Automatic content-based detection of influences in the history of Progressive Rock Music

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Abstract.

All current and future music has its roots in earlier music. Even the most avant-garde needs a prior knowledge of the foregoing in order to break it. This relationship between musician and its predecessors determines its musical characteristics. Thus, the relationship between previous, present and future musical elements determines the definition of musical influence. With this definition, we may tend to think that any music is an influence relationship. The main difficulty lies in determining what types of connections are influential and which not.

In this thesis we analyse the musical influence from a computational standpoint developing a basic algorithm that allows the finding of relationships between musical passages that can be considered as influential.

Unfortunately, the problem of influence has rarely been addressed with a computational perspective. For this reason, we present a conceptual framework that defines the needs of the problem and allows us to face analysis with guarantees. This conceptualization presents the different factors needed to discern if a musical relationship is influential or not as well as the various factors that condition relationships, the diverse musical dimensions involved and different levels of interaction.

Using this conceptual framework, we particularize the problem to a specific case: to find influences from different musical passages in Progressive Rock Music. To accomplish this, we used similarity between different music items as a measurable index of influence relationships. Our study compares a particular influenced segment against all the derived ones from a database of songs of four groups considered the most influential: King Crimson, Yes, Genesis and ELP. For our approach we use several techniques developed in other fields of MIR such as how to obtain descriptors that characterize the different levels and computing music similarity distances.

During the development of the thesis, we discuss and analyse many details as well as the problems encountered in the development of the algorithm derived from our particular approach. The results suggest that the automatic determination of influential relationships is a feasible task.

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It is difficult to quantize all the ideas, collaborations, help, advice or comments that have “influenced” this thesis. I should, at least enumerate all the people that have been involved in some sense in the development of this thesis.

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Contents.

List of tables and figures.

Tables

Figures

Chapter I. Introduction.

1. Introduction.

" Information is not knowledge,
Knowledge is not wisdom,
Wisdom is not truth,
Truth is not beauty,
Beauty is not love,
Love is not music,

and Music is THE BEST "

***- Frank Zappa**,*
1979.

To enjoy music we just need music. Everything else is supplementary. Technology has changed the way in which people enjoy music: on-line and digital music stores with egregious music collections, instant access to the songs we want *–music for every moment–*, new platform for creating and promoting music *–hear the world's sounds–*, new ways of discovering music and more information than we can assimilate. But, at the end music remains. Music, as any other art, is the result of humans' interaction with their environment. The constant inclusion of ideas and their interaction with our internal processing determine our musical view. The analysis of these interactions and, in the case of musicians, their posterior interpretations can have multiples applications from a musicology and from a music technology point of view. This thesis addresses the concept of influence from a computational perspective. Automatically, finding musical connections that can be taken as influential elements during the history of Progressive Rock Music.

1.1. Motivation.

"(...) this diversity can offer a broad palette of opportunities for those aware to listen and re-listen to music with different ears and minds on each occasion. Appreciation of music, like that of all forms of art, can only deepen with information about all of its possible meanings. Thus, music that might otherwise become stagnant can remain fresh and alive."

- David Cope
Computer Analysis of Musical Allusions

Knowing the influences of an artist changes the "ears and minds" with which we hear music, opening new possibilities to enjoy it. Our brain faces a "new dichotomy": on one side, the possibility of recognizing and anticipating links from the current experience with previous references. On the other size, being impacted for the surprising reassembles of the inspirational ideas. The balance between predictability and surprise is known to be essential for our musical enjoyment [1]. Our sensory systems perceive music as an ambiguity. Our brain is always organizing every perceived stimulus, trying to resolve it, giving it meaning and predicting what will be next. The puzzling phenomena of being "rewarded" for correct predictions and being "surprised" for unexpected

patterns establishes our enjoyment to musical pieces. Correct predictions provoke a pleasure feeling of "winning" the game while unexpected patterns "challenges us with new organizational principles" [2].

From a musicological point of view, grasping the influential process helps us to better understand a musical piece. We can "reconstruct" the creative process of the author via a sensation of familiarity through understanding the origins of the ideas and their results. Another aspect is the evolutional analysis of musical styles. The history of music can be understood as a continuous transformation of musical ideas and languages over time. We can also investigate the relationship between musicians by creating genealogies not only based on human interaction but also by means of musical connections. It also helps in the identification of recurring musical patterns looking for tracing lineages of ideas that flow from one interpretation to other. The analysis of influence relationships can provide interesting and insightful information about what musicians find important in music. More generally, influences show how musicians listen to music and therefore provide a direct insight into their inspirations and musical resources.

As mentioned before, influence is defined by the relationships of ideas. There was a time in music history when these relations were limited to physical connections (e.g. apprentice-master relationships) in a narrow context (geographical areas and cultural trends) and with restricted materials. Therefore, the breadth of musicians exposed to raw ingredients from which to draw influence was limited. Today, the circumstances are completely different. The constraining factors of influence have been blurred. Technical restrictions have been overcome. A person with a normal laptop and Internet connection can have access to the knowledge of how to compose for a whole orchestra and the materials to make it real. Thus, promising results can be achieved overcoming the geographical, cultural or financial limitations. The idea of context (geographical and cultural constraints) has changed into a "multicontext" in which lots of different scenarios coexist and it is the user who "consciously" decides which one fits better to him. All that remains the same is time. There is always a temporal directionality in influence relationships (an influential element always appears before the influenced one) and a needed distance to judge evolution and its key aspects. Today, a wide range of music is available to anybody. Ideas flow from one place to another; there are no restrictions to access to all kinds of concepts from the most various disciplines. This flow favours all sort of connections and that may improve innovation and creativity but, at the same time, it hinders the tracking of the influential ideas. All of this suggests the need of automatic computational systems that can identify influence relationships between musical elements.

Computational techniques and tools face problems from a very different perspective than the traditional ones from musicologists. What not only complements the musicological perspective but also allows us going beyond its traditional scope. Computational studies only rely on connections without any cultural or social constrains providing new applications. Some of these applications have nothing to do with music such as modelling the human rational thought or studying the creativity process. But others can provide new musical horizons like the automatic conception of future artist as a result of

current influential ideas. Certainly, applications already known can be improved based on the strong and deep connections that influence relationships provide. These are the cases of the automatic content organization systems and music recommendation systems. In the former, influence can provide new ways for organizing and presenting the musical databases analysing the evolution of artists (genealogies of bands), establishing musical connections and identifying recurring musical patterns. In the latter, recommended songs can be automatic argued based on influential links as "automatic explanations" of why those recommendations. There are other possible applications such as a system to predict the ranking of an album from the influences found and the rankings -and dispersion- of influential records used to calculate the previous measurement or websites where users can find influential relations to any queries the want to provide

1.2. Goals.

Our main goals can be summarized as:

- Highlight the scientific background of musical influence identification, make a literature summary and discuss the existing approaches.

- Propose a basic conceptual frame on which future studies and approaches can settle. The concept of influence does not refer to any existing reality itself, but to asymmetric relationships between objects of study. In this context, our conceptual frame includes a study of the different influential levels – both musical and granular –, a list of the main factors that condition musical relationships and three basic questions that define the methodology needed to correctly face each influential scenario.

- Establish a methodology to evaluate the results trying to quantify numerically the behaviour of the algorithm.

- Compile a suitable collection of influential songs and annotated influenced segments.

- Discuss all the problems and issues found during the development of this thesis and present a list of improvements in order to help future works and researches.

1.3. Structure of the thesis.

The current document is organized as follows:

Chapter 2 explains the main concepts and ideas related with influences. It gives an overview of the problem and introduces the topic in the Music Information Retrieval (MIR) field. Finally, we review the history of Progressive Rock Music, its principal traits, the history of its most relevant bands and the reason to choose it for influence detection.

Chapter 3 reviews the state of the art of the fields that relate to this work. First, it deals with the different studies conducted on influence from both, musicological and computational points of view, as well as an examination of how other disciplines face the problem. From a more computational side, we also present the most relevant techniques used in the MIR field in terms of feature extraction and similarity.

Chapter 4 explains the methodology used. That implies explaining the material used, the feature extraction process, how the common traits of the genre are modelled, how the influence extractor algorithm works along with evaluation process.

Chapter 5 shows the results for the experiments done to both validate the algorithm and find influence connections.

Chapter 6 discusses the whole process presenting a list of conclusions and extensions for future works.

Chapter 7 contains the bibliography references.

Finally, there is an Appendix with the detail of the database.

Chapter II. The problem and its contextualization.

The history of music and its evolution could not be understood without the concept of influence. Each period and genre has evolved into the next, drawing on influences from neighbouring idioms. Musical progress is a chronicle of the convergence of different influences and ideas upon key figures, normally composers, which internalize and epitomize them to create something new.

All artistic disciplines evolve thanks to the appearance of "geniuses". They contribute to this development with innovative ideas that can either accentuate and enhance known aspect or introduce unexplored conceptions. Both cases increase the limit of the artistic discipline. Innovative ideas are the consequence of a complex mechanism that involves two major aspects: the constant interaction of multiple and disparate ideas and the person's ability to absorb, process and interpret them. These two aspects are interconnected: the presence of new and different ideas improves the internal mechanism of intellectual processing and, at the same time, curious minds will constantly demand new ideas. Certainly, there is a not measurable, innate predisposition tha conditions the whole process. The relation, characterized by this complex mechanism between the external idea and the personal interior outcome, is what we call influential process. In music, as in any other artistic discipline, the interaction and interpretation of different musical and non-musical elements is an essential aspect of its existence.

The next section shows why the concept of musical influence is important, which is the role-played in the process of musical creation, and how can we classify the influential relations. Furthermore, it provides an analysis of the problem from a Music Information Retrieval point of view. Finally, as the frame of this thesis is progressive rock music, a review of its musical language and its historical evolution is made.

2.1. Musical influence: An overall point of view.

Influence. "*The capacity or faculty of producing effects by insensible or invisible means, without the employment of material force*"
- **Oxford English Dictionary**

The concept of influence has no meaning by itself, it exists only if defined as a relation between instances. Similarly, musical influence has a sense only if it considers and connects the whole world surrounding the artist and his work.

The process of listening to music, synthesizing it and creating something new is the natural way of learning and absorbing musical knowledge. An aspiration to recreate something we have enjoyed. But such recreation is no longer possible on naive or independent terms. Music does not get created in a vacuum. Musicians are influenced by what they hear. Since we are born, we interact with our surroundings. Little by little, we absorb the standards of our society, among which music is included. Music encloses us. We are in constant

contact with it: the lullabies our mother sang us, the classical music during a movie, our favourite artist out loud in the car, the top 40 pop music in a pub, musical themes of cartoons, TV shows and adds, jazz on the radio and millions of additional examples. All musical elements of our environment define our "musical world". But not only musical factors condition our musical understanding. Other aspects, such as location and epoch, determine how to interpret the received musical stimuli.

Generally, all the elements that affect and determine a musical creation can be divided into two major groups: *unconscious* and *conscious influence*. The former encompasses everything related to our automatic absorption of musical patterns and also the fact of living in a concrete geographical area, belonging to a period of time, speaking a certain language and other social factors. We are exposed to them since our first day of life and they constitute our frame of reference to interpret music. Against this gradual and unconscious absorption of context, other types of factors stand as a result of conscious decisions. The latter is associated to our personal tastes and curiosity and defines the type of music to which we will be more exposed.

Influence is a concept that is intrinsically related to the artistic creation. We are constantly -deliberately and thoughtlessly- absorbing ideas and processing them subconsciously. The combination of the outside world, "new idea" and the inner world, "processed" is central to the creative process. The acquisition of new ideas is mainly related to our musical interests and searches, therefore to the *conscious influence*. *Unconscious influence* is essentially responsible for laying the foundations of the interpretation process. This musical absorption process is complemented and enhanced by our conscious musical decisions, through constant incursion of new ideas, both musical related and unrelated. At first, our processing system is simple. Consequently the interpretation of an input idea is often very similar to the original, an imitation of the borrowed material. As we acquire more and new thoughts, our processing system is richer in ideas and complex relationships, which enables the creation of new subliminal links and connections (e.g. combining techniques from different fields, methods from other periods or unrelated concepts). The identity of the inspirational motif diminishes, as the transformation is more thorough. Hence, results are abstract, complex and innovative. The connections between the influential idea and its interpretation can rarely be detected. It is not clear by what method we can reach them. At this point, the final work is totally remote from the original inspirations, which in most cases are only a trigger, an excuse to our brain to relate underlying abstractions hidden somewhere in our universe. Acquired this “influential maturity”, influence provokes the most original and most personal work. All of this shows how musical influence can be defined according to the *conscious* and *unconscious* relation of an artist with his enclosing world. It should also be added that songs can be composed by several musicians. Therefore, the interaction between different ideas increases and complicates the relation the influential motif and its result.

In order to complete this relational model, three more aspects have to be included. They delimit and restrict the relationships between music ideas. First of all, ***time*** is a crucial concept, not only because influence can be only understood as the relation between a previous idea -past- and its result –

posterior time- but also because important influential paths –the ones that inspired and made evolve music- can be only appreciate with a sufficient temporal distance. Time, as the temporary production moment, also gives the meaning to understand works. Secondly, ***context***, comprehended as geographical location, historical period, language and cultural style, circumscribes the raw ingredients what limit the connections. The last aspect is ***technical resource***. It determinates the ways in which ideas can be transmitted - restricting the accessibility to the works-, the type of the work -not having access to certain instruments- and its quality and finally, the type of work that an author can leave for future generations. Influence from a score –which does not faithfully reflect perceptual elements that are present in the performed music- is different from the one we acquire from a record.

Additional questions arise from this conception of influence: What are the salient musical connections we want to find? What are the empirical indicators that determine these relations? How can we verify the presence of these indicators? These questions have to be answered to properly address the problem.

2.1.a. Influential factors.

Musical relations are not arbitrary but have a complex structure with a different hierarchy of levels and different musical features involved. But, not all the connections are influence-based. Three are the aspects needed to distinguish influential relations from other types of references.

Time: there is an inherent temporal hierarchy in every influential association. An influential element always appears before than the influenced one. This temporal directivity has only one direction: from a concrete moment to a posterior one. It is impossible to have an influential element that appears after in time than the influenced one. This factor only refers to musical elements, not to the artist that created them. It means that a band formed in the 80's can be influenced by innovate musical aspects from posteriors bands.

Uniqueness: to be influential, a musical element has to be unique and different from the rest of musical element. Uniqueness is correlated with the scope on which we are working. Musical elements that can be seen as unique in a specific scope could be general in another. For instance, traits that characterize a specific genre are common for the majority of artists of the genre. Detecting and isolating these singular musical elements is essential in any influential process.

Manifestation*:* it is the most difficult aspect to be modelled. It is heavily correlated with the artist and its capacity to absorb, process and create something new with it. As we have mentioned, an influential element can inspire a wide range of musical interpretations. In some of them the connection between the influential element and its result is clear. In other cases, it is almost impossible to notice it. Manifestation is a critical aspect that has to be properly modelled. Generally, we can say that an

influential aspect will appear in several influenced. Musical quotes are usually the first indication of influence but they cannot be considered as proper influences as they are conscious and near-exact reproductions of previous (usually short) passages. These quotes can be taken as indicative of a more profound influence but by themselves may be merely diversion musicians. Apart from quotations, there are a lots of musical manifestations ranging from paraphrases to something totally different and indefinable, through a great wide of form such as likenesses in musical motif, commonalities in the used of musical ideas.

2.1.b. Influential levels.

Influential relations have different hierarchical levels according to the granularity to which the problem is addressed. They can be grouped into seven layers ranging from a concrete motif present in a segment to the main traits of a genre.

Segment: it is the smallest meaningful influential element. It refers to musical motifs that are enough relevant to inspire. It includes melodies, chord progressions, cadence, modulations, counterpoint, instruments, timbre and rhythms.

Structure: it is the combination of several segments subordinate to a bigger context. It is related to the use of segments not to the segment itself. A structural influence is created by the coherence of its different segment originating a consistent and unique element.

Song: it is the union of different structures with a hierarchical order to create a "self-understandable" musical piece. It does not need any further context and has a concrete meaning. It is the most common influential element due to its coherence and its facility to be unique even with the combination of "standard" elements.

Album: it is a compilation of songs. Apart from conceptual albums, songs have a soft relation between them but they share common musical ideas as well as other non-musical aspects such as production. All these aspects can be seen as traits of the artist in a concrete moment of its career.

Band: this level refers to the main characteristic elements of the band. Normally an artist has an especial sign presented during his whole career. In other cases, the musical language of the band evolves acquiring constantly new elements. From an influential point of view, the band scope contains all of the unique signs of the band to create an especial mixture that differs from the rest of bands.

Genre: it is the result of the combination of all common elements that group together a large amount of bands. For this scope, the influential elements are the commonalities to all the bands that conform the genre.

Each upper layer includes all inferiors and contains all its influential elements. The relation between them is soft and difficult to determinate. It can be possible that the used (a especial repetitions, different development, harmony changes, etc.) of a common melody –segment level–, that has nothing unique, produce a unique and possible future influential element. As mentioned, each layer defines the uniqueness of musical elements. For instance, the musical motifs that characterize a specific artist become general traits of the musical language of its genre. Generally, every time we move up through these layers, musical ideas are global and general while going down means concrete and specific musical traits.

The influence between layers is complex and varied. A genre can influence a concrete segment or a whole song. On the other hand, there are concrete segments that, with the passing of time, have led to a new genre. In this way, we can have any relation between these seven layers.

There are many musical dimensions relevant in our perception and characterization of musical judgments among with we can highlight ***dynamics, harmony***, ***melody***, ***timbre*** and ***rhythm.*** All these dimensions might be taken into account for modelling influences. Although the interaction between these different musical levels is complex, normally it is unusual to have an element from one musical dimension inspiring other dimensions. We can assume that the influence between musical dimensions is restricted to its own dimension.

2.2. Musical influence: A narrow approach.

From the above exposed we can conclude that the problem of influence is excessively broad and vague. For this reason we must simplify it and particularize our study. In this chapter we present our narrow but manageable view of the music influence problem.

The aim of this thesis is not to model the complex mechanism involved in the uptake and processing of musical influences but to find relevant and clear connections between different musical elements that could be considered as influence relations between artists. In order to decrease the complexity of the problem, our scope is reduced to find segment-to-segment connections. Our intention is to determinate the influence of classical progressive rock songs in posterior songs of the same musical genre. The salient connections we aspire to find are the most superficial, easy, clear and direct ones. From this relationship between segments, it can be also extrapolated the influence of the most important bands of the genre in its zenith in posterior songs.

As mentioned, an important aspect to determinate if a musical connection is influential or not is the uniqueness of the musical element. In our case, uniqueness is modelled in two ways. Fist of all, we manually limited the possible influential songs selecting those that were composed for the four most important artist of the genre in its golden age. At the same time, the general features that define the genre are computationally modelled. Thus we will work only with the characteristics of the artist skipping the common trait of the genre.

Secondly, we also manually selected the influenced segment on which influential relations will be looked for. In this way, we limit the search to concrete musical elements and we can evaluate the results by means of knowing what we want to find. These selected segments constitute our ground-truth. Finally, we use an automatic method to model the traits common to Prog Rock Music in the 70's.

Although debatable, it is not totally unreasonable to use similarity as a "measurable" index of influence. Imitation is the first step in the creativity process and an important way of acquiring influence. We play the music we love. Nowadays, creating a cover band is the most common way for starting a new band. With this type of index we assume that we only can find "unprocessed" simple and direct connections between different segments. Complex, abstract and innovative influence between ideas –and probably the most interesting- will be out of our scope.

2.2.a. Influence in Music Information Retrieval.

We face the determination of influence from an empirical and computational view. Thus, this thesis is framed within the Music Information Retrieval[1] field. MIR is an interdisciplinary research field, which involves digital signal processing, machine learning, music cognition, programming, statistics, information retrieval and music theory, engaged in automated processing of music to understand, describe, retrieve and organize musical content [3].

This field draws on two sources of information: ***content*** and ***context***. ***Context*** refers to metadata and textual annotations about a musical piece, which describe its different manifestations. It includes *factual aspects*; objective truths about the music (composer, title, year, etc.); and *cultural aspects*; subjective concepts (genre or mood). It is normally obtained from the web (biographies, reviews, blogs, influences, lyrics, etc.), databases (last.fm or whosampled.com) or expert knowledge (allmusic.com). On the other hand, ***content*** regards to all the implicit information represented in the music itself. It includes all the methods and technologies that allow the automatic extraction of descriptor from the audio signal of real recordings in order to represent this implicit information.

Following the concept introduced in [3] and extended in [4] audio content-based retrieval tasks can be characterized by two aspects: ***specificity*** and ***granularity***. This kind of classification is used for the tasks that follow the query-by-example paradigm: "*given an audio query, the task is to retrieve all documents that are somehow similar or related to the query from a music collection*"[4]. Figure 1 shows various content-based music retrieval tasks in the specificity and granularity space.

Specificity alludes to the degree of similarity between the query and the database documents retrieved. A high degree of specificity includes tasks in which the retrieval result is an exact copy of the query as the case of audio

[1] From now on MIR.

identification. On the other hand, in low specificity systems, the recovery result is vague similar to the original query with respect to some musical properties. In this group we have application such as an audio recommendation system.

The second aspect of this classification method is ***granularity***. There two kinds of granularity, *internal* and *external*. The former refers to the length of the query needed to retrieve a concrete result and the later to the length of the retrieval result. Two possible scenarios are distinguished: *fragment-level* (high-level) and *document-level* (low-level). In the former, short fragments of audio are used while the latter used the global document. Figure 1 contains different content-based music retrieval scenarios that can be arranged along this classification.

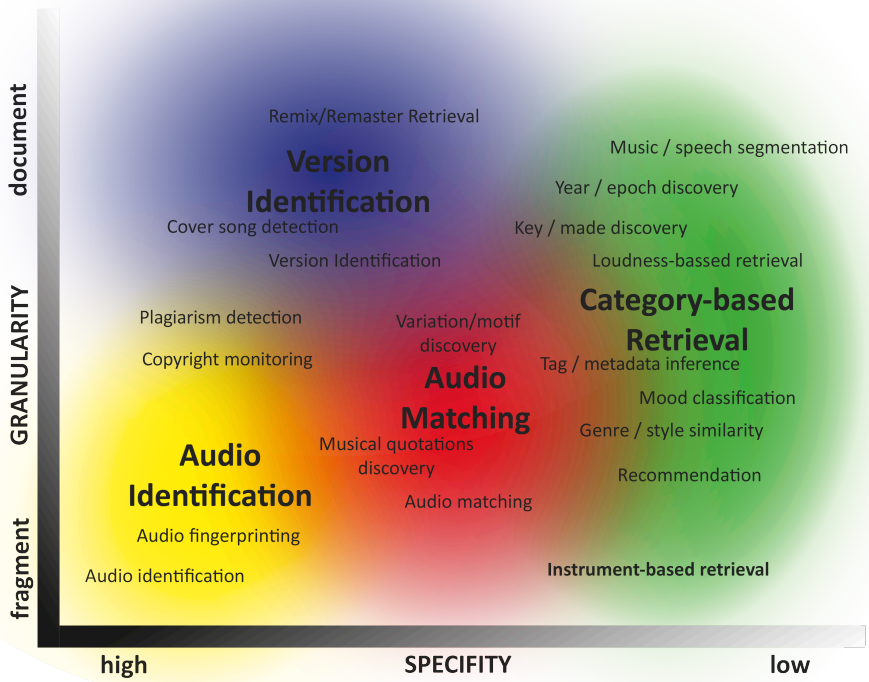

Figure 1. Specificity/granularity panel showing various facets of content-based music retrieval.

Influence covers almost the whole spectrum of ***specificity*** because an influential idea can be taken in "*a wide variety of forms, from plagiarism, borrowing, and quotation all the way to imitation and eventually to the profound but almost invisible transformation*"[5]. Regarding ***granularity*** influence cover a wide range of option. From retrieving the different motives (high *external* granularity) that have influenced a song (low *internal* granularity), to determining the influential songs (low *external* granularity) of a given segments (high *internal* granularity). It is up to the researchers and their view of the problem to define their needs and narrow it down.

2.2.b. Our approach.

It is worth to recover these principal questions suggested for tackling the problem and particularize them to our study case.

What are the salient musical connections we want to find?

In our cases we do not want to model the complex mechanism involved in the uptake and processing of musical influences but to find connections between different musical elements that could be taken as influence relations between songs. In order to simplify the problem, we only consider clear, relevant and direct musical links in a concrete genre, Progressive Rock Music. The connections we are looking for are defined manually with a selection of the influential songs and the influenced segments and computationally, modelling the generic ("universal") traits of the genre.

What are the empirical indicators that determine these relations?

As we want to find clear and direct musical relationship we can assume that similarity between songs is a valid index to measure influence.

How can we verify the presence of these indicators?

In order to verify if a musical passage is similar to others we use state-of-the-art technique for computing the musical features that characterize musical levels and for measuring the distance between elements.

To sum up, our approaches look for segment-to-segment connections between songs of key artists and posterior songs of artists from the same genre. With this temporal gap we are taking into account time that is one of the most important influential factors. The others influential factors are not modelled in this thesis. Simultaneously, the granularity is defined with the election of segment-to-segment connection. Finally, the musical levels used in our comparison are dynamics, timbre and tonal aspects musically.

So as to achieve this purpose we develop a basic algorithm based on a brute force comparison where any query segment – influenced one – is compared against of the segments of all the possible influential candidates songs[2]. It includes a method to automatically model the common traits of the genre. The approach considered here has as a query a concrete part of a song characterized by its mid-level content-audio descriptors and looks for the patterns (segments of songs) in the database that might be influential to it. Therefore, the grade of specificity is high because we do want to retrieve a re-interpretation of an influential material: something that can be completely different from query. The degree of *granularity* is low internal level (the query

[2] From now on, query and candidate will be used as synonyms of influenced and influential segments, respectively.

is the whole song) and mid external level (the retrieval results are a list of different patterns).

The corpuses we are working with contains a reduced group of influential songs and a reduced group of influenced songs. A small numbers of songs allow us to have a deep knowledge of the database which derivate in more control of our approach. It also allows us to assign manually relationships and keeping control on errors. On the other hand, working with the small dataset we can produce bias in the selection and limit the capacity of generalizing the problem and the approach.

We focus on progressive rock music because it is a genre that is constantly evolved but at the same time has a strong connection with the main influential artists [6]. Moreover, it is a challenge for MIR techniques because the level of complexity of the music is considerably higher than the popular songs normally used in many experiments. The MIR world can be divided depending of its corpuses into three different groups: classical western music, popular music and non-western music. Progressive Rock Music has the harmony and melody complexity of classical musical, the rhythmic game of some non-western music and the timbral palette of popular music.

2.3. Progressive Rock Music

Progressive Rock Music, also known as Prog Rock, is a form of rock music where lots of different musical styles, classic and contemporary, converged. Its beginnings date back to the late 60s but it is in the decade of the 70s where the genre reaches its zenith with a mature, deep and personal language. This language includes not only musical elements but also a very well defined aesthetics, with lyrical themes, vinyls presentation with incredible album arts and theatrics concert. In this chapter we present a review of the most important aspects of the genre as well as an analysis of its history with specially regard to the most important groups.

2.3.a. Musical characteristics.

Progressive Rock Music is a varied and eclectic genre. Although it was formed under the constraints of Rock Music, it goes beyond that creating a completely different genre that overcomes the technical and compositional boundaries of rock. The musical characteristics of Prog Rock cover a wide range of different aspects. Every sub-genre has its own musical traits. Even though that, a list of distinctive elements can be defined. These elements establish clear connections with posterior bands where the same foundations are shared. The musical traits present in Prog Rock include complex structures, colourful instrumentations or rich harmonies.

Structure: time is not a limit. Each song has the duration that the songs require, even longer than twenty minutes. Common structures, such as verse-

chorus-bridge, used in popular music are blurred in extended sections or inserting musical interludes. They normally use exaggerated dynamics changes to heighten contrast between sections with large crescendos or intimate pianissimos. An important aspect is instrumental passages influenced by classical music and the improvisational traditions of Jazz Music.

Timbre: the timbral palette of the traditional rock instrumentation of guitar, organ, bass, and drums is expanded with the inclusion of instruments more typical of other genres. Instruments commonly used in Jazz or Folk Music, such as flute, saxophone and violin are introduced. At the same time, new instruments were added to the timbral palette to expand the sonorous possibilities as well as many incredible electronic effects applied to traditional instruments. Some of them, such as Moog synthesizer and the Mellotron, have become closely associated with the genre. It also incorporates noises, juxtapositions, and timbral effects of the 19th century Romantic and 20th century Avant Garde Western music tradition. Summarizing, from a timbral point of view, Prog Rock mixes traditional rock instrumentation with an augmented sound palette that ranges from orchestras, synthesizers, world instruments, and choirs with an elaborate stereophonic stagings and productions.

Rhythm: it is freer than in Rock Music and includes a rich rhythm complexity. It explores other measures different than standard 4/4 or 3/4, tempo changes, metric modulation, polyrhtyhm, irregular or complex tempos and a wide variety of elements that came from Eastern, Jazz, Folk and Experimental Music.

Harmony and Melody: they are more influence by Jazz and Classical Music than by Blues or Rock Music. Its vocabulary incorporates elements such as chromaticism, mediant relationships, and neapolitans, as well as large scale harmonic structures like sonata and rondo form. Despite, the pentatonic scale is also used; melodies are more likely to be modal with developing complex passages. Chords are augmented with the 6ths, 7ths, 9ths and compound intervals. Chord progressions contain atonal or dissonant harmonies common in Classical Music, and even some rudimentary serialism. Musical arrangements may incorporate different elements that derive from Classical, Jazz and World Music.

2.3.b. Other characteristics.

Despite that in this thesis we work only with musical content, Progressive Rock Music has other traits that are worthy to mention for futures approaches or improvements.

Technology: new electronic musical instruments and technologies were constantly introduced in order to expand the timbral palette. Prog Rock bands were pioneered the use of new instruments. Mellotron was the characteristic sound of early bands, but little by little other synthesizers were developed. Bands were equipped with sequencer or tape loops

(Frippertronics), Synclavier for composing and recording, MIDI and stick guitars or electronic percussion.

Thematic: albums are not only a collection of songs, but they are unified by a theme or general history. Conceptual albums are the leading exponents where the whole album is subordinated to a historical, fantastical, and metaphysical history. Songs are acts, voices are characters with Leitmotif that represent them and even solos are parts of the plot. On the other hands, lyrics are as ambition as music. They turn from mere words to poetry trying to avoid typical rock/pop subjects such as love or dancing rather inclining towards social criticism, surreal stories, personal struggles, madness, death and themes from classical literature, fantasy, folklore, cosmos, mysticism, or futurist utopias.

Presentation: album art is an important part of the artistic concept. Cover, interiors and layout are designed to the millimetre working with particular artists and design studios that capture graphically the essence of the music. This look is integrated into the band's overall musical identity.

Performance: elaborate and flamboyant stage theatrics were incorporated into their concerts. Theatrical elements were used to describe scenes, events or other aspects of the concept. Sets included planes crashed, flying piano, rabbits that are launched from the stage, massive projection screens, exotic and colourful costumes, complex lighting, lasers or mirrors.

2.3.c. The development of Progressive Rock Music.

Most studies trace the birth of Prog Rock to Britain in the late 60's. That period was the breeding ground for the emergence of the groups that would change the art scene: King Crimson, Genesis, Yes, ELP, Pink Floyd, Jethro Tull, Soft Machine or Gentle Giant. These bands, by means of a constant mix of influences and a tireless spirit of experimentation, lead the evolution and expansion of the genre that hatched in its zenith in mid 70's. In late 70's Prog Rock disappeared in favour of other musical genre such as Punk and Disco but did not die. In the 90's, it revived and today has a very good health, with many bands and musical sub-genres. Bands like Dream Theater, Marillion, Porcupine Tree, The Flowers King´s, The Mars Volta, Spock's Beard, Anekdoten, BeardFish, Rush or Anglagard ensure the continuity of genre.

The origin: London in the 60's.

In late 60's, the musical mainstreams converged in Britain. On one hand, the international success of Indian music made that bands like The Beatles started to be fascinated by the relationship between music, emotions and mysticism. They were seduced by the sounds of Indian Raga incorporating to their musical language the sounds of Sitar and Tabla and the emphasis on repetitive circular rhythms, ornamentation.

On the other hand, young British jazz players, with relevant names like Ginger Baker, John McLaughlin, Jack Bruce, Larry Coryell, Jean Luc Ponty, Bill Bruford or David Sancious, started to mix the essence of Rock with their knowledge of jazz. They were interested in electronics and studio trickery to emphasize sound textures. They also used modern rhythms and world beat giving preference to instrumental virtuosity in the structure of the musical.

At the same time, Psychedelia had a strong impact in Rock where artists like Pink Floyd, The Jimi Hendrix Experience or Cream incorporated its essence to their compositions: oneiric elements, chaotic structures, experimentation, improvisation and extravagant sound. They focused on spontaneous and free structure incorporating elements of Indian music and early jazz and experimenting with new technologies. All of these were always complemented with a constant ingestion of hallucinogenic drugs. Concurrently, UFO, Gong or B. Eno went in depth of the Space Rock using repetitive rhythms, electronic and ambient soundscapes, guitars playing with glissando and delay, echo and cosmic themes.

Finally, Western Classical Music and Western Traditional Music were also mixed with Rock. In Symphonic Rock, The Moody Blues, Yes, Génesis, The Nice, Emerson, Lake & Palmer (ELP), Rick Wakeman, Camel, Focus or Procol Harum introduced elements from classical music such as the complexity of the bars, keyboards interventions with reminiscent to Bach or Handel, longer format of the songs and complex structure. Meanwhile, Scottish bands like, Incredible String Band, Pentangle, Fairport Convention, Quintessence, Magna Carta, Tir Na Nog or Jethro Tull, explored the relationship between Rock and Folk fused them with Blues and Jazz. As a result, acoustic and electric instruments were combined, instrumental developments had a capital importance in the pieces. They also were inspired by Medieval Music, Renaissance or Celtic.

This confluence of trends and ideas expanded the boundaries of rock creating a space where the most important thing was the expressivity of every musician and limits did not exist. The constant collaboration and exchange of musicians increased the symbiosis and feedback between trends forming what later has been described as Progressive Rock.

From 69 to 74: diffusion and Golden Age.

In early 70's Prog Rock hatched. The genre reached a marvellous musical quality, an incredible user success and a commercial gold mine. Four were the figurehead of this period: King Crimson, Yes, Genesis and ELP. It was the time of sumptuous tours, big recording with orchestras, lists of best musicians and clash of egos.

Due to this success, the essence, understood as the freedom to incorporate new musical elements, was exported to other countries creating new sub-genres and interpretations. Crossover Prog and Avant-Prog/RIO were developed in America. While the former came from Pop and Commercial Music (but maintaining the high degree of sophistication, complexity, musicality and virtuosity) the later moved to highly experimental approaches with lots of

dissonance and atonality. Krautrock appeared in Germany. It had long instrumental epics pieces with ecstatic, hypnotic and repetitive motives. Finally, in Italy, the used of trio of flute, piano and violin, the essence of the romantic melancholy enhanced by Baroque elements, the combination with opera and the lyrics in italian ended up with the Rock Progressivo Italiano.

But in mid 70's problems started. There were lots of internal problems in most of the groups. King Crimson was dissolved. Peter Gabriel left Genesis. ELP and Yes had constant discussions and arguments. 1973 was the year of the oil crisis. As a result, groups started to have financial issues and the sumptuous tours ended. Lastly, there was a generational clash. New trends appeared due to the social climate. On one hand, Punk with its "There is no future". On the other hand, Disco music as a way to disconnect of the problems. Dinosaurs had disappeared

The Resurgence: the 90's.

After a hibernation period, Prog Rock revived in the 90's decade. During the 80's a group of bands started the foundations of the resurgence. In late 80's and early 90's a series of new sub-genres appeared. They were critical in the new area of Prog Rock. It was the begging of the embryo of Progressive Metal where bands such as Queensrÿche, Fates Warning and Watchtower mixed hard rock and heavy metal with the classic elements of the 70's. It was also the time of Neo Prog, a simpler form of symphonic prog, which emphasized on the song-form with more structure melodies and rhythms. Finally, the development of the rhythmic sections of King Crimson and groups of Avant-Prog/RIO like Frank Zappa or Henry Cow and the incorporation of complex structures, angular melodies and constant abrupt changes in the tempo and time signature originally from 20th century composers such as Steve Reich and John Cage resulted in the so-called Math Rock.

In the 90's this breeding ground germinated with the explosion of Progressive Metal and the revival of Symphonic Prog. Bands like Symphony X o Dream Theater, Rush, Porcupine Tree, Tempest, Ayreon, Pain of Salvation or Riverside combined Hard Rock and Heavy Metal with the essences of the Prog Rock. Their compositions are characterized by complex rhythmic sections, distorted electric guitar and the used of keyboards as an extension of guitars. This sub-genre has achieved great commercial success. Along with Progressive Metal, groups such as Spock's Beard or The Flower Kings regained the spirit of the 70's. Symphonic Prog were back but with a more defined structure in their compositions. It supposed the revitalization of the bands of the 70's. Lots of albums were re-edited and new recorded of concerts and studio tapes appeared. It was also the reunion of King Crimson and return of Yes to the first line.

Nowadays, most of the sub-genres coexist with lots of bands that ensure their survival. But also, the spirit of experimentations and constant inclusion of new musical idea is still alive. There are new sub-genres such as, Experimental Progressive Metal, Post Metal, Eclectic Prog or Avant-grade Metal where new elements are constantly combined expanding the boundaries of Prog Rock.

The reader can appreciate the progressive rock is a constant interplay and interaction of different musical elements and trends. For this reason, it seems the perfect scenario to establish a starting point for the analysis of influence musical.

2.3.d. King Crimson, Genesis, Yes and ELP.

Of all the groups appeared, four synthesize the essence of Prog Rock: King Crimson, Genesis, Yes and ELP. Posterior musician and experts agree that these groups are essential in the genre being the most important, famous and influential groups of the period [7]. Just as an example, Jordan Rudess – probably one of the best keyboard players of our time – in his tribute album to the genre, "The Road Home", has a medley with songs from Yes, Genesis and King Crimson as well as a cover version of Tarkus, one of the most famous songs of ELP.

Each band has an internal consistency of its musical languages with a series of features that remain constant. At the same time, the election of these groups allows us to cover the most relevant traits and sub-genres. King Crimson represent the constant experimentations, ELP the connections with classical music, Genesis the mix of theatrical elements and Yes the mysticism and the grand-scale compositions.

King Crimson.

" When you want to hear where music is going in the future, you put on a King Crimson album." - Bill Bruford, 1995

King Crimson was founded in London in 1969. It is considered one of the pioneers of Progressive Rock Music and one of the pillars of the genre. It has had a great influence on many contemporary musical artists and gained a large number of followers despite having little presence on radio, television or other media. The band has adopted various sounds during its history, due to the diverse instrumentation used and the constant change of members. King Crimson has had more than nineteen members including great musicians like Ian McDonald, Greg Lake, Peter Sinfield, Keith Tippett, Mel Collins, John Wetton or Bill Bruford. Robert Fripp is the only member that has remained constant in the band. It seems that Robert Fripp is a synonym of King Crimson but as he said "*King Crimson is not Robert Fripp band ... It's a way of doing things*". He is the core of the infinite creativity madness of the band. Thus, King Crimson sounds different each time they go on stage. His music can be simple and intricate or visceral and intellectual, but it is always in constant evolutions.

During the Golden Age of the genre King Crimson has two distinct epochs. The first one covers the albums, "In the Court of the Crimson King" "In the Wake of Poseidon", "Lizard" and "Islands". The music of this period combines Pete Sinfield's lyrics with the depths of profoundness, and the eclectic music of Robert Fripp with unorthodox concepts and structure. Lots of musician, mostly from the avant-grade jazz, were part of the band. Music had

two sides. On one size, psychotic be-bop fuelled discharges, Mellotron passages, futuristic angular guitar lines and dark orchestral sound. On the other size, tranquil ethereal atmospheres with baroque touches and dramatic crescendos and decrescendos. In 1971, Pete Sinfield was fired and Robert Fripp took total control of the band. After a great number of changes the band conform a new line up with Bill Bruford on drums, David Cross on violin and John Wetton on bass and vocals. The band recorded three albums, “Larks' Tongues in Aspic”, “Starless & Bible Black” and “Red”. The sound of these albums is heavier diverging from the classical influences and the jazzy sound but maintaining the two sides of his musical language.

In 1974 King Crimson was dissolved and was inactive until 1981 when the band revive with a new line up. They recorded three albums, “Discipline”, “Beat” and “Three of a Perfect Pair”. These albums have the foundations of King Crimson though influenced by elements of New Age Music, Pop and Dance. In 1984 the band was sent indefinitely into suspended animation. In 1995 Fripp woke King Crimson up, this time with a new double trio concept which included the pairing of each instrument: two guitars, two drums and two basses. They only recorded one album: THRAK. From this period to the present the music of King Crimson had a completely different proposal with a high degree of experimentation. It is a heavy instrumental music, which displayed more musical maturity and finer execution but also incorporating ambient feel and minimalistic elements. The last two albums of the band, “The ConstruKction of Light” and “The Power To Believe” have been recorded under the quarter formation and suppose the result of year of experimentations.

Changes and new reinstatements have been happening during the history of King Crimson. But with over forty years of career, King Crimson is one of the long-standing bands in music history and probably the most innovative one. His creativity has remained as a model for all Progressive Rock bands and musicians.

Genesis.

Genesis is considered the result of creation for creation. They combined fantasy and futurism in an artistic process detached from any claims. His music is a synthesis of different trends, musical and non-musical in order to create an original product with a strong personality. Their live concerts were as important as their albums. Each concert was a play where every element was important. Clothes, dresses, make up, illuminations or positions of the musicians were thought.

Although its first album, “From Genesis to Revelation”, dates back to 1969 they had not developed its sound yet. In 1970 their first Prog album, “Trespass”, was released. The group was conformed by Peter Gabriel on the lead voice and flute, Anthony Phillips on acoustic 12-string and lead electric guitar, Anthony Banks on organs, piano, and Mellotron, Michael Rutherford on acoustic 12-string and electric bass and John Mayhew on drums, In “Trespass” the band presented its identity adding to their musical language new instruments (different organs, Mellotron, piano and flute) and the Peter Gabriel’s personal

way of singing with new resources, screams, hoarse voice and falsetto. Songs' themes were about stories and music underlined the plot with continuous rhythmic changes and instrumental passages.

In 1971 Genesis has his most known line-up with Peter Gabriel on the lead voice and flute, Steve Hackett on lead electric, Anthony Banks on organs, piano, and Mellotron, Michael Rutherford on acoustic 12-string and electric bass and Phil Collins on drums. The appearance of the album "Nursery Cryme" defined their sound signature. The entry of Steve Hackett and Phil Collins greatly enriched the music creating a wonderful instrumented album, full of subtlety, beautiful melodies and poetry. It has a complex and richness music incorporating the genuinely theatrical live performances. "Foxtrot", with great musical and literary complexity, confirmed their style and "Selling England by the Pound" showed a remarkable maturity.

The release in 1974 of the ambitious double LP "The Lamb Lies Down on Broadway" marked the last appearance of Peter Gabriel in the group. This album is considered a key work in the Prog Rock world and one of the best conceptual albums. Peter Gabriel announced that, for personal reasons, left the band, closing their best. After Peter Gabriel left, Genesis shifted their music maintaining a Progressive sound during three albums "A Trick of the Tail", "Wind & Wuthering" and "And Then There Were Three", when Steve Hackett left. At this point, the band changed completely his sound moving to Pop Music.

Yes.

Yes is a well-known and influential mainstream progressive band, which has a unique style, characterized by complex and ornate harmonies combined with melodic songs and esoteric, enigmatic and poetic lyrics. They were strongly influenced by different elements of jazz and classical music as well as the electronic and psychedelic art. The artwork of their albums has a remarkable weight in their signature. The artistic vision of his singer conditioned the musical language of the band where their brand was the mysticism and grand-scale compositions.

Their two first albums, "Yes" and "Time and Word" included rhythm changes and melodies that betrayed a clear connection with jazz and classical music, especially with the composer Igor Stravinsky. In 1971, Steve Howe was established as an integral member and the band had suddenly discovered their direction. Howe's sound is more "dynamic" playing with mastery several styles. During the tour, Rick Wakeman passed to be on keyboard what provided more variation in sounds. Wakeman was a passionate of new keyboards (Moogs and mellotrons) but had an immaculate academic technique and sensibility due to his classical education in piano and harpsichord. With this line-up the band acquired his maturity with a creative fluency and lucidity that transited from hard rock passages to coral jazzy. Two albums were recorded "Fragile" and "Closed to the Edge". The second one is considered for most people their most solid and best album. After this album, Bill Bruford, motivated by his inclination to jazz and experimental music, decided to leave Yes and to join King Crimson. The next album, "Tales From Topographic Oceans", with Alan Withe on drums, evolved

incorporating elements of jazz-fusion and varied touches of Celtic folklore and other more exotic colours to increase their musical palette.

Rick Wakeman, not satisfied with music and the mystic and eccentric character of the rest of the members, left the band. Patrick Moraz replaced him. Moraz was an Avant-grade jazz musician with an electronic and dynamic sound. In 1974, they released “Relayer”. This album has a dynamic jazz freestyle fusion that elevated their music to a sophistication multicolour and dense atmosphere not seen before in the history of band.

After the Relayer tour, the band decided to take a break for a year. From there the group's life and his music had many ups and downs caused by its numerous formation changes, which caused a loss of identity.

Emerson, Lake & Palmer.

Emerson, Lake & Palmer, also known as ELP, was one of the most significant band and probably the one that had a greater commercial success of the genre. They are a melting pot of Rock, Jazz and Classical Music at the disposal of trio virtuosity. In 1969 the trio was formed. On keyboard, organs and piano, Keith Emerson, a young classical pianist with a great interest in jazz where he could express himself with freedom. On bass, acoustic guitar and voice, Greg Lake who had been played on King Crimson’s debut album. Finally, on drums, the virtuous drummer Carl Palmer. The group was a compendium between the strong voice of Lake, and his acoustic ballad, the versatility, with eclectic compositions and orchestrations, of Emerson and the technique and polyrhythms of Palmer.

Since their first concert on 1970 they reached a great fame. Their first album, “Emerson, Lake and Palmer” defined their essence. They have constant allusions to classical composer for instance in "The Barbarian" (based on the "Allegro Barbaro" of Béla Bartók) and the "Knife Edge" (inspirited on the "Sinfonietta" of Leoš Janácek) as well as crazy and noisy keyboard solos, long polyrhythms and acoustic and melodic passages. The second album, “Tarkus”, was released on 1971. It was a conceptual album with a long suite longer than 20 minutes where Emerson explored the possibilities of the synthesizer. Their passion for classical music led them to adapt the work of composer Petrovich Mussorgsky, “Pictures at an Exhibition”, which was recorded live during its presentation on the Newcastle City Hall on the 26th of March of 1971. In the same year, they also published “Trilogy” which is probably their most compensate album. The contribution of each member was very balanced. All aspects of ELP were presented: nice ballad and songs based on classical composer such as *"Hoedown"* inspired in *"Rodeo"* of Aaron Copland.

In 1973, ELP founded their own label Manticore and in november they released “Brain Salad Surgery”. This album is considered a masterpiece of the genre. The lyrics of the album were wrote by Peter Sinfield previously in King Crimson who gave a dark and apocalyptic touch. After presenting the album in sumptuous tour, with rotating stages, screens, projections and more than forty technical, the band took a brake. Three years later a double LP was lunched, “Works, Vol.1” and “Works Vol. 2” where each member composed and decided

the music of the side of an LP. The fourth side was composed together. These records showed differences in musical ideas and supposed de facto a dissolution of the group's sound. Each band member was uncomfortable with the other, preferring to work on his own music more than working together. In 1978, after the album “Love beach”, recorded by demand of the discography, the band was dissolved.

Chapter III. Background.

3.1. Influence.

Nowadays, if we want to know who has influenced or who has been influenced by a concrete artist, we have to refer to music expert knowledge. Expert information is the best information we can get. It is reliable, precise and reinforced with plenty of arguments. A great amount of information is involved in the process of determining influences. There are millions of musical connections. Some of these links are more obvious than others. Some influences are so hidden that neither the artists themselves are conscious of them. Experts cannot cover all the relations. Normally, their approaches focus on concrete albums, periods or composers and their influenced outputs. With the proposed approach we do not want to replace this information. Moreover, this information is essential for facing properly the topic of influence.

A good example of what expert information is AllMusic.com[3]. AllMusic.com is a music guide that provides musical information such as news, discographies, genres, influence by, followers or similar artists. They try to cover all kinds of music but the quantity of information is extremely large that it is not feasible to do it. As a result, their perception of influence and similar artists is a superficial vision based on broad relation that is too general and ambiguous. There is not any justification about why an artist has been influenced by other. For instance, *21st Century Schizoid Man* by King Crimson[4] is the first track of their debut album, *In the Court of the Crimson King*. It is a noisy, chaotic and schizophrenic masterpiece, which used dissonances, loud crashing and complex rhythms to expresses frustration and anger. On the other hand, the second track of the same album, *I Talk To The Wind*, changes completely the atmosphere and mood. It is a serene, beautiful and jazzy song with relaxing flutes, placid vocals and harmonic consonances. Thus, when we talk about the influence of King Crimson, are we talking about the chaotic track or the serene one[5]? Can we talk with this generality about influence as AllMusic.com does? Probably in some cases we do not need more details, but commonly it is not a good answer.

Computational approaches can help managing large-scale information but also can provide uncovering of genuinely associations. They are not conditioned[6] by cultural or social constraints. They only rely on a set of rules previously defined that sometimes provides connections we would have never thought about them. Unfortunately, the problem of musical influence has rarely been addressed with computational perspective.

In this section, we review the salient influence approaches. We start with a musicological perspective, following with the approaches that used MIR tools and the ones that measure music influence with metadata. A review of other computational researches about social influence or cultural influence is also presented. Apart from influences, we also consider the problem of similarity.

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[3] http://www.allmusic.com/
[4] http://www.dgmlive.com/kc/
[5] This is a gross simplification because the extensive career of King Crimson has different periods with a wide range of musical properties.
[6] What is neither good nor bad, just different.

3.1.a. Musical influence: A musicological point-of-view.

Most of the work that has been done with regard to influence can be found in the musicological field. These approaches focus on influences between classical composers. They try to find links (motives, allusions, quotations, techniques, language, etc.) between different works doing an empirical analysis of concrete pieces. They look for the borrowed material that has been transformed from one composer to other to determinate how a musical piece can inspire others. These researches rely on the music history knowledge besides the investigation of a composer's surviving drafts, sketches, and letters to select the appropriate composers to investigate.

In this context, we find papers such as [5]. The author thinks that influence can lead to plagiarism or, alternatively, to inspiration, and concluded: "*the most important form of influence is that which provokes the most original and most personal work*". He worked with different pairs of composers analysing and comparing the original motives with their subsequent interpretations. The paper started inquiring the relationship between Mozart and Haydn. The influence of Haydn music in Mozart composition evolved during time. At the beginning, the young Mozart used the motives of Haydn almost identically. Then, when Mozart had acquired a more personal and deep compositional language the influence is "*so different that even the most cultivated listener is unlikely to be reminded of one by the other*". The figure of Brahms is a prime example of profound musical relationships. The connections between his musical language with the ideas of Chopin and Beethoven are so strong that it is impossible to fully appreciate his works without knowing his influences. The author fully analysed how Brahms borrowed materials form Chopin and Beethoven and incorporated them as part of his own symbolic structure and compositional language.

A similar approach can be found in [8]. In this case, the influence of Johann Christian Bach on Mozart is reviewed. Musicologists agree that Johann Christian, often presented as "*the true teacher of Mozart*", was one of the leading musical influences in Mozart's life. This study analysed how the time the young Mozart spent in London with Christian Bach created a strong musical and personal connection. This relationship is showed not only with musical examples but also with letters, which contain constant allusion to Christian by Mozart. *"For practice I have also set to music the aria "Non so d'onde viene," which has been so beautifully composed by Bach. Just because I know Bach's setting so well and like it so much, and because it is always ringing in my ears, I wished to try and see whether in spite of all this I could write an aria totally unlike his. And, indeed, mine does not resemble his in the very least". - Mozart to his father, 28 February 1778.* This is an example of how personal relation creates a strong musical connection. Personal relations can be as influential as musical connections. There are thousands of cases where strong personal ties create profound musical influences. The connection between these two factors has been deeply study in the field of musical history. Although the musical historical does not address directly the topic of influence, it is an endless source of knowledge. The analysis of personal and musical connections between

musician and their interaction with their musical and non-musical context traces the foundations of history of musical influence.

Influences can be studied with regard of the evolution of genres or concretes motives. The proposed investigation in [9] examines how a significant musical formula of the contemporary Canadian composer Claude Vivier evolves with respect to influences of the composer. This research tried to put some light in the composer internal process of creativity focusing in melodic parameters. This approach reflects the influence by means of changes in a musical motive with regard on composer style. Analogically, [10] investigates how innovator ideas of composers who expanded the jazz language interact. In this study, influence is analysed regarding its impact in the evolution of a specific genre. It focused on the importance of specific composer in jazz evolution and reviewed some major periods such as the Lindy Hop and Swing, Bebop and some important figures like Charles Mingus, Woody Herman, Stan Kenton, and the Miles Davis. The study is based on expert information and creates links between the different composers but also between composers and improvisers.

Another way to face the problem of influence is asking directly to musicians and non-musicians what they think about this topic. In [11], Nick Collins presents a review of the survey answers of 119 participants that took part on it. The survey includes 20 different questions such as "*Musical influences are an important part of musical practice*", "*Are you more than the sum of your influences?"* or "*Have you surpassed your influences?"* The study analyses the different answers and presents qualitative results of them but with no clear conclusion due to the varied and heterogeneous responses.

The work of David Cope is in a mid point between musicologists and MIR researchers. In [12], he used the computer to automatically find the presence of allusions to referential patterns in pieces. In this approach, he presented a software, called *Sorcerer,* based on pattern matching. Two different kind of patterns are used: interval and rhythmic. Interval patterns codify the distance between notes. The result is an array of number that represents the interval distance between two consecutives notes. It has positive values for ascending intervals and a negative value for descending intervals. Rhythmic patterns codify the rhythmic proportions with respect to the shortest duration. Both, target and source music, are segmented into patterns before the actual pattern matching takes place. Users control the system by means of dictating the maximum size of patterns, which are collected incrementally. That means that, if a motive has eight notes and the size pattern is fixed to three, the system will create five different patterns. Each pattern will contain the intervals that are in a group of four notes. The first group will contain the intervals between the first and the fourth note. The second group the ones that are between the second and the fifth note, etc. The same happens for rhythmic intervals. Users also control the forgiveness factor that determinate how different patterns should be to obtain a match. In this approach the evaluation of the result are up to users who must verified if results are coherent or not.

This chapter reinforces the idea that the topic of influences is extremely big and vague. There is not a clear way to face it. As it has been defined, the relation between ideas is what defines influence. The search of these

connections can be studied from a wide range of forms. But what all of them have in common is the methodology they follow. They define influential ideas as elements that are unique and characteristic for a composer/style/genre and look for their posterior interpretation. Depending on the author and the studied cases, influences are searched from different musical dimensions, although most of the studies seek for harmonic and melodic connections due to their weight in every musical piece.

3.1.b. Musical influence: Computational approaches based on audio.

Musical influence has not received too much attention from the MIR community. The Mirex 2013 is the first one that includes a task related with the detection of influences. It is called "Discovery of Repeated Themes & Sections"[7] and seeks for patterns repeated within a piece, understanding pattern as a "*set of on time-pitch pairs that occurs at least twice in a piece of music*". Unlike our study, this task does not work with audio, only with symbolic representation. Musical influence is a topic that requires a high level of abstraction both musical and interpretive. It involves many diverse aspects. Both, for a general point of view; with *temporal*, *contextual*, and *technical* constrains that have to be taken into account; and for a MIR perspective involving other major MIR tasks such as the needed of good features, temporal codification or similarity. The most abstract element is the great "distance" (nonobvious relations) between the influential motive and its subsequent interpretations. All these problems complicate the study of influence.

Nick Collins is the author who is working more actively on the analysis of the influence. In addition to the already mentioned survey (see section 2.1.a), he has also addressed the problem using computational techniques in the overall framework of MIR.

His first report on this topic was in [13]. This paper contains at the same time two different approaches, one based on metadata and other in musical features. The former is based on user-expert information collected via web scraping and web services. It looked for musicians who influenced and who were influenced by, Depeche Mode[8]. The information used is obtained from AllMusic.com, EchoNest[9], MusicBrainz[10] and last.fm[11]. Via different text mining techniques and using GraphViz[12] a graph of related artists is computed. This graph describes the connections between the different artists based around Depeche Mode. On the other hand, the second study used content-based descriptor to measure similarity. The scope is also different. In this case, he

[7] http://www.music-ir.org/mirex/wiki/2013:Discovery_of_Repeated_Themes_%26_Sections
[8] http://www.allmusic.com/artist/depeche-mode
[9] EchoNest is a company that provides music services based on web crawling, data mining and digital signal processing techniques. http://echonest.com/
[10] MusicBrainz is an open music encyclopaedia based on the collection of metadata. http://musicbrainz.org/
[11] Last.fm is a music recommendation service that collects metadata by social tagging. http://www.last.fm/
[12] GraphViz is a graph visualization software to represent structural information as diagrams of abstract graphs and networks. http://www.graphviz.org/

measured the relevant recordings that might show a strong influence to tracks on *Speak & Spell* by Depeche Mode and the early synth pop's properties in general. The database includes 37 influential albums with 364 tracks. The descriptors used in this second part are MFCC and spectral features. Both features are computed with Marsyas[13] over one minute and thirty second sections taken from the middle of each track. Descriptors are coded in a timbral summary vector of 64 dimensions. In this work Collins assumed that similarity is a measurable index of influence. Similarity is quantized using near neighbours algorithms over the timbral vector. The two different approaches are completely different and focus on different scopes of the problem sharing "Depeche Mode" as a common thread.

Up today, the last incursion of Collins in the influence problem is [14]. In this paper, he changes the scope focusing on the influence between different genres. Particularly, he centres his attention on the influence of music from mid 1960s to the early 1980s (Funk, Disco, Synth Poop, Electro, Hip Hop and Punk/Post-Punk) as precursor of the Chicago House (1986-1989) and Detroit Techno (1986-1989), which are considered the beginning of the electronic dance music. The database contains 31 representative tracks per genre. Three different types of descriptors are computed with SuperColider MIR: timbral, rhythmic and harmonic. The timbral features includes perceptual loudness, sensory dissonance (Sethares model), two transient detection measures using the wavelet method, spectral centroid, spectral percentile at 0.8% and 0.95% energy, zero crossing rate, spectral crest measure, and spectral slope. These features are codified in vectors accumulated by beats and quantised by a k-Means classifier into symbols. Rhythmic descriptors consist on inter-onset intervals from a raw onset detection function. Harmonic features are based on extracting beat-wise 12TET chroma. The final harmonic feature is the sum of differences between two consecutive chroma vectors. This approach parts from the assumption that strength of prediction is related to degree of influence. So that, influence is measured with a classification model-based on predictability using Partial-Match models (PPM), particularly a PPM-AX variant. This model encapsulates the "essence" of a genre. The PPM is created with a final token which contains the features previously computed for each song. Once the predictable model is constructed a set experiments was done to "*see how "separable" the genre groups were from one another with respect to the ability of machine learning to differentiate them, and in terms of statistical tests for their internal and paired consistency*". Experiments show a great overlap between them because genres can be predicted by others genres not only by itself. After these experiments, an automatic classification using different machine learning provided by Weka is tested. The classification was done with the 11 different timbre features. The best results had an accuracy of 28% and were obtained with k-Means cluster and naïve Bayes. After these analyses, the final model is constructed computing the prediction score of the different precursors genres up to the Chicago House and the Detroit Techno. To end up, a prediction model is constructed for each track. This allows explaining the Chicago House and the Detroit Techno by individual precursor tracks. Here is where he obtained the most interesting results because

[13] Marsyas is an open source software framework for audio processing with specific emphasis on MIR applications http://marsyasweb.appspot.com/

they provided specific links between songs and genres. The author did the evaluation of the results deciding how relevant and accurate a link between a precursor song and a genre is.

Finally, in the 30th International Conference on Machine Learning 2013, [15] was presented. The study aims to capture the essential elements that form the structure of different genres and analyse the flow of musical influence across time. In this context, they model the influence of songs in the evolution of musical genres. They want to determinate how much a song has changed the musical language of its genre. Thus, they measure the influence song-to-topic. Each song has a distribution across different genres. The goal of this approach is to compute an influence score that determines how much a song influences each genre. In order to achieve this purpose, topic models[14] [16][17] are used. These models were originally developed for text documents and used to analyse how the language of scientific papers evolves. In musical context, a song is considered influential if its musical language has been adopted by later songs of related genres. In order to adapt the principles of topic model to music, they define a musical language that contains 5000 "musical words". It is constructed using acoustic characteristics. Three different musical descriptors are used: *loudness*, *chroma* and *timbre*. To define the 5000 musical words, that form the musical dictionary, K-means is applied with k = 5000 over a set of 10 million descriptors computed for random segment of the database. Once the dictionary has been created each segment of a song is codified with one musical word. The dataset used consists of 24941 songs by 9222 artists from the years 1922 to 2010 divided into 28 time epochs but the dataset itself is heavily skewed towards later year. Songs are provided by Million Songs Dataset and they included their genre tag which allows the verification of the results. Authors conclude that this model successfully captures the evolution of popular music agreeing with human analysis provided by musical website, such as allmusic.com.

Academic studies conducted until now are very shallow and scattered. There is no deep study of how to approach the musical influence problem. There are lots of different aspects that must be thought to successfully address the question of the influence that are not properly discussed. Aspect such as: how influential ideas are modelled, the different scopes (patterns, songs, albums, artists and genres) or the different measurement indexes of influence are normally vague argued. As a result, the problem is addressed with illusory goals, and indefinite hypotheses.

3.1.c. Musical influence: Computational approaches based on metadata.

Up to now, there are only three approaches that used MIR feature to measure musical influences. On the other hand, there are many of works based on metadata information and network analysis. They treat different musical genres as well as different scopes.

[14] Originally developed for text documents and used to analyze how the language of scientific papers evolves.

For instance in [18], the author used the information provided by WhoSampled.com[15] to determine the influence between genres by means of the use of samples in current music. The database contains 42447 user-generated records of sampling. Each piece in the database has two variables: who sampled the musical material (use of the sample) and the source of the musical material sampled (original sample). Both are labelled with its genre tag on fourteen different genres. The relationship between the genre of the original sample and the genre of the resultant piece allowed the authors to construct a network graph. They also computed a genre entropy H to see how homogeneous the source material is for each destination genre. With this graph, general trends of sampling behaviour are showed. The network analysis measures the influence from each node (song, artist, or genre) and computes an influence measures index and a rank method which analyses song, artist and genre influence individually as well as how each network relates to one other. As a result, they "*can analyse how influential a given song is to an overall artist's influence or how influential an artist is to a genre by taking ratios between the respective influence graphs, among other tasks*". They weigh the influence of songs, artists and genres highlighting the most influential ones. They conclude that sampled-based influence networks follow a power-law degree distribution. In this approach there is no verification or validation of the connections, they assumed that the used of a sample is enough to establish how a genre influence other genres. This method does not directly account for influence other than explicitly using an audio sample from an earlier song.

Further study addressing popular music was done in [19]. In this case, based on the Structural Hole Theory [20]. The authors assume that artists associated with innovation and creativity have a different structural pattern than non-innovators. Another idea proposed is that the presence of structural holes in their influence network will increase the likelihood of creating innovative products. For proving that, they construct a network based on more than 14.000 "influenced by" connections supplied by AllMusic.com. The referential artists considered as innovative are the ones that have won a Grammy Award. Having these artists as a ground truth they looked for their position in the network and verified that the previous assumptions have normally been achieved. The relation between innovation and Grammy Award is highly questionable. Although, the National Academy of Recording Arts and sciences of United States claims that they award artistic achievement, year after year the results shows that Grammys are far from this purpose.

Other types of music have been studied. Jazz is a really interesting source of inspiration because it is a very broad genre with many different styles growing constantly. Apart from [10] which treated the problem from a musicological point of view, there are two more approaches that use network analysis for determining influences in Jazz. In [21], the looked for the most influenced contemporary jazz artists. They understood contemporary as artists that are currently active and started their career after the 90's. The data is also collected from AllMusic.com. They used the "influence by" and "similar to"

[15] WhoSampled.com is a website that supply to the user a great amount of sample to create new pieces. http://www.whosampled.com/

connections to compute two different networks created with GUESS[16]. A third network is also created to measure the contributions of older musicians. In this case, they used the five most influential jazz albums according with Allaboutjazz.com articles. They analysed the centrality and the community structure of these networks to conclude that musicians with the ability to play in different settings and styles bridged jazz communities. A completely different jazz approach is presented in [22]. Here, the presence of a musician in a studio session is taken as criterion of influence. This idea starts from the assumption that collaborations between musicians create strong personal and musical ties. The authors used ego-network[17] as way to organize and order the nodes avoiding occlusions. The influence is quantified according to the frequency and timing of the collaborations. The database used the information contained in the project BRIAN[18]. The result is a novel visualization of the jazz collaboration that includes: an augmented timeline for the individual recording sessions, and a circular representation where the main musician is placed in the center and it is surrounded by his close neighbours placed according to the influential measurement calculated according to the number of sessions and their frequency.

In this section we have reviewed how influence is treated from a network point of view. Networks are constructed not only to organize and visualize the influence connections but also to model what makes an artist influential. The last point is the most interesting one because it enables the identification of new influential artists. The main problem of these approaches is that they rely on previous known information to construct the network. They present a representation of influence connections previously found. To properly evaluate these approaches, we need to do a deep study of the information source they are using because it is there where the relations are constructed.

3.1.d. Influence in other disciplines.

Influence has been also studied along other disciplines. In literature we have [23] which also used similarity as a proxy of influence. Imitation as a synonym of influence is also posited. They aim to create an evolutionary model for stylistic influence. They want to cluster authors in time and by narrative theme with content-free words[19]. They used a list of 307 content-free words that included prepositions articles, conjunctions, "to be" verbs and some common nouns ad pronouns. The database is provided by to the Project Gutenberg Digital Library corpus and contains 537 authors with 7733 works. The comparison between authors is done by the symmetrized Kullback-Leibler divergence, which allows modelling the similarities as function of the temporal

[16] GUESS is an exploratory data analyser for graphs and networks.
[17] Ego-network focus on an individual node ('ego') around which the network is created adding nodes to whom ego is directly connected.
[18] BRIAN is a relational database application that compiles standard jazz discography information such as record dates, sidemen, composers or issues. http://www.jazzdiscography.com/Brian/index.php
[19] Content-free words are the bridge between words that convey meaning. They are the "syntactic glue" of a language.

distance between them. An interesting conclusion that can be drawn is that trends of diminishing influence as we move forward in time can be observed.

Sociology is also a discipline that is keen on analysing the influence. In this context, influence is understood as the behavioural change of individuals because of the perceived relationships with other persons. A general survey of the common concepts, models and algorithms of social influence can be found in [24]. Here, authors explain the basic concepts of social networks like centrality, closeness and betweenness with regard to social influences. They analyse the problem of social influence and how it is modelled. Finally, they provide a summary of different influence maximization techniques and its application for viral marketing. A similar review can be found in [25] but this time considering the problem of cultural influence. This investigation uses an extend version of the he Harrison-Carroll cultural transmissions model [26] to analyse the behaviour of the influence network.

Nowadays, Twitter is the referential source of information for social media interactions. Its directed links represent intimate friendships, common interests, passion for breaking news, celebrity gossip, etc. These flows of information indicate user's interaction, hence of user's influence on others. Researches like [27] try to measure social influence across topics and time by means of tweets intercommunications. An influence rank is measured according with the indegree (number of followers of a user, indicates the size of the audience), retweets (related with the ability of generate content), and mentions (associated with the capacity of engage conversations). Further improvement to the previous study by trying to model the motivation of human expression [28]. For this purpose, the authors develop a predictive measurement called *content transfer entropy* that quantifies the strength of the effect of one user's content on another's. This estimation quantized the relationship between the content of the original influential tweets and its subsequent influenced tweets.

The topic of social influence propagation in social networks is addressed in [29]. It starts with a criticism of the assumption that influence between users can be seen as social graphs "*with edges labeled by the probability with which a user's action will be influenced by her neighbor's actions*". Questions as from where these probabilities come, how are they computed from real social network data or can models of influence be built about these principles, are addressed by the paper. As a result, they propose two models -static and time-dependent- for capturing influence and optimizing the action log scans correlated with the probabilities of influence.

KLOUT[20] is the most famous commercial application that is ranking user's influence. It stands on an influential score derivate from user's interaction in seven different social networks: Facebook, Twitter, Google+, LinkedIn, Klout, foursquare and Wikipedia. They claim that their algorithms model and weight the interaction in order to be more accuracy and democratic giving more score to a retweet of a person that never does one than a user that does 1000 per day.

[20] http://klout.com/

Maybe, this way of measuring influence based on social network interaction can be a good approach for a sociological point of view but this perspective is not suitable for art. Social studies are related with popularity - which can be an important factor in order to change person behaviour; hence its importance in sociology- but it is nothing in arts. Sadly, there are lots of examples of important influential musicians (e.g. Charles Ives), painters (e.g. Vincent van Gogh), writers (e.g. Edgar Allan Poe), etc. that had no popularity or recognition in their days but they became a major figures in the evolution of their fields. Today it is the same, big media companies create easy products of consume and spend large sums of money in position them on top of the market. Mainstream music companies just focus on business. There are no interactions between ideas, no creativity, no effort on being innovative and attempt to experiment new paths. If a formula works, do not change it. Sorrowfully, if we have a look at the "10 most influential musicians" on Klout these are the results: 1) Justin Bieber, 2) Lady Gaga, 3) Chris Brown, 4) Rihanna, 5) Joe Jonas, 6) Miley Cyrus, 7) Selena Gomez, 8) Nicki Minaj, 9) JasmineV and 10) Katy Perry. None of them stand because of their music. As this popularity is not a result of their music, it cannot be taken as a index to measure music influence.

Influence on art is more complex than just popularity [30]. It plays an important role in the creativity process and its innovative results, which makes an artistic discipline to evolve. It is related with the characteristics of the influential ideas, their diversity, the personal tastes of the audience and above all, the ability of the influential artist to create something unique compared with the commonalties of a period by means of adding new "ingredients". It is important to note that influence should be observed from a temporal distance. From there, we can observe the important influential elements that have influenced other artists and have been essential in the evolution of field. In this temporal distance, components that seemed to be important have disappeared and other less relevant for their coetaneous have remained. Fortunately, there is always a parallel non-popular artist world that is innovative and whose results will be the future influential elements.

Conclusions.

From the exposed on this point we can see that the problem of influence has been faced from many different ways. The first thing that is remarkable is that there is a gap between conceptual and technical approaches. The problem of influence required both side. It is impossible to face a technical study without a deep conceptual analysis. And on the other side, conceptual researches are so deep and complex that it is not feasible to implement them. From a technical point of view, the problem of influence has rarely been addressed with computational perspectives. There are works in the sociologic field but their view of influence is completely distinct than the artistic view. Most of the works that has been done in music used previously known information to present relations in a more clear way. There are only four studies that try to obtain musical connection using acoustic information. From them, a few conclusions can be extracted. First of all there is no a deep study of how approach it. There also are lots of important aspects not properly discuses. Every study has a different scope, there are different ways of characterize and measure influence

relations and normally there is no quantitative evaluation. All of this is not a problem itself. The problem is that there is not a conceptual frame to group them. As a result, every study seems to fly blind.

3.2. Scientific Background.

Our work is framed within the Music Information Retrieval field. Our narrow approach of influence has the intention of automatically detecting musical relations from the audio itself using similarity as a measurable index of influences connections. In this chapter we review the main feature extraction techniques as well as the most relevant works in content-based music similarity. Note that this section is not intended to be a full compendium of these topics but a review the basic knowledge needed to properly face our view of influences.

3.2.a. Feature extraction.

Dynamic, ***harmony***, ***melody***, ***timbre*** and ***rhythm*** are the main musical facets that take part in our perception and characterization of musical judgments [31]. Obtaining reliable features to describe these musical dimensions is still one of the major tasks in MIR. These features want to capture the characteristics of the signal that are directly related to the musical content. Currently, there are many descriptors and approaches for each musical trait. Each study faces the problem from a different perspective. In of them lay the same idea: to transform the raw audio data so that the interesting information is more easily accessible. The raw audio signal subsequently passes different layers of processing and transformations. It is usually done in a short-time moving window either from a temporal or spectral representation of the audio signal. The result is a time series descriptor (or sequence) that reflects the temporal evolution of a given musical aspect.

Depending on the level of abstraction we can have three kinds of descriptors. *Low-level* audio features represent information closed to the raw signal like spectral content, pitch or vibrato/tremolo. *Mid-level* descriptors model musical concepts such as timbre, rhythm, melody, main tonality, chords, or tempo. Finally, *high-level* features contributed to the "understanding" of music and represent abstract cultural concepts like mood, genre or similarity [32]. Between mid-level descriptors and high-level descriptors exists a semantic gap –a missing connection– which arises from the difficulty of computers to extract and process abstract and cultural concepts such as genre, mood or similarity [33]. Figure 2 illustrates this classification.

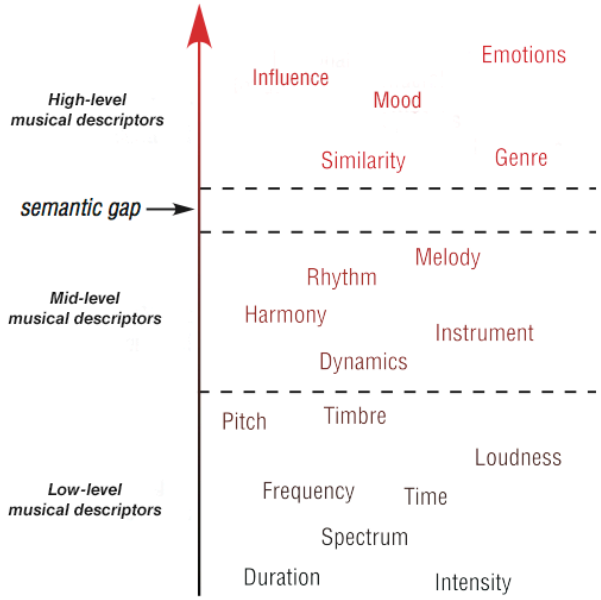

Figure 2. Three levels of abstraction for classifying features.

As explained, the main musical characteristics of Progressive Rock Music are an enormous timbral palette, a rich and varied harmony, complex melodies and polyrhythm and exaggerated dynamics changes. For this reason in this chapter we review different approaches developed in the MIR field for describing these musical facets. The techniques presented are grouped into three different topics. First of all we focus on the different studies that describe the signal from a harmonic and melodic point of view. Changes in dynamic are correlated with our perception of sound intensity, the so-called Loudness, which is presented secondly. Lastly, timbre that is a very complex problem that has been faced from different perspectives is analysed.

Harmony and melody.

Harmony and melody are the basic principles of occidental music. While harmony is the vertical organization of simultaneous notes, melody is a linear combination of sounds with different intervals and rhythms, perceiving as a single entity. Since Johan Sebastian Bach and his Well-Tempered Clavier Western music has been structured around the chromatic scale, which divide the distance between a note and its octave in twelve parts, called semitones. The combination of two or more harmonic interval[21] creates a chord. Chord progressions are a series of chords played one after other to aim a "goal" (tension Vs resolution, modulation, cadence, etc). Chords and chord progressions are basic in music because they are the structures on which music is built: they are in charge of giving the context to melodies and creating tensions. Detecting melodies, chords and chord progressions is essential to analyse and characterize music.

[21] Distance in semitones between to notes

In the MIR community, tonal descriptors are often referred to as chroma features. Chroma features are a meeting point for both musicians and engineers because they use concepts that musicologists can understand and work with, and, at the same time, it is a powerful tool for several MIR tasks like cover song detections, genre and mood classifications or similarities. The human perception of pitch has two dimensions: height (octave) and chroma (pitch class). Tones are judged to be similar if they share the chroma component. Chroma features model this phenomenon. They refer to a vector of features that describes the different tones presented in an audio signal, excerpt, or frame. Using the western tonal system a chroma feature vector has 12-component whose values express the amount of energy found for each semitone in the analysed audio. It is a powerful descriptor due to its correlation to the harmony and melody of a piece. It gives semantically meaningful relationships between notes, which, with futher postprocessing, allows the analysis of chord progression and key. There are many ways of computing and enhancing chroma features, which results in a large number of chroma variants with different properties. All of them computed as an instantaneous evolution of pitch class distributions by means of identifying pitches that differ by an octave and collapse them into the basic twelve pitch classes.

A basic approach is to estimate the instantaneous frequency (IF) as the time-derivative of the phase of the complex spectrum. The chroma feature is created using a histogram of the IF quantized [34]. Another version of chroma feature is explained in [35]. In this study Müller and Ewert want to compute a chroma descriptor that is invariant to timbre changes. Generally, lower MFCCs are closely related to the aspect of timbre. Therefore, they discard this information to achieve a timbre-invariance descriptor. This idea is combined with the concept of chroma feature to obtain a pitch-frequency cepstral coefficients (PFCCs). In this representation only the upper coefficients for each band are kept. The rest are discarded. Finally, an inverse DCT is applied to the final coefficients. They obtain a 120-dimensional vector that is quantized onto a 12-dimensional chroma vector.

According to [36] a disserved chroma feature extractor may be able to work with monophonic and polyphonic signals, have to consider the presence of harmonic frequencies, must be independent of timbre, loudness and dynamics and robust to noise. Finally, it should be independence of tuning. All of these requirements are treated in Harmonic Pitch Class Profile (HPCP) [36]. HPCP is an extension of pitch-class profile (PCP) proposed by Fujishima in [37] that measures the presence of each of the twelve semitones in a polyphonic melody. Four steps are needed to compute a HPCP representation: *preprocessing*, *reference frequency computation, frequency to pitch-class mapping and postprocessing*.

Preprocessing prepares the signal for enhancing the features that are relevant for the chroma representation. It is where the signal is represented in the frequency domain with a Discrete Fourier Transform (DFT), and also where peaks are detected. Only peaks in the interval of [100, 5000] Hz (range for most of the instrument in western music) are considered. It gives robustness to noise (ambient noise, percussive sounds, speech sounds, etc.) because avoid regions where the harmonic structure is noise. Spectral whitening is also applied to

avoid the influence of the different equalizations. Spectral whitening is a timbre normalization that normalizes the spectrum according to its spectral envelope. It converts it to a flat spectrum. Thus, notes on high octaves contribute equally to the final HPCP vector than those on low pitch range, and the results are not influenced by different equalization procedures. After this step, the method will work from now on only with the spectral peaks.

Reference frequency computation is the step in which the analyzed piece is tuned to the reference frequency A 440 Hz. The tuning needed is calculated using statistics information of the frame values. Concretely, a deviation of frequency values with respect to the A 440 Hz is mapped to a semitone scale computing a histogram of values. This step assures that HPCP vectors are independent of tuning frequency.

Frequency to pitch-class mapping is where frequency bins are mapping to a given pitch class. Each frequency contributes to its close chroma bins, not only to itself. The contribution of a peak is weighted using a $\cos^2$ function around the frequency of the bin. The value of the weight depends on the frequency distance between this frequency and the center frequency of the bin. This contribution decreases exponentially along frequency. The presence of harmonics are model considering each frequency as an f0 and as harmonics of others f0. The contribution depends of the weight of each harmonic. This point avoids the problem of finding the harmonics of the harmonic series. Finally, in the *postprocessing* step, each HPCP vector is normalized with respect to its maximum value. It gives robustness against variations on dynamics.

Dynamics.

Dynamics are changes in the sonority of musical pieces. In music, most common changes and musical level are named with Italian words such as crescendos, diminuendos, pianissimos, or forte. From a technical point of view, dynamic is related with the intensity of sounds. It is normally measured in dB_{SPL} (sound pressure level). But in every musical, humans take part of it and we do not process changes in a linear way. So that, we are interested in model our perception of sound pressures, so-called Loudness. There are different Loudness scales that relate the sound level pressure with our loudness sensation. These scales are frequency and intensity depended. Sone scale measures the amount of dB_{SPL} needed to perceive a tone of 1kHz at a level of 40 dB_{SPL} with twice loudness. On the other hand, Phons scale measures the intensity needed at certain frequency to obtain the same loudness sensation that we have for a tone of 1kHz at a level of 40 dB_{SPL}. “Equal Loudness Contours” are produced using loudness matching experiments. These contours relate both frequency and intensity dependence.

Despite it does not attempt to be compatible with standard definitions of loudness in sones or loudness level in phons Vickers’s implementations [38] is probably one of the most well known loudness representation. This method normalizes the loudness of a sound file. It compares the long-term loudness matching level (LLML) of a sound file to a desired target value that depends on the level of compression needed. LLML is a representation of global loudness

sensation that correspond reasonably well with human judgments of the relative loudness of extended audio signals. It is obtained combining a series of individual (per-frame) level estimates. The levels used are the ones computed in [39][40][41][42]. In order to obtain the LLML representation a set of rules are applied. Most of them are based on our loudness perception like being more sensitive to certain frequencies than to others, weighting heavily louder frames than softer frames (louder segments influence more our judgment of loudness) or not using non-silent parts.

Timbre.

Timbre refers to the spectral information that is correlated with the 'colour' of sounds. It is a multidimensional waste-basket category for everything that cannot be labelled as pitch or loudness. *"(...) the perception of timbre is a synthesis of several factors, and in computer-generated music considerable effort has been devoted to the creation and exploration of multi-dimensional timbral spaces The frequency spectrum of a sound, and in particular the ways in which different partials grow in amplitude during the starting transient, are of great importance in determining the timbre"*[43]. Traditionally, timbre descriptors have been characterized by the spectrum through spectral features such as *Spectral Centroid* (the barycenter point of the spectral distribution), *Spectral Flux* (frame-to-frame spectral difference), *Zero Crossing Rate* (ZCR, the number of time-domain zero crossings) or *Spectral Roll-off* (the frequency below which some percentage of the spectrum (i.e. 75%) resides) [44][45][46].

Nowadays, the most used feature for describing timber is Mel Frequency Cepstral Coefficients (MFCCs) [47]. This representation was originally developed in speech processing for automatic recognition. MFCCs are computed applying the Discrete Cosine Transform (DCT) to the original Discrete Fourier Transform (DFT) of the signal. It has the particularity that the frequency bands are equally spaced on the Mel-scale, which is an approximation of the human auditory system's response. As a result, we obtain a number of coefficients that represent, in a very uncorrelated way, the information in a spectrum but it has been proven to be useful for MIR [48].

As a conclusion, it can be said that feature extractions is not a resolved tasks yet. There is not a standard procedure to compute them. Each investigator has its own procedure and most of the descriptors are hardly limited to the topic for which were created. There are features, such as timbre that have been proved to be useful for MIR task but have not a clear connection with the musical dimension that represented. Others, such as chroma features, are a compendium of probabilities that work properly for "easy" music but fail completely for complex music such as Classical music. Therefore, each task that uses them has to take into account that it has limitations and restrictions in its base.

3.2.b. Similarity.

Our view of the influence has been presented in Chapter II. The empirical indicator we have selected to determine influential relations is similarity. Music similarity is a very active area of study in the MIR community. Similarity is a very ambiguous term that not only depends on the musical dimensions themselves, but also on different cultural context and personal aspects. The definition of the concept of music similarity involves many factors (acoustic, perceptual, cultural or subjective), and some of them (maybe the most relevant ones) are difficult to measure [49].

From an acoustic point of view, there are many musical facets (tempo, rhythm, melody, timbre, etc.) relevant in our perception and characterization of musical judgments [33]. As we have seen, these dimensions are described by musical descriptors, which try to capture the essential of each musical trait. Descriptors are obtained from the raw signal from which high levels representations close to musical facets are computed. These representation are not exact and do not characterize completely all the musical aspects involve in our perception of similarity. As a result, the computational problem of music similarity is based on arbitrary features hindering the whole process.

In general, similarity can be faced with a local or a global scope. In the former, we are looking for self-similarity in a musical piece to find similar excerpts and structures [50]. In the latter, different musical pieces are compared to determine what songs are similar. In the influence problem, as it was define as the relationship between different musical elements, similarity is related to the global scope not to local one. Most of the researches on global music similarity reduce the problem to feature vectors that describe acoustics characteristics of the song, and then, they compute distances between songs on a certain feature space [51]. Distances are computed comparing two sequences and trying to 'fit' one sequence into the other obtaining a similarity index between them. Thus, music similarity has two main aspects that define the process. First, the kind of audio descriptors used and secondly, the choice of an appropriate distance function which define what songs are close (more similar) and what songs are far (less similar).

Timbre is the most popular musical feature used in music similarity [52]. Listeners are sensitive to timbre in a global manner. The "sound the same" expression is normally more relate to timbre similarity than to melodic similarity in which a change in a single note (from major to minor) can dramatically transform our musical perception. Thus, timbre similarity is a natural way to build musical similarity connections [31]. Timbre is normally described by the well-known Mel-frequency cepstrum (MFCC) but also by spectral centroid, spectral rolloff or spectral fux. At the beginning, this timbral representation was global which means that a song was represented only by one timbre descriptor [53] but some studies introduced the codification of the temporal evolution of the timbre [54]. Nevertheless, timbre is not enough for some MIR task such as cover songs detections [52]. Little by little, other musical dimensions have slowly been used for music similarity. One of the most interesting features is tonal representation described normally by chroma. It has been successfully used to extract repetitive sub-structures for music [55][56].

Finally, other non-musical features, especially cultural aspects, are also very important in our perception of music similarity. They have to be modelled and considered in conjunction with the musical properties [57].

There exist a wide variety of approaches for providing a distance measurement between musical features. The basic is Euclidean distance, which measures the length of the path that connects two points. Euclidean distance does not cope with the problems derivate of time evolution. For dealing with these problems further distance or dissimilarity notions are needed. In this context, Dynamic Time Warping (DTW) [58] is probably the most popular one. This technique looks for the optimal alignment –path- between two sequences. It "warps" the two sequences in a non-linear way in order to handle time deformations in their temporal evolution. Although it allows the comparison between two sequences that may vary in time, its standard formulation has certain restrictions: the start and the end points of the path must be the start and end points of the two sequences and every point of each sequence must be used in the warping path. Time Warp Edit Distance (TWED) [59] is another distance to match time series but in this case, it has some time shifting tolerance. It controls the stiffness of the elastic measure along the time axis. DTW and TWED are global alignment algorithms. These algorithms compare two sequences that are similar over their entire lengths.

There are a group of distance that measure the number of operations required to transform one sequence into the other. Edit Distances weigh the distance between two strings of characters. There are several variant adapting this distance to the MIR context [60][61]. Smith-Waterman (SW) [62] was originally developed for finding similar regions between a pair of biological sequences. It is a local alignment algorithm, which allows the comparison of two sequences that share only a limited region of similarity. The cover song identification measure (Qmax) [63] adapts the principles of SW to time series. It uses dynamic programming strategies to compute an accumulated score matrix that reflects the lengths and quality of such matching sub-sequences. The highest-valued element of the score matrix corresponds to the end of the most similar matching subsequence.

Beside these distances there are other interesting measurements. Earth mover's distance (EMD) [64] was introduced in computer vision as an measurement of the distance between two colour distributions. It is calculated as the amount of changes necessary to transform one image into another. It has been widely used in content-based image retrieval systems but also in music [65].

Chapter IV. Method.

Three are the aspects we have to consider to properly approach the problem of influence: the temporal distance temporal between influenced and influential, how to detect those elements that are unique of a specific artists and the computation of a measureable index. This chapter explains the methodology followed to model these three aspects. It also contains a detailed explanation of all the procedures performed to develop and evaluate a basic algorithm that looks for influential connections between songs. First, we explain the material chosen discussing the selection criteria. Secondly, the procedure used to obtain the features that characterize the musical dimensions is explained. Then, we present our algorithm, its different parts and the proposed method to computationally model the common traits of the genre. It will used to distinguish what segments in our influential database are unique and what segments belong to the generalities of the genre. Finally, a methodology to evaluate the result is described.

4.1. Material.

The material needed contains three different databases. One that contains the influential songs, other for the posterior influenced segments and a third one used for modelling the commonalties of the genre. All of the songs contained in the datasets are mp3 at 320 kbps.

Influential database: it contains our selection of influential songs. They have been selected according to the criteria of experts and musicians of Progressive Rock Music. Both agree that King Crimson, Yes, Genesis and ELP are the most important and influential groups of the genre [6], [7]. As discussed in the Prog Rock chapter, these four groups have an internal coherence and represent the main lines of the genre. The songs selected are the ones belonging to their albums released during the golden age of the genre, from 1969 to 1974. In total we have 178 different songs.

King Crimson: seven albums, “In The Court Of The Crimson King”, “In The Wake Of Poseidon”, “Lizard”, “Islands”, “Larks' Tongues In Aspic”, “Starless And Bible Black” and “Red”. It comprises 43 songs and around 305 minutes of music.

Genesis: five albums, “Trespass”, “Nursery Cryme”, “Foxtrot” “Selling England By The Pound” and the double LP “The Lamb Lies Down On Broadway”. It comprises 60 songs and around 285 minutes of music.

Yes: seven albums, “Yes”, “Time and a Word”, “The Yes Album”, “Fragile”, “Close To The Edge”, “Tales From Topographic Oceans” and “Relayer”. It comprises 41 songs and around 320 minutes of music.

Emerson, Lake and Palmer: five albums, “Emerson Lake & Palmer”, “Tarkus”, “Pictures at an Exhibition”, “Trilogy” and “Brain

Salad Surgery". It comprises 42 songs and around 205 minutes of music.

A detailed list with all songs and its duration can be found in the Appendix Chapter. In a genre in which there are songs longer than 20 minutes the important fact is the number of minutes we have for each band. In this sense, the influential database is well balanced. Only ELP has significant fewer minutes than the others. Although the number of song is similar to the rest of groups, they are generally shorter with lots of piano interludes and ballads. Despite this difference, we think that the 205 minutes of ELP are enough representative of the main traits of the group. Figure 3 shows the song distribution per year and artist.

The selection of these songs defines the kind of influential element we are looking for. King Crimson contributes with complex and dissonant harmonies and melodies, dense and dark and multi-instrumental timbral atmospheres where stands the used of the Mellotron. Genesis has its characteristic flute and acoustic passages and its rhythm and energetic lines. Yes is the timbral magnificence with a very epic sound together with the jazzy guitar riffs of Steve Howe and the walking bass of Chris Squire. Finally, ELP has its classical piano lines mixed with crazy synthesizer parts.

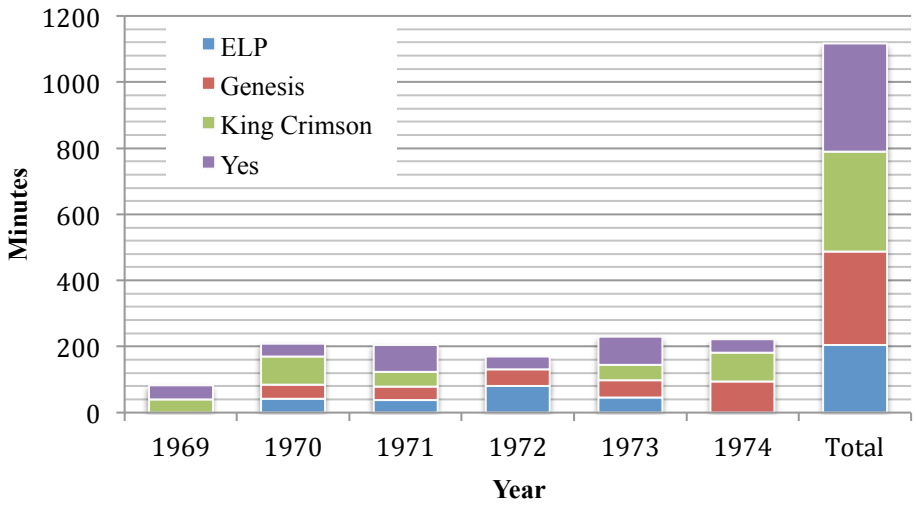

Figure 3. Influential database distribution in minutes per artist and per year.

Influenced database: it contains a list of annotated segments that correspond to songs dating from the resurgence period to our days. Each influenced segments contains a possible influential segment with its artist, album and song information. All of them constitute our ground-truth. The final list contains 123 segments distributed as shown in the figure 4. We have done our best to select unambiguous (with regard to influential artist) segments. The election of the concrete influential segment is extremely subjective. Despite this subjectivity, our own judgment has been complement by reviews read on forums, websites, and informal

documentation. In those cases, where the influential artist was clear but not a specific influential segment, we have used our algorithm to suggest possible influential segments. Each segment looks for a concrete feature of the influential artists. In this sense we have complex and dark harmony passages, classical piano parts, acoustic sections with flute solos, epic ending and a plenty of examples more. Together with the concrete influential segment annotation, each influenced segment has also assign one of the four influential artists. The detailed ground-truth with all the annotations is attached in the Appendix Chapter.

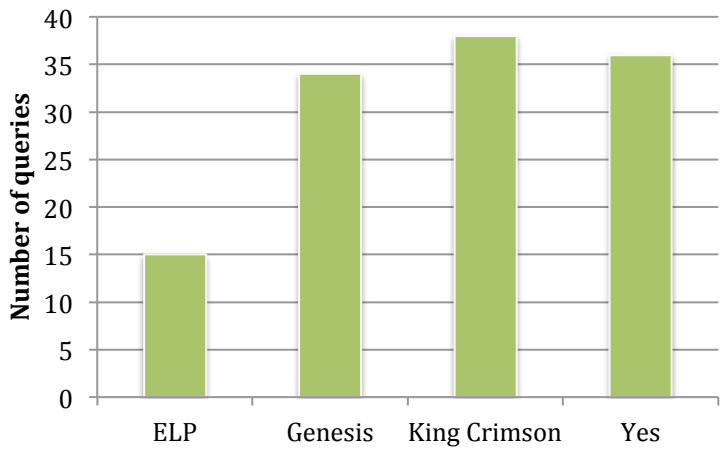

Figure 4. Distribution of the influenced segments by influential artists.

Prog Rock database: modelling the common traits of the genre requires, not just the collection of influential songs, but also complementary songs of the genre. This database contains 832 songs from relevant albums of the genre in the same period than the influential database. This list has been created according to expert knowledge using the list of most important albums compiled by Progarchives.com.

4.2. Feature extraction.

The musical dimensions we use are harmony and melody, timbre and dynamics. They are described by their related musical descriptors. As it was discussed in the Chapter III, there are many features and approaches for describing each musical dimension. In our case, we use a set of 3 state-of-the-art feature extractor algorithms. Descriptors are computed with an in-house tool specifically designed for that purpose [66].

Dynamics: it is computed with a version of the Vickers algorithm that characterized the time evolution of the loudness [38]. Each frame has only one value that represents its loudness.

Harmony and melody: in this case we use Harmonic pitch class profiles (HPCP) representation [36] which captures the tonal information quantizing the intensity of each of the 12 pitch classes of an equal tempered chromatic scale. This descriptor has 12 different components, one for each note of the western scale.

Timbre: it is described by the well-known Mel Frequency Cepstral Coefficients (MFCCs), which capture the power spectrum in 14 components skipping the DC coefficient. The implementation used in the one presented in [67] with a frequency range from 20 Hz to 22KHz to capture all the timbral richness of the genre. Each frame has 14 dimensions, each of them represent a component.

As we want to measure the influence of different patterns and segments in a given query, it has no sense to use a global descriptor. For this reason we use structure-based descriptors instead of averages over whole songs. Internally, the toolbox divides the songs in frames of 1024 samples at 44100 Hz. Each frame has a length of 23,21 milliseconds. Frames are grouped in windows. We can control the length of the window as well as the hop size, which represent the overlap between two consecutive windows. In our case we use a configuration of 10 frames per window and a hop of 5 frames. As a result, each descriptor represents the information in a mid-term temporal scope, with a resolution of 0,116 seconds. The control parameters of the toolbox allow us to define a number of settings. Each descriptor has its own configuration. The following table summarize the parameters used.

Descriptor	Averaging type	Frame normalization	Component normalization
Loudness	Median	No	No
HPCP	Mean	Division by the maximum	No
MFCC	Mean	No	Standard deviation

Table 1. Averaging type defines how the information of a window is computed from a group of frames. Frame normalization determines if the information of a frame is normalized or not and how. Finally, component normalization controls if the information of the whole song is normalize or not and how.

Each descriptor is computed separately. Once we have the three descriptors, a big matrix with all the information is created. This matrix has 27 different components where the 12 first represent the HPCP, the next 14 the MFCC and the last one the Loudness. As a result of this step each song is characterized by a matrix with dimension n x 27. Where n is the number of segments the song has, which it is defined by its duration. Each row of this matrix is a medium term representation of a concrete of 0,116 seconds segment.

From now on, as we will work with these matrixes and not with the audio itself, every time we use the term frame, it will refer to a med-term descriptor segment with a length of 0,116 seconds. Additionally, every time we use the term segment we will refer to a group of frames.

4.3. Algorithms.

In this chapter we review the different algorithms used to compute the influential connections and to model the common universal traits of the genre. The core algorithm is the same for both cases, with just only a few modules differing. This section analyses first the commonalities of the algorithm in the core algorithm section and, then, explains the specificities of the background model computation, compared to the computation of influence.

4.3.a. Core algorithm.

Our segment-to-segment scope needed to compare every influenced segment against every segments of every song in the influential database. This comparison is really slow and consumes lots of resources. Therefore, a fast computational language is required. Our election is C++ due to its fast performance.

The algorithm receives a list of queries (a concrete segment depending on the application) and a list of candidate songs (Figure 5). These lists do not address directly to the audio but to the matrixes that describe their musical dimensions. The procedure is based on a brute force comparison where each segment of the query is compared against each segment of each song of the candidate list. In each comparison a similarity distance between segments is computed. The user has control on a set of parameters. Most of the parameters depend on the application but one is common to all them. It is the number of closest connections, *k*. It determines the number of matches the output file will have. Matches will be listed according to its similarity with the query. The smaller the similarity distance is, the stronger the influence. The length of the segments, upon which the comparison is made, depends on the application.

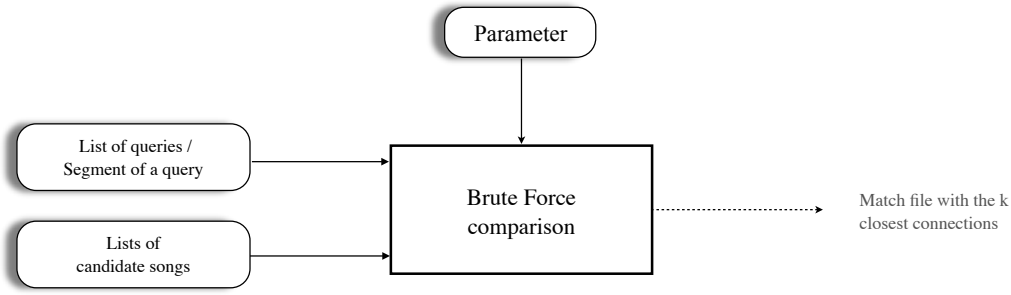

Figure 5. Basic schema of the core algorithm. Every segment of the query is compare with all the segment of the all candidate songs. Output describes the *k* closest relation found. Some parameters con be controlled, it depends on the application.

During the execution the algorithm is continuously updating a list of *k* elements sorted by its similarity distance. This list has five elements: name of the query, segment of the query, name of the candidate, segment of the candidate and similarity distance between the two segments. At the end, only the

k closest connections with its five elements are stored in a csv file. An example of the output file can be found in figure 6.

TheFloweKings_MinorGiantSteps	697	Yes_72Close_2AndYouAndI	1269	-4.9217
TheFloweKings_MinorGiantSteps	697	Yes_72Close_2AndYouAndI	1222	-4.88238
TheFloweKings_MinorGiantSteps	697	Yes_73Tales_4Ritual	3243	-4.82139
TheFloweKings_MinorGiantSteps	697	Yes_72Close_2AndYouAndI	1128	-4.73171
TheFloweKings_MinorGiantSteps	697	Yes_72Close_2AndYouAndI	1081	-4.72595

Figure 6. Example of output of the algorithm with the first four matches. The first column correspond to the name of the query, the second one with the start of the segment in frames, the third is the name of the influential song, the fourth the start of the influential segment and the last one the similarity distance between them.

Songs are characterized by only one matrix that contains all its musical information. Internally the program works with three different distances, one for each descriptor. Each distance is compute separately but then they are summed in order to end up with a single (aggregated) distance measure. In order to ensure that the three distances have the same contribution they are normalized. For the three features used, the distribution of the distances between segments divided by the length of the segment in frames resembles a Gaussian distribution. (Figure 7)

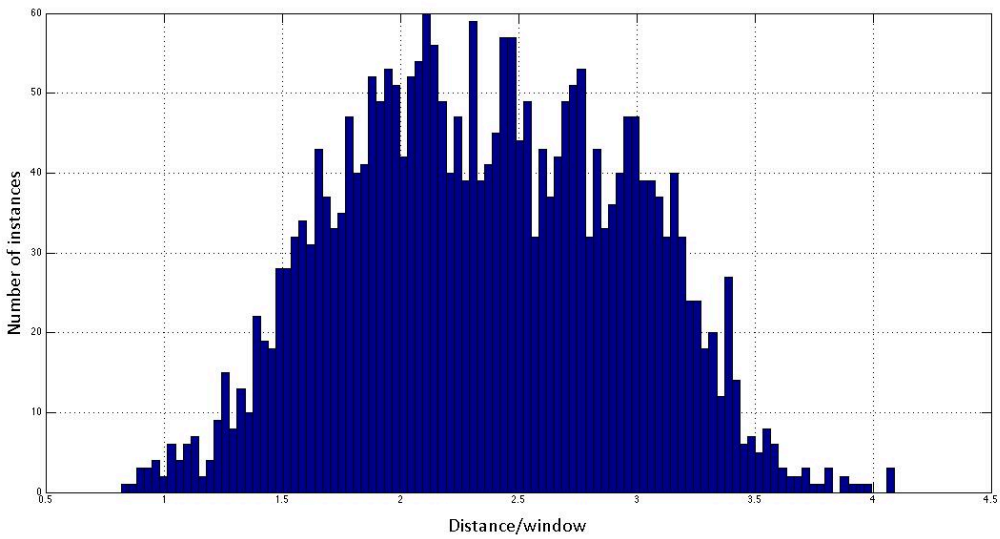

Figure 7. Example of the distances distribution for the HPCP descriptor.

It allows us to compute a standard score:

$$x = \frac{x - \mu}{\sigma}$$

where x is the distance between segments divided by the length of the segment, μ the mean of the population and σ the standard deviation of the population. This final dissimilarity is the one that defines the similarity between segments.

Users can control the weight that each descriptor will have in this final distance specifying in percentage the contribution of each distance. Two distances are implemented. The first one is a Euclidean distance. Then, in an improvement we also compute a Dynamic Time Warping distance.

Finally, for HPCP we have to have a further consideration. In order to compare two tonal representations both have to be in the same key. Before comparing the HPCP descriptors we transpose the candidate segment to the query segment key. For the transportation we compute the optimal transposition index (OTI) following the steps presented in [68]. For each pair of HPCP segments *A* and *B* of length N, its global representation g_A and g_B is obtained as:

$$g_A = \frac{\sum_{i=1}^{N} h_{A,i}}{\max(\sum_{i=1}^{N} h_{A,i})}$$

where $h_{A,i}$ is the HPCP information of the frame *i* for the segment A. A global representation of a segment is a vector with M components, where M is the HPCP size considered (usually the 12 semitones of the equal tempered scale). The next step is to obtain the dot product of g_A against all the possible transposition of g_B.

$$OTI(g_A, g_B) = \text{argmax}_{1 \leq j \leq M}(g_A \cdot Circshift_R(g_B, j-1))$$

$Circshift_R(g_B, j-1)$ is the function that performs a circular shift of the vector g_B. A circular shift permutes without altering the relative ordering the components of the vector *j* positions. For instance, a circular shift of one position moves the last component to the first position and all the other components one position to the right.

Euclidean Distance.

The Euclidean distance between two segments is the sum of the Euclidean distance of each frame contained in the segment. If we have a query segment *Q* of length *n,* with $q_1, q_2, \ldots, q_n$ frames and a candidate segment *C* also of length *n*, with $c_1, c_2, \ldots, c_n$ frames the final Euclidean distance is defined as:

$$d_{q,c} = \sum_{i=0}^{n} Euclidean(q_i, c_i)$$

where the Euclidean distance is define as:

$$Euclidean(q_i, c_i) = \sqrt{\sum_{j=1}^{d} (q_{i,j} - c_{i,j})^2}$$

being *d* the dimension of the feature and *i* the concrete frame on which the Euclidean distance is computed. A frame of the query q_i is only compared with its corresponding frame c_i of the candidate. In this distance both segments have to have the same length.

Dynamic Time Warping Distance.

Dynamic Time Warping is a method for optimally aligning two sequences to find the best match between them. Having two time series, a query Q = $q_1, q_2, \ldots, q_n$ of length n and a candidate C = $c_1, c_2, \ldots, c_m$ of length m we build a $n \times m$ matrix DTW [58]. Each element of the matrix D(i,j) is computed as the sum of its local cost, which represents the distance between the points q_i and c_j, and the minimum of the cumulative distances of the adjacent elements:

$$D(i,j) = d(q_i, c_j) + \min\{D(i-1,j-1), D(i-1,j), D(i,j-1)\}$$

In our approach, the distance between d(q_i, c_j) is measured as an Euclidean distance between q_i and c_j. There are some exceptions that do not follow the previous formula. The first element of the matrix is computed only as the local cost d(q_0, c_0). The cumulative distances of adjacent elements for the first row only have the contribution of the previous row element. Similarly, in the first column, the cumulative distances of adjacent elements have only the contribution of the previous column element.

$$D(0,j) = d(q_0, c_j) + D(0,j-1)$$

$$D(i,0) = d(q_i, c_0) + D(i-1,0)$$

Once the matrix is created we can find a path through it that minimizes the total cumulative distance between them. For our study we are not interested in the path itself rather than in the total cost of it, which corresponds with the last box of the matrix. This value represents the distance between the segments *Q* and the *C*.

Some constrains have been followed during the implementation of the algorithm. The path starts at the point (1, 1) and ends at (n, m). Every point in the query (Q) and candidate (C) must be used for the creation of the matrix. Finally, following the Sakoe-Chiba hypothesis that [69] an intuitive alignment path is unlikely to drift very far from the diagonal, elements located far away from the diagonal of D matrix are not computed.

4.3.b. Background model computation.

Determining if a musical connection is an influential relation or not is essential for our problem. With the selection of the influential database and the influenced segments we have limited the type of influential connection we are searching for. With this background algorithm we want to determine what segments of the influential database belong to the genre and what characterize the main traits of the bands. The result of this algorithm is a list of to be skipped from the influential database as we assume that these segments are not unique and they pertain to the common traits of the genre. This approach used the core algorithm to compare our influential database with the other important songs of the genre and period.

For finding the common feature of the genre we compare our influential database against the union of the Prog Rock database previously described and the influential database itself. Thereby, each segment of the influential database is compared with all the segments of the most relevant songs of the genre and period. The comparison has some constraints that respond to our conceptualization of influence Firstly, a temporality constraint imposes that musical elements of a year X cannot be influenced by elements of posterior years. Thus, the comparison can only be done between queries with candidates of the same or anterior year. It overbalances the comparison because segments of songs of posterior years are compared against more segments than segments for anterior years. This idea is not totally unreasonable because, at the beginning, when a musical style it not defined is easier to contribute to it. On the other hand, with the passing of time, when the genre has developed its general traits, musical aspects become standard and less unique. As we want to preserve the main features of bands and only skip those that are very common to the genre, we do not allow the comparison between segments of the same artist.

The final list contains *k* segments[22] of the influential database to be skipped. These segments are the ones that have the minor distance with other segments of the candidates. For each segment analysed we only keep its closest match. As a result, in this list we only have one possible connection for each of the query segments. The user can control the window length of the segments, the hop size as well as the number of final matches *k*.

With the computation of the background model, our basic approach to determine the influential elements is finished. As mentioned, it has three parts: the manual selection of the influential database, the manual selection of the influenced segments and the automatic characterization of the common traits of the genre.

4.3.c. Influential algorithm.

The goal of this algorithm is to find connections between segments that can be taken as influential. With the election of the influential database and the computation of the background model we assume that every segment that remains in our influential database can be a possible influential element. It is an idiosyncratic and not genre-specific feature of an influential artist. The manual selection of the influenced query segments assures that each of them has been influenced by some musical aspects of our influential database. With this algorithm we aspire to find the *k* closest influential segments for any specific query segment.

In this case, the query of this algorithm is a concrete influenced segment with a length *l*. Although, it is totally debatable and, as we will see in the experiment and discussion section, not true, we assume that the influential element of this segment will have the same length *l* that it has. Thus, the comparison will be done with influential segments of length *l*. In this case the user cannot control the length of segments other than selecting an influenced

[22] Number of matches factor

segment with a different length. Apart from the query, the algorithm receives a background model file, the list of candidate songs, the values that weight the contribution of each descriptor to the final distance, and the number of final matches we want to have. The result is a file with the *k* closest matches to the query segment.

4.4. Evaluation.

Establishing an objective ground-truth is a complicated assignment. Each influential connection has not a unique answer nor an objective solution. Most of the links are highly subjective and personal. Each segments has thousand and thousand of possible influential segments. Each person has his personal vision of musical relations and can have his own annotations. It depends on our personal taste. If you prefer King Crimson rather than the rest of groups, unconsciously you will find more connections to King Crimson. Even the fact of liking more some albums of King Crimson will condition your judgments.

At this point it is worth to think how we, humans, find influential connections. This task has been address from not computational perspective in the musicological field and the history of the music analysed. From their studies, we can conclude that it is a labyrinthine topic for humans being where each expert defines his list of connection [5][70]. It suggests the inclusion of an evaluation based on human listeners, much like evaluating music similarity algorithms [71].

Our methodology follows the MIR procedures where a ground-truth with the correct answer is used to verify the results obtained and then, computed statistical measurement that describe the validity of the process. In opposition to others ground-truth, the annotations have a subjective component in their foundations that hinder the process. Because if the algorithm finds a match that it is different than the one annotated it can be an error or can be a possible solution not previously taken into account.

Our ground-truth has two different annotations. The first one relates each influenced segment with a concrete influential segment. These annotations depend on the personal criteria of the author. A further improvement will need expert tests to validate them as it is explained in the discussion chapter. The second annotation connects every influenced segment with one of the four possible artists. Although this annotation is not as subjective as the previous one due to the musical differences between the four artists, there are some segments that could be influenced by two or more artists. In these cases, we have selected the artists that, in the opinion of the author, have a strong presence. Upon this ground-truth we can obtain statistical measurements and analyse the behaviour of the proposed algorithm. With this ground-truth, we can verify if our algorithm is capable to find the same segment we are thinking on when we are listening a concrete segment of a posterior song of Prog Rock. We also can measure if the relations that the algorithm found correspond with the artist that seems to be more influential to the segment.

Chapter V. Results.

The proposed experiments are divided into three groups. Each of them answers a basic question: Does the algorithm work as it should? What parameters do we use? How good are the influential connections found? Before starting with the experiments, we explain the evaluation measures used. Then, the second section verifies the behaviour of the algorithm checking if it works properly. A third section studies the effects of the involved control parameters. Finally, we present the results of the actual influential task analysing the segment-to-segment connections and the artists' influence.

5.1. Evaluation measures.

For the evaluation of the algorithm we introduce a set of performance measures that are used hereafter. The main statistic measure we have computed is the mean reciprocal rank, MRR [72]. It is a widely used measure within MIR flied. To calculate it we have to obtain the reciprocal rank (RR) of each query as the inverse of the position of the first correct answer:

$$RR = \frac{1}{rank}$$

MRR is the average of all the reciprocal ranks results for a list of Q queries:

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i}$$

Our output file orders the possible influence connections by its probability of correctness. For each query song a reciprocal rank is calculated. It corresponds to the position of the first correct influence match in our output list. If the correct answer is not in our output file we assume that the match will be in a random position between the k numbers of results computed and the number of total influential segments. A match is correct if the segment of the query and the segment of the candidate are the "same", namely, if the candidate segment is within a range marked by the length of the window and the hop size. If several correct matches are found, only the first one (minor rank) is computed.

Along with the MMR we also compute its standard deviation σ that measures how spread the results are:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{Q}(RR_i - MRR)^2}{Q}}$$

In order to estimate if our results are significantly different than random, we carry out the Wilcoxon signed-rank test [73]. It is a non-parametric (distribution free) statistical hypothesis test, which uses the ranges of the values from two independent sets of samples to test whether their population mean ranks differ. The null hypothesis to be tested is that the two populations have

equal median. The two observations have to be paired. The Wilcoxon signed-rank test is only computed to verify the statistical significance of the influential results. In this context, each possible configuration of our influential algorithm (method A) is compared against the random version of it (method B). Thus, for each configuration, Q (number of queries) different reciprocal ranks (RR) are computed. These RR are compared with the Q RR of the random version obtaining a p-value which will help us to reject the null hypothesis if its value is lower than 0.01.

5.2. Behaviour of the algorithm.

The verification of the behaviour of our algorithm in the sense that it is able to extract essential and meaningful musical descriptions of the audio content is essential to ensure that it works as it is supposed. In this scenario, we see our algorithm as a very basic cover song detector [52]. Two small databases have been used. The first one includes four modifications of the original audio of the 178 influential songs, figure 7. A total amount of 712 songs.

Type of transformation	**Explanation**
Downsample	Downsample the signal by halving its sampling rate
Equalization 1 –EQ1–	Notch filter at 15 KHz with a bandwidth of 1 H and a decay of -90dB.
Equalization 2 –EQ2–	Complex equalization that transform radically the original signal. It includes several filters, and equalizations.
Loudness changes	A gain of -10 dB is used.

Table 2. Transformations of the influential songs to test the behaviour of the algorithm.

In addition to these transformations we also use 42 cover songs of songs of the influential database. Most of the covers maintain the original tempo, rhythm, structure, key, harmony and lyrics. Only timbre might change due to the use of different instruments and the application of new recording techniques.

The experiment can be explained as follows. We randomly select one segment of 20 seconds length of each song and compute its closest 100 macthes taking as candidates. Then, we verify in which position we have found the segment that corresponds to the original segment using MRR to quantize the success of the algorithm. Each transformation has been tested separately. The hop size used is 1% of the window length, which corresponds to 1 frame. With this hop we ensure to be as comprehensive as possible. If we use a larger hop the searched segment may not be found, because our query do not "fit" with any candidate.

An important aspect is to know what the result of a random match algorithm is. For the database configuration selected the number of total influential segments is 515536. The correct answer for one query will be in a random segment between 1 and 515536, thus its RR will be:

$$RR = \frac{1}{random(1,515536)}$$

and its MRR:

$$MRR = \frac{1}{|178|} \sum_{i=1}^{|178|} \frac{1}{random(1,515536)_i}$$

it gives us a MRR equal to 2.734917e-05 and a STD of 0,000318347. Each descriptor for each transformation has been tested separately. The results presented in the following table obtained using Euclidean distance.

Task	Descriptor	MRR	STD	Number of correct segment out of 178
Downsampling	HPCP	0.99438203	0.074742129	177
	MFCC	0.06368147	0.241591893492	12
	Loudness	1.0	0	178
EQ1	HPCP	0.99438203	0.074742116	177
	MFCC	0.68409298	0.461861470	128
	Loudness	0.96860591	0.16950993849	176
EQ2	HPCP	0.98876409	0.105402094	176
	MFCC	0.04184386	0.194236672	17
	Loudness	2.8470e-05	0.000142934	0
Loudness	HPCP	1.0	0.0	178
	MFCC	0.813117	0.385561027	152
	Loudness	0.005639	0.074740833	1

Table 3. MRR and STD for the four modifications of the original audio.

These results show that our algorithm is capable to detect different transformed versions of a random segment of each song of our database. As we can see, the best results are obtained with HPCP, which is specially designed to be robust to timbral and loudness changes. The behaviour of the other two descriptors depends on the experiment.

Downsampling reduces the sampling rate from 44100Hz to 22050Hz changing the length of the spectrum of the signal from 22050Hz to 11025Hz. As our configuration of MFCC computes 14 different coefficients for a frequency

range from 20 Hz to 22KHz the downsampling process changes completely the MFCCs explaining its poor performance. EQ1 is a soft equalization where most part of the spectrum remains identical to the original one. In this case the three descriptors show results clearly above the randomness. On the other hand, when the equalization produce major changes in the spectrum, like in EQ2, only HPCP is enough roboust. Finally, when loudness changes, the Loudness descriptor is unable to perform the task correctly. The results displayed in the table 4 confirms that HPCP is the best option for the cover songs detection task, as we already know from previous work [63].

Task	Descriptor	MRR	STD	Number of correct segment out of 42
Covers	HPCP	0.90586121	0.290218148792	39
	MFCC	0.05228952	0.212702633085	5
	Loudness	0.02929621	0.153378328369	4

Table 4. MRR and STD for the small cover dataset.

The intention of this section is to verify that our algorithm is able to connect a modified segment of our influential dataset with its original. This goal is far exceeded obtaining results above randomness. This series of experiments verified that the comparison and the similarity distance computation are working correctly. Thereby, we ensure that the future influential relations found are the results of a correct brute force comparison (controlling its exhaustiveness with the hop size) where each segment has a similarity distance calculated correctly.

5.3. Selection of the settings.

As introduced in chapter V, there are different parameters that can be set to control the performance of the algorithm. In this section we carry out some experiments to find the best configuration. Two are the parameters tested: hop size and number of matches, being the latter mostly analysed in the background context computation.

5.3.a. Hop size.

Due to the brute force comparison the execution time can be extremely long. There are two parameters that can make dramatic differences on it: window length and hop size. As explained in chapter V, the window length depends on the length of the query. Thus, the only parameter we can control to vary the execution time is the hop size. In this section we perform a set of experiments to find a balance between the exhaustiveness of the search and the results obtained deciding the maximum hop size allowed for each distance. This value conditions the time execution of our process.

The dataset used is the EQ1 modification explained in the previous section. As we want to analyse how changes in the hop size affect to the results, for this experiment only the HPCP descriptor is used. This descriptor is the one, which has the best results. Both distances are tested. The results for the Euclidean distance are presented in the table 4 while table 5 contains the values for DTW distance.

Hop	MRR	STD	Number of correct segment
1% of the window length	0.99438203	0.074742116	177
5% of the window length	0.85295545	0.207336478	172
10% of the window length	0.65146860	0.429245163	154
25% of the window length	0.41379884	0.453594385	135
50% of the window length	0.33315541	0.428034541	118
75% of the window length	0.25251638	0.386826866	109
100% of the window length	0.18721187	0.335332773	99

Table 5. Hop size experiment results for Euclidean distances**.**

Hop	MRR	STD	Number of correct segment
1% of the window length	0.9935451	0.029245163	177
5% of the window length	0.9932114	0.059502233	177
10% of the window length	0.9845673	0.089951263	177
25% of the window length	0.9656832	0.104234569	176
50% of the window length	0.8338571	0.170342931	158
75% of the window length	0.7234139	0.268436565	147
100% of the window length	0.5482965	0.333927873	131

Table 6. Hop size experiment results for DTW distances.

Figure 8 shows the curve for the MMR as a function of the hop size and the type of distance (Euclidean versus DTW) with respect to different hop sizes. Logically, DTW does not need to be as exhaustive as Euclidean distance to achieve good results. Whit this figure we can establish the hop size limit for each distance. The first order derivative of the curve represents the slope the curve has in of each point. Local minimums and maximums represent abrupt changes in the curve. Euclidean distance has a local minimum at the 10% of the window size and DTW at 25% of the window size. Above these limits the algorithm will not behave correctly. Hence, even if the time execution is outsize (especially in our DTW version[23]), it is advisable not to use bigger hop sizes.

[23] There are implementations like lower-bounding techniques that allow DTW go as fast as Euclidean distance or even more.

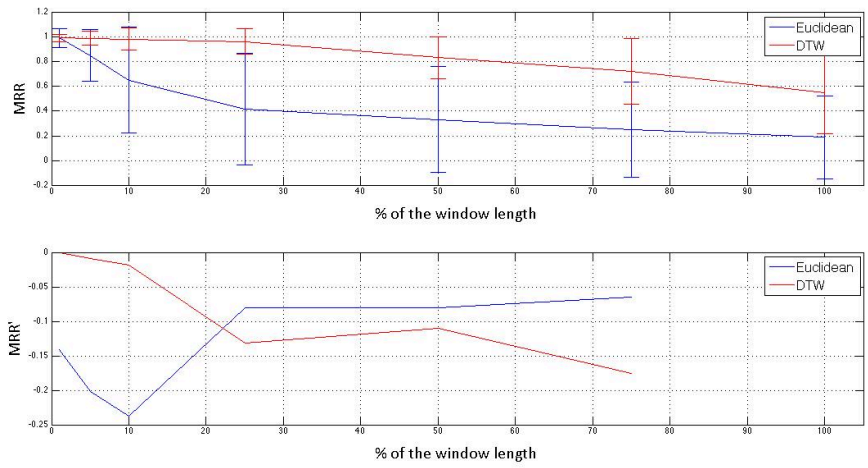

Figure 8. MRR values and its first order derivative for different hop size**.**

Time execution of the algorithm using Euclidean distance is not as problematic as using DTW. For this reason we have selected a value of hop size that permits to perform more comprehensive searches. The selected final values are 5% and 25% of the window length for Euclidean and DTW respectively.

5.3.b. Number of matches.

The election of the number of final matches *k* conditions the number of final results our algorithm computes. The analysis of the results of the experiment conducted in Section 6.1. reveals that most of the correct matches are obtained in the first position. In these experiments if the answer is not found in the first match it will not be found in posterior matches. Despite they show that the algorithm is working properly (we expected a modified segment to be closer to its original than to the rest of modified segments) this distribution does not help to determine an optimal value of *k* in the influential connections search. Although there is not any empirical reason, the chosen value we used is k = 100. This value is consistent and broad enough to find a reasonable amount of the connections that are sought.

However, for the background model computation, the *k* factor is critical because it determines how many segments of our influential database will be skipped in further performances. A high *k* can lead to a scenario in which many idiosyncratic and unique elements will be skipped. A low *k* can lead to a scenario in which everything can be seen as influential, no common elements with its genre. The goal of this experiment is to find an optimal *k* for the background to skip only those segments that belong to the genre-specific feature. The experiment consists on computing a great number of matches and finding a point in which the tendency of the calculated similarity distances changes. The settings for obtaining these values are: DTW distance, a window length of 20 seconds, a hop size of 25% and a configuration where the three descriptors have the same weight. With this configuration, the total number of possible influential segments is 6799.

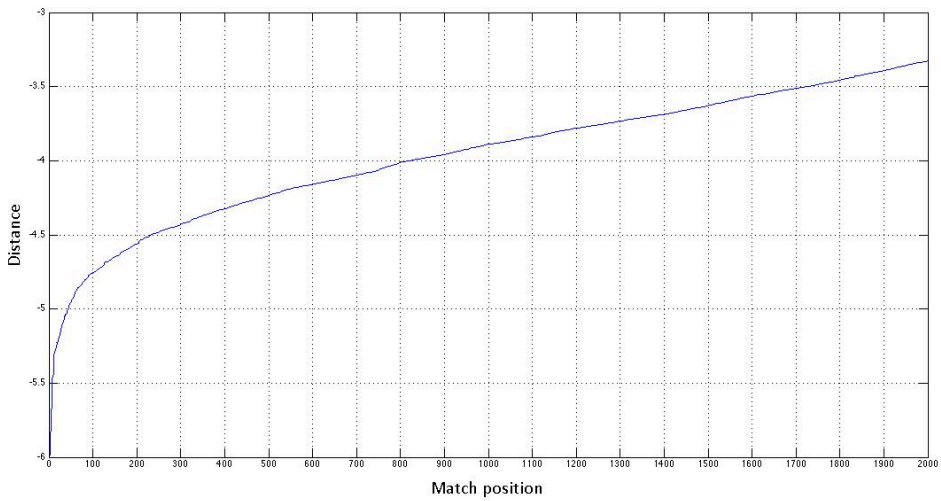

Figure 9. Similarity distance for each match.

In the figure 9 we can see how the tendency of the curve changes from 50 to 200. Looking at the first and second[24] order derivate of this curve we can find some possible solutions. As said, the searched point has to be between 50 and 200. Within this range the point 58, 89, 126, 161, 183, 189 and 204 show changes in the curve. It is up to us to select a more or less restrictive option. The last option, 204, implies to consider as progressive-genre background around the 3% of our segments, which seem reasonable.

5.3.c. Influential connections.

This section describes a set of experiments performed to analyse the extracted influential relations. The algorithm has been run with six different configurations detailed in the table 6. As discussed in section 6.2.a, the hop size used for Euclidean and DTW is 5% and 25% of the window length respectively. The window length is equal to the length of the query. This decision forces our algorithm to find influential segments with the same length of the queries complicating the problem. For this reason most of the query do not exceed a duration of 90 seconds.

We use three levels of correction to quantify the results: segment, song and artist. Each level is less restrictive than the previous one. In segment level, a match is correct if the candidate and its segment are the same (within a range defined by window length and hop size) than the annotated in the ground-truth. Song level determines a match as correct if the song of the candidate is the same that the song annotated. Finally, in artist level we measure how many instances of the final 100 matches agree with the annotated influential artist.

[24] It shows the speed change of the slope itself

Configuration	Description
Euclidean standard	Euclidean distance to compute similarity. Every descriptor has the same weight. No background.
DTW standard	DTW distance to compute similarity. Every descriptor has the same weight. No background.
DTW HPCP	DTW distance to compute similarity. HPCP has five times more weight than the rest. No background.
DTW MFCC	DTW distance to compute similarity. MFCC has five times more weight than the rest. No background.
DTW Loudness	DTW distance to compute similarity. Loudness has five times more weight than the rest. No background.
DTW standard background	DTW distance to compute similarity. Every descriptor has the same weight. Background.

Table 7. Overview of the different configuration used.

The first two levels are measured with the MRR. Each query has a reciprocal rank which indicates the position of the first correct match. Then, we calculate the MRR using the RR of each query. One last remark: each query has its own window length. Hence, there is not a specific number of possible influential segments, with each query having its own. For this reason, in the output file we also store the total number of possible influential segments for a given query. The artist level results are evaluated differently. In this case we compute a normal and a "weighted" precision. In the former, we count the number of retrieved relevant matches (matches that have the annotated artist in its influential candidate) divided by the total number of matches (100 in our case). In the "weighted" precision, the process is similar but weighting the position on which the relevant match has been found. These weights range from 100 for the first position to 1 for the last one. As a result, the maximum weight we can obtain is 5050 (sum of the first 100 numbers). The "weighted" precision sums all the weights of correct answers and divides them by 5050. As a result, in both methods, each query has its own precision that indicates how present the influential artist is in our matches. Finally, we also compute the mean of all the individual precision values obtaining a global measure of the task. In both cases, a random algorithm will get a precision of 25% (one divided by four possible artists).

In order to evaluate the results globally we use Wilcoxon signed-rank to compare the result of one method against the results of randomness. For artist level we compare the precision of each query of our algorithm against the precision of a random algorithm, which is 25%. In case of segment and song

levels, as each query has its own number of possible influential segments, the randomness level is different for each one. The p-value computed with Wilcoxon signed-rank compares our list of RR for each query against a list of RR, result of the random algorithm. The RR of each query of the random algorithm is calculated using the total number of possible influential segments for a concrete query. Table 7 shows the empirical results obtained for each configuration. From this table we can pose some basic research questions.

Comparing Euclidean distance and DTW.

First of all we can see how DTW improves results over the Euclidean distance. Despite that, for instance in song level, Euclidean distance is able to detect as many songs as DTW in the HPCP configuration, it yields lower MRR than DTW HPCP, which means that these matches are found in very far positions. At the same time, for a more restrictive task, such as finding a specific segment, the performance of Euclidean distance is much worse than the rest of configurations. Finally, for artist detection, the p-value of Euclidean distances shows that its results are closest to what it could be achieved by chance but not very likely, just 3% or 7% of probabilities. On the other hand, and in the same task, all the p-values of the DTW configurations are very far for being likely to be random.

Weighting descriptors.

As explained in Chapter V, the selected influenced segments contain different idiosyncratic and unique traits of the genre. They include timbral, tonal and dynamics elements. The analysis of the list of RR for each configuration reveals that the detected segments change depending on the descriptor used. Comparing the list of RR of the three configurations with weighted descriptors, there are some segments that are correctly detected in the three configurations but some others change. Listening to the segment that differs from one configuration to another it can be appreciated how a musical dimension has more presence than others. A If we look at the MRR we can appreciate how MFCC is the most confident descriptor. Its high MRR value indicates that most of the correct matches are found at the begging of the list. On the other hand, with the Loudness configuration the algorithm can detect even more correct segments than the MFCC configuration but its MRR values are lower than the one for MFCC. It indicates that the correct match is found in more distant positions of the output list.

Finally, opposite to what we expected, the configuration where HPCP has more weight than the rest of the descriptors has the worst performance. There are two possible explanations, technical and conceptual. From a technical point of view, it can be possible that the complex harmonies, fast solos and rich melodies cannot be properly modelled. Listening to the found connections, it can be appreciated that correct matches for this descriptor tend to fit with clear harmonic progressions with simple melodies. At the same time, the tonal complexity of the genre can end up with a scenario where most of the components have high values, complicating the comparison. On the other hand, from a conceptual point of view, the influence of tonal aspects is veiled and not

direct. It is common to have musical quotations to specific harmonic progressions or melodies. It is also possible to listen to an instrument playing a similar chord progression or melodies but normally the whole tonal context changes. Thus, tonal relations are hidden by other tonal aspects. Although we, humans, are able to detect these connections without taking into account the tonal context, our approach cannot do that. It only relies on the tonal information given the same weight to every aspect. If two melodies are similar but their context totally different, the distance between the two passages will be large.

Using a standard configuration gives the best result. It is consistent with our previous results. As said, there are some segments that are detected with one configuration but not with others. Using a configuration where all the involved descriptors are equally balanced allows for an expansion of the range of possible results. Contrastingly, the smaller MRR values observed for the standard configuration with respect to MFCC indicate that although we are able to detect more connections, the correct ones are not located at the beginning of our list.

Comparing three levels of evaluation: segment, song and artist.

The lesser restrictive criteria, the best results are obtained. Due to the subjectivity of the ground-truth the most reliable results are those computed for artist. It is consistent with our perception of influence. When we connect musical elements with its possible influential segments, first of all we think in an artist, then in a possible influential song and finally we could be able, in some cases, to spot on a specific segment. Influential connections increase their subjectivity as deep as we go into this process (artist -> song -> excerpt). The deeper we go, the more subjective the connections are. The step of going from artist to concrete song is especially critical because normally the main traits of an artist are presented in different songs and each person connects them differently.

After a manual analysis of the queries on which the song is correctly detected but not its segments we observe two scenarios. In the first and most common one, the algorithm finds connections with different versions of the annotated segment. It is common to discover connections with other version of the influential element or just with the same influential element in a different part of the annotated one. Moreover, there are cases in which the algorithm connected a query with totally different segments than the annotated one. This scenario is very likely to occur with songs that have a duration longer than 10 minute. Listening to these results we got interesting surprises by influential segments not previously thought/annotated. But in some other cases the algorithm connects the query with parts of the song that do not make sense, at least from our musical (debatable indeed) point of view.

Configuration	Segment				Song				Artist					
	MRR	**STD**	**N**[1]	**p-value**	**MRR**	**STD**	**N**	**p-value**	**Precision**	**STD**	**p-value**	**Weighted Precision**	**STD**	**p-value**
Euclidean standard	0.0090337236	0.01258781	24	4.244e-12	0.05865177756	0.16286100	74	6.1163e-15	28.04%	12.98	0.0369	27.80%	13.41	0.0752
DTW standard	0.1184559054	0.18823254	68	8.395e-17	0.2644012758	0.35963221	84	8.4224e-19	34.37%	14.87	4.2887e-09	34.92%	16.75	2.7302e-08
DTW HPCP	0.0720938010	0.10547351	53	7.594e-14	0.1982297379	0.33456334	74	5.9909e-16	32.81%	14.17	1.4413e-07	33.51%	16.15	7.8312e-07
DTW MFCC	0.1277858263	0.14672407	58	4.881e-16	0.3089431789	0.41809539	80	1.8810e-17	33.9%	16.81	2.4779e-06	33.98%	18.65	1.4998e-05
DTW Loudness	0.0978996400	0.10553753	55	3.7915e-15	0.2404398035	0.37176064	81	1.4471e-18	35.36%	16.19	2.6959e-09	35.87%	17.63	1.0070e-08
DTW standard background	0.1154496403	0.18438197	68	1.8112e-17	0.2631593407	0.36024088	84	4.0699e-19	34.37%	14.87	4.2887e-09	34.92%	16.75	2.7302e-08

Table 8. Overview with all the results for all the experiments conducted

[1] Number of detected correct queries in the 100 first matches.

Using a background model.

As expected, the results using the background files are similar to the ones calculated with the standard configuration. As explained before, only the 5% of the possible influential segments have been skipped. The fact that the results are the same indicates that there are still segments with common traits to the genre that has not been modelled. On the other hand, the results do not get worse. Thus, any characteristic segment has not been deleted.

Subjective analysis by listening to the algorithm outputs.

During development of this Thesis lots of play-lists have been created and listened to. This has made possible new and interesting hints. As described in Chapter V, in these cases in which it was not a specific influenced segments we have used our algorithm to provide possible candidates. Listening to the result is essential to properly evaluate the system because, as discussed there are lots of different possibilities not annotated in our ground-truth. Although in this thesis we have not involved users (which is essential for both, the creation of the ground-truth and the validation of the results), listening to the results give us an overview of the most common problems.

Length of the query: the constraint of being forced to find influential segments with the same length of the query complicates the problem. Intuitively, we tend to assign labels to segments based on our memories of how specific influential songs sound. This judgment is not based on any duration criterion. It is common to say "this part sounds like the song Red of King Crimson". But looking to both elements (influential and influenced) we realize that the influential element we have connected to the influential one has a duration of 20 seconds whereas we connect it with an 60 seconds' influenced excerpt. This is very likely to occur because also most of the new Prog Rock bands tend to be more structured and repetitive than the four influential one. For this reason most of the queries have a shorter-than-90-seconds length. The query excerpts on which we have found the most relevant result are in those in which the length is within the range of 5 to 30 seconds. With shorter queries, as they do not have enough identity and relevance, the algorithm tends to connect them with common elements of the genre that are dispersed on different artist and songs. In these cases we have a list with many different songs.

Influential elements: analysing the output candidates we observe that there are some influential songs that are more present than others. Listening to the results there are two cases. The first one includes relevant and idiosyncratic elements of an artist. Songs like "Red" and "One more and nightmare" from King Crimson, "The Gates of Delirium" and "And you and I" from Yes, "Tarkus" from ELP and "Supper's Ready" from Genesis are the most present in our output. This observed phenomenon could be the result of the manual selection of the influenced segments, which determine the kind of connection we are searching for. The second scenario includes simple versions of what would be characteristic

features of a band. It is striking the number of connections found with songs from the album “Yes” and “Time and A word” by Yes which are not considered to be their most representative and characteristic albums.

Coherence of the results: although a proper validation by a group of experts in the genre would be needed, the links between musical elements are consistent. Listening to the 10 first matches for each query we discover that acoustic parts are connected to acoustic parts, mellotron passages to mellotron passages, chaotic and noisy sections to chaotic and noisy sections. Despite the connection between these musical elements is coherent, it does not mean that they are influential connections. Such an evaluation would require future expert and user tests. From our experience listening to the results, there are cases on which, though connections are consistent, we will have never established them as an influential relation; but in other cases we have discover ourselves amazed after finding new surprising associations.

As mentioned above, all the ideas exposed in this subsection are extracted from a manual listening of the query results done by the author. They might be taken as possible lines and explanations that describe the behaviour the algorithm, not as facts. All of them have to be corroborated with empirical results computed from quantitative analysis proposed for future work in the next chapter.

To sum up, the results obtained agree that with our basic algorithm we can find some meaningful than can be taken as influential. They have to be ratified by the genre savvy users listening to the connections found a determining its value.

Chapter VI. Discussion, conclusion and future work.

"Funes, no lo olvidemos, era casi incapaz de ideas generales, platónicas. No sólo le constaba comprender que el símbolo genérico de perro abarcara tantos individuos dispares de diversos tamaños y diversa forma; le molestaba que el perro de las tres y catorce (visto de perfil) tuviera el mismo nombre que el perro de las tres y cuarto (visto de frente)."

- Jorge Luis Borges,
Funes el memorioso.

Along this thesis, we have introduced and detailed the problem of influence from a conceptual and computational point of view. The problem has been defined and situated in a conceptual framework exposed, where we analyse the different aspects involved. The main motivation was to find basic musical connections that can be taken as influential relations in Prog Rock music. Here we dedicate some lines to discuss issues about influence and problems associated to our method, as well as possible improvements and future work.

6.1. Discussion.

Influence involves many other tasks from both a musicological and technological viewpoint. It is related to how humans acquire and process information, which implies complex and abstract representative models. From its formalization, we can conclude that its main obstacle is the complexity of the musical relations. There is no clear connection between the influential and the influenced elements. Influential elements can take multiples forms, producing completely different results. These can range from a mere copy to something totally new and original. Knowing the kind of influences that one is seeking is essential to properly address the problem. This is not an easy responsibility. For us, humans, finding connections between ideas and its posterior interpretations is a really complicated task. There are plenty of cases on which experts do not agree. Even artists are unable to verbalize or rationalize all the elements that have influenced them.

Our intuitive way to find influences is based on the storage of high-level (platonic) ideas that represent an artist (or song or genre). These representations store our interpretation of the actual musical elements rather than specific musical motifs (no specific length, fixed harmony or exact timbre). Each person constructs its own interpretation. Thus, the original musical elements that characterize a group, genre or song are transformed to the "musical idea we have of an artist." When we determine that a musical element has been influenced by another one, it is because we are able to recognize a "version" (direct or indirect) of the idea that we have built for an artist (or song or genre) in a posterior artist (or song or genre).

On the contrary, our algorithm tries to find specific segments that have similarity to other segments. This approach is not intuitive and some times is contrary to how we find influences. During the creation of the ground-truth we

have appreciated this difficulty. Determine if a piece of music "sounds like this or that group" is relatively simple. But finding a specific example that demonstrates this relationship is an arduous task. One seems to have a very clear idea of the possible segment influential, but once we hear it, it turns out that it is not as clear as we have thought. Every time you hear the influenced segment new connections come to your mind. With every listening the connections change and what seemed clear is now diffuse. Reviewing potential influential songs, new segments appear. At the end, you are not sure if connections really exist or if they are just inventions.

Despite this non-intuitive approach (and probably because of it), the algorithm finds connections not thought before. This adds value to the system since it is not simply a confirmation of something known but also a discovery of new experiences. This aspect is the most rewarding one. Especially when you surprise yourself finding connections that you would never have imagined even though these connections are now very simple and limited due to the restrictions imposed and the actual technology used.

6.1.a. Results.

Hitherto, due to the extreme subjectivity of our ground-truth, questions the validity of the results except for the ones obtained for artists, where the annotations are quite clear. Segment-segment level requires a lot of work. Reducing the potential influential connections to a single one is only valid in cases where the musical relations are extremely clear, which does not occur in most cases. On the other hand, despite their unreliability, results indicate that this basic approach can find relationships that could be taken as influential. These connections require additional verification by genre savvy users to determine whether they can be taken as influential or not.

6.1.b. User, expert, ground-truth and evaluation.

The subjectivity of the problem indicates that the intervention of other users, particularly those skilled in the genre, is essential. Their contribution is critical and must be considered in future studies. There are two aspects in the process where their contribution is crucial: creation of the ground-truth and validation of results.

Our ground-truth is extremely subjective, unreliable (due to use of the algorithm to suggest connections) and without notes about the musical dimension that is sought. At the same time, it has few samples, which possibilities bias in its selection and a low capacity for generalization the problem and the approach. The contribution of users and experts is essential for both, verification of the annotated connections and to provide new relationships and segments. Therefore, its contribution can be divided into two parts. First, in the creation of ground-truth, providing new influential connections and adding tags about the musical dimension most involve in the influential process. Second, in the validation of those connections found for other users in order to

have a measure that indicates the reliability of a particular influential connection.

This information can be acquired either by direct contact with users through a web application where they can listen and add new connections or by data mining to get the information out there on the web to know what experts say. The Prog Rock community is very active and well organized with plenty of webs, review, interviews, books and detailed music analysis.

6.1.c. Similarity as a measurable index of influence.

Although not entirely far-fetched (and in some cases achieving good results) the use of similarity as a measurable index of influence tends to end up in a scenario in which many musical relationships found might be considered as non-influential. This thesis has dealt with this problem by performing a manual selection of the type of connections that are sought by a manual selection of influential groups and influenced segments and the use of background. Yet many of the connections found, although similar, will never be taken as influential. This hypothesis has to be verified by user tests, but our intuition (based on hearing hundreds of examples) makes us think that it is true. That is why we have to pose alternative measures. The construction of large ground-truth verified by experts and users with reliable measures of the connections is essential. Using this ground-truth we can analyse the type of relationships between the influential and influenced elements and determining alternative measurement parameters to determine if a relationship is influential or not. Intuition leads us to believe that each musical dimension has its own way to interact but again it has to be verified. Hence, it is interesting to treat each musical dimension differently. These ideas can be tested whether we have an annotated and verified ground-truth with examples for each musical dimension.

6.1.d. Background.

As showed in Chapter V, the use of background does not change the performance of the algorithm. The idea is crucial to model influence but in our approach is not entirely refined. For example, a third database to model the common elements of the period can be included. The main problem of the background, as it has been computed, is the difficulty to find a threshold. Some future experiments could be conducted to determine a relevant boundary. Different backgrounds per group could put some light on this issue. From a technical perspective, with our implementation, a segment can be skipped if it has a close similarity distance with one segment of the rest of the database. Thus, an idiosyncratic segment can be overridden just because an isolated connection. To improve the model, we would have to include probabilistic models to compute measures that determine if a segment is truly general or not according with its connections (quantity and quality) with other elements of the genre.

6.1.e. Restrictions.

Decisions made during the development of this final master thesis have direct consequences. Using global alignment techniques require the comparison of complete segments. This implies segmenting the songs in pieces forcing us to make a decision on which is the window length used. In our case we chose a size equal to the length of the influential element analysed forcing the influential element to have the same length of the influenced one. This is highly unlikely and complicated, especially in Prog Rock Music, where the actual songs are much more structured and less free than the influential ones. Everything indicates that the problem of influence is ideal for use global alignment comparing a specific query against a whole influential song.

6.1.f. Technical problems with the current implementation.

The current implementation of the algorithm is in a very early stage and has many problems. It is very slow and complex (each step is calculated separately, different operative system are needed, big amount of information, no real database, different version of the same algorithm, little modularity) delaying work. A small change consumes lot of time. To facilitate future approach we must optimize the entire process. There are implementations to reduce the execution time of the DTW, techniques to codify the database to do faster comparison and many improvements and considerations.

6.2. Future work.

As discussed, there are many open issues and ways to improve the work reported here. In this section we summarize them, in addition to mentioning future experiments and ideas that can be derived from this work.

Technical improvements.

- Upgrade the algorithm with implementations that improve the performance of DTW, the integration of all parts in one project and the creation of a database to organize all the information: materials, descriptors, ground-truth, output relations and influential playlists.

- Combination of the descriptors: the distribution of the distance between descriptors seems to be Gaussian. To be mathematically sure we should apply a BOX-COX transformation in order to linearly combined them. Another option is to empirically find the "optimal" weight for each descriptor using a regression model.

- Add new descriptors to describe other musical dimensions not here considered such as rhythm, which is an important element in Prog Rock Music.

- Implementation of local alignment algorithms like Smith-Waterman (SW) to test the kind of connections we can found using as a query a specific influenced segment and as a candidate a whole possible influential song.

Experiments.

- Experiments where we fix a specific length for the influential segments in DTW to quantify its impact on the results. Are the influential elements longer or shorter than the influenced ones?

- Experiments to find an optimal threshold for the background model. What percentage of our influential database contains unique elements? What percentage belongs to common traits of the genre?

- Experiments with users to quantify the percentage of connections found with our algorithm are influential. How good is similarity as a measurable index of influences?

- Experiments with costume configurations to determinate what musical factors are more involved in our perception of influence.

Databases.

- A revision of our song database increasing the collection, primarily the influenced queries. There are plenty of resources available on Internet that can be used. We need to introduce tags to quantize the involved musical facets. It will helpful to integrate the song database in an actual database taking advantage of its benefits.

- A revision of the annotated ground-truth increasing and validating the annotations for other users.

Ideas.

- New indexes for measuring influence. Instead of trying to find influential connections using arbitrary measurable indexes, we can used the big annotated ground-truth verified by expert previously discussed for analysing and quantifying real influential-influenced connections to determine possible measurable index of influence.

- Background model. A third dataset to model the common traits of the period can be included. New implementation to model the relation of every possible influential musical element with its coetaneous in order to better determine if it is unique or belong to the general traits of the genre.

- New ways of evaluate the results using data mining and user tests. A possible crowdsourcing[26] evaluation using Curio[27] system build by Edith Law[28].

[26] http://www.wired.com/wired/archive/14.06/crowds.html

6.3. Conclusions.

During the development of this thesis we have discussed the problem of influence from a conceptual and a technical point of view. First of all, we have presented a conceptual framework to face the problem of influence describing the aspects that condition influence relations, the different musical levels involved and the wide range of granularities it can have. Then, using this framework, we have particularized the problem to a specific study case: to find musical relations between segments in Prog Rock that can be taken as influential connections.

For this task we have complicated two datasets. The first database includes influential Prog Rock songs corresponding to songs from King Crimson, Yes, Genesis and ELP in the golden period of the genre. The second one a list of possible posterior influenced segments. In order to find possible influential connections we have used similarity as a measurable index of influence. Two different ways to compute similarity has been used: Euclidean distance and DTW. Finally, a list of experiments have been conducted to analyse the behaviour of the algorithm and to verify the connections found.

The following list summaries the main contributions of this work:

- Creation of a contextual framework of the problem of influence.
- Implementation of a basic algorithm that compares segments of songs and measures the degree of similarity to present a list of possible influential connections to that query.
- Compilation of a suitable collection of influential songs and annotated influenced segments.
- Quantitative evaluation of the results.
- A discussion of the problems found proposing new lines of work.

The problem of influence is very complex and needs a lot of abstract and adjacent areas. Each of these issues requires a detailed study. This thesis presents an overview and basic study of these aspects not delving into any of them, which gives an overview of the problem and makes us aware of all the difficulties. By contrast, the algorithm presented is very simple and crude, which models only the basic aspect of the problem and does not take full advantage of current technology. Our basic approach is only the first stepping-stone. Influence identification is still a reduced area of research with many things to improve, lot of aspects to consider and much work to do but the results obtained indicate that we are on the right track.

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[27] http://www.crowdcurio.com/
[28] http://scholar.google.es/citations?user=qqftscAAAAAJ&hl=en

Chapter VII. Bibliography.

7. Bibliography.

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Appendix. Music collections.

Appendix.

This appendix provides a list of the songs used in our datasets. It is divided in two sections: influential songs and the ground-truth used.

1. Influential songs.

Artist	Name	Album	Year	Duration	Database
ELP	The Barbarian	Emerson, Lake & Palmer	1970	04:34	ELP_70ELP_1TheBarbarian
ELP	Take A Pebble	Emerson, Lake & Palmer	1970	12:36	ELP_70ELP_2TakeAPebble
ELP	Knife-Edge	Emerson, Lake & Palmer	1970	05:08	ELP_70ELP_3Knife-Edge
ELP	The Three Fates	Emerson, Lake & Palmer	1970	07:45	ELP_70ELP_4TheThreeFates
ELP	Tank	Emerson, Lake & Palmer	1970	06:54	ELP_70ELP_5Tank
ELP	Lucky Man	Emerson, Lake & Palmer	1970	04:36	ELP_70ELP_6LuckyMan
ELP	Tarkus	Tarkus	1971	20:42	ELP_71Tarkus_1Tarkus
ELP	Jeremy Bender	Tarkus	1971	01:50	ELP_71Tarkus_2JeremyBender
ELP	Bitches Crystal	Tarkus	1971	03:58	ELP_71Tarkus_3BitchesCrystal
ELP	The Only Way (Hymn)	Tarkus	1971	03:49	ELP_71Tarkus_4TheOnlyWay
ELP	Infinite Space (Conclusion)	Tarkus	1971	03:21	ELP_71Tarkus_5InfiniteSpace
ELP	Time And A Place	Tarkus	1971	03:02	ELP_71Tarkus_6ATimeAndAPlace
ELP	Are You Ready Eddy?	Tarkus	1971	02:11	ELP_71Tarkus_7AreYouReadyEddy
ELP	Promenade	Pictures at an Exhibition	1972(1)	01:58	ELP_72(1)Picture_1Promenade
ELP	The Gnome	Pictures at an Exhibition	1972(1)	04:16	ELP_72(1)Picture_2TheGnome
ELP	Promenade	Pictures at an Exhibition	1972(1)	01:23	ELP_72(1)Picture_3Promenade
ELP	The Sage	Pictures at an Exhibition	1972(1)	04:40	ELP_72(1)Picture_4TheSage
ELP	The Old Castle	Pictures at an Exhibition	1972(1)	02:31	ELP_72(1)Picture_5TheOldCastle
ELP	Blues Variation	Pictures at an Exhibition	1972(1)	04:19	ELP_72(1)Picture_6BluesVariation
ELP	Promenade	Pictures at an Exhibition	1972(1)	01:31	ELP_72(1)Picture_7Promenade
ELP	The Hut of Baba Yaga (Part 1)	Pictures at an Exhibition	1972(1)	01:12	ELP_72(1)Picture_8TheHutOfBabaYag 1
ELP	The Curse of Baba Yaga	Pictures at an Exhibition	1972(1)	04:09	ELP_72(1)Picture_9TheCurseOfBabaY ga
ELP	The Hut of Baba Yaga (Part 2)	Pictures at an Exhibition	1972(1)	01:06	ELP_72(1)Picture_10TheHutOfBabaYa a2
ELP	The Great Gates of Kiev	Pictures at an Exhibition	1972(1)	06:37	ELP_72(1)Picture_11TheGreatGatesOf iev
ELP	Nut Rocker	Pictures at an Exhibition	1972(1)	04:24	ELP_72(1)Picture_12NutRocker
ELP	The Endless Enigma (Part One)	Trilogy	1972(2)	06:42	ELP_72(2)Trilogy_1TheEndlessEnigma
ELP	Fugue	Trilogy	1972(2)	01:57	ELP_72(2)Trilogy_2Fugue
ELP	The Endless Enigma (Part Two)	Trilogy	1972(2)	02:03	ELP_72(2)Trilogy_3TheEndlessEnigma
ELP	From The Beginning	Trilogy	1972(2)	04:16	ELP_72(2)Trilogy_4FromTheBeginnin
ELP	The Sheriff	Trilogy	1972(2)	03:23	ELP_72(2)Trilogy_5TheSheriff
ELP	Hoedown	Trilogy	1972(2)	03:47	ELP_72(2)Trilogy_6Hoedown
ELP	Trilogy	Trilogy	1972(2)	08:54	ELP_72(2)Trilogy_7Trilogy

ELP	Living Sin	Trilogy	1972(2)	03:14	ELP_72(2)Trilogy_8LivingSin
ELP	Abaddon's Bolero	Trilogy	1972(2)	08:09	ELP_72(2)Trilogy_9AbaddonsBolero
ELP	Jerusalem	Brain Salad Surgery	1973	02:45	ELP_73Brain_1Jerusalem
ELP	Toccata	Brain Salad Surgery	1973	07:23	ELP_73Brain_2Toccata
ELP	Still... You Turn Me On	Brain Salad Surgery	1973	02:53	ELP_73Brain_3StillYouTurnMeOn
ELP	Benny The Bouncer	Brain Salad Surgery	1973	02:21	ELP_73Brain_4BennyTheBouncer
ELP	Karn Evil 9 1st Impression Part 1	Brain Salad Surgery	1973	08:37	ELP_73Brain_6KarnEvil91(1)
ELP	Karn Evil 9 1st Impression Part 2	Brain Salad Surgery	1973	04:46	ELP_73Brain_6KarnEvil91(2)
ELP	Karn Evil 9 2nd Impression	Brain Salad Surgery	1973	07:07	ELP_73Brain_7KarnEvil92
ELP	Karn Evil 9 3rd Impression	Brain Salad Surgery	1973	09:07	ELP_73Brain_8KarnEvil93
Genesis	Looking for Someone	Trespass	1970	07:06	Genesis_70Trepass_1LookingForSome e
Genesis	White Mountain	Trespass	1970	06:45	Genesis_70Trepass_2WhiteMountain
Genesis	Visions of Angels	Trespass	1970	06:51	Genesis_70Trepass_3VisionsofAngels
Genesis	Stagnation	Trespass	1970	08:50	Genesis_70Trepass_4Stagnation
Genesis	Dusk	Trespass	1970	04:13	Genesis_70Trepass_5Dusk
Genesis	The Knife	Trespass	1970	08:55	Genesis_70Trepass_6TheKnife
Genesis	The Musical Box	Nursery Cryme	1971	10:30	Genesis_71Nursey_1TheMusicalBox
Genesis	For Absent Friends	Nursery Cryme	1971	01:48	Genesis_71Nursey_2ForAbsentFriends
Genesis	The Return of the Giant Hogweed	Nursery Cryme	1971	08:10	Genesis_71Nursey_3TheReturnOfTheG antHogweed
Genesis	Seven Stones	Nursery Cryme	1971	05:11	Genesis_71Nursey_4SevenStones
Genesis	Harold the Barrel	Nursery Cryme	1971	03:01	Genesis_71Nursey_5HaroldTheBarrel
Genesis	Harlequin	Nursery Cryme	1971	02:56	Genesis_71Nursey_6Harlequin
Genesis	The Fountain of Salmacis	Nursery Cryme	1971	07:54	Genesis_71Nursey_7TheFountainOfSal acis
Genesis	Watcher of the Skies	Foxtrot	1972	07:24	Genesis_72Foxtrot_1WatcherOfTheSki
Genesis	Time Table	Foxtrot	1972	04:47	Genesis_72Foxtrot_2TimeTable
Genesis	Get 'Em out by Friday	Foxtrot	1972	08:37	Genesis_72Foxtrot_3GetEmOutByFrid
Genesis	Can-Utility and the Coastliners	Foxtrot	1972	05:45	Genesis_72Foxtrot_4Can-UtilityAndTheCoastliners
Genesis	Horizon's	Foxtrot	1972	01:41	Genesis_72Foxtrot_5Horizons
Genesis	Supper's Ready	Foxtrot	1972	22:53	Genesis_72Foxtrot_6SuppersReady
Genesis	Dancing with the Moonlit Knight	Selling England by the Pound	1973	08:04	Genesis_73Selling_1DancingWithTheM onlitKnight
Genesis	I Know What I Like (In Your Wardrobe)	Selling England by the Pound	1973	04:09	Genesis_73Selling_2IKnowWhatILike(YourWardrobe)
Genesis	Firth of Fifth	Selling England by the Pound	1973	09:37	Genesis_73Selling_3FirthOfFifth
Genesis	More Fool Me	Selling England by the Pound	1973	03:10	Genesis_73Selling_4MoreFoolMe
Genesis	The Battle of Epping Forest	Selling England by the Pound	1973	11:46	Genesis_73Selling_5TheBattleOfEppin Forest
Genesis	After the Ordeal	Selling England by the Pound	1973	04:16	Genesis_73Selling_6AfterTheOrdeal
Genesis	The Cinema Show	Selling England by the Pound	1973	11:06	Genesis_73Selling_7TheCinemaShow
Genesis	Aisle of Plenty	Selling England by the Pound	1973	01:32	Genesis_73Selling_8AisleOfPlenty

Genesis	The Lamb Lies Down on Broadway	The Lamb Lies Down On Broadway	1974	04:51	Genesis_74Lamb_101TheLambLiesDo nOnBroadway
Genesis	Fly on a Windshield	The Lamb Lies Down On Broadway	1974	02:45	Genesis_74Lamb_102FlyOnAWindshie d
Genesis	Broadway Melody of 1974	The Lamb Lies Down On Broadway	1974	02:11	Genesis_74Lamb_103BroadwayMelody Of1974
Genesis	Cuckoo Cocoon	The Lamb Lies Down On Broadway	1974	02:11	Genesis_74Lamb_104CuckooCocoon
Genesis	In the Cage	The Lamb Lies Down On Broadway	1974	08:15	Genesis_74Lamb_105InTheCage
Genesis	The Grand Parade of Lifeless Packaging	The Lamb Lies Down On Broadway	1974	02:45	Genesis_74Lamb_106TheGrandParade LifelessPackaging
Genesis	Back in N.Y.C.	The Lamb Lies Down On Broadway	1974	05:42	Genesis_74Lamb_107BackInNYC
Genesis	Hairless Heart	The Lamb Lies Down On Broadway	1974	02:13	Genesis_74Lamb_108HairlessHeart
Genesis	Counting out Time	The Lamb Lies Down On Broadway	1974	03:42	Genesis_74Lamb_109CountingOutTim
Genesis	The Carpet Crawlers	The Lamb Lies Down On Broadway	1974	05:15	Genesis_74Lamb_110TheCarpetCrawle
Genesis	The Chamber of 32 Doors	The Lamb Lies Down On Broadway	1974	05:41	Genesis_74Lamb_111TheChamberOf3 Doors
Genesis	Lilywhite Lilith	The Lamb Lies Down On Broadway	1974	02:43	Genesis_74Lamb_201LilywhiteLilith
Genesis	The Waiting Room	The Lamb Lies Down On Broadway	1974	05:25	Genesis_74Lamb_202TheWaitingRoon
Genesis	Anyway	The Lamb Lies Down On Broadway	1974	03:07	Genesis_74Lamb_203Anyway
Genesis	The Supernatural Anaesthetist	The Lamb Lies Down On Broadway	1974	02:59	Genesis_74Lamb_204TheSupernatural naesthetist
Genesis	The Lamia	The Lamb Lies Down On Broadway	1974	06:57	Genesis_74Lamb_205TheLamia
Genesis	Silent Sorrow in Empty Boats	The Lamb Lies Down On Broadway	1974	03:08	Genesis_74Lamb_206SilentSorrowInE ptyBoats
Genesis	Colony of Slippermen/ The Arrival/A Visit to the Doktor/The Raven	The Lamb Lies Down On Broadway	1974	08:13	Genesis_74Lamb_207ColonyOfSlipper en
Genesis	Ravine	The Lamb Lies Down On Broadway	1974	02:05	Genesis_74Lamb_208Ravine
Genesis	The Light Dies Down on Broadway	The Lamb Lies Down On Broadway	1974	03:32	Genesis_74Lamb_209TheLightDiesDo nOnBroadway
Genesis	Riding the Scree	The Lamb Lies Down On Broadway	1974	03:57	Genesis_74Lamb_210RidingTheScree
Genesis	In the Rapids	The Lamb Lies Down On Broadway	1974	02:27	Genesis_74Lamb_211InTheRapids
Genesis	It	The Lamb Lies Down On Broadway	1974	04:16	Genesis_74Lamb_212It
King Crimson	21st Century Schizoid Man	In The Court Of The Crimson King	1969	07:20	KCrimson_69Court_1-21stCenturySchizoidMan
King Crimson	I Talk To The Wind	In The Court Of The Crimson King	1969	06:05	KCrimson_69Court_2ITalkToTheWind
King Crimson	Epitaph	In The Court Of The Crimson King	1969	08:47	KCrimson_69Court_3Epitaph
King Crimson	Moonchild	In The Court Of The Crimson King	1969	12:11	KCrimson_69Court_4Moonchild
King Crimson	The Court Of The Crimson King	In The Court Of The Crimson King	1969	09:22	KCrimson_69Court_5TheCourtOfTheC msonKing

King Crimson	Peace - A Beginning	In The Wake Of Poseidon	1970(1)	00:49	KCrimson_70(1)Poseidon_1PeaceABe nning
King Crimson	Pictures Of A City	In The Wake Of Poseidon	1970(1)	08:03	KCrimson_70(1)Poseidon_2PicturesOf City
King Crimson	Cadence And Cascade	In The Wake Of Poseidon	1970(1)	04:27	KCrimson_70(1)Poseidon_3CadenceA Cascade
King Crimson	In The Wake Of Poseidon	In The Wake Of Poseidon	1970(1)	07:56	KCrimson_70(1)Poseidon_4InTheWak OfPoseidon
King Crimson	Peace - A Theme	In The Wake Of Poseidon	1970(1)	01:15	KCrimson_70(1)Poseidon_5PeaceAThe me
King Crimson	Cat Food	In The Wake Of Poseidon	1970(1)	04:54	KCrimson_70(1)Poseidon_6CatFood
King Crimson	The Devil's Triangle: a) Merday Morn	In The Wake Of Poseidon	1970(1)	03:46	KCrimson_70(1)Poseidon_7TheDevils iangleA
King Crimson	The Devil's Triangle: b) Hand Of Sceiron	In The Wake Of Poseidon	1970(1)	04:01	KCrimson_70(1)Poseidon_8TheDevils iangleB
King Crimson	The Devil's Triangle: c) Garden Of Worm	In The Wake Of Poseidon	1970(1)	03:45	KCrimson_70(1)Poseidon_9TheDevils iangleC
King Crimson	Peace - An End	In The Wake Of Poseidon	1970(1)	02:04	KCrimson_70(1)Poseidon_10PeaceAnE d
King Crimson	Cirkus	Lizard	1970(2)	06:42	KCrimson_70(2)Lizard_1Cirkus
King Crimson	Indoor Games	Lizard	1970(2)	05:35	KCrimson_70(2)Lizard_2IndoorGames
King Crimson	Happy Family	Lizard	1970(2)	04:14	KCrimson_70(2)Lizard_3HappyFamily
King Crimson	Lady Of The Dancing Water	Lizard	1970(2)	02:48	KCrimson_70(2)Lizard_4LadyOfTheD cingWater
King Crimson	Lizard	Lizard	1970(2)	23:28	KCrimson_70(2)Lizard_5Lizard
King Crimson	Formentera Lady	Island	1971	10:17	KCrimson_71Island_1FormenteraLady
King Crimson	Sailor's Tale	Island	1971	07:34	KCrimson_71Island_2SailorsTale
King Crimson	The Letters	Island	1971	04:29	KCrimson_71Island_3TheLetters
King Crimson	Ladies Of The Road	Island	1971	05:34	KCrimson_71Island_4LadiesOfTheRoa
King Crimson	Prelude/ Song Of The Gulls	Island	1971	04:16	KCrimson_71Island_5Prelude
King Crimson	Islands	Island	1971	12:02	KCrimson_71Island_6Islands
King Crimson	Larks' Tongues in Aspic, Part 1	Larks' Tongues in Aspic	1973	13:35	KCrimson_73Larks_1LarksTongues1
King Crimson	Book of Saturday	Larks' Tongues in Aspic	1973	02:56	KCrimson_73Larks_2BookOfSaturday
King Crimson	Exiles	Larks' Tongues in Aspic	1973	07:41	KCrimson_73Larks_3Exiles
King Crimson	Easy Money	Larks' Tongues in Aspic	1973	07:53	KCrimson_73Larks_4EasyMoney
King Crimson	The Talking Drum	Larks' Tongues in Aspic	1973	07:26	KCrimson_73Larks_5TheTalkingDrum
King Crimson	Larks' Tongues in Aspic, Part 2	Larks' Tongues in Aspic	1973	07:07	KCrimson_73Larks_6LarksTongues2
King Crimson	The Great Deceiver	Starless And Bible Black	1974(1)	04:02	KCrimson_74(1)Starless_1TheGreatDe iver
King Crimson	Lament	Starless And Bible Black	1974(1)	04:01	KCrimson_74(1)Starless_2Lament
King Crimson	We'll Let You Know	Starless And Bible Black	1974(1)	03:39	KCrimson_74(1)Starless_3WeWillLetY uKnow
King Crimson	The Night Watch	Starless And Bible Black	1974(1)	04:40	KCrimson_74(1)Starless_4TheNightW ch
King Crimson	Trio	Starless And Bible Black	1974(1)	05:40	KCrimson_74(1)Starless_5Trio
King Crimson	The Mincer	Starless And Bible Black	1974(1)	04:09	KCrimson_74(1)Starless_6TheMincer
King Crimson	Starless And Bible Black	Starless And Bible Black	1974(1)	09:10	KCrimson_74(1)Starless_7StarlessAnd bleBlack
King Crimson	Fracture	Starless And Bible Black	1974(1)	11:09	KCrimson_74(1)Starless_8Fracture
King Crimson	Red	Red	1974(2)	06:16	KCrimson_74(2)Red_1Red

King Crimson	Fallen Angel	Red	1974(2)	06:03	KCrimson_74(2)Red_2FallenAngel
King Crimson	One More Red Nightmare	Red	1974(2)	07:10	KCrimson_74(2)Red_3OneMoreRedNi htmare
King Crimson	Providence	Red	1974(2)	08:10	KCrimson_74(2)Red_4Providence
King Crimson	Starless	Red	1974(2)	12:26	KCrimson_74(2)Red_5Starless
Yes	Beyond And Before	Yes	1969	04:56	Yes_69Yes_1BeyondAndBefore
Yes	I See You	Yes	1969	06:53	Yes_69Yes_2ISeeYou
Yes	Yesterday And Today	Yes	1969	02:52	Yes_69Yes_3YesterdayAndToday
Yes	Looking Around	Yes	1969	04:20	Yes_69Yes_4LookingAround
Yes	Harold Land	Yes	1969	05:46	Yes_69Yes_5HaroldLand
Yes	Every Little Thing	Yes	1969	05:57	Yes_69Yes_6EveryLittleThing
Yes	Sweetness	Yes	1969	04:35	Yes_69Yes_7Sweetness
Yes	Survival	Yes	1969	06:23	Yes_69Yes_8Survival
Yes	No Opportunity Necessary, No Experience Needed	Time And A Word	1970	04:53	Yes_70TimeWord_1NoOpportunity
Yes	Then	Time And A Word	1970	05:50	Yes_70TimeWord_2Then
Yes	Everydays	Time And A Word	1970	06:12	Yes_70TimeWord_3Everydays
Yes	Sweet Dreams	Time And A Word	1970	03:52	Yes_70TimeWord_4SweetDreams
Yes	The Prophet	Time And A Word	1970	06:39	Yes_70TimeWord_5TheProphet
Yes	Clear Days	Time And A Word	1970	02:09	Yes_70TimeWord_6ClearDays
Yes	Astral Traveler	Time And A Word	1970	05:57	Yes_70TimeWord_7AstralTraveler
Yes	Time And A Word	Time And A Word	1970	04:40	Yes_70TimeWord_8TimeAndAWord
Yes	Yours Is No Disgrace	The Yes Album	1971(1)	09:41	Yes_71(1)TheYes_1YoursIsNoDisgrac
Yes	The Clap	The Yes Album	1971(1)	03:17	Yes_71(1)TheYes_2TheClap
Yes	Starship Trooper	The Yes Album	1971(1)	09:29	Yes_71(1)TheYes_3StarshipTrooper
Yes	I've Seen All Good People	The Yes Album	1971(1)	06:55	Yes_71(1)TheYes_4IHaveSeenAllGoo eople
Yes	A Venture	The Yes Album	1971(1)	03:20	Yes_71(1)TheYes_5AVenture
Yes	Perpetual Change	The Yes Album	1971(1)	08:57	Yes_71(1)TheYes_6PerpetualChange
Yes	Roundabout	Fragile	1971(2)	08:37	Yes_71(2)Fragile_1Roundabout
Yes	Cans and Brahms	Fragile	1971(2)	01:42	Yes_71(2)Fragile_2CansAndBrahms
Yes	We Have Heaven	Fragile	1971(2)	01:40	Yes_71(2)Fragile_3WeHaveHeaven
Yes	South Side of the Sky	Fragile	1971(2)	08:00	Yes_71(2)Fragile_4SouthSideOfTheSk
Yes	Five per Cent for Nothin	Fragile	1971(2)	00:38	Yes_71(2)Fragile_5FivePerCentForNot n
Yes	Long Distance Runaround	Fragile	1971(2)	03:31	Yes_71(2)Fragile_6LongDistanceRuna und
Yes	The Fish (Shindleria Praematurus)	Fragile	1971(2)	02:42	Yes_71(2)Fragile_7TheFish
Yes	Mood for a Day	Fragile	1971(2)	03:01	Yes_71(2)Fragile_8MoodForADay
Yes	Heart of the Sunrise	Fragile	1971(2)	11:29	Yes_71(2)Fragile_9HeartOfTheSunrise
Yes	Close To The Edge	Close To The Edge	1972	18:43	Yes_72Close_1CloseToTheEdge
Yes	And You And I	Close To The Edge	1972	10:09	Yes_72Close_2AndYouAndI
Yes	Siberian Khatru	Close To The Edge	1972	09:01	Yes_72Close_3SiberianKhatru
Yes	The Revealing Science of God - Dance of the Dawn	Tales From Topographic Oceans	1973	22:37	Yes_73Tales_1The Revealing
Yes	The Remembering - High the Memory	Tales From Topographic Oceans	1973	20:53	Yes_73Tales_2TheRemembering
Yes	The Ancient -Giants Under	Tales From Topographic	1973	18:35	Yes_73Tales_3TheAncient

	the Sun	Oceans			
Yes	Ritual - Nous Sommes Du Soleil	Tales From Topographic Oceans	1973	21:52	Yes_73Tales_4Ritual
Yes	The Gates Of Delirium	Relayer	1974	21:56	Yes_74Relayer_1TheGatesOfDelirium
Yes	Sound Chaser	Relayer	1974	09:27	Yes_74Relayer_2SoundChaser
Yes	To Be Over	Relayer	1974	09:19	Yes_74Relayer_3ToBeOver

2. Ground-truth.

Influenced					**Influential**
Song	Artist	Album	Segment	Code	Segment
Rogerthe Tailor	Agents of Mercy	Dramarama	01:59 - 02:47	Genesis_73Selling_2IKnowWhatILike-InYourWardrobe	01:40 - 02:55
Rogerthe Tailor	Agents of Mercy	Dramarama	03:12 - 03:50	Genesis_74Lamb_106TheGrandParadeOfLifelessPackaging	00:00 - 01:05
The Duke Of Sadness	Agents of Mercy	Dramarama	04:16 - 04:46	Genesis_74Lamb_111TheChamberOf32Doors	03:37 - 04:46
The Duke Of Sadness	Agents of Mercy	Dramarama	07:00 - 07:43	Genesis_71Nursey_7TheFountainOfSalmacis	06:24 - 07:01
We Have Been Freed	Agents of Mercy	Dramarama	06:19 - 06:43	Genesis_71Nursey_4SevenStones	03:58 -04:30
Book Of Hours	Anekdoten	Nucleus	00:00 - 01:14	KCrimson_70Poseidon_2PicturesOfACity	04:49 - 06:55
Book Of Hours	Anekdoten	Nucleus	04:02 - 04:48	KCrimson_70Poseidon_9TheDevilsTriangle	00:00 - 01:10
Book Of Hours	Anekdoten	Nucleus	06:12 - 06:57	KCrimson_70Lizard_5Lizard	16:42 - 17:52
Harvest	Anekdoten	Nucleus	01:09 - 01:47	KCrimson_74Red_1Red	03:46 - 05:33
Harvest	Anekdoten	Nucleus	03:25 - 03:53	KCrimson_71Island_6Islands	00:00 - 01:33
Harvest	Anekdoten	Nucleus	03:55 - 04:50	KCrimson_74Red_3OneMoreRedNightmare	05:00 - 07:06
Harvest	Anekdoten	Nucleus	05:40 - 06:40	KCrimson_74Red_2FallenAngel	04:20 - 05:30
Harvest	Anekdoten	Nucleus	00:24 - 01:03	KCrimson_71Island_1FormenteraLady	01:44 - 03:03
Karelia	Anekdoten	Vemod	00:48 - 01:30	KCrimson_70Poseidon_8TheDevilsTriangleB	00:00 - 03:08
Karelia	Anekdoten	Vemod	01:57 - 02:26	KCrimson_74Red_1Red	03:46 - 05:33
Karelia	Anekdoten	Vemod	05:32 - 06:13	KCrimson_73Larks_6LarksTongues2	13:30 - 14:20
Karelia	Anekdoten	Vemod	06:40 - 07:08	KCrimson_70Lizard_3HappyFamily	01:53 - 03:53
Rubankh	Anekdoten	Nucleus	01:25 - 02:10	KCrimson_74Red_3OneMoreRedNightmare	05:00 - 07:06
Rubankh	Anekdoten	Nucleus	02:13 - 02:44	KCrimson_74Red_1Red	03:46 - 05:33
The Flow	Anekdoten	Vemod	04:49 - 05:35	KCrimson_70Lizard_3HappyFamily	01:53 - 03:53
Skogsranden	Anglagard	Epilog	02:45 - 02:52	ELP_70ELP_2TakeAPebble	06:30 - 08:30
Skogsranden	Anglagard	Epilog	03:00 - 03:29	Yes_74Relayer_1TheGatesOfDelirium	13:15 - 15:30
Skogsranden	Anglagard	Epilog	04:10 - 04:43	Yes_73Tales_4Ritual	01:45 - 02:40
Skogsranden	Anglagard	Epilog	07:10 - 08:04	Genesis_73Selling_7TheCinemaShow	02:45 - 04:04
Sole Survivor	Asia	Asia	00:00 - 00:44	Yes_72Close_3SiberianKhatru	00:00 - 00:54
Awaken The Sleeping	Beardfish	Destined Solitaire	00:13 - 00:34	ELP_71Tarkus_6ATimeAndAPlace	02:08 - 02:45
Awaken The Sleeping	Beardfish	Destined Solitaire	00:35 - 00:54	ELP_71Tarkus_1Tarkus	12:10 - 12:38
Awaken The Sleeping	Beardfish	Destined Solitaire	01:27 - 02:04	Yes_71TheYes_6PerpetualChange	05:10 - 06:36
Awaken The Sleeping	Beardfish	Destined Solitaire	02:04 - 02:45	Yes_71TheYes_6PerpetualChange	05:10 - 06:36
Destined solitaire	Beardfish	Destined	07:04 - 07:42	KCrimson_74Starless_8Fracture	04:06 - 06:04

		Solitaire			
In Real Life There Is No Algebra	Beardfish	Destined Solitaire	02:28 - 03:00	KCrimson_70Poseidon_6CatFood	01:09 - 03:30
Until You Comply Including Entropy	Beardfish	Destined Solitaire	05:44 - 06:53	Yes_73Tales_4Ritual	11:08 - 12:02
Where The Rain ComesIn	Beardfish	Destined Solitaire	00:00 - 00:54	Yes_71TheYes_6PerpetualChange	05:10 - 06:36
The Fuse	Cario	Times of legends	03:44 - 04:42	ELP_72Trilogy_6Hoedown	01:20 - 03:45
The Fuse	Cario	Times of legends	04:43 - 04:56	ELP_70ELP_5Tank	00:12 - 01:40
The Fuse	Cario	Times of legends	05:22 - 05:42	ELP_73Brain_1Jerusalem	00:00 - 02:45
The Fuse	Cario	Times of legends	05:42 - 06:14	Genesis_74Lamb_203Anyway	02:18 - 02:54
The Fuse	Cario	Times of legends	06:57 - 07:04	ELP_72Trilogy_9AbaddonsBolero	07:30 - 08:09
Somewhere But Yesterday	Citizen Cain	Somewhere but yesterday	11:30 - 13:40	Genesis_72Foxtrot_6SuppersReady	01:59 - 04:12
Naufragio	Dificil equilibrio	Dificil equilibrio	00:59 - 01:17	KCrimson_73Larks_1LarksTongues1	04:35 - 04:53
Naufragio	Dificil equilibrio	Dificil equilibrio	01:24 - 03:03	KCrimson_74Red_3OneMoreRedNightmare	05:00 - 07:06
Chronotheme	Glass hammer	Chronometree	00:00 - 00:40	Genesis_74Lamb_204TheSupernaturalAnaesthetist	00:25 - 02:05
Chronotheme	Glass hammer	Chronometree	01:13 - 01:51	Yes_71TheYes_3StarshipTrooper	06:15 - 09:27
Chronotheme	Glass hammer	Chronometree	01:51 - 02:15	Genesis_74Lamb_210RidingTheScree	00:47 - 02:10
Harvest Of Souls	IQ	Dark matter	17:50 - 18:35	Genesis_72Foxtrot_6SuppersReady	00:00 - 06:10
Harvest Of Souls	IQ	Dark matter	18:35 - 19:10	Genesis_70Trepass_6TheKnife	05:20 - 07:00
Harvest Of Souls	IQ	Dark matter	19:10 - 19:45	Genesis_70Trepass_6TheKnife	07:10 - 08:05
Medley	Jordan Rudess	The Road Home	00:00 - 01:55	Yes_74Relayer_1TheGatesOfDelirium	16:07 - 21:50
Medley	Jordan Rudess	The Road Home	01:55 - 04:05	Genesis_72Foxtrot_6SuppersReady	00:00 - 06:10
Medley	Jordan Rudess	The Road Home	04:05 - 06:15	KCrimson_69Court_2ITalkToTheWind	00:00 - 02:55
Medley	Jordan Rudess	The Road Home	06:15 - 08:21	Yes_72Close_2AndYouAndI	08:15 - 10:07
Brothers Keeper	Magellan	Hundred year flood	04:52 - 05:55	KCrimson_74Red_5Starless	10:22 - 12:00
The Great Goodnight 2	Magellan	Hundred year flood	00:00 - 00:21	Genesis_73Selling_6AfterTheOrdeal	00:00 - 00:08
The Great Goodnight 3	Magellan	Hundred year flood	00:00 - 00:20	ELP_70ELP_5Tank	00:13 - 01:05
Grendel	Marillion	Market square heroes	00:28 - 01:29	KCrimson_69Court_3Epitaph	00:43 - 01:44
Grendel	Marillion	Market square heroes	13:06 - 13:50	Genesis_73Selling_6AfterTheOrdeal	02:03 - 03:35
Grendel	Marillion	Market square heroes	15:00 - 15:25	Genesis_74Lamb_105InTheCage	04:15 - 05:25
Grendel	Marillion	Market square heroes	17:17 - 18:07	Genesis_74Lamb_212It	02:50 - 04:15
Market Square Heroes	Marillion	Market square heroes	02:37 - 03:15	Genesis_71Nursey_3TheReturnOfTheGiantHogweed	02:20 - 04:12
Al Mancato Compleanno Di Una	Maxophone	Maxophone	02:46 - 03:25	Genesis_70Trepass_4Stagnation	02:30 - 03:59

Farfalla					
Al Mancato Compleanno Di Una Farfalla	Maxophone	Maxophone	03:44 - 03:53	ELP_71Tarkus_1Tarkus	02:44 - 06:27
Al Mancato Compleanno Di Una Farfalla	Maxophone	Maxophone	05:03 - 05:17	ELP_70ELP_3Knife-Edge	02:40 - 03:21
Fase	Maxophone	Maxophone	02:12 - 02:33	KCrimson_70Poseidon_2PicturesOfACity	04:49 - 06:55
The Apocalypse Concept	Monolith	Monolith	01:07 - 01:27	ELP_72Picture_8TheHutOfBabaYaga1	00:05 - 00:35
The Apocalypse Concept	Monolith	Monolith	01:27 - 01:57	ELP_70ELP_1TheBarbarian	02:51 - 03:30
The Apocalypse Concept	Monolith	Monolith	02:46 - 03:06	ELP_70ELP_5Tank	00:12 - 01:49
Into The Gyre	Motorpsycho	The Death Defying Unicorn	05:05 - 06:07	KCrimson_74Red_1Red	03:46 - 05:33
Starhammer	Motorpsycho	Heavy Metal Fruit	09:56 - 10:50	KCrimson_73Larks_1LarksTongues1	03:05 - 07:05
The Hollow Lands	Motorpsycho	The Death Defying Unicorn	00:00 - 01:00	KCrimson_74Red_1Red	03:46 - 05:33
The Hollow Lands	Motorpsycho	The Death Defying Unicorn	04:04 - 04:58	KCrimson_69Court_1-21stCenturySchizoidMan	02:08 - 04:35
WBAT	Motorpsycho	Heavy Metal Fruit	01:20 - 02:11	KCrimson_73Larks_1LarksTongues1	03:05 - 07:05
Am I Really Losing You	Pendragon	The window of life	02:47 - 03:27	Yes_74Relayer_1TheGatesOfDelirium	16:07 - 21:50
The Walls Of Babylon	Pendragon	The window of life	04:50 - 05:05	Genesis_72Foxtrot_1WatcherOfTheSkies	02:00 - 03:53
The Walls Of Babylon	Pendragon	The window of life	04:15 - 04:46	Genesis_72Foxtrot_1WatcherOfTheSkies	02:00 - 03:53
Blacksun	Pilgrym	Pilgrimage	01:13 - 01:30	KCrimson_74Red_5Starless	06:40 - 08:43
Blacksun	Pilgrym	Pilgrimage	02:30 - 03:01	KCrimson_69Court_3Epitaph	03:58 - 04:55
Momo	Rael	Mascaras Urbanas	00:00 - 00:52	Genesis_71Nursey_2ForAbsentFriends	00:00 - 01:47
Momo	Rael	Mascaras Urbanas	01:42 - 02:36	Genesis_73Selling_6AfterTheOrdeal	01:11 - 02:14
Momo	Rael	Mascaras Urbanas	03:30 - 03:48	Genesis_73Selling_1DancingWithTheMoonlitKnight	03:42 - 05:44
Momo	Rael	Mascaras Urbanas	04:05 - 04:30	Genesis_72Foxtrot_4Can-UtilityAndTheCoastliners	02:12 - 03:12
Momo	Rael	Mascaras Urbanas	06:36 - 07:36	Genesis_72Foxtrot_6SuppersReady	09:52 - 11:05
Momo	Rael	Mascaras Urbanas	07:58 - 08:20	Genesis_74Lamb_209TheLightDiesDownOnBroadway	02:36 - 03:32
Beware Of Darkness	Spock"s Beard	Beware Of Darkness	00:00 - 01:30	Yes_73Tales_4Ritual	00:00 - 01:45
The Doorway	Spock"s Beard	Beware Of Darkness	00:00 - 01:00	ELP_70ELP_4TheThreeFates	01:50 - 04:30
The Doorway	Spock"s Beard	Beware Of Darkness	10:00 - 11:35	Yes_73Tales_2TheRemembering	13:10 - 15:50
The Great Nothing	Spock"s Beard	V	11:52 - 13:18	Genesis_72Foxtrot_1WatcherOfTheSkies	02:00 - 03:53
Walking On The Wind	Spock"s Beard	Beware Of Darkness	00:21 - 00:45	ELP_70ELP_3Knife-Edge	02:40 - 03:21
Walking On The	Spock"s Beard	Beware Of	01:32 - 02:19	Yes_69Yes_5HaroldLand	04:38 - 05:46

Wind		Darkness			
Mechanical Bride	Steve Hackett	To Watch The Storms	03:27 - 03:49	KCrimson_69Court_1-21stCenturySchizoidMan	04:39 - 05:23
Drive Home	Steven Wilson	The Raven That Refused To Sing (and other stories)	03:52 - 04:39	KCrimson_71Island_6Islands	00:00 - 05:30
Drive Home	Steven Wilson	The Raven That Refused To Sing (and other stories)	04:39 - 05:07	KCrimson_74Starless_2Lament	03:24 - 07:00
Luminol	Steven Wilson	The Raven That Refused To Sing (and other stories)	00:08 - 01:22	Yes_71Fragile_1Roundabout	00:45 - 03:20 / 07:08 - 08:13
Luminol	Steven Wilson	The Raven That Refused To Sing (and other stories)	01:59 - 02:10	KCrimson_73Larks_6LarksTongues2	03:41 - 04:27
Luminol	Steven Wilson	The Raven That Refused To Sing (and other stories)	04:35 - 04:57	KCrimson_71Island_2SailorsTale	02:30 - 04:30
Luminol	Steven Wilson	The Raven That Refused To Sing (and other stories)	08:30 - 10:00	KCrimson_70Lizard_5Lizard	14:40 - 19:27
End On A High Note	The Flower Kings	Paradox Hotel	00:00 - 01:23	Yes_72Close_2AndYouAndI	00:00 - 02:42
Love Supreme	The Flower Kings	Adam & Eve	01:22 - 01:50	Yes_73Tales_2TheRemembering	17:40 - 18:30
Love Supreme	The Flower Kings	Adam & Eve	02:18 - 03:00	Yes_73Tales_4Ritual	04:48 - 08:48
Love Supreme	The Flower Kings	Adam & Eve	03:27 - 03:40	Yes_71TheYes_1YoursIsNoDisgrace	04:46 - 06:46
Love Supreme	The Flower Kings	Adam & Eve	03:40 - 04:22	Yes_73Tales_1TheRevealing	04:48 - 08:48
Minor Giant Steps	The Flower Kings	Paradox Hotel	00:00 - 01:01	Yes_73Tales_4Ritual	17:20 - 21:52
Minor Giant Steps	The Flower Kings	Paradox Hotel	01:21 - 01:43	Yes_72Close_2AndYouAndI	00:00 - 02:42
Minor Giant Steps	The Flower Kings	Paradox Hotel	01:43 - 02:22	Yes_73Tales_2TheRemembering	13:10 - 15:50
Minor Giant Steps	The Flower Kings	Paradox Hotel	02:22 - 02:42	Yes_73Tales_1TheRevealing	03:30 - 08:00
Minor Giant Steps	The Flower Kings	Paradox Hotel	06:12 - 06:43	Yes_72Close_2AndYouAndI	00:32 - 01:18 / 02:52 - 03:23
Minor Giant Steps	The Flower Kings	Paradox Hotel	08:59 - 09:39	Yes_72Close_2AndYouAndI	00:32 - 01:18 / 02:52 - 03:23
Minor Giant Steps	The Flower Kings	Paradox Hotel	10:30 - 10:49	Genesis_70Trepass_4Stagnation	02:30 - 03:59
Timelines	The Flower Kings	Adam & Eve	00:07 - 01:00	Yes_74Relayer_1TheGatesOfDelirium	14:40 - 19:27
Timelines	The Flower Kings	Adam & Eve	02:41 - 03:00	KCrimson_70Poseidon_4InTheWakeOfPoseidon	04:34 - 06:45
Timelines	The Flower Kings	Adam & Eve	06:19 - 07:12	Yes_74Relayer_1TheGatesOfDelirium	13:15 - 15:30
InertiaticESP	The Mars Volta	De-Loused in the Comatorium	02:16 - 02:35	KCrimson_74Red_2FallenAngel	01:40 - 03:28

SoaringOn	The Watch	Timeless	00:00 - 00:30	Genesis_72Foxtrot_4Can-UtilityAndTheCoastliners	00:00 -01:08
Thunder Has Spoken	The Watch	Timeless	03:15 - 03:43	Genesis_73Selling_2IKnowWhatILike-InYourWardrobe	01:40 - 02:55
All Of The Above	Transatlantic	SMPTe	02:56 - 03:17	Yes_73Tales_4Ritual	09:00 - 13:42
Duel With The Devil	Transatlantic	Bridge Across Forever	02:33 - 02:55	Yes_73Tales_2TheRemembering	18:30 - 18:48
Duel With The Devil	Transatlantic	Bridge Across Forever	07:27 - 07:48	Yes_72Close_2AndYouAndI	00:32 - 01:18 / 02:52 - 03:23
Duel With The Devil	Transatlantic	Bridge Across Forever	16:12 - 16:39	Yes_74Relayer_1TheGatesOfDelirium	13:15 - 15:30
Duel With The Devil	Transatlantic	Bridge Across Forever	21:17 - 23:18	Yes_73Tales_4Ritual	09:00 - 13:42
Duel With The Devil	Transatlantic	Bridge Across Forever	23:45 - 24:15	Yes_73Tales_1TheRevealing	03:30 - 08:00
Stranger In Your Soul	Transatlantic	Bridge Across Forever	17:39 - 18:13	Genesis_74Lamb_212It	02:50 - 04:15
Stranger In Your Soul	Transatlantic	Bridge Across Forever	18:13 - 18:48	Yes_73Tales_4Ritual	02:50 - 04:49
Suite Charlotte Pike	Transatlantic	Bridge Across Forever	10:31 - 10:42	Yes_73Tales_4Ritual	02:50 - 04:49
End-or-fin	Unifaun	Unifaun	02:50 - 03:06	Genesis_74Lamb_102FlyOnAWindshield	01:10 -02:45