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Reducing bias in the probabilistic evaluation of Audio Music Similarity

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To my beloved brother Julio,
who was my biggest supporter…

Abstract

This thesis work conduits research toward the estimation of relevance judgments for the task of Audio Music Similarity in the context of MIREX. It is intended to improve and support the evaluation experiments run for this task from the point of view of efficiency, studying different probabilistic models and methods with the aim of reducing the cost of the annotation process. Therefore, by doing better estimations of relevance judgments, using all the tools at hand (research, literature, technology) the time used by people performing this task can be utilized in others activities.

Content

Chapter 1
Introduction

1.1 Information Retrieval

Information retrieval (IR) is the field concerned with representing, searching, and manipulating large collections of electronic text and other human-language data (Buettcher, Cormack and Clarke,2010). A user has an information need and use an IR system in order to retrieve relevant information from a document collection.

IR systems are boundless and even essential nowadays since they faciliate daily life of people supporting activities in businness, enternainment, education, medical services, and so on. Web services engines like Google, Yahoo, among others are the most popular web IR services for their great capacity of converging information from different sources. Music IR systems like Shazam, implementing music identification technology are quite popular and useful today.

These systems have been used prior the invention of computers. Before 1940's intelligence and commercial retrieve systems where already implemented and just until the appearance of the first computer-based systems, mechanical and electro-mechanical devices performed the retrieve functions. With the generalization of the computers, IR technics grew up as the increase of storage and processor speed allowed managing bigger datasets (Sanderson, M., & Croft, W. B, 2012).

IR has been widely used through the story from several fields: text and cross-language, image and multimedia, speech and music (Manning, C. D., Raghavan, P., & Schütze, H, 2008). In the case of music, Music Information Retrieval (MIR) is concerned on the extraction and inference of meaningful features of music, it's indexing and the development of different search and retrieval schemes (Downie, J. S, 2003). It started with the analysis of symbolic representations of songs (mostly MIDI scores); with the evolution of computing systems during the early

2000’s, signal processing was also included permitting the extraction of features directly from the audio. (Manning, C. D., Raghavan, P., & Schütze, H, 2008). These features are pitch, temporal, harmonic, timbral, editorial, and textual and bibliographic facets.

1.2. Information Retrieval Evaluation

Evaluation has come to play a critical role in information retrieval research (Downie, 2002) as it allows to measure how successfully an information retrieval system meets the goal of assessing users to fulfill their information needs. The IR community has paid a lot of attention to the topic, implementing evaluation standards and experimental rigor on investigations, which have been effective in moving the field forward. Music Information Retrieval initially followed the evaluation practices of text; however, not enough research has been done to properly know when this approach can be fully applied or not because music, unlike text has, a complex nature.

1.2.1 Early Work in Text Information Retrieval Evaluation

Evaluation in Text Information Retrieval has been the focus of a lot of research:

- The *Cranfield Project 2* (1962-1966) was an experiment accomplished by Cyril Cleverdon (Cleverdon, 1991) and considered as the basis that shaped the form that IR evaluation will take for the next years. In this project, experiments were conducted in order to test and compare different search strategies in a controlled laboratory environment (test collection).

- The *MEDLARS* (Medical Literature Analysis and Retrieval System) Demand Search Service (1966-1967) was one of the early operational computer-based retrieval systems. It considered the evaluation of a complete system from a user perspective, taking into consideration the user requirements (Lancaster, 1968).

- The *SMART project* (1961-1995) (System for the Mechanical Analysis and Retrieval of Text) was created both as a retrieval tool and as a vehicle for evaluating the effectiveness of a large variety of automatic search and analysis techniques, where the main evaluation viewpoint taken was the user (Kent, Lancour, Daily, 1980).

- *TREC* (Text Retrieval Conference) [1] started (1992) as an annual venue to support research within the information retrieval community by providing the necessary infrastructure for large-scale evaluation of text retrieval methodologies.

- *NTCIR* (National Institute of Informatics- Testbeds and Community for Information access Research) (1999) provided almost the same infrastructure than TREC but for Asian languages.

- *CLEF* [2] (Conference and Labs of the Evaluation Forum) (2000) was created to promote research, innovation, and development of information access systems with an emphasis on multilingual and multimodal.

- *INEX* (Evaluation of XML retrieval) (2002), which focuses on structured information.

1.2.2 Early Work in Music Information Retrieval Evaluation

Some initiatives towards the development of Music Information Retrieval evaluation frameworks took place. The organization of the first International Symposium on Music Information Retrieval *(ISMIR)* in 2000, with the intention of bringing together the MIR research community into one location to treat among other topics, the creation of formal evaluation standards for MIR (Downie, 2000) was one of them. As a consequence, some workshops on the creation of standardized test

[1] http://trec.nist.gov/overview.html

[2] http://www.clef-initiative.eu/web/clef-initiative/home

collections, tasks and metrics for music digital library (MDL) and Music Information Retrieval (MIR) Evaluation, were placed in July 2002 at the ACM/IEEE Joint Conference on Digital Libraries. The outcome of these workshops was the recognition by the Music IR community's of the creation of a periodic evaluation forum for Music Information Retrieval systems. The story of MIR evaluation has been shaped since then:

- During the 5th edition of the ISMIR in 2004, placed in Barcelona, Spain, an Audio Description Contest (ADC) [3] was realized. It proposed some tasks in order to define evaluation and statistical methods to compare systems.

- In 2005, the *MIREX* [4] *(Music Information Retrieval Evaluation eXchange)* run for the first time as the community-based framework for the formal evaluation of Music Information Retrieval (MIR) systems and algorithms. MIREX is coordinated and managed by the International Music Information Retrieval Systems Evaluation Laboratory (IMIRSEL) at the University of Illinois at Urbana- Champaign.

- *MusicClef*, which run from 2011-2013 covered multimodal music tagging (Orio, Liem, Peeters, & Schedl, 2012) and focus evaluation on professional application scenarios.

- The *Million Song Dataset Challenge* (*MSD*, 2012) was created to overcome music dataset sharing limitations (Bertin-Mahieux, Ellis, Whitman, & Lamere, 2011). With this approach, researchers could grant access to a number of features but not to the algorithm that performs the process, neither to the audio.

- *Quaero-Eval*, inspired by NIST and MIREX evaluations, since 2012 focuses on audio and music processing. In this venue the tasks are agreed first with the participants and then a common repository is shared. The algorithms are run in a

[3] http://ismir2004.ismir.net/ISMIR_Contest.html
[4] http://www.music-ir.org/mirex/wiki/

test sets with evaluation frameworks by an independent body that does not participate in the evaluation process.

- *MediaEval*, 2010, is a inititiave focuses in multimodal approaches involving human and social aspects of multimedia e.g., speech recognition, multimedia content analysis, music and audio analysis, user-contributed information (tags, tweets), etc. [5].

Fig 1 graphically encompasses both text and music evaluation initiatives.

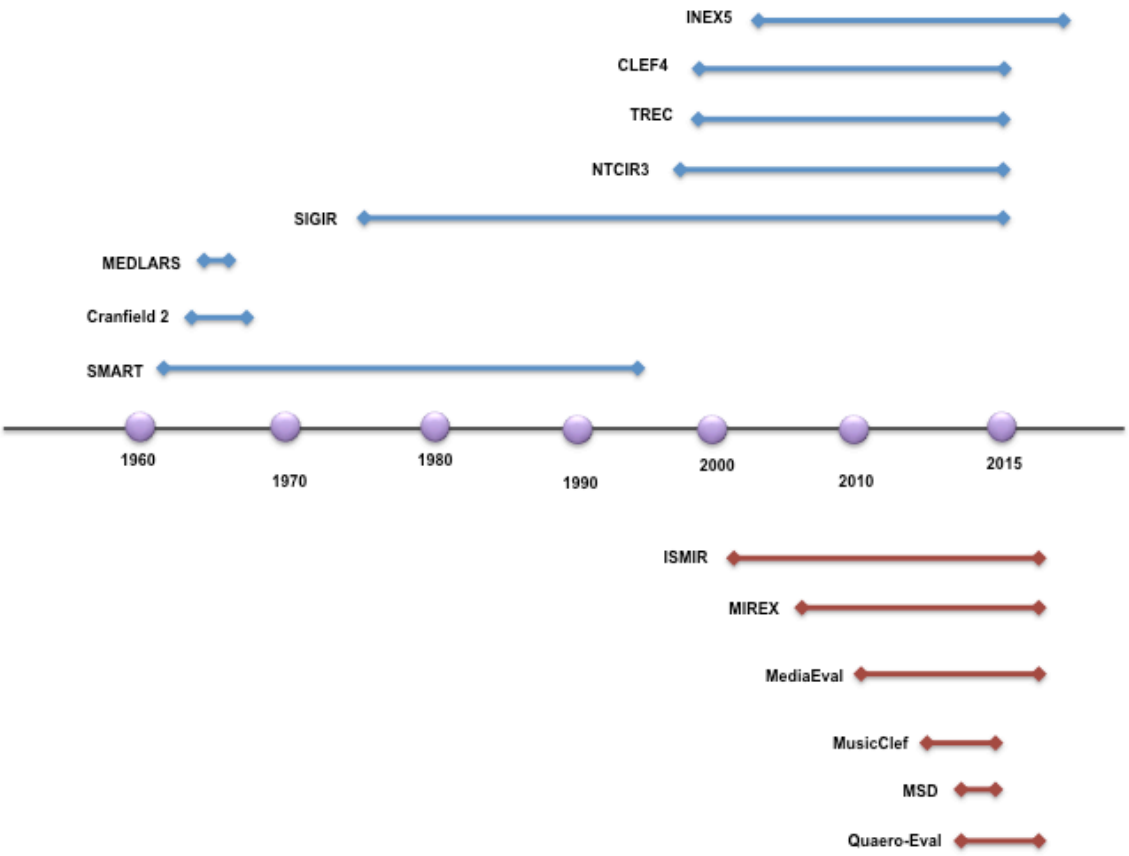


Fig 1. Timeline of Evaluation in Text IR (top) and Music IR (bottom).

[5] http://www.multimediaeval.org/about/

1.3. Audio Music Similarity

Audio Music Similarity (AMS) deals with the challenge of discovering similar songs. It is generally used in MIR task such as music recommendation, playlist generation or plagiarism detection. AMS is one of the most important tasks in MIR and has participated in MIREX since 2006, evaluating so far 85 systems. Furthermore, the same document collection with 7,000 audio documents has been used since 2007.

In the context of MIREX this task resembles the Text IR scenario: for a given audio clip (the query), a system returns a list of songs from a corpus (candidate songs), sorted by their musical similarity to the query.

1.4 Importance of Evaluation in Music Information and Retrieval and Motivation

The Roadmap for Music Information Research, created for the expansion of the context of research from the perspectives of technological advances, stated as one of the main challenges: “vi) promoting best practice evaluation methodology, defining meaningful evaluation methodologies and targeting long-term sustainability of MIR (Serra, Magas, Benetos, Chudy, Dixon, Flexer, Widmer, 2013).

In spite of all initiatives created to widen the scope of evaluation, MIR community is still concern on the way that systems are evaluated because current evaluation practices do not fully allow them to improve as much as they wish (Peeters, Urbano, & Jones, 2012). Furthermore, research by (J Urbano, Schedl, & Serra, 2013), demonstrated that evaluation in ISMIR comprised only 6% of research.

MIREX has been a significant venue to convey the study and establishment of MIR evaluation frameworks; although it was created mirroring TREC methodologies, eventually the Music IR community has realized that not everything from text applies to music. Also their evolution in time have been different; in text for instance, research in evaluation has produced an environment of continuous improvement, which has not been the case in Music IR. It seems that MIR community does not seem to pay as much attention as evaluation as it should.

Particularly, in the case of Audio Music Similarity, few studies about the influence of this TREC-like approach have been done.

The purpose of this thesis is to improve the evaluation process in Audio Music Similarity task in MIREX, studied from the perspective of efficiency with emphasis in the reduction of annotation cost.

The approach to follow twofold: first, study the literature of low cost evaluation in Audio Music Similarity. Second, study models and methods in order to propose a probabilistic framework to estimate relevance judgments in Audio Music Similarity.

Chapter 2
State of the Art

2.1 MIREX Evaluation Process

2.1.1 The Cranfield Paradigm

MIREX provides an evaluation framework for MIR researches to compare, contrast and discuss the result of their algorithms and techniques in the same way than TREC has done it to the text Information retrieval community (Downie et al., 2014). In general, MIREX and TREC use test collection with evaluation measures in order to assess effectiveness of their systems. Test collection are a resource used to test and compare search strategies in a laboratory environment. They are composed by:

1. Collection of *documents* of significant size.
2. Tasks and/or *queries* to be performed on the test collections; and,
3. *Relevance judgments* (qrels) compose of a list of document/pair describing the relevance of documents to topics.

Test collection along with evaluation measures stipulates a simulation of users in a real searching environment. They are generally used by researchers for instance to asses retrieval systems in isolation helping finding failures inside their applications and comparing effectiveness among them.

Both TREC and MIREX follow the Cranfield's paradigm, which in order to asses the performance of systems they implement a test bed consisting in a set of documents ***D***, a set of Information need statements or queries ***Q*** and a set of relevance judgments ***R*** that is compiled by human assessors ***H*** which tell what documents should be retrieved for which query (ground truth). In Music Information

Retrieval one of the task that emulate this behavior is Audio Music Similarity: for a given audio clip (the query), an AMS system returns a list of music pieces considered to be similar to it.

2.1.2. MIREX Evaluation in Audio Music Similarity

For the evaluation of system's effectiveness in the task of Audio Music Similarity in MIREX, both relevance judgments and effectiveness measures are utilized. The relevance judgments in this context are scores given to each query-candidate, representing their similarity. In a In a real scenario, the task of collecting these judgments takes several days or weeks (J Urbano & Schedl, 2013)

In general terms, the evaluation process in MIREX runs as follows:

1. ~50 [6] queries ***Q*** are selected randomly and deliver to the participants.
2. The participant systems retrieved a ranked list with the 10 [7] most similar pieces of music from a music collection ***D.*** These music pieces are 30-second audio clips of music material.
3. All the results are consolidated and evaluated this time using subjective judgments (ground truth) by human assessor using a software tool called "Evaluatron 6000" (E6K).
4. After listening to each query-candidate pair, graders were asked to rate the degree of similarity of the candidate audio excerpt to the query in two ways:

   a) By selecting one of the three BROAD categories of similarity: Not Similar (NS), Somewhat Similar (SS), and Very Similar (VS); and,

   b) By assigning a FINE[8] score between 0.0 (Least similar) and 10.0 (Most

[6] In past editions of MIREX 100 queries were used
[7] In past editions 5 of MIREX similar musical pieces were retrieved
[8] In past editions of MIREX this value was between 0 and 100

similar)

In the case of effectiveness measures, the one reported to assess effectiveness in Audio Music Similarity is **CG@10** (Average Gain after 10 audio documents retrieved) (Downie,Ehmann,Bay,Jones,2010). For an arbitrary system *A*:

$$CG@k = \frac{1}{k}\sum_{i=1}^{k} G_i \qquad (1)$$

Where G_i is the gain of the *i-th* document (song) retrieved - the similarity scored assigned- by graders, using FINE or BROAD scale. After the process of judging is done, the mean score of the gains obtained for every executed query ranks the systems. In order to minimize random effects the Friedman test is run with the Average Gain score of every system and also the Tukey's HSD to correct the experiment-wide Type I error rate. The result of this evaluation is a scale-dependent pairwise comparisons between systems, telling which one is better for the current set of queries *Q.*

2.2 Validity, Reliability and Effectiveness

Validity, reliability and effectiveness are crucial aspects of testing. All IR evaluation experiments need to be guided considering them. This thesis work will be focus from the point of view of efficiency.

Validity is the extent to which the experiment actually determines what the experimenter wishes to determine (Tague-Sutcliffe, 1992). For example, are the selected variables really representatives or the experiment? Or in an evaluation experiment, is system A better than system B?

Reliability is the extent to which the experimental results can be replicated. (Tague-

Sutcliffe, 1992). Thus, if an experiment is replicated, will we obtain similar results? There is a close relationship between validity and reliability. For example, if with one sample system A performs better than system B, but with a different sample is the opposite case, our results then can not be repeatable; hence they will be unreliable.

Efficiency is the extent to which an experiment is effective (valid and reliable) (Tague-Sutcliffe, 1992). For instance, if in an evaluation experiment the ground truth annotation process is inaccurate, the validity of the result can be affected. On the other hand, if this ground truth is not efficient enough (as stated before, this process can be tedious and expensive) the reliability of the results may be impacted as well. Therefore, evaluation experiments must find a balance between validity and reliability and the efficient cost of the annotation process. In this context, do exist others experiments related to low cost annotations process to obtain valid and reliable results?

For this reason, searching in the present literature in response to the latter question is a must.

For example, some studies presents that judgments are affected by *many characteristics of retrieved records and users*, and also by situational factors (Harter, 1996). Therefore, some research shows that *crowdsourcing* is a viable alternative for the creation of relevance judgment; however because of diversity in the backgrounds of the participants, some control methods need to be established (Alonso, Rose, & Stewart, 2008).

Another approach to this matter is to *decrease the necessary number of judgments*. For example, in the *pooling method*, a set of top ***d*** ranked documents returned by participating systems is selected to create the pool of documents that need to be judged (Spärk Jones & van Rijsbergen, 1975). Next, all the duplicates documents into the pool are eliminated (considered non-relevant) and the remaining ones are evaluated by assessors. TREC was the first event that used these partial relevance judgments. This technique has its drawbacks, for example, the existence of defective systems could affect the pooling methods and assessors can evaluate thousands of irrelevant items.

Some research is focus in how *evaluate systems with incomplete judgments* and still be confident with the results of the experiments. The idea is to use random variables to represent relevance judgments; the estimation of these values though can have some degree of error and uncertainty, but also, for most documents they are pretty good.

Let *Gi* being a Random Variable representing the relevance level assigned to document *d*. It presents a multinomial distribution and depends of the scale used by human assessors.

The expectation and variances can be defined as random variables as well:

$$E[G_i] = \sum_{l \in L} \mathrm{P}\ (\mathrm{G_i} = \mathrm{l}) \cdot \mathrm{l}$$

(2)

$$Var\ [G_i] = \sum_{l \in L} \mathrm{P}\ (\mathrm{G_i} = \mathrm{l}) \cdot \mathrm{l}^2 - E[G_i]$$

Every time a human assessor makes an annotation G_i then $E[G_i] \leftarrow g_i$ and $Var\ [G_i] = 0$; it means there is no uncertainty of $[G_i]$.

Research about incomplete judgments can be described as follows:

- (Buckley and Voorhees, 2004) investigated about *evaluation measures robust enough to cater for incomplete judgments;* this research introduced the need of a proper evaluation measure for large collections *bpref,* which calculated system's scores having into account top non-relevant judgments rejected by the traditional pooling method.

- (Carterette, Allan, & Sitaraman, 2006) conduit an investigation about *Minimal Test collections for retrieval evaluation* which has lead into an algorithm that in minimal time evaluate retrieval systems with high degree of confidence and using a minimal number of judgments.

- (Aslam, Yilmaz, 2007) have shown that giving the average precision of a minimal fraction of judge documents using a small number of relevance judgments, the *relevance of the remaining unjudged documents can be inferred*.

- (Carterette, 2007) studied *Robust Test Collections for Retrieval Evaluation*, where a model able to achieve reusability with very small sets of relevance judgments per topic was presented.

- (Carterette & Allan, 2007) proposed the use of *inter-document similarity,* in which document similarity is the key to evaluate retrieval systems with more accurate and robust results, using 99% less relevance judgments than TREC conferences.

As stated before, research in text information retrieval has been meaningful for the creation of continuous improvement in evaluation techniques. In music, this topic has received about half of the attention but still the little research conducted so far, has been significant. For example, in order to create large datasets and reduce the number of annotations needed, low-cost evaluation alternatives have been explored. For instance, (J Urbano & Schedl, 2013) applied Minimal Test Collection (MTC) algorithms to the evaluation of the Audio Music Similarity task in MIREX which reduced the annotation cost to less than 5%. Therefore, the researches investigated how to compare systems when incompletes judgments are available and still be confident about the results.

The idea is to model probabilistically the relevance judgments provided by human assessors using the same concept of random variables. Then, they created models to estimate these relevance judgments as accurately as possible and obtain good estimates of systems effectiveness even with few available judgments.

Let *Gi* being a Random Variable representing the relevance level assigned to document *d*. If the scale is *Fine*, *Gi* can take one of three values and if this is Broad, it can take one of 11 values. From (2):

$$\begin{aligned} E[G_i] &= \sum\nolimits_{l \in L} \mathrm{P}\ (\mathrm{G_i} = \mathrm{l}) \cdot \mathrm{l} \\ Var\ [G_i] &= \sum\nolimits_{l \in L} \mathrm{P}\ (\mathrm{G_i} = \mathrm{l}) \cdot \mathrm{l}^{2} - E[G_i] \end{aligned} \tag{3}$$

Relevance scale *L* where *LBroad* = {0; 1; 2} and *LFine* = {0; 1; … 11}

To estimate the relevance of a document with (3) the $\mathrm{P}\ (\mathrm{G_i} = \mathrm{l})$ needs to be known for each relevance level of *L* (the possible value giving by a human annotator using the scale L). It means, the distribution of *Gi* has to be calculated. The followed approach was the estimation of the relevance of each document individually, creating two models fitted with features about every query-document.

These features are:

i) ***Output-based:*** used when there are no judgments available; represents aspects of the system outputs. (See Table 1). For an arbitrary document *d(song)* and query *q(looking for similarity among songs).*

Feature	Description
fSYS	% of systems that retrieved *d* for *q*. If many systems return *d*, it's expected that *d* is more similar to *q*.
fTEAM	% research teams participating in MIREX that retrieved *d* for *q*
OV	Degree of overlap between systems
aRANK	Average rank in which systems retrieved *d* for *q*. Documents at the top are expected to be more similar to *q*
sGEN	Whether the musical genre of *d* is the same as *q*
fGEN	% of all documents retrieved for *q* that belong to the same musical genre than *d* does
fART	% of documents retrieved for *q* that belong to the same artist as *d* does

Table 1. Output-based features

ii) **Judgment-based features:** Utilizes known judgments (See Table 2)

Feature	Description
aSYS	Average relevance of documents retrieved by the system
aDOC	Average relevance of all the other documents retrieved for *q*
aGEN	Average relevance of all the documents retrieved for *q* that belong to the same genre as *d* does
aART	Average relevance of all the documents retrieved for *q* performed by the same artist as *d*
aART	% of documents retrieved for *q* that belong to the same artist as *d* does

Table 2. Judgment-based features

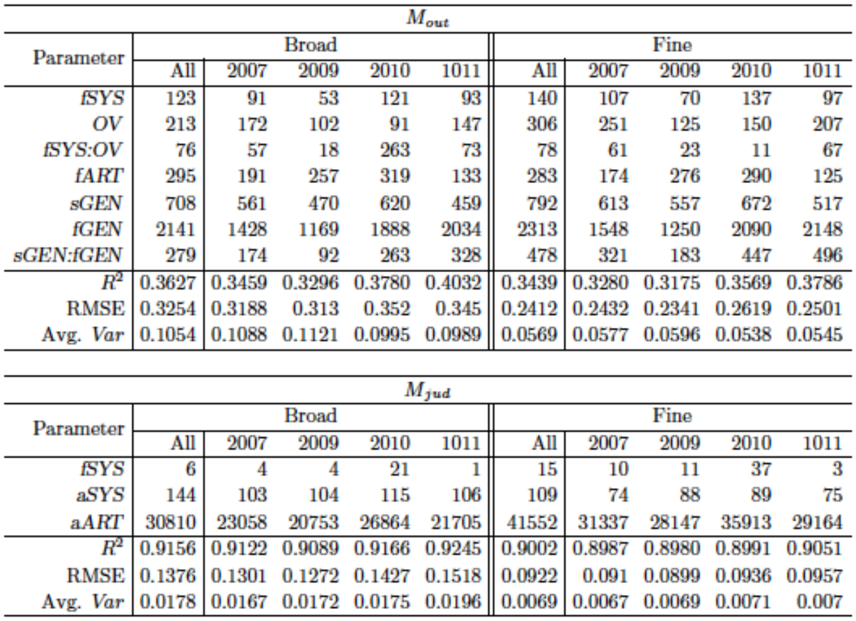
These models were created and fitted with data from the task of AMS in MIREX 2007,2009,2010 and 2011. Only those features that improve the model were selected. R^2 (coefficient of determination) was used to measure the variability of the predicted outputs, where a value of 1 means a perfect fit of the data by the model. Table 3 introduces these results.

Model	Features	R^2 Broad	R^2 Fine
M_{jud}	fTEAM, OV, aSYS, aART	0.9156	0.9002
M_{Out}	fTEAM, OV, sGEN, fART, fGEN	0.3627	0.3439

Table 3. Features for the two models

Table 3 shows that M_{jud} presents good estimates. However, the estimation of G_i has to be calculated after judging some documents to obtain aSYS and aART. For this reason M_{Out} was created in order to estimate G_i even when there is no available judgments. The latter model performed worst than the former.

Table 4 presents statistics of all features for each model. Models for year *Y* are fitted to exclude all judgments for that year.



M_{out}

Parameter	Broad					Fine				
	All	2007	2009	2010	1011	All	2007	2009	2010	1011
fSYS	123	91	53	121	93	140	107	70	137	97
OV	213	172	102	91	147	306	251	125	150	207
fSYS:OV	76	57	18	263	73	78	61	23	11	67
fART	295	191	257	319	133	283	174	276	290	125
sGEN	708	561	470	620	459	792	613	557	672	517
fGEN	2141	1428	1169	1888	2034	2313	1548	1250	2090	2148
sGEN:fGEN	279	174	92	263	328	478	321	183	447	496
R^2	0.3627	0.3459	0.3296	0.3780	0.4032	0.3439	0.3280	0.3175	0.3569	0.3786
RMSE	0.3254	0.3188	0.313	0.352	0.345	0.2412	0.2432	0.2341	0.2619	0.2501
Avg. *Var*	0.1054	0.1088	0.1121	0.0995	0.0989	0.0569	0.0577	0.0596	0.0538	0.0545

M_{jud}

Parameter	Broad					Fine				
	All	2007	2009	2010	1011	All	2007	2009	2010	1011
fSYS	6	4	4	21	1	15	10	11	37	3
a*SYS*	144	103	104	115	106	109	74	88	89	75
a*ART*	30810	23058	20753	26864	21705	41552	31337	28147	35913	29164
R^2	0.9156	0.9122	0.9089	0.9166	0.9245	0.9002	0.8987	0.8980	0.8991	0.9051
RMSE	0.1376	0.1301	0.1272	0.1427	0.1518	0.0922	0.091	0.0899	0.0936	0.0957
Avg. *Var*	0.0178	0.0167	0.0172	0.0175	0.0196	0.0069	0.0067	0.0069	0.0071	0.007

Table 4. Likehood-ratio Chi-squared (under the name of All) statistic of all features for each model, with R^2 scores, RMSE (Rooted Mean Squared Error) between predicted and actual scores, and average variance of estimates for M_{out} and $M_{jud.}$ Adapted from (Julián Urbano, 2013)

Table 4 presents results that show that:

1) In the case of M_{Out} the best results come from features fART, fGEN and sGEN, in other words, from data related to artist and genre confirming that they are good features to estimate similarity between two music excerpts (Flexer and Schnitzer 2010). For M_{jud} the best results are originated by aART demonstrating that if two songs from two artists are similar, other songs from them tend to be similar as well. This case represents the decision of MIREX of filtering out songs from the same artist than the query's because they are likely to be similar.

2) RMSE and Average Variance demonstrate how well these models estimate relevance judgments. For a better comparison across scales, they were normalized between 0 and 1, resulting in *Broad* = {0; 0.5; 1} and *Fine* = {0.05; 0.15; … 0.95}. It can be noticed that Fine scale makes better estimation of relevant judgments.

3) Although M_{jud} performs better than M_{out}, this one can still be used because the estimation's error it has can be compared to the differences expected when human assessors performs relevance judgments.

Then, after creating the probabilistic estimation of relevance judgments using random variables, effectiveness scores used to rank systems according to their performance in the evaluation of AMS needed to be predicted using random variables as well. Therefore, three possible scenarios to use according to the evaluation needs were set. In the implementation of this scenarios data from MIREX 2007, 2009, 2010 and 2011 was used. The results demonstrated that:

i) In the first scenario, when there are not relevance judgments available, M_{out} can be used and the order of systems is estimated with an average accuracy of 92% and with an average confidence in the rankings of 94%. ii) In the second scenario, when the goal is estimate system's differences, it showed that just using 2% of the judgments the differences could be correctly estimate in 93% of the cases. iii) In the third scenario, when the focus is the estimation of absolute scores, just with 25% of the relevance judgments they can estimate with an error of +-0.05. In this last scenario, effectiveness in the ranking of systems is highly overestimated. One approach to correct this issue was the use of a threshold of variance as a practical correction factor to use in the stopping condition. As a consequence, the error was reduced but at the expense of making several judgments, (between 15% and 35%). Fig 2 present this situation:

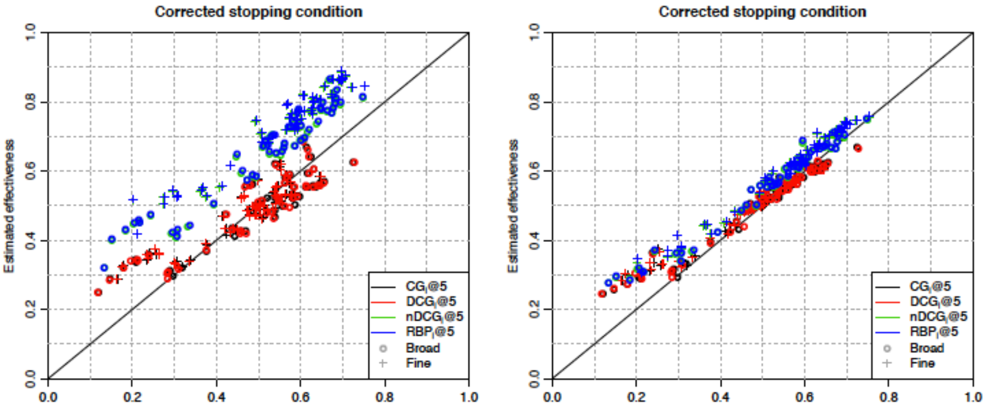


Fig 2. Estimated vs. actual absolute effectiveness scores in MIREX 2007, 2009, 2010 and 2011 when judging documents until expected error is +-0.05 with an uncorrected (left) or corrected (right) stopping condition. Adapted from (Urbano, 2013)

The objective of this thesis project is to create a probabilistic framework to estimate relevance, which is intended to improve the predictions of the ranking of systems reducing the amount of needed judgments of Figure 2.

Chapter 3
Improving the estimation of relevance

Estimating relevance judgments will reduce the annotation cost yet achieving better predictions of effectiveness measures of systems. After reviewing the literature and the available models for prediction, several approaches have been considered to obtain better estimations; data from past edition of MIREX was used:

1. Using others configurations of Ordinal Logistic Regression models.
2. Implementing others probabilistic models.
3. Improving model's attributes.
4. Implementing new attributes for models.

Each approach and its corresponding results would be described as follows:

1. Using others configurations of Ordinal Logistic Regression models.

According to the literature, (Urbano, 2013) used the regression framework with ordinal logistic regression as the main approach to predict relevance since it takes into account the order of relevance level. Using the statistical language R[9], two distinct configurations of ordinal models were tried inside the aforementioned framework: packages rms and MASS. The results of this implementation are depicted in Table 5.

[9] http://www.r-project.org

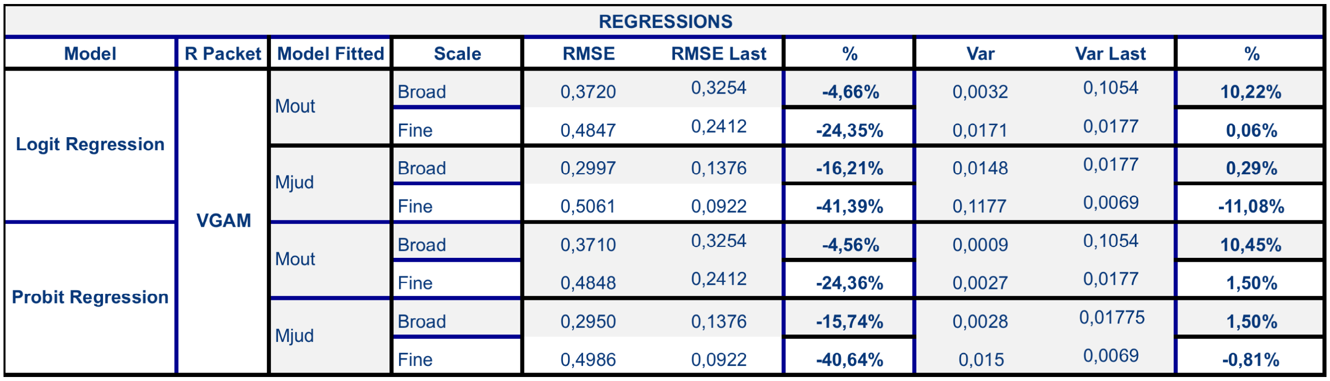
ORDINAL LOGISTIC REGRESSION												
R Packet	**Model Fitted**	**Scale**	**R2**	**Ant. R2**	**%**	**RMSE**	**Ant. RMSE**	**%**	**Var**	**Ant. Var**	**%**
rms	Mout	Broad	0,3630	0,3627	**0,03%**	0,325	0,3254	**0,00%**	0,1054	0,1054	**0,00%**
		Fine	0,3430	0,3439	**-0,09%**	0,283	0,2412	**-4,21%**	0,1067	0,0178	**-8,89%**
	Mjude	Broad	0,9160	0,9156	**0,04%**	0,138	0,1376	**0,01%**	0,0177	0,0179	**0,02%**
		Fine	0,9060	0,9000	**0,60%**	0,0900	0,0922	**0,22%**	0,0069	0,0069	**0,00%**
MASS	Mout	Broad	**This packet does not show R**			0,326	0,3254	**-0,04%**	0,1054	0,1054	**0,00%**
		Fine				0,241	0,2412	**0,04%**	0,0177	0,0178	**0,01%**
	Mjude	Broad				0,138	0,1376	**0,01%**	0,0178	0,0179	**0,01%**
		Fine				0,0900	0,0922	**0,22%**	0,0069	0,0069	**0,00%**

Table 5. Implementation of rms and MASS packages for Ordinal Logistic Regression in R. Columns Ant. R^2, Ant. RMSE and Ant. Var represent the values obtained from (Urbano, 2013). MASS package does not show the value of the coefficient of determination, R^2 .

Table 5 presents that using these configurations of ordinal models the improvement in the results were minimum. For example, proving rms for M_{out} the coefficient of determination R^2 (indicates how well data fit a statistical model and ranges from 0 to 1, "perfect fit") just increased in a 0,003% for the Broad scale and decrease in -0,009% in the case of Fine. For RMSE in Broad, no improvement was achieved and for Fine, it decreased in a -4,21%. Respect to the variance, for Broad scale no improvement was acquired in the results and for Fine, it decreased in an -8,89%. For M_{jud} the results minimum: For R^2 it got 0,04% for Broad and 0,60% for Fine scales; for RMSE, 0,01% for Broad and 0,22% for Fine; in the case of variance, 0,02% for Broad and the same result was reached for Fine. Using MASS package the results improved in a minimal amount as well. Hence, using other configurations of Ordinal Logistic Regression did not achieve significant improvements for the prediction of relevance.

2. Implementing others probabilistic models in order to obtain better results.

The reviewed literature considered that linear regression was not an appropriate approach because the predicted relevance could be outside the $[0,nL-1]$ limits (Urbano, 2013). However if the results can be truncated inside the possible values of Broad and Fine scales, this issue can be addressed. To prove this hypothesis models from the Generalized Linear Models, which can represent categorical, binary and other response types were tested: linear, probit and logit regressions. For probit and logit regressions models, the estimated relevance values need first to be mapped inside the range [0-1] and in order to interpret the results, these values need to be transformed back to the original scales; Table 6 presents the results of the evaluation using these models:

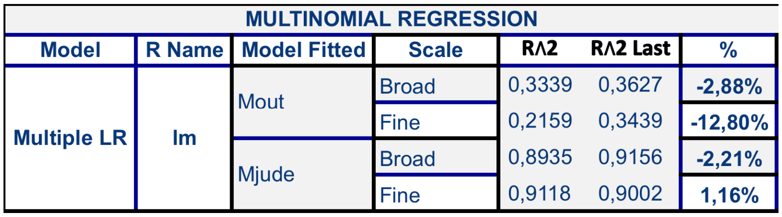


REGRESSIONS									
Model	R Packet	Model Fitted	Scale	RMSE	RMSE Last	%	Var	Var Last	%
Logit Regression	VGAM	Mout	Broad	0,3720	0,3254	**-4,66%**	0,0032	0,1054	**10,22%**
			Fine	0,4847	0,2412	**-24,35%**	0,0171	0,0177	**0,06%**
		Mjud	Broad	0,2997	0,1376	**-16,21%**	0,0148	0,0177	**0,29%**
			Fine	0,5061	0,0922	**-41,39%**	0,1177	0,0069	**-11,08%**
Probit Regression		Mout	Broad	0,3710	0,3254	**-4,56%**	0,0009	0,1054	**10,45%**
			Fine	0,4848	0,2412	**-24,36%**	0,0027	0,0177	**1,50%**
		Mjud	Broad	0,2950	0,1376	**-15,74%**	0,0028	0,01775	**1,50%**
			Fine	0,4986	0,0922	**-40,64%**	0,015	0,0069	**-0,81%**

Table 6. Implementation of Logit and Probit regression Columns Ant. R^2, Ant. RMSE and Ant. Var represent the values obtained from (Urbano, 2013).

For Logit and Probit Regression the prediction of relevance was not improved in a significant way as it is demonstrated.

In the case of Multiple Linear Regression, the predicted values sometimes do not fall in a range within [0-2] for Broad or [0-100] for Fine scale; in all these cases they need to be truncated inside the corresponding scale in order to obtain the correct mapping with the estimates values. Table 7 presents these results:



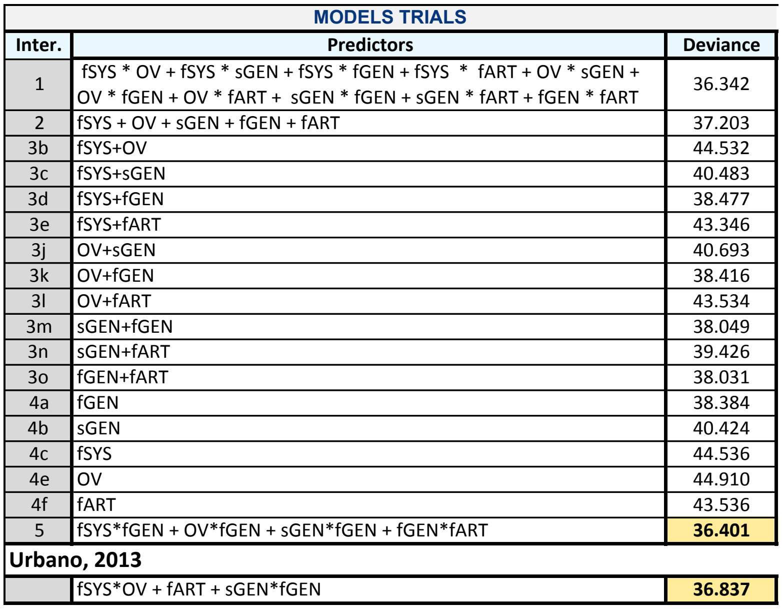
MULTINOMIAL REGRESSION						
Model	R Name	Model Fitted	Scale	R^2	R^2 Last	%
Multiple LR	lm	Mout	Broad	0,3339	0,3627	**-2,88%**
			Fine	0,2159	0,3439	**-12,80%**
		Mjude	Broad	0,8935	0,9156	**-2,21%**
			Fine	0,9118	0,9002	**1,16%**

Table 7. Implementation of Multinomial Linear Regression Columns Ant. R^2, Ant. represents the values obtained from (Urbano, 2013).

For the case of M_{jud} using the Fine scale a 1,16% of improvement was achieved. The rest of predictions did not get any improvement.

3. Improving model's attributes

To improve the prediction power of independent variables some techniques can be applied. For example, implementing a selection method, which is intended to choose the best subset of predictors (Faraway, 2004). For both models M_{out} and M_{jud} backward elimination approach was applied. In this method we start testing the interaction of all predictors (features, attributes) and then removing the predictors with less or highest value of some parameter, depending of the model (higher p-value, R^2, lowest deviance or AIC, et). In this case, the *rms* packet in R was used with ordinal logistic regression, starting with the interaction of all the predictors; therefore, in order to decrease the number of permutations, the selection of variables made by (Urbano, 2013) was followed for M_{out} (fSYS, OV, sGEN, fGEN, fART). Using the deviance as an indicator of quality of good or bad fit for the model, the results are presented in *Table 8*.   It shows that even thought the best fit was achieved by the Interaction number 1 and 5, still number 5 can be selected since it does not used as many parameters as number 1. Furthermore, if this interaction is compared with the research from Urbano, the result is almost the same, so the latter configuration can be chosen since the resulting model is less complex. Similar results were obtained for M_{jud}.



MODELS TRIALS		
Inter.	**Predictors**	**Deviance**
1	fSYS * OV + fSYS * sGEN + fSYS * fGEN + fSYS * fART + OV * sGEN + OV * fGEN + OV * fART + sGEN * fGEN + sGEN * fART + fGEN * fART	36.342
2	fSYS + OV + sGEN + fGEN + fART	37.203
3b	fSYS+OV	44.532
3c	fSYS+sGEN	40.483
3d	fSYS+fGEN	38.477
3e	fSYS+fART	43.346
3j	OV+sGEN	40.693
3k	OV+fGEN	38.416
3l	OV+fART	43.534
3m	sGEN+fGEN	38.049
3n	sGEN+fART	39.426
3o	fGEN+fART	38.031
4a	fGEN	38.384
4b	sGEN	40.424
4c	fSYS	44.536
4e	OV	44.910
4f	fART	43.536
5	fSYS*fGEN + OV*fGEN + sGEN*fGEN + fGEN*fART	**36.401**
Urbano, 2013		
	fSYS*OV + fART + sGEN*fGEN	**36.837**

Table 8. Implementation of backward elimination of predictors for M_{out} .

4. Implementing new attributes.

Another considered approach was the use of a new independent variable called Cluster; it was intended to improve the results of the prediction of relevance by clustering genres according to subjective criteria of similarity. The genres used in Mirex are (10):

Baroque, Blues, Classical, Country, Edance, Jazz, Metal, Racphiphop, Rock-and-roll, Romantic. After listen to several songs from the provided dataset from MIREX, the proposed clustering for each genre is described in Table 9:

Genres	Cluster
Baroque-Classical-Romantic	Cluster 1: ***Classical***
RapHiphop – Edance	Cluster 2: ***Electronic***
Blues-Rockandroll-Country	Cluster 3: ***Romantic***
Jazz	Cluster 4: ***Jazz***
Metal	Cluster 5: ***Metal***

Table 9. Proposed clustering of genres from data from MIREX.

Adding this new attribute to the model using a dichotomous binary variable assigning 1 if the query had the same genre as the document or 0 otherwise, the results were depicted in Table 10:

CLUSTER											
R Packet	**Model Fitted**	**Scale**	**R2**	**Ant. R2**	**%**	**RMSE**	**Ant. RMSE**	**%**	**Var**	**Ant. Var**	**%**
MASS	Mout	Broad	0,4050	0,3627	**4,23%**	0,3165	0,3254	**0,89%**	0,1001	0,1054	**0,53%**
		Fine	0,3150	0,3439	**-2,89%**	0,2488	0,2412	**-0,76%**	0,0638	0,0178	**-4,60%**
	Mjud	Broad	0,9160	0,9156	**0,04%**	0,1375	0,1376	**0,01%**	0,0177	0,0179	**0,02%**
		Fine	0,8930	0,9000	**-0,70%**	0,0934	0,0922	**-0,12%**	0,0075	0,0069	**-0,06%**

Table 10. Implementation of a new attribute into a Logistic Regression Model. Columns Ant. R^2, Ant. RMSE and Ant. Var represent the values obtained from (Urbano, 2013).

Table 10 presents that using the new attribute Cluster, the results were improved for the Broad scale in a 4% for M_{out} and in a 0,04% for M_{jud}. In the case of the Fine scale there were not improvements. Therefore, adding new attributes in order to improve the prediction of relevance was a good choice to obtain better results. For this reason, another attribute was also implemented using the media of the distances between the genre of the query and the genre of the document (song); with this new feature, one is expected to get even better results. Table 11 presents the aforementioned distances between genres and Table 12 introduces these results implemented into the models:

GENRE q	GENRE d	Distances
JAZZ	JAZZ	65,2
METAL	METAL	63,3
CLASSICAL	CLASSICAL	59,3
ELECTRONIC	ELECTRONIC	58,0
ROMANTIC	ROMANTIC	49,0
METAL	ROMANTIC	40,1
ROMANTIC	METAL	38,3
ROMANTIC	JAZZ	37,5
JAZZ	ROMANTIC	37,1

METAL	ELECTRONIC	30,9
ELECTRONIC	METAL	25,5
ELECTRONIC	ROMANTIC	20,4
CLASSICAL	JAZZ	17,5
JAZZ	CLASSICAL	16,6
ELECTRONIC	JAZZ	16,5
METAL	JAZZ	16,1
JAZZ	ELECTRONIC	13,0
ROMANTIC	ELECTRONIC	12,9
CLASSICAL	ROMANTIC	12,4
METAL	CLASSICAL	9,8
ROMANTIC	CLASSICAL	8,9
JAZZ	METAL	8,6
CLASSICAL	ELECTRONIC	6,4
CLASSICAL	METAL	4,8
ELECTRONIC	CLASSICAL	4,7

Table 11. Media of the distances between genres of the queries and the songs.

DISTANCES											
R Packet	**Model Fitted**	**Scale**	**R2**	**Ant. R2**	**%**	**RMSE**	**Ant. RMSE**	**%**	**Var**	**Ant. Var**	**%**
MASS	Mout	Broad	0,4380	0,3627	**7,53%**	0,3165	0,3254	**0,89%**	0,1001	0,1054	**0,53%**
		Fine	0,3840	0,3439	**4,01%**	0,2770	0,2412	**-3,58%**	0,1050	0,0178	**-8,72%**
	Mjud	Broad	0,9160	0,9156	**0,04%**	0,1375	0,1376	**0,01%**	0,0178	0,0179	**0,01%**
		Fine	0,8910	0,9000	**-0,90%**	0,0933	0,0922	**-0,11%**	0,0076	0,0069	**-0,07%**

Table 12. Implementation of distance as attributes into a Logistic Regression Model. Columns Ant. R^2, Ant. RMSE and Ant. Var represent the values obtained from (Urbano, 2013).

Table 12 presents a significant improvement of 7,53% for the Broad scale and of a 4% for the Fine scale for M_{out}.

These results proved that adding new attributes as independent variables is an optimal path to follow with the aim of improving the estimation of relevance.

Short-term planning

In order to improve even more the estimation of relevance with the aim to reduce the annotation cost associated to this process, several task will be done. They are depicted in Table 13.

Task	Description	Possible Date
Implementation of new features using different approaches.	Ex: Metadata from Internet Musical Databases, machine learning for clustering of genres.	*June 26th – July 15 th*
Training models to predict using different amount of available information	Training models using less data in order to consider the cases in which not much (incomplete) information will be available.	*June 26th – July 15 th*
Coding the model to be used with the system created by (Urbano, 2013) which predicts effectiveness of systems.	The studied models need to be coded using C++ or JAVA to interact (provide relevance judgments) with the aforementioned system.	July 16 th to 31 th
Finishing the monograph	Consigning the final results or the research.	August 1 th -20 th
Final Revision by Advisor		August 21 th - 31 th

Table 13. Activities intended to improve the prediction of relevance.

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