Music and Mood: Where Theory and Reality Meet

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ABSTRACT

The affective aspect of music, often referred as music mood or emotion, has been recently recognized as an important factor in organizing and accessing music information. However, music mood is far from being well studied in information science. For example, there is no consensus on whether to use *mood* or *emotion* to refer the affective aspect of music. Also, the lack of consensus on music mood categories in the Music Information Retrieval (MIR) community makes it difficult to compare classification approaches developed in different laboratories. On the other hand, there is a rich literature in music psychology that has addressed many of the issues MIR researchers want to know. This research reviews theories in music psychology and summarizes fundamental insights that can help MIR researchers in interpreting music mood. In order to investigate whether classic theories are still applicable to today's reality of music listening environment, this study also derives a set of music mood categories from social tags, using a combination of linguistic resources and human expertise, and compares it to music mood categories in psychological theories. The results verify that there are common grounds between theoretical music mood models and the reality of music listening, but theoretical models do not cover all mood categories emerged from social tags and thus need to be modified to better fit the reality of music listening.

Categories and Subject Descriptors

H.3.7 [**Information Storage and Retrieval**]: Digital Libraries – *standards, user issues.* J.5 [**Computer Applications**]: Arts and Humanities – *music*

General Terms

Human Factors, Standardization, Theory, Verification.

Keywords

Music, mood, metadata, social tags, music psychology, emotion theories, music mood categories, music information retrieval

1. INTRODUCTION

Perhaps no one, be he a music expert or casual listener, would deny the fact that music and mood can never be separated. Some music may not describe a story, but all music must express, strongly or softly, a certain emotion or a mixture of emotions. In consequence, music listeners often experience some sort of affective responses. Just as Juslin and Sloboda [15] stated:

"Some sort of emotional experience is probably the main reason behind most people's engagement with music. Emotional aspects of music should thus be at the very heart of musical science."

Nevertheless, the affective aspects of music have just started drawing attention in information science in recent years when user studies discovered that music mood is an important factor in music information seeking and organization [5][18][33]. In the Music Information Retrieval (MIR) and Music Digital Libraries (MDL) community, there are many fundamental issues on music mood remaining unresolved. For example, there is no terminology consensus on the very topic we are studying: some researchers use "music emotion", some others use "music mood" to refer the affective aspects of music. On the other hand, there is a long history of influential studies in music psychology where these issues have been well studied. Hence, MIR researchers and information scientists who are interested in music mood should learn from music psychology literature on theoretical issues such as terminology and sources of music mood.

However, not all parts of psychological theories can be borrowed into MIR research because most studies in music psychology were conducted in laboratory settings while today's music listening environment has rich social context brought by the flourishing of Web 2.0. For instance, in studying music mood classification techniques, MIR researchers have employed some influential music mood models such as Russell's two-dimensional music emotion model [25] and Watson's two level hierarchical model [34]. There are two problems in adopting various psychological models: 1) although these models have good theoretical roots, they generally lack the social context of music listening [14]. It is unknown whether the models can well fit today's reality; 2) the lack of consensus on music mood categories makes it hard to compare different automatic classification approaches. Therefore, this study strives to identify music mood categories from social tags that reflect the reality of music listening, and compare the categories to those in theoretical models.

The rest of this paper is organized as follows: Section 2 reviews and summarizes important findings in representative studies on music and mood in music psychology. In Section 3, we describe a method of deriving music mood categories from social tags. A detailed comparison between music mood categories in psychological models and those found in social tags is presented in Section 4. We then draw conclusions in Section 5.

2. THE THEORIES

2.1 Mood vs. Emotion

Since the early stage of music psychologiyl studies, researchers have paid attention to clarifying the concepts of *mood* and *emotion*. The most influential first work formally analyzing music and mood using psychological methodologies is probably Meyer's *Emotion and Meaning in Music* [23]. In this book, Meyer stated that *emotion* is "temporary and evanescent" while *mood* is "relatively permanent and stable". Sloboda and Juslin [28] followed Meyer's point after summarizing related studies during nearly a half century.

In music psychology, both *emotion* and *mood* have been used to refer to the affective effects of music, but *emotion* seems to be more popular [4][13][23][26][28]. However, in MIR, researchers tend to choose *mood* over *emotion* [7][20][21][24]. In addition, existing music repositories also use *mood* rather than *emotion* as a metadata type for organizing music (e.g., AllMusicGuide[1] and APM[2]). While we have yet to formally interview MIR researchers on why they chose to use *mood*, we hypothesize that there are at least two reasons for MIR researchers to make a different choice from their colleagues in music psychology:

First, as stated by Meyer, *mood* refers to a relatively long lasting and stable emotional state. While psychologists emphasize on human responses to various stimuli of emotion, MIR researchers, at least at current stage, are more interested in the general sentiment that music can convey. In another word, music psychologists focus on the very subjective responses to music which can be acute, momentary and fast changing, while the MIR community tries to find the common affective consequences of music that are shared by many people and are less volatile.

Second, the research purposes of the two disciplines are different. Music psychologists want to discover why a human has emotional responses to music while MIR researchers want to find a new metadata type to organize and access music objects. The former focuses on human's responses, the latter focuses on music. It is human who has *emotion*. Music does not have emotion, but it can carry a certain *mood*.

Therefore, this research continues the choice of MIR researchers and adopts the term *music mood* rather than *emotion*. However, it is noteworthy that the two concepts are not absolutely detached. To some extent, their difference mainly lies in granularity. MIR researchers can still borrow insights from music psychology studies. In fact, when MIR technologies are developed to a level where individual and transitory affective responses become the subject of study, it is possible that the MIR community may change to adopt the notion of music *emotion*.

2.2 Sources of Music Mood

Where music mood comes from is a question MIR researchers are interested in. Does it come from the intrinsic characteristics of music pieces or from the extrinsic context of music listening behaviors? The answer to this question would have significant implications on assigning mood labels to music pieces either by hand or by computer programs.

From as early as Meyer [23], there have been two contrasting views of music meanings in music psychology: the absolutist versus referentialist views. The absolutist view claimed "musical meaning lies exclusively within the context of the work itself" while the referentialist proposed "musical meanings refer to the extra-musical world of concepts, actions, emotional states, and character". Meyer acknowledged the existence of both types of musical meanings. Later, Sloboda and Juslin [28] echoed Meyer's view by presenting two sources of emotion in music: intrinsic emotion and extrinsic emotion. Intrinsic emotion is triggered by specific structural characteristics of the music while extrinsic emotion is from the semantic context related but outside the music. Therefore, the suggestion for MIR is that music mood should be a combination of music content itself and the social context where people listen to and share opinions about music. In fact, recent user studies in MIR have confirmed this point of view (e.g., [18]) and automatic music categorization systems (e.g., [2]) have started to combine music content (e.g., audio, lyrics, and symbols) and context (e.g., social tags, playlists, and reviews).

2.3 What We Know about Music Mood

Beside terminology and sources of music mood, music psychology studies on music mood have a number of fundamental generalizations that can benefit MIR research.

1. There does exist mood effect in music. Ever since early experiments (pre-1950) on psychological effects of music, studies have confirmed the existence of the functions of music in changing people's mood [4]. It is also agreed that it seems natural for listeners to attach mood labels to music pieces [28].

2. Not all moods are equally likely to be aroused by listening to music. In a study conducted by Schoen and Gatewood [26], human subjects were asked to choose from a pre-selected list of mood terms to describe their feelings while listening to 589 music pieces. Among the presented moods, sadness, joy, rest, love, and longing were among the most frequently reported while disgust and irritation were the least frequent ones.

3. There do exist uniform mood effects among different people. Sloboda and Juslin [28] summarized that listeners are often consistent in their judgment about the emotional expression of music. Early experiments in [26] have shown that "*the moods induced by each (music) selection, or the same class of selection, as reported by the large majority of our hearers, are strikingly similar in type*". Such consistency is an important ground for developing and evaluating music mood classification techniques.

4. Not all types of moods have the same level of agreement among listeners. Schoen and Gatewood [26] ranked joy, amusement, sadness, stirring, rest and love as the most consistent moods while disgust, irritation and dignity were of the lowest consistency. The implication for MIR is that some mood categories would be harder to classify than others.

5. There is some correspondence between listeners' judgments on mood and musical parameters such as tempo, dynamics, rhythm, timbre, articulation, pitch, mode, tone attacks and harmony [28]. Early experiments showed that the most important music element for excitement was swift tempo; modality was important for sadness and happiness but useless for excitement and calm; and melody played a very small part in producing a given affective state [4]. Schoen and Gatewood [26] pointed out the mood of amusement largely depended upon vocal music: *"humorous description, ridiculous words, peculiarities of voice and manner are the most striking means of amusing people through music"*. This has been evidenced by the category, "*humorous/silly/quirk*" used in the Audio Mood Classification (AMC) task in the Music

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[1] http://allmusic.com

[2] http://www.apmmusic.com

Information Retrieval Evaluation eXchange (MIREX)[3], a formal evaluation framework in the MIR community [12]. A subsequent examination on the AMC data found that music pieces which were manually labeled with this category mostly had the above mentioned quality. Such correspondence between music mood and musical parameters has very important implications for designing and developing music mood classification algorithms.

2.4 Music Mood Categories

Studies in psychology have proposed a number of models on human's emotions and music psychologists have adopted and extended a few influential models.

The six "universal" emotions defined by Ekman [6]: anger, disgust, fear, happiness, sadness, and surprise, are well known in psychology. However, since they were designed for encoding facial expressions, some of them may not be suitable for music (e.g., disgust), and some common music moods are missing (e.g., calm or soothing). In music psychology, the earliest and still best-known systematic attempt at creating music mood taxonomy was by Hevner [10]. Hevner designed an adjective circle of eight clusters of adjectives as shown in Figure 1, from which we can see: 1) the adjectives within each cluster are close in meaning; 2) the meanings of adjacent clusters would differ slightly; and 3) the difference between clusters gets larger step by step until a cluster at the opposite position is reached.

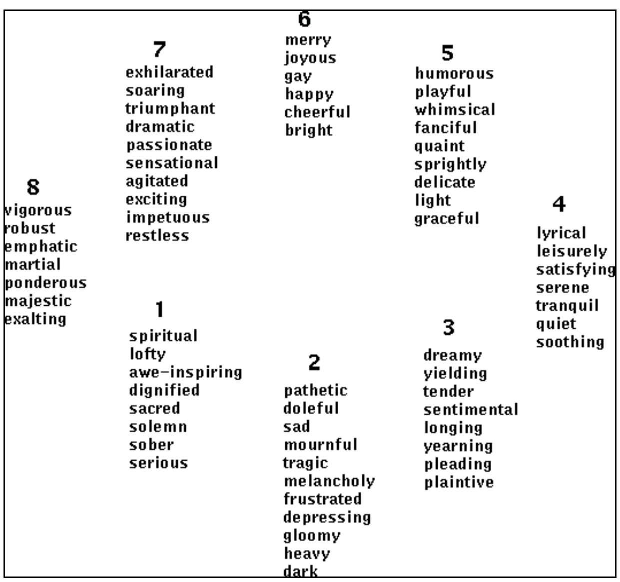

Figure 1: Hevner's adjective cycle [10].

Both Ekman's and Hevner's models belong to *categorical* models because the mood spaces consist of a set of discrete mood categories. Another well recognized kind of models is *dimensional* models where emotions are positioned in a continuous multidimensional space. The most influential ones contain such dimensions as Valence (happy-unhappy), Arousal (active-inactive), and Dominance (dominant-submissive) [22][25][31]. However, there is no consensus on how many dimensions there should be and which dimensions to consider. For example, a well cited study by Wedin identified three dimensions: Intensity-Softness, Pleasantness-Unpleasantness and Solemnity-Triviality [35], while another study by Asmus found nine dimensions: Evil, Sensual, Potency, Humor, Pastoral, Longing, Depression, Sedative, and Activity [1].

Among all these dimensional models, the Russell's model of the combination of valence and arousal dimensions [25][31] has been adopted in a few experimental studies in music psychology (e.g., [27][32]), and MIR researchers have been using similar taxonomies based on this model (e.g., [16][17][20]). As shown in Figure 2, the original Russell's model places 28 emotion denoting adjectives on a circle in a bipolar space consisting of valence and arousal dimensions.

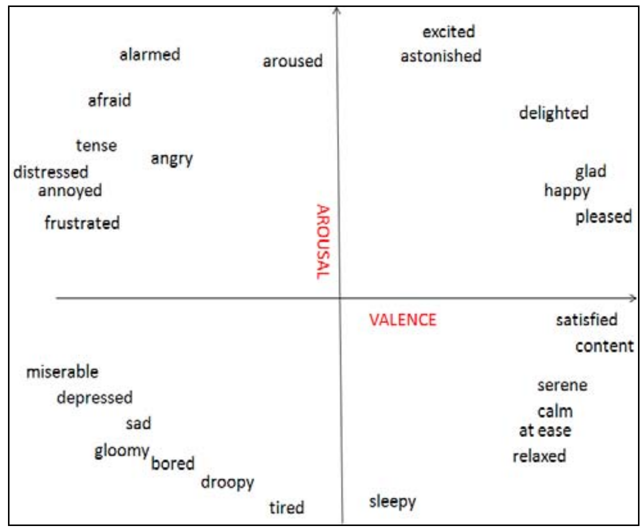

Figure 2: Russell's model with two dimensions: arousal and valence [25].

In fact, categorical models and dimensional models cannot be completely separated. Gabrielsson and Lindström [8] argued that Hevner's model suggested an implicit dimensionality similar to the combination of valence (cluster 2 – cluster 6) and arousal (clusters 7/8 – clusters 4/3).

All these psychological models were proposed in laboratory settings and thus were criticized as being lack of social context of music listening [14]. In the next section, we will derive a set of music mood categories from social tags, and in Section 4 we will compare it to those in the Hevner's model as well as the Russell's model.

3. THE REALITY

3.1 Mood Categories in Social Tags

With the birth of Web 2.0, the general public can now post text tags on music pieces and the large quantity of social tags become a unique and rich resource of discovering users' perspectives in the social context of music listening. MIR Studies have tried to find music mood or genre representations from social tags (e.g., [11][19]), but none of them have adequately addressed the following shortcomings of social tags as summarized by Guy and Tonkin [9]. First, social tags are uncontrolled and thus contain much noise or junk tags. Second, many tags have ambiguous meanings. For example, "love" can be the theme of a song or a user's attitude towards a song. Third, a majority of tags are tagged

[3] http://www.music-ir.org/mirex/2007/index.php/AMC

to only a few songs, and thus are not representative (i.e., the so called "long-tail" problem). Fourth, some tags are essentially synonyms (e.g., "cheerful" and "joyful"), and thus do not represent separate and distinguishable categories. To address these problems, we propose a new method that combines the strength of linguistic resources and human expertise to derive more realistic and user-centric mood categories from social tags.

3.1.1 *Identifying mood-related terms*

First, we identified a set of mood related terms using linguistic resources. WordNet-Affect is an affective extension of WordNet [30]. It assigns affective labels to words representing emotions, moods, situations eliciting emotions, or emotional responses. As a major resource used in text sentiment analysis, WordNet-Affect has a good coverage of mood related words. There are 1,586 unique terms in WordNet-Affect. However, some of the terms are judgmental, such as "bad", "poor", "miserable", "good", "great", and "amazing". Although these terms are related to mood, their applications on songs probably represent users' judgments towards the songs, rather than describe the moods carried by the songs. Therefore, such tags are noise for our purposes and should be eliminated. Another linguistic resource, General Inquirer [29] was consulted for a list of judgmental terms. General Inquirer is a lexicon comprised of 11,788 words organized in 182 psychological categories, two of which are about "evaluation" containing 492 words implying judgment and evaluation. Subtracting these words from terms in WordNet-Affect resulted in1,384 terms.

As a final step to ensure the quality of the term list, two human experts were consulted and manually examined the terms. Both experts are MIR researchers with a music background and native English speakers. They first identified and removed tags with music meanings that did not involve an affective aspect (e.g., "trance" and "beat"). Then, they removed words with ambiguous meanings. For example, "chill" can mean "to calm down" or "depressing", but social tags do not provide enough contexts to disambiguate the term. After this step, we got 1,249 mood related terms.

3.1.2 *Obtaining mood-related social tags*

Last.fm is one of the most popular tagging sites for Western music[4]. With 30 million users every month, it provides a good resource of studying how people tag music. We queried last.fm through its API[5] with the 1,249 mood related terms, and 476 of them have been used as tags by last.fm users as of June 2009. To untangle the "long-tail" problem mentioned above, we only included tags that were used more than 100 times. This gave us 146 terms/tags.

3.1.3 *Grouping mood-related social tags*

To solve the synonym problem of social tags, we grouped the 146 mood related tags such that synonyms were merged together into one category. We again used WordNet-Affect in this step. WordNet is a natural resource for identifying synonyms, because it organizes words into *synsets*. Words in the same synset are synonyms in the linguistic point of view. Moreover, WordNet-Affect also links each non-noun synset (verb, adjective and adverb) with the noun synset from which it is derived. For instance, the synset of "joyful" is marked as derived from the synset of "joy". Both synsets represent the same kind of mood and should be merged into the same category. Hence, mood-related tags appearing in and being derived from the same synset in WordNet-Affect were merged into one group.

Finally, human experts were again consulted to modify the grouping of tags when they saw the need of splitting or further merging some groups. As a result, 36 categories emerged. Table 1presents some of them major categories and the number of tags contained in each category[6].

Table 1: Major mood categories derived from last.fm tags

Categories	#. tags
calm, calm down, calming, calmness, comfort, quiet,..	16
gloomy, blue, dark, depress, depressed, depressing,…	10
mournful, grief, heartache, heartbreak, heartbreaking,…	9
cheerful, cheer up, cheer, cheery, festive, jolly, merry,…	8
gleeful, euphoria, euphoric, high spirits, joy, joyful,…	8
brooding, broody, contemplative, meditative, pensive,…	7
confident, encouragement, encouraging, fearless,…	6
exciting, exhilarating, stimulating, thrill, thrilling	5
anxious, angst, anxiety, jumpy, nervous	5
angry, anger, furious, fury, rage	5
compassionate, mercy, pathos, sympathy	4
desolate, desolation, isolation, loneliness	4
scary, fear, panic, terror	4
hostile, hatred, malevolent, venom	4
glad, happiness, happy	3
hopeful, desire, hope	3
sad, melancholic, sadness	3
aggression, aggressive	2
romantic	1
surprising	1

4. COMPARISONS ON MOOD CATEGORIES

The social tagging environment of Web 2.0 is very different from the laboratory settings where the music psychology studies were conducted. Hence it is interesting to compare the mood categories derived from social tags to the models developed in music psychology. Such comparison will disclose whether the theoretical models can support patterns emerged from empirical data and how much differences are between them. Specifically, the following questions are addressed:

(1) Is there any correspondence between the resultant categories and those in the psychological models?

(2) Do the distances between mood categories show similar patterns to those in the psychological models?

Both Hevner's categorical model and Russel's two-dimensional model are compared to the derived categories.

[4] http://socialmediastatistics.wikidot.com/lastfm Retrieved at July 22, 2008.

[5] http://www.last.fm/api

[6] Due to space limit, the complete list can be found at http://www.isrl.illinois.edu/~xiaohu/pub/iconf10/Table1.pdf

4.1 Categories

4.1.1 Hevner's circle vs. derived categories

Some of the terms in Hevner's circle (Figure 1) are known to be old-fashioned and are rarely used for describing moods nowadays. This is reflected by the fact that only 37 of the 66 words in Hevner's circle were found in WordNet-Affect, including matches of terms in different derived forms (e.g., "solemnity" and "solemn" were counted as a match). Comparing the clusters in Hevner's circle to the set of categories identified from social tags, we found that 33 words (50% of all) in Hevner's circle matched tags in the derived categories, as indicated in Figure 3 where matched words are surrounded by rectangles. Please note that in Figure 3 the order of words within each cluster may be changed from Figure 2, so that words in the same derived categories are within one rectangle. The observation that the rectangles never cross Hevner's clusters suggests that the boundaries of Hevner's clusters and derived categories are in accordance to each other, despite the derived categories are of a finer granularity.

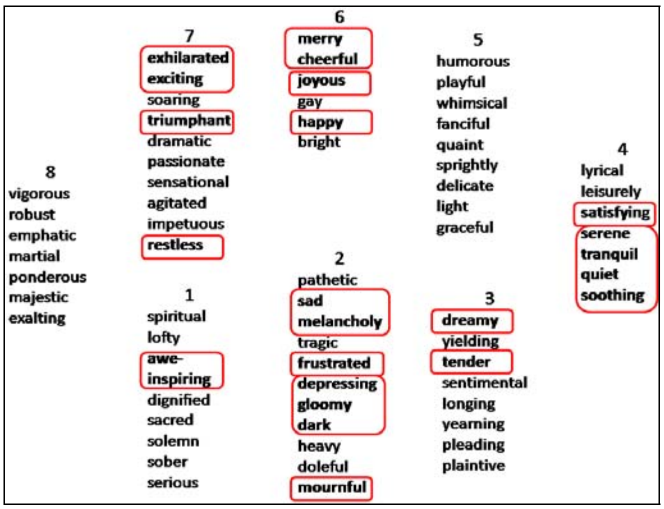

Figure 3: Words in Hevner's circle that match tags in the categories derived from last.fm tags

From Figure 3, we can also see that Clusters 2, 4, 6, 7 have the most matched words among all clusters, indicating Western popular songs (as the main music type in last.fm) mostly fall into these mood clusters. Besides exact matches, there are five categories in Table 1 with meanings close to some of the clusters in Hevner's model: categories "angry", "aggressive" are close to Cluster 8, category "desire" is close to "longing" and "yearning" in Cluster 3, and category "earnest" is close to "serious" in Cluster 1. This use of different words for the same or similar meanings indicates a vocabulary mismatch between social tags and adjectives the Hevner's model. Clusters 1 and 5 have the least matched or nearly matched words, reflecting that they are not good descriptors for Western popular songs. In fact, Hevner's circle was mainly developed for classical music for which words in Clusters 1 and 5 ("light", "dedicate" and "graceful") would be a good fit.

In total, 20 of the 36 derived categories have at least one tag contained in Hevner's circle. This is not surprising that empirical data entailed more categories since social tags were aggregated from millions of users while Hevner's model was developed by studying hundreds of subjects.

As a conclusion, after more than seven decades, Hevner's circle is still largely in accordance to categories derived from today's empirical music listening data. Admittedly, there are more mood categories in today's reality and there is a vocabulary mismatching issue, since language itself is evolving with time.

4.1.2 Russell's model vs. derived categories

Figure 4 marks the words appearing in both Russell's model and the derived sets of mood categories. Words in the same category are circled together.

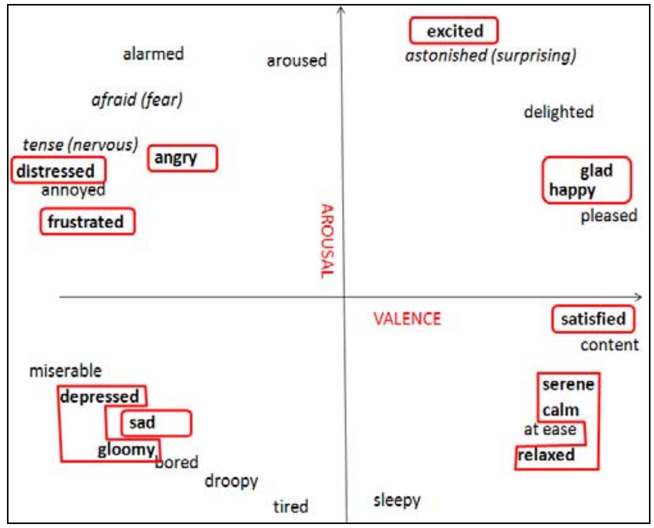

Figure 4: Words in Russell's model that match tags in the categories derived from last.fm tags

Figure 4 shows that 13 of the 28 words in Russell's model match tags in the derived categories (marked in bold), and another 3 words (marked in italic) have close meanings with tags in the derived categories (shown in parentheses). Hence, more than half of the words in Russell's model match or nearly match tags in the derived categories. For those unmatched words, there are several cases: 1) Some words in the Russell's model are synonyms according to WordNet, such as "content" and "satisfied"; "at ease" and "relaxed"; "droopy" and "tired", "pleased" and "delighted". Words in these pairs represent similar mood. 2) Some words are ambiguous and can be judgmental ("miserable", "bored", "annoyed"). If used as social tags, these terms may represent users' preferences towards the songs rather than the moods carried by the songs. Hence these terms were removed during the process of deriving mood categories from social tags. 3) 5 of the 28 adjectives in Russell's model are not in WordNet-Affect: "aroused", "tense", "droopy" and "sleepy". They are either rarely used in daily life or are not deemed as mood-related. Nevertheless, the high percentage of matched vocabulary with WordNet-Affect (23 out of 28) does reflect the fact that Russell's model is newer than Hevner's.

We can also see from Figure 4 that matched words in the same category (circled together) are placed closely in the Russell's model, and the matched words distribute evenly across the four quadrants of the two dimensional space. This indicates the derived categories have a good coverage of moods in the Russell's model. On the other hand, 2/3 of the 36 derived categories do not have matched words in the Russell's model. Therefore, this comparison tells us that the Russell model simplifies the problem in reality and the MIR experiments based on this model did help classify *some* of the mood categories used in real life but not *all* of them. Nevertheless, let us recall that Russell's model is a dimensional model instead of a categorical model, and thus theoretically it is not limited to the 28 adjectives. In fact, later studies have extended this model in many different ways [27][31][32]. It is possible (with further verifications in psycholinguistics) that most, if not all tags in the derived categories could find their places in the two-dimensional space, but it is a topic of beyond the scope of this paper.

4.2 Distances between Categories

Both Hevner's circle and Russell's space demonstrate relative distances between moods. For instance, in Russell's space, "sad" and "happy", "calm" and "angry" are at opposite places while "happy" and "glad" are close to each other.

To see if there are similar patterns in the derived categories, we calculated the distances between them. Last.fm API provides top 50 artists associated with each tag. We collected top artists for each of the 146 tags in the derived categories and calculated distances between the categories based on artist co-occurrences. Figure 5 shows the distances of the sets of categories plotted in a 2-dimensional space using Multidimensional Scaling [3].

As shown in Figure 5, categories that are intuitively close (e.g., those denoted by "glad", "cheerful", "gleeful") are positioned together, while those placed at almost opposite positions indeed represent contrasting moods (e.g., the ones denoted as "aggressive" and "calm", "cheerful" and "sad"). This evidences that the mood categories derived from social tags have similar patterns of category distances to those in psychological mood models.

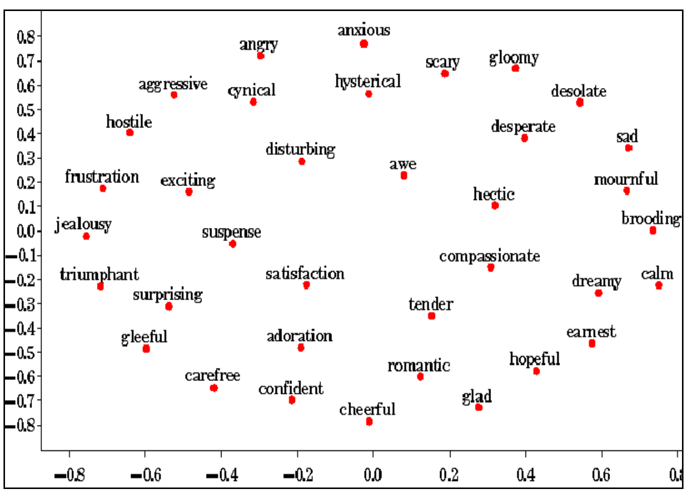

Figure 5: Distances of the 36 derived mood categories based on artist co-occurrences (each category is denoted by one tag in that category)

From the above comparisons, we can see that the derived set of categories is in accordance to common sense and is at least partially supported by classic psychological models. In addition, the derived categories are more comprehensive than psychological models and are more closely connected with the reality of music listening. It is our suggestion and recommendation for the MIR/MDL community to adopt the derived category set in music mood classification experiments, which will also facilitate comparisons across approaches.

5. CONCLUSIONS

Music mood is a newly emerged metadata type of music. Researchers in the MIR/MDL community have a lot to learn from psychology literature, from basic terminology to music mood categories. This paper reviews seminal works in the long history of psychological studies on music and mood, and summarizes fundamental points of view and their important implications on MIR/MDL research.

In MIR, one of the most debated topics on music and mood is mood categories. Theoretical models in psychology were designed from laboratory settings and may not be suitable for today's reality of music listening. By deriving a set of mood categories from social tags and comparing it to the two most representative mood models in psychology, this study finds out there are common grounds between theoretical models and categories derived from empirical music listening data in the real life. On the other hand, there are also non-neglectable differences between categories in theory and those in reality: 1) Vocabularies are different. Some words used in theoretical models are outdated, or otherwise not used in today's daily life; 2) Targeted music is different. Theoretical models were mostly designed for classical music while there are a variety of music genres in today's music listening environment; 3) While theoretical models often have a handful number of mood categories, the reality can have more categories and in a finer granularity. Therefore, in developing music mood classification techniques for today's music and users, MIR researchers should extend classical mood models according to the context of targeted users and music listening reality. For example, to classify Western popular songs, Hevner's circle can be adapted by introducing more categories found from social tags and trimming Cluster 1 and 5 which are mostly for classical music.

Information science is an interdisciplinary field. It often involves topics that have been traditionally studied in other fields. Borrowing findings from literatures in other fields is a very important research method in information science, but we need to pay attention to connecting theories in the literature to the reality and social context of the problems we investigate. The study described in this paper is a good example of connecting music psychology literature to the reality of music listening in the context of studying music mood as a new metadata type of music. In general, the methodology of literature review, analysis on empirical data and comparison of the two can help information science researchers refine or adapt theoretical models to better fit the reality of users' information behaviors.

6. ACKNOWLEDGEMENT

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