Temporal Proximity induces Attributes Similarity

Arun Kumar  
Dept. of Computer Science  
University of Minnesota Twin Cities  
kumar250@umn.edu

Karan Aggarwal  
Dept. of Computer Science  
University of Minnesota Twin Cities  
aggar081@umn.edu

Paul Schrater  
Depts. of Computer Science and Psychology  
University of Minnesota Twin Cities  
schrater@umn.edu

ABSTRACT
Users consume their favorite content in temporal proximity of consumption bundles according to their preferences and tastes. Thus, the underlying attributes of items implicitly match user preferences, however, current recommender systems largely ignore this fundamental driver in identifying matching items. In this work, we introduce a novel temporal proximity method to enable items-matching. First, we demonstrate that proximity preferences exist. Second, we present an induced similarity metric in temporal proximity driven by user tastes and third, we show that this induced similarity can be used to learn items pairwise similarity in attribute space. The proposed model does not rely on any knowledge outside users' consumption bundles and provide a novel way to devise user preferences and tastes driven novel items recommender.

KEYWORDS
Attributes similarity, Proximity filtering, Temporal proximity, Recommender systems, Taste model, Music recommendation

1 INTRODUCTION
Music industry is in a phase of massive shift in the listening styles of the music seekers, corroborated by the cheaper hosting availability and shift towards mobile devices like smart phones. With these fundamental technologies in place to bridge the gap between content providers and seekers, past decade has seen huge shift towards digital music subscription platforms like Pandora and Spotify as well as crowd-sourcing platforms like 8tracks providing direct access to the consumers to works of independent artists or bands.

With such a fundamental shift in the market as well as the consumer behaviours in the “Big” Data Generation, the recommender systems have not been able to address some fundamental issues that worked well in the era of a selected popular artists. The traditional collaborative filtering [20] recommender systems recommend users’ based on users’ with a similar history of consumption. Content based recommender systems [18], target the musical attributes or genres, recommending songs similar to what user’s listening profile history would suggest in the attribute space. Hybrid recommender systems utilize both these approaches in varying degrees to recommend songs.

These methods suffer from the "long tail" effect [8] where the recommender end up recommending popular songs or artists mainly, hence limiting the options of users, which can lead to attrition of users having faced boredom with the platform. However, these systems miss a fundamental fact—users’ tend to listen songs together—songs complement each other. Also, users’ listen songs in themes, depending on the context they reside in, like work place, study, and mood, not mutually exclusive. These themes have been inferred by providers to be represented in the genre space for a long time. There has been a push for crowd sourced curations of themed songs, leading to platforms like Stracks providing under-represented tunes [2] boasting of a user base of 5 million.

Figure 1: Collaborating filtering methods rely on finding other users with common items consumption choices to suggest items interesting to a given user. Content based methods from delve into attributes to find new items with similar attributes as previously consumed by a user. Hybrid systems combine these two methods. We present a novel proximity filtering method to learn attribute similarities.

In this work, we seek to create a fundamental framework for a system that can bridge the gap of content based liking as well as capturing the user context using latent themes, benefit of hard genre categorization. As illustrated in figure 1, we introduce a key concept of proximity filtering and attempt to answer questions like ‘what is a better way to find out which items a user might like?’ Current systems try to address this question by utilizing collaborative filtering, learning about other users who might have a similar interest and leverage on their items basket to recommend new items. Other collaborative filtering variants leverage additional information with user attributes like age, location etc or explicit feedback for items. For newly released items, consumption patterns might not be readily available.

However, a close observation of users’ music listening pattern, people listen to their favourite songs in temporal proximity, provides us insights to learn from their preferences and it can drive identification of new recommendable items. A user’s affinity to particular item attributes like beats or rhythms in musical compositions can reveal more into their latent thematic tastes. It resonates with an understanding that tastes or liking are more abstract compositional constructs. We consider an inherently deeper relationship between
users’ higher level latent thematic tastes and temporal proximity in
their consumed contents. These consumption bundles could be key
drivers for new generation recommender systems by exploiting
this immense amount of unobservable and indirect knowledge of
users’ liking to induce similarity in attributes and find matching
items.

We aim to fill this fundamental gap by introducing a novel para-
digm called ‘Temporal Proximity Filtering’ by providing a way to
learn similarity in items directly from their attributes, intrinsically
driven from their consumption patterns than exterior information.
The remainder of this article details the model. Section 2 provides
background. Section 3 explains the main proximity filtering con-
cepts. Section 4 describes induced attribute similarity. Experimental
procedure on music listening dataset is detailed in Section 5. Finally,
we discuss the results in section 6 and conclude in section 7.

2 BACKGROUND

One of the main goals of recommender systems is to suggest inter-
esting novel items to its users. There are primarily two paradigms:
collaborative filtering methods and content based methods. A ma-

ority of systems rely on collaborative filtering techniques [20],

following the availability of user provided ratings and community
data. Collaborative methods identify users whose item consump-
tion or choices history is similar to a given user and filter recommend-
able contents from similarly consumed items sets. Such methods
largely assume that a given user might also like items from this set
because their past choices have commonalities. On the other hand,
content based methods [18] attempt to find items similar in content
to previously liked item by a user. Here, emphasis is on examining
items’ history for a given user itself and find new items that might
be interesting to the user. In music domain, collaborating filtering
methods are widely used for providing recommendations, although,
content based systems found their usage in a number of applications
[18]. There have been attempts to combine both collaborating and
content methods into hybrid methods [19] so that item contents
can augment collaboratively ranked items. Although powerful, a
majority of them ignore that user preferences are dynamic and
abstract. The methods that can learn from users’ consumption con-
tent in temporal proximity and abstract level could be beneficial in
finding likable items. We attempt to address this aspect by learning
attributes similarities and these similarities are hypothesized to be
induced by temporal proximity in a latent thematic space.

In domains like music, volume of available contents is growing
rapidly, it is often difficult for people to manually select their
preferred contents. Although there is a big boost in availability
but selection difficulties encourage improvements in preferences
driven systems. Contents with diversity and small durations of each
items like music have intrinsically different consumption patterns
[21]. Moreover, consumption of such items is more unpredictable
compared to items like books etc as there can be long gaps between
listening to a similar item again or one can listen to the same music
item many times within a shorter time span. Therefore, understanding
consumption in a latent thematic space similar to [16] becomes
more important for domains with huge diversity.

Luke et al. [3] evaluate different music recommendation ap-
proaches demonstrating that collaborative filtering based recom-
mender systems produce better recommendations than the ones
based on purely artist similarity or acoustic content similarity. They
also imply that similarities between song contents can be captured
and attempt to find musical cues capturing music similarity aug-
menting traditional collaborating filtering techniques. Our work
emphasizes that user’s consumption bundles in a latent thematic
space can provide a meaningful way to find items that match user
preferences.

Overload of information led to development of information fil-
tering and retrieval methods that can supply sets of novel items for
recommendation. User preferences elicitation plays a key role in
identifying such items. Hanani et al.[10] suggested usage of explicit
elicitation like ratings or implicit elicitation from user behaviors.
Meta data for user profiles [3] generally helps in collaborating fil-
tering approaches. Jawaheer et al. [11] demonstrates that explicit
and implicit feedback can work in a complementary fashion and
they present techniques to leverage both. Bogdanov et al. [7] infer
user preferences from explicitly available information. However,
these works ignore that preferences are dynamic and abstract. In
this paper, we present methods to learn content similarity which
are based on users’ dynamic taste bundles.

Collaborating filtering methods work really well when system
has gathered item information like feedback from other users. With
ever evolving online media domains like music, new items are being
released constantly. A user might like some of these newly released
items but absence of user feedback creates difficulties for collaborat-
ing filtering methods. On the other hand, content based methods are
capable of recommending items that do not have any prior explicit
feedback like rating or comments. However, it is often difficult to
craft feature sets and methods to derive identification of recom-
mendable items and requires domain knowledge. Basic premise of
these methods lie on information retrieval to filter smaller subset of
items from a large set. Moreover, a different set of attributes could
be dominant in different items, for example, music might have
varying compositions making such retrieval process non-trivial.

Therefore, information retrieval to acquire knowledge about con-
cerned items requires incorporation of learning techniques. Given
a teaching signal, a learning system learns underlying attributes
representation and is helpful in predicting a candidate pool of items,
potentially novel and interesting to users. This work presents novel
similarities metric and learning method to retrieve recommendable
items.

3 TEMPORAL PROXIMITY FILTERING

Dynamic needs of users are largely abstract in nature and can bet-
ter be learned from their own items consumption history. Current
collaborative models fail to address users’ inherent needs and liking
[1] because they ignore either changing user preferences or latent
representations. We illustrate an analogy of the presented method
with collaborative filtering methods in figure 2. Collaborative filter-
ing methods rely on similarity in user profiles and items frequency.
User profile properties are largely assumed to be predefined and
fixed. Similarities are induced by users and items data matrices
with collaborating filtering: Collaborating filtering methods we need to augment the systems with more fundamental composi-
cation. It can be a starting point to learn similarities
gories, we would be better off learning them implicitly from users' preferences and taste? Songs in a genre might have intrinsic simi-
larities, however, a user might listen to one song from a particular
genre but he might not listen to another song from the same genre.
handcraft such features which are driven by the dynamic nature of
song or pair of songs in tandem. It opens up a question - can we
learning the intrinsic structures that make people like a particular
taste and it might be composed by different artists across genres or
genres or artist names. Users listen to music that matches their
taste and it might be composed by different artists across genres or
artists etc does not go far and we need to augment the systems with more fundamental composi-
tional properties of music attributes. Moreover, users get attached
to particular kinds of music because they start liking the inher-
ent compositional attributes like beats rather than hard-classified
genres or artist names. Users listen to music that matches their
taste and it might be composed by different artists across genres or
same artist or a mixture. A key aspect, we ought to consider, lies in
learning the intrinsic structures that make people like a particular
song or pair of songs in tandem. It opens up a question - can we
handcraft such features which are driven by the dynamic nature of
preferences and taste? Songs in a genre might have intrinsic simi-
larities, however, a user might listen to one song from a particular
genre but he might not listen to another song from the same genre.
It clearly indicates that instead of handcrafting such feature cate-
gories, we would be better off learning them implicitly from users’
content consumption. It can be a starting point to learn similarities
in items’ attributes. Such a learning ability provides us a lever to
filter recommendable and novel items matching user taste, even if
they are newly released.

We fill this gap by inducing similarity between pairs of songs in
attribute space. The attributes like beats, loudness, pitch etc have a
sequence that characterize songs or other media items. We propose
that the items consumed in temporal proximity have underlying
structural similarities at a latent level. We describe a measure to
induce similarity by proximity in consumption. Patterns of items

Although these models are popular for predicting next recom-
manded items, they do not have a reliable provision to include
temporal needs in their users or attributes feature vectors. They
try to handle it by rolling the model temporally but over the same
set of similarity inducing static features. Therefore, such methods
loose track of temporal dynamics in users’ liking or taste. In pro-
posed proximity filtering method, users’ consumption bundles are key
drivers. We propose that items similarity can be learned from
user tastes in a thematic space. It does not need users’ static profile
properties rather items consumption in a latent thematic space is an
embodiment of user profiles. The induced similarity and dy-
namic user profiling makes the presented model a dynamic hybrid
method.

Traditional recommender methods are not sufficient for diverse
and intricate domains like music. Recommending music using fixed
qualitative categories like genre, artists etc does not go far and
we need to augment the systems with more fundamental composi-
tional properties of music attributes. Moreover, users get attached
to particular kinds of music because they start liking the inher-
ent compositional attributes like beats rather than hard-classified
genres or artist names. Users listen to music that matches their
taste and it might be composed by different artists across genres or
same artist or a mixture. A key aspect, we ought to consider, lies in
learning the intrinsic structures that make people like a particular
song or pair of songs in tandem. It opens up a question - can we
handcraft such features which are driven by the dynamic nature of
preferences and taste? Songs in a genre might have intrinsic simi-
larities, however, a user might listen to one song from a particular
genre but he might not listen to another song from the same genre.
It clearly indicates that instead of handcrafting such feature cate-
gories, we would be better off learning them implicitly from users’
content consumption. It can be a starting point to learn similarities

\[
\text{Sim}_{TF}(S_x, S_y) = \frac{P(S_x) \cdot P(S_y)}{|P(S_x)| |P(S_y)|}
\]

Since the songs are composition of a variety of attributes, we can
use the taste proximity similarity measure to learn structural similari-

ties in the underlying attributes of paired songs. Users listen
to songs in taste bundles as shown in figure 3. The taste bundles
are sequence of songs listened by a user in streak. For example, a
user might want to listen to classicals at the start of the week. If
the song pairs listened by users come from the same taste, they

Figure 2: Analogy of proposed proximity filtering method
with collaborating filtering: Collaborating filtering methods
rely on similarity in user profiles and items frequency while
temporal dimension is handled loosely on a case to case ba-
is. In proposed proximity filtering method, users’ consump-
tion bundles are key drivers. It does not need users’ static
profile properties rather a latent thematic representation
provides user profile. In this work, we close the loop in other
two dimensions by attribute similarity learning using tem-
poral proximity filtering. It makes presented system a dis-
tinguishing hybrid method due to its naturally induced sim-
ilarity and dynamic user profiling.

Figure 3: Users listen to their favourite songs together, ac-
cording to their mood and taste. We propose a similarity
metric in taste space. Songs listened within a taste proximity
are deemed to be more similar than others.
are more likely to have some structural similarity than the songs from different tastes. We present this similarity in latent tastes as a learnable metric in an attribute space. The latent themes model can be run for any parametrized duration, therefore, we call such a representation of proximity in a latent thematic space as Temporal Proximity Filtering.

Essentially, users’ item consumption in a latent thematic space provides insights into the basic composition of the content itself. We propose that such similarity measure provides a novel opportunity to learn attribute structures.

4 ATTRIBUTES SIMILARITY

Discovery of novel items that match users’ tastes among millions of available items is a mammoth task. Filtering from the potential items is usually done either through explicit methods or tracking implicit user behaviors. We propose that proximity filtering in latent thematic space could be a useful way to retrieve interesting and novel potential items that match users’ tastes. As demonstrated by Knees et al. [14], there are two main components in relevant music information retrieval: features and similarity measure. For media content like songs, we need to learn higher level mixture of attributes to understand underlying characterizing structures. We use a convolution network [17][15] to extract abstract representations from attributes. Figure 4 illustrates schematic view of learning the attribute similarity for paired items.

Let X be the input and the number of filters at each level determined by [m, n] kernel configuration, \(K_i\) be a filter with kernel specification at a layer i. The output of convolution at a layer i, \(C_{X_i}\) is given by

\[
C_{X_i} = f(b_i + K_i \ast t mP(X_i))
\]

(2)

where f is activation function, \(b_i\) is bias for layer i, tmP is temporal max pooling and \(\ast\) represents a convolution operator. We use last \(C_X\) to feed a fully connected network given by

\[
O_{X_l} = f(b_l + W^T_l C_X)
\]

(3)

where \(W_l\) represents weight of hidden nodes and \(b_l\) hidden bias for layer l. Similarly, the processing of second item, Y, of the pair is given by

\[
C_{Y_l} = f(b_l + K_l \ast t mP(Y_l))
O_{Y_l} = f(b_l + W^T_l C_Y)
\]

(4)

with shared parameters between parallel networks. We compute similarity between two paired items as

\[
Sim(S_x, S_y) = \frac{O_{X_l} . O_{Y_l}}{||O_{X_l}|| ||O_{Y_l}||}
\]

(5)

where there are n output units in each of the parallel network, \(O_x\) and \(O_y\) are forward pass outputs for the respective item in the pair.

Using proximity filtering, we compute similarities between item pairs based on their consumption in a latent thematic space. Therefore, we use this cosine similarity measure as a teaching signal to train the learning model. We use mean squared error between attribute similarity and thematic teaching similarity as a loss function,

\[
L(S_x, S_y) = \frac{1}{n} \sum_{(x,y) \in S} ||Sim(S_x, S_y) - Sim_t(S_x, S_y)||^2
\]

(6)

where \(S\) is the set of pair of songs from items (songs) basket. Following this procedure, we learn similarity between paired items and the model trained using an induced similarity is capable of predicting similarity of unseen item pairs. Therefore, given an item, it is feasible to find novel items with similarity in tastes in an attribute space.

5 EXPERIMENT

In this section, we describe our dataset and the methodology, structure of our convolutional neural network used to co-learn the similarity between the songs in attribute and consumption space.

5.1 Dataset and pre-processing

We use the user data from the last.fm for the temporal music consumption history of 992 users collected by Celma [8]. The dataset contains complete temporal history of songs listened by the users from May, 2007 to May, 2009. However, the dataset does not contain the attributes of the songs. Musical attributes of songs are provided by 300 GB big Million Song Dataset [4]’s 1 million popular songs extracted by EchoNest’s song analysis [12]. These 28 features depict the audio analysis of the songs done using the “Analyze” tool [13] on raw audio to extract these derived features since raw audio data is not publicly accessible to researchers because of copyright issues. We only used the 28 audio features like beats, segments, bars, and loudness, from the song features listed at last.fm [5]. While these 28 features, some of them like segments are 2000 dimensional features. With this background, we got around 17000 dimensional space for each song, explained in next subsection.

Since, the MSD songs (EchoNest) and the songs from the last.fm’s user data don’t have a unique shared identifier, we used artist identifier field (missing in some case) in combination with the song title string similarity for correspondence between the two
datasets. The last.fm’s user data has 1.5 million unique songs, including ads/independent artist renderings. Our matching yielded correspondence between 341,039 songs across the two datasets. Out of the rest 1.16 million songs, 90% songs were listened less than once by any of the users. We use these 341,039 unique songs for our analysis of the user history, ignoring the rest, since there is no audio analysis data associated with them along with low listening frequencies.

5.2 Procedure
The proposed procedure, TASTESIM, is illustrated in algorithm 1. We use users’ consumption history dataset and song attributes from million song dataset. First, we discover latent themes using an off-the-shelf latent Dirichlet allocation package. We kept the number of themes to 20 and computed user-theme and theme-song distributions. In this experiment, we consider weekly lists that is analogous to weekly documents - imagine a large book divided into sections to be read on a weekly basis or weekly playlists.

Algorithm 1 TASTESIM: Attribute Similarity Learning by proximity in consumption bundles

\[
\begin{align*}
W & \leftarrow \{S_1, S_2, S_3 \cdots S_n\} \text{ set of songs} \\
H & \leftarrow \text{Users’ consumption history} \\
Puh, Phs & \leftarrow \text{LDA}(H, W) \\
S & \leftarrow \{(S_x, S_y) \text{ where } S_x, S_y \in W\} \\
\text{for} \ (S_x, S_y) \in S \text{ do} & \\
& \quad \text{learn attribute similarity} \\
& \quad \text{load the network model } \Theta \\
& \quad \text{while not converged or not max-iter do} \\
& \quad \quad \text{compute } \text{Sim}(S_x, S_y) \text{ via parallel + conv + fc layers} \\
& \quad \quad \text{evaluate loss } L(S_x, S_y) \text{ (refer Sec. 4)}
\end{align*}
\]

The dataset provides attributes like bars attributes, segments attributes, pitches, tatums, danceability, duration, and tempo. We consider pairs of songs and compute their cosine similarity scores using distributions from latent theme model. By limiting the scope of the taste model to weekly documents, we ensure that proximity in taste model is analogous to weekly lists. Out of all possible pairs, we used a subset of 10K pairs for taste induced similarity. We use temporal convolution to abstract features, weights act as kernel filters and are learned during network training. Filter size is kept as 5. Following [22], we use temporal max pooling and ReLU as activation in intermediate hidden layers [9]. The abstracted attributes are fed to fully connected layers with 800 and 600 hidden units. The number of output units are kept as 20 in correspondence with the number of themes. Thus, we show that taste similarity in thematic space can be used to induce similarity in learning item properties matching users’ tastes.

6 RESULTS AND DISCUSSION
We discuss the existence of temporal structure in consumption bundles and taste induced similarity for a publicly available users’ song consumption dataset and million songs dataset.

6.1 Temporal Consumption Pattern
We first examine if temporal structure does exist in user consumption patterns in taste space. We compute gap time between two songs and their similarity score as given in sec 3. This score indicates how similar are two songs in taste space. We plotted gap time with similarity scores and from figure 5, it is evident that similarity scores are higher for items consumed within a gap of couple of hours. A higher score in taste means that those pairs of songs have more commonalities in consumption and lower gap time means that they are listened more in tandem.

Moreover, as illustrated in figure 6, such pairs are not only listened in temporal proximity but also listened more frequently. A comparatively lower frequency on the left side of the plot in figure 6 and gradual decrease in the frequencies on right imply that people might not listen to pairs in immediate continuity but in a short period, it is more likely that they return to their favourite pairs of songs. It indicates that temporal proximity structure does exist and provides us an important insight into user tastes.

Traditional methods use external user attributes which might not be a good indicator of user tastes and preferences. We have illustrated that user tastes in a period are manifested in grouping of songs listened or consumed in temporal proximity. A similar argument can be made for other media consumption domains. Existence of such proximal structure can be leveraged to induce valuable knowledge in discovering novel items that a user might prefer. We now examine skip level structures, in other words, existence of Markovian structure in music listening in more details. We construct pairs of songs using n-skip levels where n indicates number of consecutive songs skipped over. For example, 0-skip would mean that we consider every consecutive song, 1-skip would mean that we consider every alternate song. A similarity score using taste model is computed for each of the n-skip pair. Boxplot (mean values with one-standard-deviation) in figure 7 illustrates cosine similarity distribution of song taste listened by users by skipping n consecutive songs. It indicates that temporal proximity structure does exist and provides us an important insight into user tastes.
This is further evidence that users listen to songs matching their tastes in temporal proximity provides a novel way to induce similarity. Since similarity between pair of songs is derived from users’ content consumption, it is viable to think that there should be an underlying implicit structure in attributes space. For example, if two items frequently co-occur within the same theme, they are more likely to have some underlying properties that encourage their co-consumption. Therefore, we should naturally exploit this implicit knowledge derived from users’ tastes to find items.

6.2 Attribute Similarity Learning through Proximity Similarity

Taking a cue from play lists, we consider temporal proximity in bundles. We create weekly listening patterns of the users from one year consumption data, i.e., 52 maximum possible weekly play-lists. For each user we only consider a weekly play-list for which they listened to a song. The intuition behind using the weekly play-lists is that the music streaming platforms usually publishes weekly charts that are used by the users to refer to the latest trendy songs. In other words, we infer users’ weekly music taste from this play-list (document) using LDA. Training the network model, fig 8, using taste or thematic similarity shows that induced taste similarity can be used to learn similarities between item-pairs in attribute space. We get a MSE of the order of $10^{-3}$ on the test set, which reflects the difference in similarity between a pair of songs from the users’ taste space and the learnt similarity calculated by the deep network from the song attributes. Hence, our deep network is able to learn a latent space of item-item similarity in the attribute space that mimics the dynamics of user driven item-item similarity.

In a nutshell, we showed that users consume media content in temporal proximity of consumption bundles which reflect users tastes. Instead of using indirect and non-reliable methods on trying to assess what a user might prefer, we propose that using these consumption bundles is a viable option to induce knowledge of users taste in attribute space. This novel view could be beneficial in developing users tastes and preferences driven recommender systems.

7 CONCLUSION

Identifying novel items is a persisting challenge in recommendation systems. While a lot of strides have been made in improving the quality of recommended items, filtering recommendable items that match user tastes and dynamic preferences is an area needing more attention. Traditional methods suffer from “long tail” effects leading to suppression of items very similar to popular ones, but not listened often. In this work, we attempt to address this issue by presenting a novel method by inducing users’ taste driven temporal proximity similarity measure into attribute space without user meta data or any explicit feedback.

We demonstrated that temporal structure exists in users consumption behavior and users consume their favourite content, matching latent theme or taste, in temporal proximity of consumption bundles. We presented an induced similarity metric from latent theme (or taste) model and showed that it is possible to harness users’ taste induced similarity for item-pairs in attribute space.

Therefore, temporal proximity in latent thematic or taste space provides a fundamentally novel view in unravelling what users implicitly prefer instead of relying on outside knowledge. This view has potential in devising recommendation systems by finding novel items that match user taste in attribute space.
REFERENCES

[1] 2016. Netflix’s Grand, Daring, Maybe Crazy Plan to Conquer the World. (2016). http://www.wired.com/2016/03/netflix-grand-maybe-crazy-plan-conquer-world/

[2] 2016. Stuck in the middle with Spotify. (2016). http://www.economist.com/blogs/prospero/2016/05/digital-music/

[3] Luke Barrington, Reid Oda, and Gert Lanckriet. 2008. Smarter than genius? human evaluation of music recommender systems. In in International Symposium on Music Information Retrieval, 2009. Oscar Celma, Music Recommendation and Discovery in the Long Tail, Ph.D. thesis, Universitat Pompeu Fabra.

[4] Thierry Bertin-Mahieux, Daniel P.W. Ellis, Brian Whitman, and Paul Lamere. 2011. The Million Song Dataset. In Proceedings of the 12th International Conference on Music Information Retrieval (ISMIR 2011).

[5] Thierry Bertin-Mahieux, Daniel P.W. Ellis, Brian Whitman, and Paul Lamere. 2014. Field list audio analysis . http://labrosa.ee.columbia.edu/millionsong/pages/field-list. (2014).

[6] David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. the Journal of machine Learning research 3 (2003), 993–1022.

[7] Dmitry Bogdanov, Martín Haro, Ferdinand Fuhrmann, Anna Xambó, Emilia Gómez, and Perfecto Herrera. 2013. Semantic audio content-based music recommendation and visualization based on user preference examples. Information Processing & Management 49, 1 (2013), 13–33.

[8] O. Celma. 2010. Music Recommendation and Discovery in the Long Tail. Springer.

[9] George E Dahl, Tara N Sainath, and Geoffrey E Hinton. 2013. Improving deep neural networks for LQCSR using rectified linear units and dropout. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 8609–8613.

[10] Uri Hanani, Bracha Shapira, and Peretz Shoval. 2001. Information filtering: Overview of issues, research and systems. User modeling and user-adapted interaction 11, 3 (2001), 203–259.

[11] Gweshe Jawaher, Martin Storozsr, and Patty Kostkova. 2010. Comparison of Implicit and Explicit Feedback from an Online Music Recommendation Service. In Proceedings of the 1st International Workshop on Information Heterogeneity and Fusion in Recommender Systems (HetRec ’10). ACM, New York, NY, USA, 47–51. https://doi.org/10.1145/1869446.1869453

[12] Tristan Jehan. 2005. Creating music by listening. Ph.D. Dissertation. Massachusetts Institute of Technology.

[13] Tristan Jehan and David DesRoches. 2014. Analyzer Documentation . http://developer.echonest.com/docs/v4_/static/AnalyzeDocumentation.pdf. (2014).

[14] Peter Knees and Markus Schell. 2016. Introduction to Music Similarity and Retrieval. In Music Similarity and Retrieval. Springer, 1–30.

[15] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems: 1097–1105.

[16] Arun Kumar and Paul Schrater. 2017. Novelty Learning via Collaborative Proximity Filtering. In Proceedings of the 22nd International Conference on Intelligent User Interfaces. ACM, 601–610.

[17] Yann LeCun and Yoshua Bengio. 1995. Convolutional networks for images, speech, and time series. The handbook of brain theory and neural networks 3361, 10 (1995), 1995.

[18] Pasquale Lops, Marco De Gemmis, and Giovanni Semeraro. 2011. Content-based recommender systems: State of the art and trends. In Recommender systems handbook. Springer, 73–105.

[19] Prem Melville, Raymond J Mooney, and Ramadas Nagarajan. 2002. Content-boosted collaborative filtering for improved recommendations. In Aisui/ai. 187–192.

[20] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th international conference on World Wide Web. ACM, 285–295.

[21] Markus Schell, Peter Knees, Brian McFee, Dmitry Bogdanov, and Marius Kaminas. 2015. Music recommender systems. In Recommender Systems Handbook. Springer, 453–492.

[22] Dominik Scherer, Andreas Müller, and Sven Behnke. 2010. Evaluation of pooling operations in convolutional architectures for object recognition. In International Conference on Artificial Neural Networks. Springer, 92–101.