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Personalized music search based  
on graph embedding

Master Thesis

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## Abstract

Due to the rise of music streaming platforms, huge collections of music are now available to users on various devices. Within these collections, users aim to find and explore songs based on certain criteria reflecting their current and context-specific preferences. Currently, users are limited to either using search facilities or relying on recommender systems that suggest suitable tracks or artists. Using search facilities requires the user to have some idea about the targeted music and to formulate a query that accurately describes this music, whereas recommender systems are traditionally geared towards long-term shifts of user preferences in contrast to ad-hoc and interactive preference elicitation. To bridge this gap, we propose Gemsearch, an approach for personalized, explorative music search based on graph embedding techniques. As the ecosystem of a music collection can be represented as a heterogeneous graph containing nodes describing e.g., tracks, artists, genres or users, we employ graph embedding techniques to learn low-dimensional vector representations for all nodes within the graph. This allows for efficient approximate querying of the collection and, more importantly, for employing visualization strategies that allow the user to explore the music collection in a 3D-space. Based on a dataset with over 1.5 million graph nodes, we show that the performance of our recommendations outperforms standard matrix factorization methods and produces results that are comparable to UserKNN techniques in terms of personalization. The strength of our system which are the seeding items to model short-term preferences, achieve even higher precision@10 values.



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# Introduction

The following master thesis presents Gemsearch, a **graph embedding** based music **search** which aims to combine flexible query mechanisms with personalized recommendations. Furthermore, the proposed method allows implicit search refinements and explorative 3D visualizations.

This thesis embraces two papers and an implementation appendix. The former paper introduces the overall Gemsearch system and in particular its embedding and query mechanism to retrieve personalized results based on seeding elements. In addition, we present here an evaluation on track prediction performance which was conducted on playlist data. The second paper is a specialization and focuses purely on the visualization of embeddings which were derived from graph embedding techniques. This paper was submitted and accepted on the Intelligent Music Interfaces for Listening and Creation congress in Tokyo, Japan, March 2018.

The implementation appendix contains specific software architecture details about the prototype system and should ease the creation of potential extensions.



# Personalized music search based on graph embedding

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## ABSTRACT

Due to the rise of music streaming platforms, huge collections of music are now available to users on various devices. Within these collections, users aim to find and explore songs based on certain criteria reflecting their current and context-specific preferences. Currently, users are limited to either using search facilities or relying on recommender systems that suggest suitable tracks or artists. Using search facilities requires the user to have some idea about the targeted music and to formulate a query that accurately describes this music, whereas recommender systems are traditionally geared towards long-term shifts of user preferences in contrast to ad-hoc and interactive preference elicitation. To bridge this gap, we propose Gemsearch, an approach for personalized, explorative music search based on graph embedding techniques. As the ecosystem of a music collection can be represented as a heterogeneous graph containing nodes describing e.g., tracks, artists, genres or users, we employ graph embedding techniques to learn low-dimensional vector representations for all nodes within the graph. This allows for efficient approximate querying of the collection and, more importantly, for employing visualization strategies that allow the user to explore the music collection in a 3D-space. Based on a dataset with over 1.5 million graph nodes, we show that the performance of our recommendations outperforms standard matrix factorization methods and produces results that are comparable to UserKNN techniques in terms of personalization. The strength of our system which are the seeding items to model short-term preferences, achieve even higher precision@10 values.

## KEYWORDS

Recommender Systems, Graph Embedding, Personalization

## 1 INTRODUCTION

In recent years, music streaming platforms have become a central means for listening to music as these allow users to access huge collections of music. This evolution has also influenced the way users search and explore music. For instance, the streaming platform Spotify currently serves 140 million active users and provides a collection of more than 30 million songs<sup>1</sup> (as of June 2017). Consequently, the primary objective for users has shifted from retrieving specific songs to finding and ultimately exploring songs that match certain criteria reflecting the user's current preferences and context [7, 11].

Currently, two paradigms allow users to explore large music collections: search and recommender systems. Utilizing naive search approaches based on simple attribute matching requires the collection data to be fully annotated with metadata. When relying

on keyword search facilities, the user is required to have some idea of his/her current preferences and must be able to formulate a query that actually describes these preferences well. More advanced search facilities are based on content similarities of items (aka "find similar artists or songs") and are rarely personalized. Especially data sparsity and the lacking ability for comparing heterogeneous items (tracks, artists, albums, etc.) makes it hard for such systems to succeed. In contrast, recommender systems propose items that might be suitable for the user (based on some collaborative filtering approach or more complex models. While recommender systems do not require the user to be able to formulate his/her current preferences, the user also is not able to directly influence recommendations by stating e.g., a starting point for his/her explorative search for music matching his/her current preferences (except for feedback mechanisms like relevance feedback and explicit ratings that influence the user model in the long term).

Only very few approaches like, e.g., the one proposed by Chen et al. [1] allow the user to specify his/her current needs and preferences in an abstract manner, where the returned results are jointly based on the query (the user's current information need) and the user's personal music preferences. However, there is still a substantial lack of systems which combine flexible search mechanisms with user interfaces that provide dynamic, exploration-driven visualization strategies for large collections of music.

Therefore, we propose the Gemsearch system, which stands for **graph embedding based music search**, to bridge this gap in explorative music search. In particular, we propose to use graph embedding techniques for computing latent representations of items contained in the graph, such as tracks, users, artists, genres or acoustic features of tracks. Using such graph embedding techniques [18], a low-dimensional latent vector representation is learned for every node. These firstly allow to create advanced search facilities as search queries can be encoded in the same vector space where every graph node is encoded. As a result, not only exact results can be retrieved, but also similar items and hence, exploiting previously unknown similarities between heterogeneous items that can be utilized to retrieve diverse search results. Secondly, the obtained vector representations can be exploited for advanced visualization paradigms, enabling explorative music search beyond traditional list-based aggregations of search results that only provide a one-dimensional view of the retrieved items.

Real world applications usually generate new data during runtime which requires to update previously learned models. To optimize this process and avoid the recreation of models from scratch, we present an extension to the Deepwalk [15] algorithm which allows to extend initially learned embeddings with new graph structures such as vertices and edges on the fly.

<sup>1</sup><http://press.spotify.com/us/about>

To evaluate the proposed system, a Spotify dataset containing 852,293 tracks is used to perform user-track recommendation and to predict the contained tracks of playlist based on its title. We show that our system outperforms state-of-the-art matrix factorization methods and is comparable to *UserKNN* recommendations. Through the incorporation of seeding items which we extract from the playlist title, even higher precision@10 values are achieved. In particular our contribution are the following:

- We propose a flexible query-system for music which incorporates personal long-term preferences with seeding items and which is based on graph embedding techniques.
- We explain an extension to the Deepwalk algorithm which allows to extend the search-underlying data-model on the fly.
- We present a innovative method to visualize search results in 3D scenes which combines implicit and explicit query-refinements.

The remainder of this paper is structured as follows. In Section 2, we describe related work and graph embedding. Section 3 presents Gemsearch a system for personalized music search. The visualization prototype for explorative music search is proposed in Section 4. Then Section 5 describes the evaluation setup which results are discussed in Section 6. We conclude the paper in Section 7 by summing up key aspects and detailing future work.

## 2 RELATED WORK AND BACKGROUND

In this section we first recap graph embedding in general because it is the fundamental aspect of our computational model. Then we describe related work from two fields: query-based recommender systems and approaches which focus on user interfaces for the exploration of new music.

Graph embedding techniques aim to transform graph structures into a low dimensional vector space. More formally, given a graph  $G = (V, E)$  with vertices  $V$  and edges  $E$ , a graph embedding is a mapping  $f : v_i \rightarrow y_i \in \mathbb{R}^d \forall i \in [n]$  such that each node  $v_i$  in the initial graph is mapped to a vector representation  $y_i$ . This resulting vector space has  $d \ll |V|$  dimensions and the function  $f$  preserves some proximity measure defined on graph  $G$  [4]. Having this coherent search space makes it much easier to calculate higher-order proximities between heterogeneous nodes. Similar items can be retrieved using nearest-neighboring searches.

Existing embedding algorithms can in general be categorized into factorization based, random walk-based and deep-walking based methods. Concerning time complexity and preserved higher order proximities, mainly random walk based methods are interesting. Others methods either only embed similarities between connected nodes or their runtime is dependent on the number of edges  $|E|$  in contrast to  $O(|V|)$  [4]. As real-world network graphs usually tend to contain more edges than vertices ( $|V| < |E|$ ), these methods scale better on large datasets.

The two most popular random walk based methods are *Deepwalk* [15] and *node2vec* [5]. For this work, *Deepwalk* was chosen because despite that *node2vec* retrieves better embeddings in theory, it is not possible to extend the graph structure after its initial creation (cf. Section 3.3).

*Deepwalk* computes embeddings in two steps: First, short random walks over edges are generated and then unsupervised feature learning is applied to compute latent representations for each node. The primary task of the random walks is to reflect neighborhood relations of the graph structure. Each node is used a fixed number of times to start path traversals over randomly selected connected edges. The length of these paths is called *window size* and can be parameterized. Using these walks as training data, a representation for each node is learned such that the co-occurrence probability among nodes within the same window is maximized. In the field of natural language processing, this method is known as word embedding and especially popular with *word2vec* [13]. Both *Deepwalk* and *node2vec* make use of *word2vec* in their algorithms and reference implementations to embed arbitrary graph structures with random walks.

Recently, graph embedding techniques have also been introduced to the field of music information retrieval. Chen et al. [1] utilize graph embeddings for realizing a query-based music recommender approach that is similar to the one presented in this paper. The main difference is that the music graph was modeled by Chen as a bipartite graph with users in one and all other items in the other set. This allows to create next track recommendations based on recent seed tracks. However, item similarities are only constructed through collaborative filtering without content relationships because music items themselves are not connected in the initial graph.

Chung et al. [2] utilize a pure text-based music retrieval on the same dataset we are using to predict the content of playlists with their title. A common latent representation of words and songs is learned with unsupervised learning based on the co-occurrence of tracks and words in playlist titles. However, in this model only tracks are included, proximities are based on playlists and the construction of queries is very limited.

For the task of building visualizations for music exploration, there are a number of relevant approaches, mostly based on proximity-preserving dimension reduction techniques.

The Islands of Music interface [14] incorporates rhythm descriptors and employs self-organizing maps for visualizing music collections based on the metaphor of geographic maps in two-dimensional space. One highly relevant extension of these maps is a browsable 3D landscape by Knees et al. [9], where tracks are clustered based on content features. Hamasaki and Goto [6] propose Songrium, a collection of visualization and exploration approaches. These include the “Music Star Map”, a visualization of songs in a graph, where placement of songs is based on audio similarity. Also, Lamere et al. [10] presented a 3D interface (Search Inside the Music) based on Multidimensional scaling techniques to visualize similarities between tracks, where each item is represented as a single colored item in the 3D space. Similarly, the Music Box visualization approach relies on principal component analyses to visualize tracks, where song similarity is used to distribute tracks on a plane. The visualization proposed in this work differs from these approaches in the fact that we base the visualization on latent representations of items within a heterogeneous graph that includes tracks, artists, albums, genres, etc. Due to the applied graph embedding techniques,

proximities within the graph visualization are not restricted to similarities between items of the same type (e.g., tracks) or similarities based on a single set of features (e.g., audio features), but rather capture the similarity of items of any type in the latent feature space.

### 3 GEMSEARCH: PERSONALIZED MUSIC SEARCH

In the following two sections, we present the Gemsearch system, a first prototype for personalized explorative music search based on latent representations of nodes of the musical ecosystem<sup>2</sup>. *Gemsearch* consists of two main components: the graph embedding and retrieval engine that computes latent representations of items and query results, and the client providing a search and visualization interface which is described in Section 4.

#### 3.1 Graph Embedding and Retrieval Engine

A music corpus can be modeled as a heterogeneous graph with tracks, artists, album and tags as nodes and relationships as edges. Using graph embedding techniques as described in the previous section, a vector space with latent representations for each item can be learned. Higher order proximities are preserved and hence, distances in the embedding represent similarities between items. This is very powerful because previously missing metadata is compensated, and also heterogeneous items can be compared.

A common task for music discovery is to retrieve similar items for one item which is given as an example. Here, simply the nearest neighbors of this seed item within the embedding has to be computed. Each node of the initial graph could possibly be used as query and consequently also tags or artists for example serve as seeding items. After retrieving similar results, a simple post filtering allows to restrict the item type to only return tracks for example. Moreover, multiple items can be combined to construct complex queries which allows to express the desired outcome in a fine granularity. To evaluate a given query on the embedding, only a vector for the nearest neighbor search is required. This means that the latent representation of each query term has to be combined and could possibly be used as positive or negative example with different weights of impact.

If user feedback is available, e.g., implicit through historic track listening behavior or explicit positive feedback on items, the user can be included into the system. In the graph, users are modeled as graph nodes and for each feedback on music items an edge is inserted between this item and the user. This improves the available graph structure and therefore, may improve the embedding quality (through collaborative filtering) and additionally makes it possible to model a user’s preference on queries. After embedding, the user itself has a latent representation in the same vector space with all other items. Because proximities have been preserved, his/her consumed and preferred items are positioned nearby this vector. Constructing a query with the user and no additional seed items retrieves general recommendations. For each user-initiated search query, the user’s latent representation is added and hence, long-term preferences partly influence the outcome. To limit this effect

to a certain margin, the user’s vector has to be downscaled.

Equation 1 formalizes the creation of a search vector  $q$  which is evaluated to retrieve nearest neighbors on embedding  $f_\theta$ . The short-term query intension may be expressed by multiple graph nodes  $x_0, x_1, \dots, x_n$  and is influenced by general preferences of user  $u$ . Each item (query nodes and user) is transformed with the embedding to retrieve the latent representations. The final vector is then produced by the weighted mean, where  $\alpha_{x_0} + \dots + \alpha_{x_n} + \alpha_u = 1$ .

$$q := \underbrace{\alpha_{x_0} * f_\theta(v_{x_0}) + \dots + \alpha_{x_n} * f_\theta(v_{x_n})}_{\text{query intension}} + \underbrace{\alpha_u * f_\theta(v_u)}_{\text{user preference}} \quad (1)$$

For the creation of the graph underlying our approach, we rely on the Spotify playlist dataset by Pichl et al. [16], containing 852,293 tracks crawled from public Spotify playlists. Graph embedding techniques can only preserve proximities in their produced embeddings which are represented by the initial graph. Therefore, we crawled Last.fm tags<sup>3</sup> for the contained tracks to introduce user created semantic information. These tags extend the feature set of tracks and in addition, they enrich the available item descriptors which users can use in their search queries. The resulting dataset is represented as a graph containing undirected edges between the following item types: user–track, track–tag, track–album, album–artist and artist–genre. For the computation of latent representations of nodes via graph embedding, we rely on the popular Deepwalk algorithm [15], where we learn representations for all nodes in a 128-dimensional vector space. The resulting latent representations provides means for flexibly computing similarities between heterogeneous items such as tracks, users or artists.

#### 3.2 Search refinement

Gemsearch allows users to interactively explore the music space to find new music. Therefore, a starting position for browsing through the items has to be determined by eliciting the user’s current musical preferences. As can be seen in the top left corner of Figure 1, a text input field (with autocompletion support) allows to select multiple items from the dataset to construct a query that reflects the user’s current preferences. Here, the search query for artist “Jimi Hendrix” may return similar and suitable artists, tracks or tags. In addition, the search result can further be restricted by adding further search terms. In Figure 1, the tag “guitar” is entered and combined with the first term.

Searching for music is not a single action where a user formulates his information needs and then consumes the results. The search can be seen as a process where query refinements are a constant part of it. Therefore, it is necessary that users are not only able to extend queries but are also supported with e.g. suggestions for possible query terms for adjustments. The user should feel like navigating through a virtual result space instead of jumping to unconnected places after manually modifying requirements. In the underlying latent vector space, any of the proposed items can be used to further extend the query and hence, refine the search to match current preferences more precisely. This means that any of

<sup>2</sup>The prototype can be accessed at <http://dbis-graphembeddings.uibk.ac.at>

<sup>3</sup><https://www.last.fm/api/show/track.getTags>

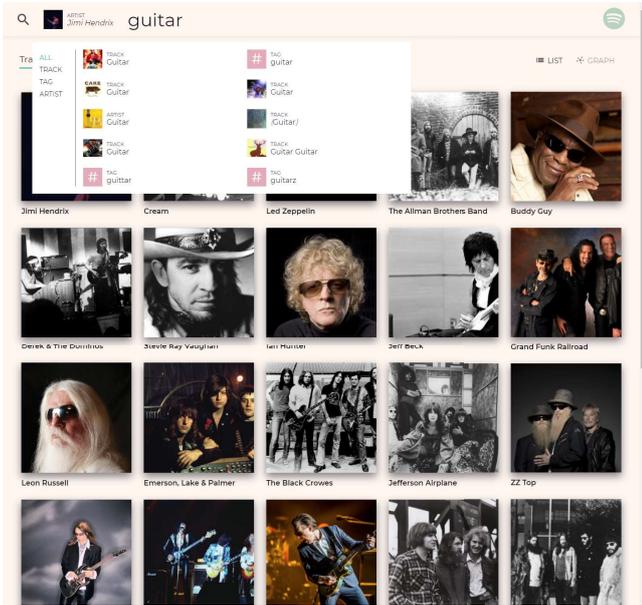


Figure 1: Gemsearch query bar with autocomplete and list results.

the proposed items which are retrieved after the initial query can be used to further extend the query and refine the search.

For example, suppose that a user inspected his/her first results of Figure 1 and the user’s search intention also matches “Jeff Beck”. Then he/she can either consume songs directly from this artist or add it to the current query. This will not limit new results to “Jeff Beck” but will return items which are similar to both artists. Using this technique, the user has not actively adapt the query through reformulating it and still gets more precise results.

### 3.3 Model extension

In real world scenarios, the dataset represents a dynamic system, constantly changing because new songs or users are added. New data can either consist of new edges, e.g. new listening events of users during the use of the system, but also of new vertices when tracks or users are added. To reflect these changes in the recommendations, this adaption has to be applied to the model. Especially if initial data is available for new users, e.g. through connecting with other services, a fast method is desirable to alleviate the cold start problem such that the system can be used right away. A naive approach could simply recreate the whole embedding from scratch, but this is not scalable for bigger sets. To solve this issue, we present an extension to the Deepwalk [15] algorithm which can include additional graph structure after creating an initial model.

Random walk based embedding techniques are mostly online algorithms [4][5] which can consume new walks during training as they are produced. This property is very powerful in general because for huge datasets, not all walks have to be generated in advance or even be kept in memory. However, the probability distribution of random walks in *node2vec* is not uniform and precomputed before walk generation, based on the graph structure. This

implies that neither edges nor vertices can be added or removed after the initial computation because it would invalidate previous transition probabilities.

On the contrary, *DeepWalk* does not impose restriction on the distribution over random walks and therefore allows graph structure extensions in theory. The presented algorithm and reference implementation does not offer this functionality, but uses *word2vec* of Gensim [17] to compute the actual embedding. Using *word2vec* in the backend makes it possible to store the current internal skip-gram model, later restore it for further learning with new sentences (walks) and additionally allows to extend the current vocabulary (vertices) during runtime. Combined, the desired options are available to partially extend the existing graph and retrieve new embeddings.

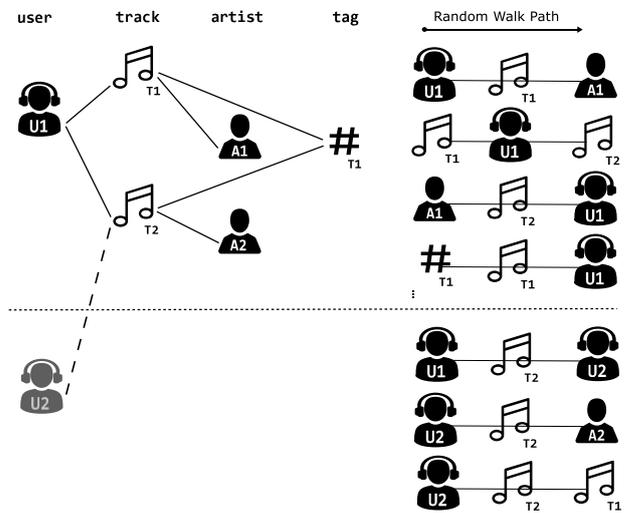


Figure 2: Graph extension example with an excerpt of potential initial walks and extended walks after user  $U_2$  and edge  $U_2 - T_2$  was added.

To extend an existing embedding, two datasets are required: added vertices and new random walks. To retrieve this set, first the initial graph is extended by the new graph structure while the system keeps track of modifications. In the next step, random walks are generated to reflect the added data in the same way as the initial walks. Here, only walks which contain new edges or vertices have to be created. This new training data is only of a small size compared to the initial data set and is proportional to the number of added structures. Figure 2 shows an example music graph and potential generated random walks for a windows size of 3. After a new user  $U_2$  and an edge between this user and the track  $T_2$  is added to graph, only three new walks needs to be generated for representing these modification.

Then, the existing *word2vec* model can be loaded and extended with the new nodes which initializes the embedded vectors with random values for those indices. Finally, learning is continued with the new random walks to retrieve an extended embedding which includes latent representations for added nodes and potential adapted

vectors for existing nodes.

With this method, the graph and its embedding can be updated with lower effort than relearning the complete model. However, even small changes can influence the whole embedding and create changed latent representations for each node. The scalability is therefore limited because for big datasets, the new embedding may impact all items contained in the graph which invalidates created indexes. Furthermore, only graph structure can be extended but it does not allow to modify or remove existing nodes or edges.

Gemsearch uses this live model updates to alleviate the cold start problem for user profiles by connecting with existing Spotify accounts. The official Spotify API supports the OAuth protocol with different scopes, allowing access to, e.g., personal playlists, playing history or saved tracks. To create a personal preference profile, *Gemsearch* retrieves the user's saved tracks as they may serve as a strong indicator for preference. After a user has connected with his/her account, the user's music library is loaded and compared with the current contents of the underlying graph. For tracks, artists, etc. that are not yet contained in the underlying graph, we gather the missing metadata from Spotify and user-curated tags describing these items from Last.fm. After the data is collected, the graph is extended with this new information to generate additional random walks. In the next step, the existing Deepwalk model is expanded and learned with the presented algorithm to compute and obtain a new latent representation which finally replaces the existing one.

#### 4 VISUALIZATION

The most common visualization for both recommendation and search results is to display a list of items ordered by the predicted relevance of the individual items for the user. This limits users to only observing the sequential order of items and hence, a one-dimensional view agnostic to distances between consecutive items. With a latent feature space underlying the system (obtained through, e.g., graph embedding techniques), similarities between arbitrary items can be expressed which permits developing more advanced interfaces. Through recent advances in browser technology, like the availability of native WebGL, just-in-time visualizations of 3D scenes can be created directly on websites without complex pre-computations or add-ons.

Using dimension reduction methods, the computed high-dimensional latent representations can be reduced to three dimensions, allowing to directly visualize items while preserving proximity. Here, we utilize principal component analysis to reduce the 128-dimensional representation of items to a three dimensional space. Instead of displaying a list of items, the recommended items can now be visualized in a 3D scene. Each track, artist or album can be positioned using its three-dimensional representation and can hence be displayed as an interactive 3D object. The positions and resulting distances reflect the relationships and proximities between items within the music collection. Beside the traditional list view for search results, the *Gemsearch* client visualizes the surrounding items in a 3D WebGL scene as depicted in Figure 3. Using such an interface does not only allow to express distance between items, but, more importantly, it allows the user to explore and browse

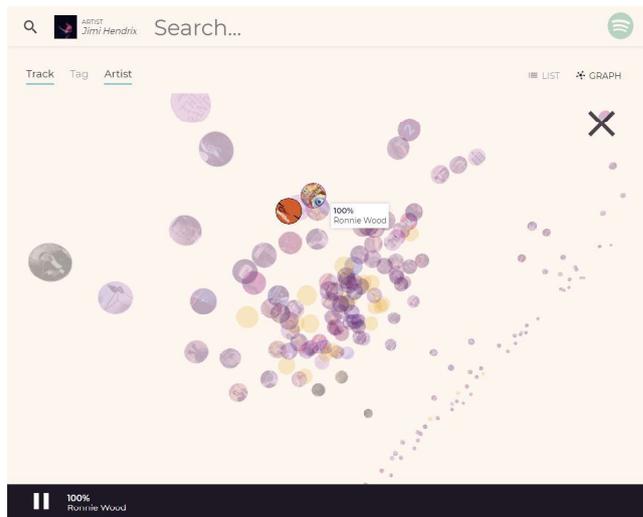


Figure 3: Web client 3D view and player bar.

through the result space interactively. Mouse gestures allow for exploring the virtual space and while navigating, additional items are lazy-loaded into the scene.

The user may first use a keyword search to express his/her current preferences (cf. section on Graph Embedding and Retrieval Engine). Based on these criteria, the first search results are retrieved and displayed in a 3D space. Beside the active manipulation of the search query which was described in Section 3.2, the 3D scene provides an even more effective process of implicit refinement. The most relevant search results are positioned around the center of the screen. When exploring additional items further away, the user has to opt for a direction in which to continue exploring. After inspecting items based on their album covers or through listening to music samples for tracks at the new position, the navigation direction can be refined. If the user detects suitable items, the direction is correct; otherwise the user will navigate in a different direction. This choice of directions and moving within the virtual result space directly translates to (implicit) query refinement.

It is crucial to simplify the inspection of single items such that huge collections of music are explorable in reasonable time. We use album covers as textures for 3D objects describing track and album items and hence, also allow for visually inspecting node textures as this has shown to be an efficient means for judging the relevance of albums and tracks [12]. To provide detailed information about selected items (e.g., artists of a given track, genres, etc.), information from the underlying graph is retrieved and displayed. Furthermore, the provide music samples for each track that allow users to immediately consume newly discovered tracks.

As similar items are located in close proximity to one another in the resulting space, distance-based clustering techniques can be applied to represent accumulations of items as annotated clusters. This allows users to decide whether a set of items might be of interest by looking at the characteristics of the cluster and not having to inspect the individual items contained in the cluster. However,

zooming in into a cluster to inspect the individual contained items is still possible. Figure 3 shows how clusters of similar items are represented as single orange circles. On click, the contained items are shown while all other elements are faded with transparency to enhance the contrast. As items within a cluster are positioned nearby, the scene is zoomed in without scaling the circle sizes to avoid overlapping elements.

## 5 EXPERIMENTS

Estimating the quality of the presented approach is one of the key challenges, because there exists no dataset which directly maps search queries with user context to results. Even having a working prototype client to test the system on real users, representative user studies require fairly big and diverse user bases. The test cases need to allow the users to estimate the results without being biased through available options or the test environment. A/B tests can model fair and solid results but require scopes in terms of number of users and participation which are only available on commercial platforms. Therefore, the common approach in research is to make use of crawled playlists which were manually created by users. As presented in [8], these evaluations are comparable to user studies. Additionally, offline experiments can be easily repeated with adapted implementations and input parameters which helps during implementation and optimization to observe and benchmark the outcome.

Manually curated playlists can be easily obtained from public platforms. They contain multiple song tracks sharing some common characteristics and are usually labeled with a short text to describe its content. In addition, they are associated to the user who has chosen the collection. In a broader sense the title of playlists can therefore be seen as queries and the contained tracks as the desired personalized results.

As there is no direct test dataset for Gemsearch, we relied on playlists to evaluate two aspects of the system. One aspect is the general embedding quality in respect to personal preferences. Here we transform the playlists to historic listening data and predict one hidden track per user. This evaluation is further described in Section 5.2. To incorporate the query mechanism with seeding elements, we use the playlist title and contained tracks as ground truth. As then explained in Section 5.3, the *playlist evaluation* tries to predict the tracks based on user context and playlist name.

### 5.1 Dataset and graph generation

The initial dataset was constructed from crawled Spotify playlists by Pichl et al. [16]. This set consists of playlists with hashed user id and multiple tracks with artist and audio features. To enrich the available query terms and gather additional graph structure, we extended the dataset with socially curated tags on tracks crawled from *Last.fm*<sup>4</sup> and artist genres from Spotify.

<sup>4</sup><https://www.last.fm/api/show/track.getTags>

**Table 1: Node count by type**

Type	Count
Playlists	21,336
Users	1,180
Tracks	852,293
Artists	110,377
Tags	395,587
Albums	189,174
Genres	1,520
Total nodes	1,571,467

**Table 2: Edge count by types (undirected)**

Type	Count
Playlist-User	21,323
User-Tracks	1,662,605
Track-Album	852,293
Track-Artists	1,027,918
Track-Tags	9,341,603
Artist-Genre	148,705
Total edges	13,054,447

Because both the playlists and *Last.fm* tags are unfiltered, user produced data, preprocessing was necessary. The playlist evaluation has to extract query terms from playlist titles. Hence, all playlists without at least one valid term were removed. We defined the smallest meaningful term to consist of either at least three alphanumeric characters or two digits (e.g. the term "80" could possible label tracks which were produced in the 1980s). Assuming that a playlist with less than four tracks represents only an incomplete list and therefore no processable information, this data was removed.

To match same tags on different tracks, the tag names are transformed to lowercase and special characters are removed. All tags which did not match the length requirement for query terms or with less than five user assignments on *Last.fm* are discarded.

Album and track titles from Spotify always satisfied those restrictions.

In total, 1,571,467 vertices and 13,054,447 are contained in the resulting graph after preprocessing which is further listed in Table 1 and 2. Within the dataset, the mode of the number of tracks in playlists is 12.

### 5.2 Track recommendation evaluation

The Gemsearch system constructs queries by combining multiple seeding elements with a potential user context to retrieve recommendations. Without seeds, the user node alone can be used to query for recommendations which are only based on his/her long-term preferences. This allows to perform a classic evaluation on user track recommendations, where implicit positive only feedback is used to determine items that a user may perform a certain action on. To reconstruct those past events, we use the playlists to produce

historic track listening data, which is split randomly into a training (80%) and test set (20%). Users with less than 8 tracks in the training set are removed because no meaningful profile could be created. Using the training data, a new graph is generated with edges between user and tracks, as well as all available metadata like artist, genres, album and tags. With Deepwalk an embedding is learned and then for each user, recommendations which are relevant and new to the user are calculated and compared with tracks in the test set of this user.

To retrieve those tracks, first the user serves as query to retrieve nearest neighbors of its latent representation in the embedding. Then these items are iterated in ascending order by their distance to filter all other items which are not tracks and to remove known samples from the user's training set. This is continued until the required amount of  $k$  elements is found and finally the results are returned.

To measure the performance  $\text{precision}@10$  and  $\text{recall}@10$  are computed and compared against five baseline scores using *MyMediaLite* [3]. Without personal context, the *Random* method returns random items and the *MostPopular* predicts tracks with the most overall listening counts. Furthermore, we conducted three collaborative filtering methods: Two state-of-the-art matrix factorization algorithms, *Weighted Regularized Matrix Factorization* (WRMF) and *Bayesian Personalized Ranking Matrix Factorization* (BPRMF), as well as *UserKNN*, a user-based collaborative filtering method that predicts  $k$ -nearest neighbor's tracks.

### 5.3 Playlist evaluation

To predict tracks of playlists based on their playlist title, two steps are required. First, a query must be constructed from the title and then this query can be used to retrieve relevant recommendations. For example, suppose the playlist title "Tommy's best of 80s rock classics" which may contains a personal best-of collection of rock songs which were produced in the 1980s. Analyzing the title multiple different queries are possible. As the embedding contains tags, the transformation could extract the tags "80s", "rock", "classics" and "rock classics". But there may also exist an album with the name "80s rock classics" which would potentially result in different recommended tracks. For this task of query term extraction, the full-text search capabilities of *Elasticsearch*<sup>5</sup> are used. Having such high-level full text search, fuzzy matching and proximity queries contribute to match terms even if they are not syntactical equivalent.

Before running the evaluation, the total set of playlists is randomly split into a training (80%) and a test set. Each user-playlist relation in the training set is used to create user-track edges in the graph which models the user preferences. With all available metadata, the graph is completed and then the embedding is computed using Deepwalk. In the evaluation phase, the title for each playlist in the test set together with the user context is combined to recommend potential relevant tracks. Those results are matched against the actual playlist tracks. For the query extraction, terms in the title must be matched against known item names. In the

training phase, all graph nodes except users and playlists are inserted into the Elasticsearch database and are then available by their title as query terms. Different techniques to extract and then combine multiple items for a final search vector are evaluated. The following list explains these methods and illustrates the possible extracted query on the example playlist title "Tommy's best of 80s rock classics" which was created by user  $u_x$ :

**one query term** The first item which is returned by the search for the playlist title is used as single query term.

Produces query: [tag:"rock classic"]

**one query term with user** Same as "one query term" but the user is added as query term which is scaled with  $\alpha_u = 0.3$  to limit the influence of long-term preferences.

Produces query: [tag:"rock classic" \* 0.7 + user: $u_x$  \* 0.3]

**first two query terms** The first two results (query extension) from the text-search for the playlist title are used to construct the query.

Produces query: [tag:"rock classic" \* 0.5 + tag:"80s" \* 0.5]

**user** Only the user is used as query term.

Produces query: [user: $u_x$ ]

**random** Random tracks are returned

Produces query: [random item]

To evaluate the performance, information retrieval measurements  $\text{precision}@k$  and  $\text{recall}@k$  are used. In addition, the metric  $\text{leastOneHit}@k$  is calculated which represents the percentage of playlists which had at least one valid hit at  $k$  proposed tracks. For baseline comparison, a random track recommender returns  $k$  random items for each playlist.

## 6 RESULTS AND DISCUSSION

As it can be seen in Table 4, Gemsearch can be used to produce personalized track recommendations which perform better than non-personalized methods and state-of-the-art matrix factorization techniques. For the task of track recommendations per user, only the UserKNN method achieved slightly better results than our approach. Because the test-listening data of this evaluation was constructed with playlist tracks, it confirms that the content of playlists are influenced by personal preferences.

Table 4: Track recommendation results

Recommender	Precision@10	Recall@10
UserKNN	0.10468	0.02010
Gemsearch	0.09469	0.00909
WRMF	0.02747	0.00192
MostPopular	0.01872	0.00175
BPRMF	0.01044	0.00088
Random	0.00017	0.00001

The results of the playlist recommender are listed in Table 3. Compared with the random track recommender, the performance does clearly outstand. Furthermore, methods relying on seeding items perform better than the track recommendations which are only based on user preferences. The best scores for precision and recall are achieved when only one query term without user context is

<sup>5</sup>www.elastic.co/products/elasticsearch

**Table 3: Playlist recommendation results**

Recommender Method	Precision@1	Precision@10	Recall@1	Recall@10
Full dataset				
one query term	0.11669	0.10014	0.00854	0.07117
first two query terms	0.11307	0.10101	0.00814	0.07140
one query term with user	0.08988	0.07637	0.00269	0.01433
user	0.01087	0.00937	0.00024	0.00208
random	0.00000	0.00014	0.00000	0.00002
Playlists with only one artist				
one query term	0.55280	0.46765	0.04258	0.34096
one query term with user	0.53981	0.45963	0.04140	0.33506
first two query terms	0.50706	0.45082	0.03852	0.32804
user	0.00169	0.00147	0.00018	0.00106
random	0.00000	0.00014	0.00000	0.00002
Playlists with multiple artists				
one query term	0.10456	0.07758	0.00495	0.03391
one query term with user	0.09897	0.07896	0.00464	0.03408
first two query terms	0.08477	0.06880	0.00391	0.02920
user	0.01979	0.01863	0.00038	0.00320
random	0.00000	0.00014	0.00000	0.00002

used. The experiments can not benchmark the query extraction and item retrieval separately. Tests on more complex query creations did not succeed because playlist titles are rather short and mostly only one query term is extracted. Therefore, not the full capacity of the Gemsearch query facilities are used in this evaluation.

Analyzing playlists without hits makes it clear that many playlist names are noisy and do not describe the contained tracks which makes it hard to predict the content. Furthermore, about 48% of the playlists contain tracks only from one artist. A nearer inspection shows, that playlists are often used to store albums or best-of collections of artists. As a consequence, pure text-based methods on the same dataset can produce better results [2]. In contrast, the proposed system *Gemsearch* is designed to discover new music and should therefore retrieve different sets of recommendations for each user. To reflect this desired property in the test data, the playlists are split into two disjunctive sets based on whether they contain tracks from multiple artists or not.

The results for these two datasets, listed in Table 3, show that for playlists with tracks from only one artist the overall performance is much better but also the user as part of the query does not improve the results. It seems that users assign more meaningful titles for such lists. Considering that the playlists were created by Spotify-Users, we suspect that users abused those lists to simply mark albums or artists for offline usage on their devices. In addition, the Spotify client currently supports to add all songs of an album to a new playlists. For this newly created list, the concatenation of the album and the artist name gets assigned as title. Many users probably keep this auto generated name and list of tracks, which makes it easier to predict the content but clearly also eliminates the influence of general user preferences on this collection. On the contrary are

playlists with a diversity of artists. All recommender methods are less efficient on this dataset except the recommendations which are only based on the user context. Both the query extraction and prediction of tracks is harder because the data is less structured. Using one single seeding element is still the best approach for short results lists but as soon as more items should be retrieved (higher  $k$ ) the long-term preferences improves the scores (precision@10 and recall@10 values for "one query term with user" are highest).

Analyzing the percentage of playlists with at least one hit in Figure 4 confirms that personalized strategies are only suitable for longer result sets. In order to predict one single item within playlists, it is more efficient to propose a "classic" example for the extracted term because it is more likely to be contained. When the user is added as additional search term to the query, most likely no direct neighbors of the initial term are retrieved anymore. This prevents the retrieval of the most popular "classic" example but is a desired effect for music exploration, because also items on the long tail are retrieved.

Figure 4: Percentage of playlists with at least one hit

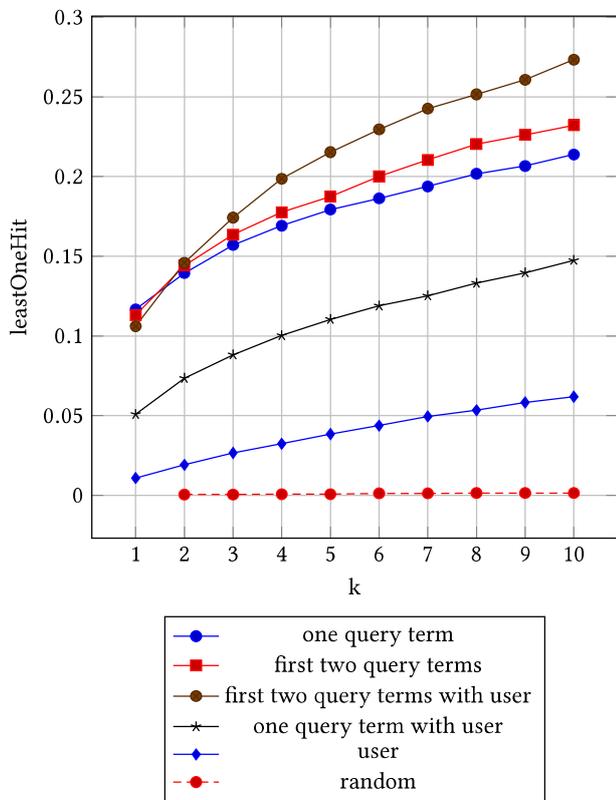


Table 5: Playlist recommendation performance on graphs with less structural data

Subset with item types	Precision@10
Tracks, Artists, User	0.03123
Tracks, Artists, User, Tags	0.03883
Tracks, Artists, User, Genres	0.04164
Tracks, Artists, User, Albums	0.06842
Tracks, Artists, User, Tags, Albums	0.07685
Tracks, Artists, User, Genres, Albums	0.08017
Tracks, Artists, User, Tags, Albums, Genres	0.08115

As expected, more structural data provided through the graph creates better embedding and therefore more meaningful results. Table 5 contains the performance measured with precision@10 on running the playlist evaluation with the extraction method "one query term". Each execution was performed on different subsets of the dataset which contained only the specified item types. Again, only playlists which contain tracks from multiple artists are included. The inclusion of album connections is responsible for the greatest performance even though most playlists were removed which probably only contained albums tracks. Tags only slightly improve the results in this evaluation but could have a stronger impact on the real use of this system because it allows to formulate queries in more natural way.

Gemsearch produces meaningful personalized recommendations, but the effect in combination with queries is currently not as strong as expected. It is not possible to explain whether the current embedding strategy or query computation lacks this personalization or if the evaluation with playlist data can not reflect the desired outcome. Especially the combination of flexible search facilities and 3D visualizations which is one of the key strength of our work could not contribute in this evaluation.

## 7 CONCLUSION

This work presented an approach to use graph embedding techniques to create a low dimensional vector space of music data. This embedding is used to create query-based music recommendations and evaluated against playlist track predictions. Combined with a 3D representation of the result items it improves the way how user find and explore new music. We believe that the proposed method is not limited to music and may be also used in different domains where application data can be represented as graph but metadata for single items is sparse.

There is still potential for future work to improve the embedding itself and the query mechanism. Weighted which are for example possible in node2vec[5] seems to be a promising approach to improve the embedded proximities in early tests. With them it could even be possible to include audio features as graph nodes in order to introduce audio similarities. However, this would make model extensions more difficult. A user study is eligible to further evaluate the performance on multi term queries and to understand how users may use such flexible search systems.

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# geMsearch: Personalized Explorative Music Search

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## ABSTRACT

Due to the rise of music streaming platforms, huge collections of music are now available to users on various devices. Within these collections, users aim to find and explore songs based on certain criteria reflecting their current and context-specific preferences. Currently, users are limited to either using search facilities or relying on recommender systems that suggest suitable tracks or artists. Using search facilities requires the user to have some idea about the targeted music and to formulate a query that accurately describes this music, whereas recommender systems are traditionally geared towards long-term shifts of user preferences in contrast to ad-hoc and interactive preference elicitation. To bridge this gap, we propose geMsearch, an approach for personalized, explorative music search based on graph embedding techniques. As the ecosystem of a music collection can be represented as a heterogeneous graph containing nodes describing e.g., tracks, artists, genres or users, we employ graph embedding techniques to learn low-dimensional vector representations for all nodes within the graph. This allows for efficient approximate querying of the collection and, more importantly, for employing visualization strategies that allow the user to explore the music collection in a 3D-space.

## ACM Classification Keywords

H.3.3. Information Search and Retrieval: Information filtering; H.4.2. 2. Information Systems Applications: Types of Systems: Decision Support

## Author Keywords

music information retrieval, search, recommender systems, visualization, graph embedding

## INTRODUCTION

In recent years, music streaming platforms have become a central means for listening to music as these allow users to access huge collections of music. This evolution has also influenced the way users search and explore music. For instance, the streaming platform Spotify currently serves 140 million active

users and provides a collection of more than 30 million songs<sup>1</sup> (as of June 2017). Consequently, the primary objective for users has shifted from retrieving specific songs to finding and ultimately exploring songs that match certain criteria reflecting the user's current preferences and context [8, 5].

Currently, two paradigms allow users to explore large music collections: search and recommender systems. Utilizing naive search approaches based on simple attribute matching requires the collection data to be fully annotated with metadata. When relying on keyword search facilities, the user is required to have some idea of his/her current preferences and has to be able to formulate a query that actually describes these preferences well. More advanced search facilities are based on content similarities of items (aka "find similar artists or songs") and are rarely personalized. Especially data sparsity and the lacking ability for comparing heterogeneous items (tracks, artists, albums, etc.) makes it hard for such systems to succeed. In contrast, recommender systems propose items that might be suitable for the user (based on some collaborative filtering approach or more complex models. While recommender systems do not require the user to be able to formulate his/her current preferences, the user also is not able to directly influence recommendations by stating e.g., a starting point for his/her explorative search for music matching his/her current preferences (except for feedback mechanisms like relevance feedback and explicit ratings that influence the user model in the long term).

Only very few approaches like the one proposed by Chen et al. [1] allow the user to specify his/her current needs and preferences in an abstract manner, where the returned results are jointly based on the query (the user's current information need) and the user's personal music preferences. However, there is still a substantial lack of user interfaces that provide dynamic, exploration-driven visualization strategies for large collections of music.

Therefore, we propose the geMsearch system to bridge this gap in explorative music search. In particular, we propose to use graph embedding techniques for computing latent representations of items contained in the graph, such as tracks, users, artists, genres or acoustic features of tracks. Using such graph embedding techniques [14], a low-dimensional latent vector representation is learned for every node. These firstly allow to create advanced search facilities as search queries can be encoded in the same vector space. As a result, not only exact results can be retrieved, but also similar items and hence,

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<sup>1</sup><http://press.spotify.com/us/about>

exploiting previously unknown similarities between heterogeneous items that can be utilized to retrieve diverse search results. Secondly, the obtained vector representations can be exploited for advanced visualization paradigms enabling explorative music search.

This work presents a preliminary study and visualization prototype based on latent representations obtained by graph embedding techniques. In contrast to traditional list-based aggregations of search results that provide a one-dimensional view of the retrieved items, we exploit the low-dimensional vector representation to generate 3D representations of the suggested items, allowing users to visually explore the music collection in a 3D-space. The user is able to specify a starting point for his/her exploration of the musical 3D-space by browsing through this space, the query is implicitly refined and the user is provided with further suitable tracks and artists.

The remainder of this paper is structured as follows. In Section 2, we describe related work. Section 3 proposes a visualization for explorative music search based on graph embeddings and presents the proposed prototype. Section 4 sums up key aspects and details future work.

## RELATED WORK

For the task of building visualizations for music exploration, there are a number of relevant approaches, mostly based on proximity-preserving dimension reduction techniques.

The Islands of Music interface [10] incorporates rhythm descriptors and employs self-organizing maps for visualizing music collections based on the metaphor of geographic maps in two-dimensional space. One highly relevant extension of these maps is a browsable 3D landscape by Knees et al. [6], where tracks are clustered based on content features. Hamasaki and Goto [4] propose Songrium, a collection of visualization and exploration approaches. These include the “Music Star Map”, a visualization of songs in a graph, where placement of songs is based on audio similarity. Also, Lamere et al. [7] presented a 3D interface (Search Inside the Music) based on Multidimensional Scaling (MDS) techniques to visualize similarities between tracks, where each item is represented as a single colored item in the 3D space. Similarly, the Music Box visualization approach relies on Principal Component Analyses to visualize tracks, where song similarity is used to distribute tracks on a plane. Stober et al. [13] also rely on MDS, however, utilize bisociative lens distortions to support serendipitous music discovery in the MusicGalaxy UI. The visualization proposed in this work differs from these approaches in the fact that we base the visualization on latent representations of items within a heterogeneous graph that includes tracks, artists, albums, genres, etc. Due to the applied graph embedding techniques, proximities within the graph visualization are not restricted to similarities between items of the same type (e.g., tracks) or similarities based on a single set of features (e.g., audio features), but rather capture the similarity of items of any type in the latent feature space.

Recently, graph embedding techniques have also been introduced to the field of music information retrieval. Chen et al. [1] utilize graph embeddings for realizing a query-based

music recommender approach that is similar to the approach presented in this paper. A similar approach has also been utilized for playlist recommendation [2] or text-based music retrieval based on playlists [3]. However, these approaches do not provide a user interface for the exploration of new music.

## GEMSEARCH: EMBEDDING-BASED VISUALIZATION

In the following section, we present the geMsearch system, a first prototype for personalized explorative music search based on latent representations of nodes of the musical ecosystem<sup>2</sup>. *geMsearch* stands for graph embedding based music search and consists of two main components, which we will detail in this section: the graph embedding and retrieval engine that computes latent representations of items and query results, and the client providing a search and visualization interface.

### Graph Embedding and Retrieval Engine

For the creation of the graph underlying our approach, we rely on the Spotify playlist dataset by Pichl et al. [12], containing 852,293 tracks crawled from public Spotify playlists. To enrich the available item descriptors for improved query performance, we also add Last.fm tags<sup>3</sup> for the contained tracks. The resulting dataset is represented as a graph containing undirected edges between the following item types: user–track, track–tag, track–album, album–artist and artist–genre. For the computation of latent representations of nodes via graph embedding, we rely on the popular Deepwalk algorithm [11], where we learn representations for all nodes in a 128 dimensional vector space. The resulting latent representations provides means for flexibly computing similarities between heterogeneous items such as tracks, users or artists.

geMsearch allows users to interactively explore the music space to find new music. Therefore, a starting position for browsing through the items has to be determined by eliciting the user’s current musical preferences. As can be seen in the top left corner of Figure 1, a text input field (with autocompletion support) allows to select multiple items from the dataset to construct a query that reflects the user’s current preferences. Here, the search query for artist “Jimi Hendrix” may return similar and suitable artists, tracks or tags. In addition, the search result can further be refined by adding further search terms. In Figure 1, the tag “guitar” is entered and combined with the first term. To create a search vector which is evaluated to retrieve nearest neighbors as search results, the mean item representation of these query terms is computed. The scaled user’s latent representation is finally added to this vector and hence, long-term preferences partly influences the outcome. The resulting vector is then used to retrieve the most similar items from the graph as search results.

### Visualization

The most common visualization for both recommendation and search results is to display a list of items ordered by the predicted relevance of the individual items for the user. This limits users to only observing the sequential order of items and

<sup>2</sup>The prototype can be accessed at <http://dbis-graphembeddings.uibk.ac.at>

<sup>3</sup><https://www.last.fm/api/show/track.getTags>

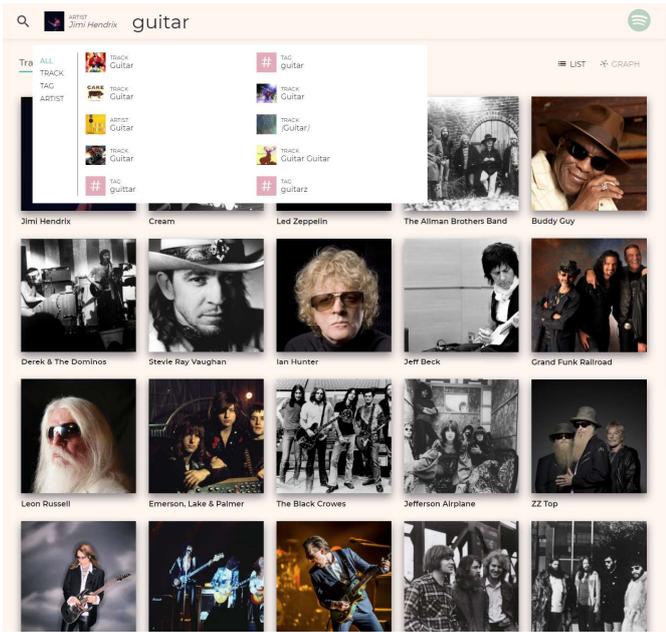


Figure 1. geMsearch query bar with autocomplete and list results.

hence, a one-dimensional view agnostic to distances between consecutive items. With a latent feature space underlying the system (obtained through, e.g., graph embedding techniques), similarities between arbitrary items can be expressed which permits developing more advanced interfaces. Through recent advances in browser technology, like the availability of native WebGL, just-in-time visualizations of 3D scenes can be created directly on websites without complex precomputations or add-ons. Using dimension reduction methods, the computed high-dimensional latent representations can be reduced to three dimensions, allowing to directly visualize items while preserving proximity. Here, we utilize principal component analysis to reduce the 128 dimensional representation of items to a three dimensional space. Instead of displaying a list of items, the recommended items can now be visualized in a 3D scene. Each track, artist or album can be positioned using its three-dimensional representation and can hence be displayed as an interactive 3D object. The positions and resulting distances reflect the relationships and proximities between items within the music collection. Beside the traditional list view for search results, the gemSearch client visualizes the surrounding items in a 3D WebGL scene as depicted in Figure 2. Using such an interface does not only allow to express distance between items, but, more importantly, it allows the user to explore and browse through the result space interactively. Mouse gestures allow for exploring the virtual space and while navigating, additional items are lazy-loaded into the scene.

The user may first use a keyword search to express his/her current preferences (cf. section on Graph Embedding and Retrieval Engine). Based on these criteria, the first search results are retrieved and displayed in a 3D space, where the user should feel like navigating through a virtual result space instead of jumping to unconnected items. In the underlying latent vector space, any of the proposed items can be used to

further extend the query and hence, refine the search to match current preferences more precisely. Besides this active manipulation, the 3D scene provides an even more effective process of implicit refinement. The most relevant search results are positioned around the center of the screen. When exploring additional items further away, the user has to opt for a direction in which to continue exploring. After inspecting items at the new position, the navigation direction can be refined. If the user detects suitable items, the direction is correct; otherwise the user will navigate in a different direction. This choice of directions and moving within the virtual result space directly translates to (implicit) query refinement.

It is crucial to simplify the inspection of single items such that huge collections of music are explorable in reasonable time. We use album covers as textures for 3D objects describing track and album items and hence, also allow for visually inspecting node textures as this has shown to be an efficient means for judging the relevance of albums and tracks [9]. To provide detailed information about selected items (e.g., artists of a given track, genres, etc.), information from the underlying graph is retrieved and displayed. Also, we provide music previews for each track that allow users to inspect and immediately consume newly discovered tracks.

As similar items are located in close proximity to one another in the resulting space, distance-based clustering techniques can be applied to represented accumulations of items as annotated clusters. This allows users to decide whether a set of items might be of interest by looking at the characteristics of the cluster and not having to inspect the individual items contained in the cluster. However, zooming in into a cluster to inspect the individual contained items is still possible. Figure 2 shows how clusters of similar items are represented as single orange circles. On click, the contained items are shown while all other elements are faded with transparency to enhance the contrast. As items within a cluster are positioned nearby, the scene is zoomed in without scaling the circle sizes to avoid overlapping elements.

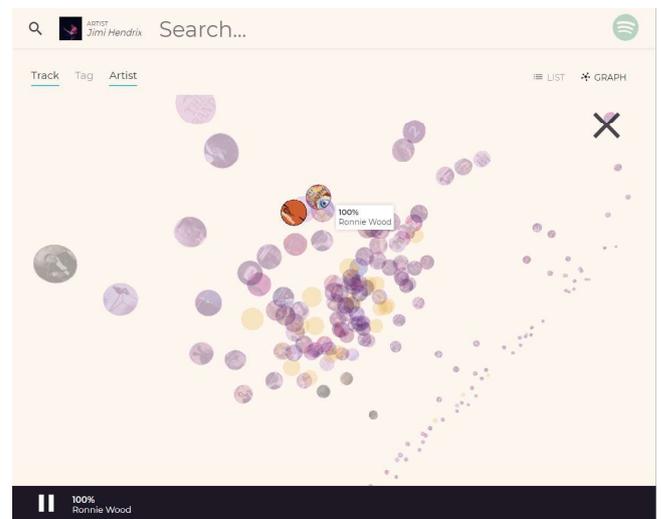


Figure 2. Web client 3D view and player bar.

To alleviate the cold start problem for user profiles, users can connect with their Spotify account. The official Spotify API supports the OAuth protocol with different scopes, allowing access to, e.g., personal playlists, playing history or saved tracks. To create a personal preference profile, *geMsearch* retrieves the user’s saved tracks as we argue that saved tracks may serve as a strong indicator for preference. After a user has connected with his/her account, the music library is loaded and compared with the current contents of the underlying graph. For tracks, artists, etc. that are not yet contained in the underlying graph, we gather the missing metadata from Spotify and user-curated tags describing these items from Last.fm. After the data is collected, the graph is extended with this new information. In a next step, latent representations have to be computed in case of new items or updated in case of items that are affected by the newly added information. Deepwalk uses short random walks to model the graph structure with an uniform distribution over nodes. Therefore, neither the complete graph structure, nor all nodes have to be known to the algorithm initially. This implies that additional nodes and edges can be added on-the-fly to continue learning and extending existing embeddings without the need to relearn the complete model from scratch when adding new users or items.

## CONCLUSION AND FUTURE WORK

In this work, we presented *geMsearch*, a preliminary prototype for personalized exploration and search of music collections. We exploit graph embedding techniques to compute a low-dimensional vector space representation of the music collection and the contained items. This allows for query-based, personalized exploration of music collections. Particularly, our approach provides users with a 3D representation to yield a visual exploration of new music; allowing the user to browse through search results and the full collection, where the distance of items (tracks, artists, genres) in the displayed graph corresponds to item similarity. Please note that the browsing through the 3D-space is not restrained to search results, the user’s query is a mere definition of a starting point for browsing for the full collection graph and hence, query refinement.

We believe that the proposed method is not necessarily limited to music and may also be used in different domains, where data can be represented as graph and metadata for single items is sparse.

As for future work, we aim to further extend the prototype by improving the visualization performance and updating user preferences on-the-fly. For computing the user profiles, we aim to look into incorporating listening histories and create more comprehensive user profiles. Also, we aim to lay a particular emphasis on interaction aspects in the prototype by, e.g., allowing the user to up- or downvote certain tracks explicitly. We further aim to perform a user-centric evaluation of the system.

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# Appendix

## A.1 Implementation Details

This appendix gives a general overview about the Gemsearch prototype which was implemented during the master thesis. The implementation can be structured into two main components. As it can be seen in figure A.1, the data management, graph embedding and recommendation computation is implemented as a Python application. With a REST interface these services are exposed and decoupled from the second component, the web client, which provides a user interface.

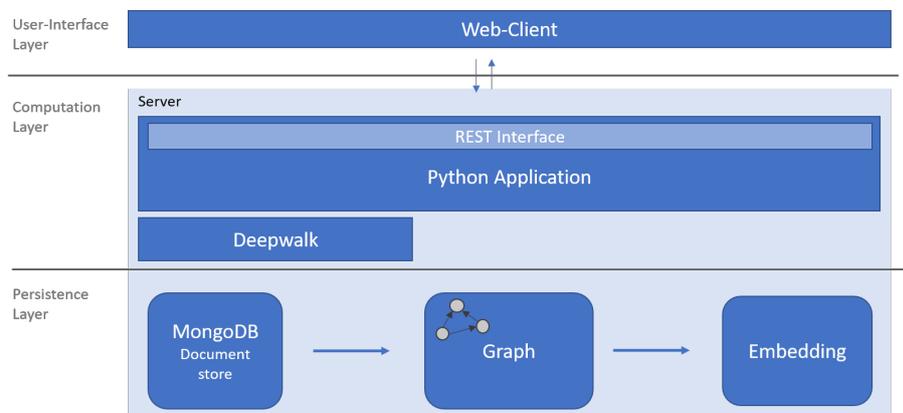


Figure A.1: Main architecture overview

### A.1.1 Python application

The actual recommender for computing and storing the required data is implemented as a Python application. We have chosen Python because there are many packages for data processing and machine learning. In addition, also the reference implementation of *Deepwalk* and the tool *word2vec* are written in Python. To achieve reasonable runtime performance, big data structures are stored and accessed with the Python

package *numpy*<sup>1</sup> and matrix computations are performed with *scipy*<sup>2</sup> which both rely on native implementations.

### A.1.2 Data management

The main data source for Gemsearch is the Spotify API where Pichl et al. [1] has already crawled a big dataset which consists of 21,336 playlists. Because this data is stored as JSON, the NoSQL document store *MongoDB*<sup>3</sup> is used to store all crawled data. This makes it easy to create data subsets for testing, performing statistical analyses and retrieving metadata to enrich the search results. Synchronized user music libraries from the Spotify connector are also stored here.

For embedding and evaluation, required data is extracted from MongoDB and stored as CSV files in an intermediate step. This makes it easier to process or split data and repeat experiments with same sub-data inputs. After potential training-test splits are applied, the music graph is constructed. When adding new data to the graph, a mapping for item ids is applied which makes sure that each node is identified by a unique unsigned integer id. These continuous ids are required for the graph embedding algorithms as input and later to transform an embedding index back to the original item. Additionally, they make sure that same items, e.g. text equal tags, are represented as single nodes in the graph.

The final graph is represented as a file in the edge list format. Each line of this file represents an edge between two integer graph node ids which are separated with whitespace. If the graph embedding algorithm supports weighted edges (e.g. *node2vec*), a third value can be used to specify the weight as float number. Deepwalk uses this file as input and produces an embedding file as output. This file contains one line per graph node to represent its latent representation. The Gemsearch recommender can load those files and stores the embedding as one single array internally. Using the previously created lookup between embedding index and object id, the representation can be transformed into both directions. Having all item vectors in one single array allows fast and efficient access during runtime which is especially important for the nearest neighbors search.

The computation of recommendation is performed on an embedding with 126 dimensions. This enables highly precise results with acceptable runtime performance. However, the 3D visualization requires rep-

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<sup>1</sup><http://www.numpy.org>

<sup>2</sup><https://www.scipy.org>

<sup>3</sup><https://www.mongodb.com>

representations in three dimensions such that items can be arranged in the scene. For this purpose, we apply PCA on the high dimensional embedding to reduce its dimension to three. In the 3D scene, the clients first evaluates the user query on the 126-dimensional embedding to retrieve the most relevant result item. This item is displayed in the scene and then additional results which are around that point are retrieved from the 3D embedding.

Each item which has a name, except playlists and users, are inserted into a *Elasticsearch*<sup>4</sup> full-text index. For the evaluation based on playlists, this service is used to extract query terms from the playlist title. Also, the client makes use of this index service to provide an autocomplete function for users while formulating queries. The service takes multiple keywords as input and returns the ids of items with the most similar names.

### A.1.3 Computation of recommendations

The interface for recommendations takes a list of object ids as input and returns items ordered by the similarity to this input. Any item of the graph can be used as seeding element. Optional the weights are assignable for each item to specify positive, negative and exceptional items. By default, each item is weighted equally as positive seeding element. To create personalized results, the user can either be specified with its ID as additional seeding item or also passed as optional parameter where the system uses defaults weights for the scaling ( $\alpha_u = 0.3$ ). To create a query vector, the latent representation for each object id is fetched and combined as described in equation 1 of the "Personalized music search based on graph embedding" paper. Then the cosine distance is computed to each item within the embedding to retrieve nearest neighbors. Ordered by distance to the search vector (similarity), this node indices are traversed and resolved with a lookup to the actual item object. In this step, optional element type filters (e.g. they restrict results to tracks) remove unwanted items. During this traversal the pagination is applied and stopped, as soon as the necessary number of items are found. Finally, metadata like album covers and preview URLs are fetched from the document store and attached to the item descriptors. This final set is returned as result.

### A.1.4 REST API

The REST-API provides access to the recommendation service via the HTTP protocol. At server startup, the whole embedding is loaded into

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<sup>4</sup><https://www.elastic.co>

memory and then shared between multiple requests to ensure fast response times. For the prototype, a Nginx web server forwards API requests via uWSGI to the Python application. Each request is handled in a separate thread to execute computations in parallel.

The most important REST endpoints are listed as follows:

#### **/api/query**

Returns a list of similar items to the given seeding elements. The computation is performed on the embedding with 128 dimensions.

Available query parameters:

- *ids* list of object ids which should be used as seeding items
- *types* list of item types to restrict the returned items
- *limit* number of elements to return
- *offset* number of elements to skip (used for pagination)
- *user* optional user id to personalize results

#### **/api/items\_near\_viz**

Returns a list of item-clusters which are around the given 3D coordinate. The computation is performed on the embedding with three dimension. This is used to lazy load additional items into the 3D scene. Each cluster consists of a 3D center position and contained elements. In addition, the total bounding box of all retrieved items is attached so that potential clients can adapt their visible scene to visualize all items at once.

Available query parameters:

- *vec* 3D coordinate to retrieve nearest neighbors for
- *types* list of item types to restrict the returned items
- *limit* number of elements to return
- *offset* number of elements to skip (used for pagination)
- *minClusterDistance* minimum distance between items. All result items which are in a closer distance to one another are grouped into a cluster.

#### **/api/suggest/<term>**

Returns suggested query term items to autocomplete the given term. Those items may be used to extend a query.

**/api/object/<id>**

This endpoint returns all available metadata for the given item uid.

**/api/neighbors/<id>**

Returns all neighbors with attached metadata for the given item id which are connected via edge in the graph. This allows to fetch the artist, genre and tags for a given track for example.

### A.1.5 Webclient

The implemented Webclient makes it possible for users to formulate queries and explore recommendations. Without the need for an installation or additional setup, the web application has many advantages over traditional desktop applications. *TypeScript*<sup>5</sup>, a programming language superset of JavaScript, was chosen for the implementation because it provides static type checking during compilation. Created and maintained by Microsoft it also enables strong autocomplete suggestions in e.g. their editor *VS Code*<sup>6</sup> which improves the development process. The JavaScript framework *React*<sup>7</sup> helps to maintain the client state and having a virtual DOM enables to program on a more abstract level as no direct DOM manipulations have to be applied. The whole client is a standalone application and the communication with the Python API is done via REST interface to retrieve search results and metadata. Hereby both components are independent and additional or different clients could possibly be introduced.

Beside the list view, results can also be explored in a 3D scene where each item is represented as a single interactive object. For performance reasons, this scene is rendered in a canvas element using WebGL which is hardware accelerated on most devices. WebGL has currently many crossbrowser issues in different browsers and requires writing shader codes for simple visualizations. The JavaScript library *ThreeJS*<sup>8</sup> fixes this issues with a common API and simplifies the development with many utility methods.

For exploring the search results, users can modify the scene camera position using their mouse and navigate through the 3D space. The whole embedding is too big as it could be transferred completely to the client. Therefore, only the most accurate query results are returned and additional items are loaded step by step with Ajax requests. After each

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<sup>5</sup><https://www.typescriptlang.org>

<sup>6</sup><https://code.visualstudio.com>

<sup>7</sup><https://reactjs.org/>

<sup>8</sup><https://threejs.org>

position change, the camera direction is unprojected to get the focused 3D position. Having the new center, additional elements can be queried and added to the existing scene. To limit the required computational and memory resources, the maximum amount of displayed elements is limited. After a fixed threshold previous items are disposed when new items are added to the scene.

### A.1.6 Spotify Connector

As described in Section 3.3 "Model extension" in the "Personalized music search based on graph embedding" paper, a Spotify account can be used to get personalized recommendations. When a user connects, access to the username and the personal music library is granted. The OAuth protocols allows to retrieve this data as a third-party application without knowing the user's login credentials. Only a token is transmitted which authorizes API request for a limited time.

After the user has connected, it is checked if he is already known to the system. For new users, the token is send to the server in order to synchronize the music library. In the database this user data is only identified by the hash of the username and prevents backtracking of personal information.

Besides the API there are two microservices on the server which execute long running tasks and prevent to block resources for further requests:

- The **Crawler service** watches the database for new tracks which are inserted through the music library synchronization. It makes sure that all necessary metadata is available to be added into the graph. For new items, the track data and artists are crawled from Spotify and tags for tracks are retrieved from Last.fm. The hereby collected data is finally stored in the shared MongoDB document store.
- The **Embedder service** waits until crawlers are finished and then extends the existing graph with the new data. This task is executed periodically and therefore may embed multiple users at once. Changes are collected and then inserted into the existing word2Vec model to retrieve a new embedding which then replaces the existing one.

The client polls for updates on these services and notifies the user as soon as all tasks are done. On subsequent requests the user context can be used to compute personal query results.

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