GDMA Project: CDDB as Graph Database

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1 Importing Data

This chapter describes design decisions made to map the relational CDDB database to a graph database. See Jupyter notebook O1_Import_Data.ipynb.

1.1 Mapping of Tables

Entries in tables <code>artists</code>, <code>albums</code>, <code>songs</code> and <code>cds</code> represent entities and are mapped to nodes of appropriate type. The cross table <code>cdtracks</code> is mapped as relations between CDs and Songs with the property <code>track</code>. The cross table <code>artist2album</code> is mapped as a triangular relationship, using six relations each to connect Artists, Albums and CDs in both directions.

1.2 Bidirectional Relations

To construct the queries necessary for subsequent tasks, it was strictly speaking not necessary to create relations for both directions. However, doing so allows for more readable queries. In addition, the relational SQL database does not define a direction for relations either, and this property is thereby preserved.

1.3 Unique Identifiers

The unique identifiers present in the SQL database are preserved as node properties. Although Neo4j automatically assigns different IDs internally, this preserves compatibility with the SQL version. It is conceivable that in the real worlds, queries may reference those IDs directly. For example, as hardcoded list as part of a GUI.

1.4 Entity Names

As in the SQL version, the actual name of a song, genre, album and artist is a property named after the entity type and therefore different per node label. This was done to map the SQL version as closely as possible to the graph

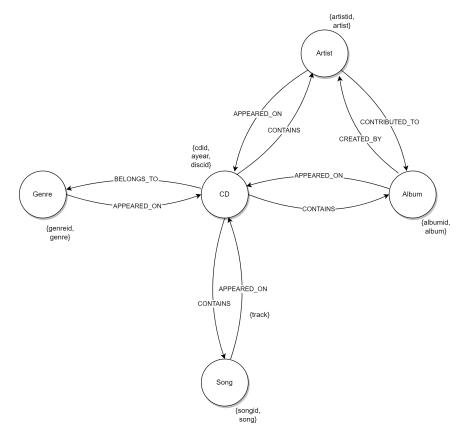


Figure 1: CDDB Graph Schema

version. In real-world scenarios, it may be beneficial to rename these properties to <code>name</code> across all nodes. This would allow for simpler queries in cases where nodes of different types are filtered by name. Also, a joint full-text index would be possible.

1.5 Indices

To speed up MERGE and MATCH operations, the IDs for nodes with label Artist, Album, Genre, Song or CD are indexed. In addition, a full-text index is used for the names of Artists, Albums and Songs to allow for imprecise searches (fuzzy search).

1.6 Importing Songs

Songs with a trailing backslash caused problems because the closing quote is escaped. To mitigate this, an extra whitespace character is added to those song

titles. Affected rows can be found with the following SQL statement:

```
SELECT *
from cddb.songs s
where song like '%\\'
and song not like '%\\\'
Statement to update the rows:

UPDATE cddb.songs
SET song = song || '_'
WHERE song LIKE '%\\'
AND song NOT LIKE '%\\\'
```

2 Cypher Queries

See Jupyter notebook 02_Cypher_Queries.ipynb.

3 SQL to Cypher

See Jupyter notebook 03_SQL_to_Cypher.ipynb.

4 Searching and Ranking

See Jupyter notebook 04_Searching_and_Ranking.ipynb.

4.1 Search Implementation Details

The search engine accepts a user supplied query string and returns an ordered list of the most relevant CDs. Three features are considered to rank CDs by relevance: Text similarity with the query string, user-preferred CDs and user-preferred genres. Since the user's preference is known prior to searching, the corresponding preference scores can be computed in advance. This leads to a two stage process:

4.1.1 Stage 1: Precompute User Preference

Preferred CDs and genres are determined based on content previously liked by the user. To find preferred CDs, a subgraph of artists, albums and songs liked by the user and associated CDs is extracted. Subsequently, a centrality score is calculated for each node in both. The basic idea is that the most relevant CDs will have a high centrality score. To determine the preferred genres, we count how often genres are associated with the user's liked nodes. The basic idea is that the user prefers content of a few genres and therefore likes many albums, artists and songs belonging to those genres.

4.1.2 Stage 2: Search based on User Input

The most significant feature is the text similarity to the search query provided by the user. By using "Full-Text Indices" of Neo4J, the text similarity between artist name, album title and song title is calculated. The similarity score of all nodes associated with a CD are aggregated and used as a "Content Match Score".

$$S_{Combined} = S_{Content} + (S_{CD} * S_{Content}) + (S_{Genre} * S_{Content}) \tag{1}$$

The "Content Match Score" is then combined with the previously computed user specific "CD Preference Score" and "Genre Preference Score". The ten CDs with the highest combined score are presented to the user.

4.2 Example Search Queries

The following example demonstrates how user 1 is searching for CDs related to "Jimmi Hendrix." See Jupyter notebook 05_Search_Demonstration.ipynb for more detailed examples.

		Score				CD Details	
	ID	Content	$^{\mathrm{CD}}$	Genre	Comb.	Genre	Artists
0	677	31.53	0.5663	0.6632	70.31	[rock]	[jimi hendrix]
1	35734	31.53	0.5541	0.6632	69.93	[rock]	[jimi hendrix]
2	136907	31.53	0.5541	0.6632	69.93	[rock]	[jimi hendrix]
3	46232	26.72	0.6927	0.6632	62.96	[rock]	[jimi hendrix]
4	162186	26.72	0.6581	0.6632	62.03	[rock]	[jimi hendrix]
5	7923	56.69	0.0000	0.0714	60.73	[blues]	[signature licks]
6	1936	24.34	0.6927	0.6632	57.35	[rock]	[jimi hendrix]
7	33321	28.27	0.2123	0.6632	53.03	[rock]	[jimi hendrix]
8	2023	26.72	0.6927	0.0714	47.14	[blues]	[jimi hendrix]
9	17266	20.76	0.3463	0.6632	41.73	[rock]	[jimi hendrix]

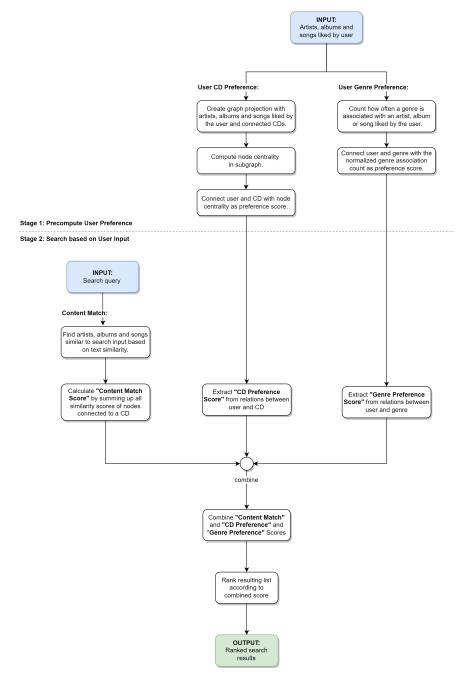


Figure 2: Two stage process of calculating a CD relevance score by using text similarity and user preference as features.