

Medium Specific Recommenders

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1 Introduction

Vinyl is an interesting medium, one which was the main way of consuming music for decades [4] and has now become a growing commodity [16, 8] for people who want to feel more content with their music in our digital world. This provides a physical manifestation of the art they enjoy the most with the wonderful side effect of supporting artists more directly.

This norm of listening has been shifted with the advent of streaming, changing how people listen to music. Therefore artists have changed the way they produce and release music focusing more on singles rather than seamless flowing albums [24] which made sense in the days of LPs. The way we discover music has clearly changed, from going through racks of albums based on genres and artists, to “Discover Weekly” playlists on Spotify giving users a mish-mash of tracks they might like: “a playlist of thirty songs they’ve never heard before”; this changes the whole dynamic. [31].

2 Problem Statement

Music taste can differ slightly from what someone streams on a day-to-day basis to what they buy on vinyl. This project will try to create a recommender system, which is developed around the specific attributes of the vinyl medium, with the further goal to hopefully quantify how well an album “flows” (sequencing) [22]. This would be particularly unique as recommender systems already use metadata such as tempo, key and “danceability” [10] to further influence an algorithms choice beyond artist and genre. To take this data further to create inferences around how well an album flows by computing the variation of BPM and harmonicity of key between subsequent songs in the tracklist.

The above is the more technical aspect of the project, in user-facing terms it will be an Apple iOS application (for iPhone), which will just be a wrapper of sorts for this recommender system. Due to multiple constraints such as: time, datasets, and the fact that this project is being undertaken independently by a single individual, it is split up into components...

1. The main iOS application:
 - Add records you own to a collection via barcode/search

- Track listening history: use the microphone in the background alongside audio fingerprinting technology
 - Apple Replay / Spotify Wrapped like statistics
2. Artist recommender system
 3. Algorithm quantifying sequencing and flow

3 Literature Review

Before starting development, researching previous works and methodologies (in the context of algorithms) allows for a justified choice backed up by relevant references.

3.1 Similar Existing Works

3.1.1 Discogs

Discogs [5] is a website developed mainly for collectors; it acts as a marketplace of sorts. It allows people to see the going price of records (and music of other mediums). Users can create accounts to store their entire collection, this then allows the user to see the total value of their collection and see how much specific items contribute to that value. Their database is huge and can be downloaded for free from their “dump” [6]. This is one of the specific datasets that will be investigated in more detail later.

To understand the scale of Discogs, consider an anecdote from a famous DJ on TikTok, who is known for finding niche tracks and “Dub-plates”, who said: “One track out my collection of 2,000 that’s not on there” [19].

Although the platform does have an amazing data source (again, more detail later). As a platform for users, it is just giving them access to this data source and allowing someone to create a collection from it. It does not cover all the points this project wants to achieve, e.g. recommendations specific to the vinyl medium. Weirdly with a user base size of around seven million (ideal for collaborative filtering) in 2020 [8], and monthly website visits up in the 10’s of millions (≈ 38 million) [6], and the extensive dataset as mentioned (ideal for content-based filtering), it has the ability to create an effective and useful recommendation algorithm.

3.1.2 Apple Music Replay / Spotify Wrapped

Most streaming services provide end-of-year statistics based on their listening history on their platform. Statistics include the most listened-to artist, song, album, genre, total listening hours, etc. This information is presented in a fun and shareable format.

Both Spotify Wrapped and Apple Music Replay have variations of this above feature. Providing this end-of-year summary to users was first implemented by Spotify. It is created by using the data which they would have already been tracking for royalty and recommendation reasons.

This feature became very popular, especially on social media where people would share their statistics (“wrapped”). A similar feature was implemented into Apple Music a few years later [27].

The way these services can provide such products, as mentioned, is due to the data they already collect, which is relatively easy for them to achieve, as it is a digital service, it's relatively straightforward for them to capture user behaviour, such as tracking when a song is played, added to a playlist, etc.

This is in complete juxtaposition to this project's focus which is on the analogue medium of vinyl. Tracking what a user listens to would be for the most part a manual process. However, minimising direct user data input is possible by taking advantage of audio fingerprinting services which can detect what is being played. This will allow the creation of a similar product within the app that's going to be developed.

3.2 Recommender Systems

The computationally complex part of this project will be how data will be manipulated and processed to give a user relevant recommendation, particularly considering that the user should not be required to interact extensively with the application before receiving a recommendation.

Many points have to be considered before choosing one specific algorithm over another:

- The data available; is there an accurate, easily accessible dataset which (in this case) is free and community-driven. This is what will be the driving force behind any chosen algorithm (a factor that will be mentioned later).
- Computing power; how long the algorithm will take to compute recommendations for one user, taking into account the processing power available and time to train if necessary.
- Ease of implementation; being transparent regarding the constraints on the time, a trade-off will have to be considered.
- Architecture considerations; how will the selected algorithm be embedded into the backend of the system should be examined, due to the front end being a mobile iOS application means there are many standard stacks (specifically Baas) [15]. A custom one can be built but that is least to be desired (detailed given later).

3.2.1 Content Based Filtering

At the core of these systems is the need for simplifying the discovery of information on products (websites, applications, etc) in a personalised manner [30].

In a more general sense, you can use this as a classification task, based on a representation of a user and an unseen item, can you classify this item as "relevant to the user" or "irrelevant to the user" [30].

An item can be described as a vector of features $X = (x_1, x_2, x_3, \dots, x_n)$. Features can be described in a variety of ways, but binary can simplify the calculation later on. An example of an index within a vector (for movies) could quantify if it's an animated movie (Boolean) [30, 23]. You also represent the user in the same feature space [21], but each index is set on whether the user aligns with that feature index (e.g. likes animated movies).

Then you use a similarity measure to compute a recommendation...

	Comedy	Action		Genre (n-1)	Genre (n)
Deadpool	1	1	[...]	1	0
Avengers	0	1		1	0
Titanic	0	0		0	1
Inside Out 2	1	0		0	0
User	0	1		1	0

Figure 1: Content-based Filtering Matrix Example {based on [23, 21]}

One example of a similarity measure is the dot product (figure 1), For X_n , each item vector, a sum is computed of how many features are present in both U_n , the user vector, and X_n . The higher the sum the more are present, thus a higher similarity. You can then select how many you want to use as a recommendation (e.g. top 10 highest).

Using the figure 1, the items with the highest dot product, and therefore the highest similarity with the user vector is Deadpool and Avengers, with a score of 1.

Below is the formula for the dot product:

$$\langle X_n, U_n \rangle = \sum_{i=1}^d x_i u_i$$

The variable d represents the dimension (i.e. the number of elements or features) of the two vectors. For each feature, the elements at that index are multiplied together (when the values are binary this gives either 0 or 1). The results are summed to give a similarity score between an item and the user.

3.2.2 Collaborative Filtering

Mainly focuses on what users $U = (u_1, u_2, \dots, u_n)$ like, and the similarity between other users U_i , and a user u_p , the user you're predicting for. There is no particular focus on the metadata behind the actual items.

The focus is entirely on... [20]

- User rating, explicit feedback from user
- User interacts with some item, inference they are interested in an item in some way, implicit feedback
- What other users like (implicitly or explicitly)

	Book 1	Book 2	Book 3	Book 4
User 1	5	4	3	4
User 2	1	2	4	5
User 3	1	2	3	null
User 4	null	4	3	1

Figure 2: Collaborative Filtering Example {based on [26]}

Notice how some of the entries in figure 2 are ‘null’, this means the user has not interacted with that specific item before. But as we know what other users liked, we can compute a guess of how a user with the ‘null’ entries will rate a specific item, by using the entries that aren’t null in said user with the other users. This process is known as Matrix Factorisation. If a user has all ‘null’ entries then no recommendation can be made, until enough of the items have been rated/interacted with in some way (similar to the cold start problem, see below). [26, 20]

Now there are two ways of doing the actual computation, model-based (machine learning), or memory-based systems, which relates to another algorithm considered later (nearest-neighbour).

No more specific details of this algorithm will be given due to a pitfall regarding mass amounts of user data. Just like CBF (content-based filtering) would require a large dataset of attributes for items (metadata). This would require a large active user base, interacting with items and rating them. Something this project will not be able to ascertain and review within a reasonable amount of time. This is more formally known as the **cold start problem** [26, 20].

3.2.3 Hybrid Method

[Look at this](#)

3.2.4 Nearest Neighbour

This specific section is more general as it is an algorithm that can be applied to other methods mentioned above (CBF and CF). The algorithm k-NN is a memory-based algorithm whose main use case is classification.

Given a dataset with labelled classes, it can compute the distances (in an n-dimensional space) between all the data points in its dataset and an unseen point. It can then classify that unseen point by totalling up which class is more prevalent in a set of k data points (e.g, the 10 closest by distance, $k = 10$, to the unseen point).

As previously, you can see this as a very loose classification task, either “relevant to the user” or not. But that could be reductive, as the focus on how this algorithm would be implemented in this context would be fully on the distance metrics, how you quantify how far a vector is from another (as you can visualise a vector coordinates in an n-dimensional space).

In the next section, we’ll discuss different distance/similarity measures...

3.3 Distance Measures

3.3.1 Euclidean Distance

This measures the shortest distance between two points (in an n-dimensional space it is known as L2-norm), by utilising the concept behind Pythagoras’ theorem. [25]

$$d(a, b) = \sqrt{\sum_{i=1}^n (a_i - b_i)^2}$$

This measure takes into account the magnitude and the relative direction of the vectors inputted [12]. Assuming you are using the same numerical attributes and not normalising your vectors [29], this comes with the caveat of normalisation in the context of removing over-representation in a dataset, making comparisons between data points more fair while still preserving essential differences.

3.3.2 Cosine Similarity

Cosine similarity measures the similarity between two vectors by using the cosine of the angle between the two vectors. Simply. It's checking if the two vectors are pointing in roughly the same direction [12]. The magnitude of vectors isn't considered in this measure (which does mean no normalisation of any kind is needed, this can save time on overall computation).

$$\cos \theta = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

Overall, as it measures the angle this means that vectors will be deemed least similar if they point directly in opposite directions. It will always give a value between -1 and 1 , higher values equals more similar [12].

As mentioned, no normalisation is required due to measuring the angle, but that means this particular measure can be useful for recommendation algorithms, like CF and CBF since overall ratings and popularity can create different distances (over-representation) [12].

3.3.3 Dot Product

Already mentioned above, Dot Product is a distance measure [21], see here for [more information \(3.2.1\)](#).

Interestingly, these metrics will in most cases produce similar results, in the case of Euclidean distance and Cosine similarity with high dimensional data, even more so with normalised data, the results of both metrics are very similar [28].

The cited paper uses vectors with a dimensional size of 64, it would be surprising if that were the case for this project, on the other hand, it's not going to be small.

Basic inference also shows how these measures are similar, as Euclidean distance concerns itself with magnitude and angle if you normalise in some cases it will remove that context (magnitude) from the dataset.

Further to this, dot product and cosine similarity are also very similar, which can be seen by the equation of CS (3.3.2), as it contains the DP (3.2.1). Again, the difference is related to whether the magnitude is taken into account, therefore after normalisation of data the two are indistinguishable [2].

It all gets a bit ridiculous on the realisation that ED (3.3.1) and DP (3.2.1) are also proportional to each other, both metrics are similar and there are no strong reasons to prefer one over another in general [18].

Picking between them might require testing/expert advice...

3.4 Available Datasets

Any algorithm that is within the capture of “artificial intelligence” requires a large amount of data to be effective. The number of features used in the computation will affect its accuracy. This is seen with the rise of large language models (LLMs). The amount of parameters and the larger the dataset the lower the error rate (which specific metric has the largest effect on performance in the case of LLMs is still widely debated) [find reference].

Looking for datasets can be quite difficult, especially free ones, which again links back to the same struggles LLMs have been having as they try to find masses of relevant information to use for training. Free datasets are hard to come across because it takes time to format and organise information in an easily computable manner, such as JSON, etc. For this project, a large amount of data on records and artists is required, and most importantly it all had to be tagged and categorised (by genre).

3.4.1 MusicBrainz

MusicBrainz is an “open music encyclopaedia that collects music metadata and makes it available to the public”. [13] It contains extensive data about artists, songs, albums, genres, and much more. With over two million artists, 42 million tracks and over a thousand genre tags the database is extensive. [3]

Trying to download a dump of these data was quite difficult, as the data wasn’t split up in the most obvious way, and all the data wasn’t needed. Due to this, the size of some dump files was 15GB zipped, which unzipped was not manageable.

Further to this complication the response from the API and data itself was hard to parse, mainly due to how extensive it was. Sub-genre names going into the absurd and obscure. One song would return many releases, obfuscating the core data required for the project, such as: artist name, name of song, album, genre, and basic simple data.

3.4.2 AcousticBrainz

Both MusicBrainz and AcousticBrainz are part of one overarching project called “MetaBrainz”. AcousticBrainz stored metadata with respect to actual songs. Such as BPM, key, danceability, mood, etc. It worked well with its big brother MusicBrainz as you could search the dataset by both artist, title, etc. as well as MusicBrainz ID. This was a significant advantage in utilising both of these datasets together, as it worked well with specific breakdown on my project (it being split into sections, different parts of the recommender algorithm).

However, after finding out the project was retired near the end of 2022 [1], and it has not been taken forward by the community, this would mean 3 years’ worth of music would not be present in that dataset. This is a huge limitation. Nevertheless, considering trends in artificial intelligence and especially LLMs, cut-offs in datasets are very common and now accepted as a limitation of trained models. For example, ChatGPT’s current cut-off (at the time of writing) for GPT-4 is October 2023. [11] This shows a precedent of this in the field. So, if taken forward, that is a major consideration.

3.4.3 Discogs

Discogs is a specific database that logs every single release of music, with a focus on vinyl. Very easy to download and was able to manipulate the data dump as required. The data set was much cleaner, especially regarding the “core” data required for the recommender.

Genres are more distinctly defined, with fifteen core genres [7] with subcategories (known as styles) [9] under it for more specific niche tracks. For example, Electronic has the style Jungle under it. As these tags are more well defined it makes defining the variety of genres in a discography of an artist easier to represent numerically.

This dataset obviously does not have the direct intergeneration with MusicBrainz/AcousticBrainz. However, that does not stop the consideration of using AcousticBrainz later on if this more detailed data is required in the later stages of this project.

3.4.4 Spotify for Developers

Firstly, this dataset cannot be downloaded. They don't have data dumps or allow scrapping in their ToS (terms of service). This is a massive limitation for using this service as it would be impossible to do inference on thousands of artists' genre-mix compared to the user-specific preferences by using API requests alone.

Spotify does provide detailed and current “audio features” [17] for all tracks in their database. This is obviously possible as they have the actual audio file in their system to allow streaming of it. This is a big advantage for Spotify as a company, as their dataset is current and accurate due to the fact they are industry leaders in the music industry, and artists are more than willing to get their copyrighted content onto the platform, which they can then analyse as much as they like.

This is a stark comparison to the AcousticBrainz cut-off. But as mentioned to access this data is only via their API which has to be authenticated by a Spotify user, and has rate limiting (which is designed to punish bursts of requests) [14] which makes retrieving all the data required to check all the songs within multiple albums to compute how well an album flows not feasible.

You can view an example API response from all these services in the appendix.

3.5 Mobile Platforms

NOTE: explain why I'm choosing to develop for iOS.

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Appendix

Example API Requests

Here are example of API requests to the various datasets mentioned in the report (data response not shown in full).

MusicBrainz

```
{
  "releases": [
    {
      "packaging-id": "ec27701a-4a22-37f4-bfac-6616e0f9750a",
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        "script": "Latn"
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        },
        "date": "2013-08-30"
      }
    ],
    "title": "The 1975",
    "packaging": "None",
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    "date": "2013-08-30",
    "text-representation": {
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      "script": "Latn"
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    "quality": "normal",
    "packaging-id": "119eba76-b343-3e02-a292-f0f00644bb9b",
    "id": "ac2b87af-2774-4575-a72a-db31c8865264"
  },
  {
    "status": "Official",
    "barcode": "602537537426",
    "release-events": [
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        "area": {
          "name": "Canada",
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            "CA"
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    ]
  }

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        "id": "71bbafaa-e825-3e15-8ca9-017dcad1748b",
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},
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    "area": {
        "iso-3166-1-codes": [
            "MX"
        ],
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        "sort-name": "Mexico",
        "type": null,
        "name": "Mexico",
        "type-id": null,
        "disambiguation": ""
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        "id": "8a754a16-0027-3a29-b6d7-2b40ea0481ed",
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        "name": "United Kingdom",
        "type-id": null,
        "disambiguation": ""
    },
    "date": "2013-09-02"
},
{
    "date": "2013-09-02",
    "area": {
        "iso-3166-1-codes": [
            "US"
        ],
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        "type": null,
        "name": "United States",
        "type-id": null,
        "disambiguation": ""
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}
}

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  "date": "2013-09-02",
  "text-representation": {
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    "language": "eng"
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        "iso-3166-1-codes": [
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        ],
        "disambiguation": "",
        "type-id": null,
        "name": "United States"
      },
      "date": "2013"
    }
  ],
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  "packaging": "Cardboard/Paper Sleeve",
  "status": "Official",
  "genres": [],
  "country": "US",
  "text-representation": {
    "language": "eng",
    "script": "Latn"
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  "date": "2013",
  "status-id": "4e304316-386d-3409-af2e-78857eec5cfe",
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  "quality": "normal",

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    "packaging-id": "f7101ce3-0384-39ce-9fde-fbbd0044d35f"
  },
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    "packaging": "Digipak",
    "release-events": [
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          ],
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          "type": null,
          "name": "Canada",
          "disambiguation": "",
          "type-id": null
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        "date": "2013"
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    "disambiguation": "deluxe edition",
    "status": "Official",
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    "quality": "normal",
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    "text-representation": {
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      "language": "eng"
    },
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    "date": "2013"
  }
],
  "id": "963ec665-106b-43d4-b92b-78fe858cddd2",
  "length": 224640,
  "first-release-date": "2013-06-04",
  "genres": [],
  "title": "Chocolate",
  "artist-credit": [
    {
      "name": "The 1975",
      "joinphrase": "",
      "artist": {
        "type": "Group",

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"id": "5b6ebfe0-f72b-4902-bba9-74c8af0f1af0",
"sort-name": "1975, The",
"genres": [
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    "id": "d3ebe947-7c03-43f5-b333-09379881b0f6",
    "name": "alternative pop",
    "count": 1
  },
  {
    "count": 1,
    "name": "alternative rock",
    "id": "ceaaa283-5d7b-4202-8d1d-e25d116b2a18",
    "disambiguation": ""
  },
  {
    "count": 2,
    "name": "ambient pop",
    "disambiguation": "",
    "id": "2cdcecfе-3e7c-4055-ab34-78eceabe4d9b"
  },
  {
    "name": "art pop",
    "count": 4,
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    "disambiguation": ""
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  {
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    "disambiguation": "",
    "name": "indie pop",
    "count": 1
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  {
    "count": 7,
    "name": "indie rock",
    "disambiguation": "",
    "id": "ccd19ebf-052c-4afe-8ad9-fbb0a73f94a7"
  },
  {
    "count": 2,
    "name": "new wave",
    "disambiguation": "",
    "id": "56407f9d-3398-4bf3-bbbd-ea372fa5adeb"
  },
  {
    "disambiguation": "",
    "id": "797e2e85-5ffd-495c-a757-8b4079052f0e",

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        "name": "pop rock",
        "count": 5
    },
    {
        "id": "988e91a3-3341-416d-b7f8-7dbef6848dac",
        "disambiguation": "",
        "name": "synth-pop",
        "count": 1
    }
],
"type-id": "e431f5f6-b5d2-343d-8b36-72607ffffb74b",
"disambiguation": "",
"name": "The 1975"
}
}
],
"disambiguation": "EP version from \"IV\"",
"video": false
}

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AcousticBrainz

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{
  "963ec665-106b-43d4-b92b-78fe858cddd2": {
    "0": {
      "highlevel": {
        "danceability": {
          "all": {
            "danceable": 0.953934967518,
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          },
          "probability": 0.953934967518,
          "value": "danceable",
          "version": {
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            "essentia_git_sha": "v2.1_beta4",
            "extractor": "music 1.0",
            "gaia": "2.4.5",
            "gaia_git_sha": "v2.4.4-44-g95f4851",
            "models_essentia_git_sha": "v2.1_beta1"
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        },
        "gender": {
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            "male": 0.181803584099
          },

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      "extractor": "music 1.0",
      "gaia": "2.4.5",
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      "models_essentia_git_sha": "v2.1_beta1"
    }
  },
  "genre_dortmund": {
    "all": {
      "alternative": 0.160485297441,
      "blues": 0.0296422634274,
      "electronic": 0.650288939476,
      "folkcountr": 0.0742783695459,
      "funksoulrnb": 0.00324602611363,
      "jazz": 0.00992484763265,
      "pop": 0.0152551233768,
      "raphiphop": 0.00269382866099,
      "rock": 0.0541852898896
    },
    "probability": 0.650288939476,
    "value": "electronic",
    "version": {
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      "extractor": "music 1.0",
      "gaia": "2.4.5",
      "gaia_git_sha": "v2.4.4-44-g95f4851",
      "models_essentia_git_sha": "v2.1_beta1"
    }
  },
  "genre_electronic": {
    "all": {
      "ambient": 0.378175705671,
      "dnb": 0.0673560276628,
      "house": 0.258274227381,
      "techno": 0.0239827632904,
      "trance": 0.272211283445
    },
    "probability": 0.378175705671,
    "value": "ambient",
    "version": {
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  }
},
"genre_rosamerica": {
  "all": {
    "cla": 0.00494982395321,
    "dan": 0.149058401585,
    "hip": 0.0384234935045,
    "jaz": 0.00734017789364,
    "pop": 0.193190515041,
    "rhy": 0.113537713885,
    "roc": 0.489368438721,
    "spe": 0.00413142517209
  },
  "probability": 0.489368438721,
  "value": "roc",
  "version": {
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    "models_essentia_git_sha": "v2.1_beta1"
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"genre_tzanetakis": {
  "all": {
    "blu": 0.0626613423228,
    "cla": 0.0348169617355,
    "cou": 0.104475811124,
    "dis": 0.0784321576357,
    "hip": 0.15692435205,
    "jaz": 0.313974827528,
    "met": 0.0448166541755,
    "pop": 0.0627359300852,
    "reg": 0.0627360641956,
    "roc": 0.0784258767962
  },
  "probability": 0.313974827528,
  "value": "jaz",
  "version": {
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    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
},
"ismir04_rhythm": {
  "all": {
    "ChaChaCha": 0.379461944103,
    "Jive": 0.081034116447,
    "Quickstep": 0.0136173907667,
    "Rumba-American": 0.012443867512,
    "Rumba-International": 0.0245444998145,
    "Rumba-Misc": 0.0139475744218,
    "Samba": 0.0879349634051,
    "Tango": 0.0764814317226,
    "VienneseWaltz": 0.299553096294,
    "Waltz": 0.0109811034054
  },
  "probability": 0.379461944103,
  "value": "ChaChaCha",
  "version": {
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    "extractor": "music 1.0",
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    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
},
"mood_acoustic": {
  "all": {
    "acoustic": 0.0333173498511,
    "not_acoustic": 0.966682672501
  },
  "probability": 0.966682672501,
  "value": "not_acoustic",
  "version": {
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  }
}

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    }
  },
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    "all": {
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      "not_aggressive": 0.554565727711
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    "value": "not_aggressive",
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      "models_essentia_git_sha": "v2.1_beta1"
    }
  },
  "mood_electronic": {
    "all": {
      "electronic": 0.29081761837,
      "not_electronic": 0.70918238163
    },
    "probability": 0.70918238163,
    "value": "not_electronic",
    "version": {
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      "gaia_git_sha": "v2.4.4-44-g95f4851",
      "models_essentia_git_sha": "v2.1_beta1"
    }
  },
  "mood_happy": {
    "all": {
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      "not_happy": 0.392959952354
    },
    "probability": 0.607040047646,
    "value": "happy",
    "version": {
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  }
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"mood_party": {
  "all": {
    "not_party": 0.379335254431,
    "party": 0.620664715767
  },
  "probability": 0.620664715767,
  "value": "party",
  "version": {
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    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
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},
"mood_relaxed": {
  "all": {
    "not_relaxed": 0.934732496738,
    "relaxed": 0.0652674883604
  },
  "probability": 0.934732496738,
  "value": "not_relaxed",
  "version": {
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    "extractor": "music 1.0",
    "gaia": "2.4.5",
    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
},
"mood_sad": {
  "all": {
    "not_sad": 0.668825507164,
    "sad": 0.331174492836
  },
  "probability": 0.668825507164,
  "value": "not_sad",
  "version": {
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    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
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"moods_mirex": {
  "all": {
    "Cluster1": 0.158346891403,
    "Cluster2": 0.374168276787,
    "Cluster3": 0.237774029374,
    "Cluster4": 0.108145728707,
    "Cluster5": 0.121565058827
  },
  "probability": 0.374168276787,
  "value": "Cluster2",
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    "essentia_git_sha": "v2.1_beta4",
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  }
},
"timbre": {
  "all": {
    "bright": 0.973818778992,
    "dark": 0.0261812321842
  },
  "probability": 0.973818778992,
  "value": "bright",
  "version": {
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    "essentia_git_sha": "v2.1_beta4",
    "extractor": "music 1.0",
    "gaia": "2.4.5",
    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
},
"tonal_atonal": {
  "all": {
    "atonal": 0.0612629503012,

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  "probability": 0.938737034798,
  "value": "tonal",
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    "essentia_git_sha": "v2.1_beta4",
    "extractor": "music 1.0",
    "gaia": "2.4.5",
    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
},
"voice_instrumental": {
  "all": {
    "instrumental": 0.0196768660098,
    "voice": 0.980323135853
  },
  "probability": 0.980323135853,
  "value": "voice",
  "version": {
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    "gaia_git_sha": "v2.4.4-44-g95f4851",
    "models_essentia_git_sha": "v2.1_beta1"
  }
}
},
"metadata": {
  "audio_properties": {
    "analysis_sample_rate": 44100,
    "bit_rate": 0,
    "codec": "flac",
    "downmix": "mix",
    "equal_loudness": 0,
    "length": 224.666671753,
    "lossless": 1,
    "md5_encoded": "3576644de669ae9c46f3e554c42e71dd",
    "replay_gain": -14.7854347229,
    "sample_rate": 44100
  },
  "tags": {
    "album": [
      "The 1975"
    ]
  }
}

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],
"albumartist": [
  "The 1975"
],
"albumartistsort": [
  "1975, The"
],
"artist": [
  "The 1975"
],
"artistsort": [
  "1975, The"
],
"asin": [
  "B01BIEFDHQ"
],
"barcode": [
  "00602537671243"
],
"bpm": [
  "99"
],
"date": [
  "2013-08-30"
],
"discnumber": [
  "1"
],
"disctotal": [
  "6"
],
"file_name": "1-04 - Chocolate.flac",
"genre": [
  "Alternative",
  "Indie Rock"
],
"isrc": [
  "GBK3W1000183"
],
"label": [
  "Dirty Hit"
],
"length": [
  "224000"
],
"media": [
  "Digital Media"
],
],
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"musicbrainz_albumartistid": [
  "5b6ebfe0-f72b-4902-bba9-74c8af0f1af0"
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  "ac2b87af-2774-4575-a72a-db31c8865264"
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  "963ec665-106b-43d4-b92b-78fe858cddd2"
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"musicbrainz_releasegroupid": [
  "cbbe5df6-08b8-4181-8aae-461a6ae9790d"
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"musicbrainz_releasetrackid": [
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"originaldate": [
  "2013-08-30"
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"originalyear": [
  "2013"
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"releasecountry": [
  "GB"
],
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  "official"
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"releasetype": [
  "album"
],
"script": [
  "Latn"
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"title": [
  "Chocolate"
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  "16"
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"tracknumber": [
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        "essentia_git_sha": "v2.1_beta4",
        "extractor": "music 1.0",
        "gaia": "2.4.5",
        "gaia_git_sha": "v2.4.4-44-g95f4851",
        "models_essentia_git_sha": "v2.1_beta1"
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    "lowlevel": {
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        "essentia_git_sha": "v2.1_beta2",
        "extractor": "music 1.0"
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},
"mbid_mapping": {}
}

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Spotify for Developers

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{
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    "danceability": 0.614,
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    "instrumentalness": 0,
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    "loudness": -4.46,
    "tempo": 100.056,
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