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# Clustering

In this assignment you have to perform clustering on the spotify dataset and develop a recommendation system for the users. You will be given a dataset of songs and their features like danceability, energy, etc. You will be asked to perform clustering on the dataset and then recommend songs to the users based on the clusters.

## Task: Music Recommendation System

In this assignment your submission should contain a main python code file, musicRecommender.py, you may use notebooks for your experiments but the main interface to your work should be from the main python code file. It takes the path to user preferences (a csv file) and outputs:

- 5 csv files, each containing the top 5 songs for each user.Tracks from each playlist should be sampled from the same cluster.
- A single playlist file containing all the songs recommended to the users. It is not important how the songs are sampled from the clusters.

## At first the given data contains 42305 rows and 22 columns, where the columns are as follow:

### **acousticness** :number<float>

**A confidence measure from 0.0 to 1.0** of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.

### **analysis_url**: string

### **danceability**: number<float>

Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. **A value of 0.0 is least danceable and 1.0 is most danceable.**

### **duration_ms**: integer

The duration of the track in milliseconds.

### **energy**: number<float>

**Energy is a measure from 0.0 to 1.0** and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

### **id**: string

The Spotify ID for the track.

### **instrumentalness**: number<float>

Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". **The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.**

### **key**: integer

The key the track is in. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value is -1.

### **liveness**: number<float>

Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.

### **loudness**: number<float>

The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.

## **mode**: integer

Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived. **Major is represented by 1 and minor is 0.**

## **speechiness**: number<float>

Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

## **tempo**: number<float>

The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.

## **time_signature**: integer

An estimated time signature. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure). The time signature ranges from 3 to 7 indicating time signatures of "3/4", to "7/4".

>= 3<= 7

## **track_href**: string

A link to the Web API endpoint providing full details of the track.

## **type**: string

The object type.

Allowed value:"audio_features"

## **uri**: string

The Spotify URI for the track.

## **valence**: number<float>

**A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track**. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

## **genre:** string

## Data Preprocessing:

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### 1) Data Cleaning

Removing unnecessary columns:
columns 'type', 'uri', 'track_href', 'analysis_url' and 'genre' are not going to be useful for us, even genre will not appear in our input so it doesn't help that much. I'm going to drop all mentioned columns.

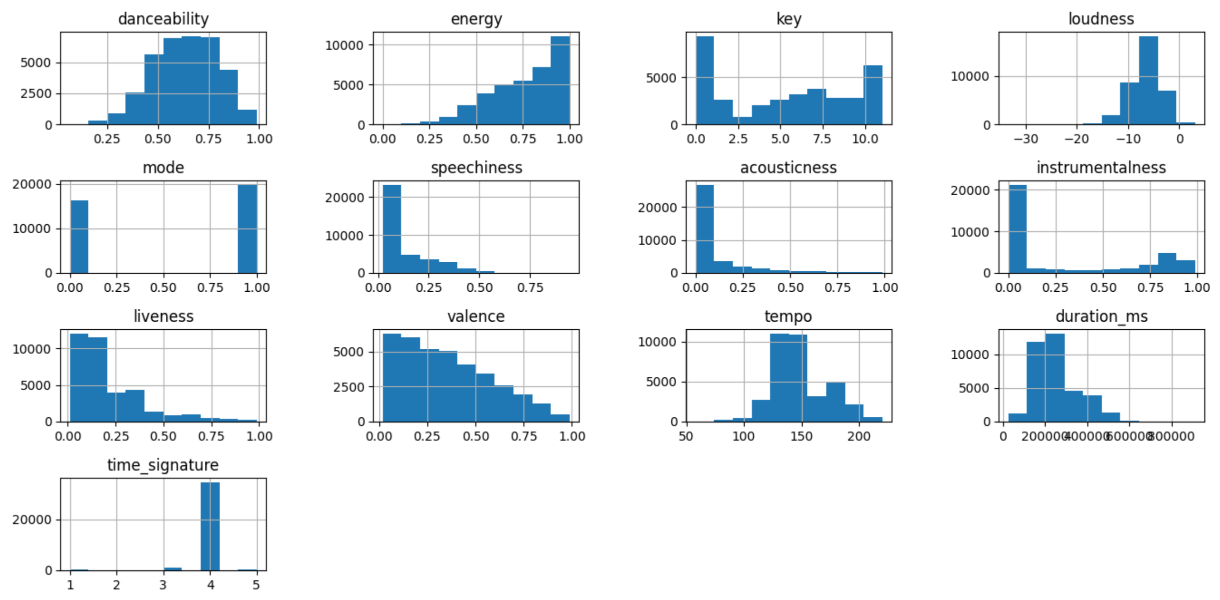
Handling missing data:
In columns 'song_name', 'Unnamed: 0' and 'title' we see lots of *NaN*s, in addition to that they are not going to be helpful for the clustering part, so I, going to drop these columns too.
It was previously mentioned that if the 'key' is not detected, its value is -1, it might be a good way of handling the missing data, but it can ruin our upcoming clustering. So I'm going to drop all the rows whose 'key' is -1.

Removing Duplicates:
It seems that we have a lot of repeated rows too. I'm going to drop them as well.

After all these data cleanings we have 36199 rows and 14 columns, all the columns are numerical but 'id' which is string. I keep this column because when I want to recommend a song to a user, I'm going to use it, But when clustering I temporarily drop it, so that it doesn't have an effect on the result.

## 2)Data Transformation

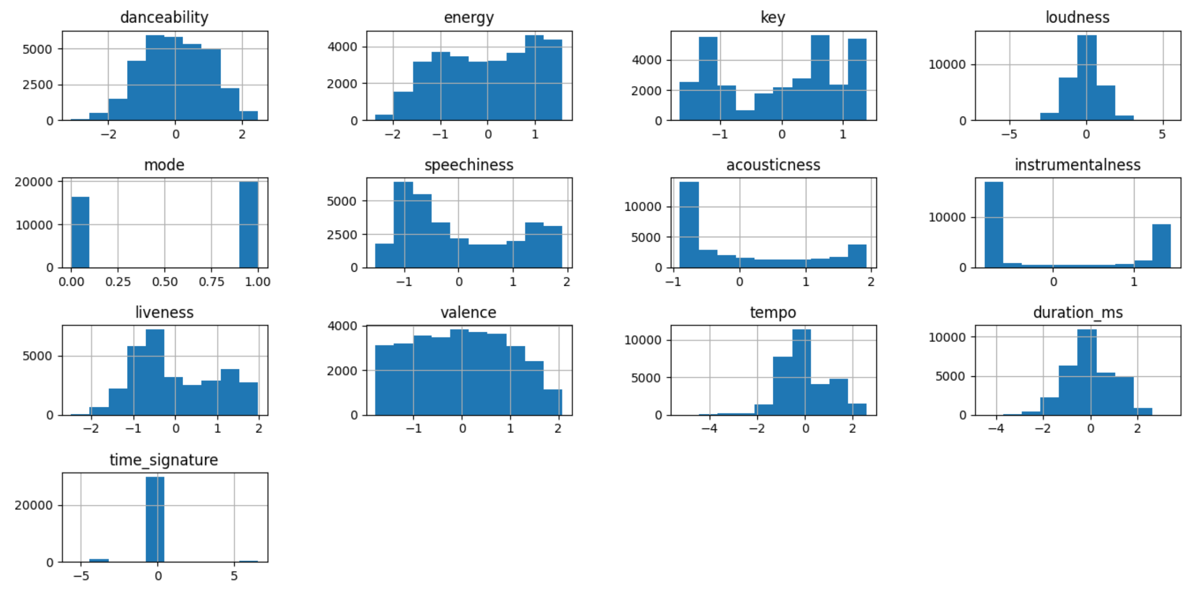
Now Let’s take a look at histogram plots of our data:



If we want to use K-means, the distribution should be symmetric.
As we can observe from the plot above, most of the features have a skewed distribution. So we should normalize them.

As many of our variables have left skewness a method like logarithm cannot help. Box-Cox is not useful either because its inputs are just positive numbers. I used Yeo-Johnson at last.The result is as follow:

- point: The variable ‘mode’ is categorical. So I didn’t use the method for that.

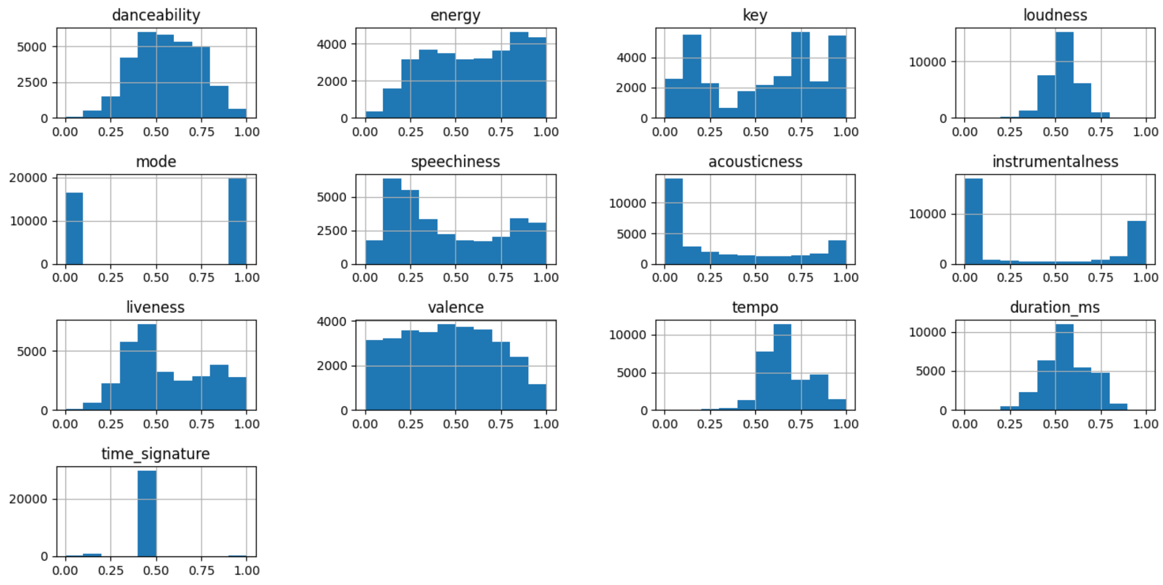


It’s better now, not completely normal but it’s better than before. What about scales of the variables?

To use K-means algorithm, all the variables should have the same mean and variance (be on the same scale). I want to transfer all of them to the range of **0.0 to 1.0**. Which means I'm going to normalize them.

An Important point that we should be careful about, is that:
**We should fit a scaler on the training data** and then use this scaler to scale **both training data and test data**. they shouldn’t have seperate scalers. Because **separate scalers will cause data leak.**

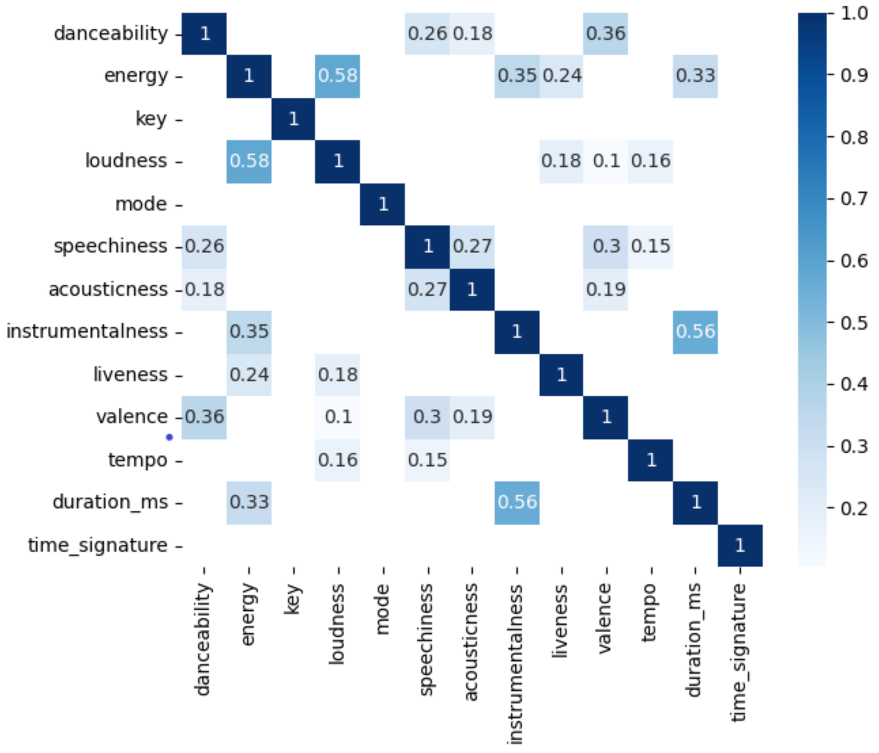
After normalizing the result is as follow:



## 3) Data Reduction

Before moving on to clustering let’s just make sure about another thing:

For a better result, we should find highly correlated variables, and if there are any, we should drop them.



None of the correlations are not very noticable. So we keep all of them.

Now, Our data is ready to be clustered…

## Clustering:

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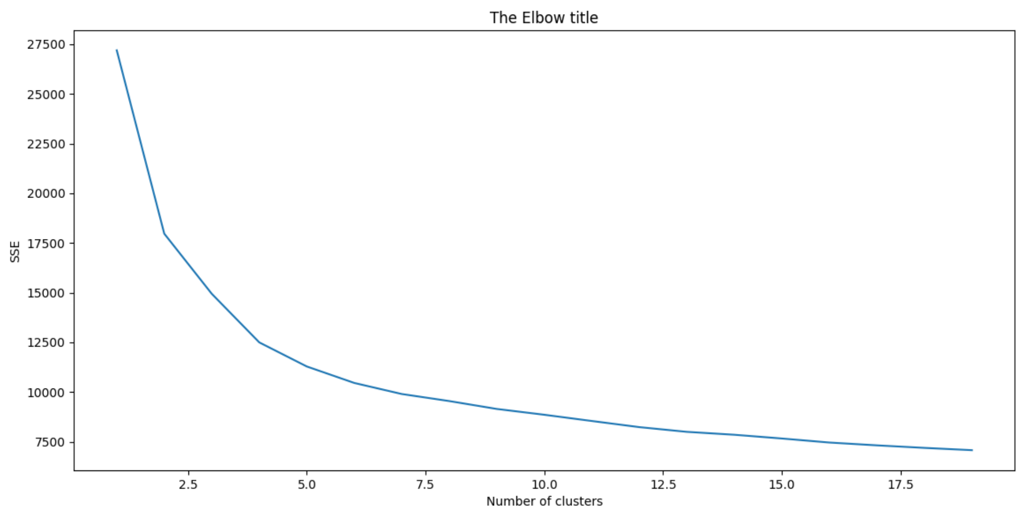
I’m going to use K-means algorithm which is an unsupervised one.
An important point about K-means, is that before running, it should be told about the value of k, which is the number of clusters that we want to have.

But how do I select a meaningful number for the clusters?

To answer this question I use the **elbow method**.



It can be concluded that **10 clusters** can work well.

After clustering now I can handle the input/output part of the assignment…

## Normalizing the input:

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The input file contains 5 preferences of the user. Before anything we have to normalize them. they should be normalized with the same scaler that we made based on our training data.

## Output:

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Output contains 6 .csv files which are as follow:

- **single_playlist.csv**

I matched each row of the user preference dataset to a cluster, and then randomly recommended one of the songs from the same cluster.

- **pl1.csv**
- **pl2.csv**
- **pl3.csv**
- **pl4.csv**
- **pl5.csv**

For pl[i].csv, I matched i'th row of the user preference dataset to a cluster, and then randomly recommended 5 songs from that cluster.

## Resources:

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- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.hist.html
- https://realpython.com/k-means-clustering-python/
- https://towardsai.net/p/data-science/how-when-and-why-should-you-normalize-standardize-rescale-your-data-3f083def38ff
- https://medium.com/@evgen.ryzhkov/5-stages-of-data-preprocessing-for-k-means-clustering-b755426f9932
- https://developer.spotify.com/documentation/web-api/reference/#/operations/get-audio-features