Sean: Intro, Data Description, Motivation

* Hi! This is Team 112’s project on music and emotions
* The data consists of 400 song excerpts split between four genres: classical, rock, pop, electronic. participants were asked to report their mood before listening and the three emotions they felt the strongest while listening. The dataset also includes personal information such as age, gender, and their mother tongue
* At the beginning of the project, we realized that music tends to be grouped in strict genres
* We were interested in seeing if we could predict a certain genre based on a user’s emotions and …
* there was a more natural grouping of songs that we could recommend to a person based on their emotional response while listening

Aidan: Ethical Considerations, bar graphs

* Ethical
  + Before we get to our visualizations, we would like to address some ethical concerns and considerations within our project, primarily addressing the bias of our dataset.
  + Firstly, we feel that it is important to note there was an uneven distribution of Mother Tongues.
    - As you can see on the graph on the right, the total number of speakers for the top 2 languages, English and Russian, was more than the lowest 38 languages.
    - In this same light, 28 languages had below 100 speakers.
    - As a result, some may not be used to songs in English and may not be able to accurately rate their emotions after the song.
  + Additionally, our data only represents four genres. This does not account for the unique music that listeners may be more exposed to.
* Bar Graphs
  + To further understand our data, we graphed the emotions of every genre. By doing this, we can better understand our results and relate to how the listeners ranked their emotions.
  + The graphs represent the average emotion rank across a whole genre. For example, in the pop genre in the bottom left, amazement, the pink bar was felt by approximately 10 percent of listeners.
  + Additionally, we can highlight the difference across genres. In rock in the bottom right, most of the emotions are largely felt the same, while in electronic in the top right, tension was a dominating emotion.
  + Now we will move on to our machine learning methods.

Mimi: Methods, managing data, classifications

* We used machine learning methods for this dataset:
* We used classification methods to analyze whether the predefined genres we know could be predicted based off the emotion one feels from a song plus personal data
* We used K-means clustering - could there be a way to cluster music based on emotion rather than the predefined genres in this dataset.
* For classification, we had to bootstrap since there were an uneven amount of samples per genre. Without bootstrapping, overprediction could occur, since classical music was the most seen sample in the dataset. So we randomly sampled the other genres to equal the genre count of classical.
* Here is our decision tree classifier, which is large because of the amount of data being used in the dataset, since we are using 15 columns to predict the genre. The max depth is at 5, which means 5 questions must be asked in order to predict a genre.
* Let’s now move onto our Random forest classifier. When looking at feature importance for this classifier, we saw the age and mood were the most important in predicting genre, which is definitely not what we were expecting to see. Emotions are not being accounted for in these classifiers as much as the user’s personal information.
* Before performing the confusion matrix, we optimized max\_depth by comparing teh depth to the accuracy score of the classifier, and we found that a max\_depth of 17 was best.
* Here is our confusion matrix for our bootstrapped data without cross validation.
* Without bootstrapping, the classifier’s accuracy score was 43.24% but after bootstrapping, it increased to 57.22%. With cross validation, there was a minimal increasing at 58.75% because our dataset is big enough with sufficient training samples
* We also tried a knn classifier, and optimization showed that k should equal 1
* With that, our knn classifier did not seem to have much of a difference from our random forest classifier, with an accuracy score of 57.15%.

Arielle: K-Means and Discussion

* We wanted to see if there was a way to cluster songs based on emotion
* We used the average emotion per track ID, by using groupBy, and finding the mean for each emotion felt.
* We then plotted 2 through 7 different clusters, and found 3 clusters to be the best, as it had the lowest mean difference
* However, you can see these still aren’t very distinct clusters, there is a lot of overlap, so there’s not an intuitive way to cluster music based on emotion

**So for what went well, what didn’t, and what we could do different**

* Our dataset was not great for this project, but bootstrapping did help us a lot and was a great tool
* Our problems with our dataset were that it is very non-linear, dealing with something subjective (emotions). It’s also mostly categorical information, consisting of 0s and 1s, which can be harder to predict. And, there was nothing keeping track of a listener ID. It would’ve been easier to make predictions if we knew that the same person was listening to different songs among genres, and how that person felt across different track IDs, whereas we just have individual listens.
* emotions are not uniform in a single genre - emotions cannot be assumed for an entire genre, what evokes tension for one person may evoke happiness for another.
* In the future, if we were to collect this data, we would keep track of a listener ID, and how they felt about different songs across genres
* Also, we would want to redefine the tracks into three clusters, and not the genres, predict which cluster a song belongs to by finding the smallest distance from the center of that cluster, instead of predicting which genre.