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IST 664: Natural Language Processing

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Final Report

Song Decade Classification

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# Introduction

Since 1940, “Billboard” has been comprising and printing lists of the most popular and best-selling singles and records across the US (Trust, 2022). What started as a meager 10 song list, whose data was collected by polling via phone calls, has since grown to be a weekly 100 song list that is considered by many to be the industry standard for discovering the most popular music listened to nationwide (Trust, 2022). The final list put out each year looks at the cumulatively most popular songs from the previous 12 months as a whole, potentially serving as a time capsule-like glimpse into how music was trending at that point in history. The following investigation attempted to see if there is any validity to this belief by analyzing the lyrics from each end-of-year top hits list from 1950 through 2019 and observing if they collectively contained any discerning features that may help identify the decade they were written. Various techniques were utilized, and multiple features were examined to perform this analysis, which will all be discussed in the following report.

# Analysis

## Data Collection

In order for this examination to take place, the lists of top songs each year from 1950-2019, as well as their respective lyrics, would all need to be collected and compiled into one central location. In a previous analysis, Comparing Corpora with Corpus Statistics (CCCS), the yearly list of tops songs from 1980-2019 had already been assembled by writing a python script that went out to Wikipedia.com, which has individual pages for each year and its respective top 100 billboard songs, then downloading the 100 song titles/artists for each year and combining them all into one data frame (Spitulnik, CCCS, 2023). This script was replicated and reused to now also collect the list of songs in the years 1960-1979. A similar script was also used to collect the list of songs in the years 1950-1959, but it had to be slightly altered since the names of the lists—and the resulting URLs where they were stored—changed from the “Top 30 Singles” in 1950-1955 to the “Top 50 Singles” in 1956-1958 to finally the “Hot 100 Singles” in 1959 that continues to exist today (Trust, 2023). With the list of songs now collected, they could all be combined into one comprehensive list of Billboard’s yearly top songs from 1950-2019. In total, the list originally contained 6,432 songs, with the song breakdown per year shown below in figure 1. The songs from the 1950’s were still used despite only 432 possible songs to choose from with the understanding that the analysis of the songs from these years may not be as strong or conclusive.

Text

Description automatically generated

*Figure 1*

With the list of songs now compiled, the song titles and song artists could now be used to create scripts for locating and exporting the song lyrics from the web. In CCCS, methods for doing this were established and are outlined in the following excerpts:

*“At a very basic level, various song lyric websites use similar formatting methods when it comes to how the webpage for each song is accessed: the name of the site/followed by the name of the artist/followed by the name of the song. Each site though has its own small intricacies that make its links slightly different; one site removed spaces from artists/titles with multiple words while another substituted them for hyphens, one site added the word ‘lyrics’ to the end of the artist and song title, one site had a /’first letter of the artists name’ before the /artist name, etc. So, for example, to find the lyrics for the song ‘Little Jeannie’ by Elton John, a script would need to be written that took the artist’s name and song title from the information in the previously created data frame and use it to construct a URL looking like one of the following three examples, depending on which page was going to be used:*

*AZlyrics.com:* [*https://www.azlyrics.com/lyrics/eltonjohn/littlejeannie.html*](https://www.azlyrics.com/lyrics/eltonjohn/littlejeannie.html)

*LyricsOnDemand.com:* [*https://www.lyricsondemand.com/e/eltonjohnlyrics/littlejeannielyrics.html*](https://www.lyricsondemand.com/e/eltonjohnlyrics/littlejeannielyrics.html)

*SongLyrics.com:* [*https://www.songlyrics.com/elton-john/little-jeannie-lyrics/*](https://www.songlyrics.com/elton-john/little-jeannie-lyrics/)

*Another issue that needed to be accounted for when creating the scripts that would collect all the song lyrics: many songs were not performed by one singular artist. In the information collected from Wikipedia, songs with multiple artists were displayed in a few different ways: ‘artist1* ***and*** *aritst2’, ‘artist1* ***&*** *artist2’, or ‘artist1* ***featuring*** *artist2’. The various song lyric websites also had their own methods for handling songs with multiple artists: some did not use additional artist names in the links for the song pages, some included them in the ‘/artist’ section of the link, some added them to the song title. To account for this, the song-collection-script needed to include some conditional statements that would test if the initially constructed URL actually worked, and if it didn’t, attempt to adjust the URL by revisiting the artist’s name or names.*

*A third issue that needed to be accounted for when collecting the song lyrics: the various lyric websites mostly had a common pattern used for each song page URL, but none of them were 100% consistent. For example, none of the sites appeared to have a full proof method to handle artists names or song titles beginning with ‘The’; sometimes they would drop it from the artist’s name but leave it on the song title, sometimes the opposite, sometimes they would drop it from both.” (Spitulnik, CCCS, 2023)*

Due to the various nuances listed above, multiple scripts needed to be built to access the lyrics from a few different sites. It was discovered that AZlyrics.com started blocking the script built to visit its site, so LyricsOnDemand.com and SongLyrics.com were inevitably used to collect a majority of the lyric data (Spitulnik, CCCS, 2023). Although the scripts were adjusted a few times to try to accommodate different patterns that were discovered in the links to the song pages, not all song lyrics could be obtained, with 6,150 of the possible 6,432 songs lyrics downloaded. This still represented almost 96% of the songs; an acceptable number to continue with the analysis. Figure 2 below shows a breakdown of the number of songs with lyrics per year:

Table

Description automatically generated

*Figure 2*

Figure 3 below shows the resulting data frame from the work performed so far:

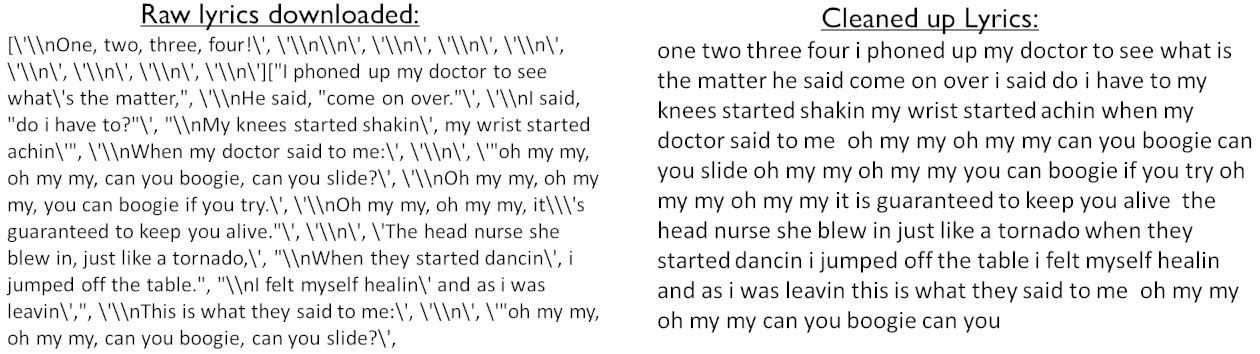


*Figure 3*

## Data Preprocessing

With all of the lyrics downloaded, preprocessing and cleanup of the data could now be performed. A “Decade” column was added to the lyrics data frame, which was based on the year the song was in the top 100, located in the “Year” column. A “SongID” column was also added, which used the index of each song’s row in the data frame to assign a unique song ID that was later utilize for merging together different feature sets.

Within the lyrics themselves specific cleanup needed to occur since the downloaded text still contained raw HTML notation. Some of the cleanup steps could be performed for all of the different analysis that took place, while some of the cleanup had to occur in a specific order to accommodate the analysis method. All of the analysis methods required the various HTML line break notations like “\n” and “\r” to be removed. They all also required word contractions such as “don’t” or “couldn’t” to be reduced to their non-contraction forms; “do not” and “could not”, respectively. This ensured these words would still be sensical after punctuation was later removed, instead of “don” and “t” or “couldn” and “t” being all that remained. For most of the analysis, all of the letters in the lyrics could now be converted to lowercase, and the punctuation could be removed. Figure 4 below shows an example of how a song lyric would have originally looked, versus how it would now look after the above listed cleanup steps:



*Figure 4*

If all of the cleanup processes previously listed were performed, each set of song lyrics would be one long string of text. For one of the analysis that was performed, however, the song lyrics needed to be broken up line by line. This could be accomplished with the “nltk.sent\_tokenize” function, but punctuation like periods, exclamation points, or question marks would need to exist where a line ended. Unfortunately, the text for each song’s lyrics did not appear this way. Figure 5 below shows how the lyrics for three songs were broken up:

![A close-up of a document

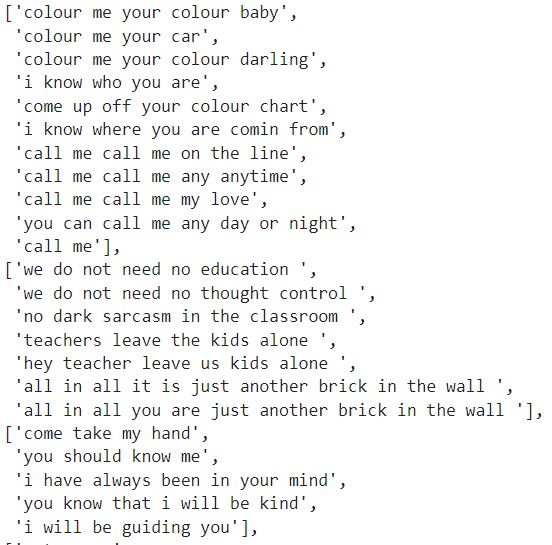
Description automatically generated with medium confidence](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAeAB4AAD/4REERXhpZgAATU0AKgAAAAgABAE7AAIAAAATAAAISodpAAQAAAABAAAIXpydAAEAAAAmAAAQ1uocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFNwaXR1bG5paywgTWF0dGhldwAAAAWQAwACAAAAFAAAEKyQBAACAAAAFAAAEMCSkQACAAAAAzU2AACSkgACAAAAAzU2AADqHAAHAAAIDAAACKAAAAAAHOoAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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*Figure 5 (Spitulnik, SAE, 2023)*

The following excerpt from another previous analysis that was performed, Sentiment and Exploratory Analysis (SAE), describes a pattern found in the format of the lyric text shown in figure 5:

*“The lyrics for each song starts with an open bracket [ and concludes with a closed bracket ]. In between [ and ] are the song lyrics. Each line of the lyrics are surrounded by either single quotes ' ' or double quotes " ", followed by a comma, unless it is the last line of a song, in which case the ' or " is followed by the ]. This pattern appeared to be consistent in every song lyric that was studied. There also did not appear to be any stray instances of ', or ", appearing in a location that was not at the end of a line/sentence. Even if an abbreviated or slang word like talkin' appeared at the end of a line, it would still be followed by another single or double quote, then a comma, appearing as so: talkin'', or talkin'",. The script that is created to place the period would still just replace the ', or ", with a period.” (Spitulnik, SAE, 2023)*

Using this observed pattern and regex commands, a period could replace all instances of a single quote or double quote followed by a comma or a closed bracket, allowing the lyrics to be broken up, line by line (Spitulnik, SAE, 2023). The lyrics could now all be converted to lowercase letters and have the punctuation removed, as seen in other analysis. Figure 6 below displays how the three songs in figure 5 now appeared:



*Figure 6*

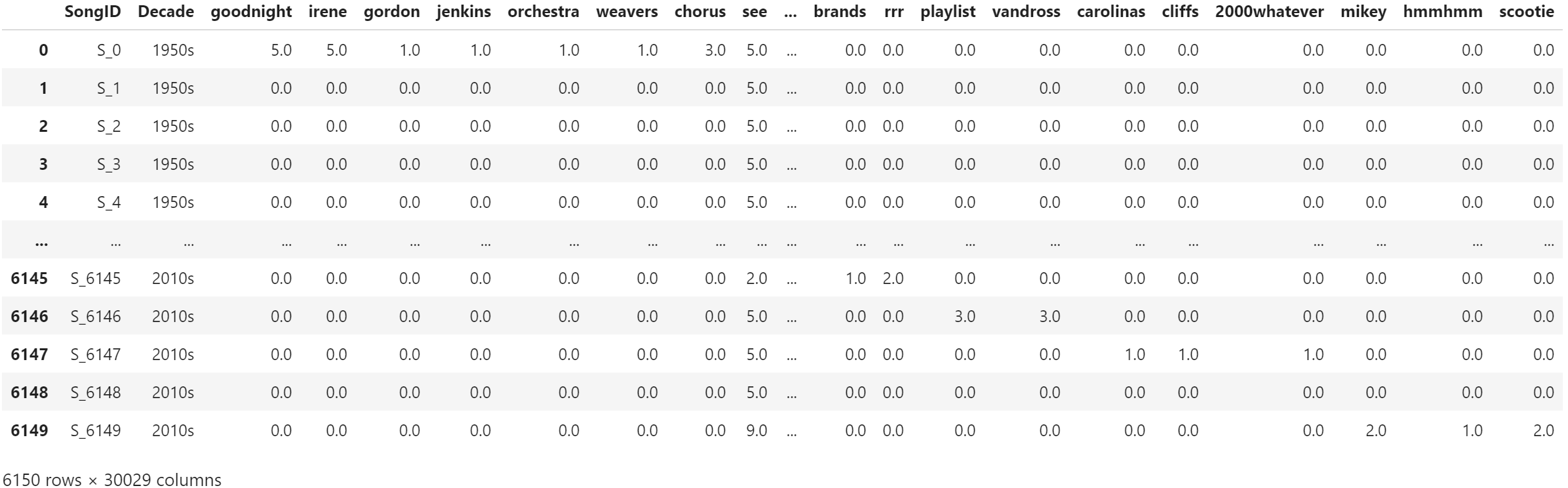
With the data now all cleaned up, the feature sets that would be created from the lyrics could now be established.

## Feature Sets/Experiments

The following is a list of the different feature sets pulled from the lyric data to use in the analysis, as well as the different experiments performed on them.

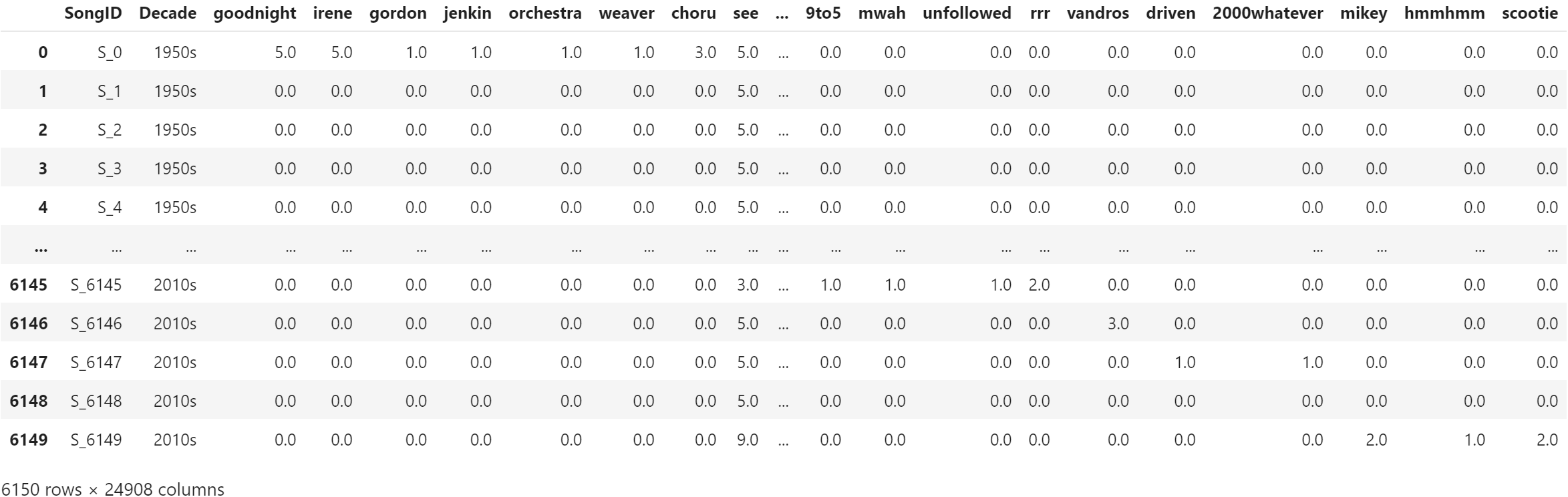
### Frequency Distributions

A frequency distribution takes a count of how often each word appears in a document or a group of documents. In the case of this analysis, frequency distributions were used to see how often a word appeared in each song. The words in each song’s lyrics were segregated using word tokenization, and then stopwords, which are words commonly used in language (is, am, to, do, etc.), were first removed in an attempt to reduce the eventual number of columns in each frequency distribution data frame. The resulting frequency distribution contained 6,150 rows, each representing one of the songs, and 30,029 columns, each representing a word that was present in at least one of the songs. Figure 7 below shows the data frame created from this frequency distribution:



*Figure 7*

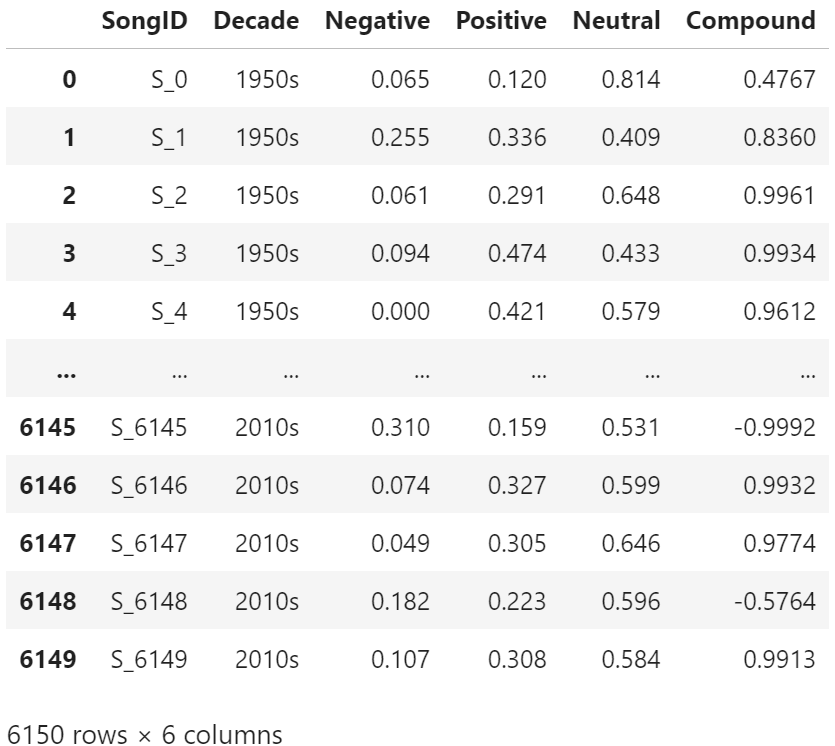
One experiment was also used on this feature set: after removing the stopwords, before creating the frequency distribution, the tense of all words were changed to their base form (referred to as lemmatization), and plural words were changed to their singular form. This meant that, in theory, words like “loves, loved, loving” would all be transformed to “love”, and words like “apples, oranges, lemons” would be changed to “apple, orange, lemon” (Saumyab271, 2022). As expected, this reduced the number of columns and unique words in the lyrics from 30,029 to 24,908, which can be seen below in figure 8:



*Figure 8*

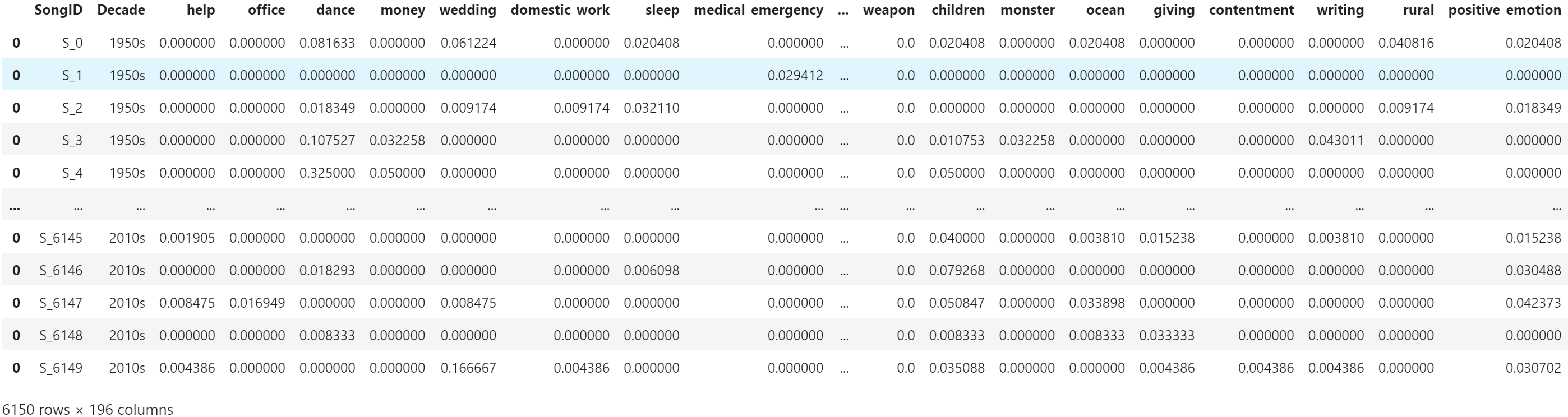
### Sentiment and Lexicon Categorical Analysis

This feature set involved 4 different experiments. In the first experiment, a sentiment analysis was performed on each song. A sentiment analysis takes all of the words in a string, document, tweet, etc., and rates how overall positive, negative, or neutral it may be (Selvaraj, 2020). The sentiment analysis technique specifically used in this experiment rated what percentage of words in each song lyric were negative, positive, or neutral, represented by a value between 0 and 1. These values were also used together to calculate a compound score ranging from -1 to 1. Songs with a score closer to -1 contained more negative lyrics, songs with a score closer to 1 contained lyrics with more positive lyrics, and songs with a score closer to 0 contained lyrics with more neutral lyrics. Figure 9 below shows the resulting sentiment analysis data frame:

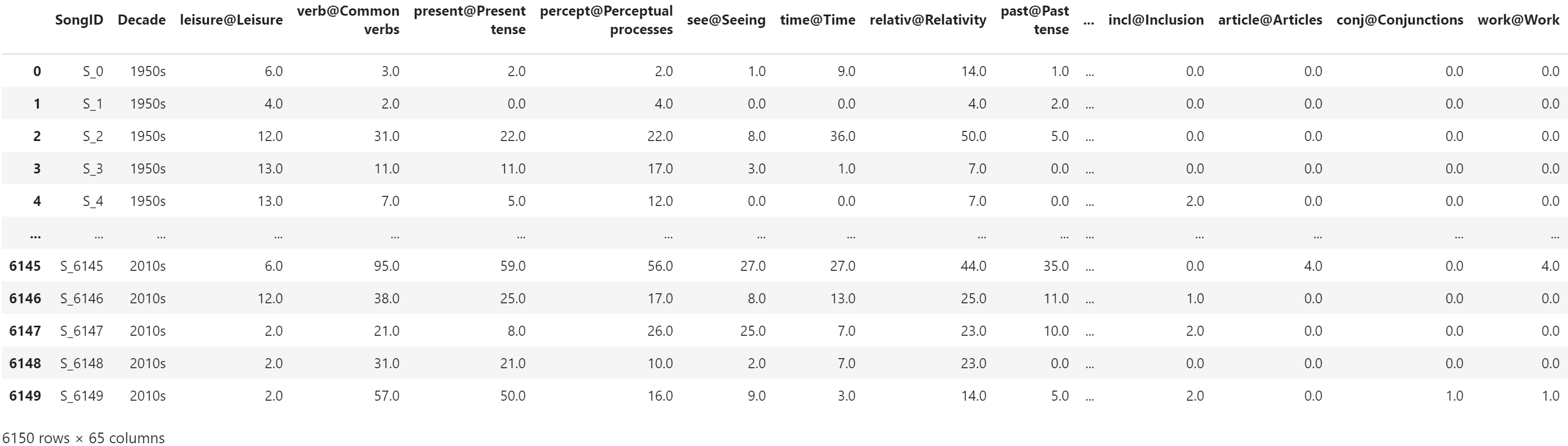


*Figure 9*

The second and third experiments applied a lexicon categorical analysis to the song lyrics. A lexical analysis breaks words down into different categories based on a predefined dictionary that establishes the meaning of a word and how it is used (Oak-Tree.tech). In some cases, after the category has been applied, the sentiment of the word can then be identified, but for these experiments, analysis was performed on the count of words in each lexical category. Experiment 2 used the empath library and its associated lexicon dictionary (figure 10), while experiment 3 used the liwc library and it’s 2007 compiled dictionary (figure 11).



*Figure 10*



*Figure 11*

The fourth experiment in this feature set combined the results from the first three experiments into one data frame to use for analysis. Figure 12 shows the resulting data set:

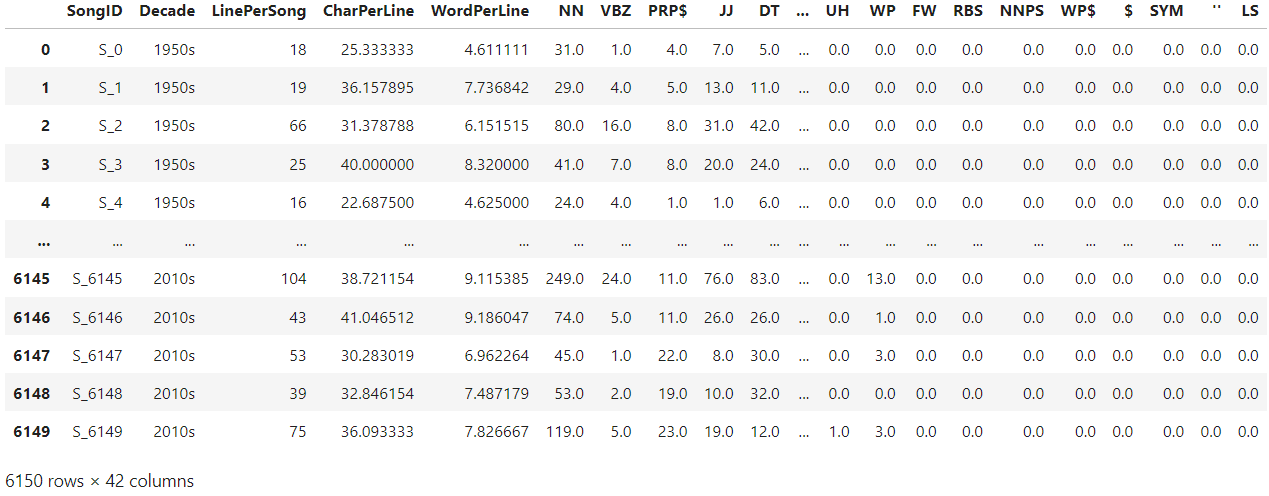


*Figure 12*

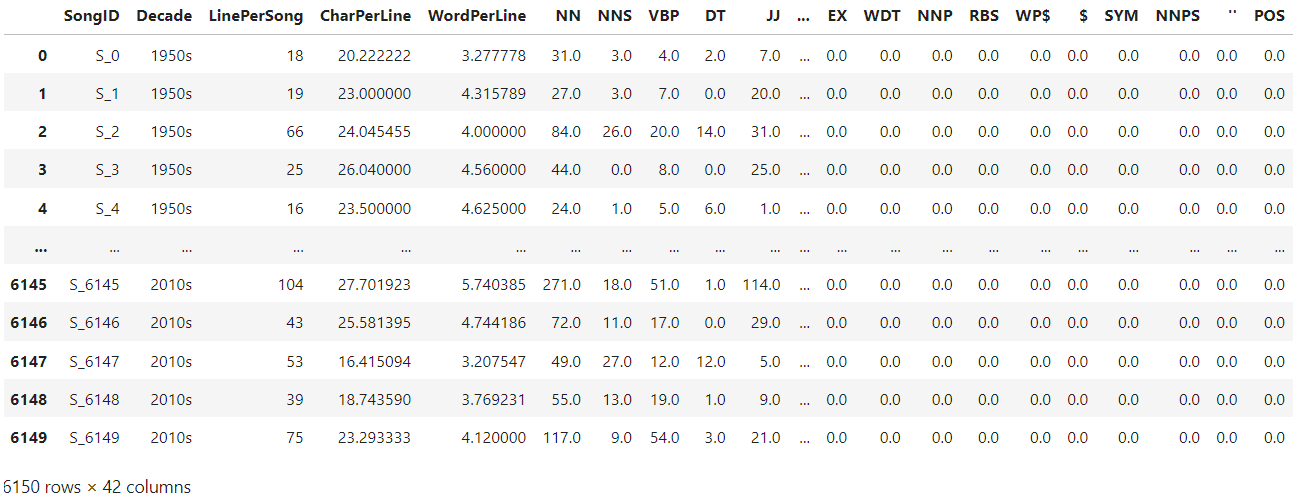
### POS Tagging and Stopword Differentiation

This feature set employed a technique called part of speech (POS) tagging. POS tagging identifies the part of speech for each word in a text, then creates a dictionary where each key is the word, and its associated value is the POS “tag” (Johnson, 2023). For this analysis, the POS tag dictionary for each song lyric was compiled and then converted into a data frame that tallied how many words were present for each part of speech. These POS tag count data frames also included the number of lines, the characters per line, and the number of words per line for each song.

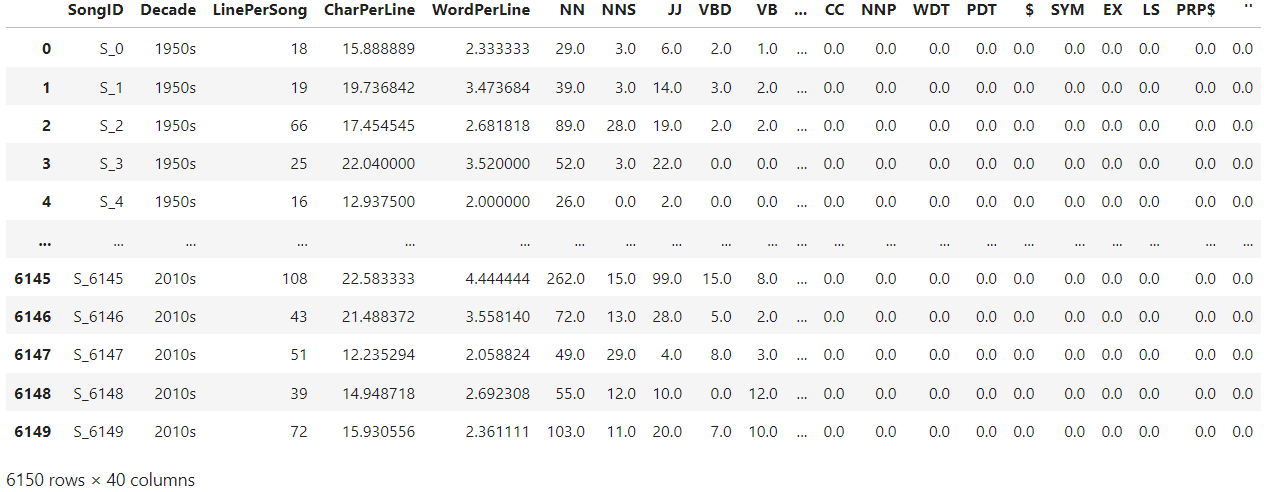
4 different experiments were also applied to this feature set. In experiment 1 (figure 13), no stopwords were removed from the lyrics. In experiment 2 (figure 14), stopwords were removed using the nltk library defined stopwords. In experiment 3 (figure 15), stopwords were removed using the spacey library defined stopwords. In experiment 4 (figure 16), stopwords were removed using the gensim library defined stopwords.



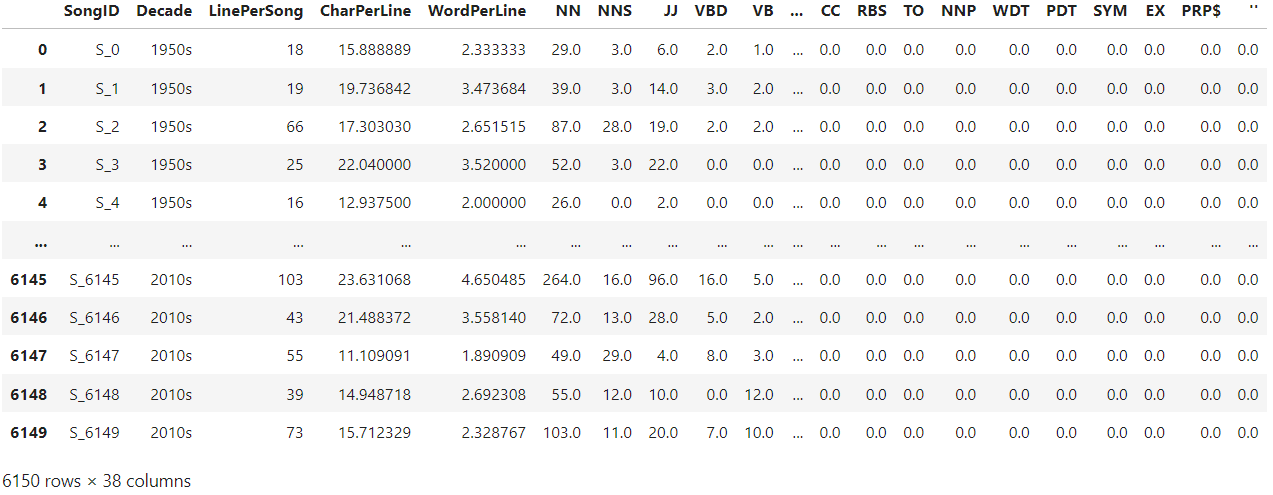
*Figure 13*



*Figure 14*



*Figure 15*



*Figure 16*

### Feature Set Combination

For this final feature set, the (subjectively) best performing experiments from each of the previous 3 feature sets were taken and combined into one feature set to be analyzed. The resulting feature set can be seen below in figure 17:



*Figure 17*

## Analysis Models and Techniques

The following models and evaluation tools were used to assess the lyrical data:

### Naïve Bayes Classifier (NLTK)

Naïve Bayes (NB) is a probabilistic machine learning model used for classifying data (Ghandi, 2018). It typically doesn’t require too much input to produce strong results and it is known to be especially useful for text and document classifications, making it a logical starting point for this analysis (Kumar, 2023). The NB classifier provided in the NLTK library was utilized for this investigation.

### Cross-validation

Cross-validation (CV) is a process of repeatedly training models using different segments of the input data to ensure as little noise, bias, and underfitting/overfitting exists as possible (Gupta, 2017). In this analysis, CV was performed on various models to confirm their reliability.

### Confusion Matrix

A confusion matrix (CM) is a table that displays how well a model is labeling its different classes (Brownlee, *What is a confusion matrix* 2020). Generally, along one side/axis of the table is the true list of data classes, while one of the perpendicular sides/axis’s displays the model’s predicted classes. Within the table, the number of times the model correctly labeled its data can be seen. If data is not being labeled correctly, the CM will also display how it is instead being labeled. This makes CMs especially insightful for data sets (like the one in this analysis) that contain more than 2 classes, where a low accuracy may show that the correct label is not being applied but does not truly show how well the model recognizes the features that separate each class.

### Precision/Recall/F1

Precision, recall, and F1 scores are additional measures that can be used to analyze the strength of model, especially when an accuracy score, for whatever reason, may not be a good representation of the model’s classification capabilities (B, 2020).

Precision examines what percentage of data points that were labeled as a certain class actually were that class (Brownlee, *How to calculate precision* 2020). A precision score of 1 would mean that all data points labeled as a certain class actually were that class. As the number of data points incorrectly labeled as that class increases (false positives in binary classes), the percentage of data points that were correctly labeled as that class goes down, and so too does the precision score.

Conversely, recall examines how many data points that are of a certain class were actually predicted to be that class (Shung, 2020). A recall score of 1 would indicate that all data points of a certain class were correctly labeled as that class. As more data points of that class are incorrectly labeled as being part of another class (false negatives in binary classes), the percentage of data points in that class that have been correctly labeled goes down, and so too does the recall.

The F1 score combines the precision and recall scores into one measurement that takes both of their observed outcomes into consideration (Brownlee, *How to calculate precision* 2020). It is possible to have a high precision with a low recall, or vice versa, so the F1 score ensures the entire picture is being seen.

### Multinomial Naïve Bayes (Sklearn)

Multinomial Naïve Bayes (MNB) is a specific form of NB that is specifically well suited for data sets containing more than 2 classifiers (Sriram, 2022). MNB is also very affective for data sets with discreet values (Educative.io), such as the number of products purchased (Zangre, 2019) or word counts (Horbonos, 2020). Similar to other NB classifiers, it also very effective in textual based analysis. This investigation implemented MNB using the Sklearn library.

### Support Vector Machines (Sklearn)

Support Vector Machine (SVM) is another machine learning model that is extremely effective in classification situations. At a very basic level, SVM looks at the data points in question on a data plane and tries to find where a line can be drawn that best separates the different classes while maximizing the distance between the line and any given points (baeldung, 2022). By default, SVM is meant to handle data sets with just two classifications, but methods like One-Vs-Rest (OvR) or One-Vs-One (OvO) can be applied that split the multi-class data into multiple binary classifications (Brownlee, 2021). OvR splits the data by applying one binary decision to each of the classes (the number of class decisions remains the same), while OvO applies a binary decision for each class against every other class (the number of class decisions most likely will increase) (Brownlee, 2021). Both OvR and OvO were used in the analysis to compare their applicability. The SVM work was all completed using Sklearn.

### Top K Accuracy Score (Sklearn)

A Top K Accuracy Score looks at whether or not the top k predicted outputs for a model contain the true label for the data point, and if they do, consider the overall prediction as correct (Petersen et al., 2022). This differentiates from a standard accuracy score, which only considers the class with the highest predicted probability as correct. A top k accuracy score is especially useful for obtaining a better understanding of how well a multi-class-based model is performing (Riva, 2021). In this analysis, the Top K Accuracy Score was calculated using the “top\_k\_accuracy\_score” function in Sklearn.

# Results

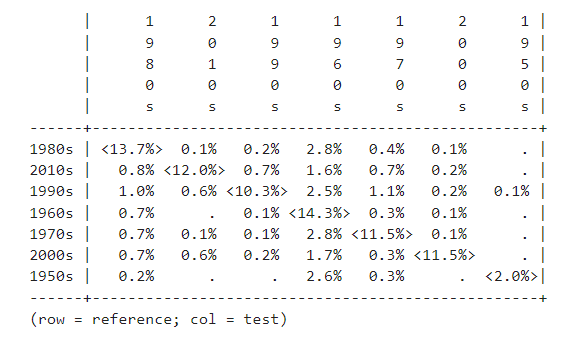
Figure 18 below displays the outputs of the various and most relevant accuracy calculations performed in this analysis:

A picture containing table

Description automatically generated

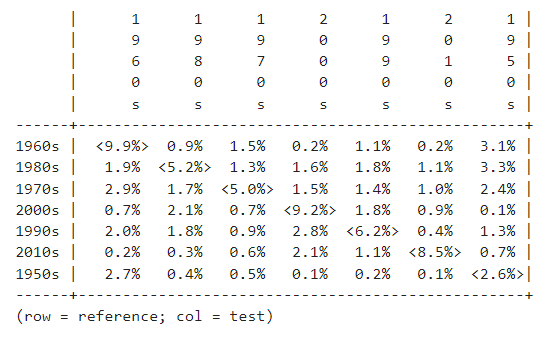
*Figure 18*

Since NB is known for being a good model to use in textual classification, this is where the analysis started. NB models were created using feature sets created from the different feature and experiment data frames and then tested using CV with 10 folds. Unfortunately, across all of the models, low accuracies were observed, ranging from .08 to .36. Decade classifications using sentiment and lexicon analysis seemed to fair the best in this category, as well as the combination of all the feature sets, but the accuracies were still on the low side. The precision, recall, and F1 scores for this model indicate that the accuracy value may not be truly representing how well the data is being classified. Besides the liwc lexicon feature set, all other feature sets have precision/recall/F1 scores over .60, with some in the high .70 to low .80 range. If a confusion matrix is looked at for the feature set with the highest F1 score, which was the feature set comprised of the three different sentiment/lexicon analysis, it can be seen that the correct decade was almost always the most highly predicted class. The only decade in which this was not the case was the 1950s, which is known to not have as much data to use. This confusion matrix can be seen below in figure 19:



*Figure 19*

Even if the confusion matrix is observed for the aforementioned liwc feature set which had the lowest F1 score (figure 20 below), it can be seen that each decade had the highest percentage of correct predictions, with the 1950s still not reaching that mark. The percentages are much closer in this confusion matrix, but the percentage of correct predictions were still the highest. Based on the results seen so far, it was clear another technique would need to be utilized to get a better understanding of whether or not this lyrical data was useful for classifying the decade the songs were written in.



*Figure 20*

After the presentation of the initial findings of this analysis during the IST 664 week 11 synchronous session, Professor Lin advised that for multi-class data sets, top k accuracy analysis provided a greater representation of a model’s classification abilities (Lin, 2023). While researching how to perform top k accuracy analysis, the “top\_k\_accuracy\_score” function offered in the Sklearn library was discovered (scikit-learn.org, *Metrics and scoring*). To calculate the “top\_k\_accuracy\_score” using the top k accuracy function, a model must be fitted, ideally using training data and an estimator. In Sklearn, estimators are essentially different machine learning methods that fit models using training data in order to make assessments of new data (scikit-learn.org, *Developing scikit-learn estimators*). Once the model is fitted, the test feature data is then passed through it to create predictions of each data point’s label. Those predictions, along with the actual test label information and the desired “top k” value, are then inputted into the “top\_k\_accuracy\_score” to produce the top k accuracy.

During the exploration of how to properly implement the “top\_k\_accuracy\_score” function, the flowchart seen below in figure 21 was stumbled upon:

Diagram

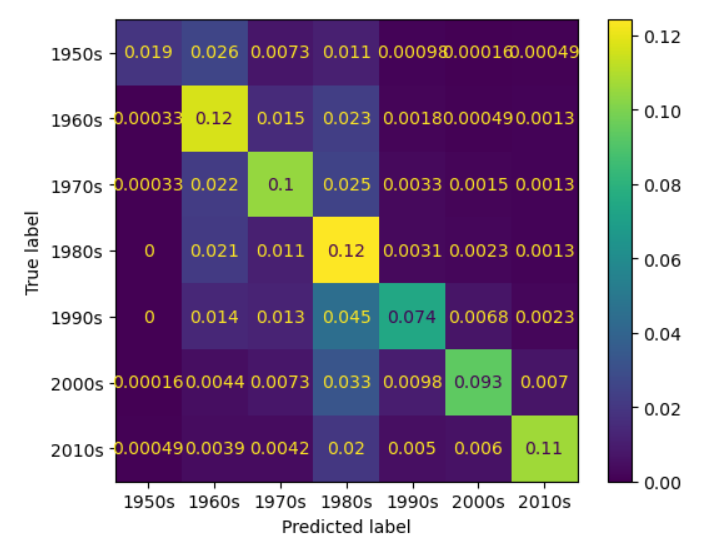
Description automatically generated

*Figure 21 (scikit-learn.org, Choosing the right estimator)*

The flowchart assists with deciding what kind of Sklearn estimators should be used for model creation based on the data set being analyzed. If the highlighted path in the flowchart is followed based on the characteristics of the data set (more than 50 samples, predicting a category, with data already labeled, less then 100K samples), the first estimator arrived at is the SVM method: Support Vector Classification (SVC). If the SVM model doesn’t work, the next estimator in the flow chart would be NB due to the text-based data that is being worked with. Knowing that SVMs and NB (specifically MNB) both have characteristics that could apply to this analysis, and both show up along the related path in the estimator flowchart, both Sklearn estimators were used for the examination.

As stated previously, in order to analyze multi-class data with SVM, either OvO or OvR needed to be utilized. In an attempt to identify which method would lead to better results, both were tested using the frequency distribution feature sets. When 2 SVM models were fitted, one with OvO and one with OvR, the resulting accuracy scores for both came in at exactly the same number: .3485. When the time came however to use these models for the top k accuracy score, the function errored out if the predictions produced from the OvO model were passed, complaining that the “*Number of classes in 'y\_true' (7) not equal to the number of classes in 'y\_score' (21).You can provide a list of all known classes by assigning it to the `labels` parameter.*” Some troubleshooting was attempted, including manually assigning the labels as the error message stated, but no matter what, a way around the issue could not be identified. Due to the nature of the OvO method, the number of classes predicted would almost always be greater then the number of actual, original classes, so it did not appear OvO could be used with the “top\_k\_accuracy\_score” function. Since the, albeit brief, accuracy score testing showed that the two methods produced extremely similar, if not identical, results, it seemed there would be no issue only using the OvR method going forward.

When the MNB and SVM models were fit using the different feature data sets and experiments, the resulting mean accuracy scores were slightly better than the mean NB CV scores (overall mean of .19 for NB CV versus .29 for MNB and .32 for SVM), but they still were not great. Between the MNB and SVM models, only the 2 frequency distribution feature sets, while being fitted by the MNB model, produced accuracies equal to or higher than .40. Those results may be attributed to MNB’s strong ability to handle discrete data, since these frequency distributions are basically long collections of that type of data. Since the ultimate goal was to arrive at top k accuracy scores, the MNB and SVM accuracies were not passed through a CV process, but as can be seen in figure 22 below, which shows the confusion matrix for the MNB model that was fitted by the original frequency distribution feature set, the same pattern is present, with the correct predictions still being the highest percentages (except for the 1950s, once again).



*Figure 22*

The top k analysis scores were now calculated using the MNB and SVM models, with a k value of the top 3 results, and CV being implemented using 10 folds. The resulting top k accuracy scores were mostly above the .60 range, with only a few falling between .50 and .60. The top k accuracy scores predicted using the SVM model appeared to do a better job, with most of the scores for the different feature sets landing at or above .70. Overall, it was pretty clear that these top k accuracy scores did in fact paint a clearer picture of the feature data’s ability to be used for distinguishing the different classes.

# Conclusions

Based on the results obtained from calculating the top k accuracy scores, it would definitely appear that intricacies in song lyrics can be pulled out, analyzed, and used as feature sets for predicting the decade that a song was written in. In fact, there is still room for improving the feature sets and models that were used to arrive at the top k accuracy scores.

To start, after seeing the consistently low numbers for the songs in the 1950s decade, it became pretty clear that the lack of data points for this decade needed to be addressed. Since additional top Billboard songs do not exist from those years to utilize, the two options would be to either collect the lyrics from other songs written in the 1950s, or just drop those songs from the analysis altogether. It would have been interesting to see how the removal of those song lyrics affected the other overall accuracies.

Some additional studying and cleaning of the feature set data also could have been done to see if it raised the accuracy and top k accuracy scores. The different feature sets, especially the frequency distributions, contained a lot of zeros, and most likely a lot of variables that were only present for a limited amount of songs, if not just 1 song. Any features that show up in a miniscule number of songs would most likely not be significant enough to have an effect on the ability to properly classify a songs decade, and in some circumstances, may even prove detrimental to that process.

On the flip side of that, the feature set data also could be further investigated to see if any variables showed up across so many songs that they became insignificant. If every single song, across all of the decades, contained the word “dance” in its lyrics at least once, the word dance wouldn’t contribute to any kind of analysis, since its appearance in a song doesn’t separate it from any other song.

Finally, when thinking about NB models and their assumptions that all variables are completely independent, the idea of needing to find the frequency of n-grams (words that frequently appear together in groups of n) instead of single, individual words, becomes clearer. Because of how sentence structure typically works, a word that appears in a sentence may be there because of another word or type of word in that sentence. For example, an adjective that appears in a sentence would most likely be there because it is describing a noun. Since the adjective is only there because the noun is there, that would mean, by definition, the adjective variable is dependent on the noun variable, thus breaking an NB models assumption of variable independence. Instead, when the words are broken up into two or more-word phrases (n-grams), the meaning and context of the words in question may be transformed, removing the dependency that existed when the words appeared singularly. This would keep the NB models assumption of variable independence in play, meaning its underlying calculations would be more effective, potentially resulting in more accurate classification results.

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