**ANL488 FINAL PROJECT REPORT**

**The Evolution of Popular Bilingual Song Lyrics**

A picture containing icon

Description automatically generated

**Submitted by**

**Name: Tan Li Lin**

**PI Number: W1882296**

**SCHOOL OF BUSINESS**

**Singapore University of Social Sciences**

**Presented to Singapore University of Social Sciences**

**in partial fulfilment of the requirements for the**

**Degree of Bachelor of Science in Business Analytics**

**2021**

**Table of Contents**

[Abstract 3](#_Toc87244562)

[Chapter 1 Introduction 4](#_Toc87244563)

[Chapter 2 Literature Review 5](#_Toc87244564)

[Chapter 3 Data Understanding and Preparation 8](#_Toc87244565)

[3.1 Data Understanding 8](#_Toc87244566)

[3.2 Data Quality 15](#_Toc87244567)

[3.3 Data Preparation 15](#_Toc87244568)

[Chapter 4 Modelling and Evaluation 18](#_Toc87244569)

[4.1 Sentiment Analysis 18](#_Toc87244570)

[4.2 Text Classification 21](#_Toc87244571)

[Chapter 5 Discussion 25](#_Toc87244572)

[5.1 Lyrical timeline (ENG) 25](#_Toc87244573)

[5.2 Lyrical timeline (CHI) 29](#_Toc87244574)

[5.3 Overview 33](#_Toc87244575)

[Chapter 6 Conclusion 34](#_Toc87244576)

[Chapter 7 Recommendations 35](#_Toc87244577)

[References 36](#_Toc87244578)

[Appendix 42](#_Toc87244579)

# **Abstract**

As the digital era dawned, songs, a combination of music and lyric, were widely accessible and gradually became a part of an individual’s daily life. Songs have changed alongside society over the decades. To discover the evolution of songs as well as understand a songwriter’s state of mind, lyrics were an ideal aspect to employ as they tend to communicate their state of being. Thus, the study examines the evolution of bilingual lyrics through sentiment analysis and text classification, as well as comprehends the shift in cultural and societal values by correlating the words used with the events in the specific decade. The aforementioned approaches were built on a total of 200 popular songs, with 100 songs each for English and Chinese, covering the years between 1970 to 2020. Due to a lack of resources in handling Chinese characters, Chinese lyrics were translated to English prior to modeling. Therefore, Support Vector Machine (SVM) and Naïve Bayes (NB) were built based on the translated lyrics. It was concluded that the SVM model outperformed the NB model in classifying song lyrics for both English and Chinese, with an overall accuracy of 60% and 56% respectively. Other evaluation metrics such as precision, recall, and F1-score were used to validate the model as the data employed was perceived to be imbalanced based on sentiment analysis findings, with the majority classified as having positive sentiment. Furthermore, as lyrics were composed under the influence of cultural, social, and emotional impact, and different songwriters express themselves differently, there are likely to be variations in the words used over decades. However, it is observable that there was a shift in the set of significant words used in English lyrics but not in Chinese. In addition, the words used in English lyrics produce positive sentiment which was aligned to the sentiment analysis findings but contrasted for Chinese lyrics. Hence, it is concluded that machine learning is not optimal in evoking the same sentiment as listeners and language is subjective for analysis.

# **Chapter 1 Introduction**

Music first originated back in the Paleolithic period, with purely instrumental sounds. It is known for its significant therapeutic effects that can reduce anxiety, promote relaxation, and improve an individual’s quality of life (Music Magic, 2008). As a result, it is regarded as an essential component in our daily life, whether for music production, performance, enjoyment, or emotional response (Galindo, 2003).

As time progressed, lyrics, also known as the text in the song, were written to complement the music. According to Winston (2017), lyrics was composed in such a way that it reflects the surrounding and communicate with listeners by introducing context to the song, enabling them to view and connect things from their perspective. However, what was communicated differs from songwriters as they express themselves differently. Thus, songs were regarded as an effective medium for non-verbal communication.

In order to comprehend the songwriter’s thoughts, text mining approach is employed. It is a technique to obtain relevant and valuable information from the text after it has been processed. Lyrics, in particular, were used to provide sentiment insights and comprehend the shift of cultural and social values.

Therefore, this study will look into various approaches to analyze textual data and aim to apply and evaluate the sentiment of popular English and Chinese song lyrics that were composed between 1970 to 2020. Furthermore, it also aims to investigate the relationship between cultural and societal values with the evolution of bilingual lyrics over time.

# **Chapter 2 Literature Review**

As songs and society are intimately connected (Music Magic, 2008), Winston (2017) mentioned that songwriters aim to produce songs based on their personal experiences. It is thus fair to assume that lyrics are composed in such a way that it gives context to a specific era.

According to Huang (2015), songs impact society in three ways: social, cultural, and emotional, which are described as follows:

**Social Impact**

Social impact refers to how songs connect and bring individuals together, such as live and street performances, concerts, festivals, which illustrate how individuals with similar interests are brought together to develop social and support networks. As a result, a community of like-minded people is formed. Furthermore, in the internet era, the internet eases the accessibility for global fans to convey their love for their musical idol easily and garner respect greater than any other differences of beliefs they have (Ford, 2020). According to Silva (2013), having the right combination of lyrics, rhythm, and instruments aided in establishing a collective identity, arousing emotions, and engaging audiences.

Hoeven and Hitters (2019) validated the factors of social and cultural impacts by performing qualitative content analysis on musical reports to analyze the cultural and societal values. They utilized ATLAS.ti software to uncover similar themes across reports, a program that does qualitative analysis on massive volumes of textual data and identifies relevant terms related to the theme. As a result, it revealed that social values are associated with social identity, public engagement, and social capital whereas musical creativity, cultural vitality, and talent development are associated with cultural values.

**Cultural Impact**

Cultural impact dictates how songs were composed in the music industry, where they reflect the culture of a particular period. The Chainsmokers’ song, “#SELFIE”, is a very spot-on example that reflected the youth and media culture in 2015.

Songs were an effective medium for non-verbal communication and can also be used as a tool to learn different languages. They are perceived as an important element in shaping cultural identity for their entertaining and captivating music and lyrics (Huang, 2015). Interestingly, despite the fact that there are few approaches for analyzing multilingual data, Yan, He, Shen, and Tang (2014) made an exception and explored models such as SVM and N-grams using English and Chinese data to determine the optimal model for text classification. Furthermore, Yan et al. (2014) addressed several significant pointers about the Chinese language, where there are several approaches to perform word segmentation and Chinese has a distinct way of conveying emotions. As a result, using English methodologies in Chinese may be inappropriate. Thus, they employed IKAnalyzer, a widely used open-source tool built on Java programming language, to analyze the Chinese language with the advantage of being efficient. The study concluded that SVM outperforms N-gram, with the Chinese model achieving an accuracy rate of 85% in classifying the data, but a slightly lower accuracy than that of the English model.

**Emotional Impact**

Emotional impact defines as the mood delivered through songs. They are known to have a direct impact on individuals in society, as reflected by how listeners feel when they listen to them. Songs are played depending on the settings. For instance, an upbeat playlist would be played during a workout, while a classical playlist would be played when calming down. Similarly, when presented in the same context, songs composed in the past differ from the present.

In addition, song lyrics represent the emotions of the songwriter. Hu, Downie, and Ehmann (2009) explored the approach of identifying the mood of lyrics by employing Music Information Retrieval (MIR) tasks and classifying them with SVM models. They collected lyrics from an online database and social tags from last.fm. After assessing the accuracy of several models, Bag-of-Words (BOW) with stemming and TF-IDF, which uses a float value-weighted vector to identify the significance of words, obtained a higher average accuracy of 0.6043. Thus, this model was used to analyze the performance of combined features. Although the performance of combined features does increase the accuracy, the study noted that purely lyrics can outperform audio if they are categorized under the appropriate mood.

Furthermore, understanding the mood of lyrics aid in predicting the emotions listeners will experience. Napier and Shamir (2018) demonstrated this understanding by collating popular songs with lyrics that were ranked by the Billboard Hot 100 from 1951 to 2016. They utilized IBM Watson Tone Analyzer (IBM WTA) to evaluate the lyrics, which employs linguistic analysis to identify emotions and musical sentiments in written text (1IBM, 2020). Additionally, Pearson correlation and linear regression tests were performed to identify the relationships between the year of composition and the tone of lyrics. It was discovered that songs associated with negative emotions like fear and despair rose with time while songs associated with joy and confidence declined. The study concluded that words used in lyrics reveal information about a songwriter’s tone and state of mind, and the impact on the mood and atmosphere.

To conclude, these papers suggest that there are several ways to evaluate lyrics. Furthermore, as society evolves, the influence on these impacts will alter to fit the society. The following research will investigate the sentiment and comprehend the shift in cultural and societal values in English and Chinese lyrics over five decades.

# **Chapter 3 Data Understanding and Preparation**

## **3.1 Data Understanding**

In this study, the lyrics of popular English and Chinese songs were used to analyze the sentiments, employ text classification, as well as comprehend the shift of cultural and societal values between decades. To begin, assumptions were developed during the data collection process. As a result, an informative list of popular songs from 1970 to 2020 was manually compiled from the internet, assuming that songs became popular after being released. In particular, English and Chinese lyrics were collected from <https://www.azlyrics.com/> and <https://baike.baidu.com/> respectively.

Before diving into data understanding, it is critical to understand the distinction between English and Chinese sentence structure. East Asian Student (2011) defined the differences as follows:

1. English sentences include whitespace between words whereas Chinese does not.
2. English is a subject-prominent language. The subject, also known as the doer of the action, would be placed first in the sentence and followed by the context. However, Chinese is a topic-prominent language. The topic, also known as the context, would be mentioned first in the sentence.

Table 1 illustrates an example of how English and Chinese sentence structure differ.

Table 1 – Example of English and Chinese sentence structure

|  |  |
| --- | --- |
| ‘I’ is the subject while ‘homework’ is the topic. | |
| English | **Chinese** |
| i.e., I have already done my homework | i.e., 作业我已经做完了  (Homework I have already done) |

Therefore, analyzing textual data in English and Chinese requires a different approach. Due to a lack of resources to analyze Chinese language, Chinese lyrics would be translated into English using the ‘googletrans’ module which leveraged on Google Translate API (PyPI, 2020) at 85% accuracy (The Language Doctors, 2021). In a song, lyrics are not the only element expressing sentiments, where music, which consists of rhythms, beats, and tempo, is also influential in contextualizing the sentiments of the song. However, as Chinese lyrics were translated automatically without taking music into account (Zivkovic, 2021), it is less precise in conveying the same meaning as the original lyrics.

Figure 1 illustrates the information of the dataset. A total of 200 records were obtained, with English and Chinese having 100 records each as illustrated in Figure 2.

Text

Description automatically generated

Figure 1 – Information of the dataset

Table

Description automatically generated

Figure 2 – Number of records for each language

In the following section, the data were grouped into five decades: 1970 – 1980, 1980 – 1990, 1990 – 2000, 2000 – 2010, 2010 – 2020.

Figures 3 and 4 illustrate the sample data for English and Chinese songs, respectively.

Graphical user interface, text, application, email

Description automatically generated

Figure 3 – Sample data for English songs

Graphical user interface, text

Description automatically generated

Figure 4 – Sample data for Chinese songs

The column, ‘ibm\_nlu\_lyrics\_sentiment’, represents the sentiment of the lyrics that was derived from IBM Watson Natural Language Understanding (IBM WNLU), a program that analyzes and extracts information such as sentiment, emotion, and keywords from text (2IBM, n.d.). Following that, the column, ‘translated\_lyrics’, consists of the translated lyrics that were performed prior to data preparation.

Figure 5 shows the color legend that was used to differentiate between English and Chinese songs in subsequent visualizations.

A picture containing text

Description automatically generated

Figure 5 – Color legend visualization

Figures 6 and 7 display the count of songs that were released each year.

Chart, bubble chart

Description automatically generated

Figure 6 – Number of English songs in each year

Chart, bubble chart

Description automatically generated

Figure 7 – Number of Chinese songs in each year

Both the size and color represent the number of songs that were popular each year. For example, the larger and darker the circle is, it represents that more songs released in that year became popular. Figure 6 depicts that there are more popular English songs, with six tracks released in 1983, followed by five tracks each in 1980, 2011, and 2012, while Figure 7 depicts that there are more popular Chinese songs, with eight tracks released in 1979, followed by six tracks in 2000 and five tracks each in 1993 and 2011.

Garrido (2011) studied how negative emotions in songs were interpreted as sorrowful. Hence, assumptions were made in this study where aggressive and mournful were regarded as negative sentiments, and pleasant, love and romance were perceived as positive sentiments.

Figure 8 illustrates the total sentiment count.

Chart

Description automatically generated with medium confidence

Figure 8 – Total count of sentiment

It is possible to conclude that Chinese and American songwriters were in a similar state, resulting in a comparable count of positive and negative sentiments.

Figure 9 illustrates a breakdown of sentiment counts.

A picture containing diagram

Description automatically generated

Figure 9 – Breakdown of Sentiment Count into five decades

With the exception of the 1990 decade, a significant difference in the number of sentiment counts could be observed in Chinese lyrics, where sentiments in other decades were comparable between English and Chinese. Furthermore, it was discovered that in the 1990s, Chinese lyrics had a more negative sentiment than English lyrics, which might be attributed to songwriters reminiscing the happenings of Tiananmen Square in the 1980s, when individuals were denied liberty.

Figure 10 illustrates the total number of YouTube views in each decade.

Chart

Description automatically generated

Figure 10 – Breakdown of the total number of views

It revealed that there was a substantial disparity in the total number of views for both English and Chinese songs across the decades. With English songs reaching over billions of views while Chinese songs reached merely millions. This implied that listeners preferred English songs over Chinese songs since English is a universally recognized language with stronger rhythms.

Furthermore, as observed, there were relatively high views in the 2010s, which could be attributed to the advancement of recording technology that happened in the twentieth century, where songs were accessible 24/7 with a click on YouTube or Spotify (Music Magic, 2008). Although the number of views may be used to evaluate a song’s popularity, it contradicts the purpose as the internet was not popular until the 2000s, and they were uploaded as technology advanced. As a result, the variable ‘no. of views’ is an unreliable indicator for assessing the popularity of songs from prior decades, thus will be eliminated.

## **3.2 Data Quality**

There were no concerns regarding data quality as the data were collected manually. However, text pre-processing was necessary to clean and analyze the data so that sentiment analysis and text classification can be performed effectively, as well as to comprehend the shift in cultural and social values over the decades.

## **3.3 Data Preparation**

The following section outlines the steps to pre-process the lyrics, by utilizing natural language toolkit (nltk) library and speller module.

Figure 11 illustrates the pre-processing stages.

Diagram

Description automatically generated

Figure 11 – Text pre-processing stages

Firstly, spelling normalization was performed by employing the speller module to transform misspelled or incomplete words to their correct spelling. For instance, the words ‘shakin’ and ‘stayin’ were corrected to ‘shaking’ and ‘staying’ respectively. In addition, a contraction dictionary was established to expand contraction words such as ‘you’ll’ to ‘you will’.

Secondly, tokenization, part-of-speech (POS) tagging and lemmatization were performed. Tokenization is the process of breaking down sentences into individual words, while POS tagging labels words with their appropriate word classes, such as a noun or a verb. Lemmatization, on the other hand, is the process of transforming words to their base form, such as ‘kicked’ to ‘kick’.

Finally, a list of common stop words was used to filter and retain words of substantial significance. The process was iterated several times, with each iteration incorporating more inconsequential words such as ‘la’, ‘em’, ‘uh’ etc.

Figures 12 and 13 illustrate the document-term and term frequency-inverse document frequency (TF-IDF) matrices respectively.

A picture containing diagram

Description automatically generated

Figure 12 – Document-term matrix

Table

Description automatically generated

Figure 13 – Term Frequency – Inverse Document Frequency

Both matrices are statistical techniques to identify the significance of a word in a document, with the former scoring words using integer count and the latter using a float-value weighted vector.

Document-term, also known as term frequency, ranks terms based on the number of occurrences in each document. This matrix will thus be used to calculate the TF-IDF.

TF-IDF, on the other hand, was calculated by multiplying term frequency and inverse document frequency, with the former representing the document-term matrix while the latter representing the scoring of the uncommon terms across documents. The final TF-IDF results will therefore define the term’s value, with a greater weight indicating that the term is significant (Góralewicz, n.d.).

# **Chapter 4 Modelling and Evaluation**

## **4.1 Sentiment Analysis**

Sentiment analysis is a technique for interpreting emotions through text by scoring the words which reflect the underlying sentiments. To compute sentiment polarity, this study used the VADER algorithm, a lexical approach, known to better perform with slang language, and achieved a high accuracy rate of 56% when compared to other sentiment algorithms (Es, 2021). The algorithm returns four values: positive, neutral, negative, and compound, with the former three being sentiment probability, which sums up to 1, and the latter returning the normalized compound score, ranging from -1 to 1 (Pipis, 2020).

Figures 14 and 15 illustrate the sample data for English and Chinese songs after performing sentiment analysis.

A picture containing application

Description automatically generated

Figure 14 – Sample data for English songs after sentiment analysis

Text

Description automatically generated

Figure 15 – Sample data for Chinese songs after sentiment analysis

The compound score was employed as a metric to analyze the sentiment of the lyrics. Following that, these scores were categorized into three categories: with scores less than 0 were labeled as ‘-1’ or ‘Negative’, scores greater than 0 were labeled as ‘1’ or ‘Positive’, and scores equal to 0 were labeled as ‘0’ or ‘Neutral’.

Figure 16 illustrates the overall sentiment count after sentiment analysis.

Chart, bar chart

Description automatically generated

Figure 16 – Overall count of sentiment after sentiment analysis

Overall, it was evident that the sentiment analysis findings contradicted the actual label count. It is possible to assume that majority of the words used in each lyric were positive, yielding a positive compound score when being aggregated, resulting in the majority of both English and Chinese lyrics conveying a positive sentiment.

Figure 17 shows the breakdown of sentiment counts in each decade.

Diagram

Description automatically generated

Figure 17 – Breakdown of sentiment count after sentiment analysis into five decade

The breakdown of sentiment count was comparable between languages in each decade, with the exception of English lyrics in the 1990s and the 2000s which illustrate a slight difference over the decades. In the 1990s, songwriters incorporated more positive words in their lyrics, with 19 songs identified as positive sentiment and only one labeled as negative sentiment. Whereas in the 2000s, songwriters incorporated more negative words, with 11 songs classified as positive and the remaining nine as negative sentiment.

However, based on the disparity between actual sentiment and sentiment analysis findings, it can be argued that machine learning cannot elicit emotions but is able to offer a gauge of the underlying sentiment of the text, although sentiment remains subjective in general.

## **4.2 Text Classification**

SVM and NB models were built to evaluate and identify the optimal classifier model for each language based on the frequency of words. SVM is a supervised machine learning technique that gathers data points and returns a hyperplane, also known as the decision boundary, that best differentiates the target for binary classification problems. Furthermore, SVM performs well with limited data (1Stecanella, 2017). NB, on the other hand, is a family of probabilistic algorithms that anticipate the target of a text using probability theory and Bayes’ Theorem. The algorithm analyzes each text and returns the tag with the highest likelihood. Moreover, despite its simplicity, NB works well and is reliable (2Stecanella, 2017).

As the dataset is limited, the above models were constructed using k-fold Cross-Validation (CV) rather than train-test split. The former approach randomly divides the data into “k” folds, with one of the folds being used as the testing data and was repeated ‘k” times. Train-test split, as opposed to k-fold CV, splits the dataset into “train” and “test” sets to construct the model. In this study, the models were built using 7-fold CV for maximum accuracy.

Figure 18 illustrates the process of a 7-fold CV.

Table

Description automatically generated

Figure 18 – 7-fold Cross-Validation process

Table 2 shows the overall accuracy of different models built for English and Chinese lyrics.

Table 2 – Accuracy of different built models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **ACCURACY** | | | | | |
|  | **MNB**  **(Multinomial Naïve Bayes)** | **SVM1**  **(Radial Basis Function)** | **SVM2**  **(Polynomial)** | **SVM3**  **(Sigmoid)** | **SVM4**  **(Linear)** |
| **ENGLISH** | 59% | 55% | 55% | 60% | 63% |
| **CHINESE** | 57% | 56% | 54% | 56% | 59% |

The term “accuracy” refers to the average performance score of the trained models in classifying lyrics their actual sentiment. In general, the overall accuracy for both English and Chinese built models yield comparable results of approximately 50% to 65%.

When comparing the various English models, Multinomial NB (MNB), SVM3, and SVM4 achieve higher accuracy of 59%, 60%, and 63% respectively. Whereas for Chinese models, MNB, SVM1, SMV3, and SVM4 yield higher accuracy of 57%, 56%, 56%, and 59% respectively. This suggested that among other built models, the aforementioned models were decent for deployment.

However, the achieved accuracies indicate that the models attained average performance and were considered relatively low. This might be attributed to the uncertainty of translation, thus affecting the accuracy of the result. Furthermore, as the dataset is imbalanced based on the sentiment analysis findings in Figure 16, accuracy may not be a reliable measure to evaluate the model. Hence, additional measures such as precision, recall, and F1-score were used to evaluate the selected models in order to identify the optimal model for each language.

Precision determines the ratio of the correctly predicted labels to the total predicted labels, while recall determines the ratio of the correctly predicted labels to their actual label. F1-score, on the other hand, is obtained by computing the average of precision and recall (Exsilio Solutions, 2016).

Logistic regression (LR) is a simple yet efficient approach for classification, it is thus appropriate to be used as the baseline model, setting a benchmark to evaluate the selected models for both English and Chinese lyrics.

Table 3 shows the precision, recall, and F1-score of the Top 3 English built models and the baseline model.

Table 3 – Evaluation measures of English Top 3 models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **ENGLISH** | | | | |
|  | **LR**  **(Logistic Regression)** | **MNB** | **SVM3 (Sigmoid)** | **SVM4**  **(Linear)** |
| **Precision** | 63% | 62% | 59% | 65% |
| **Recall** | 80% | 66% | 96% | 76% |
| **F1-score** | 69% | 63% | 73% | 69% |

In terms of precision, SVM4 was the only model that outperformed the baseline model in classifying lyrics to its label at 65% and 63%, respectively. However, in terms of recall, SVM3 outperformed the baseline model at 96%, indicating that the model was capable of predicting its actual sentiment almost accurately, whereas MNB and SVM4 performed less optimal at 66% and 76%, respectively. Furthermore, when F1-scores of the models were examined, SVM3 produced better results of 73%. As a result, despite having a slightly lower precision than the baseline model, SVM3 was regarded as the best model for its high recall of 96% and F1-score of 73%.

Table 4 shows the precision, recall, and F1-score of the Top 4 Chinese built models and the baseline model.

Table 4 – Evaluation measures of Chinese Top 4 models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **CHINESE** | | | | | |
|  | **LR (Logistic Regression)** | **MNB** | **SVM1**  **(Radial Basis Function)** | **SVM3**  **(Sigmoid)** | **SVM4**  **(Linear)** |
| **Precision** | 56% | 59% | 57% | 56% | 60% |
| **Recall** | 65% | 53% | 70% | 76% | 61% |
| **F1-score** | 59% | 55% | 63% | 64% | 59% |

The selected models except SVM3 outperformed the baseline model in categorizing lyrics to their label, by a slightly higher precision. In terms of recall, SVM1 and SVM3 marginally surpassed the baseline model at 70% and 76% respectively. Furthermore, when the F1-scores of the models were examined, SVM1 and SVM3 outperformed the baseline model and yield comparable results of 63% and 64% respectively. Although SVM1 performed slightly better for all three metrics than the baseline model, SVM3 was regarded as the best model for its high recall and F1-score despite achieving a similar precision to the baseline model.

Overall, given its high recall, the SVM3 model was regarded as the optimal model for classifying both English and Chinese lyrics to their actual sentiment accurately.

# **Chapter 5 Discussion**

## **5.1 Lyrical timeline (ENG)**

Figure 22 illustrates the Top 20 ten most representative lyrical keywords that were extracted from the English lyrics in each decade.

Timeline

Description automatically generated

Figure 22 – English lyrical timeline

Based on the findings, Americans appeared to be more individualistic, having their own opinions (“101 Characteristics of Americans/American Culture”, n.d.), as well as being upfront in expressing their views (Kelly, 2020).

**1970 – 1980**

The 1970s was regarded as a continuation of the 1960s in several aspects, including political and military conflicts that created a tumultuous decade (1Editors, 2010). With the ongoing war in Vietnam, many Americans participated in the violent protest to halt the war, risking their lives in the process. Terms such as ‘life’, ‘alive’, ‘kill’, ‘help’, ‘leave’, ‘die’ and ‘shadow’ indicated the life state in the 1970s and how songwriters utilized songs to encourage and motivate people to persevere in the face of adversity.

Whereas the terms ‘vain’ and ‘light’ suggested that Americans were entering a new phase of life following the end of the Vietnam war in 1975. In the technological aspect, the beginning of the third industrial revolution brought about the introduction of transistors and integrated circuits in the 1960s, which aided in the rise of television and the establishment of Microsoft and Apple Computer Company (The People History, n.d.).

Music had also grown in popularity from the proliferation of Discothèques (Discos) around the world, having soul music as the primary genre with a powerful bass and drum rhythm that motivate audiences to move to the groove (1RetroWaste, n.d.).

**1980 – 1990**

The 1980s was considered a watershed decade in American history, where significant transformations took place, such as the adoption of new socially, economically, and politically conservatism, as embodied in President Ronald Reagan’s policies (2Editors, 2018). For instance, the Reagan Administration intensified the War on Drugs, which was promoted through anti-drug campaigns, as drugs were a major concern in the 1980s, leading to high crime rates (3Editors, 2017). The terms ‘life’ and ‘bite’ could be crucial in such a situation where the lives of Americans were at stake, hence the administration addressed it cautiously.

Furthermore, the emergence of dance music together with the new wave in the 1980s led to a decline in the popularity of discos. The introduction of Music Television (MTV) transformed the recording industry significantly in the 1980s (ushistory, n.d.), which cause a surge in the popularity of dance-pop and rock genres (Davis, 2021). Several legendary artists, such as Michael Jackson and Prince, became iconic with their hit songs, ‘Beat It’ and ‘When Doves Cry’. These hit songs were associated with the terms ‘beat’, ‘cry’, ‘dove’, and ‘cold’ which were composed based on their personal experiences and integrated with rock music. As such, as the songs were repeatedly broadcasted on MTV, listeners were able to connect to them if they had similar experiences. While the terms ‘time’, ‘angel’, ‘heart’, and ‘play’ rose from the rise of MTV, which aided in the transition from a tumultuous decade in the 1970s to a period where individuals started to imitate their idol’s fashion sense in music videos (2Editors, 2018).

**1990 – 2000**

The 1990s was viewed as a comparatively peaceful and affluent decade with the collapse of the Soviet Union, the end of the decades-long Cold War, and the development of the internet. The advent of the internet resulted in a revolution in communication, businesses, and entertainment (“1990s”, n.d.). The quality of life of an American had thus improved significantly and developed with the popular culture, also known as ‘pop culture’. Video games, the Harry Potter series, Tamagotchi pets, and the film titled ‘Friends’ were some significant characteristics of American pop culture (Emma, 2020), which were indicated by the terms ‘joy’, ‘time’, ‘paradise’, and ’dream’.

When homosexualism peaked in America, they were being discriminated against for being different. The terms such as ‘break’, ‘tear’, and ‘lonely’ suggested that such behaviors were less masculine thus resulting in discrimination (“The 1990s Lifestyle and Social Trends: Overview”, n.d.). However, the terms ‘belong’ and ‘sign’ suggested that homosexuals were being embraced and accepted by a presidential contender in 1992 who significantly contributed to relevant campaigns (Knickerbocker, 1993).

Gangster rap and grunge, a type of hip-hop music and alternative rock genres, respectively, created significant impacts on individuals’ lifestyles in terms of their fashion sense, activity, and music preference (2RetroWaste, n.d.). For instance, in the aspect of fashion, individuals wore a flannel shirt to exhibit that they are constantly up to date with the decade’s fashion that was influenced by grunge music.

**2000 – 2010**

The 2000s was recognized as a digital decade marked by the rapid evolution of the internet, which was heavily depended on for communication. In this aspect, smartphones and text messaging had grown in popularity, introducing new forms of connection that were not feasible in the past. However, technology brought both benefits and drawbacks to individuals’ forms of communication. The formerly brought convenience in exchanging information and connecting people globally, which were associated with the terms ‘big’ and ‘good’. The latter caused social impacts such as cyberbullying and increased the number of road accidents due to distraction of the smartphones while driving, thus associating terms such as ‘leave’, ‘bleeding’, and ‘bad’.

As technology advanced, auto-tune programs were developed to adjust vocal recordings. The dominant music genre shifted from gangster rap in the 1990s to hip-hop in the 2000s, where it incorporated different elements such as rap with electronica, to achieve edgy music (Kasian, 2020) that was suggested by the terms ‘crazy’, ‘shake’, and ’rock’.

The fashion milestone of individuals shifted to ‘low’ cut following the 42nd Grammy event in 2000, where Jennifer Lopez, an American singer, showed up in a low-cut dress. Aside from that, emotional music shaped a subculture, emo parade, which caused the original emotional music to die down (Kasian, 2020), that was associated with the term ‘beat’.

**2010 – 2020**

The 2010s was perceived as a decade of social media due to the advent of a key communication game-changer, which altered the way individuals interact (Marshall, 2020). It is an online platform that stole the opportunity for face-to-face interaction. Furthermore, the increased usage of social media assisted large protest movements such as “Occupy Wall Street” and “Black Lives Matter”, connecting individuals with similar ideologies globally (Pruitt, 2019). The lyrical terms ‘happy’ and ‘deep’ implied that social media is a platform where individuals share snippets of life while fostering relationships. Whereas the terms ‘dagger’, ‘burn’, ‘hopeless’, and ‘bad’ suggested the negative influence of social media that was replaced with online interaction.

As the internet become widely accessible, social media provided a platform for content distributors to share and monetize their material. The terms ‘time’, ‘wish’, ‘perfect’, and ‘dollar’ referred to how individuals or influencers used social media as an ideal platform to monetize their content which was produced with effort and demand.

## **5.2 Lyrical timeline (CHI)**

Figure 23 illustrates the Top 20 ten most representative lyrical keywords that were extracted from Chinese lyrics in each decade.

Table, timeline

Description automatically generated

Figure 23 – Chinese lyrical timeline

In general, the Chinese were conservative, collectivistic, and self-conscious (Hays, 2021). This implied that they are resistant to change; prefer traditional over contemporary, value group over individual, and are concerned with their “mianzi” (face), which is associated with an individual’s dignity, ego, and reputation, that facilitates in establishing “guanxi” (relationships) with others.

**1970 – 1980**

The 1970s was regarded as a gloomy decade that was brought about by the Cultural Revolution (CR) and the principles of communist dictatorship (Burianek, 2009). In 1966, Mao Zedong (Mao), the founding father of the People’s Republic of China (PRC), decided to commence the “revolution”, which marked the beginning of the CR (Phillips, 2016), a social-political movement that aimed to reform China from its old ways to an ideal society. However, the act of CR was to reclaim the power and prestige Mao lost after the failure of the Great Leap Forward (Lieberthal, n.d.), and it lasted a decade until his death in 1976. During the CR, family life was disrupted as Mao saw families as institutions and kept them imprisoned thus giving orders to break down family structure, where deceased were cremated rather than buried, and ancestors’ tablets and ancestral halls were destroyed (Cao & Tom, n.d.). The terms ‘remember’, ‘miss’, ‘goodbye’, ‘forget’, ‘time’, and ‘tear’ denoted how CR had negatively impacted the lives of families, with the majority losing records of their extended families, leading to a shift to three living generations (Cao & Tom, n.d.).

Propaganda art, on the other hand, was used as a communication tool to convey information to mass audiences. Similarly, in terms of music, songwriters composed lyrics in a political manner including patriotism and revolutionary songs designed to represent a legacy. Therefore, the terms ‘dream’, ‘beautiful’, ‘wander’, and ‘breeze’ were used in a deceptive way to portray society in the 1970s.

**1980 – 1990**

The 1980s was viewed as the turning point for the Chinese when Deng Xiaoping (Deng) came to power and liberalized China’s economy after a series of significant political, economic, and cultural reforms (Gao, 2015). Individuals living in this generation were heavily engaged in democratic ideologies, in which rather than opposing the Chinese Communist Party (CCP), they yearn for the society to improve (Huang, 2019), with systems that were beneficial to them (Rosen, 2014). The terms ‘time’, ‘life’, ‘winter’, ‘fire’, ‘wind’, ‘hard’, and ‘hope’ suggested that China had gone through tough times and hoped that in the future, individuals will be given more freedom of speech thus incorporating a vibrant culture.

In the music industry, Taiwanese singers dominated the charts, prompting the music culture to evolve from patriotic songs to love ballads, as well as the internationalization of production (Huang, 2019). As a result, the once-heavily produced propaganda content faded. The terms ‘dream’, ‘sky’, and ‘smile’ signify that the individuals dream to live in a society where they will be able to exercise their privilege, rather than living under propaganda. Thereby, to live an exciting life.

**1990 – 2000**

The 1990s was regarded as a period of economic prosperity, with economic growth and political stability (Li, 2019). It was primarily due to procedures established during Deng’s era, as well as a generational change from peasant revolutionaries to well-educated, professional technocrats. The terms ‘life’, ‘happy’, ‘willing’, ‘leave’, and ‘dream’ signify that as the evolution began in the 1980s, individuals were benefitting from education where the majority with sciences-related degrees aspired to develop and live outside of China.

In the music industry, despite the fact that Chinese rock was still considered popular in the 1990s, songs of this genre were subjected to restrictions in terms of exposure and airtime after the Tiananmen Square incident that happened in 1989. The terms ‘sorrow’, ‘cold’, ‘tear’, ‘regret’, and ‘sadness’ describe how rapid economic changes influenced individuals’ lives, with the majority believed that they were denied opportunities and personal freedom.

**2000 – 2010**

With the effects of globalization and technological growth, the 2000s was regarded as a period of diversified cultures. Individuals were exposed to international cultures through movies, music, and art over the internet (velocityglobal, 2020). As a result, Chinese culture gradually gave way to world culture. Thus, the terms like ‘dragon’, ‘long’, ‘believe’, ‘old’, ‘happy’, and ‘strong’ were used to reintroduce Chinese culture through music. Furthermore, the term ‘dragon’ represents Chinese unwavering and pioneering spirit of keeping up with the times, as well as having a strong connotation of power, strength, and luck, whereas the term ‘old’ denoted how ancient Chinese dressed in Chinese Han costumes to relive the depths of China history (China, n.d.).

In addition, Hu Jintao (Hu), the CCP’s fourth-generation leader, inherited social, political, and economic inequalities left from Jiang’s era. However, Hu was more concerned with equality, focusing on areas of the Chinese populace that have been neglected by economic reform and bridged wealth disparity. Furthermore, they conducted high-profile trips to poor states of China with the aim to better understand each state and assist in the transformation. The terms ‘cry’, ‘tear’, ‘good’, and ‘alone’ were used to describe the emotions of individuals by the actions of the leaders who were philanthropic and concerned with equality for all regions, urban or rural, rather than only metropolitan regions.

**2010 – 2020**

The decade of 2010s was considered as an economic growth decade where China was the primary source of global economic development. As China is an incredibly wealthy and intellectually endowed nation that has always been deeply dedicated to learning and education, the Chinese increasingly engaged in innovative inventions, accounting for over half of all patent filings worldwide (Jacques, 2019). The term ‘dream’ was used to describe the Chinese yearning for the country’s position in terms of progress from the past to the present.

As China advanced, internet restrictions were enforced on foreigners, preventing them from accessing restricted information without the use of a Virtual Private Network (VPN). The government limits information about political opponents, free speech, sex, news, and academic research, which brought a negative impact. Hence, the term ‘afraid’ suggested that if individuals were allowed to access these contents, it would create a negative impact on the government or even the country. In addition, the term ‘crazy’ referred to how individuals used the internet on a daily basis, with an average of 125 minutes per day spent on a single app (Qu, 2021), Douyin (Chinese version of TikTok), which gained popularity in 2016 by allowing individuals to create and share short videos online, often featuring background music, resulting in the implementation of mandatory pauses to tacker viewer’s addiction.

Following the China Wind, the decade of 2010s was seen as a decade of shifting roles in Chinese popular music (Lin, 2020) as well. Songs were composed in a nostalgic emotion whilst reminiscing the past, as evidenced by the terms ‘forget’, ‘rain’, ‘end’, ‘tear’, ‘memory’, ‘pain’, and ‘miss’. For example, Chen Xi’s 2011 workpiece “where did all the time go” (时间都去哪了) was composed as though time had passed in the blink of an eye, with her source of inspiration from her mother’s 60th birthday celebration.

## **5.3 Overview**

As observed from the cultural and societal aspects of each decade, regardless of English or Chinese lyrics, they were composed related to the society which could be politically, economically, or socially influenced. Furthermore, achieved results align with Goehr’s (1994) observation that music was composed for the people by the people and if music loses its sense of community, it loses itself.

# **Chapter 6 Conclusion**

This study evaluates the sentiment of 200 popular bilingual songs using text mining on lyrics. The majority of the songs were tagged to positive sentiment, despite the fact that they have a comparable actual sentiment count for positive and negative, with the combined scores for positive words accumulated to have a higher ratio as compared to negative words.

In addition, several classification algorithms, such as SVM and NB, were examined to identify the optimal classifier model to classify their actual sentiment. Aside from computing the model’s accuracy, performance measures such as recall, precision, and F1-scores were employed as the dataset utilized was imbalanced based on the findings of sentiment analysis. As a result, the study concluded that the SVM model performed better at classifying both English and Chinese lyrics, with Sigmoid kernel, for its high recall of 96% and 76% respectively.

The study also investigates how cultural and societal values had altered through lyrics over the five decades. It was discovered that the words used in English lyrics differ from those used in Chinese. Words in English lyrics changed significantly with time, but not in Chinese. This suggested that Chinese songwriters were more sentimental than American songwriters. Furthermore, the variations in the words used were tied to the evolution of society, in which leaders who governed the country with diverse abilities had varying impacts over decades.

However, it is important to highlight that while machine learning is able to evaluate the sentiment of song lyrics, it does not indicate that listeners will have the same sentiment, considering that machine learning does not induce feelings, but listeners do.

# **Chapter 7 Recommendations**

In this study, there were several recommendations worth considering for further research. First, while Chinese lyrics were translated prior to text pre-processing, the translation may be imperfect as they were translated automatically without taking music into consideration. Hence, there is a need to either source for reliable tools that can handle Chinese characters or get in touch with an expert with a musical background to assist in the translation to achieve more accurate results.

Second, while the study provided some preliminary insights for the validity of the models, further research is required to validate the findings. For instance, the study employed a relatively small dataset, hence, there is a need to evaluate and ratify the findings by employing a larger dataset.

Third, the study employed two methodologies, sentiment analysis and text classification, with the former employing single word features, which might lead to misclassification, and the latter adopting the two most prevalent algorithms, SVM and NB. As there are various alternative approaches for sentiment analysis, such as n-grams, and text classification like K-nearest neighbors (KNN) and random forest, it is feasible to incorporate those features and/or models. Therefore, analyzing alternative text mining algorithms and identifying the most effective approach to analyze multilingual lyrics might be a future research direction to explore.

Finally, additional future work can be included in the study, such as identifying the correlation between the years composed and the tone of lyrics and incorporating audio features to make a robust comparison between the overall musical tone and the tone of lyrics.

# **References**

101 Characteristics of Americans/American Culture. (n.d.). Retrieved October 8, 2021, from <https://www.press.umich.edu/pdf/9780472033041-101AmerCult.pdf>.

1990s (n.d.). Retrieved October 13, 2021, from <https://www.history.com/topics/1990s>.

Burianek, I. E. (2009). China in the 1970s – From Cultural Revolution to Emerging World Economy. Retrieved October 19, 2021, from <https://www.grin.com/document/127244>.

Cao, Y. & Tom, M. (n.d.). The Chinese Family Under Mao. Retrieved October 19, 2021, from <https://chinachange.org/2011/03/17/the-chinese-family-under-mao/>.

China (n.d.). 2000 – 2009. Retrieved October 23, 2021, from <http://www.china.org.cn/archive/chinalifestyle/2009-09/10/content_18503582_12.htm>.

Davis, B. (2021). What was the 80s known for? Retrieved October 12, 2021, from <https://www.mvorganizing.org/what-was-the-80s-known-for/#What_was_life_in_the_80s_like>.

East Asia Student (2011). *Mandarin sentence structure: guidelines*. Retrieved August 29, 2021, from <https://eastasiastudent.net/china/mandarin/sentence-structure/>.

1Editors (2010). The 1970s. Retrieved October 10, 2021, from <https://www.history.com/topics/1970s/1970s-1>.

2Editors (2018). The 1980s. Retrieved October 11, 2021, from <https://www.history.com/topics/1980s/1980s>.

3Editors (2017). Just Say No. Retrieved October 12, 2021, from <https://www.history.com/topics/1980s/just-say-no>.

Emma, C. (2020). American Pop Culture in the 1990s. Retrieved October 13, 2021, from <https://www.throwbacks.com/american-pop-culture-in-the-1990s/>.

Es, S. (2021). Sentiment Analysis in Python: TextBlob vs Vader Sentiment vs Flair cs Building It from Scratch. Retrieved September 8, 2021, from <https://neptune.ai/blog/sentiment-analysis-python-textblob-vs-vader-vs-flair>.

Exsilio Solutions (2016). Accuracy, Precision, Recall & F1 Score: Interpretation of Performance Measures. Retrieved September 15, 2021, from <https://blog.exsilio.com/all/accuracy-precision-recall-f1-score-interpretation-of-performance-measures/>.

Ford, C. (2020). 10 ways music is intrinsically linked to our cultural identity. Retrieved October 5, 2021, from <https://www.contiki.com/six-two/10-ways-music-helps-cultural-identity/>.

Galindo, G. (2003). The Importance of Music in Our Society. Retrieved August 4, 2021, from <https://www.gilbertgalindo.com/importanceofmusic>.

Gao, G. (2015). In China, 1980 marked a generational turning point. Retrieved October 21, 2021, from <https://www.pewresearch.org/fact-tank/2015/11/12/in-china-1980-marked-a-generational-turning-point/>.

Garrido, S. (2011). Negative Emotion in Music: What is the Attraction? A Qualitative Study. Empirical Musicology Review 6(4), 214 – 230. DOI: doi.org/10.18061/1811/52950.

Goehr, L. (1994). Political Music and the Politics of Music. The Journal of Aesthetics and Art Criticism, 52(1), 99–112. DOI: doi.org/10.2307/431589.

Góralewicz, B. (n.d). The TF\*IDF Algorithm Explained. Retrieved August 31, 2021, from <https://www.onely.com/blog/what-is-tf-idf/>.

Hays, J. (2021). Chinese Personality Traits: Indirectness, Pragmatism, Competition, and Face. Retrieved October 8, 2021, from <https://factsanddetails.com/china/cat4/sub18/item116.html#chapter-6>.

Hu, X., Downie, J. S., & Ehmann, A. F. (2009). Lyric Text Mining in Music Mood Classification. Proceedings of the International Society for Music Information Retrieval Conference, 411 – 416.

Huang, B. (2015). What Kind of Impact Does Our Music Really Make on Society. Retrieved October 5, 2021, from <https://blog.sonicbids.com/what-kind-of-impact-does-our-music-really-make-on-society>.

Huang, F. (2019). China in the 1980s, when people felt free to speak their minds. Retrieved October 21, 2021, from <https://www.goldthread2.com/culture/china-1980s-censorship/article/3021028>.

1IBM (2020). About. Retrieved August 14, 2021, from <https://cloud.ibm.com/docs/tone-analyzer?topic=tone-analyzer-about>.

2IBM (n.d.). Watson Natural Language Understanding – Overview. Retrieved September 27, 2021, from <https://www.ibm.com/sg-en/cloud/watson-natural-language-understanding>.

Jacques, M. (2019). This decade belonged to China. So will the next one. Retrieved October 25, 2021, from <https://www.theguardian.com/commentisfree/2019/dec/31/decade-china-west-china-ascent>.

Kasian, M. (2020). There Were The Biggest Cultural Trends of the 2000s. Retrieved October 14, 2021, from <https://www.ask.com/culture/biggest-cultural-trends-2000s>.

Kelly, M. (2020). American Culture & Lifestyle Today: Values & Characteristics. Retrieved October 9, 2021, from <https://study.com/academy/lesson/american-culture-lifestyle-today-values-characteristics.html>.

Knickerbocker, B. (1993). Gay Rights May Be Social Issue of 1990s. Retrieved October 13, 2021, from <https://www.csmonitor.com/1993/0211/11011.html>.

Li, Z. (2019). Music, Profanity, and Subcultural Politics in 1990s China. Retrieved October 22, 2021, from <http://etheses.lse.ac.uk/4039/1/Li__Cut-out-music-profanity-China.pdf>.

Lieberthal, K. G. (n.d.). Cultural Revolution. Retrieved October 19, 2021, from <https://www.britannica.com/event/Cultural-Revolution/Rise-and-fall-of-Lin-Biao-1969-71>.

Lin, C.Y. (2020). Relocating the Functions of Chineseness in Chinese Popular Music after the China Wind. *China Perspectives*, 2020(2), 7-14. DOI: doi.org/10.4000/chinaperspectives.10068.

Marshall, E. (2020). Social media decade: shaping the 2010s in our memories. Retrieved October 14, 2021, from <https://www.evanstonian.net/feature/2020/01/31/social-media-decade-shaping-the-2010s-in-our-memories/>.

Music Magic (2008). The Powerful Role of Music in society. Retrieved August 4, 2021, from <https://musicmagic.wordpress.com/2008/07/10/music-in-society/>.

Napier, K. & Shamir, L. (2018). Quantitative Sentiment Analysis of Lyrics in Popular Music. Journal of Popular in Music Studies, 30(4), 161-176. DOI: doi.org/10.1525/jpms.2018.300411.

Phillips, T. (2016). The Cultural Revolution: all you need to know about China’s political convulsion. Retrieved October 19, 2021, from <https://www.theguardian.com/world/2016/may/11/the-cultural-revolution-50-years-on-all-you-need-to-know-about-chinas-political-convulsion>.

Pipis, G. (2020). How To Run Sentiment Analysis In Python Using VADER. Retrieved September 30, 2021, from <https://predictivehacks.com/how-to-run-sentiment-analysis-in-python-using-vader/>.

Pruitt, S. (2019). 14 Major Events of the 2010s. Retrieved October 15, 2021, from <https://www.history.com/news/2010s-decade-major-events>.

PyPI (2020). Googletrans 3.0.0. Retrieved September 27, 2021, from <https://pypi.org/project/googletrans/>.

Qu, T. (2021). TikTok’s China sibling Douyin launches mandatory five-second pauses in video feed to curb user addiction. Retrieved October 25, 2021, from <https://www.scmp.com/tech/policy/article/3153292/tiktoks-china-sibling-douyin-launches-mandatory-five-second-pauses>.

1RetroWaste (n.d.). 1970s Music: History, Pictures & Artists. Retrieved October 11, 2021, from <https://www.retrowaste.com/1970s/music-in-the-1970s/>.

2RetroWaste (n.d.). The 1990s: American Pop Culture History. Retrieved October 13, 2021, from <https://www.retrowaste.com/1990s/>.

Rosen, S. (2014). China’s Post-1980s Generation, Between the Nation and the World. Retrieved October 21, 2021, from <https://www.worldpoliticsreview.com/articles/13924/china-s-post-1980s-generation-between-the-nation-and-the-world>.

Silva, D. D. (2013). Music can change the world. Retrieved October 5, 2021, from <https://www.un.org/africarenewal/magazine/december-2013/music-can-change-world>.

1Stecanella, B. (2017). Support Vector Machines (SVM) Algorithm Explained. Retrieved October 7, 2021, from <https://monkeylearn.com/blog/introduction-to-support-vector-machines-svm/>.

2Stecanella, B. (2017). A practical explanation of a Naïve Bayes classifier. Retrieved October 7, 2021, from <https://monkeylearn.com/blog/practical-explanation-naive-bayes-classifier/>.

The 1990s Lifestyle and Social Trends: Overview. Retrieved October 13, 2021, from <https://www.encyclopedia.com/social-sciences/culture-magazines/1990s-lifestyles-and-social-trends-overview>.

The Language Doctors (2021). How Accurate is Google Translate | Updated Review 2021. Retrieved October 16, 2021, from <https://thelanguagedoctors.org/how-accurate-is-google-translate/>.

The People History (n.d.). 1970s Important News and Events, Key Technology Fashion and Popular Culture. Retrieved October 11, 2021, from <https://www.thepeoplehistory.com/1970s.html>.

Ushistory (n.d.). Life in the 1980s. Retrieved October 12, 2021, from <https://www.ushistory.org/us/59d.asp>.

Van der Hoeven, A., & Hitters, E. (2019). The social and cultural values of live music: Sustaining urban live music ecologies. *Cities,* 90, 263 – 271. DOI: doi.org/10.1016/j.cities.2019.02.015.

Velocityglobal (2020). Globalization Benefits and Challenges. Retrieved October 23, 2021, from <https://velocityglobal.com/blog/globalization-benefits-and-challenges/#section-2>.

Winston, C. (2017). Why Do Lyrics Matter? Retrieved August 4, 2021, from <https://www.nrgrecording.com/post/why-do-lyrics-matter>.

Yan, G., He, W., Shen, J., & Tang, C. (2014). A bilingual approach for conducting Chinese and English social media sentiment analysis. Computer Networks, 75, 491-503 DOI: doi.org/10.1016/j.comnet.2014.08.021.

Zivkovic, L. (2021). Translate Lyrics – Complicated Even For Simple Pop Songs. Retrieved October 17, 2021, from <https://bunnystudio.com/blog/translate-lyrics-complicated-even-for-simple-pop-songs/>.

# **Appendix**

Table 5 – Variable description

|  |  |  |
| --- | --- | --- |
| S/N | Variable | Description |
| 1 | year | The year when the song is released. |
| 2 | song title | The title of the song. |
| 3 | song artist | The singer of the song. |
| 4 | language | The language of the song. |
| 5 | genre | The genre of the song. |
| 6 | no. of views | The number of views on YouTube for each song. |
| 7 | lyrics | The lyrics of the song. |
| 8 | ibm\_nlu\_lyrics\_sentiment | The sentiment of the lyrics by IBM NLU. |
| 9 | translated\_lyrics | The translated lyrics for Chinese songs. |

Text

Description automatically generated

Figure 24 – Word Cloud for English Popular songs from 1970 to 1980

A close-up of a dollar sign

Description automatically generated with low confidence

Figure 25 – Word Cloud for English Popular songs from 1980 to 1990

Text

Description automatically generated with medium confidence

Figure 26 – Word Cloud for English Popular songs from 1990 to 2000

A close-up of a dollar bill

Description automatically generated with low confidence

Figure 27 – Word Cloud for English Popular songs from 2000 to 2010

A picture containing text, bottle

Description automatically generated

Figure 28 – Word Cloud for English Popular songs from 2010 to 2020

Logo

Description automatically generated

Figure 29 – Word Cloud for Chinese Popular songs from 1970 to 1980

Logo

Description automatically generated

Figure 30 – Word Cloud for Chinese Popular songs from 1980 to 1990

A picture containing logo

Description automatically generated

Figure 31 – Word Cloud for Chinese Popular songs from 1990 to 2000

Text

Description automatically generated with medium confidence

Figure 32 – Word Cloud for Chinese Popular songs from 2000 to 2010

Logo

Description automatically generated with medium confidence

Figure 33 – Word Cloud for Chinese Popular songs from 2010 to 2020