Faculty of Computer Science and Information Technology

DATA ANALYSIS IN TRENDING YOUTUBE VIDEOS FOR CATEGORY PEOPLE AND BLOG

TUNKU KHAIRI BIN TUNKU HANIZD

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This project is submitted in partial fulfilment of the requirements for the Degree of Bachelor of Computer Science and Information Technology with Honors.

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First and foremost, I would like to praise to Allah S.W.T, for providing good health to complete the final year project. I pray that every day I will be blessed by Allah S.W.T the ease of my tasks and always on good health.

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CHAPTER 1: INTRODUCTION

1.1 Background

YouTube was founded by Chad Hurley, Steve Chen and Jawed Karim in 2005. YouTube originally was created as a platform to post videos of ones' desire so people can publicly watch from any part of the world. Over the time, YouTube become dominant as one of the largest free video sharing websites that hosts over billions of views per day. Because of huge traffic ongoing every day, YouTube enables to invent their new special program which is called "YouTube 's Partner Program". Alongside Google's AdSense from its parent company, which is Google, YouTube has provided a career opportunity for content creators called "YouTube content creators". The content creators earn their living from ads revenue, sponsors, or paid reviews included in their uploaded videos.

YouTube as a medium of expression provides public statistics for each of uploaded videos which are upload date, number of views, number of likes and dislikes. YouTube also provides comment section for sentimental engagement of the videos. YouTube determines the high engagement videos called "*trending videos"* by indicating the level of popularity of the videos based on high number of views, likes and positive comments for each video.

Although YouTube is a platform that content creators could freely upload their videos based on YouTube 's guidelines, it is difficult to have high interactions in a single video.

YouTube categorize the videos by which topic is covered in the video. One of the categories is *"People and Blog"*. The category covers videos that is related to people's lifestyle, news about people, promotions, reviews, blogs, and topics that has correlation with people. This project aims to study the factors that can possibly give positive impacts for videos in this category to make attract the viewers' interest to interact with the videos using data analysis.

1.2 Problem Statement

According to Alexa report, YouTube has become one of the most preferred digital video platforms that intercept more than 30 million visitors in a day. The largest portion of viewers comes from USA with 16.4% of traffics followed by India (9.2%) and Japan (4.8%) respectively. Because of high traffic and more videos are being added every day, unveiling viewership pattern is considered as a complex process for a normal content creator with no Data Science background.

YouTube has massive datasets that is categorized as Big Data. If the attributes of the trending videos are thoroughly studied and analyze using data analytics, content creators could have the opportunity to greatly increase the engagement quality of their videos thus improving their marketing strategies of their videos.

To understand the causal of high interaction videos, in-depth analysis is required.

1.3 Scope of The Project

The data analysis covers trending videos from YouTube platform. Due to the massive datasets that YouTube possess, it is time consuming and potentially can be misleading when interpreting the data. Therefore, this project will focus on the trending videos from US region. This is because US contributes the largest percentage of YouTube traffic with 16.4% visitors per day. This project also focuses on trending videos in category “People and Blog”.

1.4 Aim and Objectives

The purpose of this project is to discover how videos in the category of “People and Blogs” reached a high engagement. This project intends to uncover the hidden pattern by answering various questions about the trending YouTube videos using co-related analysis of Exploratory Data Analysis and Sentiment Analysis.

In particular, the objectives are:

- To analyze the patterns of high-interaction videos in YouTube using Exploratory Data Analysis and Unsupervised Learning to build machine learning algorithms that determine the topic consisted in the video.
- To discover optimal settings needed on the posted videos in order to achieve high interactions.
- To help the small content creators gain insights from other successful content creators on how to grow more audience.

1.5 Brief Methodology

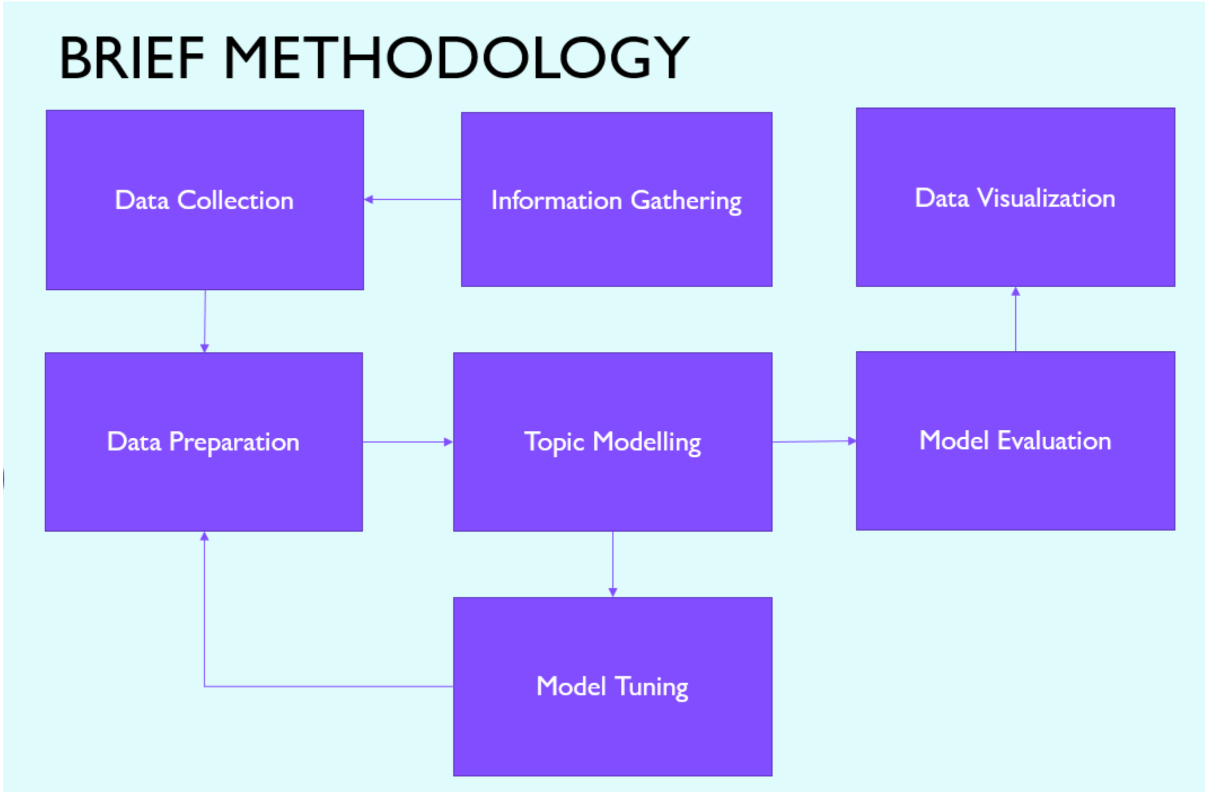

Figure 1.1:Brief Methodology of Project

Figure 1.1 shows the overview of the project workflow using flowchart. In chapter 3, each process in the project workflow is discussed thoroughly.

1.6 Significance of Project

The project is conducted to utilize YouTube as a platform to further improvise digital marketing and help content creators storyboard their future videos. The project also beneficial for content creators especially smaller channels with less viewers to grow their audience. It is done by discovering optimal settings necessary to make their videos trending and always relevant in YouTube. The project also is conducted to reveal hidden viewership patterns.

1.7 Project Schedule

Please refer to Appendix A and Appendix B for Project schedule.

1.8 Expected Outcome

At the end of this project, the analysis is expected to find the correlation and impactful attributes from trending videos. The analysis is also expected to find viewership patterns of trending videos for category “People and Blog”.

1.9 Project Outline

Chapter 1: Introduction uses to describe background of the project by defining the element of the research which is YouTube and its impact, the problem statements, scope, aim and objectives, brief methodology, significance of the project, project schedule, expected outcome and outline of project.

Chapter 2: Literature Review describes the related topics discussed on previous papers of YouTube research, methodologies involved, validations, evaluations as well as visualization. This chapter also discuss about the direction of proposed project based on previous findings.

Chapter 3: Methodology describes how the project is conducted in detail. This chapter discusses about information gathering, data collection, data pre-processing, feature extraction, data division, modelling process, evaluation, and visualization of the findings.

Chapter 4: Implementation discusses detailed methodology used in the project for according to phases mentioned in project overview.

Chapter 5: Analysis and Results Discussion consists of discussion findings based on analysis and model performance discussion.

Chapter 6: Conclusions and Future Works addresses the project achievement, contributions, limitations, and project future works.

CHAPTER 2: LITERATURE REVIEW

The study of users' behaviors on YouTube has been an interesting topic in the research world since YouTube started to rapidly grow into one of the largest video sharing platforms on internet. This literature review discusses the concept of relevant topics with the proposed project. Then the literature review covers the comparison of how related previous research is conducted. Finally, this chapter discusses the direction of proposed project and the overview of proposed project.

2.1 YouTube: A Miracle of One Video

According to Gohar Feroz Khan and Sokha Vong, YouTube is one of the most successful video-based communication mediums to express feeling, communicate with friends, and advertise business messages. YouTube was founded by Chad Hurley, Steve Chen and Jawed Karim in 2005. Snickars, P., & Vonderau, P. (2009) stated that the 2 co-founders, Chad Hurley and Steven Chen has successfully persuaded Google to invest $1.65 billion in stocks for the most-talked-about Web acquisition in October 2006. YouTube met its turning point to become one of the most preferred digital video platforms by a video featuring its third co-founder, Jawed Karim titled "Me at The Zoo". Little to his known, this spontaneous video has indicated inconspicuously that YouTube has the potential to become a proprietary platform with a new built-up online community (Snickars, P., & Vonderau, P., 2009).

2.3 The Phenomenon of Content Creation & Its Online Community

The ability to distribute content has attracted its community to upload various kind of videos on YouTube. In the summer of 2006, YouTube already has 13 million visitors in its traffic with hundreds of million videos uploaded in the platform. Mattias Holmbom (2015) said that the videos uploaded on YouTube has endless variations of cultures and interests. He added he localization of YouTube in 75 countries acquired has sparked the ability of monetization. YouTube created a partnership program with media companies to run ads alongside videos, splitting revenues with its partner. Today as a user-driven platform, the content creators have become the face of YouTube. The era of online entrepreneurship has continued to grow up until today and the main contributor of this era is called "*content creators*".

To content creators, YouTube is more than personal hub to upload videos (Holmbom, M., 2015). Alongside partnership program by YouTube, these content creators devoted their multiple hours of life every single day towards creating content and uploading it on YouTube. Although developing YouTube channel has a potential rewarding to its creator, it is difficult to have an audience big enough to provide feasible income through content creation career path. According to Mattias Holmbom, this is due to high saturation of YouTube channels, let alone YouTube videos. The rivalry for attention on this platform is so high that it may looks impossible to some minds.

According to Rowley's finding (2004) in his writing, he stated that developing a YouTube channel has a similar concept to online branding. He added that most, if not all, practical steps for developing a YouTube channel are connected to online branding. By utilizing the analytic tools provided by YouTube via its partnership program, content creators can analyse the level of attractive of their channel and videos they uploaded using metadata inserted in each video. Content creating also holds values that their videos should be plausible content for advertisers.

2.4 Social Network and Video Blogger (Vlogger) Community

YouTube as part of social media, is used to convey the creators' personality and behaviours they intend to display. In November 2010, Biel, J. I., and Gatica-Perez, D. stated that these videos in the most basic format, are usually defined as conversational videos that serves as a tool for communication and interaction alongside serves as a life documentary of the creators. Serves as a unique medium for self-presentation and interpersonal perception that surpass the use of text and still photos, conversational video blogs or its shorter term, vlogs has become a unique category video on YouTube (Biel, J. I., Aran, O., and Gatica-Perez, D., July 2011). Luers (2007) stated that vlog has several types of genres which are diary, experimental, documentary, and mash-up. According to Wauster (2010), YouTube hosts the largest number of video blogs with approximately 35% followed by Blip.tv (14%) and Vimeo (9%) in 2010.

Mitchell (1969) describes social network as "a specific set of linkage among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behaviour of the persons involved".

2.5 YouTube Advertising

With the rise of smartphones, social media has become universally accessible, making it a significant platform. As a social site, YouTube is no exception. It lets users find new songs, artists, and funny videos, for example. As a result of the increased use of YouTube, it has become an important platform for businesses to reach their target audiences. Unlike traditional commercials, YouTube endorsement marketing, also known as native advertising, is a type of marketing in which adverts are effortlessly integrated into the video content (Katrina Wu, 2016). There is a study that stated the effectiveness of YouTube advertising. Advertisers who run video ads on YouTube have increased their spending by more than 40% every year, while the top 100 advertisers on YouTube have increased their spending by more than 60% per year (Biographon, 2019).

According to Katrina Wu (2016), YouTube endorsement marketing is divided by 3 forms. The first form is when a content creator collaborates with a sponsor to generate videos, this is known as direct sponsorship. The second form called as affiliated links are those in which the content creator receives a commission from sales that are attributed to them. The third form is free product sampling which companies send things to content creators for free in exchange for them to use in a video whether to review or simply advertise explicitly or even implicitly according to consent of both party; content creators and companies.

Dugyu Firait (2019) has conducted a study about the value that YouTube advertising and its effect on purchase intention for consumers. In his study, he finds that articipants aged 40 and over believe YouTube advertisements to be more informative than those aged 18 to 29. Participants aged 30-39 believe YouTube commercials should be more interesting and trendier than those of other ages. In his findings, he concluded that the value of YouTube adverts has a beneficial impact on consumers' purchasing intention.

2.6 YouTube Algorithm

YouTube uses retrieval method as a feature for its video recommendation system. Essentially, YouTube deliver automatic suggestions to influence or assist users' decision-making processes. According to Bendersky, M., Garcia-Pueyo, L., Harmsen, J., Josifovski, V., & Lepikhin, D. (2014), algorithm used by YouTube system generates a sorted list of relevant videos for the viewer to watch in response to the video users is now watching. The collaborative filtering analysis is used in YouTube as a foundation to tailor the recommendation system by adding information about related previously watched by the user or can be based just on collective patterns of users watching videos. Most users are likely presented by the co-view videos suggested by algorithm with the videos that previously has been watched by user with same watching behaviours as them.

2.7 Latent Dirichlet Allocation (LDA) in Topic Modelling

Topic modelling is an unsupervised machine learning method of extracts themes as mathematical objects from a corpus of documents. According to Carina Jacobi et al. (2015), topic models are computer algorithms works by using the distribution of words in a collection of documents to find latent patterns of word occurrence. Equal to other topic modelling algorithm, Latent Dirichlet Allocation (LDA) algorithm is an unsupervised learning technique that create topics based on patterns of words that co-occur in when analyzing words in documents.

2.8 Review of Related Works

In this sections, related work of YouTube research is reviewed which divided into data collection, data preparation and analysis findings and evaluation, and lastly, visualization.

2.8.1 Data Collection

Several articles that discussed about digital research stated that they scraped code-based data by querying the platforms' API for data collection process referring to standards stated by Rogers (2013) discussed in his article about Digital Method.

In Choudhury, S. and Breslin, J. G. (2010) research on "*User sentiment detection: a YouTube use case*" they extracted data corpus on the most popular and relevant videos from five main categories and ten subcategories, including politics and news, science and technology, travel, music, movies, sports, gaming, people, and blogs. They gathered the 2,000 most popular videos in each category.

In the research of understanding the characteristics of internet short video sharing, Cheng, X., Dale, C., & Liu, J. (2007) scrapped data based on habits and social networks as they are of particular interest that topic. They used a mix of the YouTube API and scrapes of YouTube video web pages to crawl the YouTube site for three months and collect information on its videos.

2.8.2 Data Preparation and Analysis

2.8.2.1 Data Preparation

In Severyn, A., Uryupina, O., Plank, B., Moschitti, A., & Filippova, K. research for opinion mining on YouTube (2014), they improvised the data preparation process by instead of using traditional bag-of-word processing, they added new characteristic with features from a sentiment lexicon and features that quantify the negation in the comment.

For research “User sentiment detection: a YouTube use case” by Choudhury, S. and Breslin, J. G. (2010), They did some simple pre-processing of the text material after gathering the video data and the related comments. Stop-word removal and term stemming were applied to the comments. They stemmed the terms using Porter stemming and then used SentiWordnet to detect sentiment polarity.

In Rinaldi, E., and Musdholifah‘s article about opinion mining on Indonesian comments of youtube video using FVEC-SVM (2017), they executed preparation step in 8 phases. Emoji Removal, Slash Removal, Punctuation Removal, Slang Word Fixing, POS-tagging, Tokenizing, Tupling, and Class Selection are the 8 phases in the pre-processing stage. Frequently, video comments have included emoji that are unrelated to the message. As a result, in this study, the Unicode number was used to delete the emoji from the comment. They used FVEC approach and TF-IDF approach for feature extraction process. The FVEC method entails creating unigram and bigram words, counting negations, and calculating the cosine similarity between the comments and the title. All generated unigram and bigram words are converted into TF-IDF vectors. To extract the amount of negation terms in the comment, negative counting is used. This characteristic specifies whether the document is positive or negative in polarity. The quantity of negation words, TF-IDF of unigram and bigram words, and cosine similarity are the next features extracted from the comment.

For the research written about exploratory investigation of music on YouTube by Airoldi, M., Beraldo, D., and Gandini, A. (2016), In data preparation process, the data was acquired using the YouTube Data API v. 2.0. The data gathering procedure was divided into two parts. In the first step, we were able to acquire a generic list of videos associated to music content by querying the API for the keyword 'music' and setting the language option to English. The broad reach of the keyword allows for a wide range of musical genres to be covered, but because the search query is written in English, the results should be limited to that language. This initial batch has 500 videos since YouTube API v. 2.0 only permitted the maximum of 500 items to be extracted from one keyword. They crawled the YouTube related videos algorithm in the second phase to create a more consistent sample and a relational dataset for network research. They performed API request to collect 25 related videos for each video obtained in the first step, increasing their data variance with new videos and links between them.

2.8.2.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis is used to visually summarise and highlight the important aspects of the data to be investigated. Although EDA may or may not utilise any statistical model, but it provides insight into what the data holds beyond hypothesis testing and predictive modelling. Exploratory data analysis (EDA) is a valuable process developed in the modern era that aids in gaining familiarity with any given dataset before building a Machine Learning Algorithm or model.

Based on Heckert, N. A., Filliben, J. J., Croarkin, C. M., Hembree, B., Guthrie, W. F., Tobias, P., & Prinz, J. (2002), The EDA includes a variety of techniques for the following purposes: to gain a deeper understanding of the current dataset, to discover optimal factor settings, to develop penurious predictive models, to test fundamental assumptions, to identify outliers and anomalies in the dataset, to extract useful variables and information and to reveal hidden structures.

2.8.2.3 Sentiment Analysis

In article about opinion mining on YouTube by Severyn, A., Uryupina, O., Plank, B., Moschitti, A., and Filippova, K. (2014), the opinion mining approach they used focuses on the creation of classifiers to predict comment type and polarity. Traditionally, such classifiers have relied on bag-of-words and other complex features. They defined a baseline feature vector model and a novel structural model based on kernel approaches. Instead of using traditional bag-of word representation, they added features from a sentiment lexicon and characteristics that quantify the negation in the comment to the usual bag-of-words representation. The following feature groups are used by our model (FVEC) to encode each document:

i) Word n-gram - Over lower-cased word lemmas, they compute unigrams and bigrams, where binary values are utilised to signify the presence/absence of a given item.
ii) Lexicon – They used the MPQA Lexicon and the Hu and Liu Lexicon since both lexicon technique are manually produced sentiment lexicons that are freely available. They utilise the number of terms identified in the comment that have positive and negative sentiment as a characteristic for each of the lexicons.
iii) Negation - allows more thorough study of element of negation contained in the comments.
iv) Video Concept - Analyse the cosine similarity between a comment and the video's title/description. The majority of the videos have a title and a brief description, which may be used to decode the topicality of each comment by looking at how closely they overlap.

For structural model, they chose shallow structures with simpler and more durable components (STRUCT model). Their shallow tree structure specifically is a two-level syntactic hierarchy comprised of word lemmas (leaves) and part-of-speech tags, which are further divided into chunks.

In modelling process, they use supervised methods, such as SVM, to perform OM. The goal is to train a model that can determine the sentiment and kind of each comment automatically. They use the one-vs-all technique to create a multiclass classifier for this. For each of the classes, a binary classifier is trained, and the predicted class is determined by selecting the class with the highest prediction score.

Meanwhile on another article by Rinaldi, E., & Musdholifah, A. (2017, November) about opinion mining on Indonesian comments of youtube video using FVEC-SVM, the features of cleaned comments are extracted using FVEC, such as TF-IDF of n-gram words, negation counting, and cosine similarity. Finally, SVM is used to classify the comment based on its features. However, the Extraction Features process does not include the utilization of lexicon.

2.8.3 Findings and Evaluation

Based on YouTube data that was collected over a period of 205 days and included 40 950 videos in Khanam, S., Tanweer, S., & Khalid, S. S. (2021) research, the normalization of all the numerical attributes is conducted by implying Robust Z-score normalisation to ensure that any potential outliers have no effect on the normalisation.

The following trends and patterns were discovered in their findings based on the data features:

- Views: According to their research, 91 percent of trending videos have less than 5 million views, while 71% have 1.5 million views.
- Uniqueness: Only 6351 videos out of a total of 40 950 are unique, as some videos are trending for more than one day.
- Comments: They discovered that 93 percent of trending videos had less than 25 000 comments, and 67 percent have less than 4000 comments after studying the comments.
- For 84 percent of the videos, the 'like' count is 100 000, while for 69 percent of the videos, it is 40 000.
- Most common word: trending videos with 1 million or more views have titles that are between 35 and 55 characters long, with the most common terms being 'Trailer,' 'Official Video,' 'Audio,' and 'New.'
- Data correlation: We discovered a high positive link between the trending video's likes and views, as well as a somewhat lesser correlation between the number of comments and dislikes.

In the article wrote by Airoldi, M., Beraldo, D., & Gandini, A. (2016) about exploratory investigation of music on YouTube, they concluded that the relatedness between two music videos that may be regarded as crowd-generated music categories has been proven to be determinant in a large sample of YouTube music videos. They believe that the closely linked groupings of related music videos that emerge from a computational examination of the network's community structure could be thought of as rough miniatures of music categories as they arise "from the bottom up.". However, interestingly they added that there is a kind of situational dependent which listeners ignore the stereotype observed in the research and chose their music preference and genre by purely aesthetic and stylistic purpose. They stated that at 10% of their sample follows the logic mentioned above.

For article about opinion mining on YouTube by Severyn, A., Uryupina, O., Plank, B., Moschitti, A., & Filippova, K. (2014), they stated that Because STRUCT model can create structural patterns of sentiment, their STRUCT model is more accurate compared to FVEC model. There are some cases that which The FVEC bag-of-words model misclassifies positive evaluation because the model misinterpreted two positive expressions outweigh a single negative expression. In contradiction of STRUCT model, the structural model can accurately classify the comment as negative by identifying the product of interest and associating it with the negative expression via a structural feature.

Another article about opinion mining on YouTube comment by Rinaldi, E., & Musdholifah, A. (2017, November), using 10-fold cross validation method to evaluate each kernel function in the FVEC-SVM, they stated that FVEC-SVM that uses linear kernel function has the highest accuracy with 63.99%. They concluded that FVEC-SVM outperformed other kernel functions.

2.8.4 Visualization

In this section, observation of the visualization used to provide better insights of research. These visualizations are presented to help readers understand the context of findings.

2.8.4.1 Using Histograms

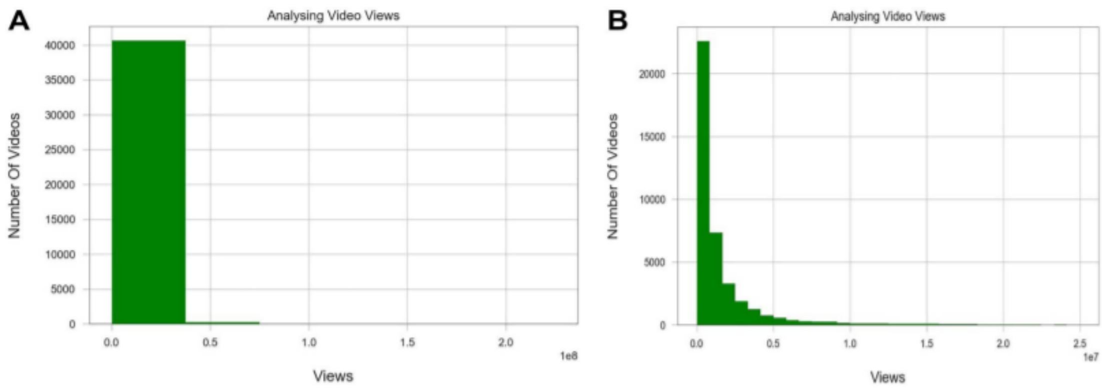

Figure 2.1: Views associated & data distribution with trending videos

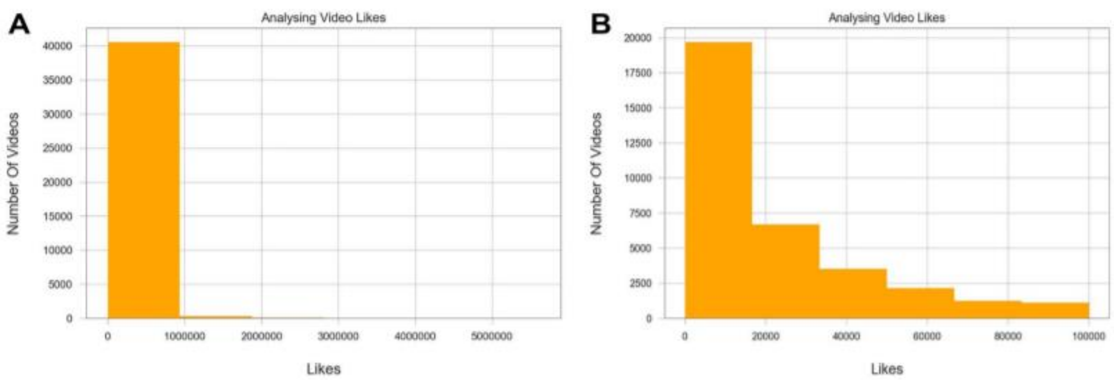

Figure 2.2: Video Likes Analysis and its Data Distribution

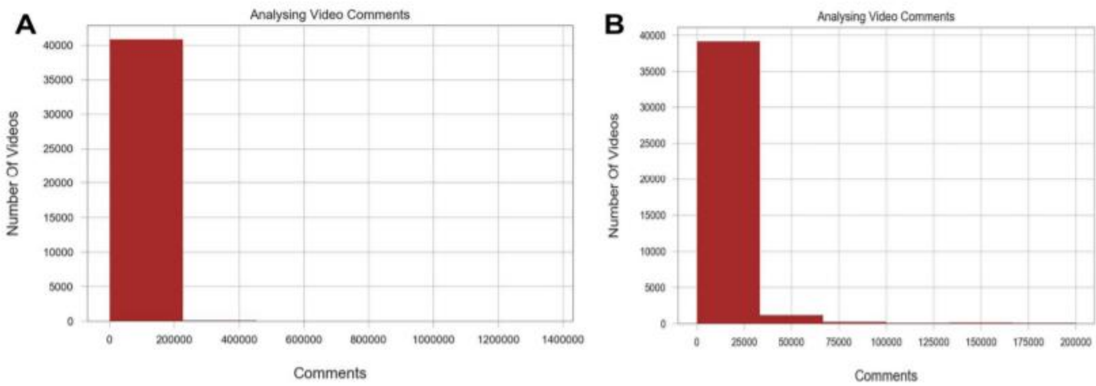

Figure 2.3: Video Comments Analysis and its Data Distribution

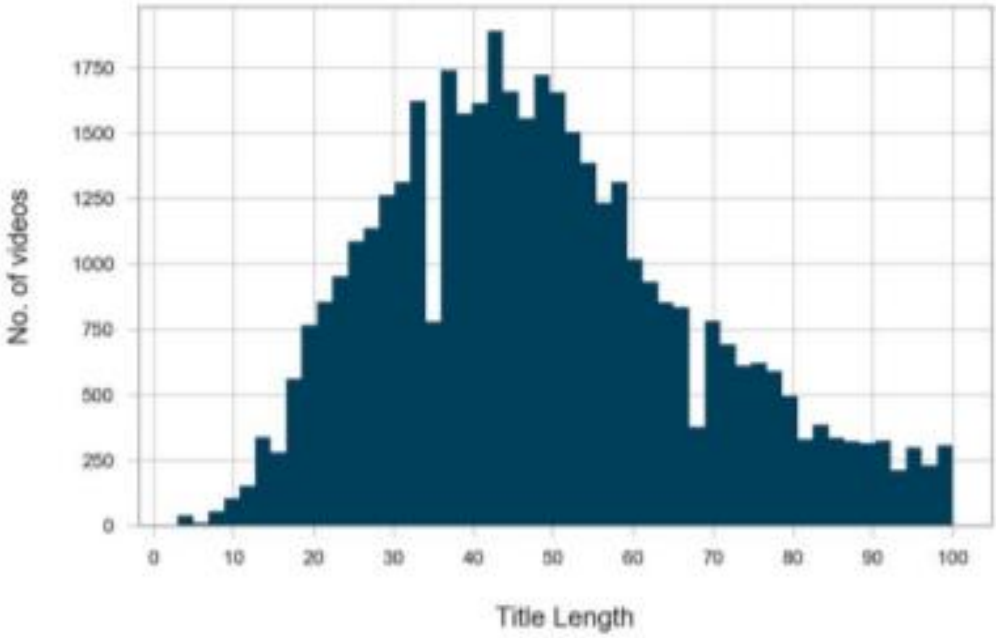

Figure 2.4: Data Distribution for Title Length

Figure 2.2, 2.3, and 2.5 shows the histogram visualizations that used to show the distribution of variables in the dataset.

2.8.4.2 Using Scatter Plot

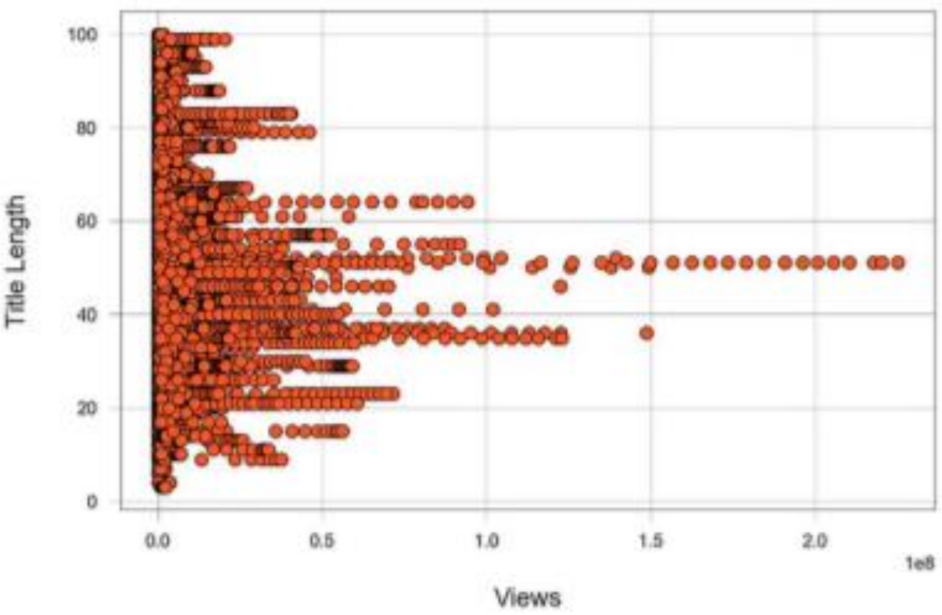

Figure 2.5: Scatter Plot for Title Length vs Views

Figure 2.5 shows that Scatter plot is used to observe and show relationships between title length of video and views.

2.8.4.3 Using Heat Map

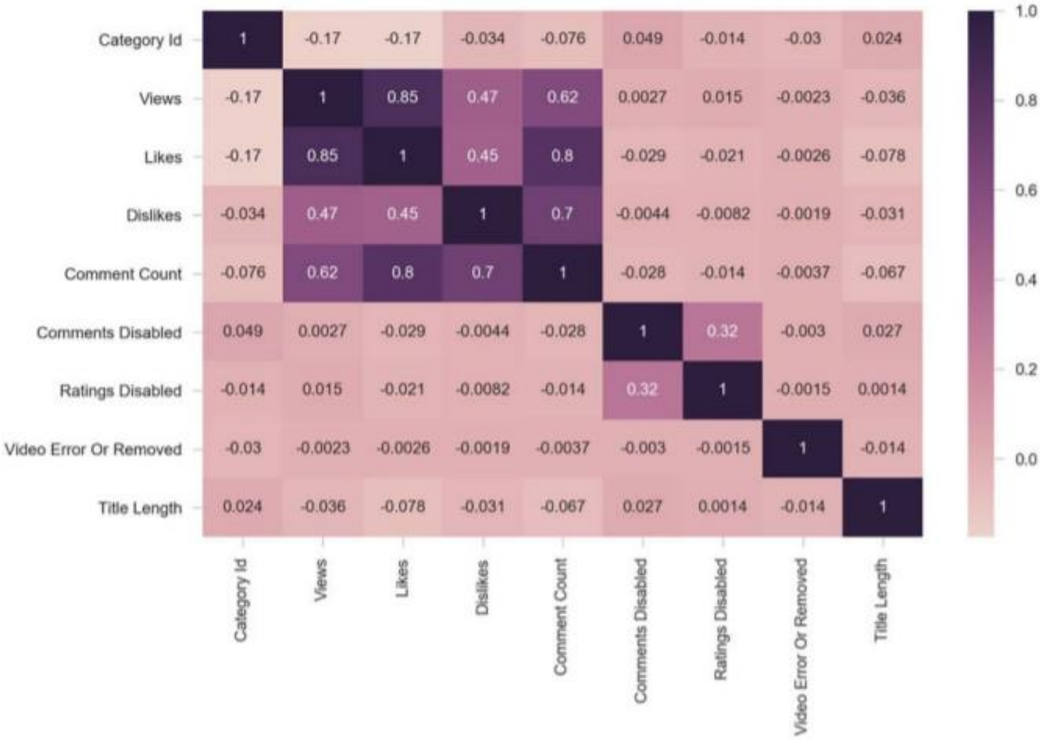

Figure 2.6: Heatmap Correlation

Figure 2.6 is a Heat map visualization that is used to find the correlation between the various YouTube attributes present including views, likes, dislikes, rating, title, etc., and hence to perform a bivariate analysis.

2.8.4.4 Using WordCloud

Figure 2.7: WordCloud for Top 30 most Common Words

Figure 2.7 shows the implementation of *WordCloud* to portray Top 30 most common words used in title of trending videos.

2.8.4.5 Using Bar Chart

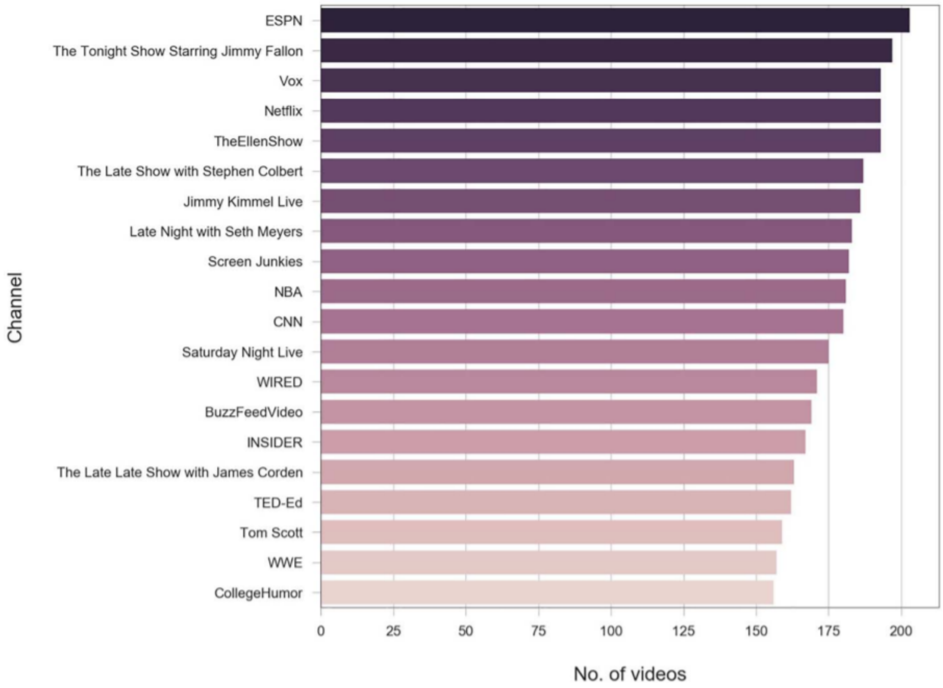

Figure 2.8: Bar Chart for Top 20 Channel

Figure 2.8 shows how Bar Chart is used to visualize the number of videos that top 20 channels has uploaded.

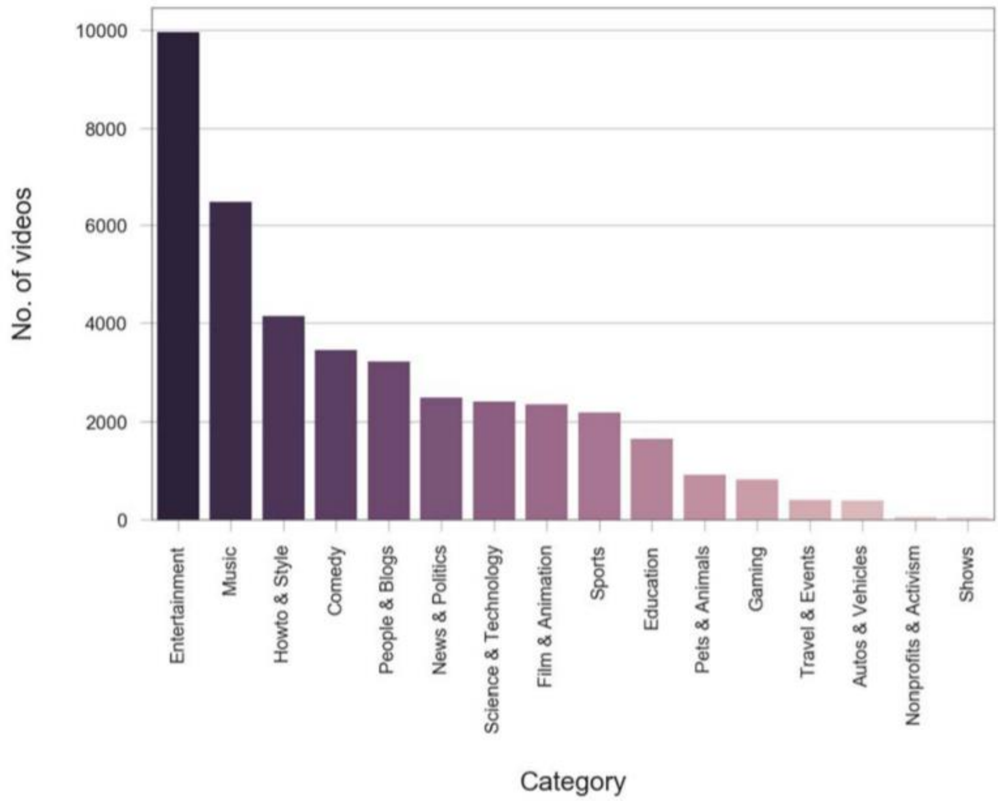

Figure 2.9: Bar Chart for Number of Videos based on Category

Figure 2.9 shows that the number of videos based on category of videos using bar chart.

2.9 Direction of the Proposed Project

After thorough reading of reviewed papers, papers from Airoldi, M., Beraldo, D., & Gandini, A. (2016), Severyn, A., Uryupina, O., Plank, B., Moschitti, A., & Filippova, K. (2014), Rinaldi, E., & Musdholifah, A. (2017, November) and Khanam, S., Tanweer, S., & Khalid, S. S. (2021) has deeply inspired me to complete the project. The topic discussed from the 4 papers are opinion mining (sentiment analysis), and exploratory analysis on YouTube.

Proposed Data Collection method: the dataset used will be a pre-crawled dataset from Kaggle website, “YouTube Trending Video Dataset (updated daily)” uploaded by Rishav Sharma because of high dimensionality of the dataset with collected data from 11 different countries which are India, USA, Great Britain, Germany, Canada, France, Russia, Brazil, Mexico, South Korea, and Japan respectively. The dataset is consisted of up to 200 listed trending videos per day. The dataset is fetched is separated by regions. List of data attribute is as below:

i) Video ID
ii) Video title
iii) Date published
iv) Channel ID
v) Channel title
vi) Category ID
vii) Trending date
viii) Video tags
ix) Count of views
x) Likes

Proposed Data Pre-processing method; use Jupyter Notebook for code documentation. Cleaning dataset will be adjusted according to usability for Exploratory Data Analysis and Sentiment Analysis on the later steps.

The dataset will be pre-processed by to removing punctuations and special characters, treating missing values, data segmentation and normalization out-of-vocabulary words in the title/description and comments in the datasets, and conversion of lowercase and data annotation.

In addition, feature extraction and feature selection will be conducted to reduce the data dimension and further pull relevant data to use for hypothesis testing.

The project will then move to data division process where data is split into training sets and testing sets.

For modelling phase, the chosen analysis for the proposed project is firstly the project will undergo unsupervised learning using LDA modelling to figure out topics for each video. Later, the obtained topics will be trained for supervised learning to evaluate the accuracy of LDA model.

The performance of analysis will be evaluated by classification report containing the confusion matrix, accuracy, precision, precision, recall and F1-score.

Finally, the findings of the project are visualized using scatter plot, pair plots, histograms, heat maps and *WordCloud.*

CHAPTER 3: METHODOLOGY

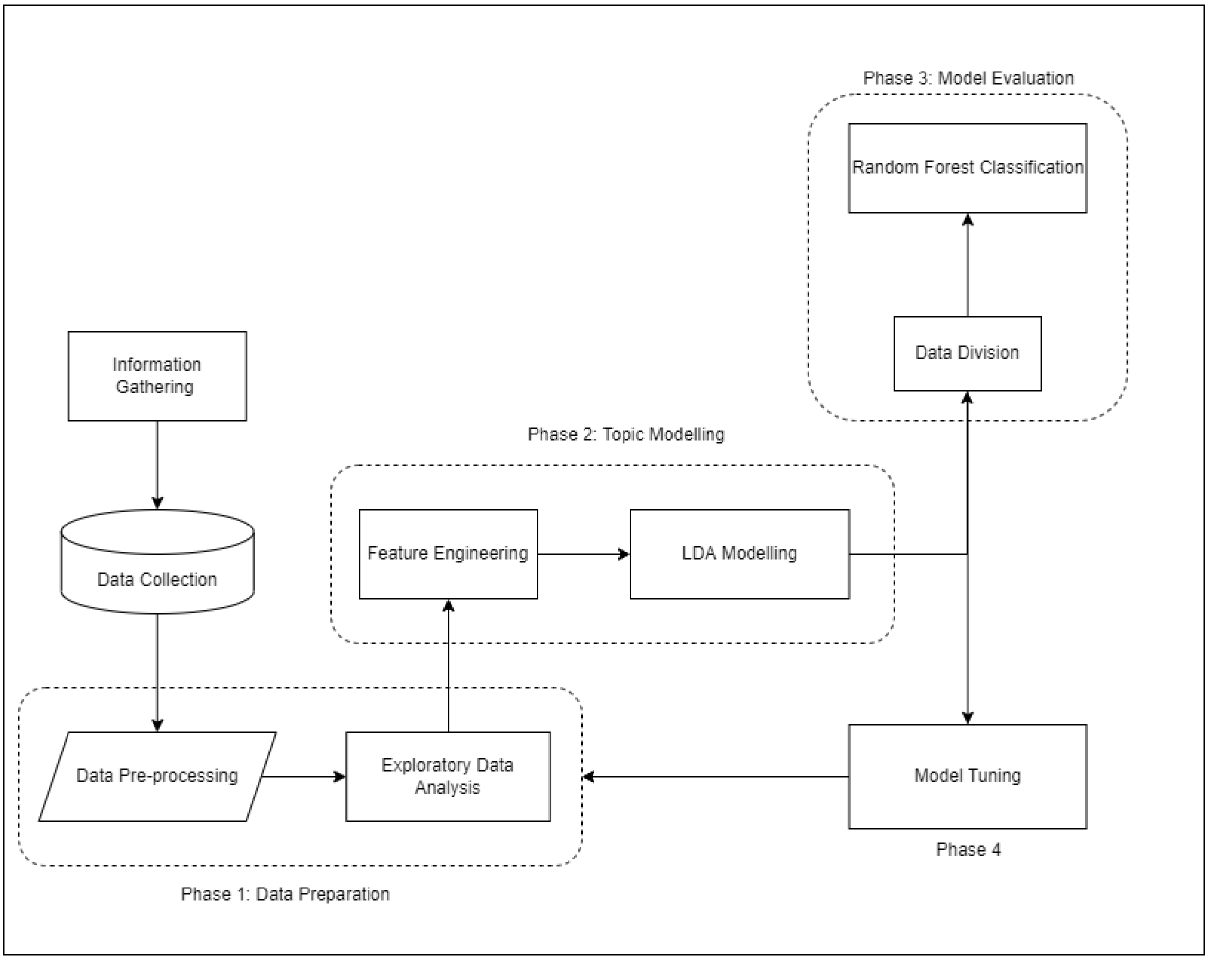

Figure 3.1: Detailed Workflow of the Project

Figure 3.1 above shows the detailed workflow of the project. This chapter will discuss the detailed methodology based on *Figure 3.1*.

3.1 Information Gathering:

i) Gather information about text classification techniques and time series analysis.

ii) Study the social and behavioral science for better understanding of the relationship between social network and user behavioral patterns.

iii) Reading similar research papers relating to YouTube

3.2 Data Collection:

i) For this project, the datasets are essentially extracted from YouTube API.

ii) The project is conducted using Python language.

The dataset is obtained from "YouTube Trending Video Dataset (updated daily)" uploaded by Rishav Sharma in Kaggle website (https://www.kaggle.com/rsrishav/YouTube -trending-video-dataset).

Kaggle.com is a crowd-sourced platform that allows developers and data scientist to write, share codes and host datasets. The purpose of Kaggle is to serve as a platform to attract data scientists all around the world, nurture, and challenges them to solve data science, machine learning and predictive analytics problems according to According to Usmani Z. (2017)

Then, the dataset acquired undergo the assessment of data quality. The assessment process of data quality is important to ensure scraped dataset using scraping bot is suitable and testable according to project requirements. This process is performed by checking the extracted data by scraping bot has scraped correct elements and fields. In this project the correct elements and field is correct comments from intended link provided in the source code.

- Video ID: ensure correct path of video ID is extracted.
- Video title: ensure video title is not merged to one another
- Date published: Ensure timestamp data extracted are true to its published date
- Channel ID: ensure all extracted rows has channel ID filled.

- Channel title: Different video may have same owner ID. Ensure that video details are not collapsed
- Category ID: Ensure all video has its categories
- Trending date: Ensure timestamp data extracted are true to its trending date
- Video tags: Ensure tags is extracted to its respective column
- Count of views: Ensure the view count is accurate according to YouTube page
- Likes and Dislike: Ensure likes and dislikes is distributed to its respective columns.

3.3 Phase 1: Data Preparation

For documentation containing notes, live codes, equations, and visualizations, the project is being documented using the classic Jupyter Notebook. Jupyter Notebook is an online application for creating and sharing computational documents. It offers a user-friendly, efficient, document-focused experience for documentation purpose.

The dataset is imported to Jupyter Notebook along with relevant libraries that will be mentioned in later process.

3.3.1 Data Pre-processing

For data pre-processing, the package tools used for this process are Pandas, Numpy and Klib from Python libraries. In data pre-process, the numerical and categorical feature is explored for better data understanding. Next step is to inspect whether the dataset has missing values or not.

Then, the missing values is treated. Next, outliers are observed and treated to avoid lower accuracy of model training later. The dataset is normalized for more consistency, which improves the model's ability to forecast results. After exploring numerical and categorical features, some features are better converted to be able to feed into machine learning algorithm later. As some columns are contained of texts, it consists of human language which has an abundance of stop words. By getting rid of these words, text columns are more focused on the key information by eliminating the low-level information. Then, punctuation and special characters is removed from columns containing texts to avoid complicacy when building model later.

3.3.2 Exploratory Data Analysis

Exploratory Data Analysis is used for more comprehensive views of what given data in the dataset is about. By doing so, the best practice of machine learning and roadmap of the project is identified. This is done by using python package such as Pandas and NumPy, along with statistical methods and data visualization packages. The purpose of doing Exploratory Data Analysis is to provide better insights from statistical evidence in Exploratory Data Analysis and utilize it to determine the results in findings.

The analysis involved are:

- Univariate Analysis
- Bivariate Analysis
- Time-series Analysis

- Multivariate Analysis

3.3.2.1 Univariate Analysis

Univariate analysis is the simplest form of analysis which involves summarization and pattern of only one "Uni" variable in the dataset dimension. This analysis is conducted to discover the meaning of each column of data, whether it is a categorical or continuous, or independent or dependent to other variables in the dataset

3.3.2.2 Bivariate Analysis

Compared to univariate analysis, Bivariate analysis is a correlation analysis that is conducted to gather insights for causal and relationship of two "Bi" variables.

3.3.2.3 Time Series Analysis

Because of the dataset containing timestamps, time series analysis is necessary to discover hidden insights based on time intervals. Time series analysis is a specific approach to analyzing a set of data points accumulated over an extended period of time. Time series analysis is done by manipulating the record the data points over a set period of time that is extracted from video published time.

3.3.2.4 Multivariate Analysis

Multivariate analysis is the statistical analysis of correlations between several measurements are made on each experimental unit and where the relationship between multivariate measurements and their structure are crucial to understanding the experiment. It is done to find suitable features to feed into machine learning models, or to decide whether the data type should be transformed or not in the feature engineering process.

3.4 Phase 2: Topic Modelling

The purpose of using topic modelling is to discover specifically what topic is used in video title, descriptions, and tags to achieve higher interaction. In phase 2, the combined text of video title, descriptions, and tags is filtered in feature engineering process and later fed into LDA model.

3.4.1 Feature Engineering

The process of feature extraction and selection is to reduce the possibility of overfitting when building models to determine the weighted polarity of the data. Based on Ghojogh, B., Samad, M. N., Mashhadi, S. A., Kapoor, T., Ali, W., Karray, F., & Crowley, M. (2019)'s paper on feature selection and feature extraction in pattern analysis, feature selection and feature extraction is used to assist the models perform better, valuable information can be in the form of better data representation or better class discrimination.

3.4.1.1 Feature Extraction

Feature extraction method used for this project are n-gram method. N-gram is the count of *n* sequence of words where *n* could be one-word level, Unigram and two-word level, Bigram. In this project, both unigram and bigram are applied.

N-gram method is used to find out the correlation between trending videos and word occurrence in the video title, tags, and video description.

3.4.1.2 Feature Selection

Feature Selection method used for reducing the dimension of data to feed into LDA model later. Reducing dimension of the data helps to improve the accuracy of the model and reduce the execution time when building and tuning model. Feature Selection include the process of lemmatization, removing stop words, removing non-readable words, and removing null rows in the dataset. The example of non-readable words is single characters or mesh of unreadable characters after lemmatization process.

This is done to ensure only meaningful words in fed into LDA model. The lemmatized document is then relayed to create a dictionary by assigning an integer value to each word in the document. Creating a dictionary of lemmatized document is necessary to create corpus Bag-of-Word needed for topic modelling.

3.4.2 LDA Modelling

For LDA modelling process, there are 2 steps involved:

- Building LDA base model
- Compute the perplexity and coherence score
- Assign each document to its predicted topic

3.4.2.1 Building LDA Base Model

The LDA base model is built by assigning reasonable initial number of topics where each topic is made up of a number of keywords, and each term has a specific weight in the topic.

3.4.2.2 Compute Perplexity and Coherence Score

The LDA model is partially evaluated using perplexity and coherence score. Perplexity is a statistical measure of how well a probability model predicts a sample in LDA model. Typically, the lower the perplexity, better LDA model is produced.

Topic modelling uses the coherence score to gauge how comprehensible the topics are to people. Generally, the higher coherence score, the better LDA model is built.

3.4.2.3 Assign Each Document to its Predicted Topics

Each row of document in the dataset is assigned and labeled to its predicted topic for later use in the supervised learning.

3.5 Phase 3: Model Evaluation

To achieve better accuracy of topic used in the video title, descriptions, and tags, the model is evaluated by cross validation process using supervised learning for Bag-Of-Word and TF-IDF model evaluation.

3.5.1 Data Division

In this process, the labeled dataset is split into two parts, training set and testing set. Training set is a subset used to train the model and testing set is a subset to test a trained model. Training set is sliced up to 80% of dataset and testing set takes 20%.

3.5.2 Random Forest Classification

Random Forest Classification is built for Bag-Of-Word model evaluation and TF-IDF model evaluation. The evaluation is observed from the value of precision, recall, F-1 score and supports obtained after cross validation process from training and testing sets.

3.6 Phase 4: Model Tuning

To increase the performance of LDA model, there are 2 steps of model tuning:

- Build LDA Mallet Model.

- Find the optimal number of topics, *k*.

3.6.1 Build LDA Mallet Model

Mallet's LDA algorithm uses Gibbs Sampling that usually returns better results for long text documents. However, emitting better accuracy, time consumed to build LDA Mallet model is higher than general LDA model. The LDA Mallet model is only chosen if it returns better coherence score than normal LDA model.

3.6.2 Find the Optimal Number of Topics, *k*

Hyperparameter is manipulated to determine the optimal number of topics, *k*. This is done by building many LDA models then plotting computed coherence score graph for range of *k*. Generally, *k* value is determined by model that has the highest coherence score before flattening out.

3.7 Conclusion

For summary, this chapter is explained based on project overview in *Figure 3.1* where there are data understanding phase along with 4 major phases involved which are:

Phase 1 – Data preparation

Phase 2 – Topic Modelling

Phase 3 – Model Evaluation

Phases 4 – Model Tuning

In Phase 3: Model Evaluation, until the optimal model that gives greatest accuracy is figured out, phase 4 which is Model Tuning will loop back to Phase 1: Data Preparation and Phase 2: Topic Modelling. The purpose of loop back process is to avoid noisy data being fed into machine learning algorithm by treat outliers and reducing dimension of data.

Lastly, all data results are visualized by its respective step. Data visualization is observed and inferred to acquire findings. Discussion of the findings is elaborated in Chapter 5. The data is visualized in various form such as histograms, correlation plot, heatmaps and *WordCloud.*

CHAPTER 4: IMPLEMENTATION

In this chapter, the project is conducted based on stated steps in project pipeline overview. Then, each phase will be discussed in detail. Chapter will consist of data understanding phase along with 4 major phases stated in Figure 4.1 below:

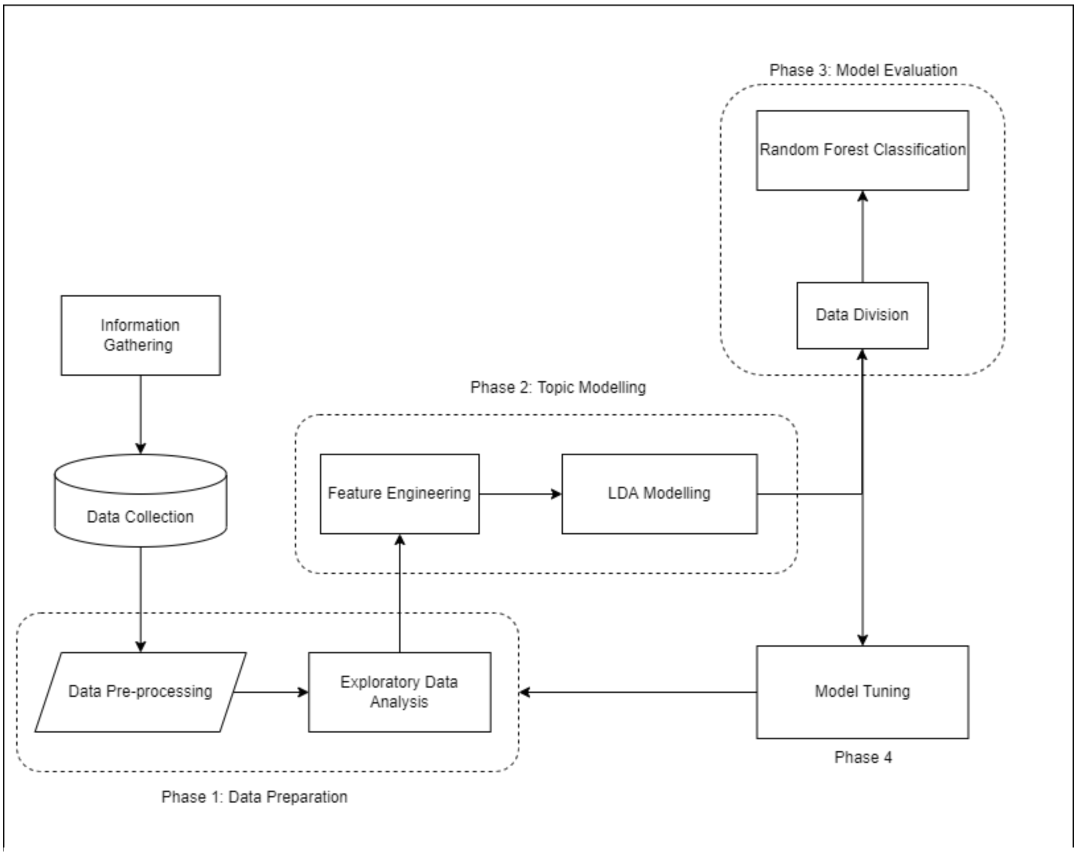

Figure 4.1 Project Pipeline Overview

Phase 1, Data preparation consist of Data Pre-processing steps and Exploratory Data Analysis. Phase 2, Topic Modelling consist of Feature Engineering step and LDA modelling. Phase 3, Model Evaluation consist of Data Division and Supervised Learning Random Forest Classification for evaluation of LDA model. Lastly, Phase 4 Model Tuning.

4.1 Data Collection

Trending YouTube videos Dataset is downloaded from link https://www.kaggle.com/datasets/rsrishav/youtube-trending-video-dataset. This dataset includes several months of data on daily trending YouTube videos. Data is included for the IN, US, GB, DE, CA, FR, RU, BR, MX, KR, and JP regions (India, USA, Great Britain, Germany, Canada, France, Russia, Brazil, Mexico, South Korea, and Japan respectively), with up to 200 listed trending videos per day where each region's data has its separate files. The category ID is stored in JSON files while video title, channel title, publish time, tags, views, likes, and dislikes, description, and comment count is stored in CSV files. *Figure 4.2* below shows the original dataset obtained from the website.

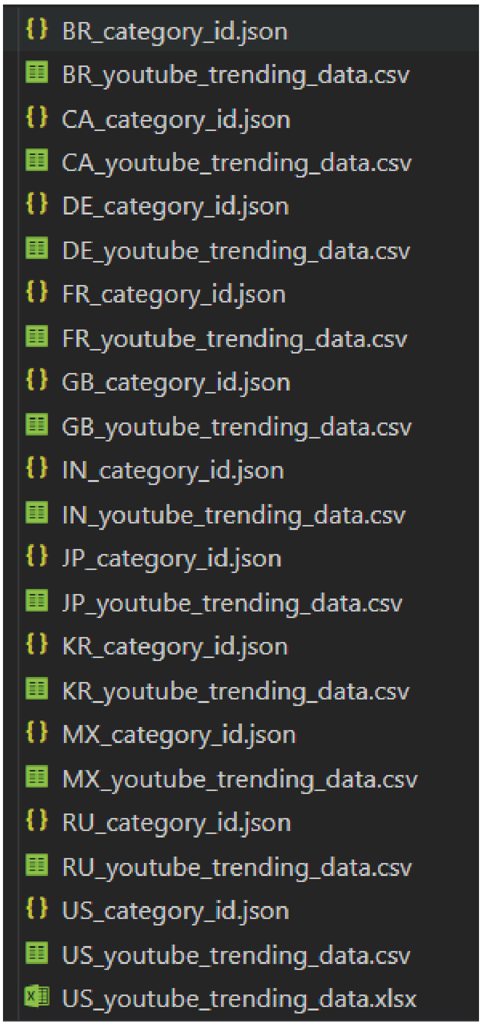

Figure 4.2: Original Dataset

4.2 Phase 1: Data Preparation

The project will be conducted using Python language version 3.9.1.2. The documentation of the project which include line of code used, results, visualizations and findings are saved in Jupyter Notebook (.ipynb File) as “FYP2 Implementation.ipynb”. *Microsoft Visual Studio* is used to connect with Jupyter Notebook. All relevant Python packages throughout this project are listed in Figure 4.3 and Figure 4.4 below:

```python
import numpy as np
import pandas as pd
import seaborn as sns
import spacy
import re
import json
pd.get_option("display.max_columns")

from datetime import datetime, timedelta, timezone
from datetime import datetime
import time
from matplotlib.dates import DateFormatter

# # Plotting tools
import pyLDAvis
import pyLDAvis.sklearn
import pyLDAvis.gensim_models as gensimvis
import matplotlib.pyplot as plt
import matplotlib.colors as colors
%matplotlib inline
from wordcloud import WordCloud
#import fot plotly
import plotly.express as px
#profile report
import klib

# Sklearn
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
from pprint import pprint
```
✓ 5.5s

Figure 4.3: Python Package used Part 1

```python
# Gensim
import gensim
import gensim.corpora as corpora
from gensim.utils import simple_preprocess
from gensim.models import CoherenceModel
from gensim.models.ldamodel import LdaModel
import pyLDAvis.gensim_models as gensimvis

#optional
import logging
logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s', level=logging.ERROR)

import warnings
warnings.filterwarnings("ignore",category=DeprecationWarning)

# NLTK Stop words
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
```

Figure 4.4: Python package used Part 2

4.2.1 Data Pre-processing

In this project, only videos in US region are observed. Dataset is called into Jupyter Notebook after importing relevant libraries.

```python
US_videos =  pd.read_csv('Dataset\\US_youtube_trending_data.csv')
US_categories = pd.read_json('Dataset\\US_category_id.json')
```
✓ 1.8s

Figure 4.5: Importing Dataset

<table>
<tr><th>video_id</th><th>title</th><th>publis...</th><th>chann...</th><th>chann...</th><th>categ...</th><th>trendi...</th><th>tags</th><th>view_c...</th><th>likes</th><th>dislikes</th><th>comm...</th><th>thum...</th><th>comm...</th><th>rating...</th></tr>
<tr><td>3C66w5Z...</td><td>I ASKED ...</td><td>2020-08-...</td><td>UCvtRTO...</td><td>Brawadis</td><td>22</td><td>2020-08-...</td><td>brawadis|...</td><td>1514614</td><td>156908</td><td>5855</td><td>35313</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>M9Pmf9...</td><td>Apex Leg...</td><td>2020-08-...</td><td>UC0ZV6...</td><td>Apex Leg...</td><td>20</td><td>2020-08-...</td><td>Apex Leg...</td><td>2381688</td><td>146739</td><td>2794</td><td>16549</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>J78aPJ3V...</td><td>I left you...</td><td>2020-08-...</td><td>UCYzPXp...</td><td>jacksepti...</td><td>24</td><td>2020-08-...</td><td>jacksepti...</td><td>2038853</td><td>353787</td><td>2628</td><td>40221</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>kXLn3Hk...</td><td>XXL 2020...</td><td>2020-08-...</td><td>UCbg_U...</td><td>XXL</td><td>10</td><td>2020-08-...</td><td>xxl fresh...</td><td>496771</td><td>23251</td><td>1856</td><td>7647</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>VIUo6ya...</td><td>Ultimate ...</td><td>2020-08-...</td><td>UCDVPcE...</td><td>Mr. Kate</td><td>26</td><td>2020-08-...</td><td>The LaBr...</td><td>1123889</td><td>45802</td><td>964</td><td>2196</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>w-aidBdv...</td><td>I Haven't ...</td><td>2020-08-...</td><td>UC5zJws...</td><td>Professor...</td><td>24</td><td>2020-08-...</td><td>Professor...</td><td>949491</td><td>77487</td><td>746</td><td>7506</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>uet14uf9...</td><td>OUR FIR...</td><td>2020-08-...</td><td>UCDSJCB...</td><td>Les Do M...</td><td>26</td><td>2020-08-...</td><td>[None]</td><td>470446</td><td>47990</td><td>440</td><td>4558</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>ua4QMF...</td><td>CGP Grey...</td><td>2020-08-...</td><td>UC2C_jS...</td><td>CGP Grey</td><td>27</td><td>2020-08-...</td><td>cgpgrey|...</td><td>1050143</td><td>89190</td><td>854</td><td>6455</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>SnsPZj91...</td><td>SURPRISI...</td><td>2020-08-...</td><td>UCZDdF_...</td><td>Louie's Life</td><td>24</td><td>2020-08-...</td><td>surprisin...</td><td>1402687</td><td>95694</td><td>2158</td><td>6613</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>SsWHMA...</td><td>Ovi x Nat...</td><td>2020-08-...</td><td>UC648rg...</td><td>Rancho ...</td><td>10</td><td>2020-08-...</td><td>Vengo D...</td><td>741028</td><td>113983</td><td>4373</td><td>5618</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>49Z6Mv4...</td><td>i don't kn...</td><td>2020-08-...</td><td>UCtinbF-...</td><td>CaseyNei...</td><td>22</td><td>2020-08-...</td><td>[None]</td><td>940036</td><td>87111</td><td>1860</td><td>7052</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>nt3VVyv5...</td><td>Try Not T...</td><td>2020-08-...</td><td>UCYJPby...</td><td>Smosh Pit</td><td>22</td><td>2020-08-...</td><td>smosh|s...</td><td>591837</td><td>44168</td><td>409</td><td>2652</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>I6hswz4rI...</td><td>Rainbow ...</td><td>2020-08-...</td><td>UCBMvc...</td><td>Ubisoft ...</td><td>20</td><td>2020-08-...</td><td>R6|R6S|Si...</td><td>320872</td><td>14288</td><td>774</td><td>2085</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>W7VK4D...</td><td>Lil Yachty...</td><td>2020-08-...</td><td>UC1X3TR...</td><td>LilYachty...</td><td>10</td><td>2020-08-...</td><td>Lil Yachty...</td><td>413372</td><td>26440</td><td>293</td><td>1495</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>W9Aen8...</td><td>When Ou...</td><td>2020-08-...</td><td>UCR9Nu...</td><td>Kyle Exum</td><td>23</td><td>2020-08-...</td><td>When Ou...</td><td>921261</td><td>124183</td><td>1678</td><td>16460</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>BNeDH6...</td><td>Ten Minu...</td><td>2020-08-...</td><td>UCMw7...</td><td>Tyler Ca...</td><td>22</td><td>2020-08-...</td><td>the bach...</td><td>105955</td><td>4511</td><td>69</td><td>673</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>6TIsR_7n...</td><td>Kylie Jen...</td><td>2020-08-...</td><td>UC2rJLq1...</td><td>Hollywoo...</td><td>24</td><td>2020-08-...</td><td>kylie jenn...</td><td>1007540</td><td>10102</td><td>7932</td><td>2763</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>gPdUsln...</td><td>Our Farm...</td><td>2020-08-...</td><td>UCuxlXCf...</td><td>Cole The ...</td><td>22</td><td>2020-08-...</td><td>farming|f...</td><td>277338</td><td>37533</td><td>197</td><td>3666</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>GTp-0S8...</td><td>Time to T...</td><td>2020-08-...</td><td>UCCgLo...</td><td>Chloe Ting</td><td>26</td><td>2020-08-...</td><td>chloe tin...</td><td>1648441</td><td>130147</td><td>1425</td><td>15773</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
<tr><td>jbGRowa...</td><td>ITZY “No...</td><td>2020-08-...</td><td>UCaO6T...</td><td>JYP Enter...</td><td>10</td><td>2020-08-...</td><td>JYP Enter...</td><td>5999732</td><td>714287</td><td>15174</td><td>31039</td><td>https://i.y...</td><td>false</td><td>false</td></tr>
</table>

Figure 4.6 Original Dataset imported as "US_videos"

Figure 4.6 above shows portion of original dataset for trending videos only in United States (US) region.

Specifically, this project analyzed videos only in category “People and Blog”. *Figure 4.7* below shows filter code for only category “People and Blog” which equals to 22

```
# select videos only in category "People and Blog"
# from US_categories, category ID for People and Blog is 22
PB_videos = US_videos.loc[US_videos['categoryId'] == 22]
✓ 0.8s
```

Figure 4.7:Filter to category People and Blog

Then, *Figure 4.8* is shown to ensure dataset is filtered to only one category

```
PB_videos.head()
```
✓ 0.8s

	video_id	title	publishedAt	channelId	channelTitle	categoryId	trending_date	
0	3C66w5Z0ixs	I ASKED HER TO BE MY GIRLFRIEND...	2020-08-11T19:20:14Z	UCvtRTOMP2TqYqu51xNrqAzg	Brawadis	22	2020-08-12T00:00:00Z	brawadis|p
10	49Z6Mv4_WCA	i don't know what im doing anymore	2020-08-11T20:24:34Z	UCtinbF-Q-fVthA0qrFQTgXQ	CaseyNeistat	22	2020-08-12T00:00:00Z	
11	nt3VVyv5pxQ	Try Not To Laugh Challenge #51	2020-08-11T17:00:31Z	UCYJPby9DRCteedh5tfxVbrw	Smosh Pit	22	2020-08-12T00:00:00Z	
15	BNeDH6UTmXw	Ten Minutes with Tyler Cameron | Q&A	2020-08-11T22:00:05Z	UCMw7m-ScQ6jV1FQzQnn1y8Q	Tyler Cameron	22	2020-08-12T00:00:00Z	the bache

Figure 4.8: People and Blog dataset

To have better comprehension about the People and Blog dataset, the data types is observed as shown in *Figure 4.9.*

```
US_videos.dtypes
```
✓ 0.6s

```
video_id             object
title                object
publishedAt          object
channelId            object
channelTitle         object
categoryId            int64
trending_date        object
tags                 object
view_count            int64
likes                 int64
dislikes              int64
comment_count         int64
thumbnail_link       object
comments_disabled      bool
ratings_disabled       bool
description          object
```

Figure 4.9: Data types

Unique channels are identified as shown below in *Figure 4.10*.

```
#How many unique channels are there?
PB_videos['channelTitle'].nunique()
✓ 0.1s

754
```

Figure 4.10: Unique Channels

Hashtag words is extracted as shown below in *Figure 4.11*

```
hash_word = PB_videos['title'].str.extractall(r"(#\S+)")
✓ 0.8s
```

Figure 4.11 Extraction of Hashtag Words

The missing values are identified using *Klib* plotting library as shown below in *Figure 4.12*

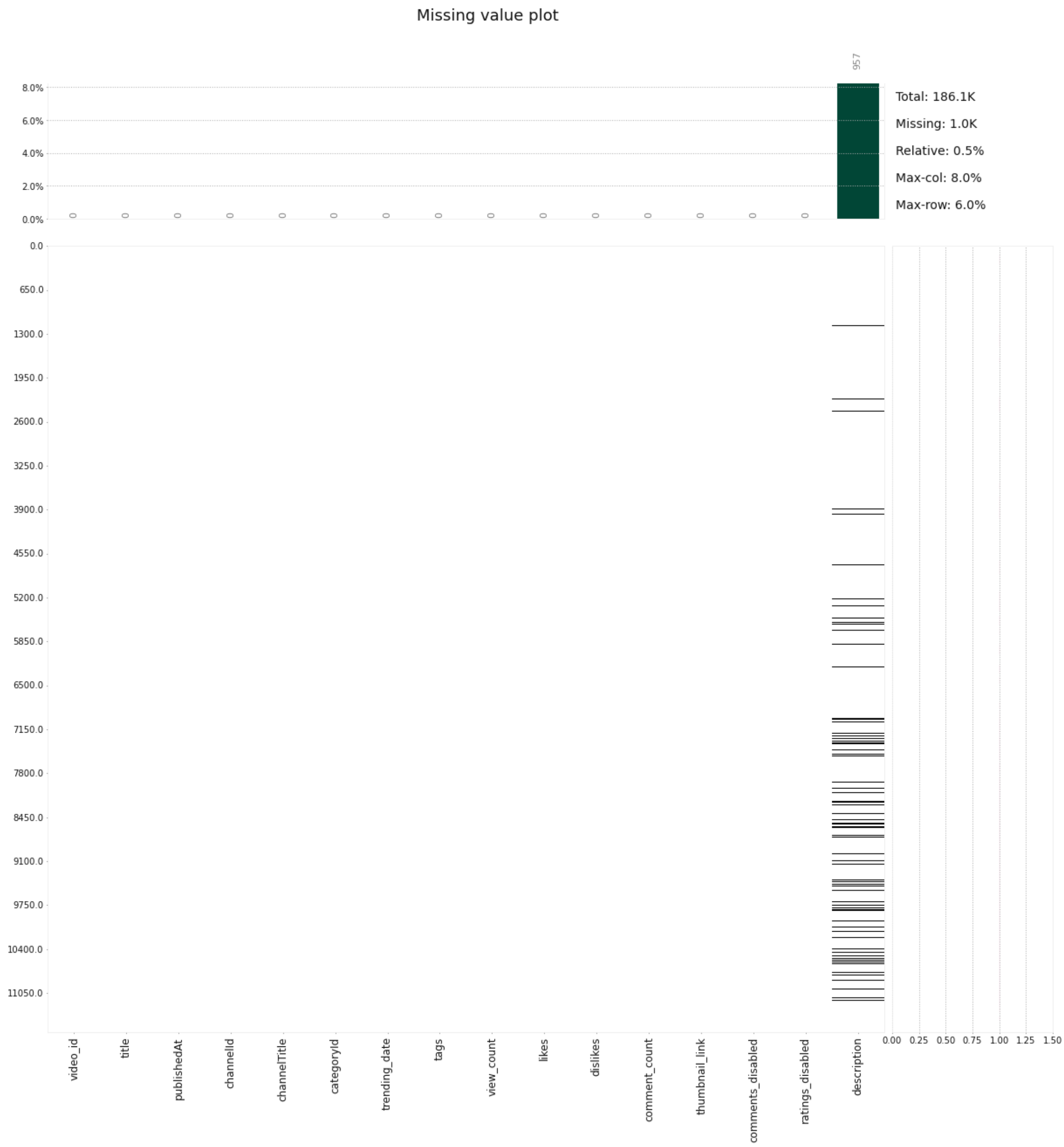

Figure 4.12: Missing Values Plot

Based on *Figure 4.12* above, missing values are detected in only in one column “description”. Next, the missing values are treated with “ “ for text sampling later as shown below in *Figure 4.13.*

```
#Treat missing value
PB_videos.description= PB_videos.description.fillna('', )
```

Figure 4.13: Treating Missing Values

When doing data cleaning it is necessary to find and remove duplicated data. The process of finding duplicated data based on column ‘video_id’ because every video ID in the dataset should be unique. The step is shown below in *Figure 4.14.*

```
PB_videos.duplicated(subset='video_id').sum()
✓ 0.4s
```

Figure 4.14: Finding Duplicated data

Based on step above, line of code returns a total of 9477 duplicated data contained in the dataset. The process of removal duplicated data is shown in *Figure 4.15* below.

```
PB_videos.drop_duplicates(subset='video_id',keep='last', inplace=True)
✓ 0.1s
C:\Users\tunku\AppData\Local\Temp\ipykernel_33592\2922947673.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  PB_videos.drop_duplicates(subset='video_id',keep='last', inplace=True)

print("Size of the original dataset: {}".format(len(US_videos.loc[US_videos['categoryId'] == 22])))
print("Number of unique videos in the dataset: {}".format(len(PB_videos)))
✓ 0.5s
Size of the original dataset: 11629
Number of unique videos in the dataset: 2152
```

Figure 4.15: Removing Duplicated data

Based on step above in *Figure 4.16*, the duplicated rows are dropped while keeping its last founded occurrence in the dataset as last occurrence has latest trending date.

Next, the columns that are meaningless to observe is dropped as shown in *Figure 4.16.*

```
PB_videos.drop(['thumbnail_link'], axis=1, inplace=True)
PB_videos.drop(['video_id'], axis=1, inplace=True)
PB_videos.drop(['categoryId'], axis=1, inplace=True)
```

Figure 4.16: Drop Irrelevant Columns

Based on *Figure 4.16,* the column 'thumbnail_link' is dropped because it is a float data type that is unlearnable by machine learning. The column 'video_id' is dropped because the dataset has its own unique index for each row. Lastly, column 'category_Id' is dropped because it provides non-observable feature since all rows in "People and Blog" dataset is filtered to category ID = 22.

Data cleaning of text columns are done to 3 columns which are:

- 'title' column
- 'description' column
- 'tags' column

Firstly, the link and punctuation from all 3 columns are removed as shown in *Figure 4.17 below.*

```python
#remove links from the description
PB_videos.description= PB_videos.description.str.replace('http\S+|www.\S+',''\
                                        ,regex= True).str.lower()
#removing Punctuation from description
PB_videos.description = PB_videos.description.str.replace(r'[^a-zA-Z0-9]+', ' ')
PB_videos.description= PB_videos.description.str.replace(r'[0-9]+', '')
```

```python
#remove links from the title
PB_videos.title= PB_videos.title.str.replace('http\S+|www.\S+',''\
                                        ,regex= True).str.lower()
#removing Punctuation from title
PB_videos.title= PB_videos.title.str.replace(r'[^a-zA-Z0-9]+', ' ')
PB_videos.title= PB_videos.title.str.replace(r'[0-9]+', '')
```

```python
#remove links from the description
PB_videos.tags= PB_videos.tags.str.replace('http\S+|www.\S+',''\
                                        ,regex= True).str.lower()
#removing Punctuation from description
PB_videos.tags= PB_videos.tags.str.replace(r'[^a-zA-Z0-9]+', ' ')
PB_videos.tags= PB_videos.tags.str.replace(r'[0-9]+', '')
```

Figure 4.17: Link and Punctuation Removal for Text Column

Secondly, from NLTK library, ‘stopwords’ library is used to define function for removing stop words from text later. The “stopwords’ library is extended with extra words as shown in *Figure 4.18 below.*

```python
# produce universal stop_words to use for cleaning
stop_words = stopwords.words("english")
stop_words.extend(['from', 'subject', 're', 'edu', 'use','none','None','follow', 'twitter', 'social', 'instagram', 'subscribe', 'snapchat', '
                  ,'channel', 'share', 'facebook', 'comment', 'like'])
print(stop_words)
```

```
✓ 0.1s                                                                                     Python

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself',
'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their',
'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be',
'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as',
'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above',
'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when',
'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same',
'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've',
'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven',
"haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't", 'from', 'subject', 're', 'edu', 'use', 'none', 'None', 'follow', 'twitter',
'social', 'instagram', 'subscribe', 'snapchat', 'youtube', 'videos', 'video', 'channel', 'share', 'facebook', 'comment', 'like']
```

Figure 4.18: Initialize Stop Words Library with Extended Word

Based on *Figure 4.18* above, extended words are the most frequent words in the text columns that provide less to no value when building topic model later.

Next, text columns ‘title’, ‘description’ and ‘tags’ are merged for data pre-processing for LDA model later as shown Figure 4.19.

```python
PB_videos['All_text'] = PB_videos.description + ' ' + PB_videos.tags + ' ' + PB_videos.title
```

Figure 4.19: Merging 3 text columns

The merged column ‘All_text’ is then converted from sentence to words using function in *Figure 4.20 below.*

```python
def sent_to_words(sentences):
    for sentence in sentences:
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))
all_words = list(sent_to_words(PB_videos['All_text']))
print(all_words[:5])
```

Figure 4.20: Function Sentence to Words

One of the results converted sentence is shown in *Figure 4.21* below.

```
[['cinemassacre', 'channel', 'update', 'recap', 'hope', 'everyone', 'is', 'safe', 'and', 'sound', 'thanks', 'for', 'watching', 'during', 'all', 'of', 'this',
'it', 'means', 'lot', 'to', 'all', 'of', 'us', 'that', 'said', 'we', 'need', 'to', 'make', 'few', 'changes', 'with', 'everything', 'going', 'on', 'in', 'the',
'world', 'james', 'and', 'mike', 'monday', 'is', 'on', 'hiatus', 'until', 'february', 'rental', 'reviews', 'is', 'cancelled', 'but', 'the', 'rr', 'guys',
'justin', 'kieran', 'tony', 'will', 'be', 'working', 'behind', 'the', 'scenes', 'and', 'will', 'guest', 'host', 'some', 'upcoming', 'videos', 'there', 'will',
'be', 'more', 'random', 'videos', 'like', 'music', 'videos', 'and', 'scripted', 'reviews', 'plus', 'monthly', 'avgn', 'and', 'ykwbs', 'the', 'new', 'release',
'schedule', 'is', 'every', 'tuesday', 'and', 'friday', 'at', 'noon', 'est', 'conventions', 'and', 'any', 'films', 'we', 'were', 'planning', 'are', 'getting',
'pushed', 'back', 'but', 'my', 'book', 'should', 'make', 'lot', 'of', 'headway', 'this', 'year', 'the', 'new', 'avgn', 'video', 'game', 'will', 'come', 'out',
'this', 'fall', 'sometime', 'on', 'all', 'systems', 'add', 'avgn', 'deluxe', 'to', 'your', 'steam', 'wishlist', 'https', 'store', 'steampowered', 'com', 'app',
'follow', 'us', 'on', 'twitter', 'james', 'https', 'twitter', 'com', 'matei', 'https', 'twitter', 'com', 'mike_mateiryan', 'https', 'twitter', 'com',
'schottrjusty', 'https', 'twitter', 'com', 'https', 'twitter', 'com', 'kieeeeerntony', 'https', 'twitter', 'com', 'shirts', 'dvds', 'and', 'blu', 'rays',
'https', 'store', 'screenwavemedia', 'com', 'collections', 'on', 'amazon', 'com', 'https', 'amzn', 'to', 'ork', 'teespring', 'exclusive', 'shirts', 'https',
'teespring', 'com', 'stores', 'to', 'subscribe', 'http', 'www', 'youtube', 'com', 'add_user', 'cinemassacre', 'jamesrolfe', 'update', 'cinemassacre',
'channel', 'update', 'cinemassacre', 'update', 'video', 'cinemassacre', 'update', 'james', 'rolfe', 'cinemassacre', 'channel', 'update']]
```

Figure 4.21Example of Converted Sentence to Words

Then, the bigram and trigram words from converted text are created. Bigrams are pairs of words that commonly appear together in a text. Meanwhile, three words are known as trigrams. Before making bigrams and trigrams, "English" natural language process is loaded into file using SpaCy to reduce the noise of words data and increase efficiency by keeping only tagger component of words. The initialization function is shown in *Figure 4.22* below.

```
# Initialize spacy 'en' model, keeping only tagger component (for efficiency)
nlp = spacy.load("en_core_web_sm", disable=['parser', 'ner'])
```

Figure 4.22: Load NLP for English Language

The English NLP model for bigrams and trigrams function is initialized as shown in *Figure 4.23* below.

```python
# make bigram function
def make_bigrams(texts):
    return [bigram_mod[doc] for doc in texts]

def make_trigrams(texts):
    return [trigram_mod[bigram_mod[doc]] for doc in texts]
```

Figure 4.23: Make Bigrams and Trigrams Function

Next, lemmatization and removing stop words function is initialized as shown in *Figure 4.24* below.

```python
def lemmatization(texts, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV']):
    """https://spacy.io/api/annotation"""
    texts_out = []
    for sent in texts:
        doc = nlp(" ".join(sent))
        texts_out.append([token.lemma_ for token in doc if token.pos_ in allowed_postags])
    return texts_out
```

```python
def remove_stopwords(texts):
    return [[word for word in simple_preprocess(str(doc)) if word not in stop_words] for doc in texts]
```

Figure 4.24: Initialization of Lemmatization and Removing Stop Words

The initialized functions are then used to do lemmatization while keeping only nouns, adjectives, verbs, and adverbs. The process of lemmatization is shown using line of code below.

```python
# Form Bigrams
title_words_bigrams = make_bigrams(all_words)

# Do lemmatization keeping only noun, adj, vb, adv
data_lemmatized_withnull = lemmatization(title_words_bigrams, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV'])

temp_df = pd.DataFrame([list(x) for x in data_lemmatized_withnull])
```

✓ 15.4s

Figure 4.25: Lemmatization process

Some of the videos is not in English, therefore there are rows that has ‘NaN’ value.The ‘NaN’ rows might affect the corpus model and later in LDA model so it is necessary to remove the rows. The ‘NaN’ rows are removed using dropping function how = ‘all’ shown in *Figure 4.26* below.

```
remove_nan_rows = temp_df.dropna(axis=0, how='all')
✓ 0.1s

temp_data_lemmatized = temp_df.to_numpy().tolist()
✓ 0.5s

data_lemmatized = remove_stopwords(temp_data_lemmatized)
✓ 2.5s
```

Figure 4.26: Remove NaN rows

Based on *Figure 4.26* above, the stop words are removed after removal NaN rows.

4.2.2 Exploratory Data Analysis (EDA)

In Exploratory Data Analysis, the process is used to summarise and highlight the important aspects of the data to be investigated. It is also to detect the feature that is plausible to fed into machine learning algorithm. The analysis involved are Univariate Analysis, Bivariate Analysis, Multivariate Analysis and Time Series Analysis.

4.2.2.1 Univariate Analysis

Firstly, the top 10 most viewed videos in category “People and Blog” are observed using line of code in *Figure 4.27* below.

```
top_10_videos_most_viewed = PB_videos.groupby(['title']).max().sort_values('view_count',ascending=False).loc[:,'view_count'][:10]
top_10_videos_most_viewed = top_10_videos_most_viewed.reset_index()
✓ 0.9s
```

Figure 4.27: Top 10 Most Viewed Video

Secondly, the top 10 most liked videos in category “People and Blog” are observed using line of code in *Figure 4.28* below

```
top_10_videos_most_liked = PB_videos.groupby(['title']).max().sort_values('likes',ascending=False).loc[:,'likes'][:10]
top_10_videos_most_liked = top_10_videos_most_liked.reset_index()
```

Figure 4.28: Top 10 Most Liked Videos

Next, the top 10 most disliked videos in category “People and Blog” are observed using line of code in *Figure 4.29* below

```
top_10_videos_most_disliked = PB_videos.groupby(['title']).max().sort_values('dislikes',ascending=False).loc[:,'dislikes'][:10]
top_10_videos_most_disliked = top_10_videos_most_disliked.reset_index()
```

Figure 4.29: Top 10 Most Disliked Videos

For text columns, the univariate analysis is conducted by observing text column ‘tags’ as shown in *Figure 4.30* below.

```python
# generate a function to make wordcloud for EDA
def generate_wordcloud(text, stopwords):
    wordcloud = WordCloud(stopwords=stop_words,max_font_size=50, max_words=150, background_color="white").generate(text)
    plt.figure()
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()
```
✓ 0.4s

```python
tag_list = " ".join(text for text in PB_videos.tags)
generate_wordcloud(tag_list, stop_words)
```
✓ 1.2s

Figure 4.30:Generate WordCloud for tags

Based on *Figure 4.30* above, the function to generate WordCloud is initialize for future use in other Exploratory Data Analysis technique.

4.2.2.2 Bivariate Analysis

Bivariate analysis is conducted to observe bicorrelation between 2 features. The bicorrelation is plotted using regression plot. The findings of the different regression plots are discussed in Chapter 5 later.

```python
sns.regplot(data=PB_videos, x='view_count', y='likes', color= 'blue')
plt.title('Regression plot for views and likes')
```

Figure 4.31: Regression Plotting for Views and Likes

Figure 4.31 above shows the plotting process for regression plot Views vs Likes

```python
sns.regplot(data=PB_videos, x='view_count', y='dislikes', color= 'red')
plt.title('Regression plot for views and dislikes')
```

Figure 4.32: Regression Plotting for Views and Dislikes

Figure 4.32 above shows the plotting process for regression plot Views vs Dislikes. Next, for the observation of channels, Top 10 channels with most trending videos on trending is observed as shown in *Figure 4.33* below.

```
trending_channels=PB_videos.groupby(['channelTitle']).size().sort_values(ascending = False).head(10)
trending_channels=trending_channels.reset_index()
trending_channels=trending_channels.rename(columns={0: 'count'})
```
✓ 0.5s

Figure 4.33: Top 10 channels with most videos on trending

4.2.2.3 Multivariate Analysis

Multivariate Analysis is statistical analysis of correlations between several feature in the dataset. In this dataset, the correlation of numerical features is plotted using heatmap from *Klib* library.

```
klib.corr_plot(PB_videos)
```

Figure 4.34: Correlation Plotting for numerical features in the dataset

Based on Figure 4.34 above, findings of the heatmap are discussed in detail later in Chapter 5.

4.2.2.4 Time Series Analysis

Time Series Analysis is used to discover hidden insights based on time intervals. In this dataset, the general topic is observed using the view counts to search for highest point of engagement across the timestamp. The time series plotting is as shown in *Figure 4.35 below*.

```
labels = {'view_count': 'View Count (Millions)', 'trending_date': 'Trending Date'}
fig = px.line(df_cat_pandblogs, x='trending_date', y='view_count', title='View Count Time Series for category: People and Blog', labels=labels)

fig.update_xaxes(rangeslider_visible=True)
fig.update_layout(title_x=0.5)
fig.show()
```

Figure 4.35: Time Series for view counts

4.4 Phase 2: Topic Modelling

In "People and Blog" category, although it is categorized by People and Blog there are various type of video can be posted in this category. From lifestyle to storytelling, the variance of topic is still in the grey area. Topic Modelling is an unsupervised machine learning algorithm that works by using the distribution of words in a collection of documents to find latent patterns of word occurrence. In this project, topic Modelling is used to discover what topic of video exactly that raised high engagements using LDA machine learning model.

4.4.1 Feature Engineering

In data pre-processing steps earlier, the text column 'title', 'description' and 'tags' is merged into new text column. This is because using only one column such as title is insufficient to predict what topic is the video about. After lemmatization process, some of the rows cleaned up until it became 'NaN' rows. Some of them also has less than 3 words after cleaning process. Therefore, to improve the dictionary corpus dimensionality, the 3 columns is transformed and merged into one single column.

```python
# Create Dictionary
id2word = corpora.Dictionary(data_lemmatized)

# Create Corpus
texts = data_lemmatized

# Term Document Frequency
dt_corpus = [id2word.doc2bow(text) for text in texts]

# View
print(dt_corpus[:1])
```

✓ 0.2s

```
[[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1), (7, 1), (8, 1), (9, 1), (1
1), (19, 1), (20, 1), (21, 1), (22, 1), (23, 1), (24, 1), (25, 1), (26, 1), (27, 1),
(36, 1), (37, 1), (38, 1), (39, 1), (40, 1), (41, 2), (42, 1), (43, 1), (44, 1), (45
1), (54, 1), (55, 1), (56, 1), (57, 1), (58, 2), (59, 1), (60, 1), (61, 1), (62, 1),
(71, 1), (72, 1), (73, 1), (74, 1)]]
```

Figure 4.36: Create dictionary, corpus of texts and TF-IDF frequency

Figure 4.36 above shows that lemmatized data is then used to create dictionary, corpus of texts and TF-IDF frequency.

4.4.2 LDA Modelling

LDA Model is built using randomly assigned number of topics, *k*. In this project, LDA Model is initialized with number of topics, $k = 10$. The snippet code is as shown in *Figure 4.37* below.

```
# Build LDA model
lda_model = gensim.models.LdaMulticore(corpus=dt_corpus,
                                       id2word=id2word,
                                       num_topics=10,
                                       random_state=100,
                                       chunksize=100,
                                       passes=10,
                                       per_word_topics=True)
```

Figure 4.37: Build base LDA Model

Then, to partially evaluate the LDA model perplexity and coherence score is computed as shown in *Figure 4.38* below.

```
# Compute Perplexity
print('\nPerplexity: ', lda_model.log_perplexity(dt_corpus))  # a measure of how good the model is. lower the better.

# Compute Coherence Score
coherence_model_lda = CoherenceModel(model=lda_model, texts=data_lemmatized, dictionary=id2word, coherence='c_v')
coherence_lda = coherence_model_lda.get_coherence()
print('\nCoherence Score: ', coherence_lda)
✓ 27.7s

Perplexity:  -8.115052082033191

Coherence Score:  0.3501204088648949
```

Figure 4.38: Compute Perplexity and Coherence Score

The base LDA model is then plotted for better visualization of topic distributions. The snippet code to plot base LDA model is as shown in *Figure 4.39* below.

```
# To plot at Jupyter notebook
pyLDAvis.enable_notebook()
plotbasemodel = pyLDAvis.gensim_models.prepare(lda_model, dt_corpus, id2word)
# Save pyLDA plot as html file
pyLDAvis.save_html(plotbasemodel, 'LDA_base_model.html')
plotbasemodel
```

Figure 4.39: Plot base LDA Model

Then, the weighted number of topics obtained is pushed into new Data Frame and later used to predict the main topic of each document based on the percentage of contribution of the document. *Figure 4.40* below shows the snippet code to

```
def format_topics_sentences(ldamodel=lda_model, corpus=dt_corpus, texts=data_lemmatized):
    # Init output
    sent_topics_df = pd.DataFrame()

    # Get main topic in each document
    for i, row in enumerate(ldamodel[corpus]):
        row = sorted(row, key=lambda x: (x[1]), reverse=True)
        # Get the Dominant topic, Perc Contribution and Keywords for each document
        for j, (topic_num, prop_topic) in enumerate(row):
            if j == 0:  # => dominant topic
                wp = ldamodel.show_topic(topic_num)
                topic_keywords = ", ".join([word for word, prop in wp])
                sent_topics_df = sent_topics_df.append(pd.Series([int(topic_num), round(prop_topic,4), topic_keywords]), ignore_index=True)
            else:
                break
    sent_topics_df.columns = ['Dominant_Topic', 'Perc_Contribution', 'Topic_Keywords']

    # Add original text to the end of the output
    contents = pd.Series(texts)
    sent_topics_df = pd.concat([sent_topics_df, contents], axis=1)
    return(sent_topics_df)
```

Figure 4.40 Function to Format Topic Sentence

Figure 4.41 below shows the snippet code of dataset of dominant topic is fetched into CSV files.

```python
df_topic_sents_keywords = format_topics_sentences(ldamodel=optimal_model, corpus=dt_corpus, texts=data_lemmatized)

# Format
df_dominant_topic = df_topic_sents_keywords.reset_index()
df_dominant_topic.columns = ['Document_No', 'Dominant_Topic', 'Topic_Perc_Contrib', 'Keywords', 'Text']

# Show
df_dominant_topic.head()
```

```python
df_dominant_topic.to_csv(r'D:\Sem 8\FYP2\temp\Dominant Topic dataset.csv', index = False)
```

Figure 4.41Dominant Topic dataset for each document

4.5 Phase 3: Model Evaluation

In this phase, based on base LDA Model's topic computed in Phase 2, all rows in column 'All_text' are assigned to its predicted dominant topic. Then, the data is divided into train and test sets. The split data is then fed into supervised learning, Random Forest Classification.

4.5.1 Data Division

Using the dominant topic discovered by base LDA model, the text is assigned according to weightage of the word occurrence in the documents. Then, the data 'Text' and 'Dominant_Topic' is split into training and testing data. The ratio of data division is 80:20 for training sets and testing set respectively. The code snippet of data split process is shown in *Figure 4.42* below.

```
X = df_dominant_topic.Text

Y = df_dominant_topic.Dominant_Topic

X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.2,random_state = 0)
```

Figure 4.42: Split Training and Testing Set

4.5.2 Random Forest Classification

To measure the performance of the model, Random Forest Classification is implemented in 2 model used:

- Bag-Of-Word (BoW) model
- TF-IDF model

BoW model is used to measure how well the document classification based on frequency occurrence of each word when it is used as feature in the model classifier.

While TF-IDF model is used to measure how well the document classification based on most relevance word in the document.

The performance of both supervised learning is using confusion matrix.

4.5.2.1 Bag-Of-Word model

BoW model is built based on snippet code in *Figure 4.43* below.

```
# Applying bag of words to features in training and testing data
bag_of_words_creator = CountVectorizer()
X_train_bow = bag_of_words_creator.fit_transform(X_train)
X_test_bow = bag_of_words_creator.transform(X_test)
```

```
cl = RandomForestClassifier(random_state = 0)
cl.fit(X_train_bow,Y_train)
```

```
y_pred = cl.predict(X_test_bow)
```

Figure 4.43: Building BoW Model

4.5.2.2 TF-IDF model

TF-IDF model is built based on snippet code in *Figure 4.44* below.

```
tfidf_creator = TfidfVectorizer()
X_train_tfidf = tfidf_creator.fit_transform(X_train)
X_test_tfidf = tfidf_creator.transform(X_test)
```

```
cl = RandomForestClassifier(random_state = 0)
cl.fit(X_train_tfidf,Y_train)
```

```
y_pred = cl.predict(X_test_tfidf)
```

Figure 4.44: Building TF-IDF Model

4.5.2.3 Classification Evaluation: Confusion Matrix

The confusion matrix is of both BoW model and TF-IDF model is computed and observed. The snippet code of confusion matrix compute is shown in *Figure 4.45* below.

```
confusion_matrix(Y_test,y_pred)
```

```
print(met.classification_report(Y_test,y_pred))
```

Figure 4.45: Compute Confusion matrix

4.6 Phase 4: Model Tuning

4.6.1 Building LDA Mallet Model

In model tuning, firstly LDA Mallet model is built and observed whether the coherence score is improved or not. The snippet code for LDA Mallet model is shown in *Figure 4.46* below.

```
import os
## Setup mallet environment change it according to your drive
os.environ.update({'MALLET_HOME':r'C:/mallet-2.0.8'})
## Setup mallet path change it according to your drive
mallet_path = 'C:/mallet-2.0.8/bin/mallet'

start_time = time.time()
##
## Train LDA with mallet
ldamallet = gensim.models.wrappers.LdaMallet(mallet_path, corpus=dt_corpus, num_topics=10, id2word=id2word)
## Print time taken to train the model
print("--- %s seconds ---" % (time.time() - start_time))
pprint(ldamallet.show_topics(formatted=False))
```

Figure 4.46: Initiate LDA Mallet Model

Based on the *Figure 4.46* above, number of topics, *k* is assigned constantly same as base LDA model. Then, after LDA Mallet Model is trained the coherence score is computed. *Figure 4.47* below shows the snippet code to compute coherence score of LDA Mallet Model.

```
# Compute Coherence Score for mallet
coherence_model_lda = gensim.models.CoherenceModel(model=ldamallet, texts=data_lemmatized, dictionary=id2word, coherence='c_v')
coherence_lda = coherence_model_lda.get_coherence()
print('\nCoherence Score: ', coherence_lda)
```

Figure 4.47: Compute Coherence Score for LDA Mallet Model

4.6.2 Finding the Optimal Number of Topics, *k*

The LDA model is tuned by adjusting hyperparameters of the model. LDA model hyperparameters are:

- alpha, α represents the density of document-topic
- Beta, β represents as the density of topic-word
- Number of topics, k

For this project, the tuning process only involves the adjusting of number of topics. Multiple models are built with different value of k assigned to each model. The results are observed by computing coherence score for each model. The initialization of function to compute multiple LDA Mallet is shown in *Figure 4.48* below.

```
def compute_coherence_values(dictionary, corpus, texts, limit, start=2, step=2):

    coherence_values = []
    model_list = []
    for num_topics in range(start, limit, step):
        model = gensim.models.wrappers.LdaMallet(mallet_path, corpus=corpus, num_topics=num_topics, id2word=id2word)
        model_list.append(model)
        coherencemodel = CoherenceModel(model=model, texts=texts, dictionary=dictionary, coherence='c_v')
        coherence_values.append(coherencemodel.get_coherence())

    return model_list, coherence_values
```

Figure 4.48: Function to Compute Coherence for Multiple LDA Mallet Model

The process of training and computing coherence score for multiple LDA Mallet Model is shown in *Figure 4.49* below.

```
model_list, coherence_values = compute_coherence_values(dictionary=id2word, corpus=dt_corpus, texts=data_lemmatized, start=2, limit=40, step=2)
```

Figure 4.49: Build and compute coherence score of multiple LDA Mallet model

The discussion of choosing optimal number of topics, *k* is discussed in detail in Chapter 5. The graph of model list is plotted for Coherence score 'c_v' vs number of topic, *k* for *k* is in range of $2 \leq k \leq 40$. Then, coherence score of models is listed as shown in *Figure 4.50* below.

```
# Show graph
limit=40; start=2; step=2;
x = range(start, limit, step)
plt.plot(x, coherence_values)
plt.xlabel("Num Topics")
plt.ylabel("Coherence score")
plt.legend(("coherence_values"), loc='best')
plt.show()
```

```
# Print the coherence scores
for m, cv in zip(x, coherence_values):
    print("Num Topics =", m, " has Coherence Value of", round(cv, 4))
```

Figure 4.50: Graph Plot for Coherence score vs Number of Topics

Model is tuned until reasonable performance is acquired in Model Evaluation process. The reasonable performance is discussed in detail in Chapter 5.

4.7 Conclusion

This chapter has discussed the configuration software used, along with Python packages involved. The implementation of this project was documented using Jupyter Notebook extension in *Microsoft VS Code.* The detailed explanation for steps involved in Phase 1, Phase 2, Phase 3, and Phase 4 is also included along with Figures contained of Snippet code used. The findings based on EDA, result analysis and modelling will be discussed in the next chapter.

CHAPTER 5: ANALYSIS & RESULTS DISCUSSION

In this chapter, findings based on Exploratory Data Analysis will be discussed on how the findings is related to real-world situations, while topic modelling will be discussed on how optimal number of topics, *k* is obtained. Lastly, the results of findings based on topic modelling will be discussed on how the findings fits the problem statement of project.

5.1 Findings Based on EDA

In this subsection, findings are described based on 4 types of analysis:

- Univariate Analysis

- Bivariate Analysis

- Multivariate Analysis

- Time Series Analysis

5.1.1 Univariate Analysis Findings

Univariate analysis is conducted based on how videos in the dataset is distributed respectively to view counts, like counts and dislikes count.

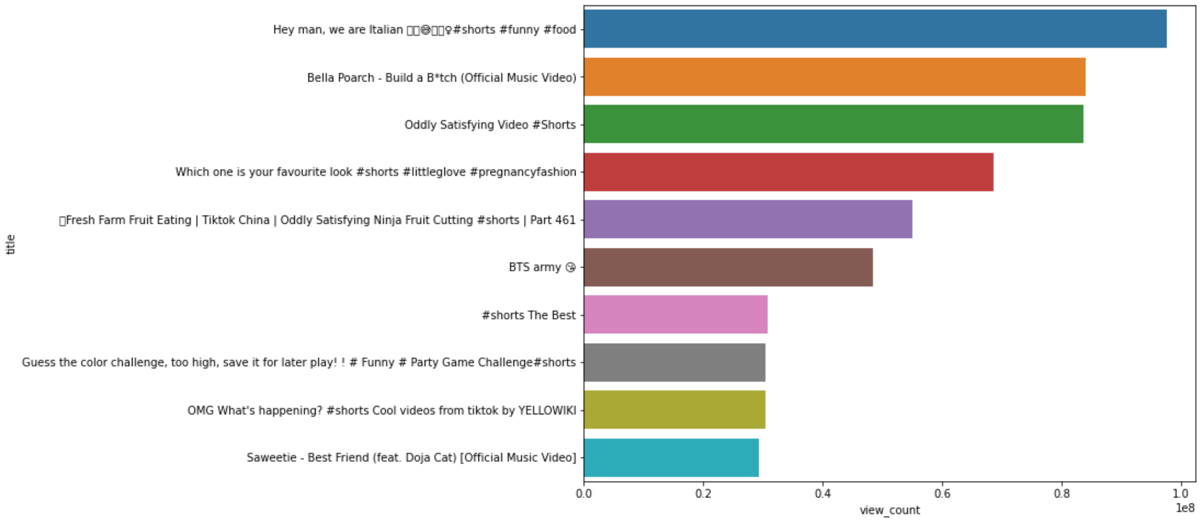

Figure 5.1: Top 10 most viewed videos in Category People and Blog

Based on *Figure 5.1* above, proves that most viewed videos from category "People and blog" have wide topics posted. Other than that, majority of the top viewed videos consist of hashtag #shorts in count of 7 out of 10 most viewed videos. Roughly, #shorts are used to indicate that the duration of video is short.

```
#shorts              697
#Shorts              121
#viral                58
#funny                47
#POV                  35
#food                 25
#4                    20
#pov                  20
#meme                 19
#trending             16
#minecraft            16
#shorts]              16
#FYP                  16
#Dpeezy2099           16
#1:                   16
#2                    13
#4!                   12
#short                12
#ad                   12
#dowehaveaproblem     11
Name: 0, dtype: int64
```

Figure 5.2: Most Frequent Hashtags used

YouTube has a new feature that enables content creators to upload their videos in a form of short videos. Based on *Figure 5.2* above, the analysis has proved that usage of the new feature is effective to attract viewers. After removing word ‘short’ along with other stop words, the WorkCloud for tags used in the videos is generated as shown in *Figure 5.3*

Figure 5.3 WorkCloud of Most Tags used

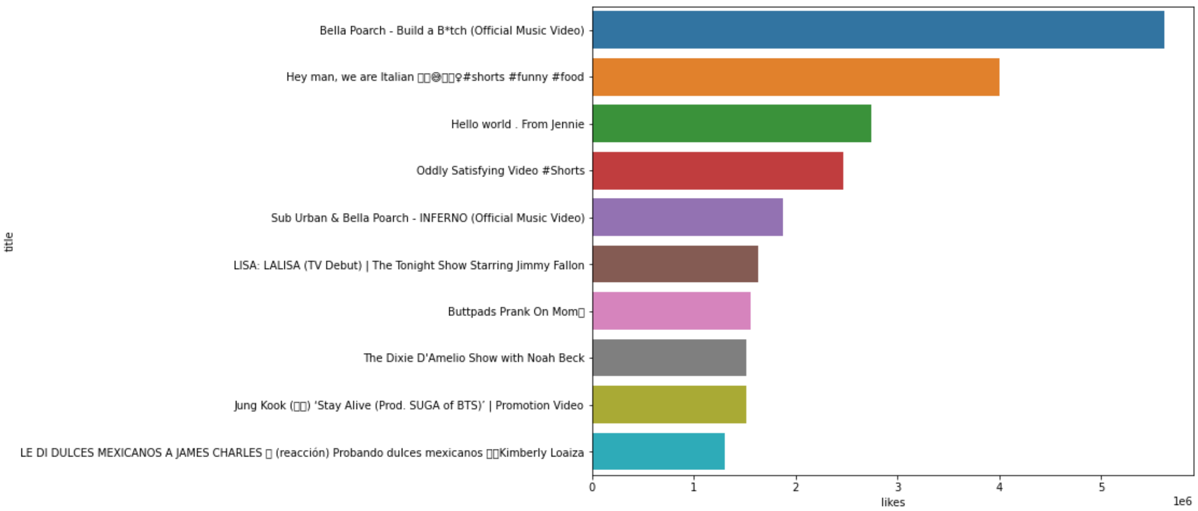

Figure 5.4: Top 10 most liked video in Category People and Blog

Based on *Figure 5.4* above, there are slight changes in order of Top 10 videos. This indicates that not every trending videos has positive feedback despite higher views.

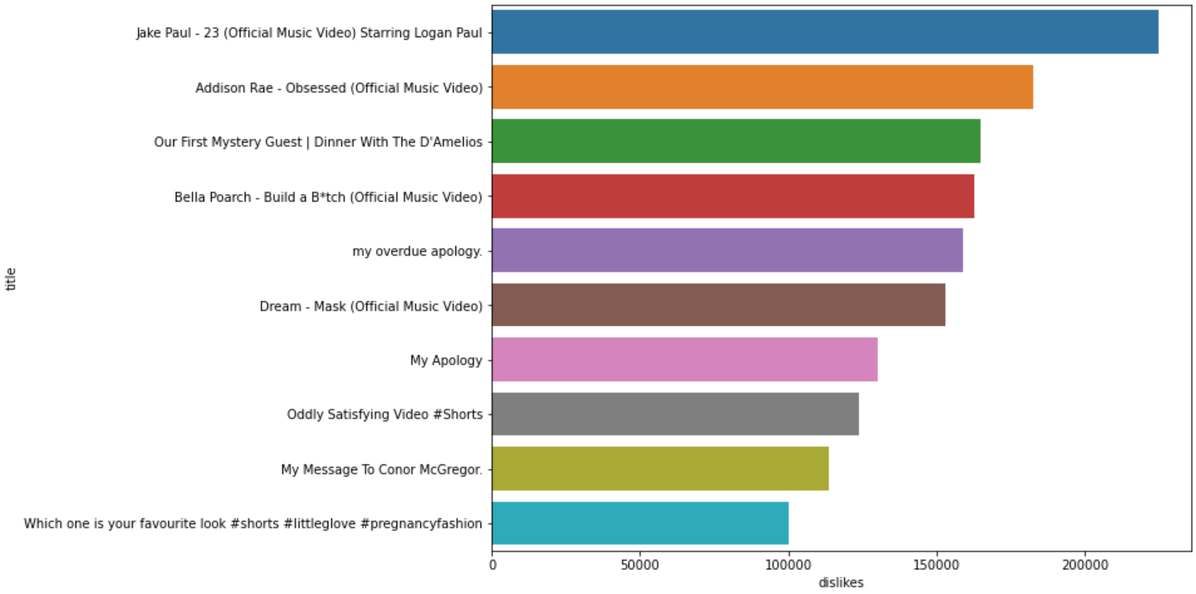

Figure 5.5: Top 10 most disliked video in Category People and Blog

Based on *Figure 5.5* above, generally videos with high views tend to have negative feedbacks too.

5.1.2 Bivariate Analysis Findings

Findings of Bivariate Analysis is conducted by bicorrelation of numeric features.

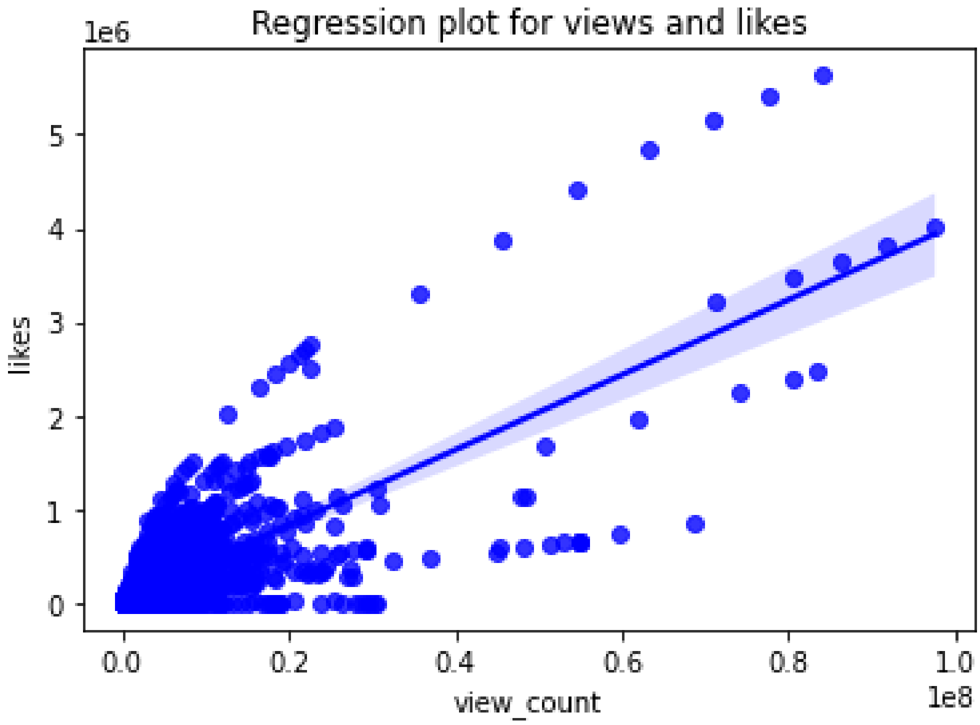

Figure 5.6: Regression plot for Views and Likes

Figure 5.6 above shows that the relationship of views and likes is linearly related. From the plot, large percentile of videos is scattered closely to the simple linear regression line while minor percentile of videos is considered outliers. However, residual value of the outliers distributed linearly too. This resulting the videos are having more than one pattern. The simple assumption can be made that likes does not always dependent to the view count. There are some possibilities taking from the scattered plot, where view counts of 2 videos are same, but one highly skewed from line of best fit likes and another one has lowly skewed from line of best fit likes.

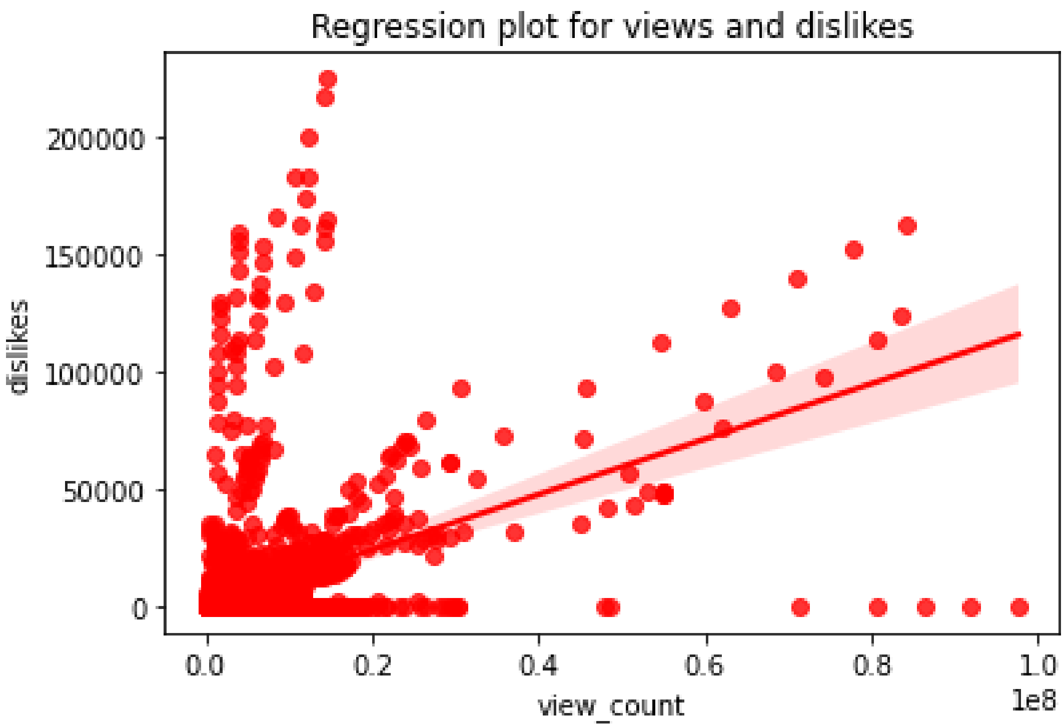

Figure 5.7: Regression Plot for views and dislikes

Figure 5.7 shows that simple linear regression line does not fit views and likes. While large percentile of videos scattered closely to the line, there are outliers that potentially show different behavioral patterns. Usual case is where the greater view counts, the greater amount of dislikes video has. However, the behavioral patterns mentioned earlier is that there are videos that despite having low views, the videos might have great number of dislikes. This can be interpreted as videos is extremely disliked by viewer, but they watch it anyway. Other behavioral pattern is there are videos that despite having high views, the videos might have lesser number of dislikes (compared to best of fit line). This can be interpreted as the videos is extremely liked by the viewers. Notes that dataset are originally extracted from only high-interacted videos where the proposition videos of low views in the statistic is assumed higher than average videos on YouTube. From assumptions made earlier, the deduction is the video does not particularly need to be likable to viewers to reach high interactions.

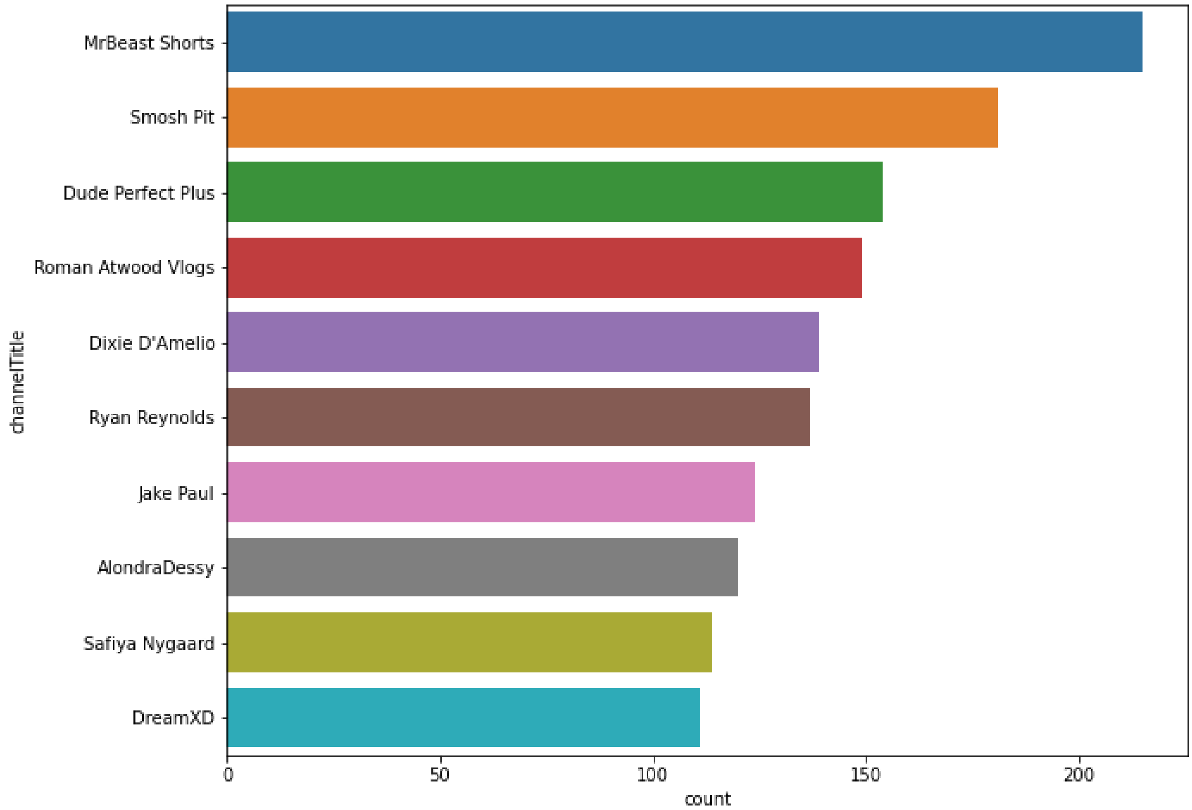

Figure 5.8: Top 10 Channels with most videos on trending

Figure 5.8 above shows that channels that has higher subscribers tends to have more their uploaded videos on trending.

5.1.3 Multivariate Analysis Findings

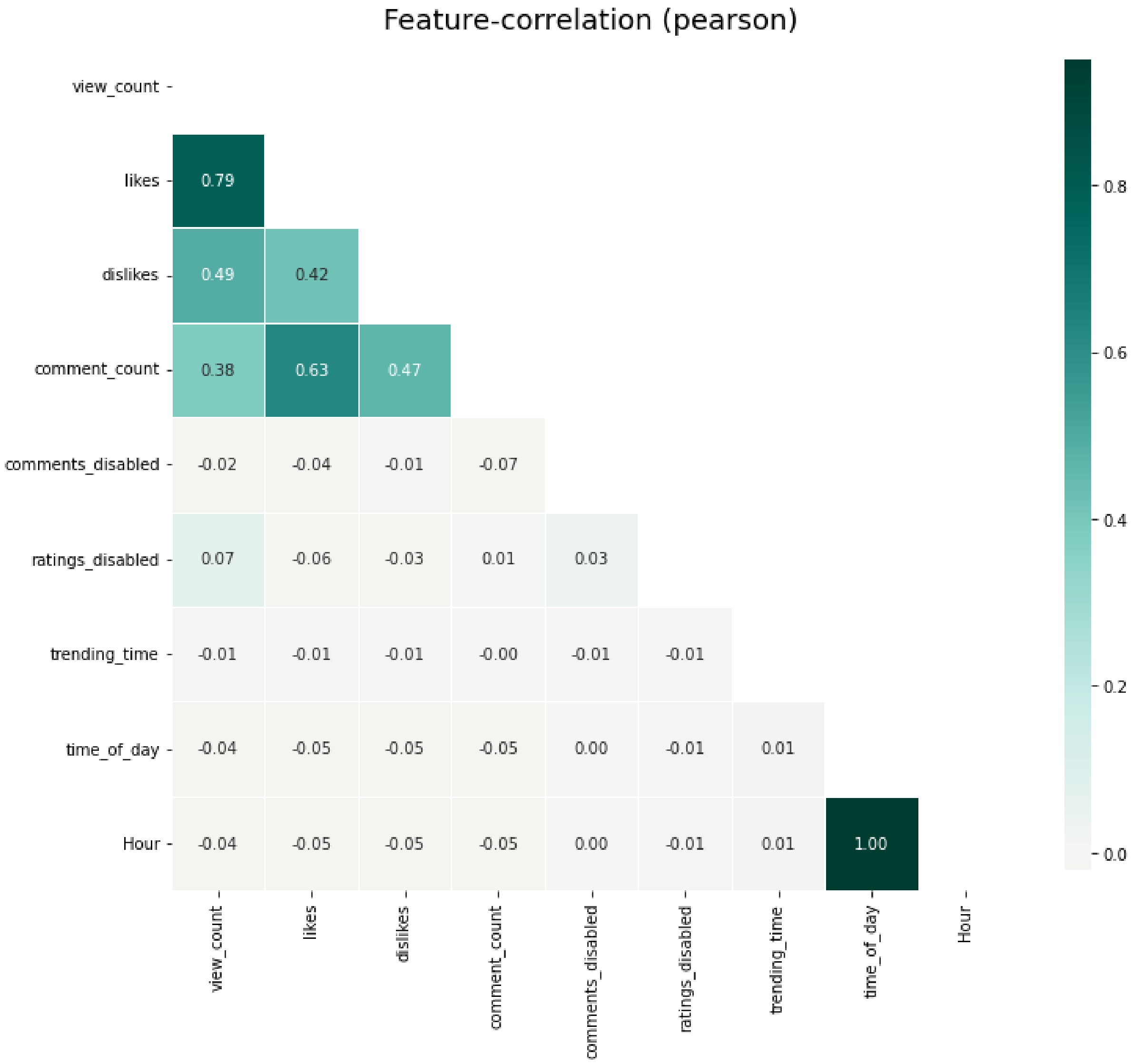

Figure 5.9: Pearson Feature Correlation Chart

Figure 5.9 shows the Pearson correlation chart for numerical features in the dataset. From the chart, some assumptions can be made. First assumption, likes is highly positive correlated to view counts with 0.79 score meanwhile dislikes is in average positively correlated to view counts. Comments counts is highly positive correlated to likes, however it has average influence on view counts and dislikes.

5.1.4 Time Series Analysis Findings

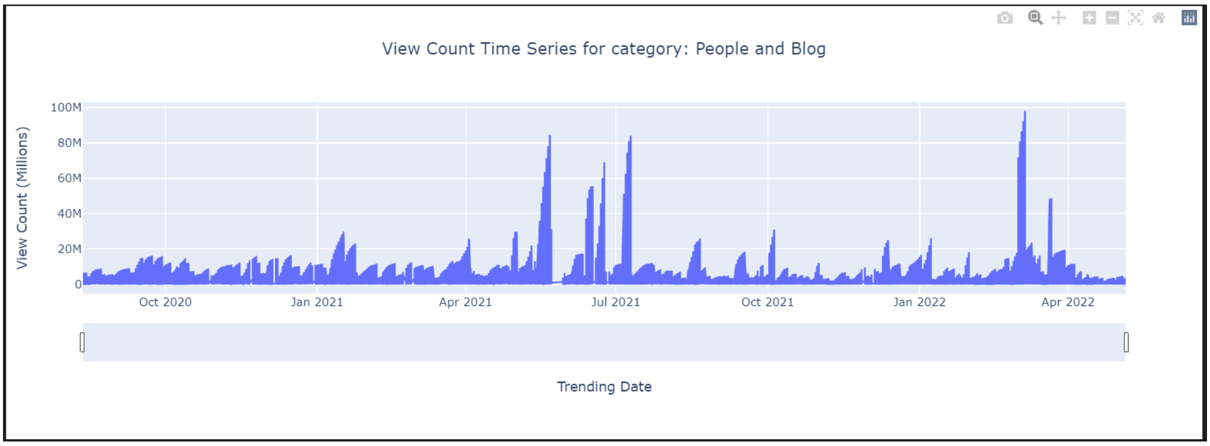

Figure 5.10: View Count Time Series for category People and Blog

Figure 5.10 shows that there are some unusual spikes of view counts over 80 million views at timeframe:

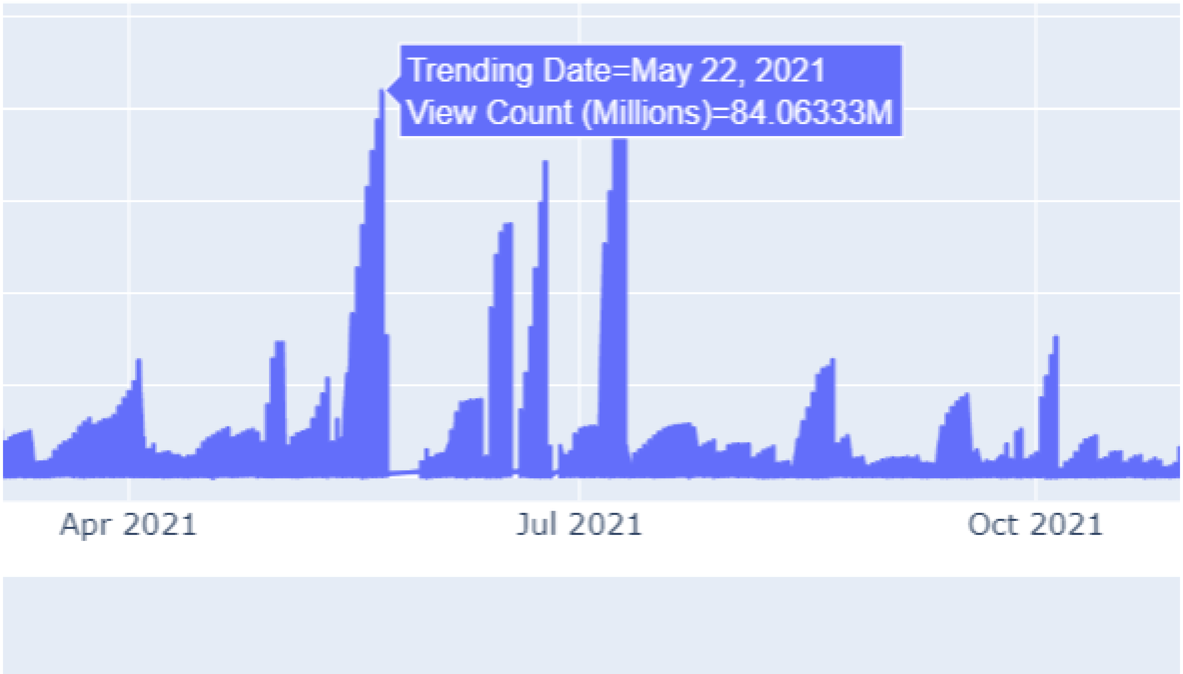

Figure 5.11: Views spike on 22 May 2021

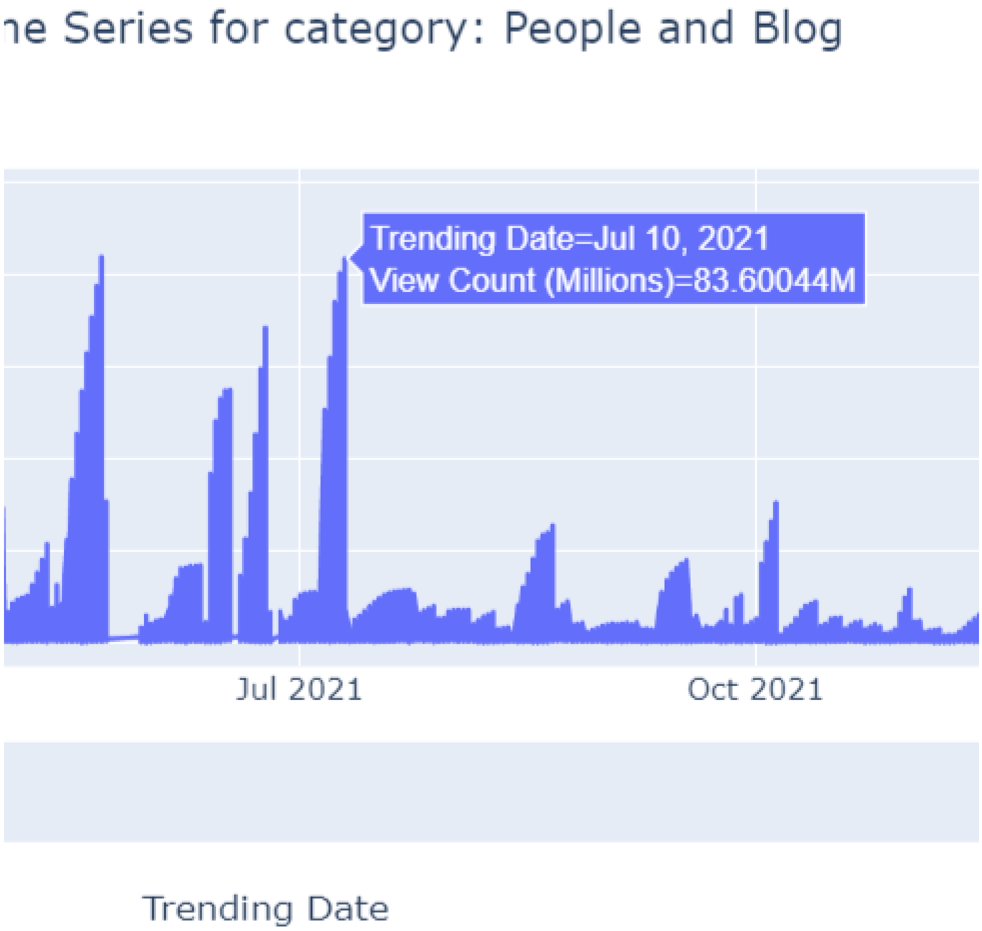

Figure 5.12: Views spike on 10 July 2021

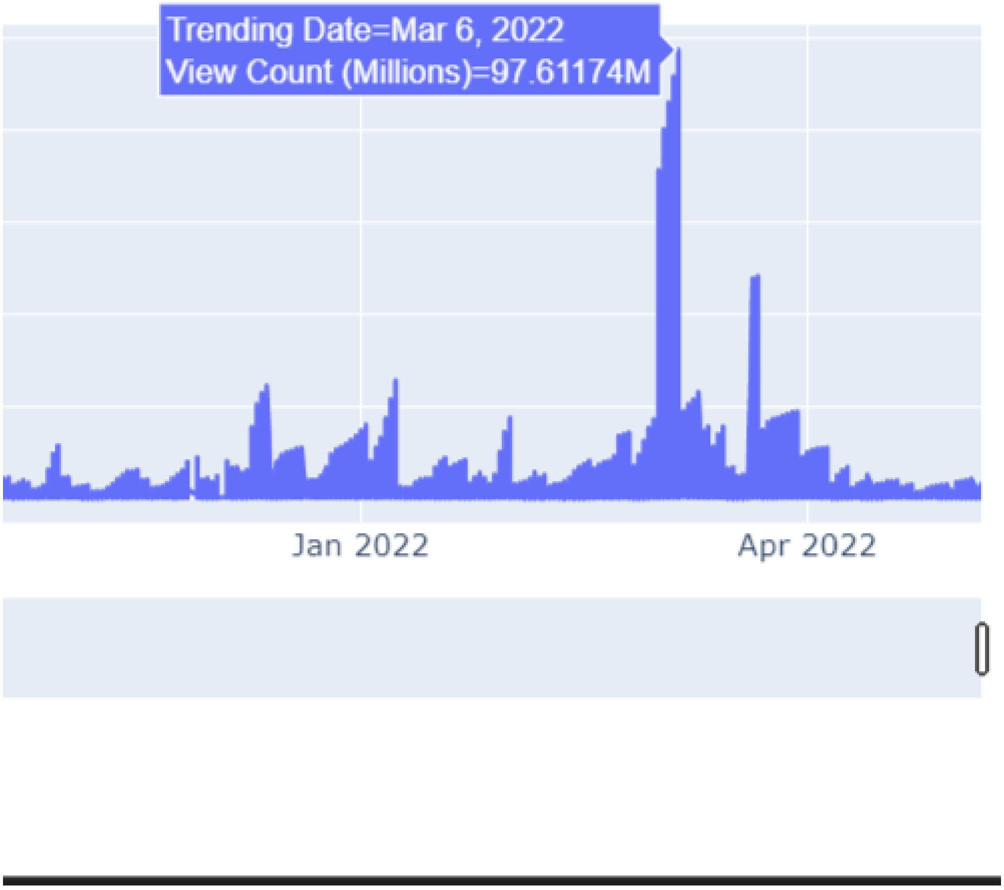

Figure 5.13:Views spike on 6March 2022

Figure 5.11, *Figure 5.12,* and *Figure 5.13* shows the exact date view count spiked on time series plot. The timeframe is:

- 16th May 2021 to 23rd May 2021
- 6th July 2021 to 10th July 2021
- 22nd March 2022 to 26th March 2022

The unusual spikes may indicate that the view counts are influenced by events on real world happened at the timeframes. WordCloud is used to illustrate what events happened on the timeframe.

Figure 5.14: WordCloud for Timeframe 16 May 2021 – 23 May 2021

Figure 5.14 above shows the WordCloud for timeframe that illustrate what videos are posted in timeframe from 16th May 2021 to 23rd May 2021. From the WordCloud, the words “Babish”, “kitchen”, and “Andrew rea” indicates that the video about cooking is trending in this timeframe. First assumption is the views are influenced by first pandemic wave that take places in the timeframe. People around the world were stuck at home and that explain why cooking videos reached high interactions at that time.

Figure 5.15: WordCloud for Timeframe 6 July 2021 to 10 July 2021

Figure 5.15 above shows the WordCloud that illustrate what videos are posted in timeframe from 6th July 2021 to 10th July 2021. Some familiar words from earlier timeframe discussed are spotted as this timeframe is not too far from first timeframe discussed earlier. Word "pasta", "Babish", "Al pesto", "chopped cheese", "luca" and "trenette" indicates that the video about cooking is trending in this timeframe. Second assumption is the views are influenced by second pandemic wave that take places in the timeframe. People around the world were stuck at home once again like first pandemic wave and that explain why cooking videos reached high interactions at that time.

Figure 5.16: WordCloud for TimeFrame 22 March 2022 until 26 March 2022

Figure 5.14 above shows the WordCloud that illustrate what videos are posted in timeframe from 22nd March 2022 to 26th March 2022. Words "Kelly Clarkson" and "Stray Kids" indicates singer. There are many assumptions can be made about why sudden spike of views based on words related to singer. For example, the singers produce new songs or reality TV shows about the singers. Words "Quitting" and "quit" may indicate many people decided to change or quit their current jobs. Word "Cardboard" may indicate the videos about manipulating cardboards are trending at the time.

From 3 generated WordCloud, the finding is real world events does impact greatly on view counts. The videos that are related to exact events of real world tends to get more interactions than videos that are not related.

5.2 Discussion of Topic Modelling

The purpose of using topic modelling is to figure out what is the topic used on trending videos in category “People and Blog”. Based on WordCloud in *Figure 5.14, Figure 5.15* and *Figure* 5.16, familiar frequent words are spotted and some of them are inter-related. For example, word “food” may consist of different topic in the video context. The example of video variation can be made is “videos about cooking food”, “videos about food reviews” or “food and hunger crisis”. Although the word “food” is used in said topic, the context of each video has a distinct values and different weightage. Topic modelling is intended to dive deep down each word in the document to predict the topic of each video.

5.3 Results and Findings Based on Topic Modelling

For base model, the number of topics is randomly assigned for k = 10 (in Python num_of_topic = 10). Result of base LDA model is shown in *Figure 5.17* below.

```
# Compute Perplexity
print('\nPerplexity: ', lda_model.log_perplexity(dt_corpus))  # a measure of how good the model is. lower the better.

# Compute Coherence Score
coherence_model_lda = CoherenceModel(model=lda_model, texts=data_lemmatized, dictionary=id2word, coherence='c_v')
coherence_lda = coherence_model_lda.get_coherence()
print('\nCoherence Score: ', coherence_lda)
```

```
Perplexity:  -8.075182183006767

Coherence Score:  0.35944259744198476
```

Figure 5.17: Perplexity and Coherence Score for base LDA model

Based on *Figure 5.17*, the perplexity and coherence score are observed. Observation is made to measure how good the LDA model is. For perplexity score, the lower the score, the higher chance that the base LDA model is good. Coherence score is used to evaluates a single topic's score by gauging the degree of semantic similarity between the topic's top-scoring words. The higher coherence score, the better chance LDA model is good.

Next, the base LDA model is compared to base LDA Mallet model that uses Gibbs Sampling method. *Figure 5.18* below shows the result of coherence score for base LDA Mallet model.

```
# Compute Coherence Score for mallet
coherence_model_lda = gensim.models.CoherenceModel(model=ldamallet, texts=data_lemmatized, dictionary=id2word, coherence='c_v')
coherence_lda = coherence_model_lda.get_coherence()
print('\nCoherence Score: ', coherence_lda)
```

```
Coherence Score:  0.365307724851063
```

Figure 5.18: Coherence score for base LDA Mallet model

Based on *Figure* 5.18, coherence score for base LDA Mallet model is slightly higher than base LDA model. Hence, LDA Mallet model is chosen to compute optimal model. Then, the next step is tuning the model by finding the optimal number of topics. This is done by computing multiple LDA Mallet models and calculate their coherence score ‘c_v’ vs number of topic, k for k is in range of $2 \leq k \leq 40$. The results are plotted in graph as shown in *Figure 5.19* below.

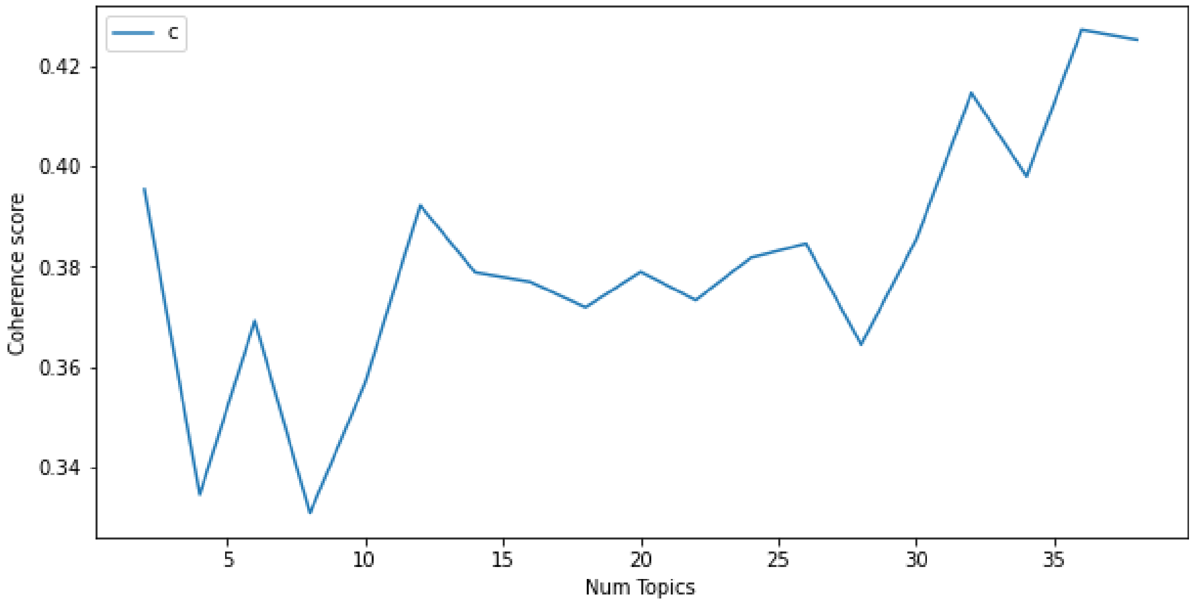

Figure 5.19: Graph Coherence Score vs Number of Topic

Based on graph in *Figure 5.19*, the optimal number of topics is chosen subjectively at the point where the coherence score is at the peak before flattening out. Hence the chosen optimal number of topics, k = 12. By choosing k = 12, the optimal LDA Mallet is then built. Next, each dominant topic is computed with weightage of the keywords as shown in *Figure 5.20* below.

```
[(0,
  [('minecraft', 0.04038652130822597),
   ('dream', 0.02985629335976214),
   ('part', 0.024405351833498512),
   ('funny', 0.02217542120911794),
   ('year', 0.01722001982160555),
   ('among_us', 0.01709613478691774),
   ('guy', 0.015237859266600595),
   ('dog', 0.014618434093161546),
   ('fashion', 0.011892963330029732),
   ('react', 0.011892963330029732)]),
 (1,
  [('story', 0.02534644083856449),
   ('getty', 0.01918749259741798),
   ('cook', 0.01587113585218524),
   ('makeup', 0.012436337794622764),
   ('cooking', 0.01172568992064432),
   ('man', 0.011251924671325358),
   ('steak', 0.010896600734336136),
   ('beauty', 0.009830628923368471),
   ('question', 0.009238422361719768),
   ('recipe', 0.007461802676773659)]),
 (2,
  [('watch', 0.047666960130801156),
...
   ('hope', 0.013437312537492502),
   ('bad', 0.01187762447510498),
   ('store', 0.011757648470305939),
   ('tik_tok', 0.011157768446310739)])]
```

Figure 5.20 Dominant Topic for Optimal Model

The dominant topics is then used to predict each video in the dataset. To evaluate performance of the optimal model, confusion matrix is calculated by feeding the dominant topic and combined text (video title, video description, and video tags) in each video into two model, Bag-of-Word model and TF-IDF model using supervised Random Forest Classification.

The classification report for Bag-of-model is shown in *Figure 5.21* below.

```
print(met.classification_report(Y_test,y_pred))
✓ 0.3s

              precision    recall  f1-score   support

           0       0.34      0.88      0.49        40
           1       0.66      0.80      0.72        50
           2       0.74      0.37      0.49        38
           3       0.57      0.77      0.66        53
           4       0.92      0.50      0.65        24
           5       0.58      0.66      0.61        29
           6       1.00      0.65      0.79        37
           7       0.96      0.57      0.72        40
           8       0.48      0.34      0.40        32
           9       0.65      0.39      0.49        28
          10       0.85      0.71      0.77        31
          11       0.87      0.45      0.59        29

    accuracy                           0.61       431
   macro avg       0.72      0.59      0.61       431
weighted avg       0.70      0.61      0.62       431
```

Figure 5.21BoW Classification Report

Based on *Figure 5.21*, the performance of BoW model is 0.62. The purpose of using BoW model is to measure how well the document classification based on frequency occurrence of each word when it is used as feature in the model classifier. While having a decent precision of model, the low recall score made F-1 score is lowered to 0.62. For TF-IDF model evaluation, the classification result is shown in *Figure 5.22* below.

```
print(met.classification_report(Y_test,y_pred))
✓ 0.6s

              precision    recall  f1-score   support

           0       0.30      0.90      0.45        40
           1       0.67      0.84      0.74        50
           2       0.61      0.37      0.46        38
           3       0.59      0.70      0.64        53
           4       0.92      0.46      0.61        24
           5       0.65      0.59      0.62        29
           6       1.00      0.62      0.77        37
           7       0.96      0.60      0.74        40
           8       0.64      0.44      0.52        32
           9       0.64      0.32      0.43        28
          10       0.96      0.74      0.84        31
          11       0.87      0.45      0.59        29

    accuracy                           0.61       431
   macro avg       0.73      0.59      0.62       431
weighted avg       0.72      0.61      0.62       431
```

Figure 5.22: Classification Report for TF-IDF model

The purpose of using TF-IDF model is to evaluate how well the document classification based on most relevance word in the document. Based on *Figure 5.22*, the performance of TF-IDF model is also 0.62. While having a decent precision of model, the low recall score made F-1 score is lowered to 0.62.

Based on two evaluation model discussed, the performance of model is assumed to be low bias but having have high variance. The model is overfit due to the fact when data pre-processing, only "English" words are selected to be fed into the model while the dataset should consist of different other languages text. In testing phase, the recall score has become low due to incapability of model to predict the text with other languages text. Hence the model only fitted for English Languages text.

5.5 Conclusion

This chapter has discussed Exploratory Data Analysis which consist of Univariate Analysis, Bivariate Analysis, Multivariate Analysis and Time Series Analysis. The analysis has covered detail reasonings of behavioral pattern for the data and relate to real world events in term of statistic. The result of analysis is visualized, and observation is explained. Other than that, the modelling process and results is discussed. Results and model performance is evaluated and compared in term of precision, recall, F-1 score and supports.

Chapter 6: Conclusion & Future Works

In this chapter, objective achievements of the whole project, contributions, and limitations of implementation of the project are outlined. The potential of future works for future project are also discussed in this chapter to further enhance the research quality.

6.1 Project Achievement & Contributions

The purpose of this project to discover how videos in the category of "People and Blogs" reached a high interaction. By the end of the project, three proposed objectives have been achieved as contributions of the project also been stated as follows:

Objective 1: To analyze the patterns of high-interaction videos in YouTube using Exploratory Data Analysis and Unsupervised Learning to build machine learning algorithms that determine the topic consisted in the video.

Objective 2: To discover optimal settings needed on the posted videos in order to achieve high interactions.

Objective 3: To help the small content creators gain insights from other successful content creators on how to grow more audience.

Exploratory Data Analysis done has shown several findings. Firstly, the usage of the new feature is effective to attract viewers. Secondly, likes do not always dependent to the view count and the deduction is the video does not particularly need to be likable to viewers to reach high interactions. There are some possibilities taking from the analysis where exceptional videos are made without having many likes. Next, the finding is real world events does impact greatly on view counts. The videos that are related to exact events of real world tends to get more interactions than videos that are not related. Using unsupervised machine learning, the main topic of trending video is discovered. Content creators might use the main topic produced as a guideline to generate title, description, and tags for their video as it was used by other successful content creators to make their video appearance stands out.

6.2 Limitations

- *Lack of computational power*

One of the limitations would be lack of computational power to train multiple LDA model. Training unsupervised Natural Language Processing learning takes a lot of resource to compute. This makes model tuning process is time consuming and cannot fully tune every hyperparameters as it will take more RAM and CPU power.

- *Lack of other language resources*

Lastly, even though the dataset is observed for trending video in United States, the dataset consists of videos from other regions that successful globally. The text cleaning process relies heavily in Natural Language Processing for English. The videos cannot be treated as outliers as the number of videos from other regions is impactful in other analysis except text columns. Removing other language beside English has proven lower recall score in cross validating process.

6.3 Future Works

As this project ended, there are future works that can be addressed as follows:

- Wider category exploration for YouTube videos
- Variance of global NLP package to use for topic modelling
- Better computational power to sustain more NLP based machine learning models

6.4 Conclusion

By the end the project, three objectives have been achieved, which patterns of high-interaction videos in YouTube is discovered using EDA and topic modelling. Second objective, optimal settings needed on the posted videos in order to achieve high interaction has been achieved by using the main topic produced by topic model. Lastly, small content creators gain insights from other successful content creators on how to grow more audience by implementing the discussion and findings made in this project.

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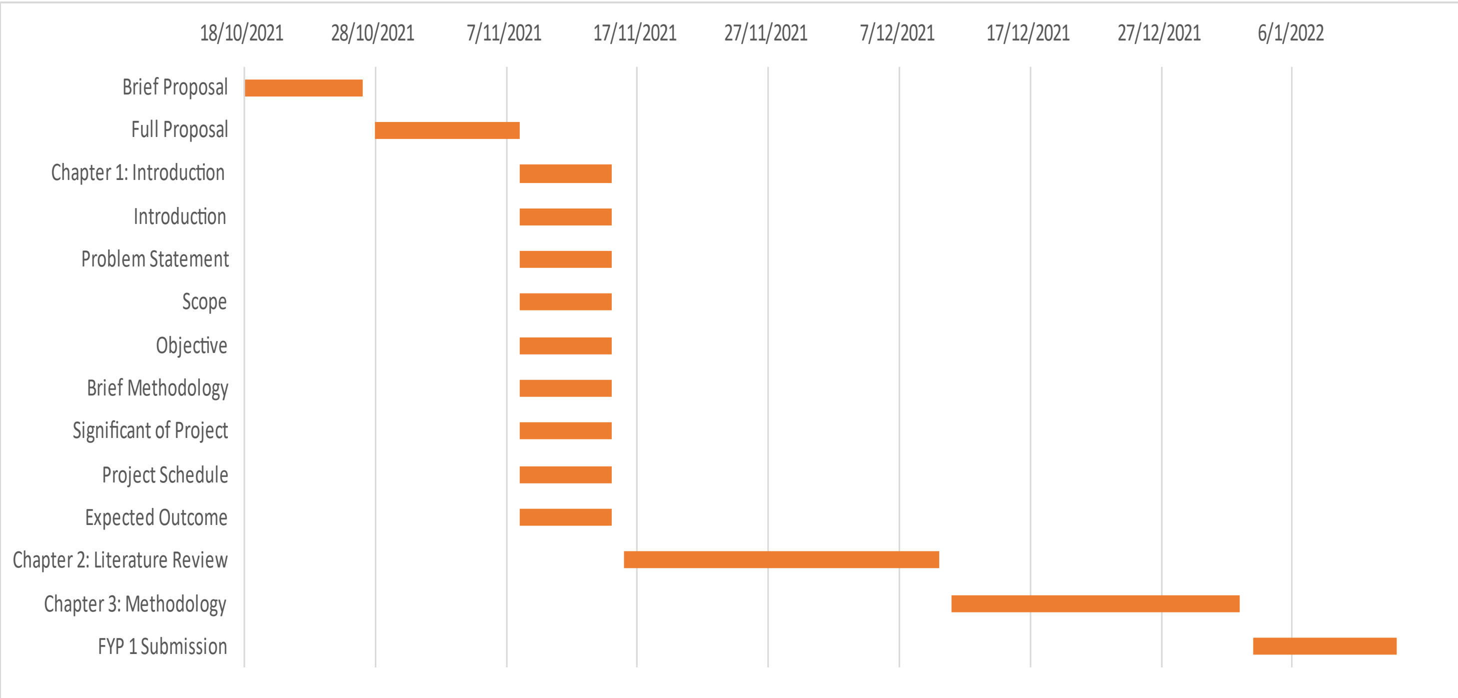
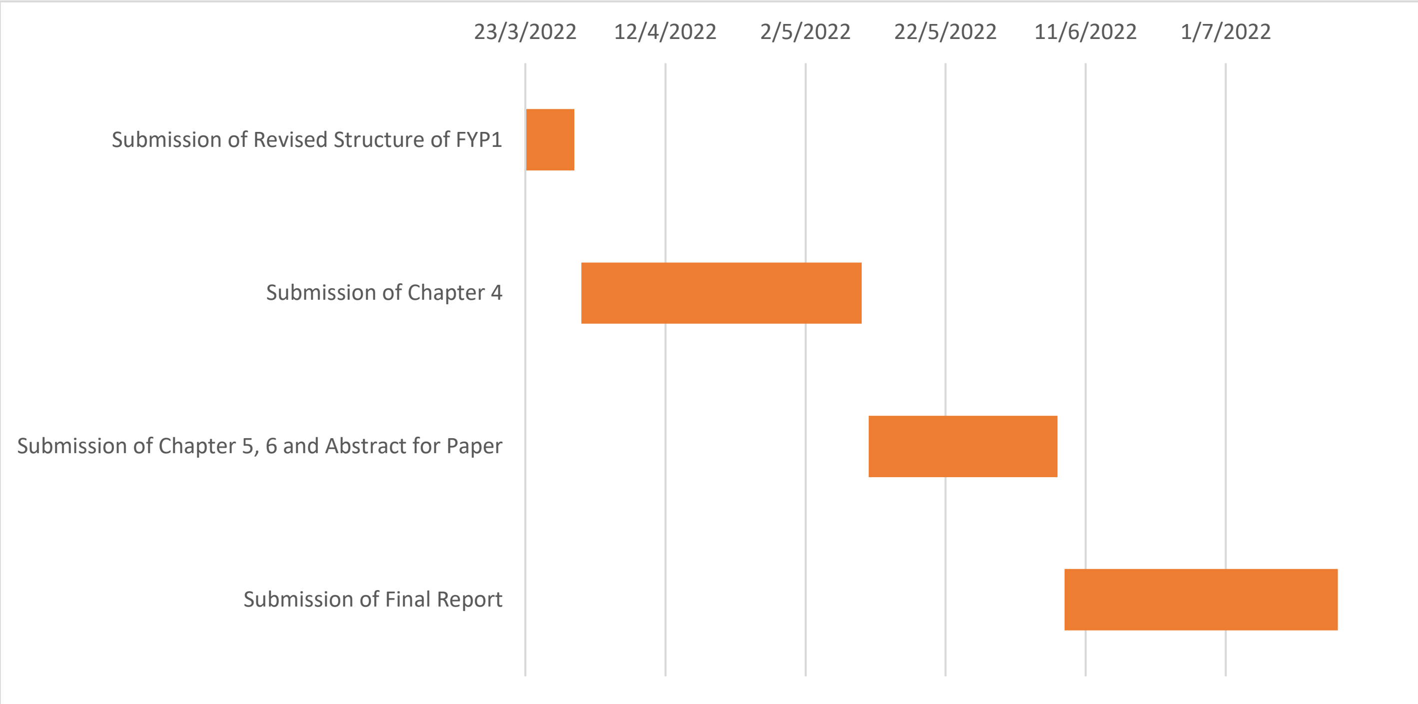
APPENDIX A

FYP 1 Project Schedule



APPENDIX B

FYP 2 Project Schedule



APPENDIX C

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