SINGAPORE UNIVERSITY OF SOCIAL SCIENCES

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[APPLICATION OF TEXT MINING ON MARKET INTELLIGENCE]

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1. Introduction

Text mining refers to "the discovery by computer of new, previously unknown information, by automatically extracting information from different written resources" (Hearst, 2003). Some examples of text data include documents, product reviews and social media captions and posts. With the rise of social media and people posting their thoughts online freely, social media platforms are a valuable source of information for companies in terms of gathering customer feedback on their products and identifying customers' pain points to improve future releases.

Furthermore, the ability to gather data from such sources also allows companies to conduct market intelligence, which is the gathering of data to get "a picture of the company's existing market, customers, problems, competition, and growth potential for new products and services" (Arline, 2019). For example, sentiment analysis on tweets regarding a product can give a company an indication of customer satisfaction on top of any reviews posted on its website. In fact, a company that proactively gathers and analyses customers' opinions even before they feedback to the company will have a competitive edge over competitors, as it is able to identify areas of growth and pain points at a faster rate (Li & Li, 2013).

However, gathering market intelligence does not come without its challenges. Given the unstructured nature of the data, a lot of work is usually required before the data can be mined and put to use. For instance, there may not always be an application programming interface (API) available for easy access to the text data, especially for data that is outside of the company. As such, web scraping will be required to scrape the target webpage. One method to do so would be to use the *BeautifulSoup* library available in Python.

Despite the challenges of text mining, it is still becoming more prevalent as companies see the benefits of investing resources into the progress to harness the data available outside their databases. With more information of the market environment, companies will be in a better position to implement campaigns and improve their products to better suit their target customers' needs. In this report, the company in focus will be Grab Singapore and its ride-hailing service, and the report will be focusing on the integration of sentiment analysis on its customer reviews gathered from its Facebook page in predicting customer churn.

2. Literature Review

De Caigny, Coussement, De Bock, and Lessmann (2020) conducted a study to use information from text data to predict customer churn for a financial services provider. The text data used was electronic conversations between customers and employees, and a convolutional neural network (CNN) was trained to extract features from the messages. The authors used three general layers for the CNN – the embedding layer for pre-processing and embedding, the convolutional layer for feature extraction, and the fully connected layer for prediction of features. There could be more than one convolutional and fully connected layer in the model. The features extracted were then added to the logistic regression model to predict customer churn. Based on the study, the best model was the logistic regression model with feature extraction of text data using a CNN, which improved the model accuracy by approximately three percentage points (De Caigny et al., 2020). This study illustrates the usefulness of investing additional resources to mine relevant text data to integrate to an existing predictive model that only had structured data. The more accurate the churn prediction model is, the more likely customer retention campaigns will be well-targeted and effective, thus leading to better business performance for the company.

Ranjan, Sood, and Verma (2018) used the sentiment of tweets containing the Twitter handles for Indian telecommunications companies to predict the rate at which the companies' number of subscribers grew. The tweets were gathered with Twitter's API on a daily basis over a period of four months. Although the paper did not go into detail about the methods used to predict the growth rate, the findings found that there was positive correlation between having a general positive sentiment and subscriber growth rate (Ranjan et al., 2018). Hence, this study shows that the sentiment of customer reviews can be a relevant factor in predicting customer satisfaction and customer churn.

Li and Li (2013) utilised opinion mining on microblog posts to classify customer sentiments on Google, Microsoft, Sony and Apple products. Microblogs are essentially mini blogposts, and an example of a microblog platform is Twitter, where every post is limited to 280 characters. In the study, the authors carried out supervised classification on the individual post's sentiment using the support vector machine (SVM) classifier and evaluated the credibility and subjectivity of the post. This evaluation was done by comparing the user's follower and following count. A user with a higher follower count than following count is deemed more credible than one with a higher following count than follower count. Hence, this study shows that apart from scraping the contents of online posts, more data on the author should also be gathered to evaluate the credibility, and individual posts can be assigned a credibility score and weighed differently in evaluating the company's position in the market.

From the literature review, it showed the effectiveness of extracting features and sentiments from text data and, after converting the information to structured data, using them as additional inputs in existing models to improve their performance. In this report, the sentiment analysis will be unsupervised, and hence it will be implemented using the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool, which is an open-sourced tool trained for social media text (Hutto & Gilbert, 2014). Additionally, on top of logistic regression, more methods of predicting customer churn were tested – multinomial Naïve Bayes, multi-layer Perceptron classifier, and an Artificial Neural Network (ANN) model trained using Keras.

3. Data Mining Process

The data mining process carried out in this report will be explained using the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework. It consists of the following phases – 1) business understanding, 2) data understanding, 3) data preparation, 4) modelling, 5) evaluation, and 6) deployment.

3.1 Business Understanding

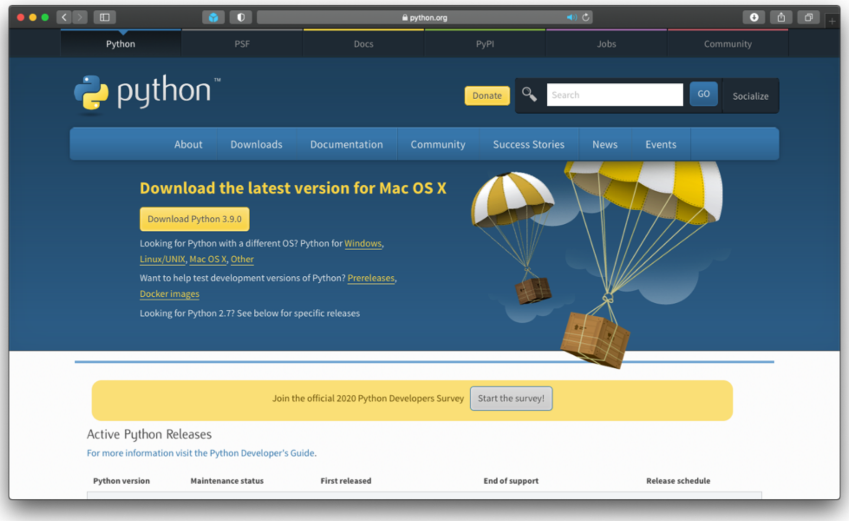
The first phase of CRISP-DM is business understanding. This phase consists of determining the business goals and objectives of the project, expressing these goals as a clear data mining problem, and outlining a plan to achieve the data mining objectives.

A business problem that Grab is facing is the increase in competition in the ride-hailing market. Since its merger with Uber in 2018, there have been new players in the ride-sharing market, from small players such as Ryde and larger, more established companies such as Gojek. Even taxi company ComfortDelGro has also recently launched its own ride-hailing app for its taxies. In 2020, the Land Transport Authority (LTA) awarded Grab, Gojek, ComfortDelGro and Tada Mobility full ride-hailing licenses to operate in Singapore (Ong, 2020). As such, consumers have more choices when it comes to which platform to use for ride-hailing. Hence, a business goal that Grab may have would be to increase customer retention by 10%.

One approach to achieve this business goal would be to predict the likelihood of a customer switching to another ride-hailing platform for his or her next ride based on factors such as gender, age, whether the customer is a subscriber of Grab's Daily Value Plan, et cetera. Hence, the data mining goal for this project is to use selected attributes of customer demographics, customers' usage of the platform and the sentiment of customer reviews to predict the likelihood of customers taking another ride with Grab in the next 30 days.

For this project, the Python programming language will be used, and the code will be executed in a Jupyter Notebook. To begin, the latest Python release will need to be downloaded.

Step 1: Download the appropriate latest Python release for the system at the following link: https://www.python.org/downloads/



Download the latest version for Mac OS X

Looking for Python with a different OS? Python for Windows, Linux/UNIX, Mac OS X, Other

Want to help test development versions of Python? Prereleases, Docker images

Looking for Python 2.7? See below for specific releases

Join the official 2020 Python Developers Survey

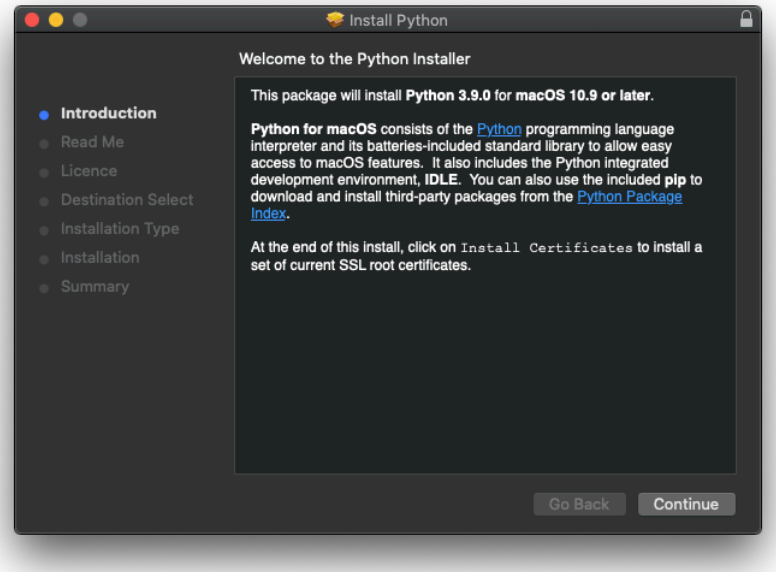
Active Python Releases

For more information visit the Python Developer's Guide.

Python version	Maintenance status	First released	End of support	Release schedule

Fig 1.1: Python website to download latest release

Step 2: Go through the instructions in the installer to install Python.



Welcome to the Python Installer

This package will install **Python 3.9.0** for **macOS 10.9 or later**.

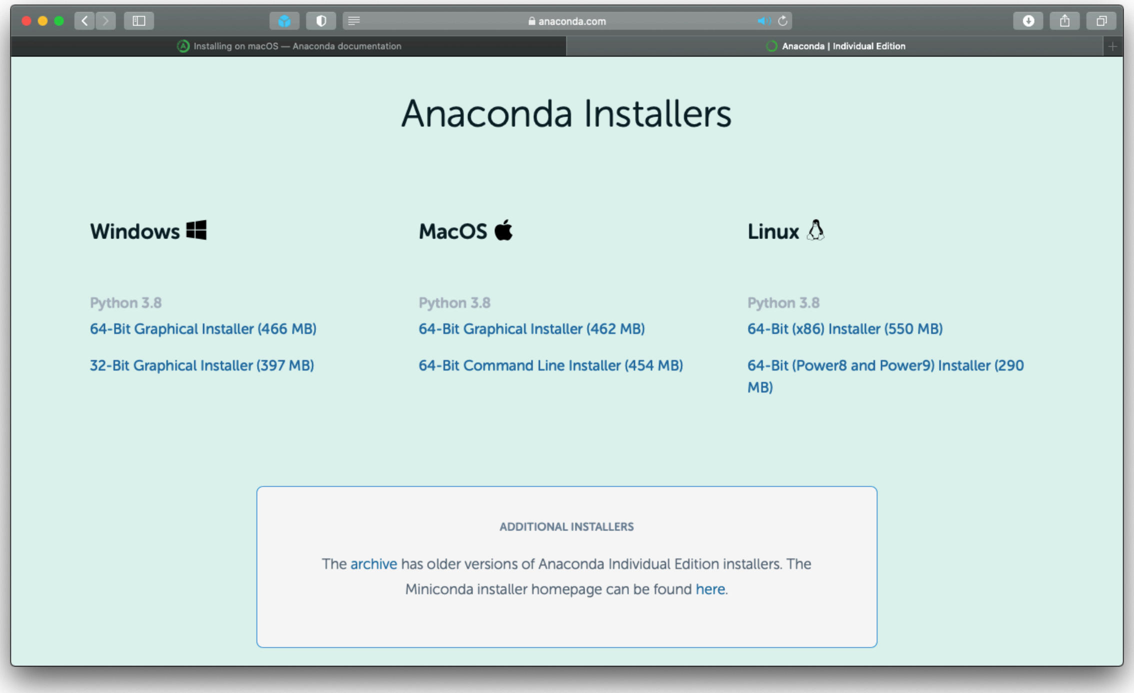
Python for macOS consists of the Python programming language interpreter and its batteries-included standard library to allow easy access to macOS features. It also includes the Python integrated development environment, **IDLE**. You can also use the included **pip** to download and install third-party packages from the Python Package Index.

At the end of this install, click on `Install Certificates` to install a set of current SSL root certificates.

Fig. 1.2: Installer for Python

After Python is installed, the next software to be installed is Anaconda to access Jupyter Notebooks.

Step 1: Download the appropriate 64-bit Graphical Installer for the system at the following link: https://www.anaconda.com/products/individual


anaconda.com
Installing on macOS — Anaconda documentation
Anaconda | Individual Edition

Anaconda Installers

Windows

Python 3.8
64-Bit Graphical Installer (466 MB)
32-Bit Graphical Installer (397 MB)

MacOS

Python 3.8
64-Bit Graphical Installer (462 MB)
64-Bit Command Line Installer (454 MB)

Linux

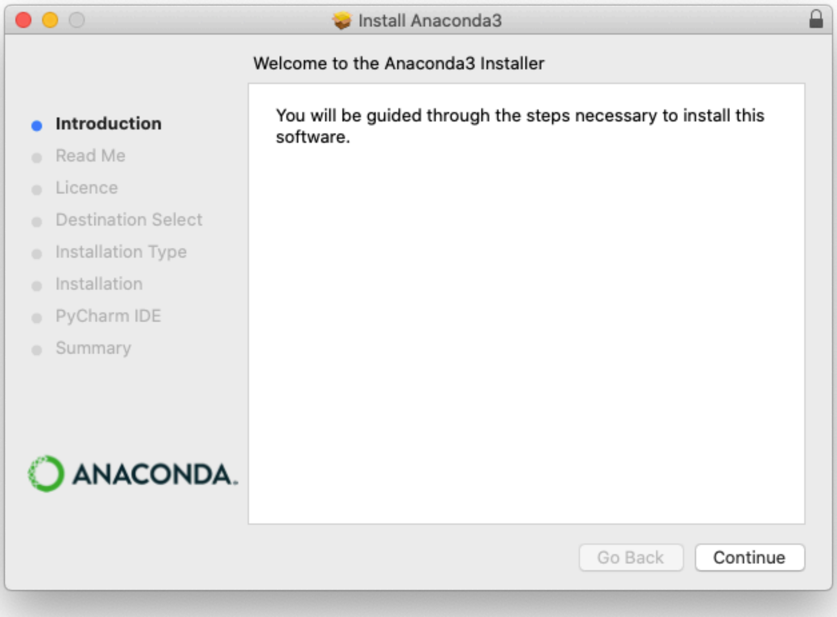
Python 3.8
64-Bit (x86) Installer (550 MB)
64-Bit (Power8 and Power9) Installer (290 MB)

ADDITIONAL INSTALLERS

The archive has older versions of Anaconda Individual Edition installers. The Miniconda installer homepage can be found here.

Fig. 1.3: Anaconda website to download the installer

Step 2: Go through the instructions in the installer to install Python.

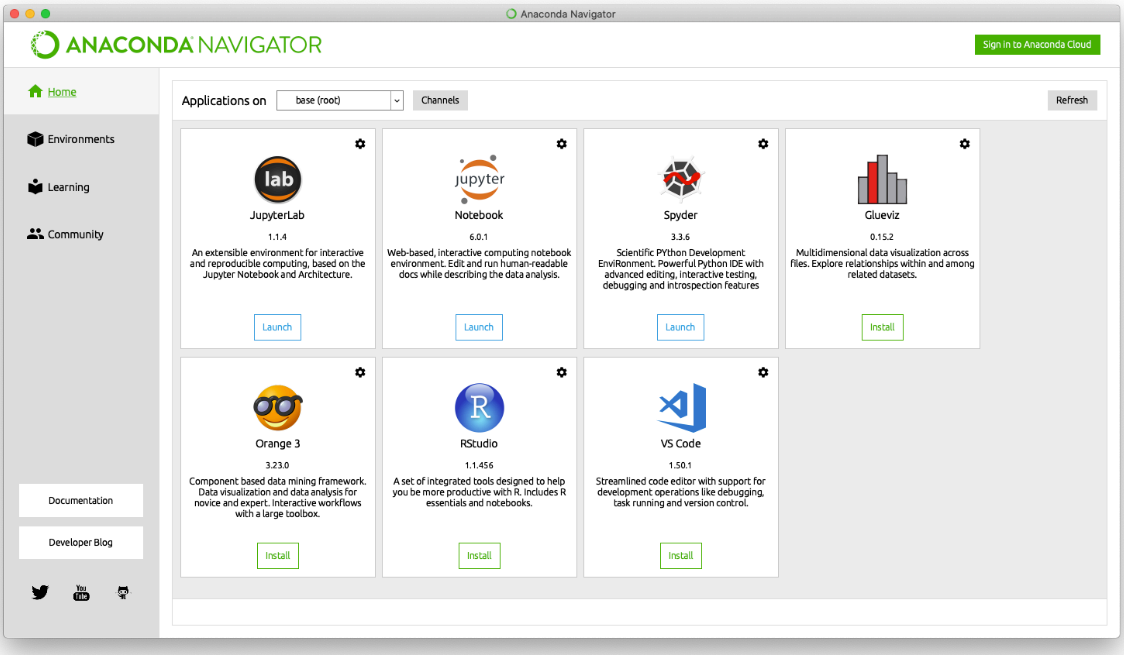


Welcome to the Anaconda3 Installer

You will be guided through the steps necessary to install this software.

Fig. 1.4: Installer for Anaconda

Step 3: Launch the Anaconda Navigator to launch Jupyter Notebook.



JupyterLab
1.1.4
An extensible environment for interactive and reproducible computing, based on the Jupyter Notebook and Architecture.

Notebook
6.0.1
Web-based, interactive computing notebook environment. Edit and run human-readable docs while describing the data analysis.

Spyder
3.3.6
Scientific PYthon Development EnviRonment. Powerful Python IDE with advanced editing, interactive testing, debugging and introspection features

Glueviz
0.15.2
Multidimensional data visualization across files. Explore relationships within and among related datasets.

Orange 3
3.23.0
Component based data mining framework. Data visualization and data analysis for novice and expert. Interactive workflows with a large toolbox.

RStudio
1.1.456
A set of integrated tools designed to help you be more productive with R. Includes R essentials and notebooks.

VS Code
1.50.1
Streamlined code editor with support for development operations like debugging, task running and version control.

Fig. 1.5: Anaconda Navigator to access Jupyter Notebook

3.2 Data Understanding

The second phase in the CRISP-DM framework is data understanding. This phase is where the data required for the model is collected, and exploratory data analysis is conducted on the collected data to understand it and evaluate the data quality, such as if there are any null or duplicate entries.

3.2.1 Data Collection

For the purposes of this project, a mock-up dataset was created from 4 sources – selected attributes from the Airline Passenger Satisfaction (Klein, 2020) and Customer Churn (Kumar, 2020) datasets on Kaggle, customer reviews posted on Grab Singapore's Facebook page obtained by web scraping, and randomised integer values generated by *numpy* in Python. The attributes in the final dataset are summarised as follows:

Attribute	Measurement	Description
Gender	Categorical	Gender of customer (Male or Female)
Age	Continuous	Age of customer
AccountWeeks	Continuous	Number of weeks that the customer has had an active account
Subscription	Flag	Whether the customer subscribed to the Daily Value Plan (Yes or No)
Reviews	Text	Text of customer review
AvgRides	Continuous	Average number of rides the customer takes per month (over 12-month period or since account opening, whichever is smaller)
AvgSpend	Continuous	Average amount (in SGD) the customer spends on Grab rides per month (over 12-month period or since account opening, whichever is smaller)
LastRating	Categorical	Rating given for the last ride (1, 2, 3, 4, or 5)
Churn	Flag	Whether the customer will book a Grab ride in the next 30 days

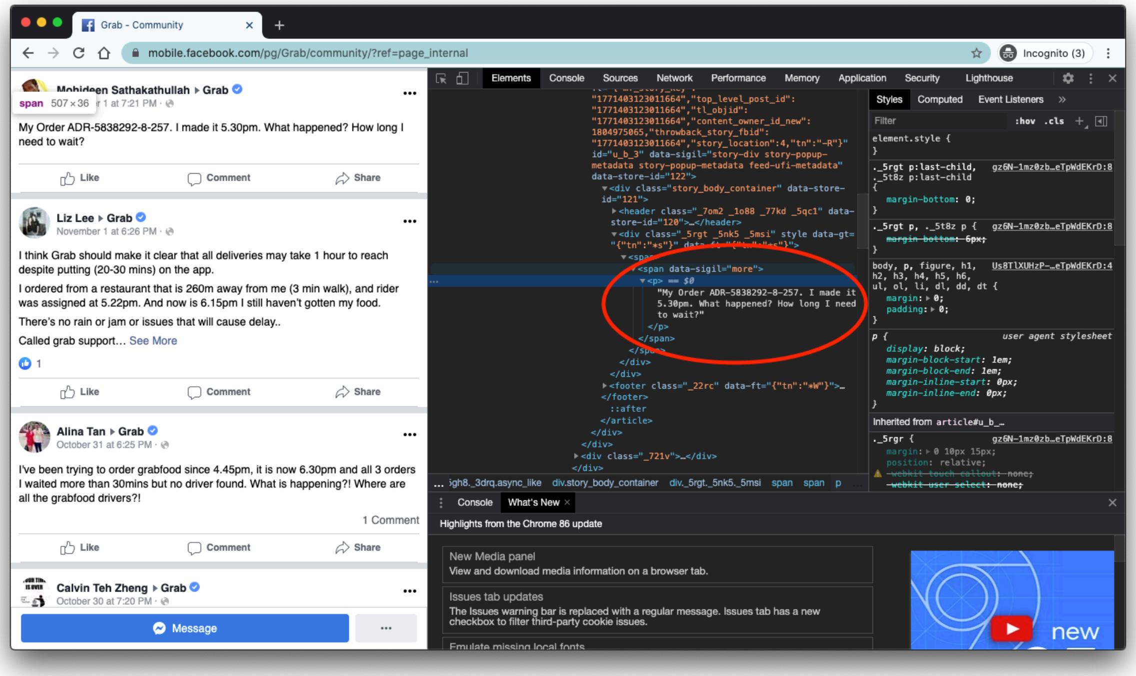
Table 1: Attributes of dataset

The steps to collect all the relevant data are as follows:

Step 1: Scrape Grab Singapore's Facebook page

Firstly, to scrape Grab Singapore's Facebook page for the customer reviews, the *selenium* and *BeautifulSoup* packages in Python were used. Although Facebook's Graph API can scrape Facebook pages, this function is now only available to the administrators of the page. As such, for this report, the scraping of the Facebook page had to be done relatively more manually.

One limitation of *BeautifulSoup* is that it can only scrape static webpages. However, for the Facebook page, to view past reviews, the page needs to be scrolled. Hence, the *selenium* package was used to control the browser and automate the scrolling.



Mohideen Sathakathullah ▸ Grab
…r 1 at 7:21 PM

My Order ADR-5838292-8-257. I made it 5.30pm. What happened? How long I need to wait?

Like Comment Share

Liz Lee ▸ Grab
November 1 at 6:26 PM

I think Grab should make it clear that all deliveries may take 1 hour to reach despite putting (20-30 mins) on the app.

I ordered from a restaurant that is 260m away from me (3 min walk), and rider was assigned at 5.22pm. And now is 6.15pm I still haven't gotten my food.

There's no rain or jam or issues that will cause delay..

Called grab support… See More

1

Like Comment Share

Alina Tan ▸ Grab
October 31 at 6:25 PM

I've been trying to order grabfood since 4.45pm, it is now 6.30pm and all 3 orders I waited more than 30mins but no driver found. What is happening?! Where are all the grabfood drivers?!

1 Comment

Like Comment Share

Calvin Teh Zheng ▸ Grab
October 30 at 7:20 PM

Message

```
"1771403123011664","top_level_post_id":
"1771403123011664","tl_objid":
"1771403123011664","content_owner_id_new":
1804975065,"throwback_story_fbid":
"1771403123011664","story_location":4,"tn":"-R"}"
id="u_b_3" data-sigil="story-div story-popup-
metadata story-popup-metadata feed-ufi-metadata"
data-store-id="122">
  ▼<div class="story_body_container" data-store-
  id="121">
    ▶<header class="_7om2 _1o88 _77kd _5qc1" data-
    store-id="120">…</header>
    ▼<div class="_5rgt _5nk5 _5msi" style data-gt=
    "{"tn":"*s"}" data-ft="{"tn":"*s"}">
      ▼<span>
        ▼<span data-sigil="more">
          ▼<p> == $0
              "My Order ADR-5838292-8-257. I made it
              5.30pm. What happened? How long I need
              to wait?"
            </p>
          </span>
        </span>
      </div>
    </div>
  ▶<footer class="_22rc" data-ft="{"tn":"*W"}">…
  </footer>
    ::after
  </article>
</div>
</div>
▶<div class="_721v">…</div>
</div>
```

… ̧gh8._3drq.async_like div.story_body_container div._5rgt._5nk5._5msi span span p

Console What's New

Highlights from the Chrome 86 update

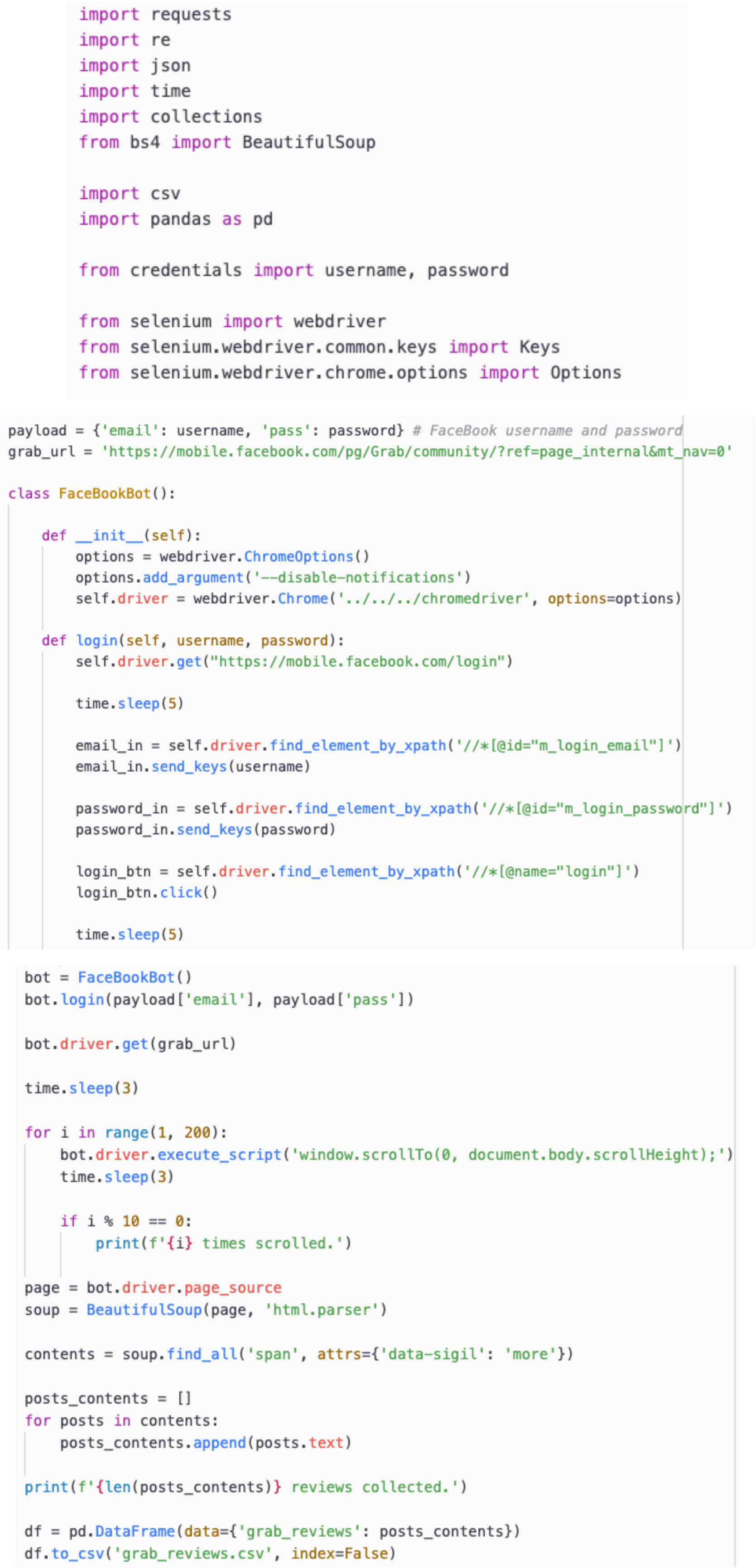
New Media panel
View and download media information on a browser tab.

Issues tab updates
The Issues warning bar is replaced with a regular message. Issues tab has a new checkbox to filter third-party cookie issues.

Emulate missing local fonts

Fig. 2.1: Inspecting the elements of the Facebook page with Google Chrome

In general, for web scraping, the mobile version of websites are easier to scrape, as the websites are made more simply with less JavaScript. Hence, the mobile version of Grab Singapore's Facebook page was scraped for this report. After inspecting the elements of the page with Google Chrome, it can be seen in the above figure that the text are under the tag '<span>' with the attribute 'data-sigil="more"'. This information was then used to scrape the page for the text reviews as follows:



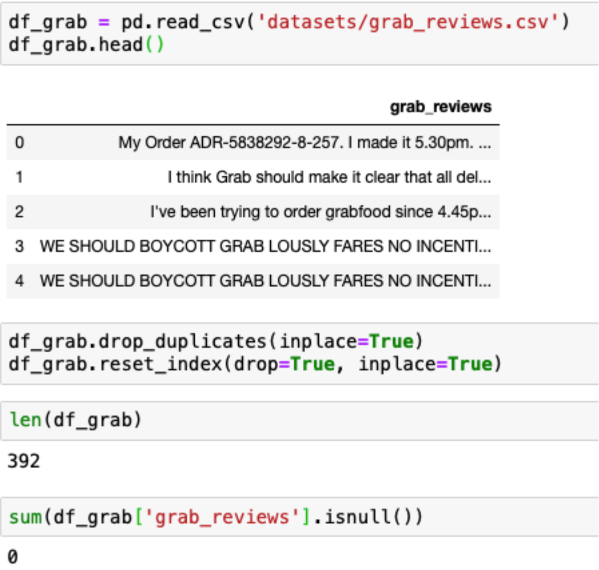
```python
import requests
import re
import json
import time
import collections
from bs4 import BeautifulSoup

import csv
import pandas as pd

from credentials import username, password

from selenium import webdriver
from selenium.webdriver.common.keys import Keys
from selenium.webdriver.chrome.options import Options
```

```python
payload = {'email': username, 'pass': password} # FaceBook username and password
grab_url = 'https://mobile.facebook.com/pg/Grab/community/?ref=page_internal&mt_nav=0'

class FaceBookBot():

    def __init__(self):
        options = webdriver.ChromeOptions()
        options.add_argument('--disable-notifications')
        self.driver = webdriver.Chrome('../../../chromedriver', options=options)

    def login(self, username, password):
        self.driver.get("https://mobile.facebook.com/login")

        time.sleep(5)

        email_in = self.driver.find_element_by_xpath('//*[@id="m_login_email"]')
        email_in.send_keys(username)

        password_in = self.driver.find_element_by_xpath('//*[@id="m_login_password"]')
        password_in.send_keys(password)

        login_btn = self.driver.find_element_by_xpath('//*[@name="login"]')
        login_btn.click()

        time.sleep(5)
```

```python
bot = FaceBookBot()
bot.login(payload['email'], payload['pass'])

bot.driver.get(grab_url)

time.sleep(3)

for i in range(1, 200):
    bot.driver.execute_script('window.scrollTo(0, document.body.scrollHeight);')
    time.sleep(3)

    if i % 10 == 0:
        print(f'{i} times scrolled.')

page = bot.driver.page_source
soup = BeautifulSoup(page, 'html.parser')

contents = soup.find_all('span', attrs={'data-sigil': 'more'})

posts_contents = []
for posts in contents:
    posts_contents.append(posts.text)

print(f'{len(posts_contents)} reviews collected.')

df = pd.DataFrame(data={'grab_reviews': posts_contents})
df.to_csv('grab_reviews.csv', index=False)
```

Fig. 2.2: Code for scraping Grab Singapore's Facebook Page – 'Community' tab

After running the above code, 405 reviews were scraped. However, due to insufficient time in between some of the scrolls, there were several duplicate entries. After removing the duplicates with the *pandas* function `drop_duplicates`, there were 392 unique reviews remaining with no null values.



```
df_grab = pd.read_csv('datasets/grab_reviews.csv')
df_grab.head()
```

	grab_reviews
0	My Order ADR-5838292-8-257. I made it 5.30pm. ...
1	I think Grab should make it clear that all del...
2	I've been trying to order grabfood since 4.45p...
3	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...
4	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...

```
df_grab.drop_duplicates(inplace=True)
df_grab.reset_index(drop=True, inplace=True)
```

```
len(df_grab)
```

```
392
```

```
sum(df_grab['grab_reviews'].isnull())
```

```
0
```

Fig. 2.3: Code to remove duplicates

Step 2: Airline Passenger Satisfaction Dataset

Two attributes in the Airline Passenger Satisfaction dataset obtained from Kaggle (Klein, 2020) were used – ‘Gender’ and ‘Age’ – to replicate customer demographics for this project. 392 rows were randomly sampled to match the number of customer reviews scraped in the previous step. In the *pandas* function `sample`, the `random_state` was set to 42 to ensure reproducibility (refer to Appendix A for the screenshot of the code).

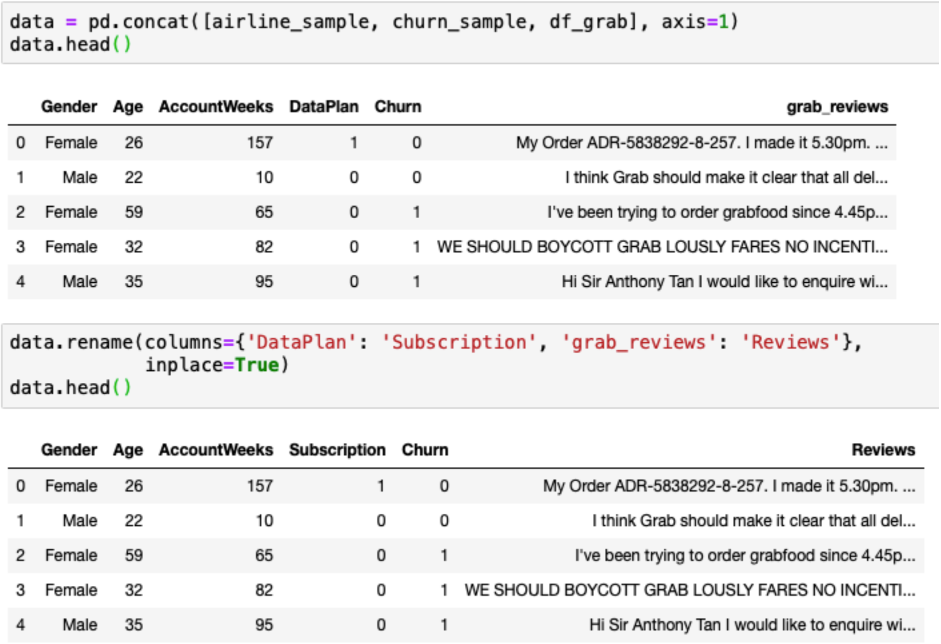
Step 3: Customer Churn Dataset

Three attributes in the Customer Churn dataset obtained from Kaggle (Kumar, 2020) were used – ‘AccountWeeks’, ‘DataPlan’, and ‘Churn’ – to replicate customer usage of the Grab ride-hailing platform and the history of customer churn. The ‘DataPlan’ attribute was then renamed to ‘Subscription’.

For this dataset, the distribution of the target, ‘Churn’, was highly imbalanced. Hence, instead of randomly sampling 392 rows from the entire dataset, half of the rows required were sampled from the rows where ‘Churn’ = 1, and the other half from the rows where ‘Churn’ = 0. Similar to the Airline Passenger Satisfaction dataset, the `random_state` was set to 42 to ensure reproducibility (refer to Appendix A for the screenshot of the code).

Step 4: Joining the above 3 DataFrames and renaming the columns

The *pandas* function `concat` was used to concatenate the three DataFrames into one. The 'DataPlan' and 'grab_reviews' columns were renamed to 'Subscription' and 'Reviews' respectively.



```
data = pd.concat([airline_sample, churn_sample, df_grab], axis=1)
data.head()
```

	Gender	Age	AccountWeeks	DataPlan	Churn	grab_reviews
0	Female	26	157	1	0	My Order ADR-5838292-8-257. I made it 5.30pm. ...
1	Male	22	10	0	0	I think Grab should make it clear that all del...
2	Female	59	65	0	1	I've been trying to order grabfood since 4.45p...
3	Female	32	82	0	1	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...
4	Male	35	95	0	1	Hi Sir Anthony Tan I would like to enquire wi...

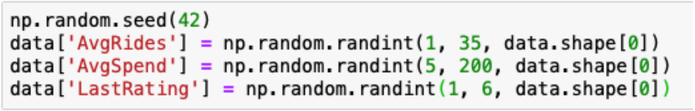
```
data.rename(columns={'DataPlan': 'Subscription', 'grab_reviews': 'Reviews'},
            inplace=True)
data.head()
```

	Gender	Age	AccountWeeks	Subscription	Churn	Reviews
0	Female	26	157	1	0	My Order ADR-5838292-8-257. I made it 5.30pm. ...
1	Male	22	10	0	0	I think Grab should make it clear that all del...
2	Female	59	65	0	1	I've been trying to order grabfood since 4.45p...
3	Female	32	82	0	1	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...
4	Male	35	95	0	1	Hi Sir Anthony Tan I would like to enquire wi...

Fig. 2.4: Code to join the DataFrames and rename the columns

Step 4: Randomised Integer Values

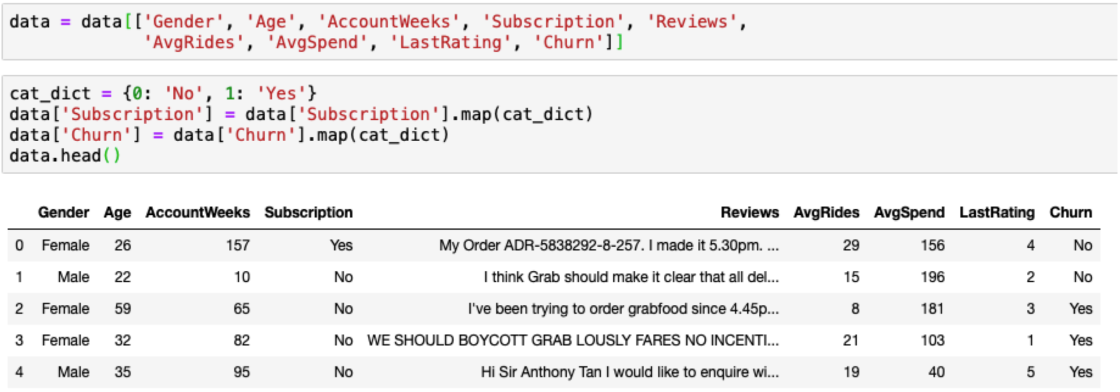
To mock-up the inputs for 'AvgRides', 'AvgSpend' and 'LastRating', the `random.randint` function from the *numpy* package was used, with the seed set at 42 to ensure reproducibility.



```
np.random.seed(42)
data['AvgRides'] = np.random.randint(1, 35, data.shape[0])
data['AvgSpend'] = np.random.randint(5, 200, data.shape[0])
data['LastRating'] = np.random.randint(1, 6, data.shape[0])
```

Fig. 2.5: Code to generate random integer values

After going through the above four steps, the dataset for the report was generated. The columns were then reordered for ease of reference and saved for use in the model.



```
data = data[['Gender', 'Age', 'AccountWeeks', 'Subscription', 'Reviews',
             'AvgRides', 'AvgSpend', 'LastRating', 'Churn']]
```

```
cat_dict = {0: 'No', 1: 'Yes'}
data['Subscription'] = data['Subscription'].map(cat_dict)
data['Churn'] = data['Churn'].map(cat_dict)
data.head()
```

	Gender	Age	AccountWeeks	Subscription	Reviews	AvgRides	AvgSpend	LastRating	Churn
0	Female	26	157	Yes	My Order ADR-5838292-8-257. I made it 5.30pm. ...	29	156	4	No
1	Male	22	10	No	I think Grab should make it clear that all del...	15	196	2	No
2	Female	59	65	No	I've been trying to order grabfood since 4.45p...	8	181	3	Yes
3	Female	32	82	No	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...	21	103	1	Yes
4	Male	35	95	No	Hi Sir Anthony Tan I would like to enquire wi...	19	40	5	Yes

Fig. 2.6: Sample of final dataset

3.2.2 Data Exploration

This step of exploring the dataset generated will provide an overview of the dataset, and Grab's customer demographic as a result, and if there are any attributes that are unbalanced. The distribution of all the attributes (excluding 'Reviews') are as follows:

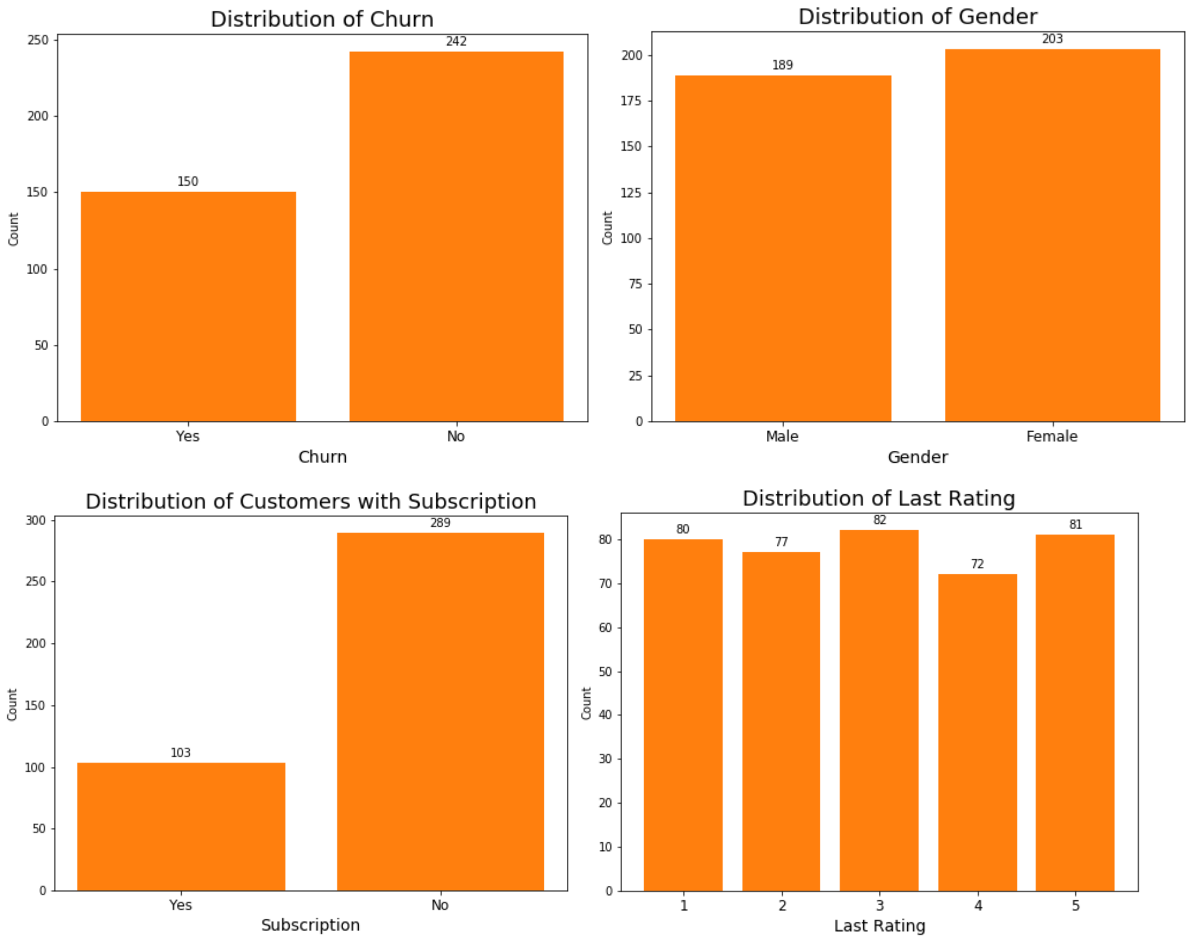
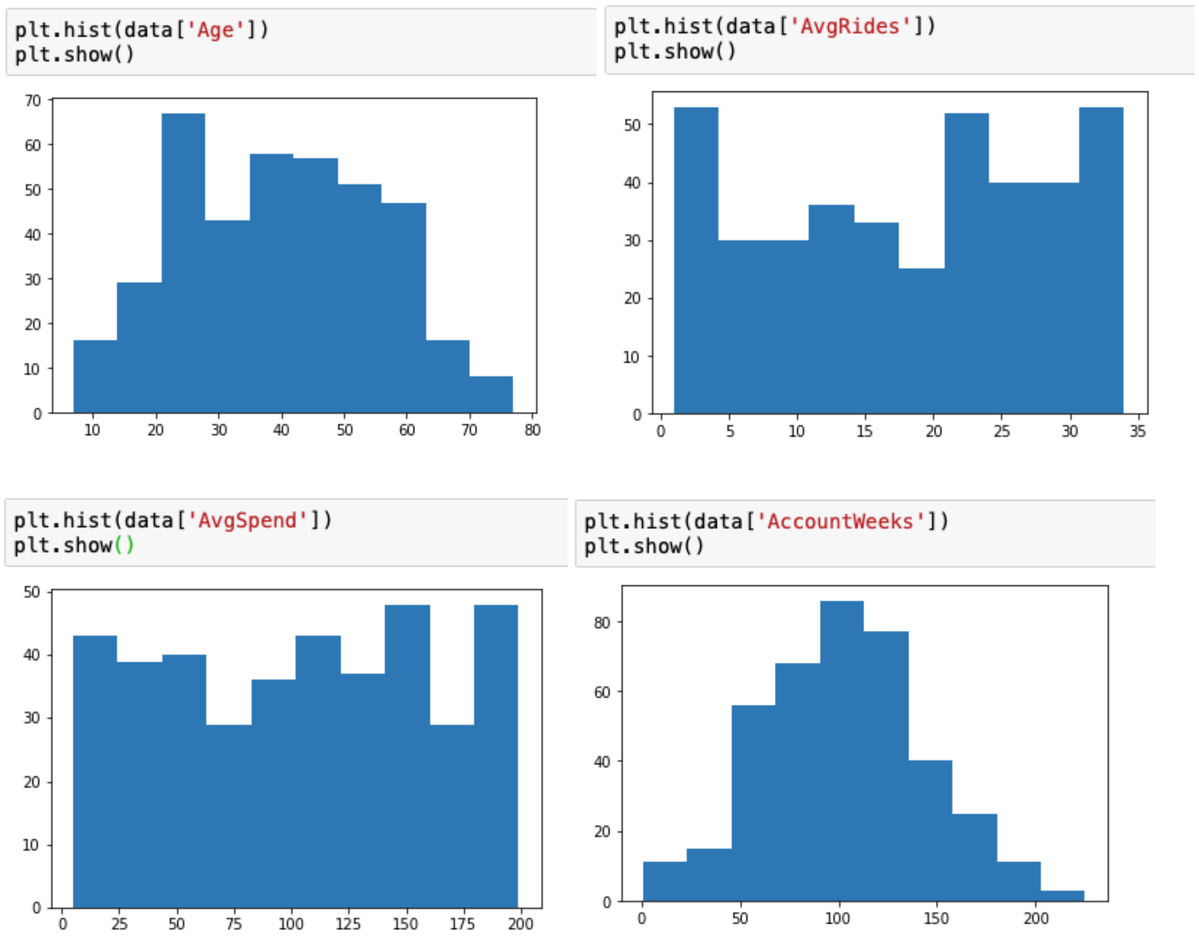


Fig. 2.7: Distribution of categorical attributes



```
plt.hist(data['Age'])
plt.show()
```

```
plt.hist(data['AvgRides'])
plt.show()
```

```
plt.hist(data['AvgSpend'])
plt.show()
```

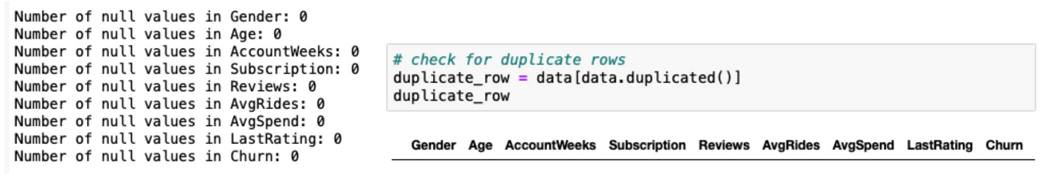
```
plt.hist(data['AccountWeeks'])
plt.show()
```

Fig. 2.8: Distribution of continuous attributes

From Fig. 2.8 above, it can be seen that the range of each continuous attribute is different. For example, ‘Age’ has a much smaller range than ‘AvgSpend’. As such, to compare between attributes with small and large ranges, data transformation will be needed in the next stage to normalise the ranges of the continuous attributes.

3.2.3 Data Quality

As seen in the figure below, there are no null values or duplicated rows in the dataset.



```
Number of null values in Gender: 0
Number of null values in Age: 0
Number of null values in AccountWeeks: 0
Number of null values in Subscription: 0
Number of null values in Reviews: 0
Number of null values in AvgRides: 0
Number of null values in AvgSpend: 0
Number of null values in LastRating: 0
Number of null values in Churn: 0
```

```
# check for duplicate rows
duplicate_row = data[data.duplicated()]
duplicate_row
```

Gender	Age	AccountWeeks	Subscription	Reviews	AvgRides	AvgSpend	LastRating	Churn

Fig. 2.9: Python check to ensure no null or duplicated rows

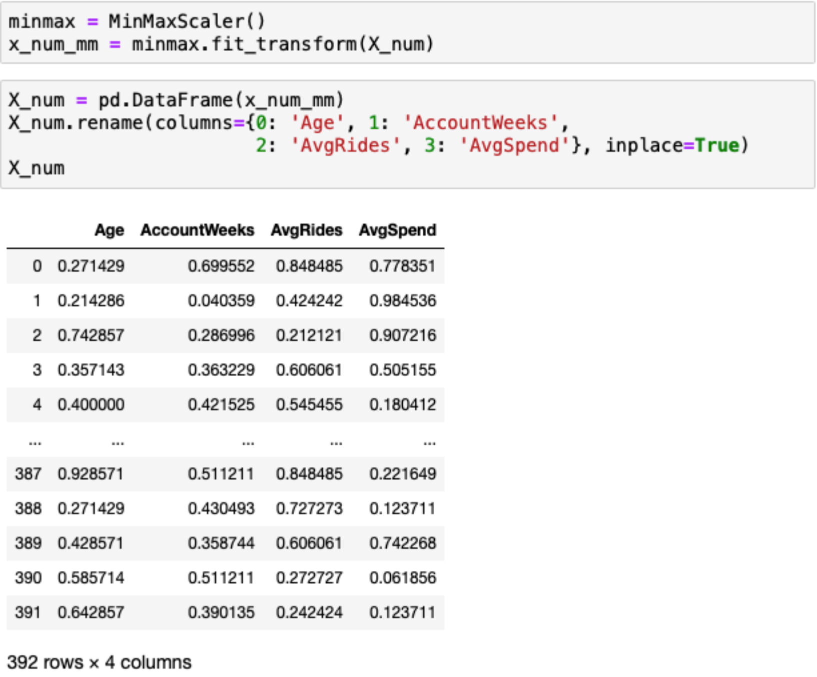
3.3 Data Preparation

The third phase of CRISP-DM is data preparation, which is the most time-consuming phase. In this stage, transformations will be applied to the data where required. For structured data, this may involve scaling the numerical values or changing the data type. For text data, this will be where the pre-processing occurs, such as case normalisation and the removal of stop words.

For the dataset used in this report, there are two types of data – structured and unstructured. As seen in Table 1, other than the 'Reviews' column, all the columns are structured data.

Structured data

For the continuous attributes, as mentioned in the previous section, data transformation will be needed to normalise the variables to a standard range. One method to do so would be to use min-max normalisation, which transforms a variable's original range into a newly specified range, namely [0, 1] in this case. The *scikit-learn* package in Python has a `MinMaxScaler` function that scales each feature to a given range, [0,1] by default.



```
minmax = MinMaxScaler()
x_num_mm = minmax.fit_transform(X_num)
```

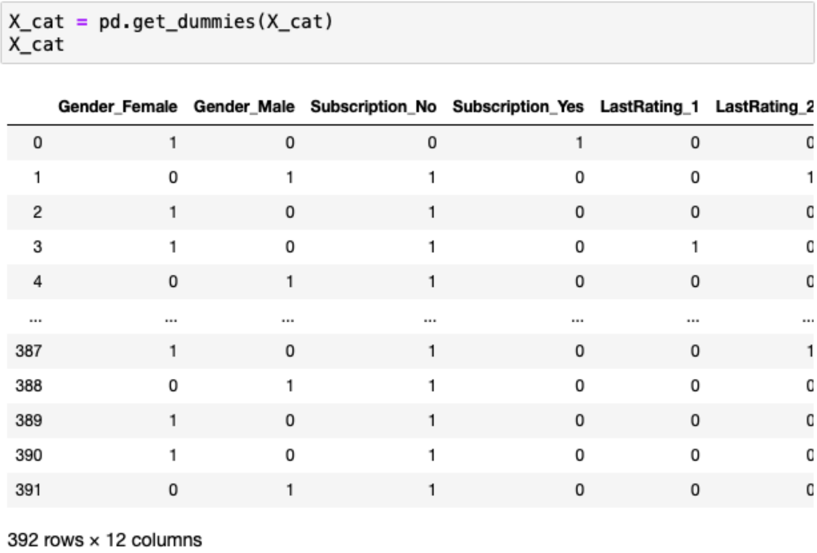
```
X_num = pd.DataFrame(x_num_mm)
X_num.rename(columns={0: 'Age', 1: 'AccountWeeks',
                      2: 'AvgRides', 3: 'AvgSpend'}, inplace=True)
X_num
```

	Age	AccountWeeks	AvgRides	AvgSpend
0	0.271429	0.699552	0.848485	0.778351
1	0.214286	0.040359	0.424242	0.984536
2	0.742857	0.286996	0.212121	0.907216
3	0.357143	0.363229	0.606061	0.505155
4	0.400000	0.421525	0.545455	0.180412
...	...	...	...	...
387	0.928571	0.511211	0.848485	0.221649
388	0.271429	0.430493	0.727273	0.123711
389	0.428571	0.358744	0.606061	0.742268
390	0.585714	0.511211	0.272727	0.061856
391	0.642857	0.390135	0.242424	0.123711

392 rows × 4 columns

Fig. 3.1: Min-Max Normalisation of Continuous Attributes

For the categorical attributes, they cannot be directly used as inputs in neural networks. Instead, dummy variables need to be created for each attribute, with each variable being binary.



```
X_cat = pd.get_dummies(X_cat)
X_cat
```

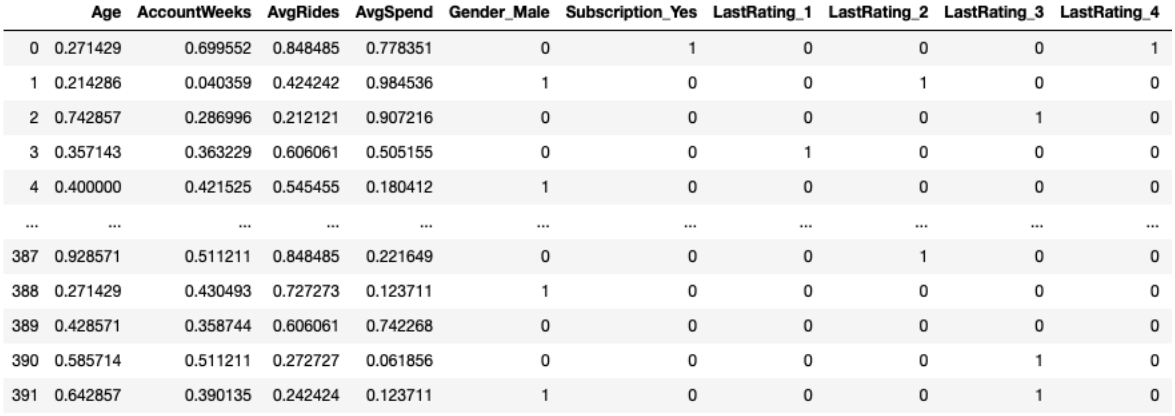
	Gender_Female	Gender_Male	Subscription_No	Subscription_Yes	LastRating_1	LastRating_2
0	1	0	0	1	0	0
1	0	1	1	0	0	1
2	1	0	1	0	0	0
3	1	0	1	0	1	0
4	0	1	1	0	0	0
...	...	...	...	...	...	...
387	1	0	1	0	0	1
388	0	1	1	0	0	0
389	1	0	1	0	0	0
390	1	0	1	0	0	0
391	0	1	1	0	0	0

392 rows × 12 columns

Fig 3.2: Dummy variable for each categorical attribute

However, creating dummy variables will result in the dummy variable trap, where there is an extra variable for each attribute. For example, for ‘Gender_Male’, 0 would indicate that the customer is a male, while 1 would indicate that the customer is female. As such, ‘Gender_Female’ is redundant, and should be removed. Similarly, for the ‘LastRating’ attribute, ‘LastRating_5’ can be removed, as 0 in all other columns – ‘LastRating_1’, ‘LastRating_2’, ‘LastRating_3’, and ‘LastRating_4’ – would mean that the customer’s last rating was 5. Hence, one dummy variable for each categorical attribute should be dropped, and the dropped variable will then be used as the benchmark.

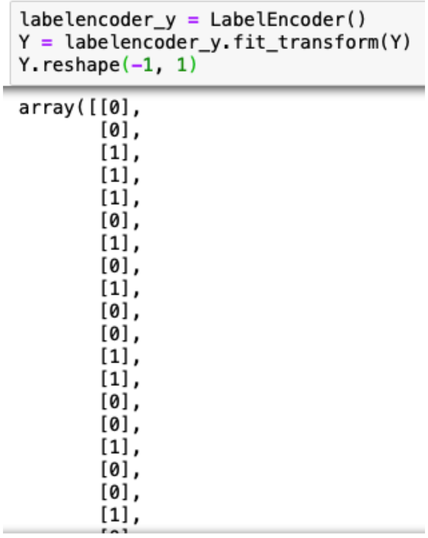
After transforming both continuous and categorical attributes, the resulting dataset is as follows:



	Age	AccountWeeks	AvgRides	AvgSpend	Gender_Male	Subscription_Yes	LastRating_1	LastRating_2	LastRating_3	LastRating_4
0	0.271429	0.699552	0.848485	0.778351	0	1	0	0	0	1
1	0.214286	0.040359	0.424242	0.984536	1	0	0	1	0	0
2	0.742857	0.286996	0.212121	0.907216	0	0	0	0	1	0
3	0.357143	0.363229	0.606061	0.505155	0	0	1	0	0	0
4	0.400000	0.421525	0.545455	0.180412	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
387	0.928571	0.511211	0.848485	0.221649	0	0	0	1	0	0
388	0.271429	0.430493	0.727273	0.123711	1	0	0	0	0	0
389	0.428571	0.358744	0.606061	0.742268	0	0	0	0	0	0
390	0.585714	0.511211	0.272727	0.061856	0	0	0	0	1	0
391	0.642857	0.390135	0.242424	0.123711	1	0	0	0	1	0

Fig. 3.3: Inputs for modelling

For the target attribute, ‘Churn’, the values were encoded with scikit-learn’s `LabelEncoder`. This function encodes the target labels, ‘Yes’ and ‘No’ with values ‘1’ and ‘0’ respectively.



```
labelencoder_y = LabelEncoder()
Y = labelencoder_y.fit_transform(Y)
Y.reshape(-1, 1)
```

```
array([[0],
       [0],
       [1],
       [1],
       [1],
       [0],
       [1],
       [0],
       [1],
       [0],
       [0],
       [1],
       [1],
       [0],
       [0],
       [1],
       [0],
       [0],
       [1],
```

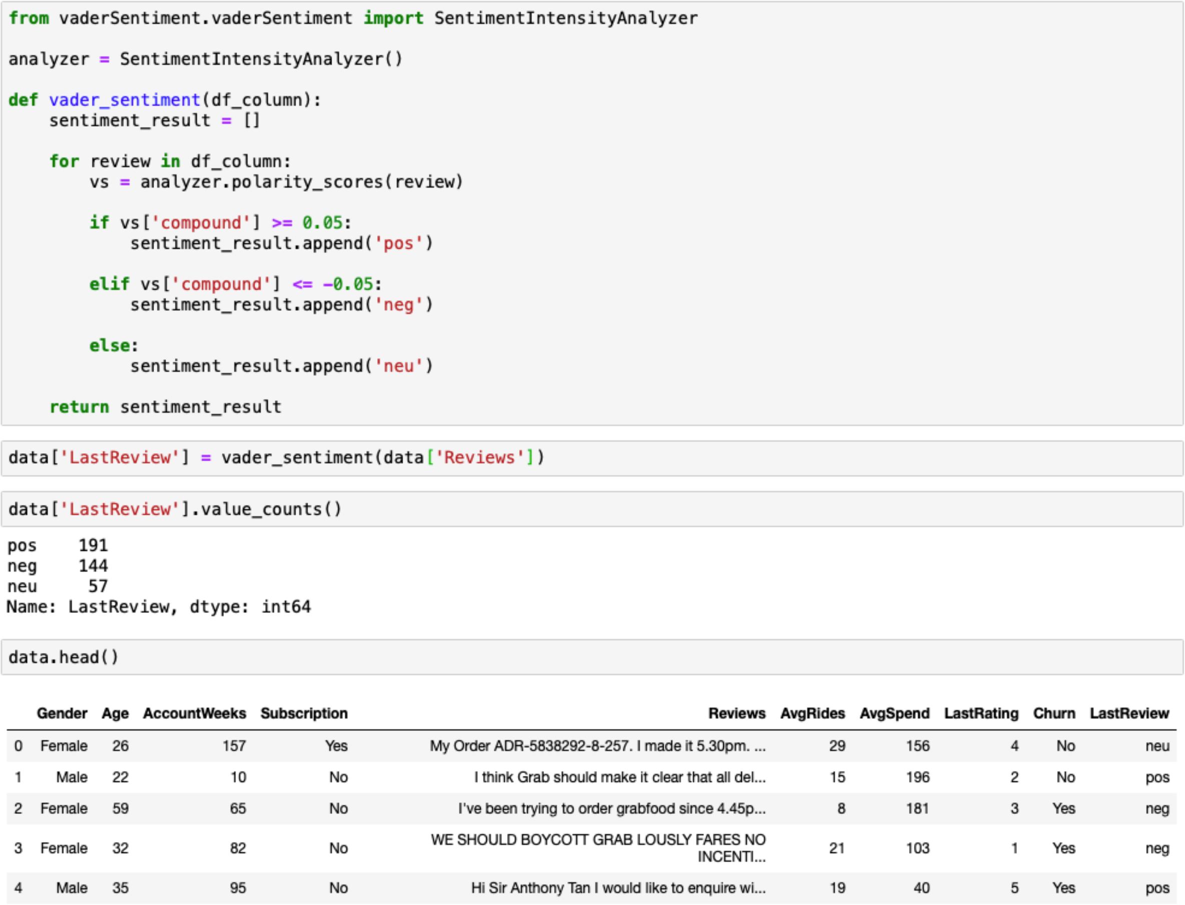
Fig. 3.4: Encoding target values

Unstructured data

Generally, an objective of the use of the text reviews is to carry out text mining on the text and obtain structured data. The result can then be used in the existing model to compare if the additional information from the text data will improve the accuracy of the predictive model.

For this report, sentiment analysis will be carried out on the text reviews scraped to obtain a categorical attribute of ‘LastReview’, where sentiment will be positive (‘pos’), neutral (‘neu’) or negative (‘neg’).

Additionally, the text reviews were obtained from Facebook, a social media platform. As such, in this report, the VADER tool was used to conduct unsupervised sentiment analysis on each review to obtain the sentiment. The rationale behind using the tool for this report is because the tool is trained for social media text, where it takes into account the emoticons, punctuation, and even commonly used acronyms (Hutto & Gilbert, 2014). As a result of using the tool, text pre-processing, such as case-normalisation, will not be essential, as VADER takes into account the case of the text in determining the sentiment of the text.



```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyzer = SentimentIntensityAnalyzer()

def vader_sentiment(df_column):
    sentiment_result = []

    for review in df_column:
        vs = analyzer.polarity_scores(review)

        if vs['compound'] >= 0.05:
            sentiment_result.append('pos')

        elif vs['compound'] <= -0.05:
            sentiment_result.append('neg')

        else:
            sentiment_result.append('neu')

    return sentiment_result
```

```
data['LastReview'] = vader_sentiment(data['Reviews'])
```

```
data['LastReview'].value_counts()
```

```
pos     191
neg     144
neu      57
Name: LastReview, dtype: int64
```

```
data.head()
```

	Gender	Age	AccountWeeks	Subscription	Reviews	AvgRides	AvgSpend	LastRating	Churn	LastReview
0	Female	26	157	Yes	My Order ADR-5838292-8-257. I made it 5.30pm. ...	29	156	4	No	neu
1	Male	22	10	No	I think Grab should make it clear that all del...	15	196	2	No	pos
2	Female	59	65	No	I've been trying to order grabfood since 4.45p...	8	181	3	Yes	neg
3	Female	32	82	No	WE SHOULD BOYCOTT GRAB LOUSLY FARES NO INCENTI...	21	103	1	Yes	neg
4	Male	35	95	No	Hi Sir Anthony Tan I would like to enquire wi...	19	40	5	Yes	pos

Fig. 3.5: Code to categorise sentiment of text reviews

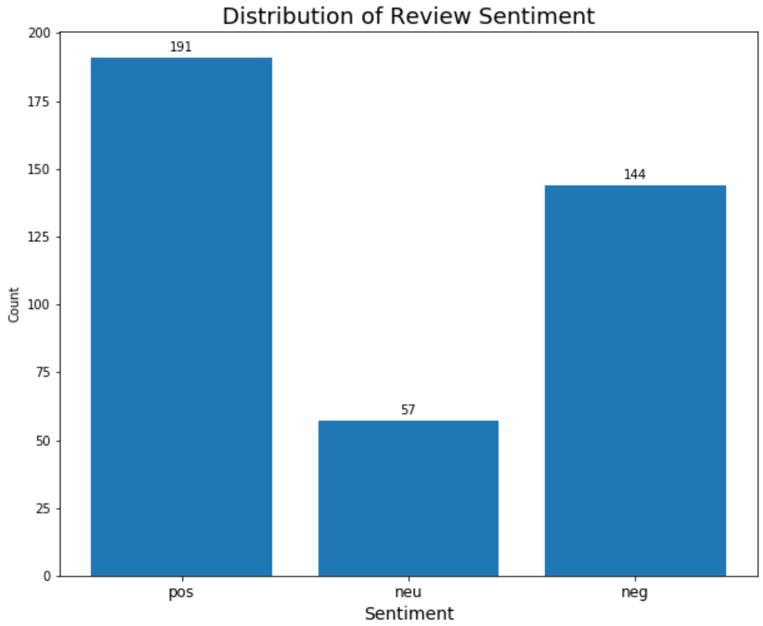
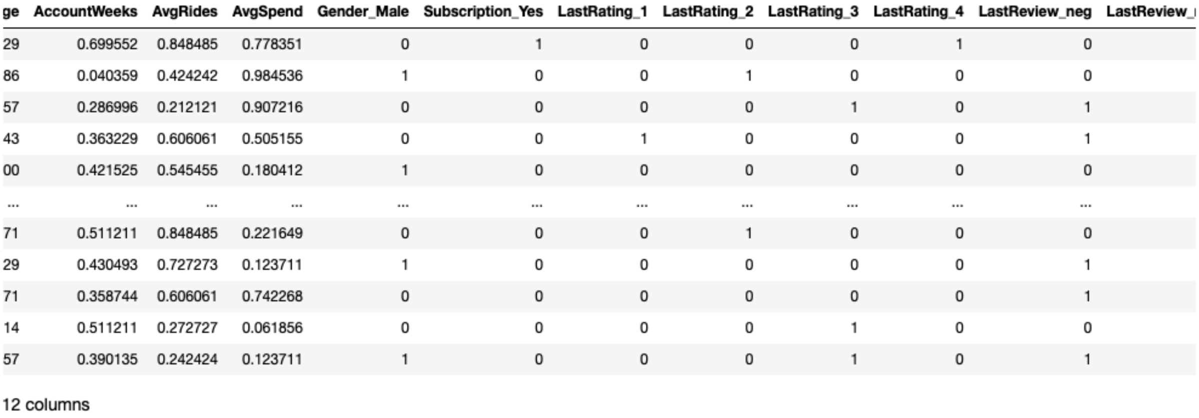


Fig. 3.6: Distribution of Sentiment

With the new categorical attribute ‘LastReview’, the step of creating dummy variables for the attribute was carried out.



ge	AccountWeeks	AvgRides	AvgSpend	Gender_Male	Subscription_Yes	LastRating_1	LastRating_2	LastRating_3	LastRating_4	LastReview_neg	LastReview_
29	0.699552	0.848485	0.778351	0	1	0	0	0	1	0	
86	0.040359	0.424242	0.984536	1	0	0	1	0	0	0	
57	0.286996	0.212121	0.907216	0	0	0	0	1	0	1	
43	0.363229	0.606061	0.505155	0	0	1	0	0	0	1	
00	0.421525	0.545455	0.180412	1	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
71	0.511211	0.848485	0.221649	0	0	0	1	0	0	0	
29	0.430493	0.727273	0.123711	1	0	0	0	0	0	1	
71	0.358744	0.606061	0.742268	0	0	0	0	0	0	1	
14	0.511211	0.272727	0.061856	0	0	0	0	1	0	0	
57	0.390135	0.242424	0.123711	1	0	0	0	1	0	1	

12 columns

Fig. 3.7: Inputs for model with sentiment

3.4 Modelling

The modelling phase of the CRISP-DM framework involves applying appropriate models to achieve the data mining goal. More than one model may be needed to compare the performance.

Predicting customer churn is a binary classification problem – whether the customer will take a Grab ride in the next 30 days. After the data preparation phase, all the inputs are now numerical. Hence, the data is suitable for most predictive modelling methods.

Several models were tested – multinomial Naïve Bayes, logistic regression, and neural networks. The training dataset consists of 70% of the dataset, with the remaining 30% used as the test dataset that was unseen by the models. Each model was run twice – once excluding the customer reviews sentiment, and once including the sentiment.

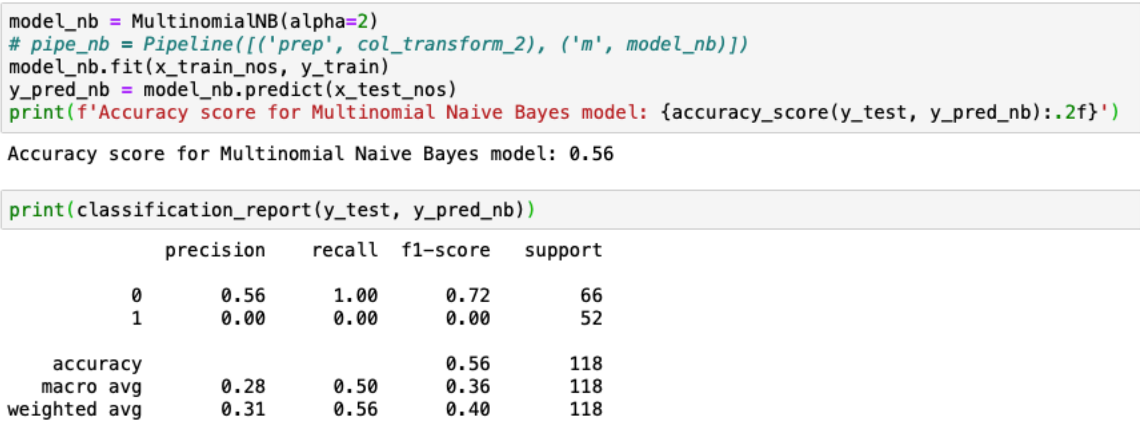
The inputs used are summarised in the following table. The sentiment inputs that were excluded in the first run of each model are indicated with an asterisk (*).

Input	**Measurement**	**Description**
Age	Continuous	Age of customer (scaled to range [0, 1])
AccountWeeks	Continuous	Number of weeks that the customer has had an active account (scaled to range [0, 1])
AvgRides	Continuous	Average number of rides the customer takes per month (over 12-month period or since account opening, whichever is smaller) (scaled to range [0, 1])
AvgSpend	Continuous	Average amount (in SGD) the customer spends on Grab rides per month (over 12-month period or since account opening, whichever is smaller) (scaled to range [0, 1])
Gender_Male	Flag	Customer is male (‘0’ = No or ‘1’ = Yes)
Subscription_Yes	Flag	Customer subscribed to the Daily Value Plan (‘0’ = No or ‘1’ = Yes)
LastRating_1	Flag	1-star rating given for the last ride (‘0’ = No or ‘1’ = Yes)
LastRating_2	Flag	2-star rating given for the last ride (‘0’ = No or ‘1’ = Yes)

LastRating_3	Flag	3-star rating given for the last ride (‘0’ = No or ‘1’ = Yes)
LastRating_4	Flag	4-star rating given for the last ride (‘0’ = No or ‘1’ = Yes)
LastReview_neg*	Flag	Sentiment of last review given was negative (‘0’ = No or ‘1’ = Yes)
LastReview_neu*	Flag	Sentiment of last review given was neutral (‘0’ = No or ‘1’ = Yes)
Churn	Flag	Whether the customer will book a Grab ride in the next 30 days (‘0’ = No or ‘1’ = Yes)

Table 2: Inputs used in the models

Multinomial Naïve Bayes



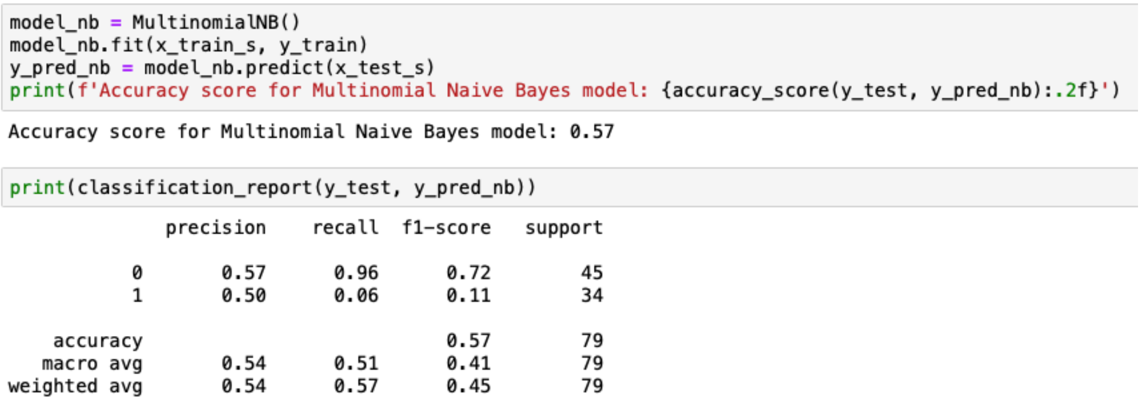
```
model_nb = MultinomialNB(alpha=2)
# pipe_nb = Pipeline([('prep', col_transform_2), ('m', model_nb)])
model_nb.fit(x_train_nos, y_train)
y_pred_nb = model_nb.predict(x_test_nos)
print(f'Accuracy score for Multinomial Naive Bayes model: {accuracy_score(y_test, y_pred_nb):.2f}')
```

```
Accuracy score for Multinomial Naive Bayes model: 0.56
```

```
print(classification_report(y_test, y_pred_nb))
```

```
              precision    recall  f1-score   support

           0       0.56      1.00      0.72        66
           1       0.00      0.00      0.00        52

    accuracy                           0.56       118
   macro avg       0.28      0.50      0.36       118
weighted avg       0.31      0.56      0.40       118
```

Fig. 4.1: Multinomial Naïve Bayes model without sentiment



```
model_nb = MultinomialNB()
model_nb.fit(x_train_s, y_train)
y_pred_nb = model_nb.predict(x_test_s)
print(f'Accuracy score for Multinomial Naive Bayes model: {accuracy_score(y_test, y_pred_nb):.2f}')
```

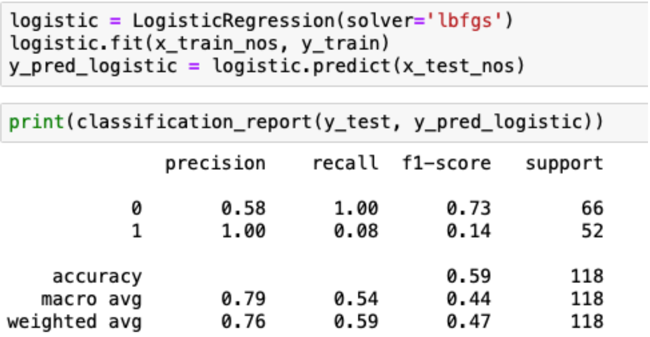
```
Accuracy score for Multinomial Naive Bayes model: 0.57
```

```
print(classification_report(y_test, y_pred_nb))
```

```
              precision    recall  f1-score   support

           0       0.57      0.96      0.72        45
           1       0.50      0.06      0.11        34

    accuracy                           0.57        79
   macro avg       0.54      0.51      0.41        79
weighted avg       0.54      0.57      0.45        79
```

Fig. 4.2: Multinomial Naïve Bayes model with sentiment

Logistic Regression

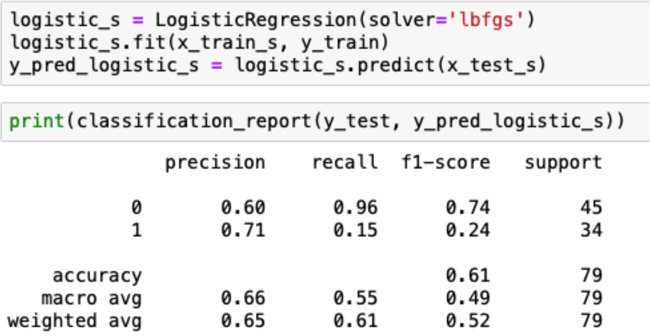


```
logistic = LogisticRegression(solver='lbfgs')
logistic.fit(x_train_nos, y_train)
y_pred_logistic = logistic.predict(x_test_nos)
```

```
print(classification_report(y_test, y_pred_logistic))
```

```
              precision    recall  f1-score   support

           0       0.58      1.00      0.73        66
           1       1.00      0.08      0.14        52

    accuracy                           0.59       118
   macro avg       0.79      0.54      0.44       118
weighted avg       0.76      0.59      0.47       118
```

Fig. 4.3: Logistic Regression model without sentiment



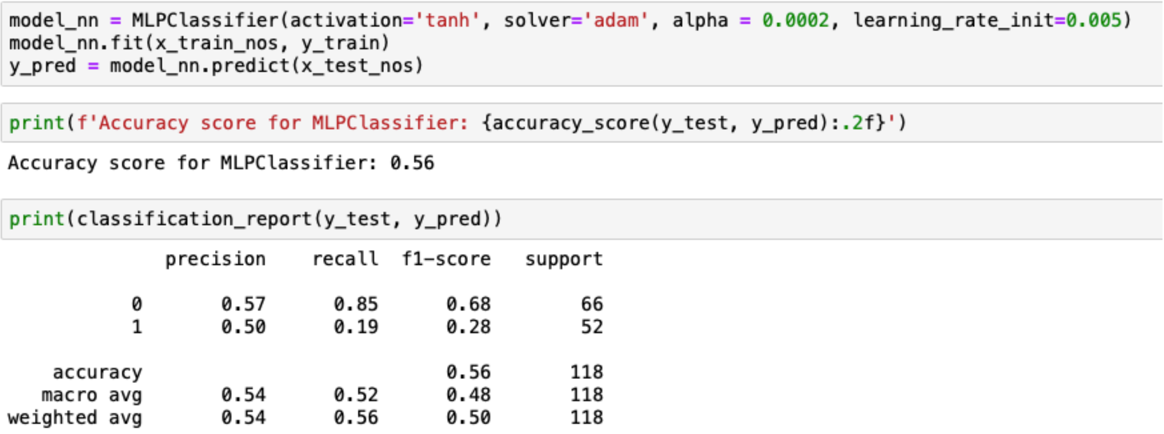
```
logistic_s = LogisticRegression(solver='lbfgs')
logistic_s.fit(x_train_s, y_train)
y_pred_logistic_s = logistic_s.predict(x_test_s)
```

```
print(classification_report(y_test, y_pred_logistic_s))
```

```
              precision    recall  f1-score   support

           0       0.60      0.96      0.74        45
           1       0.71      0.15      0.24        34

    accuracy                           0.61        79
   macro avg       0.66      0.55      0.49        79
weighted avg       0.65      0.61      0.52        79
```

Fig. 4.4: Logistic Regression with sentiment

Neural Network – Multi-layer Perceptron (MLP) Classifier



```
model_nn = MLPClassifier(activation='tanh', solver='adam', alpha = 0.0002, learning_rate_init=0.005)
model_nn.fit(x_train_nos, y_train)
y_pred = model_nn.predict(x_test_nos)
```

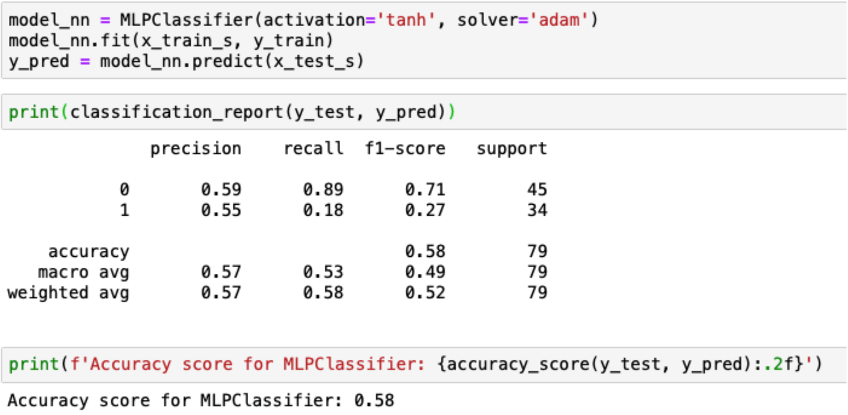
```
print(f'Accuracy score for MLPClassifier: {accuracy_score(y_test, y_pred):.2f}')
```

```
Accuracy score for MLPClassifier: 0.56
```

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.57      0.85      0.68        66
           1       0.50      0.19      0.28        52

    accuracy                           0.56       118
   macro avg       0.54      0.52      0.48       118
weighted avg       0.54      0.56      0.50       118
```

Fig. 4.5: MLP Classifier without sentiment



```
model_nn = MLPClassifier(activation='tanh', solver='adam')
model_nn.fit(x_train_s, y_train)
y_pred = model_nn.predict(x_test_s)
```

```
print(classification_report(y_test, y_pred))
```

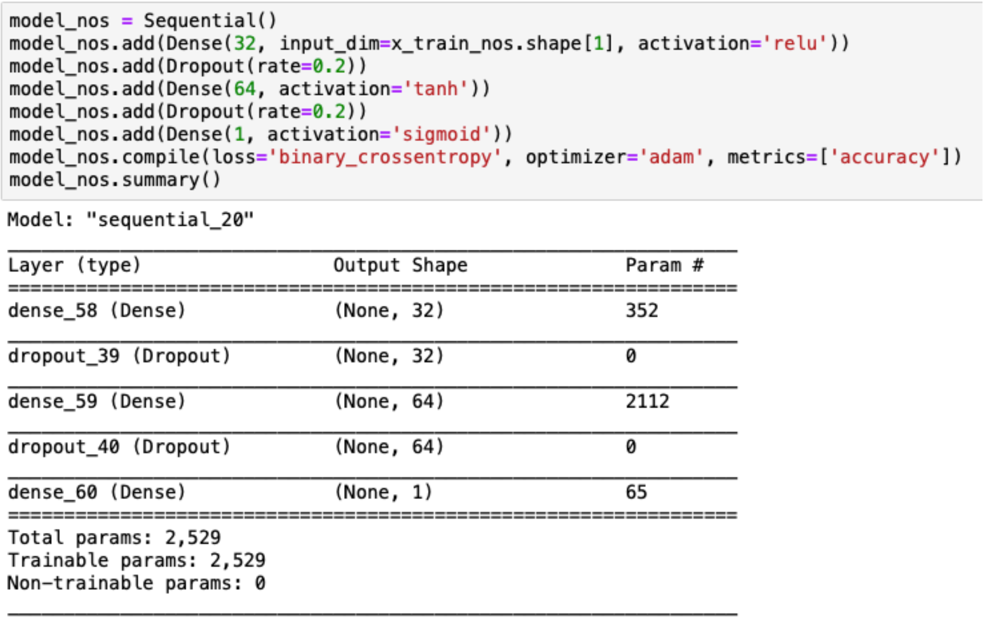
```
              precision    recall  f1-score   support

           0       0.59      0.89      0.71        45
           1       0.55      0.18      0.27        34

    accuracy                           0.58        79
   macro avg       0.57      0.53      0.49        79
weighted avg       0.57      0.58      0.52        79
```

```
print(f'Accuracy score for MLPClassifier: {accuracy_score(y_test, y_pred):.2f}')
```

```
Accuracy score for MLPClassifier: 0.58
```

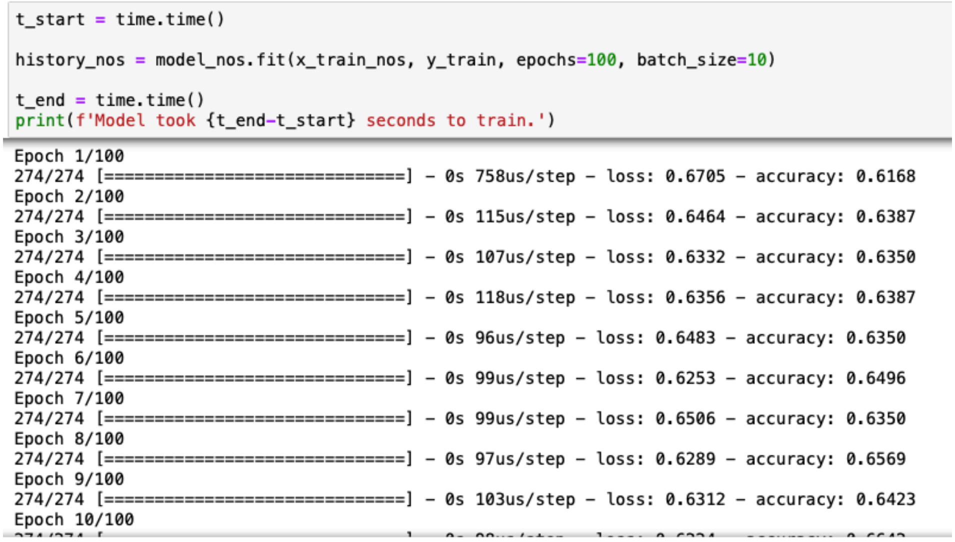
Fig. 4.6: MLP Classifier without sentiment

Neural Network – Keras



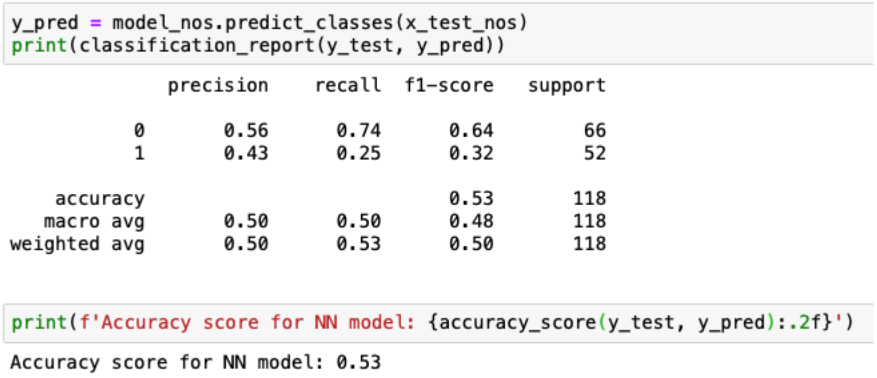
```
model_nos = Sequential()
model_nos.add(Dense(32, input_dim=x_train_nos.shape[1], activation='relu'))
model_nos.add(Dropout(rate=0.2))
model_nos.add(Dense(64, activation='tanh'))
model_nos.add(Dropout(rate=0.2))
model_nos.add(Dense(1, activation='sigmoid'))
model_nos.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model_nos.summary()
```

```
Model: "sequential_20"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_58 (Dense)             (None, 32)                352       
_________________________________________________________________
dropout_39 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_59 (Dense)             (None, 64)                2112      
_________________________________________________________________
dropout_40 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_60 (Dense)             (None, 1)                 65        
=================================================================
Total params: 2,529
Trainable params: 2,529
Non-trainable params: 0
_________________________________________________________________
```



```
t_start = time.time()

history_nos = model_nos.fit(x_train_nos, y_train, epochs=100, batch_size=10)

t_end = time.time()
print(f'Model took {t_end-t_start} seconds to train.')
```

```
Epoch 1/100
274/274 [==============================] - 0s 758us/step - loss: 0.6705 - accuracy: 0.6168
Epoch 2/100
274/274 [==============================] - 0s 115us/step - loss: 0.6464 - accuracy: 0.6387
Epoch 3/100
274/274 [==============================] - 0s 107us/step - loss: 0.6332 - accuracy: 0.6350
Epoch 4/100
274/274 [==============================] - 0s 118us/step - loss: 0.6356 - accuracy: 0.6387
Epoch 5/100
274/274 [==============================] - 0s 96us/step - loss: 0.6483 - accuracy: 0.6350
Epoch 6/100
274/274 [==============================] - 0s 99us/step - loss: 0.6253 - accuracy: 0.6496
Epoch 7/100
274/274 [==============================] - 0s 99us/step - loss: 0.6506 - accuracy: 0.6350
Epoch 8/100
274/274 [==============================] - 0s 97us/step - loss: 0.6289 - accuracy: 0.6569
Epoch 9/100
274/274 [==============================] - 0s 103us/step - loss: 0.6312 - accuracy: 0.6423
Epoch 10/100
```



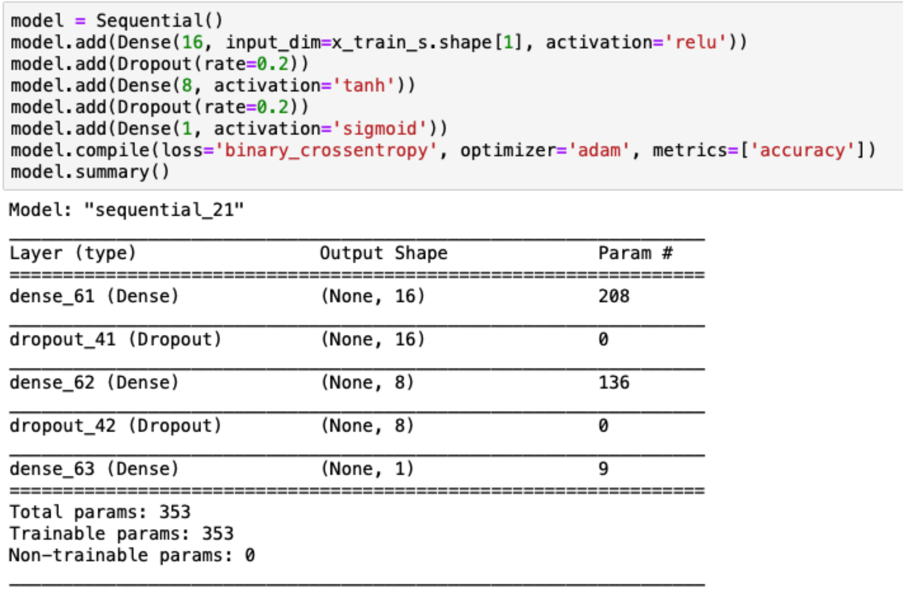
```
y_pred = model_nos.predict_classes(x_test_nos)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.56      0.74      0.64        66
           1       0.43      0.25      0.32        52

    accuracy                           0.53       118
   macro avg       0.50      0.50      0.48       118
weighted avg       0.50      0.53      0.50       118
```

```
print(f'Accuracy score for NN model: {accuracy_score(y_test, y_pred):.2f}')
```

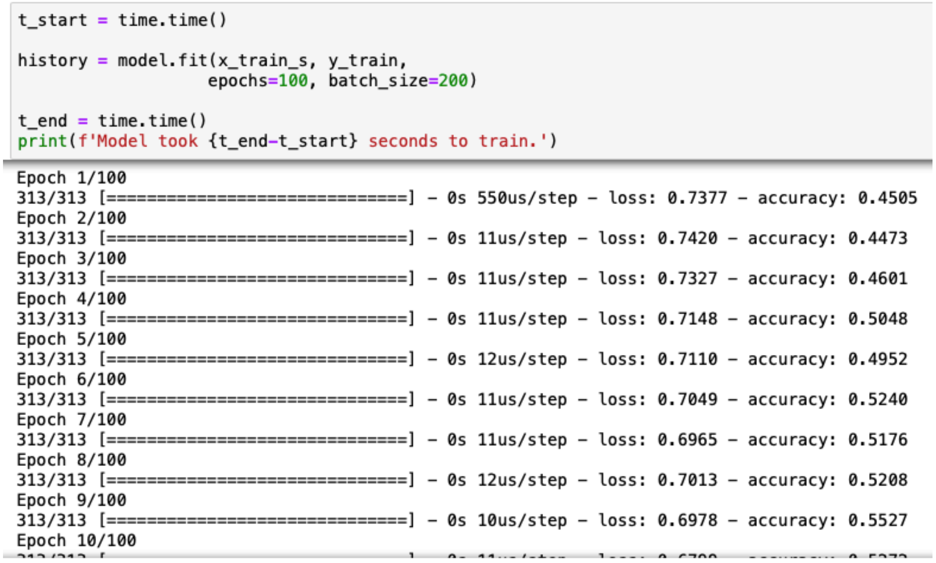
```
Accuracy score for NN model: 0.53
```

Fig. 4.7: Keras model without sentiment



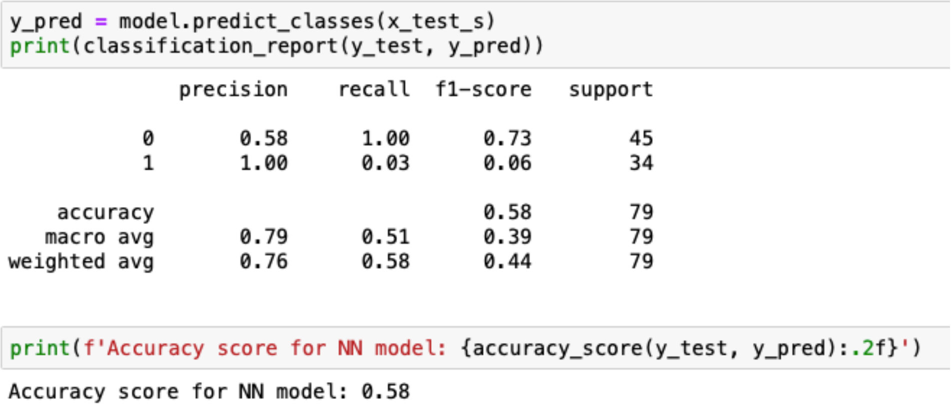
```
model = Sequential()
model.add(Dense(16, input_dim=x_train_s.shape[1], activation='relu'))
model.add(Dropout(rate=0.2))
model.add(Dense(8, activation='tanh'))
model.add(Dropout(rate=0.2))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_21"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_61 (Dense)             (None, 16)                208       
_________________________________________________________________
dropout_41 (Dropout)         (None, 16)                0         
_________________________________________________________________
dense_62 (Dense)             (None, 8)                 136       
_________________________________________________________________
dropout_42 (Dropout)         (None, 8)                 0         
_________________________________________________________________
dense_63 (Dense)             (None, 1)                 9         
=================================================================
Total params: 353
Trainable params: 353
Non-trainable params: 0
_________________________________________________________________
```



```
t_start = time.time()

history = model.fit(x_train_s, y_train,
                    epochs=100, batch_size=200)

t_end = time.time()
print(f'Model took {t_end-t_start} seconds to train.')
```

```
Epoch 1/100
313/313 [==============================] - 0s 550us/step - loss: 0.7377 - accuracy: 0.4505
Epoch 2/100
313/313 [==============================] - 0s 11us/step - loss: 0.7420 - accuracy: 0.4473
Epoch 3/100
313/313 [==============================] - 0s 11us/step - loss: 0.7327 - accuracy: 0.4601
Epoch 4/100
313/313 [==============================] - 0s 11us/step - loss: 0.7148 - accuracy: 0.5048
Epoch 5/100
313/313 [==============================] - 0s 12us/step - loss: 0.7110 - accuracy: 0.4952
Epoch 6/100
313/313 [==============================] - 0s 11us/step - loss: 0.7049 - accuracy: 0.5240
Epoch 7/100
313/313 [==============================] - 0s 11us/step - loss: 0.6965 - accuracy: 0.5176
Epoch 8/100
313/313 [==============================] - 0s 12us/step - loss: 0.7013 - accuracy: 0.5208
Epoch 9/100
313/313 [==============================] - 0s 10us/step - loss: 0.6978 - accuracy: 0.5527
Epoch 10/100
```



```
y_pred = model.predict_classes(x_test_s)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.58      1.00      0.73        45
           1       1.00      0.03      0.06        34

    accuracy                           0.58        79
   macro avg       0.79      0.51      0.39        79
weighted avg       0.76      0.58      0.44        79
```

```
print(f'Accuracy score for NN model: {accuracy_score(y_test, y_pred):.2f}')
```

```
Accuracy score for NN model: 0.58
```

Fig. 4.8: Keras model with sentiment

3.5 Evaluation

The fifth phase of the framework is the evaluation of the models trained and tested in the previous phase to select the best model that has the best performance to address the data mining problem.

Generally, the model selected should have a higher accuracy than the baseline accuracy, which is the percentage of the majority class in the dataset. This is because this would be the accuracy of a model that only predicts the majority class. For this dataset, the baseline accuracy will be 61%. As the distribution of churn in the dataset is relatively balanced, the accuracy score will be an appropriate measure to evaluate model performance.

The table below summarises the metrics in the figures in the previous section:

Model		**Accuracy**
Multinomial Naïve Bayes	*Without sentiment*	56%
	With sentiment	57%
Logistic Regression	*Without sentiment*	59%
	With sentiment	61%
Neural Network – MLP Classifier	*Without sentiment*	56%
	With sentiment	58%
Neural Network – Keras	*Without sentiment*	53%
	With sentiment	58%

Table 3: Summary of model performance

From Table 3, it can be concluded that the additional sentiment input does help with increasing the accuracy of the model. For the Keras model, it increased the accuracy by 5 percentage points. Overall, the best model is logistic regression including the sentiment input, with an accuracy of 61%, which is on par with the baseline.

3.6 Deployment

The final phase of CRISP-DM is deployment, which involves deriving a plan for using the results to introduce strategies that will achieve the business goals.

For this report, if the model above is selected to be deployed, the model will be able to tell Grab which customers are likely to churn, their demographics and their customer lifetime value. With more understanding of their customers, Grab will then be able to decide if it would to release more targeted and aggressive marketing campaigns to customers who are likely to churn (i.e. not going to book a Grab ride in the next 30 days) and have higher customer lifetime value (i.e. have a high average monthly spending) on Grab rides.

4. Summary

To conclude, this report shows that findings from text mining can be useful to a company in conducting market intelligence, as it can improve the performance of the model trained.

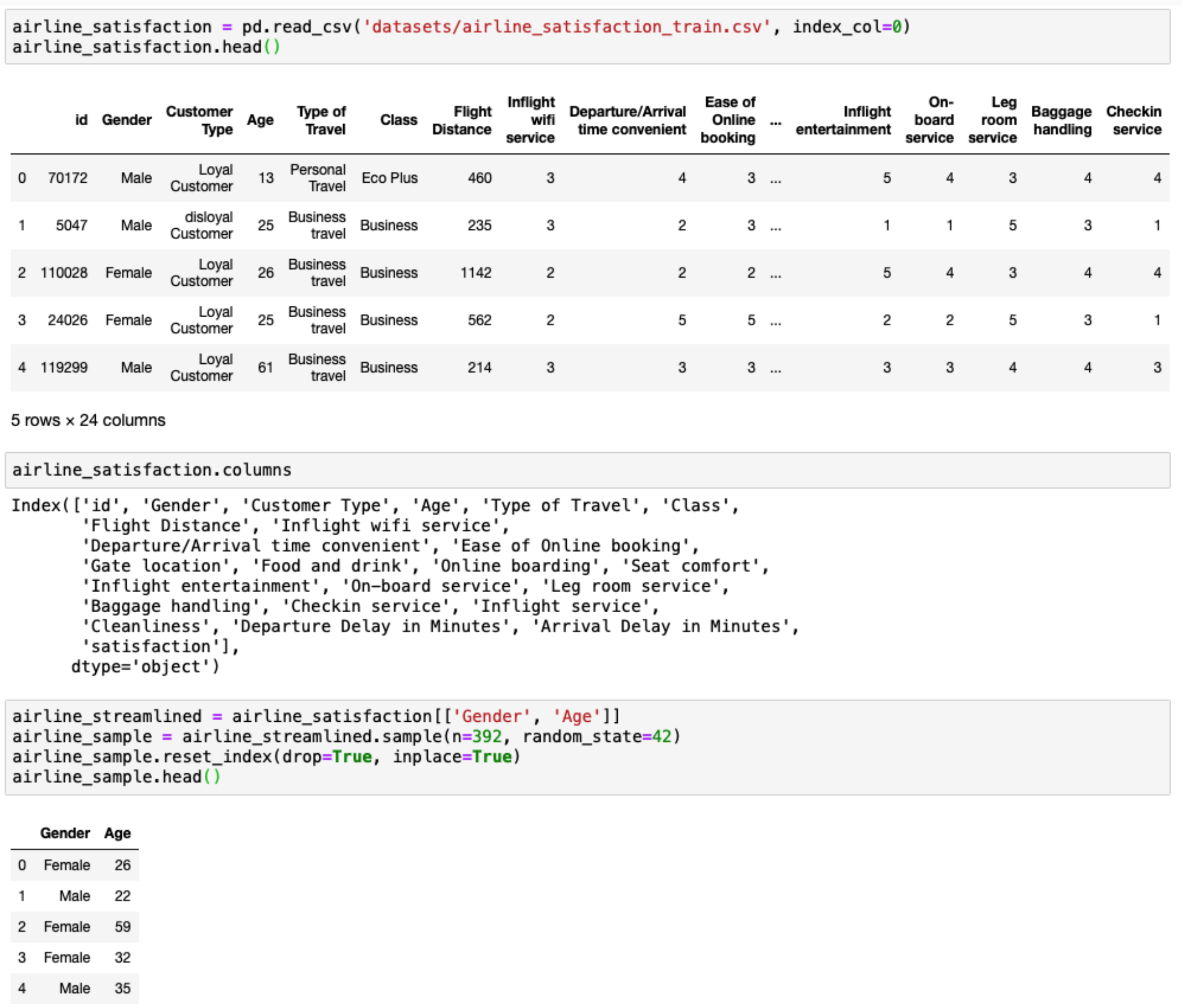
Limitations

One limitation of this report is that the dataset is relatively small in terms of attributes. For the model to perform better, more information is likely needed, such as how many days has passed since the customer last took a Grab ride, and the customer's occupation.

Another limitation is the lack of background information about the customers who posted the reviews. As mentioned in the Literature Review section of the report, the follower and following count of the user could provide further information on the credibility of the review (Li and Li, 2013). Additionally, some of the posts in the Community tab may not all be reviews. In the mix are posts in which Grab Singapore was mentioned in, such as a news site mentioning Grab Singapore in a post. Hence, with user background information, more of such posts can be filtered out to ensure that the posts scraped are truly customer reviews and feedback.

Appendix A

Code for Data Collection



```
airline_satisfaction = pd.read_csv('datasets/airline_satisfaction_train.csv', index_col=0)
airline_satisfaction.head()
```

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service
0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	3	...	5	4	3	4	4
1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	3	...	1	1	5	3	1
2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	2	...	5	4	3	4	4
3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	5	...	2	2	5	3	1
4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	3	...	3	3	4	4	3

5 rows × 24 columns

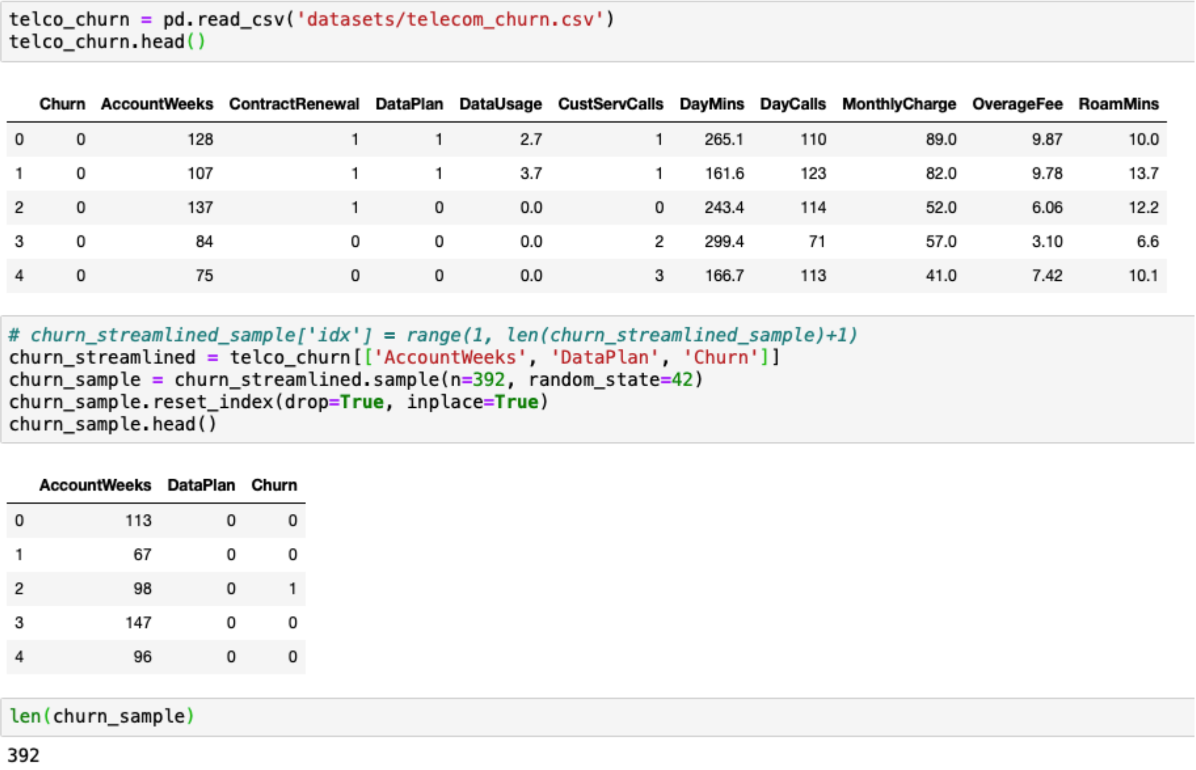
```
airline_satisfaction.columns
```

```
Index(['id', 'Gender', 'Customer Type', 'Age', 'Type of Travel', 'Class',
       'Flight Distance', 'Inflight wifi service',
       'Departure/Arrival time convenient', 'Ease of Online booking',
       'Gate location', 'Food and drink', 'Online boarding', 'Seat comfort',
       'Inflight entertainment', 'On-board service', 'Leg room service',
       'Baggage handling', 'Checkin service', 'Inflight service',
       'Cleanliness', 'Departure Delay in Minutes', 'Arrival Delay in Minutes',
       'satisfaction'],
      dtype='object')
```

```
airline_streamlined = airline_satisfaction[['Gender', 'Age']]
airline_sample = airline_streamlined.sample(n=392, random_state=42)
airline_sample.reset_index(drop=True, inplace=True)
airline_sample.head()
```

	Gender	Age
0	Female	26
1	Male	22
2	Female	59
3	Female	32
4	Male	35

Code to collect 'Gender' and 'Age' rows



```python
telco_churn = pd.read_csv('datasets/telecom_churn.csv')
telco_churn.head()
```

	Churn	AccountWeeks	ContractRenewal	DataPlan	DataUsage	CustServCalls	DayMins	DayCalls	MonthlyCharge	OverageFee	RoamMins
0	0	128	1	1	2.7	1	265.1	110	89.0	9.87	10.0
1	0	107	1	1	3.7	1	161.6	123	82.0	9.78	13.7
2	0	137	1	0	0.0	0	243.4	114	52.0	6.06	12.2
3	0	84	0	0	0.0	2	299.4	71	57.0	3.10	6.6
4	0	75	0	0	0.0	3	166.7	113	41.0	7.42	10.1

```python
# churn_streamlined_sample['idx'] = range(1, len(churn_streamlined_sample)+1)
churn_streamlined = telco_churn[['AccountWeeks', 'DataPlan', 'Churn']]
churn_sample = churn_streamlined.sample(n=392, random_state=42)
churn_sample.reset_index(drop=True, inplace=True)
churn_sample.head()
```

	AccountWeeks	DataPlan	Churn
0	113	0	0
1	67	0	0
2	98	0	1
3	147	0	0
4	96	0	0

```python
len(churn_sample)
```

```
392
```

Code to collect 'AccountWeeks', 'DataPlan' and 'Churn' rows

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