Reddit Comments about ChatGPT - EDA Analysis

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Description:

- This dataset comprises approximately 50,000 comments obtained from Reddit's Posts across four subreddits. Its main purpose is to provide valuable insights into the public's perception of ChatGPT. To achieve this, data cleaning, preprocessing, visualization and modeling are essential steps that will enable answering relevant questions about the dataset.

Strategies:

- Data Analytics steps including Data Cleaning, Data Preprocessing, Data Exploration, and Answering relevant questions.
- Each section above includes an summary for the code.

Hyperlinks:

Import packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time
import string
import re
import spacy

```

```
from tqdm.auto import tqdm
tqdm.pandas()
```

```
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('wordnet')
nltk.download('omw-1.4')
from nltk.tokenize import word_tokenize
from nltk import pos_tag
from nltk.stem import WordNetLemmatizer
from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
```

```
[nltk_data] Downloading package stopwords to /usr/share/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /usr/share/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /usr/share/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package wordnet to /usr/share/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to /usr/share/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
```

```
from sklearn.model_selection import StratifiedKFold, KFold
from statsmodels.formula.api import glm
from sklearn.metrics import mean_squared_error, accuracy_score,\
    balanced_accuracy_score, confusion_matrix
from sklearn.preprocessing import MinMaxScaler
```

```
df = pd.read_csv(
    "/kaggle/input/merged-reddit-chatgpt/Merged Reddit Database ChatGPT.csv"
)
df.head()
```

```
/opt/conda/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3553: DtypeWarni
  exec(code_obj, self.user_global_ns, self.user_ns)
```

	X	comment_id	comment_parent_id	comment_body	subreddit	parent_post	
0	0.0	iztdxuh	t3_zj2aeu	I've been shocked for days now, I don't need c...	r/ChatGPT	t3_zj2aeu	https://www.re
1	1.0	iztn0q0	t3_zj2aeu	\n\nI am so angry right now. I just wasted my...	r/ChatGPT	t3_zj2aeu	https://www.re
2	2.0	izudrph	t3_zj2aeu	chatgpt karma whoring is here folks! just when...	r/ChatGPT	t3_zj2aeu	https://www.re
3	3.0	iztfhtb	t3_zj2aeu	Worked on me, ngl.	r/ChatGPT	t3_zj2aeu	https://www.re

Data Cleanning

Data cleaning is an essential step in the data analysis process. The quality of the data can significantly impact the accuracy and reliability of the analysis results. In this case, the data is Missing Completely At Random (MCAR), which means that the missing values are not related to any of the observed or unobserved variables in the dataset. To clean the data, we follow the steps outlined below:

1. Check the percentage of missing values for each column: We need to determine the extent of missingness in the dataset to determine the appropriate imputation method. We can calculate the percentage of missing values for each column to identify the columns with the highest missingness.
2. Visualize the missing values by heat map: We can create a heat map to visualize the distribution of missing values across the dataset. This visualization can help us identify patterns of missingness, such as missing values occurring in specific rows or columns. And also there are some columns always missing together, which also show more pattens in the data.

3. Delete columns with missing values above 80%: If a column has more than 80% missing values, we may choose to delete that column. This decision is based on the assumption that a column with such high missingness may not be useful in our analysis. From the plot of the heatmap, the last 2 columns almost completely missing and no column name to describe its information.
4. Impute missing values using mean or mode for the same subreddit and parent_post: For columns with missing values that we choose to keep, we can impute the missing values using the mean or mode of the observed values for the same subreddit and parent_post. This imputation method is appropriate when the missingness is MCAR. When some post's parent_post are also missing, then impute the missing by only use the same subreddit.
5. Fill timestamp column by post_timestamp with rescaling: We observe that the column "timestamp" has a very high correlation (0.97) with another column "post_timestamp". Therefore, we can use the "post_timestamp" column to impute the missing values in "timestamp". To do this, we can fill the missing values in "timestamp" using the corresponding values in "post_timestamp". However, since "timestamp" and "post_timestamp" may have different scales, we need to rescale "post_timestamp" to the same scale as "timestamp" before filling the missing values.

Check missing values

```
1 # Null value counts
2 df.isnull().sum().sort_values(ascending = False)/df.shape[0]
```

```
Unnamed: 26           0.999504
Unnamed: 25           0.988133
post_text             0.863355
date                  0.322267
golds                 0.322267
upvotes               0.322267
score                 0.322267
timestamp             0.322267
comment_tree          0.322267
author                0.322267
post_score            0.011467
post_up_ratio         0.000591
post_comment_count    0.000095
post_cross            0.000095
post_golds            0.000095
post_author           0.000095
post_date             0.000095
post_timestamp        0.000095
post_title            0.000095
post_awards           0.000095
X                     0.000019
post_url              0.000000
```

```
comment_id            0.000000
subreddit             0.000000
parent_post           0.000000
comment_parent_id     0.000000
comment_body          0.000000
dtype: float64
```

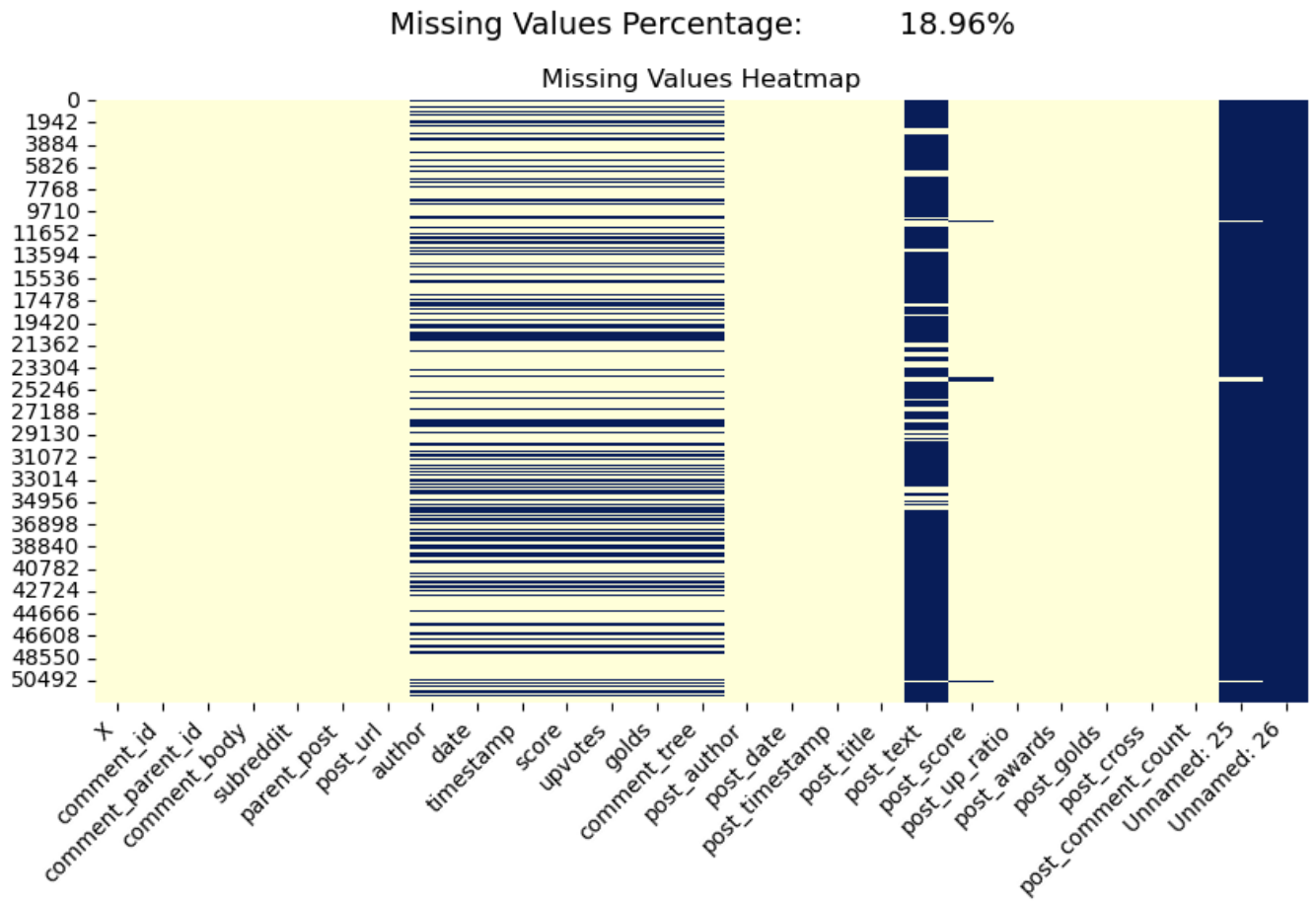
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 52413 entries, 0 to 52412
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   X                   52412 non-null  float64
 1   comment_id          52413 non-null  object 
 2   comment_parent_id   52413 non-null  object 
 3   comment_body        52413 non-null  object 
 4   subreddit           52413 non-null  object 
 5   parent_post         52413 non-null  object 
 6   post_url            52413 non-null  object 
 7   author              35522 non-null  object 
 8   date                35522 non-null  object 
 9   timestamp           35522 non-null  float64
 10  score               35522 non-null  float64
 11  upvotes             35522 non-null  float64
 12  golds               35522 non-null  float64
 13  comment_tree        35522 non-null  object 
 14  post_author         52408 non-null  object 
 15  post_date           52408 non-null  object 
 16  post_timestamp      52408 non-null  float64
 17  post_title          52408 non-null  object 
 18  post_text           7162 non-null   object 
 19  post_score          51812 non-null  object 
 20  post_up_ratio       52382 non-null  float64
 21  post_awards         52408 non-null  float64
 22  post_golds          52408 non-null  float64
 23  post_cross          52408 non-null  float64
 24  post_comment_count  52408 non-null  float64
 25  Unnamed: 25         622 non-null    float64
 26  Unnamed: 26         26 non-null     float64
dtypes: float64(13), object(14)
memory usage: 10.8+ MB
```

Visualize Missing Value by heatmap

```
1 # Total Missing Percentage
2 missing_percentage = round(df.isnull().sum().sum() / df.size * 100, 2)
3
4 plt.figure(figsize=(10, 5))
5 sns.heatmap(df.isnull(), cmap='YlGnBu', cbar=False)
```

```
plt.text(x=0.5, y=1.1, s=f"Missing Values Percentage: \
         {missing_percentage}%", fontsize=14, ha='center', \
         va='bottom', transform=plt.gca().transAxes)
plt.xticks(rotation=45, ha='right')
plt.title('Missing Values Heatmap')
plt.show()
```



For post_text, Unnamed:25, Unnamed:26, since there are very high precentage of missing values, delete them.

```
df.drop(['post_text','Unnamed: 25', 'Unnamed: 26'], axis = 1, inplace = True)
```

```
df.iloc[0:5,7:14]
```

	author	date	timestamp	score	upvotes	golds	comment_tree
0	zookeeper1797	2022-12-11	1.670784e+09	813.0	813.0	0.0	1
1	independentTeamwork	2022-12-11	1.670787e+09	184.0	184.0	0.0	2
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
df['comment_tree'] = df['comment_tree'].astype(float)
```

4	[deleted]	2022-12-11	1.670793e+09	11.0	11.0	0.0	5

```
# show one example
df.iloc[2,:]
```

```
X                                                          2.0
comment_id                                             izudrph
comment_parent_id                                    t3_zj2aeu
comment_body          chatgpt karma whoring is here folks! just when...
subreddit                                            r/ChatGPT
parent_post                                          t3_zj2aeu
post_url              https://www.reddit.com/r/ChatGPT/comments/zj2aeu
author                                                     NaN
date                                                       NaN
timestamp                                                  NaN
score                                                      NaN
upvotes                                                    NaN
golds                                                      NaN
comment_tree                                               NaN
post_author                                          hobblyhoy
post_date                                           2022-12-11
post_timestamp                                   1670782373.0
post_title            10/10, must-see moment! ChatGPT just did somet...
post_score                                           16276.0
post_up_ratio                                            1.0
post_awards                                             10.0
post_golds                                               0.0
post_cross                                               3.0
post_comment_count                                     280.0
Name: 2, dtype: object
```

For the rest of the columns such as author, date, timestamp,... this means this comment might deleted, so there is no relevant information such as upvotes.

impute missing values - discover property

First, discover each column's properties

```
df['author'].nunique()
```

```
16741
```

```
1 df.corr()['timestamp'].sort_values(ascending = False)[1:10]
```

```
post_timestamp        0.979563
post_comment_count    0.164084
post_cross            0.146889
score                 0.014424
upvotes               0.014424
comment_tree          0.011462
post_golds            0.006841
golds                 0.005222
X                    -0.002718
Name: timestamp, dtype: float64
```

```
1 df.corr()['score'].sort_values(ascending = False)[1:10]
```

```
upvotes               1.000000
golds                 0.185341
post_comment_count    0.146375
post_cross            0.113911
post_timestamp        0.019874
post_awards           0.018236
timestamp             0.014424
post_golds            0.009715
comment_tree         -0.006352
Name: score, dtype: float64
```

For the other columns, we can use mean/mode from the same subreddit and parent_post

impute missing values

```
1 # Null value counts
2 df.isnull().sum().sort_values(ascending = False)/df.shape[0]
```

```
golds                 0.322267
author                0.322267
date                  0.322267
timestamp             0.322267
score                 0.322267
upvotes               0.322267
comment_tree          0.322267
post_score            0.011467
post_up_ratio         0.000591
post_date             0.000095
post_cross            0.000095
post_golds            0.000095
post_awards           0.000095
post_title            0.000095
post_timestamp        0.000095
post_comment_count    0.000095
post_author           0.000095
X                     0.000019
```

```
comment_id            0.000000
post_url              0.000000
parent_post           0.000000
subreddit             0.000000
comment_body          0.000000
comment_parent_id     0.000000
dtype: float64
```

```
missing_count = df.isnull().sum().sort_values(ascending = False)/df.shape[0]
cols = missing_count.index
cols = cols[cols != 'timestamp']
```

Use mean/mode from the same subreddit and parent_post

```
grouped_subreddit = df.reset_index().groupby(['subreddit'])
grouped = df.reset_index().groupby(['subreddit', 'parent_post'])
for col in tqdm(cols):
    if df[col].dtype == 'object':
        mode_by_group = grouped[col].apply(lambda x: x.fillna(x.mode()[0]) if not x.mode(
        df[col] = df[col].fillna(mode_by_group)
        # if all the parent_post are missing
        mode_by_group = grouped_subreddit[col].apply(lambda x: x.fillna(x.mode()[0]) if n
        df[col] = df[col].fillna(mode_by_group)
    else:
        mean_by_group = grouped[col].transform('mean')
        df[col] = df[col].fillna(mean_by_group)
        # if all the parent_post are missing
        mean_by_group = grouped_subreddit[col].transform('mean')
        df[col] = df[col].fillna(mean_by_group)

```

```
0%|          | 0/23 [00:00<?, ?it/s]
```

```
# Null value counts
df.isnull().sum().sort_values(ascending = False)/df.shape[0]
```

```
timestamp             0.322267
X                     0.000019
author                0.000019
comment_tree          0.000019
upvotes               0.000019
score                 0.000019
date                  0.000019
golds                 0.000019
post_url              0.000000
parent_post           0.000000
subreddit             0.000000
comment_body          0.000000
comment_id            0.000000
comment_parent_id     0.000000
```

```
post_author           0.000000
post_date             0.000000
post_timestamp        0.000000
post_title            0.000000
post_score            0.000000
post_up_ratio         0.000000
post_awards           0.000000
post_golds            0.000000
post_cross            0.000000
post_comment_count    0.000000
dtype: float64
```

Impute timestamp by post_timestamp

```
# impute timestamp by post_timestamp
corr = df['timestamp'].corr(df['post_timestamp'])
df_non_na = df.dropna()
df['timestamp'] = np.where(df['timestamp'].isnull(), \
                           df['post_timestamp'] * df['timestamp'].mean()/ \
                           df_non_na['post_timestamp'].mean()\
                           , df['timestamp'])

```

```
# Null value counts
df.isnull().sum().sort_values(ascending = False)/df.shape[0]
```

```
X                     0.000019
author                0.000019
comment_tree          0.000019
upvotes               0.000019
score                 0.000019
date                  0.000019
golds                 0.000019
post_url              0.000000
post_timestamp        0.000000
post_cross            0.000000
post_golds            0.000000
post_awards           0.000000
post_up_ratio         0.000000
post_score            0.000000
post_title            0.000000
post_date             0.000000
parent_post           0.000000
post_author           0.000000
comment_parent_id     0.000000
comment_id            0.000000
comment_body          0.000000
subreddit             0.000000
timestamp             0.000000
post_comment_count    0.000000
dtype: float64
```

```
#delete the remain rows (0.0019% of total data)
df.dropna(inplace = True)
```

```
# Null value counts
df.isnull().sum().sort_values(ascending = False)/df.shape[0]
```

```
X                    0.0
comment_id           0.0
post_cross           0.0
post_golds           0.0
post_awards          0.0
post_up_ratio        0.0
post_score           0.0
post_title           0.0
post_timestamp       0.0
post_date            0.0
post_author          0.0
comment_tree         0.0
golds                0.0
upvotes              0.0
score                0.0
timestamp            0.0
date                 0.0
author               0.0
post_url             0.0
parent_post          0.0
subreddit            0.0
comment_body         0.0
comment_parent_id    0.0
post_comment_count   0.0
dtype: float64
```

Generate more information from text words:

- Length of comment
- Presence of anger
- Presence of joy
- Presence of special non alphanumeric character
- Number of stop words

```
import urllib.request
# Count Length of comment
def count_words(df, col):
    '''col is the text column'''
    df['Count_comment'] = df[col].progress_apply(lambda x: len(x.split()))
    return df

def anger_presence(df, col, angry_words):
```

```
    '''col is the text column'''

    df['anger_flag'] = df[col].progress_apply(lambda x: sum([1 for word in x.lower().split
    return df

def joy_presence(df, col, joy_words):
    '''col is the text column'''
    df['joy_flag'] = df[col].progress_apply(lambda x: sum([1 for word in x.lower().split()
    return df

def special_character(df, col):
    '''col is the text column'''
    pattern = r'[^\w\s,\.?]+' #non alphanumeric character wihtout . , ?
    df['special_character_flag'] = df[col].progress_apply(lambda x: len(re.findall(pattern
    return df

def stop_word_count(string):
    stop=set(stopwords.words('english'))
    words = sum([1 for word in string.split() if word in stop])
    return words

def num_stop_words(df, col):
    '''col is the text column'''
    df['num_stop_words'] = df[col].progress_apply(lambda x: stop_word_count(x))
    return df

# run all preprocessing functions
def preprocess_raw(df,col):
    url = "https://raw.githubusercontent.com/fnielsen/afinn/master/afinn/data/AFINN-111.tx
    urllib.request.urlretrieve(url, "AFINN-111.txt")
    afinn = pd.read_csv('AFINN-111.txt', sep='\t', header=None, names=['word', 'score'])
    # Filter for positive words
    positive_words = afinn[afinn['score'] > 0]['word'].tolist()
    negative_words = afinn[afinn['score'] < 0]['word'].tolist()
    df = count_words(df, col)
    df = anger_presence(df, col, negative_words)
    df = joy_presence(df, col, positive_words)
    df = special_character(df, col)
    df = num_stop_words(df, col)
    return df
```

```
col = 'comment_body'
df = preprocess_raw(df,col)
```

```
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
```

```
df.joy_flag.value_counts()
```

```
True     27501
False    24911
Name: joy_flag, dtype: int64
```

```
df.anger_flag.value_counts()
```

```
False    32418
True     19994
Name: anger_flag, dtype: int64
```

Preprocess the text words

- Lowercase
- Remove Numbers
- Remove extra spaces
- Convert short words such as I'm, He's
- Remove punctuations
- Remove stop words

```
# lowercase
def lower(df, cols):
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: x.lower())
    return df

# number removing
def num_remove(df, cols):
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: re.sub(r'\d+', '', x))
    return df

# white spaces removal
def space_remove(df,cols):
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: x.strip()) # remove front and end space
        df[col] = df[col].str.replace('\s+', ' ', regex=True) # remove double space
    return df

def to_sentence(df,cols):
    # join words to a sentence
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: ' '.join(x))
    return df

# punctuation removal
```

```
def punc_remove(df,cols):
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: x.translate(str.maketrans('', '', strin
    return df

# stemming
def stemming(df,cols):
    porter_stemmer  = PorterStemmer()
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: [porter_stemmer.stem(w) for w in x.spli
    df = to_sentence(df,cols)
    return df

# convert short words and urls
def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    urlPattern = r"((http://)|(https://)|( www\.)|(com)|(net)|(org))"
    phrase = re.sub(urlPattern,'',phrase)
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase

# convert cases such as he's, I'm, ...
def short_word_converter(df,cols):
    nlp = spacy.load("en_core_web_sm")
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: decontracted(x))
    return df

# stop word removal
def stop_remove(df,cols):
    stops = set(stopwords.words('english'))
    for col in tqdm(cols):
        df[col] = df[col].progress_apply(lambda x: ' '.join([word for word in x.split() if
    #df = to_sentence(df,cols)
    return df

# run all preprocessing functions
def preprocess(df,cols):
    df[cols] = lower(df,cols)[cols]
    df[cols] = num_remove(df,cols)[cols]
```

```
    df[cols] = space_remove(df,cols)[cols]
    df[cols] = short_word_converter(df,cols)[cols]
    # df[cols] = stemming(df,cols)[cols]
    df[cols] = punc_remove(df,cols)[cols]
    df[cols] = stop_remove(df,cols)[cols]
    return df
```

```
df['comment_body'][0]
```

```
"I've been shocked for days now, I don't need clickbait."
```

```
df = preprocess(df,['comment_body'])
```

```
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/52412 [00:00<?, ?it/s]
```

```
df['comment_body'][0]
```

```
'shocked days need clickbait'
```

Preprocess the date

Extract date information to year, month, day, weekdays and hour

```
df['time'] = pd.to_datetime(df['date'])
df['time']
```

```
0       2022-12-11
1       2022-12-11
2       2022-12-12
3       2022-12-11
4       2022-12-11
           ...
52408   2023-01-16
52409   2023-01-23
52410   2023-01-23
52411   2023-01-24
```

```
52412   2023-01-24
Name: time, Length: 52412, dtype: datetime64[ns]
```

```
df['month'] = df['time'].dt.month
df['year'] = df['time'].dt.year
df['day'] = df['time'].dt.day
df['hour'] = df['time'].dt.hour
df['day_of_week'] = df['time'].dt.day_name()
```

```
df[['year','month','day','hour','day_of_week']].head()
```

	year	month	day	hour	day_of_week
0	2022	12	11	0	Sunday
1	2022	12	11	0	Sunday
2	2022	12	12	0	Monday
3	2022	12	11	0	Sunday
4	2022	12	11	0	Sunday

Data Visualization

Q1

Conduct a sentiment analysis on each subreddit

In this question I provided 2 plots to show the average emotional state for each day. The first plot shows AFINN scores which between -2 and 6 to show the emotional state. Then, I simplify this into negative or positive (>0 as positive and <0 as negative). These two plots shows the similar distributions. The subpost with "Futurology" shows a higher positive rate each day, and the subpost with "dataisbeautiful" shows a lower positive rate each day

```
# sort by date
df['post_date'] = pd.to_datetime(df['post_date'])
df = df.sort_values(by='post_date')
```

```
!pip install afinn
```

```
Requirement already satisfied: afinn in /opt/conda/lib/python3.7/site-packages (0.1)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting
```

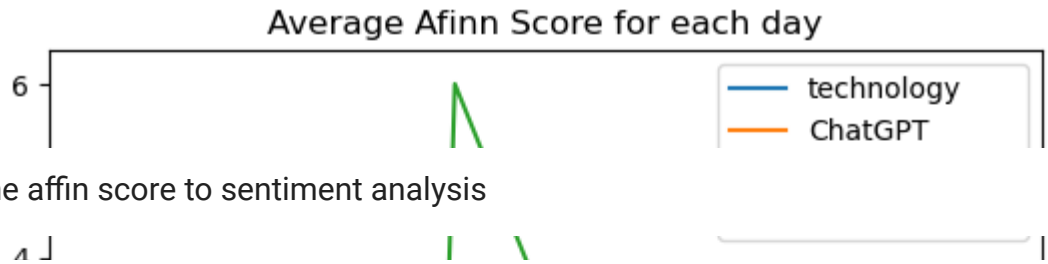
```
from afinn import Afinn
afinn = Afinn()
df['Afinn_score'] = df['comment_body'].progress_apply(lambda x: afinn.score(x))
```

```
  0%|          | 0/52412 [00:00<?, ?it/s]
```

```
df['sentiment'] = df['Afinn_score'].progress_apply(lambda x: x>0).map({True: 1, False: 0})
```

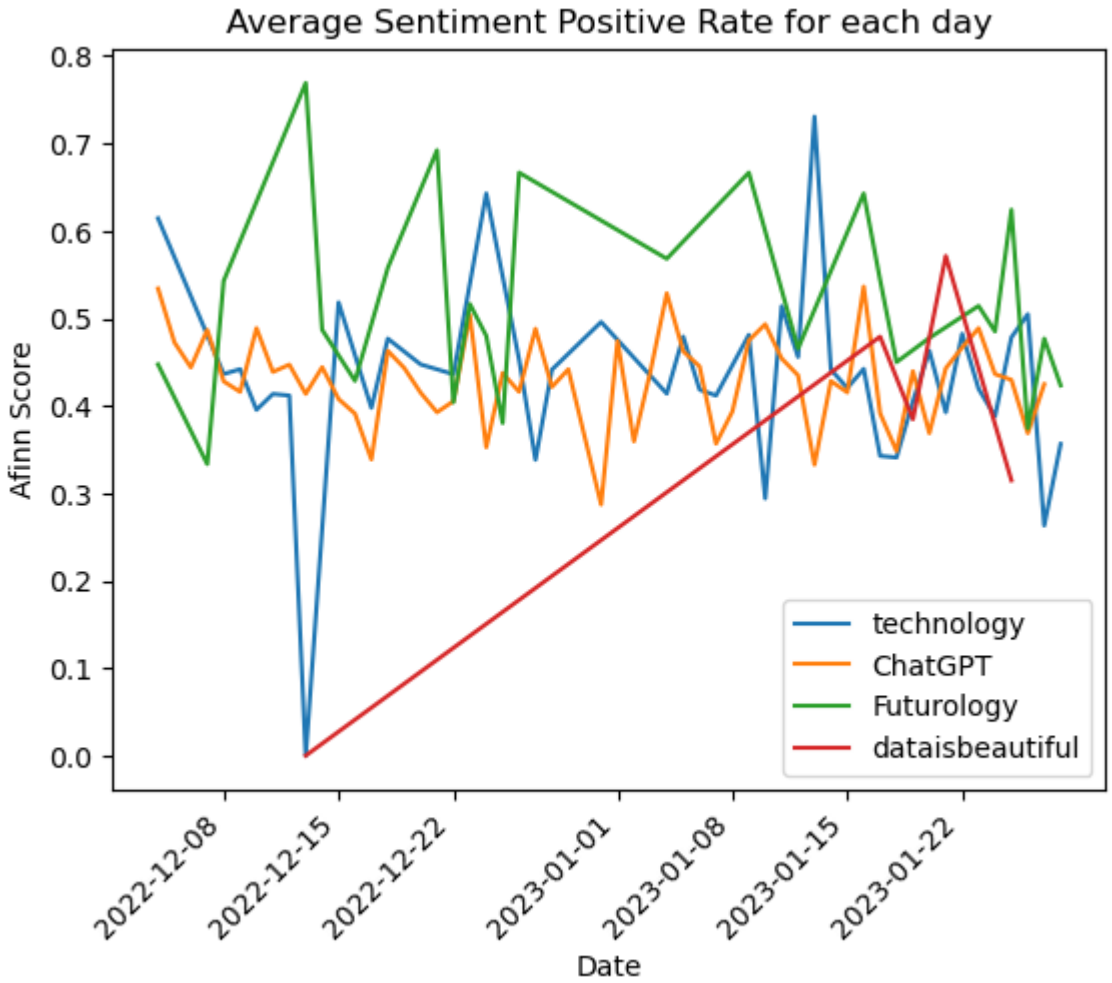
```
  0%|          | 0/52412 [00:00<?, ?it/s]
```

```
for subreddit in df['subreddit'].unique():
    subreddit_data = df[df['subreddit'] == subreddit]
    avg_scores = subreddit_data.groupby('post_date')['Afinn_score'].mean()
    date = subreddit_data['post_date'].unique()
    plt.plot(date, avg_scores, label = subreddit[2:])

plt.xlabel('Date')
plt.xticks(rotation=45, ha='right')
plt.ylabel('Afinn Score')
plt.title('Average Afinn Score for each day')
plt.legend()

plt.show()
```



Convert the affin score to sentiment analysis

```
for subreddit in df['subreddit'].unique():
    subreddit_data = df[df['subreddit'] == subreddit]
    avg_scores = subreddit_data.groupby('post_date')['sentiment'].mean()
    date = subreddit_data['post_date'].unique()
    plt.plot(date, avg_scores, label = subreddit[2:])

plt.xlabel('Date')
plt.xticks(rotation=45, ha='right')
plt.ylabel('Afinn Score')
plt.title('Average Sentiment Positive Rate for each day')
plt.legend()

plt.show()
```



Q2

Model the number of upvotes with a Poisson GLM

In this question I checked the properties of data, then removed comments with less than 0 score/net upvotes and create a temporary dataset for this question. For the information from text I selected "anger_flag + joy_flag + Count_comment + special_character_flag + num_stop_words", and for the data surrounding it I choosed "subreddit + year + month + day + hour + day_of_week + post_up_ratio + post_awards + post_cross + post_comment_count". The new column generation steps are shown in the previous steps, and other columns are the original columns in the dataset.

For the model, I provided a summary chart to show the model's information. The p-values indicate whether each independent variable is statistically significant in predicting the number of upvotes, with smaller p-values suggesting stronger evidence against the null hypothesis of no effect. Only the column "post_up_ratio" does not suggesting stronger evidence against the null hypothesis of no effect.

One other thing to tell is when apply the min-max scaler to make all numeric column's scale between 0 and 1, then the performance increase a lot. I'm using cross-validation with 5 folds to test the model performance, the score imporves from RMSE = 114.62 to 0.01

```
1 df.head()
```

	X	comment_id	comment_parent_id	comment_body	subreddit	pare
50058	14317.0	iyx9291	t3_zckhu6	best tldr could make originalwwwtheguardiantec...	r/technology	t3
50085	14344.0	iznonpd	t1_iyyqoeo	advancement neural it’s matter time someone sa...	r/technology	t3
50086	14345.0	iyxkmzd	t1_iyx91fe	tldr using chatgpt openai released chatgpt lat...	r/technology	t3
50087	14346.0	iyzh3tl	t1_iyzgu1q	also literally run roblox lua	r/technology	t3
50088	14347.0	iz0u605	t1_iz0ccgq	absolutely cases it’s great i’ve checked sever...	r/technology	t3

5 rows × 37 columns

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 52412 entries, 50058 to 35113
Data columns (total 37 columns):
```

```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   X                       52412 non-null  float64
 1   comment_id              52412 non-null  object
 2   comment_parent_id       52412 non-null  object
 3   comment_body            52412 non-null  object
 4   subreddit               52412 non-null  object
 5   parent_post             52412 non-null  object
 6   post_url                52412 non-null  object
 7   author                  52412 non-null  object
 8   date                    52412 non-null  object
 9   timestamp               52412 non-null  float64
 10  score                   52412 non-null  float64
 11  upvotes                 52412 non-null  float64
 12  golds                   52412 non-null  float64
 13  comment_tree            52412 non-null  float64
 14  post_author             52412 non-null  object
 15  post_date               52412 non-null  datetime64[ns]
 16  post_timestamp          52412 non-null  float64
 17  post_title              52412 non-null  object
 18  post_score              52412 non-null  object
 19  post_up_ratio           52412 non-null  float64
 20  post_awards             52412 non-null  float64
 21  post_golds              52412 non-null  float64
 22  post_cross              52412 non-null  float64
 23  post_comment_count      52412 non-null  float64
 24  Count_comment           52412 non-null  int64
 25  anger_flag              52412 non-null  bool
 26  joy_flag                52412 non-null  bool
 27  special_character_flag  52412 non-null  bool
 28  num_stop_words          52412 non-null  int64
 29  time                    52412 non-null  datetime64[ns]
 30  month                   52412 non-null  int64
 31  year                    52412 non-null  int64
 32  day                     52412 non-null  int64
 33  hour                    52412 non-null  int64
 34  day_of_week             52412 non-null  object
 35  Afinn_score             52412 non-null  float64
 36  sentiment               52412 non-null  int64
dtypes: bool(3), datetime64[ns](2), float64(13), int64(7), object(12)
memory usage: 14.1+ MB
```

```
1 df.post_comment_count
```

```
50058     87.0
50085     87.0
50086     87.0
50087     87.0
50088     87.0
         ...
34178    547.0
34179    547.0
34180    547.0
34204    547.0
```

```
35113    139.0
Name: post_comment_count, Length: 52412, dtype: float64
```

```
import statsmodels.api as stat
```

```
df_temp = df.copy()
df_temp = df_temp[df_temp['upvotes'] >= 0]

# data in the text
text_data = "anger_flag + joy_flag + Count_comment + special_character_flag + num_stop_wor
# data surrounding it
data_surrounding = "subreddit + year + month + day + hour + day_of_week + post_up_ratio +


formula = 'upvotes ~ ' + text_data + '+' + data_surrounding
```

```
model = glm(formula=formula, data=df_temp, family=stat.families.Poisson()).fit()
print(model.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                upvotes   No. Observations:                51151
Model:                            GLM   Df Residuals:                    51130
Model Family:                 Poisson   Df Model:                           20
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:           -1.3566e+06
Date:                Mon, 13 Mar 2023   Deviance:                  2.5279e+06
Time:                        20:38:57   Pearson chi2:                1.38e+07
No. Iterations:                     7   Pseudo R-squ. (CS):             1.000
Covariance Type:            nonrobust
=================================================================================================
                                    coef    std err          z      P>|z|      [0.025
-------------------------------------------------------------------------------------------------
Intercept                      7.224e-07   1.03e-08     70.350      0.000    7.02e-07
anger_flag[T.True]                0.1484      0.002     69.250      0.000       0.144
joy_flag[T.True]                  0.0275      0.002     12.871      0.000       0.023
special_character_flag[T.True]    0.0850      0.002     36.460      0.000       0.080
subreddit[T.r/Futurology]        -0.0414      0.004     -9.755      0.000      -0.050
subreddit[T.r/dataisbeautiful]   -0.4170      0.009    -46.754      0.000      -0.435
subreddit[T.r/technology]         0.2840      0.003    104.160      0.000       0.279
day_of_week[T.Monday]             0.1045      0.004     26.361      0.000       0.097
day_of_week[T.Saturday]          -0.3039      0.005    -65.897      0.000      -0.313
day_of_week[T.Sunday]            -0.2851      0.005    -60.840      0.000      -0.294
day_of_week[T.Thursday]          -0.2968      0.004    -73.180      0.000      -0.305
day_of_week[T.Tuesday]           -0.1752      0.004    -49.177      0.000      -0.182
day_of_week[T.Wednesday]         -0.0584      0.004    -16.367      0.000      -0.065
Count_comment                    -0.0016      0.000    -14.263      0.000      -0.002
num_stop_words                    0.0037      0.000     14.635      0.000       0.003
year                              0.0010   2.14e-06    485.777      0.000       0.001
month                             0.0047      0.000     20.440      0.000       0.004
day                               0.0065      0.000     43.658      0.000       0.006
hour                          -5.544e-17   1.32e-18    -42.110      0.000    -5.8e-17
```

```
post_up_ratio                -2.755e-05   1.99e-05     -1.385      0.166   -6.65e-05
post_awards                      0.0404      0.001     65.428      0.000       0.039
post_cross                       0.0756      0.000    217.877      0.000       0.075
post_comment_count               0.0003   1.04e-06    320.606      0.000       0.000
==============================================================================
```

Use cross-validation by stratified k folds, to estimate its performance

```
k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=1234)
rmse_array = np.zeros(k)

for i, (train_idx, test_idx) in enumerate(kf.split(df_temp)):
    train_data = df_temp.iloc[train_idx]
    test_data = df_temp.iloc[test_idx]

    # FIt the model and predict
    model = glm(formula=formula, data=train_data, family=stat.families.Poisson())
    results = model.fit()
    y_pred = results.predict(test_data)

    # RMSE
    rmse = mean_squared_error(test_data['upvotes'], y_pred, squared=False)
    rmse_array[i] = rmse

cv_rmse = np.mean(rmse_array)
print(cv_rmse)
```

```
114.6234679395154
```

Use Min-max Normalization do it again

```
# normalize df_temp
scaler = MinMaxScaler()
df_temp[df_temp.select_dtypes(include=['number']).columns] = \
    scaler.fit_transform(df_temp.select_dtypes(include=['number']))

k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=1234)
rmse_array = np.zeros(k)

for i, (train_idx, test_idx) in enumerate(kf.split(df_temp)):
    train_data = df_temp.iloc[train_idx]
    test_data = df_temp.iloc[test_idx]

    # FIt the model and predict
```

```
    model = glm(formula=formula, data=train_data, family=stat.families.Poisson())
    results = model.fit()
    y_pred = results.predict(test_data)

    # RMSE
    rmse = mean_squared_error(test_data['upvotes'], y_pred, squared=False)
    rmse_array[i] = rmse

cv_rmse = np.mean(rmse_array)
print(cv_rmse)
```

```
0.01149683730587184
```

Q3

Model whether a comment has 1 or more vs. 0 or less upvotes with a Logistic GLM

(the question title says: whether a comment has 1 or more vs. 0 or less upvote. However the question's description says: Make a Logistic (binary data) GLM that models the number of upvotes. I'm confusing for the description and my understanding is model whether True for 1 or more upvotes)

In this question I create a temporary dataset and change all upvotes > 0 to True, and no votes to False. For the information from text I selected "anger_flag + joy_flag + Count_comment + special_character_flag + num_stop_words", and for the data surrounding it I choosed "subreddit + year + month + day + hour + day_of_week + post_up_ratio + post_awards + post_cross + post_comment_count". The new column generation steps are shown in the previous steps, and other columns are the original columns in the dataset.

For the model, I provided a summary chart to show the model's information. The p-values indicate whether each independent variable is statistically significant in predicting the number of upvotes, with smaller p-values suggesting stronger evidence against the null hypothesis of no effect. The columns "day_of_week[T.Saturday]", "day_of_week[T.Sunday]", "day_of_week[T.Wednesday]" and "post_cross" does not suggesting stronger evidence against the null hypothesis of no effect.

I use balanced_accuracy_score to check the result, because the data is imbalanced, with 50074 data points positive and 2338 negative labels. I setting the weight parameter for fitting the imbalanced data. Also I tried lower sampling for the dataset, and show the result by confusion matrixes. The confusion matrixes shows the model does not have great performances, I think the data quality and model could be improve. In part 5 I will use other models and techniques.

```
1 df_temp = df.copy()
2 df_temp['upvotes'] = df['upvotes']>0
```

```
1 df_temp['upvotes'].value_counts()
```

```
True     50074
False     2338
Name: upvotes, dtype: int64
```

```
1 df_temp['upvotes'].value_counts().to_dict()
```

```
{True: 50074, False: 2338}
```

```
1 class_weights = df_temp['upvotes'].value_counts().to_dict()
```

```
1 model = glm(formula=formula, data=df_temp, family=stat.families.Binomial()).fit()
2 print(model.summary())
```

```
                          Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:     ['upvotes[False]', 'upvotes[True]']   No. Observations:
Model:                                             GLM   Df Residuals:
Model Family:                                Binomial   Df Model:
Link Function:                                  Logit   Scale:
Method:                                          IRLS   Log-Likelihood:
Date:                                Mon, 13 Mar 2023   Deviance:
Time:                                        20:39:55   Pearson chi2:                4
No. Iterations:                                     8   Pseudo R-squ. (CS):
Covariance Type:                            nonrobust
==============================================================================
                                   coef    std err          z      P>|z|      [0.025
------------------------------------------------------------------------------
Intercept                      -2.486e-06   2.07e-07    -12.024      0.000   -2.89e-06
anger_flag[T.True]                 0.3703      0.046      7.972      0.000       0.279
joy_flag[T.True]                  -0.1459      0.046     -3.143      0.002      -0.237
special_character_flag[T.True]    -0.5055      0.046    -10.948      0.000      -0.596
subreddit[T.r/Futurology]          0.1927      0.083      2.328      0.020       0.030
subreddit[T.r/dataisbeautiful]     0.9125      0.157      5.799      0.000       0.604
subreddit[T.r/technology]          0.6232      0.048     12.872      0.000       0.528
day_of_week[T.Monday]             -0.3006      0.082     -3.672      0.000      -0.461
day_of_week[T.Saturday]           -0.0550      0.082     -0.668      0.504      -0.216
day_of_week[T.Sunday]              0.0231      0.078      0.297      0.766      -0.129
day_of_week[T.Thursday]           -0.2167      0.077     -2.809      0.005      -0.368
day_of_week[T.Tuesday]            -0.3618      0.083     -4.350      0.000      -0.525
day_of_week[T.Wednesday]          -0.0254      0.077     -0.332      0.740      -0.176
Count_comment                     -0.0119      0.003     -3.877      0.000      -0.018
num_stop_words                     0.0258      0.007      3.742      0.000       0.012
year                              -0.0012   4.26e-05    -28.269      0.000      -0.001
month                             -0.0421      0.005     -8.995      0.000      -0.051
day                                0.0143      0.003      4.672      0.000       0.008
hour                           -3.572e-17   8.54e-18     -4.182      0.000   -5.25e-17
post_up_ratio                      0.0006      0.000      2.768      0.006       0.000
```

```
post_awards                -0.0720      0.023     -3.148      0.002      -0.117
post_cross                 -0.0147      0.011     -1.392      0.164      -0.036
post_comment_count         -0.0011   8.46e-05    -13.511      0.000      -0.001
==============================================================================
```

Use cross-validation by stratified k folds, to estimate its performance

```
1 train_data.head()
```

	X	comment_id	comment_parent_id	comment_body	subreddit	pare
50058	14317.0	iyx9291	t3_zckhu6	best tldr could make originalwwwtheguardiantec...	r/technology	t3
50085	14344.0	iznonpd	t1_iyyqoeo	advancement neural it's matter time someone sa...	r/technology	t3
50086	14345.0	iyxkmzd	t1_iyx91fe	tldr using chatgpt openai released chatgpt lat...	r/technology	t3
50087	14346.0	iyzh3tl	t1_iyzgu1q	also literally run roblox lua	r/technology	t3
50088	14347.0	iz0u605	t1_iz0ccgq	absolutely cases it's great i've checked sever...	r/technology	t3

5 rows × 37 columns

```
1 k = 5
2 kf = KFold(n_splits=k, shuffle=True, random_state=1234)
3 accuracy_array = np.zeros(k)
4
5 for i, (train_idx, test_idx) in enumerate(kf.split(df_temp)):
6     train_data = df_temp.iloc[train_idx]
7     test_data = df_temp.iloc[test_idx]
8
9     # FIt the model and predict
10    model = glm(formula=formula, data=train_data, family=stat.families.Binomial())
11    results = model.fit(maxiter=100, weights = class_weights)
12    y_pred = results.predict(test_data)
13    y_pred = y_pred > 0.5 # using 0.5 as threshold
14    # Accuracy
15    accuracy = balanced_accuracy_score(test_data['upvotes'], y_pred)
16    accuracy_array[i] = accuracy
17
18 cv_accuracy = np.mean(accuracy_array)
19 print(cv_accuracy)
```

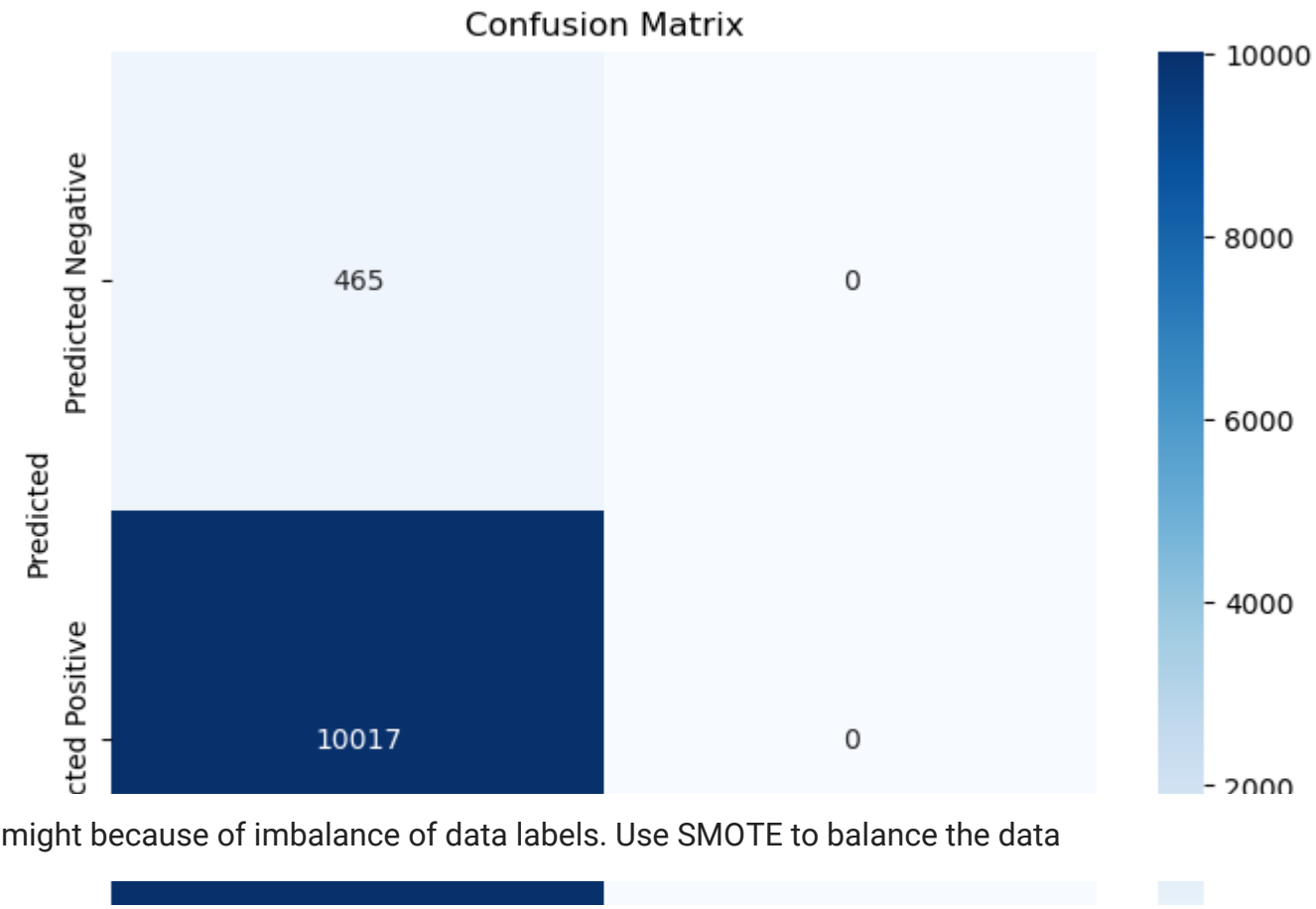
```
0.5
```

Use min-max scaler do it again

```
scaler = MinMaxScaler()
df_temp[df_temp.select_dtypes(include=['number']).columns] = \
    scaler.fit_transform(df_temp.select_dtypes(include=['number']))
k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=1234)
accuracy_array = np.zeros(k)

for i, (train_idx, test_idx) in enumerate(kf.split(df_temp)):
    train_data = df_temp.iloc[train_idx]
    test_data = df_temp.iloc[test_idx]

    # FIt the model and predict
    model = glm(formula=formula, data=train_data, family=stat.families.Binomial())
    results = model.fit(maxiter=100, weights = class_weights)
    y_pred = results.predict(test_data)
    y_pred = y_pred > 0.5 # using 0.5 as threshold
    # Accuracy
    accuracy = balanced_accuracy_score(test_data['upvotes'], y_pred)
    accuracy_array[i] = accuracy

cv_accuracy = np.mean(accuracy_array)
print(cv_accuracy)
```

```
0.5
```

```
conf_mat = confusion_matrix(test_data['upvotes'], y_pred)

# Plot confusion matrix
fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, cmap="Blues", fmt='g',
            xticklabels=['Actual Negative', 'Actual Positive'],
            yticklabels=['Predicted Negative', 'Predicted Positive'])
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title('Confusion Matrix')
plt.show()
```



This might because of imbalance of data labels. Use SMOTE to balance the data

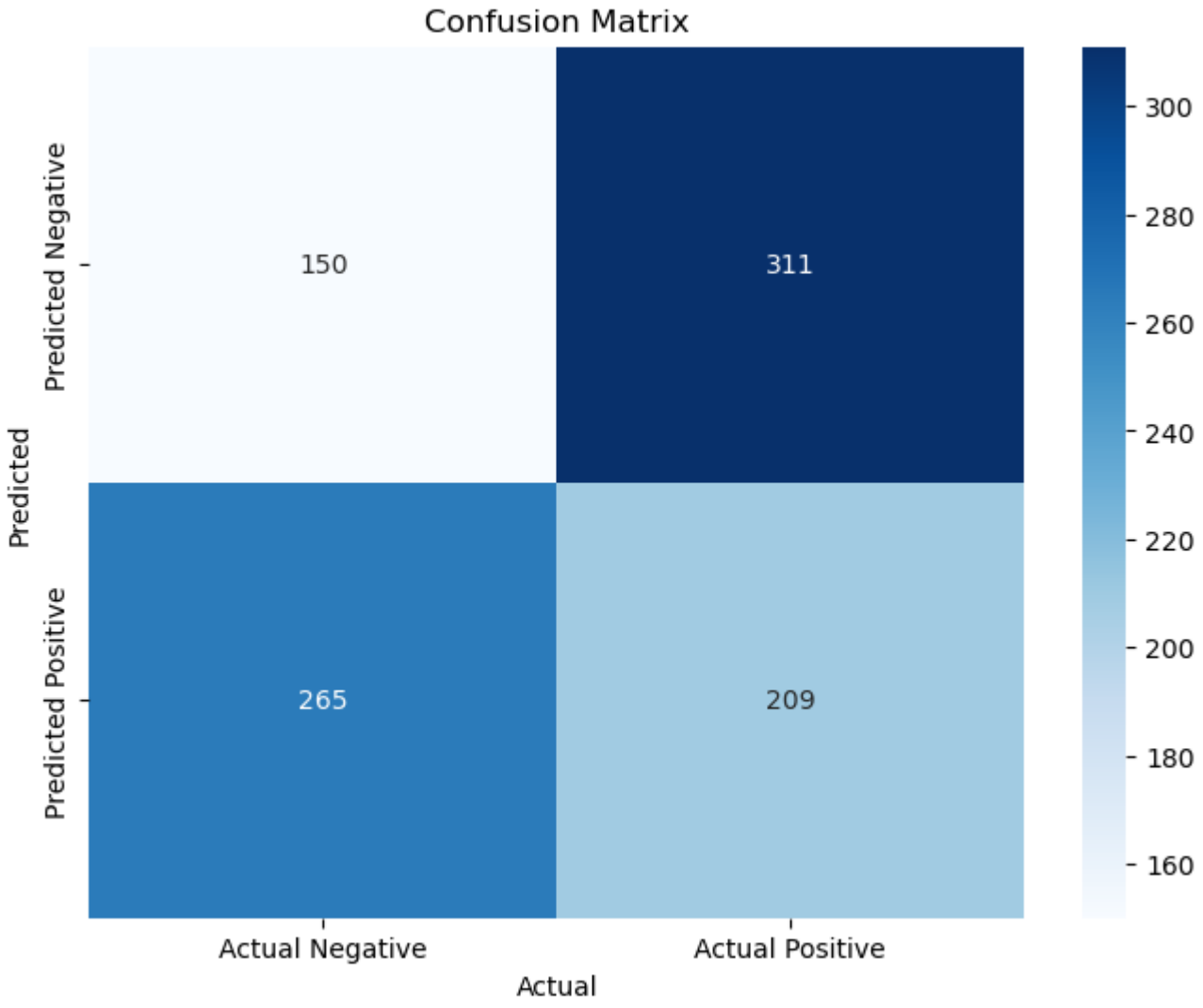
```
from imblearn.under_sampling import RandomUnderSampler

df_resampled, _ = RandomUnderSampler().fit_resample(df_temp, df_temp['upvotes'])
```

```
scaler = MinMaxScaler()
df_resampled[df_resampled.select_dtypes(include=['number']).columns] = \
    scaler.fit_transform(df_resampled.select_dtypes(include=['number']))
k = 5
kf = KFold(n_splits=k, shuffle=True, random_state=1234)
accuracy_array = np.zeros(k)

for i, (train_idx, test_idx) in enumerate(kf.split(df_resampled)):
    train_data = df_resampled.iloc[train_idx]
    test_data = df_resampled.iloc[test_idx]

    # FIt the model and predict
    model = glm(formula=formula, data=train_data, family=stat.families.Binomial())
    results = model.fit(maxiter=100)
    y_pred = results.predict(test_data)
    y_pred = y_pred > 0.5 # using 0.5 as threshold
    # Accuracy
    accuracy = balanced_accuracy_score(test_data['upvotes'], y_pred)
    accuracy_array[i] = accuracy

```

```
cv_accuracy = np.mean(accuracy_array)
print(cv_accuracy)
```

```
0.37889344158799076
```

```
conf_mat = confusion_matrix(test_data['upvotes'], y_pred)

# Plot confusion matrix
fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, cmap="Blues", fmt='g',
            xticklabels=['Actual Negative', 'Actual Positive'],
            yticklabels=['Predicted Negative', 'Predicted Positive'])
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title('Confusion Matrix')
plt.show()
```



The result is worse than before. It might better to change a model, or revise the original quality of the dataset.

Q4

Build a visualization to summarize the most common words or themes

In this part I'm using word clouds and bar charts. The word cloud provides some visual representation of the text data that summarize the word distributions by the size of text words in the plot. I seperate the wordcloud and bar charts for positive and negative upvotes.

For the word cloud, both of the charts shows some common words such as "chatgpt", "people", "ai". This means the words in positive and negative upvotes are similar. There are also some differences such as the word "google" only appears in the plot of negative words but not in positive.

The bar chart shows the top 10 occurance words in both positive and negative upvotes. By the bar charts, there is almost no significant differences between the occurence of words.

Most Common words bar chart

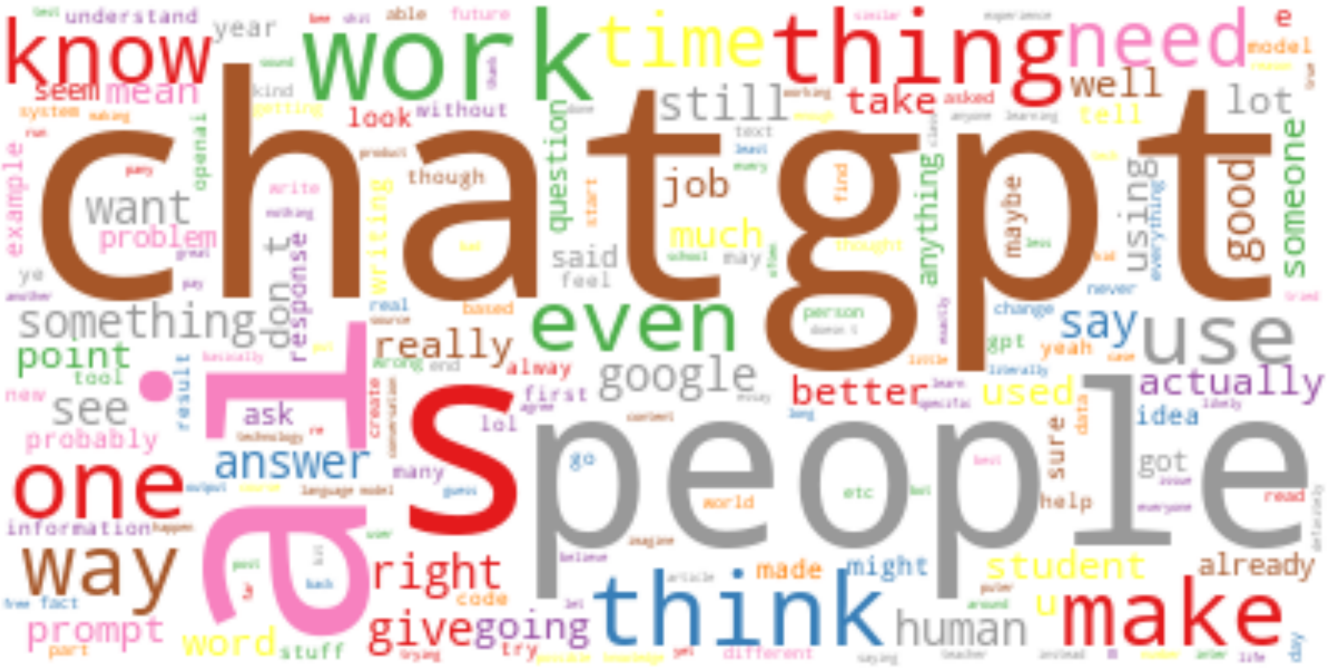
```
from wordcloud import WordCloud
```

```
word_pos = df_temp[df_temp['upvotes'] == True]['comment_body']
word_neg = df_temp[df_temp['upvotes'] == False]['comment_body']
word_pos = " ".join(i for i in word_pos)
word_neg = " ".join(i for i in word_neg)
```

```
wordcloud_pos = WordCloud(collocations = True,
                      background_color="white", colormap = "Set1").generate(word_pos)
wordcloud_neg = WordCloud(collocations = True,
                      background_color="white", colormap = "Blues").generate(word_neg)
```

```
plt.figure(figsize=(30,20))
plt.imshow(wordcloud_pos, interpolation='bilinear')
plt.axis("off")
plt.title('Word Cloud Positive', fontsize=30)
plt.savefig('word_cloud_positive.png')
plt.show()
```

Word Cloud Positive

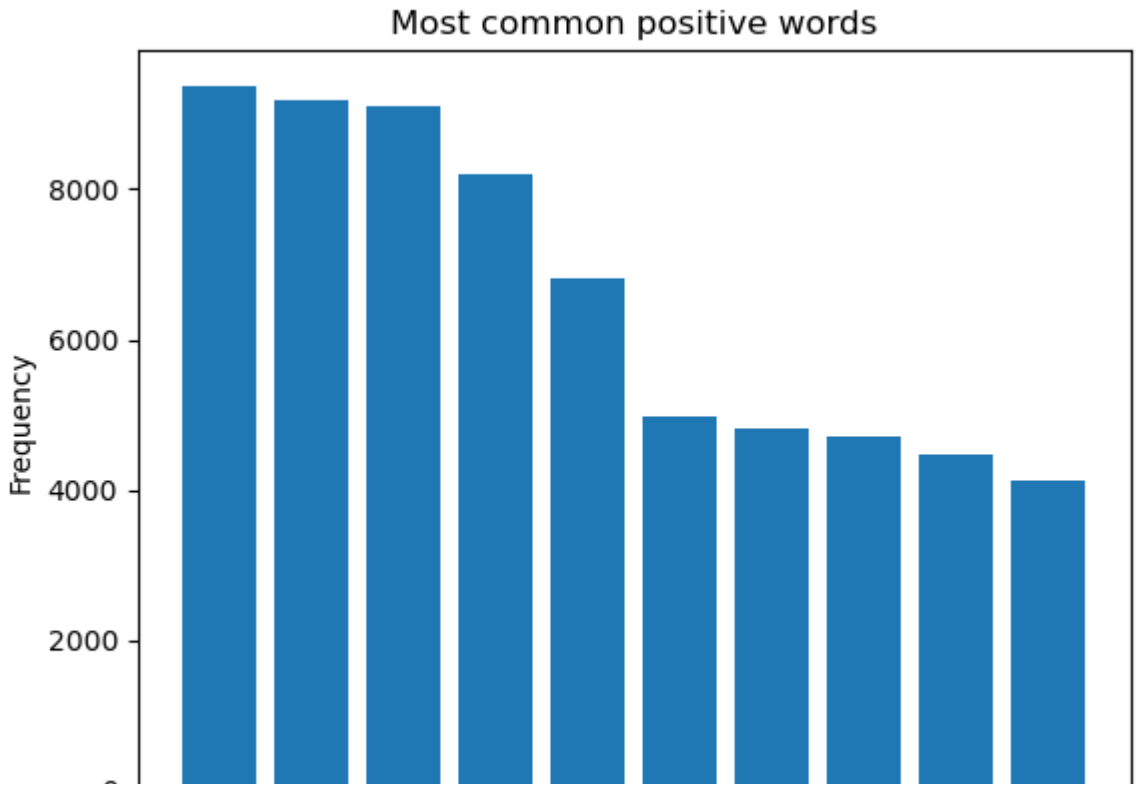



```
1 plt.figure(figsize=(30,20))
2 plt.imshow(wordcloud_neg, interpolation='bilinear')
3 plt.axis("off")
4 plt.title('Word Cloud Negative', fontsize=30)
5 plt.savefig('word_cloud_negative.png')
6 plt.show()
```

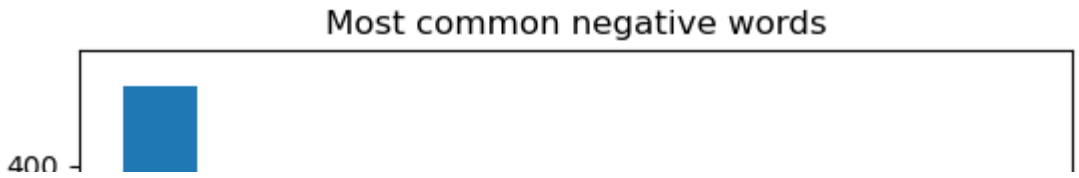
Word Cloud Negative

Most Common Words Bar Charts

```
1 word_count = pd.Series(word_pos.split()).value_counts(ascending = False)
2 n = 10
3 top_n_words = word_count[0:n]
4
5 plt.bar(range(n), top_n_words.values, tick_label=top_n_words.index)
6 plt.title('Most common positive words')
7 plt.xlabel('Words')
8 plt.ylabel('Frequency')
9 plt.show()
```




```
word_count = pd.Series(word_neg.split()).value_counts(ascending = False)
n = 10
top_n_words = word_count[0:n]

plt.bar(range(n), top_n_words.values, tick_label=top_n_words.index)
plt.title('Most common negative words')
plt.xlabel('Words')
plt.ylabel('Frequency')
plt.show()
```



Q5

Find at least two other interesting patterns in the data and comment on them. These could be relationships between data, or interesting distributions, or interesting patterns in time, or ways to split the data. You are allowed to use plots to make your point.

1. Correlation

For strong correlation between 2 variables, I found ('timestamp', 'post_timestamp'), ('score', 'upvotes'), ('Count_comment', 'num_stop_words') have high correlations. When apply model techniques, we need to delete one of each pair to avoid multicollinearity for the model.

2. PCA + K means

PCA (Principal Component Analysis） is a dimensional reduction technique, which help me select features, reduce noise and using lower feature to explain the whole dataset. Also the method helps me to visulize K means in 2-d format. This makes it easier to understand the relationship within the data.

By visualize the explain variance ratio by PCA, the first two features have very high explained variance ratio. So choose the result of K = 2.

For K-means clustering, I'm choosing the best K by with-in cluster distance and Silhouette Score. Within cluster distance measures the compactness of clusters and helps to identify the optimal number of clusters to ensure that the clusters formed are meaningful and distinct. Silhouette Score is another metric that helps to evaluate the quality of clustering. It measures how similar an object is to its own cluster compared to other clusters. For both plots the elbow point is k = 4.

For the clustering plot, the plot is well seperated with 4 clusters. For further analysis I can use the clustering result to add more features. Also by discover the similarities between each clsters for its original data, which helps us to determine the strategies and better understanding for the data.

3. Modeling

another extra thing to do is improve the model (after result of Q3). Here are some comments:

- it's better to distinguish the upvote by upvotes > 50 or 150
- Xgboost might get better result

- Model's weight functions for imbalance labels

To prove these first I plot an distribution plot for number of votes. I found the distribution is very similar between <= 0 and 0-50, so the result might not good by the seperation. I tried the seperation for < 50 and >= 50, then the model becomes much more better. The balanced accuracy for Logistic Regression is 0.74 which is > 0.5. The Xgboost works worse than Logistic Regression but still better than result in Q3.

find pairs of correlation > 0.95

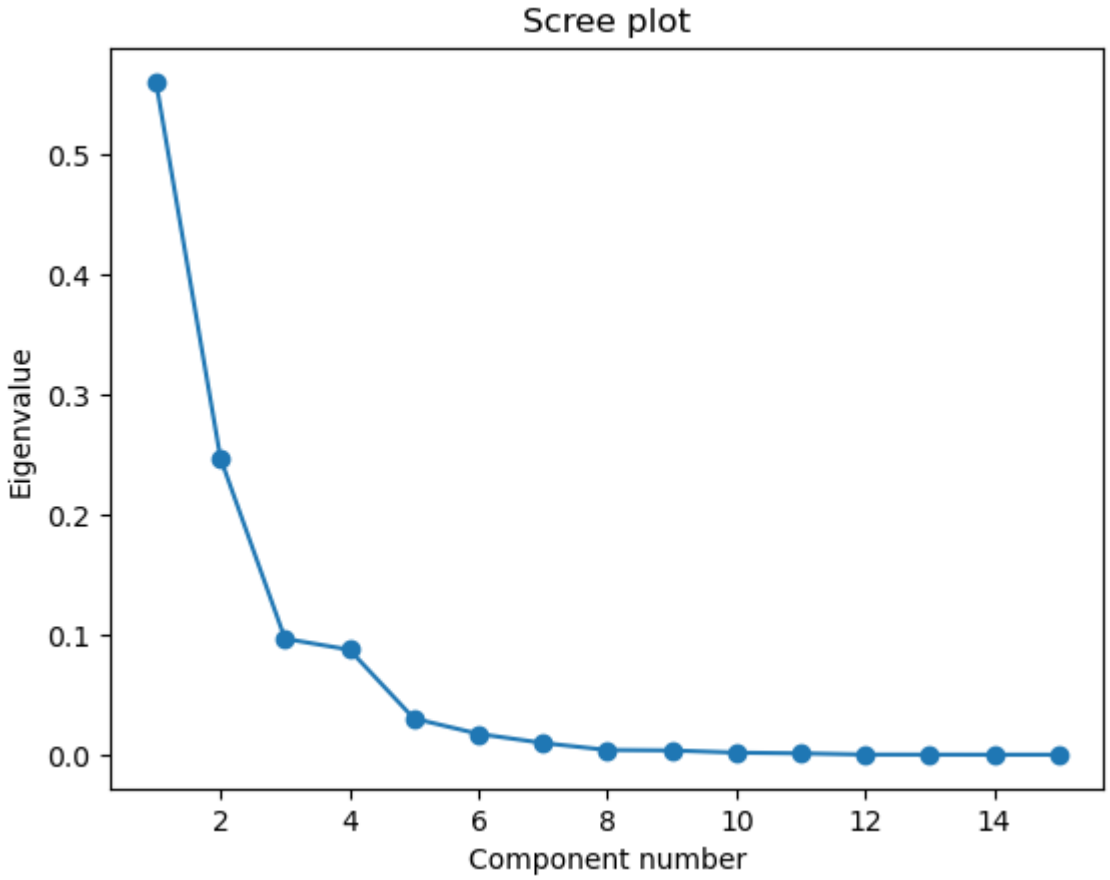
```
corr_matrix = df.corr()
high_corr_pairs = []
for i in range(len(corr_matrix.columns)):
    for j in range(i+1, len(corr_matrix.columns)):
        if corr_matrix.iloc[i, j] > 0.95 and corr_matrix.columns[i] != corr_matrix.columns
            high_corr_pairs.append((corr_matrix.columns[i], corr_matrix.columns[j]))

print(high_corr_pairs)
```

```
[('timestamp', 'post_timestamp'), ('score', 'upvotes'), ('Count_comment', 'num_stop_word
```

Dimensional Reduction

```
# normalize df
scaler = MinMaxScaler()
df[df.select_dtypes(include=['number']).columns] = \
    scaler.fit_transform(df.select_dtypes(include=['number']))
```

```
from sklearn.decomposition import PCA

n = 15
pca = PCA(n_components=n)
pca.fit(df.select_dtypes(include=['number']))

# Get the eigenvalues
eigenvalues = pca.explained_variance_

# Plot the line plot of the eigenvalues
plt.plot(np.arange(1, n+1), eigenvalues, marker='o')
plt.xlabel('Component number')
plt.ylabel('Eigenvalue')
plt.title('Scree plot')
plt.show()
```



Clustering

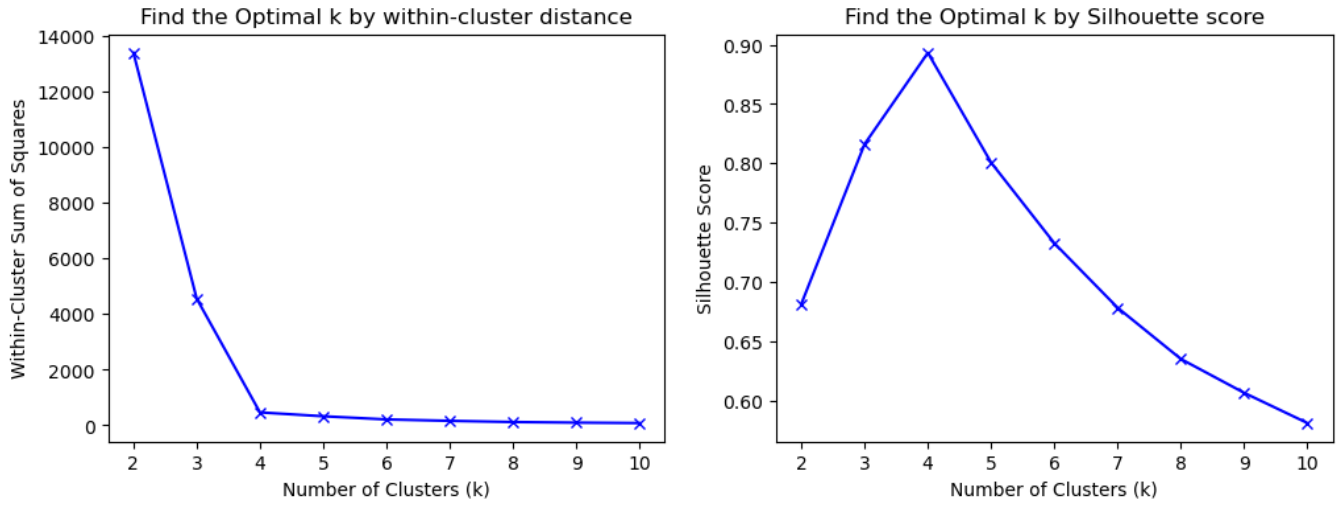
```
from sklearn.metrics import pairwise_distances
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

find the best k by intra-cluster distance

```
PCA_df = pca.fit_transform(df.select_dtypes(include=['number']))[:,0:2]
PCA_df = pd.DataFrame(data=PCA_df, columns=['PC1', 'PC2'])
wcss = []
silhouette_scores = []

k_values = range(2, 11)
for k in tqdm(k_values):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(PCA_df)
    wcss.append(kmeans.inertia_)
    if k > 1:
        score = silhouette_score(PCA_df, kmeans.labels_)
        silhouette_scores.append(score)

import matplotlib.pyplot as plt

```

```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

ax1.plot(k_values, wcss, 'bx-')
ax1.set_xlabel('Number of Clusters (k)')
ax1.set_ylabel('Within-Cluster Sum of Squares')
ax1.set_title('Find the Optimal k by within-cluster distance')

if silhouette_scores:
    ax2.plot(k_values, silhouette_scores, 'bx-')
    ax2.set_xlabel('Number of Clusters (k)')
    ax2.set_ylabel('Silhouette Score')
    ax2.set_title('Find the Optimal k by Silhouette score')

plt.show()
```

```
0%|          | 0/9 [00:00<?, ?it/s]
```

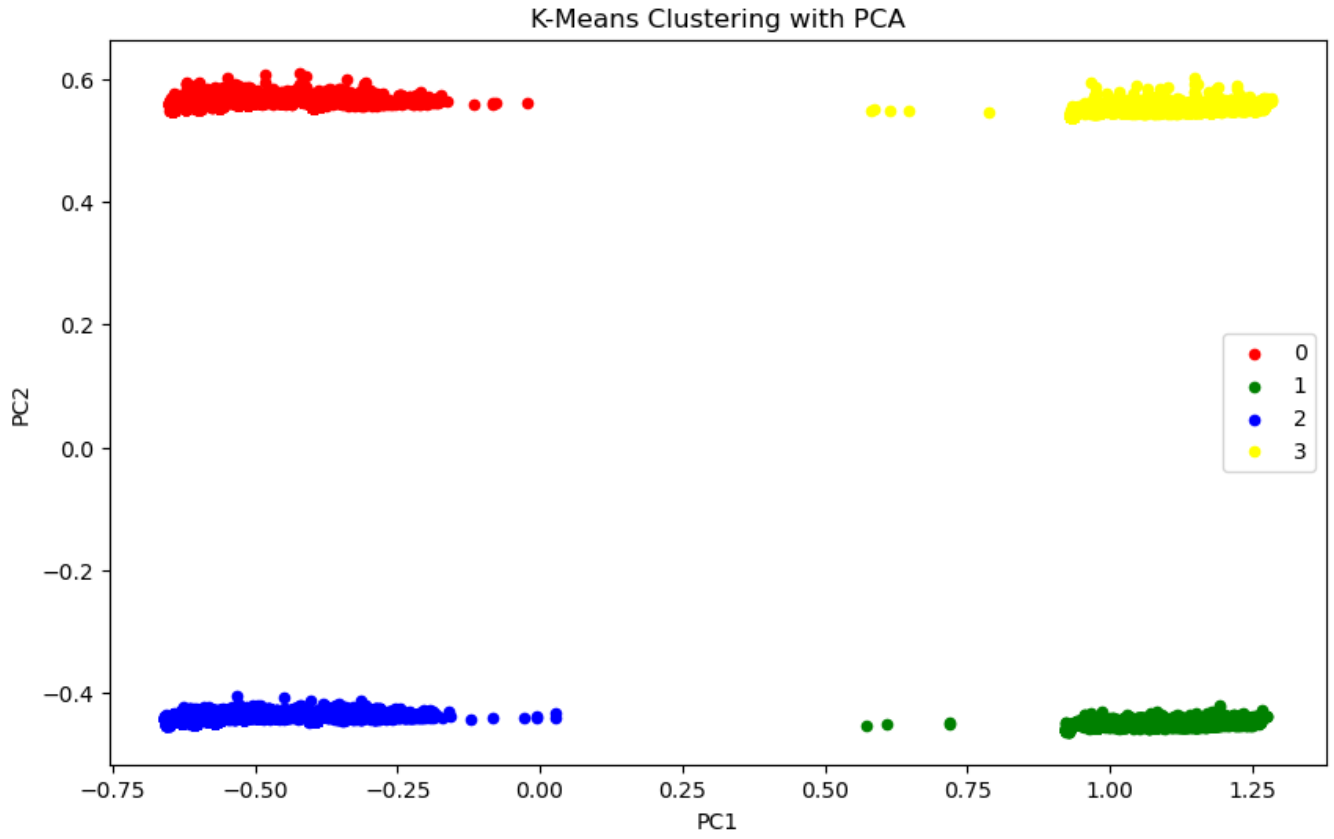


choose k = 4

```
kmeans = KMeans(n_clusters=4)
kmeans.fit(PCA_df)
labels = kmeans.predict(PCA_df)
PCA_df['Cluster'] = labels
```

```
# Plot the clusters on a scatter plot
fig, ax = plt.subplots(figsize=(10, 6))

colors = {0: 'red', 1: 'green', 2: 'blue', 3: 'yellow'}
```

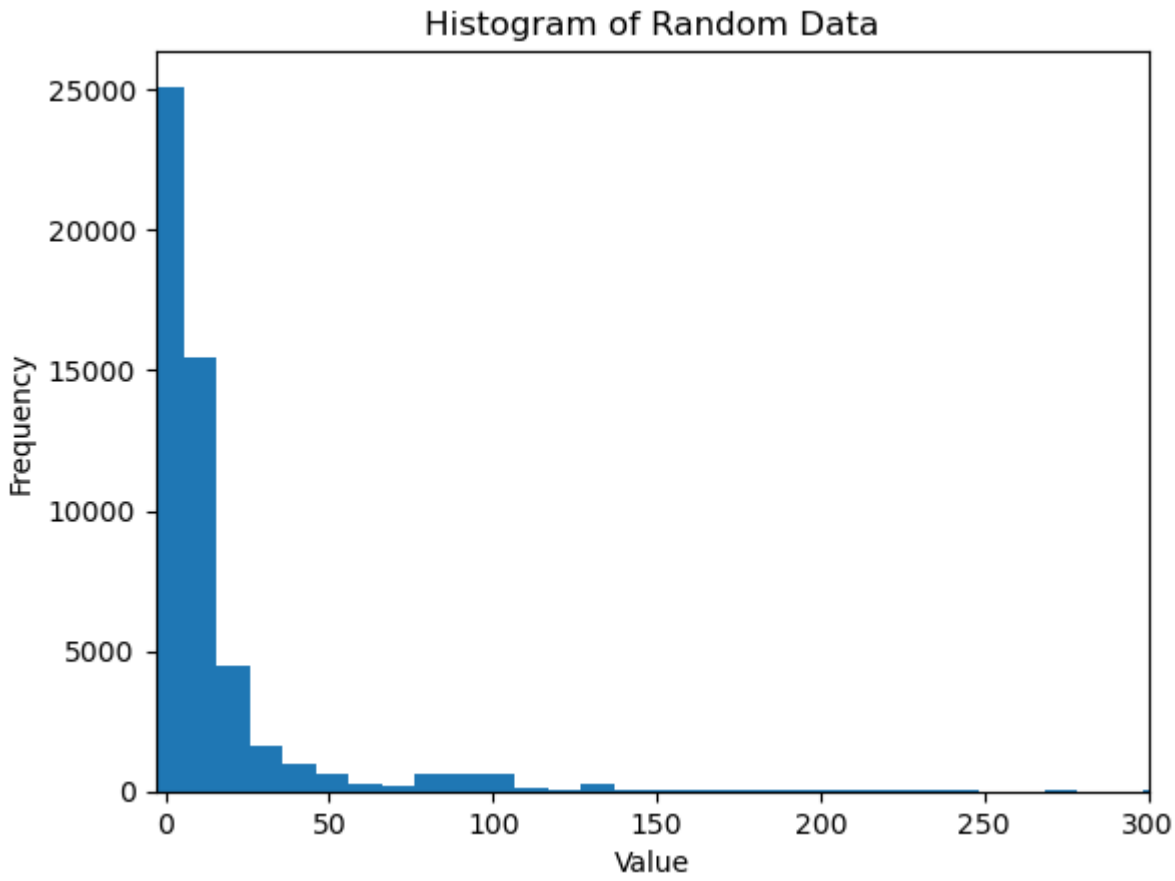
```
grouped = PCA_df.groupby('Cluster')
for key, group in grouped:
    group.plot(ax=ax, kind='scatter', x='PC1', y='PC2', label=key, color=colors[key])

plt.title('K-Means Clustering with PCA')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.show()
```



another extra thing to do is improve the model (after result of Q3). Here are some comments:

- it's better to distinguish the upvote by upvotes > 50 or 150
- Xgboost might get better result
- Model's weight functions for imbalance labels

```
df_temp = df.copy()
plt.hist(df_temp['upvotes'], bins = 1000)
plt.title('Histogram of Random Data')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.xlim([-3, 300])
plt.show()
```




```
df_temp['upvotes'] = df['upvotes'] >= 50
df_temp['upvotes'].value_counts()
```

```
False    48621
True      3791
Name: upvotes, dtype: int64
```

```
formula = text_data + ' + ' + data_surrounding
formula.split(' + ')
```

```
['anger_flag',
 'joy_flag',
 'Count_comment',
 'special_character_flag',
 'num_stop_words',
 'subreddit',
 'year',
 'month',
```

```
    'day',
    'hour',
    'day_of_week',
    'post_up_ratio',
    'post_awards',
    'post_cross',
    'post_comment_count']
```

```
X = df_temp[formula.split(' + ')]
y = df_temp['upvotes']
```

```
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_validate
```

```
X.head()
```

	anger_flag	joy_flag	Count_comment	special_character_flag	num_stop_words	sub
50058	True	True	180	True	65	r/tec
50085	True	True	109	True	50	r/tec
50086	False	True	92	True	34	r/tec
50087	False	False	7	False	2	r/tec
50088	True	True	150	True	53	r/tec

One hot encoding

```
encoded_cols = pd.get_dummies(X['subreddit'], prefix='subreddit')
encoded_cols_day = pd.get_dummies(X['day_of_week'], prefix='day_of_week')

X = pd.concat([X, encoded_cols, encoded_cols_day], axis=1)
X.drop('subreddit', axis=1, inplace=True)
X.drop('day_of_week', axis=1, inplace=True)
X.head()
```

	anger_flag	joy_flag	Count_comment	special_character_flag	num_stop_words	yeai
50058	True	True	180	True	65	202:

```
1 model = LogisticRegression(random_state=1234)
2 scoring = {'balanced_accuracy': 'balanced_accuracy', 'roc_auc': 'roc_auc'}
3 scores = cross_validate(model, X, y, cv=5, scoring=scoring)
4 print("Accuracy: %0.3f (+/- %0.3f)" % (scores['test_balanced_accuracy'].mean(), scores['te
5 print("ROC-AUC: %0.3f (+/- %0.3f)" % (scores['test_roc_auc'].mean(), scores['test_roc_auc'
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergen
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergen
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergen
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergen
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
Accuracy: 0.633 (+/- 0.158)
ROC-AUC: 0.772 (+/- 0.094)
/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818: Convergen
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

avoid warning, add max_iter to 5000. class_weight='balanced' also helps the model balance the weight.

```
model = LogisticRegression(class_weight='balanced', max_iter=5000, random_state=1234)
scoring = {'balanced_accuracy': 'balanced_accuracy', 'roc_auc': 'roc_auc'}
scores = cross_validate(model, X, y, cv=5, scoring=scoring)
print("Accuracy: %0.3f (+/- %0.3f)" % (scores['test_balanced_accuracy'].mean(), scores['te
print("ROC-AUC: %0.3f (+/- %0.3f)" % (scores['test_roc_auc'].mean(), scores['test_roc_auc'
```

```
Accuracy: 0.746 (+/- 0.066)
ROC-AUC: 0.776 (+/- 0.086)
```

```
model = XGBClassifier(random_state=1234)
scoring = {'balanced_accuracy': 'balanced_accuracy', 'roc_auc': 'roc_auc'}
scores = cross_validate(model, X, y, cv=5, scoring=scoring)
print("Accuracy: %0.3f (+/- %0.3f)" % (scores['test_balanced_accuracy'].mean(), scores['te
print("ROC-AUC: %0.3f (+/- %0.3f)" % (scores['test_roc_auc'].mean(), scores['test_roc_auc'
```

```
Accuracy: 0.545 (+/- 0.067)
ROC-AUC: 0.634 (+/- 0.168)
```

Xgboost with weight balance

```
model = XGBClassifier(scale_pos_weight = count[False]/count[True], random_state=1234)
scoring = {'balanced_accuracy': 'balanced_accuracy', 'roc_auc': 'roc_auc'}
scores = cross_validate(model, X, y, cv=5, scoring=scoring)
print("Accuracy: %0.3f (+/- %0.3f)" % (scores['test_balanced_accuracy'].mean(), scores['te
print("ROC-AUC: %0.3f (+/- %0.3f)" % (scores['test_roc_auc'].mean(), scores['test_roc_auc'
```

```
Accuracy: 0.589 (+/- 0.064)
ROC-AUC: 0.635 (+/- 0.181)
```

Save to pdf

```
pip install nbconvert
```

```
Requirement already satisfied: nbconvert in /opt/conda/lib/python3.7/site-packages (7.2
Requirement already satisfied: jupyter-core>=4.7 in /opt/conda/lib/python3.7/site-packag
Requirement already satisfied: pygments>=2.4.1 in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: traitlets>=5.0 in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: nbformat>=5.1 in /opt/conda/lib/python3.7/site-packages (
Requirement already satisfied: defusedxml in /opt/conda/lib/python3.7/site-packages (fro
Requirement already satisfied: jupyterlab-pygments in /opt/conda/lib/python3.7/site-pack
Requirement already satisfied: jinja2>=3.0 in /opt/conda/lib/python3.7/site-packages (fr
Requirement already satisfied: beautifulsoup4 in /opt/conda/lib/python3.7/site-packages
```

```
Requirement already satisfied: mistune<3,>=2.0.3 in /opt/conda/lib/python3.7/site-packag
Requirement already satisfied: markupsafe>=2.0 in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: packaging in /opt/conda/lib/python3.7/site-packages (from
Requirement already satisfied: bleach in /opt/conda/lib/python3.7/site-packages (from nb
Requirement already satisfied: tinycss2 in /opt/conda/lib/python3.7/site-packages (from
Requirement already satisfied: nbclient>=0.5.0 in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: pandocfilters>=1.4.1 in /opt/conda/lib/python3.7/site-pac
Requirement already satisfied: importlib-metadata>=3.6 in /opt/conda/lib/python3.7/site-
Requirement already satisfied: typing-extensions>=3.6.4 in /opt/conda/lib/python3.7/site
Requirement already satisfied: zipp>=0.5 in /opt/conda/lib/python3.7/site-packages (from
Requirement already satisfied: jupyter-client>=6.1.12 in /opt/conda/lib/python3.7/site-p
Requirement already satisfied: fastjsonschema in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: jsonschema>=2.6 in /opt/conda/lib/python3.7/site-packages
Requirement already satisfied: soupsieve>1.2 in /opt/conda/lib/python3.7/site-packages (
Requirement already satisfied: six>=1.9.0 in /opt/conda/lib/python3.7/site-packages (fro
Requirement already satisfied: webencodings in /opt/conda/lib/python3.7/site-packages (f
Requirement already satisfied: pkgutil-resolve-name>=1.3.10 in /opt/conda/lib/python3.7/
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in /opt/con
Requirement already satisfied: attrs>=17.4.0 in /opt/conda/lib/python3.7/site-packages (
Requirement already satisfied: importlib-resources>=1.4.0 in /opt/conda/lib/python3.7/si
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/lib/python3.7/site-p
Requirement already satisfied: tornado>=6.2 in /opt/conda/lib/python3.7/site-packages (f
Requirement already satisfied: nest-asyncio>=1.5.4 in /opt/conda/lib/python3.7/site-pack
Requirement already satisfied: pyzmq>=23.0 in /opt/conda/lib/python3.7/site-packages (fr
Requirement already satisfied: entrypoints in /opt/conda/lib/python3.7/site-packages (fr
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting
Note: you may need to restart the kernel to use updated packages.
```