Logistic Regression project

December 1, 2024

1 TikTok Project

2 Objectives

1. **Develop a Machine Learning Model**: Create a predictive model to classify TikTok videos as containing either a claim or an opinion.

2. **Enhance Efficiency in Handling User Reports**: Use the predictive model to reduce the backlog of user reports by prioritizing them based on content classification.

3. **Complete Project Development Steps**: Finalize ongoing work, including:
   - Initial action plan creation.
   - Python-based initial coding.
   - Exploratory Data Analysis (EDA).
   - Hypothesis testing.

4. **Analyze Hypothesis Testing Results**: Evaluate the relationship between user variables and verified status based on hypothesis testing.

5. **Explore Verified User Patterns**: Investigate how verified users are associated with posting opinions to refine model predictions.

6. **Conduct Logistic Regression Analysis**: Use verified status as the outcome variable to understand video characteristics linked to user verification.

7. **Refine the Final Model**: Incorporate logistic regression insights into the final machine learning model to improve claim vs opinion predictions.

8. **Support TikTok's Operations Team**: Provide actionable insights a Abadi and the operations team to enhance understanding of video characteristics and user behavior patterns.

3 Steps

1. **Demonstrate Knowledge of EDA and Regression Models**: Showcase your understanding of Exploratory Data Analysis (EDA) and logistic regression by building and evaluating a predictive model.

2. **Build a Logistic Regression Model**: Develop a logistic regression model to estimate the probability of a specific outcome using Python.

3. **Evaluate the Logistic Regression Model**: Assess the model's performance and ensure it meets the assumptions required for logistic regression-
4. **Part 1: EDA & Checking Model Assumptions**:
   - Understand the purpose of EDA before constructing a logistic regression model.
   - Identify patterns, relationships, and potential issues in the data-t.

5. **Part 2: Model Building and Evaluation**:
   - Utilize appropriate resources and methodologies to construct and evaluate the logistic regression model.
   - Document challenges and resources used during the p-cess.

6. **Part 3: Interpreting Model Results**:
   - Extract key insights from the logistic regression model.
   - Formulate business recommendations based on model results.

7. **Write an Executive Summary**:
   - Use the PACE Strategy Document to summarize findings, insights, and business recommendations effectively.

8. **Prepare for Comparison**: Complete the activity to compare your work with a provided exemplar for further learning and refinement.

3.0.1 Task 1. Imports and loading

Import the data and packages for building Logistic regression models.

[9]:
```
# Import packages for data manipulation
import pandas as pd
import numpy as np
# Import packages for data visualization
import seaborn as sns
import matplotlib.pyplot as plt
# Import packages for data preprocessing
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.utils import resample
# Import packages for data modeling
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

Load the TikTok dataset.

[10]:
```python
# Load dataset into dataframe
data = pd.read_csv("tiktok_dataset.csv")
```

EDA is the important step in data analytics, we can see the descriptive statistic, outlier, dataset info , data with duplicate and data with missing values. In Logistic Regression, we need to see the correlation between variable , to verify model assumptions such as no severe multicollinearity.

3.0.2 Task 2a. Explore data with EDA

Analyze the data and check for and handle missing values and duplicates.

[11]:
```python
# Display first few rows
data.head()
```

[11]:
```
   # claim_status    video_id  video_duration_sec  \
0  1        claim  7017666017                  59
1  2        claim  4014381136                  32
2  3        claim  9859838091                  31
3  4        claim  1866847991                  25
4  5        claim  7105231098                  19

                            video_transcription_text verified_status  \
0  someone shared with me that drone deliveries a…    not verified
1  someone shared with me that there are more mic…    not verified
2  someone shared with me that american industria…    not verified
3  someone shared with me that the metro of st. p…    not verified
4  someone shared with me that the number of busi…    not verified

  author_ban_status  video_view_count  video_like_count  video_share_count  \
0      under review          343296.0           19425.0              241.0
1            active          140877.0           77355.0            19034.0
2            active          902185.0           97690.0             2858.0
3            active          437506.0          239954.0            34812.0
4            active           56167.0           34987.0             4110.0

   video_download_count  video_comment_count
0                   1.0                  0.0
1                1161.0                684.0
2                 833.0                329.0
3                1234.0                584.0
4                 547.0                152.0
```

Get the number of rows and columns in the dataset.

[12]:
```python
# Get number of rows and columns
print(f"Total rows : {data.shape[0]}")
print(f"Total columns : {data.shape[1]}")
print(f"Size : {data.size}")
```

```
Total rows : 19382
Total columns : 12
Size : 232584
```

Get the data types of the columns.

[13]:
```
# Get data types
data.dtypes
```

[13]:
```
#                               int64
claim_status                   object
video_id                        int64
video_duration_sec              int64
video_transcription_text       object
verified_status                object
author_ban_status              object
video_view_count              float64
video_like_count              float64
video_share_count             float64
video_download_count          float64
video_comment_count           float64
dtype: object
```

Get basic information about the dataset.

[14]:
```
# Basic information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19382 entries, 0 to 19381
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   #                         19382 non-null  int64
 1   claim_status              19084 non-null  object
 2   video_id                  19382 non-null  int64
 3   video_duration_sec        19382 non-null  int64
 4   video_transcription_text  19084 non-null  object
 5   verified_status           19382 non-null  object
 6   author_ban_status         19382 non-null  object
 7   video_view_count          19084 non-null  float64
 8   video_like_count          19084 non-null  float64
 9   video_share_count         19084 non-null  float64
 10  video_download_count      19084 non-null  float64
 11  video_comment_count       19084 non-null  float64
dtypes: float64(5), int64(3), object(4)
memory usage: 1.8+ MB
```

Generate basic descriptive statistics about the dataset.

[15]:
```
# Generate basic descriptive stats
data.describe()
```

[15]:
```
                  #      video_id  video_duration_sec  video_view_count  \
count  19382.000000  1.938200e+04        19382.000000      19084.000000
mean    9691.500000  5.627454e+09           32.421732     254708.558688
std     5595.245794  2.536440e+09           16.229967     322893.280814
min        1.000000  1.234959e+09            5.000000         20.000000
25%     4846.250000  3.430417e+09           18.000000       4942.500000
50%     9691.500000  5.618664e+09           32.000000       9954.500000
75%    14536.750000  7.843960e+09           47.000000     504327.000000
max    19382.000000  9.999873e+09           60.000000     999817.000000

       video_like_count  video_share_count  video_download_count  \
count      19084.000000       19084.000000          19084.000000
mean       84304.636030       16735.248323           1049.429627
std       133420.546814       32036.174350           2004.299894
min            0.000000           0.000000              0.000000
25%          810.750000         115.000000              7.000000
50%         3403.500000         717.000000             46.000000
75%       125020.000000       18222.000000           1156.250000
max       657830.000000      256130.000000          14994.000000

       video_comment_count
count         19084.000000
mean            349.312146
std             799.638865
min               0.000000
25%               1.000000
50%               9.000000
75%             292.000000
max            9599.000000
```

[16]:
```
# Object Variable
data.describe(include='object').T
```

[16]:
```
                          count unique  \
claim_status              19084      2
video_transcription_text  19084  19012
verified_status           19382      2
author_ban_status         19382      3


                                                                         top  \
claim_status                                                           claim
video_transcription_text  a friend read  in the media a claim that badmi…
verified_status                                                 not verified
author_ban_status                                                     active
```

```
                          freq
claim_status              9608
video_transcription_text     2
verified_status          18142
author_ban_status        15663
```

Check for and handle missing values.

[17]:
```
# Check for missing values
data.isna().sum()
```

[17]:
```
#                             0
claim_status                298
video_id                      0
video_duration_sec            0
video_transcription_text    298
verified_status               0
author_ban_status             0
video_view_count            298
video_like_count            298
video_share_count           298
video_download_count        298
video_comment_count         298
dtype: int64
```

[18]:
```
data.loc[data.isna().any(axis=1)].head()
```

[18]:
```
           # claim_status    video_id  video_duration_sec  \
19084  19085          NaN  4380513697                  39
19085  19086          NaN  8352130892                  60
19086  19087          NaN  4443076562                  25
19087  19088          NaN  8328300333                   7
19088  19089          NaN  3968729520                   8

      video_transcription_text verified_status author_ban_status  \
19084                      NaN    not verified            active
19085                      NaN    not verified            active
19086                      NaN    not verified            active
19087                      NaN    not verified            active
19088                      NaN    not verified            active

       video_view_count  video_like_count  video_share_count  \
19084               NaN               NaN                NaN
19085               NaN               NaN                NaN
19086               NaN               NaN                NaN
19087               NaN               NaN                NaN
```

```
19088                NaN                 NaN                  NaN

       video_download_count  video_comment_count
19084                   NaN                  NaN
19085                   NaN                  NaN
19086                   NaN                  NaN
19087                   NaN                  NaN
19088                   NaN                  NaN
```

[19]:
```
# Drop rows with missing values
data.dropna(axis=0,inplace=True)
```

[20]:
```
# Display first few rows after handling missing values
data.head()
```

[20]:
```
   # claim_status    video_id  video_duration_sec  \
0  1        claim  7017666017                  59
1  2        claim  4014381136                  32
2  3        claim  9859838091                  31
3  4        claim  1866847991                  25
4  5        claim  7105231098                  19

                            video_transcription_text verified_status  \
0  someone shared with me that drone deliveries a…    not verified
1  someone shared with me that there are more mic…    not verified
2  someone shared with me that american industria…    not verified
3  someone shared with me that the metro of st. p…    not verified
4  someone shared with me that the number of busi…    not verified

  author_ban_status  video_view_count  video_like_count  video_share_count  \
0      under review          343296.0           19425.0              241.0
1            active          140877.0           77355.0            19034.0
2            active          902185.0           97690.0             2858.0
3            active          437506.0          239954.0            34812.0
4            active           56167.0           34987.0             4110.0

   video_download_count  video_comment_count
0                   1.0                  0.0
1                1161.0                684.0
2                 833.0                329.0
3                1234.0                584.0
4                 547.0                152.0
```

Check for and handle duplicates.

[21]:
```
# Check for duplicates
data.duplicated().sum()
```

[21]: 0

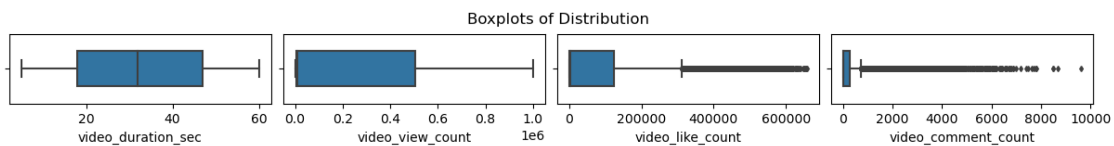
Check for and handle outliers.

[22]:
```
# Create a boxplot to visualize distribution of
#␣
↪`video_duration_sec`,`video_view_count`,`video_like_count`,`video_comment_count`

fig, ax = plt.subplots(1,4, figsize=(12,1.5), constrained_layout=True)
fig.suptitle('Boxplots of Distribution')

sns.boxplot(data=data, x='video_duration_sec', ax=ax[0], width=.5,fliersize=3)
sns.boxplot(data=data, x='video_view_count', ax=ax[1], width=.5,fliersize=3)
sns.boxplot(data=data, x='video_like_count', ax=ax[2], width=.5,fliersize=3)
sns.boxplot(data=data, x='video_comment_count', ax=ax[3], width=.5,fliersize=3)

plt.show()
```



[26]:
```
# Outliers imputation with IQR
def imputation(df,columns,iqr_factor):
    for col in columns:
        # Q1 - Q3
        q1 = df[col].quantile(0.25)
        q3 = df[col].quantile(0.75)
        # IQR
        iqr = q3 - q1
        # upper limit
        upper_limit = q3 + (iqr_factor * iqr)
        # reassign
        df.loc[df[col] > upper_limit, col] = upper_limit

        print(f"Columns : {col}")
        print(f"Upper Limit : {upper_limit}\n")
        print(f"After : ")
        print(df[col].describe())
```

[27]:
```
# Check for and handle outliers for video_like_count
data['video_like_count'].describe()
```

[27]:
```
count     19084.000000
mean      84304.636030
std      133420.546814
min           0.000000
25%         810.750000
50%        3403.500000
75%      125020.000000
max      657830.000000
Name: video_like_count, dtype: float64
```

[28]:
```
# video_like_count imputation
imputation(data,['video_like_count'],1.5)
```

```
Columns : video_like_count
Upper Limit : 311333.875

After :
count     19084.000000
mean      74323.538632
std      107103.555220
min           0.000000
25%         810.750000
50%        3403.500000
75%      125020.000000
max      311333.875000
Name: video_like_count, dtype: float64
```

[29]:
```
# video_comment_count
data['video_comment_count'].describe()
```

[29]:
```
count    19084.000000
mean       349.312146
std        799.638865
min          0.000000
25%          1.000000
50%          9.000000
75%        292.000000
max       9599.000000
Name: video_comment_count, dtype: float64
```

[30]:
```
# video_comment_count imputation
imputation(data,['video_comment_count'],1.5)
```

```
Columns : video_comment_count
Upper Limit : 728.5

After :
count    19084.000000
```

```
mean       181.023501
std        272.084766
min          0.000000
25%          1.000000
50%          9.000000
75%        292.000000
max        728.500000
Name: video_comment_count, dtype: float64
```

Check class balance of the target variable. Remember, the goal is to predict whether the user of a given post is verified or unverified.

[31]:
```
# Check class balance
data['verified_status'].value_counts(normalize=True)*100
```

[31]:
```
verified_status
not verified    93.71201
verified         6.28799
Name: proportion, dtype: float64
```

Approximately 93.7% of the dataset represents videos posted by unverified accounts and 6.3% represents videos posted by verified accounts. So the outcome variable is not very balanced.

Use resampling to create class balance in the outcome variable, if needed.

[32]:
```
# Use resampling to create class balance in the outcome variable

# Identify data points from majority and minority classes
data_majority = data.loc[data['verified_status'] == 'not verified']
data_minority = data.loc[data['verified_status'] == 'verified']

# Upsample the minority class ("verified")
minority_upsampled =␣
 ↪resample(data_minority,n_samples=len(data_majority),replace=True,␣
 ↪random_state=0)

# Combine majority class with upsampled minority class
data_upsampled = pd.concat([data_majority,minority_upsampled]).
 ↪reset_index(drop=True)

# Display new class counts
data_upsampled['verified_status'].value_counts()
```

[32]:
```
verified_status
not verified    17884
verified        17884
Name: count, dtype: int64
```

[33]:
```python
# new class percentage
print('Percentage :')
data_upsampled['verified_status'].value_counts(normalize=True)* 100
```

```
Percentage :
```

[33]:
```
verified_status
not verified    50.0
verified        50.0
Name: proportion, dtype: float64
```

Get the average video_transcription_text length for videos posted by verified accounts and the average video_transcription_text length for videos posted by unverified accounts.

[34]:
```python
# Get the average `video_transcription_text` length for claims and the average␣
↪`video_transcription_text` length for opinions
verified_and_video_transcription_text =␣
↪data_upsampled[['verified_status','video_transcription_text']]
verified_and_video_transcription_text.
↪groupby(['verified_status'])[['video_transcription_text']].agg(func= lambda␣
↪x : np.mean([len(text) for text in x ]))
```

[34]:
```
                 video_transcription_text
verified_status
not verified                    89.401141
verified                        84.569559
```

Extract the length of each video_transcription_text and add this as a column to the dataframe, so that it can be used as a potential feature in the model.

[35]:
```python
# Extract the length of each `video_transcription_text` and add this as a␣
↪column to the dataframe
data_upsampled['text_length'] = data_upsampled['video_transcription_text'].
↪apply(func=lambda x : len(x))
```

[36]:
```python
# Display first few rows of dataframe
data_upsampled.head()
```

[36]:
```
   # claim_status    video_id  video_duration_sec  \
0  1        claim  7017666017                  59
1  2        claim  4014381136                  32
2  3        claim  9859838091                  31
3  4        claim  1866847991                  25
4  5        claim  7105231098                  19

                            video_transcription_text verified_status  \
0  someone shared with me that drone deliveries a…    not verified
1  someone shared with me that there are more mic…    not verified
```

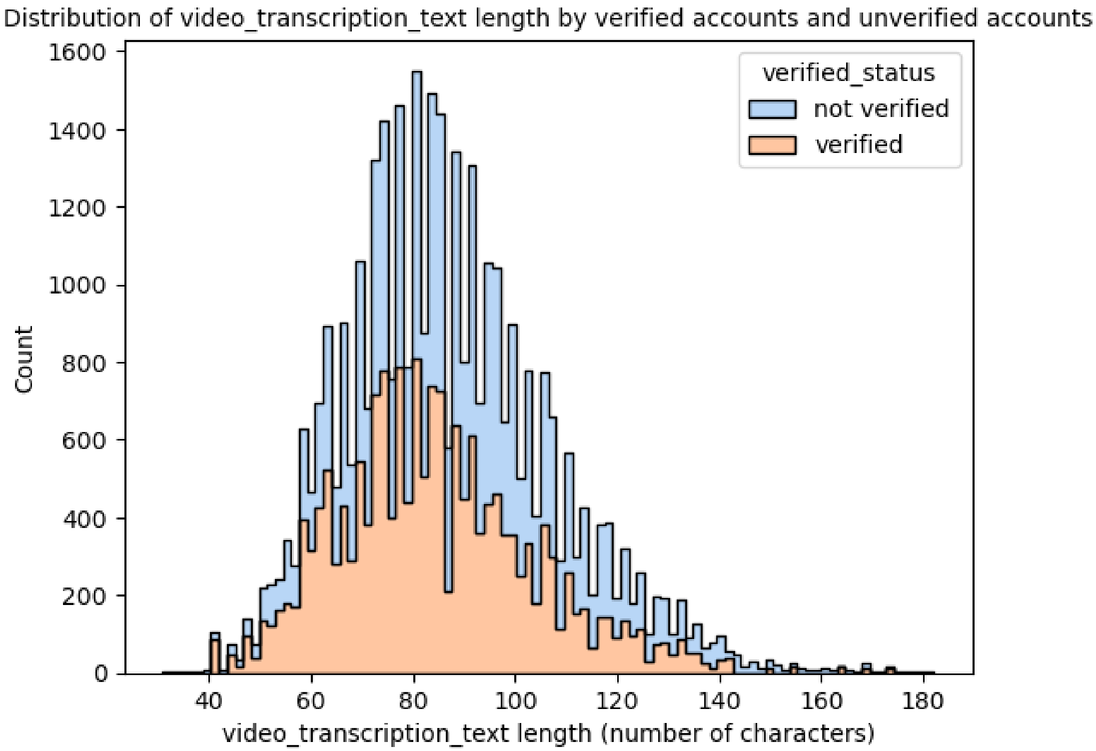
```
2  someone shared with me that american industria…    not verified
3  someone shared with me that the metro of st. p…    not verified
4  someone shared with me that the number of busi…    not verified

  author_ban_status  video_view_count  video_like_count  video_share_count  \
0      under review          343296.0           19425.0              241.0
1            active          140877.0           77355.0            19034.0
2            active          902185.0           97690.0             2858.0
3            active          437506.0          239954.0            34812.0
4            active           56167.0           34987.0             4110.0

   video_download_count  video_comment_count  text_length
0                   1.0                  0.0           97
1                1161.0                684.0          107
2                 833.0                329.0          137
3                1234.0                584.0          131
4                 547.0                152.0          128
```

Visualize the distribution of `video_transcription_text` length for videos posted by verified accounts and videos posted by unverified accounts.

[37]:
```python
# Visualize the distribution of `video_transcription_text` length by verified␣
 ↪accounts and unverified accounts
# Create two histograms in one plot
sns.histplot(data=data_upsampled,␣
 ↪x='text_length',hue='verified_status',multiple='stack',element='step',palette='pastel')
plt.xlabel('video_transcription_text length (number of characters)')
plt.title('Distribution of video_transcription_text length by verified accounts␣
 ↪and unverified accounts', fontsize=10)
plt.show()
```



3.0.3 Task 2b. Examine correlations

Next, code a correlation matrix to help determine most correlated variables.

[38]:
```
# determine most correlated variables
correlation = data_upsampled.corr(numeric_only=True,method='pearson')
correlation
```

[38]:
```
                            #  video_id  video_duration_sec  \
#                    1.000000 -0.000853           -0.011729
video_id            -0.000853  1.000000            0.011859
video_duration_sec  -0.011729  0.011859            1.000000
video_view_count    -0.697007  0.002554            0.013589
video_like_count    -0.626385  0.005993            0.004494
video_share_count   -0.504015  0.010515            0.002206
video_download_count -0.487096  0.008753           0.003989
video_comment_count -0.608773  0.012674           -0.001086
text_length         -0.193677 -0.007083           -0.002981

                      video_view_count  video_like_count  video_share_count  \
#                            -0.697007         -0.626385          -0.504015
video_id                      0.002554          0.005993           0.010515
video_duration_sec            0.013589          0.004494           0.002206
```

```
video_view_count             1.000000          0.856937          0.711313
video_like_count             0.856937          1.000000          0.832146
video_share_count            0.711313          0.832146          1.000000
video_download_count         0.690048          0.805543          0.710117
video_comment_count          0.748361          0.818032          0.671335
text_length                  0.244693          0.216693          0.171651

                      video_download_count  video_comment_count  text_length
#                                -0.487096            -0.608773    -0.193677
video_id                          0.008753             0.012674    -0.007083
video_duration_sec                0.003989            -0.001086    -0.002981
video_view_count                  0.690048             0.748361     0.244693
video_like_count                  0.805543             0.818032     0.216693
video_share_count                 0.710117             0.671335     0.171651
video_download_count              1.000000             0.793668     0.173396
video_comment_count               0.793668             1.000000     0.217661
text_length                       0.173396             0.217661     1.000000
```

[39]:

```python
correlation.style.background_gradient('crest')
```

[39]:

```
<pandas.io.formats.style.Styler at 0x76c78dae8850>
```

Visualize a correlation heatmap of the data.

[40]:

```python
# Create a heatmap to visualize how correlated variables are

plt.figure(figsize=(10,5))
sns.heatmap(data_upsampled[['video_duration_sec', 'video_view_count',␣
 ↪'video_like_count',
       'video_share_count', 'video_download_count', 'video_comment_count',
       'text_length']].corr(),annot=True,cmap='crest')
```

[40]:

```
<Axes: >
```

One of the model assumptions for logistic regression is no severe multicollinearity among the features. Take this into consideration as you examine the heatmap and choose which features to proceed with.

The above heatmap shows that the following pair of variables are strongly correlated: video_view_count and video_like_count (0.86 correlation coefficient).

3.0.4 Task 3a. Select variables

Set your Y and X variables.

[75]:
```
# Select outcome variable
y = data_upsampled['verified_status']
```

Select the features.

[76]:
```
# Select features
X = data_upsampled[["video_duration_sec", "claim_status", "author_ban_status",␣
↪"video_view_count", "video_share_count", "video_download_count",␣
↪"video_comment_count"]]

# Display first few rows of features dataframe
X.head()
```

```
[76]:    video_duration_sec claim_status author_ban_status  video_view_count  \
      0                  59        claim      under review          343296.0
      1                  32        claim            active          140877.0
      2                  31        claim            active          902185.0
      3                  25        claim            active          437506.0
      4                  19        claim            active           56167.0

         video_share_count  video_download_count  video_comment_count
      0              241.0                   1.0                  0.0
      1            19034.0                1161.0                684.0
      2             2858.0                 833.0                329.0
      3            34812.0                1234.0                584.0
      4             4110.0                 547.0                152.0
```

3.0.5 Task 3b. Train-test split

Split the data into training and testing sets.

```
[77]: # Split the data into training and testing sets
      X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.25,␣
       ↪random_state=0)
```

Confirm that the dimensions of the training and testing sets are in alignment.

```
[80]: # Get shape of each training and testing set
      X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
[80]: ((26826, 7), (8942, 7), (26826,), (8942,))
```

3.0.6 Task 3c. Encode variables

Check the data types of the features.

```
[82]: # Check data types
      X_train.dtypes
```

```
[82]: video_duration_sec        int64
      claim_status             object
      author_ban_status        object
      video_view_count        float64
      video_share_count       float64
      video_download_count    float64
      video_comment_count     float64
      dtype: object
```

```
[83]: # Get unique values in `claim_status`
      X_train['claim_status'].unique()
```

[83]: array(['opinion', 'claim'], dtype=object)

[84]:
```
# Get unique values in `author_ban_status`
X_train['author_ban_status'].unique()
```

[84]: array(['active', 'under review', 'banned'], dtype=object)

As shown above, the `claim_status` and `author_ban_status` features are each of data type `object` currently. In order to work with the implementations of models through `sklearn`, these categorical features will need to be made numeric. One way to do this is through one-hot encoding.

Encode categorical features in the training set using an appropriate method.

[85]:
```
# Select the training features that needs to be encoded
X_train_encode = X_train[['claim_status','author_ban_status']]

# Display first few rows
X_train_encode
```

[85]:

	claim_status	author_ban_status
33058	opinion	active
20491	opinion	active
25583	opinion	active
18474	opinion	active
27312	opinion	active
…	…	…
20757	opinion	active
32103	opinion	active
30403	opinion	active
21243	opinion	active
2732	claim	banned

[26826 rows x 2 columns]

[86]:
```
# Set up an encoder for one-hot encoding the categorical features
X_encoder = OneHotEncoder(drop='first', sparse_output=False)
```

[87]:
```
# Fit and transform the training features using the encoder
X_train_encoded = X_encoder.fit_transform(X_train_encode)
```

[89]:
```
# Get feature names from encoder
X_encoder.get_feature_names_out()
```

[89]: array(['claim_status_opinion', 'author_ban_status_banned',
       'author_ban_status_under review'], dtype=object)

[90]:
```
# Display first few rows of encoded training features
X_train_encoded
```

[90]:
```
array([[1., 0., 0.],
       [1., 0., 0.],
       [1., 0., 0.],
       …,
       [1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.]])
```

[91]:
```
# Place encoded training features (which is currently an array) into a dataframe
X_train_encoded_df = pd.DataFrame(X_train_encoded, columns=X_encoder.
 ↪get_feature_names_out())

# Display first few rows
X_train_encoded_df
```

[91]:
```
       claim_status_opinion  author_ban_status_banned  \
0                       1.0                       0.0
1                       1.0                       0.0
2                       1.0                       0.0
3                       1.0                       0.0
4                       1.0                       0.0
…                       …                         …
26821                   1.0                       0.0
26822                   1.0                       0.0
26823                   1.0                       0.0
26824                   1.0                       0.0
26825                   0.0                       1.0

       author_ban_status_under review
0                                 0.0
1                                 0.0
2                                 0.0
3                                 0.0
4                                 0.0
…                                 …
26821                             0.0
26822                             0.0
26823                             0.0
26824                             0.0
26825                             0.0

[26826 rows x 3 columns]
```

[92]:
```
# Display first few rows of `X_train` with `claim_status` and␣
 ↪`author_ban_status` columns dropped (since these features are being␣
 ↪transformed to numeric)
X_train.drop(columns=["claim_status", "author_ban_status"]).head()
```

[92]:
```
       video_duration_sec  video_view_count  video_share_count  \
33058                  33            2252.0               23.0
20491                  52            6664.0              550.0
25583                  37            6327.0              257.0
18474                  57            1702.0               28.0
27312                  21            3842.0              101.0

       video_download_count  video_comment_count
33058                   4.0                  0.0
20491                  53.0                  2.0
25583                   3.0                  0.0
18474                   0.0                  0.0
27312                   1.0                  0.0
```

[93]:
```python
# Concatenate `X_train` and `X_train_encoded_df` to form the final dataframe␣
↪for training data (`X_train_final`)
X_train_final = pd.concat([X_train.drop(columns=["claim_status",␣
↪"author_ban_status"]).reset_index(drop=True), X_train_encoded_df], axis=1)

# Display first few rows
X_train_final
```

[93]:
```
       video_duration_sec  video_view_count  video_share_count  \
0                      33            2252.0               23.0
1                      52            6664.0              550.0
2                      37            6327.0              257.0
3                      57            1702.0               28.0
4                      21            3842.0              101.0
…                       …                 …                  …
26821                  36            8848.0              441.0
26822                  25            8821.0              134.0
26823                  26             958.0               21.0
26824                  32            8553.0              744.0
26825                  47          484238.0             6432.0

       video_download_count  video_comment_count  claim_status_opinion  \
0                       4.0                  0.0                   1.0
1                      53.0                  2.0                   1.0
2                       3.0                  0.0                   1.0
3                       0.0                  0.0                   1.0
4                       1.0                  0.0                   1.0
…                         …                    …                     …
26821                  24.0                  1.0                   1.0
26822                   8.0                  1.0                   1.0
26823                   2.0                  0.0                   1.0
26824                  62.0                 23.0                   1.0
26825                 104.0                  1.0                   0.0
```

```
       author_ban_status_banned  author_ban_status_under review
0                           0.0                             0.0
1                           0.0                             0.0
2                           0.0                             0.0
3                           0.0                             0.0
4                           0.0                             0.0
…                            …                               …
26821                       0.0                             0.0
26822                       0.0                             0.0
26823                       0.0                             0.0
26824                       0.0                             0.0
26825                       1.0                             0.0

[26826 rows x 8 columns]
```

Check the data type of the outcome variable.

[94]:
```
# Check data type of outcome variable
y_train.dtypes
```

[94]:
```
dtype('O')
```

[95]:
```
# Get unique values of outcome variable
y_train.unique()
```

[95]:
```
array(['verified', 'not verified'], dtype=object)
```

A shown above, the outcome variable is of data type `object` currently. One-hot encoding can be used to make this variable numeric.

Encode categorical values of the outcome variable the training set using an appropriate method.

[97]:
```
# Set up an encoder for one-hot encoding the categorical outcome variable
y_encoder = OneHotEncoder(drop='first',sparse_output=False)
```

[98]:
```
# Encode the training outcome variable
#   - Adjusting the shape of `y_train` before passing into `.fit_transform()`,␣
↪since it takes in 2D array
#   - Using `.ravel()` to flatten the array returned by `.fit_transform()`, so␣
↪that it can be used later to train the model
y_train_final = y_encoder.fit_transform(y_train.values.reshape(-1, 1)).ravel()

# Display the encoded training outcome variable
y_train_final
```

[98]:
```
array([1., 1., 1., …, 1., 1., 0.])
```

3.0.7 Task 3d. Model building

Construct a model and fit it to the training set.

[99]:
```
# Construct a logistic regression model and fit it to the training set
clf = LogisticRegression(random_state=0,max_iter=800).
 ↪fit(X_train_final,y_train_final)
```

3.1 PACE: Execute

Consider the questions in your PACE Strategy Document to reflect on the Execute stage.

3.1.1 Taks 4a. Results and evaluation

Evaluate your model.

Encode categorical features in the testing set using an appropriate method.

[100]:
```
# Select the testing features that needs to be encoded
X_test_to_encode = X_test[["claim_status", "author_ban_status"]]

# Display first few rows
X_test_to_encode.head()
```

[100]:

	claim_status	author_ban_status
21061	opinion	active
31748	opinion	active
20197	claim	active
5727	claim	active
11607	opinion	active

[101]:
```
# Transform the testing features using the encoder
X_test_encoded = X_encoder.transform(X_test_to_encode)

# Display first few rows of encoded testing features
X_test_encoded
```

[101]:
```
array([[1., 0., 0.],
       [1., 0., 0.],
       [0., 0., 0.],
       …,
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.]])
```

[102]:
```
# Place encoded testing features (which is currently an array) into a dataframe
X_test_encoded_df = pd.DataFrame(data=X_test_encoded, columns=X_encoder.
 ↪get_feature_names_out())
```

```
# Display first few rows
X_test_encoded_df.head()
```

[102]:

```
   claim_status_opinion  author_ban_status_banned  \
0                   1.0                       0.0
1                   1.0                       0.0
2                   0.0                       0.0
3                   0.0                       0.0
4                   1.0                       0.0

   author_ban_status_under review
0                             0.0
1                             0.0
2                             0.0
3                             0.0
4                             0.0
```

[103]:

```
# Display first few rows of `X_test` with `claim_status` and␣
↪`author_ban_status` columns dropped (since these features are being␣
↪transformed to numeric)
### YOUR CODE HERE ###
X_test.drop(columns=["claim_status", "author_ban_status"]).head()
```

[103]:

```
       video_duration_sec  video_view_count  video_share_count  \
21061                  41            2118.0               57.0
31748                  27            5701.0              157.0
20197                  31          449767.0            75385.0
5727                   19          792813.0            56597.0
11607                  54            2044.0               68.0

       video_download_count  video_comment_count
21061                   5.0                  2.0
31748                   1.0                  0.0
20197                5956.0                728.5
5727                 5146.0                728.5
11607                  19.0                  2.0
```

[104]:

```
# Concatenate `X_test` and `X_test_encoded_df` to form the final dataframe for␣
↪training data (`X_test_final`)
X_test_final = pd.concat([X_test.drop(columns=["claim_status",␣
↪"author_ban_status"]).reset_index(drop=True), X_test_encoded_df], axis=1)

# Display first few rows
X_test_final.head()
```

[104]:

```
   video_duration_sec  video_view_count  video_share_count  \
0                  41            2118.0               57.0
```

```
1                  27          5701.0            157.0
2                  31        449767.0          75385.0
3                  19        792813.0          56597.0
4                  54          2044.0             68.0

   video_download_count  video_comment_count  claim_status_opinion  \
0                   5.0                  2.0                   1.0
1                   1.0                  0.0                   1.0
2                5956.0                728.5                   0.0
3                5146.0                728.5                   0.0
4                  19.0                  2.0                   1.0

   author_ban_status_banned  author_ban_status_under review
0                       0.0                             0.0
1                       0.0                             0.0
2                       0.0                             0.0
3                       0.0                             0.0
4                       0.0                             0.0
```

Test the logistic regression model. Use the model to make predictions on the encoded testing set.

[105]:
```python
# Use the logistic regression model to get predictions on the encoded testing set
y_pred = clf.predict(X_test_final)
```

Display the predictions on the encoded testing set.

[106]:
```python
# Display the predictions on the encoded testing set
y_pred
```

[106]:
```
array([1., 1., 0., …, 1., 0., 1.])
```

Display the true labels of the testing set.

[107]:
```python
# Display the true labels of the testing set
y_test
```

[107]:
```
21061        verified
31748        verified
20197        verified
5727     not verified
11607    not verified
             …
14756    not verified
26564        verified
14800    not verified
35705        verified
31060        verified
```

```
Name: verified_status, Length: 8942, dtype: object
```

Encode the true labels of the testing set so it can be compared to the predictions.

```
[108]: # Encode the testing outcome variable
#   - Adjusting the shape of `y_test` before passing into `.transform()`, since␣
↪it takes in 2D array
#   - Using `.ravel()` to flatten the array returned by `.transform()`, so that␣
↪it can be used later to compare with predictions
y_test_final = y_encoder.transform(y_test.values.reshape(-1, 1)).ravel()

# Display the encoded testing outcome variable
y_test_final
```

```
[108]: array([1., 1., 1., …, 0., 1., 1.])
```

Confirm again that the dimensions of the training and testing sets are in alignment since additional features were added.

```
[109]: # Get shape of each training and testing set
X_train_final.shape, y_train_final.shape, X_test_final.shape, y_test_final.shape
```

```
[109]: ((26826, 8), (26826,), (8942, 8), (8942,))
```

3.1.2 Task 4b. Visualize model results

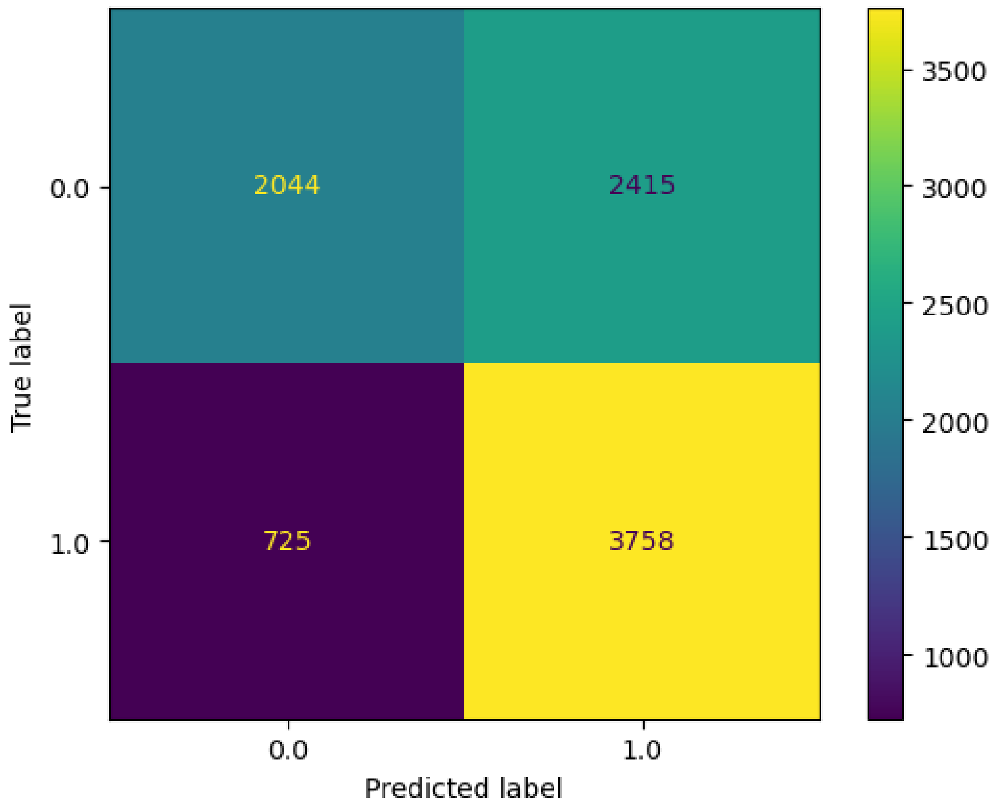
Create a confusion matrix to visualize the results of the logistic regression model.

```
[111]: # Compute values for confusion matrix
log_cm = confusion_matrix(y_test_final, y_pred, labels=clf.classes_)

# Create display of confusion matrix
log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm, display_labels=clf.
↪classes_)

# Plot confusion matrix
log_disp.plot()

# Display plot
plt.show()
```



Create a classification report that includes precision, recall, f1-score, and accuracy metrics to evaluate the performance of the logistic regression model.

[113]:
```
# Create a classification report
target_labels = ["verified", "not verified"]
print(classification_report(y_test_final, y_pred, target_names=target_labels))
```

```
              precision    recall  f1-score   support

    verified       0.74      0.46      0.57      4459
not verified       0.61      0.84      0.71      4483

    accuracy                           0.65      8942
   macro avg       0.67      0.65      0.64      8942
weighted avg       0.67      0.65      0.64      8942
```

3.1.3 Task 4c. Interpret model coefficients

[115]:
```
# Get the feature names from the model and the model coefficients (which␣
↪represent log-odds ratios)
# Place into a DataFrame for readability
pd.DataFrame(data={"Feature Name":clf.feature_names_in_, "Model Coefficient":
↪clf.coef_[0]})
```

[115]:

	Feature Name	Model Coefficient
0	video_duration_sec	8.607893e-03
1	video_view_count	-2.132079e-06
2	video_share_count	5.930971e-06
3	video_download_count	-1.099775e-05
4	video_comment_count	-6.404235e-04
5	claim_status_opinion	3.908384e-04
6	author_ban_status_banned	-1.781741e-05
7	author_ban_status_under review	-9.682447e-07

3.1.4 Task 4d. Conclusion

Key takeaways:

- The dataset has a few strongly correlated variables, which might lead to multicollinearity issues when fitting a logistic regression model. We decided to drop `video_like_count` from the model building.
- Based on the logistic regression model, each additional second of the video is associated with 0.009 increase in the log-odds of the user having a verified status.
- The logistic regression model had not great, but acceptable predictive power: a precision of 61% is less than ideal, but a recall of 84% is very good. Overall accuracy is towards the lower end of what would typically be considered acceptable.

We developed a logistic regression model for verified status based on video features. The model had decent predictive power. Based on the estimated model coefficients from the logistic regression, longer videos tend to be associated with higher odds of the user being verified. Other video features have small estimated coefficients in the model, so their association with verified status seems to be small.