TikTok User Verification Logistic Regression Model

August 11, 2023

1 TikTok User Verification Logistic Regression Model

1.0.1 Task 1. Imports and loading

[1]:
```
# 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.

[2]:
```
# Load dataset into dataframe
data = pd.read_csv("tiktok_dataset.csv")
```

1.0.2 Task 2a. Explore data with EDA

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

Inspect the first five rows of the dataframe.

[3]:
```
# Display first few rows
data.head()
```

[3]:
```
   # 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.

[4]:
```
# Get number of rows and columns
data.shape
```

[4]:
```
(19382, 12)
```

Get the data types of the columns.

[5]:
```
# Get data types of columns
data.dtypes
```

[5]:
```
#                            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.

[6]:
```
# Get 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.

[7]:
```
# Generate basic descriptive stats
data.describe(include="all")
```

[7]:

	#	claim_status	video_id	video_duration_sec	\
count	19382.000000	19084	1.938200e+04	19382.000000	
unique	NaN	2	NaN	NaN	
top	NaN	claim	NaN	NaN	
freq	NaN	9608	NaN	NaN	
mean	9691.500000	NaN	5.627454e+09	32.421732	
std	5595.245794	NaN	2.536440e+09	16.229967	
min	1.000000	NaN	1.234959e+09	5.000000	
25%	4846.250000	NaN	3.430417e+09	18.000000	
50%	9691.500000	NaN	5.618664e+09	32.000000	
75%	14536.750000	NaN	7.843960e+09	47.000000	
max	19382.000000	NaN	9.999873e+09	60.000000	

```
                                video_transcription_text verified_status  \
count                                              19084           19382
unique                                             19012               2
top     a friend read  in the media a claim that badmi…    not verified
freq                                                   2           18142
mean                                                 NaN             NaN
std                                                  NaN             NaN
min                                                  NaN             NaN
25%                                                  NaN             NaN
50%                                                  NaN             NaN
75%                                                  NaN             NaN
max                                                  NaN             NaN

       author_ban_status  video_view_count  video_like_count  \
count              19382      19084.000000      19084.000000
unique                 3               NaN               NaN
top               active               NaN               NaN
freq               15663               NaN               NaN
mean                 NaN     254708.558688      84304.636030
std                  NaN     322893.280814     133420.546814
min                  NaN         20.000000          0.000000
25%                  NaN       4942.500000        810.750000
50%                  NaN       9954.500000       3403.500000
75%                  NaN     504327.000000     125020.000000
max                  NaN     999817.000000     657830.000000

        video_share_count  video_download_count  video_comment_count
count        19084.000000          19084.000000         19084.000000
unique                NaN                   NaN                  NaN
top                   NaN                   NaN                  NaN
freq                  NaN                   NaN                  NaN
mean         16735.248323           1049.429627           349.312146
std          32036.174350           2004.299894           799.638865
min              0.000000              0.000000             0.000000
25%            115.000000              7.000000             1.000000
50%            717.000000             46.000000             9.000000
75%          18222.000000           1156.250000           292.000000
max         256130.000000          14994.000000          9599.000000
```

Check for and handle missing values.

[8]:
```
# Check for missing values
data.isnull().sum()
```

[8]:
```
#                             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
```

[9]:
```
# Drop rows with missing values
data=data.dropna(axis=0)
```

[10]:
```
# Display first few rows after handling missing values
data.head()
```

[10]:

	# 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

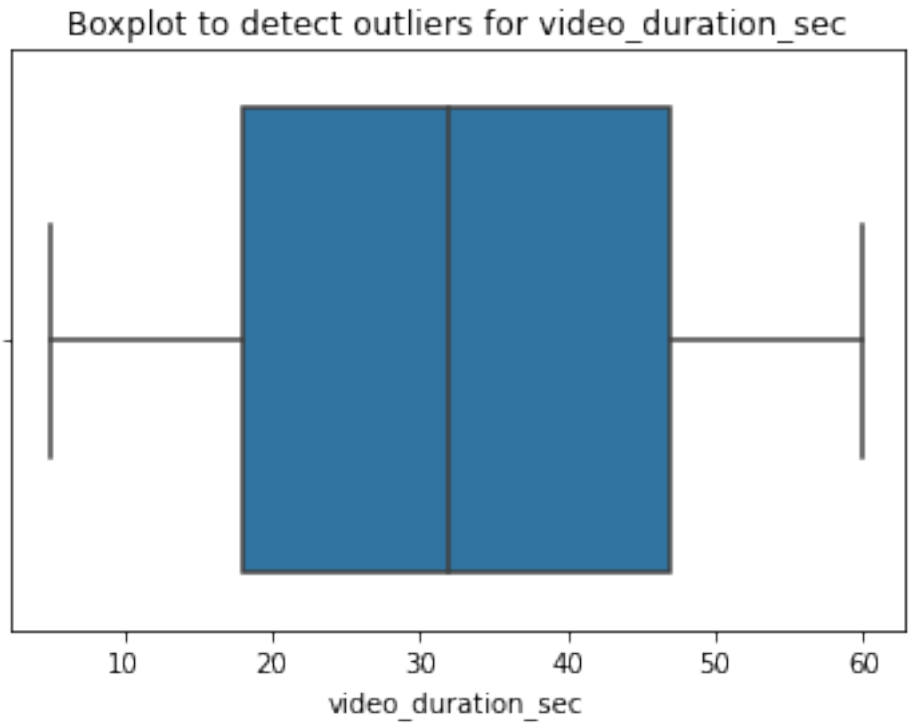
Check for and handle duplicates.

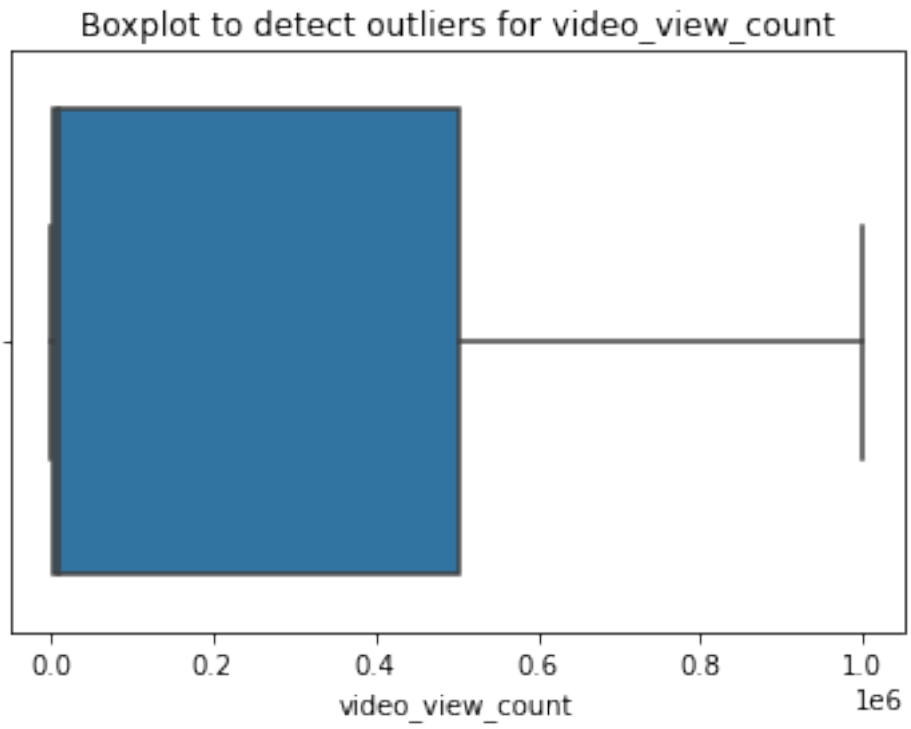
[11]:
```
# Check for duplicates
data.duplicated().sum()
```

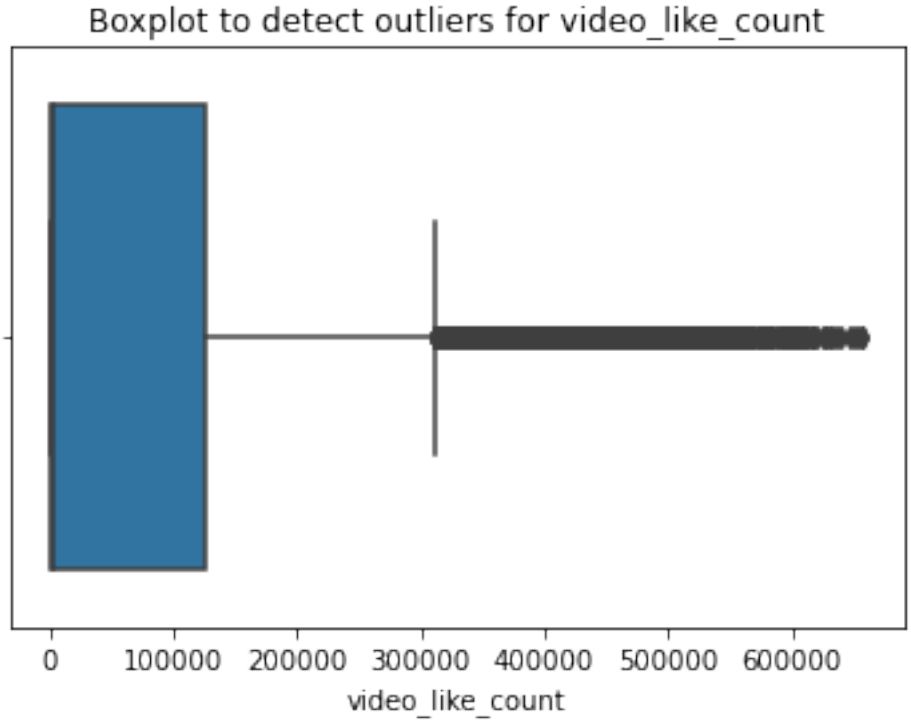
[11]:
```
0
```

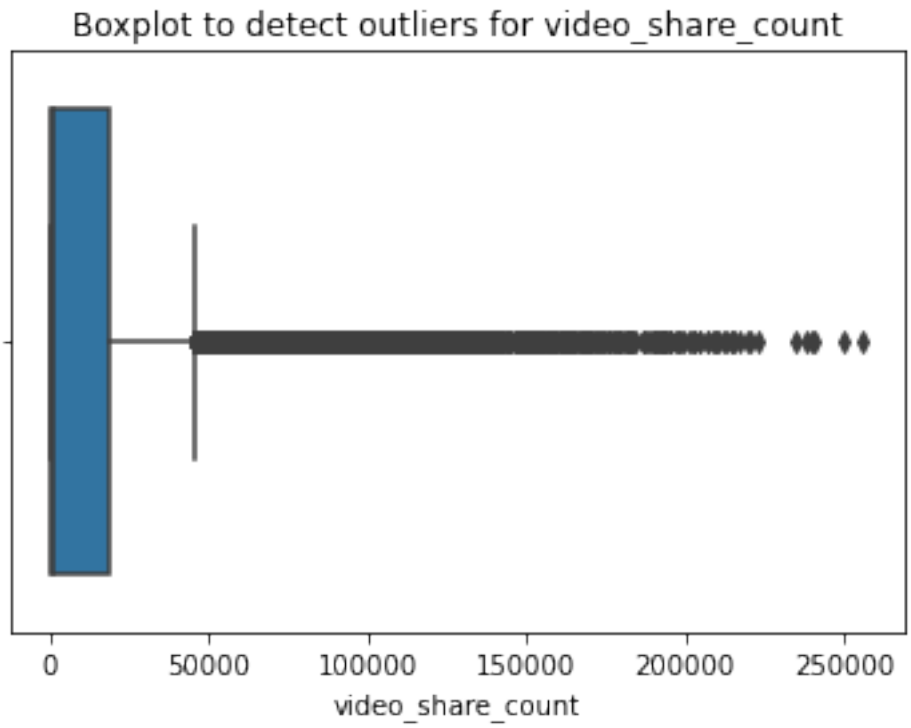
Check for and handle outliers.

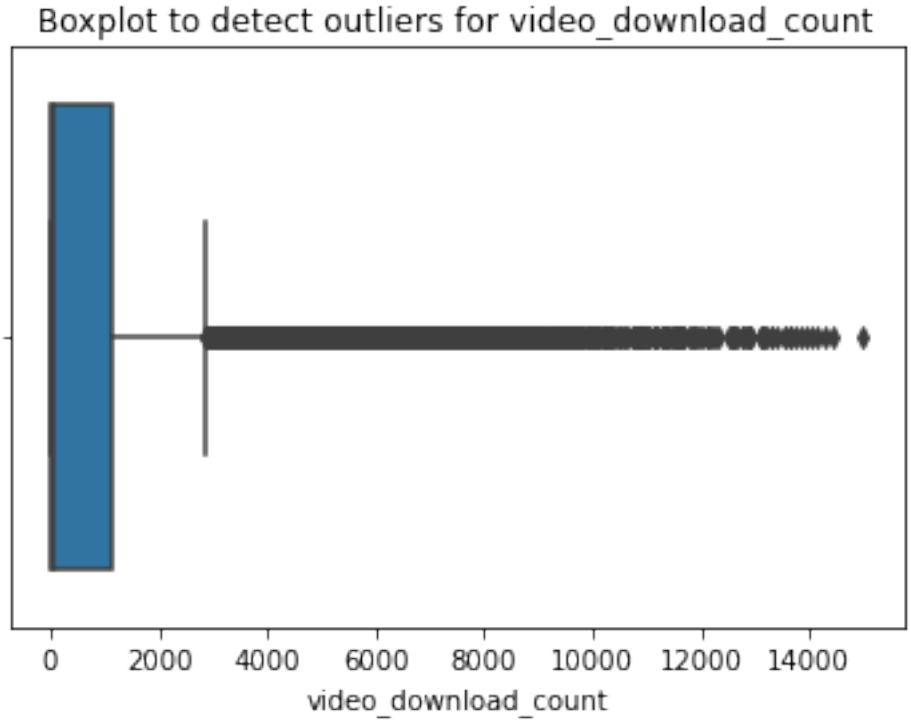
[12]:
```
# List of variables for which we want to check the outliers
ind_var_list = ["video_duration_sec", "video_view_count", "video_like_count",␣
 ↪"video_share_count", "video_download_count", "video_comment_count"]

# Loop through each variable in the list
for i in ind_var_list:
    # Create a new figure and axis for each boxplot
    fig, ax = plt.subplots()

    # Set the title for the boxplot with the current variable name
    plt.title(f"Boxplot to detect outliers for {i}", fontsize=12)

    # Create a boxplot and display it.
    sns.boxplot(data=data, x=i)
    plt.show()
```

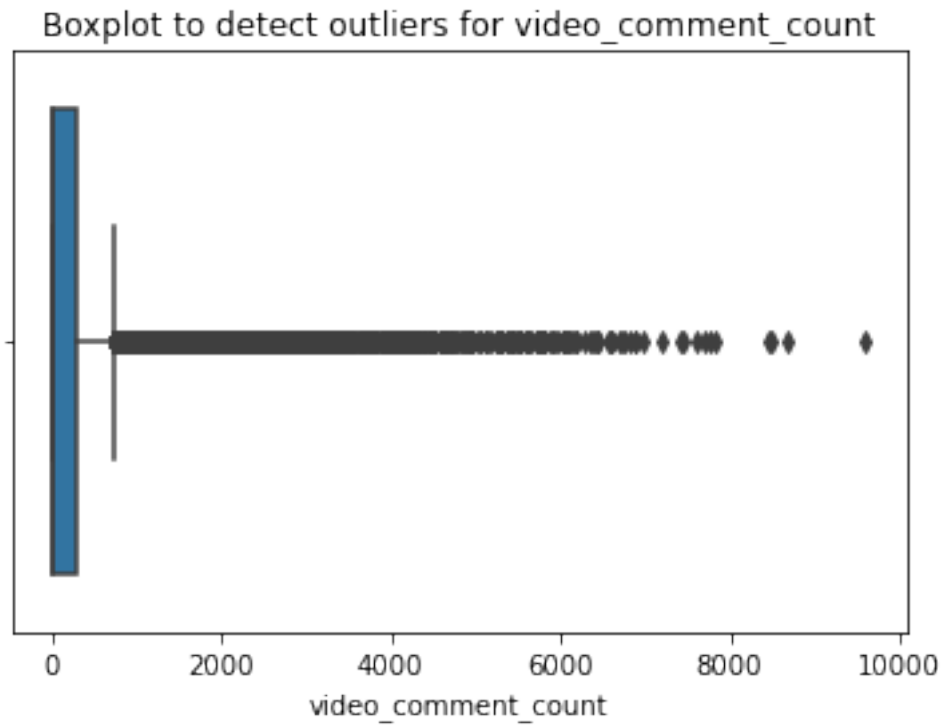



Boxplot to detect outliers for video_view_count
0.0
0.2
0.4
0.6
0.8
1.0
1e6
video_view_count


Boxplot to detect outliers for video_like_count
0
100000
200000
300000
400000
500000
600000
video_like_count


Boxplot to detect outliers for video_share_count
0
50000
100000
150000
200000
250000
video_share_count


Boxplot to detect outliers for video_download_count
0
2000
4000
6000
8000
10000
12000
14000
video_download_count



Mitigating the impact of outliers on analysis and modeling.

[13]:
```
# List of variables containing outliers
outlier_list = ["video_like_count", "video_share_count",␣
↪"video_download_count", "video_comment_count"]

# Loop through each variable in the outlier list
for o in outlier_list:
    # Calculate the 75th percentile (Q3) of the variable's data
    perc_75 = data[o].quantile(0.75)

    # Calculate the 25th percentile (Q1) of the variable's data
    perc_25 = data[o].quantile(0.25)

    # Calculate the interquartile range (IQR) for the variable
    iqr = perc_75 - perc_25

    # Calculate the upper limit for detecting outliers using 1.5 times the IQR
    upper_limit = perc_75 + 1.5 * iqr

    # Replace values in the variable's data that are above the upper limit with␣
↪the upper limit value
    data.loc[data[o] > upper_limit, o] = upper_limit
```

[14]:
```
#Find the percentage of verified status to check the class balances.
data["verified_status"].value_counts(normalize=True)
```

[14]:
```
not verified    0.93712
verified        0.06288
Name: verified_status, dtype: float64
```

Use resampling to create class balance in the outcome variable.

[15]:
```
# Use resampling to create class balance in the outcome variable.
# Identify data points from majority and minority classes

data_majority = data[data["verified_status"] == "not verified"]
data_minority = data[data["verified_status"] == "verified"]

# Upsample the minority class ("verified")
data_minority_upsampled = resample(data_minority,
                                   replace=True,                 # to sample with␣
 ↪replacement
                                   n_samples=len(data_majority), # to match␣
 ↪majority class
                                   random_state=0)               # to create␣
 ↪reproducible results

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

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

[15]:
```
not verified    17884
verified        17884
Name: verified_status, dtype: int64
```

Inserting length of transcription as a variable.

[16]:
```
# Get the average `video_transcription_text` length for verified and unverified␣
 ↪accounts.
data_upsampled.groupby("verified_status")["video_transcription_text"].
 ↪apply(lambda group: np.mean(group.str.len()))
```

[16]:
```
verified_status
not verified    89.401141
verified        84.569559
Name: video_transcription_text, dtype: float64
```

[17]:
```
# 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 text: len(text))
```

[18]:
```
# Display first few rows of dataframe after adding new column
data_upsampled.head(10)
```

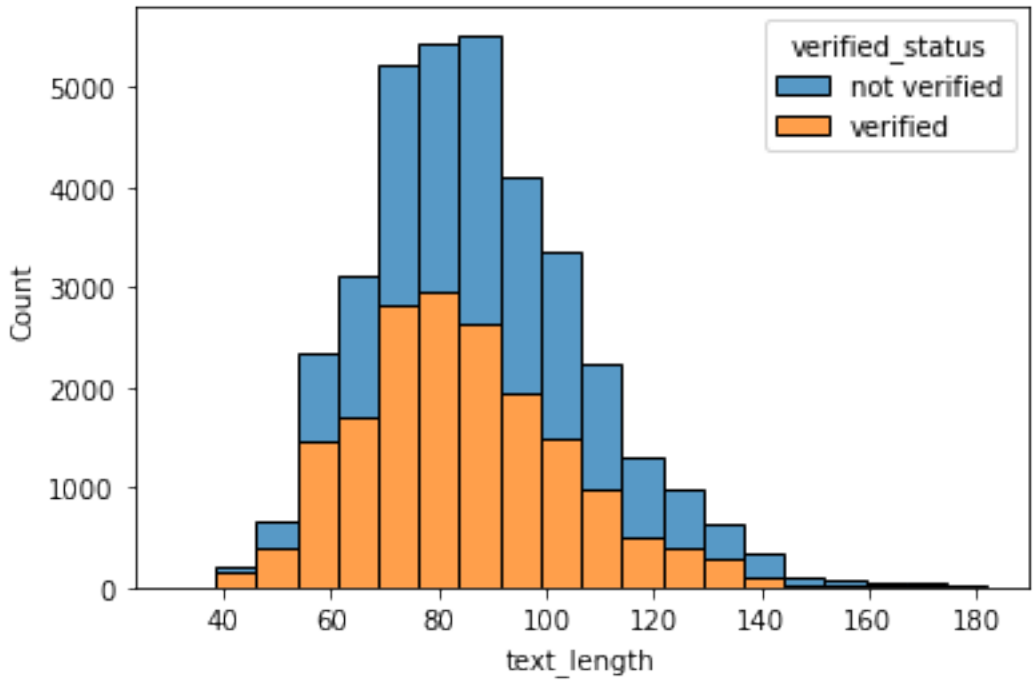
[18]:

	#	claim_status	video_id	video_duration_sec	video_transcription_text	verified_status	author_ban_status	video_view_count	video_like_count	video_share_count	video_download_count	video_comment_count	text_length
0	1	claim	7017666017	59	someone shared with me that drone deliveries a…	not verified	under review	343296.0	19425.000	241.0	1.000	0.0	97
1	2	claim	4014381136	32	someone shared with me that there are more mic…	not verified	active	140877.0	77355.000	19034.0	1161.000	684.0	107
2	3	claim	9859838091	31	someone shared with me that american industria…	not verified	active	902185.0	97690.000	2858.0			
3	4	claim	1866847991	25	someone shared with me that the metro of st. p…	not verified	active	437506.0	239954.000	34812.0			
4	5	claim	7105231098	19	someone shared with me that the number of busi…	not verified	active	56167.0	34987.000	4110.0			
5	6	claim	8972200955	35	someone shared with me that gross domestic pro…	not verified	under review	336647.0	175546.000	45382.5			
6	7	claim	4958886992	16	someone shared with me that elvis presley has …	not verified	active	750345.0	311333.875	45382.5			
7	8	claim	2270982263	41	someone shared with me that the best selling s…	not verified	active	547532.0	1072.000	50.0			
8	9	claim	5235769692	50	someone shared with me that about half of the …	not verified	active	24819.0	10160.000	1050.0			
9	11	claim	8095102436	47	someone shared with me that an average user sp…	not verified	active	695641.0	238030.000	23062.0			

2	833.000	329.0	137
3	1234.000	584.0	131
4	547.000	152.0	128
5	2880.125	728.5	127
6	2880.125	728.5	95
7	22.000	11.0	99
8	53.000	27.0	103
9	1719.000	378.0	83

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

[19]:
```
# Create two histograms in one plot

sns.histplot(data=data_upsampled, multiple="stack", x="text_length",␣
↪hue="verified_status", bins=20);
```



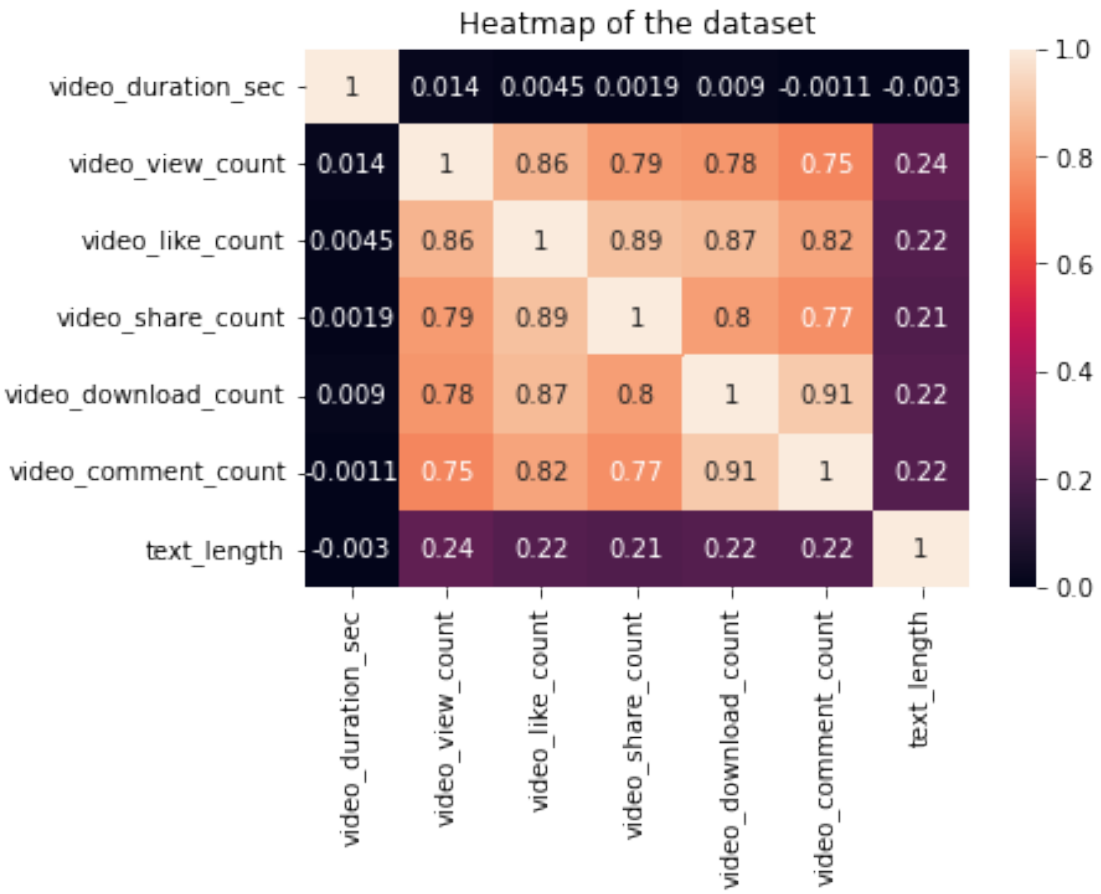
1.0.3 Task 2b. Examine correlations

[20]:
```
# Code a correlation matrix to help determine most correlated variables
data_upsampled.corr()
```

[20]:
```
                              #  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     -0.619090 -0.000888            0.001875
video_download_count  -0.611317  0.012784            0.008972
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          -0.619090
video_id                     0.002554          0.005993          -0.000888
video_duration_sec           0.013589          0.004494           0.001875
video_view_count             1.000000          0.856937           0.794957
video_like_count             0.856937          1.000000           0.888427
video_share_count            0.794957          0.888427           1.000000
video_download_count         0.782352          0.873458           0.803551
video_comment_count          0.748361          0.818032           0.766203
text_length                  0.244693          0.216693           0.208529

                      video_download_count  video_comment_count  text_length
#                                -0.611317           -0.608773    -0.193677
video_id                          0.012784            0.012674    -0.007083
video_duration_sec                0.008972           -0.001086    -0.002981
video_view_count                  0.782352            0.748361     0.244693
video_like_count                  0.873458            0.818032     0.216693
video_share_count                 0.803551            0.766203     0.208529
video_download_count              1.000000            0.911894     0.216871
video_comment_count               0.911894            1.000000     0.217661
text_length                       0.216871            0.217661     1.000000
```

Visualize a correlation heatmap of the data.

[21]:
```
# Create a heatmap to visualize how correlated variables are
sns.heatmap(data_upsampled[["video_duration_sec", "claim_status",␣
 ↪"author_ban_status", "video_view_count", "video_like_count",␣
 ↪"video_share_count", "video_download_count", "video_comment_count",␣
 ↪"text_length"]].corr(), annot=True)
plt.title("Heatmap of the dataset")
plt.show()
```



One of the model assumptions for logistic regression is no severe multicollinearity among the features. To build a logistic regression model that meets this assumption, we could exclude video_like_count as it is the variable highly correlated with other variables.

1.0.4 Task 3a. Select variables

[22]:
```
# Select outcome variable
y=data_upsampled["verified_status"]
```

[23]:
```
# 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()
```

[23]:
```
   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
```

1.0.5 Task 3b. Train-test split

[24]:
```
# 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.

[25]:
```
# Get shape of each training and testing set
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(26826, 7)
(8942, 7)
(26826,)
(8942,)
```

1.0.6 Task 3c. Encode variables

[26]:
```
# Check data types
X_train.dtypes
```

[26]:
```
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
```

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.

[27]:
```
# Select the training features that needs to be encoded
X_train_to_encode=X_train[["author_ban_status", "claim_status"]]

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

[27]:
```
      author_ban_status claim_status
33058            active      opinion
20491            active      opinion
25583            active      opinion
18474            active      opinion
27312            active      opinion
```

[28]:
```
# Set up an encoder for one-hot encoding the categorical features
X_encoder = OneHotEncoder(drop='first', sparse=False)

# Fit and transform the training features using the encoder
X_train_encoded = X_encoder.fit_transform(X_train_to_encode)

# Get feature names from encoder
X_encoder.get_feature_names()
```

[28]:
```
array(['x0_banned', 'x0_under review', 'x1_opinion'], dtype=object)
```

[29]:
```
# Display first few rows of encoded training features
X_train_encoded
```

[29]:
```
array([[0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 1.],
       …,
       [0., 0., 1.],
       [0., 0., 1.],
       [1., 0., 0.]])
```

[30]:
```
# Place encoded training features (which is currently an array) into a dataframe
X_train_encoded_df =pd.DataFrame(data=X_train_encoded, columns=X_encoder.
 ↪get_feature_names())

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

[30]:

	x0_banned	x0_under review	x1_opinion
0	0.0	0.0	1.0
1	0.0	0.0	1.0
2	0.0	0.0	1.0
3	0.0	0.0	1.0
4	0.0	0.0	1.0

[31]:
```
# Concatenate `X_train` and `X_train_encoded_df` to form the final dataframe␣
↪for training data (`X_train_final`)
# We will drop "claim_status" and "author_ban_status", since these features are␣
↪being transformed to numeric.
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.head()
```

[31]:

	video_duration_sec	video_view_count	video_share_count	video_download_count	video_comment_count	x0_banned	x0_under review	x1_opinion
0	33	2252.0	23.0	4.0	0.0	0.0	0.0	1.0
1	52	6664.0	550.0	53.0	2.0	0.0	0.0	1.0
2	37	6327.0	257.0	3.0	0.0	0.0	0.0	1.0
3	57	1702.0	28.0	0.0	0.0	0.0	0.0	1.0
4	21	3842.0	101.0	1.0	0.0	0.0	0.0	1.0

Check the data type of the outcome variable.

[32]:
```
# Check data type of outcome variable
y_train.dtype
```

[32]:
```
dtype('O')
```

[33]:
```
y_train
```

[33]:
```
33058        verified
20491        verified
25583        verified
18474        verified
27312        verified
             …
20757        verified
32103        verified
30403        verified
21243        verified
2732     not verified
Name: verified_status, Length: 26826, 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.

[34]:
```
# Set up an encoder for one-hot encoding the categorical outcome variable
y_encoder=OneHotEncoder(drop="first", sparse=False)

# Encode the training outcome variable
# Notes:
#   - 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
```

[34]:
```
array([1., 1., 1., …, 1., 1., 0.])
```

1.0.7 Task 3d. Model building

[35]:
```
# Construct a logistic regression model and fit it to the training set
log_clf=LogisticRegression(random_state=0, max_iter=800).fit(X_train_final,␣
 ↪y_train_final)
```

1.0.8 Taks 4a. Results and evaluation

Evaluate the model.

Encode categorical features in the testing set using the same method.

[36]:
```
# Select the testing features that needs to be encoded
X_test_to_encode=X_test[["author_ban_status", "claim_status"]]
```

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

[36]:

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

[37]:
```
# 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
```

[37]:
```
array([[0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 0.],
       …,
       [0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

[38]:
```
# 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())

# Display first few rows
X_test_encoded_df
```

[38]:

	x0_banned	x0_under review	x1_opinion
0	0.0	0.0	1.0
1	0.0	0.0	1.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	1.0
…	…	…	…
8937	0.0	0.0	1.0
8938	0.0	0.0	1.0
8939	0.0	0.0	1.0
8940	0.0	1.0	0.0
8941	0.0	0.0	1.0

[8942 rows x 3 columns]

[39]:
```
# Concatenate `X_test` and `X_test_encoded_df` to form the final dataframe for␣
↪testing data (`X_test_final`)
# We will drop "claim_status" and "author_ban_status", since these features are␣
↪being transformed to numeric.
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()
```

[39]:

	video_duration_sec	video_view_count	video_share_count	video_download_count	video_comment_count	x0_banned	x0_under review	x1_opinion
0	41	2118.0	57.0	5.000	2.0	0.0	0.0	1.0
1	27	5701.0	157.0	1.000	0.0	0.0	0.0	1.0
2	31	449767.0	45382.5	2880.125	728.5	0.0	0.0	0.0
3	19	792813.0	45382.5	2880.125	728.5	0.0	0.0	0.0
4	54	2044.0	68.0	19.000	2.0	0.0	0.0	1.0

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

[40]:
```
# Use the logistic regression model to get predictions on the encoded testing␣
↪set
y_pred=log_clf.predict(X_test_final)
```

Display the predictions on the encoded testing set.

[41]:
```
# Display the predictions on the encoded testing set
y_pred
```

[41]:
```
array([1., 1., 0., …, 1., 0., 1.])
```

Display the true labels of the testing set.

[42]:
```
# Display the true labels of the testing set
y_test
```

[42]:
```
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.

[43]:
```
# Encode the testing outcome variable
# Notes:
#   - 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
```

[43]:
```
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.

[44]:
```
# Get shape of each training and testing set
X_train_final.shape, X_test_final.shape, y_train_final.shape, y_test_final.shape
```

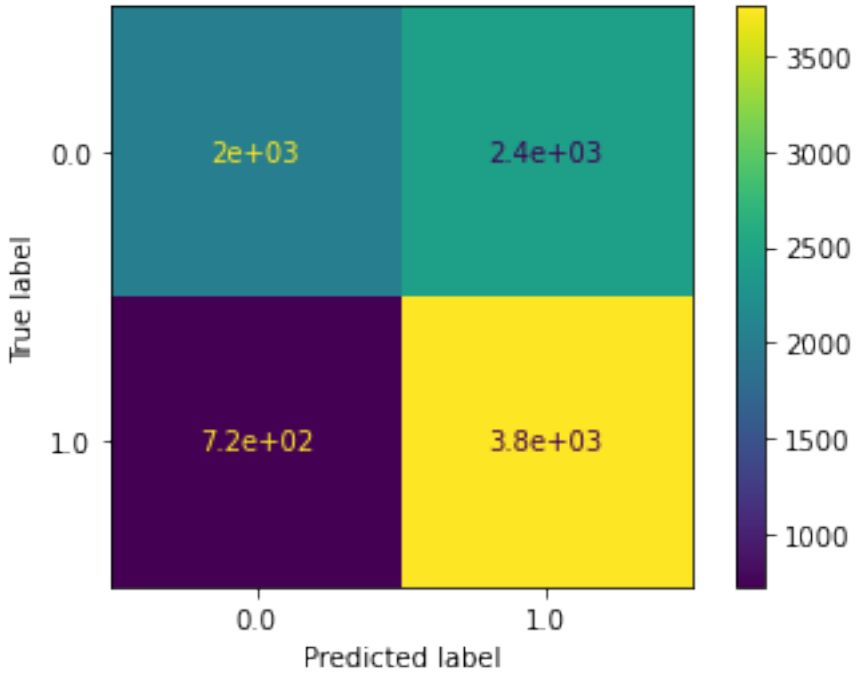
[44]:
```
((26826, 8), (8942, 8), (26826,), (8942,))
```

1.0.9 Task 4b. Visualize model results

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

[45]:
```
# Compute values for confusion matrix
log_cm=confusion_matrix(y_test_final, y_pred, labels=log_clf.classes_)

# Create display of confusion matrix
log_disp=ConfusionMatrixDisplay(confusion_matrix=log_cm, display_labels=log_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.

[46]:
```
# 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      0.45      0.56      4459
not verified       0.61      0.84      0.70      4483

    accuracy                           0.65      8942
   macro avg       0.67      0.65      0.63      8942
weighted avg       0.67      0.65      0.63      8942
```

1.0.10 Task 4c. Interpret model coefficients

[47]:
```
# 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":X_test_final.columns, "Model Coefficient":
↪log_clf.coef_[0]})
```

[47]:

	Feature Name	Model Coefficient
0	video_duration_sec	0.008507
1	video_view_count	-0.000002
2	video_share_count	0.000007
3	video_download_count	-0.000241
4	video_comment_count	0.000022
5	x0_banned	-0.000020
6	x0_under review	-0.000002
7	x1_opinion	0.000404

1.0.11 Task 4d. Conclusion

- Outliers have been identified in the variables "video_like_count," "video_share_count," "video_download_count," and "video_comment_count." To address this, we replaced the outlier values in these variables with the upper threshold of the interquartile range (IQR) for each variable.
- The dataset contains a few variables with strong correlations, raising concerns about multicollinearity in a logistic regression model. To address this, we opted to exclude "video_like_count" during model construction.
- According to the logistic regression findings, each additional second of video duration correlates with a 0.01 increase in the log-odds of a user having verified status.
- The logistic regression model exhibited reasonable predictive capability, with weighted average precision and recall values of 67% and 65% respectively, and an overall accuracy of 65%.
- We developed a logistic regression model using video features to predict verified status, achieving satisfactory predictive performance (67% precision and 65% recall).
- Based on the logistic regression coefficients, longer videos tend to be linked to higher odds of users having verified status.
- Minor estimated coefficients were observed for other video features within the model, implying a limited association with verified status.