Activity_Course 5 TikTok project lab

May 18, 2024

1 TikTok Project

Course 5 - Regression Analysis: Simplify complex data relationships

You are a data professional at TikTok. The data team is working towards building a machine learning model that can be used to determine whether a video contains a claim or whether it offers an opinion. With a successful prediction model, TikTok can reduce the backlog of user reports and prioritize them more efficiently.

The team is getting closer to completing the project, having completed an initial plan of action, initial Python coding work, EDA, and hypothesis testing.

The TikTok team has reviewed the results of the hypothesis testing. TikTok's Operations Lead, Maika Abadi, is interested in how different variables are associated with whether a user is verified. Earlier, the data team observed that if a user is verified, they are much more likely to post opinions. Now, the data team has decided to explore how to predict verified status to help them understand how video characteristics relate to verified users. Therefore, you have been asked to conduct a logistic regression using verified status as the outcome variable. The results may be used to inform the final model related to predicting whether a video is a claim vs an opinion.

A notebook was structured and prepared to help you in this project. Please complete the following questions.

2 Course 5 End-of-course project: Regression modeling

In this activity, you will build a logistic regression model in Python. As you have learned, logistic regression helps you estimate the probability of an outcome. For data science professionals, this is a useful skill because it allows you to consider more than one variable against the variable you're measuring against. This opens the door for much more thorough and flexible analysis to be completed.

The purpose of this project is to demostrate knowledge of EDA and regression models.

The goal is to build a logistic regression model and evaluate the model. *This activity has three parts:*

Part 1: EDA & Checking Model Assumptions * What are some purposes of EDA before constructing a logistic regression model?

Part 2: Model Building and Evaluation * What resources do you find yourself using as you complete this stage?

Part 3: Interpreting Model Results

- What key insights emerged from your model(s)?
- What business recommendations do you propose based on the models built?

Follow the instructions and answer the question below to complete the activity. Then, you will complete an executive summary using the questions listed on the PACE Strategy Document.

Be sure to complete this activity before moving on. The next course item will provide you with a completed exemplar to compare to your own work.

3 Build a regression model

4 PACE stages

Throughout these project notebooks, you'll see references to the problem-solving framework PACE. The following notebook components are labeled with the respective PACE stage: Plan, Analyze, Construct, and Execute.

4.1 PACE: Plan

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

4.1.1 Task 1. Imports and loading

Import the data and packages that you've learned are needed for building regression models.

[1]:
```
# Import packages for data manipulation
### YOUR CODE HERE ###
import pandas as pd
import numpy as np

# Import packages for data visualization
### YOUR CODE HERE ###
import matplotlib.pyplot as plt
import seaborn as sns

# Import packages for data preprocessing
### YOUR CODE HERE ###
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.utils import resample

# Import packages for data modeling
### YOUR CODE HERE ###
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.

Note: As shown in this cell, the dataset has been automatically loaded in for you. You do not need to download the .csv file, or provide more code, in order to access the dataset and proceed with this lab. Please continue with this activity by completing the following instructions.

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

4.2 PACE: Analyze

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

In this stage, consider the following question where applicable to complete your code response:

- What are some purposes of EDA before constructing a logistic regression model?

The purposes of EDA before constructing a logistic regression model are

1) to identify data anomalies such as outliers and class imbalance that might affect the modeling;
2) to verify model assumptions such as no severe multicollinearity.

4.2.1 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
### YOUR CODE HERE ###
data.head()
```

[3]:

	#	claim_status	video_id	video_duration_sec	video_transcription_text	verified_status	author_ban_status	video_view_count	video_like_count	video_share_count
0	1	claim	7017666017	59	someone shared with me that drone deliveries a…	not verified	under review	343296.0	19425.0	241.0
1	2	claim	4014381136	32	someone shared with me that there are more mic…	not verified	active	140877.0	77355.0	19034.0
2	3	claim	9859838091	31	someone shared with me that american industria…	not verified	active	902185.0	97690.0	2858.0
3	4	claim	1866847991	25	someone shared with me that the metro of st. p…	not verified	active	437506.0	239954.0	34812.0
4	5	claim	7105231098	19	someone shared with me that the number of busi…	not verified				

```
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
### YOUR CODE HERE ###
data.shape
```

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

Get the data types of the columns.

[5]:
```
# Get data types of columns
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
data.describe()
```

[7]:

	#	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
```

Check for and handle missing values.

[8]:
```python
# Check for missing values
data.isna().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]:
```python
# Drop rows with missing values
### YOUR CODE HERE ###
data = data.dropna(axis=0)
```

[10]:
```python
# Display first few rows after handling missing values
### YOUR CODE HERE ###
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
```

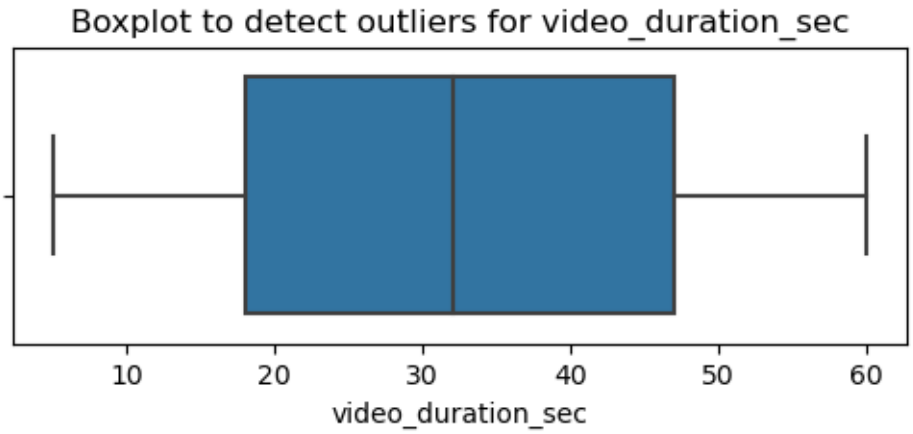
Check for and handle duplicates.

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

[11]:
```
0
```

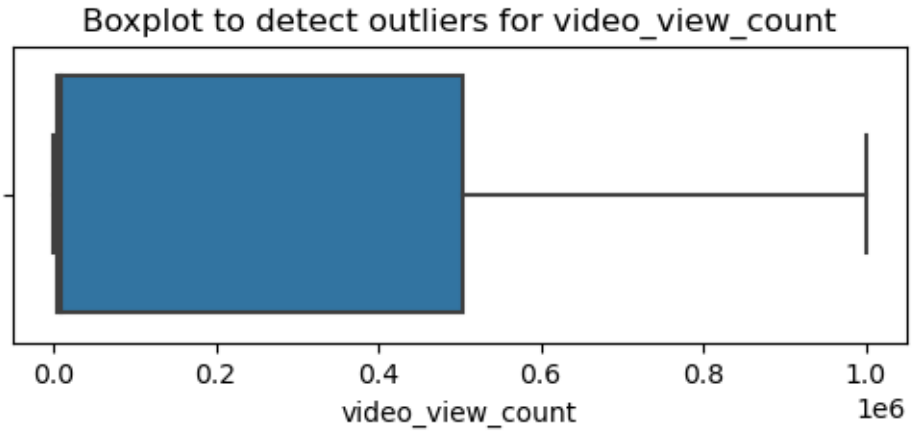
Check for and handle outliers.

[13]:
```
# Create a boxplot to visualize distribution of `video_duration_sec`
### YOUR CODE HERE ###
plt.figure(figsize=(6,2))
plt.title('Boxplot to detect outliers for video_duration_sec')
sns.boxplot(x=data['video_duration_sec'])
plt.show()
```

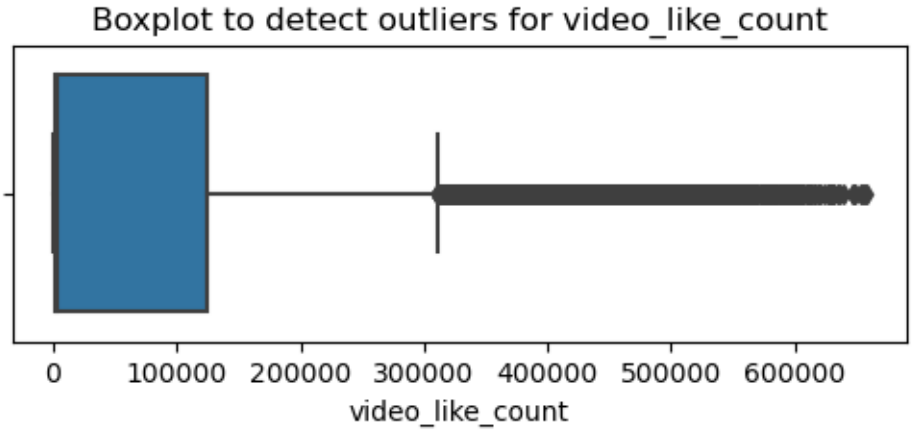


[14]:
```
# Create a boxplot to visualize distribution of `video_view_count`
### YOUR CODE HERE ###
plt.figure(figsize=(6,2))
plt.title('Boxplot to detect outliers for video_view_count')
sns.boxplot(x=data['video_view_count'])
```

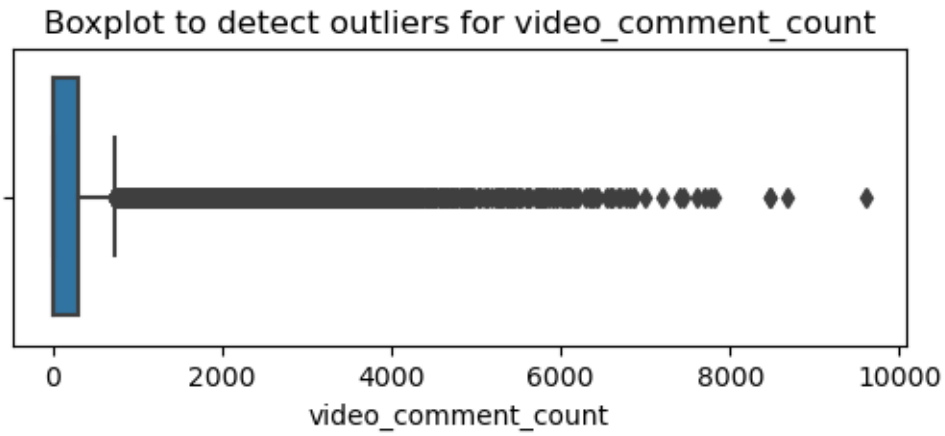
```
plt.show()
```



[15]:
```
# Create a boxplot to visualize distribution of `video_like_count`
### YOUR CODE HERE ###
plt.figure(figsize=(6,2))
plt.title('Boxplot to detect outliers for video_like_count')
sns.boxplot(x=data['video_like_count'])
plt.show()
```



[16]:
```
# Create a boxplot to visualize distribution of `video_comment_count`
### YOUR CODE HERE ###
plt.figure(figsize=(6,2))
plt.title('Boxplot to detect outliers for video_comment_count')
sns.boxplot(x=data['video_comment_count'])
plt.show()
```



[19]:
```
# Check for and handle outliers for video_like_count
### YOUR CODE HERE ###
percentile25 = data["video_like_count"].quantile(0.25)
percentile75 = data["video_like_count"].quantile(0.75)

iqr = percentile75 - percentile25
upper_limit = percentile75 + 1.5 * iqr

data.loc[data["video_like_count"] > upper_limit, "video_like_count"] =␣
 ↪upper_limit

percentile25 = data["video_comment_count"].quantile(0.25)
percentile75 = data["video_comment_count"].quantile(0.75)

iqr = percentile75 - percentile25
upper_limit = percentile75 + 1.5 * iqr

data.loc[data["video_comment_count"] > upper_limit, "video_comment_count"] =␣
 ↪upper_limit
```

Check class balance.

[20]:
```
# Check class balance for video_comment_count
### YOUR CODE HERE ###
data["verified_status"].value_counts(normalize=True)
```

[20]:
```
verified_status
not verified    0.93712
verified        0.06288
Name: proportion, dtype: float64
```

Approximately 94.2% of the dataset represents videos posted by unverified accounts and 5.8%

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.

[21]:
```
# Use resampling to create class balance in the outcome variable, if needed

# Identify data points from majority and minority classes
### YOUR CODE HERE ###
data_majority = data[data["verified_status"] == "not verified"]
data_minority = data[data["verified_status"] == "verified"]

# Upsample the minority class (which is "verified")
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
data_upsampled = pd.concat([data_majority, data_minority_upsampled]).
 ↪reset_index(drop=True)

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

[21]:
```
verified_status
not verified    17884
verified        17884
Name: count, dtype: int64
```

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.

[22]:
```
# Get the average `video_transcription_text` length for claims and the average␣
 ↪`video_transcription_text` length for opinions
### YOUR CODE HERE ###
data_upsampled[["verified_status", "video_transcription_text"]].
 ↪groupby(by="verified_status")[["video_transcription_text"]].agg(func=lambda␣
 ↪array: np.mean([len(text) for text in array]))
```

[22]:
```
                  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.

[23]:
```
# Extract the length of each `video_transcription_text` and add this as a␣
 ↪column to the dataframe
### YOUR CODE HERE ###
data_upsampled["text_length"] = data_upsampled["video_transcription_text"].
 ↪apply(func=lambda text: len(text))
```

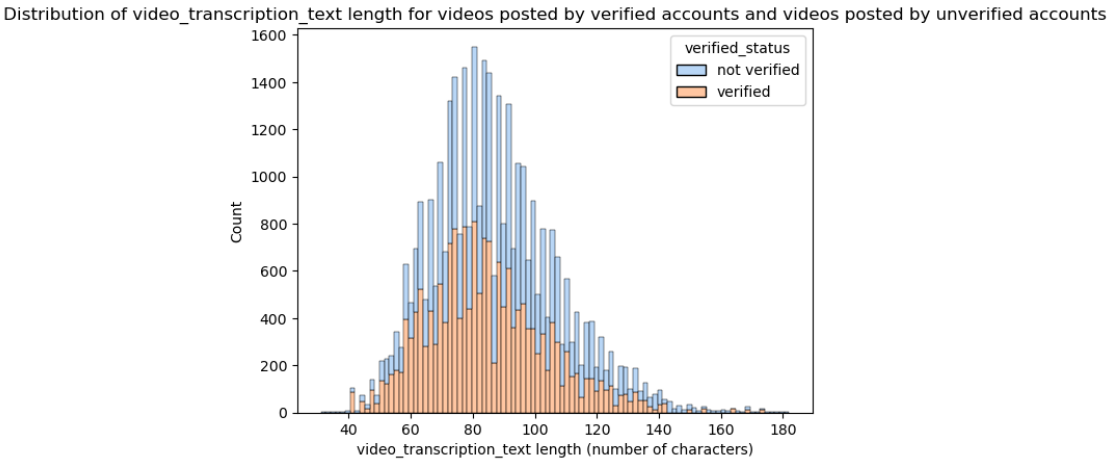
[24]:
```
# Display first few rows of dataframe after adding new column
### YOUR CODE HERE ###
data_upsampled.head()
```

[24]:

	#	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	19425.0	241.0	1.0	0.0	97
1	2	claim	4014381136	32	someone shared with me that there are more mic…	not verified	active	140877.0	77355.0	19034.0	1161.0	684.0	107
2	3	claim	9859838091	31	someone shared with me that american industria…	not verified	active	902185.0	97690.0	2858.0	833.0	329.0	137
3	4	claim	1866847991	25	someone shared with me that the metro of st. p…	not verified	active	437506.0	239954.0	34812.0	1234.0	584.0	131
4	5	claim	7105231098	19	someone shared with me that the number of busi…	not verified	active	56167.0	34987.0	4110.0	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.

[25]:
```
# Visualize the distribution of `video_transcription_text` length for videos␣
 ↪posted by verified accounts and videos posted by unverified accounts
# Create two histograms in one plot
### YOUR CODE HERE ###
sns.histplot(data=data_upsampled, stat="count", multiple="stack",␣
 ↪x="text_length", kde=False, palette="pastel",
             hue="verified_status", element="bars", legend=True)
plt.title("Seaborn Stacked Histogram")
plt.xlabel("video_transcription_text length (number of characters)")
plt.ylabel("Count")
plt.title("Distribution of video_transcription_text length for videos posted by␣
 ↪verified accounts and videos posted by unverified accounts")
plt.show()
```



4.2.2 Task 2b. Examine correlations

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

[26]:
```
# Code a correlation matrix to help determine most correlated variables
### YOUR CODE HERE ###
data_upsampled.corr(numeric_only=True)
```

[26]:

	#	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
```

Visualize a correlation heatmap of the data.

[27]:
```
# Create a heatmap to visualize how correlated variables are
### YOUR CODE HERE ###
plt.figure(figsize=(8, 6))
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(numeric_only=True),
    annot=True,
    cmap="crest")
plt.title("Heatmap of the dataset")
plt.show()
```

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.

Question: What variables are shown to be correlated in the heatmap?

4.3 PACE: Construct

After analysis and deriving variables with close relationships, it is time to begin constructing the model. Consider the questions in your PACE Strategy Document to reflect on the Construct stage.

4.3.1 Task 3a. Select variables

Set your Y and X variables.

Select the outcome variable.

[28]:
```
# Select outcome variable
### YOUR CODE HERE ###
```

```
y = data_upsampled["verified_status"]
```

Select the features.

[29]:
```
# Select features
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
X.head()
```

[29]:

	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

4.3.2 Task 3b. Train-test split

Split the data into training and testing sets.

[30]:
```
# Split the data into training and testing sets
### YOUR CODE HERE ###
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.

[31]:
```
# Get shape of each training and testing set
### YOUR CODE HERE ###
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[31]:
```
((26826, 7), (8942, 7), (26826,), (8942,))
```

4.3.3 Task 3c. Encode variables

Check the data types of the features.

[32]:
```
# Check data types
### YOUR CODE HERE ###
X_train.dtypes
```

[32]:
```
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
```

[33]:
```
# Get unique values in `claim_status`
### YOUR CODE HERE ###
X_train["claim_status"].unique()
```

[33]:
```
array(['opinion', 'claim'], dtype=object)
```

[34]:
```
# Get unique values in `author_ban_status`
### YOUR CODE HERE ###
X_train["author_ban_status"].unique()
```

[34]:
```
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.

[35]:
```
# Select the training features that needs to be encoded
### YOUR CODE HERE ###
X_train_to_encode = X_train[["claim_status", "author_ban_status"]]

# Display first few rows
### YOUR CODE HERE ###
X_train_to_encode.head()
```

[35]:

	claim_status	author_ban_status
33058	opinion	active
20491	opinion	active
25583	opinion	active
18474	opinion	active
27312	opinion	active

[36]:
```
# Set up an encoder for one-hot encoding the categorical features
### YOUR CODE HERE ###
```

```
X_encoder = OneHotEncoder(drop='first', sparse_output=False)
```

[37]:
```
# Fit and transform the training features using the encoder
### YOUR CODE HERE ###
X_train_encoded = X_encoder.fit_transform(X_train_to_encode)
```

[38]:
```
# Get feature names from encoder
### YOUR CODE HERE ###
X_encoder.get_feature_names_out()
```

[38]:
```
array(['claim_status_opinion', 'author_ban_status_banned',
       'author_ban_status_under review'], dtype=object)
```

[39]:
```
# Display first few rows of encoded training features
### YOUR CODE HERE ###
X_train_encoded
```

[39]:
```
array([[1., 0., 0.],
       [1., 0., 0.],
       [1., 0., 0.],
       …,
       [1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.]])
```

[40]:
```
# Place encoded training features (which is currently an array) into a dataframe
### YOUR CODE HERE ###
X_train_encoded_df = pd.DataFrame(data=X_train_encoded, columns=X_encoder.
 ↪get_feature_names_out())

# Display first few rows
### YOUR CODE HERE ###
X_train_encoded_df.head()
```

[40]:

	claim_status_opinion	author_ban_status_banned	author_ban_status_under review
0	1.0	0.0	0.0
1	1.0	0.0	0.0
2	1.0	0.0	0.0
3	1.0	0.0	0.0
4	1.0	0.0	0.0

[41]:
```
# Display first few rows of `X_train` with `claim_status` and␣
 ↪`author_ban_status` columns dropped (since these features are being␣
 ↪transformed to numeric)
### YOUR CODE HERE ###
X_train.drop(columns=["claim_status", "author_ban_status"]).head()
```

[41]:

	video_duration_sec	video_view_count	video_share_count	video_download_count	video_comment_count
33058	33	2252.0	23.0	4.0	0.0
20491	52	6664.0	550.0	53.0	2.0
25583	37	6327.0	257.0	3.0	0.0
18474	57	1702.0	28.0	0.0	0.0
27312	21	3842.0	101.0	1.0	0.0

[42]:
```
# Concatenate `X_train` and `X_train_encoded_df` to form the final dataframe␣
 ↪for training data (`X_train_final`)
# Note: Using `.reset_index(drop=True)` to reset the index in X_train after␣
 ↪dropping `claim_status` and `author_ban_status`,
# so that the indices align with those in `X_train_encoded_df` and `count_df`
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
X_train_final.head()
```

[42]:

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

Check the data type of the outcome variable.

[43]:
```
# Check data type of outcome variable
### YOUR CODE HERE ###
y_train.dtype
```

[43]:
```
dtype('O')
```

[44]:
```
# Get unique values of outcome variable
### YOUR CODE HERE ###
y_train.unique()
```

[44]:
```
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.

[45]:
```
# Set up an encoder for one-hot encoding the categorical outcome variable
### YOUR CODE HERE ###
y_encoder = OneHotEncoder(drop='first', sparse_output=False)
```

[46]:
```
# 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
### YOUR CODE HERE ###
y_train_final = y_encoder.fit_transform(y_train.values.reshape(-1, 1)).ravel()

# Display the encoded training outcome variable
### YOUR CODE HERE ###
y_train_final
```

[46]:
```
array([1., 1., 1., …, 1., 1., 0.])
```

4.3.4 Task 3d. Model building

Construct a model and fit it to the training set.

[47]:
```
# Construct a logistic regression model and fit it to the training set
### YOUR CODE HERE ###
log_clf = LogisticRegression(random_state=0, max_iter=800).fit(X_train_final,␣
↪y_train_final)
```

4.4 PACE: Execute

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

4.4.1 Taks 4a. Results and evaluation

Evaluate your model.

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

[49]:
```
# Select the testing features that needs to be encoded
### YOUR CODE HERE ###
X_test_to_encode = X_test[["claim_status", "author_ban_status"]]

# Display first few rows
### YOUR CODE HERE ###
X_test_to_encode.head()
```

[49]:

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

[50]:
```
# Transform the testing features using the encoder
### YOUR CODE HERE ###
X_test_encoded = X_encoder.transform(X_test_to_encode)

# Display first few rows of encoded testing features
### YOUR CODE HERE ###
X_test_encoded
```

[50]:
```
array([[1., 0., 0.],
       [1., 0., 0.],
       [0., 0., 0.],
       …,
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.]])
```

[51]:
```
# Place encoded testing features (which is currently an array) into a dataframe
### YOUR CODE HERE ###
```

```
X_test_encoded_df = pd.DataFrame(data=X_test_encoded, columns=X_encoder.
 ↪get_feature_names_out())

# Display first few rows
### YOUR CODE HERE ###
X_test_encoded_df.head()
```

[51]:
```
   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
```

[52]:
```
# 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()
```

[52]:
```
       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
```

[53]:
```
# Concatenate `X_test` and `X_test_encoded_df` to form the final dataframe for␣
 ↪training data (`X_test_final`)
# Note: Using `.reset_index(drop=True)` to reset the index in X_test after␣
 ↪dropping `claim_status`, and `author_ban_status`,
# so that the indices align with those in `X_test_encoded_df` and␣
 ↪`test_count_df`
```

```
### YOUR CODE HERE ###
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
### YOUR CODE HERE ###
X_test_final.head()
```

[53]:

	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.

[54]:
```
# Use the logistic regression model to get predictions on the encoded testing␣
 ↪set
### YOUR CODE HERE ###
y_pred = log_clf.predict(X_test_final)
```

Display the predictions on the encoded testing set.

[55]:
```
# Display the predictions on the encoded testing set
### YOUR CODE HERE ###
y_pred
```

[55]:
```
array([1., 1., 0., …, 1., 0., 1.])
```

Display the true labels of the testing set.

[56]:
```
# Display the true labels of the testing set
### YOUR CODE HERE ###
```

```
y_test
```

[56]:
```
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.

[57]:
```
# 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
### YOUR CODE HERE ###
y_test_final = y_encoder.transform(y_test.values.reshape(-1, 1)).ravel()

# Display the encoded testing outcome variable
y_test_final
```

[57]:
```
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.

[58]:
```
# Get shape of each training and testing set
### YOUR CODE HERE ###
X_train_final.shape, y_train_final.shape, X_test_final.shape, y_test_final.shape
```

[58]:
```
((26826, 8), (26826,), (8942, 8), (8942,))
```

4.4.2 Task 4b. Visualize model results

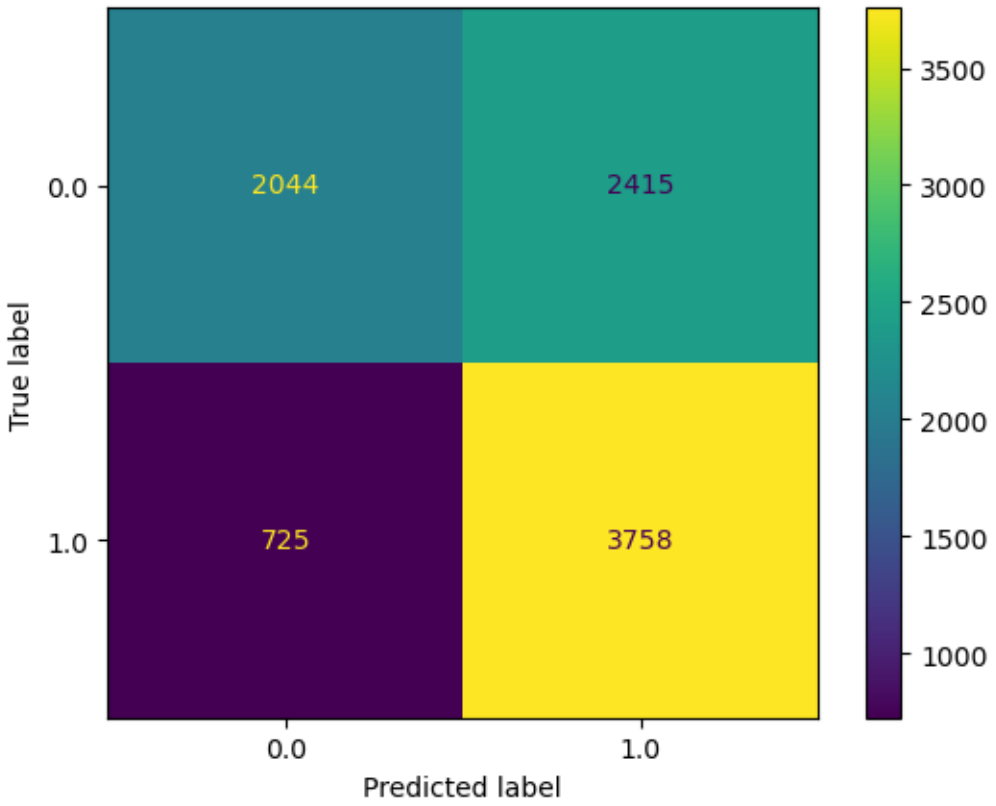
Create a confusion matrix to visualize the results of the logistic regression model.

[59]:
```
# Compute values for confusion matrix
### YOUR CODE HERE ###
log_cm = confusion_matrix(y_test_final, y_pred, labels=log_clf.classes_)
```

```
# Create display of confusion matrix
### YOUR CODE HERE ###
log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm,␣
 ↪display_labels=log_clf.classes_)

# Plot confusion matrix
### YOUR CODE HERE ###
log_disp.plot()

# Display plot
### YOUR CODE HERE ###
plt.show()
```



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

Exemplar notes:

The upper-left quadrant displays the number of true negatives: the number of videos posted by unverified accounts that the model accurately classified as so.

The upper-right quadrant displays the number of false positives: the number of videos posted by unverified accounts that the model misclassified as posted by verified accounts.

The lower-left quadrant displays the number of false negatives: the number of videos posted by verified accounts that the model misclassified as posted by unverified accounts.

The lower-right quadrant displays the number of true positives: the number of videos posted by verified accounts that the model accurately classified as so.

A perfect model would yield all true negatives and true positives, and no false negatives or false positives.

[60]:
```
# Create a classification report
### YOUR CODE HERE ###
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
```

Exemplar note: The classification report above shows that the logistic regression model achieved a precision of 61% and a recall of 84%, and it achieved an accuracy of 65%. Note that the precision and recall scores are taken from the "not verified" row of the output because that is the target class that we are most interested in predicting. The "verified" class has its own precision/recall metrics, and the weighted average represents the combined metrics for both classes of the target variable.

4.4.3 Task 4c. Interpret model coefficients

[61]:
```
# Get the feature names from the model and the model coefficients (which␣
 ↪represent log-odds ratios)
# Place into a DataFrame for readability
### YOUR CODE HERE ###
pd.DataFrame(data={"Feature Name":log_clf.feature_names_in_, "Model␣
 ↪Coefficient":log_clf.coef_[0]})
```

[61]:

	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

4.4.4 Task 4d. Conclusion

1. What are the key takeaways from this project?

2. What results can be presented from this project?

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.

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.