Activity_Course 6 TikTok project lab

February 1, 2024

1 TikTok Project

Course 6 - The Nuts and bolts of machine learning

Recall that you are a data professional at TikTok. Your supervisor was impressed with the work you have done and has requested that you build 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.

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

2 Course 6 End-of-course project: Classifying videos using machine learning

In this activity, you will practice using machine learning techniques to predict on a binary outcome variable.

The purpose of this model is to increase response time and system efficiency by automating the initial stages of the claims process.

The goal of this model is to predict whether a TikTok video presents a "claim" or presents an "opinion".

This activity has three parts:

Part 1: Ethical considerations * Consider the ethical implications of the request

- Should the objective of the model be adjusted?

Part 2: Feature engineering

- Perform feature selection, extraction, and transformation to prepare the data for modeling

Part 3: Modeling

- Build the models, evaluate them, and advise on next steps

Follow the instructions and answer the questions 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 Classify videos using machine learning

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.

In this stage, consider the following questions:

1. **What are you being asked to do? What metric should I use to evaluate success of my business/organizational objective?**
2. **What are the ethical implications of the model? What are the consequences of your model making errors?**

- What is the likely effect of the model when it predicts a false negative (i.e., when the model says a video does not contain a claim and it actually does)?
- What is the likely effect of the model when it predicts a false positive (i.e., when the model says a video does contain a claim and it actually does not)?

3. **How would you proceed?**

==> ENTER YOUR RESPONSES HERE

4.1.1 Task 1. Imports and data loading

Start by importing packages needed to build machine learning models to achieve the goal of this project.

[17]:
```
# Import packages for data manipulation
import pandas as pd
import numpy as np

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


# Import packages for data preprocessing
from sklearn.feature_extraction.text import CountVectorizer


# Import packages for data modeling
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from xgboost import plot_importance
```

```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, accuracy_score,␣
 ↪precision_score, recall_score, f1_score, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
```

Now load the data from the provided csv file into a dataframe.

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.

4.2.1 Task 2: Examine data, summary info, and descriptive stats

Inspect the first five rows of the dataframe.

[3]:
```
# Display first few rows
data.head(10)
```

[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
5   6        claim  8972200955                  35
6   7        claim  4958886992                  16
7   8        claim  2270982263                  41
8   9        claim  5235769692                  50
9  10        claim  4660861094                  45

                           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
5  someone shared with me that gross domestic pro…    not verified
6  someone shared with me that elvis presley has …    not verified
7  someone shared with me that the best selling s…    not verified
8  someone shared with me that about half of the …    not verified
9  someone shared with me that it would take a 50…        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
5      under review          336647.0          175546.0            62303.0
6            active          750345.0          486192.0           193911.0
7            active          547532.0            1072.0               50.0
8            active           24819.0           10160.0             1050.0
9            active          931587.0          171051.0            67739.0

   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
5                4293.0               1857.0
6                8616.0               5446.0
7                  22.0                 11.0
8                  53.0                 27.0
9                4104.0               2540.0
```

Get the number of rows and columns in the dataset.

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

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

Get the data types of the columns.

[5]:
```python
# Get data types of columns
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
```

Get basic information about the dataset.

[6]:
```python
# 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]:
```python
# Generate basic descriptive stats
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]:
```
# 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]:
```
# Drop rows with missing values
data = data.dropna(axis = 0)

data.isna().sum()
```

[9]:
```
#                           0
claim_status                0
video_id                    0
```

```
video_duration_sec          0
video_transcription_text    0
verified_status             0
author_ban_status           0
video_view_count            0
video_like_count            0
video_share_count           0
video_download_count        0
video_comment_count         0
dtype: int64
```

[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.

[19]:
```
### YOUR CODE HERE ###

Accoring to exemplar response:

Exemplar response: Tree-based models are robust to outliers,
so there is no need to impute or drop any values based on where they fall in␣
↪their distribution.

This makes sense due to the nature of tree model building learned in this␣
↪course.
To my understanding Tree-Building involves more of blanket binary decisions␣
↪thus not implimenting things such as
complex math on the data being used. Thus outliars are not an issue for this␣
↪section.
```

```
  Cell In[19], line 3
    Accoring to exemplar response:
             ^
SyntaxError: invalid syntax
```

Check class balance.

[12]:
```
# Check class balance
data['claim_status'].value_counts(normalize=True)
```

[12]:
```
claim_status
claim      0.503458
opinion    0.496542
Name: proportion, dtype: float64
```

4.3 PACE: Construct

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

4.3.1 Task 3: Feature engineering

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.

[20]:
```
# Extract the length of each `video_transcription_text` and add this as a␣
↪column to the dataframe
data["text_length"] = data["video_transcription_text"].str.len()
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  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
```

Calculate the average text_length for claims and opinions.

```
[21]: # Calculate the average text_length for claims and opinions
      data[['claim_status', 'text_length']].groupby('claim_status').mean()
```

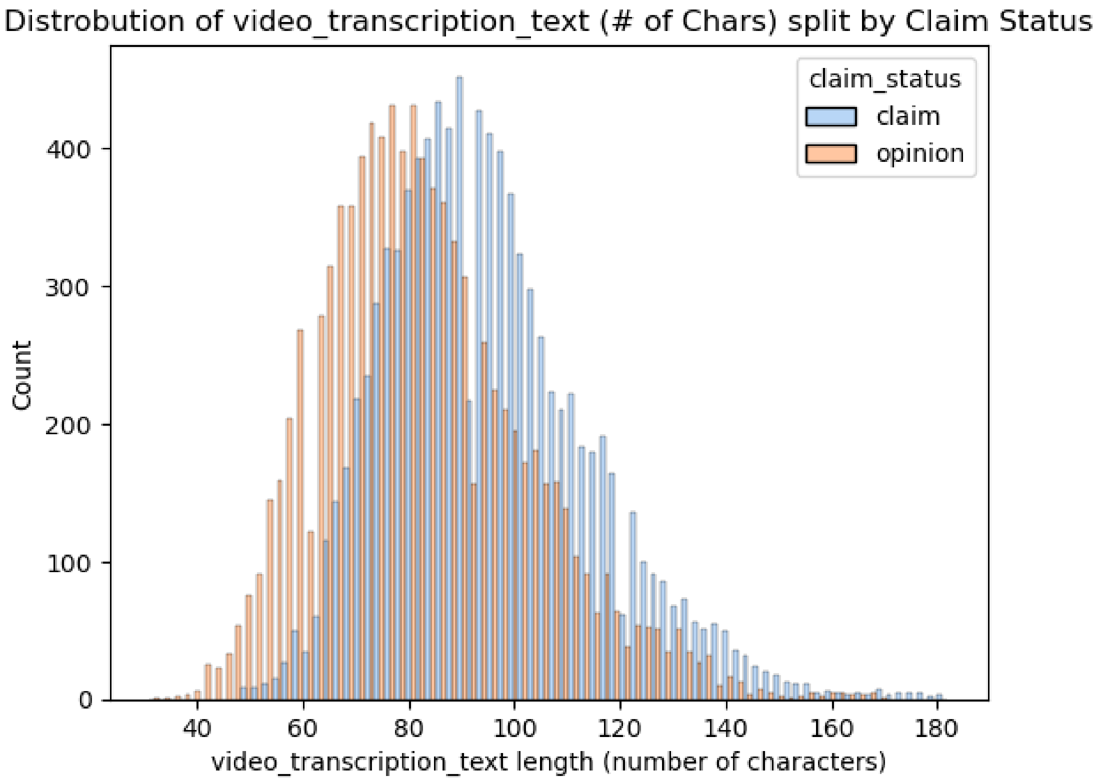
```
[21]:               text_length
      claim_status
      claim           95.376978
      opinion         82.722562
```

Visualize the distribution of `text_length` for claims and opinions.

```
[31]: # Visualize the distribution of `text_length` for claims and opinions
      # Create two histograms in one plot
      sns.histplot(data=data, stat='count', multiple='dodge', x='text_length',␣
       ↪kde=False, palette='pastel',
                   hue='claim_status', element='bars', legend=True)
      plt.title('Distrobution of video_transcription_text (# of Chars) split by Claim␣
       ↪Status')
      plt.xlabel('video_transcription_text length (number of characters)')
```

```
plt.ylabel('Count')
```

[31]: Text(0, 0.5, 'Count')



Feature selection and transformation

Encode target and catgorical variables.

[85]:
```
# Create a copy of the X data
X = data.copy()
# Drop unnecessary columns
X = X.drop(['#', 'video_id'], axis=1)

# Encode target variable
X['claim_status'] = X['claim_status'].replace({'opinion':0, 'claim':1})

# Dummy encode remaining categorical values
X = pd.get_dummies(X, columns=['verified_status', 'author_ban_status'],␣
 ↪drop_first=True)

X.head()
```

[85]:

```
   claim_status  video_duration_sec  \
0             1                  59
1             1                  32
2             1                  31
3             1                  25
4             1                  19

                             video_transcription_text  video_view_count  \
0  someone shared with me that drone deliveries a…          343296.0
1  someone shared with me that there are more mic…          140877.0
2  someone shared with me that american industria…          902185.0
3  someone shared with me that the metro of st. p…          437506.0
4  someone shared with me that the number of busi…           56167.0

   video_like_count  video_share_count  video_download_count  \
0           19425.0              241.0                   1.0
1           77355.0            19034.0                1161.0
2           97690.0             2858.0                 833.0
3          239954.0            34812.0                1234.0
4           34987.0             4110.0                 547.0

   video_comment_count  text_length  verified_status_verified  \
0                  0.0           97                     False
1                684.0          107                     False
2                329.0          137                     False
3                584.0          131                     False
4                152.0          128                     False

   author_ban_status_banned  author_ban_status_under review
0                     False                            True
1                     False                           False
2                     False                           False
3                     False                           False
4                     False                           False
```

4.3.2 Task 4: Split the data

Assign target variable.

[33]:

```python
# Isolate target variable
y = X['claim_status']
```

Isolate the features.

[34]:

```python
# Isolate features
X = X.drop(['claim_status'], axis=1)

# Display first few rows of features dataframe
```

```python
X.head()
```

[34]:

```
   video_duration_sec                           video_transcription_text  \
0                  59  someone shared with me that drone deliveries a…
1                  32  someone shared with me that there are more mic…
2                  31  someone shared with me that american industria…
3                  25  someone shared with me that the metro of st. p…
4                  19  someone shared with me that the number of busi…

   video_view_count  video_like_count  video_share_count  \
0          343296.0           19425.0              241.0
1          140877.0           77355.0            19034.0
2          902185.0           97690.0             2858.0
3          437506.0          239954.0            34812.0
4           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

   verified_status_verified  author_ban_status_banned  \
0                     False                     False
1                     False                     False
2                     False                     False
3                     False                     False
4                     False                     False

   author_ban_status_under review
0                            True
1                           False
2                           False
3                           False
4                           False
```

Task 5: Create train/validate/test sets Split data into training and testing sets, 80/20.

[75]:

```python
# Split the data into training and testing sets
X_tr, X_test, y_tr, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

Split the training set into training and validation sets, 75/25, to result in a final ratio of 60/20/20 for train/validate/test sets.

[76]:
```
# Split the training data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_tr, y_tr, test_size=0.25,␣
↪random_state=0)
```

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

[77]:
```
# Get shape of each training, validation, and testing set
X_train.shape, X_val.shape, X_test.shape, y_train.shape, y_val.shape, y_test.
↪shape
```

[77]:
```
((11450, 11), (3817, 11), (3817, 11), (11450,), (3817,), (3817,))
```

4.3.3 Task 6. Build models

4.3.4 Build a random forest model

Fit a random forest model to the training set. Use cross-validation to tune the hyperparameters and select the model that performs best on recall.

[98]:
```
# Set up a `CountVectorizer` object, which converts a collection of text to a␣
↪matrix of token counts
count_vec = CountVectorizer(ngram_range=(2, 3),
                            max_features=15,
                            stop_words='english')
count_vec


# Extract numerical features from `video_transcription_text` in the training set
count_data = count_vec.fit_transform(X_train['video_transcription_text']).
↪toarray()
count_data


# Place the numerical representation of `video_transcription_text` from␣
↪training set into a dataframe
count_df = pd.DataFrame(data=count_data, columns=count_vec.
↪get_feature_names_out())


# Concatenate `X_train` and `count_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 `video_transcription_text`,
# so that the indices align with those in `X_train` and `count_df`
X_train_final = pd.concat([X_train.drop(columns=['video_transcription_text']).
↪reset_index(drop=True), count_df], axis=1)

# Extract numerical features from `video_transcription_text` in the testing set
```

```
validation_count_data = count_vec.transform(X_val['video_transcription_text']).
 ↪toarray()
validation_count_data

# Place the numerical representation of `video_transcription_text` from␣
 ↪validation set into a dataframe
validation_count_df = pd.DataFrame(data=validation_count_data,␣
 ↪columns=count_vec.get_feature_names_out())

# Concatenate `X_val` and `validation_count_df` to form the final dataframe for␣
 ↪training data (`X_val_final`)
# Note: Using `.reset_index(drop=True)` to reset the index in X_val after␣
 ↪dropping `video_transcription_text`,
# so that the indices align with those in `validation_count_df`
X_val_final = pd.concat([X_val.drop(columns=['video_transcription_text']).
 ↪reset_index(drop=True), validation_count_df], axis=1)


# Extract numerical features from `video_transcription_text` in the testing set
test_count_data = count_vec.transform(X_test['video_transcription_text']).
 ↪toarray()

# Place the numerical representation of `video_transcription_text` from test␣
 ↪set into a dataframe
test_count_df = pd.DataFrame(data=test_count_data, columns=count_vec.
 ↪get_feature_names_out())

# Concatenate `X_val` and `validation_count_df` to form the final dataframe for␣
 ↪training data (`X_val_final`)
X_test_final = pd.concat([X_test.drop(columns=['video_transcription_text']
                                      ).reset_index(drop=True), test_count_df],␣
 ↪axis=1)




# Instantiate the random forest classifier
rf = RandomForestClassifier(random_state=0)

# Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [5, 7, None],
             'max_features': [0.3, 0.6],
            #  'max_features': 'auto'
             'max_samples': [0.7],
             'min_samples_leaf': [1,2],
             'min_samples_split': [2,3],
```

```
            'n_estimators': [75,100,200],
            }

# Define a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1'}

# Instantiate the GridSearchCV object
rf_cv = GridSearchCV(rf, cv_params, scoring=scoring, cv=5, refit='recall')

rf_cv.fit(X_train_final, y_train)
```

[98]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=0),
             param_grid={'max_depth': [5, 7, None], 'max_features': [0.3, 0.6],
                         'max_samples': [0.7], 'min_samples_leaf': [1, 2],
                         'min_samples_split': [2, 3],
                         'n_estimators': [75, 100, 200]},
             refit='recall', scoring={'f1', 'precision', 'accuracy', 'recall'})
```

[105]:
```
# Examine best recall score

rf_cv.best_score_
```

[105]:
```
0.9948228253467271
```

[104]:
```
def make_results(model_name, model_object):
    '''
    Accepts as arguments a model name (your choice - string) and
    a fit GridSearchCV model object.

    Returns a pandas df with the F1, recall, precision, and accuracy scores
    for the model with the best mean F1 score across all validation folds.
    '''

    # Get all the results from the CV and put them in a df
    cv_results = pd.DataFrame(model_object.cv_results_)

    # Isolate the row of the df with the max(mean precision score)
    best_estimator_results = cv_results.iloc[cv_results['mean_test_precision'].
 ↪idxmax(), :]

    # Extract accuracy, precision, recall, and f1 score from that row
    f1 = best_estimator_results.mean_test_f1
    recall = best_estimator_results.mean_test_recall
    precision = best_estimator_results.mean_test_precision
    accuracy = best_estimator_results.mean_test_accuracy

    # Create table of results
```

```
    table = pd.DataFrame({'Model': [model_name],
                          'F1': [f1],
                          'Recall': [recall],
                          'Precision': [precision],
                          'Accuracy': [accuracy]
                         }
                        )

    return table

rf_cv_results = make_results('Random Forest CV', rf_cv)
rf_cv_results
```

[104]:

	Model	F1	Recall	Precision	Accuracy
0	Random Forest CV	0.996014	0.992407	0.999653	0.995983

[100]:
```
# Examine best parameters
rf_cv.best_params_
```

[100]:
```
{'max_depth': None,
 'max_features': 0.6,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 200}
```

Question: How well is your model performing? Consider average recall score and precision score.

4.3.5 Build an XGBoost model

[102]:
```
# Instantiate the XGBoost classifier
xgb = XGBClassifier(objective='binary:logistic', random_state=0)

# Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [4,8,12],
             'min_child_weight': [3, 5],
             'learning_rate': [0.01, 0.1],
             'n_estimators': [300, 500]
             }

# Define a dictionary of scoring metrics to capture
scoring = {'accuracy', 'precision', 'recall', 'f1'}

# Instantiate the GridSearchCV object
xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=5, refit='recall')

xgb_cv.fit(X_train_final, y_train)
```

[102]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     feature_types=None, gamma=None,
                                     gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None,…
                                     max_delta_step=None, max_depth=None,
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=0, …),
             param_grid={'learning_rate': [0.01, 0.1], 'max_depth': [4, 8, 12],
                         'min_child_weight': [3, 5],
                         'n_estimators': [300, 500]},
             refit='recall', scoring={'f1', 'precision', 'accuracy', 'recall'})
```

[106]:
```python
def make_results(model_name, model_object):
    '''
    Accepts as arguments a model name (your choice - string) and
    a fit GridSearchCV model object.

    Returns a pandas df with the F1, recall, precision, and accuracy scores
    for the model with the best mean F1 score across all validation folds.
    '''

    # Get all the results from the CV and put them in a df
    cv_results = pd.DataFrame(model_object.cv_results_)

    # Isolate the row of the df with the max(mean precision score)
    best_estimator_results = cv_results.iloc[cv_results['mean_test_precision'].
↪idxmax(), :]

    # Extract accuracy, precision, recall, and f1 score from that row
    f1 = best_estimator_results.mean_test_f1
    recall = best_estimator_results.mean_test_recall
    precision = best_estimator_results.mean_test_precision
    accuracy = best_estimator_results.mean_test_accuracy

    # Create table of results
    table = pd.DataFrame({'Model': [model_name],
```

```
                            'F1': [f1],
                            'Recall': [recall],
                            'Precision': [precision],
                            'Accuracy': [accuracy]
                           }
                          )

    return table

xgb_cv_results = make_results('XGBoost model CV', xgb_cv)
xgb_cv_results
```

[106]:

	Model	F1	Recall	Precision	Accuracy
0	XGBoost model CV	0.994967	0.98999	1.0	0.994934

Question: How well does your model perform? Consider recall score and precision score.

4.4 PACE: Execute

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

4.4.1 Task 7. Evaluate model

Evaluate models against validation criteria.

Random forest

[107]:
```
# Use the random forest "best estimator" model to get predictions on the␣
↪encoded testing set
y_pred = rf_cv.best_estimator_.predict(X_val_final)
```

Display the predictions on the encoded testing set.

[108]:
```
# Display the predictions on the encoded testing set
y_pred
```

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

Display the true labels of the testing set.

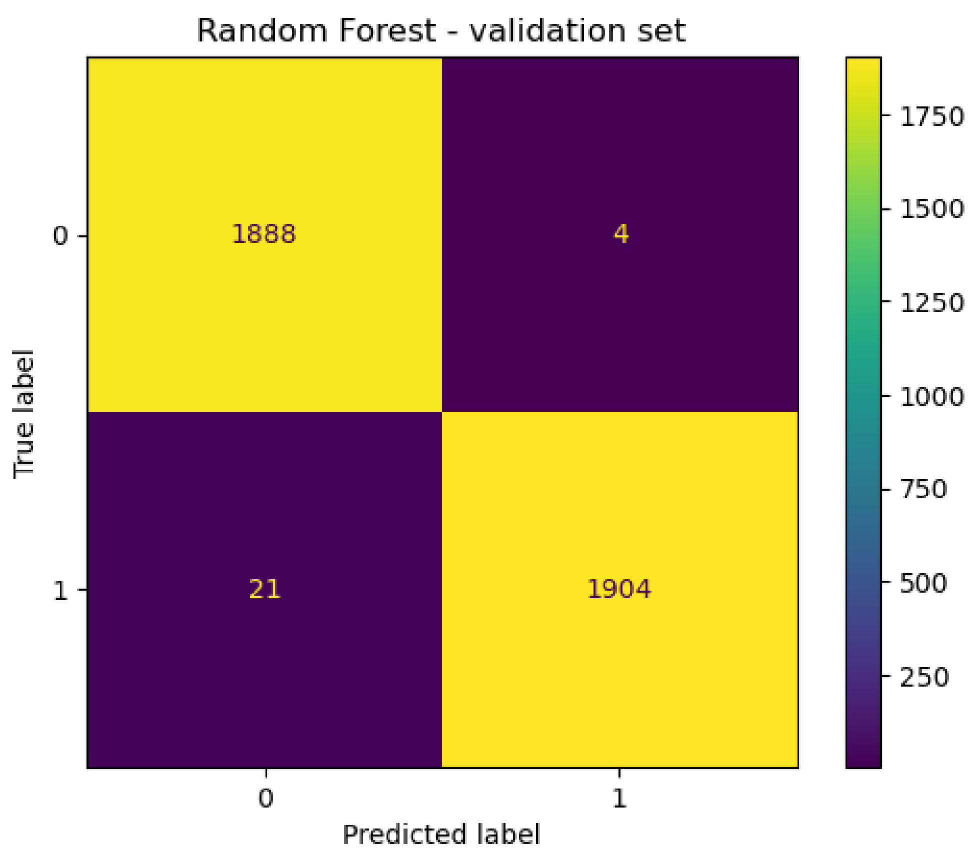
[109]:
```
# Display the true labels of the testing set
y_val
```

[109]:
```
5846     1
12058    0
2975     1
8432     1
6863     1
        ..
```

```
6036    1
6544    1
2781    1
6426    1
4450    1
Name: claim_status, Length: 3817, dtype: int64
```

Create a confusion matrix to visualize the results of the classification model.

[118]:
```python
# Create a confusion matrix to visualize the results of the classification model

# Compute values for confusion matrix
rf_cm = confusion_matrix(y_val,y_pred)

# Create display of confusion matrix
rf_disp = ConfusionMatrixDisplay(confusion_matrix=rf_cm, display_labels=None)

# Plot confusion matrix
rf_disp.plot()

# Display plot
plt.title('Random Forest - validation set');
plt.show()
```



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

[111]:
```
# Create a classification report
# Create classification report for random forest model
target_labels = ['opinion', 'claim']
print(classification_report(y_val, y_pred, target_names=target_labels))
```

```
              precision    recall  f1-score   support

     opinion       1.00      1.00      1.00      1892
       claim       1.00      1.00      1.00      1925

    accuracy                           1.00      3817
   macro avg       1.00      1.00      1.00      3817
weighted avg       1.00      1.00      1.00      3817
```

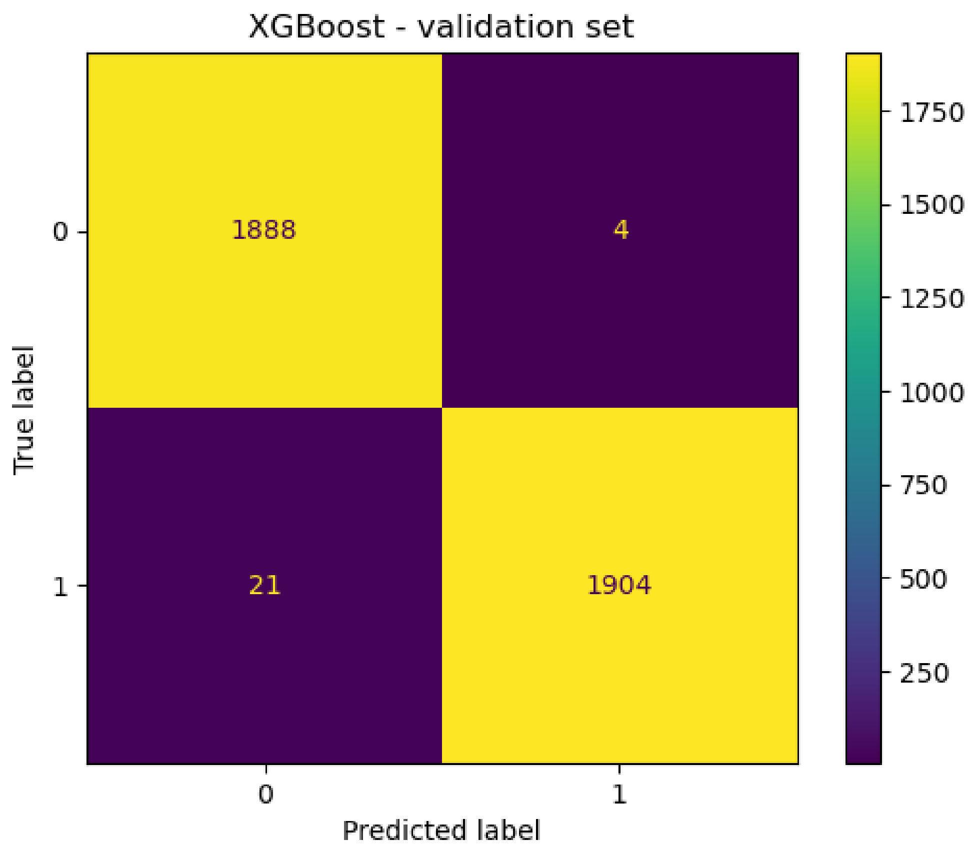
Question: What does your classification report show? What does the confusion matrix indicate?

The classification report above shows that the random forest model scores were nearly perfect. The confusion matrix indicates that there were 10 misclassifications—five false postives and five false negatives.

XGBoost

[113]:
```
#Evaluate XGBoost model
y_pred = xgb_cv.best_estimator_.predict(X_val_final)
```

[116]:
```
# Compute values for confusion matrix
xgb_cm = confusion_matrix(y_val,y_pred)

# Create display of confusion matrix
xgb_disp = ConfusionMatrixDisplay(confusion_matrix=xgb_cm, display_labels=None)

# Plot confusion matrix
xgb_disp.plot()

# Display plot
plt.title('XGBoost - validation set');
plt.show()
```



[117]:
```
# Create a classification report
target_labels = ['opinion', 'claim']
print(classification_report(y_val, y_pred, target_names=target_labels))
```

```
              precision    recall  f1-score   support

     opinion       0.99      1.00      0.99      1892
       claim       1.00      0.99      0.99      1925

    accuracy                           0.99      3817
   macro avg       0.99      0.99      0.99      3817
weighted avg       0.99      0.99      0.99      3817
```

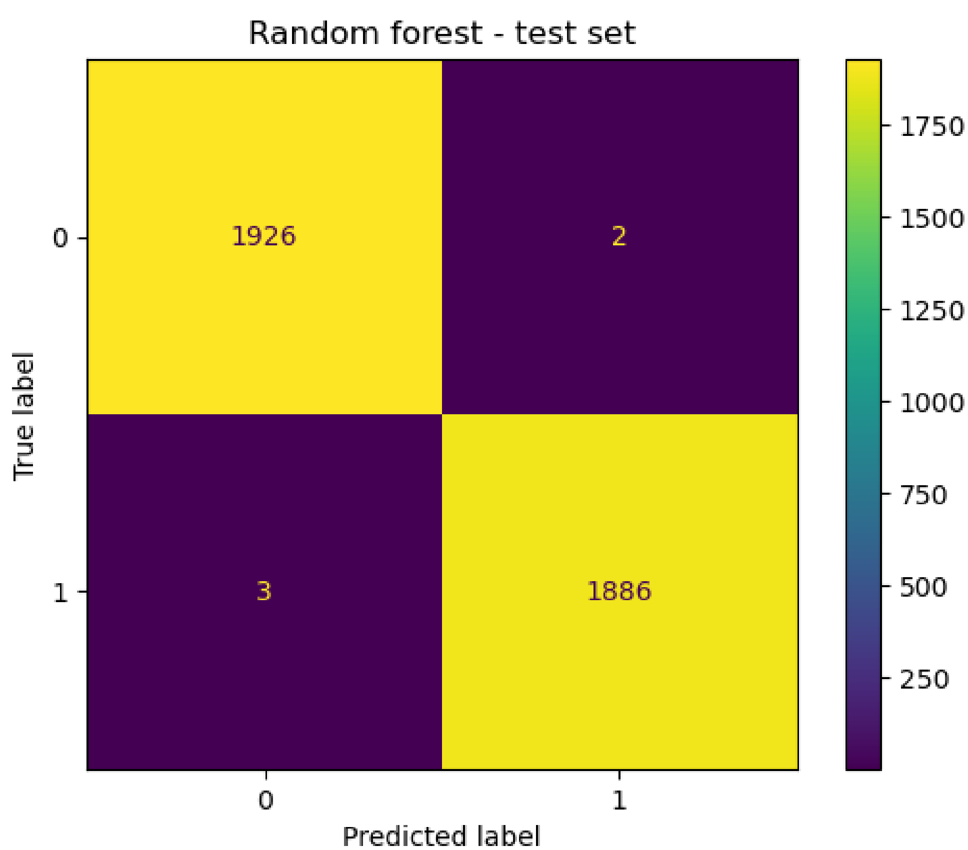
Question: Describe your XGBoost model results. How does your XGBoost model compare to your random forest model?

The results of the XGBoost model were also nearly perfect. However, its errors tended to be false negatives. Identifying claims was the priority, so it's important that the model be good at capturing all actual claim videos. The random forest model has a better recall score, and is therefore the champion model.

4.4.2 Use champion model to predict on test data

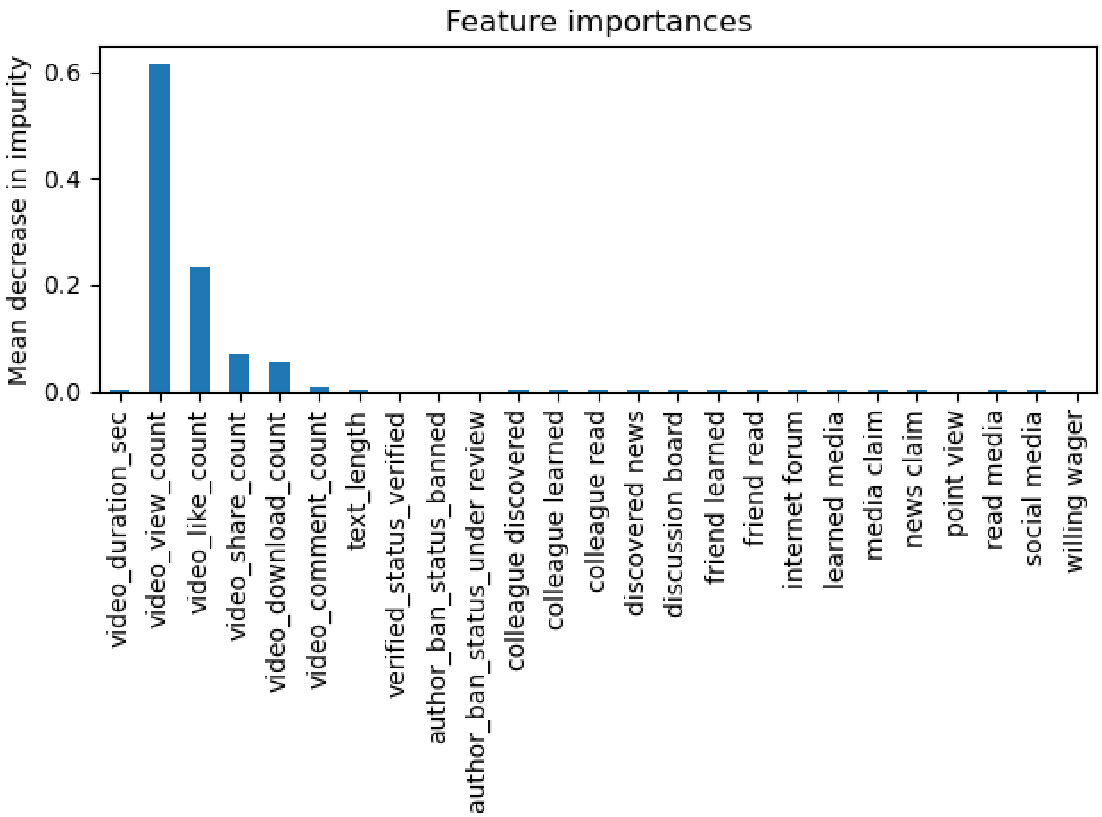
[119]:
```
### YOUR CODE HERE ###
y_pred = rf_cv.best_estimator_.predict(X_test_final)
```

[120]:
```
# Compute values for confusion matrix
log_cm = confusion_matrix(y_test, y_pred)

# Create display of confusion matrix
log_disp = ConfusionMatrixDisplay(confusion_matrix=log_cm, display_labels=None)

# Plot confusion matrix
log_disp.plot()

# Display plot
plt.title('Random forest - test set');
plt.show()
```



Feature importances of champion model

[121]:
```
importances = rf_cv.best_estimator_.feature_importances_
rf_importances = pd.Series(importances, index=X_test_final.columns)

fig, ax = plt.subplots()
rf_importances.plot.bar(ax=ax)
ax.set_title('Feature importances')
ax.set_ylabel('Mean decrease in impurity')
fig.tight_layout()
```



Question: Describe your most predictive features. Were your results surprising?

The most predictive features all were related to engagement levels generated by the video. This is not unexpected, as analysis from prior EDA pointed to this conclusion.

4.4.3 Task 8. Conclusion

In this step use the results of the models above to formulate a conclusion. Consider the following questions:

1. **Would you recommend using this model? Why or why not?**
2. **What was your model doing? Can you explain how it was making predictions?**

3. **Are there new features that you can engineer that might improve model performance?**
4. **What features would you want to have that would likely improve the performance of your model?**

Remember, sometimes your data simply will not be predictive of your chosen target. This is common. Machine learning is a powerful tool, but it is not magic. If your data does not contain predictive signal, even the most complex algorithm will not be able to deliver consistent and accurate predictions. Do not be afraid to draw this conclusion.

1) Would you recommend using this model? Why or why not? Yes, one can recommend this model because it performed well on both the validation and test holdout data. Furthermore, both precision and F1 scores were consistently high. The model very successfully classified claims and opinions.
2) What was your model doing? Can you explain how it was making predictions? The model's most predictive features were all related to the user engagement levels associated with each video. It was classifying videos based on how many views, likes, shares, and downloads they received.
3) Are there new features that you can engineer that might improve model performance? Because the model currently performs nearly perfectly, there is no need to engineer any new features.
4) What features would you want to have that would likely improve the performance of your model? The current version of the model does not need any new features. However, it would be helpful to have the number of times the video was reported. It would also be useful to have the total number of user reports for all videos posted by each author.

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.