Activity_Course 6 TikTok project lab

January 27, 2025

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. 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?**

1. We are being asked to create a random forest machine learning model that can predict whether a tiktok is considered a claim or an opinion. Given this is a binary classification model, we will use our standard binary classification metrics: precision, recall, accuracy, F1, and F-beta. We should not additionally that recall is going to be a more important evaluation metrics because it is more important to minimize false negatives. We have come to this conclusion not only because reviewing claims is more important than opinions, but also our previous reports have concluded that tiktoks identified as making claims have much larger engagement than opinions.
2. Since this model will be evaluating whether content is a terms of service violation, it is important to significantly minimize false positives and false negatives, since we neither want acceptable content censored nor unacceptable content to disperse. However, we will be extra careful to catch false negatives.
3. The dataset has about 20,000 tiktoks so we should feel confident proceeding with a split of the data which includes a validation set as well as the test and training sets. We can then perform a cross-fold validation to determine a more optimal model. We will split the data into train/validation/test proportions: (60/20/20), fit our random tree models to their respective boostrapped samples of the training data, and use the validation set to tune our hyperparameters. We evaluate our models using the above metrics, choose a the best performing champion model, and finally evaluate its predictive power on the testing set.

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.

[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.feature_extraction.text import CountVectorizer

# Import packages for data modeling
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision_score, recall_score, accuracy_score,␣
 ↪f1_score, classification_report, confusion_matrix, ConfusionMatrixDisplay

from xgboost import XGBClassifier, plot_importance
```

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()
```

[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]:
```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]:
```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
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.

Tree models are robust to negative impacts by outliers.

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.

[13]:
```python
# Extract the length of each `video_transcription_text` and add this as a␣
↪column to the dataframe
### YOUR CODE HERE ###
data['text_length'] = data['video_transcription_text'].str.len()
```

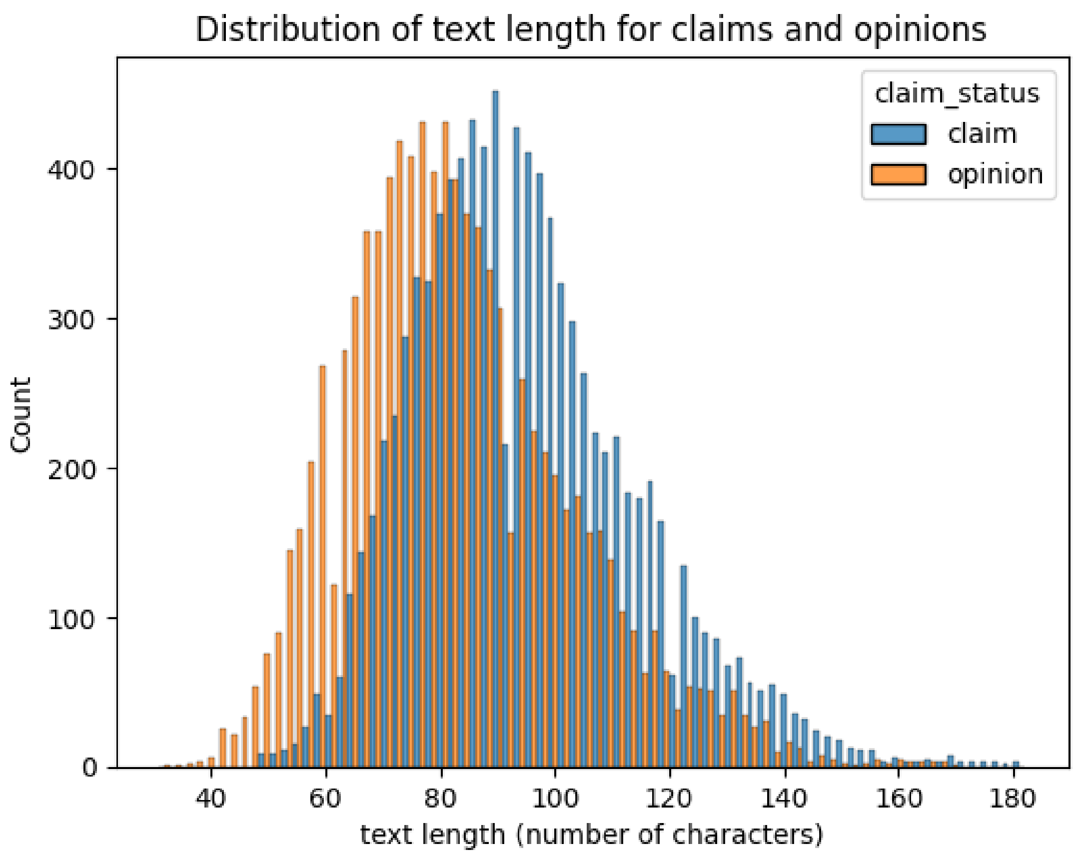
Calculate the average text_length for claims and opinions.

[14]:
```python
# Calculate the average text_length for claims and opinions
data.groupby('claim_status')['text_length'].mean()
```

[14]:
```
claim_status
claim      95.376978
opinion    82.722562
Name: text_length, dtype: float64
```

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

[15]:
```python
# Visualize the distribution of `text_length` for claims and opinions
# Create two histograms in one plot
sns.histplot(data, stat= 'count', x= 'text_length', legend = True, hue =␣
↪'claim_status', multiple = 'dodge')
plt.xlabel("text length (number of characters)")
plt.ylabel("Count")
plt.title("Distribution of text length for claims and opinions")

plt.show()
```



Feature selection and transformation

Encode target and catgorical variables.

[16]:
```python
# Create a copy of the X data
# Drop unnecessary columns
X = data.drop(['#','video_id','video_transcription_text'], axis=1)

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

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

[16]:

	claim_status	video_duration_sec	video_view_count	video_like_count	\
0	1	59	343296.0	19425.0	
1	1	32	140877.0	77355.0	
2	1	31	902185.0	97690.0	

```
3              1                   25         437506.0           239954.0
4              1                   19          56167.0            34987.0

   video_share_count  video_download_count  video_comment_count  text_length  \
0              241.0                   1.0                  0.0           97
1            19034.0                1161.0                684.0          107
2             2858.0                 833.0                329.0          137
3            34812.0                1234.0                584.0          131
4             4110.0                 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
```

4.3.2 Task 4: Split the data

Assign target variable.

[17]:
```
# Isolate target variable
y = X['claim_status']
```

Isolate the features.

[18]:
```
# Isolate features
X = X.drop('claim_status', axis = 1)

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

[18]:
```
   video_duration_sec  video_view_count  video_like_count  video_share_count  \
0                  59          343296.0           19425.0              241.0
1                  32          140877.0           77355.0            19034.0
2                  31          902185.0           97690.0             2858.0
3                  25          437506.0          239954.0            34812.0
4                  19           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.

[19]:
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .20,␣
↪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.

[20]:
```python
# Split the training data into training and validation sets
X_tr, X_val, y_tr, y_val = train_test_split(X_train, y_train, test_size = .25,␣
↪random_state = 0)
```

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

[21]:
```python
# Get shape of each training, validation, and testing set
X_test.shape, y_test.shape, X_tr.shape, X_val.shape, y_tr.shape, y_val.shape
```

[21]:
```
((3817, 10), (3817,), (11450, 10), (3817, 10), (11450,), (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.

[22]:
```python
# Instantiate the random forest classifier
rf = RandomForestClassifier(random_state=0)
```

```python
# Create a dictionary of hyperparameters to tune
cv_params = {'n_estimators': [75,100,200],
             'max_depth': [5,7,None],
             'min_samples_leaf': [1,2],
             'min_samples_split': [2,3],
             'max_features': [.3,.6],
             'max_samples': [.7]}

# Define a list of scoring metrics to capture
scoring = ['precision', 'recall', 'accuracy', 'f1']

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

[23]:
```python
%%time
rf_cv.fit(X_tr, y_tr)
```

```
CPU times: user 5min 57s, sys: 767 ms, total: 5min 58s
Wall time: 5min 58s
```

[23]:
```
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=['precision', 'recall', 'accuracy', 'f1'])
```

[24]:
```python
# Examine best recall score
rf_cv.best_score_
```

[24]:
```
0.9908534395531852
```

[25]:
```python
# Examine best parameters
rf_cv.best_params_
```

[25]:
```
{'max_depth': 5,
 'max_features': 0.6,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 75}
```

Check the precision score to make sure the model isn't labeling everything as claims. You can do this by using the `cv_results_` attribute of the fit `GridSearchCV` object, which returns a numpy array that can be converted to a pandas dataframe. Then, examine the `mean_test_precision` column of this dataframe at the index containing the results from the best model. This index can be accessed by using the `best_index_` attribute of the fit `GridSearchCV` object.

[44]:
```
# Access the GridSearch results and convert it to a pandas df
rf_results_df = pd.DataFrame(rf_cv.cv_results_)

# Examine the GridSearch results df at column `mean_test_precision` in the best
↪index
print(rf_results_df['mean_test_precision'][rf_cv.best_index_])
print(rf_results_df['mean_test_recall'][rf_cv.best_index_])
```

```
0.9994785483051682
0.9908534395531852
```

Question: How well is your model performing? Consider average recall score and precision score. The model is performing exceptionally with average recall and precision at greater than 99% on the test data. So it rarely misses a positive that should've been recognized and the reliability of a positive recognition is also incredibly strong.

4.3.5 Build an XGBoost model

[27]:
```
# Instantiate the XGBoost classifier
xgb = XGBClassifier(objective='binary:logistic', random_state=0)

# Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [3,6,9],
             'min_child_weight': [3,5],
             'learning_rate': [.01, .1],
             'n_estimators': [300, 500]}

# Define a list of scoring metrics to capture
scoring = ['precision', 'recall', 'accuracy', 'f1']

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

[28]:
```
%%time
xgb_cv = xgb_cv.fit(X_tr, y_tr)
```

```
CPU times: user 1min 1s, sys: 1.16 s, total: 1min 2s
Wall time: 32.3 s
```

[29]:
```
# Examine best recall score
xgb_cv.best_score_
```

[29]:
```
0.9898176171763818
```

[30]:
```
# Examine best parameters
xgb_cv.best_params_
```

[30]:
```
{'learning_rate': 0.1,
 'max_depth': 3,
 'min_child_weight': 5,
 'n_estimators': 300}
```

Repeat the steps used for random forest to examine the precision score of the best model identified in the grid search.

[45]:
```
# Access the GridSearch results and convert it to a pandas df
xgb_results_df = pd.DataFrame(xgb_cv.cv_results_)

# Examine the GridSearch results df at column `mean_test_precision` in the best␣
 ↪index
print(xgb_results_df['mean_test_precision'][xgb_cv.best_index_])
print(xgb_results_df['mean_test_recall'][xgb_cv.best_index_])
```

```
0.9989540877965151
0.9898176171763818
```

Question: How well does your model perform? Consider recall score and precision score. Again we have that for both average recall and precision this model is also performing exceptionally. The averages still being about 99% for both recall and precision scores.

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

[32]:
```
# Use the random forest "best estimator" model to get predictions on the␣
 ↪validation set
y_pred = rf_cv.best_estimator_.predict(X_val)
```

Display the predictions on the validation set.

[33]:
```
# Display the predictions on the validation set
y_pred
```

[33]:
```
array([1, 0, 1, …, 1, 1, 1])
```

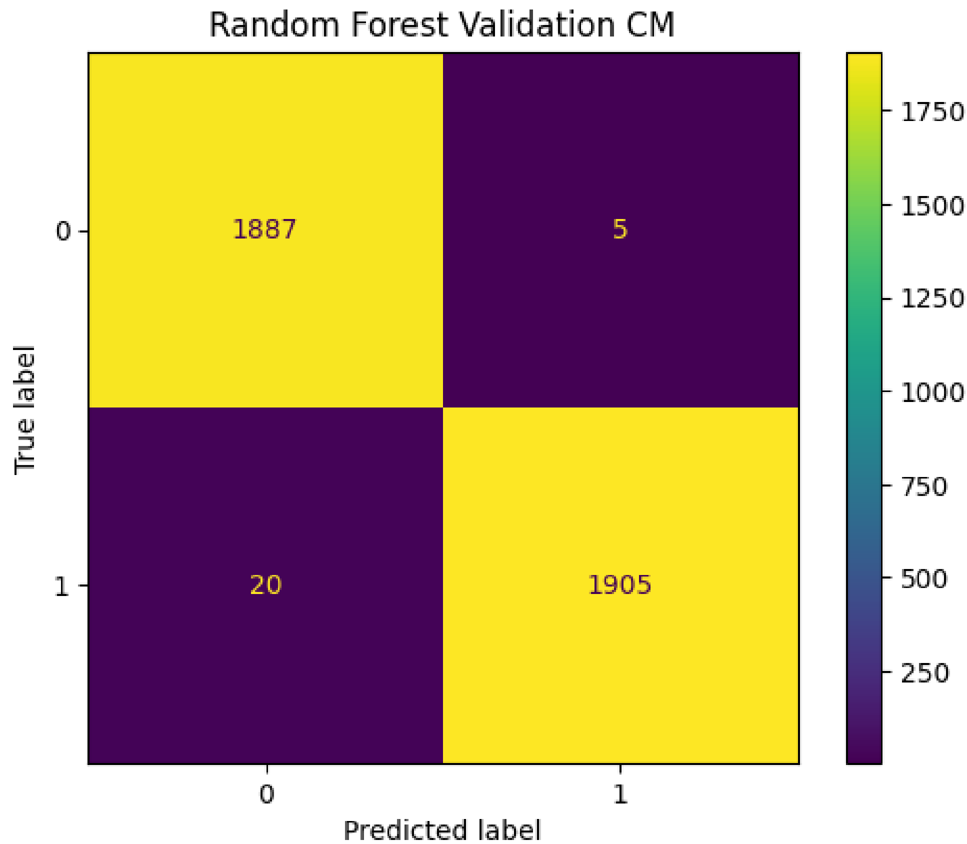
Display the true labels of the validation set.

[34]:
```
# Display the true labels of the validation set
y_val
```

[34]:
```
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.

[35]:
```
# Create a confusion matrix to visualize the results of the classification model

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

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

# Plot confusion matrix
log_disp.plot()

# Display plot
plt.title('Random Forest Validation CM')
plt.show()
```



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

Note: In other labs there was a custom-written function to extract the accuracy, precision, recall, and F1 scores from the GridSearchCV report and display them in a table. You can also use scikit-learn's built-in `classification_report()` function to obtain a similar table of results.

[36]:
```
# Create a classification report
# Create classification report for random forest model
target_labels = ['claim', 'opinion']
print(classification_report(y_val, y_pred, target_names = target_labels))
```

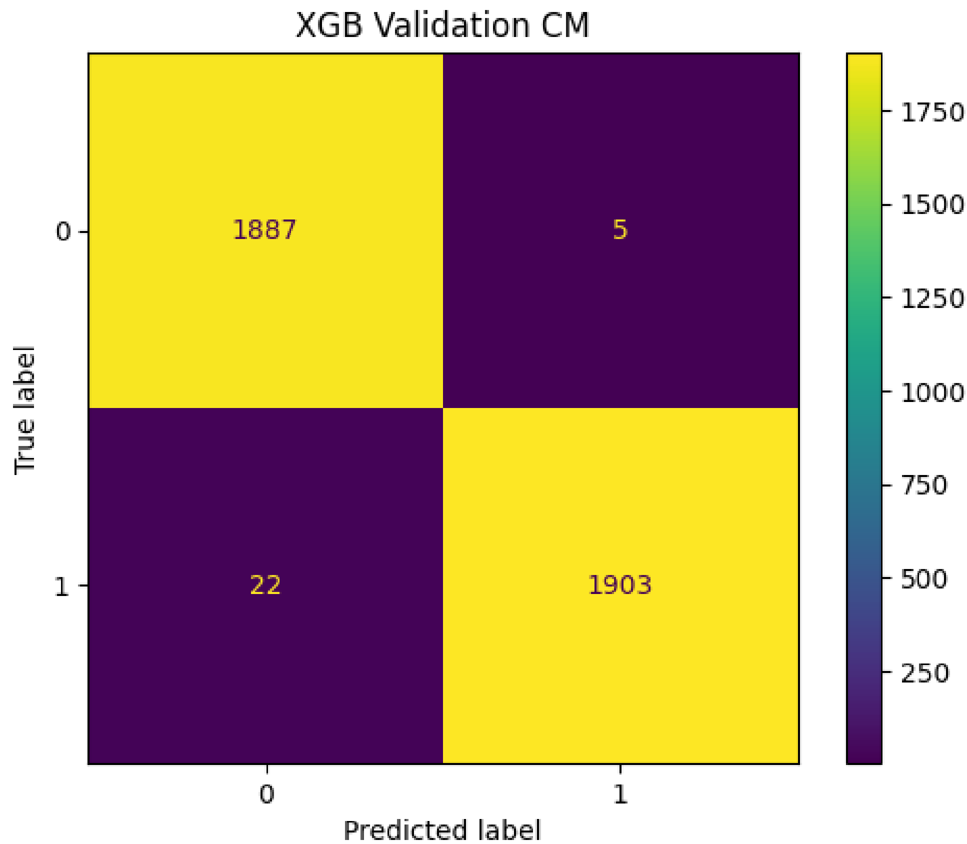
```
              precision    recall  f1-score   support

       claim       0.99      1.00      0.99      1892
     opinion       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: What does your classification report show? What does the confusion matrix indicate? The classification report shows the model had near perfect recall

XGBoost Now, evaluate the XGBoost model on the validation set.

[37]:
```
# Use the best estimator to predict on the validation data
y_pred = xgb_cv.best_estimator_.predict(X_val)
```

[38]:
```
# Compute values for confusion matrix
cm = confusion_matrix(y_val, y_pred)

# Create display of confusion matrix using ConfusionMatrixDisplay()
disp = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = None)

# Plot confusion matrix
disp.plot()

# Display plot
plt.title('XGB Validation CM')
plt.show()
```



[39]:
```
# Create a classification report
target_labels = ['claim', 'opinion']
print(classification_report(y_val, y_pred, target_names = target_labels))
```

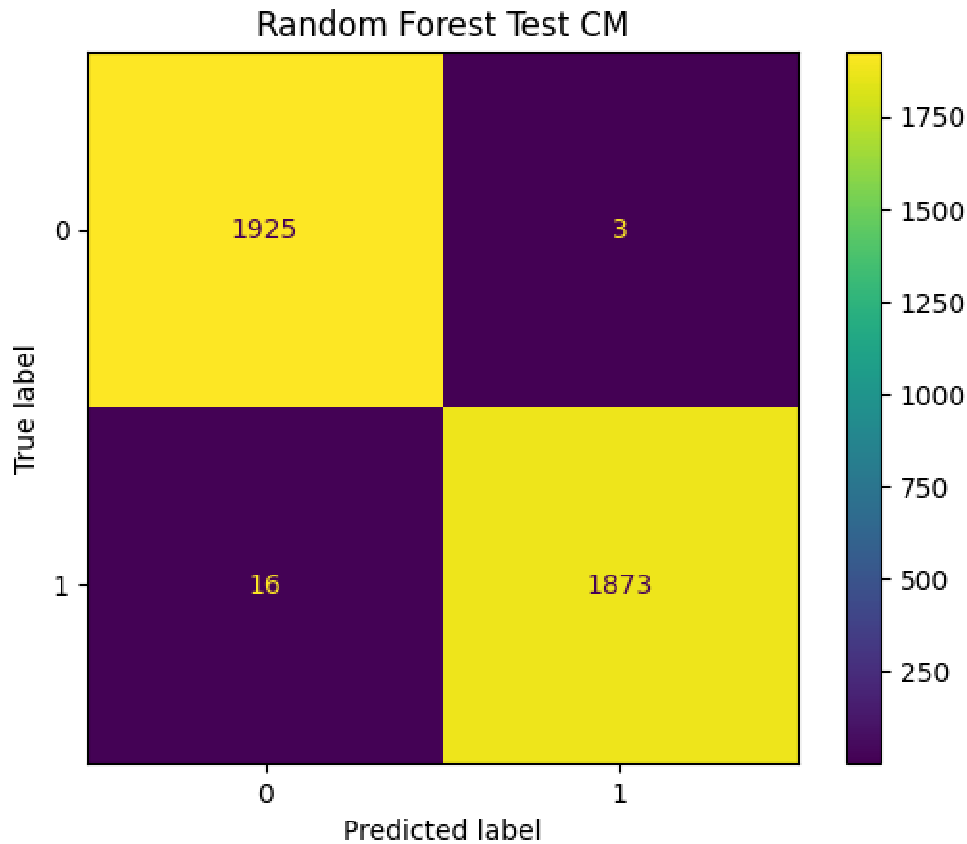
```
              precision    recall  f1-score   support

       claim       0.99      1.00      0.99      1892
     opinion       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?

4.4.2 Use champion model to predict on test data

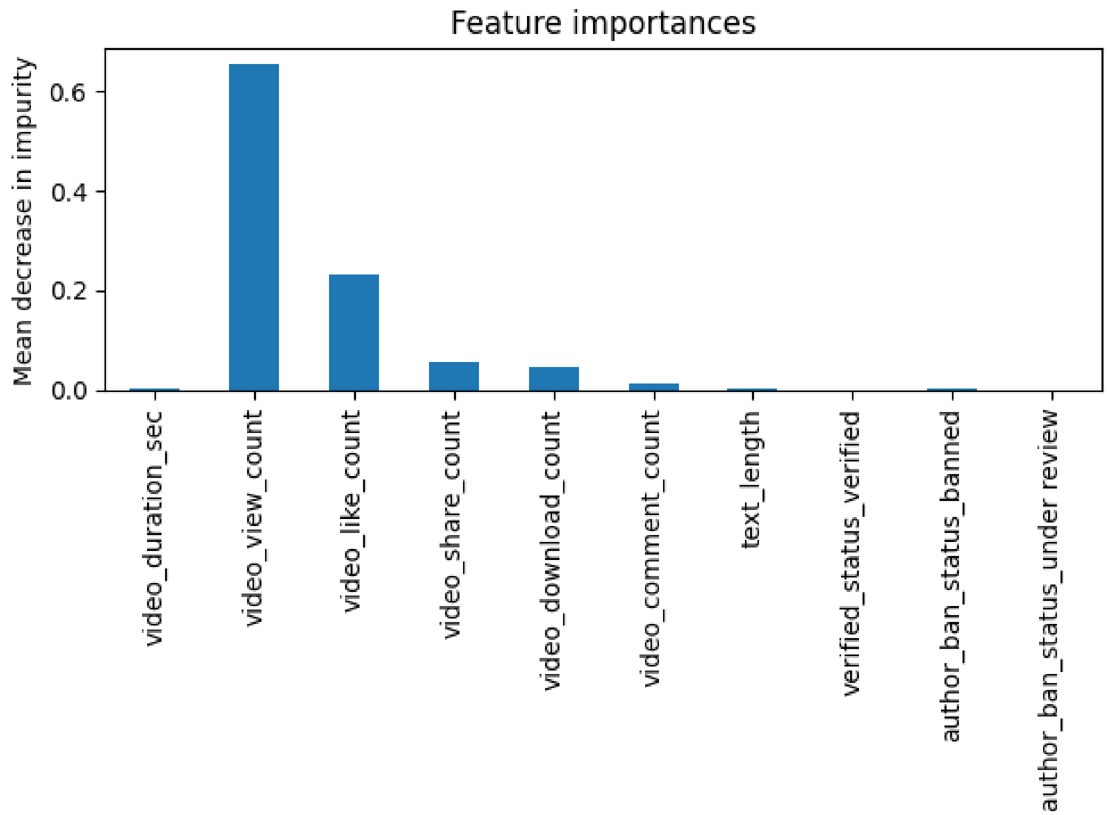
[40]:
```
y_pred = rf_cv.best_estimator_.predict(X_test)
```

[41]:
```
# Compute values for confusion matrix
test_cm = confusion_matrix(y_test, y_pred)

# Create display of confusion matrix using ConfusionMatrixDisplay()
test_disp = ConfusionMatrixDisplay(confusion_matrix = test_cm, display_labels =␣
 ↪None)

# Plot confusion matrix
test_disp.plot()

# Display plot
plt.title('Random Forest Test CM')
plt.show()
```



Feature importances of champion model

[42]:
```
importances = rf_cv.best_estimator_.feature_importances_
rf_importances = pd.Series(importances, index=X_test.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? We found that video_view_count and video_like_count were, by far, the most important features towards predicting claim_status. This is not surprising at all considering our previous analyses which showed the median view/like counts of claims being roughly 10x greater than opinions.

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. The champion random forest model was excellent at predicting claim_status, evidenced by the recall/precision scores greater than .99, so towards the goal of classifying tiktoks as claims or opinions the model is a great choice.
2. The 2 most important features were clearly video_view_count and video_like_count, followed by video_share_count and video_download_count, so our model almost entirely used these 4 features in the prediction of claim_status.
3. Any performance enhancing would be negligible given the fantastic model performance already. Further feature investigation towards a better model would be a waste of time.
4. The model requires no additional features. If we were to spend the time enhancing our already almost perfect metrics, then we could add information about reporting, such as number of reports on each tiktok or number of lifetime reports for the author's account.

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.