TikTok Project

The nuts and bolts of machine learning

In the project scenario where I am 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. Now my supervisor was impressed with the work I have done with the planning and has requested that my team should proceed with the project of 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.

Project: Classifying videos using machine learning

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

The purpose of this model is to mitigate misinformation in videos on the TikTok platform.

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

Classify videos using machine learning

PACE stages

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

Pace: Plan

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

In this stage, consider the following questions:

1. **What are we being asked to do? What metric should we use to evaluate success of my business/organizational objective?**
2. **What are the ethical implications of the model? What are the consequences of the 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 we proceed?**

Exemplar responses:

1. What are we being asked to do?

Business need and modeling objective

TikTok users can report videos that they believe violate the platform's terms of service. Because there are millions of TikTok videos created and viewed every day, this means that many videos get reported—too many to be individually reviewed by a human moderator.

Analysis indicates that when authors do violate the terms of service, they're much more likely to be presenting a claim than an opinion. Therefore, it is useful to be able to determine which videos make claims and which videos are opinions.

TikTok wants to build a machine learning model to help identify claims and opinions. Videos that are labeled opinions will be less likely to go on to be reviewed by a human moderator. Videos that are labeled as claims will be further sorted by a downstream process to determine whether they should get prioritized for review. For example, perhaps videos that are classified as claims would then be ranked by how many times they were reported, then the top x% would be reviewed by a human each day.

A machine learning model would greatly assist in the effort to present human moderators with videos that are most likely to be in violation of TikTok's terms of service.

Modeling design and target variable

The data dictionary shows that there is a column called `claim_status`. This is a binary value that indicates whether a video is a claim or an opinion. This will be the target variable. In other words, for each video, the model should predict whether the video is a claim or an opinion.

Select an evaluation metric

To determine which evaluation metric might be best, consider how the model might be wrong. There are two possibilities for bad predictions:

- **False positives:** When the model predicts a video is a claim when in fact it is an opinion
- **False negatives:** When the model predicts a video is an opinion when in fact it is a claim

2. What are the ethical implications of building the model? In the given scenario, it's better for the model to predict false positives when it makes a mistake, and worse for it to predict false negatives. It's very important to identify videos that break the terms of service, even if that means some opinion videos are misclassified as claims. The worst case for an opinion misclassified as a claim is that the video goes to human review. The worst case for a claim that's misclassified as an opinion is that the video does not get reviewed *and* it violates the terms of service. A video that violates the terms of service would be considered posted from a "banned" author, as referenced in the data dictionary.

Because it's more important to minimize false negatives, the model evaluation metric will be **recall**.

3. How would we proceed?

Modeling workflow and model selection process

Previous work with this data has revealed that there are ~20,000 videos in the sample. This is sufficient to conduct a rigorous model validation workflow, broken into the following steps:

1. Split the data into train/validation/test sets (60/20/20)
2. Fit models and tune hyperparameters on the training set
3. Perform final model selection on the validation set
4. Assess the champion model's performance on the test set

Task 1. Imports and data loading

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

In [3]:
```
# 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.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import classification_report, accuracy_score, precision_sc
recall_score, f1_score, confusion_matrix, ConfusionMatrixDisplay

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from xgboost import plot_importance
```

Load the data from the provided csv file into a dataframe.

Note: As shown in this cell, the dataset has been automatically loaded. We do not need to download the .csv file, or provide more code.

In [4]:
```
# Load dataset into dataframe
data = pd.read_csv("tiktok_dataset.csv")
```

PACE: Analyze

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

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

Inspect the first five rows of the dataframe.

In [5]:
```python
# Display first few rows
data.head()
```

Out[5]:

	#	claim_status	video_id	video_duration_sec	video_transcription_text	verified_status	auth
0	1	claim	7017666017	59	someone shared with me that drone deliveries a...	not verified	
1	2	claim	4014381136	32	someone shared with me that there are more mic...	not verified	
2	3	claim	9859838091	31	someone shared with me that american industria...	not verified	
3	4	claim	1866847991	25	someone shared with me that the metro of st. p...	not verified	
4	5	claim	7105231098	19	someone shared with me that the number of busi...	not verified	

Get the number of rows and columns in the dataset.

In [6]:
```python
# Get number of rows and columns
data.shape
```

Out[6]: (19382, 12)

Get basic information about the dataset.

In [7]:
```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.

In [8]:
```
# Generate basic descriptive stats
data.describe()
```

Out[8]:

	#	video_id	video_duration_sec	video_view_count	video_like_count	vide
count	19382.000000	1.938200e+04	19382.000000	19084.000000	19084.000000	
mean	9691.500000	5.627454e+09	32.421732	254708.558688	84304.636030	
std	5595.245794	2.536440e+09	16.229967	322893.280814	133420.546814	
min	1.000000	1.234959e+09	5.000000	20.000000	0.000000	
25%	4846.250000	3.430417e+09	18.000000	4942.500000	810.750000	
50%	9691.500000	5.618664e+09	32.000000	9954.500000	3403.500000	
75%	14536.750000	7.843960e+09	47.000000	504327.000000	125020.000000	
max	19382.000000	9.999873e+09	60.000000	999817.000000	657830.000000	

Check for and handle missing values

In [9]:
```
# Check for missing values
data.isna().sum()
```

Out[9]:
```
#                           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
```

Exemplar response: There are very few missing values relative to the number of samples in the dataset. Therefore, observations with missing values can be dropped.

In [10]:
```
# Drop rows with missing values
data = data.dropna(axis=0)
```

Check for and handle duplicates

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

Out[11]:
```
0
```

Exemplar response: There are no duplicate observations in the data.

Check for and handle outliers

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.

Check class balance.

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

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

Exemplar response: Approximately 50.3% of the dataset represents claims and 49.7% represents opinions, so the outcome variable is balanced.

PACE: Construct

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

Task 3. Feature engineering

Extract the length (character count) of each `video_transcription_text` and add this to the dataframe as a new column called `text_length` so that it can be used as a feature in the model.

In [13]:
```
# Create `text_length` column
data['text_length'] = data['video_transcription_text'].str.len()
data.head()
```

Out[13]:

	#	claim_status	video_id	video_duration_sec	video_transcription_text	verified_status	auth
0	1	claim	7017666017	59	someone shared with me that drone deliveries a...	not verified	
1	2	claim	4014381136	32	someone shared with me that there are more mic...	not verified	
2	3	claim	9859838091	31	someone shared with me that american industria...	not verified	
3	4	claim	1866847991	25	someone shared with me that the metro of st. p...	not verified	
4	5	claim	7105231098	19	someone shared with me that the number of busi...	not verified	

Calculate the average `text_length` for claims and opinions.

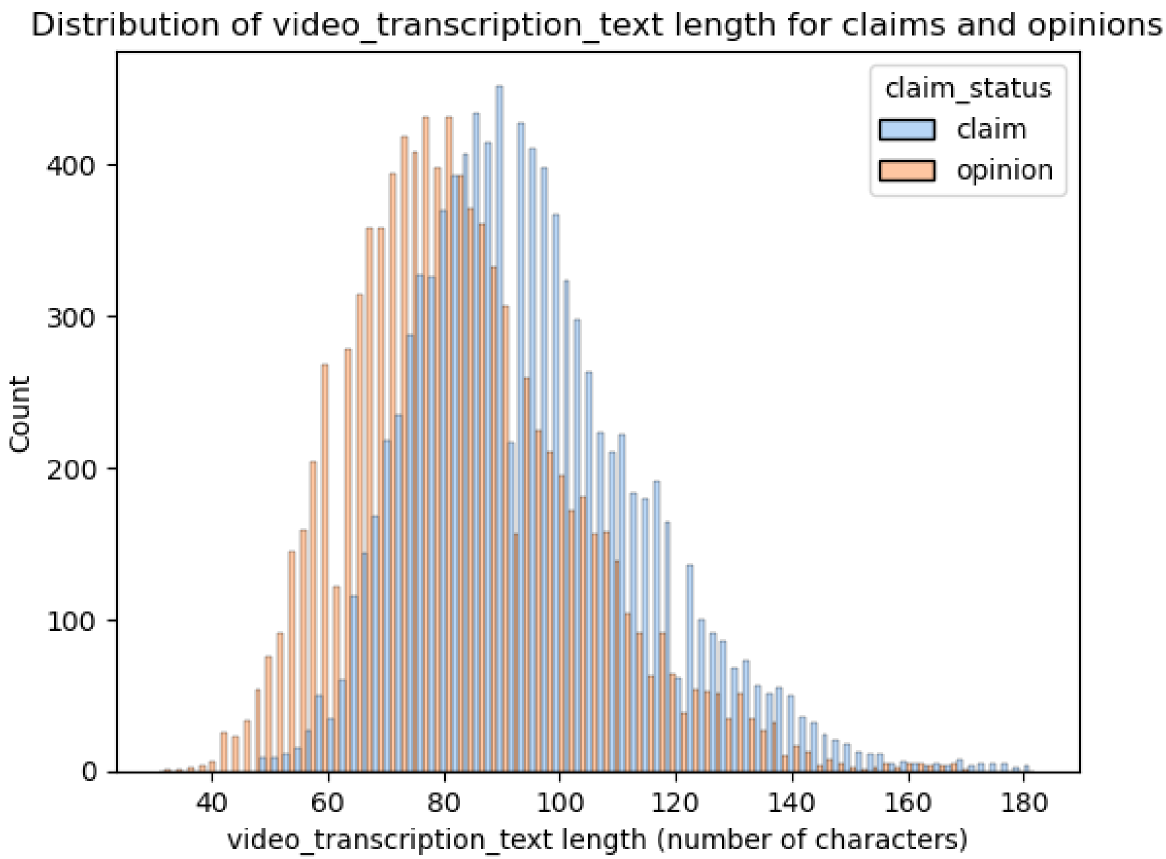
In [14]:
```
data[['claim_status', 'text_length']].groupby('claim_status').mean()
```

Out[14]:

claim_status	text_length
claim	95.376978
opinion	82.722562

Visualize the distribution of `text_length` for claims and opinions using a histogram.

In [15]:
```
# Visualize the distribution of `video_transcription_text` length for claims ar
# 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.xlabel("video_transcription_text length (number of characters)")
plt.ylabel("Count")
plt.title("Distribution of video_transcription_text length for claims and opini
plt.show()
```



Letter count distributions for both claims and opinions are approximately normal with a slight right skew. Claim videos tend to have more characters—about 13 more on average, as indicated in a previous cell.

Feature selection and transformation

Encode target and catgorical variables.

In [16]:
```
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()
```

Out[16]:

	claim_status	video_duration_sec	video_transcription_text	video_view_count	video_like_count
0	1	59	someone shared with me that drone deliveries a...	343296.0	19425.0
1	1	32	someone shared with me that there are more mic...	140877.0	77355.0
2	1	31	someone shared with me that american industria...	902185.0	97690.0
3	1	25	someone shared with me that the metro of st. p...	437506.0	239954.0
4	1	19	someone shared with me that the number of busi...	56167.0	34987.0

Task 4. Split the data

Assign target variable.

Exemplar response: In this case, the target variable is `claim_status` .

- 0 represents an opinion
- 1 represents a claim

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

Isolate the features.

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

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

Out[18]:

	video_duration_sec	video_transcription_text	video_view_count	video_like_count	video_share_
0	59	someone shared with me that drone deliveries a...	343296.0	19425.0	
1	32	someone shared with me that there are more mic...	140877.0	77355.0	19
2	31	someone shared with me that american industria...	902185.0	97690.0	2
3	25	someone shared with me that the metro of st. p...	437506.0	239954.0	34
4	19	someone shared with me that the number of busi...	56167.0	34987.0	4

Task 5: Create train/validate/test sets

Split data into training and testing sets, 80/20.

In [19]:
```
# 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
```

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.

In [20]:
```
# 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, r
```

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

In [21]:
```
# 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.sh
```

Out[21]:
```
((11450, 11), (3817, 11), (3817, 11), (11450,), (3817,), (3817,))
```

Exemplar notes:

- The number of features (`11`) aligns between the training and testing sets.
- The number of rows aligns between the features and the outcome variable for training (`11,450`) and both validation and testing data (`3,817`).

Tokenize text column

NOTE: We are not expected to do this or know this, but we might find it useful and/or interesting to understand some basic ideas behind natural language processing (NLP), because of the nature of the data provided in this TikTok project.

The feature `video_transcription_text` is text-based. It is not a categorical variable, since it does not have a fixed number of possible values. One way to extract numerical features from it is through a bag-of-words algorithm like [`CountVectorizer` (https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html)](https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html).

`CountVectorizer` works by splitting text into n-grams, which are groups of n consecutive words. For instance, "a dime for a cup of coffee" (phrase A) broken into 2-grams would result in six two-word combinations:

`a dime` | `dime for` | `for a` | `a cup` | `cup of` | `of coffee` |

Then, the next sample's text would be parsed into 2-grams. So, "ask for a cup for a child" (phrase B) would result in:

`ask for` | `for a` | `a cup` | `cup for` | `for a` | `a child` |

This process would repeat for each observation in the dataset, and each n-gram would be treated like a distinct feature. Then, the text of each observation is compared to the full array of n-grams, and the numbers of occurrences are tallied:

	a dime	dime for	for a	a cup	cup of	of coffee	ask for	cup for	a child
phrase A	1	1	1	1	1	1	0	0	0
phrase B	0	0	2	1	1	0	1	1	1
TOTAL	1	1	3	2	2	1	1	1	1

This would happen for the text of each observation in the data, and the text of each observation is parsed to get tallies for all the 2-word phrases from the entire data set for each observation, creating a large matrix.

If text is broken into 1-grams, then each feature in the matrix is an individual word.

After the count matrix has been created, `CountVectorizer` lets us choose to keep only the most frequently occurring n-grams. You specify how many. The n-grams that we select can then be used as features in a model.

Splitting text into n-grams is an example of tokenization. Tokenization is the process of breaking text into smaller units to derive meaning from the resulting tokens.

This notebook breaks each video's transcription text into both 2-grams and 3-grams, then takes the 15 most frequently occurring tokens from the entire dataset to use as features.

In [22]:
```
# Set up a `CountVectorizer` object, which converts a collection of text to a m
count_vec = CountVectorizer(ngram_range=(2, 3),
                            max_features=15,
                            stop_words='english')
count_vec
```

Out[22]:
```
CountVectorizer(max_features=15, ngram_range=(2, 3), stop_words='english')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Fit the vectorizer to the training data (generate the n-grams) and transform it (tally the occurrences). Only fit to the training data, not the validation or test data.

In [23]:
```
# Extract numerical features from `video_transcription_text` in the training se
count_data = count_vec.fit_transform(X_train['video_transcription_text']).toarr
count_data
```

Out[23]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 1, ..., 1, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]])
```

In [24]:
```
# Place the numerical representation of `video_transcription_text` from trainin
count_df = pd.DataFrame(data=count_data, columns=count_vec.get_feature_names_ou

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

Out[24]:

	colleague discovered	colleague learned	colleague read	discovered news	discussion board	friend learned	friend read	internet forum	learned media	m c
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	1	0	0	
2	0	0	0	0	0	0	1	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

In [25]:
```
# Concatenate `X_train` and `count_df` to form the final dataframe for training
# Note: Using `.reset_index(drop=True)` to reset the index in X_train after drc
# 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']).r

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

Out[25]:

	video_duration_sec	video_view_count	video_like_count	video_share_count	video_download_c
0	51	2487.0	310.0	20.0	
1	43	118512.0	3543.0	374.0	
2	22	105902.0	1885.0	229.0	
3	17	9245.0	1670.0	440.0	
4	18	3791.0	660.0	63.0	

5 rows × 25 columns

Get n-gram counts for the validation data. Notice that the vectorizer is not being refit to the validation data. It's only transforming it. In other words, the transcriptions of the videos in the validation data are only being checked against the n-grams found in the training data.

In [26]:
```
# Extract numerical features from `video_transcription_text` in the testing set
validation_count_data = count_vec.transform(X_val['video_transcription_text'])
validation_count_data
```

Out[26]:
```
array([[0, 0, 0, ..., 1, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 1, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 1, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]])
```

In [27]:
```
# Place the numerical representation of `video_transcription_text` from validat
validation_count_df = pd.DataFrame(data=validation_count_data, columns=count_ve
validation_count_df.head()
```

Out[27]:

	colleague discovered	colleague learned	colleague read	discovered news	discussion board	friend learned	friend read	internet forum	learned media	m c
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	1	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	1	0	0	0	0	0	0	

In [28]:
```
# Concatenate `X_val` and `validation_count_df` to form the final dataframe for
# Note: Using `.reset_index(drop=True)` to reset the index in X_val after dropp
# so that the indices align with those in `validation_count_df`
X_val_final = pd.concat([X_val.drop(columns=['video_transcription_text']).reset

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

Out[28]:

	video_duration_sec	video_view_count	video_like_count	video_share_count	video_download_c
0	11	578891.0	379596.0	14612.0	65
1	24	6255.0	1709.0	311.0	
2	35	410356.0	249714.0	26235.0	20
3	58	406911.0	25986.0	1230.0	5
4	47	972573.0	138167.0	25320.0	33

5 rows × 25 columns

Repeat the process to get n-gram counts for the test data. Again, don't refit the vectorizer to the test data. Just transform it.

In [29]:
```
# Extract numerical features from `video_transcription_text` in the testing set
test_count_data = count_vec.transform(X_test['video_transcription_text']).toarr

# Place the numerical representation of `video_transcription_text` from test se
test_count_df = pd.DataFrame(data=test_count_data, columns=count_vec.get_featur

# Concatenate `X_val` and `validation_count_df` to form the final dataframe for
X_test_final = pd.concat([X_test.drop(columns=['video_transcription_text']
                                       ).reset_index(drop=True), test_count_df]
X_test_final.head()
```

Out[29]:

	video_duration_sec	video_view_count	video_like_count	video_share_count	video_download_c
0	54	692084.0	135956.0	16591.0	6
1	37	5164.0	1858.0	36.0	
2	39	801951.0	344163.0	57608.0	85
3	44	6429.0	2314.0	847.0	
4	26	555780.0	106863.0	15348.0	2

5 rows × 25 columns

Task 6. Build models

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.

In [30]:
```
# 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')
```

Note this cell might take several minutes to run.

In [31]:
```
%%time
rf_cv.fit(X_train_final, y_train)
```

```
CPU times: user 5min 37s, sys: 584 ms, total: 5min 37s
Wall time: 5min 37s
```

Out[31]:
```
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={'recall', 'accuracy', 'precision', 'f
1'})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [32]:
```
# Examine best recall score
rf_cv.best_score_
```

Out[32]:
```
0.9948228253467271
```

In [33]:
```
# Examine best parameters
rf_cv.best_params_
```

Out[33]:
```
{'max_depth': None,
 'max_features': 0.6,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 200}
```

Exemplar response:

This model performs exceptionally well, with an average recall score of 0.995 across the five cross-validation folds. After checking the precision score to be sure the model is not classifying all samples as claims, it is clear that this model is making almost perfect classifications.

Build an XGBoost model

In [34]:
```
# 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')
```

Note this cell might take several minutes to run.

In [35]:
```
%%time
xgb_cv.fit(X_train_final, y_train)
```

```
CPU times: user 9min 49s, sys: 2.06 s, total: 9min 51s
Wall time: 5min 1s
```

Out[35]:
```
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=No
ne,
                                     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, 1
2],
                         'min_child_weight': [3, 5],
                         'n_estimators': [300, 500]},
             refit='recall', scoring={'recall', 'accuracy', 'precision', 'f
1'})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [36]:
```
xgb_cv.best_score_
```

Out[36]:
```
0.9906808769992594
```

In [37]:
```
xgb_cv.best_params_
```

Out[37]:
```
{'learning_rate': 0.1,
 'max_depth': 4,
 'min_child_weight': 5,
 'n_estimators': 300}
```

Exemplar response:

PACE: Execute

Consider the questions in the PACE Strategy Documentto reflect on the Execute stage.

Task 7. Evaluate models

Evaluate models against validation data.

Random forest

In [38]:
```
# Use the random forest "best estimator" model to get predictions on the valida
y_pred = rf_cv.best_estimator_.predict(X_val_final)
```

Display the predictions on the validation set.

In [39]:
```
# Display the predictions on the validation set
y_pred
```

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

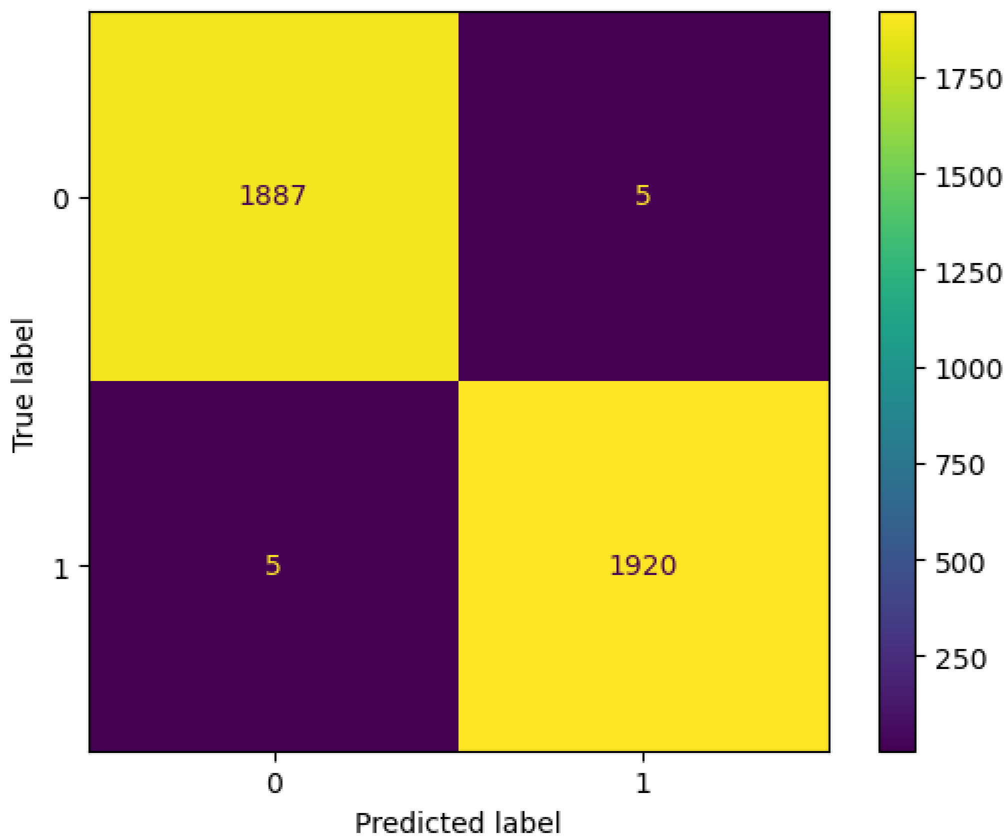
Display the true labels of the validation set.

In [40]:
```
# Display the true labels of the validation set
y_val
```

Out[40]:
```
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.

In [41]:
```
# Create a confusion matrix to visualize the results of the classification mode

# Compute values for confusion matrix
log_cm = confusion_matrix(y_val, 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.show()
```



Exemplar notes:

The upper-left quadrant displays the number of true negatives: the number of opinions that the model accurately classified as so.

The upper-right quadrant displays the number of false positives: the number of opinions that the model misclassified as claims.

The lower-left quadrant displays the number of false negatives: the number of claims that the model misclassified as opinions.

The lower-right quadrant displays the number of true positives: the number of claims 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.

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 F_1 scores from the GridSearchCV report and display them in a table. You can also use scikit-learn's built-in `classification_report()` [(https://scikit-learn.org/stable/modules/model_evaluation.html#classification-report)](https://scikit-learn.org/stable/modules/model_evaluation.html#classification-report) function to obtain a similar table of results.

In [42]:
```
# 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
```

Exemplar response:

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

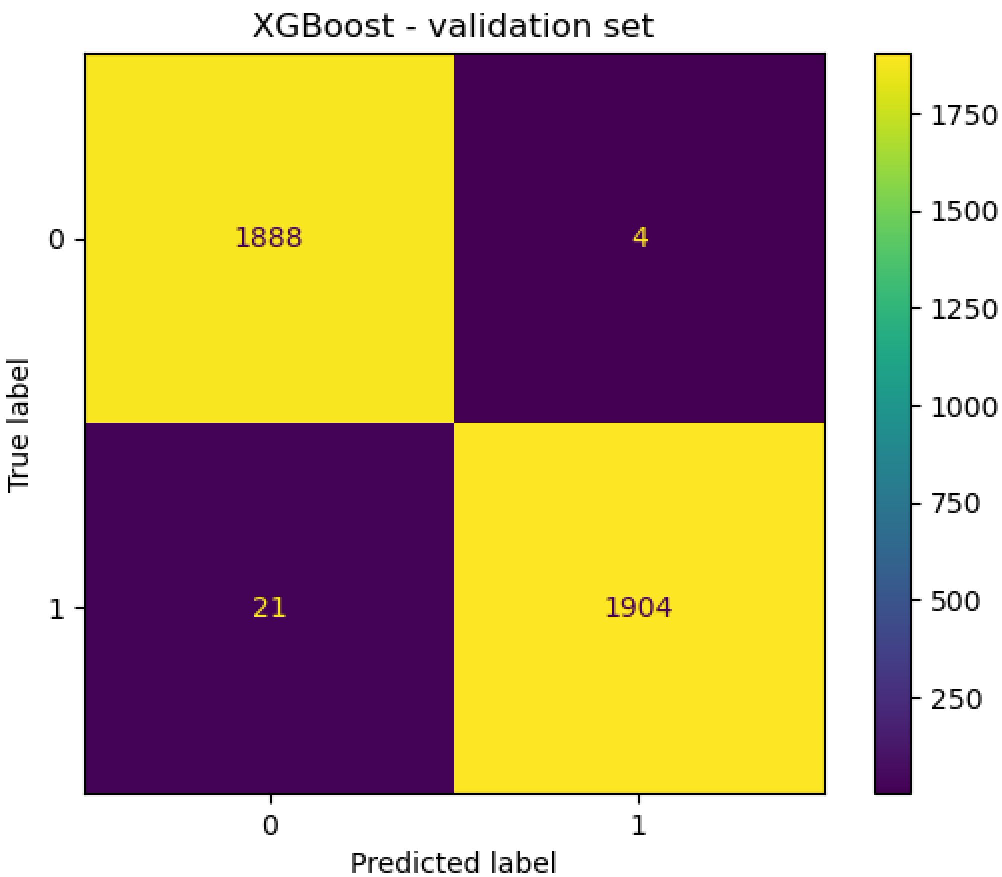
Now, evaluate the XGBoost model on the validation set.

In [43]:
```
#Evaluate XGBoost model
y_pred = xgb_cv.best_estimator_.predict(X_val_final)
```

In [44]:
```
y_pred
```

Out[44]:
```
array([1, 0, 1, ..., 1, 1, 1])
```

In [45]:
```
# Compute values for confusion matrix
log_cm = confusion_matrix(y_val, 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('XGBoost - validation set');
plt.show()
```



In [46]:
```
# 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
```

Exemplar response:

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.

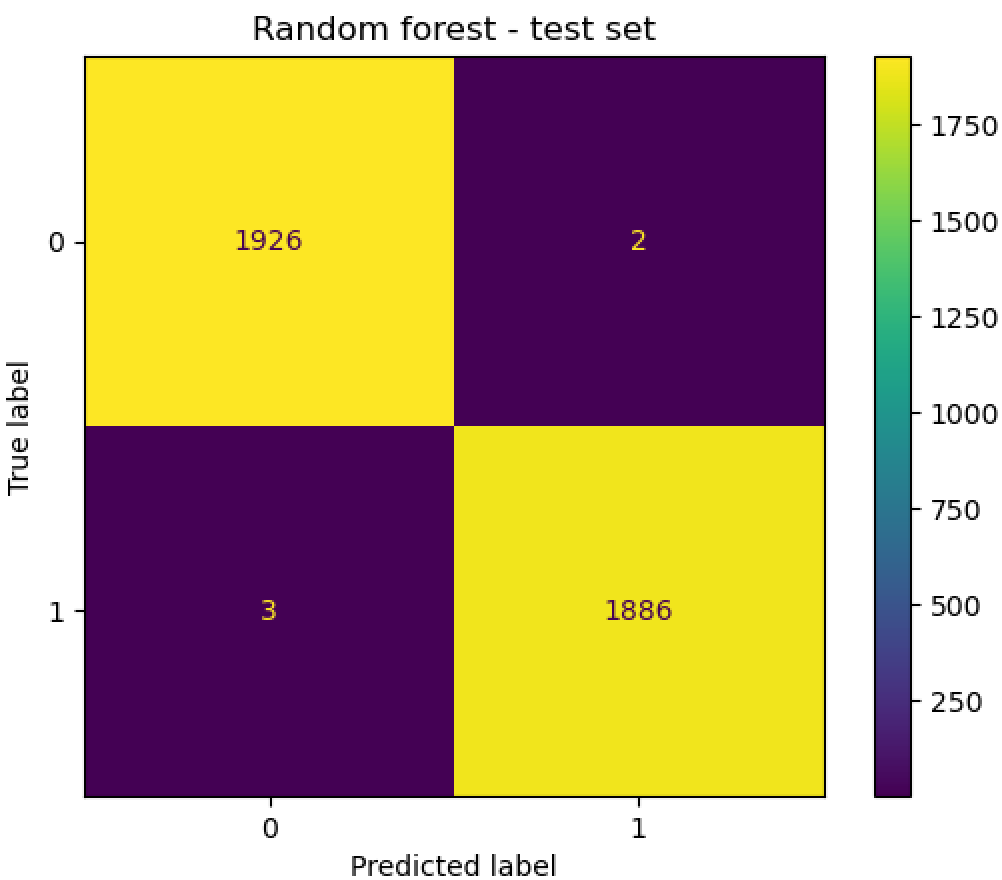
Use champion model to predict on test data

Both random forest and XGBoost model architectures resulted in nearly perfect models. Nonetheless, in this case random forest performed a little bit better, so it is the champion model.

Now, use the champion model to predict on the test data.

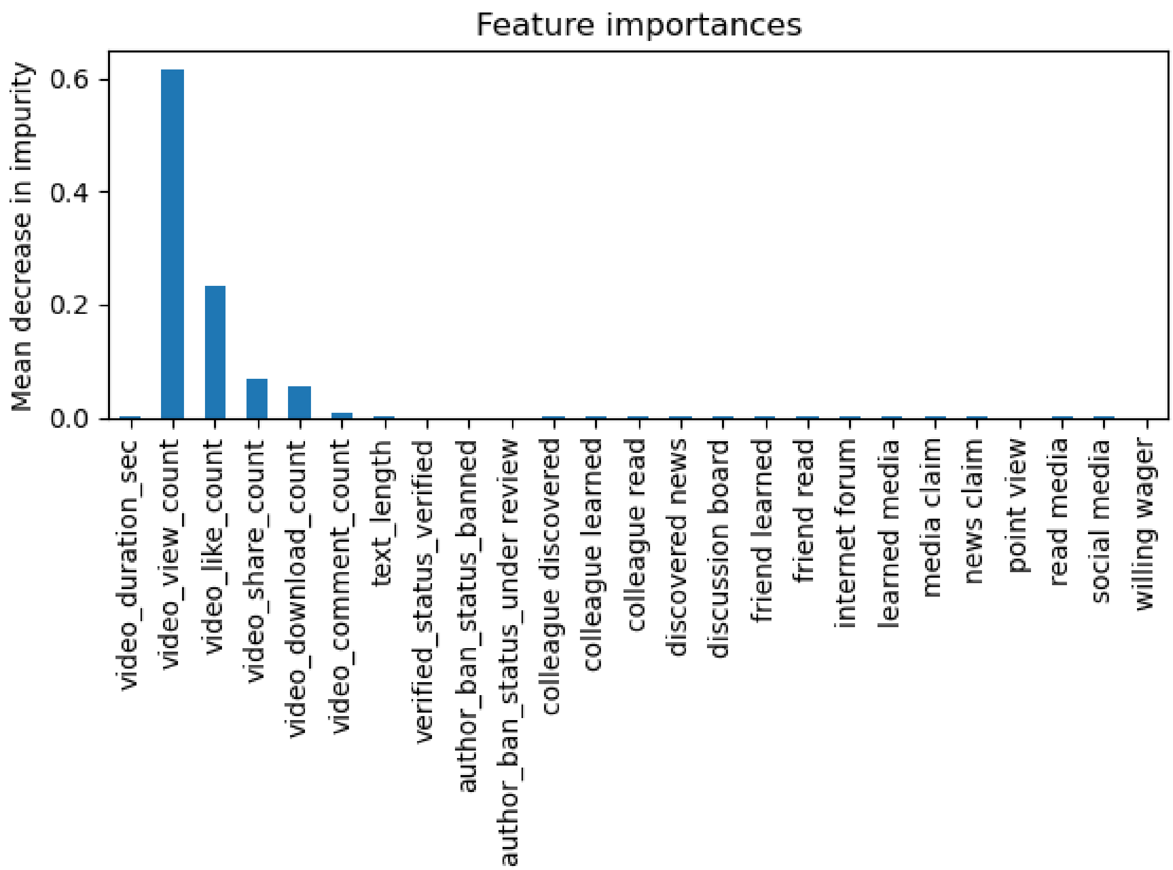
In [47]:
```
# Use champion model to predict on test data
y_pred = rf_cv.best_estimator_.predict(X_test_final)
```

In [48]:
```
# 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

In [49]:
```
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()
```



Exemplar response:

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.

Conclusion

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

1. **Would I recommend using this model? Why or why not?**
2. **What was the model doing? Can we explain how it was making predictions?**
3. **Are there new features that we can engineer that might improve model performance?**
4. **What features would we want to have that would likely improve the performance of the model?**

Remember, sometimes the data simply will not be predictive of the chosen target. This is common. Machine learning is a powerful tool, but it is not magic. If the 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.

Exemplar response:

1. *Would we 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 F_1 scores were consistently high. The model very successfully classified claims and opinions.
2. *What was the model doing? Can we 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 we 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 we want to have that would likely improve the performance of the 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.