Automatidata project lab

March 15, 2024

1 Automatidata project

Course 6 - The nuts and bolts of machine learning

Point of View : You are a data professional in a data consulting firm called Automatidata. Their client, the New York City Taxi & Limousine Commission (New York City TLC), was impressed with the work you have done and has requested that you build a machine learning model to predict if a customer will not leave a tip. They want to use the model in an app that will alert taxi drivers to customers who are unlikely to tip, since drivers depend on tips.

2 Course 6 End-of-course project: Build a machine learning model

The purpose of this model is to find ways to generate more revenue for taxi cab drivers.

The goal of this model is to predict whether or not a customer is a generous tipper.

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

3 Build a machine learning model

4 PACE stages

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

4.1 PACE: Plan

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

In this stage, consider the following questions:

1. What are you being asked to do?
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 customer will give a tip, but they actually won't)?
- What is the likely effect of the model when it predicts a false positive (i.e., when the model says a customer will not give a tip, but they actually will)?

3. Do the benefits of such a model outweigh the potential problems?
4. Would you proceed with the request to build this model? Why or why not?
5. Can the objective be modified to make it less problematic?

Exemplar responses:

Question 1:

Predict if a customer will **not** leave a tip.

Question 2:

Drivers who didn't receive tips will probably be upset that the app told them a customer would leave a tip. If it happened often, drivers might not trust the app. Drivers are unlikely to pick up people who are predicted to not leave tips. Customers will have difficulty finding a taxi that will pick them up, and might get angry at the taxi company. Even when the model is correct, people who can't afford to tip will find it more difficult to get taxis, which limits the accessibility of taxi service to those who pay extra.

Question 3:

It's not good to disincentivize drivers from picking up customers. It could also cause a customer backlash. The problems seem to outweigh the benefits.

Question 4:

No. Effectively limiting equal access to taxis is ethically problematic, and carries a lot of risk.

Question 5:

We can build a model that predicts the most generous customers. This could accomplish the goal of helping taxi drivers increase their earnings from tips while preventing the wrongful exclusion of certain people from using taxis.

Suppose you were to modify the modeling objective so, instead of predicting people who won't tip at all, you predicted people who are particularly generous—those who will tip 20% or more? Consider the following questions:

Exemplar responses:

Question 1: What features do you need to make this prediction?

Ideally, we'd have behavioral history for each customer, so we could know how much they tipped on previous taxi rides. We'd also want times, dates, and locations of both pickups and dropoffs, estimated fares, and payment method.

Question 2: What would be the target variable?

The target variable would be a binary variable (1 or 0) that indicates whether or not the customer is expected to tip 20%.

Question 3:

This is a supervised learning, classification task. We could use accuracy, precision, recall, F-score, area under the ROC curve, or a number of other metrics. However, we don't have enough information at this time to know which are most appropriate. We need to know the class balance of the target variable.

4.1.1 Task 1. Imports and data loading

Import packages and libraries needed to build and evaluate random forest and XGBoost classification models.

[1]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.metrics import accuracy_score, precision_score, recall_score,\
f1_score, confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

# This is the function that helps plot feature importance
from xgboost import plot_importance
```

[2]:
```
# RUN THIS CELL TO SEE ALL COLUMNS
# This lets us see all of the columns, preventing Juptyer from redacting them.
pd.set_option('display.max_columns', None)
```

[3]:
```
# Load dataset into dataframe
df0 = pd.read_csv('2017_Yellow_Taxi_Trip_Data.csv')

# Import predicted fares and mean distance and duration from previous course
nyc_preds_means = pd.read_csv('nyc_preds_means.csv')
```

Inspect the first few rows of `df0`.

```
[4]: # Inspect the first few rows of df0
df0.head()
```

```
[4]:    Unnamed: 0  VendorID     tpep_pickup_datetime    tpep_dropoff_datetime  \
0     24870114         2    03/25/2017 8:55:43 AM    03/25/2017 9:09:47 AM
1     35634249         1    04/11/2017 2:53:28 PM    04/11/2017 3:19:58 PM
2    106203690         1    12/15/2017 7:26:56 AM    12/15/2017 7:34:08 AM
3     38942136         2    05/07/2017 1:17:59 PM    05/07/2017 1:48:14 PM
4     30841670         2  04/15/2017 11:32:20 PM  04/15/2017 11:49:03 PM

   passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
0                6           3.34           1                  N
1                1           1.80           1                  N
2                1           1.00           1                  N
3                1           3.70           1                  N
4                1           4.37           1                  N

   PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
0           100           231             1         13.0    0.0      0.5
1           186            43             1         16.0    0.0      0.5
2           262           236             1          6.5    0.0      0.5
3           188            97             1         20.5    0.0      0.5
4             4           112             2         16.5    0.5      0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
3        6.39           0.0                    0.3         27.69
4        0.00           0.0                    0.3         17.80
```

Inspect the first few rows of `nyc_preds_means`.

```
[5]: # Inspect the first few rows of `nyc_preds_means`
nyc_preds_means.head()
```

```
[5]:    mean_duration  mean_distance  predicted_fare
0      22.847222       3.521667       16.434245
1      24.470370       3.108889       16.052218
2       7.250000       0.881429        7.053706
3      30.250000       3.700000       18.731650
4      14.616667       4.435000       15.845642
```

Join the two dataframes Join the two dataframes using a method of your choice.

[6]:

```python
# Merge datasets
df0 = df0.merge(nyc_preds_means,
                left_index=True,
                right_index=True)

df0.head()
```

[6]:

```
   Unnamed: 0  VendorID    tpep_pickup_datetime   tpep_dropoff_datetime  \
0    24870114         2   03/25/2017 8:55:43 AM   03/25/2017 9:09:47 AM
1    35634249         1   04/11/2017 2:53:28 PM   04/11/2017 3:19:58 PM
2   106203690         1   12/15/2017 7:26:56 AM   12/15/2017 7:34:08 AM
3    38942136         2   05/07/2017 1:17:59 PM   05/07/2017 1:48:14 PM
4    30841670         2  04/15/2017 11:32:20 PM  04/15/2017 11:49:03 PM

   passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
0                6           3.34           1                  N
1                1           1.80           1                  N
2                1           1.00           1                  N
3                1           3.70           1                  N
4                1           4.37           1                  N

   PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
0           100           231             1         13.0    0.0      0.5
1           186            43             1         16.0    0.0      0.5
2           262           236             1          6.5    0.0      0.5
3           188            97             1         20.5    0.0      0.5
4             4           112             2         16.5    0.5      0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount  \
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
3        6.39           0.0                    0.3         27.69
4        0.00           0.0                    0.3         17.80

   mean_duration  mean_distance  predicted_fare
0      22.847222       3.521667       16.434245
1      24.470370       3.108889       16.052218
2       7.250000       0.881429        7.053706
3      30.250000       3.700000       18.731650
4      14.616667       4.435000       15.845642
```

4.2 PACE: Analyze

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

[7]:
```python
df0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22699 entries, 0 to 22698
Data columns (total 21 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             22699 non-null  int64
 1   VendorID               22699 non-null  int64
 2   tpep_pickup_datetime   22699 non-null  object
 3   tpep_dropoff_datetime  22699 non-null  object
 4   passenger_count        22699 non-null  int64
 5   trip_distance          22699 non-null  float64
 6   RatecodeID             22699 non-null  int64
 7   store_and_fwd_flag     22699 non-null  object
 8   PULocationID           22699 non-null  int64
 9   DOLocationID           22699 non-null  int64
 10  payment_type           22699 non-null  int64
 11  fare_amount            22699 non-null  float64
 12  extra                  22699 non-null  float64
 13  mta_tax                22699 non-null  float64
 14  tip_amount             22699 non-null  float64
 15  tolls_amount           22699 non-null  float64
 16  improvement_surcharge  22699 non-null  float64
 17  total_amount           22699 non-null  float64
 18  mean_duration          22699 non-null  float64
 19  mean_distance          22699 non-null  float64
 20  predicted_fare         22699 non-null  float64
dtypes: float64(11), int64(7), object(3)
memory usage: 3.6+ MB
```

You know from your EDA that customers who pay cash generally have a tip amount of $0. To meet the modeling objective, you'll need to sample the data to select only the customers who pay with credit card.

Copy `df0` and assign the result to a variable called `df1`. Then, use a Boolean mask to filter `df1` so it contains only customers who paid with credit card.

[8]:
```python
# Subset the data to isolate only customers who paid by credit card
df1 = df0[df0['payment_type']==1]
```

Target Notice that there isn't a column that indicates tip percent, which is what you need to create the target variable. You'll have to engineer it.

Add a `tip_percent` column to the dataframe by performing the following calculation:

$$tip\ percent = \frac{tip\ amount}{total\ amount - tip\ amount}$$

Round the result to three places beyond the decimal. **This is an important step.** It affects how many customers are labeled as generous tippers. In fact, without performing this step, approximately 1,800 people who do tip   20% would be labeled as not generous.

To understand why, you must consider how floats work. Computers make their calculations using floating-point arithmetic (hence the word “float”). Floating-point arithmetic is a system that allows computers to express both very large numbers and very small numbers with a high degree of precision, encoded in binary. However, precision is limited by the number of bits used to represent a number, which is generally 32 or 64, depending on the capabilities of your operating system.

This comes with limitations in that sometimes calculations that should result in clean, precise values end up being encoded as very long decimals. Take, for example, the following calculation:

[9]:
```
# Run this cell
1.1 + 2.2
```

[9]:
```
3.3000000000000003
```

[10]:
```
# Create tip % col
df1['tip_percent'] = round(df1['tip_amount'] / (df1['total_amount'] -␣
↪df1['tip_amount']), 3)
```

Now create another column called `generous`. This will be the target variable. The column should be a binary indicator of whether or not a customer tipped   20% (0=no, 1=yes).

1. Begin by making the `generous` column a copy of the `tip_percent` column.
2. Reassign the column by converting it to Boolean (True/False).
3. Reassign the column by converting Boolean to binary (1/0).

[11]:
```
# Create 'generous' col (target)
df1['generous'] = df1['tip_percent']
df1['generous'] = (df1['generous'] >= 0.2)
df1['generous'] = df1['generous'].astype(int)
```

Create day column Next, I am going to be working with the pickup and dropoff columns.

Convert the `tpep_pickup_datetime` and `tpep_dropoff_datetime` columns to datetime.

[12]:
```
# Convert pickup and dropoff cols to datetime
df1['tpep_pickup_datetime'] = pd.to_datetime(df1['tpep_pickup_datetime'],␣
↪format='%m/%d/%Y %I:%M:%S %p')
df1['tpep_dropoff_datetime'] = pd.to_datetime(df1['tpep_dropoff_datetime'],␣
↪format='%m/%d/%Y %I:%M:%S %p')
```

Create a `day` column that contains only the day of the week when each passenger was picked up. Then, convert the values to lowercase.

[13]:
```python
# Create a 'day' col
df1['day'] = df1['tpep_pickup_datetime'].dt.day_name().str.lower()
```

Create time of day columns Next, engineer four new columns that represent time of day bins. Each column should contain binary values (0=no, 1=yes) that indicate whether a trip began (picked up) during the following times:

`am_rush` = [06:00–10:00)
`daytime` = [10:00–16:00)
`pm_rush` = [16:00–20:00)
`nighttime` = [20:00–06:00)

To do this, first create the four columns. For now, each new column should be identical and contain the same information: the hour (only) from the `tpep_pickup_datetime` column.

[14]:
```python
# Create 'am_rush' col
df1['am_rush'] = df1['tpep_pickup_datetime'].dt.hour

# Create 'daytime' col
df1['daytime'] = df1['tpep_pickup_datetime'].dt.hour

# Create 'pm_rush' col
df1['pm_rush'] = df1['tpep_pickup_datetime'].dt.hour

# Create 'nighttime' col
df1['nighttime'] = df1['tpep_pickup_datetime'].dt.hour
```

I'll need to write four functions to convert each new column to binary (0/1). Begin with `am_rush`. Complete the function so if the hour is between [06:00–10:00), it returns 1, otherwise, it returns 0.

[15]:
```python
# Define 'am_rush()' conversion function [06:00-10:00)
def am_rush(hour):
    if 6 <= hour['am_rush'] < 10:
        val = 1
    else:
        val = 0
    return val
```

Now, apply the `am_rush()` function to the `am_rush` series to perform the conversion. Print the first five values of the column to make sure it did what you expected it to do.

Note: Running this cell twice, the function will be reapplied and the values will all be changed to 0.

[16]:
```python
# Apply 'am_rush' function to the 'am_rush' series
df1['am_rush'] = df1.apply(am_rush, axis=1)
df1['am_rush'].head()
```

[16]:
```
0    1
1    0
2    1
3    0
5    0
Name: am_rush, dtype: int64
```

Creating functions to convert the three remaining columns and apply them to their respective series.

[17]:
```python
# Define 'daytime()' conversion function [10:00-16:00)
def daytime(hour):
    if 10 <= hour['daytime'] < 16:
        val = 1
    else:
        val = 0
    return val
```

[18]:
```python
# Apply 'daytime' function to the 'daytime' series
df1['daytime'] = df1.apply(daytime, axis=1)
```

[19]:
```python
# Define 'pm_rush()' conversion function [16:00-20:00)
def pm_rush(hour):
    if 16 <= hour['pm_rush'] < 20:
        val = 1
    else:
        val = 0
    return val
```

[20]:
```python
# Apply 'pm_rush' function to the 'pm_rush' series
df1['pm_rush'] = df1.apply(pm_rush, axis=1)
```

[21]:
```python
# Define 'nighttime()' conversion function [20:00-06:00)
def nighttime(hour):
    if 20 <= hour['nighttime'] < 24:
        val = 1
    elif 0 <= hour['nighttime'] < 6:
        val = 1
    else:
        val = 0
    return val
```

[22]:
```python
# Apply 'nighttime' function to the 'nighttime' series
df1['nighttime'] = df1.apply(nighttime, axis=1)
```

Create month column Creating a `month` column that contains only the abbreviated name of the month when each passenger was picked up, then convert the result to lowercase.

[23]:
```python
# Create 'month' col
df1['month'] = df1['tpep_pickup_datetime'].dt.strftime('%b').str.lower()
```

Examine the first five rows of your dataframe.

[24]:
```python
df1.head()
```

[24]:
```
   Unnamed: 0  VendorID tpep_pickup_datetime tpep_dropoff_datetime  \
0    24870114         2  2017-03-25 08:55:43   2017-03-25 09:09:47
1    35634249         1  2017-04-11 14:53:28   2017-04-11 15:19:58
2   106203690         1  2017-12-15 07:26:56   2017-12-15 07:34:08
3    38942136         2  2017-05-07 13:17:59   2017-05-07 13:48:14
5    23345809         2  2017-03-25 20:34:11   2017-03-25 20:42:11

   passenger_count  trip_distance  RatecodeID store_and_fwd_flag  \
0                6           3.34           1                  N
1                1           1.80           1                  N
2                1           1.00           1                  N
3                1           3.70           1                  N
5                6           2.30           1                  N

   PULocationID  DOLocationID  payment_type  fare_amount  extra  mta_tax  \
0           100           231             1         13.0    0.0      0.5
1           186            43             1         16.0    0.0      0.5
2           262           236             1          6.5    0.0      0.5
3           188            97             1         20.5    0.0      0.5
5           161           236             1          9.0    0.5      0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount  \
0        2.76           0.0                    0.3         16.56
1        4.00           0.0                    0.3         20.80
2        1.45           0.0                    0.3          8.75
3        6.39           0.0                    0.3         27.69
5        2.06           0.0                    0.3         12.36

   mean_duration  mean_distance  predicted_fare  tip_percent  generous  \
0      22.847222       3.521667       16.434245        0.200         1
1      24.470370       3.108889       16.052218        0.238         1
2       7.250000       0.881429        7.053706        0.199         0
3      30.250000       3.700000       18.731650        0.300         1
5      11.855376       2.052258       10.441351        0.200         1

        day  am_rush  daytime  pm_rush  nighttime month
0  saturday        1        0        0          0   mar
1   tuesday        0        1        0          0   apr
2    friday        1        0        0          0   dec
3    sunday        0        1        0          0   may
```

```
5  saturday        0        0        0          1   mar
```

Drop columns Drop redundant and irrelevant columns as well as those that would not be available when the model is deployed. This includes information like payment type, trip distance, tip amount, tip percentage, total amount, toll amount, etc. The target variable (`generous`) must remain in the data because it will get isolated as the `y` data for modeling.

[25]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15265 entries, 0 to 22698
Data columns (total 29 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             15265 non-null  int64
 1   VendorID               15265 non-null  int64
 2   tpep_pickup_datetime   15265 non-null  datetime64[ns]
 3   tpep_dropoff_datetime  15265 non-null  datetime64[ns]
 4   passenger_count        15265 non-null  int64
 5   trip_distance          15265 non-null  float64
 6   RatecodeID             15265 non-null  int64
 7   store_and_fwd_flag     15265 non-null  object
 8   PULocationID           15265 non-null  int64
 9   DOLocationID           15265 non-null  int64
 10  payment_type           15265 non-null  int64
 11  fare_amount            15265 non-null  float64
 12  extra                  15265 non-null  float64
 13  mta_tax                15265 non-null  float64
 14  tip_amount             15265 non-null  float64
 15  tolls_amount           15265 non-null  float64
 16  improvement_surcharge  15265 non-null  float64
 17  total_amount           15265 non-null  float64
 18  mean_duration          15265 non-null  float64
 19  mean_distance          15265 non-null  float64
 20  predicted_fare         15265 non-null  float64
 21  tip_percent            15262 non-null  float64
 22  generous               15265 non-null  int64
 23  day                    15265 non-null  object
 24  am_rush                15265 non-null  int64
 25  daytime                15265 non-null  int64
 26  pm_rush                15265 non-null  int64
 27  nighttime              15265 non-null  int64
 28  month                  15265 non-null  object
dtypes: datetime64[ns](2), float64(12), int64(12), object(3)
memory usage: 3.5+ MB
```

[26]:
```python
# Drop columns
drop_cols = ['Unnamed: 0', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
             'payment_type', 'trip_distance', 'store_and_fwd_flag',␣
 ↪'payment_type',
             'fare_amount', 'extra', 'mta_tax', 'tip_amount', 'tolls_amount',
             'improvement_surcharge', 'total_amount', 'tip_percent']

df1 = df1.drop(drop_cols, axis=1)
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15265 entries, 0 to 22698
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   VendorID         15265 non-null  int64
 1   passenger_count  15265 non-null  int64
 2   RatecodeID       15265 non-null  int64
 3   PULocationID     15265 non-null  int64
 4   DOLocationID     15265 non-null  int64
 5   mean_duration    15265 non-null  float64
 6   mean_distance    15265 non-null  float64
 7   predicted_fare   15265 non-null  float64
 8   generous         15265 non-null  int64
 9   day              15265 non-null  object
 10  am_rush          15265 non-null  int64
 11  daytime          15265 non-null  int64
 12  pm_rush          15265 non-null  int64
 13  nighttime        15265 non-null  int64
 14  month            15265 non-null  object
dtypes: float64(3), int64(10), object(2)
memory usage: 1.9+ MB
```

Variable encoding Many of the columns are categorical and will need to be dummied (converted to binary). Some of these columns are numeric, but they actually encode categorical information, such as `RatecodeID` and the pickup and dropoff locations. To make these columns recognizable to the `get_dummies()` function as categorical variables, you'll first need to convert them to `type(str)`.

1. Define a variable called `cols_to_str`, which is a list of the numeric columns that contain categorical information and must be converted to string: `RatecodeID`, `PULocationID`, `DOLocationID`.
2. Write a for loop that converts each column in `cols_to_str` to string.

[27]:
```python
# 1. Define list of cols to convert to string
cols_to_str = ['RatecodeID', 'PULocationID', 'DOLocationID', 'VendorID']

# 2. Convert each column to string
```

```python
for col in cols_to_str:
    df1[col] = df1[col].astype('str')
```

Now convert all the categorical columns to binary.

1. Call `get_dummies()` on the dataframe and assign the results back to a new dataframe called `df2`.

[28]:
```python
# Convert categoricals to binary
df2 = pd.get_dummies(df1, drop_first=True)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15265 entries, 0 to 22698
Columns: 347 entries, passenger_count to month_sep
dtypes: float64(3), int64(6), uint8(338)
memory usage: 6.1 MB
```

Evaluation metric Before modeling, you must decide on an evaluation metric.

1. Examine the class balance of your target variable.

[29]:
```python
# Get class balance of 'generous' col
df2['generous'].value_counts(normalize=True)
```

[29]:
```
1    0.526368
0    0.473632
Name: generous, dtype: float64
```

A little over half of the customers in this dataset were "generous" (tipped 20%). The dataset is very nearly balanced.

To determine a metric, consider the cost of both kinds of model error: * False positives (the model predicts a tip 20%, but the customer does not give one) * False negatives (the model predicts a tip < 20%, but the customer gives more)

False positives are worse for cab drivers, because they would pick up a customer expecting a good tip and then not receive one, frustrating the driver.

False negatives are worse for customers, because a cab driver would likely pick up a different customer who was predicted to tip more—even when the original customer would have tipped generously.

The stakes are relatively even. You want to help taxi drivers make more money, but you don't want this to anger customers. Your metric should weigh both precision and recall equally. Which metric is this?

Exemplar response: F1 score is the metric that places equal weight on true postives and false positives, and so therefore on precision and recall.

4.3 PACE: Construct

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

4.3.1 Task 3. Modeling

Split the data Now you're ready to model. The only remaining step is to split the data into features/target variable and training/testing data.

1. Define a variable `y` that isolates the target variable (`generous`).
2. Define a variable `X` that isolates the features.
3. Split the data into training and testing sets. Put 20% of the samples into the test set, stratify the data, and set the random state.

[30]:
```
# Isolate target variable (y)
y = df2['generous']

# Isolate the features (X)
X = df2.drop('generous', axis=1)

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪test_size=0.2, random_state=42)
```

Random forest Begin with using `GridSearchCV` to tune a random forest model.

1. Instantiate the random forest classifier `rf` and set the random state.
2. Create a dictionary `cv_params` of any of the following hyperparameters and their corresponding values to tune. The more you tune, the better your model will fit the data, but the longer it will take.

- `max_depth`
- `max_features`
- `max_samples`
- `min_samples_leaf`
- `min_samples_split`
- `n_estimators`

3. Define a set `scoring` of scoring metrics for GridSearch to capture (precision, recall, F1 score, and accuracy).
4. Instantiate the `GridSearchCV` object `rf1`. Pass to it as arguments:

- estimator=`rf`
- param_grid=`cv_params`
- scoring=`scoring`

- cv: define the number of you cross-validation folds you want (`cv=_`)
- refit: indicate which evaluation metric you want to use to select the model (`refit=_`)

Note: `refit` should be set to `'f1'`.

[31]:
```python
# 1. Instantiate the random forest classifier
rf = RandomForestClassifier(random_state=42)

# 2. Create a dictionary of hyperparameters to tune
# Note that this example only contains 1 value for each parameter for␣
↪simplicity,
# but you should assign a dictionary with ranges of values
cv_params = {'max_depth': [None],
             'max_features': [1.0],
             'max_samples': [0.7],
             'min_samples_leaf': [1],
             'min_samples_split': [2],
             'n_estimators': [300]
             }

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

# 4. Instantiate the GridSearchCV object
rf1 = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='f1')
```

Now fit the model to the training data.

Note: *Depending on how many options you include in your search grid and the number of cross-validation folds you select, this could take a very long time—even hours. If you use 4-fold validation and include only one possible value for each hyperparameter and grow 300 trees to full depth, it should take about 5 minutes. If you add another value for GridSearch to check for, say,* `min_samples_split` *(so all hyperparameters now have 1 value except for* `min_samples_split`*, which has 2 possibilities), it would double the time to ~10 minutes. Each additional parameter would approximately double the time.*

[32]:
```python
%%time
rf1.fit(X_train, y_train)
```

```
CPU times: user 3min 46s, sys: 82.9 ms, total: 3min 46s
Wall time: 3min 46s
```

[32]:
```
GridSearchCV(cv=4, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
```

```
                                                min_impurity_decrease=0.0,
                                                min_impurity_split=None,
                                                min_samples_leaf=1,
                                                min_samples_split=2,
                                                min_weight_fraction_leaf=0.0,
                                                n_estimators=100, n_jobs=None,
                                                oob_score=False, random_state=42,
                                                verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': [None], 'max_features': [1.0],
                         'max_samples': [0.7], 'min_samples_leaf': [1],
                         'min_samples_split': [2], 'n_estimators': [300]},
             pre_dispatch='2*n_jobs', refit='f1', return_train_score=False,
             scoring={'f1', 'recall', 'precision', 'accuracy'}, verbose=0)
```

If you want, use `pickle` to save your models and read them back in. This can be particularly helpful when performing a search over many possible hyperparameter values.

[33]:
```python
import pickle

# Define a path to the folder where you want to save the model
path = '/home/jovyan/work/'
```

[34]:
```python
def write_pickle(path, model_object, save_name:str):
    '''
    save_name is a string.
    '''
    with open(path + save_name + '.pickle', 'wb') as to_write:
        pickle.dump(model_object, to_write)
```

[35]:
```python
def read_pickle(path, saved_model_name:str):
    '''
    saved_model_name is a string.
    '''
    with open(path + saved_model_name + '.pickle', 'rb') as to_read:
        model = pickle.load(to_read)

        return model
```

Examine the best average score across all the validation folds.

[36]:
```python
# Examine best score
rf1.best_score_
```

[36]: 0.7136009788848705

Examine the best combination of hyperparameters.

[37]:
```
rf1.best_params_
```

[37]:
```
{'max_depth': None,
 'max_features': 1.0,
 'max_samples': 0.7,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 300}
```

Use the `make_results()` function to output all of the scores of your model. Note that it accepts three arguments.

[38]:
```
def make_results(model_name:str, model_object, metric:str):
    '''
    Arguments:
    model_name (string): what you want the model to be called in the output␣
↪table
    model_object: a fit GridSearchCV object
    metric (string): precision, recall, f1, or accuracy

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

    # Create dictionary that maps input metric to actual metric name in␣
↪GridSearchCV
    metric_dict = {'precision': 'mean_test_precision',
                   'recall': 'mean_test_recall',
                   'f1': 'mean_test_f1',
                   'accuracy': 'mean_test_accuracy',
                   }

    # 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(metric) score
    best_estimator_results = cv_results.iloc[cv_results[metric_dict[metric]].
↪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],
```

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

    return table
```

[39]:
```
# Call 'make_results()' on the GridSearch object
results = make_results('RF CV', rf1, 'f1')
results
```

[39]:

	model	precision	recall	F1	accuracy
0	RF CV	0.674919	0.757312	0.713601	0.680233

Exemplar response:

The benefit of using multiple models to predict on the test data is that you can compare models using data that was not used to train/tune hyperparameters. This reduces the risk of selecting a model based on how well it fit the training data.

The drawback of using the final test data to select a model is that, by using the unseen data to make a decision about which model to use, you no longer have a truly unbiased idea of how your model would be expected to perform on new data. In this case, think of final model selection as another way of "tuning" your model.

[40]:
```
# Get scores on test data
rf_preds = rf1.best_estimator_.predict(X_test)
```

Use the below `get_test_scores()` function you will use to output the scores of the model on the test data.

[41]:
```
def get_test_scores(model_name:str, preds, y_test_data):
    '''
    Generate a table of test scores.

    In:
    model_name (string): Your choice: how the model will be named in the output␣
 ↪table
    preds: numpy array of test predictions
    y_test_data: numpy array of y_test data

    Out:
    table: a pandas df of precision, recall, f1, and accuracy scores for your␣
 ↪model
    '''
    accuracy = accuracy_score(y_test_data, preds)
    precision = precision_score(y_test_data, preds)
```

```
    recall = recall_score(y_test_data, preds)
    f1 = f1_score(y_test_data, preds)

    table = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'F1': [f1],
                          'accuracy': [accuracy]
                          })

    return table
```

1. Use the `get_test_scores()` function to generate the scores on the test data. Assign the results to `rf_test_scores`.
2. Call `rf_test_scores` to output the results.

RF test results

[42]:
```
# Get scores on test data
rf_test_scores = get_test_scores('RF test', rf_preds, y_test)
results = pd.concat([results, rf_test_scores], axis=0)
results
```

[42]:

	model	precision	recall	F1	accuracy
0	RF CV	0.674919	0.757312	0.713601	0.680233
0	RF test	0.675297	0.779091	0.723490	0.686538

Question: How do your test results compare to your validation results?

Exemplar response: All scores increased by at most ~0.02.

XGBoost Try to improve your scores using an XGBoost model.

1. Instantiate the XGBoost classifier `xgb` and set `objective='binary:logistic'`. Also set the random state.

2. Create a dictionary `cv_params` of the following hyperparameters and their corresponding values to tune:

- `max_depth`
- `min_child_weight`
- `learning_rate`
- `n_estimators`

3. Define a set `scoring` of scoring metrics for grid search to capture (precision, recall, F1 score, and accuracy).

4. Instantiate the `GridSearchCV` object `xgb1`. Pass to it as arguments:

- estimator=`xgb`
- param_grid=`cv_params`

- scoring=`scoring`
- cv: define the number of cross-validation folds you want (`cv=_`)
- refit: indicate which evaluation metric you want to use to select the model (`refit='f1'`)

[43]:
```
# 1. Instantiate the XGBoost classifier
xgb = XGBClassifier(objective='binary:logistic', random_state=0)

# 2. Create a dictionary of hyperparameters to tune
# Note that this example only contains 1 value for each parameter for␣
↪simplicity,
# but you should assign a dictionary with ranges of values
cv_params = {'learning_rate': [0.1],
             'max_depth': [8],
             'min_child_weight': [2],
             'n_estimators': [500]
             }

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

# 4. Instantiate the GridSearchCV object
xgb1 = GridSearchCV(xgb, cv_params, scoring=scoring, cv=4, refit='f1')
```

Now fit the model to the `X_train` and `y_train` data.

[44]:
```
%%time
xgb1.fit(X_train, y_train)
```

```
CPU times: user 5min 59s, sys: 551 ms, total: 6min
Wall time: 3min
```

[44]:
```
GridSearchCV(cv=4, error_score=nan,
             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,
                                     gamma=None, gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max…
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None,
                                     objective='binary:logistic',
                                     predictor=None, random_state=0,
                                     reg_alpha=None, …),
             iid='deprecated', n_jobs=None,
```

```
             param_grid={'learning_rate': [0.1], 'max_depth': [8],
                         'min_child_weight': [2], 'n_estimators': [500]},
             pre_dispatch='2*n_jobs', refit='f1', return_train_score=False,
             scoring={'f1', 'recall', 'precision', 'accuracy'}, verbose=0)
```

Get the best score from this model.

[45]:
```python
# Examine best score
xgb1.best_score_
```

[45]:
```
0.6977560172278552
```

And the best parameters.

[46]:
```python
# Examine best parameters
xgb1.best_params_
```

[46]:
```
{'learning_rate': 0.1,
 'max_depth': 8,
 'min_child_weight': 2,
 'n_estimators': 500}
```

XGB CV results

Use the `make_results()` function to output all of the scores of your model. Note that it accepts three arguments.

[47]:
```python
# Call 'make_results()' on the GridSearch object
xgb1_cv_results = make_results('XGB CV', xgb1, 'f1')
results = pd.concat([results, xgb1_cv_results], axis=0)
results
```

[47]:

	model	precision	recall	F1	accuracy
0	RF CV	0.674919	0.757312	0.713601	0.680233
0	RF test	0.675297	0.779091	0.723490	0.686538
0	XGB CV	0.673074	0.724487	0.697756	0.669669

[48]:
```python
# Get scores on test data
xgb_preds = xgb1.best_estimator_.predict(X_test)
```

XGB test results

1. Use the `get_test_scores()` function to generate the scores on the test data. Assign the results to `xgb_test_scores`.
2. Call `xgb_test_scores` to output the results.

[49]:
```python
# Get scores on test data
xgb_test_scores = get_test_scores('XGB test', xgb_preds, y_test)
results = pd.concat([results, xgb_test_scores], axis=0)
```

```
results
```

[49]:

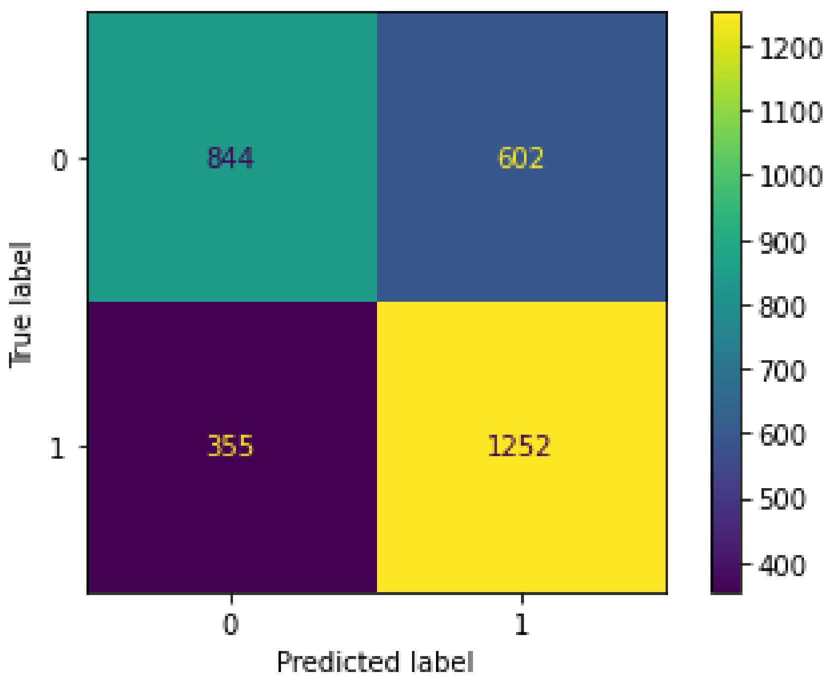
	model	precision	recall	F1	accuracy
0	RF CV	0.674919	0.757312	0.713601	0.680233
0	RF test	0.675297	0.779091	0.723490	0.686538
0	XGB CV	0.673074	0.724487	0.697756	0.669669
0	XGB test	0.675660	0.747978	0.709982	0.678349

Exemplar response: The F1 score is ~0.01 lower than the random forest model. Both models are acceptable, but the random forest model is the champion.

Plot a confusion matrix of the champion model's predictions on the test data.

[50]:
```
# Generate array of values for confusion matrix
cm = confusion_matrix(y_test, rf_preds, labels=rf1.classes_)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=rf1.classes_,
                              )
disp.plot(values_format='');
```

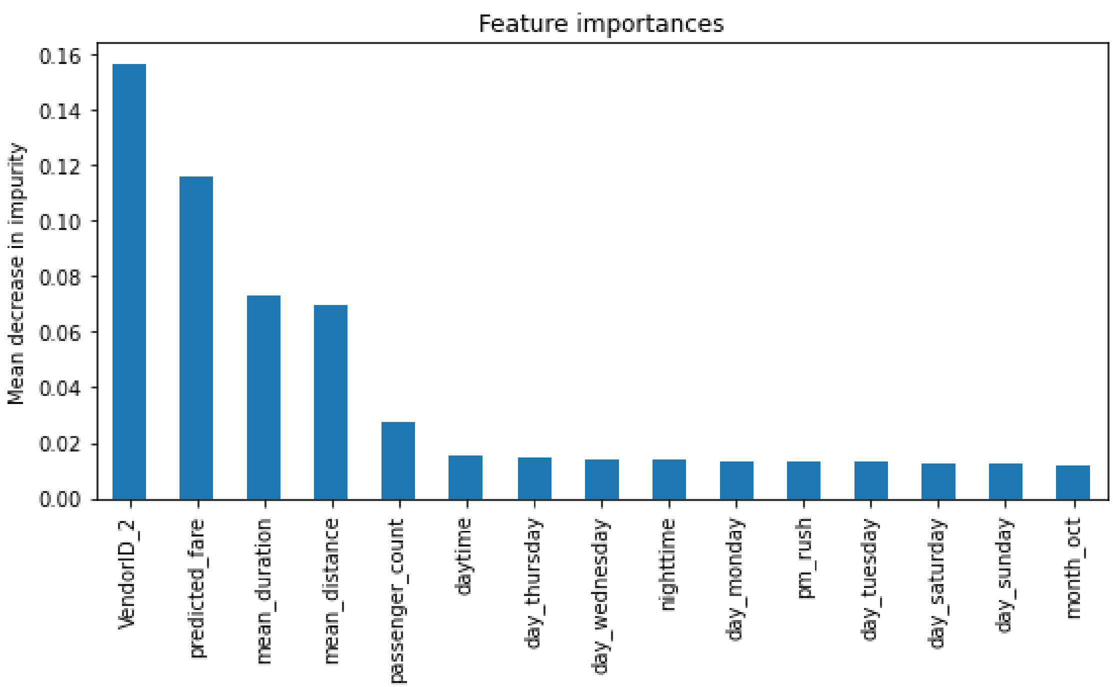


Exemplar response: The model is almost twice as likely to predict a false positive than it is to predict a false negative. Therefore, type I errors are more common. This is less desirable, because it's better for a driver to be pleasantly surprised by a generous tip when they weren't expecting one than to be disappointed by a low tip when they were expecting a generous one. However, the overall performance of this model is satisfactory.

Feature importance Use the `feature_importances_` attribute of the best estimator object to inspect the features of your final model. You can then sort them and plot the most important ones.

[51]:
```
importances = rf1.best_estimator_.feature_importances_
rf_importances = pd.Series(importances, index=X_test.columns)
rf_importances = rf_importances.sort_values(ascending=False)[:15]

fig, ax = plt.subplots(figsize=(8,5))
rf_importances.plot.bar(ax=ax)
ax.set_title('Feature importances')
ax.set_ylabel('Mean decrease in impurity')
fig.tight_layout();
```



4.4 PACE: Execute

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

4.4.1 Task 4. Conclusion

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

Exemplar responses: 1. **Would you recommend using this model? Why or why not?** Yes, this is model performs acceptably. Its F1 score was 0.7235 and it had an overall accuracy of 0.6865. It correctly identified ~78% of the actual responders in the test set, which is 48% better than a random guess. It may be worthwhile to test the model with a select group of taxi drivers to get feedback.

2. **What was your highest scoring model doing? Can you explain how it was making predictions?**
Unfortunately, random forest is not the most transparent machine learning algorithm. We know that `VendorID`, `predicted_fare`, `mean_duration`, and `mean_distance` are the most important features, but we don't know how they influence tipping. This would require further exploration. It is interesting that `VendorID` is the most predictive feature. This seems to indicate that one of the two vendors tends to attract more generous customers. It may be worth performing statistical tests on the different vendors to examine this further.

3. **Are there new features that you can engineer that might improve model performance?**
There are almost always additional features that can be engineered, but hopefully the most obvious ones were generated during the first round of modeling. In our case, we could try creating three new columns that indicate if the trip distance is short, medium, or far. We could also engineer a column that gives a ratio that represents (the amount of money from the fare amount to the nearest higher multiple of \$5) / fare amount. For example, if the fare were \$12, the value in this column would be 0.25, because \$12 to the nearest higher multiple of \$5 (\$15) is \$3, and \$3 divided by \$12 is 0.25. The intuition for this feature is that people might be likely to simply round up their tip, so journeys with fares with values just under a multiple of \$5 may have lower tip percentages than those with fare values just over a multiple of \$5. We could also do the same thing for fares to the nearest \$10.

$$round5\_ratio = \frac{amount\ of\ money\ from\ the\ fare\ amount\ to\ the\ nearest\ higher\ multiple\ of\ \$5}{fare\ amount}$$

HINT

$$= \frac{5 - (fare\ mod\ 5)}{fare\ amount}$$

4. **What features would you want to have that would likely improve the performance of your model?**
It would probably be very helpful to have past tipping behavior for each customer. It would also be valuable to have accurate tip values for customers who pay with cash. It would be helpful to have a lot more data. With enough data, we could create a unique feature for each pickup/dropoff combination.

[ ]:

```

```