Activity_Build an XGBoost model

December 31, 2023

1 Activity: Build an XGBoost model

1.1 Introduction

In this activity, you'll build on the skills and techniques you learned in the decision tree and random forest lessons to construct your own XGBoost classification model. The XGBoost model is a very powerful extension of decision trees, so having a strong working familiarity with this process will strengthen your skills and resume as a data professional.

This activity is a continuation of the airlines project in which you built decision tree and random forest models. You will use the same data, but this time you will train, tune, and evaluate an XGBoost model. You'll then compare the performance of all three models and decide which model is best. Finally, you'll explore the feature importances of your model and identify the features that most contribute to customer satisfaction.

1.2 Step 1: Imports

1.2.1 Import packages

Begin with your import statements. First, import `pandas`, `numpy`, and `matplotlib` for data preparation. Next, import scikit-learn (`sklearn`) for model preparation and evaluation. Then, import `xgboost`, which provides the classification algorithm you'll implement to formulate your predictive model.

[62]:
```python
# Import relevant libraries and modules.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle as pickle

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

from xgboost import XGBClassifier
from xgboost import plot_importance
```

1.2.2 Load the dataset

To formulate your model, `pandas` is used to import a csv of airline passenger satisfaction data called `Invistico_Airline.csv`. This DataFrame is called `airline_data`. 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.

[48]:
```
# RUN THIS CELL TO IMPORT YOUR DATA.

### YOUR CODE HERE ###

airline_data = pd.read_csv('Invistico_Airline.csv', error_bad_lines=False)
```

1.2.3 Display the data

Examine the first 10 rows of data to familiarize yourself with the dataset.

[3]:
```
# Display the first ten rows of data.

airline_data.head(10)
```

[3]:
```
  satisfaction   Customer Type  Age   Type of Travel     Class  \
0    satisfied  Loyal Customer   65  Personal Travel       Eco
1    satisfied  Loyal Customer   47  Personal Travel  Business
2    satisfied  Loyal Customer   15  Personal Travel       Eco
3    satisfied  Loyal Customer   60  Personal Travel       Eco
4    satisfied  Loyal Customer   70  Personal Travel       Eco
5    satisfied  Loyal Customer   30  Personal Travel       Eco
6    satisfied  Loyal Customer   66  Personal Travel       Eco
7    satisfied  Loyal Customer   10  Personal Travel       Eco
8    satisfied  Loyal Customer   56  Personal Travel  Business
9    satisfied  Loyal Customer   22  Personal Travel       Eco

   Flight Distance  Seat comfort  Departure/Arrival time convenient  \
0              265             0                                  0
1             2464             0                                  0
2             2138             0                                  0
3              623             0                                  0
4              354             0                                  0
5             1894             0                                  0
6              227             0                                  0
7             1812             0                                  0
8               73             0                                  0
9             1556             0                                  0

   Food and drink  Gate location  …  Online support  Ease of Online booking  \
0              0              2  …             2                       3
1              0              3  …             2                       3
2              0              3  …             2                       2
3              0              3  …             3                       1
4              0              3  …             4                       2
5              0              3  …             2                       2
6              0              3  …             5                       5
7              0              3  …             2                       2
8              0              3  …             5                       4
9              0              3  …             2                       2

   On-board service  Leg room service  Baggage handling  Checkin service  \
0                 3                 0                 3                5
1                 4                 4                 4                2
2                 3                 3                 4                4
3                 1                 0                 1                4
4                 2                 0                 2                4
5                 5                 4                 5                5
6                 5                 0                 5                5
7                 3                 3                 4                5
8                 4                 0                 1                5
9                 2                 4                 5                3

   Cleanliness  Online boarding  Departure Delay in Minutes  \
0            3                2                           0
1            3                2                         310
2            4                2                           0
3            1                3                           0
4            2                5                           0
5            4                2                           0
6            5                3                          17
7            4                2                           0
8            4                4                           0
9            4                2                          30

   Arrival Delay in Minutes
0                       0.0
1                     305.0
2                       0.0
3                       0.0
4                       0.0
5                       0.0
6                      15.0
7                       0.0
8                       0.0
9                      26.0
```

```
[10 rows x 22 columns]
```

1.2.4 Display the data type for each column

Next, observe the types of data present within this dataset.

[4]:
```python
# Display the data type for each column in your DataFrame.

airline_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 129880 entries, 0 to 129879
Data columns (total 22 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   satisfaction                       129880 non-null  object 
 1   Customer Type                      129880 non-null  object 
 2   Age                                129880 non-null  int64  
 3   Type of Travel                     129880 non-null  object 
 4   Class                              129880 non-null  object 
 5   Flight Distance                    129880 non-null  int64  
 6   Seat comfort                       129880 non-null  int64  
 7   Departure/Arrival time convenient  129880 non-null  int64  
 8   Food and drink                     129880 non-null  int64  
 9   Gate location                      129880 non-null  int64  
 10  Inflight wifi service              129880 non-null  int64  
 11  Inflight entertainment             129880 non-null  int64  
 12  Online support                     129880 non-null  int64  
 13  Ease of Online booking             129880 non-null  int64  
 14  On-board service                   129880 non-null  int64  
 15  Leg room service                   129880 non-null  int64  
 16  Baggage handling                   129880 non-null  int64  
 17  Checkin service                    129880 non-null  int64  
 18  Cleanliness                        129880 non-null  int64  
 19  Online boarding                    129880 non-null  int64  
 20  Departure Delay in Minutes         129880 non-null  int64  
 21  Arrival Delay in Minutes           129487 non-null  float64
dtypes: float64(1), int64(17), object(4)
memory usage: 21.8+ MB
```

Hint 1

Recall the methods for exploring DataFrames.

Hint 2

Recall a property of a `pandas` DataFrame that allows you to view the data type for each column.

Hint 3

Call `.dtypes` on your DataFrame `airline_data` to view the data type of each column.

Question: Identify the target (or predicted) variable for passenger satisfaction. What is your initial hypothesis about which variables will be valuable in predicting satisfaction?

My hypothesis is that in a similar way satisfaction will come from ammenities the airline provides to it's customers. Comfort included with that being said. I also think ease of flight booking will also be relevant.

1.3 Step 2: Model preparation

Before you proceed with modeling, consider which metrics you will ultimately want to leverage to evaluate your model.

Question: Which metrics are most suited to evaluating this type of model?

Seat comfort, inflight entertainment, Ease of online booking, Cleanliness, Class,

1.3.1 Prepare your data for predictions

You may have noticed when previewing your data that there are several non-numerical variables (`object` data types) within the dataset.

To prepare this DataFrame for modeling, first convert these variables into a numerical format.

[49]:
```
# Convert the object predictor variables to numerical dummies.

airline_data_dummies = pd.get_dummies(airline_data,
                                      columns=['satisfaction','Customer␣
↪Type','Type of Travel','Class'])
```

Hint 1

Refer to the content about feature engineering.

Hint 2

Use the `pandas` function for transforming categorical data into "dummy" variables.

Hint 3

Use the `get_dummies()` function on your DataFrame `airline_data` to create dummies for the categorical variables in your dataset. Note that your target variable will also need this treatment.

1.3.2 Isolate your target and predictor variables

Separately define the target variable (`satisfaction`) and the features.

[50]:
```
# Define the y (target) variable.

y = airline_data_dummies['satisfaction_satisfied']
```

```
# Define the X (predictor) variables.

X = airline_data_dummies.
↪drop(['satisfaction_satisfied','satisfaction_dissatisfied'], axis = 1)
```

Hint 1

Refer to the content about splitting your data into x and y.

Hint 2

In `pandas`, use square brackets `[]` to subset your DataFrame by specifying which column(s) to select. Also, quickly subset a DataFrame to exclude a particular column by using the `drop()` function and specifying the column to drop.

Hint 3

In this case, your target variable was split into two columns from the dummy split. Be sure to include only the column which assigns a positive (i.e., "satisfied") outcome as 1.

1.3.3 Divide your data

Divide your data into a training set (75% of the data) and test set (25% of the data). This is an important step in the process, as it allows you to reserve a part of the data that the model has not used to test how well the model generalizes (or performs) on new data.

[51]:
```
# Perform the split operation on your data.
# Assign the outputs as follows: X_train, X_test, y_train, y_test.

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,␣
↪random_state = 0)
```

Hint 1

Refer to the content about splitting your data between a training and test set.

Hint 2

To perform the splitting, call the function in the `model_selection` module of `sklearn` on the features and target variable.

Hint 3

Call the `train_test_split()` function, passing in both `features` and `target`, while configuring the appropriate `test_size`. Assign the output of this split as `X_train`, `X_test`, `y_train`, `y_test`.

1.4 Step 3: Model building

1.4.1 "Instantiate" your XGBClassifer

Before you fit your model to your airline dataset, first create the XGB Classifier model and define its objective. You'll use this model to fit and score different hyperparameters during the GridSearch cross-validation process.

[52]:
```
# Define xgb to be your XGBClassifier.

xgb =XGBClassifier(objective='binary:logistic', random_state=0)
```

Hint 1

Refer to the content about constructing a classifier model from `xgboost`.

Hint 2

Note that the target variable in this case is a binary variable.

Hint 3

Use the `XGBClassifier()` from `xgboost`. Set the objective as `binary:logistic`.

1.4.2 Define the parameters for hyperparameter tuning

To identify suitable parameters for your `xgboost` model, first define the parameters for hyperparameter tuning. Specifically, define a range of values for `max_depth`, `min_child_weight`, `learning_rate`, `n_estimators`, `subsample`, and `colsample_bytree`.

Consider a more limited range for each parameter to allow for timely iteration and model training.

[53]:
```
# Define parameters for tuning as `cv_params`.


cv_params = {'max_depth': [4, 6],
             'min_child_weight': [3, 5],
             'learning_rate': [0.1, 0.2, 0.3],
             'n_estimators': [5,10,15],
             'subsample' : [0.7],
             'colsample_bytree' : [0.7]
             }
```

Hint 1

Refer to the content about hyperparameter tuning using GridSearch cross-validation.

Hint 2

Consider a range of values for each parameter, similar to what you observed in the lesson.

Hint 3

Define these parameters using a Python dictionary in the following format: `{'parameter1': [range,of,values]}`

Question: What is the likely effect of adding more estimators to your GridSearch?

Likely the predictions will only be marginally more precise but the computing time will increase each time I add more.

1.4.3 Define how the models will be evaluated

Define how the models will be evaluated for hyperparameter tuning. To yield the best understanding of model performance, utilize a suite of metrics.

[54]:
```
# Define your criteria as `scoring`.

scoring = {'accuracy', 'precision', 'recall', 'f1'}
```

Hint 1

Recall what you've learned about using metric evaluation to determine the metrics you include.

Hint 2

Consider what you've learned about the limitations of only including a single metric, such as `accuracy`.

Hint 3

Define metrics which balance the false positives and false negatives in binary classification problems.

1.4.4 Construct the GridSearch cross-validation

Construct the GridSearch cross-validation using the model, parameters, and scoring metrics you defined. Additionally, define the number of folds and specify *which metric* from above will guide the refit strategy.

[55]:
```
# Construct your GridSearch.

xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=5, refit='f1')
```

Hint 1

Recall what you've learned about constructing a GridSearch for cross-validation.

Hint 2

Balance the time spent on validation with the number of folds you choose.

Hint 3

Choose the refit method which simultaneously balances false positives and false negatives.

1.4.5 Fit the GridSearch model to your training data

If your GridSearch takes too long, revisit the parameter ranges above and consider narrowing the range and reducing the number of estimators.

Note: The following cell might take several minutes to run.

[56]:
```
%%time
# fit the GridSearch model to training data

xgb_cv = xgb_cv.fit(X_train, y_train)
xgb_cv
```

```
CPU times: user 3min 13s, sys: 268 ms, total: 3min 13s
Wall time: 1min 40s
```

[56]:
```
GridSearchCV(cv=5, 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…
                                     predictor=None, random_state=0,
                                     reg_alpha=None, …),
             iid='deprecated', n_jobs=None,
             param_grid={'colsample_bytree': [0.7],
                         'learning_rate': [0.1, 0.2, 0.3], 'max_depth': [4, 6],
                         'min_child_weight': [3, 5],
                         'n_estimators': [5, 10, 15], 'subsample': [0.7]},
             pre_dispatch='2*n_jobs', refit='f1', return_train_score=False,
             scoring={'recall', 'accuracy', 'f1', 'precision'}, verbose=0)
```

Question: Which optimal set of parameters did the GridSearch yield?

The optimal set is ‘colsample’: 0.7, ‘learning rate’: 0.1,0.2,0.3, ‘max depth’: 4,6 ‘min child’: 3,5 ‘n estimators: 5,10,15 ’subsample’: 0.7

Hint 1

Recall what you’ve learned about the result of the GridSearch.

Hint 2

Once you’ve fitted the GridSearch model to your training data, there will be an attribute to access which yields to the optimal parameter set.

Hint 3

Access the `best_params_` attribute from your fitted model.

1.4.6 Save your model for reference using `pickle`

Use the `pickle` library you've already imported to save the output of this model.

[59]:
```
# Use `pickle` to save the trained model.

pickle.dump(xgb_cv,open('xgb_cv.sav', 'wb'))
```

Hint 1

Refer to the content about "pickling" prior models.

Hint 2

The model to be pickled is the fitted GridSearch model from above.

Hint 3

Call `pickle.dump()`, reference the fitted GridSearch model, and provide a name for the pickle file.

1.5 Step 4: Results and evaluation

1.5.1 Formulate predictions on your test set

To evaluate the predictions yielded from your model, leverage a series of metrics and evaluation techniques from scikit-learn by examining the actual observed values in the test set relative to your model's prediction.

First, use your trained model to formulate predictions on your test set.

[60]:
```
# Apply your model to predict on your test data. Call this output "y_pred".

y_pred = xgb_cv.predict(X_test)
```

Hint 1

Recall what you've learned about creating predictions from trained models.

Hint 2

Use the fitted GridSearch model from your training set and predict the predictor variables you reserved in the train-test split.

Hint 3

Call `predict()` on your fitted model and reference `X_test` to create these predictions.

1.5.2 Leverage metrics to evaluate your model's performance

Apply a series of metrics from scikit-learn to assess your model. Specifically, print the accuracy score, precision score, recall score, and f1 score associated with your test data and predicted values.

[64]:
```python
# 1. Print your accuracy score.

ac_score = metrics.accuracy_score(y_test, y_pred)
print('accuracy score:', ac_score)

# 2. Print your precision score.

pc_score = metrics.precision_score(y_test, y_pred)
print('precision score:', pc_score)

# 3. Print your recall score.

rc_score = metrics.recall_score(y_test, y_pred)
print('recall score:', rc_score)

# 4. Print your f1 score.

f1_score = metrics.f1_score(y_test, y_pred)
print('f1 score:', f1_score)
```

```
accuracy score: 0.9340314136125655
precision score: 0.9465036952814099
recall score: 0.9327170868347339
f1 score: 0.9395598194130925
```

Hint 1

Refer to the content about model evaluation for detail on these metrics.

Hint 2

Use the function in the `metrics` module in `sklearn` to compute each of these metrics.

Hint 3

Call `accuracy_score()`, `precision_score()`, `recall_score()`, and `f1_score()`, passing `y_test` and `y_pred` into each.

Question: How should you interpret your accuracy score?

It's showing a 93% accuracy score.

Question: Is your accuracy score alone sufficient to evaluate your model?

It is useful to know but all metrics are important to properly evaluate the model.

Question: When observing the precision and recall scores of your model, how do you interpret these values, and is one more accurate than the other?

These two scores evaluate correct predictions. With a precision score of 94% and a recall score of 93% these metrics show that this model is very good at predicting customer satisfaction. Evaluating both of these metrics is better than accuracy alone.

Question: What does your model's F1 score tell you, beyond what the other metrics provide?*

F1 combines precision and recall leading to how good predictions are, in this case the score is about 94% which means this is a very good model for making predictions.

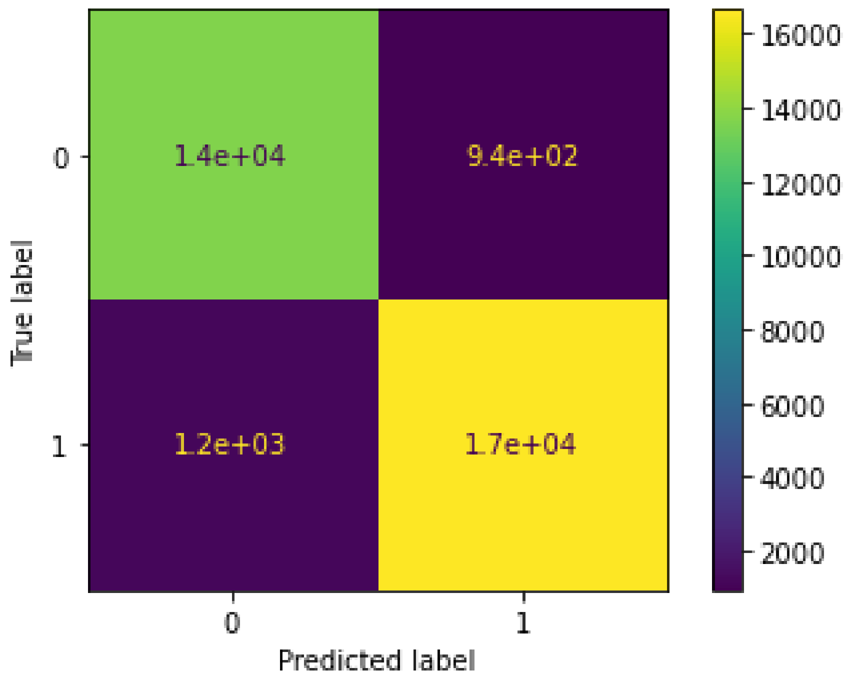
1.5.3 Gain clarity with the confusion matrix

Recall that a **confusion matrix** is a graphic that shows a model's true and false positives and true and false negatives. It helps to create a visual representation of the components feeding into the metrics above.

Create a confusion matrix based on your predicted values for the test set.

[65]:
```
# Construct and display your confusion matrix.

# Construct the confusion matrix for your predicted and test values.

cm = metrics.confusion_matrix(y_test, y_pred)

# Create the display for your confusion matrix.

disp = metrics.ConfusionMatrixDisplay(confusion_matrix=cm,␣
 ↪display_labels=xgb_cv.classes_)
# Plot the visual in-line.

disp.plot()
```

[65]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f98f0f57b10>
```



Hint 1

Refer to the content about model evaluation.

Hint 2

Use the functions in the `metrics` module to create a confusion matrix.

Hint 3

Call `confusion_matrix`, passing in `y_test` and `y_pred`. Next, utilize `ConfusionMatrixDisplay()` to display your confusion matrix.

Question: When observing your confusion matrix, what do you notice? Does this correlate to any of your other calculations?

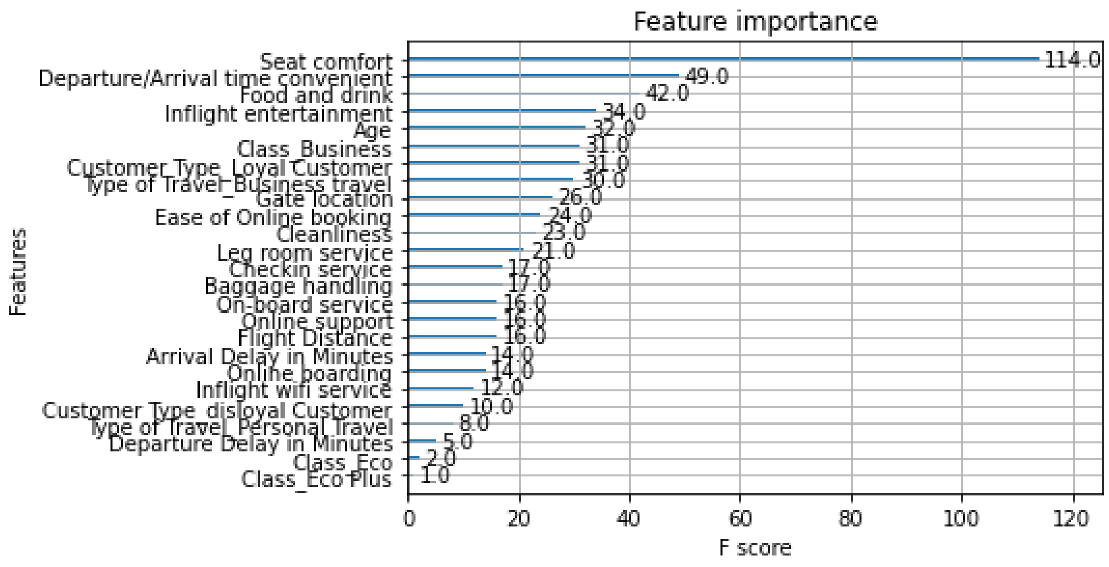
According to the matrix it is showing the true positives and true negatives stand out much more than false positives or false negatives. This does correlate and explains why the precision score is so high at 94%.

1.5.4 Visualize most important features

`xgboost` has a built-in function to visualize the relative importance of the features in the model using `matplotlib`. Output and examine the feature importance of your model.

```
[66]: # Plot the relative feature importance of the predictor variables in your model.

      plot_importance(xgb_cv.best_estimator_)
```

```
[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7f98f0cd1b50>
```



Hint 1

Recall the attributes that are provided once the model is fitted to training data.

Hint 2

Examine the `best_estimator_` attribute of your fitted model.

Hint 3

To easily visualize feature importance, call the built-in `plot_importance` function `xgboost` offers on the `best_estimator_`.

Question: Examine the feature importances outputted above. What is your assessment of the result? Did anything surprise you?

[Write your response here. Double-click (or enter) to edit.]

1.5.5 Compare models

Create a table of results to compare model performance.

```
[67]: # Create a table of results to compare model performance.

table = pd.DataFrame({'Model': ["Tuned Decision Tree", "Tuned Random Forest",␣
 ↪"Tuned XGBoost"],
                      'F1': [0.945422, 0.947306, f1_score],
                      'Recall': [0.935863, 0.944501, rc_score],
                      'Precision': [0.955197, 0.950128, pc_score],
                    'Accuracy': [0.940864, 0.942450, ac_score]
                   }
                  )
table
```

[67]:
```
                  Model        F1    Recall  Precision  Accuracy
0  Tuned Decision Tree  0.945422  0.935863   0.955197  0.940864
1  Tuned Random Forest  0.947306  0.944501   0.950128  0.942450
2        Tuned XGBoost  0.939560  0.932717   0.946504  0.934031
```

Hint 1

Create a DataFrame and using the `pd.DataFrame()` function.

Question: How does this model compare to the decision tree and random forest models you built in previous labs?

With the scores from other models it seems the Tuned Random Forest scored higher than other models aside from precision against the tuned decision tree while all of them are good and could be used, the decision tree and random forest models would be better than the tuned XGBoost.

1.6 Considerations

What are some key takeaways you learned from this lab?

Evaluating other methods of models is important because there could be higher scores and better predictions that may have not been seen before hand. As well as each metric of the scores are all important and all have their place within model evaluation. **How would you share your findings with your team?**

Show the proper examples of how well the model performed as well as explain that multiple models were made. Present the most all around effective model. Then follow up with visualization further explaining the models correct predictions. **What would you share with and recommend to stakeholders?**

The model I have made is great for the questions they want answered, customer predictions. That implementing this model can and will provide a much better insight into what will have customers feeling satisfied by the end of their flight.

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