Machine Learning

1D and 2D partial dependent plots with RandomForestClassifier and DecisionTreeClassifier

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1. Partial Dependence Plots

   - Uses

     shows how features affect prediction

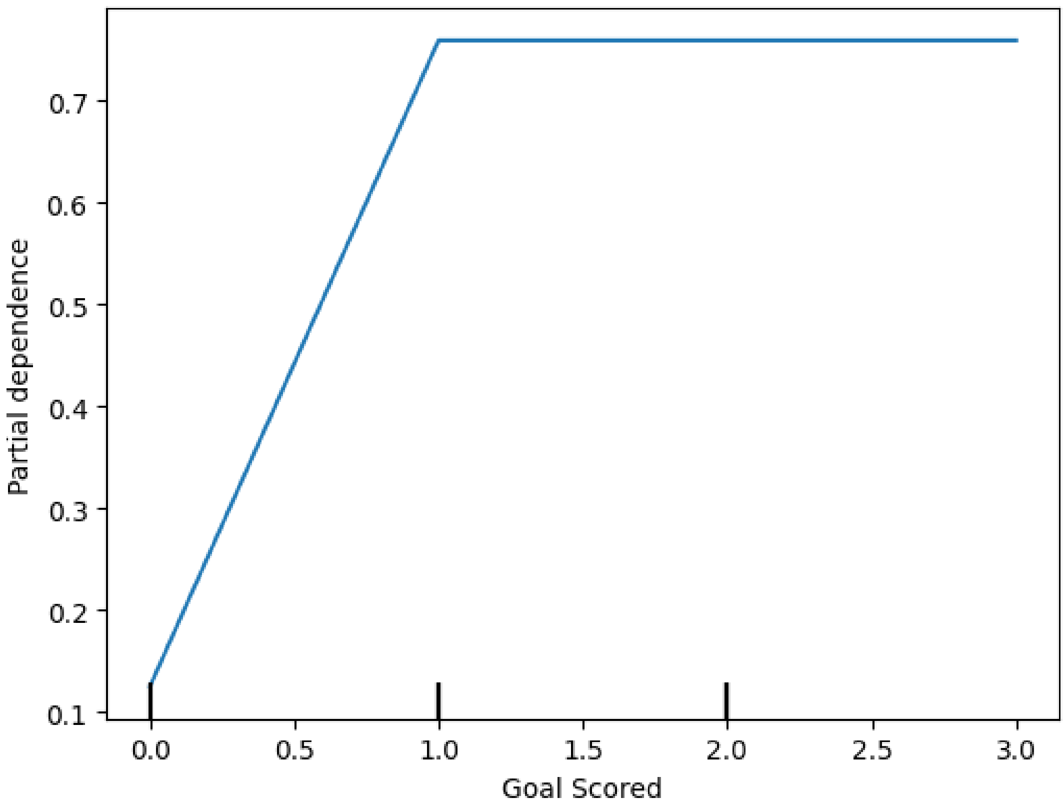
     calculated after the model has been fit

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier

data = pd.read_csv('FIFA 2018 Statistics.csv')
y = (data['Man of the Match'] == "Yes")  # Convert from string "Yes"/"No" to binary
feature_names = [i for i in data.columns if data[i].dtype in [np.int64]]
X = data[feature_names]
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state=1)
tree_model = DecisionTreeClassifier(random_state=0, max_depth=5, min_samples_split=5).fit(
```

```
from sklearn import tree
import graphviz
```

```
tree_graph = tree.export_graphviz(tree_model, out_file = None, feature_names = feature_nam
graphviz.Source(tree_graph)
```

```
from matplotlib import pyplot as plt
from sklearn.inspection import PartialDependenceDisplay

#create plot
disp1 = PartialDependenceDisplay.from_estimator(tree_model, val_X, ['Goal Scored'])
plt.show()
```

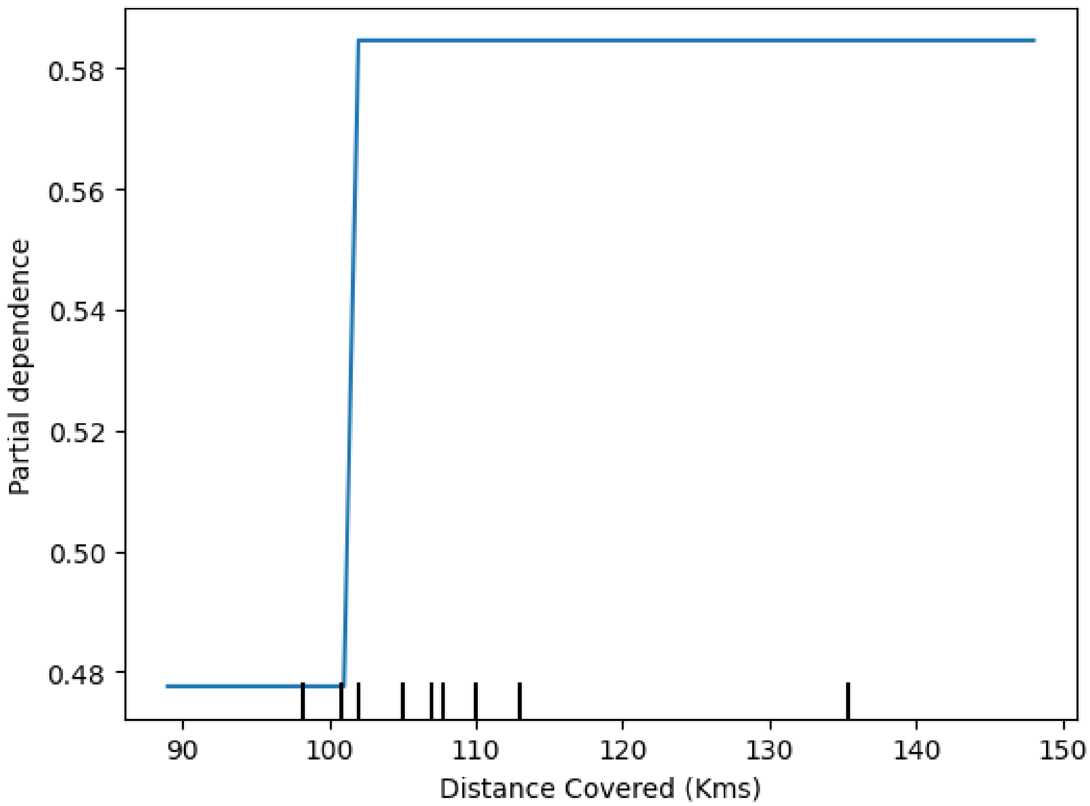


- Inference from graph-

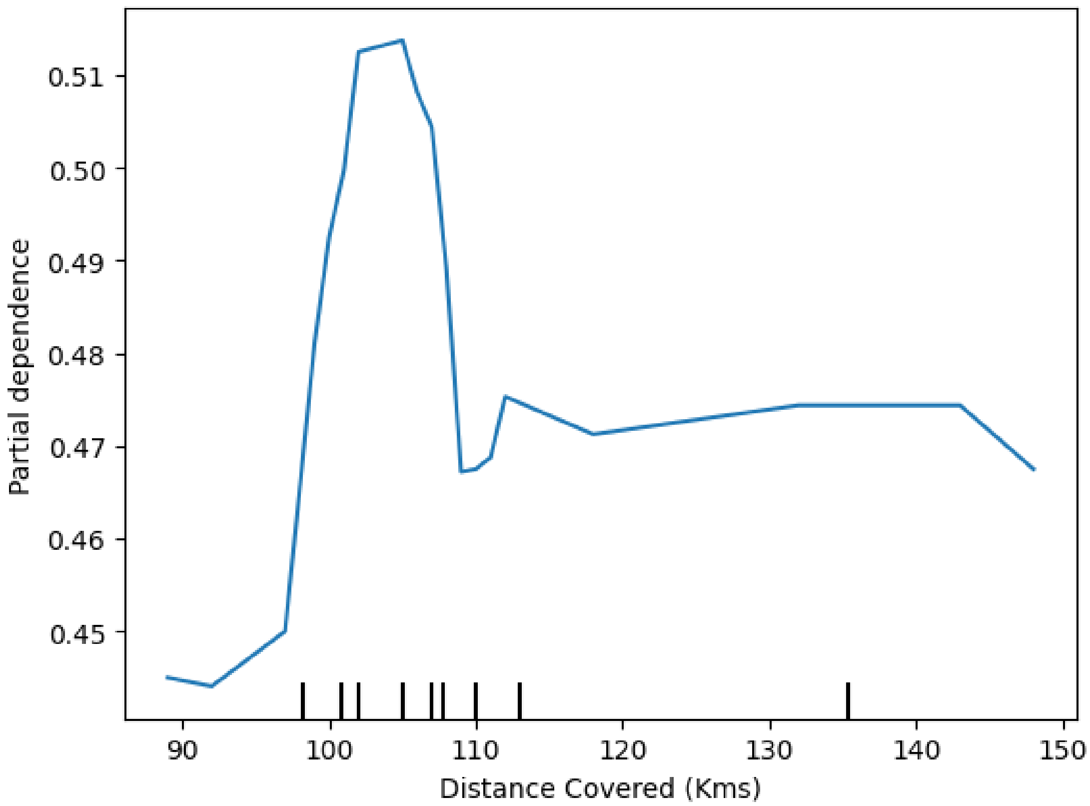
  scoring a gaol makes a person 'Man of the match'

  But extra goal seems to have no impact.

```
feature_to_plot = 'Distance Covered (Kms)'

disp2 = PartialDependenceDisplay.from_estimator (tree_model, val_X, [feature_to_plot])
plt.show()
```




```
# same plot with Random_forest

rf_model = RandomForestClassifier(random_state = 0).fit(train_X, train_y)

disp3 = PartialDependenceDisplay.from_estimator(rf_model, val_X, [feature_to_plot])
plt.show()
```



- Inference

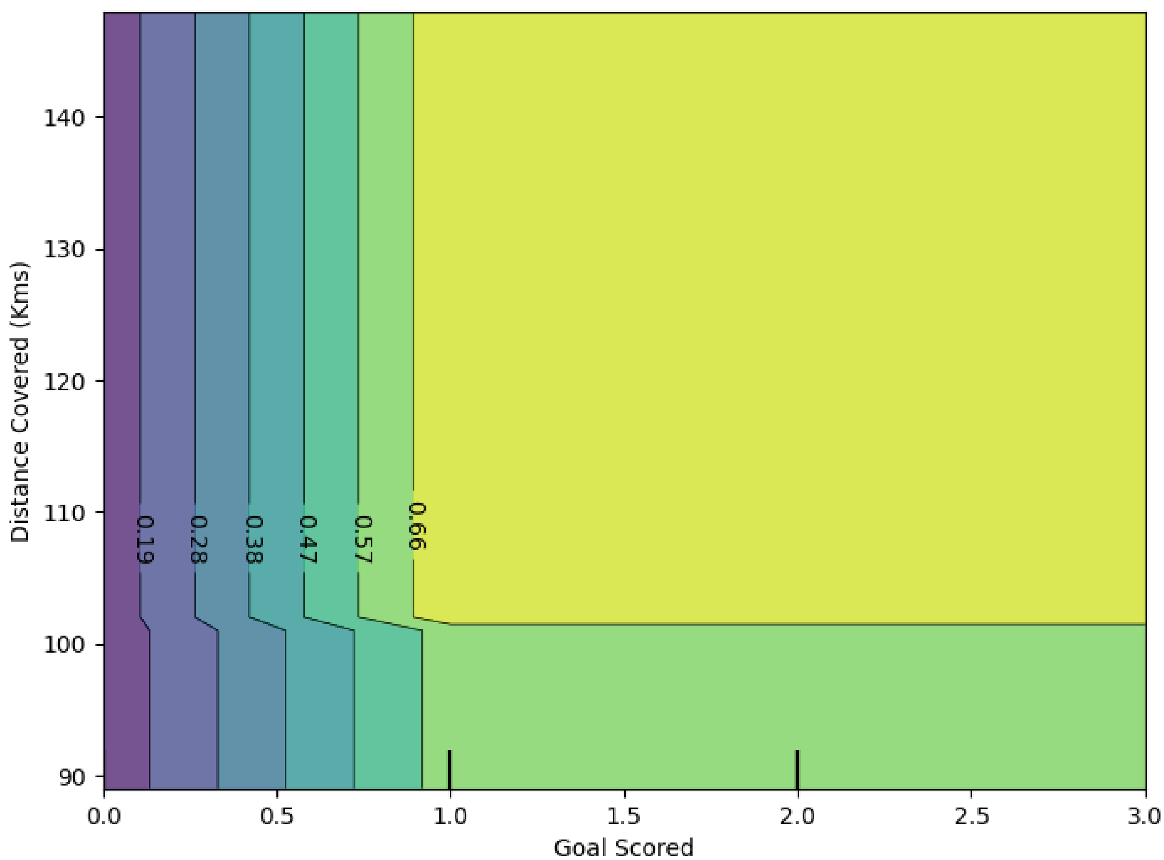
  The above graphs feature that if a player covers 100 kms, he becomes 'Man of the match'

  1st model- DecisionTreeClassifier

  2nd model - RandomForestClassifier

2. 2D Partial Dependence Plots

```
fig, ax = plt.subplots(figsize = (8,6))
f_names = [{"Goal Scored", "Distance Covered (Kms)"}]

# simiar to previous, except use use tuple features
disp4 = PartialDependenceDisplay.from_estimator(tree_model, val_X, f_names, ax = ax)
plt.show()
```



3. Practice exercise

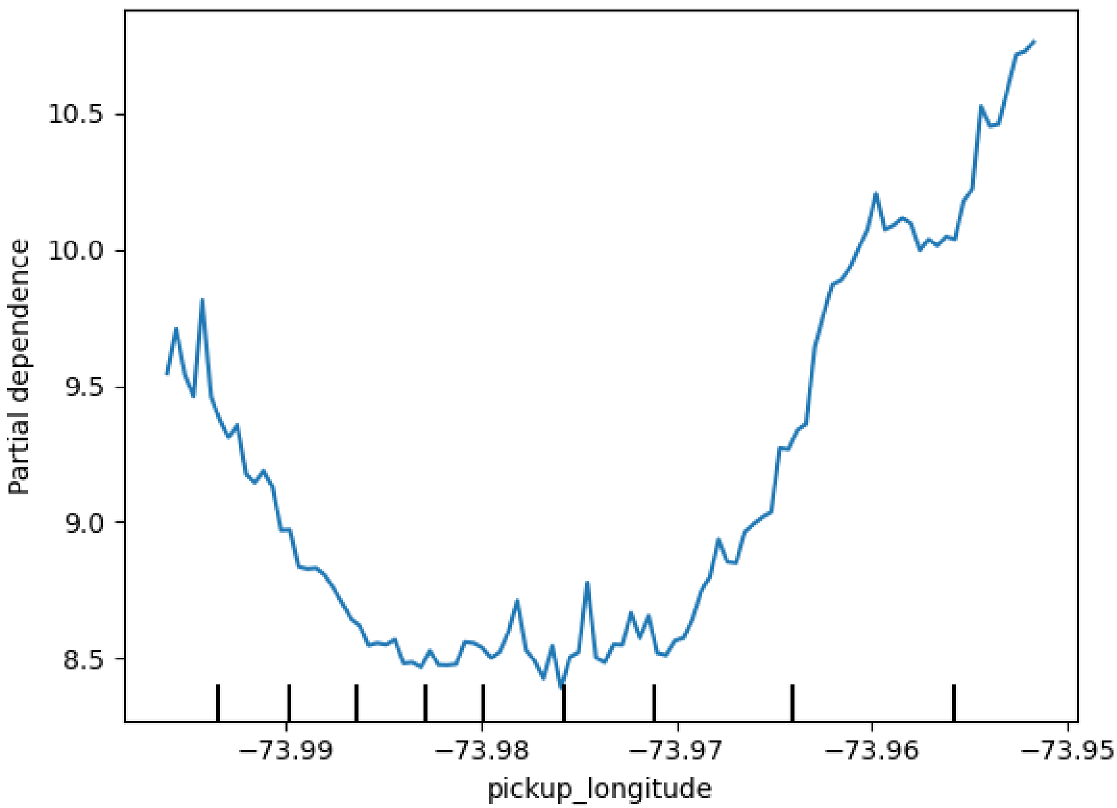
```
# import libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
from matplotlib import pyplot as plt
from sklearn.inspection import PartialDependenceDisplay

# load data
data2 = pd.read_csv('train.csv')

# Remove data with extreme outlier coordinates or negative fares
data2 = data2.query('pickup_latitude > 40.7 and pickup_latitude < 40.8 and ' +
                  'dropoff_latitude > 40.7 and dropoff_latitude < 40.8 and ' +
                  'pickup_longitude > -74 and pickup_longitude < -73.9 and ' +
                  'dropoff_longitude > -74 and dropoff_longitude < -73.9 and ' +
```

```python
                    'fare_amount > 0'
                    )

y = data2.fare_amount

base_features = ['pickup_longitude',
                 'pickup_latitude',
                 'dropoff_longitude',
                 'dropoff_latitude']

X = data2[base_features]

# train the model
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state=1)
first_model = RandomForestRegressor(n_estimators=30, random_state=1).fit(train_X, train_y)
print("Data sample:")
data2.head()
```

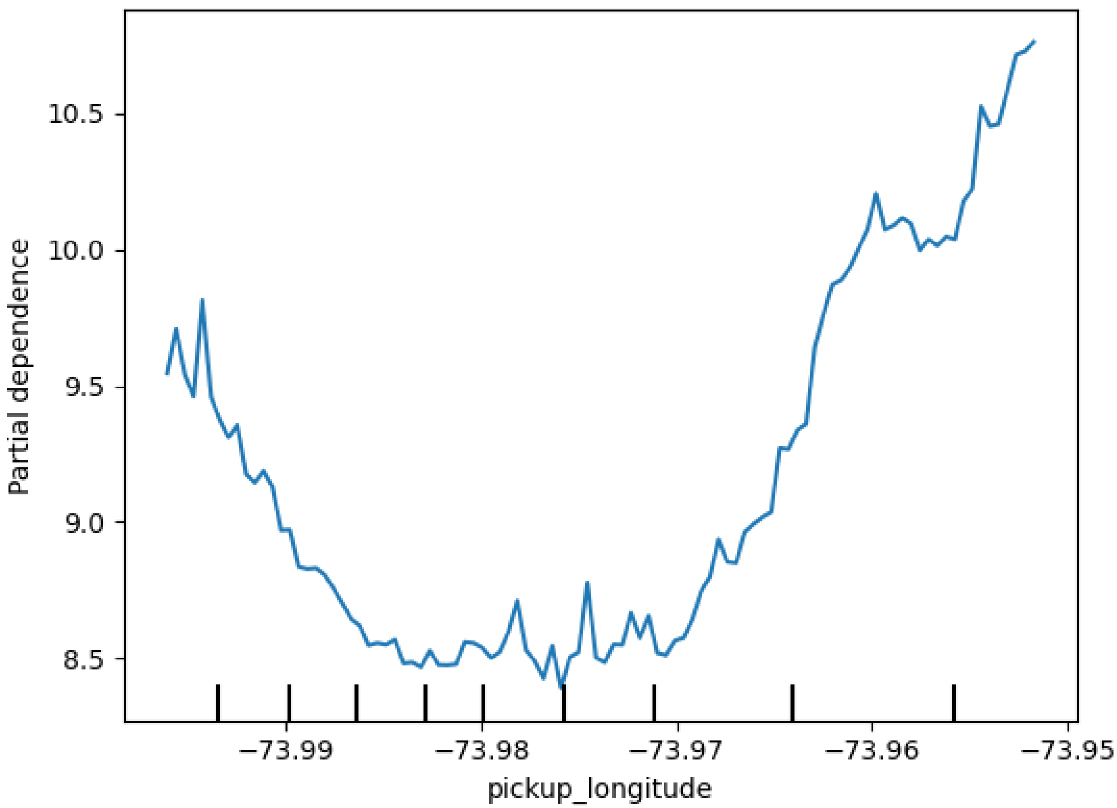
```
Data sample:
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_lat
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008
6	2012-11-20 20:35:00.0000001	7.5	2012-11-20 20:35:00 UTC	-73.980002	40.751662
7	2012-01-04 17:22:00.00000081	16.5	2012-01-04 17:22:00 UTC	-73.951300	40.774138

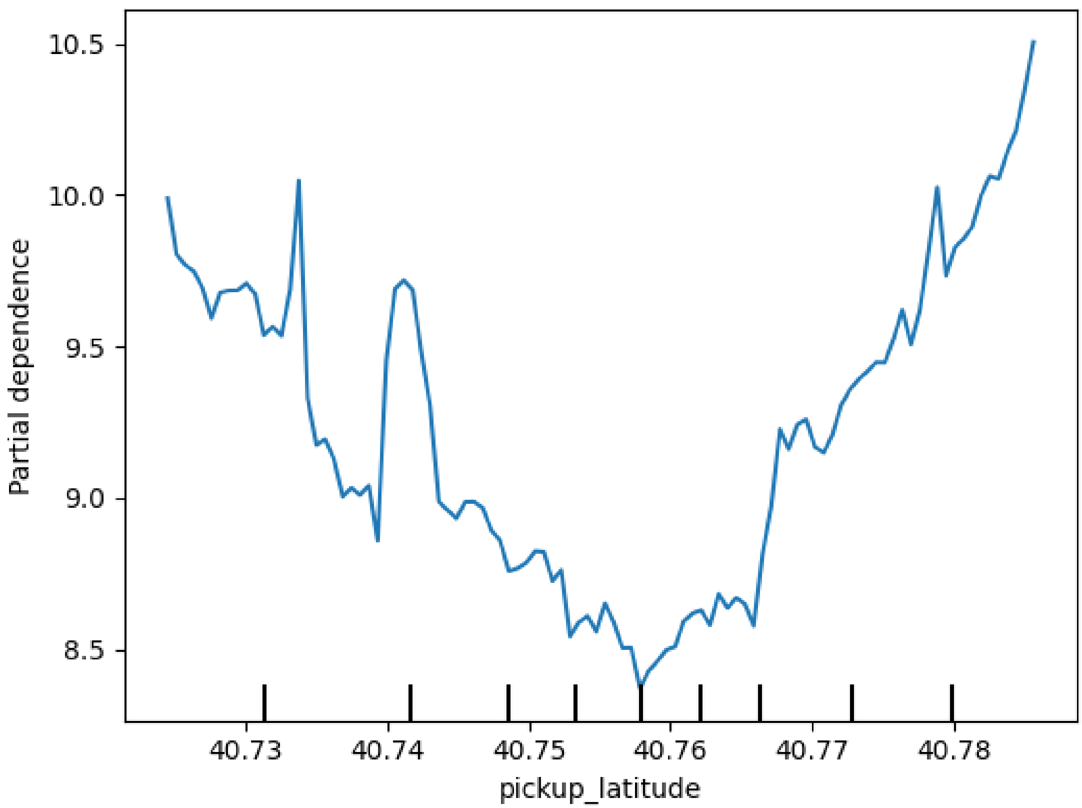
```python
feature_name = 'pickup_longitude'

PartialDependenceDisplay.from_estimator (first_model, val_X, [feature_name])
plt.show()
```

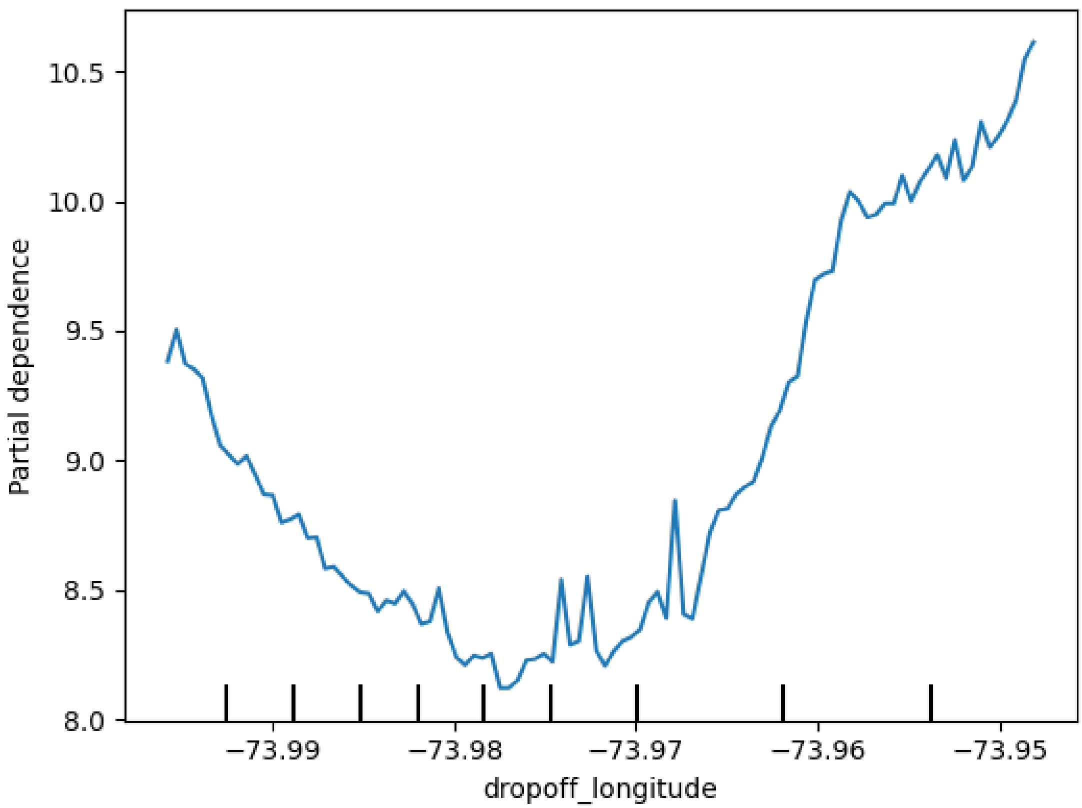


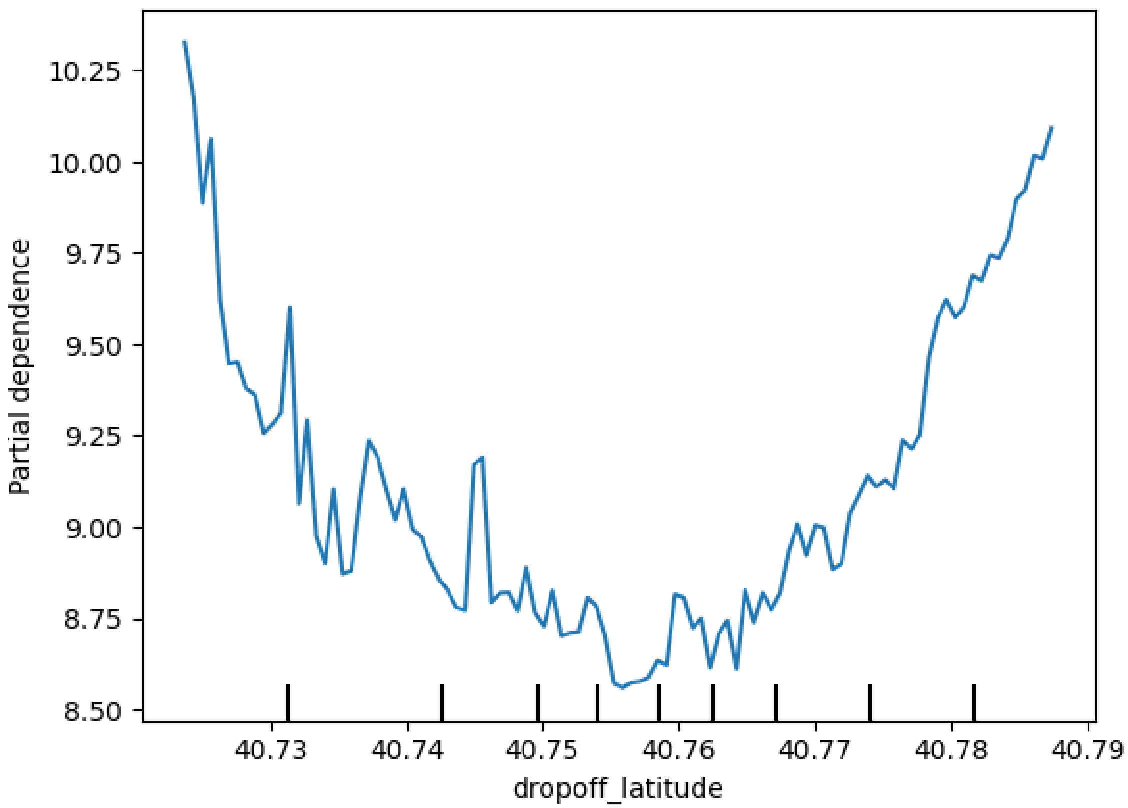

```
# apply 'for' loop for all base_features

for feature_name in base_features:
    PartialDependenceDisplay.from_estimator(first_model, val_X,  [feature_name])
    plt.show()
```



Partial dependence
10.5
10.0
9.5
9.0
8.5
−73.99
−73.98
−73.97
−73.96
−73.95
pickup_longitude

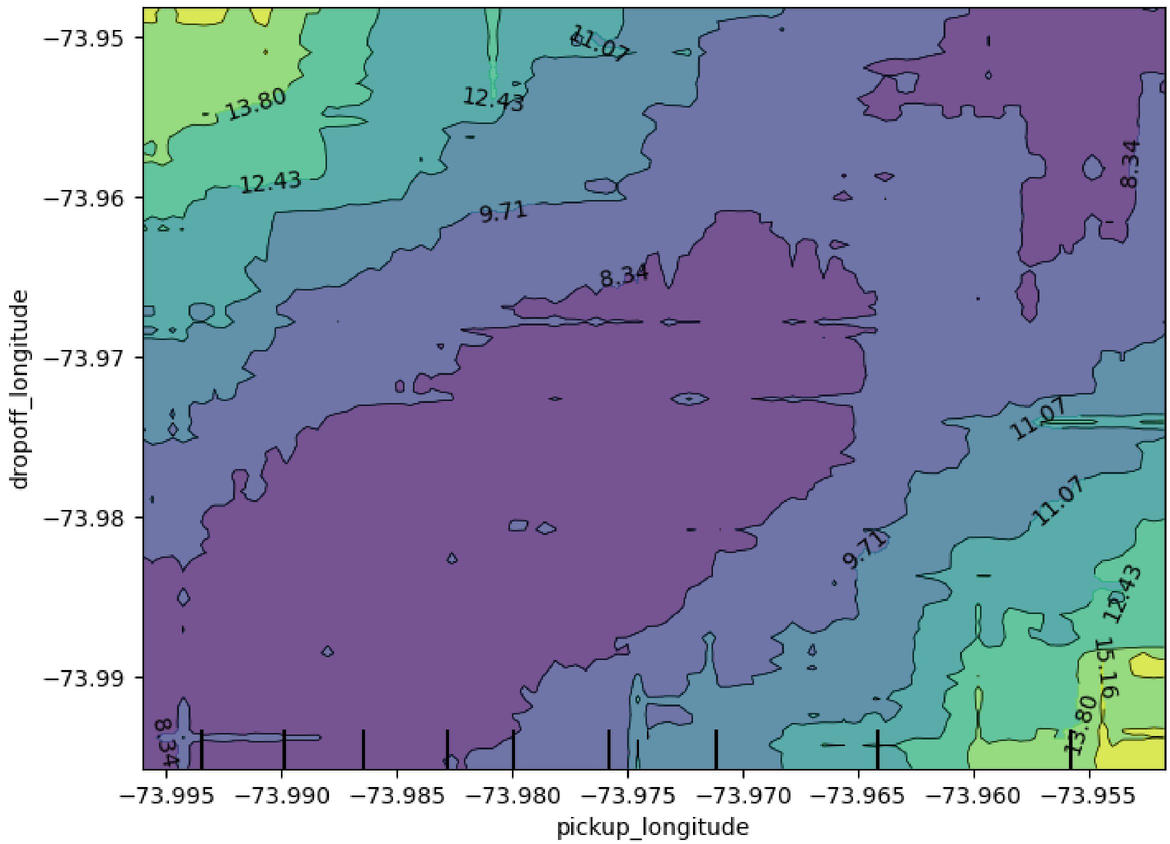

Partial dependence
10.5
10.0
9.5
9.0
8.5
40.73
40.74
40.75
40.76
40.77
40.78
pickup_latitude


Partial dependence
10.5
10.0
9.5
9.0
8.5
8.0
−73.99
−73.98
−73.97
−73.96
−73.95
dropoff_longitude




```
# 2D partial Dependence plots
fig, ax = plt.subplots(figsize = (8, 6))

feature_names = [('pickup_longitude', 'dropoff_longitude')]
PartialDependenceDisplay.from_estimator (first_model, val_X, feature_names, ax= ax)
```

```
<sklearn.inspection._plot.partial_dependence.PartialDependenceDisplay at 0x1e6ada40650>
```



Consider a scenario where you have only 2 predictive features, which we will call feat_A and feat_B.

Both features have minimum values of -1 and maximum values of 1. The partial dependence plot for feat_A increases steeply over its whole range, whereas the partial dependence plot for feature B increases at a slower rate (less steeply) over its whole range.

Does this guarantee that feat_A will have a higher permutation importance than feat_B? Why or why not_

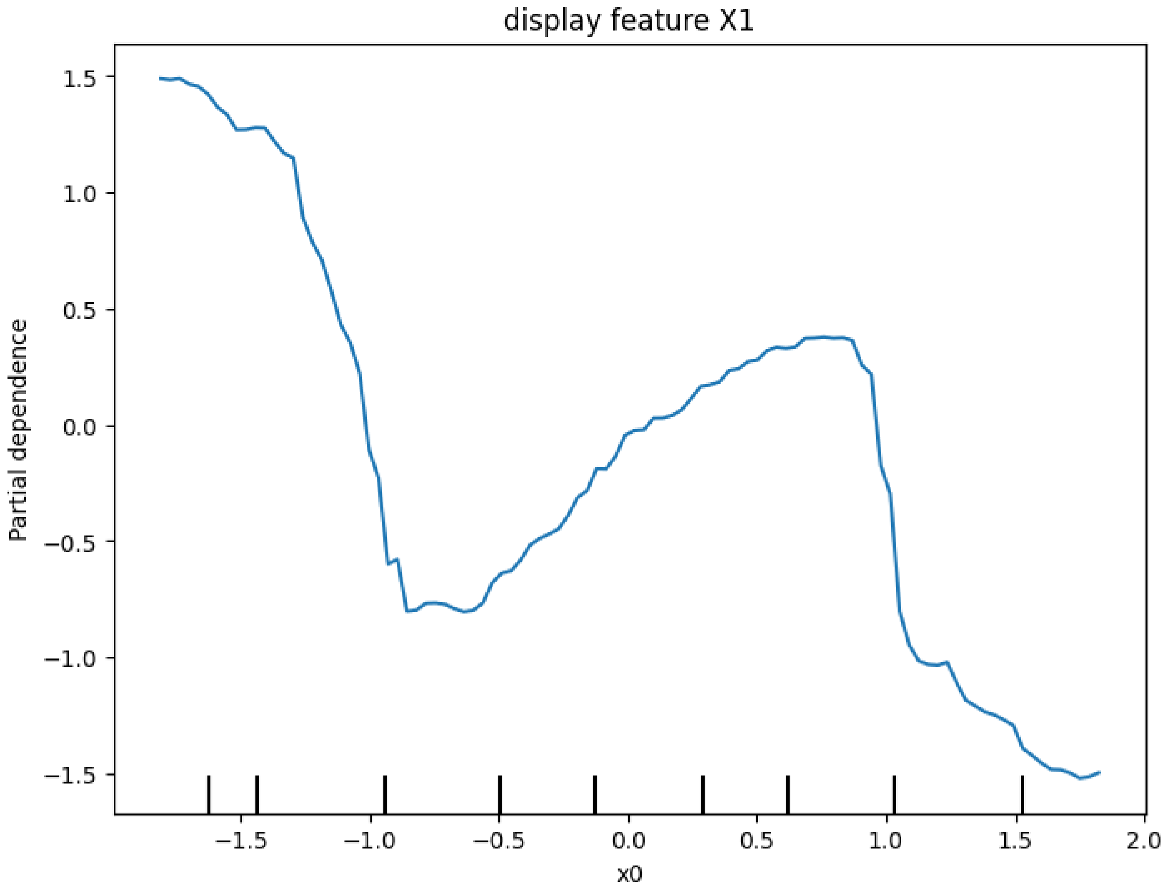
No. This doesn't guarantee feat_a is more important. For example, feat_a could have a big effect in the cases where it varies, but could have a single value 99% of the time. In that case, permuting feat_a wouldn't matter much, since most values would be unchanged.

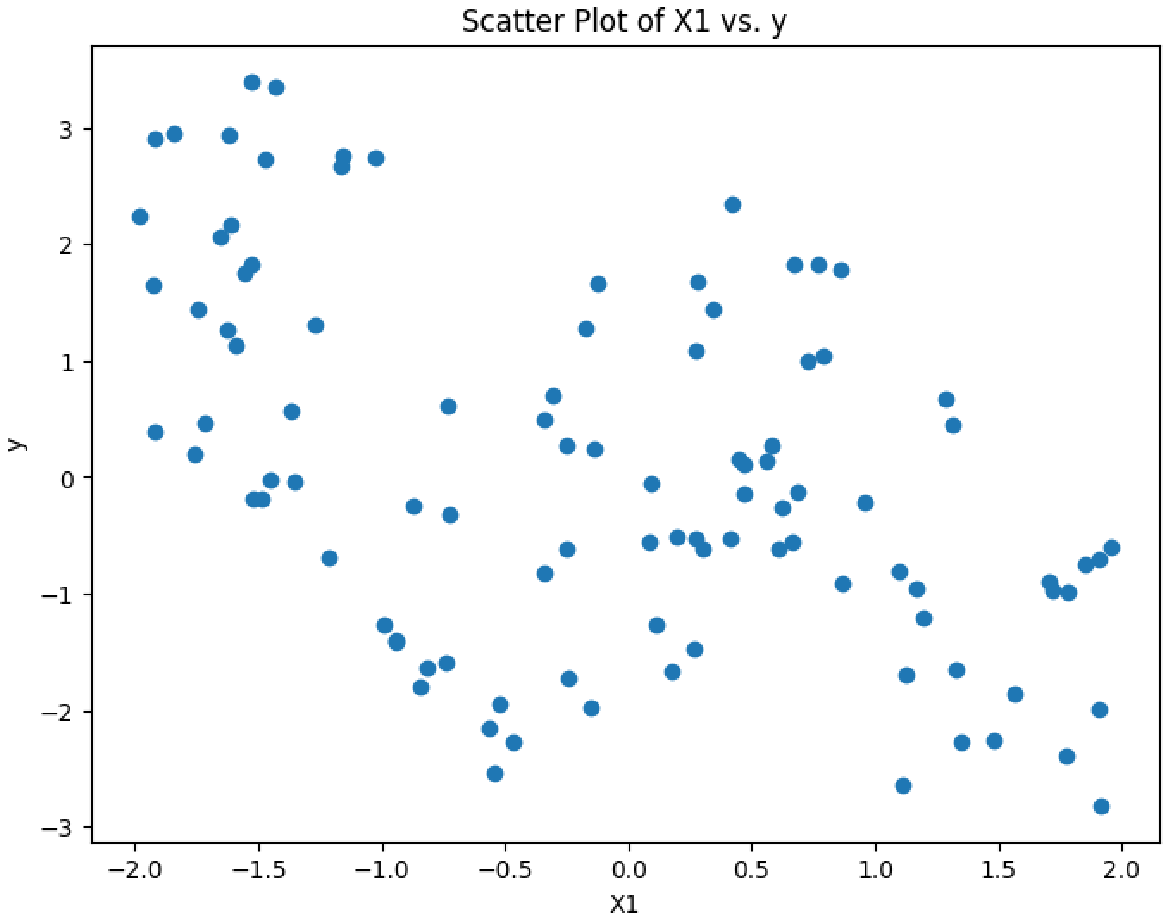
1. Creates two features, X1 and X2, having random values in the range [-2, 2].
2. Creates a target variable y, which is always 1.
3. Trains a RandomForestRegressor model to predict y given X1 and X2.

4. Creates a PDP plot for X1 and a scatter plot of X1 vs. y.

   Do you have a prediction about what the PDP plot will look like?

```
# import libraries
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.inspection import PartialDependenceDisplay
import matplotlib.pyplot as plt

# generate random data
np.random.seed(0) # for reproducibiity
X1 = np.random.uniform(-2, 2, 100)
X2 = np.random.uniform(-2, 2, 100)
X = np.column_stack([X1, X2])

# create target variable y
#y = np.ones([X.shape[0]])
y = -2 * X1 * (X1<-1) + X1 - 2 * X1 * (X1>1) - X2

# train RandomForestRegressor
model = RandomForestRegressor()
model.fit(X,y)

# plot
fix, ax = plt.subplots(figsize =(8, 6))
PartialDependenceDisplay.from_estimator (model, X, features = [0], ax= ax)
ax.set_title('display feature X1')
plt.show()

# Scatter Plot of X1 vs. y
plt.figure(figsize=(8, 6))
plt.scatter(X1, y)
plt.title("Scatter Plot of X1 vs. y")
plt.xlabel("X1")
plt.ylabel("y")
plt.show()
```


display feature X1
Partial dependence
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
x0


Scatter Plot of X1 vs. y
y
X1
3
2
1
0
−1
−2
−3
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0