Machine Learning

Permution importance with RandomForestClassifier and DecisionTreeClassifier

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Table of contents

- **Process-**

  get a trained model

  calculate the loss function

  return the data into orignal orde

```
#import eli5
#from eli5.sklearn import PermutationImportance


from sklearn.datasets import load_iris
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

```
data = pd.read_csv('FIFA 2018 Statistics.csv')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128 entries, 0 to 127
Data columns (total 27 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Date                    128 non-null    object
 1   Team                    128 non-null    object
 2   Opponent                128 non-null    object
 3   Goal Scored             128 non-null    int64
 4   Ball Possession %       128 non-null    int64
```

```
 5   Attempts                128 non-null    int64
 6   On-Target               128 non-null    int64
 7   Off-Target              128 non-null    int64
 8   Blocked                 128 non-null    int64
 9   Corners                 128 non-null    int64
 10  Offsides                128 non-null    int64
 11  Free Kicks              128 non-null    int64
 12  Saves                   128 non-null    int64
 13  Pass Accuracy %         128 non-null    int64
 14  Passes                  128 non-null    int64
 15  Distance Covered (Kms)  128 non-null    int64
 16  Fouls Committed         128 non-null    int64
 17  Yellow Card             128 non-null    int64
 18  Yellow & Red            128 non-null    int64
 19  Red                     128 non-null    int64
 20  Man of the Match        128 non-null    object
 21  1st Goal                94 non-null     float64
 22  Round                   128 non-null    object
 23  PSO                     128 non-null    object
 24  Goals in PSO            128 non-null    int64
 25  Own goals               12 non-null     float64
 26  Own goal Time           12 non-null     float64
dtypes: float64(3), int64(18), object(6)
memory usage: 27.1+ KB
```

```
data.head()
```

	Date	Team	Opponent	Goal Scored	Ball Possession %	Attempts	On-Target	Off
0	14-06-2018	Russia	Saudi Arabia	5	40	13	7	3
1	14-06-2018	Saudi Arabia	Russia	0	60	6	0	3
2	15-06-2018	Egypt	Uruguay	0	43	8	3	3
3	15-06-2018	Uruguay	Egypt	1	57	14	4	6
4	15-06-2018	Morocco	Iran	0	64	13	3	6

```
#
y = (data['Man of the Match'] == 'Yes')
feature_names = [i for i in data.columns if data[i].dtype in [np.int64]]  #choosing intege
X = data[feature_names]
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state = 1)
```

```
my_model = RandomForestClassifier(n_estimators = 100,
                                  random_state = 0).fit(train_X, train_y)
```

eli5 library for permutation importance

Practice

```
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

import seaborn as sns
import matplotlib.pyplot as plt


data2= pd.read_csv('train.csv')
```

```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   key                50000 non-null  object 
 1   fare_amount        50000 non-null  float64
 2   pickup_datetime    50000 non-null  object 
 3   pickup_longitude   50000 non-null  float64
 4   pickup_latitude    50000 non-null  float64
 5   dropoff_longitude  50000 non-null  float64
 6   dropoff_latitude   50000 non-null  float64
 7   passenger_count    50000 non-null  int64  
dtypes: float64(5), int64(1), object(2)
memory usage: 3.1+ MB
```

```
data2.columns
```

```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count'],
      dtype='object')
```

```
data2.head()
```

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_lat
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303
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

```
# 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 ' +
                  'fare_amount > 0'
                  )
```

```
# assigning prediction target

y = data2.fare_amount

base_features = ['pickup_longitude',
                'pickup_latitude',
                 'dropoff_longitude',
                'dropoff_latitude',
                'passenger_count']
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 = 50, random_state = 1).fit(train_X, trai
```

```
train_X.describe()
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	37500.000000	37500.000000	37500.000000	37500.000000	37500.000000
mean	-72.520688	39.931410	-72.514256	39.930631	1.670827
std	10.360818	6.010290	10.378988	6.014321	1.293083
min	-75.414728	-74.006893	-84.654241	-74.006377	0.000000
25%	-73.992092	40.735008	-73.991196	40.734333	1.000000
50%	-73.981811	40.752825	-73.980012	40.753397	1.000000
75%	-73.967051	40.767428	-73.963292	40.768243	2.000000
max	40.783472	42.160275	40.802437	42.168717	6.000000

```
train_y.describe()
```

```
count    37500.000000
mean        11.402322
std          9.715174
min         -5.000000
25%          6.000000
50%          8.500000
75%         12.500000
max        180.000000
Name: fare_amount, dtype: float64
```

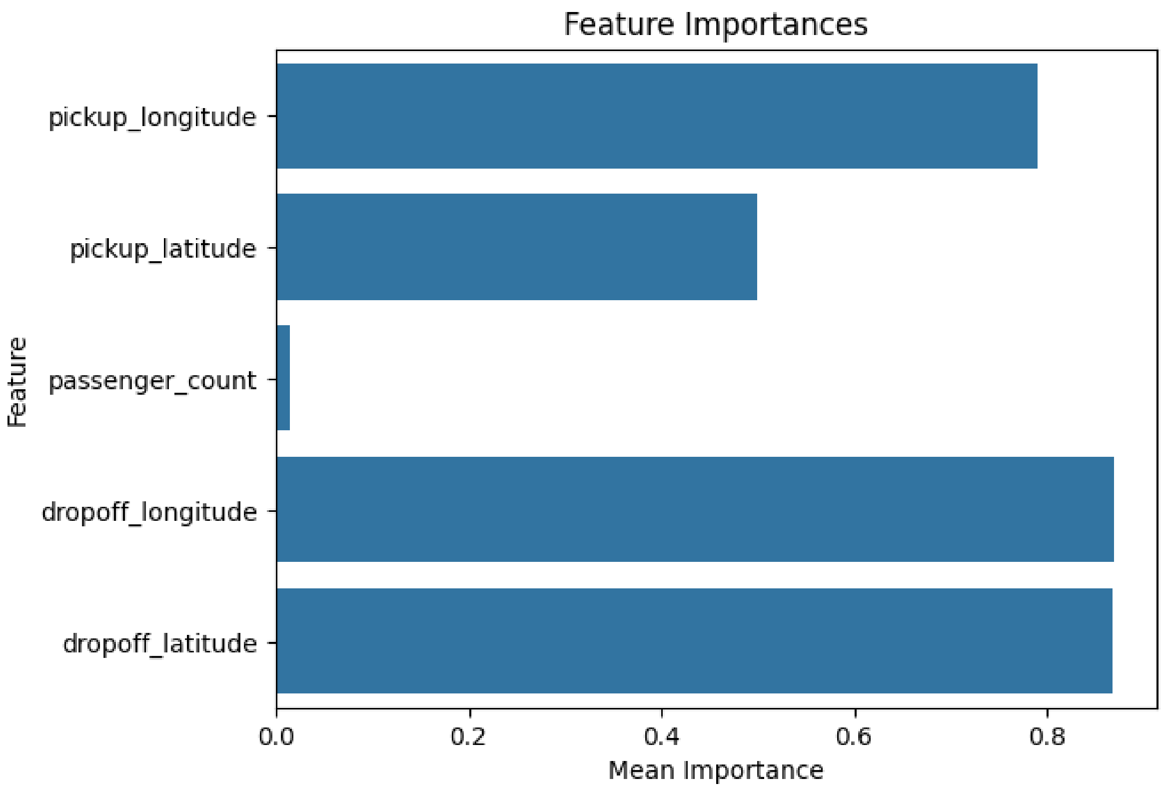
```
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state =1)
first_model = RandomForestRegressor(n_estimators = 50, random_state = 1).fit(train_X, trai
```

```
from sklearn.inspection import permutation_importance
```

```
result = permutation_importance(first_model, train_X, train_y, n_repeats=30, random_state=
```

```
# resulting importances
importance_df = pd.DataFrame({'feature': base_features,
                              'importance_mean': result.importances_mean,
                              'importance_std' : result.importances_std})
importance_df = importance_df.sort_values('feature',
                                          ascending = False)
```

```
# visualize
sns.barplot(x = 'importance_mean', y = 'feature', data= importance_df)
plt.title('Feature Importances')
plt.xlabel('Mean Importance')
plt.ylabel('Feature')
plt.show()
```



Hypothesis testing

Why are latitudes have larger effect?

1. Travel might tend to have greater latitude distances than longitude distances.
2. Different parts of the city might have different pricing rules (e.g. price per mile), and pricing rules could vary more by latitude than longitude.
3. Tolls might be greater on roads going North<->South (changing latitude) than on roads going East <-> West (changing longitude). Thus latitude would have a larger effect on

the prediction because it captures the amount of the tolls.

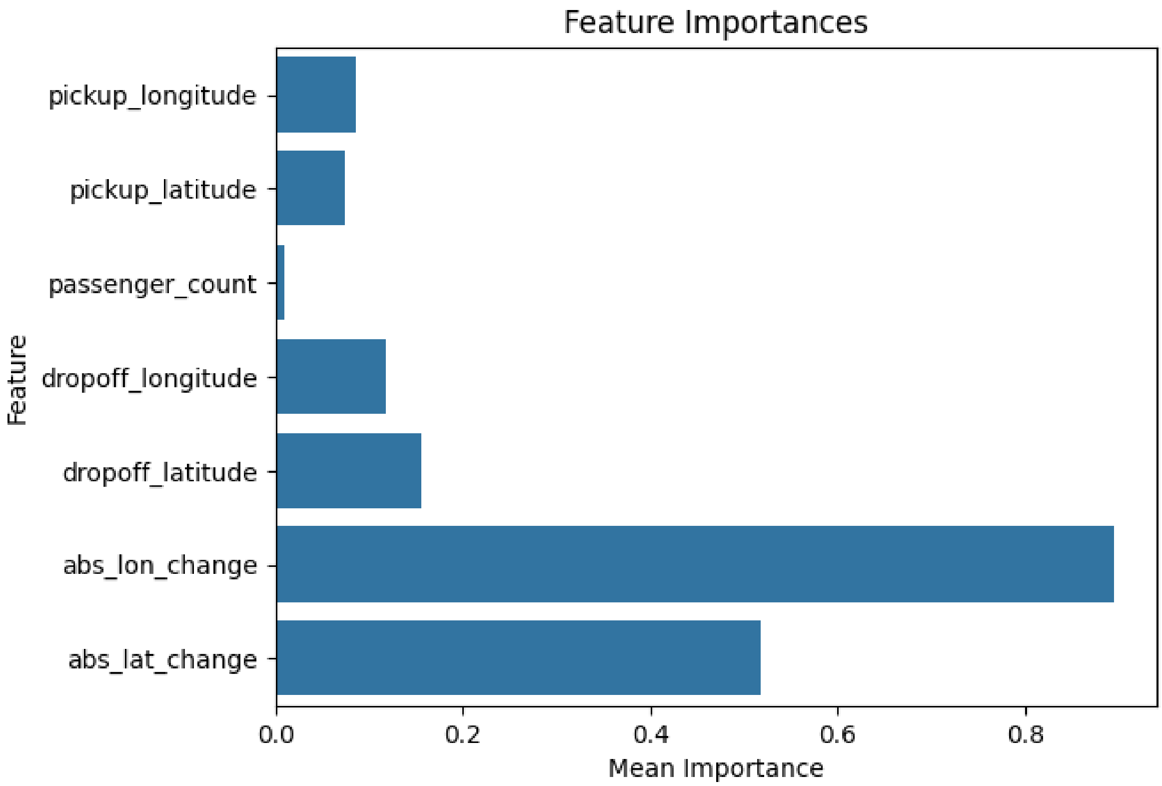
```
# reducing length of X
X_trimmed = X.iloc[:len(y)]
```

```
# create new features

data2['abs_lon_change'] = abs(data2.dropoff_longitude - data2.pickup_longitude)
data2['abs_lat_change'] = abs(data2.dropoff_latitude - data2.pickup_latitude)

features_2 = ['pickup_longitude',
                'pickup_latitude',
                 'dropoff_longitude',
                'dropoff_latitude',
                'passenger_count',
             'abs_lon_change',
             'abs_lat_change']
X= data2[features_2]

new_train_X, new_val_X, new_train_y, new_val_y = train_test_split(X, y, random_state = 1)
second_model = RandomForestRegressor(n_estimators = 50, random_state = 1).fit(new_train_X,
```

```
result2 = permutation_importance(second_model, new_train_X, new_train_y, n_repeats=30, ran
```

```
# resulting importances
importance_df2 = pd.DataFrame({'feature': features_2,
                          'importance_mean': result2.importances_mean,
                          'importance_std' : result2.importances_std})
importance_df2 = importance_df2.sort_values('feature',
                                          ascending = False)
```

```
# visualize
sns.barplot(x = 'importance_mean', y = 'feature', data= importance_df2)
plt.title('Feature Importances')
plt.xlabel('Mean Importance')
plt.ylabel('Feature')
plt.show()
```




```
X.describe()
```

	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	abs_
count	50000.000000	50000.000000	50000.000000	50000.000000	50000.000000	5000
mean	-72.509756	39.933759	-72.504616	39.926251	1.667840	0.151
std	10.393860	6.224857	10.407570	6.014737	1.289195	3.077
min	-75.423848	-74.006893	-84.654241	-74.006377	0.000000	0.000
25%	-73.992062	40.734880	-73.991152	40.734372	1.000000	0.005
50%	-73.981840	40.752678	-73.980082	40.753372	1.000000	0.012
75%	-73.967148	40.767360	-73.963584	40.768167	2.000000	0.023
max	40.783472	401.083332	40.851027	43.415190	6.000000	74.01

```
print(X.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
```

```
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   pickup_longitude   50000 non-null  float64
 1   pickup_latitude    50000 non-null  float64
 2   dropoff_longitude  50000 non-null  float64
 3   dropoff_latitude   50000 non-null  float64
 4   passenger_count    50000 non-null  int64  
 5   abs_lon_change     50000 non-null  float64
 6   abs_lat_change     50000 non-null  float64
dtypes: float64(6), int64(1)
memory usage: 2.7 MB
None
```

```
print(y.info())
```

```
<class 'pandas.core.series.Series'>
Index: 31289 entries, 2 to 49999
Series name: fare_amount
Non-Null Count  Dtype  
--------------  -----  
31289 non-null  float64
dtypes: float64(1)
memory usage: 488.9 KB
None
```