Tamas Flesch Thesis - Decision Tree step

LMJU - UpGrad - DS

Fifa 23 Ultimate Team player price prediction based on the player's attributes

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Imports

```
In [2]: # Importing the required libraries
   import pandas as pd, numpy as np
   import matplotlib.pyplot as plt, seaborn as sns
   %matplotlib inline
```

Read data

```
In [4]: # Reading the csv file and putting it into 'df' object.
df = pd.read_csv('futbin.csv')
```

Inspecting the data

```
In [5]: df.head()
```

Pace /

Shooting Passing Dribbling

Out[5]:

		Name	e Rating	Price	Skills_Star	Weak_	Foot_Sta	Pace / Diving	/ Handling	/ Kicking	/ Reflexes	/ S
	0	Pele	é 98	3270000.0	5		2	95.0	96	93	96	
	1	Lione Mess	98	4350000.0	4		2	93.0	98	97	99	
	2	Lione Mess	98	4640000.0	4		2	94.0	97	96	99	
	3	Karin Benzema	97	1850000.0	4		į	5 92.0	97	90	94	
	4	Kyliar Mbappe		9750000.0	5		2	99.0	96	88	98	
	5 rc	ows × 10)5 column	S								
4												•
In [32]:	df	_names	= df.pop(('Name')								
In [33]:	df	.head()										
Out[33]:		Rating	Price	Skills_Star	· Weak_Fo	ot_Star	Pace / Diving	Shooting / Handling	Passing / Kicking	Dribbling / Reflexes	Defense / Speed	P Pos
	0	98	3270000.0	5		4	95.0	96	93	96	60	
	1		4350000.0	4		4	93.0	98	97	99	40	
	2	98	4640000.0	4	ļ	4	94.0	97	96	99	40	
	3	97	1850000.0	4	ļ	5	92.0	97	90	94	45	
	4	97	9750000.0	5	,	4	99.0	96	88	98	44	
	5 rc	ows × 10	04 column	S								
4												•
In [34]:	df	_names.	head()									
Out[34]:	0 1 2 3 4 Na	Lio Kari Kyli	Pelé nel Messi nel Messi m Benzema an Mbappé e, dtype:	- - -								
	Вι	uild a d	lecision t	tree mod	del							
In [20]:	fr	om alala										
		OIII SKIE	arn.tree	import De	ecisionTre	eeRegre	essor					

```
np.random.seed(0)
In [35]:
          df_train, df_test = train_test_split(df, train_size=0.8, random_state=100)
          df train.shape, df test.shape
In [36]:
          ((5117, 104), (1280, 104))
Out[36]:
          df test.head()
In [37]:
                                                                Shooting Passing Dribbling
Out[37]:
                                                         Pace /
                                                                                            Defense
                                                                                                       Ph
                Rating Price Skills_Star Weak_Foot_Star
                                                        Diving
                                                                                            / Speed
                                                                                                     Posi
                                                                Handling
                                                                                   Reflexes
                                                                          Kicking
          2691
                    69 250.0
                                      3
                                                     3
                                                                                        62
                                                           60.0
                                                                      69
                                                                              51
                                                                                                 28
          3785
                    66 200.0
                                      3
                                                     3
                                                           73.0
                                                                      65
                                                                              49
                                                                                        66
                                                                                                 22
                    62 200.0
                                      0
                                                                                                 40
          4989
                                                     3
                                                           64.0
                                                                      61
                                                                              61
                                                                                        64
          1222
                    75 450.0
                                      3
                                                     3
                                                           53.0
                                                                                        79
                                                                                                 61
                                                                      53
                                                                              74
                                      2
                    66 200.0
                                                                                        64
                                                                                                 65
          3640
                                                     3
                                                           65.0
                                                                      61
                                                                              58
          5 rows × 104 columns
In [38]:
          scaler = MinMaxScaler()
          df train['Price'] = scaler.fit transform(df train[['Price']])
In [39]:
          df test['Price'] = scaler.transform(df test[['Price']])
          df_train.Price.describe()
In [40]:
                    5117.000000
          count
Out[40]:
                       0.001729
          mean
          std
                       0.022844
                       0.000000
          min
          25%
                       0.000000
          50%
                       0.000010
          75%
                       0.000053
                       1.000000
          max
          Name: Price, dtype: float64
In [41]:
          y train = df train.pop("Price")
          X_{train} = df_{train}
          y_test = df_test.pop("Price")
          X_{\text{test}} = df_{\text{test}}
          X_test.shape, X_train.shape
In [42]:
          ((1280, 103), (5117, 103))
Out[42]:
```

Fit the DT model

```
dt.fit(X_train, y_train)
In [43]:
               DecisionTreeRegressor(max_depth=4, min_samples_leaf=10, random_state=42)
Out[43]:
In [44]:
               from IPython.display import Image
                from six import StringIO
                from sklearn.tree import export graphviz
                import pydotplus, graphviz
                dot data = StringIO()
                export_graphviz(dt, out_file=dot_data, filled=True, rounded=True,
                                          feature names=X train.columns)
                graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
                Image(graph.create png())
                                                                                     Rating <= 94.5
squared_error = 0.001
samples = 5117
value = 0.002
Out[44]:
                                                                             Rating <= 91.5
squared_error = 0.0
samples = 5101
value = 0.001
                                                                Rating <= 89.5
squared_error = 0.0
samples = 5045
value = 0.0
                                                                                          Popularity <= 1135.0
squared_error = 0.004
samples = 56
value = 0.043
                                                               Pace / Diving <= 90.5
squared_error = 0.0
samples = 83
value = 0.013
                                                                                          Pace / Diving <= 91.5
squared_error = 0.001
samples = 33
value = 0.02
                                                                                                                          Pace / Diving <= 89.5
squared_error = 0.007
samples = 23
value = 0.076
                                 Rating <= 86.5
squared_error = 0.0
samples = 4962
value = 0.0
                                                  squared_error = 0.0
samples = 60
value = 0.007
                                                                   squared_error = 0.001
samples = 23
value = 0.026
                                                                                                                                             squared_error = 0.01
samples = 11
value = 0.121
                                                                                                        squared_error = 0.001
samples = 13
value = 0.033
                squared_error = 0.0
samples = 4780
value = 0.0
In [45]:
               y_train_pred = dt.predict(X_train)
In [47]:
                from sklearn.metrics import r2 score
In [48]:
                r2_score(y_train, y_train_pred)
               0.46511633392209173
Out[48]:
In [49]:
               y_test_pred = dt.predict(X_test)
In [50]:
                r2_score(y_test, y_test_pred)
               0.41381406125743336
Out[50]:
               Using Random Forest Regressor
                from sklearn.ensemble import RandomForestRegressor
In [51]:
                rf = RandomForestRegressor(random_state=42, n_jobs=-1, max_depth=5, min_samples_leaf=1
In [52]:
                rf.fit(X_train, y_train)
In [53]:
```

```
tamas_flesch_thesis project_decision_tree_step
          RandomForestRegressor(max_depth=5, min_samples_leaf=10, n_jobs=-1,
Out[53]:
                                 random state=42)
In [54]:
          sample_tree = rf.estimators_[20]
In [55]:
          dot data = StringIO()
          export graphviz(sample tree, out file=dot data, filled=True, rounded=True,
                          feature_names=X_train.columns)
          graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
          Image(graph.create png())
Out[55]:
         y_train_pred = rf.predict(X_train)
In [56]:
          y_test_pred = rf.predict(X_test)
          r2_score(y_train, y_train_pred)
In [57]:
         0.4665518871340596
Out[57]:
In [58]:
          r2_score(y_test, y_test_pred)
         0.6085673962637769
Out[58]:
In [59]:
          rf.feature_importances_
```

```
array([8.63107840e-01, 4.11047310e-03, 0.00000000e+00, 2.35199905e-02,
Out[59]:
                 1.84573743e-04, 7.48589702e-03, 7.71977045e-02, 3.47173992e-04,
                 4.02122200e-04, 1.96892230e-02, 3.62010511e-04, 9.44533176e-04,
                 4.62558964e-06, 4.77114424e-04, 8.55871299e-04, 5.08042821e-05,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 4.59991441e-07, 3.69134191e-04, 5.66323717e-04,
                 0.0000000e+00, 0.0000000e+00, 3.23781650e-07, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.0000000e+00, 0.00000000e+00,
                 0.00000000e+00, 2.36985890e-05, 2.04145436e-04, 2.39002353e-07,
                 0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 3.12153841e-05,
                 0.00000000e+00, 0.00000000e+00, 5.30923721e-05, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.0000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 1.14105389e-05,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00])
In [60]:
          imp df = pd.DataFrame({
              "Varname": X train.columns,
              "Imp": rf.feature importances })
          imp_df.sort_values(by="Imp", ascending=False)
In [61]:
Out[61]:
                              Varname
                                           Imp
            0
                                 Rating
                                       0.863108
                       Dribbling / Reflexes
            6
                                       0.077198
            3
                           Pace / Diving
                                       0.023520
            9
                              Popularity
                                       0.019689
            5
                         Passing / Kicking
                                       0.007486
           43
                     BodyType_Text_Messi
                                       0.000000
           42
                      BodyType Text Lean
                                       0.000000
           41
              BodyType_Text_High & Stocky
                                       0.000000
           40
                BodyType_Text_High & Lean
                                       0.000000
          102
                        Alt_Pos_3_missing
                                       0.000000
```

103 rows × 2 columns

Grid search for hyper-parameter tuning

```
#from sklearn.ensemble import RandomForestClassifier
In [62]:
          from sklearn.model selection import GridSearchCV
          classifier rf = RandomForestRegressor(random state=42, n jobs=-1)
In [63]:
In [64]:
          # Create the parameter grid based on the results of random search
          params = {
               'max_depth': [5, 8, 10, 13, 15, 17, 20],
               'min samples leaf': [5, 10, 20, 50, 100],
               'max features': [2,3,4],
               'n_estimators': [10, 30, 50, 100, 200]
          }
          # Instantiate the grid search model
In [85]:
          # cv=4 -> 4-fold cross validation schema
          grid search = GridSearchCV(estimator=RandomForestRegressor(), param grid=params,
                                      cv=10, n_jobs=-1, verbose=1, scoring = "r2", error_score="ra"
          X train.head()
In [70]:
Out[70]:
                                                        Shooting Passing Dribbling
                                                 Pace /
                                                                                    Defense
                                                                                              Physical /
                Rating Skills_Star Weak_Foot_Star
                                                 Diving
                                                                                            Positioning
                                                                                    / Speed
                                                                           Reflexes
                                                        Handling
                                                                  Kicking
          2556
                    69
                               2
                                              3
                                                   68.0
                                                              64
                                                                                         66
                                                                                                    71
                                                                      65
                                                                                68
          5208
                    61
                               2
                                              3
                                                   37.0
                                                              27
                                                                      39
                                                                                         58
                                                                                                    71
                                                                                39
          2567
                    69
                               2
                                              2
                                                   68.0
                                                              37
                                                                      63
                                                                                         67
                                                                                                    68
                                                                                66
          3412
                    67
                               3
                                              4
                                                   77.0
                                                                                67
                                                                                         29
                                                              66
                                                                      56
                                                                                                    56
          2673
                    69
                               2
                                              3
                                                   73.0
                                                              67
                                                                      65
                                                                                70
                                                                                         36
                                                                                                    55
         5 rows × 103 columns
In [71]:
          y_train.head()
                  0.000043
          2556
Out[71]:
          5208
                  0.000653
          2567
                  0.000113
          3412
                  0.000027
                  0.000017
          2673
          Name: Price, dtype: float64
In [81]:
          X train.shape
          (5117, 103)
Out[81]:
In [82]:
          y train.shape
          (5117,)
Out[82]:
          %%time
In [86]:
          grid_search.fit(X_train,y_train)
```

```
Fitting 10 folds for each of 525 candidates, totalling 5250 fits
         CPU times: total: 25.4 s
         Wall time: 7min 48s
         GridSearchCV(cv=10, error_score='raise',
Out[86]:
                      estimator=RandomForestRegressor(n jobs=-1, random state=42),
                      n jobs=-1,
                      param grid={'max depth': [5, 8, 10, 13, 15, 17, 20],
                                   'max_features': [2, 3, 4],
                                   'min_samples_leaf': [5, 10, 20, 50, 100],
                                   'n estimators': [10, 30, 50, 100, 200]},
                      scoring='r2', verbose=1)
         rf_best = grid_search.best_estimator_
In [87]:
         rf best
In [88]:
         RandomForestRegressor(max_depth=10, max_features=4, min_samples_leaf=5,
Out[88]:
                                n estimators=200, n jobs=-1, random state=42)
         y train pred = rf best.predict(X train)
In [89]:
         y_test_pred = rf_best.predict(X_test)
         r2_score(y_train, y_train_pred)
In [90]:
         0.42985622276084756
Out[90]:
         r2_score(y_test, y_test_pred)
In [91]:
         0.43889540025568174
Out[91]:
In [92]:
         rf_best.feature_importances_
         array([1.27692642e-01, 4.83770707e-02, 1.59748454e-02, 7.20043965e-02,
Out[92]:
                 1.25897401e-01, 6.42622827e-02, 1.44817704e-01, 2.91795004e-02,
                2.34158031e-02, 5.72564589e-02, 6.34699221e-02, 6.74117801e-02,
                1.84441807e-02, 9.71723894e-03, 1.29137152e-02, 3.04718328e-03,
                1.73705341e-04, 2.03632739e-04, 8.11418527e-04, 1.51815146e-03,
                5.67718424e-05, 4.88507780e-05, 1.98656505e-05, 3.95510989e-03,
                5.93939023e-06, 3.87282426e-04, 1.68129795e-04, 6.87949271e-05,
                 3.80398324e-06, 4.95817141e-03, 2.84880037e-03, 1.50803630e-03,
                3.05452165e-05, 2.59960910e-03, 8.65948284e-03, 2.93119221e-03,
                0.00000000e+00, 0.00000000e+00, 5.23205658e-04, 1.32026536e-04,
                0.00000000e+00, 6.17288287e-05, 7.75539661e-04, 0.00000000e+00,
                0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                2.88387919e-06, 6.88842143e-05, 5.63710998e-07, 2.78378520e-05,
                6.65866942e-03, 2.54568151e-02, 4.19120803e-04, 5.38554725e-03,
                2.72782966e-05, 7.62377128e-03, 9.41663787e-04, 2.51730785e-04,
                3.51470124e-04, 5.85266245e-03, 3.27916229e-04, 5.31958718e-03,
                1.77003759e-04, 7.05235981e-06, 4.09450579e-04, 9.20927124e-03,
                1.01654689e-04, 1.66282089e-05, 1.76081732e-03, 1.45226799e-06,
                1.26045267e-05, 6.03409815e-05, 5.95764833e-04, 8.38360790e-06,
                8.82600803e-05, 3.80730845e-04, 1.41696119e-03, 4.68024100e-07,
                1.03565768e-09, 3.25459223e-05, 1.67554247e-05, 2.54097029e-08,
                3.58939524e-04, 2.80577548e-03, 3.45847481e-07, 0.00000000e+00,
                1.96593675e-05, 8.52184913e-04, 2.81891856e-04, 5.30810895e-03,
                2.24765404e-08, 1.99289790e-06, 0.00000000e+00, 0.00000000e+00,
                7.54046813e-07, 3.89393230e-04, 1.67210044e-07, 0.000000000e+00,
                1.19433210e-08, 2.59899766e-07, 6.35997383e-04])
```

```
imp_df = pd.DataFrame({
In [93]:
                "Varname": X train.columns,
                "Imp": rf best.feature importances })
           imp df.sort values(by="Imp", ascending=False)
In [95]:
Out[95]:
                              Varname
                                           Imp
            6
                      Dribbling / Reflexes 0.144818
            0
                                Rating 0.127693
            4
                     Shooting / Handling 0.125897
            3
                           Pace / Diving 0.072004
           11
                           Ingame_Stats 0.067412
           87
                           Alt_Pos_2_RB 0.000000
           99
                          Alt_Pos_3_RM 0.000000
           37
                  BodyType_Text_Courtois 0.000000
           36
                      BodyType_Text_CR7 0.000000
           40 BodyType_Text_High & Lean 0.000000
          103 rows × 2 columns
           second grid search
            • max depth testing around 10

    max feature around 4

              sample leaf around 5

    estimator around 200

In [176...
           # Create the parameter grid based on the results of random search
           params = {
                'max_depth': [8, 9, 10, 11, 12, 13],
                'min_samples_leaf': [2,3,4,5,6,7,8],
                'max_features': [4,6,8,10],
                'n estimators': [100, 150, 200, 250, 300]
           }
           # Instantiate the grid search model
In [177...
           # cv=4 -> 4-fold cross validation schema
           grid search = GridSearchCV(estimator=RandomForestRegressor(), param grid=params,
                                       cv=10, n jobs=-1, verbose=1, scoring = "r2", error score="ra
           %%time
In [98]:
           grid_search.fit(X_train,y_train)
           Fitting 10 folds for each of 840 candidates, totalling 8400 fits
           CPU times: total: 39.3 s
           Wall time: 41min 22s
```

```
tamas_flesch_thesis project_decision_tree_step
          GridSearchCV(cv=10, error_score='raise',
 Out[98]:
                        estimator=RandomForestRegressor(n jobs=-1, random state=42),
                        n jobs=-1,
                        param_grid={'max_depth': [8, 9, 10, 11, 12, 13],
                                     'max features': [4, 6, 8, 10],
                                     'min_samples_leaf': [2, 3, 4, 5, 6, 7, 8],
                                     'n estimators': [100, 150, 200, 250, 300]},
                        scoring='r2', verbose=1)
          rf best = grid search.best estimator
 In [99]:
           rf best
In [100...
          RandomForestRegressor(max depth=8, max features=8, min samples leaf=2,
Out[100]:
                                 n jobs=-1, random state=42)
          y_train_pred = rf_best.predict(X_train)
In [102...
          y test pred = rf best.predict(X test)
In [103...
           r2_score(y_train, y_train_pred)
          0.7268290034088154
Out[103]:
In [104...
           r2_score(y_test, y_test_pred)
          0.6122313567377293
Out[104]:
In [105...
           rf best.feature importances
          array([1.38489015e-01, 4.66858447e-02, 1.51138366e-02, 8.28239884e-02,
Out[105]:
                  1.08141260e-01, 5.74164927e-02, 1.26643262e-01, 3.73862489e-02,
                  2.83327822e-02, 4.88247605e-02, 5.54882980e-02, 4.12670687e-02,
                  1.53507463e-02, 1.37700267e-02, 1.60956680e-02, 2.00895569e-03,
                  1.26215167e-04, 6.95812904e-06, 1.30401345e-03, 1.33142932e-03,
                  9.07435426e-05, 1.82934812e-04, 6.30403671e-05, 1.51820461e-02,
                  1.25060262e-06, 4.52118325e-05, 2.80795915e-04, 1.16865943e-04,
                  2.21889599e-07, 9.76897426e-03, 2.31602367e-03, 1.17541680e-04,
                  1.33593246e-05, 2.19611689e-03, 1.77063715e-02, 4.95317456e-03,
                  0.00000000e+00, 0.00000000e+00, 2.81857258e-04, 2.38660430e-05,
                  2.92761059e-07, 7.57767917e-09, 7.08016776e-04, 5.55441104e-03,
                  0.00000000e+00, 2.16383224e-02, 0.00000000e+00, 0.00000000e+00,
                  2.83678825e-06, 1.11221718e-05, 1.28650138e-07, 3.47949213e-06,
                  7.19721972e-03, 1.79522994e-02, 1.61142358e-04, 6.74598724e-03,
                  8.03629055e-05, 1.20973113e-03, 2.06139183e-03, 6.32214843e-05,
                  1.32951783e-04, 3.92989831e-03, 9.04149985e-06, 4.41874535e-03,
                  2.76849241e-04, 2.83567090e-06, 1.32693296e-03, 6.05009338e-03,
                  3.58926598e-04, 2.21020250e-05, 1.22392886e-02, 5.34552132e-10,
                  9.55474349e-05, 1.50988231e-04, 1.61348511e-03, 3.23384668e-05,
                  4.40615221e-05, 3.01687466e-04, 7.27018012e-04, 0.00000000e+00,
                  0.00000000e+00, 1.58692422e-07, 8.16173342e-06, 2.19814835e-06,
                  7.60430400e-04, 1.49256156e-03, 3.25608299e-07, 5.71065547e-09,
                  9.13209993e-09, 1.11797017e-04, 1.46286353e-04, 7.17550745e-03,
                  1.13647612e-09, 2.32284173e-05, 0.00000000e+00, 0.00000000e+00,
                  7.38528353e-06, 9.10773651e-04, 2.26690642e-09, 0.00000000e+00,
                  4.46735026e-06, 3.73632595e-07, 4.28629382e-03])
In [106...
           imp df = pd.DataFrame({
               "Varname": X train.columns,
               "Imp": rf best.feature importances })
```

0 Rating 0.138489 6 Dribbling / Reflexes 0.126643 Shooting / Handling 0.108141 3 Pace / Diving 0.082824 5 Passing / Kicking 0.057416 80 Alt_Pos_2_CDM 0.000000 95 Alt_Pos_3_LB 0.000000 BodyType_Text_R9 0.000000 44 **46** BodyType_Text_Salah 0.000000 94 Alt_Pos_3_CM 0.000000

103 rows × 2 columns

third grid search

```
In [108...
           # Create the parameter grid based on the results of random search
               'max_depth': [8, 9, 10],
               'min_samples_leaf': [1,2,3],
               'max features': [7,8,9,10],
               'n estimators': [100, 150, 200, 250, 300]
In [110...
           # Instantiate the grid search model
           # cv=4 -> 4-fold cross validation schema
           grid_search = GridSearchCV(estimator=RandomForestRegressor(), param_grid=params,
                                     cv=10, n jobs=-1, verbose=2, scoring = "r2", error score="ra
          %%time
In [111...
           grid_search.fit(X_train,y_train)
          Fitting 10 folds for each of 180 candidates, totalling 1800 fits
          CPU times: total: 8.41 s
          Wall time: 8min 35s
          GridSearchCV(cv=10, error_score='raise', estimator=RandomForestRegressor(),
Out[111]:
                        n jobs=-1,
                        param_grid={'max_depth': [8, 9, 10], 'max_features': [7, 8, 9, 10],
                                     'min_samples_leaf': [1, 2, 3],
                                     'n_estimators': [100, 150, 200, 250, 300]},
                        scoring='r2', verbose=2)
          rf_best = grid_search.best_estimator_
In [112...
```

```
rf_best
In [113...
           RandomForestRegressor(max_depth=9, max_features=10, min_samples_leaf=2)
Out[113]:
           y train pred = rf best.predict(X train)
In [114...
           y_test_pred = rf_best.predict(X_test)
           r2 score(y train, y train pred)
In [115...
          0.755998374506422
Out[115]:
In [116...
           r2_score(y_test, y_test_pred)
          0.6320821355740586
Out[116]:
          forth gridsearch
In [117...
           # Create the parameter grid based on the results of random search
           params = {
               'max_depth': [8, 9, 10],
               'min_samples_leaf': [1,2,3],
               'max features': [10,20,30,40],
               'n estimators': [100,200,300]
           }
           grid_search = GridSearchCV(estimator=RandomForestRegressor(), param_grid=params,
In [119...
                                      cv=10, n_jobs=-1, verbose=2, scoring = "r2", error_score="rates"
In [120...
           %%time
           grid search.fit(X train,y train)
          Fitting 10 folds for each of 108 candidates, totalling 1080 fits
          CPU times: total: 6.23 s
          Wall time: 9min 41s
          GridSearchCV(cv=10, error_score='raise', estimator=RandomForestRegressor(),
Out[120]:
                        n jobs=-1,
                        param grid={'max depth': [8, 9, 10],
                                     'max_features': [10, 20, 30, 40],
                                     'min_samples_leaf': [1, 2, 3],
                                     'n estimators': [100, 200, 300]},
                        scoring='r2', verbose=2)
In [121...
           rf_best = grid_search.best_estimator_
           rf_best
In [122...
           RandomForestRegressor(max_depth=10, max_features=10, min_samples_leaf=2,
Out[122]:
                                  n estimators=200)
           y_train_pred = rf_best.predict(X_train)
In [123...
           y test pred = rf best.predict(X test)
In [124...
           r2_score(y_train, y_train_pred)
          0.7601409765037306
Out[124]:
```

```
r2_score(y_test, y_test_pred)
In [125...
          0.5793143634800904
Out[125]:
          fifth gridsearch
           # Create the parameter grid based on the results of random search
In [126...
               'max_depth': [8,9,10,11],
               'min_samples_leaf': [1,2,3],
               'max_features': [9,10,11,12],
               'n estimators': [150,200,250]
           grid search = GridSearchCV(estimator=RandomForestRegressor(), param grid=params,
In [127...
                                      cv=10, n_jobs=-1, verbose=2, scoring = "r2", error_score="rates"
In [128...
           %%time
           grid search.fit(X train,y train)
          Fitting 10 folds for each of 144 candidates, totalling 1440 fits
          CPU times: total: 6.61 s
          Wall time: 7min 52s
          GridSearchCV(cv=10, error_score='raise', estimator=RandomForestRegressor(),
Out[128]:
                        n jobs=-1,
                        param_grid={'max_depth': [8, 9, 10, 11],
                                     'max_features': [9, 10, 11, 12],
                                     'min samples leaf': [1, 2, 3],
                                     'n_estimators': [150, 200, 250]},
                        scoring='r2', verbose=2)
           rf best = grid search.best estimator
In [129...
           rf best
In [130...
           RandomForestRegressor(max depth=9, max features=10, n estimators=200)
Out[130]:
In [131...
           y train pred = rf best.predict(X train)
           y_test_pred = rf_best.predict(X_test)
In [132...
           r2_score(y_train, y_train_pred)
           0.9204138340558483
Out[132]:
           r2_score(y_test, y_test_pred)
In [133...
          0.6727454133535952
Out[133]:
           Final model after grid search
           rf = RandomForestRegressor(random_state=42, n_jobs=-1, max_depth=9, n_estimators=200,
In [166...
           rf.fit(X train, y train)
In [167...
```

```
RandomForestRegressor(max_depth=9, max_features=20, n_estimators=200, n_jobs=-1,
Out[167]:
                           random state=42)
         sample_tree = rf.estimators_[2]
In [168...
In [169...
         dot data = StringIO()
         export graphviz(sample tree, out file=dot data, filled=True, rounded=True,
                      feature_names=X_train.columns)
         graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
         Image(graph.create png())
Out[169]:
                                                             y train pred = rf.predict(X train)
In [170...
        y_test_pred = rf.predict(X_test)
In [171...
         r2_score(y_train, y_train_pred)
        0.9111099629582339
Out[171]:
In [172...
         r2_score(y_test, y_test_pred)
        0.6946316867354081
Out[172]:
         rf.feature importances
In [173...
```

```
tamas flesch thesis project decision tree step
          array([1.54227577e-01, 3.38025014e-02, 6.13521060e-03, 8.57044644e-02,
Out[173]:
                  9.32105450e-02, 3.49512604e-02, 1.28418526e-01, 3.77531647e-02,
                  1.37835014e-02, 4.18185863e-02, 4.12193749e-02, 3.46733427e-02,
                  1.68488482e-02, 1.44599500e-02, 8.03670500e-03, 1.09859057e-02,
                  1.10481212e-04, 9.16481082e-07, 3.02904448e-03, 7.34819817e-04,
                  8.84070374e-05, 2.85144951e-04, 1.36549923e-06, 1.26327298e-02,
                  1.53830061e-05, 1.41996130e-04, 9.62478940e-04, 1.93141729e-05,
                  3.23521504e-06, 3.55383930e-03, 4.86880557e-03, 7.02825543e-04,
                  1.25400345e-04, 2.12460059e-03, 8.77149995e-03, 3.19316754e-03,
                  5.27790193e-08, 0.00000000e+00, 1.48310230e-03, 1.81494113e-04,
                  6.16499733e-06, 2.43354677e-07, 7.88097204e-04, 7.13182824e-03,
                  3.55364412e-02, 7.36057306e-02, 1.13237740e-05, 0.00000000e+00,
                  5.86782212e-06, 2.68740766e-04, 5.62214915e-10, 3.32833972e-05,
                  6.32531925e-03, 9.40655932e-03, 7.35020932e-04, 6.00569782e-03,
                  1.59830095e-05, 8.61977285e-05, 2.41529934e-03, 6.86376700e-05,
                  9.53154197e-04, 3.76089087e-03, 6.04007599e-05, 2.38243433e-03,
                  4.12607711e-04, 4.41674367e-07, 9.74428991e-05, 6.25883367e-03,
                  2.44342043e-03, 7.07906689e-06, 1.42692791e-02, 9.48818672e-08,
                  1.10196878e-04, 2.09647352e-04, 2.49971385e-03, 7.49555006e-06,
                  1.18550056e-04, 2.11744875e-03, 2.42444882e-04, 9.44723831e-06,
                  0.00000000e+00, 1.20490703e-05, 7.77154166e-05, 2.57502802e-07,
                  2.18234774e-03, 7.69509295e-03, 4.07886068e-07, 9.14060277e-06,
                  1.57531629e-08, 1.68586791e-03, 4.10059193e-04, 2.67185498e-03,
                  3.07371070e-08, 7.52196774e-04, 0.00000000e+00, 0.00000000e+00,
                  7.65066083e-07, 2.55677591e-03, 0.00000000e+00, 0.00000000e+00,
                  6.07311500e-06, 1.49999476e-05, 4.45731962e-03])
In [174...
           imp df = pd.DataFrame({
               "Varname": X train.columns,
               "Imp": rf best.feature importances })
           imp_df.sort_values(by="Imp", ascending=False)
In [175...
Out[175]:
```

	Varname	Imp
6	Dribbling / Reflexes	1.332667e-01
0	Rating	1.013360e-01
4	Shooting / Handling	9.981897e-02
3	Pace / Diving	6.632334e-02
45	BodyType_Text_Ronaldinho	6.168733e-02
•••		
47	BodyType_Text_Shaqiri	1.665979e-10
99	Alt_Pos_3_RM	1.368178e-13
94	Alt_Pos_3_CM	0.000000e+00
95	Alt_Pos_3_LB	0.000000e+00
80	Alt_Pos_2_CDM	0.000000e+00

103 rows × 2 columns

```
In [ ]:
```