SEENG474_project

July 1, 2023

Introduction

There are many soccer players in the world with various skills and abilities. While some players are fast but weak, others are slow but strong. The main objective of our project is to predict soccer players' positions based on their skills, such as shooting, defending, passing, crossing, dribbling, ball control, heading, vision, agility, speed and many more features. We used logistic regression to predict a soccer player's position, and obtained a high accuracy despite the low possibilities, as there are more than 25 different positions in soccer.

In addition, we also performed predictive analysis regarding the shooting scores of the players. We wanted to see if we can use attacking, ball handling, and movement attributes of players to predict how well they can score.

Questions

Given various attributes of soccer players, can we accurately predict the positions of the player? If so, how accurate can our predictions be?

Can we accurately predict how well a player is at shooting given various attributes such as movement skills, attack skills, dribbling skills?

Is it actually possible for any kind of model to predict the position of each soccer player accurately?

Which models are best at predicting positions of players/shooting scores of players?

Can the model predict a more well-suited position than what a player currently has? For example if a player is RB, but our model detects that the player is LB, does that mean the player has attributes more well-suited for LB?

[40]:
```
import numpy as np
import pandas as pd
import warnings

warnings.filterwarnings('ignore')

df = pd.read_csv("players_15.csv")
# You can pick other datasets to analyze players from different years␣
↪(2016-2019)
# df = pd.read_csv("players_16.csv")
# df = pd.read_csv("players_17.csv")
# df = pd.read_csv("players_18.csv")
# df = pd.read_csv("players_19.csv")
```

```
df.head()
```

[40]:
```
   sofifa_id                                         player_url  \
0     158023  https://sofifa.com/player/158023/lionel-messi/…
1      20801  https://sofifa.com/player/20801/c-ronaldo-dos-…
2       9014  https://sofifa.com/player/9014/arjen-robben/15…
3      41236  https://sofifa.com/player/41236/zlatan-ibrahim…
4     167495  https://sofifa.com/player/167495/manuel-neuer/…

          short_name                            long_name  age         dob  \
0           L. Messi       Lionel Andrés Messi Cuccittini   27  1987-06-24
1  Cristiano Ronaldo  Cristiano Ronaldo dos Santos Aveiro   29  1985-02-05
2          A. Robben                         Arjen Robben   30  1984-01-23
3      Z. Ibrahimović                    Zlatan Ibrahimović   32  1981-10-03
4           M. Neuer                         Manuel Neuer   28  1986-03-27

   height_cm  weight_kg  nationality            club_name  …   lwb   ldm  \
0        169         67    Argentina         FC Barcelona  …  62+3  62+3
1        185         80     Portugal          Real Madrid  …  63+3  63+3
2        180         80  Netherlands    FC Bayern München  …  64+3  64+3
3        195         95       Sweden  Paris Saint-Germain  …  61+3  65+3
4        193         92      Germany    FC Bayern München  …  36+3  40+3

    cdm   rdm   rwb    lb   lcb    cb   rcb    rb
0  62+3  62+3  62+3  54+3  45+3  45+3  45+3  54+3
1  63+3  63+3  63+3  57+3  52+3  52+3  52+3  57+3
2  64+3  64+3  64+3  55+3  46+3  46+3  46+3  55+3
3  65+3  65+3  61+3  56+3  55+3  55+3  55+3  56+3
4  40+3  40+3  36+3  36+3  38+3  38+3  38+3  36+3

[5 rows x 106 columns]
```

[17]:
```
# Get raw dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16155 entries, 0 to 16154
Columns: 106 entries, sofifa_id to rb
dtypes: float64(18), int64(44), object(44)
memory usage: 13.1+ MB
```

[18]:
```
# Get description of each feature and the values they contain
df.describe()
```

[18]:
```
            sofifa_id           age     height_cm     weight_kg   league_rank  \
count    16155.000000  16155.000000  16155.000000  16155.000000  15916.000000
mean    189284.184525     24.776230    181.083627     75.474342      1.378424
```

```
std     39749.261554    4.625321    6.618974    6.891796    0.736796
min         2.000000   16.000000  155.000000   50.000000    1.000000
25%    178042.500000   21.000000  176.000000   70.000000    1.000000
50%    200841.000000   24.000000  181.000000   75.000000    1.000000
75%    214346.000000   28.000000  186.000000   80.000000    2.000000
max    225562.000000   44.000000  204.000000  110.000000    4.000000

            overall     potential     value_eur       wage_eur  \
count  16155.000000  16155.000000  1.615500e+04   16155.000000
mean      63.830393     68.350108  1.060882e+06   13056.453110
std        7.169896      6.580610  2.819128e+06   23488.182571
min       40.000000     40.000000  0.000000e+00       0.000000
25%       59.000000     64.000000  1.200000e+05    2000.000000
50%       64.000000     68.000000  3.500000e+05    5000.000000
75%       68.000000     73.000000  8.250000e+05   10000.000000
max       93.000000     95.000000  1.005000e+08  550000.000000

       international_reputation  …  mentality_penalties  \
count              16155.000000  …         16155.000000
mean                   1.122501  …            49.648344
std                    0.396263  …            14.552244
min                    1.000000  …            20.000000
25%                    1.000000  …            39.000000
50%                    1.000000  …            50.000000
75%                    1.000000  …            61.000000
max                    5.000000  …            95.000000

       mentality_composure  defending_marking  defending_standing_tackle  \
count                  0.0       16155.000000               16155.000000
mean                   NaN          45.009037                  47.656639
std                    NaN          17.915206                  18.743105
min                    NaN          20.000000                  20.000000
25%                    NaN          25.000000                  25.000000
50%                    NaN          46.000000                  52.000000
75%                    NaN          61.000000                  64.000000
max                    NaN          90.000000                  91.000000

       defending_sliding_tackle  goalkeeping_diving  goalkeeping_handling  \
count              16155.000000        16155.000000          16155.000000
mean                  45.885918           15.869514             15.511668
std                   18.145497           17.576799             16.414173
min                   20.000000            1.000000              1.000000
25%                   25.000000            8.000000              8.000000
50%                   49.000000           11.000000             11.000000
75%                   62.000000           13.000000             14.000000
max                   95.000000           88.000000             87.000000
```

```
       goalkeeping_kicking  goalkeeping_positioning  goalkeeping_reflexes
count         16155.000000             16155.000000          16155.000000
mean             15.354875                15.504735             15.998514
std              16.010498                16.585081             17.983209
min               1.000000                 1.000000              1.000000
25%               8.000000                 8.000000              8.000000
50%              11.000000                10.000000             10.000000
75%              13.000000                13.000000             13.000000
max              92.000000                90.000000             90.000000

[8 rows x 62 columns]
```

Data Cleaning (1) The data sets we decided to use required some cleaning before we could get to the models and predictions.

The first step of the cleaning process was simply to drop the features that would not be usable/useful in our model. We did end up dropping some columns that may have been useful in the models, these are: short_name: We wanted to predict the position for a specific player but we realized that this column has no affect and simply we could just include the stats of the player in the prediction process. player_tags/player_traits: The tags just simply gives us our answer for the position that player is known for, this however is not useful to predict positions for a NEW player that is not in the dataset before. Also we wanted to focus on predicting the player position based on their current reported skills and not some tags already associated with them. work_rate: This column gets dropped later on after it gets split into attacking work rate and defending work rate which is more useful in the model for increased accuracy in predicting whether a player is assigned a defensive or offensive position.

Other features we considered dropping were: weight, height, age: we dropped these features and ran the model but did not see any significant improvement in our scores so we decided to leave them in for the final report.

[19]:
```
columns_to_drop = ['sofifa_id', 'player_url', 'short_name', 'long_name', 'dob',
            'nationality', 'club_name', 'league_name', 'league_rank',␣
 ↪'real_face',
            'release_clause_eur', 'player_tags', 'team_jersey_number',
             'loaned_from', 'joined', 'contract_valid_until',
            'nation_position', 'nation_jersey_number', 'gk_diving',␣
 ↪'gk_handling',
            'gk_kicking', 'gk_reflexes', 'gk_speed', 'gk_positioning',␣
 ↪'player_traits',
            'mentality_composure', 'goalkeeping_diving', 'goalkeeping_handling',
            'goalkeeping_kicking', 'goalkeeping_positioning',␣
 ↪'goalkeeping_reflexes',
            'ls', 'st', 'rs', 'lw', 'lf', 'cf', 'rf', 'rw', 'lam', 'cam', 'ram',␣
 ↪'lm', 'lcm', 'cm', 'rcm', 'rm',
             'lwb', 'ldm', 'cdm', 'rdm', 'rwb', 'lb', 'lcb', 'cb', 'rcb', 'rb',␣
 ↪'value_eur', 'wage_eur', 'work_rate']
```

Data Cleaning (2) The next step in the cleaning process was to decide what we were going to do with the player_positions feature, this is our initial planned target feature we want to predict.

The player_positions column contains a comma-separated string of positions that the player has played. We found that players can play in multiple positions, such as LB,CB,and RB which in general are positions in defense. We interpreted this as a list of positions a player can play, not necessarily their best positions, so in the data we only kept one position from the list for each player as the model is supposed to predict the "BEST" position for each player based on their stats and not be biased by their position list. In the end we expected this to not negatively affect our results as if a players positions were all defensive for instance, they should still be predicted as a defensive position if their stats reflect those of a defensive player.

[20]:
```
df_copy = df.copy()

for i in range(len(df.player_positions)):
    df_copy.player_positions[i] = df_copy.player_positions[i].split(',')
    df.player_positions[i] = df_copy.player_positions[i][0]

print(df['player_positions'])
```

```
0        CF
1        LW
2        RM
3        ST
4        GK
         ..
16150    CB
16151    ST
16152    LM
16153    CB
16154    CM
Name: player_positions, Length: 16155, dtype: object
```

Data Cleaning (3) Next up we removed any rows where there was only data for goal keepers as we are not predicting this position as it has a different set of skills and stats per player, and vice versa for non goal keeper players not having stats filled for any of the goal keeping features, so we decided to split the data set into GK and non-GK and only focused on non-GK for this project (some future work can include predicting for this position as well).

Here we also do the ppreviously mentioned splitting of the work_rate column before dropping it. We are simply splitting it into work_rate_atk, and work_rate_def for easier encoding later on.

finally we drop the columns marked to be dropped and also fill some missing values for positions on teams that are empty with a position called "No position" so we can also encode it later.

[21]:
```
df = df[df.team_position != 'GK']
work_rate_combo = df['work_rate']

work_rate_atk = []
work_rate_def = []
```

```python
for item in work_rate_combo:
    split = item.split('/', 1)
    work_rate_atk.append(split[0])
    work_rate_def.append(split[1])

df['work_rate_atk'] = work_rate_atk
df['work_rate_def'] = work_rate_def

df = df.drop(columns_to_drop, axis=1)
df['team_position'] = df['team_position'].fillna('No position')

df.head()
```

[21]:

```
   age  height_cm  weight_kg  overall  potential player_positions  \
0   27        169         67       93         95               CF
1   29        185         80       92         92               LW
2   30        180         80       90         90               RM
3   32        195         95       90         90               ST
5   27        181         81       89         91               ST

  preferred_foot  international_reputation  weak_foot  skill_moves  …  \
0           Left                         5          3            4  …
1          Right                         5          4            5  …
2           Left                         5          2            4  …
3          Right                         5          4            4  …
5          Right                         5          4            4  …

  mentality_aggression mentality_interceptions  mentality_positioning  \
0                   48                      22                     92
1                   63                      24                     91
2                   47                      39                     89
3                   84                      20                     86
5                   78                      41                     88

   mentality_vision  mentality_penalties  defending_marking  \
0                90                   76                 25
1                81                   85                 22
2                84                   80                 29
3                83                   91                 25
5                84                   85                 30

   defending_standing_tackle  defending_sliding_tackle  work_rate_atk  \
0                         21                        20         Medium
1                         31                        23           High
2                         26                        26           High
3                         41                        27         Medium
```

```
5                         45                         38            High

   work_rate_def
0            Low
1            Low
2            Low
3            Low
5         Medium

[5 rows x 48 columns]
```

Pipelines (1) Below we set up the numerical and catagorical pipelines for encoding the features.

for the numerical pipeline we kept it simple, only imputing with median value strategy and scaling using standardScaler().

for the catagorical pipeline we impute with “most frequent” as we found this to be sufficient, and then oneHotEncoder() for encoding the values.

[8]:
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
num_attribs = ["age", "height_cm", "weight_kg", "overall", "potential",␣
 ↪"international_reputation", "weak_foot", "skill_moves",
              "power_strength", "power_long_shots", "mentality_aggression",␣
 ↪"mentality_interceptions", "mentality_positioning", "mentality_vision",
              "mentality_penalties", "defending_marking",␣
 ↪"defending_standing_tackle", "defending_sliding_tackle"]

num_pipeline = make_pipeline(SimpleImputer(strategy="median"), StandardScaler())

cat_attribs = ["preferred_foot", "body_type", "work_rate_atk", "work_rate_def"]

cat_pipeline = make_pipeline(
    SimpleImputer(strategy="most_frequent"),
    OneHotEncoder(handle_unknown="ignore"))

preprocessing = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", cat_pipeline, cat_attribs)])

preprocessing
```

[8]:
```
ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('simpleimputer',
```

```
SimpleImputer(strategy='median')),
                                                  ('standardscaler',
                                                   StandardScaler())]),
                                 ['age', 'height_cm', 'weight_kg', 'overall',
                                  'potential', 'international_reputation',
                                  'weak_foot', 'skill_moves', 'power_strength',
                                  'power_long_shots', 'mentality_aggression',
                                  'mentality_interceptions',
                                  'mentality_positioning', 'mentality_vision',
                                  'mentality_penalties', 'defending_marking',
                                  'defending_standing_tackle',
                                  'defending_sliding_tackle']),
                                ('cat',
                                 Pipeline(steps=[('simpleimputer',
SimpleImputer(strategy='most_frequent')),
                                                  ('onehotencoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                 ['preferred_foot', 'body_type',
                                  'work_rate_atk', 'work_rate_def'])])
```

Model (1) To predict positions we went with logistic regression and split our dataset into 50/50 train and test sets and specify max_iter=1000

and train/fit the model on the training set.

[22]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

train, test = train_test_split(df, stratify=df['player_positions'],␣
 ↪train_size=0.5)
log_reg = make_pipeline(preprocessing, LogisticRegression(max_iter=1000))

y = train['player_positions']
X = train.drop(['player_positions'], axis=1)
log_reg.fit(X, y)
```

[22]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('num',
Pipeline(steps=[('simpleimputer',
SimpleImputer(strategy='median')),
('standardscaler',
StandardScaler())]),
                                                  ['age', 'height_cm',
                                                   'weight_kg', 'overall',
                                                   'potential',
                                                   'international_reputation',
                                                   'weak_foot', 'skill_moves',
                                                   'power_strength',
```

```
                                                   'power_long_shots',
                                                   'mentality_aggression',
                                                   'men…
                                                   'mentality_penalties',
                                                   'defending_marking',
                                                   'defending_standing_tackle',
                                                   'defending_sliding_tackle']),
                                                 ('cat',
Pipeline(steps=[('simpleimputer',
SimpleImputer(strategy='most_frequent')),
('onehotencoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['preferred_foot',
                                                   'body_type', 'work_rate_atk',
                                                   'work_rate_def'])])),
                ('logisticregression', LogisticRegression(max_iter=1000))])
```

Below is a snippet of the results from the prediction using log_reg.predict() with the test data set predictions are saved in a new column in the data set df["predicted"]

[23]:
```
y_test = test['player_positions']
X_test = test.drop(['player_positions'], axis=1)
test["predicted"] = log_reg.predict(X_test)
test.head()
```

[23]:

	age	height_cm	weight_kg	overall	potential	player_positions	\
4092	20	188	83	68	74	CB	
13583	25	180	70	57	60	RB	
10667	20	180	82	61	64	LM	
14443	21	185	75	55	60	ST	
11554	23	172	68	60	63	CM	

	preferred_foot	international_reputation	weak_foot	skill_moves	…	\
4092	Right	1	2	2	…	
13583	Right	1	3	2	…	
10667	Right	1	3	3	…	
14443	Right	1	3	3	…	
11554	Right	1	3	2	…	

	mentality_interceptions	mentality_positioning	mentality_vision	\
4092	72	35	39	
13583	61	51	39	
10667	25	49	58	
14443	20	56	48	
11554	57	61	61	

```
       mentality_penalties  defending_marking  defending_standing_tackle  \
```

```
4092                    49                  70                          72
13583                   28                  56                          61
10667                   58                  36                          30
14443                   54                  23                          20
11554                   43                  36                          45

       defending_sliding_tackle  work_rate_atk  work_rate_def  predicted
4092                         66         Medium           High         CB
13583                        58           High         Medium         RB
10667                        34         Medium         Medium         RM
14443                        23         Medium         Medium         ST
11554                        39         Medium         Medium         CM

[5 rows x 49 columns]
```

The classification report below shows some interesting results.

We see that the model precision and recall is very similar for each class, this can mean that it classified the same amount of players/positions as false positives and the same amount of false negatives. This could be a good thing if we have roughly the same ammount of players in each position in our dataset, which would lead to this result.

We also see a similar result for the cross validation predict scores when it comes to the precision and recall.

[24]:
```python
from sklearn.metrics import classification_report

print(classification_report(y_test, test["predicted"]))
```

```
              precision    recall  f1-score   support

         CAM       0.46      0.47      0.46       492
          CB       0.84      0.89      0.87      1349
         CDM       0.55      0.46      0.50       589
          CF       0.00      0.00      0.00        69
          CM       0.63      0.79      0.70       978
          GK       1.00      1.00      1.00       599
          LB       0.77      0.80      0.78       586
          LM       0.43      0.34      0.38       471
          LW       0.30      0.05      0.09       164
         LWB       0.00      0.00      0.00         9
          RB       0.64      0.64      0.64       610
          RM       0.38      0.31      0.34       446
          RW       0.29      0.08      0.12       184
         RWB       0.00      0.00      0.00         8
          ST       0.73      0.90      0.81      1235

    accuracy                           0.69      7789
   macro avg       0.47      0.45      0.45      7789
```

```
weighted avg       0.66      0.69      0.67      7789
```

[12]:
```python
from sklearn.model_selection import cross_val_predict
y_scores = cross_val_predict(log_reg, X, y, cv=3) #validate train set

from sklearn.metrics import confusion_matrix
confusion_matrix(y, y_scores)
```

[12]:
```
array([[ 230,    0,    0,    0,   93,    0,    2,   63,    3,    0,    1,
          42,    0,    0,   59],
       [   0, 1177,   39,    0,    7,    1,   52,    0,    0,    0,   73,
           0,    0,    0,    0],
       [   0,   66,  262,    0,  166,    0,   29,    0,    0,    0,   66,
           0,    0,    0,    0],
       [  12,    0,    0,    1,    1,    0,    0,    8,    0,    0,    0,
           7,    1,    0,   39],
       [  47,    2,  113,    0,  735,    0,   24,   12,    0,    0,   29,
           6,    0,    0,    9],
       [   0,    0,    0,    0,    0,  599,    0,    0,    0,    0,    0,
           0,    0,    0,    0],
       [   0,   46,   17,    0,   27,    0,  456,    2,    0,    0,   38,
           0,    0,    0,    0],
       [  58,    0,    2,    0,   54,    0,   23,  153,    4,    0,    2,
          66,    6,    0,  103],
       [  26,    0,    0,    1,    3,    0,    2,   41,   11,    0,    1,
          27,    5,    0,   48],
       [   0,    0,    2,    0,    1,    0,    6,    0,    0,    0,    0,
           0,    0,    0,    0],
       [   0,  115,   49,    0,   45,    0,    4,    0,    0,    0,  397,
           0,    0,    0,    0],
       [  65,    0,    6,    0,   54,    0,    0,   43,    4,    0,   19,
         143,   13,    0,   99],
       [  27,    0,    0,    0,    9,    0,    0,   16,    7,    0,    0,
          53,   14,    0,   58],
       [   1,    1,    0,    0,    1,    0,    0,    0,    0,    0,    3,
           1,    0,    0,    0],
       [  34,    0,    0,    5,   11,    0,    1,   32,    1,    0,    1,
          27,    2,    0, 1121]])
```

[25]:
```python
from sklearn.metrics import precision_score, recall_score
pred_prec_score = precision_score(y, y_scores, average=None)
pred_recall_score = recall_score(y, y_scores, average=None)
print("precision: "  + str(pred_prec_score))
print("recall: " + str(pred_recall_score))
```

```
precision: [0.064      0.16773276 0.06938776 0.         0.12427506 0.06666667
 0.0984975  0.05405405 0.03333333 0.         0.09206349 0.05913978
```

```
 0.         0.         0.15820312]
recall: [0.06490872 0.1749444  0.05762712 0.         0.15353122 0.06677796
 0.10051107 0.04255319 0.00606061 0.         0.09508197 0.04932735
 0.         0.         0.19676113]
```

[26]:
```
pd.Series(pred_prec_score).describe()
```

[26]:
```
count    15.000000
mean      0.065824
std       0.055213
min       0.000000
25%       0.016667
50%       0.064000
75%       0.095280
max       0.167733
dtype: float64
```

[27]:
```
from sklearn.metrics import classification_report

# Print the classification report
print(classification_report(y, y_scores))
```

```
              precision    recall  f1-score   support

         CAM       0.06      0.06      0.06       493
          CB       0.17      0.17      0.17      1349
         CDM       0.07      0.06      0.06       590
          CF       0.00      0.00      0.00        69
          CM       0.12      0.15      0.14       977
          GK       0.07      0.07      0.07       599
          LB       0.10      0.10      0.10       587
          LM       0.05      0.04      0.05       470
          LW       0.03      0.01      0.01       165
         LWB       0.00      0.00      0.00         8
          RB       0.09      0.10      0.09       610
          RM       0.06      0.05      0.05       446
          RW       0.00      0.00      0.00       184
         RWB       0.00      0.00      0.00         7
          ST       0.16      0.20      0.18      1235

    accuracy                           0.11      7789
   macro avg       0.07      0.07      0.07      7789
weighted avg       0.11      0.11      0.11      7789
```

Now we will perform predictive analysis of the shooting scores of players

[28]:
```
df = pd.read_csv("players_15.csv")
```

[29]:
```
df = df.filter(['shooting','dribbling','attacking_crossing',␣
↪'skill_ball_control', 'movement_acceleration', 'movement_sprint_speed',␣
↪'movement_agility', 'movement_reactions', 'movement_balance',␣
↪'power_shot_power', 'power_long_shots'])
df.head()
```

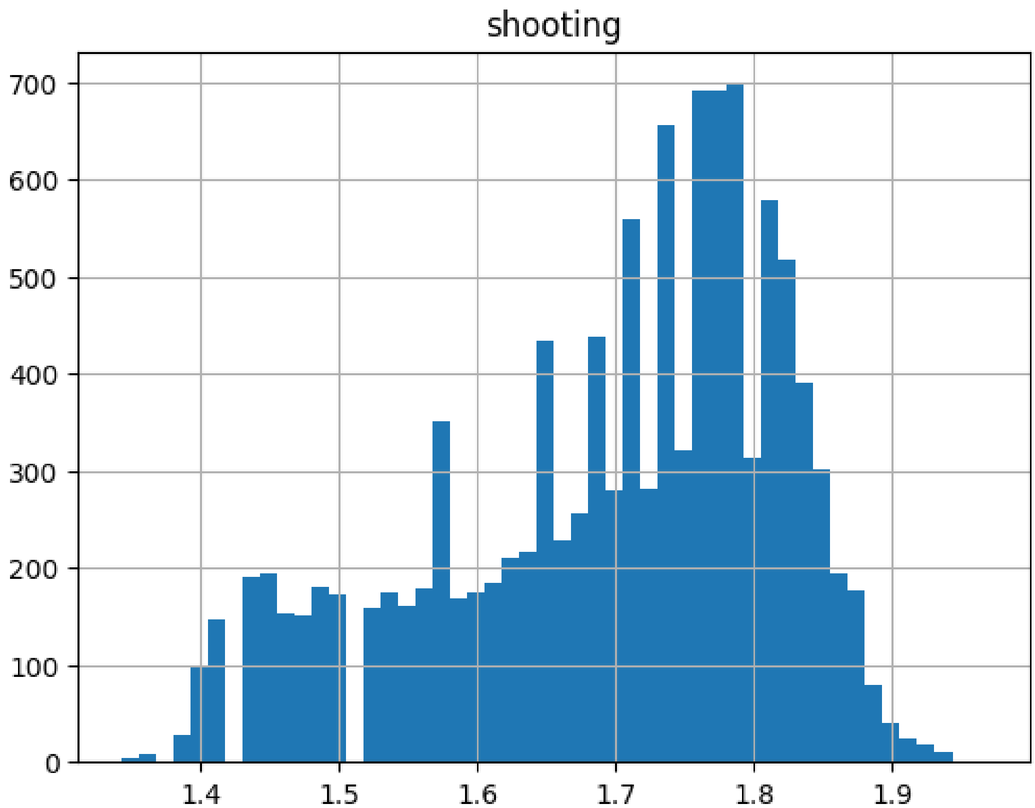
[29]:
```
   shooting  dribbling  attacking_crossing  skill_ball_control  \
0      89.0       96.0                  84                  96
1      93.0       91.0                  83                  92
2      86.0       92.0                  80                  90
3      91.0       86.0                  76                  90
4       NaN        NaN                  25                  31

   movement_acceleration  movement_sprint_speed  movement_agility  \
0                     96                     90                94
1                     91                     94                93
2                     93                     93                93
3                     74                     77                86
4                     58                     61                43

   movement_reactions  movement_balance  power_shot_power  power_long_shots
0                  94                95                80                88
1                  90                63                94                93
2                  89                91                86                90
3                  85                41                93                88
4                  89                35                42                25
```

[30]:
```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(df, test_size=0.2, random_state=42)
df = train_set.copy()
```

Our goal is to predict how well a player is at shooting based on various attributes related to attacking skills, ball handling skills, and movement

[31]:
```
np.log10(df[['shooting']]).hist(bins=50)
```

[31]:
```
array([[<Axes: title={'center': 'shooting'}>]], dtype=object)
```



[32]:
```
# Pairwise correlation of columns
df.corr()
```

[32]:
```
                        shooting  dribbling  attacking_crossing  \
shooting                1.000000   0.756930            0.471651
dribbling               0.756930   1.000000            0.714611
attacking_crossing      0.471651   0.714611            1.000000
skill_ball_control      0.719035   0.907137            0.782665
movement_acceleration   0.369534   0.589921            0.594018
movement_sprint_speed   0.327325   0.515784            0.568799
movement_agility        0.471085   0.720339            0.623276
movement_reactions      0.438431   0.527162            0.402642
movement_balance        0.286353   0.544176            0.533281
power_shot_power        0.825184   0.623296            0.634151
power_long_shots        0.895375   0.729923            0.661852

                        skill_ball_control  movement_acceleration  \
shooting                          0.719035               0.369534
dribbling                         0.907137               0.589921
attacking_crossing                0.782665               0.594018
skill_ball_control                1.000000               0.633478
```

movement_acceleration	0.633478	1.000000
movement_sprint_speed	0.620063	0.900229
movement_agility	0.664799	0.769951
movement_reactions	0.428790	0.188026
movement_balance	0.527445	0.650684
power_shot_power	0.798145	0.487176
power_long_shots	0.778555	0.501105

	movement_sprint_speed	movement_agility	\
shooting	0.327325	0.471085	
dribbling	0.515784	0.720339	
attacking_crossing	0.568799	0.623276	
skill_ball_control	0.620063	0.664799	
movement_acceleration	0.900229	0.769951	
movement_sprint_speed	1.000000	0.712415	
movement_agility	0.712415	1.000000	
movement_reactions	0.195187	0.271363	
movement_balance	0.573138	0.723925	
power_shot_power	0.496928	0.520884	
power_long_shots	0.471816	0.570193	

	movement_reactions	movement_balance	power_shot_power	\
shooting	0.438431	0.286353	0.825184	
dribbling	0.527162	0.544176	0.623296	
attacking_crossing	0.402642	0.533281	0.634151	
skill_ball_control	0.428790	0.527445	0.798145	
movement_acceleration	0.188026	0.650684	0.487176	
movement_sprint_speed	0.195187	0.573138	0.496928	
movement_agility	0.271363	0.723925	0.520884	
movement_reactions	1.000000	0.116091	0.416233	
movement_balance	0.116091	1.000000	0.367319	
power_shot_power	0.416233	0.367319	1.000000	
power_long_shots	0.418982	0.435373	0.840318	

	power_long_shots
shooting	0.895375
dribbling	0.729923
attacking_crossing	0.661852
skill_ball_control	0.778555
movement_acceleration	0.501105
movement_sprint_speed	0.471816
movement_agility	0.570193
movement_reactions	0.418982
movement_balance	0.435373
power_shot_power	0.840318
power_long_shots	1.000000

[33]:
```
# Create pipeline for preprocessing and to train model
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
num_attribs = ['dribbling','attacking_crossing', 'skill_ball_control',␣
 ↪'movement_acceleration', 'movement_sprint_speed', 'movement_agility',␣
 ↪'movement_reactions', 'movement_balance', 'power_shot_power',␣
 ↪'power_long_shots']
num_pipeline = make_pipeline(SimpleImputer(strategy="median"), StandardScaler())

preprocessing = ColumnTransformer([
("num", num_pipeline, num_attribs)])
preprocessing
```

[33]:
```
ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('simpleimputer',
SimpleImputer(strategy='median')),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['dribbling', 'attacking_crossing',
                                  'skill_ball_control', 'movement_acceleration',
                                  'movement_sprint_speed', 'movement_agility',
                                  'movement_reactions', 'movement_balance',
                                  'power_shot_power', 'power_long_shots'])])
```

[34]:
```
# Create LinearRegression model for prediction
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

lin_reg = make_pipeline(preprocessing, LinearRegression())

# Fill missing values with median
median = df["shooting"].median()
df["shooting"].fillna(median, inplace=True)

y = df['shooting']
X = df.drop('shooting', axis=1)
lin_reg.fit(X, y)
```

[34]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('num',
Pipeline(steps=[('simpleimputer',
SimpleImputer(strategy='median')),
('standardscaler',
```

```
StandardScaler())]),
                                                          ['dribbling',
                                                           'attacking_crossing',
                                                           'skill_ball_control',
                                                           'movement_acceleration',
                                                           'movement_sprint_speed',
                                                           'movement_agility',
                                                           'movement_reactions',
                                                           'movement_balance',
                                                           'power_shot_power',
                                                           'power_long_shots'])])),
                ('linearregression', LinearRegression())])
```

[35]:
```
shooting_predictions = lin_reg.predict(X)
shooting_predictions
```

[35]:
```
array([40.91925808, 52.04263897, 58.25790457, …, 64.98374848,
       43.10124071, 27.52632684])
```

[36]:
```
from sklearn.metrics import mean_squared_error

lin_rmse = mean_squared_error(y, shooting_predictions, squared=False)
lin_rmse
```

[36]: 4.671659313056307

[37]:
```
# Create DecisionTreeRegressor model for prediction
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import cross_val_score
tree_reg = make_pipeline(preprocessing, DecisionTreeRegressor())

tree_reg.fit(X, y)
tree_rmses = -cross_val_score(tree_reg,
                              X,y,
                              scoring="neg_root_mean_squared_error",
                              cv=10)
np.mean(tree_rmses)
```

[37]: 6.240264702376529

[38]:
```
# Create RandomForestRegressor model for prediction
from sklearn.ensemble import RandomForestRegressor
forest_reg = make_pipeline(preprocessing,␣
 ↪RandomForestRegressor(random_state=42))

forest_reg.fit(X, y)
shooting_predictions = forest_reg.predict(X)
```

```
shooting_predictions
```

[38]:
```
array([37.04, 52.87, 54.04, …, 61.79, 45.02, 26.45])
```

[39]:
```
forest_rmses = -cross_val_score(forest_reg,
                               X,y,
                               scoring="neg_root_mean_squared_error",
                               cv=10)
np.mean(forest_rmses)
```

[39]:
```
4.3607983619521615
```

Overall, our models seem to perform quite well. The mean square errors for all three are relatively low, with linear regression and RandomForestRegressor being the lowest with rme scores of 4.67 and 4.36 respectively.

Conclusion

In conclusion, we have used logistic regression analysis to successfully predict the position of soccer players based on the multiple attributes in the dataset. Our objective was to obtain a high accuracy. After we developed a model, and ran tests, we obtained a decent accuracy percentage. Despite some inaccuracies, we were still able to guess the position accurately in many cases. For example, in one of the tests, our prediction was RB; however, the actual position of the player was CB. Both of these positions are defensive positions but CB is a central back while the RB is Right Back. In essence, our model was able to narrow the positions down to a defensive one, but not able to exactly guess which defensive position the player had. Overall, the accuracy we got was not exactly the highest; however, we were still able to correctly estimate the general position of most players. In addition, our predictions for how well a player is at shooting was quite accurate, with our Root Square Mean Error scores quite low, thus showing high accuracy.