# Supervised Learning - FIFA 23

April 29, 2023

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1. Project Introduction

1.1 Dataset Background:

I have been playing FIFA games since 2002, all the way up to FIFA23. Over the past decade, the level of detail in FIFA games has been continuously improving, and the accuracy and reasonableness of the data have also been continuously improved, approaching the level of another football management game called FM. I hope to explore the relationships behind the data more deeply through analysis of the FIFA23 player database during this project.

1.2 Project Goals:

Exploring the realationship between a player's market value and other variables in the FIFA23 database using various models of supervised learning methods.

»Regression project: Predicting a player's market value based of the characteristics of the player.

1.3 Data Saurces:

The dataset is from Kaggle:

https://www.kaggle.com/datasets/cashncarry/fifa-23-complete-player-dataset

2. Data Cleaning

2.1 Import Library

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

2.2 Data Loading

[2]:
```
df = pd.read_csv(r'players_fifa23.csv')
print(df.shape)
```

```
(18539, 90)
```

[3]:
```
df.describe
```

[3]:
```
<bound method NDFrame.describe of            ID          Name
FullName  Age  Height  Weight  \
0      158023        L. Messi        Lionel Messi  35     169      67
1      165153      K. Benzema       Karim Benzema  34     185      81
2      188545  R. Lewandowski  Robert Lewandowski  33     185      81
3      192985    K. De Bruyne     Kevin De Bruyne  31     181      70
4      231747       K. Mbappé       Kylian Mbappé  23     182      73
…       …             …                 …  …      …       …
18534  243725      D. Collins      Darren Collins  21     174      68
18535  261933     Yang Dejiang        Dejiang Yang  17     175      60
18536  267823       L. Mullan         Liam Mullan  18     170      65
18537  267824    D. McCallion    Daithí McCallion  17     178      65
18538  261424        N. Rabha         Nabin Rabha  25     176      66

                                              PhotoUrl          Nationality  \
0      https://cdn.sofifa.net/players/158/023/23_60.png            Argentina
1      https://cdn.sofifa.net/players/165/153/23_60.png               France
2      https://cdn.sofifa.net/players/188/545/23_60.png               Poland
3      https://cdn.sofifa.net/players/192/985/23_60.png              Belgium
4      https://cdn.sofifa.net/players/231/747/23_60.png               France
…                                                    …                    …
18534  https://cdn.sofifa.net/players/243/725/23_60.png  Republic of Ireland
18535  https://cdn.sofifa.net/players/261/933/23_60.png             China PR
18536  https://cdn.sofifa.net/players/267/823/23_60.png     Northern Ireland
18537  https://cdn.sofifa.net/players/267/824/23_60.png  Republic of Ireland
18538  https://cdn.sofifa.net/players/261/424/23_60.png                India

       Overall  Potential  …  LMRating  CMRating  RMRating LWBRating  \
0           91         91  …        91        88        91        67
1           91         91  …        89        84        89        67
2           91         91  …        86        83        86        67
3           91         91  …        91        91        91        82
4           91         95  …        92        84        92        70
…          …          …  …       …        …        …        …
18534       47         56  …        50        44        50        41
18535       47         57  …        45        45        45        47
18536       47         67  …        52        49        52        46
18537       47         61  …        33        33        33        44
18538       47         50  …        44        40        44        46

      CDMRating RWBRating  LBRating  CBRating  RBRating GKRating
0            66        67        62        53        62       22
1            67        67        63        58        63       21
2            69        67        64        63        64       22
3            82        82        78        72        78       24
4            66        70        66        57        66       21
…           …         …         …         …         …        …
```

```
18534        38       41       40       36       40       15
18535        48       47       49       49       49       15
18536        44       46       46       42       46       17
18537        42       44       47       49       47       15
18538        43       46       47       47       47       19

[18539 rows x 90 columns]>
```

»Dataset Columns Include: 90 Attributes

»Dataset Rows Include: 18539 Players Attributes

2.3 Feature Description

Four different group of features as shown above:

»1. Players Details(33): Describe who the player is.

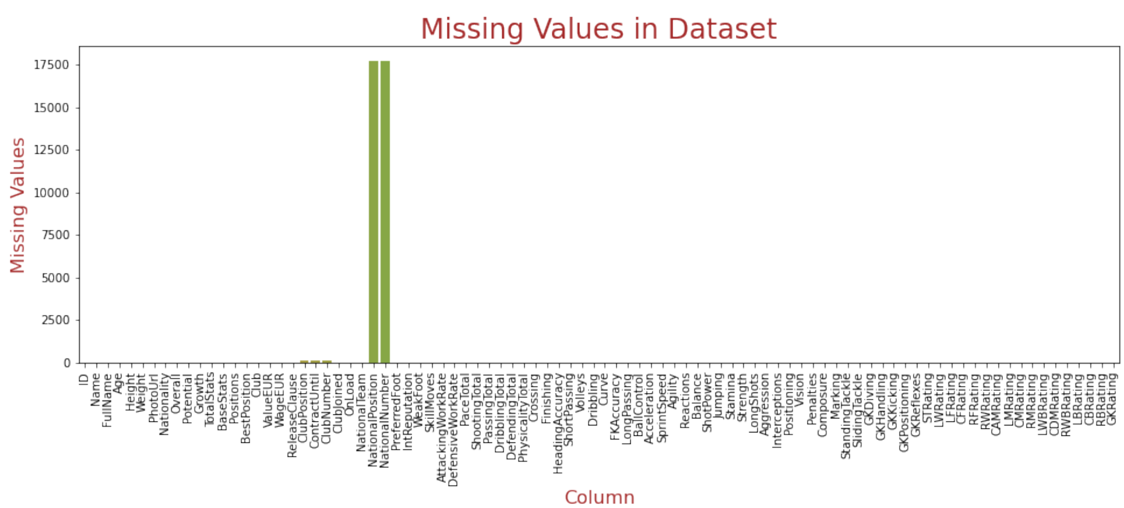
»2. General Attributes(7): Display the general rating of the player.

»3. Special Attributes(29): Contribute to the general attributes.

»4. Hidden Attributes(22): may impact the position and cannot be seen.

2.4 Missing Value Checking

[4]:
```
missing_values = df.isna().sum()

plt.figure(figsize=(16, 5))
sns.barplot(x=missing_values.index, y=missing_values.values)
plt.xticks(rotation=90)
plt.xlabel('Column', fontsize=16, color='brown')
plt.ylabel('Missing Values', fontsize=16, color='brown')
plt.title('Missing Values in Dataset', fontsize=24, color='brown')
plt.show()
```



[5]:
```
missing_contract = df[df['ContractUntil'].isnull()]
```

»There are missing values in five columns of the data: Club position, Club number, Contract until, and National position, National number.

»Because Club position, Club number, National position, and National number are all descriptive attributes of players and have no significant correlation with player value, position, or performance, we can remove them.

»They have null values in the ContractUntil column because their contracts have ended, so we can set them as 2022. This way, when calculating the remaining years of the contract in the future, it will be calculated as 0.

[6]:
```
df1 = df.drop(['ClubPosition', 'ClubNumber', 'NationalPosition',␣
 ↪'NationalNumber'], axis=1)
df1.loc[df1['ContractUntil'].isnull(), 'ContractUntil'] = 2022
print(df1.shape)
```

```
(18539, 86)
```

2.5 Duplicate Value Checking

[7]:
```
duplicate_rows = df1[df1.duplicated()]
duplicate_rows.shape
```

[7]:
```
(119, 86)
```

»There are 119 duplicate rows, which we need to remove from the dataset.

[8]:
```
df2 = df1.drop_duplicates()
print(df2.shape)
```

```
(18420, 86)
```

2.6 Unrelevant Feature Checking

»There are 22 hidden attributes that only relate to the player's position rating, which do not affect our analysis and can be removed.

»TotalStats, BaseStats, Growth, Potential, ClubJoin, NationalTeam, and PhotoUrl have no relationship with our analysis and can be removed.

[9]:
```
df3 = df2.drop(['GKDiving', 'GKHandling', 'GKKicking', 'GKPositioning',␣
 ↪'GKReflexes',
                 'STRating', 'LWRating', 'LFRating', 'CFRating', 'RFRating',␣
 ↪'RWRating',
                 'CAMRating', 'LMRating', 'CMRating', 'RMRating', 'LWBRating',␣
 ↪'CDMRating',
```

```
                 'RWBRating', 'LBRating', 'CBRating', 'RBRating', 'GKRating'],␣
 ↪axis=1)
df3 = df3.drop(['TotalStats', 'BaseStats', 'Growth', 'Potential', 'ClubJoined',␣
 ↪'NationalTeam', 'PhotoUrl'], axis=1)
print(df3.shape)
```

```
(18420, 57)
```

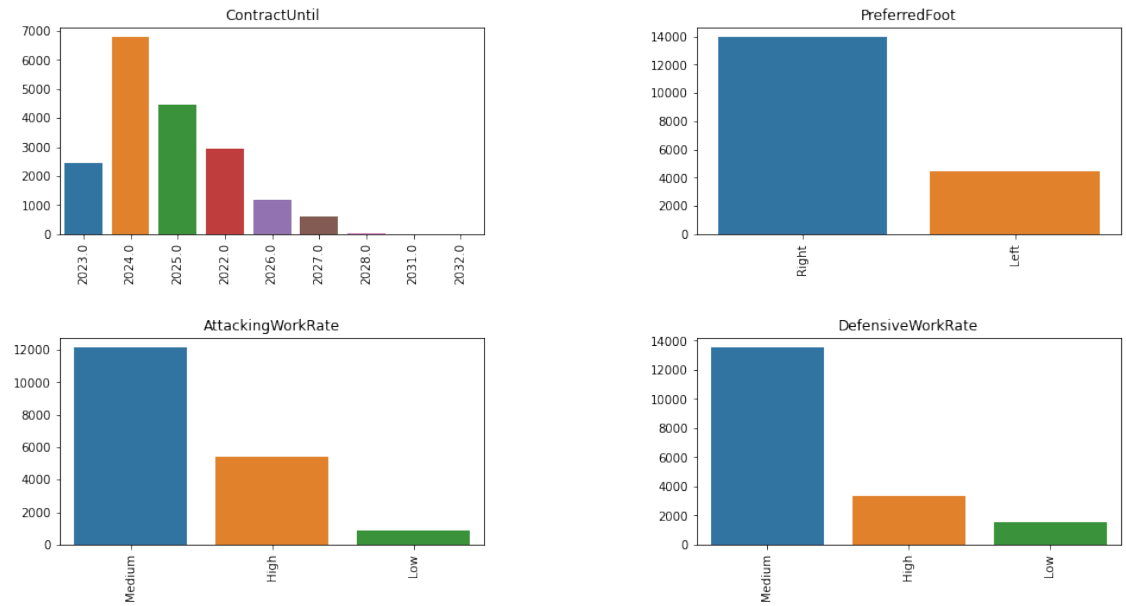
2.7 Data Conversion

»1. Change ContractUntil value to int64 as remaining years.

»2. Change PreferredFoot as right = 0 and left = 1.

»3. Change 2 WorkRate Columns as Dummy variables.

[10]:
```
# Calculation
cu_counts = df3['ContractUntil'].value_counts()
pf_counts = df3['PreferredFoot'].value_counts()
awr_counts = df3['AttackingWorkRate'].value_counts()
dwr_counts = df3['DefensiveWorkRate'].value_counts()
# Plot
fig, axs = plt.subplots(2, 2, figsize=(16, 8))
# ContractUntil
sns.barplot(x=cu_counts.index, y=cu_counts.values, ax=axs[0, 0])
axs[0, 0].set_xticklabels(cu_counts.index, rotation=90)
axs[0, 0].set_title('ContractUntil')
# PreferredFoot
sns.barplot(x=pf_counts.index, y=pf_counts.values, ax=axs[0, 1])
axs[0, 1].set_xticklabels(pf_counts.index, rotation=90)
axs[0, 1].set_title('PreferredFoot')
# AttackingWorkRate
sns.barplot(x=awr_counts.index, y=awr_counts.values, ax=axs[1, 0])
axs[1, 0].set_xticklabels(awr_counts.index, rotation=90)
axs[1, 0].set_title('AttackingWorkRate')
# DefensiveWorkRate
sns.barplot(x=dwr_counts.index, y=dwr_counts.values, ax=axs[1, 1])
axs[1, 1].set_xticklabels(dwr_counts.index, rotation=90)
axs[1, 1].set_title('DefensiveWorkRate')
# adjust
plt.subplots_adjust(wspace=0.5, hspace=0.5)
plt.show()
```




[11]:
```python
# Create a copy
df4 = df3.copy()
# Change ContractUntil value to int64 as remaining years
df4['ContractUntil']=df4['ContractUntil']-2022
# Change PreferredFoot as right = 0 and left = 1
df4['PreferredFoot'] = df4['PreferredFoot'].apply(lambda x: 0 if x=='Right' else 1)
# Change 2 WorkRate Columns as Dummy variables
awr_dummy = pd.get_dummies(df4['AttackingWorkRate'], prefix='AWR')
awr_dummy.columns = ['AWR_High', 'AWR_Low', 'AWR_Medium']
df4 = pd.concat([df4, awr_dummy], axis=1)
dwr_dummy = pd.get_dummies(df4['DefensiveWorkRate'], prefix='DWR')
dwr_dummy.columns = ['DWR_High', 'DWR_Low', 'DWR_Medium']
df4 = pd.concat([df4, dwr_dummy], axis=1)
df4[['AWR_High', 'AWR_Low', 'AWR_Medium']] = df4[['AWR_High', 'AWR_Low', 'AWR_Medium']].astype('int64')
df4[['DWR_High', 'DWR_Low', 'DWR_Medium']] = df4[['DWR_High', 'DWR_Low', 'DWR_Medium']].astype('int64')
# Remove Extra columns and change to int64
df4 = df4.drop(['AttackingWorkRate', 'DefensiveWorkRate', 'AWR_Low', 'DWR_Low'], axis=1)
df4['OnLoad'] = df4['OnLoad'].fillna(0).astype('int64')
df4['ContractUntil'] = df4['ContractUntil'].fillna(0).astype('int64')
print(df4.shape)
```

```
(18420, 59)
```

2.8 Subset Selection

Because the requirements for goalkeepers' attributes are different from those for other positions, it is not suitable to analyze them together. Therefore, goalkeepers are removed from the observations.

[12]:
```
# Remove Goalkeeper
df5 = df4[df4['BestPosition'] != 'GK']
print(df5.shape)
```

```
(16367, 59)
```

2.9 Data Cleaning Summary

»1. After data cleaning, our dataset now has 52 integer features and 5 object features and 16367 players.

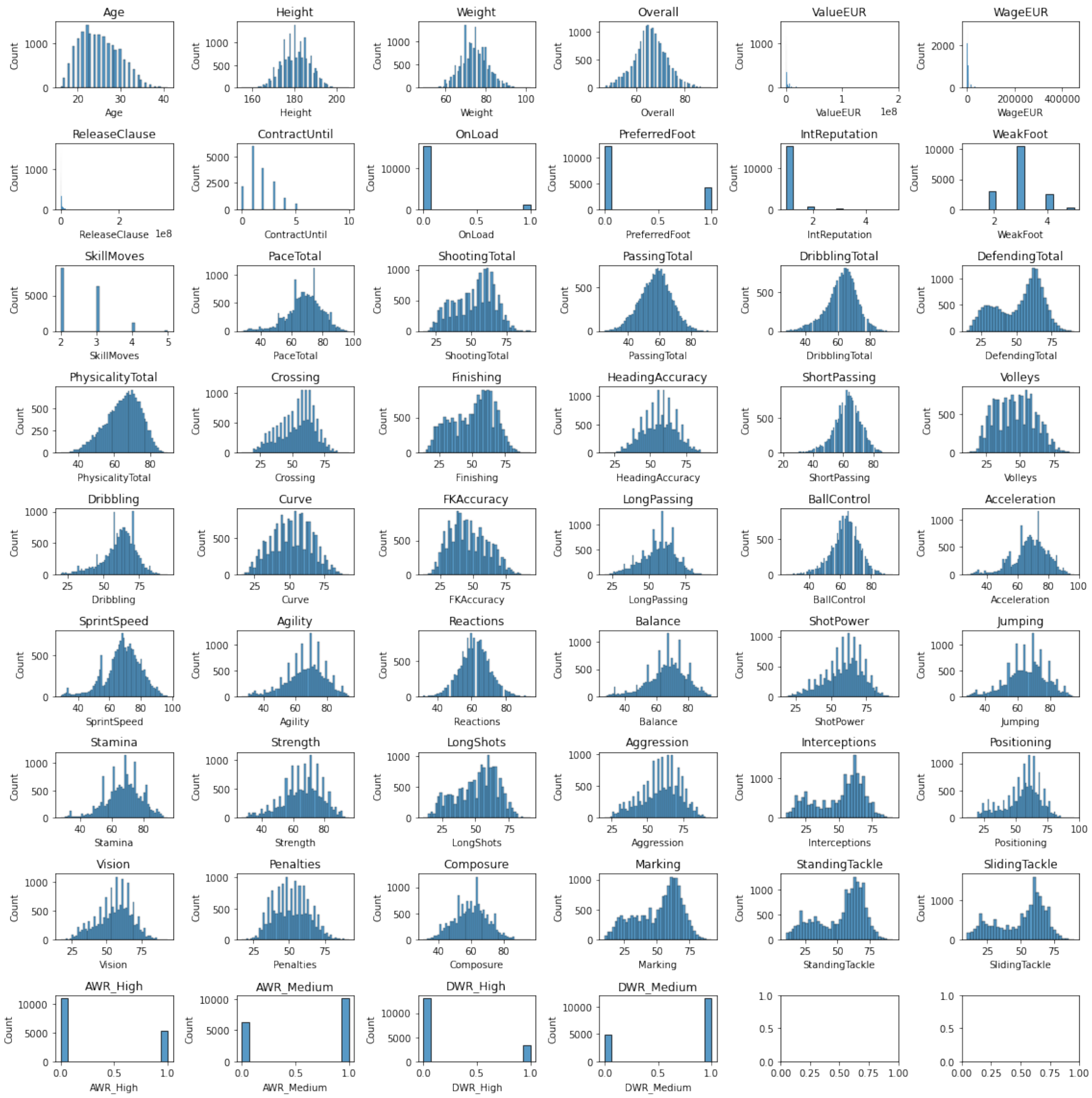
»2. We filled in missing values, removed duplicate values and irrelevant variables, and converted formats.

»3. Next, we will conduct EDA to further explore the data, which may require further cleaning.

3. Exploratory Data Analysis

3.1 Features Distribution

[13]:
```
int_features = df5.select_dtypes(include=['int']).drop(
    'ID',axis=1).columns.tolist()

# 6 x 9 row = 52 images
num_features = len(int_features)
num_cols = 6
num_rows = num_features // num_cols + (num_features % num_cols > 0)

fig, axs = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(16, 16))
for i, feature in enumerate(int_features):
    row_idx = i // num_cols
    col_idx = i % num_cols

    sns.histplot(df5[feature], kde=False, ax=axs[row_idx][col_idx])
    axs[row_idx][col_idx].set_title(feature)

plt.tight_layout()
plt.show()
```




»1. The distribution of most of the feature values satisfies normal distribution.

»2. WageEUR and ReleaseClause are greatly influenced by Value and are not suitable for use.

»3. ValueEUR, as the core variable of this analysis, requires further observation.

[14]:
```
df6 = df5.drop(['WageEUR', 'ReleaseClause'], axis=1)
print(df6.shape)
```

```
(16367, 57)
```

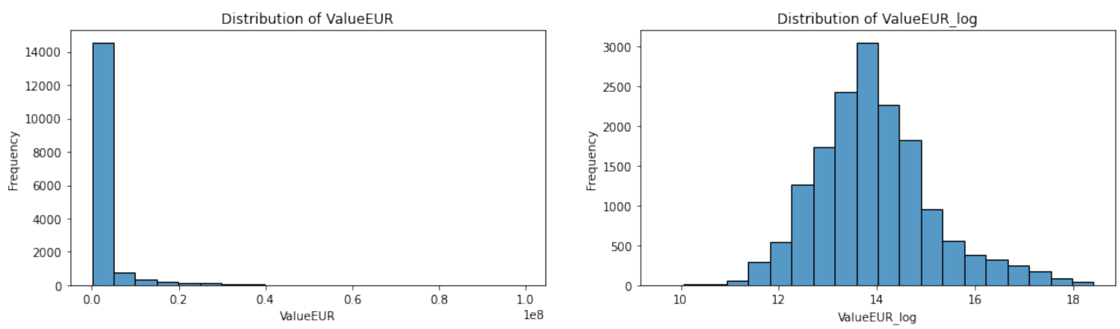
»Remove outliers: only keep between 100,000 and 100,000,000.

[15]:
```
df7 = df6.loc[(df6['ValueEUR'] >= 10000) & (df6['ValueEUR'] < 100000000)]
print(df7.shape)
```

(16271, 57)

[16]:
```
fig, axs = plt.subplots(1, 2, figsize=(16, 4))

sns.histplot(data=df7['ValueEUR'], bins=20, edgecolor='black', ax=axs[0])
axs[0].set_title('Distribution of ValueEUR')
axs[0].set_xlabel('ValueEUR')
axs[0].set_ylabel('Frequency')

df7['ValueEUR_log'] = np.log1p(df7['ValueEUR'])
sns.histplot(data=df7['ValueEUR_log'], bins=20, edgecolor='black', ax=axs[1])
axs[1].set_title('Distribution of ValueEUR_log')
axs[1].set_xlabel('ValueEUR_log')
axs[1].set_ylabel('Frequency')
```

[16]:
```
Text(0, 0.5, 'Frequency')
```



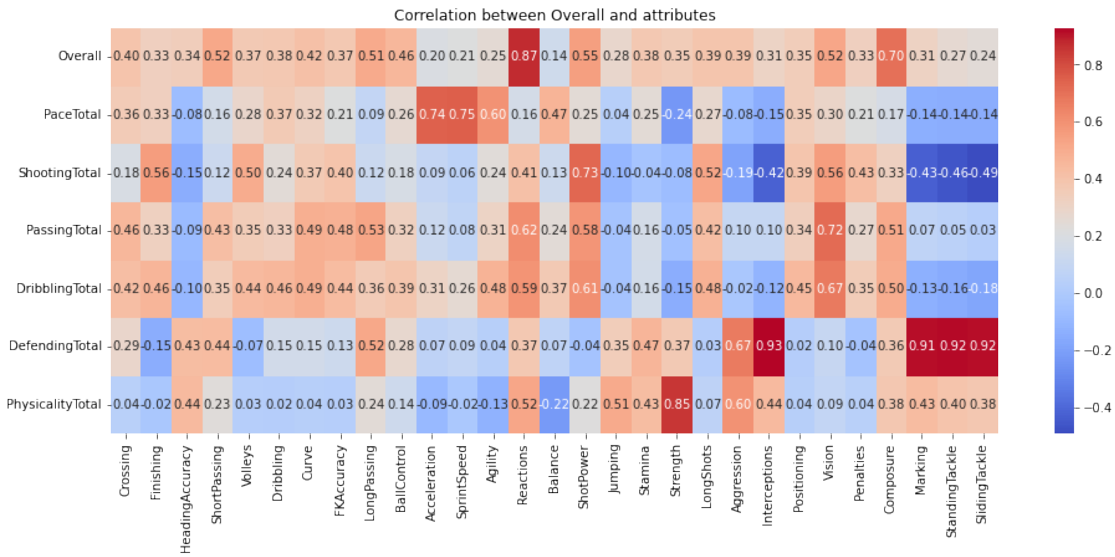

»1. The distribution of Value is left-skewed, which may impact regression performance.

»2. By transforming with logarithm, the distribution of ValueEUR approaches a normal distribution.

3.2 Features Correlation

[17]:
```
cols1 = ['Overall', 'PaceTotal', 'ShootingTotal', 'PassingTotal',
         'DribblingTotal', 'DefendingTotal', 'PhysicalityTotal']

cols2 = ['Crossing', 'Finishing', 'HeadingAccuracy', 'ShortPassing',
         'Volleys', 'Dribbling', 'Curve', 'FKAccuracy', 'LongPassing',
         'BallControl', 'Acceleration', 'SprintSpeed', 'Agility', 'Reactions',
         'Balance', 'ShotPower', 'Jumping', 'Stamina', 'Strength',
         'LongShots', 'Aggression', 'Interceptions', 'Positioning', 'Vision',
         'Penalties', 'Composure', 'Marking', 'StandingTackle', 'SlidingTackle']

# Calculation
corr_matrix = df[cols1 + cols2].corr()
corr_table = corr_matrix[cols2].loc[cols1]
```

```python
# Heatmap
fig, ax = plt.subplots(figsize=(16, 6))
sns.heatmap(corr_table, cmap='coolwarm', annot=True, fmt='.2f')
plt.title('Correlation between Overall and attributes')

plt.show()
```




»1. General Attributes (7) are all strongly correlated with some of Specific Attributes (29).

»2. Using both General Attributes and Specific Attributes could lead to multi-collinearity.

»3. Since General Attributes are calculated based on Specific Attributes, we will keep Specific Attributes.

[18]:
```python
df8 = df7.drop(['PaceTotal', 'ShootingTotal', 'PassingTotal', 'DribblingTotal',␣
↪'DefendingTotal', 'PhysicalityTotal'
               ], axis=1)
print(df8.shape)
```

```
(16271, 52)
```

3.3 EDA Summary

»1. Most features are close to normally distributed besides ValueEUR.

»2. General Attributes and Specific Attributes cannot be both in this analysis.

»3. Next, we will try different combinations to apply regression to predict the market value of football players.

4. Regression

»X: all numerical variables besides ID, ValueEUR, and Overall

»y: ValueEUR

»Split trainset and testset

[19]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
df9 = df8[df8['Club'] != 'AC Milan']

X = df9.select_dtypes(include=['int']).drop(['ID', 'ValueEUR', 'Overall'],␣
↪axis=1)
y = df9['ValueEUR']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=26)
print(X_train.shape)
print(X_test.shape)
```

```
(11370, 42)
(4874, 42)
```

[20]:
```
# Select Milan Players
milan = df8[df8['Club'] == 'AC Milan']
players = ['T. Hernández', 'F. Tomori', 'S. Kjær', 'D. Calabria', 'S. Tonali',␣
↪'R. Krunić',
           'Rafael Leão', 'I. Bennacer', 'Brahim', 'O. Giroud']
milan_players = milan.loc[milan['Name'].isin(players)].reset_index(drop=True)
X_milan = milan_players.select_dtypes(include=['int']).drop(['ID', 'ValueEUR',␣
↪'Overall'], axis=1)
y_milan = milan_players['ValueEUR']
print(X_milan.shape)
```

```
(10, 42)
```

4.1 Linear Regression

[21]:
```
# Library
from sklearn.linear_model import LinearRegression, RidgeCV, Ridge, LassoCV,␣
↪Lasso
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,␣
↪AdaBoostRegressor
from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

import time
```

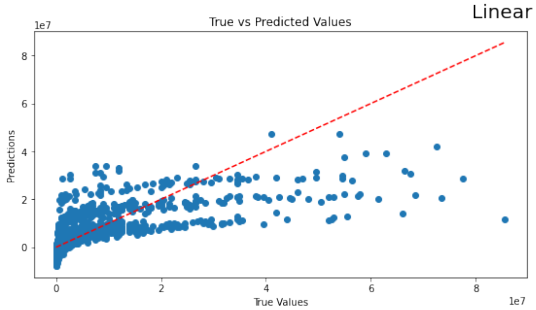
[22]:

```python
start_time = time.time()
# Linear Regression
LinearR_Model = LinearRegression()
LinearR_Model.fit(X_train, y_train)
y_pred = LinearR_Model.predict(X_test)
r2 = round(r2_score(y_test, y_pred),4)
mae = round(mean_absolute_error(y_test, y_pred),0)
mse = round(mean_squared_error(y_test, y_pred),0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Linear Regression', fontsize=20)
fig.subplots_adjust(hspace=0.3)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table non-log
milan_pred = LinearR_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.5013
MAE: 2430090.0
MSE: 21612327480836.0
```

```
Calculation Time: 0.05 seconds
```

Linear Regression




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 32798303 | -0.57 |
| F. Tomori | CB | 84 | 60500000 | 22464866 | -0.63 |
| S. Kjær | CB | 82 | 14500000 | 25443228 | 0.75 |
| D. Calabria | RB | 80 | 25500000 | 18701362 | -0.27 |
| S. Tonali | CDM | 84 | 62500000 | 13500544 | -0.78 |
| R. Krunić | CM | 77 | 10500000 | 7993384 | -0.24 |
| Rafael Leão | LW | 84 | 66500000 | 11533389 | -0.83 |
| I. Bennacer | CM | 82 | 40000000 | 20479297 | -0.49 |
| Brahim | CAM | 78 | 31500000 | 6306288 | -0.8 |
| O. Giroud | ST | 82 | 13000000 | 23231067 | 0.79 |

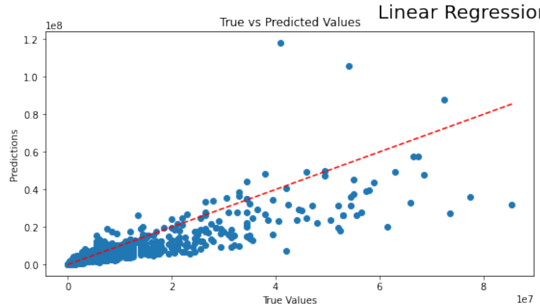
[23]:

```python
start_time = time.time()
# Linear Regression
y_train_log1p = np.log1p(y_train)
LinearR_log_Model = LinearRegression()
LinearR_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = LinearR_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred),4)
mae = round(mean_absolute_error(y_test, y_pred),0)
mse = round(mean_squared_error(y_test, y_pred),0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Linear Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = LinearR_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
```

```
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7453
MAE: 988093.0
MSE: 11036989963568.0
Calculation Time: 0.0419 seconds
```

Linear Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 90406258 | 0.19 |
| F. Tomori | CB | 84 | 60500000 | 35233327 | -0.42 |
| S. Kjær | CB | 82 | 14500000 | 12259422 | -0.15 |
| D. Calabria | RB | 80 | 25500000 | 14870996 | -0.42 |
| S. Tonali | CDM | 84 | 62500000 | 35001600 | -0.44 |
| R. Krunić | CM | 77 | 10500000 | 6839238 | -0.35 |
| Rafael Leão | LW | 84 | 66500000 | 27636803 | -0.58 |
| I. Bennacer | CM | 82 | 40000000 | 35504782 | -0.11 |
| Brahim | CAM | 78 | 31500000 | 5183491 | -0.84 |
| O. Giroud | ST | 82 | 13000000 | 11229980 | -0.14 |

4.2 Ridge Regression

alpha = ridgeCV_Model.alpha_

[24]:
```
'''
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import Ridge
# Best Hyper
ridgeCV_Model = RidgeCV(alphas=[0.001, 0.01, 0.1, 1, 10, 100], cv=5)
ridgeCV_Model.fit(X_train, y_train)
alpha = ridgeCV_Model.alpha_
print('Best Alpha:', alpha)
'''
```

[24]:
```
"\nfrom sklearn.linear_model import RidgeCV\nfrom sklearn.linear_model import
Ridge\n# Best Hyper\nridgeCV_Model = RidgeCV(alphas=[0.001, 0.01, 0.1, 1, 10,
100], cv=5)\nridgeCV_Model.fit(X_train, y_train)\nalpha =
```

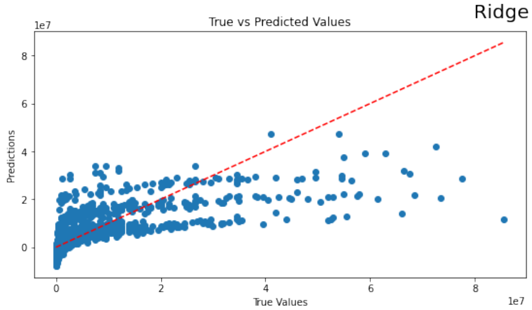
ridgeCV_Model.alpha_\nprint('Best Alpha:', alpha)\n"

[25]:
```
start_time = time.time()
#Ridge Regression
RidgeR_Model = Ridge()
RidgeR_Model.fit(X_train, y_train)
y_pred = RidgeR_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Ridge Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table non-log
milan_pred = RidgeR_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.5014
```

```
MAE: 2430157.0
MSE: 21608282867071.0
Calculation Time: 0.0324 seconds
```

Ridge Regression



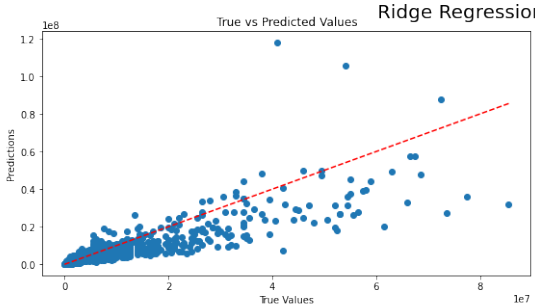

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 32783903 | -0.57 |
| F. Tomori | CB | 84 | 60500000 | 22459229 | -0.63 |
| S. Kjær | CB | 82 | 14500000 | 25428086 | 0.75 |
| D. Calabria | RB | 80 | 25500000 | 18695547 | -0.27 |
| S. Tonali | CDM | 84 | 62500000 | 13504899 | -0.78 |
| R. Krunić | CM | 77 | 10500000 | 7997178 | -0.24 |
| Rafael Leão | LW | 84 | 66500000 | 11537590 | -0.83 |
| I. Bennacer | CM | 82 | 40000000 | 20474267 | -0.49 |
| Brahim | CAM | 78 | 31500000 | 6308723 | -0.8 |
| O. Giroud | ST | 82 | 13000000 | 23219247 | 0.79 |

[26]:
```python
start_time = time.time()
y_train_log1p = np.log1p(y_train)
#Ridge Regression
RidgeR_log_Model = Ridge()
RidgeR_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = RidgeR_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Ridge Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = RidgeR_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
```

```
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7455
MAE: 988040.0
MSE: 11028654905058.0
Calculation Time: 0.0199 seconds
```

Ridge Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 90347193 | 0.19 |
| F. Tomori | CB | 84 | 60500000 | 35229287 | -0.42 |
| S. Kjær | CB | 82 | 14500000 | 12246499 | -0.16 |
| D. Calabria | RB | 80 | 25500000 | 14869734 | -0.42 |
| S. Tonali | CDM | 84 | 62500000 | 35007519 | -0.44 |
| R. Krunić | CM | 77 | 10500000 | 6841195 | -0.35 |
| Rafael Leão | LW | 84 | 66500000 | 27634360 | -0.58 |
| I. Bennacer | CM | 82 | 40000000 | 35497482 | -0.11 |
| Brahim | CAM | 78 | 31500000 | 5183609 | -0.84 |
| O. Giroud | ST | 82 | 13000000 | 11226096 | -0.14 |

[27]:
```
print(RidgeR_Model.get_params())
print(RidgeR_log_Model.get_params())
```

```
{'alpha': 1.0, 'copy_X': True, 'fit_intercept': True, 'max_iter': None,
'normalize': 'deprecated', 'positive': False, 'random_state': None, 'solver':
'auto', 'tol': 0.001}
{'alpha': 1.0, 'copy_X': True, 'fit_intercept': True, 'max_iter': None,
'normalize': 'deprecated', 'positive': False, 'random_state': None, 'solver':
'auto', 'tol': 0.001}
```

4.3 Lasso Regression

alpha = LassoCV_Model.alpha_

[28]:
```
'''
# Best Hyper
lassoCV_Model = LassoCV(alphas=[0.001, 0.01, 0.1, 1, 10, 100], cv=5)
lassoCV_Model.fit(X_train, y_train)
alpha = lassoCV_Model.alpha_
print('Best Alpha:', alpha)
'''
```

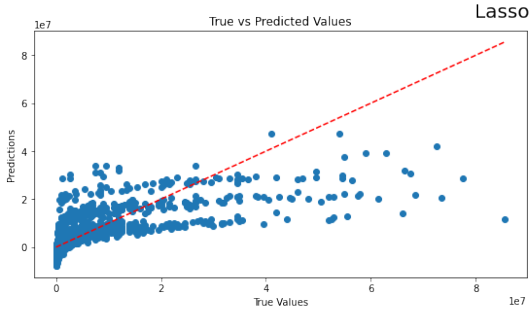
[28]:
```
"\n# Best Hyper\nlassoCV_Model = LassoCV(alphas=[0.001, 0.01, 0.1, 1, 10, 100],
cv=5)\nlassoCV_Model.fit(X_train, y_train)\nalpha =
lassoCV_Model.alpha_\nprint('Best Alpha:', alpha)\n"
```

[29]:
```
start_time = time.time()
# Lasso Regression
LassoR_Model = Lasso()
LassoR_Model.fit(X_train, y_train)
y_pred = LassoR_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Lasso Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table non-log
milan_pred = LassoR_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
```

```
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
    ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
    ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.5013
MAE: 2430089.0
MSE: 21612323298719.0
Calculation Time: 0.3467 seconds
```

Lasso Regression



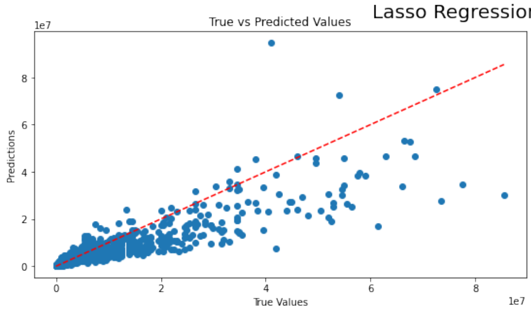

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 32798281 | -0.57 |
| F. Tomori | CB | 84 | 60500000 | 22464863 | -0.63 |
| S. Kjær | CB | 82 | 14500000 | 25443177 | 0.75 |
| D. Calabria | RB | 80 | 25500000 | 18701359 | -0.27 |
| S. Tonali | CDM | 84 | 62500000 | 13500541 | -0.78 |
| R. Krunić | CM | 77 | 10500000 | 7993388 | -0.24 |
| Rafael Leão | LW | 84 | 66500000 | 11533382 | -0.83 |
| I. Bennacer | CM | 82 | 40000000 | 20479287 | -0.49 |
| Brahim | CAM | 78 | 31500000 | 6306307 | -0.8 |
| O. Giroud | ST | 82 | 13000000 | 23231049 | 0.79 |

[30]:
```
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Lasso Regression
LassoR_log_Model = Lasso(alpha=0.005)
LassoR_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = LassoR_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
```

```python
fig.suptitle('Lasso Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = LassoR_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],
    milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',
    'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,
    9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
    values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',
    loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7632
MAE: 985644.0
MSE: 10262798943037.0
Calculation Time: 0.3176 seconds
```

Lasso Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 80676120 | 0.06 |
| F. Tomori | CB | 84 | 60500000 | 35084292 | -0.42 |
| S. Kjær | CB | 82 | 14500000 | 10167717 | -0.3 |
| D. Calabria | RB | 80 | 25500000 | 15018728 | -0.41 |
| S. Tonali | CDM | 84 | 62500000 | 35939508 | -0.42 |
| R. Krunić | CM | 77 | 10500000 | 7229295 | -0.31 |
| Rafael Leão | LW | 84 | 66500000 | 26750446 | -0.6 |
| I. Bennacer | CM | 82 | 40000000 | 34065247 | -0.15 |
| Brahim | CAM | 78 | 31500000 | 5058760 | -0.84 |
| O. Giroud | ST | 82 | 13000000 | 10868574 | -0.16 |

[31]:
```python
print(LassoR_Model.get_params())
print(LassoR_log_Model.get_params())
```

```
{'alpha': 1.0, 'copy_X': True, 'fit_intercept': True, 'max_iter': 1000,
'normalize': 'deprecated', 'positive': False, 'precompute': False,
```

```
'random_state': None, 'selection': 'cyclic', 'tol': 0.0001, 'warm_start': False}
{'alpha': 0.005, 'copy_X': True, 'fit_intercept': True, 'max_iter': 1000,
'normalize': 'deprecated', 'positive': False, 'precompute': False,
'random_state': None, 'selection': 'cyclic', 'tol': 0.0001, 'warm_start': False}
```

4.3 Multi-nominal Regression

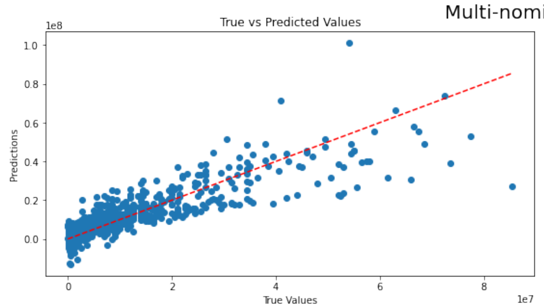
Create poly_features.fit_transform

[32]:
```
start_time = time.time()
# Multi-nominal
poly_features = PolynomialFeatures(degree=2)
X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.transform(X_test)
# Multi-nominal Regression
MNR_Model = LinearRegression()
MNR_Model.fit(X_train_poly, y_train)
y_pred = MNR_Model.predict(X_test_poly)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred),4)
mae = round(mean_absolute_error(y_test, y_pred),0)
mse = round(mean_squared_error(y_test, y_pred),0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Multi-nominal Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table non-log
milan_poly = poly_features.fit_transform(X_milan)
milan_pred = MNR_Model.predict(milan_poly)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
```

```
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
 ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7785
MAE: 1663694.0
MSE: 9601522135004.0
Calculation Time: 2.204 seconds
```

Multi-nominal Regression



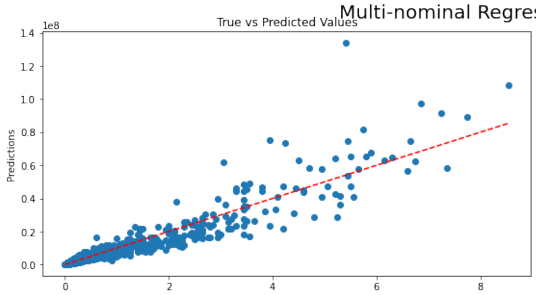

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 58743909 | -0.23 |
| F. Tomori | CB | 84 | 60500000 | 44969386 | -0.26 |
| S. Kjær | CB | 82 | 14500000 | 23378888 | 0.61 |
| D. Calabria | RB | 80 | 25500000 | 23555256 | -0.08 |
| S. Tonali | CDM | 84 | 62500000 | 27822052 | -0.55 |
| R. Krunić | CM | 77 | 10500000 | 11520291 | 0.1 |
| Rafael Leão | LW | 84 | 66500000 | 26959942 | -0.59 |
| I. Bennacer | CM | 82 | 40000000 | 36305158 | -0.09 |
| Brahim | CAM | 78 | 31500000 | 15287227 | -0.51 |
| O. Giroud | ST | 82 | 13000000 | 19093691 | 0.47 |

[33]:
```
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Multi-nominal
poly_features = PolynomialFeatures(degree=2)
X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.transform(X_test)
# Multi-nominal Regression
MNR_log_Model = LinearRegression()
MNR_log_Model.fit(X_train_poly, y_train_log1p)
y_pred_log1p = MNR_log_Model.predict(X_test_poly)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred),4)
mae = round(mean_absolute_error(y_test, y_pred),0)
mse = round(mean_squared_error(y_test, y_pred),0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')
```

```python
# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Multi-nominal Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_poly = poly_features.fit_transform(X_milan)
milan_pred = MNR_log_Model.predict(milan_poly)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'], milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall', 'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2, 9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center', loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.8763
MAE: 629980.0
MSE: 5359653235589.0
Calculation Time: 2.0877 seconds
```

Multi-nominal Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 85850671 | 0.13 |
| F. Tomori | CB | 84 | 60500000 | 71796361 | 0.19 |
| S. Kjær | CB | 82 | 14500000 | 10413846 | -0.28 |
| D. Calabria | RB | 80 | 25500000 | 18096195 | -0.29 |
| S. Tonali | CDM | 84 | 62500000 | 48456526 | -0.22 |
| R. Krunić | CM | 77 | 10500000 | 8529566 | -0.19 |
| Rafael Leão | LW | 84 | 66500000 | 54273957 | -0.18 |
| I. Bennacer | CM | 82 | 40000000 | 50930576 | 0.27 |
| Brahim | CAM | 78 | 31500000 | 31173055 | -0.01 |
| O. Giroud | ST | 82 | 13000000 | 12546486 | -0.03 |

[34]:
```
print(MNR_Model.get_params())
print(MNR_Model.get_params())
```

```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize':
'deprecated', 'positive': False}
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize':
'deprecated', 'positive': False}
```

4.5 KNN Regression

best_k = knn_Model.best_params_['n_neighbors']

[35]:
```
'''
# Best Hyper
param_grid = {'n_neighbors': range(1, 11)}
knn_Model = GridSearchCV(KNeighborsRegressor(), param_grid, cv=5)
knn_Model.fit(X_train, y_train)
best_k = knn_Model.best_params_['n_neighbors']
print('Best K:', best_k)
'''
```

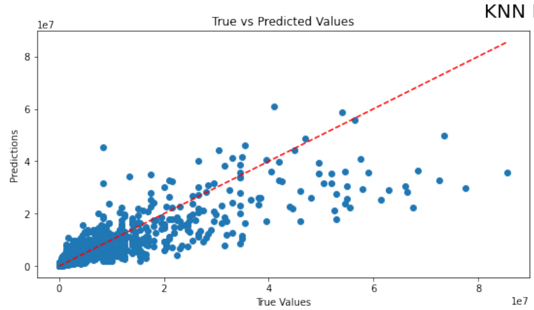
[35]:
```
"\n# Best Hyper\nparam_grid = {'n_neighbors': range(1, 11)}\nknn_Model =
GridSearchCV(KNeighborsRegressor(), param_grid, cv=5)\nknn_Model.fit(X_train,
y_train)\nbest_k = knn_Model.best_params_['n_neighbors']\nprint('Best K:',
best_k)\n"
```

[36]:
```
start_time = time.time()
# KNN Regression
KNN_Model = KNeighborsRegressor()
KNN_Model.fit(X_train, y_train)
y_pred = KNN_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('KNN Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
```

```python
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = KNN_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7428
MAE: 1094924.0
MSE: 11145900528328.0
Calculation Time: 2.9687 seconds
```

KNN Regression



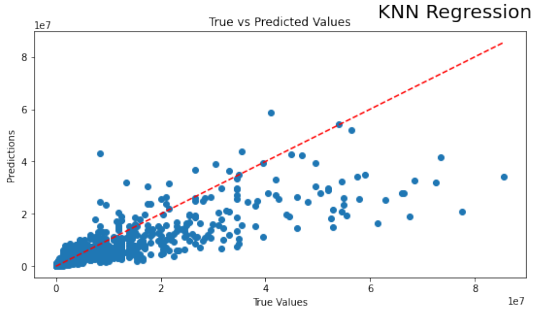

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 32500000 | -0.57 |
| F. Tomori | CB | 84 | 60500000 | 33800000 | -0.44 |
| S. Kjær | CB | 82 | 14500000 | 24500000 | 0.69 |
| D. Calabria | RB | 80 | 25500000 | 12900000 | -0.49 |
| S. Tonali | CDM | 84 | 62500000 | 39700000 | -0.36 |
| R. Krunić | CM | 77 | 10500000 | 6060000 | -0.42 |
| Rafael Leão | LW | 84 | 66500000 | 31500000 | -0.53 |
| I. Bennacer | CM | 82 | 40000000 | 32800000 | -0.18 |
| Brahim | CAM | 78 | 31500000 | 10360000 | -0.67 |
| O. Giroud | ST | 82 | 13000000 | 8875000 | -0.32 |

[37]:
```python
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# KNN Regression
KNN_log_Model = KNeighborsRegressor()
KNN_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = KNN_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
```

```
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('KNN Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = KNN_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
 ↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
 ↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
 ↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
 ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.6932
MAE: 1122900.0
MSE: 13296664187068.0
Calculation Time: 2.7817 seconds
```

KNN Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 28210426 | -0.63 |
| F. Tomori | CB | 84 | 60500000 | 31379146 | -0.48 |
| S. Kjær | CB | 82 | 14500000 | 18175163 | 0.25 |
| D. Calabria | RB | 80 | 25500000 | 12441990 | -0.51 |
| S. Tonali | CDM | 84 | 62500000 | 34170311 | -0.45 |
| R. Krunić | CM | 77 | 10500000 | 5096906 | -0.51 |
| Rafael Leão | LW | 84 | 66500000 | 28920604 | -0.57 |
| I. Bennacer | CM | 82 | 40000000 | 29612781 | -0.26 |
| Brahim | CAM | 78 | 31500000 | 8924959 | -0.72 |
| O. Giroud | ST | 82 | 13000000 | 5778875 | -0.56 |

[38]:
```python
print(KNN_Model.get_params())
print(KNN_log_Model.get_params())
```

```
{'algorithm': 'auto', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params':
None, 'n_jobs': None, 'n_neighbors': 5, 'p': 2, 'weights': 'uniform'}
{'algorithm': 'auto', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params':
None, 'n_jobs': None, 'n_neighbors': 5, 'p': 2, 'weights': 'uniform'}
```

4.6 Decision Tree Regression

[39]:
```python
'''
# Best Hyper
param_grid = {
    'max_depth': [5, 10, 15],
    'min_samples_split': [15, 30, 45],
    'min_samples_leaf': [5, 10, 15],
    'max_leaf_nodes': [15, 30, 45]}
dt_Model = GridSearchCV(DecisionTreeRegressor(), param_grid, cv=5)
dt_Model.fit(X_train, y_train)
best_params = dt_Model.best_params_
print('Best Parameters:', best_params)
'''
```

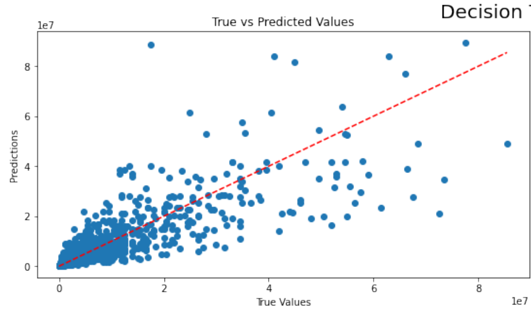
[39]:
```
"\n# Best Hyper\nparam_grid = {\n    'max_depth': [5, 10, 15],\n
'min_samples_split': [15, 30, 45],\n    'min_samples_leaf': [5, 10, 15],\n
'max_leaf_nodes': [15, 30, 45]}\ndt_Model =
GridSearchCV(DecisionTreeRegressor(), param_grid, cv=5)\ndt_Model.fit(X_train,
y_train)\nbest_params = dt_Model.best_params_\nprint('Best Parameters:',
best_params)\n"
```

[40]:
```python
start_time = time.time()
# Decision Tree Regression
DT_Model = DecisionTreeRegressor(random_state=26)
DT_Model.fit(X_train, y_train)
y_pred = DT_Model.predict(X_test)
# Evaluate R2 MAE and MSE
```

```python
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Decision Tree Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = DT_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7162
MAE: 1082433.0
MSE: 12298368109027.0
Calculation Time: 0.9766 seconds
```

Decision Tree Regression



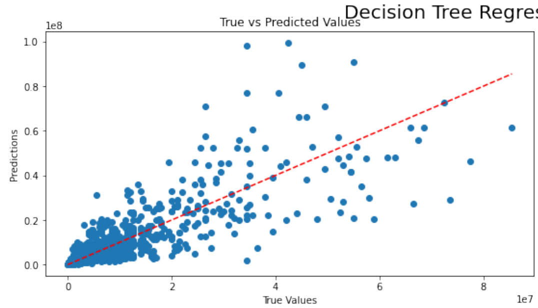

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 72000000 | -0.05 |
| F. Tomori | CB | 84 | 60500000 | 68500000 | 0.13 |
| S. Kjær | CB | 82 | 14500000 | 24000000 | 0.66 |
| D. Calabria | RB | 80 | 25500000 | 36000000 | 0.41 |
| S. Tonali | CDM | 84 | 62500000 | 35000000 | -0.44 |
| R. Krunić | CM | 77 | 10500000 | 14000000 | 0.33 |
| Rafael Leão | LW | 84 | 66500000 | 49000000 | -0.26 |
| I. Bennacer | CM | 82 | 40000000 | 38000000 | -0.05 |
| Brahim | CAM | 78 | 31500000 | 23500000 | -0.25 |
| O. Giroud | ST | 82 | 13000000 | 55500000 | 3.27 |

[41]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV

start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Decision Tree Regression
DT_log_Model = DecisionTreeRegressor(random_state=26)
DT_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = DT_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Decision Tree Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = DT_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],
    milan_players['ValueEUR'])-1),2)
```

```python
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
 ↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
 ↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
 ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.705
MAE: 1097749.0
MSE: 12784446504883.0
Calculation Time: 0.9305 seconds
```

Decision Tree Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 37500000 | -0.51 |
| F. Tomori | CB | 84 | 60500000 | 46000000 | -0.24 |
| S. Kjær | CB | 82 | 14500000 | 5500000 | -0.62 |
| D. Calabria | RB | 80 | 25500000 | 35500000 | 0.39 |
| S. Tonali | CDM | 84 | 62500000 | 20000000 | -0.68 |
| R. Krunić | CM | 77 | 10500000 | 18500000 | 0.76 |
| Rafael Leão | LW | 84 | 66500000 | 61500000 | -0.08 |
| I. Bennacer | CM | 82 | 40000000 | 23000000 | -0.43 |
| Brahim | CAM | 78 | 31500000 | 38000000 | 0.21 |
| O. Giroud | ST | 82 | 13000000 | 77500000 | 4.96 |

[42]:
```python
print(DT_Model.get_params())
print(DT_log_Model.get_params())
```

```
{'ccp_alpha': 0.0, 'criterion': 'squared_error', 'max_depth': None,
'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0,
'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0,
'random_state': 26, 'splitter': 'best'}
{'ccp_alpha': 0.0, 'criterion': 'squared_error', 'max_depth': None,
'max_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0,
'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0,
'random_state': 26, 'splitter': 'best'}
```

4.7 Random Forest Regression

[43]:
```python
'''# Best Hyper
param_grid = {
    'n_estimators': [50, 100],
```

```
    'max_depth': [10],
    'min_samples_split': [45],
    'min_samples_leaf': [15],
    'max_leaf_nodes': [45]}
rf_Model = GridSearchCV(RandomForestRegressor(), param_grid, cv=5)
rf_Model.fit(X_train, y_train)
best_params = rf_Model.best_params_
print('Best Parameters:', best_params)
'''
```

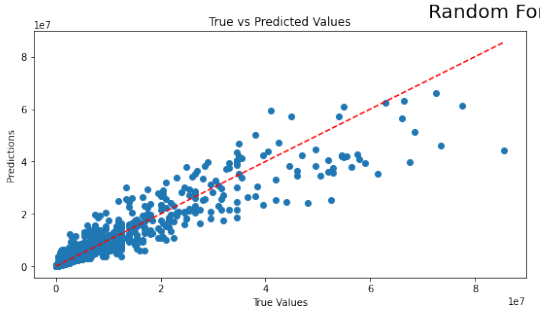
[43]: "# Best Hyper\nparam_grid = {\n    'n_estimators': [50, 100],\n    'max_depth': [10],\n    'min_samples_split': [45],\n    'min_samples_leaf': [15],\n 'max_leaf_nodes': [45]}\nrf_Model = GridSearchCV(RandomForestRegressor(), param_grid, cv=5)\nrf_Model.fit(X_train, y_train)\nbest_params = rf_Model.best_params_\nprint('Best Parameters:', best_params)\n"

[44]:
```
start_time = time.time()
# Random Forest Regression
RF_Model = RandomForestRegressor(random_state=26)
RF_Model.fit(X_train, y_train)
y_pred = RF_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Random Forest Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = RF_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],
 ↪milan_players['ValueEUR'])-1),2)
```

```
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
 ↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
 ↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
 ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.8933
MAE: 697402.0
MSE: 4623413076250.0
Calculation Time: 51.14 seconds
```

Random Forest Regression



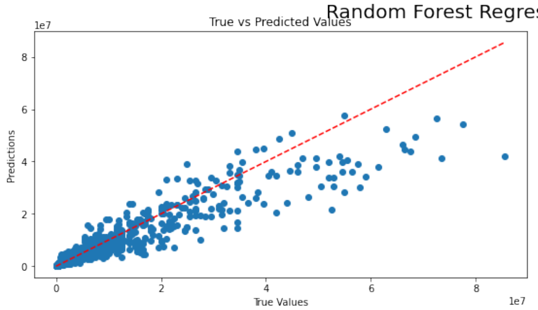

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 50520000 | -0.34 |
| F. Tomori | CB | 84 | 60500000 | 50435000 | -0.17 |
| S. Kjær | CB | 82 | 14500000 | 13396000 | -0.08 |
| D. Calabria | RB | 80 | 25500000 | 35290000 | 0.38 |
| S. Tonali | CDM | 84 | 62500000 | 43585000 | -0.3 |
| R. Krunić | CM | 77 | 10500000 | 14270000 | 0.36 |
| Rafael Leão | LW | 84 | 66500000 | 47930000 | -0.28 |
| I. Bennacer | CM | 82 | 40000000 | 40185000 | 0.0 |
| Brahim | CAM | 78 | 31500000 | 18438000 | -0.41 |
| O. Giroud | ST | 82 | 13000000 | 24874000 | 0.91 |

[45]:
```
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Random Forest Regression
RF_log_Model = RandomForestRegressor(random_state=26)
RF_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = RF_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')
```

```
# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Random Forest Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = RF_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.8769
MAE: 679591.0
MSE: 5334894705692.0
Calculation Time: 41.3601 seconds
```

Random Forest Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 35643163 | -0.53 |
| F. Tomori | CB | 84 | 60500000 | 40566843 | -0.33 |
| S. Kjær | CB | 82 | 14500000 | 10747536 | -0.26 |
| D. Calabria | RB | 80 | 25500000 | 22864615 | -0.1 |
| S. Tonali | CDM | 84 | 62500000 | 39461508 | -0.37 |
| R. Krunić | CM | 77 | 10500000 | 14718839 | 0.4 |
| Rafael Leão | LW | 84 | 66500000 | 46122708 | -0.31 |
| I. Bennacer | CM | 82 | 40000000 | 42309847 | 0.06 |
| Brahim | CAM | 78 | 31500000 | 14553277 | -0.54 |
| O. Giroud | ST | 82 | 13000000 | 17153776 | 0.32 |

[46]:
```
print(RF_Model.get_params())
print(RF_log_Model.get_params())
```

```
{'bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'squared_error', 'max_depth':
None, 'max_features': 'auto', 'max_leaf_nodes': None, 'max_samples': None,
'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_jobs': None,
'oob_score': False, 'random_state': 26, 'verbose': 0, 'warm_start': False}
{'bootstrap': True, 'ccp_alpha': 0.0, 'criterion': 'squared_error', 'max_depth':
None, 'max_features': 'auto', 'max_leaf_nodes': None, 'max_samples': None,
'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_jobs': None,
'oob_score': False, 'random_state': 26, 'verbose': 0, 'warm_start': False}
```

4.8 Gradient Boosting Regression

[47]:
```
'''# Best Hyper
param_grid = {
    'n_estimators': [50],
    'learning_rate': [0.1, 0.5],
    'max_depth': [5, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 3],
    'max_features': ['auto', 'sqrt', 'log2']}
gb_Model = GridSearchCV(GradientBoostingRegressor(), param_grid, cv=5)
gb_Model.fit(X_train, y_train)
best_params = gb_Model.best_params_
print('Best Parameters:', best_params)
'''
```

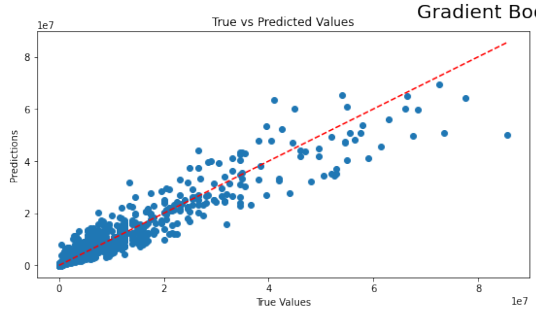
[47]:
```
"# Best Hyper\nparam_grid = {\n    'n_estimators': [50],\n    'learning_rate':
[0.1, 0.5],\n    'max_depth': [5, 10],\n    'min_samples_split': [2, 5],\n
'min_samples_leaf': [1, 3],\n    'max_features': ['auto', 'sqrt',
'log2']}\ngb_Model = GridSearchCV(GradientBoostingRegressor(), param_grid,
cv=5)\ngb_Model.fit(X_train, y_train)\nbest_params =
gb_Model.best_params_\nprint('Best Parameters:', best_params)\n"
```

[48]:
```
start_time = time.time()
# Gradient Boosting Regression
GB_Model = GradientBoostingRegressor(random_state=26)
GB_Model.fit(X_train, y_train)
y_pred = GB_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
```

```python
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Gradient Boosting Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = GB_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'], milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall', 'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2, 9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center', loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.9147
MAE: 741671.0
MSE: 3694760751632.0
Calculation Time: 13.4689 seconds
```

Gradient Boosting Regression

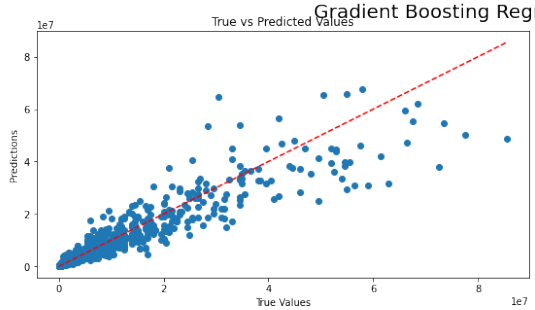



| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 55908096 | -0.26 |
| F. Tomori | CB | 84 | 60500000 | 61268103 | 0.01 |
| S. Kjær | CB | 82 | 14500000 | 15196081 | 0.05 |
| D. Calabria | RB | 80 | 25500000 | 27881194 | 0.09 |
| S. Tonali | CDM | 84 | 62500000 | 48487332 | -0.22 |
| R. Krunić | CM | 77 | 10500000 | 12329032 | 0.17 |
| Rafael Leão | LW | 84 | 66500000 | 53672626 | -0.19 |
| I. Bennacer | CM | 82 | 40000000 | 46750962 | 0.17 |
| Brahim | CAM | 78 | 31500000 | 15086508 | -0.52 |
| O. Giroud | ST | 82 | 13000000 | 30277181 | 1.33 |

[49]:
```python
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Gradient Boosting Regression
GB_log_Model = GradientBoostingRegressor(random_state=26)
GB_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = GB_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Gradient Boosting Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = GB_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
```

```
plt.show()
```

```
R2 Score: 0.8883
MAE: 650905.0
MSE: 4839335412423.0
Calculation Time: 13.1533 seconds
```




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 62187288 | -0.18 |
| F. Tomori | CB | 84 | 60500000 | 37877854 | -0.37 |
| S. Kjær | CB | 82 | 14500000 | 9881741 | -0.32 |
| D. Calabria | RB | 80 | 25500000 | 21225838 | -0.17 |
| S. Tonali | CDM | 84 | 62500000 | 61059199 | -0.02 |
| R. Krunić | CM | 77 | 10500000 | 14740135 | 0.4 |
| Rafael Leão | LW | 84 | 66500000 | 53888861 | -0.19 |
| I. Bennacer | CM | 82 | 40000000 | 44239651 | 0.11 |
| Brahim | CAM | 78 | 31500000 | 12442301 | -0.61 |
| O. Giroud | ST | 82 | 13000000 | 8889471 | -0.32 |

[50]:
```
print(GB_Model.get_params())
print(GB_log_Model.get_params())
```

```
{'alpha': 0.9, 'ccp_alpha': 0.0, 'criterion': 'friedman_mse', 'init': None,
'learning_rate': 0.1, 'loss': 'squared_error', 'max_depth': 3, 'max_features':
None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf':
1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100,
'n_iter_no_change': None, 'random_state': 26, 'subsample': 1.0, 'tol': 0.0001,
'validation_fraction': 0.1, 'verbose': 0, 'warm_start': False}
{'alpha': 0.9, 'ccp_alpha': 0.0, 'criterion': 'friedman_mse', 'init': None,
'learning_rate': 0.1, 'loss': 'squared_error', 'max_depth': 3, 'max_features':
None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf':
1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100,
'n_iter_no_change': None, 'random_state': 26, 'subsample': 1.0, 'tol': 0.0001,
'validation_fraction': 0.1, 'verbose': 0, 'warm_start': False}
```

4.9 Adaboost Regression

[51]:
```
'''# Best Hyper
param_grid = {
    'n_estimators': [50],
    'learning_rate': [0.1, 0.5],
    'base_estimator': [DecisionTreeRegressor(max_depth=5),␣
 ↪DecisionTreeRegressor(max_depth=10)],
    'loss': ['linear', 'square', 'exponential']}
ab_Model = GridSearchCV(AdaBoostRegressor(), param_grid, cv=5)
ab_Model.fit(X_train, y_train)
best_params = ab_Model.best_params_
print('Best Parameters:', best_params)
```

```
'''
```

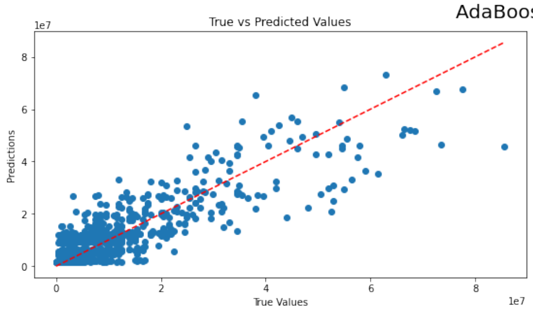
[51]: "# Best Hyper\nparam_grid = {\n    'n_estimators': [50],\n    'learning_rate': [0.1, 0.5],\n    'base_estimator': [DecisionTreeRegressor(max_depth=5), DecisionTreeRegressor(max_depth=10)],\n    'loss': ['linear', 'square', 'exponential']}\nab_Model = GridSearchCV(AdaBoostRegressor(), param_grid, cv=5)\nab_Model.fit(X_train, y_train)\nbest_params = ab_Model.best_params_\nprint('Best Parameters:', best_params)\n"

[52]:
```
start_time = time.time()
# Adaboosting Regression
AB_Model = AdaBoostRegressor(random_state=26, learning_rate=0.1,␣
 ↪n_estimators=100)
AB_Model.fit(X_train, y_train)
y_pred = AB_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('AdaBoost Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = AB_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
 ↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
 ↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
 ↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
```

```
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',
    loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7859
MAE: 1571494.0
MSE: 9279481735867.0
Calculation Time: 17.2452 seconds
```

AdaBoost Regression

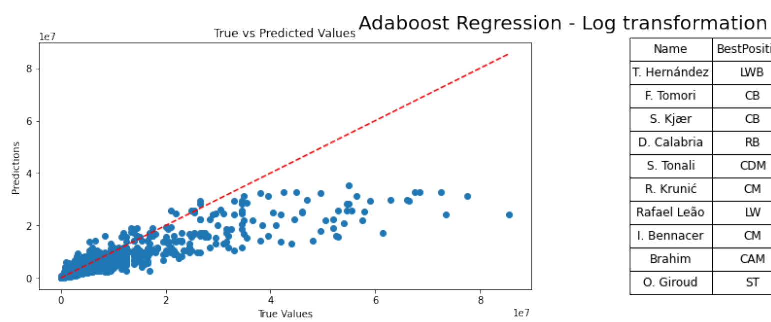



| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 51857650 | -0.32 |
| F. Tomori | CB | 84 | 60500000 | 50327391 | -0.17 |
| S. Kjær | CB | 82 | 14500000 | 17750000 | 0.22 |
| D. Calabria | RB | 80 | 25500000 | 19703064 | -0.23 |
| S. Tonali | CDM | 84 | 62500000 | 39408911 | -0.37 |
| R. Krunić | CM | 77 | 10500000 | 16380311 | 0.56 |
| Rafael Leão | LW | 84 | 66500000 | 51857650 | -0.22 |
| I. Bennacer | CM | 82 | 40000000 | 55468127 | 0.39 |
| Brahim | CAM | 78 | 31500000 | 12022335 | -0.62 |
| O. Giroud | ST | 82 | 13000000 | 32379545 | 1.49 |

[53]:
```
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Adaboosting Regression
AB_log_Model = AdaBoostRegressor(random_state=26, learning_rate=1,
    n_estimators=100)
AB_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = AB_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Adaboost Regression - Log transformation', fontsize=20)
```

```
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = AB_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.7171
MAE: 1009320.0
MSE: 12259157098032.0
Calculation Time: 16.2221 seconds
```




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 31231143 | -0.59 |
| F. Tomori | CB | 84 | 60500000 | 19141124 | -0.68 |
| S. Kjær | CB | 82 | 14500000 | 6745907 | -0.53 |
| D. Calabria | RB | 80 | 25500000 | 11187801 | -0.56 |
| S. Tonali | CDM | 84 | 62500000 | 25864989 | -0.59 |
| R. Krunić | CM | 77 | 10500000 | 14310380 | 0.36 |
| Rafael Leão | LW | 84 | 66500000 | 24620630 | -0.63 |
| I. Bennacer | CM | 82 | 40000000 | 25807299 | -0.35 |
| Brahim | CAM | 78 | 31500000 | 8599779 | -0.73 |
| O. Giroud | ST | 82 | 13000000 | 4490831 | -0.65 |

[54]:
```
print(AB_Model.get_params())
print(AB_log_Model.get_params())
```

```
{'base_estimator': None, 'learning_rate': 0.1, 'loss': 'linear', 'n_estimators':
100, 'random_state': 26}
{'base_estimator': None, 'learning_rate': 1, 'loss': 'linear', 'n_estimators':
```

100, 'random_state': 26}

4.10 Support Vector Regression

[55]:
```
'''
# Best Hyper
param_grid = {
    'kernel': ['linear', 'poly', 'rbf'],
    'C': [0.1, 1, 10],
    'gamma':[0.1, 1 ,10]
    'epsilon': [0.1, 0.5, 1]}
svm_Model = GridSearchCV(SVR(), param_grid, cv=5)
svm_Model.fit(X_train, y_train)
best_params = svm_Model.best_params_
print('Best Parameters:', best_params)
'''
```

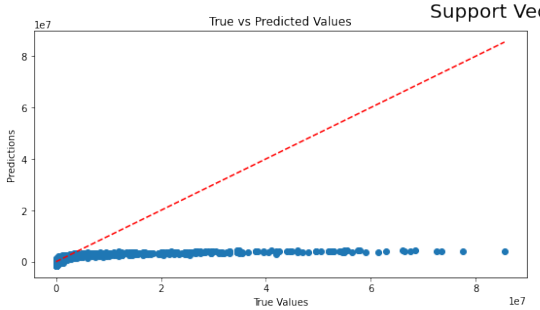
[55]:
```
"\n# Best Hyper\nparam_grid = {\n    'kernel': ['linear', 'poly', 'rbf'],\n
'C': [0.1, 1, 10],\n    'gamma':[0.1, 1 ,10]\n    'epsilon': [0.1, 0.5,
1]}\nsvm_Model = GridSearchCV(SVR(), param_grid, cv=5)\nsvm_Model.fit(X_train,
y_train)\nbest_params = svm_Model.best_params_\nprint('Best Parameters:',
best_params)\n"
```

[56]:
```
start_time = time.time()
# Support Vector Regression
SVM_Model = SVR(kernel='linear',C=10, gamma=10)
SVM_Model.fit(X_train, y_train)
y_pred = SVM_Model.predict(X_test)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Support Vector Regression', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
```

```
milan_pred = SVM_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round((milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.1109
MAE: 1798853.0
MSE: 38534497655933.0
Calculation Time: 32.242 seconds
```

Support Vector Regression



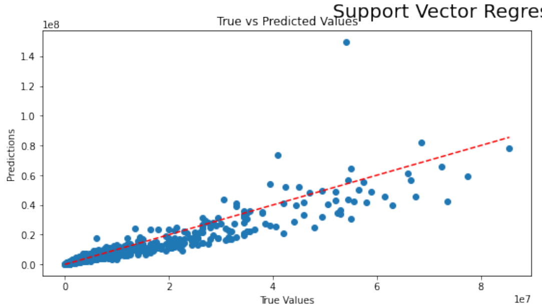

| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 4736240 | -0.94 |
| F. Tomori | CB | 84 | 60500000 | 4225045 | -0.93 |
| S. Kjær | CB | 82 | 14500000 | 2896976 | -0.8 |
| D. Calabria | RB | 80 | 25500000 | 3458996 | -0.86 |
| S. Tonali | CDM | 84 | 62500000 | 4444666 | -0.93 |
| R. Krunić | CM | 77 | 10500000 | 3190694 | -0.7 |
| Rafael Leão | LW | 84 | 66500000 | 4249835 | -0.94 |
| I. Bennacer | CM | 82 | 40000000 | 4144423 | -0.9 |
| Brahim | CAM | 78 | 31500000 | 2574281 | -0.92 |
| O. Giroud | ST | 82 | 13000000 | 3062481 | -0.76 |

[57]:
```
start_time = time.time()
y_train_log1p = np.log1p(y_train)
# Support Vector Regression
SVM_log_Model = SVR()
SVM_log_Model.fit(X_train, y_train_log1p)
y_pred_log1p = SVM_log_Model.predict(X_test)
y_pred = np.expm1(y_pred_log1p)
# Evaluate R2 MAE and MSE
r2 = round(r2_score(y_test, y_pred), 4)
mae = round(mean_absolute_error(y_test, y_pred), 0)
mse = round(mean_squared_error(y_test, y_pred), 0)
```

```
print('R2 Score:', r2)
print('MAE:', mae)
print('MSE:', mse)
end_time = time.time()
print('Calculation Time:', round(end_time - start_time, 4), 'seconds')

# Update Scatter
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 4))
fig.subplots_adjust(bottom=0)
fig.suptitle('Support Vector Regression - Log transformation', fontsize=20)
ax1.scatter(y_test, y_pred)
ax1.plot([0, max(y_test)], [0, max(y_test)], color='red', linestyle='--')
ax1.set_xlabel("True Values")
ax1.set_ylabel("Predictions")
ax1.set_title('True vs Predicted Values')
# Update Table log
milan_pred = SVM_log_Model.predict(X_milan)

milan_players['Pred_Value'] = np.round(np.expm1(milan_pred), 0).astype(int)
milan_players['Accuracy'] = np.round((np.divide(milan_players['Pred_Value'],␣
 ↪milan_players['ValueEUR'])-1),2)
milan_players_selected = milan_players[['Name', 'BestPosition', 'Overall',␣
 ↪'ValueEUR', 'Pred_Value', 'Accuracy']]
milan_players_selected = milan_players_selected.reindex(index=[0, 3, 6, 7, 2,␣
 ↪9, 1, 4, 8, 5])
table_data = [list(milan_players_selected.columns)] + milan_players_selected.
 ↪values.tolist()
table = ax2.table(cellText=table_data, colLabels=None, cellLoc='center',␣
 ↪loc='center')
table.auto_set_font_size(False)
table.set_fontsize(12)
table.scale(1, 2)
plt.axis('off')
plt.show()
```

```
R2 Score: 0.8662
MAE: 643371.0
MSE: 5796886799482.0
Calculation Time: 35.816 seconds
```

Support Vector Regression - Log transformation




| Name | BestPosition | Overall | ValueEUR | Pred_Value | Accuracy |
|---|---|---|---|---|---|
| T. Hernández | LWB | 85 | 76000000 | 58175942 | -0.23 |
| F. Tomori | CB | 84 | 60500000 | 43172952 | -0.29 |
| S. Kjær | CB | 82 | 14500000 | 8134915 | -0.44 |
| D. Calabria | RB | 80 | 25500000 | 13117539 | -0.49 |
| S. Tonali | CDM | 84 | 62500000 | 54184809 | -0.13 |
| R. Krunić | CM | 77 | 10500000 | 9555092 | -0.09 |
| Rafael Leão | LW | 84 | 66500000 | 56171556 | -0.16 |
| I. Bennacer | CM | 82 | 40000000 | 42067200 | 0.05 |
| Brahim | CAM | 78 | 31500000 | 17029543 | -0.46 |
| O. Giroud | ST | 82 | 13000000 | 8788990 | -0.32 |

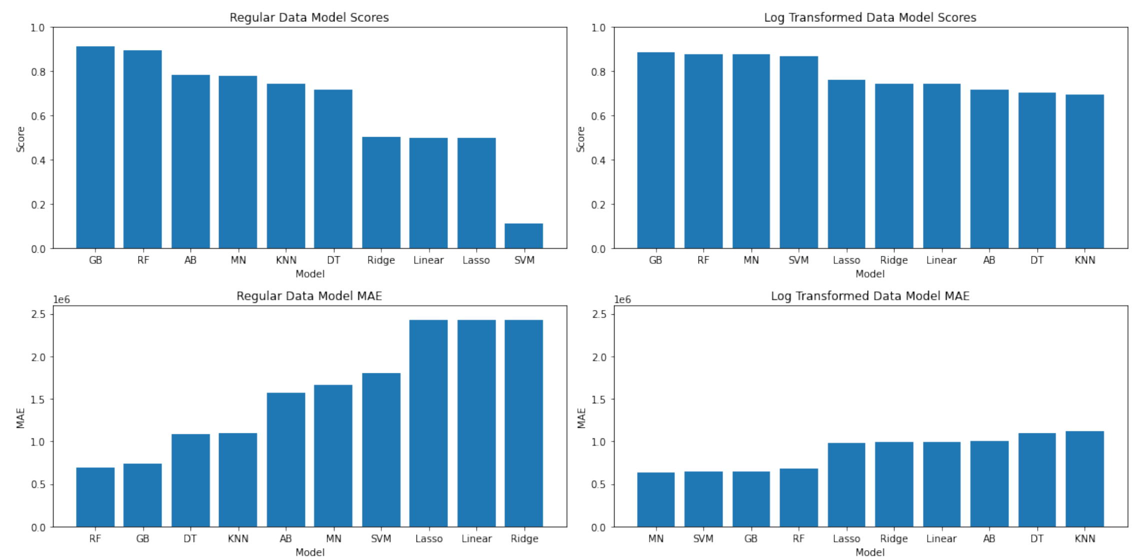
[58]:
```python
print(SVM_Model.get_params())
print(SVM_log_Model.get_params())
```

```
{'C': 10, 'cache_size': 200, 'coef0': 0.0, 'degree': 3, 'epsilon': 0.1, 'gamma':
10, 'kernel': 'linear', 'max_iter': -1, 'shrinking': True, 'tol': 0.001,
'verbose': False}
{'C': 1.0, 'cache_size': 200, 'coef0': 0.0, 'degree': 3, 'epsilon': 0.1,
'gamma': 'scale', 'kernel': 'rbf', 'max_iter': -1, 'shrinking': True, 'tol':
0.001, 'verbose': False}
```

5. Model Comparision

[59]:
```python
# Score data
regS_models = ['Linear', 'Ridge', 'Lasso', 'MN', 'KNN', 'DT', 'RF', 'GB', 'AB',␣
↪'SVM']
regS_scores = [0.5013, 0.5014, 0.5013, 0.7785, 0.7428, 0.7162, 0.8933, 0.9147,␣
↪0.7859, 0.1109]
regS = pd.DataFrame({'Regular Model': regS_models, 'Score': regS_scores})

logS_models = ['Linear', 'Ridge', 'Lasso', 'MN', 'KNN', 'DT', 'RF', 'GB', 'AB',␣
↪'SVM']
logS_scores = [0.7453, 0.7455, 0.7632, 0.8763, 0.6932, 0.705, 0.8769, 0.8883, 0.
↪7171, 0.8662]
logS = pd.DataFrame({'Log Transformed Model': logS_models, 'Score':␣
↪logS_scores})

regM_models = ['Linear', 'Ridge', 'Lasso', 'MN', 'KNN', 'DT', 'RF', 'GB', 'AB',␣
↪'SVM']
regM_mae = [2430090, 2430157, 2430089, 1663694, 1094924, 1082433, 697402,␣
↪741671, 1571494, 1798853]
regM = pd.DataFrame({'Regular Model': regM_models, 'MAE': regM_mae})

logM_models = ['Linear', 'Ridge', 'Lasso', 'MN', 'KNN', 'DT', 'RF', 'GB', 'AB',␣
↪'SVM']
```

```
logM_mae = [988093, 988040, 985644, 629980, 1122900, 1097749, 679591, 650905,␣
↪1009320, 643371]
logM = pd.DataFrame({'Log Transformed Model': logM_models, 'MAE': logM_mae})

# Chart Frame
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(nrows=2, ncols=2, figsize=(16, 8))
# Regular
regS_sorted = regS.sort_values(by='Score', ascending=False)
ax1.bar(regS_sorted['Regular Model'], regS_sorted['Score'],␣
↪color=['C0']*10+['C3']*0+['C0']*0+['C3']*0)
ax1.set_ylim(0, 1)
ax1.set_xlabel('Model')
ax1.set_ylabel('Score')
ax1.set_title('Regular Data Model Scores')
# Log Transformed
logS_sorted = logS.sort_values(by='Score', ascending=False)
ax2.bar(logS_sorted['Log Transformed Model'], logS_sorted['Score'],␣
↪color=['C0']*10+['C3']*10+['C0']*0)
ax2.set_ylim(0, 1)
ax2.set_xlabel('Model')
ax2.set_ylabel('Score')
ax2.set_title('Log Transformed Data Model Scores')
# Regular
regM_sorted = regM.sort_values(by='MAE', ascending=True)
ax3.bar(regM_sorted['Regular Model'], regM_sorted['MAE'],␣
↪color=['C0']*10+['C3']*0+['C0']*6)
ax3.set_ylim(0,2600000)
ax3.set_xlabel('Model')
ax3.set_ylabel('MAE')
ax3.set_title('Regular Data Model MAE')
# Log Transformed
logM_sorted = logM.sort_values(by='MAE', ascending=True)
ax4.bar(logM_sorted['Log Transformed Model'], logM_sorted['MAE'],␣
↪color=['C0']*10+['C3']*10+['C0']*0)
ax4.set_ylim(0,2600000)
ax4.set_xlabel('Model')
ax4.set_ylabel('MAE')
ax4.set_title('Log Transformed Data Model MAE')

fig.tight_layout()
plt.show()
```




Based on the Score and MAE of 10 regression models, we can make the following conclusion:

»1. Gradient Boosting and Random Forest regression models achieve scores of around 90% and low MAE values on both the original and log-transformed targets.

»2. The Multi-nominal and SVM regression models have the lowest MAE on log transformation, but they perform poorly on the original dataset.

»3. Linear regression model fits poorly on this dataset, and neither Ridge nor Lasso provide a significant improvement.

»4. Decision Tree and KNN regression perform better on the original dataset than on the log-transformed dataset, which means that log transformation still loses some of the original data information..

»5. Overall, the MAE of the models after log transformation is much lower, indicating that log transformation should be considered for variables with severe skewness when performing regression prediction.

6. Conclusion

Through this analysis, we successfully predicted the market prices of FIFA23 players using their attributes with an accuracy of over 90%. From our analysis, we can also draw the following conclusions:

»No free lunch theorem: in the field of machine learning, no algorithm is superior to others, and we can only find the most suitable method through continuous experimentation.

»Ensemble methods have a wider range of applicability and are more likely to produce better results. Compared to traditional SVM algorithms, Ensemble methods do not require spending a lot of time searching for optimal hyperparameters.

»Feature engineering is more important than model selection. Choosing the right features directly affects the success of the final model.

Next Step:

»I will combine unsupervised learning methods and classification learning methods to explore the relationship between player skills and their position on the field.