Data Viz - FIFA Dataset

June 1, 2023

[1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

sns.set_theme(style='whitegrid', font_scale=2, palette='viridis_r')
```

[2]:
```python
path = 'FIFA Dataset.csv'
FIFA = pd.read_csv(path)
```

1 Before visualizing our data, let's have a general overview

[3]:
```python
FIFA.shape
```

[3]:
```
(17588, 53)
```

[4]:
```python
FIFA.head()
```

[4]:
```
                Name Nationality National_Position  National_Kit  \
0  Cristiano Ronaldo    Portugal                LS           7.0
1       Lionel Messi   Argentina                RW          10.0
2             Neymar      Brazil                LW          10.0
3        Luis Suárez     Uruguay                LS           9.0
4       Manuel Neuer     Germany                GK           1.0

           Club Club_Position  Club_Kit Club_Joining  Contract_Expiry  Rating  \
0   Real Madrid            LW       7.0   07/01/2009           2021.0      94
1  FC Barcelona            RW      10.0   07/01/2004           2018.0      93
2  FC Barcelona            LW      11.0   07/01/2013           2021.0      92
3  FC Barcelona            ST       9.0   07/11/2014           2021.0      92
4     FC Bayern            GK       1.0   07/01/2011           2021.0      92

   … Long_Shots Curve Freekick_Accuracy Penalties  Volleys GK_Positioning  \
0  …         90    81                76        85       88             14
1  …         88    89                90        74       85             14
2  …         77    79                84        81       83             15
3  …         86    86                84        85       88             33
```

```
4  …          16    14                11         47        11               91

   GK_Diving  GK_Kicking  GK_Handling  GK_Reflexes
0          7          15           11           11
1          6          15           11            8
2          9          15            9           11
3         27          31           25           37
4         89          95           90           89

[5 rows x 53 columns]
```

[5]:
```
FIFA.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17588 entries, 0 to 17587
Data columns (total 53 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Name                17588 non-null  object
 1   Nationality         17588 non-null  object
 2   National_Position   1075 non-null   object
 3   National_Kit        1075 non-null   float64
 4   Club                17588 non-null  object
 5   Club_Position       17587 non-null  object
 6   Club_Kit            17587 non-null  float64
 7   Club_Joining        17587 non-null  object
 8   Contract_Expiry     17587 non-null  float64
 9   Rating              17588 non-null  int64
 10  Height              17588 non-null  object
 11  Weight              17588 non-null  object
 12  Preffered_Foot      17588 non-null  object
 13  Birth_Date          17588 non-null  object
 14  Age                 17588 non-null  int64
 15  Preffered_Position  17588 non-null  object
 16  Work_Rate           17588 non-null  object
 17  Weak_foot           17588 non-null  int64
 18  Skill_Moves         17588 non-null  int64
 19  Ball_Control        17588 non-null  int64
 20  Dribbling           17588 non-null  int64
 21  Marking             17588 non-null  int64
 22  Sliding_Tackle      17588 non-null  int64
 23  Standing_Tackle     17588 non-null  int64
 24  Aggression          17588 non-null  int64
 25  Reactions           17588 non-null  int64
 26  Attacking_Position  17588 non-null  int64
 27  Interceptions       17588 non-null  int64
 28  Vision              17588 non-null  int64
 29  Composure           17588 non-null  int64
```

```
 30  Crossing           17588 non-null  int64
 31  Short_Pass         17588 non-null  int64
 32  Long_Pass          17588 non-null  int64
 33  Acceleration       17588 non-null  int64
 34  Speed              17588 non-null  int64
 35  Stamina            17588 non-null  int64
 36  Strength           17588 non-null  int64
 37  Balance            17588 non-null  int64
 38  Agility            17588 non-null  int64
 39  Jumping            17588 non-null  int64
 40  Heading            17588 non-null  int64
 41  Shot_Power         17588 non-null  int64
 42  Finishing          17588 non-null  int64
 43  Long_Shots         17588 non-null  int64
 44  Curve              17588 non-null  int64
 45  Freekick_Accuracy  17588 non-null  int64
 46  Penalties          17588 non-null  int64
 47  Volleys            17588 non-null  int64
 48  GK_Positioning     17588 non-null  int64
 49  GK_Diving          17588 non-null  int64
 50  GK_Kicking         17588 non-null  int64
 51  GK_Handling        17588 non-null  int64
 52  GK_Reflexes        17588 non-null  int64
dtypes: float64(3), int64(38), object(12)
memory usage: 7.1+ MB
```

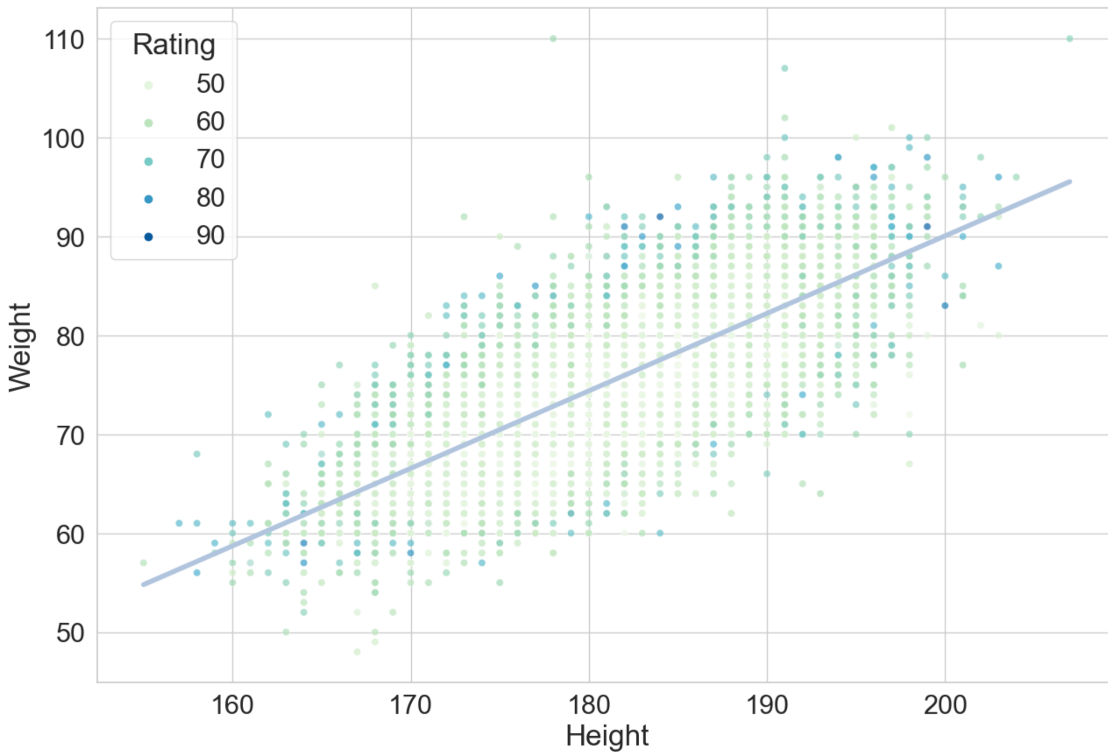
[6]:
```
# Casting height and weight columns into int
FIFA['Height'] = FIFA['Height'].str.replace(' cm', '').astype(int)
FIFA['Weight'] = FIFA['Weight'].str.replace(' kg', '').astype(int)
```

2 Visualization starts here...

2.1 Players ratings depending on their height and weight

[7]:
```
plt.subplots(figsize=(15, 10))
sns.scatterplot(data=FIFA, x='Height', y='Weight', hue='Rating',␣
 ↪palette='GnBu', alpha=.7)
sns.regplot(data=FIFA, x='Height', y='Weight', scatter=False, color='#B0C4DE',␣
 ↪line_kws={'linewidth': 4})
```

[7]:
```
<AxesSubplot:xlabel='Height', ylabel='Weight'>
```

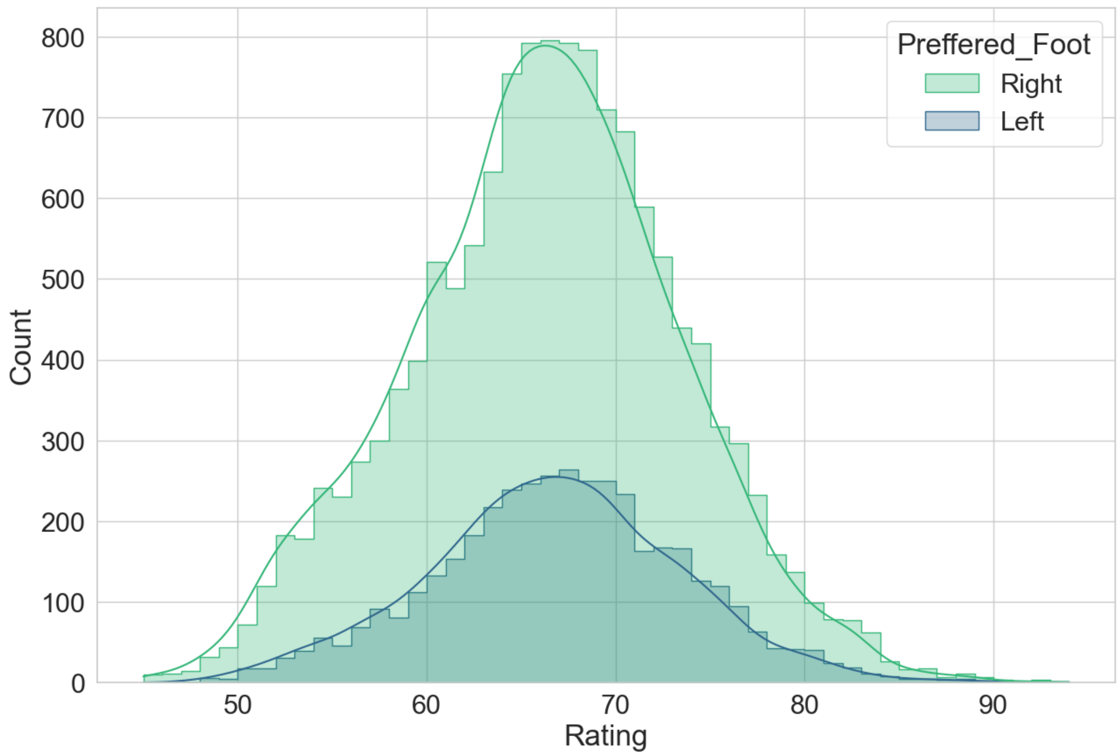


Globally, players height and weight are positively correlated. Furthermore, the subtle gradient around the regression line suggest that some ellipses having the regression line as major axis can be used to estimate a player's rating. The larger the minor axis, the more likely the player is to have a great rating.

2.2 Rating distribution based on the preffered foot

[8]:
```
plt.subplots(figsize=(15, 10))
sns.histplot(data=FIFA, x='Rating', hue='Preffered_Foot', kde=True,␣
 ↪element='step', multiple='layer', binwidth=1, alpha=.3, palette='viridis_r')
```

[8]: <AxesSubplot:xlabel='Rating', ylabel='Count'>



According to these overlaid histograms, left-handed players represents around 20 and 25% of the entire dataset and ratings seems to be normally distributed, with a mean around 68, regardless of the players preferred foot.

The ratings lower bound is established around 45 and the upper one near 95.

Considering the third statement of the empirical rule which predicts that 99.7% of observations falls within the first three standard deviations, we can make the hypothesis of a standard deviation around $\frac{68-45}{3} \approx 7.67$.

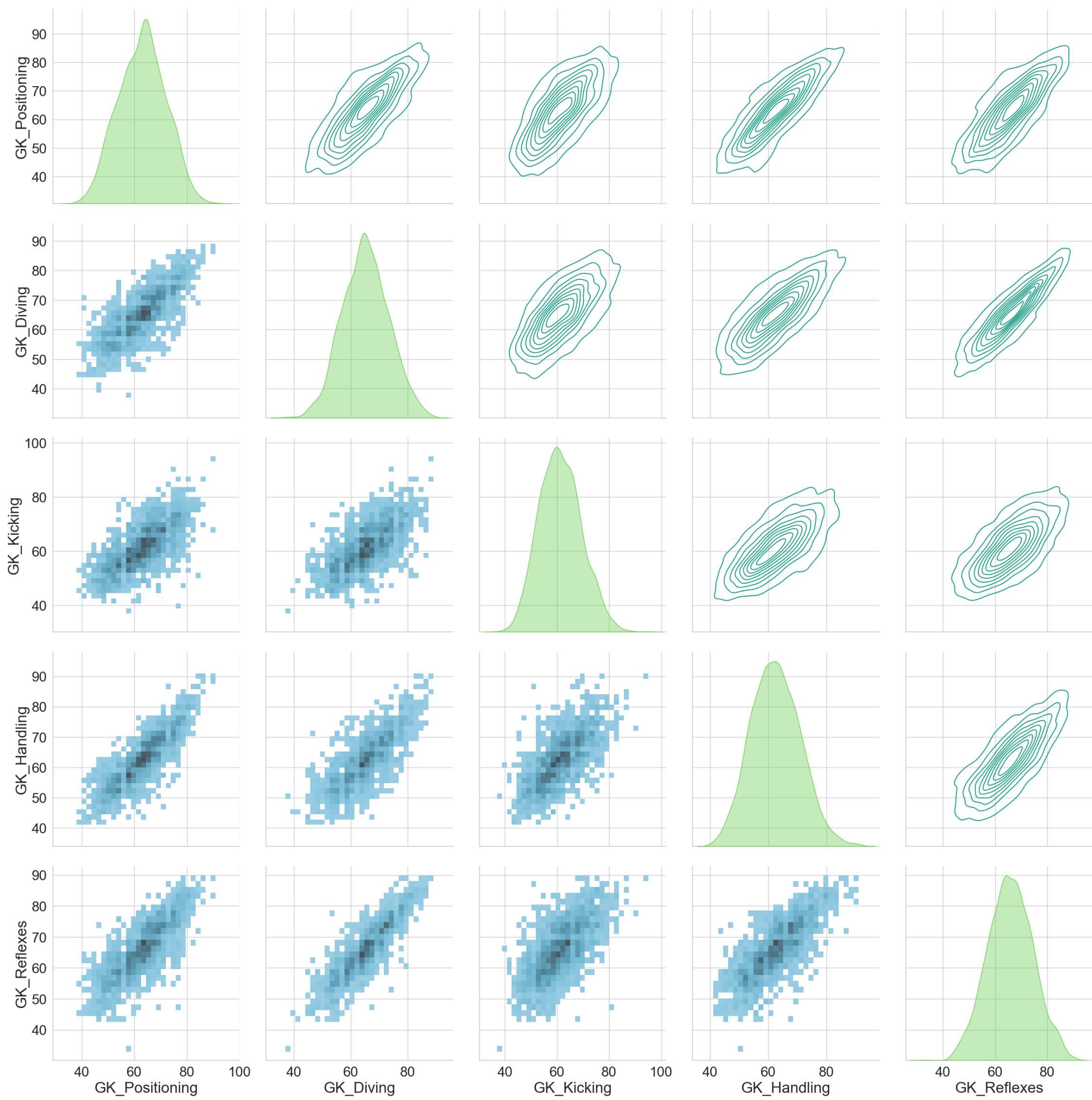
So, we come up with this hypothesis: $rating \sim \mathcal{N}(68, 7.67)$

2.3 Goal keepers' skills (GK skills)

[9]:
```
GK = FIFA[FIFA['Preffered_Position'] == 'GK']
GK_skills = ['GK_Positioning', 'GK_Diving', 'GK_Kicking', 'GK_Handling',␣
 ↪'GK_Reflexes']

g = sns.PairGrid(data=GK, vars=GK_skills, diag_sharey=False, height=5)
g.map_lower(sns.histplot, color='#87CEEB')
g.map_diag(sns.kdeplot, fill=True, color='#6ECE58', alpha=.4)
g.map_upper(sns.kdeplot, color='#1F9E89')
```

[9]: <seaborn.axisgrid.PairGrid at 0x220019cbdf0>



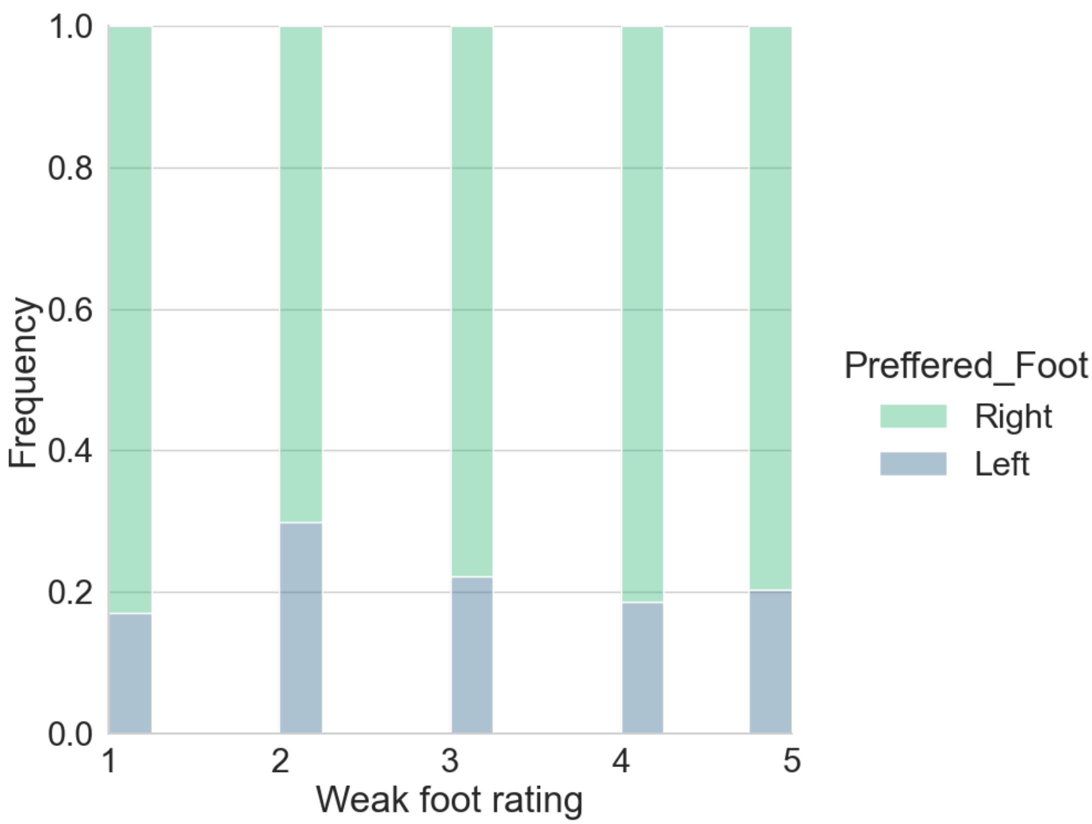
The previous grid summarises goal keepers' skills (the analysis has been restricted to GK for relevance purposes). Two principal facts are highlighted:

- Each GK skill appears to be normally distributed with almost values in range [30, 90].
- All GK skills are positively correlated. A deeper analysis could tell us wether the skills evolve together for a single GK or they may move on differently, meaning that each GK has its strengths and weaknesses, but the fact that they don't all focus on the same skill creates the overall balance observed.

2.4 Making the best with the worst

[10]:
```
g = sns.displot(data=FIFA, x='Weak_foot', hue='Preffered_Foot',␣
↪palette='viridis_r', multiple='fill', height=8, alpha=.4)
g.set_axis_labels('Weak foot rating', 'Frequency')
```

[10]: <seaborn.axisgrid.FacetGrid at 0x22002eeddc0>



Here we wanted to answer the following question: which of the left or right-handed players perform better with their weak foot?

The distribution plot above shows that none of the two groups stand out in particular, since the 20/80 ratio - which may be the actual ratio among left and right-handed in the dataset - is almost respected. There's no real upward or downward trend when the weak foot rating moves.

2.5 Clubs evaluation

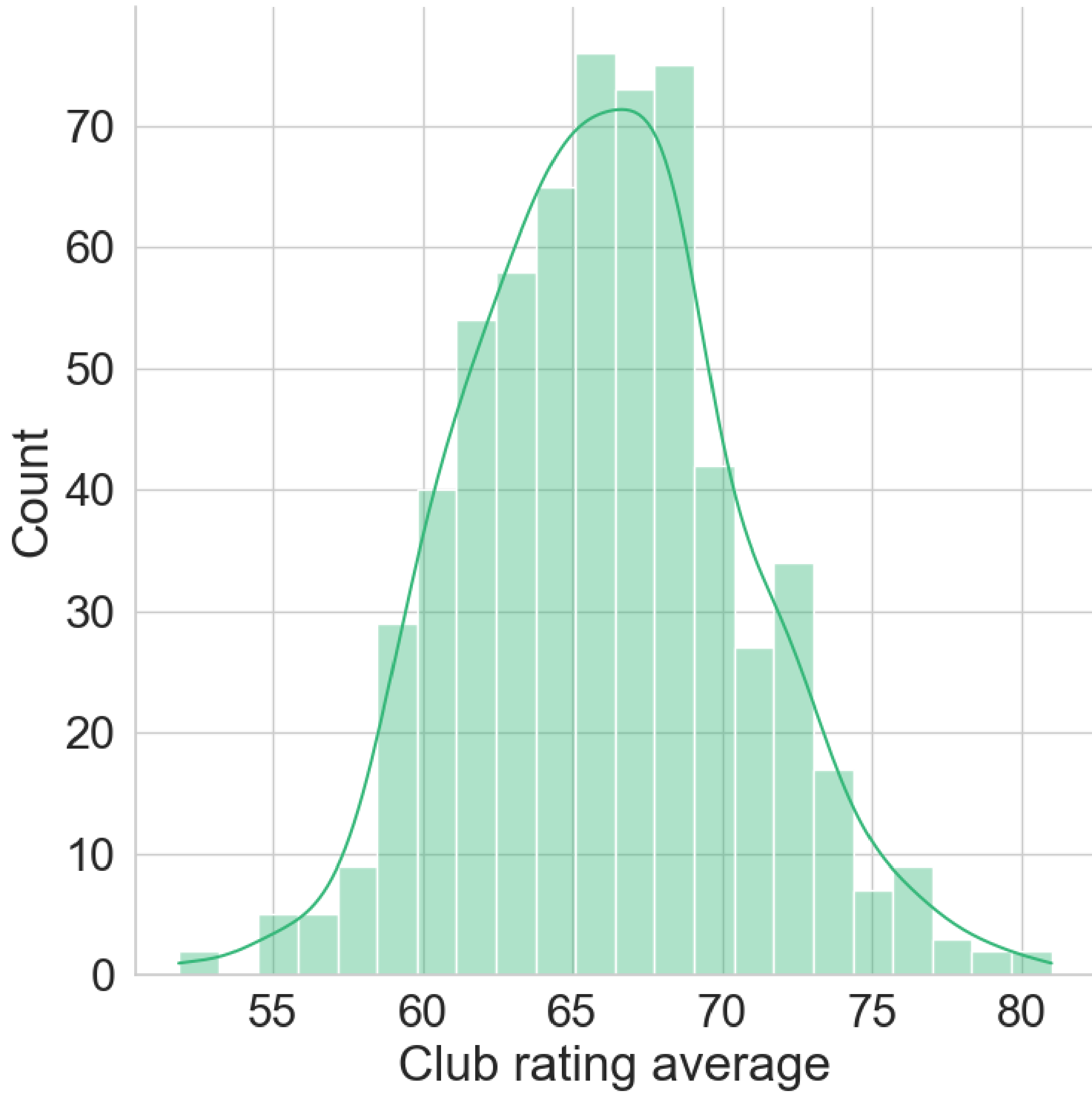
For this section, a new statistic is computed: we associate to each club, the rating average of its players.

[11]:
```
club_ratings = FIFA[['Club', 'Rating']].groupby('Club').mean('Rating')
```

2.5.1 Club rating average distribution

```
[12]: g = sns.displot(data=club_ratings, x='Rating', kde=True, color='#35B779',␣
        ↪alpha=.4, height=8)
      g.set_axis_labels('Club rating average', 'Count')
```

```
[12]: <seaborn.axisgrid.FacetGrid at 0x22002ee5ca0>
```



We're going to create 3 club clusters depending on their rating average:

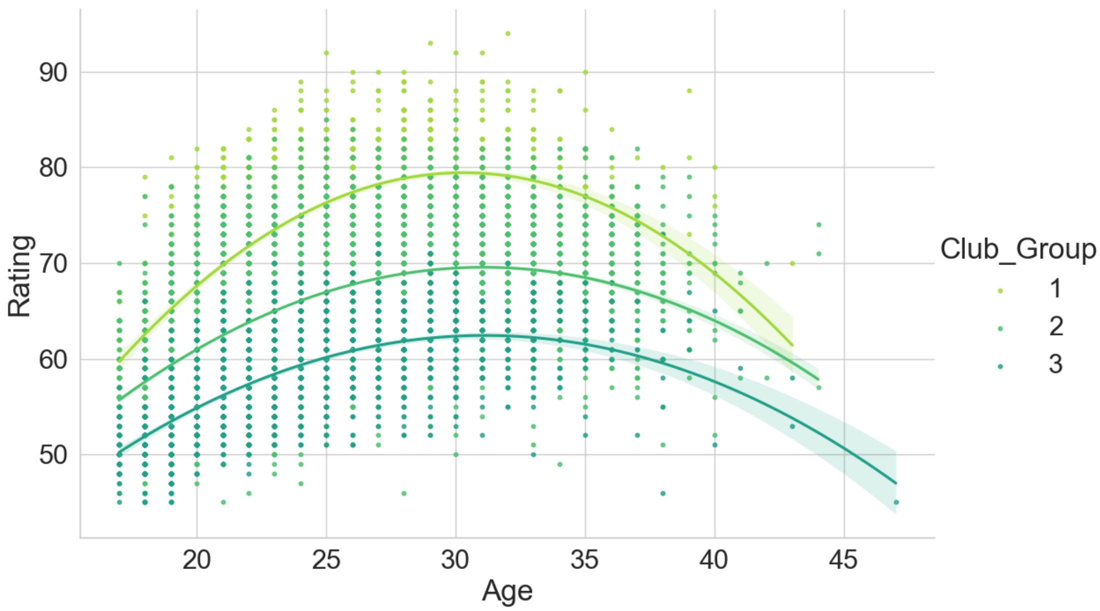
- Group 1 - rating average >= 72
- Group 2 - rating average in [60, 72[
- Group 3 - rating average < 60

[13]:
```
club_ratings['Club_Group'] = 1
club_ratings.loc[club_ratings.Rating < 72, 'Club_Group'] = 2
club_ratings.loc[club_ratings.Rating < 60, 'Club_Group'] = 3
club_ratings.drop('Rating', axis=1, inplace=True)
FIFA = FIFA.merge(club_ratings, left_on='Club', right_on='Club')
```

2.5.2 Age vs. rating average scatterplot

[14]:
```
sns.lmplot(data=FIFA, x='Age', y='Rating', order=2, hue='Club_Group', height=7.
 ↪5, aspect=1.5, scatter_kws={'s': 10})
```

[14]:
```
<seaborn.axisgrid.FacetGrid at 0x22002ef5fd0>
```



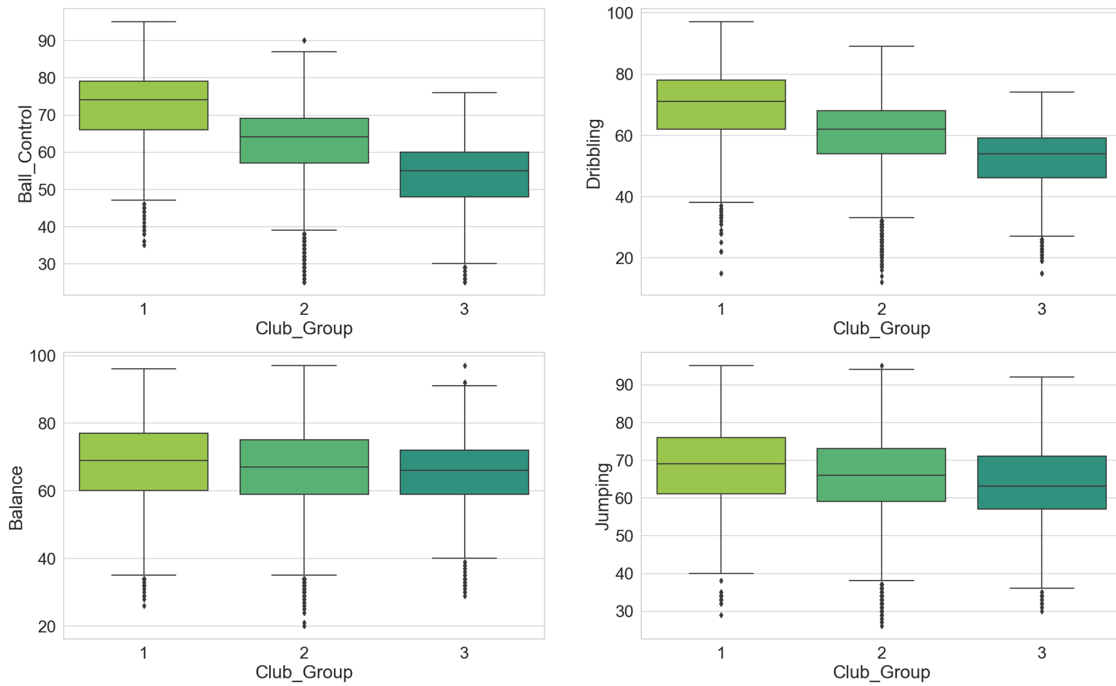
The scatterplot above suggests a quadratic relationship between a player's age and its performance level; globally, the performance increases until 30 years old and then starts going down. Another remark is that whatever their age, the best players are in the best teams.

2.5.3 What makes some teams better than the others?

[15]:
```
not_GK = FIFA[FIFA['Preffered_Position'] != 'GK']

fig, ax = plt.subplots(2, 2, figsize=(25, 15))
sns.boxplot(data=not_GK, x='Club_Group', y='Ball_Control', ax=ax[0, 0])
sns.boxplot(data=not_GK, x='Club_Group', y='Dribbling', ax=ax[0, 1])
sns.boxplot(data=not_GK, x='Club_Group', y='Balance', ax=ax[1, 0])
sns.boxplot(data=not_GK, x='Club_Group', y='Jumping', ax=ax[1, 1])
```

[15]: <AxesSubplot:xlabel='Club_Group', ylabel='Jumping'>



Although it is established that the teams of group 1 are better than those of group 2, which are better than those of group 3, the previous boxplots reveal that a specific set of skills creates this demarcation (ball control and dribbling for instance), while for others skills, the teams seems to have approximately the same level, regardless the different groups (balance, jumping, etc.). Identifying these would likely allow low-ranking teams to better focus their efforts to achieve higher levels of performance.