FIFA 20 EXPLORATORY DATA ANALYSIS

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ABSTRACT: We have carried out exploratory data analysis on the FIFA 20 player database making useful inferences and predictions.

The graphs we used for useful visualizations are namely pie-chart, count plots, bar graph, box plot, co-relation heatmap. We have also carried out hypothesis testing, t-test hypothesis namely.

For carrying out predictions we have used K Nearest Neighbours predefined model(algorithm='kdtree') from sklearn package. The trained model was able to predict similar players with maximum accuracy, given a player as an input.

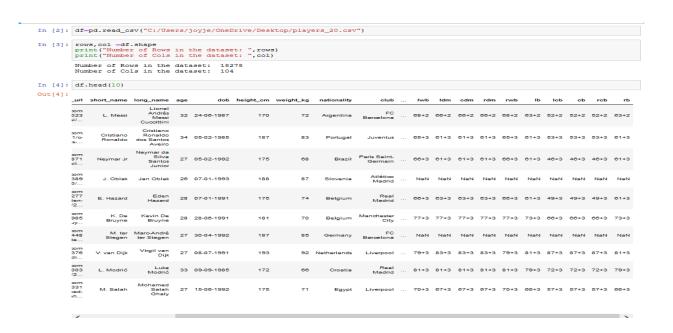
Normalization and standardization were performed on the numeric data and plotted corresponding graphs.

INTRODUCTION: Football is a game played on a field between two teams of 11 players each with the object to propel a round ball into the opponent's goal by kicking or by hitting it with any part of the body except the hands and arms.

FIFA 20 is a football simulation video game published by Electronic Arts as part of the FIFA series. It is the 27th instalment in the FIFA series, and was released on 27 September 2019 for Microsoft Windows, PlayStation 4, Xbox One, and Nintendo Switch.

We have carried out interesting club analysis focused on Liverpool inferring useful and meaningful results.

We have also built a model that recommends five similar players to the given player.



Dataset: The datasets provided include the players data for the Career Mode of FIFA 20 ("players_20.csv"). The data allows multiple comparison of various attributes of a player of the videogame. The dataset was taken from Kaggle.

Data has been scraped from the publicly available website https://sofifa.com. The various features of the dataset are the player name, respective country, attributes of the particular player(i.e. lwb , lw, ldm,lb, rwb, rb , rdm etc.).

Pre-processing and Data

cleaning: There were close to 7k NaN values in the dataset. Few columns of less importance were also dropped. The NaN values were imputed to zero or median depending on the attribute types.

After imputation and removing columns with less importance there was zero NaN values. The code snippets for the corresponding cleaning and imputations have been added in the subsequent slides.

After cleaning the number of columns was reduced to 97 from 104.

After cleaning

```
In [5]: df.isnull().sum()
Out[5]: sofifa id
                     0
       player url
       short name
                     0
       long_name
                     0
                     0
       age
       1b
                   2036
                  2036
       1cb
       cb
                  2036
       rcb
                  2036
                   2036
       rb
       Length: 104, dtype: int64
```

```
In (8): cols = ["dribbling", "defending", "physic", "passing", "shooting", "pace"]

for col in cols:
    df[col]-df[col].fillna(df[col].median())

df=df.fillna(0)
df.ismull().sum()

Out[8]: sofifa_id 0
    player_url 0
    short name 0
    long_name 0
    age 0
    ...
lb 0
    lcb 0
    cb 0
    rcb 0
    rcb 0
    rcb 0
    Length: 104, dtype: int64
```

```
df[stats] = df[stats].fillna(0)
df[stats]=df[stats].astype(int)
df[stats].head(10)
Out[7]:
             Is st rs lw If cf rf rw lam cam ... lwb ldm cdm rdm rwb lb lcb cb rcb rb
          0 89 89 89 93 93 93 93 93 93 93 ... 68 66 66 66 68 63 52 52 52 63

    1
    91
    91
    98
    90
    90
    88
    88
    ...
    65
    61
    61
    61
    65
    61
    53
    53
    53
    61

    2
    84
    84
    84
    90
    89
    89
    90
    90
    ...
    66
    61
    61
    61
    66
    61
    46
    46
    46
    46

           3 0 0 0 0 0 0 0 0 0
          4 83 83 83 89 88 88 88 89 89 89 ... 66 63 63 63 66 61 49 49 49 61
           5 82 82 82 87 87 87 87 87 88 88 ... 77 77
                                                                     77 77 77 73 66 66 66 73
          7 69 69 69 67 69 69 69 67 69 69 69 69 ... 79 83 83 83 79 81 87 87 87 81 8 77 77 77 84 83 83 84 86 86 ... 81 81 81 81 81 81 79 72 72 72 79
           9 84 84 84 88 88 88 88 88 87 87 ... 70 67 67 70 66 57 57 57 66
          10 rows × 26 columns
In [8]: cols = ["dribbling", "defending", "physic", "passing", "shooting", "pace"]
    for col in cols:
        df[col]=df[col].fillna(df[col].median())
        df=df.fillna(0)
         df.isnull().sum()
Out[8]: sofifa_id player_url
          short name
          long_name
          age
          1b
          cb
rcb
          Length: 104, dtype: int64
```

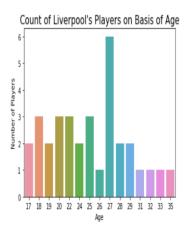
Exploratory Data Analysis:

Few interesting insights we obtained from our EDA are:

- The average age of the players from team Liverpool was 24.5 which was also inferred from the count plot.
- Team Liverpool had most of it's players from England.
- The overall rating of a player was directly proportional to their weekly wages, i.e. more the overall rating, higher the wage.
- Another interesting inference made was there is no relation between BMI and the player's nationality, which was something usually misunderstood.
- We also inferred that left foot and right foot attributes are two independent groups using boxplot and hypothesis testing.

```
In [23]: plt.figure()
    ax = sns.countplot(x='age', data=liverpool)
    ax.set_title(label='Count of Liverpool\'s Players on Basis of Age', fontsize=16)
    ax.set_xlabel(xlabel='Age')
    ax.set_ylabel(ylabel='Number of Players')
```

Out[23]: Text(0, 0.5, 'Number of Players')

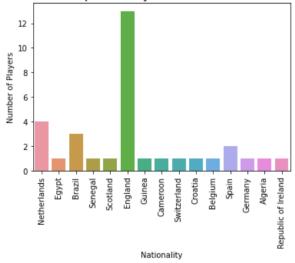


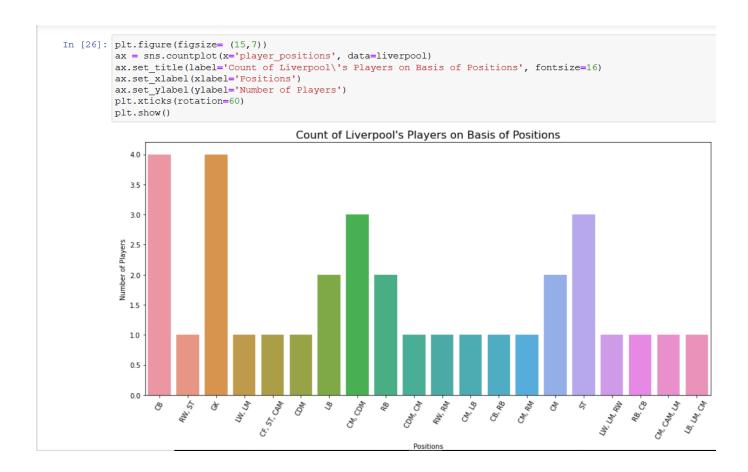
```
In [24]: avg_age = liverpool["age"].mean()
    avg_age = round(avg_age,1)
    print('Liverpool Squad\'s have an average age of ',avg_age, ' Years')
```

Liverpool Squad's have an average age of 24.5 Years

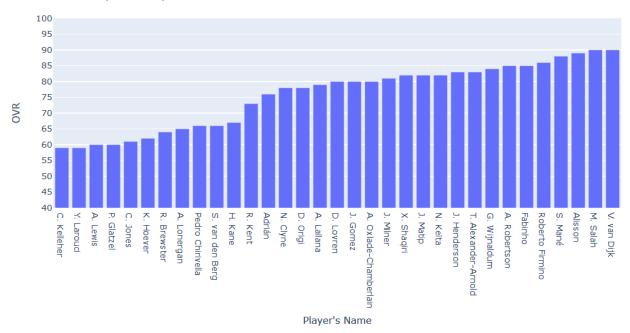
```
In [25]: plt.figure()
    ax = sns.countplot(x='nationality', data=liverpool)
    ax.set_title(label='Count of Liverpool\'s Players on Basis of NATIONALITY', fontsize=16)
    ax.set_xlabel(xlabel='Nationality')
    ax.set_ylabel(ylabel='Number of Players')
    plt.xticks(rotation=90)
    plt.show()
```

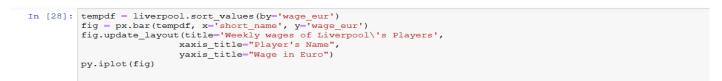
Count of Liverpool's Players on Basis of NATIONALITY



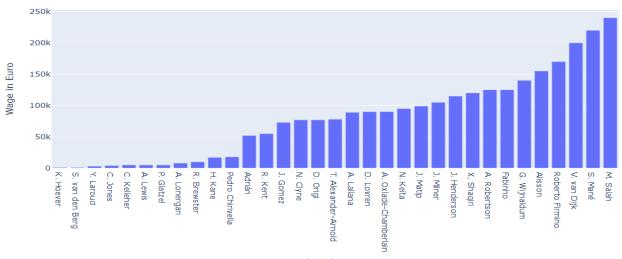


OVR of Liverpool's Players





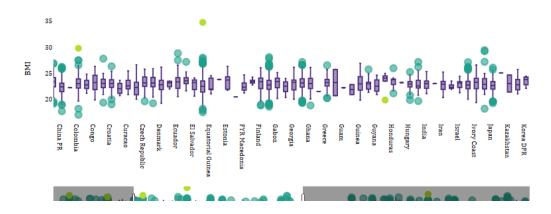
Weekly wages of Liverpool's Players



Player's Name

```
In [29]: df['bmi'] = df['weight_kg'] / (df['height_cm']/100)**2
In [30]: fig = go.Figure()
           sample = df.sort_values(by='nationality')
           fig.add_trace(go.Box(
               x = sample['nationality'],
y = sample['bmi'],
                name="Suspected Outliers",
                boxpoints='suspectedoutliers',
                marker=dict(
                    size=12,
color='rgb(180, 222, 43)',
                     outliercolor='rgba(31, 158, 137, 0.6)',
                     line=dict(
                          outliercolor='rgba(31, 158, 137, 0.6)',
               outlierwidth=2)),
line_color='rgb(72, 40, 120)',
text= sample['short_name']
           fig.update_layout(title='Box Plot - Nationality vs BMI',
                                 xaxis_title='Nationality',
                                 yaxis_title='BMI',
                                 paper_bgcolor='rgba(0,0,0,0)',
                                 plot bgcolor='rgba(0,0,0,0)',
font=dict(family='Cambria, monospace', size=12, color='#000000'),
xaxis_rangeslider_visible=True)
           fig.show()
```

Box Plot - Nationality vs BMI



Lime: Confirmed Outliers

Green: Suspected Outliers

Hypothesis Testing: A t-test is a type of inferential statistic used to determine if there is a significant difference between the means of two groups, which may be related in certain features.

Two Sample independent t-test is used to compare the means of two independent groups. For example, we have two different playing foots (Left foot and Right foot)

and would like to compare if the overall rating of left-foot is significantly different from right-foot.

- Null hypotheses: Two group means are equal
- Alternative hypotheses: Two group means are different (two-tailed)

```
In [32]: from scipy import stats
          a = df[df['preferred_foot']=='Left'][['skill_ball_control','power_shot_power', 'attacking_finishing']]
b = df[df['preferred_foot']=='Right'][['skill_ball_control','power_shot_power', 'attacking_finishing']]
In [54]: new_a = a['skill_ball_control'].sample(n=30)
    new_b = b['skill_ball_control'].sample(n=30)
           t1, p1 = stats.ttest_ind(new_a,new_b, equal_var=False)
          print("t = " + str(t1))
print("p = " + str(p1))
if p1 <0.05:</pre>
            print("we reject null hypothesis")
          print("we accept null hypothesis")
          t = -0.32771421072049556
          p = 0.7444670991417686
          we accept null hypothesis
In [34]: data = [new_a, new_b]
          fig = plt.figure(figsize =(10, 7))
ax = fig.add_subplot(111)
          bp = ax.boxplot(data, patch_artist = True,
                            notch ='True', vert = 0)
          colors = ['#0000FF', '#00FF00', '#FFFF00', '#FFF00FF']
```

t-test is performed when sample size is less than equal to 30 and for non-Gaussian distributions.

Here in our case we reject null hypothesis.

Correlation matrix: Is a table showing correlation coefficients between variable(features of the dataset). Each cell in the matrix shows the correlation between two variables. A correlation matrix is used to summarize data, as an input into a more advanced analysis,

and as a diagnostic for advanced analysis.

```
In [34]: plt.figure(figsize=(12,12))
corr = sample.corr()
sns.heatmap(corr, vmax=.4, center=0,
square=True, linewidths=.7, cbar_kws=("shrink": 0.8))

Out[34]: (AxesSubplot:)

Out[34]: (AxesSubplot
```

In [37]: scaled = StandardScaler()

Predictions: For further useful predictions we used K Nearest Neighbours predefined model from sklearn. We performed unsupervised learning techniques for our models training, after which our model was able predict or recommend five similar players given a player as an input.

```
X = scaled.fit transform(sample)
recommendations = WearestWeighbors(n_neighbors=7,algorithm='kd_tree')
recommendations.fit(X)
player_index = recommendations.kmeighbors(X)[1]

In [60]: def player_name(x):
    return df(df('short_name')=x].index.tolist()[0]

def recommend_similar(player):
    print("These are 5 players similar to {} : ".format(player))
    index = player_name(player)
    for i im player_index[index[]1:]:
        print("Wame: {}\nOwerall: {}\nMarket Walue: {}\nAge: {}\nAge: {}\nAge: {}\n^*.format(df.iloc[i]['short_name'],df.iloc(companies).
```

```
In [61]: recommend similar('E. Hazard')
         These are 5 players similar to E. Hazard :
         Name: L. Messi
         Overall: 94
         Market Value: €95500000
         Age: 32
         BMI: 24.91
         Name: K. De Bruyne
         Overall: 91
         Market Value: €90000000
         Age: 28
         BMI: 21.37
         Name: A. Griezmann
         Overall: 89
         Market Value: €69000000
         Age: 28
         BMI: 23.57
         Name: Neymar Jr
         Overall: 92
         Market Value: €105500000
         Age: 27
         BMI: 22.20
         Name: M. Salah
         Overall: 90
         Market Value: €80500000
         Age: 27
         BMI: 23.18
```

Results and discussion: The following conclusions were made from performing EDA on the dataset:

- 1) We could infer the average of age of all players of a particular team.
- 2) We came to the conclusion that higher the rating of the player higher is his weekly salary.
- 3) We also saw that most of the players from Liverpool were from England.

- 4) We made an assumption that there is a relationship between bmi and nationality of a player, but that was proven wrong from the box plot that was plotted
- 5) We have normalized and standardized our data to obtain 0 mean and 1 variance.
- 6) We could also recommend 5 players of similar attributes given a player.

Possible analysis with our dataset:

- Historical comparison
 between Messi and Ronaldo
 (what skill attributes
 changed the most during
 time compared to real-life
 stats);
- Ideal budget to create a competitive team (at the level of top n teams in Europe) and at which point the budget does not allow to buy significantly better players for the 11-men lineup. An extra is the same comparison with the Potential attribute for the line-up instead of the Overall attribute;
- Sample analysis of top n% players (e.g. top 5% of the player) to see if some important attributes as

Agility or BallControl or Strength have been popular or not across the FIFA versions. An example would be seeing that the top 5% players of FIFA 20 are more fast (higher Acceleration and Agility) compared to FIFA 15. The trend of attributes is also an important indication of how some attributes are necessary for players to win games (a version with more top 5% players with high BallControl stats would indicate that the game is more focused on the technique rather than the physical aspect).

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THANK YOU