FIFA 21 DATA ANALYSIS

The topic for my STAT 5000 project is Soccer Data Analysis. The dataset I used for my project is a Kaggle dataset. The dataset consists of 18000+ rows and 106 columns describing various features.The dataset is a collection of various attributes of players from the FIFA 2021 game by EA Sports. This notebook is an in depth analysis of various attributes of player, how are they related to each other, some story telling through data visualizations and finally predicition of attributes. We will be answering some important questions through data analysis to get some useful insights from the dataset.

Data Exploration and Cleaning

Importing necessary libraries

In [8]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
pd.options.mode.chained_assignment = None
```

We will be using Numpy, Pandas, Matplotlib, Seabrorn and Sci-Kit Learn libraries.

Reading the dataset

In [9]:
```
fifa = pd.read_csv("players_21.csv")
```

The file is in CSV format.

Checking the head of the dataset

In [10]:
```
fifa.head()
```

Out[10]:

	sofifa_id	player_url	short_name	long_name	age	dob	height_cm	weight_kg	nationality	club_name	league_na
0	158023	https://sofifa.com/player/158023/lionel-messi/...	L. Messi	Lionel Andrés Messi Cuccittini	33	1987-06-24	170	72	Argentina	FC Barcelona	Spain Prin Divi
1	20801	https://sofifa.com/player/20801/c-ronaldo-dos-...	Cristiano Ronaldo	Cristiano Ronaldo dos Santos Aveiro	35	1985-02-05	187	83	Portugal	Juventus	Italian Ser
2	200389	https://sofifa.com/player/200389/jan-oblak/210002	J. Oblak	Jan Oblak	27	1993-01-07	188	87	Slovenia	Atlético Madrid	Spain Prin Divi
3	188545	https://sofifa.com/player/188545/robert-lewand...	R. Lewandowski	Robert Lewandowski	31	1988-08-21	184	80	Poland	FC Bayern München	Germa Bundes
4	190871	https://sofifa.com/player/190871/neymar-da-sil...	Neymar Jr	Neymar da Silva Santos Júnior	28	1992-02-05	175	68	Brazil	Paris Saint-Germain	French Li

5 rows × 106 columns

Listing all the columns in the dataset

In [11]:
```
fifa.columns
```

Out[11]:
```
Index(['sofifa_id', 'player_url', 'short_name', 'long_name', 'age', 'dob',
       'height_cm', 'weight_kg', 'nationality', 'club_name',
       ...
       'lwb', 'ldm', 'cdm', 'rdm', 'rwb', 'lb', 'lcb', 'cb', 'rcb', 'rb'],
      dtype='object', length=106)
```

Removing irrelevant columns

In [12]:
```
l = fifa[['sofifa_id','player_url','long_name','dob','real_face','body_type',
          'player_tags','team_jersey_number','loaned_from',
        'contract_valid_until','nation_jersey_number','player_traits','ls', 'st', 'rs',
       'lw', 'lf', 'cf', 'rf', 'rw', 'lam', 'cam', 'ram', 'lm', 'lcm', 'cm',
       'rcm', 'rm', 'lwb', 'ldm', 'cdm', 'rdm', 'rwb', 'lb', 'lcb', 'cb',
       'rcb', 'rb','nation_position','defending_marking','joined','goalkeeping_diving',
       'goalkeeping_handling', 'goalkeeping_kicking','goalkeeping_positioning', 'goalkeeping_reflexes']]
fifa = fifa.drop(labels = l, axis = 1)
```

Removed all the unecessary columns like long name, dob, player traits ls,st,rs,etc. They were not necessary as they depicted how would every player play at different positions.

In [13]:
```
fifa.head(2)
```

Out[13]:

	short_name	age	height_cm	weight_kg	nationality	club_name	league_name	league_rank	overall	potential	value_eur	wage_eur	player_po
0	L. Messi	33	170	72	Argentina	FC Barcelona	Spain Primera Division	1.0	93	93	67500000	560000	RW,
1	Cristiano Ronaldo	35	187	83	Portugal	Juventus	Italian Serie A	1.0	92	92	46000000	220000	

This is the cleaned dataset containing all the useful columns.

Checking for columns that have null values

In [14]:
```
null = fifa.isnull().sum()
print(null[null>0])
```

```
club_name                225
league_name              225
league_rank              225
release_clause_eur       995
team_position            225
pace                    2083
shooting                2083
passing                 2083
dribbling               2083
defending               2083
physic                  2083
gk_diving              16861
gk_handling            16861
gk_kicking             16861
gk_reflexes            16861
gk_speed               16861
gk_positioning         16861
dtype: int64
```

Removing all the null values in the columns

In [15]:
```
fifa['club_name'] = fifa['club_name'].fillna('Free Agent')
fifa['league_name'] = fifa['league_name'].fillna('No League')
fifa['league_rank'] = fifa['league_rank'].fillna('No Rank')
fifa['team_position'] = fifa['team_position'].fillna('No Position')
fifa['release_clause_eur'] = fifa['release_clause_eur'].fillna(0)
fifa['pace'] = fifa['pace'].fillna(fifa['pace'].mean())
fifa['shooting'] = fifa['shooting'].fillna(fifa['shooting'].mean())
fifa['passing'] = fifa['passing'].fillna(fifa['passing'].mean())
fifa['defending'] = fifa['defending'].fillna(fifa['defending'].mean())
fifa['dribbling'] = fifa['dribbling'].fillna(fifa['dribbling'].mean())
fifa['physic'] = fifa['physic'].fillna(fifa['physic'].mean())
```

We inserted mean values wherever there were numerical missing values and called players having no clubs as 'Free Agents'.

In [16]:
```
null = fifa.isnull().sum()
print(null[null>0])
```

```
gk_diving         16861
gk_handling       16861
gk_kicking        16861
gk_reflexes       16861
gk_speed          16861
gk_positioning    16861
dtype: int64
```

There are too many missing values for Goalkeeper columns, so we leave them as it is.

Generating Descriptive Statistics

In [17]:
```
fifa.describe()
```

Out[17]:

	age	height_cm	weight_kg	overall	potential	value_eur	wage_eur	international_reputation	weak_foot
count	18944.000000	18944.000000	18944.000000	18944.000000	18944.000000	1.894400e+04	18944.000000	18944.000000	18944.000000
mean	25.225823	181.190773	75.016892	65.677787	71.086729	2.224813e+06	8675.852513	1.091850	2.936603
std	4.697354	6.825672	7.057140	7.002278	6.109985	5.102486e+06	19654.774894	0.361841	0.667132
min	16.000000	155.000000	50.000000	47.000000	47.000000	0.000000e+00	0.000000	1.000000	1.000000
25%	21.000000	176.000000	70.000000	61.000000	67.000000	3.000000e+05	1000.000000	1.000000	3.000000
50%	25.000000	181.000000	75.000000	66.000000	71.000000	6.500000e+05	3000.000000	1.000000	3.000000
75%	29.000000	186.000000	80.000000	70.000000	75.000000	1.800000e+06	7000.000000	1.000000	3.000000
max	53.000000	206.000000	110.000000	93.000000	95.000000	1.055000e+08	560000.000000	5.000000	5.000000

Describe() method will give you all the important statistics like mean, standard deviation, median and different percentiles.

Summary of the Dataframe

In [18]:
```
fifa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18944 entries, 0 to 18943
Data columns (total 60 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   short_name                  18944 non-null  object 
 1   age                         18944 non-null  int64  
 2   height_cm                   18944 non-null  int64  
 3   weight_kg                   18944 non-null  int64  
 4   nationality                 18944 non-null  object 
 5   club_name                   18944 non-null  object 
 6   league_name                 18944 non-null  object 
 7   league_rank                 18944 non-null  object 
 8   overall                     18944 non-null  int64  
 9   potential                   18944 non-null  int64  
 10  value_eur                   18944 non-null  int64  
 11  wage_eur                    18944 non-null  int64  
 12  player_positions            18944 non-null  object 
 13  preferred_foot              18944 non-null  object 
 14  international_reputation    18944 non-null  int64  
 15  weak_foot                   18944 non-null  int64  
 16  skill_moves                 18944 non-null  int64  
 17  work_rate                   18944 non-null  object 
 18  release_clause_eur          18944 non-null  float64
 19  team_position               18944 non-null  object 
 20  pace                        18944 non-null  float64
 21  shooting                    18944 non-null  float64
 22  passing                     18944 non-null  float64
 23  dribbling                   18944 non-null  float64
 24  defending                   18944 non-null  float64
 25  physic                      18944 non-null  float64
 26  gk_diving                   2083 non-null   float64
 27  gk_handling                 2083 non-null   float64
 28  gk_kicking                  2083 non-null   float64
 29  gk_reflexes                 2083 non-null   float64
 30  gk_speed                    2083 non-null   float64
 31  gk_positioning              2083 non-null   float64
 32  attacking_crossing          18944 non-null  int64  
 33  attacking_finishing         18944 non-null  int64  
 34  attacking_heading_accuracy  18944 non-null  int64  
 35  attacking_short_passing     18944 non-null  int64  
 36  attacking_volleys           18944 non-null  int64  
 37  skill_dribbling             18944 non-null  int64  
 38  skill_curve                 18944 non-null  int64  
 39  skill_fk_accuracy           18944 non-null  int64  
 40  skill_long_passing          18944 non-null  int64  
 41  skill_ball_control          18944 non-null  int64  
 42  movement_acceleration       18944 non-null  int64  
 43  movement_sprint_speed       18944 non-null  int64  
 44  movement_agility            18944 non-null  int64  
 45  movement_reactions          18944 non-null  int64  
 46  movement_balance            18944 non-null  int64  
 47  power_shot_power            18944 non-null  int64  
 48  power_jumping               18944 non-null  int64  
 49  power_stamina               18944 non-null  int64  
 50  power_strength              18944 non-null  int64  
 51  power_long_shots            18944 non-null  int64  
 52  mentality_aggression        18944 non-null  int64  
 53  mentality_interceptions     18944 non-null  int64  
 54  mentality_positioning       18944 non-null  int64  
 55  mentality_vision            18944 non-null  int64  
 56  mentality_penalties         18944 non-null  int64  
 57  mentality_composure         18944 non-null  int64  
 58  defending_standing_tackle   18944 non-null  int64  
 59  defending_sliding_tackle    18944 non-null  int64  
dtypes: float64(13), int64(38), object(9)
memory usage: 8.7+ MB
```

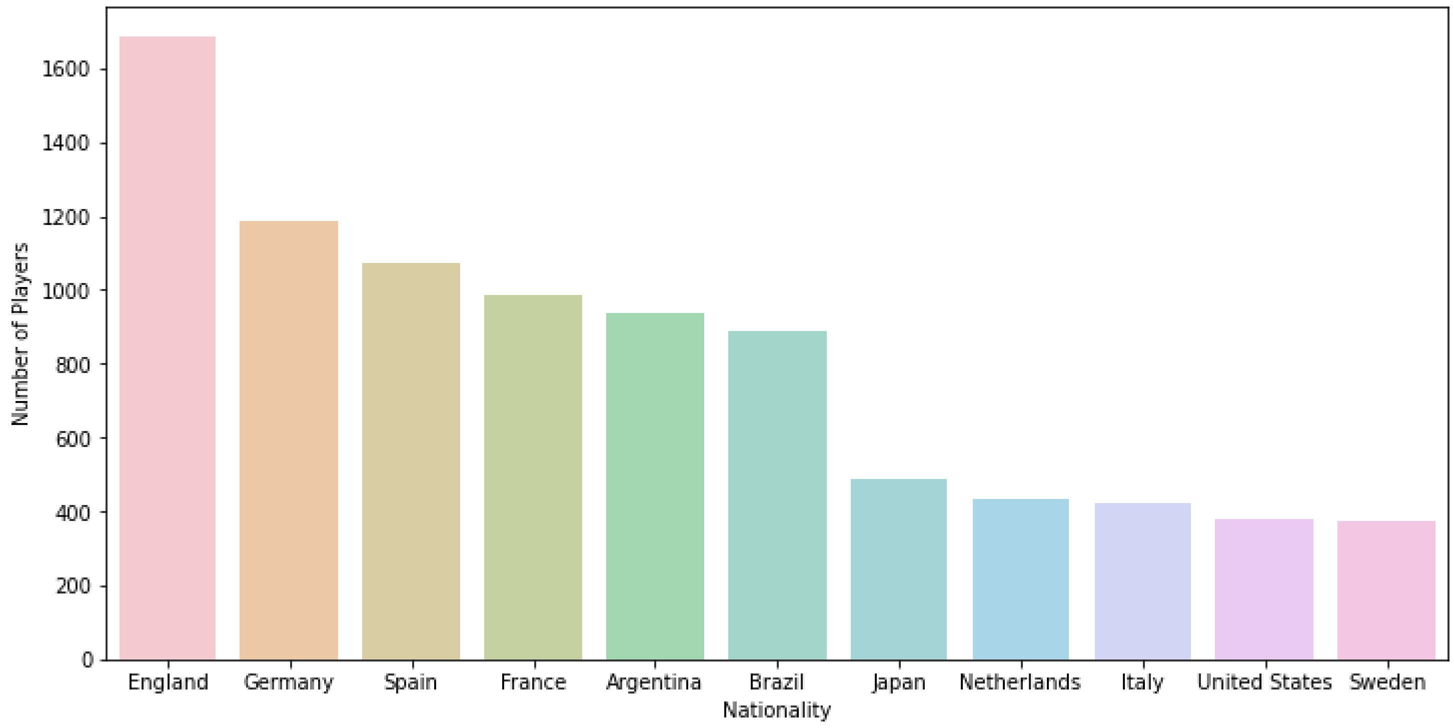
Info() will provide you a short summary of the dataset with the count of the rows and data types of the columns.

Exploratory Data Analysis

Countries having most number of players in the dataset

In [19]:
```
country = fifa['nationality'].value_counts()
country = country[0:11]
plt.figure(figsize = (12,6))
sns.barplot(x=country.index,y=country.values,alpha=0.5)
plt.xlabel("Nationality")
plt.ylabel("Number of Players")
```

Out[19]: Text(0, 0.5, 'Number of Players')

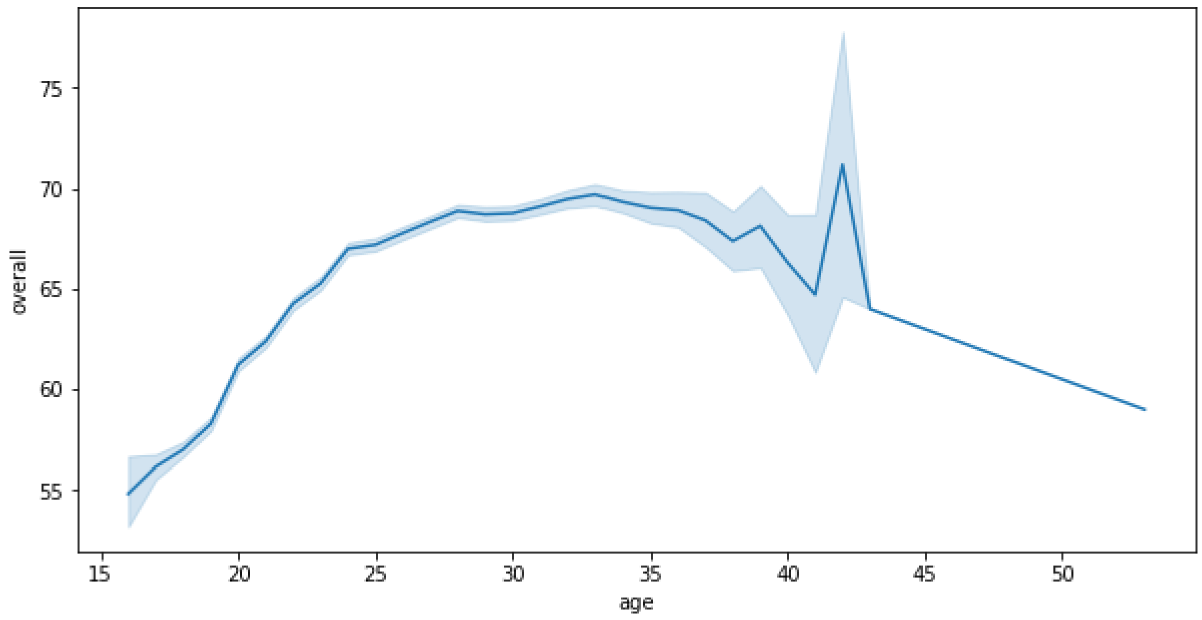


As we can see from the barplot that England has the maximum number of players in the dataset followed by Germany, Spain, France, Argentina. Japan is the only Asian country in the top 10 which means soccer is not that prominent in Asia.

Relation between Overall and the Age of the players

In [20]:
```
plt.figure(figsize=(10,5))
sns.lineplot(x='age',y='overall',data=fifa)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7efee1af5e90>



As you can see from the graph that as age goes on increasing the overall increases as well to a certain point. After 30 the graph gradually goes on decreasing. So as age goes on increasing the overall of a player goes on decreasing.

Scouting out the youngest star in the dataset

In [21]:
```
youngsters = fifa[fifa['age']==fifa['age'].min()]
you_over = youngsters[youngsters['overall'] == youngsters['overall'].max()]
best_potential = you_over[you_over['potential'] == you_over['potential'].max()]
best_potential[['short_name','nationality','age','potential','overall']]
```

Out[21]:

	short_name	nationality	age	potential	overall
7314	R. Cherki	France	16	88	67

R.Cherki from France is the youngest and the best talent with a potential of 88.

Best oldest player in the dataset

In [22]:
```
old = fifa[fifa['age'] > 37]
best_old = old[old['overall'] == old['overall'].max()]
best_old[['short_name','nationality','age','overall']]
```

Out[22]:

	short_name	nationality	age	overall
168	Z. Ibrahimović	Sweden	38	83

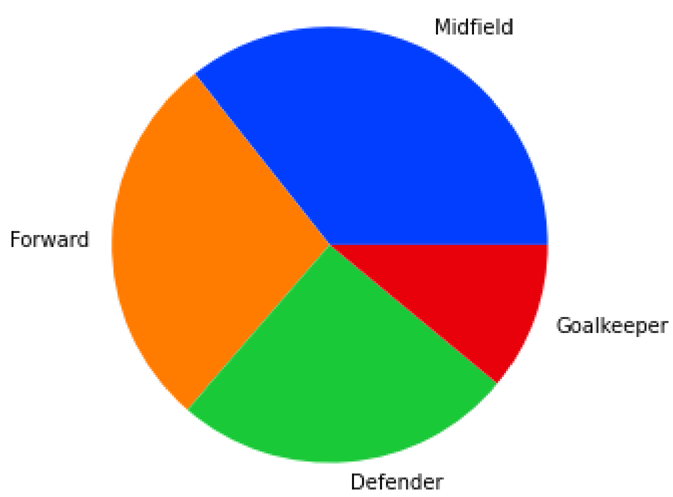
Zlatan Ibrahimovic is one of the finest old talent in the world of soccer. Currently he is playing for AC Milan and his age is 40. Playing for a top tier team in the age of 40 is a very big thing because Italian football is very competetive and tough.

Dividing the dataset into Attackers, Midfield, Defenders and Goalkeepers and storing them in different Dataframes

In [23]:
```
football = []
l=[]
for i in fifa['player_positions']:
  l.append(i.replace(" ",''))
for j in l:
  if 'ST' in j or 'CF' in j or'LW' in j or 'RW' in j:
    football.append("Forward")
  elif 'CAM'in j or 'CDM' in j or 'CM' in j or 'RM' in j or 'LM' in j:
    football.append('Midfield')
  elif 'GK' in j:
    football.append('Goalkeeper')
  elif 'CB' in j or 'RB' in j or 'LB' in j or 'LWB' in j or 'RWB' in j:
    football.append("Defender")
fifa['Positions'] = football
```

In [24]:
```
pos = fifa['Positions'].value_counts()
```

In [25]:
```
plt.figure(figsize = (10,5))
color = sns.color_palette('bright')
plt.pie(x = pos.values, labels = pos.index, colors = color  )
plt.show()
```



In [26]:
```
Attack = fifa[fifa['Positions'] == 'Forward']
Mid = fifa[fifa['Positions'] == 'Midfield']
Defence = fifa[fifa['Positions'] == 'Defender']
Goalkeepers = fifa[fifa['Positions'] == 'Goalkeeper']
```

This is a pie chart distribution of Attackers, Midfield, Defenders and Goalkeepers. We observe more number of Midfield in the dataset.

Calculating the Mean Age of all the categories of the players

In [27]:
```
Attack.nlargest(50,'age')['age'].mean()
```

Out[27]: 38.1

In [28]:
```
Mid.nlargest(50,'age')['age'].mean()
```

Out[28]: 37.4

In [29]:
```
Defence.nlargest(50,'age')['age'].mean()
```

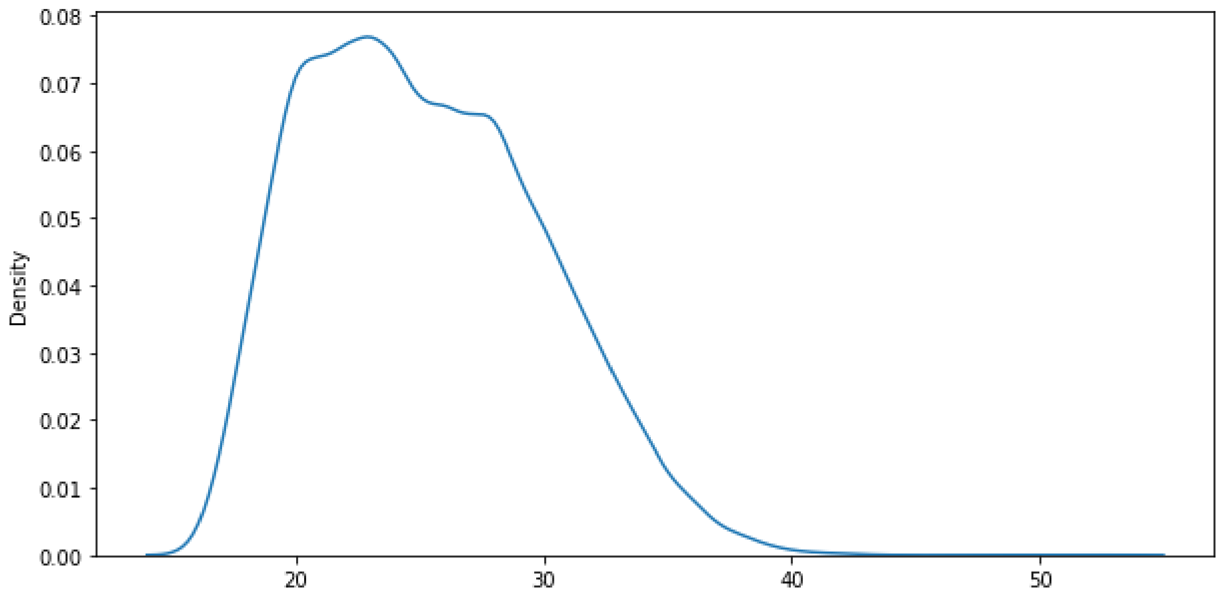
Out[29]: 37.32

In [30]:
```
Goalkeepers.nlargest(50,'age')['age'].mean()
```
Out[30]: 39.04

From the above analysis we can conclude that Goalkeepers can play soccer for a longer time.

Age Distribution of Players

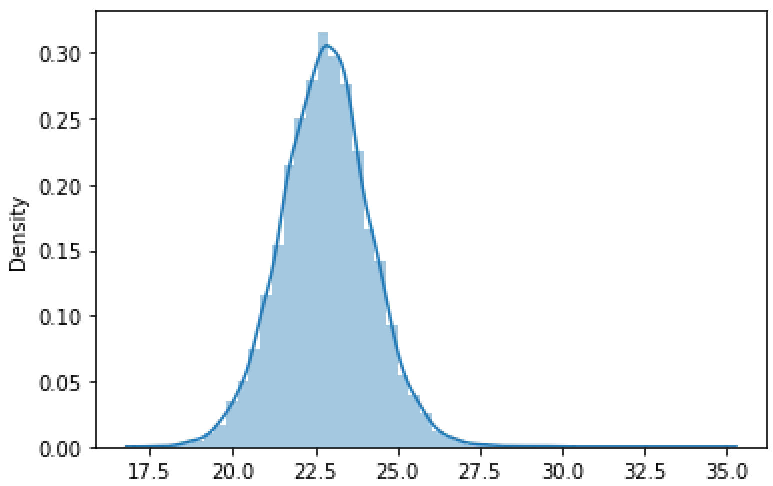
In [31]:
```
plt.figure(figsize=(10,5))
sns.distplot(x=fifa['age'],hist=False)
```
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated funct
ion and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7efedf184690>



Age has a normal distribution with a mean of 25.

Calculation and Distribution of BMI

In [32]:
```
fifa['BMI'] = (fifa['weight_kg']*10000)/(fifa['height_cm']*fifa['height_cm'])
sns.distplot(x=fifa['BMI'],kde=True)
```
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated funct
ion and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7efed4929e90>



BMI also follows a normal distribution with a mean of 22.5. Most of the soccer players will have BMI between 20-24.9(according to Google).This is also evdient from the graph as well.

Net Worth of top clubs in the world

In [33]:
```
RealMadrid = fifa[fifa['club_name'] == 'Real Madrid']
Barca = fifa[fifa['club_name'] == 'FC Barcelona']
PSG = fifa[fifa['club_name'] == 'Paris Saint-Germain']
Manc = fifa[fifa['club_name'] == 'Manchester City']
Manu = fifa[fifa['club_name'] == 'Manchester United']
Liv = fifa[fifa['club_name'] == 'Liverpool']
Bayern = fifa[fifa['club_name'] == 'FC Bayern München']
Juve = fifa[fifa['club_name'] == 'Juventus']
Che = fifa[fifa['club_name'] == 'Chelsea']
ATM = fifa[fifa['club_name'] == 'Atlético Madrid']
valRM = RealMadrid['value_eur'].sum()
wageRM = RealMadrid['wage_eur'].sum()
valBAR = Barca['value_eur'].sum()
wageBAR = Barca['wage_eur'].sum()
valPSG = PSG['value_eur'].sum()
wagePSG = PSG['wage_eur'].sum()
valMC = Manc['value_eur'].sum()
wageMC = Manc['wage_eur'].sum()
valMU = Manu['value_eur'].sum()
wageMU = Manu['wage_eur'].sum()
valLIV = Liv['value_eur'].sum()
wageLIV = Liv['wage_eur'].sum()
valBM = Bayern['value_eur'].sum()
wageBM = Bayern['wage_eur'].sum()
valJUV = Juve['value_eur'].sum()
wageJUV = Juve['wage_eur'].sum()
valCHE = Che['value_eur'].sum()
wageCHE = Che['wage_eur'].sum()
valATM = ATM['value_eur'].sum()
wageATM = ATM['wage_eur'].sum()
values = [valRM,valBAR,valPSG,valMC,valMU,valLIV,valBM,valJUV,valCHE,valATM]
wages = [wageRM,wageBAR,wagePSG,wageMC,wageMU,wageLIV,wageBM,wageJUV,wageCHE,wageATM]
```

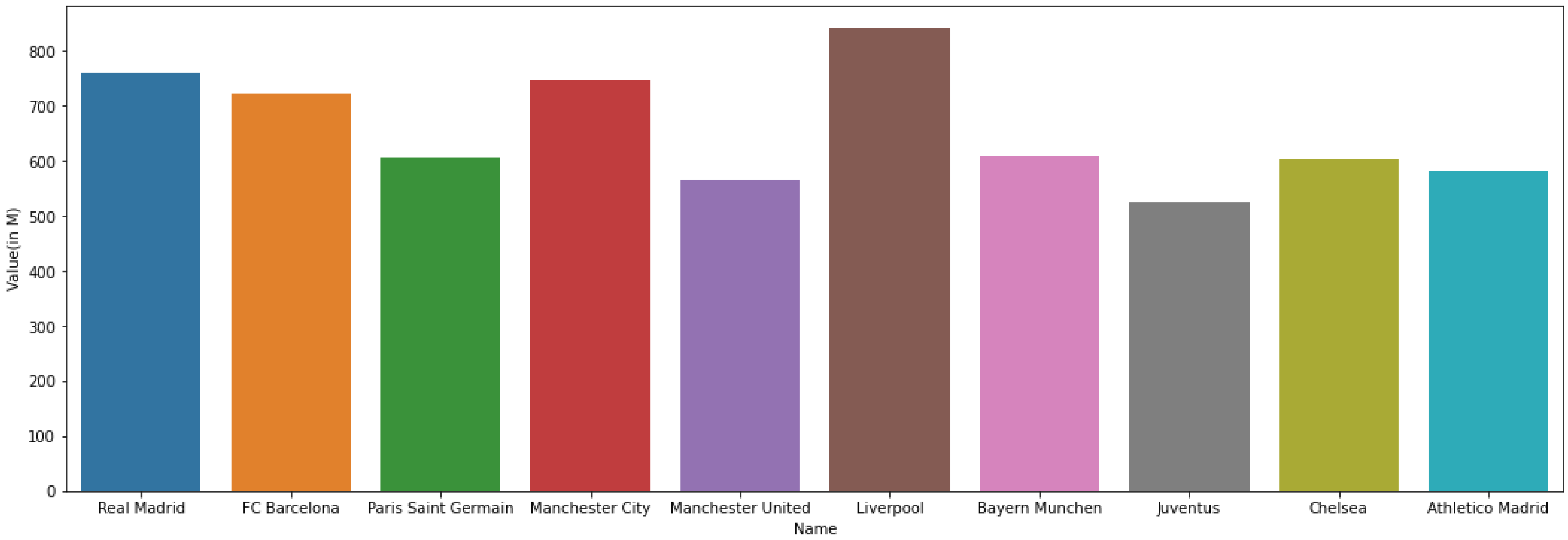
In [34]:
```
net = {'Name':['Real Madrid','FC Barcelona','Paris Saint Germain','Manchester City','Manchester United','Liverpool','B
ayern Munchen',
       'Juventus','Chelsea','Athletico Madrid'],'Value':values,'Wages':wages}
Net_worth = pd.DataFrame(data=net)
Net_worth['Value(in M)'] = Net_worth['Value']/1000000
Net_worth['Wages(in M)'] = Net_worth['Wages']/1000000
Net_worth
```

Out[34]:

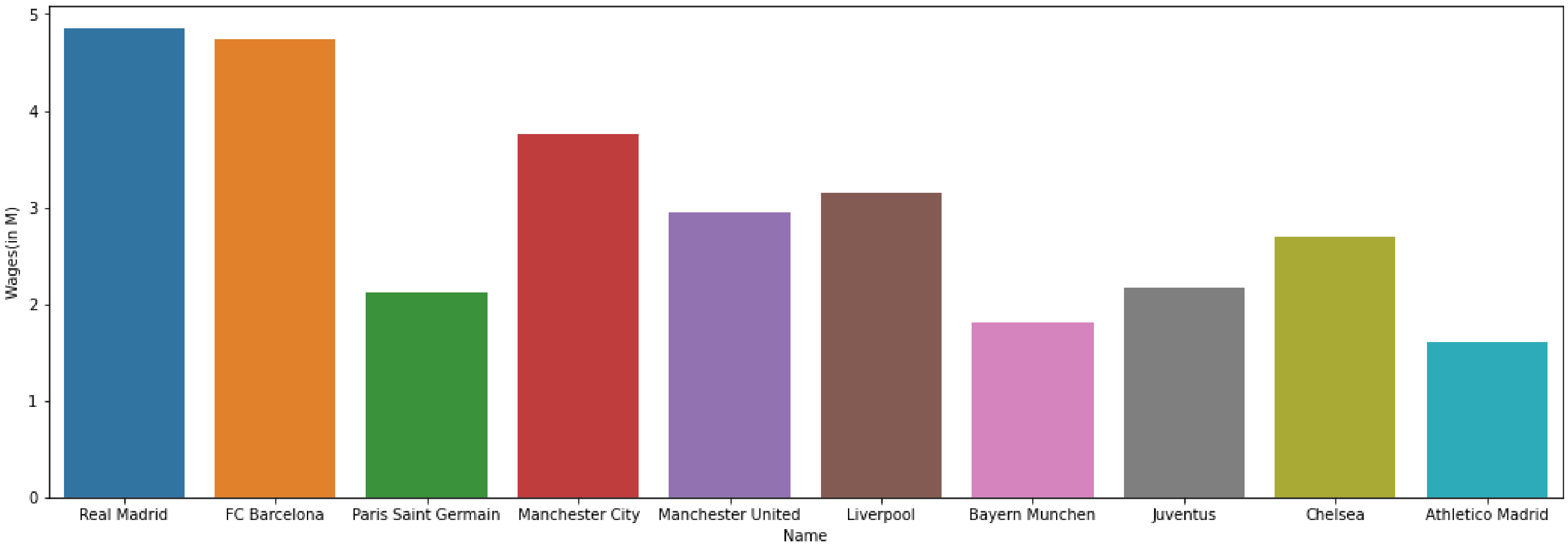
	Name	Value	Wages	Value(in M)	Wages(in M)
0	Real Madrid	760850000	4848000	760.850	4.84800
1	FC Barcelona	722200000	4738000	722.200	4.73800
2	Paris Saint Germain	605675000	2125550	605.675	2.12555
3	Manchester City	747275000	3765000	747.275	3.76500
4	Manchester United	564130000	2950000	564.130	2.95000
5	Liverpool	840625000	3154000	840.625	3.15400
6	Bayern Munchen	609700000	1802000	609.700	1.80200
7	Juventus	524450000	2161000	524.450	2.16100
8	Chelsea	602275000	2698000	602.275	2.69800
9	Athletico Madrid	582500000	1597000	582.500	1.59700

Players Value(in M) VS Wages paid by their clubs

In [35]:
```
plt.figure(figsize = (18,6))
sns.barplot(x=Net_worth['Name'],y=Net_worth['Value(in M)'])
plt.show()
plt.figure(figsize = (18,6))
sns.barplot(x=Net_worth['Name'],y=Net_worth['Wages(in M)'])
```



Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7efed476f350>



Liverpool wins the race in Values of its players with the highest of 840.625 Millions. But the interesting fact is that Liverpool is not the leading club in terms of Wages. The stratergy which Liverpool used was that they bought players for a cheap transfer value and won the UEFA Champions League. So because of this Liverpool's player value increased drastically. But thier Wages remained same. Wages are depenedent on the price at which the players are bought from the transfer market. Real Madrid pays the highest Wages to their players.

Forming my own 'DREAM TEAM'

```
    LW           ST              RW

         LCM                 RCM
                 CDM

   LB          LCB        RCB        RB

                  GK
```

In [36]:
```
dtgoal = Goalkeepers[Goalkeepers['overall']>=85][['short_name','overall','team_position','age','potential','nationality','club_name','pace','shooting','passing','dribbling','defending']]
dtdef = Defence[Defence['overall']>=85][['short_name','overall','team_position','age','potential','nationality','club_name','pace','shooting','passing','dribbling','defending']]
dtmid = Mid[Mid['overall']>=85][['short_name','overall','team_position','age','potential','nationality','club_name','pace','shooting','passing','dribbling','defending']]
dtattack = Attack[Attack['overall']>=85][['short_name','overall','team_position','age','potential','nationality','club_name','pace','shooting','passing','dribbling','defending']]
```

In [37]:
```
dtgoal.head(5)
```

Out[37]:

	short_name	overall	team_position	age	potential	nationality	club_name	pace	shooting	passing	dribbling	defending
2	J. Oblak	91	GK	27	93	Slovenia	Atlético Madrid	67.66811	52.274954	57.139434	62.45543	51.316292
7	M. ter Stegen	90	GK	28	93	Germany	FC Barcelona	67.66811	52.274954	57.139434	62.45543	51.316292
9	Alisson	90	GK	27	91	Brazil	Liverpool	67.66811	52.274954	57.139434	62.45543	51.316292
12	T. Courtois	89	GK	28	90	Belgium	Real Madrid	67.66811	52.274954	57.139434	62.45543	51.316292
16	M. Neuer	89	GK	34	89	Germany	FC Bayern München	67.66811	52.274954	57.139434	62.45543	51.316292

In [38]:
```
dtgoal = dtgoal[dtgoal['short_name'] == 'J. Oblak']
```

In [39]:
```
dtdef.head(5)
```

Out[39]:

	short_name	overall	team_position	age	potential	nationality	club_name	pace	shooting	passing	dribbling	defending
8	V. van Dijk	90	LCB	28	91	Netherlands	Liverpool	76.0	60.0	71.0	71.0	91.0
14	Sergio Ramos	89	LCB	34	89	Spain	Real Madrid	71.0	70.0	76.0	73.0	88.0
26	K. Koulibaly	88	LCB	29	88	Senegal	Napoli	75.0	28.0	55.0	68.0	89.0
29	T. Alexander-Arnold	87	RB	21	92	England	Liverpool	80.0	66.0	87.0	80.0	80.0
31	A. Laporte	87	LCB	26	90	France	Manchester City	63.0	50.0	72.0	68.0	88.0

In [40]:
```
dtdef = dtdef[(dtdef['short_name'] == 'A. Robertson') | (dtdef['short_name'] == 'V. van Dijk')
       | (dtdef['short_name'] == 'R. Varane') | (dtdef['short_name'] == 'T. Alexander-Arnold') ]
```

In [41]:
```
dtmid.head(5)
```

Out[41]:

	short_name	overall	team_position	age	potential	nationality	club_name	pace	shooting	passing	dribbling	defending
5	K. De Bruyne	91	RCM	29	91	Belgium	Manchester City	76.0	86.0	93.0	88.0	64.0
17	Casemiro	89	CDM	28	89	Brazil	Real Madrid	65.0	73.0	76.0	72.0	86.0
20	J. Kimmich	88	RDM	25	90	Germany	FC Bayern München	71.0	72.0	86.0	84.0	81.0
24	T. Kroos	88	LCM	30	88	Germany	Real Madrid	54.0	81.0	91.0	81.0	71.0
27	N. Kanté	88	RDM	29	88	France	Chelsea	77.0	66.0	76.0	81.0	86.0

In [42]:
```
dtmid = dtmid[(dtmid['short_name'] == 'T. Kroos') | (dtmid['short_name'] == 'K. De Bruyne')| (dtmid['short_name'] ==
'Casemiro')]
```

In [43]:
```
dtattack.head(5)
```

Out[43]:

	short_name	overall	team_position	age	potential	nationality	club_name	pace	shooting	passing	dribbling	defending
0	L. Messi	93	CAM	33	93	Argentina	FC Barcelona	85.0	92.0	91.0	95.0	38.0
1	Cristiano Ronaldo	92	LS	35	92	Portugal	Juventus	89.0	93.0	81.0	89.0	35.0
3	R. Lewandowski	91	ST	31	91	Poland	FC Bayern München	78.0	91.0	78.0	85.0	43.0
4	Neymar Jr	91	LW	28	91	Brazil	Paris Saint-Germain	91.0	85.0	86.0	94.0	36.0
6	K. Mbappé	90	LS	21	95	France	Paris Saint-Germain	96.0	86.0	78.0	91.0	39.0

In [44]:
```
dtattack = dtattack[(dtattack['short_name'] == 'Neymar Jr') | (dtattack['short_name'] == 'R. Lewandowski')| (dtattack[
'short_name'] == 'M. Salah')]
```

In [45]:
```
DreamTeam = pd.concat([dtattack,dtmid,dtdef,dtgoal],ignore_index=True)
```

In [46]:
```
DreamTeam
```

Out[46]:

	short_name	overall	team_position	age	potential	nationality	club_name	pace	shooting	passing	dribbling	defending
0	R. Lewandowski	91	ST	31	91	Poland	FC Bayern München	78.00000	91.000000	78.000000	85.00000	43.000000
1	Neymar Jr	91	LW	28	91	Brazil	Paris Saint-Germain	91.00000	85.000000	86.000000	94.00000	36.000000
2	M. Salah	90	RW	28	90	Egypt	Liverpool	93.00000	86.000000	81.000000	90.00000	45.000000
3	K. De Bruyne	91	RCM	29	91	Belgium	Manchester City	76.00000	86.000000	93.000000	88.00000	64.000000
4	Casemiro	89	CDM	28	89	Brazil	Real Madrid	65.00000	73.000000	76.000000	72.00000	86.000000
5	T. Kroos	88	LCM	30	88	Germany	Real Madrid	54.00000	81.000000	91.000000	81.00000	71.000000
6	V. van Dijk	90	LCB	28	91	Netherlands	Liverpool	76.00000	60.000000	71.000000	71.00000	91.000000
7	T. Alexander-Arnold	87	RB	21	92	England	Liverpool	80.00000	66.000000	87.000000	80.00000	80.000000
8	A. Robertson	87	LB	26	89	Scotland	Liverpool	82.00000	62.000000	80.000000	80.00000	81.000000
9	R. Varane	86	RCB	27	88	France	Real Madrid	82.00000	49.000000	64.000000	64.00000	87.000000
10	J. Oblak	91	GK	27	93	Slovenia	Atlético Madrid	67.66811	52.274954	57.139434	62.45543	51.316292

Mean Age and Mean of my Dream Team

In [47]:
```
DreamTeam['overall'].mean()
```

Out[47]: 89.18181818181819

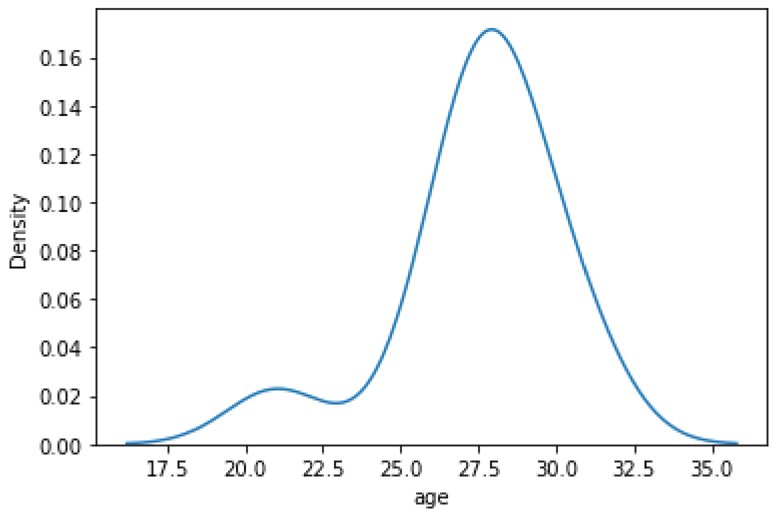
In [48]:
```
DreamTeam['age'].mean()
```

Out[48]: 27.545454545454547

Distribution of Age and Overall of the players in the Dream Team

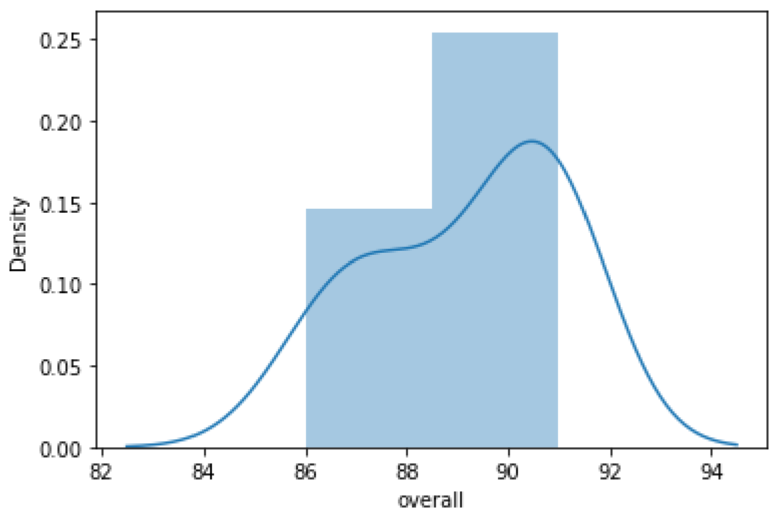
In [49]:
```
sns.distplot(a=DreamTeam['age'],hist=False)
plt.show()
sns.distplot(a=DreamTeam['overall'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated funct
ion and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```




```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated funct
ion and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

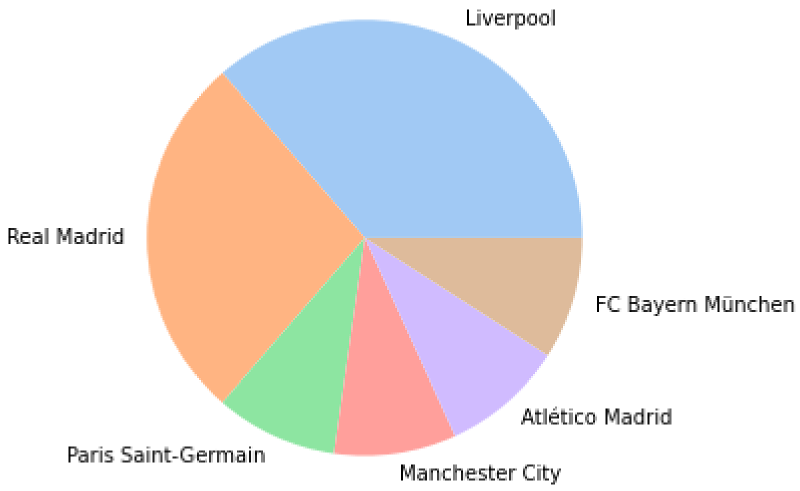
Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x7efed462e7d0>

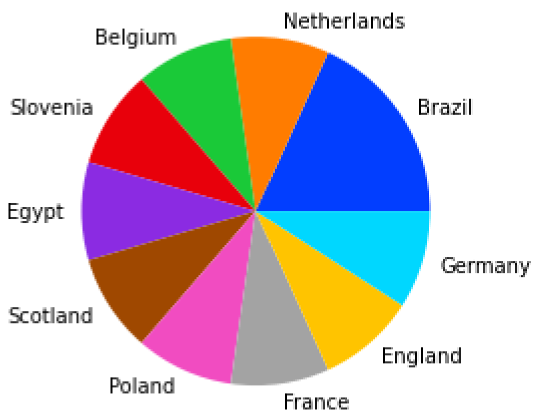


Most number of players from any country and club

In [50]:
```
dtclub = DreamTeam['club_name'].value_counts()
dtcountry = DreamTeam['nationality'].value_counts()
```

In [51]:
```
plt.figure(figsize = (10,5))
col = sns.color_palette(palette='pastel')
colo = sns.color_palette(palette='bright')
plt.pie(x= dtclub.values,labels = dtclub.index,colors = col)
plt.show()
plt.pie(x=dtcountry.values,labels=dtcountry.index,colors=colo)
plt.show()
```



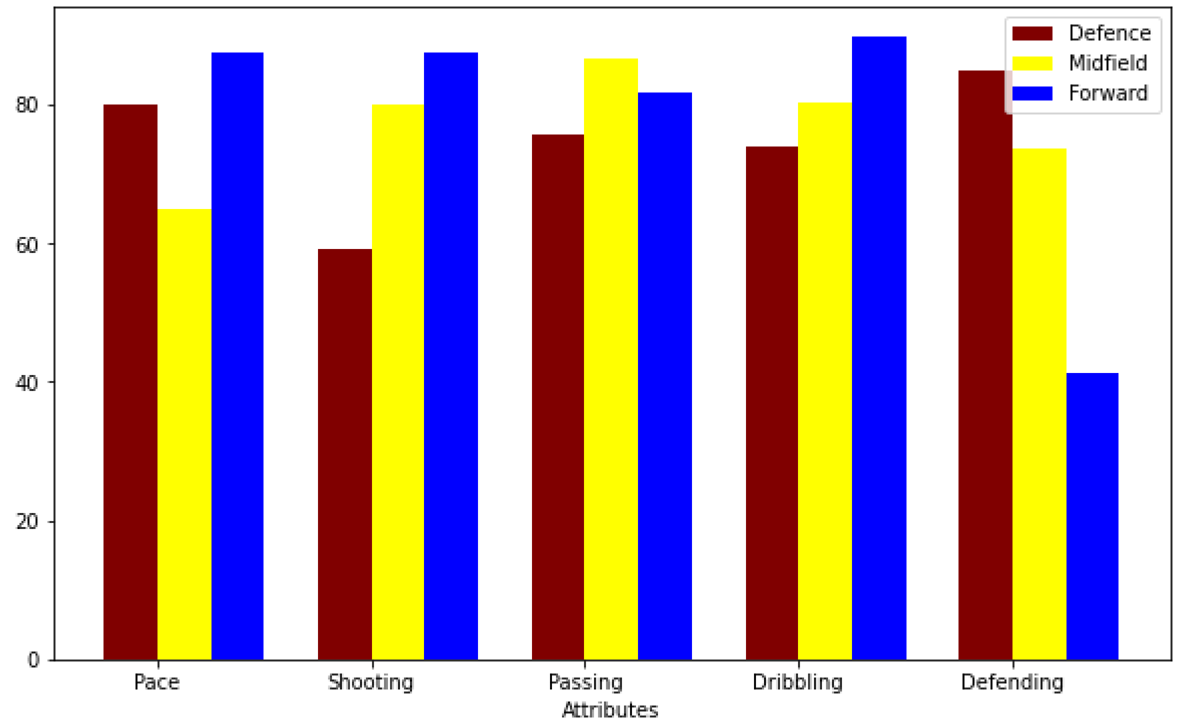


My Dream Team contains maximum number of players from Liverpool.

Plotting important attributes according to Attackers, Midfield, Defenders

In [52]:
```
Defdt = DreamTeam.iloc[6:10]
MDefdt = Defdt[['pace','shooting','passing','dribbling','defending']].mean()
Middt = DreamTeam.iloc[3:6]
MMiddt = Middt[['pace','shooting','passing','dribbling','defending']].mean()
Attackdt = DreamTeam.iloc[0:3]
MAttackdt = Attackdt[['pace','shooting','passing','dribbling','defending']].mean()
```

In [53]:
```
mvaldef = list(MDefdt.values)
mvalmid = list(MMiddt.values)
mvalatt = list(MAttackdt.values)
plt.figure(figsize = (10,6))
N=5
r = np.arange(N)
width = 0.25
bar1 =plt.bar(r,mvaldef,width = 0.25,color = 'maroon',label='Defence')
bar2 = plt.bar(r+width,mvalmid,width = 0.25,color='yellow',label='Midfield')
bar3 = plt.bar(r+width*2,mvalatt,width = 0.25,color='blue',label='Forward')
plt.xlabel('Attributes')
plt.xticks(r + width/2,['Pace','Shooting','Passing','Dribbling','Defending'])
plt.legend()
plt.show()
```



1) Forwards should have good pace. This is evident form our graph.

2) Shooting and finishing skills should be prominent in Forwards.

3) Midfield should be excellent in Passing.

4) Forwards again beat others in Dribbling skills.

5) Its pretty obvious that Defenders have to be the best in Defending.

Exploratory Data Analysis on Goalkeepers

Creating a Goalkeeper Dataset

In [54]:
```
Goalkeepers.columns
```

Out[54]:
```
Index(['short_name', 'age', 'height_cm', 'weight_kg', 'nationality',
       'club_name', 'league_name', 'league_rank', 'overall', 'potential',
       'value_eur', 'wage_eur', 'player_positions', 'preferred_foot',
       'international_reputation', 'weak_foot', 'skill_moves', 'work_rate',
       'release_clause_eur', 'team_position', 'pace', 'shooting', 'passing',
       'dribbling', 'defending', 'physic', 'gk_diving', 'gk_handling',
       'gk_kicking', 'gk_reflexes', 'gk_speed', 'gk_positioning',
       'attacking_crossing', 'attacking_finishing',
       'attacking_heading_accuracy', 'attacking_short_passing',
       'attacking_volleys', 'skill_dribbling', 'skill_curve',
       'skill_fk_accuracy', 'skill_long_passing', 'skill_ball_control',
       'movement_acceleration', 'movement_sprint_speed', 'movement_agility',
       'movement_reactions', 'movement_balance', 'power_shot_power',
       'power_jumping', 'power_stamina', 'power_strength', 'power_long_shots',
       'mentality_aggression', 'mentality_interceptions',
       'mentality_positioning', 'mentality_vision', 'mentality_penalties',
       'mentality_composure', 'defending_standing_tackle',
       'defending_sliding_tackle', 'Positions'],
      dtype='object')
```

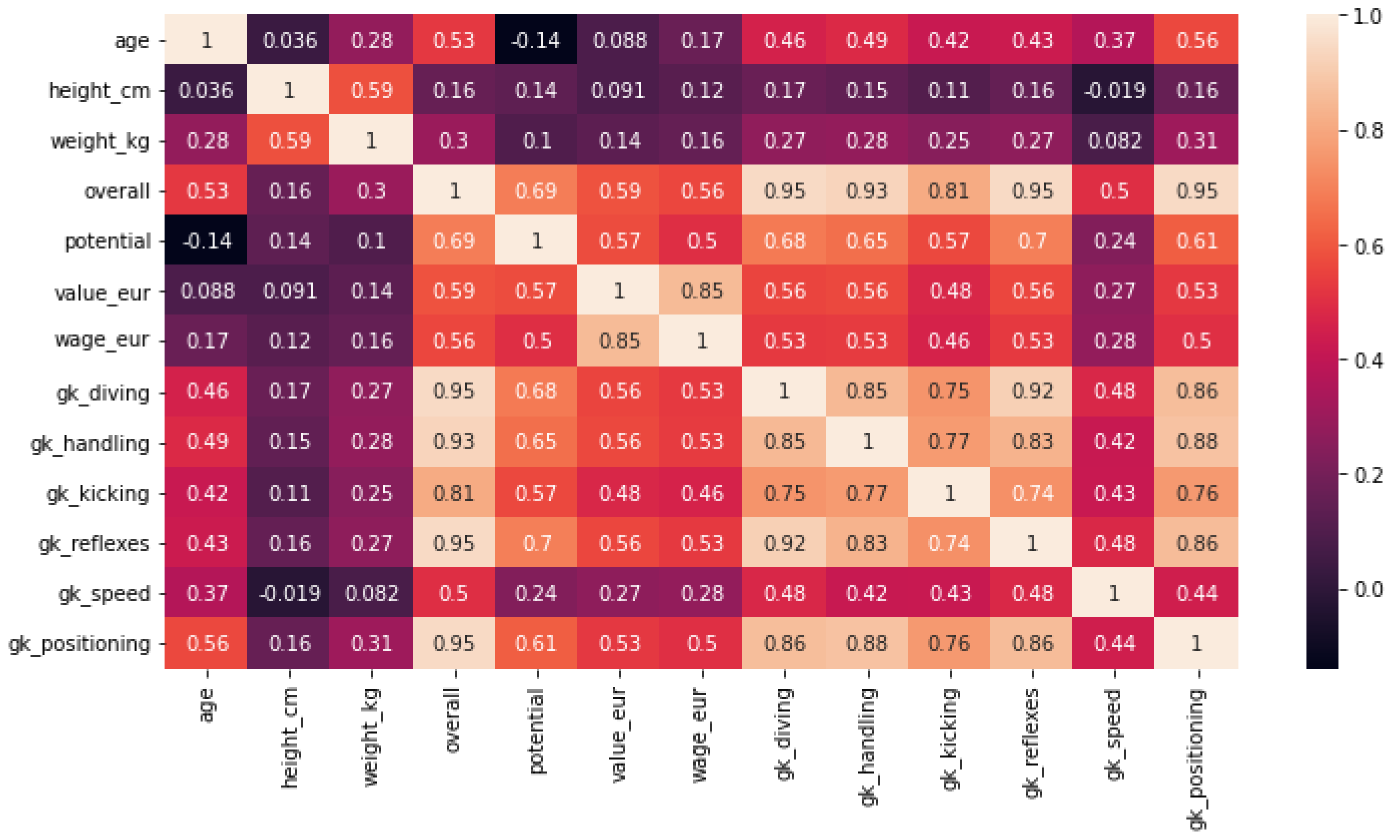
In [55]:
```
Keeper = ['player_positions', 'preferred_foot','international_reputation', 'weak_foot', 'skill_moves', 'work_rate',
       'release_clause_eur', 'team_position', 'pace', 'shooting','passing', 'dribbling', 'defending', 'physic','attack
ing_crossing', 'attacking_finishing',
       'attacking_heading_accuracy', 'attacking_short_passing',
       'attacking_volleys', 'skill_dribbling', 'skill_curve',
       'skill_fk_accuracy', 'skill_long_passing', 'skill_ball_control',
       'movement_acceleration', 'movement_sprint_speed', 'movement_agility',
       'movement_reactions', 'movement_balance', 'power_shot_power',
       'power_jumping', 'power_stamina', 'power_strength', 'power_long_shots',
       'mentality_aggression', 'mentality_interceptions',
       'mentality_positioning', 'mentality_vision', 'mentality_penalties',
       'mentality_composure', 'defending_standing_tackle',
       'defending_sliding_tackle','Positions','league_rank',]
```

In [56]:
```
Goalkeeper = Goalkeepers.drop(labels = Keeper, axis = 1)
```

Visualizing Correlation between attributes for top 100 Goalkeepers

In [57]:
```
plt.figure(figsize = (12,6))
sns.heatmap(Goalkeeper.corr(),annot = True)
```

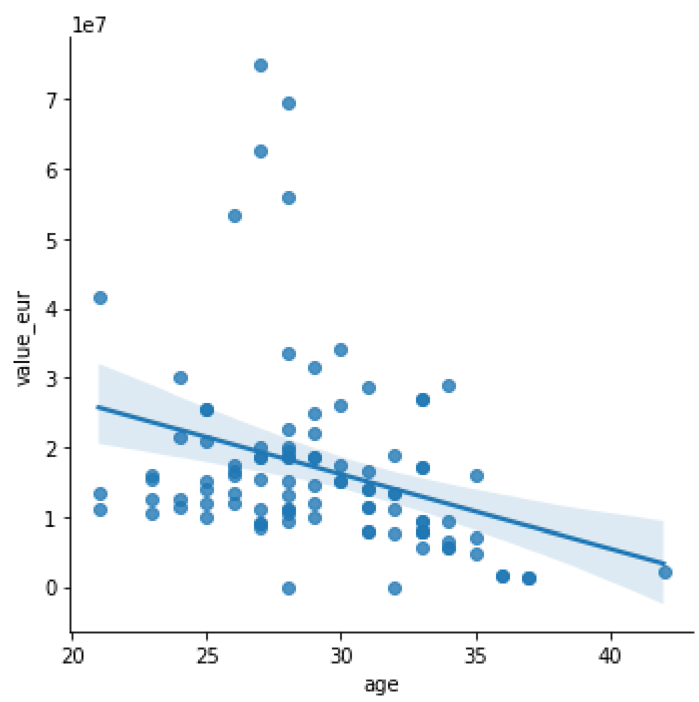
Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7efed44dc590>



Relation between Age and Player Value in Euros

In [58]:
```
goal = Goalkeeper['overall'].nlargest(100)
top100 = Goalkeeper.loc[goal.index]
sns.lmplot(x='age',y='value_eur',data=top100)
```

Out[58]: <seaborn.axisgrid.FacetGrid at 0x7efed440ff10>

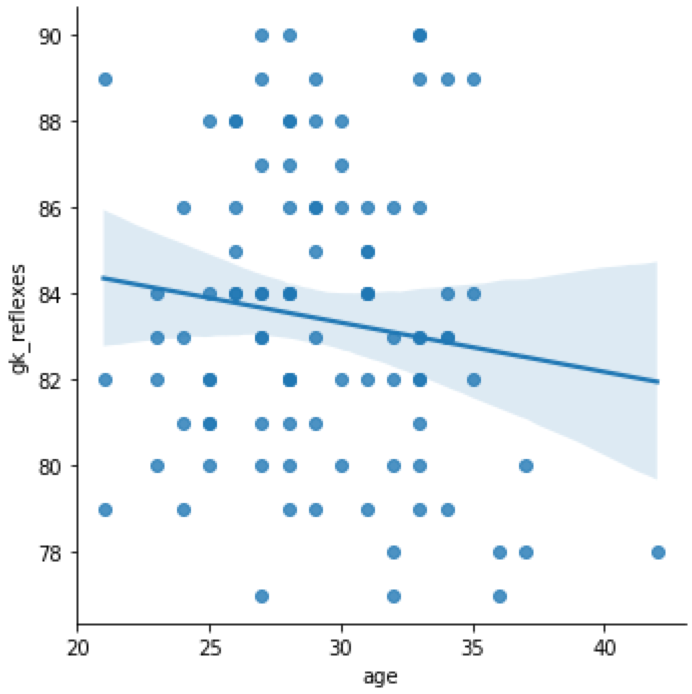


As the age increases the value of a goalkeeper decreases.

Relation between Age and Golakeeper Reflexes

In [59]:
```
sns.lmplot(x='age',y='gk_reflexes',data=top100)
```

Out[59]: <seaborn.axisgrid.FacetGrid at 0x7efed2ba7bd0>

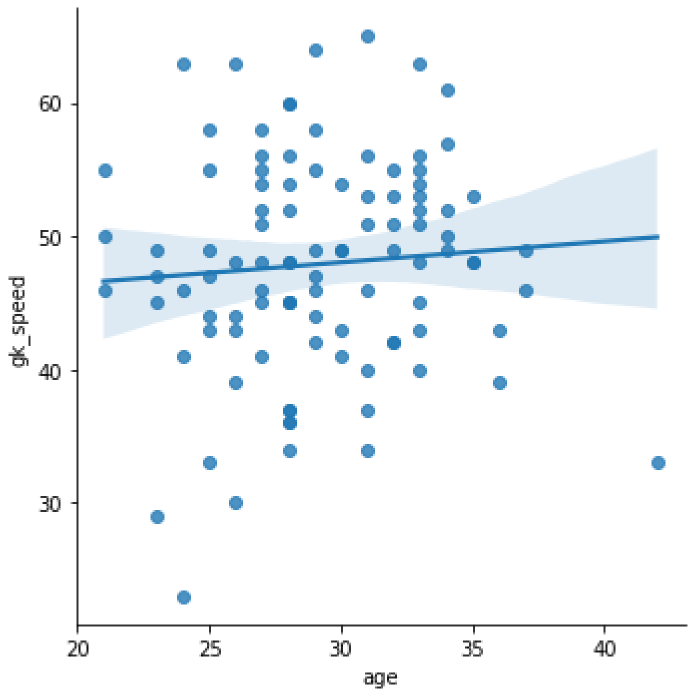


Goalkeeper Reflexes decrease as the age increases.

Relation between Age and Goalkeeper Speed

In [60]:
```
sns.lmplot(x='age',y='gk_speed',data=top100)
```

Out[60]: <seaborn.axisgrid.FacetGrid at 0x7efed2b2c210>



Overall trend observed was a constant. Goalkeeper speed is not dependent on his Age. This some what makes sense as Goalkeepers have to save the ball from entering the goal and not score any goals.

Chi Square Test for various Categorical Features

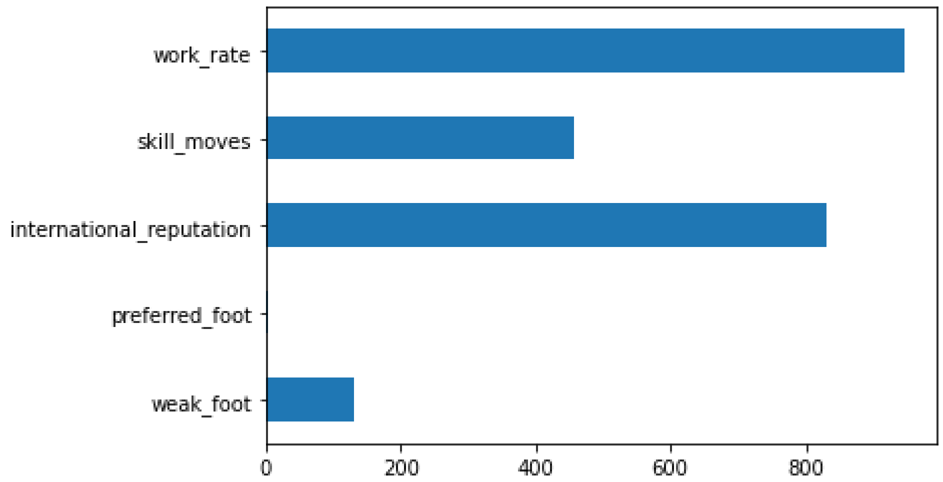
For chi-square distribution we require categorical variables. So we decided to implement a chi-square test on the categorical variables present in the dataset. Chi-Square test is mainly used for Feature Importance. We want to calculate feature importance with respect to the Overall of the player. So I decided to convert Overall to a categorical variable and apply a Chi-Square test on the variables.

In [61]:
```
fifa.loc[(fifa['overall']<50,'Overall_Desc')] = 'Poor'
fifa.loc[(fifa['overall']>=50) & (fifa['overall']<=69.9),'Overall_Desc'] = 'Below Average'
fifa.loc[(fifa['overall']>=70) & (fifa['overall']<=79.9),'Overall_Desc'] = 'Average'
fifa.loc[(fifa['overall']>=80) & (fifa['overall']<89.9),'Overall_Desc'] = 'Good'
fifa.loc[(fifa['overall']>=90) & (fifa['overall']<100),'Overall_Desc'] = 'Best'
```

In [62]:
```
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
col = ['weak_foot','preferred_foot','international_reputation','skill_moves','work_rate','Overall_Desc']
categ = pd.DataFrame(data = fifa, columns=col)
categ['weak_foot'] = le.fit_transform(categ['weak_foot'])
categ['preferred_foot'] = le.fit_transform(categ['preferred_foot'])
categ['work_rate'] = le.fit_transform(categ['work_rate'])
categ['Overall_Desc'] = le.fit_transform(categ['Overall_Desc'])
X = categ.drop('Overall_Desc',axis = 1)
Y = categ['Overall_Desc']
```

In [63]:
```
from sklearn.feature_selection import chi2
chi_scores = chi2(X,Y)
chi_scores = pd.Series(chi_scores[0], index = X.columns)
chi_scores.plot(kind = 'barh')
```

Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x7efece8adb90>



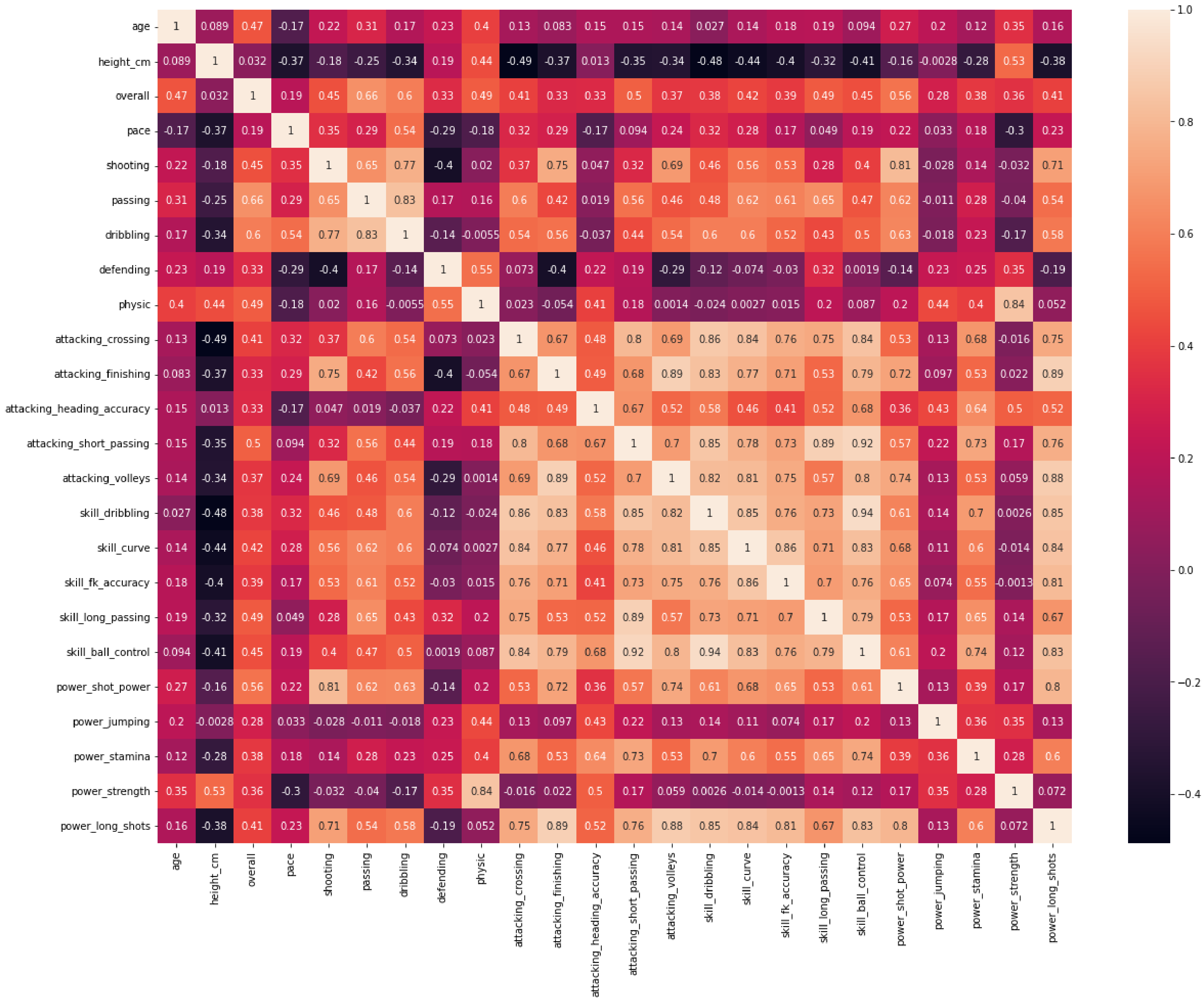
We selected 5 best categorical features that affected the 'Overall' the most. Work Rate is the best parameter to decide the Overall of a player. Work rate is followed by international reputation. International Reputation is of utmost importance as well depicting how a player plays for his own country. Preferred foot is of no use as it does not make any sense with which foot a player plays.

Pearson Correlation between various important Features

In [64]:
```
pearson = fifa[['age','height_cm','overall','pace','shooting','passing','dribbling','defending','physic','attacking_crossing',
'attacking_finishing','attacking_heading_accuracy','attacking_short_passing','attacking_volleys','skill_dribbling','skill_curve',
'skill_fk_accuracy','skill_long_passing','skill_ball_control','power_shot_power','power_jumping','power_stamina',
'power_strength','power_long_shots']]
plt.figure(figsize = (20,15))
sns.heatmap(pearson.corr(),annot = True)
pearson.corr()
```

Out[64]:

	age	height_cm	overall	pace	shooting	passing	dribbling	defending	physic	attacking_crossing
age	1.000000	0.089297	0.468197	-0.168214	0.222164	0.312271	0.168493	0.234109	0.404695	0.127915
height_cm	0.089297	1.000000	0.031579	-0.369787	-0.175334	-0.247290	-0.344262	0.189149	0.442275	-0.487854
overall	0.468197	0.031579	1.000000	0.188862	0.454391	0.662090	0.596558	0.333616	0.493539	0.410530
pace	-0.168214	-0.369787	0.188862	1.000000	0.350496	0.294917	0.541006	-0.286393	-0.180699	0.315519
shooting	0.222164	-0.175334	0.454391	0.350496	1.000000	0.654703	0.769547	-0.402365	0.020286	0.365566
passing	0.312271	-0.247290	0.662090	0.294917	0.654703	1.000000	0.834238	0.173119	0.164542	0.597197
dribbling	0.168493	-0.344262	0.596558	0.541006	0.769547	0.834238	1.000000	-0.142760	-0.005488	0.537464
defending	0.234109	0.189149	0.333616	-0.286393	-0.402365	0.173119	-0.142760	1.000000	0.551949	0.072896
physic	0.404695	0.442275	0.493539	-0.180699	0.020286	0.164542	-0.005488	0.551949	1.000000	0.022720
attacking_crossing	0.127915	-0.487854	0.410530	0.315519	0.365566	0.597197	0.537464	0.072896	0.022720	1.000000
attacking_finishing	0.082528	-0.371722	0.325413	0.287464	0.753205	0.424693	0.556242	-0.397700	-0.053713	0.671433
attacking_heading_accuracy	0.148629	0.012558	0.327239	-0.172865	0.047090	0.018609	-0.036524	0.220852	0.408769	0.483909
attacking_short_passing	0.147002	-0.353814	0.502191	0.094084	0.320596	0.557348	0.437664	0.185412	0.180037	0.804440
attacking_volleys	0.139521	-0.343877	0.374330	0.238581	0.686418	0.460477	0.538344	-0.291382	0.001407	0.693095
skill_dribbling	0.027099	-0.479083	0.378455	0.320611	0.464997	0.478467	0.595984	-0.118332	-0.023829	0.864583
skill_curve	0.141459	-0.438664	0.420495	0.277243	0.555318	0.616756	0.595232	-0.074266	0.002689	0.839114
skill_fk_accuracy	0.182622	-0.402411	0.385617	0.172614	0.529931	0.609378	0.518969	-0.030111	0.015031	0.763700
skill_long_passing	0.188678	-0.318615	0.487147	0.048670	0.277961	0.651050	0.432517	0.320839	0.204556	0.746818
skill_ball_control	0.094226	-0.410529	0.449372	0.193036	0.397779	0.466566	0.502123	0.001918	0.086931	0.841641
power_shot_power	0.267956	-0.158181	0.558372	0.215542	0.810232	0.617167	0.626448	-0.141436	0.202177	0.527564
power_jumping	0.202541	-0.002795	0.282440	0.032880	-0.028292	-0.011254	-0.017518	0.233794	0.435904	0.125847
power_stamina	0.121206	-0.283207	0.381869	0.179436	0.140138	0.278456	0.232559	0.245052	0.398834	0.678117
power_strength	0.350908	0.529385	0.358049	-0.300066	-0.031963	-0.039611	-0.170905	0.345165	0.843849	-0.015983
power_long_shots	0.156099	-0.379300	0.407525	0.229682	0.709929	0.544656	0.576198	-0.187946	0.052076	0.746340



The above Heatmap shows the Pearson Correlation between various features of the dataset.

Prediciton and Modelling

Predciting the Player Value in Euros using Linear Regression

In [65]:
```
fifa['value_eur'] = fifa['value_eur'] / 1000000
```

In [66]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
X = pearson.drop('height_cm',axis = 1)
y = fifa['value_eur']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
lr = LinearRegression()
lr.fit(X_train, y_train)
predict = lr.predict(X_test)
print('Slopes :',lr.coef_)
print('Intercept',lr.intercept_)
```

```
Slopes : [-2.85606930e-01  5.59571539e-01  6.72547872e-03  1.01874877e-01
  1.68531290e-02 -9.17910458e-02  8.14693094e-03 -4.33222211e-03
 -2.12886366e-02 -2.27885257e-02 -6.35568000e-04  5.09519529e-03
  2.21154218e-02  3.22105381e-02  1.51560081e-02 -2.95634679e-04
  1.02962583e-02  2.82033945e-03 -4.03250555e-02  2.40788774e-03
 -3.63271556e-03 -1.57494500e-02 -3.58395022e-02]
Intercept -25.678650273766582
```

In [67]:
```
from sklearn import metrics
print("Mean Squared Error:",metrics.mean_squared_error(y_test,predict))
print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,predict))
print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,predict)))
```

```
Mean Squared Error: 15.593645526525657
Mean Absolute Error: 2.018147291607448
Root Mean Squared Error: 3.9488790215104914
```

We decided to predict the Player Value in Euros using Linear Regression. Used the Linear Regression model form the Sci-Kit Learn package. We also used the Train-Test-Split as well as different metrics from Sci-Kit Learn to check the accuracy. We observed that the mean squared error came up to be 15.59, mean absolute error was 2.018 and the root mean squared error was 3.94887. We did pretty well in terms of error.

Resources-

Dataset - https://www.kaggle.com/stefanoleone992/fifa-21-complete-player-dataset (https://www.kaggle.com/stefanoleone992/fifa-21-complete-player-dataset)

Libraries - https://scikit-learn.org/stable/ (https://scikit-learn.org/stable/), https://seaborn.pydata.org/,https://matplotlib.org/ (https://seaborn.pydata.org/,https://matplotlib.org/), https://pandas.pydata.org/,https://numpy.org/ (https://pandas.pydata.org/,https://numpy.org/)