Machine Learning Project 2

In [ ]:

```
# Predicting players rating:
# In this project you are going to predict the overall rating of soccer player based on the
# such as 'crossing', 'finishing etc.

# The dataset you are going to use is from European Soccer Database
# (https://www.kaggle.com/hugomathien/soccer) has more than 25,000 matches and more than
# 10,000 players for European professional soccer seasons from 2008 to 2016.
# Download the data in the same folder and run the following commmand to get it in the envi

# About the Dataset:
# The ultimate Soccer database for data analysis and machine learning:
# The dataset comes in the form of an SQL database and contains statistics of about 25,000
# matches, from the top football league of 11 European Countries. It covers seasons from 20
# 2016 and contains match statistics (i.e: scores, corners, fouls etc...) as well as the te
# with player names and a pair of coordinates to indicate their position on the pitch.
# +25,000 matches
# +10,000 players
# 11 European Countries with their lead championship
# Seasons 2008 to 2016
# Players and Teams' attributes* sourced from EA Sports' FIFA video game series, including
# weekly updates
# Team line up with squad formation (X, Y coordinates)
# Betting odds from up to 10 providers
# Detailed match events (goal types, possession, corner, cross, fouls, cards etc...) for +1
# matches

# The dataset also has a set of about 35 statistics for each player, derived from EA Sports
# games. It is not just the stats that come with a new version of the game but also the wee
# updates. So for instance if a player has performed poorly over a period of time and his s
# impacted in FIFA, you would normally see the same in the dataset.

# Import Libraries:
# # import sqlite3
# # import pandas as pd
# # from sklearn.tree import DecisionTreeRegressor
# # from sklearn.linear_model import LinearRegression
# # from sklearn.model_selection import train_test_split
# # from sklearn.metrics import mean_squared_error
# # from math import sqrt

# Read Data from the Database into pandas:
# # # Create your connection.
# # cnx = sqlite3.connect('database.sqlite')
# # df = pd.read_sql_query("SELECT * FROM Player_Attributes", cnx)
```

Libraries

In [5]:

```
import pandas as pd
import numpy as np
import math
from math import sqrt
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
import sklearn

## Importing train_test_split,cross_val_score,GridSearchCV,KFold, RandomizedSearchCV - Vali
from sklearn.model_selection import ShuffleSplit, train_test_split,cross_val_score,GridSear

# Importing Regressors - Modelling
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor, AdaBoostRegr

# Importing Regression Metrics - Performance Evaluation
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

import pickle
```

In [6]:

```
%matplotlib inline
```

In [7]:

```
# Create your connection
cnx = sqlite3.connect('database.sqlite')
```

In [8]:

```
# Loading the dataframe with the data from the Player_Attributes Table
player_attrib = pd.read_sql_query("SELECT * FROM Player_Attributes", cnx)
```

In [9]:

```
player_attrib.head()
```

Out[9]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacki
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	

5 rows × 42 columns

Understand Dataset and Data

```
Get the basic information about the dataset
```

In [10]:

```
print(player_attrib.columns)
```

```
Index(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'overall_ratin
g',
       'potential', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate', 'crossing', 'finishing', 'heading_accuracy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accurac
y',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamin
a',
       'strength', 'long_shots', 'aggression', 'interceptions', 'positionin
g',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackl
e',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes'],
      dtype='object')
```

In [11]:

```
print(player_attrib.shape)
```

```
(183978, 42)
```

In [12]:

```
player_attrib.head()
```

Out[12]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacki
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	

5 rows × 42 columns

In [13]:

```
print(player_attrib.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 42 columns):
id                     183978 non-null int64
player_fifa_api_id     183978 non-null int64
player_api_id          183978 non-null int64
date                   183978 non-null object
overall_rating         183142 non-null float64
potential              183142 non-null float64
preferred_foot         183142 non-null object
attacking_work_rate    180748 non-null object
defensive_work_rate    183142 non-null object
crossing               183142 non-null float64
finishing              183142 non-null float64
heading_accuracy       183142 non-null float64
short_passing          183142 non-null float64
volleys                181265 non-null float64
dribbling              183142 non-null float64
curve                  181265 non-null float64
free_kick_accuracy     183142 non-null float64
long_passing           183142 non-null float64
ball_control           183142 non-null float64
acceleration           183142 non-null float64
sprint_speed           183142 non-null float64
agility                181265 non-null float64
reactions              183142 non-null float64
balance                181265 non-null float64
shot_power             183142 non-null float64
jumping                181265 non-null float64
stamina                183142 non-null float64
strength               183142 non-null float64
long_shots             183142 non-null float64
aggression             183142 non-null float64
interceptions          183142 non-null float64
positioning            183142 non-null float64
vision                 181265 non-null float64
penalties              183142 non-null float64
marking                183142 non-null float64
standing_tackle        183142 non-null float64
sliding_tackle         181265 non-null float64
gk_diving              183142 non-null float64
gk_handling            183142 non-null float64
gk_kicking             183142 non-null float64
gk_positioning         183142 non-null float64
gk_reflexes            183142 non-null float64
dtypes: float64(35), int64(3), object(4)
memory usage: 59.0+ MB
None
```

___There are null values in the dataset which need to be removed or imputed___

In [14]:

```
player_attrib.get_dtype_counts()
```

Out[14]:

```
float64    35
int64       3
object      4
dtype: int64
```

Data Cleaning

__Find rows containing null values or zeros(that don't belong in the dataset) and then either impute or remove them__

___Checking for columns containing null values___

In [15]:

```
player_attrib.isna().any() # To look for null element in atleast one row in the dataframe
```

Out[15]:

```
id                     False
player_fifa_api_id     False
player_api_id          False
date                   False
overall_rating          True
potential               True
preferred_foot          True
attacking_work_rate     True
defensive_work_rate     True
crossing                True
finishing               True
heading_accuracy        True
short_passing           True
volleys                 True
dribbling               True
curve                   True
free_kick_accuracy      True
long_passing            True
ball_control            True
acceleration            True
sprint_speed            True
agility                 True
reactions               True
balance                 True
shot_power              True
jumping                 True
stamina                 True
strength                True
long_shots              True
aggression              True
interceptions           True
positioning             True
vision                  True
penalties               True
marking                 True
standing_tackle         True
sliding_tackle          True
gk_diving               True
gk_handling             True
gk_kicking              True
gk_positioning          True
gk_reflexes             True
dtype: bool
```

All columns in the dataframe have null values except the id, player_fifa_api_id, player_api_id, date columns

In [17]:

```
#Performing a check to understand the number of null values in each column
null_info_df = pd.DataFrame(player_attrib.isna().sum())  # Identifying the number of nulls
null_info_df
```

Out[17]:

	0
id	0
player_fifa_api_id	0
player_api_id	0
date	0
overall_rating	836
potential	836
preferred_foot	836
attacking_work_rate	3230
defensive_work_rate	836
crossing	836
finishing	836
heading_accuracy	836
short_passing	836
volleys	2713
dribbling	836
curve	2713
free_kick_accuracy	836
long_passing	836
ball_control	836
acceleration	836
sprint_speed	836
agility	2713
reactions	836
balance	2713
shot_power	836
jumping	2713
stamina	836
strength	836
long_shots	836
aggression	836
interceptions	836
positioning	836
vision	2713
penalties	836

	0
marking	836
standing_tackle	836
sliding_tackle	2713
gk_diving	836
gk_handling	836
gk_kicking	836
gk_positioning	836
gk_reflexes	836

In [18]:

```
# Performing a check to understand the percentage of null values in each column
null_info_df["null_percentage"] = (player_attrib.isna().sum()/player_attrib.shape[0])*100
null_info_df
```

Out[18]:

	0	null_percentage
id	0	0.000000
player_fifa_api_id	0	0.000000
player_api_id	0	0.000000
date	0	0.000000
overall_rating	836	0.454402
potential	836	0.454402
preferred_foot	836	0.454402
attacking_work_rate	3230	1.755645
defensive_work_rate	836	0.454402
crossing	836	0.454402
finishing	836	0.454402
heading_accuracy	836	0.454402
short_passing	836	0.454402
volleys	2713	1.474633
dribbling	836	0.454402
curve	2713	1.474633
free_kick_accuracy	836	0.454402
long_passing	836	0.454402
ball_control	836	0.454402
acceleration	836	0.454402
sprint_speed	836	0.454402
agility	2713	1.474633
reactions	836	0.454402
balance	2713	1.474633
shot_power	836	0.454402
jumping	2713	1.474633
stamina	836	0.454402
strength	836	0.454402
long_shots	836	0.454402
aggression	836	0.454402
interceptions	836	0.454402
positioning	836	0.454402
vision	2713	1.474633
penalties	836	0.454402

	0	null_percentage
marking	836	0.454402
standing_tackle	836	0.454402
sliding_tackle	2713	1.474633
gk_diving	836	0.454402
gk_handling	836	0.454402
gk_kicking	836	0.454402
gk_positioning	836	0.454402
gk_reflexes	836	0.454402

In [ ]:

```
** there are approx 1.5% null values i.e. is very less , so droping those values
```

In [19]:

```
# Dropping rows containing null values in the dataframe
player_attrib.dropna(axis = 0, inplace = True)
```

In [20]:

```
player_attrib.shape
```

Out[20]:

```
(180354, 42)
```

3624 rows containing one or more null values removed

In [21]:

```
# Cross checking if the rows containing null values were removed
player_attrib.isna().sum()
```

Out[21]:

```
id                     0
player_fifa_api_id     0
player_api_id          0
date                   0
overall_rating         0
potential              0
preferred_foot         0
attacking_work_rate    0
defensive_work_rate    0
crossing               0
finishing              0
heading_accuracy       0
short_passing          0
volleys                0
dribbling              0
curve                  0
free_kick_accuracy     0
long_passing           0
ball_control           0
acceleration           0
sprint_speed           0
agility                0
reactions              0
balance                0
shot_power             0
jumping                0
stamina                0
strength               0
long_shots             0
aggression             0
interceptions          0
positioning            0
vision                 0
penalties              0
marking                0
standing_tackle        0
sliding_tackle         0
gk_diving              0
gk_handling            0
gk_kicking             0
gk_positioning         0
gk_reflexes            0
dtype: int64
```

Checking if there are any row values = zero that need our consideration so that we can decide to study those rows

In [22]:

```
player_attrib.loc[(player_attrib==0).all(axis=1)].shape
```

Out[22]:

```
(0, 42)
```

No zeroes in the dataframe to consider

In [23]:

```
player_attrib.head()
```

Out[23]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacki
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	

5 rows × 42 columns

In [24]:

```
# Moving overall_rating column to the end of the dataframe
cols = list(player_attrib.columns.values)
cols.pop(cols.index('overall_rating'))
player_attrib = player_attrib[cols+['overall_rating']]
```

In [25]:

```
player_attrib.columns.values
```

Out[25]:

```
array(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'potential',
       'preferred_foot', 'attacking_work_rate', 'defensive_work_rate',
       'crossing', 'finishing', 'heading_accuracy', 'short_passing',
       'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping',
       'stamina', 'strength', 'long_shots', 'aggression', 'interceptions',
       'positioning', 'vision', 'penalties', 'marking', 'standing_tackle',
       'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
       'gk_positioning', 'gk_reflexes', 'overall_rating'], dtype=object)
```

Cleaning Categorical Columns

In [26]:

```
# Getting a  list of the categorical columns
categorical_cols = player_attrib.select_dtypes(include='object').columns.values
categorical_cols
```

Out[26]:

```
array(['date', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate'], dtype=object)
```

In [27]:

```
# Getting a list of all the
player_attrib[categorical_cols].get_dtype_counts()
```

Out[27]:

```
object    4
dtype: int64
```

In [28]:

```
# Checking the number of unique values in the categorical columns
player_attrib[categorical_cols].nunique()
```

Out[28]:

```
date                   197
preferred_foot           2
attacking_work_rate      8
defensive_work_rate     18
dtype: int64
```

In [29]:

```
# Checking the distribution of the values in the preferred_foot column
player_attrib["preferred_foot"].value_counts()
```

Out[29]:

```
right    136247
left      44107
Name: preferred_foot, dtype: int64
```

The preferred_foot column doesn't need cleaning

In [26]:

```
# Checking the distribution of date column
player_attrib["date"].value_counts()
```

Out[26]:

```
2007-02-22 00:00:00    10410
2011-08-30 00:00:00     6520
2015-09-21 00:00:00     6518
2013-09-20 00:00:00     6513
2012-08-31 00:00:00     6491
2014-09-18 00:00:00     6429
2013-02-15 00:00:00     6373
2010-08-30 00:00:00     6232
2012-02-22 00:00:00     6134
2011-02-22 00:00:00     5340
2009-08-30 00:00:00     5312
2008-08-30 00:00:00     4873
2010-02-22 00:00:00     4160
2007-08-30 00:00:00     3921
2009-02-22 00:00:00     3048
2013-03-22 00:00:00     1945
2013-02-22 00:00:00     1487
2015-01-09 00:00:00     1480
2015-10-16 00:00:00     1469
2013-03-08 00:00:00     1292
2014-02-07 00:00:00     1244
2014-10-02 00:00:00     1217
2015-04-10 00:00:00     1188
2014-11-14 00:00:00     1187
2016-03-10 00:00:00     1180
2014-01-31 00:00:00     1064
2015-11-06 00:00:00     1060
2013-04-19 00:00:00     1048
2016-04-21 00:00:00     1044
2014-04-04 00:00:00     1036
                       ...
2014-08-22 00:00:00       52
2016-06-23 00:00:00       52
2013-09-13 00:00:00       51
2015-01-28 00:00:00       50
2016-06-30 00:00:00       46
2015-08-07 00:00:00       45
2015-01-26 00:00:00       45
2014-09-19 00:00:00       43
2016-02-19 00:00:00       42
2013-09-06 00:00:00       34
2015-04-01 00:00:00       30
2013-03-04 00:00:00       30
2015-09-04 00:00:00       29
2014-12-27 00:00:00       28
2015-08-27 00:00:00       26
2015-06-26 00:00:00       24
2014-08-29 00:00:00       23
2015-06-19 00:00:00       22
2015-08-21 00:00:00       20
2014-09-26 00:00:00       19
2014-09-05 00:00:00       19
2015-10-19 00:00:00       12
2016-07-07 00:00:00        9
```

```
2015-12-30 00:00:00        7
2015-03-10 00:00:00        7
2014-11-26 00:00:00        6
2015-09-10 00:00:00        5
2015-09-01 00:00:00        5
2016-02-13 00:00:00        1
2014-07-20 00:00:00        1
Name: date, Length: 197, dtype: int64
```

The date column item values don't need cleaning

In [30]:

```
# Checking the distribution of the values in the attacking_work_rate column
player_attrib["attacking_work_rate"].value_counts()
```

Out[30]:

```
medium    125070
high       42823
low         8569
None        3317
norm         317
y             94
stoc          86
le            78
Name: attacking_work_rate, dtype: int64
```

The attacking_work_rate column item values need to be set to medium, low or high as those are the only possible values for attacking_work_rate.

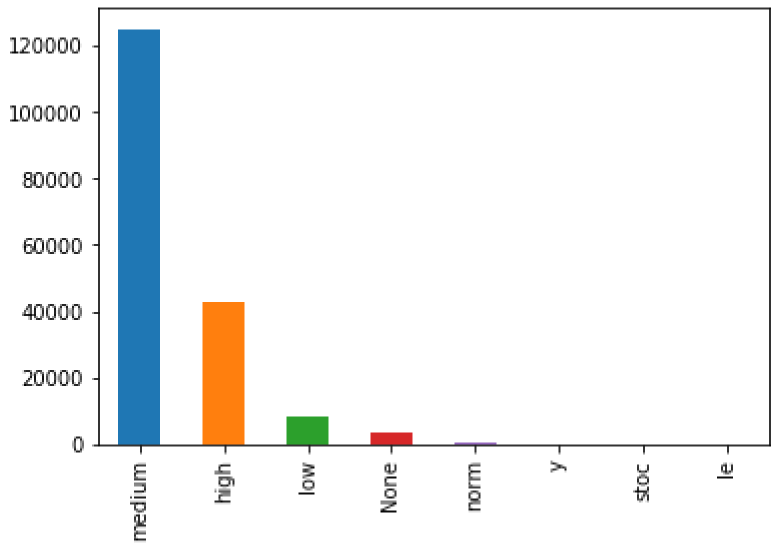
Reference: http://www.fifplay.com/encyclopedia/work-rate/ (http://www.fifplay.com/encyclopedia/work-rate/)

In [31]:

```
# Plotting the distribution of the values in the attacking_work_rate column
player_attrib["attacking_work_rate"].value_counts().plot.bar()
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b3c923c8>
```



We can choose to drop the columns where the categorical values do not make sense or we can replace those values into the three categories, medium, high, low

Ignore this - Dropping rows with gibberish values in attacking_work_rate

In [32]:

```
# To delete the rows which have the gibberish values
cleaned = player_attrib[~(player_attrib.attacking_work_rate.isin(['None','norm','y','stoc',

(1- cleaned.shape[0]/player_attrib.shape[0])*100
```

Out[32]:

```
2.1579781984319757
```

2.15% Data Loss

To replace gibberish values with medium, low, high

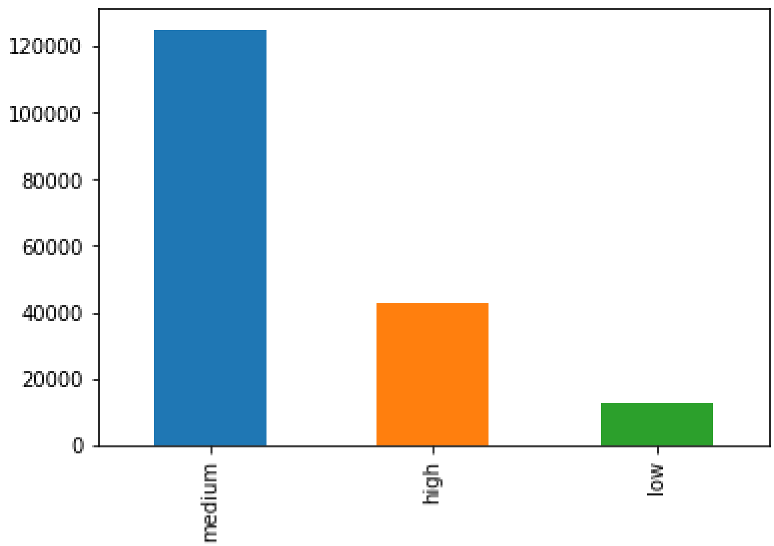
In [34]:

```
# Choosing to replace only with low because it can improve the variance of the column
player_attrib.replace( ['None','norm','y','stoc','le'],'low', inplace = True)
print(player_attrib["attacking_work_rate"].value_counts())
player_attrib["attacking_work_rate"].value_counts().plot.bar()
```

```
medium    125070
high       42823
low        12461
Name: attacking_work_rate, dtype: int64
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194ac879a90>
```



In [35]:

```
# Checking the distribution of the values in the defensive_work_rate column
player_attrib["defensive_work_rate"].value_counts()
```

Out[35]:

```
medium    130846
high       27041
low        18432
o           1328
1            421
2            334
ormal        317
3            243
5            231
7            207
0            188
6            179
9            143
4            116
es            94
tocky         86
ean           78
8             70
Name: defensive_work_rate, dtype: int64
```

The defensive_work_rate column items need to be set into medium, low or high as those are the only possible values for defensive_work_rate.

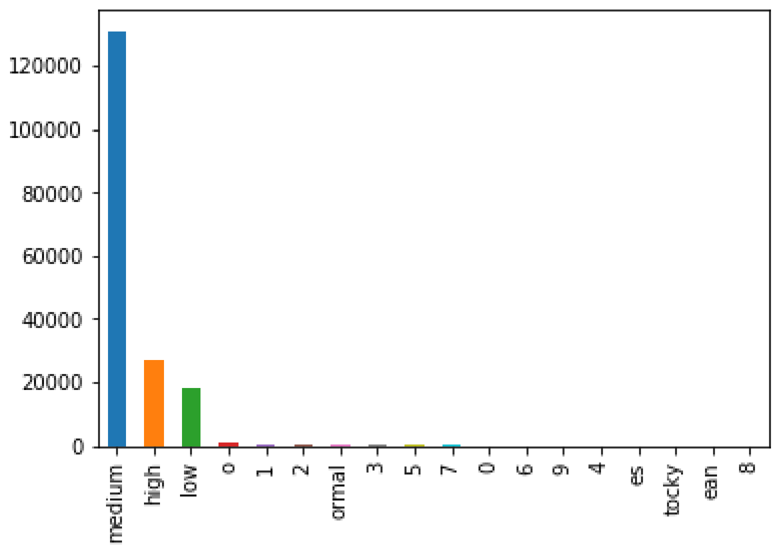
Reference: [http://www.fifplay.com/encyclopedia/work-rate/ (http://www.fifplay.com/encyclopedia/work-rate/)](http://www.fifplay.com/encyclopedia/work-rate/)

In [36]:

```
# Plotting the distribution of the values in the defensive_work_rate column
player_attrib["defensive_work_rate"].value_counts().plot.bar()
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194ab6ca9b0>
```



WE can choose to drop the columns where the categorical values do not make sense or we can re-

organize those values into the three categories, medium, high, low

Ignore this - Dropping rows with gibberish values in defensive_work_rate

In [37]:

```
# To delete the rows which have the gibberish values
cleaned1 = player_attrib[~(player_attrib.defensive_work_rate.isin(['o', '1', '2', 'ormal',
                                                          '6', '9', '4', 'es', 'tocky', 'ear
```

In [38]:

```
(1- cleaned1.shape[0]/player_attrib.shape[0])*100
```

Out[38]:

```
2.2372667088060183
```

2.2% Data Loss

OR

To replace gibberish values with medium, low, high

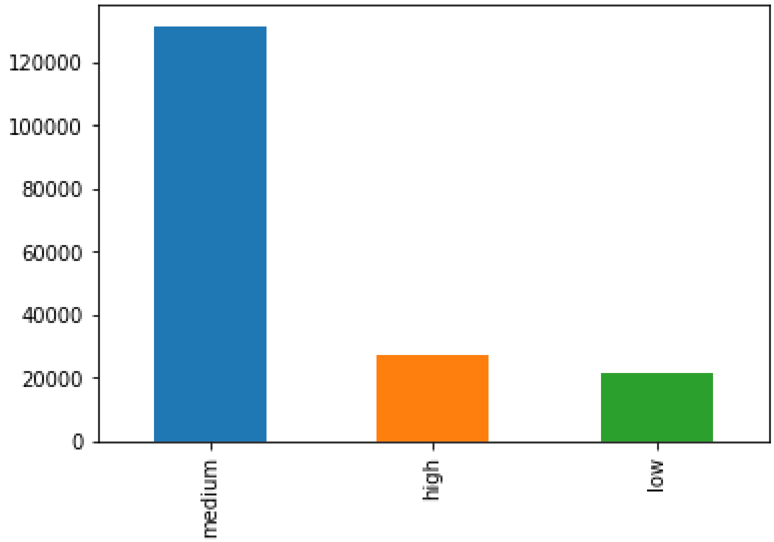
In [39]:

```
player_attrib.replace(['o', '1', '2', 'ormal', '3', '0', 'es', 'tocky', 'ean'],'low',inplac
player_attrib.replace(['5',  '6', '4'],'medium', inplace = True)
player_attrib.replace([ '7', '9', '8'],'high', inplace = True)
print(player_attrib["defensive_work_rate"].value_counts())
player_attrib["defensive_work_rate"].value_counts().plot.bar()
```

```
medium    131372
high       27461
low        21521
Name: defensive_work_rate, dtype: int64
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b2a06d30>
```



Basic Statistical Information

In [40]:

```
# Getting basic statistical information about the numerical columns
player_attrib.describe() # Only numerical columns
```

Out[40]:

	id	player_fifa_api_id	player_api_id	potential	crossing	fin
count	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.0
mean	91995.886274	166822.125803	137653.145514	73.479457	55.142071	49.9
std	53092.657914	52821.443279	137599.735284	6.581963	17.247231	19.0
min	1.000000	2.000000	2625.000000	39.000000	1.000000	1.0
25%	46074.250000	156616.000000	35451.000000	69.000000	45.000000	34.0
50%	92003.500000	183792.000000	80291.000000	74.000000	59.000000	53.0
75%	137935.750000	200138.000000	192841.000000	78.000000	68.000000	65.0
max	183978.000000	234141.000000	750584.000000	97.000000	95.000000	97.0

8 rows × 38 columns

In [41]:

```
# Getting correlation between various numerical columns
player_attrib.corr()
```

Out[41]:

	id	player_fifa_api_id	player_api_id	potential	crossing	finishing
id	1.000000	0.003744	0.002048	0.000837	-0.020231	-0.008171
player_fifa_api_id	0.003744	1.000000	0.556557	-0.021252	-0.065631	-0.029836
player_api_id	0.002048	0.556557	1.000000	0.010588	-0.113365	-0.062312
potential	0.000837	-0.021252	0.010588	1.000000	0.277284	0.287838
crossing	-0.020231	-0.065631	-0.113365	0.277284	1.000000	0.576896
finishing	-0.008171	-0.029836	-0.062312	0.287838	0.576896	1.000000
heading_accuracy	-0.011781	-0.103500	-0.130282	0.206063	0.368956	0.373459
short_passing	-0.006701	-0.065311	-0.090237	0.382538	0.790323	0.580245
volleys	-0.006916	-0.088726	-0.131262	0.301678	0.637527	0.851482
dribbling	-0.014784	0.047551	0.015616	0.339978	0.809747	0.784988
curve	-0.019523	-0.052501	-0.099430	0.296050	0.788924	0.691082
free_kick_accuracy	-0.008396	-0.108735	-0.152683	0.262842	0.708763	0.633274
long_passing	-0.008137	-0.111272	-0.139584	0.343133	0.685649	0.341121
ball_control	-0.013976	-0.024942	-0.053940	0.401803	0.807721	0.720694
acceleration	-0.008212	0.178267	0.101536	0.338820	0.599439	0.529355
sprint_speed	-0.011897	0.178343	0.094236	0.340698	0.579506	0.509647
agility	-0.000947	0.116309	0.026467	0.293714	0.599561	0.554396
reactions	-0.005740	-0.233465	-0.312538	0.580991	0.384999	0.354769
balance	-0.009909	0.008350	0.021300	0.202232	0.519778	0.394978
shot_power	-0.010371	-0.080175	-0.126514	0.325459	0.656740	0.727835
jumping	-0.004279	-0.073277	-0.141646	0.174532	0.021270	0.008948
stamina	-0.010506	0.015277	-0.109958	0.259432	0.565935	0.347853
strength	-0.008954	-0.178351	-0.234866	0.122392	-0.072915	-0.054596
long_shots	-0.010382	-0.068652	-0.119638	0.313059	0.716515	0.806895
aggression	-0.018034	-0.170147	-0.212509	0.162137	0.324625	0.044465
interceptions	-0.008480	-0.169307	-0.185482	0.163292	0.306446	-0.152560
positioning	-0.015643	-0.078862	-0.105157	0.326898	0.684803	0.803687
vision	-0.007928	-0.163099	-0.188087	0.379278	0.693978	0.652376
penalties	-0.011751	-0.175255	-0.162481	0.315207	0.574208	0.726234
marking	-0.010329	-0.075568	-0.089772	0.054094	0.234886	-0.285416
standing_tackle	-0.012515	-0.071128	-0.086706	0.082073	0.285018	-0.230453
sliding_tackle	-0.011101	-0.055218	-0.073595	0.063284	0.274673	-0.262144
gk_diving	0.014251	-0.092945	-0.071825	-0.012283	-0.604567	-0.479370
gk_handling	0.010911	-0.138844	-0.125345	0.005865	-0.595646	-0.465135

	id	player_fifa_api_id	player_api_id	potential	crossing	finishing
gk_kicking	0.008758	-0.248222	-0.229704	0.092299	-0.356728	-0.292349
gk_positioning	0.014015	-0.140925	-0.125525	0.004472	-0.597742	-0.470758
gk_reflexes	0.014671	-0.131531	-0.121947	0.004936	-0.601696	-0.473302
overall_rating	-0.003738	-0.278703	-0.328315	0.765435	0.357320	0.330079

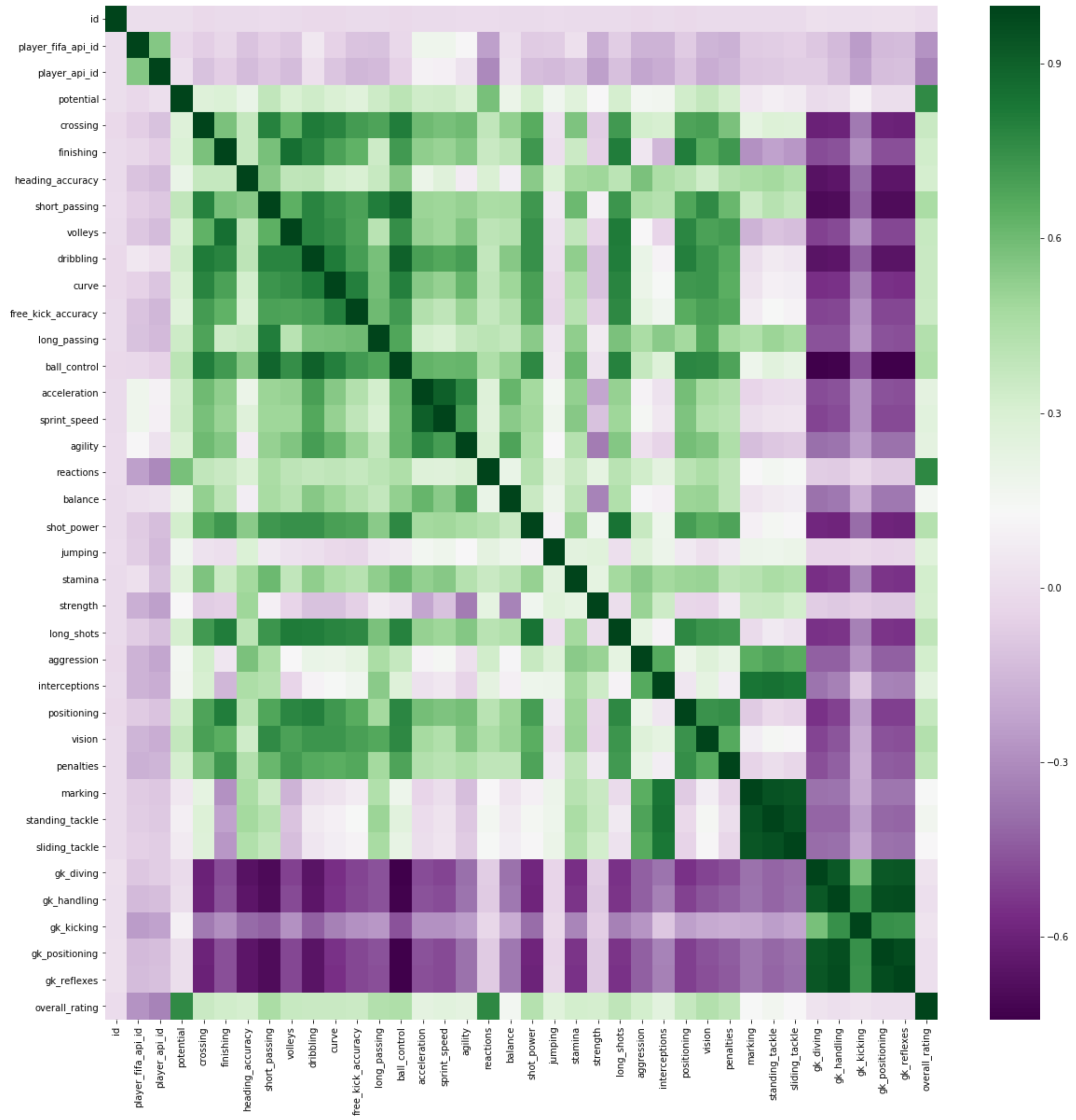
38 rows × 38 columns

In [42]:

```
# Checking for correlations using HEATMAP
plt.figure(figsize=(20,20))
sns.heatmap(player_attrib.corr(), cmap="PRGn")
```

Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b3bf1518>
```



In [43]:

```
player_attrib.corr().loc['overall_rating']
```

Out[43]:

```
id                    -0.003738
player_fifa_api_id    -0.278703
player_api_id         -0.328315
potential              0.765435
crossing               0.357320
finishing              0.330079
heading_accuracy       0.313324
short_passing          0.458243
volleys                0.361739
dribbling              0.354191
curve                  0.357566
free_kick_accuracy     0.349800
long_passing           0.434525
ball_control           0.443991
acceleration           0.243998
sprint_speed           0.253048
agility                0.239963
reactions              0.771856
balance                0.160211
shot_power             0.428053
jumping                0.258978
stamina                0.325606
strength               0.315684
long_shots             0.392668
aggression             0.322782
interceptions          0.249094
positioning            0.368978
vision                 0.431493
penalties              0.392715
marking                0.132185
standing_tackle        0.163986
sliding_tackle         0.128054
gk_diving              0.027675
gk_handling            0.006717
gk_kicking             0.028799
gk_positioning         0.008029
gk_reflexes            0.007804
overall_rating         1.000000
Name: overall_rating, dtype: float64
```

overall_rating is highly correlated with the reactions and potential columns(Correlation>0.7). It is moderately correlated with short_passing, long_passing,ball_control, shot_power,vision (correlation >0.4)

Exploratory Data Analysis

Univariate - Visual Analysis - Distribution and countplots etc.

Univariate Analysis of Categorical Data

In [44]:

```
categorical_cols
```

Out[44]:

```
array(['date', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate'], dtype=object)
```

In [45]:

```
player_attrib[categorical_cols].head()
```

Out[45]:

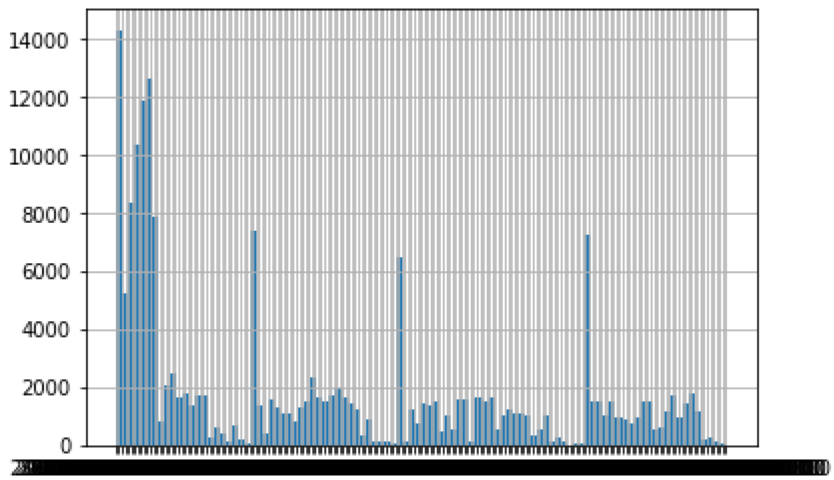
	date	preferred_foot	attacking_work_rate	defensive_work_rate
0	2016-02-18 00:00:00	right	medium	medium
1	2015-11-19 00:00:00	right	medium	medium
2	2015-09-21 00:00:00	right	medium	medium
3	2015-03-20 00:00:00	right	medium	medium
4	2007-02-22 00:00:00	right	medium	medium

In [46]:

```
player_attrib.date.hist(bins=100)
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b3976358>
```

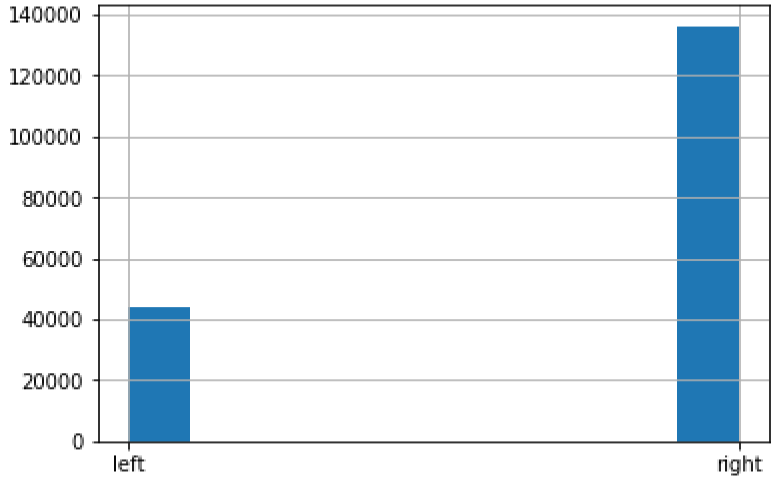


In [43]:

```
player_attrib.preferred_foot.hist()
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e15cc22400>
```



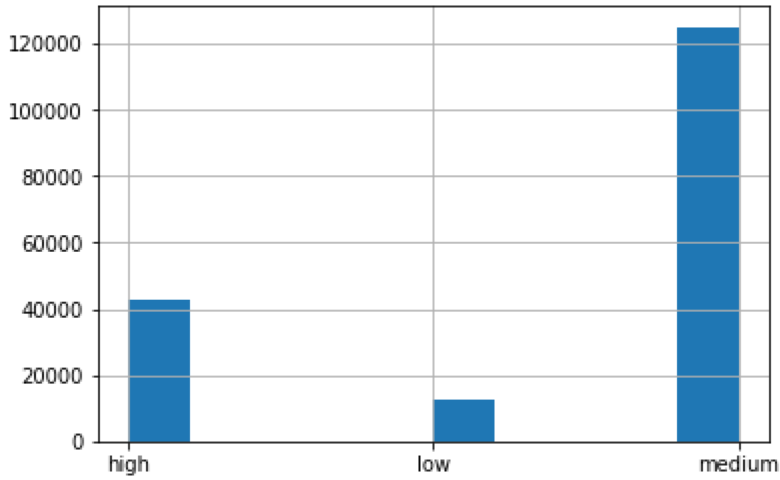
Majority of the players' preferred foot is the right leg

In [47]:

```
player_attrib.attacking_work_rate.hist()
```

Out[47]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b24d5e48>
```



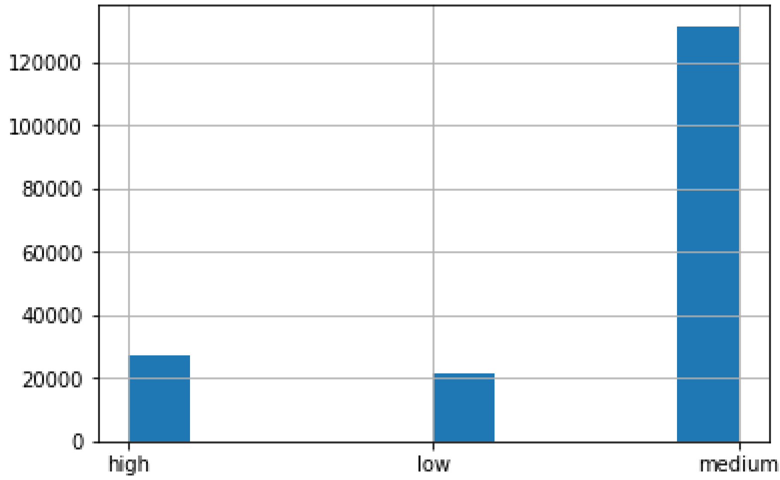
Majority of the players' attacking work rate is medium

In [45]:

```
player_attrib.defensive_work_rate.hist()
```

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e15dff1cc0>
```



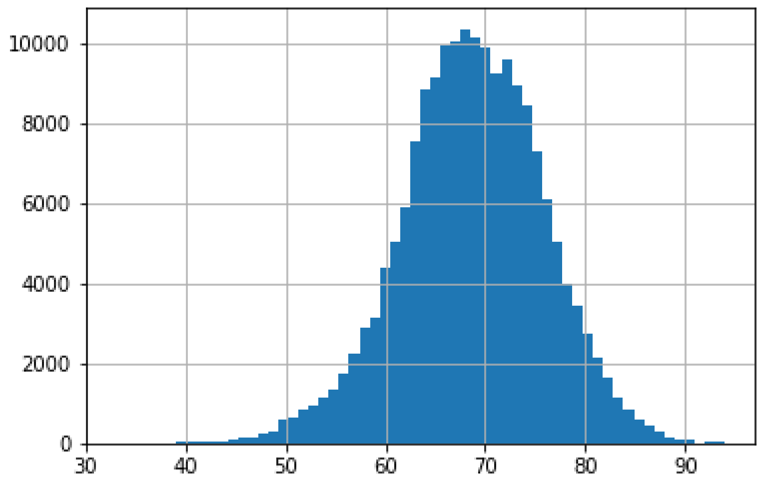
Majority of the players' defensive work rate is medium

In [48]:

```
player_attrib['overall_rating'].hist(bins=60)
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x194b1585c88>
```

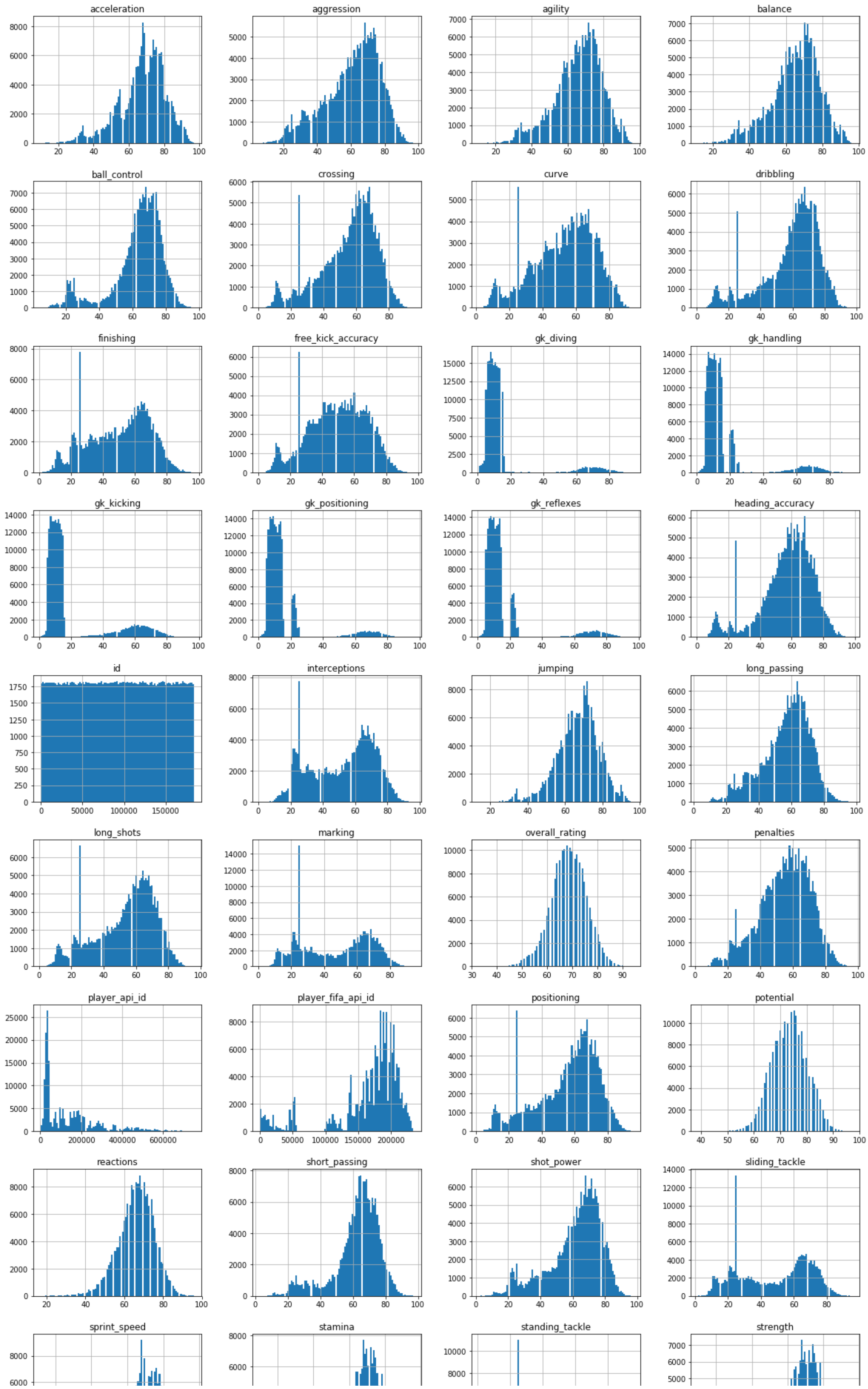


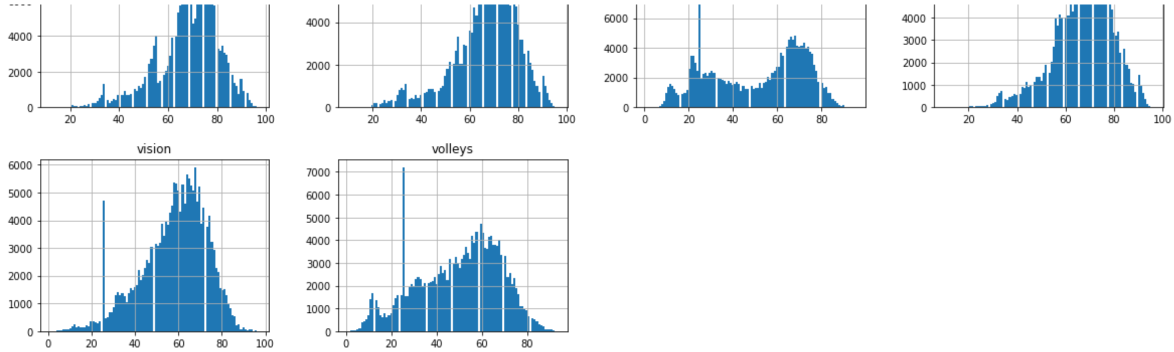
Players' overall rating is normally distributed

Univariate Analysis of Numerical Data

In [49]:

```
# Plotting the histograms of numerical columns to understand their distribution
player_attrib.hist(bins=100,figsize=(20,40),layout=(10,4))
plt.show()
```





The interception, marking, standing_tackle and diving_tackle column values follow bimodal distribution

The gk_diving, gk_relexes, gk_positioning, gk_kicking, gk_handling column values follow also bimodal distribution but are imbalanced

All other player attributes column values roughly follow normal distribution. This is to be expected as majority of the players have reasonably attributes but only some have exceptional attributes

Bi-variate - Statistical and Visual Analysis

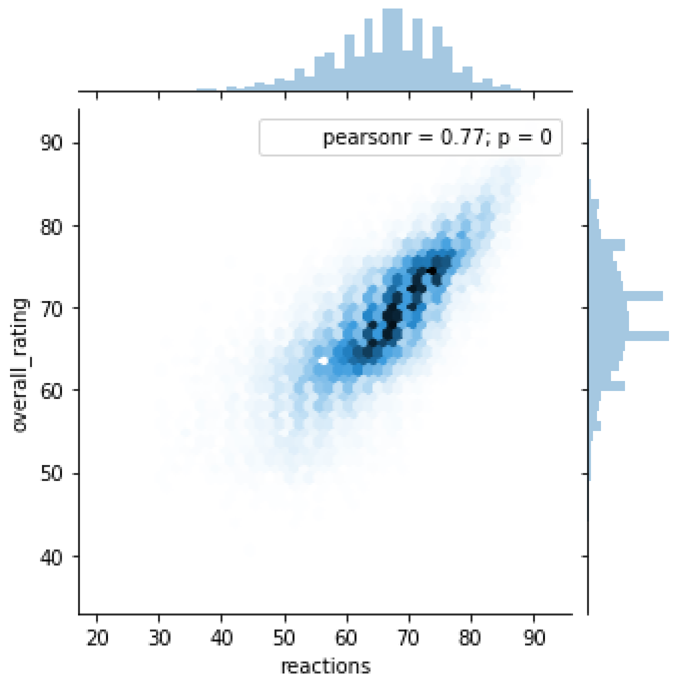
Plotting: overall_rating vs reactions and potential columns(Correlation>0.7) and short_passing, long_passing, ball_control, shot_power,vision (correlation >0.4)

In [54]:

```
sns.jointplot(x=player_attrib["reactions"], y=player_attrib["overall_rating"], kind='hex',s
```

Out[54]:

```
<seaborn.axisgrid.JointGrid at 0x194acb40cc0>
```

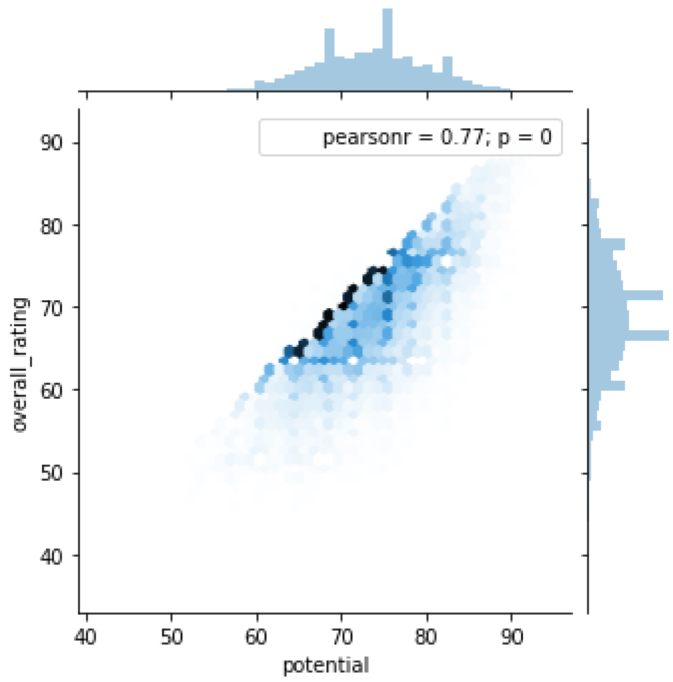


In [55]:

```
sns.jointplot(x=player_attrib["potential"], y=player_attrib["overall_rating"], kind='hex',s
```

Out[55]:

```
<seaborn.axisgrid.JointGrid at 0x194ac6bc5f8>
```

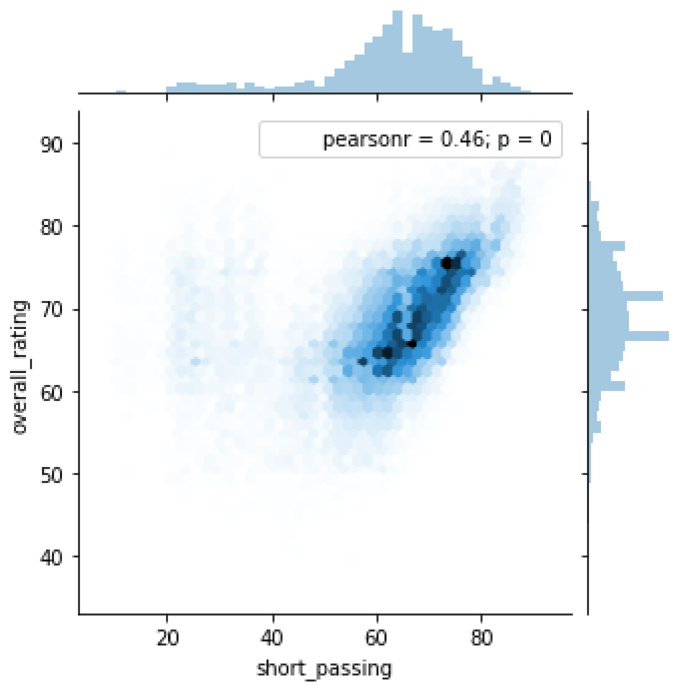


In [56]:

```
sns.jointplot(x=player_attrib["short_passing"], y=player_attrib["overall_rating"], kind='he
```

Out[56]:

```
<seaborn.axisgrid.JointGrid at 0x194abd89d68>
```

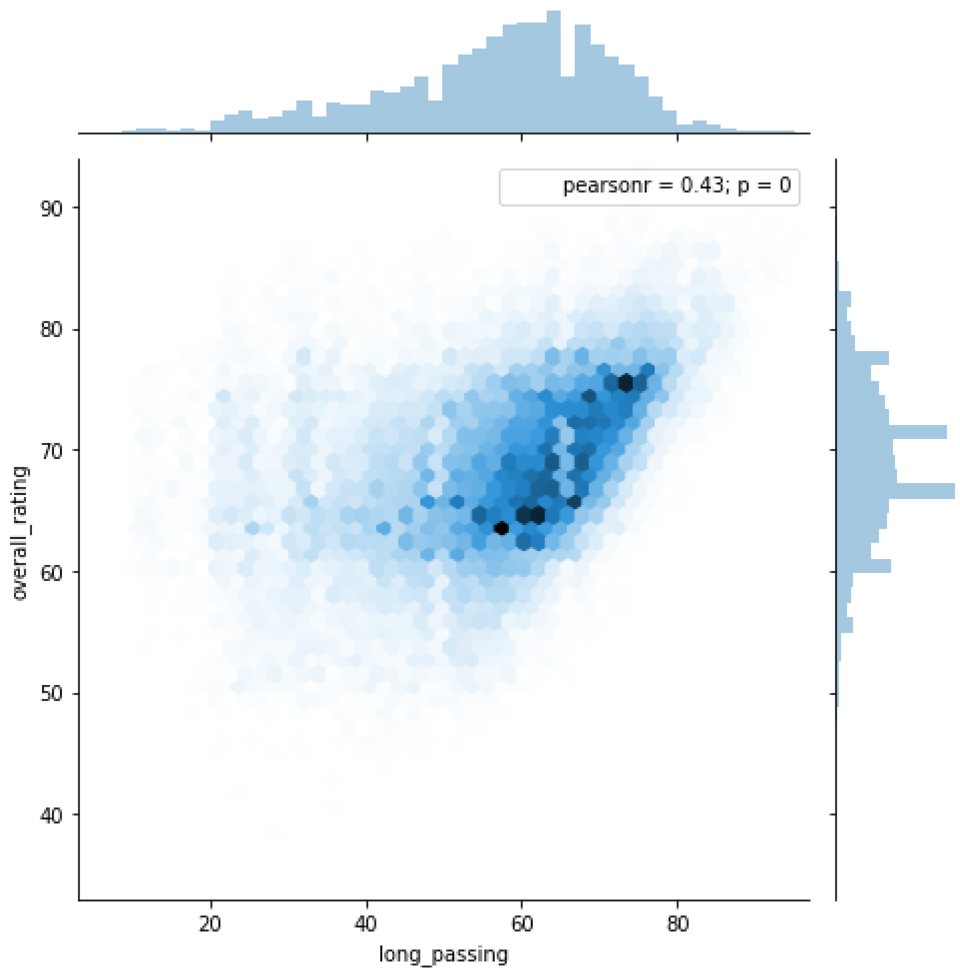


In [51]:

```
sns.jointplot(x=player_attrib["long_passing"], y=player_attrib["overall_rating"], kind='hex
```

Out[51]:

```
<seaborn.axisgrid.JointGrid at 0x1e160e6c390>
```



Feature Engineering - Preparing Data for Modeling

Preparing the input vector X

In [60]:

```
X = player_attrib.drop("overall_rating",axis = 1)
X.shape, X.columns
```

Out[60]:

```
((180354, 41),
 Index(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'potential',
        'preferred_foot', 'attacking_work_rate', 'defensive_work_rate',
        'crossing', 'finishing', 'heading_accuracy', 'short_passing', 'volle
ys',
        'dribbling', 'curve', 'free_kick_accuracy', 'long_passing',
        'ball_control', 'acceleration', 'sprint_speed', 'agility', 'reaction
s',
        'balance', 'shot_power', 'jumping', 'stamina', 'strength', 'long_sho
ts',
        'aggression', 'interceptions', 'positioning', 'vision', 'penalties',
        'marking', 'standing_tackle', 'sliding_tackle', 'gk_diving',
        'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes'],
       dtype='object'))
```

Dropping the various ids in the dataset as they do not contribute to the regression model

In [61]:

```
X.drop("id",axis = 1, inplace = True)
X.drop("player_fifa_api_id",axis = 1, inplace = True)
X.drop("player_api_id",axis = 1, inplace = True)
```

Modifying the date column in the input vector

In [62]:

```
X['year'] = pd.DatetimeIndex(X.date).year
X['month'] = pd.DatetimeIndex(X.date).month
X['day'] = pd.DatetimeIndex(X.date).day
X.drop('date',axis=1, inplace=True)
```

Selecting columns for label encoding and encoding them

In [63]:

```
X_cat_cols = X.select_dtypes(include='object').columns.tolist()
X_cat_cols
```

Out[63]:

```
['preferred_foot', 'attacking_work_rate', 'defensive_work_rate']
```

In [64]:

```
# LabelEncoding the preferred_foot, attacking_work_rate, defensive_work_rate
from sklearn.preprocessing import LabelEncoder
for i in X_cat_cols:
    lbl_enc = LabelEncoder()
    X[i] = lbl_enc.fit_transform(X[i])
```

In [65]:

```
# Checking the columns and the shape of the input vector after encoding
X.columns, X.shape
```

Out[65]:

```
(Index(['potential', 'preferred_foot', 'attacking_work_rate',
        'defensive_work_rate', 'crossing', 'finishing', 'heading_accuracy',
        'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accurac
y',
        'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
        'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamin
a',
        'strength', 'long_shots', 'aggression', 'interceptions', 'positionin
g',
        'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackl
e',
        'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
        'gk_reflexes', 'year', 'month', 'day'],
       dtype='object'), (180354, 40))
```

In [66]:

```
X.head()
```

Out[66]:

	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finishing	headi
0	71.0	1	2	2	49.0	44.0	
1	71.0	1	2	2	49.0	44.0	
2	66.0	1	2	2	49.0	44.0	
3	65.0	1	2	2	48.0	43.0	
4	65.0	1	2	2	48.0	43.0	

5 rows × 40 columns

Preparing the Output Y

In [67]:

```
Y = player_attrib["overall_rating"]
Y.shape
```

Out[67]:

```
(180354,)
```

In [68]:

```
Y.head()
```

Out[68]:

```
0    67.0
1    67.0
2    62.0
3    61.0
4    61.0
Name: overall_rating, dtype: float64
```

Splitting the data into Train and Test

In [69]:

```
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.25, random_state = 100)
```

Fitting the models and collecting the metrics

Linear Regression

In [70]:

```
lm  = LinearRegression()
model  = lm.fit(x_train,y_train)
y_train_pred = model.predict(x_train)
y_test_pred = model.predict(x_test)

print('Linear Regression -', 'RMSE Train:', math.sqrt(mean_squared_error(y_train_pred, y_tr
print('Linear Regression -', 'RMSE Test:' ,math.sqrt(mean_squared_error(y_test_pred, y_test
print('Linear Regression -', 'R2_score Train:', r2_score(y_train_pred, y_train))
print('Linear Regression -', 'R2_score Test:' ,r2_score(y_test_pred, y_test))
```

```
Linear Regression - RMSE Train: 2.7309026846988043
Linear Regression - RMSE Test: 2.730777350395378
Linear Regression - R2_score Train: 0.8216028424294087
Linear Regression - R2_score Test: 0.8219679620041507
```

Other Regressors

In [71]:

```
regressors = [
            ("Linear - ", LinearRegression(normalize=True)),
            ("Ridge - ",  Ridge(alpha=0.5, normalize=True)),
            ("Lasso - ",  Lasso(alpha=0.5, normalize=True)),
            ("ElasticNet - ",  ElasticNet(alpha=0.5, l1_ratio=0.5, normalize=True)),
            ("Decision Tree - ",  DecisionTreeRegressor(max_depth=5)),
            ("Random Forest - ",  RandomForestRegressor(n_estimators=100)),
            ("AdaBoost - ",  AdaBoostRegressor(n_estimators=100)),
            ("GBM - ", GradientBoostingRegressor(n_estimators=100))]
```

In [72]:

```
for reg in regressors:
    reg[1].fit(x_train, y_train)
    y_test_pred= reg[1].predict(x_test)
    print(reg[0],"\n\t R2-Score:", reg[1].score(x_test, y_test),
                 "\n\t RMSE:", math.sqrt(mean_squared_error(y_test_pred, y_test)),"\n")
```

```
Linear - 
         R2-Score: 0.8501969196523183 
         RMSE: 2.73077735039538 

Ridge - 
         R2-Score: 0.8094085593573674 
         RMSE: 3.080190780589965 

Lasso - 
         R2-Score: -4.220879563199276e-06 
         RMSE: 7.0554844132901415 

ElasticNet - 
         R2-Score: -4.220879563199276e-06 
         RMSE: 7.0554844132901415 

Decision Tree - 
         R2-Score: 0.7786783353651396 
         RMSE: 3.3192341052560117 

Random Forest - 
         R2-Score: 0.9824041194635779 
         RMSE: 0.9359042568169555 

AdaBoost - 
         R2-Score: 0.8186531942844436 
         RMSE: 3.004559959795495 

GBM - 
         R2-Score: 0.9380248854563253 
         RMSE: 1.7564451379448531 
```

Feature Selection

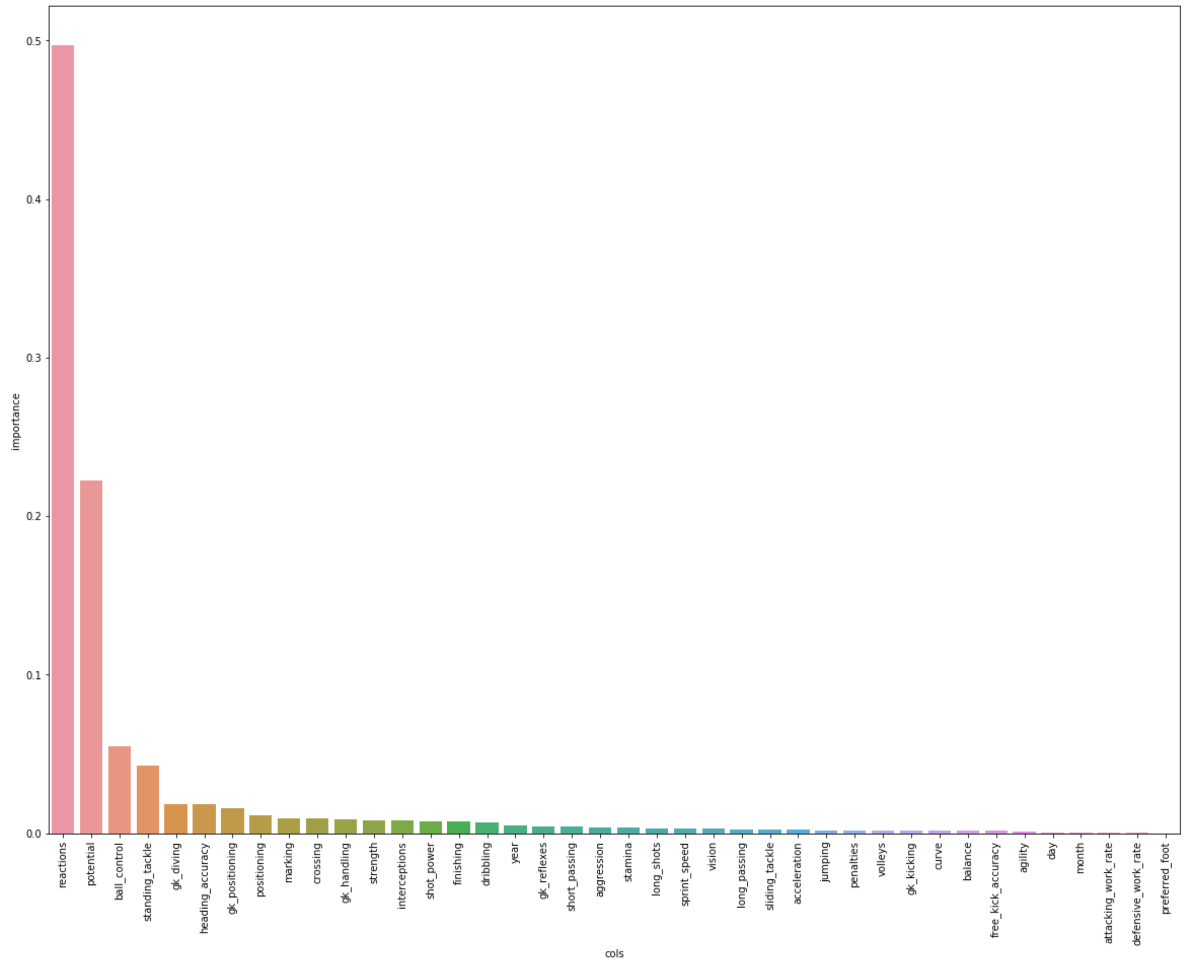
Feature Selection using feature importances from RandomForestRegressor model

In [73]:

```
rndf = RandomForestRegressor(n_estimators=150)
rndf.fit(x_train, y_train)
importance = pd.DataFrame.from_dict({'cols':x_train.columns, 'importance': rndf.feature_imp
importance = importance.sort_values(by='importance', ascending=False)
plt.figure(figsize=(20,15))
sns.barplot(importance.cols, importance.importance)
plt.xticks(rotation=90)
```

Out[73]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39]), <a list of 40 Text xticklabel objects>)
```



In [74]:

```
imp_cols = importance[importance.importance >= 0.005].cols.values
imp_cols
```

Out[74]:

```
array(['reactions', 'potential', 'ball_control', 'standing_tackle',
       'gk_diving', 'heading_accuracy', 'gk_positioning', 'positioning',
       'marking', 'crossing', 'gk_handling', 'strength', 'interceptions',
       'shot_power', 'finishing', 'dribbling', 'year'], dtype=object)
```

In [75]:

```
# Fitting models with columns where feature importance>=0.005
x_train, x_test, y_train, y_test = train_test_split(X[imp_cols],Y,test_size=0.75, random_st
for reg in regressors:
    reg[1].fit(x_train, y_train)
    y_test_pred= reg[1].predict(x_test)
    print(reg[0],"\n\t R2-Score:", reg[1].score(x_test, y_test),
                 "\n\t RMSE:", math.sqrt(mean_squared_error(y_test_pred, y_test)),"\n")
```

```
Linear - 
	 R2-Score: 0.8431273415851339 
	 RMSE: 2.783681625409858 

Ridge - 
	 R2-Score: 0.8003978321538426 
	 RMSE: 3.1399921438596183 

Lasso - 
	 R2-Score: -1.776966378042033e-06 
	 RMSE: 7.028235745736134 

ElasticNet - 
	 R2-Score: -1.776966378042033e-06 
	 RMSE: 7.028235745736134 

Decision Tree - 
	 R2-Score: 0.7741592409557474 
	 RMSE: 3.340004846504886 

Random Forest - 
	 R2-Score: 0.9653283748637406 
	 RMSE: 1.3086786997820135 

AdaBoost - 
	 R2-Score: 0.8305763922158786 
	 RMSE: 2.8928965089035215 

GBM - 
	 R2-Score: 0.9356063522104895 
	 RMSE: 1.7834767352457117 
```

In [76]:

```
imp_cols = importance[importance.importance >= 0.001].cols.values
imp_cols
```

Out[76]:

```
array(['reactions', 'potential', 'ball_control', 'standing_tackle',
       'gk_diving', 'heading_accuracy', 'gk_positioning', 'positioning',
       'marking', 'crossing', 'gk_handling', 'strength', 'interceptions',
       'shot_power', 'finishing', 'dribbling', 'year', 'gk_reflexes',
       'short_passing', 'aggression', 'stamina', 'long_shots',
       'sprint_speed', 'vision', 'long_passing', 'sliding_tackle',
       'acceleration', 'jumping', 'penalties', 'volleys', 'gk_kicking',
       'curve', 'balance', 'free_kick_accuracy', 'agility'], dtype=object)
```

In [77]:

```
# Fitting models with columns where feature importance>=0.001
x_train, x_test, y_train, y_test = train_test_split(X[imp_cols],Y,test_size=0.75, random_st
for reg in regressors:
    reg[1].fit(x_train, y_train)
    y_test_pred= reg[1].predict(x_test)
    print(reg[0],"\n\t R2-Score:", reg[1].score(x_test, y_test),
                 "\n\t RMSE:", math.sqrt(mean_squared_error(y_test_pred, y_test)),"\n")
```

```
Linear -
         R2-Score: 0.8485016231507021
         RMSE: 2.735583178429208

Ridge -
         R2-Score: 0.8097666691702011
         RMSE: 3.065414734954621

Lasso -
         R2-Score: -1.776966378042033e-06
         RMSE: 7.028235745736134

ElasticNet -
         R2-Score: -1.776966378042033e-06
         RMSE: 7.028235745736134

Decision Tree -
         R2-Score: 0.7741592409557474
         RMSE: 3.340004846504886

Random Forest -
         R2-Score: 0.9680321135002367
         RMSE: 1.256616902141094

AdaBoost -
         R2-Score: 0.8387281543247305
         RMSE: 2.8224432127521553

GBM -
         R2-Score: 0.9385145861893729
         RMSE: 1.7427375335042703
```

RandomForest and GBM provide us with the best RMSE and R2-Score when selecting columns with feature importance >= 0.001

Validation of the Models

Validating our models using K-Fold Cross Validation for Robustness

In [78]:

```
scoring = 'neg_mean_squared_error'
results=[]
names=[]
for modelname, model in regressors:
    kfold = KFold(n_splits=10, random_state=7)
    cv_results = cross_val_score(model, x_train,y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(modelname)
    print(modelname,"\n\t CV-Mean:", cv_results.mean(),
                    "\n\t CV-Std. Dev:",  cv_results.std(),"\n")
```

```
Linear -
         CV-Mean: -7.577425402593292
         CV-Std. Dev: 0.1881652662073941

Ridge -
         CV-Mean: -9.527694490104617
         CV-Std. Dev: 0.3104263221463401

Lasso -
         CV-Mean: -49.38186544635581
         CV-Std. Dev: 1.092422030903323

ElasticNet -
         CV-Mean: -49.38186544635581
         CV-Std. Dev: 1.092422030903323

Decision Tree -
         CV-Mean: -11.465003716652667
         CV-Std. Dev: 0.34653675521956645

Random Forest -
         CV-Mean: -1.717148459139164
         CV-Std. Dev: 0.10152873437301052

AdaBoost -
         CV-Mean: -7.988006847478836
         CV-Std. Dev: 0.3337065566539398

GBM -
         CV-Mean: -3.1420739651710514
         CV-Std. Dev: 0.1394835771508512
```

RandomForest and GBM provide us with the best validation score, both w.r.t. CV-Mean and CV-Std. Dev

Therefore we choose these two models to optimize. We do this by finding best hyper-parameter values which give us even better R2-Score and RMSE values

Tuning Model for better Performance -- Hyper-Parameter Optimization

Tuning the RandomForestRegressor, GradientBoostingRegressor Hyper-Parameters using GridSearchCV

In [79]:

```
regressors
```

Out[79]:

```
[('Linear - ',
  LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Tru
e)),
 ('Ridge - ', Ridge(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=Non
e,
     normalize=True, random_state=None, solver='auto', tol=0.001)),
 ('Lasso - ', Lasso(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=100
0,
     normalize=True, positive=False, precompute=False, random_state=None,
     selection='cyclic', tol=0.0001, warm_start=False)),
 ('ElasticNet - ',
  ElasticNet(alpha=0.5, copy_X=True, fit_intercept=True, l1_ratio=0.5,
        max_iter=1000, normalize=True, positive=False, precompute=False,
        random_state=None, selection='cyclic', tol=0.0001, warm_start=Fals
e)),
 ('Decision Tree - ',
  DecisionTreeRegressor(criterion='mse', max_depth=5, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             presort=False, random_state=None, splitter='best')),
 ('Random Forest - ',
  RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
             max_features='auto', max_leaf_nodes=None,
             min_impurity_decrease=0.0, min_impurity_split=None,
             min_samples_leaf=1, min_samples_split=2,
             min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
             oob_score=False, random_state=None, verbose=0, warm_start=Fals
e)),
 ('AdaBoost - ',
  AdaBoostRegressor(base_estimator=None, learning_rate=1.0, loss='linear',
          n_estimators=100, random_state=None)),
 ('GBM - ',
  GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
               learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
               max_leaf_nodes=None, min_impurity_decrease=0.0,
               min_impurity_split=None, min_samples_leaf=1,
               min_samples_split=2, min_weight_fraction_leaf=0.0,
               n_estimators=100, presort='auto', random_state=None,
               subsample=1.0, verbose=0, warm_start=False))]
```

Warning: Running the following optimization algorithms takes very long to complete.

Random Forest Regressor

In [80]:

```
RF_Regressor =  RandomForestRegressor(n_estimators=100, n_jobs = -1, random_state = 100)

CV = ShuffleSplit(test_size=0.25, random_state=100)

param_grid = {"max_depth": [5, None],
              "n_estimators": [50, 100, 150, 200],
              "min_samples_split": [2, 4, 5],
              "min_samples_leaf": [2, 4, 6]
             }
```

In [81]:

```
rscv_grid = GridSearchCV(RF_Regressor, param_grid=param_grid, verbose=1)
```

In [82]:

```
rscv_grid.fit(x_train, y_train)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=1)]: Done 216 out of 216 | elapsed: 54.7min finished
```

Out[82]:

```
GridSearchCV(cv=None, error_score='raise',
       estimator=RandomForestRegressor(bootstrap=True, criterion='mse', max_
depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=-1,
           oob_score=False, random_state=100, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'max_depth': [5, None], 'n_estimators': [50, 100, 150, 20
0], 'min_samples_split': [2, 4, 5], 'min_samples_leaf': [2, 4, 6]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=1)
```

In [83]:

```
rscv_grid.best_params_
```

Out[83]:

```
{'max_depth': None,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 200}
```

In [84]:

```
model = rscv_grid.best_estimator_
model.fit(x_train, y_train)
```

Out[84]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=2, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=200, n_jobs=-1,
           oob_score=False, random_state=100, verbose=0, warm_start=False)
```

In [85]:

```
model.score(x_test, y_test)
```

Out[85]:

```
0.9677172492931098
```

In [86]:

```
RF_reg = pickle.dumps(rscv_grid)
```

Gradient Boosting Regressor

In [87]:

```
GB_Regressor =  GradientBoostingRegressor(n_estimators=100)

CV = ShuffleSplit(test_size=0.25, random_state=100)

param_grid = {'max_depth': [5, 7, 9],
              'learning_rate': [0.1, 0.3, 0.5]
             }
```

In [88]:

```
rscv_grid = GridSearchCV(GB_Regressor, param_grid=param_grid, verbose=1)
```

In [89]:

```
rscv_grid.fit(x_train, y_train)
```

```
Fitting 3 folds for each of 9 candidates, totalling 27 fits

[Parallel(n_jobs=1)]: Done  27 out of  27 | elapsed: 15.6min finished
```

Out[89]:

```
GridSearchCV(cv=None, error_score='raise',
       estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_ms
e', init=None,
             learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             n_estimators=100, presort='auto', random_state=None,
             subsample=1.0, verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'max_depth': [5, 7, 9], 'learning_rate': [0.1, 0.3, 0.
5]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=1)
```

In [90]:

```
rscv_grid.best_params_
```

Out[90]:

```
{'learning_rate': 0.1, 'max_depth': 9}
```

In [91]:

```
model = rscv_grid.best_estimator_
model.fit(x_train, y_train)
```

Out[91]:

```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.1, loss='ls', max_depth=9, max_features=None,
             max_leaf_nodes=None, min_impurity_decrease=0.0,
             min_impurity_split=None, min_samples_leaf=1,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             n_estimators=100, presort='auto', random_state=None,
             subsample=1.0, verbose=0, warm_start=False)
```

In [91]:

```
model.score(x_test, y_test)
```

Out[91]:

```
0.9738262886317136
```

In [92]:

```
GB_reg = pickle.dumps(rscv_grid)
```

Comparing performance metric of the different models

In [93]:

```
RF_regressor = pickle.loads(RF_reg)
GB_regressor = pickle.loads(GB_reg)
```

In [95]:

```
print("RandomForestRegressor - \n\t R2-Score:", RF_regressor.score(x_test, y_test),
                 "\n\t RMSE:", math.sqrt(mean_squared_error(RF_regressor.predict(x_test), y

print("GradientBoostingRegressor - \n\t R2-Score:", GB_regressor.score(x_test, y_test),
                 "\n\t RMSE:", math.sqrt(mean_squared_error(GB_regressor.predict(x_test), y
```

```
RandomForestRegressor -
         R2-Score: 0.9677101265725686
         RMSE: 1.2629294945564922

GradientBoostingRegressor -
         R2-Score: 0.9738262886317136
         RMSE: 1.1370474512785247
```

Select the model

We can see that Gradient Boosting Regressor gives better result with an R2-Score of more than 97% and while keeping RMSE value low(=1.1370474). So, XGBoost Regressor should be used as the regression model for this dataset.