Project 2

Predicting players rating

In this project you are going to predict the overall rating of soccer player based on their attributessuch as 'crossing', 'finishing etc.

The dataset you are going to use is from European Soccer Database ([https://www.kaggle.com/hugomathien/soccer (https://www.kaggle.com/hugomathien/soccer)](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 environment

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 football matches, from the top football league of 11 European Countries. It covers seasons from 2008 to 2016 and contains match statistics (i.e: scores, corners, fouls etc...) as well as the team formations, 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 the 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 +10,000 matches

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

Python skills required to complete this project

SQL:

The data is in SQL database so students need to retrive using query language. They also need to know how to connect SQL database woth python. The library we are using for this in 'sqlite3'. SQLite3 can be integrated with Python using sqlite3 module, which was written by Gerhard Haring. It provides an SQL interface compliant with the DB-API 2.0 specification described by PEP 249. You do not need to install this module separately because it is shipped by default along with Python version 2.5.x onwards.

To use sqlite3 module, you must first create a connection object that represents the database and then optionally you can create a cursor object, which will help you in executing all the SQL statements.

Pandas:

Pandas is an open-source, BSD-licensed Python library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.In this tutorial, we will learn the various features of Python Pandas and how to use them in practice.

Scikit Learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python.

The library is built upon the SciPy (Scientific Python) that must be installed before you can use scikit-learn. This stack that includes:

- `NumPy` : Base n-dimensional array package
- `SciPy` : Fundamental library for scientific computing
- `Matplotlib` : Comprehensive 2D/3D plotting
- `IPython` : Enhanced interactive console
- `Sympy` : Symbolic mathematics
- `Pandas` : Data structures and analysis

Extensions or modules for SciPy care conventionally named SciKits. As such, the module provides learning algorithms and is named scikit-learn.

The vision for the library is a level of robustness and support required for use in production systems. This means a deep focus on concerns such as easy of use, code quality, collaboration, documentation and performance.

Machine Learning skills required to complete the project

Supervised learning

Supervised learning deals with learning a function from available training data. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples.

Regression

Regression is a parametric technique used to predict continuous (dependent) variable given a set of independent variables. It is parametric in nature because it makes certain assumptions (discussed next) based on the data set. If the data set follows those assumptions, regression gives incredible results.

Model evaluation

Student must know how to judge a model on unseen data. What metric to select to judge the performance

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Let's get started.....

Import Libraries

In [1]:

```
## Importing required libraries
# Core Libraries - Data manipulation and analysis
import pandas as pd
import numpy as np
import math
from math import sqrt
import matplotlib.pyplot as plt
import seaborn as sns

# Core Libraries - Loading data from sqlite database
import sqlite3

# Core Libraries - Machine Learning
import sklearn

## Importing train_test_split,cross_val_score,GridSearchCV,KFold,  - Validation and Optimiza
from sklearn.model_selection import ShuffleSplit, train_test_split,cross_val_score,GridSearc

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

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

# Importing libraries  for train test split the data

from sklearn import model_selection




##############################################################################################
##############################################################################################

#from sklearn.pipeline import Pipeline
import warnings

#warnings.simplefilter("ignore")
```

In [2]:
```
## Read Data from the Database into pandas
# Create your connection.
import sqlite3
cnx = sqlite3.connect('database.sqlite')
player_attrib = pd.read_sql_query("SELECT * FROM Player_Attributes", cnx)

player_attrib.head()
```

Out[2]:

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

5 rows × 42 columns

Understand Dataset and Data

Get the basic information about the dataset

Basic Data about the dataframe are the columns, shape, top 5 and bottom 5 rows, its column types and null(and non-null) values

In [3]:
```
player_attrib.columns
```

Out[3]:
```
Index(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'overall_rating',
       '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'],
      dtype='object')
```

In [4]:
```
player_attrib.shape
```

Out[4]:
```
(183978, 42)
```

In [5]:
```
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
```

There are null values in the dataset which need to be removed or imputed, We have to check the data properly if data size is very small data can be removed from the data set.

In [6]:
```
player_attrib.groupby(['attacking_work_rate'])['attacking_work_rate'].count()
```

Out[6]:
```
attacking_work_rate
None        3639
high       42823
le           104
low         8569
medium    125070
norm         348
stoc          89
y            106
Name: attacking_work_rate, dtype: int64
```

In [7]:
```
player_attrib.get_dtype_counts()
```

Out[7]:
```
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 [8]: player_attrib.isna().any() # To look for null element in atleast one row in the dataframe
```

```
Out[8]: 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 [9]:
```
#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 i
# OR
# player_attrib.isnull().sum() # This will also work directly
null_info_df.columns = ["total_null_values"]
null_info_df
```

Out[9]:

	total_null_values
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
marking	836

	total_null_values
standing_tackle	836
sliding_tackle	2713
gk_diving	836
gk_handling	836
gk_kicking	836
gk_positioning	836
gk_reflexes	836

In [10]:
```
# 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[10]:

	total_null_values	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
marking	836	0.454402
standing_tackle	836	0.454402
sliding_tackle	2713	1.474633

	total_null_values	null_percentage
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 [11]:
```
# Performing a check to understand the number of rows which has null values
player_attrib.isnull().T.any().T.sum()
```

Out[11]: 3624

In [12]:
```
# Performing a check to understand the percentage of rows which has null values
rows = (player_attrib.isnull().T.any().T.sum()/player_attrib.shape[0])*100
rows
```

Out[12]: 1.9698007370446464

In [13]:
```
player_attrib.shape[0]
```

Out[13]: 183978

Since the number of rows with null values in every column is less than `2% of the data`, dropping those rows won't have a bearing on the regression model. It also, is better to not impute because we have insufficient information about the data. Deleting `3624` rows from `183978`

In [14]:
```
# Dropping rows containing null values in the dataframe
player_attrib.dropna(axis = 0, inplace = True)
```

In [15]:
```
player_attrib.shape
```

Out[15]: (180354, 42)

3624 rows containing one or more null values are being removed, hence remaining rows are `180352` which is also a quite large number

In [16]:
```
# Cross checking if the rows/columns containing null values were removed
player_attrib.isna().sum()
```

Out[16]:
```
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
```

In [17]:
```
# Cross checking if the rows/columns containing null values were removed
player_attrib.isnull().T.any().T.sum()
```

Out[17]:
```
0
```

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

In [18]:
```
player_attrib.loc[(player_attrib==0).all(axis=1)].shape
```

Out[18]:
```
(0, 42)
```

No zeroes in the dataframe to consider

In [19]:
```
player_attrib.head()
```

Out[19]:

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

5 rows × 42 columns

In [20]:
```
# 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 [21]:
```
player_attrib.columns.values # Checking the column sequence
```

Out[21]:
```
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)
```

In [22]:
```
# Getting a  list of the categorical columns
categorical_cols = player_attrib.select_dtypes(include='object').columns.values
categorical_cols
# OR
# categorical_cols = player_attrib.dtypes[player_attrib.dtypes == 'object'].index
# categorical_cols
```

Out[22]:
```
array(['date', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate'], dtype=object)
```

In [23]:
```
# Getting a list of all the
player_attrib[categorical_cols].get_dtype_counts()
```

Out[23]:
```
object    4
dtype: int64
```

In [24]:
```python
# Checking the number of unique values in the categorical columns
player_attrib[categorical_cols].nunique()
```

Out[24]:
```
date                   197
preferred_foot           2
attacking_work_rate      8
defensive_work_rate     18
dtype: int64
```

In [25]:
```python
# Checking the distribution of the values in the preferred_foot column
player_attrib["preferred_foot"].value_counts()
```

Out[25]:
```
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
                        ...
2016-06-23 00:00:00       52
2014-08-22 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
2015-03-10 00:00:00        7
2015-12-30 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
2014-07-20 00:00:00        1
```

```
2016-02-13 00:00:00        1
Name: date, Length: 197, dtype: int64
```

The date column item values don't need cleaning

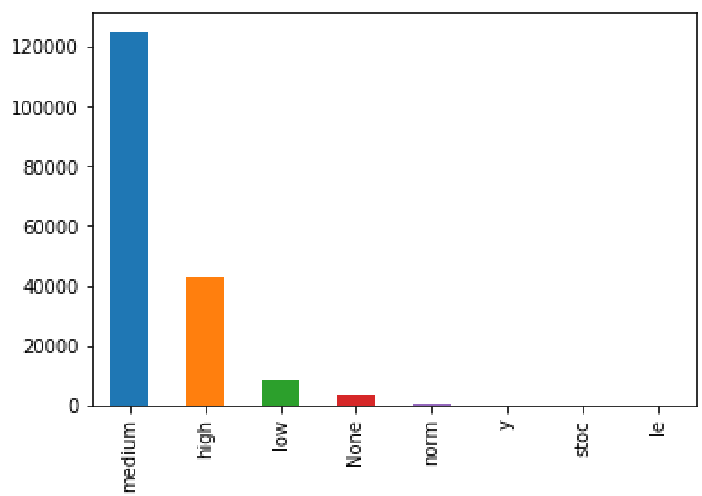
In [27]:
```
# Checking the distribution of the values in the attacking_work_rate column
player_attrib["attacking_work_rate"].value_counts()
```

Out[27]:
```
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.

In [28]:
```

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

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x206b82e62b0>
```



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 [29]:
```
# 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
```

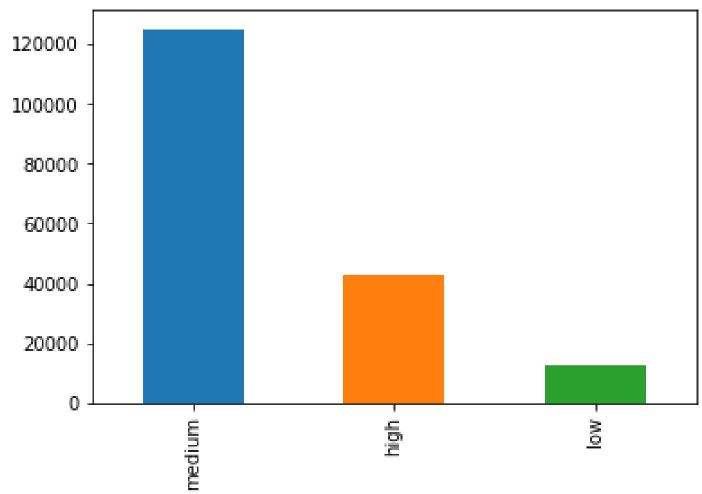
Out[29]:
```
2.1579781984319757
```

To replace gibberish values with medium, low, high

In [30]:
```
# 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[30]: `<matplotlib.axes._subplots.AxesSubplot at 0x206b8fcbc50>`



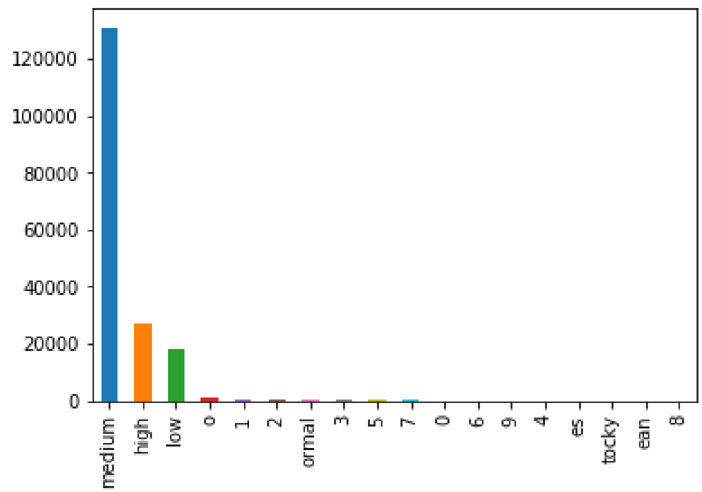
In [31]:
```
# Checking the distribution of the values in the defensive_work_rate column
player_attrib["defensive_work_rate"].value_counts()
```

Out[31]:
```
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.

In [32]:
```
# Plotting the distribution of the values in the defensive_work_rate column
player_attrib["defensive_work_rate"].value_counts().plot.bar()
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x206ba117ef0>



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 [33]:
```
# 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', 'ean'
```

In [34]:
```
(1- cleaned1.shape[0]/player_attrib.shape[0])*100
```

Out[34]: 2.2372667088060183

2.2% Data Loss

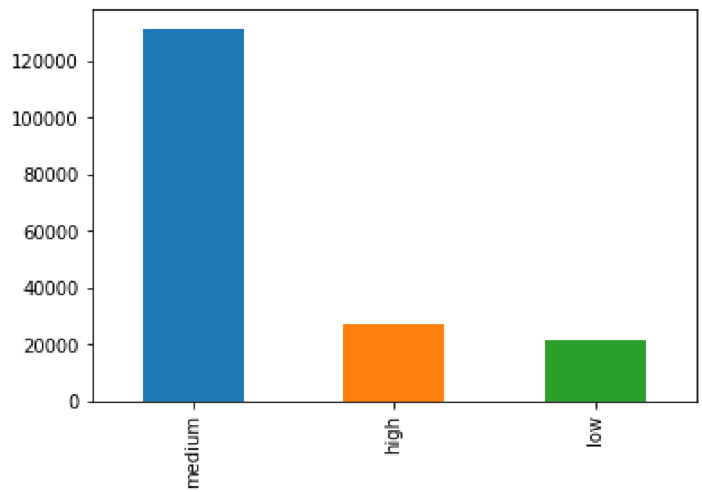
OR

To replace gibberish values with medium, low, high

In [35]:
```python
player_attrib.replace(['o', '1', '2', 'ormal', '3', '0', 'es', 'tocky', 'ean'],'low',inplace
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[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x206b8fcb7b8>
```



Basic Statistical Information

In [36]:
```python
# Getting basic statistical information about the numerical columns# Gettin
player_attrib.describe() # Only numerical columns
```

Out[36]:

	id	player_fifa_api_id	player_api_id	potential	crossing	finishing	heading_a
count	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	18035
mean	91995.886274	166822.125803	137653.145514	73.479457	55.142071	49.962136	5
std	53092.657914	52821.443279	137599.735284	6.581963	17.247231	19.041760	1
min	1.000000	2.000000	2625.000000	39.000000	1.000000	1.000000	
25%	46074.250000	156616.000000	35451.000000	69.000000	45.000000	34.000000	4
50%	92003.500000	183792.000000	80291.000000	74.000000	59.000000	53.000000	6
75%	137935.750000	200138.000000	192841.000000	78.000000	68.000000	65.000000	6
max	183978.000000	234141.000000	750584.000000	97.000000	95.000000	97.000000	9

8 rows × 38 columns

In [37]:

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

Out[37]:

	id	player_fifa_api_id	player_api_id	potential	crossing	finishing	heading_accuracy
id	1.000000	0.003744	0.002048	0.000837	-0.020231	-0.008171	-0.011781
player_fifa_api_id	0.003744	1.000000	0.556557	-0.021252	-0.065631	-0.029836	-0.103500
player_api_id	0.002048	0.556557	1.000000	0.010588	-0.113365	-0.062312	-0.130282
potential	0.000837	-0.021252	0.010588	1.000000	0.277284	0.287838	0.206063
crossing	-0.020231	-0.065631	-0.113365	0.277284	1.000000	0.576896	0.368956
finishing	-0.008171	-0.029836	-0.062312	0.287838	0.576896	1.000000	0.373459
heading_accuracy	-0.011781	-0.103500	-0.130282	0.206063	0.368956	0.373459	1.000000
short_passing	-0.006701	-0.065311	-0.090237	0.382538	0.790323	0.580245	0.548435
volleys	-0.006916	-0.088726	-0.131262	0.301678	0.637527	0.851482	0.391129
dribbling	-0.014784	0.047551	0.015616	0.339978	0.809747	0.784988	0.400803
curve	-0.019523	-0.052501	-0.099430	0.296050	0.788924	0.691082	0.320384
free_kick_accuracy	-0.008396	-0.108735	-0.152683	0.262842	0.708763	0.633274	0.306013
long_passing	-0.008137	-0.111272	-0.139584	0.343133	0.685649	0.341121	0.362741
ball_control	-0.013976	-0.024942	-0.053940	0.401803	0.807721	0.720694	0.550956
acceleration	-0.008212	0.178267	0.101536	0.338820	0.599439	0.529355	0.198164
sprint_speed	-0.011897	0.178343	0.094236	0.340698	0.579506	0.509647	0.265430
agility	-0.000947	0.116309	0.026467	0.293714	0.599561	0.554396	0.068570
reactions	-0.005740	-0.233465	-0.312538	0.580991	0.384999	0.354769	0.295601
balance	-0.009909	0.008350	0.021300	0.202232	0.519778	0.394978	0.077255
shot_power	-0.010371	-0.080175	-0.126514	0.325459	0.656740	0.727835	0.541365
jumping	-0.004279	-0.073277	-0.141646	0.174532	0.021270	0.008948	0.286305
stamina	-0.010506	0.015277	-0.109958	0.259432	0.565935	0.347853	0.477830
strength	-0.008954	-0.178351	-0.234866	0.122392	-0.072915	-0.054596	0.493543
long_shots	-0.010382	-0.068652	-0.119638	0.313059	0.716515	0.806895	0.406003
aggression	-0.018034	-0.170147	-0.212509	0.162137	0.324625	0.044465	0.577304
interceptions	-0.008480	-0.169307	-0.185482	0.163292	0.306446	-0.152560	0.454187
positioning	-0.015643	-0.078862	-0.105157	0.326898	0.684803	0.803687	0.408972
vision	-0.007928	-0.163099	-0.188087	0.379278	0.693978	0.652376	0.336472
penalties	-0.011751	-0.175255	-0.162481	0.315207	0.574208	0.726234	0.431291
marking	-0.010329	-0.075568	-0.089772	0.054094	0.234886	-0.285416	0.460831
standing_tackle	-0.012515	-0.071128	-0.086706	0.082073	0.285018	-0.230453	0.480054
sliding_tackle	-0.011101	-0.055218	-0.073595	0.063284	0.274673	-0.262144	0.441134
gk_diving	0.014251	-0.092945	-0.071825	-0.012283	-0.604567	-0.479370	-0.665600
gk_handling	0.010911	-0.138844	-0.125345	0.005865	-0.595646	-0.465135	-0.649145
gk_kicking	0.008758	-0.248222	-0.229704	0.092299	-0.356728	-0.292349	-0.402865
gk_positioning	0.014015	-0.140925	-0.125525	0.004472	-0.597742	-0.470758	-0.648981
gk_reflexes	0.014671	-0.131531	-0.121947	0.004936	-0.601696	-0.473302	-0.652494

	id	player_fifa_api_id	player_api_id	potential	crossing	finishing	heading_accuracy
overall_rating	-0.003738	-0.278703	-0.328315	0.765435	0.357320	0.330079	0.313324

38 rows × 38 columns

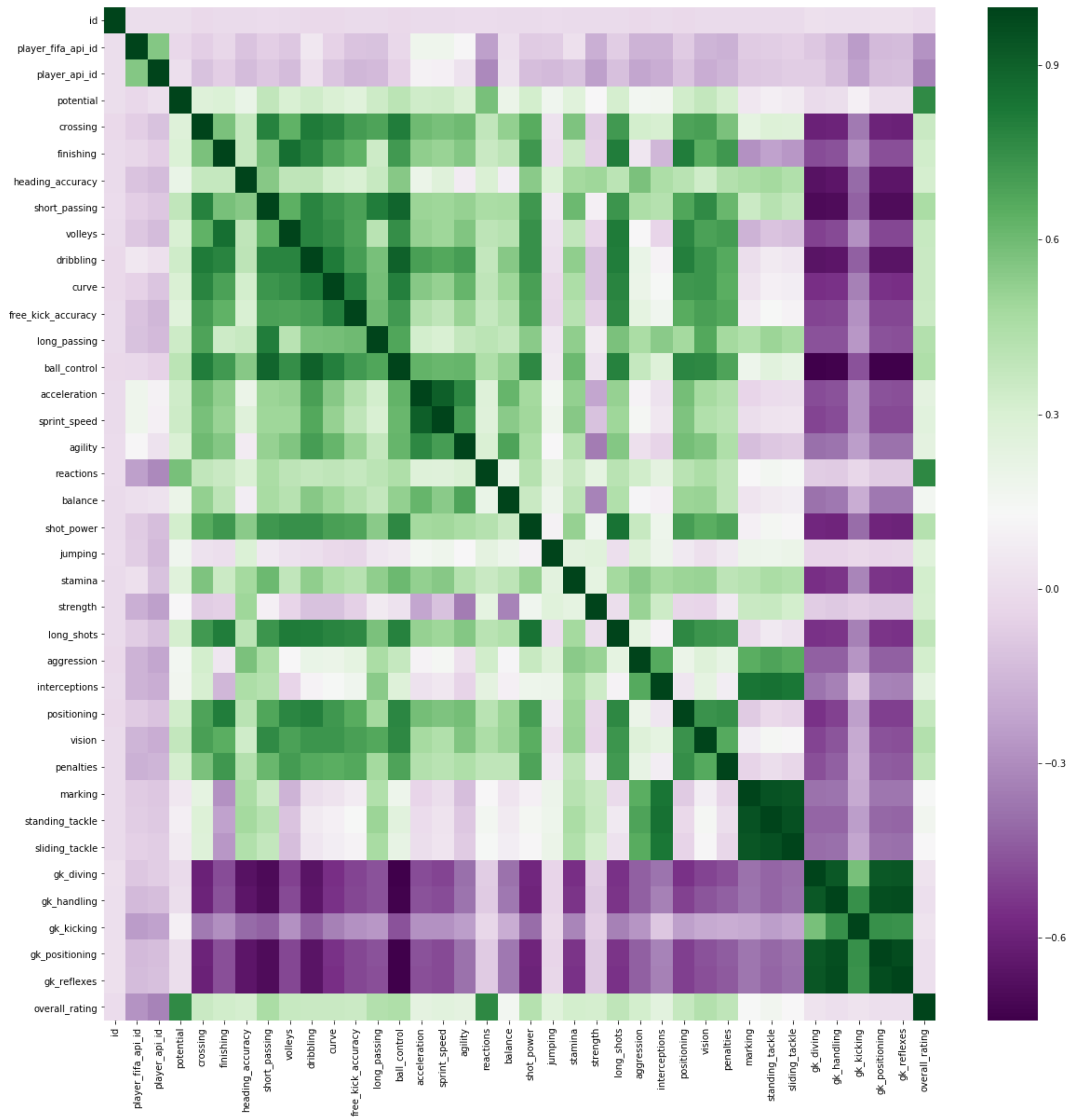
Since data is very large its difficult to find the relation among the independent variable.

One can find the relation with the Overall_Rating. It seems potential has very strong relationship with the Overall_Rating (0.765435) . Other features are not very much related, we may ignore some of them.

Coorelation is good if we have less not of features i.e. approx 20

In [38]:
```python
# Checking for correlations using HEATMAP
plt.figure(figsize=(20,20))
sns.heatmap(player_attrib.corr(), cmap="PRGn")
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x206bc165d68>



Here is it much easier to find the relationship among the independent variable.

One can find the relationship with the Overall_Rating. It seems potential has very strong relationship with the Overall_Rating (0.765435) . Reactions also has strong relationship. Other features are not very much related, we may ignore some of them.

Heatmap is better if we have medium no of features to visualize, such as 50 to 60 features

In [39]:
```python
player_attrib.corr().loc['overall_rating']
```

Out[39]:
```
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 [40]:
```
categorical_cols
```

Out[40]:
```
array(['date', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate'], dtype=object)
```

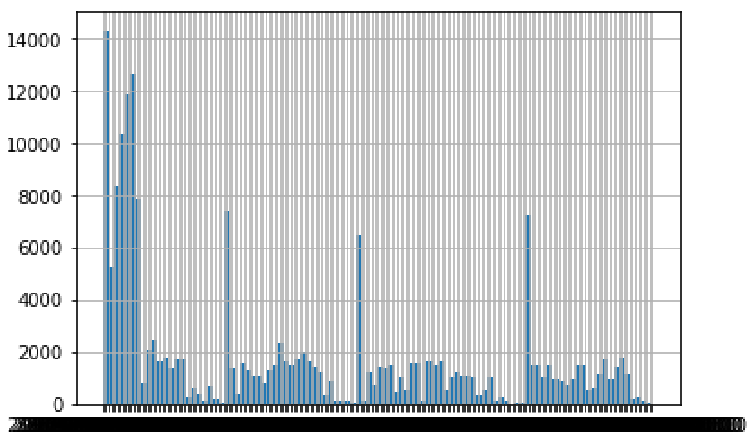
In [41]:
```
player_attrib[categorical_cols].head()
```

Out[41]:

	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

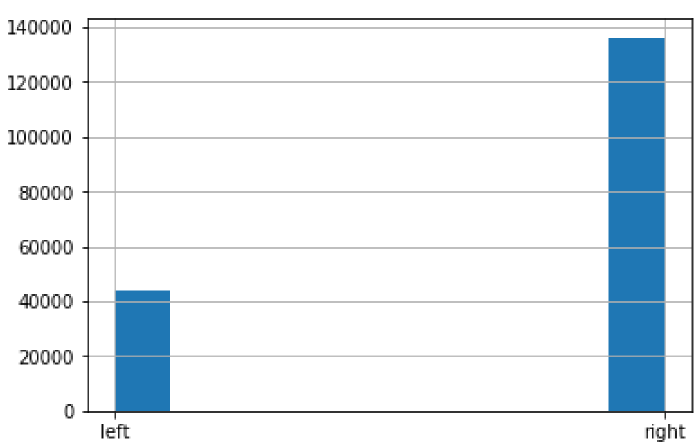
In [42]:
```
player_attrib.date.hist(bins=100)
```

Out[42]:
```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x206b75d91d0&gt;
```



In [43]:
```
player_attrib.preferred_foot.hist()
```

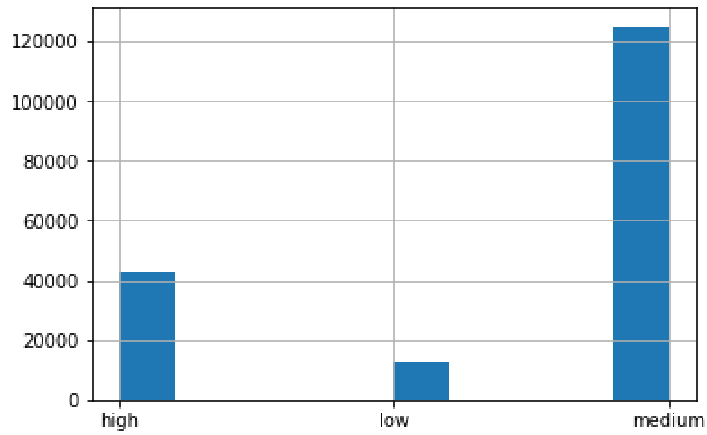
Out[43]:
```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x206b632ec88&gt;
```



Majority of the players' preferred foot is the `right leg`

In [44]:
```
player_attrib.attacking_work_rate.hist()
```

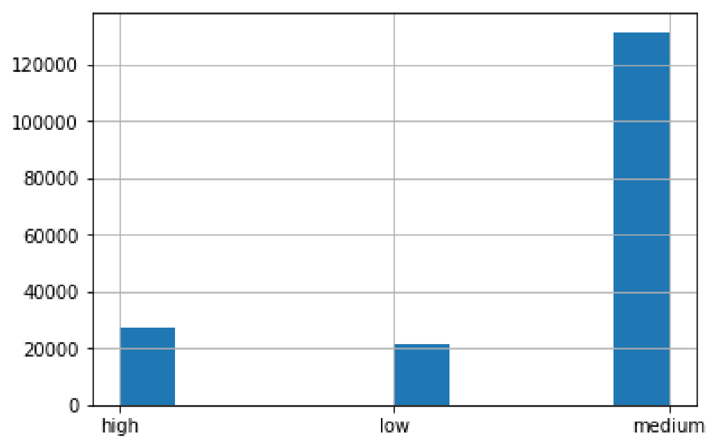
Out[44]: `<matplotlib.axes._subplots.AxesSubplot at 0x206b60aa048>`



Majority of the players' attacking work rate is `medium`

In [45]:
```
player_attrib.defensive_work_rate.hist()
```

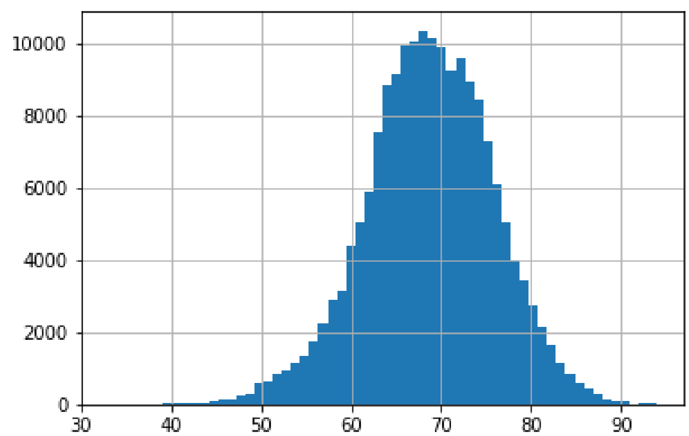
Out[45]: `<matplotlib.axes._subplots.AxesSubplot at 0x206b52d7160>`



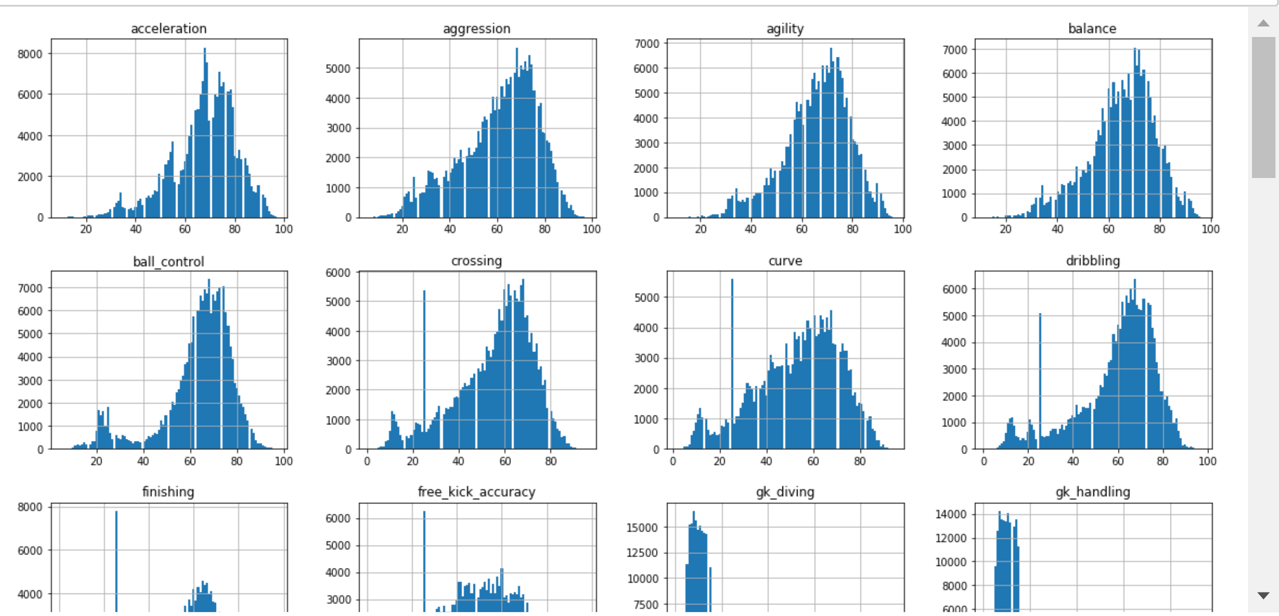
Majority of the players' defensive work rate is `medium`

In [46]:
```python
player_attrib['overall_rating'].hist(bins=60)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x206b5eb9908>



In [47]:
```python
# Plotting the histograms of numerical columns to understand their distribution# Plotti
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-Modal distribution can be treated as the binary values. The downside is if you don’t have multiple other independent variables(predictors), then this might cause too much inaccuracy (unacceptable) and variance in your prediction.
- Bi-Modal distribution can be converted into 2 different variables. One problem with this is that, it might exaggerate the effect of this variable on the outcome(predicted) variable

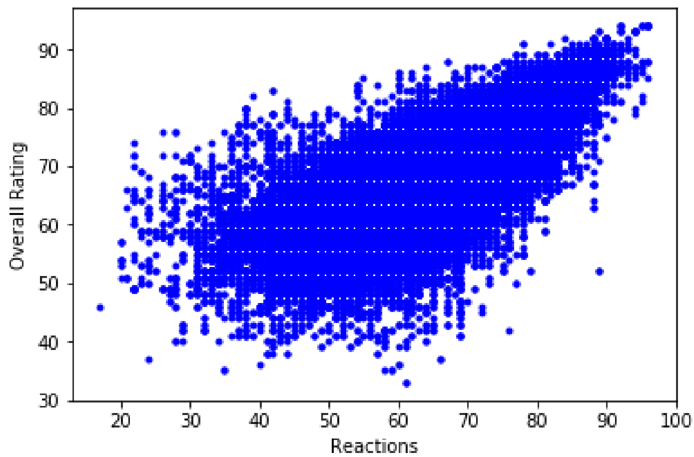
- Due to lack of time I am not considering Bi-Model distribution as the binary values or 2 different variables, but just ignoring them and keep the variable as id.

--

Bi-variate - Statistical and Visual Analysis

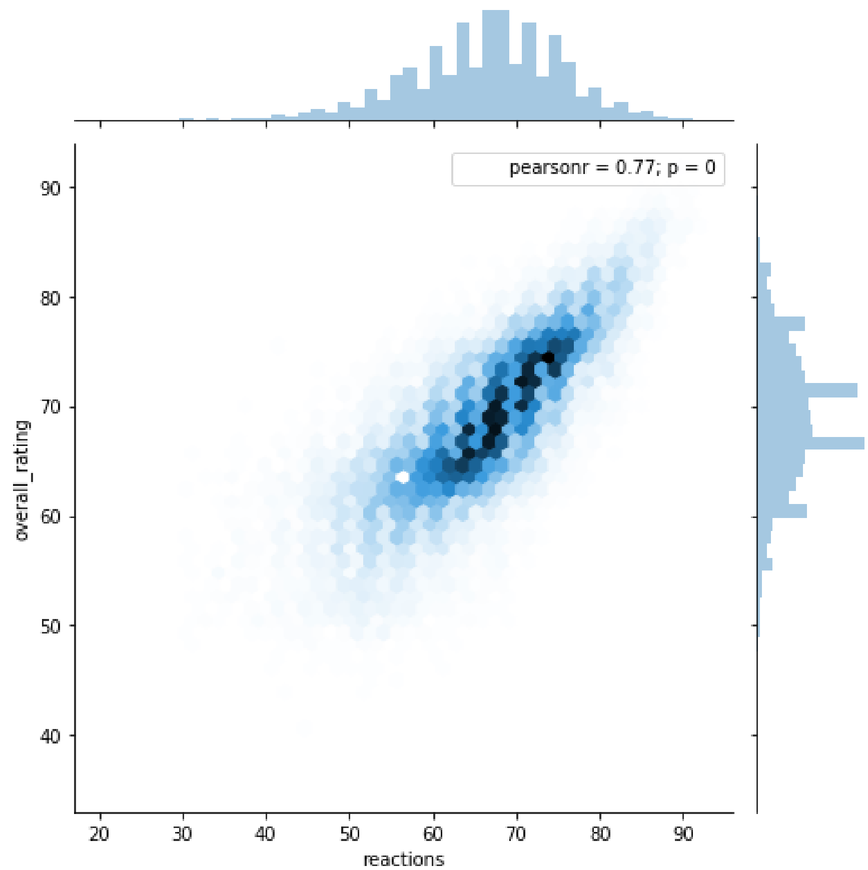
Plotting: overall_rating vs reactions and potential columns(Correlation>0.7) and short_passing, long_passing, ball_control, shot_power,vision (correlation >0.4)

In [48]:
```
plt.plot(player_attrib["reactions"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Reactions')
plt.show()
```

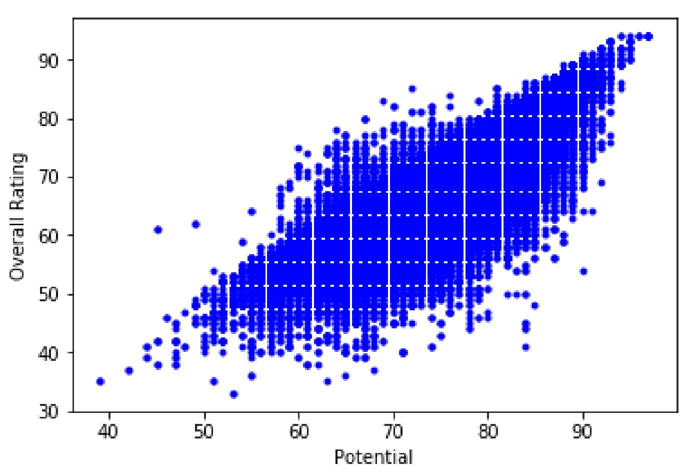


In [49]:
```
sns.jointplot(x=player_attrib["reactions"], y=player_attrib["overall_rating"], kind='hex',si
```

Out[49]: <seaborn.axisgrid.JointGrid at 0x206b9706eb8>

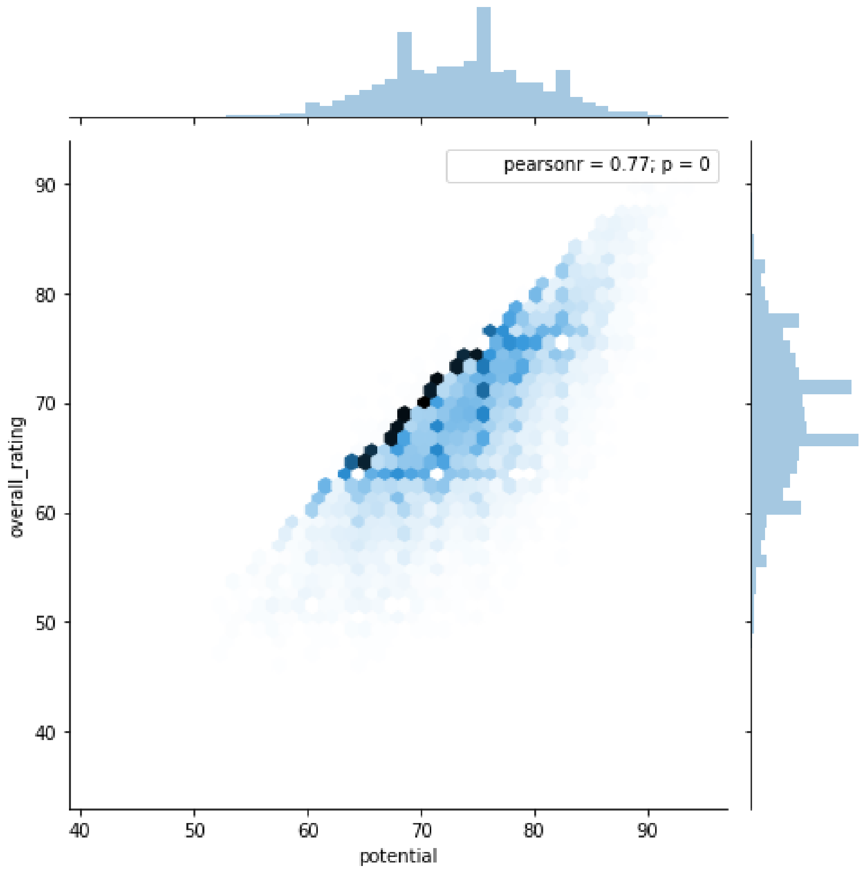


In [50]:
```
plt.plot(player_attrib["potential"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Potential')
plt.show()
```

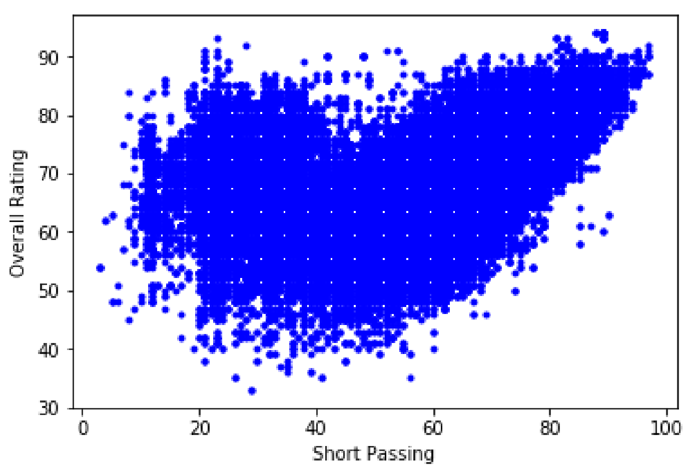


In [51]:
```
sns.jointplot(x=player_attrib["potential"], y=player_attrib["overall_rating"], kind='hex',si
```

Out[51]: <seaborn.axisgrid.JointGrid at 0x206bac994e0>

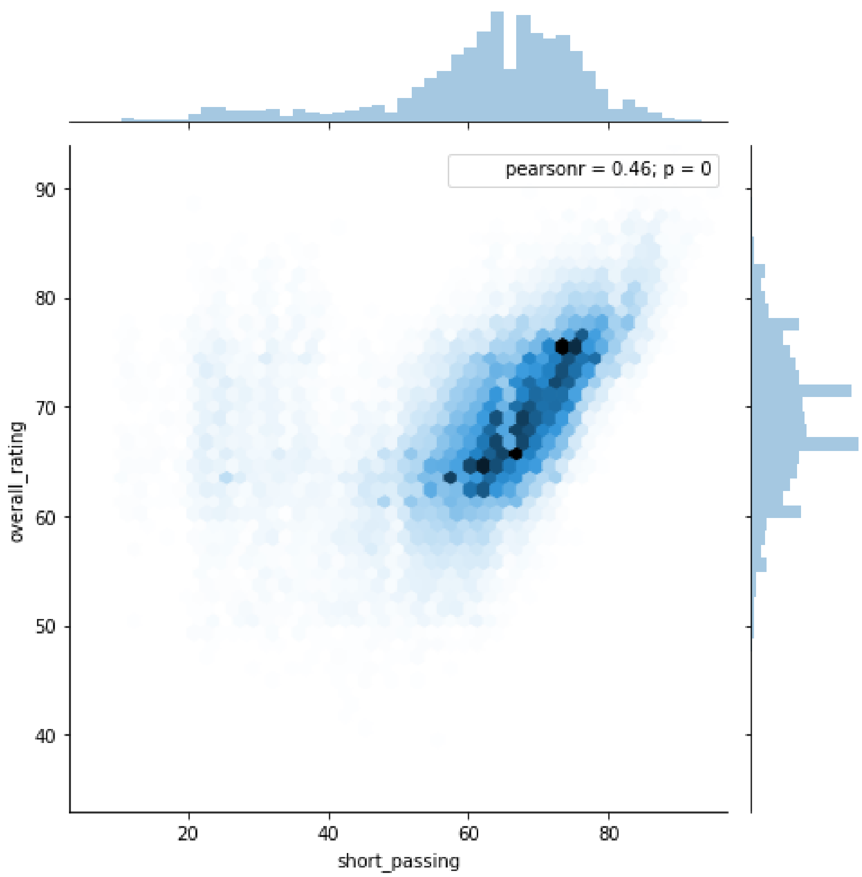


In [52]:
```
plt.plot(player_attrib["short_passing"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Short Passing')
plt.show()
```

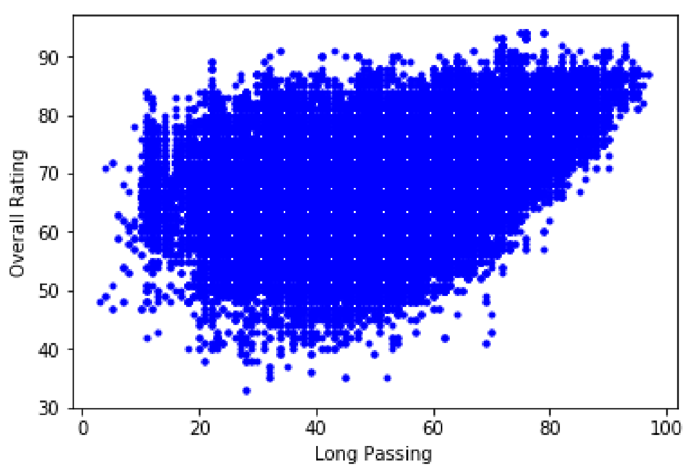


In [53]:
```
sns.jointplot(x=player_attrib["short_passing"], y=player_attrib["overall_rating"], kind='hex
```

Out[53]: <seaborn.axisgrid.JointGrid at 0x206b8a65d30>

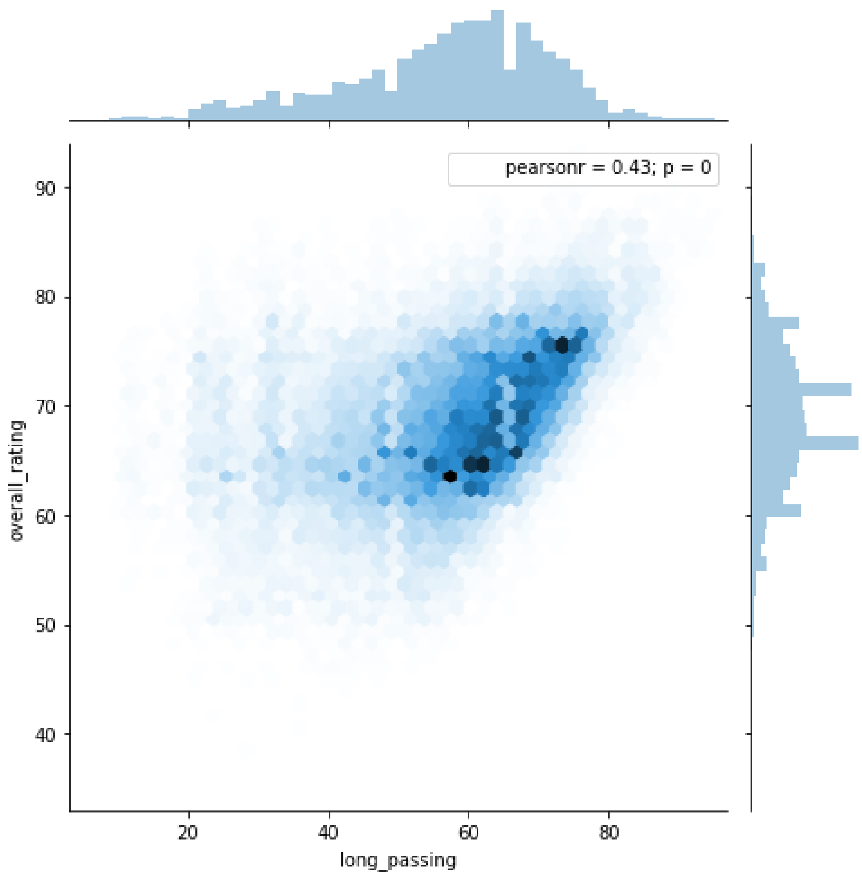


In [54]:
```
plt.plot(player_attrib["long_passing"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Long Passing')
plt.show()
```

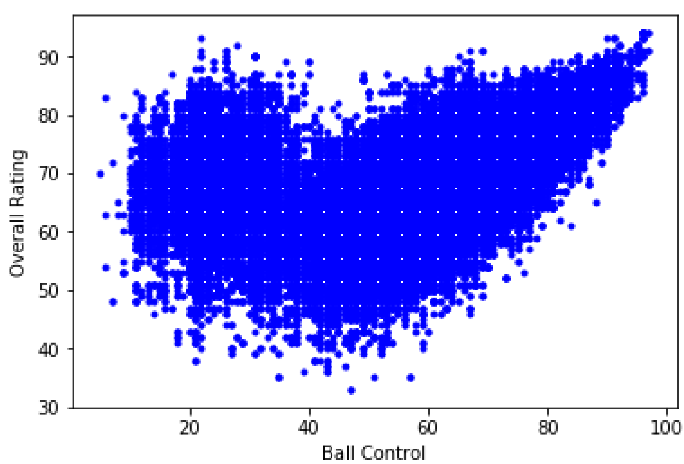


In [55]:
```
sns.jointplot(x=player_attrib["long_passing"], y=player_attrib["overall_rating"], kind='hex'
```

Out[55]: <seaborn.axisgrid.JointGrid at 0x206b96f3048>

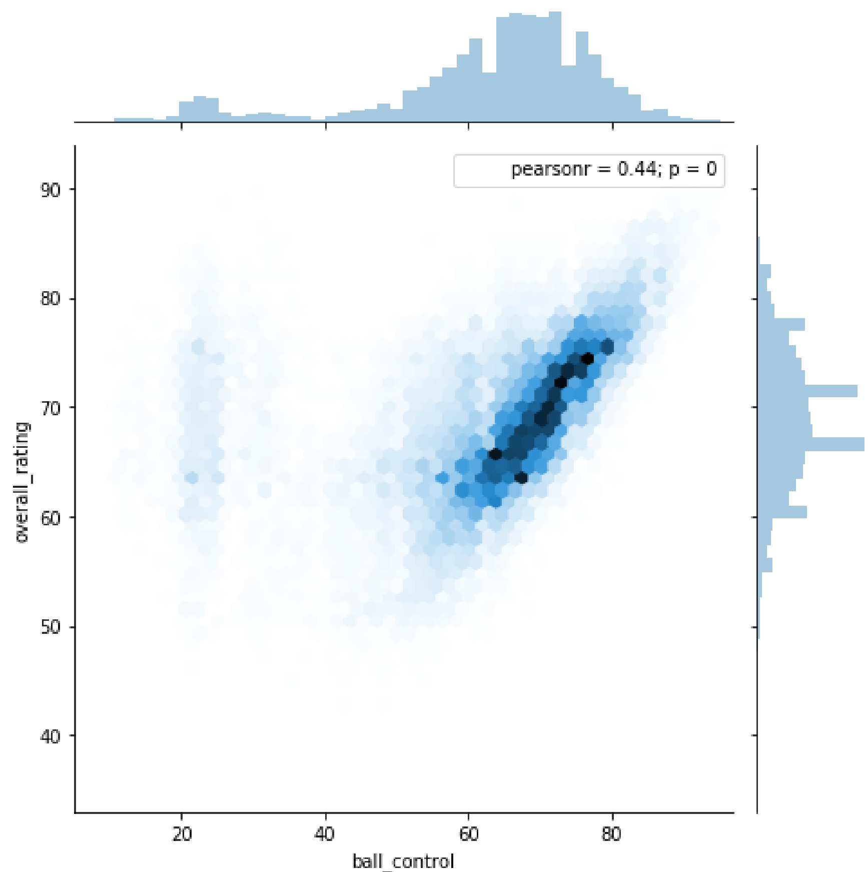


In [56]:
```
plt.plot(player_attrib["ball_control"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Ball Control')
plt.show()
```

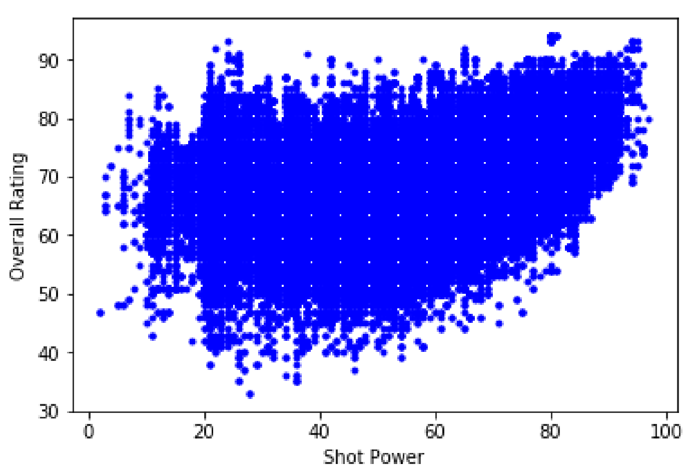


In [57]:
```
sns.jointplot(x=player_attrib["ball_control"], y=player_attrib["overall_rating"], kind='hex'
```

Out[57]: <seaborn.axisgrid.JointGrid at 0x206b984bc88>

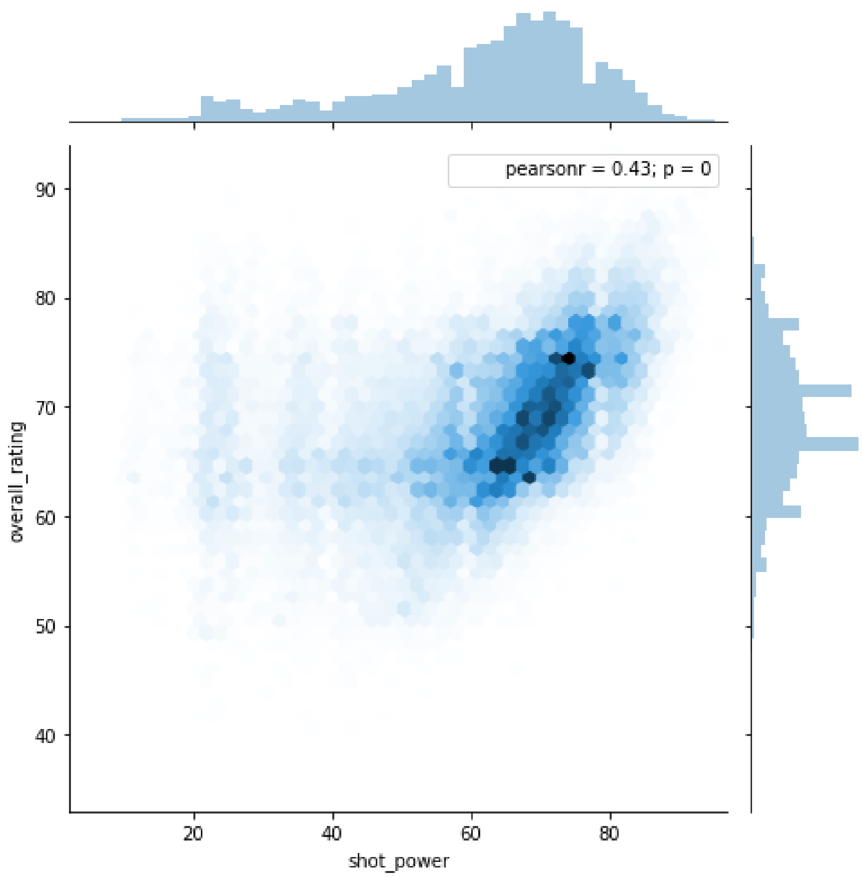


In [58]:
```
plt.plot(player_attrib["shot_power"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Shot Power')
plt.show()
```

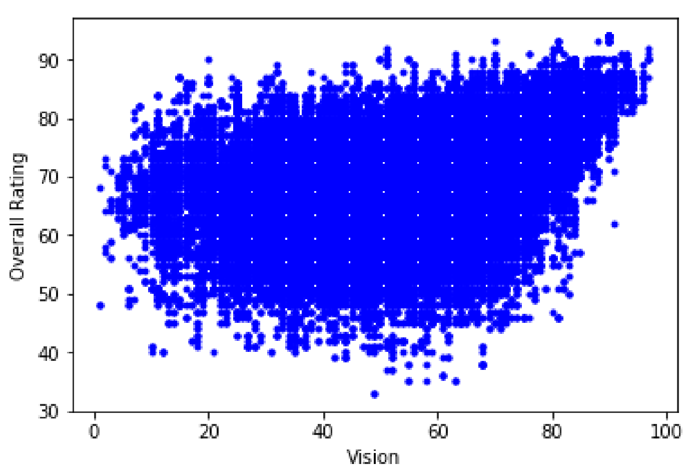


In [59]:
```
sns.jointplot(x=player_attrib["shot_power"], y=player_attrib["overall_rating"], kind='hex',s
```

Out[59]: <seaborn.axisgrid.JointGrid at 0x206bc1594e0>

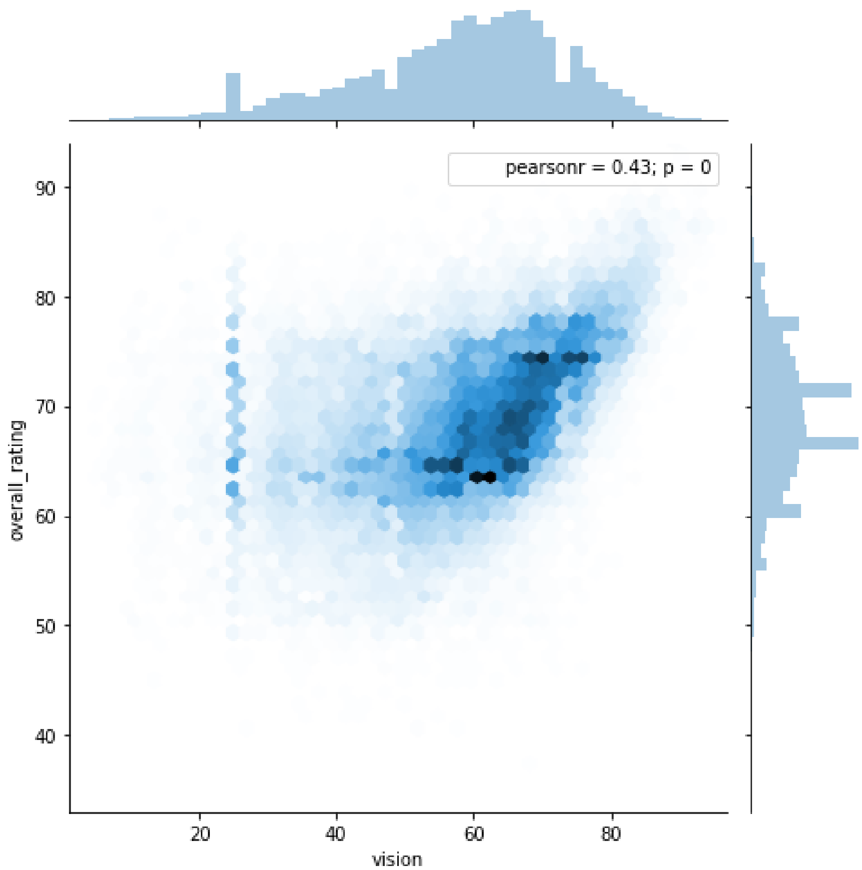


In [60]:
```
plt.plot(player_attrib["vision"], player_attrib["overall_rating"], 'b.')
plt.ylabel('Overall Rating')
plt.xlabel('Vision')
plt.show()
```



In [61]:
```
sns.jointplot(x=player_attrib["vision"], y=player_attrib["overall_rating"], kind='hex',size
```

Out[61]: <seaborn.axisgrid.JointGrid at 0x206b8de8dd8>



From the above diagram its very clear that reactions and potential have good relation with Overall Rating whereas short_passing, long_passing, ball_control, shot_power,vision have moredate relation with Overall Rating.

We may choose only those variable and discard the other variables if need so

---

Feature Engineering - Preparing Data for Modeling

Preparing the input vector X

In [62]:
```python
X  =  player_attrib .drop("overall_rating",axis = 1)
X.shape, X.columns
```

Out[62]:
```
((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', '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'],
       dtype='object'))
```

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

In [63]:
```python
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 [64]:
```python
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 [65]:
```python
X_cat_cols  = X.select_dtypes(include='object').columns.tolist()
X_cat_cols
```

Out[65]:
```
['preferred_foot', 'attacking_work_rate', 'defensive_work_rate']
```

In [66]:
```python
# 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 [67]:
```python
# Checking the columns and the shape of the input vector after encoding
X.columns, X.shape
```

Out[67]:
```
(Index(['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', 'year', 'month', 'day'],
       dtype='object'), (180354, 40))
```

In [68]:
```
X.head()
```
Out[68]:

	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finishing	heading_accuracy	sho
0	71.0	1	2	2	49.0	44.0	71.0	
1	71.0	1	2	2	49.0	44.0	71.0	
2	66.0	1	2	2	49.0	44.0	71.0	
3	65.0	1	2	2	48.0	43.0	70.0	
4	65.0	1	2	2	48.0	43.0	70.0	

5 rows × 40 columns

In [ ]:
```
## list(set(X.defensive_work_rate))
```

Preparing the Output Y

In [69]:
```
Y  =  player_attrib ["overall_rating"]
Y.shape
```
Out[69]:
```
(180354,)
```

In [70]:
```
Y.head()
```
Out[70]:
```
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 [71]:
```
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 [72]:
```
import math
from math import sqrt
# Importing Regression Metrics - Performance Evaluation
# from sklearn.metrics import mean_squared_error
# from sklearn.metrics import r2_score

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_tra
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: 2.7309026846988056
Linear Regression - RMSE Test: 2.7307773503953796
Linear Regression - R2_score Train: 0.8216028424294082
Linear Regression - R2_score Test: 0.8219679620041501
```

In [73]:
```
# Importing Regressors - Modelling


## Other Regressors
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)),
            ("XGB - ", xgb.XGBRegressor(n_estimators=200,learning_rate=1))
        ]
```

In [74]:
```python
for reg in regressors:
    print(reg[1])
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=True)
Ridge(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=True, random_state=None, solver='auto', tol=0.001)
Lasso(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=True, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)
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=False)
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')
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=False)
AdaBoostRegressor(base_estimator=None, learning_rate=1.0, loss='linear',
         n_estimators=100, random_state=None)
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)
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [75]:
```
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")
```

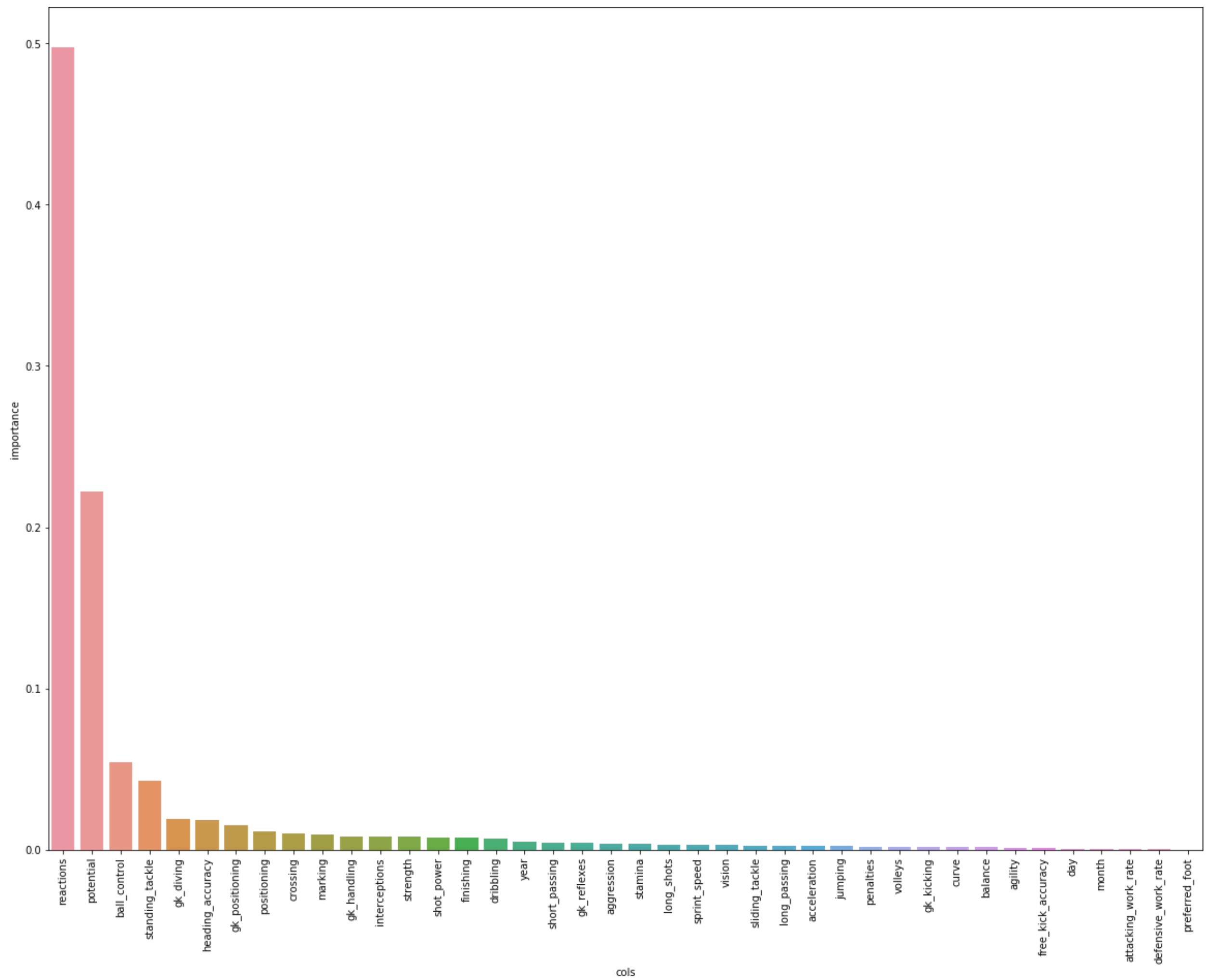
```
Linear -
         R2-Score: 0.8501969196523184
         RMSE: 2.7307773503953783

Ridge -
         R2-Score: 0.8094085593573674
         RMSE: 3.080190780589964

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: 0.9824651937364285
         RMSE: 0.9342786104743287

AdaBoost -
         R2-Score: 0.8282613883191218
         RMSE: 2.92388235296507

GBM -
         R2-Score: 0.938030029613183
         RMSE: 1.7563722408080826

XGB -
         R2-Score: 0.9631756543925616
         RMSE: 1.3539213577226723
```

Feature Selection

Feature Selection using feature importances from RandomForestRegressor model

In [77]:
```python
rndf = RandomForestRegressor(n_estimators=150)
rndf.fit(x_train, y_train)
importance = pd.DataFrame.from_dict({'cols':x_train.columns, 'importance': rndf.feature_impo
importance = importance.sort_values(by='importance', ascending=False)
plt.figure(figsize=(20,15))
sns.barplot(importance.cols, importance.importance)
plt.xticks(rotation=90)
```

Out[77]:
```
(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 [78]:
```python
imp_cols = importance[importance.importance >= 0.005].cols.values
imp_cols
```

Out[78]:
```
array(['reactions', 'potential', 'ball_control', 'standing_tackle',
       'gk_diving', 'heading_accuracy', 'gk_positioning', 'positioning',
       'crossing', 'marking', 'gk_handling', 'interceptions', 'strength',
       'shot_power', 'finishing', 'dribbling', 'year'], dtype=object)
```

In [79]:
```
# 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=0.25, random_sta
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: 0.8439523739633608
	 RMSE: 2.7871125268704837

Ridge -
	 R2-Score: 0.7994287233124309
	 RMSE: 3.1598050560318725

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: 0.980490370600706
	 RMSE: 0.9854859343885751

AdaBoost -
	 R2-Score: 0.8174079536142944
	 RMSE: 3.014857906597178

GBM -
	 R2-Score: 0.9355259334874624
	 RMSE: 1.7915067617699374

XGB -
	 R2-Score: 0.9523672514463974
	 RMSE: 1.539851148876016
```

In [80]:
```
imp_cols = importance[importance.importance >= 0.001].cols.values
imp_cols
```

Out[80]:
```
array(['reactions', 'potential', 'ball_control', 'standing_tackle',
       'gk_diving', 'heading_accuracy', 'gk_positioning', 'positioning',
       'crossing', 'marking', 'gk_handling', 'interceptions', 'strength',
       'shot_power', 'finishing', 'dribbling', 'year', 'short_passing',
       'gk_reflexes', 'aggression', 'stamina', 'long_shots',
       'sprint_speed', 'vision', 'sliding_tackle', 'long_passing',
       'acceleration', 'jumping', 'penalties', 'volleys', 'gk_kicking',
       'curve', 'balance', 'agility', 'free_kick_accuracy'], dtype=object)
```

In [81]:
```
# 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=0.25, random_sta
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: 0.8493748941033852
         RMSE: 2.7382594986062605

Ridge -
         R2-Score: 0.8087308612133917
         RMSE: 3.085662136620677

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: 0.9826982210176765
         RMSE: 0.9280498399569246

AdaBoost -
         R2-Score: 0.8298627251134251
         RMSE: 2.910218897011034

GBM -
         R2-Score: 0.9380248854563256
         RMSE: 1.7564451379448505

XGB -
         R2-Score: 0.9627608150501934
         RMSE: 1.3615262025560475
```

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 [82]:
```
scoring = 'neg_mean_squared_error'
results=[]
names=[]
## Importing train_test_split,cross_val_score,GridSearchCV,KFold, - Validation and Optimizat
# from sklearn.model_selection import ShuffleSplit, train_test_split,cross_val_score,GridSea

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: -7.502232234604968
         CV-Std. Dev: 0.08893915474142117

Ridge -
         CV-Mean: -9.420622277052178
         CV-Std. Dev: 0.14233002834191066

Lasso -
         CV-Mean: -49.263172179987876
         CV-Std. Dev: 0.5729685439130466

ElasticNet -
         CV-Mean: -49.263172179987876
         CV-Std. Dev: 0.5729685439130466

Decision Tree -
         CV-Mean: -11.046032706937625
         CV-Std. Dev: 0.2758550814988682

Random Forest -
         CV-Mean: -0.9268602015596414
         CV-Std. Dev: 0.04055290498875436

AdaBoost -
         CV-Mean: -8.76928628751411
         CV-Std. Dev: 0.3262764726552419

GBM -
         CV-Mean: -3.120115134070597
         CV-Std. Dev: 0.0751762497199429

XGB -
         CV-Mean: -1.9854456042823068
         CV-Std. Dev: 0.06066003977911336
```

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 [83]:
```
regressors
```

Out[83]:
```
[('Linear - ',
  LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=True)),
 ('Ridge - ', Ridge(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=None,
     normalize=True, random_state=None, solver='auto', tol=0.001)),
 ('Lasso - ', Lasso(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=1000,
     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=False)),
 ('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=False)),
 ('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)),
 ('XGB - ', XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
         colsample_bytree=1, gamma=0, learning_rate=1, max_delta_step=0,
         max_depth=3, min_child_weight=1, missing=None, n_estimators=200,
         n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
         reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
         silent=True, subsample=1))]
```

Warning: Run the following optimization algorithms only if you have a powerful processor or GPU. Even then it may take more than 3 - 4 hours to run completely.

Random Forest Regressor

In [84]:
```
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 [85]:
```
rscv_grid = GridSearchCV(RF_Regressor, param_grid=param_grid, verbose=1)
```

In [86]:
```
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: 182.9min finished
```

Out[86]:
```
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, 200], 'min_sampl
es_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 [87]:
```
rscv_grid.best_params_
```

Out[87]:
```
{'max_depth': None,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 200}
```

In [88]:
```
model = rscv_grid.best_estimator_
model.fit(x_train, y_train)
```

Out[88]:
```
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 [89]:
```

model.score(x_test, y_test)
```

Out[89]:
```
0.9819081379353162
```

In [90]:
```
import pickle
RF_reg = pickle.dumps(rscv_grid)
```

Gradient Boosting Regressor

In [91]:
```
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 [92]:
```
rscv_grid = GridSearchCV(GB_Regressor, param_grid=param_grid, verbose=1)
```

In [93]:
```
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: 63.2min finished
```

Out[93]:
```
GridSearchCV(cv=None, error_score='raise',
       estimator=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),
       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 [94]:
```
rscv_grid.best_params_
```

Out[94]:
```
{'learning_rate': 0.1, 'max_depth': 9}
```

In [95]:
```
model = rscv_grid.best_estimator_
model.fit(x_train, y_train)
```

Out[95]:
```
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 [96]:
```
model.score(x_test, y_test)
```

Out[96]:
```
0.9802665463529842
```

In [97]:
```
GB_reg = pickle.dumps(rscv_grid)
```

Comparing performance metric of the different models

In [98]:
```
RF_regressor = pickle.loads(RF_reg)
GB_regressor = pickle.loads(GB_reg)
```

In [99]:
```
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: 0.9819081379353162
         RMSE: 0.9490029319800807

GradientBoostingRegressor -
         R2-Score: 0.9802665463529842
         RMSE: 0.9911228075439812
```

Choosing the model

We can see that RandomForest Regressor gives better result with an R2-Score of more than 98% and while keeping RMSE value low(=0.948617596). So, RandomForest Regressor should be used as the regression model for this dataset. However Gradient Boosting Regressor fares well too ¶