FIFA18_Analyze

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CS584: FIFA18 data Analysis *Ting Jiang Chen Gong Yizhi Hong*

****

Part 1: Data pre-processing

```
In [1]: import numpy as np
        import sys
        import pandas as pd
        from datetime import datetime
        import matplotlib.pyplot as plt
        import glob
        import warnings
        warnings.filterwarnings("ignore")
```

```
In [2]: import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegression,LinearRegression
        from sklearn.linear_model import Lasso
        from sklearn.linear_model import Ridge
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.cross_validation import cross_val_score, cross_val_predict
        from sklearn import metrics
        from sklearn.model_selection import GridSearchCV, KFold
        from sklearn.feature_extraction.text import CountVectorizer
        from scipy.sparse import csr_matrix, hstack, vstack
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.pipeline import make_pipeline
        sns.set_style("dark")
```

```
/Users/Chi.Hong/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: Deprecati
  "This module will be removed in 0.20.", DeprecationWarning)
```

****

look up data firt 10 columns

In [3]:
```
dataframe = pd.read_csv('../data/fifa-18-demo-player-dataset/CompleteDataset.csv')
dataframe.head(10)
```

Out[3]:

	Unnamed: 0	Name	Age	Photo	Nationality	Flag	Overall	Potential	Club	Club Logo	...
0	0	Cristiano Ronaldo	32	https://cdn.sofifa.org/48/18/players/20801.png	Portugal	https://cdn.sofifa.org/flags/38.png	94	94	Real Madrid CF	https://cdn.sofifa.org/24/18/teams/243.png	...
1	1	L. Messi	30	https://cdn.sofifa.org/48/18/players/158023.png	Argentina	https://cdn.sofifa.org/flags/52.png	93	93	FC Barcelona	https://cdn.sofifa.org/24/18/teams/241.png	...
2	2	Neymar	25	https://cdn.sofifa.org/48/18/players/190871.png	Brazil	https://cdn.sofifa.org/flags/54.png	92	94	Paris Saint-Germain	https://cdn.sofifa.org/24/18/teams/73.png	...
3	3	L. Suárez	30	https://cdn.sofifa.org/48/18/players/176580.png	Uruguay	https://cdn.sofifa.org/flags/60.png	92	92	FC Barcelona	https://cdn.sofifa.org/24/18/teams/241.png	...
4	4	M. Neuer	31	https://cdn.sofifa.org/48/18/players/167495.png	Germany	https://cdn.sofifa.org/flags/21.png	92	92	FC Bayern Munich	https://cdn.sofifa.org/24/18/teams/21.png	...
5	5	R. Lewandowski	28	https://cdn.sofifa.org/48/18/players/188545.png	Poland	https://cdn.sofifa.org/flags/37.png	91	91	FC Bayern Munich	https://cdn.sofifa.org/24/18/teams/21.png	...
6	6	De Gea	26	https://cdn.sofifa.org/48/18/players/193080.png	Spain	https://cdn.sofifa.org/flags/45.png	90	92	Manchester United	https://cdn.sofifa.org/24/18/teams/11.png	...
7	7	E. Hazard	26	https://cdn.sofifa.org/48/18/players/183277.png	Belgium	https://cdn.sofifa.org/flags/7.png	90	91	Chelsea	https://cdn.sofifa.org/24/18/teams/5.png	...
8	8	T. Kroos	27	https://cdn.sofifa.org/48/18/players/182521.png	Germany	https://cdn.sofifa.org/flags/21.png	90	90			
9	9	G. Higuaín	29	https://cdn.sofifa.org/48/18/players/167664.png	Argentina	https://cdn.sofifa.org/flags/52.png	90	90			

```
8       Real Madrid CF  https://cdn.sofifa.org/24/18/teams/243.png  ...
9             Juventus   https://cdn.sofifa.org/24/18/teams/45.png  ...

     RB   RCB   RCM   RDM    RF    RM    RS    RW   RWB    ST
0  61.0  53.0  82.0  62.0  91.0  89.0  92.0  91.0  66.0  92.0
1  57.0  45.0  84.0  59.0  92.0  90.0  88.0  91.0  62.0  88.0
2  59.0  46.0  79.0  59.0  88.0  87.0  84.0  89.0  64.0  84.0
3  64.0  58.0  80.0  65.0  88.0  85.0  88.0  87.0  68.0  88.0
4   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
5  58.0  57.0  78.0  62.0  87.0  82.0  88.0  84.0  61.0  88.0
6   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN
7  59.0  47.0  81.0  61.0  87.0  87.0  82.0  88.0  64.0  82.0
8  76.0  72.0  87.0  82.0  81.0  81.0  77.0  80.0  78.0  77.0
9  51.0  46.0  71.0  52.0  84.0  79.0  87.0  82.0  55.0  87.0

[10 rows x 75 columns]
```

```
In [4]: dataframe.columns
```

```
Out[4]: Index(['Unnamed: 0', 'Name', 'Age', 'Photo', 'Nationality', 'Flag', 'Overall',
               'Potential', 'Club', 'Club Logo', 'Value', 'Wage', 'Special',
               'Acceleration', 'Aggression', 'Agility', 'Balance', 'Ball control',
               'Composure', 'Crossing', 'Curve', 'Dribbling', 'Finishing',
               'Free kick accuracy', 'GK diving', 'GK handling', 'GK kicking',
               'GK positioning', 'GK reflexes', 'Heading accuracy', 'Interceptions',
               'Jumping', 'Long passing', 'Long shots', 'Marking', 'Penalties',
               'Positioning', 'Reactions', 'Short passing', 'Shot power',
               'Sliding tackle', 'Sprint speed', 'Stamina', 'Standing tackle',
               'Strength', 'Vision', 'Volleys', 'CAM', 'CB', 'CDM', 'CF', 'CM', 'ID',
               'LAM', 'LB', 'LCB', 'LCM', 'LDM', 'LF', 'LM', 'LS', 'LW', 'LWB',
               'Preferred Positions', 'RAM', 'RB', 'RCB', 'RCM', 'RDM', 'RF', 'RM',
               'RS', 'RW', 'RWB', 'ST'],
              dtype='object')
```

**** take the attribute that we need to use ****
The attribute needs to be predicted: 'Overall','Preferred Positions'
The attribute use to predict: rest of the attributes

```
In [5]: # only consider non goalkeeper's position.

        col_needed = ['Overall','Acceleration', 'Aggression', 'Agility', 'Balance', 'Ball conti
               'Composure', 'Crossing', 'Curve', 'Dribbling', 'Finishing',
               'Free kick accuracy', 'Heading accuracy', 'Interceptions',
               'Jumping', 'Long passing', 'Long shots', 'Marking', 'Penalties',
               'Positioning', 'Reactions', 'Short passing', 'Shot power',
               'Sliding tackle', 'Sprint speed', 'Stamina', 'Standing tackle',
               'Strength', 'Vision', 'Volleys', 'Preferred Positions']

        # rearrange the attributes. The attribute need to be predicted: Overall, Preferred Pos
```

```
# rearrange as ST -> CM -> CB

recol_needed = ['Overall','Finishing', 'Shot power', 'Positioning', 'Dribbling', 'Long
                'Acceleration', 'Agility','Sprint speed', 'Curve',

       'Free kick accuracy', 'Heading accuracy',
       'Short passing', 'Long passing', 'Vision',
       'Strength', 'Stamina', 'Balance', 'Ball control','Composure','Jumping',
       'Crossing','Reactions',
       'Aggression','Interceptions', 'Marking', 'Sliding tackle', 'Standing tackle','Pe

dataframe = dataframe[recol_needed]
dataframe.head(10)
```

Out[5]:

	Overall	Finishing	Shot power	Positioning	Dribbling	Long shots	Penalties
0	94	94	94	95	91	92	85
1	93	95	85	93	97	88	74
2	92	89	80	90	96	77	81
3	92	94	87	92	86	86	85
4	92	13	25	12	30	16	47
5	91	91	88	91	85	83	81
6	90	13	31	12	18	12	40
7	90	83	79	85	93	82	86
8	90	76	87	79	79	90	73
9	90	91	88	92	84	82	70

	Volleys	Acceleration	Agility	...	Composure	Jumping	Crossing
0	88	89	89	...	95	95	85
1	85	92	90	...	96	68	77
2	83	94	96	...	92	61	75
3	88	88	86	...	83	69	77
4	11	58	52	...	70	78	15
5	87	79	78	...	87	84	62
6	13	57	60	...	64	67	17
7	79	93	93	...	87	59	80
8	82	60	71	...	85	32	85
9	88	78	75	...	86	79	68

	Reactions	Aggression	Interceptions	Marking	Sliding tackle	Standing tackle
0	96	63	29	22	23	31
1	95	48	22	13	26	28
2	88	56	36	21	33	24
3	93	78	41	30	38	45
4	85	29	30	10	11	10
5	91	80	39	25	19	42
6	88	38	30	13	13	21
7	85	54	41	25	22	27
8	86	60	85	63	69	82

```
9        88         50             20      12              18              22

  Preferred Positions
0              ST LW
1                 RW
2                 LW
3                 ST
4                 GK
5                 ST
6                 GK
7                 LW
8             CDM CM
9                 ST

[10 rows x 31 columns]
```

In [6]:
```
dataframe['Preferred Positions'] = dataframe['Preferred Positions'].str.strip()
#remove Goalkeeper from dataframe

dataframe = dataframe[dataframe['Preferred Positions'] != 'GK']
dataframe.head(10)
```

Out[6]:

	Overall	Finishing	Shot power	Positioning	Dribbling	Long shots	Penalties	\
0	94	94	94	95	91	92	85	
1	93	95	85	93	97	88	74	
2	92	89	80	90	96	77	81	
3	92	94	87	92	86	86	85	
5	91	91	88	91	85	83	81	
7	90	83	79	85	93	82	86	
8	90	76	87	79	79	90	73	
9	90	91	88	92	84	82	70	
10	90	60	79	52	61	55	68	
11	89	83	85	84	85	86	77	

	Volleys	Acceleration	Agility	...	Composure	Jumping	\
0	88	89	89	...	95	95	
1	85	92	90	...	96	68	
2	83	94	96	...	92	61	
3	88	88	86	...	83	69	
5	87	79	78	...	87	84	
7	79	93	93	...	87	59	
8	82	60	71	...	85	32	
9	88	78	75	...	86	79	
10	66	75	79	...	80	93	
11	82	76	80	...	84	65	

	Crossing	Reactions	Aggression	Interceptions	Marking	Sliding tackle	\
0	85	96	63	29	22	23	

```
1        77        95        48        22        13        26
2        75        88        56        36        21        33
3        77        93        78        41        30        38
5        62        91        80        39        25        19
7        80        85        54        41        25        22
8        85        86        60        85        63        69
9        68        88        50        20        12        18
10       66        85        84        88        86        91
11       90        88        68        56        30        40

   Standing tackle Preferred Positions
0               31                ST LW
1               28                   RW
2               24                   LW
3               45                   ST
5               42                   ST
7               27                   LW
8               82               CDM CM
9               22                   ST
10              89                   CB
11              51           RM CM CAM

[10 rows x 31 columns]
```

**** Check the data ****

```
In [7]: # make sure no null value.
        dataframe.isnull().values.any()

Out[7]: False

In [8]: # Check all the positions we have.
        positions = dataframe['Preferred Positions'].str.split().apply(lambda x: x[0]).unique()
        positions

Out[8]: array(['ST', 'RW', 'LW', 'CDM', 'CB', 'RM', 'CM', 'LM', 'LB', 'CAM', 'RB',
               'CF', 'RWB', 'LWB'], dtype=object)

In [9]: # handle multiple positions
        df_fifa = dataframe.copy()
        df_fifa.drop(df_fifa.index, inplace=True)

        for position in positions:
            temp = dataframe[dataframe['Preferred Positions'].str.contains(position)]
            temp['Preferred Positions'] = position
            df_fifa = df_fifa.append(temp, ignore_index=True)

        df_fifa.iloc[::1000, :]
```

Out[9]:

	Overall	Finishing	Shot power	Positioning	Dribbling	Long shots
0	94	94	94	95	91	92
1000	70	68	66	75	67	63
2000	64	53	50	61	67	42
3000	56	61	53	49	48	49
4000	62	57	59	60	61	52
5000	61	46	70	72	60	54
6000	71	57-3	73-5	63-3	67-1	68-4
7000	65	60	55	66	63	55
8000	78	65	77	59	64	64
9000	70	22	62	44	58	44
10000	65	19	40	22	32	13
11000	59	19	38	29	50	22
12000	72	65	63	53	79	63
13000	66	61	68	58	72	65
14000	50	35	53	52	45	32
15000	71	53	56+2	68	73	55+5
16000	66	52	68	66	69	61
17000	60	32	60	50	56	51
18000	74	67	76	68	74	83
19000	67	38	40	67	67	40
20000	57	39	43	50	58	47
21000	67	43	58	40	63	60
22000	58	23	23	45	52	24
23000	70	57	61	65	68	58
24000	62	50	56	54	57	56
25000	70	53	64	70	69	61
26000	62	22	38	41	43	23
27000	64	36	35	38	62	33

	Penalties	Volleys	Acceleration	Agility	...	Composure
0	85	88	89	89	...	95
1000	67	63	63	68	...	67
2000	51	48	86	81	...	44
3000	53	47	56	58	...	49
4000	57	45	79	70	...	49
5000	63	67	76	74	...	58
6000	69	49	45	68	...	77
7000	65	51	66	61	...	57
8000	50	56	58	52	...	67
9000	62	21	51	39	...	61
10000	17	18	53	60	...	56
11000	32	26	68	58	...	55
12000	75	68	77	76	...	69
13000	59	58	77	86	...	67
14000	44	37	69	62	...	46
15000	45	46	63	75	...	72
16000	49	59	78	79	...	60

17000	47	34	69	56	...	51
18000	48	64	85	80	...	74
19000	35	21	78	76	...	61
20000	39	44	71	72	...	58
21000	55	39	72	59	...	59
22000	38	26	77	73	...	33
23000	61	53	78	80	...	60
24000	55	49	59	81	...	58
25000	51	33	78	67	...	65
26000	39	29	44	62	...	45
27000	46	34	76	60	...	54

	Jumping	Crossing	Reactions	Aggression	Interceptions	Marking	\
0	95	85	96	63	29	22	
1000	72	62	68	70	56	21	
2000	60	59	58	32	17	23	
3000	78	31	53	42	28	22	
4000	54	59	65	41	26	22	
5000	51	47	58	34	13	17	
6000	73	61-3	72	68	69-4	68	
7000	66	66	60	61	55	45	
8000	74	53	72	77	78	75	
9000	57	57	68	73	72	72	
10000	80	34	54	60	57	62	
11000	64	45	56	56	59	56	
12000	60	64	71	74	28	22	
13000	46	58	55	48	37	40	
14000	63	51	51	48	39	39	
15000	53	61	70	61	60	59	
16000	59	65	64	67	52	47	
17000	60	48	48	64	60	58	
18000	56	72	69	41	68	72	
19000	60	66	66	68	59	61	
20000	78	47	53	33	43	42	
21000	64	54	62	65	68	65	
22000	59	54	54	60	54	55	
23000	55	67	62	52	36	45	
24000	73	57	58	58	52	47	
25000	81	71	63	76	66	64	
26000	75	27	54	53	56	65	
27000	70	41	59	57	64	70	

	Sliding tackle	Standing tackle	Preferred Positions
0	23	31	ST
1000	25	31	ST
2000	26	24	ST
3000	19	24	ST
4000	20	19	RW

```
5000              17              17                LW
6000            66-3            69-2               CDM
7000              58              64               CDM
8000              76              81                CB
9000              65              70                CB
10000             66              68                CB
11000             56              59                CB
12000             17              18                RM
13000             26              34                RM
14000             45              47                RM
15000             43              64                CM
16000             52              53                CM
17000             50              61                CM
18000             76              72                LM
19000             62              63                LM
20000             41              39                LM
21000             60              66                LB
22000             55              59                LB
23000             47              46               CAM
24000             45              57               CAM
25000             70              67                RB
26000             62              58                RB
27000             72              73               RWB

[28 rows x 31 columns]
```

```
In [10]: cols = [col for col in df_fifa.columns if col not in ['Preferred Positions']]

         for i in cols:
             df_fifa[i] = df_fifa[i].apply(lambda x: eval(x) if isinstance(x,str) else x)

         df_fifa.iloc[::1000, :]
```

```
Out[10]:        Overall  Finishing  Shot power  Positioning  Dribbling  Long shots  \
         0           94         94          94           95         91          92
         1000        70         68          66           75         67          63
         2000        64         53          50           61         67          42
         3000        56         61          53           49         48          49
         4000        62         57          59           60         61          52
         5000        61         46          70           72         60          54
         6000        71         54          68           60         66          64
         7000        65         60          55           66         63          55
         8000        78         65          77           59         64          64
         9000        70         22          62           44         58          44
         10000       65         19          40           22         32          13
         11000       59         19          38           29         50          22
         12000       72         65          63           53         79          63
         13000       66         61          68           58         72          65
```

14000	50	35	53	52	45	32
15000	71	53	58	68	73	60
16000	66	52	68	66	69	61
17000	60	32	60	50	56	51
18000	74	67	76	68	74	83
19000	67	38	40	67	67	40
20000	57	39	43	50	58	47
21000	67	43	58	40	63	60
22000	58	23	23	45	52	24
23000	70	57	61	65	68	58
24000	62	50	56	54	57	56
25000	70	53	64	70	69	61
26000	62	22	38	41	43	23
27000	64	36	35	38	62	33

	Penalties	Volleys	Acceleration	Agility	...	\
0	85	88	89	89	...	
1000	67	63	63	68	...	
2000	51	48	86	81	...	
3000	53	47	56	58	...	
4000	57	45	79	70	...	
5000	63	67	76	74	...	
6000	69	49	45	68	...	
7000	65	51	66	61	...	
8000	50	56	58	52	...	
9000	62	21	51	39	...	
10000	17	18	53	60	...	
11000	32	26	68	58	...	
12000	75	68	77	76	...	
13000	59	58	77	86	...	
14000	44	37	69	62	...	
15000	45	46	63	75	...	
16000	49	59	78	79	...	
17000	47	34	69	56	...	
18000	48	64	85	80	...	
19000	35	21	78	76	...	
20000	39	44	71	72	...	
21000	55	39	72	59	...	
22000	38	26	77	73	...	
23000	61	53	78	80	...	
24000	55	49	59	81	...	
25000	51	33	78	67	...	
26000	39	29	44	62	...	
27000	46	34	76	60	...	

	Composure	Jumping	Crossing	Reactions	Aggression	Interceptions	\
0	95	95	85	96	63	29	
1000	67	72	62	68	70	56	

2000	44	60	59	58	32	17
3000	49	78	31	53	42	28
4000	49	54	59	65	41	26
5000	58	51	47	58	34	13
6000	77	73	58	72	68	65
7000	57	66	66	60	61	55
8000	67	74	53	72	77	78
9000	61	57	57	68	73	72
10000	56	80	34	54	60	57
11000	55	64	45	56	56	59
12000	69	60	64	71	74	28
13000	67	46	58	55	48	37
14000	46	63	51	51	48	39
15000	72	53	61	70	61	60
16000	60	59	65	64	67	52
17000	51	60	48	48	64	60
18000	74	56	72	69	41	68
19000	61	60	66	66	68	59
20000	58	78	47	53	33	43
21000	59	64	54	62	65	68
22000	33	59	54	54	60	54
23000	60	55	67	62	52	36
24000	58	73	57	58	58	52
25000	65	81	71	63	76	66
26000	45	75	27	54	53	56
27000	54	70	41	59	57	64

	Marking	Sliding tackle	Standing tackle	Preferred Positions
0	22	23	31	ST
1000	21	25	31	ST
2000	23	26	24	ST
3000	22	19	24	ST
4000	22	20	19	RW
5000	17	17	17	LW
6000	68	63	67	CDM
7000	45	58	64	CDM
8000	75	76	81	CB
9000	72	65	70	CB
10000	62	66	68	CB
11000	56	56	59	CB
12000	22	17	18	RM
13000	40	26	34	RM
14000	39	45	47	RM
15000	59	43	64	CM
16000	47	52	53	CM
17000	58	50	61	CM
18000	72	76	72	LM
19000	61	62	63	LM

```
20000       42              41              39              LM
21000       65              60              66              LB
22000       55              55              59              LB
23000       45              47              46             CAM
24000       47              45              57             CAM
25000       64              70              67              RB
26000       65              62              58              RB
27000       70              72              73             RWB

[28 rows x 31 columns]
```

****

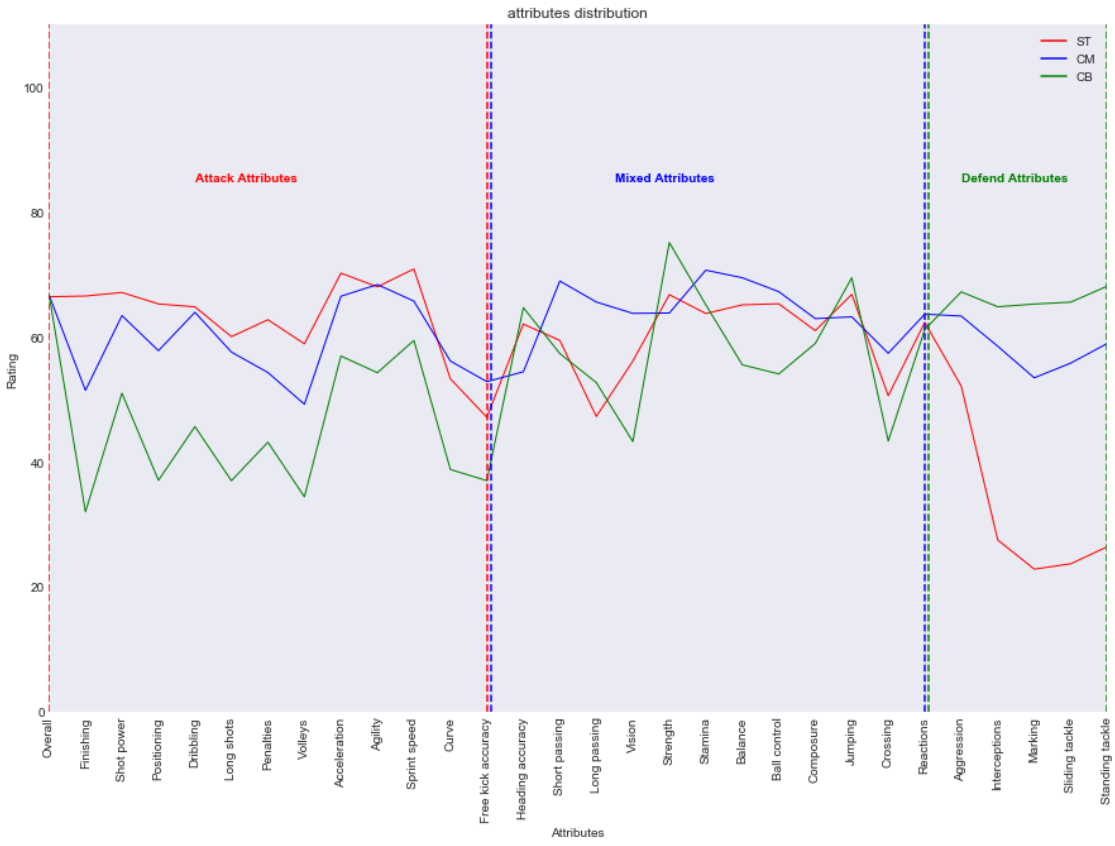
Part2: Data Analyze

****

The plot below shows how the attributes contribute the position.

In [11]:
```
fig, fs = plt.subplots()

## show the 3 main positions
df_ST = df_fifa[df_fifa['Preferred Positions'] == 'ST'].iloc[::10,:-1]
np.mean(df_ST).T.plot.line(color = 'red', figsize = (15,10), legend = 'ST',label='ST'

df_CM = df_fifa[df_fifa['Preferred Positions'] == 'CM'].iloc[::10,:-1]
np.mean(df_CM).T.plot.line(color = 'blue', figsize = (15,10), legend = 'CM',label='CM

df_CB = df_fifa[df_fifa['Preferred Positions'] == 'CB'].iloc[::10,:-1]
np.mean(df_CB).T.plot.line(color = 'green', figsize = (15,10), legend = 'CB',label='C



fs.set_xlabel('Attributes')
fs.set_ylabel('Rating')

fs.set_xticks(np.arange(len(cols)))
fs.set_xticklabels(labels = cols, rotation=90)

for l in fs.lines:
    l.set_linewidth(1)

fs.axvline(0, color='red', linestyle='--')
fs.axvline(12, color='red', linestyle='--')

fs.axvline(12.1, color='blue', linestyle='--')
fs.axvline(24, color='blue', linestyle='--')
```

```
fs.axvline(24.1, color='green', linestyle='--')
fs.axvline(29, color='green', linestyle='--')

fs.text(4, 85, 'Attack Attributes', color = 'red', weight = 'bold')
fs.text(15.5, 85, 'Mixed Attributes', color = 'blue', weight = 'bold')
fs.text(25, 85, 'Defend Attributes', color = 'green', weight = 'bold')
plt.show()
```



**** we can see above there is obvious margin between attacker's attributes and defender's attributes ****

***

1. Logistic Regression

***** predict the Attacker or the Defender *****
**** Set the ST/RW/LW/RM/CM/LM/CAM/CF as an Attacker group --> 1 ****
**** Set the CDM/CB/LB/RB/RWB/LWB as an Defender group --> 0 ****

```
In [12]: # Set the baseline of the prediction
         baseline = 1/2
         print('The baseline is', baseline)
```

The baseline is 0.5

In [13]:
```
df_fifa_normalized = df_fifa.iloc[:,:-1].div(df_fifa.iloc[:,:-1].sum(axis=1), axis=0)
mapping = {'ST': 1, 'RW': 1, 'LW': 1, 'RM': 1, 'CM': 1, 'LM': 1, 'CAM': 1, 'CF': 1, '

df_fifa_normalized['Preferred Positions'] = df_fifa['Preferred Positions']

df_fifa_normalized = df_fifa_normalized.replace({'Preferred Positions': mapping})
df_fifa_normalized.iloc[::1000,]
```

Out[13]:

	Overall	Finishing	Shot power	Positioning	Dribbling	Long shots	\
0	0.039847	0.039847	0.039847	0.040271	0.038576	0.039000	
1000	0.037797	0.036717	0.035637	0.040497	0.036177	0.034017	
2000	0.040842	0.033823	0.031908	0.038928	0.042757	0.026803	
3000	0.039773	0.043324	0.037642	0.034801	0.034091	0.034801	
4000	0.039241	0.036076	0.037342	0.037975	0.038608	0.032911	
5000	0.038293	0.028876	0.043942	0.045198	0.037665	0.033898	
6000	0.036960	0.028110	0.035398	0.031234	0.034357	0.033316	
7000	0.036171	0.033389	0.030607	0.036728	0.035058	0.030607	
8000	0.038825	0.032354	0.038328	0.029368	0.031857	0.031857	
9000	0.042735	0.013431	0.037851	0.026862	0.035409	0.026862	
10000	0.044338	0.012960	0.027285	0.015007	0.021828	0.008868	
11000	0.039651	0.012769	0.025538	0.019489	0.033602	0.014785	
12000	0.038585	0.034834	0.033762	0.028403	0.042337	0.033762	
13000	0.037671	0.034817	0.038813	0.033105	0.041096	0.037100	
14000	0.034530	0.024171	0.036602	0.035912	0.031077	0.022099	
15000	0.038213	0.028525	0.031216	0.036598	0.039290	0.032293	
16000	0.035503	0.027972	0.036579	0.035503	0.037117	0.032813	
17000	0.036496	0.019465	0.036496	0.030414	0.034063	0.031022	
18000	0.036010	0.032603	0.036983	0.033090	0.036010	0.040389	
19000	0.038373	0.021764	0.022910	0.038373	0.038373	0.022910	
20000	0.036822	0.025194	0.027778	0.032300	0.037468	0.030362	
21000	0.037160	0.023849	0.032169	0.022185	0.034942	0.033278	
22000	0.039510	0.015668	0.015668	0.030654	0.035422	0.016349	
23000	0.037413	0.030465	0.032603	0.034741	0.036344	0.030999	
24000	0.034714	0.027996	0.031355	0.030235	0.031915	0.031355	
25000	0.035678	0.027013	0.032620	0.035678	0.035168	0.031091	
26000	0.042234	0.014986	0.025886	0.027929	0.029292	0.015668	
27000	0.039192	0.022045	0.021433	0.023270	0.037967	0.020208	

	Penalties	Volleys	Acceleration	Agility	...	\
0	0.036032	0.037304	0.037728	0.037728	...	
1000	0.036177	0.034017	0.034017	0.036717	...	
2000	0.032546	0.030632	0.054882	0.051691	...	
3000	0.037642	0.033381	0.039773	0.041193	...	
4000	0.036076	0.028481	0.050000	0.044304	...	
5000	0.039548	0.042059	0.047709	0.046453	...	

6000	0.035919	0.025508	0.023425	0.035398	...
7000	0.036171	0.028381	0.036728	0.033945	...
8000	0.024888	0.027875	0.028870	0.025884	...
9000	0.037851	0.012821	0.031136	0.023810	...
10000	0.011596	0.012278	0.036153	0.040928	...
11000	0.021505	0.017473	0.045699	0.038978	...
12000	0.040193	0.036442	0.041265	0.040729	...
13000	0.033676	0.033105	0.043950	0.049087	...
14000	0.030387	0.025552	0.047652	0.042818	...
15000	0.024220	0.024758	0.033907	0.040366	...
16000	0.026358	0.031737	0.041958	0.042496	...
17000	0.028589	0.020681	0.041971	0.034063	...
18000	0.023358	0.031144	0.041363	0.038929	...
19000	0.020046	0.012027	0.044674	0.043528	...
20000	0.025194	0.028424	0.045866	0.046512	...
21000	0.030505	0.021631	0.039933	0.032723	...
22000	0.025886	0.017711	0.052452	0.049728	...
23000	0.032603	0.028327	0.041689	0.042758	...
24000	0.030795	0.027436	0.033035	0.045353	...
25000	0.025994	0.016820	0.039755	0.034149	...
26000	0.026567	0.019755	0.029973	0.042234	...
27000	0.028169	0.020821	0.046540	0.036742	...

	Composure	Jumping	Crossing	Reactions	Aggression	Interceptions	\
0	0.040271	0.040271	0.036032	0.040695	0.026706	0.012293	
1000	0.036177	0.038877	0.033477	0.036717	0.037797	0.030238	
2000	0.028079	0.038290	0.037652	0.037013	0.020421	0.010849	
3000	0.034801	0.055398	0.022017	0.037642	0.029830	0.019886	
4000	0.031013	0.034177	0.037342	0.041139	0.025949	0.016456	
5000	0.036409	0.032015	0.029504	0.036409	0.021343	0.008161	
6000	0.040083	0.038001	0.030193	0.037480	0.035398	0.033837	
7000	0.031720	0.036728	0.036728	0.033389	0.033945	0.030607	
8000	0.033350	0.036834	0.026381	0.035839	0.038328	0.038825	
9000	0.037241	0.034799	0.034799	0.041514	0.044567	0.043956	
10000	0.038199	0.054570	0.023192	0.036835	0.040928	0.038881	
11000	0.036962	0.043011	0.030242	0.037634	0.037634	0.039651	
12000	0.036977	0.032154	0.034298	0.038049	0.039657	0.015005	
13000	0.038242	0.026256	0.033105	0.031393	0.027397	0.021119	
14000	0.031768	0.043508	0.035221	0.035221	0.033149	0.026934	
15000	0.038751	0.028525	0.032831	0.037675	0.032831	0.032293	
16000	0.032275	0.031737	0.034965	0.034427	0.036041	0.027972	
17000	0.031022	0.036496	0.029197	0.029197	0.038929	0.036496	
18000	0.036010	0.027251	0.035036	0.033577	0.019951	0.033090	
19000	0.034937	0.034364	0.037801	0.037801	0.038946	0.033792	
20000	0.037468	0.050388	0.030362	0.034238	0.021318	0.027778	
21000	0.032723	0.035496	0.029950	0.034387	0.036051	0.037715	
22000	0.022480	0.040191	0.036785	0.036785	0.040872	0.036785	
23000	0.032068	0.029396	0.035810	0.033137	0.027793	0.019241	

```
24000   0.032475  0.040873  0.031915  0.032475  0.032475  0.029115
25000   0.033129  0.041284  0.036188  0.032110  0.038736  0.033639
26000   0.030654  0.051090  0.018392  0.036785  0.036104  0.038147
27000   0.033068  0.042866  0.025107  0.036130  0.034905  0.039192

        Marking  Sliding tackle  Standing tackle  Preferred Positions
0      0.009326        0.009750         0.013141                    1
1000   0.011339        0.013499         0.016739                    1
2000   0.014678        0.016592         0.015316                    1
3000   0.015625        0.013494         0.017045                    1
4000   0.013924        0.012658         0.012025                    1
5000   0.010672        0.010672         0.010672                    1
6000   0.035398        0.032795         0.034878                    0
7000   0.025042        0.032276         0.035615                    0
8000   0.037332        0.037830         0.040319                    0
9000   0.043956        0.039683         0.042735                    0
10000  0.042292        0.045020         0.046385                    0
11000  0.037634        0.037634         0.039651                    0
12000  0.011790        0.009110         0.009646                    1
13000  0.022831        0.014840         0.019406                    1
14000  0.026934        0.031077         0.032459                    1
15000  0.031755        0.023143         0.034446                    1
16000  0.025282        0.027972         0.028510                    1
17000  0.035280        0.030414         0.037105                    1
18000  0.035036        0.036983         0.035036                    1
19000  0.034937        0.035510         0.036082                    1
20000  0.027132        0.026486         0.025194                    1
21000  0.036051        0.033278         0.036606                    0
22000  0.037466        0.037466         0.040191                    0
23000  0.024051        0.025120         0.024586                    1
24000  0.026316        0.025196         0.031915                    1
25000  0.032620        0.035678         0.034149                    0
26000  0.044278        0.042234         0.039510                    0
27000  0.042866        0.044091         0.044703                    0

[28 rows x 31 columns]
```

In [14]:
```
# perform 5 cross validation
clf = LogisticRegression()
x = df_fifa_normalized.iloc[:,:-1]
y = df_fifa_normalized.iloc[:,-1]
scores = cross_val_score(clf, x, y, cv=5)
print ('Logistic Regression Accuracy: {}'.format(np.mean(scores)))
```

```
Logistic Regression Accuracy: 0.8247060870911659
```

**** Tune the features by lasso ****

```
In [15]: # Perform lasso to get rid of the attribute that unnecessary influence the decision o
         clf = Lasso(alpha=0.00001)
         clf.fit(x,y)
         Feature_Coef_list = list(sorted(zip(recol_needed, abs(clf.coef_)),key=lambda x: -x[1])
         Feature_Coef_table = pd.DataFrame(np.array(Feature_Coef_list).reshape(-1,2), columns =
         print(Feature_Coef_table)
```

	Attributes	Coefficient
0	Marking	11.13209727
1	Finishing	9.8962076159
2	Vision	6.8567879403
3	Overall	6.34613490803
4	Interceptions	4.77723878996
5	Crossing	4.69090655742
6	Sliding tackle	4.6484871289
7	Short passing	4.36900008552
8	Heading accuracy	4.13270382179
9	Positioning	3.92430870186
10	Volleys	2.32842916586
11	Long passing	2.26317284857
12	Balance	2.01616090561
13	Jumping	1.73687147151
14	Free kick accuracy	1.65818299991
15	Reactions	1.40307357195
16	Ball control	0.808624901334
17	Agility	0.748758074388
18	Strength	0.523559227578
19	Dribbling	0.507372774338
20	Curve	0.506313190176
21	Acceleration	0.464846463463
22	Stamina	0.172440802888
23	Penalties	0.132479441118
24	Shot power	0.0
25	Long shots	0.0
26	Sprint speed	0.0
27	Composure	0.0
28	Aggression	0.0
29	Standing tackle	0.0

**** now we try to enumerate the features to get the highest performance ****

```
In [16]: max_score = 0
         n_features = 0

         for i in range(1,len(Feature_Coef_table['Attributes'])):
             clf_lasso = LogisticRegression()
             lasso_cols = Feature_Coef_table[:i]['Attributes'].tolist()
```

```
            x_lasso = df_fifa_normalized.iloc[:,:-1][lasso_cols]
            scores_lasso = cross_val_score(clf_lasso, x_lasso,y , cv=5)
            if np.mean(scores_lasso) > max_score:
                max_score = np.mean(scores_lasso)
                n_features = i

        print ('Logistic Regression Accuracy (' + str(n_features) +' features):' + str(max_sc

Logistic Regression Accuracy (7 features):0.833513325558
```

**** As we can see here. we are improve the accuracy slightly ****
**** And it is higher than baseline 0.5 ****

```
In [17]: imp_features = Feature_Coef_table[:n_features]['Attributes'].tolist()
         print('The important features to determine the 1/0 is')
         print(imp_features)

The important features to determine the 1/0 is
['Marking', 'Finishing', 'Vision', 'Overall', 'Interceptions', 'Crossing', 'Sliding tackle']
```

***

2. Random Forest

***** predict all the position *****

```
In [18]: # Set the baseline of the prediction
         baseline = 1/len(positions)
         print('The baseline is', baseline)

The baseline is 0.07142857142857142
```

```
In [19]: df_fifa_all_pos = df_fifa.copy()
         mapping_all = {'ST': 0, 'RW': 1, 'LW': 2, 'RM': 3, 'CM': 4, 'LM': 5, 'CAM': 6, 'CF':

         df_fifa_all_pos = df_fifa_all_pos.replace({'Preferred Positions': mapping_all})
         df_fifa_all_pos.iloc[::1000,]
```

Out[19]:

	Overall	Finishing	Shot power	Positioning	Dribbling	Long shots	\
0	94	94	94	95	91	92	
1000	70	68	66	75	67	63	
2000	64	53	50	61	67	42	
3000	56	61	53	49	48	49	
4000	62	57	59	60	61	52	
5000	61	46	70	72	60	54	

6000	71	54	68	60	66	64
7000	65	60	55	66	63	55
8000	78	65	77	59	64	64
9000	70	22	62	44	58	44
10000	65	19	40	22	32	13
11000	59	19	38	29	50	22
12000	72	65	63	53	79	63
13000	66	61	68	58	72	65
14000	50	35	53	52	45	32
15000	71	53	58	68	73	60
16000	66	52	68	66	69	61
17000	60	32	60	50	56	51
18000	74	67	76	68	74	83
19000	67	38	40	67	67	40
20000	57	39	43	50	58	47
21000	67	43	58	40	63	60
22000	58	23	23	45	52	24
23000	70	57	61	65	68	58
24000	62	50	56	54	57	56
25000	70	53	64	70	69	61
26000	62	22	38	41	43	23
27000	64	36	35	38	62	33

	Penalties	Volleys	Acceleration	Agility	...	\
0	85	88	89	89	...	
1000	67	63	63	68	...	
2000	51	48	86	81	...	
3000	53	47	56	58	...	
4000	57	45	79	70	...	
5000	63	67	76	74	...	
6000	69	49	45	68	...	
7000	65	51	66	61	...	
8000	50	56	58	52	...	
9000	62	21	51	39	...	
10000	17	18	53	60	...	
11000	32	26	68	58	...	
12000	75	68	77	76	...	
13000	59	58	77	86	...	
14000	44	37	69	62	...	
15000	45	46	63	75	...	
16000	49	59	78	79	...	
17000	47	34	69	56	...	
18000	48	64	85	80	...	
19000	35	21	78	76	...	
20000	39	44	71	72	...	
21000	55	39	72	59	...	
22000	38	26	77	73	...	
23000	61	53	78	80	...	

```
24000         55       49            59       81         ...
25000         51       33            78       67         ...
26000         39       29            44       62         ...
27000         46       34            76       60         ...

       Composure  Jumping  Crossing  Reactions  Aggression  Interceptions  \
0             95       95        85         96          63             29
1000          67       72        62         68          70             56
2000          44       60        59         58          32             17
3000          49       78        31         53          42             28
4000          49       54        59         65          41             26
5000          58       51        47         58          34             13
6000          77       73        58         72          68             65
7000          57       66        66         60          61             55
8000          67       74        53         72          77             78
9000          61       57        57         68          73             72
10000         56       80        34         54          60             57
11000         55       64        45         56          56             59
12000         69       60        64         71          74             28
13000         67       46        58         55          48             37
14000         46       63        51         51          48             39
15000         72       53        61         70          61             60
16000         60       59        65         64          67             52
17000         51       60        48         48          64             60
18000         74       56        72         69          41             68
19000         61       60        66         66          68             59
20000         58       78        47         53          33             43
21000         59       64        54         62          65             68
22000         33       59        54         54          60             54
23000         60       55        67         62          52             36
24000         58       73        57         58          58             52
25000         65       81        71         63          76             66
26000         45       75        27         54          53             56
27000         54       70        41         59          57             64

       Marking  Sliding tackle  Standing tackle  Preferred Positions
0           22              23               31                    0
1000        21              25               31                    0
2000        23              26               24                    0
3000        22              19               24                    0
4000        22              20               19                    1
5000        17              17               17                    2
6000        68              63               67                    8
7000        45              58               64                    8
8000        75              76               81                    9
9000        72              65               70                    9
10000       62              66               68                    9
11000       56              56               59                    9
```

```
12000       22              17              18              3
13000       40              26              34              3
14000       39              45              47              3
15000       59              43              64              4
16000       47              52              53              4
17000       58              50              61              4
18000       72              76              72              5
19000       61              62              63              5
20000       42              41              39              5
21000       65              60              66              10
22000       55              55              59              10
23000       45              47              46              6
24000       47              45              57              6
25000       64              70              67              11
26000       65              62              58              11
27000       70              72              73              12

[28 rows x 31 columns]
```

```
In [20]: # perform 5 cross validation
         clf = LogisticRegression()
         x = df_fifa_all_pos.iloc[:,:-1]
         y = df_fifa_all_pos.iloc[:,-1]
         log_scores = cross_val_score(clf, x, y, cv=3)
         print ('Logistic Regression Accuracy: {}'.format(np.mean(log_scores)))
```

```
Logistic Regression Accuracy: 0.45080732796136597
```

```
In [21]: clf = RandomForestClassifier(random_state=0)
         x = df_fifa_all_pos.iloc[:,:-1]
         y = df_fifa_all_pos.iloc[:,-1]
         rf_scores = cross_val_score(clf, x, y, cv=3)
         print ('Random Forest Accuracy: {}'.format(np.mean(rf_scores)))
```

```
Random Forest Accuracy: 0.32505937892358683
```

**** Tune the features by ridge ****

```
In [22]: # Perform ridge to get the importance of the feature when determining the position.
         clf = Ridge(alpha=0.001)
         clf.fit(x,y)
         Feature_Coef_list = list(sorted(zip(recol_needed, abs(clf.coef_)),key=lambda x: -x[1])
         Feature_Coef_table = pd.DataFrame(np.array(Feature_Coef_list).reshape(-1,2), columns =
         print(Feature_Coef_table)
```

```
   Attributes        Coefficient
0     Overall    0.0717080168083
```

```
1            Finishing    0.0522304336032
2             Crossing    0.0433288377307
3              Marking    0.0314207616489
4         Ball control    0.0304023274928
5       Sliding tackle    0.0256481212323
6        Short passing    0.0219442536492
7          Positioning    0.0209245070663
8        Interceptions    0.0163144373453
9               Vision    0.0162954778204
10           Penalties    0.0136074977623
11     Standing tackle    0.0131716395467
12          Shot power    0.0112859824342
13               Curve   0.00912983517573
14        Long passing   0.00851227891875
15    Heading accuracy   0.00806576156269
16             Volleys   0.00764793997365
17  Free kick accuracy    0.0076164430895
18          Aggression   0.00754916691825
19           Composure    0.0073492387795
20          Long shots    0.0063430751331
21            Strength   0.00427936412214
22             Stamina   0.00339006056184
23             Balance   0.00321063647673
24             Jumping   0.00225932031214
25        Acceleration    0.0017792794071
26           Dribbling   0.00112446965917
27           Reactions  0.000953019137569
28        Sprint speed  0.000765540510496
29             Agility  0.000505710571809
```

**** now we try to enumerate the features to get the highest performance ****

```
In [23]: max_score = 0
         n_features = 0

         for i in range(1,len(Feature_Coef_table['Attributes'])):
             clf_ridge = RandomForestClassifier(random_state=0)
             ridge_cols = Feature_Coef_table[:i]['Attributes'].tolist()
             x_ridge = df_fifa_normalized.iloc[:,:-1][ridge_cols]
             scores_ridge = cross_val_score(clf_ridge, x_ridge,y , cv=3)
             if np.mean(scores_ridge) > max_score:
                 max_score = np.mean(scores_ridge)
                 n_features = i

         print ('Random Forest Accuracy (' + str(n_features) +' features):' + str(max_score))
```

```
Random Forest Accuracy (22 features):0.395765861155
```

```
In [24]: imp_features = Feature_Coef_table[:n_features]['Attributes'].tolist()
         print('The important features to determine the positon is')
         print(imp_features)

The important features to determine the positon is
['Overall', 'Finishing', 'Crossing', 'Marking', 'Ball control', 'Sliding tackle', 'Short passi
```

**** As we can see here. we are improve the accuracy slightly ****
**** And 0.395765861155 is higher than baseline 0.07142857142857142 ****
***

3. Linear Regression

***** predict the overall of the player. *****

**** define a new cross validation ****

```
In [25]: def cross_Validation_reg(reg, X, y, k = 3):

             tMSE = list()

             for train_index, test_index in KFold(n_splits=k, random_state=None, shuffle=False
                 X_train, X_test = X[train_index], X[test_index]
                 y_train, y_test = y[train_index], y[test_index]
                 regm = reg.fit(X_train, y_train)
                 tMSE.append(np.mean((y_test - regm.predict(X_test)) ** 2))
             return np.mean(tMSE)

In [26]: ## set y overall
         overall = np.array(df_fifa.iloc[:,0:1])[:,0]
         Xb = csr_matrix(df_fifa.iloc[:, 1:-1])
         Xb.toarray()

Out[26]: array([[94, 94, 95, ..., 22, 23, 31],
                [94, 87, 92, ..., 30, 38, 45],
                [91, 88, 91, ..., 25, 19, 42],
                ...,
                [35, 27, 51, ..., 55, 57, 55],
                [38, 53, 39, ..., 29, 36, 30],
                [34, 44, 44, ..., 49, 43, 48]], dtype=int64)

In [27]: class baseline:

             def fit(self, X, y):
                 return self
```

```
            def predict(self, X):
                n = X.shape[0]
                res = np.zeros(n)
                for i in range(n):
                    res[i] = np.mean(X[i,:])
                return res

        # set the baseline class for certain player
        bl = baseline()
```

```
In [28]: # test baseline for all
         cross_Validation_reg(bl, Xb, overall, 5)
```

```
Out[28]: 84.765765665367482
```

**** Perform linear model ****

```
In [29]: overall = np.array(df_fifa.iloc[:,0:1])[:,0]
         X = csr_matrix(df_fifa_all_pos.iloc[:, :])
         lr = LinearRegression()

         ## ignore the positions
         accuracy = cross_Validation_reg(lr, Xb,overall, 5)
         print('The linear model Accuracy(ignore the positions):' + str(accuracy))

         lr = LinearRegression()
         ## fatorize the positions
         accuracy_f = cross_Validation_reg(lr, X, overall, 5)
         print('The linear model Accuracy(fatorize the positions):' + str(accuracy_f))
```

```
The linear model Accuracy(ignore the positions):24.1899472391
The linear model Accuracy(fatorize the positions):21.6724222569
```

```
In [30]: lrm = lr.fit(X, overall)
         print('The coef are ' + str(lrm.coef_))
         print('The intercept is ' + str(lrm.intercept_))
```

```
The coef are [ 0.50296368 -0.0088104  -0.00452567  0.01011129  0.01096997  0.05972182
 -0.08519162  0.02961537 -0.05606899 -0.04137218 -0.04830314  0.03610987
 -0.01101434 -0.05770672 -0.07897779  0.01758256 -0.05891234 -0.24378331
  0.02476237 -0.27168061  0.02807166  0.07749302 -0.00907431  0.07296686
  0.10880582  0.03459514  0.06388949  0.00142567 -0.04639001 -0.01173554
 -0.25987998]
The intercept is 66.9109023522
```

**** Perform polynomial model ****

```
In [31]: model = make_pipeline(PolynomialFeatures(2), Ridge(copy_X = False))
         accuracy_p = cross_Validation_reg(model, X.toarray(), overall, 5)
         print('The polyomial model accuracy (factorize the positions):' + str(accuracy))

The polyomial model accuracy (factorize the positions):24.1899472391


In [32]: nX = X.toarray()
         modelp = model.fit(nX , overall)
         result = modelp.predict(nX)
         print('To predict all the player overall rating by our model')
         print(result)

To predict all the player overall rating by our model
[ 94.00029641  92.00053072  91.00084033 ...,  53.00020395  51.00029448
  47.00097197]
```

**** we get a very good accuracy in polynomial model ****