Investigate_a_Dataset

November 14, 2018

1 Project: Investigate a soccer dataset extracted from *Kaggle*

1.1 Table of Contents

Introduction

> Soccer dataset extracted from Kaggle web site, The database is stored in a SQLite database with 8 tables that contains players and teams attributes sourced from EA Sports and different sites, +25,000 matches, +10,000 players, 11 European Countries with their lead championship, Seasons 2008 to 2016

- Some players are missing from the lineup (NULL values). This is because no source to their attributes from FIFA.
- After quick review using sqlite, i had been interested in players attributes.
- SQL were used to extract data i need and save it to csv file formate.

1.1.1 Questions :

1- Considering players improvement during their career, what is the most potential age range that they could improve the most?

2- What is the most important attribute that must be exist in the attackers overall rating among the famous skills like dribbling, sprint speed, vision, heading accuracy and shot power ?

```
In [1]: # Seting up import statements for all of the packages that we plan to use.

        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        % matplotlib inline
```

Data Wrangling

In this section of the report, loading the data, checking for cleanliness, and then trimming and cleaning the dataset for analysis.

1.1.2 General Properties

In [2]:
```
# using sqlite to extract Player and Player_Attributes in 1 table, joining them with pla
# saving the data to Soccer_players.csv

# reading the uploaded csv file
df = pd.read_csv('Soccer_players.csv')

print(df.columns) # print all coulmns names

df.head(3) # display headers
```

```
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', 'id.1', 'player_api_id.1', 'player_name',
       'player_fifa_api_id.1', 'birthday', 'height', 'weight'],
      dtype='object')
```

Out[2]:
```
   id  player_fifa_api_id  player_api_id                 date  overall_rating  \
0   1              218353         505942  2016-02-18 00:00:00            67.0
1   2              218353         505942  2015-11-19 00:00:00            67.0
2   3              218353         505942  2015-09-21 00:00:00            62.0

   potential preferred_foot attacking_work_rate defensive_work_rate  crossing  \
0       71.0          right              medium              medium      49.0
1       71.0          right              medium              medium      49.0
2       66.0          right              medium              medium      49.0

     ...    gk_kicking  gk_positioning  gk_reflexes  id.1  player_api_id.1  \
0    ...          10.0             8.0          8.0     1           505942
1    ...          10.0             8.0          8.0     1           505942
2    ...          10.0             8.0          8.0     1           505942

          player_name  player_fifa_api_id.1             birthday  height  \
0  Aaron Appindangoye                218353  1992-02-29 00:00:00  182.88
1  Aaron Appindangoye                218353  1992-02-29 00:00:00  182.88
2  Aaron Appindangoye                218353  1992-02-29 00:00:00  182.88

   weight
0     187
1     187
```

```
2     187

[3 rows x 49 columns]
```

In [3]:
```python
# since the data are extensive, i need to drop un-needed columns, as i will focus on att
# then start to look closely to the datafram

# drop all cloumns except what i need (foucs on attacker's attributes)
# using df.index.difference but for column instead of index to return other columns name
df.drop(df.columns.difference(['player_fifa_api_id','date', 'overall_rating', 'attacking
                               'heading_accuracy', 'dribbling', 'shot_power', 'sprint_spe
                               'vision', 'birthday']), axis=1, inplace = True)
# re-display the header
df.head(3)
```

Out[3]:
```
   player_fifa_api_id                 date  overall_rating  \
0              218353  2016-02-18 00:00:00            67.0
1              218353  2015-11-19 00:00:00            67.0
2              218353  2015-09-21 00:00:00            62.0

  attacking_work_rate  heading_accuracy  dribbling  sprint_speed  shot_power  \
0              medium              71.0       51.0          64.0        55.0
1              medium              71.0       51.0          64.0        55.0
2              medium              71.0       51.0          64.0        55.0

   vision             birthday
0    54.0  1992-02-29 00:00:00
1    54.0  1992-02-29 00:00:00
2    54.0  1992-02-29 00:00:00
```

In [4]:
```python
# confirm the unique data of attacking_work_rate
# to select the unique value of attackers
print('unique values are: ', df.attacking_work_rate.unique())
```

```
unique values are:  ['medium' 'high' nan 'low' 'None' 'le' 'norm' 'stoc' 'y']
```

In [5]:
```python
# confrim how many rows assigned for high attacking rate
print('count of high attacking rate evaluations: ', df.attacking_work_rate.value_counts(

# extract attackers dataframe using query of high attacking rate
# assign query result to attacker_df
attacker_df = df.query('attacking_work_rate == "high"')
```

```
count of high attacking rate evaluations:  42823
```

In [6]:
```python
# check for nulls values and duplicates in attacker_df
print(attacker_df.shape, df.duplicated().sum())

attacker_df.isnull().sum() # print total nulls in each column
```

```
(42823, 10) 91
```

```
Out[6]: player_fifa_api_id     0
        date                   0
        overall_rating         0
        attacking_work_rate    0
        heading_accuracy       0
        dribbling              0
        sprint_speed           0
        shot_power             0
        vision                 0
        birthday               0
        dtype: int64
```

```
In [7]: # check for data types to select which column we need to convert its format
        attacker_df.dtypes
```

```
Out[7]: player_fifa_api_id       int64
        date                    object
        overall_rating         float64
        attacking_work_rate     object
        heading_accuracy       float64
        dribbling              float64
        sprint_speed           float64
        shot_power             float64
        vision                 float64
        birthday                object
        dtype: object
```

1.1.3 Data Cleaning

Cleaning steps : - 91 duplicated row were found and it will not affect the datafram if dropped. - drop attacking_work_rate column from attacker_df as its single unique value. - rename evaluation date column & player_fifa_api_id columns to eval_date & id. - convert evaluation date column and birthday column to datetime formate. - keep only ids with evalouations more than 10.

```
In [12]: # make a copy of attacker datafram to apply all the cleaning
         # to avoid any pandas warnings regading changing original data
         eval_df = attacker_df.copy()

         # since no null values, i will drop duplicats (91) that will not affect my analysis
         eval_df.drop_duplicates(inplace = True)

         # drop attacking_work_rate column as we no longer need it
         eval_df.drop(['attacking_work_rate'],axis =1 , inplace=True)

         # rename evaluation date & player_fifa_api_id columns
         # 'date' does not describe its purpose and 'player_fifa_api_id' is too long
         eval_df.rename(columns={'date': 'eval_date', 'player_fifa_api_id' :'id'}, inplace=True)
```

In [13]:
```python
# convert date col in datetime format
eval_df.eval_date = pd.to_datetime(eval_df.eval_date)

# convert birthday col in datetime format
eval_df.birthday = pd.to_datetime(eval_df.birthday)

# extract the birth year from birthday column using Series.dt.year
eval_df['birth_year'] = pd.to_datetime(eval_df.birthday).dt.year

eval_df.head(3) # display data frame
```

Out[13]:
```
       id  eval_date  overall_rating  heading_accuracy  dribbling  \
5  189615 2016-04-21            74.0              58.0       73.0
6  189615 2016-04-07            74.0              58.0       73.0
7  189615 2016-01-07            73.0              57.0       71.0

   sprint_speed  shot_power  vision   birthday  birth_year
5          78.0        71.0    66.0 1989-12-15        1989
6          78.0        71.0    66.0 1989-12-15        1989
7          78.0        71.0    65.0 1989-12-15        1989
```

In [14]:
```python
eval_df.dtypes # recheck data types
```

Out[14]:
```
id                           int64
eval_date           datetime64[ns]
overall_rating             float64
heading_accuracy           float64
dribbling                  float64
sprint_speed               float64
shot_power                 float64
vision                     float64
birthday            datetime64[ns]
birth_year                   int64
dtype: object
```

In [15]:
```python
# using groupby to group the dataframe by id
# using transform to calucate length of each id (how many evaluations)
# assign the grouped and selected id that has more than 10 evaluation to cleaned_df

cleaned_df = eval_df[eval_df.groupby('id').id.transform(len) > 10]

print('average evaluation count after trimming :', cleaned_df.id.value_counts().mean())
```

```
average evaluation count after trimming : 19.3007990868
```

Exploratory Data Analysis

Data now is trimmed and cleaned and ready to move on to exploration.

1.1.4 Research Question 1 :

What is the most potential age range that they could improve the most?

- create age at evaluation column that calculate player's age at each date of their evaluation.
- set range of age as follow (under_23 , between 23_28, above_28) .
- create ranking column that contains players rating according to their overall rating during the evaluation period.
- set ranking as performance (best , better than normal, normal)
- visualize bars chart and single chart that represent ranking of players at each range of age and overall rating.

For the range of age and ranking rate, i will use 'pandas cutting' for once and use 'for loop' as alternative method to avoid repetitive code.

```
In [16]: # answering question1
         # group the players by id and evaluated dates
         q1_df = cleaned_df.groupby(['id', 'eval_date'])['overall_rating', 'eval_date','birthday

         q1_df.head()
```

```
Out[16]:                  overall_rating  eval_date   birthday  birth_year
         id eval_date
         27 2007-02-22              87.0 2007-02-22 1981-11-08        1981
            2007-08-30              86.0 2007-08-30 1981-11-08        1981
            2008-08-30              84.0 2008-08-30 1981-11-08        1981
            2009-02-22              83.0 2009-02-22 1981-11-08        1981
            2009-08-30              83.0 2009-08-30 1981-11-08        1981
```

```
In [17]: # create palyer age at each evaluation date
         # substracting date of evaluation from player's birthday
         q1_df['age_at_eval'] = q1_df.eval_date - q1_df.birthday

         q1_df.head(1) # display the new result
```

```
Out[17]:                  overall_rating  eval_date   birthday  birth_year age_at_eval
         id eval_date
         27 2007-02-22              87.0 2007-02-22 1981-11-08        1981   9237 days
```

```
In [18]: # once the format is timedelta (with days) we need to converte it into years
         # divide number of days by 1 year (365 day) return float results
         # using np.timedelta64(1, 'Y') as 1 year
         q1_df['age_at_eval'] = q1_df['age_at_eval'] / np.timedelta64(1, 'Y')

         # check age at eval data type
         q1_df.age_at_eval.dtypes
         q1_df.head(1)
```

```
Out[18]:                  overall_rating  eval_date   birthday  birth_year  age_at_eval
         id eval_date
         27 2007-02-22              87.0 2007-02-22 1981-11-08        1981    25.290047
```

```
In [19]: # create bins & label name to be used in cutting birth year column

         # set the in and medium and max values
         bins = [q1_df.age_at_eval.min()-1 , 23 , 28 , q1_df.age_at_eval.max()]
         labels_list=[ 'under_23' , '23_28' ,'above_28' ] # groups name

         # cut age at eval column into 3 mentioned group
         q1_df['age_group'] = pd.cut(q1_df['age_at_eval'] , bins , labels = labels_list)

In [20]: # create column to be used in ranking evalution
         q1_df['ranking'] = q1_df['overall_rating']

         # useing different method other than pd.cut
         # create list with rankng score for each player during his evalutaion with "for" loop
         # for every row in index of ranking column, divide the cell by avergae rate of selected
         score_list= [q1_df.overall_rating[(index, row)]/q1_df.overall_rating[index].mean() for

         # add the list as rank_score column to datafram using pd.Series with same overall ratin
         q1_df['rank_score'] = pd.Series(score_list, index= q1_df.overall_rating.index)
```

IMP note: pandas cutting is much faster than 'for loop' in dealing with large dataframe

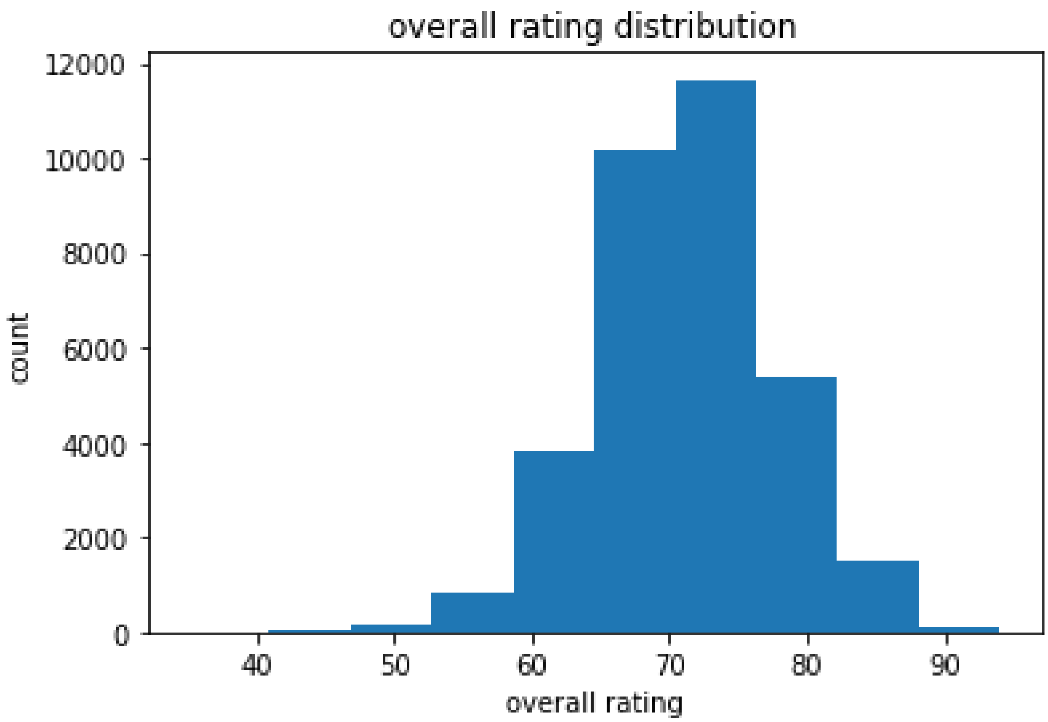
```
In [21]: # assign rank rate description to score
         # score above 1.04 (104%) 'best', under 0.97 (97%) 'normal', else is 'better'
         q1_df.loc[q1_df.rank_score > 1.04, 'ranking'] = 'best'
         q1_df.loc[q1_df.rank_score < 0.97, 'ranking'] = 'normal'
         q1_df.loc[(0.97 <= q1_df.rank_score) & (q1_df.rank_score <= 1.04) , 'ranking'] = 'bette

         q1_df.head(7) # check results
```

```
Out[21]:                  overall_rating  eval_date   birthday  birth_year  age_at_eval  \
         id eval_date
         27 2007-02-22            87.0 2007-02-22 1981-11-08        1981    25.290047
            2007-08-30            86.0 2007-08-30 1981-11-08        1981    25.807511
            2008-08-30            84.0 2008-08-30 1981-11-08        1981    26.809585
            2009-02-22            83.0 2009-02-22 1981-11-08        1981    27.291457
            2009-08-30            83.0 2009-08-30 1981-11-08        1981    27.808921
            2010-08-30            80.0 2010-08-30 1981-11-08        1981    28.808258
            2011-02-22            79.0 2011-02-22 1981-11-08        1981    29.290129

                       age_group ranking  rank_score
         id eval_date
         27 2007-02-22     23_28    best    1.121375
            2007-08-30     23_28    best    1.108485
            2008-08-30     23_28    best    1.082707
            2009-02-22     23_28    best    1.069817
            2009-08-30     23_28    best    1.069817
            2010-08-30  above_28  better    1.031149
            2011-02-22  above_28  better    1.018260
```

In [22]:
```
# drop the extra evaluation date column
# 2 column with the same name (1 as index and other as column)
q1_df.drop(labels = ['eval_date'], axis=1, inplace = True)

# reset the index to normal
q1_df.reset_index(inplace = True)
```

In [23]:
```
# explore overall rating histogram

plt.hist(q1_df.overall_rating) # selecting data
plt.title('overall rating distribution') # assign title
plt.xlabel('overall rating') # set x label name
plt.ylabel('count') # set y label name
```

Out[23]:
```
Text(0,0.5,'count')
```

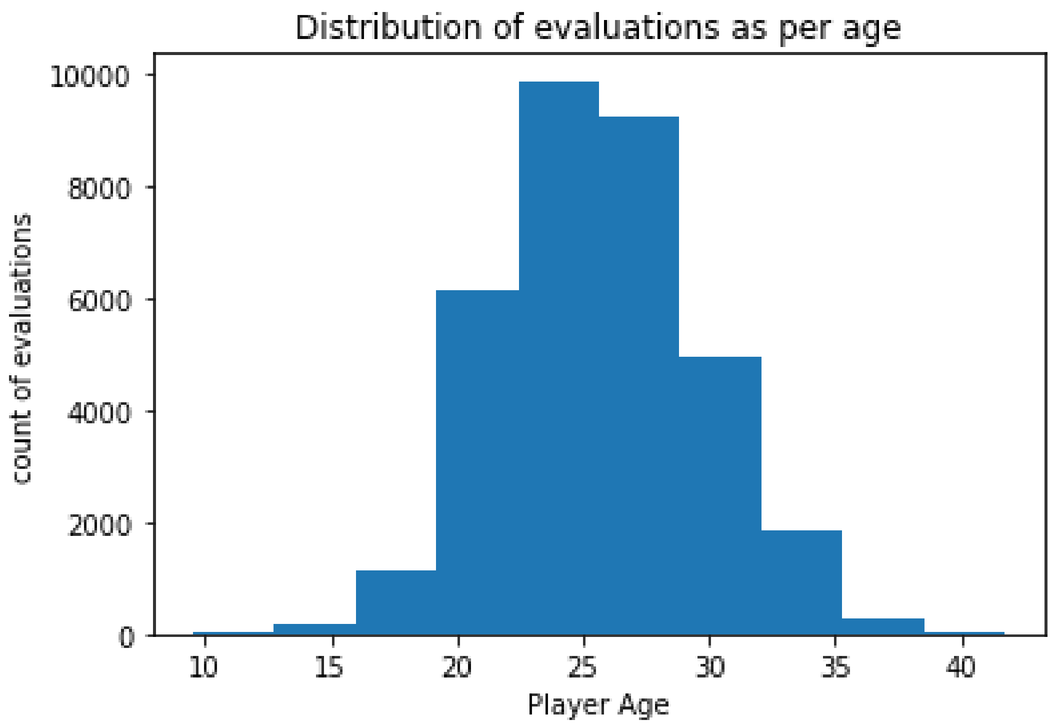


looking at overall rating histogram, find the distribution is skewed left with highest distribution between 70 and 75

In [24]:
```
# explore age histogram

plt.hist(q1_df.age_at_eval)
plt.title('Distribution of evaluations as per age')
plt.xlabel('Player Age')
plt.ylabel('count of evaluations')
```

```
print('Average player age at evaluation dates: ', q1_df.age_at_eval.mean())
```

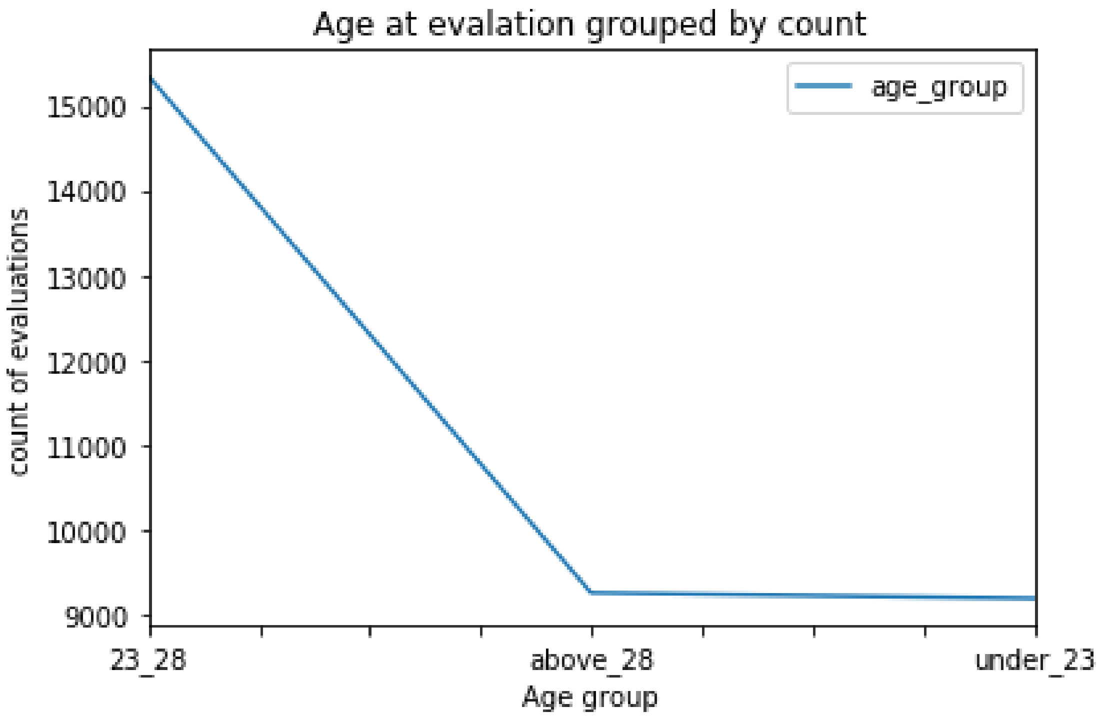
```
Average player age at evaluation dates:  25.6302549841
```



Almost symmetric distributions, i find that most of the evaluations made for players around age 25

```
In [25]: # explore distribution of age_group

         # group by data frame by age_group and set values count to be plotted
         q1_df.age_group.value_counts().plot(title = 'Age at evalation grouped by count', legend
         plt.xlabel('Age group')
         plt.ylabel('count of evaluations')
```

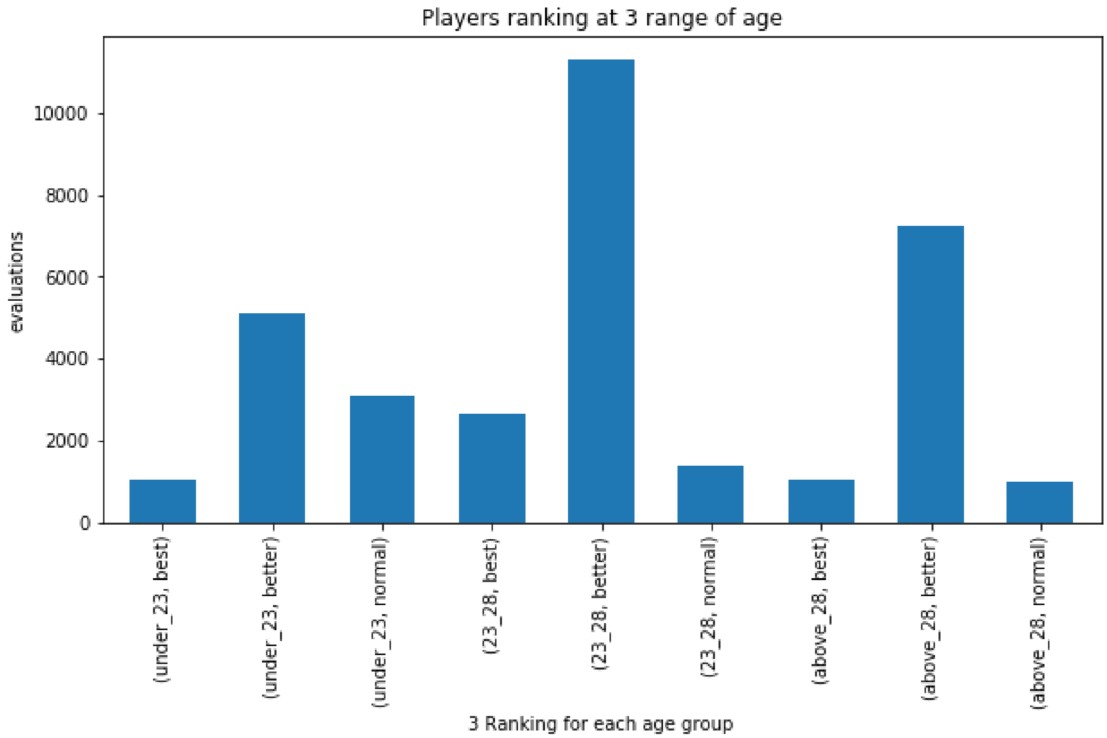
```
Out[25]: Text(0,0.5,'count of evaluations')
```



age group line plot show clearly the gap of evaluations between age between 23 & 28 and age under 23 or above 28 - more than 15000 evaluation located between age 23 and 28, while allocated slightly above 9000 for under 23 and above 28 each.

In [26]:
```
# which age group has the best player's ranking

plt.subplots(figsize = (10 ,5)) # set the layout size

# group both age_group and ranking togather for plotting
q1_df.groupby(['age_group','ranking']).size().plot(kind = 'bar', width = 0.6)
plt.title('Players ranking at 3 range of age')
plt.xlabel('3 Ranking for each age group')
plt.ylabel('evaluations')
```

Out[26]:
```
Text(0,0.5,'evaluations')
```



1.1.5 Challenges and limitations thourgh question 1:

- Data is incomplete as players position were not included and i had been forced to use only high attacking rate players to select the attackers, also count of evaluation varies for each player.
- Using different method other than 'pandas cut' to rank players score into (best, better, normal) was harder than what i expected, it takes long time from me to pass this issue by using 'for loop' because in big dataset it could be very challenging to succeed.

Conclusion Q1
First, its very important to mention that most of the evaluations made for the players at age 25 which is located in range between 23 & 28, which may affect the results regarding the count of evaluations.

Second, I selected attackers for investigation by selected high attacking rate which means that some players are not strikers or forwards which leads that their attributes may be change according to their position.

- Chart has been grouped by age order (under_23 , 23_28, above_28) then ranking performance (best, better, normal)
- Considering my question regarding the best players improvement, it will be at age between 23 & 28, its very clear that 'best' bar at range between 23 & 28 is obvious higher than above 28 & under 23.
- Regarding the players better improvement, also its obvious that players do a better improvement at age between 23 & 28 if its not their best.

- At age under 23 most of the palyers are doing normal or better performance.

Before exploring the data, I thought that the best improvment will be after 28 but it was wrong

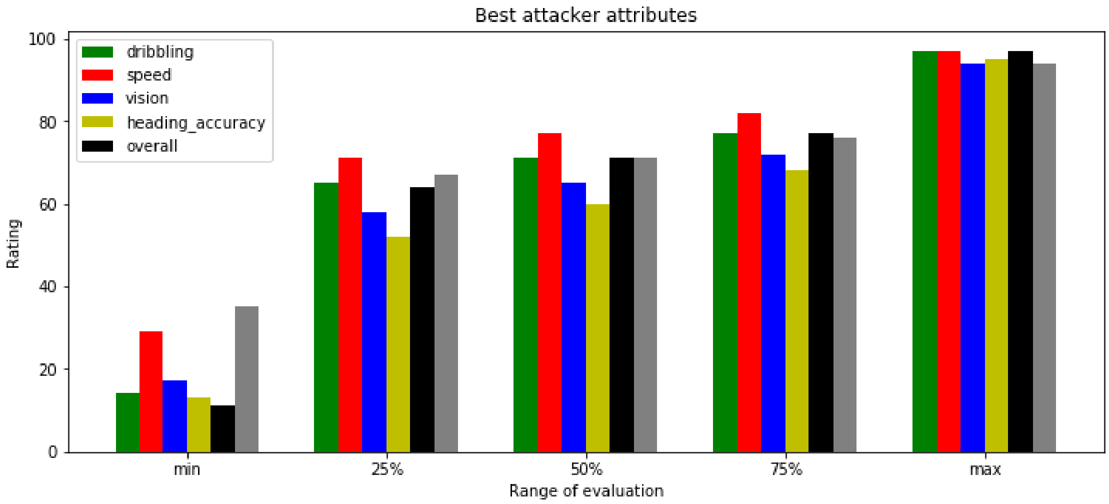
1.1.6 Research Question 2

What is the most important attribute that must be exist in the attackers overall rating among the famous skills like dribbling, sprint speed, vision, heading accuracy and shot power ?

- using dribbling, sprint speed, vision, heading accuracy and shot power columns along with overall rating.
- use describe() to extract our data from each column from min to max.

In [27]:
```
# the most important attribute for the players

# set index, locations, titles
ind = np.arange(5)
plt.subplots(figsize = (12 ,5)) # set the layout size
plt.title('Best attacker attributes')
plt.xlabel('Range of evaluation')
plt.ylabel('Rating')
width = 0.12  # for bar width

# set label name just like the result of describe() min, 25%, 50%, 75%, max
labels = cleaned_df.loc[:, 'overall_rating'].describe()['min':'max'].index
locations = ind + width*5/2 # set location of label names
plt.xticks(locations, labels) # set the location and label on the chart

# set bars data by selecting column of each bar
# and create list from discribe() that shows descriptive statistics at min, 25%, 50%, 7
dribbling = cleaned_df.loc[:, 'dribbling'].describe()['min':'max'].values
speed = cleaned_df.loc[:, 'sprint_speed'].describe()['min':'max'].values
vision = cleaned_df.loc[:, 'vision'].describe()['min':'max'].values
heading = cleaned_df.loc[:, 'heading_accuracy'].describe()['min':'max'].values
shot = cleaned_df.loc[:, 'shot_power'].describe()['min':'max'].values
overall = cleaned_df.loc[:, 'overall_rating'].describe()['min':'max'].values

# create the bars and assign different color to each
plt.bar(ind, dribbling, width, color = 'g')
plt.bar(ind+width, speed, width, color = 'r')
plt.bar(ind+width*2, vision, width,color = 'b')
plt.bar(ind+width*3, heading, width,color = 'y')
plt.bar(ind+width*4, shot, width,color = 'black')
plt.bar(ind+width*5, overall, width ,color = 'grey')

# set legends names
plt.legend(('dribbling', 'speed', 'vision','heading_accuracy','overall'))
```

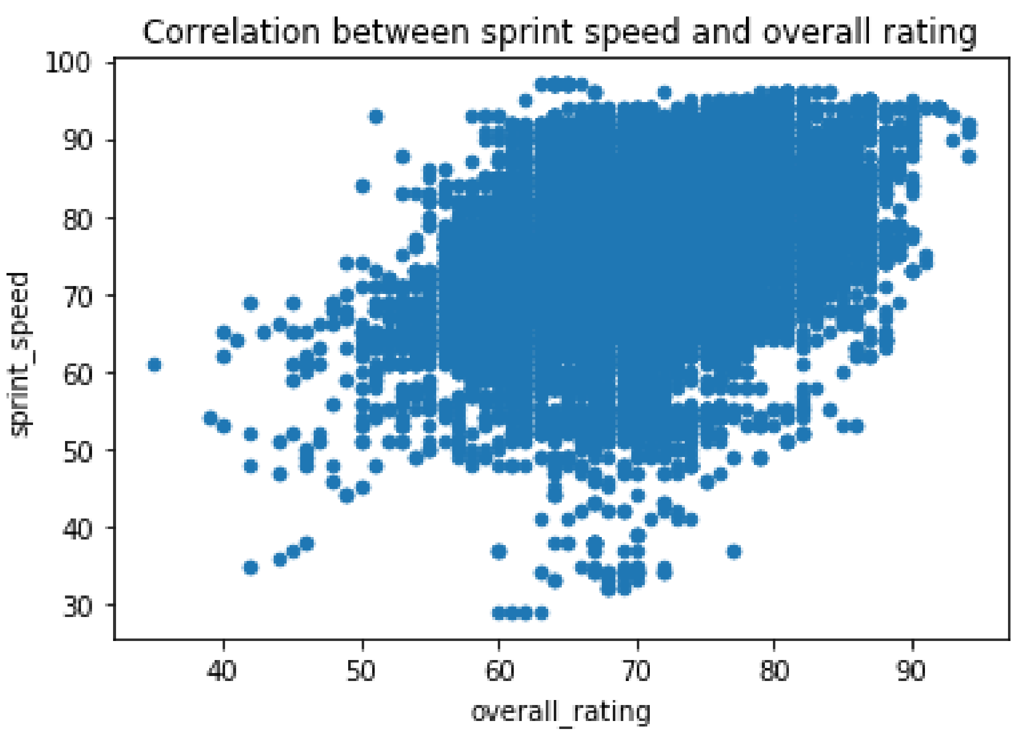
Out[27]: <matplotlib.legend.Legend at 0x7f7c49c3d320>



For the selected attributes: sprint speed(red bar) shows the highest rating among other attribute

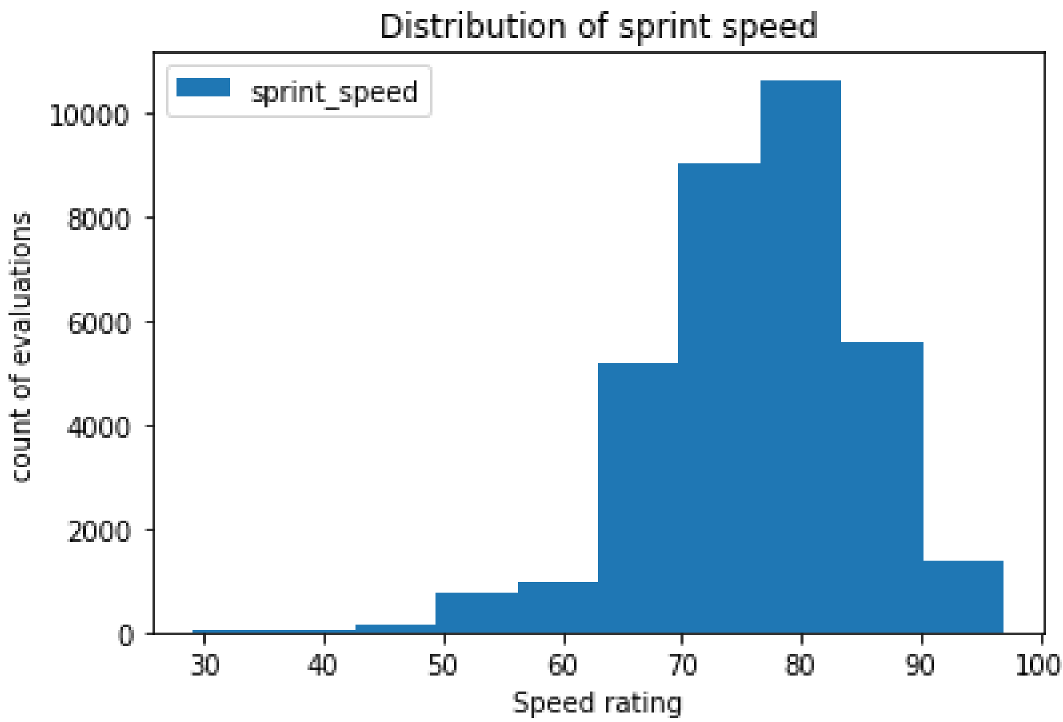
In [28]:
```
# sactter plot the correlation between sprint speed and overall rating
cleaned_df.plot(x= 'overall_rating' , y= 'sprint_speed' , kind = 'scatter', title = 'Co
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7c49c096d8>
```



Postive correlation between sprint speed and overall rating but shows high overall rate for some players with medium speed rate and vice versa

```
In [29]: # explore distribution of sprint speed

         cleaned_df.sprint_speed.plot(kind= 'hist',title = 'Distribution of sprint speed', legen
         plt.xlabel('Speed rating')
         plt.ylabel('count of evaluations')

Out[29]: Text(0,0.5,'count of evaluations')
```



Above chart shows the important of sprint speed for attackers, the distribution skewed left with long left tail and highest distribution rate located between 80 and 85

1.1.7 Challenges and limitations thourgh question 1:

- Trying to find most attributes related to strikers takes long time to explore about each of very large list of attributes (as per my opinion)

Conclusion Q2
Only 4 attributes have been selected as the most popular attributes, other attributes related to each one of selected may change the results, such ball control, finishing and volleys amy be realted to dribbling and acceleration, stamina and strength may related to sprint speed.

- Considering question2, the above bar chart show that the sprint speed is the most common attribute that all attackers need.

- Sprint speed exceeded the overall rating at evaluation except the minimum player's performance.
- At max bars, we can see that most of attributes are close to its others, because its the best player's performance that could reach a 100%.
- Below the max performance, we can see that the heading accuracy is the lowest attribute that players have.

In [30]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[30]: 0