International Soccer Player Ratings

DSC 530 FINAL PROJECT

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Fédération Internationale de Football Association(FIFA) publishes Player rating data set which contains over 85 features about 18000 players. The feaures and players are updated annually and players are rated from 1(worst) to 100(best) . The data set can be used for various purposes, one of which is in the gaming industry.

The goal of this study is to explore the 2019 publication of this dataset using statistical and programatic techniques.

Dataset description

- Single csv file
- 18209 observations
- 89 features
- 34 features recording each player’s skills with rating of 1(bad) to 100(good)
- ‘Potential’, ‘Overall’ features show the ratings based on various features such as skills, age, etc.. Their value ranges from 1(bad) to 5(good)
- Other features of interest:
  - Age, weight, height

Data Preparation

- Import Dataset
- Replace ‘lbs’ from the weight and convert to integer
- Convert height from “ft’inch” to Inches as type integer place in new column(Height_Inch)
- Compute experience in years from signing date

Question

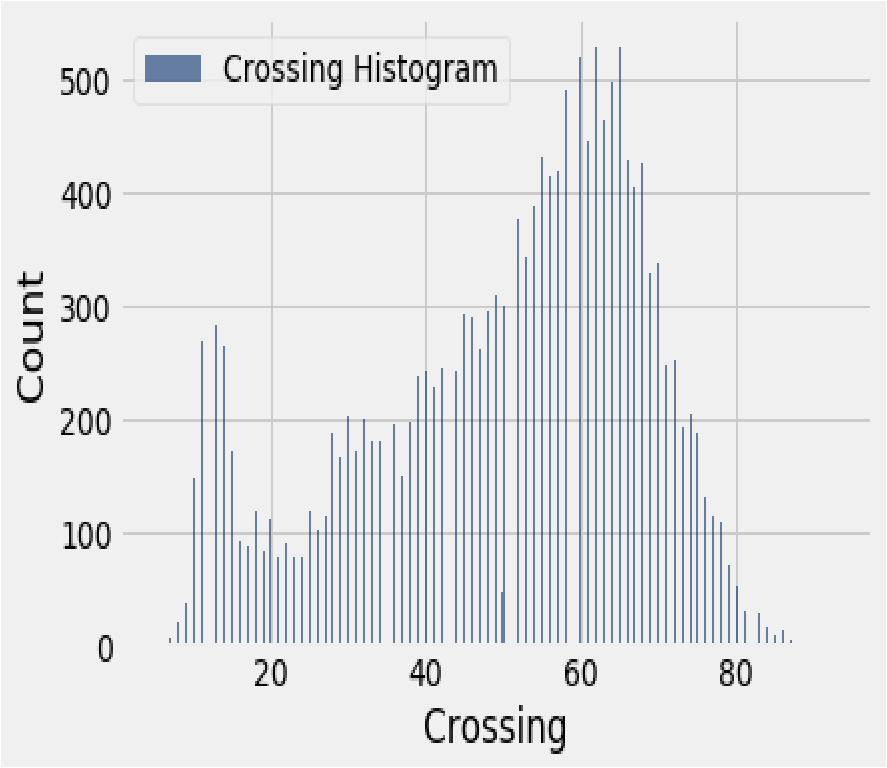
- Is the overall rating of players govern by their skill set.

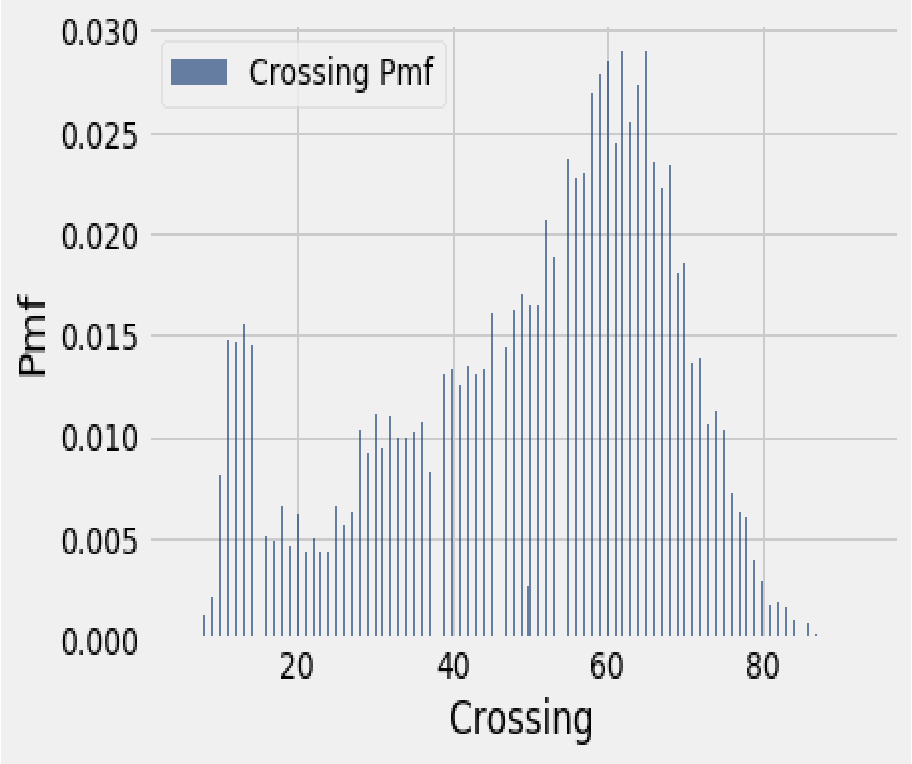
Data Exploration-Best in skill

```
Best Crossing : K. De Bruyne from Belgium
Best Finishing : L. Messi from Argentina
Best HeadingAccuracy : Naldo from Brazil
Best ShortPassing : L. Modrić from Croatia
Best Volleys : E. Cavani from Uruguay
Best Dribbling : L. Messi from Argentina
Best Curve : Quaresma from Portugal
Best FKAccuracy : L. Messi from Argentina
Best LongPassing : T. Kroos from Germany
Best BallControl : L. Messi from Argentina
Best Acceleration : Douglas Costa from Brazil
Best SprintSpeed : K. Mbappé from France
Best Agility : Neymar Jr from Brazil
Best Reactions : Cristiano Ronaldo from Portugal
Best Balance : Bernard from Brazil
Best ShotPower : Cristiano Ronaldo from Portugal
Best Jumping : Cristiano Ronaldo from Portugal
Best Stamina : N. Kanté from France
Best Strength : A. Akinfenwa from England
Best LongShots : L. Messi from Argentina
Best Aggression : B. Pearson from England
Best Interceptions : N. Kanté from France
Best Positioning : Cristiano Ronaldo from Portugal
Best Vision : L. Messi from Argentina
Best Penalties : M. Balotelli from Italy
Best Composure : L. Messi from Argentina
Best Marking : A. Barzagli from Italy
Best StandingTackle : G. Chiellini from Italy
Best SlidingTackle : Sergio Ramos from Spain
Best GKDiving : De Gea from Spain
Best GKHandling : J. Oblak from Slovenia
Best GKKicking : M. Neuer from Germany
Best GKPositioning : G. Buffon from Italy
Best GKReflexes : De Gea from Spain
```

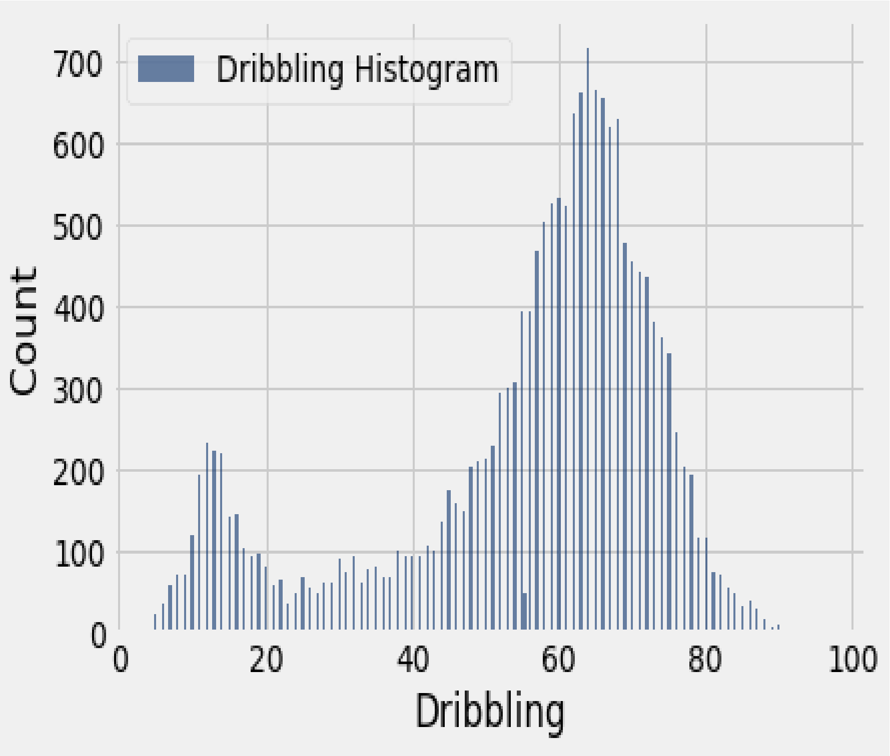
Best player in each skill category. Lionel Messi is the best overall player and is best rated in more skills than others.

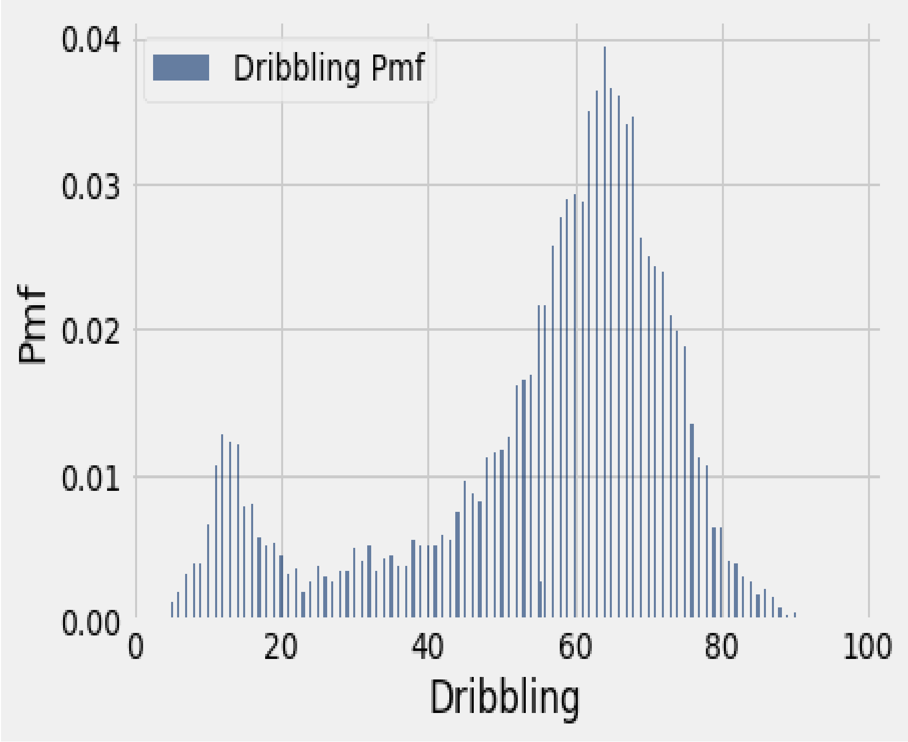
Data Exploration- Distributions



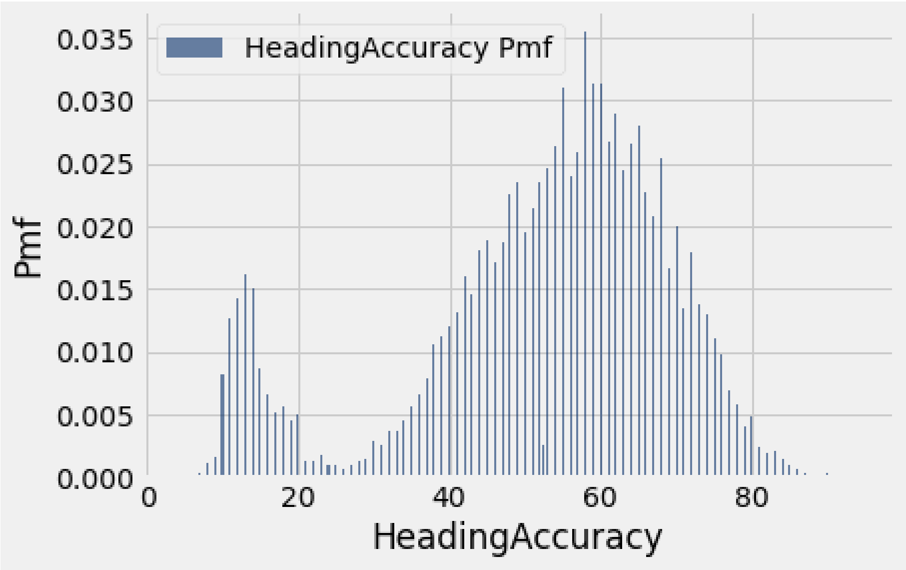


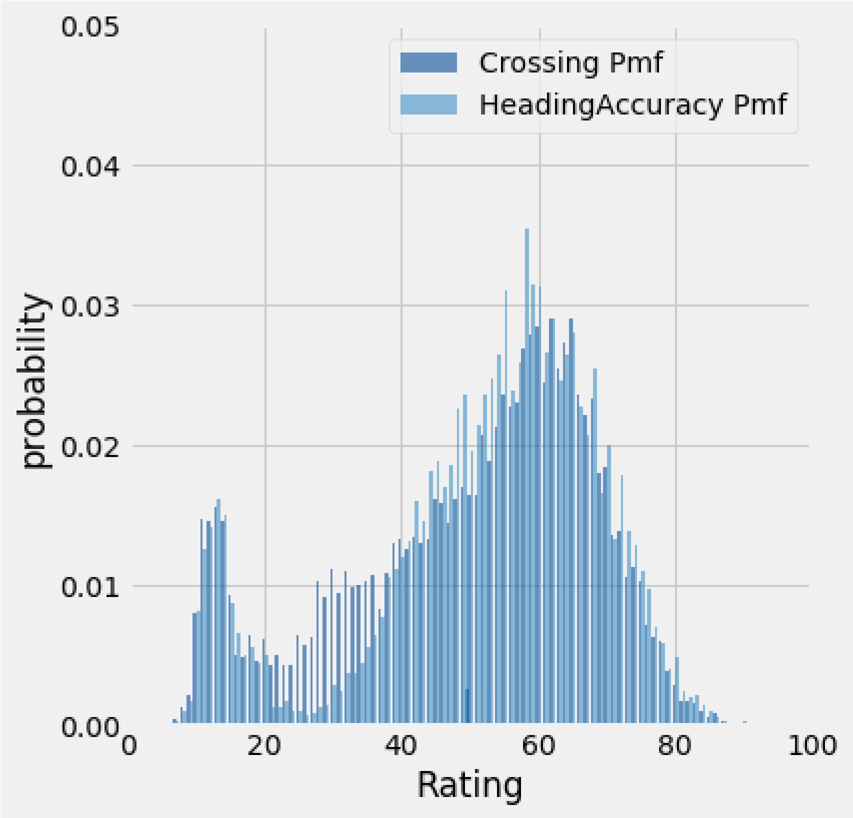
Data Exploration- Distributions

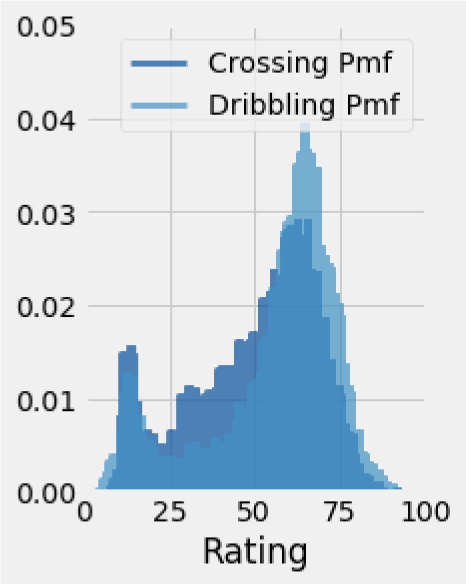




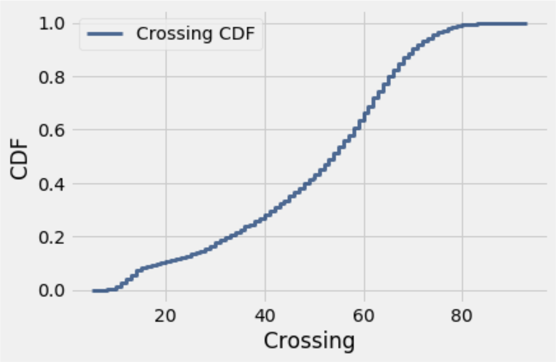
Data Exploration- Distribution comparison







Data Exploration- Distribution

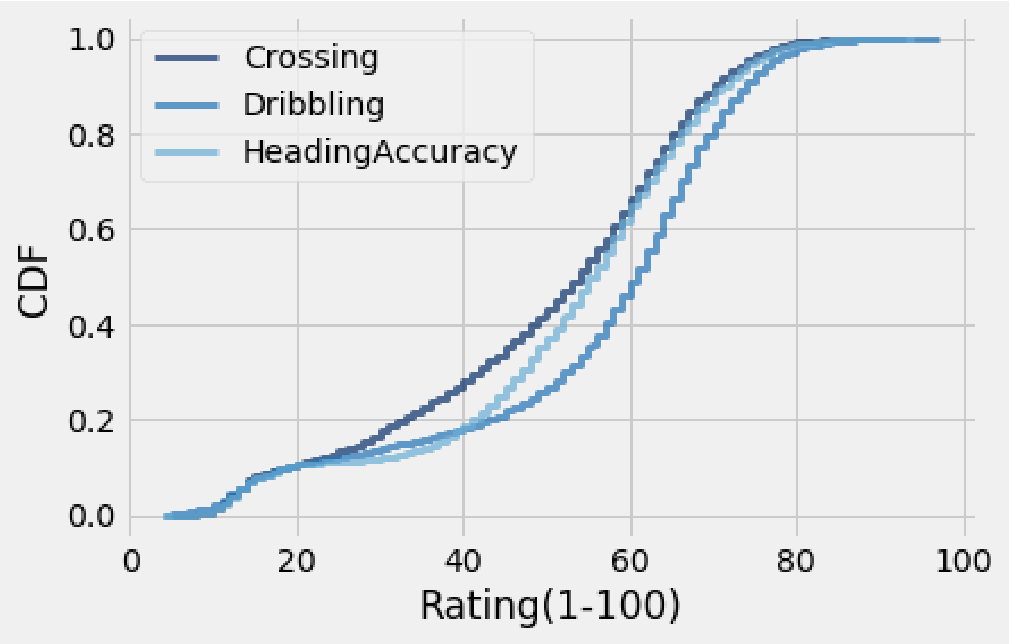



```
cdf.Prob(40),cdf.Prob(80)
#this means that 28 percent of the players have rating of 40 and 99 percent have rating of 80
```

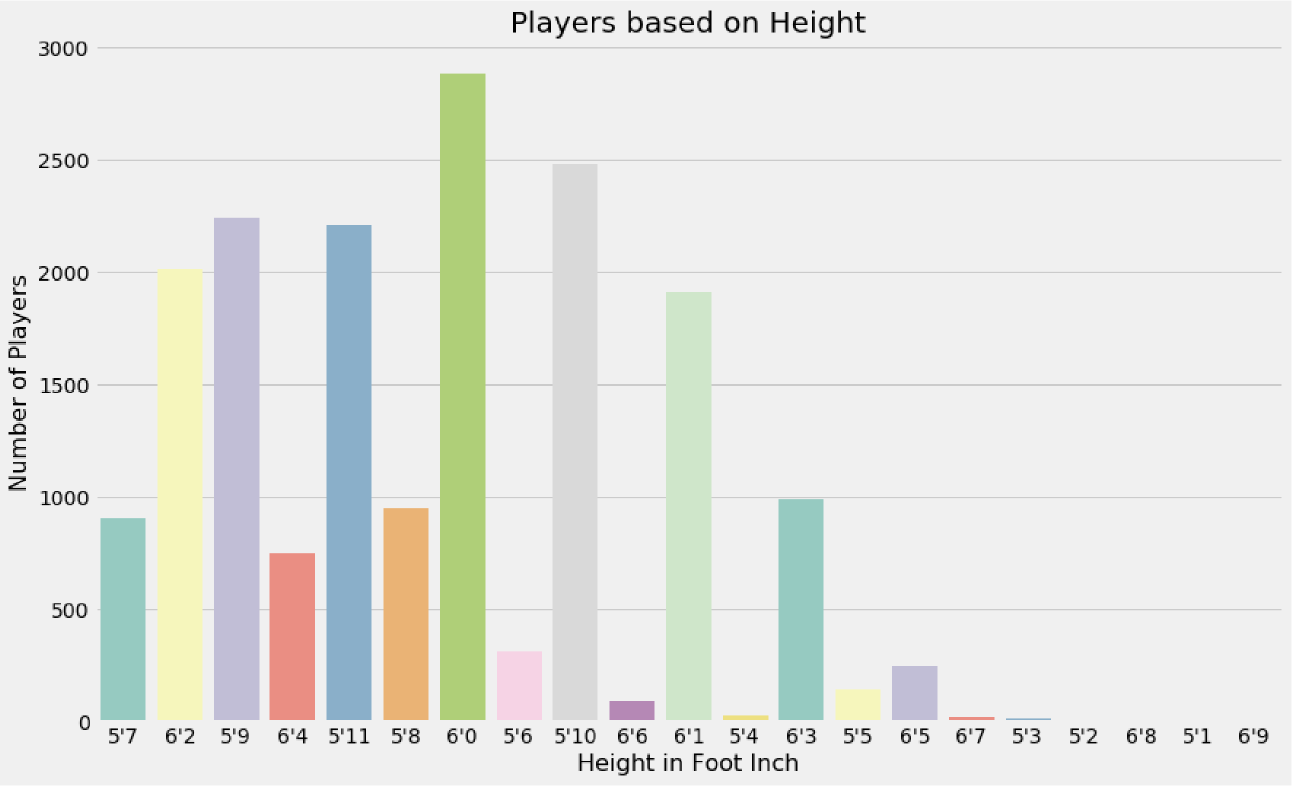
```
(0.28280331740539355, 0.9913220190036799)
```

```
cdf.Value(.5)
# This means that 50 percent have rating of 54
cdf.Prob(54)
# this shows that.
```

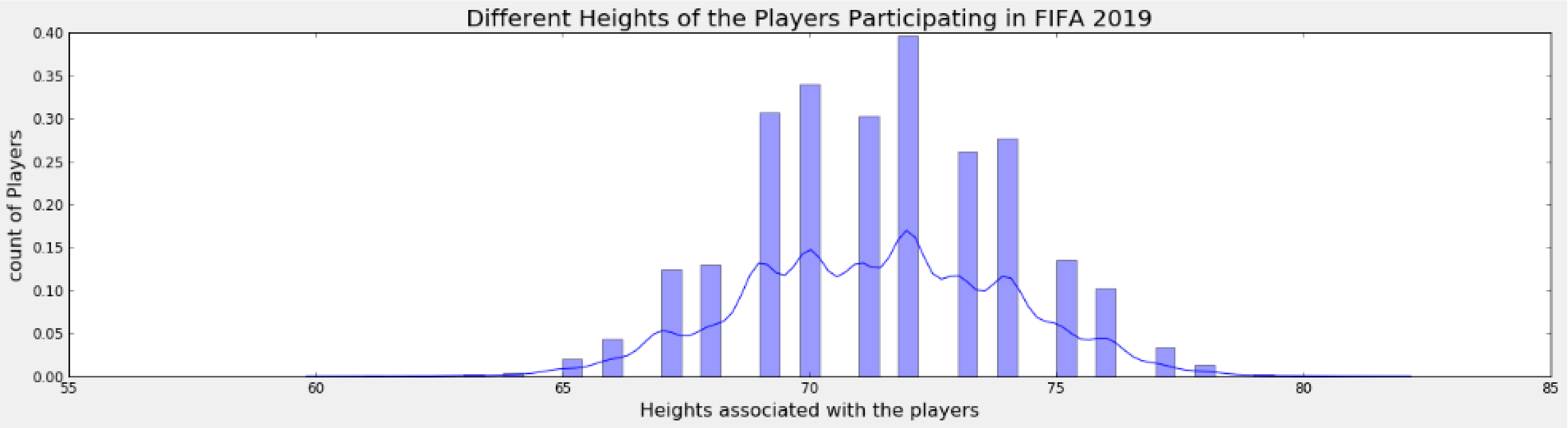
```
0.5113967155489647
```



Data Exploration- Distribution



Data Exploration- Distribution

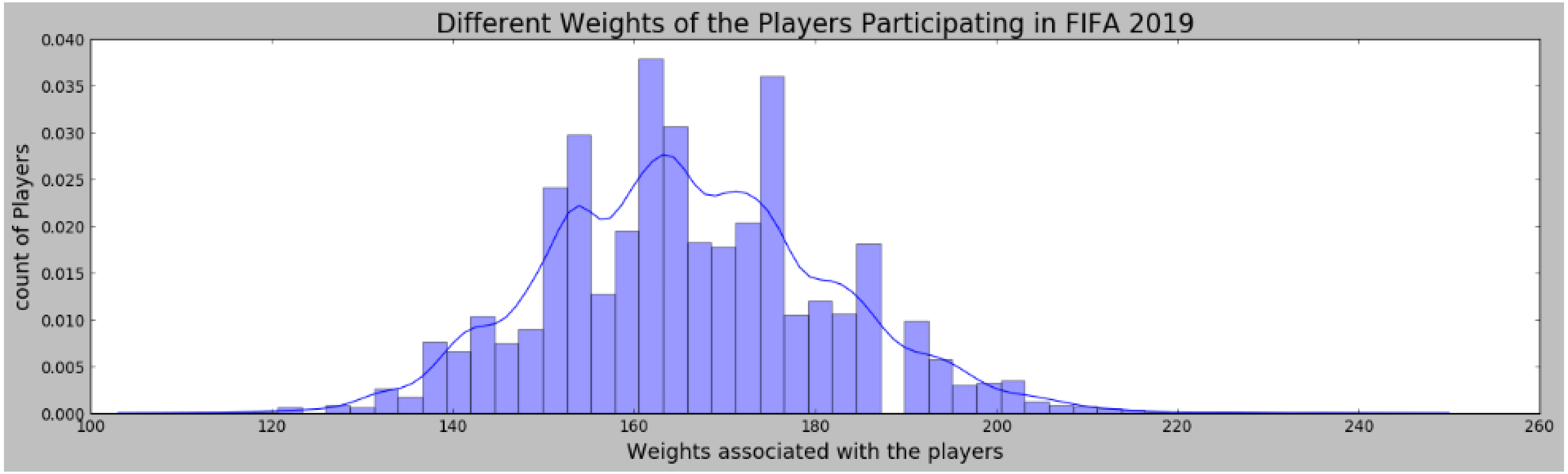



```
# Normal distribution in above graph shows to be 71.36 as shown here

statistics.mean(data['Height_Inch'])
```

71.3612533729831

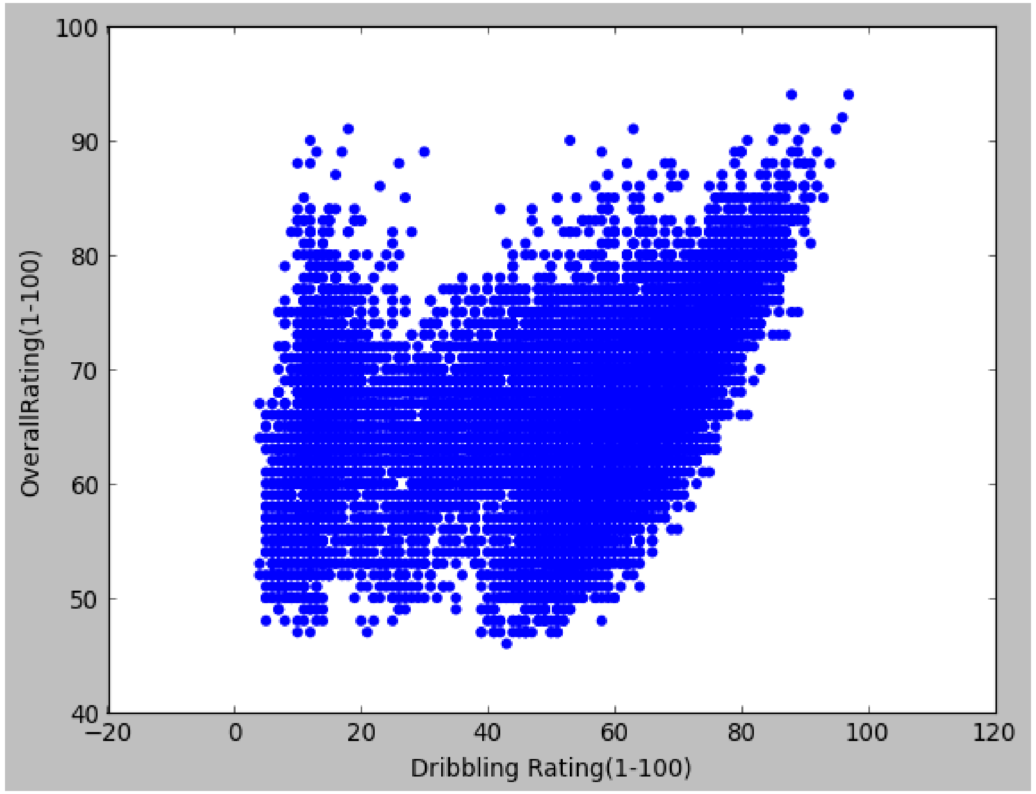
Data Exploration- Distribution




```
: statistics.mean(data['Weight'])
```

: 165.97912880665234

Data Exploration- Scatter plot



Modeling Coefficients

```
: statsmodels.formula

a = 'Overall ~ Cross
= smf.ols(formula, d
s = model.fit()
s.summary()
```

FKAccuracy	0.0005	0.002	0.223	0.824	-0.004	0.005
BallControl	0.1459	0.005	28.653	0.000	0.136	0.156
Acceleration	0.0325	0.004	8.332	0.000	0.025	0.040
SprintSpeed	0.0314	0.004	8.624	0.000	0.024	0.038
Agility	-0.0086	0.003	-3.073	0.002	-0.014	-0.003
Reactions	0.2833	0.004	75.435	0.000	0.276	0.291
ShotPower	0.0146	0.003	5.468	0.000	0.009	0.020
Jumping	0.0012	0.002	0.594	0.552	-0.003	0.005
Stamina	0.0030	0.002	1.278	0.201	-0.002	0.008
Strength	0.0434	0.002	19.147	0.000	0.039	0.048
Penalties	0.0008	0.003	0.297	0.767	-0.005	0.006
Composure	0.1164	0.003	38.078	0.000	0.110	0.122
Marking	0.0343	0.002	13.851	0.000	0.029	0.039
StandingTackle	0.0055	0.002	2.202	0.028	0.001	0.010
GKDiving	0.0744	0.006	12.536	0.000	0.063	0.086
GKHandling	0.0768	0.006	12.790	0.000	0.065	0.089
GKKicking	0.0334	0.006	6.035	0.000	0.023	0.044

Modeling Correlations

Acceleration	0.0292	0.004	7.771	0.000	0.022	0.037
SprintSpeed	0.0306	0.004	8.442	0.000	0.023	0.038
Reactions	0.2824	0.004	75.374	0.000	0.275	0.290
ShotPower	0.0141	0.003	5.345	0.000	0.009	0.019
Jumping	-0.0001	0.002	-0.056	0.955	-0.004	0.004
Stamina	0.0023	0.002	0.984	0.325	-0.002	0.007
Strength	0.0450	0.002	20.304	0.000	0.041	0.049
Penalties	0.0003	0.003	0.124	0.902	-0.005	0.006
Composure	0.1154	0.003	37.927	0.000	0.109	0.121
Marking	0.0346	0.002	13.967	0.000	0.030	0.039
StandingTackle	0.0063	0.002	2.533	0.011	0.001	0.011
GKDiving	0.0744	0.006	12.540	0.000	0.063	0.086
GKHandling	0.0770	0.006	12.832	0.000	0.065	0.089
GKKicking	0.0337	0.006	6.085	0.000	0.023	0.045
GKPositioning	0.0683	0.006	11.633	0.000	0.057	0.080
GKReflexes	0.0775	0.006	13.162	0.000	0.066	0.089

Omnibus:	45.524	Durbin-Watson:	1.680
Prob(Omnibus):	0.000	Jarque-Bera (JB):	57.150
Skew:	0.027	Prob(JB):	3.89e-13
Kurtosis:	3.269	Cond. No.	2.89e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.89e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
Remove features with negative coefficient
port statsmodels.formula.api as smf

rmula = 'Overall ~ Crossing+Finishing+HeadingAccuracy+ShortPassing+Curve+FKAccuracy+BallControl+Acceleration+SprintSpeed+Reacti
del = smf.ols(formula, data=data)
sults = model.fit()
sults.summary()
```

Modeling

```
]: #Split dataset into test and train datasets
from sklearn.model_selection import train_test_split
# Create test and train data set. Training data set is 80% of the total and test is 20%
X_train, X_test, y_train, y_test = train_test_split(Model_Independent_Variables, Model_Dependent_Variable, test_size=0.2,random_s

#One Hot Encoding
X_train = pd.get_dummies(X_train)
X_test = pd.get_dummies(X_test)
print(X_test.shape,X_train.shape)
print(y_test.shape,y_train.shape)
```

```
(3642, 34) (14565, 34)
(3642,) (14565,)
```

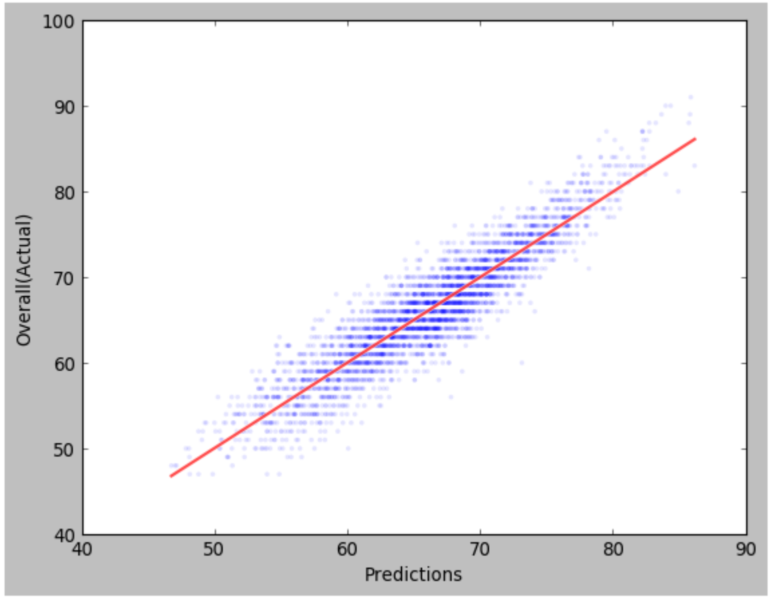
```
: #Apply Linear Regression
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)

#Finding the r2 score and root mean squared error
from sklearn.metrics import r2_score, mean_squared_error
print('r2 score: '+str(r2_score(y_test, predictions)))
print('RMSE : '+str(np.sqrt(mean_squared_error(y_test, predictions))))
```

```
r2 score: 0.8514783362139567
RMSE : 2.6485407085072126
```

Modeling – All Skills

```
thinkplot.Scatter(predictions, y_test, color='blue', alpha=0.1, s=10)
thinkplot.Plot(fit_xs, fit_ys, color='white', linewidth=3)
thinkplot.Plot(fit_xs, fit_ys, color='red', linewidth=2)
thinkplot.Config(xlabel="Predictions",
                 ylabel='Overall(Actual)',
                 legend=False)
```



Modeling – Less Skills

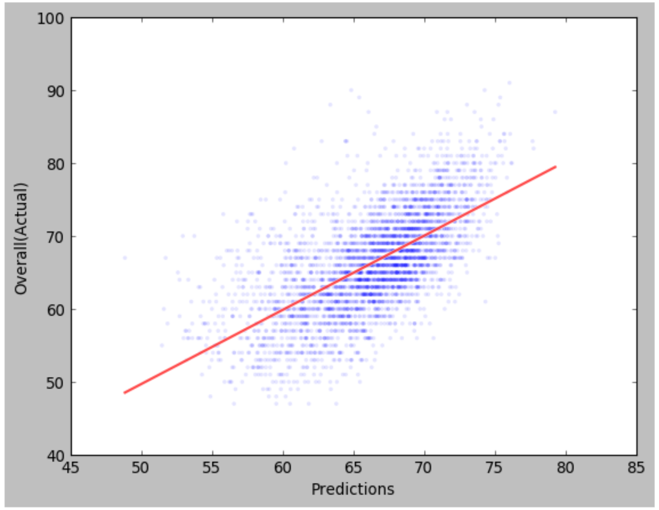
```python
# reduce features
Model_Independent_Variables = data[["Crossing","Finishing","HeadingAccuracy","ShortPassing","Volleys","Dribbling","Curve","LongPa
```

```python
inter, slope = LeastSquares(predictions, y_test)
inter,slope
```

```
(-1.1423557380204983, 1.0164462486903685)
```

```python
fit_xs, fit_ys = FitLine(predictions, inter, slope)
```

```python
thinkplot.Scatter(predictions, y_test, color='blue', alpha=0.1, s=10)
thinkplot.Plot(fit_xs, fit_ys, color='white', linewidth=3)
thinkplot.Plot(fit_xs, fit_ys, color='red', linewidth=2)
thinkplot.Config(xlabel="Predictions",
                 ylabel='Overall(Actual)',
                 legend=False)
```



Summary

The focus of this analysis was to determine which of the attributes in the dataset contribute the most to players rating. We focused on the 34 skills and found that even though there were collinearity among them, they are a good predictors of the overall rating.

We analyzed distributions, correlations, and ran the data through ordinary least square model and charted the result. When all skills were included the model fit better.

Further evaluation of data and other attributes would reveal more insight to not just overall rating, but also player selection, positioning and other aspects of the game.

It would be interesting to see if height can be a predictor of heading accuracy, or weight with speed and/or stamina.

The main challenge of this study was lack of experience interpreting statistical findings. With more experience and using tools available, I believe I can overcome this challenge.

Conclusions

You need all the skills you can get to be number one.

The skills rating had multicollinearity. We can eliminate them using a backward elimination technique by evaluating the coefficients, R2 and p-value at each iteration.

The prediction model was run with all skills and a subset. The prediction suffered when some skills were removed.

The dataset and its analysis can answer many other questions related to whether a player should be signed, what rate should the compensated, how long a contract to offer, can be a starter or better be on the bench until certain point in the game.