What Predicts Quality Starts in Tough Ballparks?

A Capstone by Tad Inglesby

Identify the Problem

- Unlike in other sports, baseball stadiums have unique factors that affect the outcome of games such as weather conditions and ballpark dimensions
- Coors Field (Denver)/Chase Field(Phoenix): Elevation and thin air
- Rogers Center (Toronto): Astro Turf
- Miller Park(Milwaukee): Field Dimensions
- Camden Yards and Globe Life Park: Summer humidity
- These conditions help create positive run-scoring environments for home and away hitters, adversely affect pitchers
- Convention: Ground Ball Pitchers → More success in these environments
- What explains quality starts, ground balls or something else?

Acquire the Data

- Averaged Park Factor Rankings by Runs from 2011-2016 and categorized top 10 as “Hard” Ballpark Dataset, and bottom 20 as “Easy” Ballpark
- Scraped starting pitching lines from box scores for every game from 2014-2016, grouping them into the hard or easy ballparks categories

MLB Park Factors - 2011

RK	PARK NAME	RUNS	
1	Globe Life Park in Arlington (Arlington, Texas)	1.409	1
2	Coors Field (Denver, Colorado)	1.347	1
3	Fenway Park (Boston, Massachusetts)	1.173	0
4	Rogers Centre (Toronto, Ontario)	1.152	1
5	Chase Field (Phoenix, Arizona)	1.146	1
6	Yankee Stadium (New York, New York)	1.131	1
7	Minute Maid Park (Houston, Texas)	1.100	1
8	Great American Ball Park (Cincinnati, Ohio)	1.082	1
9	Comerica Park (Detroit, Michigan)	1.061	0
10	Miller Park (Milwaukee, Wisconsin)	1.041	1

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Pitching	IP	H	R	ER	BB	SO	HR	ERA	BF	Pit	Str	Ctct	StS	StL	GB	FB	LD
Miguel Gonzalez, L (0-1)	5.2	3	1	1	5	5	0	1.59	23	98	59	35	9	15	10	3	1

Ballparks

Parse/Mine/Refine the Data

Dropped one row of data with an infinite FIP valueUsed RegEx to eliminate Game Record in name column

Dropped irrelevant columns and derived new target columns from existing ones

	Name	IP	H	R	ER	BB	K	HR	ERA	BF	...	StS	StL	GB	FB	LD	GB_rate	FB_rate	LD_rate	QS	FIP
0	Wade Miley	5.0	3	3	3	2	8	1	5.40	22	...	11.0	15.0	6.0	7.0	3.0	0.375000	0.437500	0.187500	0	3.800000
1	Trevor Cahill	4.0	8	5	5	4	1	0	11.25	23	...	3.0	10.0	8.0	9.0	6.0	0.347826	0.391304	0.260870	0	5.700000
2	Brandon McCarthy	6.2	6	5	5	1	4	1	6.75	27	...	7.0	20.0	11.0	11.0	5.0	0.407407	0.407407	0.185185	0	4.490323
3	Wade Miley	7.0	6	4	4	1	5	1	5.25	28	...	12.0	18.0	11.0	11.0	5.0	0.407407	0.407407	0.185185	0	4.057143
4	Trevor Cahill	6.0	4	2	2	3	3	0	6.30	25	...	7.0	16.0	9.0	10.0	5.0	0.375000	0.416667	0.208333	1	3.700000
5	Bronson Arroyo	4.1	5	2	2	2	3	1	4.15	20	...	2.0	17.0	6.0	9.0	4.0	0.315789	0.473684	0.210526	0	6.370732
6	Brandon McCarthy	7.0	10	6	6	1	4	1	7.78	31	...	10.0	12.0	18.0	8.0	8.0	0.529412	0.235294	0.235294	0	4.342857
7	Wade Miley	5.0	8	5	5	3	4	1	5.04	25	...	6.0	20.0	8.0	10.0	7.0	0.320000	0.400000	0.280000	0	6.000000
8	Trevor Cahill	4.0	5	7	6	5	8	2	9.17	22	...	16.0	17.0	5.0	4.0	1.0	0.500000	0.400000	0.100000	0	9.450000
9	Josh Collmenter	4.0	5	3	3	1	3	0	3.75	18	...	4.0	12.0	6.0	8.0	3.0	0.352941	0.470588	0.176471	0	2.450000

Parse/Mine/Refine the Data

Features

```
['Name', 'IP', 'H', 'R','ER','BB','K','HR','ERA','BF','Pit','Str', 'Ctct', 'StS', 'StL', 'GB', 'FB', 'LD']
```

```
['H', 'HR','BB','K', 'Ctct', 'StS', 'StL', 'GB', 'FB', 'LD']]
```

```
['BB','K', 'Ctct', 'StS', 'StL', 'GB', 'FB', 'LD']]
```

Quality Starts

```
#Create a column for Quality Starts
QS = []

for x,y in zip( baseball4['IP'].values,baseball4['ER'].values):
    if x >= 6.0:
        if y <= 3.0:
            QS.append(1)
        else:
            QS.append(0)
    else:
        QS.append(0)
```

Build a Model: Logistic Regression, Tough Parks

```
X = baseball16[['BB','K', 'Ctct', 'StS', 'StL', 'GB',
```

```
#logreg scorewith IP, ER, Pit R, H,HR, BF, ERA, HR out, test size = 0
```

```
0.73259820813232257
```

	precision	recall	f1-score	support
0	0.76	0.75	0.75	793
1	0.70	0.71	0.71	658
avg / total	0.73	0.73	0.73	1451

```
cross_val_score(logreg, X_scaled, y2, cv=5)
```

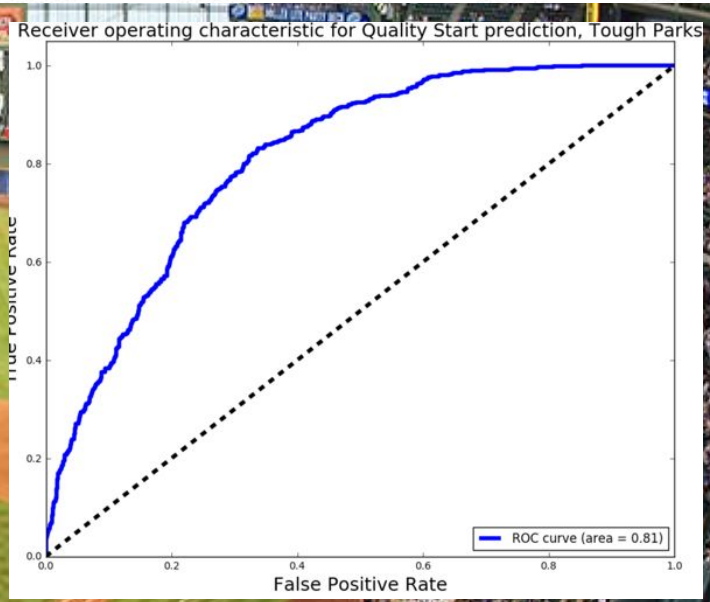
```
array([ 0.7375    ,  0.75312856,  0.72696246,  0.73265074,  0.74601367])
```

```
baseball6_scores = cross_val_score(logreg, X_scaled, y2, cv=5, scoring='roc
print np.mean(baseball6_scores)
```

```
0.820343432046
```

```
from sklearn.metrics import confusion_matrix
confusion = np.array(confusion_matrix(y_test, y_pred))
print(confusion)
```

```
[[596 197]
 [191 467]]
```



Build a Model: Logistic Regression, Easy Parks

```
#Easy Park Score, scaled, test size = 0.33, C = 0.1, penalty = 'l1'
```

```
0.73163841807909602
```

```
from sklearn.metrics import confusion_matrix
confusion = np.array(confusion_matrix(y_test, y_pred))
print(confusion)
```

```
[[1048  463]
 [ 392 1283]]
```

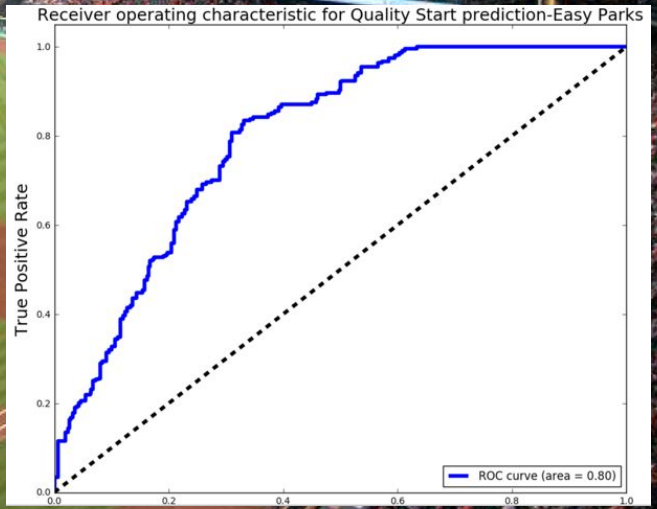
```
cross_val_score(logreg, X_scaled, y2, cv=5)
```

```
array([ 0.73706004,  0.72901554,  0.75544041,  0.72901554,  0.72746114])
```

```
easy_baseball4_scores = cross_val_score(logreg, X_scaled, y2, cv=5, scoring
print np.mean(easy_baseball4_scores)
```

```
0.794116798582
```

	precision	recall	f1-score	support
0	0.73	0.69	0.71	1511
1	0.73	0.77	0.75	1675
avg / total	0.73	0.73	0.73	3186



Decision Tree, Tough Ballparks

```
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)
```

```
0.15745768125199611
```

```
rt = tree.DecisionTreeClassifier(
 min_samples_split=30, min_samples_leaf=5,
  random_state=0)
rt.fit(X_scaled,y2)
```

```
if current_score < best_score or best_score == 0:
    best_score = current_score
    best_depth = i
```

```
Best score:
0.56089626926
Best depth:
6

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```

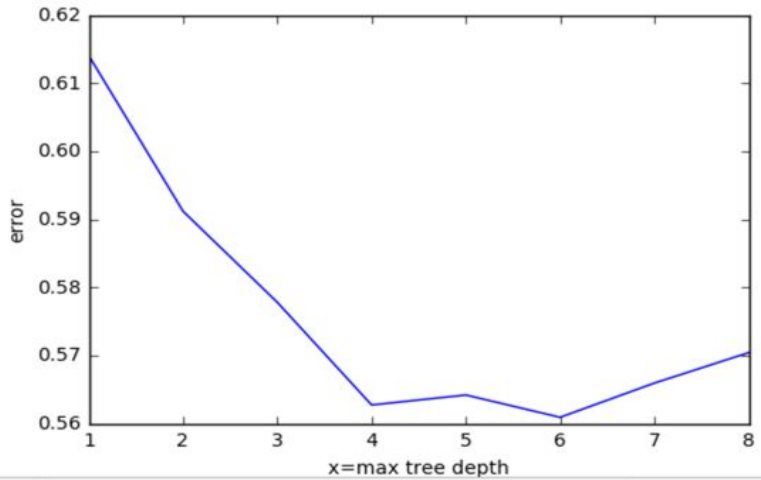

Decision Trees, Easy Ballparks

```
rt = tree.DecisionTreeClassifier(
 min_samples_split=30, min_samples_leaf=5,
  random_state=0)
rt.fit(X_scaled,y2)
```

```
if current_score < best_score or best_score == 0:
    best_score = current_score
    best_depth = i
```

```
Best score:
0.41541799521
Best depth:
8

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```
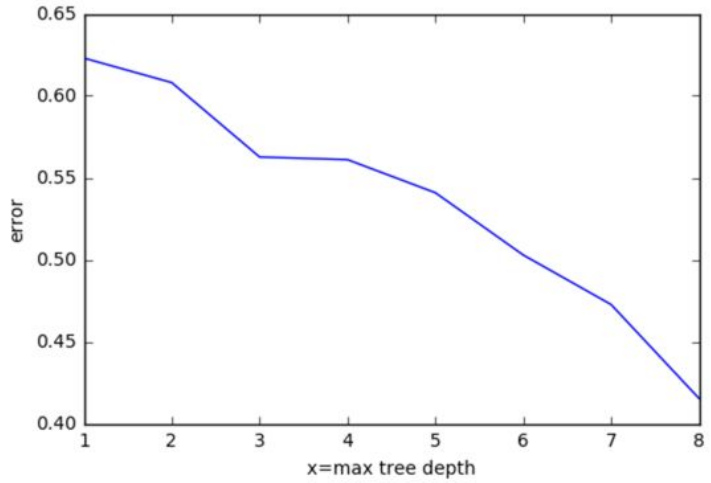
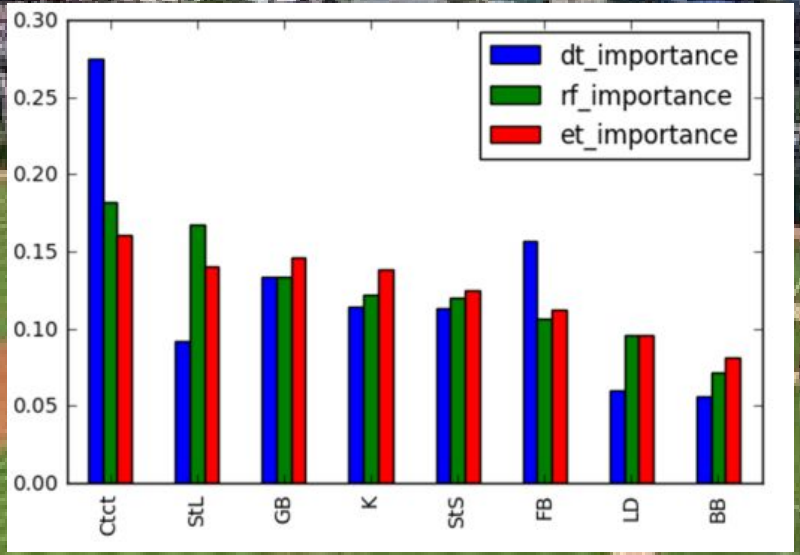



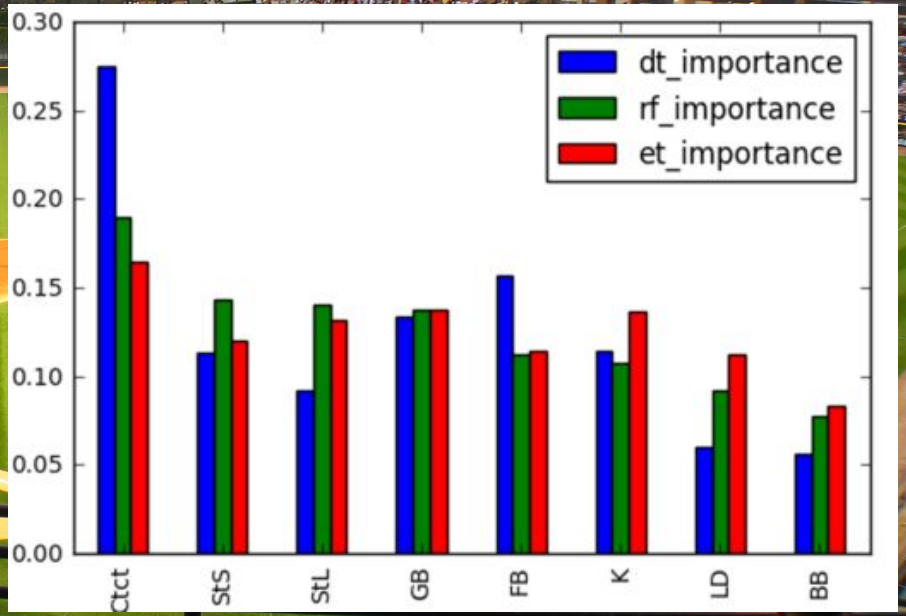
Tough Ballpark Feature Importances

	dt_importance	rf_importance	et_importance
Ctct	0.274694	0.182055	0.160359
StL	0.091903	0.167701	0.140590
GB	0.133592	0.133249	0.146049
K	0.113881	0.121727	0.138641
StS	0.112903	0.120510	0.125079
FB	0.156794	0.106501	0.112496
LD	0.059687	0.096271	0.095496
BB	0.056546	0.071985	0.081291



Feature Importances, Easy Parks, H & HR excluded

	dt_importance	rf_importance	et_importance
Ctct	0.274694	0.189599	0.164411
StS	0.112903	0.142824	0.120166
StL	0.091903	0.140711	0.131473
GB	0.133592	0.137693	0.137140
FB	0.156794	0.111928	0.114359
K	0.113881	0.107485	0.136465
LD	0.059687	0.092341	0.112603
BB	0.056546	0.077418	0.083382



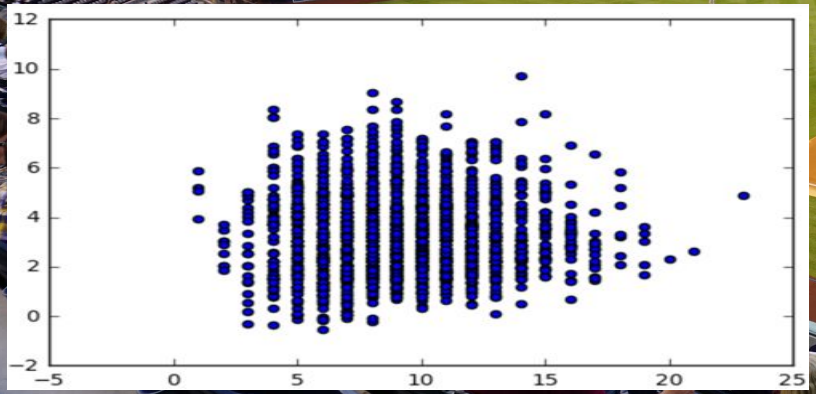
Ground Balls vs. FIP and Linear Regression

```
[['Ctct', 'StS', 'StL', 'GB', 'FB', 'LD']]
```

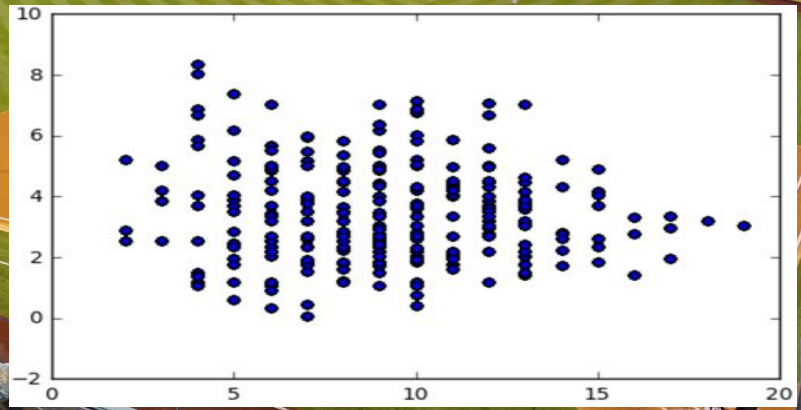
```
print linreg.coef_

[-0.04245273 -0.12568147 -0.07458922  0.02743294  0.12025419 -0.1082011 ]
```

```
[ 0.37614754 -0.33857451 -0.03239205  0.00564134 -0.01709578 -0.05902336
  0.06926775 -0.07827734]
```

```
baseball4['FIP'] = ((((13*baseball4.HR)+(3*baseball4.BB)-(2*baseball4.K))/baseball4.IP)+3.2)
```



Hard



Easy

Decision Trees on Quality Starts and FIP

```
Best score:
1.5171059667
Best depth:
3

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```
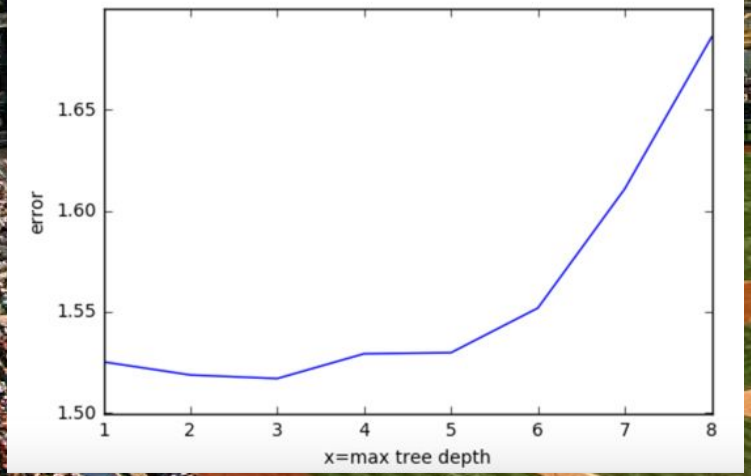
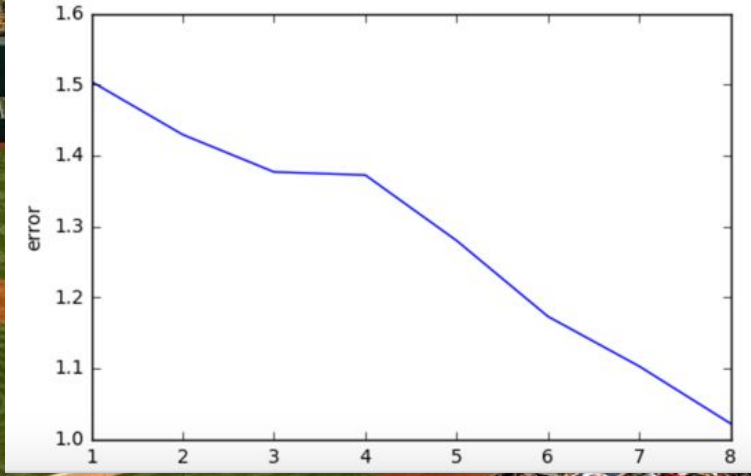



Hard

Easy

```
Best score:
1.02186245132
Best depth:
8

<matplotlib.text.Text at 0x7f3635c71a50>
```



Easy

Features Importances: DT Regression Quality Starts=1 and FIP

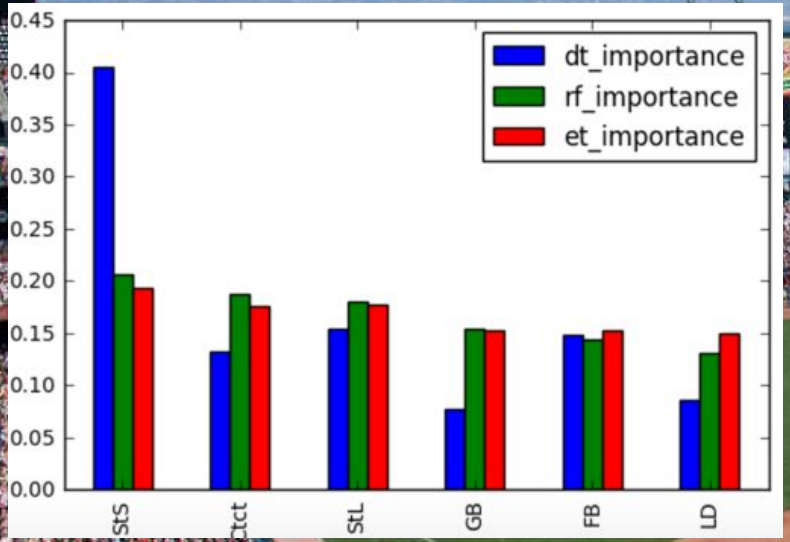
	dt_importance	rf_importance	et_importance
StS	0.405409	0.205797	0.193260
Ctct	0.131516	0.187460	0.175738
StL	0.153462	0.179468	0.176985
GB	0.077070	0.153711	0.152995
FB	0.147500	0.143096	0.151949
LD	0.085043	0.130469	0.149073

Hard

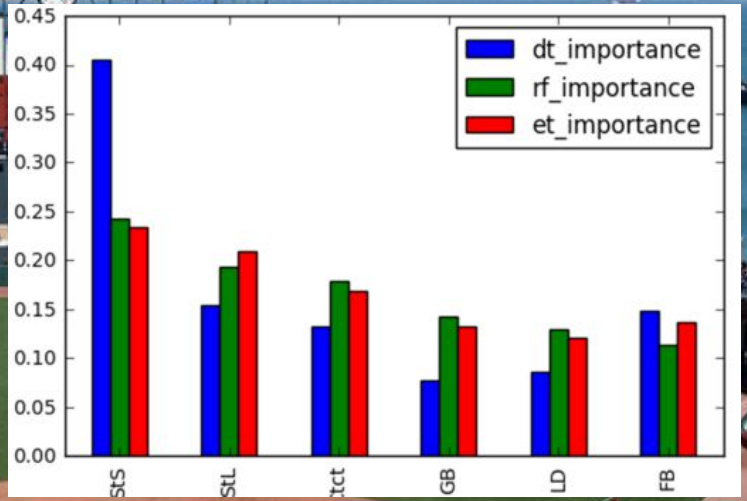
	dt_importance	rf_importance	et_importance
StS	0.405409	0.242929	0.234188
StL	0.153462	0.193710	0.208585
Ctct	0.131516	0.178751	0.167889
GB	0.077070	0.142677	0.132890
LD	0.085043	0.128903	0.120062
FB	0.147500	0.113031	0.136386

Easy

Features Importances: Quality Starts and FIP



Hard



Easy

Present Results

- Swing most “important feature in predicting Quality Starts
- Ground Balls important, but not the most important in logistic regression and Decision Tree/Random Forest/Extra Trees Classification
- Once Quality Starts stripped out, and regressed against FIP, Ground Balls shown to not be predictive in linear regression context
    - Also not shown to have substantial feature importance in decision tree, random forest, and extra trees regression when examining FIP in quality starts only
    - Swinging Strikes and Strikes by Contact most important
- Future expansion on this study would account for quality of contact data
    - Hard, Medium, Soft