

```
In [335]: %matplotlib inline
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
from sklearn import metrics
from sklearn.model_selection import train_test_split
from pandas import Series

import pandas as pd
import numpy as np
```

```
In [336]: data = pd.read_csv('/Users/juanrquilesjr/Documents/Machine_Learning-Spring_2019/assignment-6/nba.csv')
```

```
In [337]: data.head(5)
```

```
Out[337]:
```

	age	g	gs	mp	fg	fga	fg.	x3p	x3pa	x3p.	...	ft.	orb	drb	trb	ast	stl	blk	tov	pf	pts
0	23	63	0	847	66	141	0.468	4	15	0.266667	...	0.660	72	144	216	28	23	26	30	122	1
1	20	81	20	1197	93	185	0.503	0	0	0.000000	...	0.581	142	190	332	43	40	57	71	203	1
2	27	53	12	961	143	275	0.520	0	0	0.000000	...	0.639	102	204	306	38	24	36	39	108	1
3	28	73	73	2552	464	1011	0.459	128	300	0.426667	...	0.815	32	230	262	248	35	3	146	136	3
4	25	56	30	951	136	249	0.546	0	1	0.000000	...	0.836	94	183	277	40	23	46	63	187	1

5 rows × 26 columns

```
In [338]: data.columns
```

```
Out[338]: Index(['age', 'g', 'gs', 'mp', 'fg', 'fga', 'fg.', 'x3p', 'x3pa', 'x3p.',
              'x2p', 'x2pa', 'x2p.', 'efg.', 'ft.', 'fta', 'ft.', 'orb', 'drb', 'trb',
              'ast', 'stl', 'blk', 'tov', 'pf', 'pts'],
              dtype='object')
```

```
In [339]: #feature variables
X = data.drop('pts',axis =1).values

#target variables
y = data['pts'].values
```

\*\*\*\* L1 Regularization \*\*\*\*

```
In [350]: # data divide into train and testing sets
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=5)
```

```
In [351]: #instantiate the LR model
lr = LogisticRegression(multi_class='multinomial', penalty = 'l1', solver='saga', tol=0.1)

# fit the model with data
lr.fit(X_train,y_train)
```

```
Out[351]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                             intercept_scaling=1, max_iter=100, multi_class='multinomial',
                             n_jobs=1, penalty='l1', random_state=None, solver='saga',
                             tol=0.1, verbose=0, warm_start=False)
```

```
In [352]: y_pred = lr.predict(X_test)
```

```
In [353]: accuracy = metrics.accuracy_score(y_test,y_pred)

micro = f1_score(y_test, y_pred, average = 'micro')
macro = f1_score(y_test, y_pred, average = 'macro')
weighted = f1_score(y_test, y_pred, average = 'weighted')

#f1 score/accuracy with l1 regularization
print('l1 accuracy: %.2f' % accuracy)
print('l1 Micro f1_score: %.2f' % micro)
print('l1 Micro f1_score: %.2f' % macro)
print('l1 Micro f1_score: %.2f' % weighted)

l1 accuracy: 0.81
l1 Micro f1_score: 0.81
l1 Micro f1_score: 0.45
l1 Micro f1_score: 0.80

/Users/juanrquilesjr/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricWarning: F-score is ill-defined
and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

```
In [354]: lr.coef_
```

```
Out[354]: array([[ 5.89972602e-03,  5.02549318e-03, -1.60039136e-03,
 3.71475227e-03, -3.29426162e-03, -4.58889455e-03,
 8.78728239e-05, -8.61213090e-04, -1.59313959e-03,
 3.88798976e-05, -2.43101789e-03, -2.99373159e-03,
 9.34367276e-05,  9.62770675e-05, -2.15718567e-03,
-2.33539817e-03,  1.28258697e-04,  8.55167851e-04,
-1.01348852e-04,  7.54995488e-04, -1.15384321e-03,
 4.07726515e-05,  3.93268264e-04,  2.18328828e-04,
 3.56244957e-03],
 [-1.62157761e-03, -9.85808088e-04,  1.42453229e-04,
 2.86859550e-03, -6.93181636e-04, -2.09886661e-03,
-2.26219512e-05, -6.02993211e-05, -1.77574557e-05,
-9.90828939e-06, -6.31006895e-04, -2.08032073e-03,
-2.39680588e-05, -2.47715212e-05, -1.42907103e-03,
-1.73182916e-03, -3.20167611e-05,  5.44023997e-04,
-4.06319232e-05,  5.04888794e-04, -1.93070116e-03,
 1.43455892e-04, -6.52331435e-05, -8.00355908e-04,
 4.98733001e-04],
 [-1.86604900e-03, -1.91917858e-03,  7.62196570e-04,
-4.49928074e-05,  3.83946030e-04,  9.95433257e-04,
-2.68968307e-05,  6.73092640e-05,  1.26630303e-04,
-1.04030588e-05,  3.14644427e-04,  8.66805244e-04,
-2.87690642e-05, -2.97062778e-05,  6.25399798e-05,
 3.17556468e-04, -4.22899879e-05, -2.15487437e-06,
 7.26158225e-05,  6.88416894e-05,  4.77985389e-04,
-2.20382360e-04,  1.33318696e-04,  4.05776215e-05,
-1.77497830e-03],
 [-1.34003396e-03, -1.24229996e-03,  5.00848363e-04,
-3.38919689e-03,  1.98473566e-03,  3.36339327e-03,
-1.83665155e-05,  4.76865052e-04,  7.41923832e-04,
-7.56351015e-06,  1.50588987e-03,  2.61949174e-03,
-1.97373343e-05, -2.03039282e-05,  1.73641607e-03,
 1.79218246e-03, -2.75731256e-05, -9.09108761e-04,
-1.38875639e-04, -1.05002204e-03,  2.01132886e-03,
 4.09006910e-05, -2.92844160e-04,  3.02581280e-04,
-1.21980584e-03],
 [-1.06594858e-03, -8.72124424e-04,  1.89359643e-04,
-3.14728784e-03,  1.61699784e-03,  2.32723158e-03,
-1.38848111e-05,  3.75772441e-04,  7.39598788e-04,
-5.00855410e-06,  1.23962047e-03,  1.58605091e-03,
-1.48557314e-05, -1.53926250e-05,  1.78561677e-03,
 1.95582350e-03, -2.02913289e-05, -4.85887207e-04,
 2.08524590e-04, -2.77071396e-04,  5.93639997e-04,
-6.55188890e-06, -1.66647139e-04,  2.34727221e-04,
-1.06435863e-03]])
```

```
In [363]: features = data.drop('pts' ,axis =1).columns
          for i in lr.coef_:
              print(Series(i,features).sort_values())
```

fga	-0.004589
fg	-0.003294
x2pa	-0.002994
x2p	-0.002431
fta	-0.002335
ft	-0.002157
gs	-0.001600
x3pa	-0.001593
ast	-0.001154
x3p	-0.000861
drb	-0.000101
x3p.	0.000039
stl	0.000041
fg.	0.000088
x2p.	0.000093
efg.	0.000096
ft.	0.000128
tov	0.000218
blk	0.000393
trb	0.000755
orb	0.000855
pf	0.003562
mp	0.003715
g	0.005025
age	0.005900
dtype:	float64
fga	-0.002099
x2pa	-0.002080
ast	-0.001931
fta	-0.001732
age	-0.001622
ft	-0.001429
g	-0.000986
tov	-0.000800
fg	-0.000693
x2p	-0.000631
blk	-0.000065
x3p	-0.000060
drb	-0.000041
ft.	-0.000032
efg.	-0.000025
x2p.	-0.000024
fg.	-0.000023
x3pa	-0.000018
x3p.	-0.000010
gs	0.000142
stl	0.000143
pf	0.000499
trb	0.000505
orb	0.000544
mp	0.002869
dtype:	float64
g	-0.001919
age	-0.001866
pf	-0.001775
stl	-0.000220
mp	-0.000045
ft.	-0.000042
efg.	-0.000030
x2p.	-0.000029
fg.	-0.000027
x3p.	-0.000010
orb	-0.000002
tov	0.000041
ft	0.000063
x3p	0.000067
trb	0.000069
drb	0.000073
x3pa	0.000127
blk	0.000133
x2p	0.000315
fta	0.000318
fg	0.000384
ast	0.000478
gs	0.000762
x2pa	0.000867
fga	0.000995
dtype:	float64
mp	-0.003389
age	-0.001340
g	-0.001242
pf	-0.001220
trb	-0.001050
orb	-0.000909
blk	-0.000293
drb	-0.000139
ft.	-0.000028
efg.	-0.000020
x2p.	-0.000020
fg.	-0.000018
x3p.	-0.000008
stl	0.000041
tov	0.000303
x3p	0.000477
gs	0.000501
x3pa	0.000742
x2p	0.001506
ft	0.001736
fta	0.001792
fg	0.001985
ast	0.002011
x2pa	0.002619
fga	0.003363
dtype:	float64
mp	-0.003147
age	-0.001066

```

pf      -0.001064
g       -0.000872
orb     -0.000486
trb     -0.000277
blk     -0.000167
ft.     -0.000020
efg.    -0.000015
x2p.    -0.000015
fg.     -0.000014
stl     -0.000007
x3p.    -0.000005
gs      0.000189
drb     0.000209
tov     0.000235
x3p     0.000376
ast     0.000594
x3pa    0.000740
x2p     0.001240
x2pa    0.001586
fg      0.001617
ft      0.001786
fta     0.001956
fga     0.002327
dtype: float64

```

\*\*\*\* Coefficient Visualizations(least and most important) \*\*\*\*

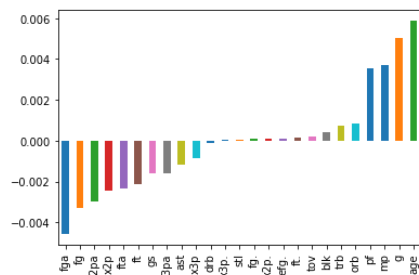
```

In [356]: coef = Series(lr.coef_[0],features).sort_values()
coef.plot(kind = 'bar')

# Top 3 features:  mp, g, age

```

Out[356]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1a24524630>



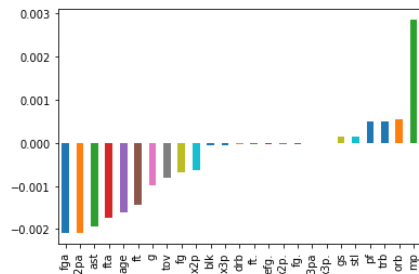
```

In [357]: coef = Series(lr.coef_[1],features).sort_values()
coef.plot(kind = 'bar')

#Top 3 features:  trb, orb, mp

```

Out[357]: <matplotlib.axes.\_subplots.AxesSubplot at 0x117f62e80>

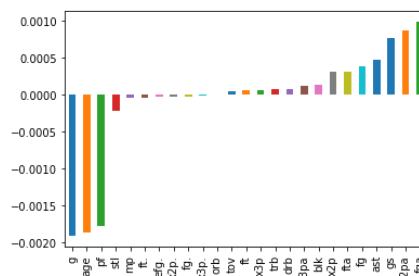


```

In [358]: coef = Series(lr.coef_[2],features).sort_values()
coef.plot(kind = 'bar')

```

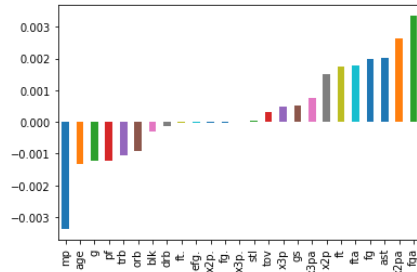
Out[358]: <matplotlib.axes.\_subplots.AxesSubplot at 0x117d78e80>



```
In [359]: coef = Series(lr.coef_[3],features).sort_values()
coef.plot(kind = 'bar')
```

```
#top 3 features:  ast, x2pa, fga
```

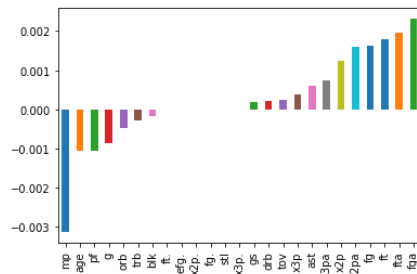
```
Out[359]: <matplotlib.axes._subplots.AxesSubplot at 0x117d97d68>
```



```
In [360]: coef = Series(lr.coef_[4],features).sort_values()
coef.plot(kind = 'bar')
```

```
#top 3 features:  ft, fta, fga
```

```
Out[360]: <matplotlib.axes._subplots.AxesSubplot at 0x1180479e8>
```



\*\*\*\* L2 Regularization \*\*\*\*

```
In [364]: # data divide into train and testing sets
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=5)
```

```
In [365]: #instantiate the LR model
lr = LogisticRegression(multi_class='multinomial', penalty = 'l2', solver='saga', tol=0.1)

# fit the model with data
lr.fit(X_train,y_train)
```

```
Out[365]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
intercept_scaling=1, max_iter=100, multi_class='multinomial',
n_jobs=1, penalty='l2', random_state=None, solver='saga',
tol=0.1, verbose=0, warm_start=False)
```

```
In [366]: y_pred = lr.predict(X_test)

accuracy = metrics.accuracy_score(y_test,y_pred)

micro = f1_score(y_test, y_pred, average = 'micro')
macro = f1_score(y_test, y_pred, average = 'macro')
weighted = f1_score(y_test, y_pred, average = 'weighted')

#f1 score/accuracy with l2 regularization
print('l2 accuracy: %.2f' % accuracy)
print('l2 Micro f1_score: %.2f' % micro)
print('l2 Micro f1_score: %.2f' % macro)
print('l2 Micro f1_score: %.2f' % weighted)

l2 accuracy: 0.77
l2 Micro f1_score: 0.77
l2 Micro f1_score: 0.42
l2 Micro f1_score: 0.76

/Users/juanrquilesjr/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricWarning: F-score is ill-defined
and being set to 0.0 in labels with no predicted samples.
'precision', 'predicted', average, warn_for)
```

```
In [367]: lr.coef_
```

```
Out[367]: array([[ 2.96888374e-03,  2.64774640e-03, -8.62457354e-04,
 2.73977248e-03, -2.04163540e-03, -3.25124393e-03,
 4.50394978e-05, -4.91606230e-04, -9.24648392e-04,
 2.11642790e-05, -1.55002917e-03, -2.32659554e-03,
 4.81767598e-05,  4.93970246e-05, -1.43276168e-03,
-1.59107716e-03,  6.62735319e-05,  5.12569886e-04,
 1.29869750e-04,  6.42439636e-04, -7.98654421e-04,
 8.71803367e-05,  2.64448298e-04, -3.30603814e-05,
 2.00067068e-03],
 [-7.51805426e-04, -4.01962990e-04,  8.62620375e-05,
 1.98185599e-03, -5.21767364e-04, -1.25169810e-03,
-1.13006997e-05,  7.99367335e-05,  2.48081710e-04,
-5.54871170e-06, -6.01704097e-04, -1.49977981e-03,
-1.20017235e-05, -1.22344907e-05, -9.73117449e-04,
-1.18094317e-03, -1.55303999e-05,  4.30788486e-04,
 8.20501201e-05,  5.12838606e-04, -1.21368227e-03,
-1.58825330e-05, -3.27618370e-05, -4.56375811e-04,
 3.70021381e-04],
 [-9.47024490e-04, -1.03259040e-03,  4.26940675e-04,
-3.73991721e-04,  4.89043220e-04,  1.14423416e-03,
-1.46657383e-05,  3.46682150e-05,  6.09270384e-05,
-6.59887393e-06,  4.54375005e-04,  1.08330712e-03,
-1.57212449e-05, -1.61858940e-05,  3.31589937e-04,
 5.08525200e-04, -2.27024038e-05, -1.32556389e-04,
-1.20950531e-04, -2.53506921e-04,  4.73918379e-04,
-9.50569055e-05,  5.45229958e-05,  1.08432318e-04,
-1.02204961e-03],
 [-7.24027525e-04, -7.35245702e-04,  2.60605443e-04,
-2.32697150e-03,  1.30219521e-03,  2.25461754e-03,
-1.09870180e-05,  2.35578898e-04,  3.70065308e-04,
-5.21452149e-06,  1.06661631e-03,  1.88455224e-03,
-1.17991362e-05, -1.20686980e-05,  1.19380784e-03,
 1.29762518e-03, -1.63438841e-05, -5.66224867e-04,
-1.27500279e-04, -6.93725146e-04,  1.26135043e-03,
 4.61758653e-05, -1.91843472e-04,  2.72826343e-04,
-7.67181662e-04],
 [-5.46026302e-04, -4.77947301e-04,  8.86491990e-05,
-2.02066525e-03,  7.72164335e-04,  1.10409032e-03,
-8.08604175e-06,  1.41422384e-04,  2.45574336e-04,
-3.80217194e-06,  6.30741951e-04,  8.58515985e-04,
-8.65465528e-06, -8.90794193e-06,  8.80481349e-04,
 9.65869955e-04, -1.16968441e-05, -2.44577116e-04,
 3.65309406e-05, -2.08046176e-04,  2.77067884e-04,
-2.24167636e-05, -9.43659850e-05,  1.08177532e-04,
-5.81460795e-04]])
```

\*\*\*\* Coefficient Visualizations (least and most important) \*\*\*\*

```
In [371]: features = data.drop('pts' ,axis =1).columns
          for i in lr.coef_:
              print(Series(i,features).sort_values())
```



fga	-0.003251
x2pa	-0.002327
fg	-0.002042
fta	-0.001591
x2p	-0.001550
ft	-0.001433
x3pa	-0.000925
gs	-0.000862
ast	-0.000799
x3p	-0.000492
tov	-0.000033
x3p.	0.000021
fg.	0.000045
x2p.	0.000048
efg.	0.000049
ft.	0.000066
stl	0.000087
drb	0.000130
blk	0.000264
orb	0.000513
trb	0.000642
pf	0.002001
g	0.002648
mp	0.002740
age	0.002969
dtype:	float64
x2pa	-0.001500
fga	-0.001252
ast	-0.001214
fta	-0.001181
ft	-0.000973
age	-0.000752
x2p	-0.000602
fg	-0.000522
tov	-0.000456
g	-0.000402
blk	-0.000033
stl	-0.000016
ft.	-0.000016
efg.	-0.000012
x2p.	-0.000012
fg.	-0.000011
x3p.	-0.000006
x3p	0.000080
drb	0.000082
gs	0.000086
x3pa	0.000248
pf	0.000370
orb	0.000431
trb	0.000513
mp	0.001982
dtype:	float64
g	-0.001033
pf	-0.001022
age	-0.000947
mp	-0.000374
trb	-0.000254
orb	-0.000133
drb	-0.000121
stl	-0.000095
ft.	-0.000023
efg.	-0.000016
x2p.	-0.000016
fg.	-0.000015
x3p.	-0.000007
x3p	0.000035
blk	0.000055
x3pa	0.000061
tov	0.000108
ft	0.000332
gs	0.000427
x2p	0.000454
ast	0.000474
fg	0.000489
fta	0.000509
x2pa	0.001083
fga	0.001144
dtype:	float64
mp	-0.002327
pf	-0.000767
g	-0.000735
age	-0.000724
trb	-0.000694
orb	-0.000566
blk	-0.000192
drb	-0.000128
ft.	-0.000016
efg.	-0.000012
x2p.	-0.000012
fg.	-0.000011
x3p.	-0.000005
stl	0.000046
x3p	0.000236
gs	0.000261
tov	0.000273
x3pa	0.000370
x2p	0.001067
ft	0.001194
ast	0.001261
fta	0.001298
fg	0.001302
x2pa	0.001885
fga	0.002255
dtype:	float64
mp	-0.002021
pf	-0.000581

```

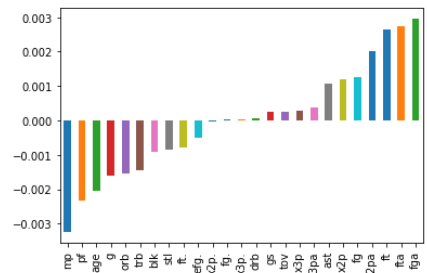
age      -0.000546
g        -0.000478
orb      -0.000245
trb      -0.000208
blk      -0.000094
stl      -0.000022
ft.      -0.000012
efg.     -0.000009
x2p.     -0.000009
fg.       -0.000008
x3p.     -0.000004
drb       0.000037
gs        0.000089
tov       0.000108
x3p       0.000141
x3pa      0.000246
ast       0.000277
x2p       0.000631
fg        0.000772
x2pa      0.000859
ft         0.000880
fta       0.000966
fga       0.001104
dtype: float64

```

```

In [376]: features = data.drop('pts',axis=1).columns
          for i in lr.coef_:
              Series(i,features).sort_values().plot(kind = 'bar')

```



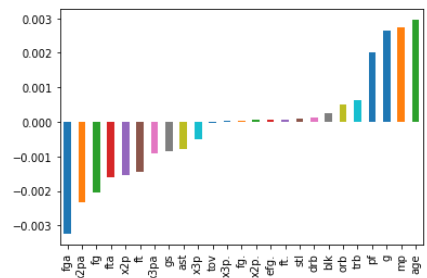
```

In [369]: coef = Series(lr.coef_[0],features).sort_values()
          coef.plot(kind = 'bar')

          #Top 3 features:  g, mp, age

```

Out[369]: <matplotlib.axes.\_subplots.AxesSubplot at 0x11811b780>



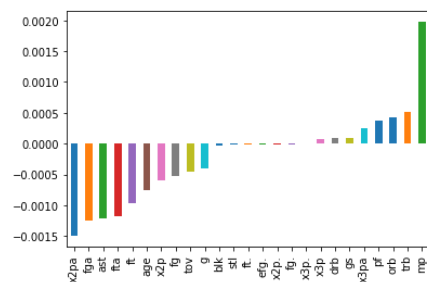
```

In [370]: coef = Series(lr.coef_[1],features).sort_values()
          coef.plot(kind = 'bar')

          #Top 3 features:  orb, trb, mp

```

Out[370]: <matplotlib.axes.\_subplots.AxesSubplot at 0x117dd4550>



```
#Top 3 features:  fta, x2pa, fga
```

A bar chart showing the distribution of the number of non-zero elements in the matrix A for different values of n. The x-axis represents the number of non-zero elements (log scale) and the y-axis represents the frequency. The distribution is skewed to the right, with most non-zero elements concentrated at higher values.

Number of non-zero elements	Frequency
1	-0.0010
2	-0.0005
3	-0.0002
4	-0.0001
5	-0.0001
6	-0.0001
7	-0.0001
8	-0.0001
9	-0.0001
10	-0.0001
11	-0.0001
12	-0.0001
13	-0.0001
14	-0.0001
15	-0.0001
16	-0.0001
17	-0.0001
18	-0.0001
19	-0.0001
20	-0.0001
21	-0.0001
22	-0.0001
23	-0.0001
24	-0.0001
25	-0.0001
26	-0.0001
27	-0.0001
28	-0.0001
29	-0.0001
30	-0.0001
31	-0.0001
32	-0.0001
33	-0.0001
34	-0.0001
35	-0.0001
36	-0.0001
37	-0.0001
38	-0.0001
39	-0.0001
40	-0.0001
41	-0.0001
42	-0.0001
43	-0.0001
44	-0.0001
45	-0.0001
46	-0.0001
47	-0.0001
48	-0.0001
49	-0.0001
50	-0.0001
51	-0.0001
52	-0.0001
53	-0.0001
54	-0.0001
55	-0.0001
56	-0.0001
57	-0.0001
58	-0.0001
59	-0.0001
60	-0.0001
61	-0.0001
62	-0.0001
63	-0.0001
64	-0.0001
65	-0.0001
66	-0.0001
67	-0.0001
68	-0.0001
69	-0.0001
70	-0.0001
71	-0.0001
72	-0.0001
73	-0.0001
74	-0.0001
75	-0.0001
76	-0.0001
77	-0.0001
78	-0.0001
79	-0.0001
80	-0.0001
81	-0.0001
82	-0.0001
83	-0.0001
84	-0.0001
85	-0.0001
86	-0.0001
87	-0.0001
88	-0.0001
89	-0.0001
90	-0.0001
91	-0.0001
92	-0.0001
93	-0.0001
94	-0.0001
95	-0.0001
96	-0.0001
97	-0.0001
98	-0.0001
99	-0.0001
100	-0.0001
101	-0.0001
102	-0.0001
103	-0.0001
104	-0.0001
105	-0.0001
106	-0.0001
107	-0.0001
108	-0.0001
109	-0.0001
110	-0.0001
111	-0.0001
112	-0.0001
113	-0.0001
114	-0.0001
115	-0.0001
116	-0.0001
117	-0.0001
118	-0.0001
119	-0.0001
120	-0.0001
121	-0.0001
122	-0.0001
123	-0.0001
124	-0.0001
125	-0.0001
126	-0.0001
127	-0.0001
128	-0.0001
129	-0.0001
130	-0.0001
131	-0.0001
132	-0.0001
133	-0.0001
134	-0.0001
135	-0.0001
136	-0.0001
137	-0.0001
138	-0.0001
139	-0.0001
140	-0.0001
141	-0.0001
142	-0.0001
143	-0.0001
144	-0.0001
145	-0.0001
146	-0.0001
147	-0.0001
148	-0.0001
149	-0.0001
150	-0.0001
151	-0.0001
152	-0.0001
153	-0.0001
154	-0.0001
155	-0.0001
156	-0.0001
157	-0.0001
158	-0.0001
159	-0.0001
160	-0.0001
161	-0.0001
162	-0.0001
163	-0.0001
164	-0.0001
165	-0.0001
166	-0.0001
167	-0.0001
168	-0.0001

```
#Top 3 features: fg, x2pa, fga
```

```
#Top 3 features:  ft, fta, fga
```

Symbol	Relative Frequency
me	-0.0019
pl	-0.0001
agie	-0.0006
g	-0.0004
orb	-0.0005
io	-0.0002
bli	-0.0001
si	0.0000
ft	0.0000
ffg	0.0000
zp	0.0000
fj	0.0000
cp	0.0000
orb	0.0001
lvo	0.0001
x3p	0.0002
pas	0.0003
ast	0.0001
x2p	0.0006
fg	0.0000
zpa	0.0008
fia	0.0009
fia	0.0010