

## EE239AS Project 4

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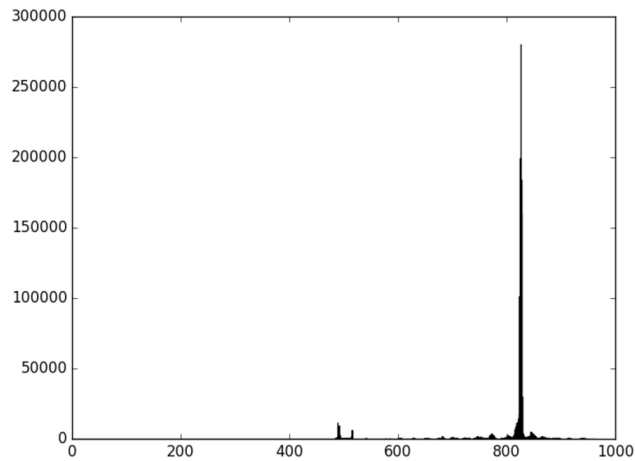
1) Calculate these statistics for each hashtag: average number of tweets per hour, average number of followers of users posting the tweets, and average number of retweets. Plot "number of tweets in hour" over time for #SuperBowl and #NFL

	average number of tweets per hour	number of followers of users posting the tweets*	average number of retweets**
#gohawks	193.36	1593.83	2.01
#gopatriots	38.35	1324.11	1.40
#nfl	279.42	4122.14	1.54
#patriots	498.69	1830.33	1.78
#sb49	1418.44	2379.09	2.51
#superbowl	1400.59	3983.87	2.39

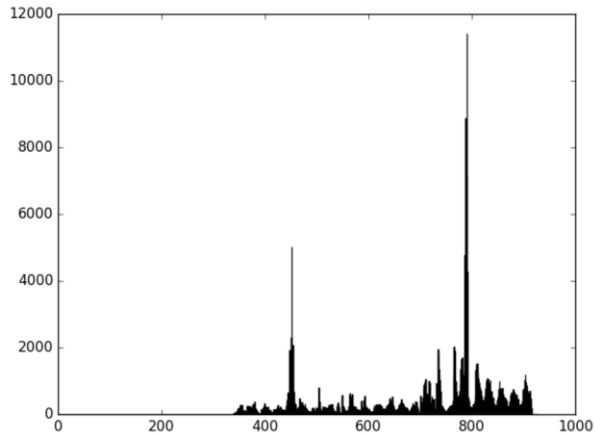
\*Number of followers of users: ['author']['followers']

\*\*Number of retweets: ['metrics']['citations']['total']

"number of tweets in hour" over time for #superbowl



"number of tweets in hour" over time for #NFL



2)

### **Process:**

While reading every line of the file, based on the time of the tweet, we put the target variables into different element of target arrays. For example, the first element of *num\_tweet* array stores the number of tweets in first hour, every time we ready a tweet belong to the first hour, we increase the first element of *num\_tweet* array by one.

After obtaining arrays contains target value in each hour, we use 1 to n-1 row for X and 2 to n row for Y.

Statsmodels.OLS is used for linear regression and analysis. x1, x2, x3, x4 and x5 represent total tweet number, total retweet number, total follower, max follower and hour of the day respectively.

### **Results:**

**#gohawks**

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.625			
Model:	OLS	Adj. R-squared:	0.623			
Method:	Least Squares	F-statistic:	321.4			
Date:	Fri, 18 Mar 2016	Prob (F-statistic):	1.26e-202			
Time:	17:37:28	Log-Likelihood:	-7610.8			
No. Observations:	972	AIC:	1.523e+04			
Df Residuals:	966	BIC:	1.526e+04			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	-0.3289	40.016	-0.008	0.993	-78.858	78.200
x1	1.1189	0.097	11.520	0.000	0.928	1.310
x2	-0.1802	0.036	-4.940	0.000	-0.252	-0.109
x3	2.428e-06	6.64e-05	0.037	0.971	-0.000	0.000
x4	-0.0002	0.000	-1.642	0.101	-0.000	3.67e-05
x5	0.1321	0.071	1.867	0.062	-0.007	0.271
Omnibus:	1023.673	Durbin-Watson:	2.207			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2074156.023			
Skew:	3.759	Prob(JB):	0.00			
Kurtosis:	229.180	Cond. No.	3.35e+06			

The R-squared number is low so the training accuracy is low. The total tweet number (x1) has the largest coefficient, t and zero p-value. So it is the most significant feature. Total follower and max follower have p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, tweet number > total retweet number > hour of the day > max follower total > total follower

**#gopatriots**

### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.506
Model:                  OLS    Adj. R-squared:       0.502
Method:                 Least Squares    F-statistic:       138.6
Date:                  Fri, 18 Mar 2016    Prob (F-statistic): 4.13e-101
Time:                  17:26:13    Log-Likelihood:    -4615.3
No. Observations:      683    AIC:               9243.
Df Residuals:          677    BIC:               9270.
Df Model:              5
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
const	-8.8065	16.474	-0.535	0.593	-41.152 23.539
x1	-2.0493	0.255	-8.035	0.000	-2.550 -1.549
x2	2.8243	0.286	9.864	0.000	2.262 3.386
x3	-0.0010	0.000	-3.915	0.000	-0.001 -0.000
x4	0.0005	0.000	2.320	0.021	8.42e-05 0.001
x5	0.0268	0.041	0.657	0.511	-0.053 0.107

```

=====
Omnibus:                1063.589    Durbin-Watson:          2.379
Prob(Omnibus):          0.000    Jarque-Bera (JB):       1157808.922
Skew:                   8.449    Prob(JB):               0.00
Kurtosis:               203.995    Cond. No.               7.15e+05
=====

```

The R-squared number is low so the training accuracy is low. The total retweet number (x2) has the largest coefficient, t and zero p-value. So it is the most significant feature. Hour of the day has p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, total retweet number > tweet number > total follower > max follower > hour of the day

#nfl

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.700			
Model:	OLS	Adj. R-squared:	0.698			
Method:	Least Squares	F-statistic:	428.5			
Date:	Fri, 18 Mar 2016	Prob (F-statistic):	2.36e-237			
Time:	17:42:19	Log-Likelihood:	-6847.0			
No. Observations:	926	AIC:	1.371e+04			
Df Residuals:	920	BIC:	1.373e+04			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	-34.5568	27.148	-1.273	0.203	-87.837	18.723
x1	0.8388	0.102	8.215	0.000	0.638	1.039
x2	0.0151	0.057	0.266	0.791	-0.096	0.126
x3	-2.164e-05	2.36e-05	-0.915	0.360	-6.8e-05	2.48e-05
x4	9.736e-06	3.04e-05	0.320	0.749	-5e-05	6.94e-05
x5	0.1880	0.054	3.492	0.001	0.082	0.294
Omnibus:	870.752	Durbin-Watson:	1.932			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	472504.198			
Skew:	3.325	Prob(JB):	0.00			
Kurtosis:	113.463	Cond. No.	5.51e+06			

The R-squared number is higher than previous two cases so the training accuracy is higher. The total tweet number (x1) has the largest coefficient, t and zero p-value. So it is the most significant feature. Total number of retweets, total follower and max follower have p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, total tweet number > hour of the day > total follower > max follower > total retweet number

**#patriots**

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.721			
Model:	OLS	Adj. R-squared:	0.719			
Method:	Least Squares	F-statistic:	503.1			
Date:	Fri, 18 Mar 2016	Prob (F-statistic):	6.15e-267			
Time:	17:39:44	Log-Likelihood:	-8741.9			
No. Observations:	980	AIC:	1.750e+04			
Df Residuals:	974	BIC:	1.753e+04			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	-36.0310	118.675	-0.304	0.761	-268.920	196.858
x1	1.7815	0.090	19.792	0.000	1.605	1.958
x2	-0.8256	0.086	-9.559	0.000	-0.995	-0.656
x3	0.0002	4.6e-05	3.890	0.000	8.86e-05	0.000
x4	-7.705e-05	9.38e-05	-0.821	0.412	-0.000	0.000
x5	0.3621	0.212	1.705	0.089	-0.055	0.779
Omnibus:	1689.614	Durbin-Watson:	1.801			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1391405.015			
Skew:	11.167	Prob(JB):	0.00			
Kurtosis:	186.239	Cond. No.	1.06e+07			

The R-squared number is higher than previous three cases so the training accuracy is higher. The total tweet number (x1) has the largest coefficient, t and zero p-value. So it is the most significant feature. Max follower and hour of the day have p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, total tweet number > total retweet number > total follower > hour of the day > max follower

#sb49

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.852			
Model:	OLS	Adj. R-squared:	0.850			
Method:	Least Squares	F-statistic:	661.1			
Date:	Fri, 18 Mar 2016	Prob (F-statistic):	6.82e-236			
Time:	17:36:11	Log-Likelihood:	-5633.5			
No. Observations:	582	AIC:	1.128e+04			
Df Residuals:	576	BIC:	1.131e+04			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	73.1629	327.728	0.223	0.823	-570.524	716.850
x1	1.1678	0.048	24.233	0.000	1.073	1.262
x2	-0.3485	0.039	-8.837	0.000	-0.426	-0.271
x3	0.0002	2.76e-05	7.079	0.000	0.000	0.000
x4	-0.0002	6.97e-05	-2.562	0.011	-0.000	-4.17e-05
x5	-0.7862	1.045	-0.752	0.452	-2.840	1.267
Omnibus:	888.041	Durbin-Watson:	1.487			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	573029.125			
Skew:	8.141	Prob(JB):	0.00			
Kurtosis:	155.856	Cond. No.	6.25e+07			

The R-squared number is higher than previous four cases so the training accuracy is higher. The total tweet number (x1) has the largest coefficient, t and zero p-value. So it is the most significant feature. Hour of the day has p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, total tweet number > total retweet number > total follower > hour of the day > max follower

**#superbowl**

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.713			
Model:	OLS	Adj. R-squared:	0.711			
Method:	Least Squares	F-statistic:	474.5			
Date:	Fri, 18 Mar 2016	Prob (F-statistic):	5.18e-256			
Time:	17:48:26	Log-Likelihood:	-9950.2			
No. Observations:	962	AIC:	1.991e+04			
Df Residuals:	956	BIC:	1.994e+04			
Df Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[95.0% Conf. Int.]	
const	334.6198	506.203	0.661	0.509	-658.777	1328.017
x1	2.9367	0.308	9.534	0.000	2.332	3.541
x2	-0.9485	0.152	-6.249	0.000	-1.246	-0.651
x3	1.99e-06	3.46e-05	0.058	0.954	-6.59e-05	6.99e-05
x4	0.0007	0.000	3.988	0.000	0.000	0.001
x5	-1.7830	1.037	-1.719	0.086	-3.819	0.253
Omnibus:	1063.801	Durbin-Watson:	1.720			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	912756.093			
Skew:	4.405	Prob(JB):	0.00			
Kurtosis:	153.645	Cond. No.	9.08e+07			

The R-squared number is high so the training accuracy is high. The total tweet number (x1) has the largest coefficient, t and zero p-value. So it is the most significant feature. Total follower has p-value > 0.05 so the null hypothesis cannot be rejected. In terms of significance, total tweet number > total retweet number > max follower > hour of the day > total follower

### 3)

Four new features are used, they are:

Author count (A):

Number of authors ([‘author’][‘name’]). This feature can be used to recognize those hashtags automatically posted by some fake accounts.

Mention count (B):

Sum of times been mentioned of each tweet ([‘tweet’][‘entities’][‘user\_mentions’])). If a user was mentioned in a tweet with a hashtag, he probably took part in the topic, especially when this mention came from his friends.

Co-occurrence times of other hashtags (C):

Number of tweets that has one or more hashtags ([‘tweet’][‘entities’][‘hashtags’])). More hashtag together may indicate higher popularity.

Url ratio (D):



Number of tweets that has URL/total number of tweets (['tweet']['entities']['urls']). High ratio of tweets with urls may indicate an interesting topic

Together with features in 2), all 9 features are used.

Random Forrest Tree model is used as regression model for this problem for better accuracy compared with linear regression model.

x1, x2, x3, x4, x5, x6, x7, x8, x9 represent author number, mentioned number, hashtag co-occurrence, URL ratio, total tweet number, total retweet number, total follower, max follower, hour of the day

**sklearn.ensemble.RandomForestClassifier** was used and its `feature_importances_` and `score` functions are used to evaluate feature importance and regression accuracy.

### Results:

**#gohawks**

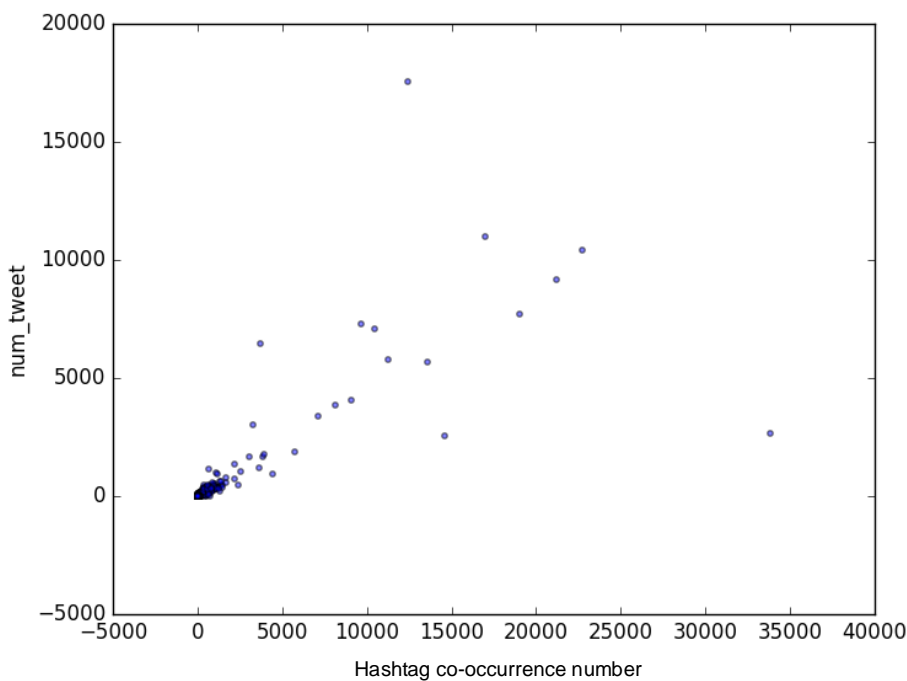
Accuracy:

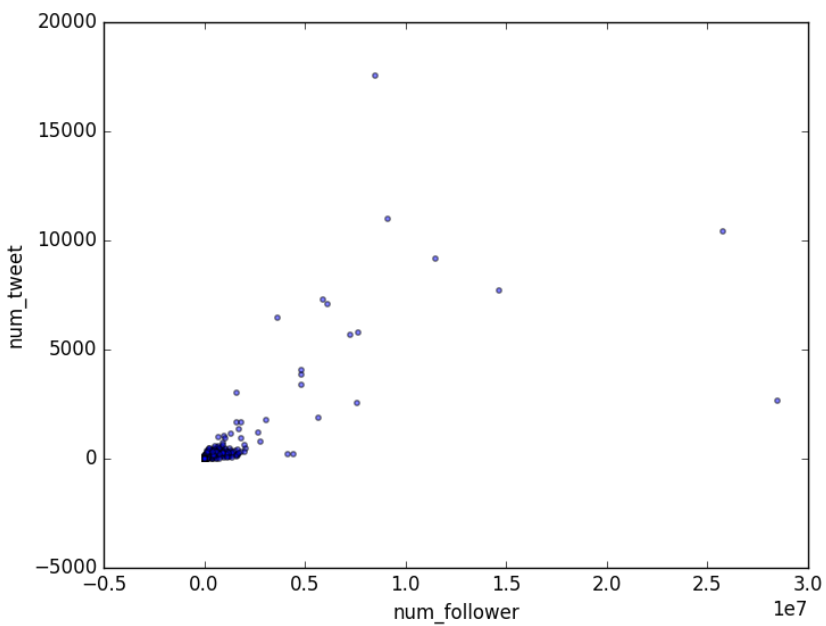
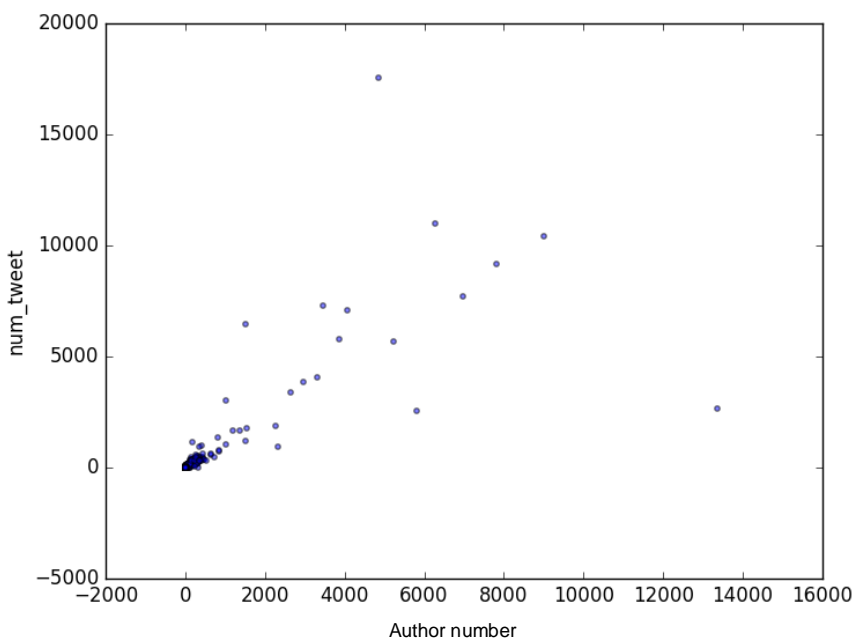
Mean accuracy score is 0.94953120160.

Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
1.59e-1	1.39e-1	1.88e-1	3.16e-9	1.04e-1	5.80e-2	2.78e-1	3.70e-2	3.65e-2

Follower number, author number, mentioned number, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.





**#gopatriots**

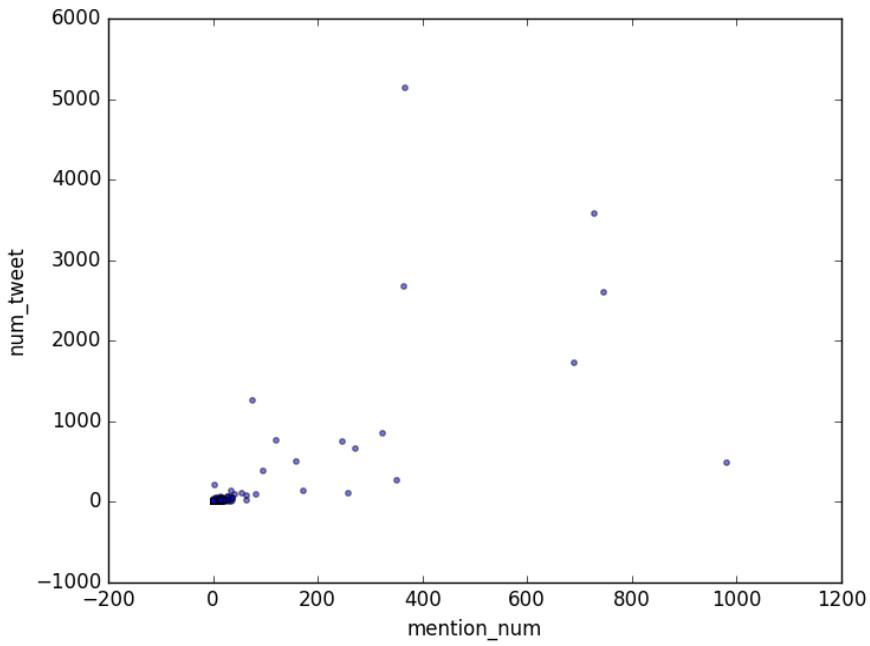
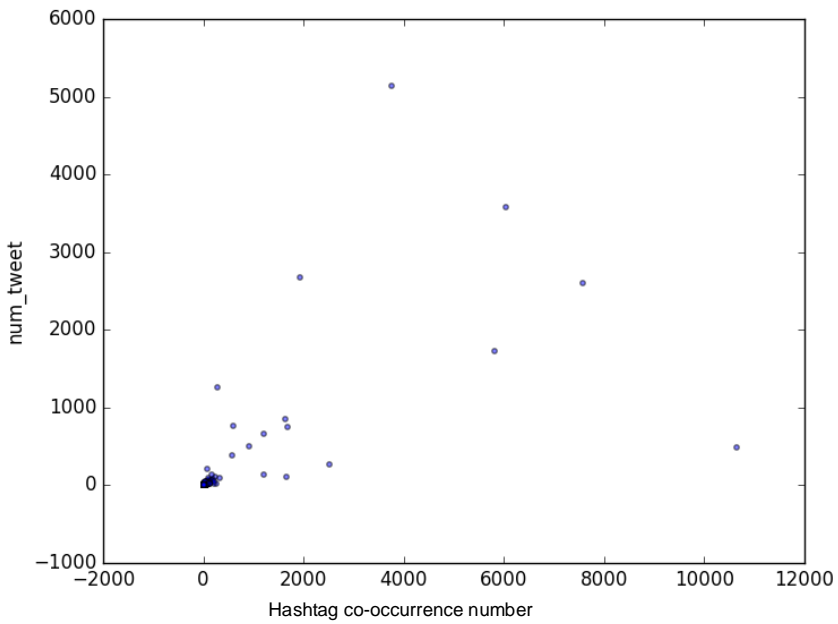
Accuracy:

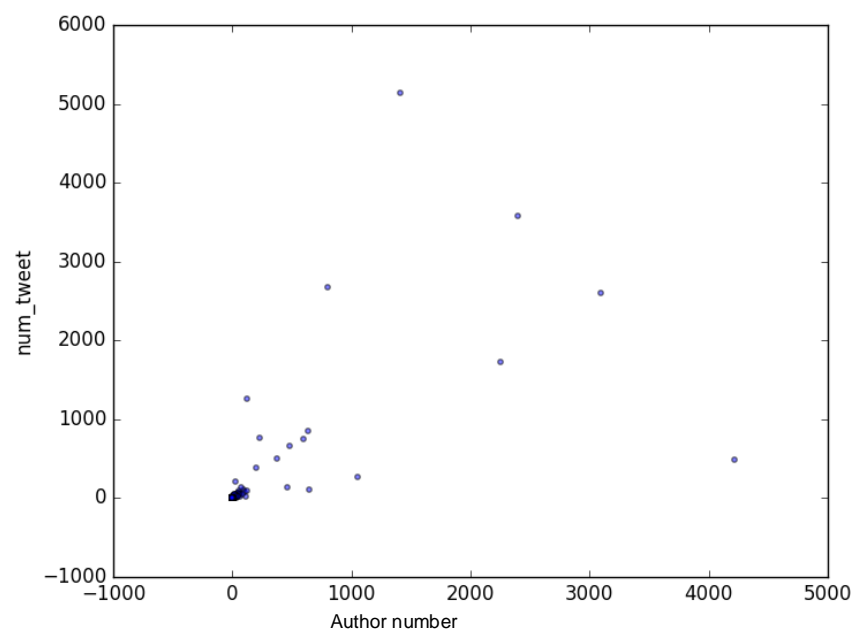
Mean accuracy score is 0.933574203546

Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
1.19e-1	4.30e-1	1.82e-1	2.61e-7	8.44e-2	6.95e-2	1.47e-2	5.25e-2	4.74e-2

Author number, mentioned number, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.





**#nfl**

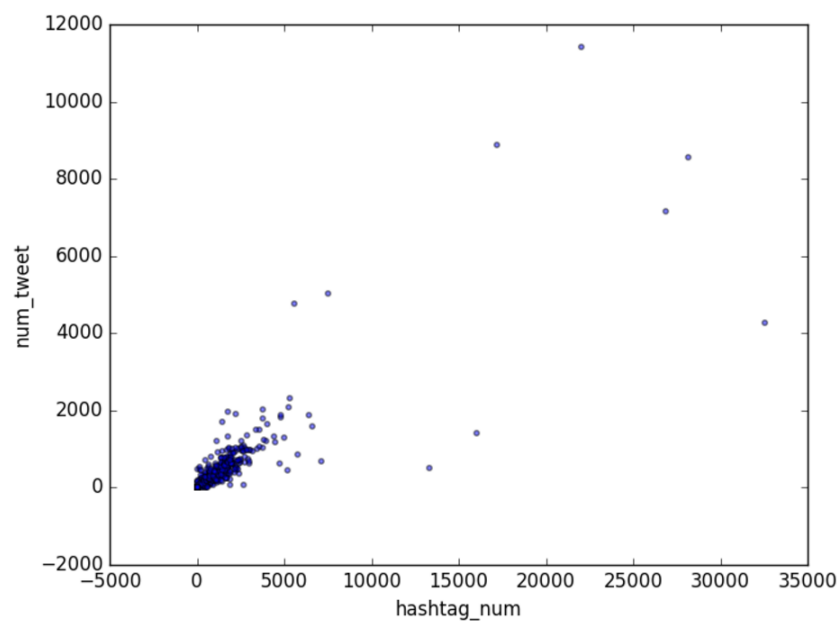
Accuracy:

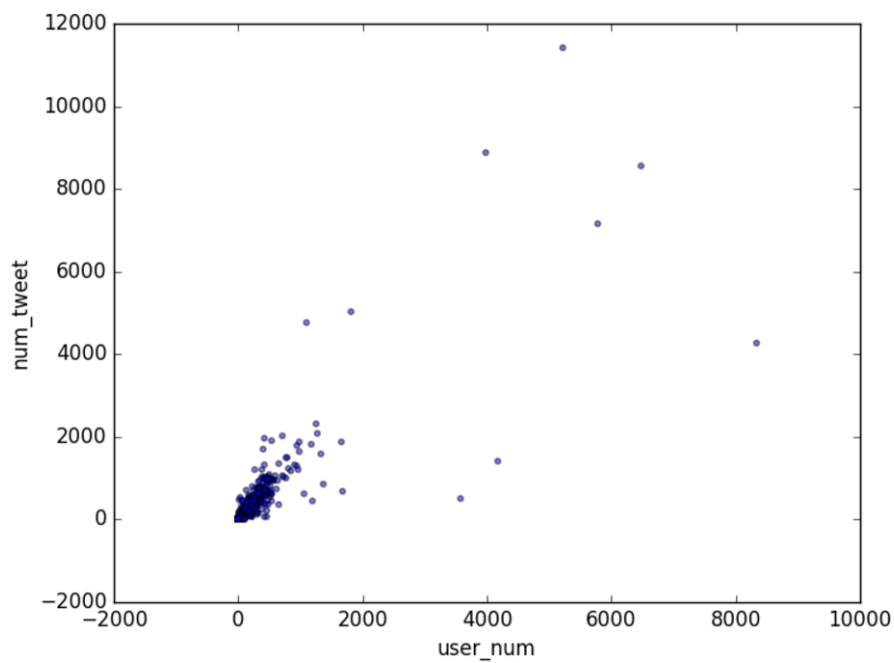
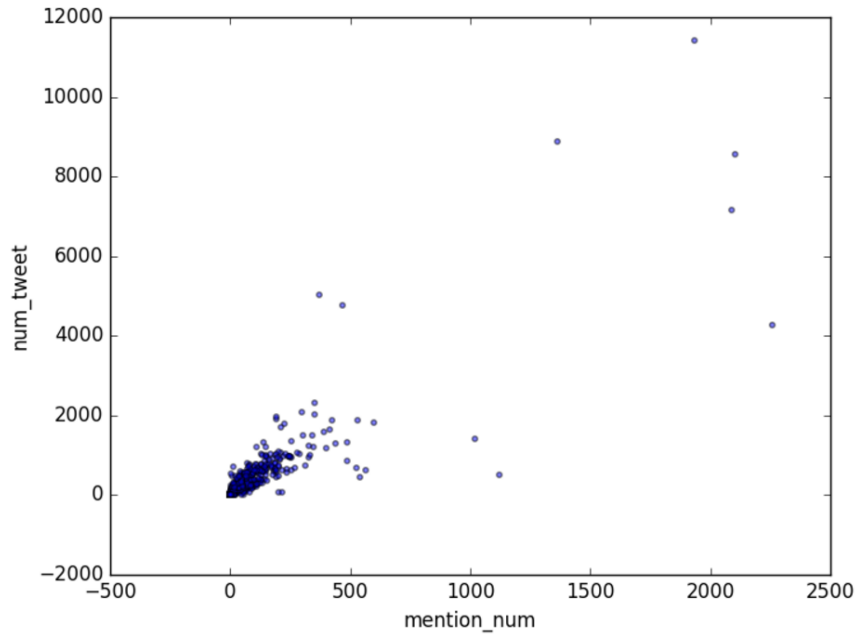
Mean accuracy score is 0.949531201604

Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
2.1e-1	1.97e-1	2.6e-1	2.69e-8	1.08e-1	1.27e-1	4.91e-2	2.22e-2	2.55e-2

Hashtag co-occurrence, author number, mentioned number, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.





**#patriots**

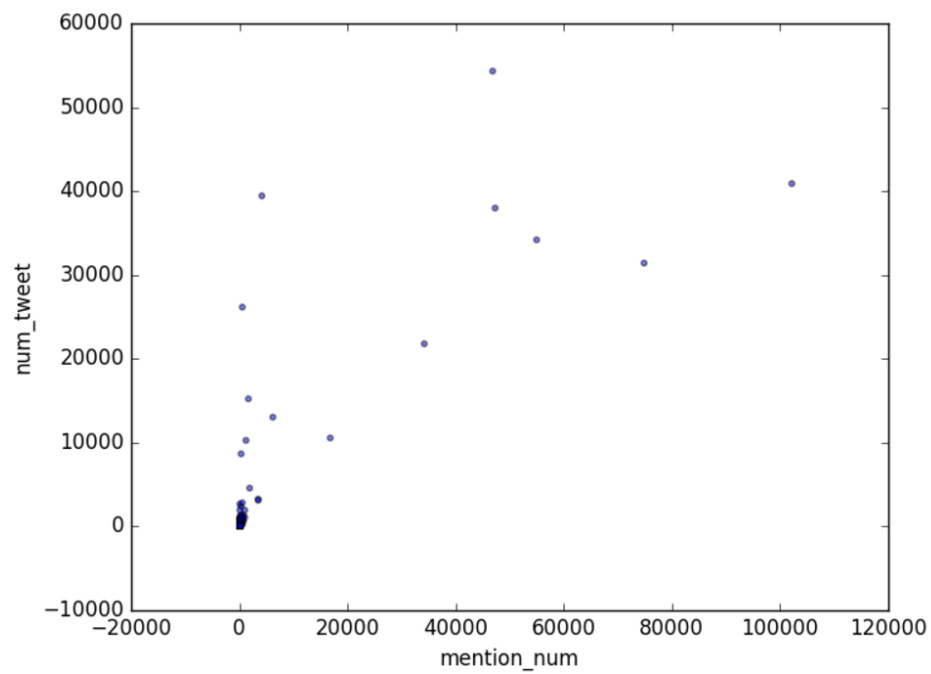
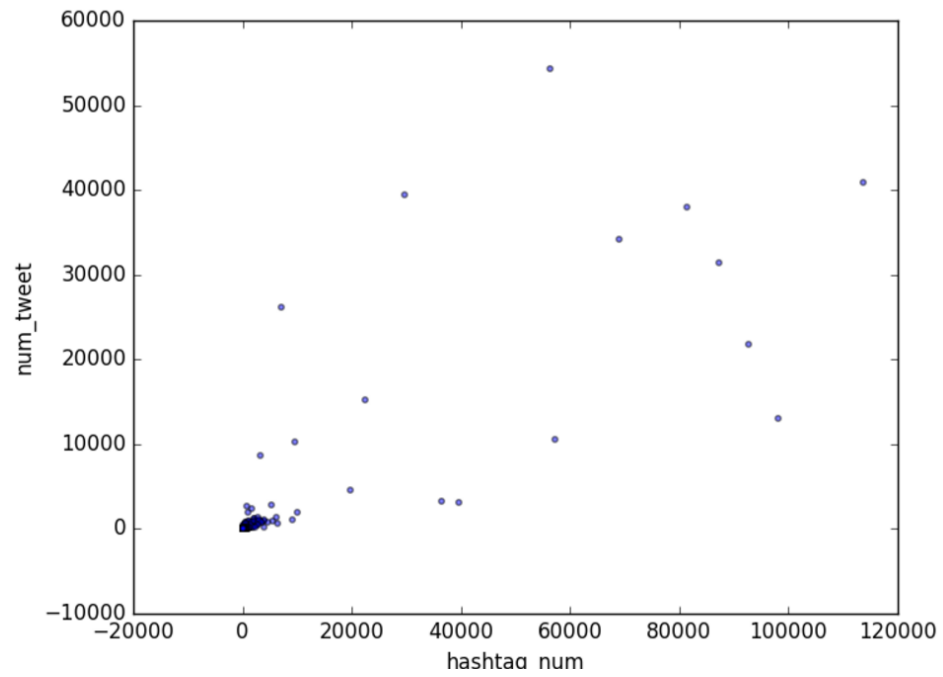
Accuracy:

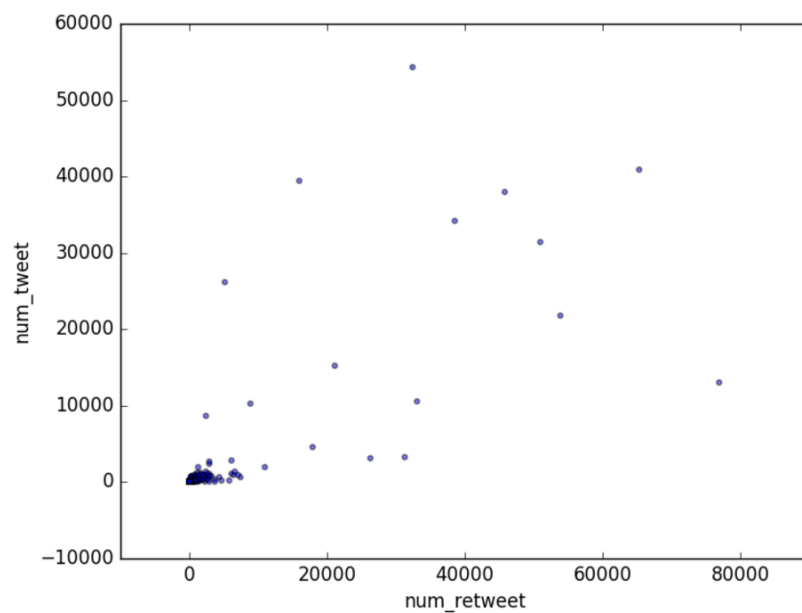
Mean accuracy score is 0.950926015404

Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
3.83e-2	6.58e-1	9.59e-2	5.8e-12	4.94e-2	7.89e-2	4.7e-2	2.09e-2	1.15e-2

Hashtag co-occurrence, number of retweets, mentioned number, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.





**#sb49**

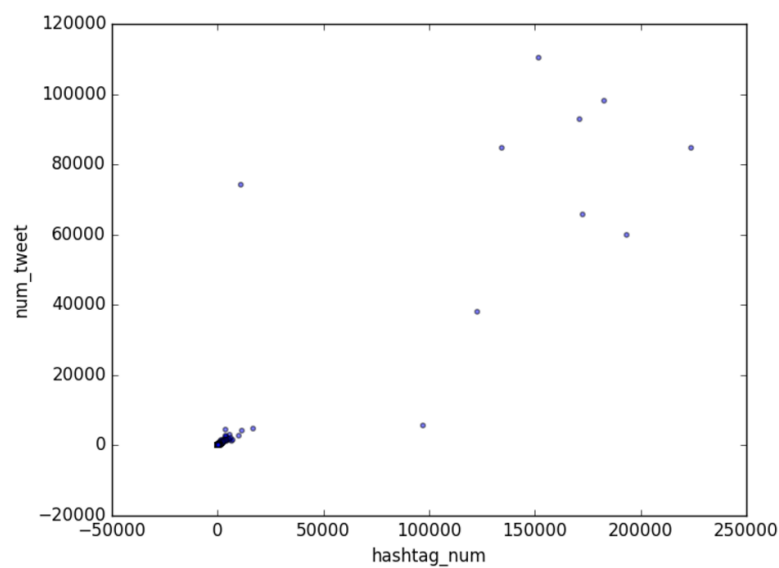
Accuracy:

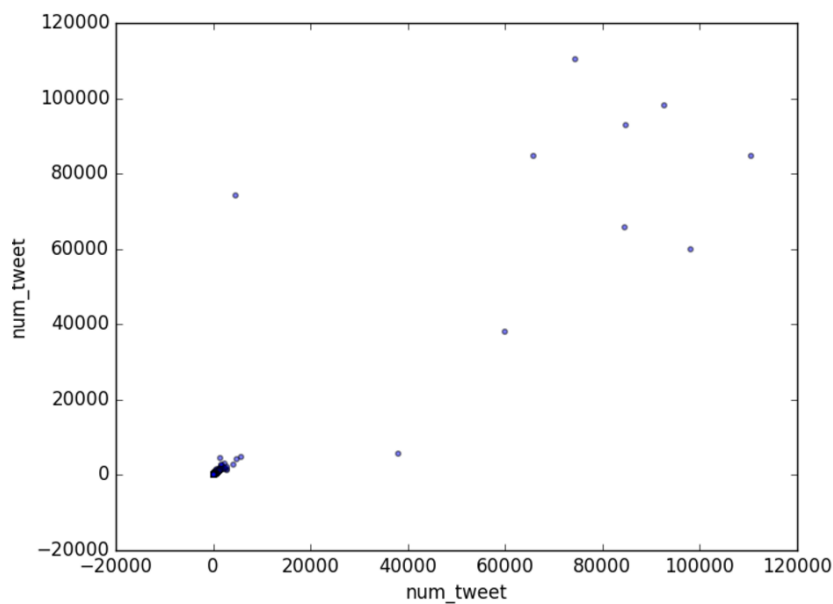
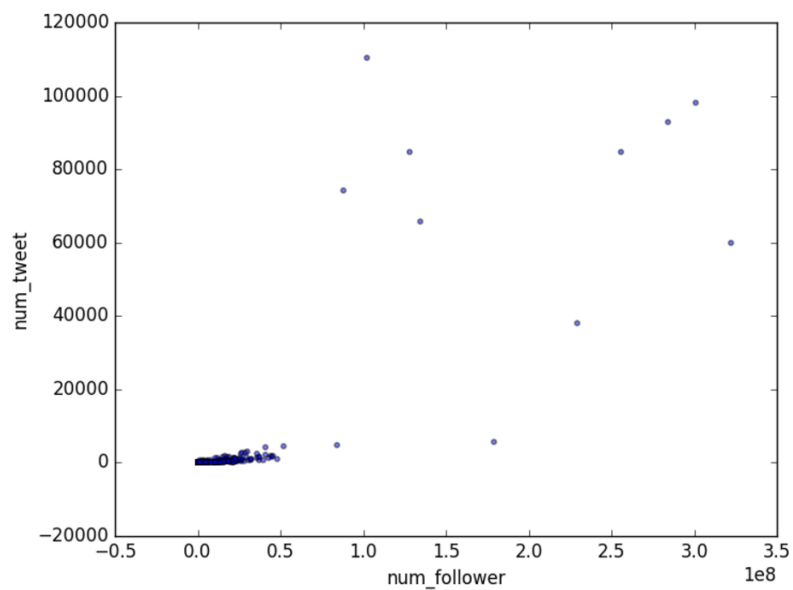
Mean accuracy score is 0.964792397543

Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
5.02e-2	7.81e-2	1.45e-1	3.6e-11	2.31e-1	1.2e-1	4.41e-1	1.54e-2	1.94e-2

Hashtag co-occurrence, number of follower, number of tweet, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.





### #superbowl

Accuracy:

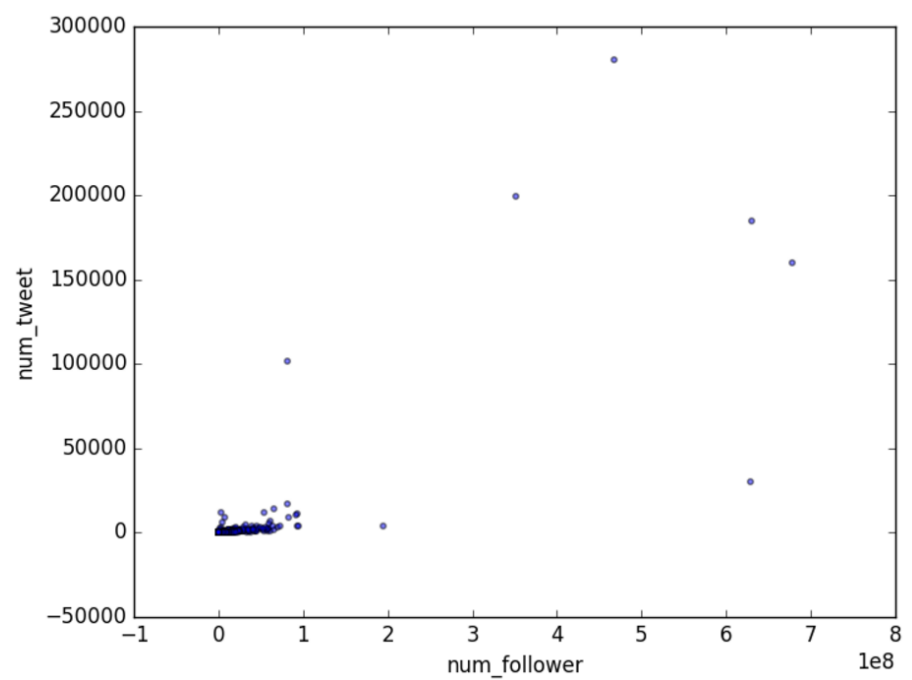
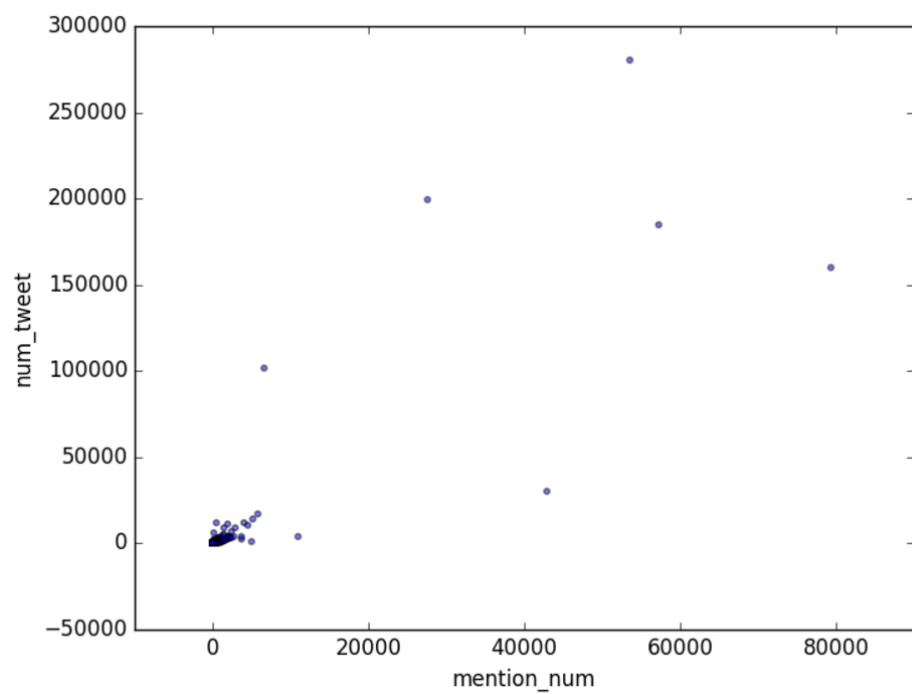
Mean accuracy score is 0.965857619053

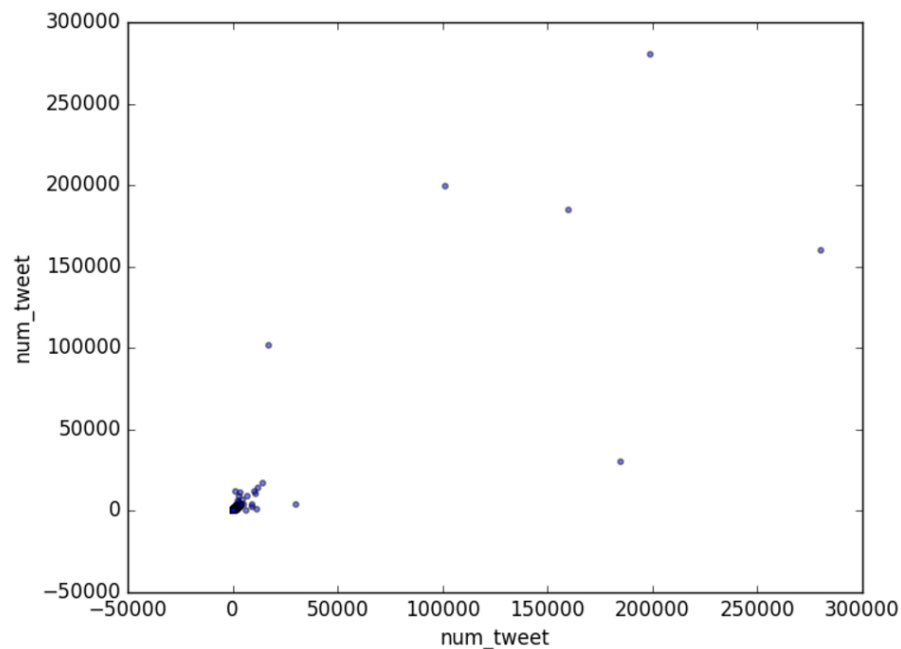
Feature importance:

x1	x2	x3	x4	x5	x6	x7	x8	x9
0.103	0.162	0.113	0	0.214	0.103	0.143	0.088	0.073

Mention number, number of follower, number of tweet, hashtag co-occurrence are the top three features. URL ratio is the least importance feature.







4)

10 part cross validation:

Cross\_validation in sklearn is used, for example:

`X_train, X_test, y_train, y_test = cross_validation.train_test_split(X, Y, test_size=0.1)`

To avoid overfitting, URL ratio feature is removed since it is not related from previous problem.

**Cross-validation error:**

#gohawks	93.4550819439
#gopatriots	19.1288128799
#nfl	92.4687694997
#patriots	244.781287531
#sb49	490.957822444
#superbowl	836.040754656

The error is about half of the average value.

**Cross-validation error in different time range:**

Before Feb. 1, 8:00 a.m.

#gohawks	58.8963910282
#gopatriots	11.0605621615
#nfl	60.2011197581
#patriots	86.2837751873
#sb49	42.7552721268
#superbowl	173.75410161

Between Feb. 1, 8:00 a.m. and 8:00 p.m.

#gohawks	193.36
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#gopatriots	1430.1275
#nfl	1155.68875
#patriots	11561.355
#sb49	18296.5725
#superbowl	35740.46375

After Feb. 1, 8:00 p.m.

#gohawks	15.8492142378
#gopatriots	1.53445339069
#nfl	134.013681186
#patriots	46.0447061913
#sb49	107.301734095
#superbowl	198.991091879

## 5)

For each time period, we have already obtained 6 models in previous problem. In this problem, first we need to decide which model to use.

We tested each sample in corresponding 6 models of its period and calculate the mean accuracy\* score. Then we pick the model that produce the largest score as the model to be used to predict the number in 7<sup>th</sup> hour.

\*mean accuracy =  $1 - u/v$ , where  $u$  = regression sum of squares:  $((y\_true - y\_pred) ** 2).sum()$  and  $v$  = residual sum of squares:  $((y\_true - y\_true.mean()) ** 2).sum()$ . Best possible value is 1.

	Model to use	Mean accuracy	hour 7 predict
sample1_period1	#sb49	-1.41997031919	157.7960901
sample2_period2	#superbowl	0.385764909431	142108.8
sample3_period3	#superbowl	-1.38192630731	717.45
sample4_period1	#sb49	-3.20574389085	217.06458333
sample5_period1	#gopatriots	-0.827388461522	429.15294118
sample6_period2	# patriots	0.10577786725	29402.625
sample7_period3	#gohawk	0.0378589322475	205.475
sample8_period1	#gopatriots	0.0656369334582	12.97919207
sample9_period2	# patriots	-0.927428431502	19482.724
sample10_period3	#gohawk	-9.03937851124	72.95

Due to the limitation of our random forest model and feature selection, the mean accuracy is relatively low.

## 6)

Problem: sentiment analysis of fans in both teams

Description: before, during and after the game, we can see the emotion of the fans based on the contents of their tweets. The ideal process is:

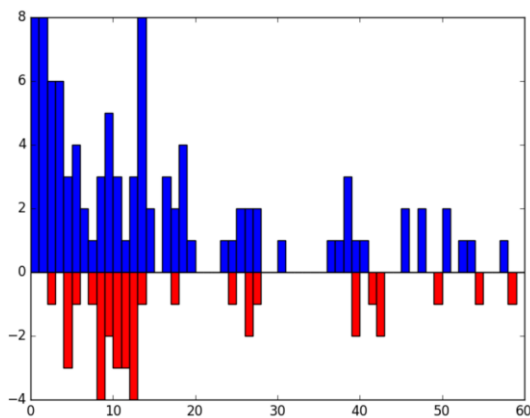
1. Scan all the tweets, find all the tweets with positive and negative emoticon

2. Summarize all the useful words in positive emoticon as positive words collection, and all the useful words in negative emoticon as negative words collection
3. Scan all the tweets, for each tweets, based on how many positive words and negative words, rate the emotion score

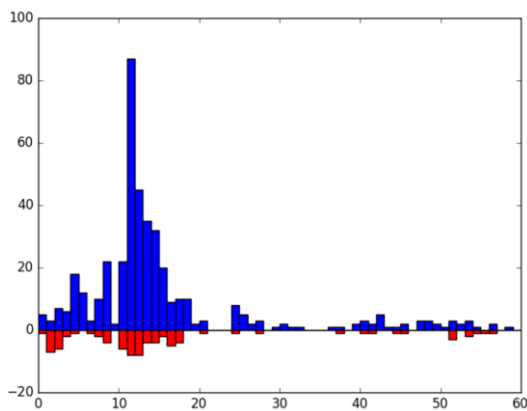
In this project, we simplified this process and only focused on the game night. For the game period, we summarize all the number of positive emoticon and negative emoticon in each ten minutes.

Emotion over the game period (red is negative, blue is positive), starting time is Feb 01, 6pm and ending time is Feb 02, 0 am

**Seahawks fan**



**Patriots fan**



As can be see, the seahawks fan were clearly more exited at the beginning of the game, however, since they were behind for most of the game, so there are more negative emotions. When the game ended at around 20, the seahawks fan were clearly more disappointed that patriots fans,