

ECE 219 Project5

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1 Introduction

Twitter is a good platform for social network analysis. We want to predict future tweet activity using current tweet activity for a hashtag. The Twitter data used in this project is from 2015 Super Bowl, ranging from 2 weeks before the game to a week after the game. Data from some related hashtags will be used to train a regression model. Then, the model will be used to make predictions for other hashtags. Lastly, we defined several new problems and implemented them.

2 Q1

2.1 Q1.1

#gohawks: Average number of tweets per hour: 324.933

#gohawks: Average number of followers of users posting the tweets: 2203.932

#gohawks: Average number of retweets: 2.015

#sb49: Average number of tweets per hour: 1418.441

#sb49: Average number of followers of users posting the tweets: 10267.317

#sb49: Average number of retweets: 2.511

#gopatriots: Average number of tweets per hour: 45.621

#gopatriots: Average number of followers of users posting the tweets: 1401.896

#gopatriots: Average number of retweets: 1.400

#patriots: Average number of tweets per hour: 834.264

#patriots: Average number of followers of users posting the tweets: 3309.979

#patriots: Average number of retweets: 1.783

#superbowl: Average number of tweets per hour: 2297.729

#superbowl: Average number of followers of users posting the tweets: 8858.975

#superbowl: Average number of retweets: 2.388

#nfl: Average number of tweets per hour: 441.267

#nfl: Average number of followers of users posting the tweets: 4653.252

#nfl: Average number of retweets: 1.539

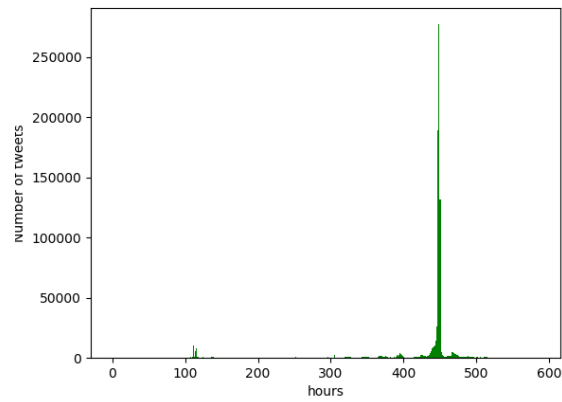


Figure 1: **number of tweets in hour over time for #superbowl**

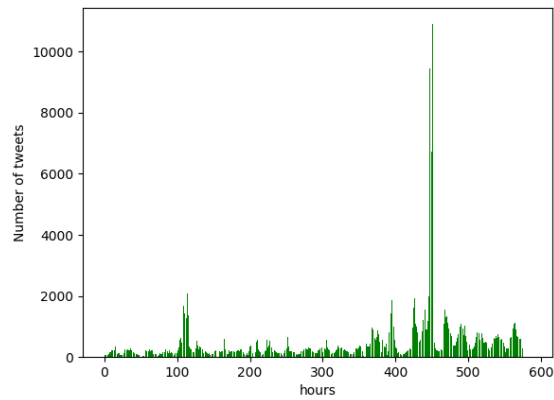


Figure 2: **number of tweets in hour over time for #nfl**

2.2 Q1.2

For each hashtag, fit a linear regression model using 5 features (number of tweets, total number of retweets, sum of number of followers, maximum number of followers, time of the day) to predict the number of tweets in the next hour with features from the previous hour.

For each model (hashtag), we report model's RMSE, R-squared measure. We also analyzed the significance of each feature with t-test and P-value. We used statsmodels.api. Specifically, we use linear regression model OLS for fitting and prediction.

To interpret the OLS output (screenshots), x1 to x5 stands for different features. Specifically, x1=tweet count, x2=retweet count, x3=follower count, x4=max followers, x5=time of the day. For each tag, RMSE and test R-square are shown in the chart. t-value and P-value for each feature for each tag are shown in the screenshots. t-value is under "t" column, and P-value is under " $P > |t|$ " column.

	RMSE	Test R-squared
#gohawks	969.32	0.505
#nfl	585.32	0.647
#sb49	4357.89	0.818
#gopatriots	174.47	0.680
#patriots	2517.04	0.684
#superbowl	8330.89	0.789

Table 1: **Metrics of linear regression model**

category: #gohawks						
rmse: 969.320823613694						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.505			
Model:	OLS	Adj. R-squared:	0.501			
Method:	Least Squares	F-statistic:	117.1			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	3.33e-85			
Time:	16:35:29	Log-Likelihood:	-4794.8			
No. Observations:	578	AIC:	9600.			
DF Residuals:	573	BIC:	9621.			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	1.2371	0.127	9.746	0.000	0.988	1.486
x2	-0.1557	0.045	-3.454	0.001	-0.244	-0.067
x3	-0.0005	0.000	-3.151	0.002	-0.001	-0.000
x4	0.0002	0.000	1.026	0.305	-0.000	0.000
x5	6.7740	3.401	1.992	0.047	0.094	13.454
Omnibus:	933.725	Durbin-Watson:	2.248			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	780386.888			
Skew:	9.065	Prob(JB):	0.00			
Kurtosis:	182.096	Cond. No.	9.06e+04			

(a) #gohawks

category: #sb49 rmse: 4357.88677897403						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.818			
Model:	OLS	Adj. R-squared:	0.817			
Method:	Least Squares	F-statistic:	519.2			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	7.23e-211			
Time:	16:37:06	Log-likelihood:	-5702.8			
No. Observations:	582	AIC:	1.142e+04			
DF Residuals:	577	BIC:	1.144e+04			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	0.9355	0.058	16.180	0.000	0.822	1.049
x2	-0.1610	0.026	-6.343	0.000	-0.212	-0.112
x3	0.0003	4.9e-05	5.693	0.000	0.000	0.000
x4	-3.613e-05	5.13e-05	-0.705	0.481	-0.000	6.45e-05
x5	2.5998	14.464	0.180	0.857	-25.809	31.009
Omnibus:	1240.740	Durbin-Watson:	1.772			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2871768.756			
Skew:	16.329	Prob(JB):	0.000			
Kurtosis:	345.574	Cond. No.	1.01e+06			

(c) #sb49

category: #patriots rmse: 2517.0436225246235						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.684			
Model:	OLS	Adj. R-squared:	0.681			
Method:	Least Squares	F-statistic:	251.0			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	1.51e-142			
Time:	16:37:46	Log-Likelihood:	-5420.4			
No. Observations:	586	AIC:	1.085e+04			
DF Residuals:	581	BIC:	1.087e+04			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	0.9805	0.079	12.624	0.000	0.845	1.154
x2	-0.0450	0.056	-0.824	0.410	-0.155	0.063
x3	-0.0002	9.15e-05	-2.243	0.025	-0.000	-2.55e-05
x4	0.0003	0.000	3.043	0.002	0.000	0.001
x5	1.8266	8.749	0.209	0.835	-15.356	19.009
Omnibus:	888.931	Durbin-Watson:	1.980			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	704259.297			
Skew:	7.952	Prob(JB):	0.00			
Kurtosis:	172.087	Cond. No.	3.02e+05			

(e) #patriots

category: #nfl rmse: 585.3194207979475						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.647			
Model:	OLS	Adj. R-squared:	0.644			
Method:	Least Squares	F-statistic:	213.2			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	6.76e-129			
Time:	16:35:54	Log-Likelihood:	-4565.6			
No. Observations:	586	AIC:	9141.			
DF Residuals:	581	BIC:	9163.			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	1.0581	0.110	9.662	0.000	0.843	1.273
x2	-0.1392	0.063	-2.213	0.027	-0.263	-0.016
x3	-8.332e-05	2.84e-05	-2.936	0.003	-0.000	-2.76e-05
x4	5.726e-05	2.4e-05	2.392	0.017	1.03e-05	0.000
x5	4.6344	2.151	2.154	0.032	0.409	8.860
Omnibus:	476.493	Durbin-Watson:	2.185			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	357011.437			
Skew:	2.283	Prob(JB):	0.000			
Kurtosis:	123.935	Cond. No.	1.69e+05			

(b) #nfl

category: #gopatriots						
rmse: 174.47405664592223						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.680			
Model:	OLS	Adj. R-squared:	0.672			
Method:	Least Squares	F-statistic:	241.7			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	3.80e-138			
Time:	16:37:09	Log-likelihood:	-3777.3			
No. Observations:	574	AIC:	7565.			
DF Residuals:	569	BIC:	7586.			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	0.5720	0.241	2.377	0.018	0.099	1.045
x2	-0.2377	0.211	-1.127	0.260	-0.652	0.176
x3	0.0010	0.000	8.356	0.000	0.001	0.001
x4	-0.0010	0.000	-8.813	0.000	-0.001	-0.001
x5	1.0705	0.566	1.890	0.059	-0.042	2.183
Omnibus:	522.450	Durbin-Watson:	2.036			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	271437.437			
Skew:	2.948	Prob(JB):	0.000			
Kurtosis:	109.370	Cond. No.	2.32e+04			

(d) #gopatriots

category: #superbowl rmse: 8330.894601699181						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.789			
Model:	OLS	Adj. R-squared:	0.787			
Method:	Least Squares	F-statistic:	434.8			
Date:	Sat, 10 Mar 2018	Prob (F-statistic):	1.12e-193			
Time:	16:41:22	Log-Likelihood:	-6121.7			
No. Observations:	586	AIC:	1.225e+04			
DF Residuals:	581	BIC:	1.228e+04			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	1.9462	0.082	23.825	0.000	1.786	2.107
x2	-0.4753	0.027	-17.686	0.000	-0.528	-0.423
x3	5.429e-05	5.83e-05	0.931	0.352	-6.02e-05	0.000
x4	9.771e-05	0.000	0.814	0.416	-0.000	0.000
x5	-5.1482	30.563	-0.168	0.866	-65.175	54.879
Omnibus:	901.649	Durbin-Watson:	2.246			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1783902.692			
Skew:	7.797	Prob(JB):	0.00			
Kurtosis:	272.848	Cond. No.	1.90e+06			

(f) #superbowl

Figure 3: Statistics for Linear Regression

2.3 Q1.3

After studying several papers, we designed following new features: mention count, rank score, passivity, co-occurrence of tags, and unique authors.

Mention count. Mention is a directional sharing behavior in Twitter by using @ as the prefix of the user's name. If a user was mentioned in a tweet with a hashtag, he probably took part in the topic. Thus, mention count is one of the new features we tried.

Rank score. Rank score measures the degree of relevance of a tweet to a topic. If there were many tweets related to a specific topic, then these tweets should have high relevance scores to this topic. Thus, mention count is one of the new features we tried.

Passivity. Active users often post or retweet tweets following some hashtags. On the other hand, passive users rarely do so unless the topics are attractive enough. The passivity is defined as following equation:

$$P_{sv}(u_i) = \frac{N_d(u_i)}{1.0 + N_t(u_i)}$$

where $N_d(u_i)$ denotes the number of days since the user account was created, and $N_t(u_i)$ denotes the total number of tweets posted by this user.

Co-occurrence of tags. Sometimes, several hashtags are used together by users if the topic is hot. The co-occurrence of tags is defined as the number of hashtags used in a tweet.

Unique authors. We also consider the unique number of authors who posted tweets containing the hashtag. This feature can help recognize tweets automatically posted by some fake accounts.

We combine these new features, and apply the OLS linear model of stats api to fit our data. We obtain following fitting accuracy metrics:

	RMSE	Test R-squared
#gohawks	904.084	0.570
#nfl	528.773	0.712
#sb49	4224.850	0.829
#gopatriots	136.285	0.806
#patriots	2468.086	0.698
#superbowl	8391.092	0.785

Table 2: Metrics of linear regression model (New designed features)

#gohawks						
OLS Regression Results						
Dep. Variable:	y		R-squared:	0.570		
Model:	OLS		Adj. R-squared:	0.566		
Method:	Least Squares		F-statistic:	152.0		
Date:	Sun, 11 Mar 2018		Prob (F-statistic):	1.30e-102		
Time:	14:14:31		Log-Likelihood:	-4754.5		
No. Observations:	578		AIC:	9519.		
DF Residuals:	573		BIC:	9541.		
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	0.8433	0.425	1.985	0.048	0.009	1.678
x2	-0.1611	0.189	-1.483	0.139	-0.374	0.052
x3	-0.1132	0.028	-4.111	0.000	-0.167	-0.059
x4	1.3609	0.281	6.759	0.000	0.965	1.756
x5	74.3725	988.958	0.082	0.935	-1718.924	1859.669
Omnibus:	1190.014		Durbin-Watson:	2.247		
Prob(Omnibus):	0.000		Jarque-Bera (JB):	2389786.138		
Skew:	15.106		Prob(JB):	0.000		
Kurtosis:	311.213		Cond. No.	4.95e+05		

(a) #gohawks

#nfl						
OLS Regression Results						
Dep. Variable:	y		R-squared:		0.712	
Model:	OLS		Adj. R-squared:		0.710	
Method:	Least Squares		F-statistic:		287.3	
Date:	Sun, 11 Mar 2018	Prob (F-statistic):		1.96e-154		
Time:	14:14:31	Log-Likelihood:		-4506.0		
No. Observations:	586		AIC:		9022.	
DF Residuals:	581		BIC:		9044.	
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	1.7904	0.559	3.205	0.001	0.693	2.887
x2	-0.3588	0.056	-6.400	0.000	-0.469	-0.249
x3	-0.0719	0.008	-8.615	0.000	-0.088	-0.056
x4	0.9315	0.085	10.963	0.000	0.765	1.098
x5	-37.6525	531.067	-0.071	0.944	-1080.698	1005.993
Omnibus:	664.862		Durbin-Watson:		2.551	
Prob(Omnibus):	0.000		Jarque-Bera (JB):		175209.298	
Skew:	4.784		Prob(JB):		0.000	
Kurtosis:	87.168		Cond. No.		3.16e+05	

(b) #nfl

#sb49											
OLS Regression Results											
Dep. Variable:	y	R-squared:	0.829								
Model:	OLS	Adj. R-squared:	0.828								
Method:	Least Squares	F-statistic:	359.9								
Date:	Sun, 11 Mar 2018	Prob (F-statistic):	1.19e-218								
Time:	14:14:31	Log-Likelihood:	-5684.8								
No. Observations:	582	AIC:	1.138e+04								
DF Residuals:	577	BIC:	1.140e+04								
DF Model:	5										
Covariance Type:	nonrobust										
	coef	std err	t	P> t	[0.025	0.975]					
x1	0.6792	0.067	10.124	0.000	0.547	0.811					
x2	-0.0444	0.093	-0.476	0.634	-0.228	0.139					
x3	0.1961	0.027	7.135	0.000	0.144	0.249					
x4	-0.8169	0.158	-4.127	0.000	-1.206	-0.428					
x5	3.5228	4243.116	0.001	0.999	-8330.313	8337.357					
Omnibus:	1232.685	Durbin-Watson:	1.538								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2865975.814								
Skew:	16.071	Prob(JB):	0.00								
Kurtosis:	345.274	Cond. No.	2.62e+06								

(c) #sb49

#gopatrics						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.806			
Model:	OLS	Adj. R-squared:	0.804			
Method:	Least Squares	F-statistic:	472.7			
Date:	Sun, 11 Mar 2018	Prob (F-statistic):	6.69e-200			
Time:	14:14:31	Log-Likelihood:	-3635.5			
No. Observations:	574	AIC:	7281.			
DF Residuals:	569	BIC:	7303.			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	2.4558	0.484	5.070	0.000	1.504	3.407
x2	-1.0718	0.127	-8.414	0.000	-1.322	-0.822
x3	0.3020	0.010	15.651	0.000	0.286	0.342
x4	0.7340	0.274	2.677	0.008	0.196	1.272
x5	8.4249	136.883	0.062	0.951	-260.432	277.282
Omnibus:	232.846	Durbin-Watson:	2.221			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	100874.859			
Skew:	-0.107	Prob(JB):	0.000			
Kurtosis:	69.848	Cond. No.	9.94e+04			

(d) #gopatrics

#patriots						
OLS Regression Results						
Dep. Variable:	y	R-squared:	0.698			
Model:	OLS	Adj. R-squared:	0.695			
Method:	Least Squares	F-statistic:	268.5			
Date:	Sun, 11 Mar 2018	Prob (F-statistic):	2.04e-145			
Time:	14:14:31	Log-Likelihood:	-5406.9			
No. Observations:	586	AIC:	1.083e+04			
DF Residuals:	581	BIC:	1.085e+04			
DF Model:	5					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
x1	0.1819	0.049	3.712	0.000	0.086	0.278
x2	0.2747	0.116	2.371	0.018	0.047	0.502
x3	-0.0653	0.033	-1.999	0.046	-0.130	-0.001
x4	0.0233	0.192	0.122	0.903	-0.353	0.400
x5	105.9916	2478.995	0.043	0.966	-4762.892	4974.875
Omnibus	1003.460	Durbin-Watson	2.011			
Prob(Omnibus):	0.000	Jarque-Bera (JB)	782869.545			
Skew:	10.409	Prob(JB)	0.00			
Kurtosis:	171.364	Cond. No.	1.19e+06			

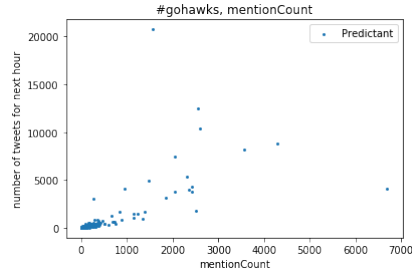
(e) #patriots

#superbowl											
OLS Regression Results											
Dep. Variable:	y	R-squared:	0.785								
Model:	OLS	Adj. R-squared:	0.783								
Method:	Least Squares	F-statistic:	423.4								
Date:	Sun, 11 Mar 2018	Prob (F-statistic):	4.81e-191								
Time:	14:14:31	Log-Likelihood:	-6126.0								
No. Observations:	586	AIC:	1.226e+04								
DF Residuals:	581	BIC:	1.228e+04								
DF Model:	5										
Covariance Type:	nonrobust										
	coef						std err	t	P> t	[0.025	0.975]
x1	-5.9103	0.668	-8.848	0.000	-7.222	-4.598					
x2	0.6314	0.127	4.981	0.000	0.382	0.880					
x3	-0.4438	0.031	-14.262	0.000	-0.505	-0.383					
x4	2.6111	0.242	10.770	0.000	2.135	3.087					
x5	-104.7545	8427.143	-0.012	0.990	-1.67e+04	1.64e+04					
Omnibus:	850.822	Durbin-Watson:	2.515								
Prob(Omnibus):	0.000	Jarque-Bera (JB):	434552.954								
Skew:	7.449	Prob(JB):	0.000								
Kurtosis:	135.573	Cond. No.	5.70e+06								

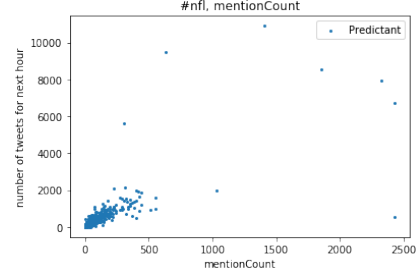
(f) #superbowl

Figure 4: Statistics for Linear Regression (New designed features)

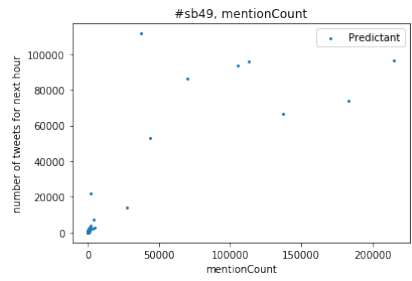
These are statistic results of OLS model for each hashtag. To choose the top 3 features, we simply did majority votes among 5 new features based on the p value of each feature. We found that features x1 (mention count), x2 (passivity), and x4 (co-occurrence of tags) are most significant 3 features. Then, we plot scatter plots (predictant versus the value of feature) for each of top 3 features, and for each hashtag.



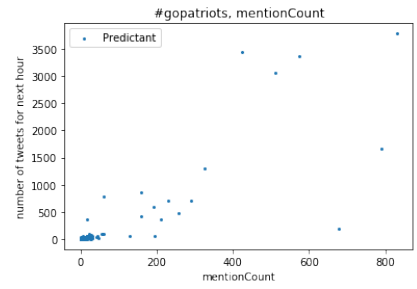
(a) #gohawks



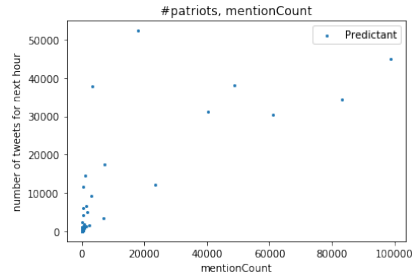
(b) #nfl



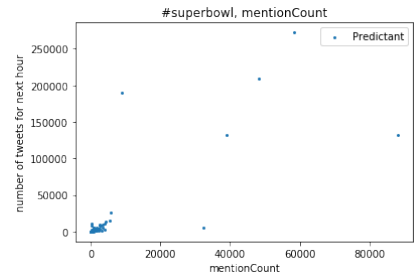
(c) #sb49



(d) #gopatrics



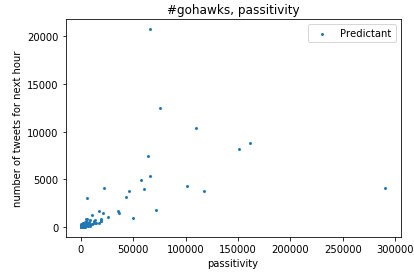
(e) #patriots



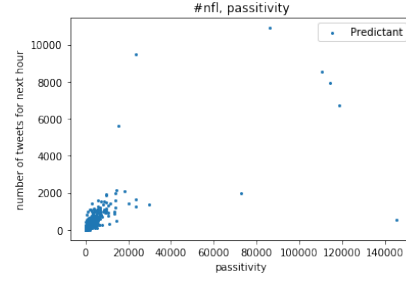
(f) #superbowl

Figure 5: **Scatter plot of predictant versus value of feature (Mention Count)**

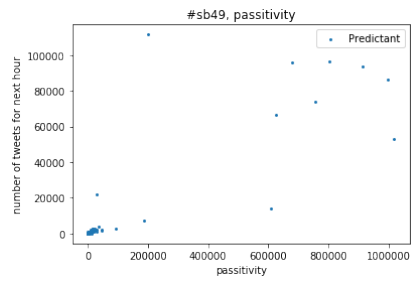
These are scatter plots for predictant versus value of mention count, for each hashtag. We conclude that there is a relatively linear relationship between our mention count feature and the number of tweets for next hours, despite of some extreme points.



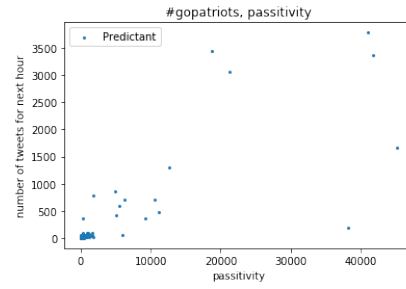
(a) #gohawks



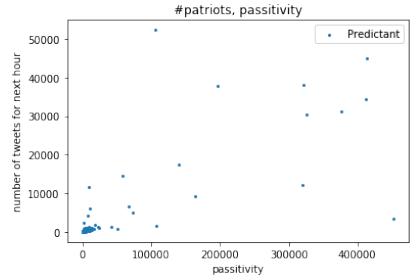
(b) #nfl



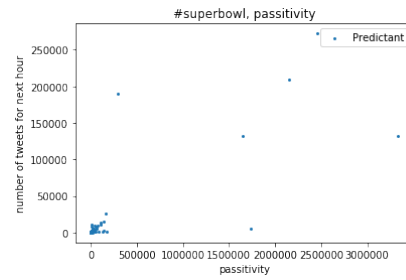
(c) #sb49



(d) #gopatients



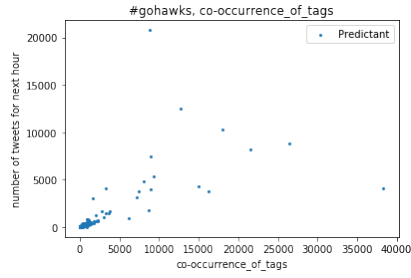
(e) #patriots



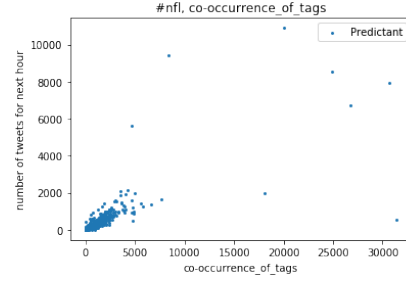
(f) #superbowl

Figure 6: **Scatter plot of predictant versus value of feature (Passivity)**

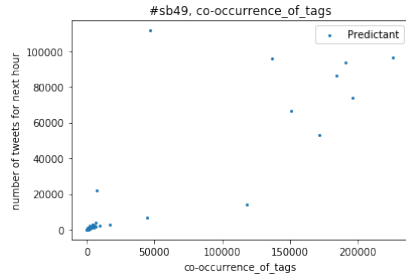
These are scatter plots for predictant versus value of passivity, for each hashtag. We conclude that there is a relatively linear relationship between our passivity feature and the number of tweets for next hours, despite of some extreme points.



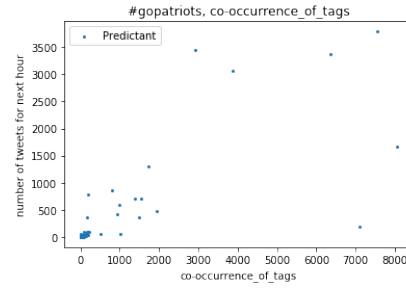
(a) #gohawks



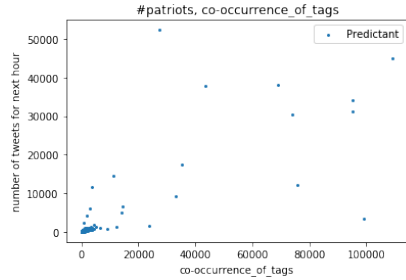
(b) #nfl



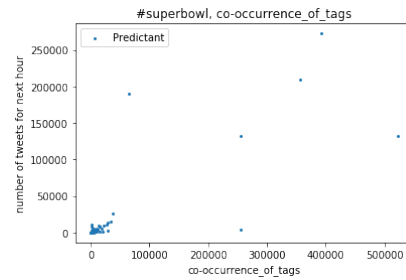
(c) #sb49



(d) #gopatriots



(e) #patriots



(f) #superbowl

Figure 7: Scatter plot of predictant versus value of feature (Co-occurrence of tags)

These are scatter plots for predictant versus value of co-occurrence of tags, for each hashtag. We conclude that there is a relatively linear relationship between our co-occurrence of tags feature and the number of tweets for next hours, despite of some extreme points.

2.4 Q1.4

In this part, we use three different models, Random Forest Regressor, Support Vector Regressor, and Linear SVR for cross validation. We use the same features as part 1.3. As we can see, the MAE is particularly large in the second period (the day when the final happens). This is expected since the number of tweets is the largest during that period.

Hashtag	Model	MAE Period 1	MAE Period 2	MAE Period 3
#gohawks	Random Forest Regressor	224.805	2961.000	32.771
#gohawks	Support Vector Regressor	162.873	2057.769	29.308
#gohawks	Linear SVR	230.735	4961.248	19.039
#nfl	Random Forest Regressor	189.435	3360.846	296.178
#nfl	Support Vector Regressor	113.409	1862.838	161.894
#nfl	Linear SVR	131.304	6610.062	184.607
#sb49	Random Forest Regressor	104.355	43000.962	340.302
#sb49	Support Vector Regressor	45.973	24142.238	133.946
#sb49	Linear SVR	50.603	102436.941	85.322
#gopatriots	Random Forest Regressor	12.830	1407.308	4.932
#gopatriots	Support Vector Regressor	11.654	884.046	4.226
#gopatriots	Linear SVR	13.230	1474.449	3.717
#patriots	Random Forest Regressor	265.085	20316.308	143.657
#patriots	Support Vector Regressor	223.789	13326.308	104.829
#patriots	Linear SVR	211.170	59552.666	60.537
#superbowl	Random Forest Regressor	441.546	75255.077	598.250
#superbowl	Support Vector Regressor	248.277	48557.815	256.598
#superbowl	Linear SVR	338.001	69712.643	300.267

Table 3: **MAE of three different models in different periods for 6 hash-tags**

Hashtag	Model	MAE Period 1	MAE Period 2	MAE Period 3
total	Random Forest Regressor	1642.051	77828.077	1239.598
total	Support Vector Regressor	1525.975	72535.892	370.987
total	Linear SVR	1386.803	103832.673	408.831

Table 4: **MAE of three different models in different periods using aggregate data**

Hashtag	Model	MAE Period 1	MAE Period 2	MAE Period 3
total	Random Forest Regressor	1238.056	146301.5	1416.091
total	Support Vector Regressor	794.296	95530.546	643.571
total	Linear SVR	818.874	289569.02	603.722

Table 5: **sum of MAE of three different models in different periods using each hashtag**

The first table is generated with the cross-validated MAE of aggregate data, and the second one is simply the sum of errors from all 6 tags. We can observe that the first table is much smaller than the second one. This is expected, since we might over-estimate or under-estimate the result, and aggregating the data will counteract some of this effect.

2.5 Q1.5

The best model we found in Q1.4 is the random forest regressor model and we apply this model here. We set time window of features to 5 hours instead of 1 hour, and predict for the hour after each window. We use the 'first_postdate' instead of 'citation_date', because the test data are collected based on 'first_postdate'. All test samples have 6 hour span except for sample8 which only has 5 hour span. We trained our model by aggregating the data of all hashtags, with time window of 5 hours. Because most each test sample file spans over 6 hours, so we use the first 5 hours data (first 4 hours data for sample8) as the input to the model, and compare the predicted number of tweets in the 6th hour (the 5th hour for sample 8) with the true number of tweets in the 6th hour of each test sample file. Both the true value and the predicted value are listed in the following table.

Hour 6	True value	Predicted Value
Sample1	178	225.5
Sample2	82892	30163.2
Sample3	524	547.9
Sample4	203	426.45
Sample5	211	699.5
Sample6	37279	67951
Sample7	121	224.7
Sample8	12	255.5
Sample9	2791	2349.6
Sample10	62	475

Table 6: **Number of tweets in the next hour (Use 5 hour interval to predict)**

There are some situations where the predicted value (5 hour window) is close to the true value: sample 3 (524 versus 547.9) and sample 9 (2791 versus 2349.6). Also, there are situations where the predicted value based on 5-hour window is much closer to the true value than the predicted value based on 1-hour window. For example, in sample 6, the true value is 37279, the predicted value based on 5-hour window is 67951, and the predicted value based on 1-hour window is 159763.9 which is far from the true value.

In general, predicting number of tweets in the next hour based on 5-hour window is a fair choice. But since this prediction task is hard, it is difficult for training data based on 5-hour window to reach a perfect performance.

3 Q2

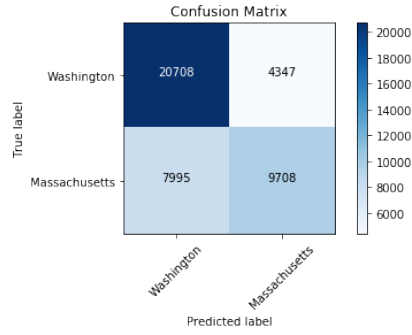
Leveraging the techniques in Project 1, we transform the textual content of the text into matrix with latent semantic information. After preprocessing the data, we tried 6 classification algorithms. These algorithms are **random forest classifier, linear support vector machine classifier, logistic regression classifier, k nearest neighbors, multiple layer perceptron, and decision tree**.

For each classification algorithm, we plot confusion matrix, ROC curve, and calculate accuracy, recall and precision scores. Following table shows the metric scores of 6 classification algorithms. Analysis will be made at the end of this part (Q2).

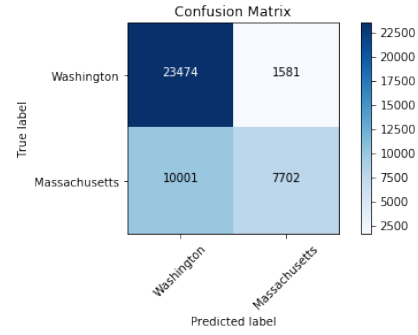
	Accuracy	Recall	Precision
Random Forest	0.7114	0.5484	0.6907
Support Vector	0.7291	0.4351	0.8297
Logistic Regression	0.7300	0.4351	0.8329
K Nearest Neighbors	0.6884	0.5989	0.6302
Multi Layer Perceptron	0.7345	0.5162	0.7664
Decision Tree	0.6710	0.6048	0.6022

Table 7: **Test Metrics of Classification Algorithm (Fan Base Prediction)**

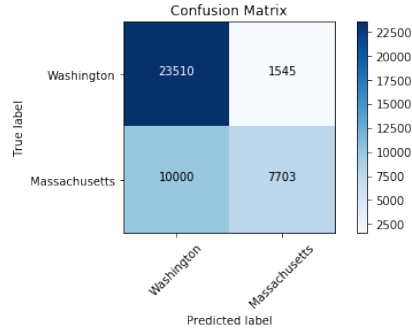
Followings are plots of confusion matrix for each classification algorithm. Analysis will be made at the end of this part (Q2).



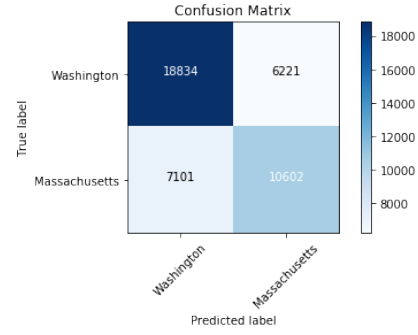
(a) Random Forest Classifier



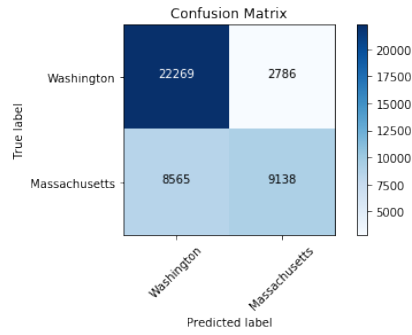
(b) Support Vector Machine Classifier



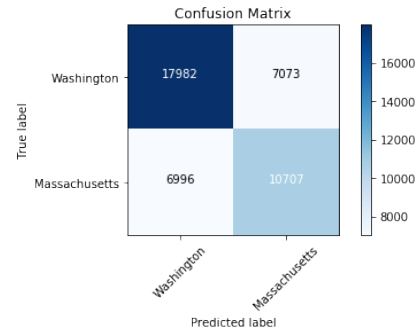
(c) Logistic Regression



(d) K Nearest Neighbors



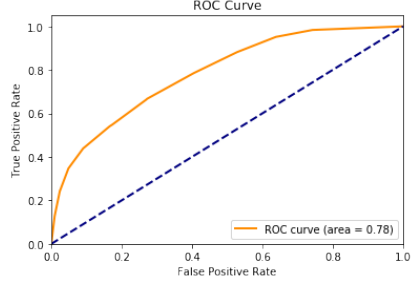
(e) Multi Layer Perceptron



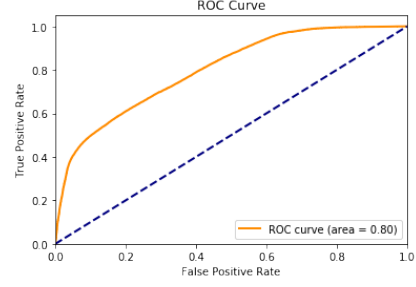
(f) Decision Tree

Figure 8: Confusion matrix plots for fan base prediction

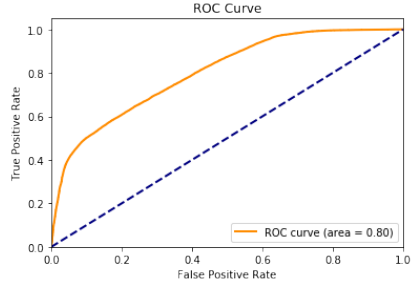
Followings are plots of ROC curve for each classification algorithm. Analysis will be made at the end of this page.



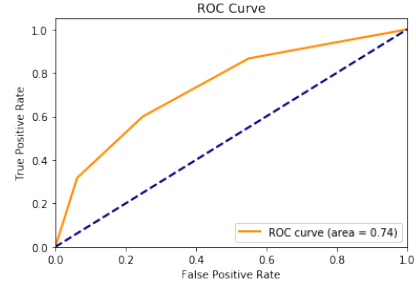
(a) Random Forest Classifier



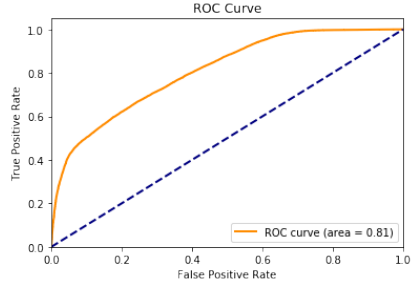
(b) Support Vector Machine Classifier



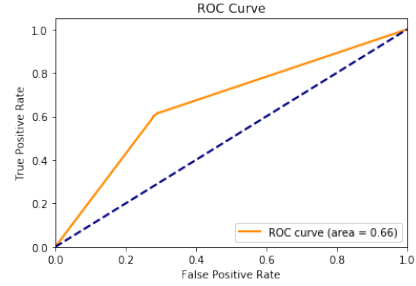
(c) Logistic Regression



(d) K Nearest Neighbors



(e) Multi Layer Perceptron



(f) Decision Tree

Figure 9: ROC plots for fan base prediction

All 6 classification algorithms have not bad performances. But based on metric scores (accuracy, recall, precision), ROC curve and confusion matrix, the multiple layer perceptron classification algorithm is the best one among all six classification algorithms.

4 Q3

4.1 Quantitative Sentiment Analysis

For part 3, we are analyzing the change of tweet sentiments for fans of the two teams (hawks and patriots) in the superbowl match. We first plot positive and negative sentiment versus time. The sentiments (y-axis) are obtained from `SentimentIntensityAnalyzer` from `nlk` and I use the tweet content (`tweet['title']`) to analyze the sentiment polarity score.

The time (x-axis) is the number of hours passed from the beginning of the data collection, which is two weeks before the game match. To approximate the time of the game match we can deduct a week from the last data, so the time would be around the middle of 400 500 hours on x-axis.

If we carefully analyze the two sentiment vs time plots, we can see that the negative sentiment polarity score has a peak at around 450 hours on the x-axis for `#gohawks` and positive sentiment polarity score has a peak around 450 hours on the x-axis for `#patriots`. This makes sense because The New England Patriots team won Superbowl in 2015, which causes the peak of positive sentiment for the patriots (winner) tag and the peak of negative sentiment for the hawks (loser) tag.

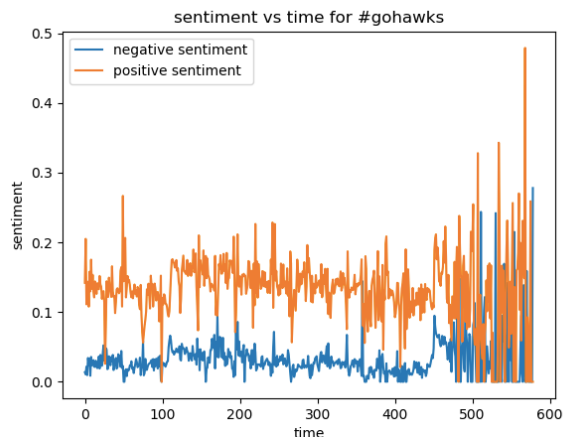


Figure 10: **Sentiment vs time for #gohawks**

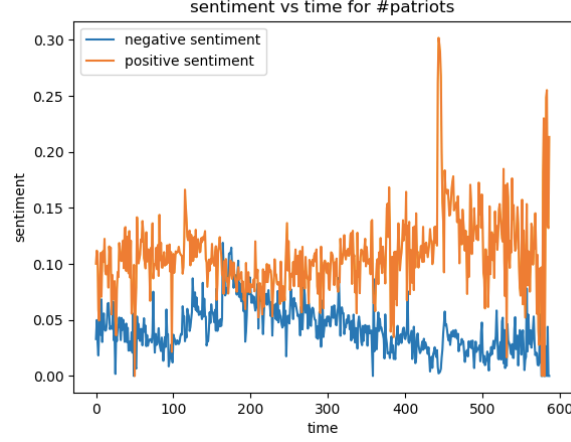


Figure 11: **Sentiment vs time for #patriots**

4.2 Relative Sentiment Analysis

Different from the previous analysis which estimated the exact quantity sum of sentiment coefficient and plotted all the positive and negative sentiments, this time, we took another insight. That is, we consider those who have sentiment quantity > 0 are considered "positive tweets", those who have sentiment quantity < 0 are considered "negative tweets", and those who holds neutral opinion will have the sentiment equal to zero. In other words, there is no "strong sentiment" in this scenario.

In addition, the sentiment quantity is calculated using TextBlob, a python package for Natural Language Processing, in which the `sentiment.polarity` was invoked, from the `sentiment()` function. The polarity ranges from -1 to 1, with -1 being most negative texts and 1 being the opposite.

Next, since there are only two teams involved in this data set, we consider those who hold "negative sentiment" against team "hawk" are supporting their opponent team, that is "patriots". Similarly, those who hold "positive sentiment" for "patriots" are essentially "negative sentiment" for the "hawk". Once this concept is established, we conclude that, from the hawk's perspective, tweets supporting hawk = positive sentiment for hawk + negative sentiment for patriots; tweets against hawk = positive sentiment towards patriots + negative sentiment for hawk.

Thereafter, four arrays of data are collected, for positive sentiment hawk, negative sentiment hawk, positive sentiment patriots, negative sentiment patriots. Then based in the formula mentioned above, we plot the diagram for relative negative and positive tweets from the hawk's perspective.

As we can see from the diagram below, at around hour 450, there is a huge peak for relative positive response on hawk's perspective, one can easily deduce that hawk was the winner at that moment.

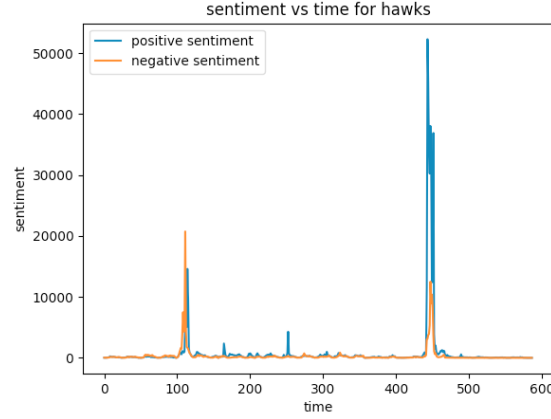


Figure 12: relative responses from hawk's perspective

4.3 Comparison between method 4.1 and method 4.2

The sentiment values were calculated differently, due to package differences. In "Quantitative Sentiment Analysis", the sentiment values were computed by the sentiment intensity analyzer, from the nltk package; whereas in "Relative Sentiment Analysis", the sentiment.polarity from TextBlob was used. The later method took around 3 hours to run through the entire data set, taking 2 hours and 30 min longer than the nltk package. Both TextBlob and nltk are part of Natural Language Processing, but TextBlob was designed to bring more benefits that was not in nltk. In other words, TextBlob is enhanced super set that is build off of nltk. This leads to the reason why TextBlob took significantly longer than nltk, though the data we were interested in were the same - sentiment quantity. Also, the algorithm was a bit different, in that the "Relative Sentiment Analysis" has to run over the data set for 4 times, whereas "Quantitative Sentiment Analysis" only run for twice (see details in implementation). Another difference is that 4.1 is per tweet sentiment. As y-axis in graphs in 4.1 indicates, the sentiments are between 0 and 1. On the other hand, 4.2 is adding up the sentiment scores and so the y-axis is much larger.

4.4 Changes of top words before, during and after the super bowl game

For this newly designed problem, we want find some interesting changes of top words in tweets before, during and after the super bowl game. To perform this experiment, we firstly aggregate tweet contents based on following three time periods (PST times):

1. Before Feb. 1, 8:00 a.m. (i.e. before game)
2. Between Feb. 1, 8:00 a.m. and 8:00 p.m. (i.e. game time)
3. After Feb. 1, 8:00 p.m. (i.e. after game)

Then we perform TfIDF vectorization (the technique we mastered from Project 1) to extract top 20 words.

1. Before the game

['gohawks', 'http', 'superbowlxlix', 'seattle', 'seahawks', 'superbowl', 'nfl', 'new', 'amp', 'game', 'win', 'football', 'super', 'bowl', 'patriots', 'el', 'sb49', 'colts', 'brady', 'deflategate']

2. During the game

['gohawks', 'http', 'just', 'super', 'bowl', 'sb49', 'seahawks', 'patriots', 'game', 'superbowl', 'superbowlxlix', 'winning', 'got', 'nfl', 'el', 've', 'half-time', 'katyperry', 'seahawkswin', 'patriotswin']

3. After the game

['brady', 'http', 'rt', 'seahawks', 'super', 'bowl', 'superbowl', 'sb49', 'superbowlxlix', 'amp', 'win', 'game', 'football', 'nfl', 'patriots', 'https', 'year', 'katyperry', 'new', '2015']

We can find many interesting facts from the change of top words in tweets. For example, 'halftime' and 'katyperry' shows up in the top words from tweets during the game, as Katy Perry was featured in the half time show. Also, 'brady' jumps to the top 1 from tweets after the super bowl game, as Tom Brady was the key person that led New England Patriots win the game!

5 Conclusion

In this project, we used Twitter data for social network analysis. We did popularity prediction using linear regression and other regression models. We designed good features for the regression models. We also used k-fold cross validation for different models. Lastly, we designed our own problems analyzing sentiments and change of top words and implemented them.