Geolocation Classifier for Tweets

1 Introduction

People from different countries or cities use language differently. The spelling of some words in British English is different from in American English. Also, dialects and slangs are different from regions to regions. So, it is possible to infer a person's home geolocation by looking at what (s)he writes and how (s)he writes. This project aims to build a Geolocation Classifier Model, which able to classify a user's geolocation into one of the three cities (New York, California or Georgia) with decent accuracy. The dataset used in this project is the tweets dataset (Eisenstein and Jacob, 2010; Rahimi, 2018) which includes 96585 instances from the training set and 34028 instances from the development set. The software used in this project is the Waikato Environment for Knowledge Analysis (Ian, 2011).

2 Literature review

Some works have been done in this area. In 2010, Eisenstein Jacob developed a model, which assumes the topic varies from regions to regions, to identify words that have "high regional affinity". In 2018, Afshin Rahimi proposed three semi-supervised models (GCN, DCCA, and MLP-TXT+NET) to identify users' locations, which achieved good results.

3 Method

First, we select the dataset for analysis. We use bestXX instead of mostXX since bestXX contains the features with the greatest Mutual Information and Chi-Square values, while mostXX contains the most frequent terms, which do not indicate locations.

Second, we select classifiers that are suitable for this project. Since the problem is a classification problem as we need to classify the tweet instances into one of the three cities (multiclass). Also, it is Supervised Learning as we have the desired output class in our training set and development set. ZeroR, OneR, J48, LMT, Random Forest, Naïve Bayes, Naïve Bayes Multinomial and Logistic Regression are selected for analysis. Although some are binary classifiers by definition, such as Logistic Regression, sometimes they work well with the multiclass problems.

Third, base on the previous results and analysis, we sum the vectors by the same user id, which reduced the number of instances. After that, we run the selected classifiers again using 10-Fold Cross-validation for further analysis.

3.1 ZeroR

ZeroR is a simple classifier, which always predicts the majority class. In this project, ZeroR is used as a baseline.

3.2 OneR

OneR uses one feature which has the lowest error rate for prediction. In this project, OneR is used as a baseline.

3.3 K-NN

K-Nearest Neighbors (Altman, 1992) compared one instance to other instances and classify the instance by looking at its K nearest neighbors. A common way of choosing K value is K = sqrt(n).

3.4 J48

J48 (C4.5) is a decision tree algorithm (Ross 1993) for classification.

3.5 Random Forest

Random Forest (Ho, 1995), which randomly selects features and construct different decision trees, uses the results (voting) from a collection of trees to make predictions.

3.6 Naïve Bayes and Naïve Bayes Multinomial

Naïve Bayes (Maron, 1961), which based on Bayes' theorem and assume each feature is independent of other features, is a way of classification based on the probabilities. Naïve Bayes Multinomial uses multinomial distribution for each feature.

3.7 Logistic Regression

Logistic Regression (Walker, 1967), which uses the Logistic Model, has an 'S' shape logistic regression curve range from 0 to 1, which predicts based on the probabilities.

3.8 LMT

logistic model tree (Niels, 2003) is based on the decision tree (C4.5) and logistic regression.

4 Measurement

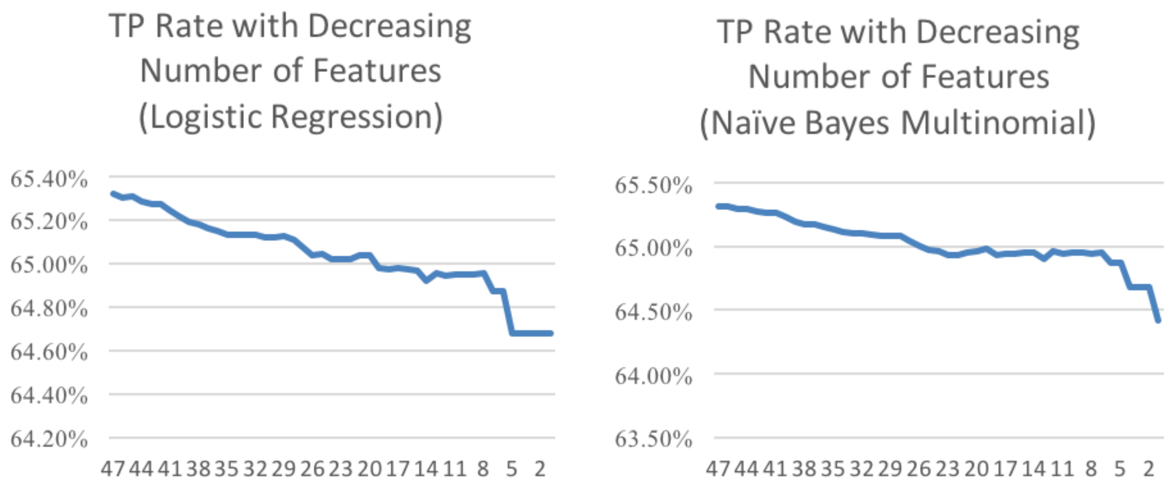
There are several measurements provided by Weka: TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, ROC Area, and PRC Area. In this project, we mainly look at the TP rate (Powers, 2011), Receiver Operating Characteristic Area (Fewcett, 2006) and Precision-Recall Curves Area because of the TP rate indicates accuracy while ROC and PRC Area indicates the benefits of the model compared to the baseline.

Experiment 1: Results of best 10, 20, 50 and 200 data with tweet-id and user-id removed (Hold-out)								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
ZeroR	0.644	0.644	-	0.644	-	-	0.500	0.479
OneR	0.647	0.633	-	0.647	-	-	0.507	0.483
Best 10								
K-NN(185)	0.649	0.628	-	0.649	-	-	0.560	0.524
J48	**0.651**	0.620	0.658	0.651	0.529	0.114	0.517	0.489
Random Forest	**0.651**	0.620	0.645	0.651	0.529	0.113	**0.562**	**0.527**
Naïve Bayes	0.632	0.612	0.513	0.632	0.519	0.045	0.550	0.505
Naïve Bayes Multinomial	**0.651**	0.619	0.650	0.651	0.530	0.115	**0.561**	**0.527**
Logistic Regression	**0.651**	0.620	0.655	0.651	0.529	0.114	**0.563**	**0.528**
LMT	**0.651**	0.620	0.656	0.651	0.529	0.114	**0.563**	**0.528**
Best 20								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
K-NN(185)	0.649	0.629	0.616	0.649	0.520	0.084	0.583	0.542
J48	**0.653**	0.615	0.657	0.653	0.533	0.130	0.521	0.493
Random Forest	0.650	0.609	0.603	0.650	0.535	0.115	0.583	0.542
Naïve Bayes	0.621	0.590	0.508	0.621	0.527	0.056	0.564	0.515
Naïve Bayes Multinomial	**0.653**	0.613	0.647	0.653	0.535	0.130	**0.588**	**0.550**
Logistic Regression	**0.653**	0.614	0.652	0.653	0.535	0.130	**0.589**	**0.551**
LMT	**0.653**	0.615	0.657	0.653	0.534	0.130	**0.588**	**0.550**
Best 50								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
K-NN(185)	0.648	0.629	0.613	0.648	0.519	0.081	0.608	0.564
J48	**0.651**	0.598	0.601	0.651	0.544	0.133	0.549	0.511
Random Forest	0.636	0.576	0.549	0.636	0.547	0.107	0.593	0.551
Naïve Bayes	0.601	0.550	0.513	0.601	0.535	0.071	0.574	0.525
Naïve Bayes Multinomial	**0.654**	0.593	0.620	0.654	0.549	0.148	**0.623**	**0.583**
Logistic Regression	**0.656**	0.597	0.626	0.656	0.547	0.151	**0.624**	**0.584**
LMT	-	-	-	-	-	-	-	-
Best 200								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
K-NN(185)	0.648	0.631	0.532	0.648	0.518	0.074	0.626	0.581
J48	-	-	-	-	-	-	-	-
Random Forest	-	-	-	-	-	-	-	-
Naïve Bayes	0.582	0.514	0.515	0.582	0.538	0.083	0.579	0.532
Naïve Bayes Multinomial	**0.654**	0.552	0.603	0.654	0.572	0.178	**0.662**	**0.618**
Logistic Regression	**0.658**	0.571	0.616	0.658	0.565	0.176	**0.661**	**0.618**
LMT	-	-	-	-	-	-	-	-

Table 1 - Results of best 10, 20, 50 and 200 data with tweet-id and user-id removed

Experiment 2: Information Gain Ranking of train-best20 Features								
No	IG	Feature	No	IG	Feature	No	IG	Feature
1	0.005166	haha	17	0.001222	dead	33	0.000702	gw
2	0.002894	inhighschool	18	0.001187	dat	34	0.000669	flirty
3	0.002771	lmaoo	19	0.001135	atlanta	35	0.000643	san
4	0.002493	lml	20	0.001104	iight	36	0.000629	ahaha
5	0.002183	hahaha	21	0.000964	will	37	0.000619	coo
6	0.002007	da	22	0.000958	dis	38	0.000607	thatisall
7	0.001982	hella	23	0.000945	deadass	39	0.000596	lowkey
8	0.001932	lmaooo	24	0.000944	willies	40	0.000555	famu
9	0.001757	rt	25	0.000925	just	41	0.000517	frequency
10	0.001709	the	26	0.000911	finna	42	0.0005	juss
11	0.001542	and	27	0.00091	ga	43	0.000498	gsu
12	0.00154	ii	28	0.000832	la	44	0.000498	tinos
13	0.001421	are	29	0.000825	a	45	0.00049	parody
14	0.001287	atl	30	0.000799	know	46	0.000452	famusextape
15	0.001287	that	31	0.00072	bomb	47	0.000424	wet
16	0.001261	smh	32	0.00072	childplease			

Table 2 - Information Gain Ranking for Best 20 Features (tweet-id and user-id removed)



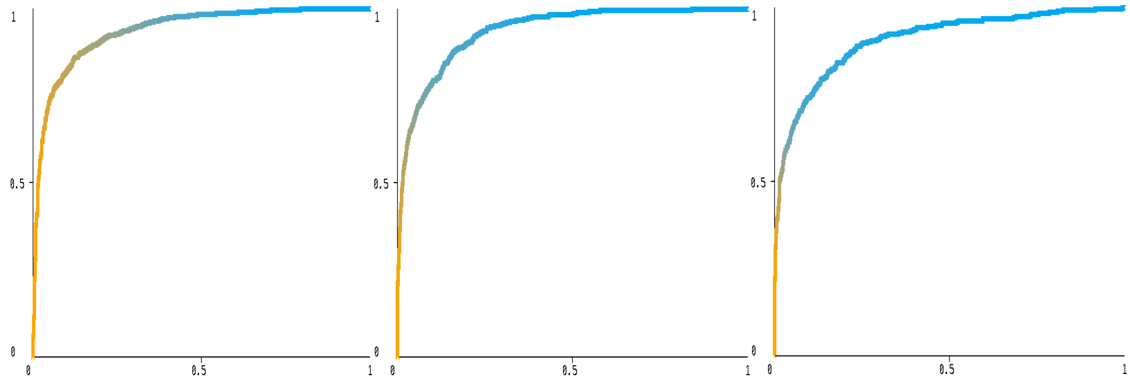
Graph 1 - TP Rate with Decreasing Number of Features (Logistic Regression and Naïve Bayes Multinomial)

Experiment 3: Results of best200 (train+dev), 10-Fold Cross-validation								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
ZeroR	0.633	0.633	-	0.633	-	-	0.500	0.470
OneR	0.636	0.622	-	0.636	-	-	0.507	0.474
Naïve Bayes Multinomial	0.653	0.533	0.617	0.653	0.574	0.206	0.678	0.627

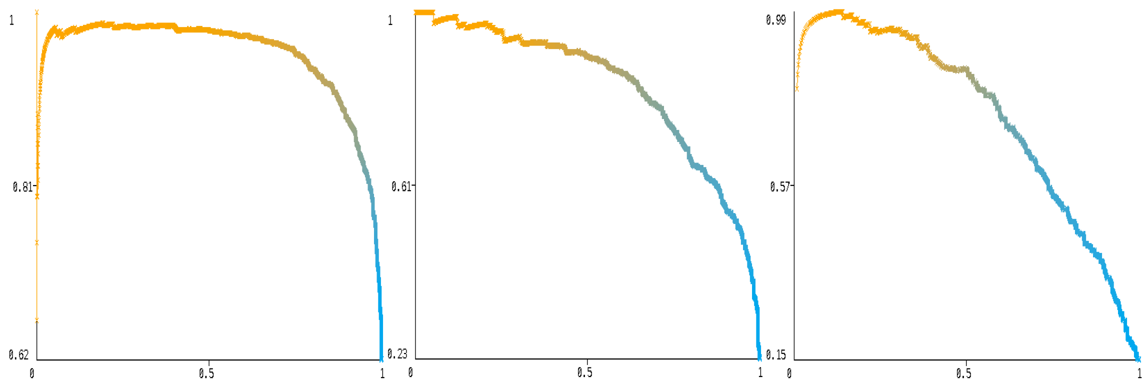
Table 3 - Results of Naïve Bayes Multinomial (10-Fold Cross-validations on all data)

Experiment 4: Results of best200 (train+dev), 10-Fold Cross-validation, sum feature vectors by user_id								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
ZeroR	0.624	0.624	-	0.624	-	-	0.498	0.463
OneR	0.651	0.536	-	0.651	-	-	0.558	0.501
K-NN(17)	0.661	0.549	0.731	0.661	0.563	0.258	0.791	0.710
J48	0.716	0.236	0.713	0.716	0.715	0.483	0.735	0.635
Random Forest	0.715	0.431	0.737	0.715	0.664	0.411	0.895	0.840
Naïve Bayes	0.657	0.126	0.761	0.657	0.675	0.507	0.862	0.782
Naïve Bayes Multinomial	**0.766**	0.111	0.804	0.766	0.775	0.621	**0.897**	**0.857**
Logistic Regression	**0.789**	0.166	0.790	0.789	0.790	0.622	**0.891**	**0.841**
LMT	**0.828**	0.189	0.823	0.828	0.822	0.674	**0.930**	**0.893**

Table 4 - Results of best200 (train+dev), 10-Fold Cross-validation, sum feature vectors by user_id



Graph 2 - ROC Areas (New York: 0.935, California: 0.934, Georgia: 0.905)



Graph 3 - PRC Areas (New York: 0.953, California: 0.831, Georgia: 0.734)

5 Result

For the first experiment, we removed twee-id and user-id as they would not reappear in the test and used 8 models for analysis. From the results in Table 1, we can see some classifiers perform better than the baseline. Logistic Regression, Naïve Bayes Multinomial and Logistic Model Tree have the best TP Rate, ROC Area and PRC Area. Random Forest, J48 and K-NN(185) are slightly better than the baseline while Naïve Bayes is worse than the baseline. So, for the second experiment, we mainly focus on Logistic Regression, Naïve Bayes Multinomial and Logistic Model Tree.

For the second experiment, we first analyzed the information gain (Quinlan, 1986) of each feature, rankings can be seen from table 2. Then we remove the feature with the lowest IG one by one (e.g. 'wet', 'famusextape' etc.) and calculate TP Rate for each remaining feature set. The results are shown in graph 1. We can see TP Rate is positively correlated with the Number of Features and Training Instances. So, removing features with less information gain may improve Over-fitting models, but not helpful to improve accuracy since the features are selected using Mutual Information and Chi-Square values.

For the third experiment, we combined the train-best200 data with dev-best200 data (130613 instances in total). Then, we use the 10-Fold Cross-validation to train our NBM model. We can see the results from table 3 that TP Rate improved by 2%, ROC Area improved by 17.8% and PRC Area improved by 15.7%.

For the fourth experiment, we sum the feature vectors by the same user id because there are too many '0's in our dataset, which is not good for building models. After that, the number of instances got reduced to 3190 (train+dev), so I chose to use 10-Fold Cross-validations for analysis. Since we sum the feature vectors, most feature values would be non-zero, so we use the best200 dataset. The result can be seen in table 4 and graphs 2 and 3. We can see the result got improved a lot for most classifiers. LMT has the highest TP rate (82.8%), which is 20% more than the baseline. Also, LMT has 93.0% ROC Area and 89.3% PRC Area, which is surprisingly good. Logistic Regression and Naïve Bayes Multinomial have solid performance as well.

6 Discussion

There are several things I learned from this project. First, Machine Learning is not only about using Machine Learning Algorithms. Pre-processing the data properly is crucial. My first three experiments did not show much improvement on TP Rate because of the training data are mostly filled with '0'. After we pre-process the data in experiment 4, we can see improvements in almost every classifier.

Second, trying out different classifiers are necessary. Before doing the project, I think K-NN might be the best classifier because of the "closeness" of language habits of people in the same region, but it turns out NBM, LR, and LMT are much better.

From the results of this project, I would recommend using Naïve Bayes Multinomial, Logistic Model Tree and Logistic Regression.

For Naïve Bayes Multinomial, it is a linear classifier, fast, and highly scalable. We can put more instances in our dataset and train our model in a relatively short time. Also, unlike decision trees, it is not likely to have an over-fitting problem because of its conditional independence hypothesis.

For Logistic Regression, I think one of the reasons LR did well in this project is because of good Feature Engineering. Since the features in bestXX are meaningful, they work well with LR's decision boundary even though LR was mainly a binary classifier.

For Logistic Model Tree, it combined benefits of LR and the decision tree. The decision tree uses Information Gain to select the best features for the LR model. I think that is the reason it has the highest accuracy in this project.

7 Conclusion

The model developed for this project are Naïve Bayes Multinomial, Logistic Model Tree and Logistic Regression.

Naïve Bayes Multinomial is fast, scalable and unlikely to get over-fitting problems. A large number of instances can be used to train the model to improve accuracy. Logistic Regression works well if the features are properly selected. Logistic Model Tree can select the best features for its LR model, which performed best in this project.

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