Geolocation Classifier for Tweets

1 Introduction

People from different countries or cities use language differently. For example, 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 geolocation by looking at what (s)he writes and how (s)he writes. This project aims to build a Geolocation Classifier Model using Machine Learning algorithms, 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 [1][2], which includes 96585 instances from the training set and 34028 instances from the development set. The software used in this project is Waikato Environment for Knowledge Analysis (Weka) [8].

2 Literature review

Some previous works have been done in this area. In 2010, Eisenstein Jacob [1] develop a model, which assumes the topic varies from regions to regions, to identify words that have "high regional affinity". In 2018, Afshin Rahimi [2] proposed three semi-supervised models (GCN, DCCA, and MLP-TXT+NET) to identify a user's location, which achieved some good results.

3 Method

First, we select a 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 just contains the most common terms, which do not indicate a location.

Second, we select machine learning methods 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 (New York, California or Georgia). Also, it is Supervised Learning as we have the desired output city in our training set and development set. As a result, ZeroR, OneR, J48, Random Forest, Naïve Bayes, Naïve Bayes Multinomial and Logistic Regression are selected for analysis.

Third, base on the results in the first step, we use Attribute Evaluator to select features with high values and use Filter to remove features that might cause misleading results.

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 attribute (feature) which has the lowest error rate for prediction. It is a simple classifier but sometimes performs better than other classifiers.

3.3 K-NN

K-Nearest Neighbors (k-NN) [3] 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). In this project, n = 34028 instances in the development set, so the K = 184.46. As we need an odd number of K, 185 is chosen for this project.

3.4 J48

J48 (C4.5) is a decision tree algorithm (by Ross Quinlan [4]) for classification.

3.5 Random Forest

Random Forest [5], 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 [6], 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 [7], which uses the Logistic Model (a math function of the logarithm), has an 'S' shape logistic regression curve range from 0 to 1, which can be used to make predictions based on the probabilities.

4 Measurement

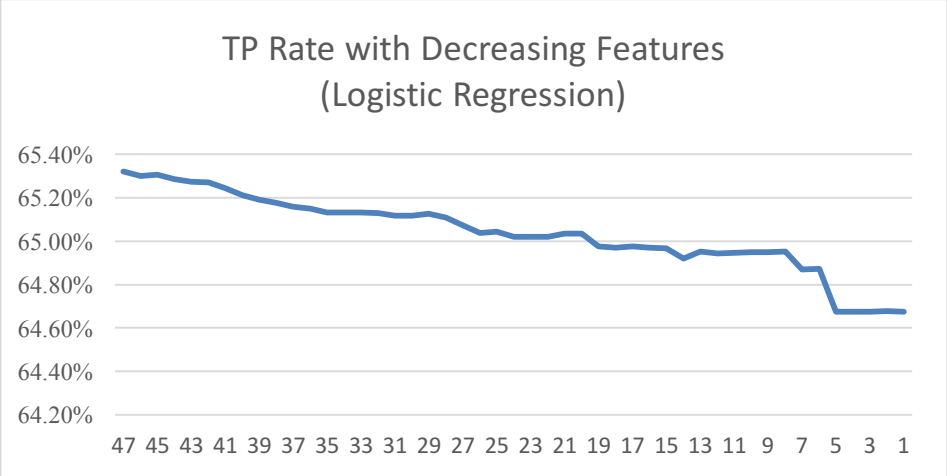
There are several measurements provided by Weka: TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, ROC Area, and PRC Area. In this project, we mainly look at Weighted TP rate [9] (Percent of correctly classified instances), Receiver Operating Characteristic (ROC) [10] Area and Precision-Recall Curves (PRC) Area because TP rate indicates accuracy, ROC and PRC Area indicate benefits of the algorithm compared to the baseline.

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
Best 10								
OneR	0.647	0.633	-	0.647	-	-	0.507	0.483
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**
Best 20								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
OneR	0.647	0.633	-	0.647	-	-	0.507	0.483
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**
Best 50								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
OneR	0.647	0.633	-	0.647	-	-	0.507	0.483
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**
Best 200								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
OneR	0.647	0.633	-	0.647	-	-	0.507	0.483
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**

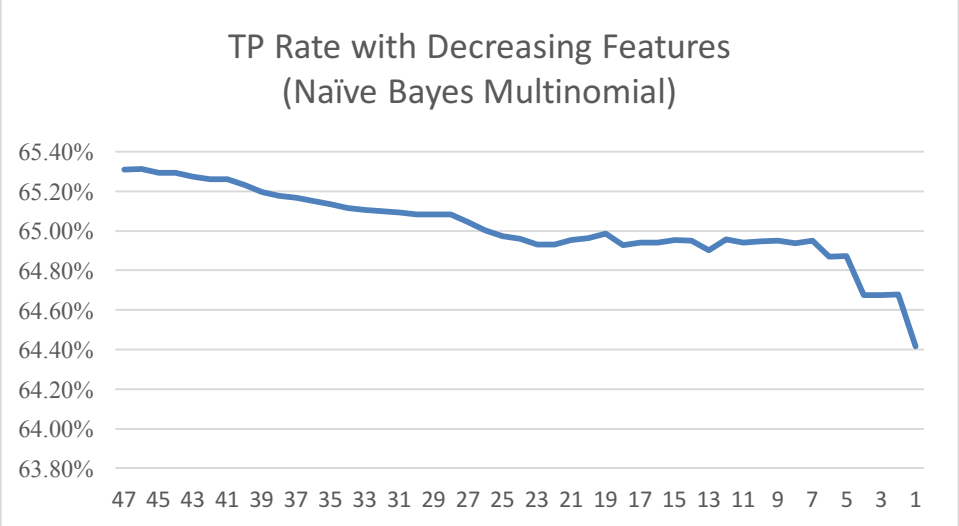
Table 1 - Results of best 10, 20, 50 and 200 data with tweet-id and user-id removed

Information Gain Ranking for train-best20 Features (tweet-id and user-id removed)								
No	IG	Attribute	No	IG	Attribute	No	IG	Attribute
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)



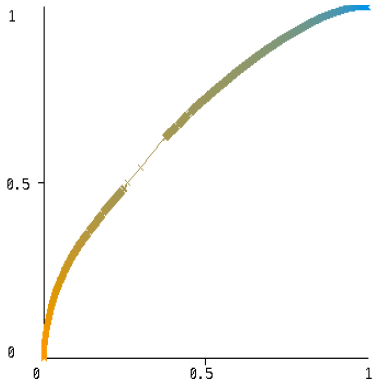
Graph 1 - TP Rate with Decreasing Number of Features (Logistic Regression)



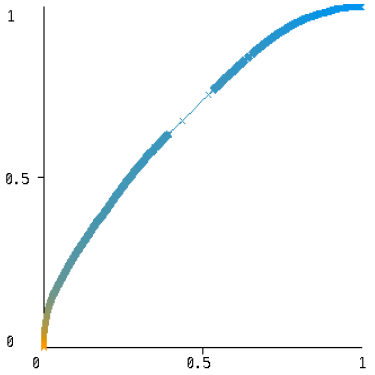
Graph 2 - TP Rate with Decreasing Number of Features (Naïve Bayes Multinomial)

Results of Naïve Bayes Multinomial (10-Fold Cross-validations on all data)								
	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
ZeroR	0.633	0.633	-	0.633	-	-	0.500	0.470
Naïve Bayes Multinomial	0.653	0.533	0.617	0.653	0.574	0.206	0.678	0.627

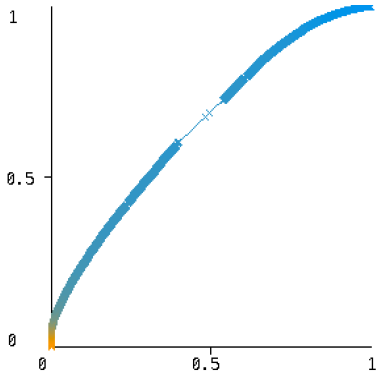
Table 3 - Results of Naïve Bayes Multinomial (10-Fold Cross-validations on all data)



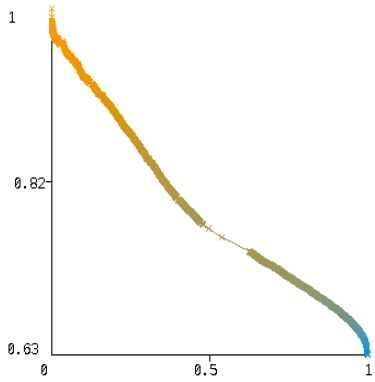
Graph 3 - New York (ROC)



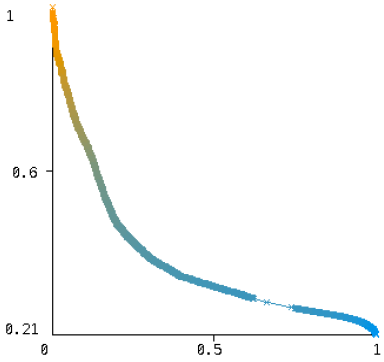
Graph 4 - California (ROC)



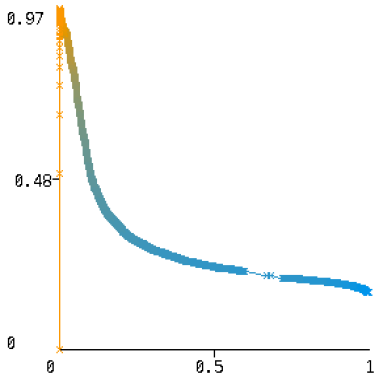
Graph 5 - Georgia (ROC)



Graph 6 - New York (PRC)



Graph 7 - California (PRC)



Graph 8 - Georgia (PRC)

5 Result

For the first experiment, we removed twee-id and user-id from the dataset as they would not reappear in the testing set and used 8 models for analysis. From the results in Table 1, we can see some classifiers perform better than the baseline (ZeroR), which includes Logistic Regression, Naïve Bayes Multinomial, Random Forest, J48, K-NN(185) and OneR. Logistic Regression and Naïve Bayes Multinomial have the best TP Rate, ROC Area and PRC Area. Random Forest, J48, K-NN(185) and OneR 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 and Naïve Bayes Multinomial.

For the second experiment, we first analyzed the information gain (IG) [11] of each attribute, rankings can be seen from table 2. Then we remove the attribute with the lowest IG one by one (e.g. 'wet', 'famusextape', 'parody' etc.) and calculate TP Rate for each attributes set. The results are shown in graph 1 and graph 2. We can see TP Rate is positively correlated with the Number of Features and training instances. So, removing attributes with less information gain may improve Over-fitting models, but not helpful to improve accuracy when we use Naïve Bayes Multinomial and Logistic Regression in this dataset. So, for the third experiment, we try to train our model with more features and instances. Since Naïve Bayes Multinomial is faster, we continue the third experiment with it.

For the third experiment, we combined the train-best200 data with dev-best200 data, which contains 130613 instances in total. Then, we use the 10-Fold Cross-validation to train our model. We can see the results from table 3 and graph 3-8 that TP Rate improved by 2%, ROC Area improved by 17.8% and PRC Area improved by 15.7%.

In addition, we combined Naïve Bayes Multinomial with other models using ensembling, boosting and bagging, but the results are not ideal. Furthermore, we used J48 for feature selection and NBM for classification. We removed 'wet', 'gsu', 'ii', 'lmao', 'lmaooo', 'lml' and 'parody' from the best10 dataset and the weighted TP Rate got improved by 0.01% (3 instances), but at the cost of ROC Area and PRC Area. So, this approach might not be suitable for this dataset as well. And building trees for the best200 dataset is computationally expensive.

6 Discussion

From the results and the nature of this project, I would recommend using machine learning models based on the probability, such as Naïve Bayes Multinomial. There are several reasons.

First, Naïve Bayes Multinomial is fast. It is a linear classifier and highly scalable. We can put more instances in our dataset and train our model in a relatively short time.

Second, Naïve Bayes Multinomial is unlikely to have an over-fitting problem with massive training data because of its feature conditional independence hypothesis. While a J48 decision tree is likely to get this issue if we use a large amount of data to train our model.

However, it is not easy to make Naïve Bayes Multinomial work well with other models. So I think pre-processing is the key step for the NBM model to achieve better results.

7 Conclusion

The model developed for is project is Naïve Bayes Multinomial, which is fast, scalable and unlikely to get over-fitting problems. A large number of instances and features have been used to train the model to improve accuracy and reliability.

References

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