Automatically Generate Tags for Questions Posted on StackExchange.com

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Abstract

In this project, the problem of how to automatically generate tags for questions posted on StackExchange websites is discussed. There are certain needs for this task since not all the users can tag their questions accurately due to the lack of understanding of the question or the website. An evaluation of $Fscore_M$ is utilized to meet the specific requirement of the task. After carefully studied the current multi-classification approaches in text mining, term frequency is selected for featurization, three different methods, SVM, Naive Bayes, and Decision Tree, are chosen to compare with each other in fulfilling the requirements. By analysing the results, imbalance is found to be the major problem for this task. (Not finished yet:)An over-sampling technique (SMOTE) is implemented to balance the data. The final result with SVM + SMOTE is satisfying.

1 Introduction

Now a days, more and more people post their questions and find their answers on StackExchange.com. With the help of tags, every user can find the questions they are most confident to solve. However, not all the users can tag their questions accurately due to the lack of understanding of the question or the website. This certain needs of automatically generate tags motivates the author to conduct this experiment. Without loss of generality, the experiment is conducted on one single site of StackExchange.com, which is http://anime.stackexchange.com/.

One significant characteristic of the data is imbalance. There are only 22 documents with the most minority tag "resources" while 1609 documents with the most majority tag "others". To evaluate the performance, we use the $Fscore_M$ [1] across the tags to equally reflect the performance across each tag. The $Fscore_\mu$ [1] is also calculated as another view of the performance since it favors majority classes much more than the minority ones. Our target is to achieve highest $Fscore_M$.

In order to achieve a high $Fscore_M$, data needs to be balanced before the training of the classifier. Synthetic minority over-sampling technique (SMOTE) [2] is a widely accepted technique to tackle imbalance problems with great improvements reported in literature [3-5]. After the implementation of SMOTE in the experiment, an increase in $Fscore_M$ is reported without sacrificing the $Fscore_\mu$.

1.1 Data

All the data used in this project is in a single file called anime.txt. It is collected from http://anime.stackexchange.com/ and formated by RAISE Lab. It contains 4827 documents with tags. For each document, the first tag is treated as its label. All material of this project can be found

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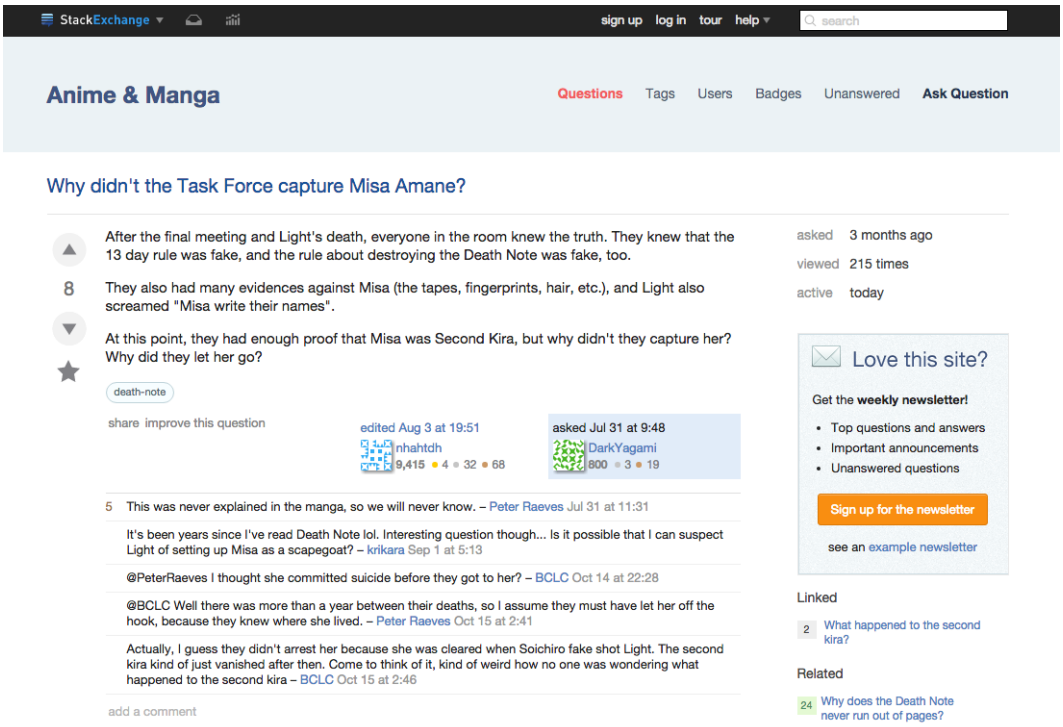


Figure 1: Example of post

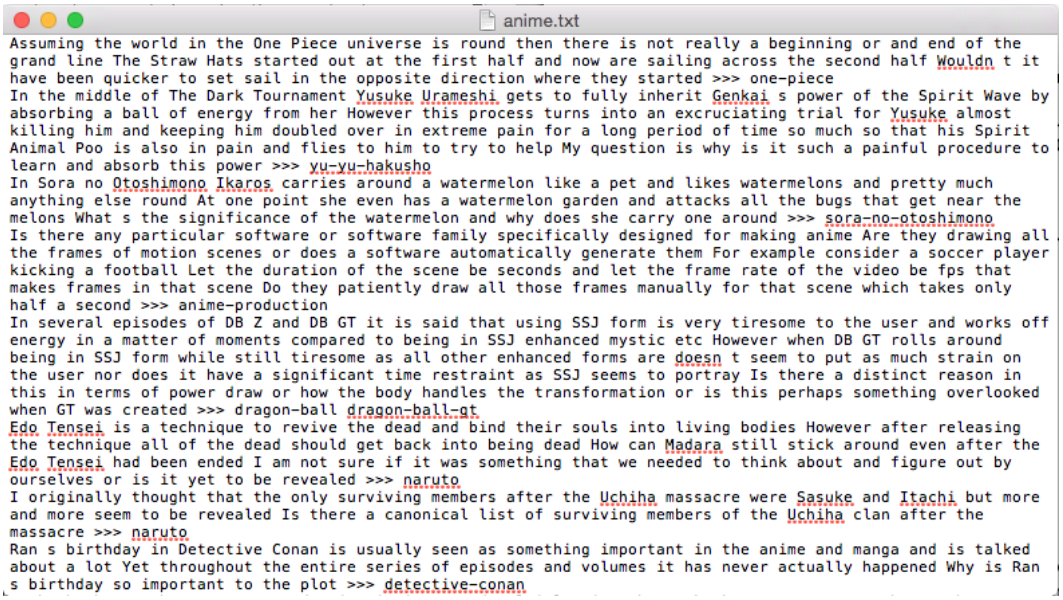


Figure 2: Example of anime.txt

at https://github.com/azhe825/AGT.git. An example of document on anime.stackexchange.com is shown in Figure 1. An example of the processed data in anime.txt is shown in Figure 2.

The number of documents in each tag is: {'others': 1609, 'identification-request': 1099, 'naruto': 547, 'one-piece': 204, 'anime-production': 164, 'fullmetal-alchemist': 114, 'tropes': 110, 'bleach': 87, 'death-note': 86, 'fairy-tail': 78, 'dragon-ball': 66, 'code-geass': 51, 'japanese-language': 49, 'sword-art-online': 48, 'monogatari-series': 46, 'madoka-magica': 46, 'culture': 45, 'pokemon':

45, 'fate-stay-night': 43, 'shingeki-no-kyojin': 40, 'hunter-x-hunter': 38, 'anime-history': 35, 'manga-production': 33, 'from-the-new-world': 26, 'terminology': 25, 'neon-genesis-evangelion': 24, 'music': 24, 'toaru-majutsu-no-index': 23, 'resources': 22}.

1.2 Related works

Clayton and Byrne, 2013 [6] have worked on StackOverflow tag prediction and developed an ACT-R inspired Bayesian probabilistic model. This approach achieves a 65% of accuracy by choosing the tag that has the highest log odds of being correct, given the tags prior log odds of occurrence and adjusting for the log likelihood ratio of the words in the post being associated with the tag.

Kuo, 2011 [7] has also worked on StackOverflow tag prediction. Kuo uses a co-occurrence model that predicts tags based on the relation (co-occurrence) between the words and tags. Initially built for next-word prediction in large documents, this model is adapted to the StackOverflow dataset by constraining the next word predicted to only tags. A 47% classification accuracy is achieved.

Another model called SNIF-ACT (Fu & Pirolli, 2007 [8]) also uses co-occurrences and can predict link traversal for search queries. The model predicts the most likely link that a person will click on by a search query (goal state) and fetched results.

2 Method

As suggested by [9] and [10], term frequency is calculated as feature and term frequency inverse document frequency (tf-idf) is used to select the most effective features. Inspired by CSC 522, three of the most famous classification methods, SVM, Naive Bayes, and Decision Tree, are used to conduct the experiments. In the second part of the experiment, SMOTE is implemented to balance the data before training.

2.1 Preprocessing

Term frequency: Simple term frequency count is utilized to construct the feature matrix. The value in feature matrix $M_{i,j}$ represents the number of appearance of the j_{th} token in the i_{th} document.

Tf-idf selection: Tf-idf score of each token is calculated as $tfidf(token_i) = \frac{WordCount(token_i)}{\Sigma WordCount(token_j)} log(\frac{TotalNumberofDocs}{NumberofDocs(token_i)})$. Tokens are then sorted by their tf-idf scores and tokens with the largest n tf-idf scores are selected to form the new feature matrix.

L2 Normalization: L2 Normalization is implemented on each row of the feature matrix to eliminate the difference between long documents and short documents.

SMOTE: SMOTE with five nearest neighbors is implemented to over-sample documents in each tag to reach the number of majority tag. That is, SMOTE is implemented on each training set and after SMOTE, each tag will have the same number of documents.

2.2 Classifiers

Support Vector Machine: linear kernel with primal problem solving is chosen since state-of-art accuracy on text classification is reported in [11].

Naive Bayes: multinomial model is chosen according to the performance report in [12].

Decision Tree: CART [13].

2.3 Performance Metrics

Cross validation: 5 by 5 cross validation, each time the classifier is trained on 80% of the data and tested on the rest 20%. For each classifier with each number of features, there are 25 results. The median and iqr of the 25 results represent the performance. A low iqr means that we can trust the result.

$Fscore_M$**:** F-score on each tag can be calculated after the trained classifier is tested on test set. The mean of F-score on each tag is then calculated to represent the overall performance of the classifier. Regardless of the population within each tag, the $Fscore_M$ represents performance on each tag equally [1].

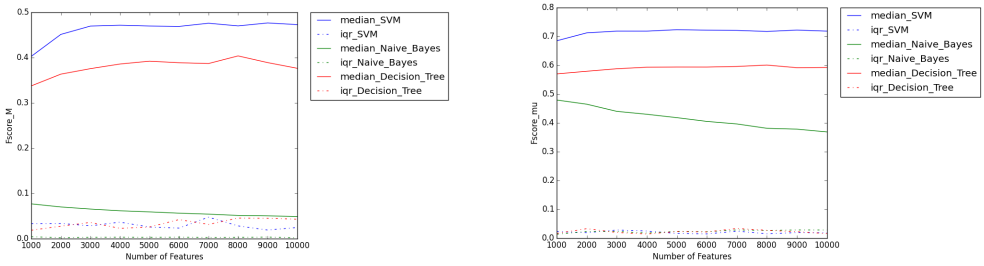
$Fscore_\mu$**:** The $Fscore_\mu$ on each tag is calculated by multiply F-score on each tag by its population. Classifiers are trained to achieve high in this score by default, which is not desired in this task and therefore over-sampling methods like SMOTE is introduced in the later experiment [1].

3 Experiments

In the first experiment, SMOTE is not implemented. The performances of SVM, Naive Bayes, and Decision Tree are compared against each other by their $Fscore_M$ and $Fscore_\mu$.

In the second experiment, SMOTE is implemented to over-sample documents in each tag to reach the number of majority tag. The performances of SVM, Naive Bayes, and Decision Tree, with or without SMOTE are compared against each other by their $Fscore_M$ and $Fscore_\mu$.

3.1 Without SMOTE



(a) $Fscore_M$ (b) $Fscore_\mu$

Figure 3: F-scores without SMOTE

SVM outperforms Naive Bayes and Decision Tree in both $Fscore_M$ and $Fscore_\mu$, according to Figure 3. However, even though SVM can achieve a 0.7 $Fscore_\mu$, its $Fscore_M$ is below 0.5, which is definitely not good enough.

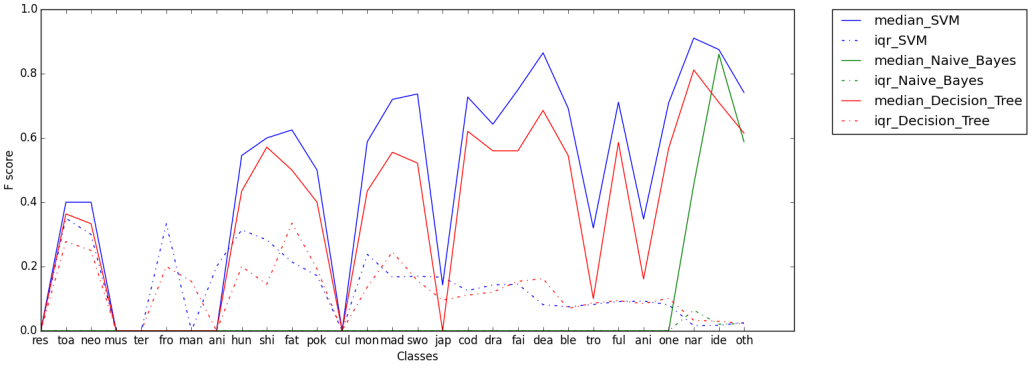
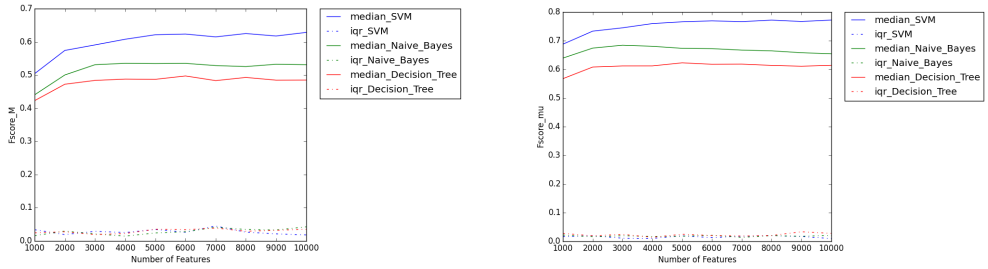


Figure 4: F-scores of each tag without SMOTE, sorted by population

As we can see from Figure 4, most of the tags are actually ignored (low median or high iqr) by all the classifiers due to their small population. This implies that a) $Fscore_\mu$ cannot correctly represent the true performance; b) over-sampling is essential and promising in achieving a better $Fscore_M$. Another fact is that SVM wins on every tag.

3.2 With SMOTE



(a) $Fscore_M$ (b) $Fscore_\mu$

Figure 5: F-scores with SMOTE

SVM still outperforms Naive Bayes and Decision Tree in both $Fscore_M$ and $Fscore_\mu$, according to Figure 5. The major difference is that with SMOTE, Naive Bayes outperforms Decision Tree while it is the opposite without SMOTE.

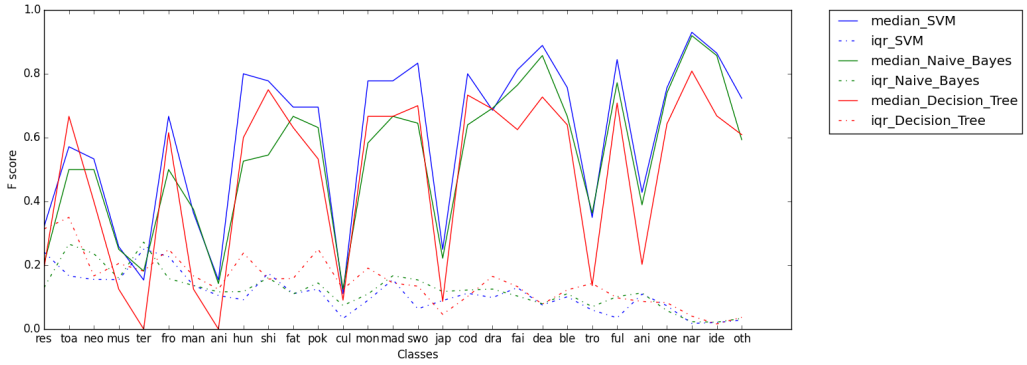
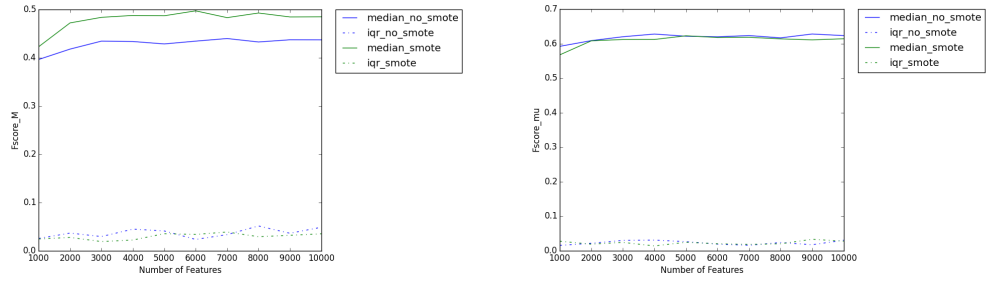


Figure 6: F-scores of each tag with SMOTE, sorted by population

As we can see from Figure 6, tags with small population are not totally ignored by classifiers any more. This implies that the data is well balanced by SMOTE. Still, SVM wins on most of the tags.

3.3 Comparison between SMOTE and No-SMOTE



(a) $Fscore_M$ (b) $Fscore_\mu$

Figure 7: F-scores of Decision Tree

Decision Tree: from Figure 7 we can see that SMOTE improves the $Fscore_M$ without sacrificing $Fscore_\mu$. It is also suggested by Figure 8 that performance of Decision Tree on most of the tags with

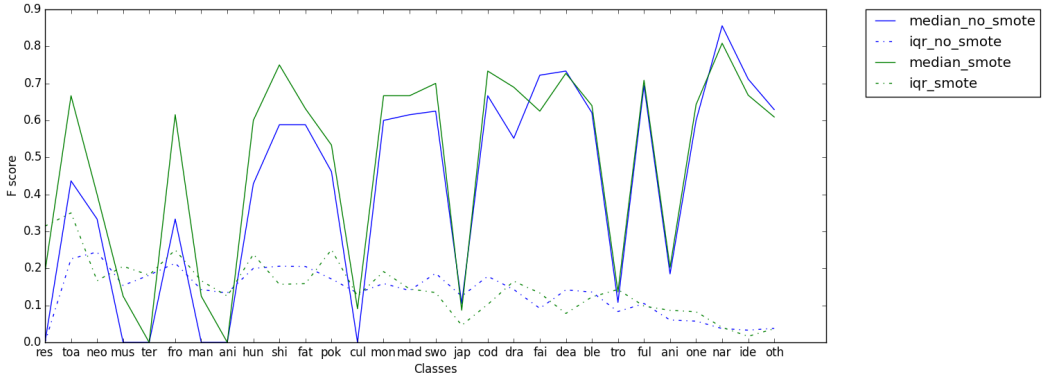
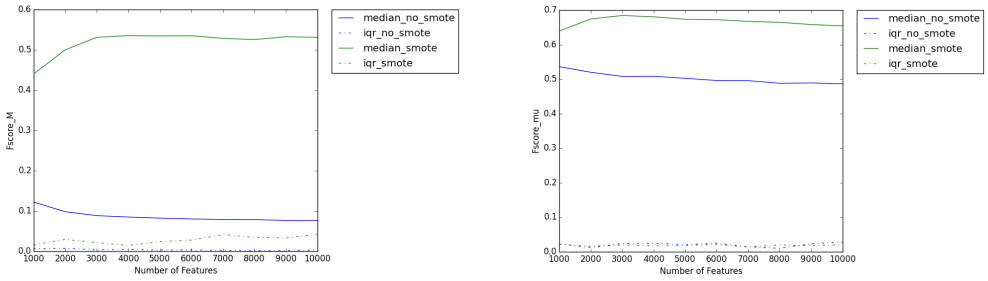


Figure 8: F-scores of each tag with Decision Tree, sorted by population

small population is improved by SMOTE (higher median or lower iqr of F score). The performance of Decision Tree (CART) with SMOTE, 3000 features can achieve 0.49 in $Fscore_M$ and 0.61 in $Fscore_\mu$.



(a) $Fscore_M$ (b) $Fscore_\mu$

Figure 9: F-scores of Naive Bayes

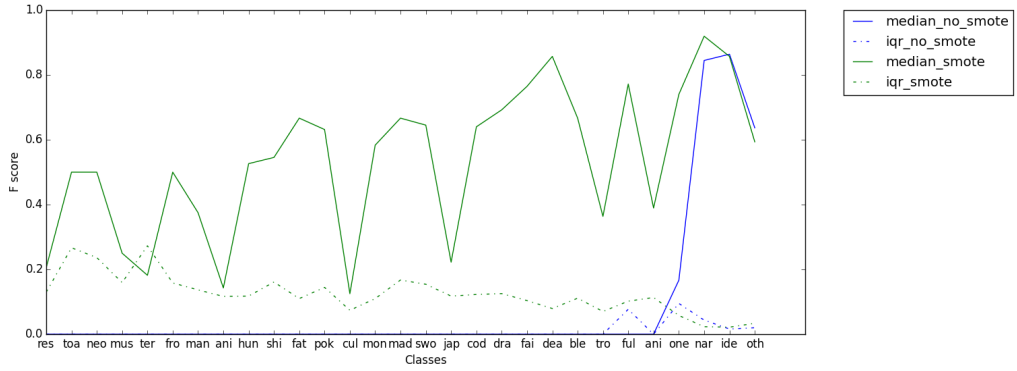
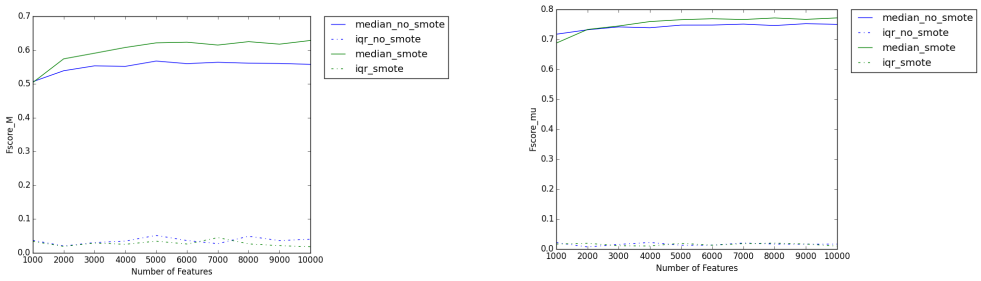


Figure 10: F-scores of each tag with Naive Bayes, sorted by population

Naive Bayes: SMOTE impacts a lot on the performance of Naive Bayes. As we can see from Figure 9, without SMOTE, the $Fscore_M$ is about 0.1 while it reaches above 0.5 with SMOTE. Even the $Fscore_\mu$ is improved by about 0.2 after SMOTE is implemented. It is shown in Figure 10 that Naive Bayes totally ignores the tags with low population (0 in median of F score) while all the tags are considered after SMOTE. This explains the huge improvement of $Fscore_M$ in Figure 9(a).

The performance of Naive Bayes (multinomial) with SMOTE, 3000 features can achieve 0.53 in $Fscore_M$ and 0.69 in $Fscore_\mu$.



(a) $Fscore_M$ (b) $Fscore_\mu$

Figure 11: F-scores of Support Vector Machine

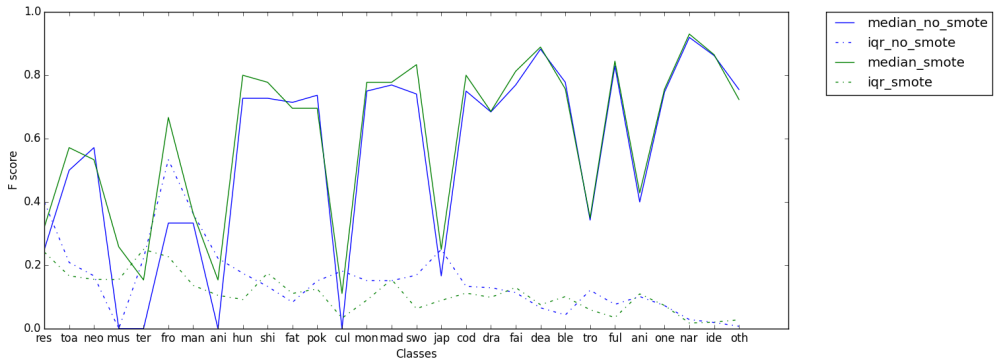


Figure 12: F-scores of each tag with Support Vector Machine, sorted by population

Support Vector Machine: SVM is still the best classifier for this task. As shown in Figure 11, SMOTE improves the $Fscore_M$ by approximate 0.1 without sacrificing $Fscore_\mu$. Although 0.6 in $Fscore_M$ and 0.7 in $Fscore_\mu$ do not seem enough, this result is actually comparable to the state-of-art result [6]. Similar as the result of Decision Tree, Figure 12 shows that the F scores on minority tags improves after SMOTE, which leads to the improvement of $Fscore_M$. The performance of linear SVM with SMOTE, 5000 features can achieve 0.62 in $Fscore_M$ and 0.76 in $Fscore_\mu$.

4 Conclusions and Future Works

Conclusions of this paper are: a) $Fscore_M$ is a good and reliable performance metric regarding to multi-classification problems; b) linear SVM outperforms Naive Bayes and Decision Tree in this task; c) SMOTE improves the result of $Fscore_M$ significantly without sacrificing $Fscore_\mu$, which also implies that imbalance is indeed a problem in this tag generation task; d) 5000 features are enough for this tag generation task. With SMOTE, linear SVM can achieve an $Fscore_M$ of 0.62 and $Fscore_\mu$ of 0.76 with feature number 5000. The result is reliable since it is repeated 25 times and the iqr is lower than 0.04. This is the method we suggest for this certain tag generation task.

In our next step, different kernels of SVM can be tested to see if further improvement is available. There are other promising classifiers, artificial neural network with deep learning for example, as well. Another possible way to improve the performance can be: a) first divide the multi-classification problem to k (k is the number of different classes) binary classification problems (one class as positive and all the other classes as negative); b) implement SMOTE on each binary classification problem to over-sample the documents of positive class to match the population of negative documents; c) train a linear SVM classifier on each of the binary classification problem; d) aggregate the trained classifiers to predict unknown tags based on scores of each SVM output (distance from decision boundary).

The result of this project can be implemented to automatically generate tag for posts or simply providing users suggestions of tag options if the result is not considered reliable enough.

References

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A Plan of Activities

Old plan:

a) preprocess the data, generate feature matrix with term frequency or tf-idf;

b) try different classification methods (decision tree, Naive Bayes, Adaboost, SVM, ...) to predict labels, cross validation will be applied; c) evaluate results from b) by comparing F_1 scores and confusion matrix;

d) use SMOTE to improve the result.

Revised plan:

a) preprocessing: generate feature matrix with term frequency and select features with top tf-idf scores;

b) Decision Tree, Naive Bayes, and SVM are implemented to predict tags, cross validation is applied;

c) $Fscore_M$ is justified for a better representation of the performance in this task. Both $Fscore_\mu$ and $Fscore_M$ are shown to compare the three classifiers;

d) SMOTE is implemented to improve the result.

Member activities:

all the works are done by Zhe Yu.

Resources:

all the materials of this project can be found at https://github.com/azhe825/AGT.git.