Feature Selection and Parameter Tuning on Age and Gender Classification for English Tweets using SVMs
A report for Automatic Classification and Kernel Methods

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1 Introduction

Author profiling has been of importance in the recent years. From a forensic standpoint for example, it could be used to determine potential suspects by getting linguistic profiles and identifying characteristics. From a business intelligence perspective, companies could target specific people through online advertising. By knowing the profile of the authors, companies would easily find what a specific group of people talk about online and device strategies to advertise to these people. They could also analyze product reviews and know what types of products are liked or disliked by certain people.

Part of the reason why the interest in author profiling grows is because the growth of the internet where text is one of the main forms of communication. Through this growth, various corpora could be extracted, curated, assembled from different sources such as blogs, websites, customer reviews, and even twitter posts. Of course, this presents some problems. For example, people from different countries who use the same online platform such as Twitter or Blogger could behave differently in terms of text usage. This presents a difficulty in profiling. This work tries to take this difficulty into account by studying which kind of features are useful for different languages.

The aim of this work is to investigate the parameters for support vector machines in terms of classification using the dataset given in PAN 2015 [11]. The dataset contains twitter data from 4 different languages which are used to profile an author based on age, gender, and 5 personality traits - agreeability, conscientiousness, extrovertedness, openness, and stability. The four languages are English, Dutch, Italian, and Spanish. However, the focus of this work is on English alone and only in age and gender classification. Furthermore, the investigation is more on using different kernels and different parameters for the classification.

2 State of the Art

One of the first few works on author profiling is that of Argamon et al. in [1] where texts are categorized base on gender, age, native language, and personality. For personality, only neuroticism was checked. The corpus comes from different sources. The age and gender have the same corpus taken from blog postings. The native language corpus was taken from International Corpus of Learner English. Personality was taken from essays of pyschology students from University of Texas in Austin. Two types of features were obtained: content-based features and style-based features and Bayesian Multinomial Regression was used as a classifier. Argamon et al. had some interesting results where from the gender task, they were able to achieve 76.1% accuracy using style and content features. For age task with 3 classes, the accuracy was at 77.7% also using style and content features. For the native language task, the classifiers were able to achieve 82.3% using only content features. And finally, in checking for neuroticism, the highest obtained was 65.7% using only style features.

There has also been some research that uses datasets collected from social media. A particular example is that of Schler et al. in [13] where writing styles in blogs are related to age and gender. Stylistic and content features were extracted from 71,000 different blogs and a Multi-Class Real Winnow was used to learn the models to classify the blogs. Stylistic features included parts-of-speech tags, function words, hyperlinks, and non-dictionary words. Content features included word unigrams with high information gain. The accuracy achieved was around 80% for gender classification and 75% for age identification.

The work or Argamon et al. [1] became the basis for the work in PAN. It is an ongoing project from CLEF with author profiling as one of its tasks. It currently has three editions. In the first edition of PAN [10] in 2013, the task was age and gender profiling for English and Spanish blogs. There were a variety of methods used. One set includes content-based features such as bag of words, named entities, dictionary words, slang words, contractions, sentiment words, and emotion words. Another would be stylistic features such as frequencies, punctuations, POS, HTML use, readability measures, and other various statistics. There are also features that are n-grams based, IR-based, and collocations-based. Named entities, sentiment words, emotion words, and slang, contractions and words with character flooding were also considered. After extracting the features, the classifiers that were used were the following - decision trees, Support Vector Machines, logistic regression, Naïve Bayes, Maximum Entropy, Stochastic Gradient Descent, and random forests. The work of Lopez-Monroy in [4] was considered the winner for the task although they placed second for both English and Spanish with an accuracy of 38.13% and 41.58% respectively. They used second order representation based on relationships between documents and profiles. The work of Meina et al. [7] used collocations and placed first for English with a total accuracy of 38.94%. On the other hand, the work of Santosh et al. in [12] gave a total accuracy of 42.08% after using POS features for Spanish.

In PAN 2014 [9], the task was profiling authors with text from four different sources - social media, twitter, blogs, and hotel reviews. Most of the approaches used in this edition are similar to the previous year. In [3], the method used to represent terms in a space of profiles and then represent the documents in the space of profiles and subprofiles were built using expectation maximization clustering. This is the same method as in the previous year in [4]. In [5], ngrams were used with stopwords, punctuations, and emoticons retained, and then idf count was also used before placed into a classifier. Liblinear logistic regression returned with the best result. In [15], different features were used that were related to length (number of characters, words, sentences), information retrieval (cosine similarity, okapi BM25), and readability (Flesch-Kincaid readability, correctness, style). Another approach is to use term vector model representation as in [14]. For the work of Marquardt et al. in [6], they used a combination of content-based features (MRC, LIWC, sentiments) and stylistic features (readability, html tags, spelling and grammatical error, emoticons, total number of posts, number of capitalized letters number of capitalized words). Classifiers also varied for this edition. There was the use of logistic regression, multinomial Naïve Bayes, liblinear, random forests, Support Vector Machines, and decision tables. The method of Lopez-Monroy in [3] gave the best result with an average accuracy of 28.95% on all corpus-types and languages.

3 Dataset and Tools

The dataset for the problem at hand is composed of a set of tweets for English. Different models were made for each classification task - age and gender. There were 4 categories for the age classification - 18-24, 25-34, 35-49, and 50 and above. Gender has two categories - male and female. There were 152 users for English. Each user has different number of tweets. The dataset is balanced based on gender. Processing the data was done through Python using the scikits-learn [8] library.

4 Methodology

The focus of this study is to determine optimal parameters for classification using support vector machines. The approach is to do preprocessing, feature extraction, feature selection, then use the optimal features into support vector machines with different parameters. Evaluation was made through 10 fold cross validation and Wilcoxon signed rank test was used to compare the statistical significance of the results. A confidence interval of 95% was used. Therefore, if there was an experiment between two settings and the returned p-value after a Wilcoxon signed rank test yields less than 0.05, the null hypothesis is rejected. This means that the values are statistically different. If it yields a value greater than 0.05, it means that values between the two experiments are not statistically different. The study will look on the polynomial kernels and radial basis function kernels. It will also explore the effect of using one classification as an additional feature for the other. And this study will also explore the use of ensemble methods.

4.1 Preprocessing and Feature Extraction

For each language, xml files from each user are read. Then the tweets taken from each user are extracted and concatenated into one line to form one training example. The examples are then transformed by putting them all in lower case. No stop words are removed. Hashtags, numbers, mentions, shares, and retweets were not processed or transformed to anything else. The resulting file is used for feature extraction. Features extracted were simply *tfidf* features.

4.2 Feature Selection

After extracting *tfidf* features, we want to reduce the number of features in the text. To do that, classification was done using Support Vector Machines [2] with a linear kernel, choosing C=1 as the default. But instead of using all the *tfidf* features, different number of features were tested. The number of features were ranked by either information gain or gain ratio. The results for the accuracies by varying the feature set is given in table 1 in the succeeding chapter. However, it is suffice to say that for the succeeding experiment on polynomial kernels and radial basis function kernels, the number of features selected will be 9000 and 7000 for age and gender classification respectively. The discussion on settling for the features is given in the succeeding chapter.

4.3 Exploring different Kernels

Using Support Vector Machines [2] entails the use of kernels that maps the features into a different space such that separation would be done in the new space. In the earlier section, only the linear kernel was used but we further used polynomial kernels and radial basis function kernels. Polynomial kernels maps the input features to another feature space that uses the polynomial function over the similarity of the input features. Mathematically, the kernel is given by equation 1 but scikits-learn implementation has a gamma to scale the dot product as in equation 2.

$$K(x, y) = (x^T y + c)^d \tag{1}$$

$$K(x) = (\gamma(x^T x) + c)^d \tag{2}$$

For our experiments, we set the gamma to be equal to 1 but the degrees d to vary between 1, 2, and 3. For age classification, c varies between 0.0001, 0.001, 0.1, 1, 10, 1000, 10000. For gender classification however, c varies between 0.0001, 0.1, 1, 10, 10000.

Radial basis function kernel is another kernel explored. Mathematically, it is given by equation 3. It is similar the scikits implementation but with a regularization factor c.

$$K(x, x') = exp\left(-\frac{\parallel x - x' \parallel^2}{2\sigma^2}\right) \tag{3}$$

For both age and gender classification, σ and c were chosen to be one among 0.0001, 0.001, 0.1, 1, 10, 1000, and 10000.

4.4 Classification with string substitution

One of the interesting experiments is to check if the addition of some twitter specific features could affect the classification. For this experiment we only look into hashtags and links because user mentions are already handled previously since users have been anonymized. The treatment is simple and done in the preprocessing side. After taking the text from the html and converting them into lowercase, string substitution was performed on links and hashtags. All links were transformed into the text " LINK_HERE " while hashtags were turned into " HASHTAG_HERE ". The idea is that each link and hashtag wont be considered as a unique and that it would just add to the number of links or hashtags. After string substitution, *tfidf* was used and then features were ranked based on information gain. Top 9000 and 7000 words were used age and gender classification respectively. Finally, classification was done using the optimal settings given by the previous experiments and that given in the succeeding chapter.

4.5 Using Classification Priors as a Feature

Another interesting experiment is that of classifcation when using the ouput of the other classification as a feature. For example, the results of gender classification will be used as a feature for age classification. And this will be done vice-versa with gender classification.

4.6 Exploring Ensemble Methods

Finally, a comparison with ensemble methods was also done. Two different ensemble methods were considered - Random Forests and AdaBoost

5 Results and Discussion

5.1 Feature Selection

The results for feature selection are given in table 1. When using all the different features, the highest accuracy could be attained. However, to check if the other accuracies are not statistically different, Wilcoxon signed rank test was done. The p-value results are given in table 2. For age classication with words ranked with information gain and gain ratio, the results begin to be statistically different when the number of features were 8000. The number of features chosen for further age classification experiments was 9000. On the other hand the results become statistically different when the number of features was 5000 for gender classification. Therefore, The number of features chosen for further age classification experiments was 7000.

	Age		Gender	
Num Features	info gain	gain ratio	info gain	gain ratio
26263	0.6913	0.6913	0.6825	0.6825
10000	0.6321	0.6321	0.6167	0.6167
9000	0.6321	0.6321	0.6163	0.6163
8000	0.6188	0.6188	0.6233	0.6233
7000	0.6188	0.6188	0.6300	0.6300
5000	0.6188	0.6188	0.4863	0.4863
2000	0.6188	0.6188	0.4983	0.4983
1000	0.6188	0.6188	0.4983	0.4983
700	0.6188	0.6188	0.4921	0.4921
500	0.6188	0.6188	0.4921	0.4921
300	0.6188	0.6188	0.4921	0.4921
200	0.6188	0.6125	0.4921	0.4921
100	0.6188	0.3950	0.4921	0.4921

Table 1. Accuracies that result from using different number of important features ranked by information gain and gain ratio. SVM linear kernel with C=1 was used.

	Age		Gender	
Num Features	info gain	gain ratio	info gain	gain ratio
26263	1.0000	1.0000	1.0000	1.0000
10000	0.0757	0.0757	0.1212	0.1212
9000	0.0757	0.0757	0.1124	0.1124
8000	**0.0211**	**0.0211**	0.1306	0.1306
7000	0.0211	0.0211	0.1859	0.1859
5000	0.0211	0.0211	**0.0002**	**0.0002**
2000	0.0211	0.0211	0.0012	0.0012
1000	0.0211	0.0211	0.0015	0.0015
700	0.0211	0.0211	0.0006	0.0006
500	0.0211	0.0211	0.0006	0.0006
300	0.0211	0.0211	0.0006	0.0006
200	0.0211	0.0211	0.0006	0.0006
100	0.0211	0.0002	0.0006	0.0006

Table 2. Wilcoxon signed rank test results comparing accuracies give by the highest number of features and those with lower number of features.

5.2 Different Kernels

The results for age classification using support vector machines with polynomial kernel is given by table 3. The highest accuracy obtained was 80.92% which is shown in boldface. This was obtained from three different settings, degree 3 with C to be either 10, 1000, 10000. However, checking on Wilcoxon signed rank test, these results are not statistically significant to 80.25% given by settings with degree 2 and C to be either 10, 1000, 10000. These results are also not statistically significant against 75% with degree 3 and C to be 1.

C	degree		
	1	2	3
0.0001	0.6321	0.6192	0.5121
0.001	0.6321	0.6192	0.5121
0.1	0.6321	0.6254	0.5992
1	0.6321	0.7104	0.7500
10	0.6321	0.8025	**0.8092**
1000	0.6321	0.8025	**0.8092**
10000	0.6321	0.8025	**0.8092**

Table 3. Accuracy results of using SVM with polynomial kernel on age classication task with different C and degree parameters using top 9000 informative features ranked by information gain.

The results for age classification using support vector machines with radial basis function kernel is given by table 4. Results show that the highest achieved accuracy was 80.92% which is shown in boldface in the table. It was obtained from the kernel with gamma to be 0.001 and with a C to be 10000. This wasnt statistically different from the settings that gave 80.25%.

C	gamma						
	0.0001	0.001	0.1	1	10	1000	10000
0.0001	0.3950	0.3950	0.3950	0.3950	0.3950	0.3950	0.3950
0.001	0.3950	0.3950	0.3950	0.3950	0.3950	0.3950	0.3950
0.1	0.3950	0.3950	0.3950	0.4746	0.3950	0.3950	0.3950
1	0.3950	0.3950	0.6054	0.6517	0.5933	0.3950	0.3950
10	0.3950	0.3950	0.6846	0.8025	0.6196	0.3950	0.3950
1000	0.6188	0.6971	0.8025	0.8025	0.6196	0.3950	0.3950
10000	0.6971	**0.8092**	0.8025	0.8025	0.6196	0.3950	0.3950

Table 4. Accuracy results of using SVM with radial basis function kernel for age classification with different C and gamma parameters using top 9000 informative features ranked by information gain.

The results for gender classification using support vector machines with polynomial function kernel is given by table 5. Results show that the highest achieved accuracy was 79.54% which is shown boldface in the table. This comes from four different settings. The first two were when the degree is 2 and C was chosen to be 10 or 10000. The last two settings were when degree is 3 with C also either 10 or 10000.

C	degree		
	1	2	3
0.0001	0.6300	0.4983	0.4733
0.1	0.6300	0.5233	0.4733
1	0.6300	0.6367	0.7025
10	0.6300	**0.7954**	**0.7954**
10000	0.6300	**0.7954**	**0.7954**

Table 5. Accuracy results of using SVM with polynomial kernel for gender classification with different C and degree parameters using the top 7000 informative features ranked by information gain.

The results for gender classification using support vector machines with radial basis function kernel is given by table 6. Results show that the highest achieved accuracy was 80.79% as shown boldface in the table. This comes from the settings with gamma to be 1 and C to be 10. However, these arent statistically different from settings which gave 80.21% and 80.13% accuracy.

C	gamma						
	0.0001	0.001	0.1	1	10	1000	10000
0.0001	0.5233	0.5233	0.5233	0.5171	0.4921	0.5171	0.4733
0.001	0.5233	0.5233	0.5233	0.5171	0.4921	0.5171	0.4733
0.1	0.5233	0.5233	0.5233	0.5171	0.4921	0.5171	0.4733
1	0.5233	0.5233	0.5233	0.6167	0.6629	0.4796	0.4733
10	0.5233	0.5233	0.6238	**0.8079**	0.7025	0.4796	0.4733
1000	0.5233	0.6367	0.8021	0.8013	0.7025	0.4796	0.4733
10000	0.6367	0.7954	0.8021	0.8013	0.7025	0.4796	0.4733

Table 6. Accuracy results of using SVM with radial basis function kernel for gender classification with different C and gamma parameters using the top 7000 informative features ranked by information gain.

5.3 String Substitution

Comparisons between the the best from previous parameter tuning experiments and that where links and hashtags were substituted with a different string tag is shown in tables 7 and 8. We can see that using the same parameters for the classifier, the performance drops when there's string substitution but the results are not statistically different.

Method	Accuracy	settings			
		kernel	gamma	degree	C
Age with String Sub	0.7892	rbf	1	N/A	10
Best Among Age	0.8079	rbf	1	N/A	10
P-value	0.8206				

Table 7. Comparison between the best accuracy for age classification from previous experiments against a classifier trained with links and hashtags string substitution.

Method	Accuracy	settings			
		kernel	gamma	degree	C
Gender with String Sub	0.7742	rbf	1	N/A	10
Best Among Gender	0.8079	rbf	1	N/A	10
P-value	0.4963				

Table 8. Comparison between the best accuracy for gender classification from previous experiments against a classifier trained with links and hashtags string substitution.

5.4 Using Classification Priors

Comparisons between the the best from previous parameter tuning experiments and another method where the training set features is augmented by the results of another classification is given by tables 9 and 10. We can see that age classification with features augmented by gender classification results has 2% increased accuracy but it is not statistically different. For gender classification, the results are almost the same and are also not statistically different.

Method	Accuracy	settings			
		kernel	gamma	degree	C
Age with Gender Prior	0.8292	poly	N/A	3	10
Best Among Age	0.8092	poly	N/A	3	10
P-value	0.5453				

Table 9. Comparison between the best accuracy for age classification from previous experiments against a classifier trained with a feature set added with gender classification results.

Method	Accuracy	settings			
		kernel	gamma	degree	C
Gender with Age Prior	0.8021	rbf	1	N/A	10
Best Among Age	0.8079	rbf	1	N/A	10
P-value	0.8206				

Table 10. Comparison between the best accuracy for gender classification from previous experiments against a classifier trained with a feature set added with age classification results.

5.5 Ensemble Methods

Accuracy results for random forests are given in table 11.

n-estimators	Accuracy
10	0.5917
100	0.6175
1000	0.6108
2000	0.6108
5000	0.6308
10000	0.6242

Table 11. Accuracy results for forests of randomized trees.

n-estimators	Accuracy
10	
100	
1000	
2000	
5000	
10000	

Table 12. Accuracy results for forests of AdaBoost.

6 Conclusions and Future Work

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