Twitter User Classification using Ambient Metadata

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ABSTRACT
Microblogging websites, especially Twitter have become an important means of communication, in today’s time. Often these services have been found to be faster than conventional news services. With millions of users, a need was felt to classify users based on ambient metadata associated with their user accounts. We particularly look at the effectiveness of the ‘profile description’ field in order to carry out the task of user classification. Our results show that such metadata can be an effective feature for any classification task.

Categories and Subject Descriptors
I.2 [Artificial Intelligence]: Miscellaneous

General Terms
Verification

Keywords
Twitter, Classification, Machine Learning

1. INTRODUCTION
Twitter, over the years has gained immense popularity with millions of registered users. As a microblogging website, Twitter allows users to post terse 140 character long ‘tweets’ or status updates. For any information retrieval or recommendation task, user classification can be an effective pre-processing step. Previous work [5] have utilised profile features and some tweets of a user to bring about the task of user classification, in our study we do not consider the tweets of a user, but utilise other features like followers count, following count, number of tweets and the profile description of a user. The profile description is a short 160 character alphanumeric field. To the best of our knowledge no previous attempt at user classification has utilised this feature. We train two classifiers, OUC, to classify profiles as Organisations, Users and Others and MPS, to classify users on the basis of interest towards Music, Politics and Sports. In order to train the classifier we utilise Decision Trees, Naive Bayes and Support Vector Machines. Comparative results are provided in Section 3.

2. FEATURE SET
Any classifier, requires a set of features to be trained upon, for our classifier, as mentioned earlier, we utilise a) The followers count, b) The following count, c) The number of Tweets, d) Ratio of Followers to Following count and the e) Profile Description. Features a,b,c are whole numbers whereas the Profile Description is a 160 character alphanumeric field.

Profile Description
We analysed a corpus of over 70,000 user profiles, which were aggregated using the Twitter Streaming API [1] and found that about 85% provide at least one or more character of user description. We removed all punctuation marks and special characters from all the descriptions. Out of the users that do provide profile description , the average length was found to be 59 characters while the average number of words was approximately 6.

We analysed our corpus of user profiles and extracted the top 50 most frequently occurring words in the profile description. These words were used for creating binary features to train our algorithms.

Numerical Features
Since, the range of values for the numerical features was large, binning was required to reduce dimensionality of our
features. This was carried out using the function
\[ H(n) = \lfloor \log_{10} n \rfloor \] (1)

Here \( n \) is the whole number value associated with the particular feature and \( \lfloor \rfloor \) is the greatest integer function. Figures 2 to 5 visualise the features after binning using the function described above.

We also define another derived feature, ‘ratio’ which is essentially the ratio of the followers count and the following count. Since this produces a fractional term, to this we apply the function as described above to perform binning.

3. TRAINING & RESULTS

We trained two classifiers, OUC to classify users as Organisations, Users and Celebrities and MPC, Music, Politics and Sports. We aggregated 1200 user profiles and labelled them as OUC and MPS. For each classification we trained Decision Trees (DT), Naive Bayes (NB) and Linear Support Vector Machines (SVM). For DT & NB we utilise the NLTK Python package [2], while for SVM we utilise SciKit [4].

For each classification we perform 4-cross validation, and present the most accurate confusion matrix out of the four iterations. We also provide the average accuracy of the entire classifier.

3.1 OUC Classifier

3.1.1 Decision Trees

|       | U  | O  | C  |
|-------|----|----|----|
| U     | 36.8% | 1.9% | 0.9% |
| O     | 7.5% | 16.0% | 15.1% |
| C     | 0.9% | 1.9% | 18.9% |

Accuracy: 71.7%

Table 1: Confusion Matrix for DT in OUC

3.1.2 Support Vector Machines

|       | U  | O  | C  |
|-------|----|----|----|
| U     | 36.8% | 2.8% | .   |
| O     | 7.5% | 17.9% | 13.2% |
| C     | 0.9% | .   | 20.8% |

Accuracy: 75.5%

Table 2: Confusion Matrix for SVM in OUC

3.1.3 Naive Bayes

|       | U  | O  | C  |
|-------|----|----|----|
| U     | 37.1% | .   | 1.9% |
| O     | 1.9% | 22.9% | 4.8% |
| C     | 1.9% | 2.9% | 27.6% |

Accuracy: 87.6%

Table 3: Confusion Matrix for NB in OUC
| Feature | Label | Ratio |
|--------|-------|-------|
| 1 followers = 6 | c : u | 34.1 : 1.0 |
| 2 ratio = 4 | c : u | 26.9 : 1.0 |
| 3 ratio = 3 | c : u | 15.6 : 1.0 |
| 4 contains(my) | u : o | 14.1 : 1.0 |
| 5 contains(news) | o : u | 13.1 : 1.0 |
| 6 contains(from) | o : c | 13.0 : 1.0 |
| 7 contains(i) | u : o | 9.9 : 1.0 |
| 8 followers = 3 | u : o | 8.7 : 1.0 |

Table 4: Most Significant Features in Naive Bayes

| Features | DT | SVM | NB |
|----------|----|-----|----|
| numerical | 65.6% | 66.7% | 64.8% |
| numerical+ratio | 64.6% | 65.6% | 66.3% |
| numerical+ratio+description | 69.6% | 72.9% | 80.9% |

Table 5: Average Results for OUC classification

3.2 MPS Classifier

3.2.1 Decision Trees

| M | P | S |
|--|----|----|
| 30.9% | 1.4% | 2.2% |
| 2.9% | 32.5% | 4.1% |
| 3.8% | 2.2% | 20.1% |

Accuracy: 83.4%

Table 6: Confusion Matrix for DT in MPS

3.2.2 Naive Bayes

| M | P | S |
|--|----|----|
| 23.8% | 2.9% | 7.6% |
| 4.8% | 29.5% | 3.8% |
| 10.5% | 5.7% | 11.4% |

Accuracy: 76.8%

Table 7: Confusion Matrix for NB in MPS

4. CONCLUSIONS

We find that ambient profile metadata associated with user profiles, is an efficient feature set to bring about user classification. For both classifiers, MPS and OUC we get reasonably high accuracies after 4 cross validation. As expected, from Table 4 we can infer that the OUC classifier depends more on numerical features like followers count whereas, from Table 5 it is clear that the MPS classifier relies more on the lexical features of the profile description. We can thus conclude that any future twitter classifier, must incorporate these features, in its training.

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6. REFERENCES

[1] Twitter Developer API. [http://dev.twitter.com/]

[2] S. Bird, E. Klein, and E. Loper. Natural Language Processing with Python. O’Reilly Media, Inc., 1st edition, 2009.

[3] C. D. Manning, P. Raghavan, and H. Schütze. Introduction to Information Retrieval. Cambridge University Press, New York, NY, USA, 2008.

[4] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine Learning in Python . Journal of Machine Learning Research, 12:2825–2830, 2011.

[5] M. Pennacchiotti and A.-M. Popescu. A machine learning approach to twitter user classification. In L. A. Adamic, R. A. Baeza-Yates, and S. Counts, editors, ICWSM. The AAAI Press, 2011.

[6] D. Ramage, S. T. Dumais, and D. J. Liebling. Characterizing microblogs with topic models. In W. W. Cohen and S. Gosling, editors, ICWSM. The AAAI Press.

[7] A. Ritter, S. Clark, Mausam, and O. Etzioni. Named entity recognition in tweets: An experimental study. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP ’11, pages 1524–1534, Stroudsburg, PA, USA, 2011. Association for Computational Linguistics.

[8] W. X. Zhao, J. Jiang, J. He, Y. Song, P. Achanaanuparp, E.-P. Lim, and X. Li. Topical keyphrase extraction from twitter. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies - Volume 1, HLT ’11, pages 379–388, Stroudsburg, PA, USA, 2011. Association for Computational Linguistics.