Topic models and n-gram language models for author profiling

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1. Task

- ► A set of Twitter users and their posts were provided.
- Set was divided into four languages: Italian, English, Dutch, Spanish.
- Each user's gender, age and personality were given.
- Task was to predict age, gender and personality of unseen users; given a single set of these known users.

2. Data and processing

Users were equally balanced by author gender. No guarantee of equal balance for other attributes, i.e. age had a marked imbalance.

5. Results

| | | Englich | Spanich | Italian | Dutch |
|----------|-----------------------|----------|---------|----------|--------|
| | | Linglish | Spanish | Italiali | Dutti |
| | Global Ranking | 0.6743 | 0.6918 | 0.8061 | 0.6796 |
| | Average RMSE | 0.1725 | 0.1619 | 0.1378 | 0.1409 |
| | Gender | 0.6901 | 0.8409 | 0.7500 | 0.5000 |
| Accuracy | Age | 0.7394 | 0.5909 | N/A | N/A |
| | Joint | 0.5211 | 0.5455 | N/A | N/A |
| | E | 0.1381 | 0.1669 | 0.1279 | 0.1752 |
| | Ν | 0.2223 | 0.2285 | 0.1923 | 0.1511 |
| RMSE | Α | 0.1918 | 0.1398 | 0.1257 | 0.1444 |
| | C | 0.1749 | 0.1412 | 0.1187 | 0.1344 |
| | 0 | 0.1352 | 0.1329 | 0.1243 | 0.0993 |

- As authors may have different numbers of tweets. Up- (and down-) weighting of users was tested to avoid over-fitting to particular authors.
- Investigating effects of Hyperlinks was addressed in two ways:
 - Collecting domain of hyperlinks,
 - ▷ replacing hyperlinks with special token.
- ► The effect of shares and retweets were not considered in this approach.
- A single document representing each user was formed by aggregating their respective tweets.
- Each document was tokenized with a Twitter-aware tokenizer.

3. Feature extraction

- ► N-gram language model:
 - ▷ Word n–grams with n in the range 1–3 were extracted.
 - ▷ Weighted using TF-IDF (term frequency–inverse document frequency).
 - Character level n-grams were not considered.
- ► Topic model:
 - ▷ Topic models identify hidden themes in a document.
- LDA (Latent Dirichlet Allocation) was employed. This is a generative model in which documents are treated as a finite mixture of topics, such that each word in a document must be generated by one of its topics.
 A topic model trained on input data was used to label every topic as present or not present within each document.

Table 1: Results of final software submission including global rankings and individual attribute performance.

- Age, gender and their combination were scored using the accuracy metric for each of the four languages.
- Personality aspects (E=Extraversion, N=Neuroticism, A=Agreeableness, C=Conscientiousness and O=Openness) were scored with RMSE (root mean squared error). An average RMSE for each language is also provided.
- Global ranking is a combination of the joint (age, gender) accuracy and the average personality RMSE.
- These results show that n-grams and topic models are useful in developing multiple language compatible author profiling systems, as consistent results are achieved over the four languages.
- Manipulating hyperlinks was found to have no affect on system performance.
- Up- (and down-) weighting of users to avoid author over-fitting also had no affect on performance.

6. Further Work

Attempt to generate more robust topic models by training on a large external corpus.

4. Architecture

- Two feature sets—n–grams and topics—were combined to train Support Vector Machines with a linear kernel from package scikit-learn.
- Resulting model was then presented with previous unseen documents; performing judgements on the author attributes it was trained with.



- Assess effect of additional stylometric features such as readability.
- Investigate network and behavioural features for author profiling on social media.

References

- D.M. Blei, A.Y. Ng, M.I. Jordan (2003) Latent Dirichlet Allocation J. Mach. Learn. Res. (3) pp. 993–1022
- C. Manning, R. Prabhakar, H. Schutze (2008) Introduction to Information Retrieval, *Cambridge University Press*
- F. Pedregosa, et al. (2011) Scikit-learn: Machine Learning in Python J. Mach. Learn. Res. (12) pp. 2825–30
- F. Rangel, P. Rosso, M. Potthast, B. Stein, W. Daelemans (2015) Overview of the 3rd author profiling task at PAN 2015 in L. Cappellato, N. Ferro, J. Gareth, E. San Juan (Eds.) CLEF 2015 Labs and Workshops, Notebook Papers
- R. Řehůřek and P. Sojka (2010) Software Framework for Topic Modelling with Large Corpora *in* Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks *ELRA* pp. 45–50

Figure 1: Architecture of presented system.

Acknowledgments

This material is based upon work supported by the Air Force Office of Scientific Research, Air Force Material Command, USAF under Award No. FA9550-14-1-0333.

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