A Comparative Analysis of Social Network Pages by Interests of Their Followers

Elena Mikhalkova · Nadezhda Ganzherli · Yuri Karyakin

Received: date / Accepted: date

Abstract Being a matter of cognition, user interests should be apt to classification independent of the language of users, social network and content of interest itself. To prove it, we analyze a collection of English and Russian Twitter and Vkontakte community pages by interests of their followers. First, we create a model of Major Interests (MaIs) with the help of expert analysis and then classify a set of pages using machine learning algorithms (SVM, Neural Network, Naive Bayes, and some other). We take three interest domains that are typical of both English and Russian-speaking communities: football, rock music, vegetarianism. The results of classification show a greater correlation between Russian-Vkontakte and Russian-Twitter pages while English-Twitter pages appear to provide the highest score.

Keywords Interest discovery · Social networks · Natural language processing · Classification

1 Introduction

Social networks provide people with an opportunity to form social clusters that share interests not only sporadically but on a regular basis (circles of fans of different music, books, kinds of sports, etc.). Every circle communicates these interests creating lots of linguistic data to attract new followers and support
interests of the existing ones. Researchers often use these data in content-based user models to classify interests of particular users. As a rule, such models are tested on a corpus of one language downloaded from one social network. However, being a matter of cognition, user interests should be independent of the language in which they are expressed and the network where users communicate them, when we try to process them with different algorithms. To see if the performance of machine learning algorithms is the same for two different languages and two networks, we will test them in three internationally popular interest domains: football, rock music, vegetarianism. For the present research, we collected three datasets from two different networks: the English (I) and Russian (II) corpora from Twitter and the Russian corpus (III) from Vkontakte, and built a linguistic model of user interests. Then, we tested the model with such machine learning instruments as SVM, Neural Network, Naive Bayes etc. to classify datasets according to the interests of users.

2 Interest discovery by means of NLP

In present, there exists a variety of content-based models of user interests. These models make use of keywords, interests enlisted in profiles, tags attached to posts etc. Such data serve as the classification basis in works of Bonhard and Sasse (2006), Firan et al (2007), Dugan et al (2007), Li et al (2008), Sen et al (2009), Guy et al (2010), and many others. However, as these data are often very unreliable and hard to formalize, classifying social network pages by interests of their users is not a trivial task.

Interest discovery has now become a separate branch of user modelling. In regard to social networks, Natural Language Processing provides several approaches to interest discovery: collecting interests as topics or terms from tweets, posts and messages; defining semantic relations between keywords and searching for their correspondences in ontologies. Piao and Whittle (2011) view interests as terms and named entities extracted from a collection of user tweets.

In works of McCallum et al. (2005), Ramage et al. (2010), Ahmed et al. (2011), interests are viewed as topics distributed across users’ tweets. The authors apply variations of Latent Dirichlet Allocation suggested by Blei et al. (2003) as the main method of topic analysis to scale user messages down to a particular topic. Wang et al. (2014) describe the User Message Model that is designed particularly for microblogs to reduce data sparseness and topic diversity.

---

1 In recommender systems, tags and keywords in profiles define a scope of users that share similar interests. According to Guy et al. (2009), this process is called collaborative filtering. Pazzani (1999) suggests demographic filtering that infers types of users with a common interest based on their age, gender, education etc. mentioned in profiles. With the rise of the social network analysis, many researchers, for example Groh and Ehme (2007), attempt to objectivize real-world communities and build recommender systems with the help of social graphs (social filtering). A more detailed account of these approaches is given by Burke (2002).
Interests can be represented as concepts in an ontology. The latter often includes named entities. Bakalov et al. (2009) suggest a hybrid user model that makes use of ontologies to specify user interests. Interests are either extracted as keywords from the content of visited pages or can be manually specified by a user. Al-Kouz and Albayrak (2012) describe another approach where the system creates a semantic graph of interests based on the “entities” mentioned in tweets. Entities are words denoting real-world phenomena that have an encyclopaedic description. For reference, the authors used the currently deprecated knowledge base Freebase.

A recent study of Piao and Breslin (2016) demonstrates that “concept-based representations of user interests using a KB” add efficiency to the model, but then there is no need to add “rich semantic information from a KB to extend the interests of users.”

3 Modelling social nature of interests

It appears that interest discovery in social networks is a two-sided problem. First, regarding the number of published posts and comments, although in social networks linguistic content is abundant, it is often very hard to structure. Second, user interests themselves are an arcane matter: some researchers view them as topics, tags, keywords, etc. We will call the interest that attracts users to a page, the Major Interest (MaI). In the present research, we will attempt to classify a number of community pages based on three MaIs: football, rock music, vegetarianism.

3.1 Community pages

In our research, we will focus on community pages, e.g. accounts of public value that represent institutions, authorities, famous people, leaders of social groups, events, etc. They exist in all networks known to us (Twitter, Vkontakte, Facebook, LiveJournal etc.). Many researchers already use data from such pages together with a user’s individual page content but view them as complementary material. Usually, but not necessarily, such accounts have many followers (typically, more than 1,000).

Concerning the content downloaded for analysis, from Vkontakte, we obtained posts, comments to posts, and comments from the so-called “board”. As for Twitter, the only content available there is tweets.

---

2 http://www.freebase.com. Before the widespread use of knowledge bases, linguists often referred to WordNet, for example Stefani and Strapparava (1999). More recent approaches like Shen et al. (2013) use DBpedia.

3 https://vk.com/. One of the most popular Russian social networks.
3.2 Data survey

Observations show that for an expert it is quite easy to bind a community page to one certain MaI based on user comments and tweets and to find other pages with a similar MaI (the same kind of sports, music style, etc.). Many pages even provide links to other recommended pages. However, on the same page, users can mention a variety of different interest domains especially if they are related hyponymically (a style of music and its substyles), antonymically (a football team vs. its opponent in a championship), pragmatically (a football team and a stadium where it trains). Therefore, to define the basis of classification, i.e. MaIs that are not just microtopics and the pages that are devoted to these MaIs, we conducted an expert-based survey.

First, we downloaded comments from 20,000 random Vkontakte community pages. 4,460 pages contained texts of size from 1 to 100,523 words. We cut down the number of pages to 4,000 leaving out pages with the smallest number of words. So far, there was no automatic sorting of pages into spammed, flooded etc. Next, we asked a sociologist and a marketing specialist to look through these pages and find several active communities with common interests, i.e. such community pages where people actively interact about something they share an interest for. The result set included four communities whose MaI is one of the following 1. rock music, 2. historical reenactment, 3. football, 4. vegetarianism. In addition, all these MaIs are international and can be represented by pages in Russian as well as in English. We chose sample discussions from Vkontakte pages where people talk about things related to these MaIs. For control, a sample with several disparate objects of interest was chosen.

10 experts (linguists, sociologists, marketing specialists) gave their opinion on what community manifests itself in every sample. We instructed experts to define if authors in the sample dialogue are a community and, if yes, explain why they think so. Thus, the expert answers were formulated freely without the aim of interest attribution. Some of them preferred to just name the community (“vegans”, “rockers”); some stated the object of interest (“vegetarianism”, “rock music”). If these keywords were mentioned, we assigned 1 point to the answer (a True Positive answer); if no or some other keywords were mentioned (“music addicts” instead of “rockers”), we assigned 0 points. The answers were put in a ranking table. To see which samples relate to the most unanimous decision, we calculated percentage of True Positive answers in every column (percent agreement).

Determining adherence of the authors of comments to communities of football fans, vegetarians, and historical reenactors, the raters showed perfect agreement. Fans of rock music were not as easy to define (50% of raters recognized them). The control group also provided a highly reliable result that allows us to state that the raters were not apt to see communities in any text we offer them.

\footnote{We assigned 1 point for this sample if the expert directly expressed doubt in describing the community or just wrote “Don’t know” or left the field blank.}
Table 1  Percent agreement for expert analysis of community adherence

| Expert No. | Rock | Reenactment | Football | Vegetarianism | Control |
|------------|------|-------------|----------|---------------|---------|
| 1          | 1    | 1           | 1        | 1             | 0       |
| 2          | 0    | 1           | 1        | 1             | 1       |
| 3          | 1    | 1           | 1        | 1             | 1       |
| 4          | 1    | 1           | 1        | 1             | 1       |
| 5          | 0    | 1           | 1        | 1             | 1       |
| 6          | 1    | 1           | 1        | 1             | 1       |
| 7          | 1    | 1           | 1        | 1             | 1       |
| 8          | 0    | 1           | 1        | 1             | 1       |
| 9          | 0    | 1           | 1        | 1             | 1       |
| 10         | 0    | 1           | 1        | 1             | 1       |

Agreement, % 50 100 100 100 90

4 Community pages classification

We used several machine learning algorithms to classify community pages that represent one of the mentioned MIs. As these interest domains are popular in the both English and Russian-speaking communities, we used Twitter to create the text collection in English and Russian, and Vkontakte, a very popular Russian social network, for the dataset in Russian. However, we were unable to find any popular Twitter accounts devoted to historical reenactment (clubs, regiments, well-known reenactors) in Russian. Consequently, we had to exclude this MI from the further research. That leaves us with the three MIs: 1. football, 2. rock music, 3. vegetarianism.

For each class in the three corpora (I. English-Twitter, II. Russian-Twitter, III. Russian-Vkontakte), we prepared 30 texts downloaded from community pages. To normalize texts, we converted them to lowercase and removed punctuation marks, hashtags and emoji.

4.1 Interclass classification

To test performance of supervised machine learning algorithms on our collection, we randomly split the dataset into two equal sets of 15 texts (training and test sets) so that these sets do not overlap. For vectors, we picked up the first 1,000 most frequent keywords including stop-words. We experimented with two vector models: Bernoulli (a simple absence or presence of a keyword in a text denoted by 0 or 1 correspondingly) and frequency distribution. We used plain frequencies of keywords in a text denoted by a whole number in the interval $[0; +\infty)$ and also normalized frequencies in the interval $[0; 1]$.

Classification algorithms that we chose for the survey are often met in NLP tasks like spam detection, sentiment analysis and the like: Naive Bayes, 5

---

5 We could also transform every text into a set of microtopics or keywords, for example by using Latent Dirichlet Allocation, but, as the reader will see later, the current result was high enough without it.
Support Vector Machine, Neural Network etc. In particular, we used their implementation in the Python library Scikit-learn described by Pedregosa et al. (2011). Table 4.1 demonstrates average results of F1-score in five tests. In every new test, train and test sets were randomly created anew.

Table 4.1 shows that Bernoulli model is the most effective one by mode: it has 29 scores of 1.0 when the two other models have only 8 such scores each, and by mean: 0.958 against 0.819 for plain and 0.872 for normalized frequencies. The best performing algorithm is Linear Regression with Bernoulli model. The sum of its F1-scores equals 8.976. The second best score (8.95) belongs to the Neural Network (lbfgs). Multinomial Naive Bayes has the third best score (8.938) which is the same in all the three models. Hence, we can assume that in our research this classifier is most insensitive to the model type, although initially it was designed for word frequencies. But for Multinomial NB, Bernoulli models take the first 8 places in the ranking table. All things considered, we believe that Bernoulli models are the best solution for the tested linguistic model of interest classification.

Concerning normalization, it appears to be necessary for such algorithms as SVM with RBF and sigmoid kernels. Without it, they show the lowest results (their sums of F1-scores are 5.324 and 2.156 correspondingly). However, even with normalization, their performance remains low compared to the winning solutions. Some well-performing models like Neural Network slightly increase their result with normalization. As for Naive Bayes, it either gives the same result (Gaussian and Multinomial) or derates it (Bernoulli NB). Effects of normalization on the rest of the algorithms are not so obvious. For example, Linear Regression with normalization underperforms slightly in most of the cases, but even without normalization it is far below the top-score of Bernoulli model.

4.2 Statistical analysis

We will now try to analyze differences in classification of the three datasets according to the MaI, the language of user communication and the network where the texts were posted. For the analysis we will use the F1-scores from Table 4.1. First, we will normalize Table 4.1 excluding classifiers that gave lower results in the either of the two frequency models. That leaves us with SVM (linear), Bernoulli NB, Linear Regression, Decision Trees with plain frequencies, and SVM (polynomial, sigmoid, RBF), and Neural Networks with

---

6 Scikit-learn implementation of Neural Network for supervised learning is a type of Multi-layer Perceptron classifier with different optimization tools. As mentioned in the documentation, “lbfgs is an optimizer in the family of quasi-Newton methods” and adam is “a stochastic gradient-based optimizer”. For more references to particular methods, see Scikit-learn documentation at [http://scikit-learn.org](http://scikit-learn.org).

7 Some of the algorithms appeared to give similar results regardless of what texts went to the train set. This is most obvious with the Multinomial Bayes that returned the same result with the three models (Bernoulli and frequency). Results of some other algorithms varied more around the mean.
Table 2  Interclass classification: $\bar{F}_1$-score. F - football, R - rock music, V - vegetarianism, T - Twitter, Vk - Vkontakte, En - English, Ru - Russian, SVM - Support Vector Machine, lin. - linear kernel, pol. - polynomial kernel, rad. - Radial Basis Function kernel, sig. - sigmoid kernel, Neur. - Neural Network, NB - Naive Bayes, Bern. - Bernoulli, Mult. - Multinomial, Gaus. - Gaussian, LR - Logistic Regression, DT - Decision Trees, K-N - K-Neighbours. $\dagger$ marks cases where normalization was more effective compared to plain frequencies.

|          | Bernoulli model | Frequency model | Normalized frequency |
|----------|-----------------|-----------------|----------------------|
|          | Vk | Ru | T | En | Vk | Ru | T | En | Vk | Ru | T | En | Vk | Ru | T | En |
|          |    |    |   |    |    |    |   |    |    |    |   |    |    |    |   |    |
|          |    |    |   |    |    |    |   |    |    |    |   |    |    |    |   |    |
| SVM lin. | 0.908 | 0.974 | 0.968 | 0.986 | 0.988 | 0.988 | 0.994 | 0.994 | 0.994 | 0.994 | 0.994 | 0.994 | 0.994 | 0.994 | 0.994 |
| SVM pol. | 0.822 | 0.854 | 0.898 | 0.918 | 0.898 | 0.86 | 0.994 | 0.988 | 0.994 | 0.988 | 0.994 | 0.988 | 0.994 | 0.988 | 0.994 |
| SVM rad. | 0.952 | 0.954 | 0.994 | 1.0 | 0.982 | 0.982 | 1.0 | 0.994 | 0.994 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| SVM sig. | 0.952 | 0.954 | 0.994 | 1.0 | 0.988 | 0.988 | 1.0 | 0.994 | 0.994 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| Neur. lbfgs | 0.986 | 0.994 | 0.994 | 1.0 | 0.988 | 0.988 | 1.0 | 0.994 | 0.994 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| Neur. adam | 0.988 | 0.994 | 0.994 | 0.994 | 0.976 | 0.968 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| Bern. NB | 0.988 | 1.0 | 0.988 | 1.0 | 0.914 | 0.886 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| Mult. NB | 0.982 | 0.98 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| Gauss. NB | 0.968 | 0.988 | 0.982 | 1.0 | 0.982 | 0.978 | 1.0 | 0.982 | 0.982 | 1.0 | 0.988 | 0.988 | 1.0 | 0.988 | 0.988 |
| LR | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| DT | 0.836 | 0.882 | 0.792 | 0.98 | 0.988 | 0.968 | 0.924 | 0.872 | 0.9 |
| K-N | 0.84 | 0.904 | 0.864 | 0.53 | 0.41 | 0.632 | 1.0 | 0.982 | 0.982 |

Normalized frequency:
Table 3: Sums of MaI scores: F1-score. F - football, R - rock music, V - vegetarianism, T - Twitter, Vk - Vkontakte, En - English, Ru - Russian. \(\bar{x}\) denotes that the value is given as the mean of the scores due to differences in the size of arrays (e.g. there are 48 F1-scores per a MaI in Russian - Russian-Twitter and Russian-Vkontakte, and only 24 in English).

| MaI | Total | Vk | Ru | T | En | Vk, \(\bar{x}\) | Ru, \(\bar{x}\) | En, \(\bar{x}\) |
|-----|-------|----|----|---|----|-------------|-------------|-------------|
| F   | 67.04 | 20.57 | 22.81 | 23.65 | 0.85 | 0.968 | 0.904 | 0.986 |
| R   | 66.7  | 21.73 | 21.90 | 23.06 | 0.90 | 0.937 | 0.909 | 0.961 |
| V   | 66.81 | 21.85 | 21.71 | 23.24 | 0.91 | 0.937 | 0.908 | 0.966 |

normalized frequencies. Multinomial and Gaussian NB have the same result in both models.

For every MaI, the total sum of F1-scores and sum dependent on the language and network is shown in Table 4.2.

To analyze significance of differences in the total scores, we used Mann-Whitney test. The median values of the three sets are F=0.982, R=0.971, V=0.968, the size of each set is 72. Football has the best total score. Mann-Whitney U for Rock and Vegetarian sets demonstrates that they are likely to come from the same distribution: statistic=2562.0, p-value=0.904, two-sided. However, there are significant differences in Rock-Football (statistic=3130.5, p-value=0.03) and Vegetarianism-Football (statistic=3107.5, p-value=0.038) scores. Hence, we can assume that Football as a MaI was more supple to classification. It was also well-classified by the experts in the experiment.

However, there is one case where Football got the lowest score: the Russian-Vkontakte set. Mann-Whitney U for Russian-Vkontakte and Russian-Twitter Football sets shows a significant difference in the two distributions (statistic=151.5, p-value=0.004, two-sided). Meanwhile, Russian-Twitter and English-Twitter Football sets are more similar (statistic=334.5, p-value=0.3, two-sided) as well as Russian-Vkontakte and Russian-Twitter Rock sets (statistic=269.0, p-value=0.695, two-sided). This prompts us to conclude that the Russian-Vkontakte Football set is not so representative as other sets although the reasons of its defects are unclear.

Concerning the correlation between the experiment and classification, in case of Rock music, it did provide the lowest total result of percent agreement (50%) as well as of F1-score (66.7). However, in automatic classification the difference is not as significant as in experiment where it is twice lower than for the other two MaIs). There can be two explanations: either there was a flaw in the experiment (e.g. the text suggested for the expert analysis was not so representative in features, some experts were unfamiliar with rock music, etc.) or some MaIs (like Rock music) are less supple to classification. Nevertheless, as we showed previously, Mann-Whitney U for Rock and Vegetarianism demonstrates similarity in their scores. Hence, the experiment settings are more likely to have caused the discrepancy.

As for the factors of language and network, it appears that the mean values for Twitter are greater than those for Vkontakte, and the mean values for English are greater than those for Russian in case of all the MaIs. Lower
Vkontakte results can be caused by more noise features like spam, URLs, flood-messages compared to Twitter, as we used different software to clean the texts in Twitter and Vkontakte. However, considered separately, Russian-Vkontakte and Russian-Twitter sets are more similar to each other than to English-Twitter by mean (0.953 and 0.963 versus 0.982 correspondingly) and median (0.891 and 0.923 versus 0.972), which leads us to the idea that it is the language that brings more noise to the analysis. We conducted a series of tests with normalization of the Russian text (stemming and part-of-speech classification), but they decreased results.

5 Conclusion

Summing up, the assumption about classification neutrality has proved wrong. First of all, there are slight changes in interest classification across networks, which can be due to amounts of noise features coming from spam, flood, attached content, etc. Second, there are greater differences bound to the language: as far as our language model of MaI is concerned, pages in Russian are harder to classify than pages in English. As for the interests themselves, it is hard to draw any strict conclusion. Some of the MaIs we took for research show a strong correlation of classification results, some stand aside. This is also an issue in expert classification.

Concerning the algorithms of classification, we faced the efficiency of the Bernoulli model. I.e. word frequencies are not as important in classification as the absence or presence of characteristic features. And the more unique features are present in a page, the better. Hence, Linear Regression also came out to be the most effective algorithm. As for the frequency model, tests showed that with some classifiers it needs normalization, but even normalized frequencies are not so representative. Generally speaking, we tend to think that MaIs are more like umbrella terms to a variety of topics discussed by communities rather than a class term semantically bound to page subtopics. Therefore, common NLP techniques do not work with them as they do in other NLP tasks.

We also discovered that objects of interest even though they can be spread in different parts of the world and communicated in different languages do not necessarily appear in all popular networks. In case with the historical reenactors, Twitter abounds in their accounts in English, but, as far as we know, does not have a single reenactment account in Russian. Russian vegetarian accounts are also scarce in Twitter. Unsurprisingly, Vkontakte has no living accounts of English-speaking reenactors and vegetarians. However, there are some English-language football fans accounts. There are also some concerns in regard to the size of the dataset. Due to the mentioned peculiarities, pages with veracious content representing certain MaIs are not easy to collect (except, probably, football).
References

Ahmed A, Low Y, Aly M, Josifovski V, Smola AJ (2011) Scalable distributed inference of dynamic user interests for behavioral targeting. In: Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, pp 114–122

Al-Kouz A, Albayrak S (2012) An interests discovery approach in social networks based on semantically enriched graphs. In: Advances in Social Networks Analysis and Mining (ASONAM), 2012 IEEE/ACM International Conference on, IEEE, pp 1272–1277

Bakalov F, König-Ries B, Nauerz A, Welsch M (2009) A hybrid approach to identifying user interests in web portals. In: HCS, pp 129–134

Blei DM, Ng AY, Jordan MI (2003) Latent dirichlet allocation. Journal of machine Learning research 3(Jan):993–1022

Bonhard P, Sasse MA (2006) ‘knowing me, knowing you’—using profiles and social networking to improve recommender systems. BT Technology Journal 24(3):84–98

Burke R (2002) Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction 12(4):331–370

Dugan C, Muller M, Millen DR, Geyer W, Brownholtz B, Moore M (2007) The dogear game: a social bookmark recommender system. In: Proceedings of the 2007 international ACM conference on Supporting group work, ACM, pp 387–390

Firan CS, Nejdl W, Pain R (2007) The benefit of using tag-based profiles. In: Web Conference, 2007. LA-WEB 2007. Latin American, IEEE, pp 32–41

Groh G, Ehming C (2007) Recommendations in taste related domains: collaborative filtering vs. social filtering. In: Proceedings of the 2007 international ACM conference on Supporting group work, ACM, pp 127–136

Guy I, Zwerdling N, Carmon D, Ronen I, Uziel E, Yogev S, Ofek-Koifman S (2009) Personalized recommendation of social software items based on social relations. In: Proceedings of the third ACM conference on Recommender systems, ACM, pp 53–60

Guy I, Zwerdling N, Ronen I, Carmon D, Uziel E (2010) Social media recommendation based on people and tags. In: Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval, ACM, pp 194–201

Li X, Guo L, Zhao YE (2008) Tag-based social interest discovery. In: Proceedings of the 17th international conference on World Wide Web, ACM, pp 675–684

McCallum A, Corrada-Emmanuel A, Wang X (2005) Topic and role discovery in social networks. Computer Science Department Faculty Publication Series

Pazzani MJ (1999) A framework for collaborative, content-based and demographic filtering. Artificial intelligence review 13(5-6):393–408

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

Piao G, Breslin JG (2016) Interest Representation, Enrichment, Dynamics, and Propagation: A Study of the Synergetic Effect of Different User Modeling Dimensions for Personalized Recommendations on Twitter, Springer International Publishing, Cham, pp 496–510

Piao S, Whittle J (2011) A feasibility study on extracting twitter users’ interests using nlp tools for serendipitous connections. In: Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on, IEEE, pp 910–915

Ramage D, Dumais ST, Liebling DJ (2010) Characterizing microblogs with topic models. ICWSM 10:1–1

Sen S, Vig J, Riedl J (2009) Tagommenders: connecting users to items through tags. In: Proceedings of the 18th international conference on World wide web, ACM, pp 671–680

Shen W, Wang J, Luo P, Wang M (2013) Linking named entities in tweets with knowledge base via user interest modeling. In: Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, pp 68–76

Stefani A, Strapparava C (1999) Exploiting nlp techniques to build user model for web sites: the use of wordnet in sitelf project. In: Proc. 2nd Workshop on Adaptive Systems and
User Modeling on the WWW
Wang Q, Xu J, Li H (2014) User message model: A new approach to scalable user modeling on microblog. In: Asia Information Retrieval Symposium, Springer, pp 209-220