Inferring Semantic Interest Profiles from Twitter Followees

Does Twitter know better than your Friends?

Christoph Besel
University of Passau
Innstraße 41
Passau, Germany
beselch@fim.uni-passau.de

Jörg Schlötterer
University of Passau
Innstraße 41
Passau, Germany
joerg.schloetterer@uni-passau.de

Michael Granitzer
University of Passau
Innstraße 41
Passau, Germany
michael.granitzer@uni-passau.de

ABSTRACT

Social media based recommendation systems infer users' interests from their social network activity in order to provide personalised recommendations. Typically, the user profiles are generated by analysing the users' posts or tweets. However, there might be a significant difference between what a user *produces* and what she *consumes*. We propose an approach for inferring user interests from followees (the accounts the user follows) rather than tweets. This is done by extracting named entities from a user's followees using the English Wikipedia as knowledge base and regarding them as interests. Afterwards, a spreading activation algorithm is performed on a Wikipedia category taxonomy to aggregate the various interests to a more abstract interest profile. With over 7 out of 10 items being relevant to the users in our evaluation, we show that this approach can compete with the state of the art and performs even better in predicting the users' interests than their human friends do.

CCS Concepts

•**Information systems** → **Personalization;** •**Human-centered computing** → *Social networks;*

Keywords

Personalization, Twitter User Profile

1. INTRODUCTION

We have seen a rapid increase in the amount of published information and data since the rise of the Internet. Obviously, it is not possible for humans to process all the information available, a problem known as "information overload" [3]. At the same time more and more people reveal their interests explicitly in and implicitly by using social networks. The goal of social media based recommendation systems is to infer users' interests and preferences from their social network activity and use the thereby generated interest profiles for making personalized content recommendations. Using social information for recommendation systems is also connected to the hope of solving the cold start problem which correlation based approaches suffer from, especially for smaller web pages. Most of the related work infers the interest profiles from a user's posts or tweets. However, there might be a significant difference between what a user *produces* and what she *consumes*. Moreover the passive use of social network sites is on the rise. Now four in ten users browse Facebook only passively, without posting anything [5]. We address this problem by inferring semantic interest profiles from the twitter followees (the accounts, the user follows) rather than her tweets. The rationale for this approach is that many famous people maintain a Twitter account and a lot of Twitter users follow these accounts. For those accounts, the likelihood that a Wikipedia article about this person exists is very high. Moreover, Wikipedia articles are typically linked to higher level categories (e.g. the article about the football player "Thomas Müller" is linked to the category "German footballers"). Making use of those categories, following an account that can be linked to a Wikipedia article can be seen as implicit expression of interests. In addition, the assigned categories are organised in some kind of hierarchy in Wikipedia, thus they can be traversed in order to provide a more fine- or coarse-grained profile. This approach immediately raises the question of whether a sufficient number of followees can be linked to Wikipedia entities. Specifically, the contribution of this paper is the following:

(i) *We evaluate the coverage of followee lists in terms of named entities in the English Wikipedia and show that the followee lists provide enough input to infer comprehensive semantic interest profiles.*
(ii) *We propose a followee-based approach to create user interest profiles, which can compete with state of the art tweet-based approaches.*

The rest of the paper is organized as follows: In the next section, we present related work in the field of social media based recommendation systems. Then we provide an overview of the approach, followed by the evaluation of named entity coverage in followee lists and the evaluation of the overall quality of the approach by a user study. Finally, we conclude the paper and provide an outlook on future work.

SAC 2016, April 04 - 08, 2016, Pisa, Italy

ACM 978-1-4503-3739-7/16/04…$15.00
DOI: http://dx.doi.org/10.1145/2851613.2851819

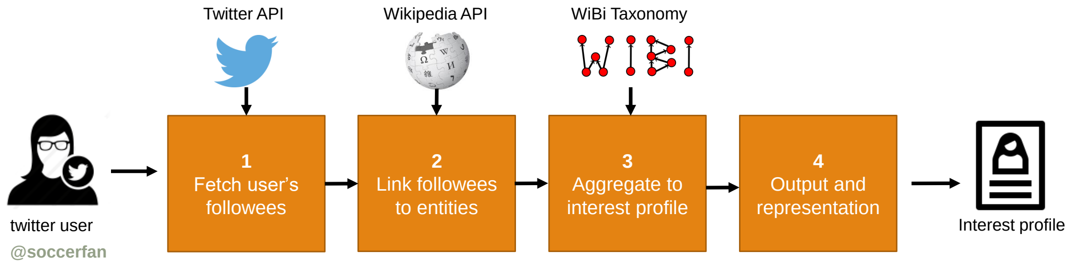

Figure 1: Overview approach

2. RELATED WORK

Research on user profiling and personalized content recommendation has been done for many years since the beginning of the web [9]. Early approaches focused on the web [9, 8] and search history [15] of the user. Recently, with the emergence of social networks like Twitter, research has shifted to analyze user activities on these platforms. For instance Siehndel and Kawase [14] introduced *TwikiMe*, a prototype for generating user profiles by extracting entities from the user's tweets and linking them to the 23 top-level categories of the English Wikipedia. This leads to abstract interest profiles with a fixed size represented as a 23-length vector. Abel et. al. [1] in their work compared hastag-based, topic-based (bag-of-words) and entity-based user models generated from the user's tweets, for news recommendation. In this approach the scoring of the extracted concepts and interests is based on a simple term frequency technique. The results of their comparative evaluation showed that the simple bag-of-words and hashtag-based approaches, which did not consider the semantics of a tweet, were clearly outperformed by the (semantic) entity-based strategy (precision of 0.71 compared to 0.4 and 0.1). Based on these results Tao et. al. [16] presented *TUMS*, a Twitter-based User Modeling Service, that tries to infer semantic user profiles from the messages people post on Twitter. However, the focus of *TUMS* is to make use of semantic web technologies for providing a standardized representation of the interest profiles allowing an easy exchange between different web services. This is connected with the hope to solve the so-called ramp up or cold start problem, a downside of approaches like content based or collaborative filtering [16, 11], which usually depend on the build-up of a user history before making personalized content recommendations. In terms of the applied algorithm and the knowledge base, the approach introduced by Kapnipathi et. al [6] is the closest to our work. They used the English Wikipedia to spot entities in tweets and leveraged the hierarchical relationships by performing a spreading activation on the Wikipedia Category Graph to infer user interests. The result, a weighted hierarchical interest profile (expressed as a so-called *Hierarchical Interest Graph*), was evaluated by a user study which showed an average of approximately eight out of the ten interests in the graph being relevant to a user. Even though Siehndel and Kawase [14] suggested investigating other types of inputs for inferring user interests, most of the related work only makes use of the content posted by a user (e.g. the tweets). Apart from [10] that presented a basic approach for classifying celebrities followed by a user to high-level Wikipedia categories, up to now, no published work known to us has yet made use of the accounts followed by a user to infer his or her interests.

3. GENERAL APPROACH

The generation of interest profiles in this paper can be seen as a four-step process which is shown in fig. 1. In the following, each step is described in more detail and a fictional user called *@soccerfan* will be used as an illustrating example.

Fetch user's followees In the first step the followees are crawled via Twitter's RESTful Web API[1]. The fictional user *@soccerfan* might, among others, follow the accounts *@Cristiano (Cristiano Ronaldo)*, *@BSchweinsteiger (Basti Schweinsteiger)*, *@neymarjr (Neymar Jr)*, *@esmuellert_ (Thomas Müller)* and *@FIFAcom (FIFA.com)*.

Link followees to entities The objective of this step is to link the user's followees to corresponding entities represented by Wikipedia articles. This entity linking includes handling coincidental homonymy and ambiguity (for instance there are several famous "Thomas Müllers" with their own Wikipedia page). For that purpose the MediaWiki Web API[2] is used and several disambiguation heuristics are applied. They include syntactical measures (overlap coefficient of last 20 tweets and article summary) and probabilistic heuristics (Sense Prior and a reverse linking of Wikipedia articles to Twitter search results).
In our example the following entities might be extracted: *WikipediaPage:Christiano Ronaldo*, *WikipediaPage:Bastian Schweinsteiger* and *WikipediaPage:Thomas Mueller (footballer)*. As you can see, "Thomas Müller" was correctly linked to the famous football player.

Aggregate to interest profile The extracted Wikipedia article entities are assigned to Wikipedia categories. These categories are hierarchically structured (at least to some extent) and used to represent particular interests of the user. By performing a spreading activation algorithm on the Wikipedia Bitaxonomy (a taxonomy based on the Wikipedia page and category hierarchy [4]) the single interest entities are aggregated to a more

[1]https://dev.twitter.com/rest/public
[2]https://www.mediawiki.org/wiki/API

abstract and broader interest profile. The categories of the Wikipedia page entities extracted in the previous step represent the set of initially activated nodes. Their activation is spread during several iterations to neighboring nodes connected by outgoing edges. Formally the activation $a(v)$ of a node v can be written as:

$$a_t(j) \leftarrow a_{t-1}(j) + d \cdot a_{t-1}(i) \tag{1}$$

where j is being activated by node i and $0 < d < 1$ represents the decay factor. If a node is activated by more than one node the activation is accumulated in this node. Apart from that, a normalization with the number of incoming edges and a so-called Intersection Boost (see [6] for more details), boosting nodes that are intersections of different paths are applied.

In our example the entities (pages) are assigned to categories such as *2014 FIFA World Cup players* or *German footballers*. Performing spreading activation identifies *sports* and *footballers* as two of the most suitable overall interest categories for the example user.

Output and representation As the output of step three is a graph data structure with weighted nodes, the objective of this last step is to convert this representation to a common exchange format. Therefore, the top-k interests are extracted and can be represented in an arbitrary format, such as for example the *Weighted Interests Vocabulary*[3]. This also allows the provision of the interest profiles to other applications and web services through standardized interfaces.

4. ENTITY COVERAGE EVALUATION

The first question we need to address is whether the followee list of a Twitter user is sufficient input for inferring his or her interest profile. This mainly depends on the number of followees which could be linked to an entity and the quality of that entity linking. We evaluated both issues on a sample dataset.

4.1 Method and sample description

We conducted experimental research by crawling the profiles of 3000 twitter accounts (with over 350 000 followees in total) chosen randomly from an updated data set based on [2, 7]. Afterwards we analyzed the number of followees that could be linked to an entity and assessed the quality of that entity linking by applying the disambiguation heuristics mentioned in the second step of section 3.

A first analysis of the sample showed that over 72 % of the users in the sample are friends with more than 50 other accounts. More than half of the Twitter accounts examined had between 50 and 200 followees. The overwhelming majority (91 %) used the English language version of Twitter.

4.2 Quantitative results

For analyzing the number of followees that could be linked to a corresponding Wikipedia page entity we used the MediaWiki Web API[2]. As this API allows search on the English

[3]http://purl.org/ontology/wi/core

Table 1: Quantitative results (auto suggest on)

Selection	followees in % linked: unambiguously	ambiguously	not at all
None	69.89	7.14	22.72
Number of followees > 50	71,08	7.11	21.65
Number of followees < 50	66.77	7.23	25.51
English language version	71.24	7.24	21.27
Other language version	54.84	6.05	38.87
EN & #followees > 50	72.44	7.20	20.22

Wikipedia with an auto suggest feature enabled or disabled, we did the calculation for both. Table 1 and table 2 show the results for different selections on the sample. The numbers include the shares of followees which could be linked to an entity unambiguously, the followees that could be linked to more than one page (ambiguity) and the followees that could not be linked to any entity at all. On average about 70 % of the total number of followees could be linked unambiguously to an entity by the MediaWiki API with the auto suggest feature enabled. In less than every tenth case (7.14 %) more than one disambiguation (articles of the same name) was possible. About a fifth of the followees could not be linked to any entity even with the auto suggest feature enabled. Considering only accounts using the English language version the share of followees linked unambiguously is significantly higher (71.24 %) than with other language versions (54.84 %). The same effect, even though to a lesser extent, can be seen when comparing accounts that have more and less than 50 followees. The best success rate (72.44 %) is achieved by a combined selection of accounts using the English language version of Twitter with more than 50 followees. With auto suggest feature disabled the share of followees that could be linked to an entity is, as one could expect, lower (41.23 % compared to 69.89 %). However the trends for the different sections are very similar. For accounts with more than 50 followees that use the English language version barely half could be linked to an entity (6 % of these ambiguously).

Table 2: Quantitative results (auto suggest off)

Selection	followees in % linked: unambiguously	ambiguously	not at all
None	41.23	5.73	52.93
Number of followees > 50	42.74	5.81	51.35
Number of followees < 50	37.24	5.54	57.08
English language version	42.61	5.88	51.39
Other language version	25.84	4.06	69.99
EN & #followees > 50	44.17	5.95	49.79

4.3 Qualitative results

The quantitative results may not necessarily imply that the quality of the entity linking is sufficient. This depends on whether the followee was linked with the semantically cor-

Table 3: Qualitative results (overlap coefficient)

	Entity Linking $n = 7500$		Baseline $n = 7500$	
	M	SD	M	SD
no normalization	0.2325	0.0910	0.2168	0.0871
normalization	0.0609	0.0643	0.0369	0.0365

M: mean, SD: standard deviation

rect entity. For instance "common" people that share the name with a celebrity coincidentally might be linked to a Wikipedia page. To assess the quality of the entity linking we applied some of the disambiguation heuristics mentioned in section 3:

Overlap coefficient.

We calculated the overlap coefficient as a simple syntactic measure for assessing the link quality. This was done by collecting the last 20 tweets for 7500 randomly chosen Twitter users that could be linked to a Wikipedia page by the MediaWiki Web API[2] (auto suggest enabled) and the summary of the linked page (usually the very first section). Afterwards we tokenized the crawled input and converted it into a set of words, which also removed duplicates. On that basis we calculated the overlap coefficient as shown in eq. (2) (where X and Y are the two word token sets compared).

$$overlap(X, Y) = \frac{|X \cap Y|}{min(|X|, |Y|)} \tag{2}$$

The overlap coefficient was calculated for both, a random mapping of tweets and page summaries (the baseline) and for the linking suggested by the MediaWiki Web API. This was done with and without text normalization (stop word removal and stemming). With text normalization the results show (see table 3) that the mean overlap coefficient for the entity linking is twice as high as for the random baseline mapping (Cohen's $d = 0.47$). Without text normalization the effect (Cohen's $d = 0.18$) is clearly smaller. All value differences were highly statistically significant ($p < 0.001$). The observed difference is probably due to the falsifying effect of stop words, which inevitably increase the overlap and are removed by the text normalization.

Reverse Linking.

A quick way to estimate the entity linking quality is to search on Twitter for accounts with the name of the Wikipedia page title (entity). By doing this reverse linking we ended up in about 80 % of the cases with the account we started the entity linking from. Both Twitter and Wikipedia have optimized search indices and the article title sometimes contains additional disambiguation information (e.g. "footballer" for "Thomas Müller"). A high success rate could be seen as indicator of a good entity linking, but as the search algorithms and indices of Twitter and Wikipedia are black boxes for us this could only be a first clue.

Sense Prior.

Sense Prior is a probabilistic approach which assumes that the most frequent word meaning dominates the others [13]. For that purpose the relative frequencies of so-called surface forms linking to an entity are calculated and the most frequent one is assumed to be the correct disambiguation. In this evaluation we used a dataset based on the internal link structure of the English Wikipedia to calculate the frequencies. Let $l = (s, a)$ be an internal link which points to article a with the link text (surface form) s and let $n(s)$ describe the number of occurrences of that surface form in all articles then

$$P(a|s) = \frac{l(s, a)}{n(s)} \tag{3}$$

is the probability that entity a is the correct disambiguation for surface form s.
We calculated that probability for 10 000 randomly chosen followee names (the surface form in this case) of our sample (no auto suggest, English language version and more than 50 followees) and compared the entity with the highest probability to the linked entity.
If the Sense Prior dataset could provide a disambiguation (the case in 78 %) it corresponded with a probability of over 90 % with the linked entity.

4.4 Analysis and Discussion

The results of our empirical research show that without auto suggest almost half of the followees and with auto suggest over two thirds of the accounts a user is following could be linked to Wikipedia page entities successfully. This implies that the Twitter followees of a user actually could be a sufficient and broad basis for inferring interest profiles. As ambiguity does occur only in about one out of ten cases it should have little effect. With an overlap coefficient twice as high as for a random baseline mapping and success rates of ca. 80 % and 90 % for the probabilistic disambiguation heuristics the entity linking quality could be seen as sufficient as well.
To conclude, the results suggest that the Twitter followees of a user are already a sufficient input, both quantitatively and qualitatively, for inferring meaningful interest profiles.

5. USER STUDY

Even though the groundwork in the last section showed that the Twitter followees are a sufficient base for inferring interest profiles, the evaluation of personalization and/or recommendation systems typically involves a user study [6].
For that purpose we implemented the approach presented in section 3 and evaluated it with real users. The source code of the application can be found on the project repository[4].

5.1 Experimental Setup

For our evaluation we generated four different profile types defined by the number of iterations, the decay factor and the application of disambiguation heuristics (see table 4). After

[4]The project repository includes application source code, evaluation scripts and screenshots: https://bitbucket.org/beselch/interest_twitter_acmsac16

Table 4: Evaluated profile types

	Iterations	Decay	Disambiguation
Profile type 1	5	0.2	No
Profile type 2	5	0.2	Yes
Recommendations	3	0.2	Yes
Comparative Eval.	5	0.2	Yes

the users had registered by providing their Twitter screenname and e-mail, they were notified by a mail providing a link to their personalized questionnaire. This questionnaire had four pages that corresponded with the four different interest profile types shown in table 4. For screenshots of the registration form and questionnaire pages please see the project repository[4].

On the first page the user was presented the top 20 interest categories (most weighted nodes) of the first profile type. The participants were asked to indicate their strength of interest for each category on a four-point Likert scale ranging from "very interesting" to "not interesting at all".

The second page was pretty much the same presenting the top 20 interests of profile type 2 that mainly differed in whether disambiguation heuristics were applied or not.

On the third page five Wikipedia articles that were assigned to the interest categories of the third interest profile (a smaller number of iterations was used to get more specific results) were shown. Again the participants were asked to indicate their strength of interest in the topics covered by these articles.

The last page showed the users ten interest categories randomly picked from the profiles of other users. As the categories did not appear in their interest profiles, no interest of the users in these categories was assumed and they were asked to evaluate whether this was correct or not. Afterwards the participants were provided with a link they were asked to send a friend of theirs. This link lead to a one-paged survey that presented the user's friend with 20 interest categories. One half consisted of the top 10 interests of profile type 2 and the other half were the randomly picked interest categories that our approach assumed to be not interesting. Now the user's friend was asked to evaluate the interest of his or her friend in these interest categories. Following [17] these answers were used to compare the performance of the friend and our algorithm in predicting the user's interests. Whereas the pages one and two were obligatory the last two steps could be skipped by the participants.

5.2 Sample description

During the evaluation period from 30 June to 10 July 2015 64 Twitter users registered for the user study and 52 of them completed the survey (response rate of 81.25 %). A participant had 205 followees on average, while the median (114) was considerably lower. The used Twitter language versions were half German and half English. Barely half of the users posted fewer than 100 tweets (over 15 % nothing), which means that approaches based on the tweets would fail to generate interest profiles for that users. 46 participants submitted the optional third page and 17 people took part in the fourth step (comparative evaluation).

5.3 Results

Evaluation of Likert scale items.

The possible answers of the Likert scale were encoded with values ranging from 1 for "not interesting at all" to 4 for "very interesting". Whereas the top 20 interests of profile type 1 scored 2.38 ± 0.33, the same selection of interest categories for profile type 2 scored higher with 2.80 ± 0.39. This trend could be found for all n-best selections (see table 5) reaching a maximum difference of 0.7 for the top 5 interests. The recommended Wikipedia articles (profile type *recommendations*) have been evaluated with an average score of 2.46 ± 0.33 by the participants.

Table 5: Mean scores of Likert scale items

	Type 1 $n = 52$		Type 2 $n = 52$	
	M	SD	M	SD
Top 5 interests	2.3808	0.3302	3.0840	0.4361
Top 10 interests	2.3923	0.3318	2.946	0.4166
Top 15 interests	2.3859	0.3309	2.8645	0.4050
Top 20 interests	2.3798	0.3300	2.8021	0.3963

M: mean, SD: standard deviation

Precision.

For calculating the precision we considered items rated as "very interesting" and "interesting" as relevant to the user (true positive) and items rated as "hardly interesting" and "not interesting at all" were considered irrelevant (false positive). Figure 2 depicts the precision curves for different n-best selections of profile type 1 (red curve, dashed) and profile type 2 (blue curve, solid). Again profile type 2 (disambiguation heuristics applied) dominates profile type 1 (no disambiguation) in each n-best selection: Regarding the top 5 interests, users indicated a correct assignment for over 80%. For all inferred topics (top 20), at least two thirds are considered relevant by the users. Similarly, two of the top 3 Wikipedia articles recommended in the third step are considered relevant.

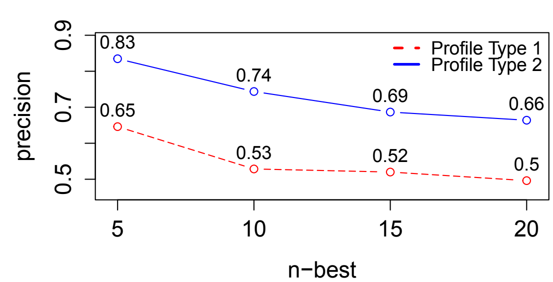

Figure 2: Precision curves profile type 1 and 2

MAP and MRR.

Mean Average Precision and Mean Reciprocal Rank answer the question of how well the interests are ranked at top-k and how early relevant results appear [12]. Again both MAP and MRR scored higher for profile type 2 (0.72 and 0.85) than for profile type 1 (0.50 and 0.68).

Comparative evaluation with a user's friend.

Profile type 4 was built up with top-10 interest categories of profile type 2 and 10 interest categories where no interest was assumed. The users were asked to evaluate this profile and send a link to a friend of theirs to do the same. The performance of our algorithm and the friend's assessment was compared by the user's evaluation (benchmark). Table 6 shows the confusion matrix comparing the performance of the algorithm introduced in this paper and the user's friends (in brackets). With a combined success rate of 74 % versus 60 % our approach clearly outperforms the friend in predicting the user's interests. Differences in the above mean values are statistically significant ($p < 0.01$).

Table 6: Algorithm vs. friend (in brackets)

	Recommended	Not recommended
Relevant	73 % (55 %)	27 % (55 %)
Not Relevant	24 % (35 %)	76 % (65 %)

5.4 Analysis and Discussion

The results of the user study show that a user's followees are not only a sufficiently broad basis for inferring interest profiles but these interest profiles are also a valid representation of the user's interests. Profile type 2 scored better than profile type 1 in all quality measures calculated. This implies that the disambiguation heuristics have a significant impact on the quality of the generated interest profiles. With over 7 out of 10 items being relevant to the users our approach could achieve state of the art results and performed even better in predicting the users' interests than their friends (thus humans) did.

6. CONCLUSION AND FUTURE WORK

In this paper we introduced an approach for inferring semantically meaningful interest profiles from the accounts a user follows on Twitter. With followees as the only input used, it is possible to generate interest profiles even for users that posted no tweets. By conducting an extensive user study we could show that our approach achieved state of the art (and superhuman) results in predicting a user's interests. We plan to extend our approach to other social networks such as Facebook (for which "likes" should be semantically equivalent to followees on Twitter). Another interesting research focus could be a comparison of profiles derived from tweets and those derived from followees. The evaluation showed that the disambiguation heuristics had a significant impact on the profile quality so it also appears promising to use more sophisticated disambiguation and entity linking algorithms in future.

7. ACKNOWLEDGMENTS

The presented work was developed within the EEXCESS project funded by the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement number 600601.

References

[1] F. Abel et al. "Analyzing user modeling on twitter for personalized news recommendations". In: *UMAP*. 2011, pp. 1–12.

[2] C. G. Akcora et al. "Detecting anomalies in social network data consumption". In: *SNAM* 4.1 (2014), pp. 1–16.

[3] A. Edmunds and A. Morris. "The problem of information overload in business organisations: a review of the literature". In: *IJIM* 20.1 (2000), pp. 17–28.

[4] T. Flati et al. "Two is bigger (and better) than one: the Wikipedia Bitaxonomy Project". In: *ACL*. 2014, pp. 945–955.

[5] S. Gunelius. *Facebook's Growing Problem - Passive Users*. http://www.corporate-eye.com/main/facebooks-growing-problem-passive-users/. 2015.

[6] P. Kapanipathi et al. "User Interests Identification on Twitter Using a Hierarchical Knowledge Base". In: *ESWC*. 2014, pp. 99–113.

[7] H. Kwak et al. "What is Twitter, a social network or a news media?" In: *WWW*. 2010, pp. 591–600.

[8] S. LeMole et al. "Method and system for presenting customized advertising to a user on the world wide web". Patent US6009410 A (US). A. Corporation. 1999.

[9] H. Lieberman et al. "Letizia: An agent that assists web browsing". In: *IJCAI (1)* 1995 (1995), pp. 924–929.

[10] K. H. Lim and A. Datta. "Interest classification of Twitter users using Wikipedia". In: *OpenSym*. 2013, p. 22.

[11] C. Lu, W. Lam, and Y. Zhang. "Twitter user modeling and tweets recommendation based on wikipedia concept graph". In: *Workshops at the 26. AAAI Conf. on Artificial Intelligence*. 2012.

[12] C. D. Manning, P. Raghavan, H. Schütze, et al. *Introduction to information retrieval*. Vol. 1. Cambridge university press Cambridge, 2008.

[13] P. Resnik. "Using information content to evaluate semantic similarity in a taxonomy". In: *arXiv preprint cmp-lg/9511007* (1995).

[14] P. Siehndel and R. Kawase. "TwikiMe! User profiles that make sense." In: *ISWC (posters and demos)*. 2012.

[15] L. Tamine-Lechani, M. Boughanem, and N. Zemirli. "Inferring the user interests using the search history". In: *LWA '06*. 2006, pp. 108–110.

[16] K. Tao et al. "Tums: twitter-based user modeling service". In: *ESWC Workshops*. 2012, pp. 269–283.

[17] W. Youyou, M. Kosinski, and D. Stillwell. "Computer-based personality judgments are more accurate than those made by humans". In: *PNAS* 112.4 (2015), pp. 1036–1040.