Web Science & Engineering

WSE 2017

Geert-Jan Houben

October 16

1. Web
2. Web *& paper*
3. Web engineering intro
4. Web engineering hands-on
5. Web data, Semantic Web
6. ***Example paper & final paper***

7. Social web data analytics
8. User modeling, User adaptation
9. Social Web, Social Web data
10. Data Science on the Social Web
11. Data Science on the Social Web
12. *Final paper*
13. *Final paper*

Paper

WSE 2017, October 16

Paper

- How does a **scientific** paper [on this type of subject] look like, and how it is **structured**?
- The goal here is to **know** that, and then to use when you write a paper yourself, e.g. this course's final paper.
- We take a look at the **UMAP2011** paper by Abel et al., that happened to win the best paper prize.
  - NB I do not claim this paper is the best, but use it to discuss the paper structure ☺.

Analyzing User Modeling on Twitter for Personalized News Recommendations

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Abstract. How can micro-blogging activities on Twitter be leveraged for user modeling and personalization? In this paper we investigate this question and introduce a framework for user modeling on Twitter which enriches the semantics of Twitter messages (tweets) and identifies topics and entities (e.g. persons, events, products) mentioned in tweets. We analyze how strategies for constructing hashtag-based, entity-based or topic-based user profiles benefit from semantic enrichment and explore the temporal dynamics of those profiles. We further measure and compare the performance of the user modeling strategies in context of a personalized news recommendation system. Our results reveal how semantic enrichment enhances the variety and quality of the generated user profiles. Further, we see how the different user modeling strategies impact personalization and discover that the consideration of temporal profile patterns can improve recommendation quality.

Title & Abstract

- A title must be **descriptive** and **specific**, and inviting to read.
- A title is used for **finding** the paper and for **remembering** it.

- An abstract addresses:
  - **Why**? – motivation, relevance, scientific & application
  - **What**? – the concrete research challenge or question
  - **How**? – the approach to address that challenge, incl. evaluation
  - **Results**? – the outcomes and the contributions

- Abstract serves as a short summary, used to enhance finding the paper and for advertising it. And reviewing.

1 Introduction

With more than 190 million users and more than 65 million postings per day, Twitter is today the most prominent micro-blogging service available on the Web[1]. People publish short messages (tweets) about their everyday activities on Twitter and lately researchers investigate feasibility of applications such as trend analysis [1] or Twitter-based early warning systems [2]. Most research initiatives study network structures and properties of the Twitter network [3,4]. Yet, little research has been done on understanding the semantics of individual Twitter activities and inferring user interests from these activities. As tweets are limited to 140 characters, making sense of individual tweets and exploiting tweets for user modeling are non-trivial problems.

In this paper we study how to leverage Twitter activities for user modeling and evaluate the quality of user models in the context of recommending

In this paper we study how to leverage Twitter activities for user modeling and evaluate the quality of user models in the context of recommending news articles. We develop a framework that enriches the semantics of individual Twitter activities and allows for the construction of different types of semantic

[1] http://techcrunch.com/2010/06/08/twitter-190-million-users/

Joseph A. Konstan et al. (Eds.): UMAP 2011, LNCS 6787, pp. 1–12, 2011.

user profiles. The characteristics of these user profiles are influenced by different design dimensions and design alternatives. To better understand how those factors impact the characteristics and quality of the resulting user profiles, we conduct an in-depth analysis on a large Twitter dataset of more than 2 million tweets and answer research questions such as the following: how does the semantic enrichment impact the characteristics and quality of Twitter-based profiles (see Section 4.2)? How do (different types of) profiles evolve over time? Are there any characteristic temporal patterns (see Section 4.3)? How do the different user modeling strategies impact personalization (personalized news article recommendations) and does the consideration of temporal patterns improve the accuracy of the recommendations (see Section 5)?

Introduction

- An introduction addresses, the same 4 main aspects.

- **Why**?
  - To motivate the work and show its scientific (& application) relevance. Be careful not to make it too long. Use references.
- **What**?
  - To specify the concrete research challenge or question. Precise.
- **How**?
  - To indicate the approach that the paper will follow to address that challenge, incl. evaluation. Connect to paper structure (at end).
- **Results**?
  - To indicate the goals (outcomes & contributions).

- Last two are in the introduction more forward looking.

2 Related Work

With the launch of Twitter in 2007, micro-blogging became highly popular and researchers started to investigate Twitter's information propagation patterns [3] or analyzed structures of the Twitter network to identify influential users [4]. Dong et al. [5] exploit Twitter to detect and rank fresh URLs that have possibly not been indexed by Web search engines yet. Lately, Chen et al. conducted a

Related Work

- Serves a few purposes.
- To inform the reader about the **background** and **state of the art** for motivation and relevance.
- To show that the authors know the state of the art, and can justify the **relevance** and **innovation** of this paper.
- Related work can be related by being the foundations or stepping stones on which this work is **built**, or it can be related as it is aiming for the same or similar goals and is therefore relevant for **comparison**.
- Prevent the obvious. Show that you know the SotA.

3 Twitter-Based User Modeling

The user modeling strategies proposed and discussed in this paper vary in three design dimensions: (i) the type of profiles created by the strategies, (ii) the data sources exploited to further enrich the Twitter-based profiles and (iii) temporal constraints that are considered when constructing the profiles (see Table 1). The generic model for profiles representing users is specified in Definition 1.

Definition 1 (User Profile). *The profile of a user $u \in U$ is a set of weighted concepts where with respect to the given user u for a concept $c \in C$ its weight $w(u, c)$ is computed by a certain function w.*

$$P(u) = \{(c, w(u, c))|c \in C, u \in U\}$$

Here, C and U denote the set of concepts and users respectively.

In particular, following Table 1 we analyze three *types* of profiles that differ with respect to the type of concepts C: entity-, topic- and hashtag-based pro-

3.1 Twitter-Based User Modeling Framework

We implemented the profiling strategies as a Twitter-based user modeling framework that is available via the supporting website of this paper [12]. Our framework features three main components:

1. **Semantic Enrichment.** Given the content of Twitter messages we extract entities and topics to better understand the semantics of Twitter activities. Therefore we utilize OpenCalais[2], which allows for the detection and identification of 39 different types of entities such as persons, events, products or music groups and moreover provides unique URIs for identified entities as well as for the topics so that the meaning of such concepts is well defined.
2. **Linkage.** We implemented several strategies that link tweets with external Web resources and news articles in particular. Entities and topics extracted from the articles are then propagated to the linked tweets. In [11] we showed that for tweets which do not contain any hyperlink the linking strategies identify related news articles with an accuracy of 70-80%.
3. **User Modeling.** Based on the semantic enrichment and the linkage with external news articles, our framework provides methods for generating hashtag-based, entity-based, and topic-based profiles that might adhere to specific temporal constraints (see above).

Main Proposal

- Depends on type of approach, but often the **design** of your approach/system or the **definition** of your strategy.

- Use (formal) **definitions** where appropriate.
- Create **structure** for the reader to understand your approach, and to be able to follow what is coming up in the next parts of the paper.
- Avoid lengthy **prose**.

- Make the elements and aspects of your proposal stand out, showing implicitly the (design) **decisions** that you had to make, and that in fact reflect the smartness (and uniqueness) that underlies this proposal.

4 Analysis of Twitter-Based User Profiles

To understand how the different user modeling design choices influence the characteristics of the generated user profiles, we applied our framework to conduct an in-depth analysis on a large Twitter dataset. The main research questions to be answered in this analysis can be summarized as follows.

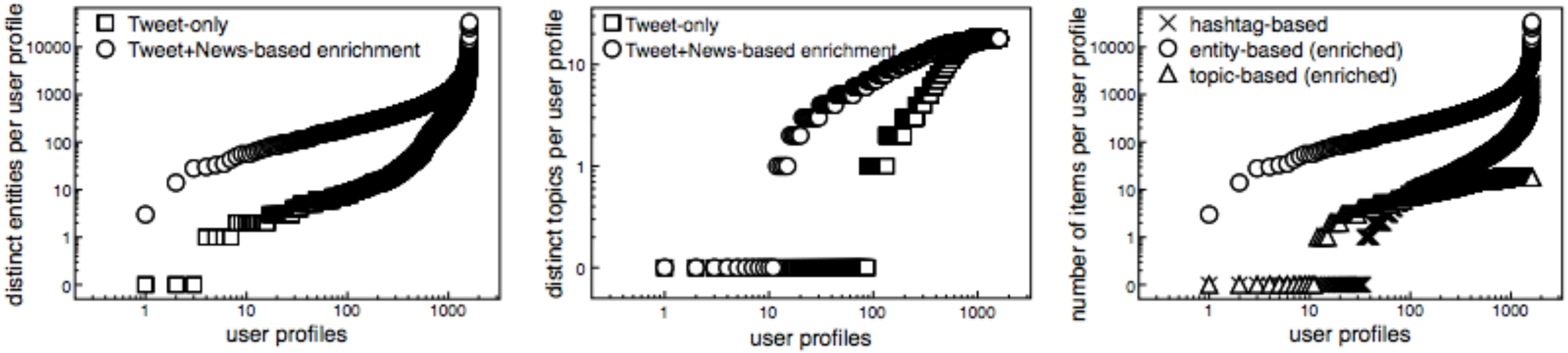
1. How do the different user modeling strategies impact the *characteristics* of Twitter-based user profiles?
2. Which *temporal characteristics* do Twitter-based user profiles feature?

Analysis

- Increase the **contributions** and value of your paper, by adding an analysis where this brings (new) insights.

- Even if the later evaluation of your proposal brings not too spectacular results (these are still results), doing an analysis **in the process** of performing this work can bring interesting insights.
- These insights can put the evaluation in perspective and **context**, and can fire other and **future** work.

- Try to include relevant and non-trivial analyses, and think of how to do them well. It could be that others work on top of these analyses and therefore they should be **solid**.



(a) Entity-based profiles (b) Topic-based profiles (c) Comparison of different types of profiles

Fig. 1. Comparison between different user modeling strategies with tweet-only-based or news-based enrichment

Figures

- Figures are very important elements of a paper, as they are most often used to report on **findings** from analyses or evaluations.

- It depends on the type of work, but keep 'illustrations' (to sketch the proposal) in balance with findings (to present results).
  - Figures and their nature tell reviewers often about the stage of the work: idea vs. completed work.

- Think early on about the **graphs**, their dimensions etc.
- Relate these to your **research questions**.
- See in **other** papers, that these are the good graphs to use. If you are the only one, that usually is odd.

4.1 Data Collection and Data Set Characteristics

Over a period of more than two months we crawled Twitter information streams of more than 20,000 users. Together, these people published more than 10 million tweets. To allow for linkage of tweets with news articles we also monitored more than 60 RSS feeds of prominent news media such as BBC, CNN or New York Times and aggregated the content of 77,544 news articles. The number of Twitter messages posted per user follows a power-law distribution. The majority of users published less than 100 messages during our observation period while only a small fraction of users wrote more than 10,000 Twitter messages and one user produced even slightly more than 20,000 tweets (no spam). As we were interested in analyzing also temporal characteristics of the user profiles, we created a sample of 1619 users, who contributed at least 20 tweets in total and at least one tweet in each month of our observation period. This sample dataset contained 2,316,204 tweets in total.

We processed each Twitter message and each news article via the semantic enrichment component of our user modeling framework to identify topics and

Dataset or Context Characteristics

- Describe the characteristics and properties of the **data** used in your proposal, or more in general the **context** in which you do the analysis, design and evaluation.
- For others to know exactly what you did: to understand the **conditions** that influence your results, and to be able to **reproduce** the work.

4.2 Structural Analysis of Twitter-Based Profiles

To validate our hypothesis and explore how the exploitation of linked external sources influences the characteristics of the profiles generated by the different user modeling strategies, we analyzed the corresponding profiles of the 1619 users

from our sample. In Figure 1 we plot the number of distinct (types of) concepts in the topic- and entity-based profiles and show how this number is influenced by the additional news-based enrichment.

For both types of profiles the enrichment with entities and topics obtained from linked news articles results in a higher number of distinct concepts per profile (see Fig. 1(a) and 1(b)). Topic-based profiles abstract much stronger from the

Approach Characteristics

- Describe the characteristics and properties of the approach and the **techniques** you were working with to do the analysis, design and evaluation.

- For others to know exactly what you did: to understand the **conditions** that influence your results, and to be able to **reproduce** the work.

defines the meaning of the entity and topic respectively.

The advantages of well-defined semantics as exposed by the topic- and entity-based profiles also depend on the application context, in which these profiles are used. The results of the quantitative analysis depicted in Fig. 1 show that entity- and topic-based strategies allow for higher coverage regarding the number of users, for whom profiles can be generated, than the hashtag-based strategy. Further, semantic enrichment by exploiting news articles (implicitly) linked with tweets increases the number of entities and topics available in the profiles significantly and improves the variety of the profiles (the number of profile facets).

Analysis

- As result of the analysis, you give the 'clean results', like in the graphs, but you also 'interpret' them: you formulate what the analysis has brought in terms of a verbal, easy to communicate **lesson learned**.
- This can be one of the contributions of your paper, specially if you learn something that is **interesting**, surprising or new, or triggers new and future research.
- Remember that you often only can see what you are looking at, so make sure that you look for things in an **organized** manner.

4.3 Temporal Analysis of Twitter-Based Profiles

In the temporal analysis we investigate (1) how the different types of user profiles evolve over time and (2) which temporal patterns occur in the profiles. Regarding temporal patterns we, for example, examine whether profiles generated on the weekends differ from those generated during the week. Similar

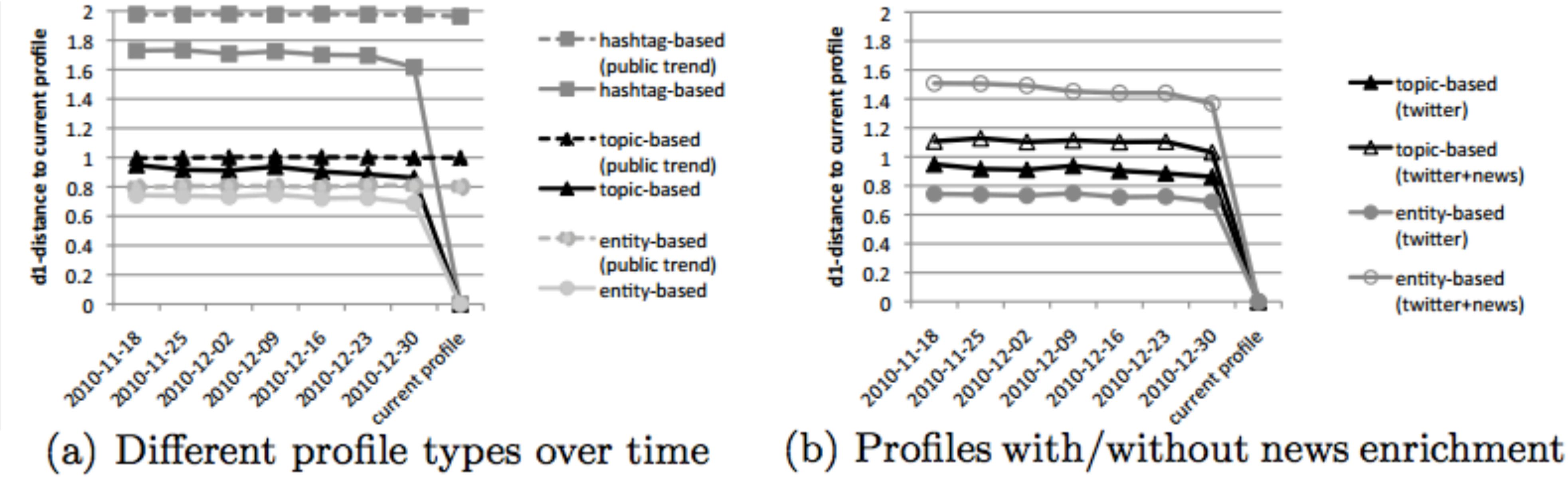
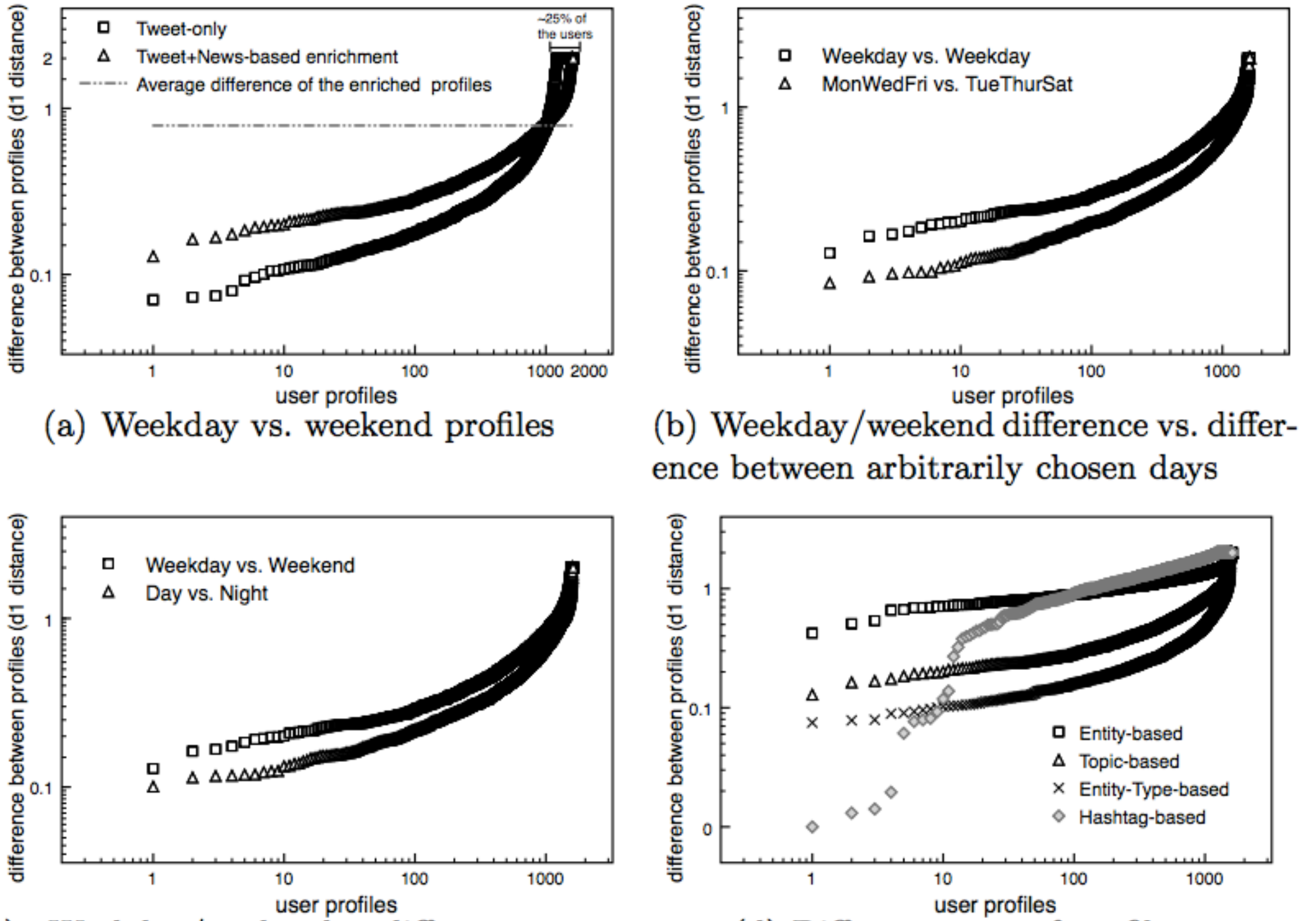


Fig. 2. Temporal evolution of user profiles: average d_1-distance of current individual user profiles with corresponding profiles in the past



(a) Weekday vs. weekend profiles

(b) Weekday/weekend difference vs. difference between arbitrarily chosen days

(c) Weekday/weekend difference vs. day/night difference

(d) Different types of profiles

Fig. 3. Temporal patterns: comparison between weekend and weekday profiles by means of d_1-distance ((a)-(c): topic-based profiles)

Analysis Structure

- Make the structure clear and easy to follow, so identify and formulate clear **questions** and associate them with fitting **graphs**.

- Think early on the definitions, measures and visualizations needed to tell the story, and how they are in **sync** with the state of the art.
- Inventing your own measures of the quality of your own proposal is very often a bad idea: using the commonly accepted **standards** is much more convincing.

5 Exploitation of User Profiles for Personalized News Recommendations

In this section, we investigate the impact of the different user modeling strategies on recommending news articles:

1. To which degree are the profiles created by the different user modeling strategies appropriate for recommending news?
2. Can the identified (temporal) patterns be applied to improve recommendation accuracy?

5.1 News Recommender System and Evaluation Methodology

Recommending news articles is a non-trivial task as the news items, which are

Evaluation

- For a good evaluation, you need to explain **carefully** what you are doing, just like for the analysis.

- Again, the objectives (questions) and the results (graphs) need to be in **sync** with each other and in **sync** with how this is commonly done.
- One of the **first** steps in your research.

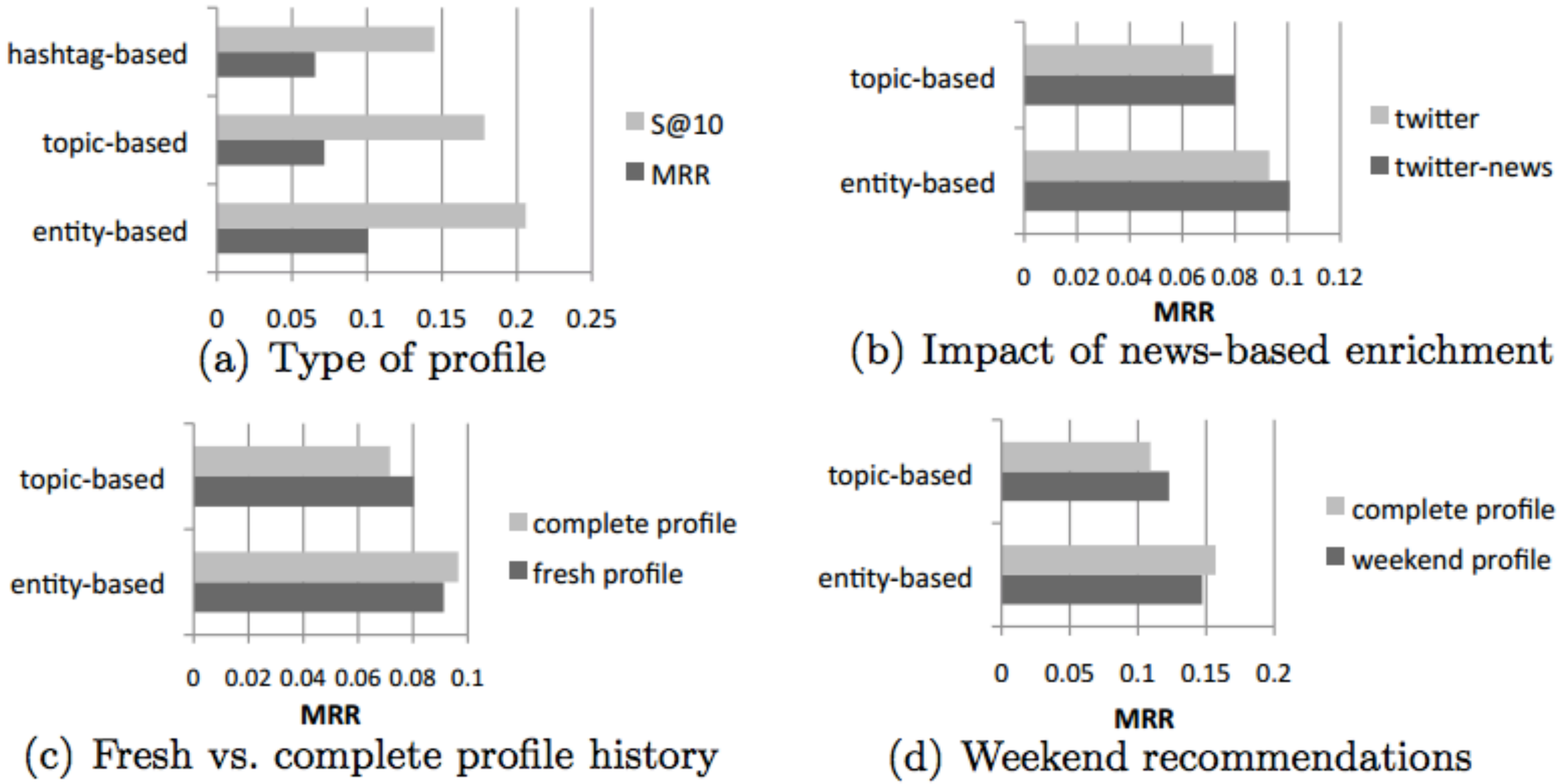


Fig. 4. Results of news recommendation experiment

given user profile. We thus cast the recommendation problem into a search and ranking problem where the given user profile, which is constructed by a specific user modeling strategy, is interpreted as query.

Definition 2 (Recommendation Algorithm). *Given a user profile vector* $\mathbf{p}(u)$ *and a set of candidate news items* $N = \{\mathbf{p}(n_1), ..., \mathbf{p}(n_n)\}$*, which are represented via profiles using the same vector representation, the recommendation algorithm ranks the candidate items according to their cosine similarity to* $\mathbf{p}(u)$.

Given the Twitter and news media dataset described in Section 4.1, we considered the last week of our observation period as the time frame for computing recommendations. The ground truth of news articles, which we consider as *rel-*

Results

- The value of the results are as good as the **confidence** in the approach to get the results.

- Make sure therefore that the way to get the results is **solid** and **convincing**.

- **Balance** this explanation and the results accordingly.
- Consider having detailed results published in an accompanying website

5529 items. We then applied the different user modeling strategies together with the above algorithm (see Def. 2) and set of candidate items to compute news recommendations for each user. The user modeling strategies were only allowed to exploit tweets published before the recommendation period. The quality of the recommendations was measured by means of *MRR* (Mean Reciprocal Rank), which indicates at which rank the first item relevant to the user occurs on average, and *S@k* (Success at rank k), which stands for the mean probability that a relevant item occurs within the top k of the ranking. In particular, we will focus on S@10 as our recommendation system will list 10 recommended news articles to a user. We tested statistical significance of our results with a two-tailed *t*-Test where the significance level was set to $\alpha = 0.01$ unless otherwise noted.

5.2 Results

The results of the news recommendation experiment are summarized in Fig. 4 and validate findings of our analysis presented in Section 4. Entity-based user modeling (with news-based enrichment), which produces according to the quantitative analysis (see Fig. 1) the most valuable profiles, allowed for the best recommendation quality and performed significantly better than hashtag-based user modeling (see Fig. 4(a)). Topic-based user modeling also performed better than the hashtag-based strategy – regarding S@10 the performance difference is significant. Since the topic-based strategy models user interests within a space of

Results & Discussion

- Presenting results to the world correctly can already bring a contribution.
- Aim to do that as '**objectively**' as possible.
- Even if people would agree with your subjective views on what the results tell, they should be able to use the solid numbers from your findings.

- Follow up the Results section with a Discussion section or paragraph.
- To have a more '**subjective**' interpretation of the results and speculate about what they tell or trigger.

- "Results is for the numbers, Discussion is for the words"

6 Conclusions

In this paper we developed a user modeling framework for Twitter and investigated how the different design alternatives influence the characteristics of the generated user profiles. Given a large dataset consisting of more than 2 million tweets we created user profiles and revealed several advantages of semantic entity- and topic-based user modeling strategies, which exploit the full functionality of our framework, over hashtag-based user modeling. We saw that further enrichment with semantics extracted from news articles, which we correlated with the users' Twitter activities, enhanced the variety of the constructed profiles and improved accuracy of news article recommendations significantly.

Further, we analyzed the temporal dynamics of the different types of profiles. We observed how profiles change over time and discovered temporal patterns such as characteristic differences between weekend and weekday profiles. We also showed that the consideration of such temporal characteristics is beneficial to recommending news articles when dealing with topic-based profiles while for entity-based profiles we achieve better performance when incorporating the entire user history. In future work, we will further research the temporal specifics

Conclusion(s)

- The last section wraps up and summarizes.

- Often the first paragraph is used to **look back** at what the reader has read. Also to accommodate the process of determining whether to read the paper in full.
- Then it is the time to highlight the **main results and contributions**. In words that stick.
- Finally, there is the indication of **future work**. To indeed inspire others, but also to show one's mastery of the subject and the stage of the work (tricky).

References

1. Lerman, K., Ghosh, R.: Information contagion: an empirical study of spread of news on Digg and Twitter social networks. In: Cohen, Gosling (eds.) Proc. of 4th Int. Conf. on Weblogs and Social Media (ICWSM). AAAI Press, Menlo Park (2010)
2. Sakaki, T., Okazaki, M., Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors. In: Rappa, et al. (eds.) Proc. of 19th Int. Conf. on World Wide Web (WWW), pp. 851–860. ACM, New York (2010)
3. Kwak, H., Lee, C., Park, H., Moon, S.: What is Twitter, a social network or a news media? In: Rappa, et al. (eds.) Proc. of 19th Int. Conf. on World Wide Web (WWW), pp. 591–600. ACM, New York (2010)
4. Weng, J., Lim, E.P., Jiang, J., He, Q.: TwitterRank: Finding topic-sensitive influential Twitterers. In: Davison, et al. (eds.) Proc. of 3rd Int. Conf. on Web Search and Web Data Mining (WSDM), pp. 261–270. ACM, New York (2010)
5. Dong, A., Zhang, R., Kolari, P., Bai, J., Diaz, F., Chang, Y., Zheng, Z., Zha, H.: Time is of the essence: improving recency ranking using twitter data. In: Rappa, et al. (eds.) Proc. of 19th Int. Conf. on World Wide Web (WWW), pp. 331–340. ACM, New York (2010)
6. Chen, J., Nairn, R., Nelson, L., Bernstein, M., Chi, E.: Short and tweet: experiments on recommending content from information streams. In: Mynatt, et al. (eds.) Proc. of 28th Int. Conf. on Human factors in Computing Systems (CHI), pp. 1185–1194. ACM, New York (2010)
7. Laniado, D., Mika, P.: Making sense of Twitter. In: Patel-Schneider, P.F., Pan, Y.,

References

- Include a good set of **relevant** references.
- Correctly referenced, according to the **practice** in the community.
- Avoid **general** literature, and focus on the audience of the paper and conference or journal.
- Show how you have mastered the **subject**.

Semantic Web Conference (ESWC), Springer, Heraklion (2011)

12. Abel, F., Gao, Q., Houben, G.J., Tao, K.: Supporting website: code, datasets and additional findings (2011), http://wis.ewi.tudelft.nl/umap2011/
13. Liu, J., Dolan, P., Pedersen, E.R.: Personalized news recommendation based on

Website

- Consider publishing the details on an accompanying website.

- To publish **data** – open data.
- To publish **software** – open software.

- To advertise the work.
- To update it beyond a single paper and as part of ongoing experimentation – **research line**.

Final Paper

WSE 2017, October 16

Delft
University of
Technology

Topic

- You can choose a topic for your paper that is related to the subjects we have covered in class.
- It means that it is fitting within the scope of **Web Engineering and/or Web Science** in the spirit of what we have seen in class, and preferably considers the role of Web data for science or engineering.

Contributions

- When approaching a topic, either for review or for research, think about the objectives you have in terms of **contributions** you intend to make.
- Imagine that you contribute with:
  - New knowledge
  - New methods
  - New datasets
- Science is all about **to understand** and **to create**. Formulate what you intend to understand and create with your research steps and questions.

Style/type

- (*review paper*) The paper **reviews relevant literature** and provides a structured perspective on a given subject, driven by a specific objective for this review.

- (*research paper*) The paper is a ‘real’ **research paper**, like we know it from literature, as the result of really having completed the research yourself.

- (*research draft*) The paper is a **‘draft’ research paper**, which means that the paper looks like a ‘real’ paper but as the research has not yet been completed, the results sections of the paper contain some placeholders to be filled in – the design of the research is completed though.

Deadline

- The deadline for the final paper is **January 15**, 2018.
- Handing in by email, mentioning “WSE Final Paper” in the subject.

Length

- The paper length would be **around 3 pages** (in our familiar ACM double column style), without the references. It is 5 pages, without references, if the paper is a review paper.

Proposal

- In order to get approval for your final paper, you hand in **BY DECEMBER 15**, through email (mention "WSE topic proposal" in the subject field of the mail) a small description of the final paper that you propose to write, with a clear indication of:
  - Descriptive title,
  - Subject description (abstract-size)
  - Style/type,
  - The objectives and contributions that you target in the paper,
  - At least three references of papers that you will use for your paper.