

# An Adaptive Technique for Weighting Multiple Factors in Followee Recommendation Algorithms

Antonela Tommasel and Daniela Godoy



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# Followee Recommendation

## Motivation

- The accurate suggestion of potentially interesting friends or followees is a crucial issue in recommendation systems, accentuated by the overload of available information.
  - Most followee selection approaches are only based on topological, content of other independent factors, which are assumed to be equally important to each user.
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- A technique is proposed for adapting the followee selection criteria to the decisions of each particular user regarding user preferences.

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# Computing Factor Weights

$$\text{Similarity}(u, v) = \alpha_1 * \text{sim}_1(u, v) + \dots + \alpha_n * \text{sim}_n(u, v) = \sum_{i=1}^n \alpha_i * \text{sim}_i(u, v)$$

- Weights should be defined to accurately capture user preferences. (the characteristics of previously selected followees)
- Followees are assumed to be chosen by a determined factor if the similarity between the followee and the target user is higher than a pre-defined threshold.
- The percentage of followees selected by each factor is used as the factor's weight.

# Updating Factor Weights

- The target user is presented with a set of recommended followees, i.e. the most similar potential followees.
- For each potential followee the target user has accepted or manifested interest in, weights are updated accordingly to reflect the new interests of the target user.

# Ranking Recommended Followees

- As all recommended candidates are similar to the target user, they are likely to be similar to each other.
- Algorithms will never uncover certain items, which although less similar to the target user, are nevertheless important to him/her.
- Novelty is a component that could be introduced to the similarity-based algorithms in the ranking of potential followees.
- This component tries to balance both:
  - The relevance of a candidate followee.
  - The diversity or novelty of recommendations.

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# Ranking Recommended Followees

## Novelty

- The novelty of an item can be measured in terms of the degree to which is unusual regarding the target user normal interests.

$$\text{novelty}(\textit{pf}) = \frac{\sum_{i \in \text{followees}(u)} \text{abs}(\text{Similarity}(u, i) - \text{Similarity}(u, \textit{pf}))}{|\text{followees}(u)|}$$

- No need to compute the dissimilarity between the potential followee and each of the previously selected followees.

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## Evaluation Settings

## Factors for Followee Recommendation

## Topology

- The similarity between nodes is based on their neighbourhoods or ensembles of paths.

## Common Followees

$$\frac{|\Gamma_{out}(x) \cap \Gamma_{out}(y)|}{|\Gamma_{out}(x) \cup \Gamma_{out}(y)|}$$

## Sørensen

$$\frac{2|\Gamma(x) \cap \Gamma(y)|}{k_x + k_y}$$

## Content

- A content-based followee recommendation should match the *reading profile* of a user with the *publishing profile* of their potential followees.
  - publishing profile.* The information users create and publish
  - reading profile.* The information users read and consider interesting.

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# Baseline Comparison

- The proposed technique (***adaptive***) for personalising the followee recommendations was compared against four baselines.
  - ***pure-topology***. Followee recommendation exclusively based on topology.
  - ***pure-content***. Followee recommendation exclusively based on content.
  - ***half-topology-content***. A combination of both recommendation factors in which they are assigned static and equal weights.
  - ***adaptive-no-novelty***. A version of the proposed technique in which the novelty factor is not considered.

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## Evaluation Settings

# Evaluation

- For each user, their actual followees and a equal proportion of randomly selected non-followees were added to the pool of potential followees to be recommended.
- Potential followees in the same order in which the user started following them to simulate the actual behaviour of target users.
- Items that were not originally part of the followee set are assumed to be uninteresting for the user.

## Experimental Results

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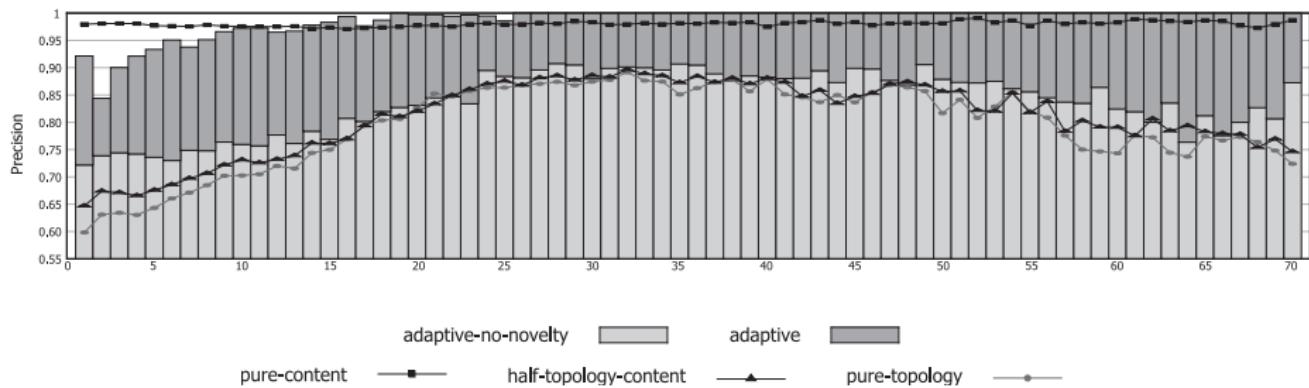
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## Experimental Results

## Comparison of Precision Results

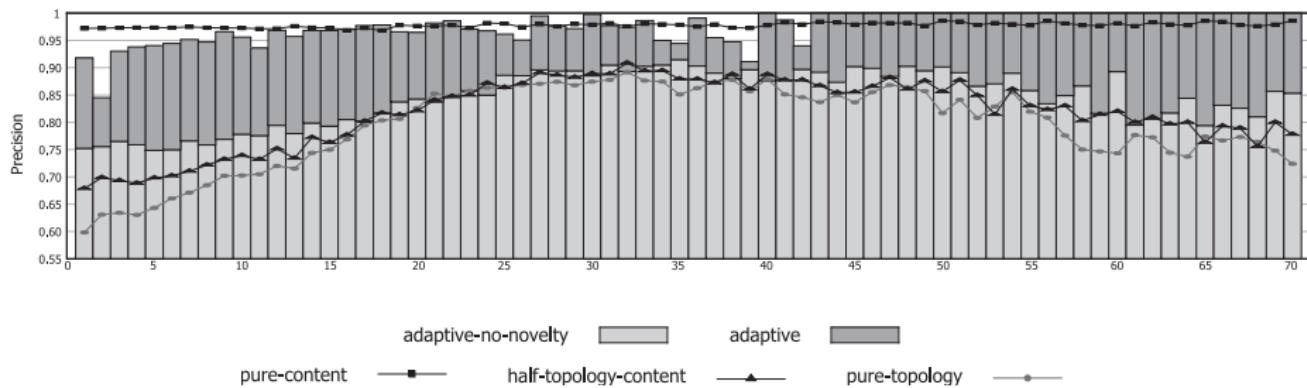
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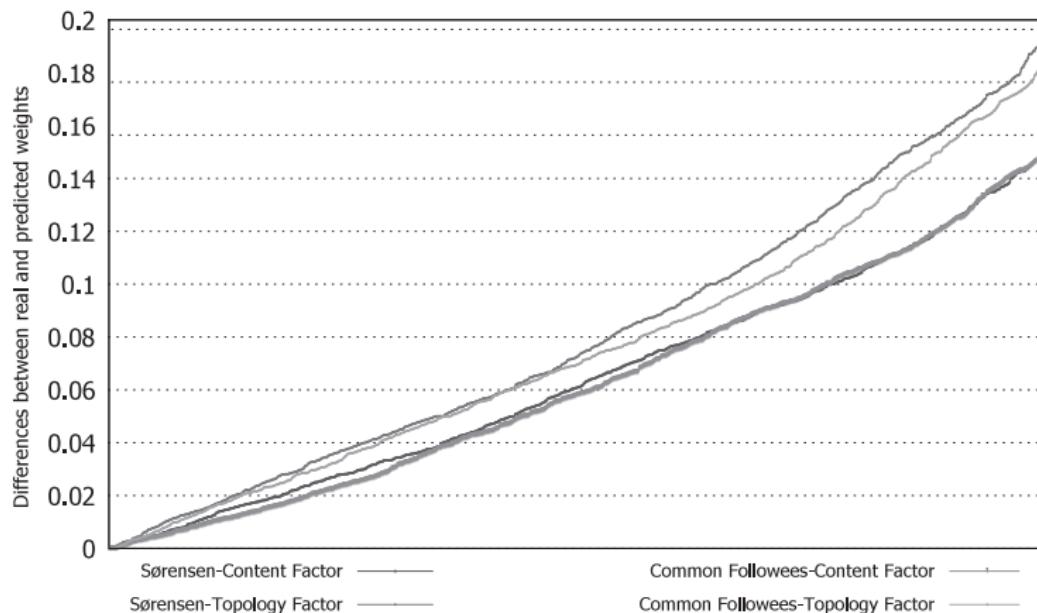
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# Summary of Precision Improvements

	<i>Adaptive Followee Recommendation</i>		
	<i>Minimum</i>	<i>Maximum</i>	<i>Average</i>
<i>pure-topology</i>	4.48	<b>60</b>	25.78
<i>pure-content</i>	-13.96	<b>11.11</b>	3.35
<i>half-topology-content</i>	9.10	53.99	26.38
<i>adaptive-no-novelty</i>	9.38	49.42	24.82

## Experimental Results

## Difference between Predicted and Real Weights



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- The search and ranking of users should not be only guided by a similarity ranking, but also by a novelty component.
- It is important not only recommending similar followees, but also recommending novel or diverse followees.
- Results emphasised the importance of adapting the relevance of recommendation factors to changes of user preferences over time.

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# Questions



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# Dataset

Total number of Twitter users	3,453
Total number of tweets	3,227,782
Average number of tweets per user	935.86
Total number of followee relations	1,650,208
Average number of followee relations per user	478.46
Total number of follower relations	23,626,904
Average number of follower relations per user	6,850.36

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