Social Context Contribution to Group Recommender Systems

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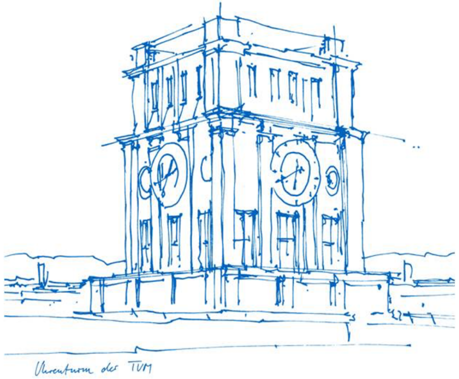

IARIA

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About

- Safey A.Halim - PhD student – Technische Universität München – Social Computing Research Group
  - Research Interests:
    - Recommender Systems
    - Group Recommendation
    - Social Networks
    - Activity Recognition and social situation detection
- TUM - Social Computing Group (https://www.in.tum.de/social/group/)
  - Social Signal Processing
  - Social Network Analysis
  - Social Media and Web Mining

Social Context & Group Recommendation - Motivation

- Group Recommendation is becoming an increasingly important research topic in the area of recommender systems
- Group recommender systems currently cover multiple domains such as music, movies, and travel [1-5]
- Social relationships play an important role in group decision making. Group recommendation to groups can be considered a group decision outcome.
- Awareness of the social dynamics surrounding the group recommendation represents an interesting approach
- Different social factors have been considered in building group recommenders. Most importantly: Trust [6] and the notion of social influence [7]

Research Question

- How can the **social context** incorporation into a group recommender system affect the recommendation quality?
- **Long-term Social Context:** Group’s social network
    - The relationships between the group members
    - Long time to build and long time to break
- **Short-term Social Context:** Group’s current activity
    - Quick to build and quick to break
- **Social context = Long-term Social Context + Short-term Social Context**

Focus: Long-term Social Context

1. Relationship (Free-text)
2. Social Capital (willingness to help under any circumstances)
3. Tie Strength
4. Social Similarity (personality and lifestyle)
5. Social Context (Social setting: school, course, common friends, etc…)
6. Social Sympathy (likability)
7. Social Hierarchy
8. Domain Expertise

Long-term Social Context, contd.

9. Personality type through the conflict mode instrument (TKI) [8]

- How an individual behave in case of a conflict:
    - Competing (forcing)
    - Cooperating (problem solving)
    - Compromising (sharing)
    - Avoiding (withdrawal)
    - Accommodating (smoothing)

Approach – Social Network and Restaurant Rating Platform

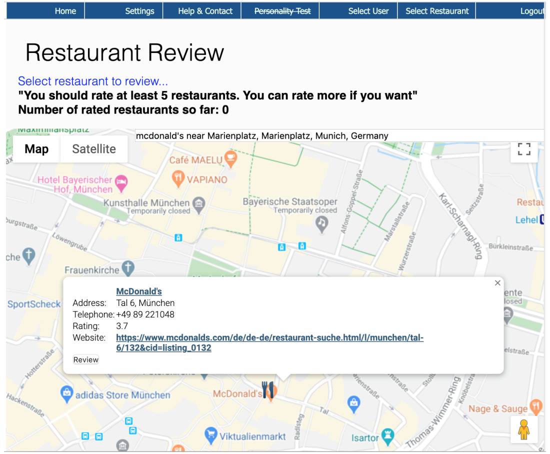
- Social networking Platform: to establish the social graph between which incorporates the long term social context

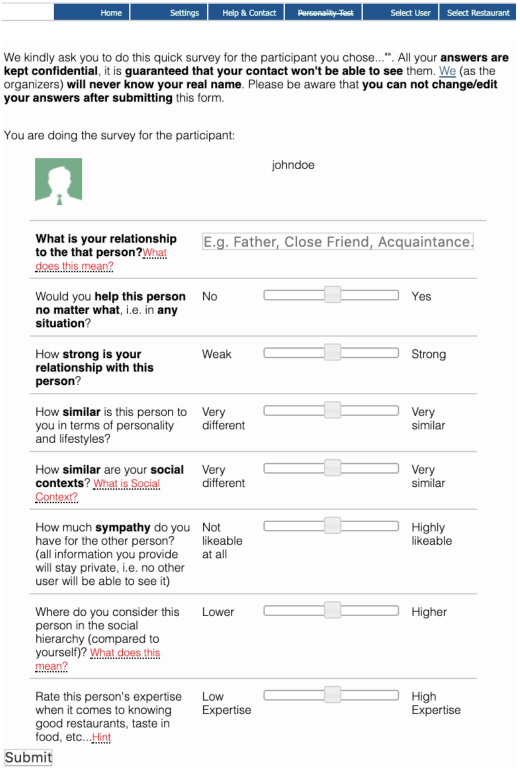
- Restaurant Rating Platform: Allows users to evaluate restaurants according different criteria (both as individuals and as groups)

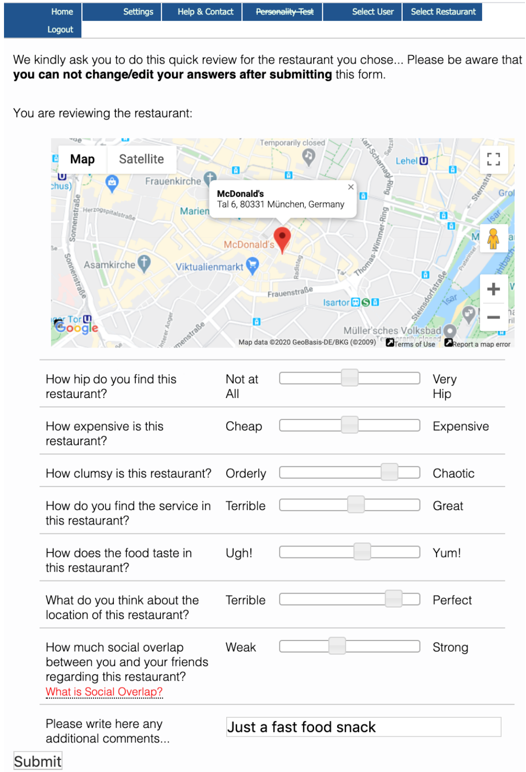
- The outcome is a ground truth dataset that can be used for offline evaluation of individual and group recommender systems

Approach – Social Network and Restaurant Rating Platform, contd.

- Picking and rating users and restaurants







Recommendation Model – Single Social Context Attribute

$$pred_{soc}(u,i) = \frac{1}{\left|\sum_{v \in G} attr_{u,v}\right|} \sum_{v \in G \wedge v \neq u} attr_{u,v} \cdot (\mathrm{pred}(v,i) + p_v)$$

- Individual’s social predicted rating is weighted by an single social context attribute of choice. This generates 8 different recommendation models (recommenders)
- The selected social context attribute together with the personality types reflect the degree of social influence exercised by the other group members on the user in question

Recommendation Model – Full Social Context

$$pred_{soc}(u,i) = \frac{1}{\left|\sum_{v \in G}(\sum_{attr \in soctxt} attr_{u,v})\right|} \sum_{v \in G \wedge v \neq u} \left(\sum_{attr \in soctxt} attr_{u,v}\right) \cdot (\mathrm{pred}(v,i) + p_v)$$

- Individual's social predicted rating is weighted by the aggregation of the social context attributes as rated by the user in question towards the other members group members and the personality type of the other group's members
- The social context attributes and the personality types reflect the degree of social influence exercised by the other group members on the user in question

Group Recommendation Aggregation

- We chose 4 different group recommendation aggregation strategies: [9]
  - **Average:** average individual predicted ratings as the group’s predicted ratings
  - **Least Misery:** The degree of the group’s satisfaction with an item is determined by its least satisfied member with that item
  - **Most Pleasure (Maximum satisfaction):** The degree of the group’s satisfaction with an item is determined by the its most satisfied member with that item
  - **Dictatorship:** the group’s predicted rating of an item is the item’s predicted rating of the group’s dictator
    - We chose the individual social context attributes to elect the group’s dictator

Group Recommendation Platform

- With the different possible recommendation models and aggregation strategies, we are able to build 38 different group recommenders
- The baseline recommender against which we compare the social context based recommender is based on an item-item collaborative filtering prediction and recommendation algorithm
- We have 8 different single social context attributes recommenders
- 1 full social context recommender (that employs all the social context attributes together)
- For each of the recommenders, 3 different aggregation strategies are used to generate group recommendation
- The Dictatorship strategy is only used with the single social context attributes recommenders

Experimental Setup

- Internal participants: TUM students
- External participants: invited to join the experiment by the students
- Building two types of groups:
  - **Internal Groups:** consist of students only (weaker social ties)
  - **External Groups:** consist normally of students and external participants (relatively stronger social ties)
- 363 participants (178 students and 185 externals)
- 80 participants were older than 45 years old
- 45 internal groups
- 92 external groups

Evaluation

- Evaluation metrics: NDCG, precision(n), and recall(n) [10]
- n values: 100, 10, 5, and 3
- Examined the individual social context attributes based group recommenders and compared them against the collaborative filtering baseline
- Examined the full social context based recommenders and compared them against the collaborative filtering baseline
- Examined the results for two different datasets:
  - The full dataset
  - The external groups dataset (characterized by the stronger social ties)

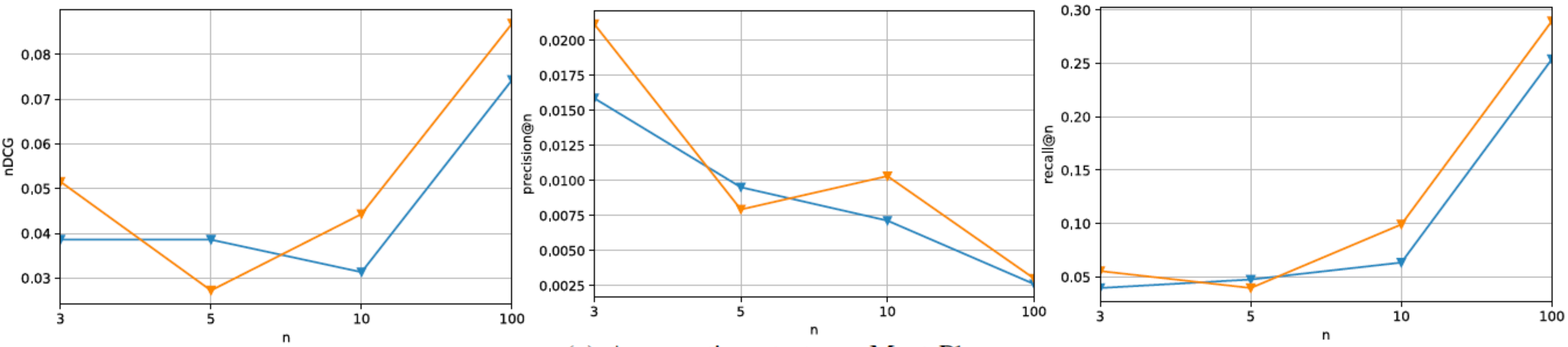
Evaluation – Key Findings

- Social context-based recommenders outperfom the baseline for all metrics and for all the aggregation strategies
- We cannot conclude a single social context attribute that performs consistently better than all the other social context attributes
- Trust and relationship based recommenders are always among the top best recommenders with respct to average NDCG, Precision@n, and Recall@n
- Outperforming percentages for the external dataset are significantly higher which indicates links stronger social ties to the strength of the social context attributes effects on the recommenders

Percentages by which Full Social Context Recommenders outperforming the baseline

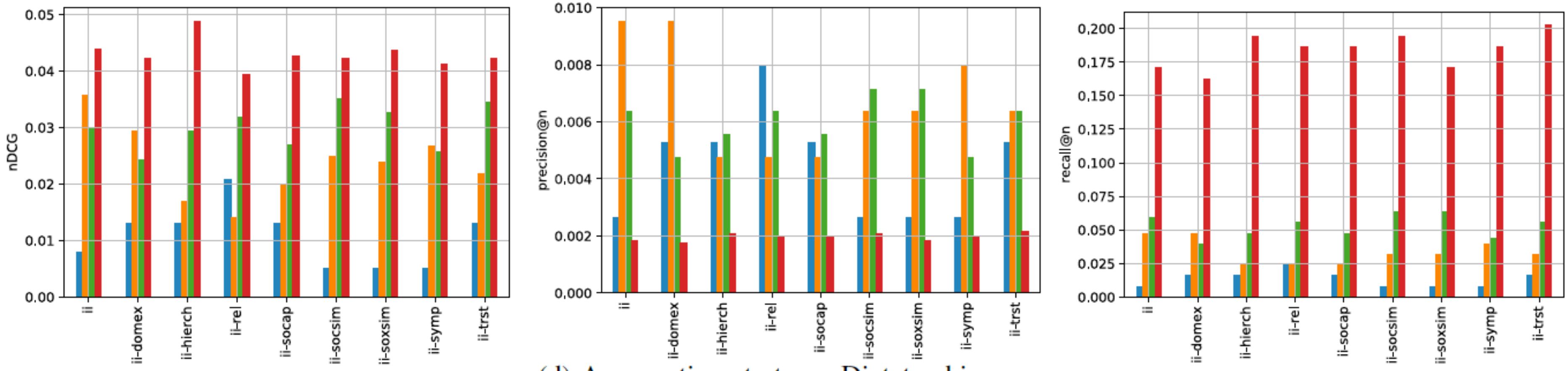
	NDCG(n)	Precision(n)	Recall(n)
Full dataset	57.16%	72.41%	57.83%
External groups dataset	75.87%	90.23%	66.67%

Evaluation – Exception of Better Baseline Performance



(c) Aggregation strategy: Most Pleasure

Evaluation – Exception of Better Baseline Performance (2)



(d) Aggregation strategy: Dictatorship

Conclusion & Future Work

- We employed a multitude of long term social context attributes and examined their effect on the quality of group recommendation
- Our method outperformed the baseline in almost all settings with all aggregation strategies
- The effect of social context contribution to group recommendation is significantly stronger for groups with stronger social ties
- In the future we will consider an online approach and closed user feedback and dynamic recommendation
- Short term social context should also be combined with long term social context

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