How to best support users in social learning platforms with recommendations?

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A socially-powered, multilingual open learning infrastructure in Europe

Recommendations!

Which recommender approach best fits ODS platform?

Limitations in learning domain:
Too sparse data
Too few 5-star ratings
No proper tags and annotations
Learning domain has its own data and limitations, expectations

- Too sparse data
- Too few 5-star ratings
- No proper tags and annotations
- Can not use only popular reference datasets like MovieLens, Netflix, etc.

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• **RQ:** How to best support users in social learning platforms with recommendations by using the data originating from social activities of users within the platform?

  • Performance metrics commonly used in recsys
  • Social network analysis
  • User satisfaction
Recommender algorithms

1. Content-based

![Diagram showing a user likely to buy a product based on similar preferences.]

2. Collaborative filtering ✓

![Diagram showing a network of users and their preferences.]

The images are not clearly visible due to the resolution, but they represent the concepts of content-based and collaborative filtering.
Similarity

Sparsity!
Improving prediction accuracy of recommendations

Trustworthy users == like-minded users
• Golbeck’s TidalTrust
• Trust-aware recommender by Massa and Avesani
• Andersen et al’s axiomatic approach
• T-BAR by Bellaachia and Alathel
• And many more…

All require users to give explicit trust ratings!
• Lathia et al.’s trust-based recommender #neal-lathia #recsys
• Trust model by O’Donovan and Smyth
A social recommender system: T-index approach

1. Description

- Trust networks: a graph
  - Nodes: users
  - Edges: trust relationships
  - Weights: trust values originating from similarity
- Each user can be assumed as an agent
- Improve the process of finding nearest neighbors
  - T-index
  - TopTrustee
A social recommender system: T-index approach

2. Trust propagation mechanism

• A new trust relationship between two far unconnected users is inferred if and only if:
  • Condition 1:
    • Mutual trust value between intermediate users is higher than a certain threshold ($v$)
  • Condition 2:
    • The number of connecting edges is lower than an upper bound ($L$)
if A trusts B and B trusts C, then A trusts C if and only if condition 1 is met and condition 2 is met
A social recommender system: T-index approach

3. T-index?

- **T-index**: measure of users’ trustworthiness
- **H-index**: the impact of publications of an author

Indegree \((u_a) = 7\)

Indegree \((u_b) = 5\)

T-index \((u_a) = 2\)

T-index \((u_b) = 4\)

*Note! Cluster*: a group of users who all trust a common user as the most trustworthy one (central user)
A social recommender system: T-index approach

3. T-index?

Algorithm 1 Computing T-index

1: procedure COMPUTE-T-index(user, TrustedList)
2:    TrusteValueList ← TrustedList.sort(trustValue, desc)
3:    for all trustValue in TrusteValueList do
4:        trustValue ← multiply(trustValue, Max_T-index)
5:    end for
6:    Counter ← 1
7:    for all trustValue in TrusteValueList do
8:        if Counter < trustValue then
9:            Counter ← Counter + 1
10:        else
11:            break
12:    end if
13:    end for
14:    T-index ← Counter - 1
15:    return T-index
16: end procedure
A social recommender system: T-index approach

4. What T-index is for?

- TopTrustee: a list of top raters of an item sorted by T-index
- Helps the process of finding nearest neighbors
  - Providing access to trustworthy users across the trust network including even those outside the traversal path length limit (L)
A social recommender system: T-index approach

4. Results using MovieLens 100k

MAE with and without T-index

Coverage with and without T-index
Data-driven study
1. Method

• Testing recommender algorithms
  • Trust-based recommender
    • If explicit trust is available (Epinion)
    • If not available: similarity measures + walking algorithm (modified BFS)

• Datasets
  • MovieLens 100k– reference dataset
  • MACE, OpenScout – quite similar to the future ODS dataset
Data-driven study

3. Setting

- $v = 0.1$ (Condition 1), $L = 3$ (Condition 2)
- Training set 80% and test set 20%
- Sizes of neighborhoods $k = (3, 5, 7, 10, 20)$
- Size of TopTrustee list $m = 5$
Data-driven study

4. Tools
## Data-driven study

### 5. Data

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Data-driven study

6. Results

F1 of the K+NN and baseline CFs based on the size of neighborhoods
Data-driven study
7. Implicit social networks for MovieLens
Data-driven study

3. In-degree centrality

In-degree distribution of the users in the implicit social networks for different datasets using graph-based approach; k=10
Data-driven study
4.2. Created trust network

Without T-index

With T-index
Conclusion

• The aim is to support user in social platforms to find the novel and relevant recommendations on resources

• Trust-based recommender systems can be a solution
Ongoing and Further work

• Go online with the ODS platform (October 2013)
• User evaluation study (December 2013)
• Evaluating trust-aware recommenders based on explicit trust ratings given by users: Massa et al., Golbeck, and T-index
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Joint paper proposal

- Trust-based recommenders
  - Many of them are memory-based
  - A few studies on model-based
    - Using MF methods (Jamali et al., 2010)
      - Explicit trust e.g. Epinion
      - Evaluation only on common metrics: RMSE, Precision
    - MF + inferred trust
    - Explicit trust vs. inferred trust
    - Evaluation also in terms of SNA metrics
    - User satisfaction
• Hao Ma
  • Comparing implicit Trust-based recsys; explicit trust

• Diverse recommendations; not only similar ones
  • Initial recommendations
  • Filtering and refining recommendations using tree structures for item’s content features
  • Aim: To make diverse recommendations