RECOMMENDATIONS ON A KNOWLEDGE GRAPH

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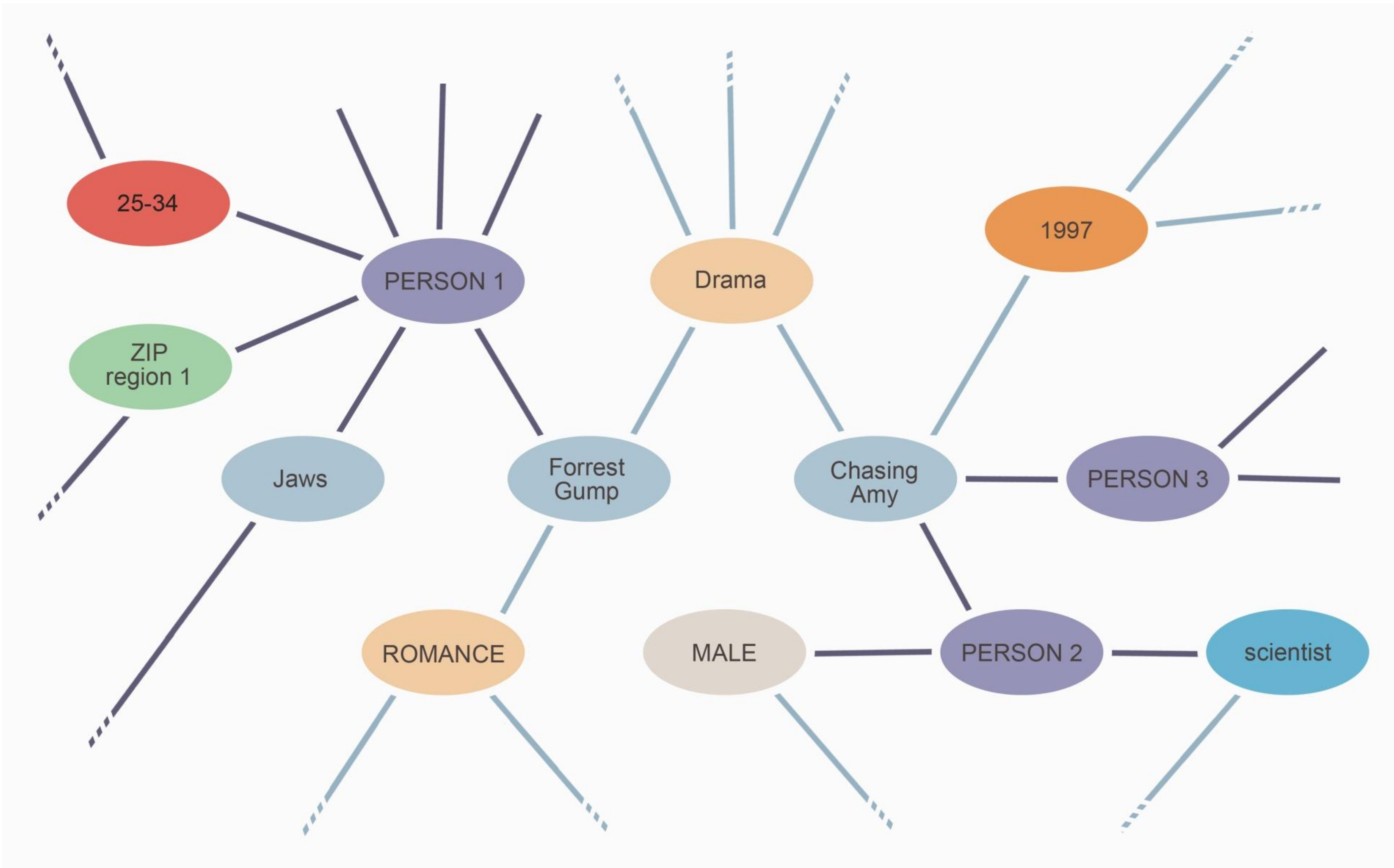
I. MOTIVATION

WHY GRAPH BASED REPRESENTATION?

- Pros
  - Can represent **heterogeneous information sources**, which leads to a high coverage **avoiding cold start**.
  - Potential to be more accurate as the knowledge base **represents detailed information**.
  - **Social network** integration.
- Cons
  - Calculation methods easily run into **exponential problems**.
  - Does not compress the information. **Storage / memory problems**.

SAMPLE REPRESENTATION (MovieLens Dataset)



II. RELATED WORK

INFORMATION SOURCES

- Konstas et al. – On Social Networks and Collaborative Recommendation (2009)
  - Information source: **users**, **tracks** and **tags**.
  - Representation: **partitioned matrix**.

- Hidasi et al. – Fast ALS-based tensor factorization for context-aware recommendation from implicit feedback (2012)
  - Information source: **users**, **items** and **context info**.
  - Representation: **tensor**.

- Kazienko et al. – Multidimensional Social Network in the Social Recommender System (2013)
  - Information source: **contact lists**, **tags**, **groups**, **favourites**, **opinions** and **social network**.
  - Representation: **layered graph**.

NETWORKS

- Guy et al. – Personalized Recommendation of Social Software Items Based on Social Relations (2009)
  - Method: **collaborative formula** with explicit weighting scheme.
  - **User similarity** is based on the **social network** (SONAR).
- Jeong et al. – Personalized Recommendation Based on Collaborative Filtering with Social Network Analysis (2012)
  - Involvement of **network science measures**.
- Salakhutdinov et al. - **Restricted Boltzmann** machines for collaborative filtering (2007)
- Huang - A Graph-based Recommender System for Digital Library (2002)
  - **Hopfield network**

III. RECOMMENDATION SPREADING

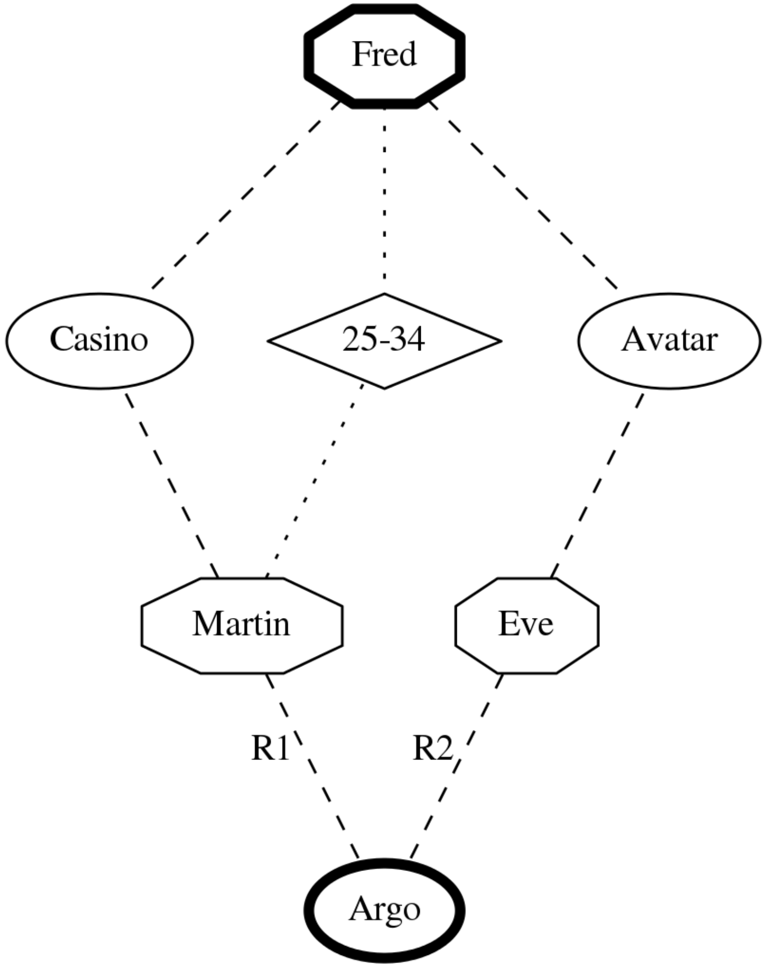
RECOMMENDATION SPREADING

- Spreading activation based method.
- The termination criteria is a step limit.
- For each rating edge the flown through activation is accumulated.
- The accumulated values are used as weights for user ratings in the collaborative filtering formula.

$$pred(a,p) = \bar{r_a} + \frac{\sum_{b \in N} sim(a, r_{b,p})(r_{b,p} - \bar{r_b})}{\sum_{b \in N} sim(a, r_{b,p})}$$

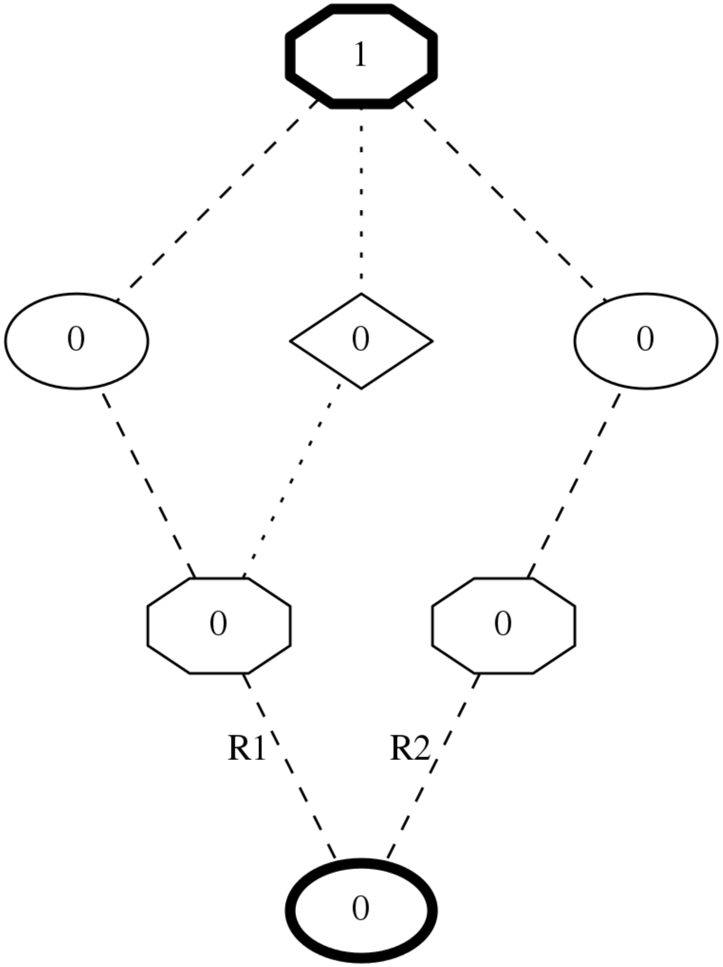
A SAMPLE NETWORK

We'd like to provide a rating estimation for Fred on Argo.



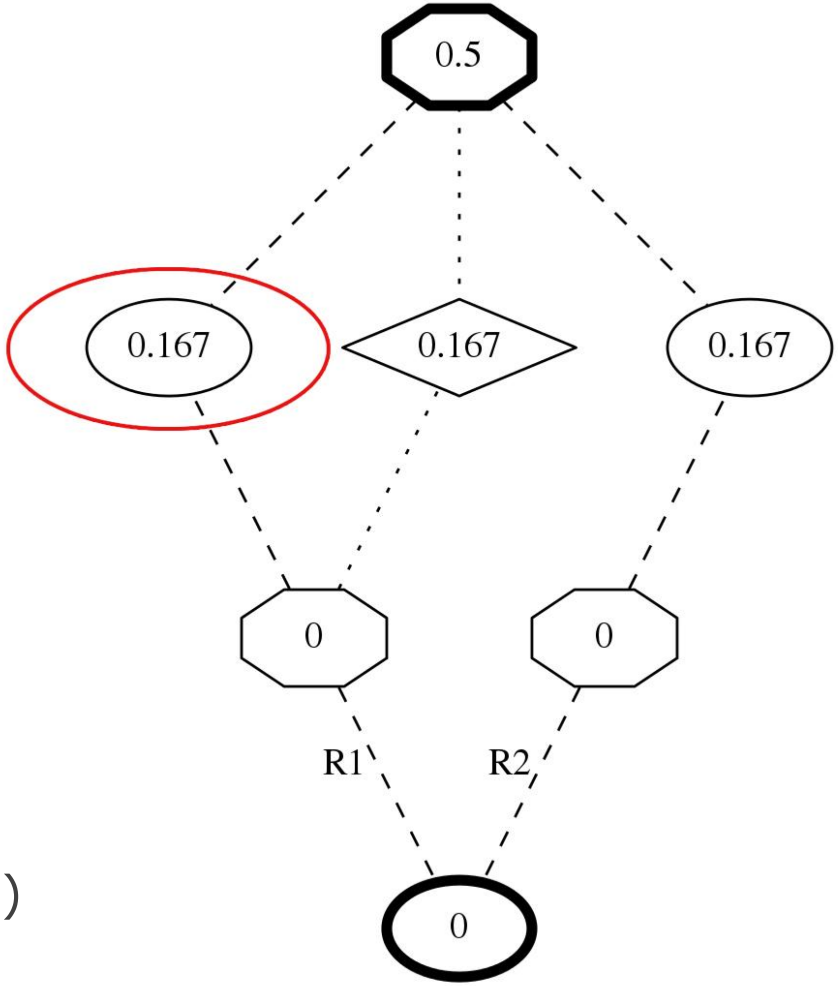
INITIAL ITERATION STEP

- The iteration is initialized.
- The activation of the nodes is initialized to 0.
- Except to source node. Its activation is initialized to 1.



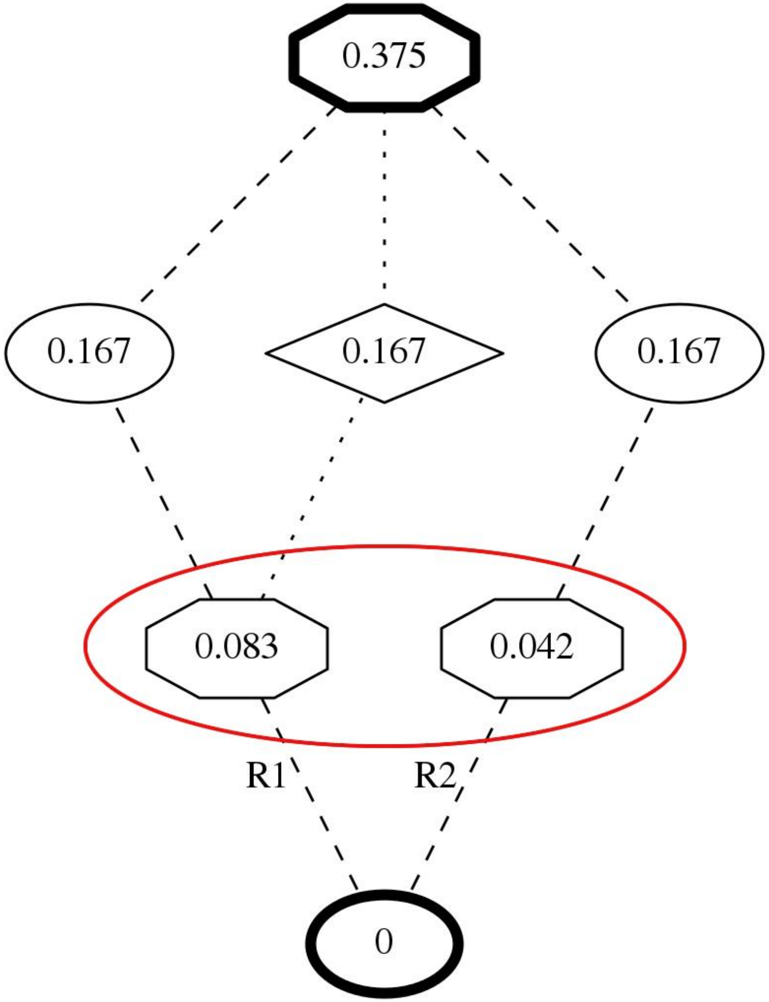
ITERATION STEP 1

- A part of the activation is kept at the node
  - activation relax is 0.5.
- A part of the activation is spreading to the neighbours distributed equally.
  - Spreading relax is 0.5.
- Fred (top node)
  - 0.5 = 1 x 0.5 (activations relax) stays at the node
- Casino (leftmost node)
  - 0.167 = 1 x 0.5 (spreading relax) x 1/3 (3 neighbours)



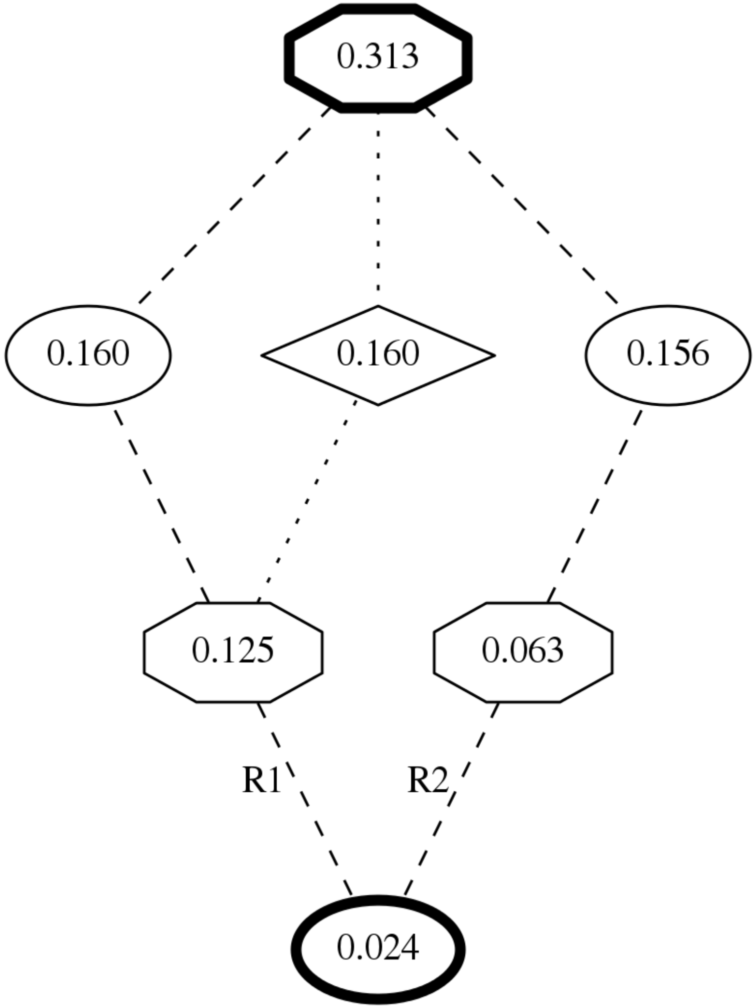
ITERATION STEP 2

- The spreading continues.
- Martin and Eve also receive activation.
- Martin (left octagon) receives more because there are 2 parallel paths to the node representing Martin.



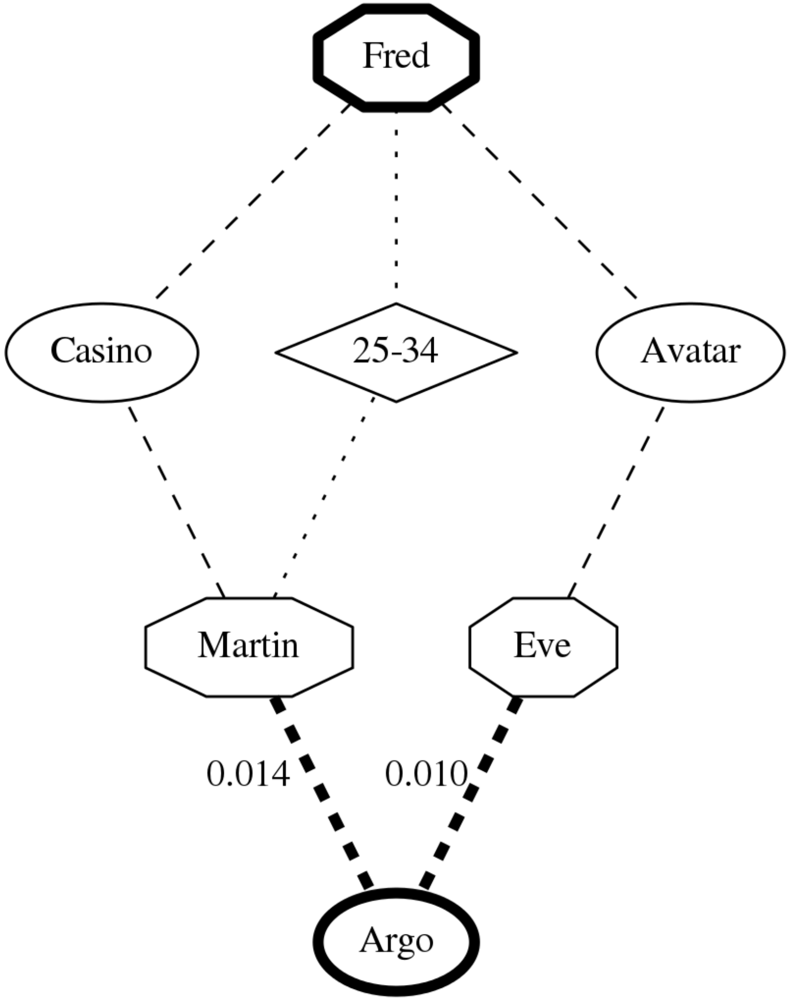
ITERATION STEP 3

- Argo (bottom node) received 0.024 activation.
- The activation arrived from Martin and Eve via rating edge R1 and R2.
- We stop the iteration with a step limit (in this case 3).



RATING WEIGHTS

- Activation received
- From Martin
  - 0.014 = 0.083 x 0.5 (spreading relax) x 1/3 (3 edges from Martin)
- From Eve
  - 0.010 = 0.042 x 0.5 (spreading relax) x ½ (2 edges from Eve)



ESTIMATING THE RATING VALUE

- LETS ASSUME
- The average ratings for
  - Fred: 4
  - Martin: 3
  - Eve: 4
- The rating values for
  - Martin: 5 (the difference from the mean is 2)
  - Eve: 3 (the difference from the mean is -1)
- Rating value similarities (from previous slide)
  - Martin: 0.014
  - Eve: 0.010

- THE FINAL RATING ESTIMATION IS
- 4 +
  (0.014 x (5-3) +
  0.010 x (3-4)) /
  (0.014 + 0.010) =
- 4 +
  (0.014 x 2 +
  0.010 x -1) /
  (0.024) =
- 4 + 0.75 =
- 4.75

IV. EVALUTATION

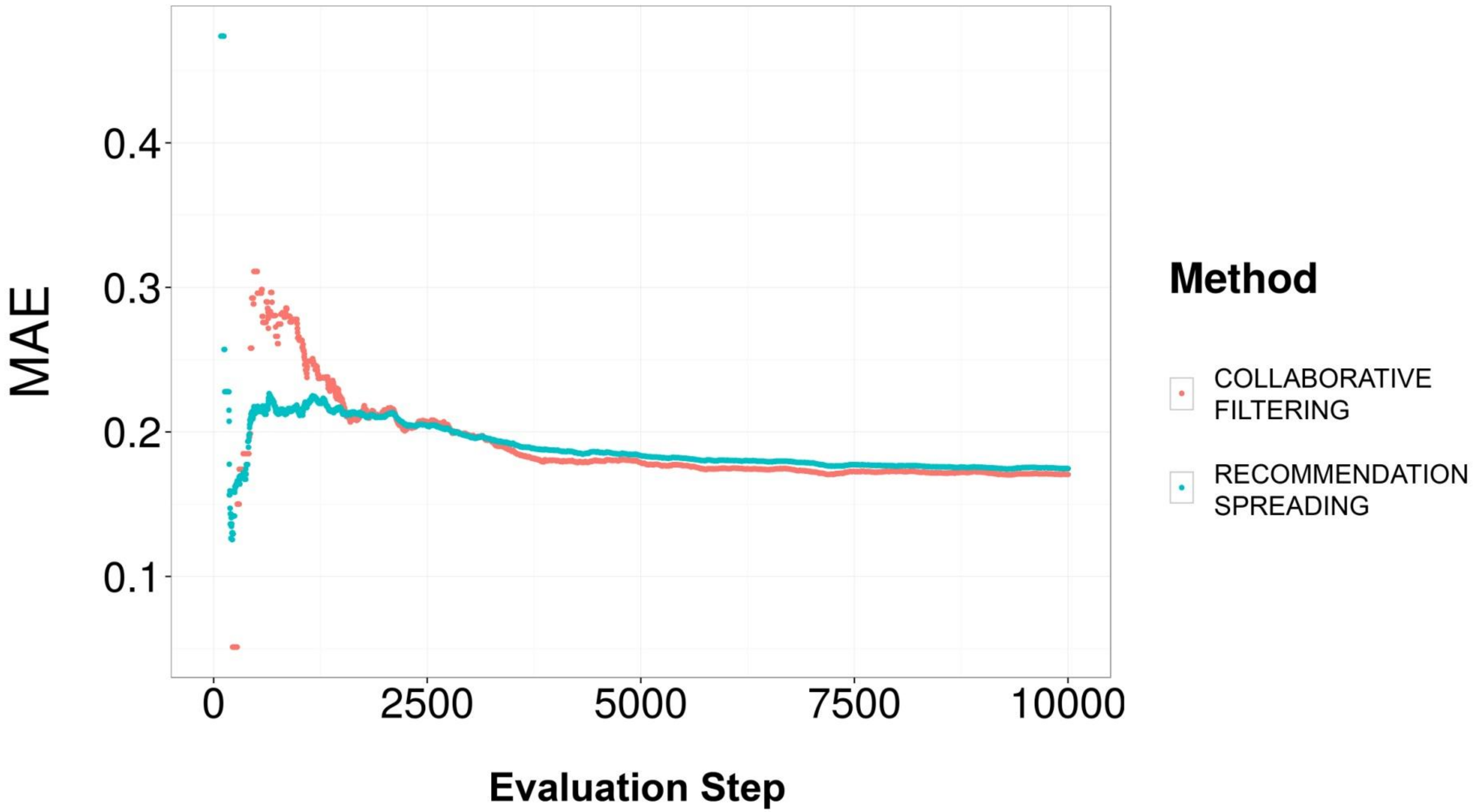
MOVIELENS DATASET

- Node types – AgeCategory, Gender, Genre, Item (Movie), Occupation, Person, YearOfPublishing, ZipCode
- Relation types – ItemGenre, ItemRating, ItemYearOfPublishing, PersonAgeCategory, PersonGender, PersonOccupation, PersonZipCodeRegion
- Main numbers on the dataset
  - 6 040 persons
  - 3 883 items (movies)
  - 1 000 209 ratings
- The ratings are time-stamped
  - The rating process can be simulated.

EVALUATION

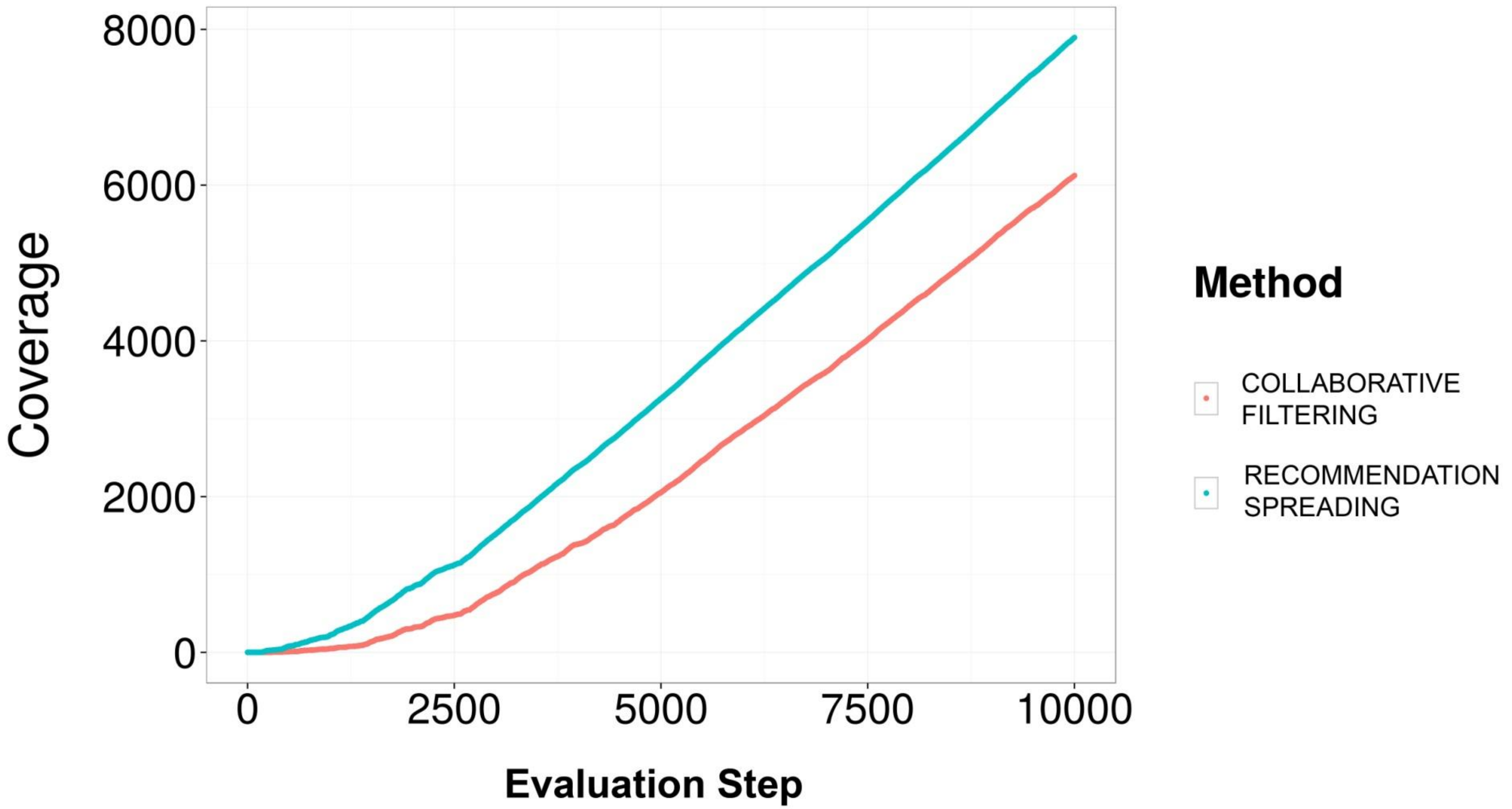
- All rating edges are eliminated from the database
- In each iteration step
  - The **next rating** record **is taken** (user, item, rating value) from the dataset in timestamp ascending order.
  - An **estimation is asked** from the method under evaluation.
  - Evaluation **measures are recorded**.
  - The **rating edge is added** to the knowledge base.
- The knowledge base is filled during the evaluation process with rating edges.
- MAE and coverage is recorded.
  - Coverage is the number of cases the method could provide an estimation.
  - MAE is the mean of the absolute error at the corresponding evaluation step. Absolute error is the absolute value of the difference between the true and estimated rating value.

MAE



MAE
0.4
0.3
0.2
0.1
0
2500
5000
7500
10000
Evaluation Step
Method
COLLABORATIVE FILTERING
RECOMMENDATION SPREADING

COVERAGE



8000
6000
4000
2000
0
Coverage
0
2500
5000
7500
10000
Evaluation Step
Method
COLLABORATIVE FILTERING
RECOMMENDATION SPREADING

V. Summary

SUMMARY

- The trend of **increasing** number of **information sources** and emerging **graph based methods** is shown.
- Graph based representation is presented.
- Recommendation spreading is described.
  - A **spreading activation** based method.
  - **Distance between source nodes and rating edges**.
  - Does an **average weighting** based on edge distance.
- Evaluation is presented
  - **Rating estimation is better** in **short terms** than collaborative filtering, the same in long terms as collaborative filtering.
  - **Coverage** is definitely **higher** than in the case of collaborative filtering.
- Heterogeneous information sources can be combined leading to increased recommendation quality.

THANK YOU FOR YOUR ATTENTION

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