Exploiting weak ties in trust-based recommender systems using regular equivalence

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Problem

Trust-aware Recommender Systems incorporate social trust with the goal of improving the quality of recommendations.

Trust connections can **explicitly** exist between two users (**strong tie**) or can be **implicitly** created by utilizing the transitive property of trust (**weak tie**).

In this paper we wanted to **model** and **measure the impact of weak ties** in a Trust-based Recommender System.

Approach

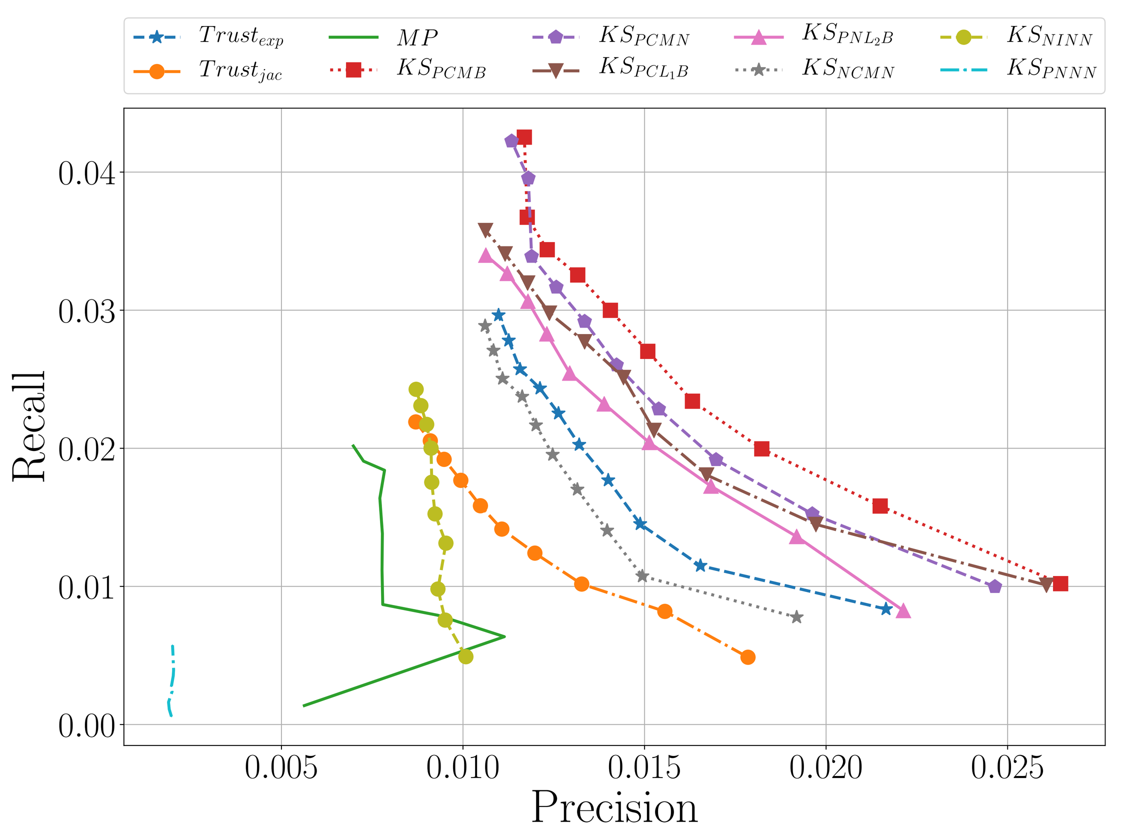
- Using **trust connections**, we create an **adjacency matrix** $\boldsymbol{A}$ where each entry represents a directed trust link between two users.
- From $\boldsymbol{A}$, we create a *user-to-user* similarity matrix by calculating the **"Katz Similarity"** on the trust adjacency matrix using the iterative approach:

$$\boldsymbol{\sigma}^{(l_{max}+1)} = \sum_{l=0}^{l_{max}} (\alpha \boldsymbol{A})^l$$

- This approach gives us the ability to **define the maximum path length** l_{max} used for forming weak ties between users which are not directly connected.

Conclusion

- "Katz-similarity", a **regular equivalence** measure from **network science** is a useful method for modeling and quantifying the impact of weak ties in a Trust-based CF approach.
- **Using weak ties almost always greatly improves the recommendation results with respect to recommendation accuracy compared to using only strong ties.**

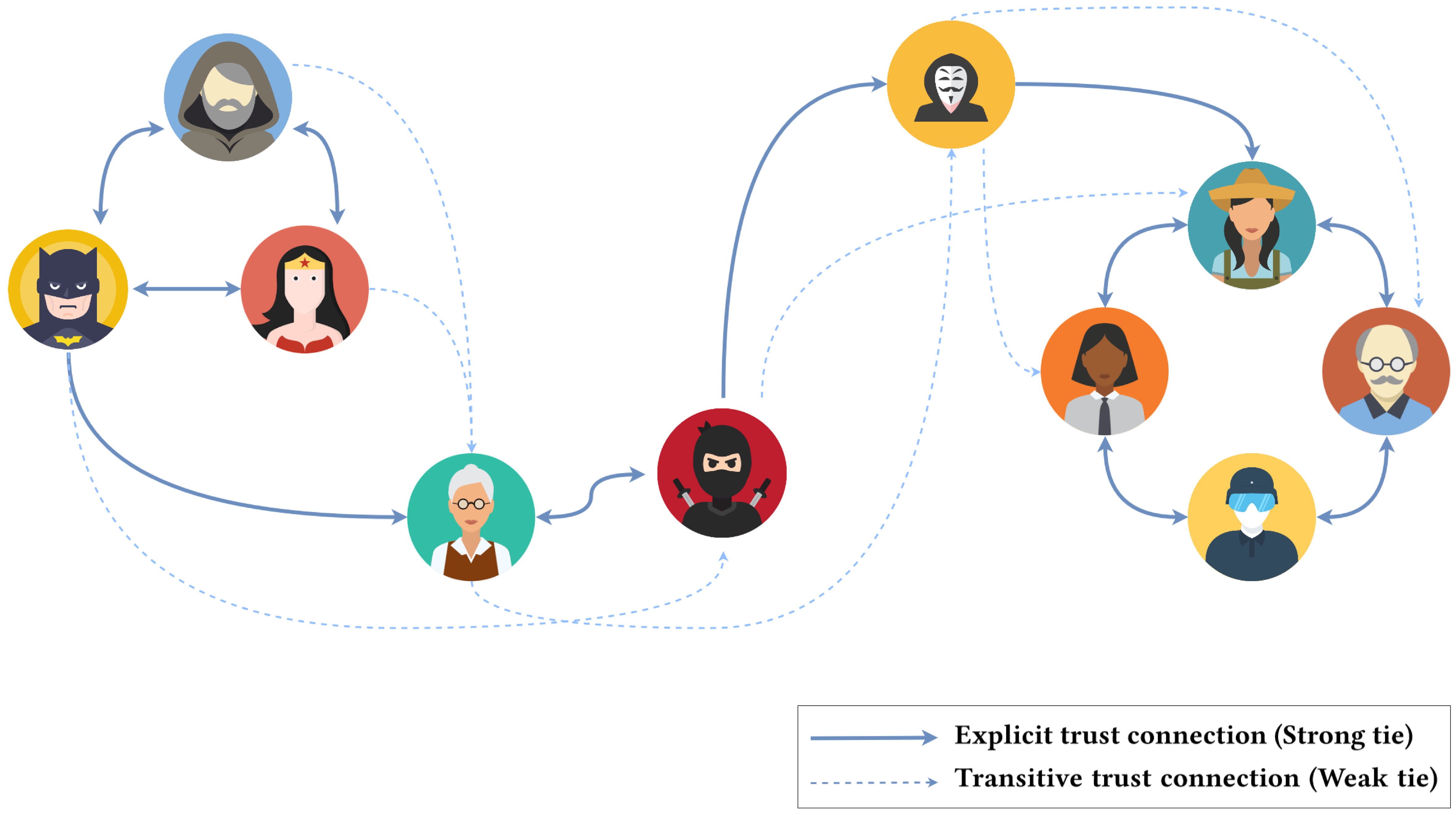


References

[1] T. Duricic, E. Lacic, D. Kowald and E. Lex. (2019) Exploiting weak ties in trust-based recommender systems using regular equivalence. arXiv preprint arXiv:1907.11620

[2] T. Duricic, E. Lacic, D. Kowald and E. Lex. (2018) Trust-Based Collaborative Filtering: Tackling the Cold Start Problem Using Regular Equivalence. In *Proc.* of the 12th ACM Conference on Recommender Systems (RecSys'18).

Trust, tie strengths and recommender systems



Trust theory defines a number of distinct properties which can be attributed to trust:

- **Assymetry** – Trust is personal and subjective, different people may hold various opinions on a target user. If user u trusts user v, user u does not have to trust user v. Therefore, in a trust network, edges are directed.
- **Transitivity** – It says if user u trusts v, and v trusts p, it can be inferred that user u trusts p to some extent, i.e. people tend to trust the friend of a friend rather than a stranger. Using transitivity, we may identify more trusted nodes and hence improve the predictive performance of recommender systems.
- Dynamicity – Trust is built in a continuous way and can change over time.
- Context Dependence – Trust is context-specific, meaning that a user which is trustworthy in one domain may not be trusted in another.

A **strong tie** can be viewed as a close friend and a **weak tie** as a remote friend or an acquaintance. If we translate this to **network theory**, a strong tie can be viewed as an edge between two nodes in a network. On the other hand, a weak tie would mean that there exists a path of length ≥ 2 between two nodes in a network. The higher the path length, the weaker the tie.

If we have a network of users and know who trusts whom, we can use this information to form a **trust network** in which each node represents a user and each directed (possibly weighted) edge represents a trust connection between two users where the strength of a tie is depicted by the weight of an edge. A trust network can be utilized in many different ways, one of which is in **Collaborative Filtering (CF)**, an algorithm used in **Recommender Systems**.

Evaluation results

- Offline evaluation study conducted on cold-start users (users which rated at most 10 items) from the *Epinions* dataset, a total of 25,393 users.
- We show that by using weak ties from paths of maximum length 2 (i.e. adding friends of friends into the user's neighborhood), we can improve the quality of the recommendations in terms of recommendation accuracy with the best approach being the KS_{PCMB}.
- We applied various normalization techniques on KS and compared them with simple baselines as shown in the Table below.

Approach	l_{max}	Degree normalization	Row normalization	Boost	nDCG	Recall	Precision
$Trust_{exp}$					.0224	.0296	.0110
$Trust_{jac}$					.0176	.0219	.0087
MP					.0134	.0202	.0070
KS_{PCMB}	2	Combined	Max	Yes	**.0303**	**.0425**	**.0117**
KS_{PCMN}	2	Combined	Max	No	.0295	.0422	.0113
KS_{PCL_1B}	2	Combined	L1	Yes	.0273	.0358	.0106
KS_{PNL_2B}	2	No degree	L2	Yes	.0257	.0340	.0106
KS_{NCMN}	1	Combined	Max	No	.0213	.0289	.0106
KS_{NINN}	1	In degree	N/A	No	.0161	.0243	.0087
KS_{PNNN}	2	No degree	N/A	No	.0036	.0057	.0020