**TRUST, TIE STRENGTHS AND RECOMMENDER SYSTEMS**

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.

**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.

**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.

<table>
<thead>
<tr>
<th>Approach</th>
<th>l_{max}</th>
<th>Degree normalization</th>
<th>Row normalization</th>
<th>Boost</th>
<th>nDCG</th>
<th>Recall</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust_{exp}</td>
<td>0.0224</td>
<td>0.0296</td>
<td>0.010</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trust_{jac}</td>
<td>0.0176</td>
<td>0.0219</td>
<td>0.0007</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MP</td>
<td>0.0134</td>
<td>0.0202</td>
<td>0.070</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>2</td>
<td>Combined</td>
<td>Max</td>
<td>Yes</td>
<td>0.0303</td>
<td>0.425</td>
<td>0.117</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>2</td>
<td>Combined</td>
<td>Max</td>
<td>No</td>
<td>0.0295</td>
<td>0.422</td>
<td>0.013</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>2</td>
<td>Combined</td>
<td>L1</td>
<td>Yes</td>
<td>0.0273</td>
<td>0.358</td>
<td>0.016</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>2</td>
<td>No degree</td>
<td>L2</td>
<td>Yes</td>
<td>0.0257</td>
<td>0.340</td>
<td>0.016</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>1</td>
<td>Combined</td>
<td>Max</td>
<td>No</td>
<td>0.0213</td>
<td>0.289</td>
<td>0.016</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>1</td>
<td>In degree</td>
<td>N/A</td>
<td>No</td>
<td>0.0161</td>
<td>0.243</td>
<td>0.087</td>
</tr>
<tr>
<td>KS_{PCMB}</td>
<td>2</td>
<td>No degree</td>
<td>N/A</td>
<td>No</td>
<td>0.0036</td>
<td>0.057</td>
<td>0.020</td>
</tr>
</tbody>
</table>

**REFERENCES**


**PROBLEM**

Trust-aware Recommender Systems incorporate social trust with the goal of improving the quality of recommendations. Trust is personal and subjective, different people may hold various opinions. Trust is context-specific, meaning that a user which is trustworthy in one domain may not be trusted in another.

**APPROACH**

- Using trust connections, we create an adjacency matrix \(A\) where each entry represents a directed trust link between two users.
- From \(A\), we create a user-to-user similarity matrix by calculating the "Katz Similarity" on the trust adjacency matrix using the iterative approach:
  \[
  \sigma_{\text{iter}}(l_{\text{max}} + 1) = \sum_{l=0}^{l_{\text{max}}} \sigma_{\text{iter}}(l) A^l
  \]
- This approach gives us the ability to define the maximum path length \(l_{\text{max}}\) used for forming weak ties between users which are not directly connected.

**TRUST THEORY**

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

- **Asymmetry** – 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 \(\geq 2\) 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.