Query	Type	X-Rank		RWR		HITS		CrossQuery	
		Mean	STD	Mean	STD	Mean	STD	Mean	STD
Ghost World	Book	**3.43**	1.30	3.23	1.08	3.07	1.10	3.02	0.92
The Making of Pride and Prejudice	Book	**4.02**	0.87	3.80	0.94	3.66	0.90	3.61	0.96
Fear and Loathing in Las Vegas	Book	**3.77**	0.97	3.63	0.91	3.43	1.12	3.16	0.93
Lost Horizon	DVD	**4.10**	0.95	4.05	0.88	3.22	0.76	3.0	0.95
Tai Chi Music - Dr. Paul Lam	Music	**4.36**	0.68	4.11	0.91	3.57	1.05	3.81	0.68
The American Experience	Video	3.50	1.03	**3.64**	0.96	3.00	0.93	3.11	1.09

Table 1: Results of user study. The term 'STD' in the table stands for standard deviation.

as they are more representative of the demo paper's primary user group. In addition, all experiments were performed in Windows 10 with a 3.4GHz i7-6700 CPU and 32GB memory.

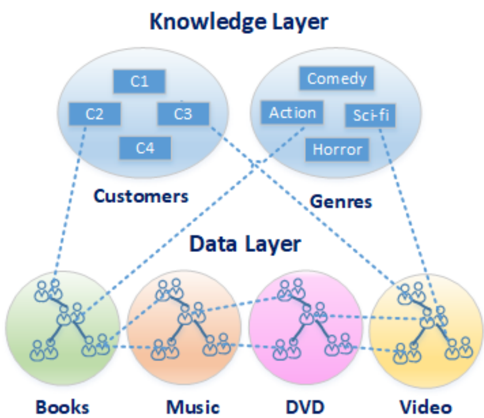

Figure 3: Example of the multi-layered network in Amazon co-purchase dataset.

Dataset. We utilize the Amazon co-purchase dataset (548,552 nodes and 1,788,725 edges) from [9] to conduct the user study. The co-purchase network contains four categories (book, DVD, music and video), each of which is used to construct a data graph as shown in Figure 3. Cross network connections (dotted lines) represent a co-purchase between different categories. In addition, we utilize the genre and customer review metadata contained in the dataset to construct the knowledge layer. Cross layer connections between knowledge and data layers represent the corresponding genre(s) and customer(s) of each product.

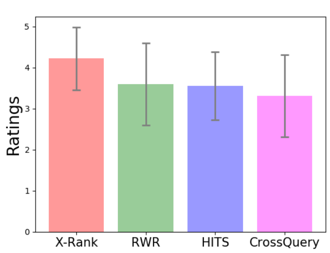

Figure 4: Explainability ratings of all compared methods. Higher is better.

Results. Findings from the user study are reported in Table 1. From this table we offer the following observations: (1) in 5 out of 6 queries, X-Rank performs the best among all compared methods; (2) comparing X-Rank and CrossQuery, the significant improvement indicates the effectiveness of adding knowledge layers. Furthermore, when measuring the usefulness of explanations from X-Rank, the users gave the explanations an average rating of 4.22 (out of 5). This is significantly higher than the ratings for RWR, HITS and CrossQuery—which are 3.60, 3.55, 3.31, respectively. Results are shown in Figure 4. This demonstrates the potential of the proposed X-Rank algorithm to provide useful and intuitive explanations. In addition, the X-Rank algorithm is capable of scaling to large networks due to its linear complexity. To see this, we note that LocalProximity, CrossQuery, Aurora-E and Aurora-N all have linear complexities, which renders a linear time complexity of the overall X-Rank algorithm.

5 CONCLUSION

The goal of this work is to develop a web-based prototype (X-Rank) for researchers and practitioners to visually explore and interact with the proposed explainable ranking algorithm. We believe the platform and algorithm will be of particular interest to both researchers and practitioners in the fields of information retrieval and data mining. In addition, an operational prototype of the X-Rank platform is currently online (http://www.x-rank.net), along with a demonstration video (https://youtu.be/EAKPaCWJQxQ). Source code will be made publicly available by the conference date.

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