Table 2: Offline Runtime (in sec)

	ML_100K	ML_1M	ML_10M	Jester2	Yelp
FTSC	712.503	>1day	>1day	>1day	>1day
FTSC_hybrid	610.728	>1day	>1day	>1day	>1day
FTSC_den	370.040	>1day	>1day	>1day	>1day
GraphRec	0.050	0.223	0.769	0.191	6.441
GraphRec*	0.050	0.223	0.769	0.191	6.441
GraphRec**	1.965	21.689	188.297	24.576	17.767

Table 3: Online Runtime (in msec)

	ML_100K	ML_1M	ML_10M	Jester2	Yelp
FTSC	0.868	—	—	—	—
FTSC_hybrid	0.649	—	—	—	—
FTSC_den	0.017	—	—	—	—
GraphRec	5.932	66.221	461.610	114.690	89.991
GraphRec*	1.540	10.858	14.117	27.361	70.226
GraphRec**	0.381	4.312	3.022	12.913	2.877

Table 4: MAE (normalized)

	ML_100K	ML_1M	ML_10M	Jester2	Yelp
FTSC	0.799	—	—	—	—
FTSC_hybrid	0.797	—	—	—	—
FTSC_den	0.946	—	—	—	—
GraphRec	0.802	0.731	0.677	0.836	0.977
GraphRec*	0.832	0.802	0.891	0.925	1.068
GraphRec**	0.834	0.770	0.815	0.925	1.032

a sparse and diversified sets like Yelp. GraphRec**, however, scales well regardless the structure of the data and remains relatively accurate compared to GraphRec.

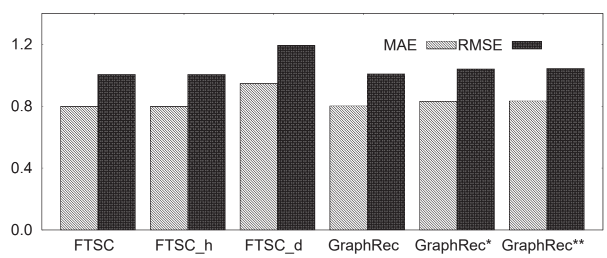
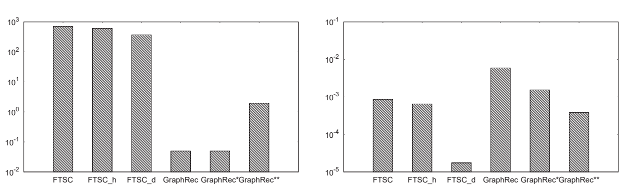


Figure 1: MAE & RMSE for User Recommendation in ML-100k Dataset



(a) Offline Runtime (sec) **(b) Online Runtime (sec)**

Figure 2: Offline & Online Runtime for ML-100k Dataset

3.2.2 Quality of Group Recommendations. Since there is no ground truth in group recommendations, we use the individual group members ratings to asses the quality. We randomly generate 1,000 user groups from the ML-100K dataset and use the average rating for commonly rated items as ground truth. Each group consists of 5 members and we test all common items for each group. The parameter settings are the same as our experiments of user recommendations. The runtimes of algorithms are linear to the runtime in user recommendations with respect to the group size. Therefore we do not report the runtime of group recommendation experiments. In terms of effectiveness, as shown in Figure 3, our methods are similar to FTSC algorithms.

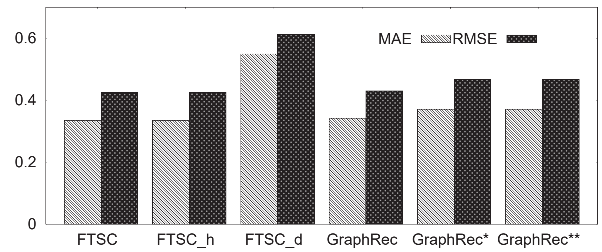


Figure 3: MAE & RMSE for Group Recommendation in ML-100k Dataset

4 CONCLUSION

In this paper, we show the connection between fault-tolerant group recommendation and graph search. Based on it, we propose an efficient fault-tolerant group recommendation method, GraphRec, and its two variants which are based on the concept of α-β-core. Our experiments demonstrate the efficiency of our solutions, compared to the state-of-the-art. In the future, we plan to investigate the adoption of other graph structures to approximate α-β-cores, in order to further improve efficiency. Another interesting direction is to scale GraphRec algorithms up by applying a distributed computing setting.

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