

User-based graph regularisers

1. Collaborative filtering

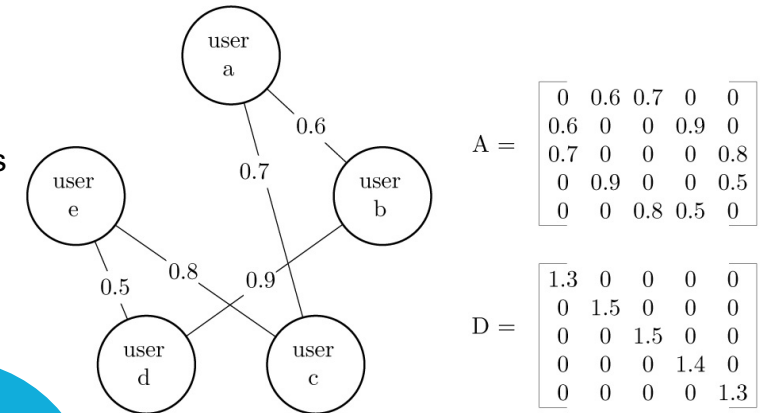
What: Predicting ratings based on ratings of similar users.
How: Taking the weighted average of the ratings of the most similar users



Research question: How the Tikhonov regulariser performs for user-based KNN collaborative filtering.
Additional research question: How the Sobolev regulariser performs for user-based KNN collaborative filtering

3. MovieLens to Graph

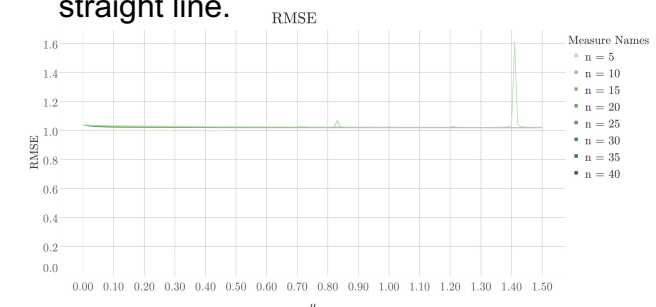
Represent a user as node
 The similarity between users are the edge weights
 The ratings are represented as the graph signal



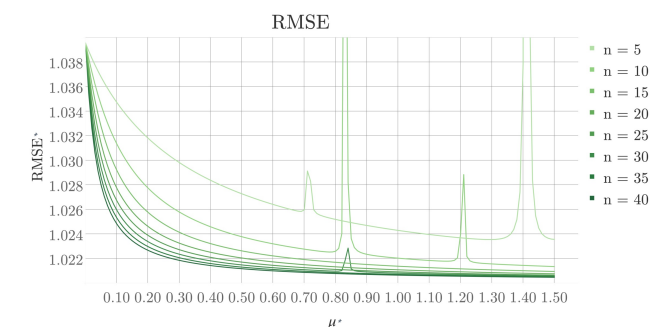
4. Tikhonov regulariser

$$\hat{X} = (I + \mu L)^{-1} Y$$

The results for the different metrics for the Tikhonov regulariser are almost identical. The graphs show a nearly straight line.



Zoomed in we see some minor variation



6. Comparison

Overview of the best performance for each algorithm for the different metrics.

	RMSE	Recall@5	Recall@10	Recall@20	Precision@5	Precision@10	Precision@20	NDCG@5	NDCG@10	NDCG@20
CF	1.092	0.521	0.715	0.864	0.640	0.692	0.593	0.914	0.892	0.932
Tikhonov	1.020	0.516	0.711	0.861	0.682	0.636	0.593	0.885	0.908	0.928
Sobolev	1.021	0.517	0.711	0.864	0.684	0.635	0.593	0.884	0.907	0.928

5. Sobolev regulariser

$$\hat{X} = (I + \mu(L + \epsilon I)^\beta)^{-1} Y$$

The results show the same trends as Tikhonov. That is the variations between the different parameter sets on the different metrics are very small.

7. Conclusion



With RMSE of 1 on a scale of 1 to 5 and all the algorithms have almost identical results. It is an indication that the underlying assumption that the Pearson correlation as similarity measure is useful for prediction user ratings might not hold true for this data set.