Hungarian Academy of Sciences
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Recommendation systems on Nomao data

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Rating vs. binary matrix
Sparsity: <1% of known values
Overfitting

Singular Value Decomposition

dense representation
no regularization

Stochastic Gradient Descent

sparse representation
vs. conjugate (ALS)
regularization

Both optimize RMSE

Evaluation?

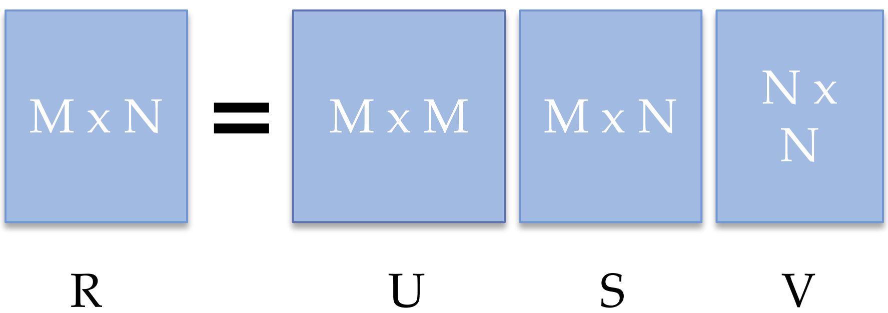
User/Movie	Napoleon Dynamite	Monster Inc.	Cindarella	Life on Earth
David	1	?	?	3
Dora	5	3	5	5
Peter	?	4	3	?

User/Movie	Napoleon Dynamite	Monster Inc.	Cindarella	Life on Earth
David	1	0	0	1
Dora	1	1	1	1
Peter	0	1	1	0

User/Movie	Napoleon Dynamite	Monster Inc.	Cindarella	Life on Earth
David	1			1
Dora	1	1	1	1
Peter		1	1	

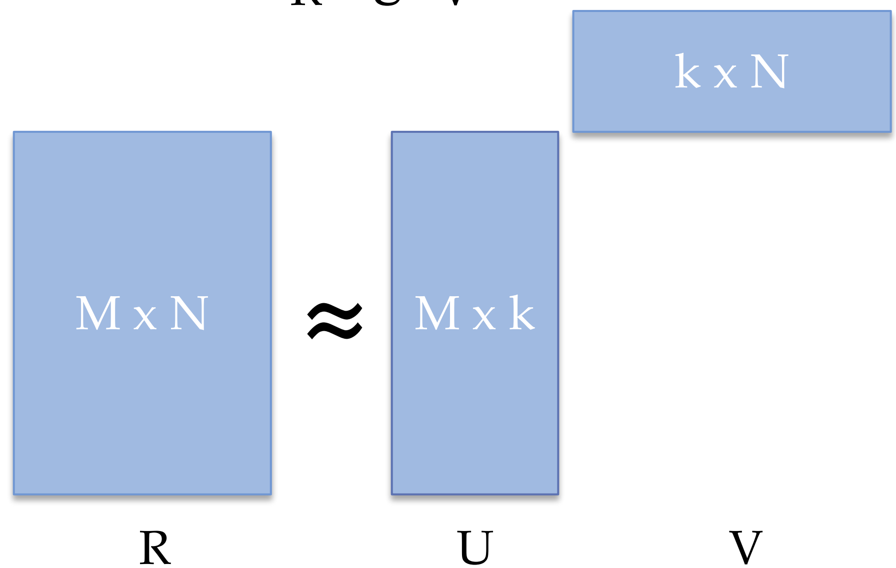
Singular Value Decomposition

$$R = U^T S V$$



Stochastic Gradient Descent

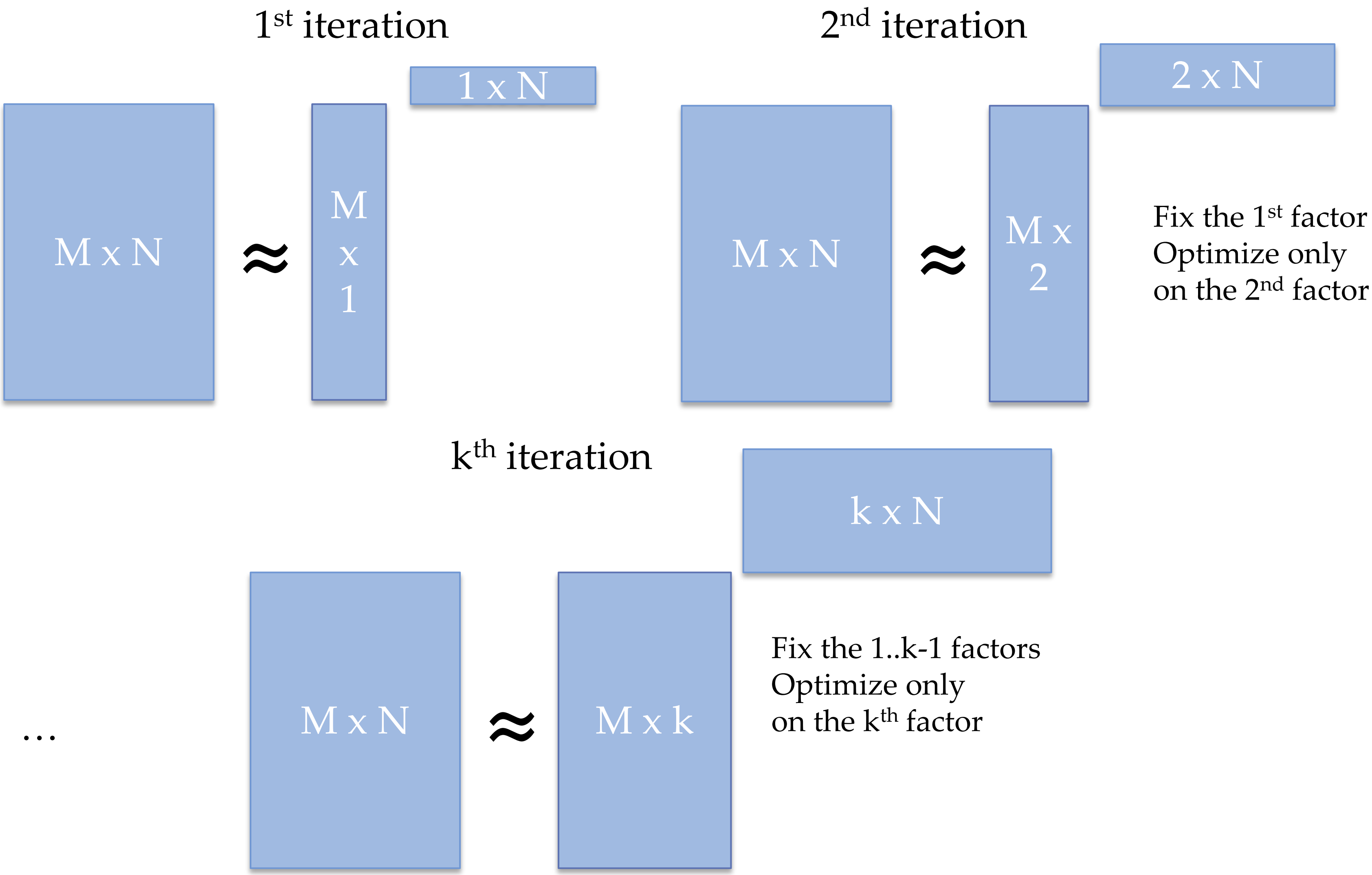
$$R = U^T V$$



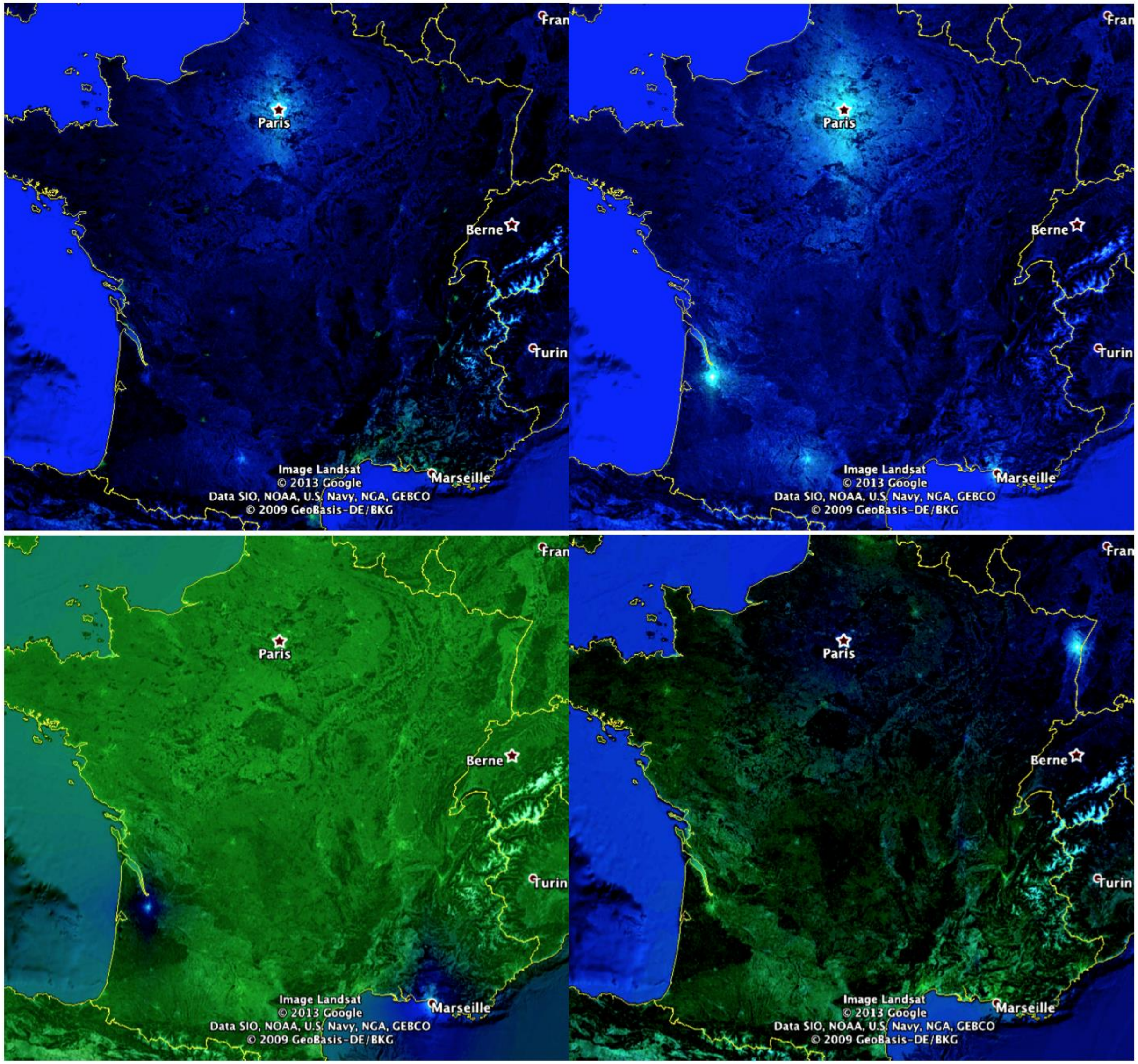
In our case:
M: number of users
N: number of items
R: the original (<1% known) rating matrix

In comparison to SVD, the SGD factors are not ranked
Ranked factors: iterative SGD optimize only on a single factor at a time

Iterative Stochastic Gradient Descent (by Simon Funk)



Singular Value Decomposition

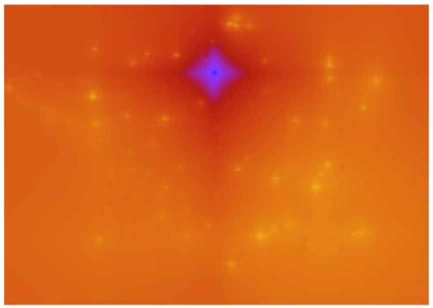
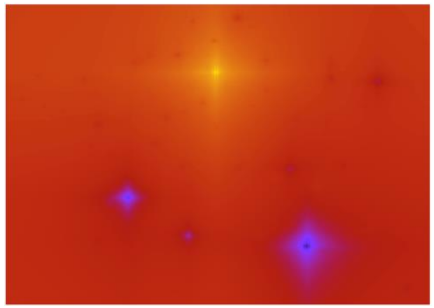
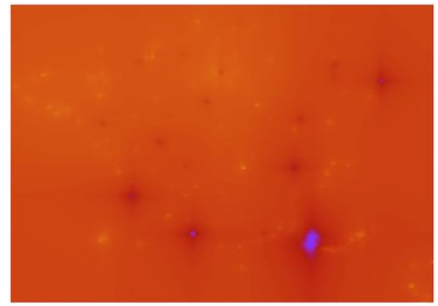
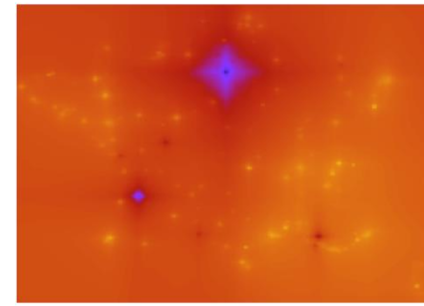
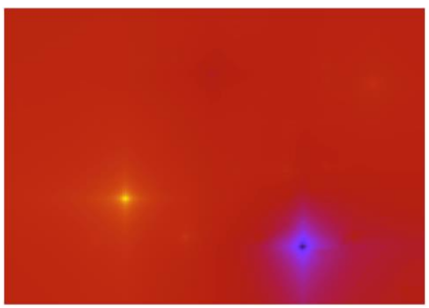
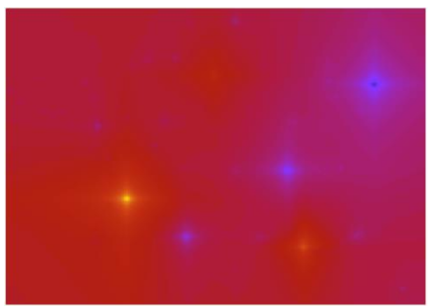
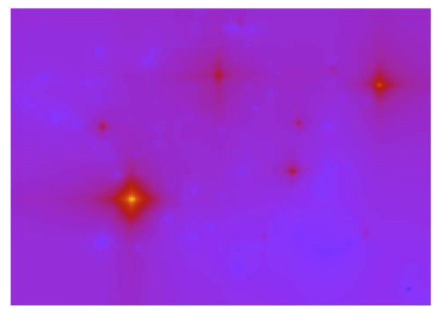
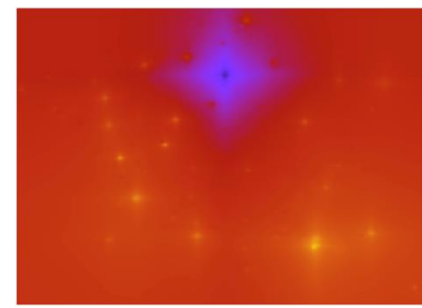
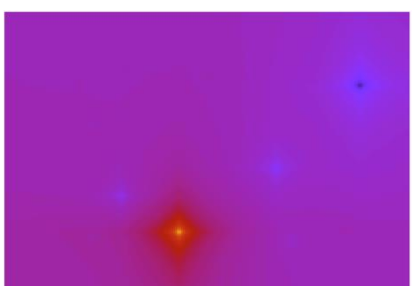


The first 4 factors mapped over France

The first 5 factors mapped over France

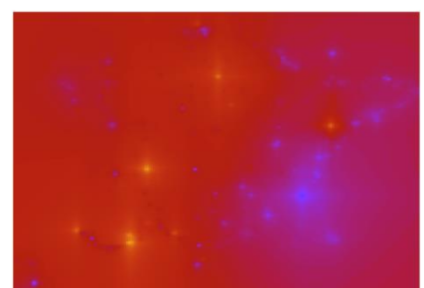
Singular Value Decomposition

Stochastic Gradient Descent not ranked!

Smoothness

képlet



Recommend locations near to already visited places
vs.
Expand/modify the training set or regularization

Expansion via locality

- SVD vs. SGD
- Binary vs. Rating matrix
- identifying neighbors: k-nearest vs. radius , travel time?
- number of neighbors (n)?

Let be E the set of known ratings and N_j the neighbors of the location j, than we can modify the training set as follows. For all (u,i)

$$\hat{r}_{u,i} = \begin{cases} r_{u,i} & \text{if } (u,i) \in \mathrm{E} \\ f(R_u, N_{u,i}) & \text{if } (u,i) \notin \mathrm{E} \text{ and } \exists\, j \text{ with } (u,j) \in \mathrm{E} \text{ and } i \in N_j \\ 0 \text{ or don't care} & \text{otherwise} \end{cases}$$

where f is function of R_u, the set of known ratings by user "u" and $N_{u,i}$, the set locations visited by "u"where "i" is a place of their neighorhood.

Model 1: expand the list of locations per user with the neighbors of visited places

a) learn the ratings

$$f(R_u, N_{u,i}) = \frac{1}{|N_{u,i}|} \sum_{j \in N_{u,i}} r_{u,j}$$

or a constant

$$f(R_u, N_{u,i}) = c$$

b) learn the occurrence

$$f(R_u, N_{u,i}) = 1$$

Model 2: adaptive distance based expansion, smoothed with local density

a) learn the ratings

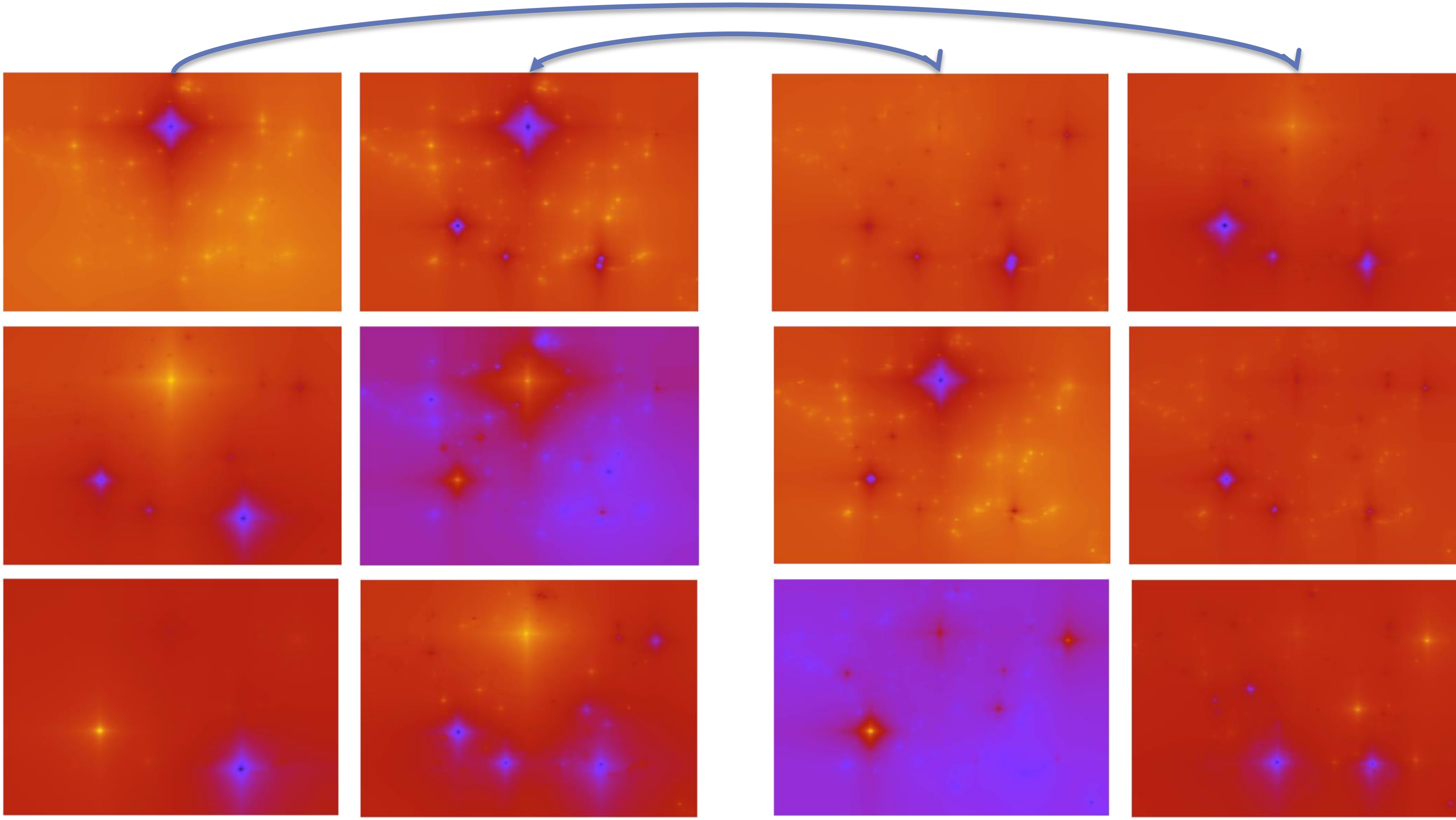
$$f(R_u, N_{u,i}) = \frac{1}{|N_{u,i}|} \sum_{j \in N_{u,i}} \hat{r}_{u,j} \mathrm{e}^{-\frac{d_{L2}(i,j)}{\hat{d}_{L2}(j)}}$$

b) learn the occurrence

$$f(R_u, N_{u,i}) = \mathrm{e}^{-\frac{d_{L2}(i,j)}{\hat{d}_{L2}(j)}}$$

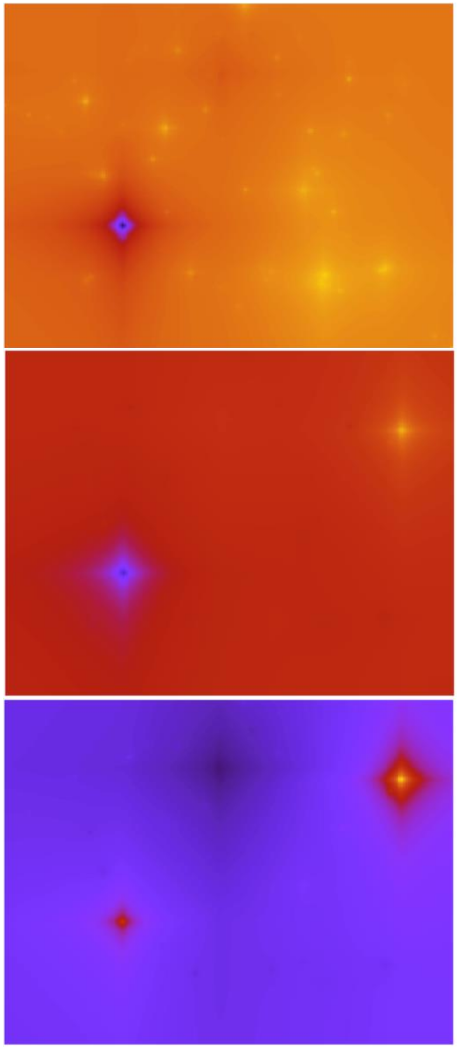
Effect of “n”, The first 5 factors mapped over France

Singular Value Decomposition | Stochastic Gradient Descent



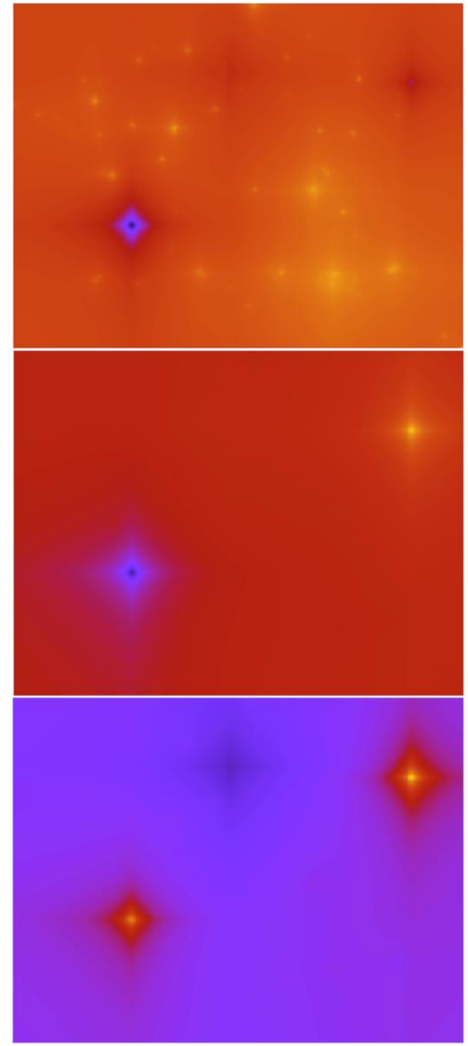
original | n=1 | original | n=1

Effect of "n"



n=1

≈



n=20

Performance measures

RMSE: $RMSE = \sqrt{\sum_{(u,i)} (r_{u,i} - r^*_{u,i})^2}$

$$RMSE_{sparse} = \sqrt{\sum_{(u,i)\in E} (r_{u,i} - r^*_{u,i})^2)}$$

Recall @ K: number of hits/number of relevant items

$$Recall(K) = \frac{1}{|U|} \sum_u Recall_u(K)$$

per user

$$Recall_u(K) = \frac{1}{|R_u|} \sum_{i=1}^{K} rel_{u,i}$$

Normalized Discounted Cumulative Gain @ K

$$nDCG(K) = \frac{1}{|U|} \sum_u nDCG_u(K)$$

per user

$$nDCG_u(K) = \frac{DCG_u(K)}{iDCG_u(K)} \quad \text{where} \quad DCG_u(K) = rel_{u,1} + \sum_{i=2}^{K} \frac{rel_{u,i}}{log_2(i)}$$

Item	Rank for a user	Relevance to the user
item1	0	0
item2	1	1
…	…	0
		1
		0
		0
		1
item K-1	K-2	0
item K	K-1	1

Relevance ($rel_{u,i}$)?

Binary or real

Preliminary results

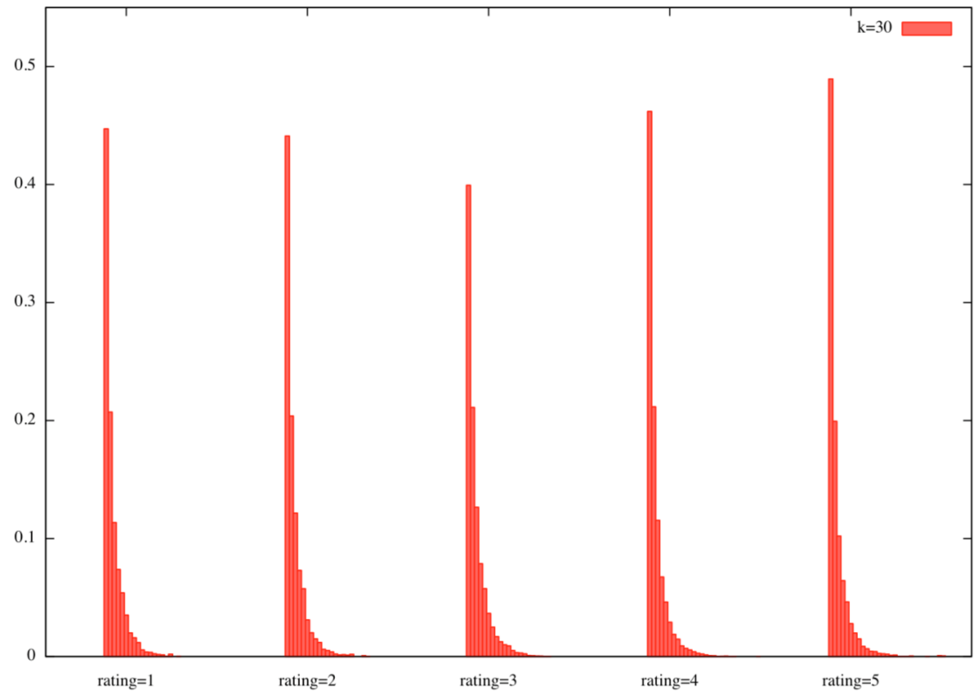
Datasets

Nomao: France, mostly Paris
7605 location
9471 users
97453 known ratings

Yelp: U.S.A
45981 users
11537 locations
227906 known ratings

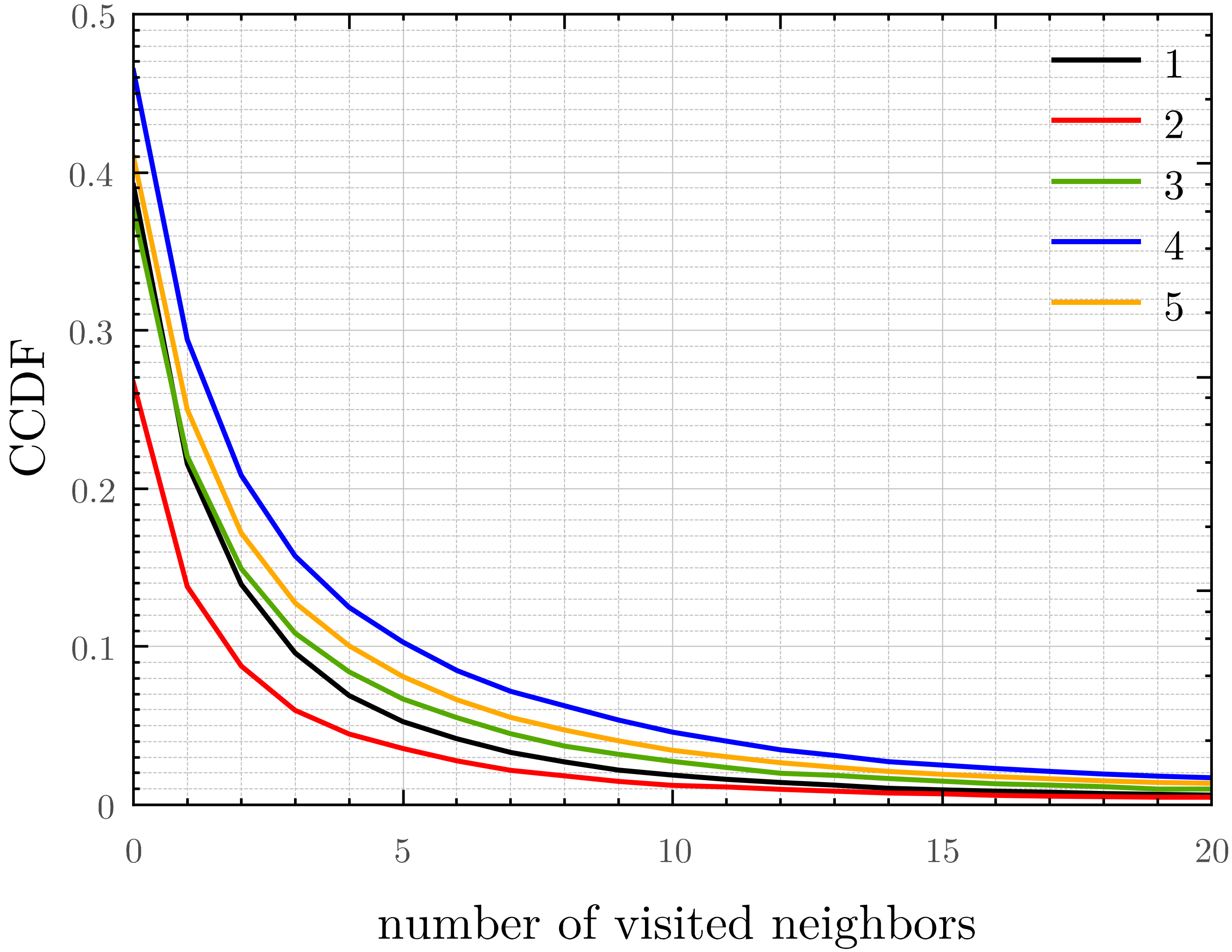
"Rating effect"

For a given user the neighbors of "average" rated places are more-likely visited as the neighbors of "extremely" rated places

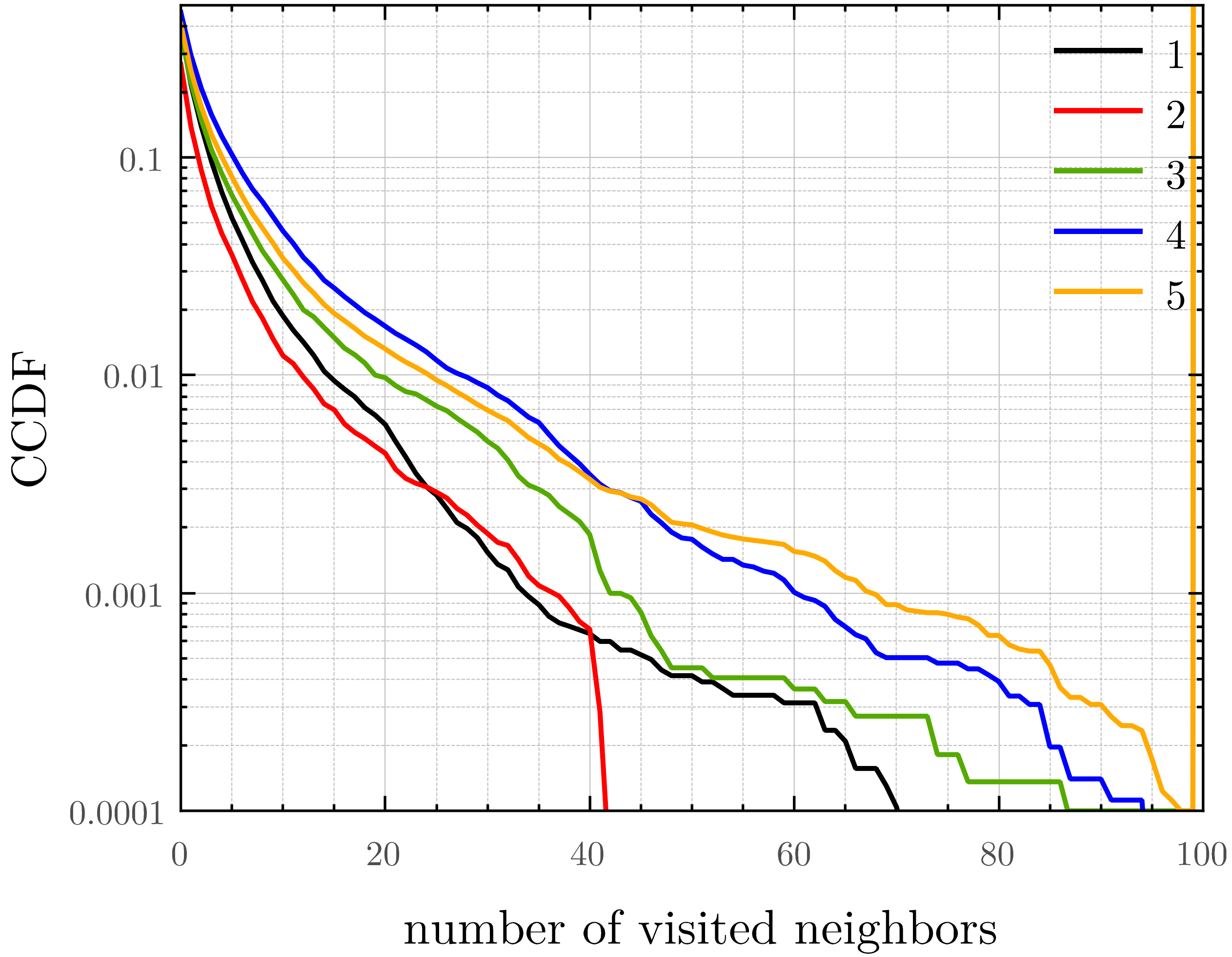


Refine recommendation: regularization or re-ranking
Location adaptive expansion via the ratings of the visited places

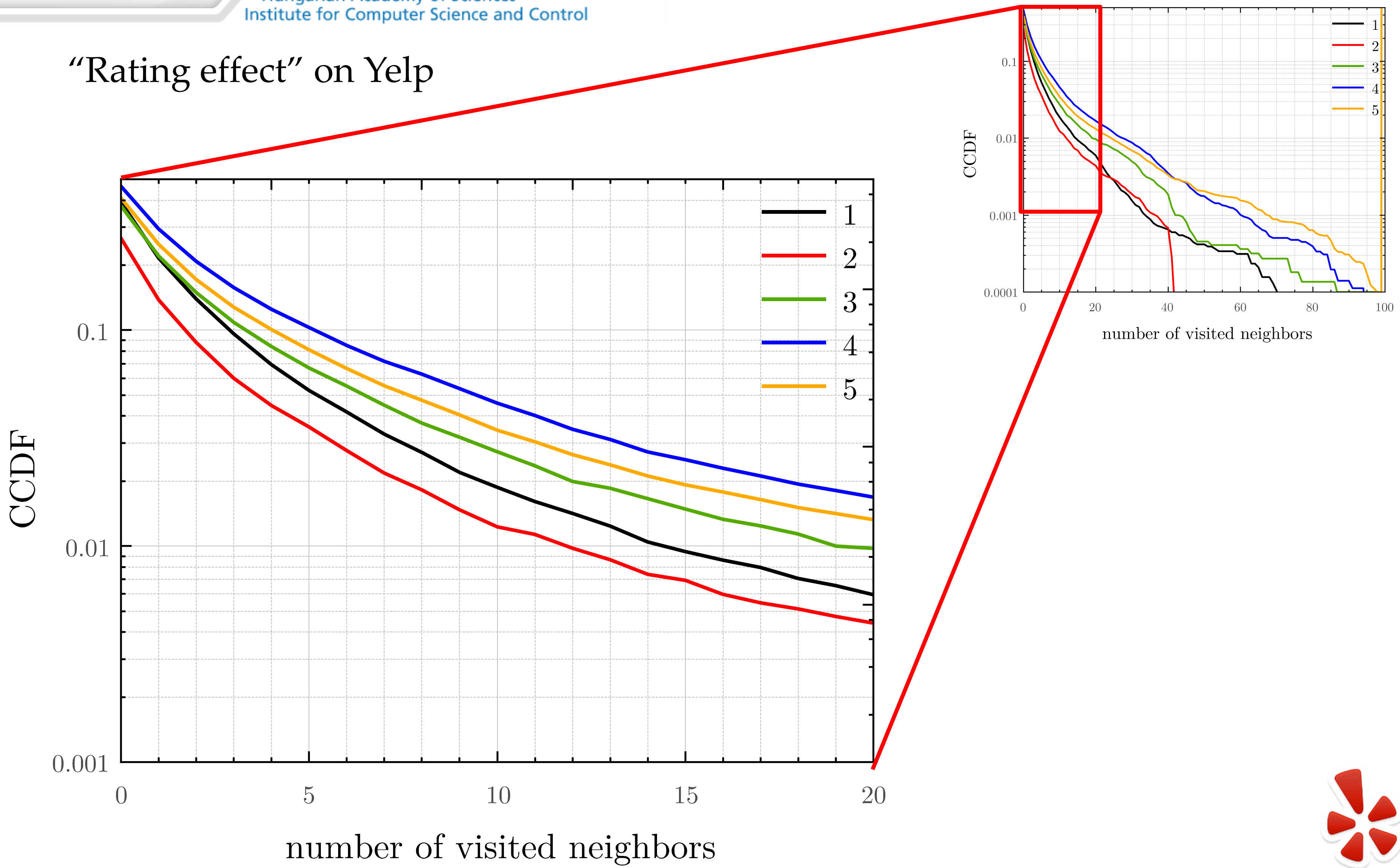
"Rating effect" on Yelp



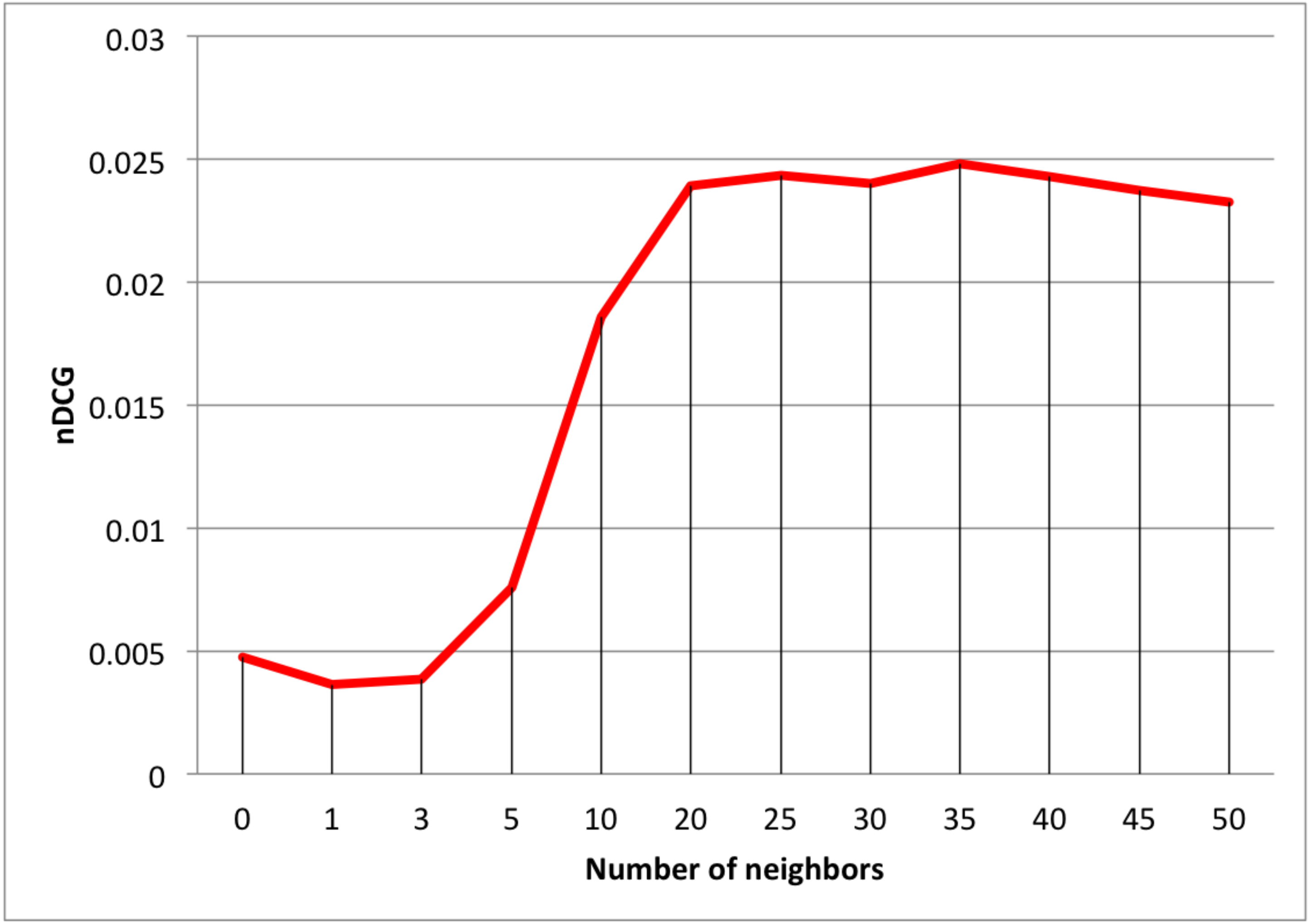
"Rating effect" on Yelp (log-scale)



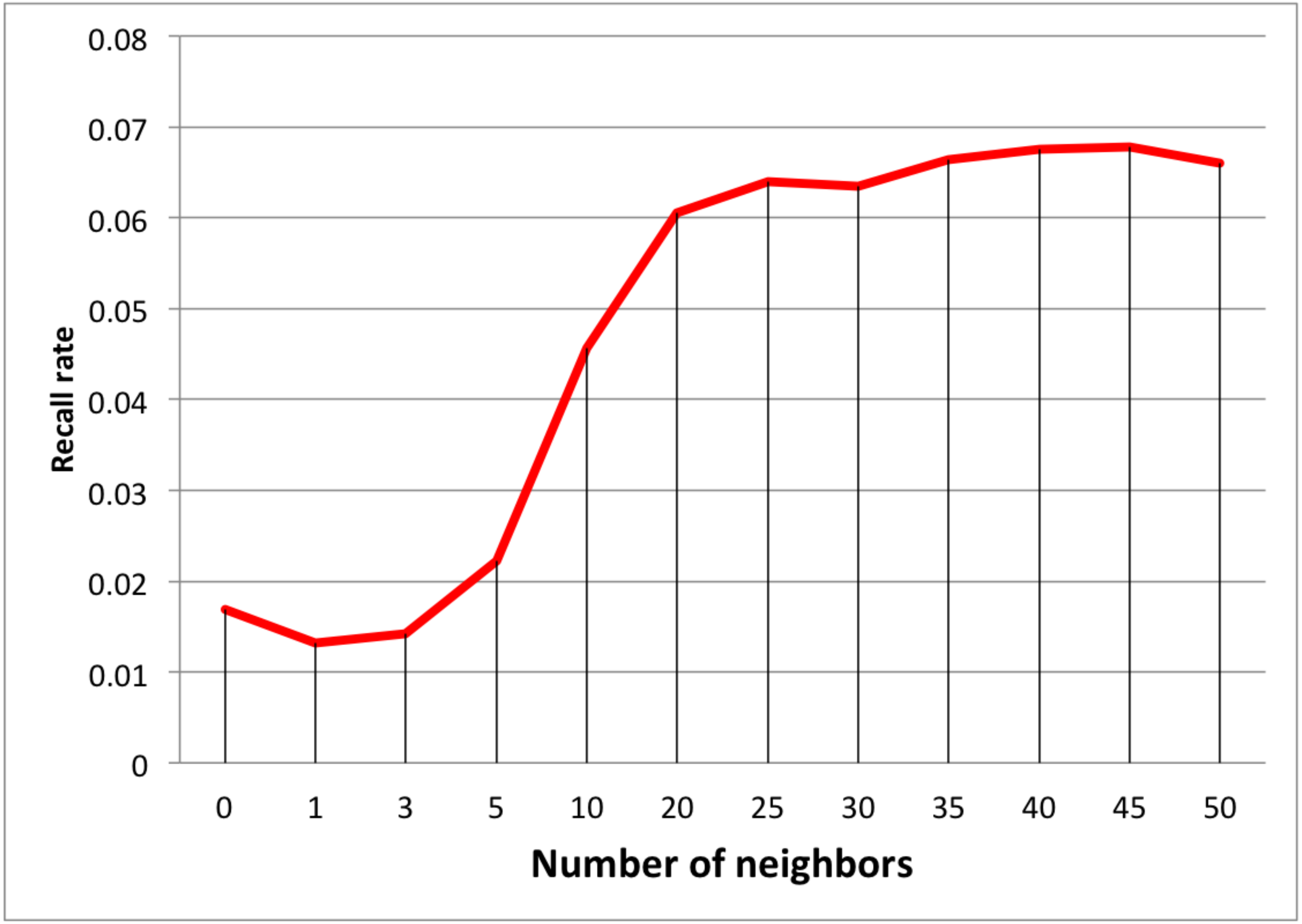
“Rating effect” on Yelp



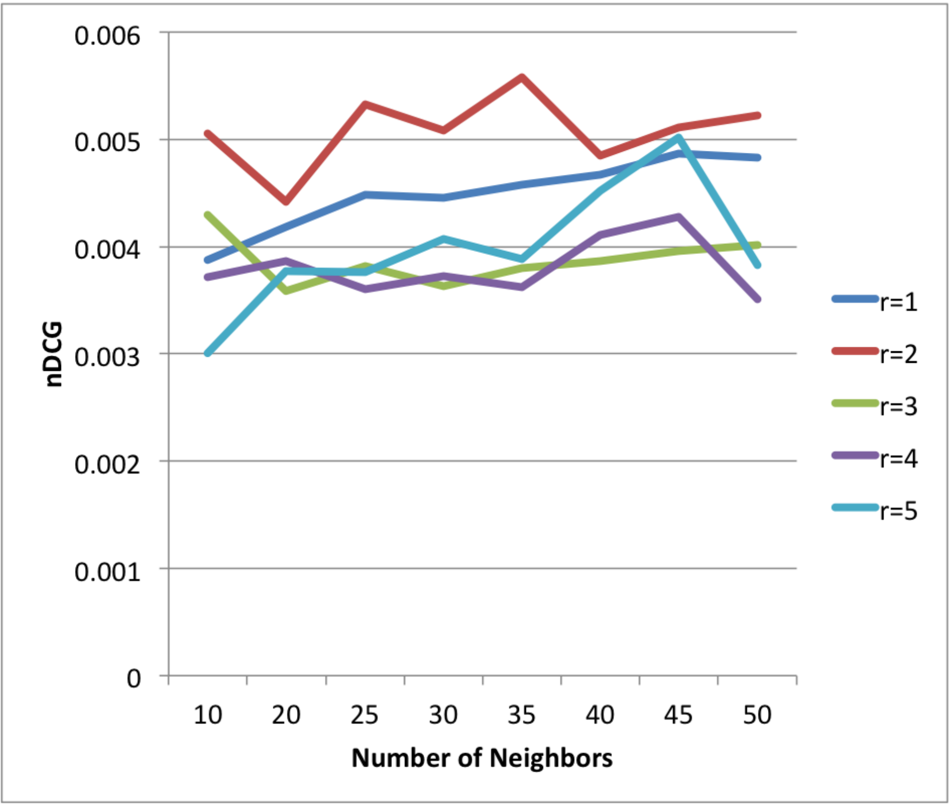
M1a: Expansion with the original ratings (nDCG@100)

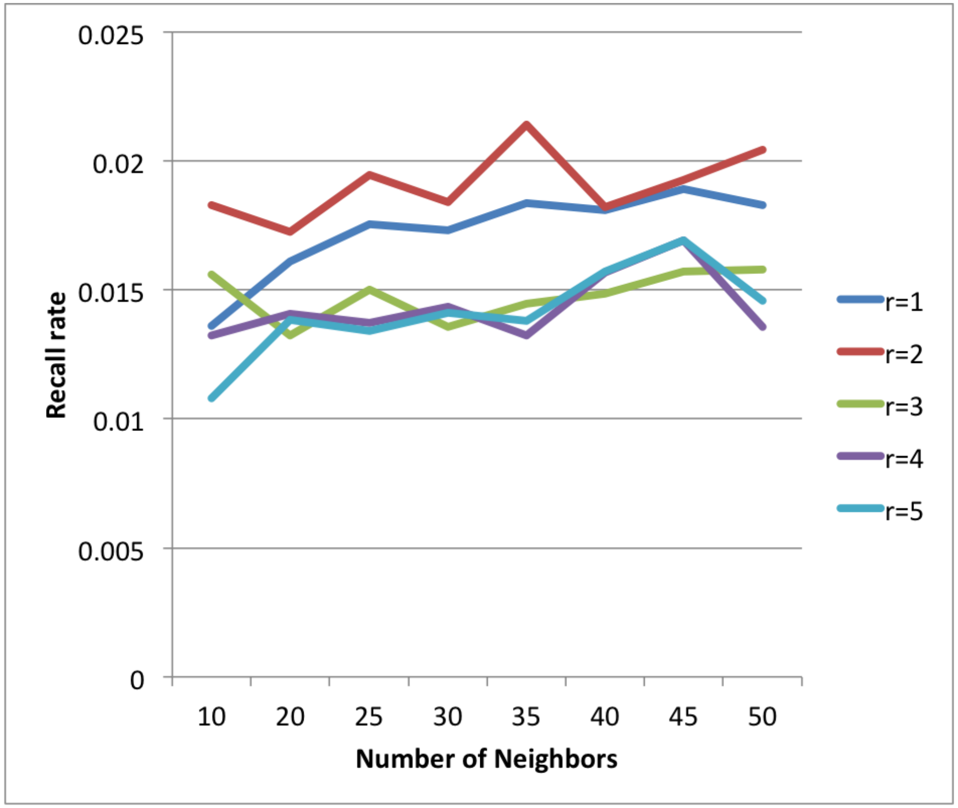


M1a: Expansion with the original ratings (Recall@100)

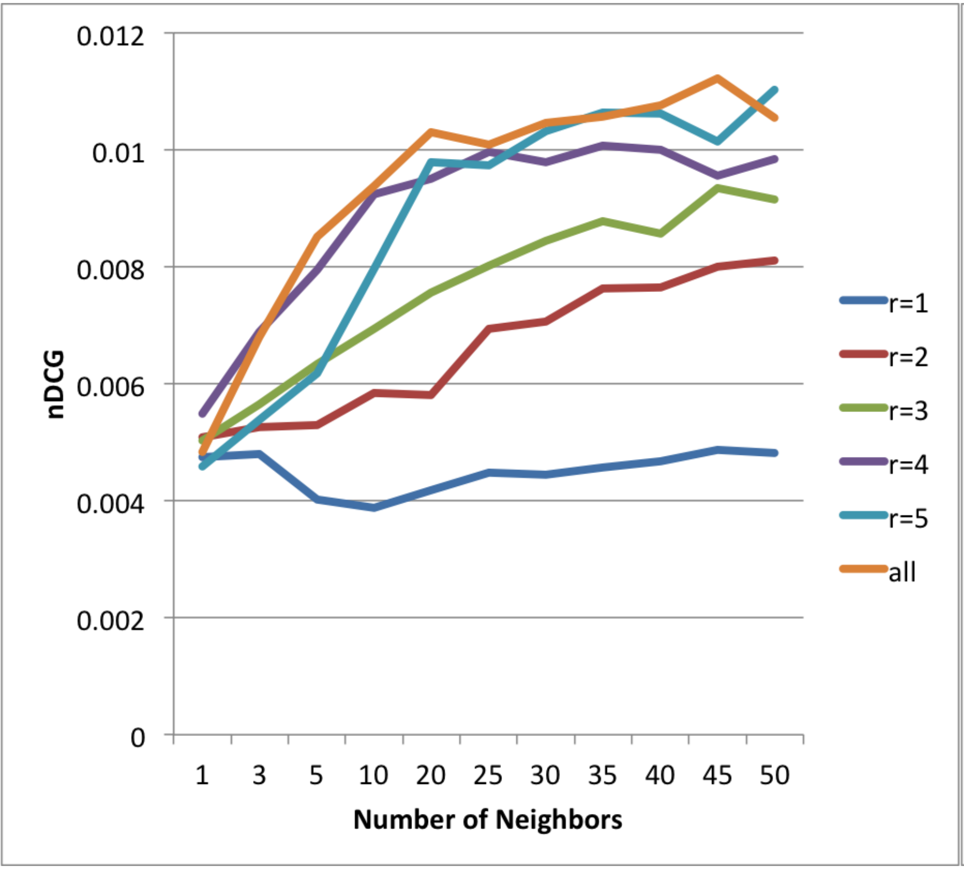


M1a: Weighted expansion per rating (nDCG@100 and Recall rate)
Note: we lower the test predicitions if the original rating was “low”

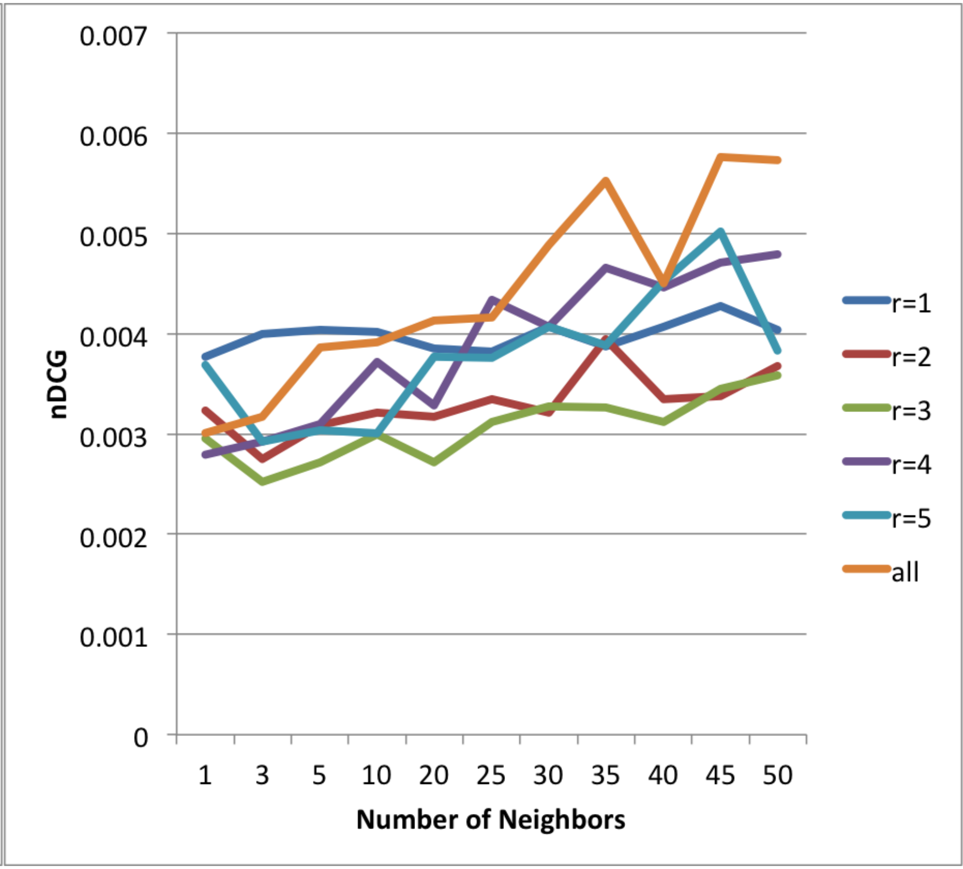




M1a: Constant expansion per rating (nDCG@100)

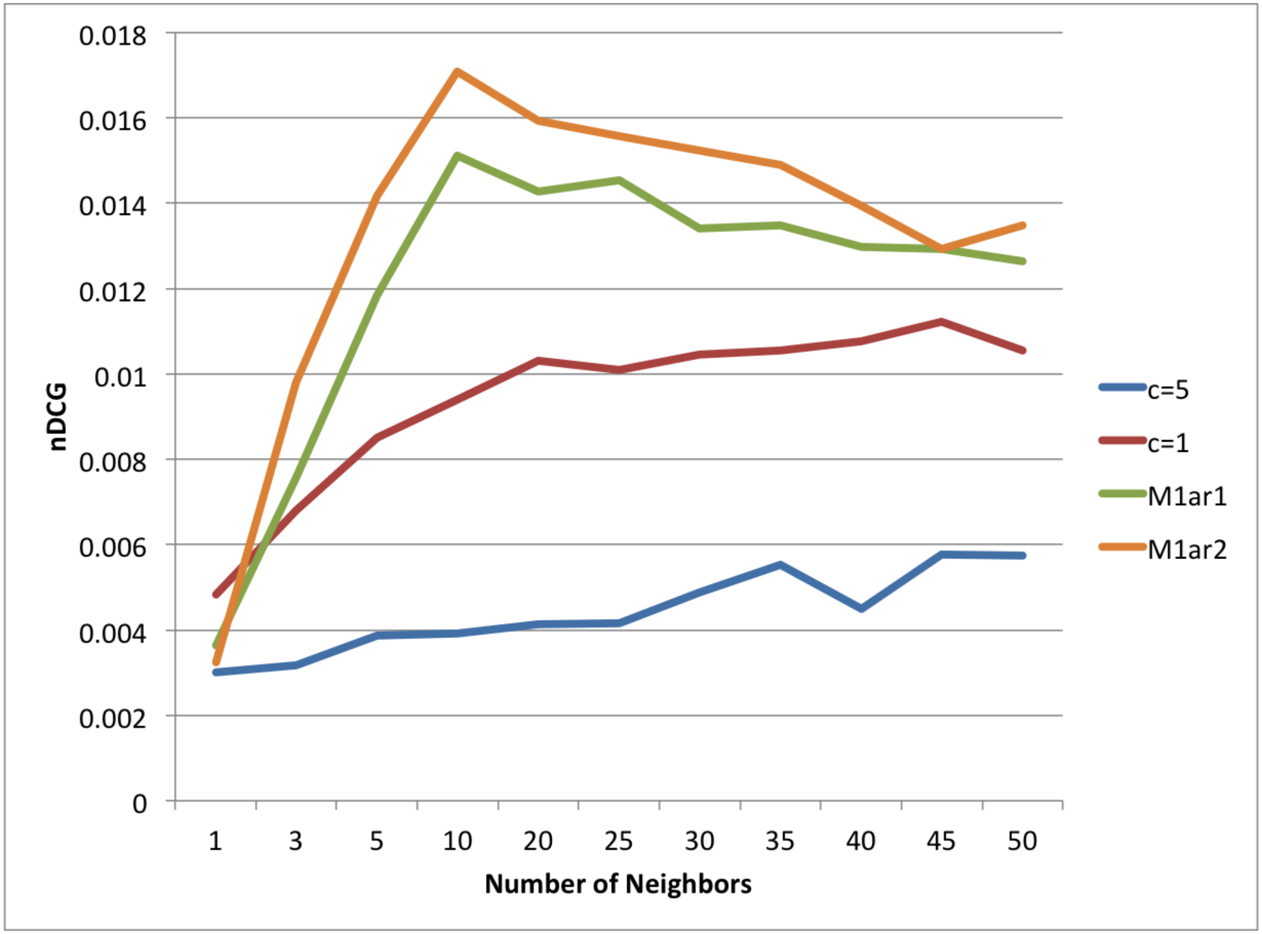


c=1



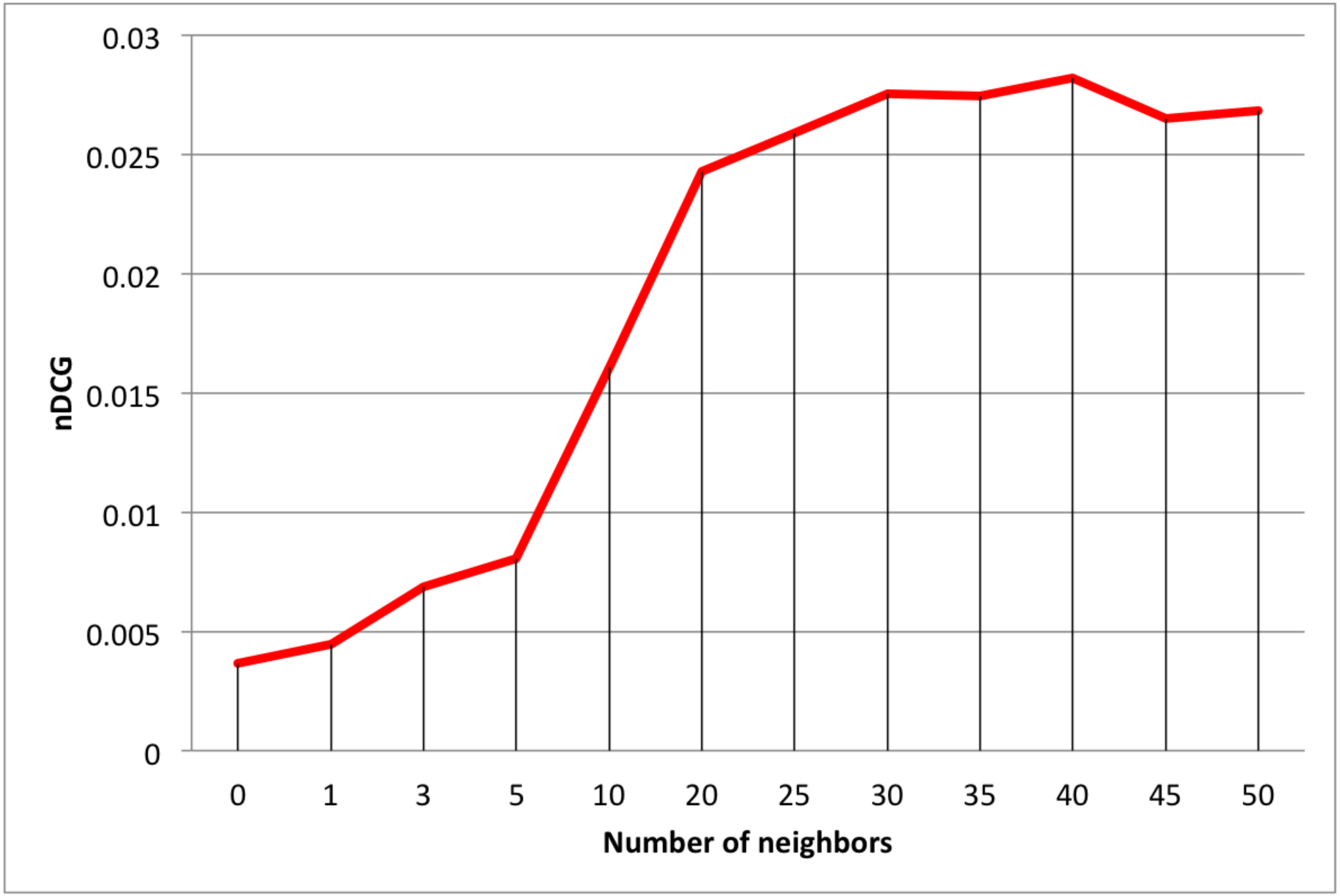
c=5

M1ar: Rating dependent constant expansion per rating (nDCG@100)

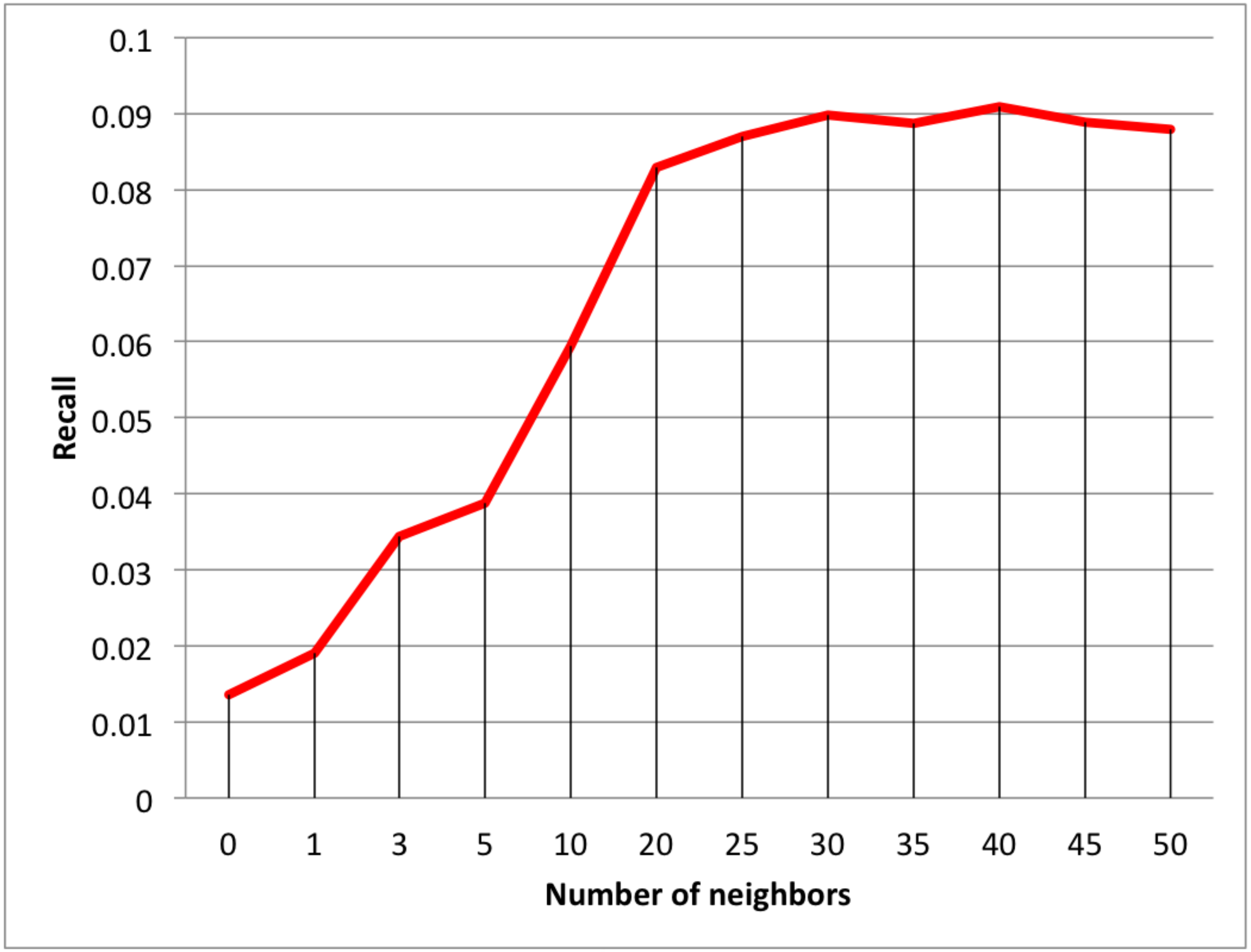


M1ar1: c=1 if r=1,2,3 and c=5 if r=4,5
M1ar2: c=1 if r=1,5 and c=5 if r=2,3,4

M1b: Expansion the list of visited locations with neighbors (nDCG@100)



M1b: Expansion the list of visited locations with neighbors (Recall@100)



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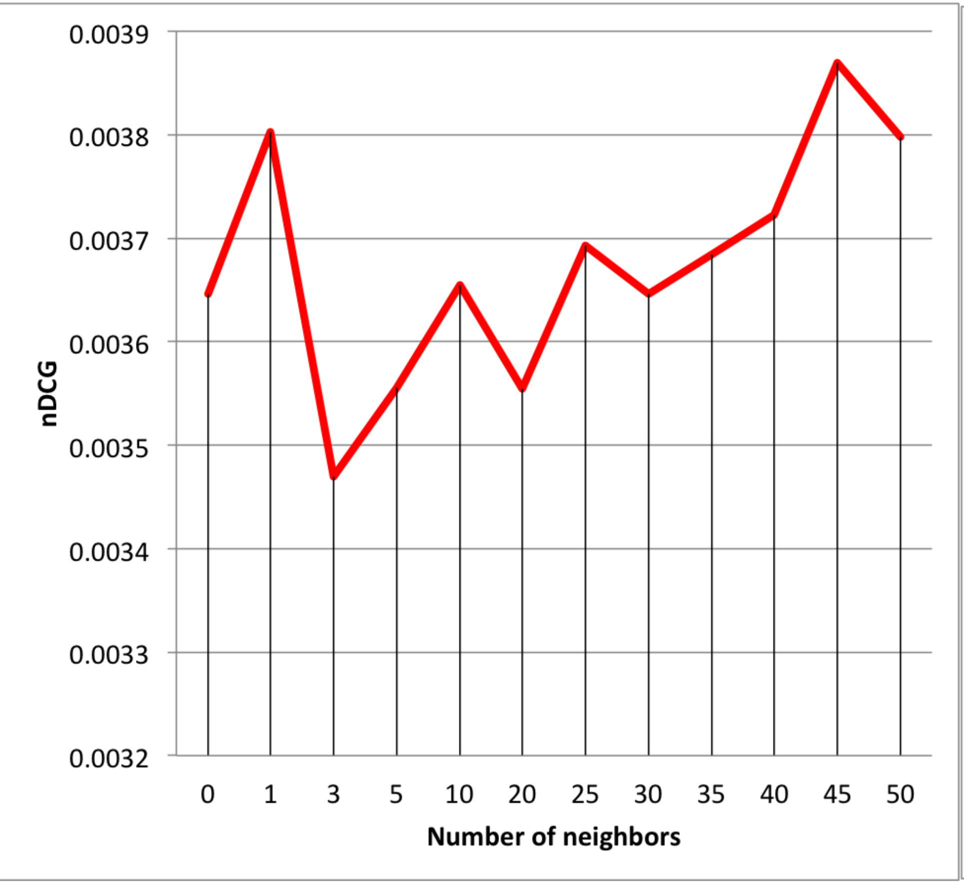
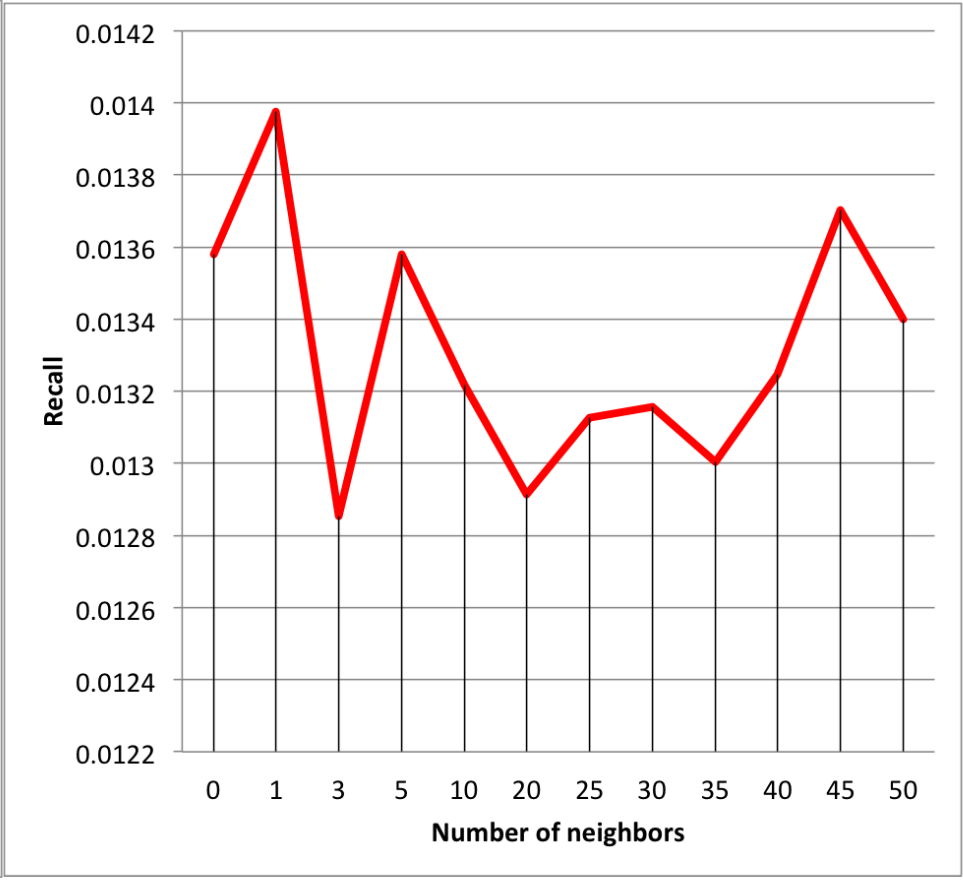
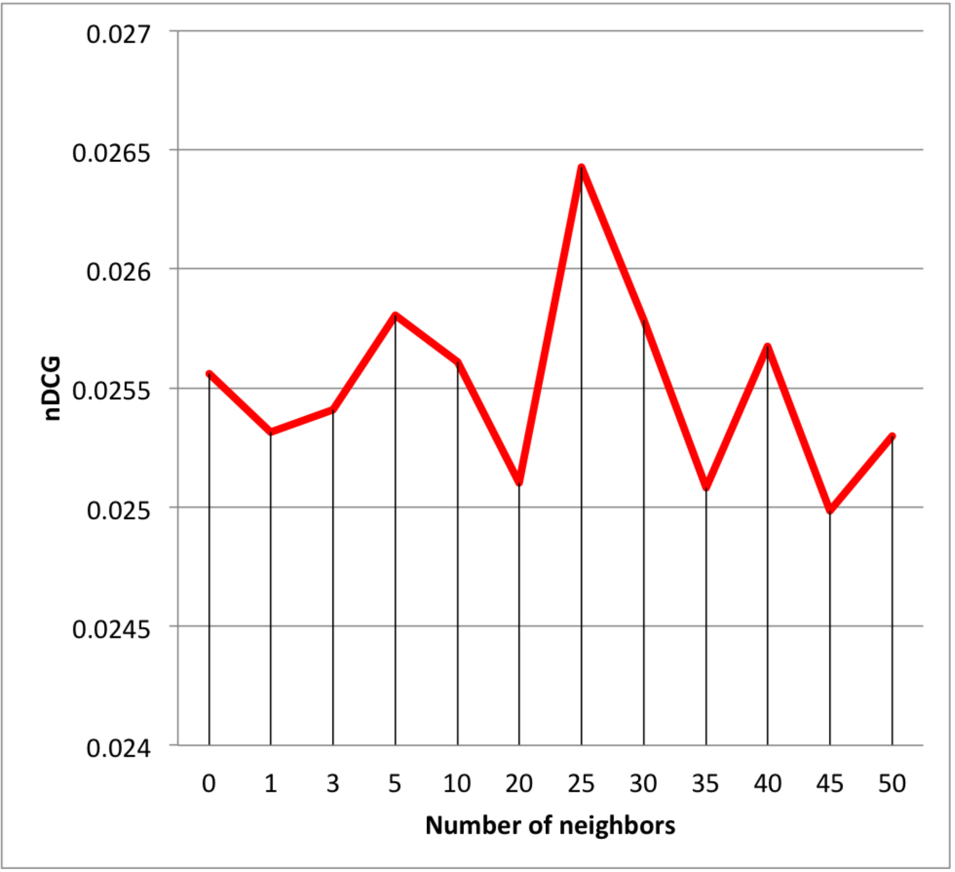
nomad

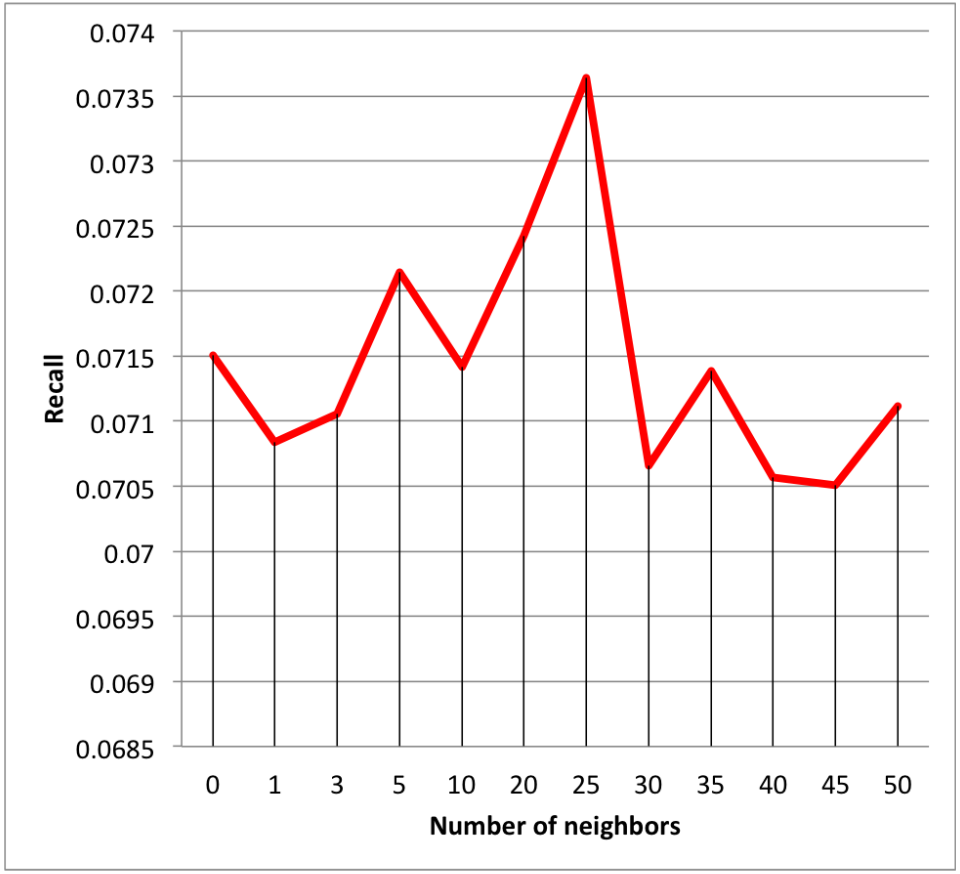
M2b: Distance adaptive expansion of visited locations , smoothed (nDCG@100 and Recall)



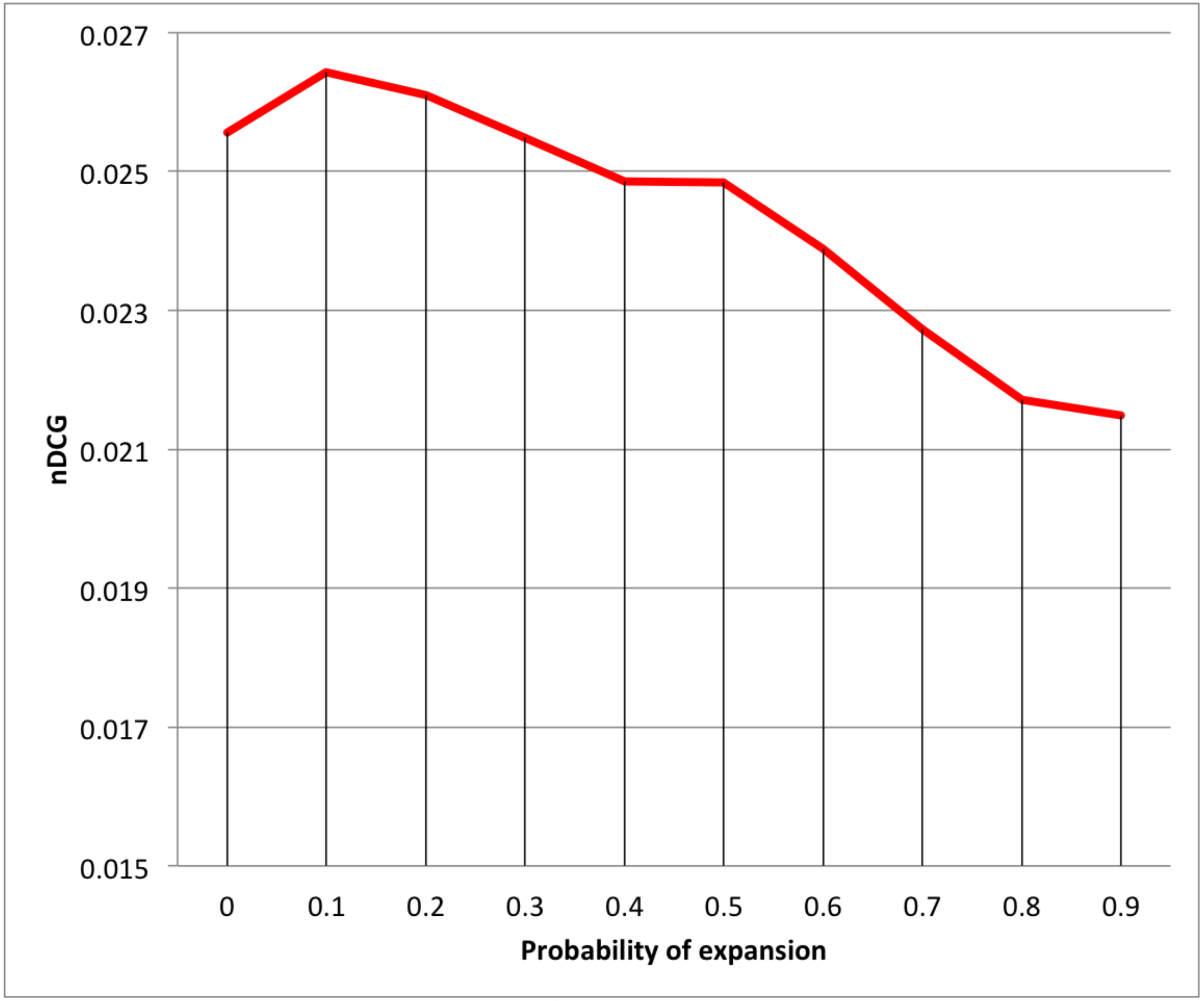


M2a: Distance adaptive expansion of ratings , smoothed (nDCG@100 and Recall)





M2a: Probability of expansion



Conclusions and future work

- SGD and SVD “factors” are similar
  - factors with highest eigenvalue are mostly correlated with a particular place
- “Rating effect”
  - rating dependent distribution of visited neighbors
  - observed over Nomao and Yelp too
- In some cases expansion via neighbors of visited places could increase the performance

Next steps:

- Combination of non-factor and factor models
- We just started to use the “rating effect”: probabilistic models
- MultiMF: Learn where to expand

Thank you! Questions?