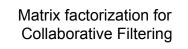


## Matrix factorization motivation

- Discover/use latent factors – attributes, topics, features
- Factor matrices to uncover latent factors
- Don't know what latent factors represent – can conjecture

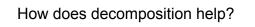


- Give ratings matrix R: M users X N items
   R has holes- R<sub>ij</sub> with no value
- Want to fill in holes => predict ratings
- Idea: decompose R:

## R=P\*Q<sup>⊤</sup>

- P is M X f; Q is N X f
- f dimensions are latent factors
- no interpretation but can add one

must choose f



2

- estimate P and Q, leaving no holes
- get estimate of R as R<sub>f</sub> = PQ<sup>T</sup>
   R<sub>f</sub> has holes of R filled in
- Several methods for estimation, e.g. – Gradient descent
  - Stochastic gradient descent
    - Koren et al. Matrix Factorization Techniques for Recommender Systems, IEEE Computer, Aug 2009
  - Least squares based calculations
     Bell et al Modeling Relat'ships at Multiple Scales to Improve Accuracy of Large Recom. Sys., KDD Aug 2007.

## Optimization

• Minimize least squares error:

err(P,Q) is defined as

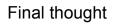
$$\sum_{(u,i) \text{ in } K} (R_{(u,i)} - (PQ^T)_{(u,i)})^2$$

for K the set of (u,i) for which  $\mathsf{R}_{(u,i)}$  has a value

Simple Step: Gradient Descent
Minimize for one element change:
(choose one element of P or one element of Q to vary, say P(r,g) (PQ<sup>2</sup>)(r,j) = (∑<sub>k,k±3</sub>) P(r,k) \* Q<sub>1</sub>(k, j) + x \* Q<sub>1</sub>(k, g))
ent(P,Q) becomes equation with one unknown
look at only terms involving x
et sum over j for which R<sub>(r,j</sub>) has a value of:
(R<sub>(r,j</sub>) - (PQ<sup>T</sup>)(r,j)<sup>2</sup> = (R<sub>(r,j</sub>) - (∑<sub>k,k±3</sub>) P(r,k) \* Q<sub>1</sub>(k, g)) - x \* Q<sub>1</sub>(k, g)<sup>2</sup>)<sup>2</sup>
take derivative wrt x, set to 0, solve



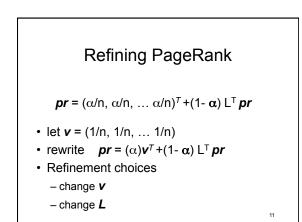
- · Looked at several techniques to modify search
- · explicit user feedback
- user behavior: history
   user history
  - crowd history
- collaborative history: "people like you"
- · role of social networks
  - general analysis
  - relationships
- · models of recommender systems

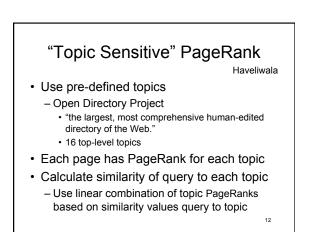


All techniques we've seen behavior or topic oriented

What about links? What about PageRank?

10





## Personalized PageRank Kamvar et. al.

- Random leaps are biased by personal interests change  $\pmb{v}$
- Combined with use of block structure to make more efficient:
  - Divide Web graph into blocks (clusters)
  - Use high-level domains (e.g. princeton.edu)
  - Calc. local PageRank within each block
  - Collapse each block into 1 node new graph
    Weighted edges between nodes
  - Calc. PageRank with biased leaps for block structure

13

Weight local PageRanks with block PageRank
Use to initialize power calculation