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THINKING OF THE WORLD

Probabilistic Graphical Models for Recommendation in Social Media

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- Social networks have been used widely in the social and behavioral sciences, in economics, marketing, . . .

- Directed or undirected graph

  nodes: actors
  edges: social relationships or interactions

Introduction

- Explicit social network
  relationships provided by users

- Implicit social network
  relationships inferred from user interactions
  - Email network
  - Co-worker network

Introduction

- Emergence of online social networks
- Among the top websites http://www.alexa.com/topsites

  . . .
  2. FaceBook
  . . .
  8. LinkedIn
  . . .
  10. Twitter
  . . .

→ Availability of very large datasets

Introduction

- Users want to have personalized results.
- But are not willing to spend a lot of time to specify their personal information needs.
- Recommender systems
automatically identify information relevant for a given user, learning from available data.
- Recommender systems play a crucial role in the evolution of online social networks, e.g. 50% of the links in LinkedIn were recommended by an algoritm.

→ [Ester, Tutorial at RecSys 2013]

Introduction

Outline

- Introduction
- Item recommendation
- matrix factorization [RecSys 2010]
- stochastic block model [RecSys 2011]
- Location recommendation
- spatial topic model [RecSys 2013]
- spatio-temporal topic model [ICDM 2013]
- Future work

Introduction

- Social rating network (SRN)
  (online) social network, where users are associated with item ratings.
- Item ratings can be numeric [1..5]
  or Boolean (bookmark photo, like article, . . .).
- Examples: Epinions, Flixster, last.fm,
  flickr, Digg.
- Two types of user actions:
  (1) social actions,
  (2) rating actions.

Social rating networks

- Social influence
  ratings are influenced by ratings of friends,
  i.e. friends are more likely to have similar ratings than strangers.
- Correlational influence
  ratings are influenced by ratings of users with similar ratings,
  i.e. if some ratings are similar, further ratings are more likely also similar.

Social rating networks

- Selection
  users relate to users with similar ratings,
  i.e. users with similar ratings are more likely to become friends.
- Transitivity
  users relate to friends of their friends,
  i.e. users are more likely to relate to indirect friends than to strangers.

Social rating networks

- Rating prediction
  - Given user *u* and target item *i.*
  - Predict the rating $r_{u,i}$.
- Link prediction
  - Given users *u* and *v.*
  - Predict the probability $p_{u,v}$ of a link from *u* to *v*.
- Top-N recommendation
  - Given user *u.*
  - Rank the items *i* w.r.t. $r_{u,I}$ / the users *v* w.r.t. $p_{u,v}$.

Recommendation

- Collaborative filtering (CF)
- Memory-based approach

  Determine *k* users most similar to *u*
  and aggregate their ratings of item *i*.
- Model-based approach
  - Training: learn model parameters.
  - Test: apply model for rating prediction or top-N recommendation.
- Cold-start problem

  Cannot deal with new users / users with few ratings.

Recommendation

- Observed ratings R_{ui} are governed by latent variables (factors) of users and items.
- Latent factors for users

$$U \in \mathbb{R}^{K \times N}$$

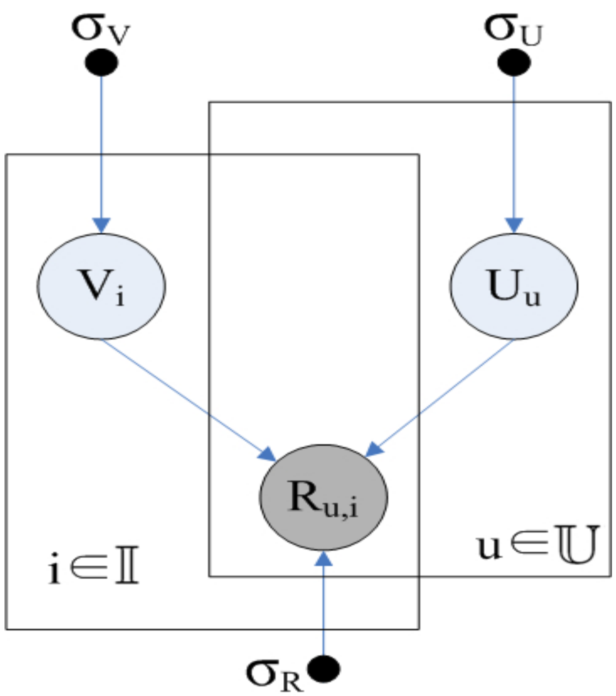
- Latent factors for items

$$V \in \mathbb{R}^{K \times M}$$

- User item ratings

$$p(R|U,V,\sigma_R^2) = \prod_{u=1}^{N} \prod_{i=1}^{M} \left[\mathcal{N}\left(R_{u,i}|g(U_u^T V_i), \sigma_r^2\right)\right]^{I_{u,i}^R}$$

g: logistic function, σ_u, σ_V , σ_R : normal priors



Matrix factorization

- Motivation for social network-based recommendation:
  - social influence, selection, and other effects
  - can deal with cold-start users,
    as long as they are connected to the social network.
- Memory-based approach
  MoleTrust,
  TrustWalker, . . .
- Model-based approach
  Matrix factorization (MF)

Recommendation in social networks: a matrix factorization approach

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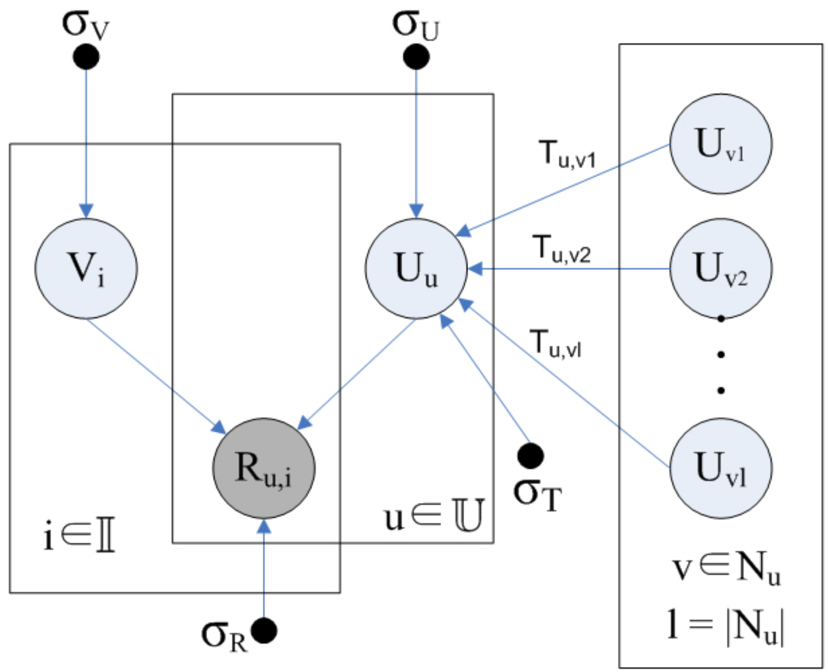
- Social correlation
  behavior of a user u *is* correlated with that of his direct neighbors N_u.
- Latent factors of a user depend on those of his neighbors.

$$\widehat{U}_u = \sum_{v \in N_u} T_{u,v} U_v$$

- $T_{u,v}$ is the normalized trust value.
- Trust propagation to indirect neighbors.

Recommendation in social networks: a matrix factorization approach



$$\sum_{all\ observed\,(u,i)} (R_{ui} - \hat{R}_{ui})^2 + \lambda(\|U\|^2 + \|V\|^2)$$

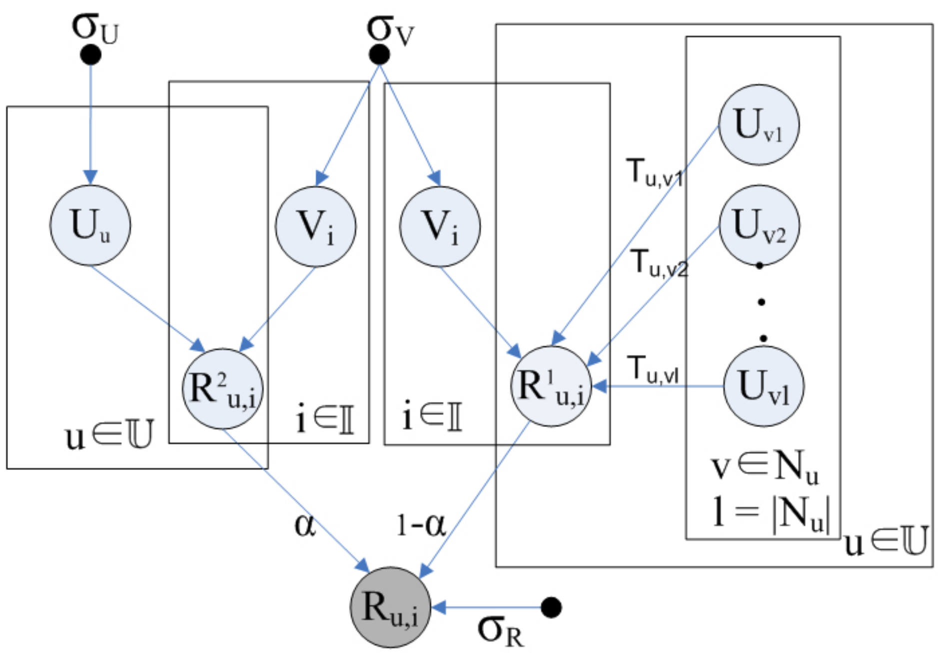
$$+\beta(\sum_{u}((U_u - \sum_{v} T_{u,v}U_v)(U_u - \sum_{v} T_{u,v}U_v)^T)$$

Recommendation in social networks: a matrix factorization approach

- Comparison partners:
  - CF
  - Baseline MF
  - STE (Social Trust Ensemble) [Ma et al. 2009]
  - SocialMF (our method)
- Datasets:
  - Epinions
  - Flixster
- Number *k* of factors:
  - 5 or 10

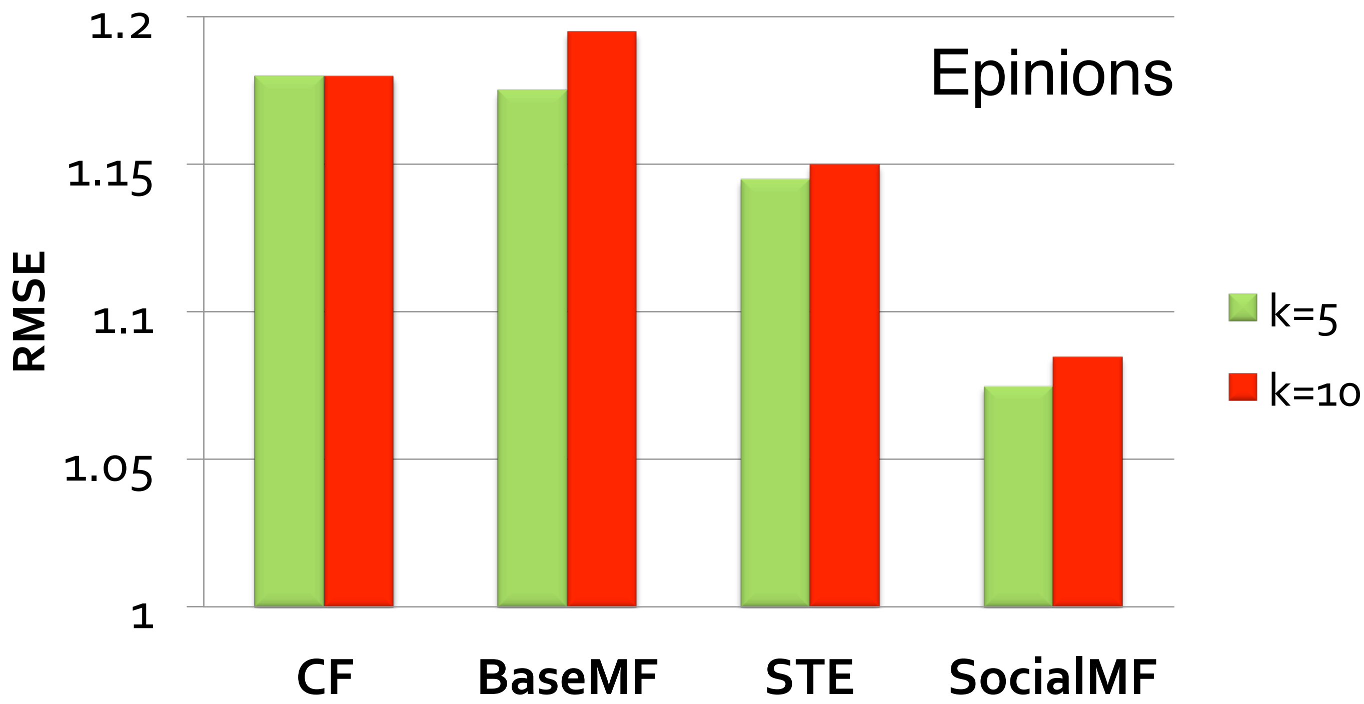
Recommendation in social networks: a matrix factorization approach

STE



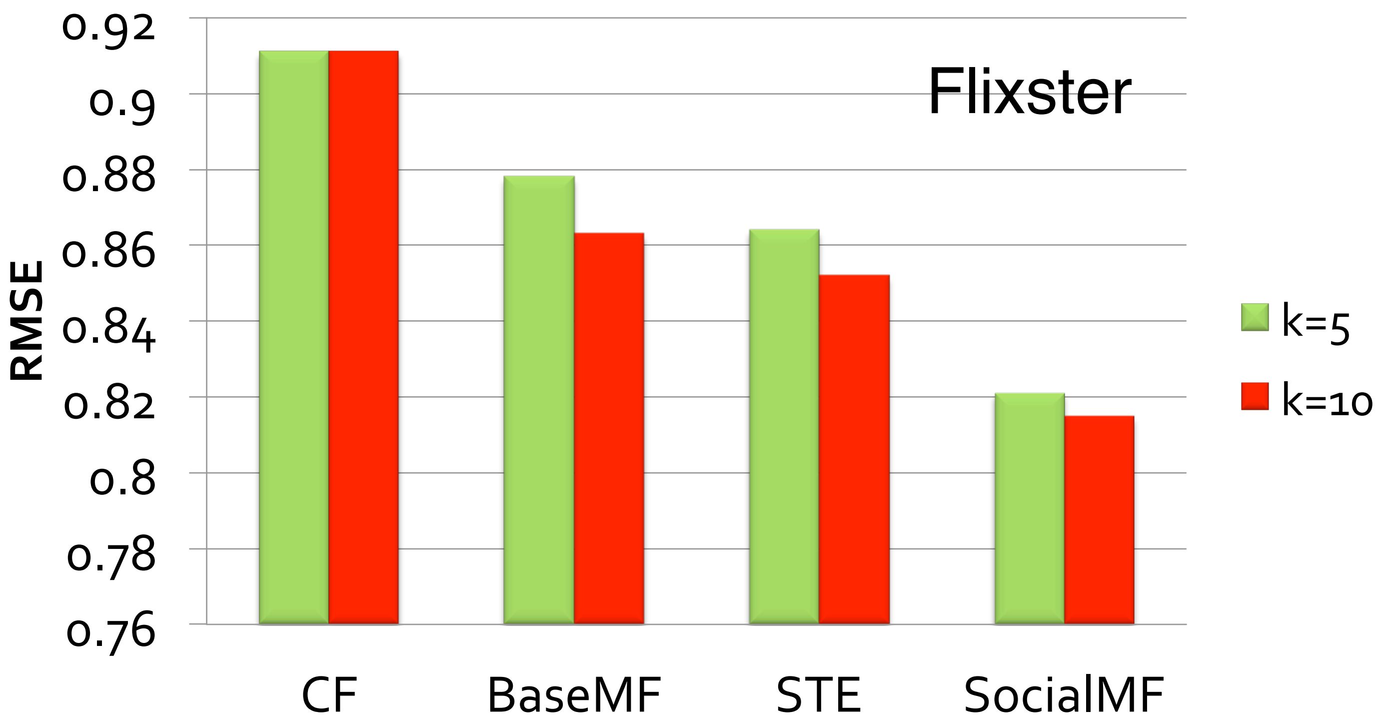
$$\hat{R}_{u,i} = \alpha U_u^T V_i + (1-\alpha) \sum_{v \in N_u} T_{u,v} U_v^T V_i$$

Recommendation in social networks: a matrix factorization approach



- Gain over STE: 6.2%. for K=5 and 5.7% for K=10

Recommendation in social networks: a matrix factorization approach



- SocialMF gain over STE (5%) is 3 times the STE gain over BasicMF (1.5%)

Recommendation in social networks: a matrix factorization approach

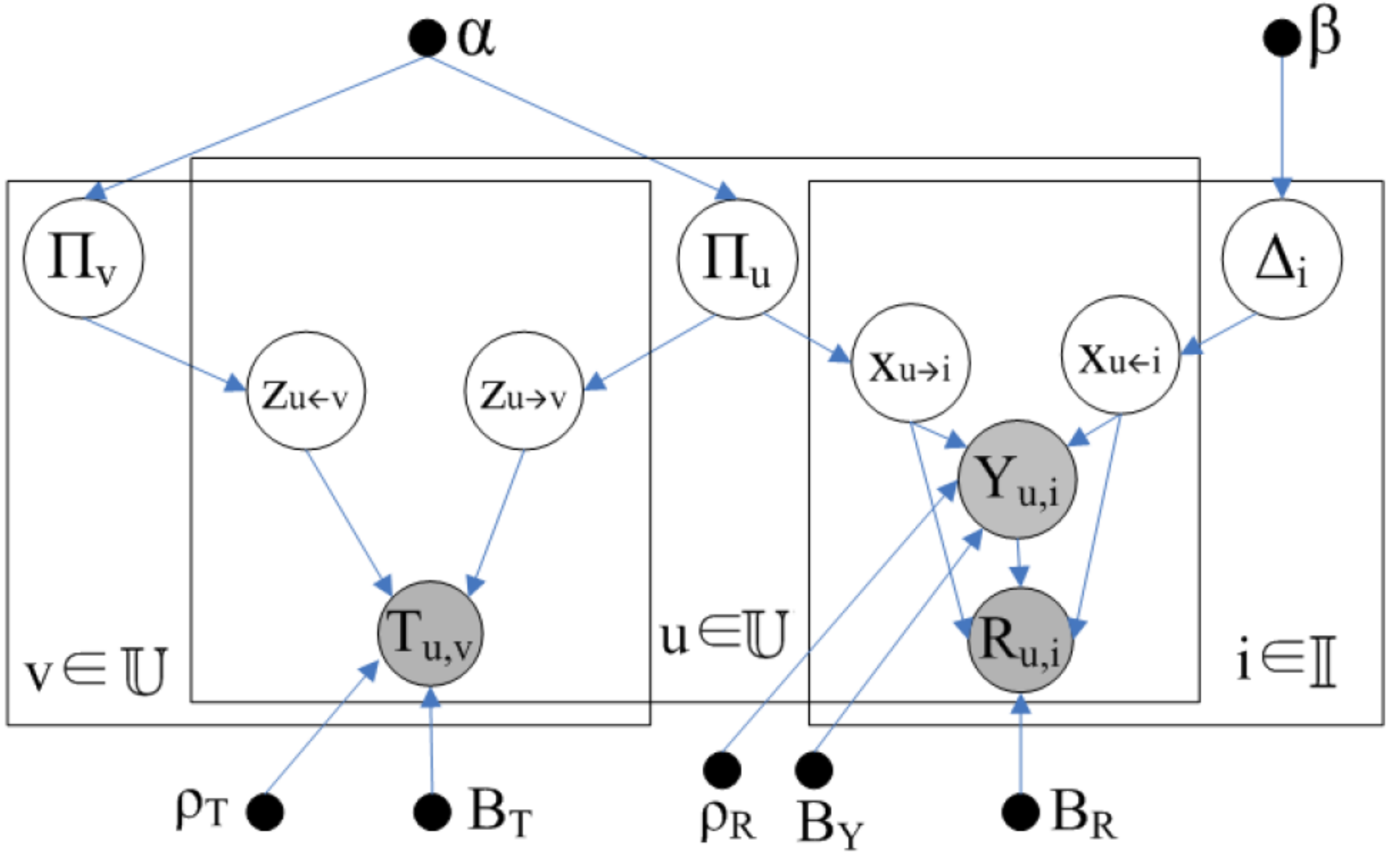
- Social influence and selection happen simultaneously.
- Leads to formation of communities/clusters.
- Users within a cluster have similar patterns of actions.
- Users may belong to different clusters for different types of actions.

→ Clustering-based method for recommendation

Recommendation in social networks: a generalized stochastic block model

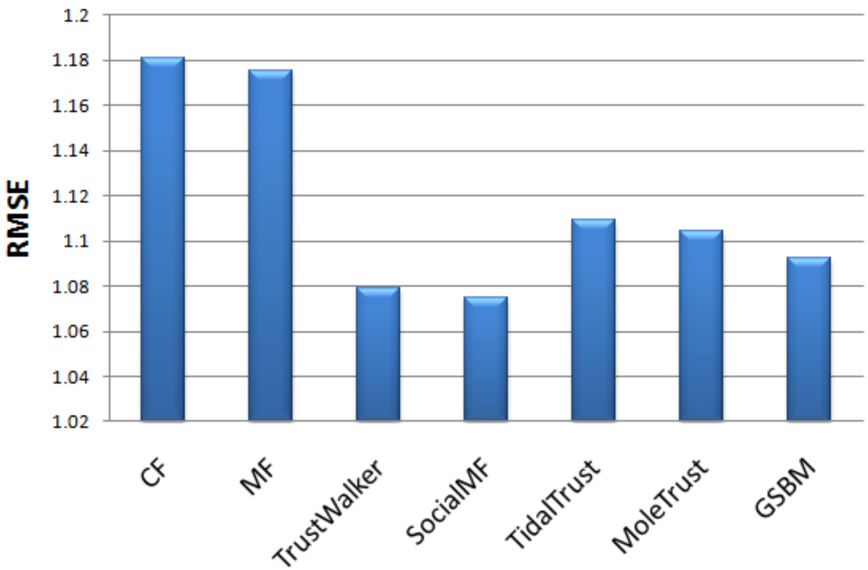
- We extend the mixed membership stochastic block model [Airoldi et al. 2008].
- In each action, users probabilistically act as a member of one of the latent clusters.
- Every item is considered to belong to a latent cluster when it is being rated.
- The relationships between users and items are governed by the relationships between clusters.

Recommendation in social networks: a generalized stochastic block model

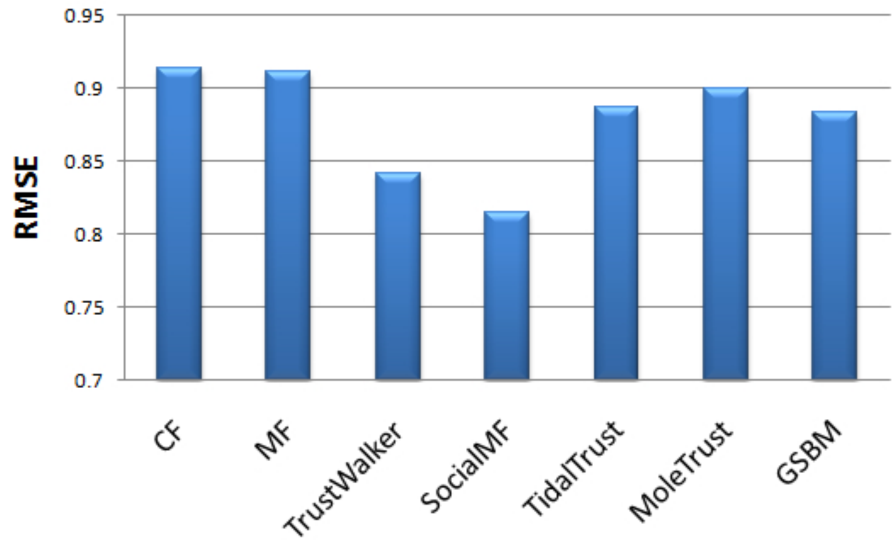


Recommendation in social networks: a generalized stochastic block model

Rating prediction



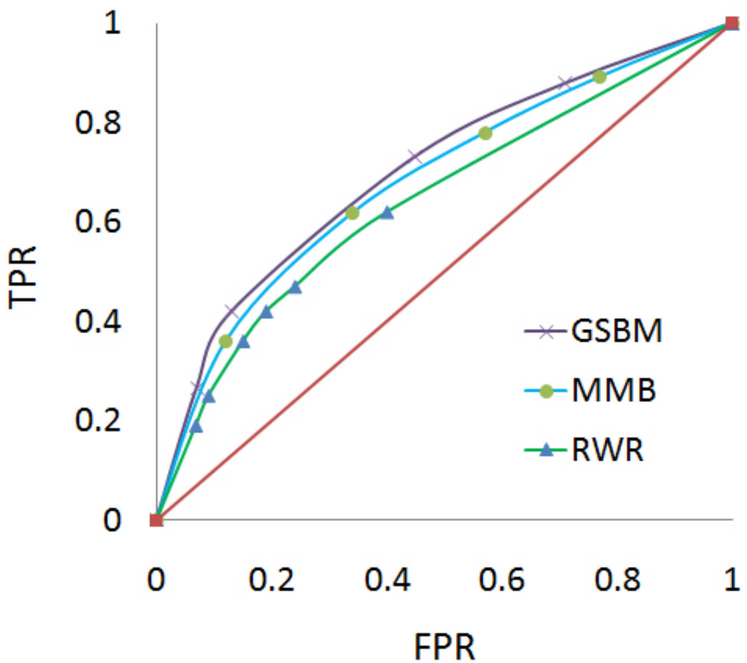
Epinions



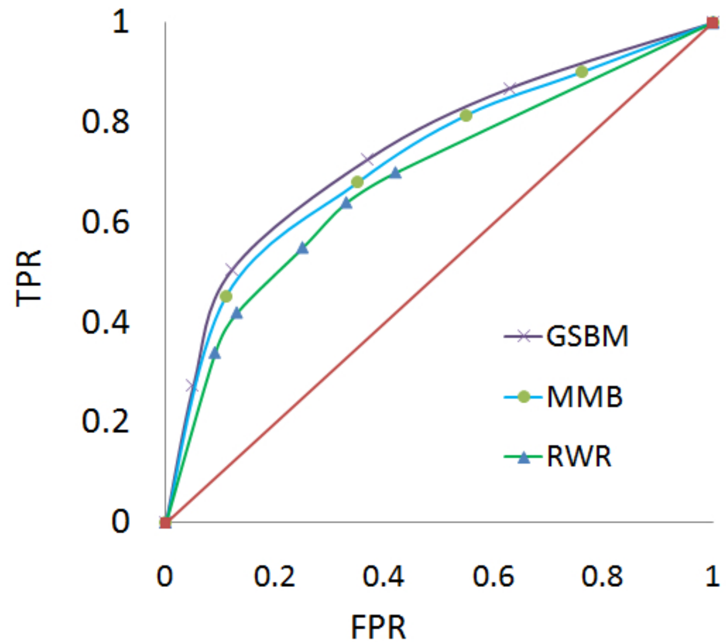
Flixster

Recommendation in social networks: a generalized stochastic block model

Link prediction



Epinions



Flixster

Recommendation in social networks: a generalized stochastic block model

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- Location-based social network (LBSN)
  online social network, where users check in at locations (points of interest).
- Check-in:
  User: @XXX
  Time: 2012-04-23 12:04:09
  Coordinates: 40.7244 -74.0020
  Location: a825251e7c560c1e
  →unique id = store, restaurant, mall, school, . . .
  (Post:
  Close to the equator, perfect soil and high elevation make @CafeD produce the perfect cup of Coffee!! #Honduras!)
- Examples: Twitter, Foursquare, Gowalla, Yelp,. . .

Location-based social networks

- LBSNs bridge the gap between the online world and the physical world.
- Two types of user actions:
  (1) social actions,
  (2) check-in actions: user links to location.
- Locality of users
  Users tend to visit locations close to their activity space (home, work, . . .).
- Interests of users
  Users tend to visit locations that match their interests (posts).

Location-based social networks

- Geographical influence
  Nearby locations have similar check-in probabilities.
- Multinomial distribution does not capture it.
- Use Gaussian distribution.

Location-based social networks

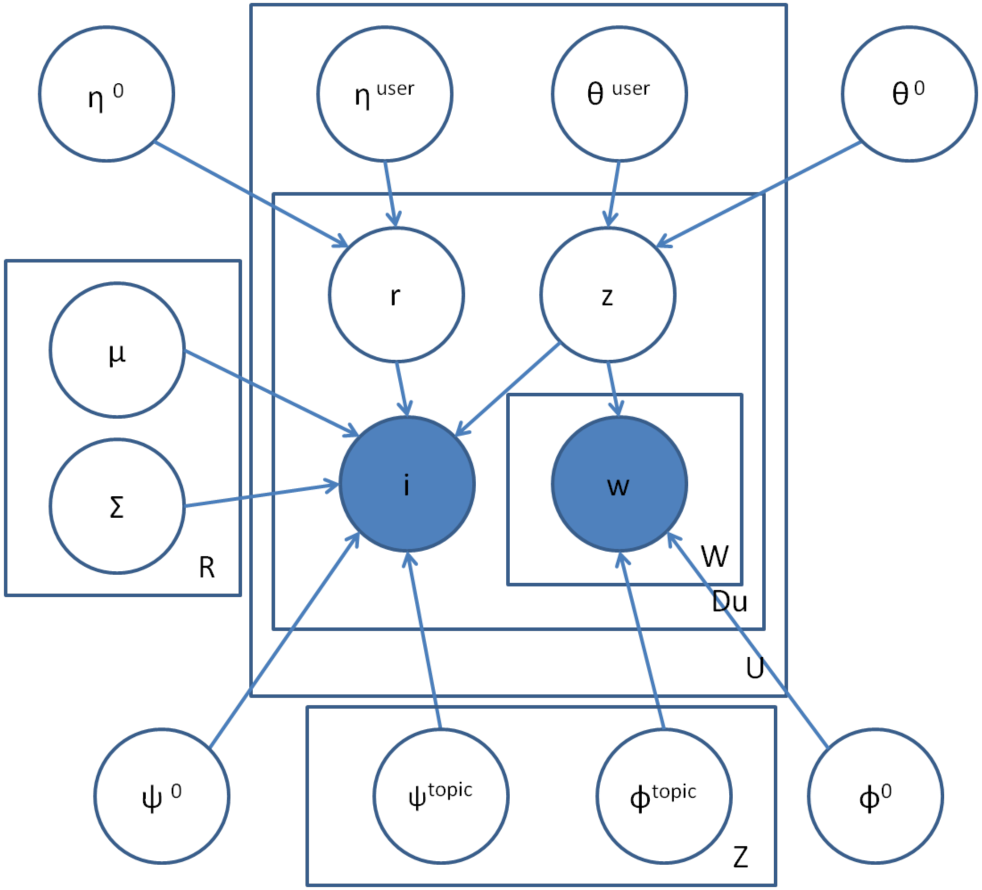
- Text-based location recommendation
  - Given user u and post (query) $\{w\}$.
  - Rank the locations i w.r.t. the probability $p_{u,i}$ of u visiting i.
- Time-based location recommendation
  - Given user u and time t.
  - Rank the locations i w.r.t. the probability $p_{u,i}$ of u visiting i.

Location recommendation

- Probabilistic Graphical Model
- Observed variables: locations and words.
- Latent variables:
  - regions with (Gaussian) coordinate distributions,
  - topics with (multinomial) location distributions and word distributions.
- Users associated with region distribution and topic distribution.
- Check-in location depends on
  - region of user,
  - topic (interest) of user.

Spatial Topic Model

Spatial Topic Model (ST)



Spatial Topic Model

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To generate a check-in:

– Sample a region
  User + global region distribution
– Sample a topic
  User + global topic distribution
– Sample the words
  Word distribution + global word distribution
– Sample the location
  Topic's multinomial distribution
  + region's 2D Gaussian distribution

Spatial Topic Model

- Sparse coding
- Multiple factors
  - No “switch” variable
  - Model the log-frequency difference from the global distribution
- E.g., for word distributions
  - A global word distribution
  - Topic word distribution (sparse)

Spatial Topic Model

- Parameter learning
- P(w,i|ϴ) hard to be maximized
- Maximize P(z,r,w,i|ϴ)
- Monte Carlo EM
  - E step: sample z and r
  - M step: learn ϴ that maximizes P(z,r,w,i|ϴ)
- PSSG (Projected Scaled Sub Gradient)
  [Schmidt et al., AAAI 2007]
  Quasi-Newton with L1 regularization

Spatial Topic Model

Experimental design

- Data split

  For each user, 70% check-ins for training, 30% for test

- Recommendation task

  given user and post

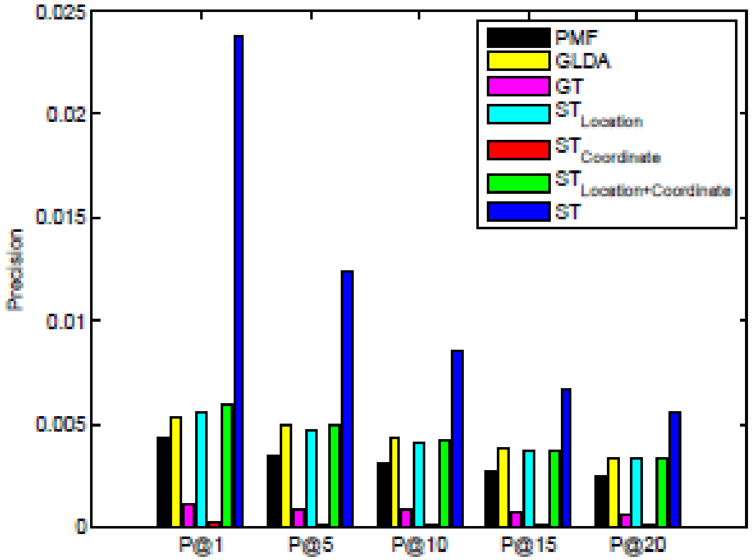
- Evaluation metric: precision@N

– top N locations are recommended by the model

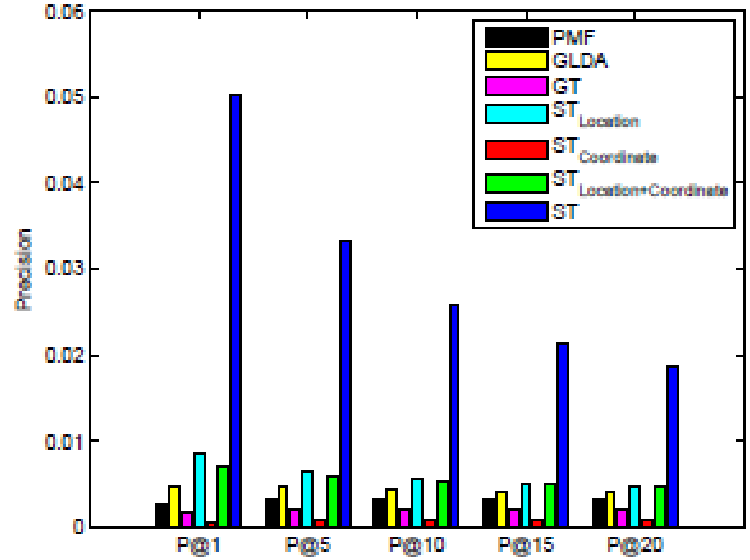
– for each test check-in: if the ground truth location is among the recommended N locations:1/N, otherwise: 0

Spatial Topic Model

Experimental results



(a) Twitter data set.



(b) Yelp data set.

Spatial Topic Model

- Why does ST outperform the comparison partners?
- Compared to PMF and GLDA
  - ST also models the text, PMF/GLDA only the location.
    - Use topics to connect users and locations.
- Compared to GT
  - ST models the location (POI), GT only the coordinates.
    - GT only predicts the approximate area, not the exact location.

Spatial Topic Model

- Check-in location also depends on time,
  in particular on the relative time,
  i.e. hour of the day or weekday.
- Discrete time
  1-24 (hour)
  or 1-7 (weekday).
- Check-in location depends on
  - region of user and coordinates of location,
  - topic (interests) of user, and
  - time.

Spatio-Temporal Topic Model

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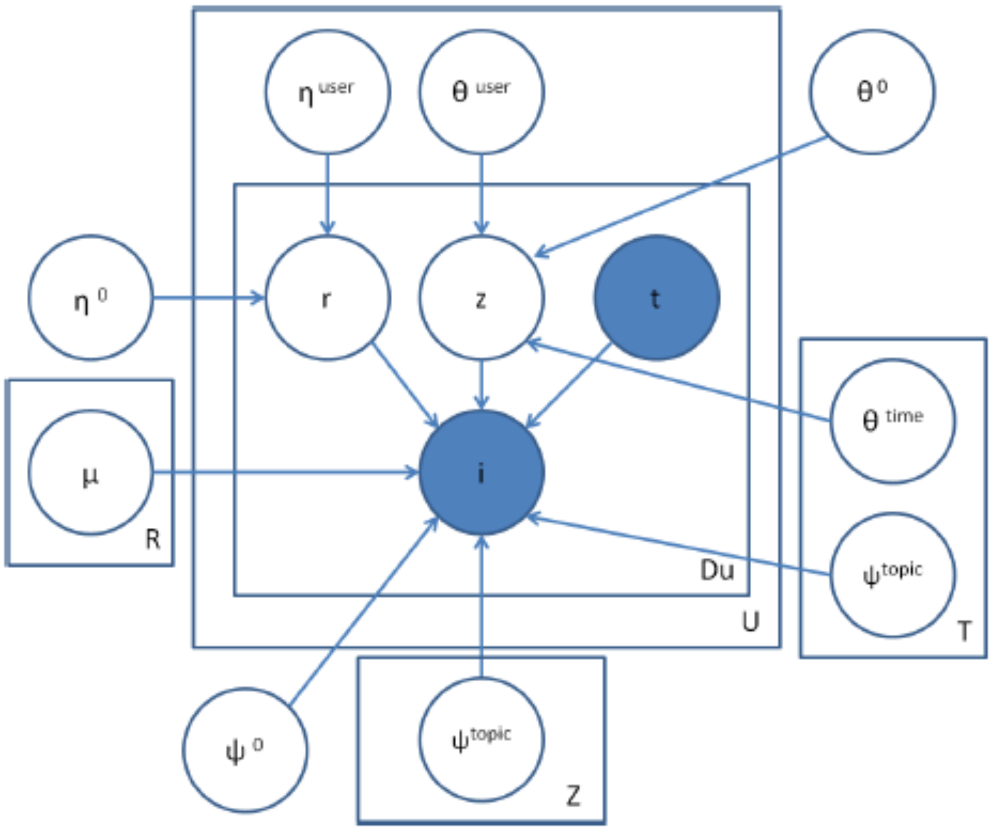
Spatio-Temporal
Topic Model
(STT)



Spatio-Temporal Topic Model

Experimental design

- Data split
  For each user, 70% check-ins for training, 30% for test
- Recommendation task
  given user and time
- Evaluation metric: accuracy@N

– top N locations are recommended by the model
– for each test check-in: if the ground truth location is among the recommended N locations: 1, otherwise: 0

Spatio-Temporal Topic Model

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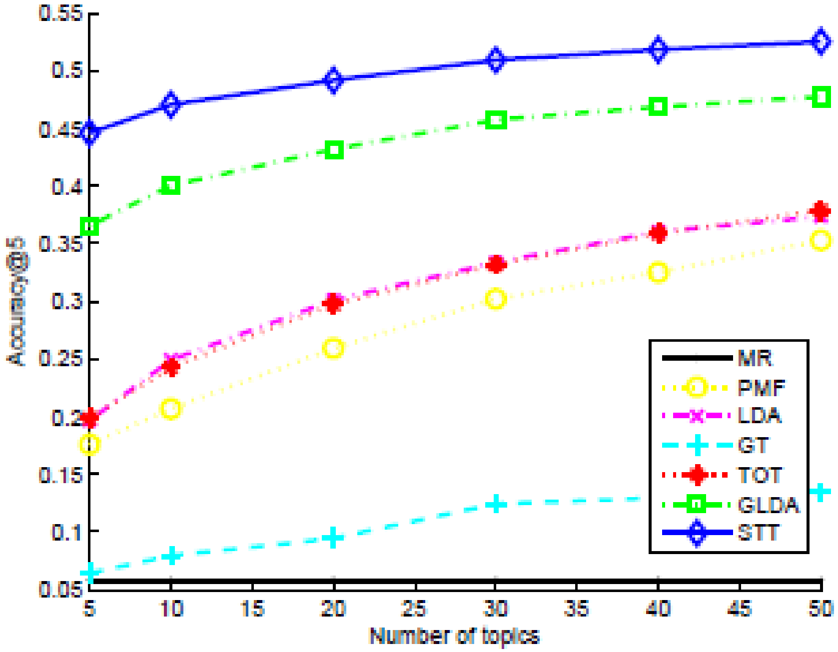
Experimental results



Spatio-Temporal Topic Model

- Why does STT outperform the comparison partners?
- GLDA
  Does not model the time.
- TOT
  Does not model the location.
- LDA
  Does not model the time, does not model geographic distances.
- GT
  Does not model locations, only coordinates.

Spatio-Temporal Topic Model

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Future Work

- Inference of latent edge weights
  from observed user interactions
- Recommendation in heterogeneous social networks
  multiple node types
- Explanation of social recommendations
  persuasiveness and informativeness
- Recommendation with trust and distrust information
- Privacy-preserving recommendation in social networks
- Analysis of co-offender networks
  prediction of co-offenders in a crime,
  prediction of crime locations

Martin Ester: Recommendation in Social Networks, Tutorial at RecSys 2013

Mohsen Jamali, Martin Ester: A matrix factorization technique with trust propagation for recommendation in social networks, RecSys 2010.

Mohsen Jamali, Tianle Huang, Martin Ester: A generalized stochastic block model for recommendation in social rating networks, RecSys 2011.

Bo Hu, Martin Ester: Spatial topic modeling in online social media for location recommendation, RecSys 2013

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References