

Dynamic Poisson Factorization

Laurent Charlin

Joint work with: Rajesh Ranganath, James McInerney, David M. Blei
McGill & Columbia University

Presented at RecSys 2015



Learning

Authors and titles for recent submissions

- [Mon, 25 Aug 2014](#)
- [Fri, 22 Aug 2014](#)
- [Thu, 21 Aug 2014](#)
- [Tue, 19 Aug 2014](#)
- [Mon, 18 Aug 2014](#)

[total of 21 entries: 1-21]

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Mon, 25 Aug 2014

[1] [arXiv:1408.5389](#) [[pdf](#), [other](#)]

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[Zhensong Qian](#), [Oliver Schulte](#), [Yan Sun](#)

Comments: 11pages, 8 figures, 8 tables, CIKM'14, November 3--7, 2014, Shanghai, China

Subjects: **Learning (cs.LG)**; Databases (cs.DB)

[2] [arXiv:1408.5246](#) [[pdf](#)]

Improving the Interpretability of Support Vector Machines-based Fuzzy Rules

[Duc-Hien Nguyen](#), [Manh-Thanh Le](#)

Comments: 8 pages, 2 figures

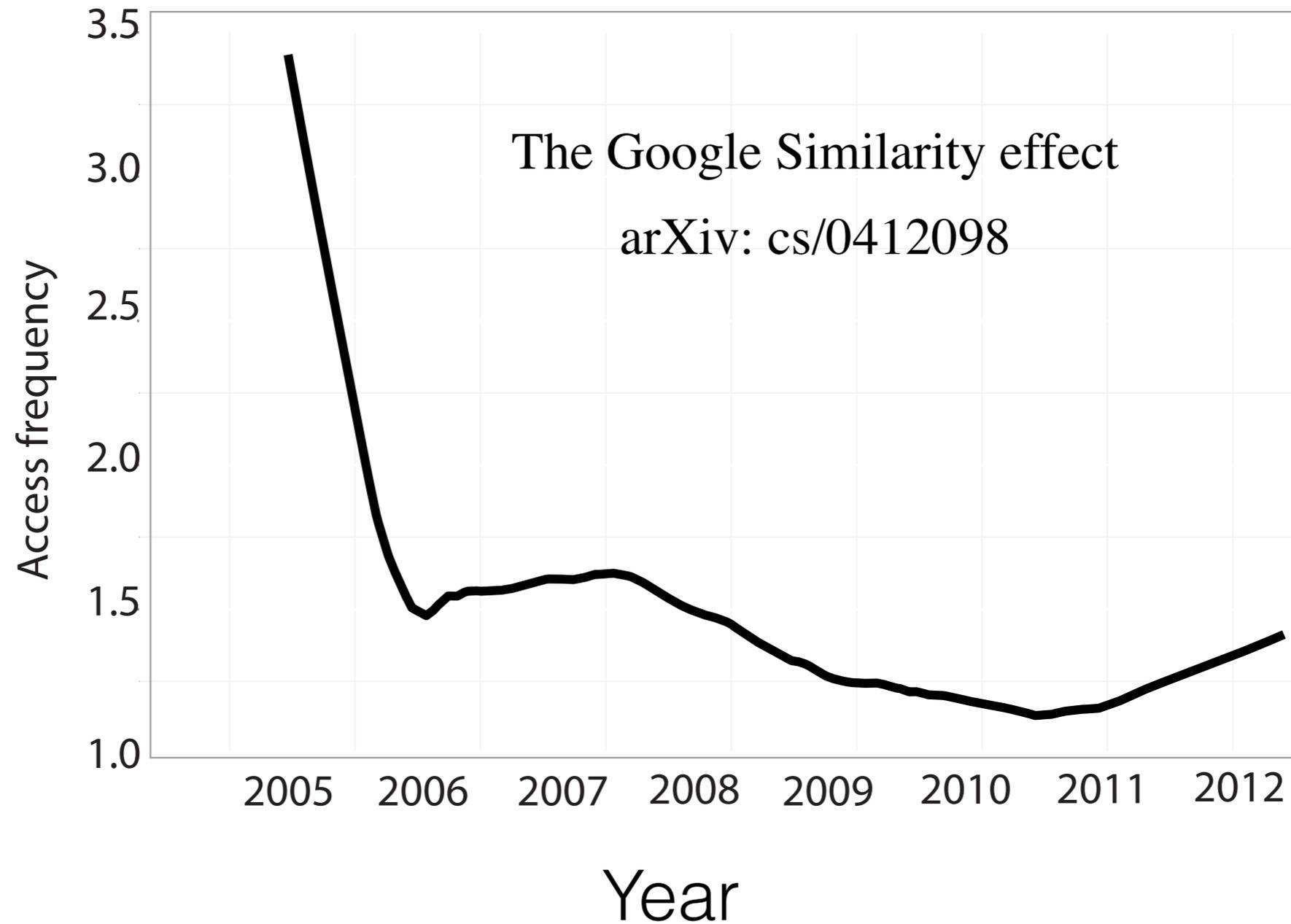
Subjects: **Learning (cs.LG)**; Artificial Intelligence (cs.AI)

[3] [arXiv:1408.5352](#) (cross-list from stat.ML) [[pdf](#), [other](#)]

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Click Data for a paper

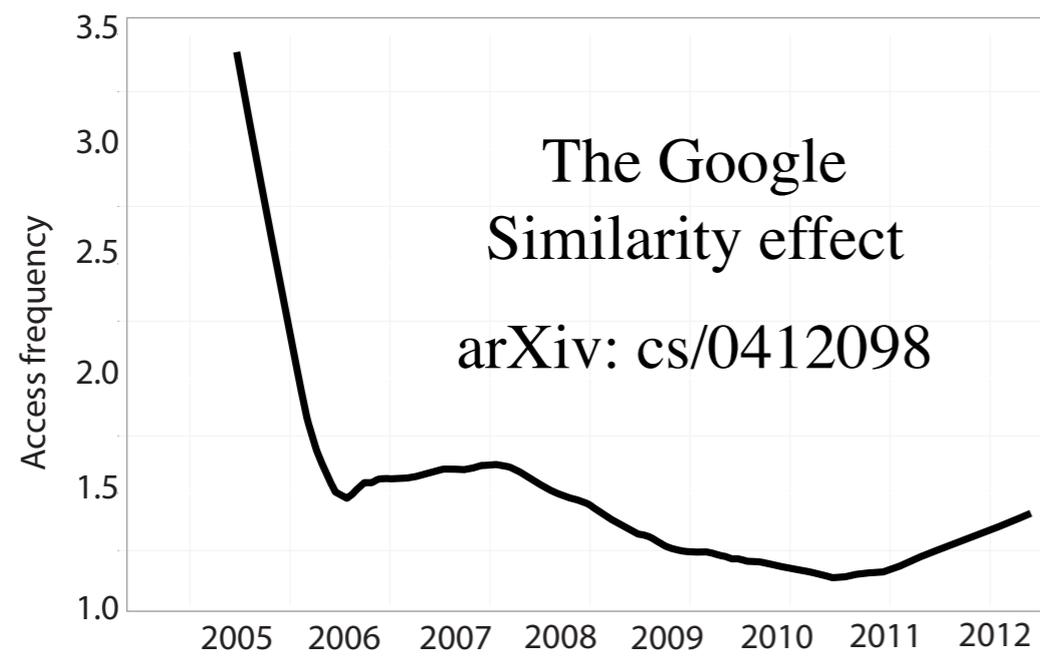


arXiv evolves over time

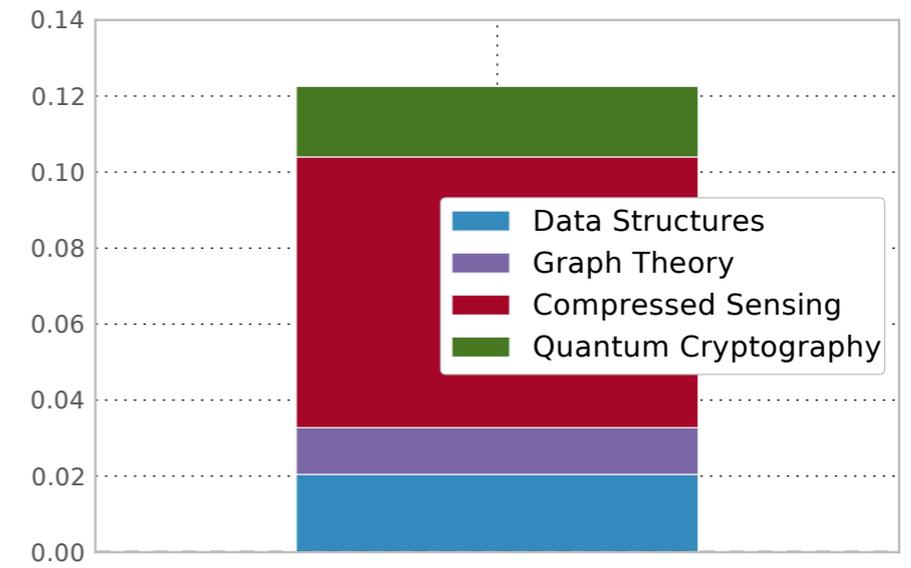
- Click data evolves over time
 - Popularity of papers change over time
 - Users' interests change over time
- The same is also true of other datasets

Recommendations should evolve over time

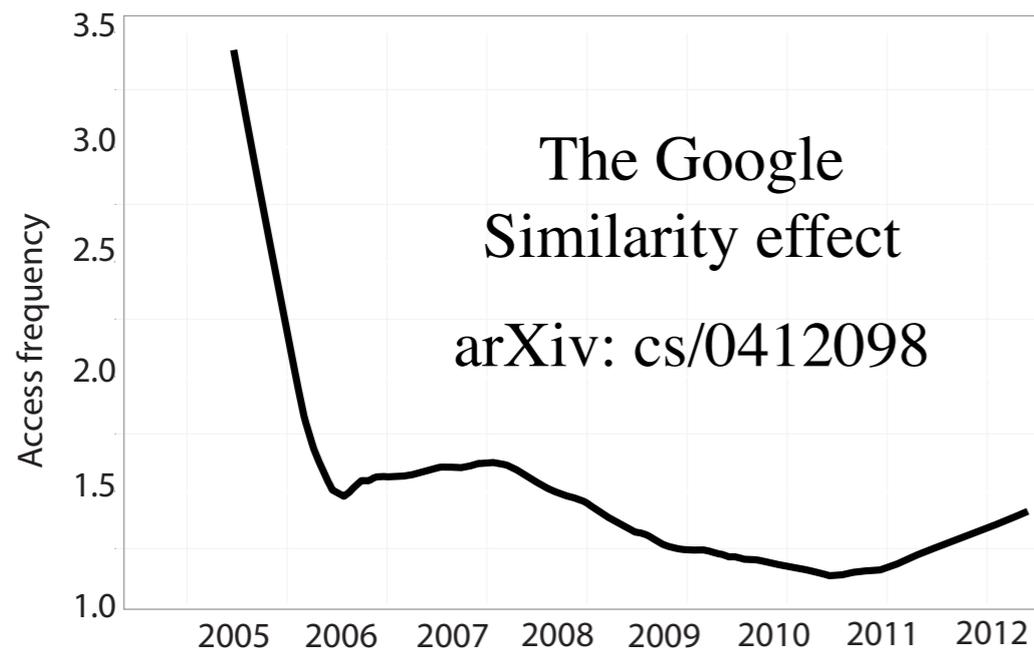
Raw Data



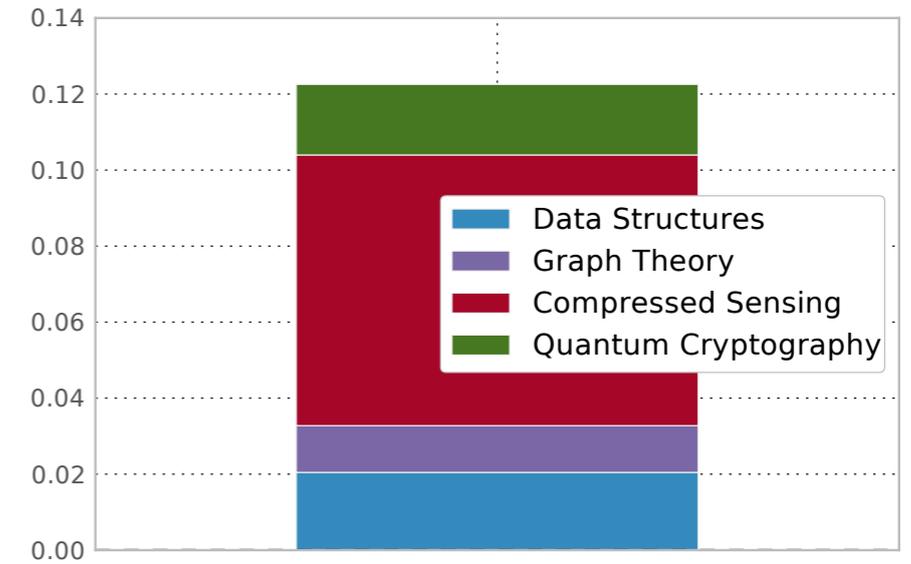
Modeled Data (e.g., Matrix Factorization)



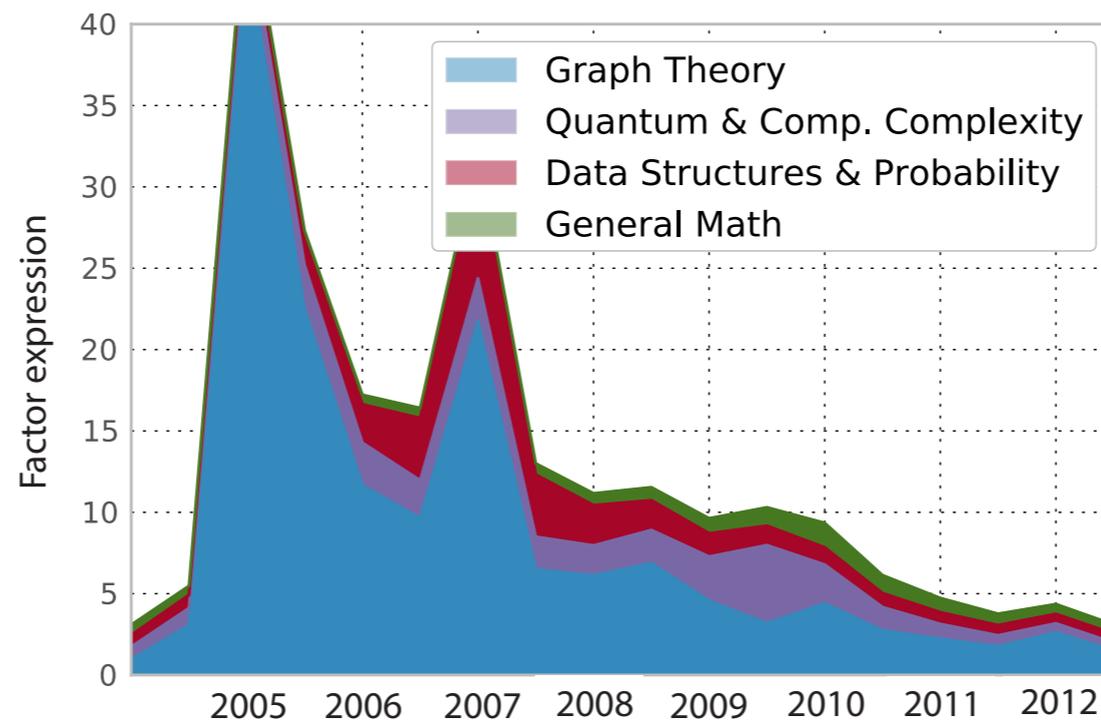
Raw Data



Modeled Data (e.g., Matrix Factorization)



Time-aware Modeled Data



Objectives

- Understand click data over time
 - Better predictions of future user interests
 - Explore how (large) datasets evolve over time
- Motivated by the arXiv
 - Study other datasets

Technical approach

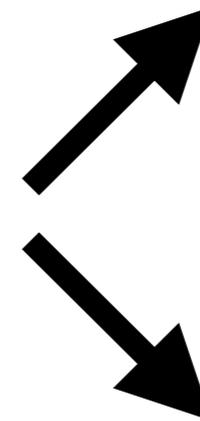
- Dynamic model of user preferences
 - Poisson matrix factorization [Gopalan et al. UAI'15]
 - User and item latent factors evolve over time
 - Develop inference procedure
- Fit this model using data
- Explore fits

Data
(e.g., clicks)



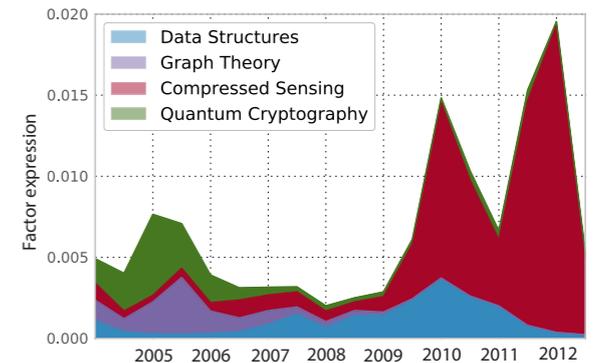
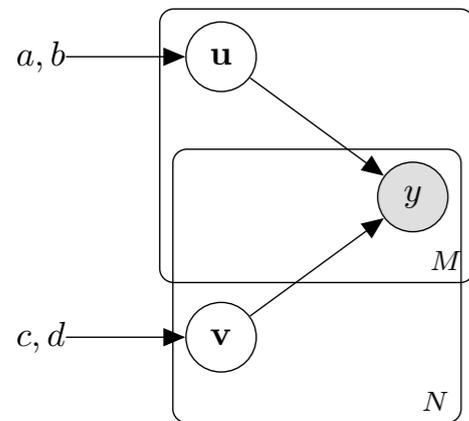
Learning & Inference

Recommendations



Exploration
(latent factors)

Generative Model



Background

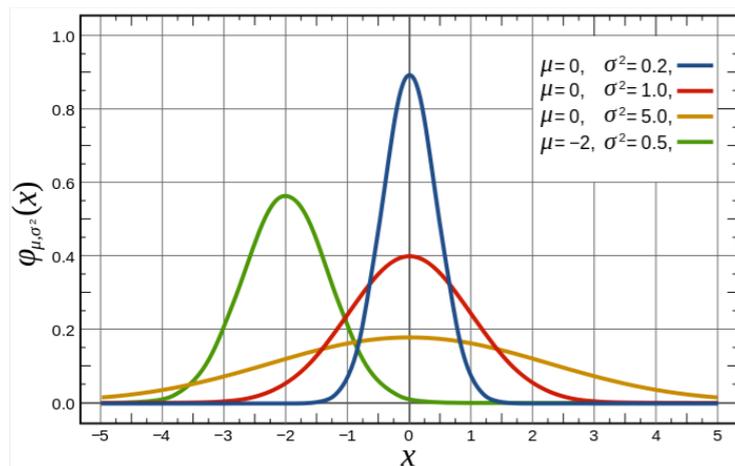
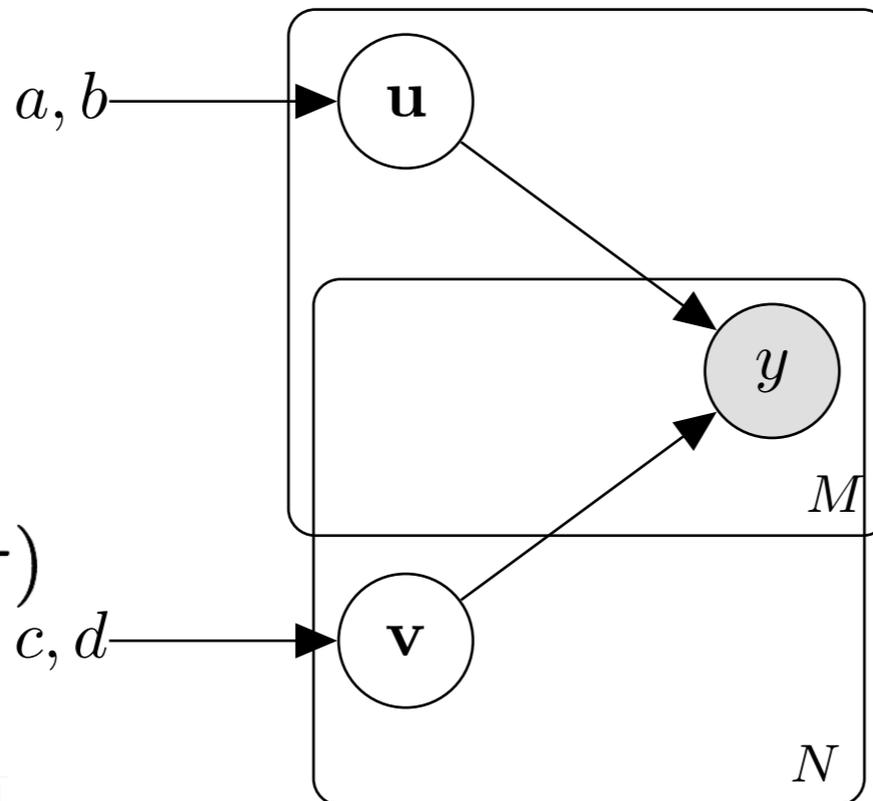
Gaussian Matrix Factorization

[Salakhutdinov et al. '15]

$$\mathbf{u}_m \sim \mathcal{N}(a, b)$$

$$\mathbf{v}_n \sim \mathcal{N}(c, d)$$

$$y_{mn} \sim \mathcal{N}(u_m^\top v_n, \sigma)$$



[wikipedia]

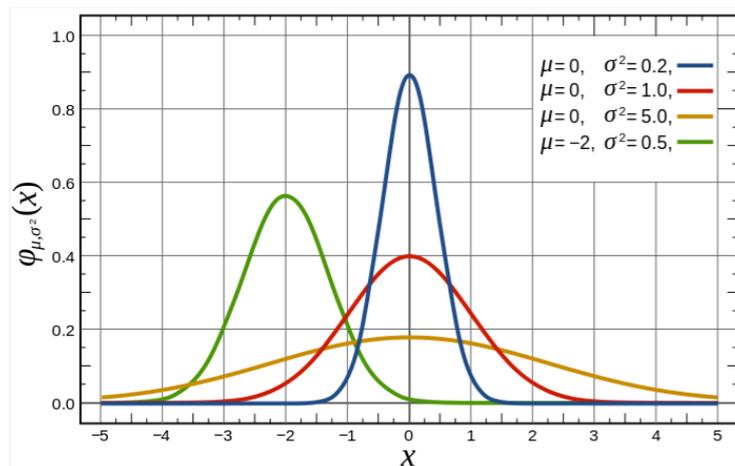
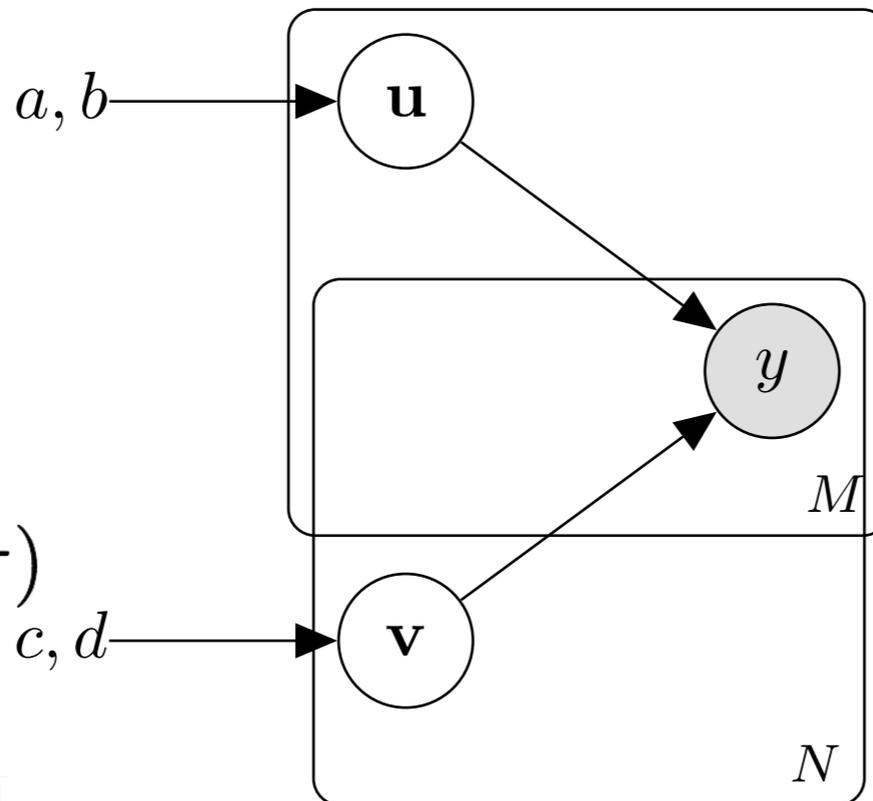
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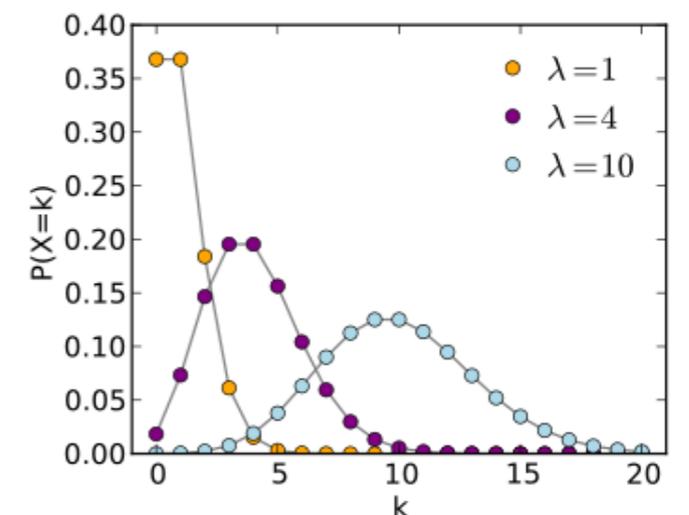
Poisson Matrix Factorization (PF)

[Gopalan et al. '15]

$$\mathbf{u}_m \sim \text{Gamma}(a, b)$$

$$\mathbf{v}_n \sim \text{Gamma}(c, d)$$

$$y_{mn} \sim \text{Poisson}(u_m^\top v_n)$$

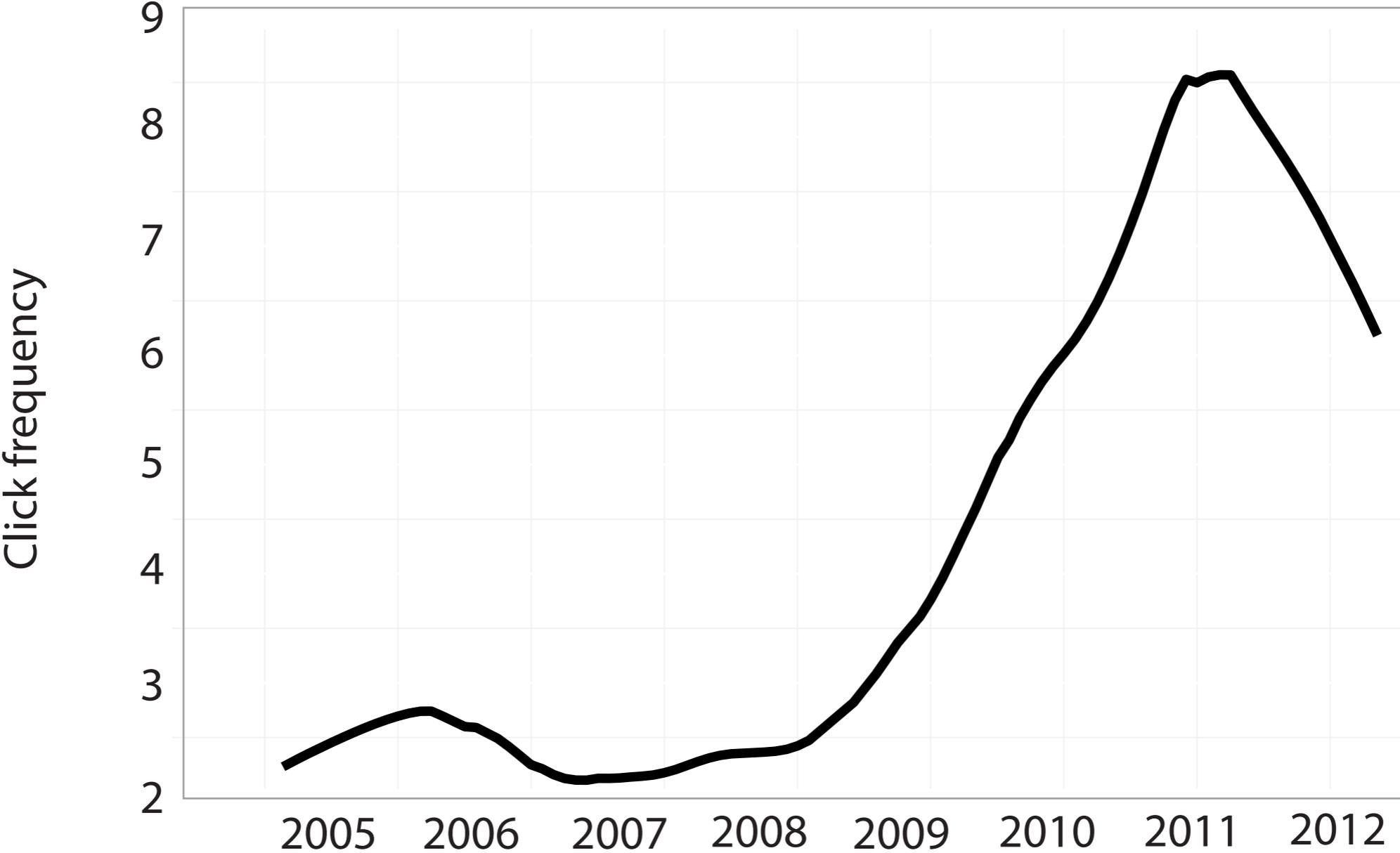


[wikipedia]

Properties of PF

- Suitable for implicit and explicit data
- Model can be fit to massive datasets

User 755



Dynamic Poisson factorization

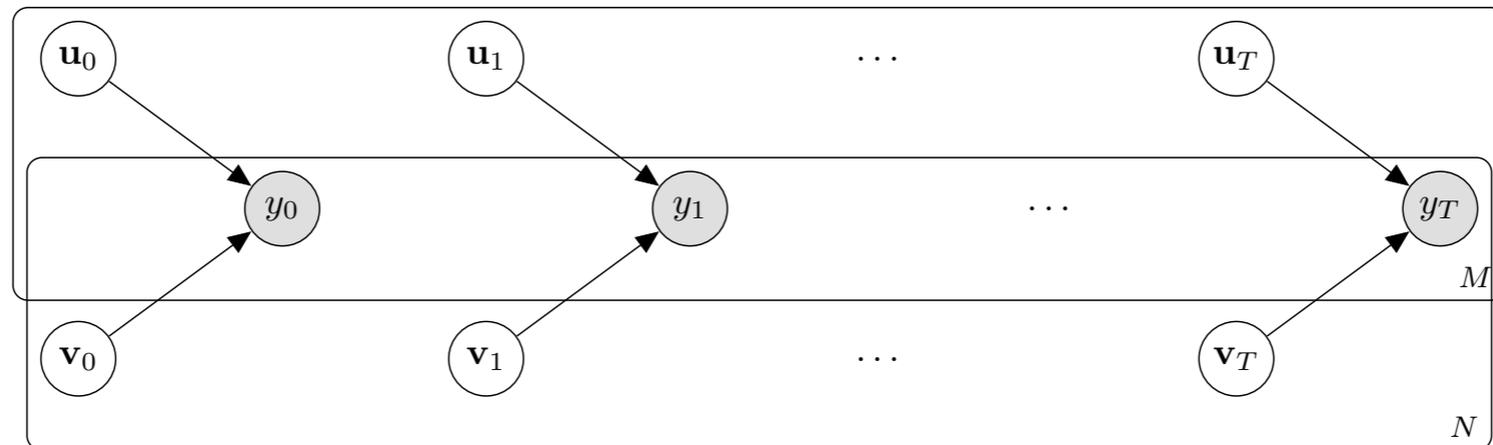
- Users' preferences evolve over time
 - Item popularity evolves over time
- ➔ Ratings are not exchangeable over time

Dynamic Matrix Factorization (DPF)

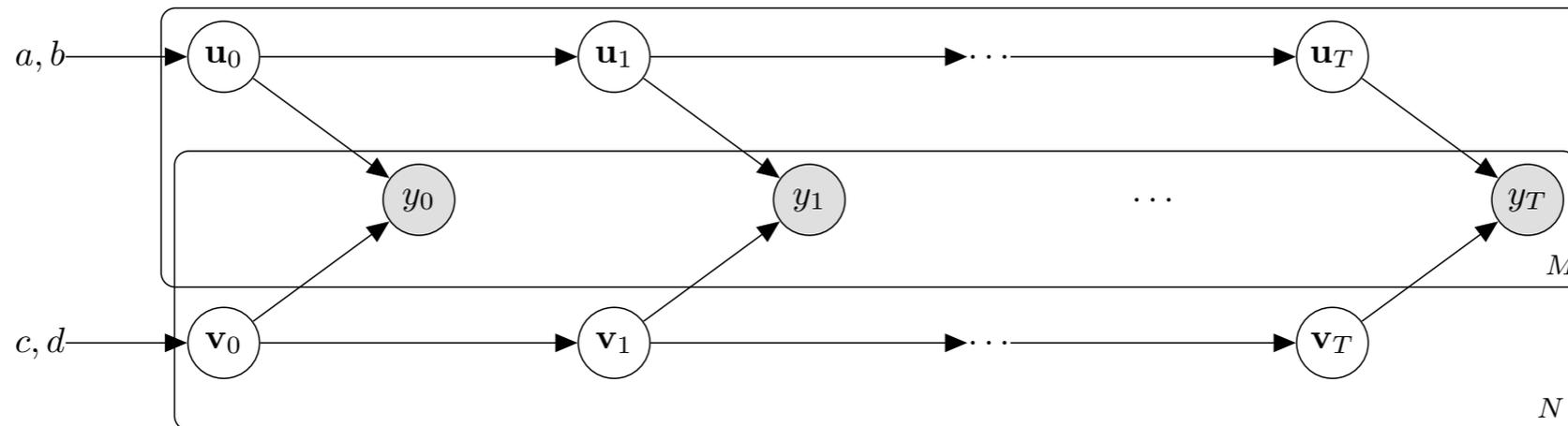
Dynamic Matrix Factorization (DPF)



Dynamic Matrix Factorization (DPMF)



Dynamic Matrix Factorization (DPMF)



- Modeling: Smooth evolution through time

Smooth Evolution through time

- Gaussian time series model

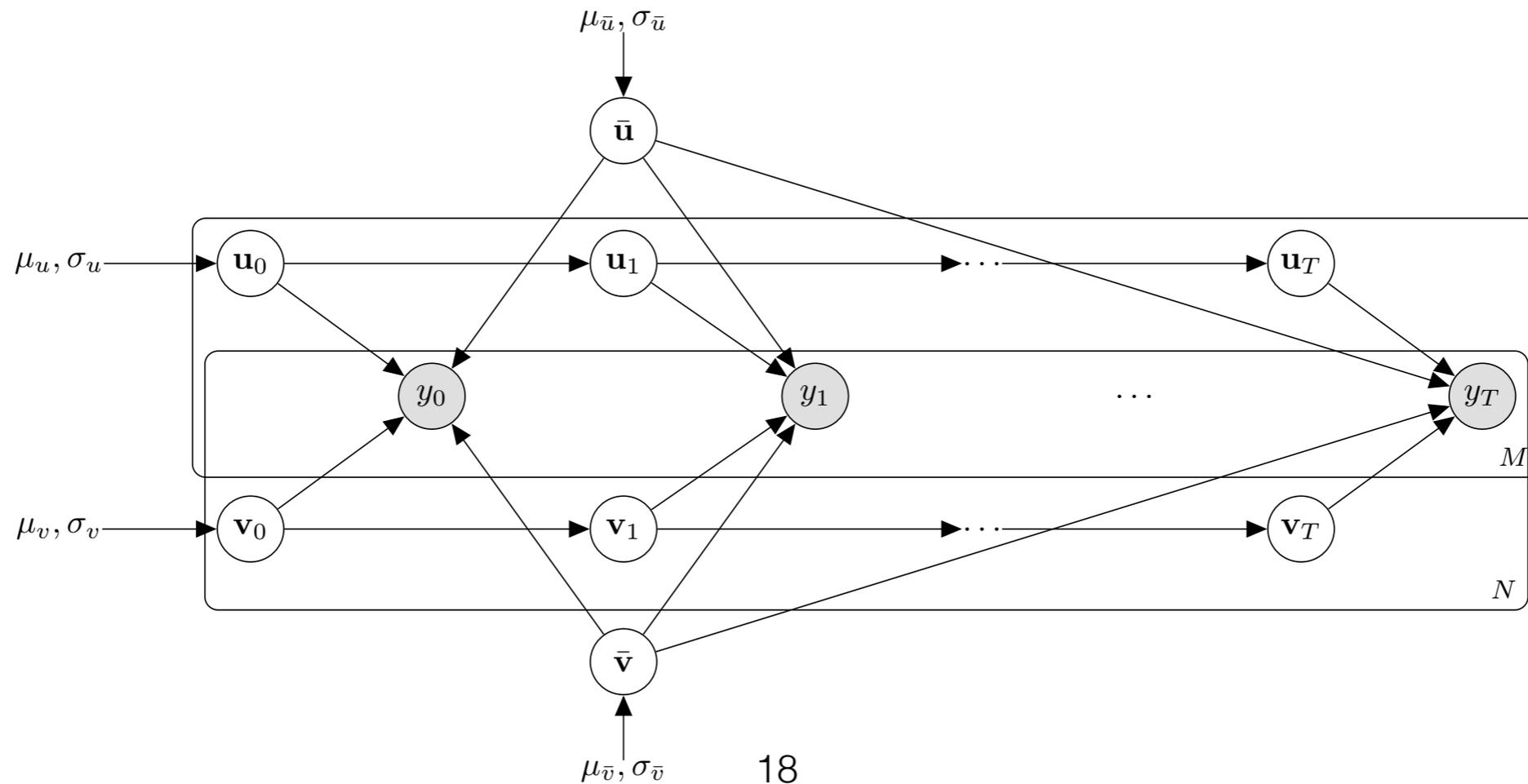
$$\mathbf{u}_{m,t} \mid \mathbf{u}_{m,t-1} \sim \mathcal{N}(\mathbf{u}_{m,t-1}, \sigma_u^2 I)$$

- Exponentiate to obtain positive Poisson rates

$$y_{mn,t} \sim \text{Poisson} \left(\sum_{k=1}^K e^{u_{mk,t}} e^{v_{nk,t}} \right)$$

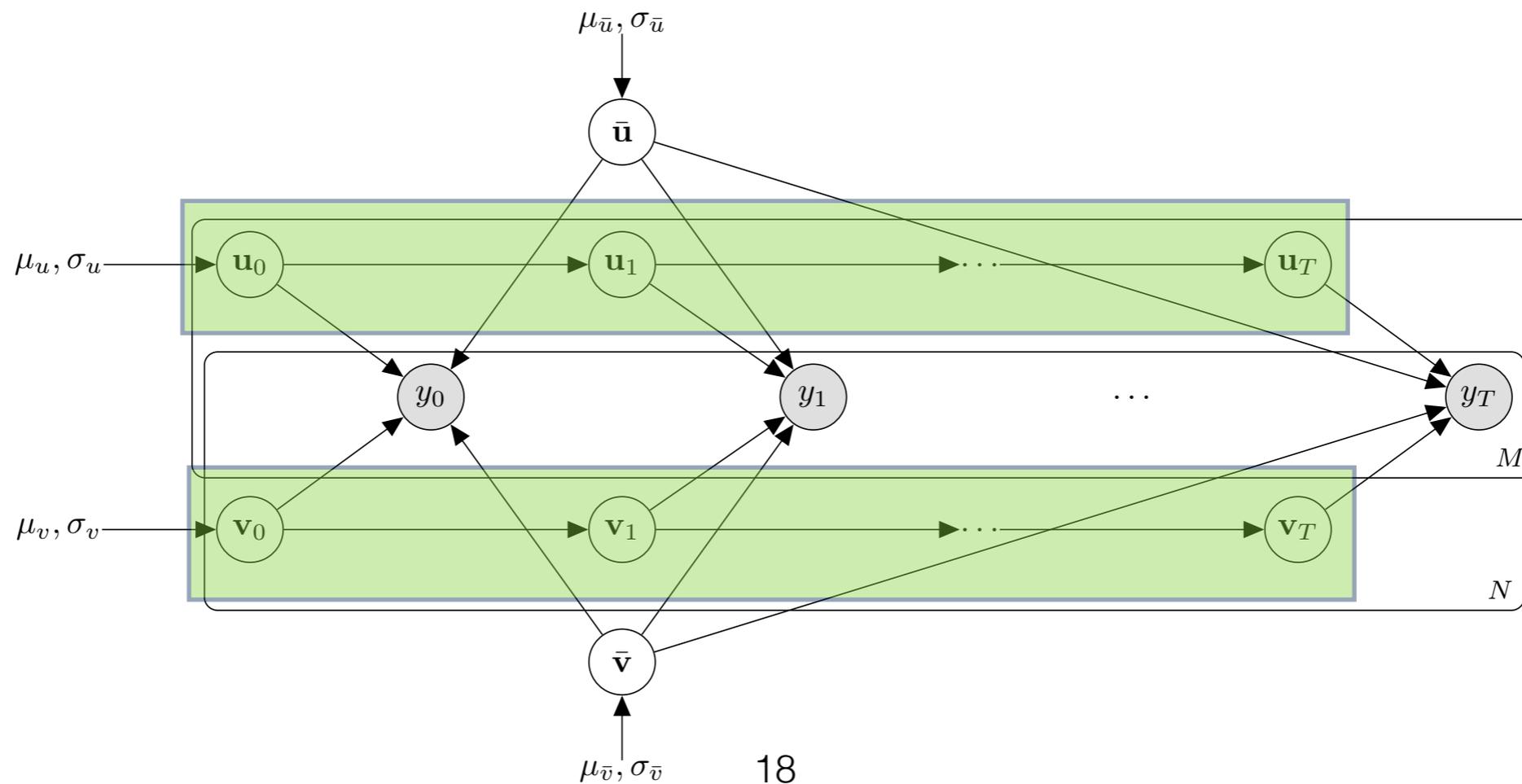
Local and Global factors

- Two levels of modeling:
 - **Local factors:** model evolution through time
 - **Global factors:** model constant preferences wrt time



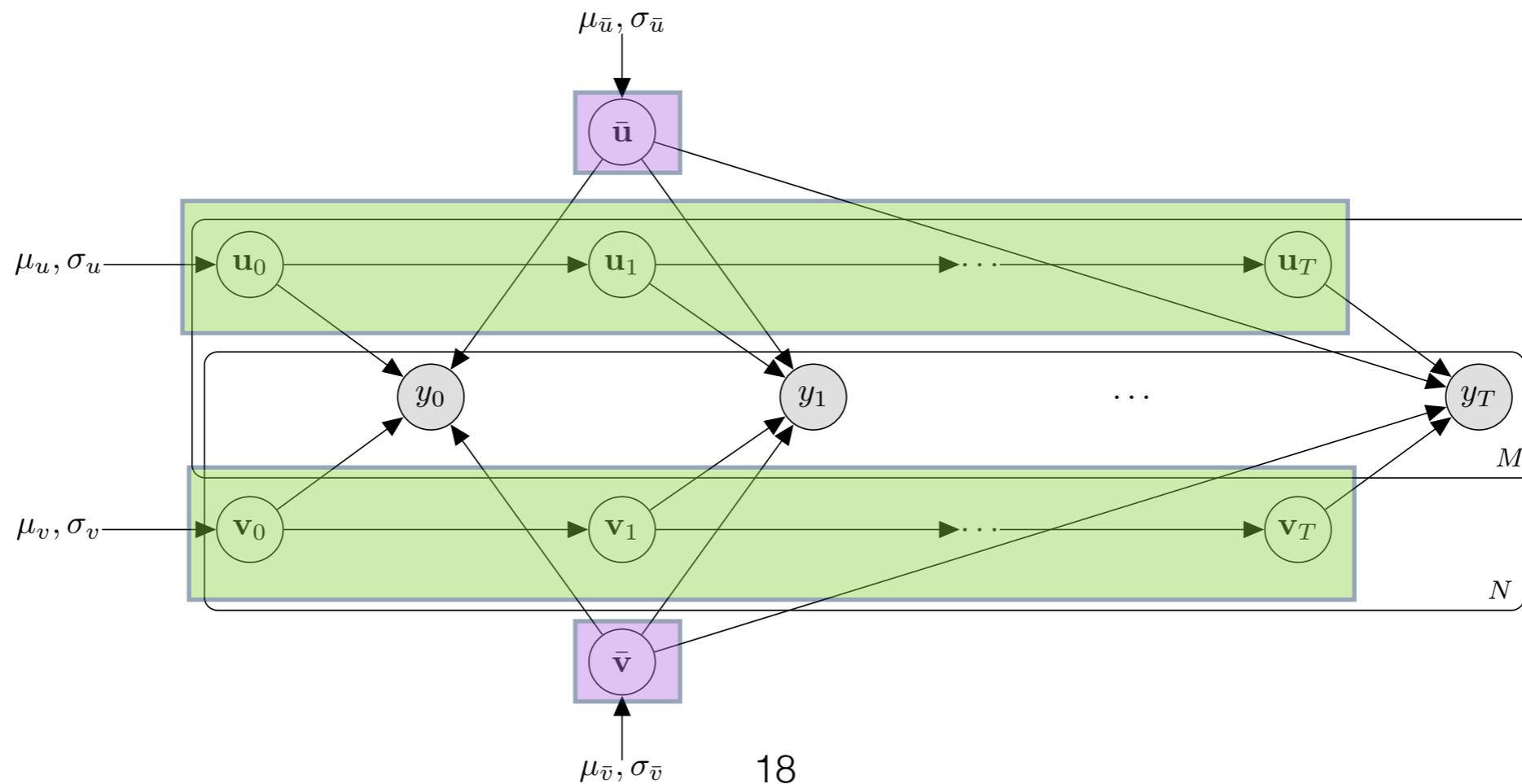
Local and Global factors

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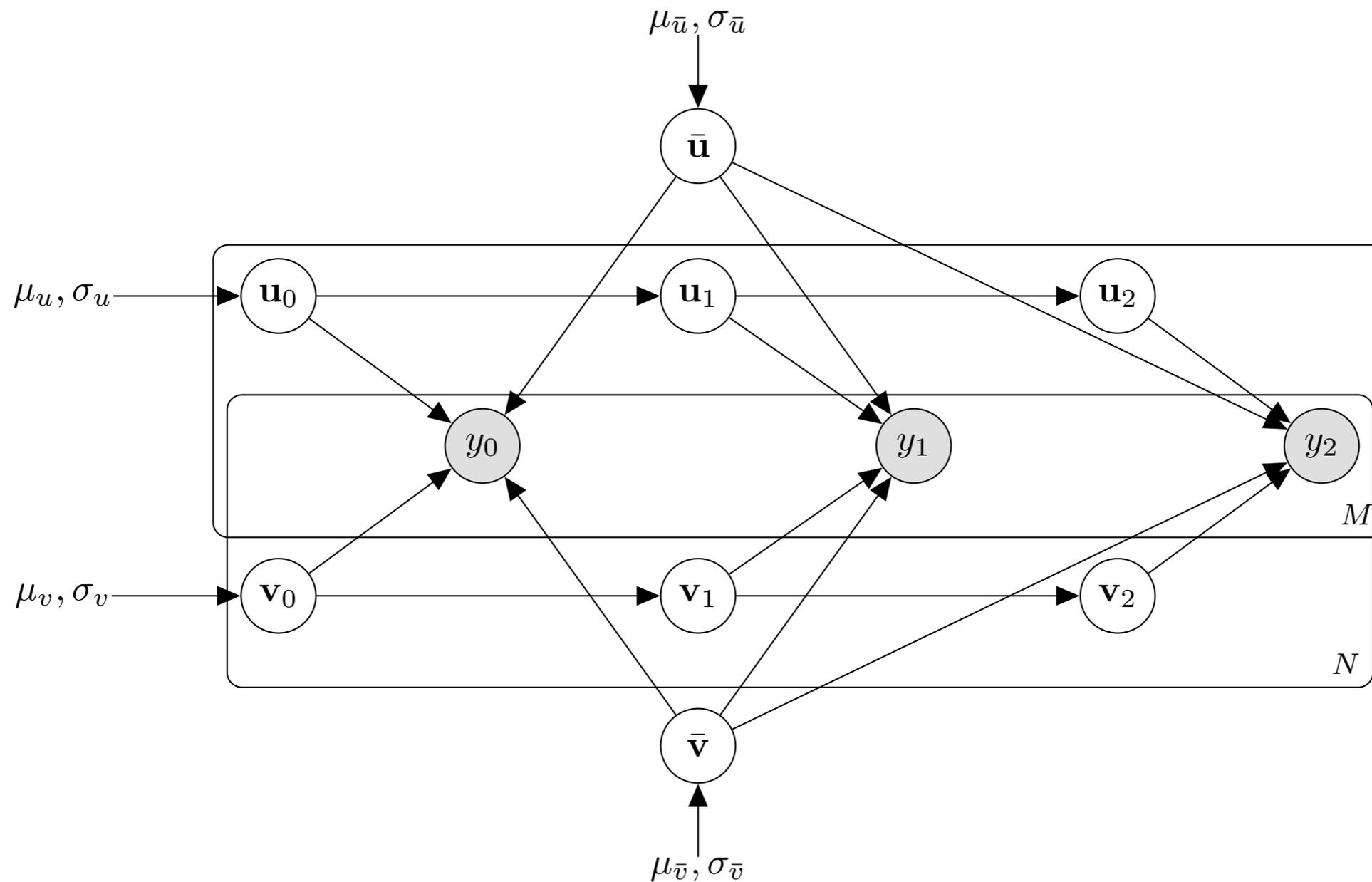


Local and Global factors

- Two levels of modeling:
 - **Local factors:** model evolution through time
 - **Global factors:** model constant preferences wrt time



A 3 timeslice Dynamic PF



Inference

- Variational inference algorithm
 - Mean-field (factorized) approximation
 - Non-conjugacy between $P(\mathbf{u}_t | \mathbf{u}_{t-1})$ and $P(\mathbf{y}_t | \mathbf{u}_t, \mathbf{v}_t)$
 - Use an additional approximation
- See the paper for details on the algorithm
- Scales linearly in time, we provide a parallel implementation

Empirical results

- Explicit data
 - Augmented matrix factorization [Koren'10, Li'11, Gultekin'14]
 - Tensor factorization [Karatzoglou'10]
 - **Bayesian Tensor Probabilistic Factorization [Xiong'10]**
- Implicit data
 - HMM [Sahoo'12]
 - Gamma process MF [Acharya'15]
- DPF (us):
 - User and item dynamicity
 - Implicit and explicit
 - Scalable

Experimental setup

- Test on multiple time steps
 - Train data: clicks up to time slice t
 - Predict held-out clicks at time $t+1$
- Metrics for implicit data
 - Ranking-based (NDCG, Recall, MAR, MRR)

Netflix-time

	Recall@50	MAR	MRR	NDCG
dPF	0.170	640	0.027	0.294
BPTF [Xiong'10]	0.148	668	0.020	0.277
PF-all [Gopalan'15]	0.145	691	0.021	0.280
PF-last [Gopalan'15]	0.065	807	0.019	0.268

- 7.5K users, 3.6K items, 2M non-zero ratings, binarized
- 3 months per time slice

Netflix

	Recall@50	MAR	MRR	NDCG
dPF	0.156	1605	0.021	0.358
PF-all [Gopalan'15]	0.120	1807	0.015	0.338
PF-last [Gopalan'15]	0.138	1635	0.018	0.351

- 225K users, 14K items, 6.9M non-zero ratings, binarized
- 6 months per time slice

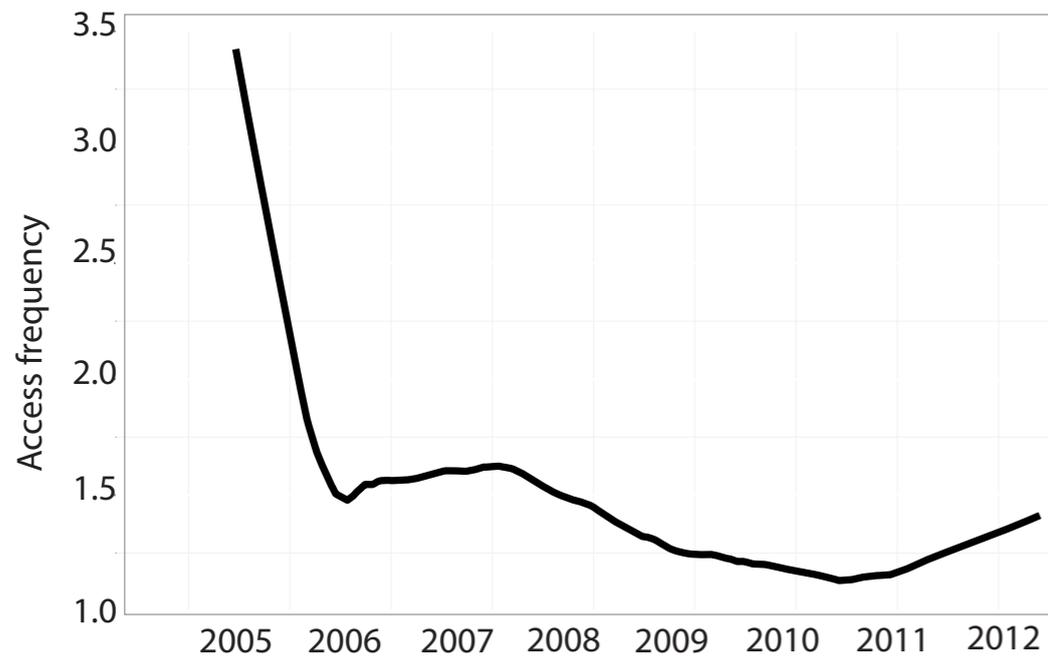
arXiv

	Recall@50	MAR	MRR	NDCG
dPF	0.035	21822	0.0062	0.186
PF-all [Gopalan'15]	0.032	22402	0.0056	0.182
PF-last [Gopalan'15]	0.023	25616	0.0040	0.168

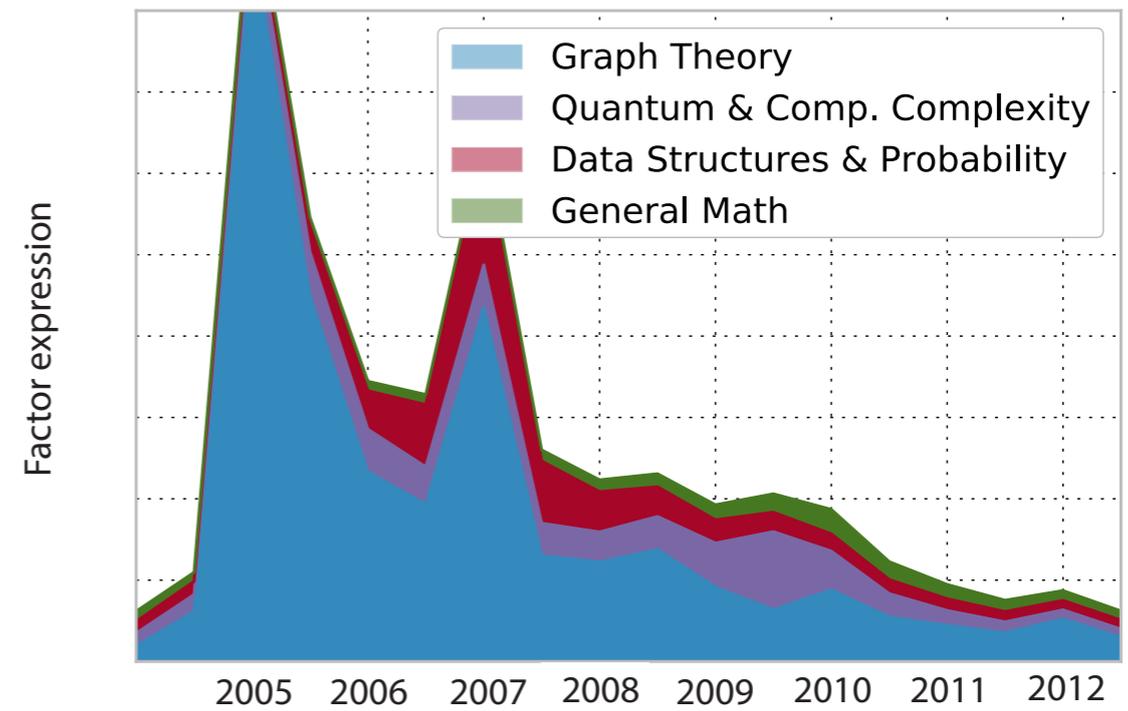
- 75K users, 5K items, 1.3M clicks
- 18 months per time slice

Usage Data

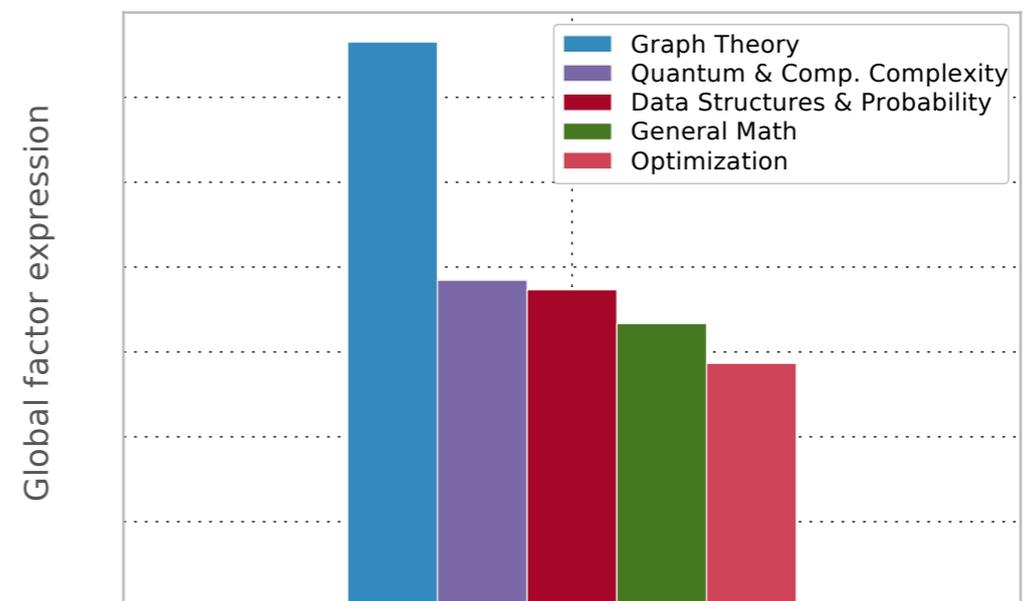
The Google Similarity effect
arXiv: cs/0412098



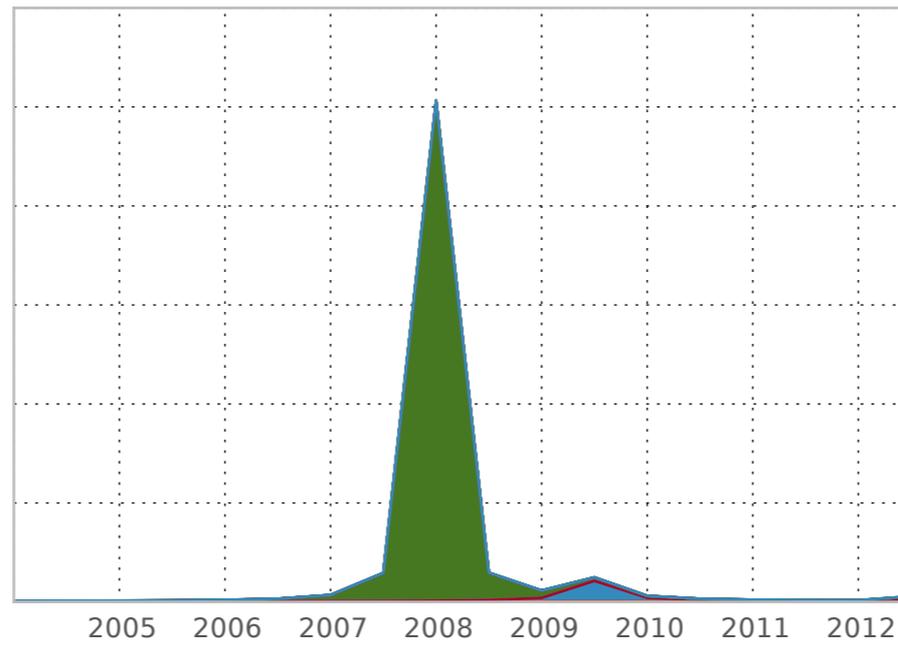
DPF Factors

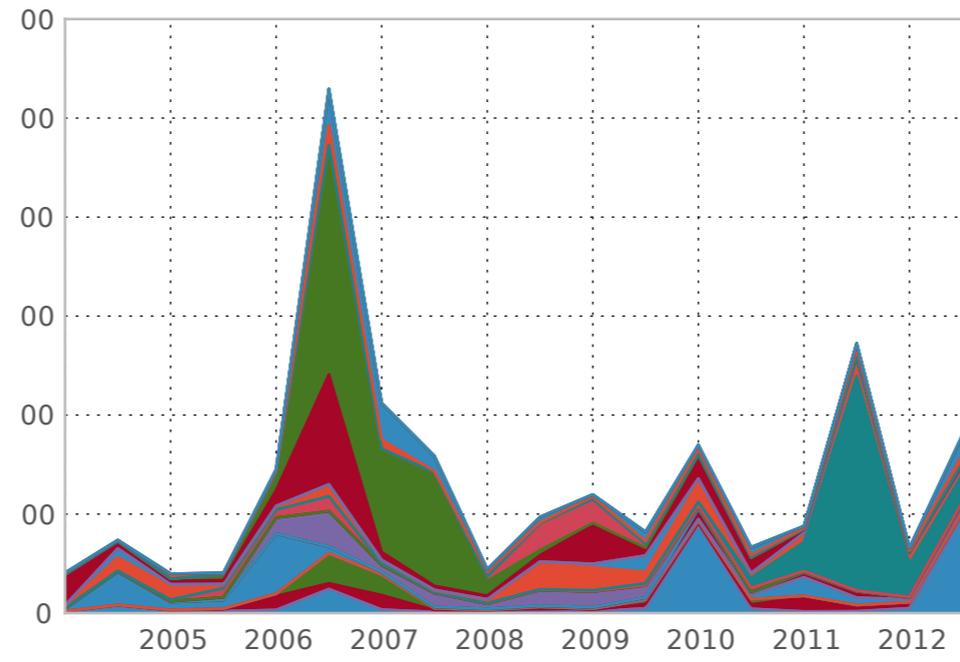


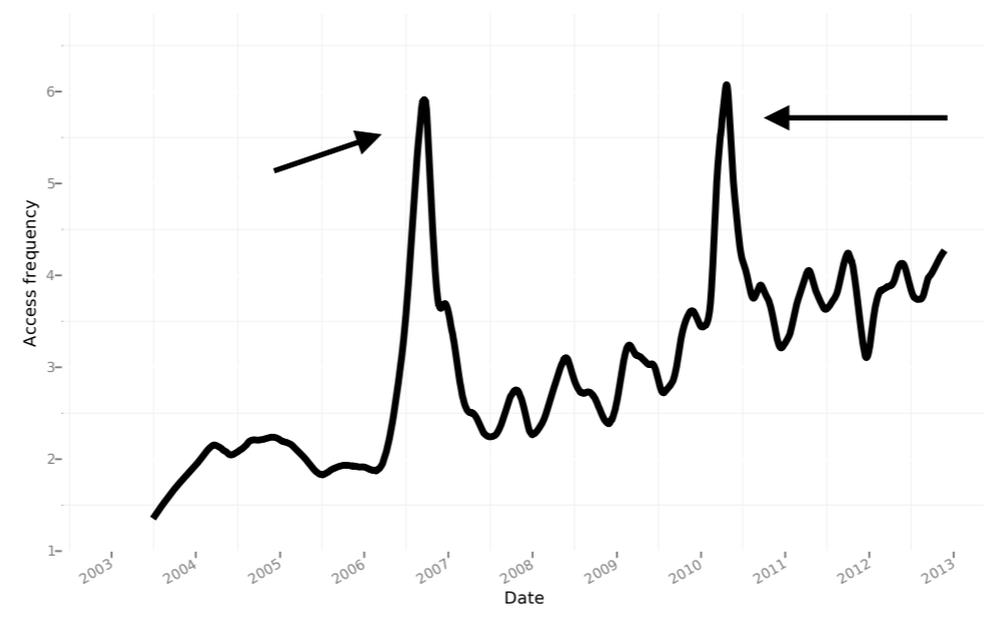
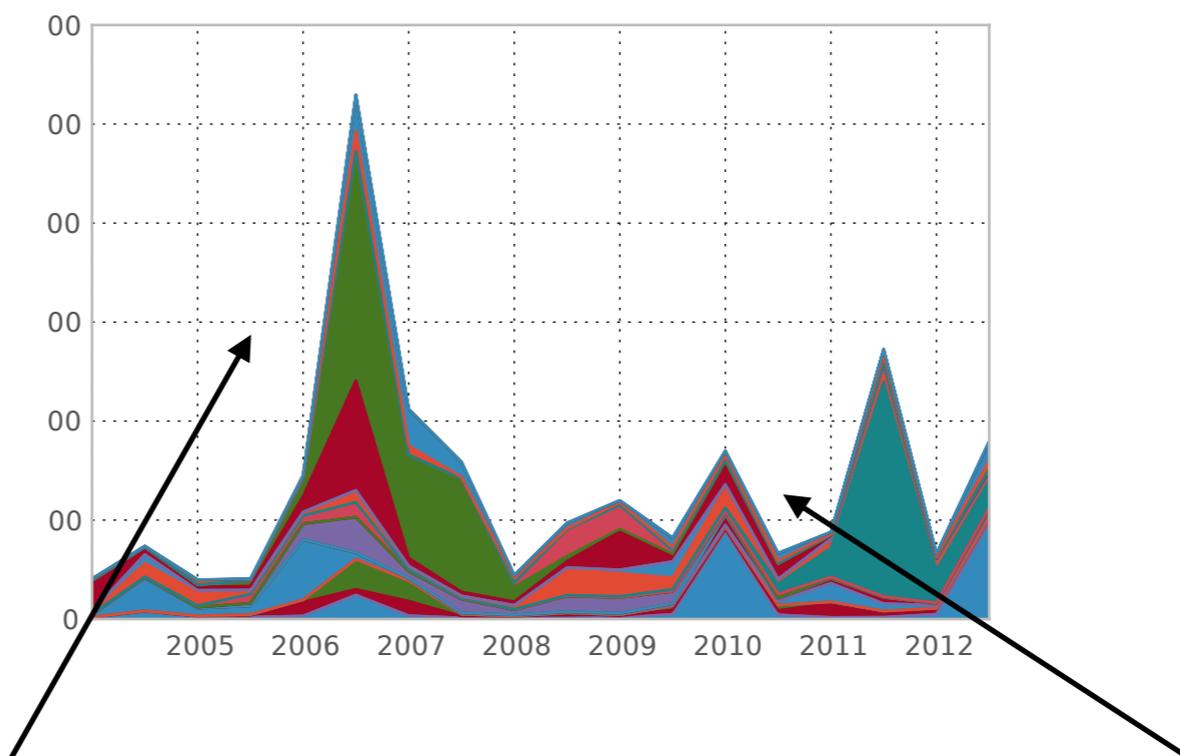
DPF Global Factors



Paper Selected at Random

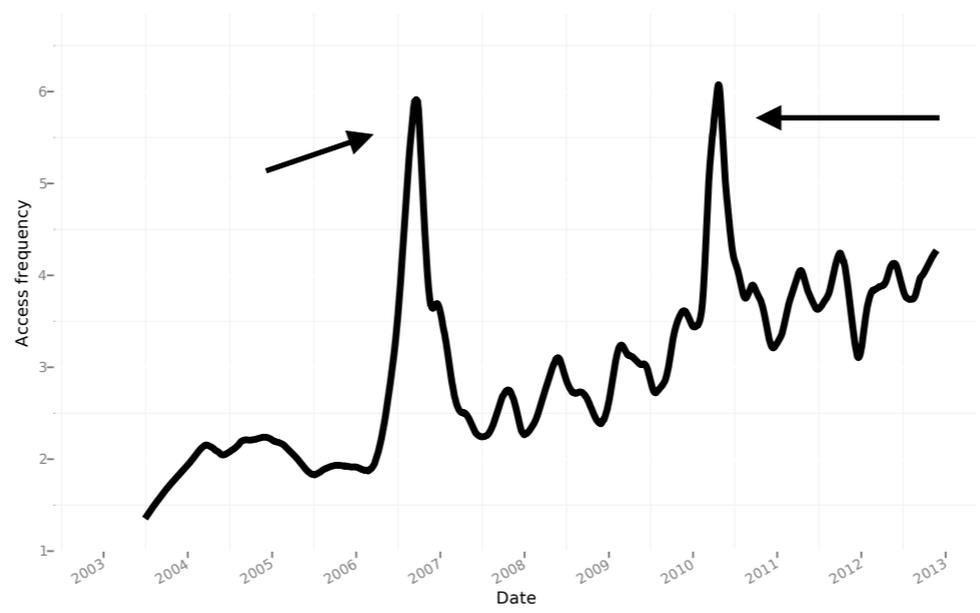
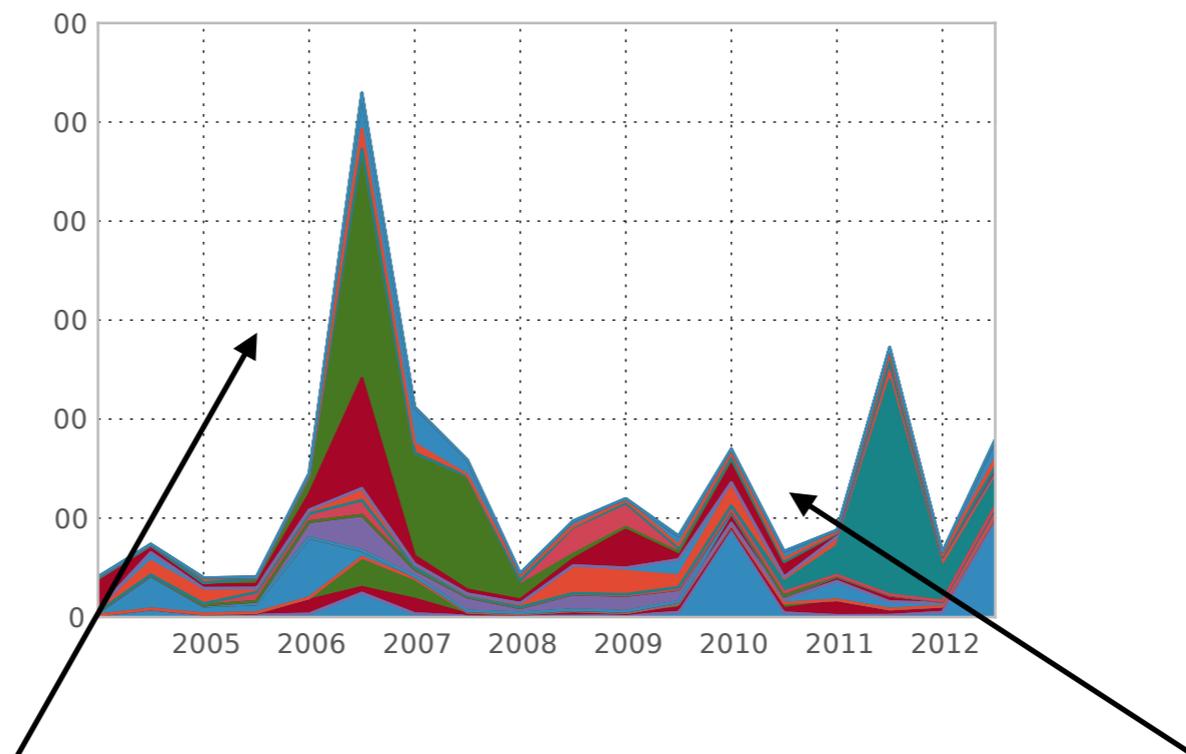






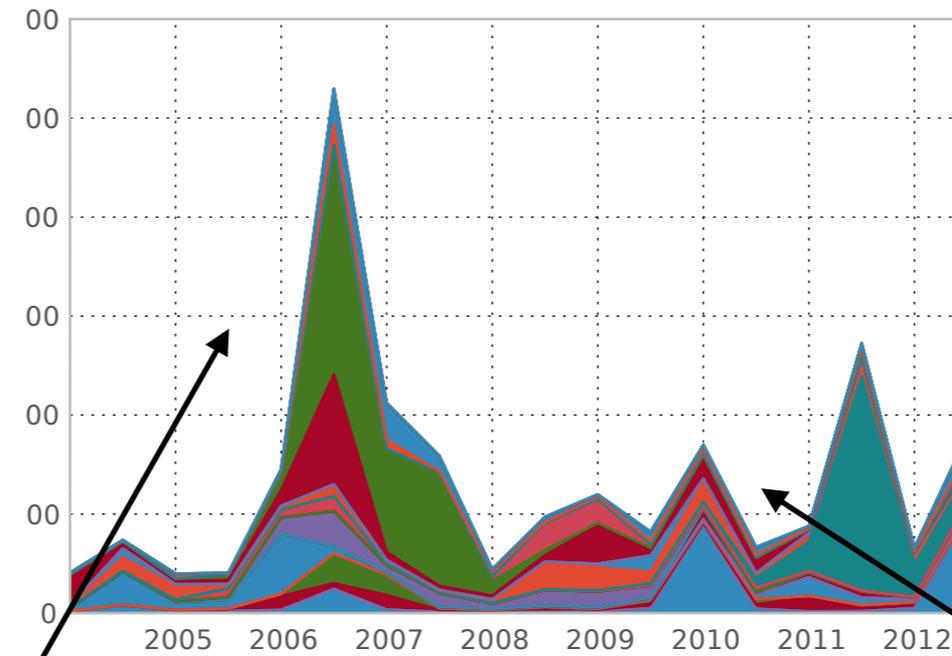
The entropy formula for the Ricci flow and its geometric applications

Grisha Perelman

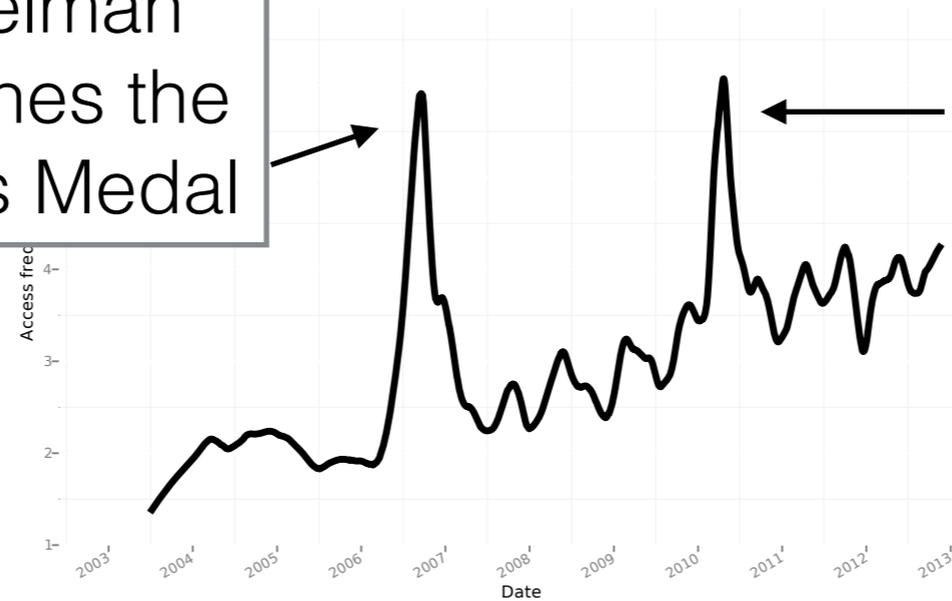


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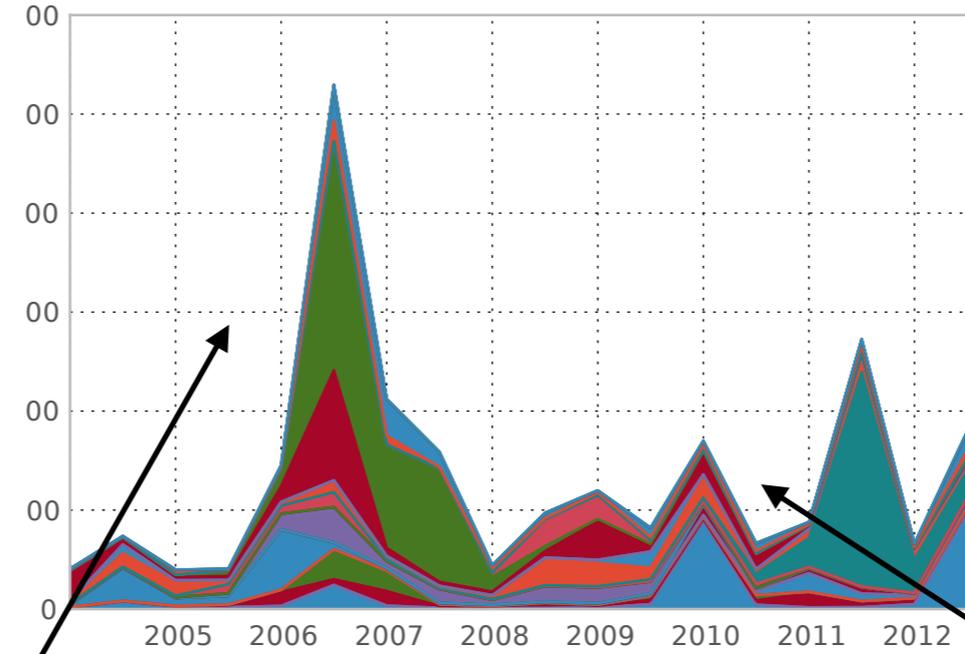


Perelman declines the Fields Medal



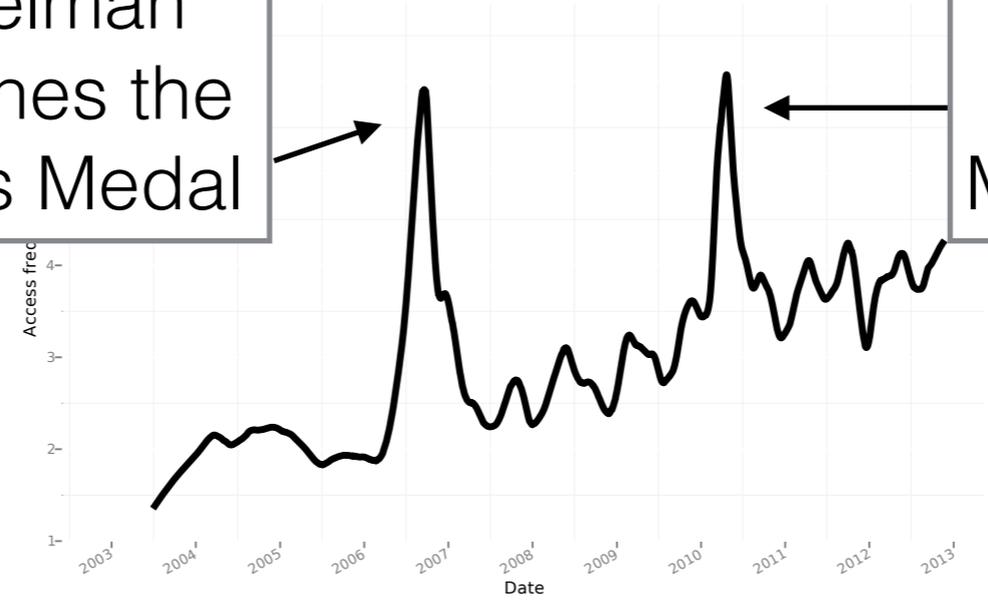
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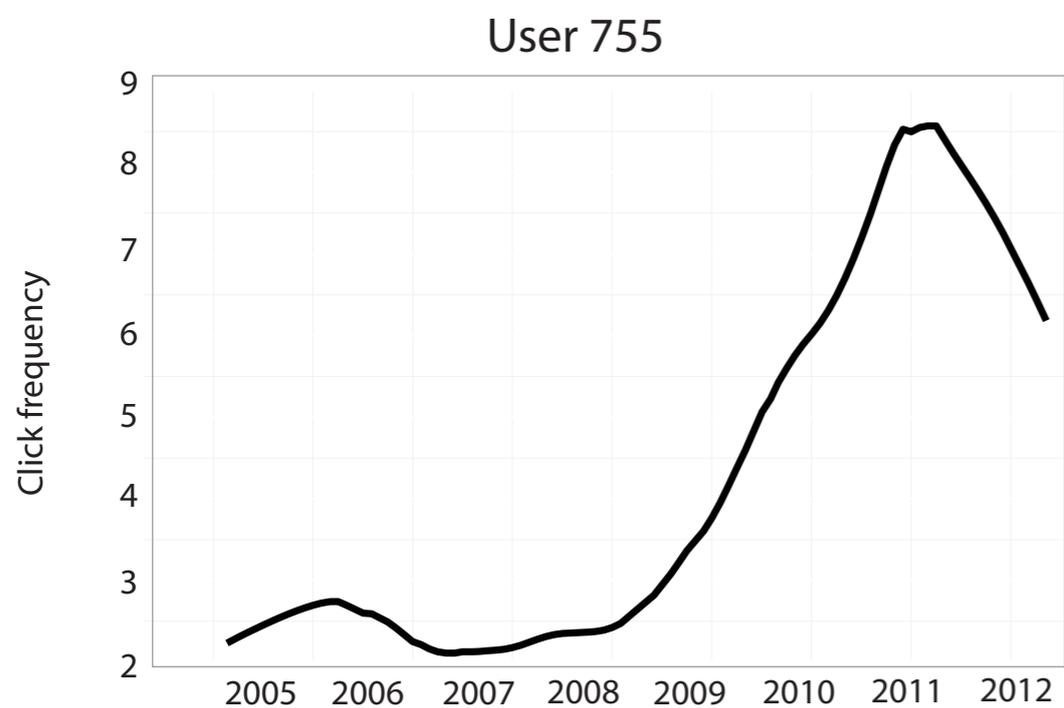


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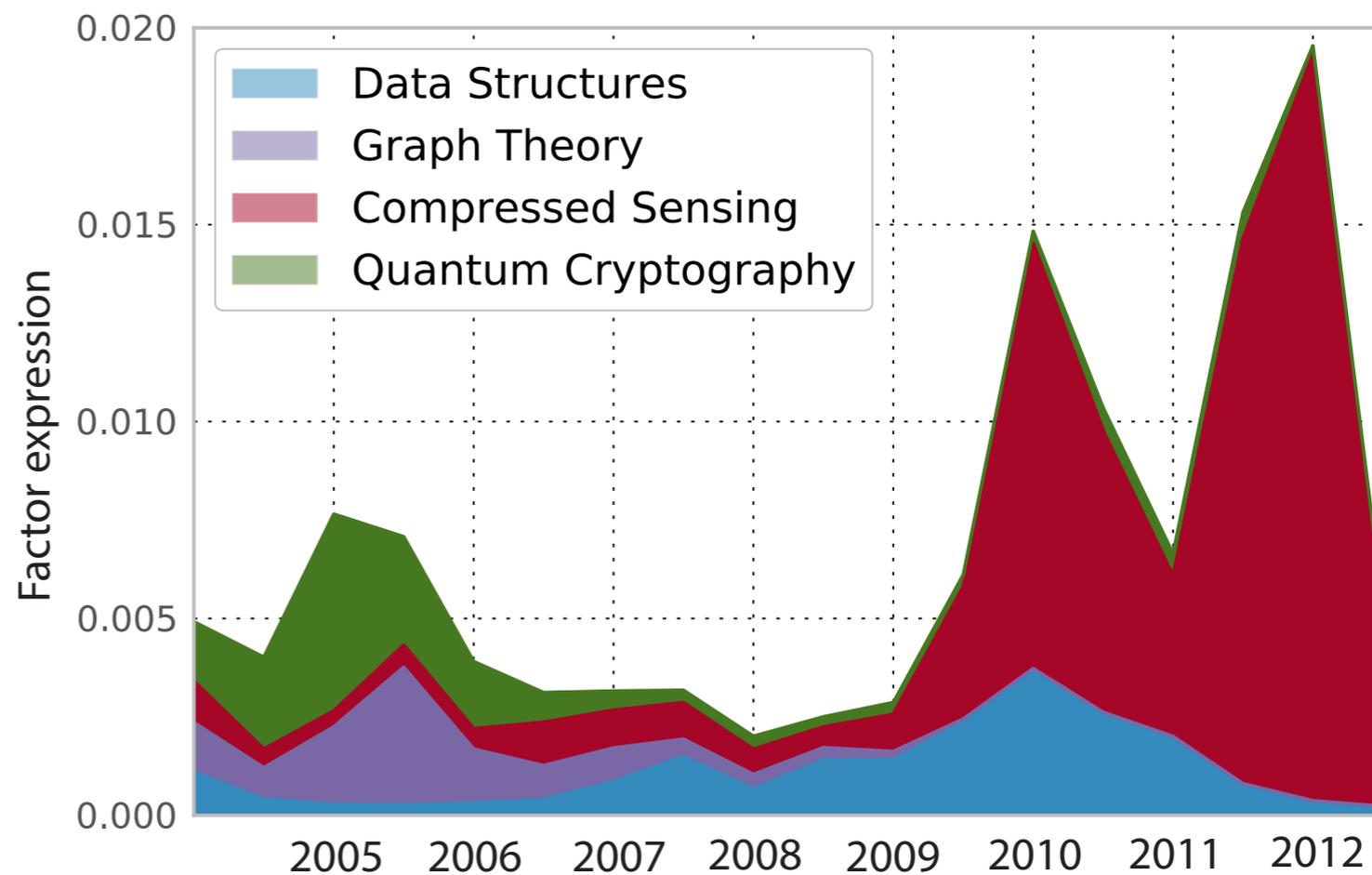
Perelman rejects the Millenium Prize



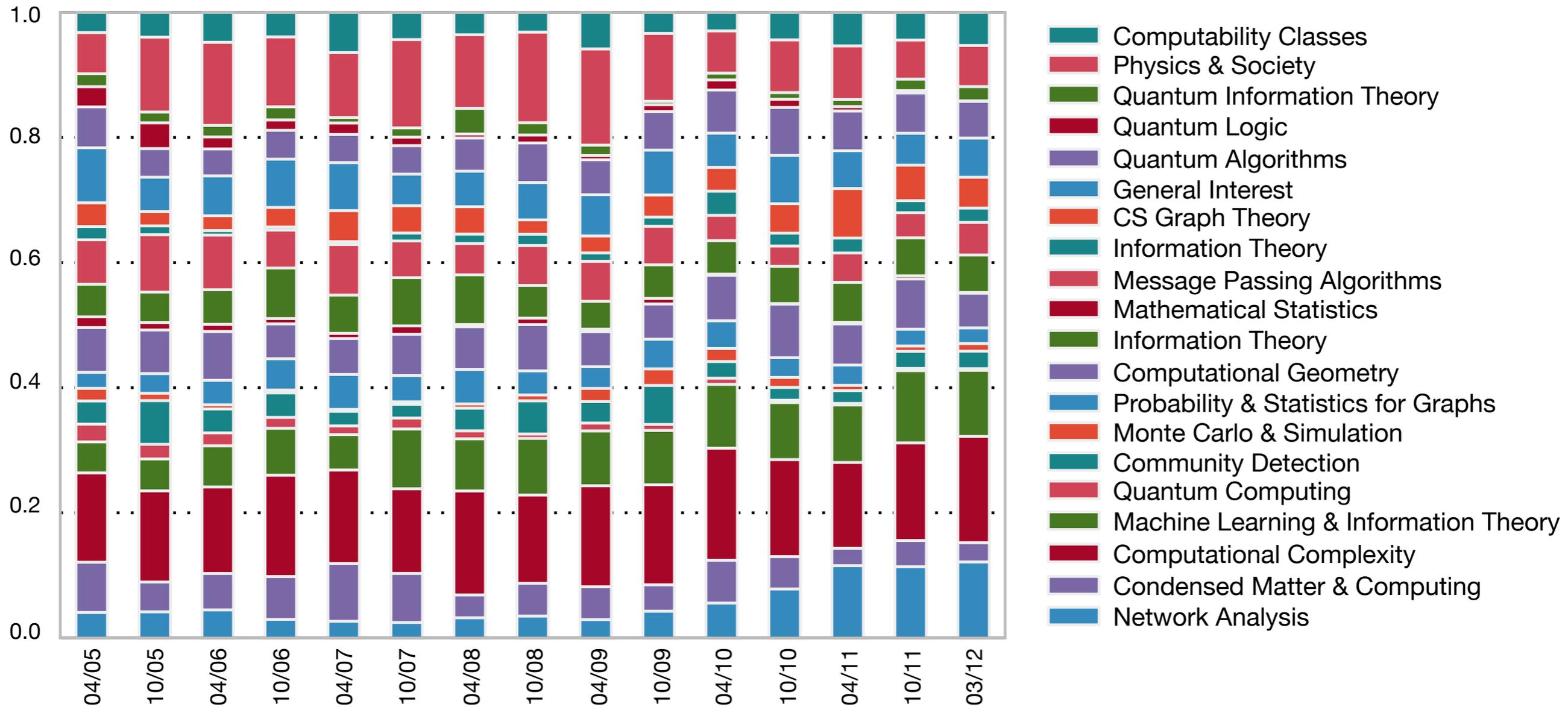
Usage Data



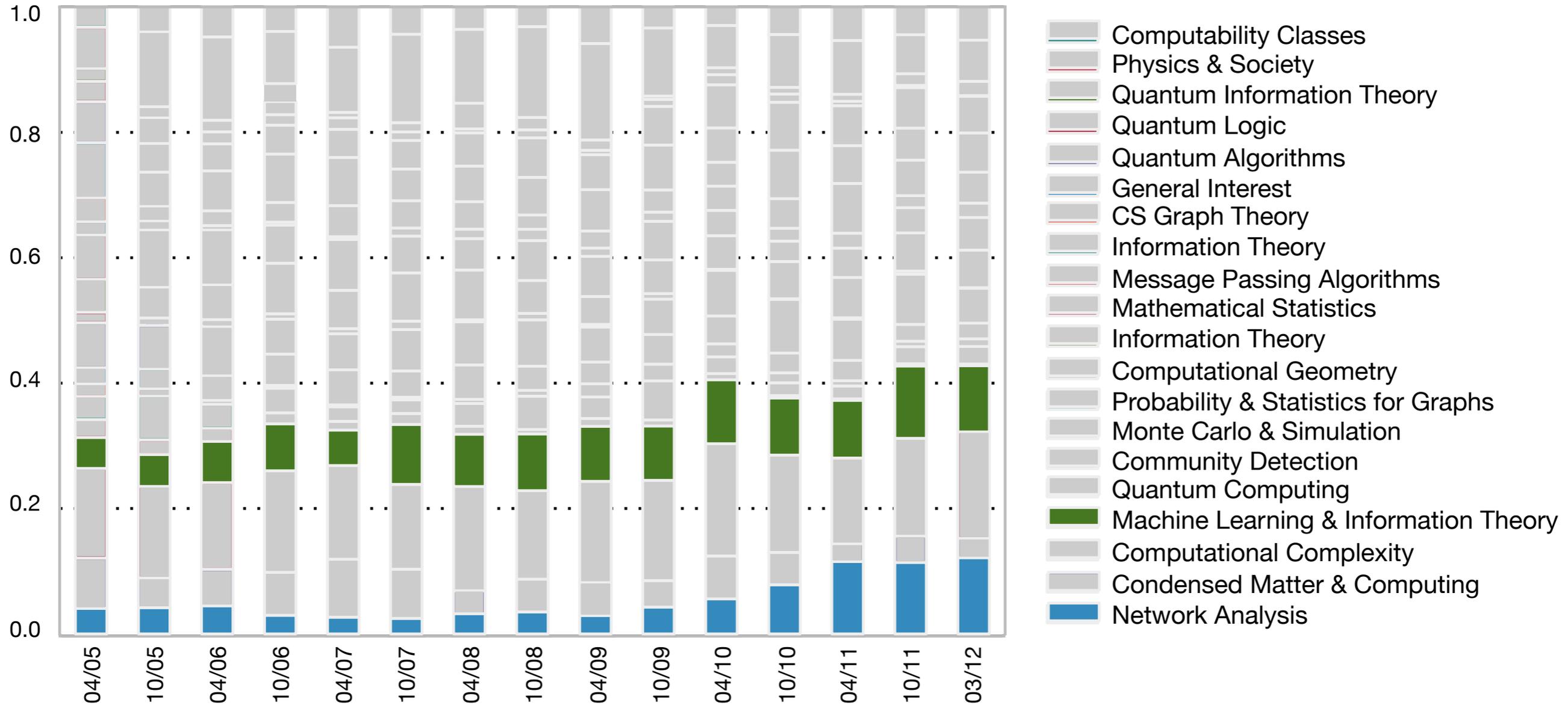
DPF Factors



Fields evolve over time

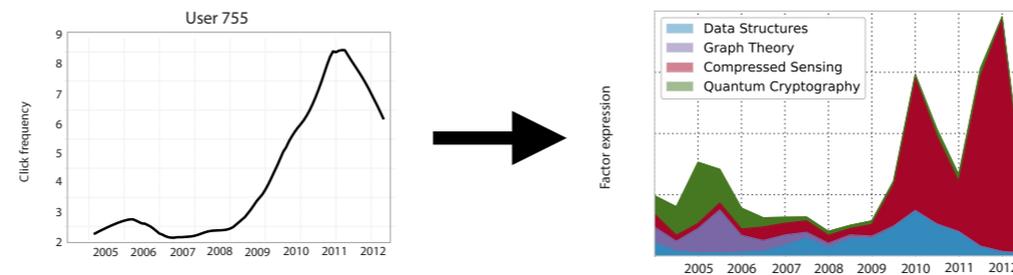


Fields evolve over time



Conclusions

- Dynamic Poisson factorization (DPF)



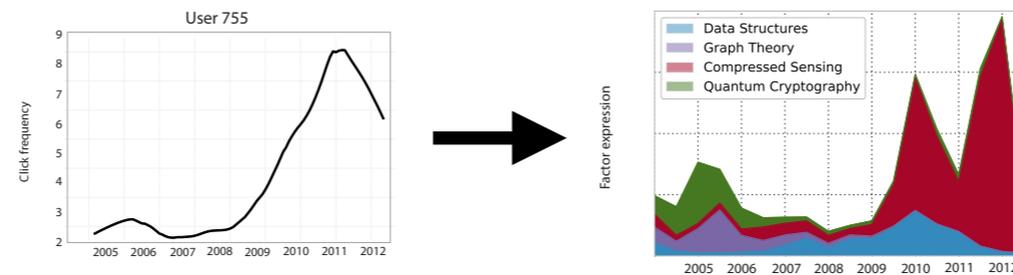
- Implicit data, scalable
- Open source implementation is available:

github.com/Blei-Lab/

- Future work: levels of granularities, continuous time

Thank you!

- Dynamic Poisson factorization (DPF)



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