Tumblr Blog Recommendation with Boosted Inductive Matrix Completion

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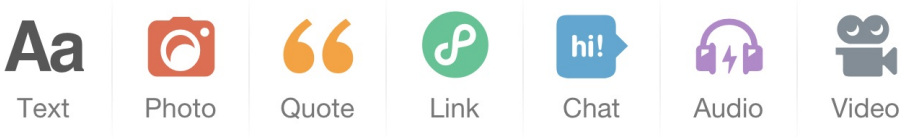
Thanks to the SIGIR Student Travel Grant!

Tumblr Blog Recommendation

Tumblr

Microblogging service:

- No limit on length of posts.
- Supports various types of posts:



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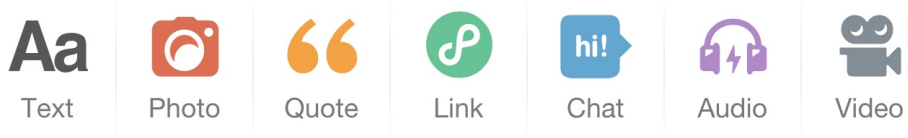
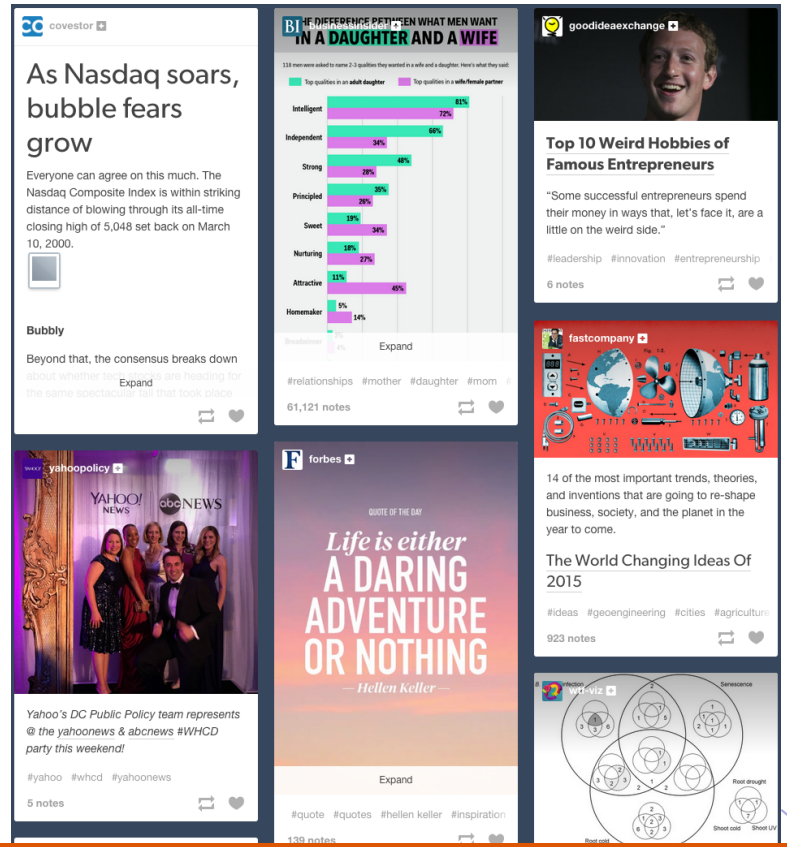


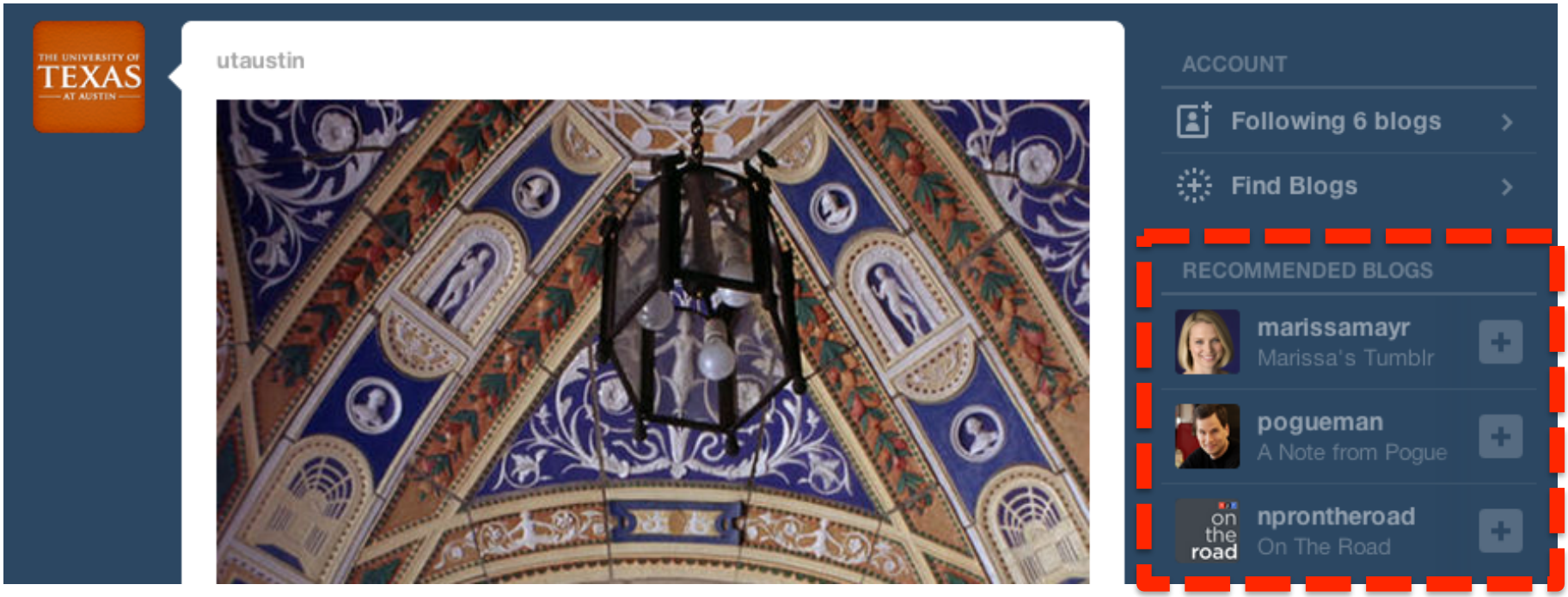
Social network service:

- *Follow* other blogs – 260M blogs
- Like or reblog other posts – 122B posts



Blog Recommendation

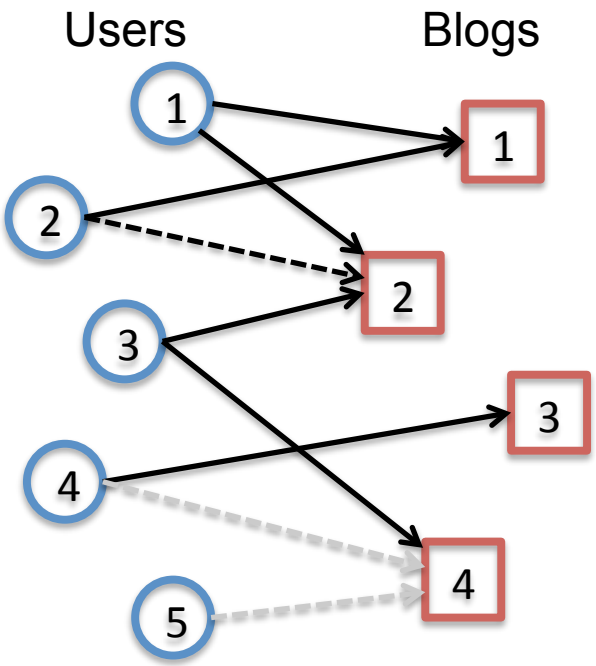
Who to follow?

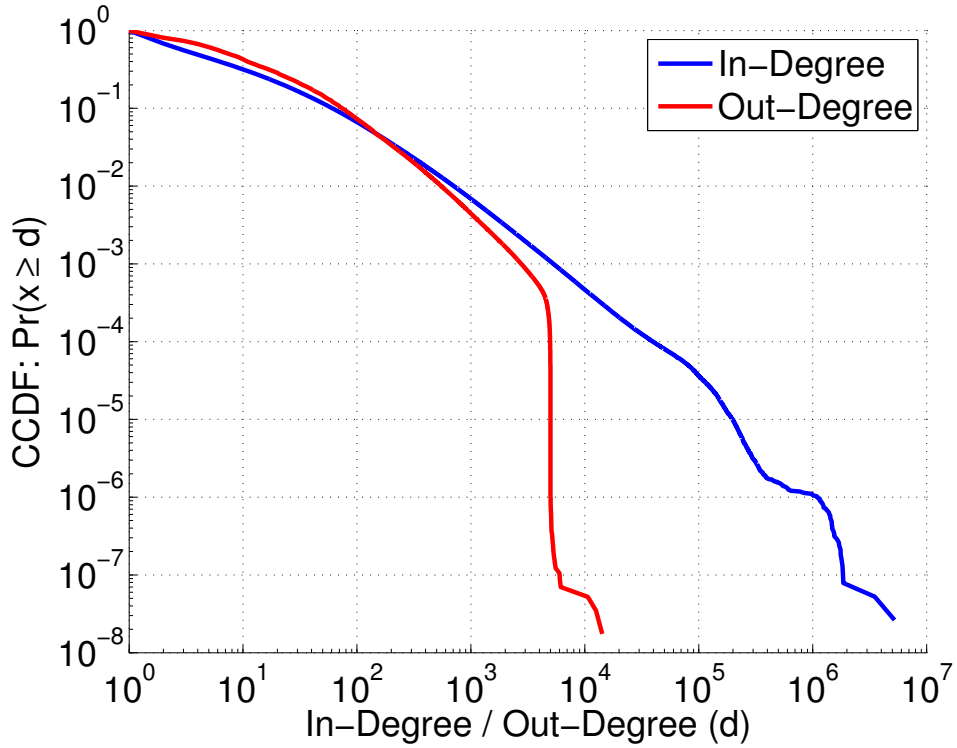


- Help users find content they want $\Rightarrow$ enhance user experience and engagement
- Help increase followers for sponsored or advertiser blogs

Follower Graph

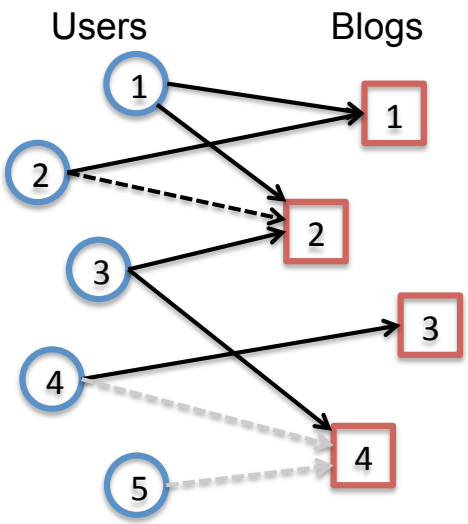
- Snapshot from Jun. 2014
- Directed graph: 76.86M nodes (users/blogs) and 2.27B edges (follows) with timestamps
- 50% have 0 in-degree, 25% have 0 out-degree

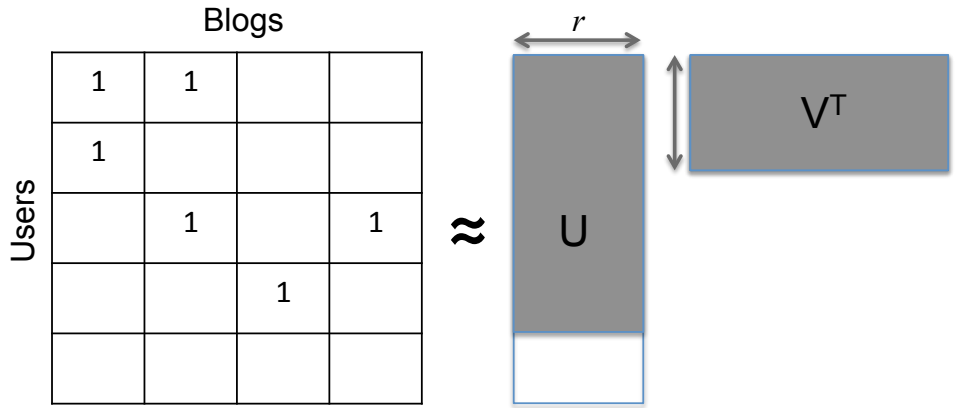




Existing Methods

- Global ranking: recommend most popular blogs
- Graph proximity: Common Neighbors, Katz, etc
- Standard matrix completion
- ...





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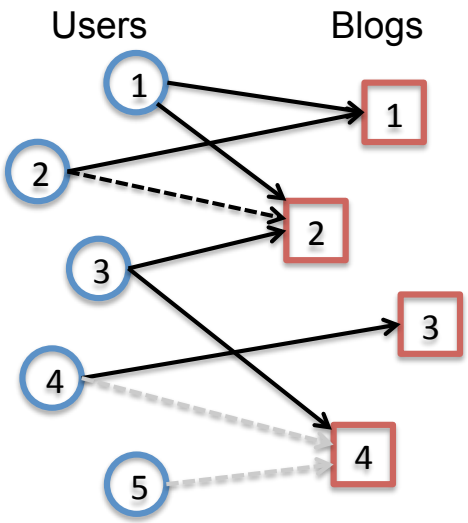

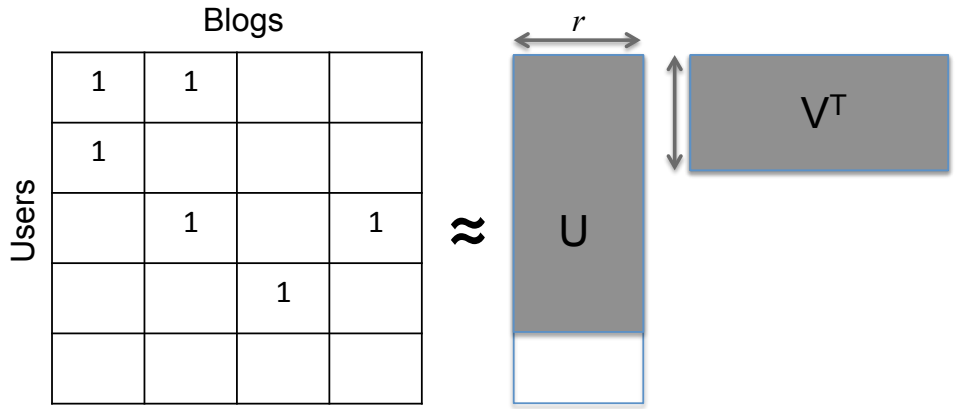

Can NOT make meaningful recommendations for users or blogs with no follow information (e.g., user 5)

Additional Information from Posts

Tumblr Posts

Various sources of additional information:

Tumblr Posts

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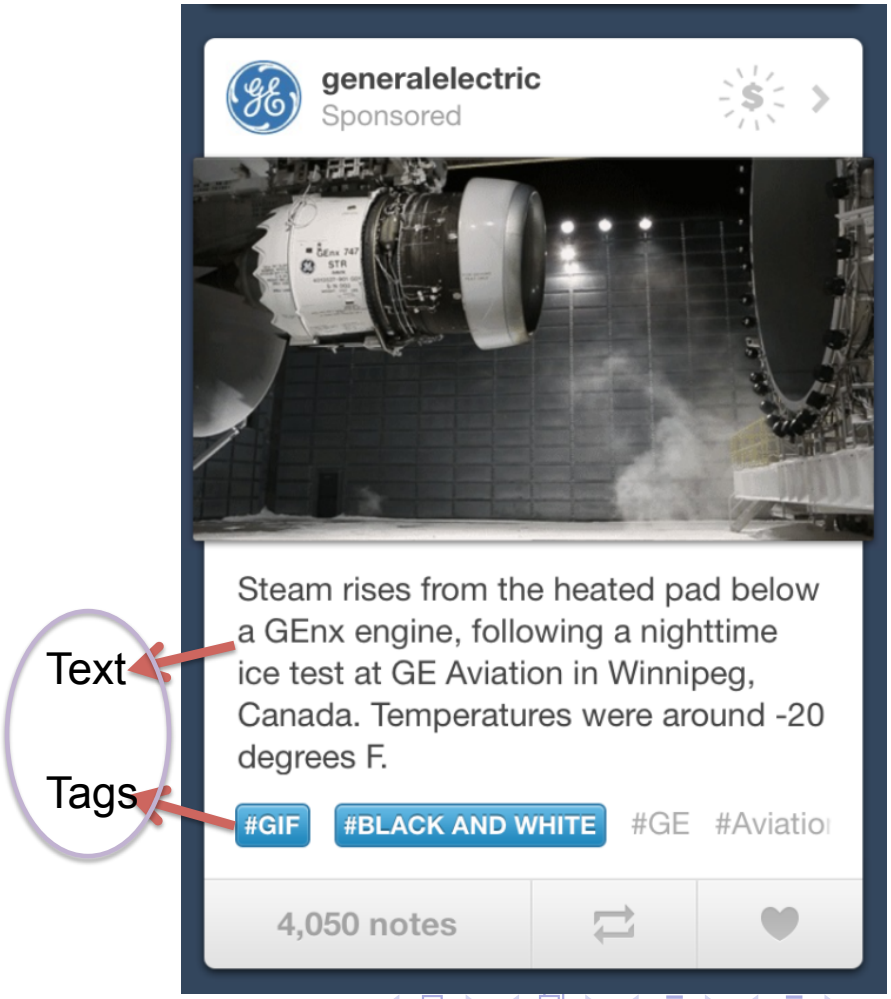
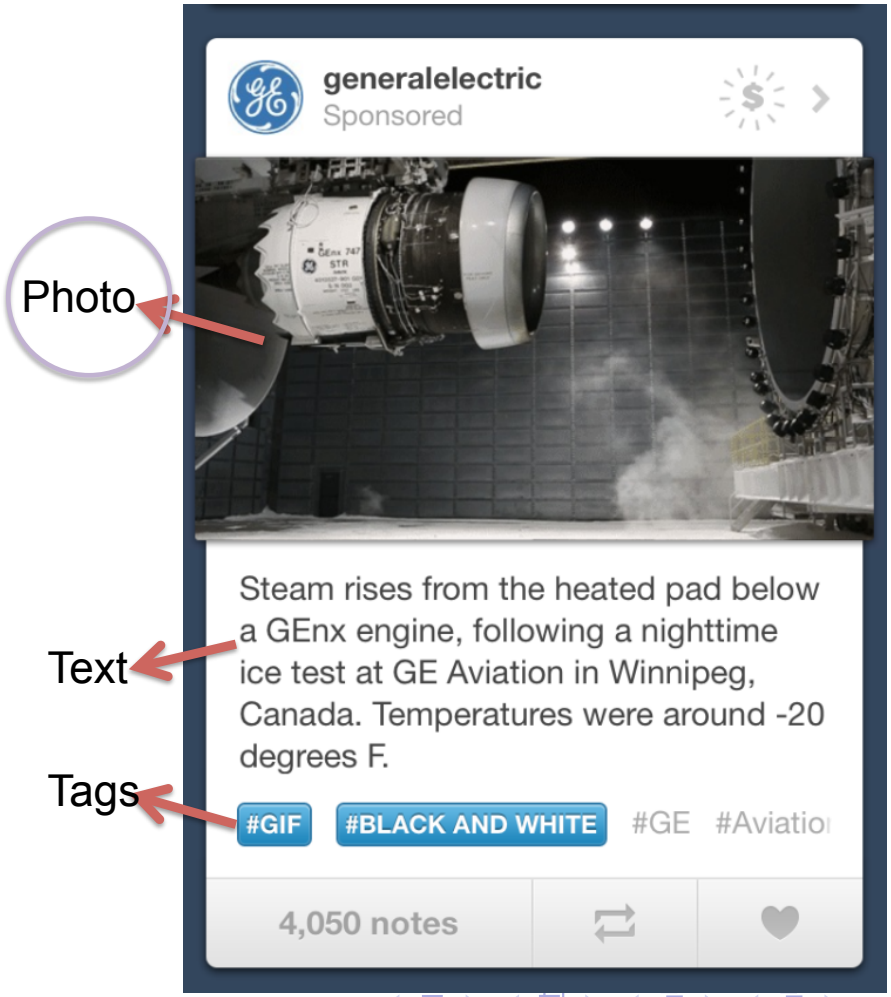
- Textual: text and tags



Tumblr Posts

Various sources of additional information:

- Textual: text and tags
- Visual: photos (and videos)



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Various sources of additional information:

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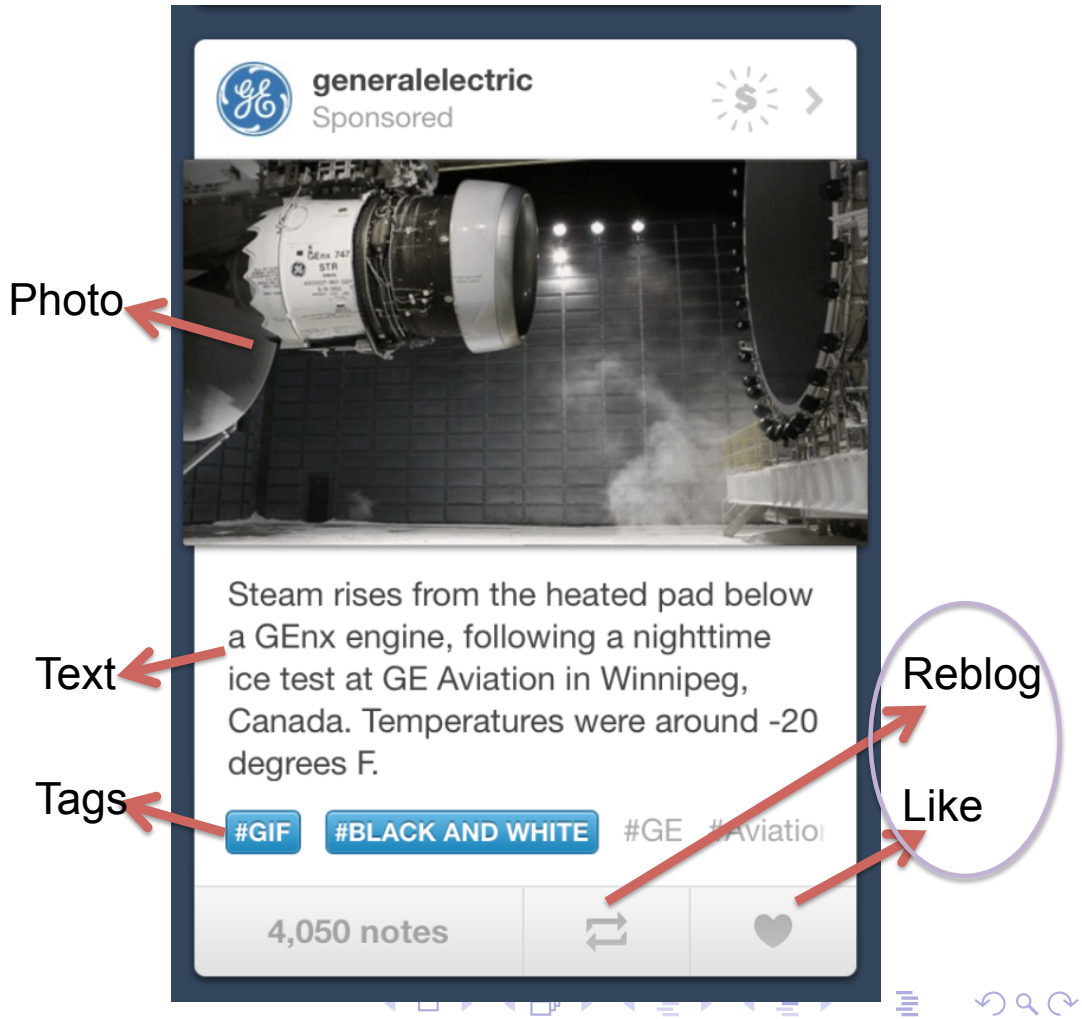
- Activity: reblog and like



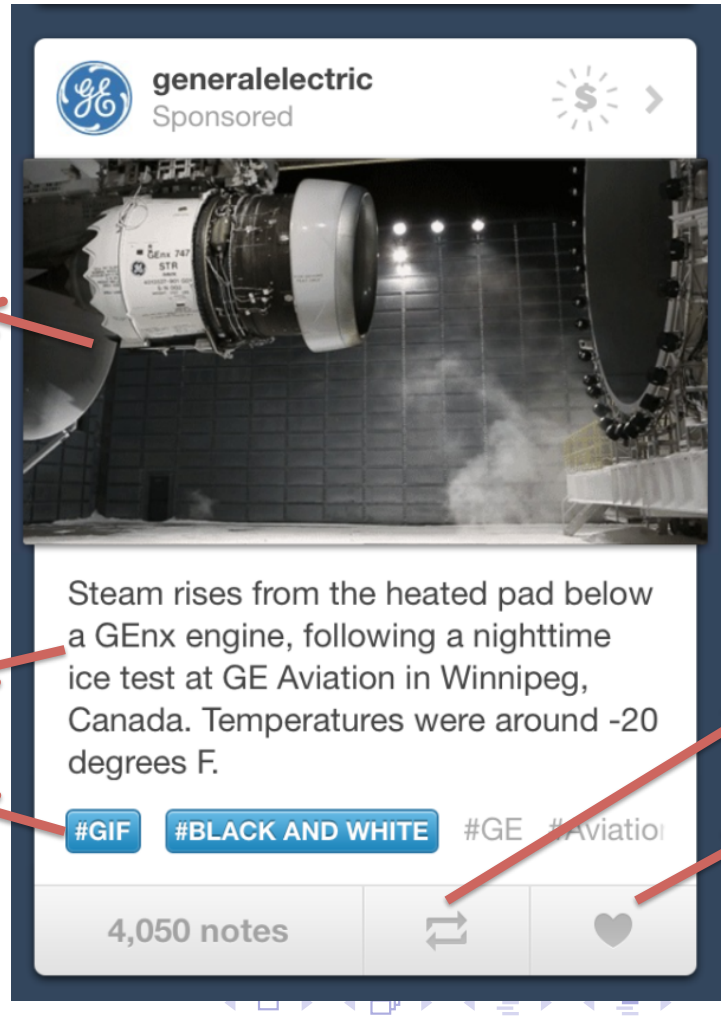
Tumblr Posts

Various sources of additional information:

- Textual: text and tags
- Visual: photos (and videos)
- Activity: reblog and like

User and blog features are generated from each source.

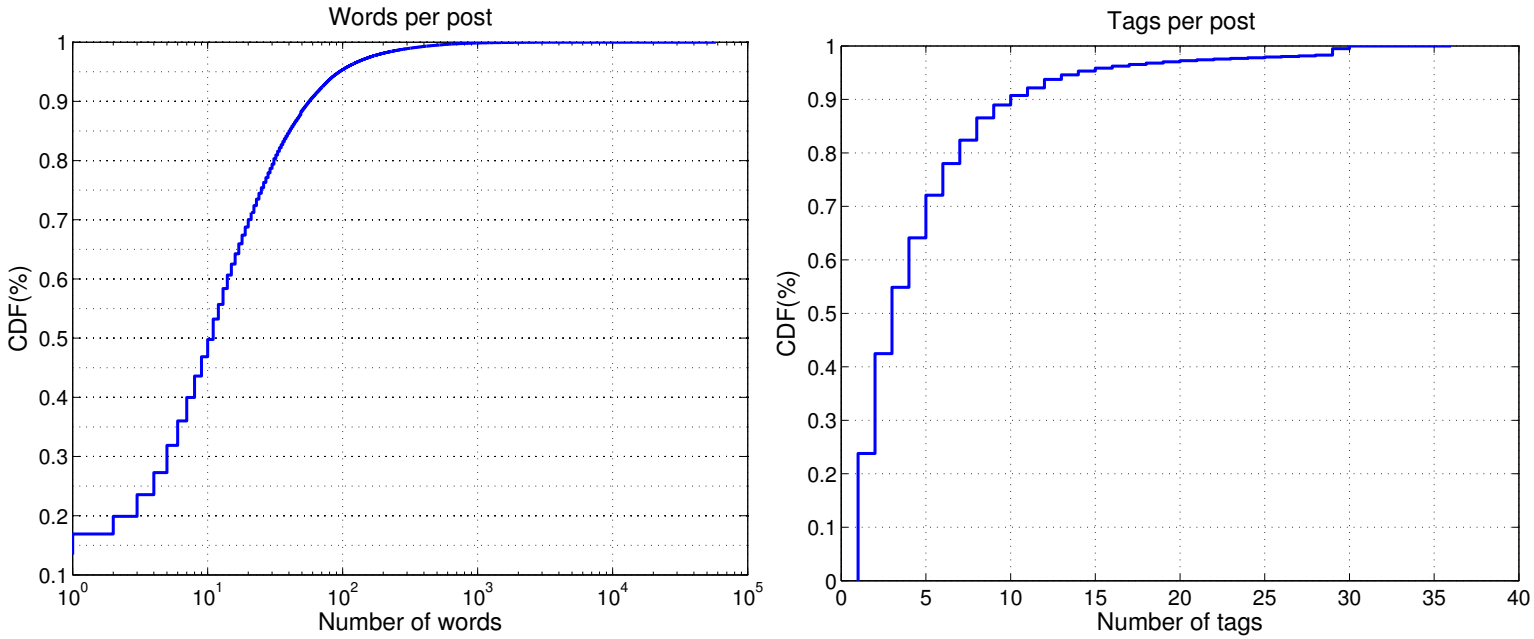
- 150M new posts per month
- Collected over a 5 month period: more than 7.5 TB of data



User and Blog Features – Textual

Text and Tags:

- Extremely sparse and noisy – 28.7 words / 4.8 tags per post on average



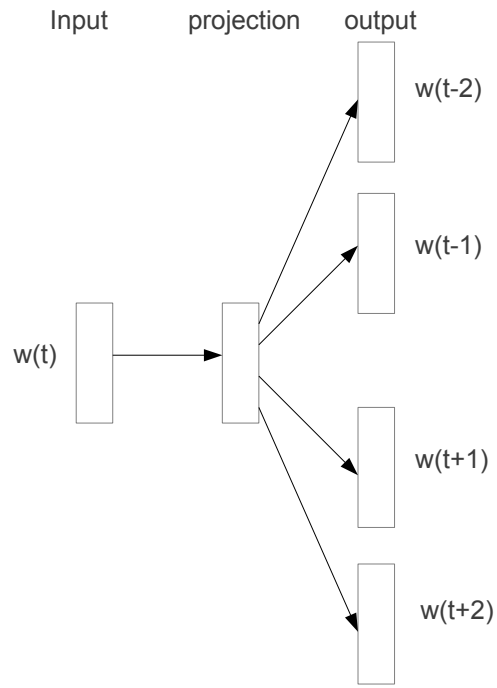
Problematic for existing bag-of-words models (LSA, LDA, etc).

User and Blog Features – Textual

Text and Tags: extract features using word2vec

[Mikolov et.al. 2013]

- Learns a vector representation of each word, such that words in similar context are close to each other



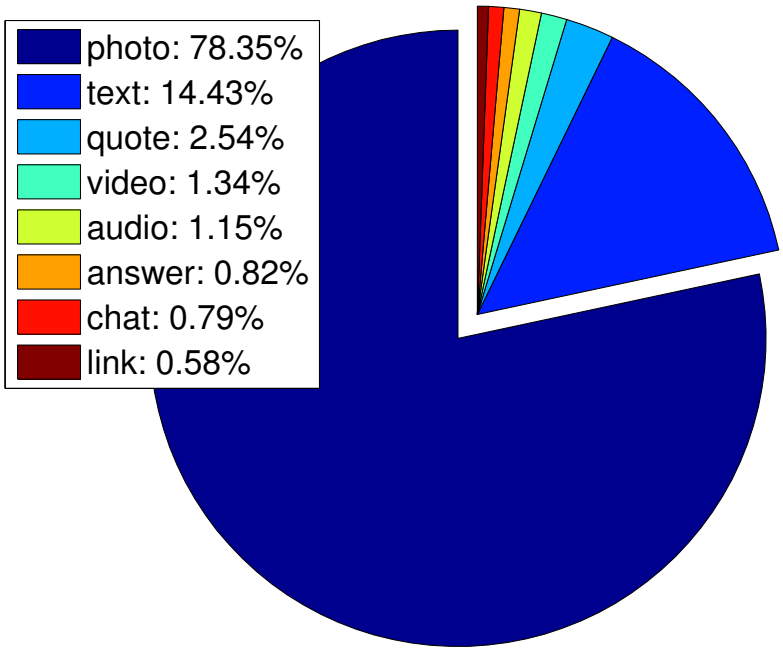
Textual features:

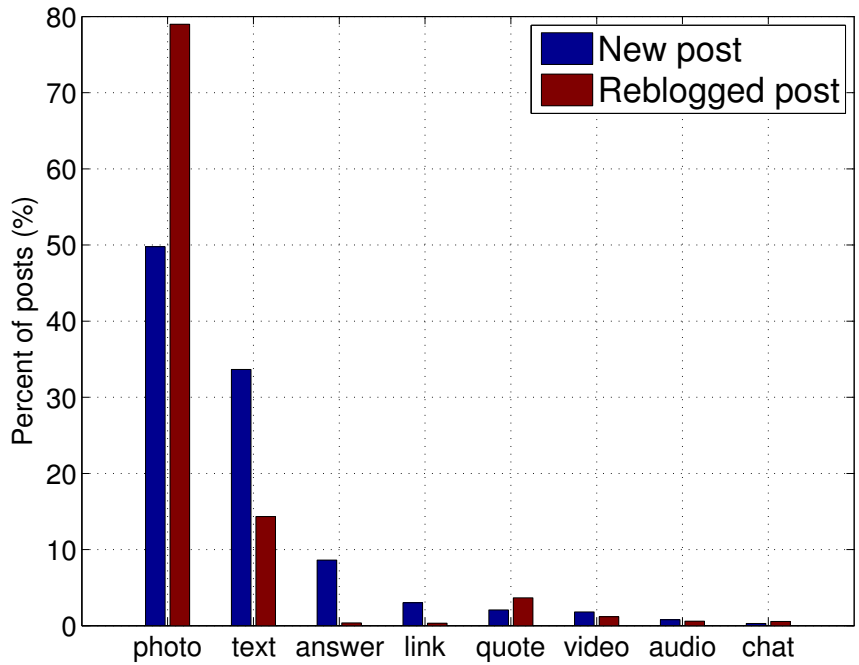
1. Learn d-dimensional vector representations of each word
2. Cluster words into c clusters via k-means
3. Compute histogram of word clusters for each post
4. Take average of histograms as features of users and blogs

User and Blog Features – Visual

Photos:

- About 78% of total posts are photo posts.
- Majority of reblogged posts are also photo posts.

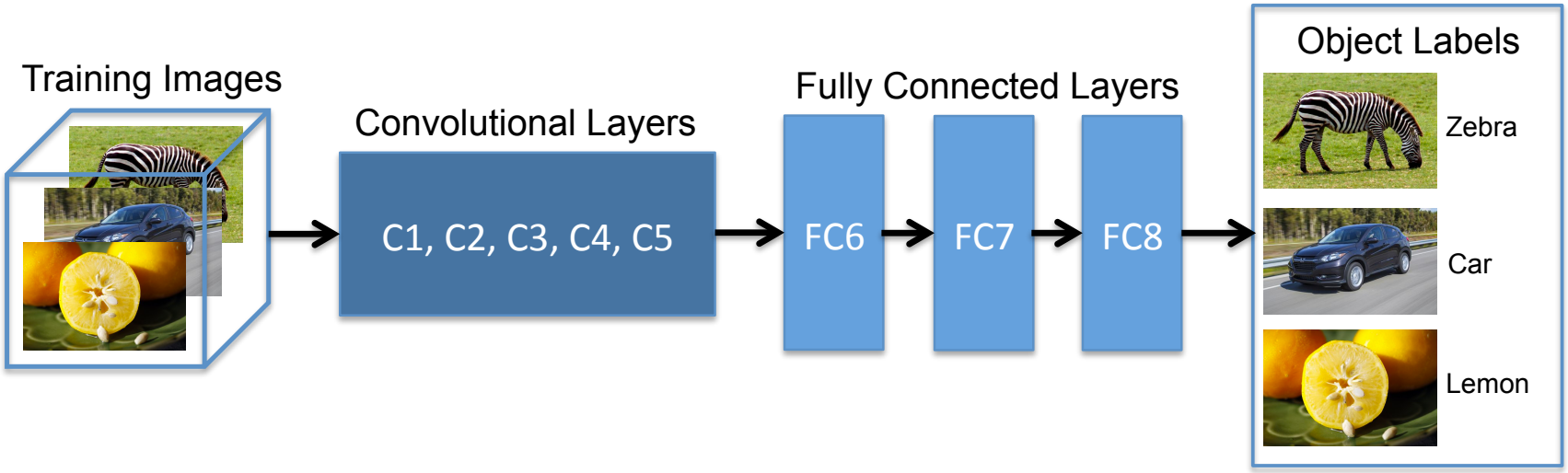




User and Blog Features – Visual

Photos: extract features using deep learning

- Used a convolutional neural network with a total of 8 layers – 7 hidden layers and a soft-max layer [Donahue et.al. 2014]
  - Trained on 1.5M Flickr images (labels unavailable for Tumblr images)



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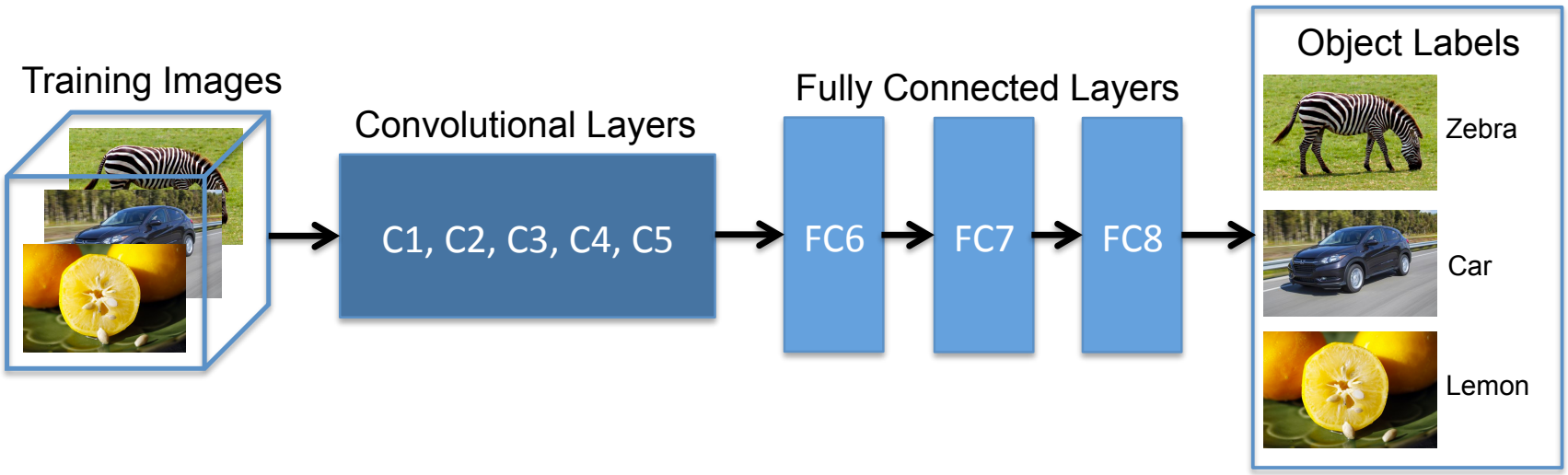
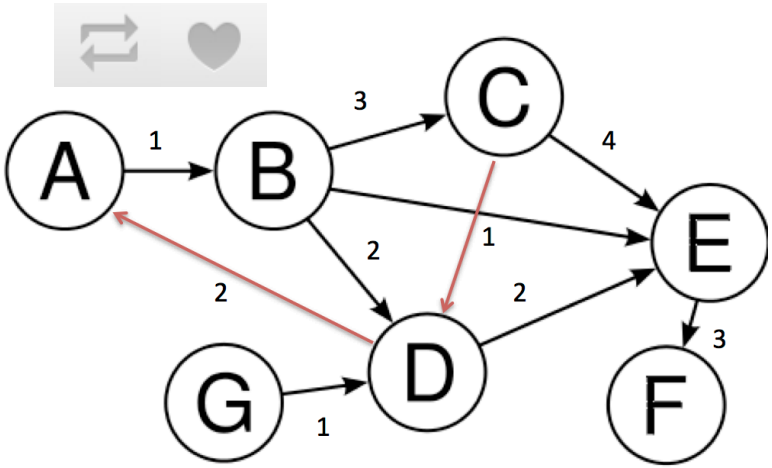


- Final output is a 958-dimensional vector of confidence scores over pre-defined categories
  - Averaged over photos that were posted/liked/reblogged

User and Blog Features – Activity

Both like and reblog activity can be represented as a graph W:

- W_{ij}: number of reblogged/liked posts of blog j by user i.

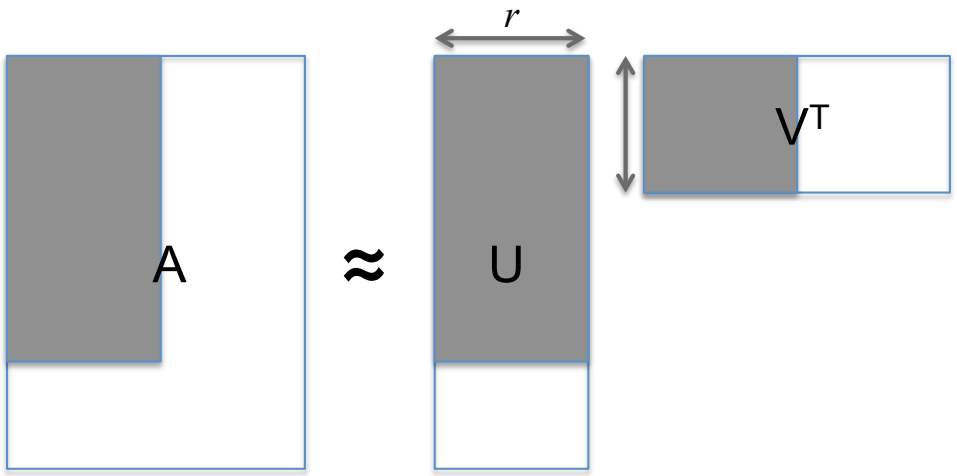


We extract principal components of the reblog/like graph.

Proposed Method:
Boosted Inductive Matrix Completion

Standard Matrix Completion

Model A_{ij} with low-rank matrix: $A_{ij} = \mathbf{u}_i \mathbf{v}_j^T$

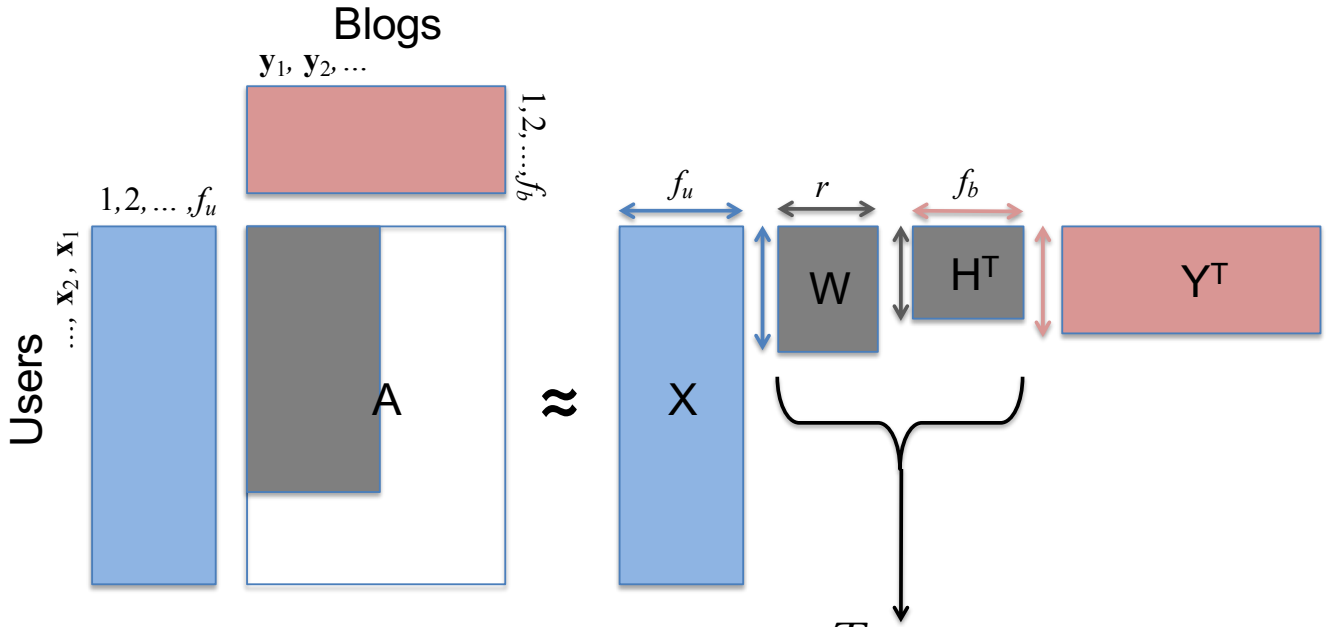


$$\min_{U,V} \sum_{(i,j)\in\Omega} (A_{ij} - \mathbf{u}_i \mathbf{v}_j^T)^2 + \frac{\lambda}{2}(\|U\|_F^2 + \|V\|_F^2),$$

- Theoretically well-understood + Fast solvers [Jain et.al. 2013, Yu et.al. 2014a]
- Restricted to transductive setting: predictions can only be made for existing users/items
- Suffers performance with extreme sparsity in data

Inductive Matrix Completion

Model A_{ij} with user and item feature vectors: $A_{ij} = \mathbf{x}_i^T Z \mathbf{y}_j$



$$A_{ij} = \mathbf{x}_i^T Z \mathbf{y}_j$$

$$\min_{W,H} \sum_{(i,j)\in\Omega} (A_{ij} - \mathbf{x}_i^T W H^T \mathbf{y}_j)^2 + \frac{\lambda}{2}(\|W\|_F^2 + \|H\|_F^2)$$

- Utilizes side information – alleviate data sparsity issues
- Inductive setting: can make predictions for new users and items
- Theoretical guarantees + Fast solver [Yu et.al. 2014b, Zhong et.al. 2015]

Inductive Matrix Completion

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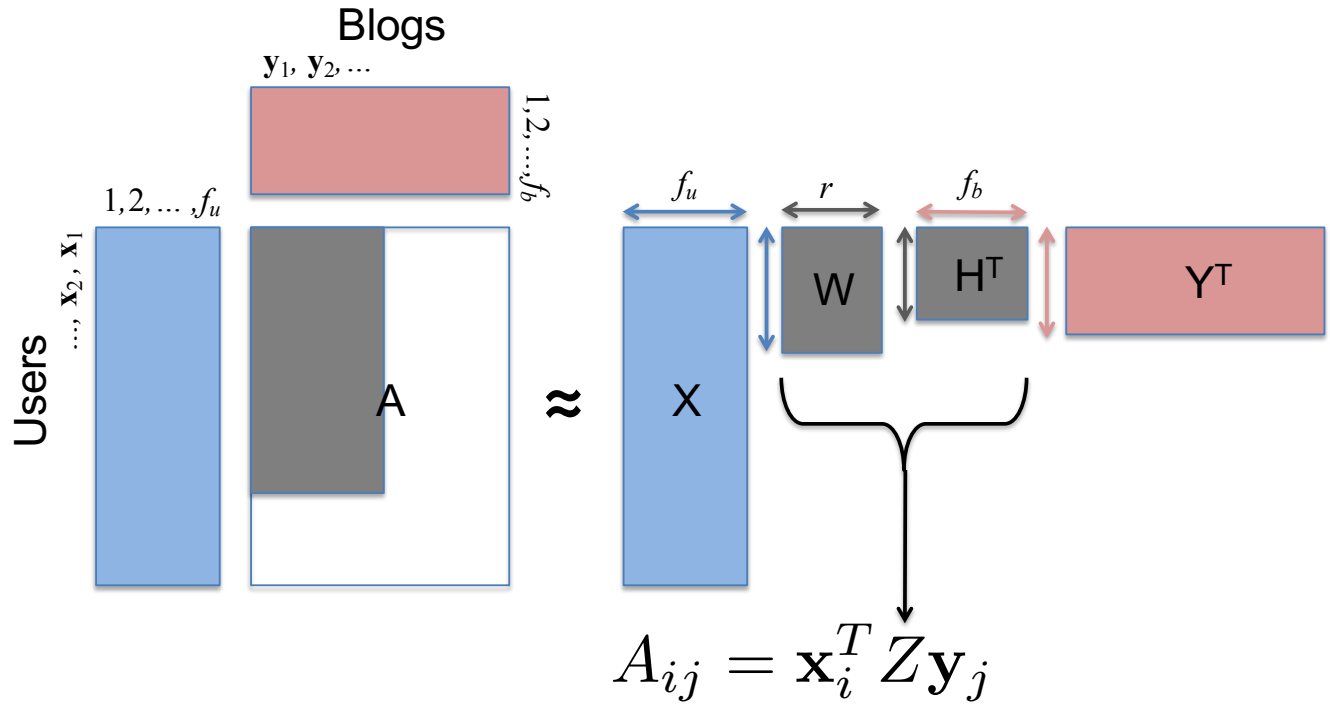

- IMC model is too rigid as it heavily depends on user/item features:

$$A = XZY^T \quad \Rightarrow \quad col(A) \subseteq col(X), \quad col(A^T) \subseteq col(Y)$$

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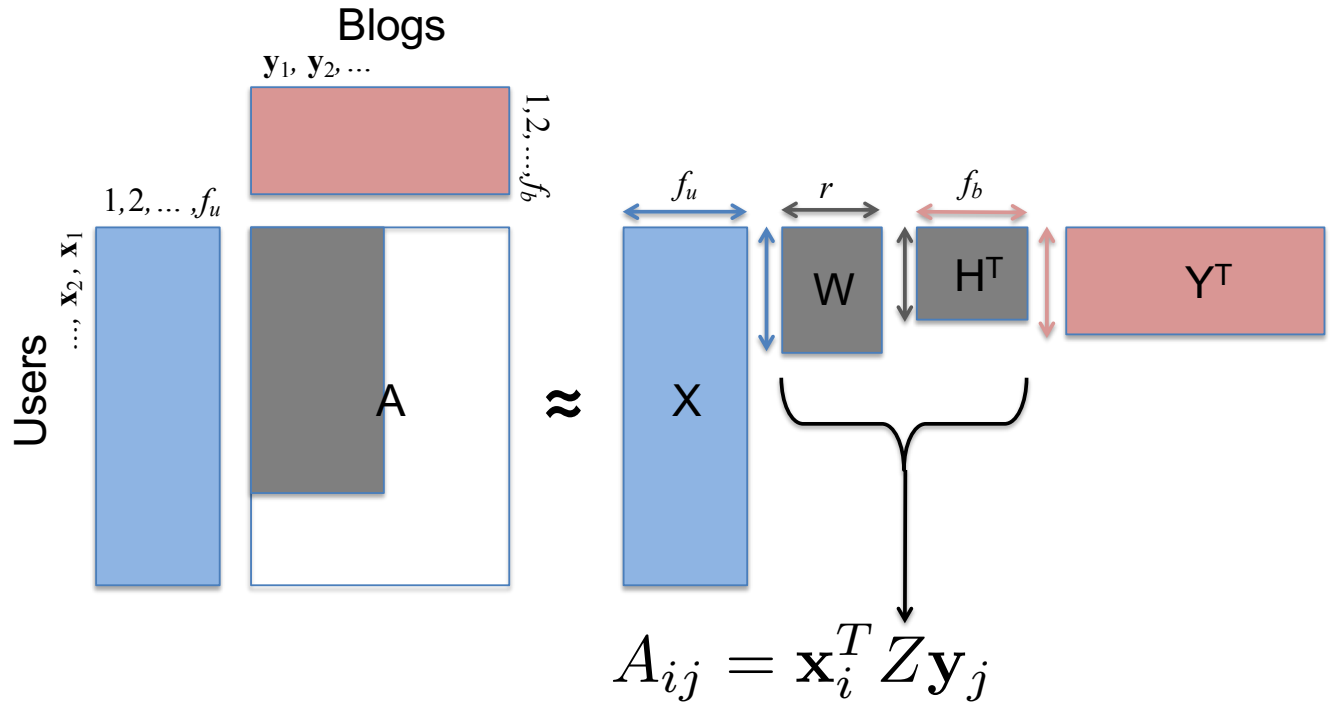

- IMC model is too rigid as it heavily depends on user/item features:

$$A = XZY^T \quad \Rightarrow \quad col(A) \subseteq col(X), \quad col(A^T) \subseteq col(Y)$$

  - Noisy or weakly informative features that do not support A
  - Users or items without any features (e.g., users without any posts)

Boosted Inductive Matrix Completion

Combine MC and IMC and utilize the power of both methods:

$$A_{ij} = \mathbf{u}_i \mathbf{v}_j^T + \alpha \mathbf{x}_i^T Z \mathbf{y}_j$$

- Exploits both observation and feature information – α controls the contribution of features
- Can handle sparsity issues in either source

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Caveats:

- Tuning for a good α is difficult
- Jointly optimizing for all factor matrices can be inefficient

Boosted Inductive Matrix Completion

Our approach: focus on the residual in an additive manner

$$R_{ij} = A_{ij} - \mathbf{u}_i \mathbf{v}_j^T = \mathbf{x}_i^T Z \mathbf{y}_j$$

1. First find the support of A with U and V
2. Then focus on the part that cannot be modeled by MC

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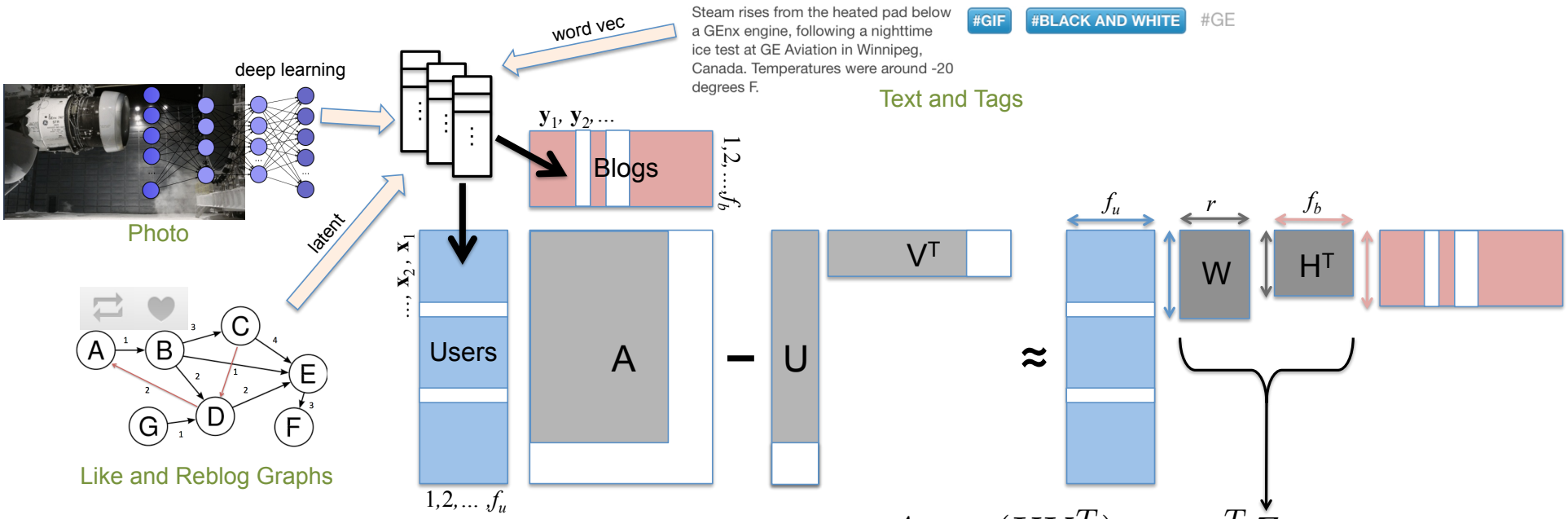
Combine effectiveness of both MC and IMC models:

- Captures low-rank structure of A + latent structure using features
- Captures entries in A where MC fails to learn – especially useful when $\|R\|$ is large
- No need to fine tune α
- Can utilize fast MC/IMC solvers

Boosted Inductive Matrix Completion

1. Learn U and V via standard MC
2. Train IMC on the residual $R = A - UV^T$



$$A_{ij} - (UV^T)_{ij} = \mathbf{x}_i^T Z \mathbf{y}_j$$

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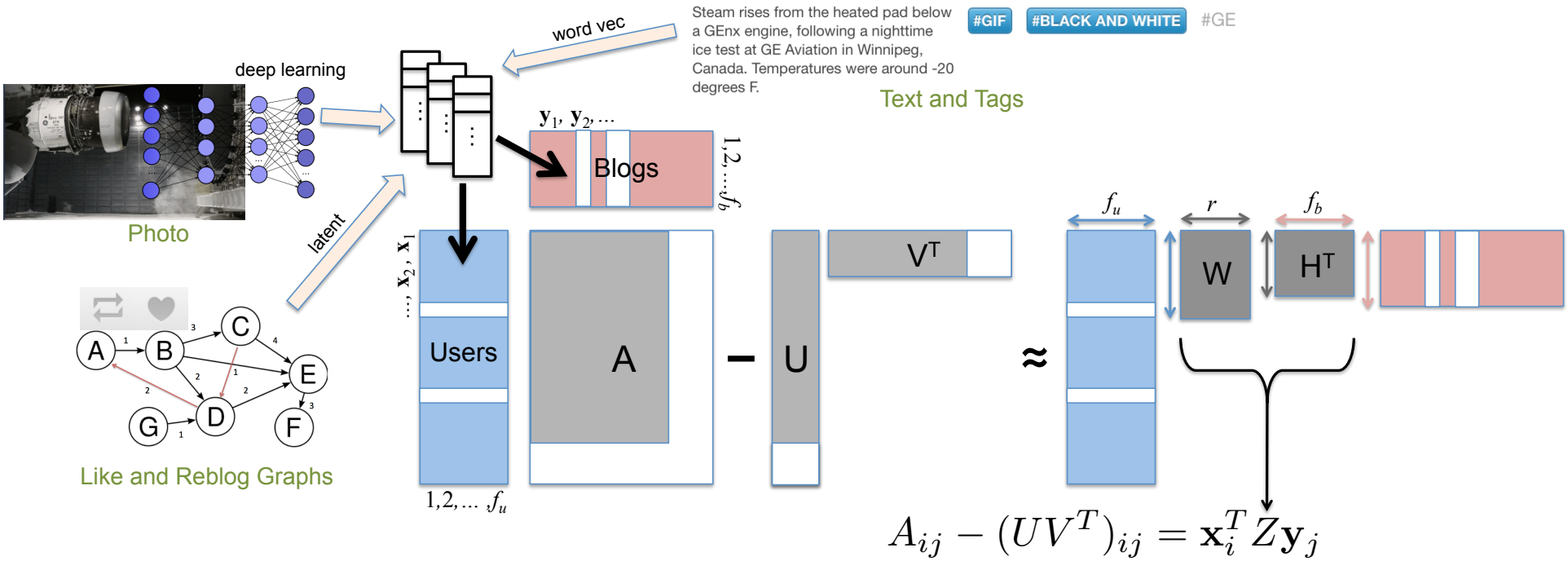


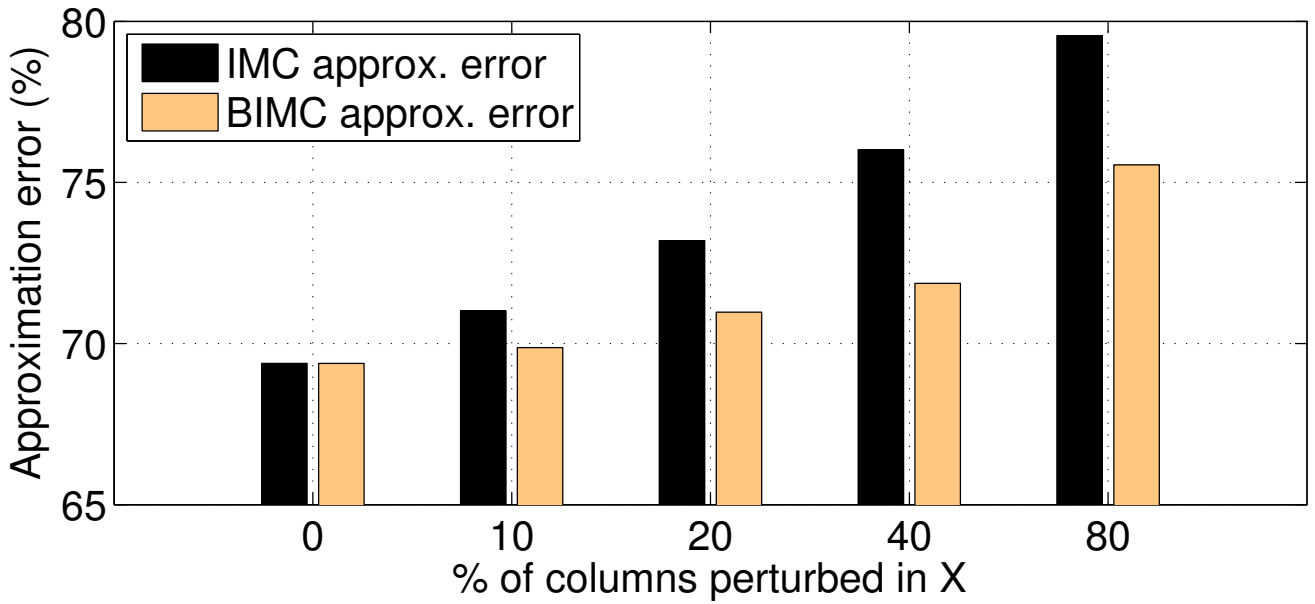
$$A_{ij} - (UV^T)_{ij} = \mathbf{x}_i^T Z \mathbf{y}_j$$

- Converse approach (IMC⇒MC) gives comparable results.

Robustness to Noisy Features

Dataset: MovieLens-100K (100K ratings from 1,000 users on 1,700 movies)

- Compute the rank-20 SVD of $A \approx U_A \Sigma_A V_A$.
- Set $X = U_A$ and $Y = V_A$ for both IMC and BIMC.
- Perturb columns of X by adding random noise.



Experimental Results

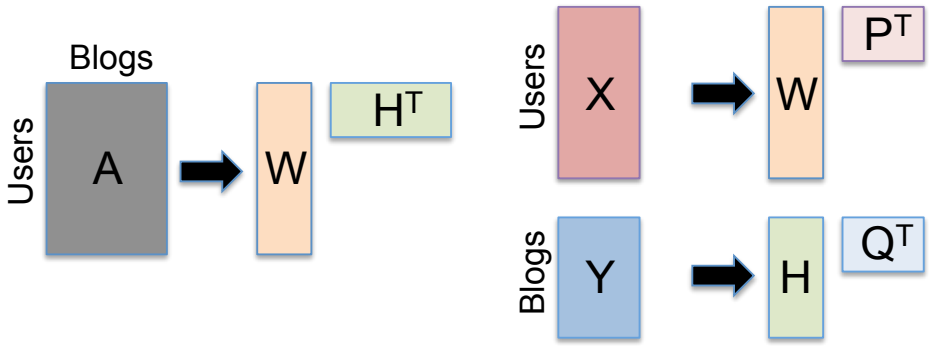
Comparison Methods

Baselines:

- Global ranking, SVD, Matrix Completion (MC)

Methods incorporating side-information:

- Inductive Matrix Completion (IMC)
- Collective Matrix Completion (CMC) [Gunasekar et.al. 2015]
  - Jointly recover a collection of matrices with shared low rank structure



- Graph-based proximity measure between users and blogs (Katz):
  - Compute Katz scores using $C = \begin{bmatrix} U & A \\ A^T & B \end{bmatrix}$, where U and B are similarity matrices computed from user and blog features, respectively.

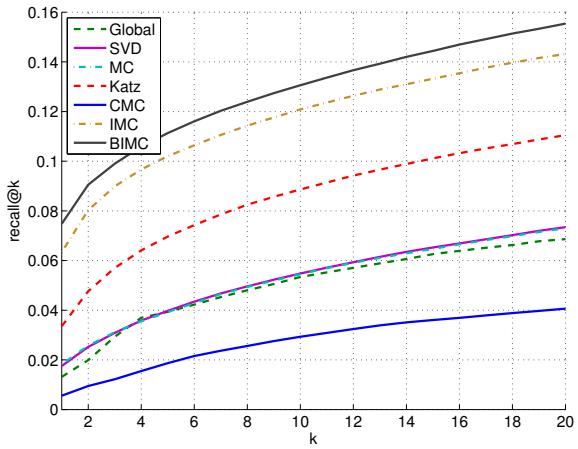
Experimental Results

- 1M sampled users and blogs
- 10-fold cross-validation (similar results with temporal evaluation)

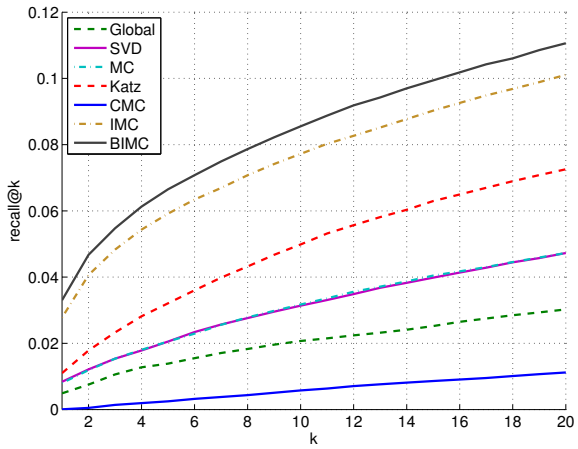
Method	PRC@10	RCL@10	AUC
Global	1.03%	4.80%	0.8687
SVD	1.28%	5.10%	0.8530
MC	1.28%	5.07%	0.8515
Katz	1.90%	8.15%	0.9209
CMC	0.49%	2.41%	0.8996
IMC	2.93%	11.33%	0.9075
BIMC	**3.21%**	**12.28%**	**0.9221**

User and Blog Groups

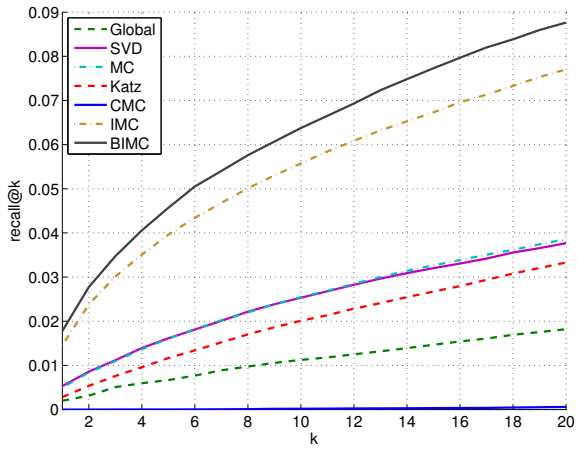
User groups with different number of followees ($n_f \leq 40$, $40 < n_f \leq 100$, $100 < n_f$)



(a) Low (89.4%)

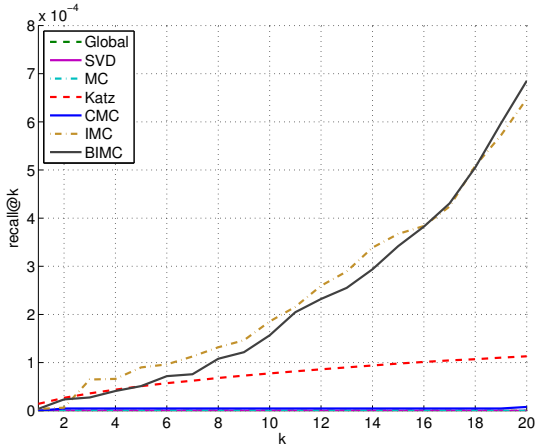


(b) Medium (7.8%)

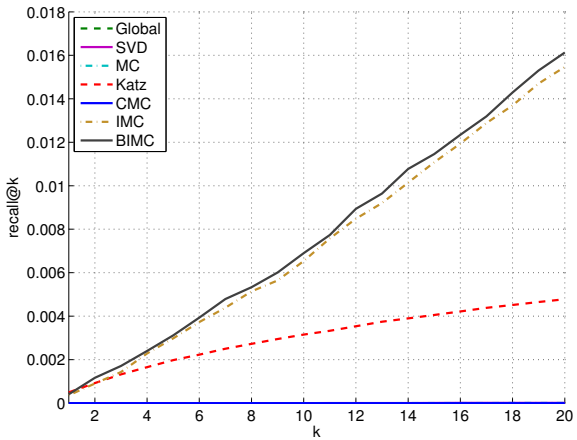


(c) High (2.8%)

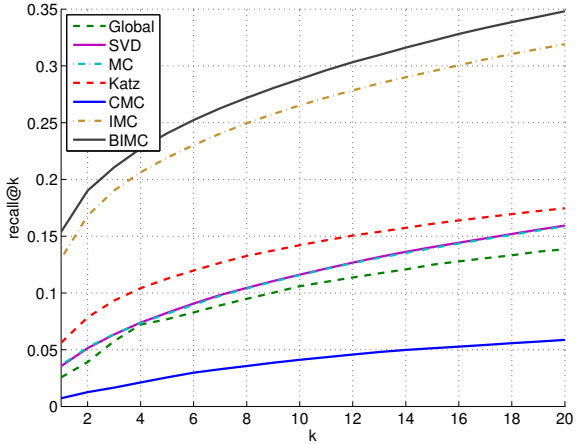
Blog groups with different number of followers ($n_f \leq 40$, $40 < n_f \leq 100$, $100 < n_f$)



(d) Low (95.1%)

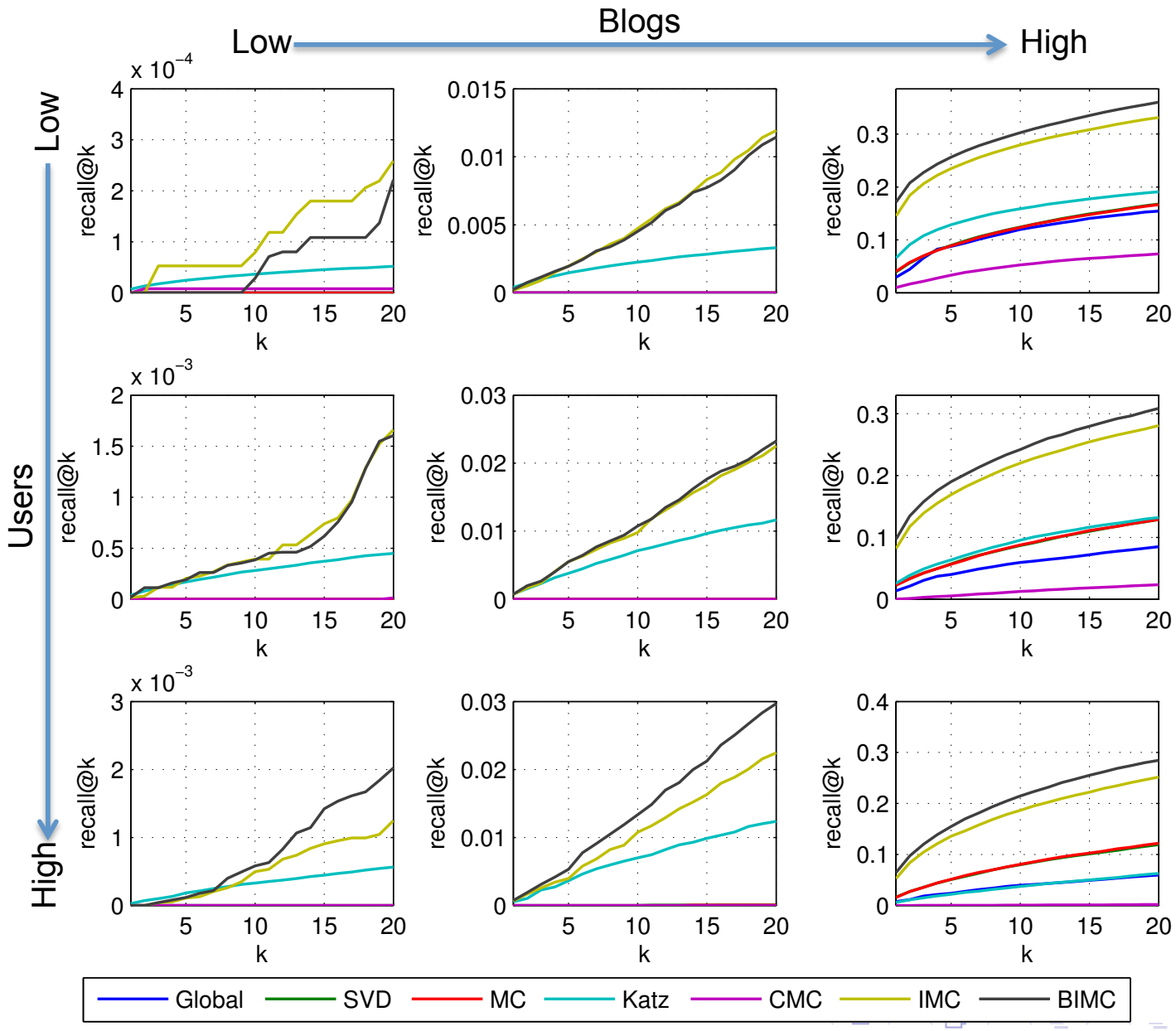


(e) Medium (3.3%)



(f) High (1.6%)

Recall@k


Blogs
Low
High
Users
Low
High
x 10^-4
x 10^-3
x 10^-3
recall@k
k
Global
SVD
MC
Katz
CMC
IMC
BIMC

Conclusion

Tumblr Blog Recommendation

- Incorporate features extracted from various side information (text, image and activity) with state-of-the-art deep learning approaches.
- BIMC: effectively combining the power of both MC and IMC
  - Exploits both observation and feature information
  - Can deal with sparsity issues in either source
  - Can make predictions for new users and items
  - Scalable due to fast MC/IMC solvers
  - Yields the best recommendation performance

Thanks!

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