Ratings Meet Reviews, a Combined Approach to Recommend

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Presented by: Guang Ling

The ACM Conference Series on
Recommender Systems

Recommender Systems are everywhere

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- Amazon
  Recommends books

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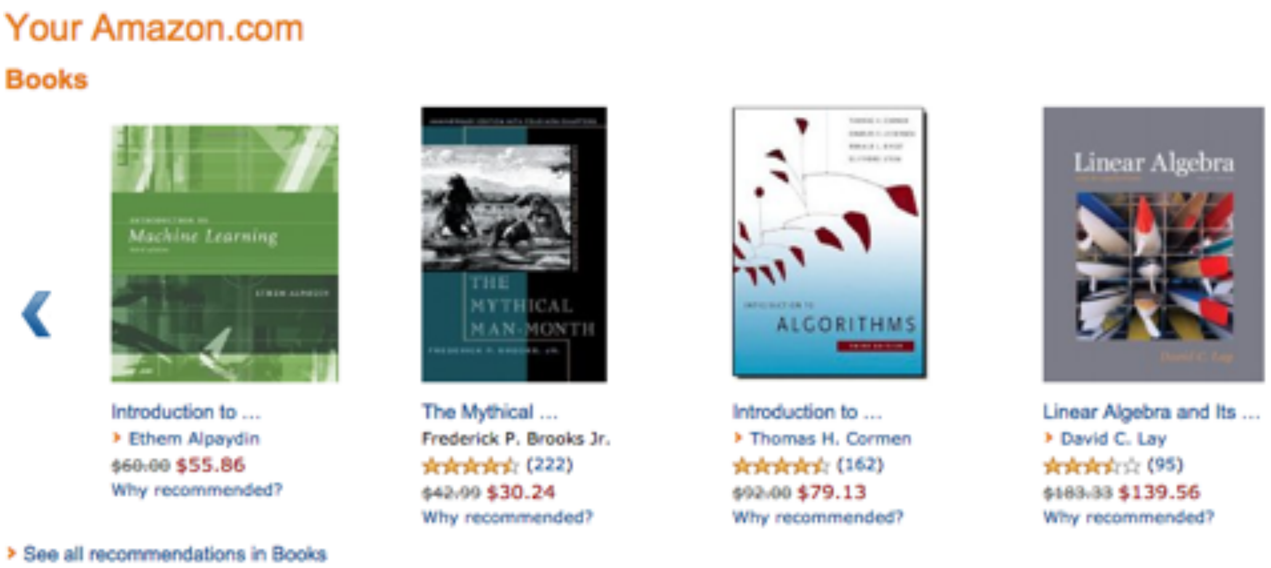

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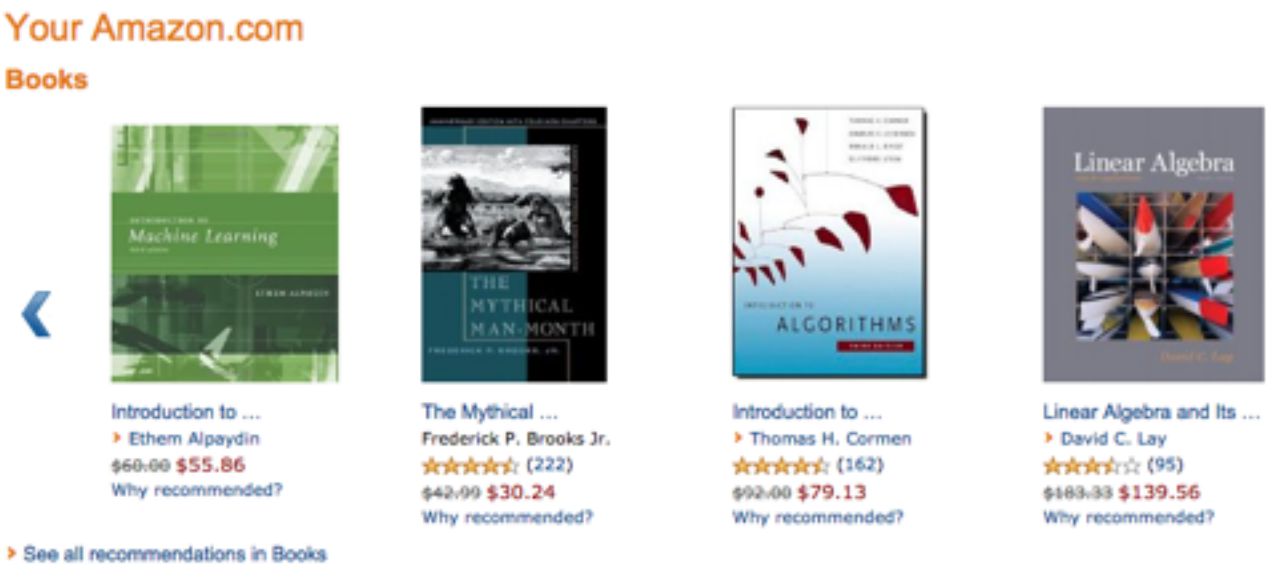

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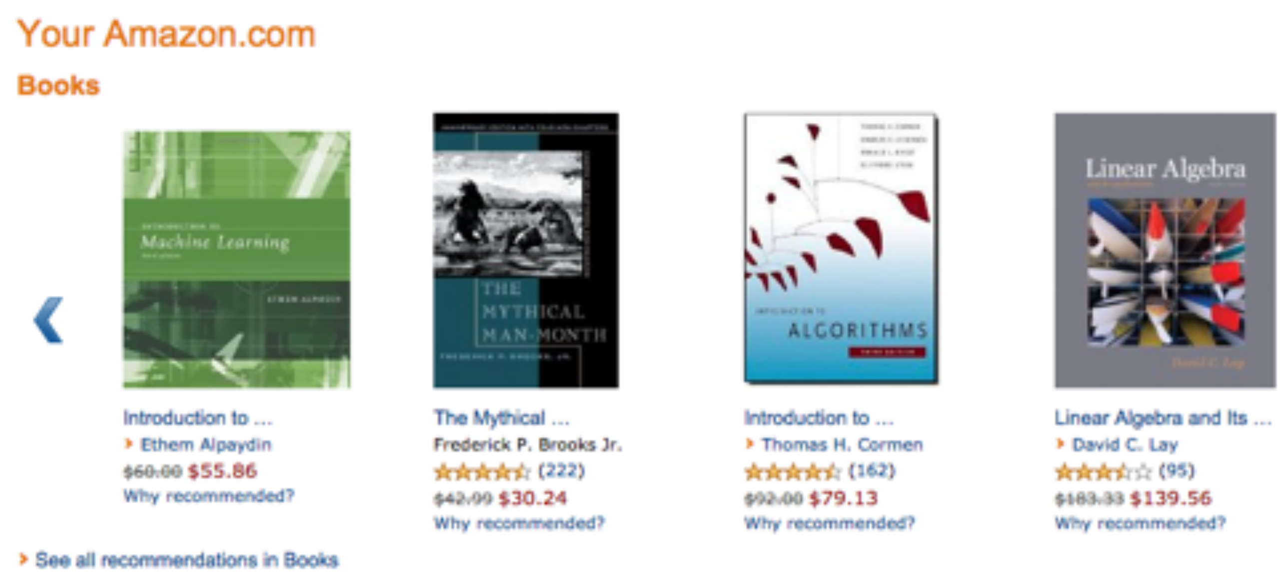

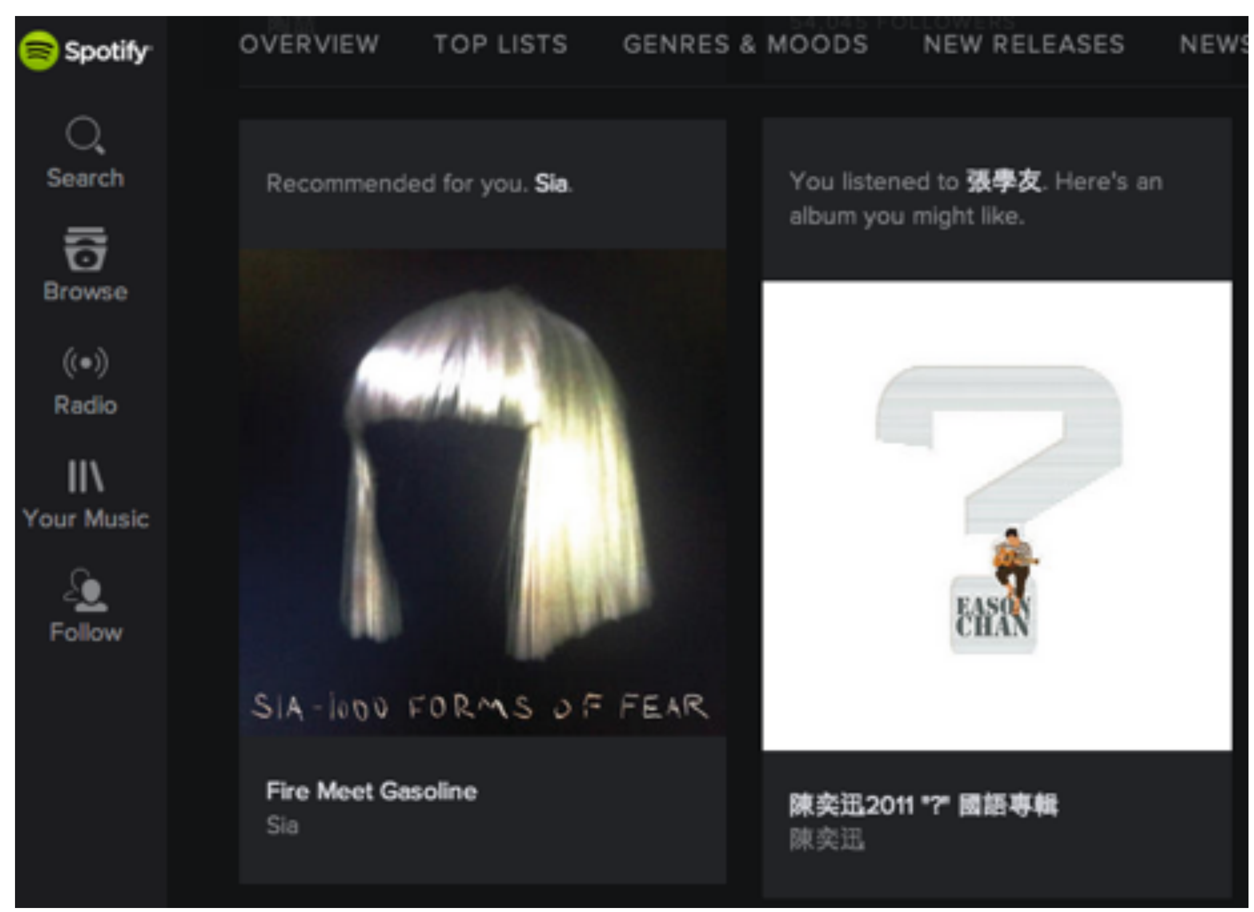

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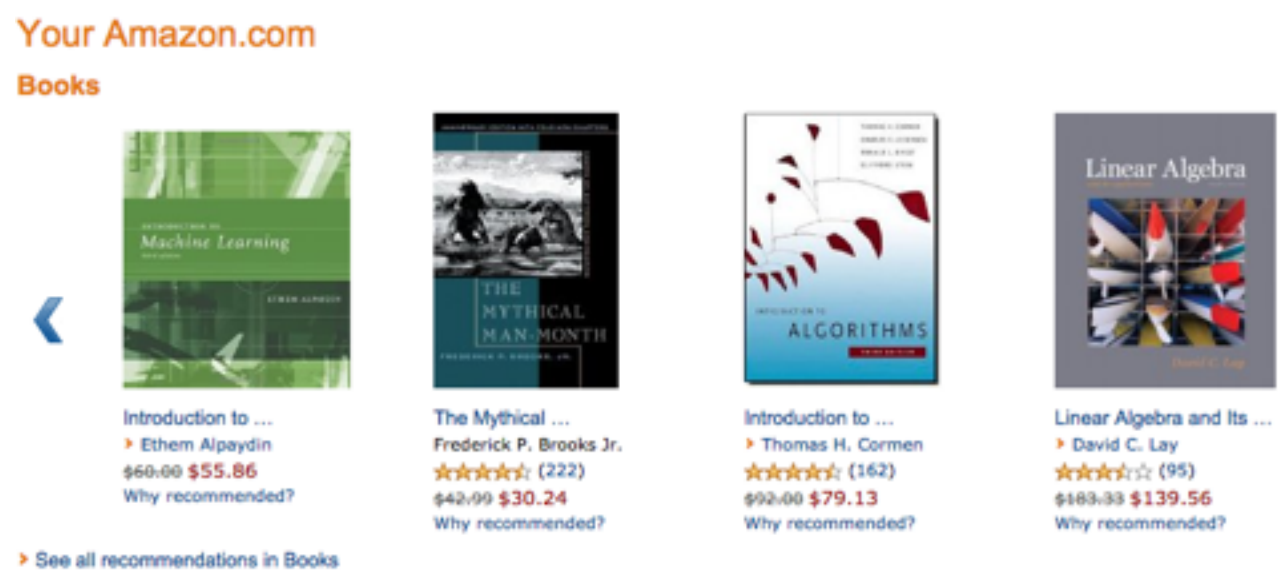

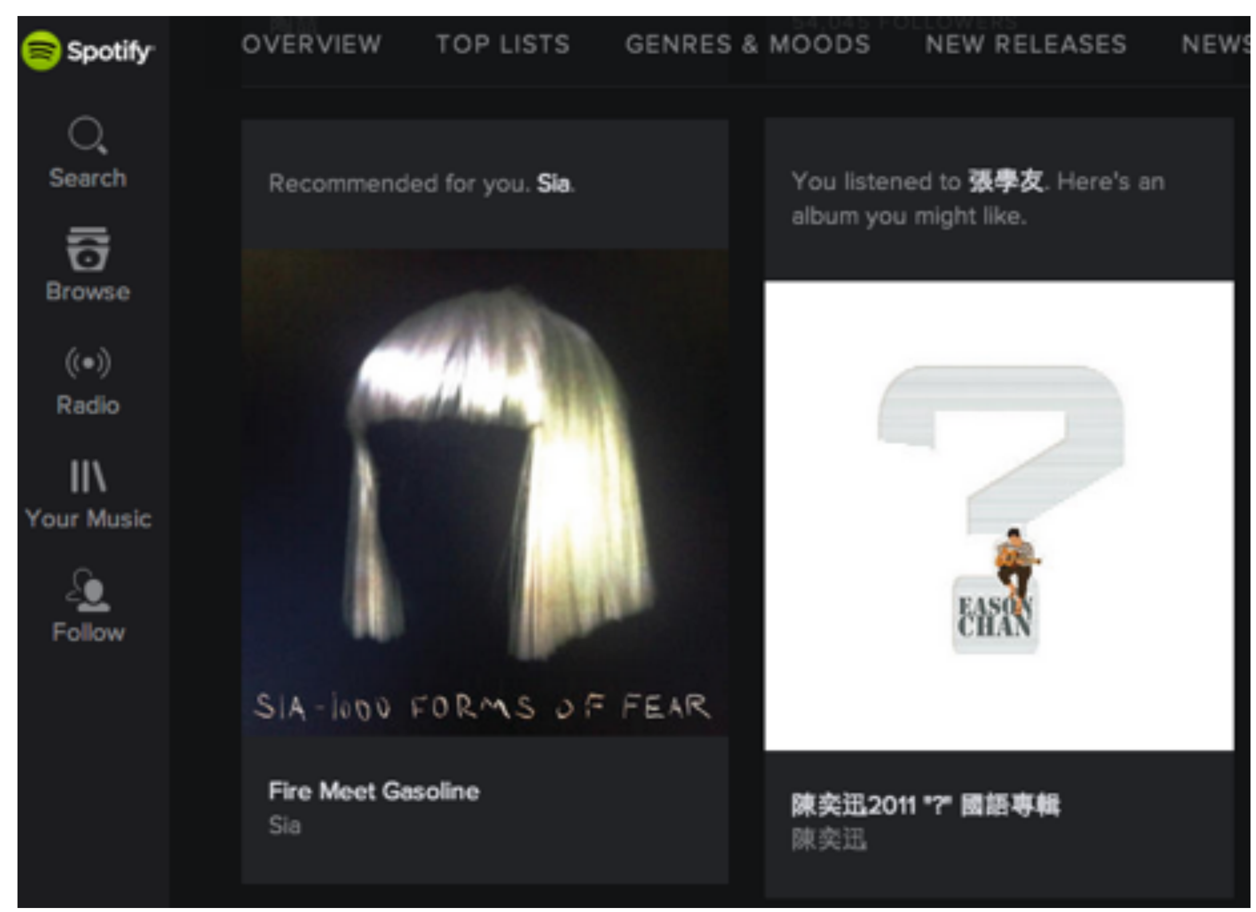

Recommender Systems are everywhere

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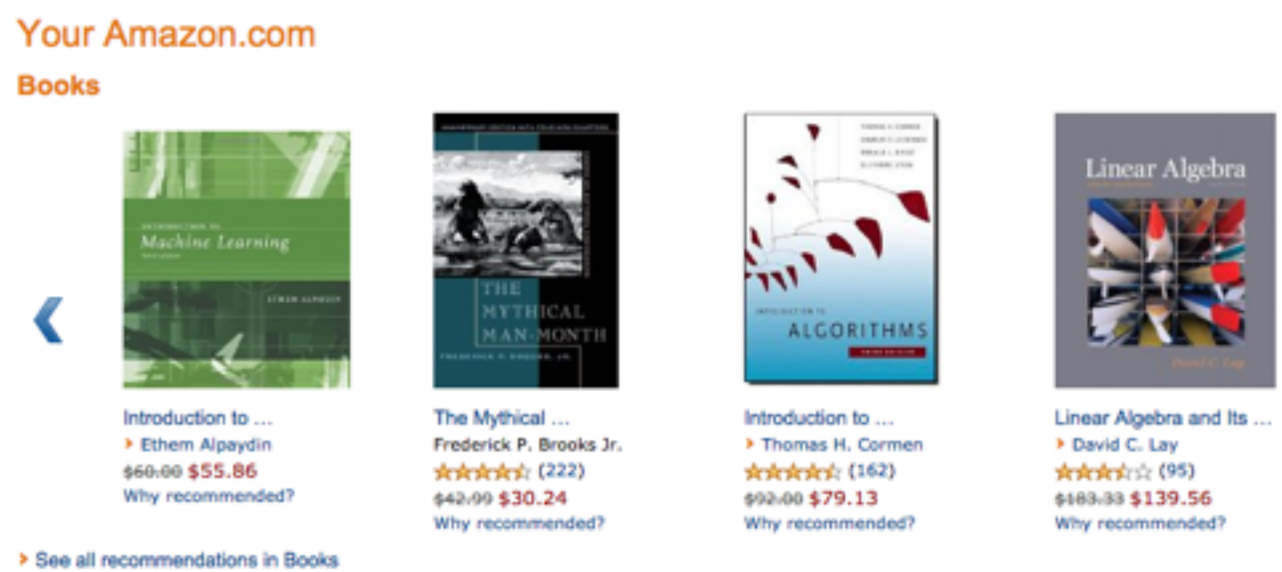
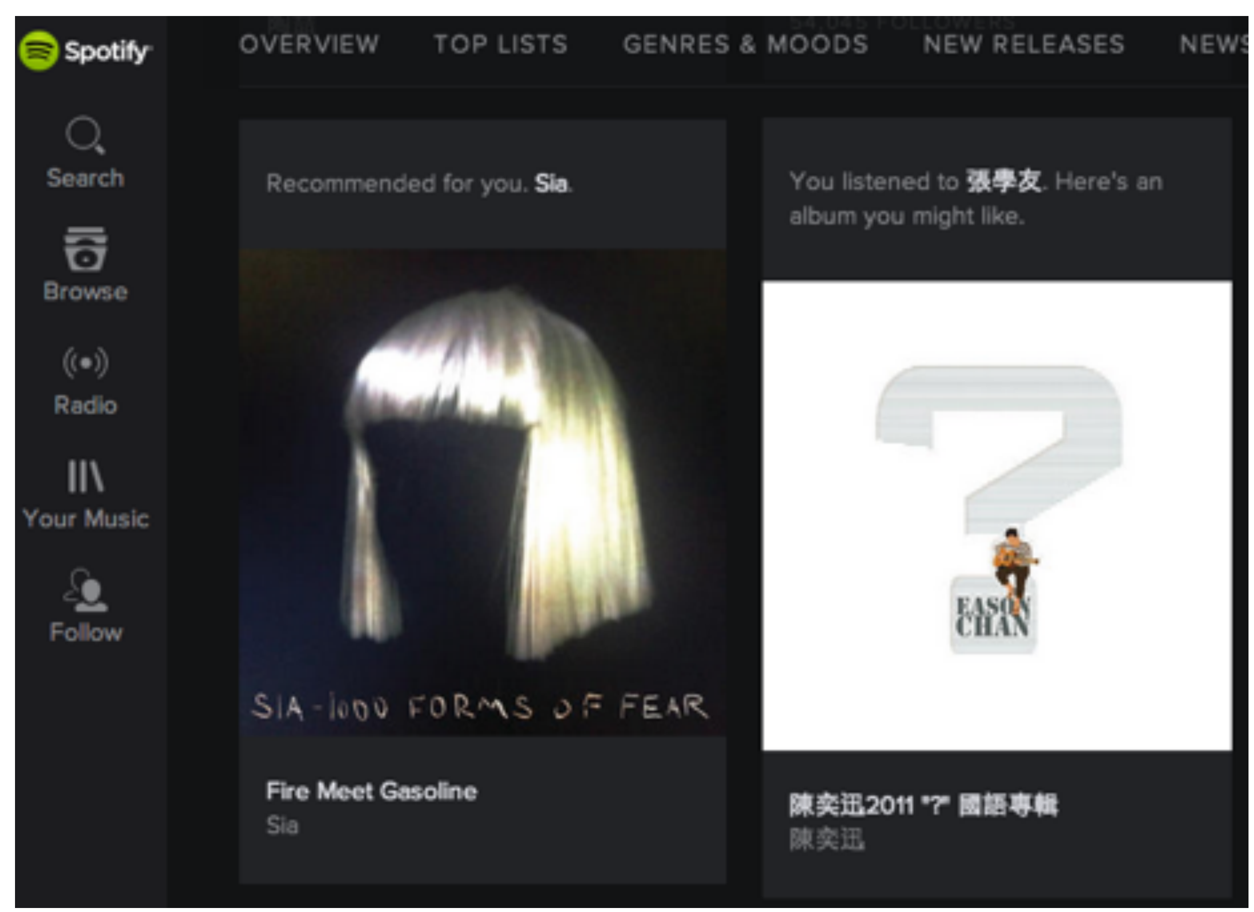
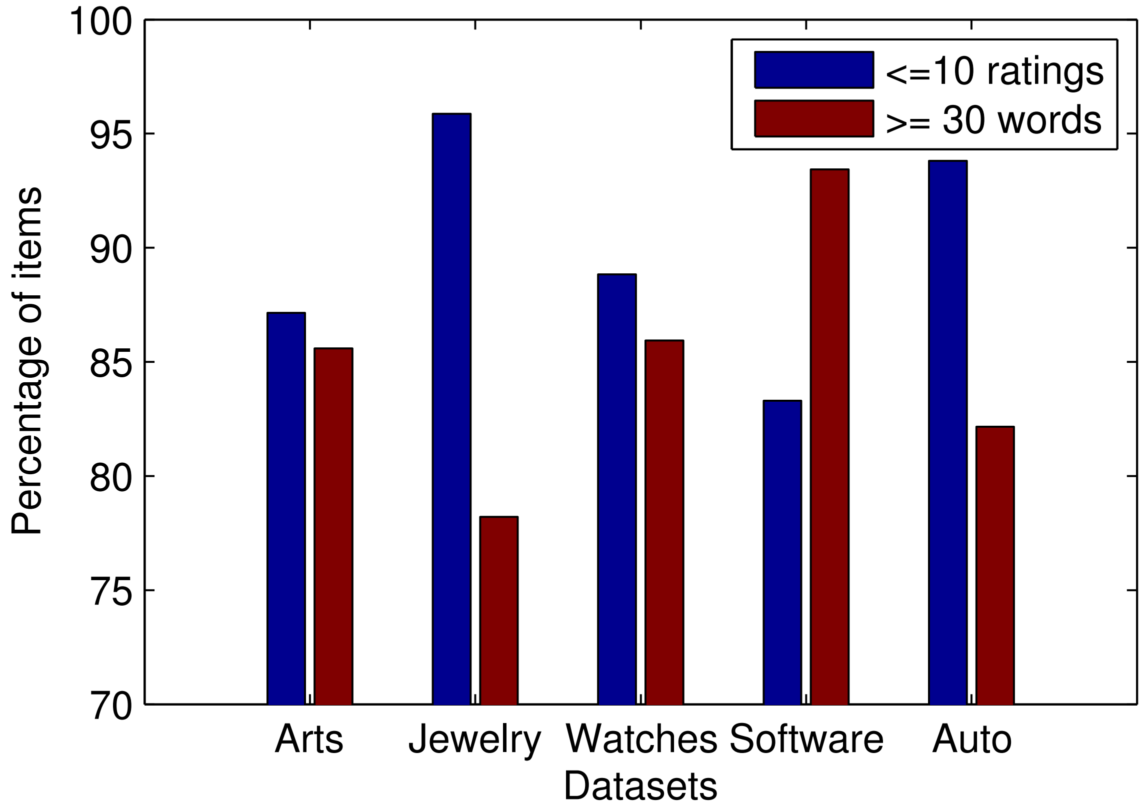
  Recommends books
- Spotify recommends music
- IMDb recommends movies to watch
- Twitter and Facebook suggest whom to follow and friend





Recommender Systems are not perfect

- Cold-start problem
  - Recommender system has too little information concerning a user or an item to make accurate predictions
  - Severe problem in real system



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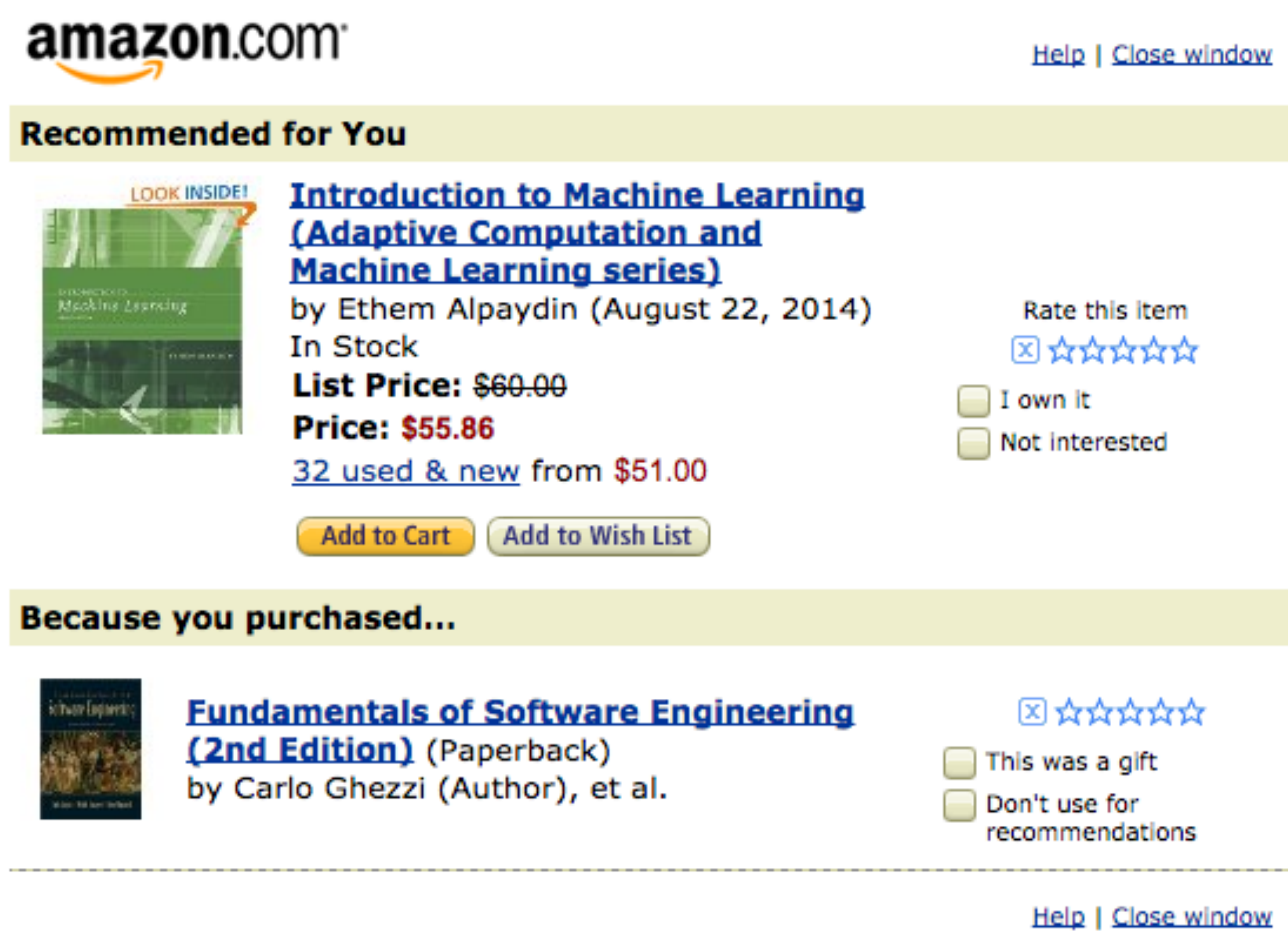

Recommender Systems are not perfect

- Why these items are recommended?

Recommender Systems are not perfect

- Why these items are recommended?
- Explanations on why such items are recommended can be useful.
- Existing recommender systems do not provide adequate explanations.

Reviews can help

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Did not disappoint life-long Trekkie

By Emily Eagon on July 27, 2013

Format: DVD

I had a major argument with a fellow Trekkie about the merits of this film. He continued to argue that the movie was good until the end, in which case it was a cop out of something that had already been done before (those who have seen other Star Trek motion pictures know what I'm talking about. Being sensitive to spoilers) This was my argument:

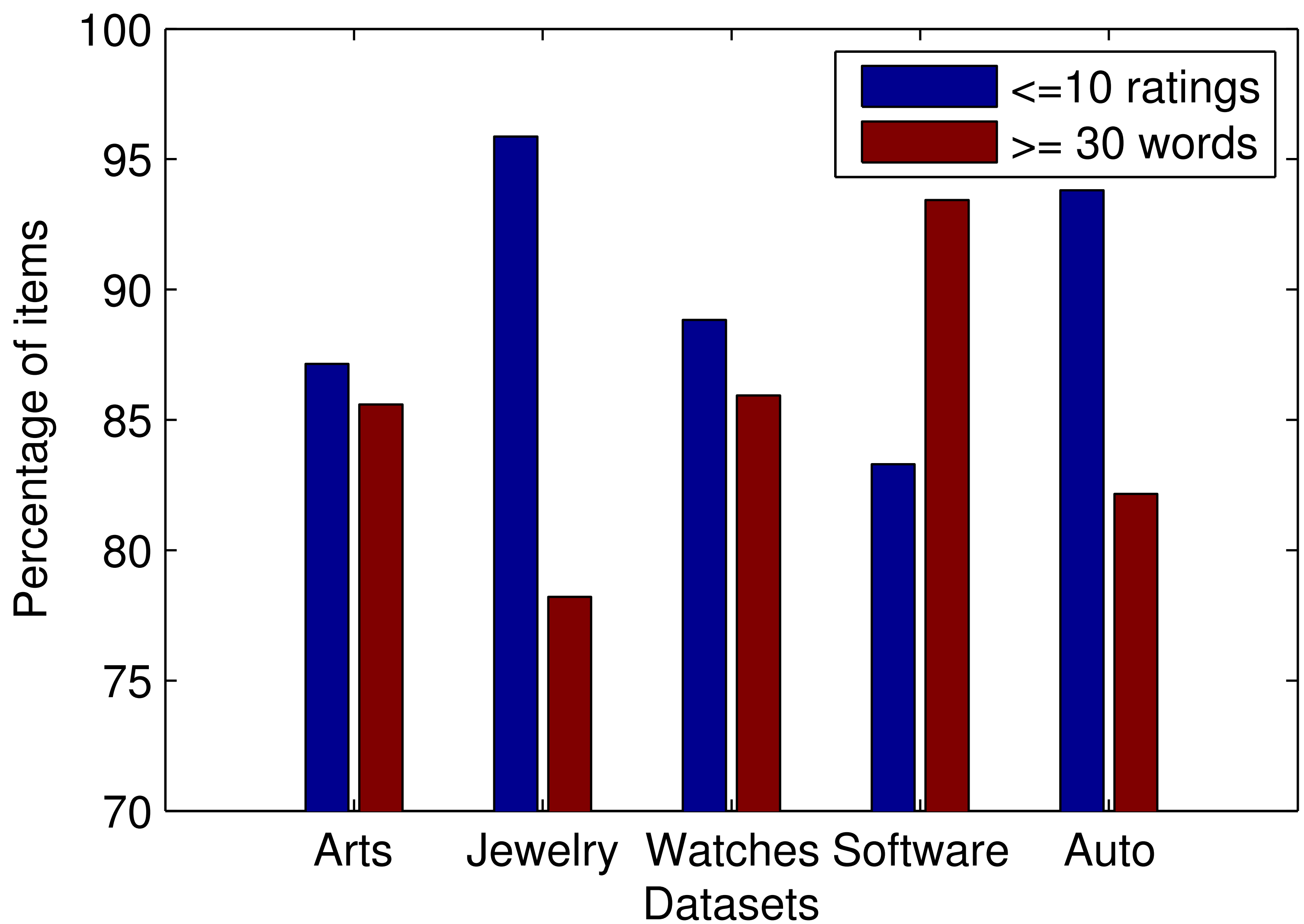
Yes it does mirror some previously established Star Trek plots, but the twists that accompanied the mirages are COMPLETELY important to what makes this film unique. The changes that were made to story lines from the original series completely change the way that the characters react and open them up to future discoveries that could not have been made in the original series (I'm mostly referring to Spock's emotional availability)

Even in the tiniest details it connects to the original series, down to the Tribbles, making any Trekkie feel right at home for the majority of the movie. The film was filled with the sass, wit, and banter that the characters in this show are known for and keep the audience on their toes with the surprises built in.

Maybe one or two other times in my life have I wanted to stand up in the theater or my living room (or wherever I was watching whatever I was watching) and root for a character so badly. The line from the trailer sums it all up. "Is there anything you would not do for your family?" This movie shows exactly how much of a family they truly are and I could not have been happier with this film.

By the way I NEVER see a movie multiple times in theaters due to the obscene prices, but I was willing to go three times to see this film, if that tells you anything.

Reviews can help

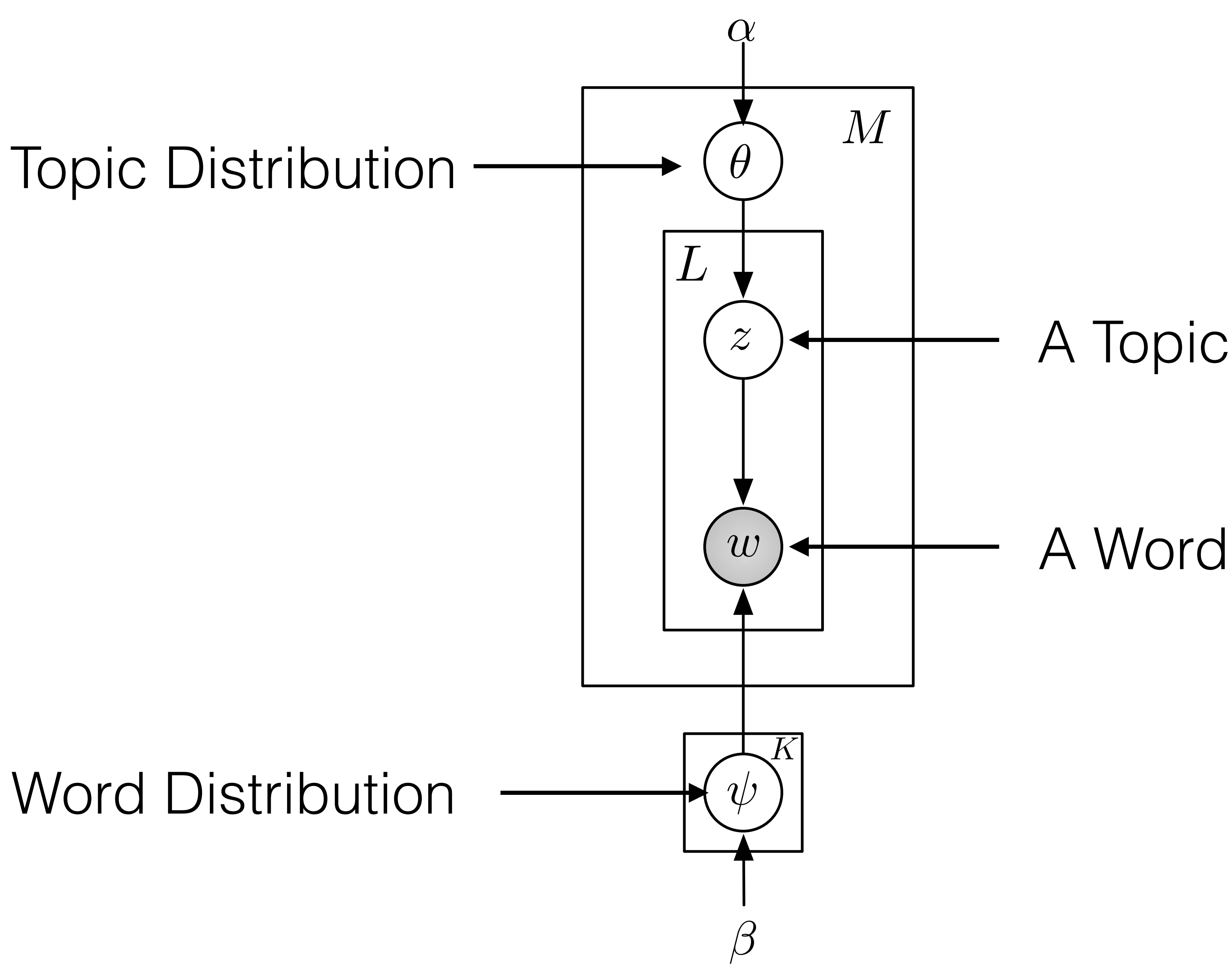


Ratings Meet Reviews, a Combined Approach to Recommend

- Harness the information in BOTH the ratings and the reviews
    - Alleviate the Cold-Start Problem
    - Interpret the recommendations
- How to model the ratings, reviews and combine them?

Modelling the reviews

- Latent Dirichlet Allocation



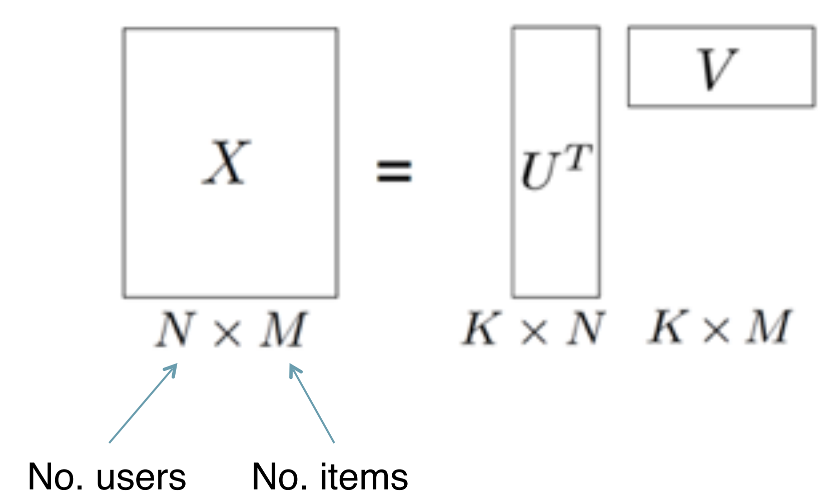
Modelling the ratings

- Most popular method is low-rank matrix factorisation

- Factorize X into $U^T V$

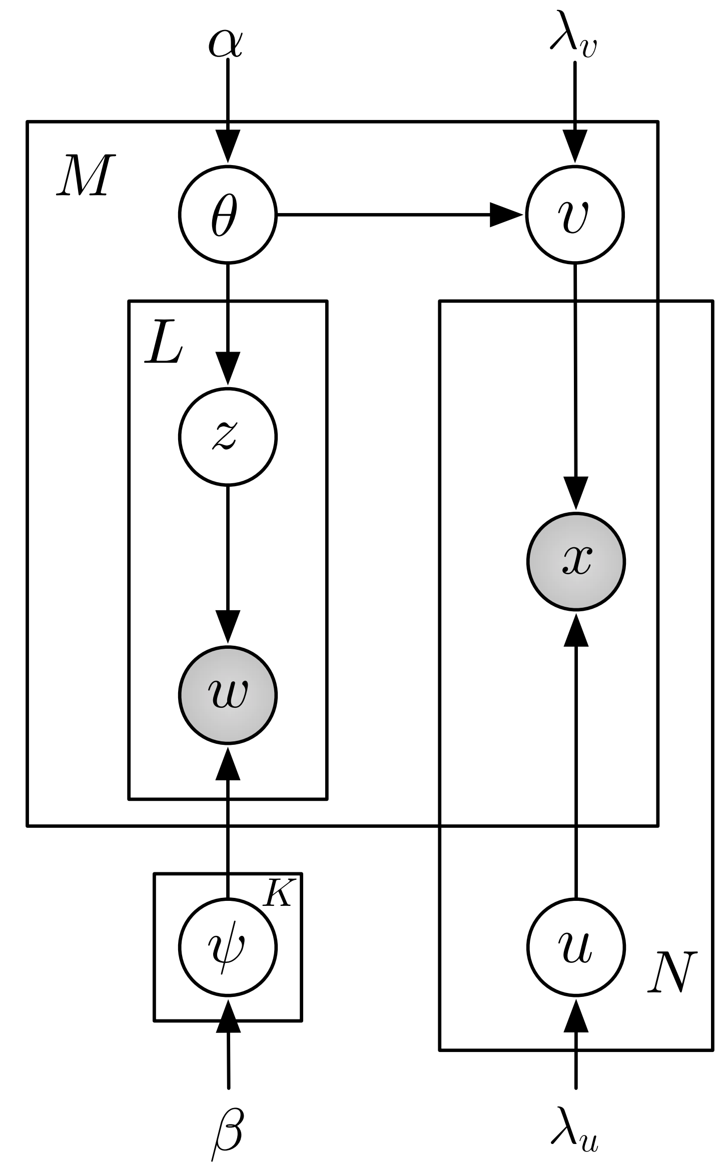
	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8
u_1	5	2		3		4		
u_2	4	3			5			
u_3	4		2				2	4
u_4								
u_5	5	1	2		4	3		
u_6	4	3		2	4		3	5

$$\mathcal{L} = \sum_{i,j \in \text{observation}} (X_{i,j} - U_i^T V_j)^2 + \|U\|_F^2 + \|V\|_F^2$$



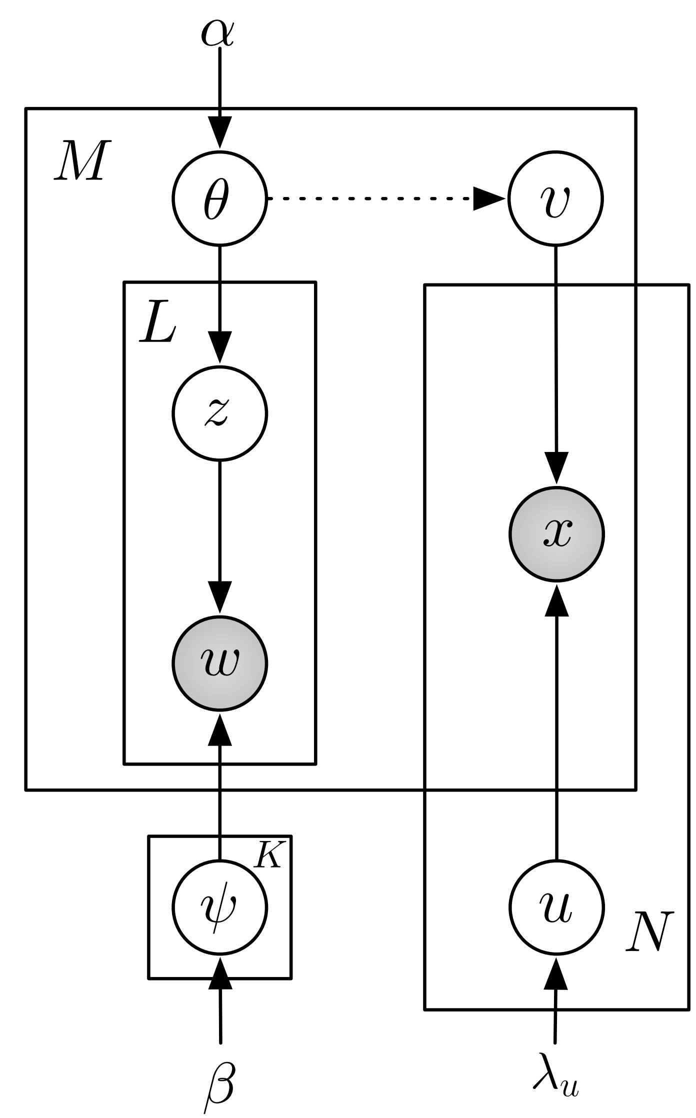
Related works

- CTR model (Wang 2011)
    - Take the topic distribution as the base for the item vectors
    - The topics distribution vector and the item feature vector does not necessarily align with one another



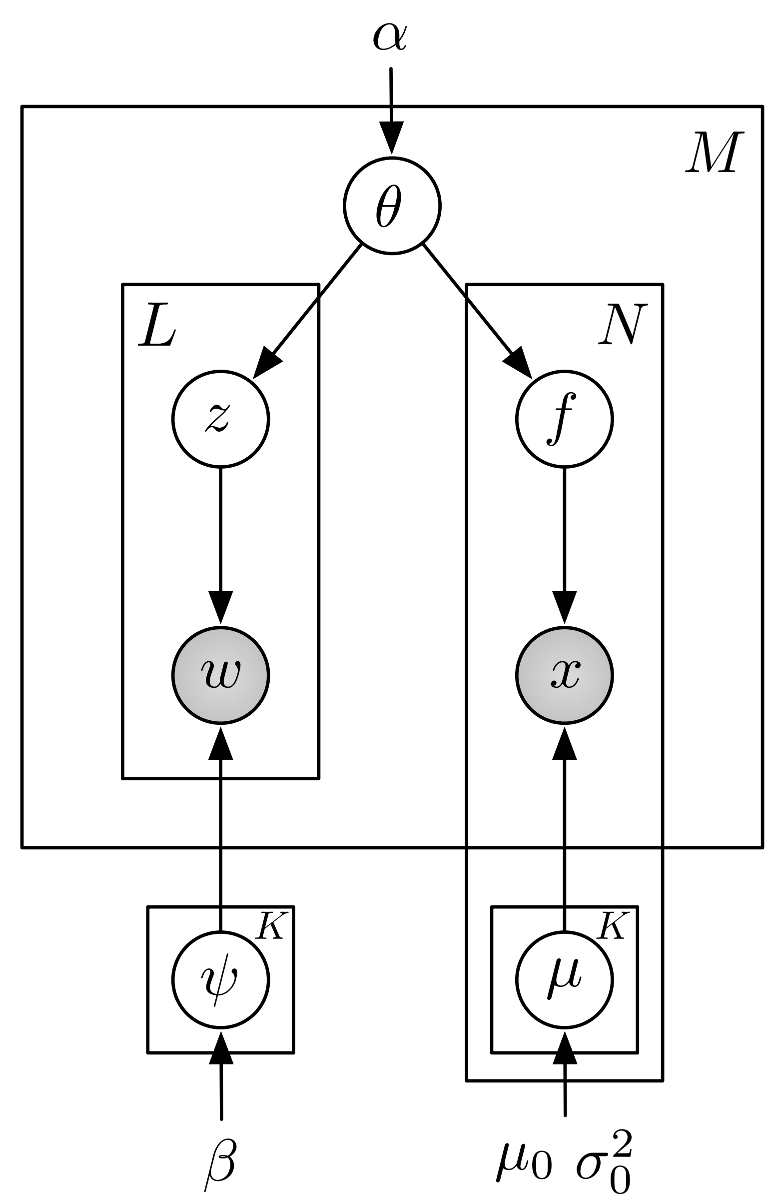
Related works

- HFT (McAuley 2013)
  - Adopt a transformation function to link the topic distribution and the item feature vector
  - Transformation parameter is hard to choose and restrictive



Ratings Meet Reviews, a Combined Approach to Recommend

- Our model, called RMR
  - Use mixture of Gaussians rather than matrix factorisation to model ratings
  - Use LDA to model reviews
  - Combine ratings and reviews by sharing the same topic distribution



Ratings Meet Reviews

- Generative Process:

1. For each user $u \in \mathcal{U}$:
   (a) For each latent topic dimension $k \in [1, K]$:
      i. Draw $\mu_{u,k} \sim$ Gaussian(μ_0, σ_0^2)
2. For each latent topic dimension $k \in [1, K]$:
   (a) Draw $\psi_k \sim$ Dirichlet(β)
3. For each item $v \in \mathcal{V}$:
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   (b) For each description word $w_{v,n}$:
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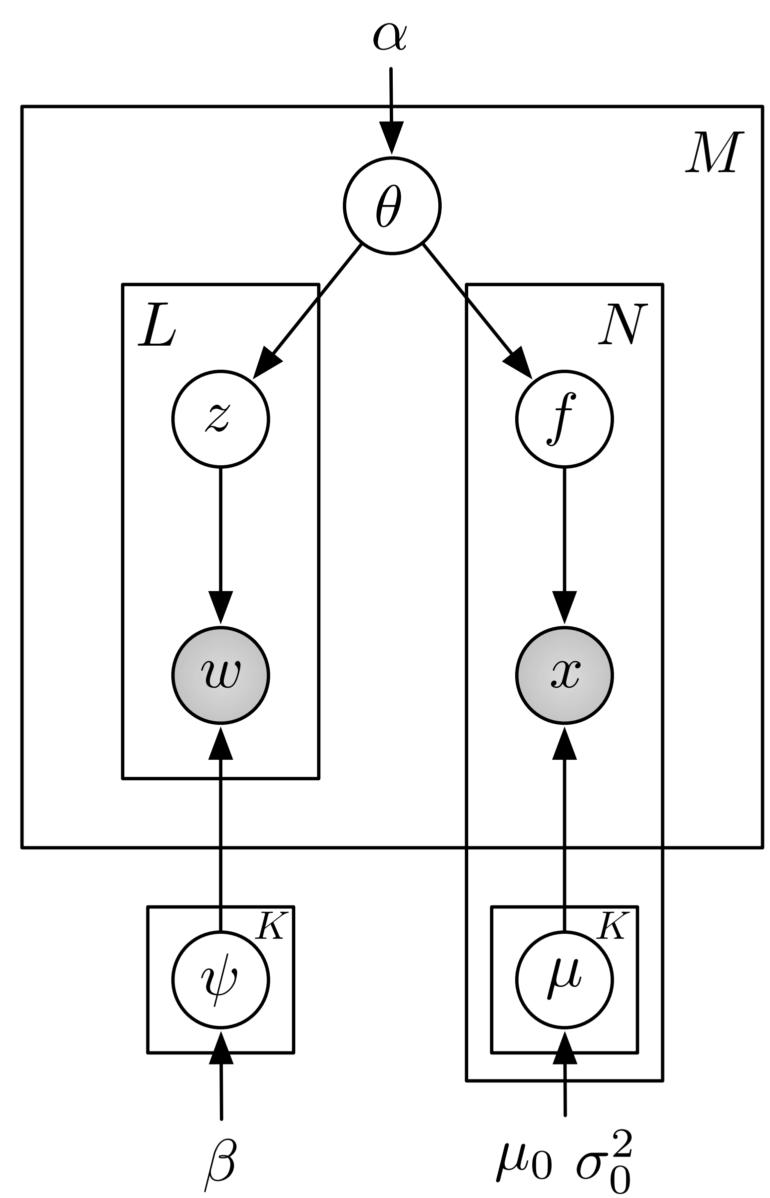

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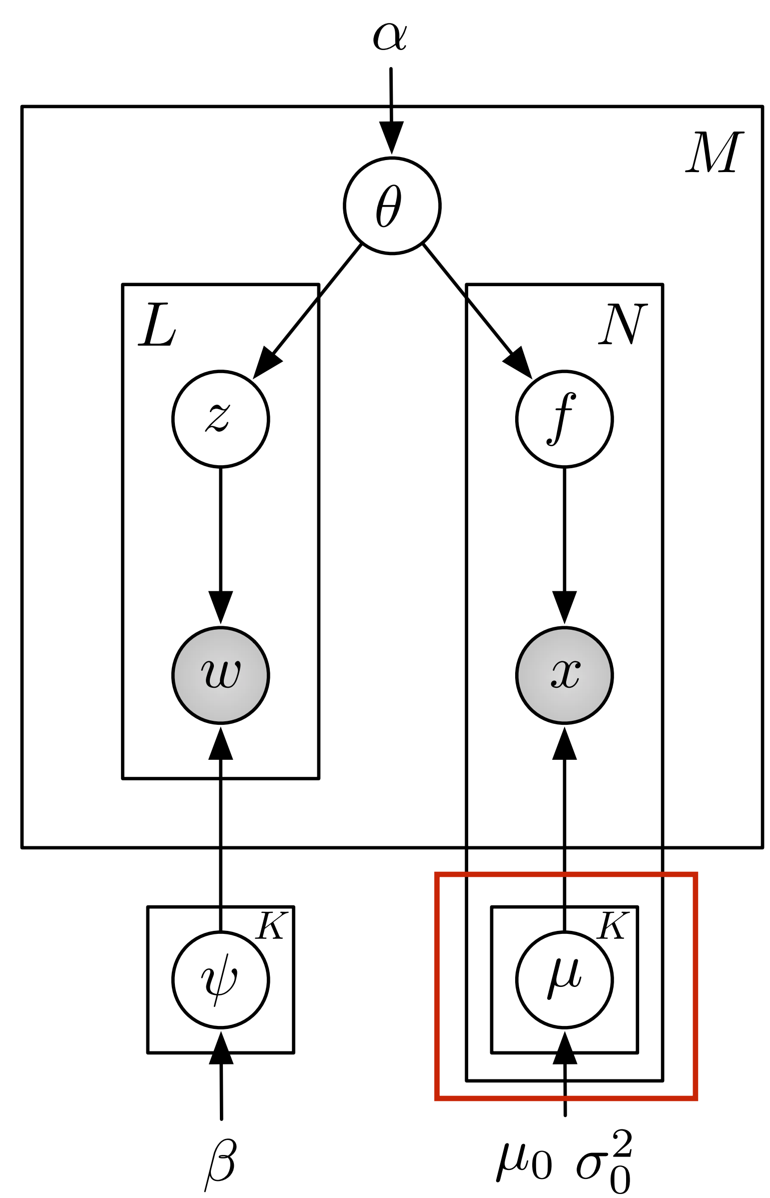

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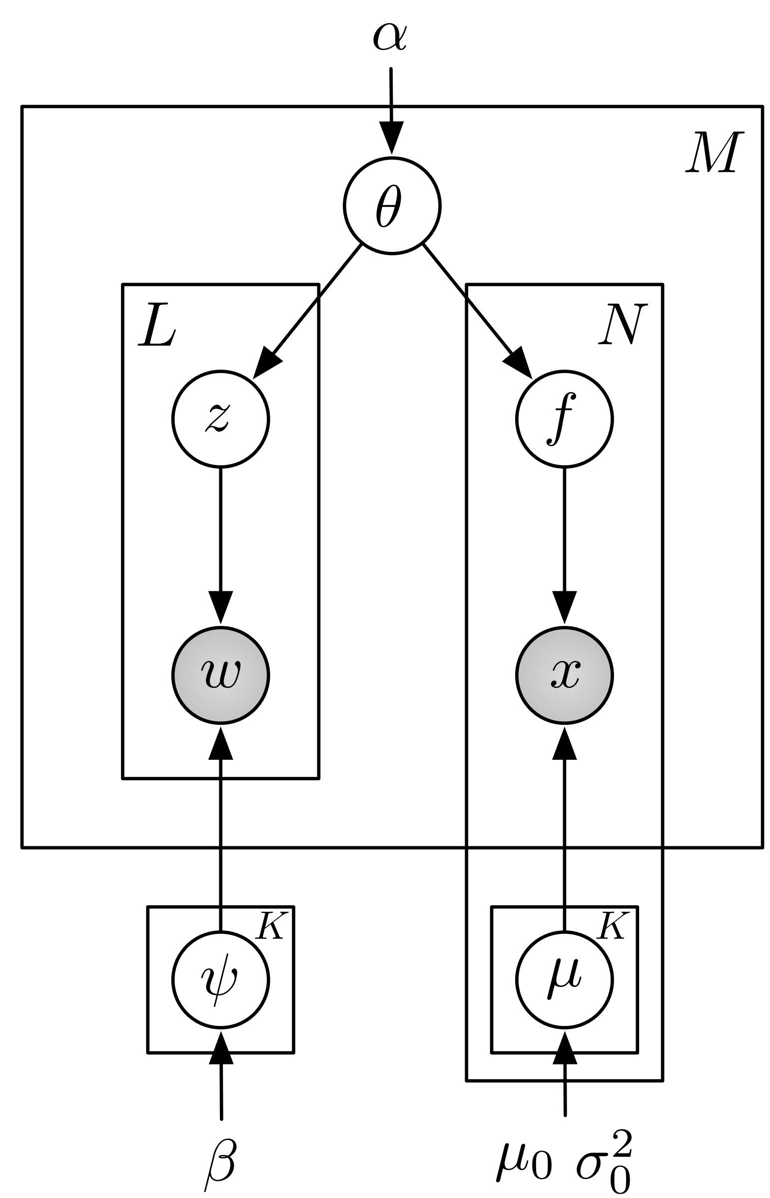

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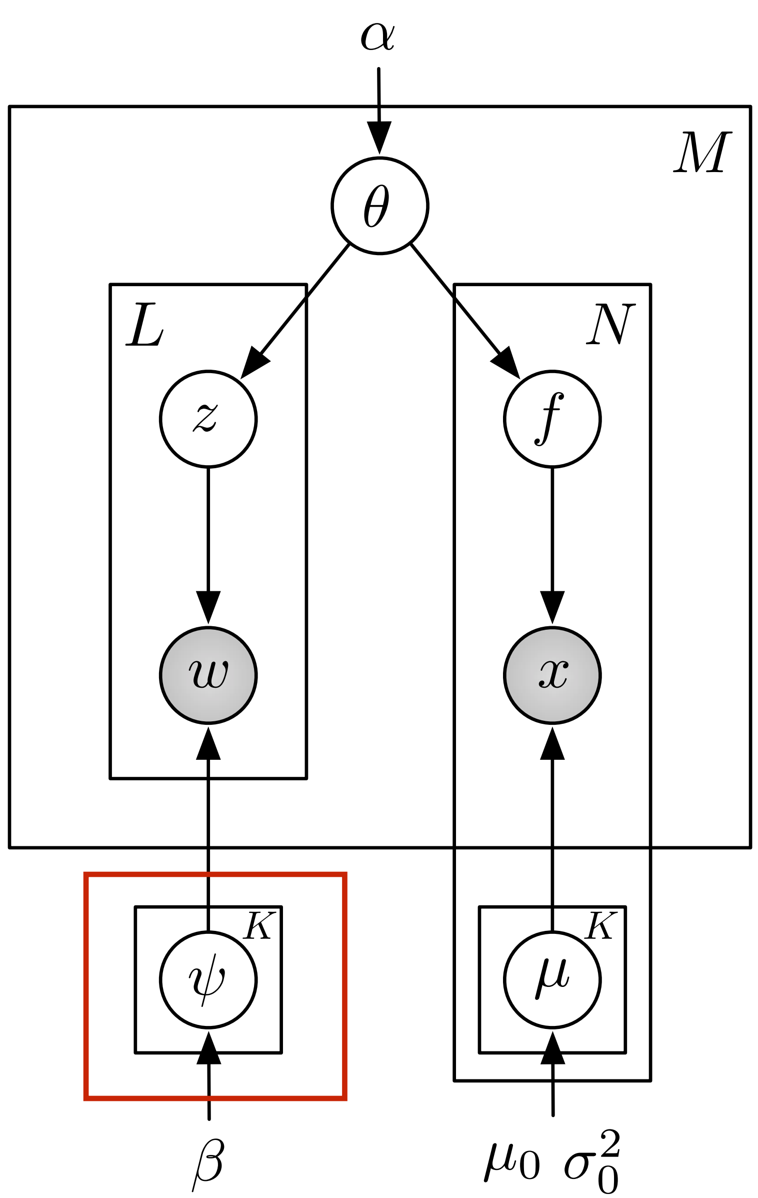

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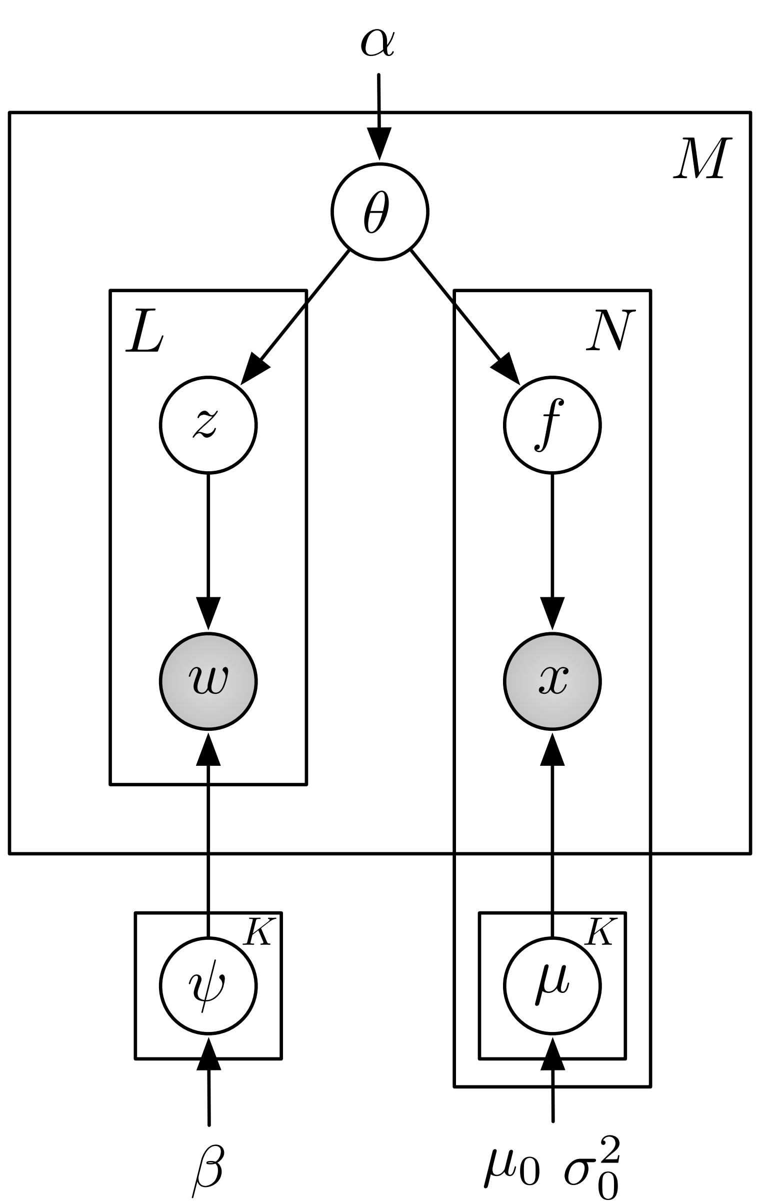

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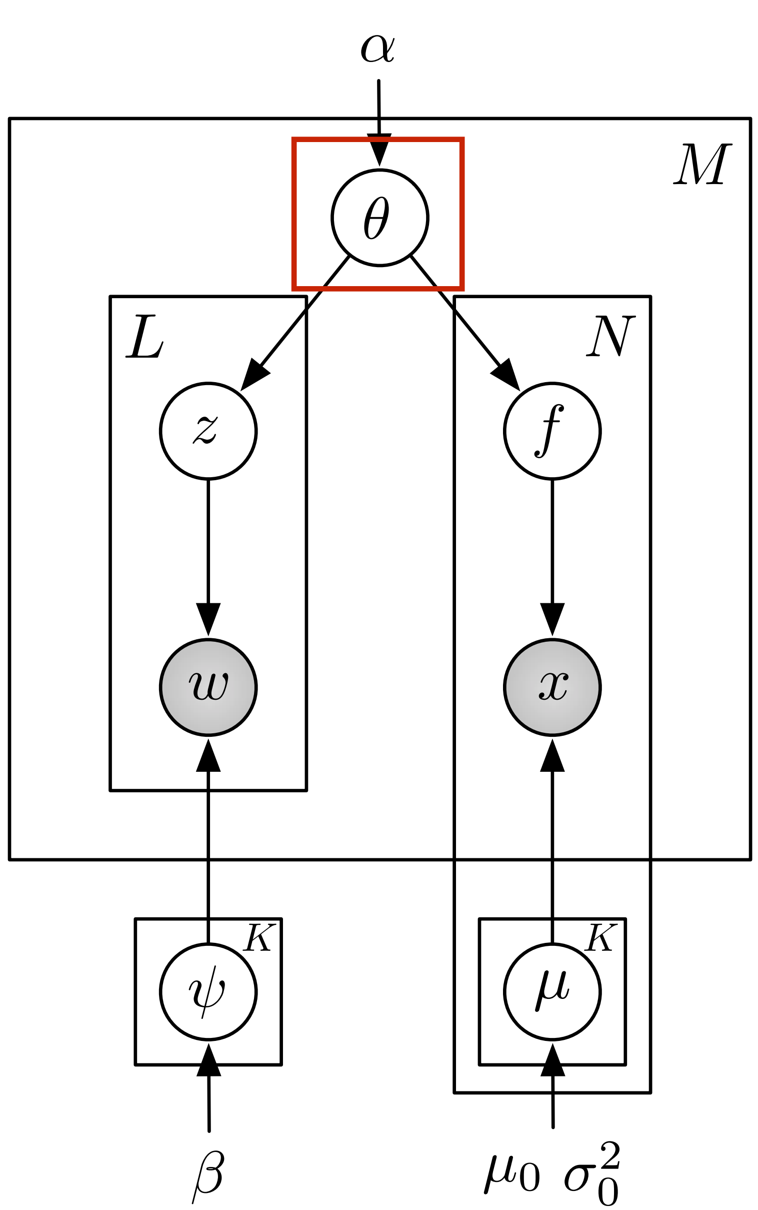

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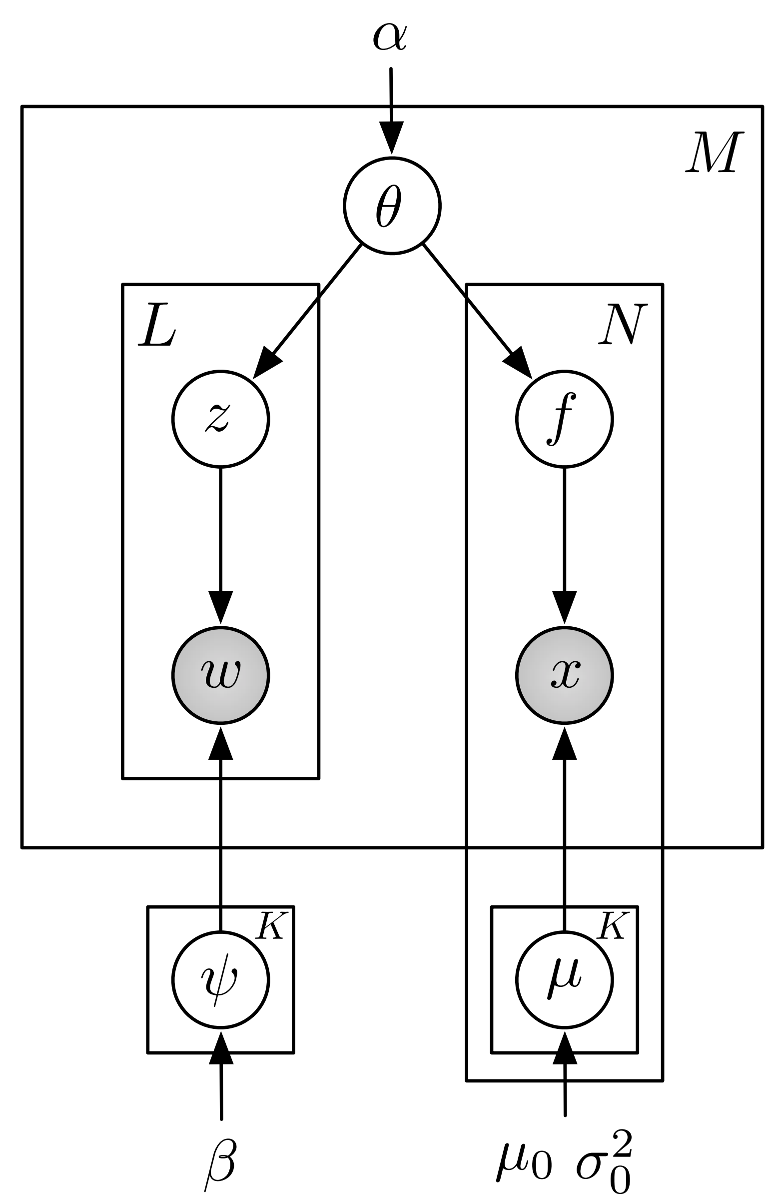

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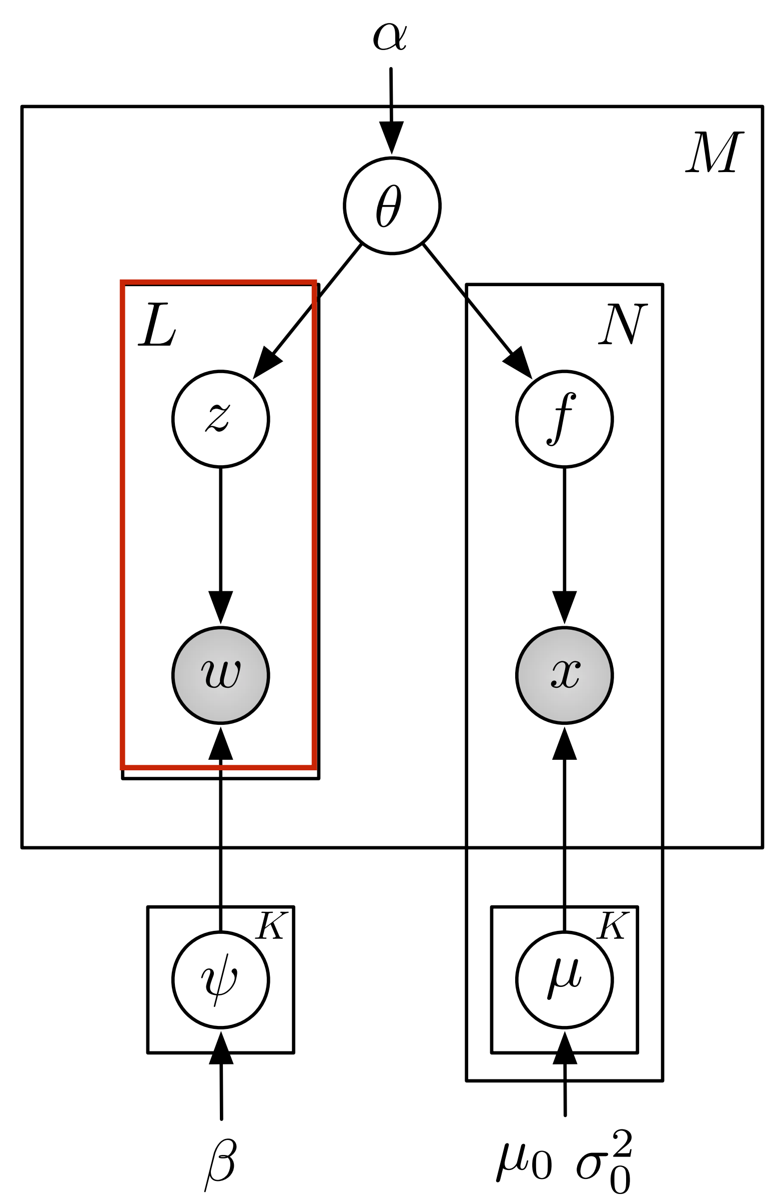

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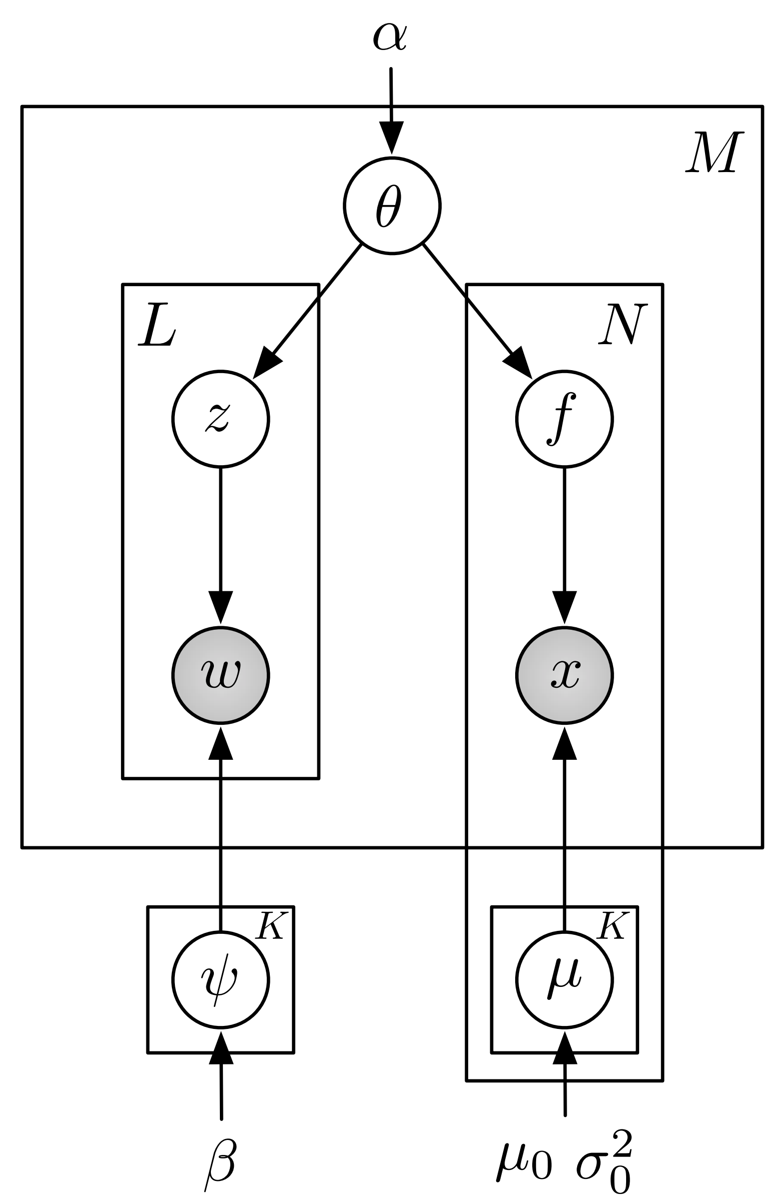

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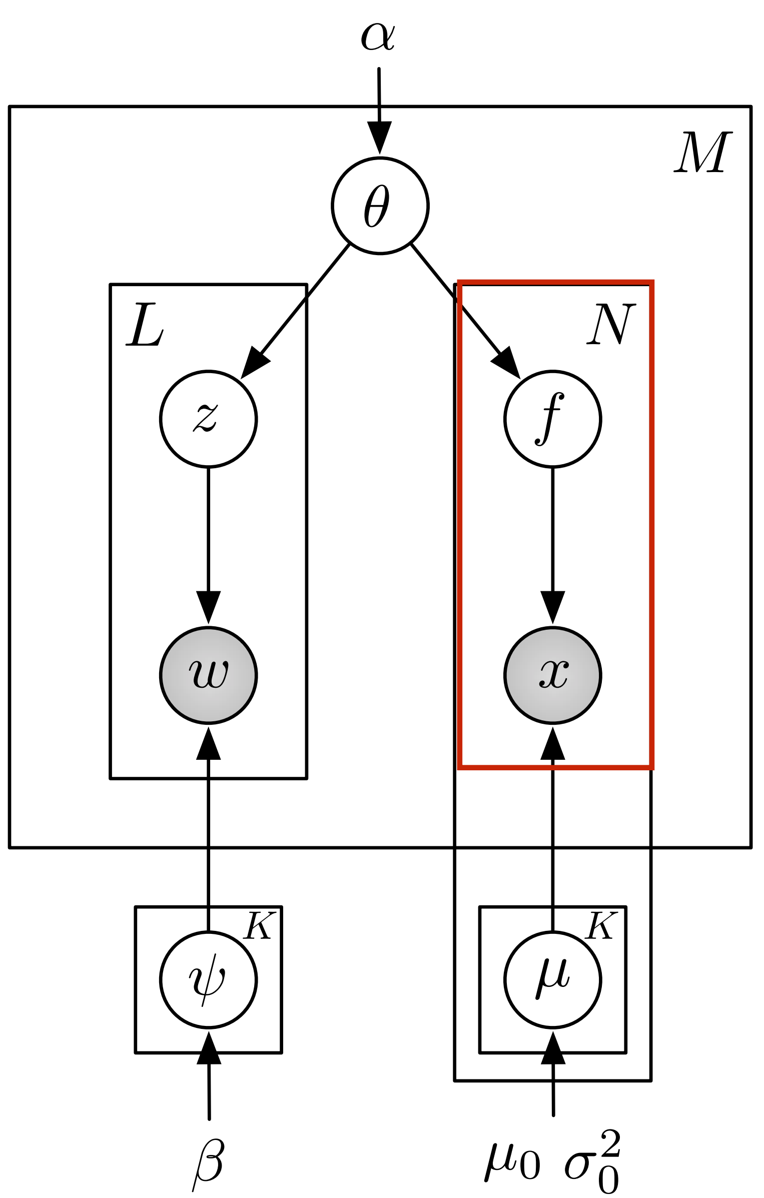

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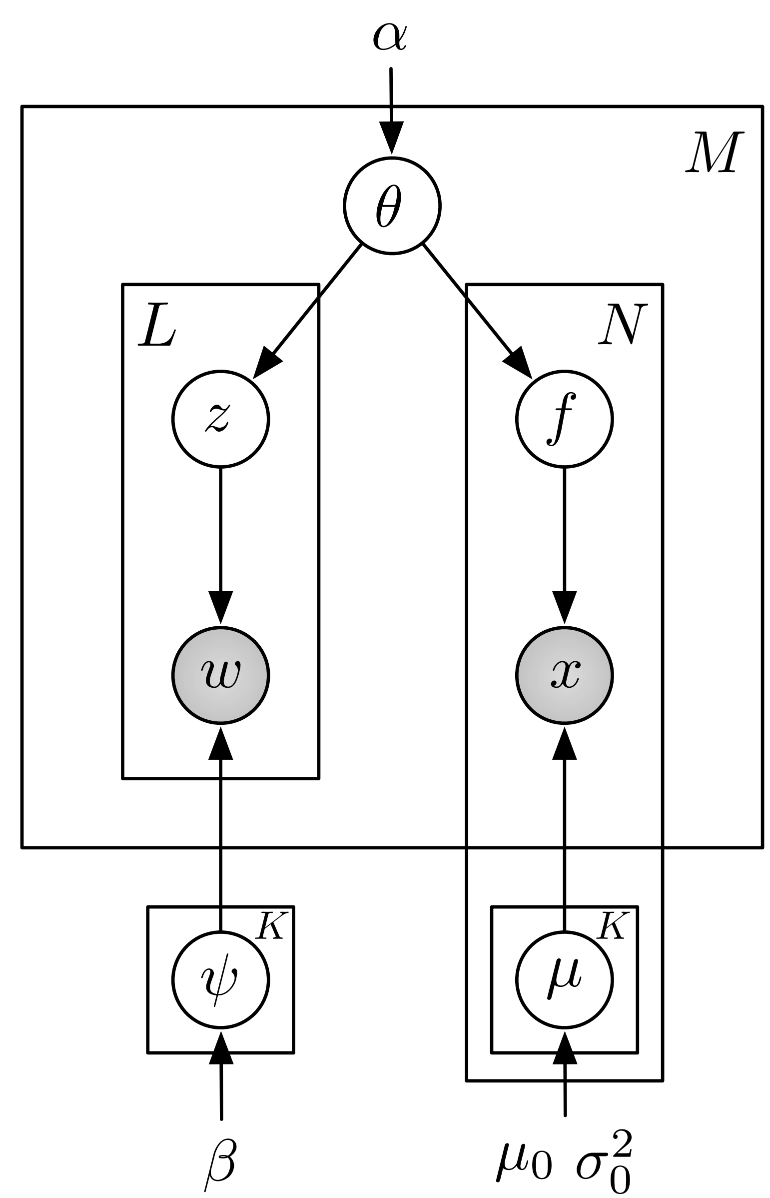

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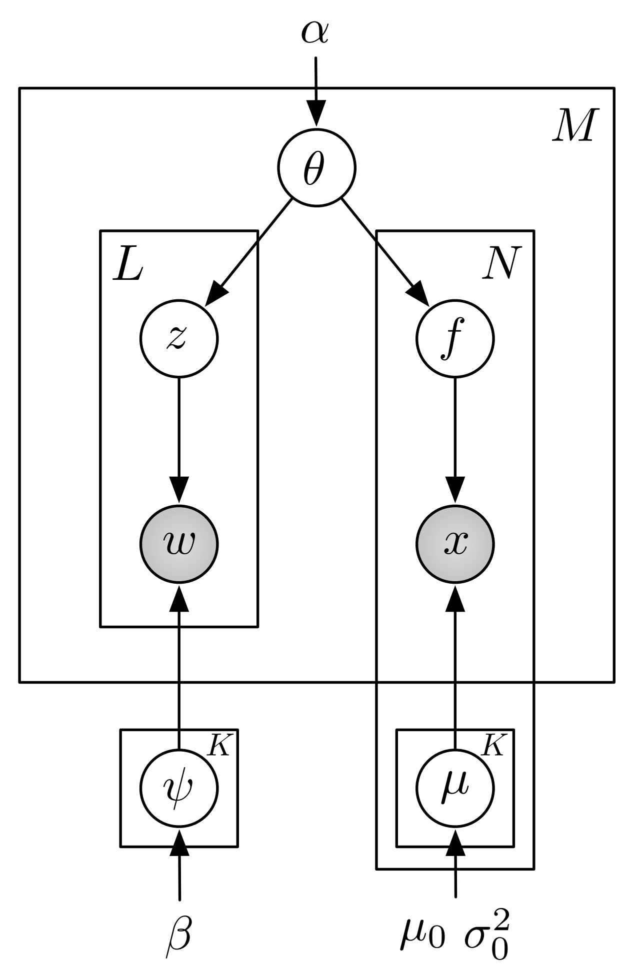

$$P(\mathbf{w}, \mathbf{x}|\Theta; \alpha, \beta, \mu_0, \sigma_0^2, \sigma^2) \propto \prod_{j=1}^{M} P(\theta_j|\alpha) \prod_{i \in \mathcal{U}_j} \left(\prod_{l=1}^{L_{i,j}} \sum_{z=1}^{K} P(z|\theta_j) P(w_l|\psi_z) \right) \left(\sum_{f=1}^{K} P(f|\theta_j) P(x_{i,j}|\mu_{i,f}, \sigma^2) \right)$$

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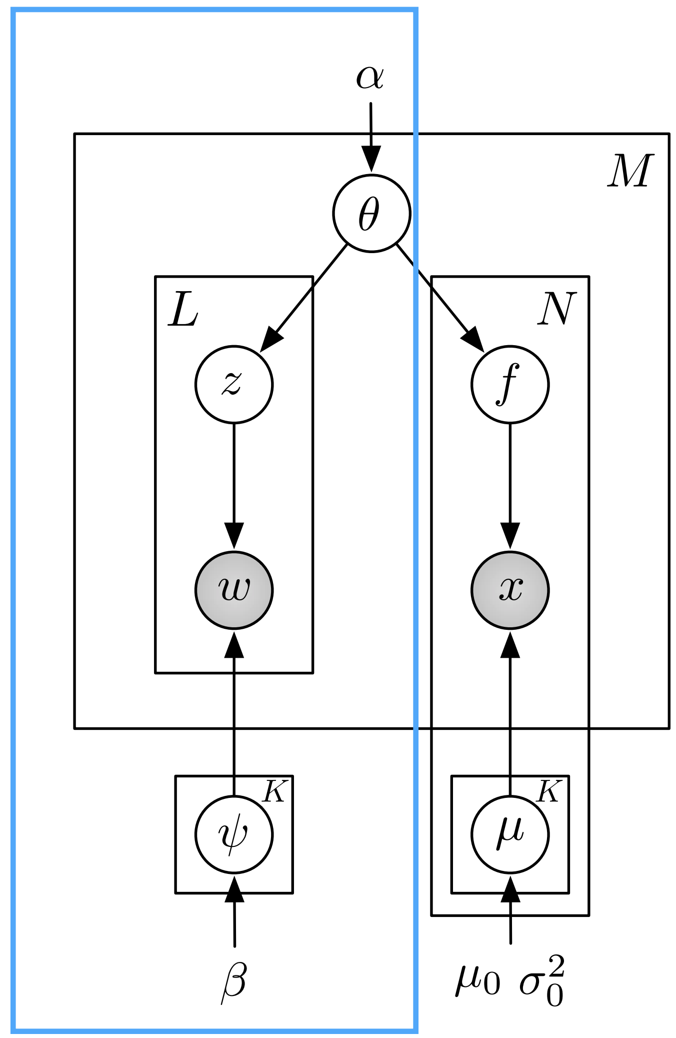

Use LDA to model the reviews

$$P(\mathbf{w}, \mathbf{x} | \Theta; \alpha, \beta, \mu_0, \sigma_0^2, \sigma^2) \propto \prod_{j=1}^{M} P(\theta_j|\alpha) \boxed{\prod_{i \in \mathcal{U}_j} \left(\prod_{l=1}^{L_{i,j}} \sum_{z=1}^{K} P(z|\theta_j) P(w_l|\psi_z) \right)} \left(\sum_{f=1}^{K} P(f|\theta_j) P(x_{i,j}|\mu_{i,f}, \sigma^2) \right)$$

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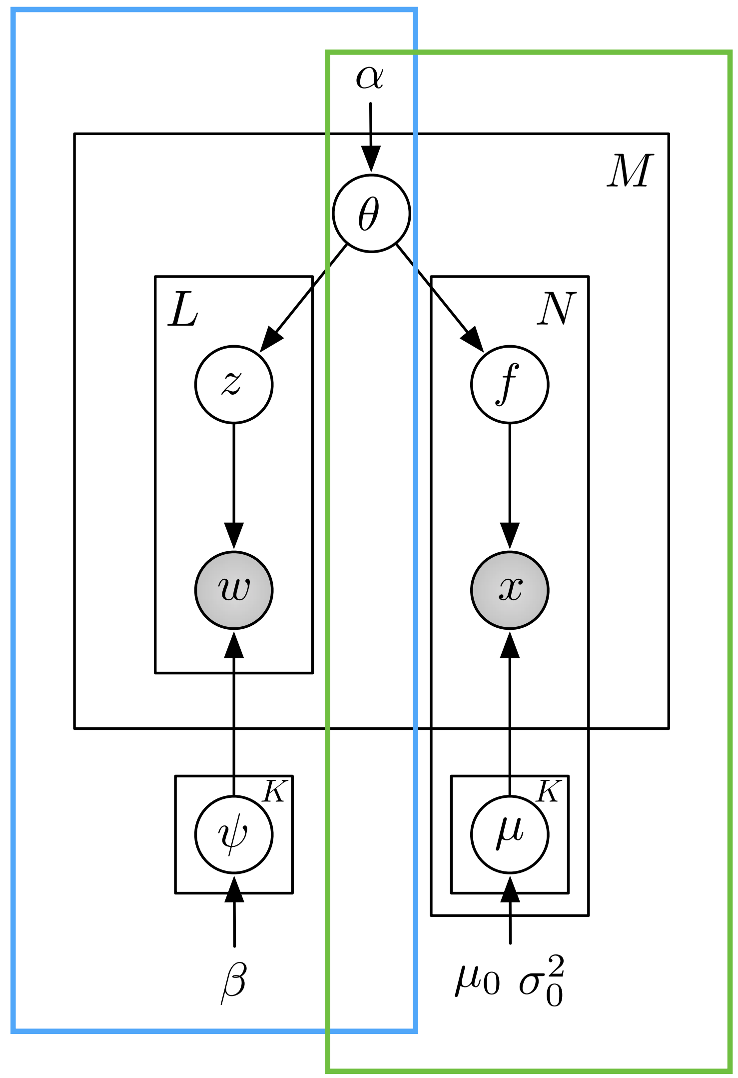
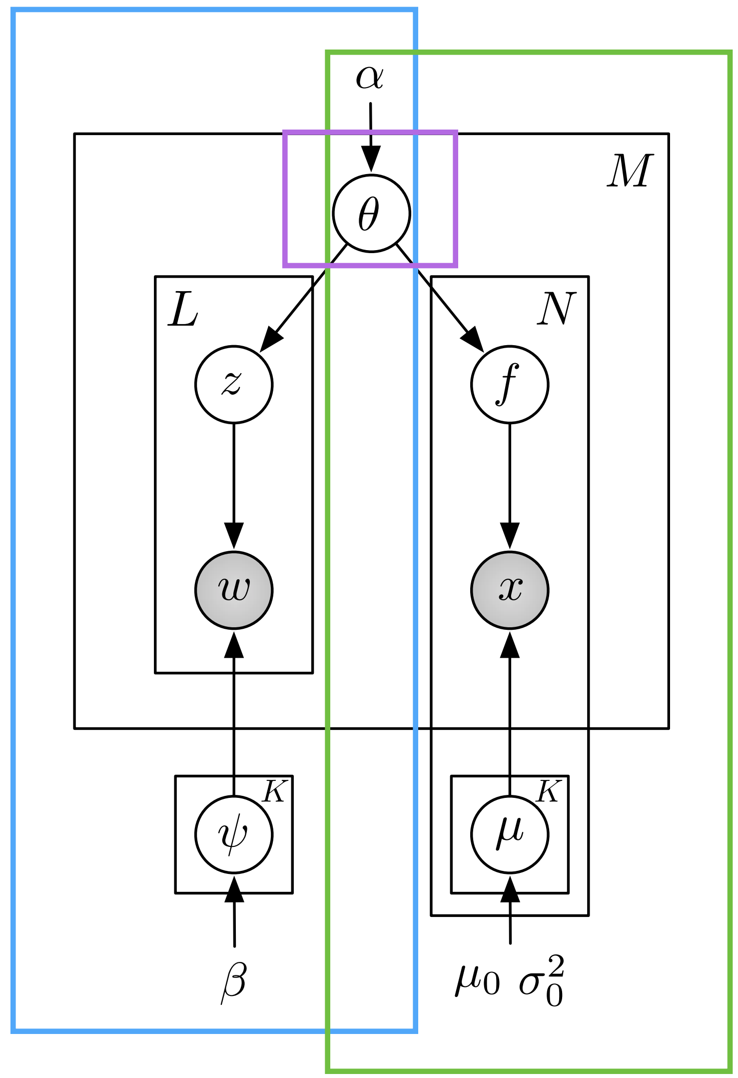


Use LDA to model the reviews

Use mixture of Gaussians to model the ratings

$$P(\mathbf{w}, \mathbf{x} | \Theta; \alpha, \beta, \mu_0, \sigma_0^2, \sigma^2) \propto \prod_{j=1}^{M} P(\theta_j | \alpha) \prod_{i \in \mathcal{U}_j} \left(\prod_{l=1}^{L_{i,j}} \sum_{z=1}^{K} P(z|\theta_j) P(w_l | \psi_z) \right) \left(\sum_{f=1}^{K} P(f|\theta_j) P(x_{i,j} | \mu_{i,f}, \sigma^2) \right)$$

Ratings Meet Reviews



Use the same topic distribution to connect rating part and review part

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Use mixture of Gaussians to model the ratings

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Ratings Meet Reviews

- We developed Collapsed Gibbs Sampler for RMR

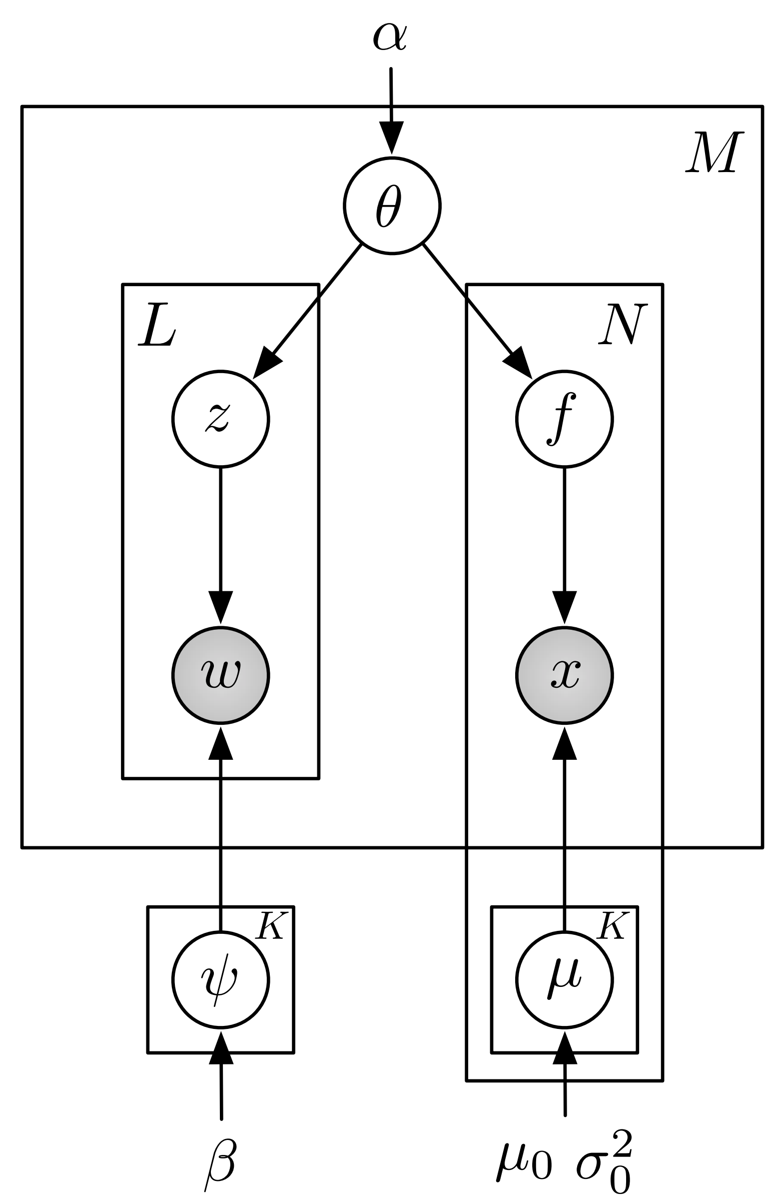
- Space Complexity

  $O((M+N+V)\times K)$

- Time Complexity

  $O(K)$

- Details can be found in paper



Experiments

- How RMR performs compared with other models?
- How can "cold-start" items/users benefit from the incorporation of reviews?
- Can we learn interpretable latent topics?

Experiments

- Use the Amazon dataset collected by HFT (McAuley 2013)
  - 27 categories
  - 6,643,669 users
  - 2,441,053 items
  - 34,686,880 reviews
  - 4,053,795,667 words in reviews
  - On average
    - 116.87 words per review
    - 14.21 reviews per item

Experiments

- Compare RMR with 4 baseline methods
  - Matrix Factorization
  - LDAMF (baseline method in McAuley 2013)
  - CTR (Wang 2011)
  - HFT (McAuley 2013)

Experiments

- USE Mean Squared Error (MSE) as evaluation metric.
- Split datasets into training (80% up to 2 million reviews) and testing (remaining).
- Hyper-parameters are grid searched and the best performance are reported for all models.

Experiments

Experiments

- Results

Dataset	a MF	b LDAMF	c CTR	d HFT	e RMR	Improvement of RMR versus min(a,b)	 c	 d
Arts	1.565 (0.04)	1.575 (0.04)	1.471 (0.04)	1.390 (0.04)	**1.371 (0.04)**	14.15%	7.29%	1.39%
Jewelry	1.257 (0.03)	1.279 (0.03)	1.206 (0.03)	1.177 (0.02)	**1.160 (0.02)**	8.36%	3.97%	1.47%
Industrial Scientific	0.461 (0.02)	0.462 (0.02)	0.382 (0.02)	**0.359 (0.02)**	0.362 (0.02)	27.35%	5.52%	-0.83%
Watches	1.535 (0.03)	1.518 (0.03)	1.491 (0.03)	1.488 (0.03)	**1.458 (0.02)**	4.12%	2.26%	2.06%
Cell Phones and Accessories	2.230 (0.04)	2.308 (0.04)	2.177 (0.04)	2.135 (0.03)	**2.085 (0.03)**	6.95%	4.41%	2.40%
Musical Instruments	1.506 (0.02)	1.520 (0.02)	1.422 (0.02)	1.395 (0.02)	**1.374 (0.02)**	9.61%	3.49%	1.53%
Software	2.409 (0.02)	2.214 (0.02)	2.254 (0.02)	2.219 (0.02)	**2.173 (0.02)**	1.89%	3.73%	2.12%
Gourmet Foods	1.515 (0.01)	1.491 (0.01)	1.482 (0.01)	**1.457 (0.01)**	1.465 (0.01)	1.77%	1.16%	-0.55%
Office Products	1.814 (0.01)	1.796 (0.01)	1.733 (0.01)	1.669 (0.01)	**1.638 (0.01)**	9.65%	5.80%	1.89%
Automotive	1.570 (0.01)	1.585 (0.01)	1.492 (0.01)	1.432 (0.01)	**1.403 (0.01)**	11.90%	6.34%	2.07%
Patio	1.771 (0.01)	1.793 (0.01)	1.720 (0.01)	1.698 (0.01)	**1.669 (0.01)**	6.11%	3.06%	1.74%
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Beauty	1.399 (0.01)	1.414 (0.01)	1.361 (0.01)	1.358 (0.01)	**1.334 (0.01)**	4.87%	2.02%	1.80%
Shoes	0.305 (0.00)	0.335 (0.00)	0.271 (0.00)	**0.247 (0.00)**	0.251 (0.00)	21.51%	7.97%	-1.59%
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Electronics	1.828 (0.00)	1.823 (0.00)	1.764 (0.00)	**1.722 (0.00)**	**1.722 (0.00)**	5.87%	2.44%	0.00%
Music	**0.956 (0.00)**	0.958 (0.00)	0.959 (0.00)	0.980 (0.00)	0.959 (0.00)	-0.31%	0.00%	2.19%
Movies and TV	1.119 (0.00)	1.117 (0.00)	**1.114 (0.00)**	1.119 (0.00)	1.120 (0.00)	-0.27%	-0.54%	-0.09%
Books	1.107 (0.00)	1.109 (0.00)	**1.106 (0.00)**	1.138 (0.00)	1.113 (0.00)	-0.54%	-0.63%	2.25%
Average on all datasets						7.79%	3.28%	1.22%

Experiments

- Results

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Electronics	1.828 (0.00)	1.823 (0.00)	1.764 (0.00)	**1.722 (0.00)**	**1.722 (0.00)**	5.87%	2.44%	0.00%
Music	**0.956 (0.00)**	0.958 (0.00)	0.959 (0.00)	0.980 (0.00)	0.959 (0.00)	-0.31%	0.00%	2.19%
Movies and TV	1.119 (0.00)	1.117 (0.00)	**1.114 (0.00)**	1.119 (0.00)	1.120 (0.00)	-0.27%	-0.54%	-0.09%
Books	1.107 (0.00)	1.109 (0.00)	**1.106 (0.00)**	1.138 (0.00)	1.113 (0.00)	-0.54%	-0.63%	2.25%
Average on all datasets						7.79%	3.28%	1.22%

Experiments

- Results
  - Performs the best on 19 out of 27 categories
  - Performs better on 26 out of 27 datasets compared with matrix factorisation
  - On average, improve 8% over MF, 3.3% over CTR and 1.2% over HFT

	a	b	c	d	e	Improvement of RMR versus		
Dataset	MF	LDAMF	CTR	HFT	RMR	min(a,b)	c	d
Arts	1.565 (0.04)	1.575 (0.04)	1.471 (0.04)	1.390 (0.04)	**1.371 (0.04)**	14.15%	7.29%	1.39%
Jewelry	1.257 (0.03)	1.279 (0.03)	1.206 (0.03)	1.177 (0.02)	**1.160 (0.02)**	8.36%	3.97%	1.47%
Industrial Scientific	0.461 (0.02)	0.462 (0.02)	0.382 (0.02)	**0.359 (0.02)**	0.362 (0.02)	27.35%	5.52%	-0.83%
Watches	1.535 (0.03)	1.518 (0.03)	1.491 (0.03)	1.488 (0.03)	**1.458 (0.02)**	4.12%	2.26%	2.06%
Cell Phones and Accessories	2.230 (0.04)	2.308 (0.04)	2.177 (0.04)	2.135 (0.03)	**2.085 (0.03)**	6.95%	4.41%	2.40%
Musical Instruments	1.506 (0.02)	1.520 (0.02)	1.422 (0.02)	1.395 (0.02)	**1.374 (0.02)**	9.61%	3.49%	1.53%
Software	2.409 (0.02)	2.214 (0.02)	2.254 (0.02)	2.219 (0.02)	**2.173 (0.02)**	1.89%	3.73%	2.12%
Gourmet Foods	1.515 (0.01)	1.491 (0.01)	1.482 (0.01)	**1.457 (0.01)**	1.465 (0.01)	1.77%	1.16%	-0.55%
Office Products	1.814 (0.01)	1.796 (0.01)	1.733 (0.01)	1.669 (0.01)	**1.638 (0.01)**	9.65%	5.80%	1.89%
Automotive	1.570 (0.01)	1.585 (0.01)	1.492 (0.01)	1.432 (0.01)	**1.403 (0.01)**	11.90%	6.34%	2.07%
Patio	1.771 (0.01)	1.793 (0.01)	1.720 (0.01)	1.698 (0.01)	**1.669 (0.01)**	6.11%	3.06%	1.74%
Pet Supplies	1.700 (0.01)	1.700 (0.01)	1.613 (0.01)	1.583 (0.01)	**1.562 (0.01)**	8.83%	3.27%	1.34%
Beauty	1.399 (0.01)	1.414 (0.01)	1.361 (0.01)	1.358 (0.01)	**1.334 (0.01)**	4.87%	2.02%	1.80%
Shoes	0.305 (0.00)	0.335 (0.00)	0.271 (0.00)	**0.247 (0.00)**	0.251 (0.00)	21.51%	7.97%	-1.59%
Kindle Store	1.553 (0.01)	1.561 (0.01)	1.457 (0.01)	1.437 (0.01)	**1.412 (0.01)**	9.99%	3.19%	1.77%
Clothing and Accessories	0.393 (0.00)	0.406 (0.00)	0.355 (0.00)	0.349 (0.00)	**0.336 (0.00)**	16.96%	5.65%	3.87%
Health	1.615 (0.01)	1.608 (0.01)	1.552 (0.01)	1.538 (0.01)	**1.512 (0.01)**	6.35%	2.65%	1.72%
Toys and Games	1.467 (0.01)	1.395 (0.01)	1.389 (0.01)	**1.370 (0.01)**	1.372 (0.01)	1.68%	1.24%	-0.15%
Tools and Home Improvement	1.600 (0.01)	1.610 (0.01)	1.513 (0.01)	1.510 (0.01)	**1.491 (0.01)**	7.31%	1.48%	1.27%
Sports and Outdoors	1.219 (0.01)	1.223 (0.01)	1.150 (0.01)	1.138 (0.01)	**1.129 (0.01)**	7.97%	1.86%	0.80%
Video Games	1.610 (0.01)	1.608 (0.01)	1.572 (0.01)	1.528 (0.01)	**1.510 (0.01)**	6.49%	4.11%	1.19%
Home and Kitchen	1.628 (0.05)	1.610 (0.05)	1.577 (0.05)	1.531 (0.04)	**1.501 (0.04)**	7.26%	5.06%	2.00%
Amazon Instant Video	1.330 (0.01)	1.328 (0.01)	1.291 (0.01)	**1.260 (0.01)**	1.270 (0.01)	4.57%	1.65%	-0.79%
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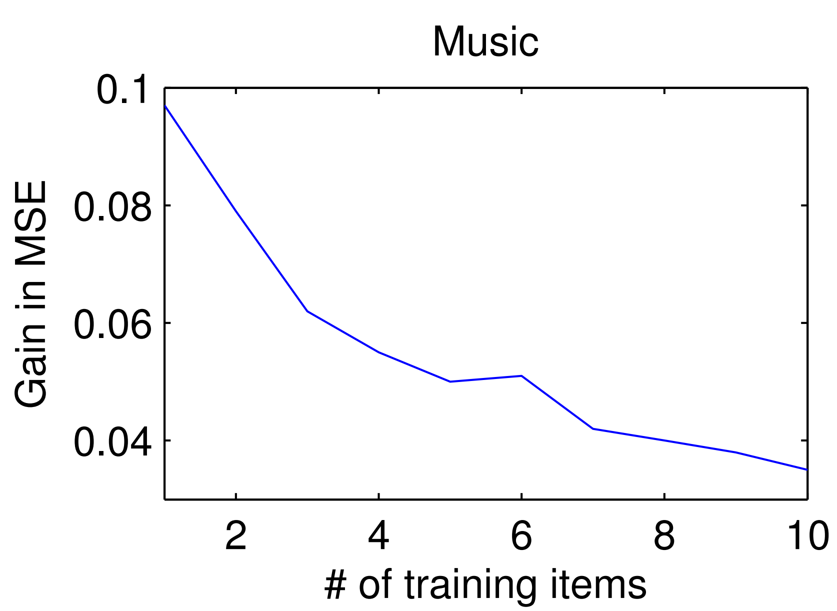
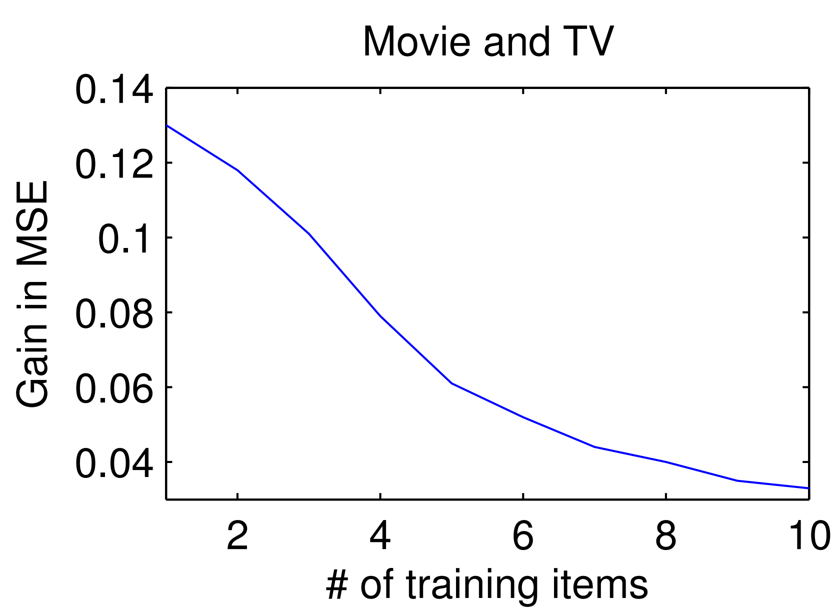
Music	**0.956 (0.00)**	0.958 (0.00)	0.959 (0.00)	0.980 (0.00)	0.959 (0.00)	-0.31%	0.00%	2.19%
Movies and TV	1.119 (0.00)	1.117 (0.00)	**1.114 (0.00)**	1.119 (0.00)	1.120 (0.00)	-0.27%	-0.54%	-0.09%
Books	1.107 (0.00)	1.109 (0.00)	**1.106 (0.00)**	1.138 (0.00)	1.113 (0.00)	-0.54%	-0.63%	2.25%
Average on all datasets						7.79%	3.28%	1.22%

Experiments

- Cold-start Settings
    - Users with fewer ratings gain more from the reviews





Experiments

- Interpretability
  - We recommend “Star Trek” to you because you are interested in “batman, effects, alien, harry, matrix, edition”

Top words in category Software

roxio	quicken	leopard	office	suse
contacted	son	os	excel	accounts
perfect	pick	parallels	2007	2004
burning	given	apple	student	nav
dvds	spanish	turbo	activation	federal
care	starting	tiger	microsoft	symantec

Top words in category Movie & TV

workout	season	batman	disney	godzilla
yoga	match	effects	christmas	hitchcock
workouts	episodes	alien	animation	kidman
videos	seasons	harry	kids	murder
exercises	vs	matrix	shrek	densel
cardio	episode	edition	animated	nicole

Conclusion

- We proposed RMR, which takes advantage of the information in both the ratings and the reviews.
- We developed efficient collapsed Gibbs sampler for RMR.
- We demonstrated that RMR can produce more accurate recommendations, especially under cold-start situations and provide interpretability to recommendations.

Thanks!

Extra slides

- Statistics of the datasets

Dataset	#users	#items	#review	#words	words/review	reviews/item
Arts	24,071	4,211	27,980	2,006,874	71.73	6.64
Jewelry	40,594	18,794	58,621	3,100,948	52.90	3.12
Industrial Scientific	29,590	22,622	13,7042	6,920,151	50.50	6.06
Watches	62,041	10,318	68,356	5,436,671	79.53	6.62
Cell Phones and Accessories	68,041	7,438	78,930	7,567,961	95.88	10.61
Musical Instruments	67,007	14,182	85,405	7,442,294	87.14	6.02
Software	68,464	11,234	95,084	11,012,882	115.82	8.46
Gourmet Foods	112,544	23,476	154,635	10,542,984	68.18	6.59
Office Products	110,472	14,224	138,084	11,206,338	81.16	9.71
Automotive	133,256	47,577	188,728	13,249,641	70.21	3.97
Patio	166,832	19,531	206,250	17,290,881	83.83	10.56
Pet Supplies	160,496	17,523	217,170	18,684,153	86.03	12.39
Beauty	167,725	29,004	252,056	17,889,577	70.97	8.69
Shoes	73,590	48,410	389,877	23,604,059	60.54	8.05
Kindle Store	116,191	4,372	160,793	21,533,201	133.92	36.78
Clothing and Accessories	128,794	66,370	581,933	34,267,151	58.89	8.77
Health	311,636	39,539	428,781	33,277,423	77.61	10.84
Toys and Games	290,713	53,600	435,996	35,034,001	80.35	8.13
Tools and Home Improvement	283,514	51,004	409,499	34,591,409	84.47	8.03
Sports and Outdoors	329,232	68,293	510,991	38,898,738	76.12	7.48
Video Games	228,570	21,025	463,669	55,532,148	119.77	22.05
Home and Kitchen	644,509	79,006	991,794	81,923,017	82.60	12.55
Amazon Instant Video	312,930	22,204	717,651	88,958,349	123.96	32.32
Electronics	811,034	82,067	1,241,778	124,064,510	99.91	15.13
Music	1,134,684	556,814	6,396,350	774,791,468	121.13	11.49
Movies and TV	1,224,267	212,836	7,850,072	997,261,969	127.04	36.88
Books	2,588,991	929,264	12,886,488	1,613,603,531	125.22	13.87
All categories	6,643,669	2,441,053	34,686,880	4,053,795,667	116.87	14.21

Extra slides

- MSE results

	a	b	c	d	e	Improvement of RMR versus		
Dataset	MF	LDAMF	CTR	HFT	RMR	min(a,b)	c	d
Arts	1.565 (0.04)	1.575 (0.04)	1.471 (0.04)	1.390 (0.04)	**1.371 (0.04)**	14.15%	7.29%	1.39%
Jewelry	1.257 (0.03)	1.279 (0.03)	1.206 (0.03)	1.177 (0.02)	**1.160 (0.02)**	8.36%	3.97%	1.47%
Industrial Scientific	0.461 (0.02)	0.462 (0.02)	0.382 (0.02)	**0.359 (0.02)**	0.362 (0.02)	27.35%	5.52%	-0.83%
Watches	1.535 (0.03)	1.518 (0.03)	1.491 (0.03)	1.488 (0.03)	**1.458 (0.02)**	4.12%	2.26%	2.06%
Cell Phones and Accessories	2.230 (0.04)	2.308 (0.04)	2.177 (0.04)	2.135 (0.03)	**2.085 (0.03)**	6.95%	4.41%	2.40%
Musical Instruments	1.506 (0.02)	1.520 (0.02)	1.422 (0.02)	1.395 (0.02)	**1.374 (0.02)**	9.61%	3.49%	1.53%
Software	2.409 (0.02)	2.214 (0.02)	2.254 (0.02)	2.219 (0.02)	**2.173 (0.02)**	1.89%	3.73%	2.12%
Gourmet Foods	1.515 (0.01)	1.491 (0.01)	1.482 (0.01)	**1.457 (0.01)**	1.465 (0.01)	1.77%	1.16%	-0.55%
Office Products	1.814 (0.01)	1.796 (0.01)	1.733 (0.01)	1.669 (0.01)	**1.638 (0.01)**	9.65%	5.80%	1.89%
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Patio	1.771 (0.01)	1.793 (0.01)	1.720 (0.01)	1.698 (0.01)	**1.669 (0.01)**	6.11%	3.06%	1.74%
Pet Supplies	1.700 (0.01)	1.700 (0.01)	1.613 (0.01)	1.583 (0.01)	**1.562 (0.01)**	8.83%	3.27%	1.34%
Beauty	1.399 (0.01)	1.414 (0.01)	1.361 (0.01)	1.358 (0.01)	**1.334 (0.01)**	4.87%	2.02%	1.80%
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Music	**0.956 (0.00)**	0.958 (0.00)	0.959 (0.00)	0.980 (0.00)	0.959 (0.00)	-0.31%	0.00%	2.19%
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Books	1.107 (0.00)	1.109 (0.00)	**1.106 (0.00)**	1.138 (0.00)	1.113 (0.00)	-0.54%	-0.63%	2.25%
Average on all datasets						7.79%	3.28%	1.22%