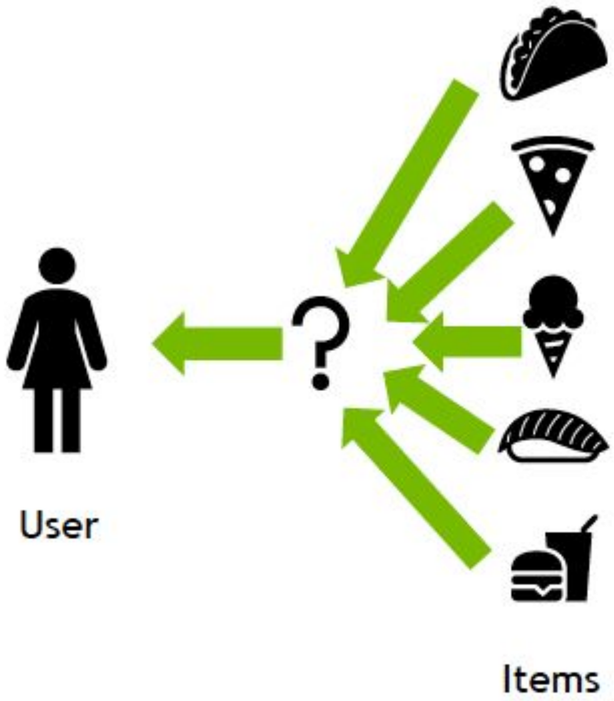
Topic Analysis in Recommendation Systems

By John Bogacz & Nicholas Pang

What are Recommendation Systems

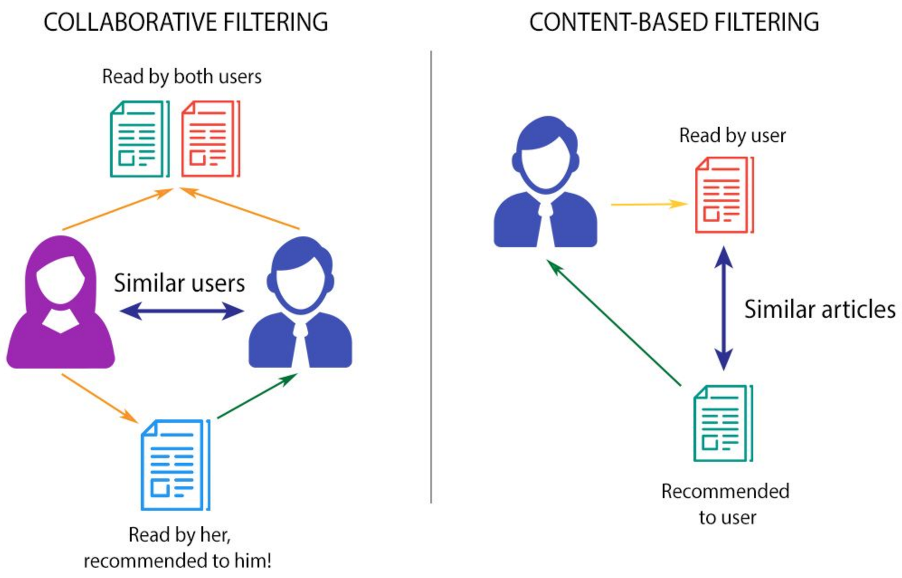


Motivation

Online services provide a plethora of options

- Filtering takes time, and becomes harder the larger the dataset is
- Humans may not recognize their own patterns

Background on Recommendation Systems



Existing solutions

- Collaborative Filtering
  - Users with similar activity are likely to have similar preferences
- Content-Based Filtering
  - Users are likely to like items similar to their previous activity
- Hybrid Filtering
  - A combination of collaborative and content-based

Challenges & problems

- Cold Start
- Latency
- Sparsity
- Diversity
- Scalability

[3],[11],[12]

Matrix Factorization

	Feature 1	Feature 2
User 1	?	?
User 2	?	?
User 3	?	?
User 4	?	?
User 5	?	?

x

	Item 1	Item 2	Item 3	Item 4	Item 5
Feature 1	?	?	?	?	?
Feature 2	?	?	?	?	?

=

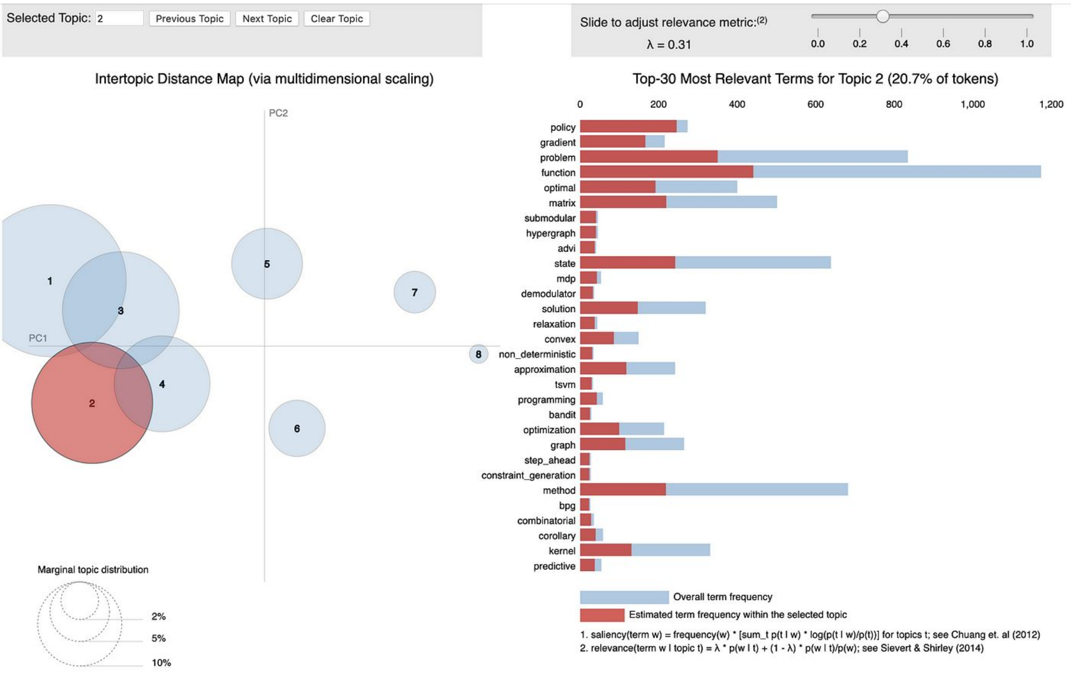
	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	0?	3	0?	3	0?
User 2	4	0?	0?	2	0?
User 3	0?	0?	3	0?	0?
User 4	3	0?	4	0?	3
User 5	4	3	0?	4	0?

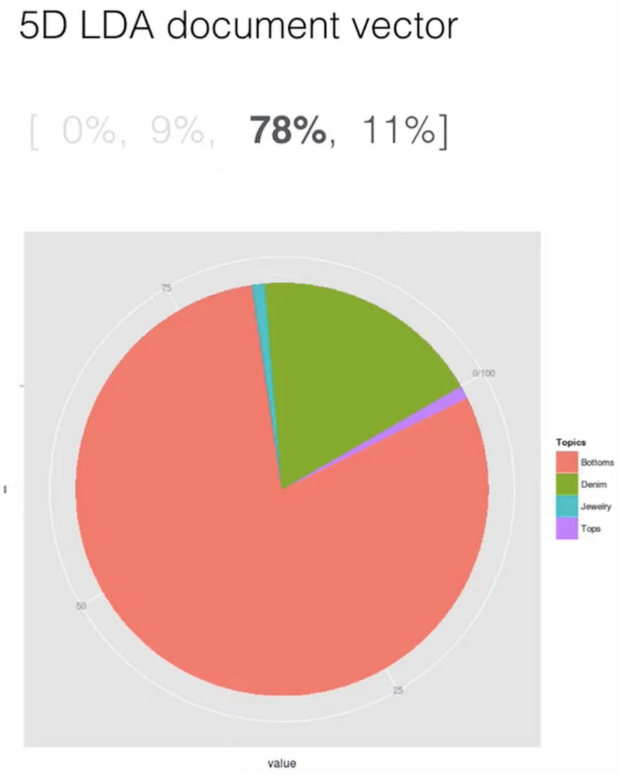
$$R(u,i) = p_u \cdot q_i^T + u_b + i_b + g_b$$

- p_u is the embedding of user u from P.
- q_i is the embedding of item i from Q.
- u_b and i_b are user and item biases.
- g_b is the global bias.

[1],[2],[5]

Latent Dirichlet Allocation (LDA)





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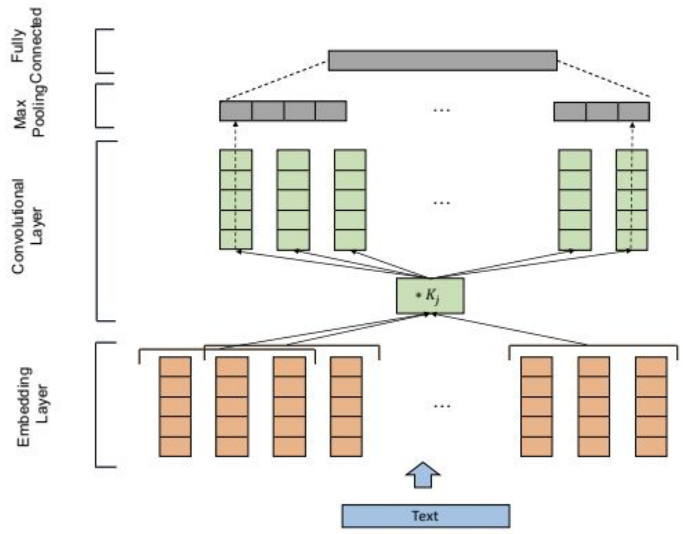
Neural Attentional Rating Regression with Review-level Explanations (NARRE)



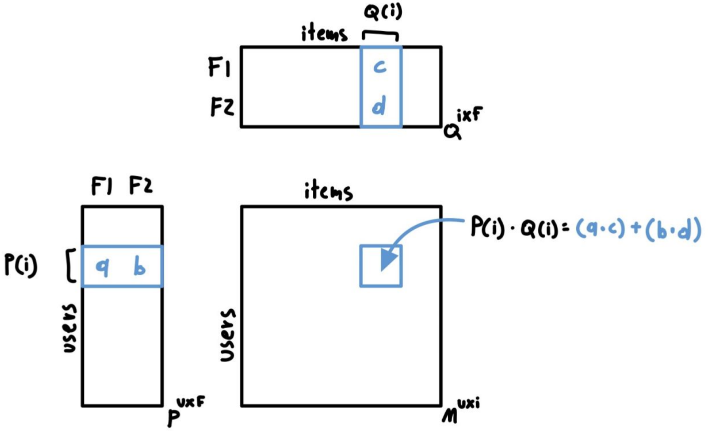
Reviews play an active role in predicting ratings

- Uses attention mechanisms & text processing models to provide rankings for reviews
- Those rankings help determine the weight of the review in rating calculation

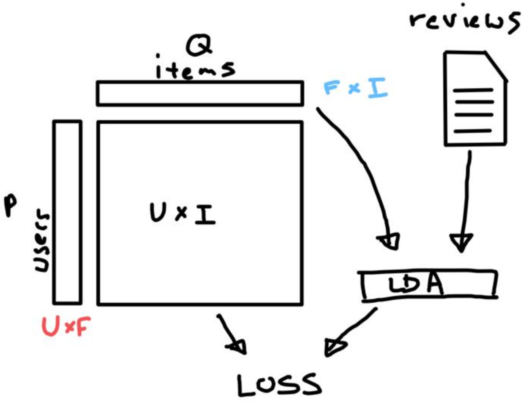
[9]

New Design & Components

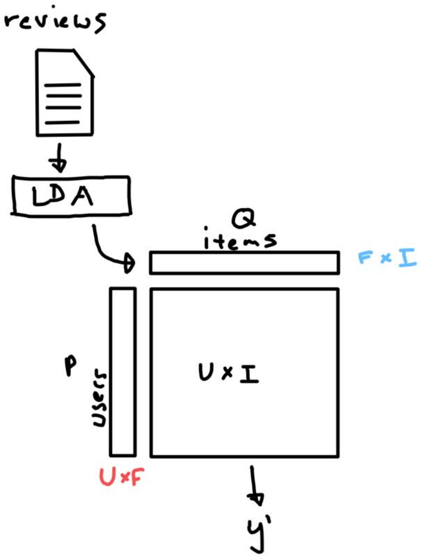
Matrix Factorization (original)



Regularization



Weight Initialization



[2]

Important Formulas

$$L(u,i) = (R(u,i) - y)^2$$

MSE

- Loss function used for regular MF and MF with LDA weight initialization

$$L(u,i) = (R(u,i) - y)^2 - \alpha \ell(T|\theta, \phi)$$

MSE w/ LDA

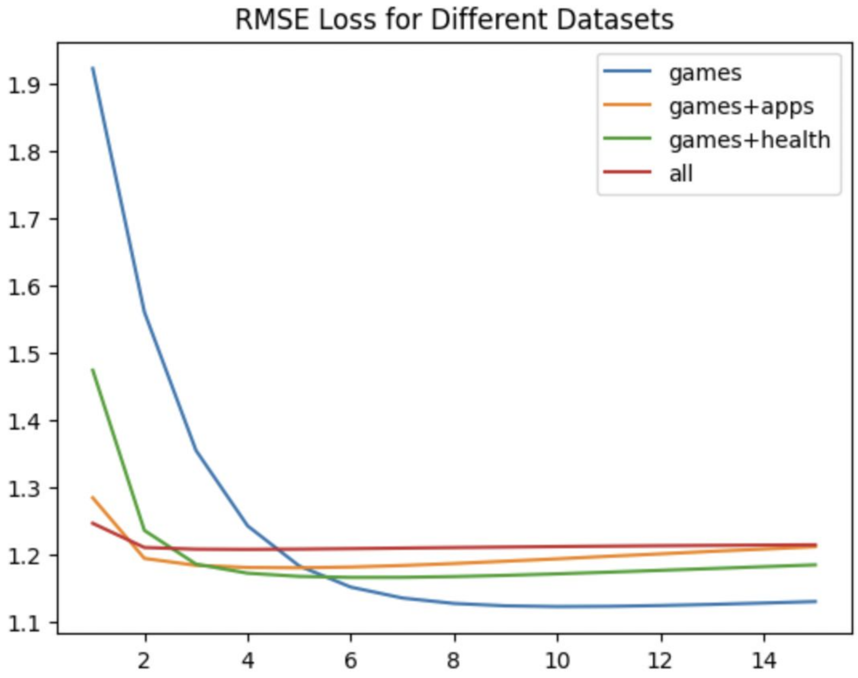
- ℓ is the likelihood of corpus T given the topic distribution per document θ and word distribution per topic ϕ
- α is a regularization parameter for the likelihood
- Only used in gradient descent

Dataset

TABLE I
SIZES OF PROPOSED DATASETS

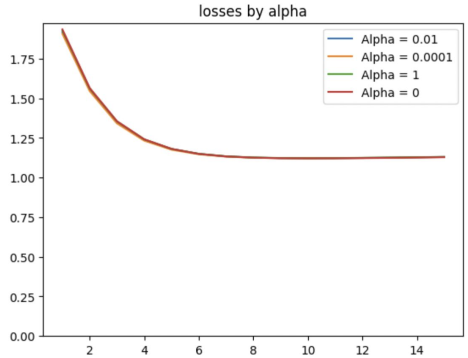
Category	#Users	#Items	#Reviews
Video Games	24303	10672	231780
Android Applications	87271	13209	752937
Health and Personal Care	38609	18534	346355

Results - LDA on Different Datasets



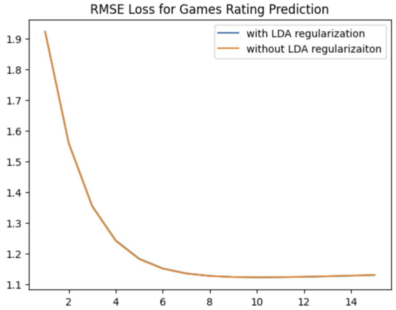
- More diverse datasets led to worse losses overall
- Combining datasets tended to lead to faster convergence
- Combining games with health led to better results than games with apps

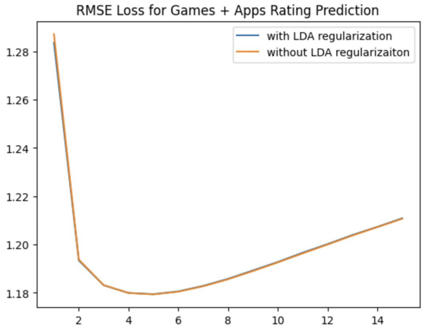
Results - LDA as Regularization

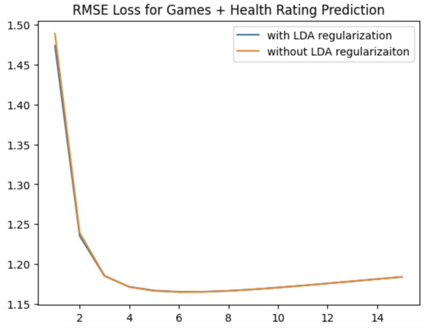


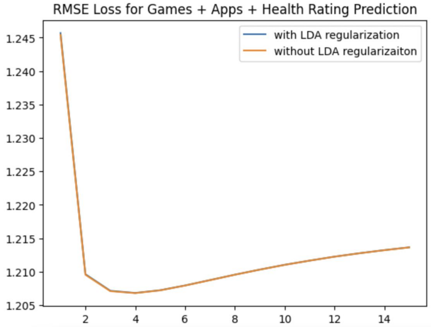
LDA as a regularizer does not appear to impact overall loss

- Changing alpha value does not lead to faster or better convergence

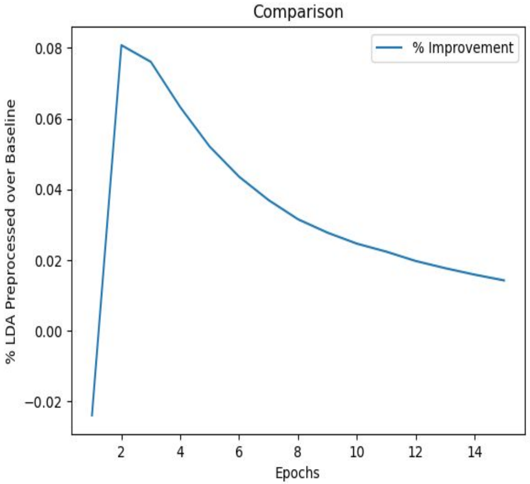


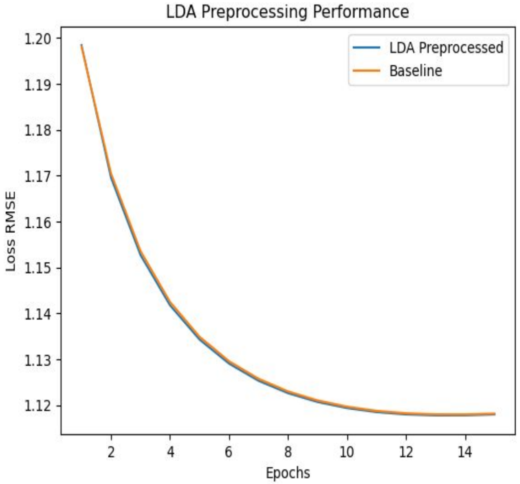


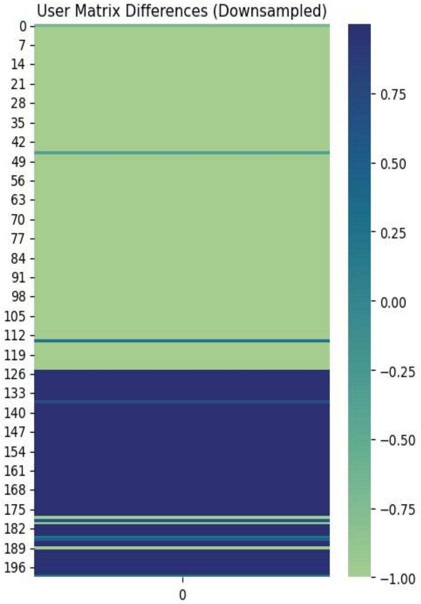


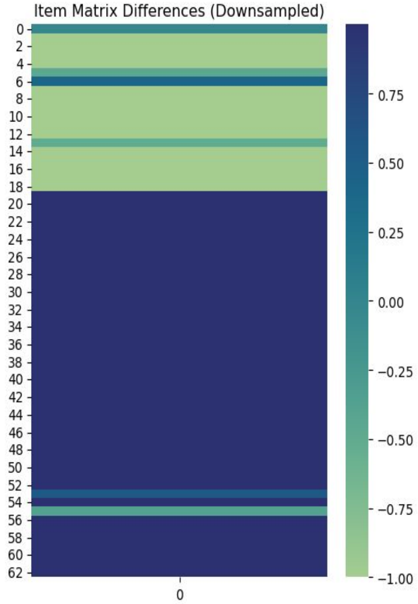


Results - LDA as Weight Initialization









- Faster convergence
- No significance improvements on overall accuracy in the long-term

Discussion

Pros

- LDA can help reach faster convergence
- Weight initialization is faster than regularization

Cons

- Time complexity increase with LDA is significant
- No loss improvements

Potential Future Directions

- More features
    - Since time is a limiting factor, running more diverse datasets with more latent factors was difficult. Combining the model with multithreading and GPUs for more optimal parameters may reveal different results
- Different LDA's for users and items
    - Users and items may have different subsets of relevant terms. Having a different LDA model for each may yield better corpus likelihood and potentially more accurate results.
- Content-based analysis rather than review-based
    - Creating topic distributions from item descriptions may be more accurate than creating them from reviews.

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