

A Lightweight Method for Modeling Confidence in Recommendations with Learned Beta Distributions (LBD)

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Outline

1. Introduction

Why have a confidence level?

Related Work

2. Method: Learned Beta Distributions (LBD) for Rating Prediction

From Beta Distribution to a Discrete Rating Distribution

Modeling means and confidences

Modeling biases and discretization strategies

Overview of the LBD method

Comparison with existing methods

3. Experimental Setup and Procedure

Research questions

Baselines, metrics and parameter tuning

4. Results & Discussion

Parametrization of the LBD model

Recommendation performance

Evaluating Prediction Confidence

5. Conclusion & Future Work

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Parametrization of the LBD model

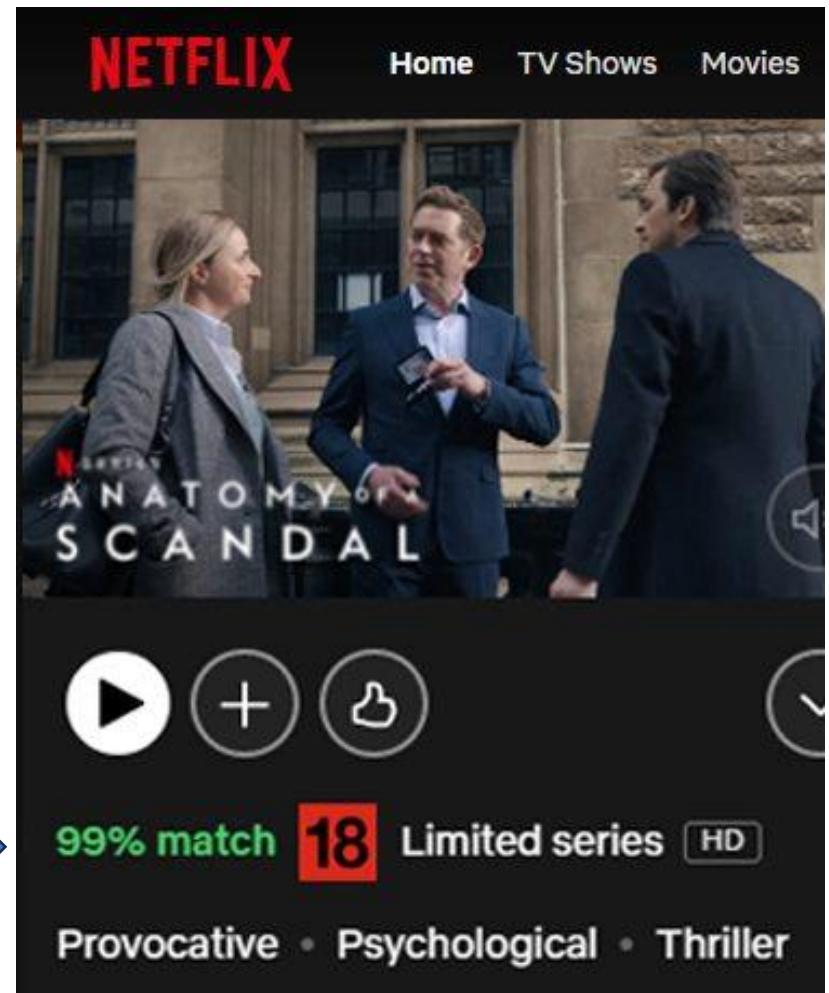
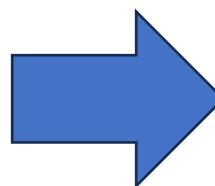
Recommendation performance

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Why have a confidence level?

- It provide insights into the reliability of recommendations
- Personalization



Related work

Method	Confidence	Distribution	Ranking bounding
CMF	Yes	Gaussian	No
OrdRec	Yes	Logistic	Yes
MF	No	N/A	Yes
<u>LBD</u>	<u>Yes</u>	<u>Beta (discrete)</u>	<u>Yes</u>

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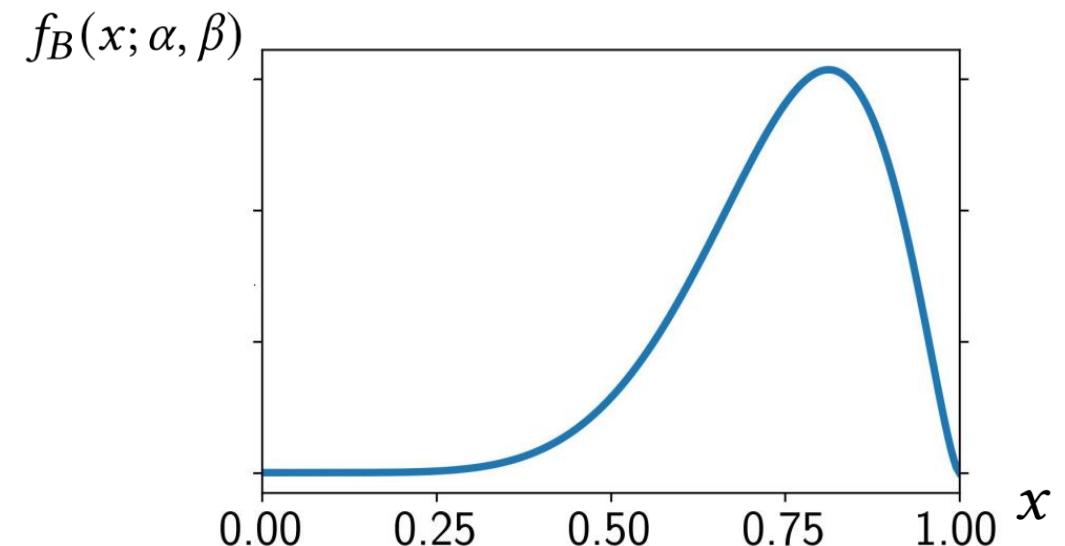
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From Beta Distribution to a Discrete Rating Distribution

Beta Distribution

$$f_B(x; \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$$



- Parameters: $\alpha, \beta > 0$. Normalization factor: $B(\alpha, \beta) = \int_0^1 f_B(t; \alpha, \beta) dt$

Parametrization by mean μ and sample size ν

$$\mu = \alpha / (\alpha + \beta)$$

$$\nu = \alpha + \beta$$

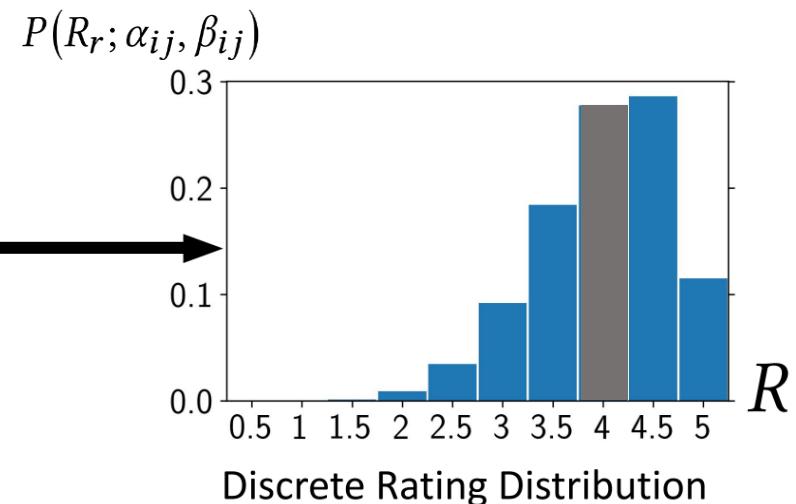
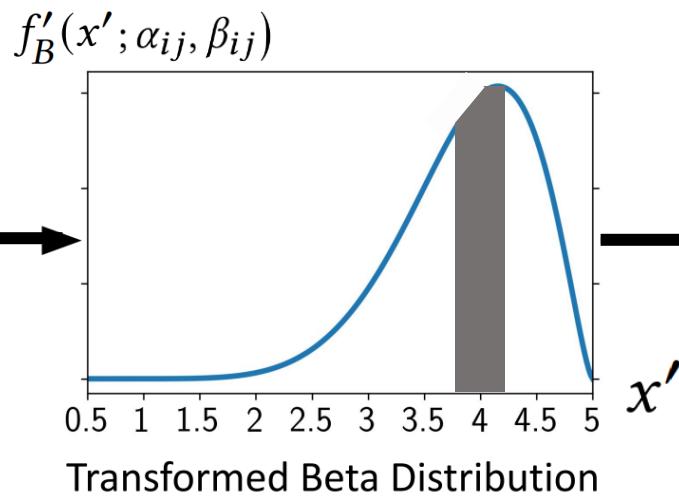
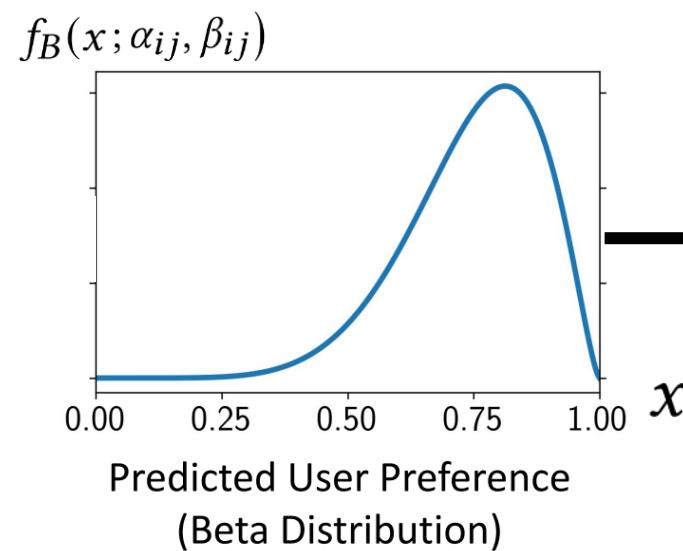
$$\mu \in (0, 1)$$

$$\nu \in (0, \infty)$$

- ν as “confidence”

From Beta Distribution to a Discrete Rating Distribution

- Assuming that user i provides ratings: $R \in \{R_1, R_2, \dots, R_n\}$ for an item j:



$$x' = x(R^{\max} - R^{\min}) + R^{\min}$$

Modeling Means and Confidences

Mean and confidence parameters proposed

$$\mu_{ij} = \frac{1}{2} + \frac{1}{2} \text{Cosine-similarity}(U_i, V_j) = \frac{1}{2} + \frac{1}{2} \frac{U_i^\top V_j}{\|U_i\| \|V_j\|}$$

$$\nu_{ij}^{\text{norm}} = \|U_i\| \|V_j\|, \quad \nu_{ij}^{\text{sum}} = \|U_i + V_j\|, \quad \nu_{ij}^{\text{dot}} = |U_i^\top V_j|$$

- Where $U_i \in \mathbb{R}^D$ and $V_j \in \mathbb{R}^D$ are embeddings for each user i and item j

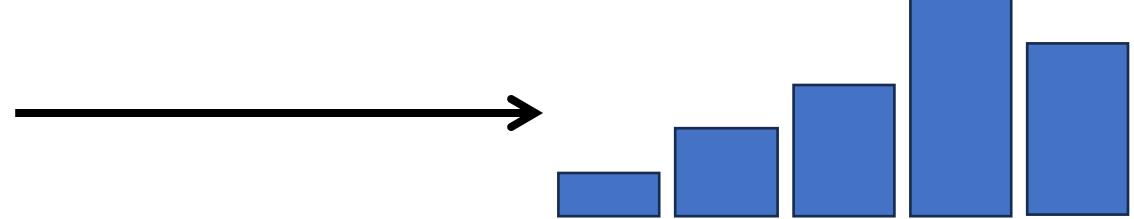
Modeling biases and discretization strategies

Modeling User and items biases

- Weights for α_{ij}, β_{ij} : $\longrightarrow f_B(a_0 + a_i + a_j + \alpha_{ij}, b_0 + b_i + b_j + \beta_{ij})$
- Weights for $\mu_{ij} \nu_{ij}$: $\longrightarrow u_0 u_i u_j v_0 v_i v_j$

Modeling static and adaptive discretization strategies

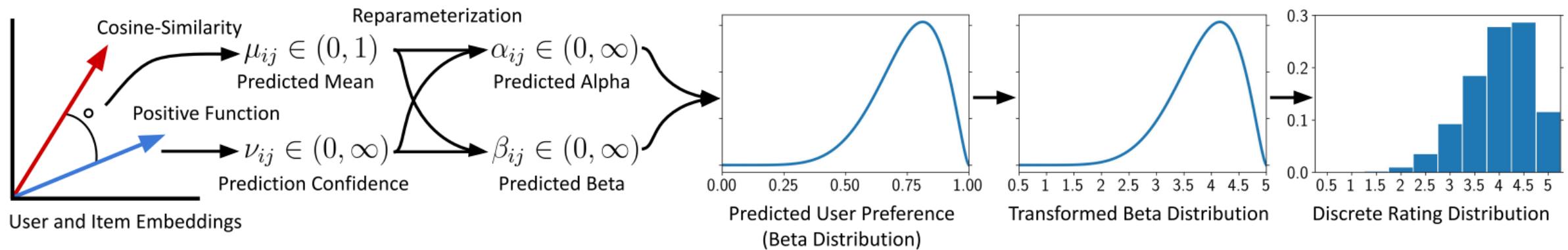
- Static Strategy (LBD-S) makes each bin equisized



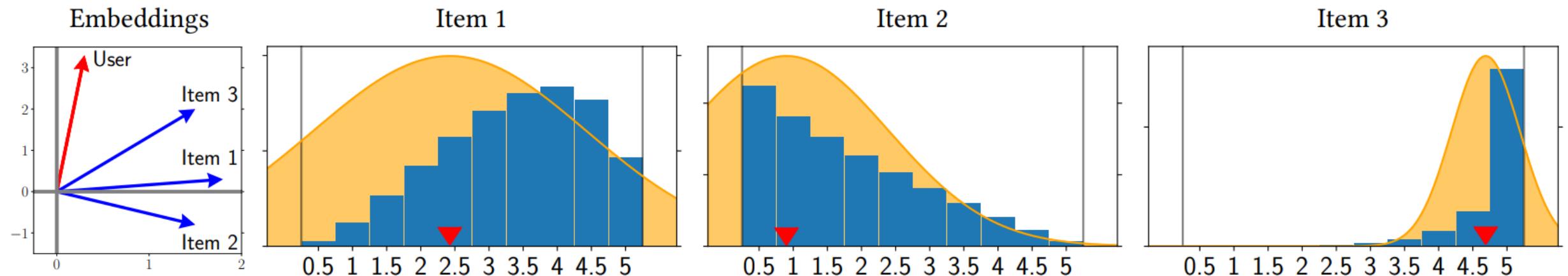
- Adaptative Strategy (LBD-A) varies the bin widths per rating, user and item.



Overview of the LBD Method



Comparison with existing methods



- The prediction of MF is pointwise; CMF is a Gaussian distribution; and LBD is a discrete rating prediction.

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Research questions

- What modeling of the parameters of LBD results in the highest predictive performance for rating prediction?
- Does our LBD approach provide rating prediction performance that is competitive with MF, CMF and OrdRec?
- Is there a stronger correlation between the confidence and accuracy of predictions by LBD than for CMF and OrdRec?
- Does the confidence modeling of LBD translate to higher performance compared to MF, CMF and OrdRec in a highprecision targeted recommendation task?

Baselines, metrics and parameter tuning

Baseline and metrics

Baselines

- MF
- CMF
- OrdRec

Metrics

RMSE
Accuracy
NDCG@k

Performance

New Methods

- LBD-S
- LBD-A

Parameter tuning

- Extensive random search
- Different embedding sizes
- RMSE on validation test

- Classification
- Regression
- Ranking

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Parametrization of the LBD Model

- What modeling of the parameters of LBD results in the highest predictive performance for rating prediction?

Size	$\nu(\cdot)$	Bias	RMSE	MAE	Accuracy	Ave. Log-L.	NDCG@3	NDCG@10
512	<i>sum</i>	-	0.7932 (0.0005)	0.6130 (0.0004)	0.3016 (0.0005)	-1.769 (0.001)	0.9330 (0.004)	0.9568 (0.0002)
512	<i>sum</i>	μ, v	0.7864 (0.0005)	0.6058 (0.0003)	0.3092 (0.0003)	-1.760 (0.001)	0.9339 (0.0003)	0.9568 (0.0001)
512	<i>sum</i>	α, β	0.7761 (0.0005)	0.5895 (0.0005)	0.3139 (0.0003)	-1.755 (0.003)	0.9357 (0.0003)	0.9583 (0.0001)
512	<i>norm</i>	α, β	0.7852 (0.0007)	0.5942 (0.0005)	0.3140 (0.0005)	-1.818 (0.004)	0.9336 (0.0002)	0.9572 (0.0002)
512	<i>dot</i>	α, β	0.8387 (0.0005)	0.6391 (0.0006)	0.2972 (0.0005)	-1.865 (0.005)	0.9330 (0.0004)	0.9495 (0.0001)
256, 256	<i>sum</i>	α, β	0.7850 (0.0006)	0.5964 (0.0006)	0.3133 (0.0006)	-1.774 (0.002)	0.9331 (0.0003)	0.9570 (0.0001)
512 + 10	<i>sum</i>	α, β	0.7759 (0.0004)	0.5875 (0.0004)	0.4356 (0.0006)	-1.432 (0.002)	0.9351 (0.0003)	0.9579 (0.0001)

Best Results: confidence function ν^{sum} , α and β bias terms, both with and without dynamic binning

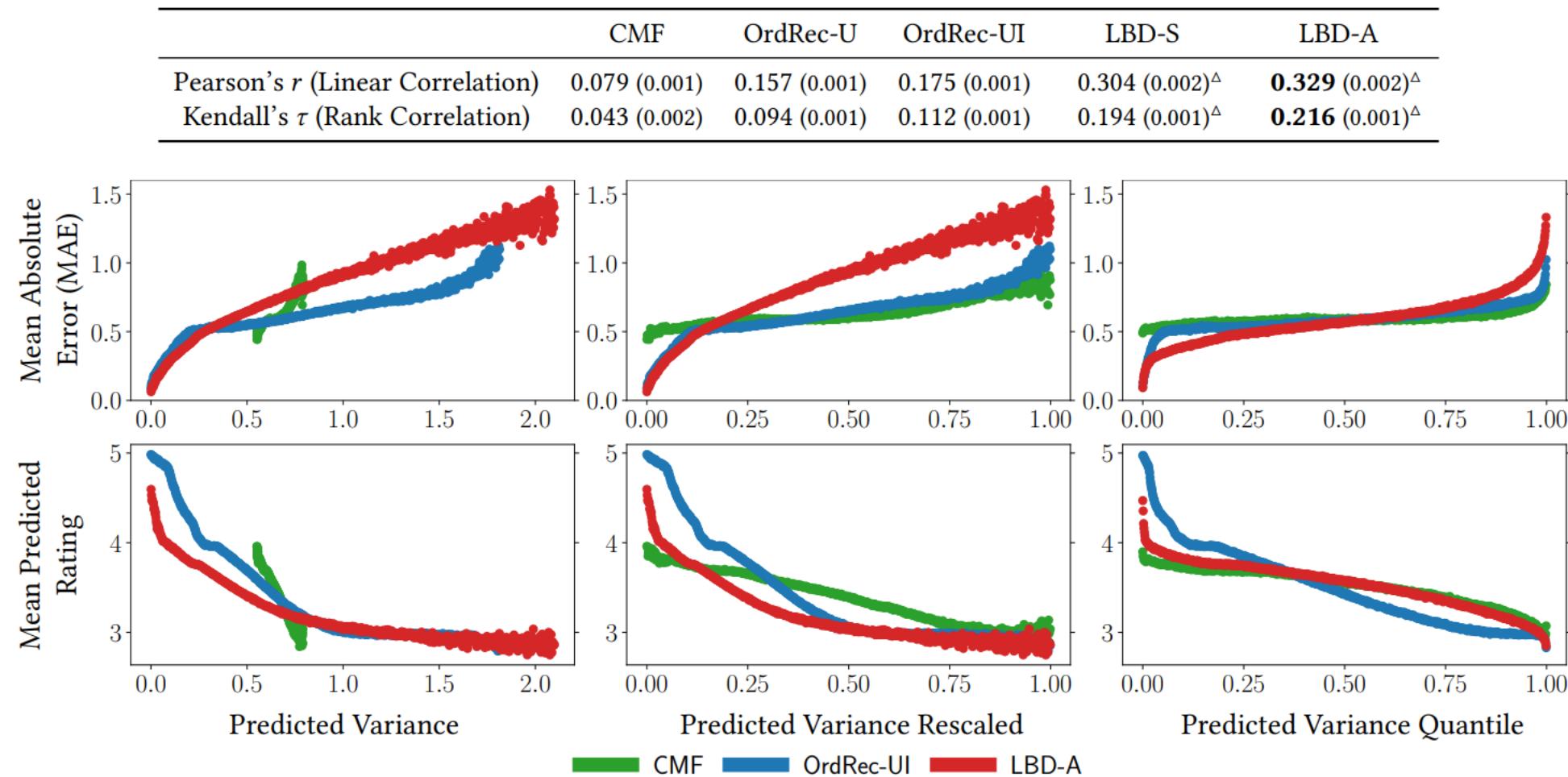
Recommendation Performance

- Does our LBD approach provide rating prediction performance that is competitive with MF, CMF and OrdRec?

Model	RMSE	MAE	Accuracy	Ave. Log-L.	NDCG@3	NDCG@10
MF (128)	0.7802 (0.0006)	0.5984 (0.0005)	0.2923 (0.0005)	-2.004 (0.002)	0.9334 (0.0002)	0.9570 (0.0001)
MF (512)	0.7883 (0.0006)	0.6022 (0.0005)	0.2934 (0.0004)	-2.022 (0.002)	0.9321 (0.0002)	0.9560 (0.0001)
CMF (128)	0.7760 (0.0007)	0.5936 (0.0004)	0.3226 (0.0004) [▽]	-1.777 (0.001)	0.9338 (0.0002)	0.9573 (0.0001)
CMF (512)	0.7820 (0.0005)	0.5967 (0.0003)	0.2849 (0.0015)	-1.801 (0.001)	0.9329 (0.0003)	0.9567 (0.0001)
OrdRec-U (512)	0.7821 (0.0006)	0.6043 (0.0004)	0.2322 (0.0007)	-1.881 (0.001)	0.9343 (0.0003)	0.9575 (0.0001)
OrdRec-UI (512)	0.7765 (0.0006)	0.5896 (0.0005)	0.4187 (0.0006) [▽]	-1.569 (0.001) [▽]	0.9349 (0.0003)	0.9578 (0.0001)
LBD-S (512)	0.7761 (0.0005)	0.5895 (0.0005)	0.3139 (0.0003)	-1.755 (0.003)	0.9357 (0.0003) [△]	0.9583 (0.0001) [△]
LBD-A (512)	0.7759 (0.0004)	0.5875 (0.0004) [△]	0.4356 (0.0006) [△]	-1.432 (0.002) [△]	0.9351 (0.0003)	0.9579 (0.0001)

Evaluating prediction Confidence

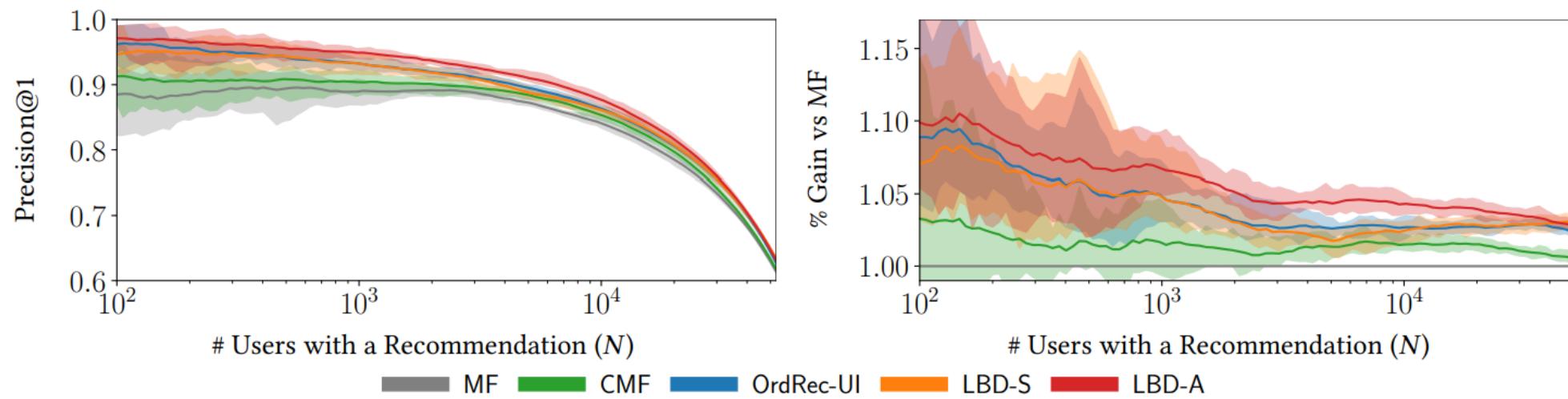
- Is there a stronger correlation between the confidence and accuracy of predictions by LBD than for CMF and OrdRec?



High precision targeted Recommendation

- Does the confidence modeling of LBD translate to higher performance compared to MF, CMF and OrdRec in a highprecision targeted recommendation task?

Model	Precision@1 for top N users					
	$N = 100$	$N = 320$	$N = 1000$	$N = 3200$	$N = 10000$	$N = 32000$
MF	0.885 (0.034)	0.893 (0.019)	0.889 (0.011)	0.886 (0.004)	0.841 (0.004)	0.726 (0.002)
CMF	0.913 (0.030)	0.907 (0.016)	0.904 (0.013)	0.895 (0.005)	0.853 (0.005)	0.733 (0.002)
OrdRec-UI	0.962 (0.016)	0.949 (0.007)	0.932 (0.006)	0.910 (0.003)	0.863 (0.003)	0.747 (0.002)
LBD-S	0.947 (0.019)	0.944 (0.013)	0.932 (0.009)	0.908 (0.006)	0.861 (0.004)	0.747 (0.003)
LBD-A	0.971 (0.012)	0.962 (0.011) ^Δ	0.949 (0.005) ^Δ	0.925 (0.004) ^Δ	0.877 (0.004) ^Δ	0.751 (0.003) ^Δ



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Conclusions and Future Work

Conclusions:

- Low model complexity
- Strong correlation between correlation and accuracy
- Higher precision in recommendation task

Future work:

- Understanding User Preferences and Dataset Uncertainty using LBD
- Confidence Modeling for Implicit Feedback Signals

Gracias 