Non-Compensatory Psychological Models for Recommender Systems

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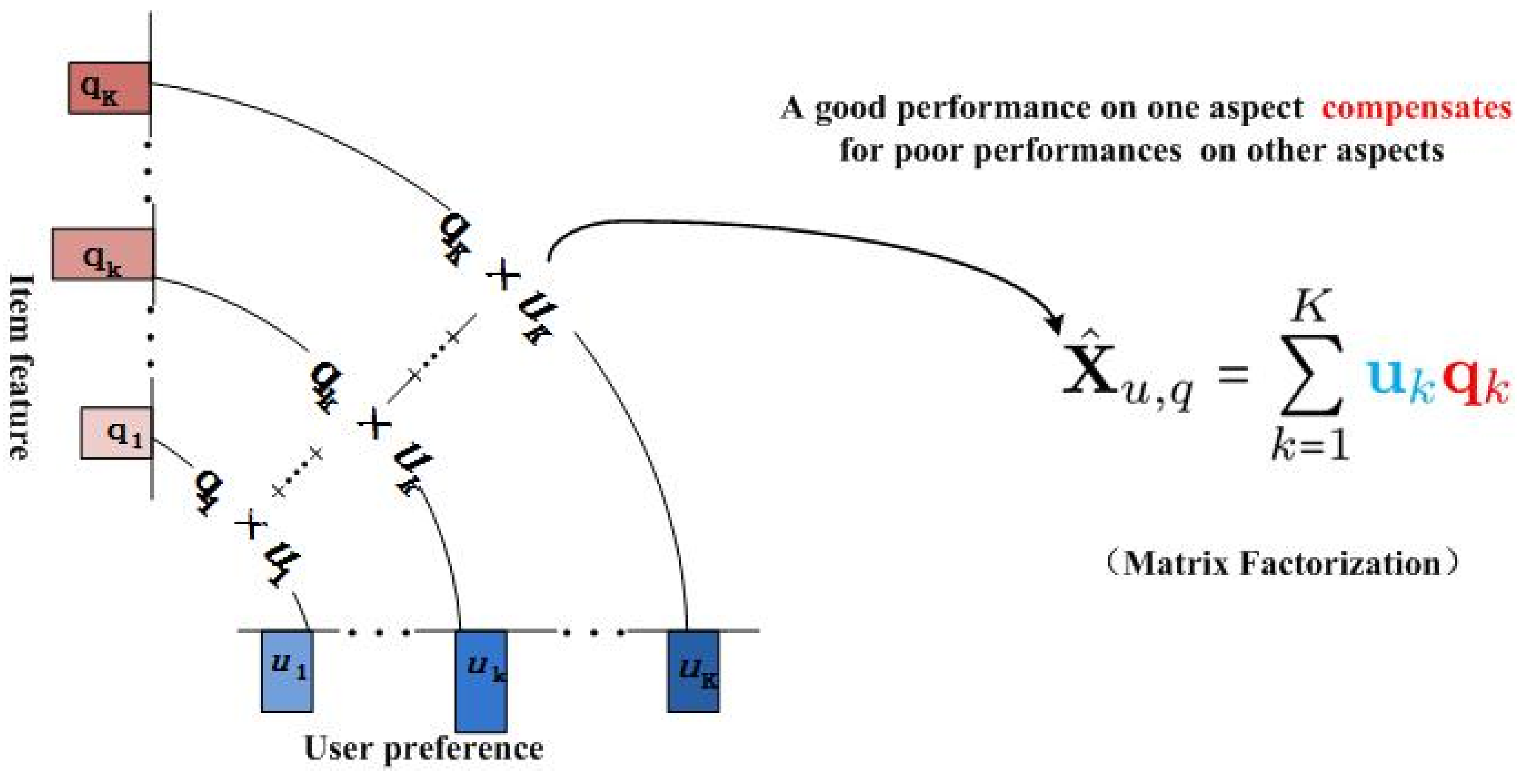
Research Question

- Q1: How do we explain existing recommendation models from a psychological perspective?
- Q2: How can we develop explainable and accurate recommendation models that operate differently from existing models?

Compensatory Models

- Compensatory Decision Rule



- Other Rating Models

AMF@KDD'08: $\hat{\mathbf{X}}_{u,q} = \sum_{k=1}^{K} \left(\sum_{\mathbf{p}\in R(u)} \mathbf{p}_k / \sqrt{|R(u)|}\right)\mathbf{q}_k$

LLORMA@JMLR'16:

$$\hat{\mathbf{X}}_{u,q} = \sum_{t=1}^{S}\sum_{k=1}^{K} \mathbf{u}_{t,k} \frac{K((\mathbf{u}_t,\mathbf{i}_t),(\mathbf{u},\mathbf{q}))}{\sum_{s=1}^{S} K((\mathbf{u}_s,\mathbf{i}_s),(\mathbf{u},\mathbf{q}))} \mathbf{q}_{t,k}$$

- Pair-wise Ranking Models

Thurstone Model: BPR@UAI'09,FSBPR@AJSE'18,LCR@WWW'14

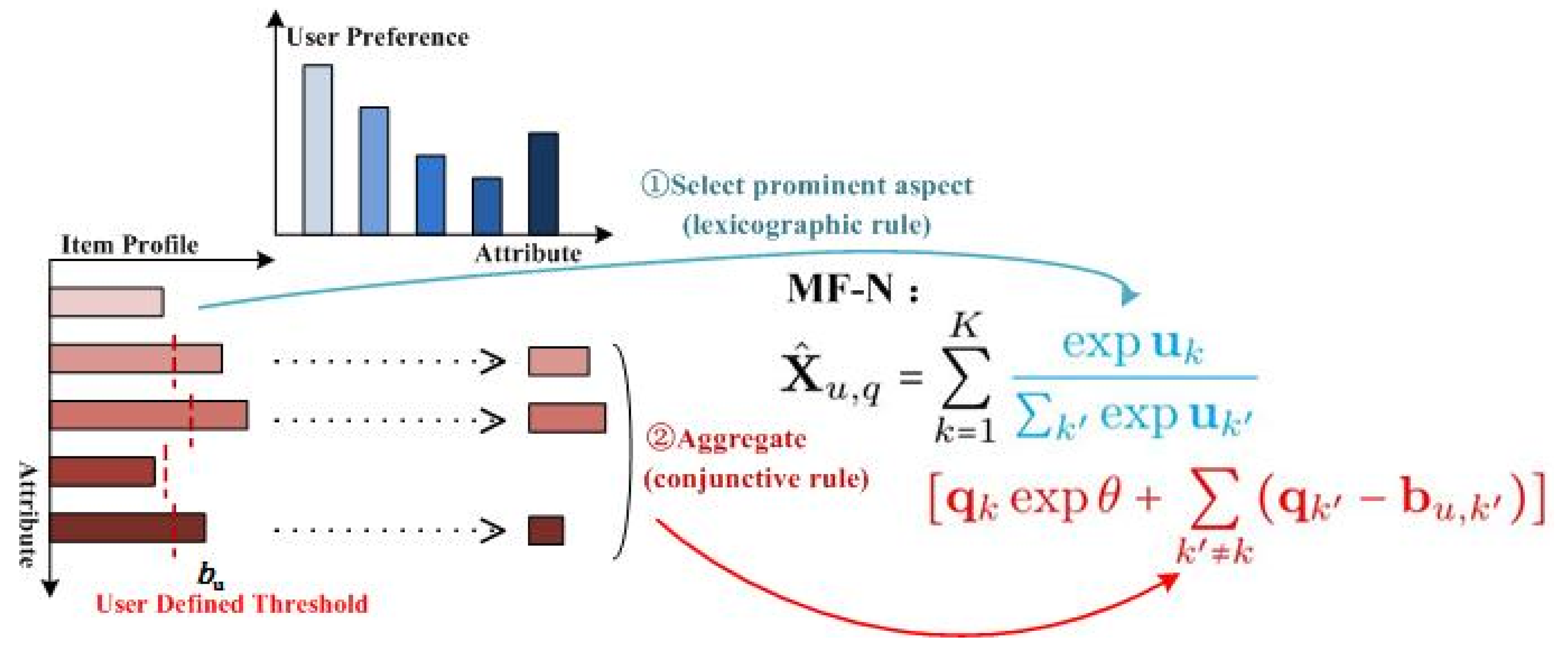
$Pr(p >_u q) = \frac{1}{1+\exp[-(\hat{\mathbf{X}}_{u,p}+\hat{\mathbf{X}}_{u,q})]}$, $\hat{\mathbf{X}}_{u,p,q}$ by MF, AMF, or LLORMA

Bradley-Terry Model: BT@ICDM'16

$$Pr(p >_u q) = \frac{\hat{\mathbf{X}}_{u,p}}{\hat{\mathbf{X}}_{u,p} + \hat{\mathbf{X}}_{u,q}}, \quad \text{where} \quad \hat{\mathbf{X}}_{u,q} = \sum_{k=1}^{K} \mathbf{u}_k \mathbf{q}_k$$

Non-Compensatory Models

- Non-Compensatory Decision Rule



- Other Non-Compensatory Rating Models

AMF-N: $\hat{\mathbf{X}}_{u,q} = \sum_{k=1}^{K} \frac{\exp(\sum_{\mathbf{p}\in R(u)} \mathbf{p}_k)}{\sum_{k'}\exp(\sum_{p\in R(u)} \mathbf{p}_{k'})} [\mathbf{q}_k \exp\theta + \sum_{k'\neq k}(\mathbf{q}_{k'} - \mathbf{b}_{u,k'})]$

LLORMA-N:

$$\hat{\mathbf{X}}_{u,q} = \sum_{t=1}^{S}\sum_{k} \frac{\exp \mathbf{u}_k}{\sum_{k'}\exp \mathbf{u}_{k'}} \frac{K((\mathbf{u}_t,\mathbf{i}_t),(\mathbf{u},\mathbf{q}))}{\sum_{s=1}^{S} K((\mathbf{u}_s,\mathbf{i}_s),(\mathbf{u},\mathbf{q}))} [\mathbf{q}_{t,k}\exp\theta + \sum_{k'\neq k}(\mathbf{q}_{t,k'} - \mathbf{b}_{u,k'})]$$

- Non-Compensatory Pair-wise Ranking Models

Thurstone Model - N:

$$\hat{\mathbf{X}}_{u,p,q} = \sum_{k=1}^{K} \frac{\exp(\mathbf{u}_k)}{\sum_{k'}\exp(\mathbf{u}_{k'})} [\exp\theta(\mathbf{p}_k - \mathbf{q}_k) + \sum_{k'\neq k}(\mathbf{p}_{k'} - \mathbf{q}_{u,k'})]$$

Bradley Terry Model - N:

$$Pr(p >_u q) = \sum_{k=1}^{K} \mathbf{u}_k \left[\frac{\mathbf{p}_k}{\mathbf{p}_k + \theta\mathbf{q}_k} \prod_{k'\neq k} \frac{\theta\mathbf{p}_{k'}}{\mathbf{q}_{k'} + \theta\mathbf{p}_{k'}}\right]$$

Rating Prediction

∘ Comparative experiments on rating prediction.
∘ Non-compensatory rules universally increase prediction accuracy.

Method	AUC	Imp	NDCG	Imp	MRR	Imp
Movielens		(%)		(%)		(%)
MF	0.6729		0.6925		0.8300	
MF-N	0.7108	5.62	0.7166	3.48	0.8633	4.01
AMF	0.6901		0.7107		0.8747	
AMF-N	0.7027	1.83	0.7138	0.44	0.8790	0.49
LLORMA	0.7265		0.8734		0.7015	
LLORMA-N	0.7299	0.47	0.8999	3.03	0.7187	2.45
Filmtrust		(%)		(%)		(%)
MF	0.6507		0.5229		0.7011	
MF-N	0.6710	3.12	0.5241	0.23	0.7071	0.86
AMF	0.5971		0.5137		0.7411	
AMF-N	0.6133	2.71	0.5253	2.25	0.7619	2.80
LLORMA	0.6240		0.8596		0.7857	
LLORMA-N	0.6345	1.68	0.8684	1.02	0.8068	2.69
CiaoDVD		(%)		(%)		(%)
MF	0.7431		0.7949		0.8910	
MF-N	0.7903	6.34	0.8127	2.25	0.9154	2.74
AMF	0.6489		0.6612		0.8741	
AMF-N	0.6993	7.77	0.6878	4.02	0.8967	2.58
LLORMA	0.6752		0.7827		0.8267	
LLORMA-N	0.6845	1.38	0.7984	2.00	0.8384	1.42

∘ $b_{u,k}$ significantly positive suggests aspect specific cut-off thresholds.
∘ Moderate θ suggests a combination of lexicographic and conjunctive rules.

Dataset	Imp.(%)	$\sigma(\mathbf{b}_u)$	θ
Movielens	5.37	0.0095 ± 0.0024	0.608 ± 0.105
FilmTrust	2.21	0.0095 ± 0.0023	0.667 ± 0.016
CiaoDVD	28.97	0.0093 ± 0.0022	0.773 ± 0.051

Explicit Feedback

∘ Comparative results for ranking reconstruction, pairwise ranking observed from explicit feedback, i.e. a higher rating is considered to be superior than a lower rating.
∘ Non-compensatory rules generally improve ranking performance.

Method	AUC	Imp	NDCG	Imp	MRR	Imp
Movielens		(%)		(%)		(%)
BT	0.6453		0.5329		0.8227	
BT-N	0.8511	31.89	0.5795	8.74	0.9256	12.51
BPR	0.7976		0.5674		0.8988	
BPR-N	0.8361	4.82	0.5761	1.53	0.9180	2.14
FSBPR	0.5048		0.5011		0.7524	
FSBPR-N	0.8272	63.86	0.5740	14.56	0.9136	21.42
LCR	0.7191		0.8555		0.9461	
LCR-N	0.7360	2.35	0.8605	0.58	0.9515	0.57
FIlmtrust		(%)		(%)		(%)
BT	0.5405		0.5092		0.7702	
BT-N	0.6969	28.94	0.5446	6.95	0.8485	10.15
BPR	0.6412		0.5319		0.8206	
BPR-N	0.6729	4.94	0.5391	1.35	0.8364	1.93
FSBPR	0.4857		0.4968		0.7428	
FSBPR-N	0.6717	38.29	0.5388	8.47	0.8358	12.52
LCR	0.5977		0.9034		0.7511	
LCR-N	0.6144	2.79	0.9063	0.32	0.7635	1.65
CiaoDVD		(%)		(%)		(%)
BT	0.6063		0.5240		0.8031	
BT-N	0.9334	53.95	0.5981	14.1	0.9666	20.36
BPR	0.6344		0.5304		0.8172	
BPR-N	0.8987	41.66	0.5902	11.28	0.9493	16.17
FSBPR	0.7537		0.5574		0.8769	
FSBPR-N	0.8992	19.30	0.5903	5.91	0.9496	8.30
LCR	0.6260		0.9408		0.7889	
LCR-N	0.6349	1.42	0.9451	0.46	0.7988	1.25

Implicit Feedback

∘ Comparative results for ranking reconstruction, pairwise ranking observed from implicit feedback which is graded, i.e. a purchase is considered superior than a click, more details refer to our paper.

∘ Non-compensatory rules generally improve ranking performance on implicit feedback.

	Method	AUC	Imp.(%)	NDCG	Imp.(%)	MRR	Imp.(%)	MAP	Imp.(%)	Prec	Imp.(%)
Tmall-single											
	BT	0.5304		0.2804		0.4870		0.4327		0.2778	
	BT-N	0.5400	1.82	0.2840	1.28	0.4948	1.61	0.4386	1.34	0.2801	0.84
	BPR	0.5181		0.2794		0.4854		0.4297		0.2767	
	BPR-N	0.5349	3.24	0.2848	1.92	0.4960	2.18	0.4401	2.41	0.2806	1.41
	FSBPR	0.5265		0.2824		0.4913		0.4350		0.2794	
	FSBPR-N	0.5389	2.35	0.2863	1.39	0.4988	1.53	0.4432	1.90	0.2818	0.87
	LCR	0.5200		0.8190		0.4277		0.3568		0.2534	
	LCR-N	0.5290	1.73	0.8213	0.28	0.4360	1.94	0.3648	2.24	0.2586	2.05
Tmall-hybrid											
	BT	0.5867		0.3015		0.5373		0.4929		0.2904	
	BT-N	0.6568	11.94	0.3279	8.75	0.5990	11.48	0.5527	12.13	0.3036	4.53
	BPR	0.6183		0.3183		0.5792		0.5318		0.2973	
	BPR-N	0.6460	4.48	0.3276	2.92	0.5990	3.41	0.5524	3.87	0.3030	1.94
	FSBPR	0.6334		0.3246		0.5916		0.5442		0.3026	
	FSBPR-N	0.6544	3.31	0.3309	1.94	0.6062	2.48	0.5603	2.95	0.3047	0.69
	LCR	0.5398		0.6644		0.4519		0.3745		0.2597	
	LCR-N	0.5649	4.65	0.6790	2.20	0.4809	6.42	0.3988	6.49	0.2720	4.74
Yoochoose											
	BT	0.6027		0.4734		0.7151		0.6361		0.4560	
	BT-N	0.7000	16.15	0.5160	8.99	0.7869	10.04	0.7084	11.37	0.4785	4.92
	YBPR	0.6700		0.5065		0.7713		0.6895		0.4737	
	BPR-N	0.6920	3.28	0.5131	1.31	0.7812	1.29	0.7027	1.91	0.4771	0.74
	FSBPR	0.3272		0.3658		0.5062		0.4599		0.4006	
	FSBPR-N	0.6198	89.45	0.4822	31.83	0.7169	41.62	0.6448	40.22	0.4650	16.08
	LCR	0.5842		0.9725		0.8009		0.7934		0.7677	
	LCR-N	0.6315	8.10	0.9754	0.30	0.8231	2.77	0.8161	2.86	0.7881	2.66

Conclusion

- Existing recommendation models are based on compensatory decision rules. However,consumers adopt non-compensatory rules more often.
- We propose a non-compensatory framework which can be easily embedded in latent factor models. We experimentally show that it universally improves recommendation performances of different existing models.
- This contribution sheds insight to developing explainable shallow models.

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