Learning And Mining from DatA
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About the Author(分栏显示)

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Latest works

- NeurPIS
- ICML
- ICLR
- TPAMI
- PRML

Outline

Preliminary(公式展示)

- **Learning Strategy**

Optimization methods: Pointwise loss (binary cross-entropy, mean square error), pairwise loss (BPR, WARP), and softmax loss

$$\mathcal{L}_0 = -\sum_{(u,i)\in O^+} \log \frac{\exp\left(\cos(\hat{\theta}_{ui})/\tau\right)}{\exp\left(\cos(\hat{\theta}_{ui})/\tau\right) + \sum_{j\in N_u} \exp\left(\cos(\hat{\theta}_{uj})/\tau\right)},$$

Outline

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Related Work(多级列表)

SOTA debiasing strategies

- **Sample re-weighting methods** (e.g. IPS-CN)
  exploit the item popularity's inverse to re-weight loss of each instance.
- **Causal inference methods** (e.g. MACR, CausE)
  - specify the role of popularity bias in assumed causal graphs
  - mitigate the bias effect on the prediction.
- **Regularization-based frameworks** (e.g. Sam-reg)
  - Provides a tunable mechanism for controlling the trade-off between recommendation accuracy and coverage.
  - **Sam-reg** regularizes the biased correlation between user-item relevance and item popularity

Outline

Methodology of BC Loss BC Loss(二级标题)

- **BC Loss**

$$\mathcal{L}_{\mathrm{BC}} = -\sum_{(u,i)\in O^+} \log \frac{\exp\left(\cos(\hat{\theta}_{ui} + M_{ui})/\tau\right)}{\exp\left(\cos(\hat{\theta}_{ui} + M_{ui})/\tau\right) + \sum_{j\in N_u} \exp\left(\cos(\hat{\theta}_{uj})/\tau\right)},$$

M_{ui}: the bias-aware angular margin for the interaction (u, i)

$$M_{ui} = \min\{\hat{\xi}_{ui}, \pi - \hat{\theta}_{ui}\}$$

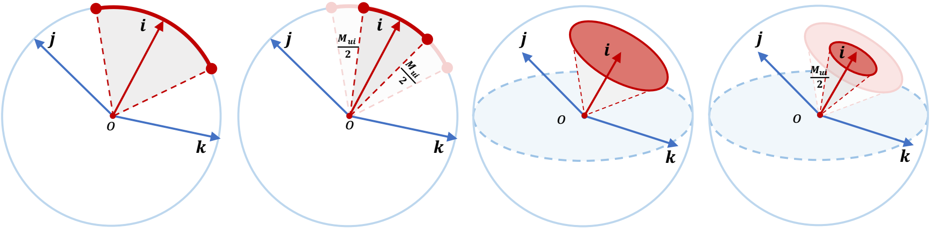
- **Intuition**

  If a user-item pair is the hard interaction that can hardly be reconstructed by its popularity statistics, it holds a high value of ξ_{ui} and leads to a high value of M_{ui}. Henceforward, BC loss imposes the large angular margin M_{ui} between the negative item j and positive item i.

Outline

- **Geometric Interpretation**

  User u with one observed item i and two unobserved items j and k.



(a) Softmax Loss (2D) (b) BC Loss (2D) (c) Softmax Loss (3D) (d) BC Loss (3D)

- **Theoretical Properties**

Proof.

1. There exists an upper bound m, s.t. $-1 < \cos(\hat{\theta}_{ui} + M_{ui}) \leq v_u^T v_i - m < 1$
2.
3.
4.
5.
6.

$\square$

Outline

Baselines

- Backbone: only use softmax loss
- IPS-CN: sample re-weighting methods
- CausE: bias removal by causal inference
- sam + reg: regularization-based framework
- MACR: bias removal by causal inference

Datasets

	KuaiRec	Douban Movie	Tencent	Amazon-Book	Alibaba-iFashion	Yahoo!R3	Coat
#Users	7175	36,644	95,709	52,643	300,000	14382	290
#Items	10611	22,226	41,602	91,599	81,614	1000	295
#Interactions	1062969	5,397,926	2,937,228	2,984,108	1,607,813	129,748	2,776
Sparsity	0.01396	0.00663	0.00074	0.00062	0.00007	0.00902	0.03245

Outline

Conclusion(脚注使用)

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- **Contribution**
  - (Originality) Popular bias extractor has an intuitive geometric interpretation.
  - (Quality) Outperforms existing methods in various evaluation protocols.
  - (Clarity) Well-written and easy to understand. Theoretical proof is quite solid.
- **Limitation**
  - The technical contribution of this paper is limited.It only proposes to employ an extra popularity-based predictor and combine the results with an existing CF model [1].
  - Overclaims the strength of the proposed BC loss in theoretical analysis. The geometric interpretability and the hard-negative mining ability are actually the same thing[2, 3]

[1] Kaiming He et al. "Momentum contrast for unsupervised visual representation learning". In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020, pp. 9729–9738.

References I

[1] Kaiming He et al. "Momentum contrast for unsupervised visual representation learning". In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2020, pp. 9729–9738.

[2] Tongzhou Wang and Phillip Isola. "Understanding Contrastive Representation Learning through Alignment and Uniformity on the Hypersphere". In: Proceedings of Machine Learning Research. PMLR, 2020, pp. 9929–9939.

[3] Fajie Yuan et al. "One person, one model, one world: Learning continual user representation without forgetting". In: *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2021, pp. 696–705.

Acknowledgement

Thank you!