指出,用户在对商品打分时关注商品特性多于关注自身的偏好.实验结果表明,HFT(item)效果优于HFT(user).

- TopicMF 方法是更换了主题发现的评论集主体,采用单条评论作为主题模型的输入.而 HFT(user)和HFT(item)的对主题偏好的学习是通过整体评论集使用主题发现,定义了主题偏好分布与用户潜在因子向量和商品潜在因子向量的映射.实验结果表明,TopicMF 方法均优于 HFT(item)和 HFT(user),单条评论能够更精准地表达某用户对某商品的个性偏好.
- 本文提出的 PreferenceMF 是在 TopicMF 基础上加入了主题偏好的引导.经过实验验证,该引导项可以进一步提升推荐质量.后续有待进一步研究该方法在解决冷启动问题的能力.

4 总结和展望

本文提出了融合评分与评论文本的推荐方法,即加入了偏好引导的 PreferenceMF 方法.从不同角度进行分析后,给出了模型的数学表述形式和参数拟合求解的算法.最后,在 28 组 Amazon 数据子集上与多种相关的推荐方法进行实验对比,结果表明,本文提出的 PreferenceMF 方法的推荐质量相对于目前主流的方法有进一步提升.并分析了各个方法的实验结果以及存在的问题.今后可以对隐因子数量和映射关系做进一步研究.本文在融合方法中假设主题发现的主题数量与潜在因子数相等,并且具有相同的权重,可以考虑不同权重的情况.在解决数据稀疏性、模型冷启动和长尾现象等问题上,都有待进一步展开研究.此外,本文是从最大化似然的角度来使推荐模型适应数据,今后可以采用贝叶斯估计,从最大化后验分布的角度来对模型进行建模和求解.

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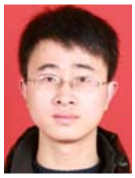

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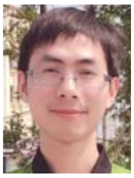

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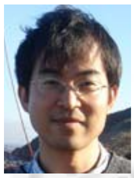

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