(6) 社交推荐模型快速求解

高效、快速地求解推荐模型,一直是推荐系统研究人员关注的热点问题.大数据时代,庞大数据量的产生为推荐模型求解带来了极大的挑战.与此同时,多源信息的引入(如社交信息等)尽管能够为推荐系统提供强有力的数据支持,但也加剧了推荐模型的复杂度.社交推荐的主流模型是基于矩阵分解的协同过滤,其主要思想是:通过矩阵分解获得用户和物品在隐特征空间上的表示,并用其拟合评分信息来设定目标优化函数.这类目标函数的优化求解往往采用随机梯度下降法[10].随机梯度下降法由于其计算复杂度低且易于并行化在推荐领域受到广泛关注.并行化随机梯度下降法能够在很大程度上加快推荐模型的求解,目前已有多种相关算法被提出来[81,82].然而社交信息的引入,往往使得基于矩阵分解的推荐模型更加复杂,从而无法而合理有效地对数据进行划分而达到并行加速效果.因此,如何有效地划分数据、设计融合多源信息的并行优化算法、高效而快速地为用户提供高质量推荐结果,成为推荐时代面临的核心问题.

(7) 社交信息动态变化的影响

用户行为信息具有动态变化的特点,已有文献开始关注基于时序行为的推荐方法的研究[83−85].然而现实生活中,由于人际关系的复杂性与网络环境的实时性,决定了社交网络同样具有动态变化性[86],即真实社交网络中个体间的关系及个体状态都是动态变化的.已有社交推荐方法往往基于静态社交关系设计,忽略了推荐数据的动态变化特点,从而无法实时地为社交推荐提供可靠的资源.因此,如何有效地刻画社交网络动态变化的特点,提出基于动态社交网络的社交推荐模型,将成为社交推荐研究的难点之一.

(8) 用户隐私信息的保护

个性化推荐系统利用用户行为信息、个人属性信息等为用户提供推荐,这种个人信息具备较强的隐私性,用户可能会出于对隐私泄露的担心而放弃对推荐系统的信任[87].Netflix prize 比赛极大地推动了推荐系统的发展.然而由于美国联邦政府交易委员会认为大赛会损害用户隐私,同时,Netflix 为了防止官司缠身,遂于 2010 年 3 月宣布取消 Netflix prize 大赛.由此可见,对于用户隐私信息的保护极其重要.针对个性化推荐中隐私保护方法的研究,也将成为研究者关注的热点.

(9) 前沿理论与方法在推荐上的应用

近年来,深度学习在语音和图像上的巨大成功引起了人们的强烈关注.推荐系统作为一支独立的学科,如何与深度学习相结合,创造出更大价值,也成为推荐系统研究领域的一大方向.在基于矩阵分解方法使得 Netflix prize 比赛陷入僵局之时,受限玻尔兹曼机(restricted Boltzmann machine,简称 RBM)的出现为推荐方法提供了新的思路[88].此后,陆续有相关基于深度学习的推荐方法被提出来[85,89,90].2016 年,推荐系统大会 RecSys 还专门针对深度学习与推荐系统设立了专门研讨会.由此可见,深度学习在推荐上的应用具有广阔的前景.

6 总 结

作为推荐领域的重要研究方向,社交推荐方法近年来在推荐领域获得了广泛的关注,尤其是基于矩阵分解的社交推荐方法得到了快速发展.社交信息的引入,为推荐系统的研究提供了新的方向,也极大促进了推荐系统的发展.本文依据社交推荐模型构建方式的不同对其进行了分类综述,其目的在于全面完善地了解基于矩阵分解的社交推荐模型构建过程,为新的社交推荐模型构建提供思路.其次,通过在真实数据集上的实验对比,验证典型基于矩阵分解的社交推荐模型的性能,分析社交信息对推荐性能的影响.最后,指出现有社交推荐模型在数据稀疏性、可解释性、快速求解等方面存在的问题.希望本文对基于矩阵分解的社交推荐模型的综述能够为相关学者提供一定程度的帮助,同时更好地促进社交推荐方法的研究.

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