从结果中可以看到:在神经网络中附加传统特征选择方法,可以优化神经网络在文本分类任务上的效果,其中,附加经过 Sigmoid 归一化的 Pearson 和 Chi2 评价值的模型效果显著优于无附加神经网络的效果.这表明了本文提出的增强特征选择的神经网络模型的有效性.

5 结论与展望

本文从理解神经网络特征选择的角度出发,提出了基于感受野的特征贡献度分析方法来显式地挖掘神经网络模型对不同特征的重要性判断和选择.进而通过比较传统特征选择方法和神经网络对特征的选择能力,我们发现:以卡方检验、皮尔逊相关系数为代表的传统特征选择方法在提取高重要性特征、过滤噪声特征方面具有优势,尤其当样本量并非海量时.因此,可以在神经网络中结合传统特征选择方法来提高神经网络的特征选择能力和分类效果.据此,本文设计了增强特征选择的神经网络.与通常将特征选择放于模型训练之前的做法不同,该模型将特征选择直接加入网络训练过程中,使得网络可以更有效地进行特征选择.在社交媒体用户建模数据集上的实验结果验证了模型的有效性.本文提出的分析方法和改进模型为理解神经网络特征选择能力、改进神经网络在高维特征问题上的效果提供了一种思路.

神经网络的黑箱特性使我们对其工作原理知之甚少,本文通过对网络权重的分析,尝试打开神经网络的黑箱,从特征选择的角度理解和评价神经网络的特点和不足.未来我们会进一步从理论的角度对本文的分析方法和结论进行验证.近年来,许多研究者尝试将传统机器学习的成果加入神经网络中.我们初步尝试了将传统特征评价方法作为先验知识来辅助神经网络的学习.未来我们会进一步从实验和理论的角度探究不同的结合方法来优化神经网络的效果.

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