表 1 显示处理和隐式处理算法优缺点总结

处理方式	方法		不同方法优缺点
显示处理	清理噪声		文献[18]处理方式简单, 但数据容易缺失; 文献[19]解决数据严重缺失问题, 但也容易误删某些正确的实例; 文献[20]可以和不同的半监督损耗兼容, 却在噪声比较高情况下表现不好; 文献[21]训练集很小的情况下可防止网络过度拟合, 但标签分布固定无法更新; 文献[22]易部署, 噪声较高时会失效.
	ANVC		文献[23]适用于二分类, 多分类下性能低
	重加权		文献[24]适用对称噪声标签, 权重并不易估计
	样本选择		文献[27]减少时间、降低存储成本, 但易忽略反馈信息, 且对小批量SGD训练困难
	小损失		文献[28]克服了损坏标签的过度拟合情况, 但容易累积错误信息; 文献[29]解决了累积错误问题, 但训练时间太长, 两个网络容易达到收敛共识; 文献[30]鲁棒性好, 但在噪声率极高时, 难适用于小批量训练.
隐式处理	损失函数	0-1损失[31]、非铰链损失[32,33]、斜坡和S型损失[33]	适用于二分类, 不适用于多分类
		DAC[36]、SL[37]	文献[36]易于实现, 可以和现有任意DNN架构一起使用, 但若随机标签中存在不明显噪声, 则该方法并不适用; 文献[37]在手动损坏的嘈杂标签上有很好的性能, 但真实数据下比较相似的类容易混淆.
		CCE、TCCE[38]	CCE收敛速度快, 但对标签噪声比较敏感; 文献[38]较大噪声水平下性能好, 但噪声过高时, 其性能没有CCE好, 且无法获得干净数据标签的最高准确度.
		MAE[34]、截断Lq[35]	文献[34]鲁棒性好, 但数据集复杂时性能下降; 文献[35]鲁棒性好收敛速度快, 但修剪时计算过于复杂, 且会错误标记非常相似的类.
	其他	转移学习	很好地避免过拟合, 但必须保证两任务之间存在很大的相关性, 不能过于松散.
		前后向校正[39]	文献[39]该方式与应用程序和网络体系结构无关, 但现实中非一直可用的, 而且难以准确估计.
		通用框架[40]	文献[40]可以处理一般情况下的标签噪声的同时也可以处理多类分类问题, 但在只有嘈杂标签时, 模型会漂移.

3 展望与进一步挑战

3.1 展望

3.1.1 数量趋势

本文针对 2015~2019 年顶级会议上的论文进行调研, 统计并分析和标签噪声相关论文数如图 5 所示.

(1) 图 5(a) 中可以很明显地看出, 有关标签噪声的各类会议在 2015 年屈指可数, 但这之后其呈现出快速增长的趋势, 虽然每年都存在小幅度波动, 但丝毫不影响其整体性发展.

(2) 图 5(b) 中可以发现, 2015~2019 年中关于噪声的研究文献明显增长, 特别是在 2019 年, 其研究文献已经达到 2015 年的 4 倍, 可以预计, 未来对标签噪声的研究会越来越多, 亦有可能呈现爆发性增长, 其将会成为人工智能领域的一个热门研究对象.

(3) 上述顶级会议论文中, 针对标签噪声的学习不仅仅是关于理论知识的研究, 同时也包含其实际应用中的研究, 理论与应用两方面的研究从侧面体现了关于标签噪声学习的重要性.

3.1.2 热点趋势

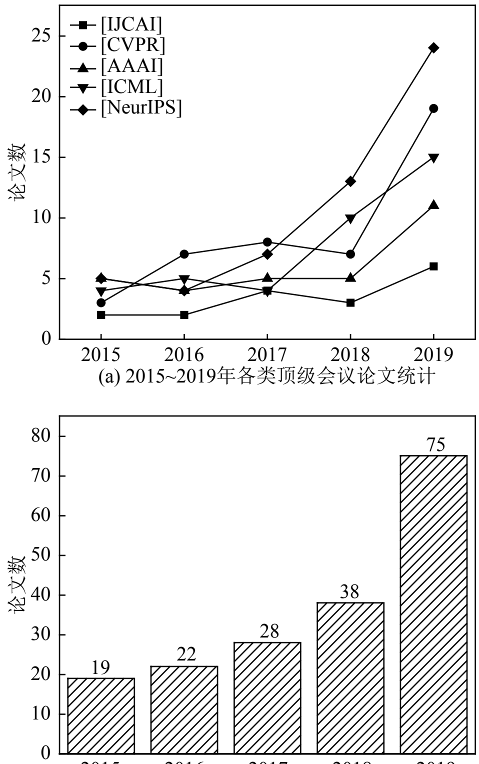
处理标签噪声是一个开放性问题, 本文根据其特点和实际应用性将其热点趋势大致分为 4 种情况:

(1) 多角度性: 参阅文献可以看出, 针对标签噪声研究方法多种多样, 但大部分研究主要针对以下几方面, 如: 处理噪声敏感的标签; 类的相似性过高下的误判; 训练过程中的过拟合; 不同噪声比下的误差过大; 不同网络间优势相结合等等. 显而易见, 从算法不同角度及其本身进行剖析一直是该领域研究热点.

(2) 通用性: 有文献设计出与应用程序和网络体系都无关的方法, 也有设计出可以和任意 DNN 架构一起使用的方法, 这些设计从侧面反映出其方法对环境的非依赖性, 同时方法的通用性会进一步减少研究成本, 由此可推断出学者会针对此方面做进一步研究.

(3) 适用性: 上述研究基本针对人工合成噪声数据, 其准确率虽然不错, 但并未对真实数据研究, 为增强噪声数据的适用性, 可以预测未来将逐渐针对如网络爬虫、众包等真实数据或更复杂的环境进行研究.

(4) 易于实现性: 虽然现有框架下的研究对标签噪声处理取得了不错效果, 但若应用到实际情况, 其效果不尽其然, 因此如何设计出能够有效处理标签噪声且易于实现的方法必将成为研究热点.



(a) 2015~2019年各类顶级会议论文统计

(b) 2015~2019年顶级会议论文统计

图 5　顶级会议相关文献统计

3.2　标签噪声处理的进一步挑战

虽然标签噪声的研究在理论层面和工程领域都有丰硕的研究成果, 但其在实际应用中仍存在很多问题.

(1) 虽然标签噪声清理方法能够用去除或纠正错误标签的实例, 但这些方法很难将信息丰富的示例与有害的错误贴标签的示例明显区分, 同时过度清洗也可能会将分类器的性能降低.

(2) 大多数损失函数对标签噪声并不是完全鲁棒且有些对异常值敏感, 对于处理方式过于复杂的损失函数, 容易产生过拟合现象.

(3) 现有方法对标签噪声的相关研究假设了一定的不实际的前提条件, 同时有很少文献针对一般情况下的标签噪声进行研究, 如大多数研究并不是基于网络爬虫等进行研究, 无法将其一般化于各类数据情况下的标签噪声.

(4) 多分类情况下, 标签噪声在破坏原始干净数据分布的同时会导致标签浮动噪声问题, 其容易限制模型的泛化能力; 且多特征数据中有些标签相关性能比较微弱, 需要仔细辨别.

(5) 有关标签噪声的应用问题, 在不同场景下应对策略也有所不同, 需要针对标签噪声的场景适用性问题作出进一步研究.

4　总结

本文根据噪声结构的建模方式对标签噪声的处理方法从显式和隐式两大方面做出系统性梳理和总结. 从众多文献可以看出, 在训练前直接删除数据会造成数据严重缺失, 目前大部分研究主要使用“训练-清洗数据-再训练”此种迭代方式进行研究, 且逐渐倾向于多网络方式结合、监督和非监督技术结合或损失函数相关处理方面等; 但大部分研究都有相应的特定场景, 且最终效果并不乐观, 和实际情况下不同场景的应用有很大差距. 因此需要研究出一种具有通用性好、适用性强并且易于实现的方法来处理不同场景下的标签噪声.

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