可以看到,SDN 流量感知的研究已转向复杂条件下的智能流量分类和预测.此外,研究人员也在研究 5G 核心网络、接入网、内容中心网络、物联网等场景下,将 SDN 集中控制和深度学习出色的感知能力结合,在上述新型场景下解决更具体的感知问题.为了深度学习模型能在更苛刻的 SDN 场景中部署,研究人员尝试了一些新的机制,如将模型部署在单独的服务器,监听交换机网络信息,并通过 OpenFlow 协议与控制器进行通信;或者将模型分布式部署到数据平面的交换设备上,利用交换设备上少量的计算能力完成模型的运行,减少控制器的压力,并且控制器可以通过 OpenFlow 协议的可编程特性完成模型在交换机上的动态部署、更改等.

7 其他应用

除了上述 SDN 中深度学习应用较多的领域,还有诸如信道分配、网络功能虚拟化(NFV)选择、控制器同步、流表冲突检测等领域也零星分布有深度学习的应用,这些应用可以松散地分类为控制器相关和交换机相关两大类.相比较智能路由、入侵检测、流量感知等研究方向,深度学习在上述领域的应用成果很少,一方面是因为 SDN 中的深度学习应用还处于探索阶段,上述领域还未全面将深度学习引入到相关研究中,另一方面也要看到,随着深度学习的参与,上述领域本身的特点特使得深度学习的引入较为困难,相关领域应用较少.

7.1 控制器

SDN 中 NFV 的研究由来已久,Pei 等人[94]提出了一种基于 DBN 的深度学习方法来解决 VNF 选择和链接问题[95],并在 SDN 网络中设计高性能路由策略,这是用深度学习技术研究 VNF 选择和链接问题的第一次尝试.该方案时间效率很高,端到端延迟小,服务功能链请求(SFCR)接受率高,证明深度学习技术可以解决高性能网络的 VNF 选择和链接问题.

针对软件定义工业物联网(SDIIoT)中的控制器同步问题,Qiu 等人[96]给出了一个基于 DRL 的区块链系统.他们综合考虑了区块链节点和控制器的信任特征,以及区块链系统的计算能力,将视图改变、访问选择和计算资源分配制定为联合优化问题.采用 DRL 方法来解决这一问题,并得到了基于 DRL 的控制器同步区块链系统.

7.2 交换机

针对 SDN 中应用的流表冲突问题,Li 等人[97]提出了一种新的方法以检测流表冲突.该方法采用第 1 级 CNN 模型定性判断是否存在流表冲突,并采用同样的第 2 级深度学习模型定位出具体冲突的流表项.当 OpenFlow 网络中存在大量的流表时,该方法在检测冲突流表上所花费的时间远小于传统的流表冲突检测方法,非常适合于对超大规模流表进行冲突检测.

无线软件定义物联网中(SDN-IoT)交换机的信道分配问题非常重要.Tang 等人[98]设想了预测未来网络流量负载,然后分别根据预测的流量负载自适应地分配信道的策略,并采用 CNN 模型一次性解决这两个问题.该模型分为特征抽取部分和分类部分,SDN 控制器收集整个网络的历史数据线下训练该模型用于信道分配,并在分配信道后收集实时数据更新该模型,从而实现智能地分配信道.该方法信道分配的准确率高,算法收敛时间远远小于传统算法,在网络的吞吐量和时延这两个性能上也有所提高.

在后来的工作中,Tang 等人[99]又提出一种新颖的智能信道分配算法,可以自动避免潜在的拥塞并在 SDN-IoT 中快速分配合适的信道.该算法包括两个部分:流量预测和信道分配,其中,基于深度学习的流量负载预测算法预测网络中未来的流量负载和拥塞,而基于深度学习的部分信道分配算法被称为 DLPOCA,可以智能地将信道分配给 SDN-IoT 网络中的每个链路.在经过多次实验以后,他们选择了 CNN 作为深度学习模型,仿真结果表明,该方案明显优于传统的信道分配算法,准确率接近 100%,并且收敛时间大大缩短.

7.3 其他应用分析

除了重点的 SDN 研究领域以外,深度学习方法在其他 SDN 相关的研究中也有引入,很好地促进了相关研究的发展,见表 6.可以看到,在其他应用这一部分,需要解决的问题较为复杂,已经没有了成熟的研究路线和应用深度学习方法的模式,需要针对具体问题具体分析,深度学习模型更多的是作为核心步骤被引入.与此同时,面对不规则的问题,研究人员倾向于采用 CNN 进行原始特征的特征提取和高级抽象,并在模型的最后附加 softmax

分类器进行标签学习.在训练数据方面,因为所研究的问题相对较为小众和特殊,缺乏现成数据集,需要通过模拟生成的方式来获得训练数据.

另外,这一部分的深度学习应用机制更加复杂,需要配合其他技术联合解决问题,这有别于入侵检测、流量感知等 SDN 研究领域直接应用深度学习模型的情况.面对更细化的特定研究问题,深度学习模型的引入更加困难,需要针对具体问题详细设计和适配,这无疑给研究人员提出了更大的挑战.

Table 6 Other applications

表 6 其他应用

文献	目标	模型/层	特征	开发平台	数据集	准确率(%)	优点	缺点
[94]	SDN 中 VNF 选择	DBN/4	资源状态	Matlab	模拟生成	100.0	SFCR 映射的时效性可扩展性较好	请求增加时性能急剧下降
[96]	SDIIoT 控制器同步	DRL/–	综合特征	Tensorflow	模拟生成	–	提出基于区块链的第三方控制器同步机制	未解决信任特征的获取问题
[97]	SDN 流表冲突检测	CNN/8 CNN/4	流表字段	Keras scikit-learn	模拟生成	97.0 99.9	采用两级检测机制,检测时间线性增长	数据集模拟生成,无参考性
[98]	SDN-IoT 信道分配	CNN/7	历史负载	–	模拟生成	90.0	可动态进行信道分配,提高网络吞吐量	准确率有待提高
[99]	SDN-IoT 信道分配	CNN/6	负载矩阵	WILL	模拟生成	100.0	跨层联动预测,大幅提高系统性能	机制复杂,部署难度大

8 问题与展望

本文对SDN中的深度学习应用进行了详尽的介绍和分析,不难看出,在SDN中引入深度学习是一个值得研究的领域,复杂且更加强大的深度模型能够深刻揭示网络环境所承载的信息,并对复杂的网络任务做出更精准的决策,将有效促进智能化的计算机网络管控.但是深度学习与 SDN 的结合是 2016 年左右才开始兴起的,还处于探索阶段,与其他成熟的深度学习应用领域相比,尚存在许多问题和不足,需要投入更多的时间和精力.在未来的工作中,可从以下几个方向入手,对深度学习的引入进行必要的基础性准备研究,更好地支持深度学习与SDN 的深度融合,促进关键研究的深入开展,提升计算机网络的智能化水平.

(1) SDN 网络数据获取

在 SDN 中部署深度学习,需要大量数据来训练深度学习模型,数据的轻松获取有助于促进相关研究的广泛开展.现有网络数据集对 SDN 和深度学习的支持度极其有限,需要在 SDN 网络数据获取方面进行深入研究.除了采用过时的网络数据集训练和评估模型效果外,在 SDN 中实时收集训练数据是许多现有研究的选择,然而这需要更多的资源投入和复杂的系统设计.如何设计高效、便捷的网络监测和大规模网络数据收集框架,减少系统资源消耗,是一大难题.原始网络数据获取后需要进行预处理,研究大规模 SDN 网络数据的批量处理,高效存储,快速获取是引入深度学习后,顺利部署相关模型需要面对的挑战之一.此外,建立大型、公开、支持深度学习研究的标准网络数据库也将推进在 SDN 中引入深度学习的研究.

(2) 深度学习模型适配

与其他成熟领域相比,SDN研究中深度学习的引入到目前为止还只是一种粗浅的尝试,深度学习与SDN研究并未完全适配.现有研究多采用成熟的深度学习模型,模型结构和训练设置并未根据 SDN 研究的特点灵活修改.此外,深度学习模型输入和输出设计的好坏会直接影响到模型的训练效率和问题求解的准确性,因此对网络数据的筛选和处理就变得尤为重要.在 SDN 中,做出复杂决策的输入数据至少应包含网络本身的信息(节点+链路)和网络中流量的信息(包+流).同时还需要对模型的输出设计进行深入考量,不同的输出程式对任务解决方案的简化能力是不同的.未来应注重深度学习模型与 SDN 网络环境的深度融合,在充分理解模型特点和设计原理的基础上进行修改,以适配具体的 SDN 任务,发挥深度学习的潜力.

(3) SDN 接口协议设计

SDN 架构中,北向接口没有公认的通用协议,而南向接口普遍采用的 OpenFlow 协议也经历了多次更改,以支持不断变化的研究和部署需求,然而对深度学习机制的支持极其有限,只能实现简单的模型嵌入和消息传递,

无法支持复杂的深度学习机制和个性化部署.在未来的工作中,需要对接口协议进行重新设计,在协议内部原生支持深度学习,并保留开放接口机制,以接入不断变化的深度学习模型,增加部署的自由度和开放性,促进创新型研究的开展.

(4) SDN 实验平台设计

SDN 研究工作离不开模拟实验平台的支持.现有的 SDN 研究实验平台 Mininet、OMNeT++等只能搭建简单拓扑,对小规模 SDN 场景进行模拟.在未来,随着研究场景的扩大和大型深度学习模型的引入,需要对混合场景、异形设备、自定义网络架构等复杂 SDN 环境进行模拟,因此需要开展综合实验平台的研究设计.综合实验平台需要有足够的可扩展性和自由度,支持对复杂环境自定义建模,提供深度学习的嵌入机制,更好地支持基于深度学习的复杂 SDN 场景下的研究.

(5) SDN 网络安全

随着社会生活、生产越来越依赖于网络,网络安全问题日益突出,对 SDN 网络安全的研究未来将成为重点.未来 SDN 网络安全研究更为复杂多变,网络侵入、零日攻击、新型攻击等安全问题使用传统方法难以应对,需要借助深度学习强大的特征学习和决策能力,对网络攻击进行有效反应,快速处理,持续保护互联网应用和用户数据的安全.并且,SDN 架构本身也极易成为攻击的目标,特别是针对控制器资源和应用层软件漏洞的攻击,需要引入深度学习进行感知,持续保护网络架构本身的安全,保证持续提供网络服务的能力.

(6) SDN 大规模部署

实现大规模部署,促进 SDN 技术落地一直是研究人员的目标,却面临不少挑战.挑战之一便是 SDN 控制平面的可扩展性.分布式控制器可以增强 SDN 对大规模网络的管理能力,但如何使用深度学习进行多控制器视图同步以及控制权限分配尚有待深度研究.随着网络规模的扩大,网络资源的管理和服务部署变得困难,设计高效的网络管控机制,综合优化网络数据传输成为亟需解决的问题.深度学习的引入对控制器的计算资源提出了挑战.除了使用性能更强的控制器之外,另一个方向则是 SDN 中深度学习的分布式部署,对 OpenFlow 流表的结构加以扩展,将深度学习网络实现到了分布式交换机体系中,既降低了控制器的负担,也增强了网络的安全性和可扩展性.研究深度学习的分布式控制机制将成为深度学习应用于 SDN 大规模控制的关键.

(7) SDN 应用领域拓展

深度学习在 SDN 中的应用范围较窄,集中在路由、流量感知和入侵检测等方面,这与研究还处于探索阶段有关.未来,需要对不同应用领域的 SDN 研究进行深入分析,寻找深入学习引入的切入点,将深度学习在 SDN 中的应用范围扩展到更为广阔的领域.与此同时,随着 SDN 的持续发展,SDN 与 5G 网、无线传感器网络、物联网等新型网络的融合成为一种趋势,借助深度学习的决策能力和 SDN 集中控制的优势,可以进行复杂网络的管理,拓展 SDN 的应用领域.SDN 与新型网络的融合需要结合 SDN 和新型架构的优点,重新设计网络架构,设计过程中如何提高架构适用性,增强对异种设备的管理,引入对深入学习机制的支持需要进一步加以研究.

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