终身机器学习

Lifelong Machine Learning

课程指南

主讲：梁国强
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课程基本情况

- 课程名称：终身机器学习
- 课程编号：M10M11013
- 课时/学分：32课时/2学分
- 时间：11-18周周三下午1-4节
- 地点：长安校区-教东B2-105
- 课程QQ群：732900760
- 授课教师：梁国强、张世周

群名称：终身机器学习课程群

课程内容安排

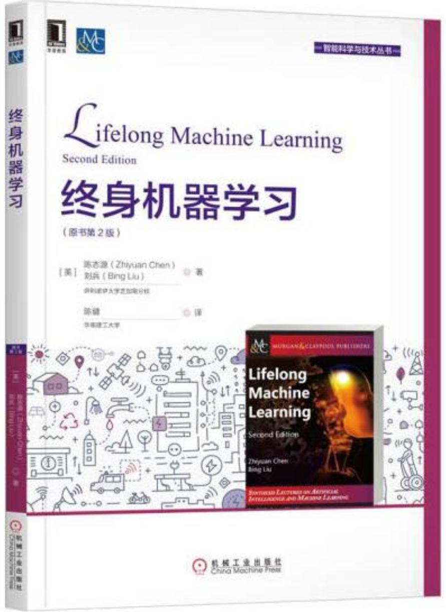
章节	基本内容
第一章 绪论	介绍终身学习定义、发展和主要挑战
第二章 相关学习范式	介绍与相关机器学习范式的区别
第三章 类增量学习	介绍面向图像分类的持续学习方法
第四章 持续学习	介绍面向目标检测、图像分割的持续学习方法
第五章 开放环境持续学习	介绍开放环境持续学习算法
第六章 文本终身学习	介绍终身主题建模和终身信息提取
第七章 聊天机器人	以聊天机器人为主，介绍持续学习系统
第八章 强化终身学习	介绍强化终身学习算法

时间进度安排

<table>
<tr><th>周次</th><th colspan="2">基本内容</th></tr>
<tr><td>11、12周</td><td colspan="2">老师讲授</td></tr>
<tr><td rowspan="3">13-18周</td><td colspan="2">1-2节老师讲授</td></tr>
<tr><td rowspan="2">3-4节课堂汇报讨论</td><td>13-17周个人汇报（11.29日起）</td></tr>
<tr><td>18周小组展示</td></tr>
</table>

参考资料

■教材



陈志源、刘兵著，陈键译，终身机器学习，2020，机械工业出版社

https://www.cs.uic.edu/~liub/lifelong-machine-learning.html

■相关在线资源

论文资源

https://github.com/xialeiliu/Awesome-Incremental-Learning

李宏毅 机器学习 课程——Life-long Learning

http://speech.ee.ntu.edu.tw/~tlkagk/courses_ML20.html

参考资料

A Comprehensive Survey of Continual Learning: Theory, Method and Application

Liyuan Wang, Xingxing Zhang, Hang Su, Jun Zhu, *Fellow, IEEE*

Abstract—To cope with real-world dynamics, an intelligent agent needs to incrementally acquire, update, accumulate, and exploit knowledge throughout its lifetime. This ability, known as continual learning, provides a foundation for AI systems to develop themselves adaptively. In a general sense, continual learning is explicitly limited by catastrophic forgetting, where learning a new task usually results in a dramatic performance drop of the old tasks. Beyond this, increasingly numerous advances have emerged in recent years that largely extend the understanding and application of continual learning. The growing and widespread interest in this direction demonstrates its realistic significance as well as complexity. In this work, we present a comprehensive survey of continual learning, seeking to bridge the basic settings, theoretical foundations, representative methods, and practical applications. Based on existing theoretical and empirical results, we summarize the general objectives of continual learning as ensuring a proper stability-plasticity trade-off and an adequate intra/inter-task generalizability in the context of resource efficiency. Then we provide a state-of-the-art and elaborated taxonomy, extensively analyzing how representative strategies address continual learning, and how they are adapted to particular challenges in various applications. Through an in-depth discussion of continual learning in terms of the current trends, cross-directional prospects and interdisciplinary connections with neuroscience, we believe that such a holistic perspective can greatly facilitate subsequent exploration in this field and beyond.

Index Terms—Continual Learning, Incremental Learning, Lifelong Learning, Catastrophic Forgetting.

第 49 卷 第 3 期 自 动 化 学 报 Vol. 49, No. 3
2023 年 3 月 ACTA AUTOMATICA SINICA March, 2023

类别增量学习研究进展和性能评价

朱 飞[1,2] 张煦尧[1,2] 刘成林[1,2]

摘 要 机器学习技术成功地应用于计算机视觉、自然语言处理和语音识别等众多领域. 然而, 现有的大多数机器学习模型在部署后类别和参数是固定的, 只能泛化到训练集中出现的类别, 无法增量式地学习新类别. 在实际应用中, 新的类别或任务会源源不断地出现, 这要求模型能够像人类一样在较好地保持已有类别知识的基础上持续地学习新类别知识. 近年来新兴的类别增量学习研究方向, 旨在使得模型能够在开放、动态的环境中持续学习新类别的同时保持对旧类别的判别能力 (防止"灾难性遗忘"). 本文对类别增量学习方法进行了详细综述. 根据克服遗忘的技术思路, 将现有方法分为基于参数正则化、基于知识蒸馏、基于数据回放、基于特征回放和基于网络结构的五类方法, 对每类方法的优缺点进行了总结. 此外, 本文在常用数据集上对代表性方法进行了实验评估, 并通过实验结果对现有算法的性能进行了比较分析. 最后, 对类别增量学习的研究趋势进行展望.

关键词 增量学习, 持续学习, 灾难性遗忘, 机器学习, 深度学习

引用格式 朱飞, 张煦尧, 刘成林. 类别增量学习研究进展和性能评价. 自动化学报, 2023, **49**(3): 1−26

DOI 10.16383/j.aas.c220588

Three scenarios for continual learning

Gido M. van de Ven[1,2] & Andreas S. Tolias[1,3]
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Abstract

Standard artificial neural networks suffer from the well-known issue of catastrophic forgetting, making continual or lifelong learning difficult for machine learning. In recent years, numerous methods have been proposed for continual learning, but due to differences in evaluation protocols it is difficult to directly compare

An Introduction to Lifelong Supervised Learning

Shagun Sodhani
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Mojtaba Faramarzi
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Sanket Vaibhav Mehta
Carnegie Mellon University
Pranshu Malviya
Polytechnique Montréal
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This paper has been accepted for publication at the
IEEE Transactions on Pattern Analysis and Machine Intelligence, 2022. ©IEEE

Class-incremental learning: survey and performance evaluation on image classification

Marc Masana, Xialei Liu, Bartłomiej Twardowski, Mikel Menta, Andrew D. Bagdanov, Joost van de Weijer

Deep Class-Incremental Learning: A Survey

Da-Wei Zhou, Qi-Wei Wang, Zhi-Hong Qi, Han-Jia Ye, De-Chuan Zhan, Ziwei Liu

Abstract—Deep models, *e.g.*, CNNs and Vision Transformers, have achieved impressive achievements in many vision tasks in the closed world. However, novel classes emerge from time to time in our ever-changing world, requiring a learning system to acquire new knowledge continually. For example, a robot needs to understand new instructions, and an opinion monitoring system should analyze emerging topics every day. Class-Incremental Learning (CIL) enables the learner to incorporate the knowledge of new classes incrementally and build a universal classifier among all seen classes. Correspondingly, when directly training the model with new class instances, a fatal problem occurs — the model tends to *catastrophically forget* the characteristics of former ones, and its performance drastically degrades. There have been numerous efforts to tackle catastrophic forgetting in the machine learning community. In this paper, we survey comprehensively recent advances in deep class-incremental learning and summarize these methods from three aspects, *i.e.*, data-centric, model-centric, and algorithm-centric. We also provide a rigorous and unified evaluation of 16 methods in benchmark image classification tasks to find out the characteristics of different algorithms empirically. Furthermore, we notice that the current comparison protocol ignores the influence of memory budget in model storage, which may result in unfair comparison and biased results. Hence, we advocate fair comparison by aligning the memory budget in evaluation, as well as several memory-agnostic performance measures. The source code to reproduce these evaluations is available at https://github.com/zhoudw-zdw/CIL_Survey/.

考核方式

成绩组成

- 考勤 10%
- 个人汇报30%

  选取近2年的高水平论文进行30分钟课堂汇报

  依据论文水平、报告质量、问题回答等进行打分

- 大作业及汇报60%

  题目：课程组给的题目或者自选题目

  要求：小组不超过3人

  提交代码和论文（IEEE期刊格式双栏>5页）

个人汇报.xlsx

谢　　谢！