Google Brain 研發工程師 李冠輝先生演講

Learn Representations That Generalize for Vision and RL

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講者李冠輝先生是來自 Google Brain 的研究人員。主要研究領域為強化學習 (Reinforcement Learning)、資訊理論 (information theory) 和表徵學習於感知及決策之應用 (representation learning for perception and decision making)。講者近年參與多項由 Google 所主導之深度學習機器人計畫。曾在 2016 至 2019 年間，擔任微軟電腦視覺及相關產品的研發工程師。畢業於國立臺灣大學，並於卡內基美隆大學取得資訊科學碩士學歷。

幾乎在所有機器學習應用的相關領域裡，使用適當的神經網路模型和明確的學習目標，去提取大量且多樣化數據所內藏之資訊，已成為泛用且有效的方法。在本次演講中，講者李冠輝從資料和目標（objective）的角度來切入並探索電腦視覺與強化學習領域。內容包括自督導式學習 (self-supervised representation learning)、如何更有效的利用模擬器所取得的經驗、虛實轉換 (sim-to-real) 方法以及一些尚未克服的難題。講者希望可以透過本次的內容拋磚引玉，讓相關領域的研究人員可以從全新的角度去思考如何利用現有的資料與目標，為電腦視覺與強化學習領域帶來下一次的重大突破。

演講內容主要分為三個主題：自督導式學習（self-supervised representation learning）、預測性表徵（predictive representation）、以及如何更有效的提取並利用學習經驗 (agent experience)。

提到自督導式學習，講者首先提出在面對不同機器學習任務時，此方法最根本的問題：如何在沒有人為監督下，去學習泛用且有效的視覺表徵 (visual representation)?

現今自督導式學習的方法為嘗試找出一個表徵，使經過不同轉換影像之間的相互關聯資訊得以最大化。因為這些資訊概括影像背後共享的訊息，所以提取出的表徵也有利於後續的應用。透過重構 SimCLR，一個目前位於 state-of-the-art 的對比學習方法（contrastive learning）和新的目標函數 Conditional Entropy Bottleneck-CEB，即便面臨不同情境下所引發的域遷移問題 (domain shift)，仍然可以大幅提升神經網路的準確度與穩定性。

強化學習也可以使用與自督導式學習的相近的概念。預測性資訊 (Predictive Information) 為聯繫起過去與未來的相互關連資訊，同時也代表著對未來的掌握程度。講者提出一個構想，認為強化學習在面對不同的任務時，成敗的關鍵取決於機器學習模型否能有效地抓取這些預測性資訊，並準確的判斷即將發生的事件。在他的研究中可以看到，相較於未壓縮過的表徵，壓縮過後的表徵能更有效的去概括未見過的任務。

講者也提到，強化學習距離解決任務移轉（transferring tasks）、多任務（multitask）等真實世界裡的開放性問題仍然有許多努力空間。在特定領域內，電腦視覺、自然語言處理和強化學習均可以找到有效解決相對映問題的方法，例如 2016 年 AlphaGo，一個基於強化學習的電腦程式，已經能超越人類表現，勝過頂尖圍棋手李世乭。在任務繁多且複雜的真實世界裡，電腦視覺與自然語言處理已經找出使用大型資料集的演算法，例如電腦視覺的監督式學習與自監督式學習，或是在自然語言處理的 GTP, BERT 等神經網路模型，相較於前者，強化學習則尚未找到一個有效的模型來解決問題。

最後，面對如何為強化學習領域帶來下一次的重大突破， 講者提出三個方向，第一：如何收集大量且多樣的資料讓強化學習可以進行離線訓練，第二：如何擴大並提升多任務，非監督試線上訓練資料的蒐集規模與效率。第三：如何開創出全新的強化學習演算法，使學習資料能更有效的被利用。

演講結束後，講者與 CGI Lab 的 DeepRacer 團隊與 Robotics 團隊做了一場深度的對談，並對目前團隊研究上面臨的挑戰提出了一些建議。我們非常感謝有這個機會，聆聽來自 Google Brain 的研發工程師李冠輝所帶給我們的寶貴研究經驗。

Research Engineer from Google Brain Kuang-Huei Lee Delivered a Speech:

Learn Representations That Generalize for Vision and RL

Kuang-Huei Lee is a research engineer at Google Brain. His research focuses on reinforcement learning, information theory, and representation learning for perception and decision making. He has been involved in various robot learning projects at Google. From 2016 to 2019, he was a research engineer at Microsoft where he works on computer vision related products. He received his Masters degree in computer science from Carnegie Mellon University and his Bachelor's degree from National Taiwan University.

In almost all machine learning application domains, using capable models and expressive learning objectives to absorb large amounts of diverse data has now become a common narrative of generalization success. In this talk, Kuang-Huei will explore the data and objective aspects of this narrative for vision and reinforcement learning. He will discuss several ideas for self-supervised representation learning, improving uses of agent experience and simulator, the sim-to-real problem, as well as future challenges. The goal of the presentation is to motivate scientists to make the next major breakthrough by rethinking the data and objectives that they used for learning vision and reinforcement learning models.

His talk mainly focused on three topics: self-supervised visual representation learning, how to build better reinforcement learning with predictive representation, and how to collect and use agent experience efficiently.

Discussing self-supervised representation learning, Mr.Lee said that Learning effective visual representations that generalizes well without human supervision is a fundamental problem to apply machine learning to a wide variety of tasks.

The current self-supervised learning approach attempts to find a representation that maximizes the mutual information between features extracted from multiple images.The mutual information comprising a general shared context is assumed to be effective for various downstream tasks. By reformulating SimCLR, the state-of-the-art contrastive representation method, and adding a new objective function (Conditional Entropy Bottleneck-CEB), the proposed model yields significant improvements in accuracy and robustness to domain shifts across a number of scenarios.

Reinforcement learning is similar to self-supervised learning. Predictive Information, the mutual information between the past and the future, measures how much our observations of the past can tell us about the future. Lee's work hypothesized that capturing the predictive information is useful in reinforcement learning since the ability to model what will happen next is necessary for success on many tasks. Moreover, he showed that compressed representation outperformed uncompressed representation in generalizing to unseen tasks.

Mr.Lee pointed out that reinforcement learning still has a long way to go with real-world problems such as transferring tasks and multi-task.Computer vision (CV), natural language processing (NLP), and reinforcement learning (RL) have been used for solving specific problems. For example, in 2016, AlphaGo, a computer program with the use of a reinforcement learning algorithm, defeated Lee Sedol, the best Go player in the world. For the transferring task and multi-task in the real world,CV and NLP have developed algorithms for large-scale dataset, such as supervised/self-supervised learning in CV, and GTP, BERT models in NLP. Compared with the above mentioned, RL methods have not yet found an effective model to solve them.

At the end of the talk, Mr. Lee raised three research questions, which may lead to the next major breakthrough in reinforcement learning. First, how to collect large and diverse offline data for offline reinforcement learning. Second, how to expand the scale and and improve efficiency of collecting multi-task and unsupervised dataset. And third, how to develop a novel reinforcement learning algorithm in which data can be used more efficiently.

After the talk, Mr. Lee had a deep discussion with DeepRacer and the Robotic group from CGI Lab and gave some comments on the problems that we are dealing with. We are very grateful for such a great opportunity to meet a research engineer from Google Brain, and we appreciate him taking the time to share his valuable research experiences with us.