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Lifelong learning of neural networks

Uczenie ciagłe sieci neuronowych

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1. Introduction

The integration of AI and machine learning into robotics has not only increased the capabilities of robots but has also opened up new possibilities for their application. Robotics is now being used in areas that were once considered challenging or impossible for machines to navigate, such as healthcare, space exploration, and even disaster response. The ability for robots to perform tasks with precision and without fatigue has transformed industries, making them more efficient and reducing human error. In manufacturing, robots are capable of assembling products faster than humans while maintaining consistent quality, while in logistics, robots streamline supply chain operations, ensuring the timely delivery of goods. These advancements are reshaping industries, making robots indispensable tools in optimizing operations and enhancing safety across various sectors.

As the capabilities of robots continue to advance, the demands for greater autonomy and adaptability grow. In many applications, robots are required to perform tasks in dynamic, unpredictable environments where they must adapt to new situations on the fly. For instance, robots operating in manufacturing plants must handle a wide variety of products, each requiring different handling techniques and tasks. The ability to learn autonomously, without needing human supervision, is a key factor in ensuring that robots remain effective in such environments. This need for continual adaptation presents an enormous challenge, as traditional learning methods require extensive retraining to accommodate new tasks, which is often impractical in real-world scenarios.

Continual learning, also known as lifelong learning, offers a promising solution to this issue. This concept aims to allow robots to learn new tasks incrementally, without forgetting previously learned ones, enabling them to adapt to new challenges over time. In theory, continual learning could help robots become more flexible and versatile, allowing them to handle new tasks with minimal human intervention. The key advantage of continual learning is that it enables robots to build upon prior experiences while adapting to new data, without the need for retraining the entire model from scratch. This approach could significantly reduce the time and cost involved in deploying robots in new environments or with new products.

Moreover, while theoretical models of continual learning have been developed, there is a lack of comprehensive studies and empirical evidence demonstrating its practical effectiveness in real-world settings. Much of the existing research is based on small-scale experiments or simulations, which may not fully capture the challenges that arise when deploying robots in complex, dynamic environments. As such, further research is needed to evaluate the scalability and effectiveness of continual learning in real-world robotic systems.

By addressing these issues, continual learning could unlock new possibilities for the future of robotics, enabling machines to operate autonomously in an ever-evolving world.

1.1. The aim of the job

The primary goal of this role is to showcase the effectiveness of the continual learning model in practical applications. This will be achieved by evaluating and identifying the most suitable model for accurately classifying images of rooms, taking into account various real-world challenges and constraints that might affect model performance. Through this process, the aim is to demonstrate the model's capability to learn and adapt to new data continuously while maintaining high classification accuracy.

2. State of the Art

Unlike conventional machine learning, continual learning focuses on training models on a sequence of data, enabling them to learn new tasks while retaining knowledge of previously learned ones. This chapter explores the advancements in continual learning, highlighting established methods and the challenges that continue to shape the field.

2.1. Approaches

The problem of continual learning can be addressed from three primary approaches that have been developed over the years: regularization-based methods, memory-based methods, and dynamic architecture-based methods.

2.1.1. Regularization-Based Methods:

These methods focus on modifying the model's weight adjustment strategy to mitigate catastrophic forgetting. Common techniques in this category include fine-tuning and Elastic Weight Consolidation (EWC). In fine-tuning, the model's final layer weights are updated during new task learning while the previous layers remain unchanged. EWC, on the other hand, adjusts the importance of model weights after training is complete, ensuring that only the least significant weights are updated during the learning of new tasks. However, while these methods can help to some extent, they often result in catastrophic forgetting, where the model forgets previously learned tasks when trained on new ones.

2.1.2. Memory-Based Methods:

Memory-based techniques, such as Rainbow Memory and memory replay, are designed to store and recall previously learned tasks. This can be achieved by saving key data to disk or generating memory data using another model, enabling the continual learning system to refer back to these memories as needed. The major drawback of these methods lies in the quality and availability of stored data, as well as the challenge of maintaining a sufficient memory bank for recalling previous knowledge. This can lead to issues such as low-quality data, poor memory management, and computational inefficiency, all of which may hinder the model's overall performance.

2.1.3. Dynamic Architecture-Based Methods:

In this approach, the structure of the neural network itself is modified to accommodate new tasks. One method is the Dynamically Expandable Network (DEN), which allows for the addition of new neurons to the network as new tasks are encountered. This dynamic modification of the architecture enables continual learning without overwriting or forgetting old tasks, though it may lead to increased model complexity and potentially higher computational costs over time.

While these approaches focus on different strategies for mitigating catastrophic forgetting, they all aim to improve a model's ability to adapt over time. To understand how these methods work in practice, it's essential to consider the specific scenarios in which continual learning is applied. These approaches can be applied to three main continual learning scenarios: class-incremental, task-incremental, and domain-incremental learning, each presenting different challenges in how the model adapts to new data and tasks.

2.2. Continual Learning Scenarios:

Continual learning is applied in various real-world contexts, where the model must adapt to new information over time. Additionally, more complex scenarios may arise, requiring further considerations. Three main continual learning scenarios are:

1. **Class-Incremental Learning (CIL):** The model learns new classes sequentially, but cannot access previous data. The challenge is to prevent catastrophic forgetting of old classes while learning new ones.

2. **Task-Incremental Learning (TIL)**: The model learns new tasks over time, where each task may involve different classes or problems. The challenge is to avoid task interference, where learning a new task negatively affects performance on older tasks.

3. **Domain-Incremental Learning (DIL):** The model encounters new data distributions (domains) over time. The main challenge is adapting to new domains without forgetting the old ones, requiring domain adaptation techniques.

2.3. Related Work

In the paper "When continual learning meets robotic grasp detection: a novel benchmark on the Jacquard dataset" (Yang et al., 2023), a comparative analysis was conducted to evaluate several continual learning methods that do not apply memory. These methods include: EWC, fine-tuning, Synaptic Intelligence (SI), Learning without Forgetting (LWF), and PodNet. The study also considered methods with memory, such as Memory Replay, A-GEM, LWF, and PodNet. The results revealed a clear advantage for memory-based approaches:

models that used memory significantly outperformed those without memory, achieving accuracy levels exceeding 90%, compared to the 50-75% accuracy achieved by memory-less methods. These findings were obtained through experiments conducted on a benchmark for grasp detection based on the Jaquard dataset, which was developed by the authors.[1]

”Rainbow Memory: Continual Learning with a Memory of Diverse Samples” (Bang et al., 2021) presents a novel method called Rainbow Memory addressed to the blurry-class incremental learning (blurry-CIL) scenario, where tasks may overlap and share classes at different points in time. Rainbow Memory demonstrates superior performance compared to established methods such as EWC, RWalk, iCaRL, BiC, and GDumb. The proposed approach employs two key strategies: Diversity Aware Sampling, which selects samples based on classification uncertainty to enhance representational diversity, and Mixed-Label Data Augmentation (CutMix), which further boosts performance by creating mixed-label training samples. These techniques work synergistically to improve learning efficiency and adaptability in blurry-CIL scenarios. Additionally, the results demonstrated that the combination of augmentation techniques, specifically CutMix and AutoAugmentation, resulted in optimal outcomes on the evaluated datasets.[2]

In the paper ”Imbalanced data robust online continual learning based on evolving class aware memory selection and built-in contrastive representation learning” (Yang et al., 2024) is presented a comprehensive analysis of memory-based methods for learning from imbalanced data, including Experience Replay, Gradient-Based Sample Selection, Class-Balancing Reservoir Sampling, Maximally Interfering Retrieval, Online Coreset Selection, and a newly proposed approach, Memory Selection with Contrastive Learning (MSCL). Evaluated on datasets such as MNIST, Cifar-100, mini-ImageNet, PACS, and DomainNet, MSCL proved to be the most effective method, particularly for imbalanced scenarios. MSCL utilizes a feature-distance-based sample selection mechanism, where new inputs are assigned weights based on their distance in feature space to existing memory samples. This ensures a diverse and representative memory buffer. Additionally, the integration of IWL (Contrastive Learning Loss) enhances learning by separating class representations in the feature space, further boosting performance on imbalanced datasets.[3]

In conclusion, continual learning has made substantial progress in addressing the problem of catastrophic forgetting, with memory-based methods showing significant promise. However, challenges remain in managing memory efficiently and ensuring models can handle overlapping and evolving tasks effectively.

3. Research section

4. Conclusions

Bibliography

[1] Rui Yang et al. "When continual learning meets robotic grasp detection: a novel benchmark on the Jacquard dataset". In: (2023).

[2] Jihwan Bang et al. "Rainbow Memory: Continual Learning with a Memory of Diverse Samples". In: (2021).

[3] Rui Yang et al. "Imbalanced data robust online continual learning based on evolving class aware memory selection and built-in contrastive representation learning". In: (2024).