Stanford University

CS 330:
Deep Multi-Task and Meta Learning

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0 Course Introduction, Problem Definitions, Applications

0.1 Agents learning skills in real world environments should achieve generalization

In the future, we desire to develop physical agents that interact with the real world, also known as *robots*, which can,

- generalize across tasks, objects, and environments
- possess some common sense understanding of the environment
- learn without supervision, as a labeled training set does not accompany every task

Research in robotics in 2016-2017 produced robots that were *specialists*, or robots that could perform a single task for a single environment well, but could not generalize beyond their training task and environment.

How do we build robots that are *generalists* like humans, who learn simple tasks before complex tasks, and apply their skills over a variety of environments?

0.2 Standard machine learning paradigm is insufficient for generalization

Deep learning introduced deep neural networks into the machine learning toolkit, achieving impressive results.

- Deep learning models significantly decreased error rates in the ImageNet competition compared to prior SOA models based on SVMs
- In 2016, Google translate switched to deep learning-based models, yielding improvements in translation accuracy ranging from 50% to 90% across several languages.

This success comes at the cost of a large amount of training data per task, but this standard paradigm is,

- impractical when acquiring sufficient training data is too costly
- impractical to generalize to small data domains of data distributions with long-tails
- not leveraging prior knowledge like humans do to learn over a small number of examples

0.3 Definition of a task

$$\{\mathcal{L}, \mathcal{D}\} \mapsto f_\theta$$

This is an introductory problem definition that will be formalized later. A task is a mapping from a dataset $\mathcal{D}$ and a loss function $\mathcal{L}$ to a model f_θ with weights θ. For example, we can define different tasks by holding $\mathcal{L}$ constant, yet using different datasets $\mathcal{D}_i$, where each $\mathcal{D}_i$ consists of different objects, people, lighting conditions, words, languages, etc.

0.4 Evaluating the critical assumption of meta learning

The *critical assumption of meta learning* is, if a set of different tasks share some structure, then meta learning on this set of tasks may yield a more general and useful model for all tasks within the set when compared to training a single task learning model to each individual task in the set .

Many tasks have a shared structure. For example, screwing a cap on a jar, a lid on a water bottle, and the top of a pepper grinder all have similar structure. Even if tasks are seemingly unrelated, there are often common underlying structures within the tasks, considering,

- the laws of physics underlie real data
- people are all organisms with intentions
- the rules of English underlie English language data
- all languages develop for a similar purpose

0.5 Problem definitions

The multi-task learning problem and meta learning problem are two distinct problems.

- The *multi-task learning problem* is learning all tasks more quickly or more proficiently than learning them independently
- The *meta learning problem* is, given data/experience on previous tasks, learning a new task more quickly and/or more proficiently than learning the task independently.

These definitions do not cover the algorithm definitions for multi-task and meta learning. A similar problem that is often discussed is the the transfer learning problem. Although it is not specified here, the transfer learning problem is a higher-level problem definition that contains both of these problem definitions.

0.6 Notable recent applications of meta learning

Bengio et al. (1992), Caruana (1997) , and Thrun (1998) all looked at ways to solve multi-task and meta learning problems. With the advent of fast computing technologies and deep neural networks as general function approximators, recent research yielded successful applications of meta learning.

- a multi-lingual neural machine translation model trained on 102 languages, surpassed the performance of strong bilingual baselines Aharoni et al. (2019).
- using one-shot imitation learning, robot was able to learn to place fruit into a bowl from a single human demonstration Yu et al. (2018).
- a quadcopter was able to learn to navigate real environments from learning on simulation data only Sadeghi and Levine (2016).
- the YoutTube recommendation engine builds next-video recommendations based on multiple objective functions Zhao et al. (2019).

0.7 Prediction on the importance of meta learning in the future

Meta learning's success will be critical for the democratization of deep learning, which requires scaling deep learning to tasks with small datasets.

1 First Topics

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