ECEN 743: Reinforcement Learning

Meta Learning

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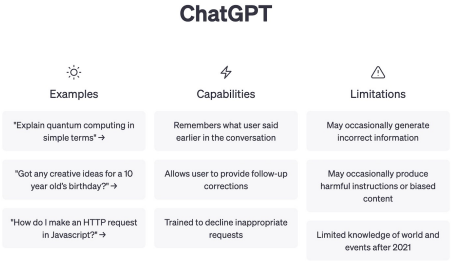
References

- Acknowledgment: Most of the materials for this lecture are taken from the lecture slides of Stanford CS 330: Deep Multi-Task and Meta Learning course by Prof. Chelsea Finn [Link], with permission.

- All the figures in the slides, unless otherwise stated, are also from the Stanford's CS 330 course.

Deep Learning with Limited Data

- Standard deep learning algorithms require very large and diverse set of data samples, and large (deep) neural network models



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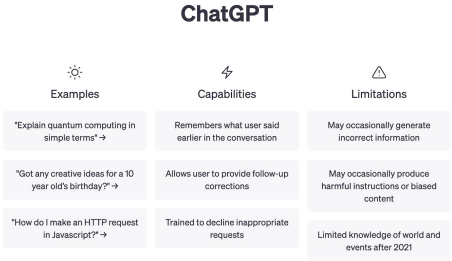

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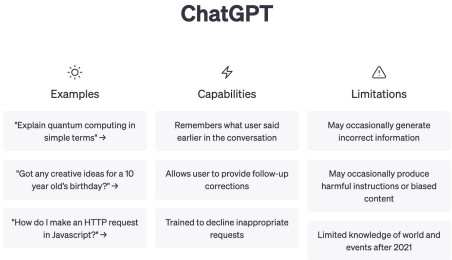

- What if we don't have a large dataset?
  - medical imaging, robotics, personalized education, recommendations

Learning with Limited Data

- Humans learn new concepts and skills efficiently with very limited data

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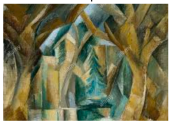
training data

Braque



Cezanne

test datapoint

By Braque or Cezanne?

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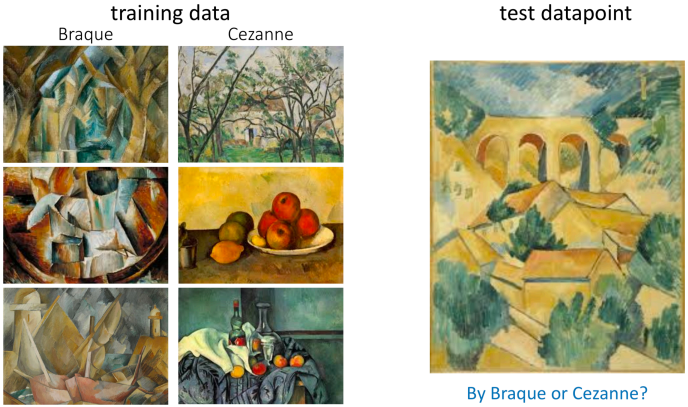

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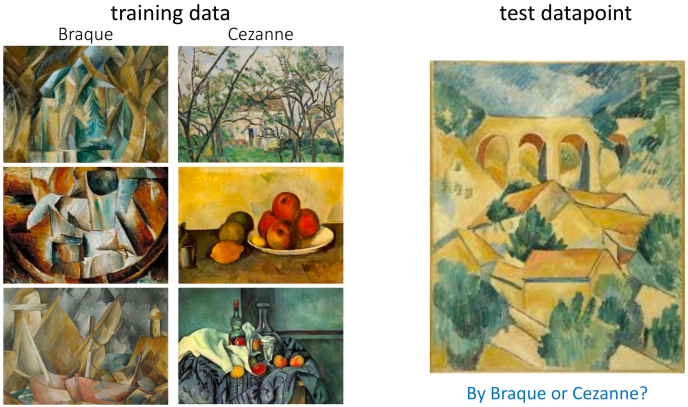

- Arguably, human are leveraging on the prior experiences
- Can we design ML algorithms that can learn new tasks with a few training examples by leveraging on prior experience/data from other tasks?

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- Objective: $\min_\theta \ L_i(\theta, \mathcal{D}_i)$
- Task: $\mathcal{T}_i = \{p_i, \mathcal{D}_i, L_i\}$

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  - This can be characterized in a number of ways
- Examples: per-language handwriting recognition, personalized recommendation, face attribute recognition, scene understanding, ...

Multi-Task Learning

- Basic vanilla multi-task learning objective: $\min_\theta \sum_{i=1}^{M} L_i(\theta, \mathcal{D}_i)$
  - Goal is to learn a single parameter for all tasks

Image from Ruder, 17. [Link]

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- A better objective

$$\min_{\theta_{\text{sh}}, (\theta_i)_{i=1}^{M}} \sum_{i=1}^{M} L_i(\theta_{\text{sh}}, \theta_i, \mathcal{D}_i)$$

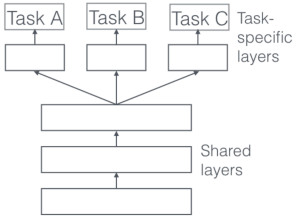

Figure 1: Hard parameter sharing for multi-task learning in deep neural networks

Image from Ruder, 17. [Link]

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- Transfer learning is typically achieved by fine-tuning of a pre-trained model parameter

$$\phi_{\text{new-task},k+1} = \phi_{\text{new-task},k} - \alpha \nabla_{\phi} L(\phi, \mathcal{D}_{\text{new-task}})|_{\phi_{\text{new-task},k}}, \quad \text{with } \phi_{\text{new-task},0} = \theta_{\text{pre-trained}}$$

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- Where do you get the pre-trained parameters?
  - ImageNet classification models (VGG19, Inceptionv3, ResNet); LLMs (BERT, LLaMA), ...

Transfer Learning by Fine Tuning

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Common design choices:

- Fine-tune with a smaller learning rate
- Smaller learning rate for earlier layers
- Freeze earlier layers, gradually unfreeze
- Reinitialize last layer
- Search over hyperparameters via cross-val
- Architecture choices matter (e.g. ResNets)

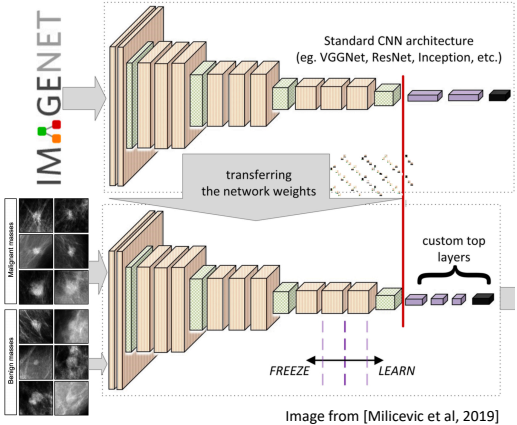
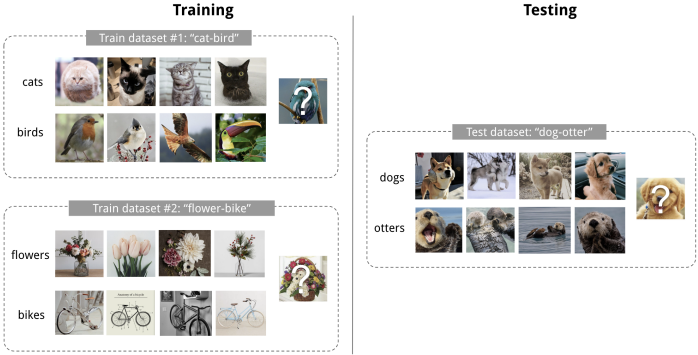


Image from [Milicevic et al, 2019]

Meta Learning

- Meta Learning: Given data from tasks $\mathcal{T}_1, \ldots, \mathcal{T}_n$, learn to solve a new task $\mathcal{T}_{\text{test}}$ with only few data samples



- k-shot learning: learning with k examples per class

Image from [Weng, 2018]

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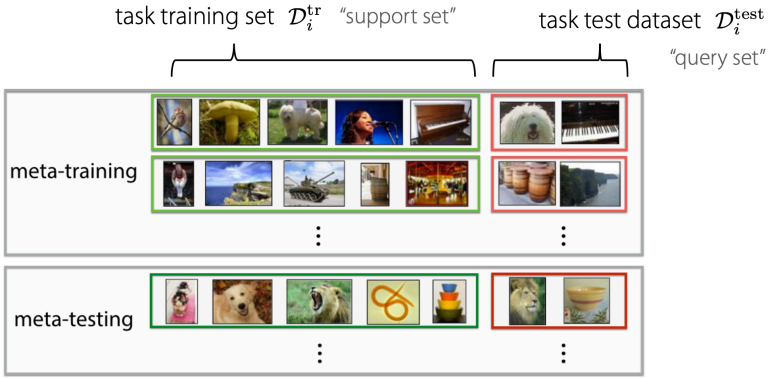

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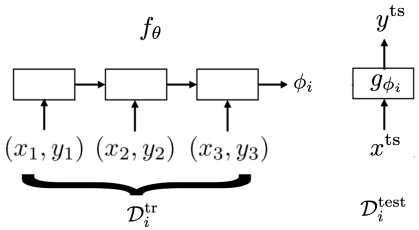
- Meta Learning: Given data from tasks $\mathcal{T}_1, \ldots, \mathcal{T}_n$, learn a model parameter θ that can be used to solve a new task $\mathcal{T}_{\text{test}}$ with only few data samples
- Meta-learning can be through as a transfer Learning with many source tasks where the real objective is to solve a new test task using only a small number of samples

Black-Box Adaptation Meta Learning

Key idea:

- Train a neural network θ to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$
- Use ϕ_i as the parameter for test data points $y^{\text{ts}} = g_{\phi_i}(x^{\text{ts}})$



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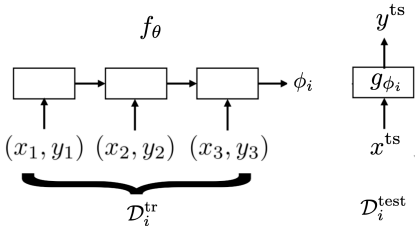

- Training objective:

$$\min_\theta \sum_{\mathcal{T}_i} \underbrace{\sum_{(x,y)\sim\mathcal{D}_i^{\text{test}}} -\log g_{\phi_i}(y \mid x)}_{\mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})}$$

$$\min_\theta \sum_{\mathcal{T}_i} \mathcal{L}(f_\theta(\mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

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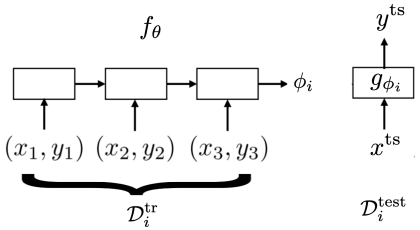

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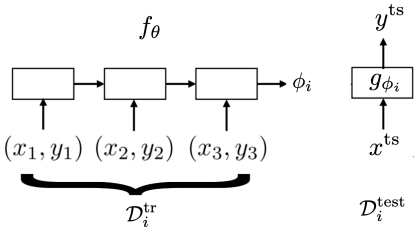

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1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$
3. Compute $\phi_i \leftarrow f_\theta(\mathcal{D}_i^{\text{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})$

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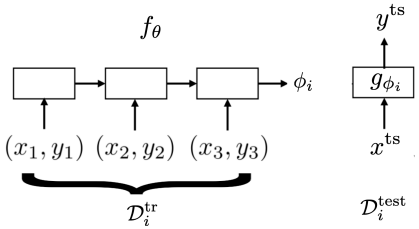

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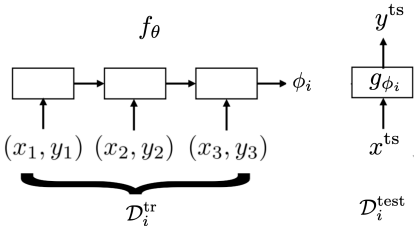

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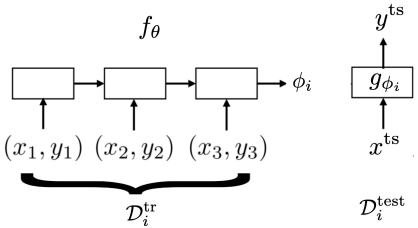

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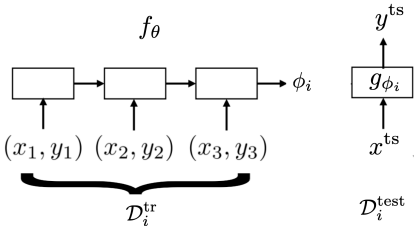

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- Outputting all neural net parameters may not be scalable
- The optimization problem is typically challenging and often data-inefficient

Optimization based Meta Learning

- Model Agnostic Meta Learning (MAML)[3]

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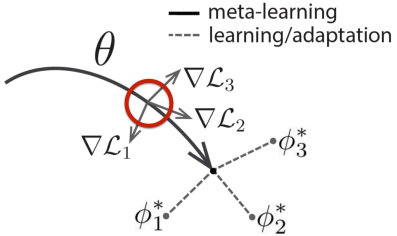
θ parameter vector being meta-learned

ϕ_i^* optimal parameter vector for task i



[3]Finn et al, "Model-agnostic meta-learning for fast adaptation of deep networks", ICML, 2017

Model Agnostic Meta Learning (MAML)

Algorithm Model-Agnostic Meta-Learning

1: **for** $i = 1, 2, \ldots$ **do**
2: Sample a task $\mathcal{T}_i \sim p(\mathcal{T})$
3: Sample disjoint datasets $\mathcal{D}_i^{\text{train}}$ and $\mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$
4: Update $\phi_i \leftarrow \theta - \alpha \nabla_\theta L(\theta, \mathcal{D}_i^{\text{train}})$
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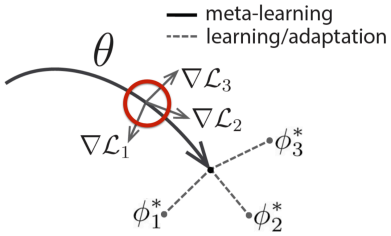

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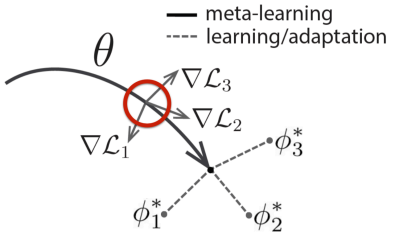

- Test time adaptation of MAML:
  Given the new task $\mathcal{T}_{\text{new}}$, the data $\mathcal{D}_{\text{new}}^{\text{tr}}, \mathcal{D}_{\text{new}}^{\text{ts}}$, and the trained meta-parameter θ_{meta}, perform one (or a few) gradient update to get the task specific parameter

$$\phi_{\text{new}} = \theta_{\text{meta}} - \alpha \nabla_\theta L(\theta, \mathcal{D}_i^{\text{tr}})|_{\theta=\theta_{\text{meta}}}$$

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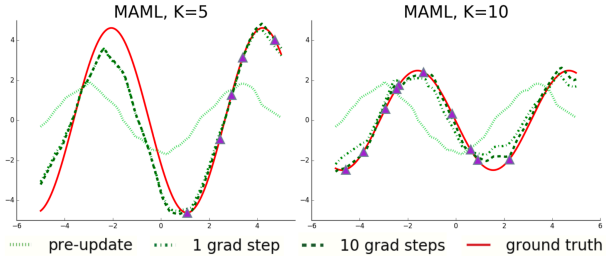

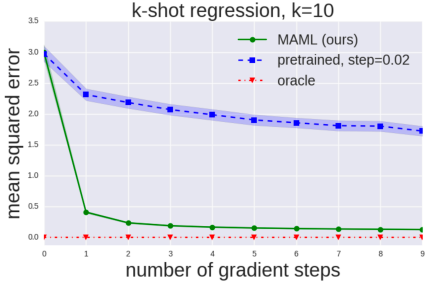

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- See [Finn et al., 2017] for more examples of MAML in supervised learning (image classification) and reinforcement learning

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- Bi-level optimization algorithms can exhibit oscillations and non-convergence when tried to solve through gradient descent approaches
- There are many heuristic solutions now available that can address this issue: Meta-SGD [Li et al., 2017], CAVIA [Zintgraf et al., 2019], MAML++ [Antoniou et al., 2018]

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- Implicit MAML [Rajeswaran et al., 2019]
  - Derives an analytical meta-gradient using the implicit function theorem

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- In Meta RL, each task $\mathcal{T}_i$ is an MDP $\mathcal{M}_i$
- Assumption: MDPs $\mathcal{M}_i$s are drawn according to a distribution $p(\mathcal{M})$

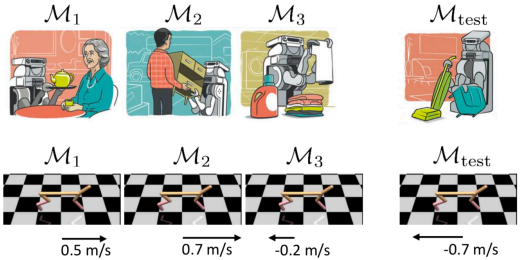

Image from UC Berkeley CS 285: Deep Reinforcement Learning course slides [Link]

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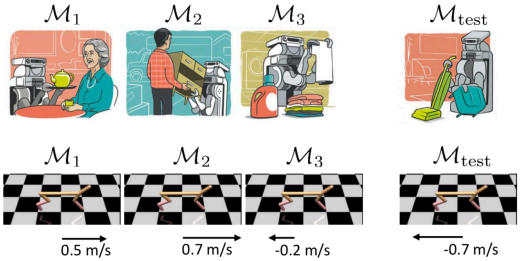

- Meta RL problem

$$\max_{\theta} \sum_{i=1}^{n} V_{\pi_{\phi_i}, \mathcal{M}_i} \quad \text{where,} \quad \pi_{\phi_i} = \text{Alg}(\theta, \mathcal{M}_i)$$

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- Meta parameter update is done as

$$\theta \leftarrow \theta + \beta \nabla_\theta \sum_{i=1}^n V(\theta + \alpha \nabla_\theta V(\theta, \mathcal{M}_i), \mathcal{M}_i)$$

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