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Transfer Learning using Meta-learning

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Technical Aspects of Multimodal Systems

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Outline

Traditional DL Model vs Transfer Learning

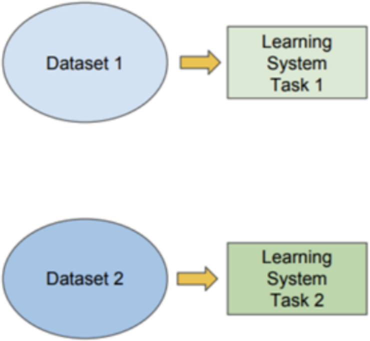
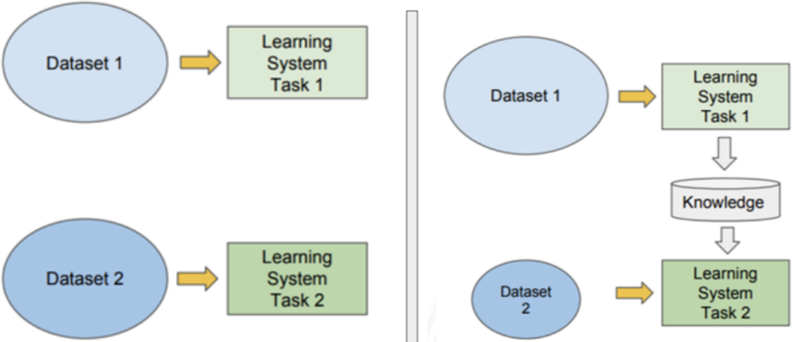


Image Credits: Sarkar D. for medium post on 'A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications in Deep Learning'

Motivation

Traditional DL Model vs Transfer Learning



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Motivation

- Is Deep Learning Bio-inspired?
- Problems with DL
  - Data hungry
  - Long training time
  - No progressive learning like humans

How can we learn like Humans do?

- Learn with few samples(Few-shot Learning)
- Leverage prior knowledge

What is Transfer Learning?

- Transfer the knowledge from one task to another

Why Transfer Learning?

- Can help in learning quicker and with fewer examples
- Provides a way for few-shot learning

Few-Shot Learning

Using Data Augmentation *Using Meta Learning*

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What is Meta-Learning?

- Meta Learning is learning from multiple tasks
- Also referred as "Learning To Learn"

Supervised Learning: $f(x) \rightarrow y$
Meta-Supervised Learning: $f(D_{train}, x) \rightarrow y$

Meta-Learning Model

1. Given Dataset D, split the tasks into D_{train} and D_{test}
2. Train the network for some epochs on D_{train}
3. Test the network on D_{test}

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A Simple View On Meta Learning Problem

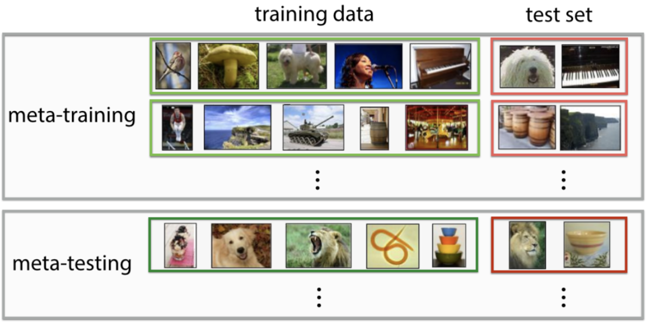

image credit: Ravi & Larochelle 2017

image credit: S. Levine. Taken from deeprlcourse-fa17 Lec 16

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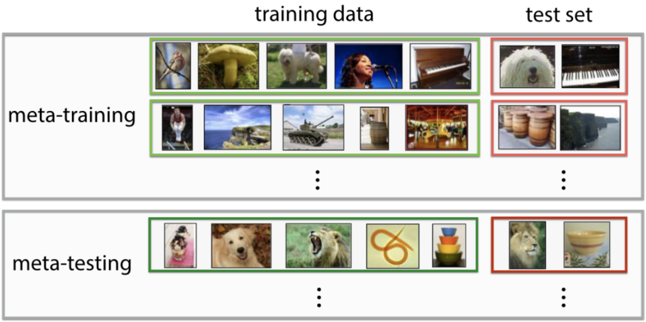

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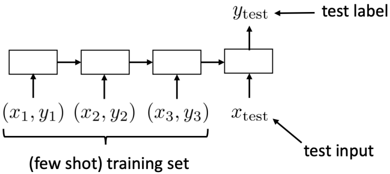

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Meta Learning Approaches

- Three Approaches for Meta-Learning

- Meta Learning
  - *Metric Learning*
    - Learn embeddings
  - *Memory Based*
    - Store experience
  - *Gradient Based*
    - Using RNNs
    - MAML

Meta Learning Approaches

- Three Approaches for Meta-Learning

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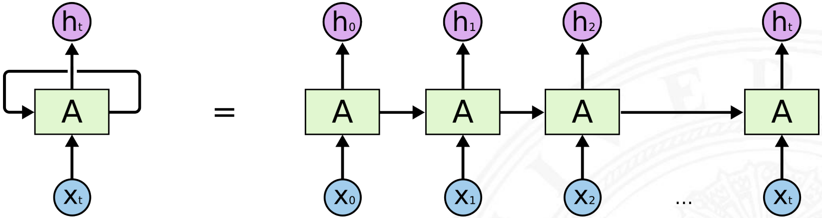
Recurrent Neural Networks

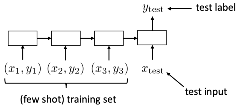
- RNNs consider info from prev timesteps
- Used for sequence modelling



Unfolded RNNs: Image taken from http://colah.github.io/posts/2015-08-Understanding-LSTMs/

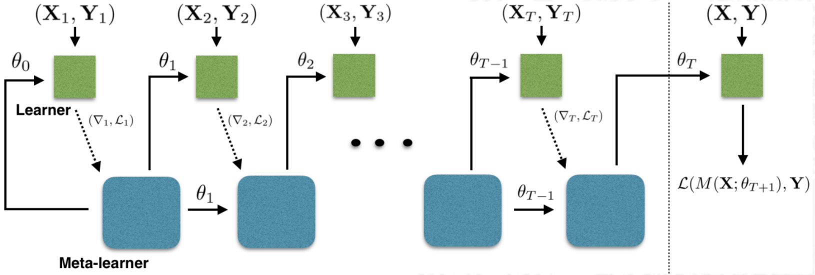
Meta-Learning Using RNN

Learn the optimizer that guides the model to learn different tasks eg. Using RNN



Makes use of two deep networks

1. Meta-Learner(to learn the task independent features)
2. Base-Learner(to learn the task-dependent features)



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Another Method: MAML

Learn the good initialization weights for the model which could be easily fine-tuned eg. using MAML

- Goal is to provide a model which once fine tuned on a particular task, can learn rapidly and can generalize well
- MAML, provides a good initialization for the model which needs to be fine tuned(similar to tranfer learning on ImageNet)

Image credits: Finn et al. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

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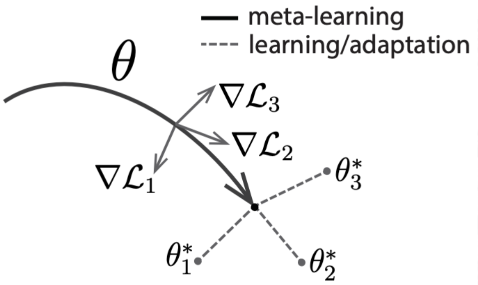

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Pseudo code

Algorithm 1 Train MAML

Input:Data p(τ): Distribution over tasks, model params θ

$\theta \leftarrow$random initialization
while not done **do**:
  Sample batch of tasks $T_i \sim p(\tau)$
  for i=1 to N **do**:
    Sample K datapoints for Task T$_i$
    $\theta'_i \leftarrow \theta - \alpha \nabla_\theta L_{T_i}(f_\theta)$ ▷ Gradient wrt K examples
    Sample Datapoints $D' = \{x^j, y^j\}$ for meta-update
  end for
  $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\tau \sim p(\tau)} L_{T_i}(f_{\theta'_i})$ ▷ Update Meta-Learner wrt D'
end while

MAML: cont'd

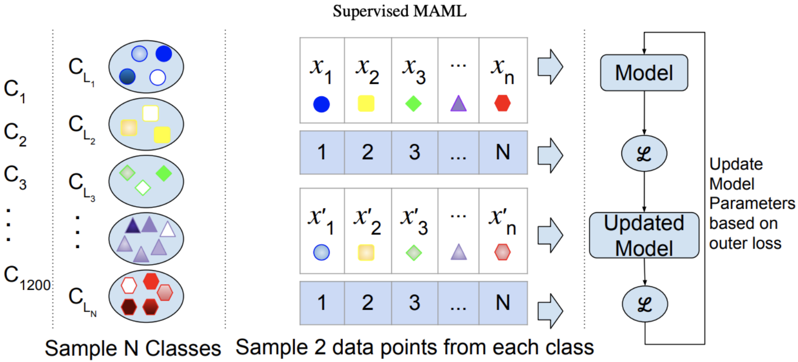


Image credits: Khodadadeh S. et al. Unsupervised Meta-Learning For Few-Shot Image and Video Classification

MAML: cont'd

- Suitable for any kind of ML problem , regression, classification and RL
- Need to adapt the loss function as per problem

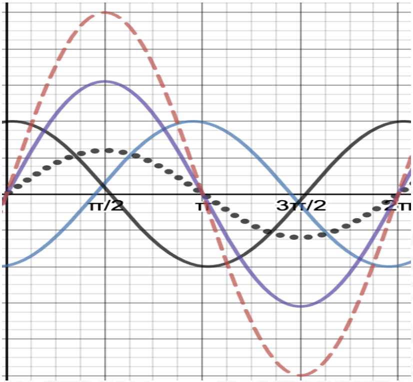
Common Loss Functions

- Regression loss: Mean squared error
  $$L_{T_i}(f_\phi) = \sum_{x^{(j)},y^{(j)} \sim T_i} ||f_\phi(x^{(j)}) - y^{(j)}||^2$$
- Classification loss: cross-entropy loss
  $$L_{T_i}(f_\phi) = \sum_{x^{(j)},y^{(j)} \sim T_i} y^{(j)} \log f_\phi(x^{(j)}) - (1 - y^{(j)}) \log(1 - f_\phi(x^{(j)}))$$
- RL loss: negative avg episodic reward
  $$L_{T_i}(f_\phi) = -\mathbb{E}_{x^t, a^t \sim f_{\phi, q_{T_i}}} \sum_{t=1}^{T} R_i(x_t, a_t)$$

Experiments-Simple Regressor

Training Dataset:

- 70000 random Sinusoid Wave
- amplitude $\in$ [0.1, 5.0]
- Phase varies within $[0, \pi]$
- datapoints x $\sim$ [-5.0, 5.0]



MAML training:

- take N=70000
- sample k=5 datapoints for each sinwave
- Train MAML learner

Meta-Testing:

- take random sine wave $\rightarrow$ [0.1, 5]
- sample k=5 datapoints for the selected sinwave
- Fine-tune the model for the task and measure performance

Experiments-Cont'd

Trained Baseline Models

- Oracle Model(fed with amplitude and phase beforehand)
- pre-trained on the randomly generated sine waves and fit a regressor

Evaluation:

- Select 600 points at random i.e.$x_{test} \in [-5, 5]$
- Calculate y_{test} for the selected task for meta-testing
- get y_{pred} from the models for x_{test}
- Calculate MSE loss between y_{test} and y_{pred}

Model Details:

- 2 layer NN with 40 neurons in each hidden Layer and Relu in between
- Trained with ADAM optimizer

Results

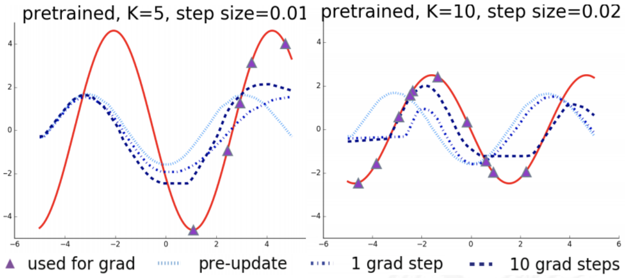


image courtesy: Finn C. et al [1]

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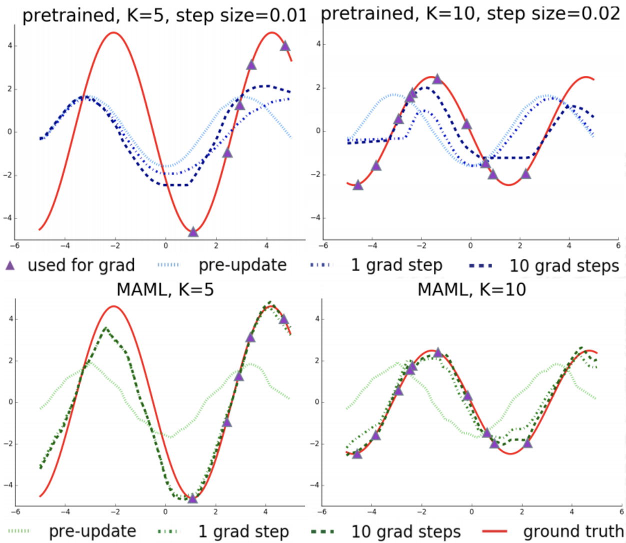
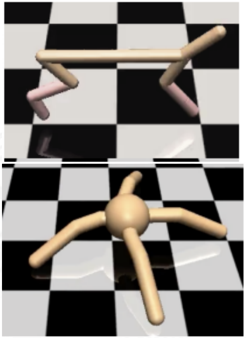


image courtesy: Finn C. et al [1]

Experiment-Robot Locomotion

Task:

- Robot(e.g. 2 legged cheetah or 4 legged ant) locomotion in simple 3D world
- Tasks are to attain a target speed or walk in a particular direction



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MDP details:

- Observation space –> current coordinates
- Action space –> joint angles to move
- Rewards:
  - **For goal velocity tasks:** negative of absolute diff of goal velocity and current velocity
  - **For goal direction tasks:** magnitude of goal velocity in desired direction

Experiment-Robot Locomotion Cont'd

meta-training:

- Sample a task for goal velocity from $\sim [0.0, 2.0]$
- For each task, generate k=20/40 policy rollouts(samples) and fit the learner
- For each task, generate the meta-test observations and update the meta learner using loss on meta-testset.

meta-test:

- Sample a task for goal velocity from $\sim [0.0, 2.0]$
- Generate k=20/40 samples policy rollouts and fine tune the learner

Experiment-Robot Locomotion Results

1. Randomly trained policy
2. MAML trained policy

Conclusion

+ Meta-Learning shows potential for more human like learning
+ Works with only few samples(Saves effort on data labelling)
+ Algorithms like MAML show early success in field on related tasks
– Still in early phase, and requires the tasks to be related and similar.
– Requires large number of similar tasks
– Uses shallow networks to avoid overfitting which restricts the representational powers of model
– Need for more mature algorithms for more human like learning

Thank You For Your Attention!

Questions??

References

1. Finn C., Abbeel P., Levine S. in CoRR 2017, Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks, http://arxiv.org/abs/1703.03400
2. Ravi S., Larochelle H. in ICLR 2017, Optimization As a Model for Few-shots learning https://openreview.net/forum?id=rJY0-Kcll
3. Finn Chelsea, Learning to Learn https://bair.berkeley.edu/blog/2017/07/18/learning-to-learn/

Pseudo code

Algorithm 2 Train Meta-Learner

Input:Data D_{train}, Learner(M) params θ, Meta-learner(R) params ϕ

$\phi_0 \leftarrow$random initialization
for d=1,n **do**
  D_{train}, D_{test} gets random dataset from $D_{MetaTrain}$
  $\theta_0 \leftarrow c_0$ ▷ Initialize learner parameters
  for t=1,T **do**
    X_t, Y_t gets random batch from D_{train}
    $L_t \leftarrow L(M(X_t; \theta_{t-1}), Y_t)$ ▷ learner loss on train batch
    $c_t \leftarrow R((\nabla_{\theta_{t-1}} L_t, L_t); \phi_{d-1})$ ▷ output of meta-learner
    $\theta_t \leftarrow c_t$ ▷ Update learner parameters
  end for
  $X, Y \leftarrow D_{test}$
  $L_{test} \leftarrow L(M(X; \theta_t), Y)$ ▷ learner loss on test batch
  Update ϕ_t using $\nabla_{\Theta_{d-1}} L_{test}$ ▷ Update meta-learner params
end for