Learning how to learn

Machine Learning and Data Mining

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Meta-learning

Traditional learning:

- given problem $D = (X_i, Y_i)_{i=1}^N$, $X_i, Y_i \sim P(x, y)$
- find decision function f
- that minimizes error $R(f, P)$.

Meta-learning:

- given family of problems $D_j = (X_i^j, Y_i^j)_{i=1}^{N_j}$,
- $D_j \sim P_\theta^{N_j}(x, y)$, $\theta \sim P(\theta)$
- find mapping $g : D \to f$
- such that minimizes error $\mathbb{E}_\theta \, \mathbb{E}_{D \sim P_\theta^N} \, R(g(D), P_\theta)$

This definition is not commonly accepted.

Meta-learning

$$\text{data} = \underbrace{\underbrace{\text{shared knowledge}}_{\text{pre learn}} + \underbrace{\text{concept}}_{\text{learn to infer}}}_{\text{learn to combine}}$$

Meta-learning flavors

- concept learning, few-shot learning;
- learning optimization procedure;
- learning model:
  - hyper-parameter optimization.

While in practice these are quite distinct areas, theoretically, the lines are blurry.

Few-shot learning

Weight sharing

- model $f(\psi, \theta_i)$ with two sets of parameters:
  - ψ — independent of task;
  - θ_i — parameters for i-th task.

Train:

$$\psi^* = \arg\min \min_{\theta_1, \theta_2, \ldots} \sum_i \mathcal{L}(f(\psi, \theta_i), D_i)$$

Test:

$$\theta^* = \arg\min_\theta \mathcal{L}(f(\psi^*, \theta), D)$$

Also known as 'replace-head-of-an-already-trained-network' or transfer learning.

'Soft' weight sharing

Train:

$$\psi^* = \arg\min_{\psi} \left[\min_{\theta_1,\theta_2,\ldots} \sum_i \mathcal{L}(f(\theta_i), D_i) + \sum_i \|\psi - \theta_i\|^2 \right]$$

Test:

$$\theta^* = \arg\min_{\theta} \left[\mathcal{L}(f(\theta), D) + \|\psi^* - \theta\|^2 \right]$$

Also known as fine-tuning of a pretrained network or transfer learning.

Model Agnostic Meta-Learning

- 'soft' weight sharing constrains weights to be close to each other in l_2 space;
- instead let's directly incorporate test weights inference into training:

$$\psi^* = \arg\min_{\psi} \left[\sum_i \mathcal{L}(f(\psi_i), D_i) \right]$$

where:

$$\psi_i = \psi - \alpha \left. \frac{\partial \mathcal{L}(f(\theta), D_i)}{\partial \theta} \right|_{\theta=\psi}$$

Model Agnostic Meta-Learning

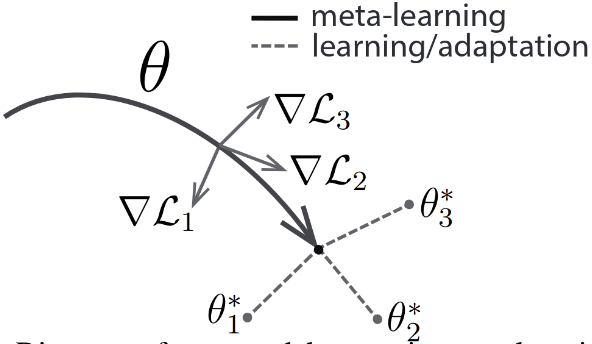
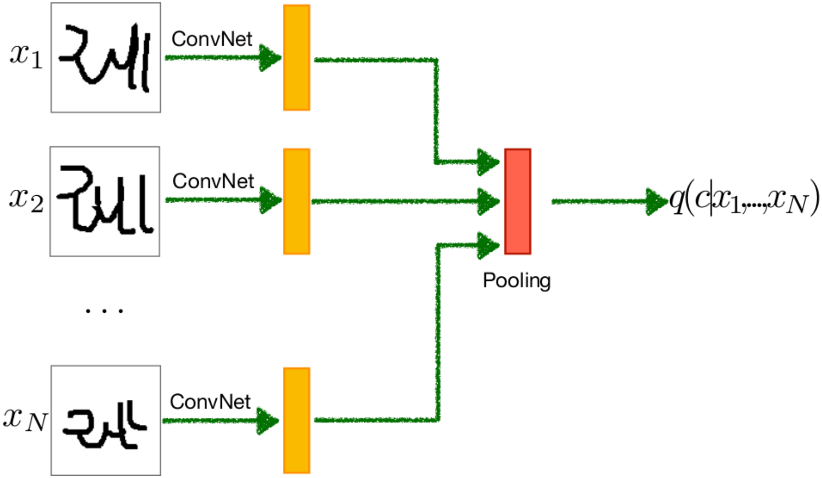


Figure 1. Diagram of our model-agnostic meta-learning algorithm (MAML), which optimizes for a representation θ that can quickly adapt to new tasks.

Generative models

Neural Statistician



Neural Statistician

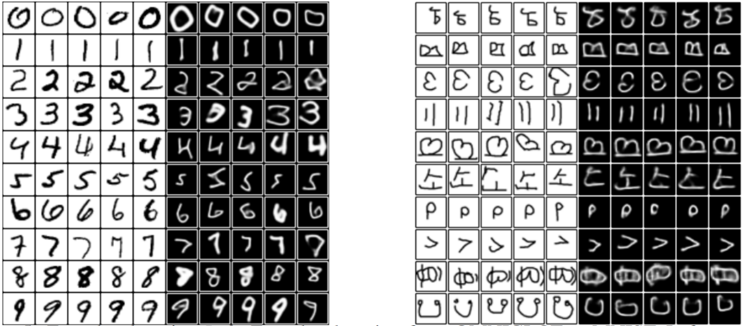
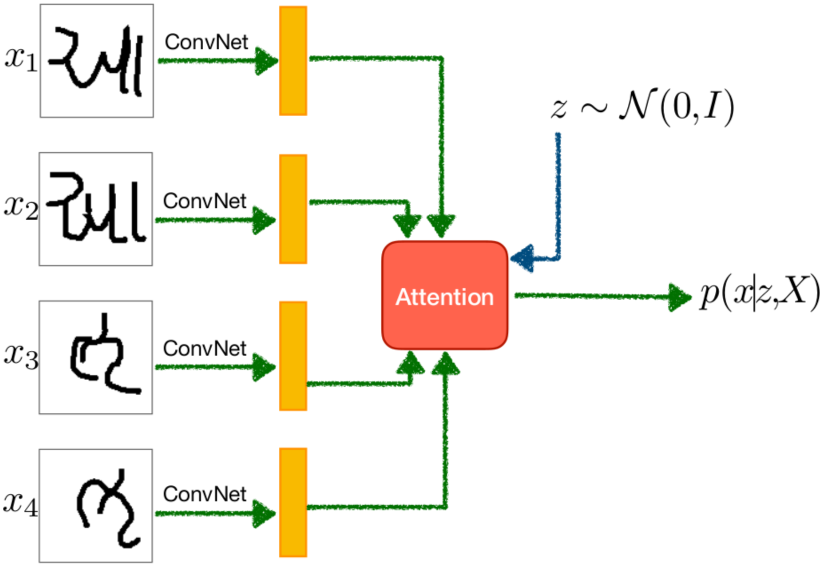


Figure 5: Few-shot learning *Left*: Few-shot learning from OMNIGLOT to MNIST. Left rows are input sets, right rows are samples given the inputs. *Right*: Few-shot learning from with OMNIGLOT data to unseen classes. Left rows are input sets, right rows are samples given the inputs. Black-white inversion is applied for ease of viewing.

Neural Statistician

Figure 6: Few-shot learning for face data. Samples are from model trained on Youtube Faces Database. *Left*: Each row shows an input set of size 5. *Center*: Each row shows 5 samples from the model corresponding to the input set on the left. *Right*: Imagined new faces generated by sampling contexts from the prior. Each row consists of 5 samples from the model given a particular sampled context.

Generative Matching Networks



Generative Matching Networks

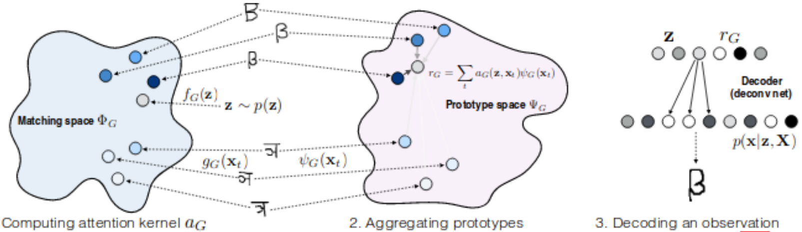
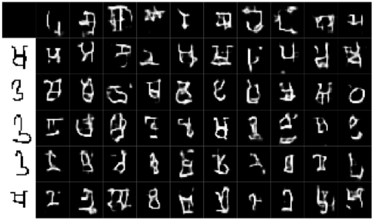


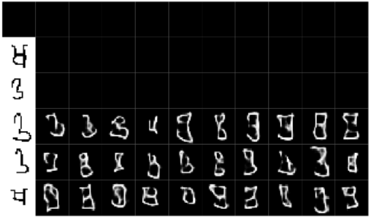
Figure 1: Generation of a new sample in a basic generative matching network, see section $\boxed{3.1}$ for the description of functions f, g and ψ.

Generative Matching Networks

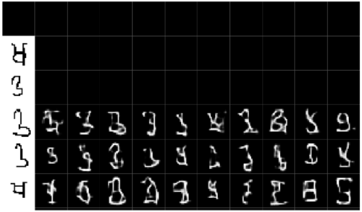
(a) GMN (no pseudo-input)



(b) GMN (one pseudo-input)



(c) GMN (no attention, no pseudo-input)



(d) Neural statistician

Learning optimizers

Replacing gradient descent

$$\theta^{t+1} = \theta^{t} + g_{\psi}(\nabla f(\theta_t))$$

$$\mathcal{L}(\psi) = \mathop{\mathbb{E}}_{f}\left[w_t f(\theta_t)\right]$$

Replacing gradient descent

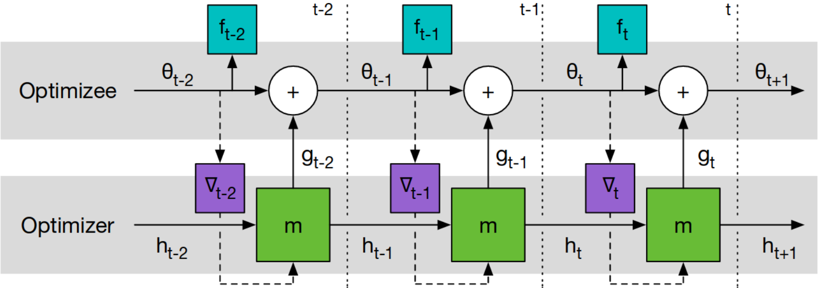


Figure 2: Computational graph used for computing the gradient of the optimizer.

Replacing gradient descent

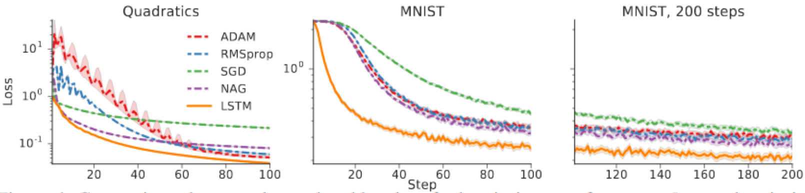


Figure 4: Comparisons between learned and hand-crafted optimizers performance. Learned optimizers are shown with solid lines and hand-crafted optimizers are shown with dashed lines. Units for the y axis in the MNIST plots are logits. **Left:** Performance of different optimizers on randomly sampled 10-dimensional quadratic functions. **Center:** the LSTM optimizer outperforms standard methods training the base network on MNIST. **Right:** Learning curves for steps 100-200 by an optimizer trained to optimize for 100 steps (continuation of center plot).

Replacing gradient descent

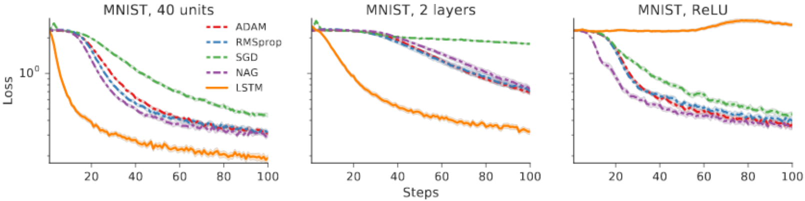


Figure 5: Comparisons between learned and hand-crafted optimizers performance. Units for the y axis are logits. **Left:** Generalization to the different number of hidden units (40 instead of 20). **Center:** Generalization to the different number of hidden layers (2 instead of 1). This optimization problem is very hard, because the hidden layers are very narrow. **Right:** Training curves for an MLP with 20 hidden units using ReLU activations. The LSTM optimizer was trained on an MLP with sigmoid activations.

References

References

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