Parameter Prediction Paper: Learning to Learn by gradient descent by gradient descent

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https://qdata.github.io/deep2Read/

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Optimizer

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$$\theta t + 1 = \theta_t - \alpha_t \nabla f(\theta_t) \tag{2}$$

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Optimization strategies tailored to different classes of tasks:

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Generally, hand designed update rules.

Learning to Learn

Meta-learning / Learning to Learn

Replace hand designed update rules with learned update rule

$$\theta_{t+1} = \theta_t + g_t(\nabla(f(\theta_t)), \phi) \tag{3}$$

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g_t is the optimizer with its own parameters

g_t is a recurrent neural network that predicts update at each timestep, parameterised by ϕ

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Find an optimizer with learned updates (instead of hand designed updates) that performs well on a class of optimization problems.

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Generalization in 'Learning to Learn' context: Optimizer should perform well in unseen problems of the same 'type':

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Generalization in 'Learning to Learn' context: Optimizer should perform well in unseen problems of the same 'type':

transfer learning

Learning to Learn with Recurrent Neural Networks

1. When can you say an optimizer is good?
2. θ^* (optimal parameters) is a function of the class of functions f being optimized and the optimizer parameters

$$\theta^*(f, \phi) \tag{4}$$

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$$\mathbb{L}(\phi) = \mathbb{E}_f \Big[\sum_{t=1}^{T} w_t f(\theta_t) \Big] \tag{6}$$

$$\theta_{t+1} = \theta_t + g_t \tag{7}$$

$$\begin{pmatrix} g_t \\ h_{t+1} \end{pmatrix} = m(\nabla_t, h_t, \phi)$$

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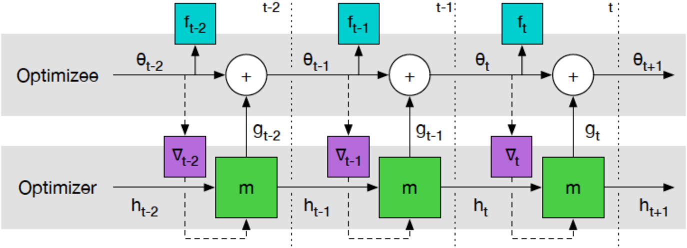
5. Generate updates at each timestep using a recurrent neural network

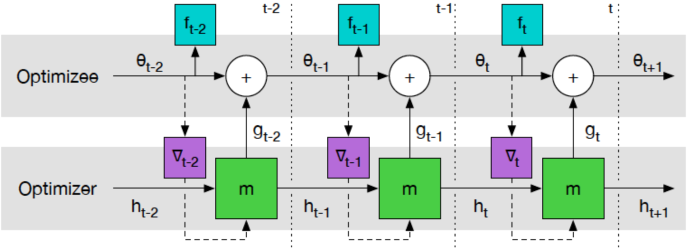
Optimizing the optimizer



Computational Graph used for computing the gradient

1. Minimize loss $\mathbb{L}(\phi)$w.r.t the parameters of the optimizer (ϕ)
2. calculate $\frac{\delta \mathbb{L}}{\delta \phi}$ and backpropagate through time

Optimizing the optimizer



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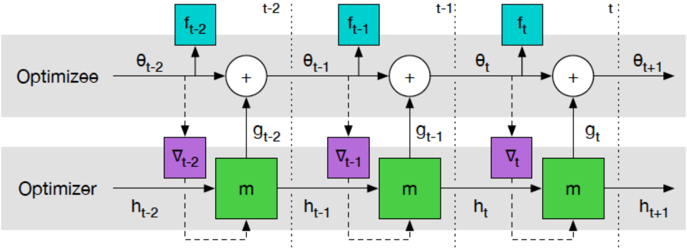

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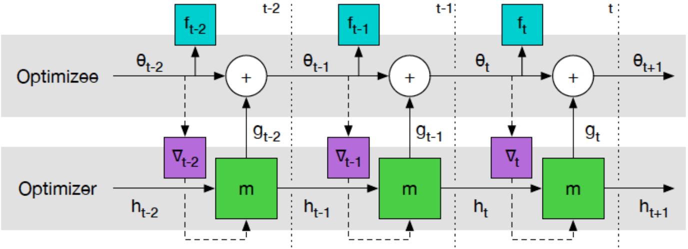

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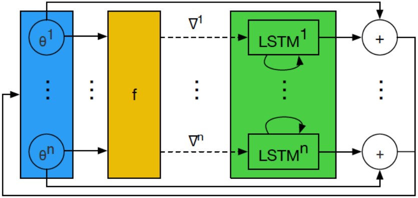
1. Issue: Huge hidden state RNN if we want an update for each parameter

$$\theta_{t+1} = \theta_t + g_t \tag{8}$$

$$\begin{pmatrix} g_t \\ h_{t+1} \end{pmatrix} = m(\nabla_t, h_t, \phi)$$

2. Solution: use an RNN to get an update coordinate wise
3. Coordinate wise LSTM shares the weights across all parameters

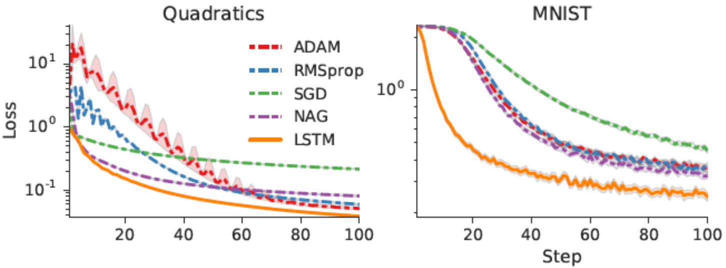


Separate hidden states, but shared parameters

Experiments and Results: Quadratic Functions

1. Quadratic Functions:

$$f(\theta) = ||W\theta - y||_2^2 \tag{9}$$

2. Optimzer trained on random functions from this family
3. Test on a random function sampled from this family distribution
4. 

Learning Curves