Learning to Optimize

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Recent Trends in Automated Machine-Learning

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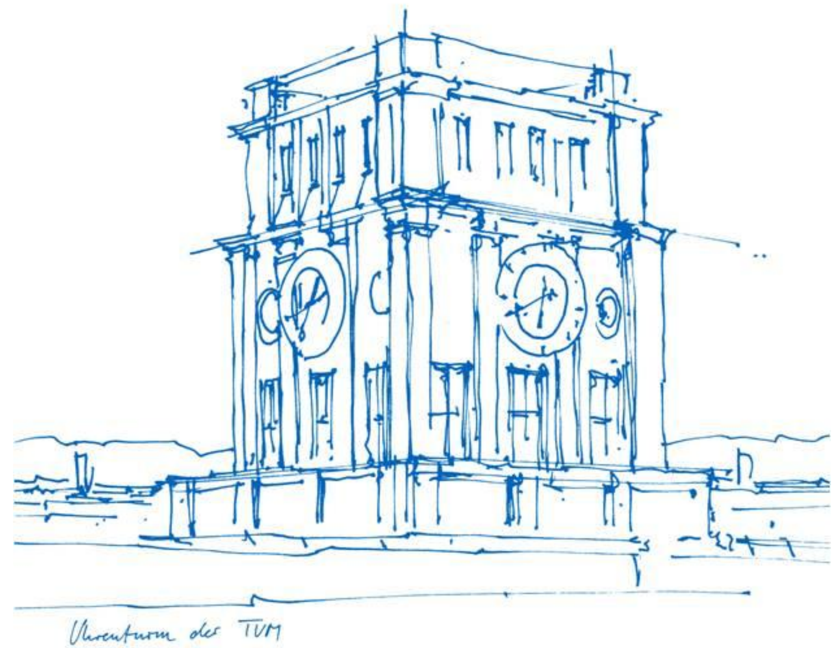
Thursday, 11th July, 2019



Motivation

- Improvement with automated machine learning
  - data augmentation
  - architecture
  - activation functions
- learn an optimizer
  - faster convergence
  - lower final loss value
  - more stable training
  - no hyperparameter optimisation

Optimizer

Algorithm 1 General structure of optimization algorithms

Require: Objective function f
  $x^{(0)} \leftarrow$ random point in the domain of f
  for $i = 1, 2, \ldots$ **do**
    $\Delta x \leftarrow \pi(f, \{x^{(0)}, \ldots, x^{(i-1)}\})$
    if stopping condition is met **then**
      return $x^{(i-1)}$
    end if
    $x^{(i)} \leftarrow x^{(i-1)} + \Delta x$
  end for

- can be rewritten in general form
- update rule can be seen as a policy

- known handcrafted examples:
  - gradient descent: $\pi(f, \{x^{(0)}, \ldots, x^{(i-1)}\}) = -\gamma \nabla f(x^{(i-1)})$
  - gradient descent with momentum: $\pi(f, \{x^{(0)}, \ldots, x^{(i-1)}\}) = -\gamma \left(\sum_{j=0}^{i-1} \alpha^{i-1-j} \nabla f(x^{(j)}) \right)$

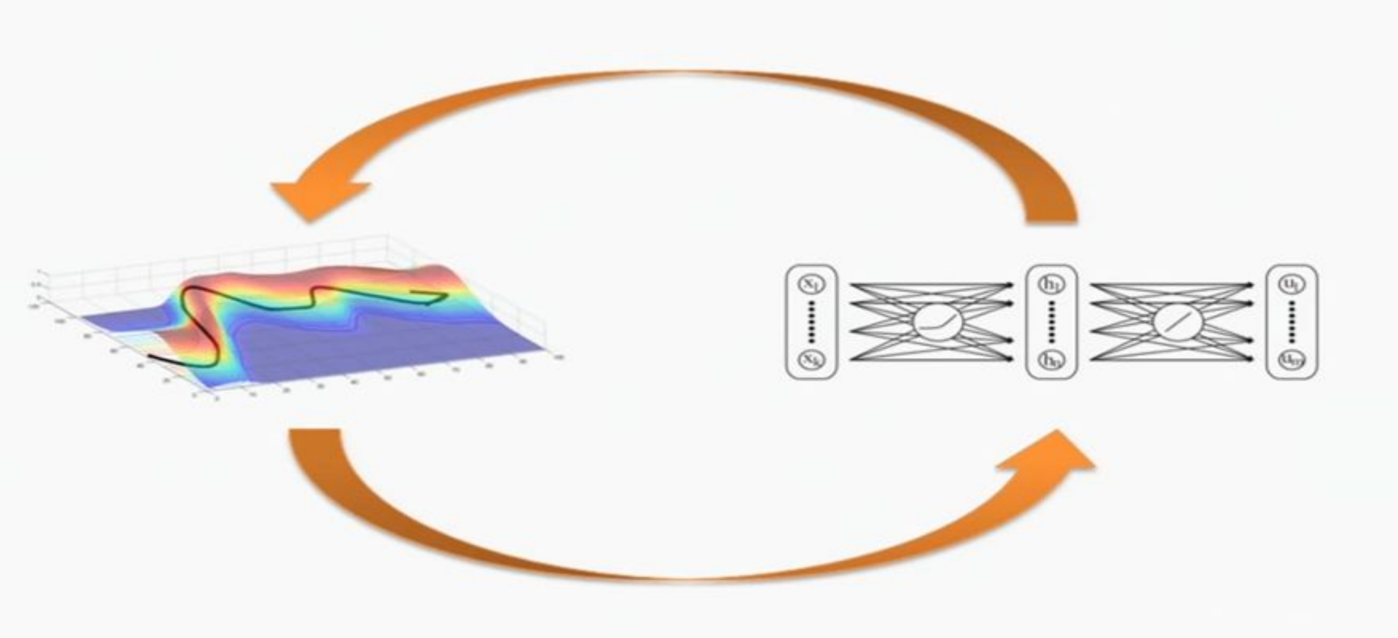
Reinforcement Learning

- negative loss of the child network as reward
  - encurage fast convergence and low final loss value
  - undiscounted reward
- learn the policy in continous state and action space
- using Guided Policy Search

$$R = \sum_{t=1}^{T} -l_t(x)$$

Guided Policy Search

- Trajectory Optimization (learn dynamics)
- Supervised Learning (optimize policy)



Guided Policy Search - Trajectory Optimization

- dynamics calculates the response of the system when changing the variables
- trajectory is the path of optimization steps during training
- initial trajectory is chosen to behave like SGD with momentum
- trajectory distributions are more stable, especially for discontinous dynamics
- need to approximate dynamics
    - sample distribution and linearize at each time step
    - number of samples can be reduced with knowledge of previous samples
- trajectories musn't deviate to much for good linear approximation

$$\min_{p(\tau)\in\mathcal{N}(\tau)} E_p[\ell(\tau)] \text{ s.t. } D_{\mathrm{KL}}(p(\tau)\|\hat{p}(\tau)) \leq \epsilon$$

- solve with lagrangian with dual gradient descent

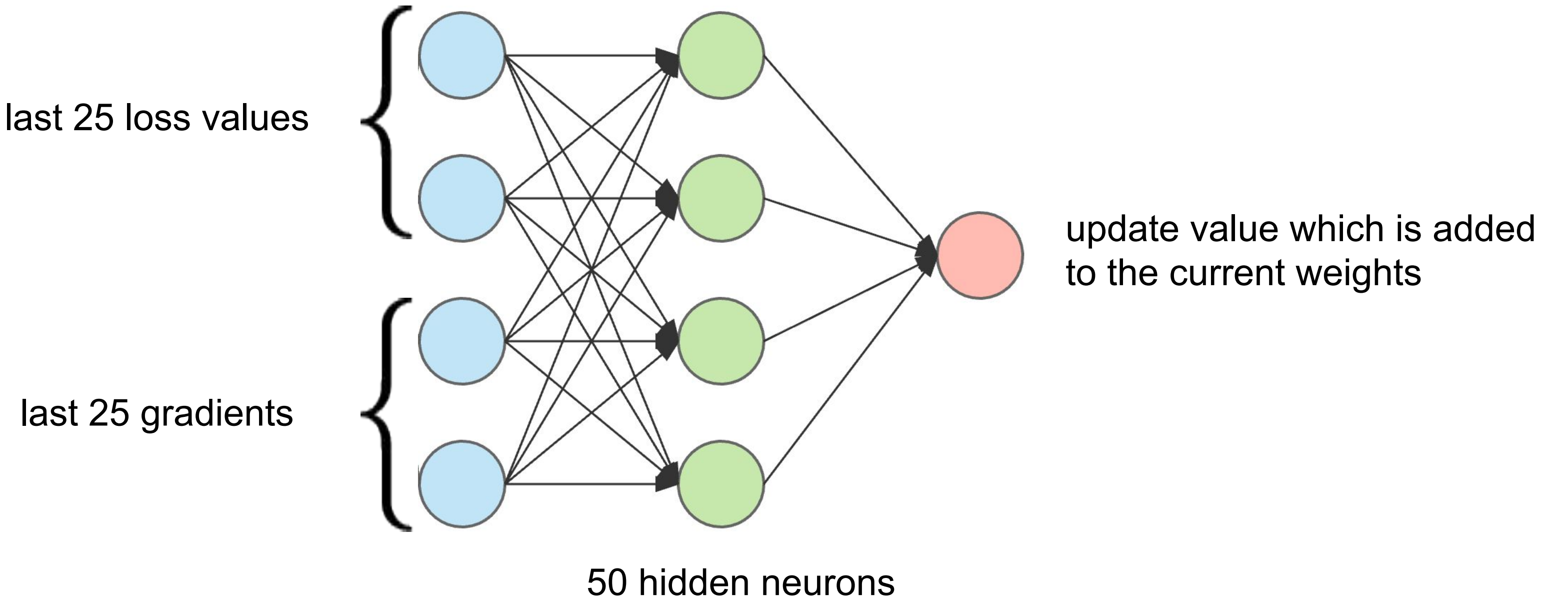
Guided Policy Search - Supervised Learning

- take the samples of the trajectory distribution
- learn policy supervised by minimizing

$$\sum_{t=1}^{T} \lambda_t D_{\mathrm{KL}}(p(\mathbf{x}_t)\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)\|p(\mathbf{x}_t, \mathbf{u}_t))$$

  - minimize the difference between the optimized trajectory and the policy
  - converges to a policy which produces the trajectory

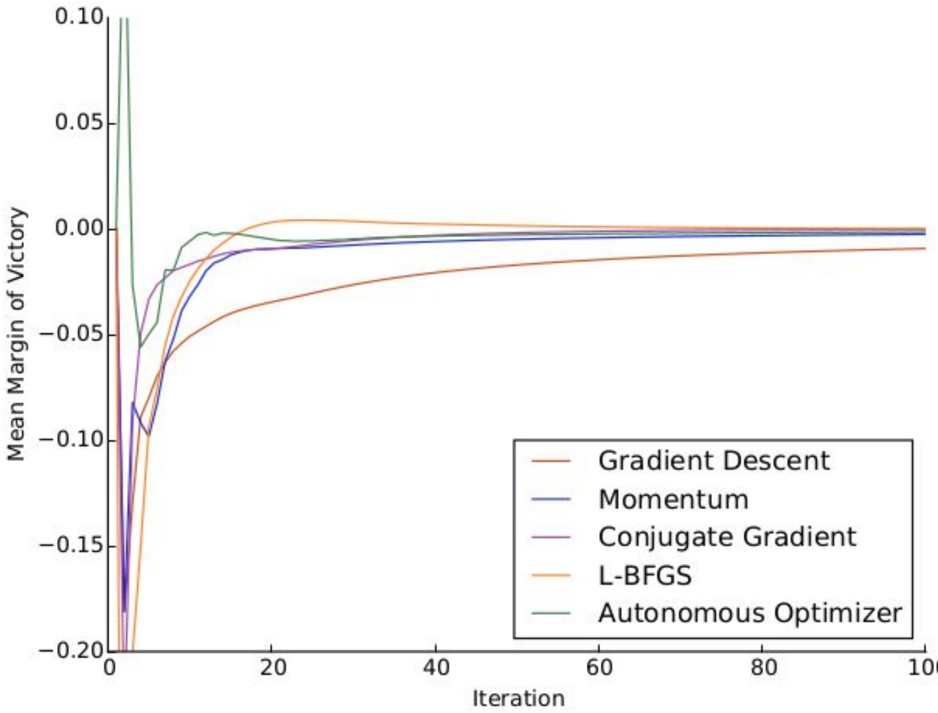
Network for the Policy



Experiment Logistic Regression

- convex optimization surface $\min_{w,b} -\frac{1}{n}\sum_{i=1}^{n} y_i log\, \sigma(w^T x_i + b) + (1 - y_i) log(1 - \sigma(w^T x_i + b)) + \frac{\lambda}{2}||w||_2^2$
- artificial data
  - single set created based on two multivariant gausians, 50 samples each
  - 90 of these sets for training
  - 100 of these sets for testing

- only L-BFGS converges faster
  - known for fast convergence with convex problems



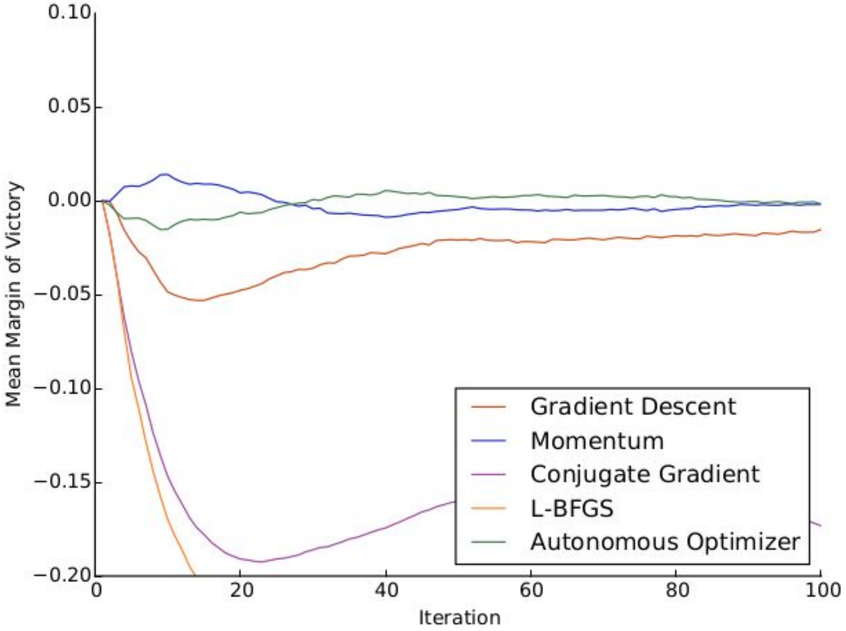
Experiment Robust Linear Regression

- nonconvex problem $$\min_{\mathbf{w},b} \frac{1}{n} \sum_{i=1}^{n} \frac{\left(y_i - \mathbf{w}^T \mathbf{x}_i - b\right)^2}{c^2 + \left(y_i - \mathbf{w}^T \mathbf{x}_i - b\right)^2}$$
- artificial data
  - datapoints: 100 samples from 4 multivariate gaussians per trainings set
  - labels: datapoins of each gaussian projected on a different random vector,

    a random bias is added

    perturbed with i.i.d. gaussian noise
  - 120 sets for training
  - 100 sets for testing

- outperfoms other policies after 30 epochs



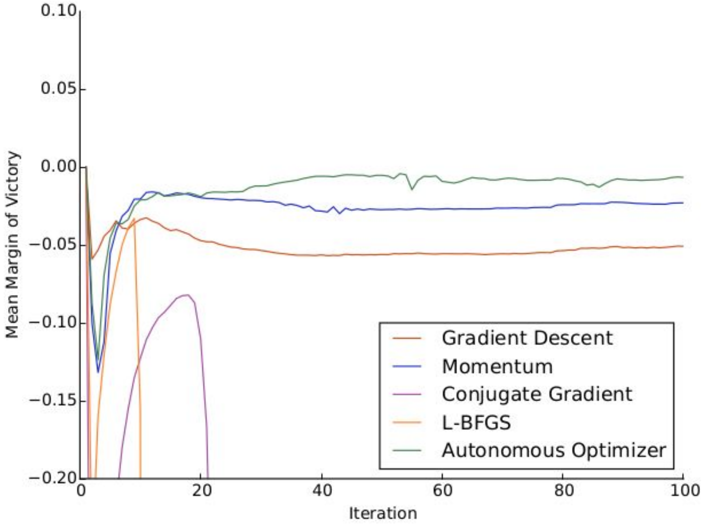
Experiment Neural Net Classifier

- complex optimization surface with multiple local optima

$$\min_{W,U,b,c} -\frac{1}{n}\sum_{i=1}^{n} log(\frac{exp((Umax(Wx_i+b,0)+c)_{y_i})}{\sum_j exp((Umax(Wx_i+b,0)+c)_j)}) + \frac{\lambda}{2}||W||_F^2 + \frac{\lambda}{2}||U||_F^2$$

- Fully Conected NN with 2 input, 2 hidden and 2 output neurons and regularization
- artificial data
  - datapoints are sampled from 4 differnt gaussians
  - labels randomly 0 or 1 assinged per gaussian

    at least 1 gaussian of each lable
  - 120 sets for training
  - 100 sets for testing
- outperforms all other policies
  - the first epochs similar to SGD with momentum



Conclusion

- Strength
  - simple idea to learn the policy
  - outperformed other optimizer
  - no hyperparameter tuning
- Weaknesses
  - only toy problems, no real data or application
  - scalability problem, need to cache 25 gradients and 25 loss values per weight
  - guided policy search not straight forward to train