Applied Deep Learning

Optimization

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Vanilla Gradient Descent

- Computes the gradient of the cost function w.r.t. to the parameters θ for the entire training dataset.
- As we need to calculate the gradients for the whole dataset to perform just one update, batch gradient descent can be very slow and is intractable for datasets that don't fit in memory.
- Batch gradient descent also doesn't allow us to update our model *online*, i.e. with new examples on-the-fly.

$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta)$$

Stochastic Gradient Descent

- Stochastic gradient descent (SGD) in contrast performs a parameter update for *each* training example.
- It is therefore usually much faster and can also be used to learn online.

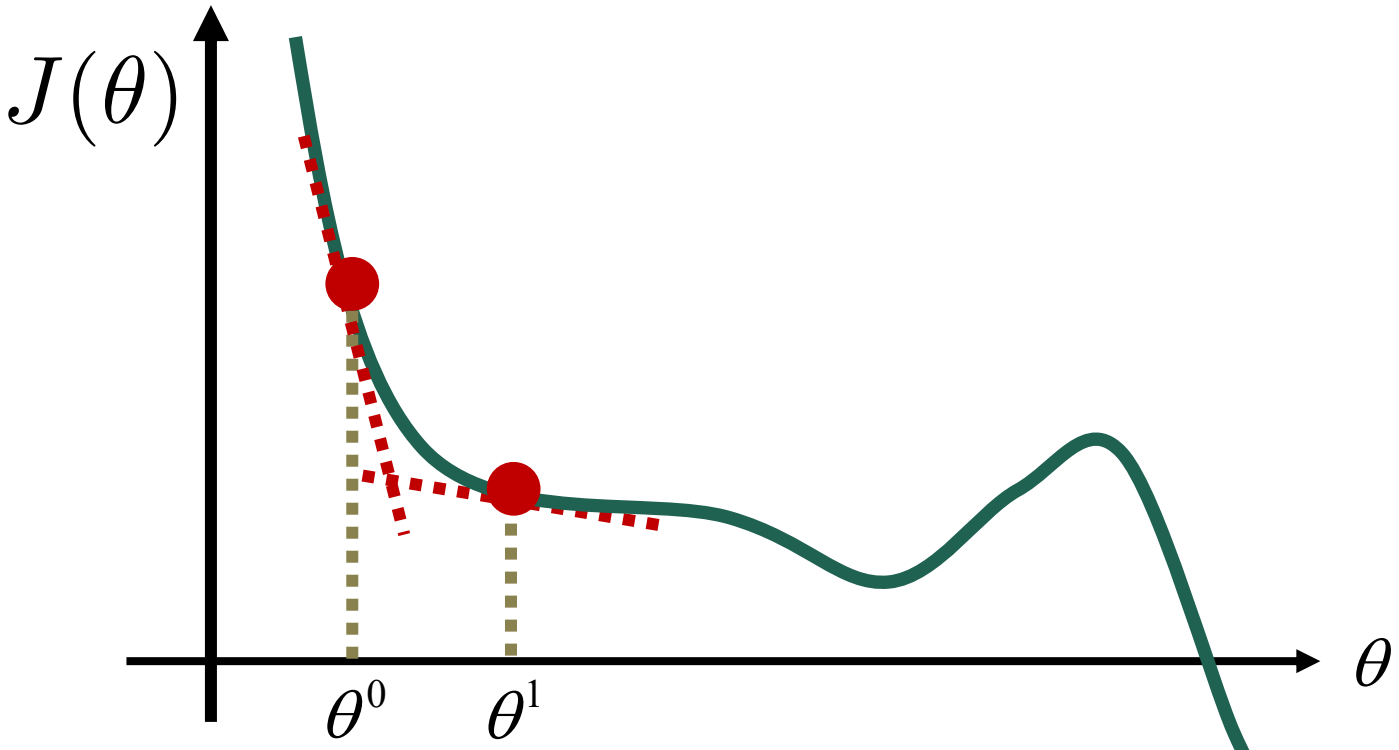
$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i)}; y^{(i)})$$

Mini-batch Stochastic Gradient Descent

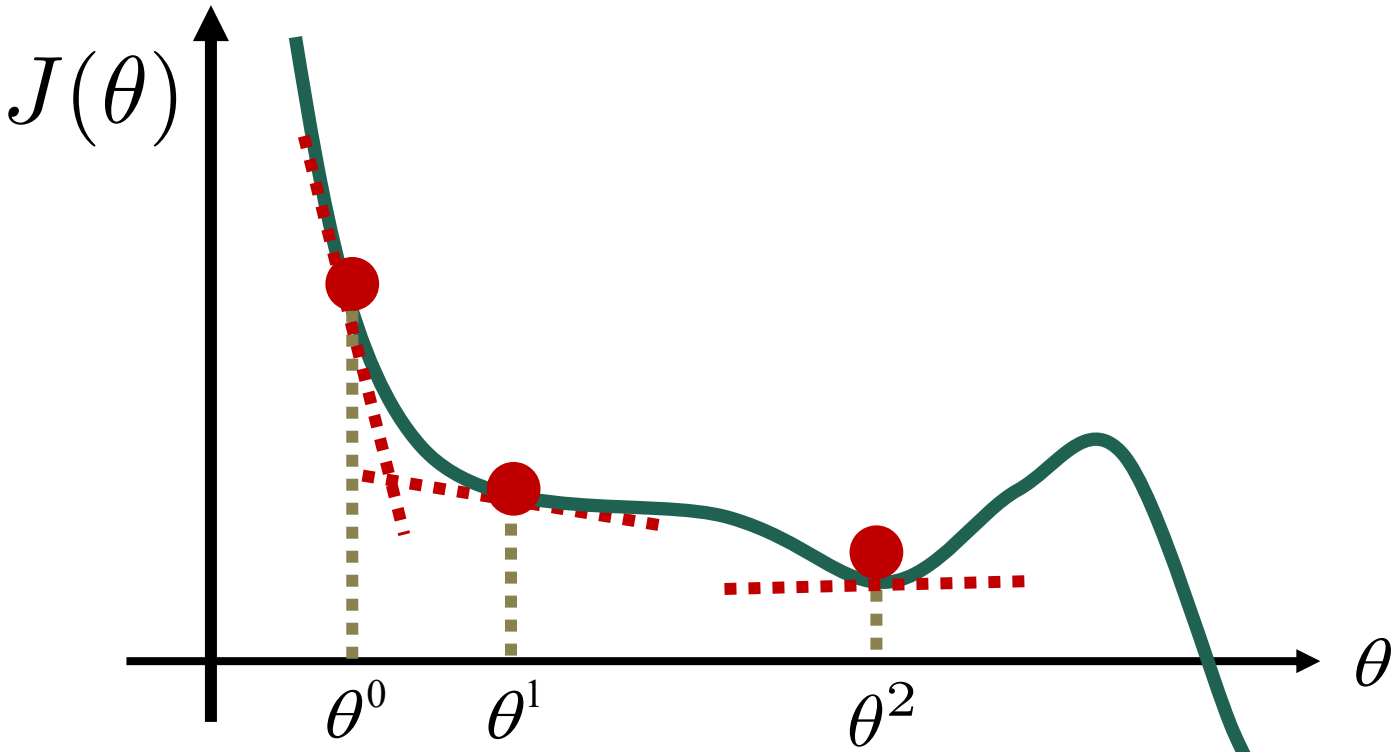
- Mini-batch gradient descent finally takes the best of both worlds and performs an update for every mini-batch of n training examples.
- This way reduces the variance of the parameter updates, which can lead to more stable convergence.
- **On modern hardware 16 operations of size 1 is much slower than 1 operation of size 16 (parallelization on GPUs)**

$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i:i+n)}; y^{(i:i+n)})$$

Local Minimum



Local Minimum



Challenges

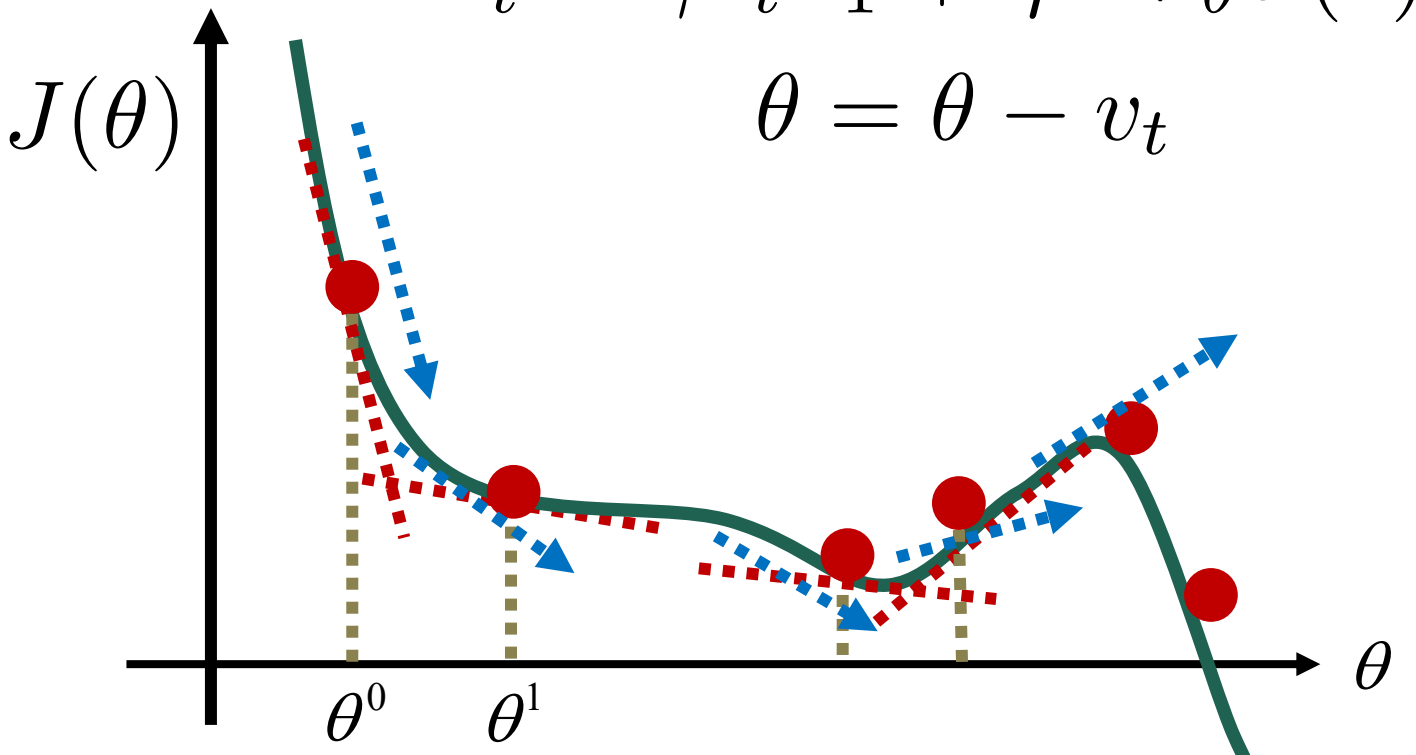
- Choosing a proper learning rate can be difficult.
- Learning rate schedules try to adjust the learning rate during training by e.g. annealing, i.e. reducing the learning rate according to a pre-defined schedule or when the change in objective between epochs falls below a threshold.
- These schedules and thresholds, however, have to be defined in advance and are thus unable to adapt to a dataset's characteristics

Beyond SGD

Momentum

$$v_t = \gamma v_{t-1} + \eta \cdot \nabla_\theta J(\theta)$$

$$\theta = \theta - v_t$$



Momentum

- Mini-batch accumulates the gradient of the past steps to determine the direction to go.
- faster convergence and reduced oscillation.

SGD without momentum

Image 2: SGD without momentum

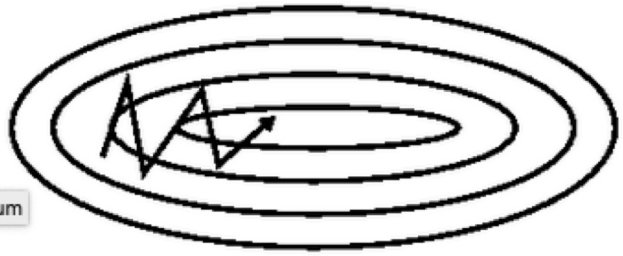


Image 3: SGD with momentum

SGD with Momentum

- Remember gradients from past time steps

$$v_t = \gamma v_{t-1} + \eta g_t$$

Momentum

Momentum Conservation Parameter

Previous Momentum

Gradient

- **Intuition**: Prevent instability resulting from sudden changes

$$\theta_{t+1} = \theta_t - v_t$$

Adagrad

- It adapts the learning rate to the parameters, performing smaller updates (i.e. low learning rates) for parameters associated with frequently occurring features, and larger updates (i.e. high learning rates) for parameters associated with infrequent features.
- For this reason, it is well-suited for dealing with sparse data.
- G is the accumulation of previous gradient values.

$$G_t = G_{t-1} + g_t \odot g_t$$ ← Squared Current Gradient

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t + \epsilon}} \odot g_t$$

Small Constant

RMSProp

- Instead of inefficiently storing all previous squared gradients, the sum of gradients is recursively defined as a decaying average of all past squared gradients (rolling average).
- resolve Adagrad's radically diminishing learning rates
- **Best choice for RNN…?**

$$E[g^2]_t = \gamma E[g^2]_{t-1} + (1-\gamma) g_t^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} \odot g_t$$

Adam

- **Most standard optimization option in NLP and beyond**
- first moment + second moment (momentum + RMSprop)

$$m_t = \gamma_1 m_{t-1} + (1 - \gamma_1) g_t$$

$$v_t = \gamma_2 v_{t-1} + (1 - \gamma_2) g_t^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

Miscellaneous

Adam is the best?

- Issue of non-convergence

Published as a conference paper at ICLR 2018

ON THE CONVERGENCE OF ADAM AND BEYOND

Sashank J. Reddi, Satyen Kale & Sanjiv Kumar
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Missing Global-Optima

- The solutions found by **adaptive methods generalize worse (often significantly worse) than SGD**, even when these solutions have better training performance. These results suggest that practitioners should reconsider the use of adaptive methods to train neural networks

The Marginal Value of Adaptive Gradient Methods in Machine Learning

Ashia C. Wilson[♯], Rebecca Roelofs[♯], Mitchell Stern[♯], Nathan Srebro[†], and Benjamin Recht[♯]
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Adam + SGD

- prior period : Adam for fast convergence
- last period: SGD for gradually seeking the global optima

Improving Generalization Performance by Switching from Adam to SGD

Nitish Shirish Keskar [1] Richard Socher [1]

Back to the Data

算法固然美好，数据才是根本。

另一方面，Adam之流虽然说已经简化了调参，但是并没有一劳永逸地解决问题，默认参数虽然好，但也不是放之四海而皆准。因此，在充分理解数据的基础上，依然需要根据数据特性、算法特性进行充分的调参实验，找到自己炼丹的最优解。而这个时候，不论是Adam，还是SGD，于你都不重要了。

少年，好好炼丹吧。

references

- http://ruder.io/optimizing-gradient-descent/
- http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2016/Lecture/Gradient%20Descent%20(v2).pdf
- http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2016/Lecture/DNN%20tip.pdf