

Control Batch Size and Learning Rate to Generalize Well: Theoretical and Empirical Evidence



Challenge: How to tune the hyper-parameters of SGD to make deep learning generalize well?

Theoretical analysis: We analyse the generalizationability of SGD via stochastic differential equation:

Model the updates of SGD as a Ornstein-Uhlenbeck process;

$$\Delta\theta(t) = \theta(t+1) - \theta(t) = -\eta g(\theta) + \frac{\eta}{|S|} B\Delta W, \Delta W \sim \mathcal{N}(0,I),$$
 where $\theta(t)$ is the weight in time (step) t , η is the step size, $|S|$ is the batch size.

Use the stationary distribution to express the output of SGD; $q(\theta) = M \exp \left\{ -\frac{1}{2} \theta^{\top} \Sigma^{-1} \theta \right\},$

where

$$\Sigma A + A\Sigma = \frac{\eta}{|S|} B B^{\top},$$

and A expresses the local geometry around the global minima:

$$\mathcal{R}(\theta) = \frac{1}{2} \theta^{\top} A \theta.$$

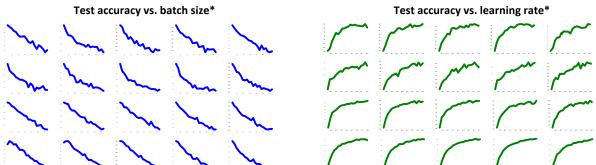
Finally, we get a PAC-Bayesian generalization bound for SGD:

$$R(Q) \leq \hat{R}(Q) + \sqrt{\frac{d \log \left(\frac{|S|}{\eta}\right) + \log \left(\frac{\det(A)}{\det(B)^2}\right) + \frac{1}{2}tr(\Sigma - I) + 2\log \frac{1}{\delta} + 5\log N + 1}{4N - 2}}$$

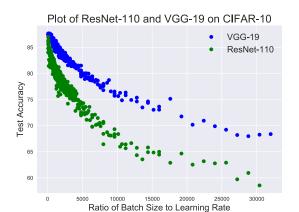
Results: The generalization ability of SGD has

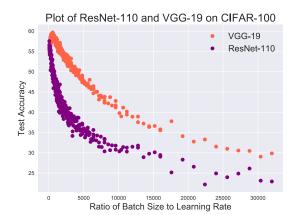
- A negative correlation with batch size;
- A positive correlation with learning rate;
- A negative correlation with the ratio of batch size to learning rate.

Empirical analysis: We trained around 1,600 models based on the architectures ResNet-19 and VGG-110 on the datasets CIFAR-10 and CIFAR-100. The results fully support the theoretical results.



*Every curve is drawn based on the basis that strictive controls irrelevant variables. From top to bottom, the four lines are respectively (1) ResNet-110 on CIFAR-10. (2) ResNet-110 on CIFAR-100. (3) VGG-19 on CIFAR-10. and (4) VGG-19 on CIFAR-10.





He, Liu, and Tao, "Control Batch Size and Learning Rate to Generalize Well: Theoretical and Empirical Evidence", NeurIPS, 2019.