MLDS HW1-2

TAs ntu.mldsta@gmail.com

Outline

- Timeline
- Task Descriptions
- Q&A

Timeline

Three Parts in HW1

- (1-1) Deep vs Shallow:
 - Simulate a funtion.
 - Train on actual task using shallow and deep models.
- (1-2) Optimization
 - Visualize the optimization process.
 - Observe gradient norm during training.
 - What happens when gradient is almost zero?
- (1-3) Generalization

Schedule

- 3/9:
 - Release HW1-1
- 3/16:
 - Release HW1-2
- 3/23:
 - Deadline to team-up by yourselves
 - Release HW1-3
- 3/30:
 - Deadline to team-up by TAs
- 4/6:
 - All HW1 due (including HW1-1, HW1-2 and HW1-3)

Task Descriptions

HW1-2: Optimization

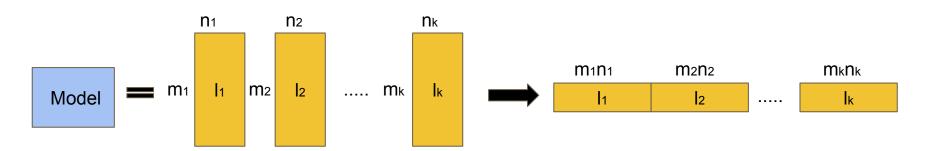
- Three subtask
 - Visualize the optimization process.
 - Observe gradient norm during training.
 - What happens when gradient is almost zero?
- Train on designed function, MNIST or CIFAR-10...

Visualize the Optimization Process 1/3

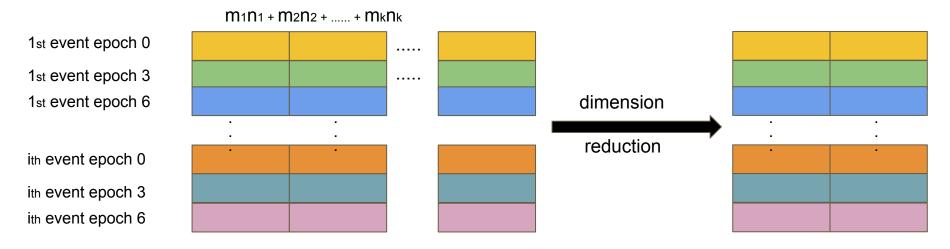
- Requirement
 - Collect weights of the model every n epochs.
 - Also collect the weights of the model of different training events.
 - Record the accuracy (loss) corresponding to the collected parameters.
 - Plot the above results on a figure.

Visualize the Optimization Process 2/3

• Collect parameters of the model:

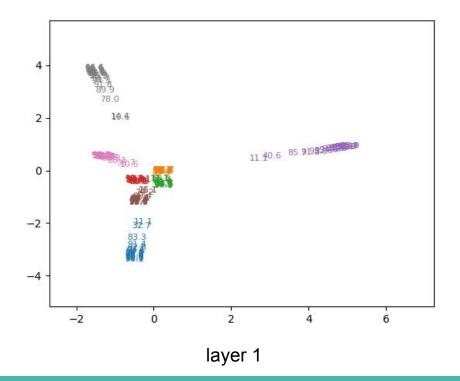


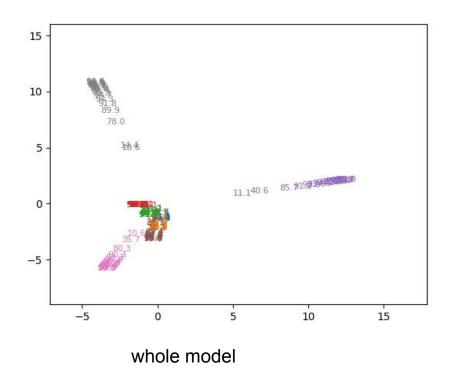
Reduce the dimension



Visualize the Optimization Process 3/3

- DNN train on MNIST
- Collect the weights every 3 epochs, and train 8 times. Reduce the dimension of weights to 2 by PCA.





Requirement

- Record the gradient norm and the loss during training.
- Plot them on one figure.
- p-norm

$$\left\| \mathbf{x}
ight\|_p := igg(\sum_{i=1}^n |x_i|^p igg)^{1/p}$$

In PyTorch:

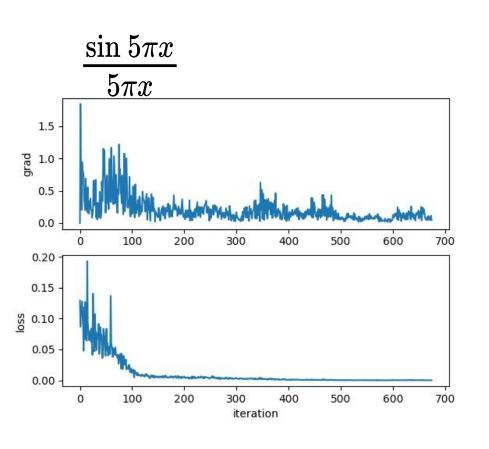
```
grad_all = 0.0

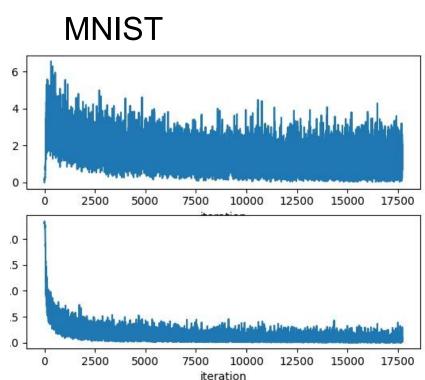
for p in model.parameters():
    grad = 0.0
    if p.grad is not None:
        grad = (p.grad.cpu().data.numpy() ** 2).sum()
    grad_all += grad

grad_norm = grad_all ** 0.5
```

Other packages: The similar code can be applied.

Observe Gradient Norm During Training 2/2





What Happened When Gradient is Almost Zero 1/3

Requirement

- Try to find the weights of the model when the gradient norm is zero (as small as possible).
- Compute the "minimal ratio" of the weights: how likely the weights to be a minima.
- Plot the figure between minimal ratio and the loss when the gradient is almost zero.

Tips

Train on a small network.

What Happened When Gradient is Almost Zero 2/3

1. How to reach the point where the gradient norm is zero?

First, train the network with original loss function.

- i. Change the objective function to gradient norm and keep training.
- ii. Or use second order optimization method, such as Newton's method or Levenberg-Marquardt algorithm (more stable)

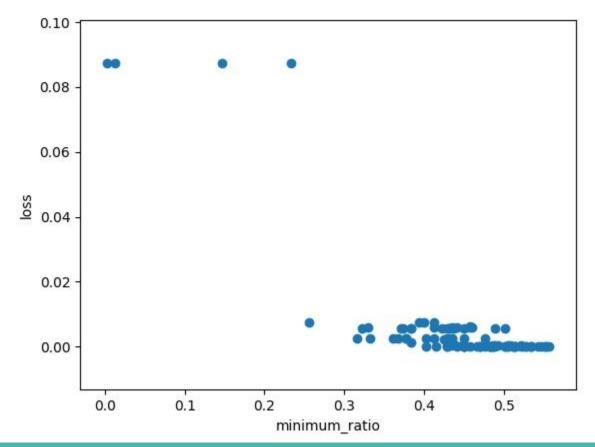
2. How to compute minimal ratio?

- i. Compute $H(L(\theta_{norm=0}))$ (hessian matrix), and then find its eigenvalues. The proportion of the eigenvalues which are greater than zero is the minimal ratio.
- ii. Sample lots of weights around $\theta_{norm=0}$, and compute $L(\theta_{sample})$. The minimal ratio is the proportion that $L(\theta_{sample}) > L(\theta_{norm=0})$

What Happened When Gradient is Almost Zero 3/3

$\sin 5\pi x$

- $5\pi x$
 - Train 100 times.
 - Find gradient norm equal to zero by change objective function.
 - Minimal ratio is defined as the proportion of eigenvalues greater than zero.

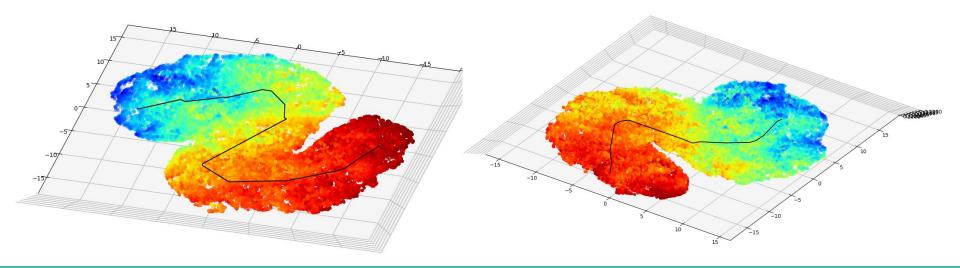


HW1-2 Report Questions (10%)

- Visualize the optimization process.
 - Describe your experiment settings. (The cycle you record the model parameters, optimizer, dimension reduction method, etc) (1%)
 - Train the model for 8 times, selecting the parameters of any one layer and whole model and plot them on the figures separately. (1%)
 - Comment on your result. (1%)
- Observe gradient norm during training.
 - Plot one figure which contain gradient norm to iterations and the loss to iterations. (1%)
 - Comment your result. (1%)
- What happens when gradient is almost zero?
 - State how you get the weight which gradient norm is zero and how you define the minimal ratio. (2%)
 - Train the model for 100 times. Plot the figure of minimal ratio to the loss. (2%)
 - Comment your result. (1%)
- Bonus (1%)
 - Use any method to visualize the error surface.
 - o Concretely describe your method and comment your result.

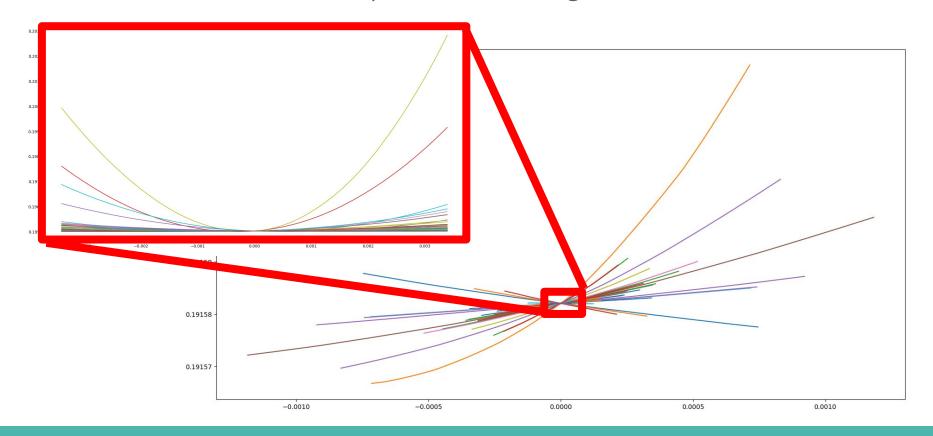
Example of Bonus 1/3

- Similar method as $\underline{\text{pg.}10}$, but use TSNE to reduce dimensionality.
- First train with gradient descent, then use second order optimization, finally train for about 10 epochs furthur by second order optimization.
- During the 10 epochs, randomly plot nearby parameters.
- Tips:
 - Use small model (less than 50 parameters) on small tasks (simulate function)
 - Fixed number of possible input (thus number of possible output is also fixed)
 - Scale the range of randomness according to each parameters' rate of descending
 - Non-linear coloring



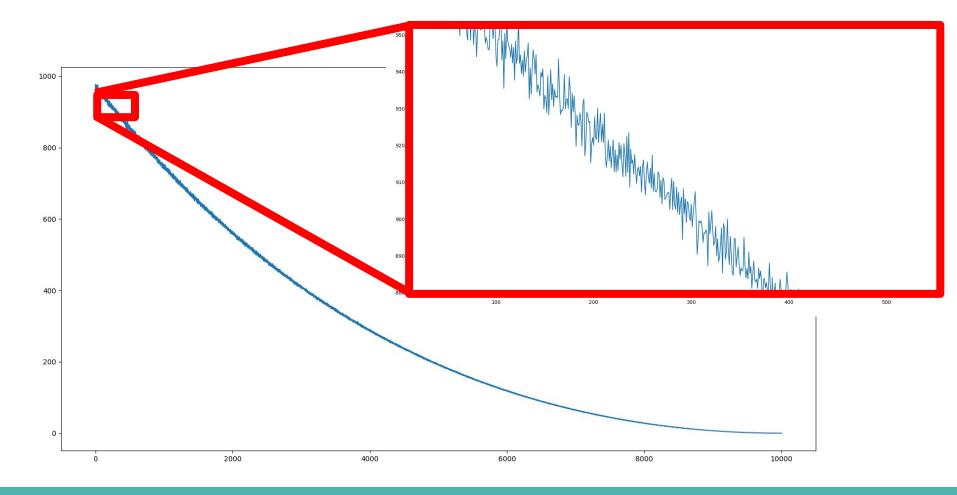
Example of Bonus 2/3

- Perturb each parameter randomly within a small range and plot the resulting loss.
- Scale differences between parameters are significant.



Example of Bonus 3/3

Plot the error surface between start and end point.



Allow Packages

- python 3.6
- TensorFlow r1.6
- PyTorch 0.3 / torchvision
- Keras 2.0.7 (TensorFlow backend only)
- MXNet 1.1.0
- CNTK 2.4
- matplotlib
- scikit-learn 0.19.1
- Python Standard Library
- If you want to use other packages, please ask TAs for permission first!

Submission

- Deadline: 2018/4/6 23:59 (GMT+8)
- Write the questions of HW1-1, HW1-2 and HW1-3 in **one** report.
- Chinese unless you are not familiar with Chinese
- At most 10 pages for HW1-1, HW1-2 and HW1-3
- Your github must have several files under directory hw1/
 - Readme.*
 - Report.pdf
 - other code
- In your Readme, state clearly how to run your program to generate the results in your report.
- Files for training is required.

Q&A

ntu.mldsta@gmail.com