

# Teacher-Student Learning

Eric He



## Who is this guy?

- My name is Eric He
- Third-year student at NYU
- Grew up in Bay Area, Evergreen Valley High School
- Wanted to do marketing, now studying mathematics and data science
- Strong interest in explanatory modeling



## What is Teacher-Student Learning?

- An alternative method of training neural nets
- Normal loss functions penalize deviation of student model from the ground truth label
- Teacher-Student loss penalizes deviation of student model from the teacher's predictions, or soft labels

	Panther	Cat	Truck	Goose
Ground Truth	1	0	0	0
Soft Labels	0.7	0.28	0.015	0.005



Dark Knowledge: A panther is more like a cat than a truck or a goose



## Potential of Teacher-Student Learning

- Data flexibility
  - May not need to expend resources to label training data
  - Customers do not need to hand over proprietary data used to train models
- Model compression
  - train a smaller model for deployment
- Model diversity
  - Different architectures learn different features, which can all be transferred onto the student model



### Infrastructure

Machine Learning





#### Hardware







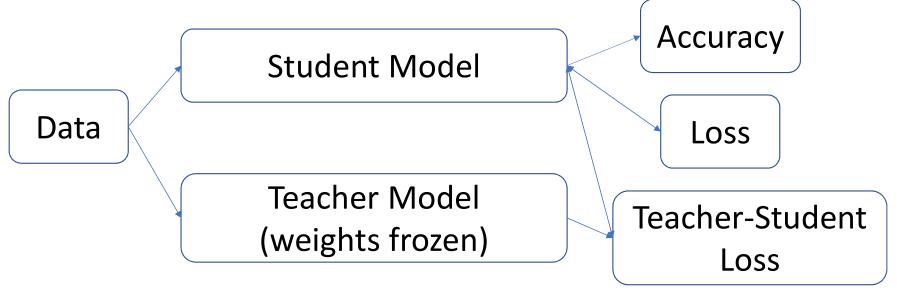
#### **Graphics**







## Setting up Teacher-Student Modeling



Method: Stack both teacher and student models into one .prototxt file Problems: Highly memory intensive, both models require same data dimensions

 Batch size of 20 with AlexNet teacher and VGG16 student takes 12 GB of GPU memory



### Three Performance Metrics

Accuracy

Proportion of predicted top1 labels in concordance with the true labels

Loss

Sum of softmax crossentropy scores between studentgenerated probability distributions and true labels **Teacher-Student Loss** 

Sum of softmax crossentropy scores between student and teacher-generated probability distributions

**Cross Entropy Loss** 

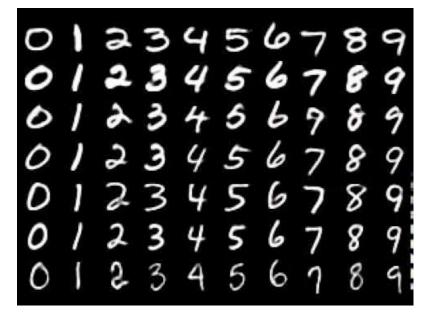
$$\mathcal{L}(y, \hat{y}) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

For the purposes of visualization, Loss and Teacher-Student Loss are graphed as percentages of their maximum.



#### **MNIST**

- 60000 training images
- 20 x 20 x 1 (grayscale)
- 10 categories



#### CIFAR10

- 60000 training images
- 32 x 32 x 3 (color)
- 10 categories

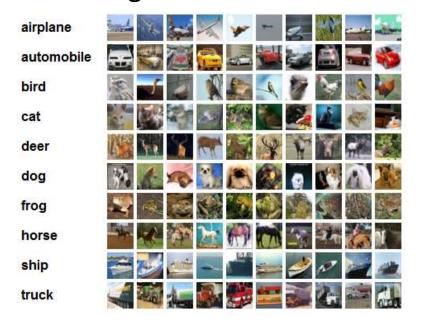
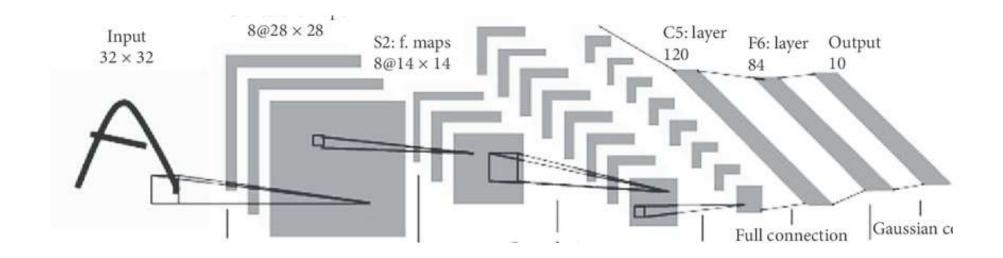


Image sources: https://github.com/cazala/mnist, http://karpathy.github.io/2011/04/27/manually-classifying-cifar10/

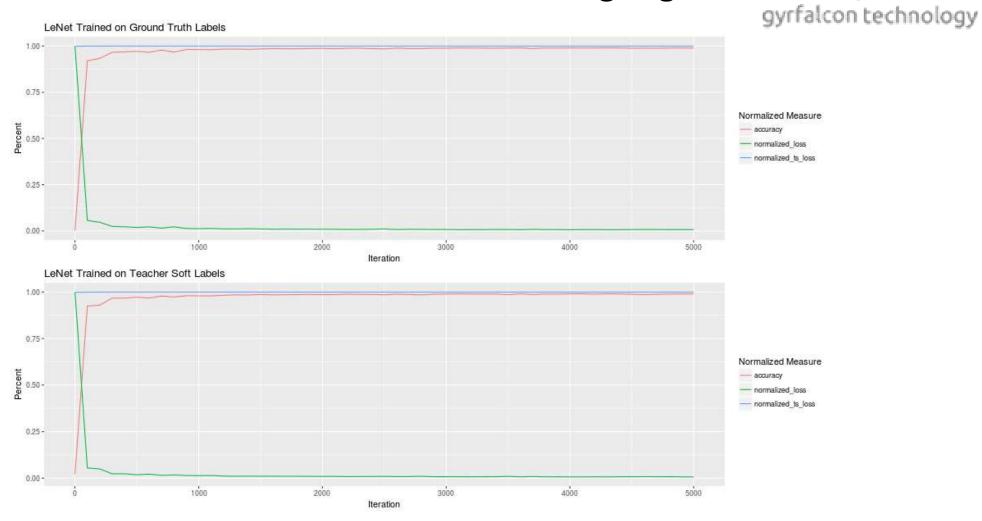


### LeNet Structure



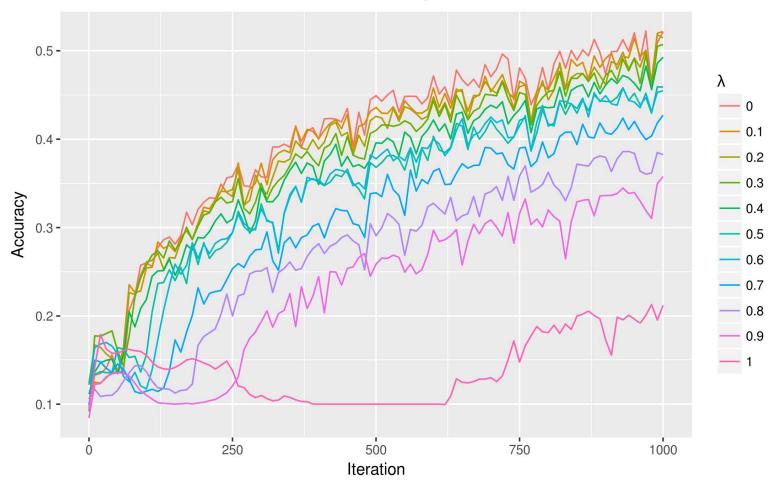
 $Image\ source: https://www.researchgate.net/figure/303857877\_fig1\_Figure-1-Architecture-of-CNN-by-LeCun-et-al-LeNet-5-1-Architecture-of-CNN-by-LeCun-et-al$ 

## No obvious differences between training regimes



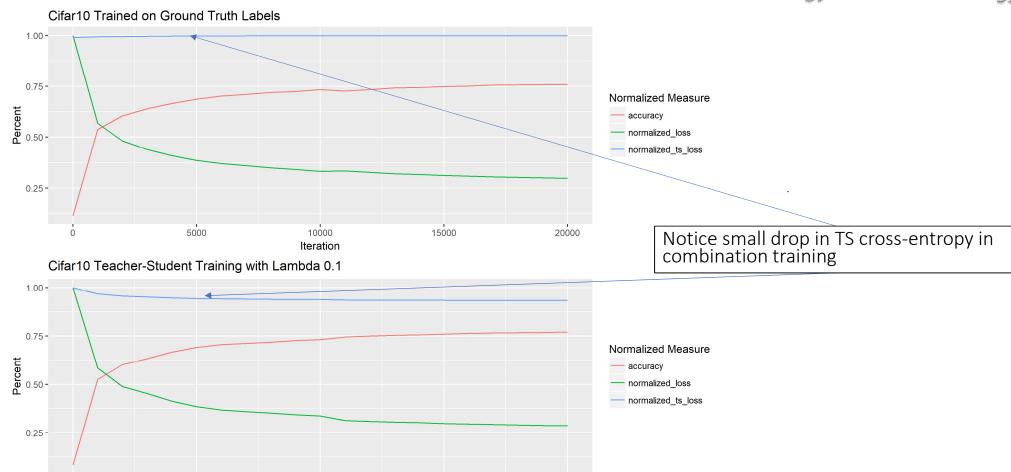


## Soft labels slow training on MNIST!



# Combination Training works on CIFAR10 as well gyrfalcon technology

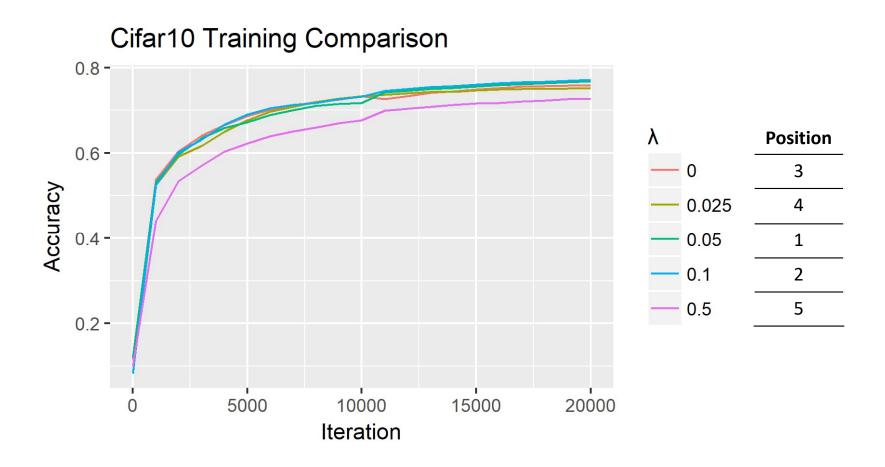




Iteration



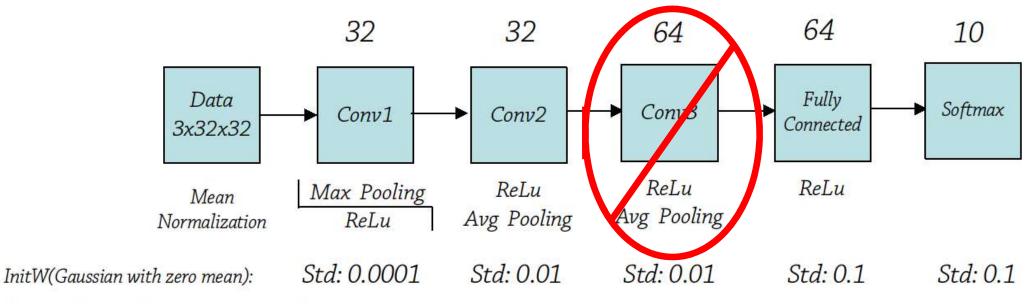
In fact, low-weighted soft labels are faster for early epochs gyrfalcon technology





### What about a smaller student model?

Cifar-10 Fast Model(5 epochs with 25% Validation Error Rate)

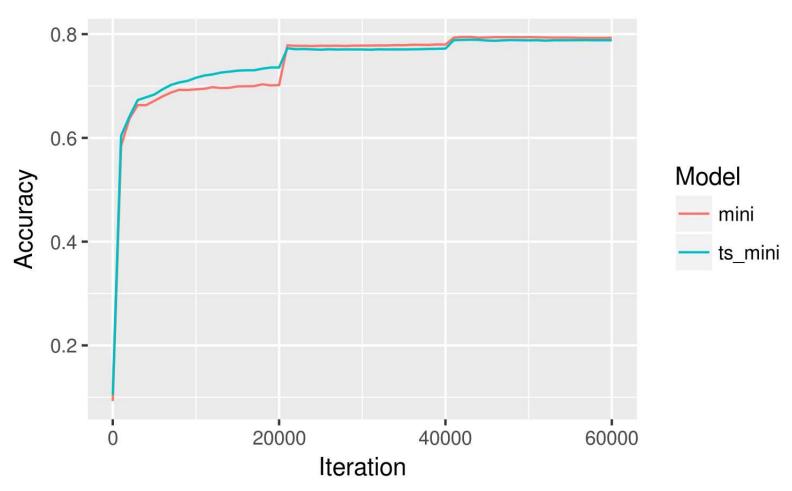


Notes: All Convs Padding: 2 Kernel: 5 / All Poolings Overlapping (Kernel: 3 Stride: 2)

Image source: http://www.cnblogs.com/yymn/p/4589133.html

## Training is faster for early epochs, but plateaus earlier







### Conclusions

- Teacher-Student training IS possible!
- In combination with hard labels, soft labels appear to be a training speedup for larger datasets, slowdown for smaller datasets
- Student model is unable to make close approximation of teacher decision surface
  - Student-teacher cross-entropy remains large despite classification accuracies being about the same
  - Student and teacher models do not learn features the same way!



## Looking forward

- Bigger datasets; ImageNet
  - Two of three months of the internship was spent trying and failing to make VGG16 model converge.
  - Teacher-Student training question remains unresolved for big datasets, where its potential is largest
- Best temperature for teacher soft labels?
  - A lower temperature raises the top1 probability of soft label towards 1 and decreases other class label probabilities towards 0
    - Makes teacher soft label more like hard label
  - A higher temperature makes all class probabilities closer to each other
    - Teacher models with low top1 accuracy but high top5 accuracy will be more informative
- Better loss function?
  - Cross-entropy is combination of entropy and KL-divergence
  - KL-divergence measures "distance" between two probability distributions
  - Paper-recommended loss function uses only KL-divergence for TS training

Questions?