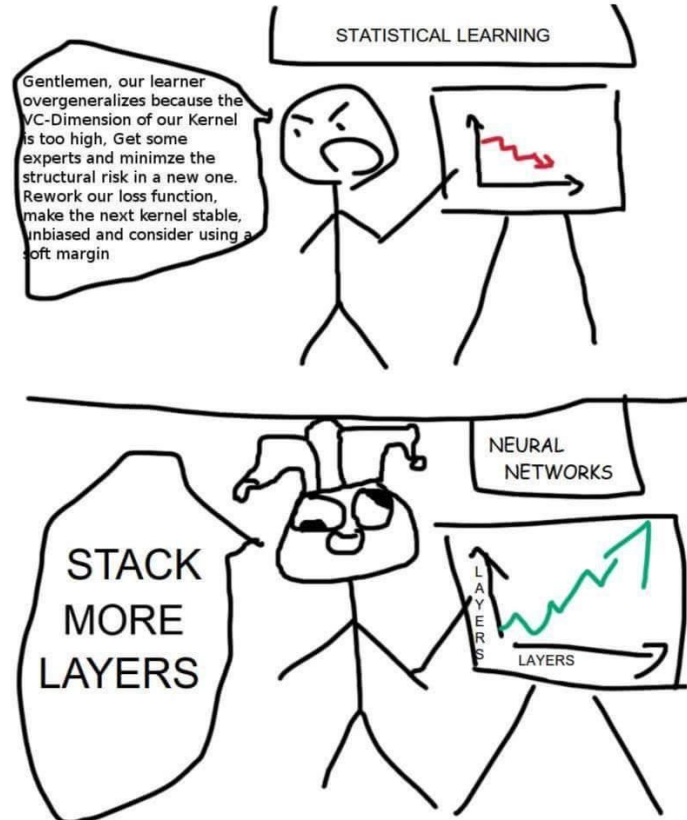


# Tips and tricks for tuning NNs

Apr 20  
Fei & Nish

# Tuning NNs can be a dark art



# When NNs don't work, you have many choices

Your choices: (from Andrew Ng's talk at Bay Learn'17)

- *Fetch more data*
- *Add more layers to Neural Network*
- *Try some new approach in Neural Network*
- *Train longer (increase the number of iterations)*
- *Change batch size*
- *Try Regularization*
- *Check Bias Variance trade-off to avoid under and overfitting*
- *Use more GPUs for faster computation*
- *...*

How to systematically attempt to fix a NN?

# Abstraction of hyperparameter tuning

Your input : Hyper parameters

- Architecture (#layers, #kernels, stride, kernel size)
- Learning rate, optimizer (momentum)
- Regularizations (weight decay rate, dropout probability)
- Batchnorm / no batchnorm

Your output: Some diagnostic statistics:

- Loss curves
- Gradient norms
- Accuracy / Visual output (generative models)
- Performance on training vs validation set
- Other abnormal behaviors

# Architecture

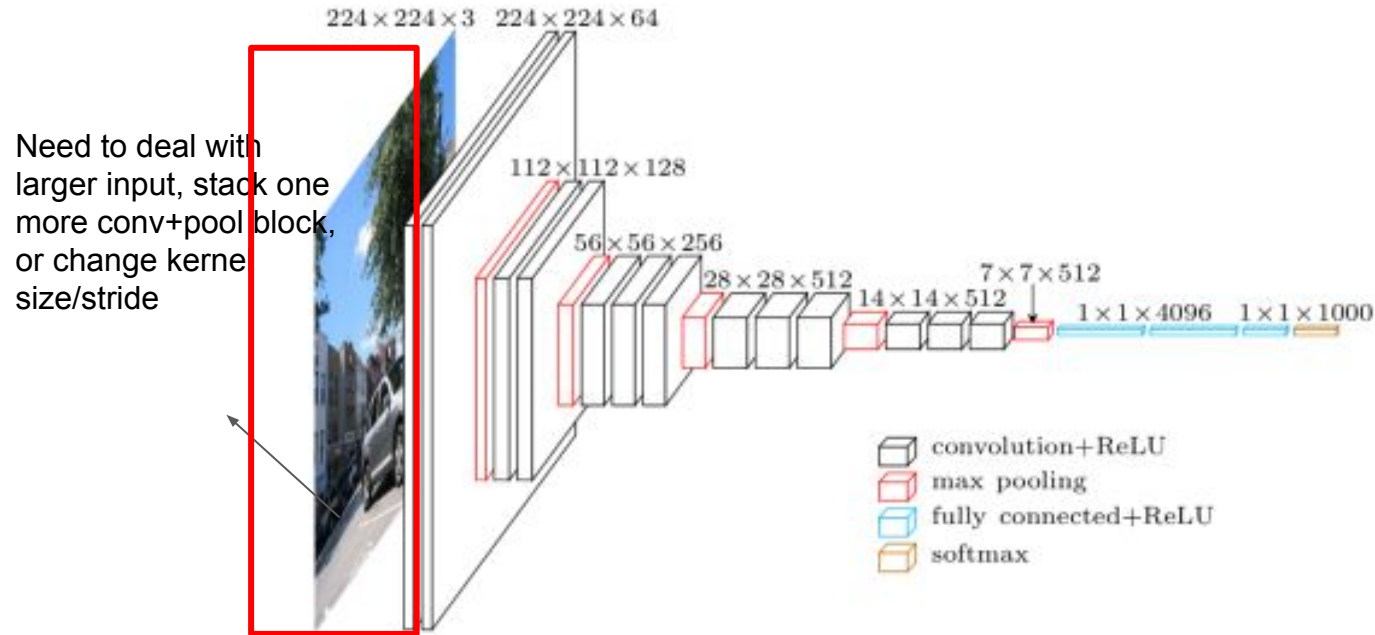
Using or adapt from established networks (will see more later this quarter)

- Classification: AlexNet, VGG, ResNet, DenseNet, ...
- Segmentation: FCN, Dilated Convolution, Mask RCNN
- Detection: Faster-RCNN, YOLO, SSD
- Image Generation: UNet, Dilated Convolution, DCGAN, WGAN
- ...

How to adapt:

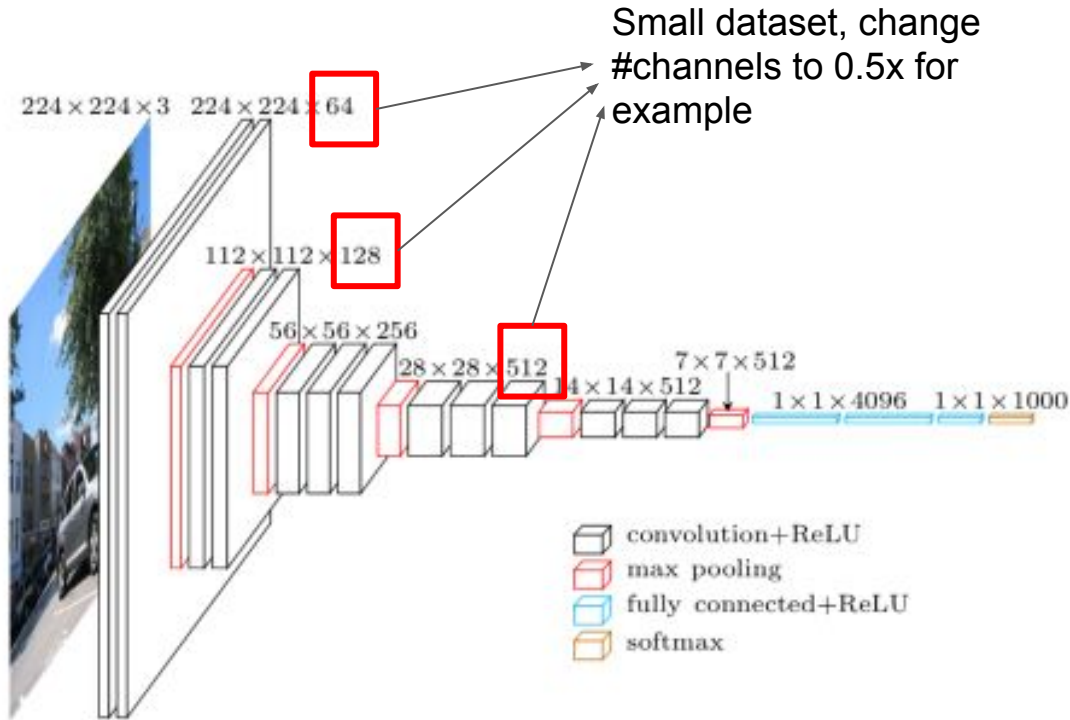
- Change number of kernels to ideal numbers
- Remove / add layers
- Change the structure of last few layers for your task

# Architecture: adapt to different input



Let's say you saw this awesome network on some related work, but the input is not the same.

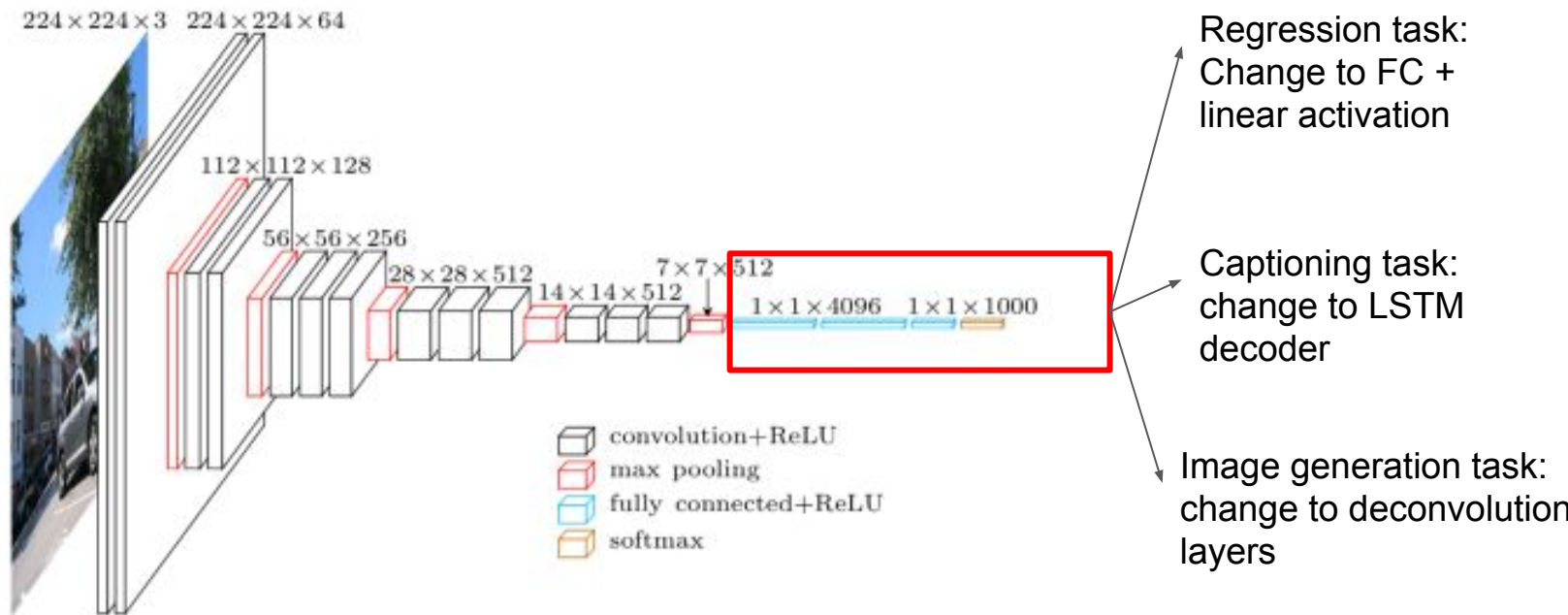
# Architecture: for different size of dataset



Let's say you saw this awesome network on some related work, but the dataset you have is much smaller



# Architecture: for tasks



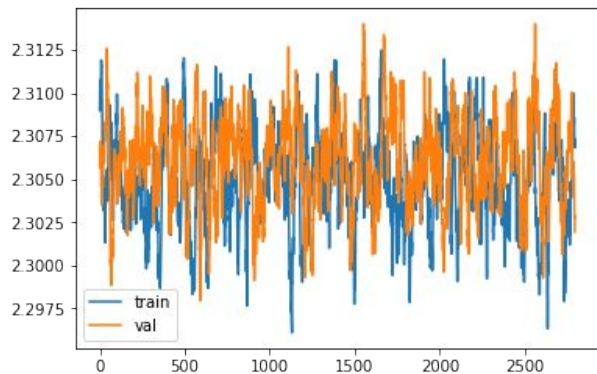
Let's say you saw this awesome network on some related work, but the task is not the same.

# Fast iteration

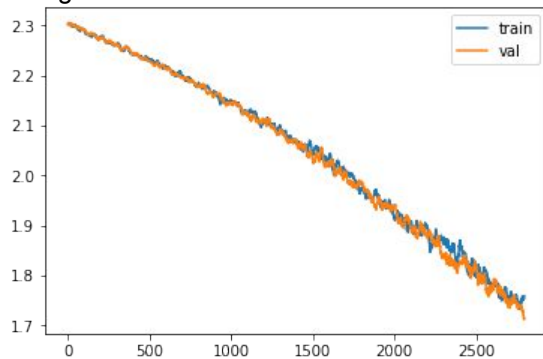
1. When tuning parameters, only use a small portion of the dataset for fast iteration.
2. Start from a larger learning rate for fast prototyping.

```
Class YourAwesomeDataset(torch.data.Dataset):  
  
    def __init__(root_dir, debug=False):  
  
        ...  
  
        if debug:  
  
            train_files = train_files[:len(train_files)//10]  
  
            val_files = val_files[:len(val_files)//10]
```

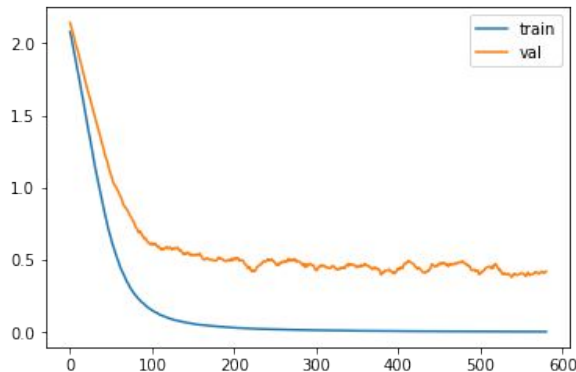
# Loss curves: what are the problems?



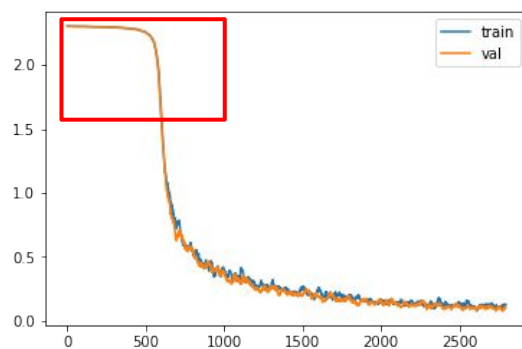
Not learning: gradients not applied to weights



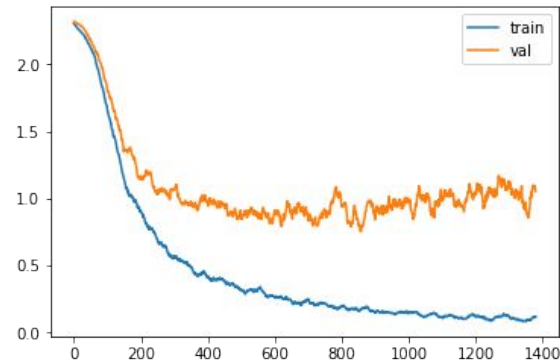
Not converged yet: need longer training



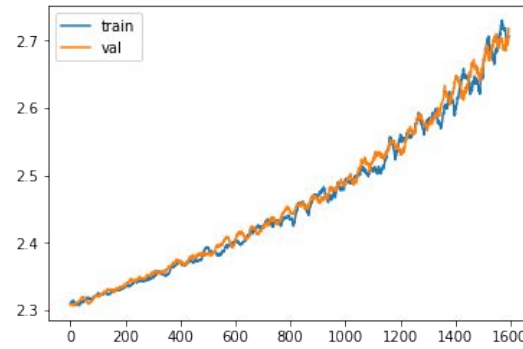
Overfit: model too large/dataset too small  
slow start



Slow start: initialization weights too small

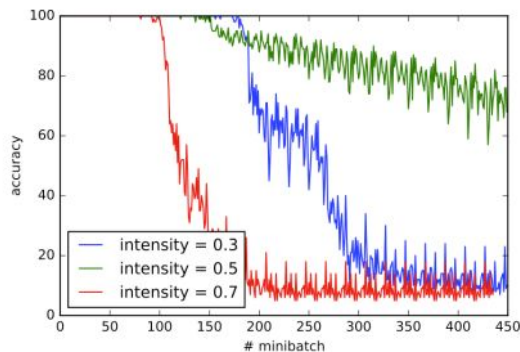


More extreme case of overfitting

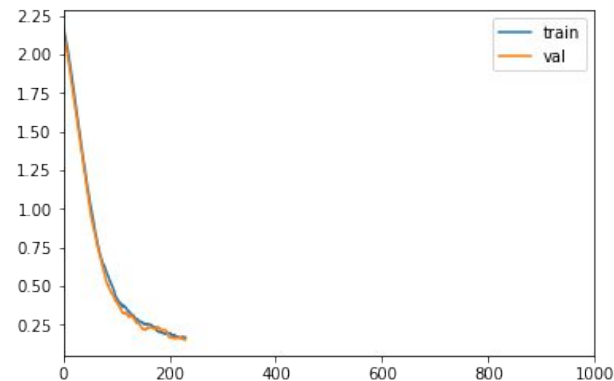
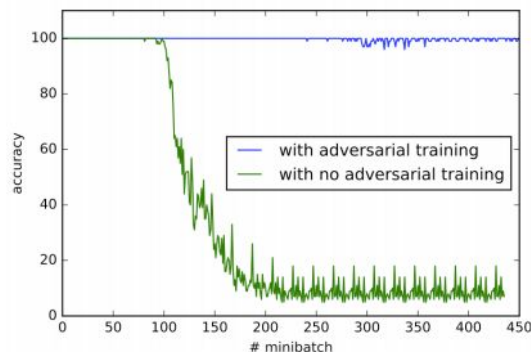


Applied the negative of gradients

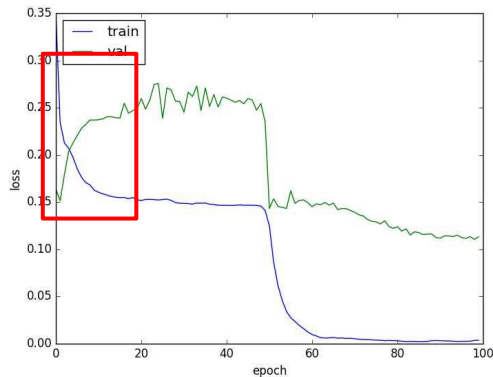
# Loss curves: more examples (or more epic fails)



Problem: Not shuffling data, periodical patterns in loss curve

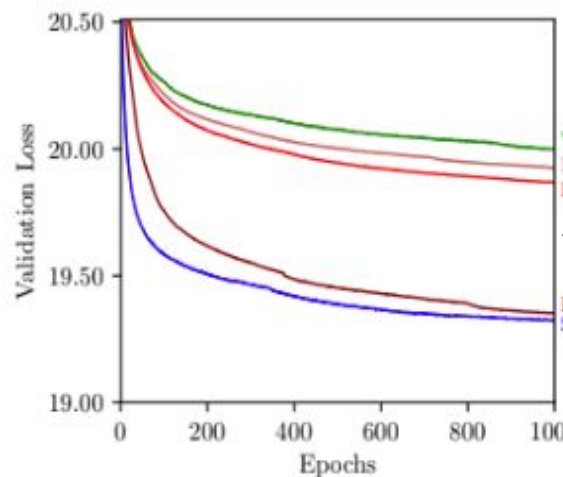


Get nans in the loss after a number of iterations: caused by numerical instability in models

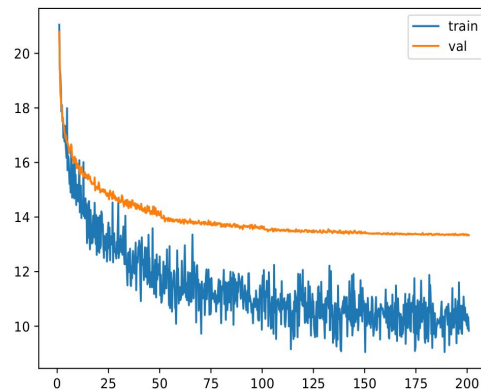


Problem: val set too small, statistics not meaningful

# Loss curves: more examples



Problem: applied nonlinear  
activation before softmax



Make sure to optimize correct loss

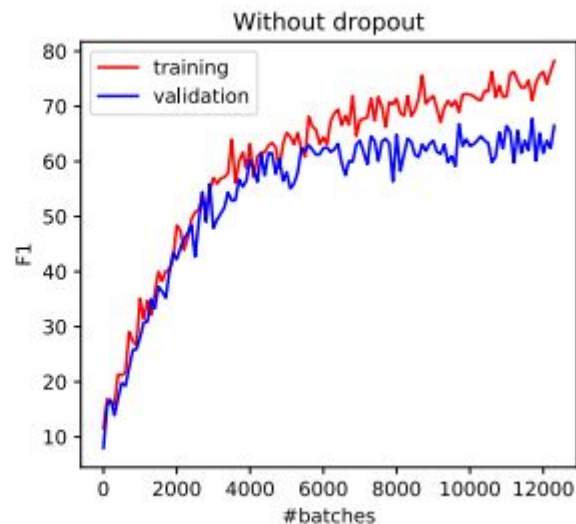
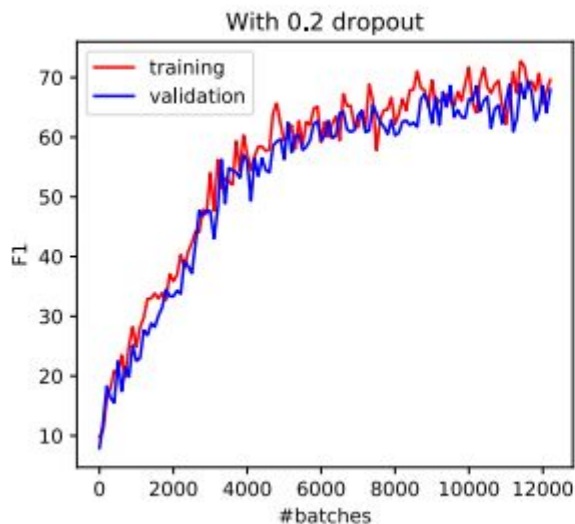
$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^k e^{z_k}} \text{ for } j = 1, \dots, k$$

# Summary

- Loss curve is one powerful indicator when debugging NNs
- Abnormal loss curves can be caused by
  - Wrong implementation of data loading
  - Wrong implementation/choice of losses
  - Optimizer problems
  - Suboptimal hyper-parameters
- Some back of the envelope calculation can help:
  - What do you expect the loss to start at?
  - What do you expect the loss to converge to?
  - Any ideas of how many iterations are required?

# Regularization

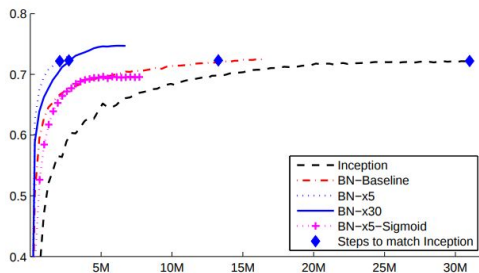
Dropout, weight decay, use a smaller model



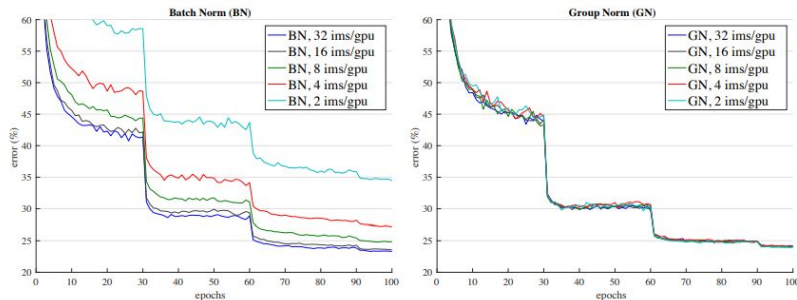
Tip: try overfit first, then try to close the gap between train and val.

# Normalization

- You will explore in PS2
- Trains faster
- Robust to initializations
- Remember to do change to evaluation mode at testing time `model.eval()`



Batch normalization



Group normalization



# Generative models

- Looking at loss curves is still insightful
- Looking at visual output for pathological issues
  - Grid patterns
  - Blurry output
  - Inductive bias
  - ...

Examples:



# Generative models: useful references

<https://github.com/soumith/ganhacks>

<https://distill.pub/2016/deconv-checkerboard/>



# Live code

Let's try training a neural network on a chest xray dataset!