CPSC 340:
Machine Learning and Data Mining

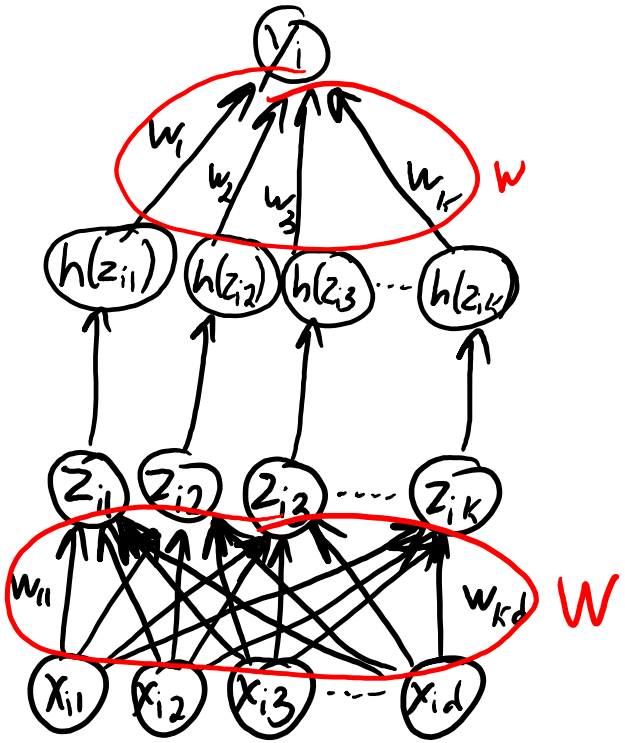
Deep Learning

Admin

- Tutorials
  - Tutorials this week have been turned into office hours (Bita).
  - You can go to any of them, doesn't have to be the one you're registered in.
  - My office hours this week are Friday after class.
- Assignment 5:
  - Due Friday.
- Assignment 6:
  - Out this week.
  - Due next Friday.
  - If you want to work with a partner, open the issue asap.

Last Time: Deep Learning

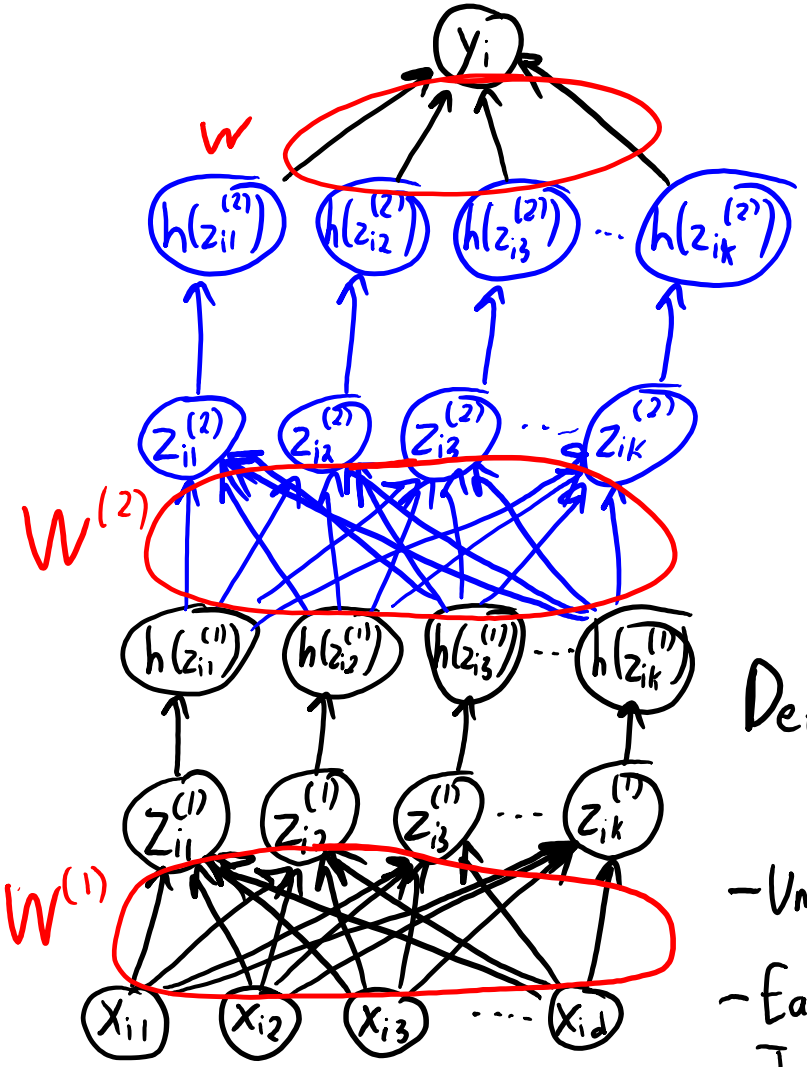
Neural network:



$$y_i = w^T h(Wx_i)$$

Learn 'W' and 'w' together.

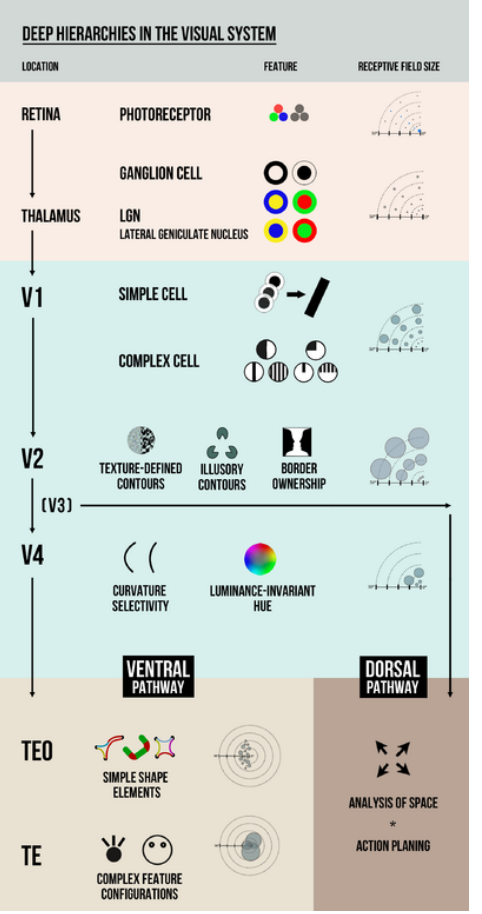
- Learn features for supervised learning.
- Non-linear 'h' makes it a universal approximator for large 'K'



Deep neural networks:

$$y_i = w^T h(W^{(2)} h(W^{(1)} x_i))$$

- Unprecedented performance on difficult problems.
- Each layer combines "parts" from previous layer.
- Train all layers together.
- Multiple layers allow more "efficient" representations



Artificial Neural Networks

- With squared loss, our objective function is:

$$f(w, W) = \frac{1}{2} \sum_{i=1}^{n} (w^T h(Wx_i) - y_i)^2$$

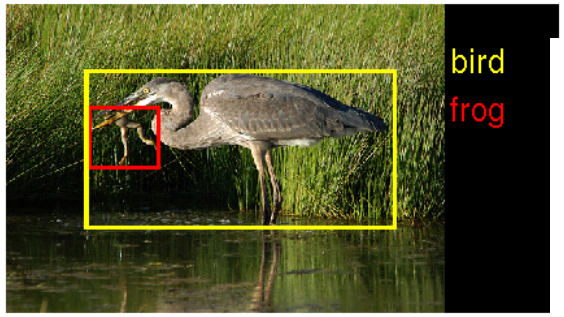
- At each unit we add a bias variable explicitly/implicitly like with OLS
- Usual training procedure: stochastic gradient.
  - Compute gradient of random example 'i', update both 'w' and 'W'.
  - Highly non-convex and can be difficult to tune.
- Computing the gradient is known as "backpropagation".
  - This is basically the chain rule applied backwards through the layers.
  - We do some careful book-keeping to avoid re-computing quantities
    - Sort of like dynamic programming

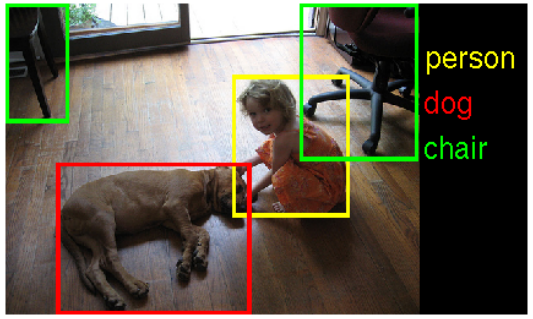
Backpropagation derivations

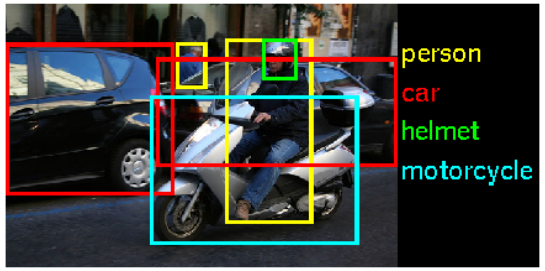
- I am skipping the detailed derivations
  - I think it'd be very hard to follow/digest them at our breakneck lecture pace
  - I prefer to spend lectures on high-level ideas
- Some people disagree with me on skipping this material
    - https://medium.com/@karpathy/yes-you-should-understand-backprop-e2f06eab496b
- I agree it's useful to know, but me teaching ≠ student knowing
  - I have plenty of personal experience with this as a student ☺
  - And we have limited time.
- Hopefully this slide is a good compromise
  - "Knowing what you don't know"
- You can read about it on your own if you're interested.
  - Bonus slides and many free online resources.

Application: ImageNet Challenge

- Millions of labeled images, 1000 object classes.







Easy for humans but hard for computers.

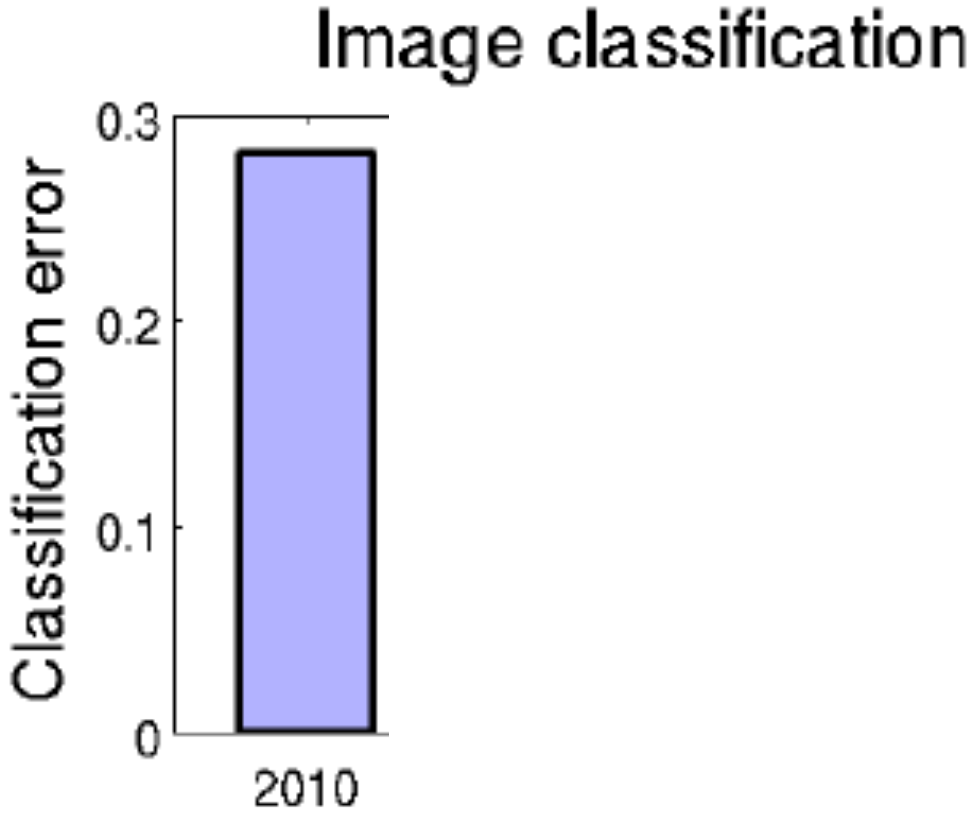
http://www.image-net.org/challenges/LSVRC/2014/

ImageNet Challenge

- Object detection task:
  - Single label per image.
  - Humans: ~5% error.

(a) Siberian husky

(b) Eskimo dog



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http://arxiv.org/pdf/1409.0575v3.pdf
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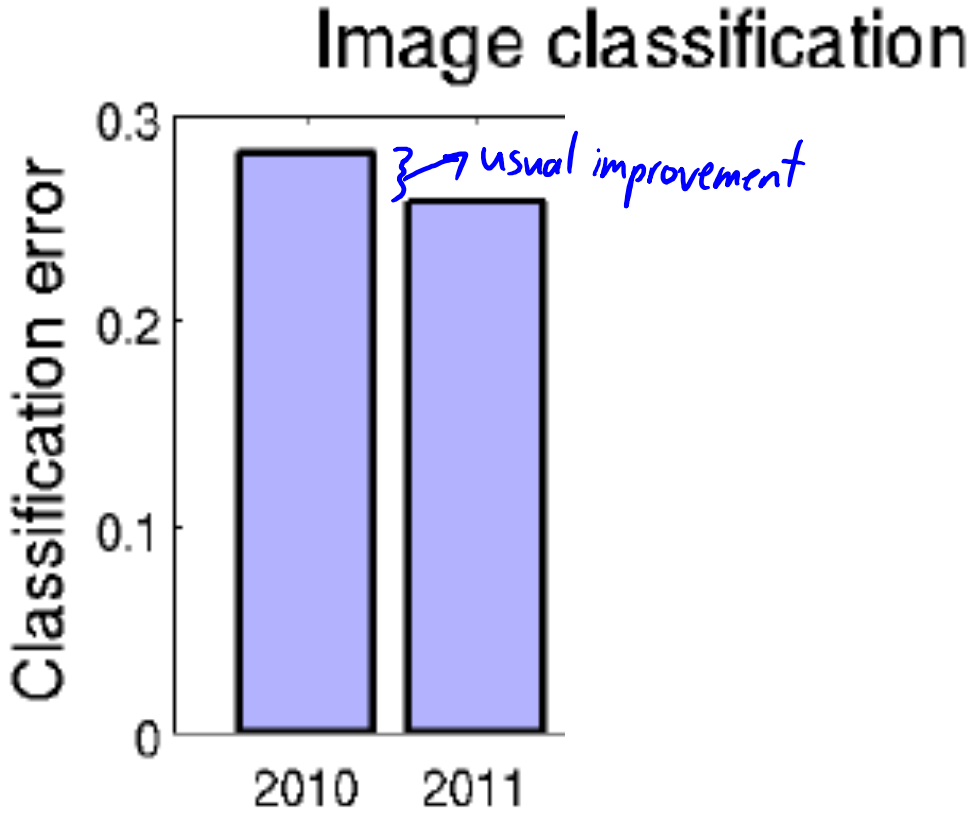

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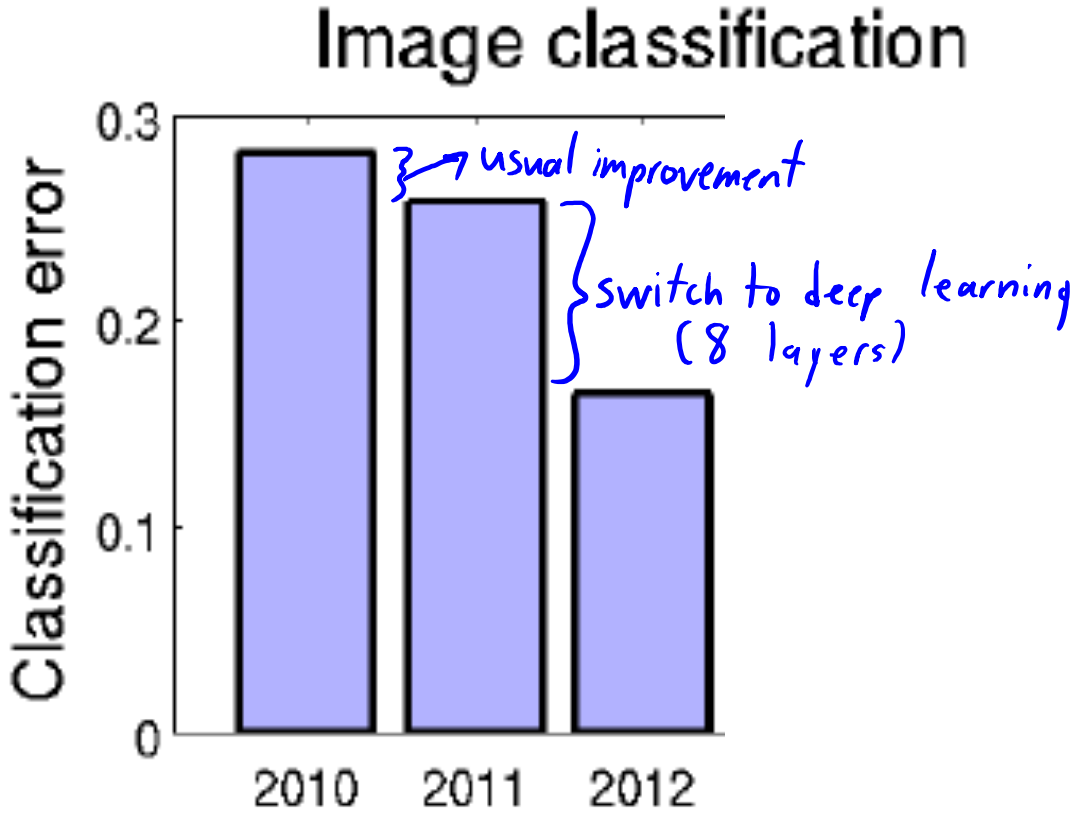

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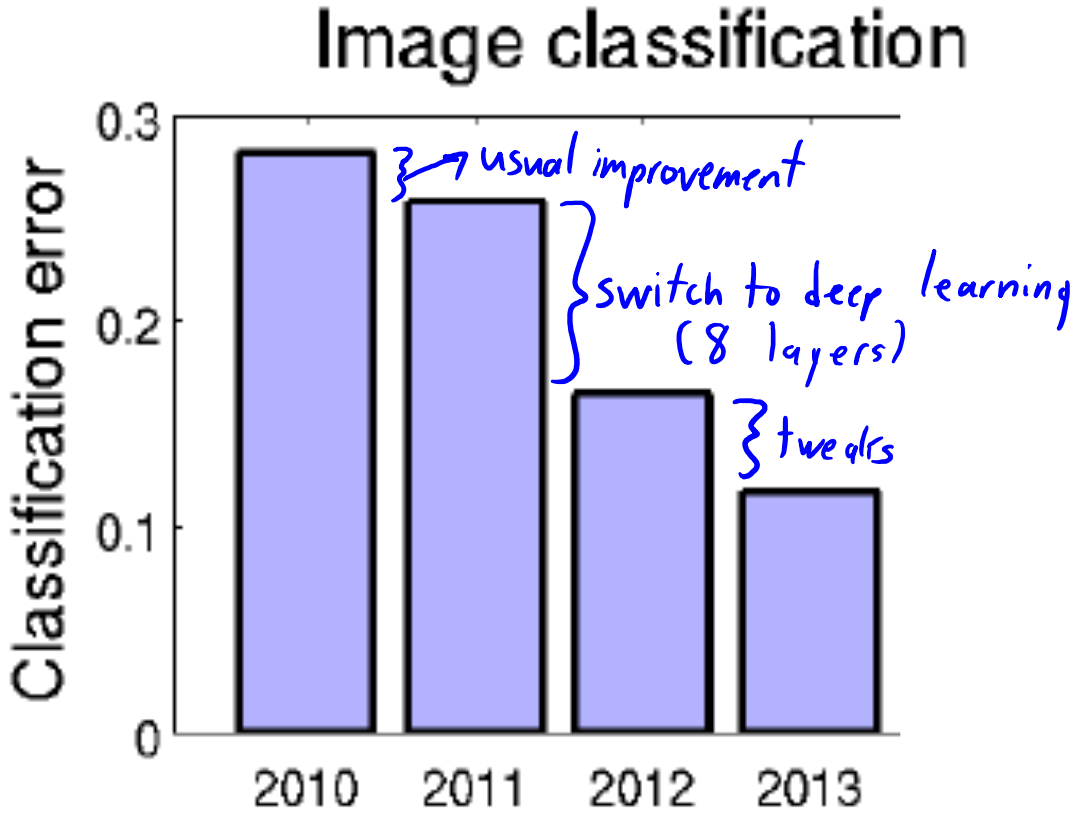

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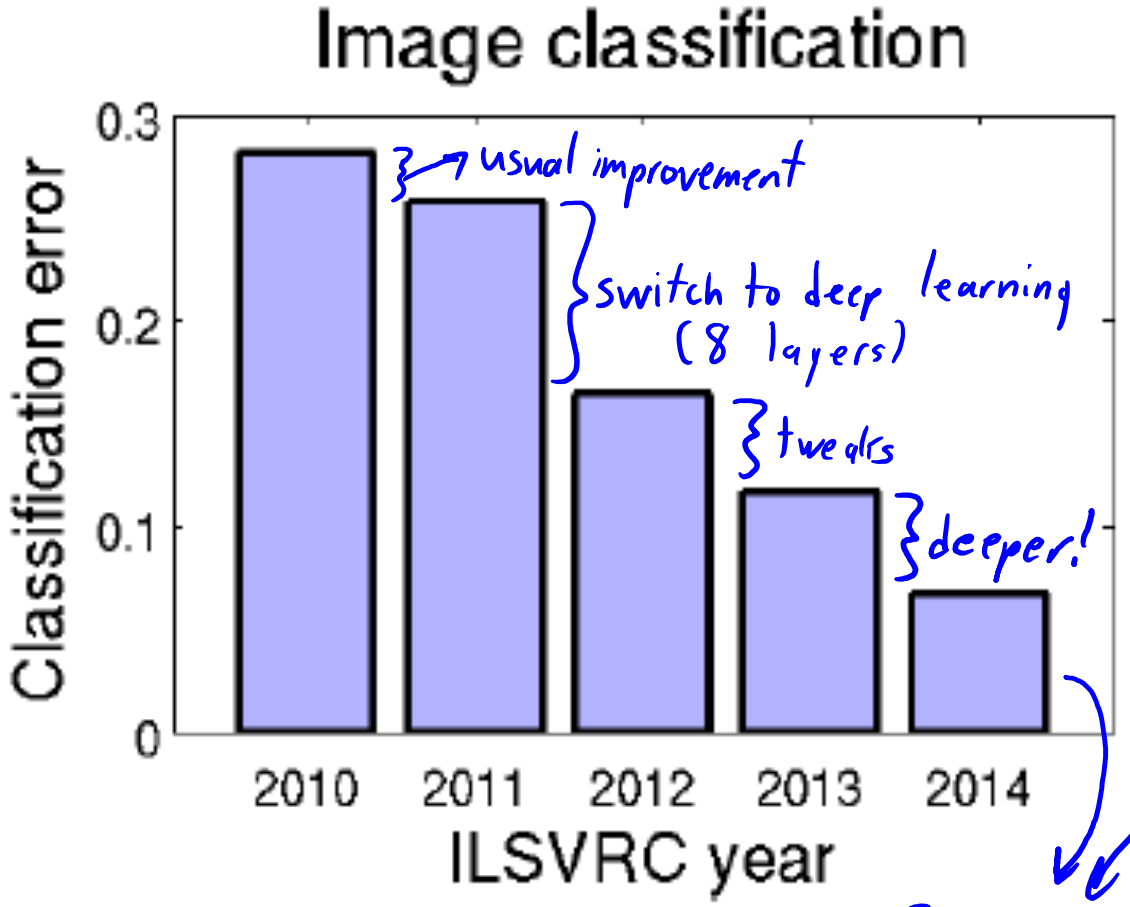

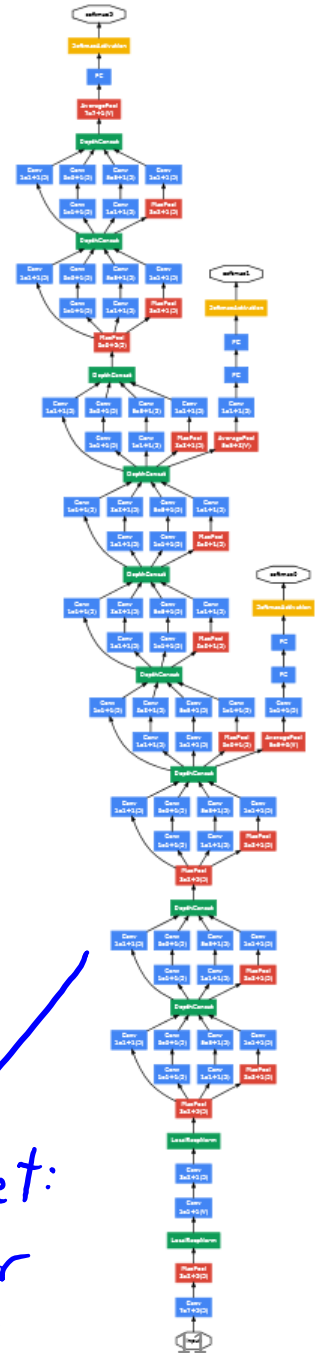

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ImageNet Challenge

- Object detection task:
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  - Humans: ~5% error.

(a) Siberian husky

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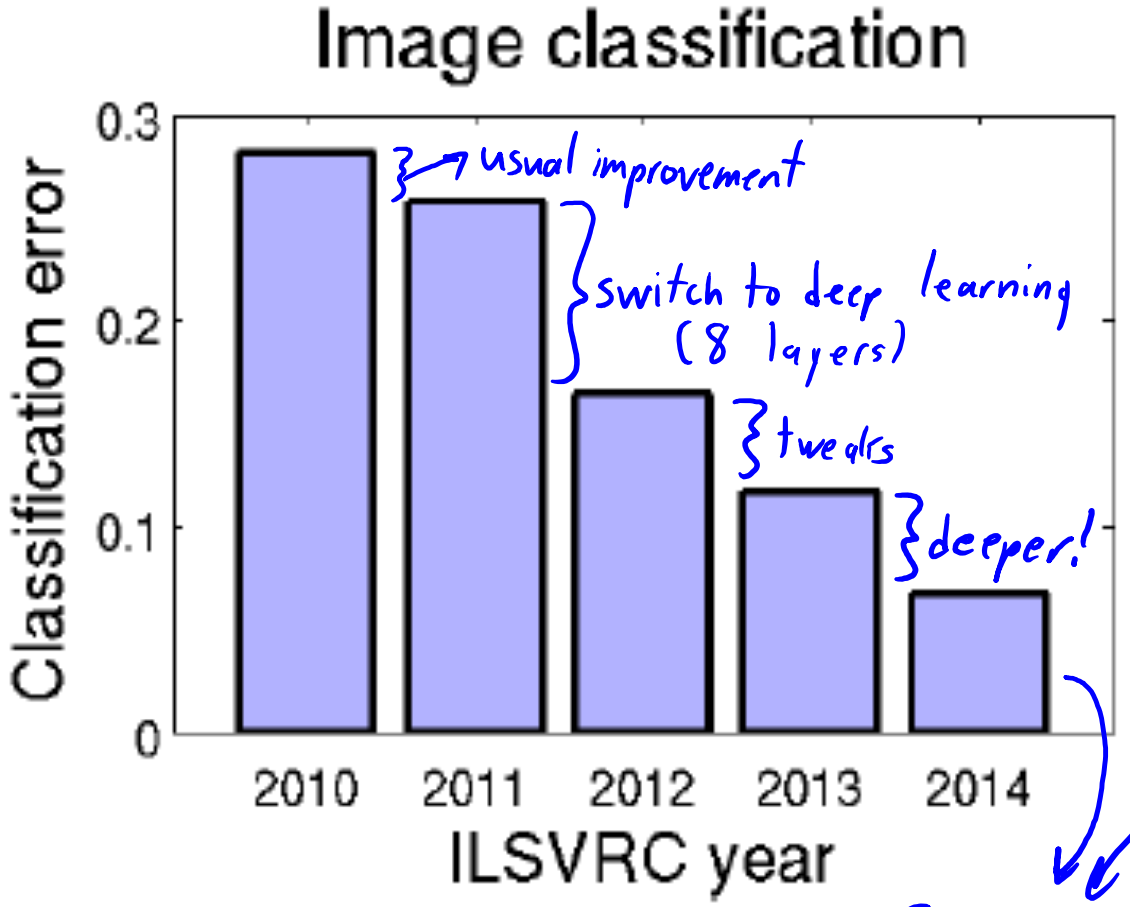
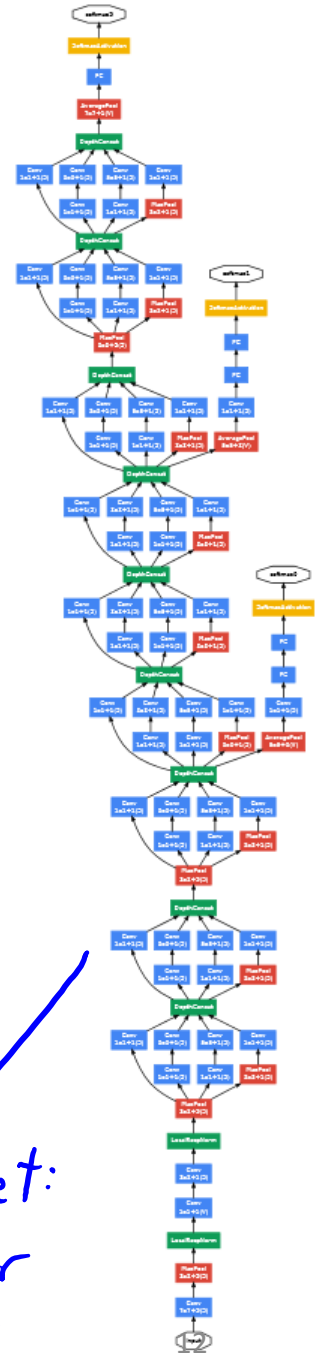
- 2015 winner: Microsoft
  - 3.6% error.
  - 152 layers.





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ImageNet Challenge

- ImageNet challenge:
  - Use millions of images to recognize 1000 objects.
- ImageNet organizer visited UBC summer 2015.
- "Besides huge dataset/model/cluster, what is the most important?"
  1. Image transformations (translation, rotation, scaling, lighting, etc.).
  2. Optimization.
- Why would optimization be so important?
  - Neural network objectives are highly non-convex (and worse with depth).
  - Optimization has huge influence on quality of model.
  - Bad optimization → underfitting
    - (and what about good optimization? Coming up in a few minutes…)

Stochastic Gradient Training

- Standard training method is stochastic gradient (SG, lecture 20):
  - Choose a random example 'i'.
  - Use backpropagation to get gradient with respect to all parameters.
  - Take a small step in the negative gradient direction.
- Challenging to make SG work:
  - Often doesn't work as a "black box" learning algorithm.
  - But people have developed a lot of tricks/modifications to make it work.
- Highly non-convex, so is the problem local minima?
  - Some empirical/theoretical evidence that local minima are not the problem.
  - If the network is "deep" and "wide" enough, we think all local minima are good.
  - But it can be hard to get SG to even find a local minimum.

Parameter Initialization

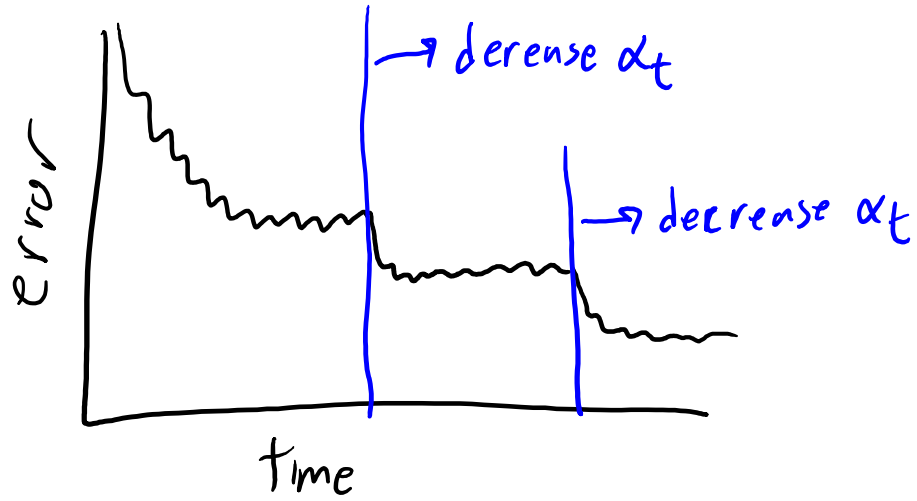
- Parameter initialization is crucial:
  - Can't initialize weights in same layer to same value, or they will stay same.
  - Can't initialize weights too large, it will take too long to learn.
- A traditional random initialization:
  - Initialize bias variables to 0.
  - Sample from standard normal, divided by 10^5 (0.00001*randn).
  - Performing multiple initializations does not seem to be important.
    - Personally, I find this surprising. But it's good news!
- Popular approach from 10 years ago:
  - Initialize with deep unsupervised model (like autoencoders, coming up).

Parameter Initialization

- Parameter initialization is crucial:
  - Can't initialize weights in same layer to same value, or they will stay same.
  - Can't initialize weights too large, it will take too long to learn.
- Also common to standardize data:
  - Subtract mean, divide by standard deviation, "whiten", standardize y_i.
- More recent initializations try to standardize initial z_i:
  - Use different initialization in each layer.
  - Try to make variance of z_i the same across layers.
  - Use samples from standard normal distribution, divide by sqrt(2*nInputs).
  - Use samples from uniform distribution on [-b,b], where $b = \frac{\sqrt{6}}{\sqrt{k^{(m)} + k^{(m-1)}}}$

Setting the Step-Size

- Stochastic gradient is very sensitive to the step size in deep models.
- Common approach: manual "babysitting" of the step-size.
  - Run SG for a while with a fixed step-size.
  - Occasionally measure error and plot progress:



  - If error is not decreasing, decrease step-size.

Setting the Step-Size

- Stochastic gradient is very sensitive to the step size in deep models.
- More automatic method is Bottou trick:
  1. Grab a small set of training examples (maybe 5% of total).
  2. Do a binary search for a step size that works well on them.
  3. Use this step size for a long time (or slowly decrease it from there).

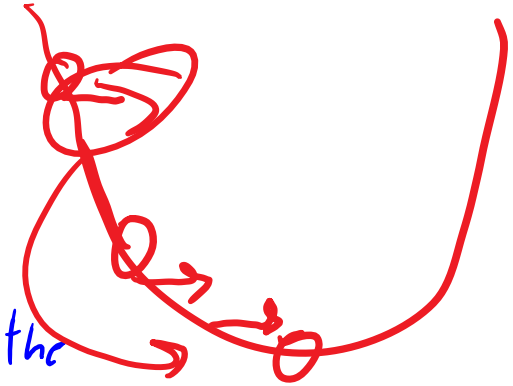
- Several recent methods use a step size for each variable:
  - AdaGrad, RMSprop, Adam.

Setting the Step-Size

- Stochastic gradient is very sensitive to the step size in deep models.
- Bias step-size multiplier: use bigger step-size for the bias variables.
- Momentum:
  - Add term that moves in previous direction:

$$w^{t+1} = w^t - \alpha^t \nabla f_i(w^t) + \beta^t (w^t - w^{t-1})$$

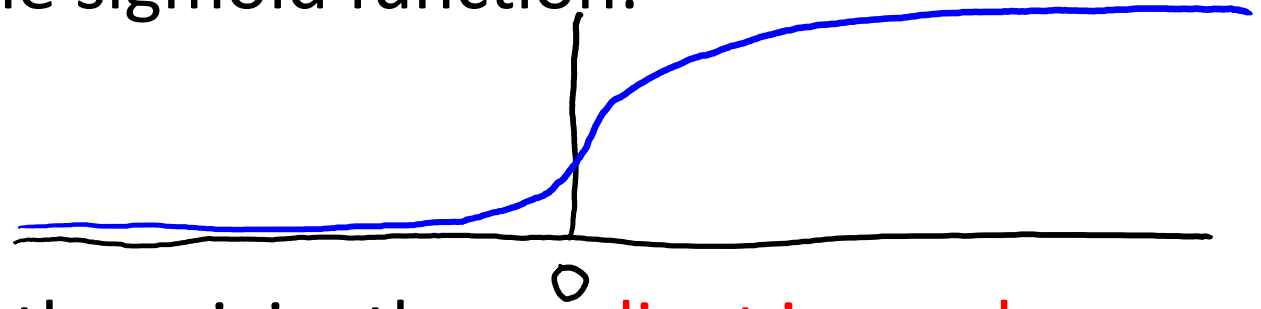
keep going in the old direction



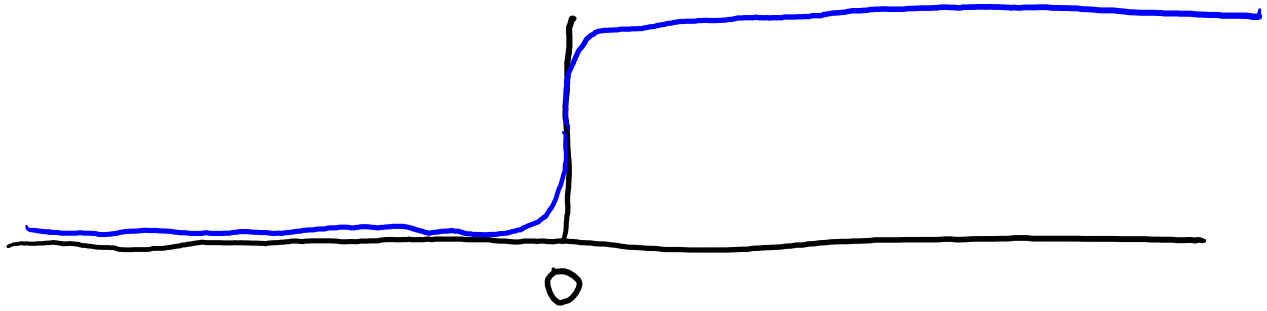
- Batch size (number of random examples) also influences results.
- Another recent trick is batch normalization:
  - Try to "standardize" the hidden units within the random samples as we go.

Vanishing Gradient Problem

- Consider the sigmoid function:



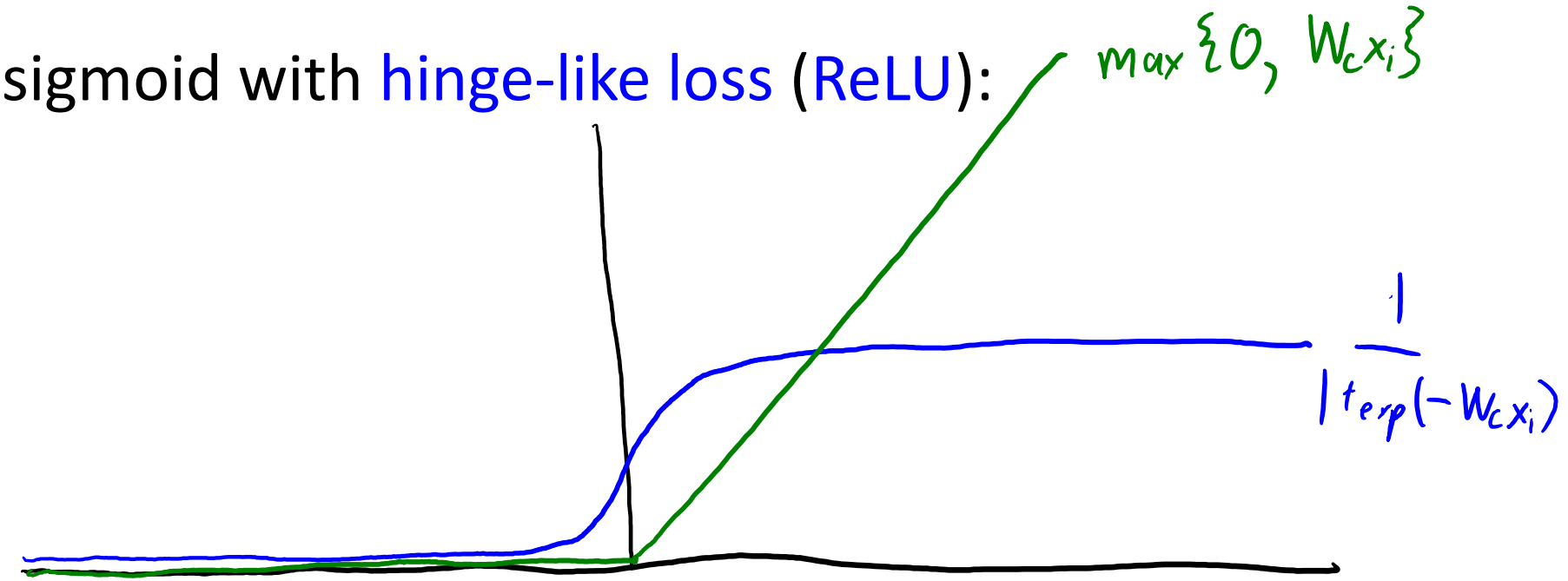
- Away from the origin, the gradient is nearly zero.
- The problem gets worse when you take the sigmoid of a sigmoid:



- In deep networks, many gradients can be nearly zero everywhere.

Rectified Linear Units (ReLU)

- Replace sigmoid with hinge-like loss (ReLU):



- The gradient is zero or x_i, depending on the sign.
  - Fixes vanishing gradient problem.
  - Gives sparser of activations.
  - Not really simulating binary signal, but could be simulating rate coding.

Deep Learning and the Fundamental Trade-Off

- Neural networks are subject to the fundamental trade-off:
  - As we increase the depth, training error decreases.
  - As we increase the depth, training error no longer approximates test error.

- We want deep networks to model highly non-linear data.
  - But increasing the depth leads to overfitting.

- How could GoogLeNet use 22 layers?
  - Many forms of regularization and keeping model complexity under control.

Standard Regularization

- We typically add our usual L2-regularizers:

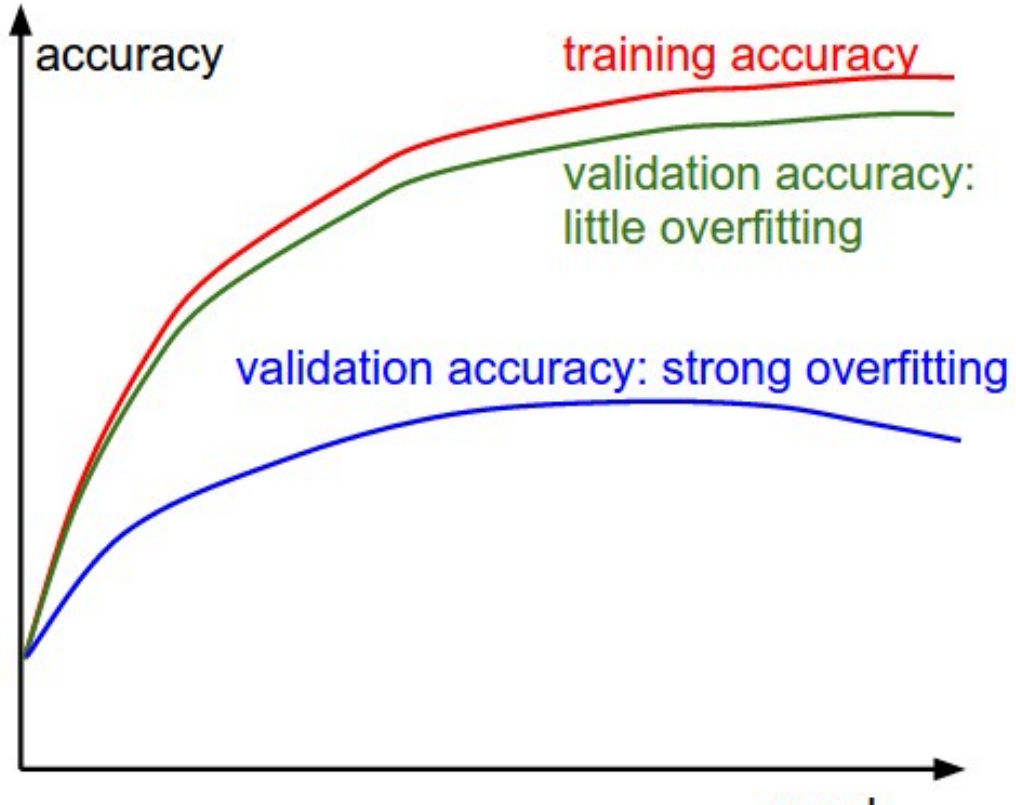
$$f(w, W^{(3)}, W^{(2)}, W^{(1)}) = \frac{1}{2}\sum_{i=1}^{n}(w^T h(W^{(3)} h(W^{(2)} h(W^{(1)} x_i))) - y_i)^2 + \frac{\lambda_4}{2}\|w\|^2 + \frac{\lambda_3}{2}\|W^{(3)}\|_F^2 + \frac{\lambda_2}{2}\|W^{(2)}\|_F^2 + \frac{\lambda_1}{2}\|W^{(1)}\|_F^2$$

- L2-regularization is called "weight decay" in neural network papers.
  - Could also use L1-regularization.
- "Hyper-parameter" optimization:
  - Try to optimize validation error in terms of λ_1, λ_2, λ_3, λ_4.

- Unlike linear models, typically use multiple types of regularization.

Early Stopping

- Second common type of regularization is "early stopping":
  - Monitor the validation error as we run stochastic gradient.
  - Stop the algorithm if validation error starts increasing.



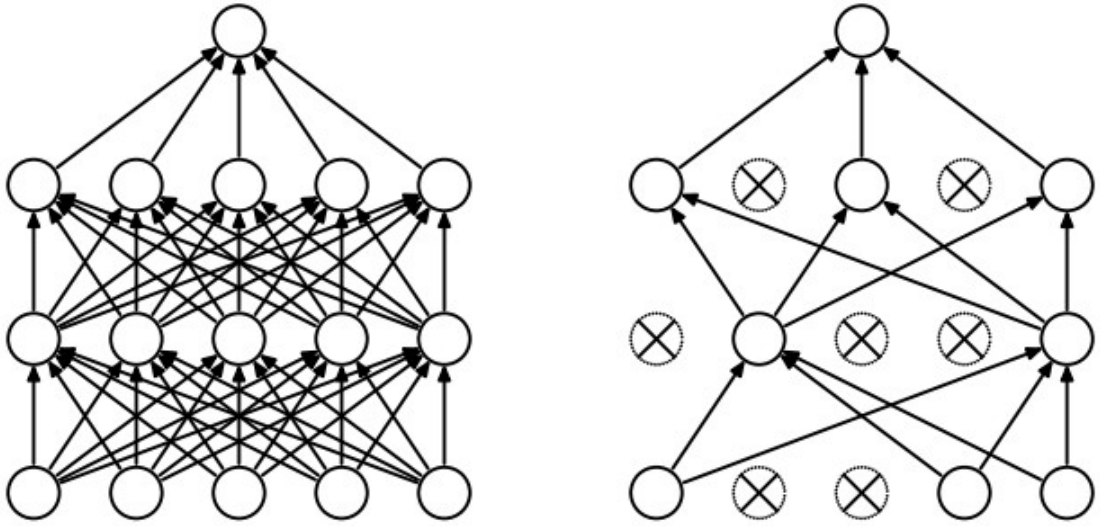
http://cs231n.github.io/neural-networks-3/

Early stopping

- Philosophical debate: do you want the modeling and optimization to be completely decoupled?
  - If they were, we could take the best optimization software and apply it to our model.
  - Early stopping violates this “modularity”. Is that bad?
  - Regularization is supposed to make the objective function something we actually want to minimize.
  - But if early stopping helps, why not use it?

Dropout

- Dropout (2012) is a more recent form of regularization:
  - On each iteration, randomly set some x_i and z_i to zero (often use 50%).



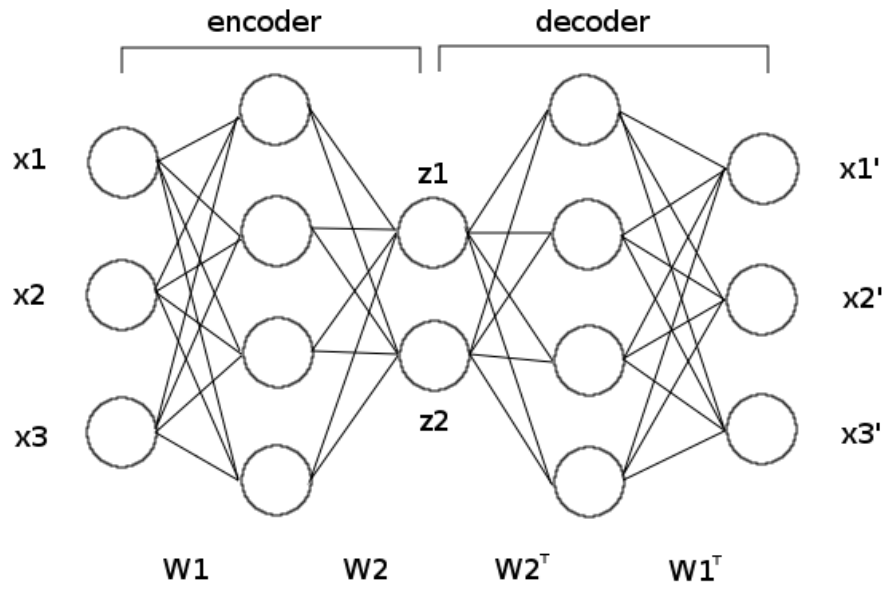
(a) Standard Neural Net (b) After applying dropout.

  - Encourages distributed representation rather than using specific z_i.
  - Like ensembling a lot of models but without the high computational cost.
  - After a lot of success, dropout may already be going out of fashion.

http://www.cs.toronto.edu/~rsalakhu/papers/srivastava14a.pdf

Autoencoders

- Autoencoders are an unsupervised deep learning model:
  - Use the inputs as the output of the neural network.



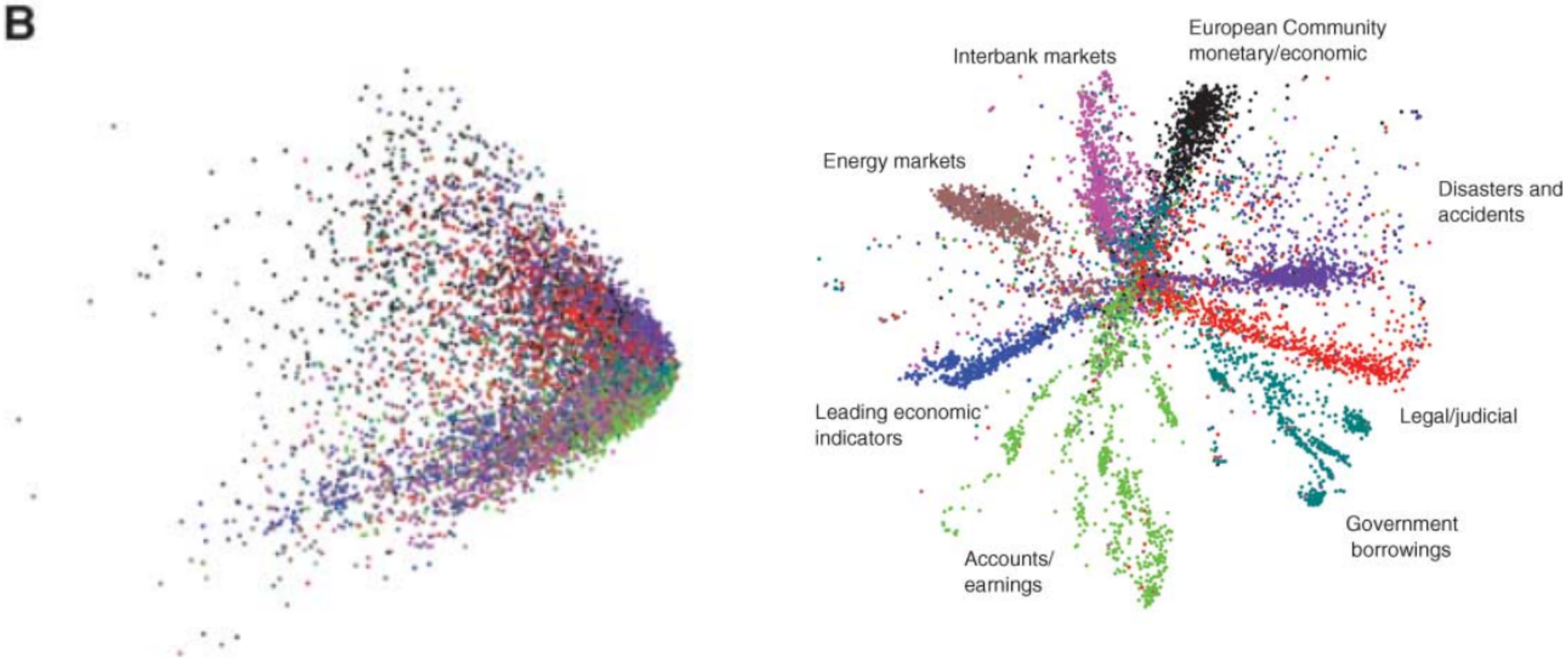
  - Middle layer could be latent features in non-linear latent-factor model.
    - Can do outlier detection, data compression, visualization, etc.
  - A non-linear generalization of PCA.

http://inspirehep.net/record/1252540/plots

Autoencoders

PCA

Autoencoder



https://www.cs.toronto.edu/~hinton/science.pdf

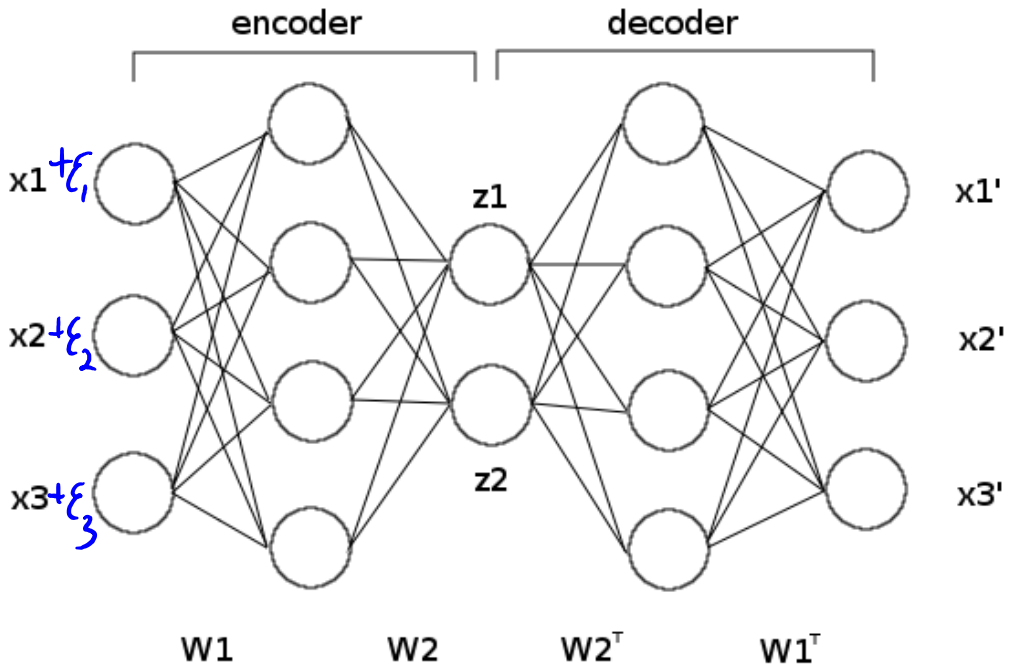
Summary

- Parameter initialization is crucial to neural net performance.
- Optimization and step size are crucial to neural net performance.
- Regularization is crucial to neural net performance:
  - L2-regularizaiton, early stopping, dropout.
- Autoencoders are unsupervised neural net latent-factor models.

- Next time:
  - Convolutions, convolutional neural networks, and rating selfies.

Denoising Autoencoder

- Denosing autoencoders add noise to the input:



  - Learns a model that can remove the noise.

http://inspirehep.net/record/1252540/plots