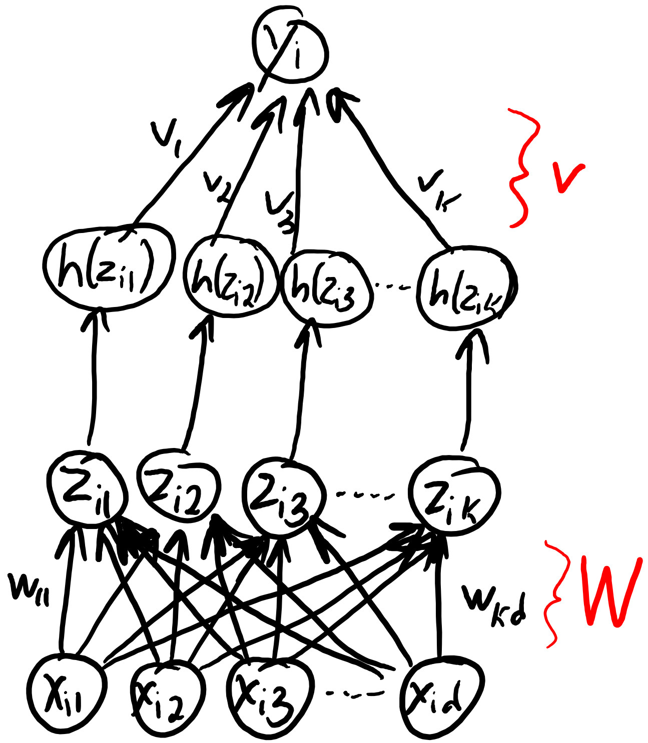
# CPSC 340: Machine Learning and Data Mining

More Deep Learning

Fall 2018

# Last Time: Deep Learning

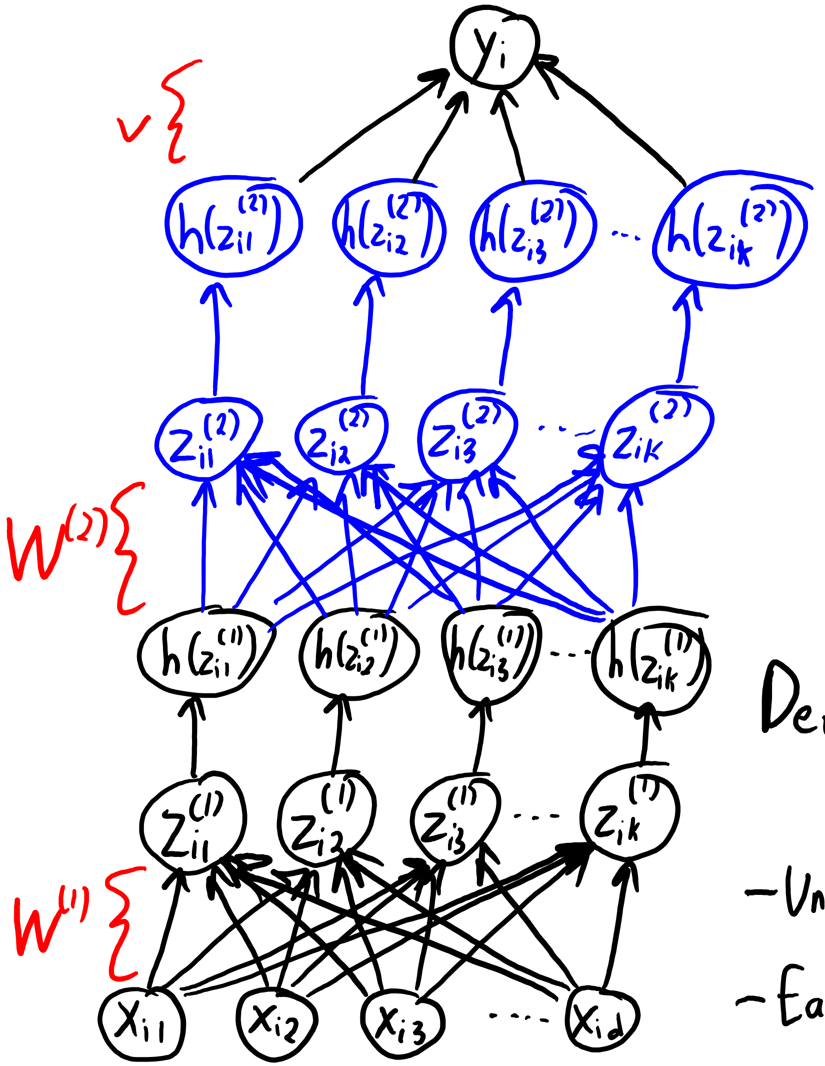
Neural network:

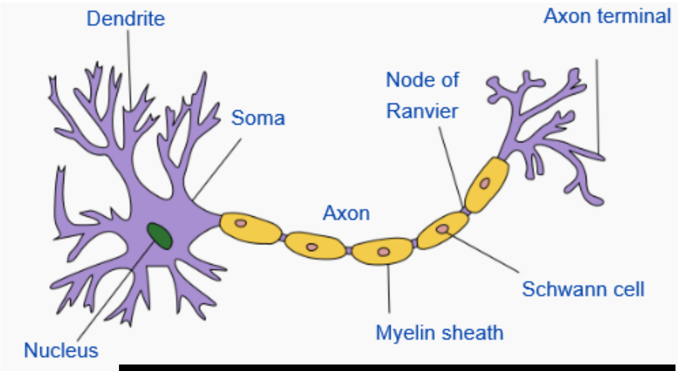


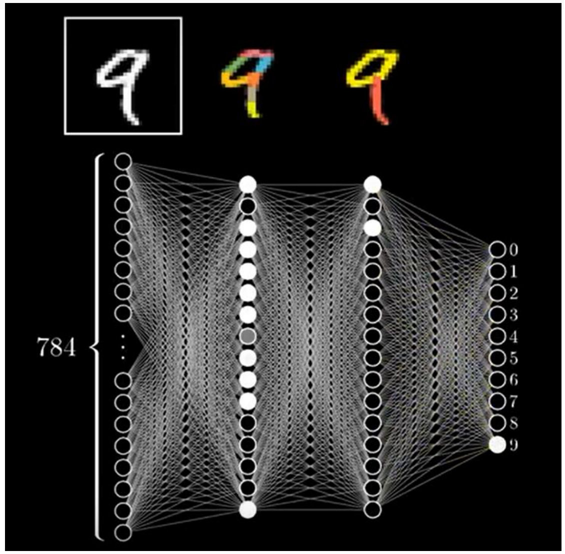

$$y_i = v^T h(Wx_i)$$

Learn 'W' and 'v' together.

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




Deep neural networks:

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

- Unprecedented performance on difficult problems.
- Each layer combines "parts" from previous layer.

https://en.wikipedia.org/wiki/Neuron
https://www.youtube.com/watch?v=aircAruvnKk

# Deep Learning

Linear model:

$$\hat{y}_i = w^T x_i$$

Neural network with 1 hidden layer:

$$\hat{y}_i = v^T h(\underbrace{W x_i}_{z_i})$$

Neural network with 2 hidden layers:

$$\hat{y}_i = v^T h(\underbrace{W^{(2)} h(\underbrace{W^{(1)} x_i}_{z_i^{(1)}})}_{z_i^{(2)}})$$

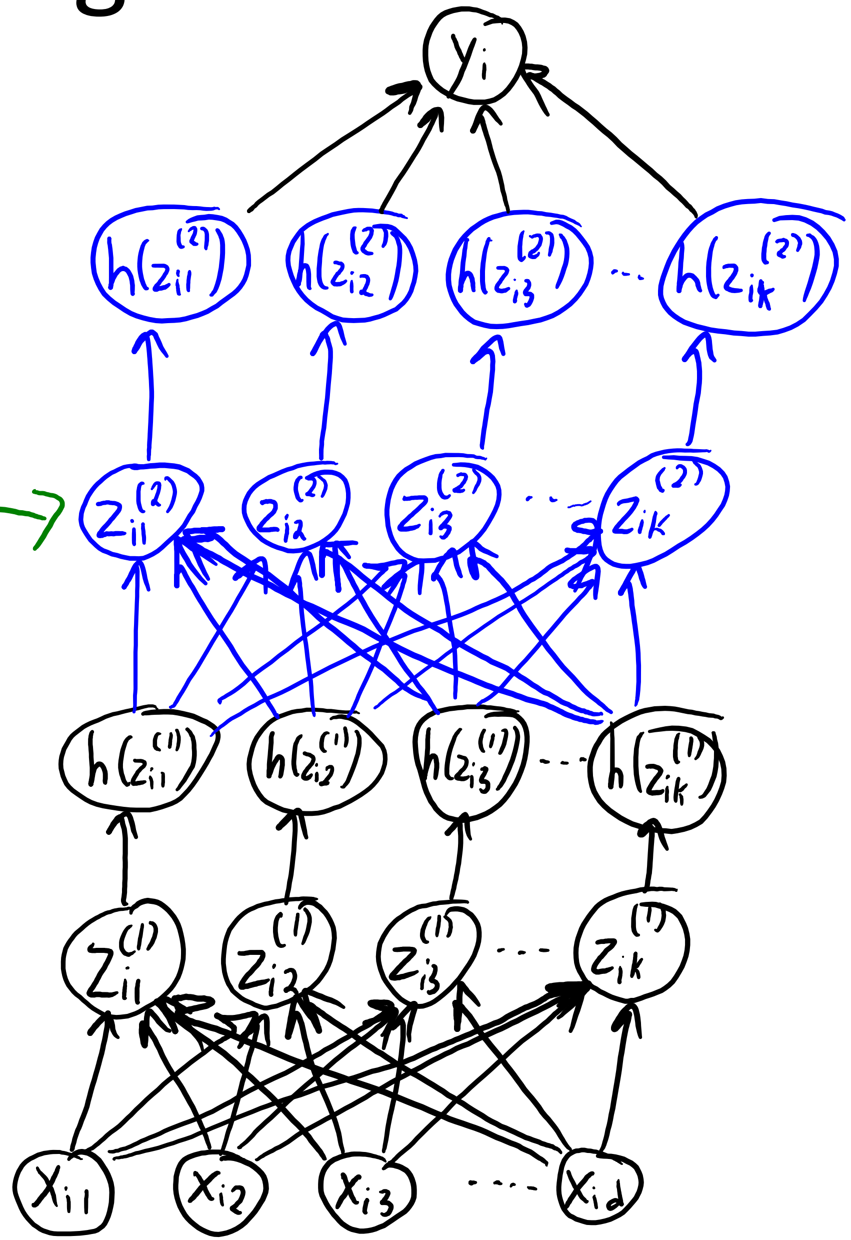
Neural network with 3 hidden layers

$$\hat{y}_i = v^T h(\underbrace{W^{(3)} h(\underbrace{W^{(2)} h(\underbrace{W^{(1)} x_i}_{z_i^{(1)}})}_{z_i^{(2)}})}_{z_i^{(3)}})$$

Deep learning:

Second "layer" of latent features

You can add more "layers" to go "deeper"



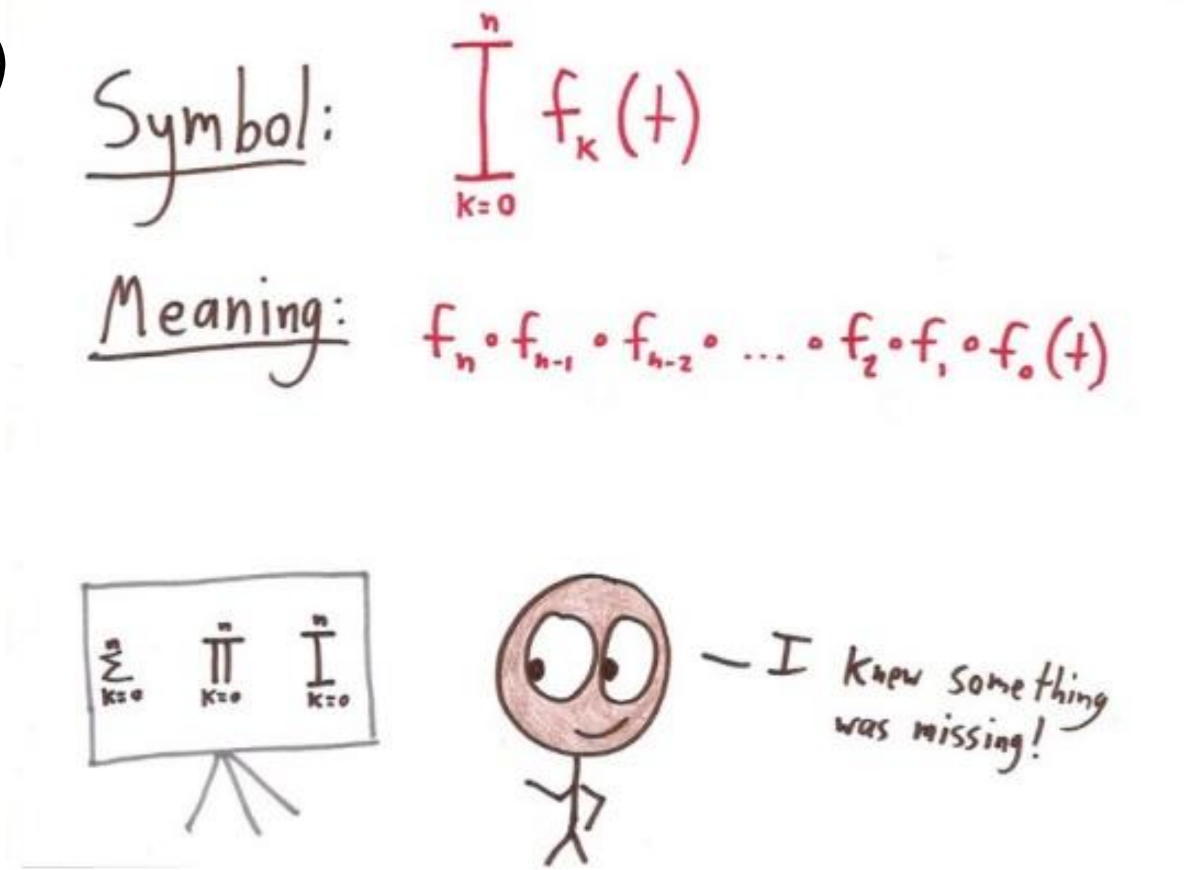
# Deep Learning

- For 4 layers, we could write the prediction as:

$$\hat{y}_i = v^T h(W^{(4)} h(W^{(3)} h(W^{(2)} h(W^{(1)} x_i))))$$

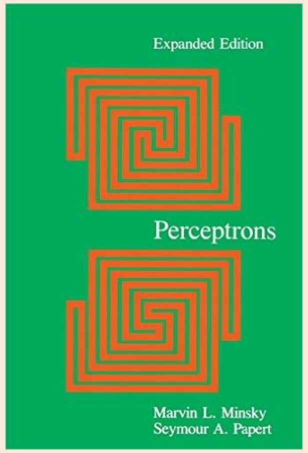
- For 'm' layers, we could use:

$$\hat{y}_i = w^T \left( \underset{\ell=1}{\overset{m}{\mathrm{I}}} h(W^{(\ell)} x_i) \right)$$

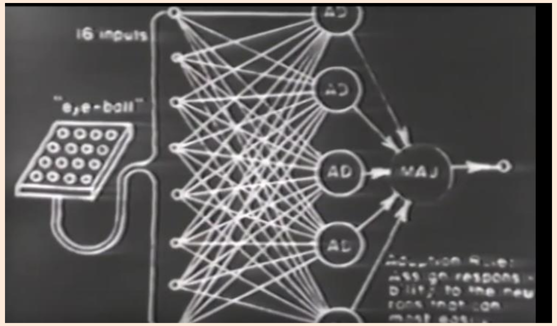


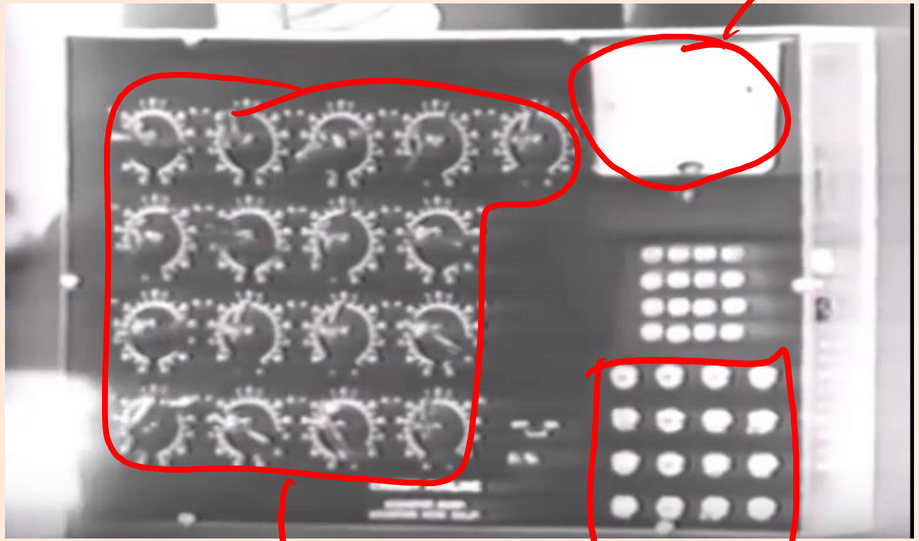

https://mathwithbaddrawings.com/2016/04/27/symbols-that-math-urgently-needs-to-adopt

# ML and Deep Learning History




- 1950 and 1960s: Initial excitement.
  - Perceptron: linear classifier and stochastic gradient (roughly).
  - "the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence." New York Times (1958).
    - https://www.youtube.com/watch?v=IEFRtz68m-8
  - Marvin Minsky assigns object recognition to his students as a summer project

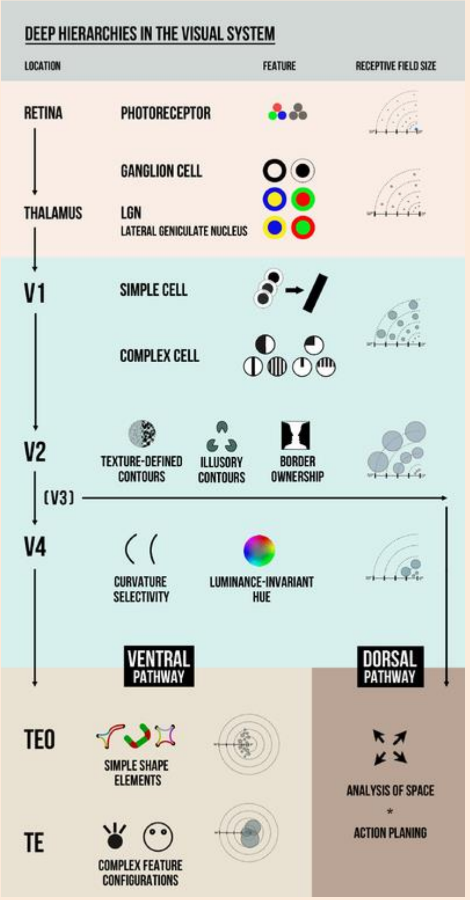


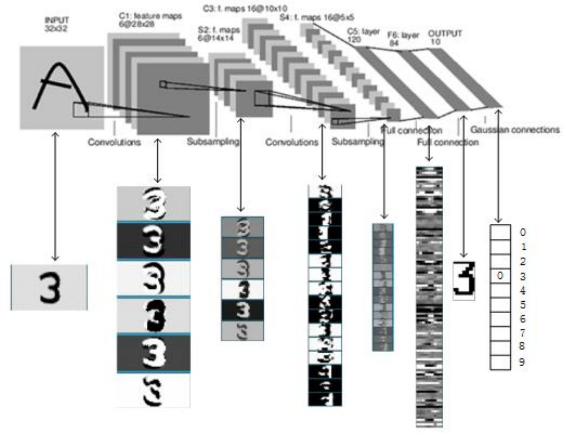

- Then drop in popularity:
  - Quickly realized limitations of linear models.

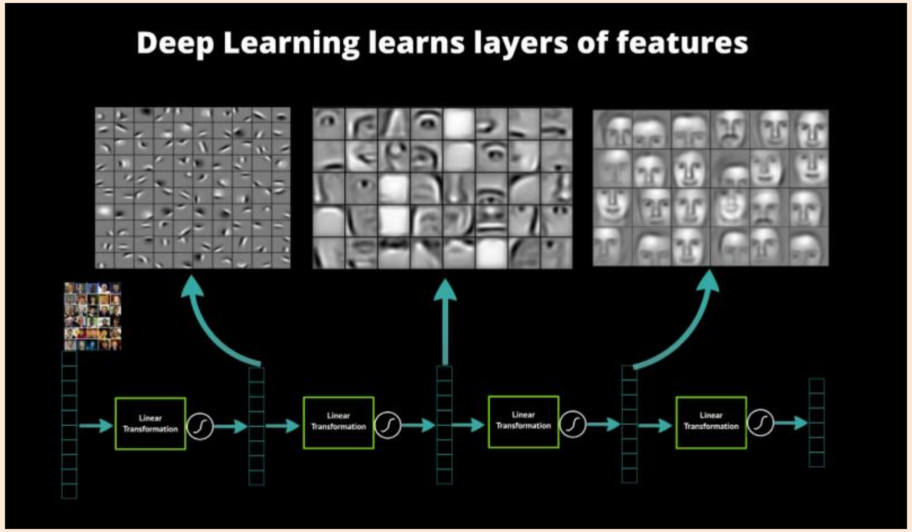
https://mitpress.mit.edu/books/perceptrons/

# ML and Deep Learning History




- 1970 and 1980s: Connectionism (brain-inspired ML)
  - Want "connected networks of simple units".
    - Use parallel computation and distributed representations.
  - Adding hidden layers $z_i$ increases expressive power.
    - With 1 layer and enough sigmoid units, a universal approximator.
  - Success in optical character recognition.



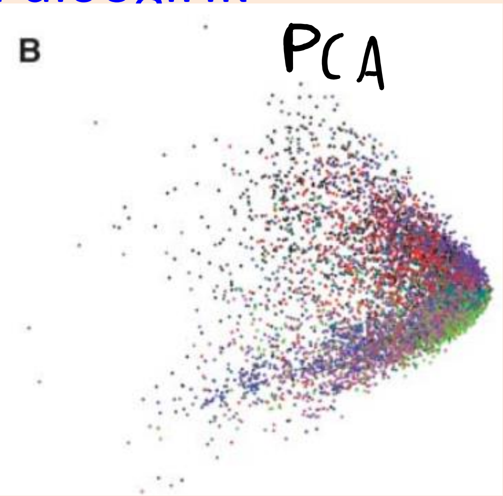

https://en.wikibooks.org/wiki/Sensory_Systems/Visual_Signal_Processing
http://www.datarobot.com/blog/a-primer-on-deep-learning/
http://blog.csdn.net/strint/article/details/44163869

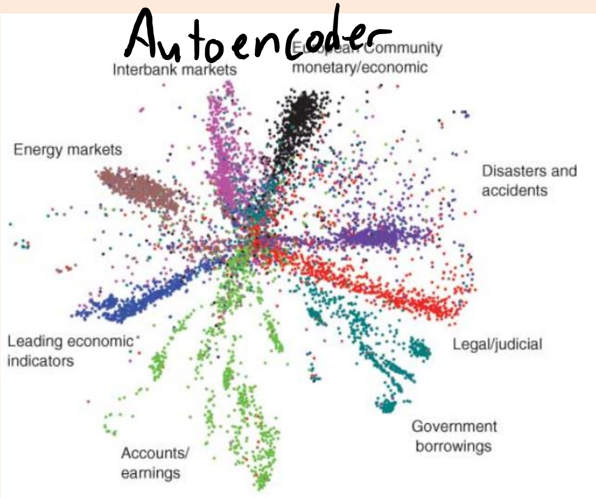
# ML and Deep Learning History

- 1990s and early-2000s: drop in popularity.
  - It proved really difficult to get multi-layer models working robustly.
  - We obtained similar performance with simpler models:
    - Rise in popularity of logistic regression and SVMs with regularization and kernels.
  - ML moved closer to other fields (CPSC 540):
    - Numerical optimization.
    - Probabilistic graphical models.
    - Bayesian methods.

# ML and Deep Learning History

- Late 2000s: push to revive connectionism as "deep learning".
  - Canadian Institute For Advanced Research (CIFAR) NCAP program:
    - "Neural Computation and Adaptive Perception".
    - Led by Geoff Hinton, Yann LeCun, and Yoshua Bengio ("Canadian mafia").
  - Unsupervised successes: "deep belief networks" and "autoencoders".
    - Could be used to initialize deep neural networks.
    - https://www.youtube.com/watch?v=KuPai0ogiHk

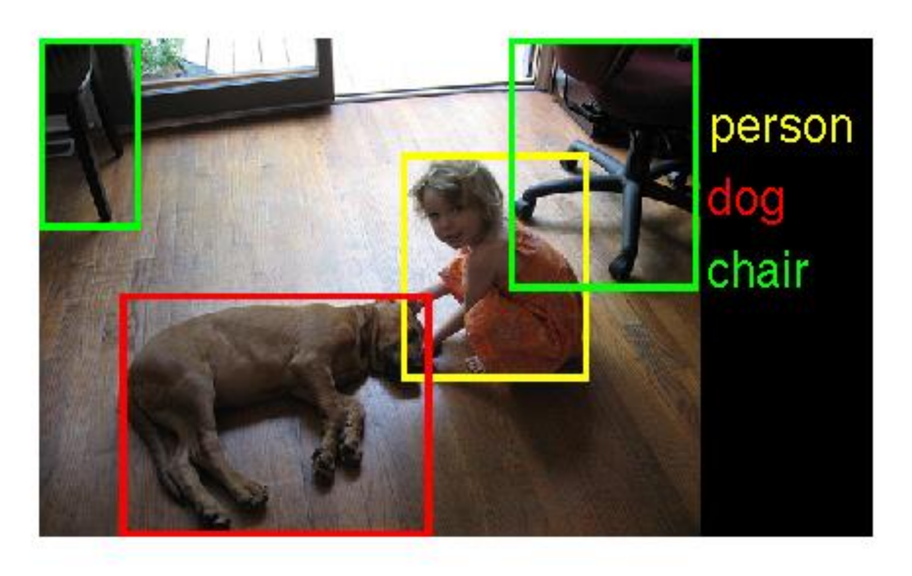



https://www.cs.toronto.edu/~hinton/science.pdf

# 2010s: DEEP LEARNING!!!

- Bigger datasets, bigger models, parallel computing (GPUs/clusters).
  - And some tweaks to the models from the 1980s.
- Huge improvements in automatic speech recognition (2009).
  - All phones now have deep learning.
- Huge improvements in computer vision (2012).
  - Changed computer vision field almost instantly.
  - This is now finding its way into products.




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

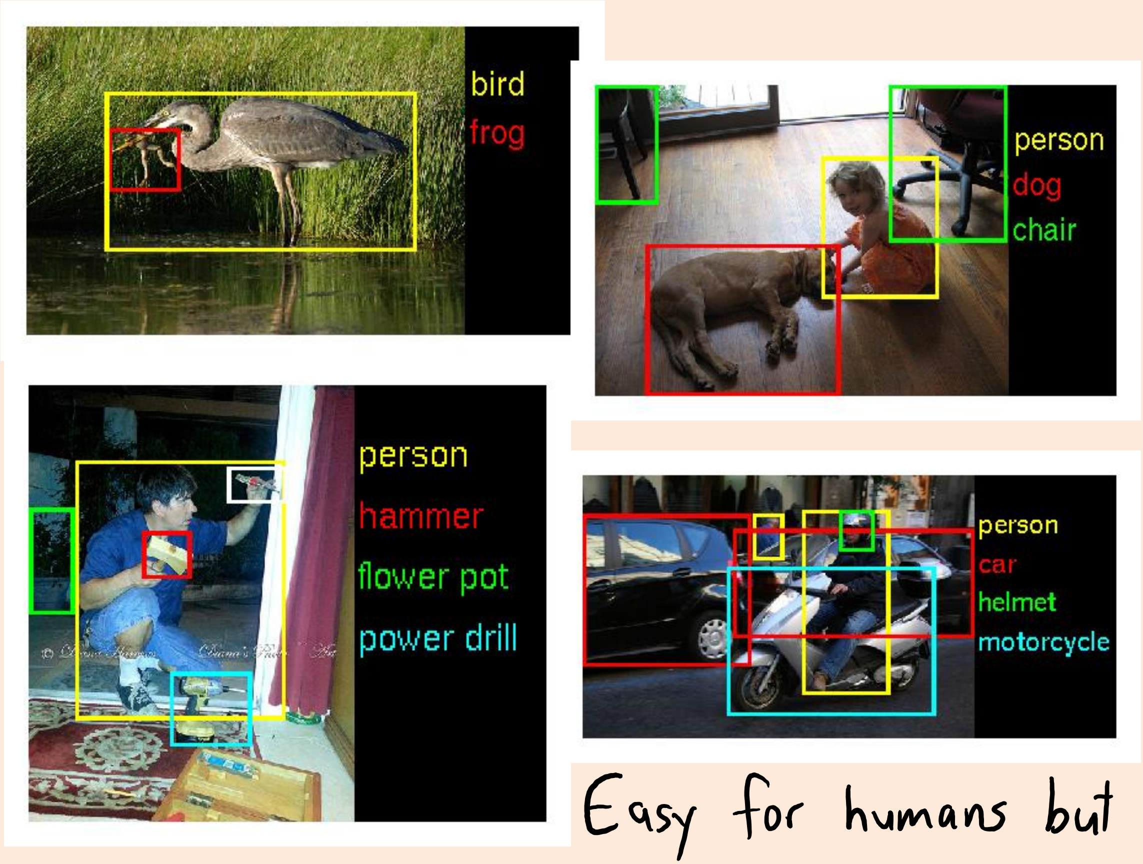
# 2010s: DEEP LEARNING!!!

- Media hype:
  - "How many computers to identify a cat? 16,000"
    New York Times (2012).
  - "Why Facebook is teaching its machines to think like humans"
    Wired (2013).
  - "What is 'deep learning' and why should businesses care?"
    Forbes (2013).
  - "Computer eyesight gets a lot more accurate"
    New York Times (2014).

- 2015: huge improvement in language understanding.

# ImageNet Challenge

- Millions of labeled images, 1000 object classes.



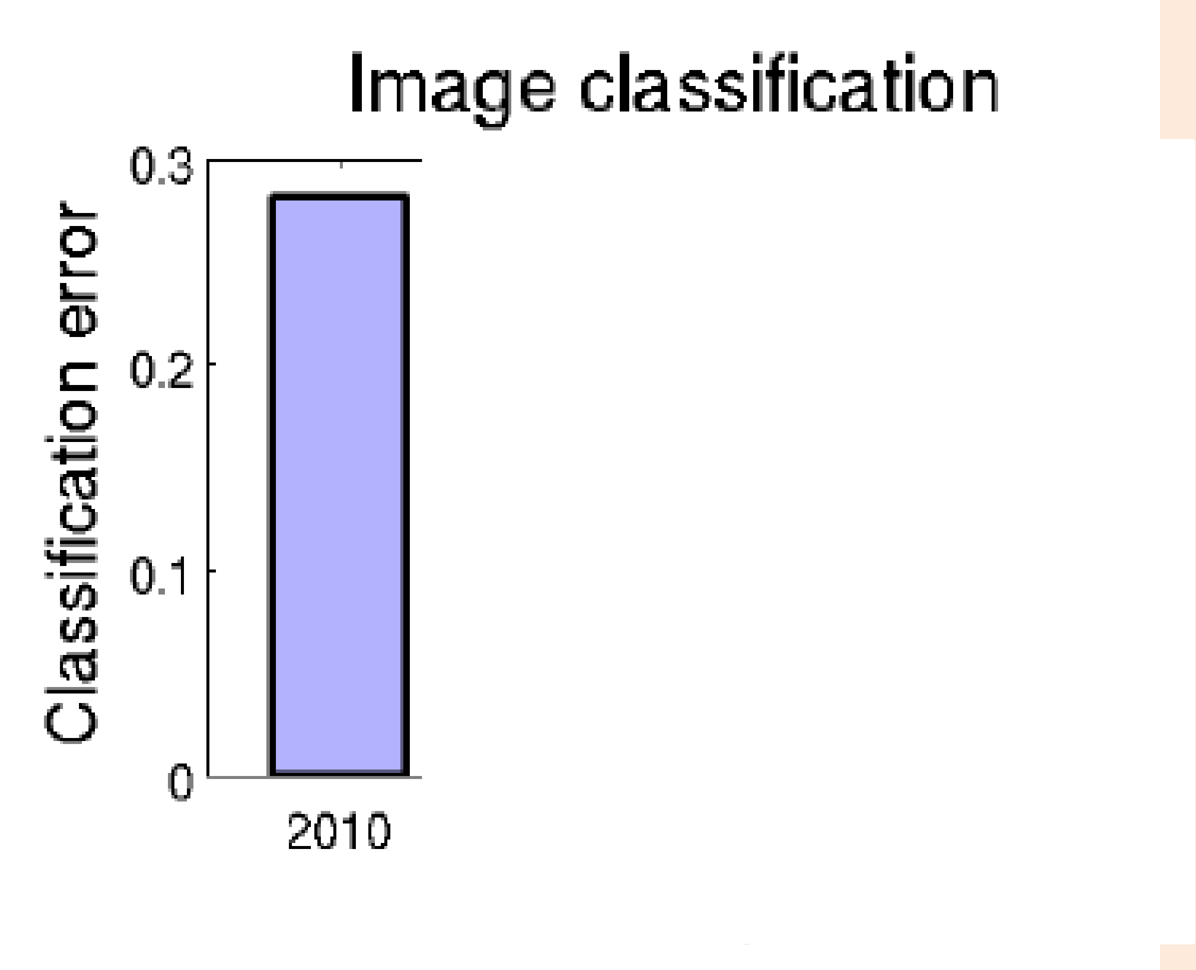

Easy for humans but <u>hard</u> for computers.

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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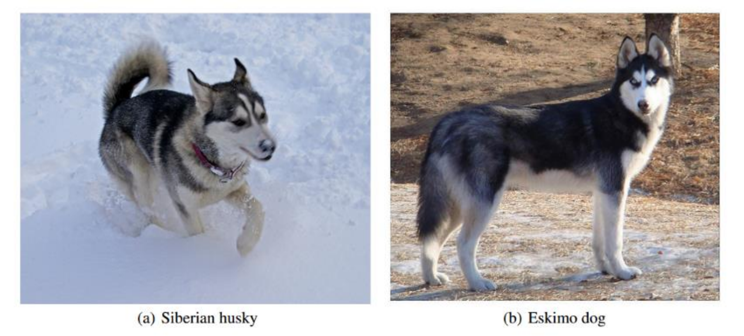


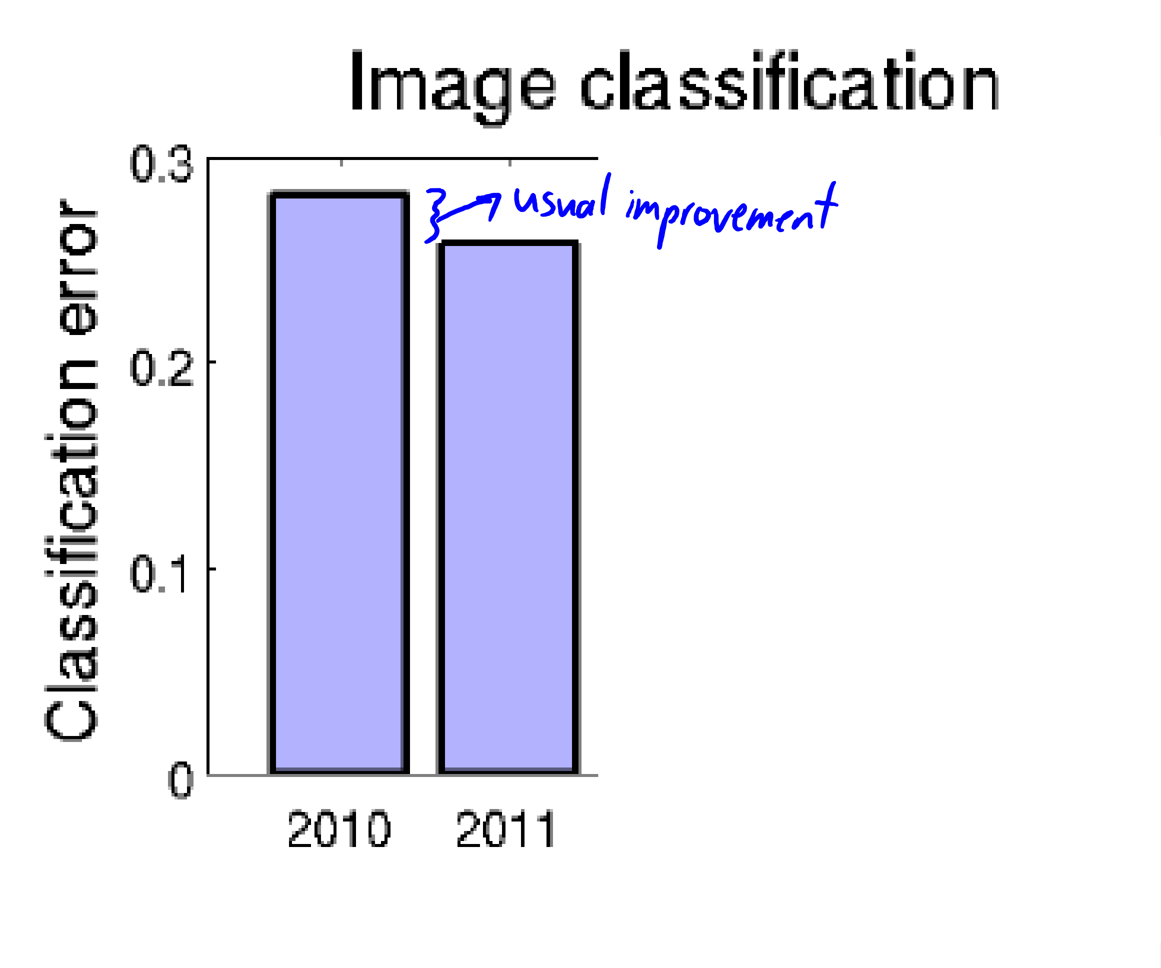


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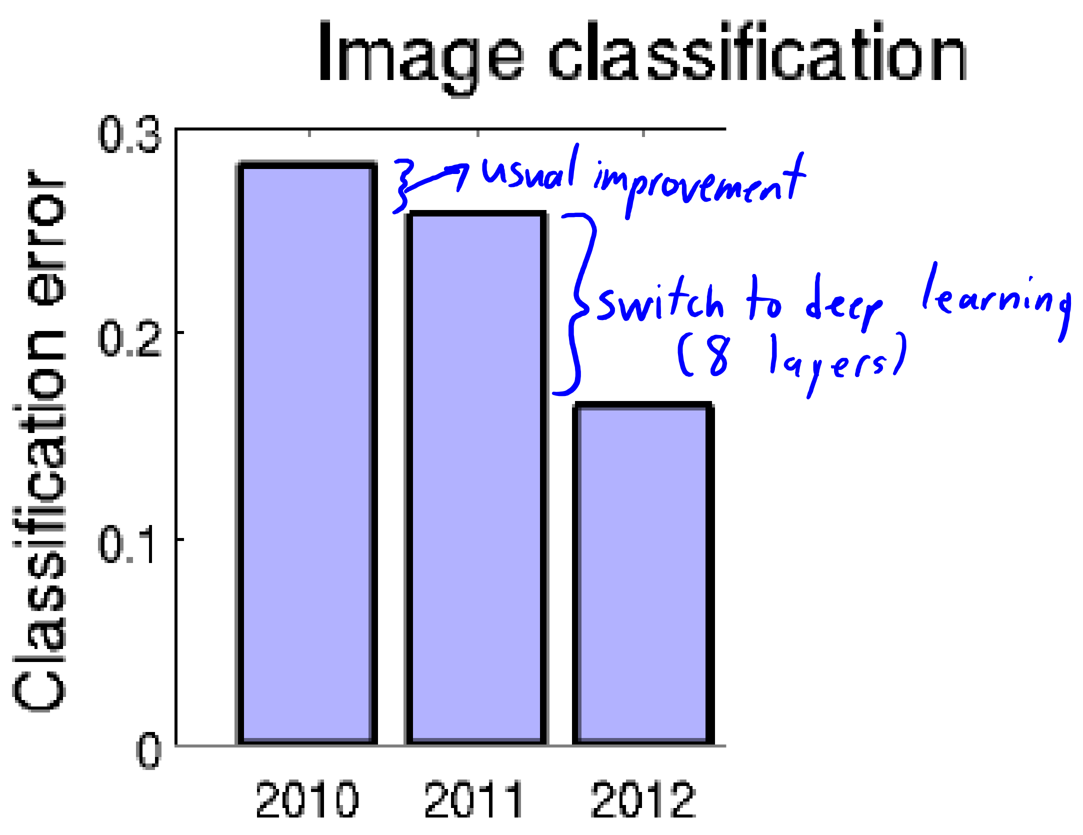


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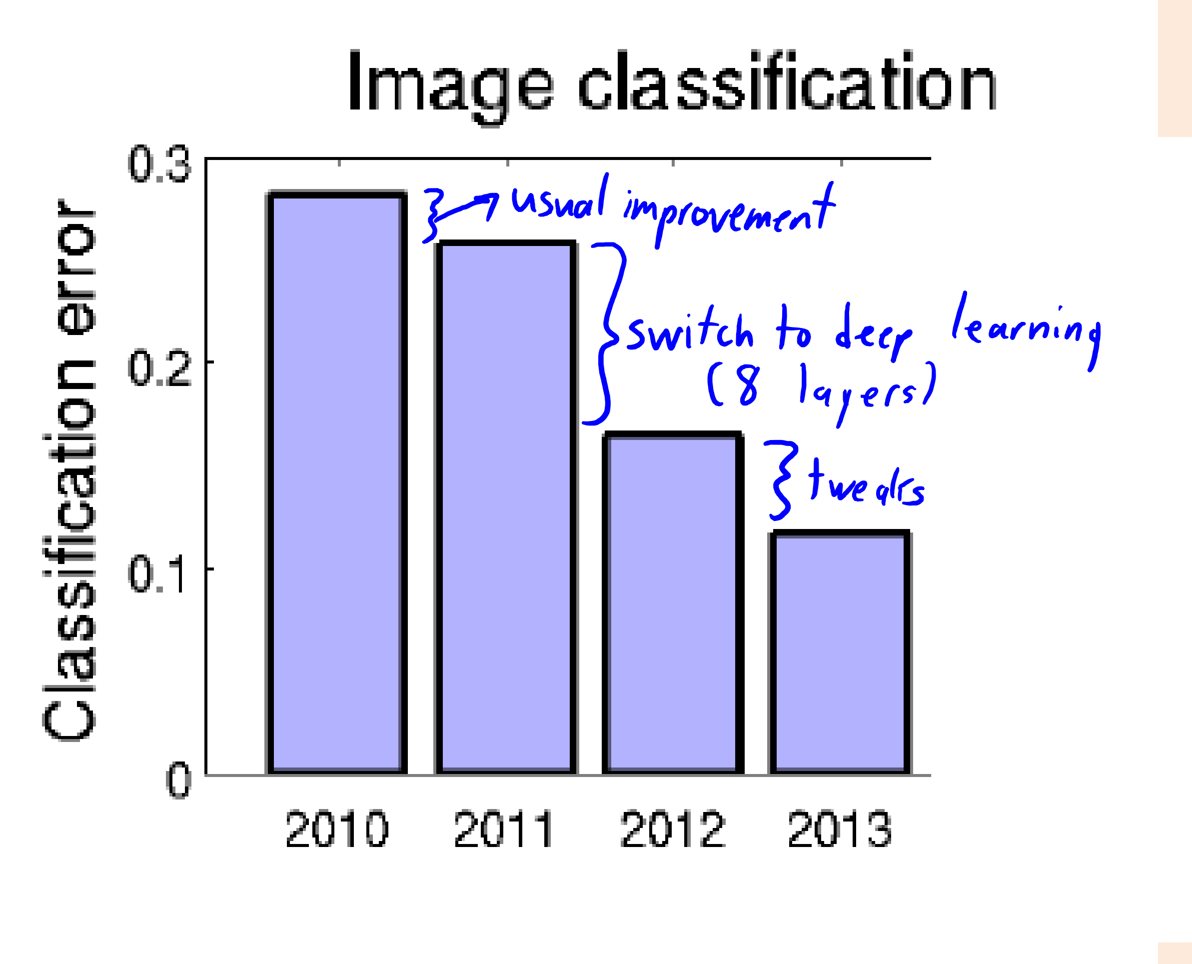


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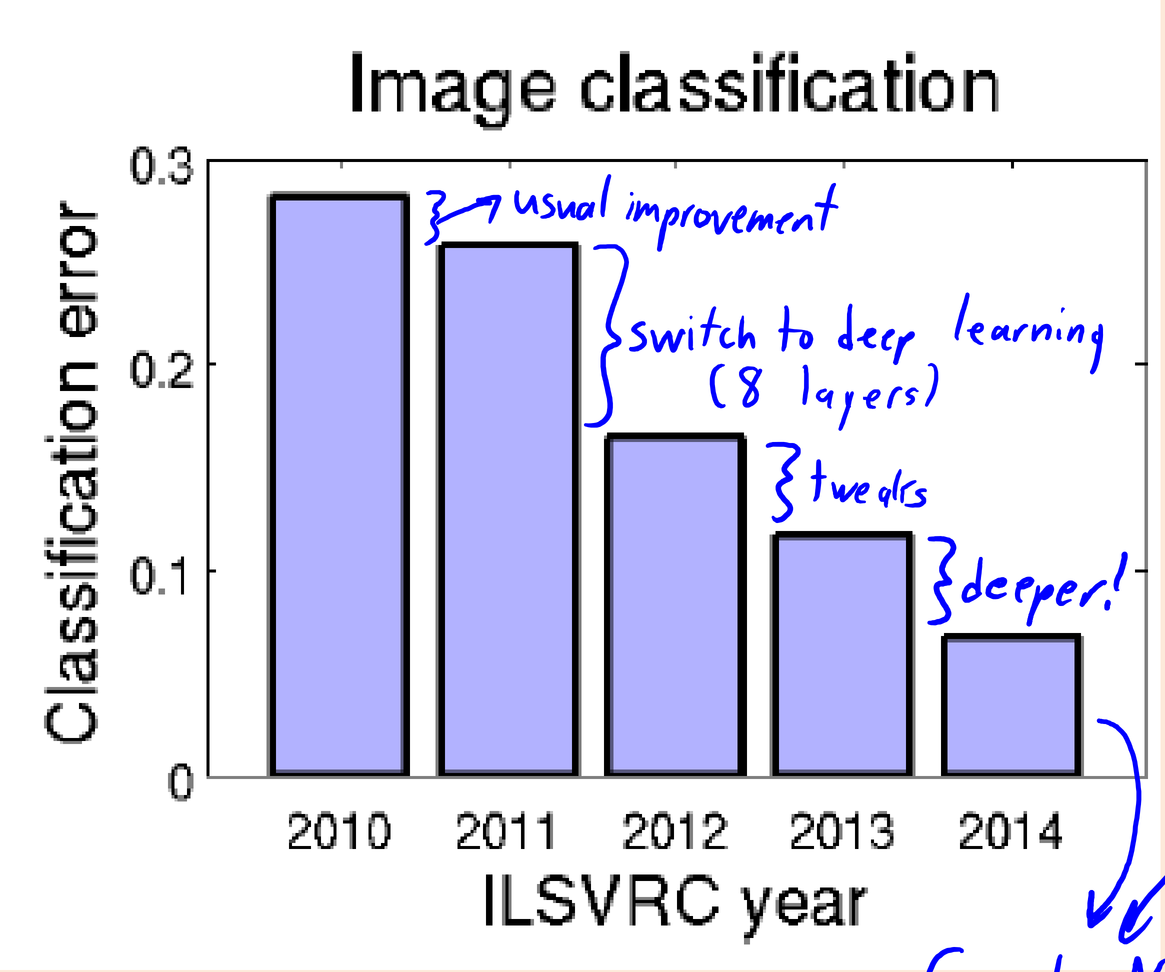
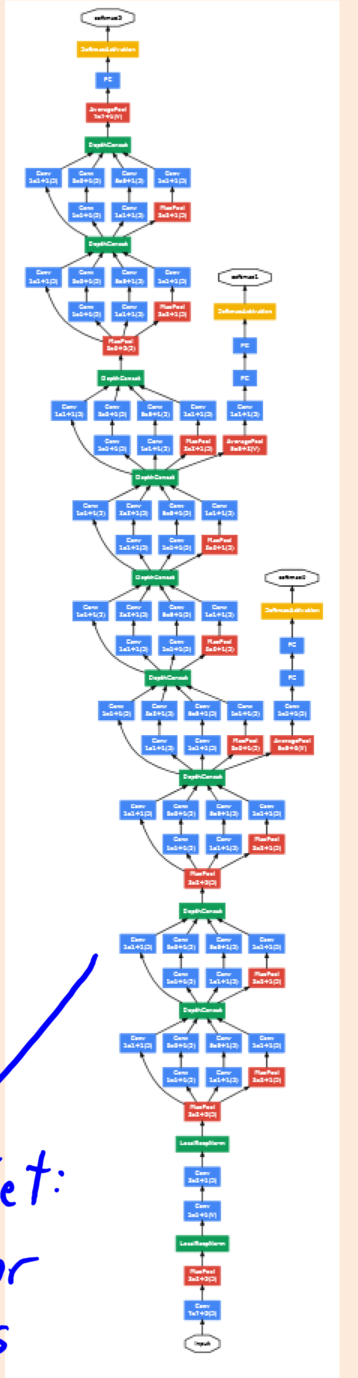



GoogLeNet:
6.7% error
22 layers



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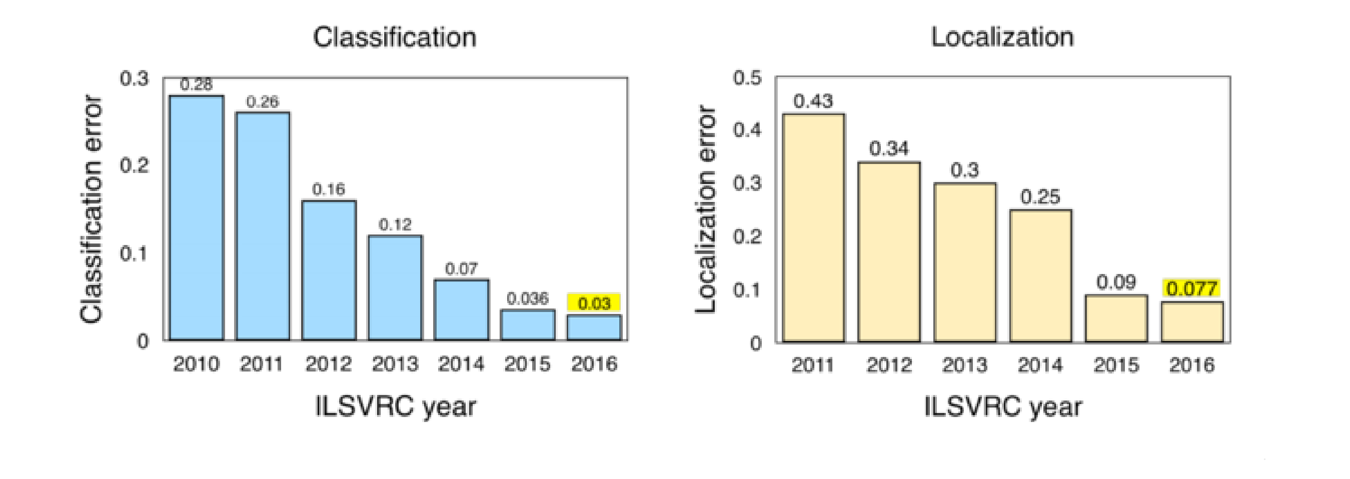



- 2015: Won by Microsoft Asia
  - 3.6% error.
  - 152 layers, "resnet" architecture.
  - Also won "localization" (finding location of objects in images).
- 2016: Chinese University of Hong Kong:
  - Ensembles of previous winners and other existing methods.
- 2017: fewer entries, organizers decided this would be last year.

http://www.themtank.org/a-year-in-computer-vision

(pause)

# Deep Learning Practicalities

- This lecture focus on deep learning practical issues:
  - Backpropagation to compute gradients.
  - Stochastic gradient training.
  - Regularization to avoid overfitting.

- Next lecture:
  - Special ‘W’ restrictions to further avoid overfitting.

# But first: Adding Bias Variables

- Recall fitting line regression with a bias:

$$\hat{y}_i = \sum_{j=1}^{d} w_j x_{ij} + \beta$$

  – We avoided this by adding a column of ones to X.

- In neural networks we often want a bias on the output:

$$\hat{y}_i = \sum_{c=1}^{k} v_c h(w_c^T x_i) + \beta$$

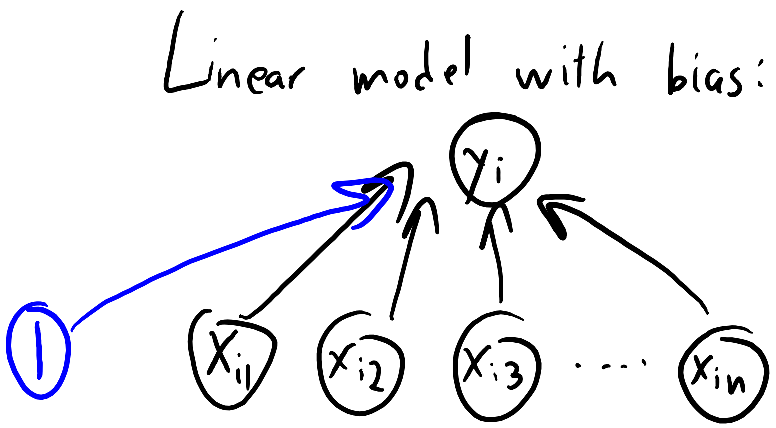
- But we also often also include biases on each $z_{ic}$:

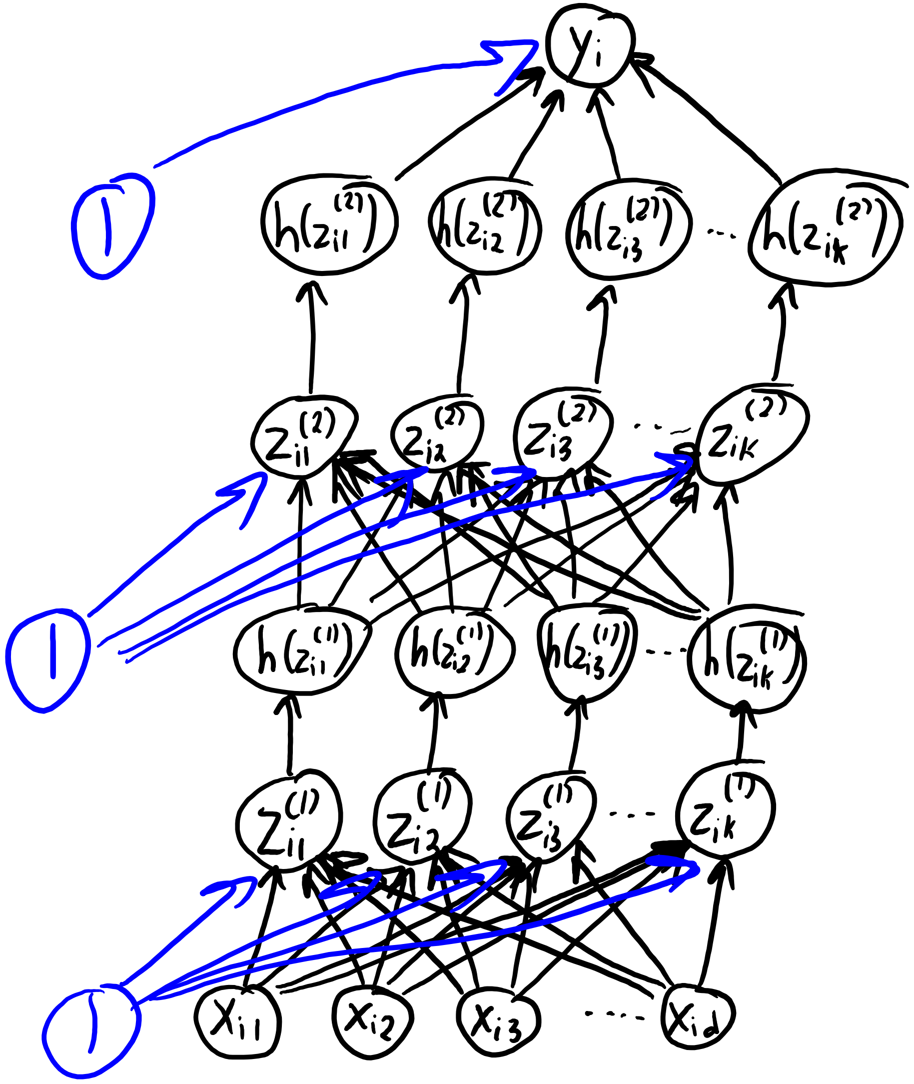
$$\hat{y}_i = \sum_{c=1}^{k} v_c h(w_c^T x_i + \beta_c) + \beta$$

  – A bias towards this $h(z_{ic})$ being either 0 or 1.

- Equivalent to adding to vector $h(z_i)$ an extra value that is always 1.
  – For sigmoids, you could equivalently make one row of $w_c$ be equal to 0.

# But first: Adding Bias Variables



# Artificial Neural Networks

- With squared loss, our objective function is:

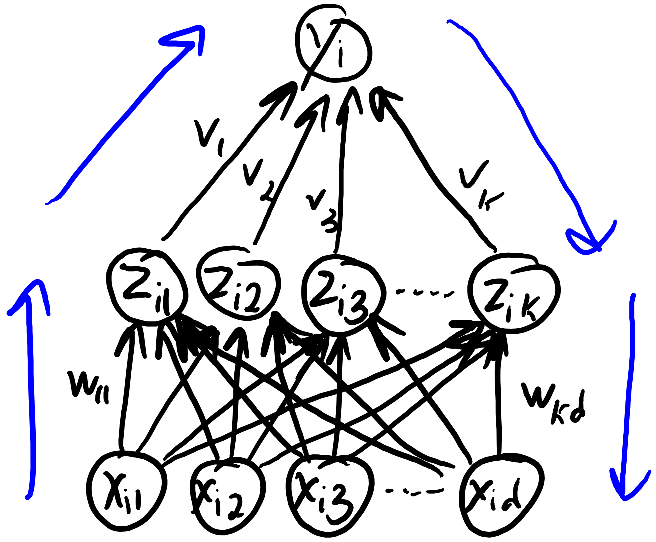
$$f(w, W) = \frac{1}{2}\sum_{i=1}^{n}(v^T h(Wx_i) - y_i)^2$$

- Usual training procedure: stochastic gradient.
  - Compute gradient of random example ‘i’, update both ‘v’ and ‘W’.
  - Highly non-convex and can be difficult to tune.

- Computing the gradient is known as “backpropagation”.
  - Video giving motivation here.

# Backpropagation

- Overview of how we compute neural network gradient:
  - Forward propagation:
    - Compute $z_i^{(1)}$ from $x_i$.
    - Compute $z_i^{(2)}$ from $z_i^{(1)}$.
    - …
    - Compute $\hat{y}_i$ from $z_i^{(m)}$, and use this to compute error.
  - Backpropagation:
    - Compute gradient with respect to regression weights ‘v’.
    - Compute gradient with respect to $z_i^{(m)}$ weights $W^{(m)}$.
    - Compute gradient with respect to $z_i^{(m-1)}$ weights $W^{(m-1)}$.
    - …
    - Compute gradient with respect to $z_i^{(1)}$ weights $W^{(1)}$.
- “Backpropagation” is the chain rule plus some bookkeeping for speed.



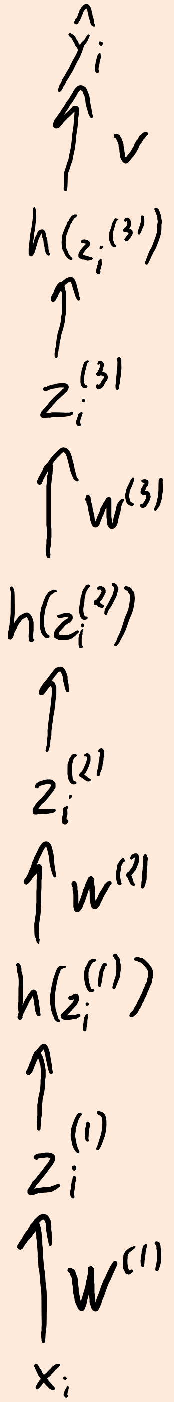
# Backpropagation

- Let's illustrate backpropagation in a simple setting:
  - 1 training example, 3 hidden layers, 1 hidden "unit" in layer.

$$f(W^{(1)}, W^{(2)}, W^{(3)}, v) = \frac{1}{2}(\underbrace{\hat{y}_i - y_i}_{r})^2 \quad \text{where} \quad \hat{y}_i = v h(W^{(3)} h(W^{(2)} h(W^{(1)} x_i)))$$

$$\frac{\partial f}{\partial v} = r\, h(W^{(3)} h(W^{(2)} h(W^{(1)} x_i))) = r\, h(z_i^{(3)})$$

$$\frac{\partial f}{\partial W^{(3)}} = r\, v h'(W^{(3)} h(W^{(2)} h(W^{(1)} x_i))) h(W^{(2)} h(W^{(1)} x_i)) = r\, v h'(z_i^{(3)}) h(z_i^{(2)})$$



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$$\frac{\partial f}{\partial v} = r\, h(W^{(3)}h(W^{(2)}h(W^{(1)}x_i))) = r\, h(z_i^{(3)})$$

$$\frac{\partial f}{\partial W^{(3)}} = r\, v\, h'(W^{(3)}h(W^{(2)}h(W^{(1)}x_i)))\, h(W^{(2)}h(W^{(1)}x_i)) = \underbrace{r\, vh'(z_i^{(3)})}\, h(z_i^{(2)})$$

$$\frac{\partial f}{\partial W^{(2)}} = r\, v\, h'(W^{(3)}h(W^{(2)}h(W^{(1)}x_i)))\, W^{(3)}h'(W^{(2)}h(W^{(1)}x_i))\, h(W^{(1)}x_i) = \underbrace{r^{(3)} W^{(3)} h'(z_i^{(2)})}\, h(z_i^{(1)})$$

$$\frac{\partial f}{\partial W^{(1)}} = r\, v\, h'(W^{(3)}h(W^{(2)}h(W^{(1)}x_i)))\, W^{(3)}h'(W^{(2)}(W^{(1)}x_i))\, W^{(2)}h'(W^{(1)}x_i)\, x_i = r^{(2)} W^{(2)} h'(z_i^{(1)})\, x_i$$

# Backpropagation

- Let's illustrate backpropagation in a simple setting:
  - 1 training example, 3 hidden layers, 1 hidden "unit" in layer.

$$\frac{\partial f}{\partial v} = r\, h(z_i^{(3)})$$

$$\frac{\partial f}{\partial W^{(3)}} = r\, v\, h'(z_i^{(3)})\, h(z_i^{(2)})$$

$$\frac{\partial f}{\partial W^{(2)}} = r^{(3)} W^{(3)} h'(z_i^{(2)})\, h(z_i^{(1)})$$

$$\frac{\partial f}{\partial W^{(1)}} = r^{(2)} W^{(2)} h'(z_i^{(1)})\, x_i$$

$$\frac{\partial f}{\partial v_c} = r\, h(z_{ic}^{(3)})$$

$$\frac{\partial f}{\partial W^{(3)}_{c'c}} = r\, v_c\, h'(z_{ic'}^{(3)})\, h(z_{ic}^{(2)})$$

$$\frac{\partial f}{\partial W^{(2)}_{c'c}} = \left[\sum_{c''=1}^{k} r^{(3)}_{c''} W^{(3)}_{c''c'}\right] h'(z_{ic'}^{(2)})\, h(z_{ic}^{(1)})$$

$$\frac{\partial f}{\partial W^{(1)}_{cj}} = \left[\sum_{c''=1}^{k} r^{(2)}_{c''} W^{(2)}_{c''c}\right] h'(z_{ic}^{(1)})\, x_j$$

  - Only the first 'r' changes if you use a different loss.
  - With multiple hidden units, you get extra sums.
    - Efficient if you store the sums rather than computing from scratch.

# Backpropagation

- I've marked those backprop math slides as bonus.
- Do you need to know how to do this?
  - Exact details are probably not vital (there are many implementations).
  - "Automatic differentiation" is becoming standard and has same cost.
  - But understanding basic idea helps you know what can go wrong.
    - Or give hints about what to do when you run out of memory.
  - See discussion here by a neural network expert.

- You should know cost of backpropagation:
  - Forward pass dominated by matrix multiplications by $W^{(1)}$, $W^{(2)}$, $W^{(3)}$, and 'v'.
    - If have 'm' layers and all $z_i$ have 'k' elements, cost would be $O(dk + mk^2)$.
  - Backward pass has same cost as forward pass.
- For multi-class or multi-label classification, you replace 'v' by a matrix:
  - Softmax loss is often called "cross entropy" in neural network papers.

# Deep Learning Vocabulary

- "Deep learning": Models with many hidden layers.
  - Usually neural networks.
- "Neuron": node in the neural network graph.
  - "Visible unit": feature.
  - "Hidden unit": latent factor $z_{ic}$ or $h(z_{ic})$.
- "Activation function": non-linear transform.
- "Activation": $h(z_i)$.
- "Backpropagation": compute gradient of neural network.
  - Sometimes "backpropagation" means "training with SGD".
- "Weight decay": L2-regularization.
- "Cross entropy": softmax loss.
- "Learning rate": SGD step-size.
- "Learning rate decay": using decreasing step-sizes.
- "Vanishing gradient": underflow/overflow during gradient calculation.

(pause)

# ImageNet Challenge and Optimization

- 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.

# Stochastic Gradient Training

- Standard training method is stochastic gradient (SG):
  - 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 are the problem local mimina?
  - 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 close to a local minimum in reasonable time.

# 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).
    - w = .00001*randn(k,1)
  - Performing multiple initializations does not seem to be important.

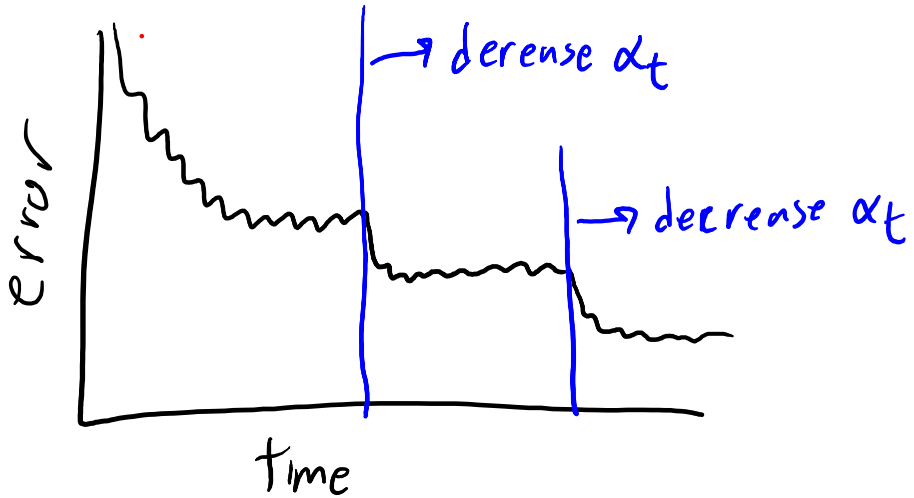
- Popular approach from 10 years ago:
  - Initialize with deep unsupervised model (like "autoencoders" – see bonus).

# 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, "whitten", 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.

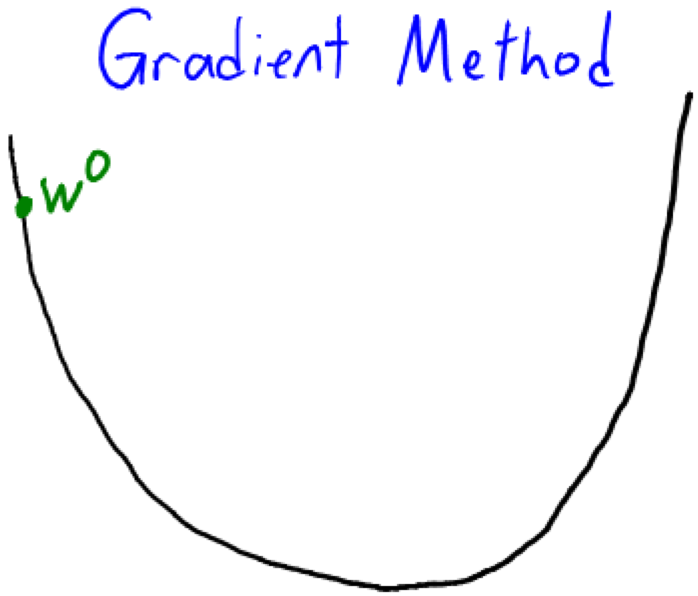
# Setting the Step-Size

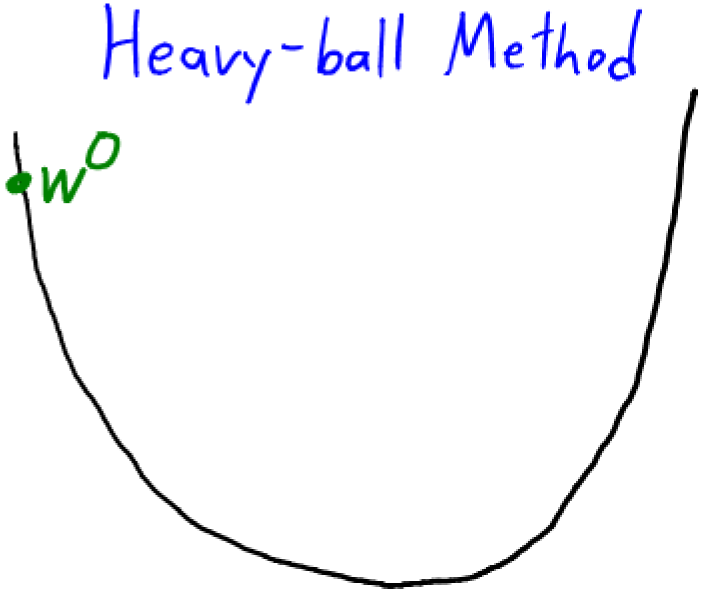
- Stochastic gradient is very sensitive to the step size in deep models.
- Bias step-size multiplier: use bigger step-size for the bias variables.
- Momentum (stochastic version of "heavy-ball" algorithm):
  - Add term that moves in previous direction:

$$w^{t+1} = w^t - \alpha^t \nabla f_i(w^t) + \underbrace{\beta^t(w^t - w^{t-1})}_{\text{keep going in the old direction}}$$

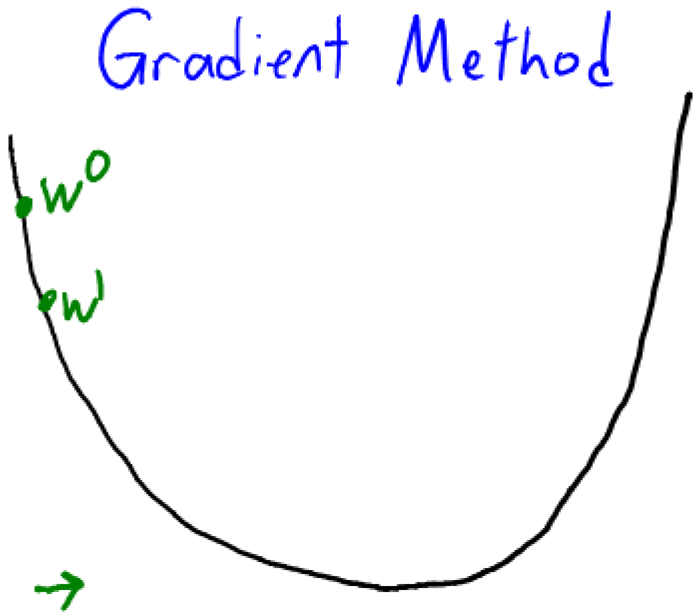
  - Usually $\beta^t = 0.9$.

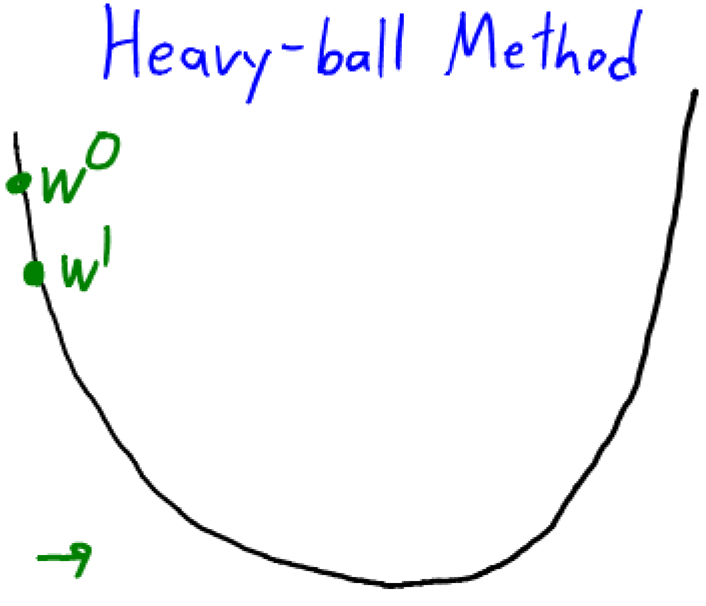
# Gradient Descent vs. Heavy-Ball Method



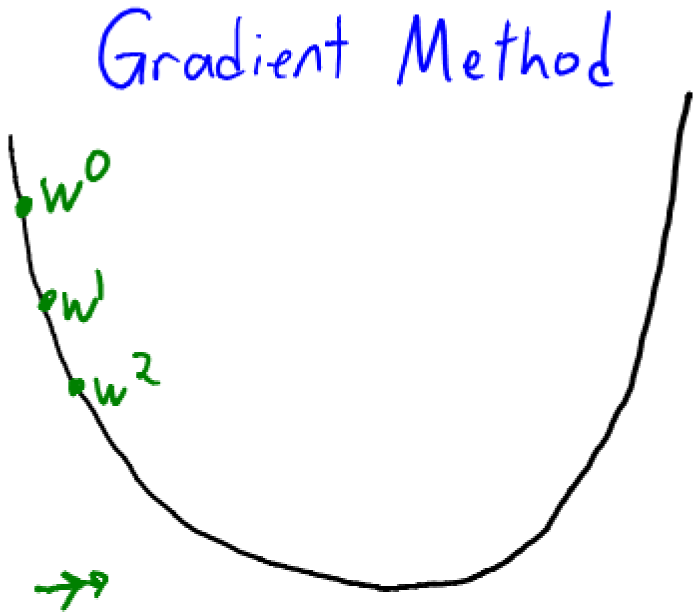



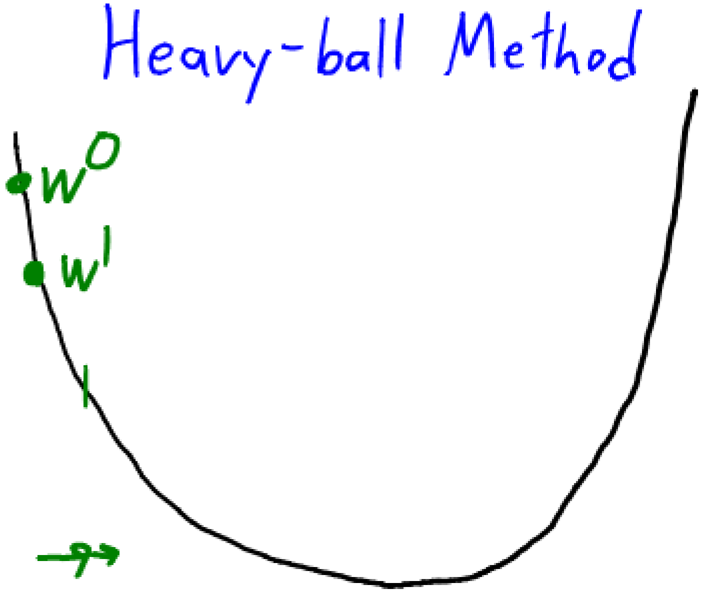
# Gradient Descent vs. Heavy-Ball Method



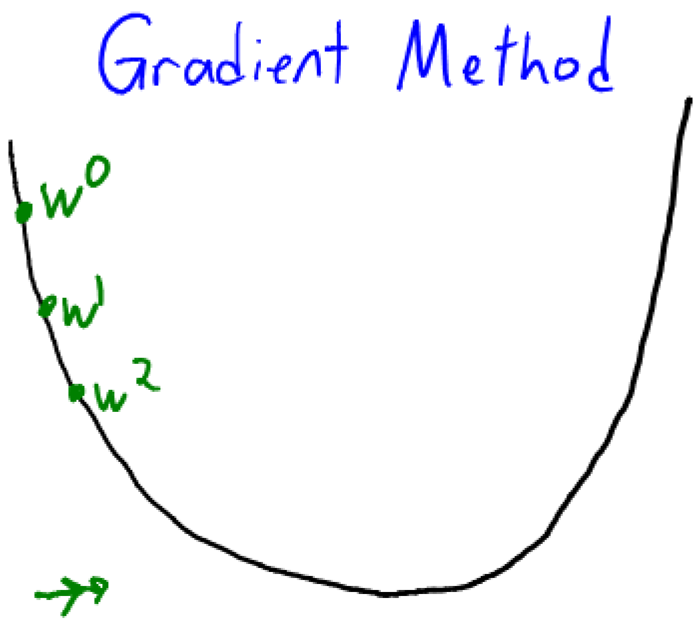



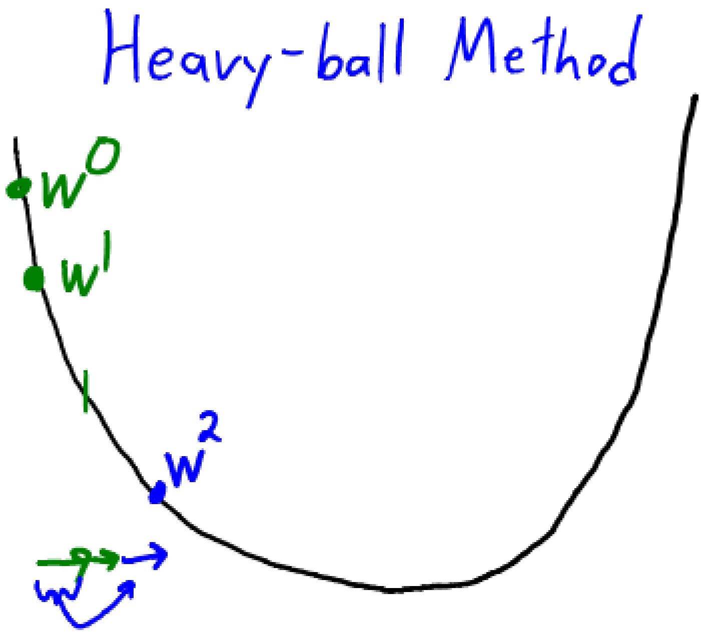
# Gradient Descent vs. Heavy-Ball Method



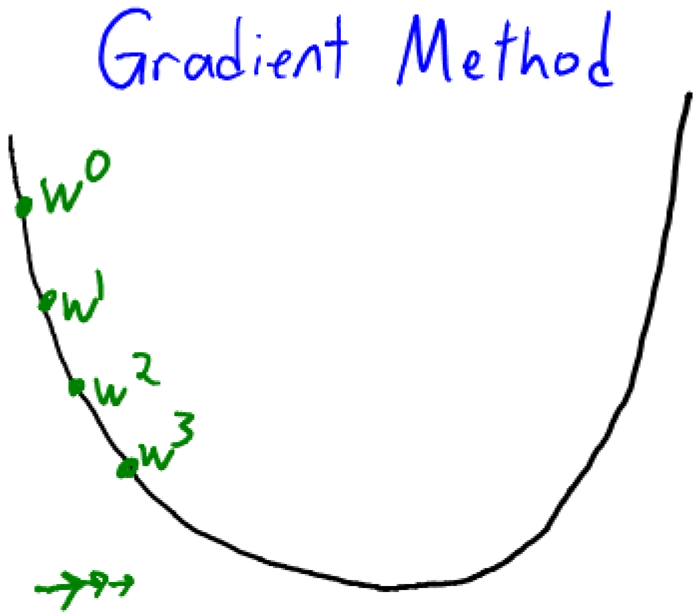



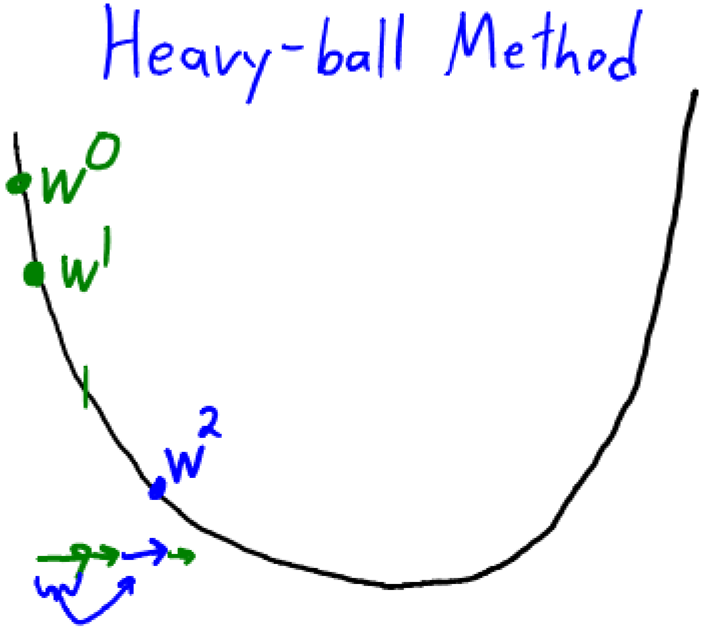
# Gradient Descent vs. Heavy-Ball Method



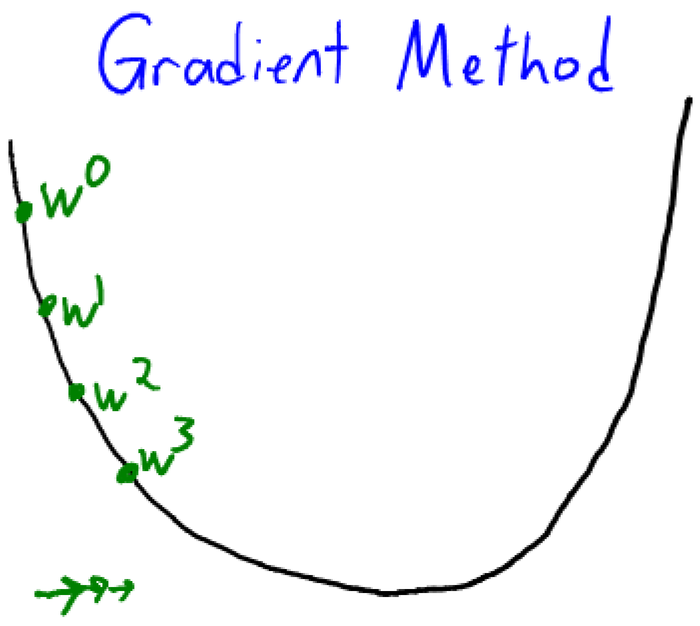



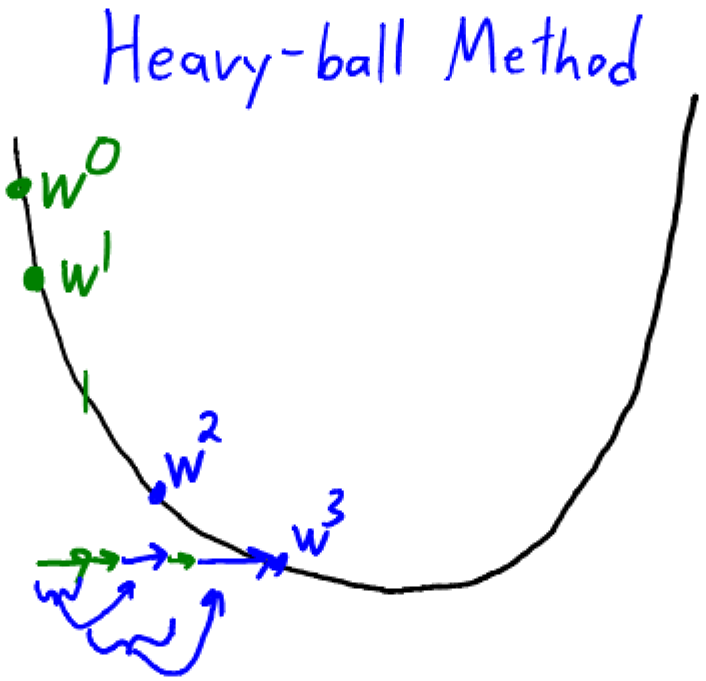
# Gradient Descent vs. Heavy-Ball Method



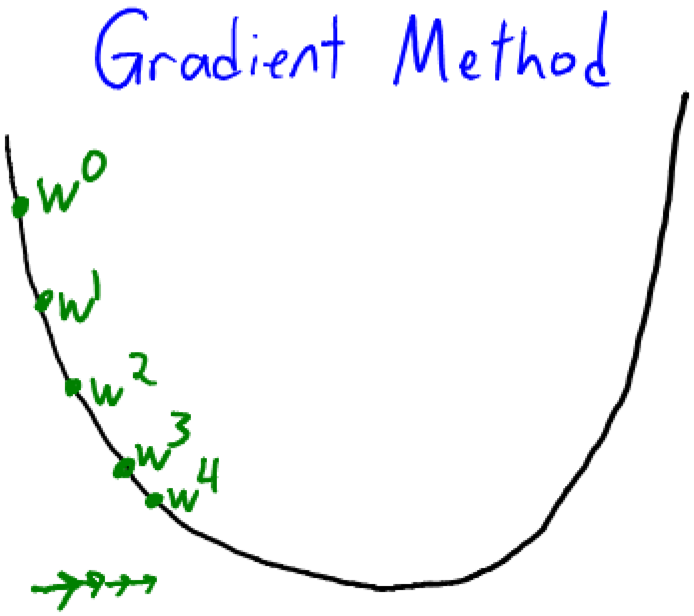



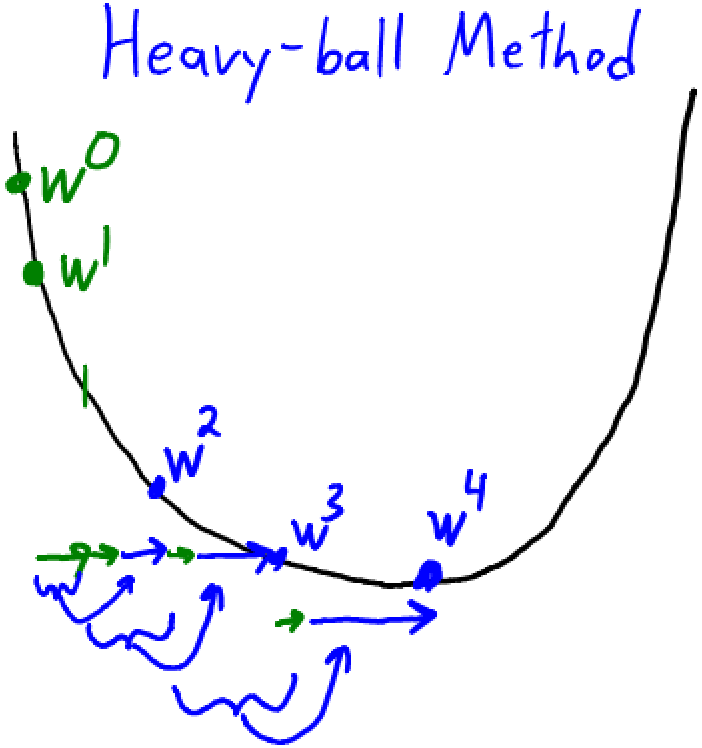
# Gradient Descent vs. Heavy-Ball Method



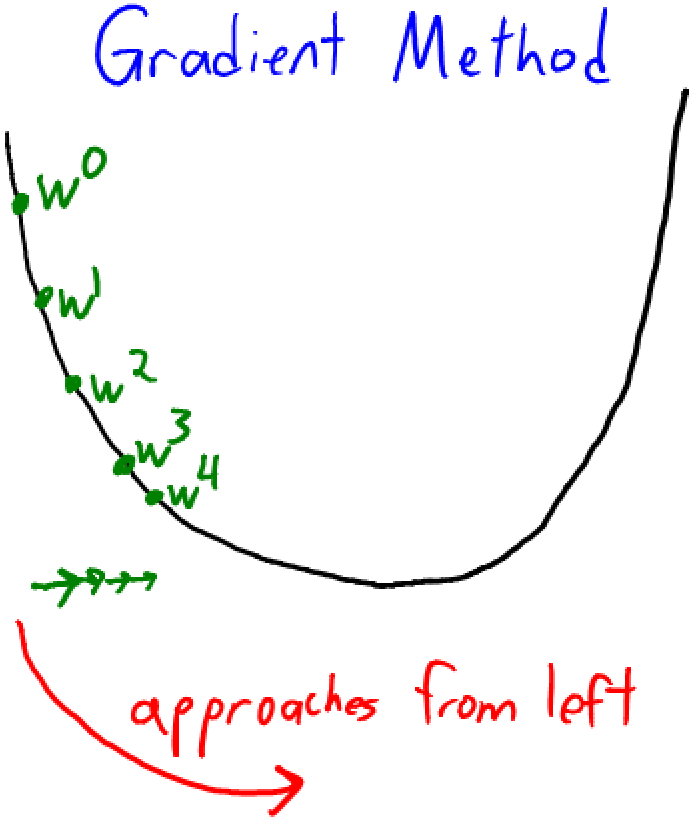



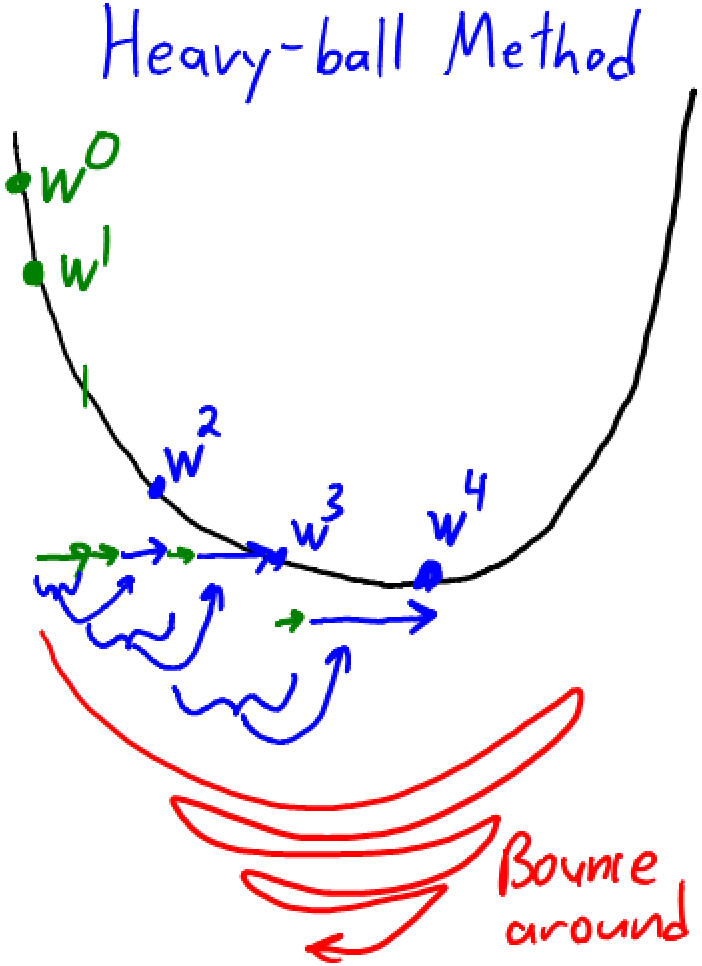
# Gradient Descent vs. Heavy-Ball Method



# Gradient Descent vs. Heavy-Ball Method



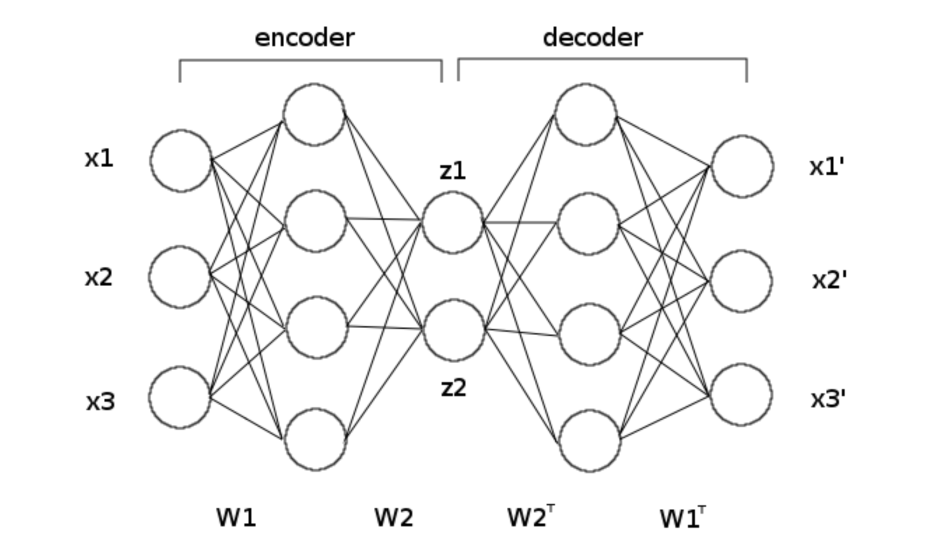
# Summary

- Unprecedented performance on difficult pattern recognition tasks.
- Backpropagation computes neural network gradient via chain rule.
- Parameter initialization is crucial to neural net performance.
- Optimization and step size are crucial to neural net performance.
  - "Babysitting", momentum.

- Next time:
  - Regularization, and getting these working for vision problems.

# Autoencoders

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

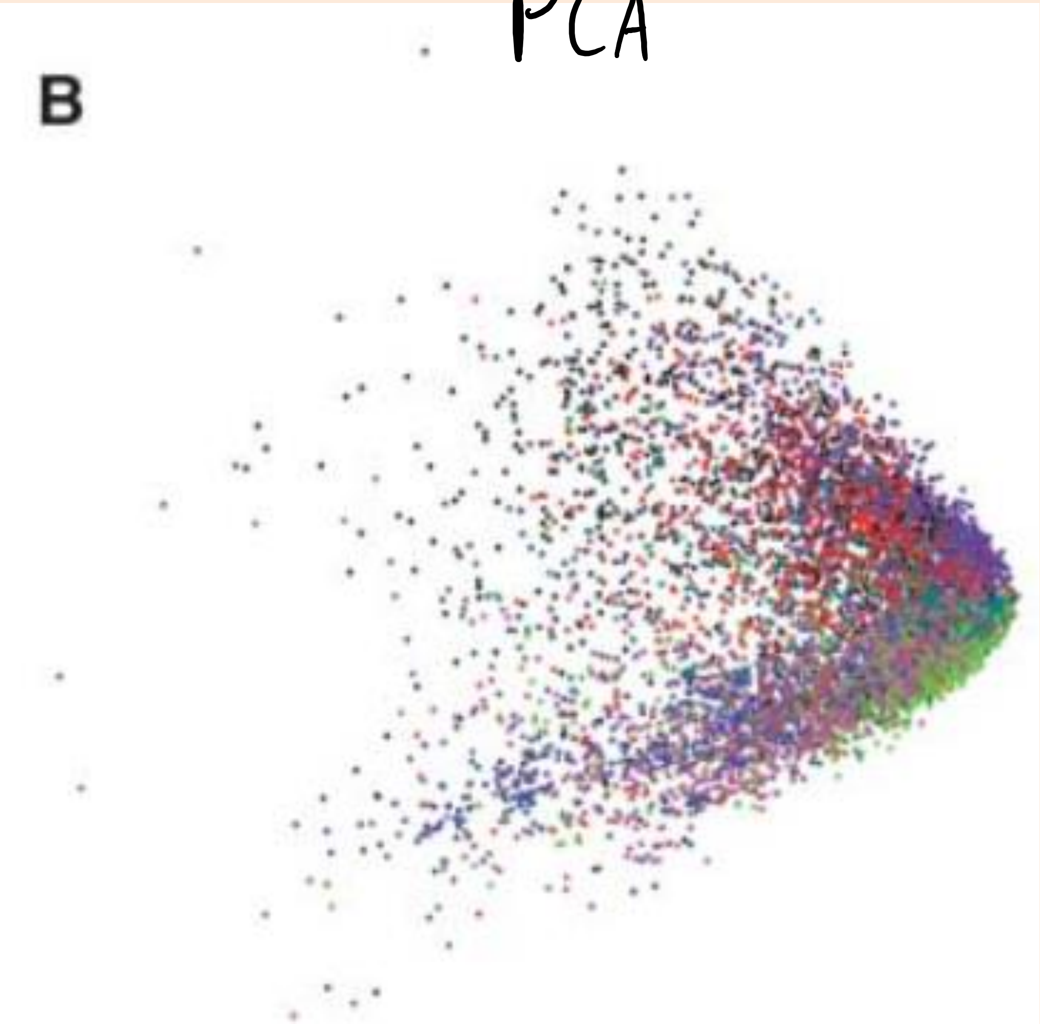



  - Middle layer could be latent features in non-linear latent-factor model.
    - Can do outlier detection, data compression, visualization, etc.
  - A non-linear generalization of PCA.
    - Equivalent to PCA if you don't have non-linearities.

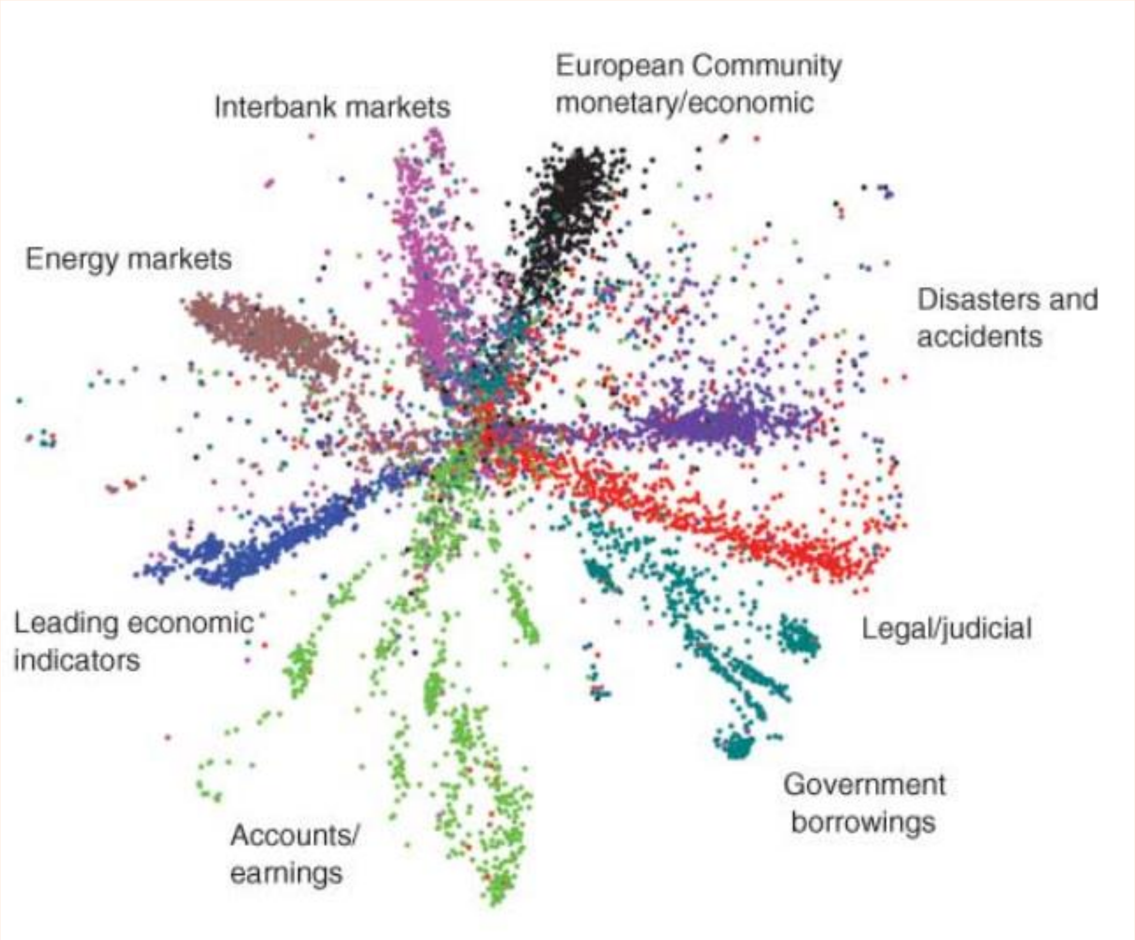
http://inspirehep.net/record/1252540/plots

# Autoencoders

PCA



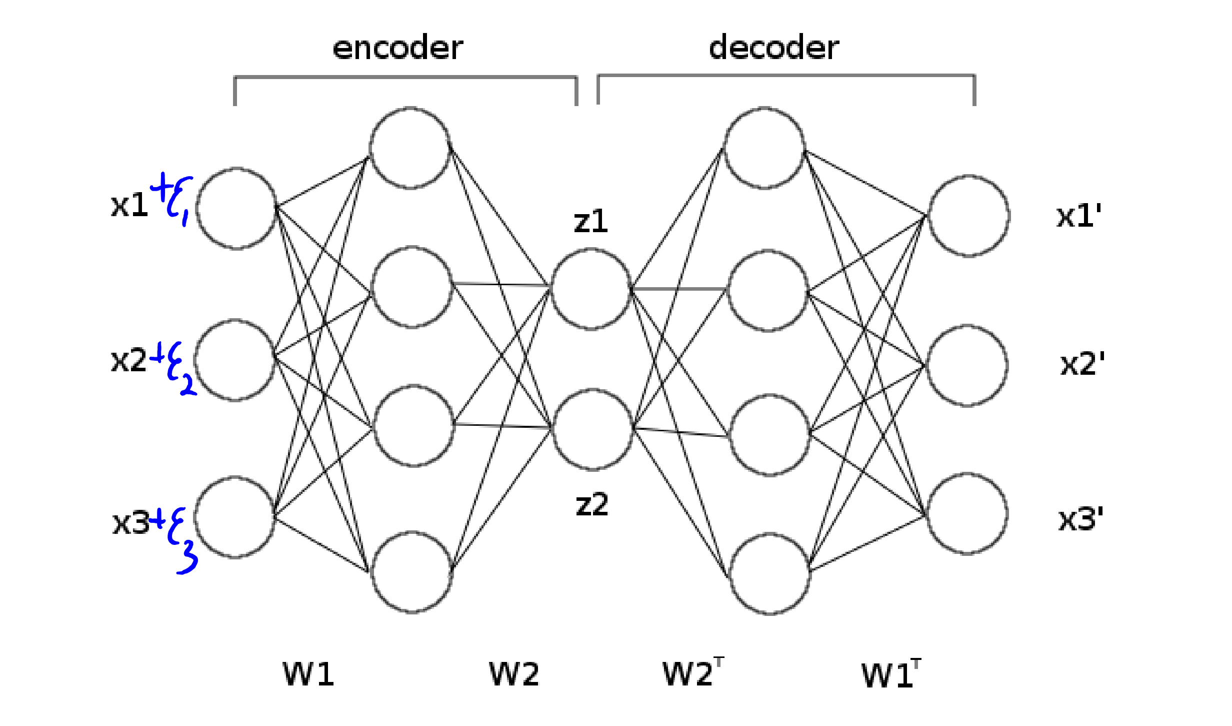

Autoencoder




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

# Denoising Autoencoder

- Denoising autoencoders add noise to the input:




  – Learns a model that can remove the noise.