Fundamentals of Deep Learning

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Agenda

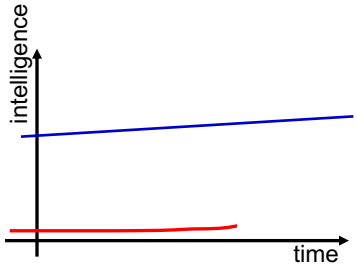
- Part I- Intuition and Theory
  - 8:35-9:15pm: Introduction
  - 9:15-10:00pm: Convolutional Neural Networks
  - 10:00-10:40pm: Recurrent Neural Networks
- 10:40-11:00pm: Break
- Part II- Hands on
  - 11:00am-12:45pm: Hands-on exercises

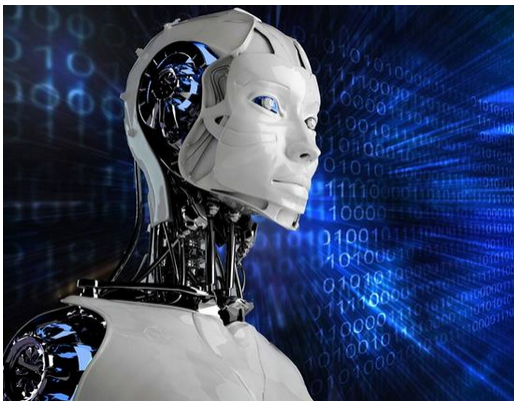
Machine Learning

- Machine learning is giving computers the ability to analyze, generalize, think/reason/behave like humans.
- Machine learning is transforming medical research, financial markets, international security, and generally making humans more efficient and improving quality of life.
- Inspired by the mammalian brain, deep learning is machine learning on steroids- bigger, faster, better!

The point of Singularity

- The point of singularity is when computers become smarter than humans.





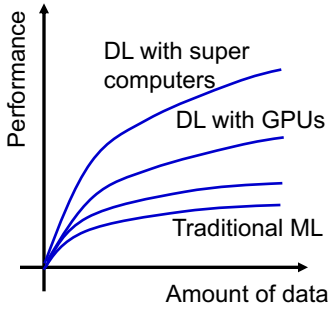
Evolution of biology
Advancement of technology

Unleashing of Intelligence

- Machines will slowly match, then quickly surpass human capabilities.
- Today it is exciting/scary/fun to drive next to an autonomous car.
- Tomorrow it may be considered irresponsible for a human to relinquish control from a car that has faster reaction times, doesn't drink/text/get distracted/tired, and is communicating with surrounding vehicles and objects.

Why is AI (Deep Learning) Just Now Becoming Practical in Many Day-to-Day Situations?

- Availability of data;
- Sustained advances in hardware capabilities (including GPUs running machine learning workloads);
- Omnipresent connectivity;
- Lower cost and power consumption;
- Sustained advances in algorithmic learning techniques.



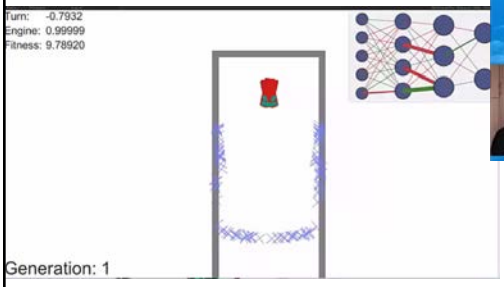
Hot trend:
High performance architecture experts teaming up with deep learning experts

2017: The Year of AI:

The Wall Street Journal, Forbes, and Fortune

NEC Face Recognition

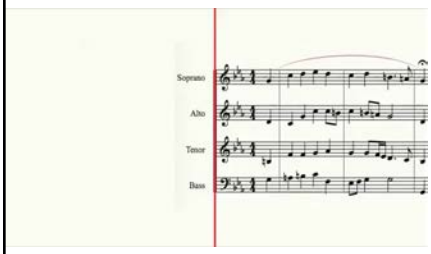
SONY Playstation Virtual Reality



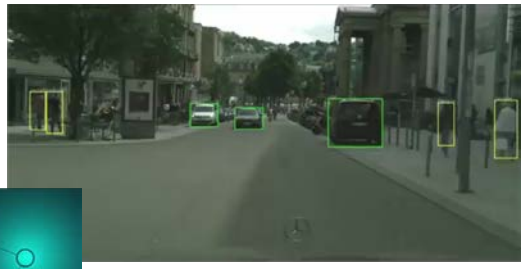
Evolutionary Reinforcement Learning

2017: The Year of AI:

The Wall Street Journal, Forbes, and Fortune



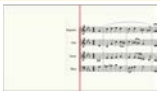
DeepBach



NVIDIA Autonomous Car
Detection & Segmentation

YOLO v2 Object Detection

Awesome 2018 Technology



CelebA-HQ
1024 × 1024

Progressive growing

CelebA-HQ
1024 × 1024

Latent space interpolations

http://research.nvidia.com/sites/default/files/pubs/2017-10_Progressive-Growing-of/karras2017gan-paper.pdf

Awesome 2018 Technology

Faceshift GDC

Apple iPhone X, Animoji Yourself

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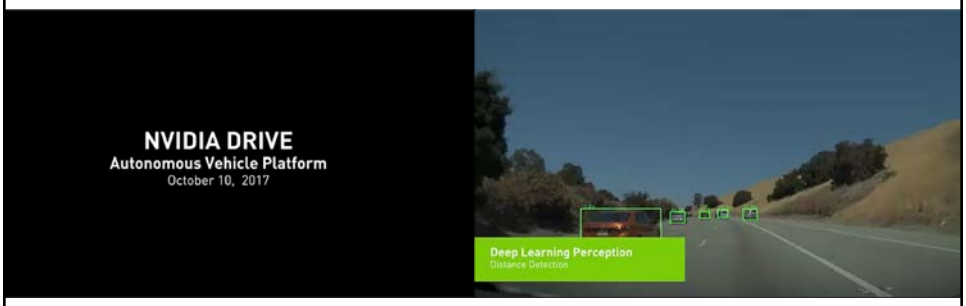
Awesome 2018 Technology



NVIDIA Drive

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Awesome 2018 Technology

Email smart compose sentence completion

https://ai.googleblog.com/2018/05/smart-compose-using-neural-networks-to.html?m=1

ML Trends

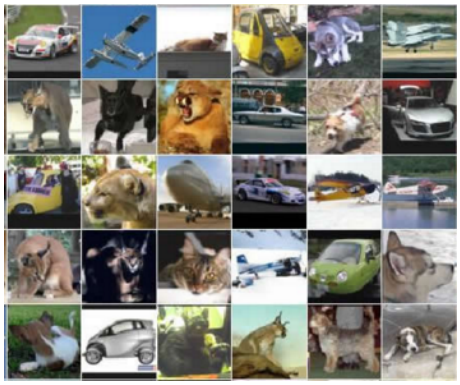
- If 2013/2014 were the year of CNNs, 2015/2016 were LSTMs, 2018 was GANs.
- In 2017 AI fear mongering peaked, in 2018 press has come to terms with AI limitations.
- In 2018 focus started to turn to fairness, bias, interpretability.
- Deep learning continues to infiltrate more applications/markets.
- While current deep learning is not capable of achieving general AI, it may form building blocks.

The Human Brain

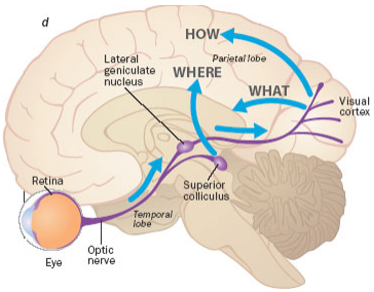
- We've learned more about the brain in the last 5 years than we have learned in the last 5000 years!
- It controls every aspect of our lives, but we still don't understand exactly how it works.

The Brain on Pattern Recognition

- Airplane, Cat, Car, Dog



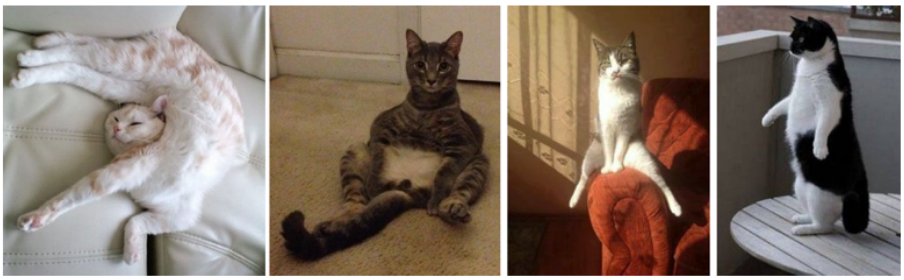
STL-10 dataset



http://thebraingeek.blogspot.com/2012/08/blindsight.html

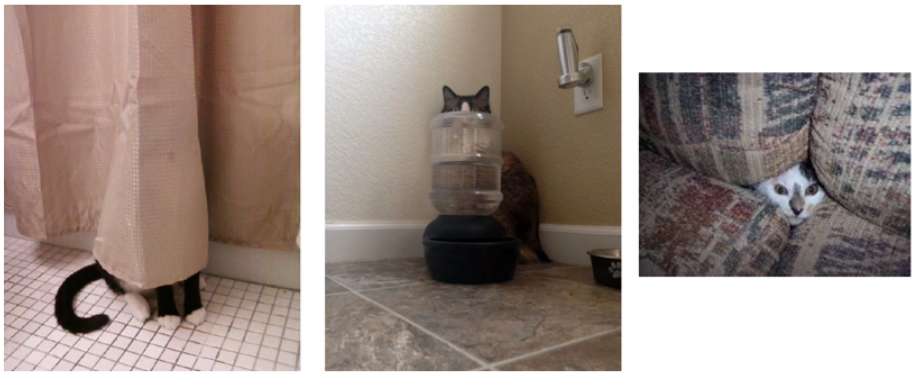
The Brain on Pattern Recognition

Despite Changes in Deformation:



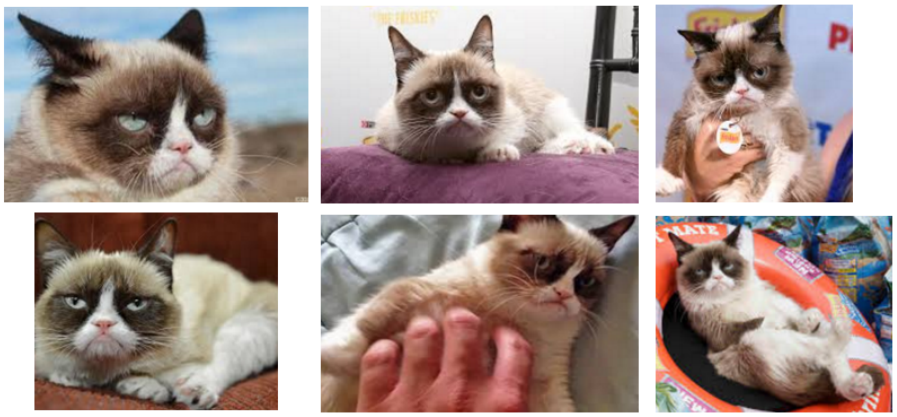
The Brain on Pattern Recognition

Despite Changes in Occlusion:



The Brain on Pattern Recognition

Despite Changes in Size, Pose, Angle:



Tardar Sauce “Grumpy Cat”

The Brain on Pattern Recognition

Despite Changes in Background Clutter:

The Brain on Pattern Recognition

Despite Changes in Class Variation…

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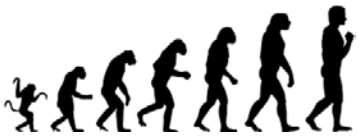
Teaching Computers to See

- It took evolution 540M years to develop the marvel of the eye-brain.



- Lets say a child collects a new image every 200msec.
- By age 3, this child has processed over 100M images.

$$(5\ images/sec)(60sec/min)(60min/hr)(12hr/day)(365days/yr)(3yrs) = 236M$$

- Today's computers can do this in a few days…

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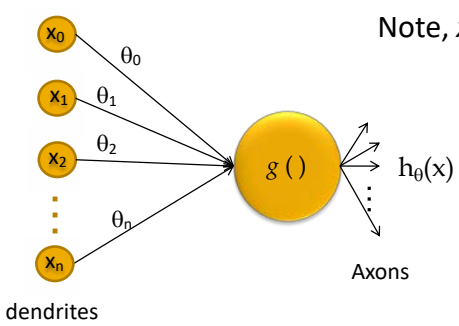
Neural Nets on Pattern Recognition

- Instead of trying to code simple intuitions/rules on what makes an airplane, car, cat, and dog…
- We feed neural networks a large number of training samples, and it will automatically learn the rules!
- We will learn the magic behind this today!

Artificial Neuron



Note, x_0 is the bias unit, x_0=1

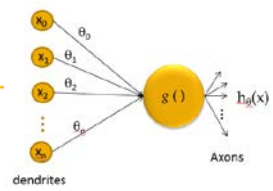
$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix}$$

Activation function

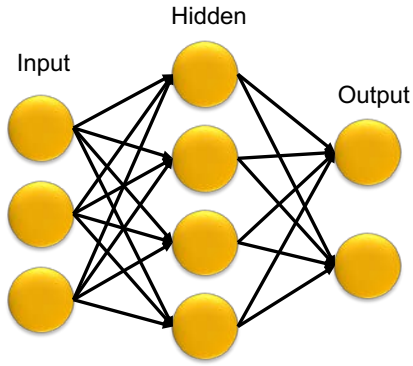
$$h_\theta(x) = g(x_0\theta_0 + x_1\theta_1 + \ \dots + x_n\theta_n) = g\left(\sum_{i=0}^{n} x_i\theta_i\right)$$

$$h_\theta(x) = g(\theta^T x)$$

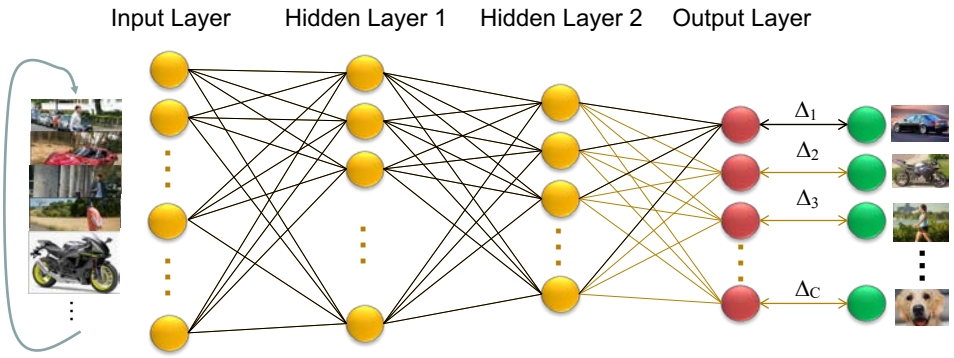
Artificial Neural Networks



- <u>Artificial Neural Network (ANN)</u> – A network of interconnected nodes that "mimic" the properties of a biological network of neurons



4-Layer ANN Fully Connected Topology



A 20x20 image would have 400 input nodes

a nodes

b nodes

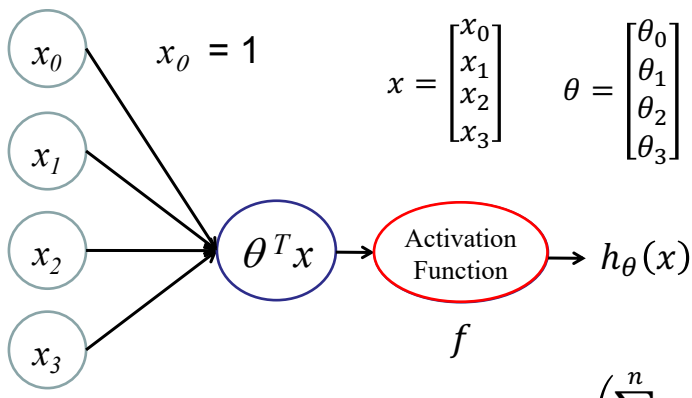
C nodes, where *C* is the number of classes

Backpropagation (~1985) uses $\frac{\partial \Delta}{\partial w}$ for learning

Learning happens in the weights- each line is a weight.

Neuron Model

Bias unit



$x_0 = 1$

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

$$h_\theta(x) = g(x_0\theta_0 + x_1\theta_1 + \ \dots + x_n\theta_n) = g\left(\sum_{i=0}^{n} x_i\theta_i\right)$$

$$h_\theta(x) = g(\theta^T x)$$

Activation Function

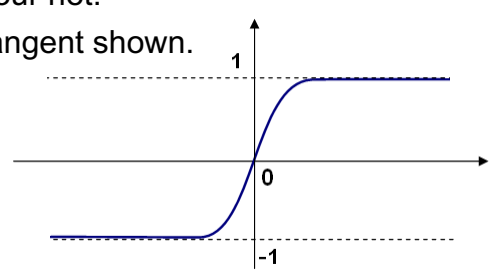
- Basic operation of an artificial neuron involves summing its weighted input signal and applying a threshold, called an activation function.
- If the sum is greater than threshold, fire, otherwise don't.
- A linear activation function is unbounded and limits the nonlinear properties of our net.
- Non-linear hyperbolic tangent shown.

Sigmoid:

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

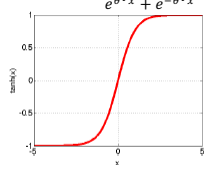
Hyperbolic tangent:

$$h_\theta(x) = \frac{e^{\theta^T x} - e^{-\theta^T x}}{e^{\theta^T x} + e^{-\theta^T x}}$$

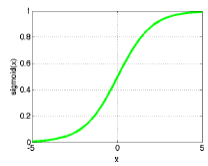


Activation Function Comparison

$$h_\theta(x) = \frac{e^{\theta^T x} - e^{-\theta^T x}}{e^{\theta^T x} + e^{-\theta^T x}}$$



$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

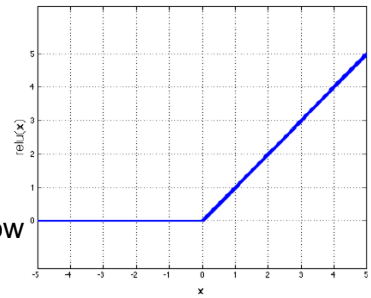


- Tanh
- Sigmoid

Gradient of both saturates at zero. Sigmoid also non-zero centered, so in practice tanh performs better.

- Rectified Linear Units (ReLU)
  - Better for high dynamic range
  - Faster learning
  - Overall better result
  - Neurons can "die" if allowed to grow unconstrained

$$h_\theta(x) = max(0, x)$$



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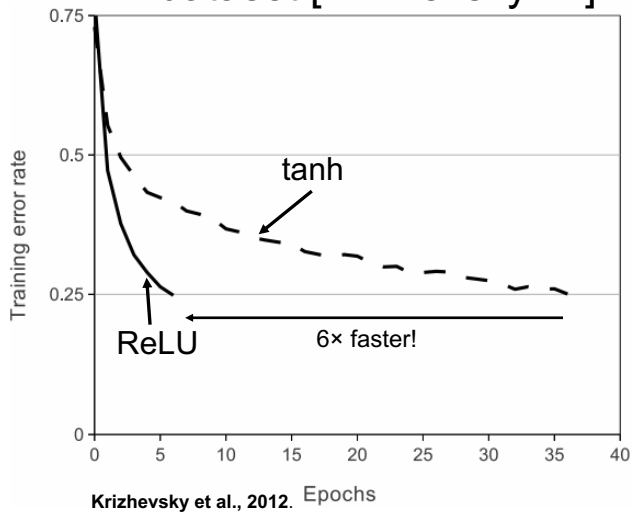
Tanh vs. ReLU on CIFAR-10 dataset [Krizhevsky'12]



Krizhevsky et al., 2012.

ReLU reaches 25% error 6× faster!
Note: Learning rates optimized for each, no regularization, four layer CNN.

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Where Do Weights Come From?

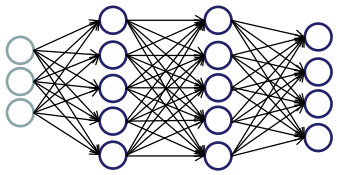
- The weights in a neural network need to be learned such that the errors are minimized.
- Just like logistic regression, we can write a cost function.
- Similar to gradient descent, we can write an iterative procedure to update weights, with each iteration decreasing our cost.
- These iterative methods may be less efficient than a direct analytical solution, but are easier to generalize.

Backpropagation

- We need to solve weights of a network so that the error is minimized.
- Weights can be refined by changing each weight by an amount proportional to the partial derivative of the error with respect to each weight.
- Partial derivatives can be calculated by iteratively changing each weight and measuring the corresponding change in error.
- Hard to do with millions of weights!
- In 1986, a technique called back-propagation was introduced (D. E. Rumelhart, G. E. Hinton, and R. J. Williams "Learning representations by back-propagating errors," J. *Nature* 323, 533-536, 1986).

Hyperparameters vs. parameters

- Hyperparameters are the tuning parameters for a nnet- say number of layers, nodes per layer, learning rate, momentum, regularization, etc.
- Parameters are the weights that are being learned. Ignoring bias terms, the below network has 3x5+5x5+5x4 = 60 parameters.
  - If we include bias terms, we have 4x5+6x5+6x4=74 learnable parameters.



Note: deep nets may contain 100M parameters with 20 layers!

Cost Function

Add regularization to prevent overfitting to the training set.

Logistic Regression Cost Function:

$$J(\theta) = \left[-\frac{1}{n}\sum_{i=1}^{n} y^{(i)} log\left(h_\theta\left(x^{(i)}\right)\right) + \left(1-y^{(i)}\right) log\left(1-h_\theta\left(x^{(i)}\right)\right)\right] + \frac{\lambda}{2n}\sum_{j=1}^{D}\theta_j^2$$

n = number training samples, D is the dimension of each sample

Foreach sample

Foreach class (or foreach output node)

C = number of classes
L = number of layers
s_l = number of nodes in layer l

Neural Network Cost Function:

$$J(\theta) = \left[-\frac{1}{n}\sum_{i=1}^{n}\sum_{c=1}^{C} y^{(i,c)} log\left(h_\theta\left(x^{(i)}\right)\right)_c + \left(1-y^{(i,c)}\right) log\left(1-h_\theta\left(x^{(i)}\right)\right)_c\right] +$$

$$\frac{\lambda}{2n}\sum_{l=1}^{L}\sum_{i=1}^{s_{l-1}}\sum_{j=1}^{s_l}\left(\theta_{ji}^{[l]}\right)^2$$

For L layers
Each layer l has s_l nodes
θ between layer l-1 and layer l
Note: we don't regularize bias term

To From

Initialization of Weights

- We initialize weights to small ± values centered on 0.
- If they were all initialized to 0, the network wouldn't learn anything.
  - ie: the output of each node would be equal, therefore the update would update each term identically.
- If they were all initialized to large values (values > +1 or < -1), the inputs to each node would be saturated.
- If they were all initialized to small values around 0, we would be in the linear portion of the activation function.
  - W1 = 0.001*rand(length(h1),length(h2))

Initialization of Weights

- Although the uniform distribution is good, the more inputs to a node, the greater its variance.
- To set output distribution of all nodes equal (this empirically improves convergence), use
  "X
  –

Transfer Learning

h1=# input nodes

- Other solutions restrict weights: $-\epsilon_{init} < \theta_{ji}^{(l)} < \epsilon_{init}$

  $\epsilon_{init} = \sqrt{6}/\sqrt{s_l + s_{l+1}}$ s_l , s_{l+1} are the No. nodes in layers around $\theta^{(l)}$
- For deep ReLU networks, He2015 showed:
  - **W1 = 0.001*rand(length(h1),length(h2))./sqrt(2*length(h1))**
- Works best and is recommended for them

Multiclass Loss Functions

input

Nnet model (w/ 3 outputs)

-96.8	Bunny score
437.9	Cat score
61.95	Dog score

- The input image scores highest against cat, but is also somewhat similar to dog.
- How do we assign a loss function?

Activation Function of Output Layer

- Sigmoid returns 0 or 1 for each output node.
- What if you wanted a confidence interval?
- Use a linear activation function for regression: $a^{(l)}=z^{(l)}$
- Softmax often used for classification:

$$a_c^{(L)} = h_\theta(x)_c = g\left(z_c^{(L)}\right) = \frac{exp\left(z_c^{(L)}\right)}{\sum_{c=1:C} exp\left(z_c^{(L)}\right)}$$

← *exp()* of each output node

← Sum of all output nodes

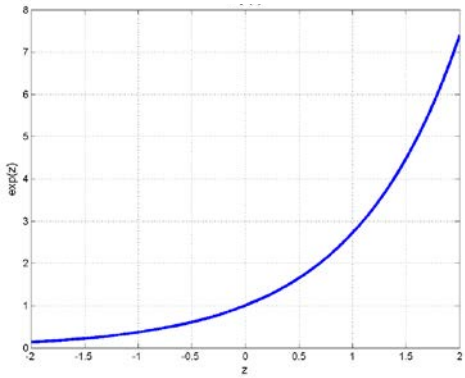
- Note: Only the output layer activation function changes- all hidden layer nodes activation functions would be the sigmoid/tanh/ReLU function.

input

Nnet model (w/ 3 outputs)

Bunny score	-0.97	0.38	0.46
Cat score	4.38	79.8	97.3
Dog score	0.62	1.86	2.26

exp(z), where z is each output node



$$exp\left(z_c^{(L)}\right)$$

$$\frac{exp\left(z_c^{(L)}\right)}{\sum_{c=1:C} exp\left(z_c^{(L)}\right)} \times 100$$

exp() take in values +/- values and returns all positive values.

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Most Common Loss Functions

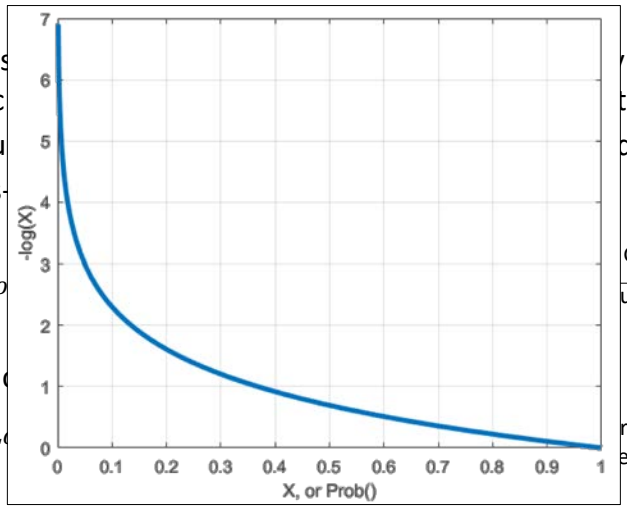
- The cos ... from logistic ... tion.
- For mu ... ds:

1. Cross- ... GT node) ... ut) of all nodes

$Loss^{(i)} = -lo$

2. Multi ... rect – ... es

L



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Most Common Loss Functions

- The cost function we previously used was a direct copy from logistic regression and works great for binary classification.
- For multi-class, there are two popular data loss methods:

1. Cross-entropy loss, which uses softmax:

$$Loss^{(i)} = -log\left(\frac{exp\left(out_{yi}^{(i)}\right)}{\sum_{c=1:C} exp\left(out_c^{(i)}\right)}\right)$$

Loss for sample i = $\frac{\text{exp(output of GT node)}}{\text{Sum of exp(output) of all nodes}}$

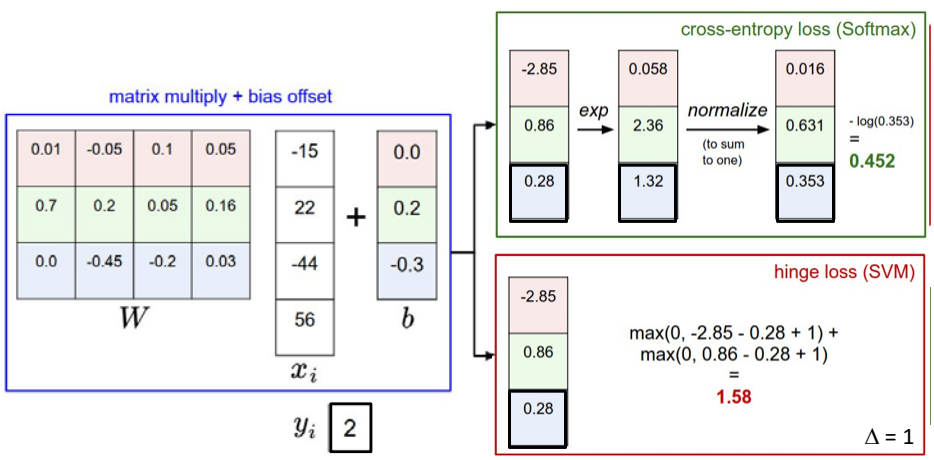
2. Multiclass SVM Loss (Weston Watkins formulation):

$$Loss^{(i)} = \sum_{j \neq yi} max\left(0, out_j - out_{yi} + \Delta\right)$$

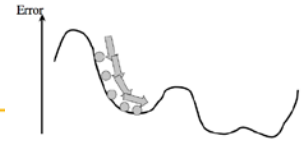
Sum of incorrect – correct classes

Loss Example

(based on cs231n, Li/Karpathy 2016)



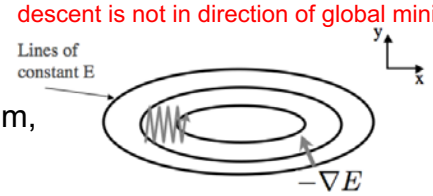
Local Minima



Marsland: Machine Learning

- Back propagation modifies the weights to minimize the cost function.
- It does this by approximating the gradient of the error and following it downhill.
- We could of course get stuck at a local minima.
- If we start near the global minimum, we often end up there.
- If we start at a local minimum, we often end up there!

Sometimes the direction of steepest descent is not in direction of global minima

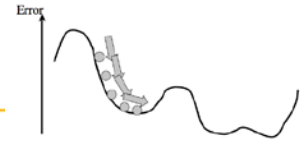


Marsland: Machine Learning

Learning Rates

- Like gradient descent, we incorporate a learning rate so we don't take full steps in any one direction.
- In its simplest form, we have $w_{ij} = w_{ij} - \eta\, dw_{ij}$
- As training progresses, we generally anneal the learning rate over time, going from large to small steps. Three common approaches:
  1. Step decay: Either watch validation error and reduce learning rate whenever validation error stops improving, or automatically reduce by ~0.1 every ~20 epochs
  2. Exponential decay: $\alpha = \alpha_0 e^{-kt}$ (α_0 *and k are* hyperparameters, *t* is epoch.
  3. 1/*t* decay: $\alpha = \alpha_0/(1+kt)$ (α_0 *and k are* hyperparameters, *t* is epoch.

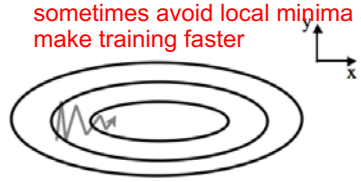
Momentum



Marsland: Machine Learning

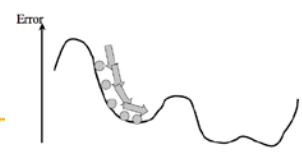
- One solution is to train several networks, each at a different initialization.
- Another is to add a momentum term.
- Imagine a ball rolling down a hill- if it had little energy, it may get stuck in little dips.
- If it had a lot of energy, it would be more likely to skip over little dips, and keep rolling until it hopefully hits a global minimum.

Adding a momentum term can sometimes avoid local minima and make training faster



Marsland: Machine Learning

Momentum



Marsland: Machine Learning

- Momentum adds a contribution of our previous weight change to our current weight change.
- Change:

$$\Delta_{ij}^{(l)} = \Delta_{ij}^{(l)} + a_j^{(l)} \delta_i^{(l+1)}$$

- To:

$$\Delta_{ij}^{(l)}{}_t = \Delta_{ij}^{(l)}{}_{t-1} + a_j^{(l)} \delta_i^{(l+1)} + \alpha \Delta_{ij}^{(l)}{}_{t-1} \quad , 0 \le \alpha \le 1$$

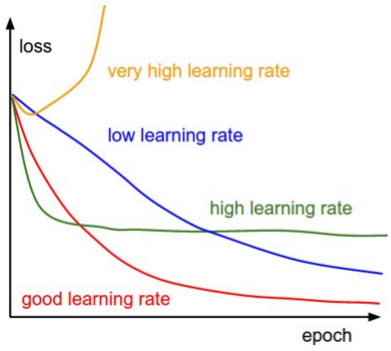
Caution- these methods are quite effective, but more of an art than science!

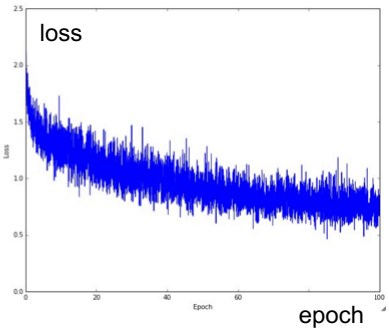
The use of *t* and *t-1* emphasize the previous and current derivatives
A typical value of α is 0.9

Sequential vs. Batch Training

- Back propagation can be done:
  - Sequential: one sample at a time,
    - Weights are shifted back and forth quite a bit
  - Group (minibatch): a group of samples at a time, or
  - Batch: all training samples at once
    - Weights are shifted in direction that makes most input samples better
    - Generally converges the fastest
- Recommended to use largest minibatch possible and stay within memory constraints of hardware.

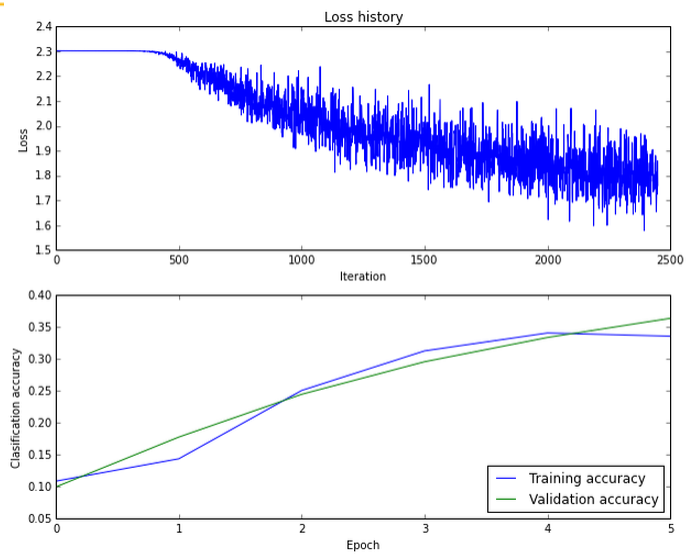
Examples of Learning Rate and Batch Size





This batch size could be made a little larger to shrink the variance

Tuning Parameters



Curve too linear- increase learning rate.

Train and Test sets too similar- increase model complexity. Be careful, larger models susceptible to overfitting. Perhaps increase regularization

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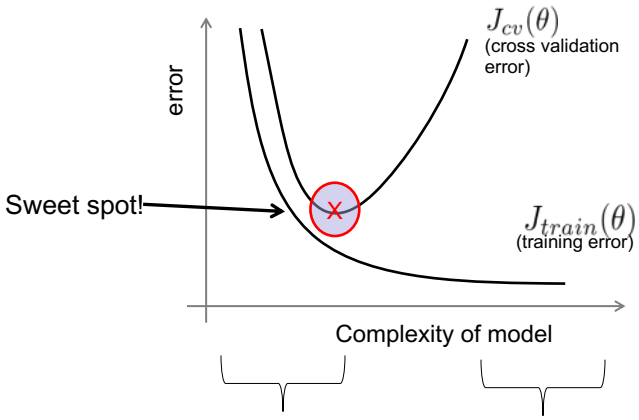
Bias (underfit) vs. Variance (overfit) errors



Model too simple. Too high error on train and test

Model too complex. Overfitting to training set

Adopted from: Andrew Ng, ML class

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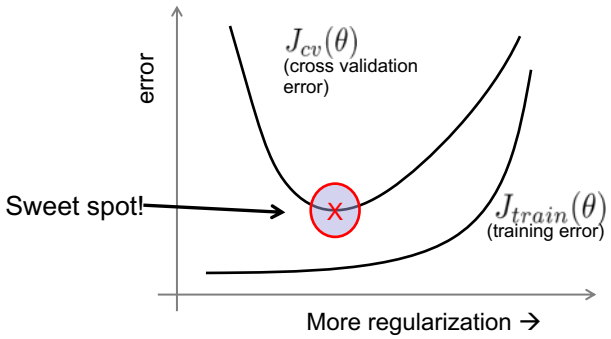
Regularization Tuning



Adopted from:
Andrew Ng, ML class

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