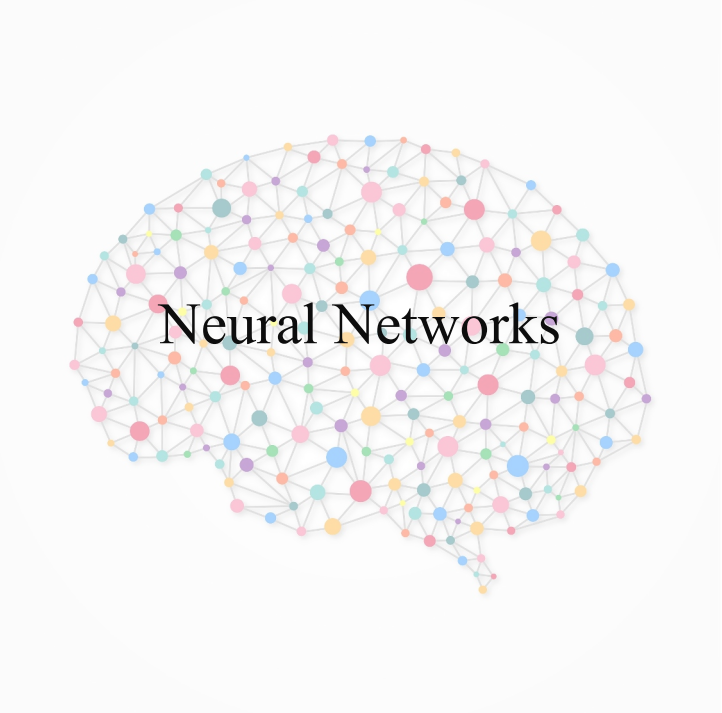
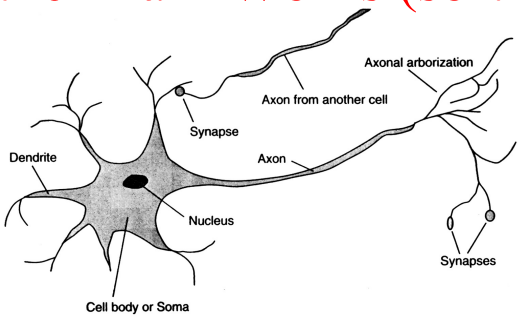


1

How the Brain Works (sort of…)



- Neuron is fundamental functional unit
  - Soma: cell body
  - Axon: long single fiber that connects to other neurons
  - Dendrites: connected to axons from other neurons
  - Synapse: connecting junction
- A collection of simple cells can lead to thought, action, and consciousness ("bottom-up" statement)

2

2

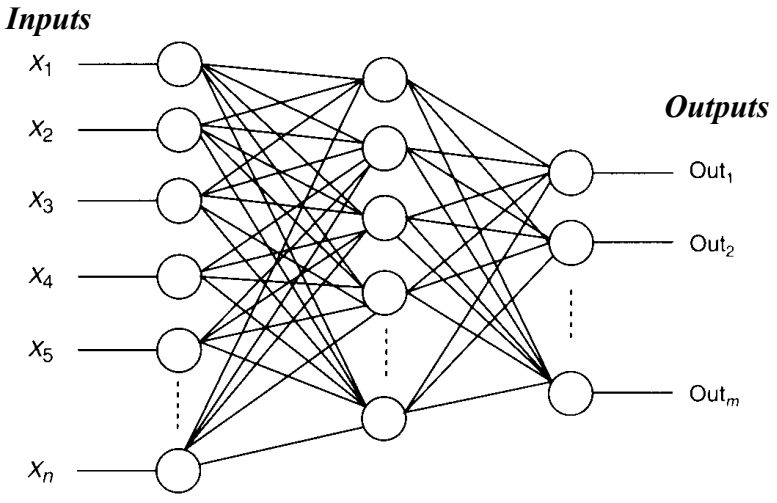
Network Structures

- Two main varieties
  - Feed-forward
    - Unidirectional links with no cycles
    - Directed acyclic graph (DAG)
    - Not like the brain!
      - We have memory
      - Many back connections
  - Recurrent
    - Links can form arbitrary topologies

3

3

Feed-Forward Neural Network



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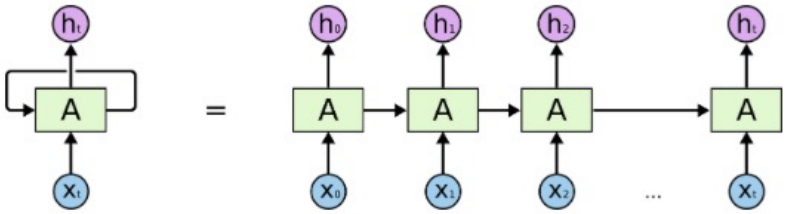
Recurrent Neural Network



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Neural Networks

- Neural net is composed of nodes (units)
  - Some connected to outside world as input or output units
- Nodes are connected by links
  - Input and output links
- Each link has numeric weight associated with it
  - Primary means of **long-term storage/memory**
  - Weights are modified to bring network's input/output behavior to goal response
- Nodes have activation level
  - Given its inputs and weights
  - Local computation based on inputs from neighbors (no global control)

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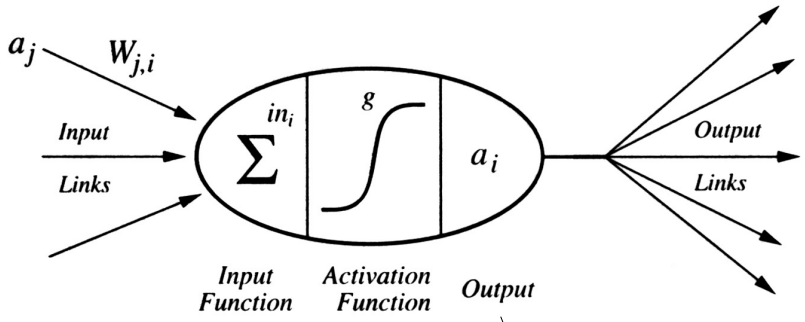
Node Computation



$$\sum_j W_{j,i} a_j = \boldsymbol{W} \cdot \boldsymbol{a}$$ linear

$$g(\sum_j W_{j,i} a_j)$$ non-linear

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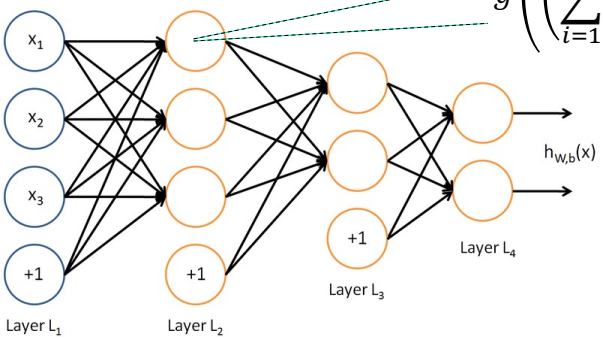
Additive Bias Terms

linear term bias

$$g\left(\left(\sum_{i=1}^{3} W_{i,1} \cdot x_i\right) + \left(B_{L_1} \cdot 1\right)\right)$$



Common to have a "bias" term <u>for each node</u> to "*shift*" linear inputs into good place for activation function (learn best bias values)

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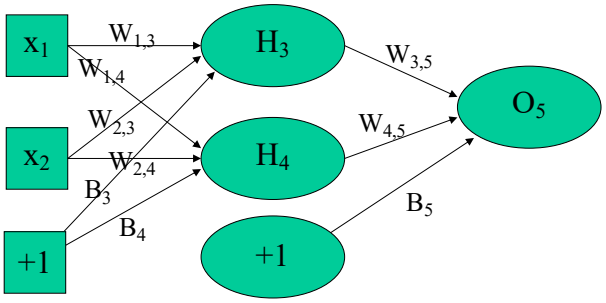
Simple Feed-Forward Neural Network



$$O_5 = g(\ W_{3,5} \cdot g(W_{1,3} \cdot x_1 + W_{2,3} \cdot x_2 + B_3) + W_{4,5} \cdot g(W_{1,4} \cdot x_1 + W_{2,4} \cdot x_2 + B_4) + B_5\ )$$

Learning just becomes a process of tuning parameters to fit data in training set!!!

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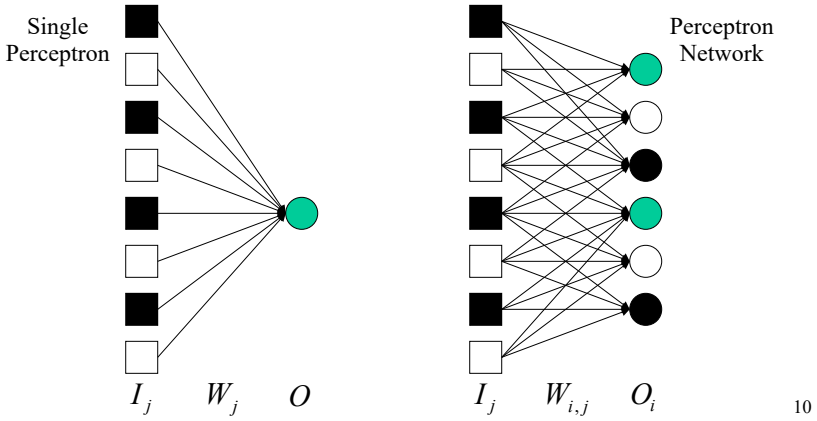
"Perceptrons"

- First studied in late 1950's
- Single-layer, feed-forward network



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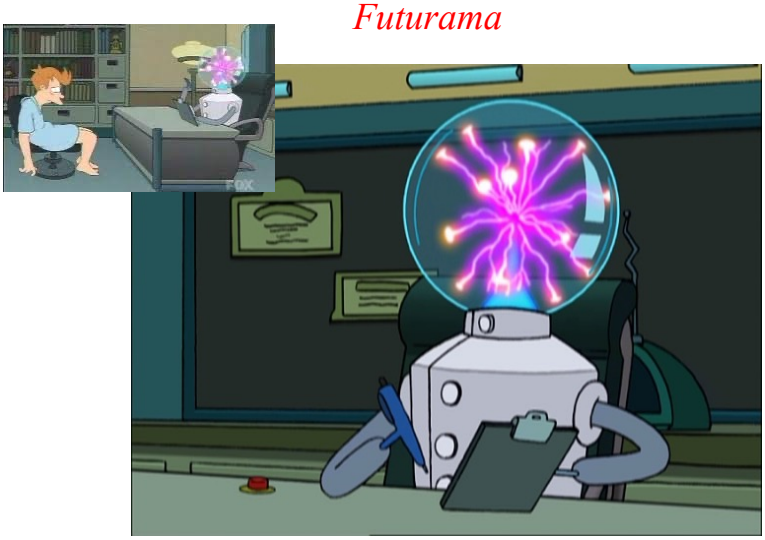
Dr. Perceptron

Futurama



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Perceptrons

- Consider simple "*Threshold*" (sign) activation function:

$$g\left(\sum_j W_{j,i}a_j\right) = g\left(\langle W_{1,i}, W_{2,i}, W_{3,i}\rangle \cdot \langle a_1, a_2, a_3\rangle\right)$$

where $g = 1$ if $\langle W_{1,i}, W_{2,i}, W_{3,i}\rangle \cdot \langle a_1, a_2, a_3\rangle > 0$

$g = -1$ if $\langle W_{1,i}, W_{2,i}, W_{3,i}\rangle \cdot \langle a_1, a_2, a_3\rangle \leq 0$

- Now consider equation for a line

$$y = mx + b$$
$$0 = mx + b - y$$
$$0 = \langle m, b, -1\rangle \cdot \langle x, 1, y\rangle$$

$$0 = \langle W_{1,i}, W_{2,i}, W_{3,i}\rangle \cdot \langle a_1, a_2, a_3\rangle$$

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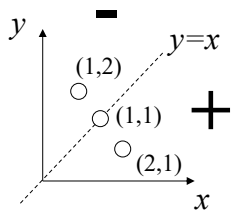
Dividing the Space (+,-)

$y = x \longrightarrow 0 = x - y \longrightarrow 0 = \langle 1, -1 \rangle \langle x, y \rangle$

(1,2):

-1 = 1 - 2



(2,1):

+1 = 2 - 1

Threshold perceptrons represent functions that are **linearly separable** ***

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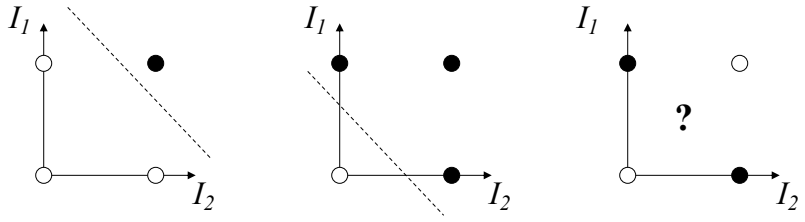
Linear Separability in Perceptrons

Limited in Boolean functions they can represent
AND, OR, but not XOR
(True = solid circle)



I_1 AND I_2 I_1 OR I_2 I_1 XOR I_2

"A perceptron can represent a function only if some line can separate all white dots from black dots"

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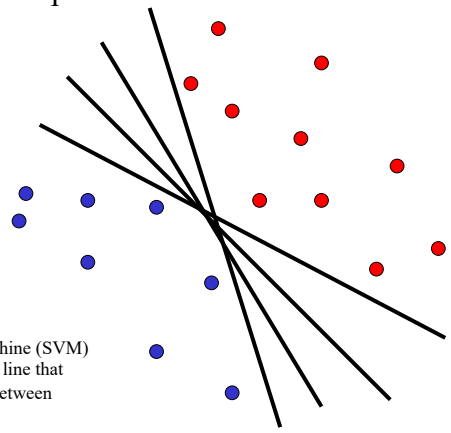
Linear Classifiers

- Multiple Perceptron solutions to separate positive and negative examples



Note: Support Vector Machine (SVM) approach seeks to find the line that maximizes the "margin" between classes – better!

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Perceptron Learning Algorithm

- Initially assign random weights
  - More on this later…
- Update network to try to make consistent with examples
  - Make small adjustments in weights to reduce difference between observed and predicted values
  - Updating process divided into "epochs"
    - One epoch involves updating all weights for all examples

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Error ("Loss") Function

Squared-Error function (**to be summed over <u>all</u> training examples – here only shown for 1 example**): [Note: there are <u>multiple</u> types of error/loss functions]

$$E = \frac{1}{2} Err^2 = \frac{1}{2}\left[O - g\left(\sum_j W_j a_j \right) \right]^2$$

Desired output value

Perceptron output value

Find the weights W_j that minimize this error (for all training examples)

How determine these weight values????

Gradient Descent method

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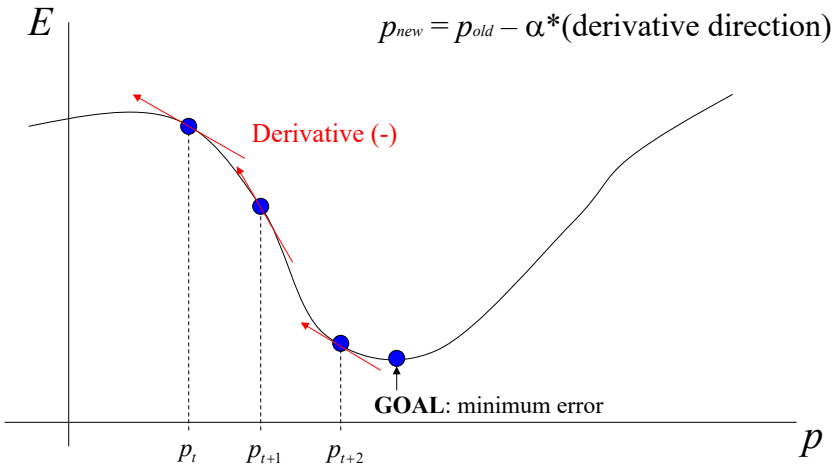
Gradient Descent Visualization (1-D)



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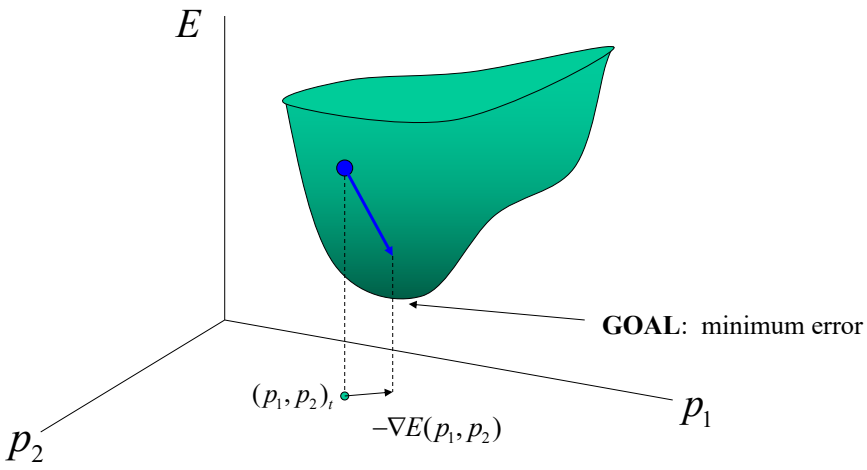
2-D Visualization



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Weight Updating via Gradient Descent

Squared-Error function (**again, to be summed over <u>all</u> training examples**):

$$E = \frac{1}{2} Err^2 = \frac{1}{2}\left[O - g\left(\sum_j W_j a_j \right) \right]^2$$

Desired output value

Perceptron output value

$$\begin{aligned} \frac{\partial E}{\partial W_j} &= \frac{1}{2}\frac{\partial Err^2}{\partial W_j} = Err \cdot \frac{\partial Err}{\partial W_j} \\ &= Err \cdot \frac{\partial}{\partial W_j}\left[O - g\left(\sum_j W_j a_j \right) \right] \\ &= Err \cdot g'() \cdot (-a_j) \end{aligned}$$

Note: $g'()$ is omitted from "threshold" perceptrons

$$\begin{aligned} W_j &= W_j - \alpha \cdot \frac{\partial E}{\partial W_j} \\ &= W_j + \alpha \cdot Err \cdot g'() \cdot a_j \end{aligned}$$

Note: Save the <u>new</u> weight values and do all weight updates **together** <u>at the end</u> of the epoch

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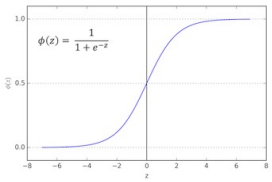
Common Activation Functions

Sigmoid

$$Sig(x) = \frac{1}{1 + e^{-x}}$$

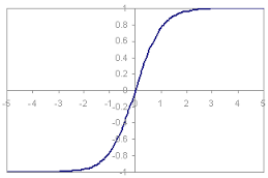
0 to 1



TANH

$$tanh(x) = 2sig(2x) - 1$$

-1 to +1



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Issues

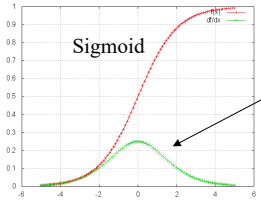
- Sigmoid can have "saturation" problems when input is composed of high (+/-) weights

$$output = \frac{1}{1 + e^{-input}}$$

$(input = x_1 * w_1)$

If $|w_1|$ is large, then *output* is near 0 or 1

$$\frac{\partial out}{\partial net} = out * (1 - out)$$



Thus the gradient will be near zero… **Bad for learning** with Gradient Descent (slows down or makes no changes)!

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"Vanishing Gradient" Problem

- In some cases, some neurons can even "die" in the training and become ineffective
- Gradient signals from the error function decrease exponentially as they are backpropogated to earlier layers (more on this later…)
  - Derivative of certain activation functions (sigmoid, tanh) is small (<1), which when stacked in network layers get smaller, and smaller
- Can be problematic for deep networks!

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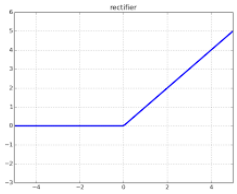
Common Activation Functions

Rectified Linear Unit (ReLU)

$\text{ReLU}(x) = \max(0, x)$

0 to Inf



- Pros:
  - Non-saturating (like sigmoid)
    - ReLU overcomes this particular issue (derivative=1 when signal >0)
  - Faster convergence
  - Efficient computation
  - Resulting representation is "sparse" (not all having nodes have non-zero activations), removing redundancies
- "Leaky" ReLU
  - Use small negative slope around 0

ReLU works as a detector, with a particular signal being detected when the corresponding input (x) is large enough (greater than zero). In practice, the inputs are usually centered (zero-mean) and therefore a threshold of zero is reasonable. But generally use an additive bias term/value to enable a "shift" if needed.

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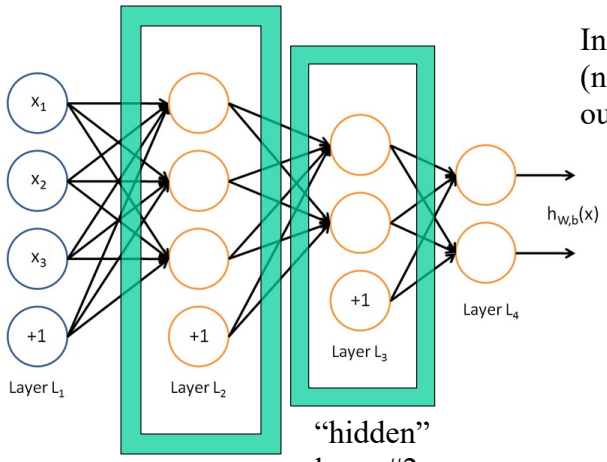
How Handle **Multilayer** Feed-Forward Networks?



Includes "hidden" layers (not containing input or output nodes)

"hidden" layer #1

"hidden" layer #2

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Learning/Training in Multilayer Feed-Forward Networks

- **Back-propagation** learning algorithm
  - Divide error "locally" among contributing weights and update layer-by-layer backwards
- Example

  https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/

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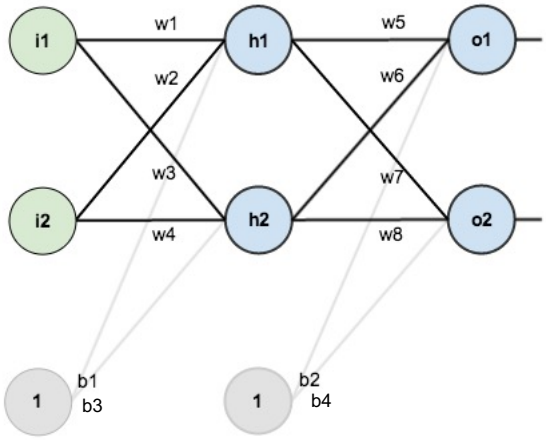
Example Network w/ 1 Hidden Layer



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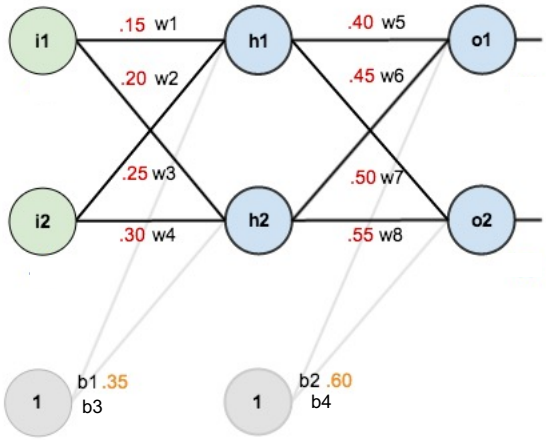
Initialize Weights/Biases



Note: common to start with zero bias value

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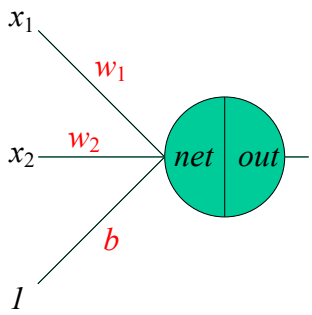
Node Computations: "net" and "out"



Sigmoid activation:

$$net = x_1 * w_1 + x_2 * w_2 + b$$

linear

$$out = \frac{1}{1 + e^{-net}}$$

non-linear

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"Forward Pass"

Note: updating with only 1 training example

- **Input (2-D):** i1=.05, i2= 0.1
  - Desired "target" output (o1=0.01, o2=0.99)
- **Output (2-D):** out_{o1}=0.7569, out_{o2}=0.7677
- **Error/Loss:**

$$E_{total} = \sum \frac{1}{2}(target - output)^2 = E_{o1} + E_{o2} = 0.3037$$

$$E_{o1} = \frac{1}{2}(0.01 - 0.7569)^2 = 0.2790$$

$$E_{o2} = \frac{1}{2}(0.99 - 0.7677)^2 = 0.0247$$

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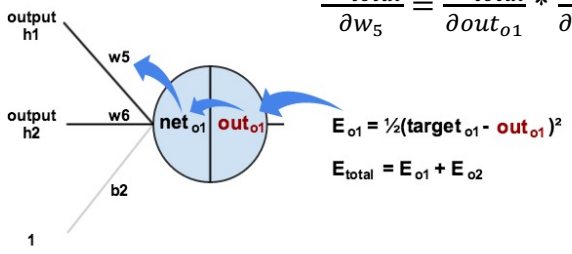
"Backward Pass"

- At final Output Layer (initially)
  - Want to know how much a change in each of w_5, w_6, w_7, w_8, b_2 , b_4 affect Total Error (for gradient descent)
  - So for w_5, we want to know $\frac{\partial E_{total}}{\partial w_5}$
  - Using the chain rule!!!

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$



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Partial Derivative Terms

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

$$E_{total} = \frac{1}{2}(target_{o1} - out_{o1})^2 + \frac{1}{2}(target_{o2} - out_{o2})^2$$

$$\frac{\partial E_{total}}{\partial out_{o1}} = -(target_{o1} - out_{o1})$$

$$= -(0.01 - 0.7569) = \mathbf{0.7469}$$

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Partial Derivative Terms

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \boxed{\frac{\partial out_{o1}}{\partial net_{o1}}} * \frac{\partial net_{o1}}{\partial w_5}$$

$$out_{o1} = \frac{1}{1 + e^{-net_{o1}}}$$

$$\frac{\partial out_{o1}}{\partial net_{o1}} = out_{o1} * (1 - out_{o1}) = \mathbf{0.1840}$$

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Partial Derivative Terms

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \boxed{\frac{\partial net_{o1}}{\partial w_5}}$$

$$net_{o1} = w_5 * out_{h1} + w_6 * out_{h2} + b_2$$

$$\frac{\partial net_{o1}}{\partial w_5} = out_{h1} = \mathbf{0.5945}$$

Note: Uses current inputs and weights to compute sigmoid response at node $h1$ (know this value **from forward pass**)

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Putting it Together…

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

$$\frac{\partial E_{total}}{\partial w_5} = 0.7469 * 0.1840 * 0.5945$$
$$= \mathbf{0.0817}$$

Alternatively see written as "delta rule":

$$\frac{\partial E_{total}}{\partial w_5} = \partial_{o1} * \frac{\partial net_{o1}}{\partial w_5} = \partial_{o1} * out_{h1}$$

where

$$\partial_{o1} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} = \frac{\partial E_{total}}{\partial net_{o1}}$$

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Updating via Gradient Descent

$$w_5 = w_5 - \alpha \cdot \frac{\partial E_{total}}{\partial w_5}$$

$$w_5 = 0.4 - \underset{\textit{given}}{(0.5)} \cdot 0.0817 = 0.3592$$

Repeat entire process for w_6, w_7, w_8, b_2, and b_4

Note: Save these new weight values and do all weight updates together at the end of the epoch (after all new weight values are collected, in this example)

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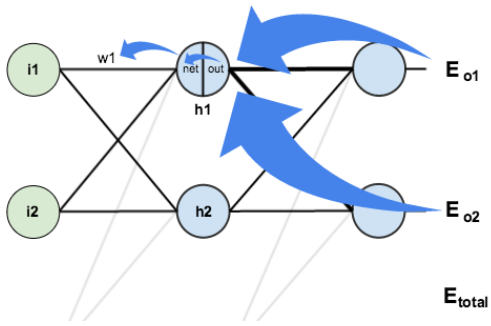
Now Update for "Hidden Layer(s)"

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} * \frac{\partial out_{h1}}{\partial net_{h1}} * \frac{\partial net_{h1}}{\partial w_1}$$

$$\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{o1}}{\partial out_{h1}} + \frac{\partial E_{o2}}{\partial out_{h1}}$$

"This is a bit more tricky!"



$E_{total} = E_{o1} + E_{o2}$

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$$\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{o1}}{\partial out_{h1}} + \frac{\partial E_{o2}}{\partial out_{h1}}$$

$$\frac{\partial E_{o1}}{\partial out_{h1}} = \underbrace{\frac{\partial E_{o1}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}}}_{\text{Have already for } w_5 \text{ ("delta" term)}} * \frac{\partial net_{o1}}{\partial out_{h1}}$$

$$\frac{\partial net_{o1}}{\partial out_{h1}} = w_5 = 0.4$$

Note: $net_{o1} = w_5 * out_{h1} + w_6 * out_{h2} + b_2$

Note: $\frac{\partial E_{o1}}{\partial out_{o1}}$ same as $\frac{\partial E_{total}}{\partial out_{o1}}$

$$= \underbrace{(0.7469 * 0.1840)}_{\text{Already have these values from layer just analyzed}} * 0.4 = \mathbf{0.0550}$$

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$$\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{o1}}{\partial out_{h1}} + \frac{\partial E_{o2}}{\partial out_{h1}}$$

$$\frac{\partial E_{o2}}{\partial out_{h1}} = \underbrace{\frac{\partial E_{o2}}{\partial out_{o2}} * \frac{\partial out_{o2}}{\partial net_{o2}}} * \frac{\partial net_{o2}}{\partial out_{h1}}$$

Have already from updating w_7 ("delta" term)

$$\frac{\partial net_{o2}}{\partial out_{h1}} = w_7 = 0.5$$

Note: $net_{o2} = w_7 * out_{h1} + w_8 * out_{h2} + b_4$

$$= (\mathbf{-0.2223 * 0.1783}) * \mathbf{0.5} = \mathbf{-0.0198}$$

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$$\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{o1}}{\partial out_{h1}} + \frac{\partial E_{o2}}{\partial out_{h1}}$$

$$\frac{\partial E_{total}}{\partial out_{h1}} = 0.0550 - 0.0198 = \mathbf{0.0352}$$

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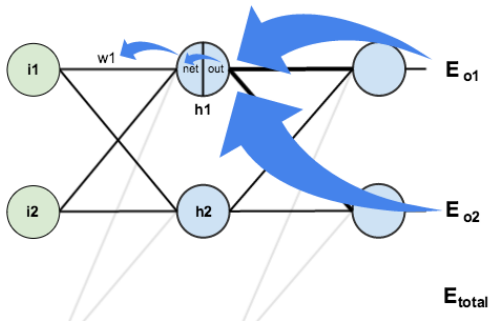
Now Update for "Hidden Layer(s)"

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} * \frac{\partial out_{h1}}{\partial net_{h1}} * \frac{\partial net_{h1}}{\partial w_1}$$

$$\frac{\partial out_{h1}}{\partial net_{h1}} = out_{h1} * (1 - out_{h1}) = \mathbf{0.2411}$$



$E_{total} = E_{o1} + E_{o2}$

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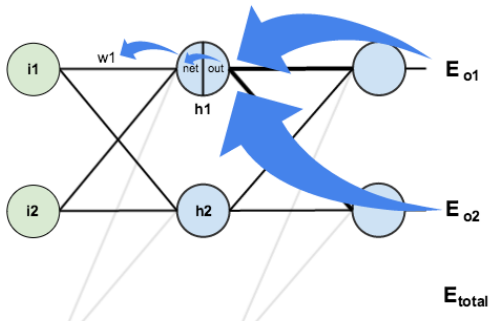
Now Update for "Hidden Layer(s)"

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} * \frac{\partial out_{h1}}{\partial net_{h1}} * \frac{\partial net_{h1}}{\partial w_1}$$

$$\frac{\partial net_{h1}}{\partial w_1} = i_1 = \mathbf{0.05}$$

$$net_{h1} = w_1 * i_1 + w_2 * i_2 + b_1$$



$E_{total} = E_{o1} + E_{o2}$

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Putting it Together…

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} * \frac{\partial out_{h1}}{\partial net_{h1}} * \frac{\partial net_{h1}}{\partial w_1}$$

$$\frac{\partial E_{total}}{\partial w_1} = 0.0352 * 0.2411 * 0.05$$
$$= \mathbf{0.0004243}$$

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Updating via Gradient Descent

$$w_1 = w_1 - \alpha \cdot \frac{\partial E_{total}}{\partial w_1}$$

$$w_1 = 0.15 - (0.5) \cdot 0.0004243 = 0.1498$$

Repeat entire process for w_2, w_3, w_4, b_1, and b_3

Note: Save these new weight values and do all weight updates together at the end of the epoch

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More on Loss Functions…

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SoftMax Output

- If target output is a vector of **dependent multi-class membership**, it can be desirable to train the network to output a "*probability distribution*" across the classes
  - Multinomial "hard targeting" [1 0 0], [0 1 0], [0 0 1]
    - Also called "**1-hot**" vectors, used as **ground-truth targets**
  - Network outputs: [.99 0 .01], [.15 .85 0], [.2 .1 .7]
- Use normalized exponential of outputs out_{oi}
  - Sums to 1 (probability)
  - "Peaky" distribution

$$p_{oi} = \frac{e^{out_{oi}}}{\sum_j e^{out_{oj}}}$$

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Multi-Class "*Categorical*" **Cross Entropy** Error/Loss Function

- Softmax output: $p_{oi} = \frac{e^{out_{oi}}}{\sum_j e^{out_{oj}}}$

$$E = -\sum_i target_{oi} * \ln(p_{oi})$$

Note: only one $target_{oi}$ is 1 (rest are 0)

$$\frac{\partial E}{\partial out_{oi}} = (p_{oi} - target_{oi})$$

Used in Gradient Descent

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Calibration and Temperature Scaling

- Would like to have Softmax be representative of true posterior probability
  - If largest softmax output of a class is .8, then want that to mean "*there is an 80% chance of this classification being correct*" [this is perfect calibration]
- There exist methods to assess the calibration quality
  - "On Calibration of Modern Neural Networks"
  - https://arxiv.org/pdf/1706.04599.pdf
- If uncalibrated (typical), can attempt to calibrate model
  - Temperature (T) scaling
  - Either soften or sharpen softmax vals
  - Can learn or search for best T

$$p_{oi} = \frac{e^{out_{oi}/T}}{\sum_j e^{out_{oj}/T}}$$

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Training Particulars

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Data Preprocessing

- Mean subtraction
  - Subtract the mean across every individual *feature/dimension* in the data
  - Method 1: Compute from dataset
  - Method 2: From fixed value of data range (e.g., 128 for 8-bit values)
- Normalization (after mean subtraction)
  - Scale the data so they have same range
    - Method 1: Divide each dimension by its standard deviation
    - Method 2: Normalize each dimension so that the *min* and *max* values along the dimension is -1 and 1
    - Method 3: Divide by shifted data range extent (e.g., $128)_{50}$

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Weight Initialization

(for "link" weights, biases are set to 0)

- Method 1a: Gaussian
  - Sample from Gaussian with $\sigma^2=1$, then scale
    - Scale with a small value (e.g., .001)
- Method 1b: Gaussian (Xavier/Glorot)
  - For the set of weights that go in/out of a node (N_{in}, N_{out}), sample from Gaussian with $\sigma^2 = 2 / (N_{in}+N_{out})$
  - Not designed for ReLU activations, better with Sigmoid
- Method 1c: Gaussian (Kaiming/He)
  - Use $\sigma^2 = 2 / N_{in}$ or $\sigma^2 = 2 / N_{out}$
  - Designed for ReLU
- Others…

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Random Seed Initialization

- Training is highly affected by the initial **random seed** used to set the initial network weights and selection of data order
  - Can give large difference in results with different seed
- Can training multiple times, each time with a different random seed initialization, and choose final model giving best results
  - Could also make into an ensemble of models
- Should report accuracy **mean, stdev** for multiple trained models to truly understand performance (not just one run/model)
  - Use statistical test to prove one method is better than another

"Revisiting Batch Norm Initialization"
J. Davis and L. Frank
European Conference on Computer Vision, October 2022

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Learning Rate α

$$w_5 = w_5 - \boxed{\alpha \cdot} \frac{\partial E_{total}}{\partial w_5}$$

How to choose/set learning rate α?

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"Step" Reduction

- Begin with a selected starting learning rate

  $\alpha = 0.1$

- At pre-selected epochs intervals (e.g., 30th, 60th, 90th, …), divide current learning rate by 10

  $\alpha^{new} = \alpha^{old} / 10$

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"Poly" Learning Rate Adaptation

- Begin with a selected starting learning rate

$$\alpha = 0.1$$

- The learning rate is multiplied by a changing rate (decay) at each iteration (e.g., epoch)

$$\alpha^{new} = \alpha^{old} * \left(1 - \frac{iter}{max\ iter}\right)^{power}$$

$power = 0.9$

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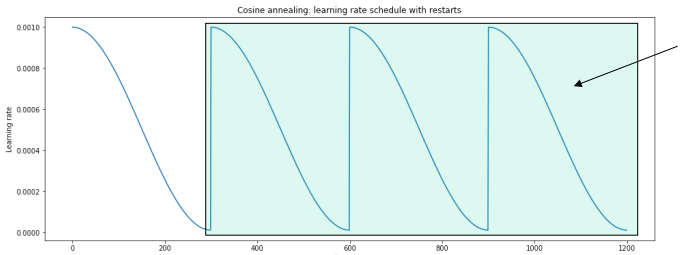
Cosine Learning Rate



Note: can do only 1 reduction w/ no cycles

$$\eta_t = \eta^i_{\min} + \frac{1}{2}\left(\eta^i_{\max} - \eta^i_{\min}\right)\left(1 + \cos\left(\frac{T_{current}}{T_i}\pi\right)\right)$$

where η_t is the learning rate at timestep t (incremented each mini batch), $\eta^i_{\max}$ and $\eta^i_{\min}$ define the range of desired learning rates, $T_{current}$ represents the number of epochs since the last restart (this value is calculated at every iteration and thus can take on fractional values), and T_i defines the number of epochs in an cycle.

"By drastically increasing the learning rate at each restart, we can essentially exit a local minima and continue exploring the loss landscape."

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"Stochastic" Gradient Descent

- Perform a parameter update for **each** training data example only (instead of all data)
  - Usually much faster, can learn online

while not converged
  shuffle/randomize data examples x
  for **each** training example x_j
    for each parameter $p_i \in p$
      compute gradient (using only x_j) $\nabla_{pi}E(p, x_j)$
      update p_i with $p_i = p_i - \alpha * \nabla_{pi}E(p, x_j)$

***** Note: do simultaneous update of all parameters p_i at end of each iteration (after each training example)!**

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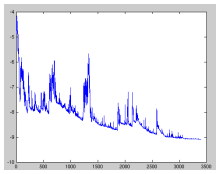
Stochastic Gradient Descent



- Performance
  - Fluctuates
    - Can jump to better local minima
    - However can keep overshooting (better if slowly decrease learning rate)
- **"Mini-Batch" Gradient Descent**
  - Perform an update using mini-batch of **N data examples** (e.g., 32-256 examples instead of just 1)
  - Can have **more stable/smoother convergence**, more efficient
  - Use batch sampler to get appropriate batches during training
    - Configure to get equal % of examples from each class when have unbalanced training classes

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Momentum

- Can oscillate across slopes of ravine while only making small progress along weaker bottom slope towards local minima
- Solution: Remember the update at each iteration, and determine next update as combination of current gradient and previous update:

Old: $p_i = p_i - \alpha * \nabla E(p_i)$

$$\Delta p_i = (\alpha * \nabla E(p_i) + \beta * \Delta p_i)$$

current remember last time

update p_i with $p_i = p_i - \Delta p_i$

(typically start with $\beta = .5$ then increase to $\beta = .9$)

New: $p_i = p_i - (\alpha * \nabla E(p_i) + \beta * \Delta p_i)$

- Result: Tends to keep traveling in same direction, preventing oscillations

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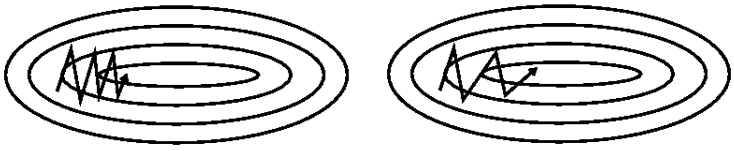
Momentum

- Analogy: push a ball down a hill. It accumulates momentum as it rolls downhill, becoming faster and faster on the way
- Hence, momentum term increases for dimensions whose gradients point in same directions and reduces updates for dimensions whose gradients change direction (cancel out)
  - Gain faster convergence and reduced oscillation



w/o momentum w/ momentum

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Batch Normalization (BN)

- Technique to provide any (each) layer with inputs that are zero mean and unit variance
  - Also has learnable parameters of scale, shift
  - Makes the data comparable across features
- Normalize for each feature going into a node using the input mini-batch examples
- Helps in two ways: faster learning and higher overall accuracy

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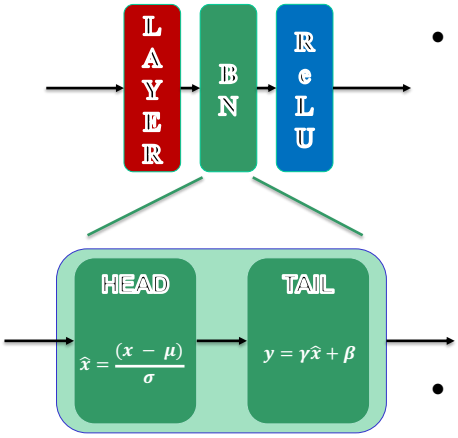
Batch Normalization (BN)



- Frequently used in NN before activation
  - **Head**: Normalize / whiten data
    - Mean = 0
    - Variance = 1
  - **Tail**: Learnable affine transformation (scale and shift)
    - Scale initialized to 1
    - Shift initialized to 0
- Helps to stabilize data through network

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Batch Normalization (BN)

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

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Batch Normalization (BN)

- Need to transform the batch means and variances statistics into population statistics
  - Required for new test data (single example)
- Compute and use the average across mini-batches
- NOTE: Better initialization can yield improved performance!

"Revisiting Batch Norm Initialization"
J. Davis and L. Frank
European Conference on Computer Vision, October 2022

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L2 Regularization

- Helps to reduce overfitting
- Preference to learn smaller weights w_i and spread weights as not to have only a few weights with large values and the rest with zero
  - Keeps the network from focusing on specific non-generalized items

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L2 Regularization ("*Weight Decay*")

Loss = E_0 "standard loss" + E_1 "weight regularization"

Note: Typically for "link" weights, not biases or BN

$$E = E_0 + E_1 = E_0 + \frac{\lambda}{2}\sum_i w_i^2$$

In Gradient Descent:

$$w_i = w_i - \alpha\frac{\delta E}{\delta w_i} = w_i - \alpha\left(\frac{\delta E_0}{\delta w_i} + \frac{\delta E_1}{\delta w_i}\right) = w_i - \alpha\frac{\delta E_0}{\delta w_i} - \alpha\lambda w_i$$

$$w_i = (1 - \alpha\lambda)w_i - \alpha\frac{\delta E_0}{\delta w_i}$$

Note: Typical values of λ are 0.001 or 0.0001, but really tied to size of network!

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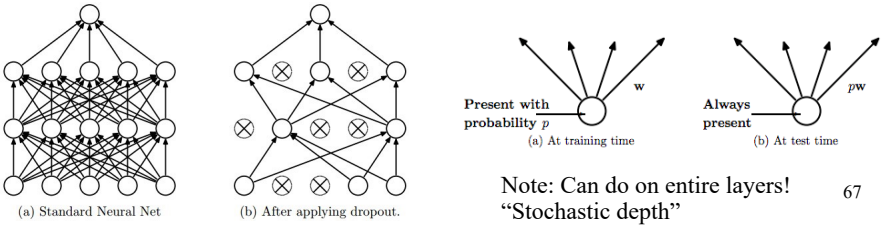
Dropout

- Another way to prevent overfitting to training data
  - Samples a network within the full network, and only updates the parameters of the sampled network based on the input data
    - Keeps a neuron **active** with some probability (e.g., p = .5 to .9), otherwise set it to zero
    - For each training example/batch a different set of units to drop is chosen
- No dropout at test time, only during training
  - Approximate average of dropped-out networks by using the full network with each node's output weighted by p
  - Interpretation: evaluate an averaged prediction across ensemble of sub-networks



(a) Standard Neural Net (b) After applying dropout. (a) At training time (b) At test time

Note: Can do on entire layers!
"Stochastic depth"

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"Deep Learning"

- Algorithms that attempt to model high-level abstractions in data by using a deep graph with multiple processing layers, composed of multiple linear and non-linear transformations
  - Exploits hierarchical explanatory factors where higher level, more abstract concepts are learned from lower level one
- Deep neural network (DNN), with "*many*" hidden layers
  - G. Hinton: **>1 hidden layer**

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Convolutional Neural Networks (CNNs)

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CNNs

- Type of neural network designed to take advantage of the 2D structure of "image" data
- Composed of one or more "convolutional" (with activations) and "pooling" layers, and may have fully-connected layers (as in typical artificial neural networks) at end for classification
  - Uses tied/shared weights at convolutional layers
- Can be trained with standard backpropagation

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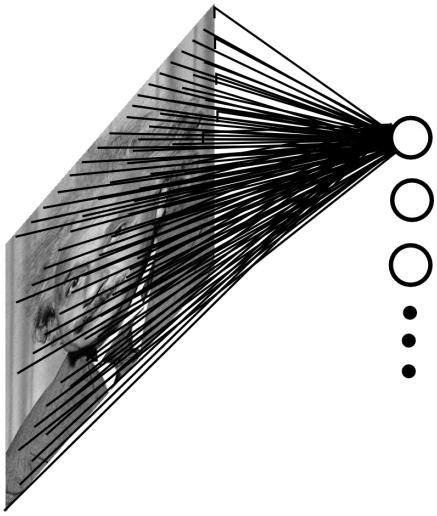
Naïve Connection



- Could connect every pixel to each node in the first hidden layer
  - Too many weights!
  - Not have enough training examples!

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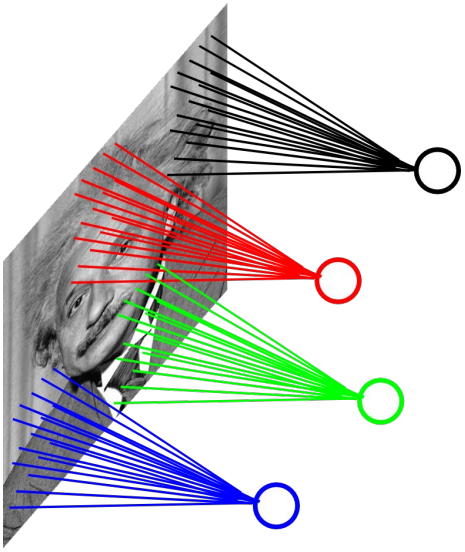
Locally Connected



- Good when input image is registered
  - Certain visual features/patterns are in same area of the image
    - e.g., aligned "mug shot" for face recognition (nose, mouth, eyes are in same image locations)

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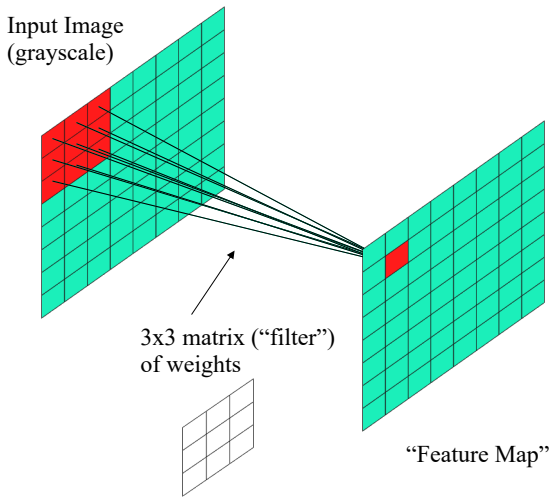
Turn Local into "Convolution"



Can think of this as each location in the "Feature Map" as a node in a neural network layer, with 3x3=9 weights coming into each node. But here all of these nodes have the same "shared" weights (i.e., the feature map has a total of 9 weights associated with it to learn)

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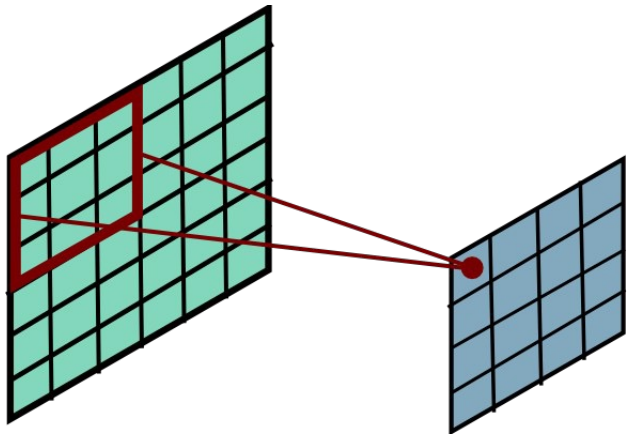
Convolution Operation (w/ 3x3 links to node)



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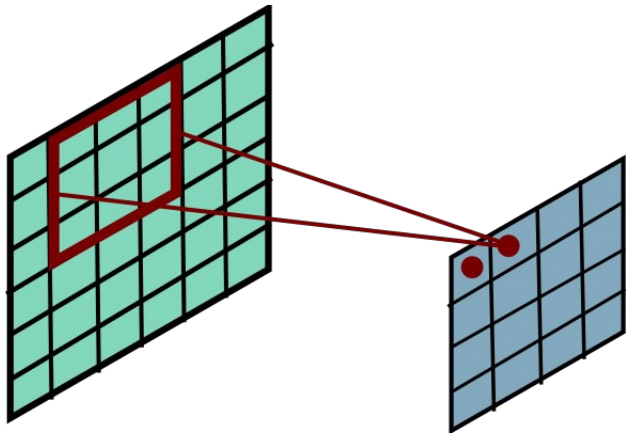
Convolution Operation
(w/ 3x3 links to node)



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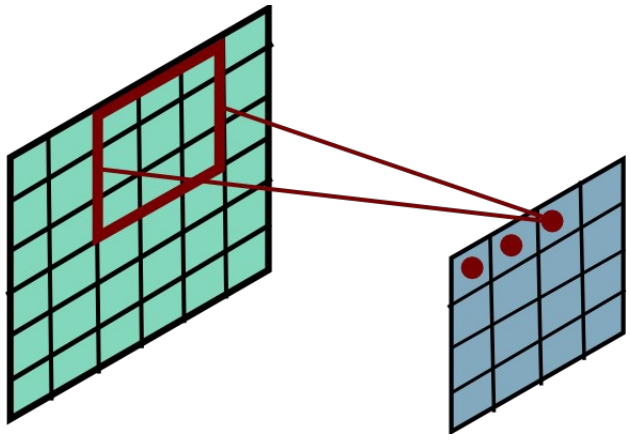
Convolution Operation
(w/ 3x3 links to node)



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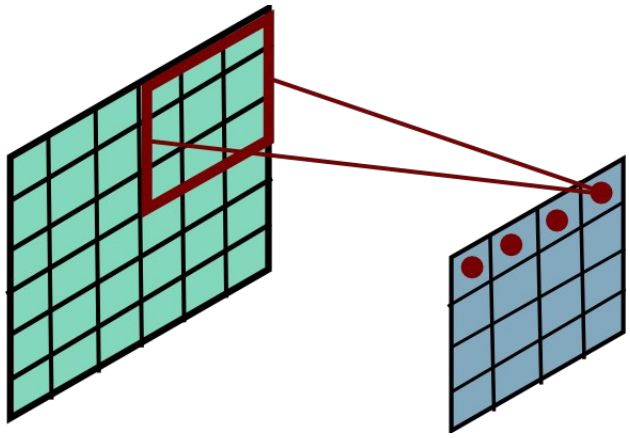
Convolution Operation
(w/ 3x3 links to node)



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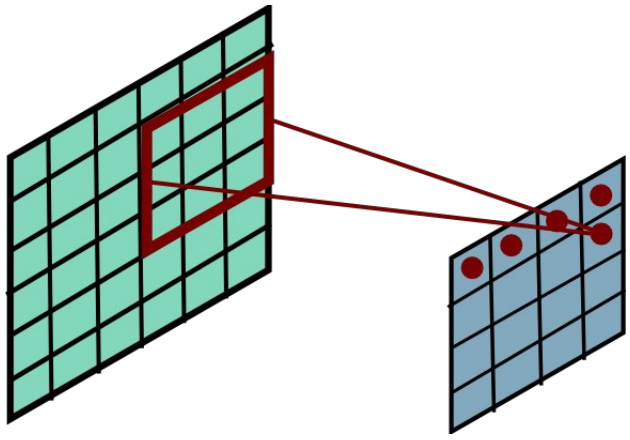
Convolution Operation
(w/ 3x3 links to node)



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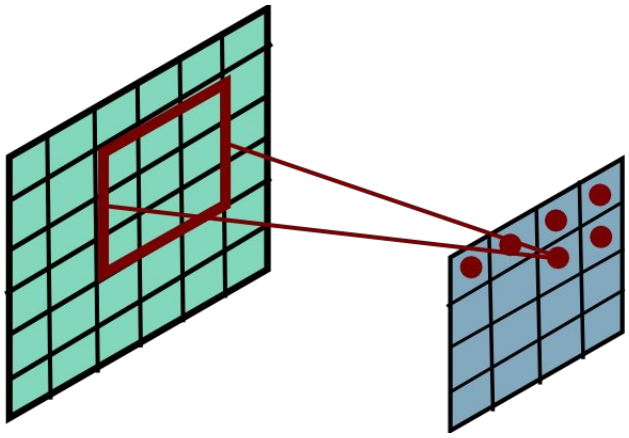
Convolution Operation
(w/ 3x3 links to node)



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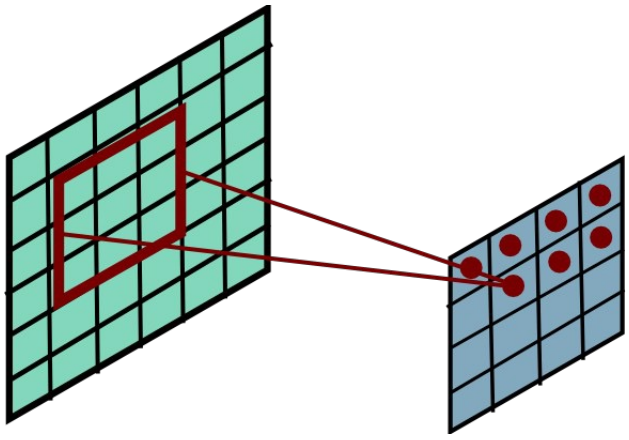
Convolution Operation
(w/ 3x3 links to node)



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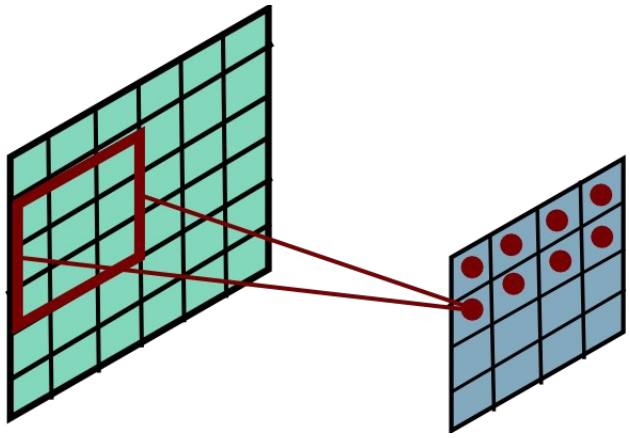
Convolution Operation
(w/ 3x3 links to node)



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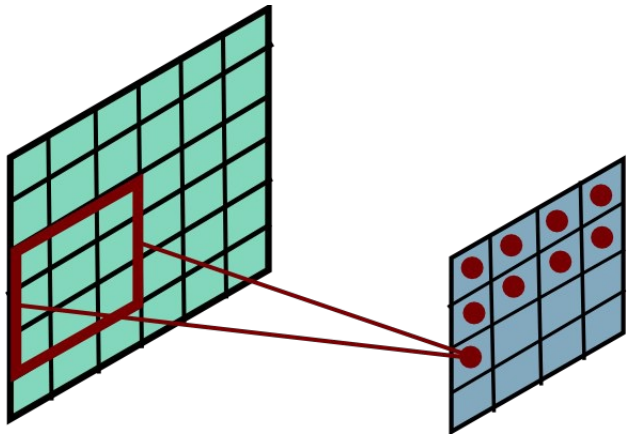
Convolution Operation
(w/ 3x3 links to node)



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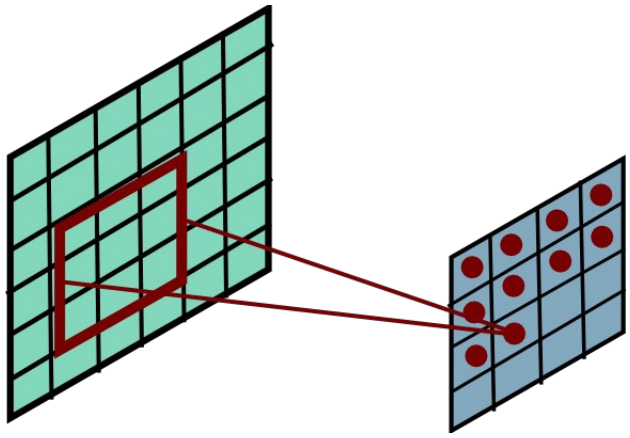
Convolution Operation
(w/ 3x3 links to node)



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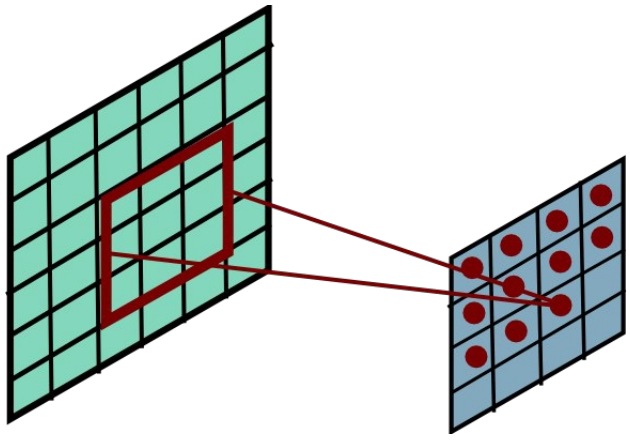
Convolution Operation
(w/ 3x3 links to node)



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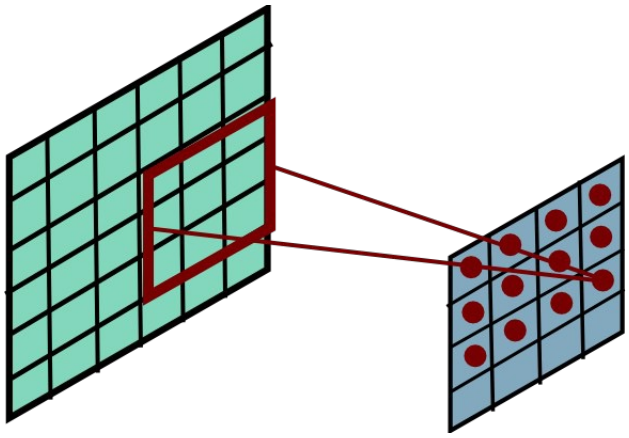
Convolution Operation
(w/ 3x3 links to node)



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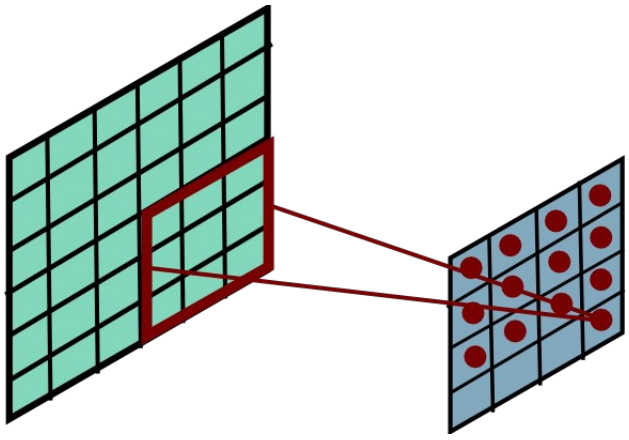
Convolution Operation
(w/ 3x3 links to node)



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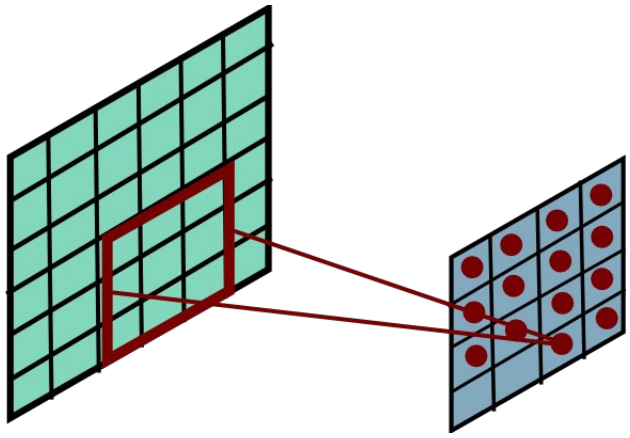
Convolution Operation
(w/ 3x3 links to node)



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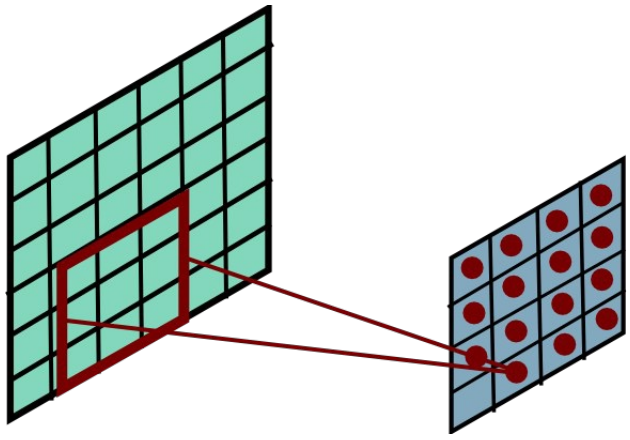
Convolution Operation
(w/ 3x3 links to node)



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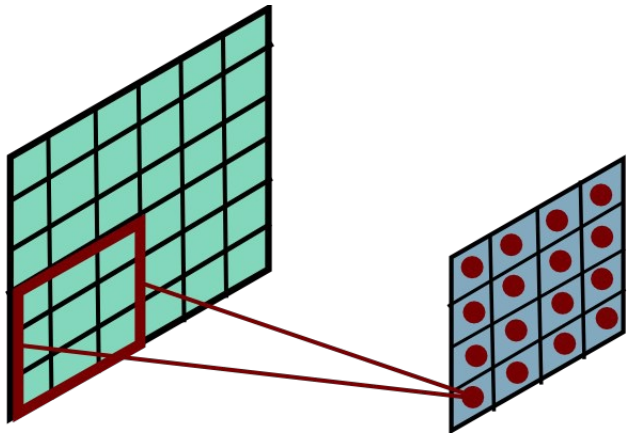
Convolution Operation (w/ 3x3 links to node)



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"Stride"

- "Stride" is the number of shifts in pixels over the input matrix
  - Stride = 1: moves the filter in steps of 1 pixel at a time
  - Stride = 2: moves the filter in steps of 2 pixels at a time

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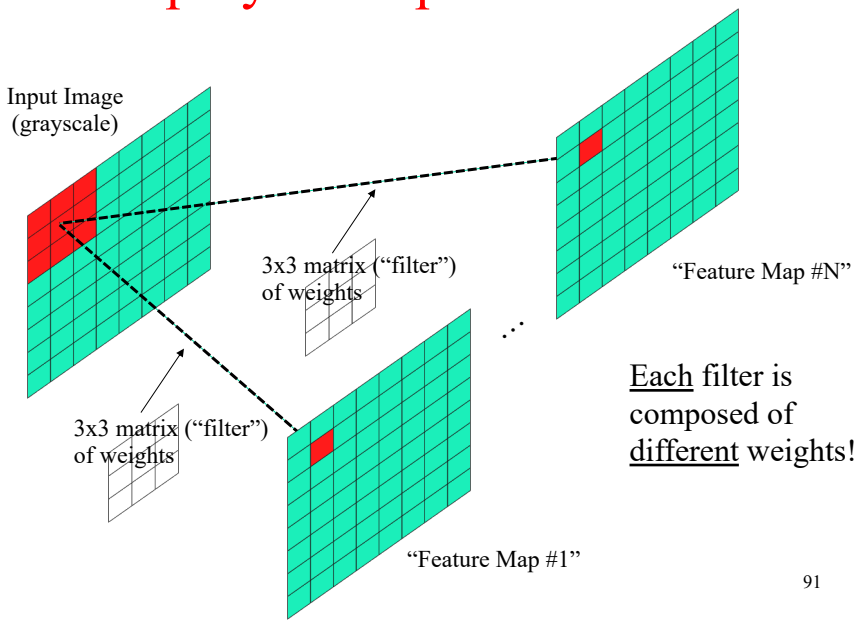
Employ Multiple "Filters"…



Each filter is composed of different weights!

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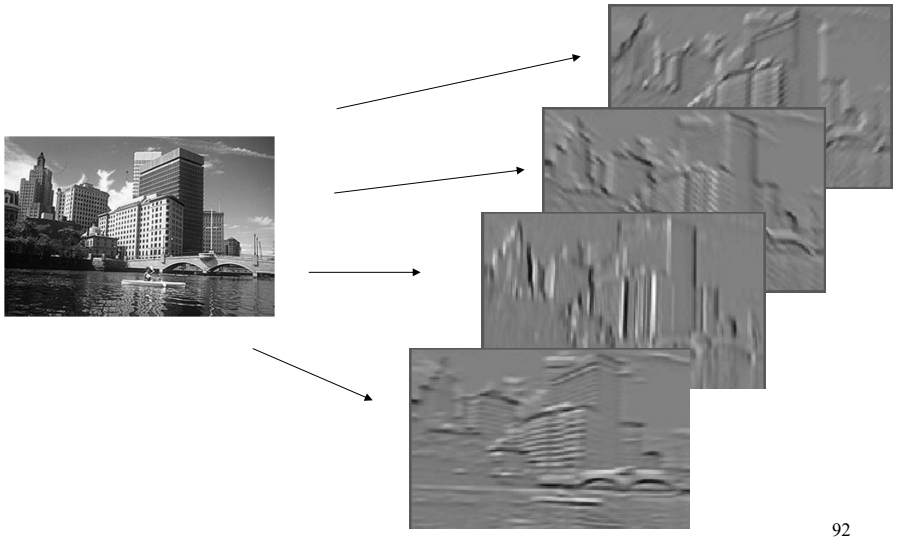
"Convolutional Layer"

Multiple Filters to Create Feature Maps



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Filter Sizes

- Can choose sizes of 1x1, 3x3, 5x5, or 7x7, etc. throughout the network layers
- Some networks have larger-sized convolution filters (and possibly with larger strides) in earlier network layers
- **Training will "fill-in" (learn) the necessary filter weights/values**

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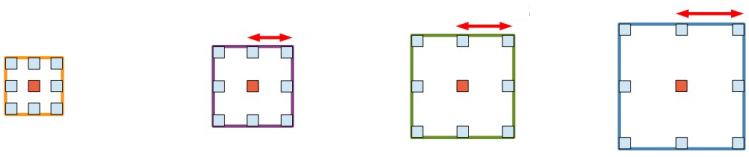
Atrous Convolutions

- Convolution with upsampled filters ("Atrous convolution")
- Method to effectively enlarge the field-of-view of filters (larger context) without increasing the number of parameters or the amount of computation.



Also referred to as "dilation"

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What About Input with Color (Multi-Channel) Image/Input?

- For grayscale image, may use 3x3 filter
  - Output is same row,col size as input
- As color image has 3 channels (RGB), use 3x3x3 filter (cube)
  - Output is same row,col size as input with only 1 channel (not 3)
- So if desire 64 feature maps with 3x3 spatial filter in initial conv layer for RGB input image:
  - Will have 64 filters of size 3x3x3 to learn
  - This "cube" concept extends to deeper layers…

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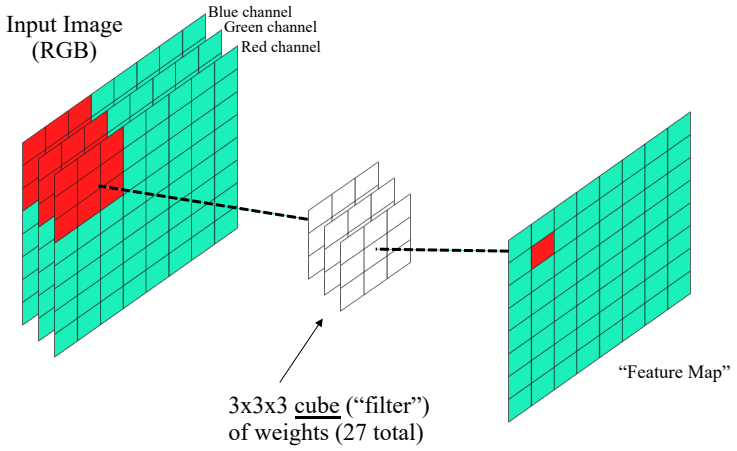
Filter "Cube"



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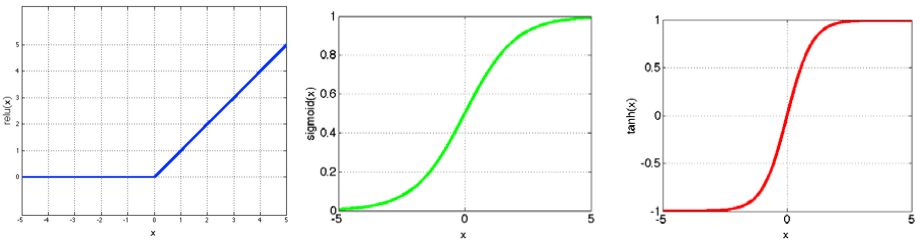
Activation Function

- On each feature map element (independently)
  - **ReLU**, Sigmoid, TANH
  - Also include additive bias term as parameter/weight (one per feature map in feature map volume)



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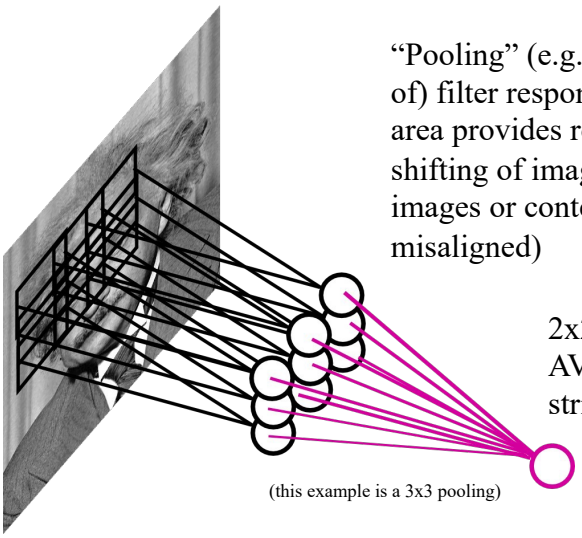
Spatial Pooling



"Pooling" (e.g., taking a summary of) filter responses within local area provides robustness to slight shifting of image features (e.g., if images or content slightly misaligned)

2x2 MAX (or AVERAGE) pooling w/ stride of 2 is common

(this example is a 3x3 pooling)

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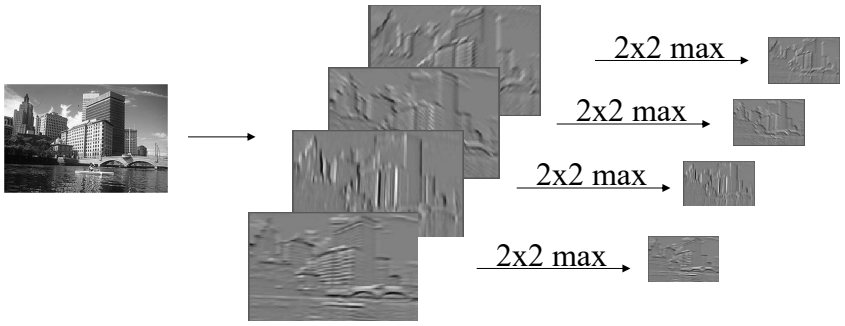
“Pooling Layer”



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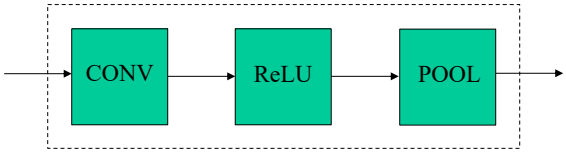
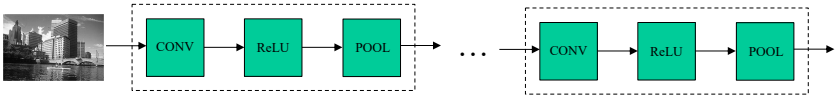
Staging

Single Stage:





Note: Can have multiple convolution/ReLU layers before pooling

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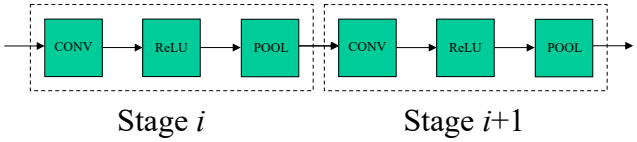
From Pooling to Next Convolution



- A convolutional filter at Stage i+1 filters across all output maps from Stage i
  - Considered as a 3-D filter (e.g., 3 x 3 x #maps)

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"Classification" Layers

- Lastly, for a classification network, employ fully-connected neural network at the end (1-D vector output)
- Output class labels for the input image
  - e.g., SoftMax output for hard-target class labels
  - Typically no activation function at final layer

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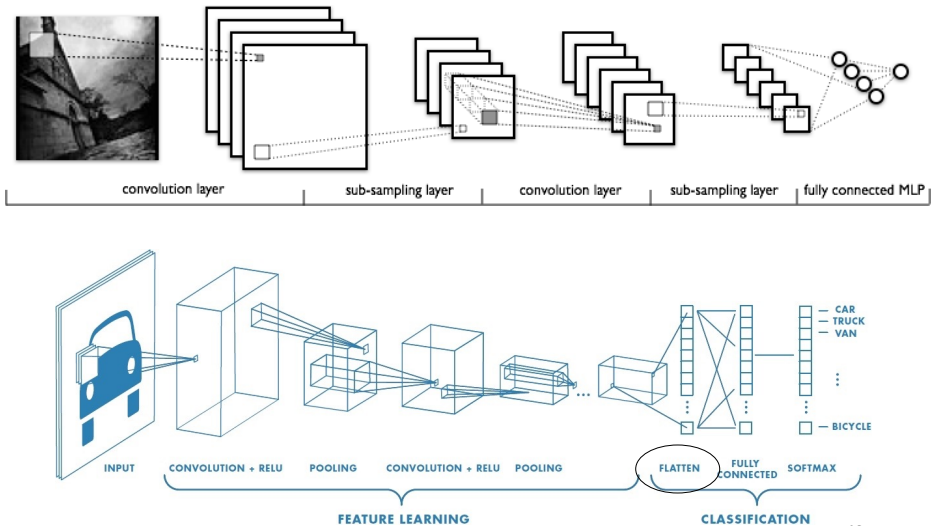
Putting it all together…



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"Fully-Convolutional" CNN
(FCN)

- Use convolutions (perhaps with pooling) all the way to the end
  - No fully-connected 1-D classification layer at end
- With multiple feature maps at the end, learn to output a "vector of values" per spatial location
  - Semantic Segmentation (vector of class probabilities at each pixel)

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What if Input Image is Larger/Smaller?

- Method #1: Crop to fixed-size input
- Method #2: Scale to fixed-size input
  - Isotropic (if same aspect ratio, else clip out center)
  - Anisotropic (but aspect ratio will change)

OR USE…

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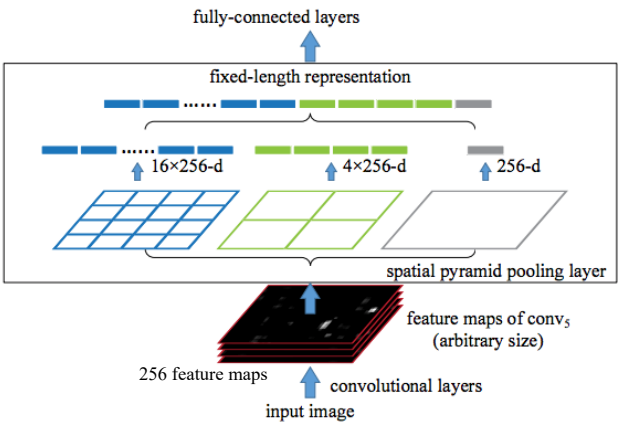
Spatial Pyramid Pooling

Handles varying sized images by pooling into a spatial hierarchy (e.g., 4x4, 2x2, 1x1), rasterizing (e.g., 16x1, 4x1, 1x1), then concatenating into a single vector (e.g., 21x1)



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How to Train?

- Given input images and target labels
  - e.g., scene type, primary object type present
- Normal NN backpropagation techniques
- Many, many, many weights
  - Though shared weights at convolutional layer filters
  - Most weights are at final stages of a **fully-connected** classification CNN
    - For the fully-connected nodes

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Input

- Mean-subtract input image (make zero mean)
  - Pixel-wise mean
    - Single aveR, aveG, aveB subtracted from each pixel
  - Could also consider "mean image" (not pixel)
- Scale each pixel (to be between around +/-1)
  - By standard deviation of pixels in dataset
  - Or by fixed range of pixels

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Input Augmentation

- Augment/distort the image during training to add more variability
- Methods
  - Scale
  - Crop
  - Flip (possibly rotate)
  - Brightness (gamma)
  - Color perturbation
  - Patch dropout (set a small region to 0)
  - etc.

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Filter Values After Training: "What are they?"

- Represent low-level, mid-level, high-level feature extraction at convolutional layers
  - The filters define the features
- Highly non-linear feature extraction, so simpler (linear) classifier at end may even be sufficient

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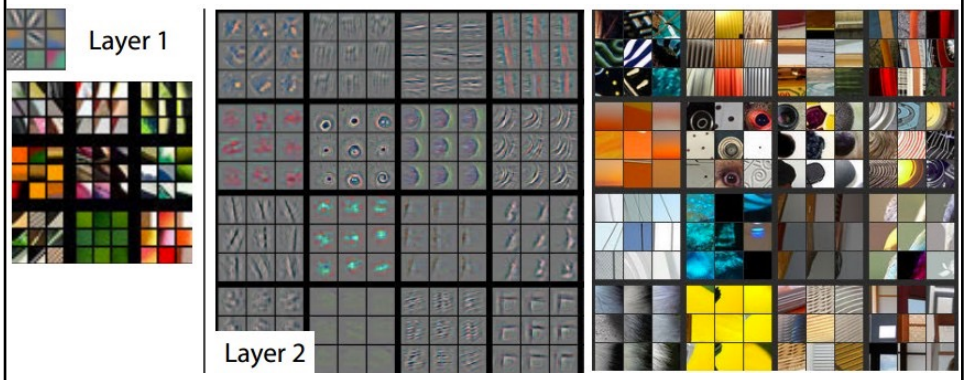
Simple-to-Complex Filters…



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"Transfer Learning" or "Network Re-use" for Different Classification Tasks

- Use trained model (on a specific task)
- Push new dataset through, and take outputs *before* final classifier
- Treat those *outputs* as input features for this new classification task
- Train a new classifier (just the classifier portion) with these features
  - Re-use of features for different tasks

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Classic and Modern Networks

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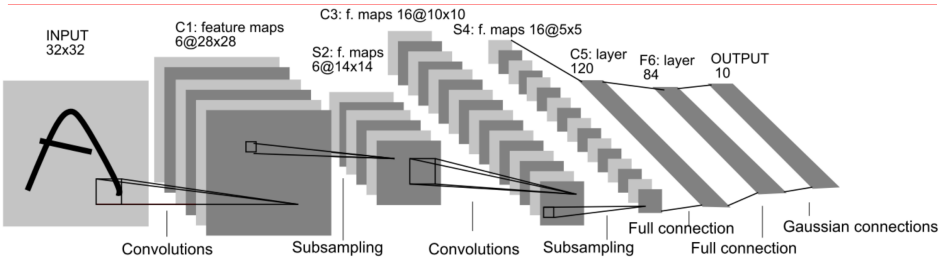
Early (1998) CNN: Le-Net 5

Handwritten digit recognition



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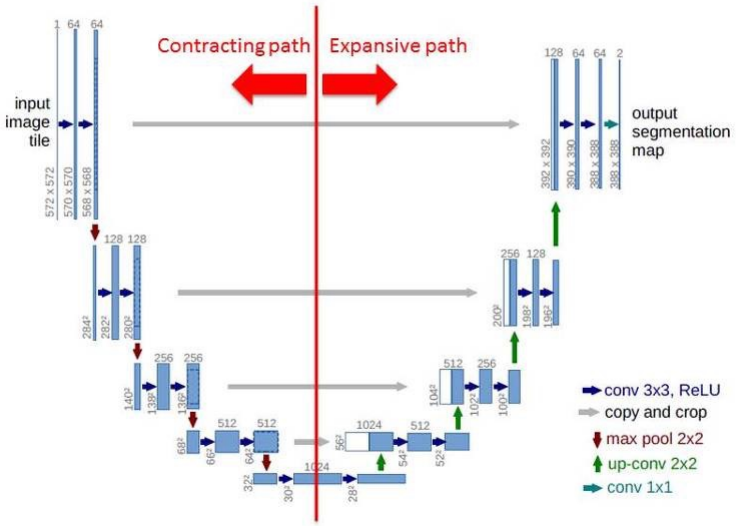
U-Net Architecture

(…for pixel-wise classification, e.g., Semantic Segmentation)



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ResNet

- ***Why do very deep nets perform <u>worse</u> as you keep adding layers*?**
  - Intuitively, deeper nets should perform no worse than their shallower counterparts
  - Say a net with *n* layers is learned that achieves a certain accuracy
  - A net with *n+1* layers should be able to achieve same accuracy, by copying over the same first *n* layers and performing an **identity mapping** for the last layer
    - Similarly, nets of *n+2*, *n+3*, and *n+4* layers could all continue performing **identity mappings** and achieve the same accuracy
  - In practice, however, these deeper nets almost always degrade in performance
  - Authors: *direct mappings are hard to learn*. Instead, learn a "residual" function

https://medium.com/towards-data-science/an-intuitive-guide-to-deep-network-architectures-65fdc477db41

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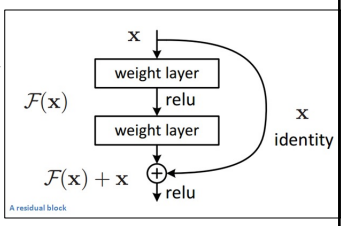
ResNet



- An ultra-deep 152-layer CNN
- Build on "residual blocks"
  - Skip connections
- It's much easier to learn to push F(x) to 0 and leave the output as x, than to learn an **identity transformation** from scratch.
- State-of-the-art model, many/most new CNNs are still based on this approach

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However…

- As gradient flows through the network, there is nothing to force it to go through residual block weights and it can avoid learning anything during training
- Therefore it is possible that there is either **only a few blocks that learn useful representations** or **many blocks share very little information with small contribution** to the final goal

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Popular ResNet Sizes

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				

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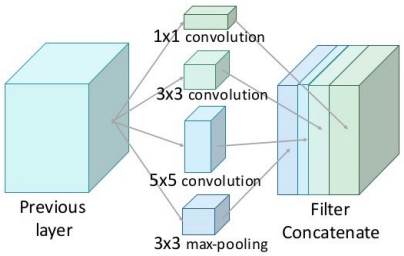
"Inception" Style Networks

- ResNet was about going deeper, the Inception network is all about going wider
- Run multiple filters over the same input map in parallel, then concatenating their results into a single output
- The next layer of the model gets to decide if (and how) to use each piece of information



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ResNeXt

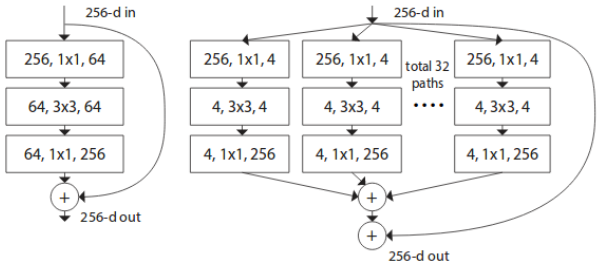

Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

ResNet (left) and ResNeXt (right) Architecture.

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EfficientNet

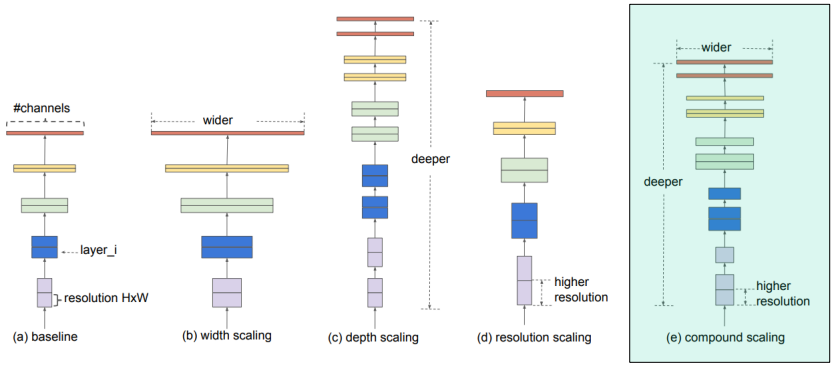

Figure 2. **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

Offers a method to scale up a baseline CNN to target resource constraints (larger) in a more principled way, while maintaining model efficiency, to achieve better results.

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Neural Architecture Search (NAS)

- Most model architectures are designed (or borrowed) by humans, and can be ad hoc
- Neural Architecture Search methods can be used to *explore* different network architecture spaces and choose best
  - For a specific need/requirement or dataset
  - Computationally expensive

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IMAGENET
Classification Challenge(s)

- Goal is to "estimate the content" of photographs for the purpose of retrieval and automatic annotation
  - ImageNet dataset has approx 10,000,000 labeled images depicting 10,000+ object categories
- 2012 classification challenge had 5 guesses
  - Algorithms produced a list of at most 5 object categories in the descending order of confidence (compared to single ground truth label for image)

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ImageNet “Hammers”

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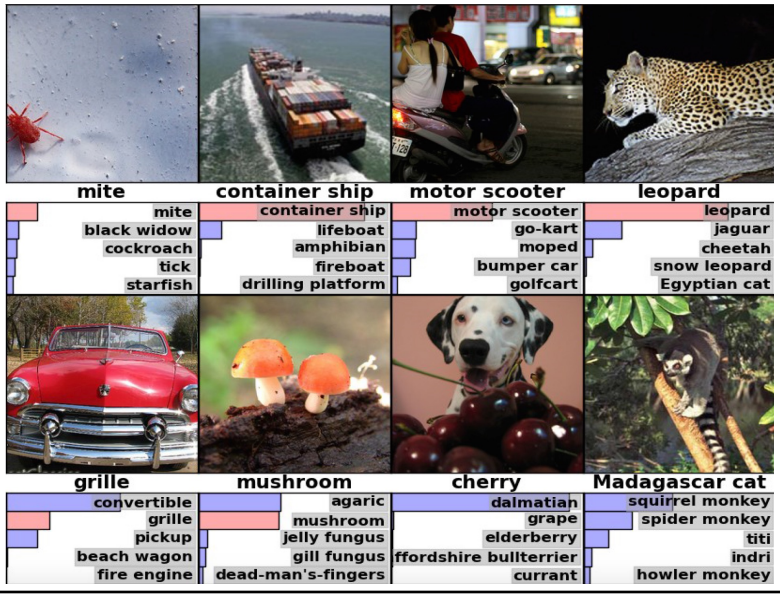
“5-best” Examples (AlexNet)



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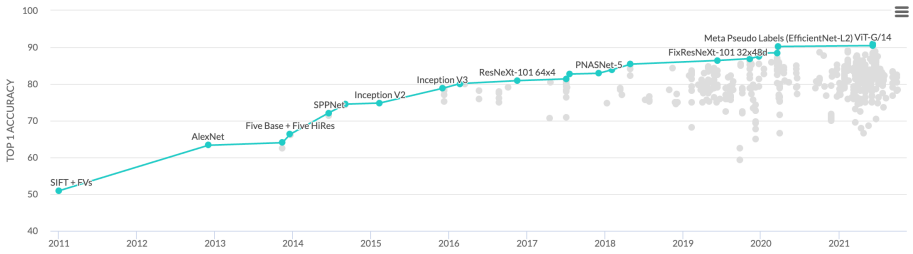
History of ImageNet Top-1 Accuracy



https://paperswithcode.com/sota/image-classification-on-imagenet

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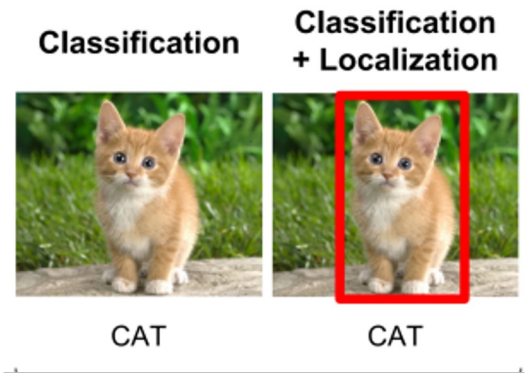
Object Detection
(Classification + Localization)



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"You Only Look Once" (YOLO)

- Single end-to-end network
- Reframes the object detection problem as a single regression task
- Straight from image pixels to bounding box coordinates and class probabilities

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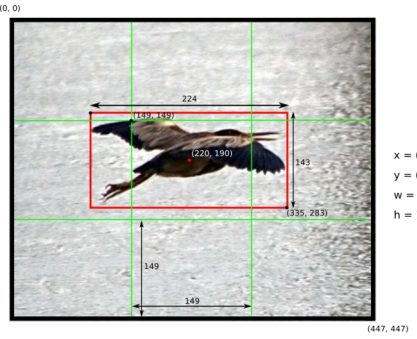
YOLO Details



x = (220-149) / 149 = 0.48
y = (190-149) / 149 = 0.28
w = 224 / 448 = 0.50
h = 143 / 448 = 0.32

- Partitions input/output into an S x S grid of cells
- Each grid cell predicts
  - B bounding boxes (leads to predictor specialization)
  - C class probabilities
- Each bounding box predicts (x, y, w, h, confidence)
  - **(x, y)**: center of box (normalized)
  - **(w, h)**: width, height of box (normalized)
  - **confidence:** Prob(object)
- Class probabilities: Prob(class | object)
- Overall, final output is a tensor of size
  S x S x (B*5 + C)

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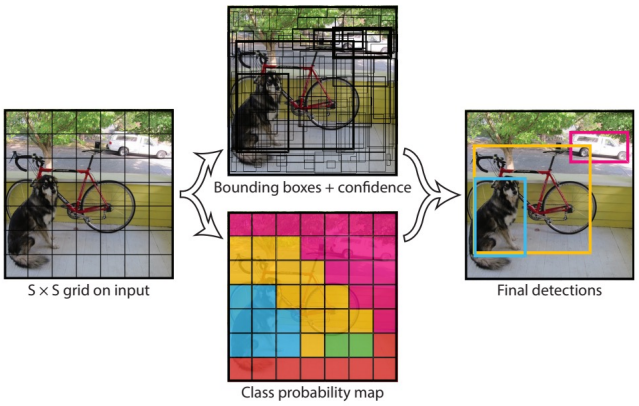

Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

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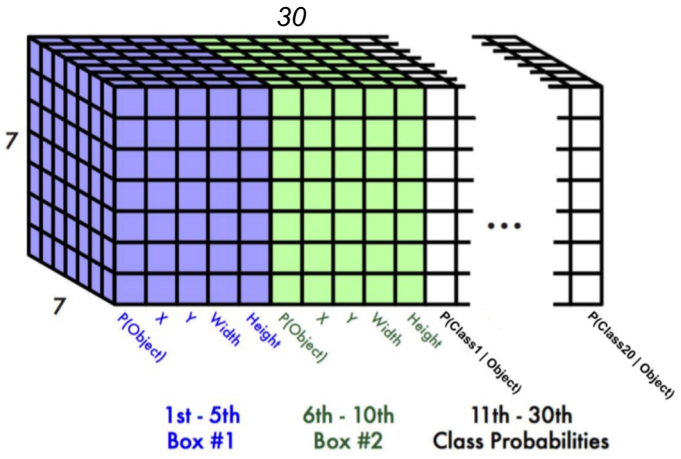
Yolo Output Interpretation

(S=7, B=2, C=20)



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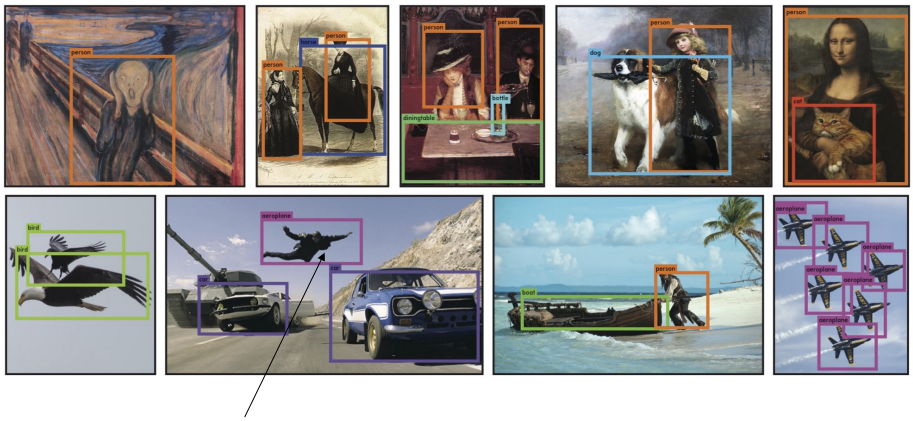
Example Results



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Inference and Extensions

- Final prediction via post-processing
  - Uses a Non-Maximal Suppression method
  - Note: Bounding boxes that do not "confidently" describe an object (e.g., all class probabilities are below a threshold) can be ignored/removed
- YOLOv2: Refined the design and made use of predefined "anchor" boxes to improve bounding box proposal
  - Learn offsets/scales to pre-defined box sizes/aspects (priors on object shapes – learned by clustering ground truth boxes)
- YOLOv3: Further refined the model architecture and training process

Good overview:
https://jonathan-hui.medium.com/real-time-object-detection-with-yolo-yolov2-28b1b93e2088

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Final Terminology to Remember…

- Deep Learning ≠ CNN
  - Other deep neural network architectures that are not CNN
- But CNN is a form of Deep Learning
  - Think of CNN ⊂ Deep Learning

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Complexity of Biological Neuron

"… showed that a deep neural network requires between five and eight layers of interconnected `neurons' to represent the complexity of one single biological neuron."

https://www.quantamagazine.org/how-computationally-complex-is-a-single-neuron-20210902/

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Summary

- Neural net components
- Feed-forward network
- Back-propagation for multilayer networks
- Training particulars
- Deep learning
- CNNs

But soooooo much more to talk about!

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