CSC 411: Lecture 11: Neural Networks II

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Today

- Forward propagation
- Backward propagation
- Deep learning

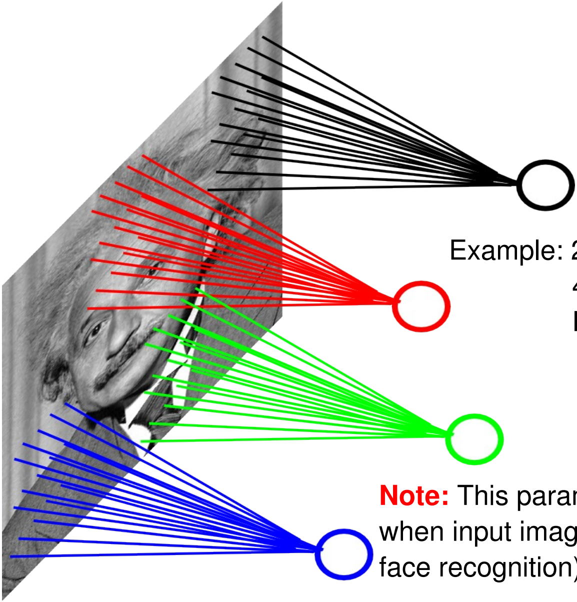
Neural Nets for Object Recognition

- People are very good at recognizing shapes
  - Intrinsically difficult, computers are bad at it
- Some reasons why it is difficult:
  - Segmentation: Real scenes are cluttered
  - Invariances: We are very good at ignoring all sorts of variations that do not affect shape
  - Deformations: Natural shape classes allow variations (faces, letters, chairs)
  - A huge amount of computation is required

How to deal with large Input Spaces

- Images can have millions of pixels, i.e., $\mathbf{x}$ is very high dimensional
- Prohibitive to have fully-connected layer
- We can use a locally connected layer
- This is good when the input is registered

Locally Connected Layer



Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

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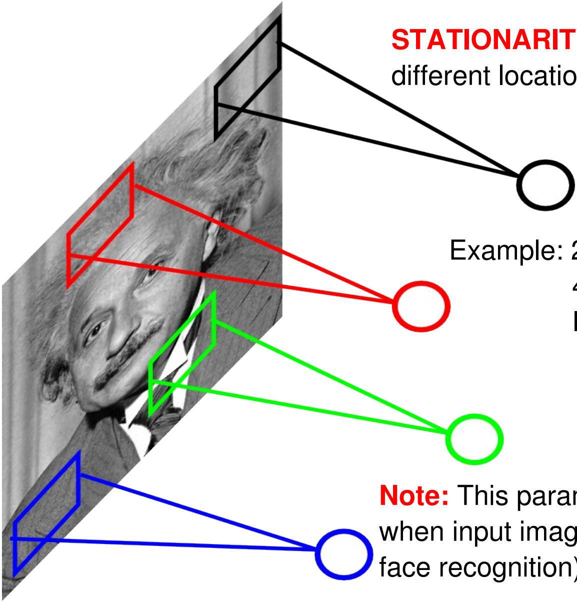
The invariance problem

- Our perceptual systems are very good at dealing with invariances
  - translation, rotation, scaling
  - deformation, contrast, lighting, rate
- We are so good at this that its hard to appreciate how difficult it is
  - Its one of the main difficulties in making computers perceive
  - We still don't have generally accepted solutions

Locally Connected Layer



STATIONARITY? Statistics is similar at different locations

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

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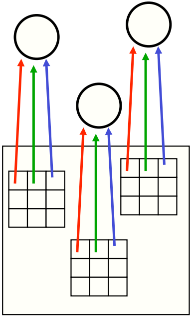
The replicated feature approach

The red connections all have the same weight.



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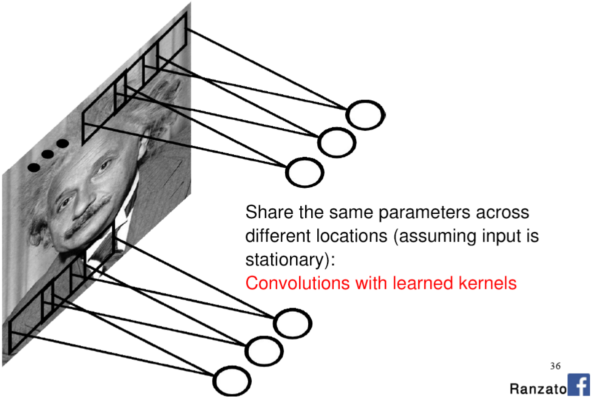
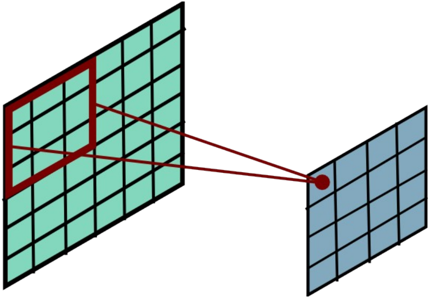
- Adopt approach apparently used in monkey visual systems
- Use many different copies of the same feature detector.
  - Copies have slightly different positions.
  - Could also replicate across scale and orientation.
    - Tricky and expensive
  - Replication reduces number of free parameters to be learned.
- Use several different feature types, each with its own replicated pool of detectors.
  - Allows each patch of image to be represented in several ways.

Convolutional Neural Net

- Idea: statistics are similar at different locations (Lecun 1998)
- Connect each hidden unit to a small input patch and share the weight across space
- This is called a convolution layer and the network is a convolutional network



Convolutional Layer



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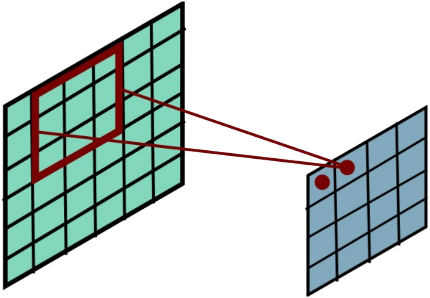
$$h_j^n = \max(0, \sum_{k=1}^{K} h_k^{n-1} * w_{jk}^n)$$

Convolutional Layer



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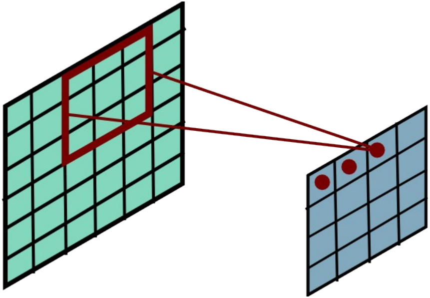
Convolutional Layer



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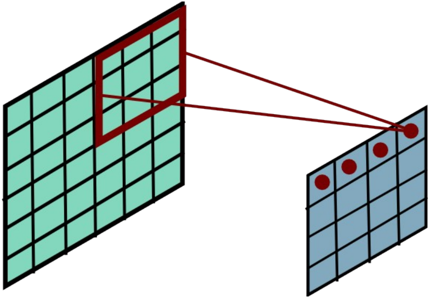
Convolutional Layer



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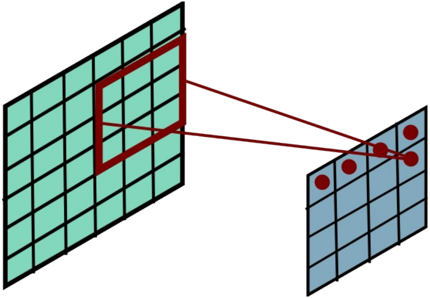
Convolutional Layer



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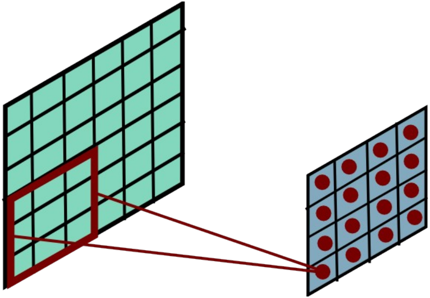
$$h_j^n = \max(0, \sum_{k=1}^{K} h_k^{n-1} * w_{jk}^n)$$

Convolutional Layer



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$$h_j^n = \max(0, \sum_{k=1}^{K} h_k^{n-1} * w_{jk}^n)$$

Backpropagation with weight constraints

- It is easy to modify the backpropagation algorithm to incorporate linear constraints between the weights

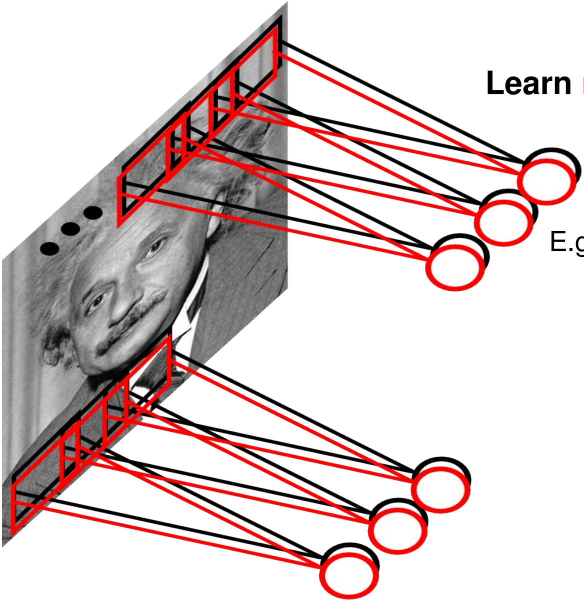
$$\begin{aligned} \text{To constrain:} \quad w_1 &= w_2 \\ \text{we need:} \quad \Delta w_1 &= \Delta w_2 \end{aligned}$$

- We compute the gradients as usual, and then modify the gradients so that they satisfy the constraints.

$$\begin{aligned} \text{compute:} \quad & \frac{\partial E}{\partial w_1} \text{ and } \frac{\partial E}{\partial w_1} \\ \text{use:} \quad & \frac{\partial E}{\partial w_1} + \frac{\partial E}{\partial w_2} \text{ for } w_1 \text{ and } w_2 \end{aligned}$$

- So if the weights started off satisfying the constraints, they will continue to satisfy them.

Convolutional Layer



Learn multiple filters.

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters

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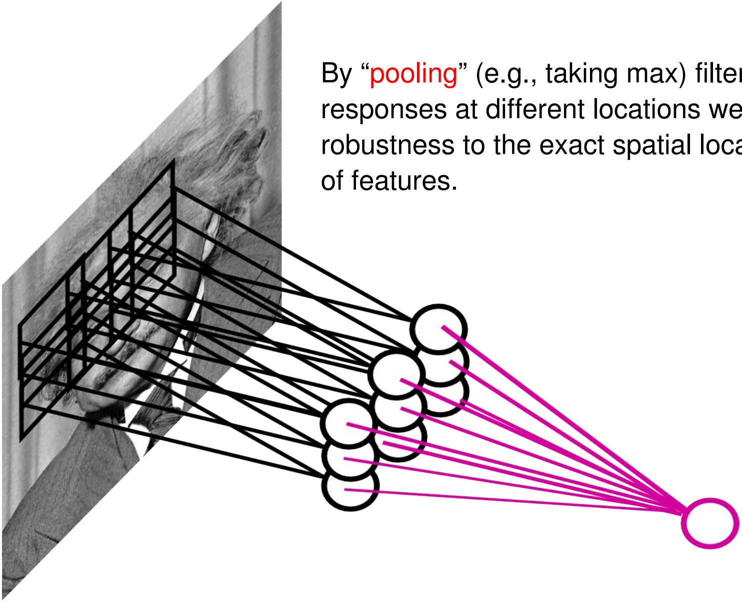
Pooling Layer

By "pooling" (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.



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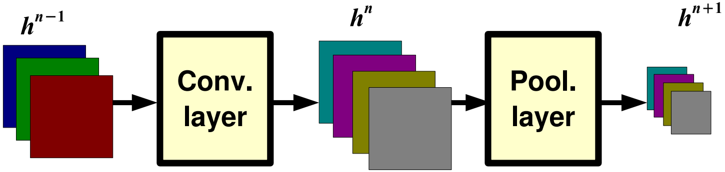
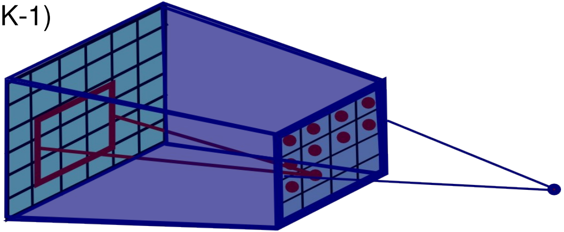
Pooling Options

- Max Pooling: return the maximal argument
- Average Pooling: return the average of the arguments
- Other types of pooling exist.

Pooling Layer: Receptive Field Size



If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: (P+K-1)x(P+K-1)



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Now let's make this very deep to get a real state-of-the-art object recognition system

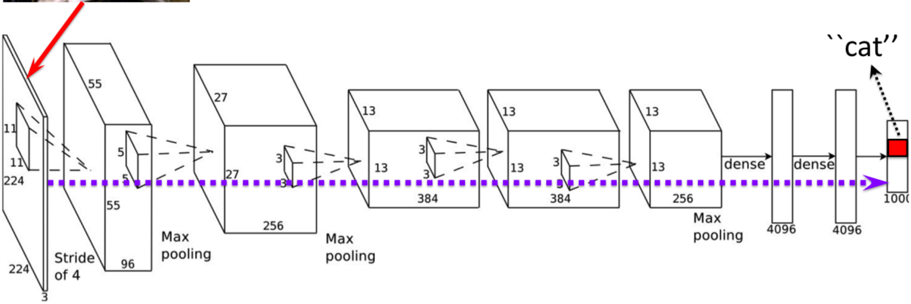
Convolutional Neural Networks (CNN)

- Remember from your image processing / computer vision course about filtering?
- If our filter was $[-1, 1]$, we got a vertical edge detector
- Now imagine we want to have many filters (e.g., vertical, horizontal, corners, one for dots). We will use a filterbank.
- So applying a filterbank to an image yields a cube-like output, a 3D matrix in which each slice is an output of convolution with one filter.
- Do some additional tricks. A popular one is called max pooling. Any idea why you would do this?
- Do some additional tricks. A popular one is called max pooling. Any idea why you would do this? To get invariance to small shifts in position.
- Now add another "layer" of filters. For each filter again do convolution, but this time with the output cube of the previous layer.

Classification

- Once trained we feed in an image or a crop, run through the network, and read out the class with the highest probability in the last (classif) layer.

What's the class of this object?

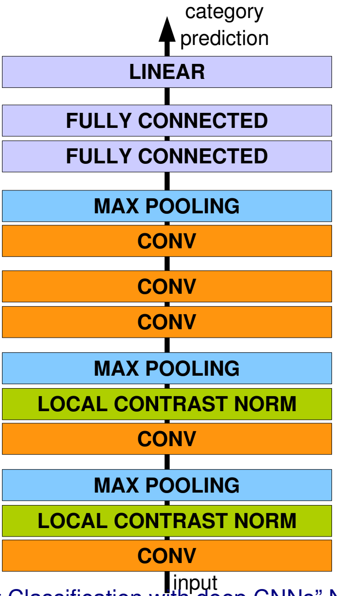


[Slide Credit: Sanja Fidler]

Classification Performance

- Imagenet, main challenge for object classification: `http://image-net.org/`
- 1000 classes, 1.2M training images, 150K for test

Architecture for Classification



Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

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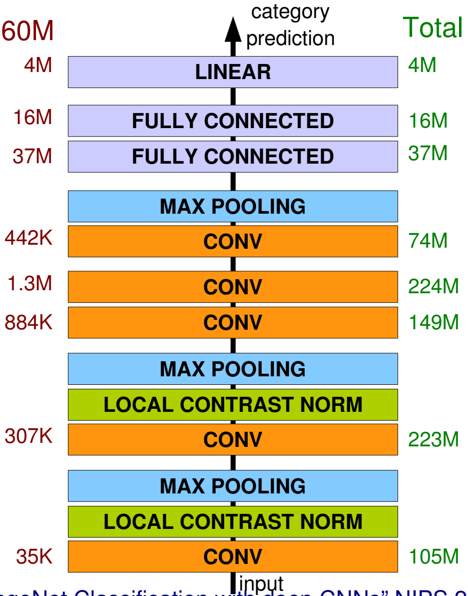
Architecture for Classification

Total nr. params: 60M

Total nr. flops: 832M



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Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012

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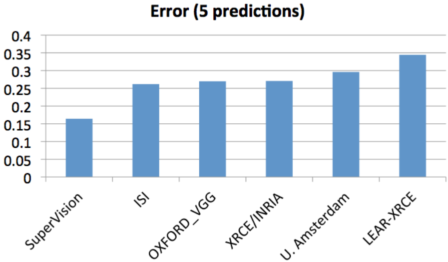
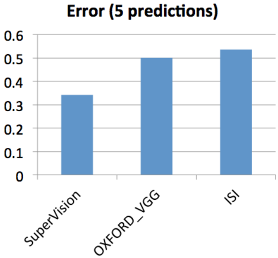
The 2012 Computer Vision Crisis



(Classification)



(Detection)

So Neural Networks are Great

- So networks turn out to be great.
- Everything is deep, even if it's shallow!
- Companies leading the competitions as they have more computational power
- At this point Google, Facebook, Microsoft, Baidu "steal" most neural network professors/students from academia

- But to train the networks you need quite a bit of computational power (e.g., GPU farm). So what do you do?

- And train more layers. 16 instead of 7 before. 144 million parameters.
- Buy even more.

Overfitting

- The training data contains information about the regularities in the mapping from input to output. But it also contains noise
  - The target values may be unreliable.
  - There is sampling error. There will be accidental regularities just because of the particular training cases that were chosen
- When we fit the model, it cannot tell which regularities are real and which are caused by sampling error.
  - So it fits both kinds of regularity.
  - If the model is very flexible it can model the sampling error really well. This is a disaster.

Preventing overfitting

- Use a model that has the right capacity:
  - enough to model the true regularities
  - not enough to also model the spurious regularities (assuming they are weaker)
- Standard ways to limit the capacity of a neural net:
  - Limit the number of hidden units.
  - Limit the size of the weights.
  - Stop the learning before it has time to overfit.

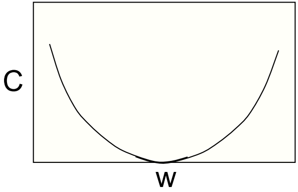
Limiting the size of the weights

- Weight-decay involves adding an extra term to the cost function that penalizes the squared weights.

$$C = \ell + \frac{\lambda}{2} \sum_i w_i^2$$

- Keeps weights small unless they have big error derivatives.

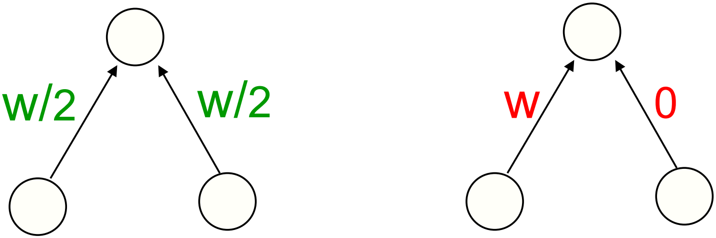
$$\frac{\partial C}{\partial w_i} = \frac{\partial \ell}{\partial w_i} + \lambda w_i$$



$$\text{when } \frac{\partial C}{\partial w_i} = 0, \quad w_i = -\frac{1}{\lambda} \frac{\partial \ell}{\partial w_i}$$

The effect of weight-decay

- It prevents the network from using weights that it does not need
  - This can often improve generalization a lot.
  - It helps to stop it from fitting the sampling error.
  - It makes a smoother model in which the output changes more slowly as the input changes.
- But, if the network has two very similar inputs it prefers to put half the weight on each rather than all the weight on one $\rightarrow$ other form of weight decay?



Deciding how much to restrict the capacity

- How do we decide which limit to use and how strong to make the limit?
  - If we use the test data we get an unfair prediction of the error rate we would get on new test data.
  - Suppose we compared a set of models that gave random results, the best one on a particular dataset would do better than chance. But it won't do better than chance on another test set.
- So use a separate validation set to do model selection.

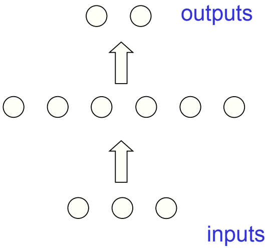
Using a validation set

- Divide the total dataset into three subsets:
  - Training data is used for learning the parameters of the model.
  - Validation data is not used for learning but is used for deciding what type of model and what amount of regularization works best
  - Test data is used to get a final, unbiased estimate of how well the network works. We expect this estimate to be worse than on the validation data
- We could then re-divide the total dataset to get another unbiased estimate of the true error rate.

Preventing overfitting by early stopping

- If we have lots of data and a big model, its very expensive to keep re-training it with different amounts of weight decay
- It is much cheaper to start with very small weights and let them grow until the performance on the validation set starts getting worse
- The capacity of the model is limited because the weights have not had time to grow big.

Why early stopping works



- When the weights are very small, every hidden unit is in its linear range.
  - So a net with a large layer of hidden units is linear.
  - It has no more capacity than a linear net in which the inputs are directly connected to the outputs!
- As the weights grow, the hidden units start using their non-linear ranges so the capacity grows.