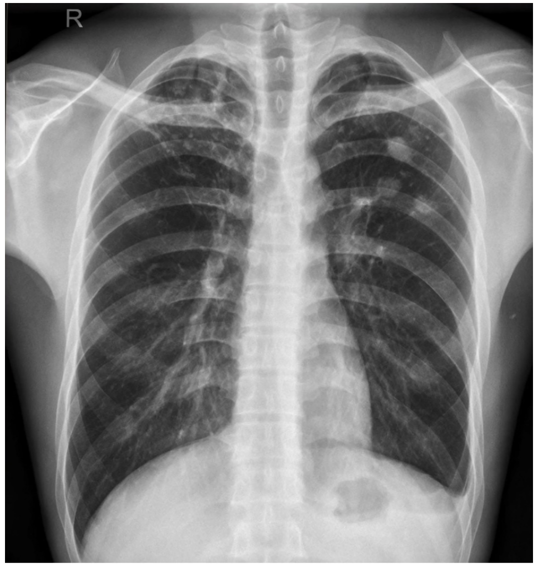
CPSC 440/540: Machine Learning

Convnets, Autoencoders, Multi-label classification

Winter 2023

Motivation: X-Ray Abnormality Detection

- Want to build a system that recognizes abnormalities in x-rays:



"Abnormality detected"
(binary classification)

- Applications:
  - Fast detection of tuberculosis, pneumonia, lung cancer, and so on.
- Deep learning has led to incredible progress on computer vision tasks.
  - Much of this progress has been driven by convolutional neural networks (CNNs).

Convolutional Neural Network (CNN) Motivation

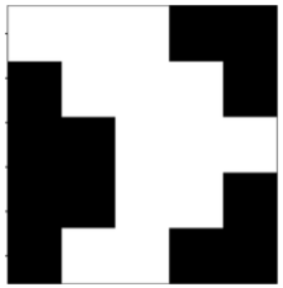
- Consider training neural networks on 500 pixel by 500 pixel images.
  - So the number of inputs d to first layer is 250,000 (more if colour).
- If first layer has k=10,000, then W has 2.5 billion parameters.
  - We want to avoid this huge number (due to storage and overfitting).

- CNNs drastically reduce the number of parameters by:
  - Having activations only depend on a small number of inputs.
  - Using the same parameters on the connections of many activations.
- Done using layers that look like "convolutions" in signal processing.

Illustration of 2D Convolution

- 2D convolution:
  - Inputs: an "input" image x and a "filter" image w.
  - Output: new image z whose pixels are dot products of filter and image region).

Input image **Filter image** **Output image**



$$\underset{x}{\begin{array}{|c|c|c|c|c|}\hline 1 & 1 & 1 & 0 & 0 \\ \hline 0 & 1 & 1 & 1 & 0 \\ \hline 0 & 0 & 1 & 1 & 1 \\ \hline 0 & 0 & 1 & 1 & 0 \\ \hline 0 & 1 & 1 & 0 & 0 \\ \hline \end{array}} * \underset{w}{\begin{array}{|c|c|c|}\hline 1 & 0 & 1 \\ \hline 0 & 1 & 0 \\ \hline 1 & 0 & 1 \\ \hline \end{array}} = \underset{z}{\begin{array}{|c|c|c|}\hline 4 & 3 & 4 \\ \hline 2 & 4 & 3 \\ \hline 2 & 3 & 4 \\ \hline \end{array}}$$

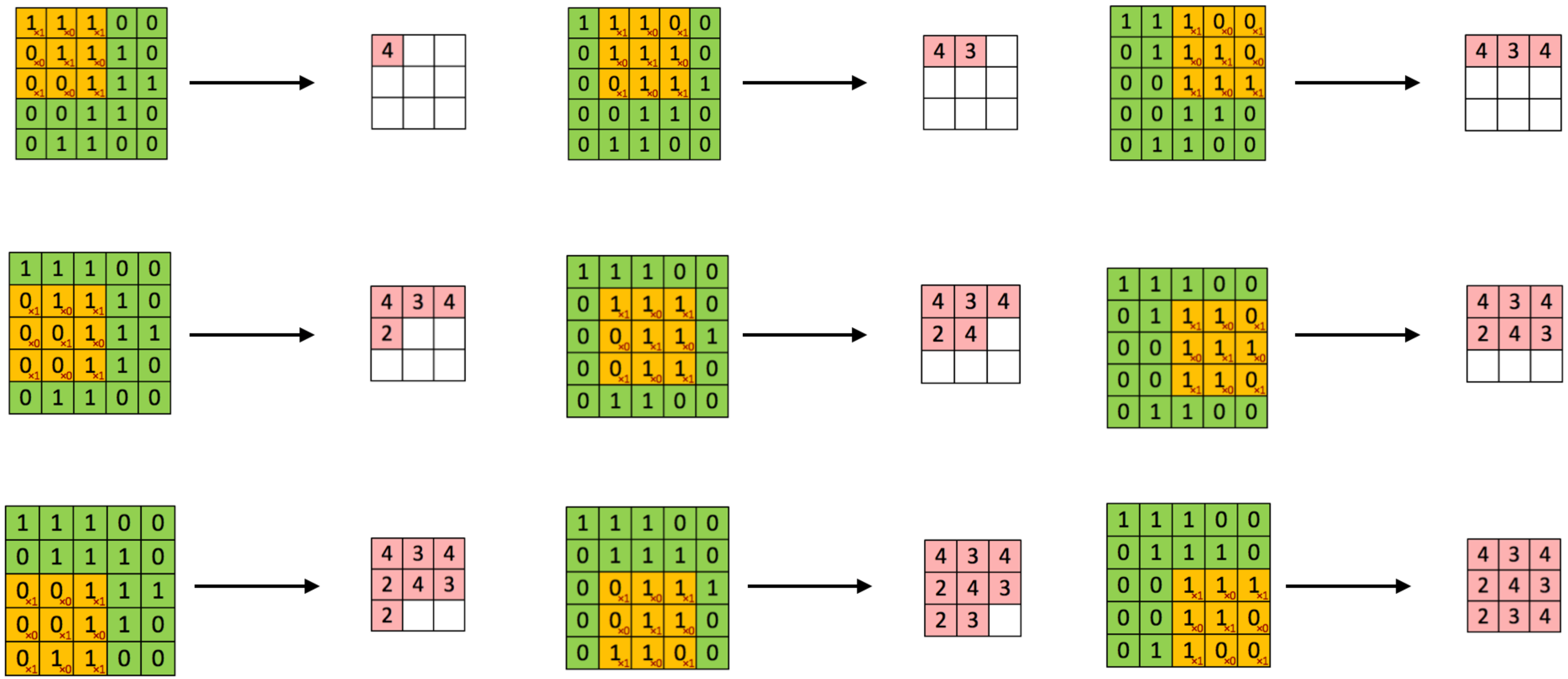
https://scientistcafe.com/ids/convolutional-neural-network.html

Illustration of 2D Convolution

- 2D convolution:
  - Inputs: an “input” image *x* and a “filter” image *w*.
  - Output: new image *z* whose pixels are dot products of filter and image region).

Filter image

1	0	1
0	1	0
1	0	1

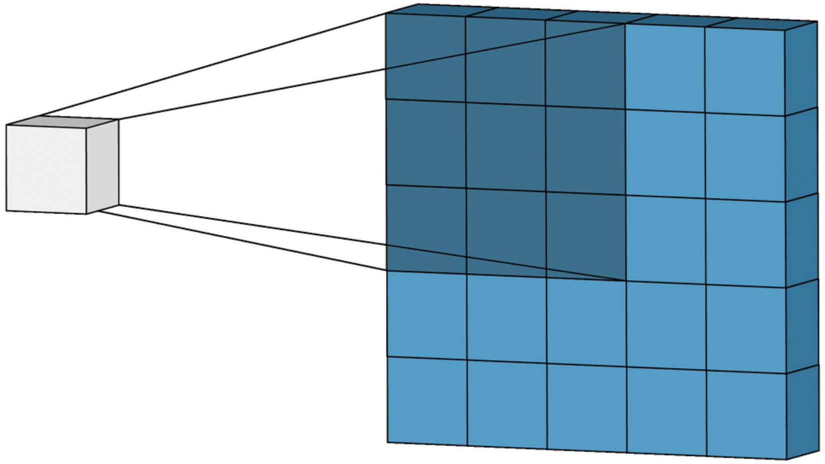


https://scientistcafe.com/ids/convolutional-neural-network.html

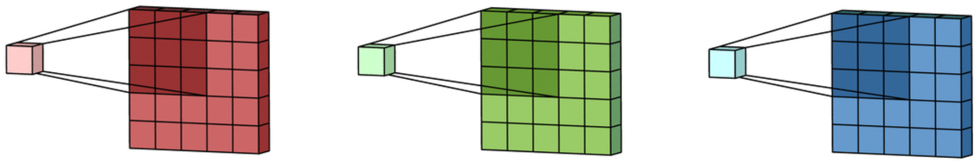
Illustration of 2D Convolution

- 2D convolution:
  - Inputs: an "input" image *x* and a "filter" image *w*.
  - Output: new image *z* whose pixels are dot products of filter and image region).
- As a formula:

$$z[i_1,i_2] = \sum_{j_1=-m}^{m} \sum_{j_2=-m}^{m} w[j_1,j_2]\, x[i_1+j_1, i_2+j_2]$$



  - Final image *z* can be written as usual *z=W' x*.
    - *W'* will be sparse, with filter values in *W* repeated.
- 3D convolution (for colour images):
  - Weighted dot product across all three dimensions.



https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

bonus!

Formal Convolution Definition

- We have defined the convolution as:

$$z_i = \sum_{j=-m}^{m} w_j x_{i+j}$$

- In other classes you may see it defined as:

$$z_i = \sum_{j=-m}^{m} w_j x_{i-j}$$

(reverses 'w')

$$z_i = \int_{-\infty}^{\infty} w_j x_{i-j} \, dj$$

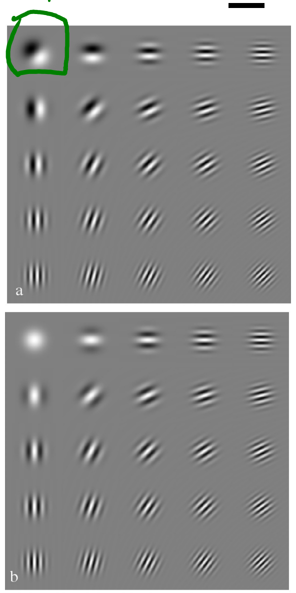
(assumes signal + filter are continuous)

- For simplicity we're skipping the "reverse" step, and assuming *w* and *x* are sampled at discrete points (not functions).
- But keep this mind if you read about convolutions elsewhere.

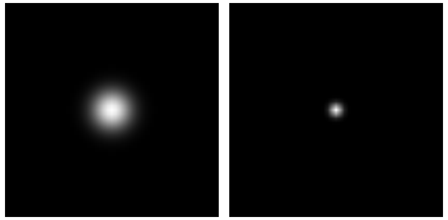
"signed" image:
- gray means 0
- white means 1
- dark means -1

Convolutions

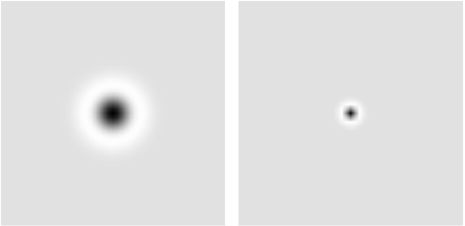
- Pre-2012, people often designed the filters by hand.
  - Filters can approximate "derivatives" or "integrals" of the image regions.
    - Derivative filters will up to 0, integral filters will add up to 1.
  - Three of the most-common filters that people used:



    - Gaussian filters: integral filter, giving the average brightness in a region.
      - Variance of the Gaussian controls the amount of smoothness.
      - This produces a pixel feature that is less sensitive to noise than pixel's raw value.



    - Gabor filters: derivative filters, measuring changes in brightness along a direction.
      - We typically compute these for different orientations and "frequencies".
      - This gives a set of features that is useful in describing edges in the image.

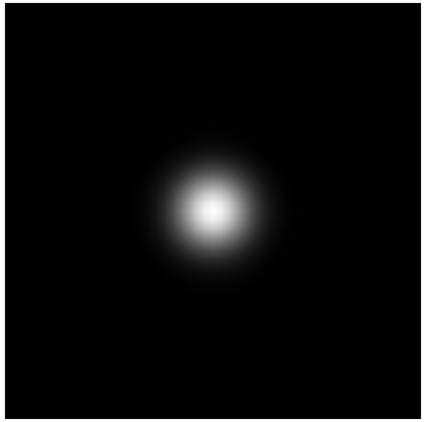


    - Laplacian of Gaussian filter: total second-derivative filter.
      - Complements Gabor filters: helps describe if change is due to an edge, line, or continuous change.
  - Similar filters may be used early in the eyes visual processing.
  - I think of the results of convolutions as the "bag of words" making up images.

Image Convolution Examples

Gaussian Convolution:

$*$



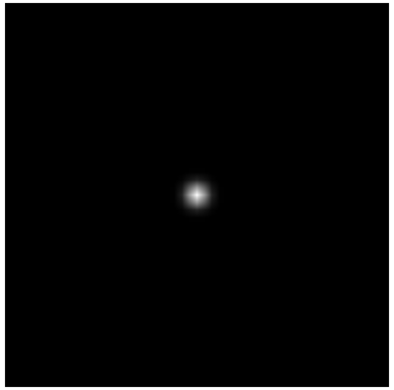
$=$

blurs image to represent average (smoothing)

Image Convolution Examples

Gaussian Convolution:

$*$



(smaller variance)

$=$

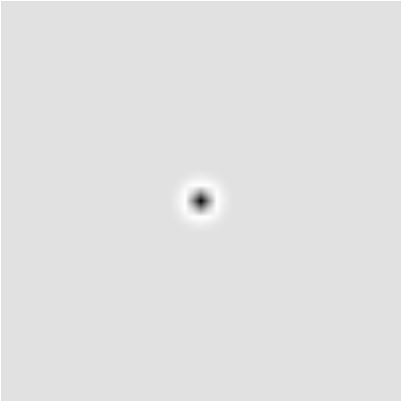
<u>blurs</u> image to represent average (smoothing)

Image Convolution Examples

"signed" image (gray is 0)

Laplacian of Gaussian

$*$



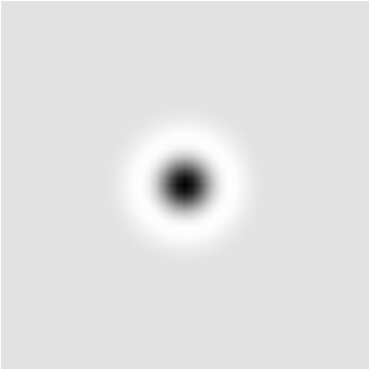
$=$

"How much does it look like a black dot surrounded by white?"

Image Convolution Examples

Laplacian of Gaussian

$*$



(larger variance)

$=$

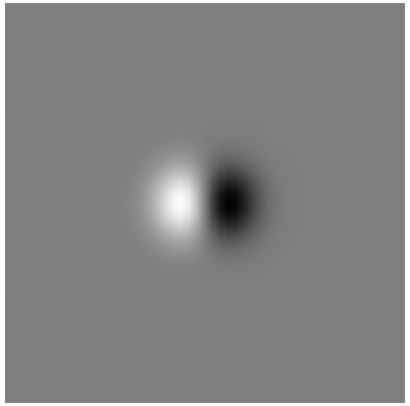
Black/white as sides of edge

Similar preprocessing may be done in basal ganglia and LGN.

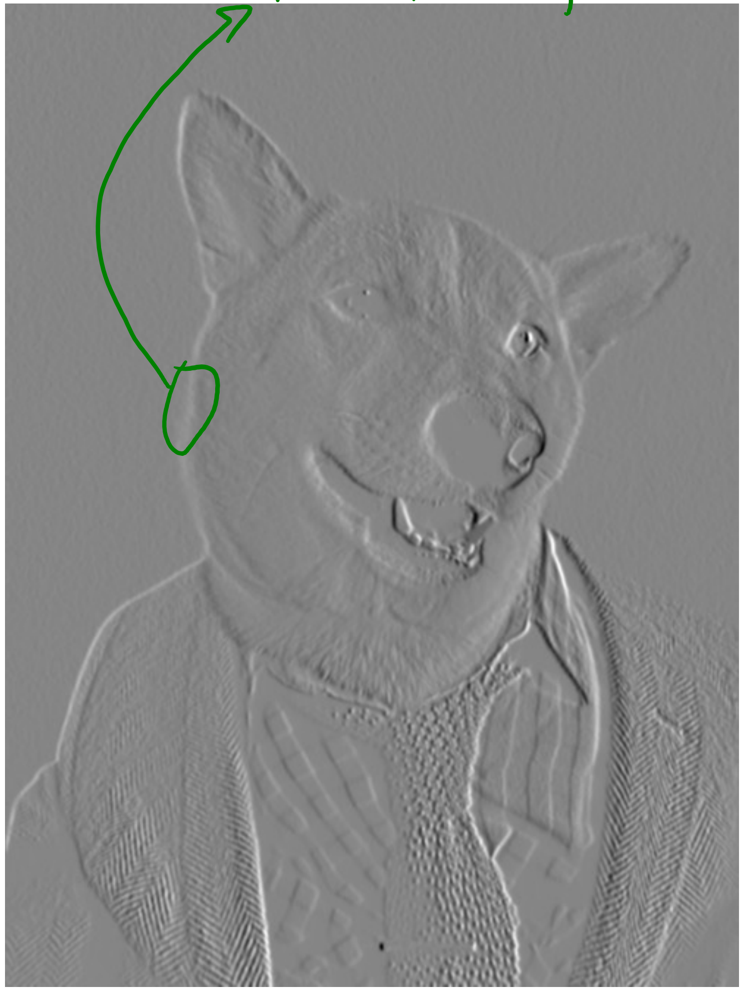
Image Convolution Examples

Gabor Filter
(Gaussian multiplied by sine or cosine)

*

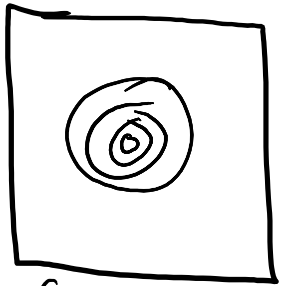


=



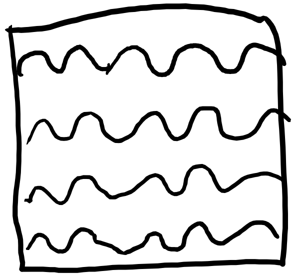
Horizontal "bright to dark"

=



Gaussian

.*



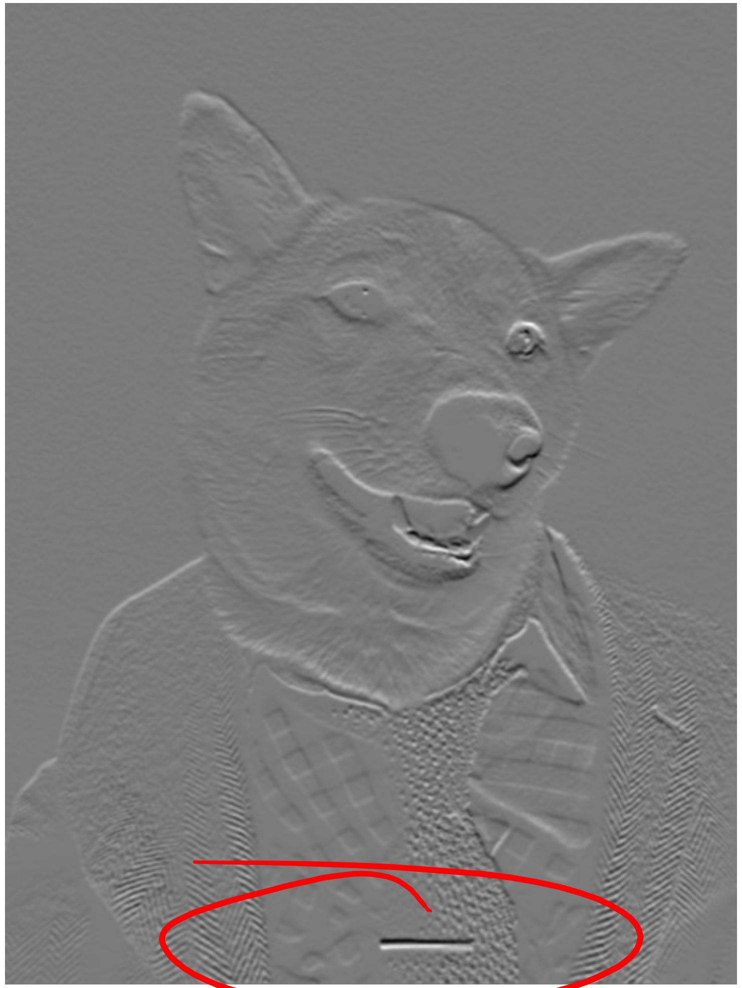
Parallel Sine functions

Image Convolution Examples

Gabor Filter
(Gaussian multiplied by sine or cosine)

$*$

$=$



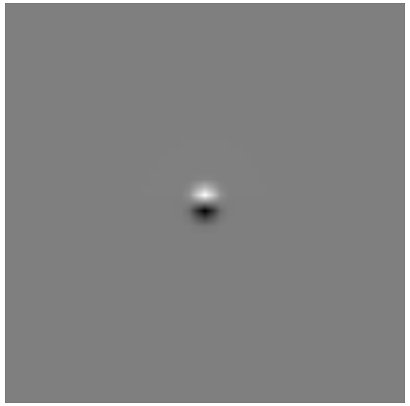
Different orientations of the sine/cosine let us detect changes with different orientations.

2d derivatives have a direction.

Image Convolution Examples

Gabor Filter
(Gaussian multiplied by sine or cosine)

$*$



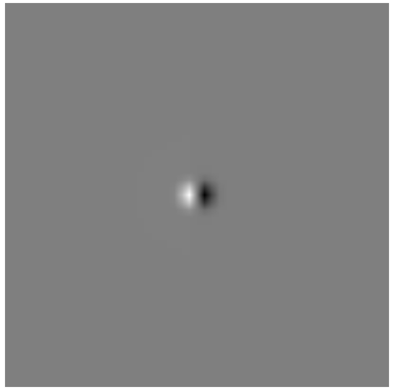
(smaller variance)

$=$

Image Convolution Examples

Gabor Filter
(Gaussian multiplied by sine or cosine)

$*$



$=$

(smaller variance)

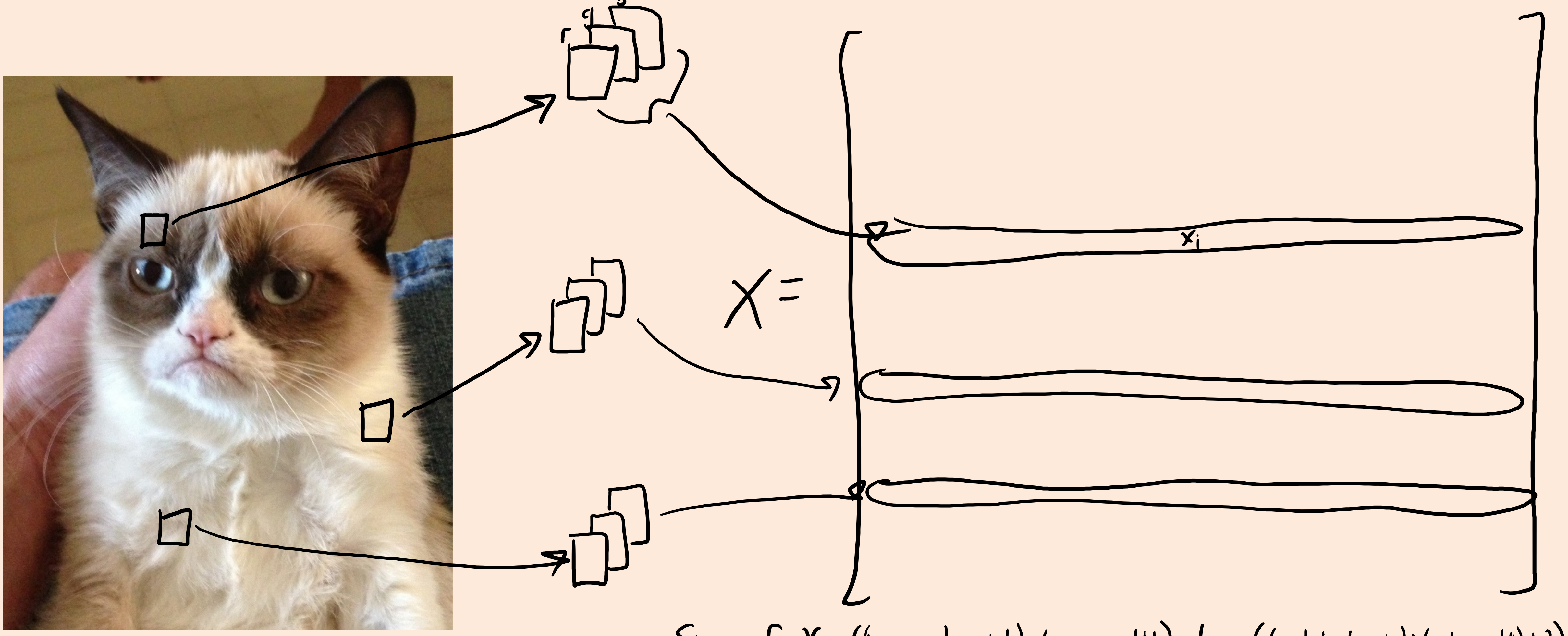
Vertical orientation

- Can obtain other orientations by rotating.
- May be similar to effect of V1 "simple cells."

bonus!

Unsupervised Learning of Filters for Image Patches

- Consider building an unsupervised model of image patches:

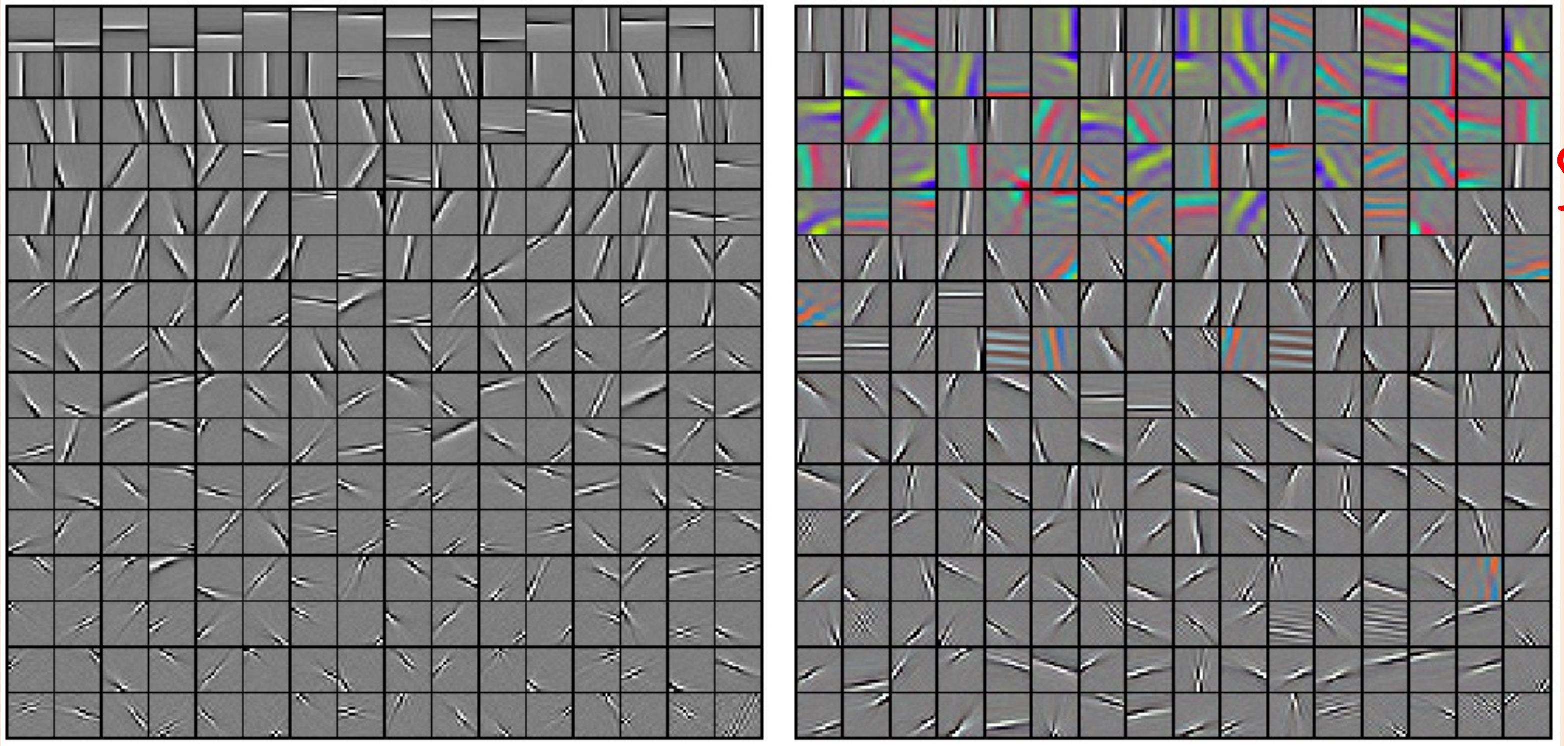


Size of X: (image height)×(image width) by ((patch height)×(patch width)×3)

Unsupervised Learning of Filters for Image Patches

bonus!

- Some methods to do this generate Gaussian/LoG/Gabor filters:
  - These filters are motivated from both neuroscience and ML experiments.



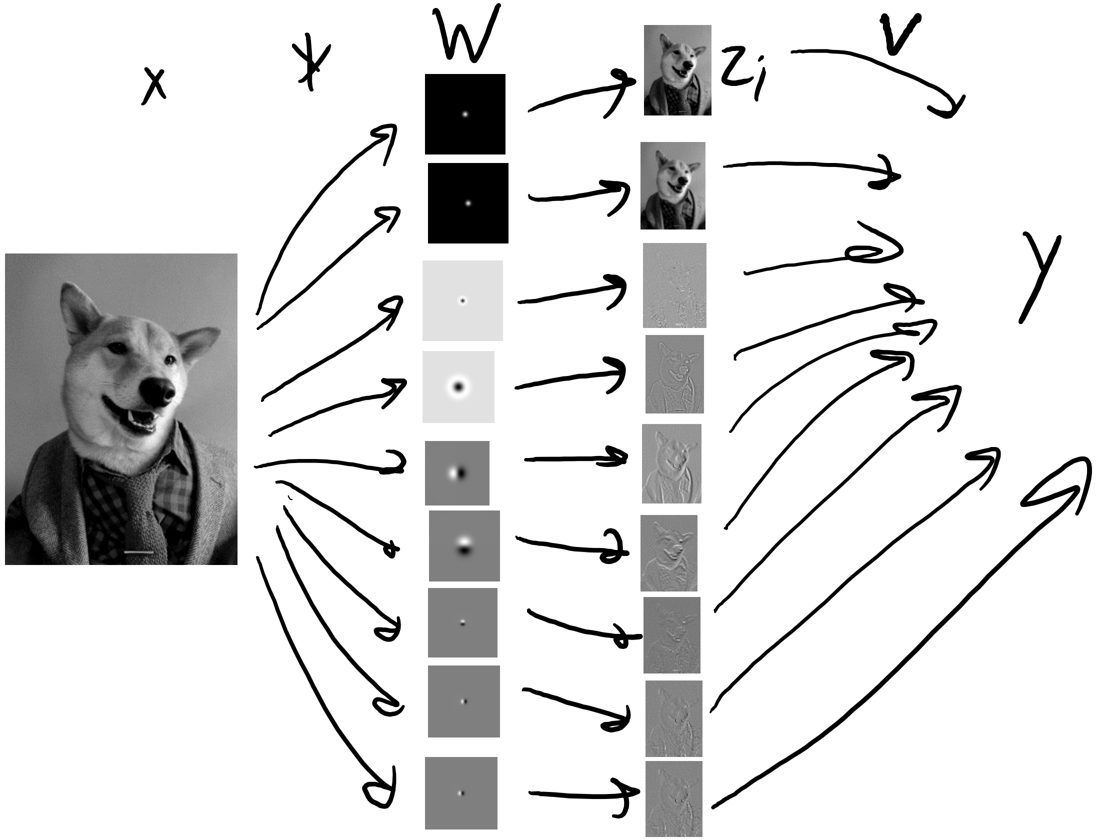
(c) With whitening - gray.   (d) With whitening - RGB.

"colour opponency"

http://lear.inrialpes.fr/people/mairal/resources/pdf/review_sparse_arxiv.pdf

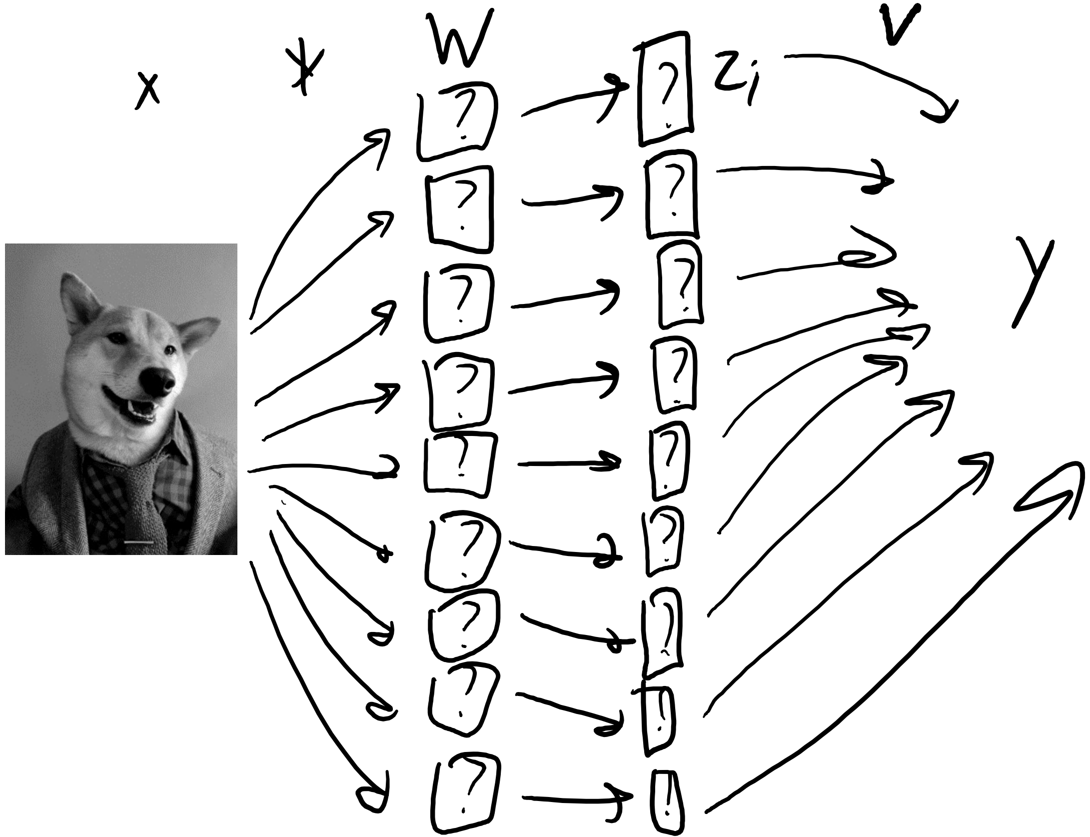
Motivation for Convolutional Neural Networks

- Classic vision methods uses fixed convolutions as features:
  - Usually have different types/variances/orientations.
  - Can do subsampling or take maxes across locations/orientations/scales.



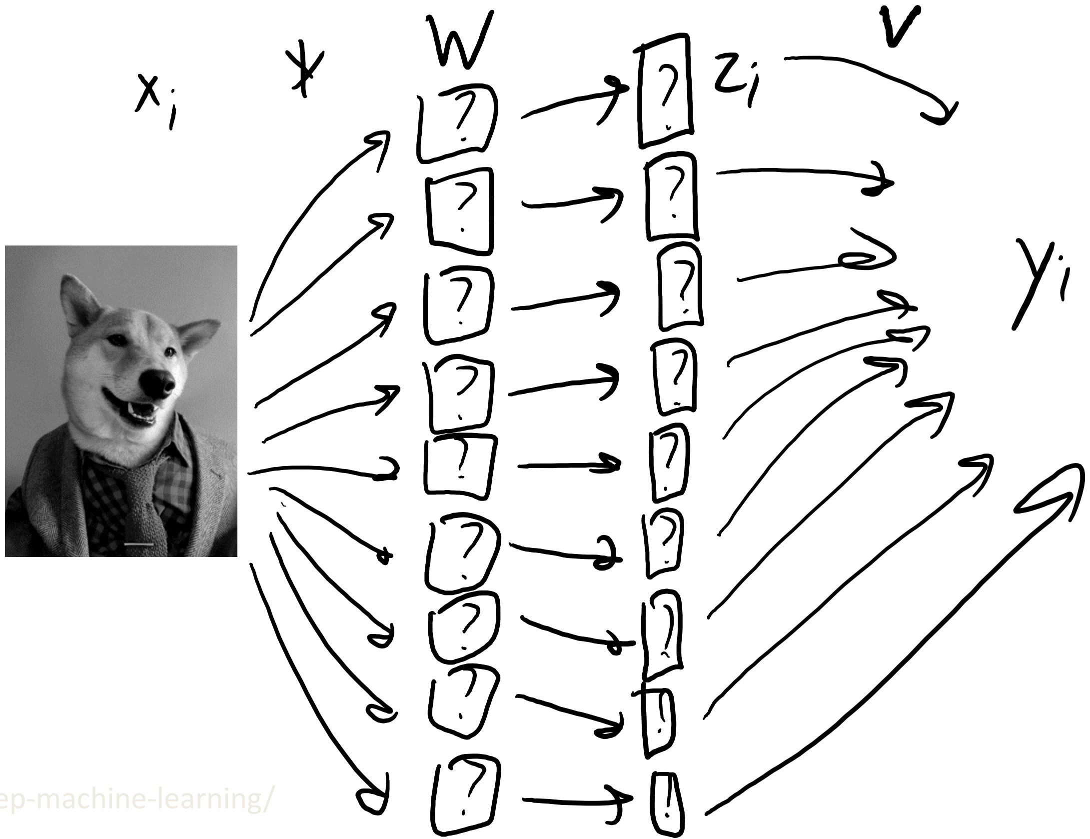
Motivation for Convolutional Neural Networks

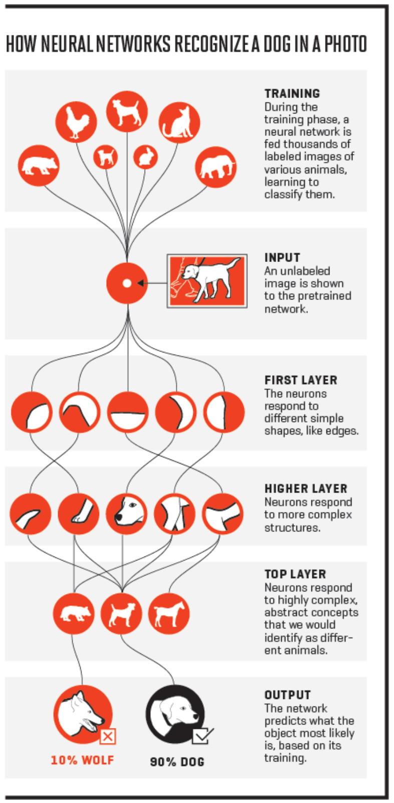
- Convolutional neural networks learn the convolutions:
  - Learning *W* and *v* automatically chooses types/variances/orientations.
  - Don't pick from fixed convolutions, but learn the elements of the filters.



Motivation for Convolutional Neural Networks

- Convolutional neural networks learn the convolutions:
  - Learning *W* and *v* automatically chooses types/variances/orientations.
  - Can do multiple layers of convolution to get deep hierarchical features.

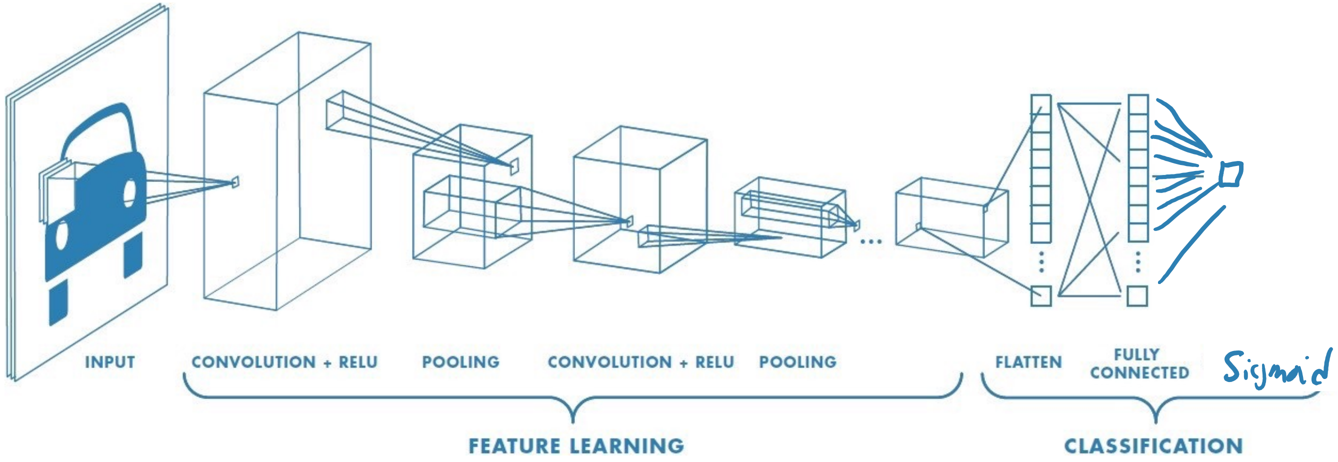




http://fortune.com/ai-artificial-intelligence-deep-machine-learning/

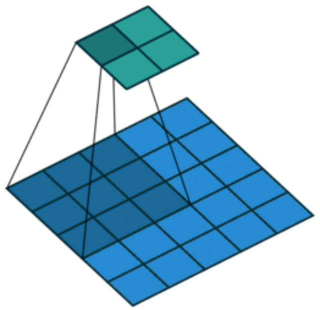
Convolutional Neural Networks

- Classic architecture of a convolutional neural network:



- Convolution layers:
  - Apply convolution with several different filters.
  - Sometimes these have a "stride": skip several pixels between applying filter.
- Pooling layers:
  - Aggregate regions to create smaller images (usually "max pooling").
- Fully-connected layers: usual "multiplication by W^l" in layer.

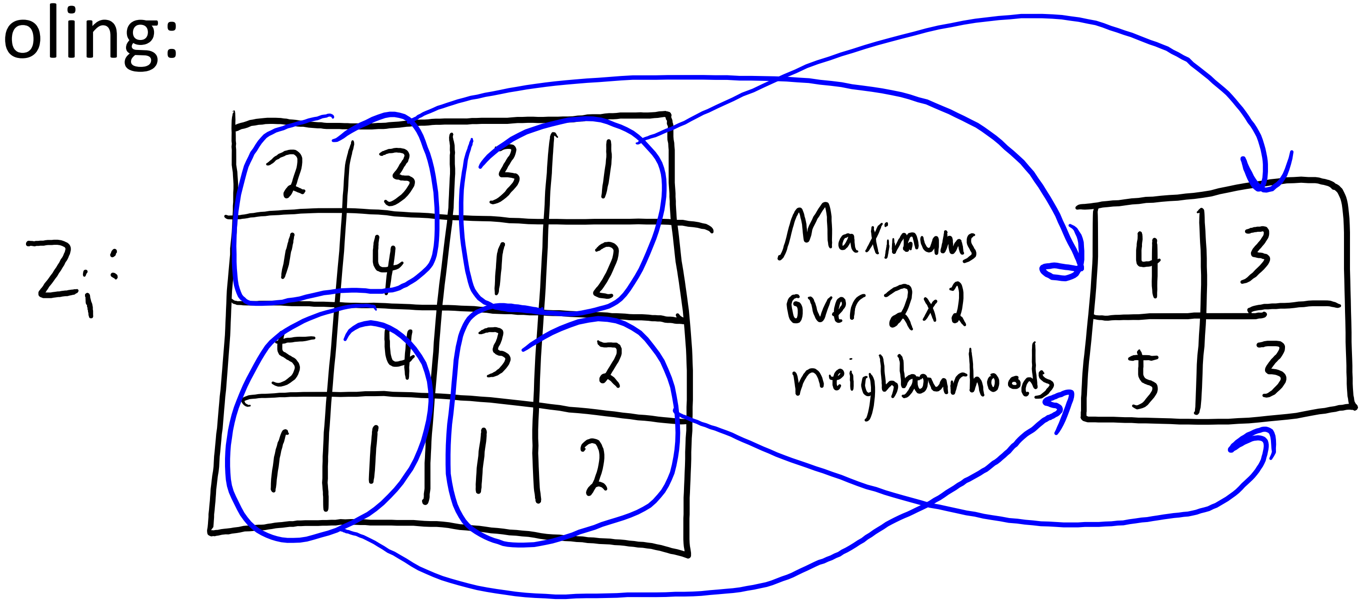
"Stride" of 2



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53
https://github.com/vdumoulin/conv_arithmetic

Max Pooling Example

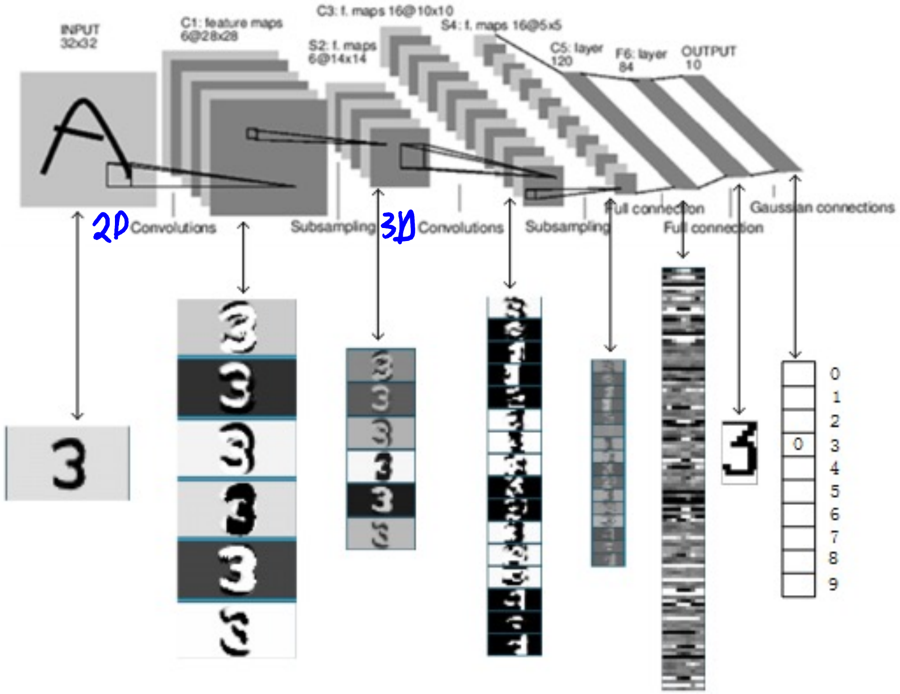
- Max pooling:



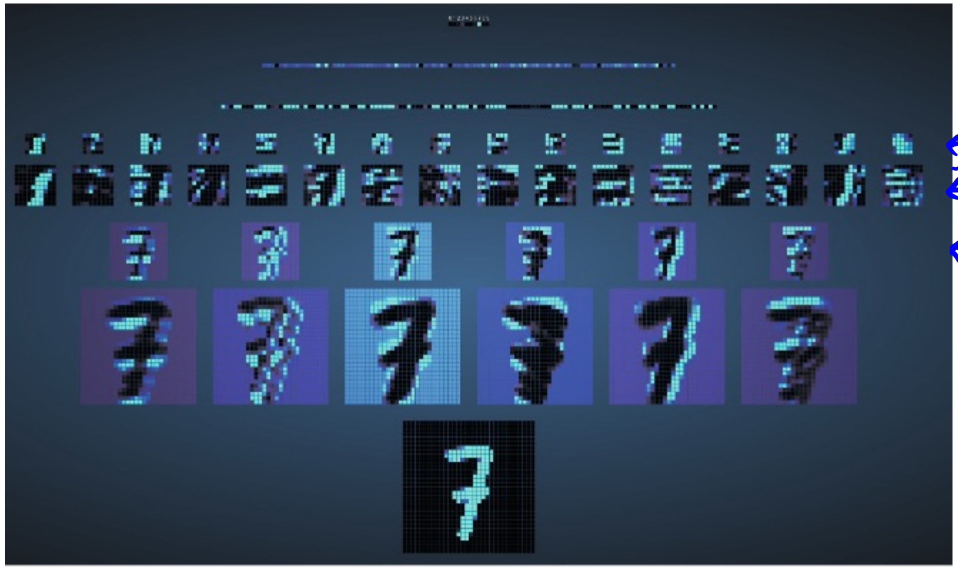
- Decreases size of hidden layer, so we need fewer parameters.
  - Gives some local translation invariance:
    - The precise location of max is not important.
- This is continuous and piecewise-linear but non-differentiable.
  - Like ReLU, we can still optimize this type of objective with SGD.

LeNet Convolutional Neural Networks

- Classic convolutional neural network (LeNet):



- Visualizing the "activations":
  - http://scs.ryerson.ca/~aharley/vis/conv
  - http://cs231n.stanford.edu



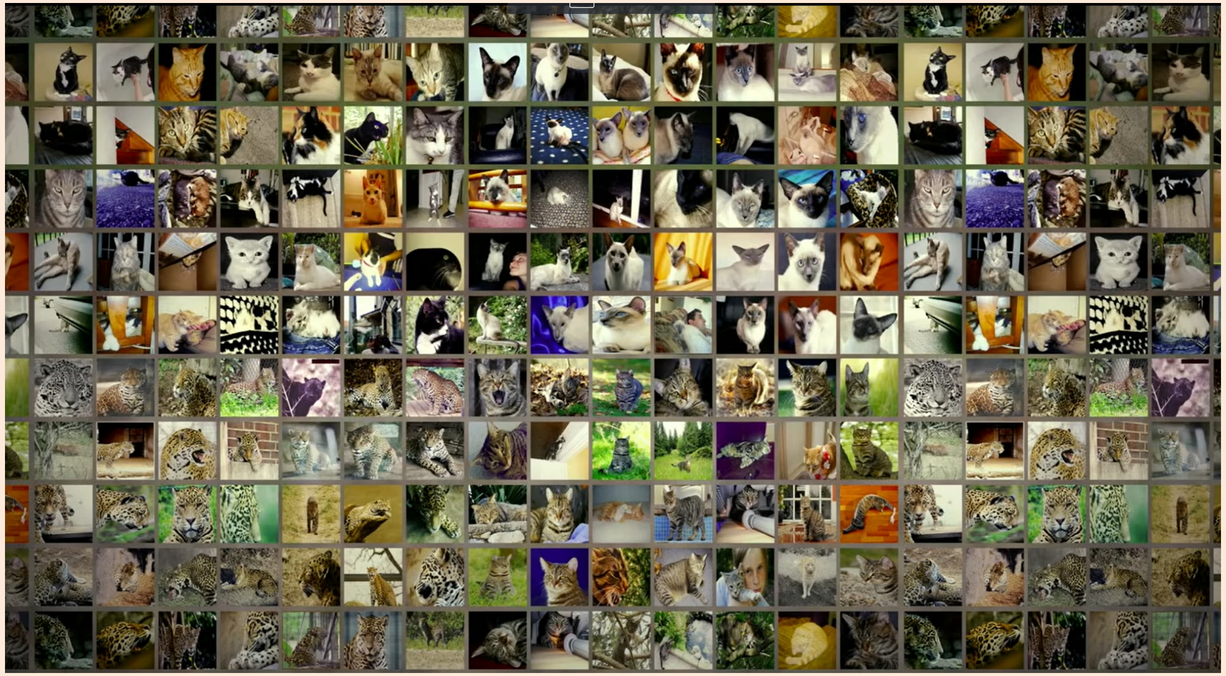
softmax
2 "fully-connected"
max pooling
3D convolutions
max pooling
2D convolutions

http://scs.ryerson.ca/~aharley/vis/harley_vis_isvc15.pdf

bonus!

ImageNet Competition

- ImageNet: Millions of labeled images, 1000 object classes.
  - Task is to classify images into one of the 1000 class labels.
    - We will discuss multi-class classification in Part 2 of the course.
  - Everyone submits their "best" model, winners announced.



https://www.youtube.com/watch?v=40riCqvRoMs

bonus!

AlexNet Convolutional Neural Network

- Modern CNN era started with AlexNet (won 2012 competition):
  - 15.4% error vs. 26.2% for closest competitor.
  - 5 convolutional layers.
  - 3 fully-connected layers.
  - SG with momentum.
  - ReLU non-linear functions.
  - Data translation/reflection/ cropping.
  - L2-regularization + Dropout.
  - 5-6 days on two GPUs.

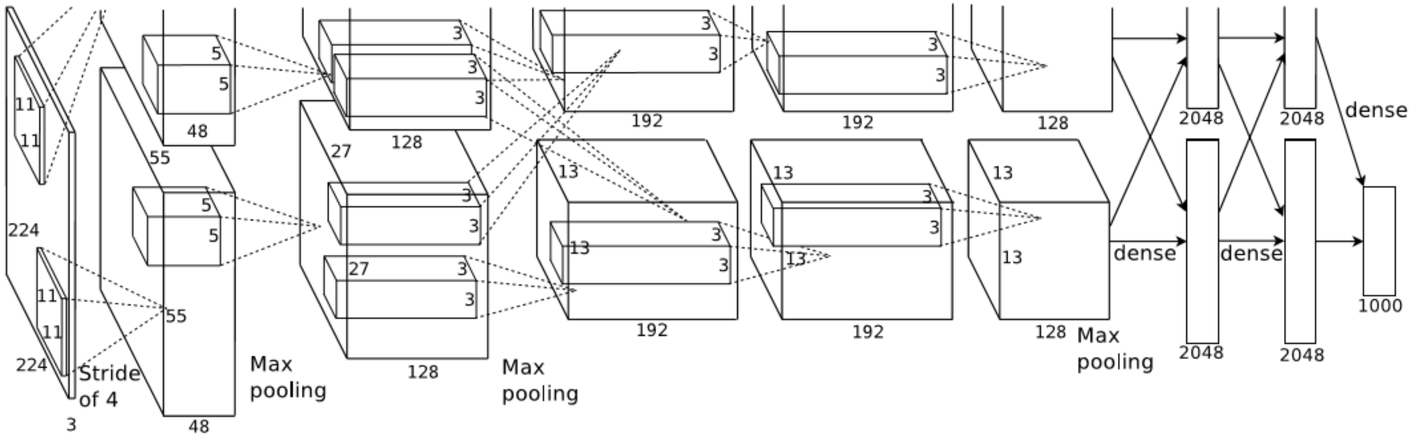


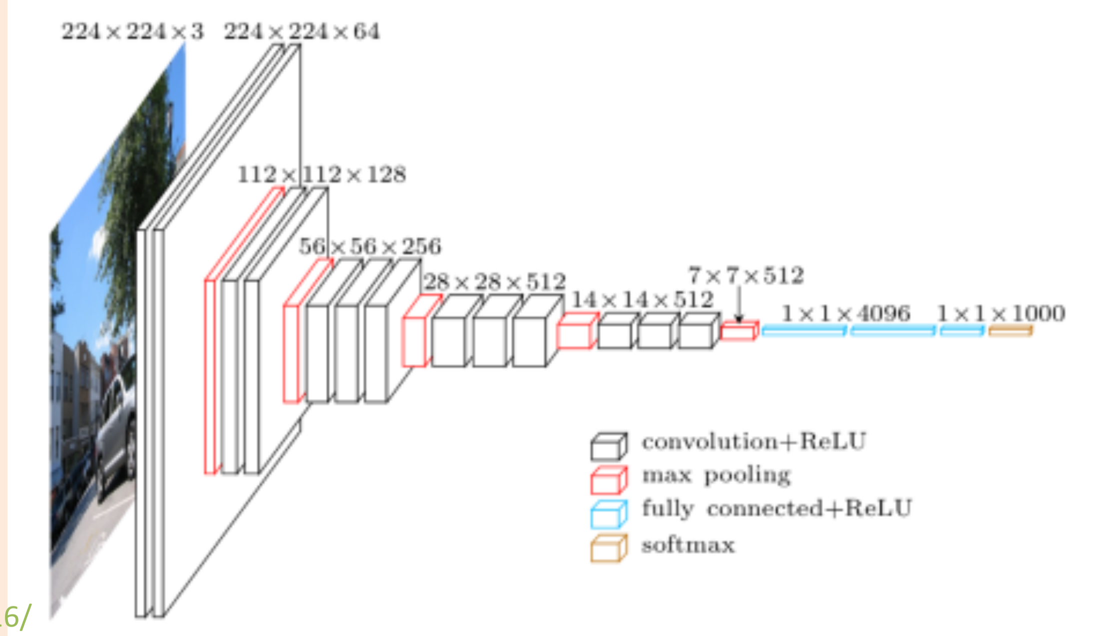
Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

bonus!

ImageNet Insights

- Filters and stride got smaller over time.
  - Popular VGG approach uses 3x3 convolution layers with stride of 1.
    - 3x3 followed by 3x3 simulates a 5x5, and another 3x3 simulates a 7x7, and so on.
    - Speeds things up and reduces number of parameters.
    - Also increases number of non-linear ReLU operations.

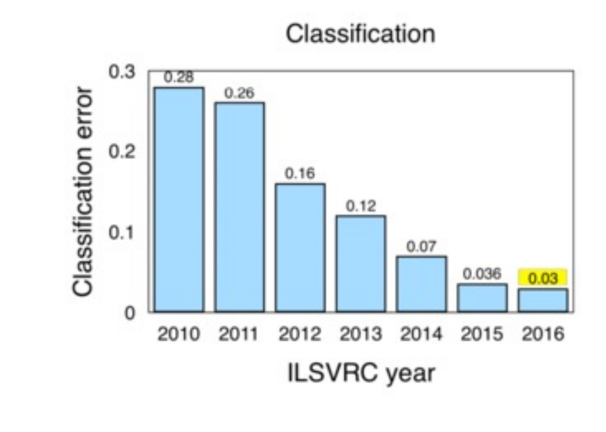


https://www.cs.toronto.edu/~frossard/post/vgg16/

bonus!

ImageNet Insights

- Filters and stride got smaller over time.
  - Popular VGG approach uses 3x3 convolution layers with stride of 1.
  - GoogLeNet used multiple filter sizes (“inception layer”), but not as popular.
- Eventual switch to “fully-convolutional” networks.
  - No fully connected layers.
- ResNets allow easier training of deep networks.
  - Won all 5 tasks in 2015, training 152 layers for 2-3 weeks on 8 GPUs.
- Ensembles help.
  - 2016 winner combined predictions of previous networks.
- Competition ended in 2017!



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

Discussion of CNNs

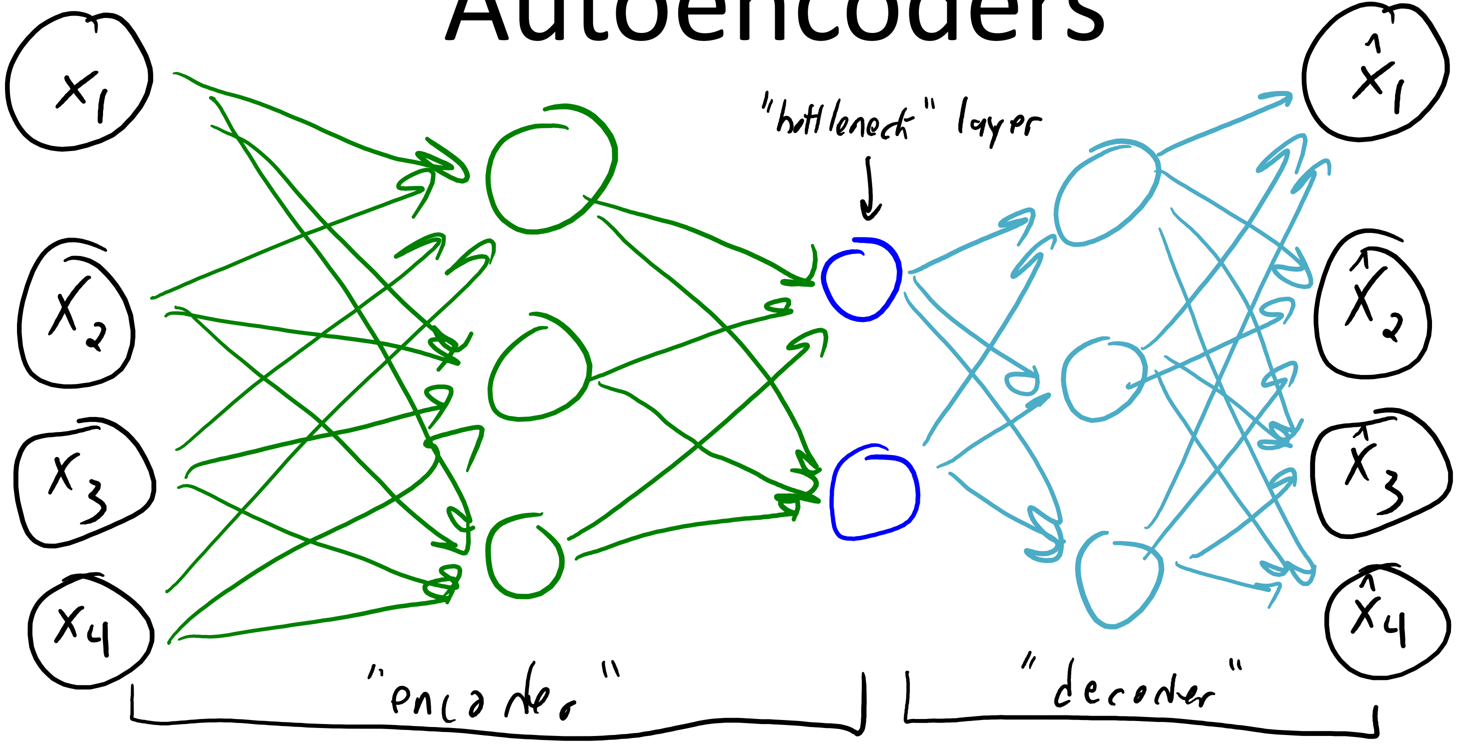
- Convolutional layers reduce the number of parameters in two different ways:
  - Each hidden unit only depends on small number of inputs from previous layer.
  - We use the same filters across the image.
    - So we do not learn a different weight for each "connection" like in classic neural networks.

- CNNs give some amount of translation invariance:
  - Because the filters are used across the image, they can detect a pattern anywhere in the image.
    - Even in image locations where the pattern has never been seen.
  - The pooling layer can also give some local invariance, against small translations of the image.

- CNNs are not only for images!
  - Can use CNNs for 1D sequences like sound or language.
  - Can use CNNs for 3D objects like videos or medical image volumes.
  - Can use CNNs for graphs.
- But you do need some notion of "neighbourhood" for convolutions to make sense.

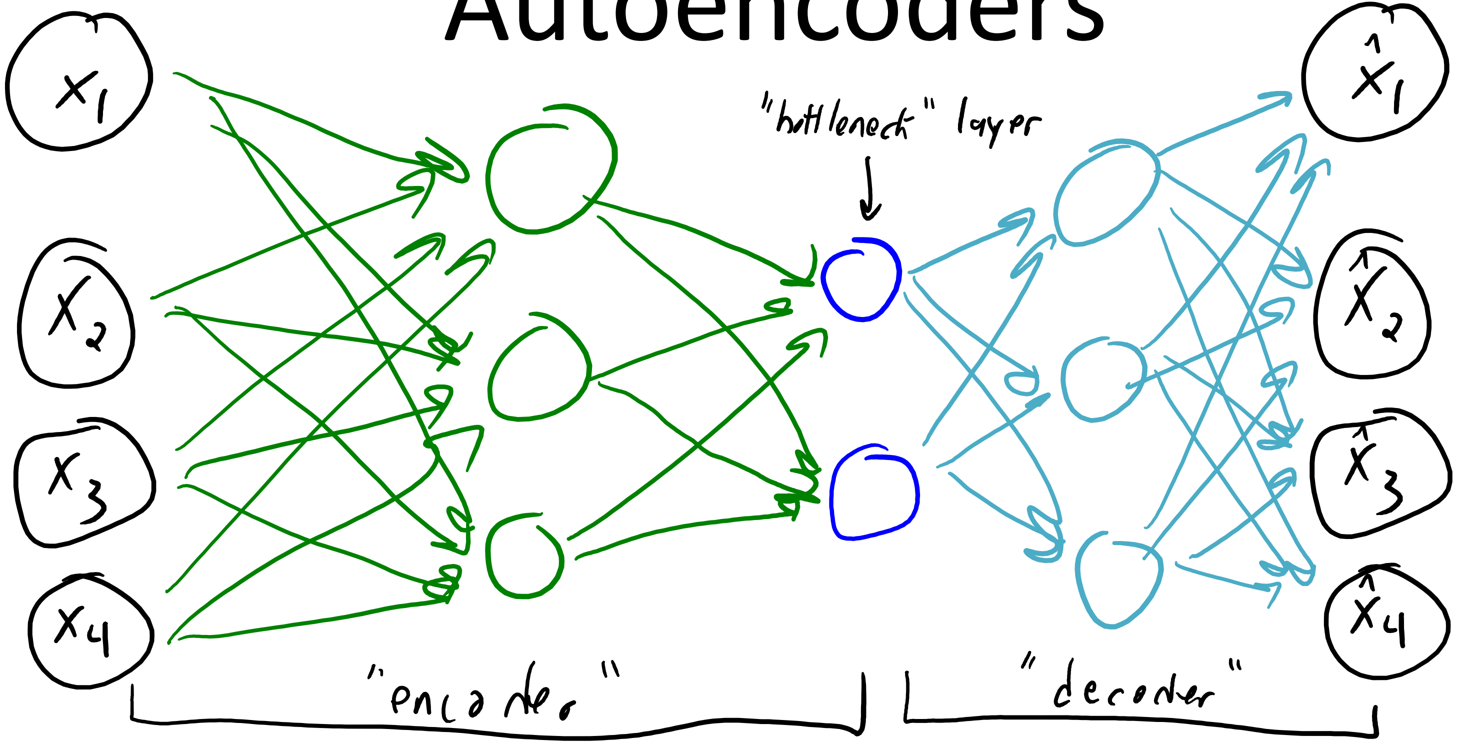
Next Topic: Autoencoders

Autoencoders



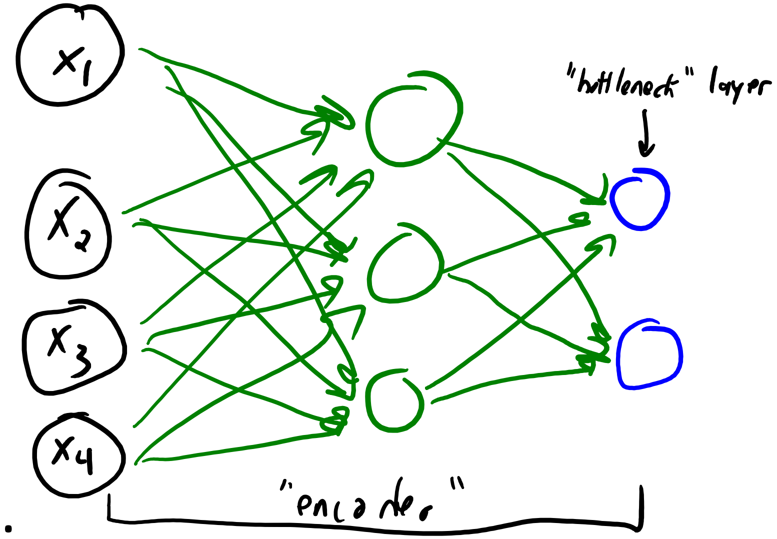
- Autoencoders are neural networks with same input and output.
  - Includes a bottleneck layer: with dimension *k* smaller than input *d*.
  - First layers "encode" the input into bottleneck.
  - Last layers "decode" the bottleneck into a (hopefully valid) input.

Autoencoders



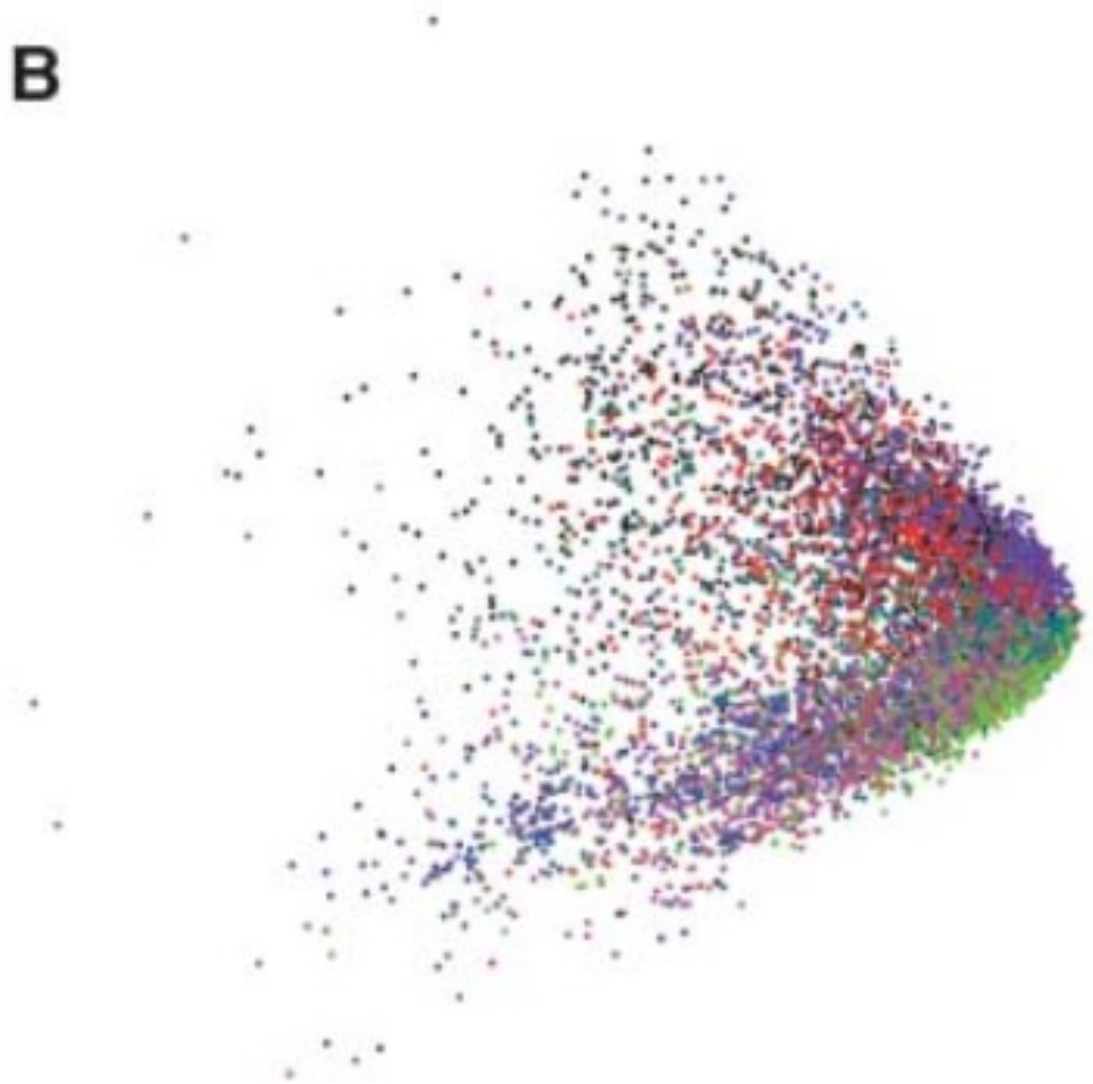
- This is an unsupervised learning method.
  - There are no labels *y*.
- Relationship to principal component analysis (PCA):
  - With squared error and linear network, equivalent to PCA.
    - Size of bottleneck layer gives number of latent factors *k* in PCA.
  - With non-linear transforms: a non-linear/deep generalization of PCA.

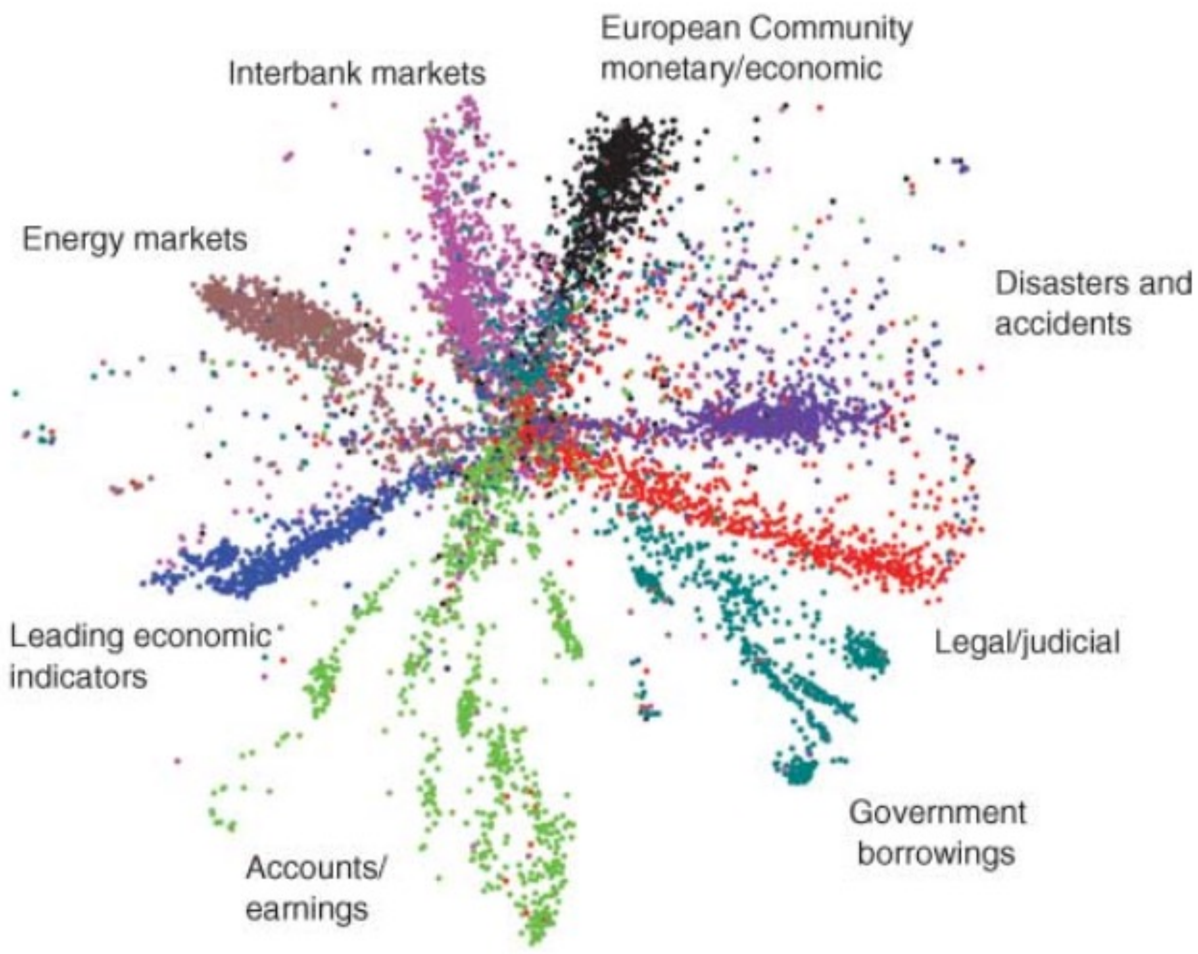
Encoder as Learning a Representation



- Consider the encoder part of the network:
  - Takes features x^i and makes low-dimensional z^i.
- Ways you could use the encoder:
  - Use z^i as compressed input (reduce memory needed).
  - Set bottleneck size to 2, and plot the z^i to visualize the data.
  - Try to interpret what the bottleneck features z^i mean.
  - Use the z^i as features for supervised learning.
    - For the special case of PCA and regression with L2 loss, this is called "partial least squares".
  - You could add a supervised y^i to final layer of trained autoencoder + fit with SGD.
    - This is called "unsupervised pre-training".
    - If you use unlabeled data to do this initialization, an example of "self-supervised" learning.
      - Usually it is easier to get a lot of unlabeled data than it is to get labeled data.

PCA vs. Deep Autoencoder (Document Data)



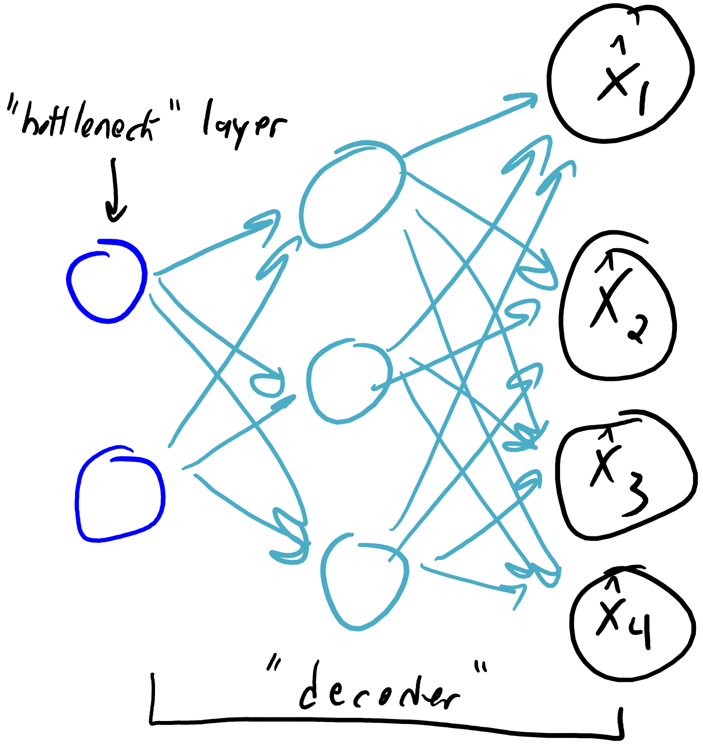


https://www.cs.toronto.edu/~hinton/science.pdf

(these days t-SNE is the usual way to make visualizations like this; see these guidelines)

Decoder as Generative Model

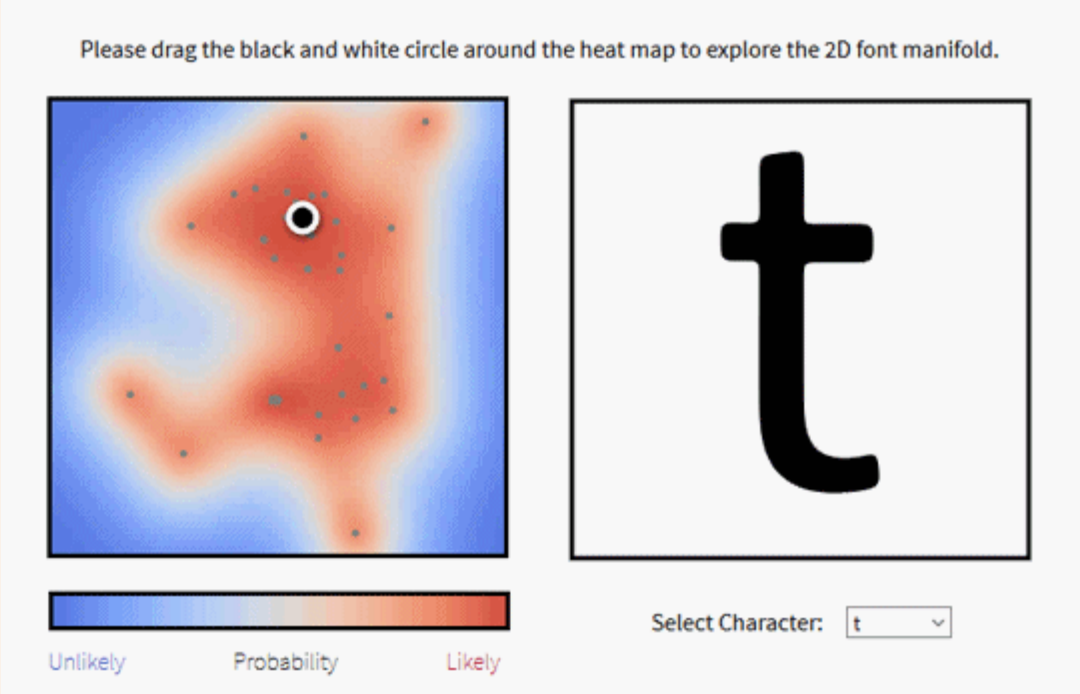
- Consider the decoder part of the network:
  - Takes low-dimensional z^i and makes features $\hat{x}^i$.
- Can be used for outlier detection:
  - Check distance to original features to detect outliers.
- Can be used to generate new data:
  - The z close to training examples should generate new valid "samples."
  - But this is not actually sampling, since we aren't modeling p(z) yet.



bonus!

Font Manifold

- Going from encoding to decoding for different fonts:

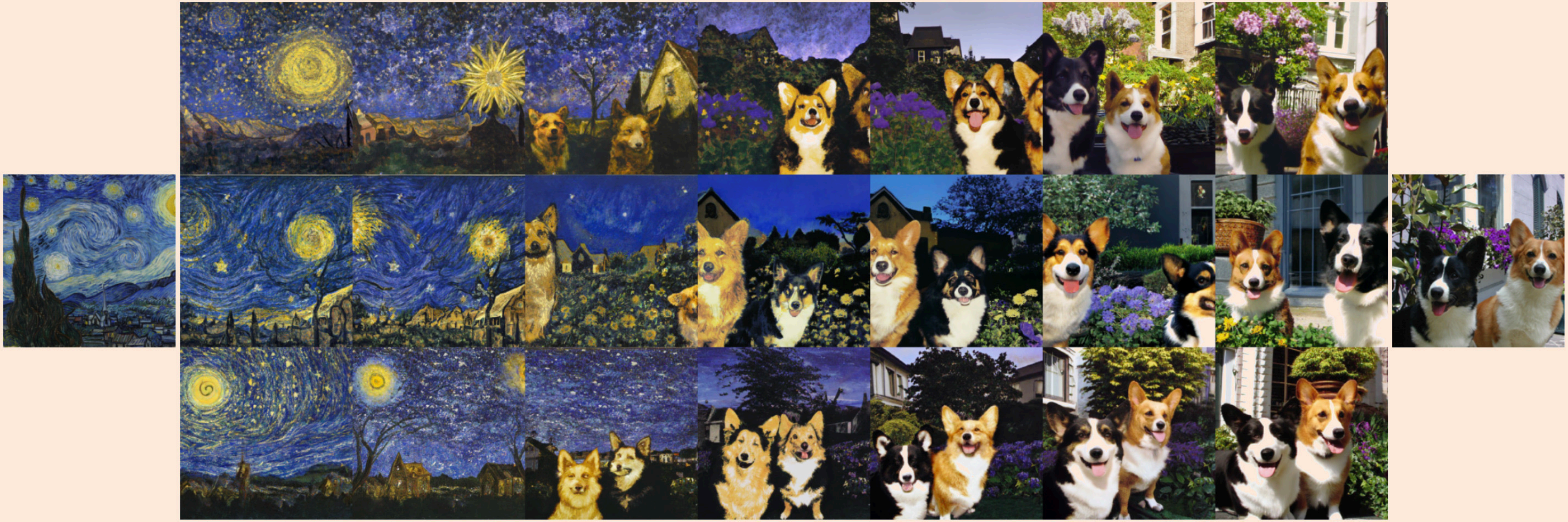


- Demo [here](#).
  - The above was generated by a Gaussian process and not an autoencoder.
  - But the decoder part of autoencoders is trying to do something like this.

http://entangled.systems/fragments/20160729-learning-a-manifold-of-fonts-machine-learning-research-from-2014-by-dr-neill-campbell-provides-an-interactive-exploration-of.html

bonus!

Latent Space Interpolation



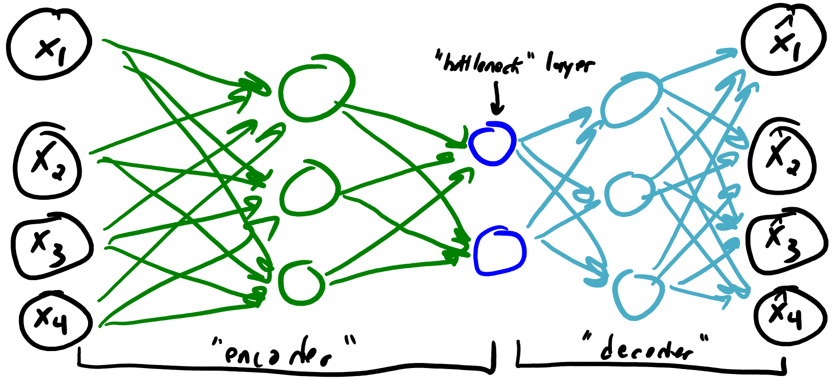
- Encode both ends; decode various points on a line between

https://arxiv.org/abs/2204.06125

Neural Networks with Multiple Outputs

- Previous neural networks we have seen only have 1 output y.
- In autoencoders, we have d outputs (one for each feature).

$$\left.\begin{aligned} \hat{x}_1 &= v_1^T h(W^3 h(W^2 h(W^1 x))) \\ \hat{x}_2 &= v_2^T h(W^3 h(W^2 h(W^1 x))) \\ &\vdots \\ \hat{x}_d &= v_d^T h(W^3 h(W^2 h(W^1 x))) \end{aligned}\right\} \hat{x} = V h(W^3 h(W^2 h(W^1 x)))$$



- For training, we add up the loss across all j:

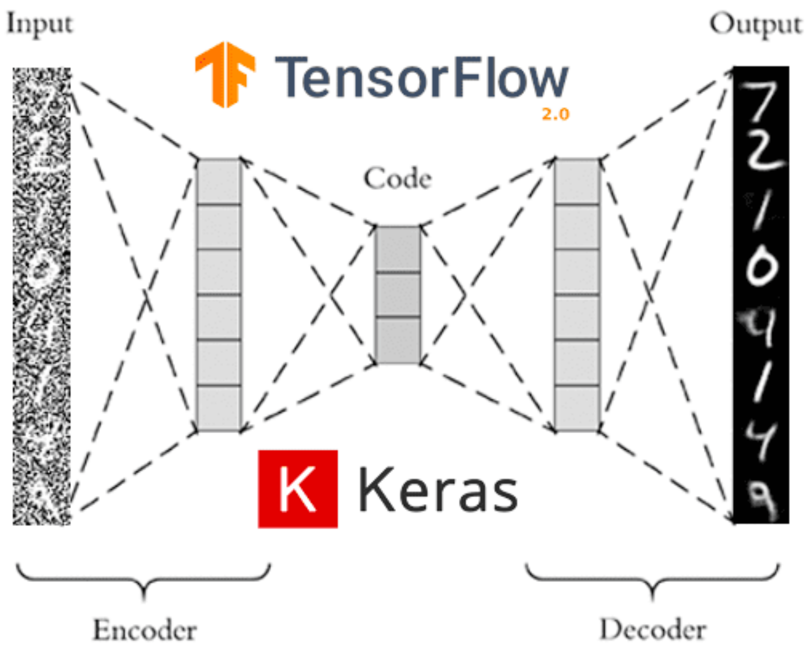
$$\hat{x}_j^i = v_j^T h(W^3 h(W^2 h(W^1 x^i)))$$

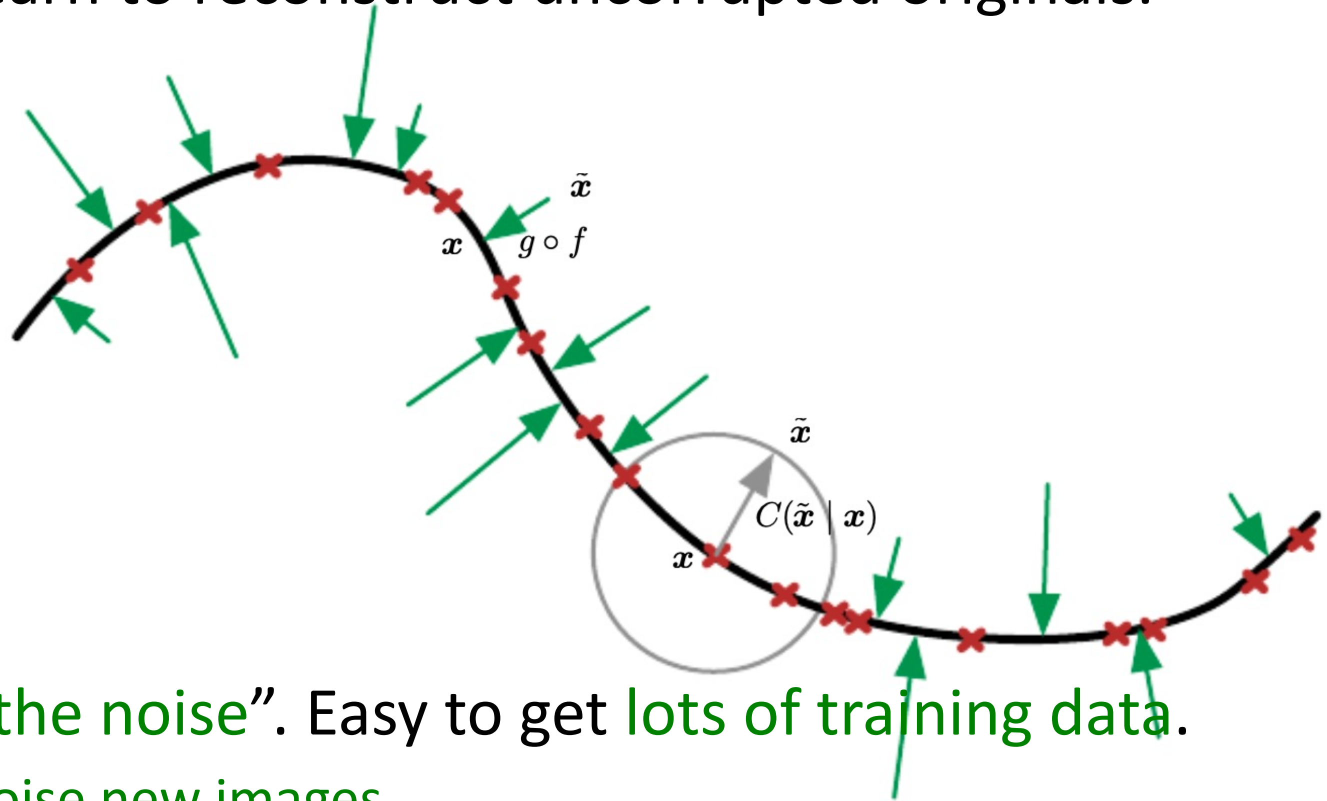
$$f(W^1, W^2, V) = \underbrace{\sum_{i=1}^n \sum_{j=1}^d (\hat{x}_j^i - x_j^i)^2}_{\text{squared error for continuous } x_j^i} \qquad f(W^1, W^2, V) = \sum_{i=1}^n \sum_{j=1}^d \underbrace{\log(1 + \exp(-\hat{x}_j^i x_j^i))}_{\text{logistic loss for binary } x_j^i \in \{-1, +1\}}$$

- Fit with SGD (sampling random i), and usual deep learning tricks can be used.
  - Even though network has multiple outputs, f is a scalar so autodiff works as before.
  - For images, may want to use convolution layers.

Denoising Autoencoders

- A common variation on autoencoders is denoising autoencoders:
  - Use “corrupted” inputs, and learn to reconstruct uncorrupted originals.





  - “Learn a model that removes the noise”. Easy to get lots of training data.
    - You can apply the model to denoise new images.
    - Do not necessarily need a “bottleneck” layer.

https://www.pyimagesearch.com/2020/02/24/denoising-autoencoders-with-keras-tensorflow-and-deep-learning/
https://www.deeplearningbook.org/contents/autoencoders.html

bonus!

What Denoising Autoencoders Learn

Theorem 1 *Let p be the probability density function of the data. If we train a DAE using the expected quadratic loss and corruption noise $N(x) = x + \epsilon$ with*

$$\epsilon \sim \mathcal{N}\left(0, \sigma^2 I\right),$$

then the optimal reconstruction function $r^*(x)$ will be given by

$$r^*(x) = \frac{\mathbb{E}_\epsilon\left[p(x-\epsilon)(x-\epsilon)\right]}{\mathbb{E}_\epsilon\left[p(x-\epsilon)\right]} \tag{3}$$

for values of x where $p(x) \neq 0$.

Moreover, if we consider how the optimal reconstruction function $r^*_\sigma(x)$ behaves asymptotically as $\sigma \to 0$, we get that

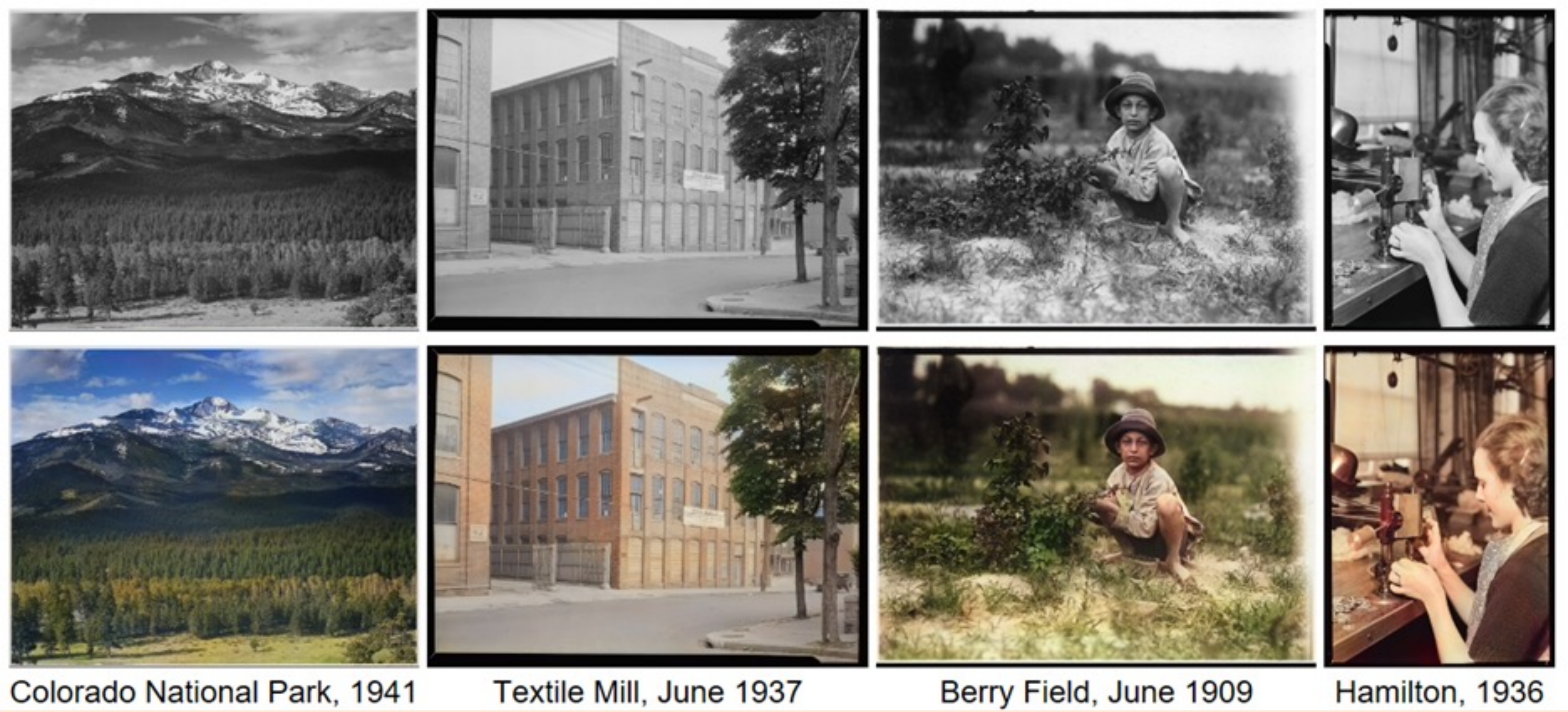
$$r^*_\sigma(x) = x + \sigma^2 \frac{\partial \log p(x)}{\partial x} + o(\sigma^2) \quad as \quad \sigma \to 0. \tag{4}$$

Alain and Bengio (2012)

- Can use to estimate "Hyvärinen score" $\frac{(r^*_\sigma(x) - x)}{\sigma^2} \approx \nabla_x \log p(x)$
- Closely related to diffusion models (later in the course!)

bonus!

Image Colourization



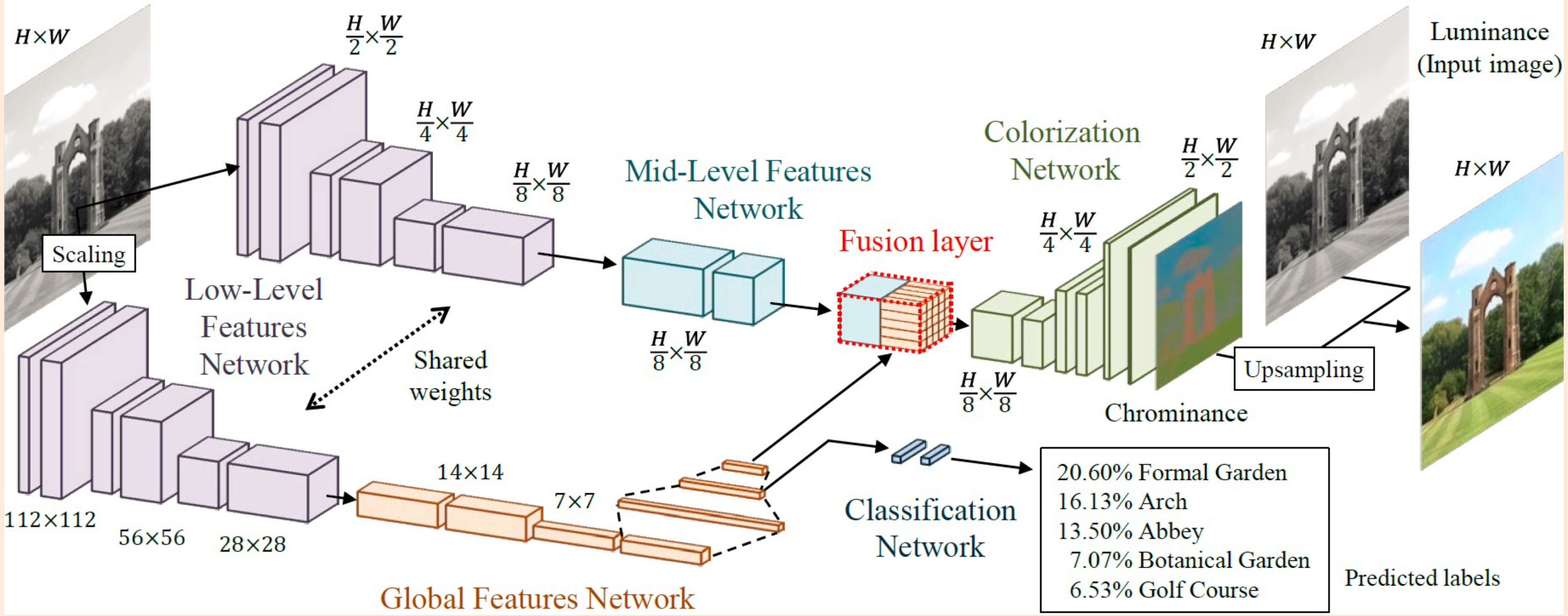
- Gallery: http://iizuka.cs.tsukuba.ac.jp/projects/colorization/extra.html
- Video: https://www.youtube.com/watch?v=ys5nMO4Q0iY

http://iizuka.cs.tsukuba.ac.jp/projects/colorization/en/

bonus!

Image Colourization

- Instead of noisy inputs, you use de-coloured inputs:



- Another application is super-resolution:
  - Learn to output a high-resolution image based on low-resolution images.

http://iizuka.cs.tsukuba.ac.jp/projects/colorization/en/

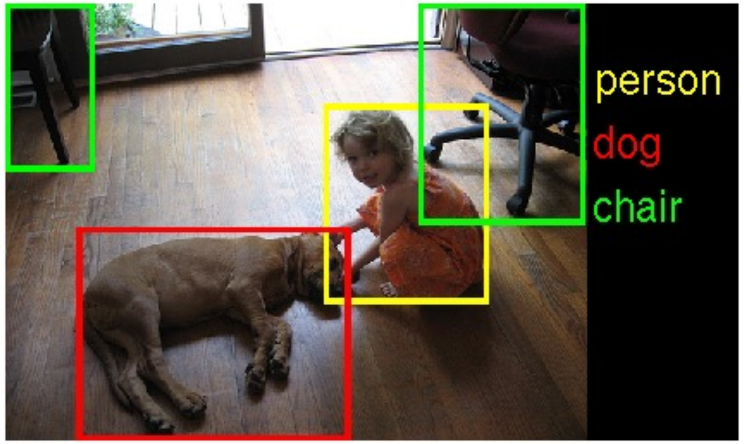
Next Topic: Multi-Label Classification

Motivation: Multi-Label Classification

- Consider multi-label classification:

$$X = \underbrace{\begin{bmatrix} \quad & \quad & \quad \\ & & \\ & & \end{bmatrix}}_{d} \Big\} n \qquad Y = \underbrace{\begin{array}{c} \begin{array}{ccccc} \text{cat} & \text{dog} & \text{person} & \text{chair} & \text{mouse} \end{array} \\ \begin{bmatrix} 1 & -1 & 1 & 1 & 1 \\ -1 & -1 & 1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 \\ 1 & 1 & -1 & 1 & -1 \\ -1 & -1 & 1 & 1 & -1 \\ 1 & -1 & 1 & -1 & 1 \end{bmatrix} \end{array}}_{k} \Big\} n$$

- Which of the *k* objects are in this image?
  – There may be more than one "correct" class label.



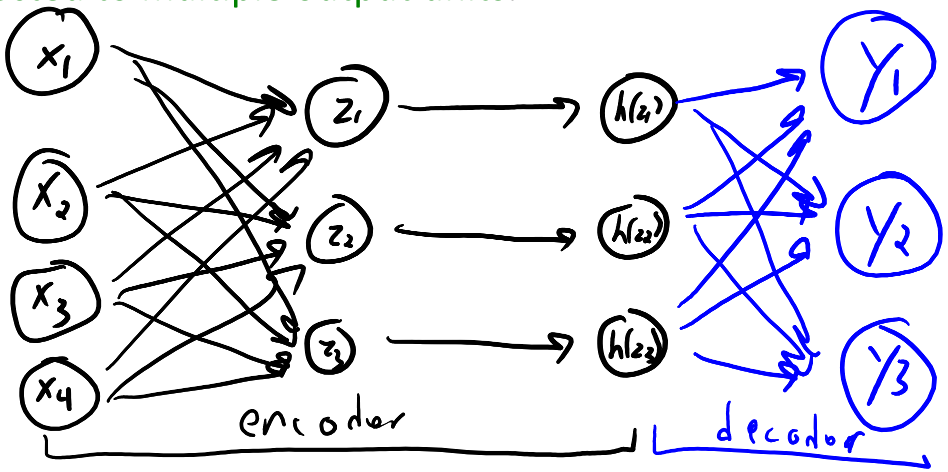
http://image-net.org/challenges/LSVRC/2013/

Independent Classifier Approach

- One way to build a multi-label classifier:
  - Train a classifier for each label.
    - Train a neural network that predicts +1 if the image contains a dog, and -1 otherwise.
    - Train a neural network that predicts +1 if the image contains a cat, and -1 otherwise.
    - …
  - To make predictions for the *k* classes, concatenate predictions of the *k* models.
- Can think of this as a "product of independent classifiers".
- Drawbacks:
  - Lots of parameters: *k**(number of parameters for base classifier).
  - Each classifier needs to "relearn from scratch".
    - Each classifier needs to learn its own Gabor filters, how corners and light works, and so on.
    - A lot of visual features for "dog" might also help us predict "cat".

Encoding-Decoding for Multi-Label Classification

- Multi-label classification with an encoding-decoding approach:
  - Input is connected to a hidden layer.
  - Hidden layer is connected to multiple output units.



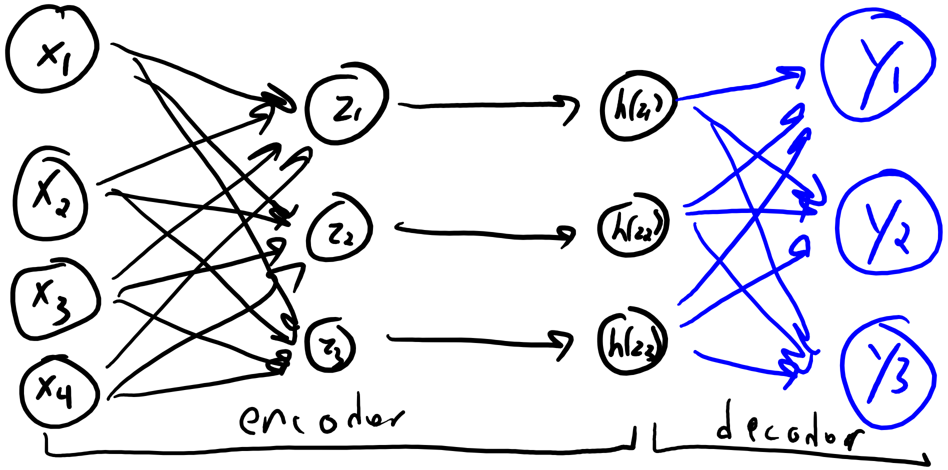
$$\hat{y}_1 = v_1^T h(Wx)$$
$$\hat{y}_2 = v_2^T h(Wx)$$
$$\hat{y}_3 = v_3^T h(Wx)$$

- Prediction: compute hidden layer, compute activations, compute output:

$$\hat{y} = V h(Wx)$$

- Number of parameters and cost is $O(dm + mk)$ for k classes and m hidden units.
  - If we trained a separate network for each class, number of parameters and cost would be $O(kdm)$ (for ‘W’ for each class)
- Might have multiple layers, convolution layers, and so on. And no need to have a “bottleneck” layer.

Encoding-Decoding for Multi-Label Classification



- We usually assume that the classes are independent given last layer:

$$p(y_1, y_2, \dots, y_k \mid x_1, x_2, \dots, x_d, W, V) = p(y_1 \mid x_1, x_2, \dots, x_d, W, v_1)\, p(y_2 \mid x_1, x_2, \dots, x_d, W, v_2) \cdots p(y_k \mid x_1, x_2, \dots, x_d, W, v_k)$$

with: $$p(y_1 = 1 \mid x, W, v) = \underbrace{\frac{1}{1+\exp(-v_1^T h(Wx))}}_{\theta_1} \qquad p(y_2 = 1 \mid x, W, v) = \underbrace{\frac{1}{1+\exp(-v_2^T h(Wx))}}_{\theta_2} \quad \dots$$

  - Conditioned on features/parameters, this is ultimately a fancy product of Bernoullis model:
    - $p(y_1, y_2, \dots, y_k \mid x, W, V) = p(y_1 \mid x, W, V)p(y_2 \mid x, W, V) \cdots p(y_k \mid x, W, V)$, where $p(y_c = 1 \mid x, W, V) = \theta_c$.
    - This makes decoding and other inference problems easy: you do inference on each y_c independently.

Encoding-Decoding for Multi-Label Classification

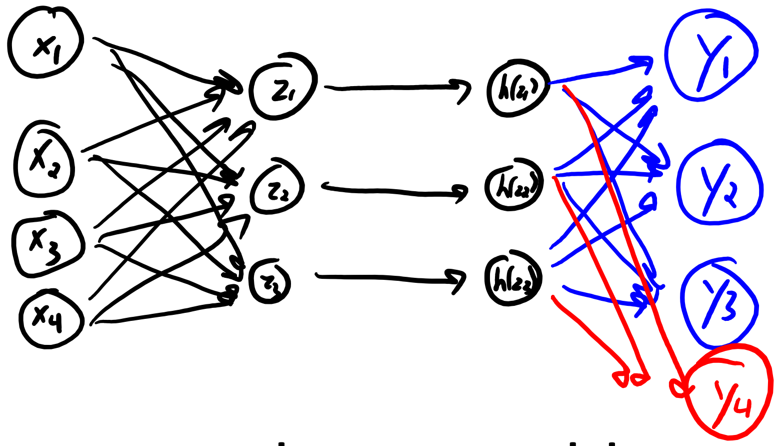
- The negative log-likelihood we optimize for MLE:

$$f(W,V) = \sum_{i=1}^{n} \sum_{c=1}^{k} \log\left(1 + \exp\left(-y_c^i v_c^T h(Wx^i)\right)\right)$$

- Use backpropagation or AD to compute gradient, train by SGD.
  - You randomly sample a training example *i* and compute gradient for all labels.
  - The updates of *W* lead to features that are useful across classes.
  - The updates of *V* focus on getting the class labels right given the features.
- Important:
  - We assumed independence of labels given the last layer.
  - But the last layer can reflect dependencies.
    - If “dog” and “human” are frequently together, this should be reflected in the hidden layer.
      - For example, θ_{human} might be higher when the features give a high value for θ_{dog}.

Pre-Training for Multi-Label Classification

- Consider a scenario where we get a new class label.
  - For example, we get new images that contain horses (not seen in training).



- Instead of training from scratch, we could:
  - Add an extra set of weights v_{k+1} to the final layer for the new class.
  - Train these weights with the encoding weights W fixed.
    - This is a simple/convex logistic regression problem.
    - If we already have "features" that are good for many classes, we may be able to learn a new class with very-few training examples!

Pre-Training for Multi-Label Classification

- Using an existing network for new problems is called "pre-training"
  - Typically, we start with a network trained on a large dataset.
  - We use this network to give us features to fit a smaller dataset.
    - "Few-shot learning".

- Depending the setup, you may also update W and the other v_c.
  - Useful if you have a lot of data on the new class.
  - In this case, would typically mix in new examples with old ones.

- Increasing trend in vision and language to using pre-training a lot.
  - No need to learn everything about language for every language task!

Summary

- Convolutions are flexible class of signal/image transformations.
  - Can approximate derivatives and integrals at different scales/orientations.
- Convolutional neural networks:
  - Include layers that apply several (learned) convolutions.
  - Significantly decreases number of parameters.
  - Achieves a degree of translation invariance.
  - Often combined with pooling operations like max pooling.
- Autoencoders:
  - Neural network where the output is the input.
  - Non-linear generalization of PCA.
  - Encode data into a bottleneck layer, then decode predict original input.
  - Can be used for visualization, compression, outlier detection, pre-training.
- Denoising autoencoders train to uncorrupt/enhance images.
  - Can be used for removing noise, adding colour, super-resolution, and so on.
- Multi-label classification:
  - Classification with more than one label per example.
- Encoding-Decoding approach to multi-label classification:
  - Have all classes shared the same hidden layer(s).
  - Reduces number of parameters.
  - Models dependencies between classes, while keeping inference easy.
- Pre-training:
  - Use parameters from model trained a on large diverse dataset, to initialize SGD for new dataset.

- Next time: helping teach fish to drive?