Fundamentals of Machine Learning:

Convolutional Neural Networks

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Outline

A Critique of Pure Reason

What makes a cow, a *cow*?

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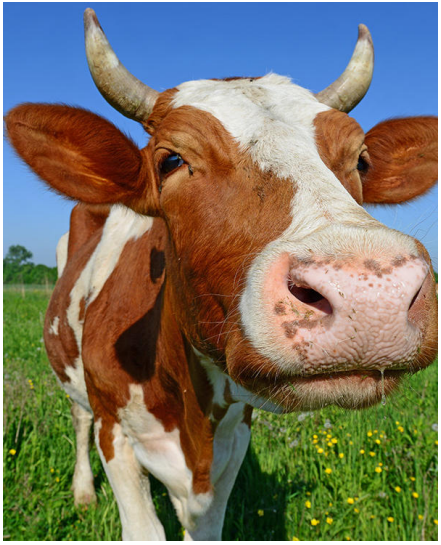

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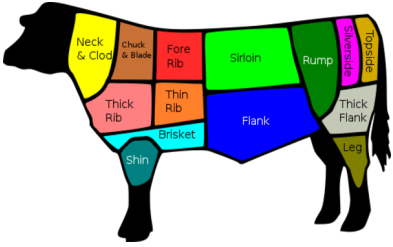

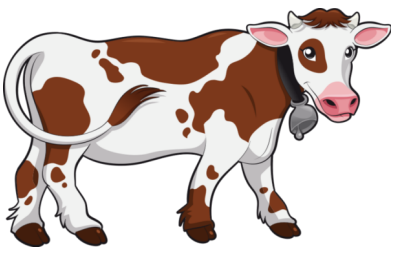

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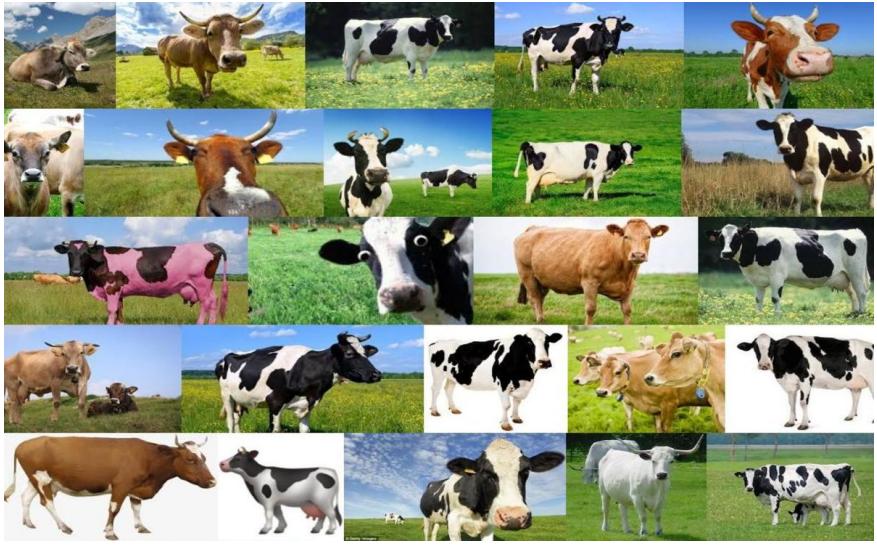
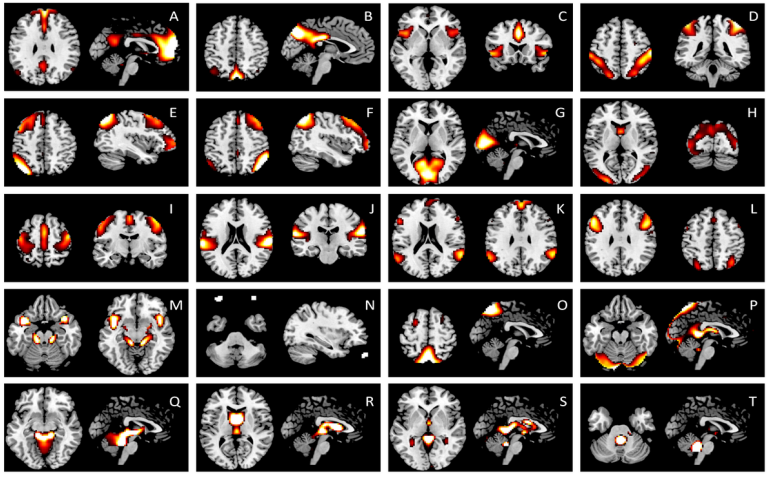
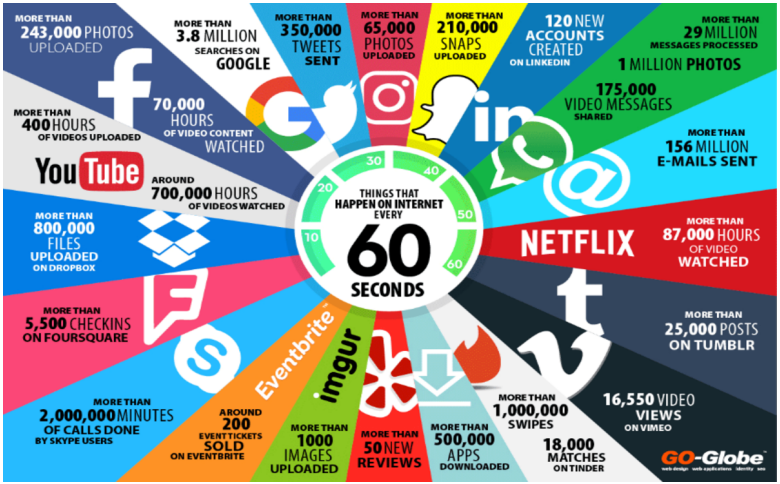


A picture is worth a thousand words...



[Cabral et al., 2013]

Content crash: why do we care?

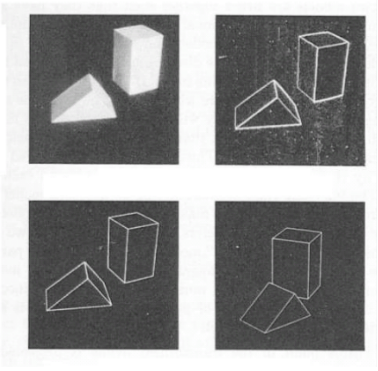


[GO-Gulf Web Design, 2017]

Visual recognition: explicit models

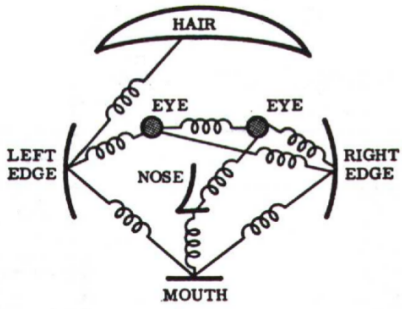
- Early works on visual recognition used (very) explicit models [Roberts, 1963].
- They are significant as first steps and appeal to our analytic beliefs about image understanding.

L. Roberts



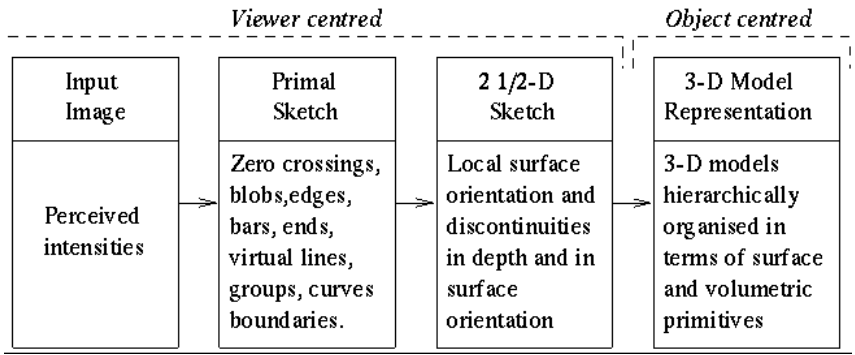
Visual recognition: explicit models

- This type of explicit model of recognition gave way to part-based representations [Fischler and Elschlager, 1973].
- An object was represented by a set of parts arranged in an elastic configuration.
- The trend: move away from models and move towards the image.



Visual recognition: Marr's Vision

- In his book, Marr developed a modular framework for computervision [Marr, 1982].
- This framework consists of three representations that are created, maintained, and interpreted by the process of vision:



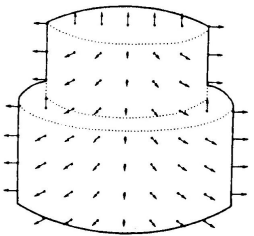
Visual recognition: Marr's Vision

- The Primal Sketch is a description of the intensity changes in the image and their local geometry.
- It is based on the assumption that intensity variations are likely to correspond to physical realities like object boundaries.

Vision: A computational investigation into the human representation and processing of visual information

Visual recognition: Marr's Vision

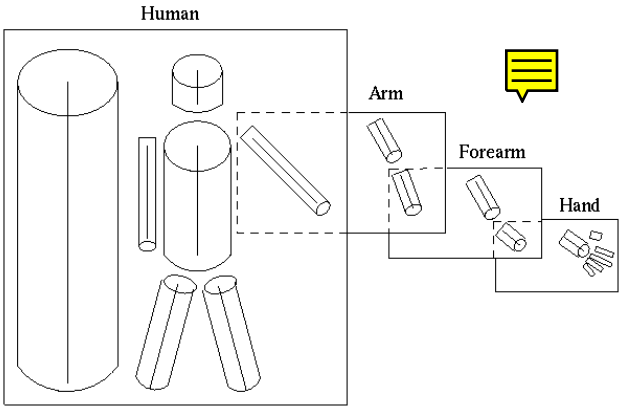
- The 2.5D Sketch is a viewer-centric representation of orientation and depth of visible surfaces drawing from the primal sketch.
- Note that no grouping is done yet: we are only associating weak geometry to image elements.
- Hence the metaphor 2.5D sketch.



Vision: A computational investigation into the human representation and processing of visual information

Visual recognition: Marr's Vision

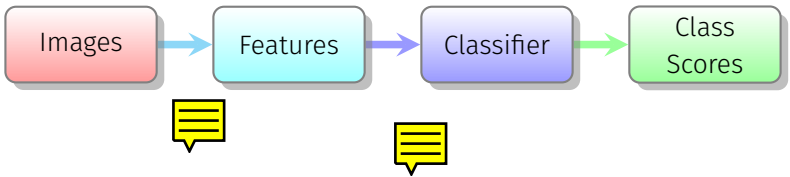
- The 3D Model is an object-centric representation of 3D objects in the image.
- The goal of this model is to enable object manipulation and recognition.



Vision: A computational investigation into the human representation and processing of visual information

Visual recognition: implicit models

- Let's consider a more-or-less Standard setup of supervised learning for visual classification.
- We can imagine a simple pipeline like below.
- Each stage has it's own design space and critical choices to be made.
- This appeals to the computer scientist in us since we are effectively dividing, modularizing, and (hopefully) conquering.



Visual recognition: implicit models

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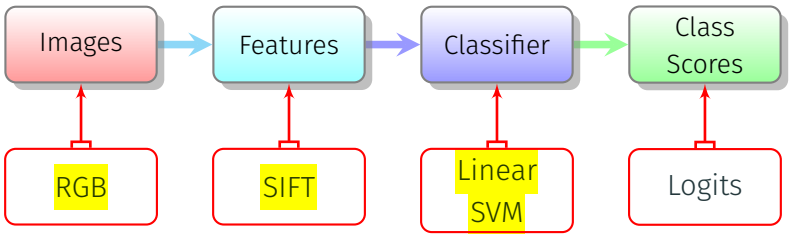


Visual recognition: why is this hard?

- A paper appeared in 2000 that summarized the state-of-the-art in visual recognition [Smeulders et al., 2000].
- It introduced sensory gap into the conversation on visual recognition:

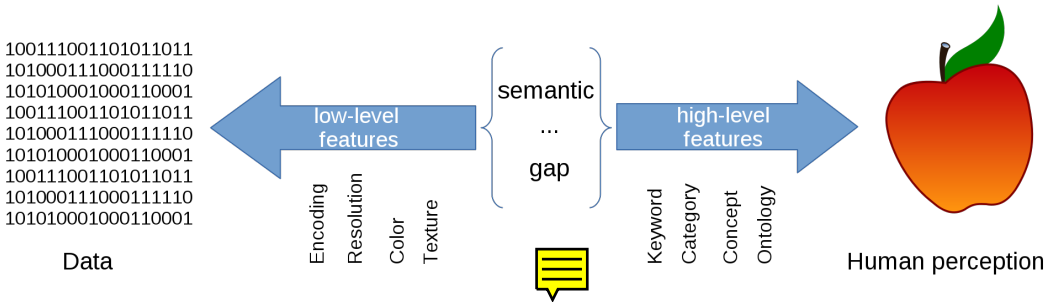
  The sensory gap is the gap between the object in the world and the information in a (computational) description derived from a recording of that scene.

- Think about this for a moment: we are always working with an imperfect reconstruction of the real world.
- Images have finite resolution, they are subject to noise, they are acquired with a sensor which is another free object in the world.
- This sensory gap must be surpassed in order to render object recognition invariant to scene-incidental artifacts.

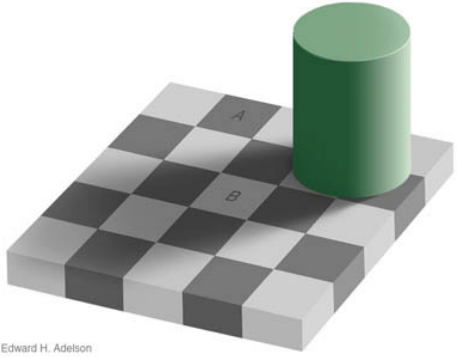
The semantic gap

- The other key concept is the semantic gap:

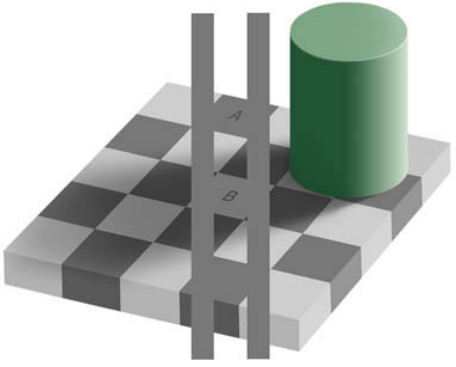
The semantic gap is the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation.



The semantic gap

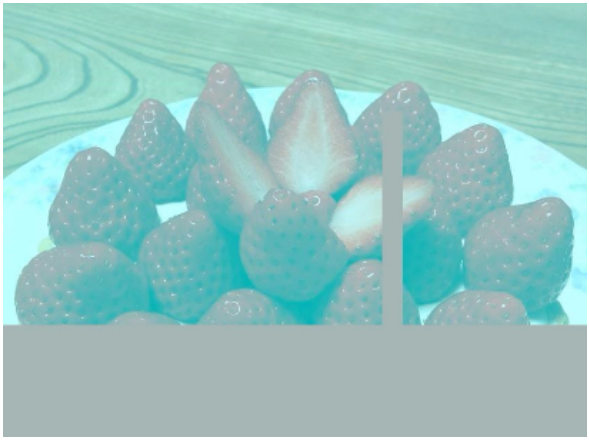


Edward H. Adelson



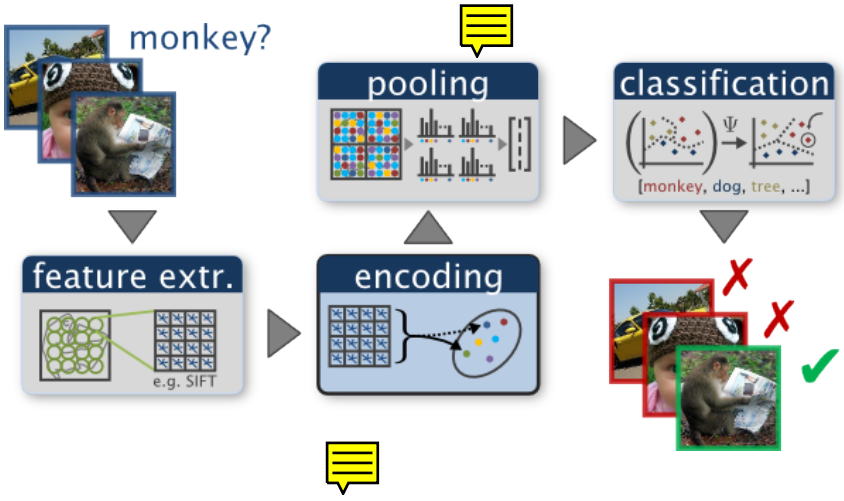
The semantic gap

The semantic gap

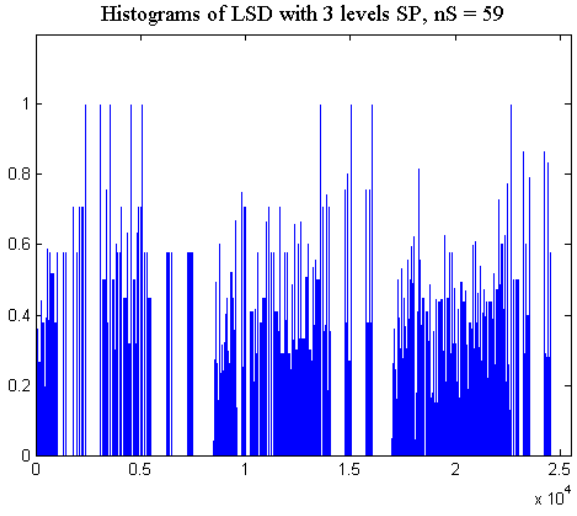


Historical context: Bags of Features

- This was the state-of-the-art in 2011:

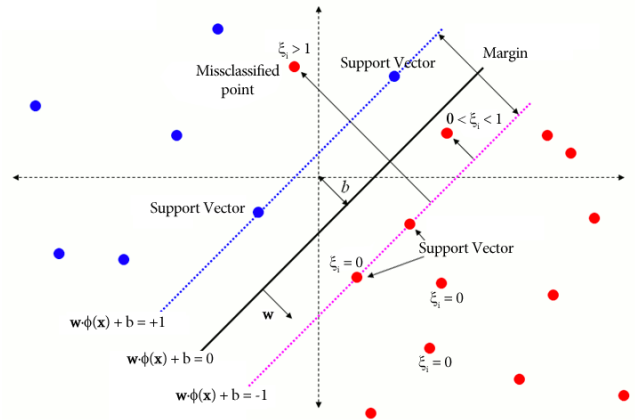


Historical context: This was a “cat”



Historical context: Now “learn”

- To each image representation was associated one (or more) labels.
- Then we feed these into a multi-class SVM.



Historical context: A recipe

- Then returned the optimal decision boundaries between all classes (and all the others).
- The process is important:
  1. First: extract a handcrafted representation of fiducial points.
  2. Then: encode these into a global image representation.
  3. Then: fit an SVM (with or without kernel).
- Pro: the actual learning has few hyperparameters (usually just one).
- Con: many handcrafted elements with many (basically infinitely many) hyperparameters.
- Con: learning is separate from representation.

Lecture objectives

At the end of the lecture you should:

- Understand the historical motivations of the *general problem of computer vision* and the central role played by the semantic gap.
- Understand the differences and similarities between the Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) model architectures.
- Understand some of the recent historical developments and technological innovations that made the *Deep Learning Renaissance* possible.
- Understand the two fundamental families of CNN architectures and what distinguishes them from each other.
- Understand some of the "tricks" needed to make CNNs effective in practice.

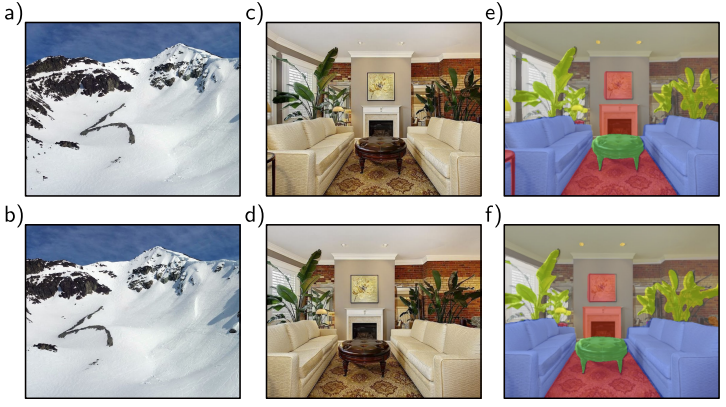
Connectionism: From MLPs to CNNs

The attractiveness of end-to-end learning

- MLPs have a number extremely attractive features:
  - It is an end-to-end model: we can train everything in the model using a single optimization algorithm.
  - MLPs learn representations of input and classifier.
- Why can't we just use this model for image recognition problems?
- An MLP should be able to learn feature representations that are in turn good representations for classification.
- Why is this problematic?
- NOTE: The treatment and many figures in this section I have taken from the excellent book *Understanding Deep Learning*, by Simon Prince.
- I highly recommend this book.

On invariance and equivariance

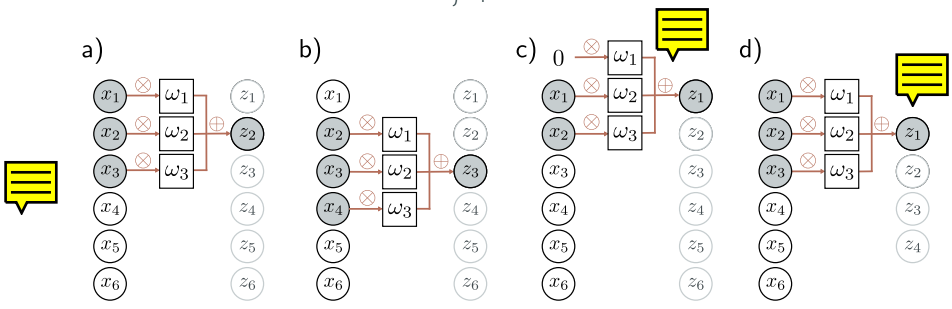
- A function f[x] is invariant to transformation t[x] if $f[t[x]] = f[x]$.
- A function f[x] is equivariant to transformation t[x] if $f[t[x]] = t[f[x]]$.



One dimensional convolutions

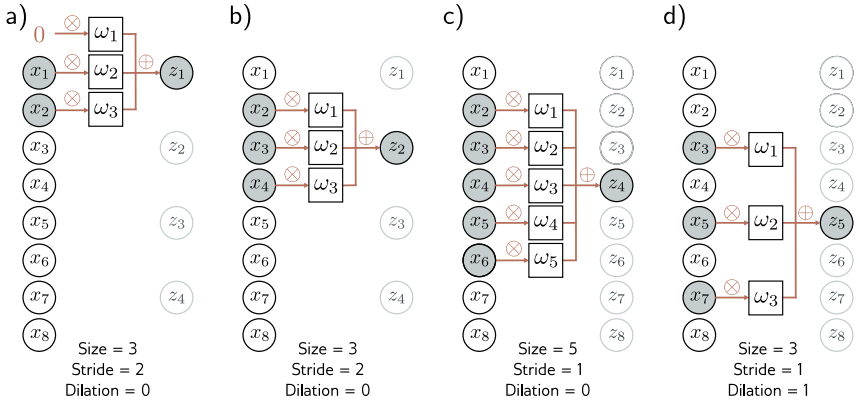
- The convolution operator computes a weighted sum of neighboring values:

$$
\begin{aligned}
h_i &= \sigma[\beta_i + w_1 x_{i-1} + w_2 x_i + w_3 x_{i+1}] \\
&= \sigma[\beta + \sum_{j=1}^{3} w_j x_{i+j-1}]
\end{aligned}
$$



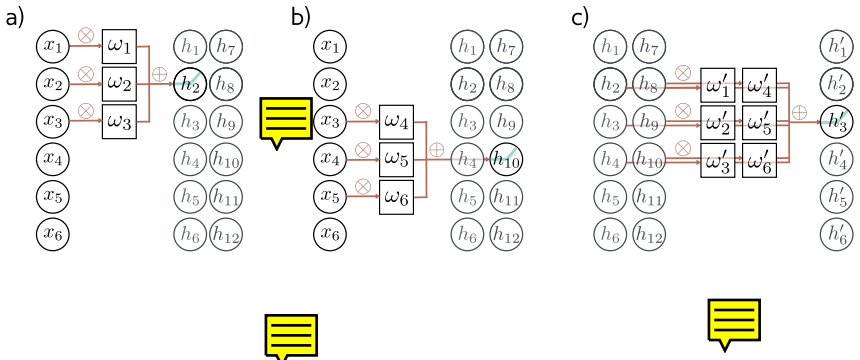
One dimensional convolution (continued)

- The convolution is very flexible (at the cost of hyperparameters):



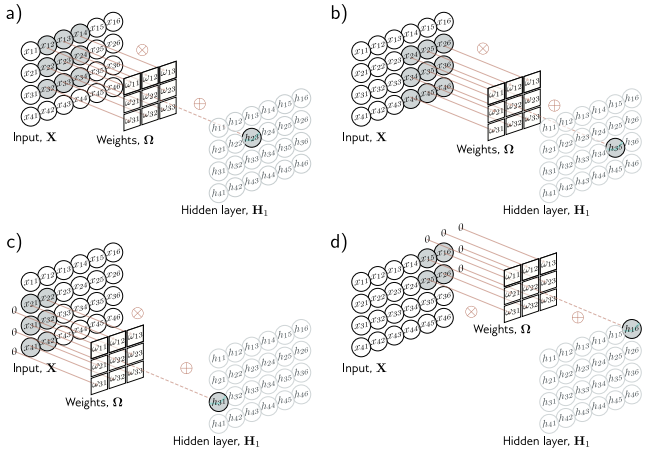
Multichannel one dimensional convolutions

- We can compute multiple convolutions and convolve multiple inputs:



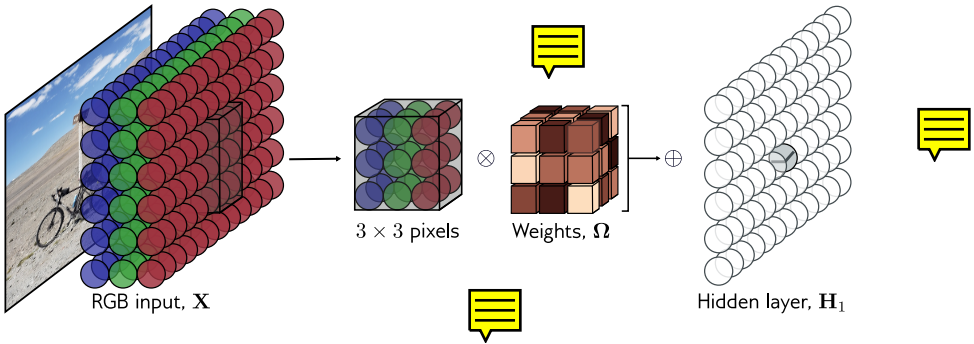
Two dimensional convolution

- Exactly the same operation is naturally extended to two spatial dimensions:



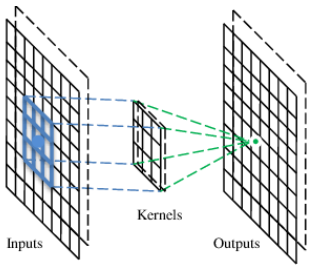
Multichannel two dimensional convolutions

- And to multichannel images (or feature maps):



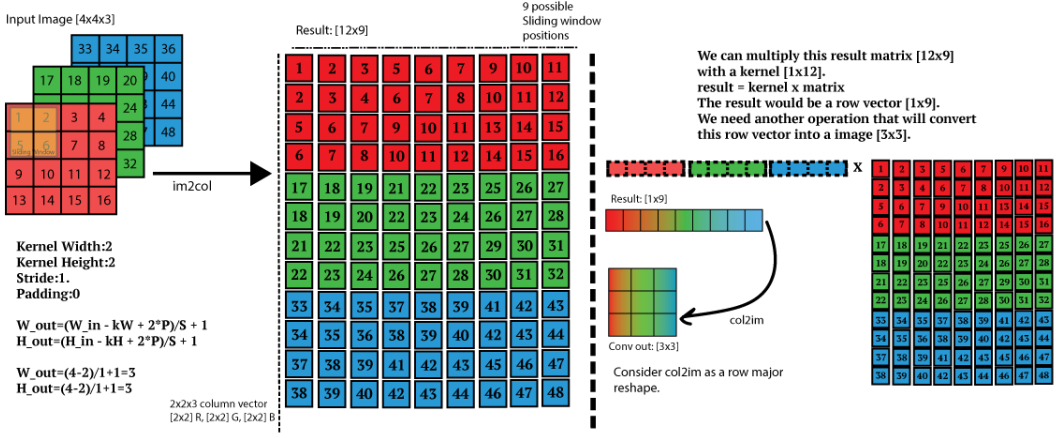
From MLPs to CNNs (which are really still MLPs)

- A convolutional layer is a fully-connected layer with weights *shared across locations of the image*.
- The input of size $w \times h \times c$ is transformed into an output of size $w \times h \times c'$.
- The outputs are called feature maps and they are derived by convolving the image with d' 3D tensors of size $u \times v \times d$.
- So, the number of parameters is "merely" $(u * v * c' * c) + c'$.



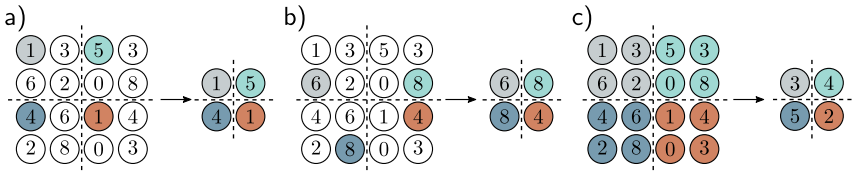
A CNN is really an MLP (in disguise)

- That sure doesn't look like an MLP...



The final ingredient: Pooling Layers

- Representation learning works by creating an semantic bottleneck.
- We force the network to extract meaningful representations that capture semantic features.
- In CNNs we do this by Subsampling, Max Pooling, and Mean Pooling:



- We will now look at some actual CNN architectures which will make this clearer.

AlexNet: The Shot Heard ’Round the World

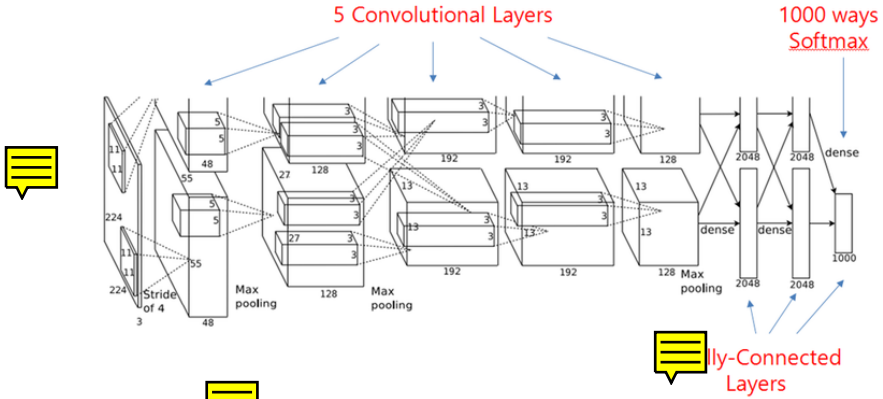
AlexNet: Context

- We will now take a look at the International Large Scale Visual Recognition Competition (ILSVRC) submission that changed everything [Krizhevsky et al., 2012].
- This architecture systematically addresses most of the problems with training large network architectures on large datasets.
- It is a Convolutional Neural Network (CNN) that is universally called AlexNet.
- It is also a Deep Network because it has many hidden layers.

ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: The Architecture

- Let's look first at the overall architecture and then analyze in detail how each component addresses specific problems.
- It is also helpful to examine how data flows through the network.



ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: Pooling Features

- Like in the Bag-of-Words model, we can pool local features.
- AlexNet uses 3×3 pooling regions with a stride of 2 pixels.
  - This means that after some convolutional layers the feature map size is reduced by a factor of 2.
  - They use max pooling: in each feature map, keep the maximum value in each overlapping 3×3 pooling region (in each feature map).
  - This helps to contain the size of feature maps propagated through the network.
  - And it also helps to build higher-level representations of the image.
  - This is because, halving the image resolution is the same as doubling the size of subsequent convolutions.

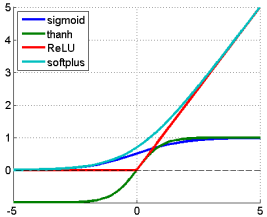
ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: Unit Saturation

- Another innovation in AlexNet is the use of the Rectified Linear Unit (ReLU) activation function.

$$\sigma(\mathbf{x}) = max(0, \mathbf{x})$$

- This activation function does not saturate like sigmoids.
- The result is a 6x speedup in training.



ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: Reducing Overfitting

- Even with convolutional weight sharing, AlexNet still has 60M parameters.
- To reduce overfitting, the authors use two extra (now standard) tricks:

  - Data augmentation: random translations and reflections of input images are generated, plus random variation in principal directions of RGB space.
  - Dropout: an advanced trick from the Neural Network community which randomly removes half of the inputs to select layers at training time.

ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: More Tricks

- The AlexNet paper is an excellent resource because it explains all of the tricks necessary to get a deep network to learn:
  - Local response normalization: keep local variation in feature maps under control (section 3.3).
  - Momentum: limits the "skateboard" effect when following valleys in the loss surface, equivalent to L1 (or L2) regularization of weights (section 5).
  - Mini-batch Stochastic Gradient Descent (SGD): with 1.2M training samples, we cannot consider the entire dataset in one batch; instead, randomly sample mini-batches of 128 images (section 5).
  - Multiple GPUs: AlexNet was too big to fit in a single GPU (in 2012), so feature maps are split over two GPUs (section 3.2).
  - Model averaging: state-of-the-art results are obtained by training multiple CNNs and averaging outputs.

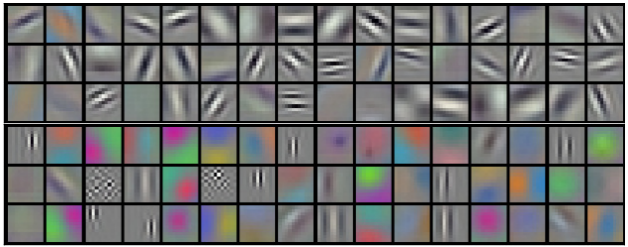
ImageNet Classification with Deep Convolutional Neural Networks

AlexNet: Results

- The proof is in the pudding:

Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SIFT + FVs [7]	—	—	*26.2%*
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	**16.4%**
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	**15.3%**

- And in the representations the network learns:

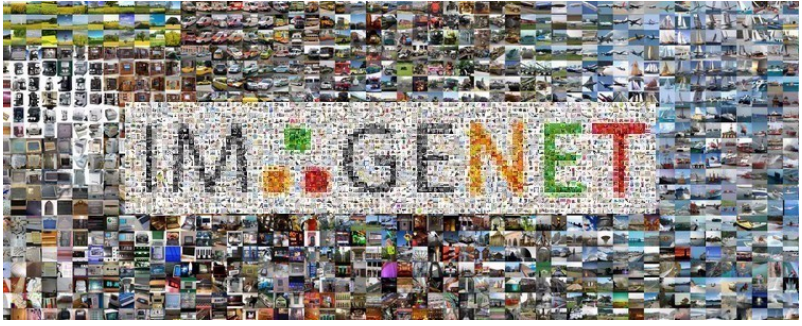


AlexNet: Reflections

- AlexNet took the object recognition world by storm.
- Many of the elements of the model are not really new.
- However, this was the first work to convincingly demonstrate how state-of-the-art object recognition systems can be trained end-to-end on real problems.
- This was made possible by a number of confluent development:
  - The availability of enormous amounts of annotate data (ImageNet, with 1.2M training images).
  - Modern GPUs, which make convolutions super fast.
  - Decades of persistent theoretical development (ReLUs, fast backprop, dropout, etc).

Reflections: CNNs are really big

- One of the first observations one can make about CNNs is that they have a HUGE number of parameters.
- Even modestly-sized, state-of-the-art networks can have on the order of *150 million trainable parameters*.
- Fitting such models requires massive amounts of labeled training data.



The Family of Very Deep Networks

VGG: Small convolutions, more depth

- Now that we have AlexNet as a point of reference, we can look at some other state-of-the-art CNN architectures.
- The VGG Family of Networks (VGG = Visual Geometry Group from Oxford) is a refinement of the AlexNet style of CNN [Simonyan and Zisserman, 2014].
- In this work the authors performed a thorough exploration of the architectural parameter space.
- They varied hyperparameters (e.g. number of layers, size of convolutions, etc).
- And established a new baseline for CNN-based object recognition.

Very deep convolutional networks for large-scale image recognition

VGG: The setup

- Input to the networks is a fixed, $224 \times 224 \times 3$ image tensor.
- The mean RGB value is first subtracted from all training images to center the data.
- All convolutions are $3 \times 3 \times d$ or $1 \times 1 \times d$ in size (d is an arbitrary number of feature maps) with a stride of 1.
- The idea is: if you need larger convolutions, just go deeper.
- Max pooling is done over non-overlapping 2×2 windows with a stride of 2 (2x reduction in size).
- All hidden layers use a ReLU activation function, but do not do local response normalization.

Very deep convolutional networks for large-scale image recognition

VGG: The configurations

- The following configurations were considered:

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224×224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Very deep convolutional networks for large-scale image recognition

VGG: training

- The training procedure is similar to AlexNet:
  - The training is carried out by optimizing the multinomial logistic regression objective using mini-batch gradient descent.
  - Training was regularised by weight decay and dropout on the first two fully-connected layers.
  - The learning rate was initially set to 10^{-2} and decreased by a factor of 10 when the validation set accuracy stopped improving.
  - Learning was stopped after 370K iterations (74 epochs).
- Initialization:
  - CNNs are extremely sensitive to initialization of the weights.
  - For training VGG networks, the authors use a combination of random initialization and pre-training.

Very deep convolutional networks for large-scale image recognition

VGG: Training image size

- Note that training images are all scaled to 224×224 pixels before passing them through the network.
- This is the same as AlexNet, and clearly can affect the image content by introducing artifacts (consider portrait images).
- In VGG networks, images are isotropically scaled so that the smallest dimension has fixed size.
- Then a subimage of size 224×224 is randomly cropped from the scaled image.
- The authors evaluated randomly scaling to between 256 and 384 pixels for the smallest dimension.

Very deep convolutional networks for large-scale image recognition

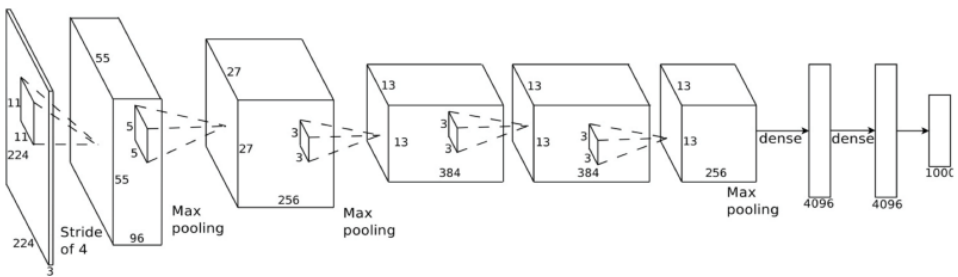
VGG: Testing image size

- At testing time, five strategies for image scaling are evaluated:
  - Dense: the network is fully convolutionalized (I will explain this on the next slide), evaluated densely on the input image, and results are globally pooled.
  - Single-scale: a single isotropic scale is used.
  - Multi-scale: like at training time, images are scaled to three discrete isotropic scales.
  - Multi-crop: multiple, random crops are taken from the fully-convolutional output for average pooling.

Very deep convolutional networks for large-scale image recognition

VGG: Fully-convolutionalization

- Below is a diagram of a typical ConvNet.
- How can we make it independent of the image size?



Very deep convolutional networks for large-scale image recognition

VGG: Results

- Even when only considering a single input scale, the results are impressive.
- Note: deeper is better, LRN doesn't help, scale jittering at test time does.

ConvNet config. (Table 1)	smallest image side		top-1 val. error (%)	top-5 val. error (%)
	train (S)	test (Q)		
A	256	256	29.6	10.4
A-LRN	256	256	29.7	10.5
B	256	256	28.7	9.9
C	256	256	28.1	9.4
	384	384	28.1	9.3
	[256;512]	384	27.3	8.8
D	256	256	27.0	8.8
	384	384	26.8	8.7
	[256;512]	384	25.6	8.1
E	256	256	27.3	9.0
	384	384	26.9	8.7
	[256;512]	384	**25.5**	**8.0**

Very deep convolutional networks for large-scale image recognition

VGG: Results

- Using multiple scales leads to even better performance:

ConvNet config. (Table 1)	smallest image side		top-1 val. error (%)	top-5 val. error (%)
	train (S)	test (Q)		
B	256	224,256,288	28.2	9.6
C	256	224,256,288	27.7	9.2
	384	352,384,416	27.8	9.2
	[256; 512]	256,384,512	26.3	8.2
D	256	224,256,288	26.6	8.6
	384	352,384,416	26.5	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**
E	256	224,256,288	26.9	8.7
	384	352,384,416	26.7	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**

- As does fusing multiple cropping strategies:

ConvNet config. (Table 1)	Evaluation method	top-1 val. error (%)	top-5 val. error (%)
D	dense	24.8	7.5
	multi-crop	24.6	7.5
	multi-crop & dense	**24.4**	**7.2**
E	dense	24.8	7.5
	multi-crop	24.6	7.4
	multi-crop & dense	**24.4**	**7.1**

VGG: Us versus Them

- Finally, model averaging over multi-scale, multi-crop models leads to state-of-the-art performance:

Method	top-1 val. error (%)	top-5 val. error (%)	top-5 test error (%)
VGG (2 nets, multi-crop & dense eval.)	**23.7**	**6.8**	**6.8**
VGG (1 net, multi-crop & dense eval.)	24.4	7.1	7.0
VGG (ILSVRC submission, 7 nets, dense eval.)	24.7	7.5	7.3
GoogLeNet (Szegedy et al., 2014) (1 net)	-	7.9	
GoogLeNet (Szegedy et al., 2014) (7 nets)	-	**6.7**	
MSRA (He et al., 2014) (11 nets)	-	-	8.1
MSRA (He et al., 2014) (1 net)	27.9	9.1	9.1
Clarifai (Russakovsky et al., 2014) (multiple nets)	-	-	11.7
Clarifai (Russakovsky et al., 2014) (1 net)	-	-	12.5
Zeiler & Fergus (Zeiler & Fergus, 2013) (6 nets)	36.0	14.7	14.8
Zeiler & Fergus (Zeiler & Fergus, 2013) (1 net)	37.5	16.0	16.1
OverFeat (Sermanet et al., 2014) (7 nets)	34.0	13.2	13.6
OverFeat (Sermanet et al., 2014) (1 net)	35.7	14.2	-
Krizhevsky et al. (Krizhevsky et al., 2012) (5 nets)	38.1	16.4	16.4
Krizhevsky et al. (Krizhevsky et al., 2012) (1 net)	40.7	18.2	-

VGG: Analysis

- In this paper the authors significantly improved over the previous generation by going deeper.
- Again, most of the ideas are not new, but systematic exploration of the design space led to significant improvements.
- Note that the networks are deeper, but have a smaller memory footprint at training time due to carefully balancing the size of feature maps.
- Dense evaluation of the network at test time can also increase performance, leading to fully convolutional networks that are independent of input image size.
- The architecture is still a classical ConvNet.

Deep Residual Networks: Deeper and Deeper

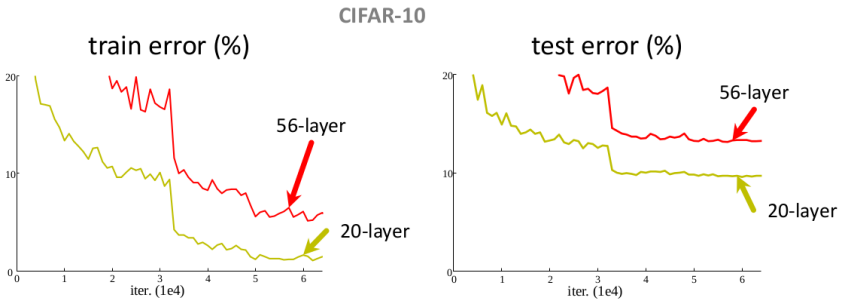
ResNets: Introduction

- From what we have seen so far, it seems like deeper networks generalize better.
- So, can we just keep stacking more and more layers onto the end of our CNNs?
- Aside from the computational complications (GPU memory is finite), this seems like it should "just work".
- We will now look at our last state-of-the-art network architecture (known as ResNet) which looks at this question in detail [He et al., 2016].

Deep residual learning for image recognition

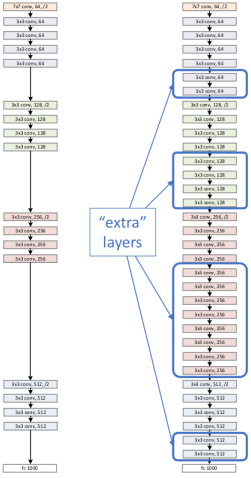
ResNets: Deeper isn't better?

- Pre-ResNet Thinking: *Deeper networks should always perform better – at least on the training data.*



Deep residual learning for image recognition

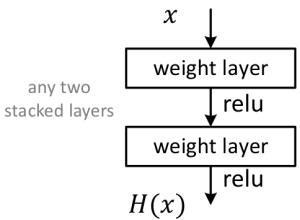
ResNets: Wait, shouldn't training error be lower?



- Using an artificial construction, we see that the training error at least shouldn't increase with depth.
- Just copy pre-trained weights from plain network into a deeper network with new, randomly initialized weights.

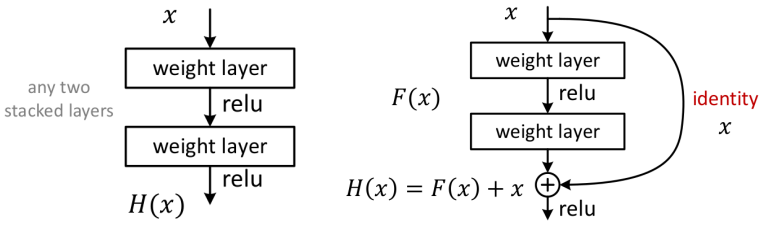
ResNets: Targets and Residuals

- Let's say that the network is learning towards some optimal feature representation $H(x)$.
- The compositional and feed-forward nature of the CNN isn't really helping.



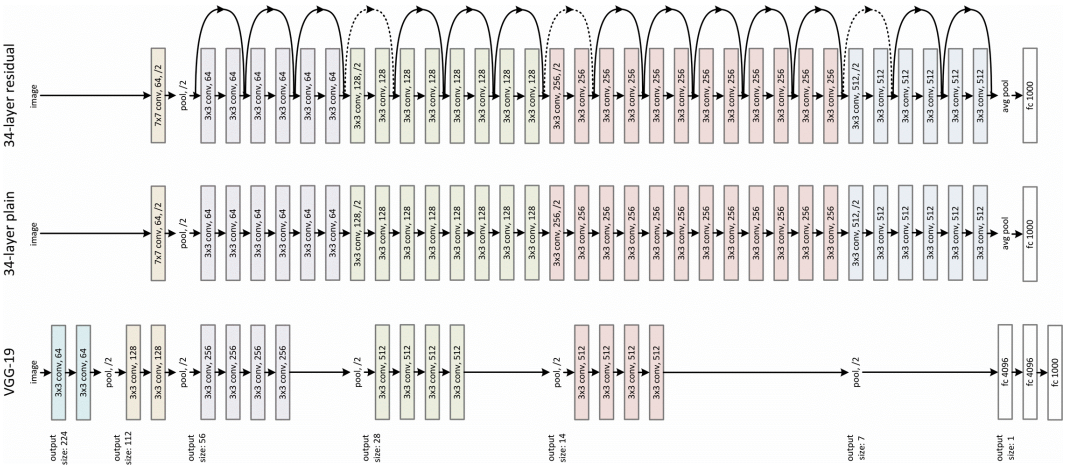
ResNets: Targets and Residuals

- Let's say that the network is learning towards some optimal feature representation $H(x)$.
- The compositional and feed-forward nature of the CNN isn't really helping.
- Instead, we can help the network out by not requiring it to pass through as much information.
- Pass x forward and add it to the output of the residual block – now we "only" need to learn $H(x) - x$.



ResNets: Comparison

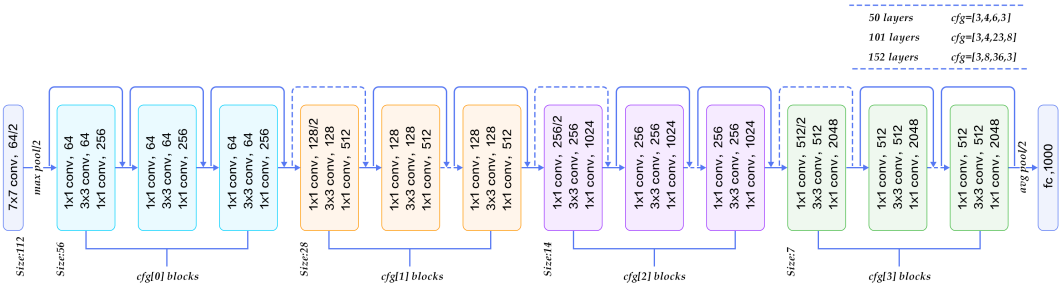
- Here is a comparison of VGG19 and ResNet-34:



Deep residual learning for image recognition

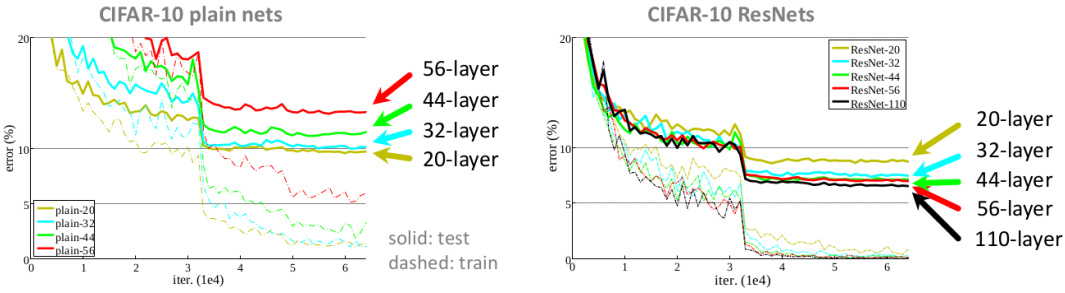
ResNets: Parametric Modularity

- And this is a common way of parametrically representing the various ResNet configurations:



ResNets: Results

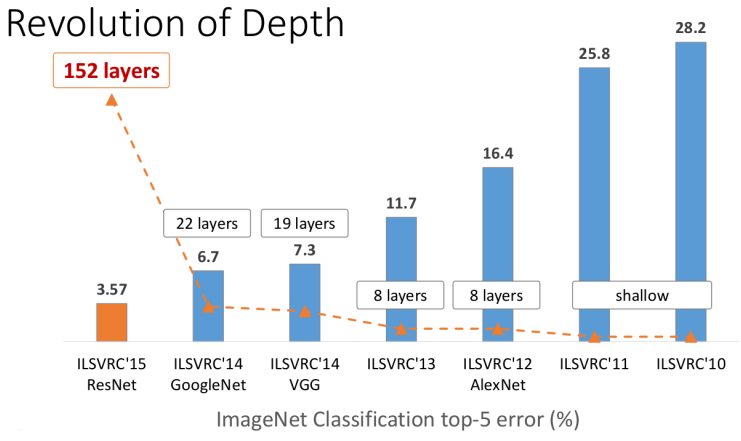
- Residual connections are extremely effective:



Deep residual learning for image recognition

ResNet: Results

- And the proof, as always, is in the pudding:



CNNs: Tricks of the Trade

CNNs: How do you train CNNs?

- CNNs work great, but it's not always sunshine and lollipops trying to get them to work.
- The community has developed a number of tricks, techniques, and heuristics that are proven to help.
- Let's look at a few of them.

CNNs: Batch Normalization

- Attention to the data distribution (through the whole network) and normalization are critical [Ioffe and Szegedy, 2015]:

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

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

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

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

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

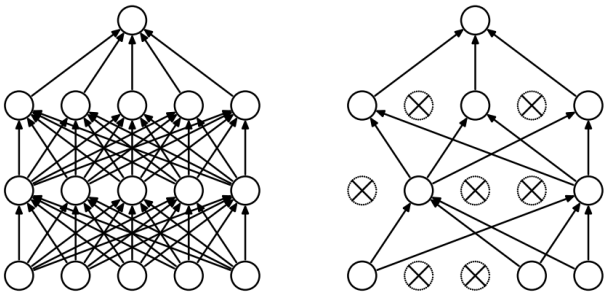
Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

Input: Network N with trainable parameters Θ;
subset of activations $\{x^{(k)}\}_{k=1}^{K}$
Output: Batch-normalized network for inference, $N^{\mathrm{inf}}_{\mathrm{BN}}$

1: $N^{\mathrm{tr}}_{\mathrm{BN}} \leftarrow N$ // Training BN network
2: **for** $k = 1 \ldots K$ **do**
3: Add transformation $y^{(k)} = \mathrm{BN}_{\gamma^{(k)},\beta^{(k)}}(x^{(k)})$ to $N^{\mathrm{tr}}_{\mathrm{BN}}$ (Alg. 1)
4: Modify each layer in $N^{\mathrm{tr}}_{\mathrm{BN}}$ with input $x^{(k)}$ to take $y^{(k)}$ instead
5: **end for**
6: Train $N^{\mathrm{tr}}_{\mathrm{BN}}$ to optimize the parameters $\Theta \cup \{\gamma^{(k)}, \beta^{(k)}\}_{k=1}^{K}$
7: $N^{\mathrm{inf}}_{\mathrm{BN}} \leftarrow N^{\mathrm{tr}}_{\mathrm{BN}}$ // Inference BN network with frozen // parameters
8: **for** $k = 1 \ldots K$ **do**
9: // For clarity, $x \equiv x^{(k)}, \gamma \equiv \gamma^{(k)}, \mu_{\mathcal{B}} \equiv \mu^{(k)}_{\mathcal{B}}$, etc.
10: Process multiple training mini-batches $\mathcal{B}$, each of size m, and average over them:
$\mathrm{E}[x] \leftarrow \mathrm{E}_{\mathcal{B}}[\mu_{\mathcal{B}}]$
$\mathrm{Var}[x] \leftarrow \frac{m}{m-1}\mathrm{E}_{\mathcal{B}}[\sigma^2_{\mathcal{B}}]$
11: In $N^{\mathrm{inf}}_{\mathrm{BN}}$, replace the transform $y = \mathrm{BN}_{\gamma,\beta}(x)$ with $y = \frac{\gamma}{\sqrt{\mathrm{Var}[x]+\epsilon}} \cdot x + \left(\beta - \frac{\gamma\,\mathrm{E}[x]}{\sqrt{\mathrm{Var}[x]+\epsilon}}\right)$
12: **end for**

Algorithm 2: Training a Batch-Normalized Network

CNNs: Dropout (another “crazy” idea)



(a) Standard Neural Net (b) After applying dropout.

With unlimited computation, the best way to “regularize” a fixed-sized model is to average the predictions of all possible settings of the parameters, weighting each setting by its posterior probability given the training data.

– *Srivastava et al. [2014]*

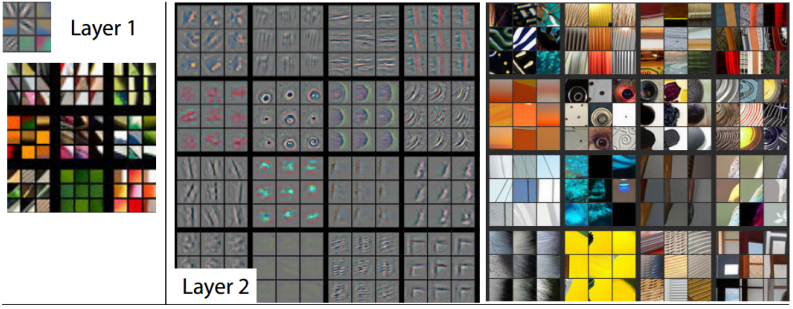
Dropout: A Simple Way to Prevent Neural Networks from Overfitting

CNNs: What's Going On?

- Remember earlier I mentioned that one of the biases against using neural networks was that lack of interpretability.
- As soon as the spectacular results of CNNs on object recognition started coming in, researchers began inventing new ways to interpret the innards of these huge networks.
- Nowadays there are many tools and tricks you can use to understand what the network has learned.

CNNs: What's Going On

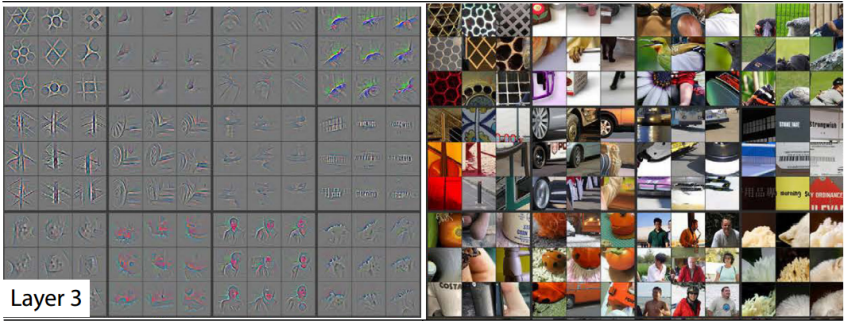
- An early work looked at just this problem and the paper has a ton of interesting analysis of how these networks work [Zeiler and Fergus, 2014].
- I am only going to talk about how visualizations of feature map activations demonstrate what's going on.



Visualizing and understanding convolutional networks

CNNs: What's Going On

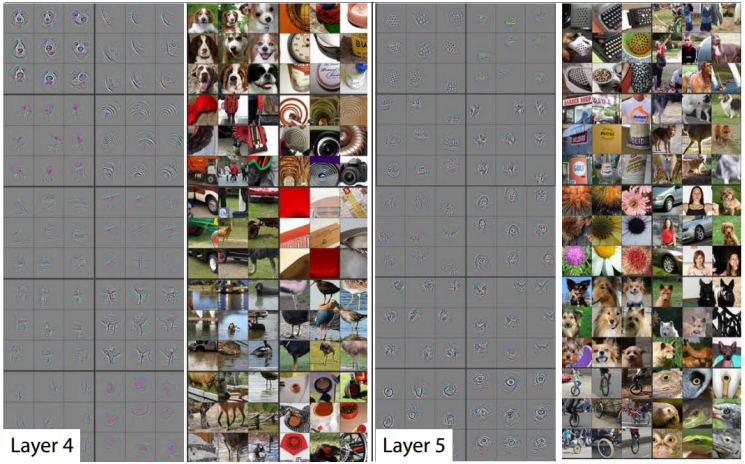
- As we go deeper into the network, feature activations correspond to higher-level semantics.



Visualizing and understanding convolutional networks

CNNs: What's Going On

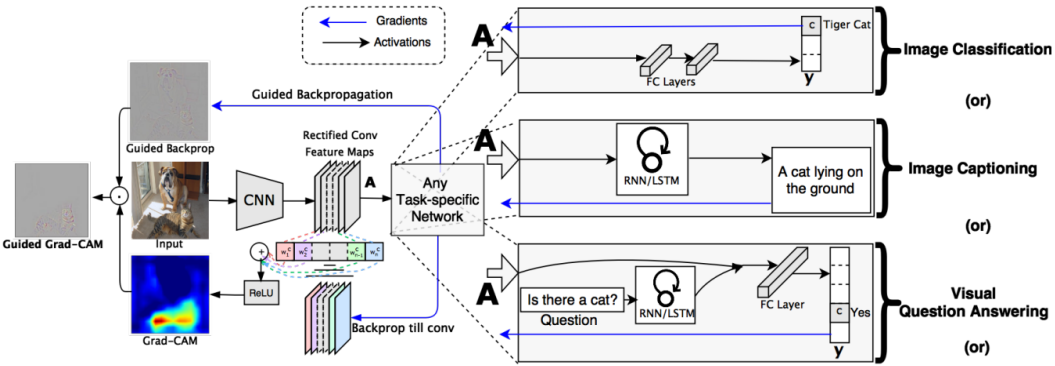
- Until features are really indicating the presence of "eyes" and "cat faces", etc.



Visualizing and understanding convolutional networks

CNNs: What's Going On

- The Grad-CAM algorithm is an intuitive way to visualize, well, what makes a cow, a cow [Selvaraju et al., 2017]:



CNNs: What's Going On

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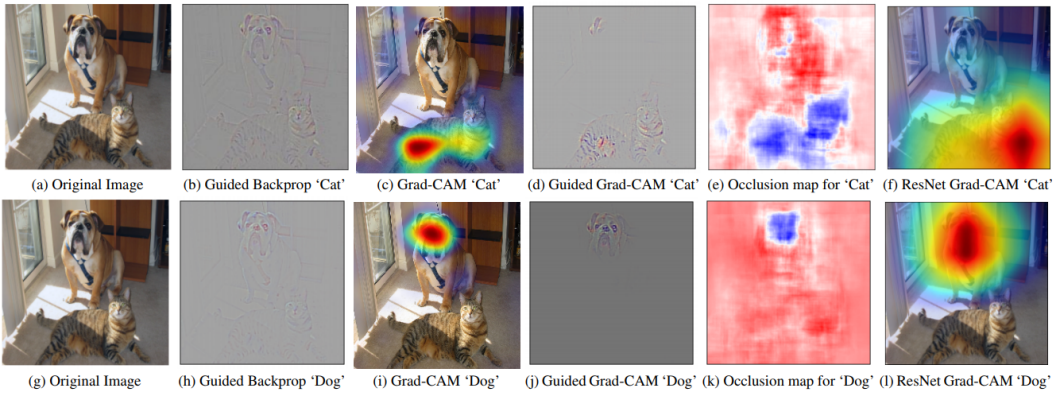
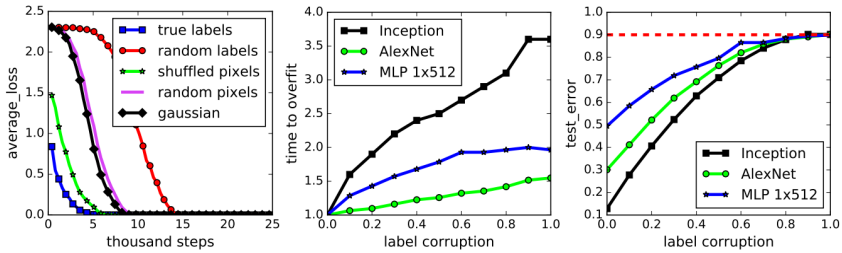


Discussion

Discussion: The burden of supervision

- What is 1.5M annotations really worth [Zhang et al., 2016]?
- If labels are equally probable, a randomly shuffled set of ImageNet labels contains about $1.5\text{M} * \log_2(1000) \approx 15\text{Mbits}$.



(a) learning curves (b) convergence slowdown (c) generalization error growth

Understanding deep learning requires rethinking generalization

Discussion: The state-of-the-art

- We have come a long way in a few years.

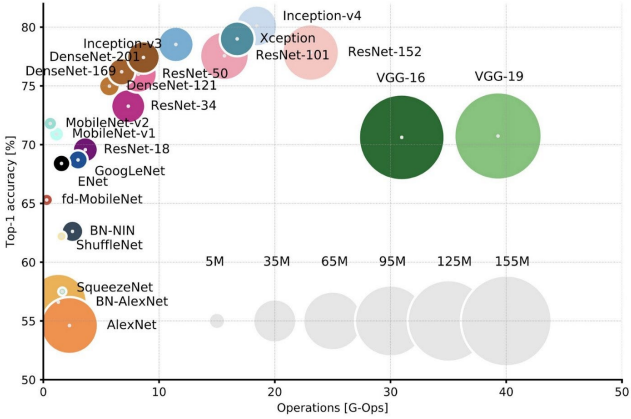
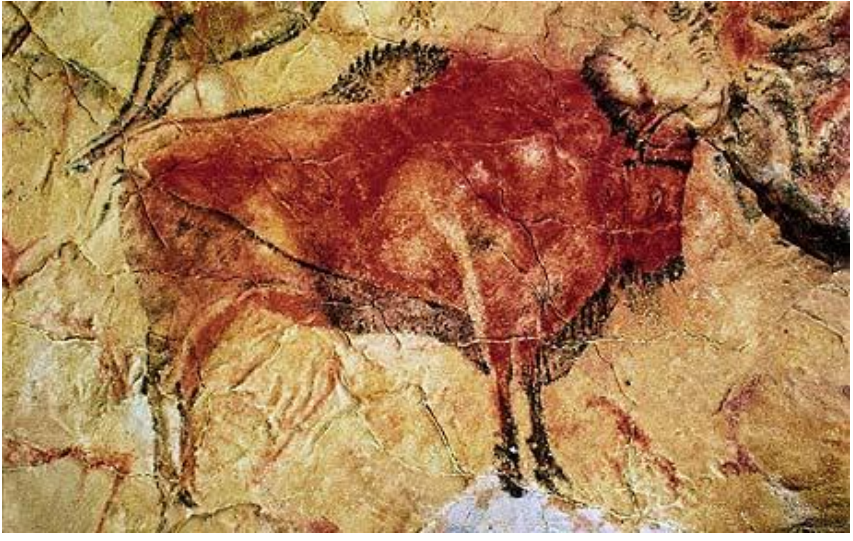


Figure from: [Canziani et al., 2016]

Discussion: CNNs and the way forward



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