Lecture 7: Convolutional Neural Networks

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Deep Learning Course, Winter 2022-2023

Outline

Convolutional Neural Networks

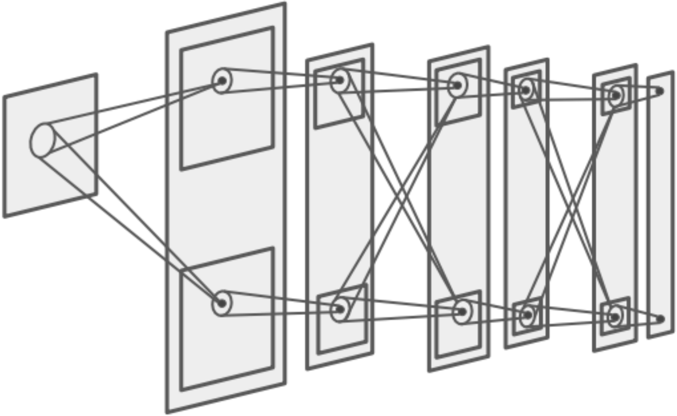
What is a convolutional neural network (CNN)?

...just a NN with a special connectivity structure.

Roadmap:

- Parameter tying/sharing
- 2D CNNs for object recognition
- Pooling layers
- Classical CNNs: ImageNet, AlexNet, GoogLeNet
- One-dimensional CNNs for NLP

Neocognitron (Fukushima and Miyake, 1982)



(Credits: Fei-Fei Li, Johnson, Yeung)

- "Sandwich" architecture, alternating between simple cells with modifiable parameters and complex cells which perform pooling

Neocognitron (Fukushima and Miyake, 1982)

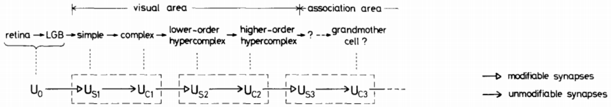


Fig. 1. Correspondence between the hierarchy model by Hubel and Wiesel, and the neural network of the neocognitron

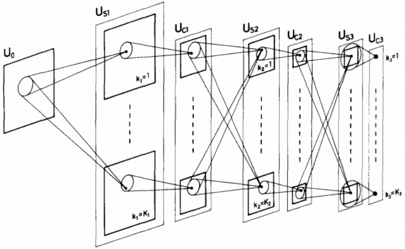
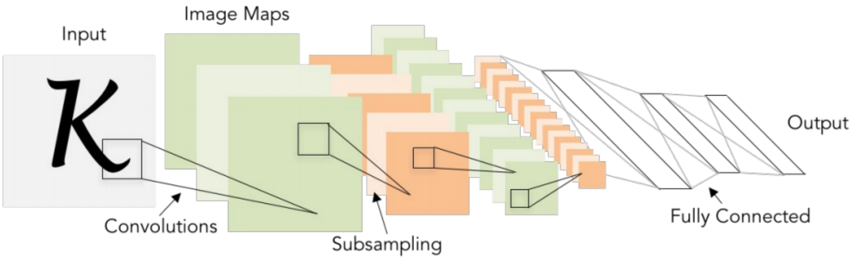


Fig. 2. Schematic diagram illustrating the interconnections between layers in the neocognitron

- Inspired by the multi-stage hierarchy model of the visual nervous system (Hubel and Wiesel, 1965)

ConvNet (LeNet-5) (LeCun et al., 1998)

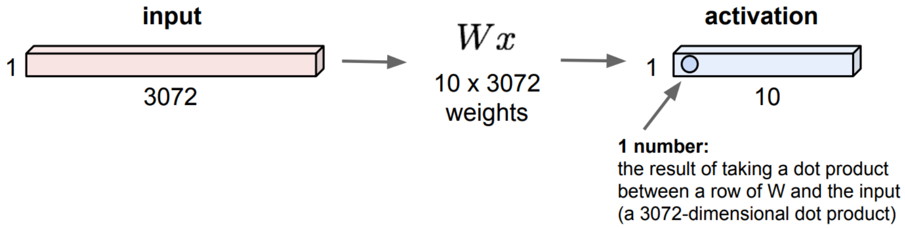


Convolutional Networks

- How is a CNN different from a standard feedforward NN?
- What is a convolutional layer?
- How is it different from a fully connected layer?

Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

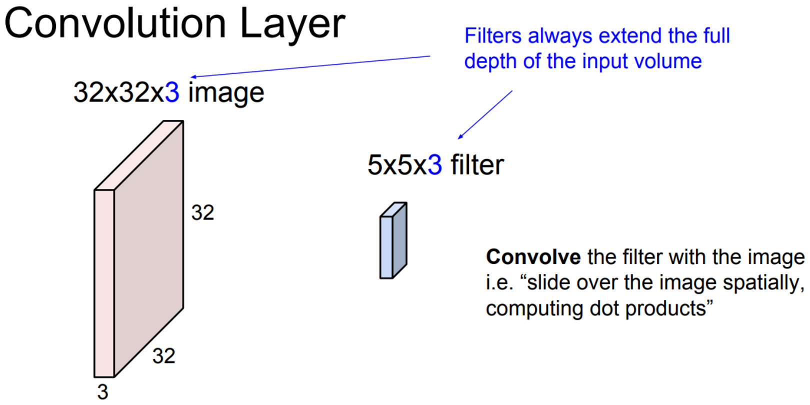


(Credits: Fei-Fei Li, Johnson, Yeung)

All activations depend on all inputs.

Convolutional Layer

Don't stretch/reshape: preserve the spacial structure!

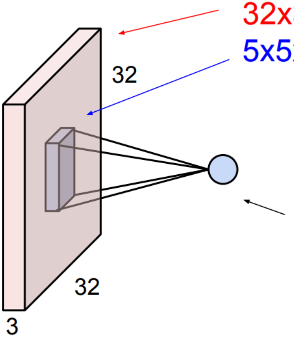


(Credits: Fei-Fei Li, Johnson, Yeung)

Convolutional Layer

32x32x3 image

5x5x3 filter w



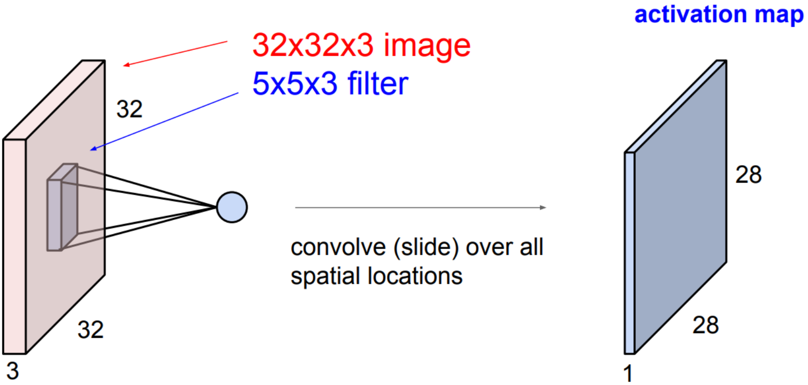
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

(Credits: Fei-Fei Li, Johnson, Yeung)

Convolutional Layer

Apply the same filter to all spatial locations (28x28 times, why?):



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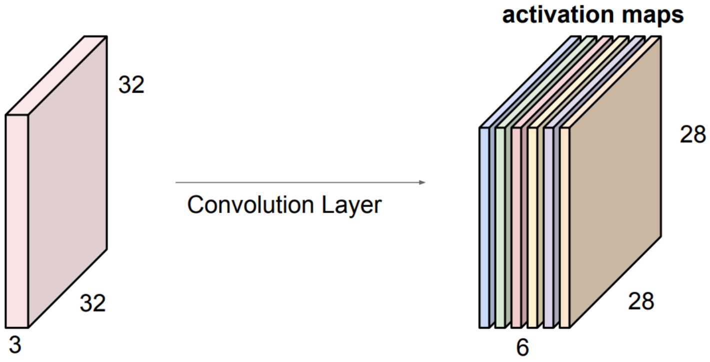
Convolutional Layer

- For example, if we have **6** 5x5x3 filters, we get **6** activation maps:



(Credits: Fei-Fei Li, Johnson, Yeung)

- We stack these up to get a new "image" of size 28x28x6!

Image Size, Filter Size, Stride, Channels

Stride: shift in pixels between two consecutive windows.

In the previous illustrations: stride $= 1$.

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Given an $N \times N \times D$ image, $F \times F \times D$ filters, K channels, and stride S, the resulting output will be of size $M \times M \times K$, where

$$M = (N - F)/S + 1$$

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Examples:

- $N = 32$, $D = 3$, $F = 5$, $K = 6$, $S = 1$ results in an $28 \times 28 \times 6$ output
- $N = 32$, $D = 3$, $F = 5$, $K = 6$, $S = 3$ results in an $10 \times 10 \times 6$ output

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Padding: append zeros around the images.

Common padding size: $(F - 1)/2$, which preserves spatial size: $M = N$.

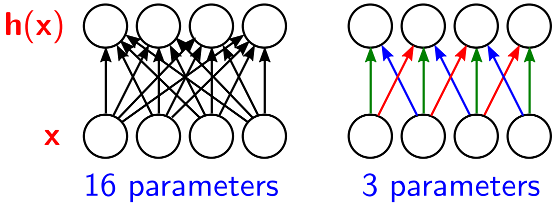
CNNs and Convolutions

Why is this called "convolutional"?

The convolution of a signal x and a filter w, denoted $x * w$, is:

$$h[t] = (x * w)[t] = \sum_{a=-\infty}^{\infty} x[t-a]w[a].$$

Basic idea: sparse/local connectivity and parameter tying/sharing.



Convolutions with Padding

Expression above is for infinite-support signal x and filter w.

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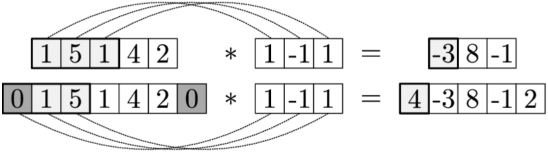
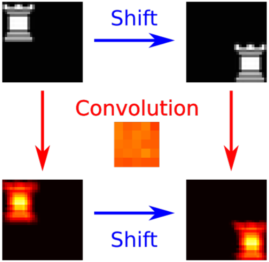
Padding: append $D = (F - 1)/2$ zeros at each side of x.



Convolutions and Parameter Tying

Leads to translation/shift equivariance



Why do we want to tie (share) parameters?

- Reduce the number of parameters to be learned
- Deal with arbitrary long, variable-length, sequences: rather than shifting the filters, shift the input

Can also be done in 1D (e.g., text data, signals, ...)

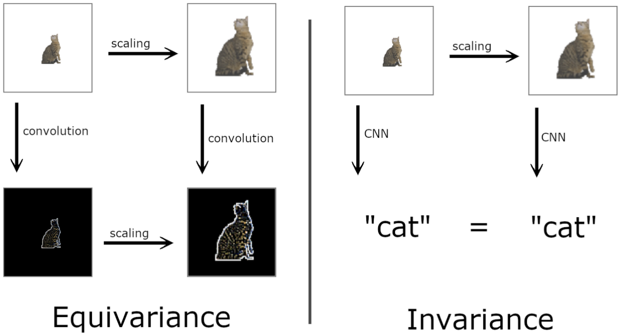
Convolutions and Pooling

The second component of CNNs is pooling

Common CNNs alternate convolutional layers and pooling layers.

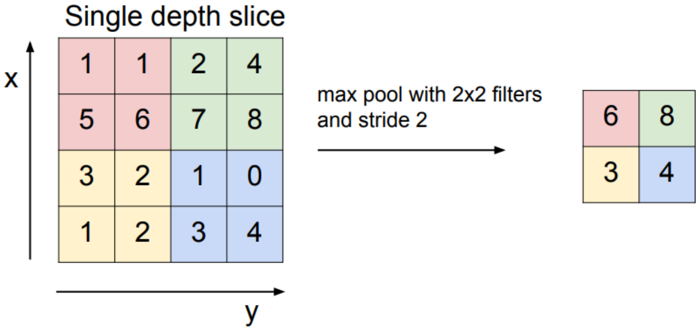
Pooling layers provide invariance.

Equivariance vs Invariance



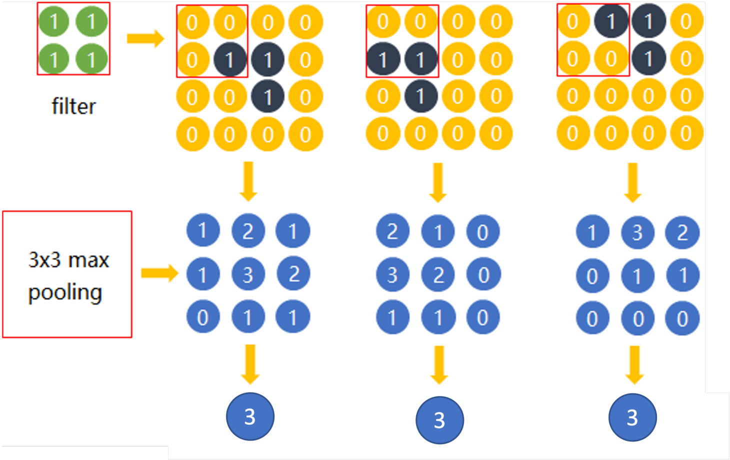
Pooling Layer

- Makes the representations smaller, more manageable.
- Operates over each activation map (each channel) independently
- Max-pooling:

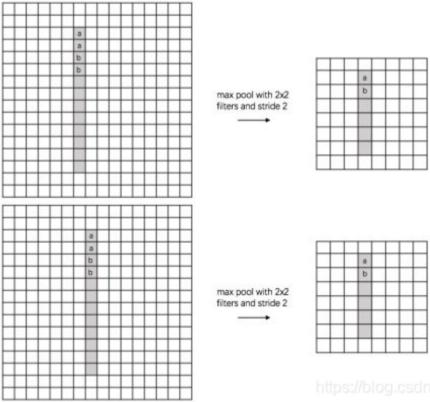


(Credits: Fei-Fei Li, Johnson, Yeung)

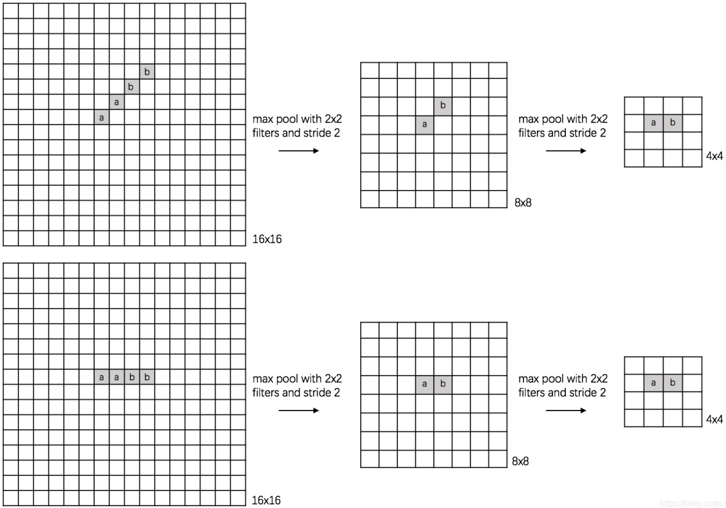
Max Pooling: Shift Invariance



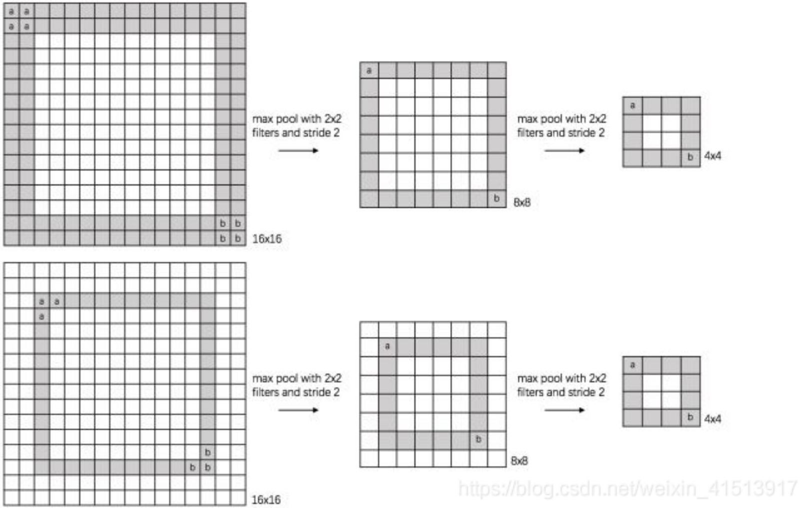
Max Pooling: Shift Invariance (II)



Max Pooling: Rotation Invariance

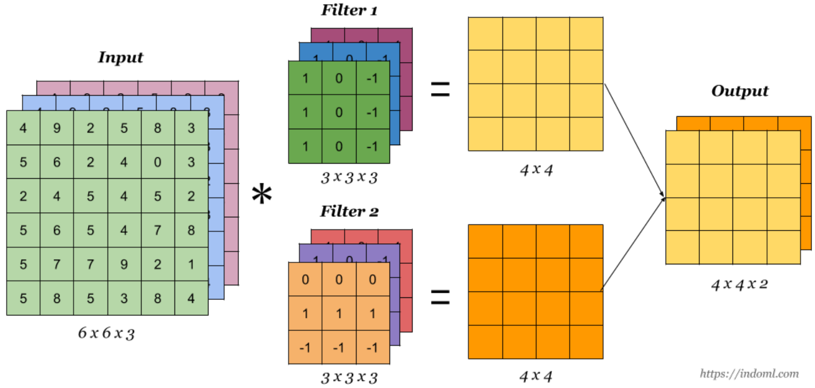


Max Pooling: Scale Invariance



Multiple Convolution Filters: Feature Maps

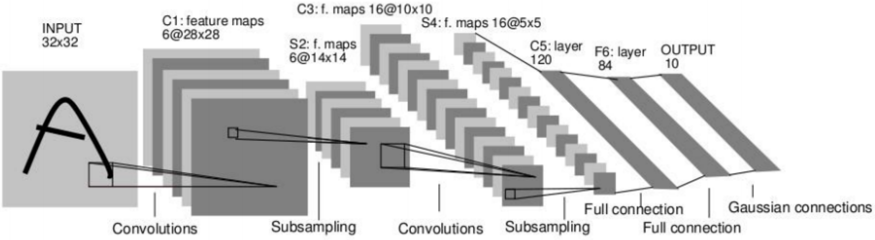
- Different filter for each channel, but keeping spatial invariance:



(Figure credit: Andrew Ng)

2D Convolutional Nets (LeCun et al., 1989)

- Inspired by "Neocognitron" (Fukushima, 1980)
- 2D Convolutions: the same filter (e.g. 3x3) is applied to each location of the image
- The filter weights are learned (as tied parameters)
- Multiple filters
- Alternates convolutional and pooling layers.



ConvNet Successes: MNIST

Handwritten text/digits:

- MNIST (0.35% error (Ciresan et al., 2011b))
- Arabic and Chinese (Ciresan et al., 2011a)

ConvNet Successes: CIFAR-10, Traffic Signs

Simpler recognition benchmarks:

- CIFAR-10 (9.3% error (Wan et al., 2013))
- Traffic signs: 0.56% error vs 1.16% for humans (Cireşan et al., 2011)

Less good at more complex tasks, e.g., Caltech-101/256 (few training samples).

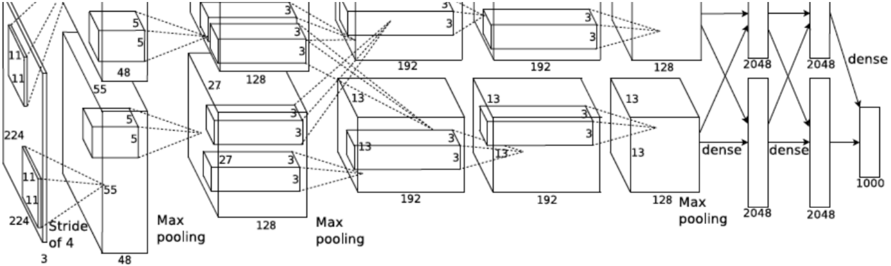
ImageNet Dataset

- 14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk

(Slide credit to Rob Fergus)

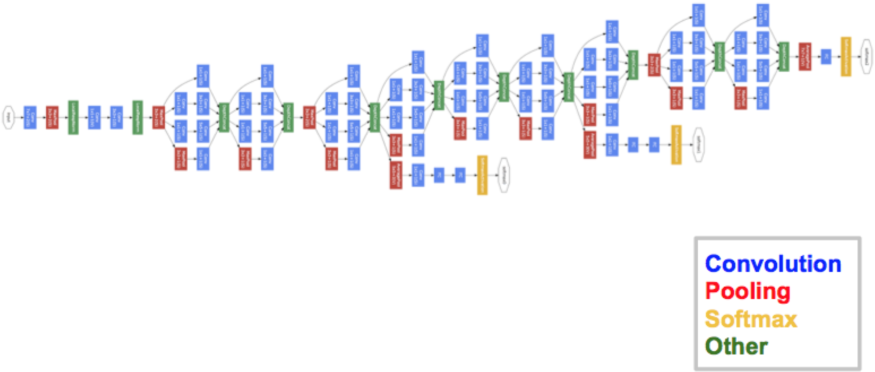
AlexNet (Krizhevsky et al., 2012)

- 54M parameters; 8 layers (5 conv, 3 fully-connected)
- Trained on 1.4M ImageNet images
- Trained on 2 GPUs for a week (50x speed-up over CPU)
- Dropout regularization
- Test error: 16.4% (second best team was 26.2%)



GoogLeNet (Szegedy et al., 2015)

- GoogLeNet inception module: very deep convolutional network, fewer (5M) parameters



Residual Networks (ResNets)

- Add skip-connections; tends to lead to more stable learning.

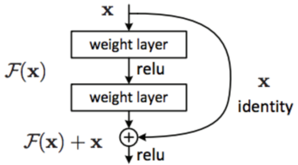


Figure 2. Residual learning: a building block.

(He et al., 2016)

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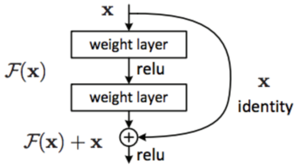


Figure 2. Residual learning: a building block.

(He et al., 2016)

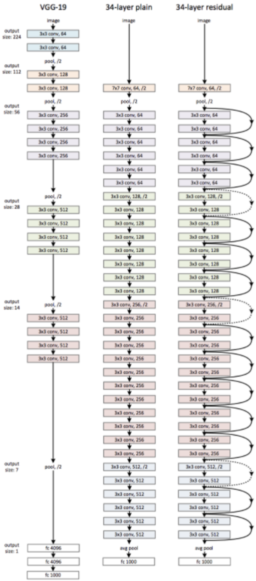
Key (not unique) motivation: mitigate the vanishing gradient problem

With $H(\boldsymbol{x}) = \mathcal{F}(\boldsymbol{x}) + \lambda \boldsymbol{x}$, the gradient back-propagation becomes

$$\frac{\partial L}{\partial \boldsymbol{x}} = \frac{\partial L}{\partial H}\frac{\partial H}{\partial \boldsymbol{x}} = \frac{\partial L}{\partial H}\left(\frac{\partial \mathcal{F}}{\partial \boldsymbol{x}} + \lambda\right)$$

Residual Networks (ResNets)

- Very deep network (34 layers here, but up to 152 layers!)
- VGG-19 ("Visual Geometry Group") by Simonyan and Zisserman (2014) (19 layers, but more FLOPs)



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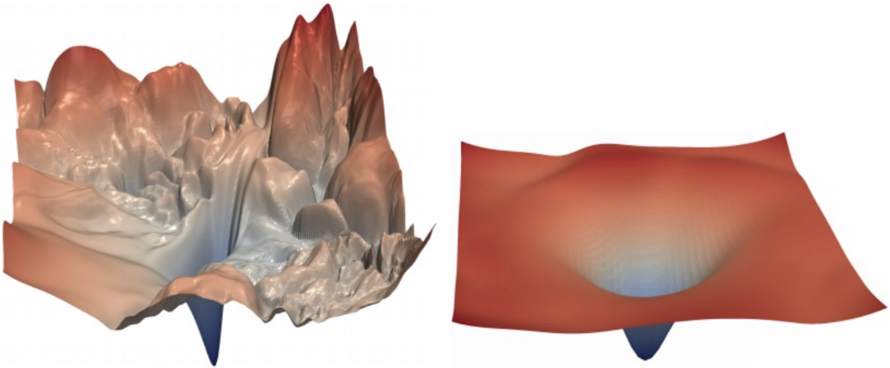

(a) without skip connections   (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

(Li et al., 2018)

Convolutional Nets in NLP

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- Are CNNs also used in NLP? Not as much, but...

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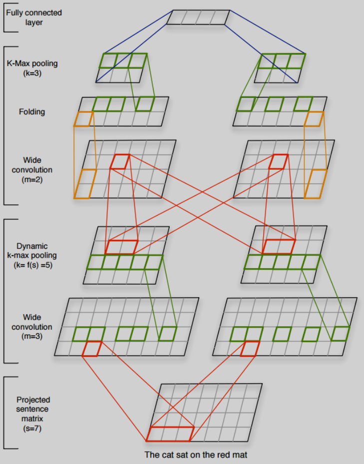
- Are CNNs also used in NLP? Not as much, but...
- Yoav Goldberg in the Representation Learning Workshop (ACL 2018):

  "NLP's ImageNet moment has arrived."

  (not referring to CNNs, in particular, but to big NNs for NLP.

Convolutional Nets in NLP

- 1D convolutions (text is a sequence)



Kalchbrenner et al. (2014)

Convolutional Nets in NLP

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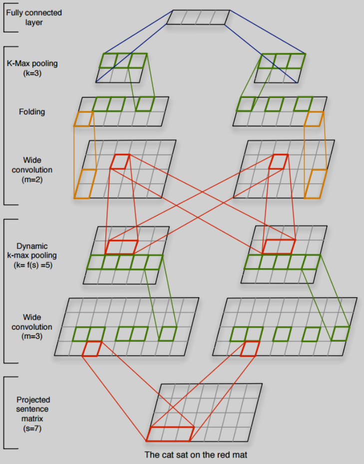

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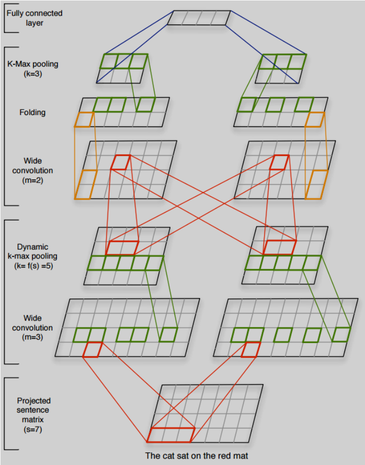
- For word embeddings $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_L$, the filter response for word i is:

$$\boldsymbol{h}_i = \boldsymbol{g}(\boldsymbol{W}[\boldsymbol{x}_{i-h} \oplus \ldots \oplus \boldsymbol{x}_i \oplus \ldots \boldsymbol{x}_{i+h}] + \boldsymbol{b}),$$

where $\oplus$ denotes vector concatenation and $\boldsymbol{W}$ are shared parameters



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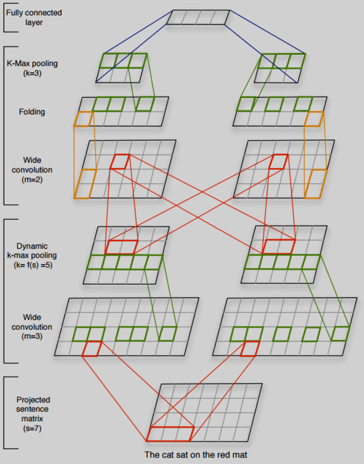
- Can pad left and right with special symbols if needed.



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Variable Input Length

- Most computation in CNNs can be done in parallel.
- GPUs can leverage this and achieve great speed-ups!
- But, unlike images, which have fixed size, sentences have different lengths, which makes batching a bit trickier!

Mini-Batching, Padding, and Masking

Mini-batching is necessary to speed up training in GPUs

How to cope with different sentence lengths?

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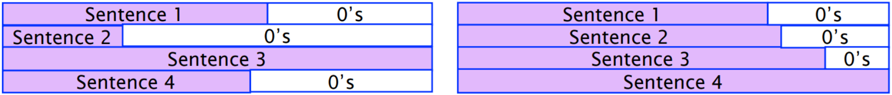

(Image credit: Thang Luong, Kyunghyun Cho, Chris Manning)

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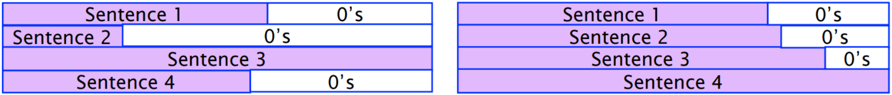

(Image credit: Thang Luong, Kyunghyun Cho, Chris Manning)

Masking is needed to ensure the padding is not affecting the results.

Beyond Convolutions

- Other architectures have been proposed which offer alternatives to convolutions
- For example: transformers.
- This is somewhat similar to "dynamic convolutions".
- Covered in another lecture.

Outline

1. Convolutional Neural Networks
2. Visualizing Representations
3. Conclusions

What Representations Are We Learning?

- Which neurons fire for recognizing a particular object?
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- To answer this, visualize what is happening inside the network.

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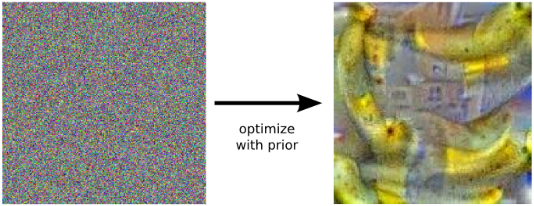

(from `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`)

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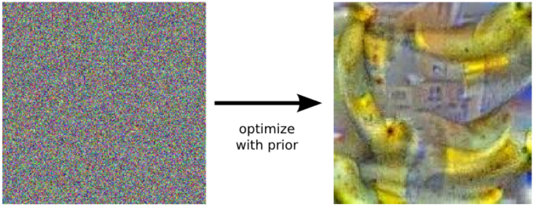

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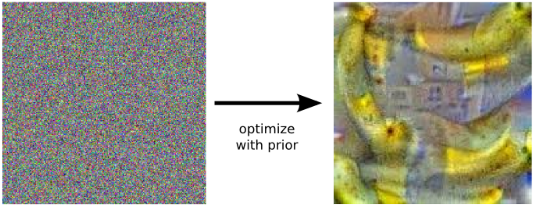

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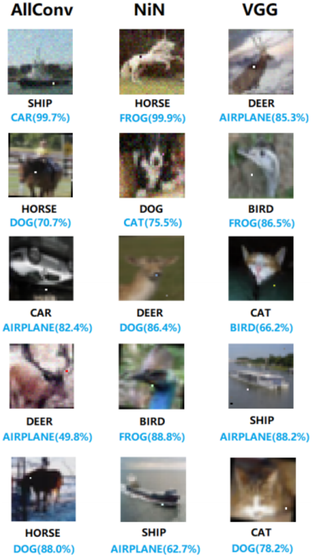
- Can also specify an inner layer and tune the input to maximize its activations: useful to see what kind of features it is representing.
- Specifying a higher layer produces more complex representations...

Google DeepDream

(from https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html)

Adversarial Attacks

- How can we perturb an input slightly to fool a classifier?
- For example: 1-pixel attacks
- Glass-box model: assumes access to the model
- Backpropagate to the inputs to find pixels which maximize the gradient
- There's also work for black-box adversarial attacks (don't have access to the model, but can query it).



(Credits: Su, Vargas, Sakurai (2018))

Even Worse: Perturb Object, Not Image

- Print the model of a turtle in a 3D printer.
- Perturbing the texture fools the model into thinking it's a rifle, regardless of the pose of the object!

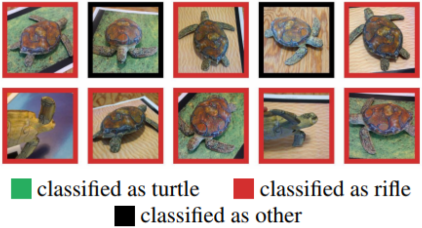


Figure 1. Randomly sampled poses of a 3D-printed turtle adversarially perturbed to classify as a rifle at every viewpoint[2]. An unperturbed model is classified correctly as a turtle nearly 100% of the time.

(Credits: Athalye, Engstrom, Ilyas, Kwok (2018))

Neural networks are still very brittle!

Outline

1. Convolutional Neural Networks
2. Visualizing Representations
3. Conclusions

Conclusions

- CNNs are a very powerful architecture for computer vision
- CNNs take advantage of parameter sharing and sparse connectivity
- They are extremely useful to capture translational invariances in images
- Typically, convolution layers are alternated with max-pooling layers
- Lower layers capture more low-level representations (edges, corners)
- Higher layers have more "semantic" representations (objects, scenes)

Thank you!

Questions?

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