Recurrent and convolutional networks

Statistical Methods in NLP 2
ISCL-BA-08

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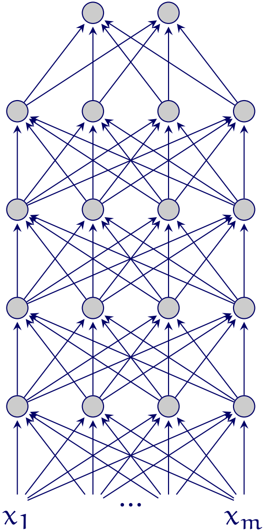
Deep neural networks



- Deep neural networks have recently been successful in many tasks
- They often use sparse connectivity and shared weights
- We will focus on two important architectures: recurrent and convolutional networks

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- We saw that a feed-forward network with a single hidden layer is a *universal approximator*
- However, this is a theoretical result – it is not clear how many units one may need for the approximation
- Successive layers may learn different representations
- Deeper architectures have been found to be useful in many tasks

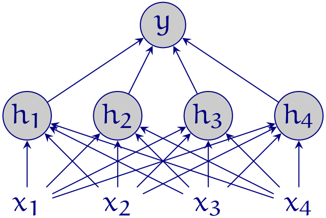
Why now?

- Increased computational power, especially advances in graphical processing unit (GPU) hardware
- Availability of large amounts of data
  - mainly unlabeled data (more on this later)
  - but also labeled data through 'crowd sourcing' and other sources
- Some new developments in theory and applications

Recurrent neural networks

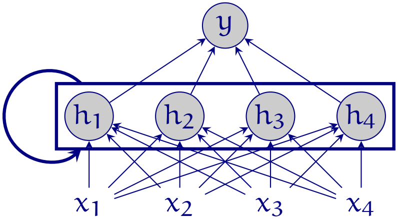
- Feed forward networks
  - can only learn associations
  - do not have memory of earlier inputs
  - if used for sequences, learning strongly depends on location of items
- Recurrent neural networks model sequences
- This is achieved by ‘recurrent’ connections in the network

Recurrent neural networks



- Recurrent neural networks are similar to the standard feed-forward networks

Recurrent neural networks



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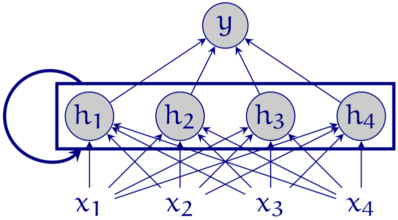
- They include loops that use previous output (of the hidden layers) as well as the input

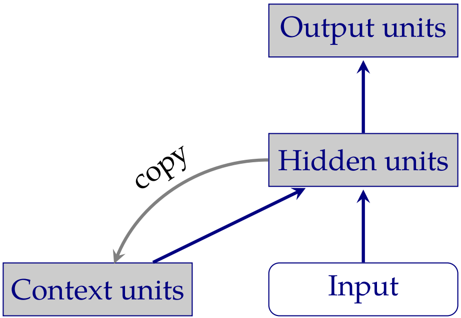
Recurrent neural networks



- Recurrent neural networks are similar to the standard feed-forward networks
- They include loops that use previous output (of the hidden layers) as well as the input
- Forward calculation is straightforward, learning becomes somewhat tricky

A simple version: SRNs

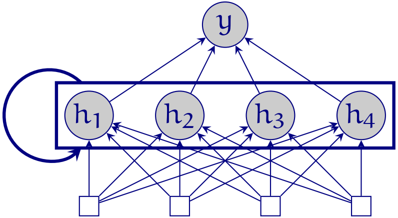
Elman (1990)



- The network keeps previous hidden states (context units)
- The rest is just like a feed-forward network
- Training is simple, but cannot learn long-distance dependencies

Processing sequences with RNNs

- RNNs process sequences one unit at a time
- The earlier inputs affect the output through recurrent links



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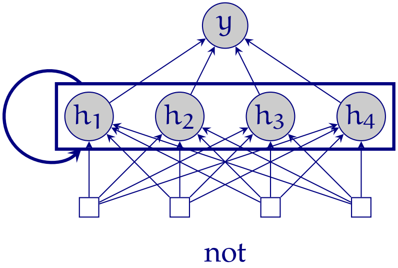

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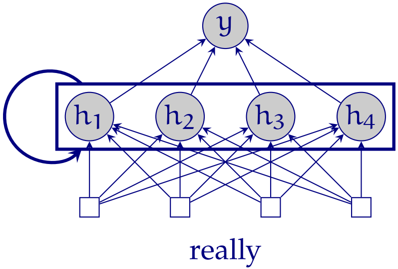

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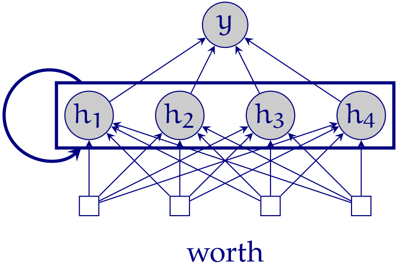

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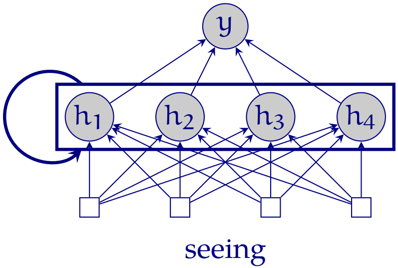
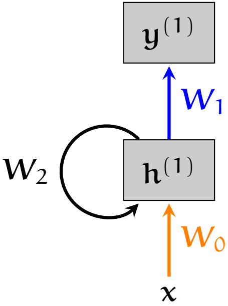


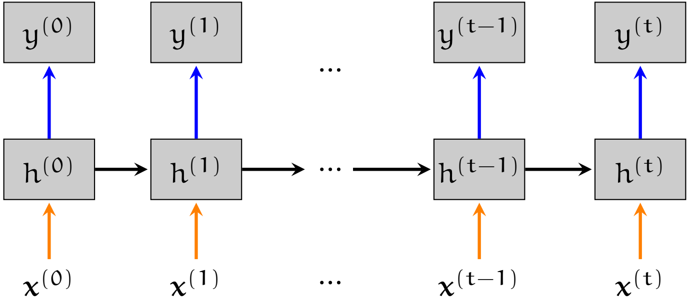
Learning in recurrent networks



- We need to learn three sets of weights: W_0, W_1 and W_2
- Backpropagation in RNNs are at first not that obvious
- The main difficulty is in propagating the error through the recurrent connections

Unrolling a recurrent network

Back propagation through time (BPTT)



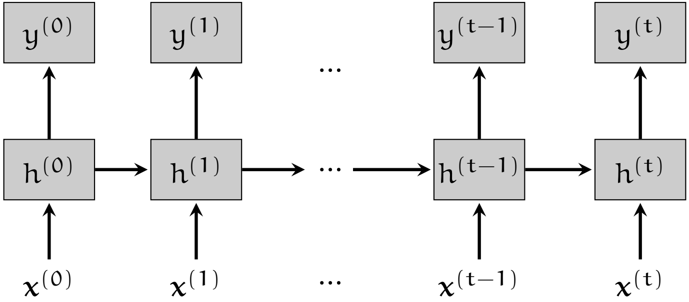
Note: the weights with the same color are shared.

Unstable gradients

- A common problem in deep networks is *unstable gradients*
- The patial derivatives with respect to weights in the early layers calculated using the chain rule
- A long chain of multiplications may result in
  - *vanishing gradients* if the values are in range $(-1, 1)$
  - *exploding gradients* if absolute values larger than 1
- A practical solution for exploding gradients is called *gradient clipping*
- The solution to vanishing gradients is more involved (coming soon)

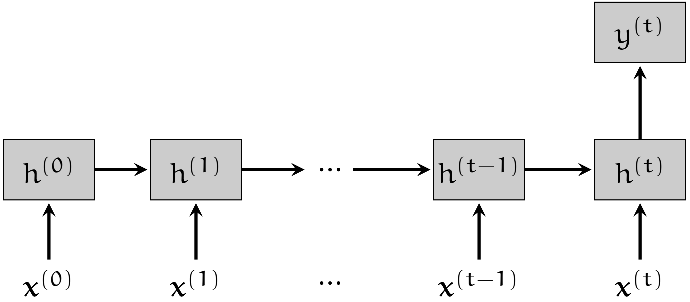
RNN architectures

Many-to-many (e.g., POS tagging)



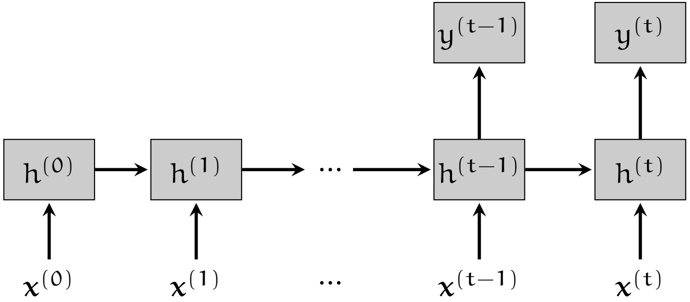
RNN architectures

Many-to-one (e.g., document classification)

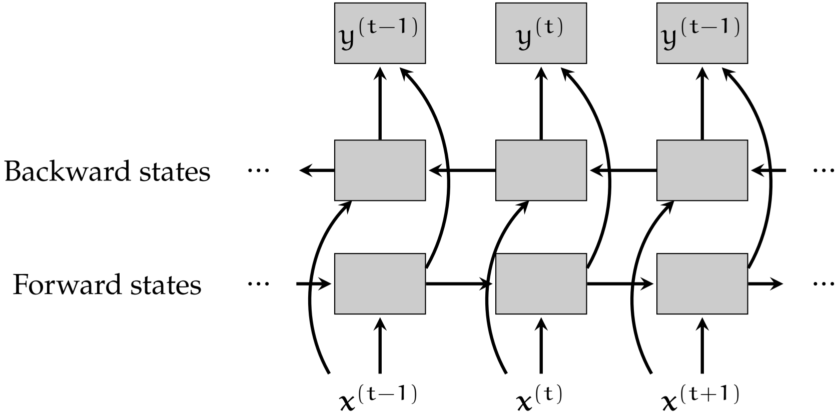


RNN architectures

Many-to-many with a delay (e.g., machine translation)



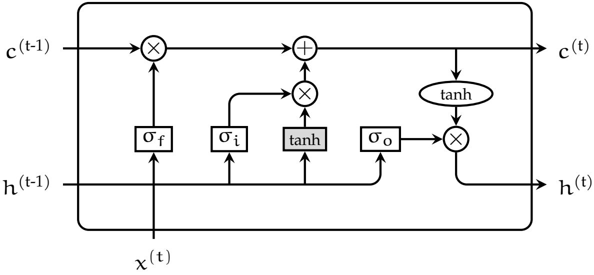
Bidirectional RNNs



Unstable gradients revisited

- We noted earlier that the gradients may *vanish* or *explode* during backpropagation in deep networks
- This is especially problematic for RNNs since the effective dept of the network can be extremely large
- Although RNNs can theoretically learn long-distance dependencies, this is affected by unstable gradients problem
- The most popular solution is to use *gated* recurrent networks

Gated recurrent networks



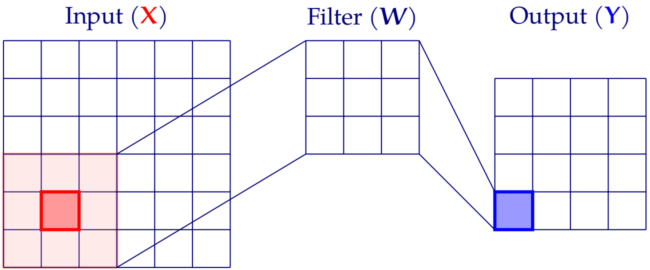
- Most modern RNN architectures are 'gated'
- The main idea is learning a mask that controls what to remember (or forget) from previous hidden layers
- Two popular architectures are
  - Long short term memory (LSTM) networks (above)
  - Gated recurrent units (GRU)

Convolutional networks

- Convolutional networks are particularly popular in image processing applications
- They have also been used with success some NLP tasks
- Unlike feed-forward networks we have discussed so far,
  - CNNs are not fully connected
  - The hidden layer(s) receive input from only a set of neighboring units
  - Some weights are shared
- A CNN learns features that are *location invariant*
- CNNs are also computationally less expensive compared to fully connected networks

Convolution in image processing

- Convolution is a common operation in image processing for effects like edge detection, blurring, sharpening, ...
- The idea is to transform each pixel with a function of the local neighborhood



$$y = \sum_i w_i x_i$$

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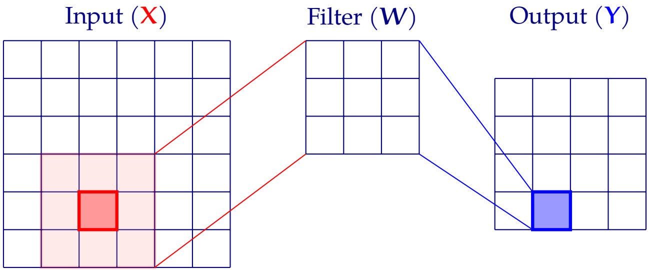

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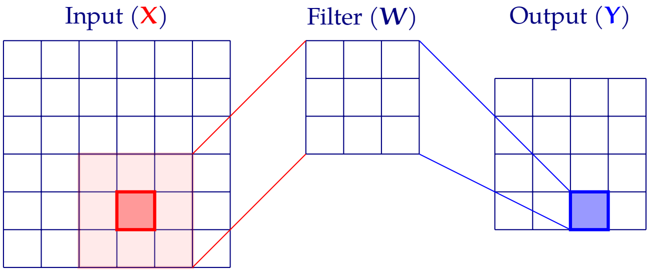

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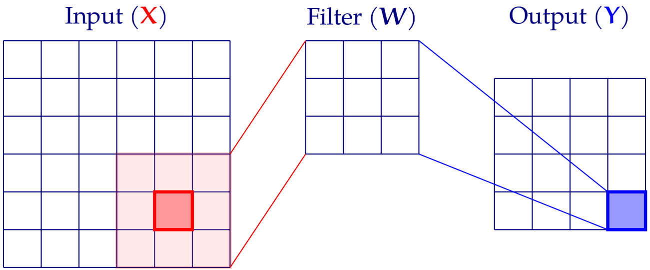

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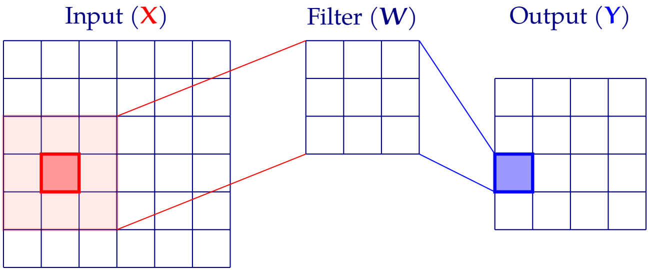

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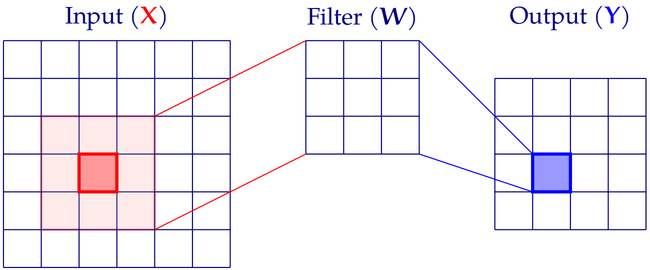

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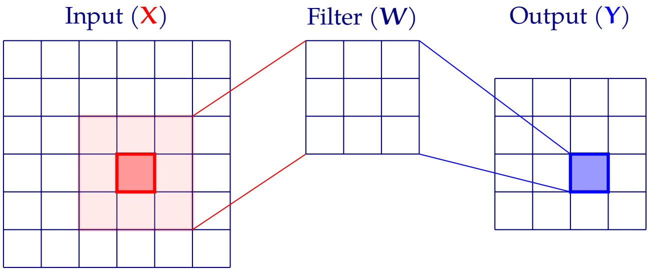

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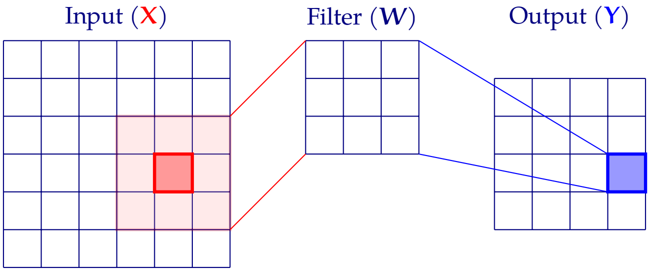

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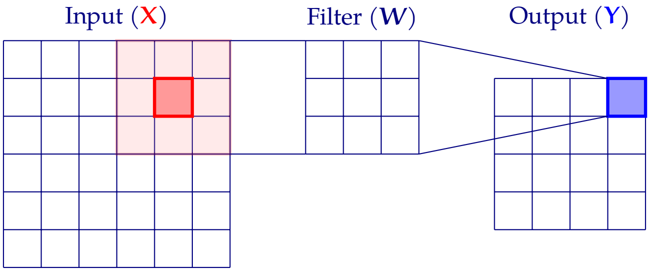

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Example convolutions

- Blurring

$$\frac{1}{16}\begin{bmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{bmatrix}$$

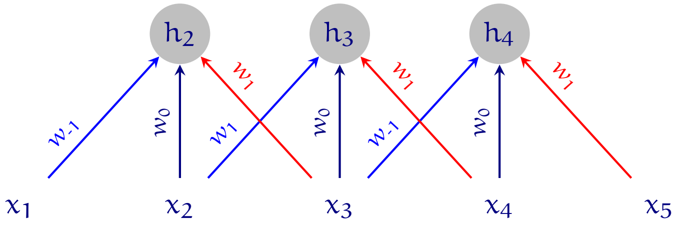
- Edge detection

$$\begin{bmatrix}-1 & -1 & -1\\ -1 & 8 & -1\\ -1 & -1 & -1\end{bmatrix}$$

Learning convolutions

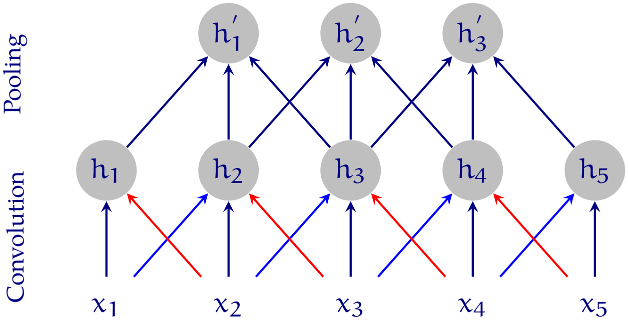
- Some filters produce features that are useful for classification (e.g., of images, or sentences)
- In machine learning we want to *learn* the convolutions
- Typically, we learn multiple convolutions, each resulting in a different feature map
- Repeated application of convolutions allow learning higher level features
- The last layer is typically a standard fully-connected classifier

Convolution in neural networks



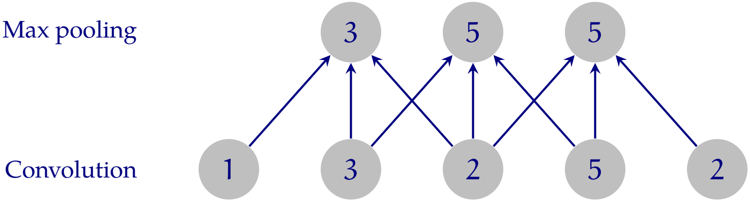
- Each hidden unit corresponds to a local window in the input
- Weights are shared: each convolution detects the same type of features

Pooling



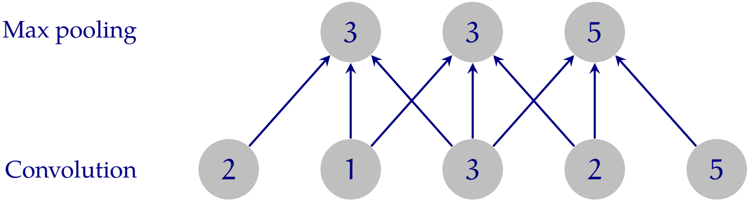
- Convolution is combined with *pooling*
- Pooling 'layer' simply calculates a statistic (e.g., max) over the convolution layer
- Location invariance comes from pooling

Pooling and location invariance



- Note that the numbers at the pooling layer are stable in comparison to the convolution layer

Pooling and location invariance



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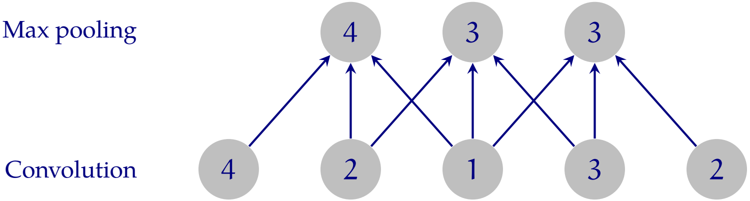
Pooling and location invariance



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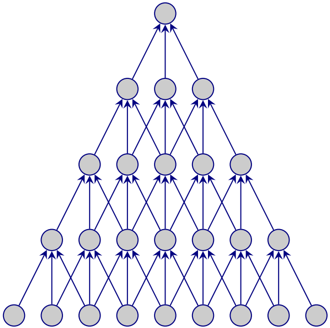
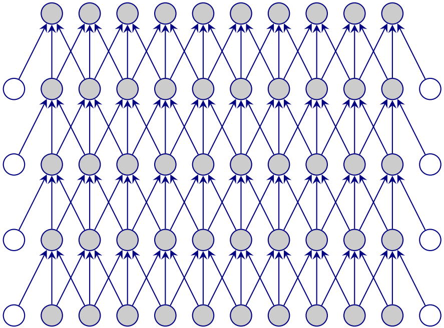
Padding in CNNs

- With successive layers of convolution and pooling, the later layers shrink



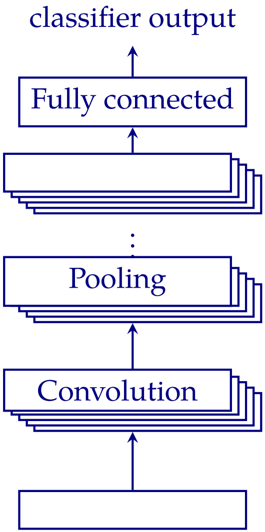
Padding in CNNs

- With successive layers of convolution and pooling, the later layers shrink
- One way to avoid this is *padding* the input and hidden layers with enough number of zeros

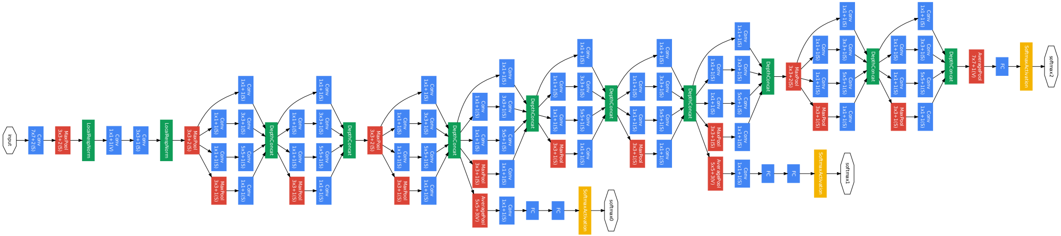


CNNs: the bigger picture

- At each convolution/pooling step, we often want to learn multiple feature maps
- After a (long) chain of hierarchical feature maps, the final layer is typically a fully-connected layer (e.g., softmax for classification)



Real-world examples are complex



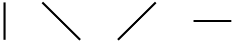
The real-world CNNs tend to be complex

- Many layers (sometimes with repetition)
- Large amount of branching

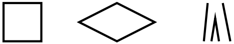
* Diagram describes an image classification network, GoogLeNet (Szegedy et al. 2014).

CNNs in natural language processing

- The use of CNNs in image applications is rather intiutive
  - the first convolutional layer learns local features, e.g., edges

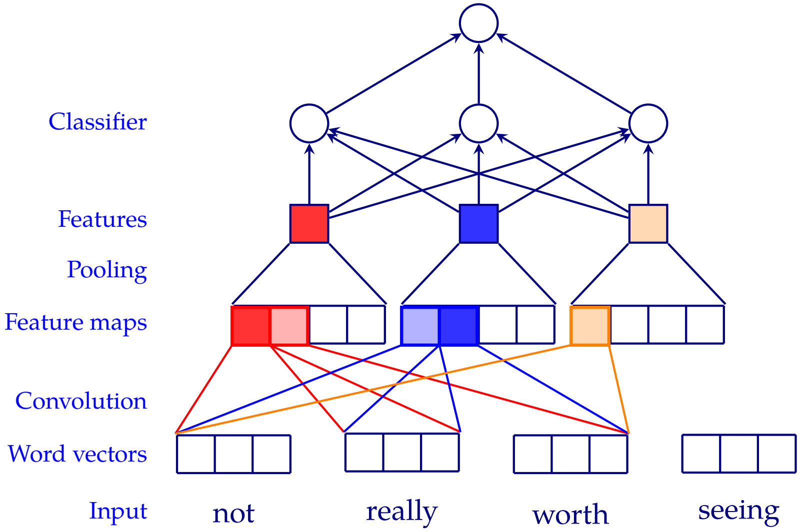


  - successive layers learn more complex features that are combinations of these features



- In NLP, it is a bit less straight-forward
  - CNNs are typically used in combination with word vectors
  - The convolutions of different sizes correspond to (word) n-grams of different sizes
  - Pooling picks important ‘n-grams’ as features for classification

An example: sentiment analysis



Some (important) architectures we did not cover (yet)

- It is common to use RNNs (and other networks) in combination with *attention*
  - Instead of relying on the (final) representation built for the whole input sequence, selectively relevant intermediate representations in the decoder
- Transformers: no recurrent networks, rely mainly on attention mechanism
  - These networks became the standard for the last couple of years, mainly because they can be trained on large amounts of data in parallel (using many GPUs)

Summary

RNN models of sequences with (short term) memory

CNN shared feed-forward weights, location invariance

- Reading: Jurafsky and Martin (2025, Chapter 8)

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RNN models of sequences with (short term) memory

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Next:

- Unsupervised learning

References & further reading

Jurafsky, Daniel and James H. Martin (2025). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. 3rd. Online manuscript released January 12, 2025. URL: https://web.stanford.edu/~jurafsky/slp3/.