Natural Language Understanding

Lecture 15: Convolutional Neural Networks

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Outline

What is Convolution?

Convolution is an important operation in signal and image processing; it operates on two signals (1D) or two images (2D). Think of one as the input signal and the other, the kernel as a filter on the input producing an output.

Definition

$$(f * g)(i) = \sum_{j=1}^{m} g(j) \cdot f(i - j + m/2)$$

- f is the input vector and g is the kernel
- f has length n and g has length m
- We are sliding the kernel over input vector!

1D Convolution Example

Suppose we have 1D input vector denoted by f:

$f \quad =$

10	50	60	10	20	40	30

and our kernel is $g \quad =$

1/3	1/3	1/3

Let's call the output vector h. What is the value of $h(3)$?

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1D Convolution Example

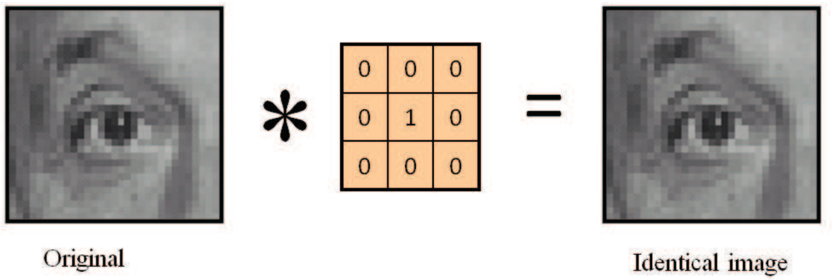
What is the kernel doing?

- The kernel is computing a windowed average of the input vector
- The kernel replaces each entry with the average of that entry and its left and right neighbor.
- We can compute the other values of h as well.

$$h = \begin{array}{|c|c|c|c|c|c|c|}\hline 20 & 40 & 40 & 30 & 20 & 30 & 23.333 \\ \hline\end{array}$$

2D Convolution Example

- Our images and kernels are now 2D functions (aka matrices).
- We slide the kernel over each pixel of the image, multiply the corresponding entries of the input and kernel, and add them up.



http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

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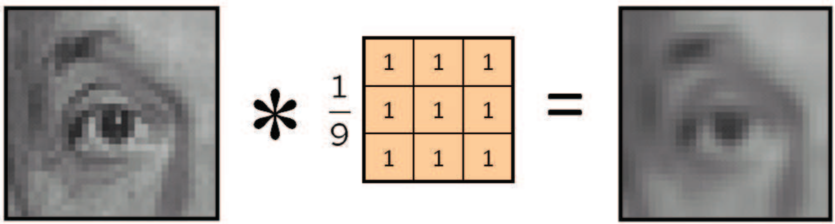

Original

Blur (with a mean filter)

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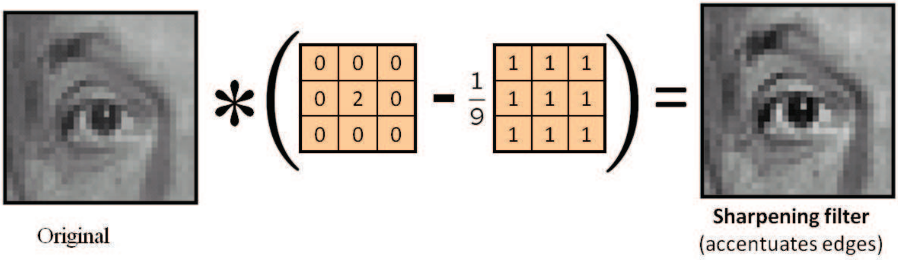

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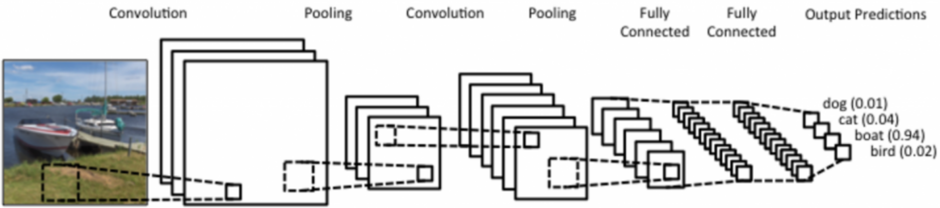
What are Convolutional Neural Networks?

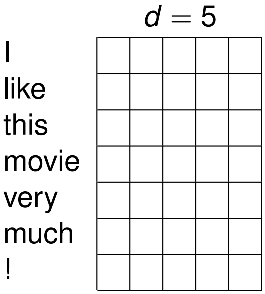
- In feedforward NNs each input neuron is connected to each output neuron in the next layer.
- CNNs use convolutions over the input layer to compute the output.
- This results in local connections: each region of the input is connected to a neuron in the output
- Each layer applies different filters (hundreds or thousands) and combines their results
- A CNN automatically learns the values of its filters based on the task you want to perform.

What are Convolutional Neural Networks?



So What this have to do with NLU?

- We begin with a tokenized sentence and convert it into a matrix.
- Rows are d-dimensional word vectors for each token
- Let s denote sentence length, then matrix is $s \times d^2$
- Sentence looks like an image now, we can apply convolutions.



What are Filters for Sentences?

- In vision filters slide over local patches of an image.
- In NLP filters slide over full rows of the matrix (words).
- The width of the filter is same as d width of input matrix.
- The height h or region size of the filter is number of adjacent rows.
- Sliding windows over 2-5 words at a time is typical.

$d = 5$

I					
like					
this					
movie					
very					
much					
!					

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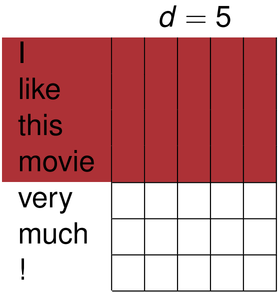

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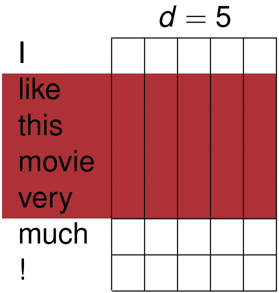

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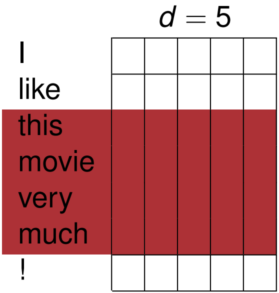

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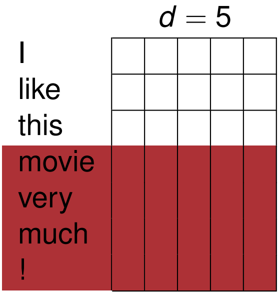

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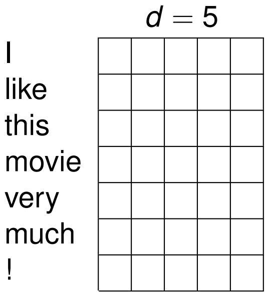

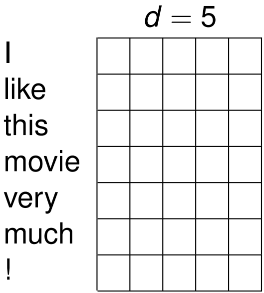

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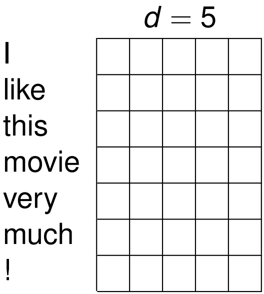

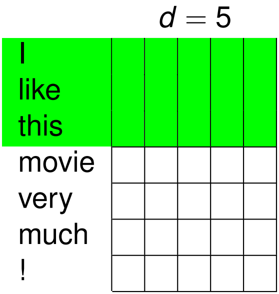

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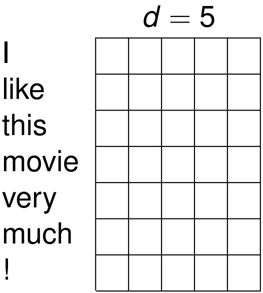

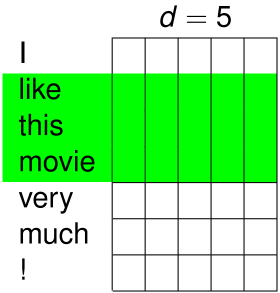

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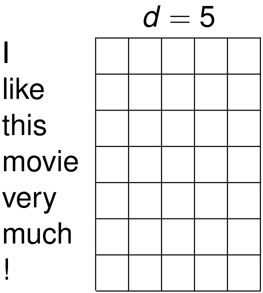

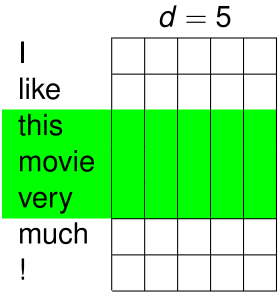

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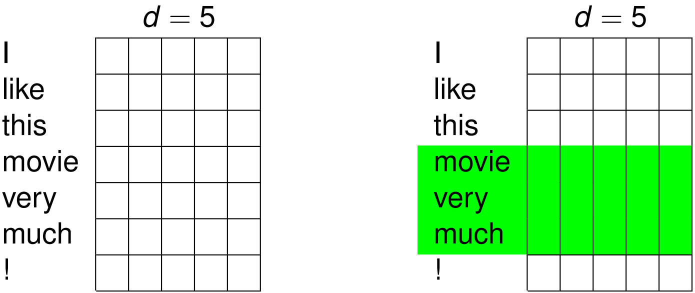

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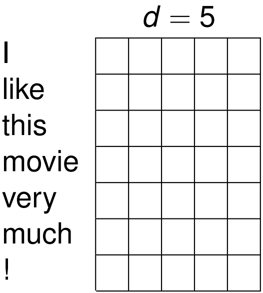
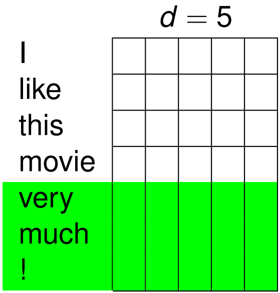




What are Filters for Sentences?

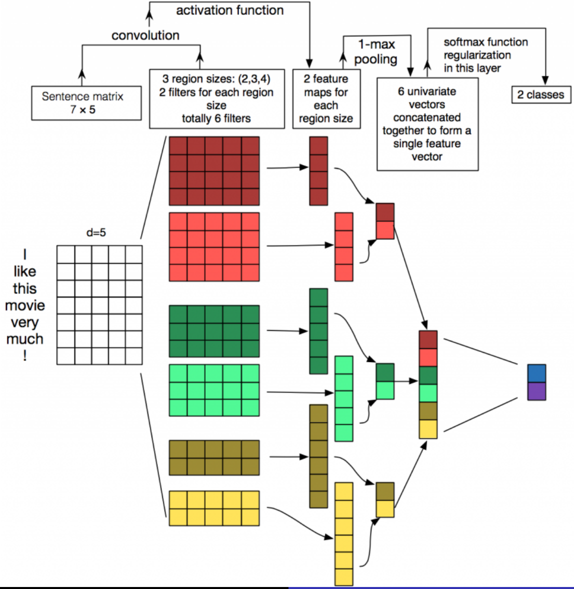
- A filter is parameterized by weight vector $\mathbf{w} \in \mathbb{R}^{h \times d}$
- Let $\mathbf{A} \in \mathbb{R}^{s \times d}$ denote a sentence matrix.
- Let $A[i : j]$ denote sub-matrix of $\mathbf{A}$ from row i to row j.
- Obtain output sequence of convolution operator by repeatedly applying filter on submatrices of $\mathbf{A}$.
- Include a bias term b and an activation function f to each o_i inducing feature map $\mathbf{c} \in \mathbb{R}^{s-h+1}$ for the filter

$$o_i = \mathbf{w} \cdot \mathbf{A}[i : i + h - 1]$$

$i = 1 \cdots - h + 1$ and $\cdot$ is dot product between sub-matrix and filter (sum over element-wise multiplications)

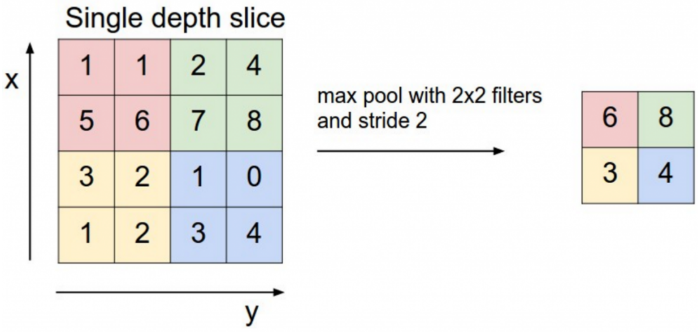
$$c_i = f(o_i + b)$$

Illustration of CNN



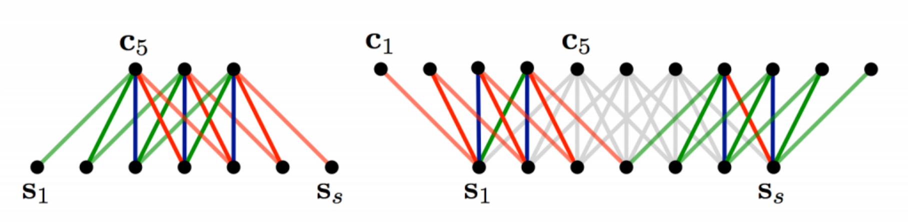
Pooling

- The dimensionality of feature map **c** will vary with sentence length.
- A pooling function is applied to each map to reduce dimensionality and number of parameters
- Most common pooling operator is 1-max pooling function
- Captures feature with the highest value for each feature map



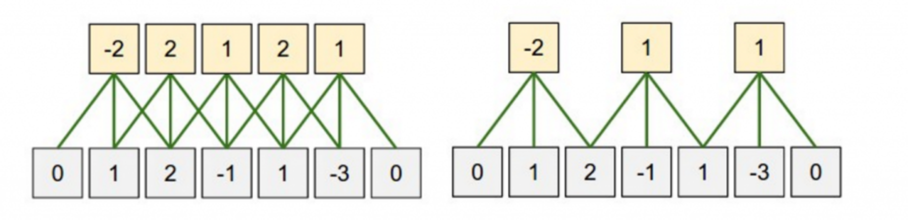
CNN Hyperparameters

- Applying a 3×3 filter at the center of the matrix works fine.
- But how would you apply the filter to the first element of a matrix that doesn't have any neighboring elements to the top and left?
- zero-padding: all elements that fall outside of the matrix are zero.
- wide convolution vs narrow convolution.



CNN Hyperparameters

- stride size: how much do you want to shift your filter at each step
- If stride size is 1, consecutive applications of the filter overlap
- A larger stride size leads to fewer applications of the filter and a smaller output size

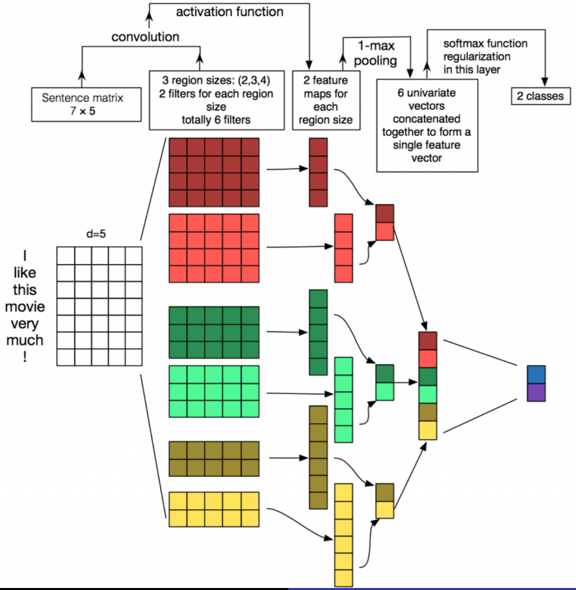


Source: `http://cs231n.github.io/convolutional-networks/`

Final Model

- Each sentence represented by feature vector and fed through a softmax function to generate final classification.
- You may apply dropout or *l*2 norm constraint.
- Training objective: minimize cross-entropy loss.
- Parameters: weight vector(s) of the filter(s), bias term in activation function, and weight vector in softmax.
- Word vectors can be fixed or inferred.

Illustration of CNN



Evaluation (Kim, EMNLP-2014)

Data	c	l	N	$\lvert V \rvert$	$\lvert V_{pre} \rvert$	*Test*
MR	2	20	10662	18765	16448	CV
SST-1	5	18	11855	17836	16262	2210
SST-2	2	19	9613	16185	14838	1821
Subj	2	23	10000	21323	17913	CV
TREC	6	10	5952	9592	9125	500
CR	2	19	3775	5340	5046	CV
MPQA	2	3	10606	6246	6083	CV

MR: movie reviews, one sentence per review; SST: Stanford sentiment treebank; Subj: sentence subjective or objective; TREC: question classification; CR: customer reviews, positive/negative sentences; MPQA: opinion polarity detection for sentences.

Model Comparisons (Kim, EMNLP-2014)

- **CNN-rand**: baseline model where all words are randomly initialized and then modified during training.
- **CNN-static**: model with pre-trained `word2vec` vectors; unknown words are inititalized randomly.
- **CNN-non-static**: pretrained vectors are fine-tuned for each task.
- **CNN-multichannel**: two sets of word vectors (one static, on non-static), each is a channel; each filter is applied to both channels (form of fine-tuning).
- **Hyperparameters**: filter windows (*h*) of 3, 4, 5 with 100 feature maps each.

Results (Kim, EMNLP-2014)

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (Socher et al., 2012)	79.0	44.4	82.9	–	–	–	–
RNTN (Socher et al., 2013)	–	45.7	85.4	–	–	–	–
DCNN (Kalchbrenner et al., 2014)	–	48.5	86.8	–	93.0	–	–
Paragraph-Vec (Le and Mikolov, 2014)	–	**48.7**	87.8	–	–	–	–
CCAE (Hermann and Blunsom, 2013)	77.8	–	–	–	–	–	87.2
Sent-Parser (Dong et al., 2014)	79.5	–	–	–	–	–	86.3
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3
MNB (Wang and Manning, 2012)	79.0	–	–	**93.6**	–	80.0	86.3
G-Dropout (Wang and Manning, 2013)	79.0	–	–	93.4	–	82.1	86.1
F-Dropout (Wang and Manning, 2013)	79.1	–	–	**93.6**	–	81.9	86.3
Tree-CRF (Nakagawa et al., 2010)	77.3	–	–	–	–	81.4	86.1
CRF-PR (Yang and Cardie, 2014)	–	–	–	–	–	82.7	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

Discussion

- CNNs often used for classification tasks (e.g., sentiment analysis)
- Simple architectures perform well across the board.
- Features are learned through filters and pooling operations.
- A window-size-k kernel extracts local features from k-grams
- Max pooling reduces dimensions, forcing the network to discriminate important features.