Natural Language Processing

Lecture 1.6

Convolutional neural networks

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Limitations of the bag-of-words representation

- The bag-of-words representation is unable to account for meaning that emerges from interactions between words.

  not pleasant, hardly a generous offer

- One approach to overcoming this limitation is to introduce explicit features for word pairs, triplets, and longer *n*-grams.

- However, this would result in very large embedding matrices, and suffer from data sparsity.

  The *n*-grams *quite good* and *very good* would be completely independent.

Convolutional neural networks

- **Convolutional neural networks (CNNs)** learn to extract *n*-gram features from a text.

- In a first step, a set of *filter functions* transform a sequence of embeddings into a matrix.

  filter = parameterized convolution + non-linear transfer function

- In a second step, a *pooling operation* reduces this matrix to a single vector, which we can view as a summary of the text.

The convolution operation

$$\boldsymbol{X} * \boldsymbol{K} = \sum_i \sum_j \left(\boldsymbol{X}_{ij} \cdot \boldsymbol{K}_{ij} \right)$$

0.08	0.95	0.85
0.98	0.78	0.02
0.32	0.13	0.82

input X

0.50	0.10	0.10
1.00	0.20	0.20
0.50	0.10	0.10

kernel K

The convolution operation

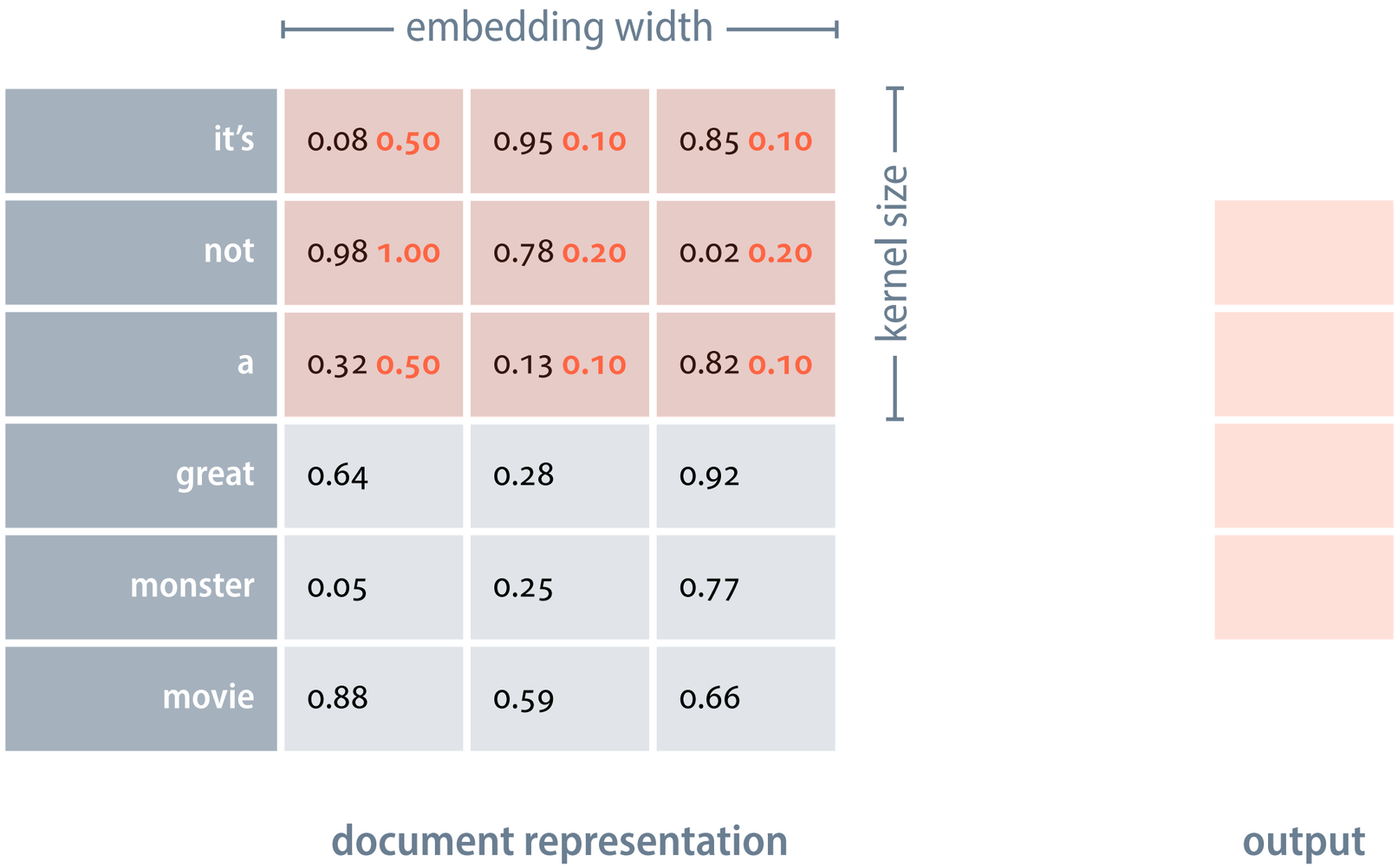
$$\boldsymbol{X} * \boldsymbol{K} = \sum_i \sum_j \left(\boldsymbol{X}_{ij} \cdot \boldsymbol{K}_{ij} \right)$$

0.08 **0.50**	0.95 **0.10**	0.85 **0.10**
0.98 **1.00**	0.78 **0.20**	0.02 **0.20**
0.32 **0.50**	0.13 **0.10**	0.82 **0.10**

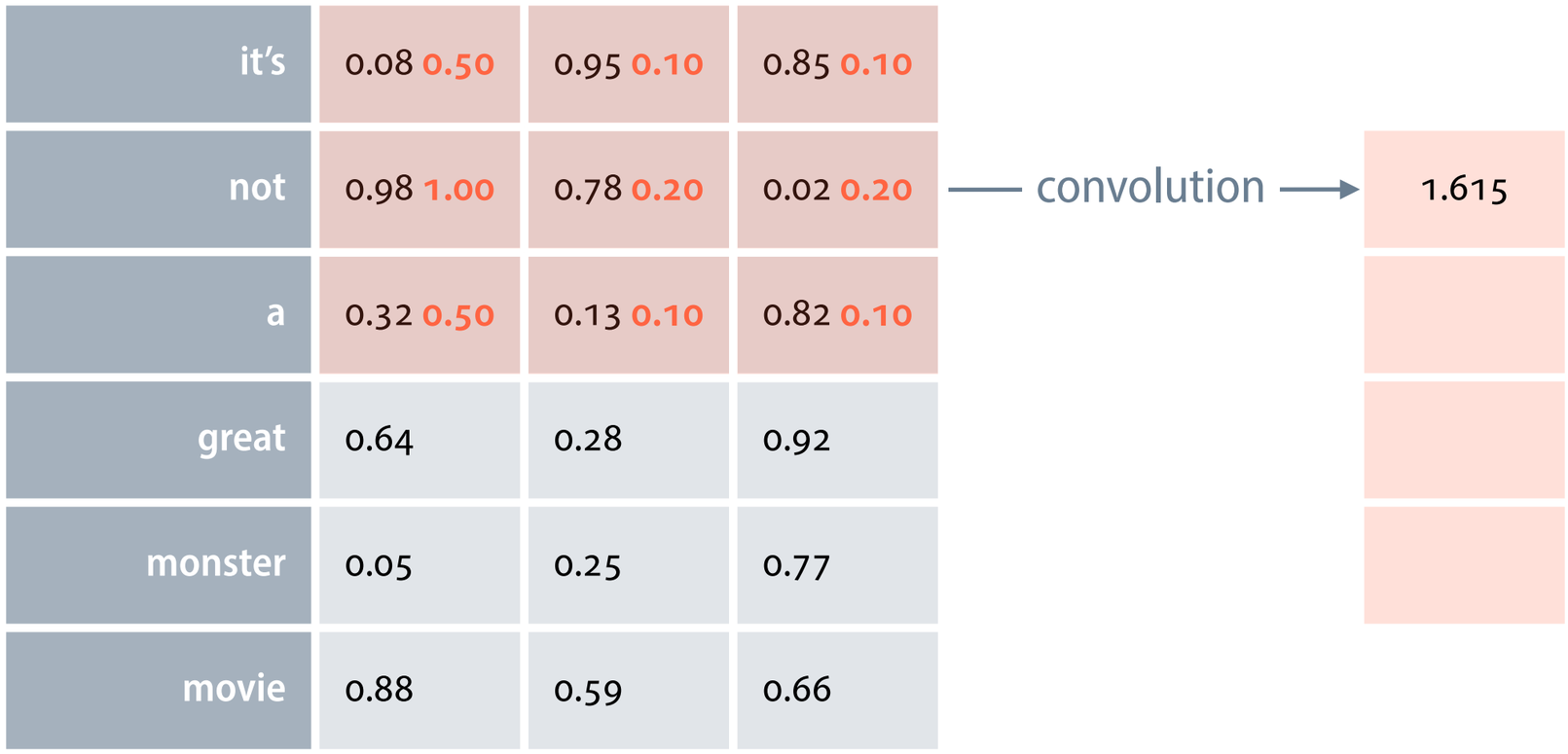
convolution

1.615

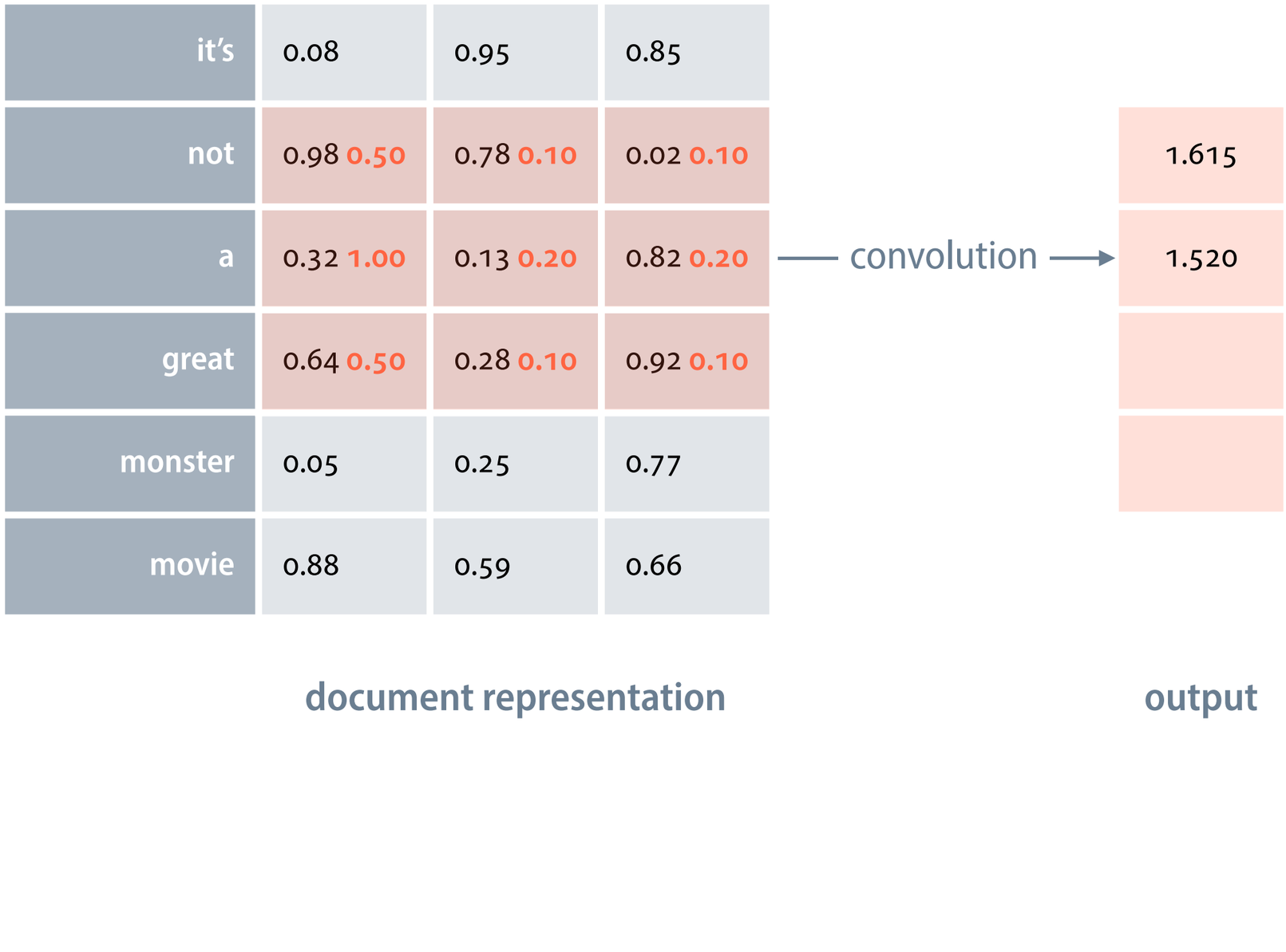
One-dimensional convolutions over text



One-dimensional convolutions over text



One-dimensional convolutions over text



One-dimensional convolutions over text

it's	0.08	0.95	0.85
not	0.98	0.78	0.02
a	0.32 0.50	0.13 0.10	0.82 0.10
great	0.64 1.00	0.28 0.20	0.92 0.20
monster	0.05 0.50	0.25 0.10	0.77 0.10
movie	0.88	0.59	0.66

document representation

1.615
1.520
1.262

output

One-dimensional convolutions over text

it's	0.08	0.95	0.85
not	0.98	0.78	0.02
a	0.32	0.13	0.82
great	0.64 0.50	0.28 0.10	0.92 0.10
monster	0.05 1.00	0.25 0.20	0.77 0.20
movie	0.88 0.50	0.59 0.10	0.66 0.10

document representation

1.615
1.520
1.262
1.259

output

Narrow convolutions versus wide convolutions

- When using kernels of size two or more, the output of a convolution will be smaller than the input.

  narrow convolution

- To produce output of the same size as the input, we may pad the input; this is typically done symmetrically on both ends.

  wide convolution

Wide convolutions

<pad>	0.00 **0.50**	0.00 **0.10**	0.00 **0.10**	
it's	0.08 **1.00**	0.95 **0.20**	0.85 **0.20**	1.010
not	0.98 **0.50**	0.78 **0.10**	0.02 **0.10**	1.615
a	0.32	0.13	0.82	1.520
great	0.64	0.28	0.92	1.262
monster	0.05	0.25	0.77	1.259
movie	0.88	0.59	0.66	1.257
<pad>	0.00	0.00	0.00	

Multiple channels

- We can view the dimensions of the word embeddings as separate **input channels**, similar to the colour channels in images.
- By applying several different filters to the same input, we can also get multiple **output channels**.

  several feature maps for the same input

- In deep learning libraries such as PyTorch, we can match input channels to output channels in flexible ways.

  documentation for nn.Conv1d

Multiple channels

<pad>	0.00 **0.50**	0.00 **0.10**	0.00 **0.10**			
it's	0.08 **1.00**	0.95 **0.20**	0.85 **0.20**		1.010	
not	0.98 **0.50**	0.78 **0.10**	0.02 **0.10**		1.615	
a	0.32	0.13	0.82		1.520	
great	0.64	0.28	0.92		1.262	
monster	0.05	0.25	0.77		1.259	
movie	0.88	0.59	0.66		1.257	
<pad>	0.00	0.00	0.00			

Multiple channels

<pad>	0.00 **0.10**	0.00 **0.50**	0.00 **0.10**			
it's	0.08 **0.20**	0.95 **1.00**	0.85 **0.20**	1.010	1.626	
not	0.98 **0.10**	0.78 **0.50**	0.02 **0.10**	1.615	1.727	
a	0.32	0.13	0.82	1.520	1.144	
great	0.64	0.28	0.92	1.262	0.978	
monster	0.05	0.25	0.77	1.259	1.159	
movie	0.88	0.59	0.66	1.257	1.050	
<pad>	0.00	0.00	0.00			

Multiple channels

<pad>	0.00 **0.10**	0.00 **0.10**	0.00 **0.50**			
it's	0.08 **0.20**	0.95 **0.20**	0.85 **1.00**	1.010	1.626	1.242
not	0.98 **0.10**	0.78 **0.10**	0.02 **0.50**	1.615	1.727	1.355
a	0.32	0.13	0.82	1.520	1.144	1.648
great	0.64	0.28	0.92	1.262	0.978	1.974
monster	0.05	0.25	0.77	1.259	1.159	1.859
movie	0.88	0.59	0.66	1.257	1.050	1.369
<pad>	0.00	0.00	0.00			

Pooling

- **Pooling** reduces a feature map to a single scalar by an operation such as taking the maximum or the average.

  max pooling, average pooling

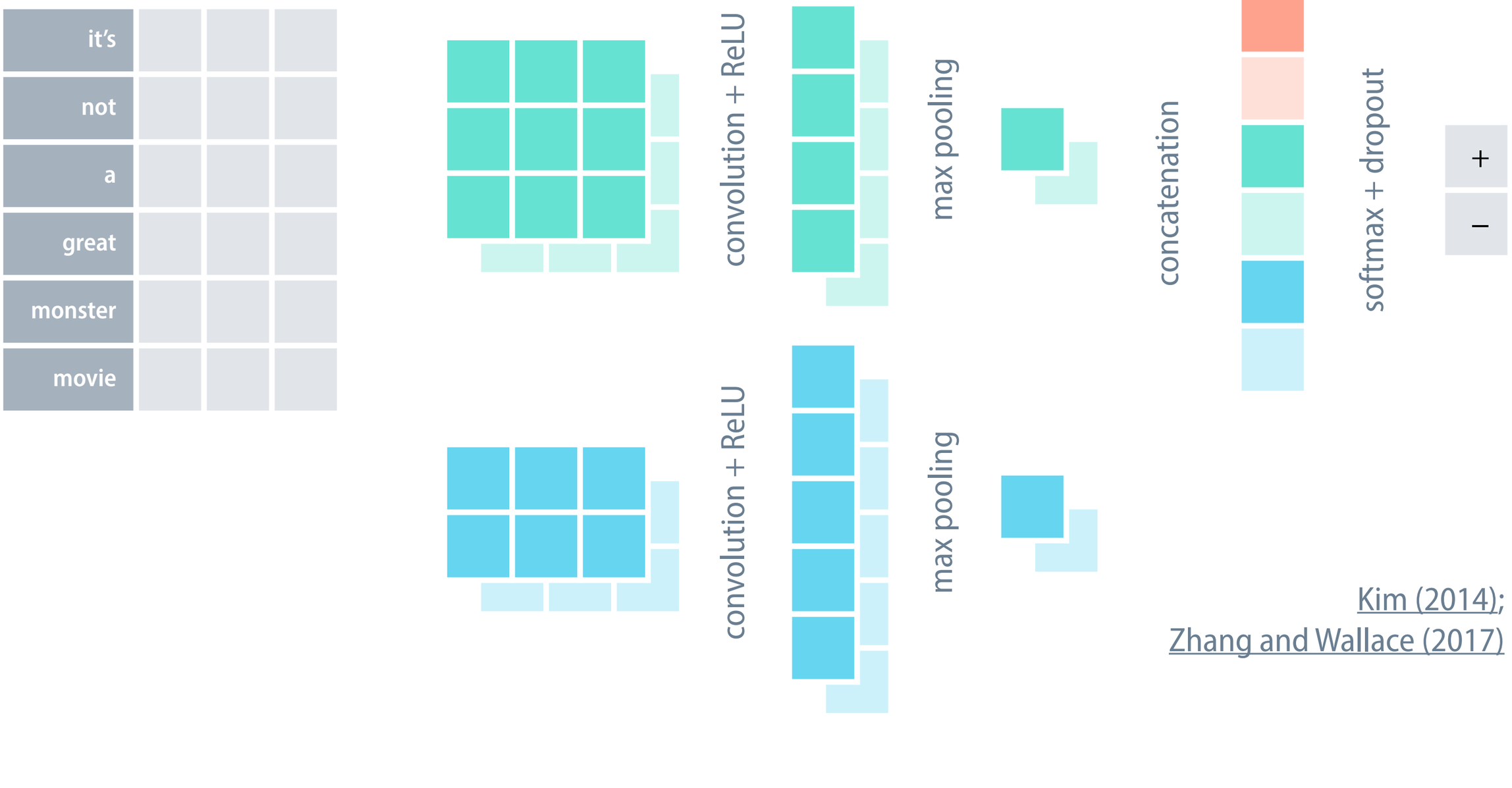
- When performed on all channels, this gives us a single vector representing the entire input document.

- The hope is that this vector summarizes the most important information for the classification task at hand.

Max pooling

<pad>	0.00	0.00	0.00			
it's	0.08	0.95	0.85	1.010	1.626	1.242
not	0.98	0.78	0.02	1.615	1.727	1.355
a	0.32	0.13	0.82	1.520	1.144	1.648
great	0.64	0.28	0.92	1.262	0.978	1.974
monster	0.05	0.25	0.77	1.259	1.159	1.859
movie	0.88	0.59	0.66	1.257	1.050	1.369
<pad>	0.00	0.00	0.00	*max*	*max*	*max*
				1.615	1.727	1.974

CNN architecture for sentence classification



Kim (2014);
Zhang and Wallace (2017)