Natural Language Processing (CS-472) Spring-2023

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Overview of this week’s lecture

Convolutional Neural Networks

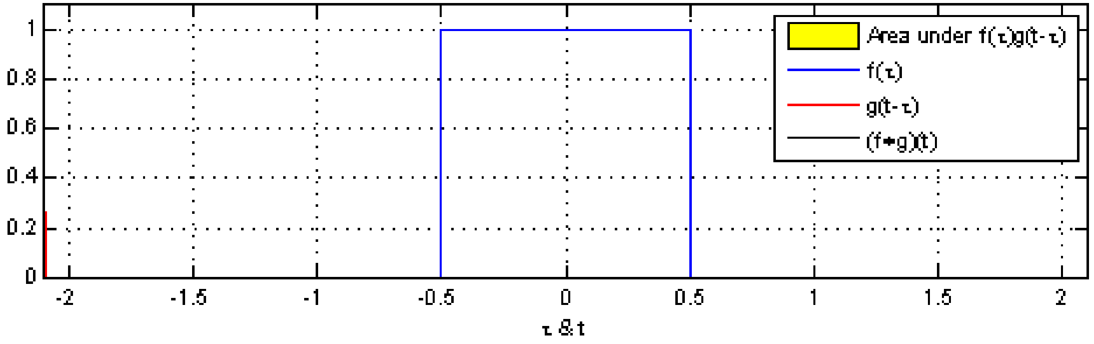
- Fundamentals of CNNs

- Applications of CNNs in NLP

What is convolution?

- Mathematically, convolution is an operation on two functions that shows how one function is modified by the other.

$$f[n] * g[n] = \sum_{m=-M}^{M} f[n]\, g[n-m]$$



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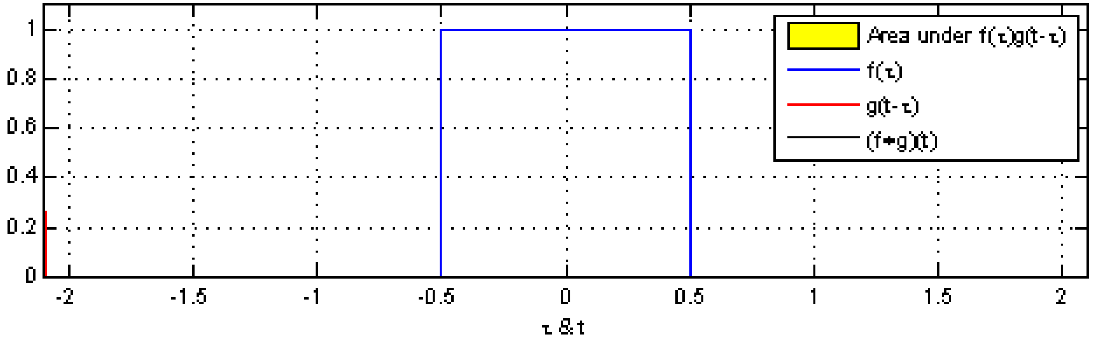

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- In computer vision, convolution finds features that are translation invariant.

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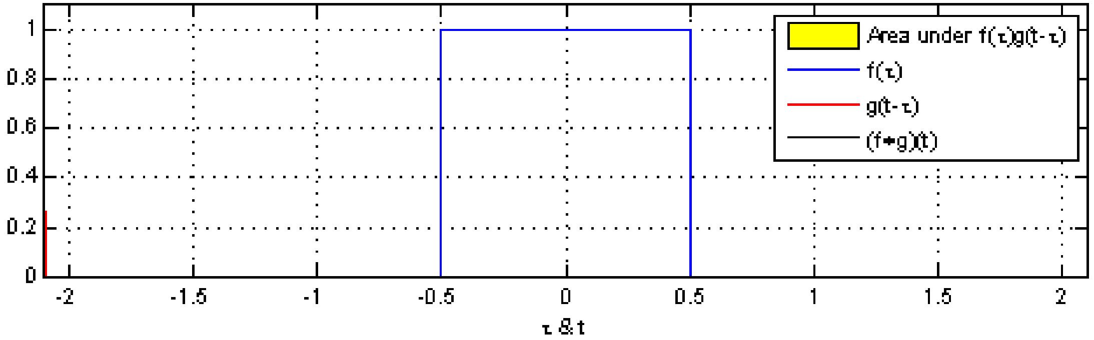

- In computer vision, convolution finds features that are translation invariant.

- In AI, the operation normally referred to as convolution is actually cross-correlation.

$$f[n] \star g[n] = \sum_{m=-M}^{M} f[n]\, g[n+m]$$

  - Correlation is a measure of similarity.

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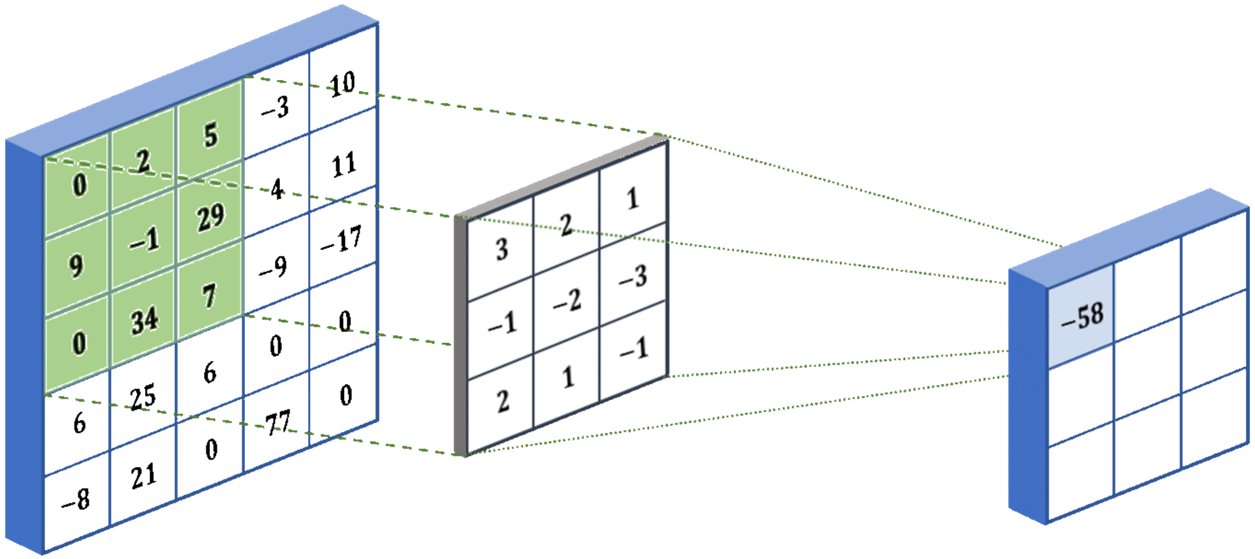
2D Convolution is inspired from visual cortex

- Take dot product between part of an image (receptive field) and a kernel or filter.



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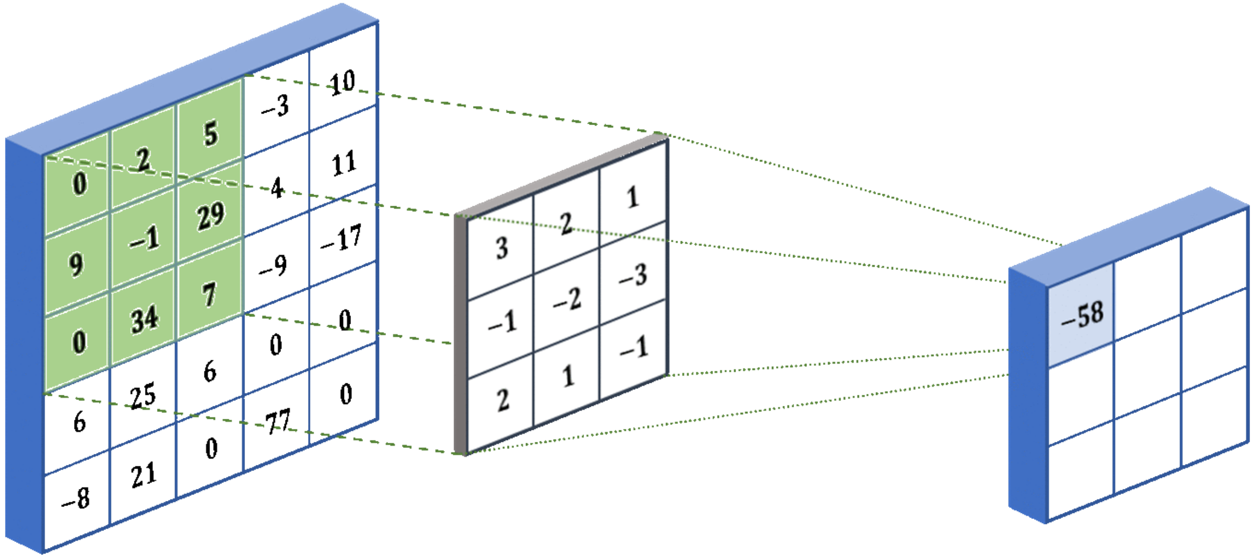
2D Convolution is inspired from visual cortex

- Take dot product between part of an image (receptive field) and a kernel or filter.

- The output of this operation (activation map) is, most of the times, a smaller image which finds a particular feature in the input.



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1D convolution is used for text processing

- Let we have a sequence of words, each represented by a 4-dimentional dense vector.

Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3

1D convolution is used for text processing

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That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3

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1D convolution is used for text processing

- Let we have a sequence of words, each represented by a 4-dimentional dense vector.
- In CNN, 4-dimensions of these word vectors may be referred to as 4-channels.
- Let we have a filter of size 3 (arbitrary number). The filter must have the same number of channels as the input (word vectors).

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Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let's put a	-1.0

1D convolution is used for text processing

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That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let's put a	-1.0
Put a smile	-0.5

1D convolution is used for text processing

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- In CNN, 4-dimensions of these word vectors may be referred to as 4-channels.

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Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let’s put a	-1.0
Put a smile	-0.5
A smile on	-3.6

1D convolution is used for text processing

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Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let’s put a	-1.0
Put a smile	-0.5
A smile on	-3.6
Smile on that	-0.2

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Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let's put a	-1.0
Put a smile	-0.5
A smile on	-3.6
Smile on that	-0.2
On that face	0.3

How to preserve the dimension of output?

Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Let's put a	-1.0
Put a smile	-0.5
A smile on	-3.6
Smile on that	-0.2
On that face	0.3

How to preserve the dimension of output?

- Use zero-padding on one or both ends of the signal.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Ø Let's put	-0.6
Let's put a	-1.0
Put a smile	-0.5
A smile on	-3.6
Smile on that	-0.2
On that face	0.3
That face Ø	-0.5

How to preserve the dimension of output?

- Use zero-padding on one or both ends of the signal.

- Apply multiple filters.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

How to preserve the dimension of output?

- Use zero-padding on one or both ends of the signal.
- Apply multiple filters.
  - Each filter learns a specific aspect of the text.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

Pooling over time helps summarise the text using features

- Max-pooling checks whether a feature learnt by a filter is present anywhere in the text.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Max-pool	**0.3**	**1.6**
Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

Pooling over time helps summarise the text using features

- Max-pooling checks whether a feature learnt by a filter is present anywhere in the text.

- Average-pooling estimates the average strength of a feature in a piece of text.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Avg-pool	**-0.87**	**0.26**
Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

Pooling over time helps summarise the text using features

- Max-pooling checks whether a feature learnt by a filter is present anywhere in the text.
- Average-pooling estimates the average strength of a feature in a piece of text.
  - Average pooling is not widely used.

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
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Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

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Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

How to compress the feature map?

- Some of the following may be used to compress the feature map.
  - Kernel stride of greater than 1

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
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That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Put a smile	-0.5	-0.1
Smile on that	-0.2	-0.1
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Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Put a smile	-0.5	-0.1
Smile on that	-0.2	-0.1
That face Ø	-0.5	-0.9

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That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
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Smile on that	-0.2	-0.1
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Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Put a smile	-0.5	-0.1
Smile on that	-0.2	-0.1
That face Ø	-0.5	-0.9

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How to compress the feature map?

- Some of the following may be used to compress the feature map.
  - Kernel stride of greater than 1
  - Local pooling

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

How to compress the feature map?

Ø Let's put a	-0.6	1.6

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  - Kernel stride of greater than 1
  - Local pooling

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Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
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That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
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Question

1	0	1	1
1	0	-1	-1
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Ø Let's put	-0.6	0.2
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On that face	0.3	0.6
That face Ø	-0.5	-0.9

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  - Kernel stride of greater than 1
  - Local pooling

Ø Let's put a	-0.6	1.6
Let's Put a smile	-0.5	1.6

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

How to compress the feature map?

- Some of the following may be used to compress the feature map.
  - Kernel stride of greater than 1
  - Local pooling

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put a	-0.6	1.6
Let's Put a smile	-0.5	1.6
Put a smile on	-0.5	0.3
A smile on that	-0.2	0.3
Smile on that face	0.3	0.6
On that face Ø	0.3	0.6

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
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That face Ø	-0.5	-0.9

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How to compress the feature map?

- Some of the following may be used to compress the feature map.
  - Kernel stride of greater than 1
  - Local pooling
  - k-max pooling

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

2-Max-pool	-0.2	1.6
	0.3	0.6

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

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How to compress the feature map?

- Some of the following may be used to compress the feature map.
  - Kernel stride of greater than 1
  - Local pooling
  - k-max pooling
  - Dilated Convolution

Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

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1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
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Ø	0.0	0.0	0.0	0.0
Let's	0.2	0.1	-0.3	0.4
Put	0.5	0.2	-0.3	-0.1
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Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
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Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
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Let's	0.2	0.1	-0.3	0.4
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A	-0.1	-0.3	-0.2	0.4
Smile	0.3	-0.3	0.1	0.1
On	0.2	-0.3	0.4	0.2
That	0.1	0.2	-0.1	-0.1
Face	-0.4	0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Politeness

-3	1	2	-3
-1	2	1	-3
1	1	-1	1

Question

1	0	1	1
1	0	-1	-1
0	1	0	1

Ø Let's put	-0.6	0.2
Let's put a	-1.0	1.6
Put a smile	-0.5	-0.1
A smile on	-3.6	0.3
Smile on that	-0.2	-0.1
On that face	0.3	0.6
That face Ø	-0.5	-0.9

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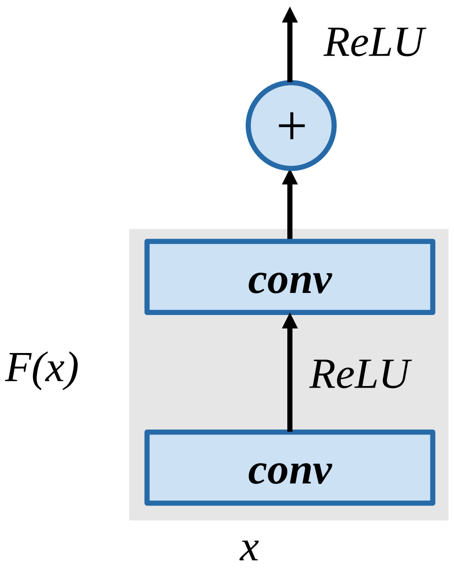
Training deeper CNNs requires some tricks to avoid vanishing gradients

- The idea of gating/skipping an input as seen in LSTMs can also be used in CNNs.

Training deeper CNNs requires some tricks to avoid vanishing gradients

- The idea of gating/skipping an input as seen in LSTMs can also be used in CNNs.

- Summing candidate updates with shortcut connections is required for deeper networks to train.



Residual Block

Training deeper CNNs requires some tricks to avoid vanishing gradients

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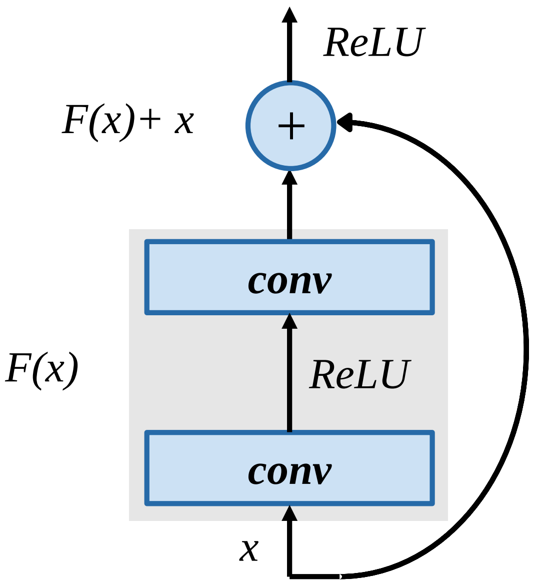
- Summing candidate updates with shortcut connections is required for deeper networks to train.



Residual Block

Training deeper CNNs requires some tricks to avoid vanishing gradients

- The idea of gating/skipping an input as seen in LSTMs can also be used in CNNs.

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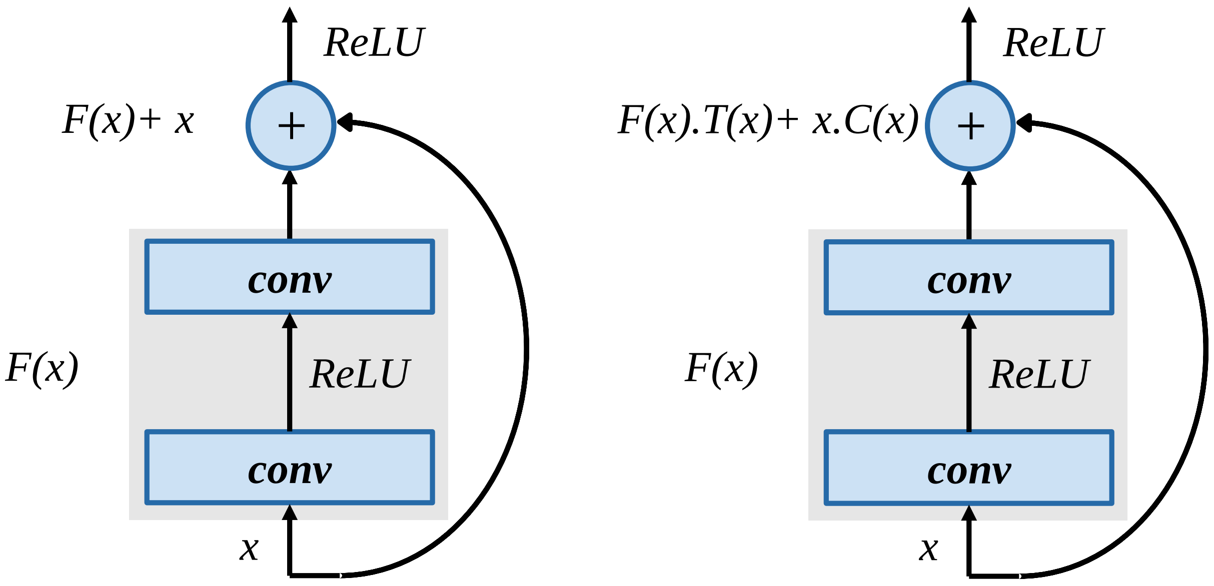
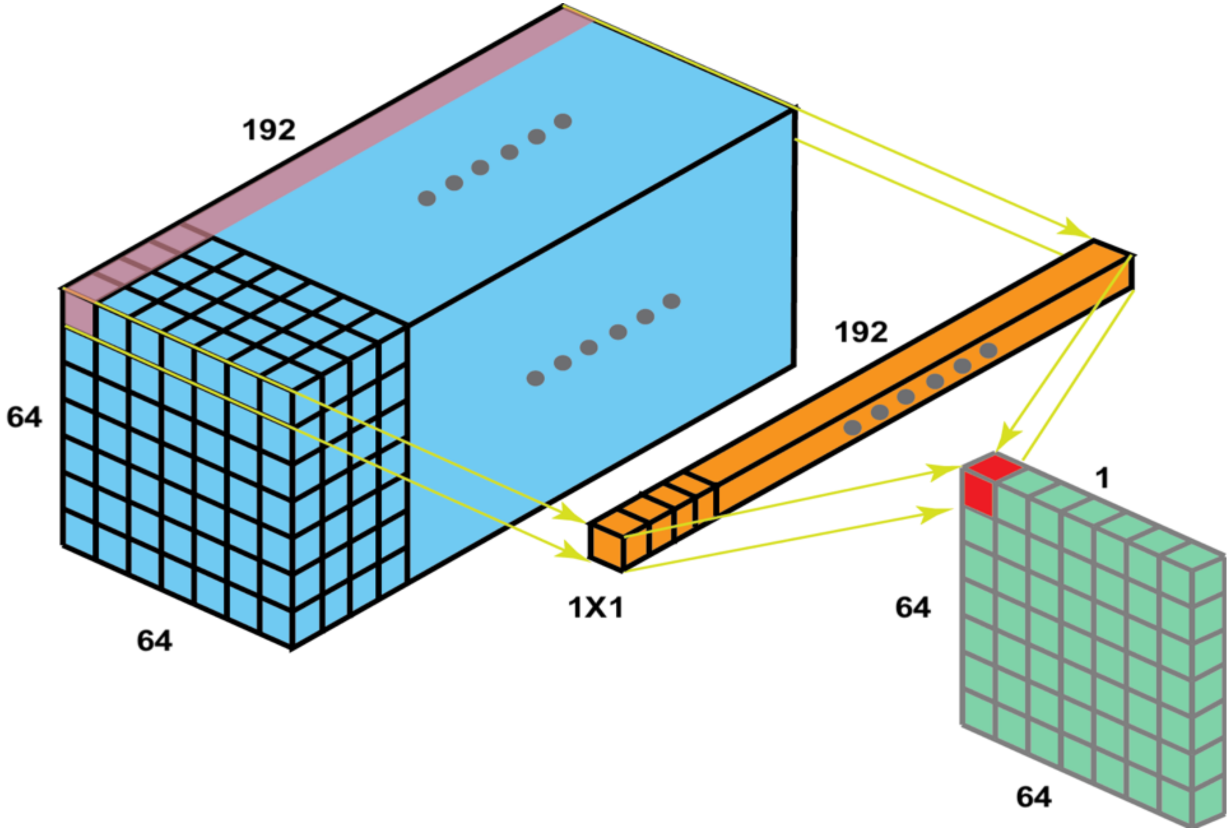


Residual Block **Highway Block**

Does 1 × 1 convolution actually make sense?

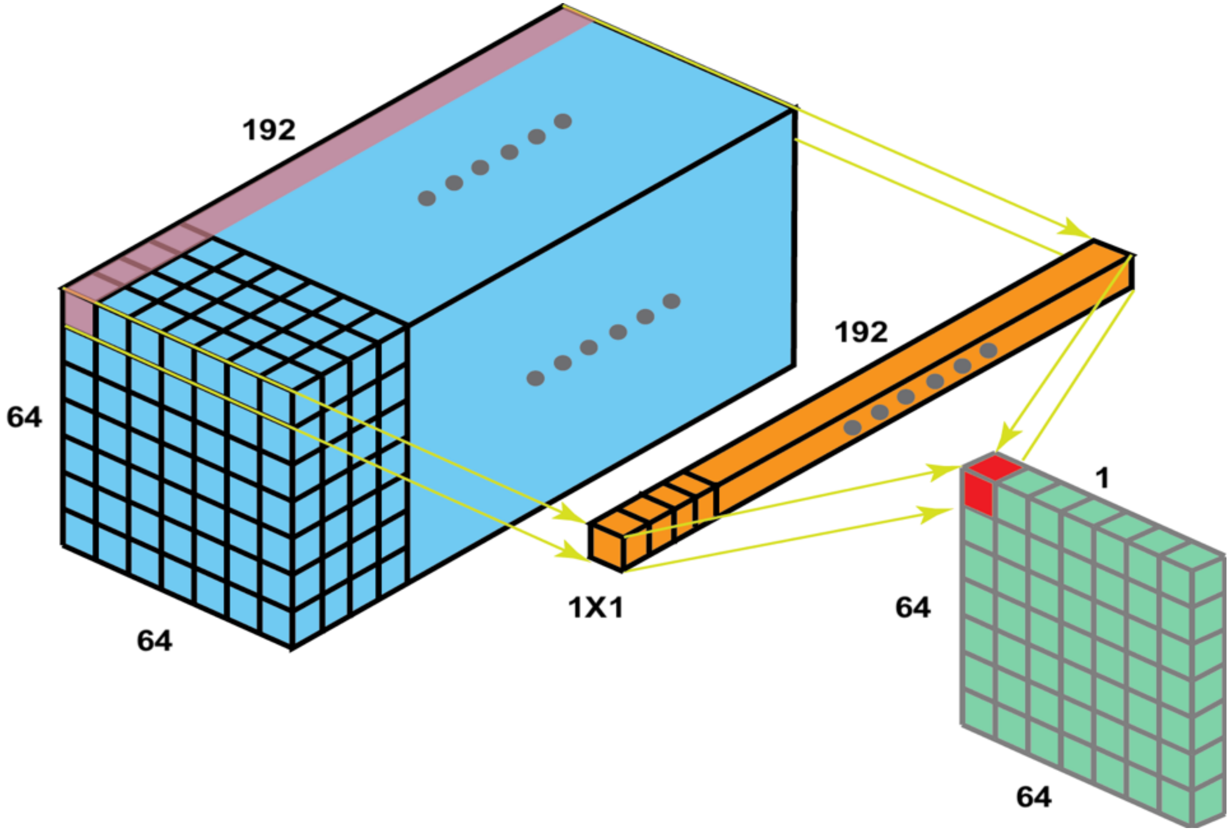
Does 1×1 convolution actually make sense?

- Kernels have size 1 but have depth equal to the input channels.



Does 1×1 convolution actually make sense?

- Kernels have size 1 but have depth equal to the input channels.
    - Also known as a Network-in-Network connections.
    - Acts as a fully connected layer across channels.
    - Adds additional NN layer with only a few parameters.
    - May be used to compress channels.



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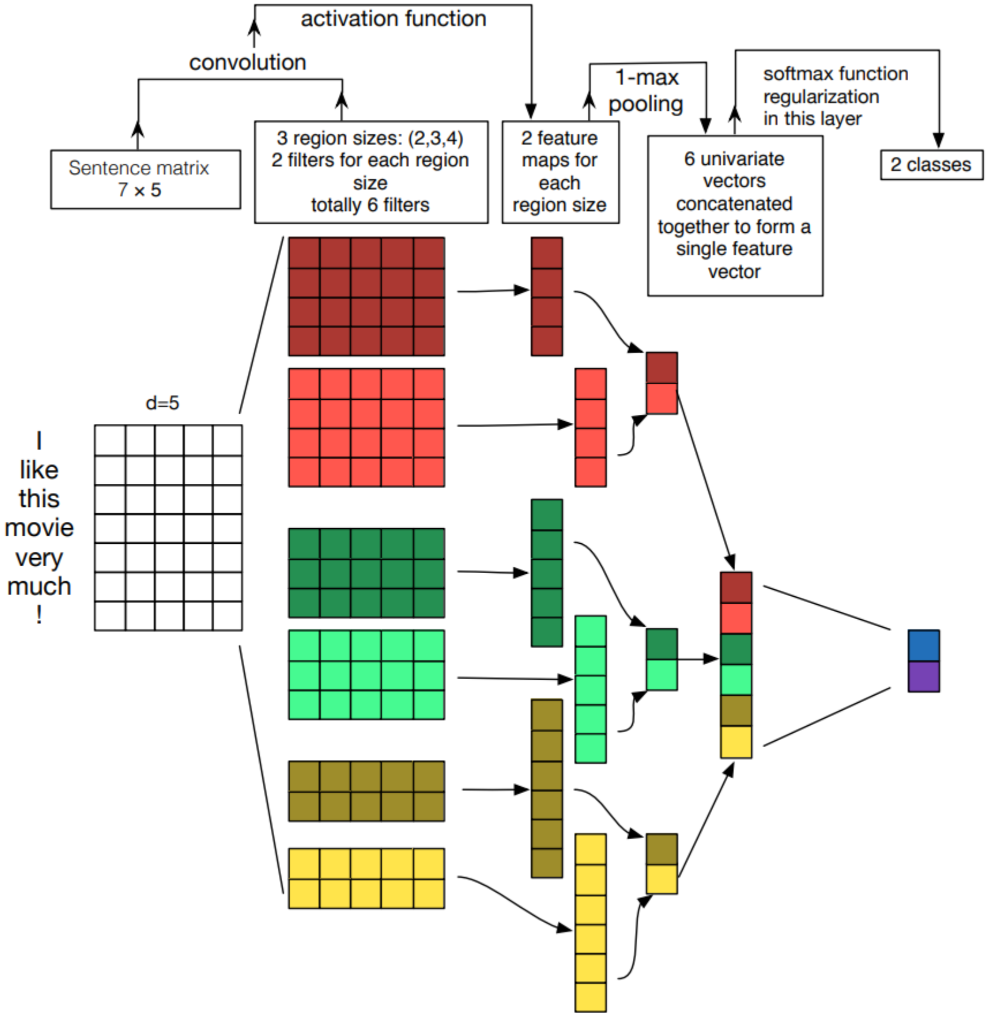
A simple application of CNN for text classification



Zhang, Y., & Wallace, B. (2015). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. arXiv preprint arXiv:1510.03820.

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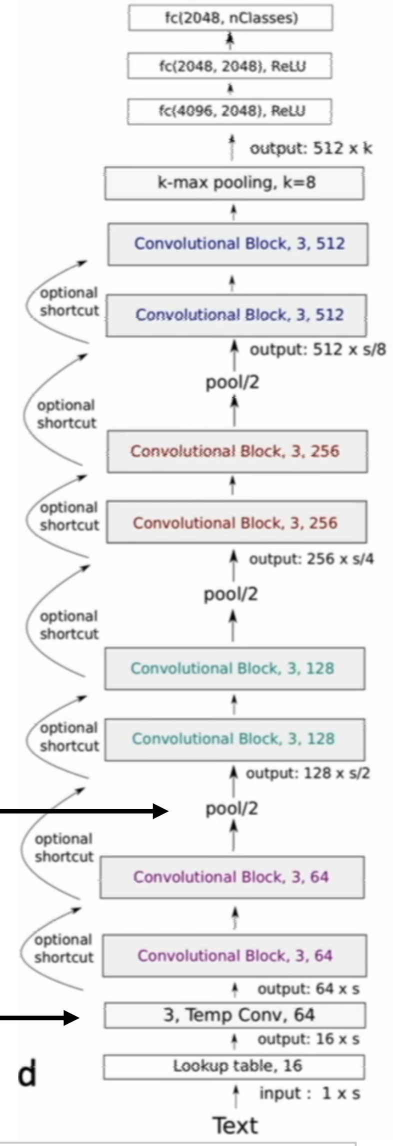
A very deep CNN architecture

- A CNN based DNN for text classification built over characters.
  - Input is taken as a fixed sequence of 1024 characters.
  - Each character is represented by an embedding of size 16.
  - k-max pooling is used after convolutional backbone ($k = 8$).

Local pooling at each stage halves temporal resolution and doubles number of features

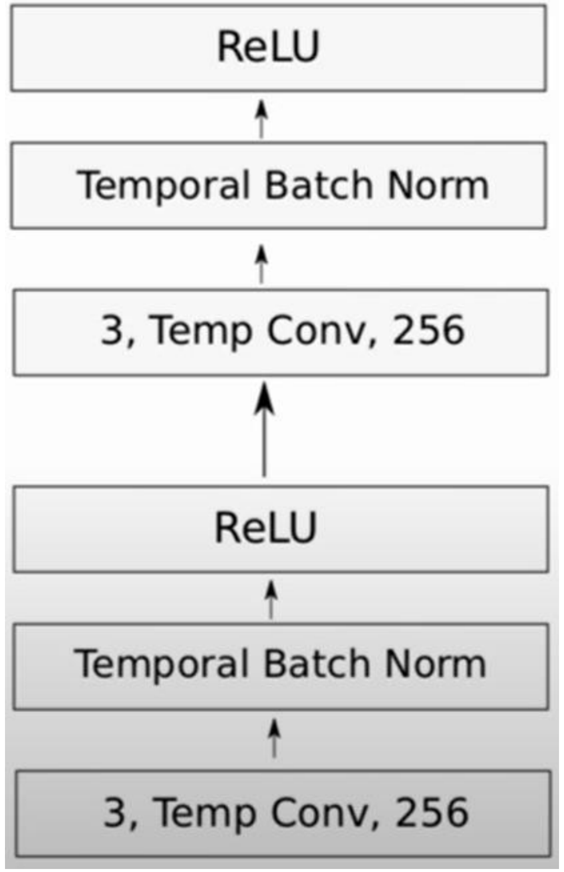
64 kernels of size 3



Conneau, A., Schwenk, H., Barrault, L., & Lecun, Y. (2016). Very deep convolutional networks for text classification. arXiv preprint arXiv:1606.01781.

A very deep CNN architecture

- Each convolutional block consists of
  - Two $1d$ convolutional layers
  - Each $conv$ layer is followed by a batch norm and a $ReLU$.
  - Kernel size is 3.
  - Number of kernels differ in different blocks.
  - Padding is used to set the dimensions as per requirement.



Conneau, A., Schwenk, H., Barrault, L., & Lecun, Y. (2016). Very deep convolutional networks for text classification. arXiv preprint arXiv:1606.01781.

Do you have any problem?

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