Neural networks for text

What is text?

You can think of text as a sequence of

- Characters
- **Words**
- Phrases and named entities
- Sentences
- Paragraphs
- …

Bag of words way (sparse)

~100k columns

	good	movie	very	a	did	like
very	0	0	**1**	0	0	0
good	**1**	0	0	0	0	0
movie	0	**1**	0	0	0	0

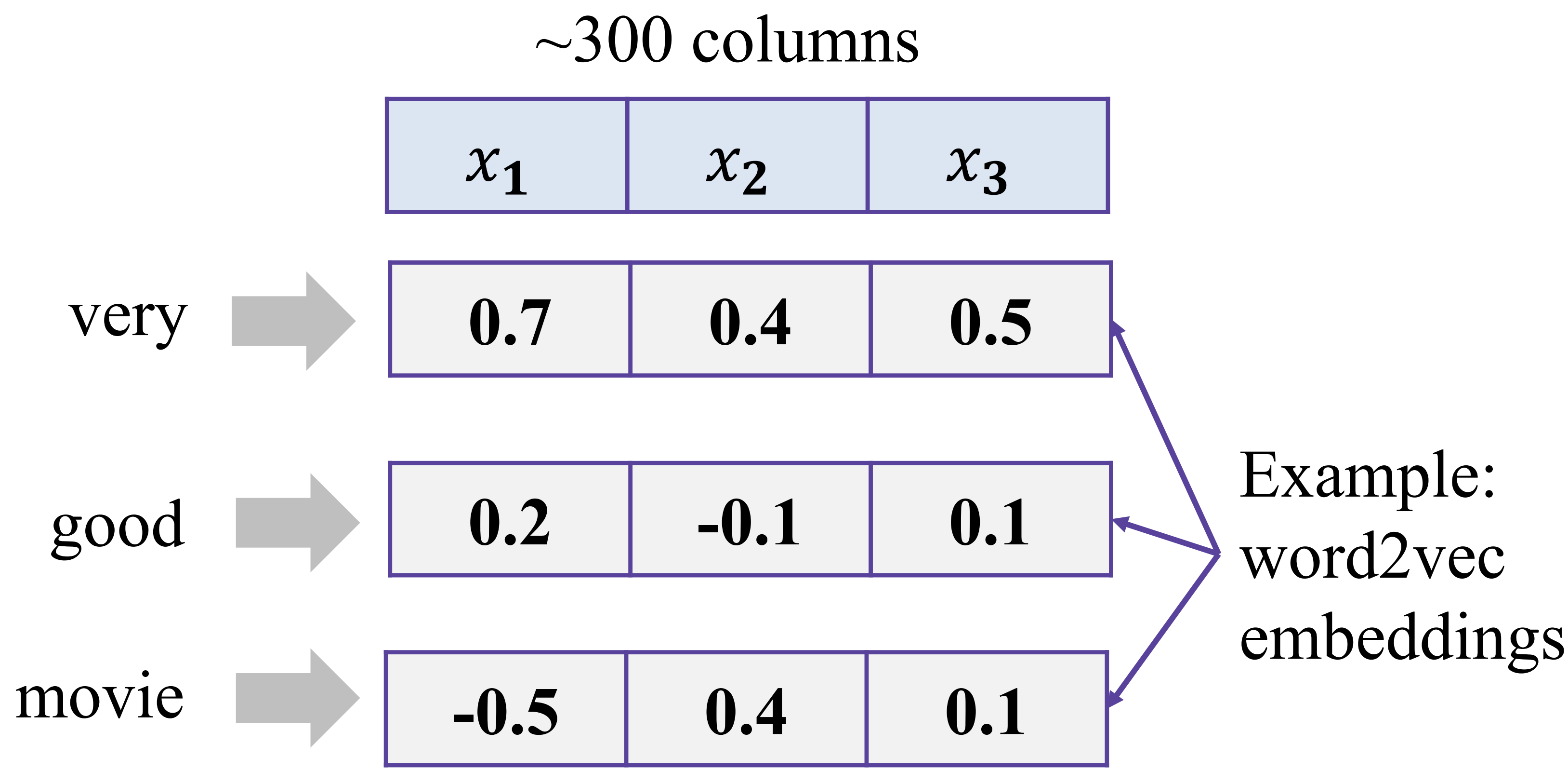
Bag of words way (sparse)

~100k columns

	good	movie	very	a	did	like
very	0	0	**1**	0	0	0
good	**1**	0	0	0	0	0
movie	0	**1**	0	0	0	0
very good movie	**1**	**1**	**1**	0	0	0

Bag of words representation
is a sum of sparse one-hot-encoded vectors

Neural way (dense)



Word2vec property:

Words that have similar context tend to have collinear vectors

Neural way (dense)

~300 columns

	x_1	x_2	x_3
very	**0.7**	**0.4**	**0.5**
+			
good	**0.2**	**-0.1**	**0.1**
+			
movie	**-0.5**	**0.4**	**0.1**
=			
very good movie	**0.4**	**0.7**	**0.7**

Example: word2vec embeddings

Sum of word2vec vectors
can be a good text descriptor already!

A better way: 1D convolutions

Word embeddings

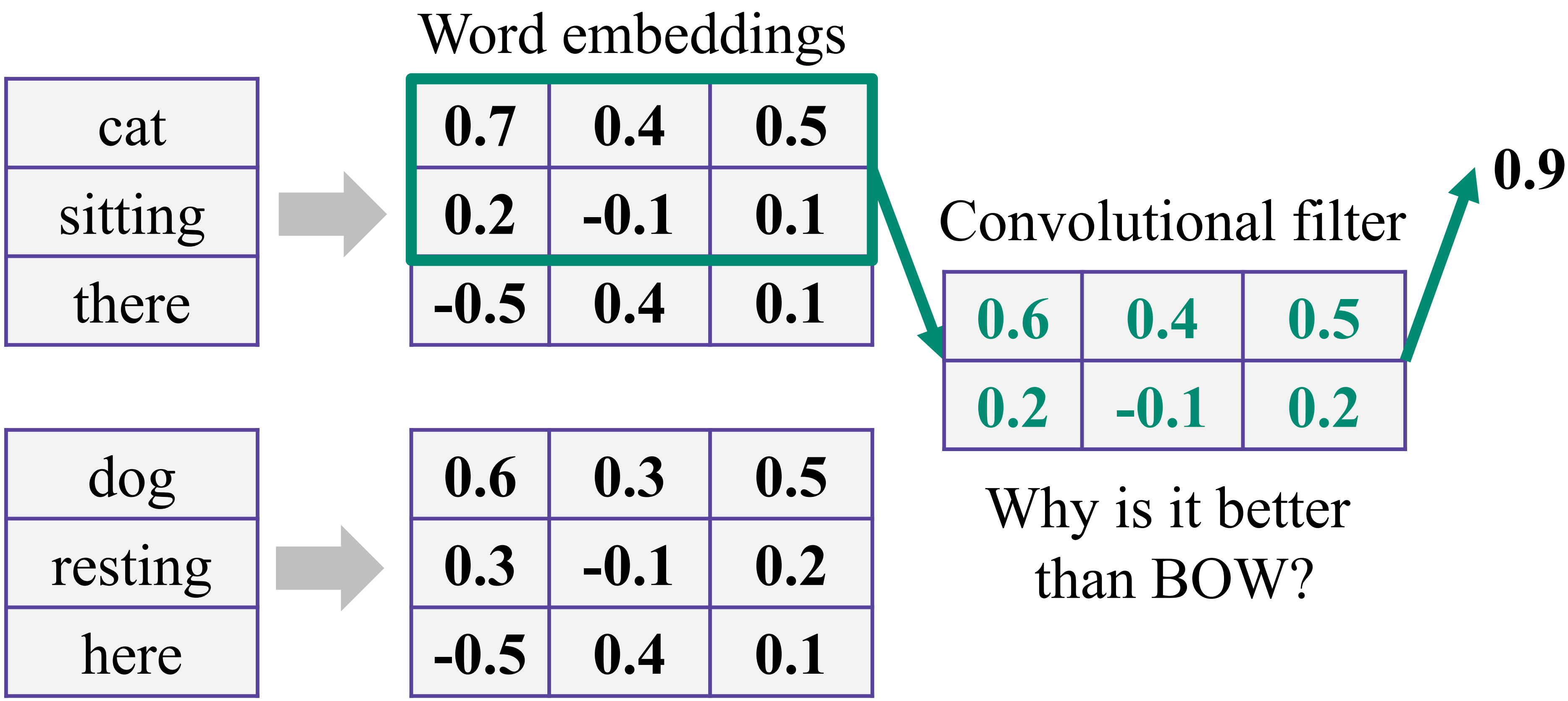
cat	**0.7**	**0.4**	**0.5**
sitting	**0.2**	**-0.1**	**0.1**
there	**-0.5**	**0.4**	**0.1**

How do we make 2-grams?

dog	**0.6**	**0.3**	**0.5**
resting	**0.3**	**-0.1**	**0.2**
here	**-0.5**	**0.4**	**0.1**

http://bionlp-www.utu.fi/wv_demo/

A better way: 1D convolutions

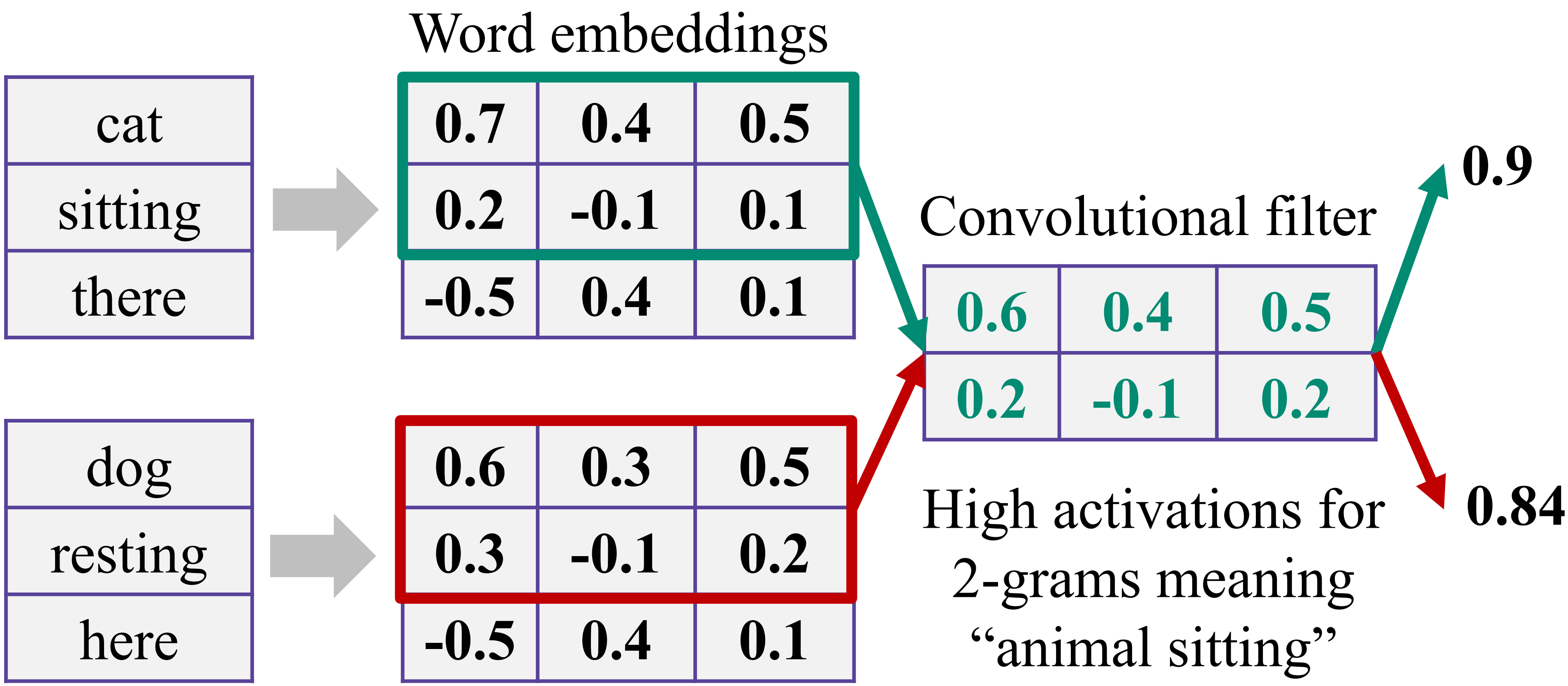


Why is it better than BOW?

- This convolution provides high activations for 2-grams with certain meaning

http://bionlp-www.utu.fi/wv_demo/

A better way: 1D convolutions



- This convolution provides high activations for 2-grams with certain meaning
- Word2vec vectors for similar words are similar in terms of cosine distance (similar to dot product)

http://bionlp-www.utu.fi/wv_demo/

1D convolutions

- Can be extended to 3-grams, 4-grams, etc.
- One filter is not enough, need to track many n-grams
- They are called 1D because we slide the window only in one direction

cat
sitting
there
or
here

0.7	**0.4**	**0.5**
0.2	**-0.1**	**0.1**
-0.5	**0.4**	**0.1**
-0.1	**0.8**	**-0.3**
-0.5	**0.3**	**0.2**

0.1

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-0.5	**0.3**	**0.2**

0.1
0.3

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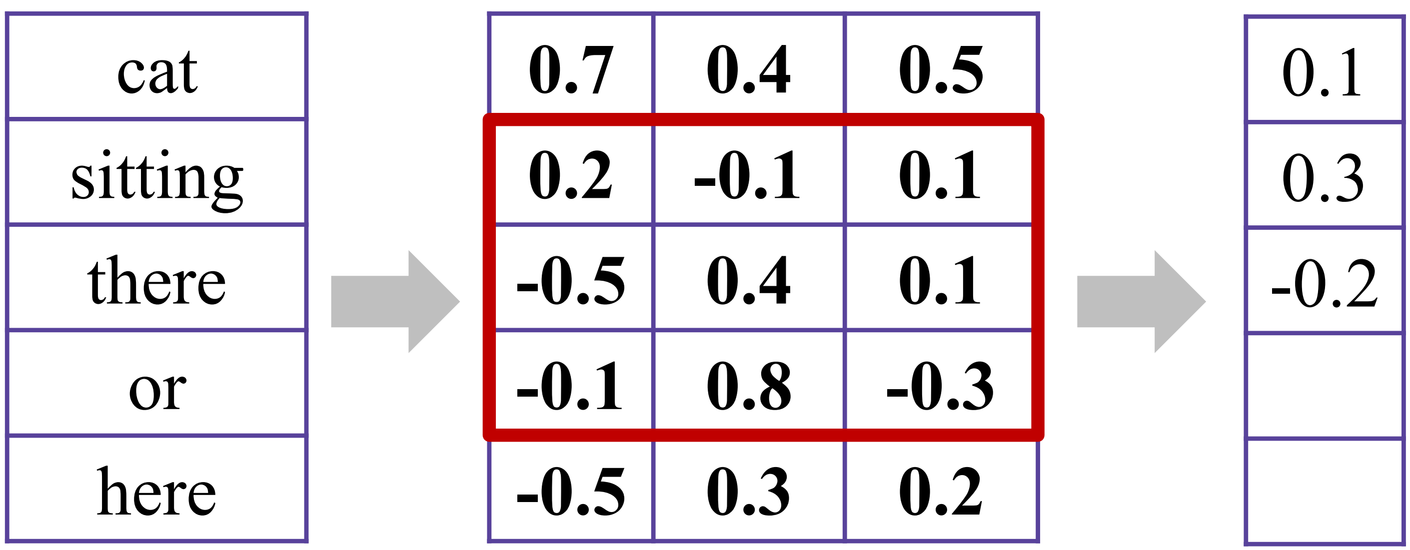

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-0.1	**0.8**	**-0.3**
-0.5	**0.3**	**0.2**

0.1
0.3
-0.2
0.7

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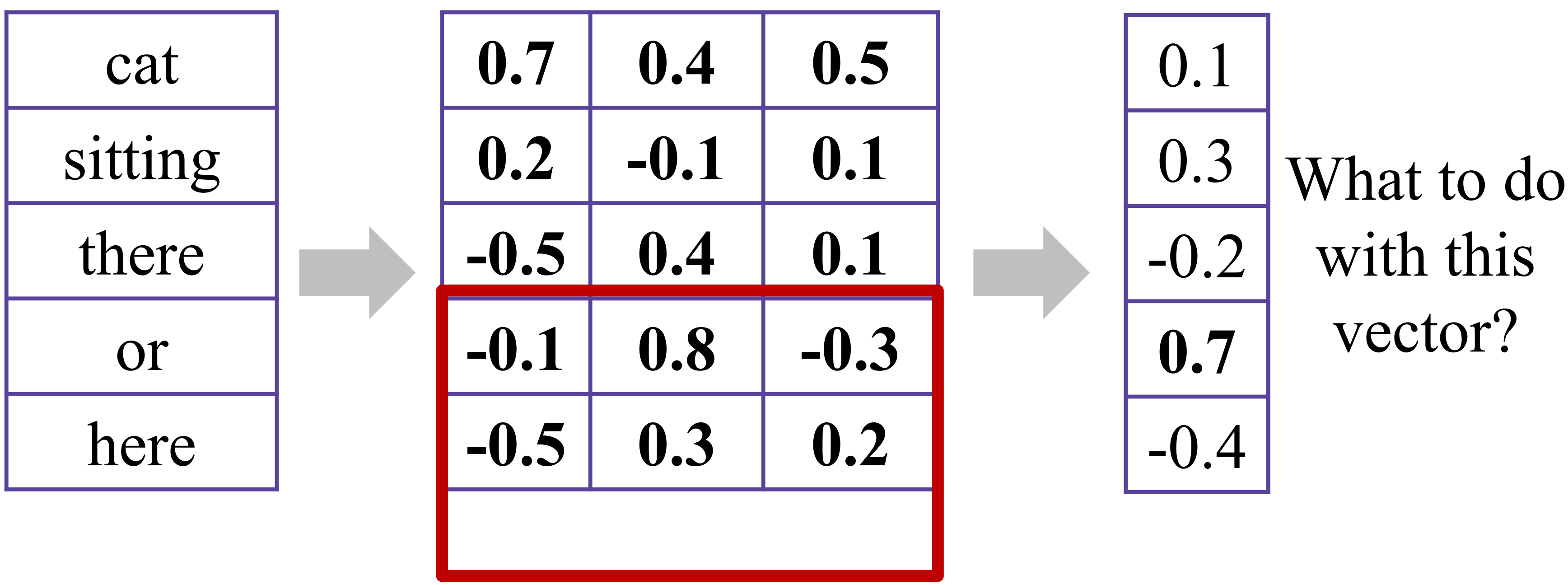

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-0.1	**0.8**	**-0.3**
-0.5	**0.3**	**0.2**

0.7

Maximum pooling over time!

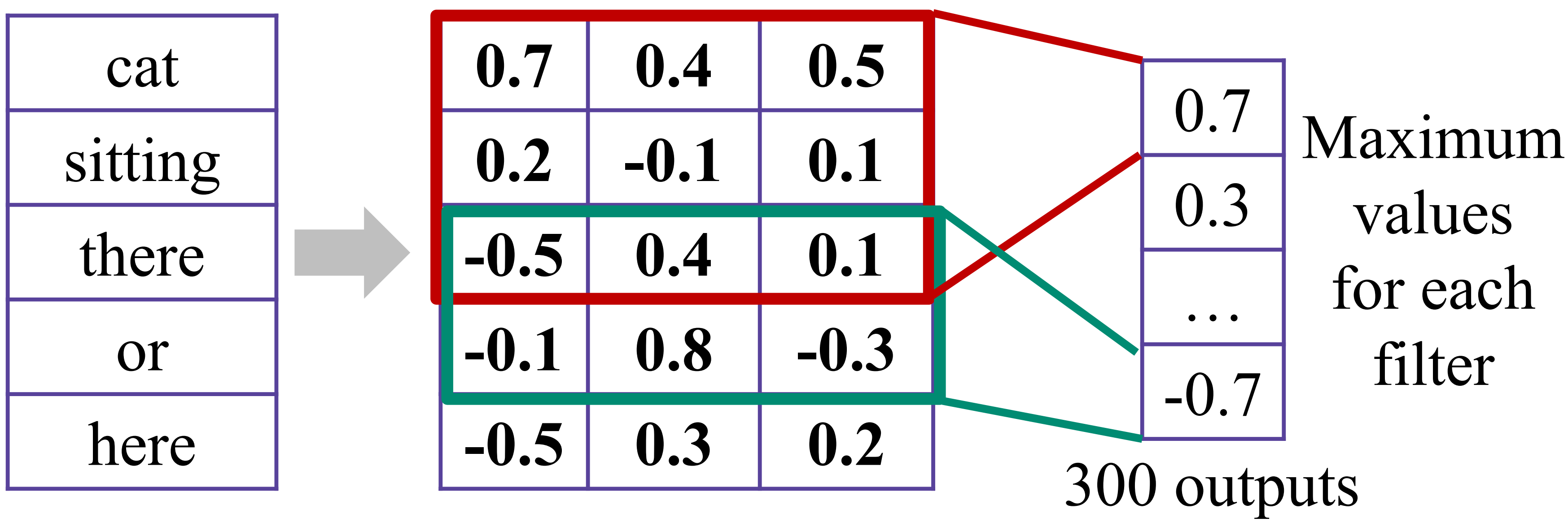
Let's train many filters

Final architecture

- 3,4,5-gram windows with 100 filters each
- MLP on top of these 300 features

Quality comparison on customer reviews (CR)

- Naïve Bayes on top of 1,2-grams – 86.3% accuracy
- 1D convolutions with MLP – 89.6% (+3.8%) accuracy



http://www.jmlr.org/papers/volume12/collobert11a/collobert11a.pdf https://arxiv.org/pdf/1408.5882.pdf

Going deeper with text

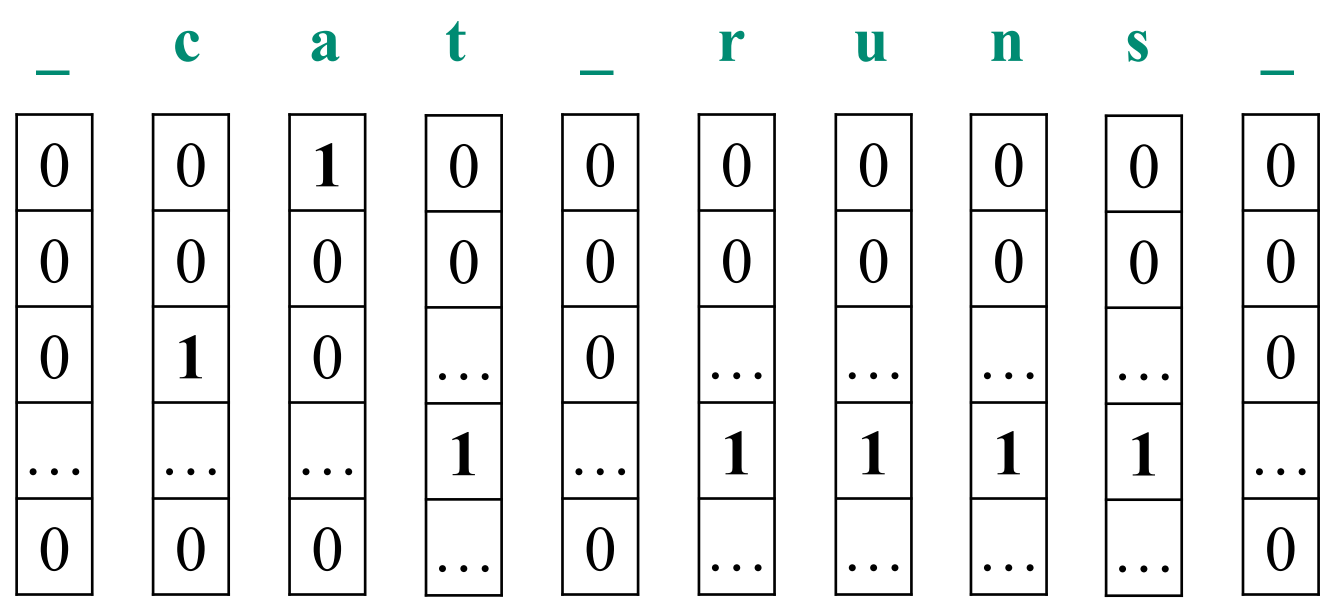
What is text?

You can think of text as a sequence of

- **Characters**
- Words
- Phrases and named entities
- Sentences
- Paragraphs
- …

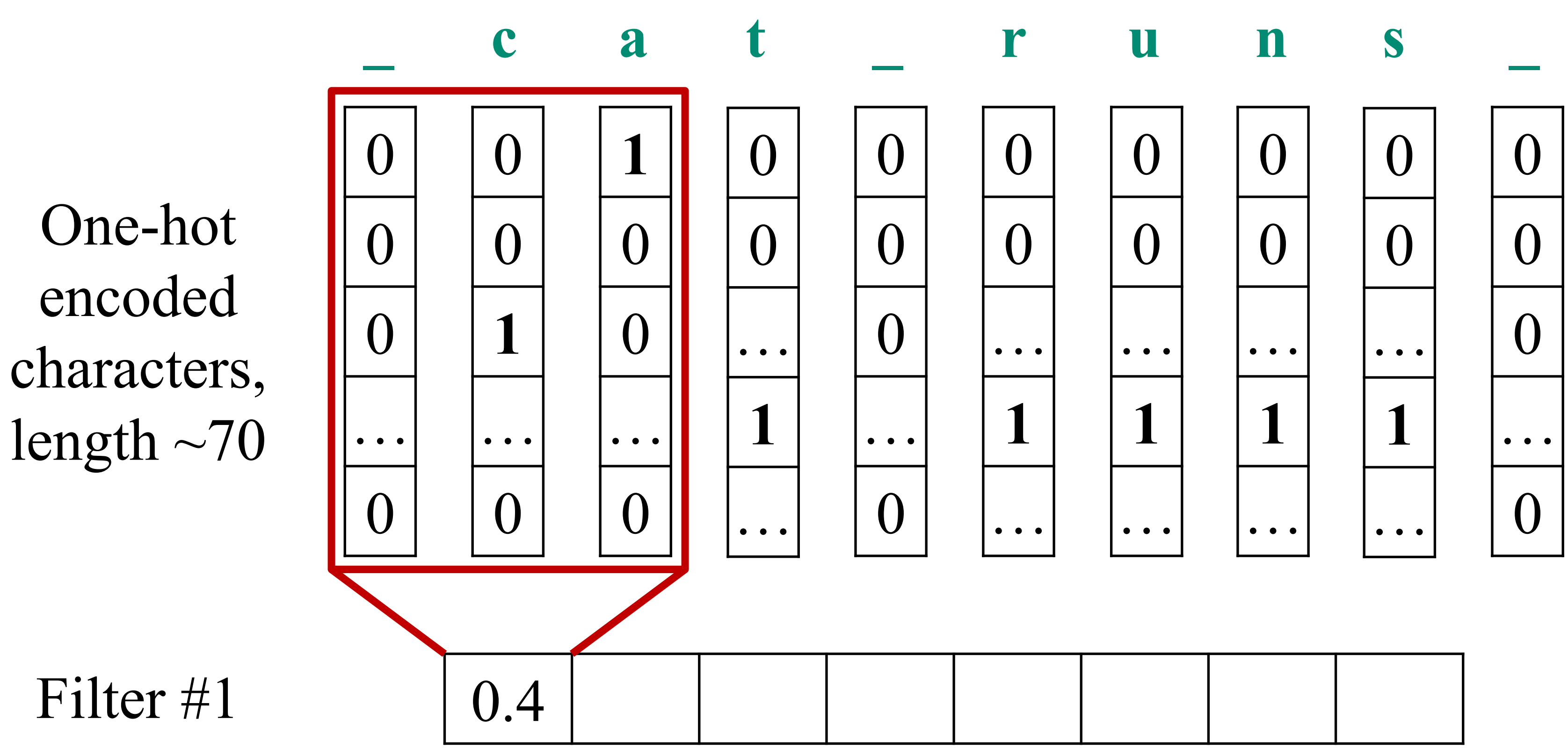
Text as a sequence of characters

One-hot encoded characters, length ~70

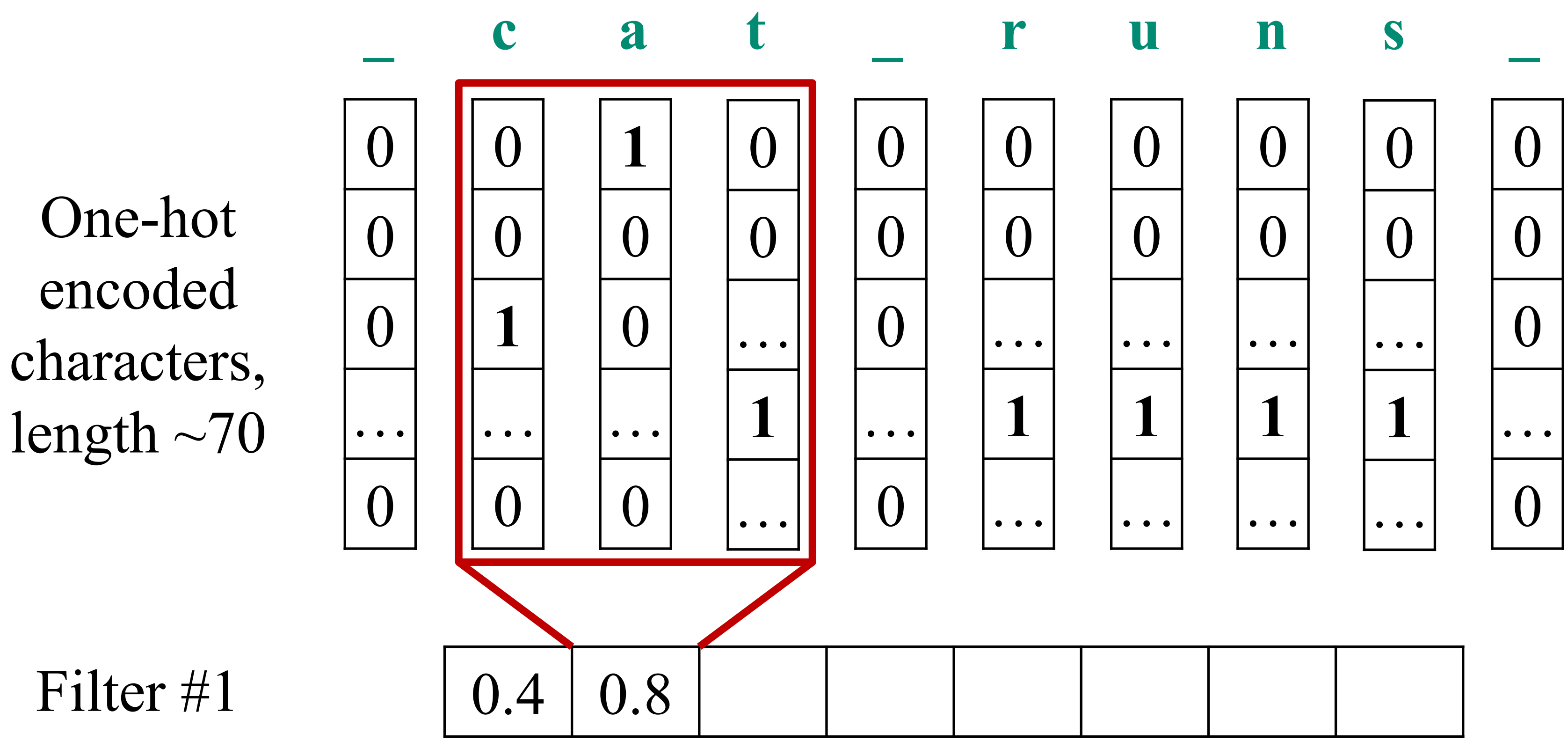


Let's start with character *n*-grams!

1D convolutions on characters

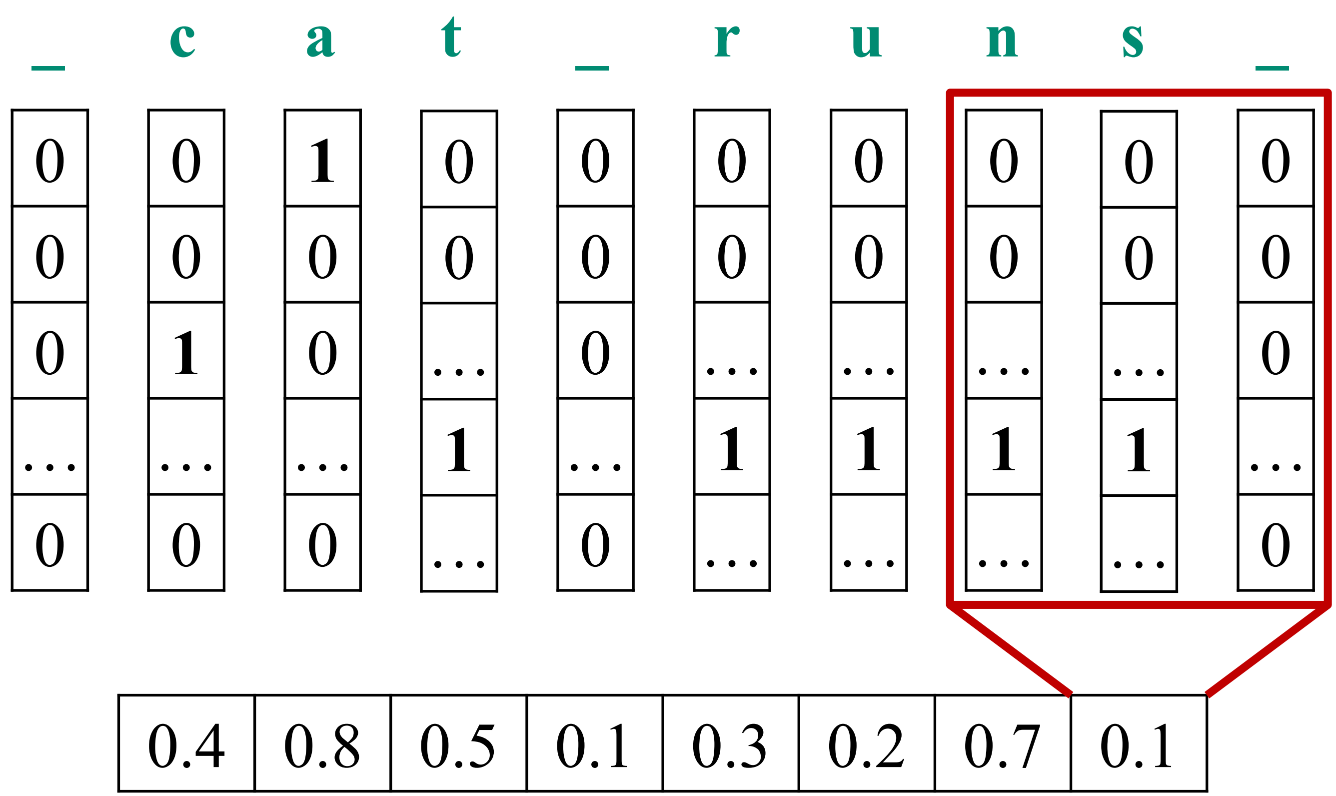


1D convolutions on characters



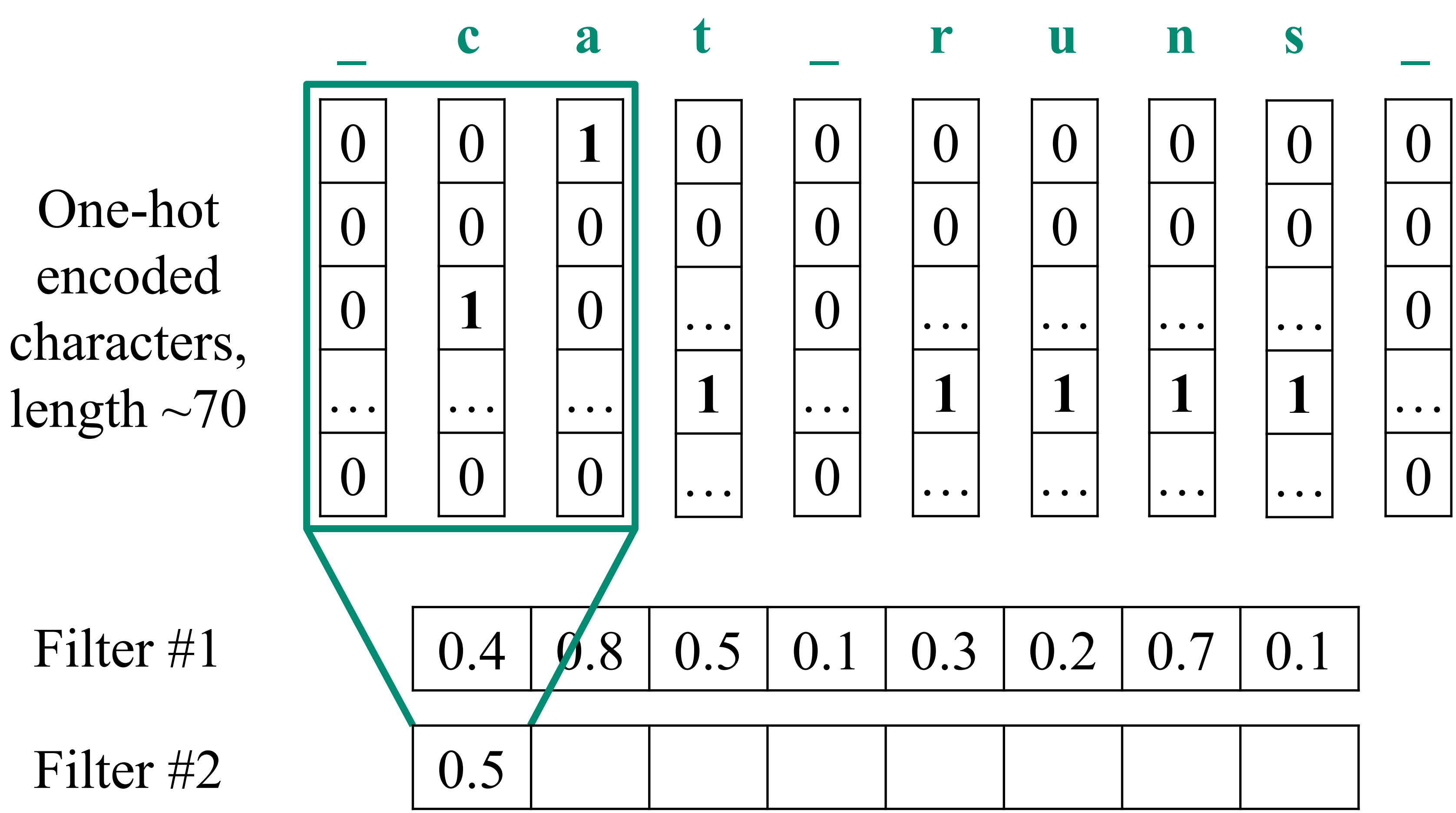
1D convolutions on characters

One-hot encoded characters, length ~70

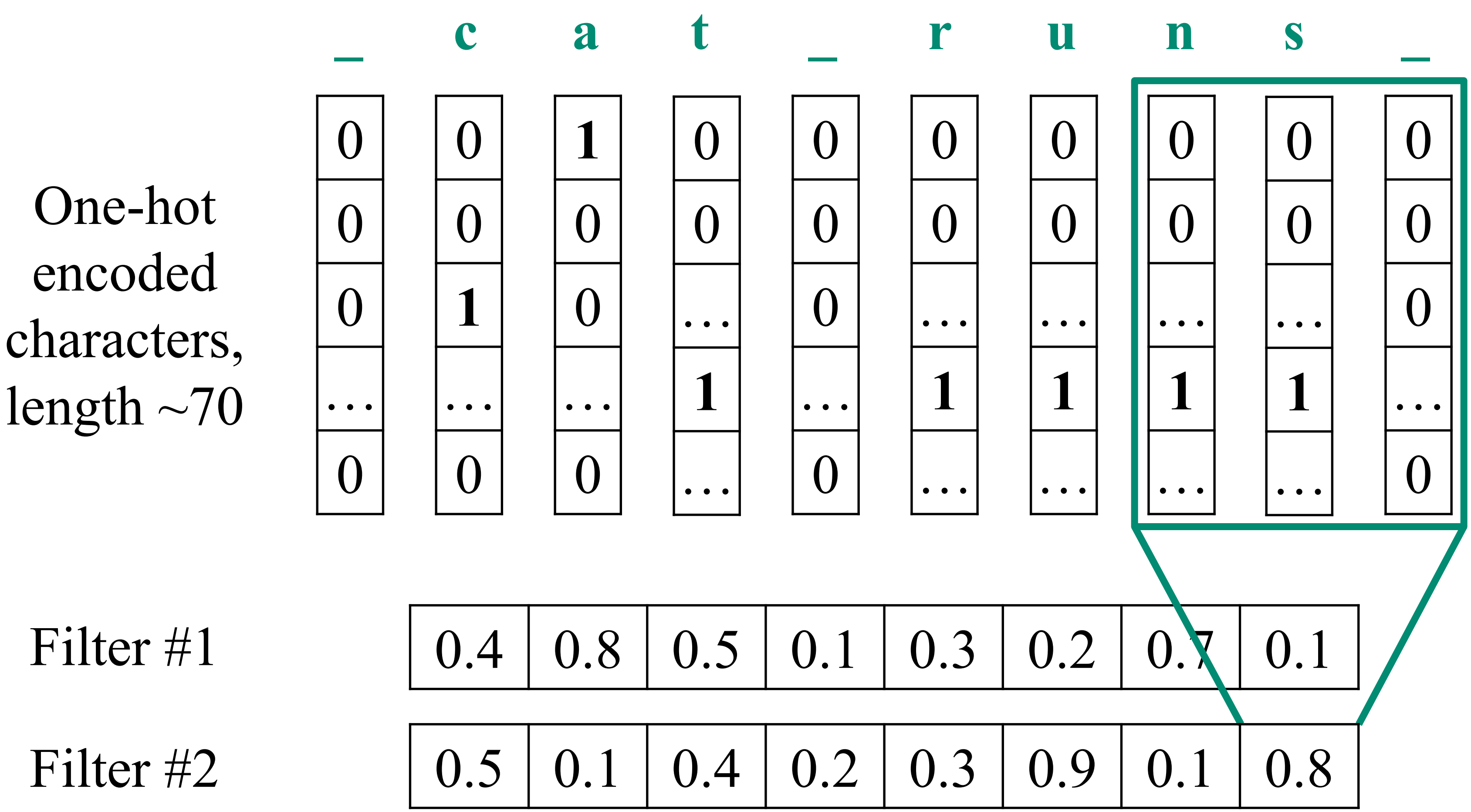


Filter #1

1D convolutions on characters



1D convolutions on characters



1D convolutions on characters

One-hot encoded characters, length ~70

_	c	a	t	_	r	u	n	s	_
0	0	**1**	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	**1**	0	…	0	…	…	…	…	0
…	…	…	**1**	…	**1**	**1**	**1**	**1**	…
0	0	0	…	0	…	…	…	…	0

Filter #1	0.4	0.8	0.5	0.1	0.3	0.2	0.7	0.1
Filter #2	0.5	0.1	0.4	0.2	0.3	0.9	0.1	0.8
Filter #3	0.4	0.7	0.3	0.7	0.5	0.5	0.9	0.4

~1024 filters

What's next? Let's add pooling!

Max pooling

Filter #1	0.4	0.8	0.5	0.1	0.3	0.2	0.7	0.1
Filter #2	0.5	0.1	0.4	0.2	0.3	0.9	0.1	0.8
Filter #3	0.4	0.7	0.3	0.7	0.5	0.5	0.9	0.4

0.8			

Max pooling

Filter #1	0.4	0.8	0.5	0.1	0.3	0.2	0.7	0.1
Filter #2	0.5	0.1	0.4	0.2	0.3	0.9	0.1	0.8
Filter #3	0.4	0.7	0.3	0.7	0.5	0.5	0.9	0.4

0.8	0.5		

Max pooling

Filter #1	0.4	0.8	0.5	0.1	0.3	0.2	0.7	0.1
Filter #2	0.5	0.1	0.4	0.2	0.3	0.9	0.1	0.8
Filter #3	0.4	0.7	0.3	0.7	0.5	0.5	0.9	0.4

0.8	0.5	0.3	0.7

Max pooling

Filter #1	0.4	0.8	0.5	0.1	0.3	0.2	0.7	0.1
Filter #2	0.5	0.1	0.4	0.2	0.3	0.9	0.1	0.8
Filter #3	0.4	0.7	0.3	0.7	0.5	0.5	0.9	0.4

Pooling output

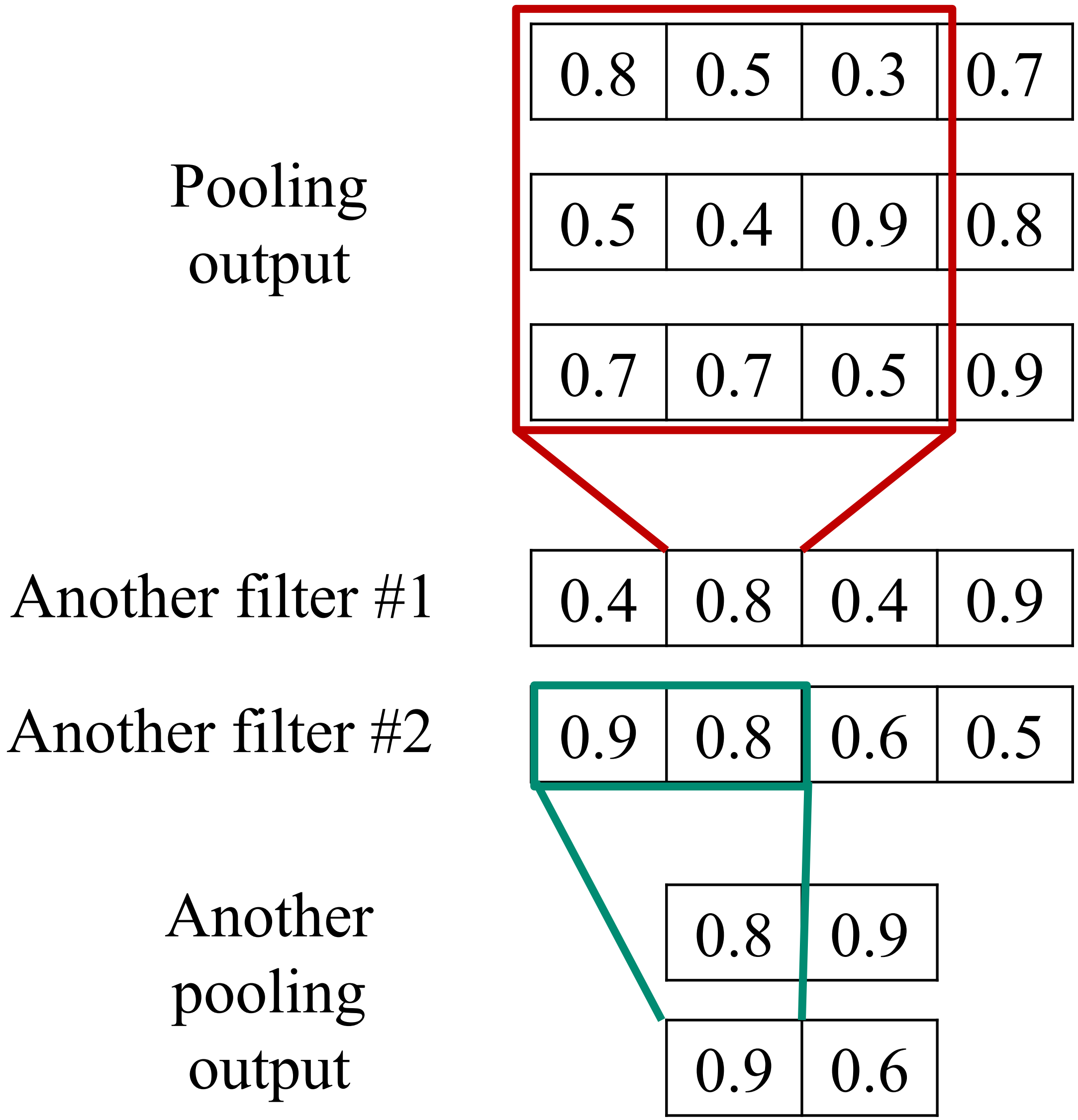
0.8	0.5	0.3	0.7
0.5	0.4	0.9	0.8
0.7	0.7	0.5	0.9

Provides a little bit of position invariance for character n-grams

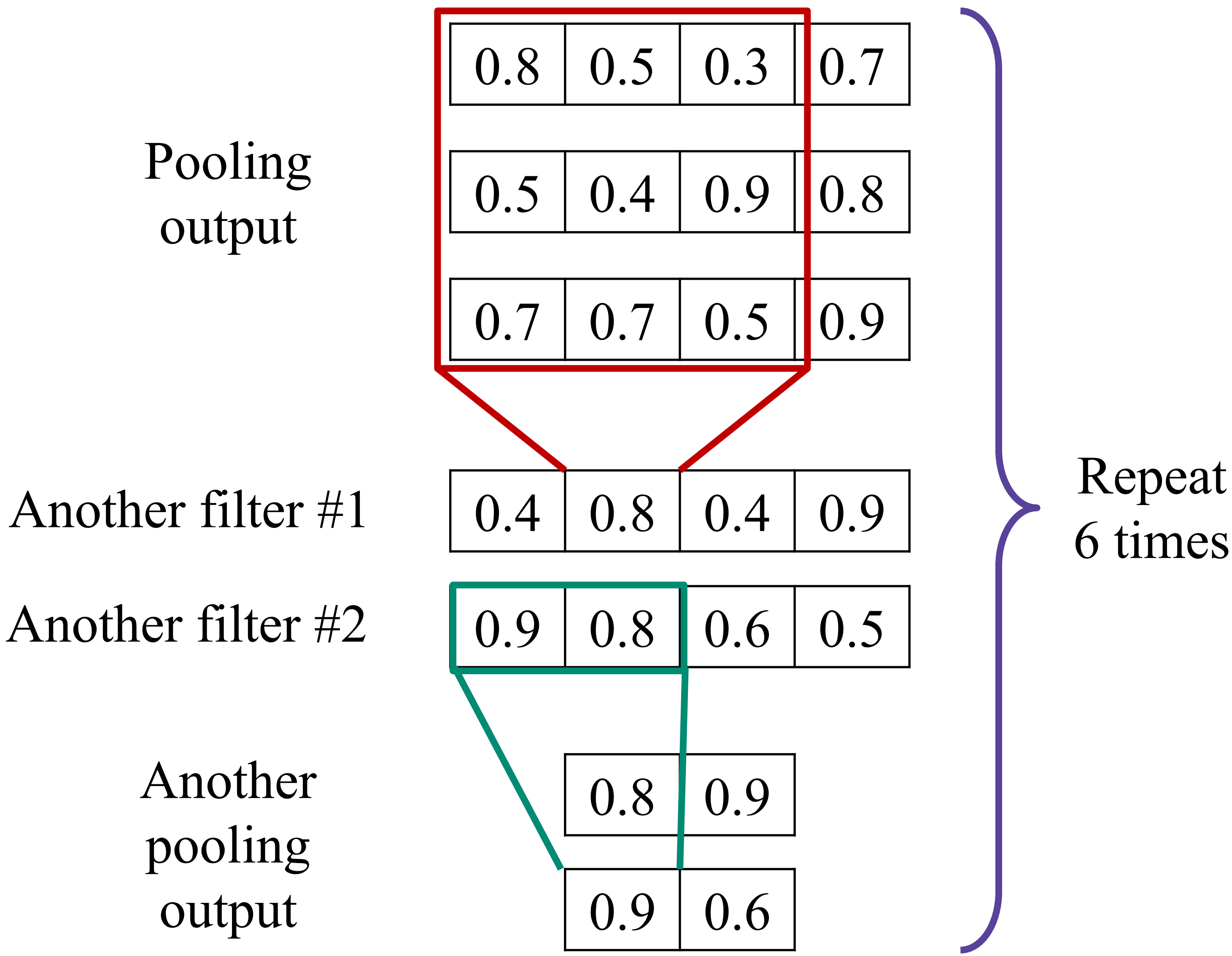
Repeat 1D convolution + pooling

Pooling output	0.8	0.5	0.3	0.7
	0.5	0.4	0.9	0.8
	0.7	0.7	0.5	0.9
Another filter #1	0.4	0.8	0.4	0.9
Another filter #2	0.9	0.8	0.6	0.5

Repeat 1D convolution + pooling



Repeat 1D convolution + pooling



Final architecture

- Let's take only first **1014** characters of text
- Apply 1D convolution + max pooling **6** times
  - Kernels widths: 7, 7, 3, 3, 3, 3
  - Filters at each step: 1024
- After that we have a $\mathbf{1024 \times 34}$ matrix of features
- Apply MLP for your task

https://arxiv.org/pdf/1509.01626.pdf

Experimental datasets

Categorization or sentiment analysis

	Dataset	Classes	Train Samples
Smaller	AG's News	4	120,000
	Sogou News	5	450,000
	DBPedia	14	560,000
	Yelp Review Polarity	2	560,000
Bigger	Yelp Review Full	5	650,000
	Yahoo! Answers	10	1,400,000
	Amazon Review Full	5	3,000,000
	Amazon Review Polarity	2	3,600,000

https://arxiv.org/pdf/1509.01626.pdf

Experimental results

Errors on test set for classical models:

Model	AG	Sogou	DBP.	Yelp P.	Yelp F.	Yah. A.	Amz. F.	Amz. P.
BoW	11.19	7.15	3.39	7.76	42.01	31.11	45.36	9.60
BoW TFIDF	10.36	6.55	2.63	6.34	40.14	28.96	44.74	9.00
ngrams	7.96	2.92	1.37	**4.36**	43.74	31.53	45.73	7.98
ngrams TFIDF	**7.64**	**2.81**	**1.31**	4.56	45.20	31.49	47.56	8.46

Errors on test set for deep models:

LSTM	13.94	4.82	1.45	5.26	41.83	29.16	40.57	6.10
Sm. Full Conv.	11.59	8.95	1.89	5.67	38.82	30.01	40.88	5.78
Lg. Full Conv. Th.	9.51	-	1.55	4.88	38.04	29.58	40.54	5.51
Sm. Full Conv. Th.	10.89	-	1.69	5.42	**37.95**	29.90	40.53	5.66
Lg. Conv.	12.82	4.88	1.73	5.89	39.62	29.55	41.31	5.51
Sm. Conv.	15.65	8.65	1.98	6.53	40.84	29.84	40.53	5.50
Lg. Conv. Th.	13.39	-	1.60	5.82	39.30	**28.80**	40.45	**4.93**
Sm. Conv. Th.	14.80	-	1.85	6.49	40.16	29.84	**40.43**	5.67

Deep models work better for large datasets!

https://arxiv.org/pdf/1509.01626.pdf

Summary

- You can use convolutional networks on top of characters (called learning from scratch)
- It works best for large datasets where it beats classical approaches (like BOW)
- Sometimes it even beats LSTM that works on word level