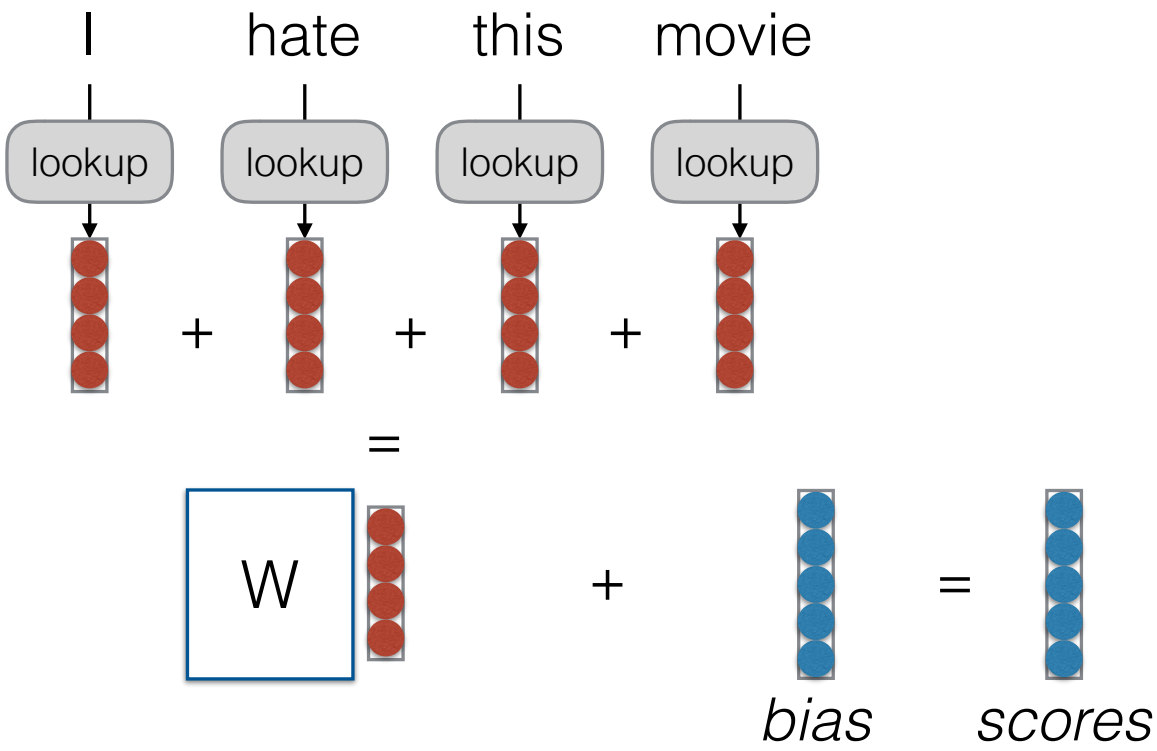
Continuous Bag of Words (CBOW)



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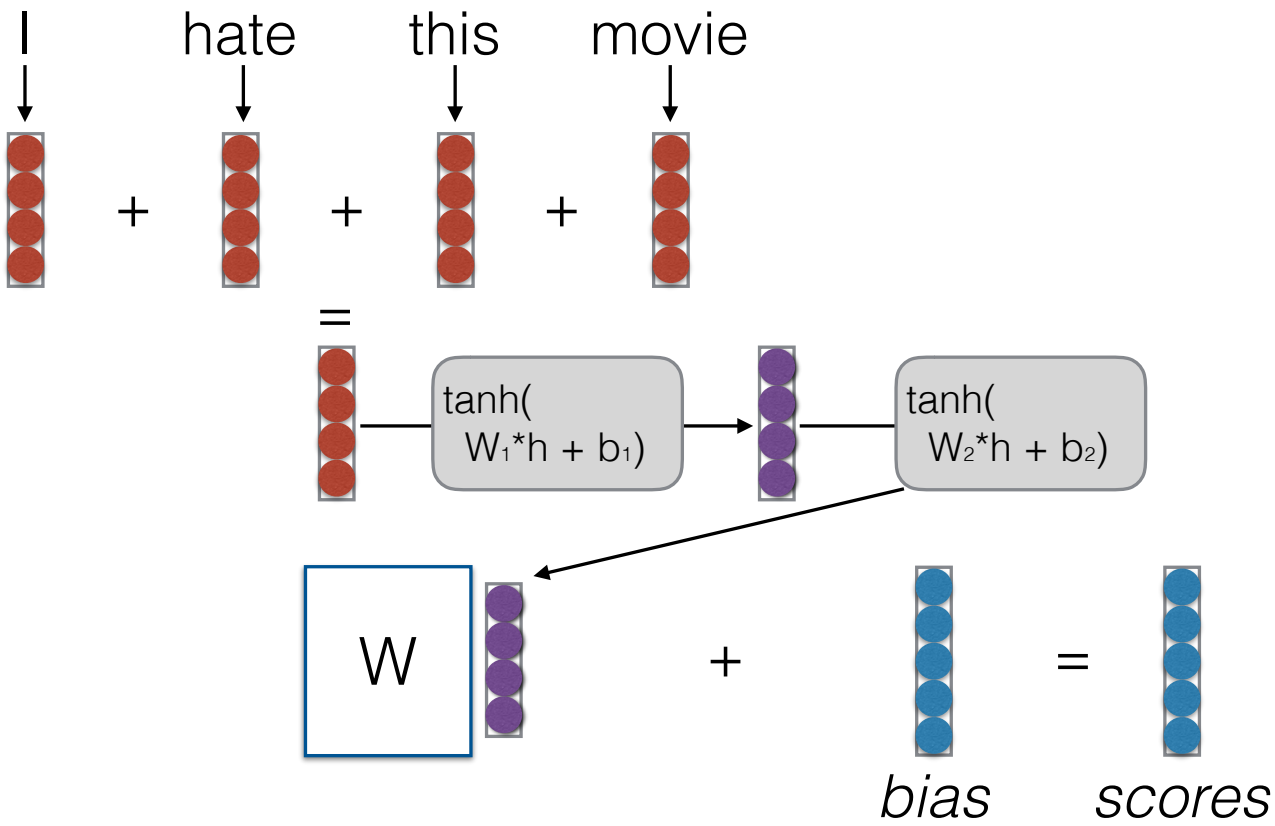
Deep CBOW



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What do Our Vectors Represent?

- We can learn feature combinations (a node in the second layer might be “feature 1 AND feature 5 are active”)
- e.g. capture things such as “not” AND “hate”
- BUT! Cannot handle “not hate”

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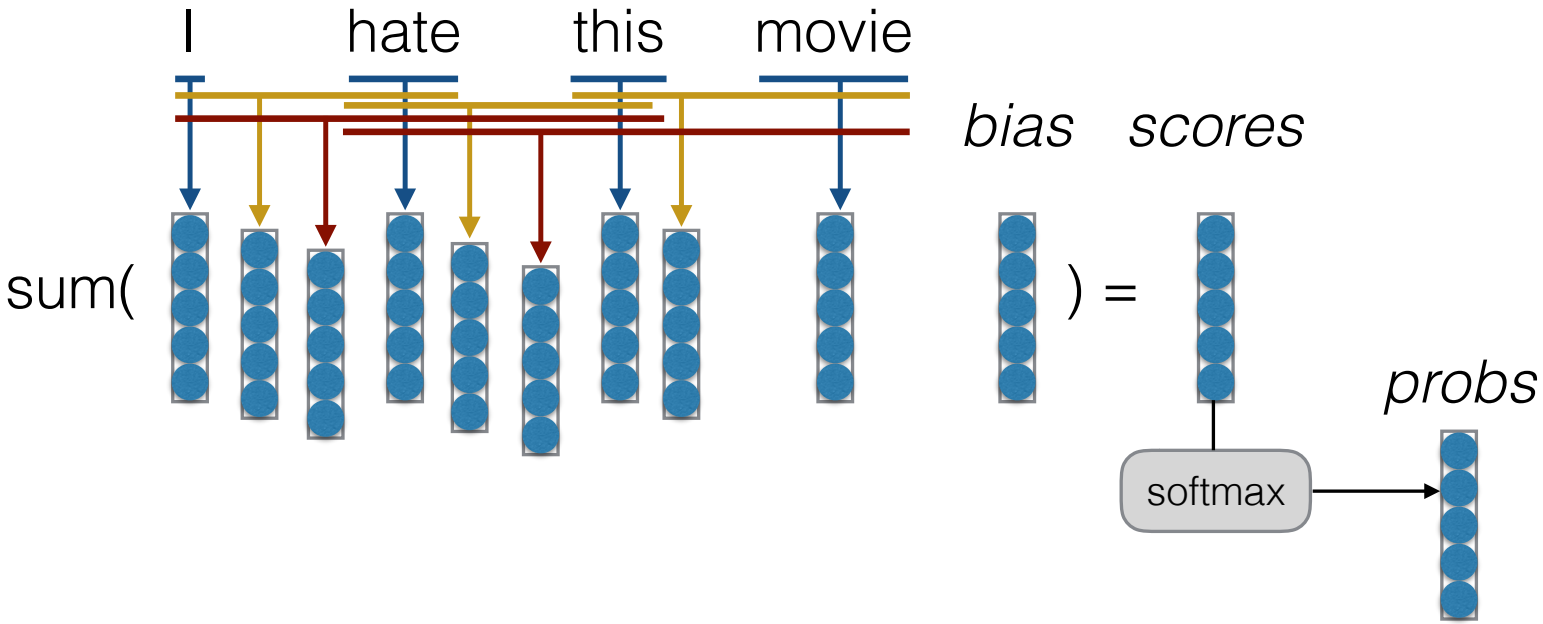
Content

Bag of n-grams



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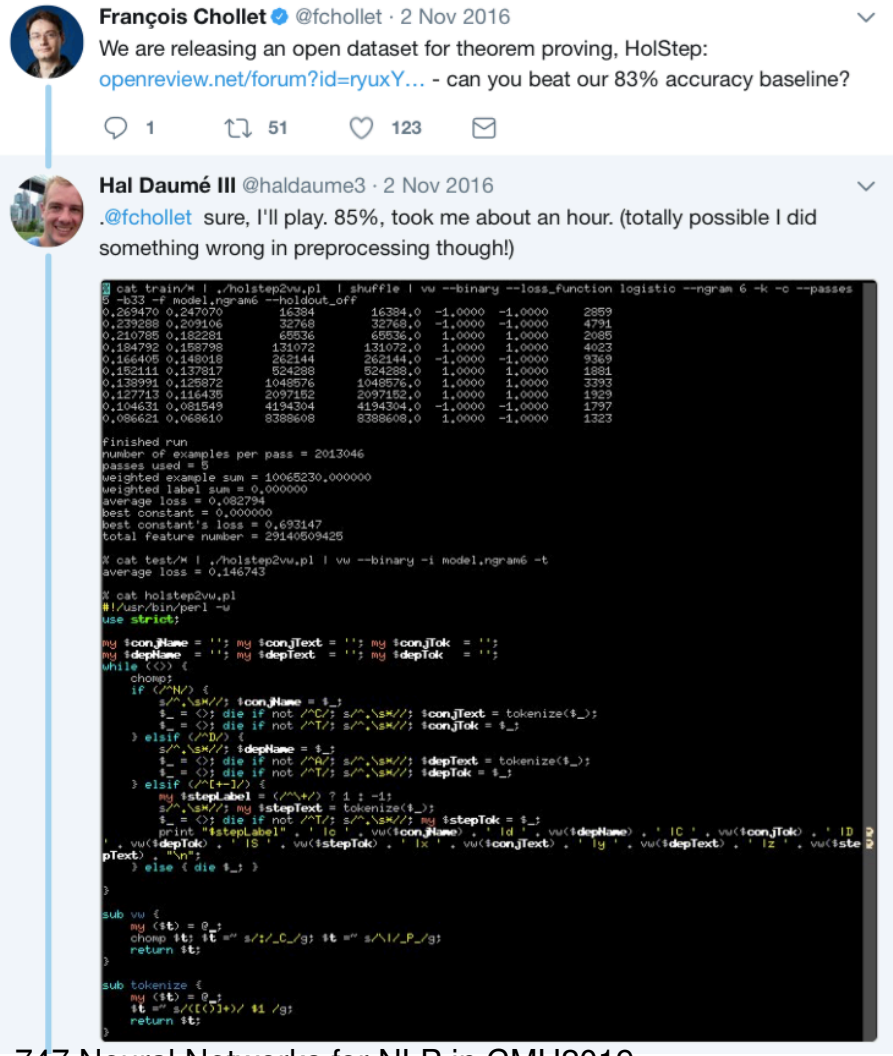
Why Bag of n-grams?

- Allow us to capture combination features in a simple way “don’t love”, “not the best”
- Works pretty well



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What Problems w/ Bag of n-grams?

- Same as before: parameter explosion
- No sharing between similar words/n-grams

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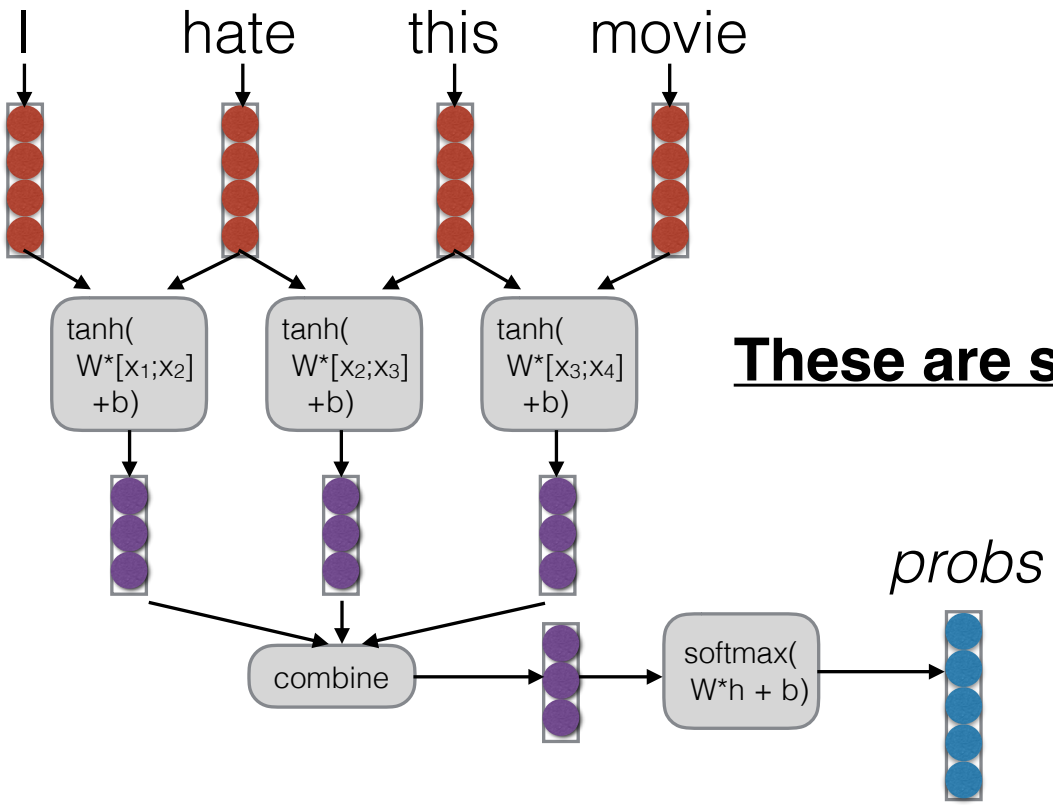
Content

1-dimensional Convolutions / Time-delay Networks

(Waibel et al. 1989)



These are soft 2-grams!

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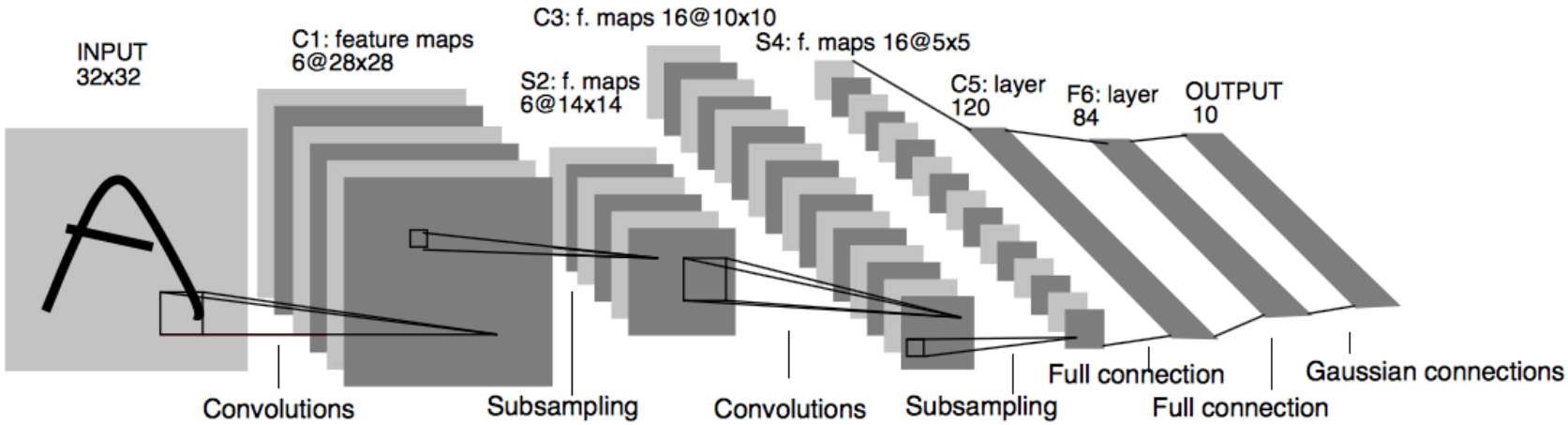
2-dimensional Convolutional Networks

(LeCun et al. 1997)



Parameter extraction performs a 2D sweep, not 1D

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CNNs for Text
(Collobert and Weston 2011)

- Generally based on 1D convolutions
  - But often uses terminology/functions borrowed from image processing for historical reasons
- Two main paradigms:
  - **Context window modeling:** For tagging, etc. get the surrounding context before tagging
  - **Sentence modeling:** Do convolution to extract n-grams, pooling to combine over whole sentence

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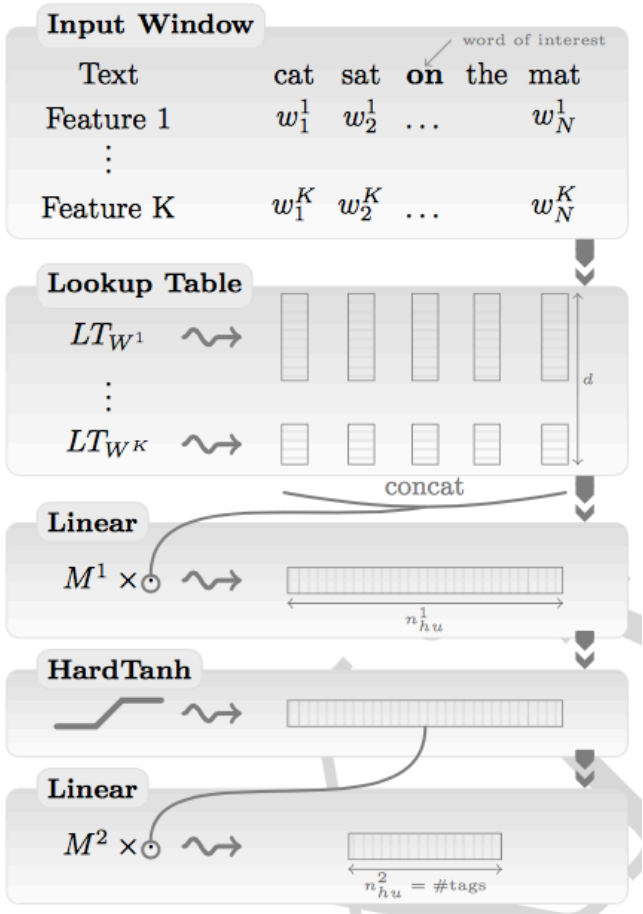
CNNs for Tagging

(Collobert and Weston 2011)



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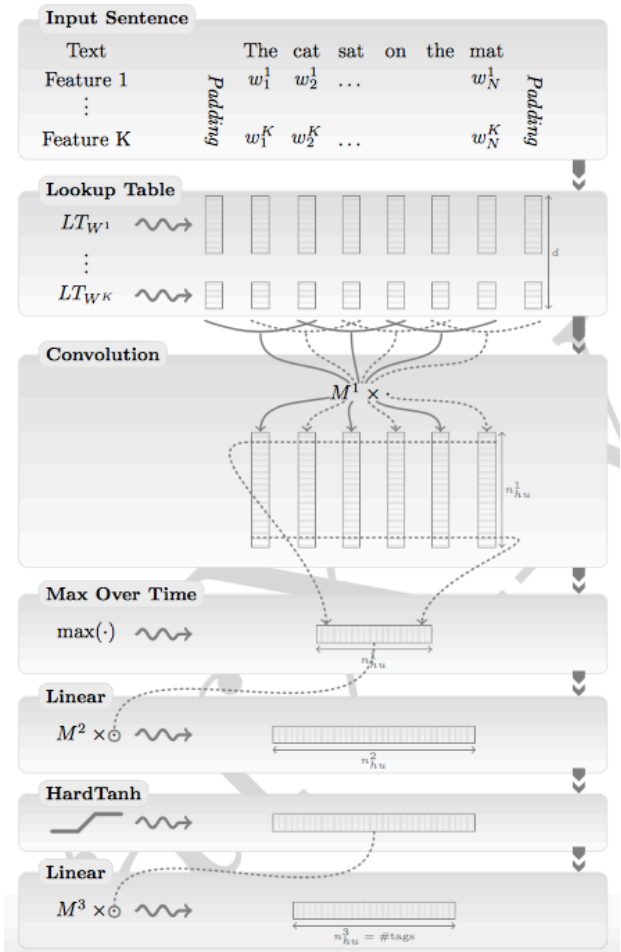
CNNs for Sentence Modeling

(Collobert and Weston 2011)



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Standard conv2d Function

- 2D convolution function takes input + parameters
- **Input:** 3D tensor
  - rows (e.g. words), columns, features ("channels")
- **Parameters/Filters:** 4D tensor
  - rows, columns, input features, output features

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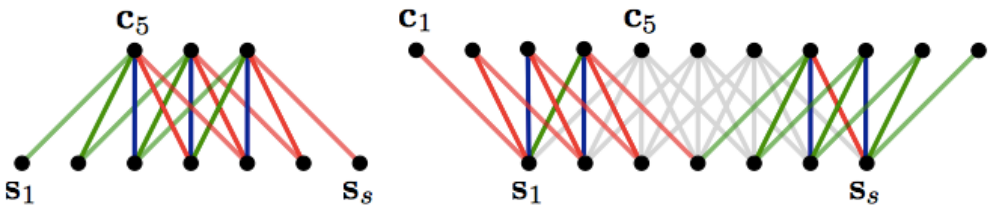
Padding

- After convolution, the rows and columns of the output tensor are either
  - = to rows/columns of input tensor (*"same"* convolution)
  - = to rows/columns of input tensor minus the size of the filter plus one (*"valid"* or *"narrow"*)
  - = to rows/columns of input tensor plus filter minus one (*"wide"*)

Narrow →



← Wide

Image: Kalchbrenner et al. 2014

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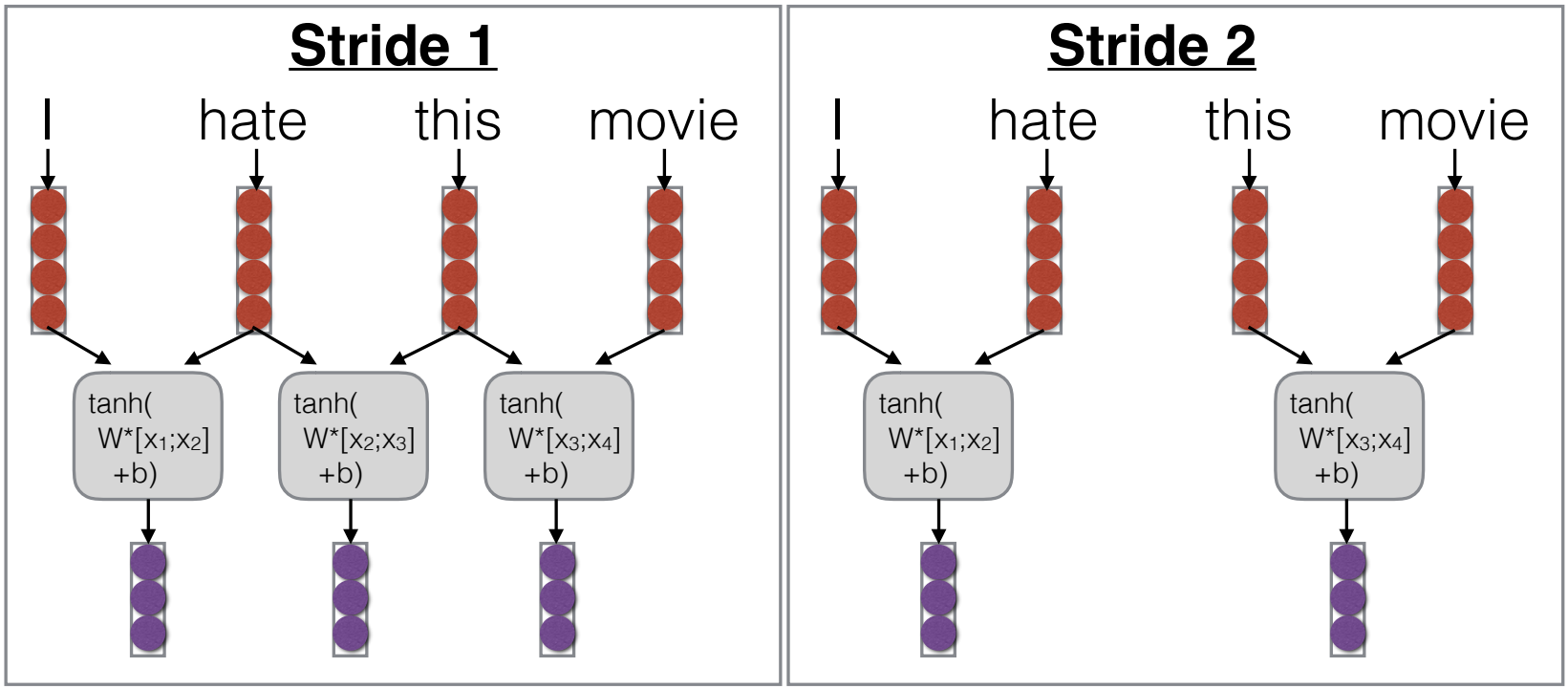
Striding

- Skip some of the outputs to reduce length of extracted feature vector



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Pooling

- Pooling is like convolution, but calculates some reduction function feature-wise
- **Max pooling:** "Did you see this feature anywhere in the range?" (most common)
- **Average pooling:** "How prevalent is this feature over the entire range"
- **k-Max pooling:** "Did you see this feature up to k times?"
- **Dynamic pooling:** "Did you see this feature in the beginning? In the middle? In the end?"

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Content

Stacked Convolution

- Feeding in convolution from previous layer results in larger area of focus for each feature

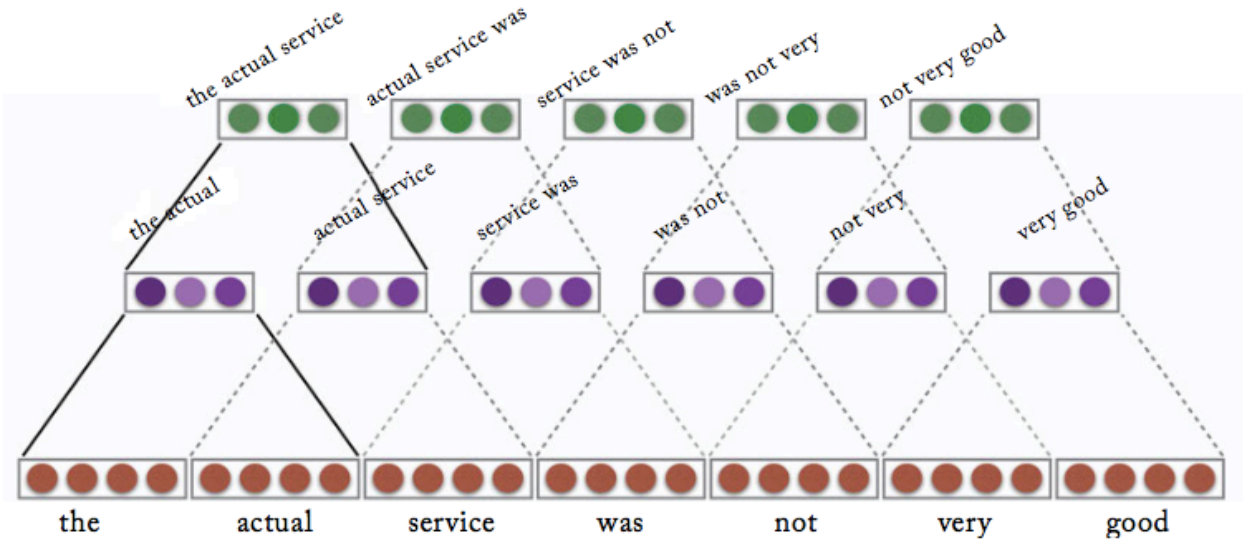

Image Credit: Goldberg Book

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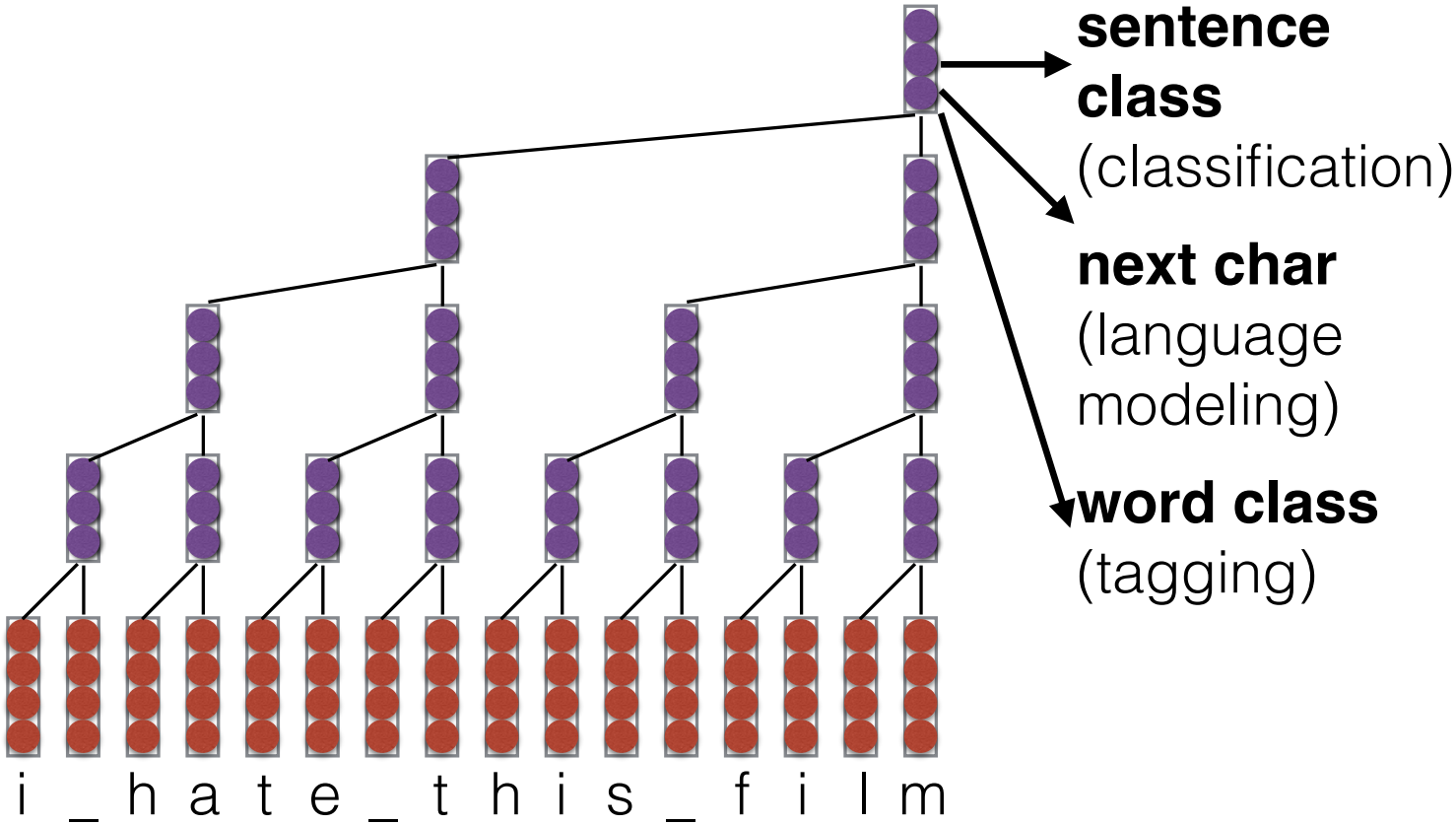
Dilated Convolution

(e.g. Kalchbrenner et al. 2016)

- **Gradually increase stride**, every time step (no reduction in length)



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Why (Dilated) Convolution for Modeling Sentences?

- In contrast to recurrent neural networks (next class)
- **+** Fewer steps from each word to the final representation: RNN O(N), Dilated CNN O(log N)
- **+** Easier to parallelize on GPU
- **-** Slightly less natural for arbitrary-length dependencies
- **-** A bit slower on CPU?

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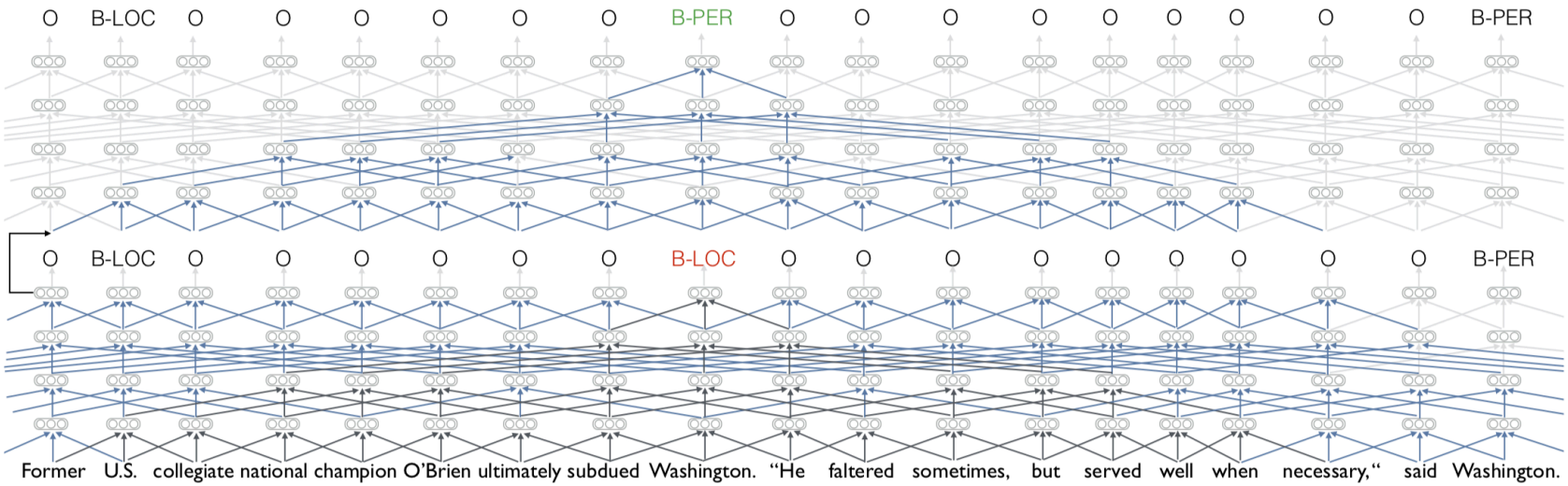
Iterated Dilated Convolution

(Strubell+ 2017)

- Multiple iterations of the same stack of dilated convolutions



- Wider context, more parameter efficient

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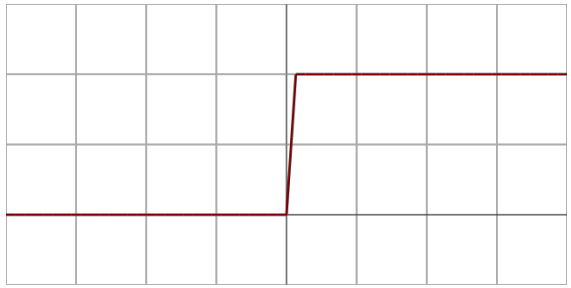
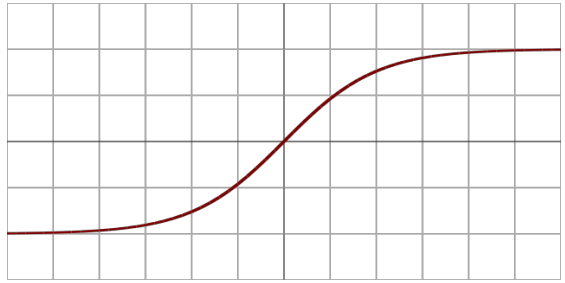
Content

Non-linear Functions

- Proper choice of a non-linear function is essential in stacked networks

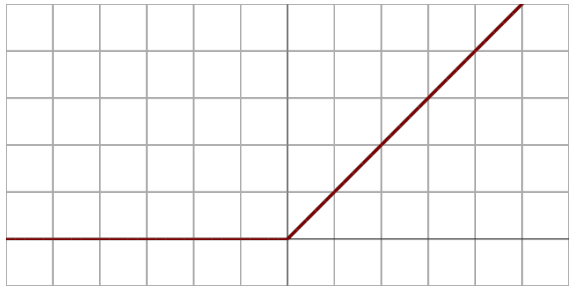
step

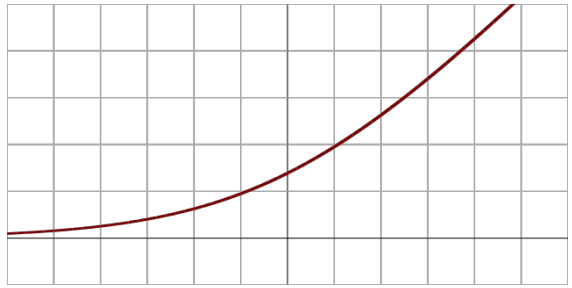




tanh

rectifier (RelU)





soft plus

- Functions such as RelU or softplus allegedly better at preserving gradients

Image: Wikipedia

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Which Non-linearity Should I Use?

- Ultimately an empirical question
- Many new functions proposed, but search by Eger et al. (2018) over NLP tasks found that standard functions such as tanh and relu quite robust

sigmoid	$f(x) = \sigma(x) = 1/(1+\exp(-x))$
swish	$f(x) = x \cdot \sigma(x)$
maxsig	$f(x) = \max\{x, \sigma(x)\}$
cosid	$f(x) = \cos(x) - x$
minsin	$f(x) = \min\{x, \sin(x)\}$
arctid	$f(x) = \arctan(x)^2 - x$
maxtanh	$f(x) = \max\{x, \tanh(x)\}$
lrelu-0.01	$f(x) = \max\{x, 0.01x\}$
lrelu-0.30	$f(x) = \max\{x, 0.3x\}$
penalized tanh	$f(x) = \begin{cases} \tanh(x) & x > 0, \\ 0.25\tanh(x) & x \leq 0 \end{cases}$

best	penalized tanh (6), swish (6), elu (4), relu (4), lrelu-0.01 (4)
mean	penalized tanh (16), tanh (13) sin (10)

Table 5: Top-3 winner statistics. In brackets: number of times within top-3, keeping only functions with four or more top-3 rankings.

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Content

A 1D convolution for text

tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3

t,d,r	−1.0
d,r,t	−0.5
r,t,k	−3.6
t,k,g	−0.2
k,g,o	0.3

Apply a **filter** (or **kernel**) of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

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1D convolution for text with padding

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Ø,t,d	−0.6
t,d,r	−1.0
d,r,t	−0.5
r,t,k	−3.6
t,k,g	−0.2
k,g,o	0.3
g,o,Ø	−0.5

Apply a **filter** (or **kernel**) of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

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3 channel 1D convolution with padding = 1

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1

Apply 3 **filters** of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

Could also use (zero) padding = 2

Also called “wide convolution”

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conv1d, padded with max pooling over time

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1
max p	0.3	1.6	1.4

Apply 3 **filters** of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

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conv1d, padded with ave pooling over time

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1
ave p	−0.87	0.26	0.53

Apply 3 **filters** of size 3

	3	1	2	−3
	−1	2	1	−3
14	1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

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Other less useful notions: stride = 2

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Ø,t,d	−0.6	0.2	1.4
d,r,t	−0.5	−0.1	0.8
t,k,g	−0.2	0.1	1.2
g,o,Ø	−0.5	−0.9	0.1

Apply 3 **filters** of size 3

	3	1	2	−3
	−1	2	1	−3
16	1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

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Less useful: local max pool, stride = 2

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Apply 3 **filters** of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1
Ø	−Inf	−Inf	−Inf

Ø,t,d,r	−0.6	1.6	1.4
d,r,t,k	−0.5	0.3	0.8
t,k,g,o	0.3	0.6	1.2
g,o,Ø,Ø	−0.5	−0.9	0.1

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conv1d, *k*-max pooling over time, *k* = 2

Ø	**0.0**	**0.0**	**0.0**	**0.0**
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	**0.0**	**0.0**	**0.0**	**0.0**

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1

2-max p	−0.2	1.6	1.4
	0.3	0.6	1.2

Apply 3 **filters** of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

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Other somewhat useful notions: dilation = 2

Ø	0.0	0.0	0.0	0.0
tentative	0.2	0.1	−0.3	0.4
deal	0.5	0.2	−0.3	−0.1
reached	−0.1	−0.3	−0.2	0.4
to	0.3	−0.3	0.1	0.1
keep	0.2	−0.3	0.4	0.2
government	0.1	0.2	−0.1	−0.1
open	−0.4	−0.4	0.2	0.3
Ø	0.0	0.0	0.0	0.0

Apply 3 **filters** of size 3

3	1	2	−3
−1	2	1	−3
1	1	−1	1

1	0	0	1
1	0	−1	−1
0	1	0	1

1	−1	2	−1
1	0	−1	3
0	2	2	1

Ø,t,d	−0.6	0.2	1.4
t,d,r	−1.0	1.6	−1.0
d,r,t	−0.5	−0.1	0.8
r,t,k	−3.6	0.3	0.3
t,k,g	−0.2	0.1	1.2
k,g,o	0.3	0.6	0.9
g,o,Ø	−0.5	−0.9	0.1

1,3,5	0.3	0.0
2,4,6		
3,5,7		

2	3	1
1	−1	−1
3	1	0

1	3	1
1	−1	−1
3	1	−1

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Content

3. Single Layer CNN for Sentence Classification

- Yoon Kim (2014): Convolutional Neural Networks for Sentence Classification. EMNLP 2014. https://arxiv.org/pdf/1408.5882.pdf Code: https://arxiv.org/pdf/1408.5882.pdf [Theano!, etc.]
- A variant of convolutional NNs of Collobert, Weston et al. (2011)

- Goal: Sentence classification:
  - Mainly positive or negative sentiment of a sentence
  - Other tasks like:
    - Subjective or objective language sentence
    - Question classification: about person, location, number, …

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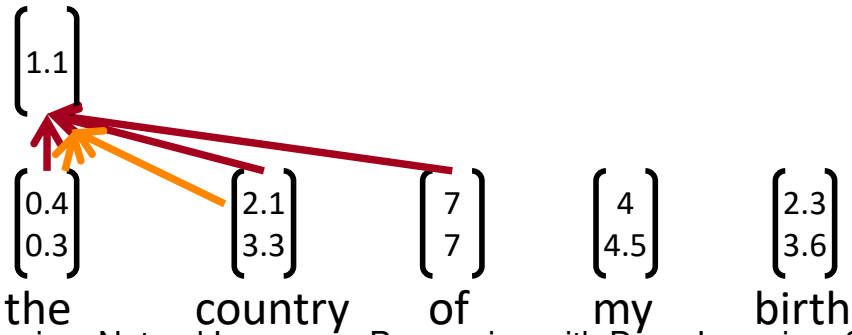
Single Layer CNN for Sentence Classification

- A simple use of one convolutional layer and **pooling**
- Word vectors: $\mathbf{x}_i \in \mathbb{R}^k$
- Sentence: $\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus x_2 \oplus \cdots \oplus \mathbf{x}_n$ (vectors concatenated)
- Concatenation of words in range: $\mathbf{x}_{i:i+j}$ (symmetric more common)
- Convolutional filter: $\mathbf{w} \in \mathbb{R}^{hk}$ (over window of *h* words)
- Note, filter is a vector!
- Filter could be of size 2, 3, or 4:



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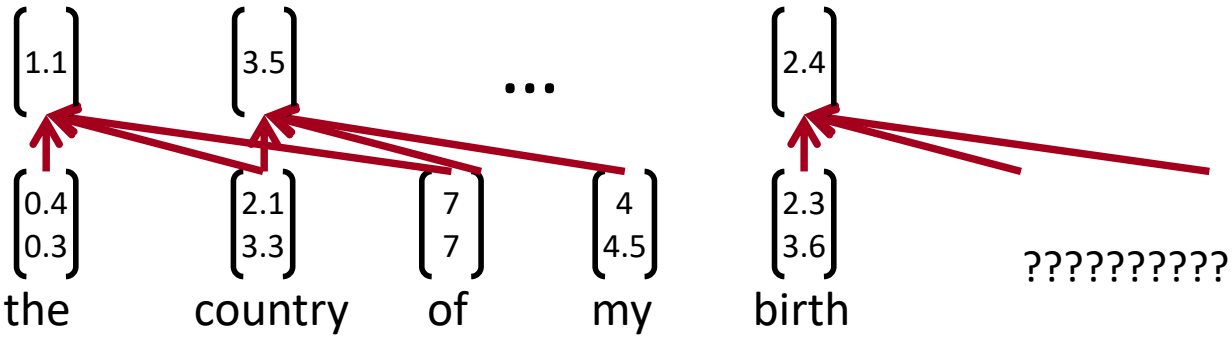
Single layer CNN

- Filter **w** is applied to all possible windows (concatenated vectors)
- To compute feature (one *channel*) for CNN layer:

$$c_i = f\left(\mathbf{w}^T \mathbf{x}_{i:i+h-1} + b\right)$$

- Sentence: $\mathbf{x}_{1:n} = \mathbf{x}_1 \oplus \mathbf{x}_2 \oplus \ldots \oplus \mathbf{x}_n$
- All possible windows of length *h*: $\{\mathbf{x}_{1:h}, \mathbf{x}_{2:h+1}, \ldots, \mathbf{x}_{n-h+1:n}\}$
- Result is a feature map: $\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$



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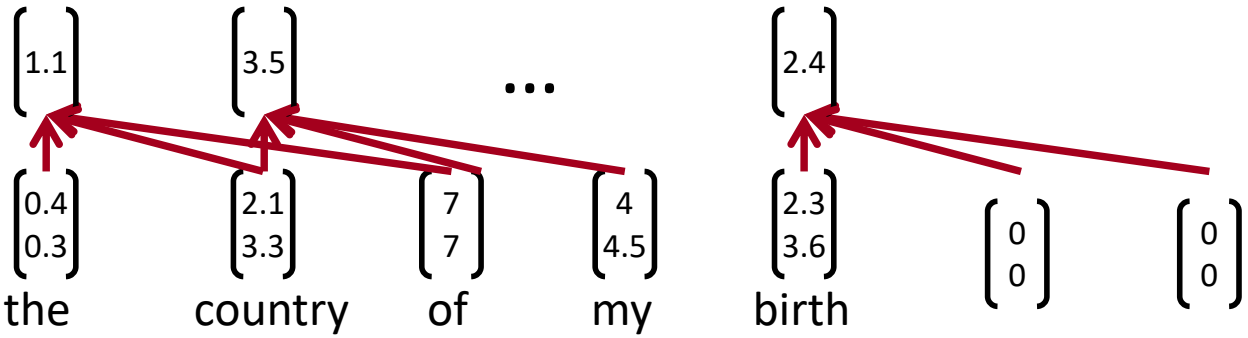

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Pooling and channels

- Pooling: max-over-time pooling layer
- Idea: capture most important activation (maximum over time)
- From feature map $\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$
- Pooled single number: $\hat{c} = \max\{\mathbf{c}\}$

- Use multiple filter weights **w**
- Useful to have different window sizes *h*
- Because of max pooling $\hat{c} = \max\{\mathbf{c}\}$, length of **c** irrelevant

$$\mathbf{c} = [c_1, c_2, \ldots, c_{n-h+1}] \in \mathbb{R}^{n-h+1}$$

- So we could have some filters that look at unigrams, bigrams, tri-grams, 4-grams, etc.

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Multi-channel input idea

- Initialize with pre-trained word vectors (word2vec or Glove)
- Start with two copies
- Backprop into only one set, keep other “static”
- Both channel sets are added to c_i before max-pooling

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Classification after one CNN layer

- First one convolution, followed by one max-pooling
- To obtain final feature vector: $\mathbf{z} = [\hat{c}_1, \ldots, \hat{c}_m]$ (assuming *m* filters **w**)
  - Used 100 feature maps each of sizes 3, 4, 5
- Simple final softmax layer $y = softmax\left(W^{(S)}z + b\right)$

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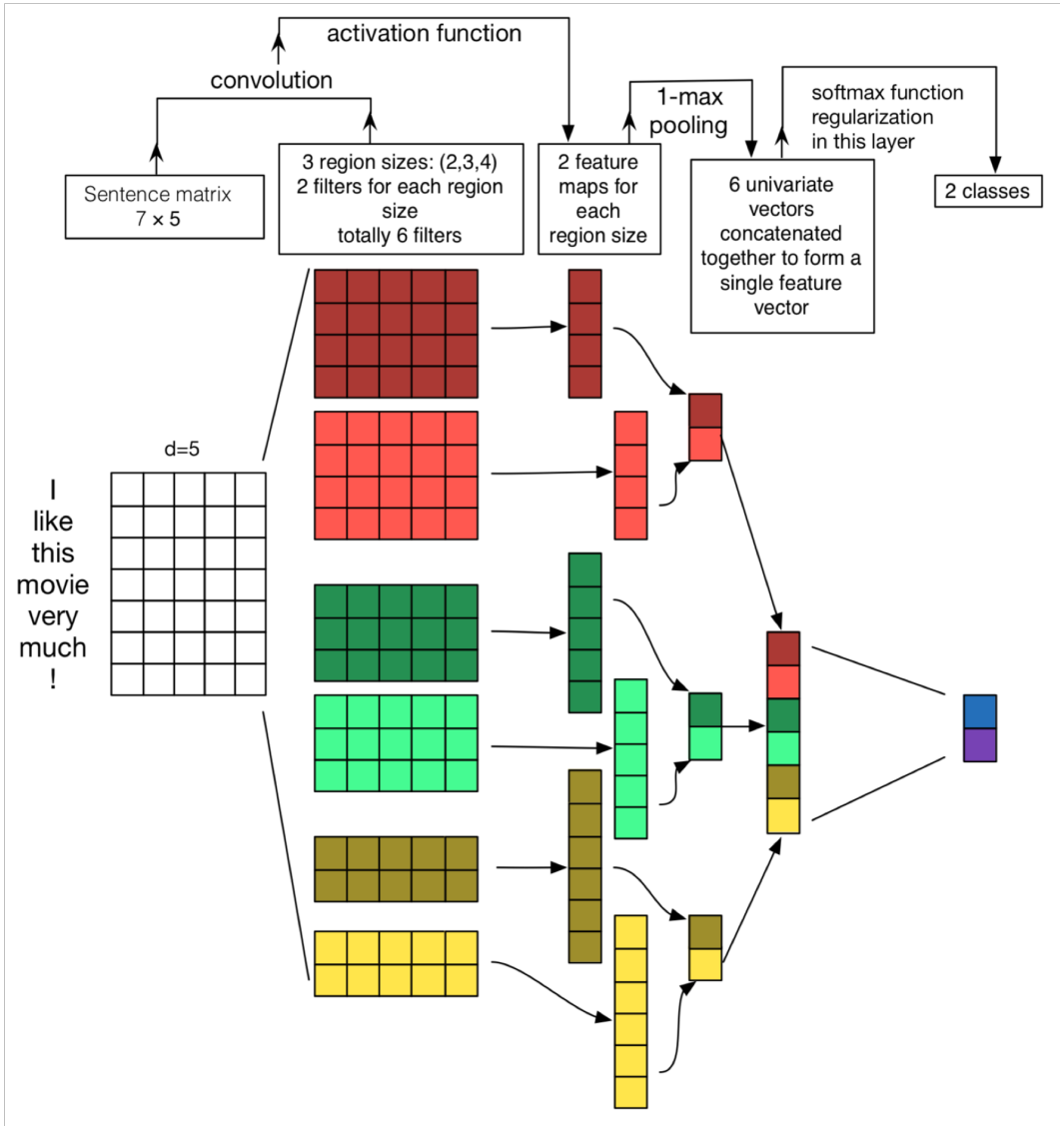
From:

Zhang and Wallace (2015) A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification

https://arxiv.org/pdf/1510.03820.pdf

(follow on paper, not famous, but a nice picture)



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Regularization

- Use **Dropout**: Create masking vector *r* of Bernoulli random variables with probability *p* (a hyperparameter) of being 1
- Delete features during training:

$$y = softmax\left(W^{(S)}(r \circ z) + b\right)$$

- Reasoning: Prevents co-adaptation (overfitting to seeing specific feature constellations) (Srivastava, Hinton, et al. 2014)
- At test time, no dropout, scale final vector by probability *p*

$$\hat{W}^{(S)} = pW^{(S)}$$

- **Also:** Constrain l_2 norms of weight vectors of each class (row in softmax weight $W^{(S)}$) to fixed number *s* (also a hyperparameter)
- If $\|W_{c\cdot}^{(S)}\| > s$, then rescale it so that: $\|W_{c\cdot}^{(S)}\| = s$
- Not very common

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All hyperparameters in Kim (2014)

- Find hyperparameters based on dev set
- Nonlinearity: ReLU
- Window filter sizes h = 3, 4, 5
- Each filter size has 100 feature maps
- Dropout p = 0.5
  - Kim (2014) reports **2–4%** accuracy improvement from dropout
- L2 constraint *s* for rows of softmax, *s* = 3
- Mini batch size for SGD training: 50
- Word vectors: pre-trained with word2vec, *k* = 300

- During training, keep checking performance on dev set and pick highest accuracy weights for final evaluation

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Experiments

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**	–	–

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Content

1. Artificial neural networks (ANNs)
2. Multilayer perceptron (MLP)
3. Convolutional neural networks (CNNs)
4. Convolutional Networks for Text Classification