# Deep Learning for NLP
# Convolutional Neural Networks

**Nils Reimers**

TECHNISCHE
UNIVERSITÄT
DARMSTADT

## Course-Website: www.deeplearning4nlp.com

# Recommended Readings

TECHNISCHE UNIVERSITÄT DARMSTADT

- https://www.youtube.com/watch?v=EevTPpQvxiU
- Kim, 2014, *Convolutional Neural Networks for Sentence Classification*
- http://cs231n.github.io/convolutional-networks/

# Convolutional Neural Network

TECHNISCHE UNIVERSITÄT DARMSTADT

- Universal architecture achieving state-of-the-art performance (in 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** | – | – |

Kim, 2014. Performance on Sentence Classification Tasks

# Some notes on Conv. Neural Networks

TECHNISCHE UNIVERSITÄT DARMSTADT

- Convolutional Neural Networks are dominating computer vision

- For NLP, they became popular in ~2014
  - But became less popular in 2015 / 2016, as everyone is using LSTM
  - Some papers in 2017 from Facebook Research show that they often can achieve similar performance to LSTM, requiring a lot less computational time

- Understanding the notation is quite difficult in computer vision
  - Images are typically 3 dimensional (width x height x color)
  - In NLP, we mainly deal with 1 dimensional data (our sentence / document)
  - Notation for 1 dimensional data is much simpler

# Convolutional Neural Networks solve 2 crucial Challenges

TECHNISCHE UNIVERSITÄT DARMSTADT

- **First Challenge:**
  - In a lot of cases, we have variable sized input data, e.g. length of sentence / length of document.
  - Our network / our hidden layers are of fixed sizes
  - Solution 1: Window Approach (Collobert et al.), but we don't capture information outside of the window
  - Solution 2: Recursive & Recurrent Neural Networks

- **Second Challenge:**
  - Increasing the window in the window approach allows us to capture more context information, but increases dramatically the number of parameters
  - Often the position in the context window is of minor importance:
    - Jim $[\text{sells}]_{\text{Pred}}$ his car for $[\$5{,}000]_{???}$
    - Jim $[\text{sells}]_{\text{Pred}}$ his car, which he inherited from his dad, for $[\$5{,}000]_{???}$

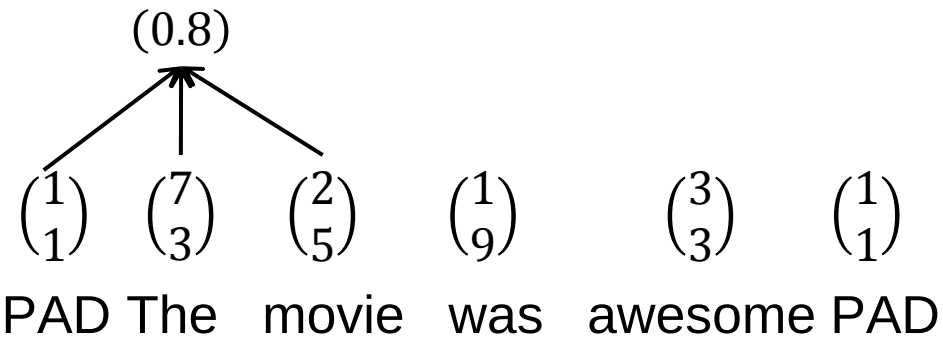
# Single Layer CNN – Single Filter

TECHNISCHE UNIVERSITÄT DARMSTADT

- We compute a single filter for a window size of n (here n=3):

Word Vectors: $w_i \in \mathbb{R}^2$
Weight Matrix: $W \in \mathbb{R}^{1 \times 6}$
Bias: $b \in \mathbb{R}$

$$\text{output} = \tanh\left(W \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} + b\right)$$

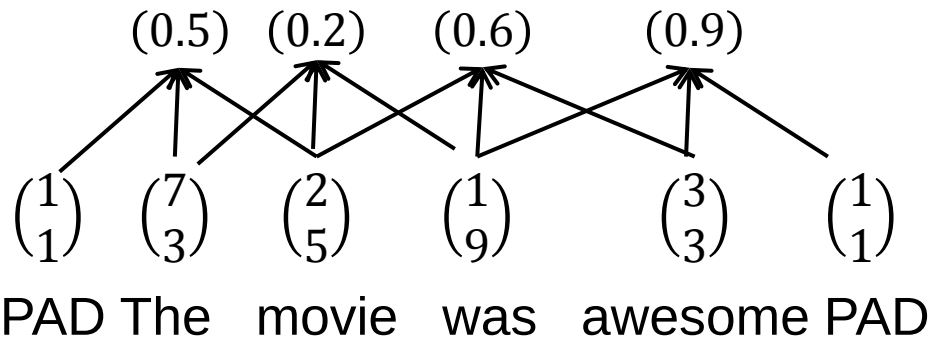





UKP

# Single Layer CNN – Single Filter

- Compute the output for all windows of size n (in our case n=3)
- For each window use the same weight and bias values (shared weights)
- This gives us the same number of digits as the length of the sentence



# Single Layer CNN – Pooling Layer

TECHNISCHE UNIVERSITÄT DARMSTADT

- New building block: Pooling
- Idea: Capture the most important activation

- Let $o_1, o_2, ... \in \mathbb{R}$ denote the output values for our filter

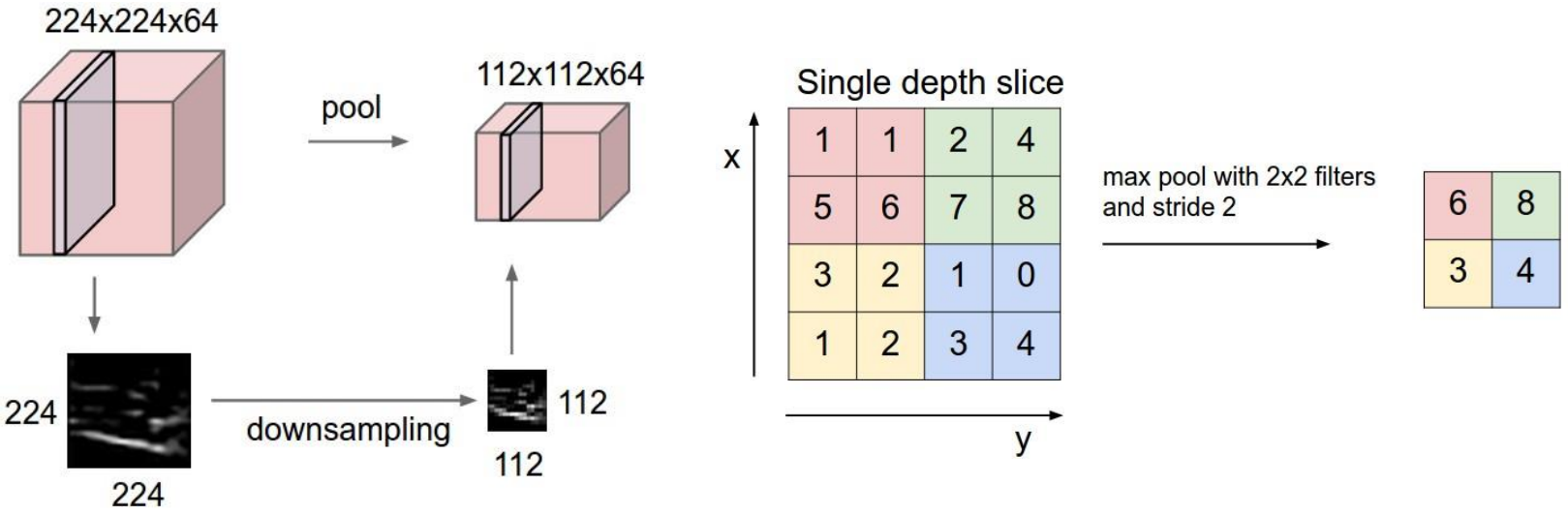
- Compute a max-over-time pooling layer:

$$c = \max_i(o_i) \in \mathbb{R}$$

- Because of max-over-time pooling, length of input sequence is irrelevant.
- We could use the output *c* and forward it to a softmax classifier and derive a sentiment class for the sentence
- Max-pooling most common in NLP. In Computer Vision, min-pooling and mean-pooling also common.

# Excursion: Max Pooling in Computer Vision

- In computer vision, pooling is often applied over fixed windows (e.g. 2x2)
- Be careful, don't confuse max pooling and max-over-time pooling




Example:

- 224x224 pixel gray scale images, 64 images / batch
- 2x2 max-pooling reduces each image it to 112 x 112 dimensions

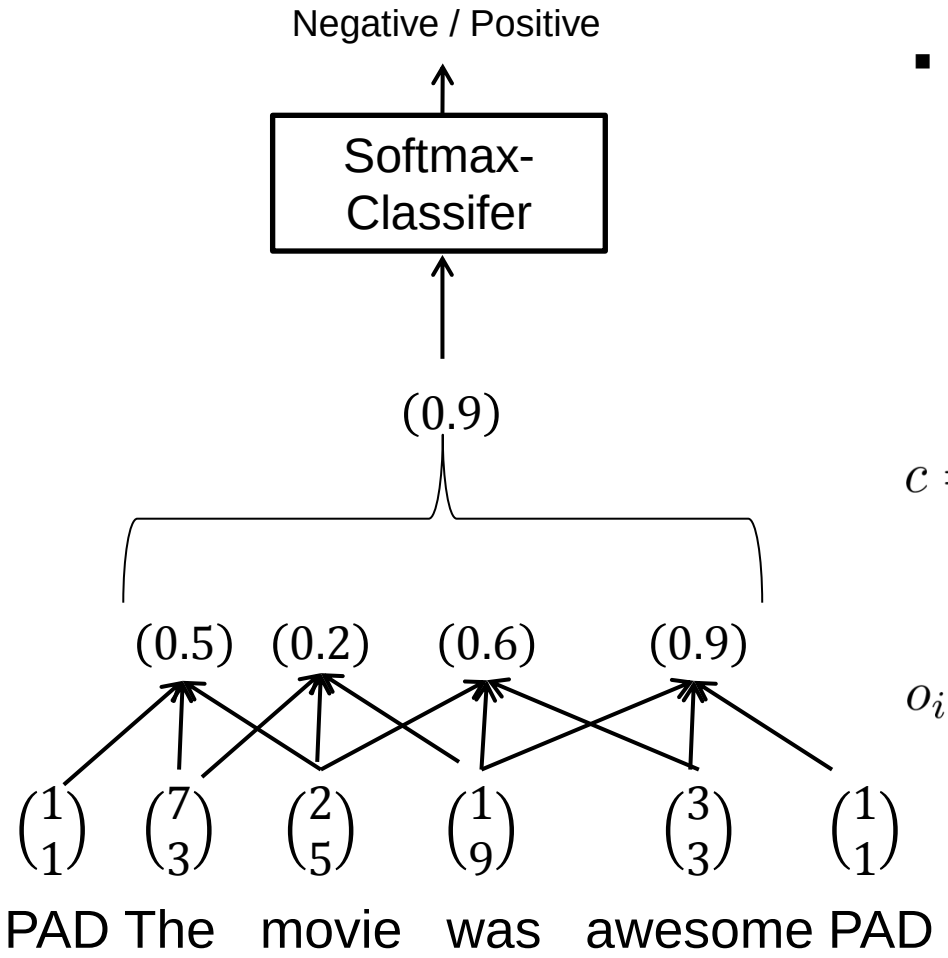
Img-Source: http://cs231n.github.io/convolutional-networks/

# Max Pooling vs. Max-over-Time


- Max pool with 2x2 filters on variable sized input generates variable sized output
- Max-over-time generates fixed-sized output
- In NLP, mostly max-over-time is used
  (as presented by Collobert et al., NLP almost from scratch, section 3.2.2)

- A lot of literature on max pooling originated from computer vision
  - Be careful with different terminology and hyper parameters for those pooling layers
- Keras supports both:
  - MaxPooling1D: for fixed-size max pooling
  - GlobalMaxPooling1D: for max-over-time pooling

# Single Layer CNN + Classification

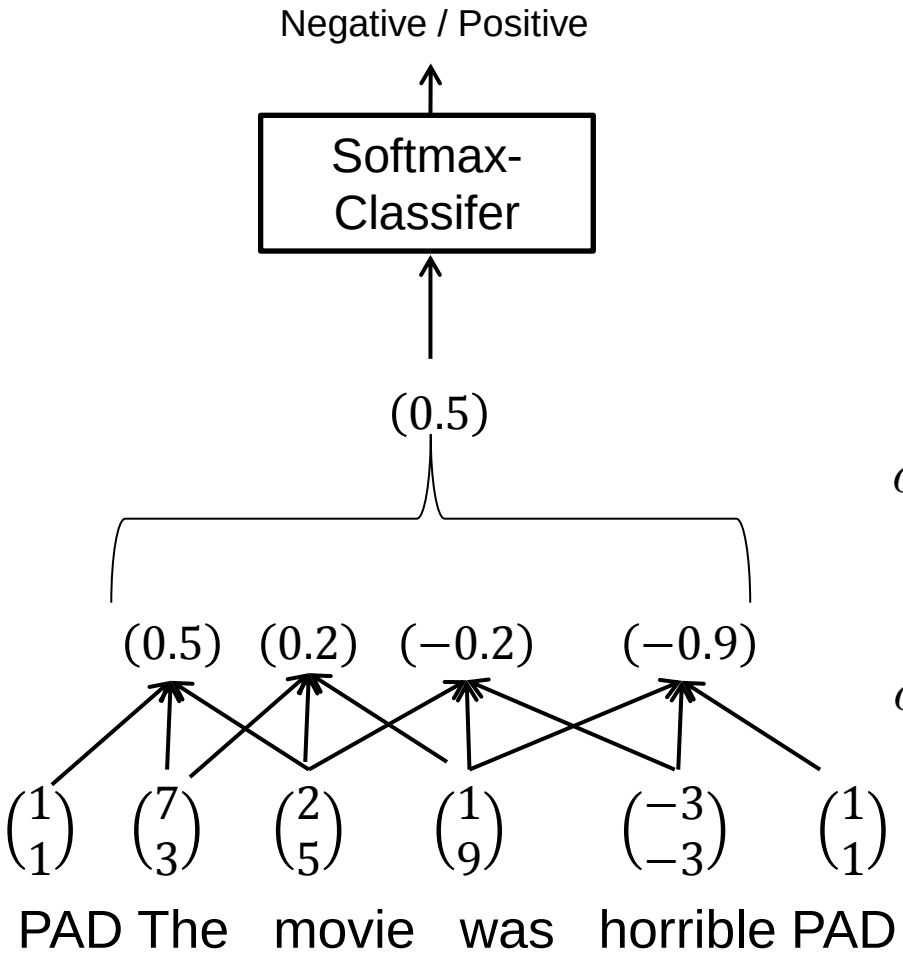



- You can train this like any other neural network

$$c = \max_i(o_i)$$

$$o_i = \tanh\left(W \begin{pmatrix} w_{i-1} \\ w_i \\ w_{i+1} \end{pmatrix} + b\right)$$

# 1 Dimension – not enough information

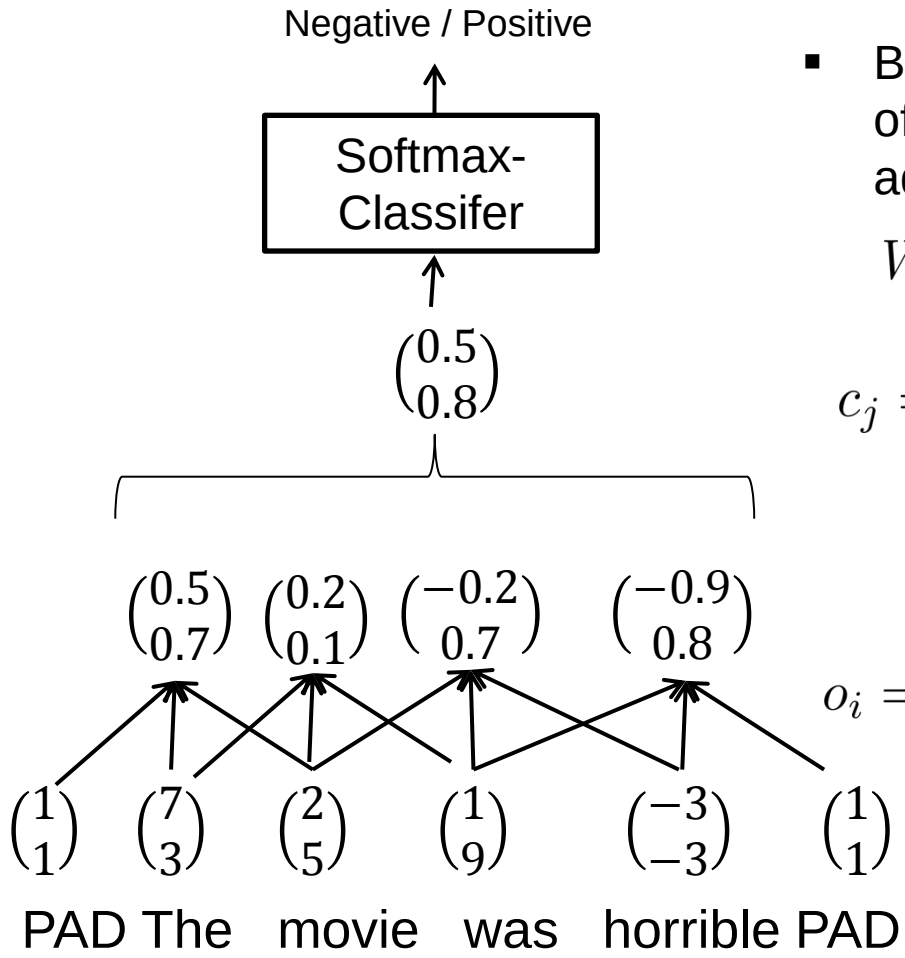



- With only a single filter our possibilities are limited

$$c = \max_i(o_i)$$

$$o_i = \tanh\left(W \begin{pmatrix} w_{i-1} \\ w_i \\ w_{i+1} \end{pmatrix} + b\right)$$

# Single Layer CNN – Multiple Filters




- By changing the dimensionality of the weight matrix, we can add further filters:

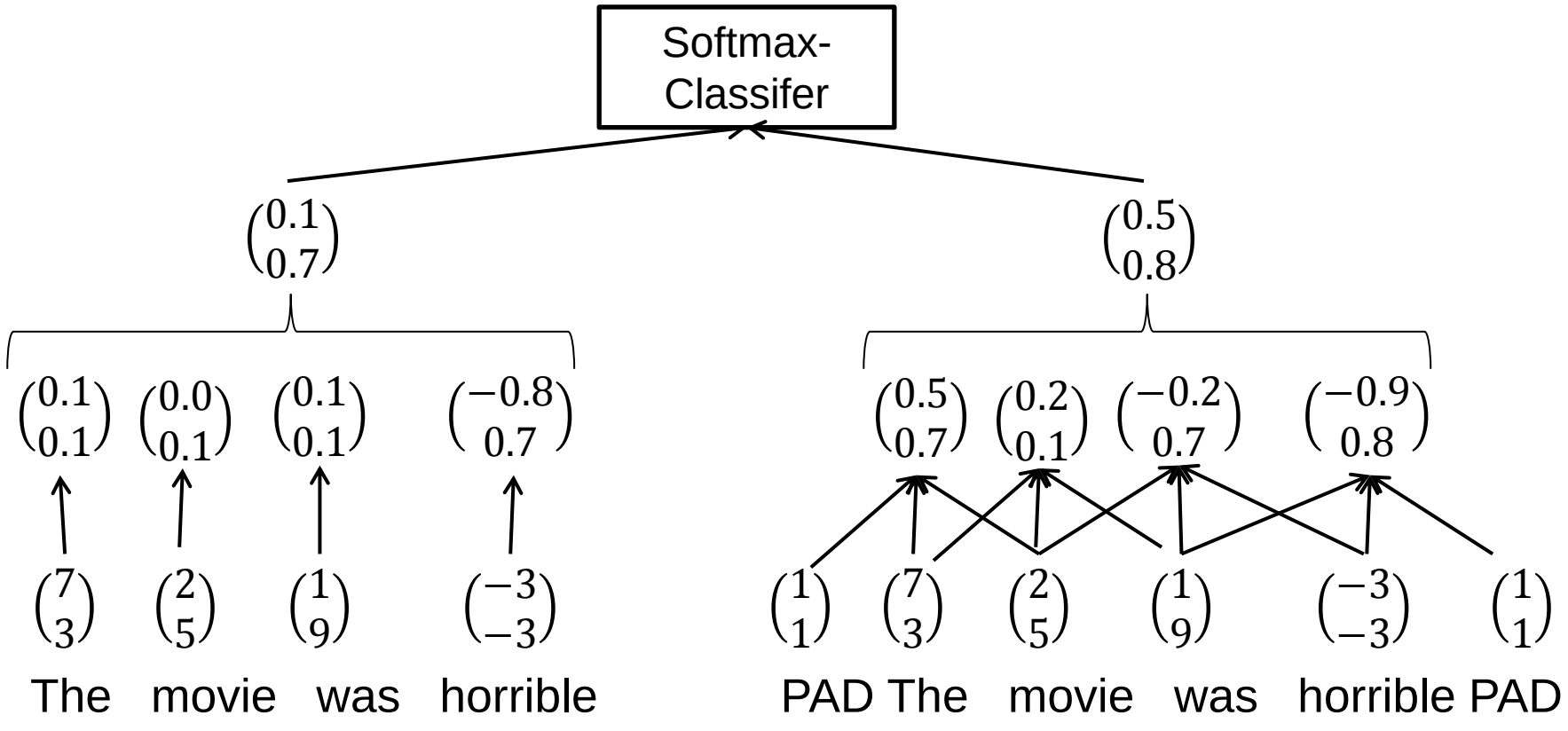
$$W \in \mathbb{R}^{k \times 6}$$

$$c_j = \max_i(o_{i,j}) \text{ for } 0 < j < k$$

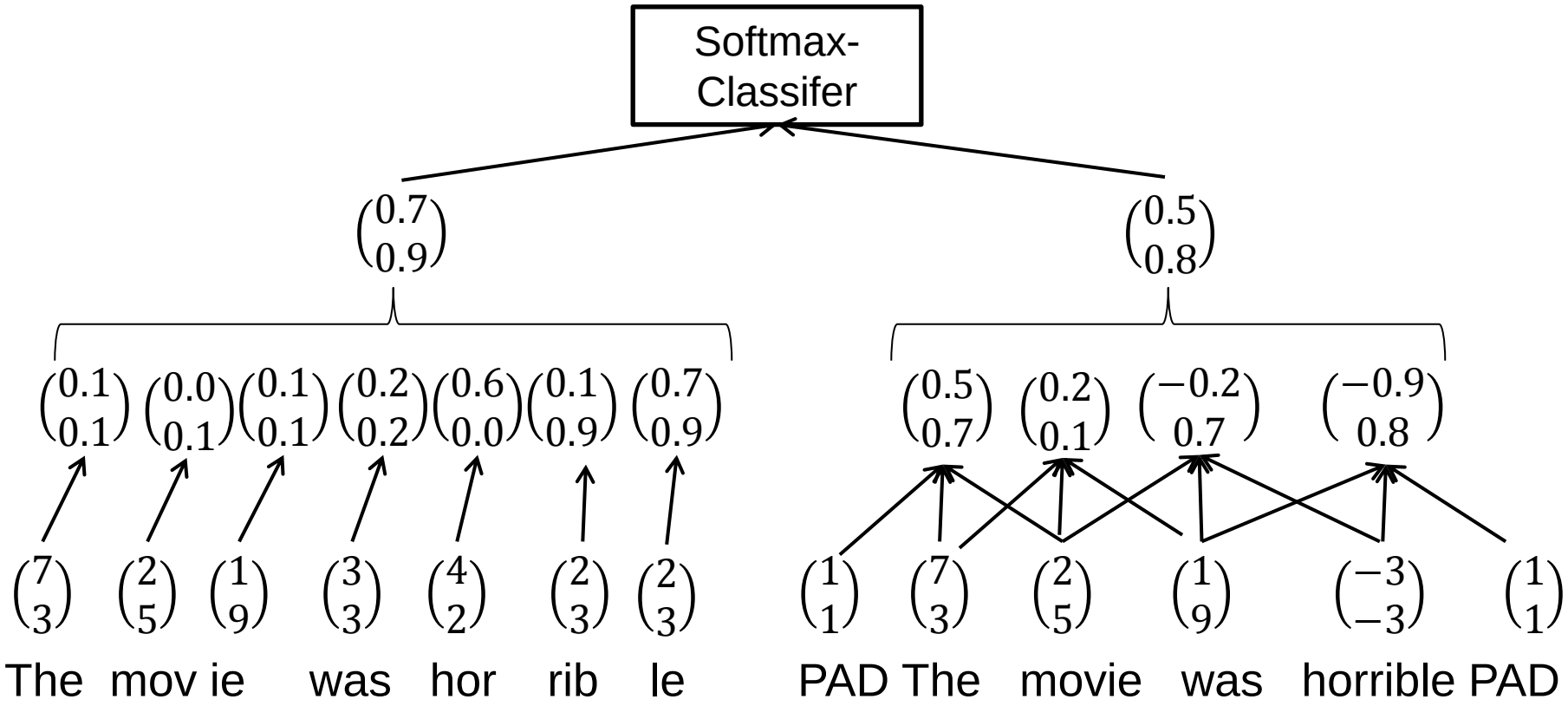
$$o_i = \tanh\left(W \begin{pmatrix} w_{i-1} \\ w_i \\ w_{i+1} \end{pmatrix} + b\right) \in \mathbb{R}^k$$

# Going further with Filters

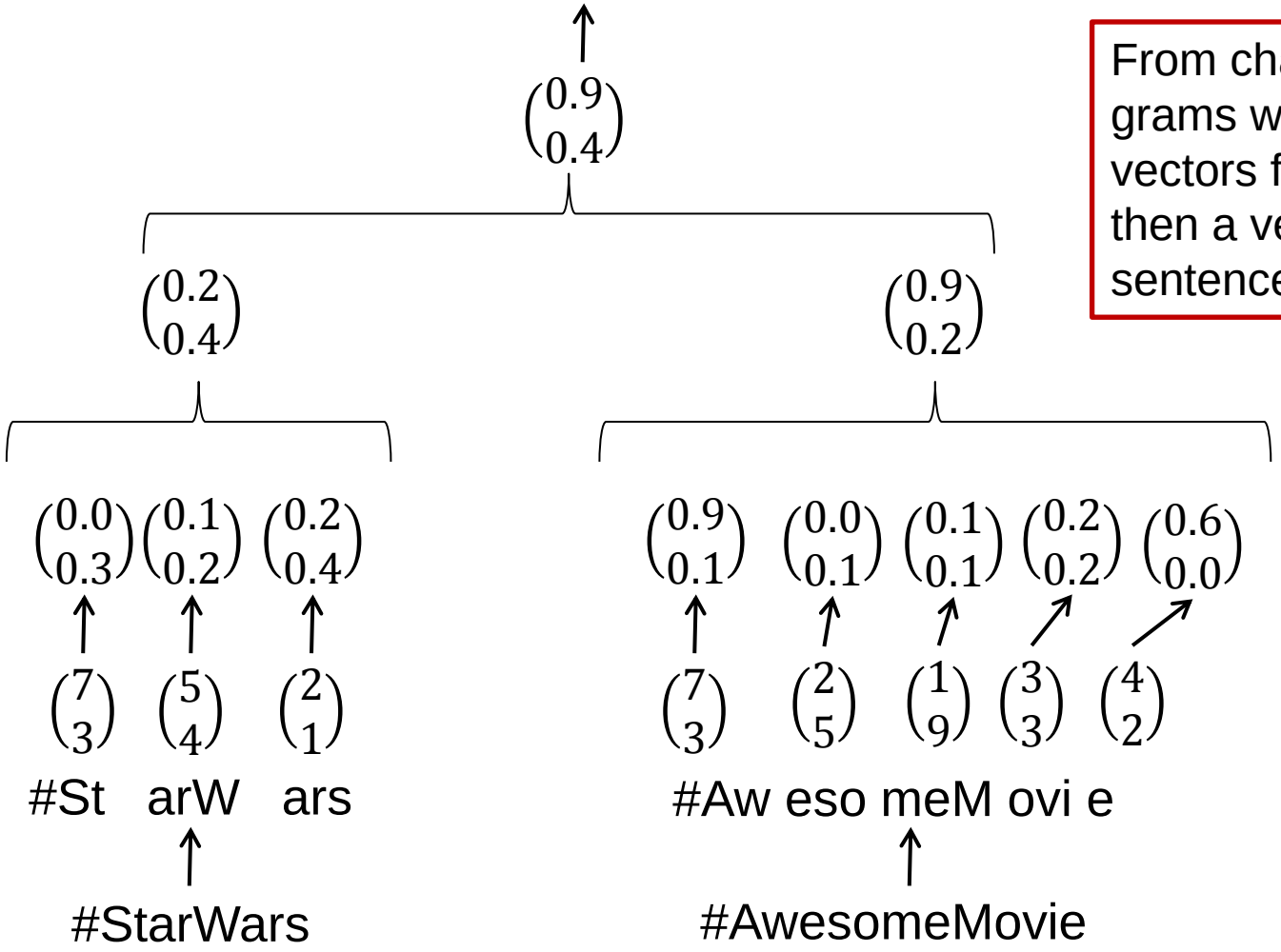
- We can create convolutional layers working on unigrams, bigrams, trigrams etc. and combine their output



# Or work on a different granularity



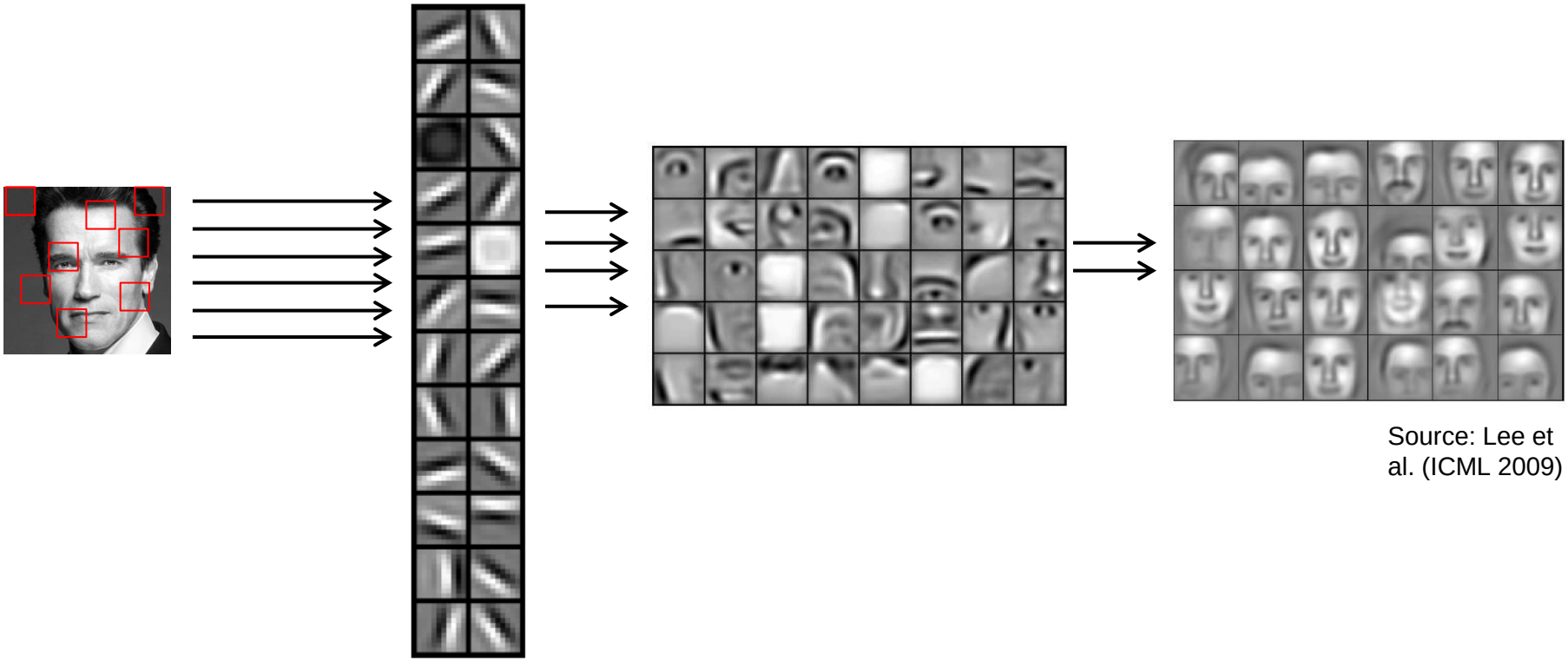
# Stacking Convolutional Layers




From character n-grams we could derive vectors for words and then a vector for the sentence

# Stacked Convolutional Layers

- Computer vision uses stacked convolutional layers to derive from simple representations high level representations



Source: Lee et al. (ICML 2009)

Input
e.g. 40 000 dim

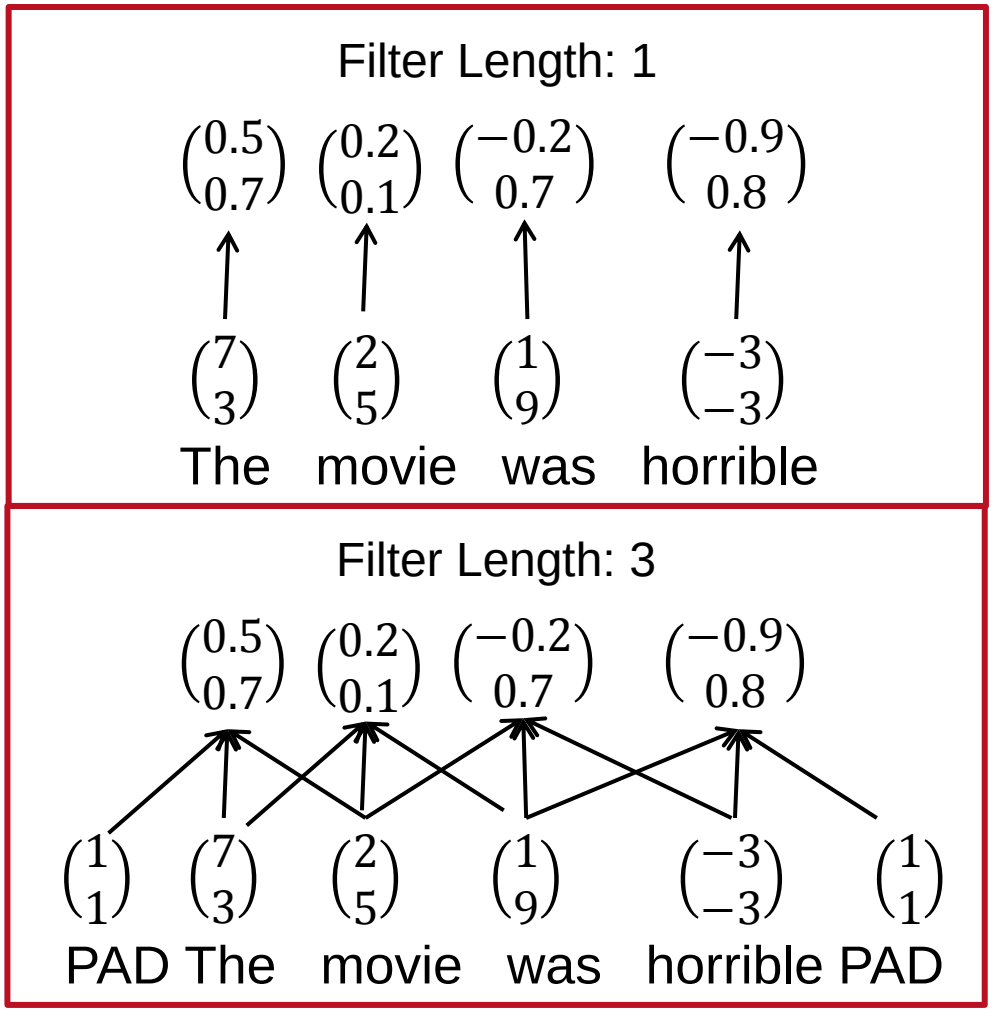
Layer 1
9 600 dim

Layer 2
3800 dim

Layer 3
900 dim

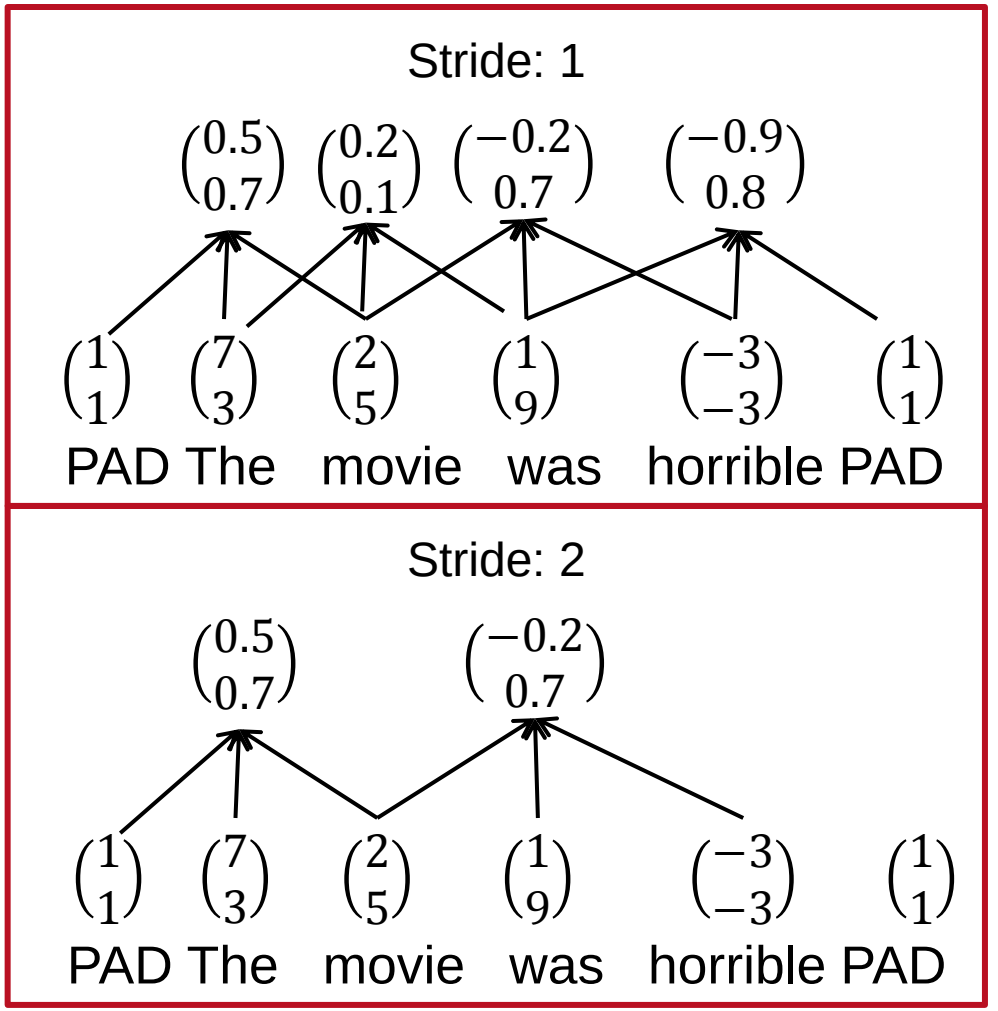
# Terminology: Filter Length

- The filter length is the extension of each filter
- Mainly inspired by Computer Vision where we work on spatial close pixels
- In NLP we are more flexible:
  - Use a context window of size *n*
  - Use dependency links / syntax tree



# Terminology: Stride

- The *stride* specifies the steps size we move across a sentence
- In NLP: Typically stride=1
- In computer vision: Other values can be used



# How to choose the embeddings?

TECHNISCHE UNIVERSITÄT DARMSTADT

- When we use words, how should we initialize the embeddings?

| 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 |

- Rand: Random initialization
- Static: word2vec, no updates during training
- Non-static: word2vec with updates
- Multichannel: next slide

Source: Kim, 2014. Performance on Sentence Classification Tasks

# Multi-Channel Idea

- We start with 2 copies for the word vectors, both initialized with word2vec/GloVe etc.
- Only one version of them is updated, the other is static
- We apply the same filters to both channels before we apply the pooling

- The one channel can learn task specific embeddings
  - E.g. for sentiment, *good* and *bad* should be far away in vector space

- So far mixed results
- Different Idea: Use differently pre-trained word embeddings
  - E.g. based on local context, on dependency trees, on relations from knowledge bases etc.

- Reference: Kim, 2014. *Performance on Sentence Classification Tasks*

# Hints on the Implementation

TECHNISCHE UNIVERSITÄT DARMSTADT

- Numpy and Theano cannot work with variable sized rows
- How to model a dataset like this?
  [ [This is my first sentence .]
  [This is my second , longer sentence .]
  [Super short ]]
- 2 Approaches:
  - Ignore minibatches, just input 1 sentence at a time for training / testing
    - Bad for performance
  - Pad the sentences with 0 to make them of the same length
    - Be careful with the padding, that the max-pooling does not choose your padded values
    - Be careful with the runtime, that a single super long sentence does not create too much padding for all other sentences.
    - Great to run on GPU (convolutions can be computed easily in parallel)

# Hints on the Implementation II

TECHNISCHE UNIVERSITÄT DARMSTADT

- Most implementation for convolutional layers are targeted for computer vision
- They introduce a lot more hyper parameters.
- Keras.Convolution1D:
  - filters: Number of filters that should be applied / dimensionality of the output
  - kernel_size: The extension (spatial or temporal) of each filter.
  - padding: How are vales at the border handled. ‘valid' or ‘same'. ‘valid’ does not pad the borders, ‘same’ ensures that the output is as long as the input. ‘same’ usually works better for NLP