# CS 4248 Natural Language Processing

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# **Materials**

• NNM4NLP Chapter 13

- Specialized for dealing with language data
  - Sequence data
  - Long distance dependency
    - "John, who is a student at NUS which is a top university in Asia located in a region experiencing high growth which is attributed to rapidly industrializing nations which ..., is my best friend."

- Convolutional neural networks (CNN)
  - Identify informative ngrams
  - Consider local ordering patterns
- Recurrent neural networks (RNN)
  - Capture subtle patterns and regularities in sequences
  - Model non-Markovian dependencies
  - Consider infinite window and zoom in on informative sequential patterns in the window

- CNN and RNN are used as feature extractors
- Each network produces a vector (or a sequence of vectors) that is then fed into further parts of the network that eventually leads to prediction

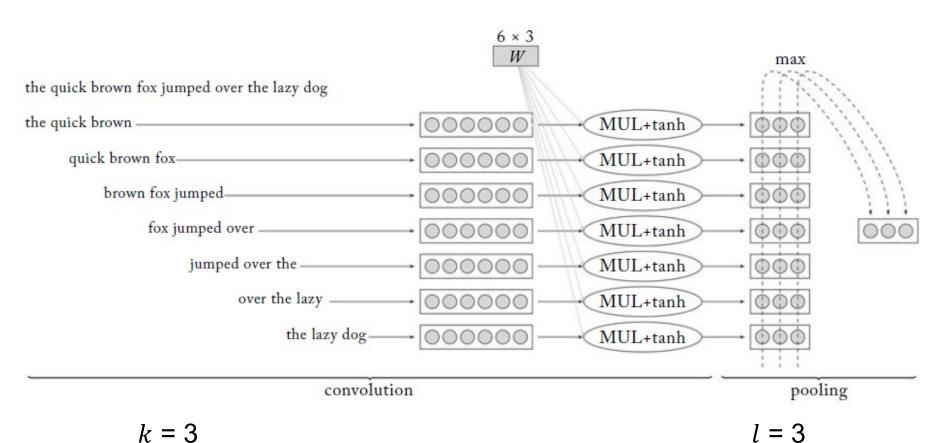
- The network is trained end-to-end (the predicting part and the convolutional/recurrent architectures are trained jointly)
- The vectors from the convolutional/recurrent part capture aspects of the input useful for the prediction task
- Computation graph setup allows easy mixing of MLPs, CNNs, and RNNs as components

- Word order is important in NLP
- Feed-forward NN using CBOW (continuous bag-of-words representation) ignores word order
- "It was not good, it was actually quite bad."
- "It was not bad, it was actually quite good."

- Naïve solution: produce word vectors for bigrams and trigrams rather than words
- Problems:
  - Huge embedding matrix, and does not scale to longer ngrams
  - Data sparsity: no sharing between different ngrams (e.g., "quite good" and "very good" are completely independent ngrams)

- CNN: a feature-extracting architecture
  - Extract meaningful substructures useful for the overall prediction task
- CNN was first successfully applied in computer vision as object detector, to recognize an object from a pre-defined category
- CNN terminology borrowed from computer vision community
- We focus here on 1D (sequence) convolutions

- Apply a nonlinear, learned function (a filter) over each k-word sliding window in the sentence
- l filters are applied to produce an l-dimensional vector for each sliding window of k words
- A pooling operation (e.g., max or average) then combines the vectors from the different windows into a single *l*-dimensional vector
- The single *l*-dimensional vector is fed further into a neural network for prediction



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- Filter function learns to identify informative k-grams
- Pooling enables focusing on the most important aspects of a sentence, regardless of location

- Sentence (sequence of words)  $w_{1:n} = w_1, ..., w_n$
- Word embedding matrix  $E_{[w_i]} = w_i$   $E \in \mathbb{R}^{|V| \times d}$
- Sliding window of size k (receptive field)
- $x_i = \bigoplus (w_{i:i+k-1}) = [w_i; w_{i+1}; ...; w_{i+k-1}] \ x_i \in \mathbb{R}^{k \cdot d}$
- u: a convolution filter or kernel
- g: nonlinear activation function
- $p_i = g(\mathbf{x_i} \cdot \mathbf{u})$   $p_i \in \mathbb{R}$   $\mathbf{u} \in \mathbb{R}^{k \cdot d}$

- l different filters  $u_1, ..., u_l$
- $\boldsymbol{U} = \left[\boldsymbol{u}_{1}^{\mathrm{T}} \cdots \boldsymbol{u}_{l}^{\mathrm{T}}\right]$
- $p_i = g(x_i \cdot U + b)$   $p_i \in \mathbb{R}^l$   $U \in \mathbb{R}^{k \cdot d \times l}$   $b \in \mathbb{R}^l$
- $p_i$  is a collection of l values representing the ith window
- Each dimension of  $p_i$  captures a different kind of indicative information

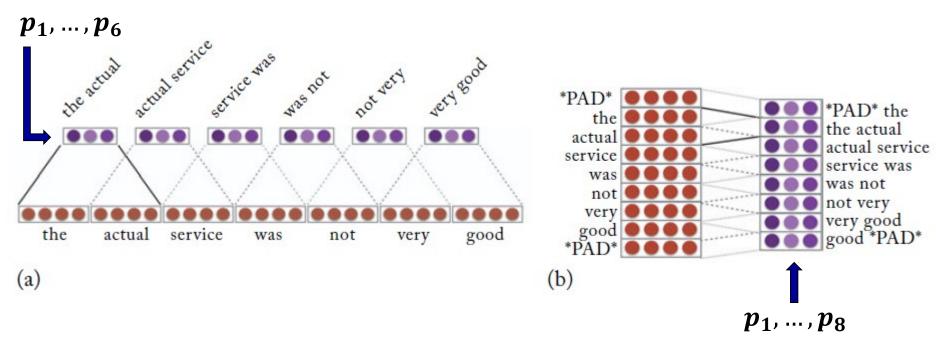
- The convolution layer applies the same parameterized function (filters) *U* over all *k*-grams in the sentence
- Each  $p_i$  vector represents a particular k-gram in the sentence
- The representation  $p_i$  is sensitive to the identity and order of the words within a k-gram
- The same representation  $p_i$  is extracted for the same k-gram regardless of its position within the sentence

- m: number of  $p_i$  vectors (i = 1, ..., m)
- Narrow convolution (no padding)

$$m = n - (k - 1) = n - k + 1$$

• Wide convolution (pad k-1 words to each side)

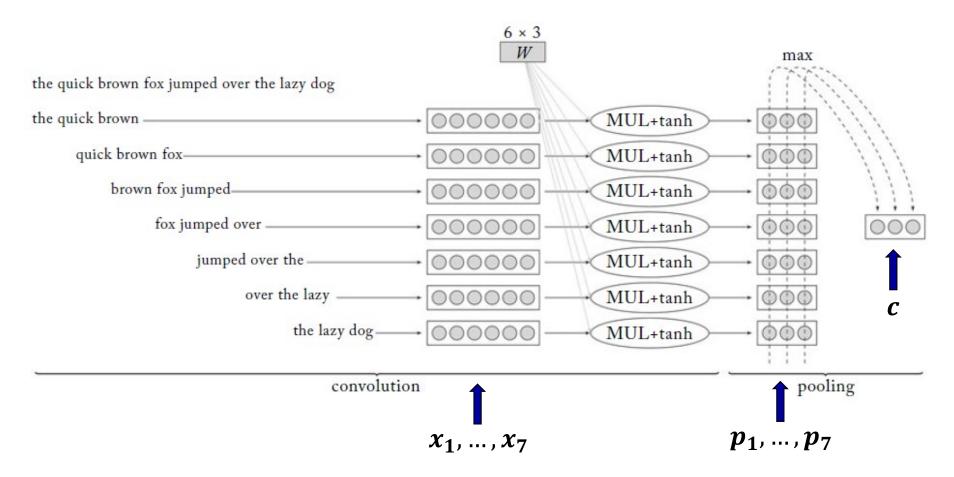
$$m = n + (k - 1) = n + k - 1$$



$$n = 7, d = 4, k = 2, l = 3$$

(a): Narrow convolution, m = 6 = n - (k - 1)

(b): Wide convolution, m = 8 = n + (k - 1)



Narrow convolution, n = 9, d = 2, k = 3, l = 3, m = 7

- Pooling: Combining  $p_1, ..., p_m$  into a single vector c
- c captures the essence of the important information in the sentence
- c is fed to downstream feed-forward NN (MLP) for prediction
- Training tunes the parameters in MLP, *U*, *b*,
   *E* such that *c* encodes information relevant to the prediction task

Max pooling

$$\boldsymbol{c}_{[j]} = \max_{1 \le i \le m} \boldsymbol{p_{i}}_{[j]} \quad \forall j \in [1, l]$$

Average pooling

$$c = \frac{1}{m} \sum_{i=1}^{m} p_i$$

Continuous bag of words (CBOW) of the k-gram representations