

92586 Computational Linguistics

15. Convolutions in Text

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Previously

- doc2vec
- CNN over images

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Chapter 7 of Lane et al. (2019)

Quick Reminders on CNNs

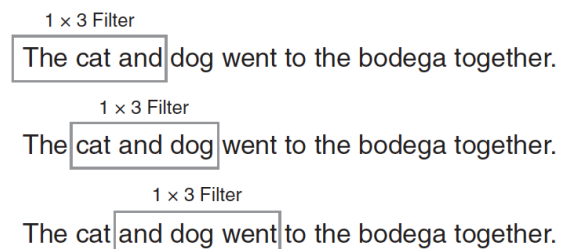
Quick Reminders on CNNs

- Sliding —or convolving— a window over the sample
- Filters (kernels; matrices) slide over fragments of the image
- “Snapshots” of different areas of the image are taken and processed
- Multiple filters produce multiple images
- Multiple convolution layers can be added
- At the end, we can plug a “standard” fully-connected NN

CNNs for NLP

Back to Text

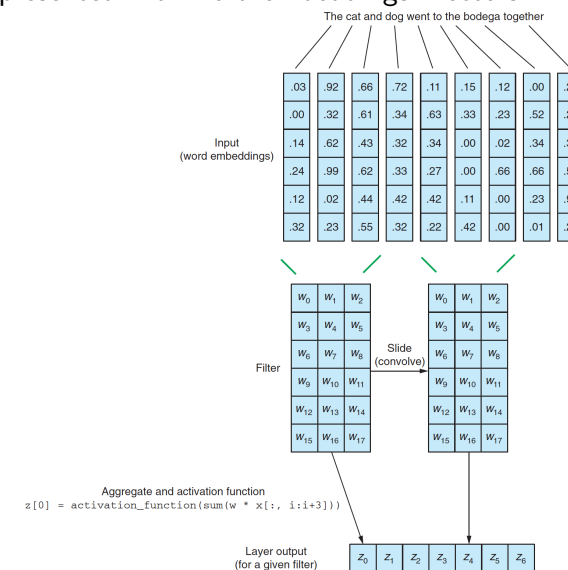
- In images both vertical and horizontal relationships are relevant
- In text only horizontal ones do¹
- **We need “1D” filters**



¹|2r or r2l; for some languages it's the vertical direction that matters (e.g., Japanese) (Lane et al., 2019, p. 229)

But we do have 2D “filters”


Words are represented with word embeddings: vectors



(Lane et al., 2019, p. 229)

The convolution is (practically) the same as for images

- We now *convolve* in one dimension (not two)
- The computation order is irrelevant, but the outputs have to be fed in the same order
- The filters' weights are fixed for a full sample (parallel computation)
- Their output becomes the features for the classifier


 Let us see

Padding

- (In general) in image processing the inputs are of fixed size, regardless of the image (same source!)
- Texts are not fixed length (regardless of their source)
- Instances longer than `maxlen` will be truncated
- Instances shorter than `maxlen` will be **padded**

$x_0, x_1, x_2, x_3, \dots, x_{398} x_{399}$ $\times_{400} \times_{401}$

$x_0, x_1, x_2, x_3, \dots, x_{397}$ PAD PAD

 Let us see

Pooling

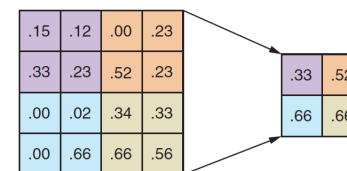
- For each filter one new version of the instance is produced (250 in the example)
- Pooling evenly divides the output of each filter into subsections
- It selects (or computes) a representative value for each subsection

Pooling

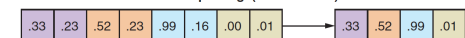
Pooling is “the CNN path to dimensionality reduction [...] by learning higher-order representations of the source data” (Lane et al., 2019, p. 236)

- The filters job is finding patterns → relationships between words and their neighbours
- Pooling in text: a 1D window (e.g., 1×2 or 1×3)

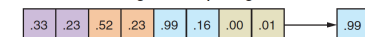
2D max pooling (2 x 2 window)



1D max pooling (1 x 2 window)



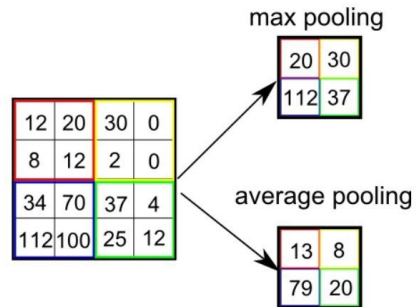
1D global max pooling



(Lane et al., 2019, p. 237)

Pooling

Max vs Average Pooling



- Average is more intuitive: retaining most of the info
- Max is better: the NN keeps the most prominent feature


 Let us see

Image borrowed from

www.quora.com/What-is-max-pooling-in-convolutional-neural-networks

Recap

- Each filter will produce a 1×398
- For each of the 250 filter outputs, we take the single maximum value for each 1D vector
- Output: one 1×250 vector


This is a crude semantic representation of the text

Dropout: Preventing Overfitting

On each training pass **turn off** a percentage of the input of a layer; it will become 0

- Chosen randomly on each pass
- It will not rely heavily on any feature
- It will generalize better
- Dropout is applied on training only



 Let us see

Photogram of "The Platform" (2019)

Workhorse Loss Functions

Out of the 13+ available loss functions:

`binary_crossentropy`: the output neuron is either on or off

`categorical_crossentropy`: the output is one out of many classes

 Let us see

Closing Remarks

- Your input is a series of max 400 words; 300 elements each
- Nothing prevents you from stacking other embeddings (think of RGB)
- The output of the convolution layer is tied to the task (in this case, sentiment analysis)
- A CNN is more efficient, thanks to the pooling process and the filters
- You can add many convolution layers

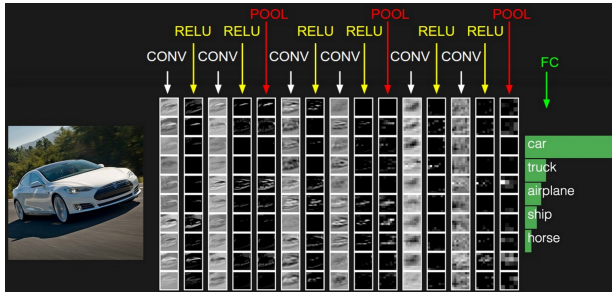


Image borrowed from <https://blog.mapillary.com>

Next time

- Recurrent Neural Networks

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY:
Manning Publication Co.