91258 Natural Language Processing

Lesson 15. Convolutions in Text

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Quick Keras Reminder

Keras

Sequential()

- Python class
- Neural network abstraction
- Grants access to the basic Keras API

Sequential.compile()

- Builds the underlying weights
- Builds the interconnected relationships

Sequential.fit()

- Computes the training errors (loss)
- Applies backpropagation (weight adjustment)

Some "cooking" hyperparameters

epochs number of iterations over the data
batch_size number of instances before adjusting
optmizer function

Prologue to CNN and RNN

Prologue

- We have learned to build embedding spaces for words and texts
- We are considering the neighborhood of the words ($\sim$the bag)
- We are not considering *actual* connections yet
- The downstream application is usually classification or regression

We will start heading towards text generation

Words have relations and influence each other

Word order

$$s_1 = \text{The dog chased the cat.}$$
$$s_2 = \text{The cat chased the dog.}$$

$$\begin{aligned} sim(tfidf(s_1), tfidf(s_2)) &= 1 \\ sim(wv(s_1), wv(s_2)) &= 1 \\ sim(dv(s_1), dv(s_2)) &= 1 \end{aligned}$$

But s_1 and s_2 are not the same!

Word proximity

$s =$ His mother, besides her son's willingness to amend the issue, decided to punish him

mother. . . decided | son. . . him

(Lane et al., 2019, p. 220)

Words have relations and influence each other

Spatial relation
Consider the position of words ($\sim$written)

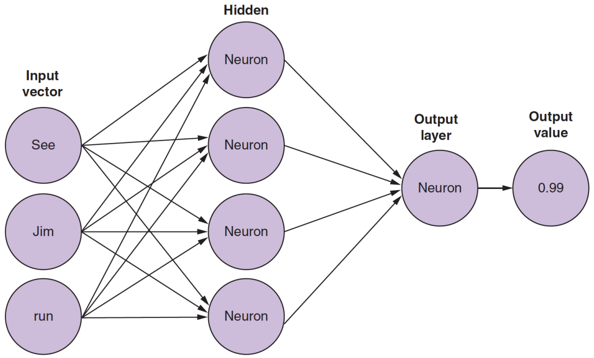
$\rightarrow$ fixed-width window
convolutional neural networks

Temporal relation
Consider words as time series ($\sim$spoken)

$\rightarrow$ ongoing (unk) amount of time
recurrent neural networks

(Lane et al., 2019, p. 220)

Multiple Input Words



- Three tokens are passed at a time
- Two input alternatives
  - one-hot vector
  - pre-trained word vector

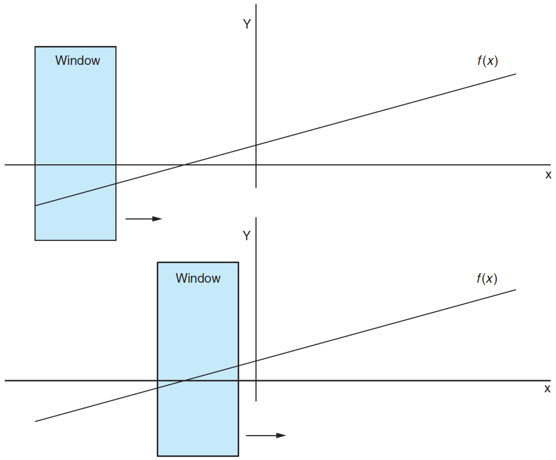
`See Jim run` $\neq$ `run See Jim` (!)

(Lane et al., 2019, p. 221)

CNN

Convolutional Neural Networks

Sliding —or convolving[1]— a window over the sample

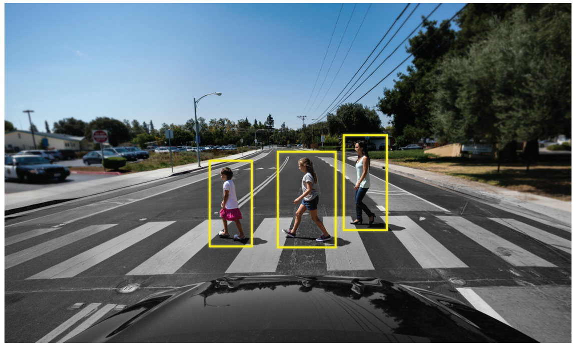


[1] To roll or wind together (Webster's)
(Lane et al., 2019, p. 222)

Convolutional Neural Networks

Back to the roots: image recognition

- Input: pixels of an image
- Output: the image contains x

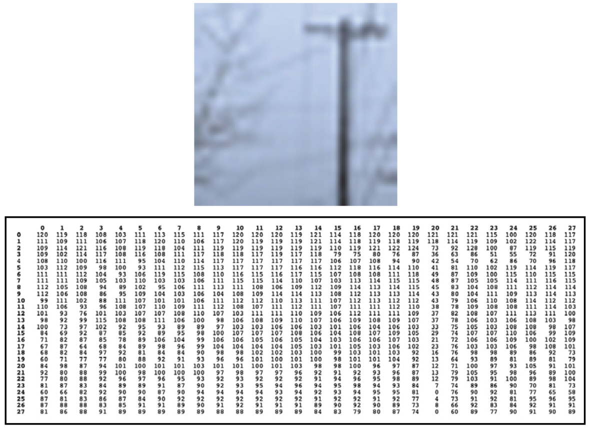


https://blogs.nvidia.com/wp-content/uploads/2019/04/ADAS-IMG_0052.jpg

Convolutional Neural Networks

When the input is an image

- B&W: [0,1] (with a smooth binariser)
- Grayscaled: [0, 255]
- Colour: R: [0, 255] G: [0, 255] B: [0, 255]



(Lane et al., 2019, p. 223)

Convolutional Neural Networks

When the input is an image

An image is just a bunch of numbers

- Appropriate as input for a NN
- But one single pixel has no real meaning

$\rightarrow$ **Sliding over fragments of the image**

The convolution defines a set of filters (aka kernels) to do just that

- Take "snapshots" of different areas of the image
- Process them, one at a time

Convolutional Neural Networks

Strides and filters

Stride

- The distance "traveled" when sliding
- Yet another parameter
- Never bigger than the size of the filter $\rightarrow$ overlapping areas

Sounds familiar? *n*-**grams!**

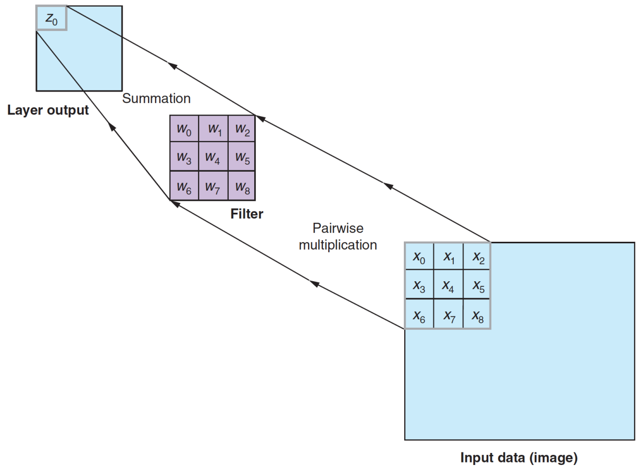
Filter

- $n \times m$ surfaces
- Typically $n = m = 3$ (often $n \neq m$)
- Includes a set of weights (fix for the whole image)
- Includes an activation function: usually ReLU

$$z = \max\left(sum(x * w), 0\right)$$

Convolutional Neural Networks

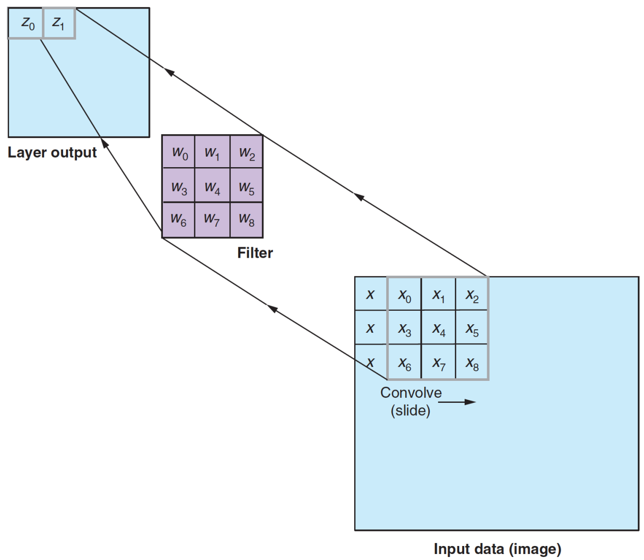
Convolutional step



(Lane et al., 2019, p. 225)

Convolutional Neural Networks

Convolution



(Lane et al., 2019, p. 226)

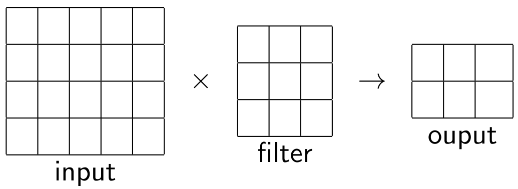
Convolutional Neural Networks

Producing multiple images

- k filters exist which carry out different operations
- Every filter will produce a new image, combination of source and filter

Convolutional Neural Networks

Padding



We are producing smaller images

"I don't care": Keras' argument `padding='valid'`
The edges of the image are undersampled

"I do care": Keras' padding argument `padding='same'`

In NLP **we care**

Convolutional Neural Networks

Pipeline

Input: an image, text
Output: a class, a real number

- Produce k new images through k filters
- Wire the filtered images to a feed-forward network
- Proceed as usual

We can add multiple convolution layers
A full path of learning layers and abstractions

- Edges
- Shapes
- Colours
- **Concepts**

What is learned

- Good filters
- "Standard" weights

Convolutional Neural Networks
Keras premier

```
from keras.models import Sequential
from keras.layers import Conv1D

model = Sequential()

model.add(Conv1D(filters=16,
                 kernel_size=3,
                 padding='same',
                 activation='relu',
                 strides=1,
                 input_shape=(100, 300))
)
```

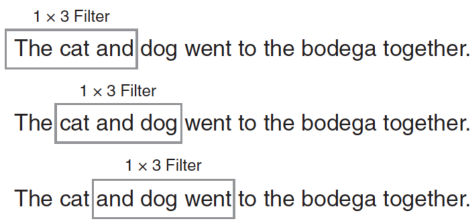
CNN Wrap up

- 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 do[2]
- **We need "1D" filters**

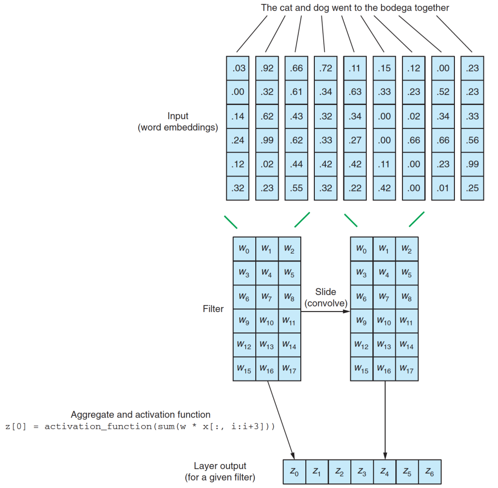


[2] l2r or r2l; for some languages it's the vertical direction that matters (e.g., Japanese)

(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 instance (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**

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

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

📓 Let us see

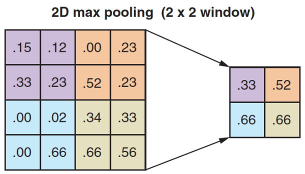
Pooling

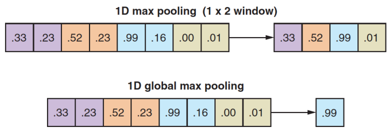
- For each filter one new version of the instance is produced (250 in the example)
- Pooling evenly divides the output of each filter into subsections
- It selects (or computes) a representative value for each subsection

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)

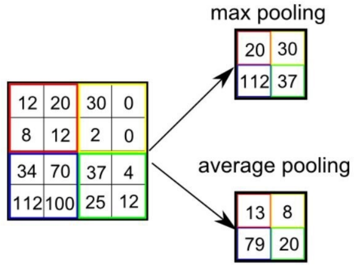




(Lane et al., 2019, p. 237)

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 vector
- 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 generalise better
- Dropout is applied during training only

Let us see

Photogram from the film "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

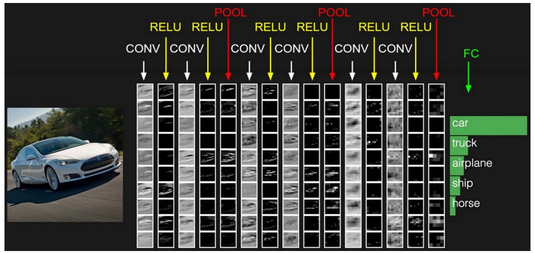


Image borrowed from `https://blog.mapillary.com`

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.