Convolution for text

A Recurrent Neural Network may be an ideal mechanism for dealing with sequential data like text.

But a one dimensional CNN may be an even simpler mechanism.

We briefly introduce the idea as it may deepen our understanding of the particular issues of text.

An *n-gram* is a sequence of n consecutive tokens that encapsulates a single concept (*phrase*) such as:

- "New York City" versus ["New", "York", "City"]

An n-gram can also capture subtleties of ordering

- ["hard", "not", "easy"] versus ["easy", "not", "hard"]

How does one identify consecutive tokens that may improve prediction ?

There are two approaches.

The first is statistical

- The joint frequency of consecutive tokens being higher than the frequency assuming independence
- $p(\text{"New York City"}) > p(\text{"New"})p(\text{"York"})p(\text{"City"})$

The second way: use Machine Learning !

We have spoken about convolutions as

- Identifying the presence/absence of a feature
- At a *spatial* location

The one-dimensional convolution, when applied to a sequence of tokens

- Identifies the presence/absence of a feature
- At a *temporal* location (index within the sequence)

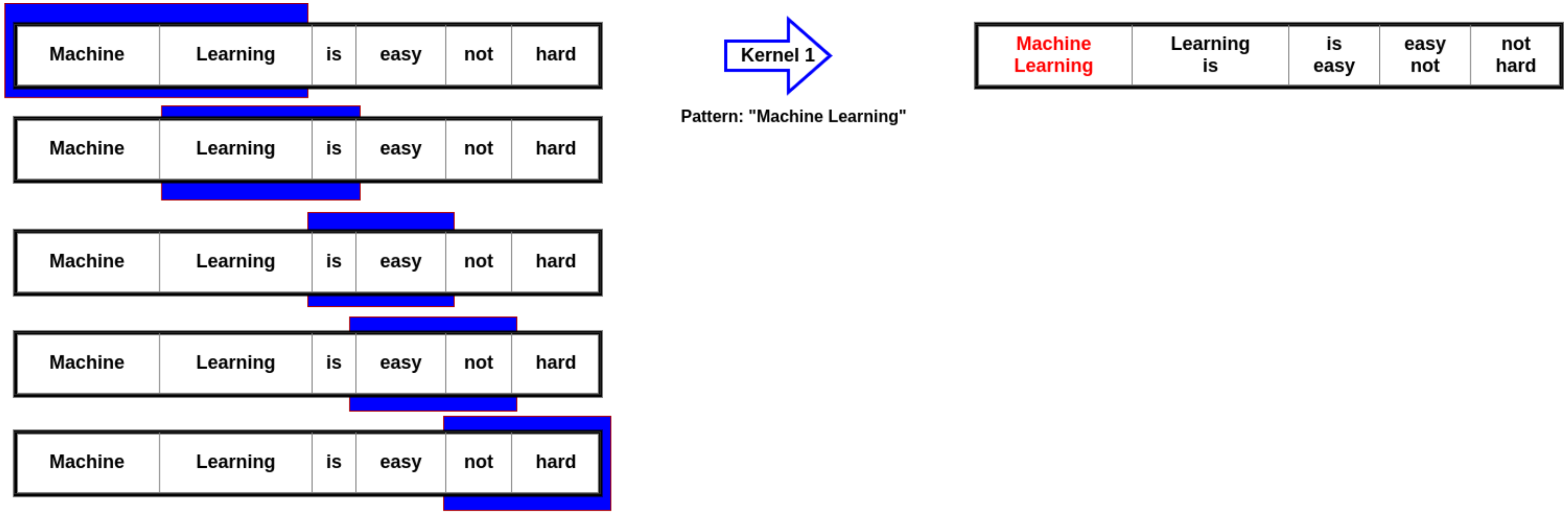
This is just an ordinary convolution, applied to a sequence.

It is only able to capture *local* relationships that occur within the width of the convolutional kernel.

Here is a picture:

- A kernel of size 2 (blue) recognizing the pattern "Machine Learning"
- Being slid over the input sequence
- Producing a high output (red) when the consecutive tokens match the pattern

One dimensional convolution
Slide blue kernel over input



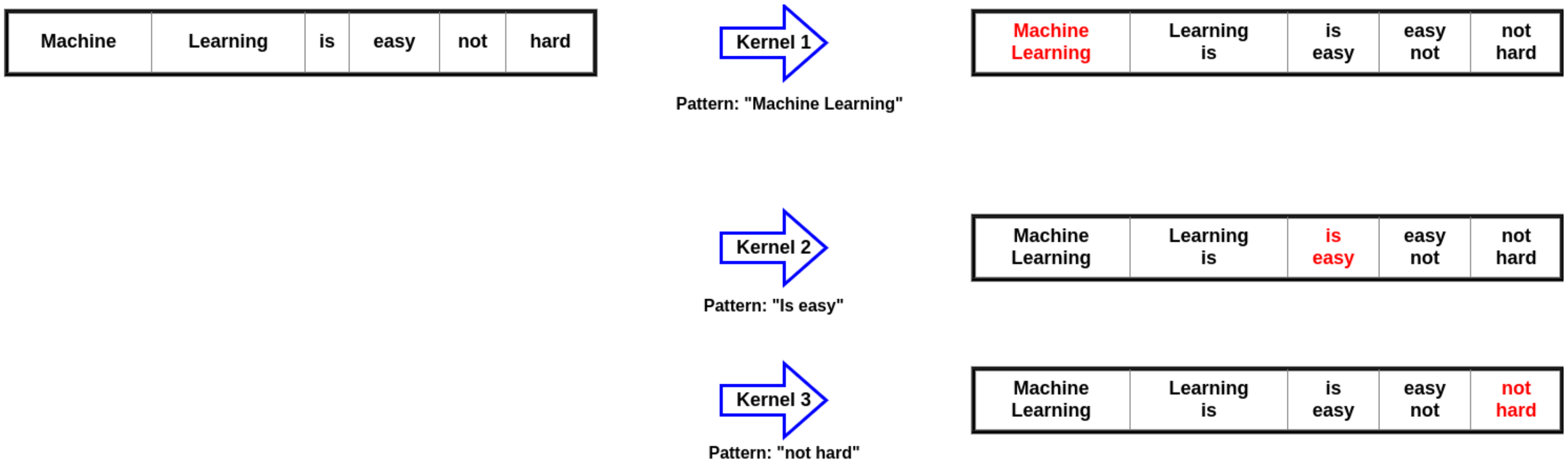
Using one dimensional convolution with kernel size n

- The convolution creates an n-gram feature
- At each (temporal) location in the sequence

As with any other CNN, we can apply multiple kernels

- Each matching a different pattern
- To identify a different feature (n-gram)
- At each location in the sequence

One dimensional convolution
multiple kernels



Convolutional Layer l thus produces $\mathbf{y}_{(l)}$

- Of the same temporal/spatial dimension as $\mathbf{y}_{(l-1)}$
- With $n_{(l)}$ features

After constructing n-gram features at layer l

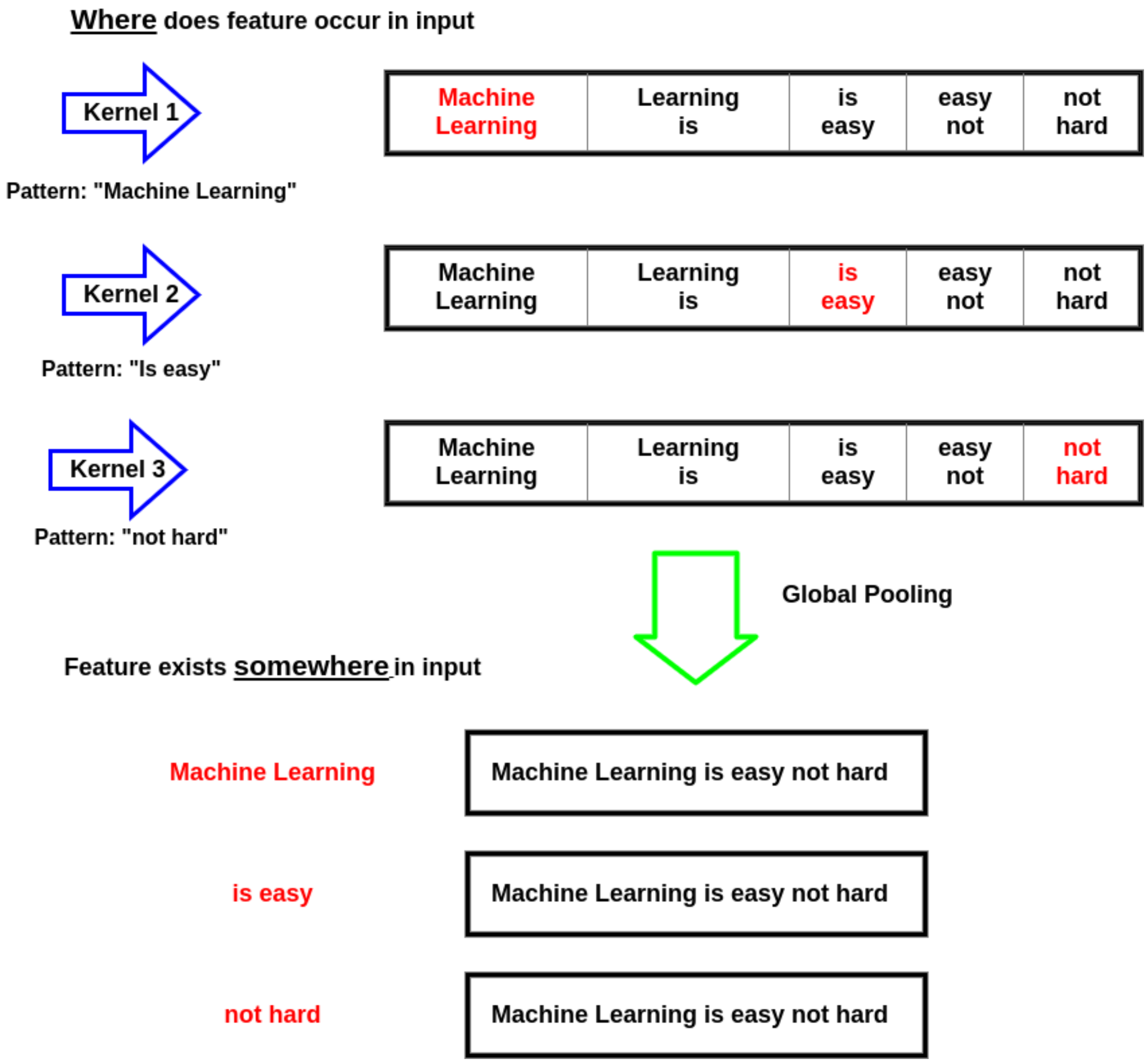
- We get $\mathbf{y}_{(l)}$
- Of the same spatial/temporal shape as $\mathbf{y}_{(l-1)}$

That is: we transform a sequence of tokens into an equal sequence of n-grams

Here is a picture

- Using 3 kernels of width 2 to identify
- 3 synthetic features ("2-gram") at each location in the sequence
- Followed by Global Pooling to reduce the sequence for each feature
- To a single value per feature

Global Pooling
3 features over spatial locations
to 3 features over one location



The resulting vector of 3 features can then be fed into a Classical ML layer such as Classification.

Our notebook will demonstrate code for the entire process.

Conclusion

Ordering of tokens is important for understanding text.

Convolutional Layers

- By capturing temporally local relationships
- May create features ("n-grams") that are more useful
- Than isolated tokens

This is important in general, but particularly when a subsequent layer (e.g., Global Pooling) loses ordering.

In [2]:

```
print("Done")
```

Done