Course

Knowledge-based Systems

Lecture 12 – Deep Learning 2

Dr. Mohsen Mesgar

Universität Duisburg-Essen

Deep Learning Architectures

Deep learning architectures

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Processing images

- Convolutional neural networks

Processing sequences (e.g., text)

- Recurrent neural networks

Generating data

- Generative adversarial networks

Convolutional Neural Networks

Variable input in image recognition

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The 1d convolution operation

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$$(f * g)[i] = \sum_{m=-M}^{M} f[i-m]\,g[m]$$

- ◊ $*$ is the convolution operator
- ◊ $f(x)$ is the input representation
- ◊ i is the current position in the input representation
- ◊ M is the window size
- ◊ $g[m]$ is the weight for an input element with distance m to the current input
- ◊ → it is also often referred to as the filter.

- ◊ Careful! You will find many terminological alternatives in the literature: w (for weights) instead of g, n or t (for time) instead of i, a (for age) instead of m, …

1-D Convolution

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$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} ? & ? & ? \end{bmatrix}$$

Input representation f | Filter g (also 'kernel') | Convolved output

(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

1-D Convolution

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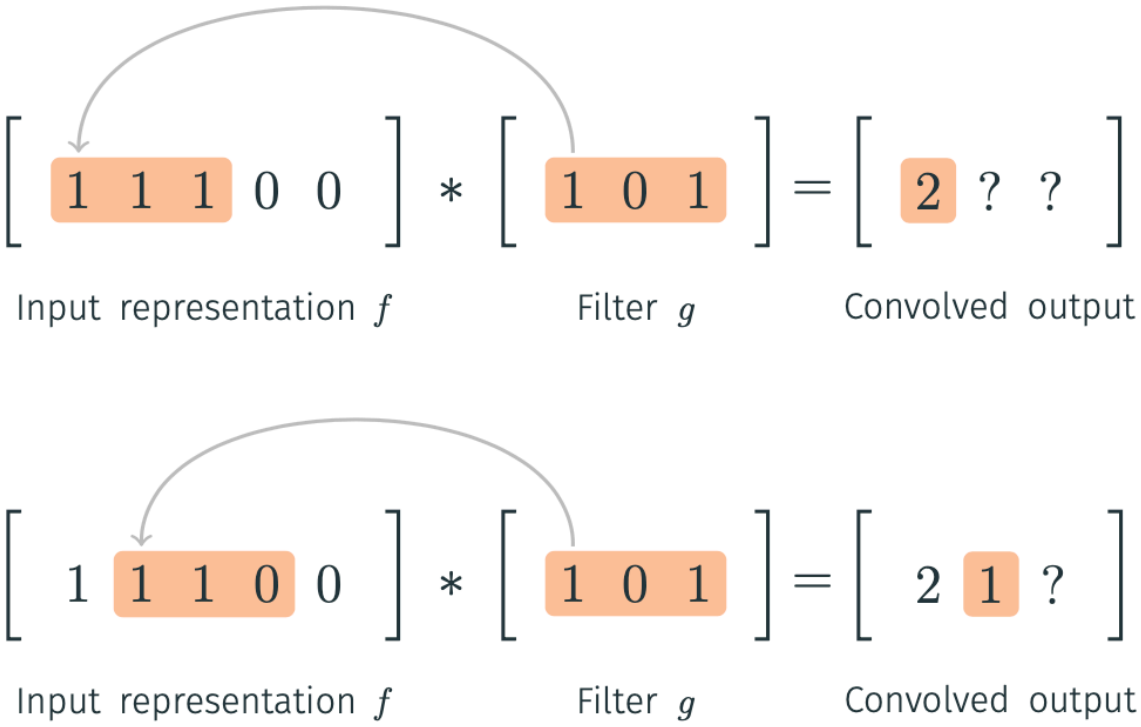


(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

2-D Convolution

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} ? & ? & ? \\ ? & ? & ? \\ ? & ? & ? \\ ? & ? & ? \end{bmatrix}$$

Input representation f

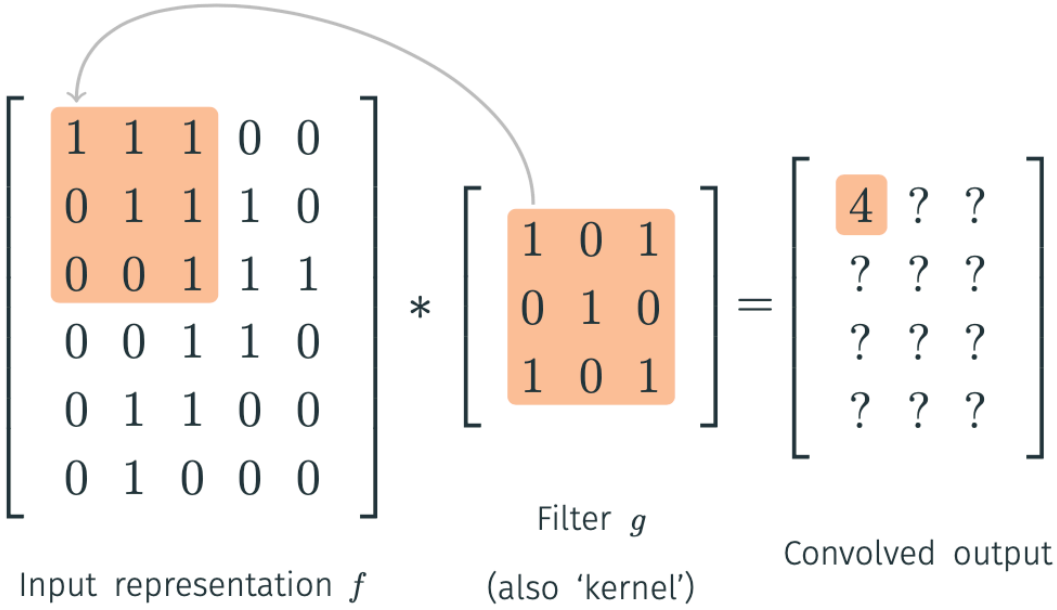
Filter g

(also 'kernel')

Convolved output

(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

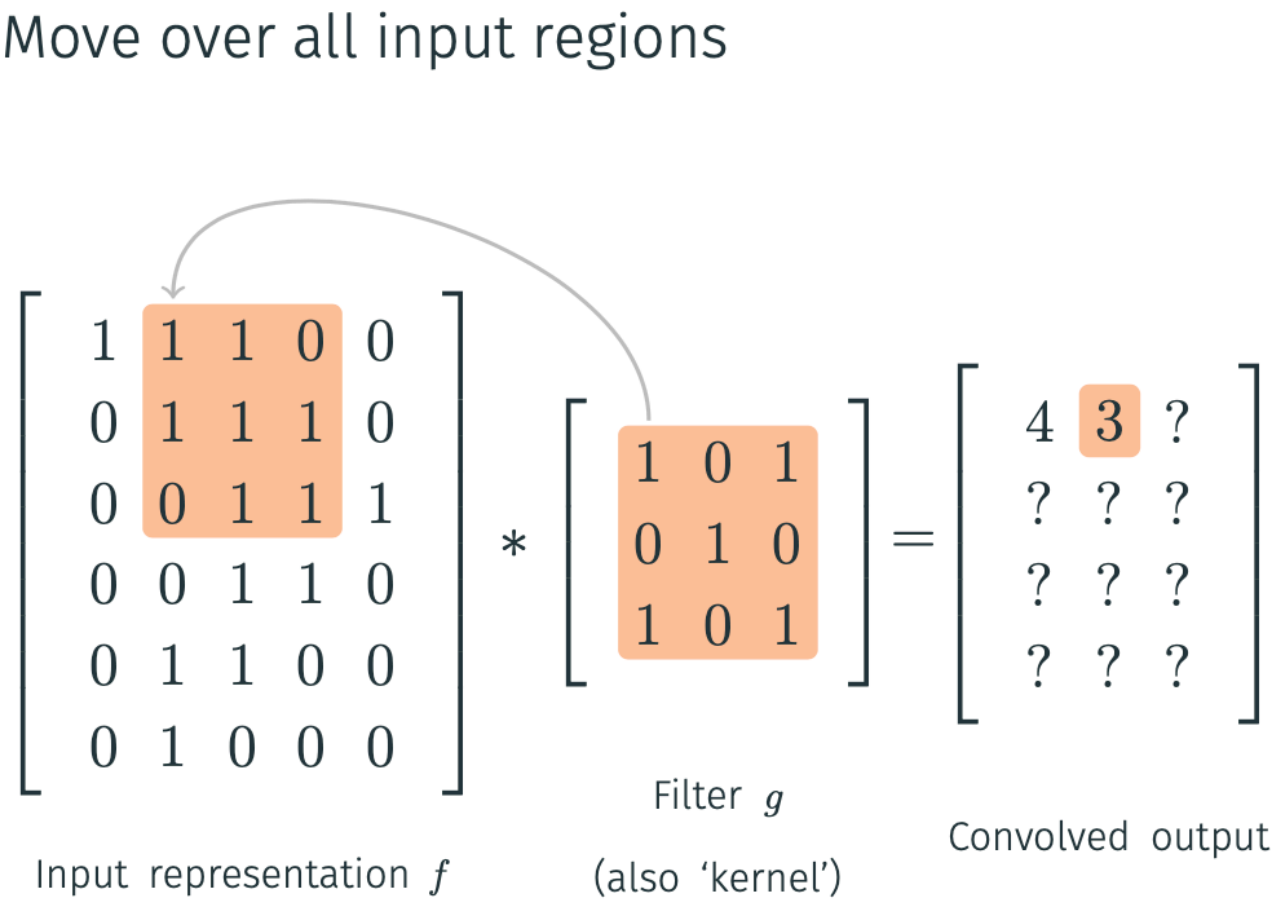
2-D Convolution



$$\underbrace{1 \cdot 1 + 1 \cdot 0 + 1 \cdot 1}_{\text{1st row}} + \underbrace{0 \cdot 0 + 1 \cdot 1 + 1 \cdot 0}_{\text{2nd row}} + \underbrace{0 \cdot 1 + 0 \cdot 0 + 1 \cdot 1}_{\text{3rd row}} = 4$$

(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

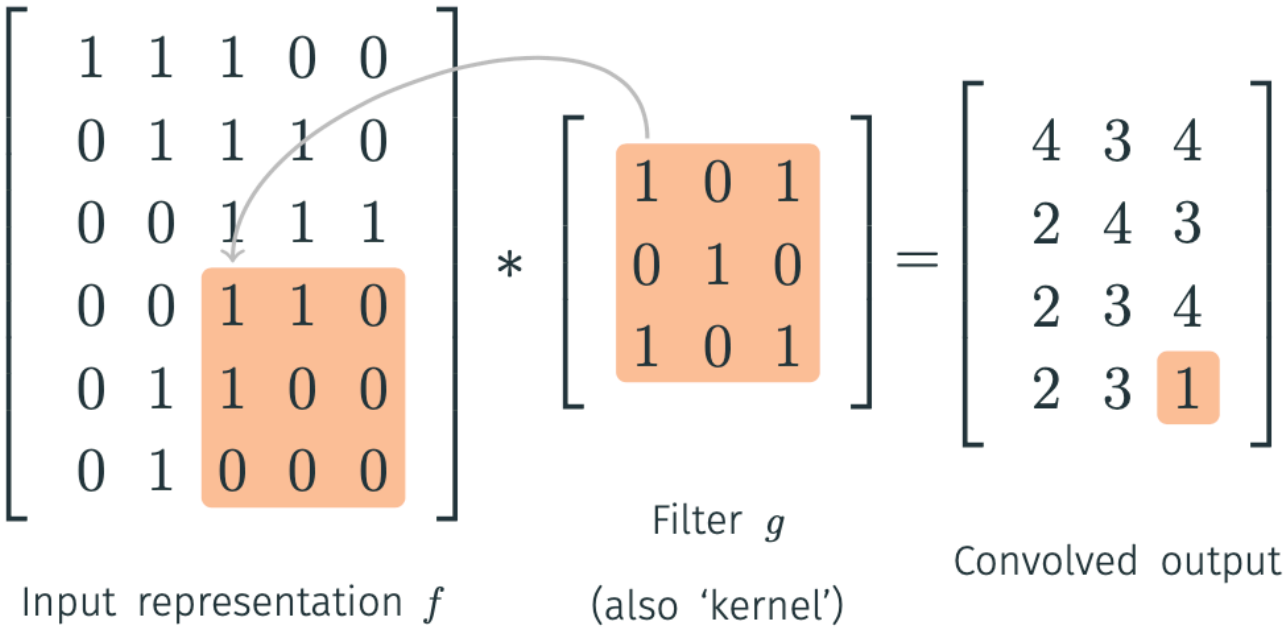
2-D Convolution



(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

2-D Convolution

The goal is to **learn** good kernels (filter parameters)



(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

Convolutional networks in speech recognition

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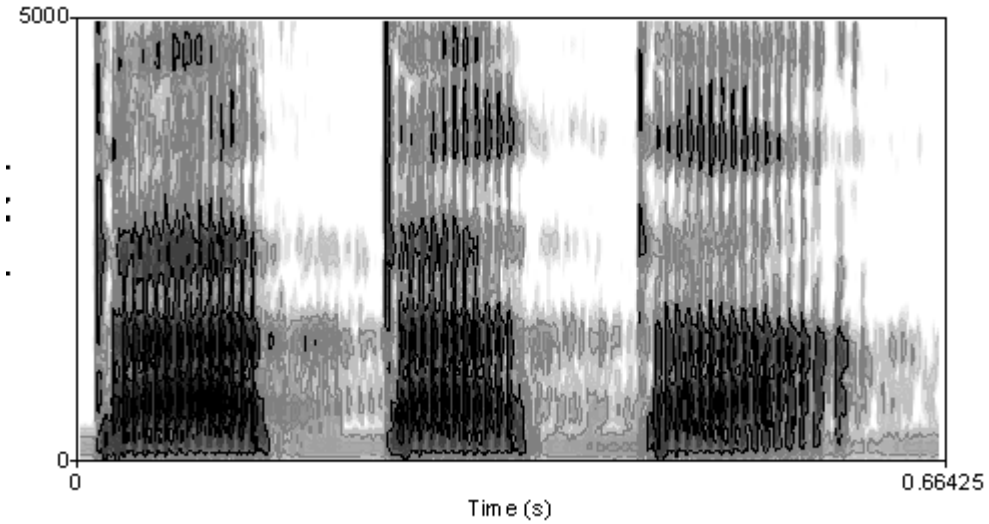
- Convolution over frequency to account for variations in the vocal tracts of different speakers



And in texts?

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- Sentiment classification
  - The movie was **really good**.
  - We saw this **really good** movie.
  - The movie, which we saw yesterday with all the colleagues in this tiny movie theatre next to the bridge, was (despite my expectations) **really good**.

- For this task, position information is not very relevant.

Dimensionality

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- Advantages of text flow:
  - Usually only one dimension
    as opposed to two dimensions in images

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Aenean …

Convolution operation

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- Input sentence $\mathbf{x}_{i:i+n}$ are stacked word embeddings of dimensionality d

- Convolutional filter $\mathbf{w} \in \mathbb{R}^{h \times d}$

where h is the filter size (how many neighboring words are convoluted)

- Convolution operation $\mathbf{w} * \mathbf{x}_{i:i+n}$

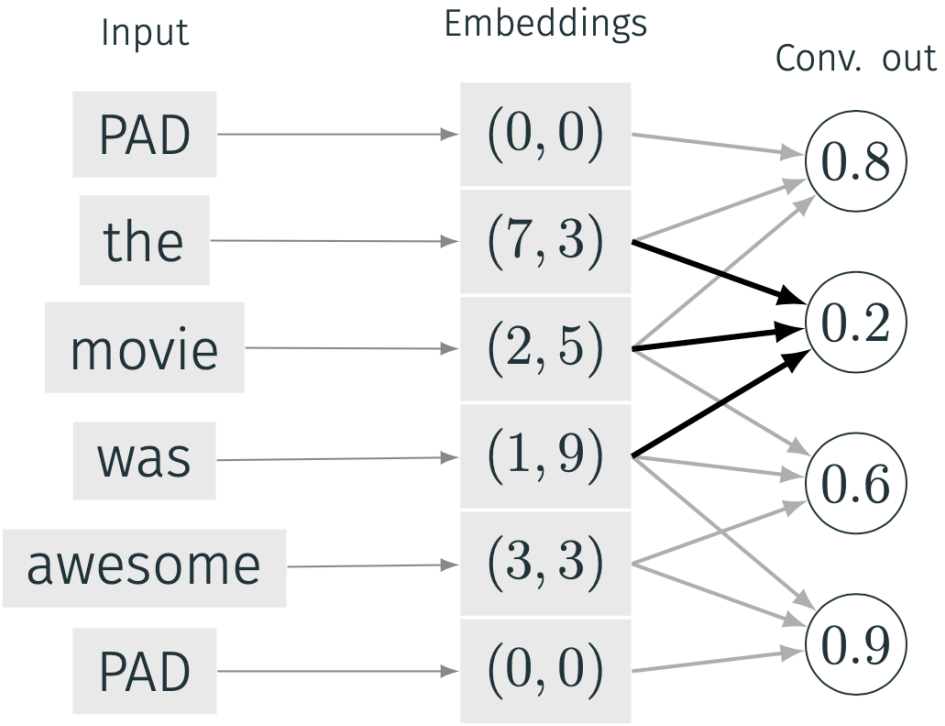
- Non-linear operation

$$c_i = \mathrm{ReLU}(\mathbf{w} * \mathbf{x}_{i:i+n} + b)$$

(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

Example

$d = 2 \qquad h = 3$



(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

CNN vs FeedForward

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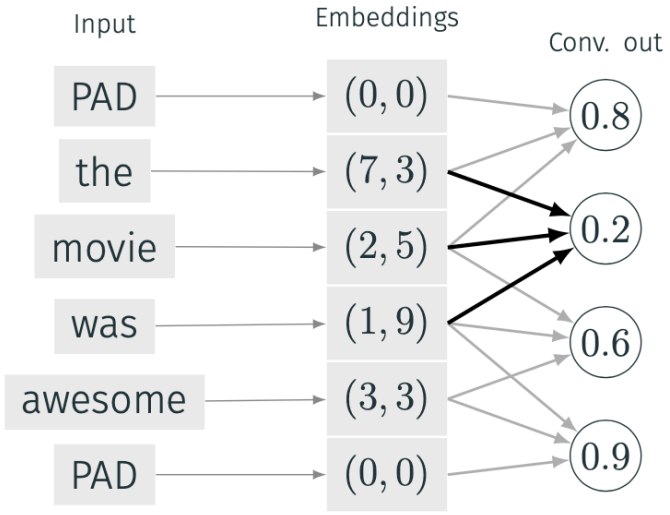
Not every input is connected to every output in the following layer

- **sparse connectivity** (vs fully-connected/dense layers)

For each window, we use the same weights and bias values

- **parameter sharing**



(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

Stride

Stride: the step size for moving over the sentence

- Stride 1 common in NLP; other values in comp. vision

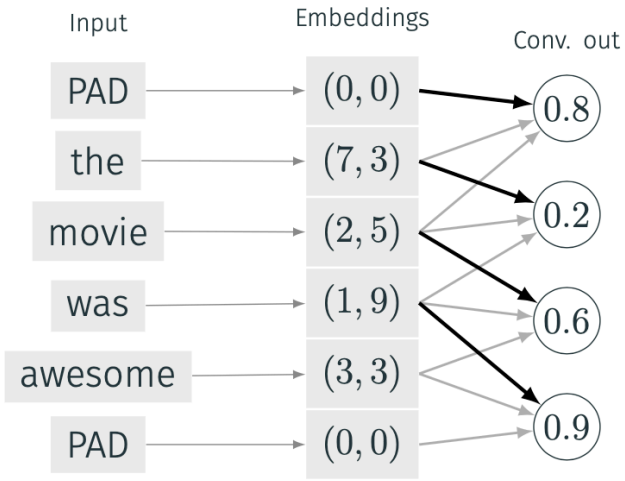


Figure 1: Stride = 1

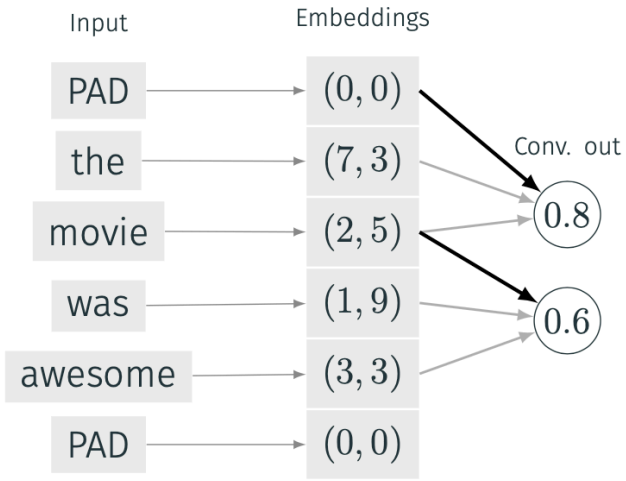


Figure 2: Stride = 2

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Pooling

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Another new building block: pooling layer

- Idea: capture the most important activation

Let $c_1, c_2, \ldots, \in \mathbb{R}$ denote the output values of the convolutional filter

Compute output o for a **max-over-time pooling** layer as

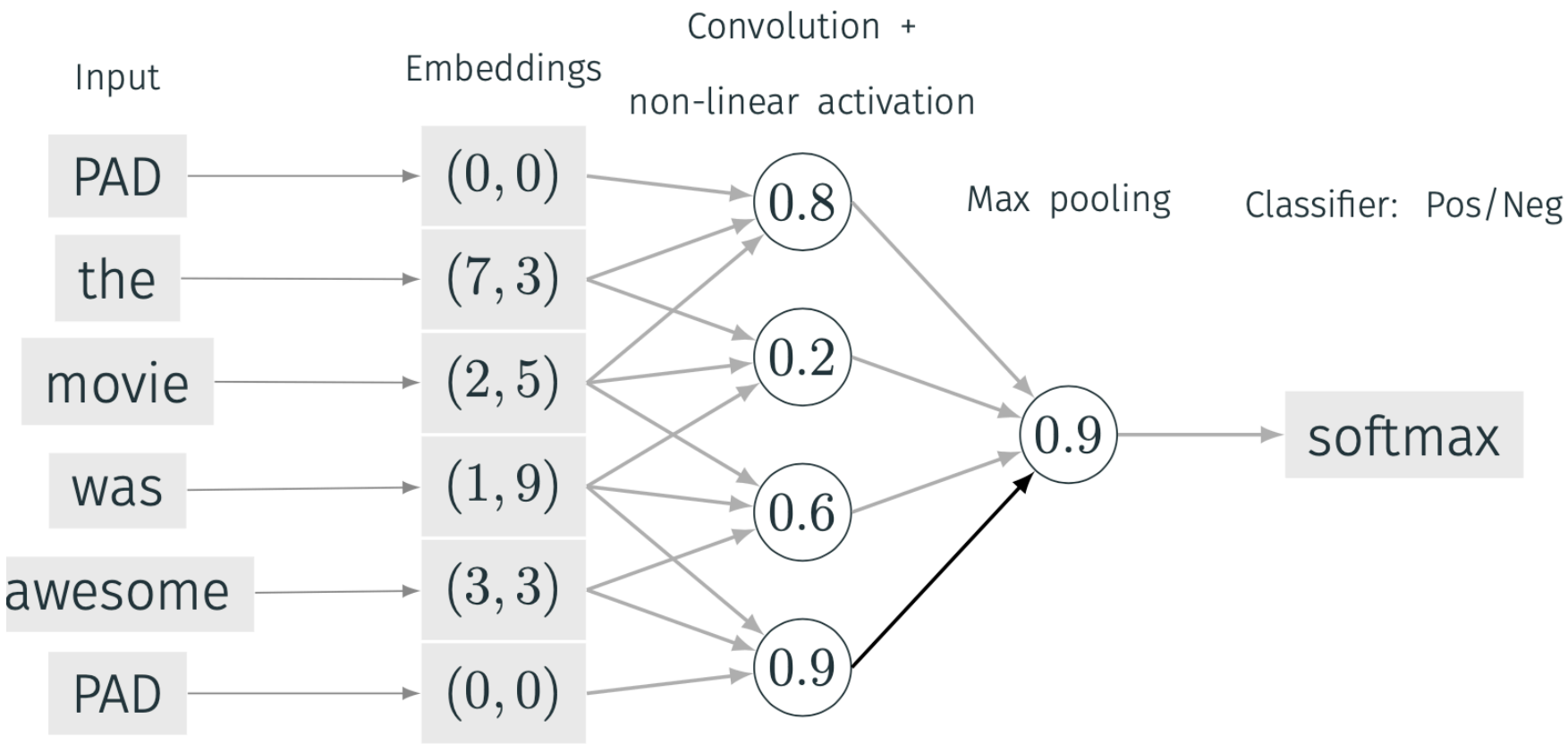
$$o = \max_i c_i$$

Max-over-time pooling is most common in NLP. You can also find min-pooling and mean-pooling in other areas. Could also use some other averaging

Note that there are no associated weights

(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

Pooling



(Taken from the DL4NLP course 2021 (Ivan Habernal and Mohsen Mesgar)

Stacked convolutional layers

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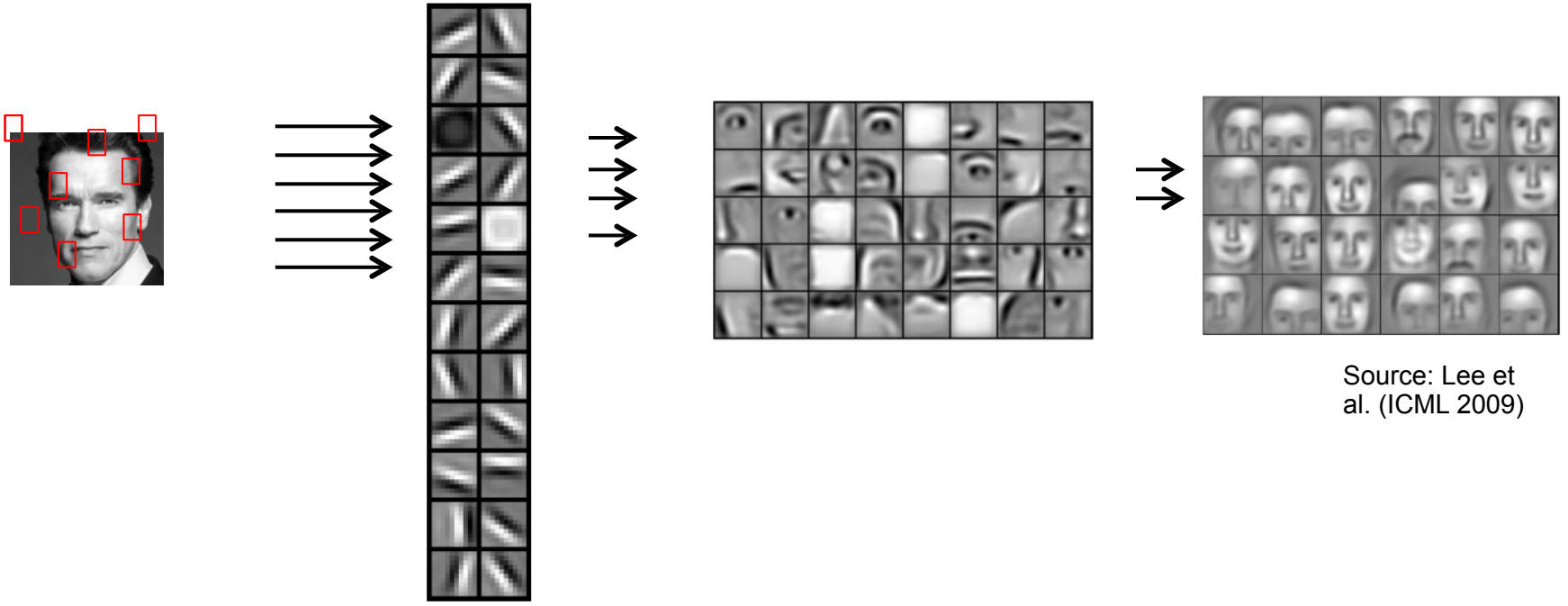
- Convolutional layers can be stacked to derive high-level representations from simple representations
- In images: edge detection → identifying facial features (eyes, nose, lips) → face recognition



Source: Lee et al. (ICML 2009)

Stacked convolutional layers

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- Convolutional layers can be stacked to derive high-level representations from simple representations
- In images: edge detection → identifying facial features (eyes, nose, lips) → face recognition
- In NLP?
- Polarity of words → Identifying polarity of phrase (negated positive phrase) → sentiment classification

- This is only a very rough approximation, usually features in neural networks are hard to interpret (if at all)

Recurrent Neural Networks

Representation of Language

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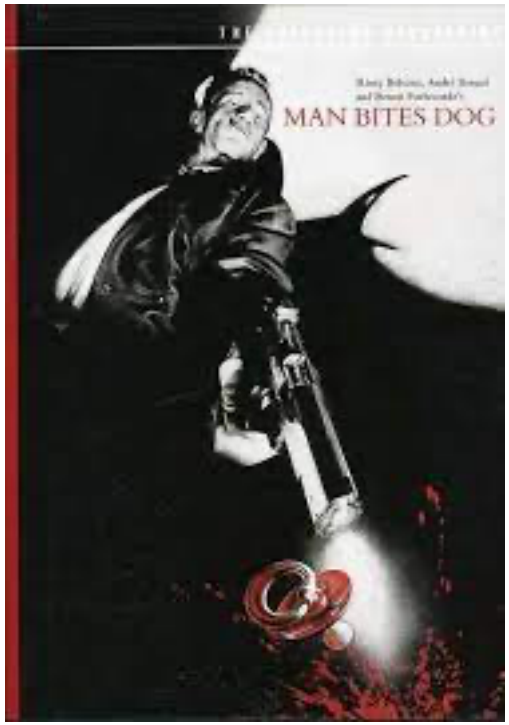
Neural networks need vectorized/numerical input

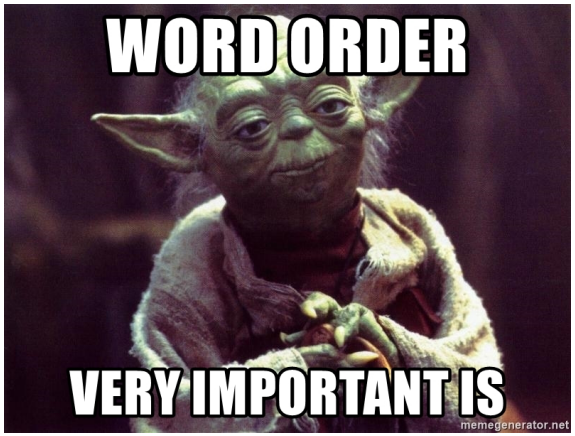
- `This is an example sentence .`
- `[ 35, 5, 3, 134, 96, 10 ]`

Fixed number of input neurons → fixed size

- `[ 0 0 0 0 15 16 2 19 178 32]`
- `[ 52 154 462 33 89 78 285 16 145 95] 108 7 4 2`
- `[ 0 0 624 35 534 6 227 7 129 113]`
- `[ 26 49 2 15 566 30 579 21 64 2]`
- `[ 19 14 5 2 6 226 251 7 61 113] 4 226 65 12 10 10`

Word order matters ...





„Man bites dog“
„Dog bites man“

Long-range Dependencies

e.g. Sentiment classification

- I like the new iPhone but it doesn‘t have any new features and it is much too expensive.

Long-range Dependencies

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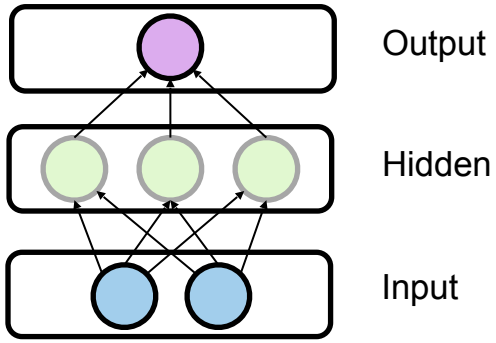
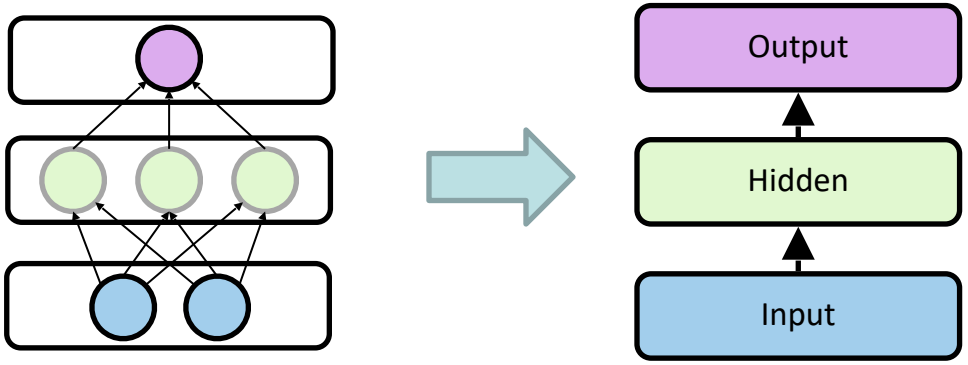
e.g. Sentiment classification

- **[I like the new iPhone but it doesn't have any new features and it is]** ~~much too expensive.~~



How to model long input sequences?

Collapsed View



From Feed-forward to Recurrent Nets

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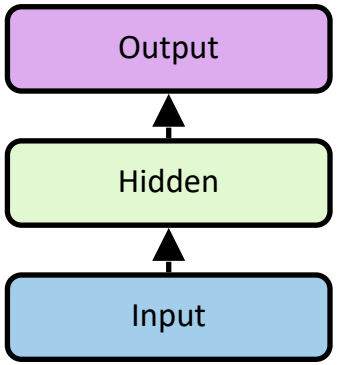
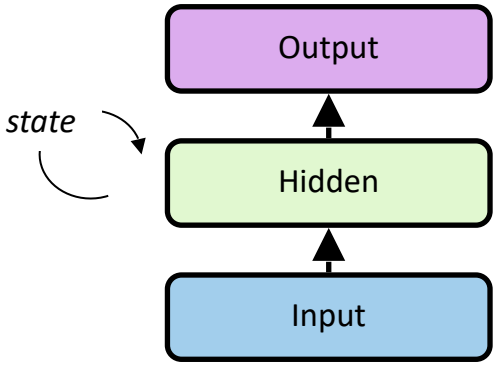
Feed-forward



Recurrent



Unrolling in time

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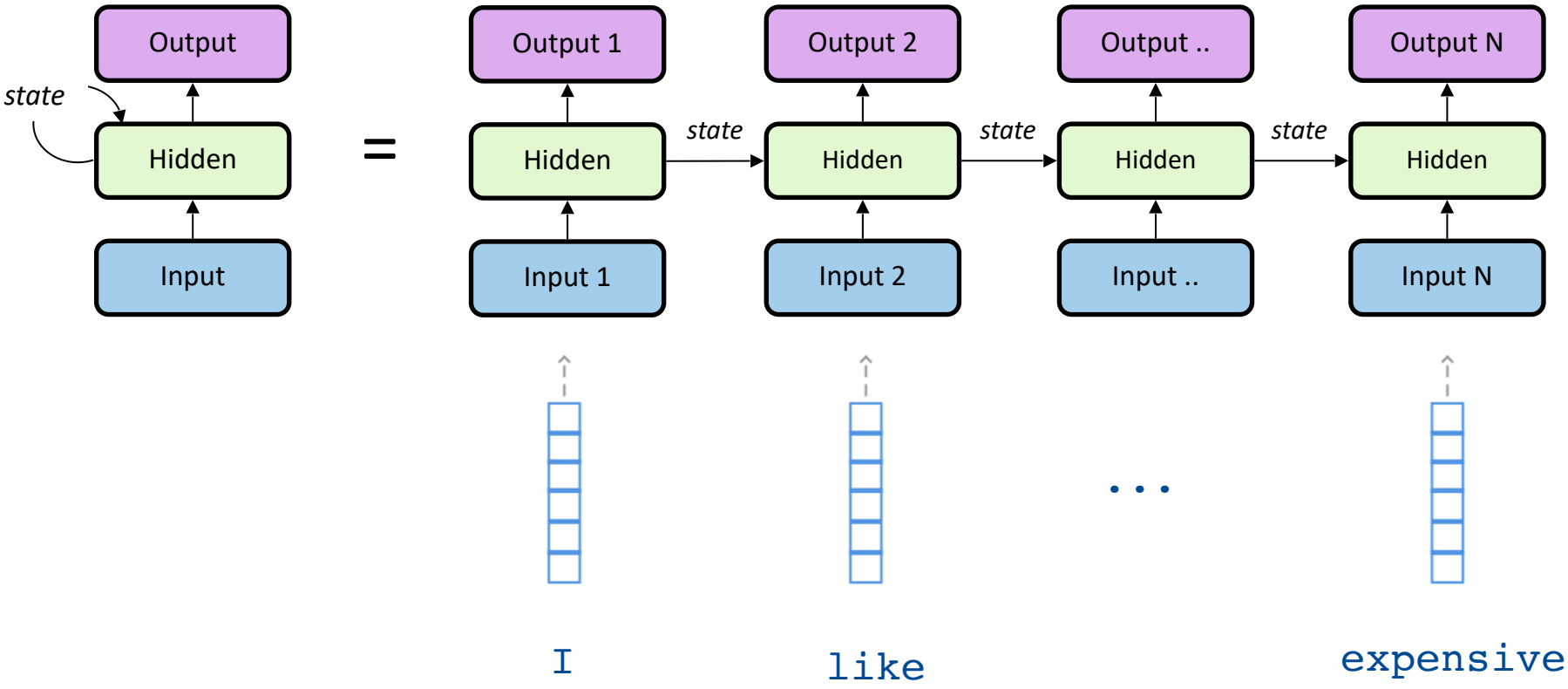
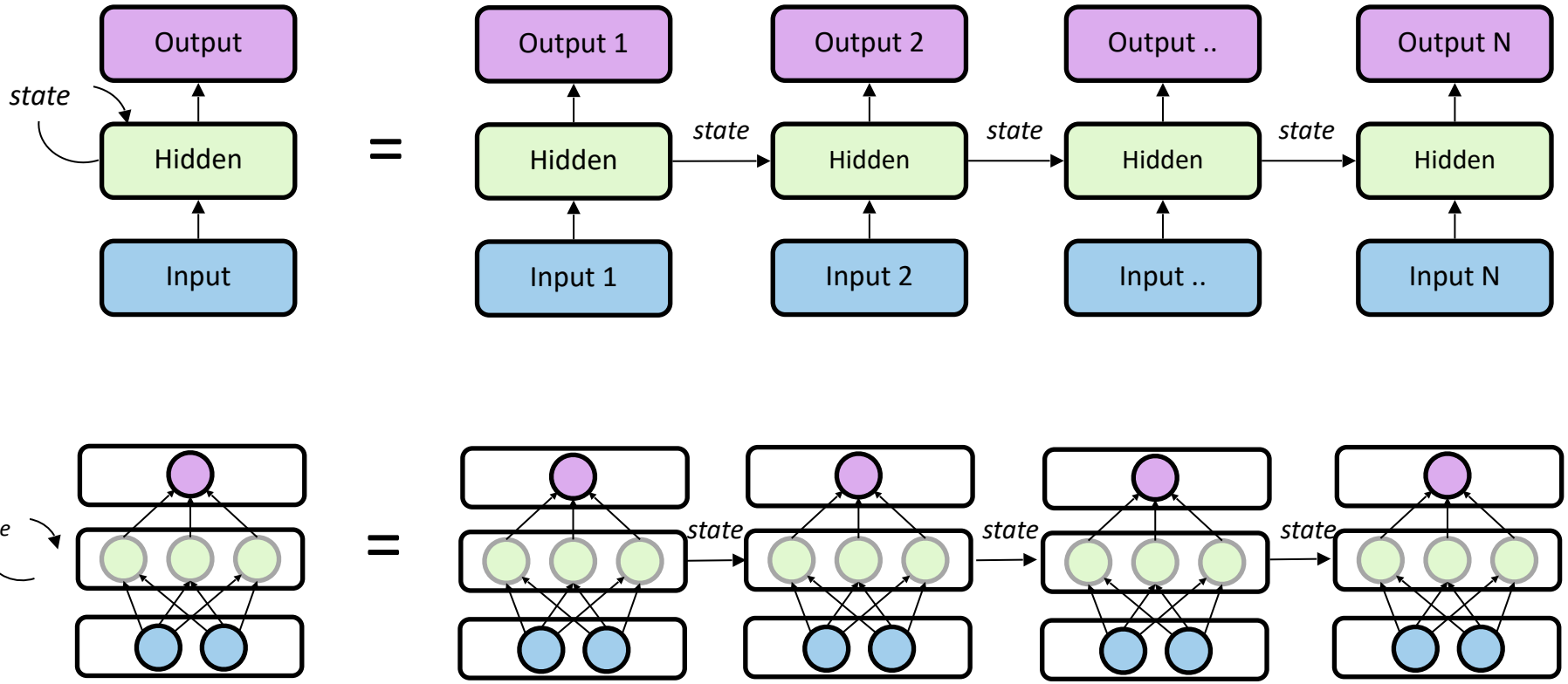
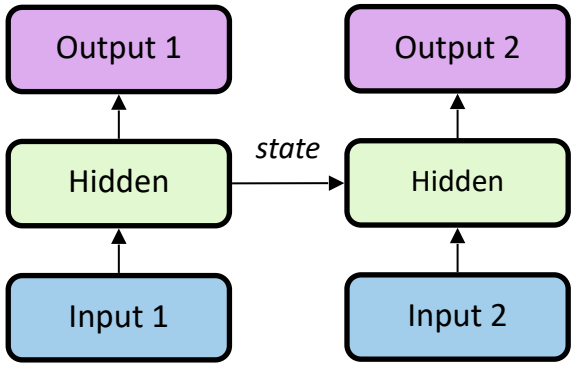
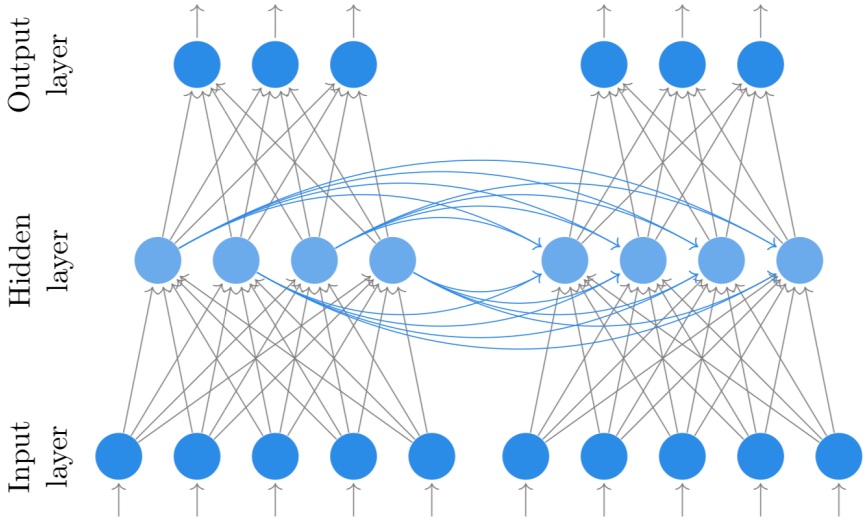


Unrolling in time



Zoomed-in View





Variants

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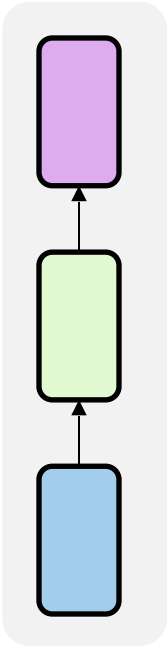
one to one



Vanilla Feed-Forward

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ & http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Variants

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one to one

one to many

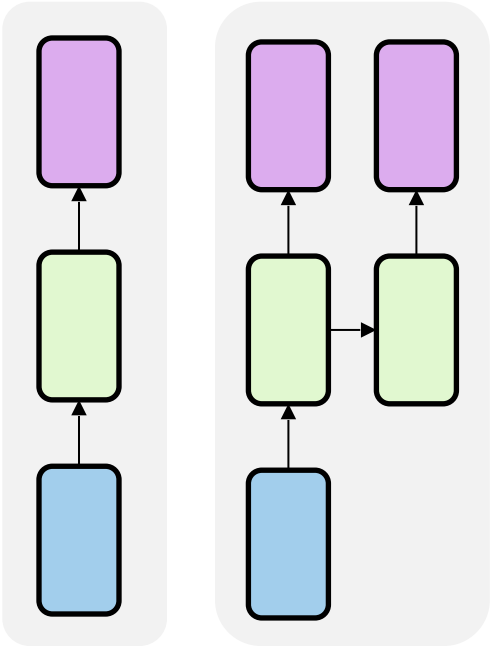
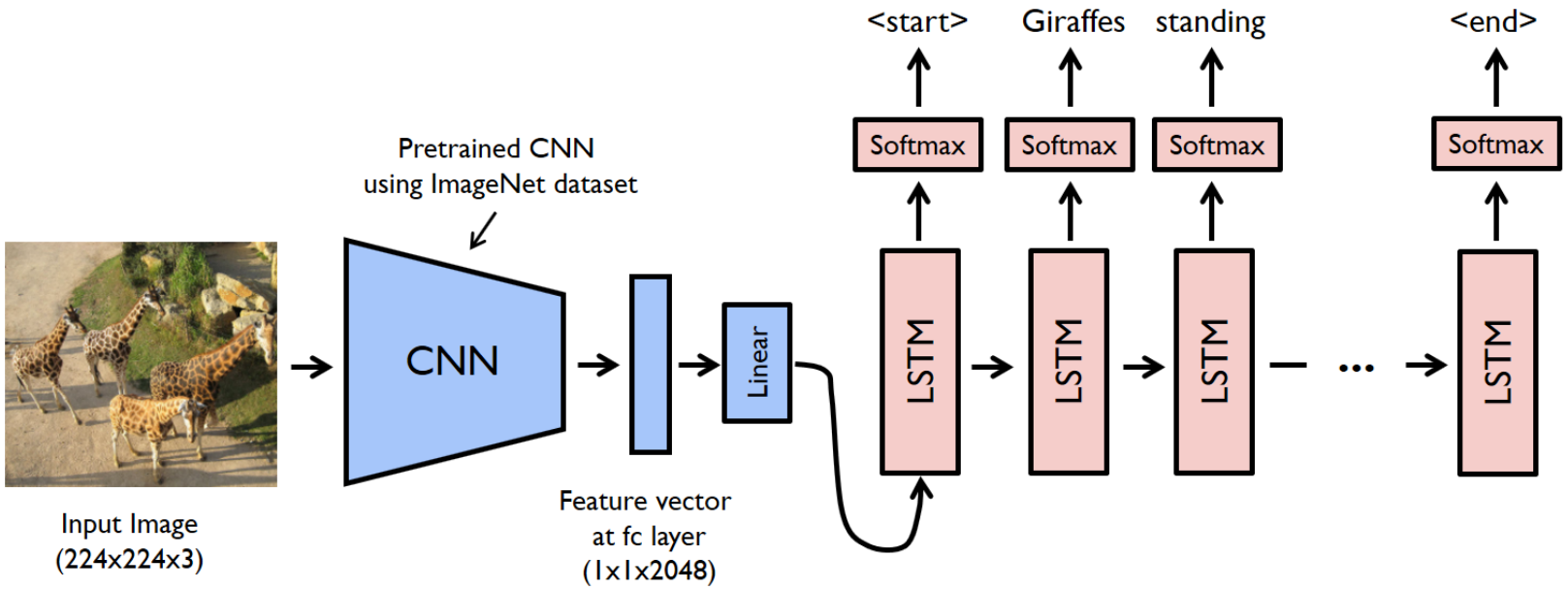


Image Captioning

- *one* image to *many* words

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ & http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Image Captioning



https://www.analyticsvidhya.com/blog/2018/04/solving-an-image-captioning-task-using-deep-learning/

Variants

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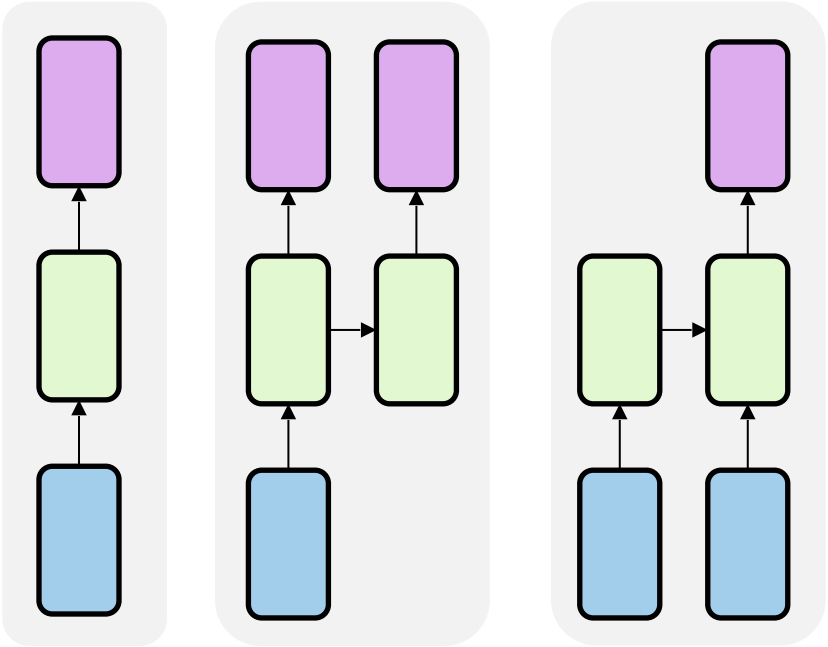
one to one | one to many | many to one

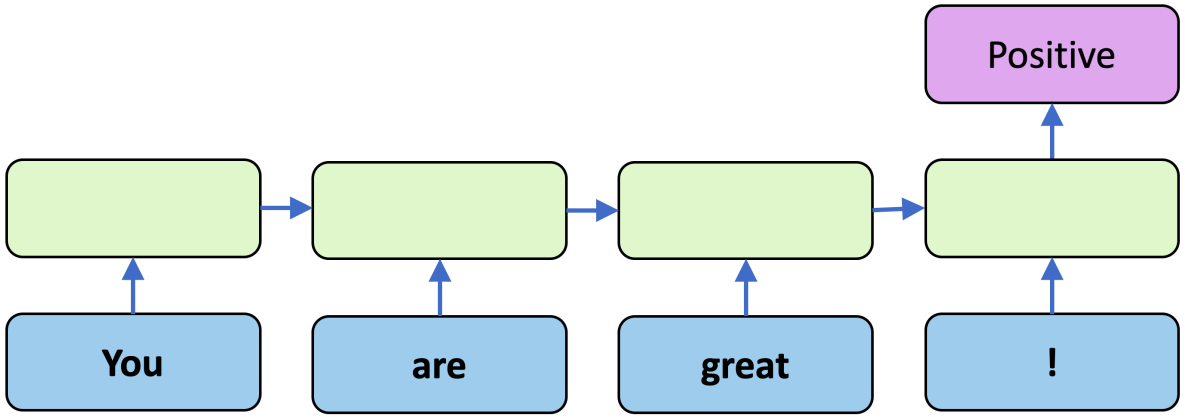


Sentiment Classification

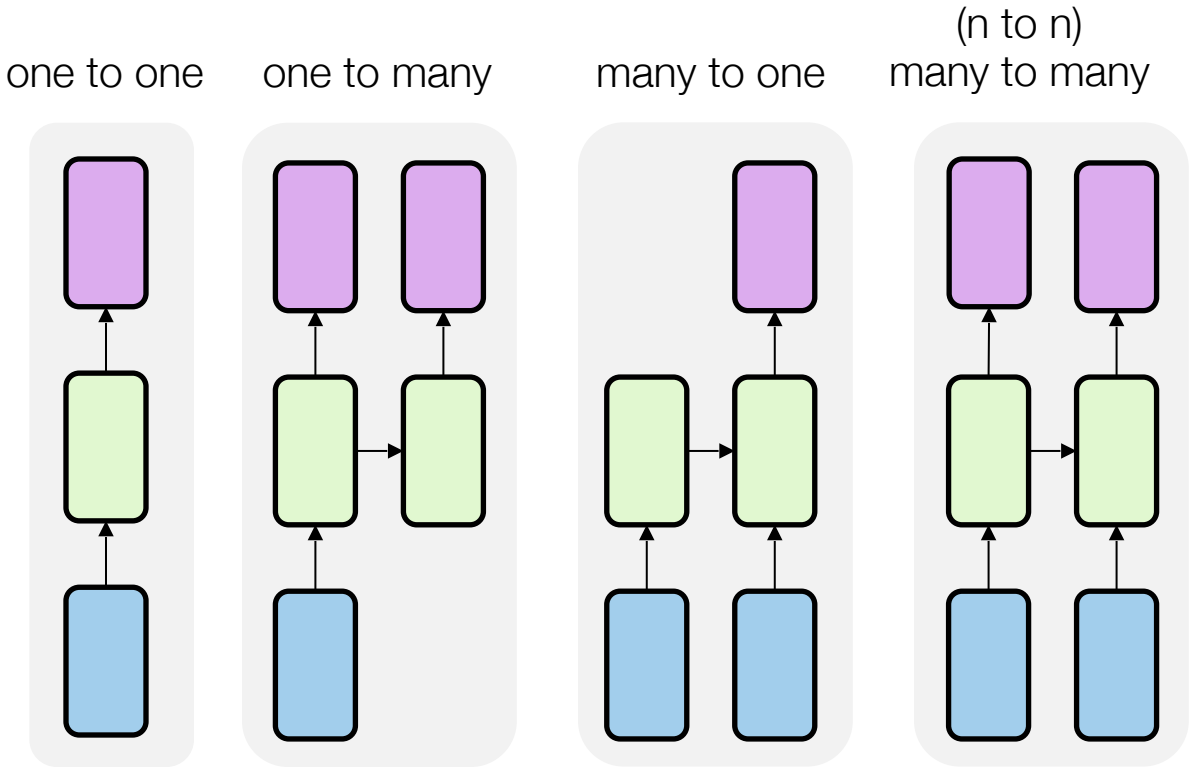
- *many* words to *one* category

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ & http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Sentiment Classification



Variants



POS Tagging

- *many* words to *many tags*

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ & http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

POS Tagging

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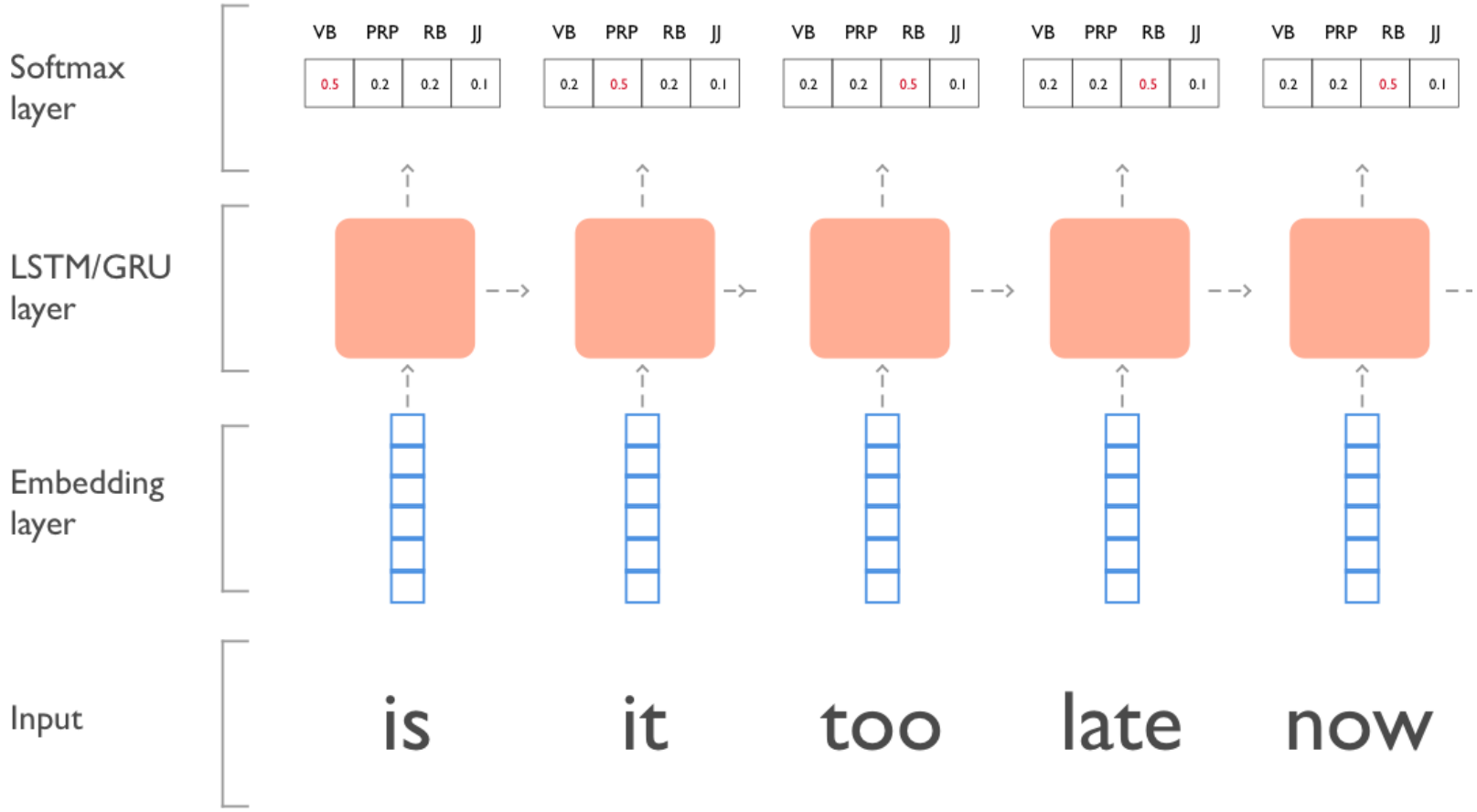

https://towardsdatascience.com/taming-lstms-variable-sized-mini-batches-and-why-pytorch-is-good-for-your-health-61d35642972e

Variants

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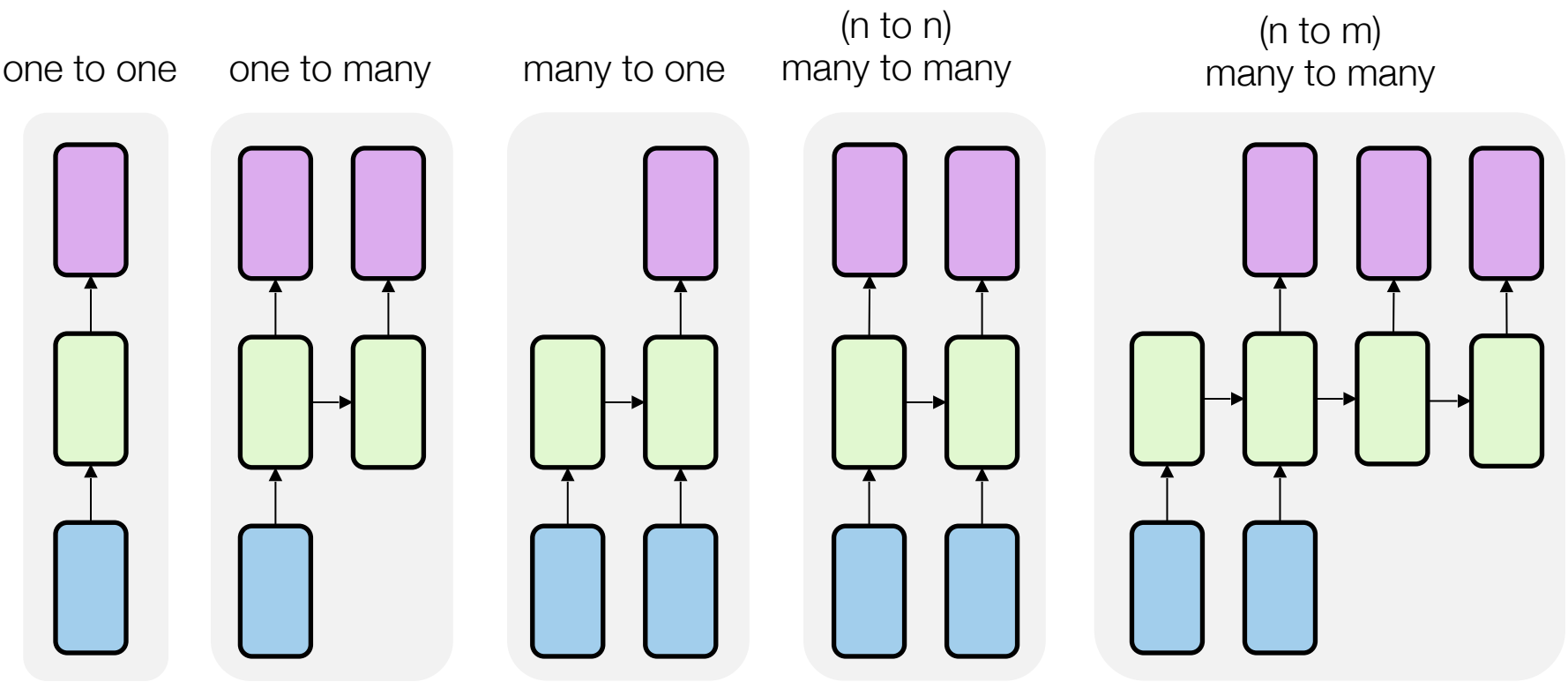
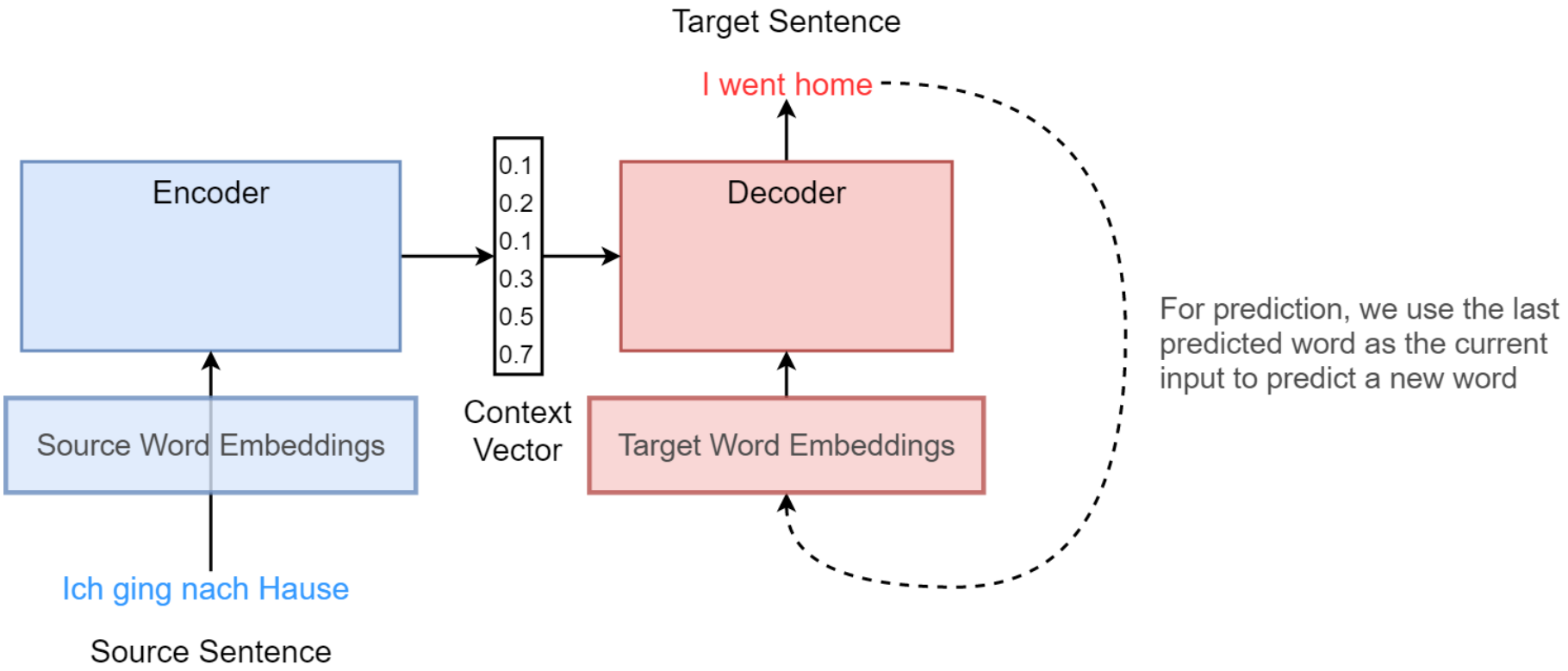


Machine Translation

- *many* words to *many words*

http://karpathy.github.io/2015/05/21/rnn-effectiveness/ & http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Machine Translation



Generative Adversarial Networks (GANs)

Generative networks

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- The networks we have seen so far, read an input matrix of data and modify it by using weights and activation functions.
- In the final layer, we run a softmax over the modified matrix to receive classification probabilities.

- The input matrix represents the input data.
- Could we modify the matrix such that it represents new data?
  → generative model

- For many tasks, we encounter the problem that we do not have enough training data.
  Couldn't we just generate it?

Generator-discriminator competition

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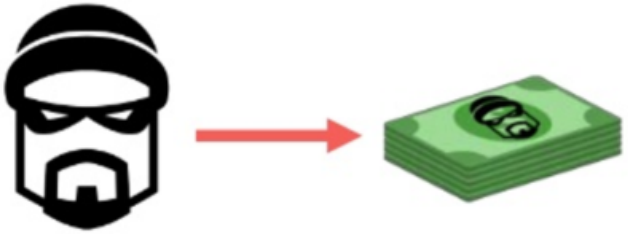
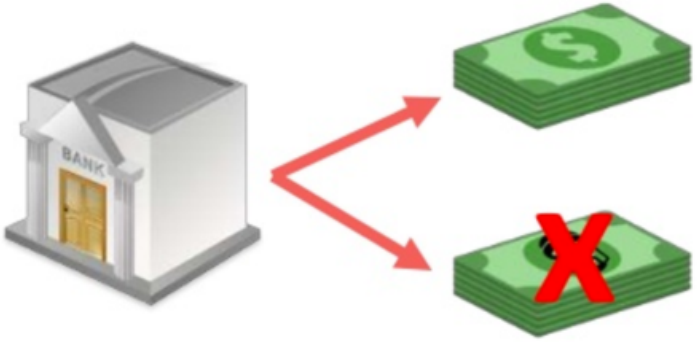
- Generator: try to generate authentic looking instances.
- Discriminator: distinguish between the real and generated instances.

Generator



Goal: produce counterfeit money that is as similar as real money.

Discriminator (Classifier)



Goal: distinguish between real and counterfeit money.

Generative Adversarial Networks (GAN)

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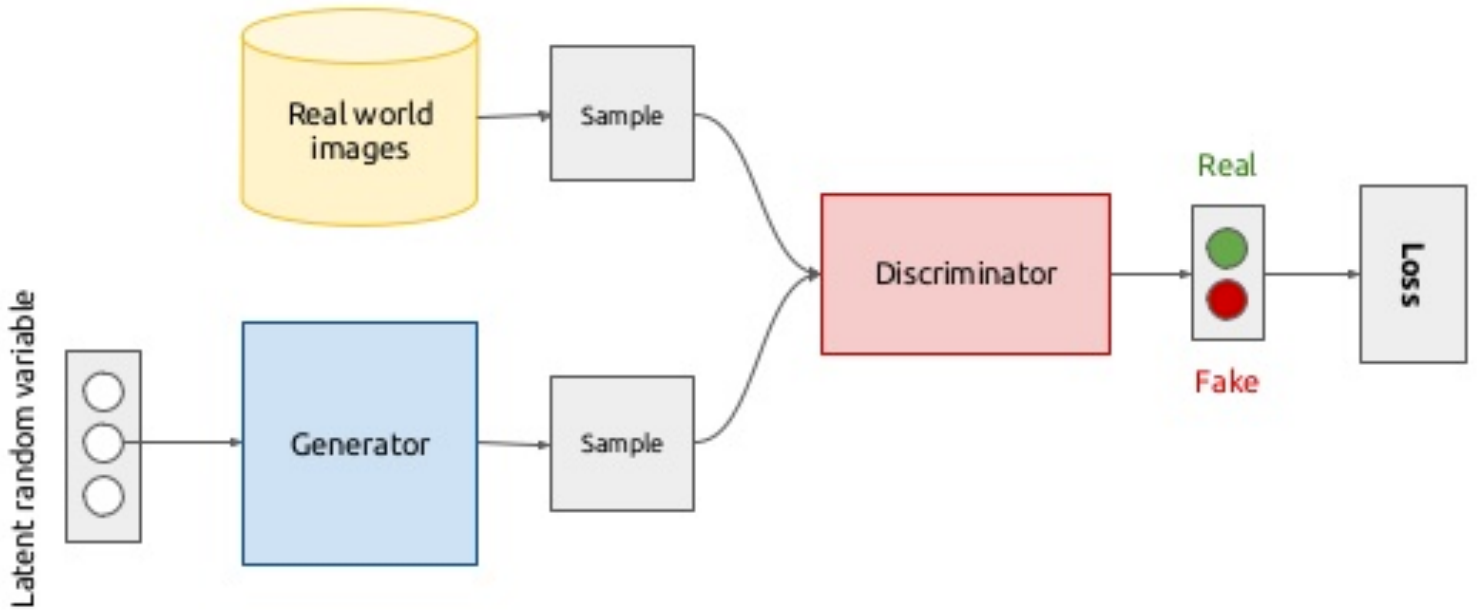
- During training, both the discriminator and the generator improve.



5

Objective

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Generator:

Input

100 numbers

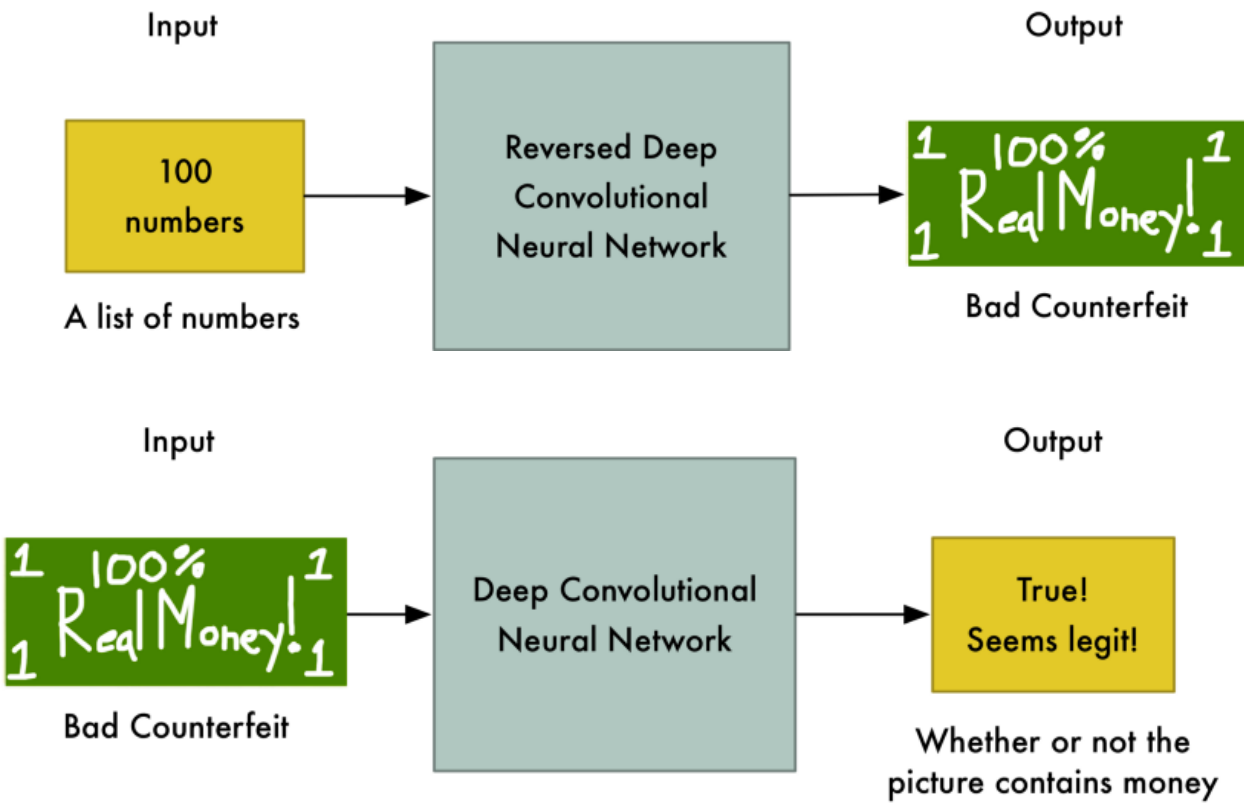
A list of numbers

Reversed Deep Convolutional Neural Network

Discriminator:

Deep Convolutional Neural Network

GAN: Start


Input
100 numbers
A list of numbers
Reversed Deep Convolutional Neural Network
Output
100% Real Money!
Bad Counterfeit
Input
100% Real Money!
Bad Counterfeit
Deep Convolutional Neural Network
Output
True! Seems legit!
Whether or not the picture contains money

GAN: Improve classification

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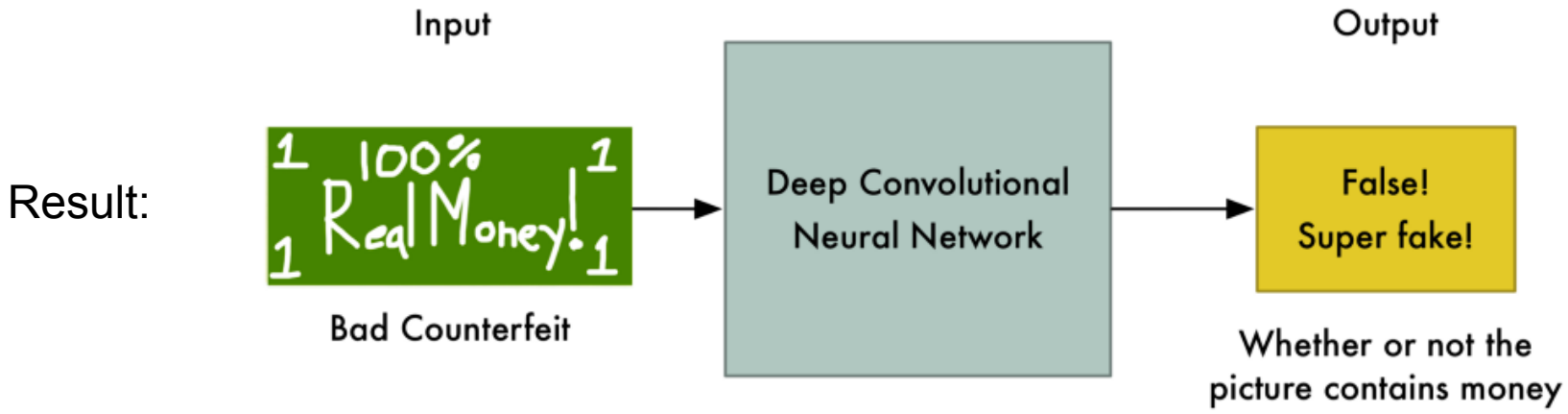
- The discriminator learns from sample data to distinguish between real and fake money.
  - e.g. real money has a picture of a person on it



GAN: Improve generation

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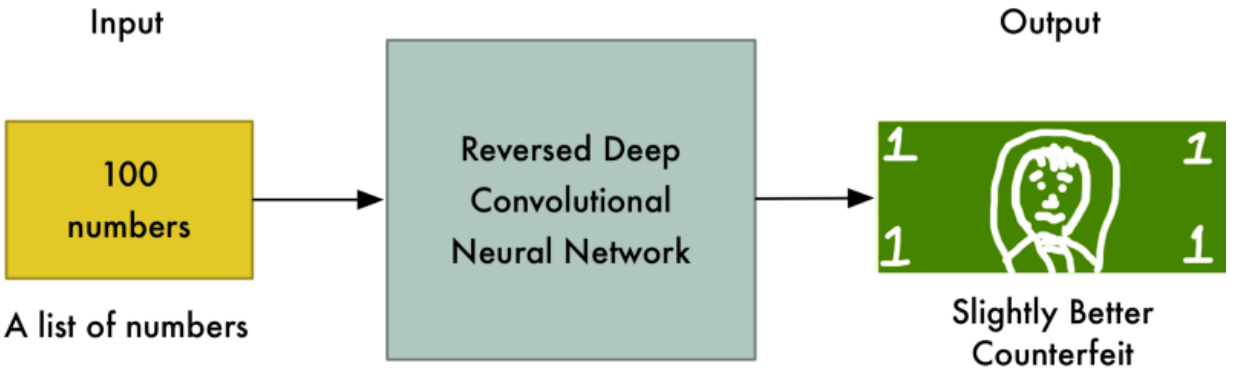
- The generator learns that the generated samples are getting rejected.
- It learns which features the discriminator is looking for (pictures of people) and improves the generation.

Result:



- Now: iterate!
- An improved generator leads to an improved discriminator leads to an improved generator...

Face aging

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Zhang et al: https://arxiv.org/pdf/1702.08423.pdf

Generating art

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Elgammal et al.: https://arxiv.org/pdf/1706.07068.pdf

Summary

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- Different architectures serve different purposes:

- Convolutional neural networks
  → Image processing, document classification

- Recurrent neural network
  → Sequence processing

- Generative adversarial neural networks
  → Artificial data generation

Reading

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Mandatory:

- Ian Goodfellow, Yoshua Bengio, Aaron Courville:
- Deep Learning, *Chapter 9*, 9.1 to 9.3.
- Deep Learning, *Chapter 10*, 10.2 and 10.4
  http://www.deeplearningbook.org/

Optional:

- http://colah.github.io/posts/2015-08-Understanding-LSTMs/
- https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/