Machine Learning I 60629A

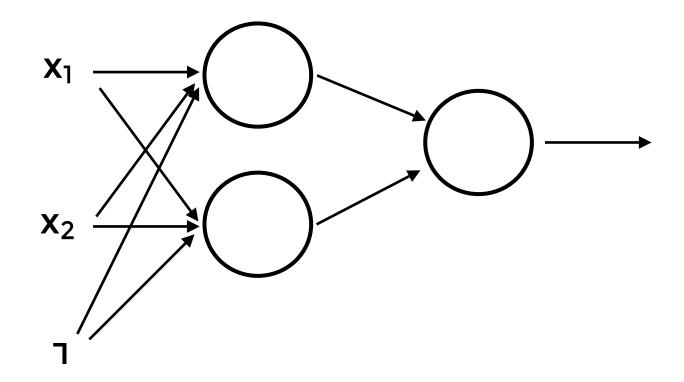
Summary

CNNs and RNNs

— Week #5

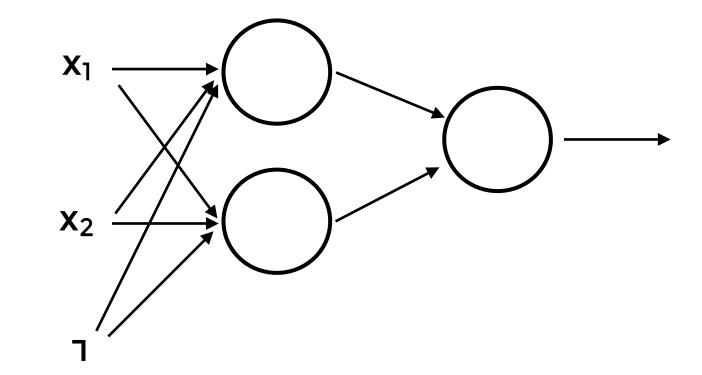
Neural Network models (architectures)

- Feed-forward neural networks are standard
 - Input & Output: Fixed-length
 - Data is processed in parallel



Neural Network models (architectures)

- Feed-forward neural networks are standard
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 - Data is processed in parallel



- We can "specialize" neural networks
 - Different data have different characteristics

Text Classification

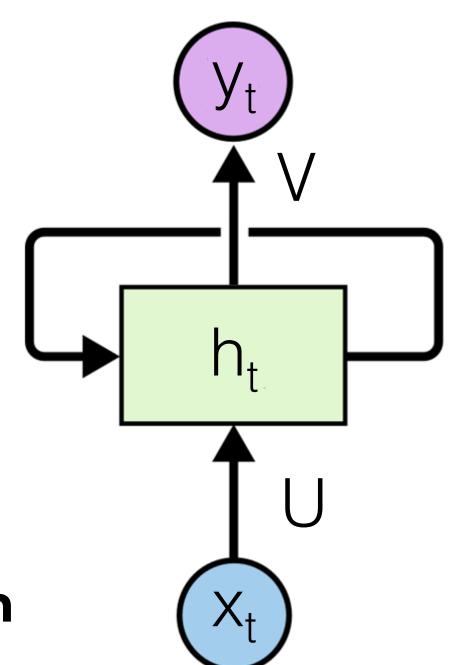
```
From: bcash@crchh410.NoSubdomain.NoDomain (Brian Cash)
Subject: Re: free moral agency
Nntp-Posting-Host: crchh410
Organization: BNR, Inc.
Lines: 17
In article <735295730.25282@minster.york.ac.uk>, cjhs@minster.york.ac.uk writes:
|> : Are you saying that their was a physical Adam and Eve, and that all
|> : humans are direct decendents of only these two human beings.? Then who
|> : were Cain and Able's wives? Couldn't be their sisters, because A&E
|> : didn't have daughters. Were they non-humans?
|> Genesis 5:4
|> and the days of Adam after he begat Seth were eight hundred years, and
> he begat sons and daughters:
|> Felicitations -- Chris Ho-Stuart
Yeah, but these were not the wives. The wives came from Nod, apparently
a land being developed by another set of gods.
| Brian /-|-\
```

→ SPAM / HAM

Basic idea (with parameters)

Process through time (t)

- U, V, W: parameters
 - Shared through time
- Simplest parametrization



W

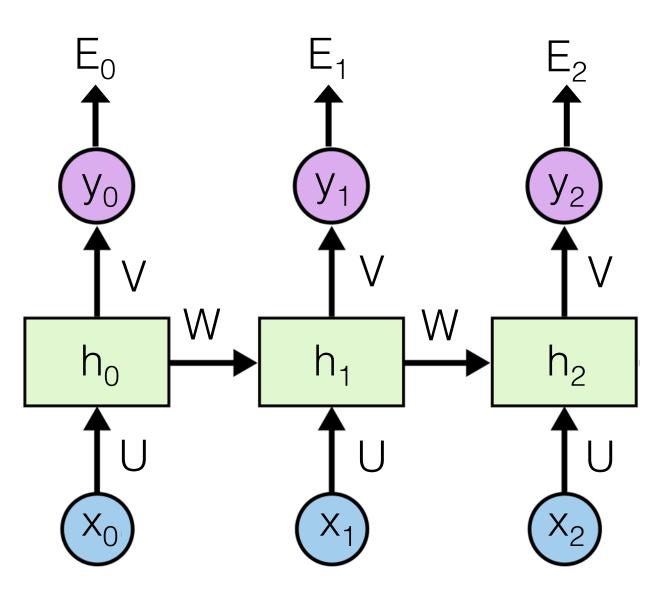
 $h_t = \tanh(Ux_t + Wh_{t-1})$ $y_t = f(Vh_t)$

Training RNNs

• Gradient descent from the loss $E = \sum (y_t - \hat{y}_t)^2$

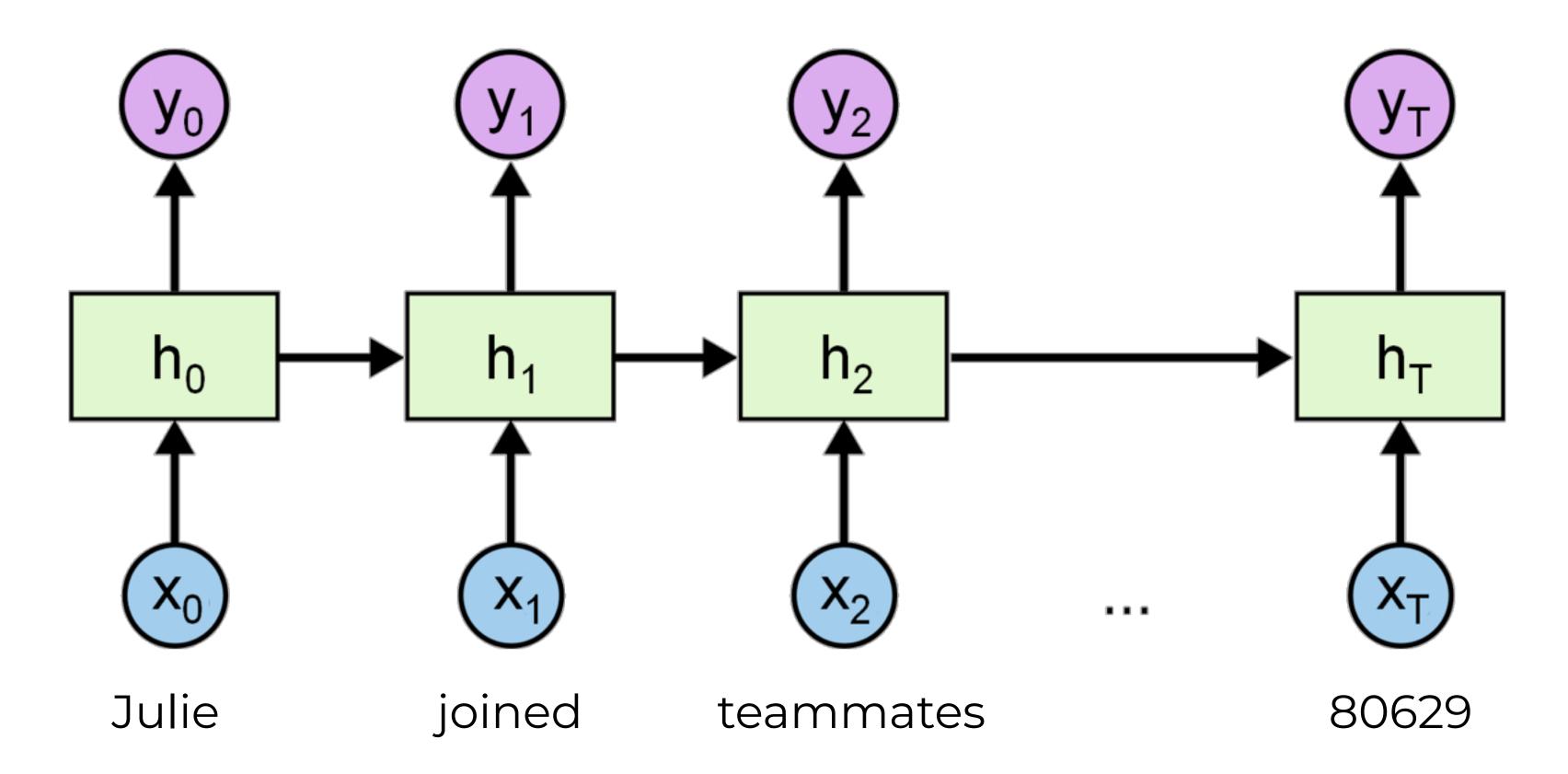
$$E = \sum_{t} (y_t - \hat{y}_t)^2$$

 Following the structure the gradient is back propagated through time



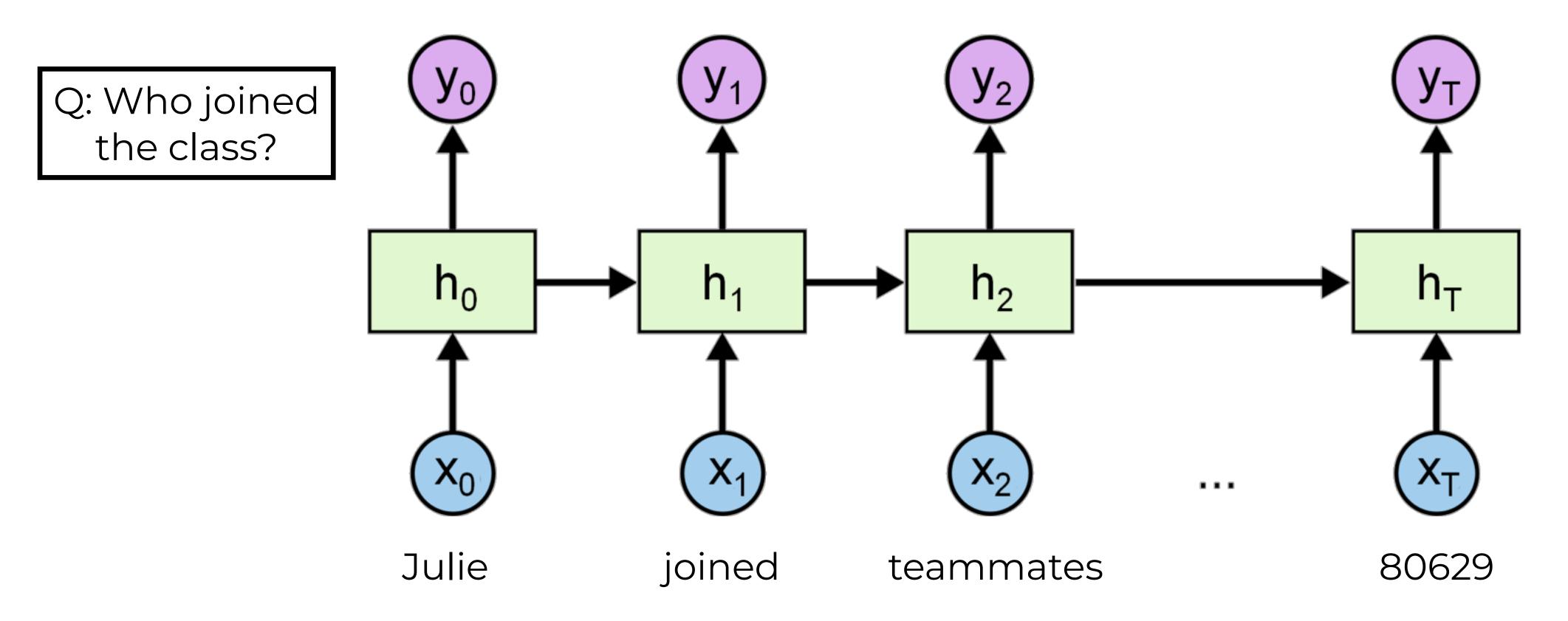
Limitations

• Long-term dependencies are difficult to learn



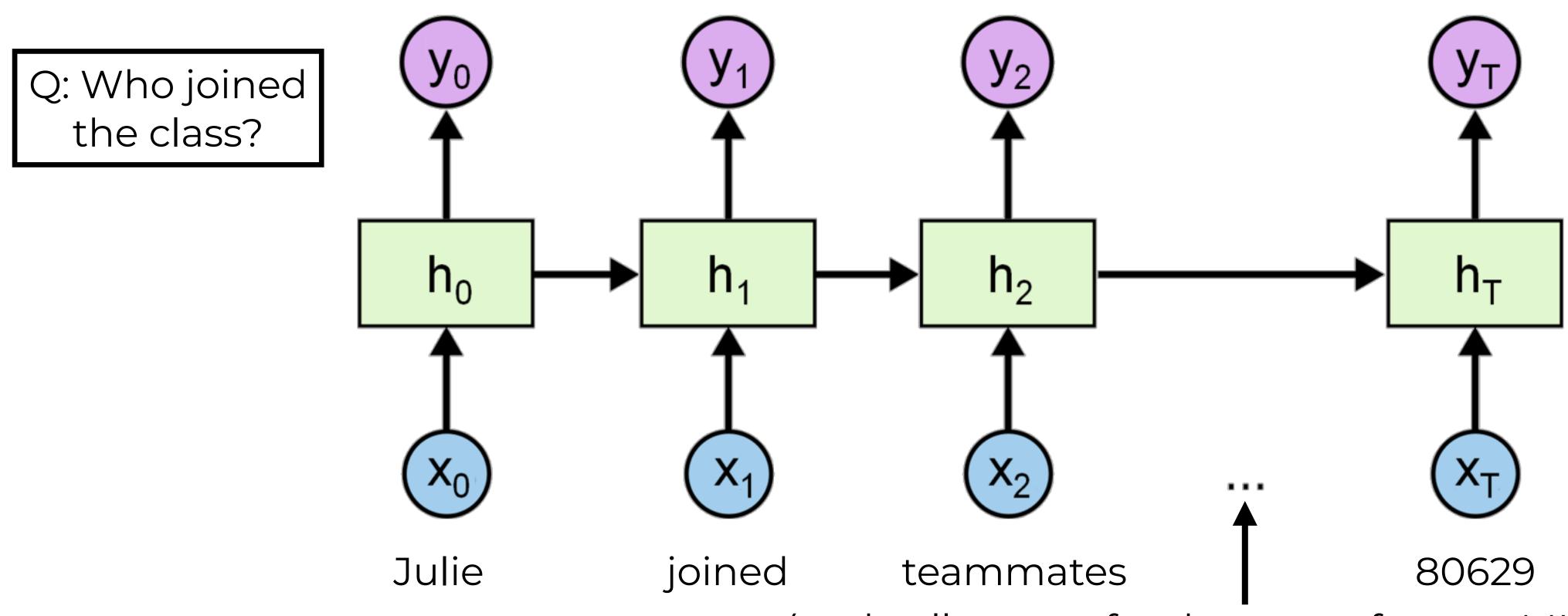
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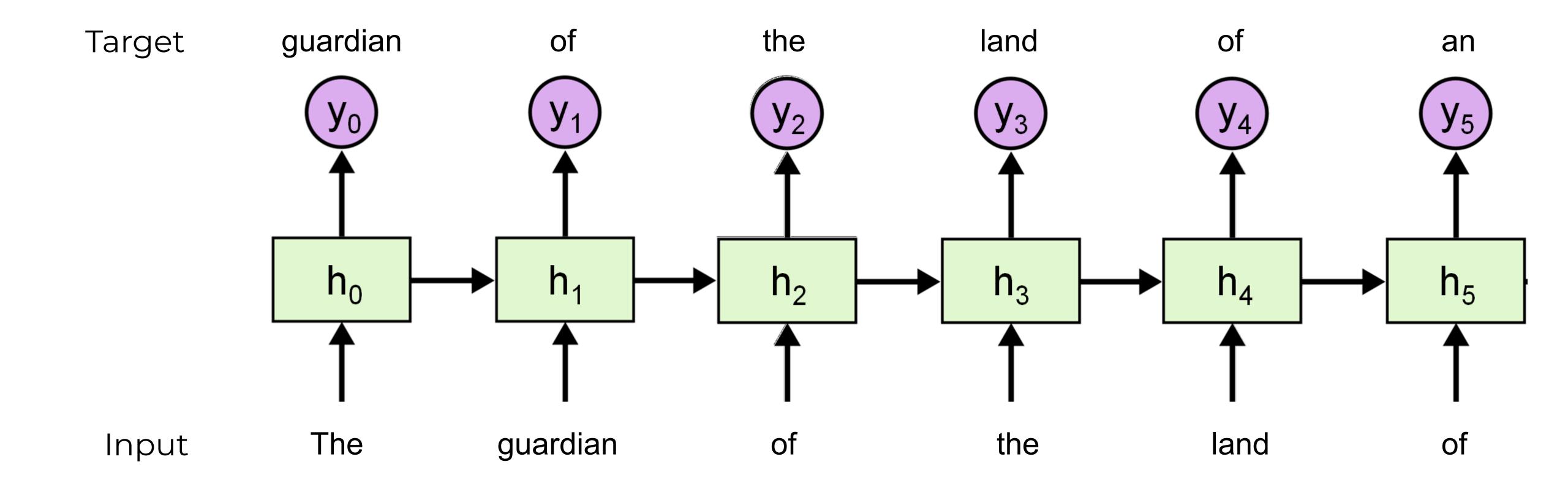
Long-term dependencies are difficult to learn



http://colah.github.io/

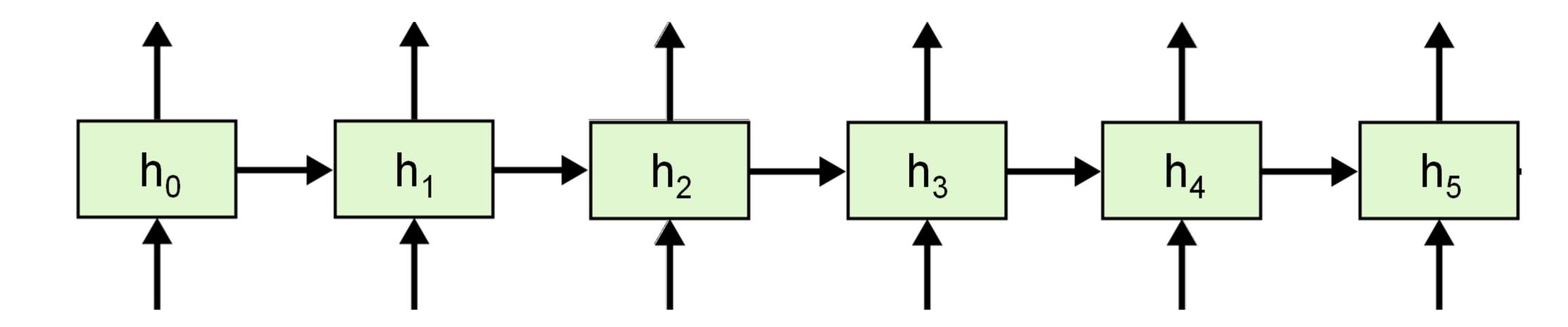
(and colleagues for the start of a new ML class)

Training.
Given previous words,
predict the next word



- 1. Predict One word at a time.
- 2. Feed the prediction back to the model

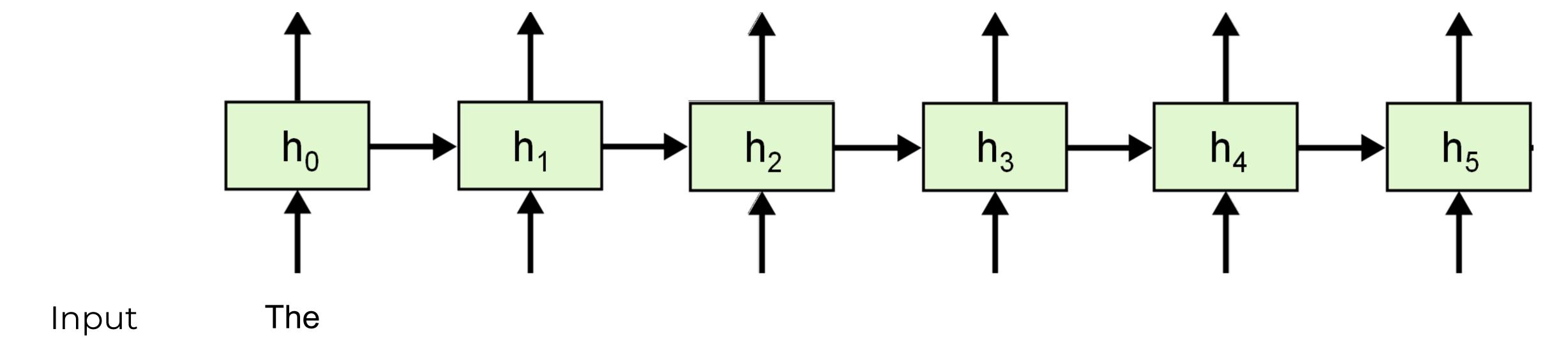
Prediction



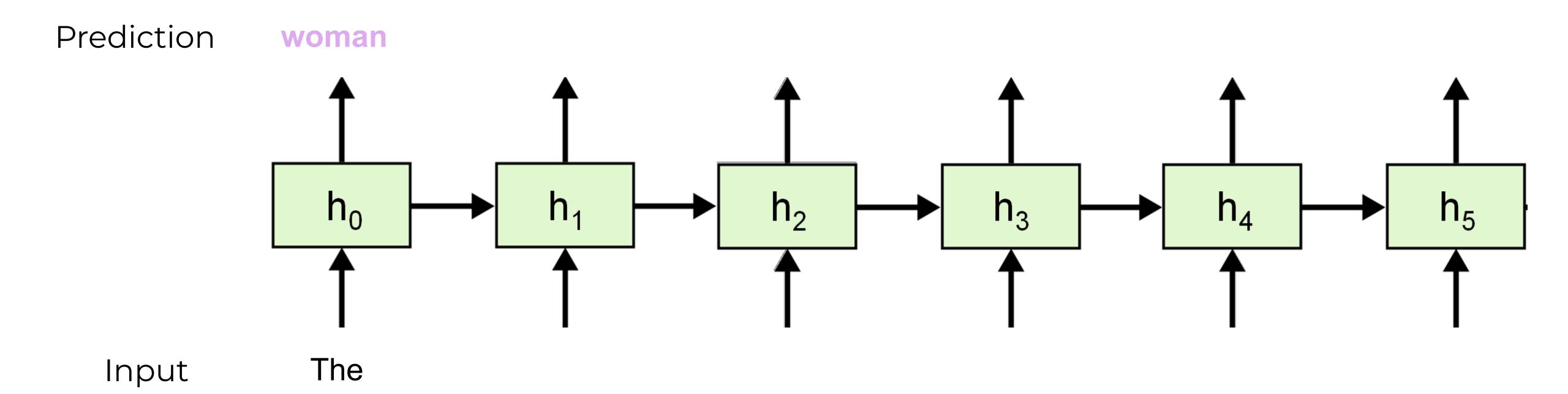
Input

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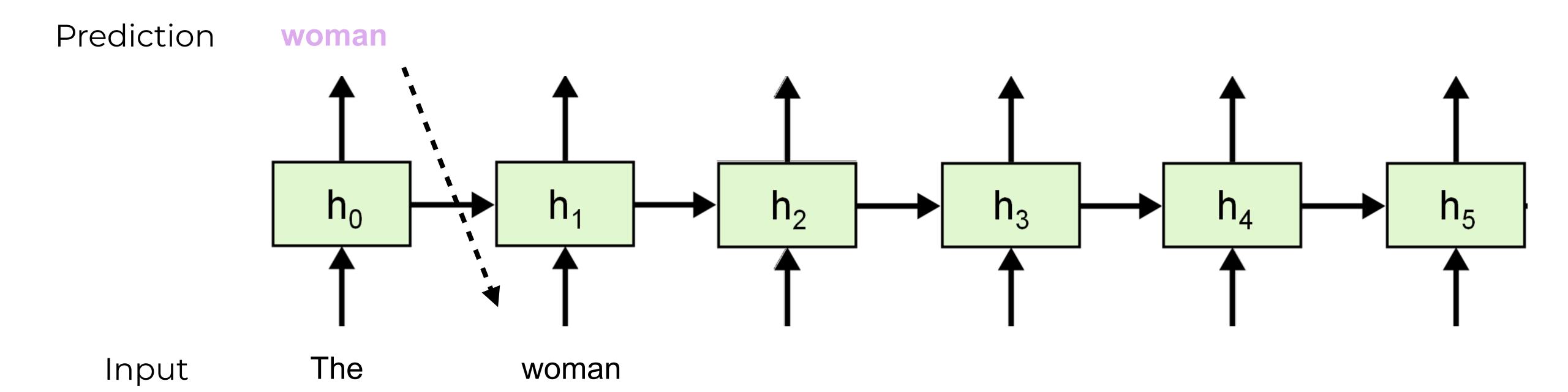
Prediction



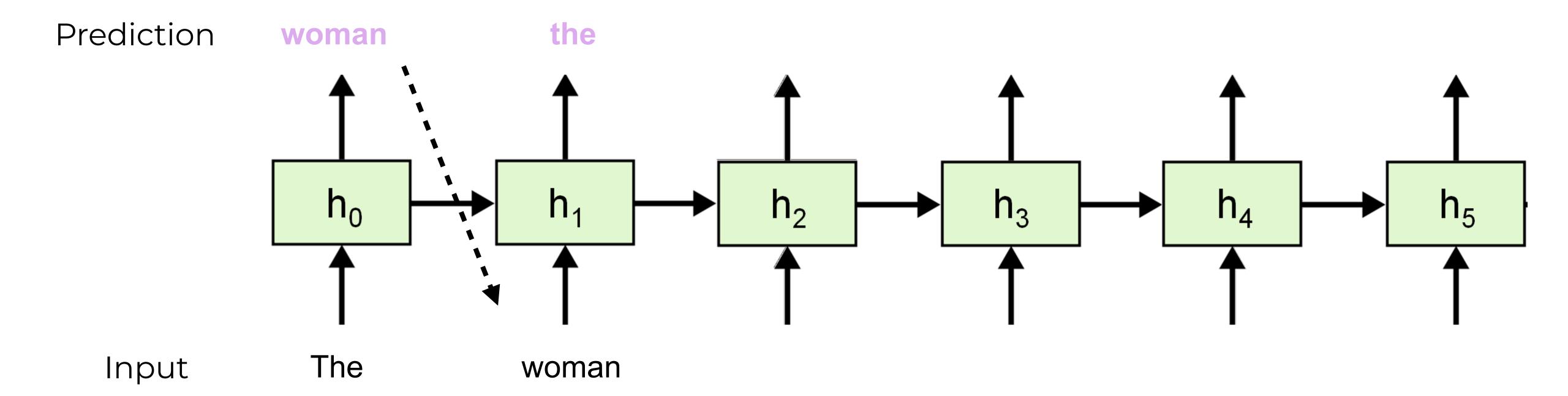
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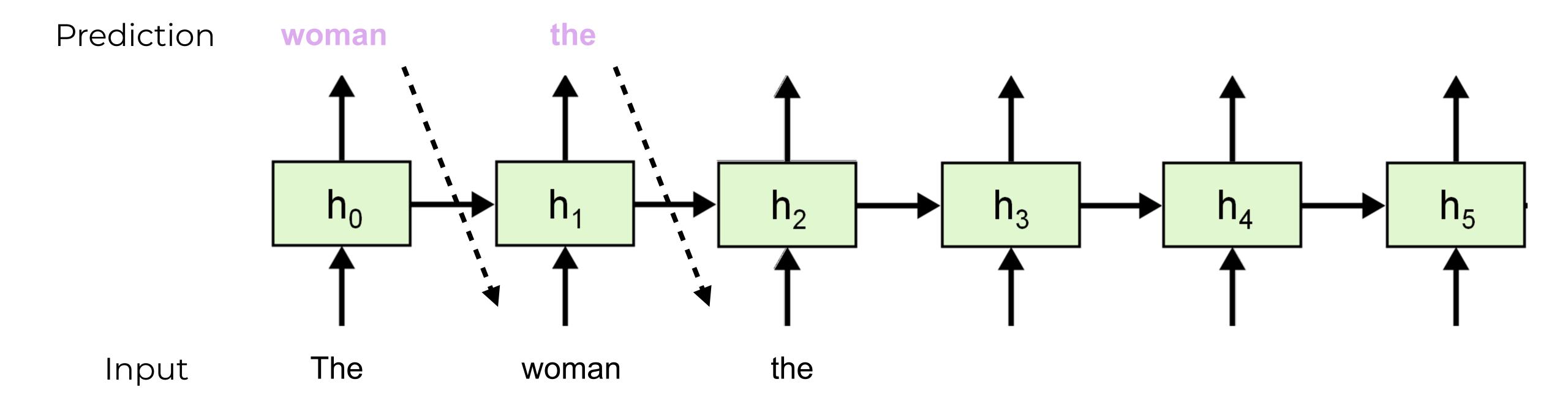
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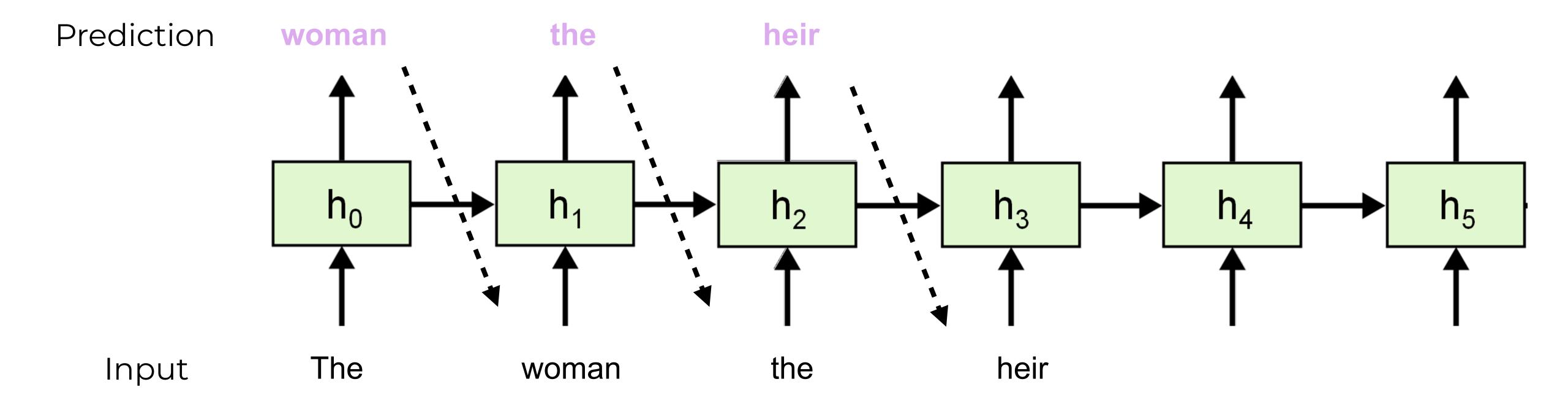
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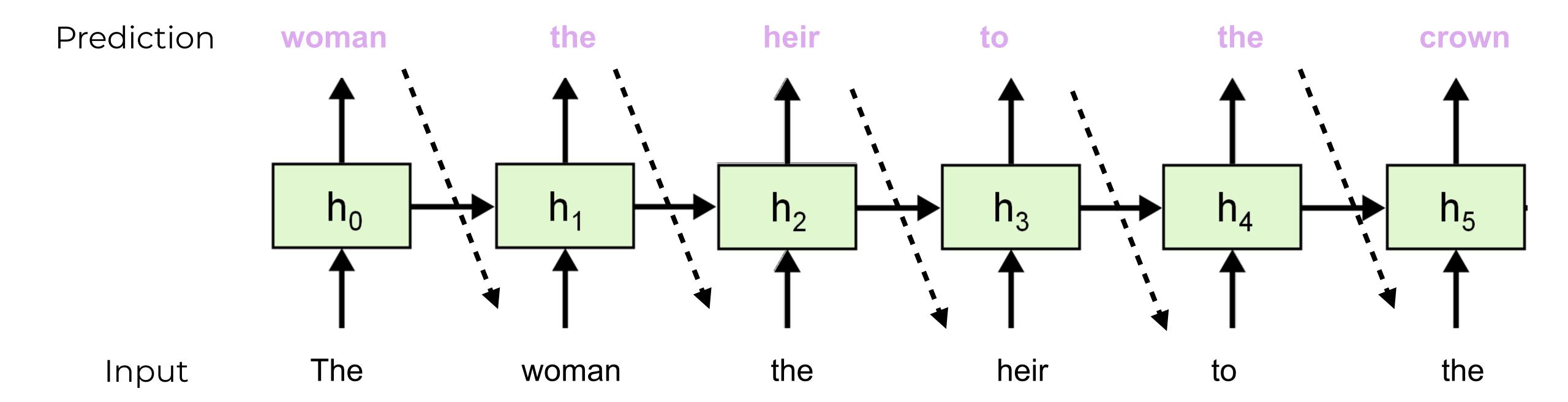
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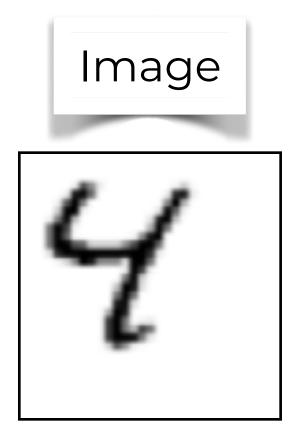


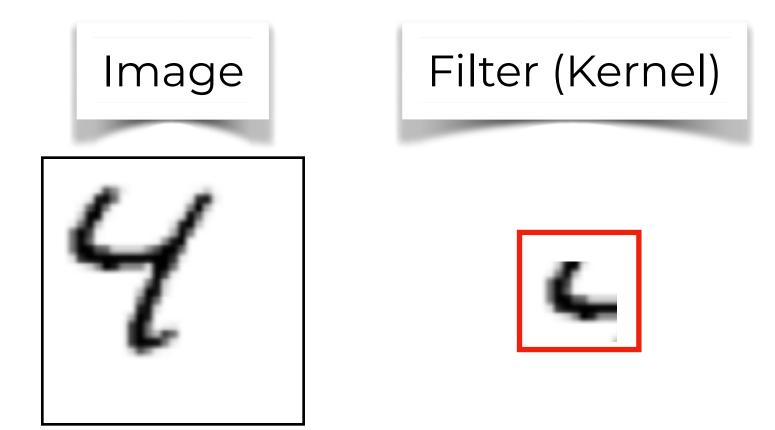
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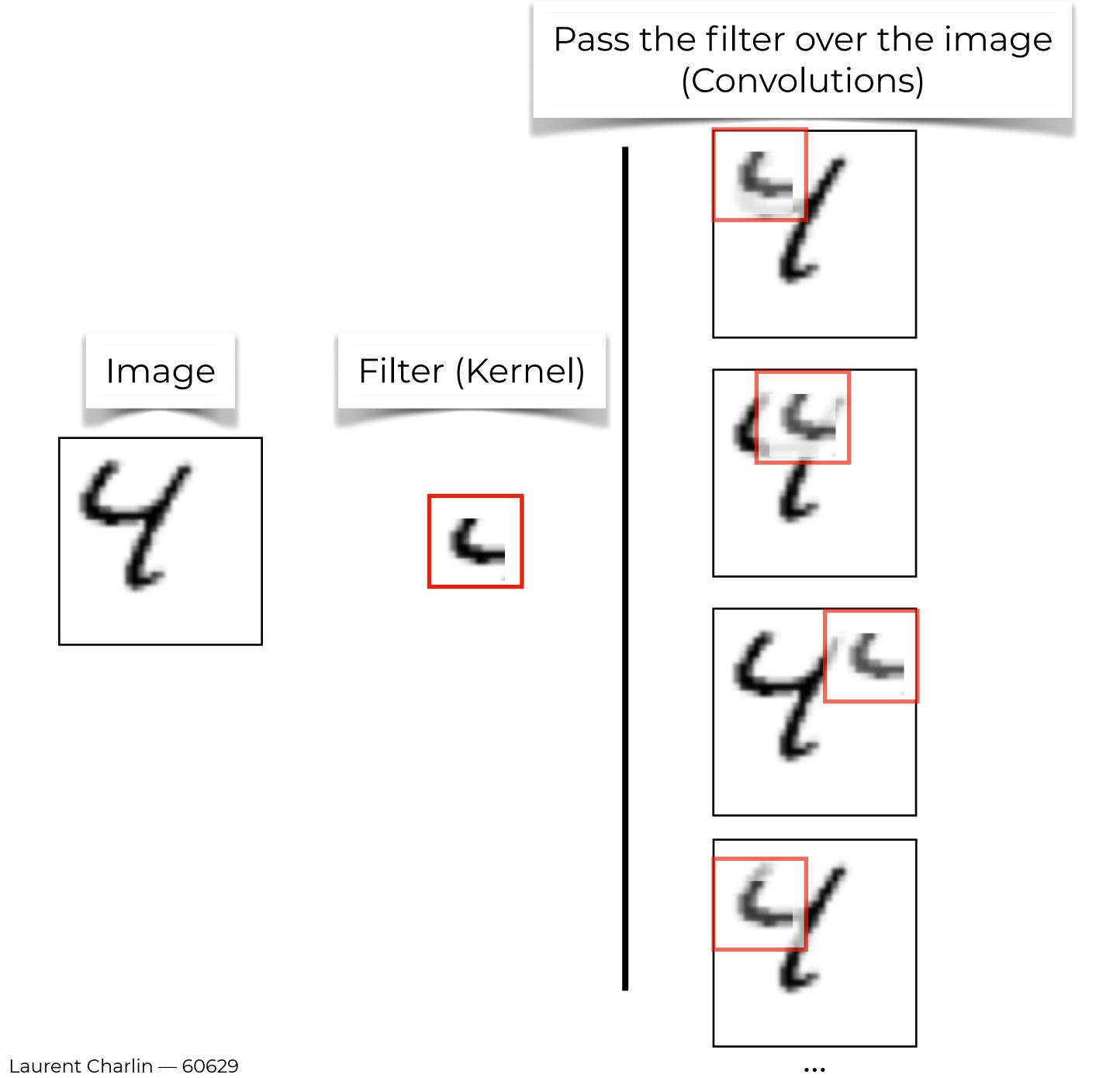


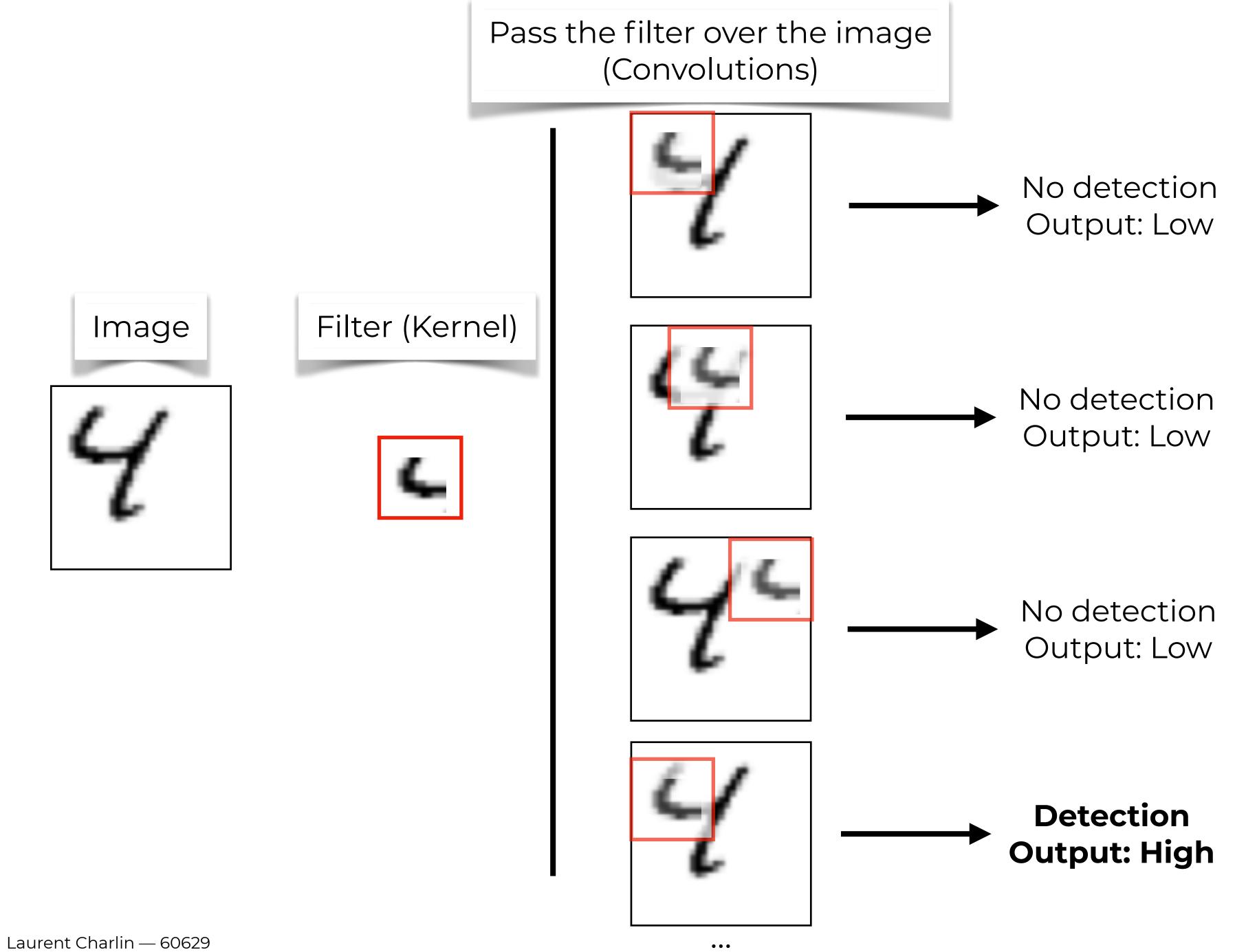
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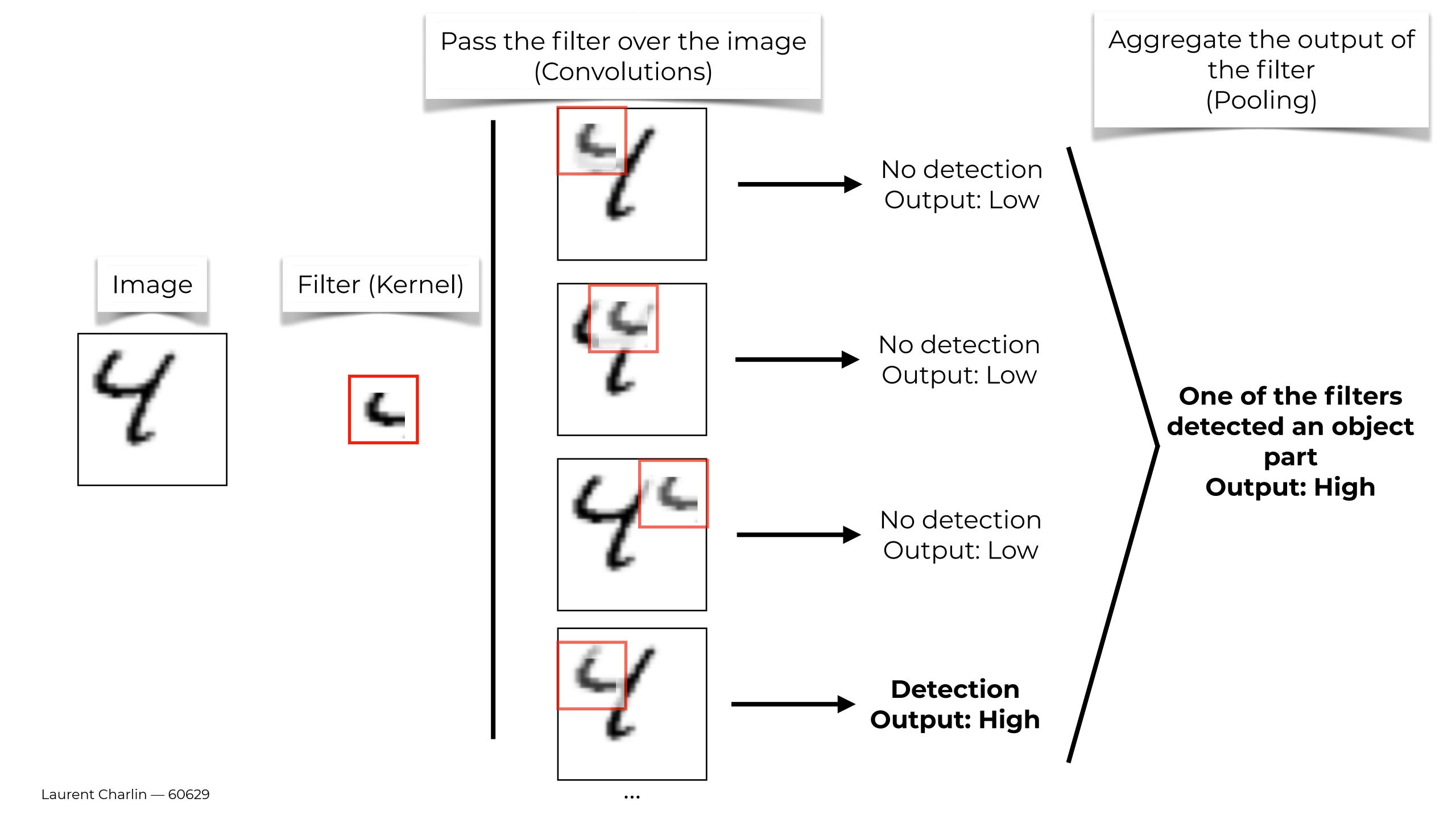


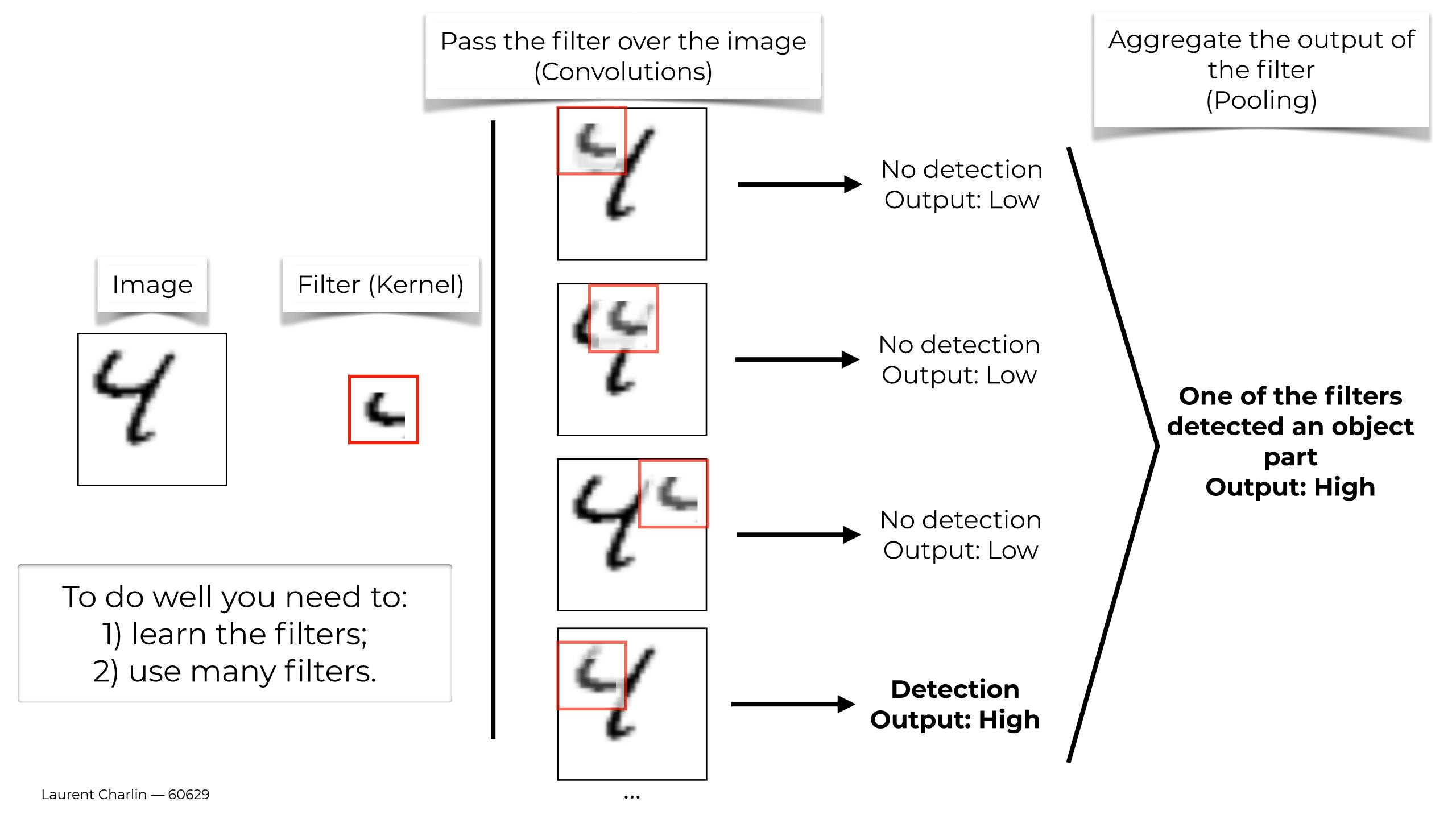


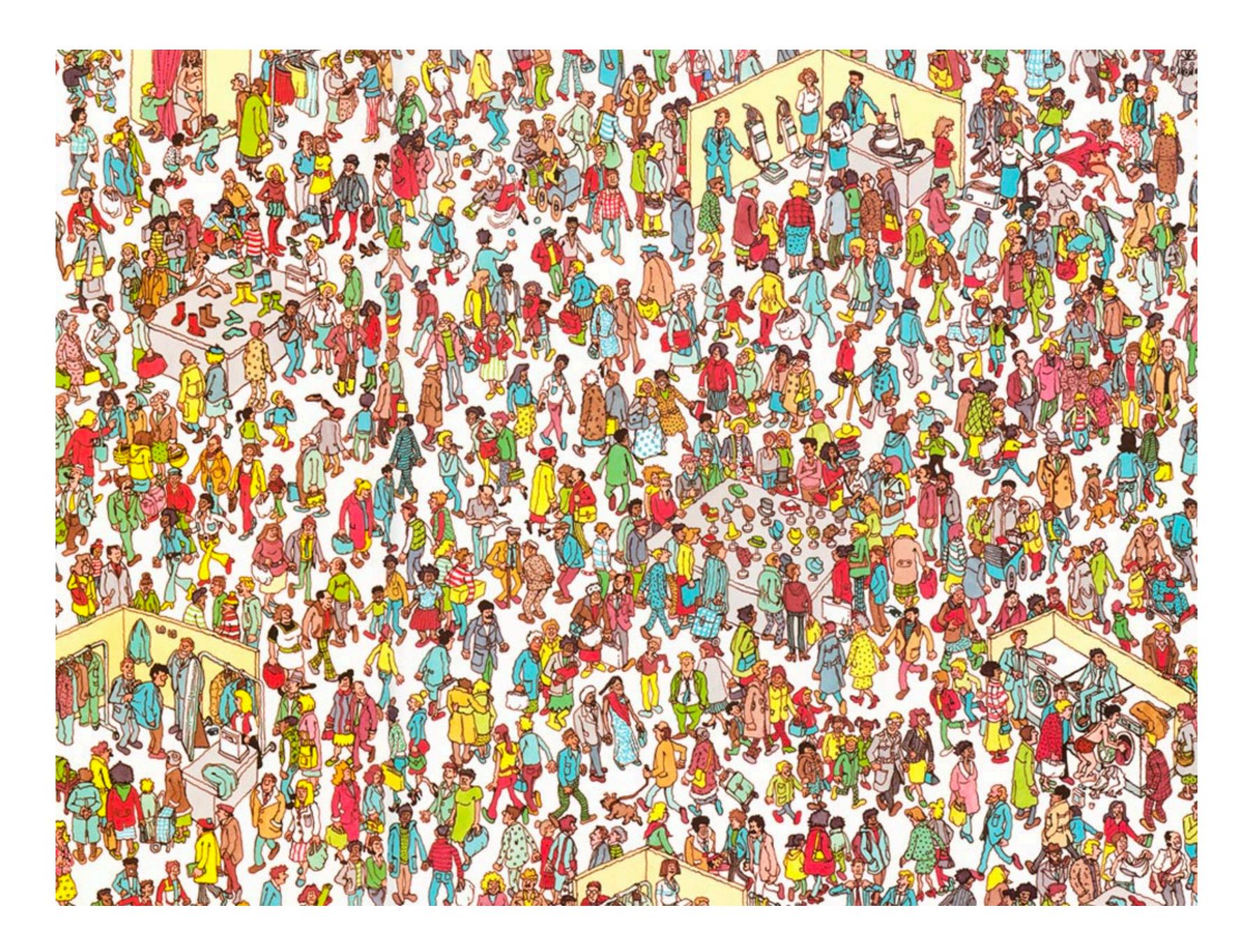










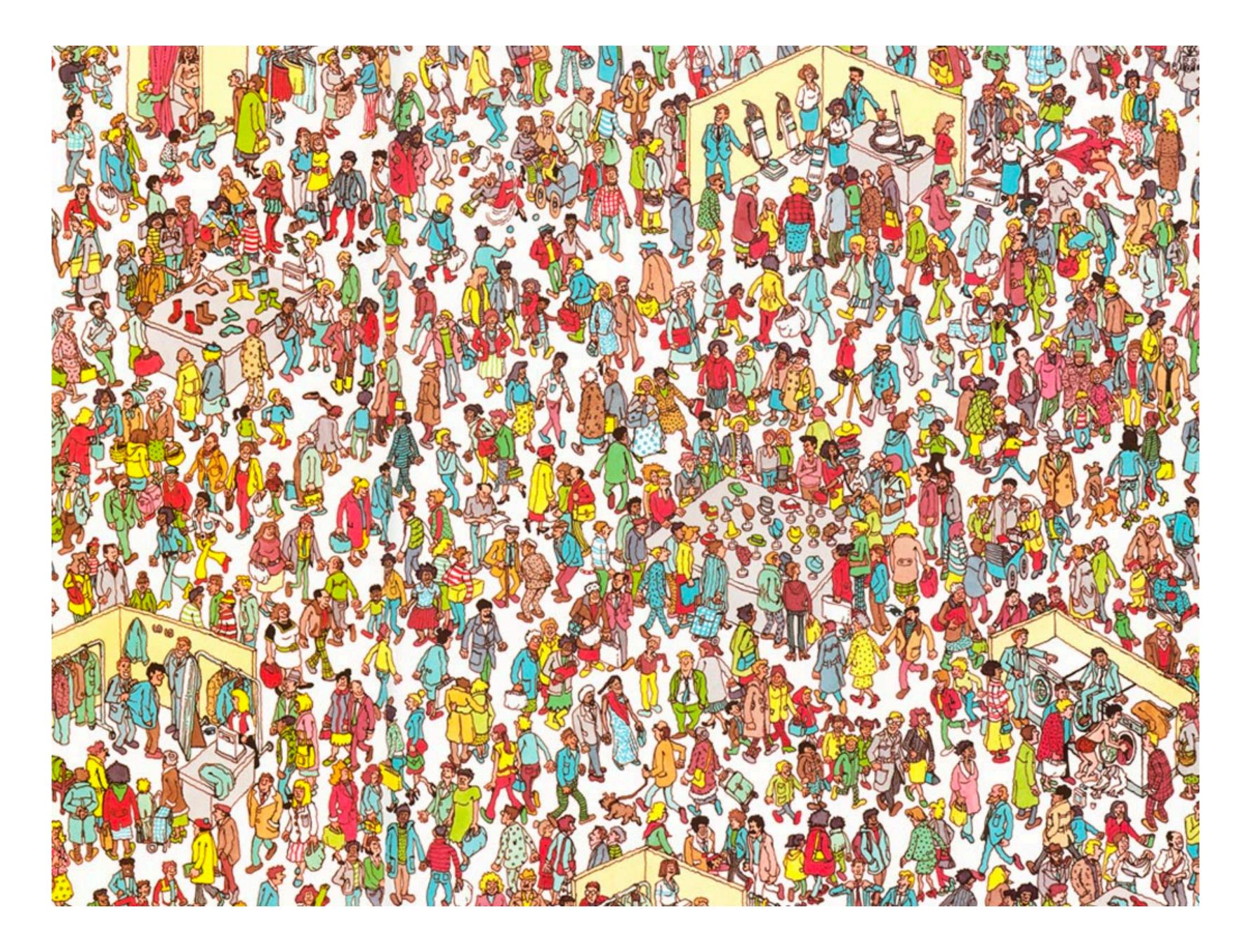




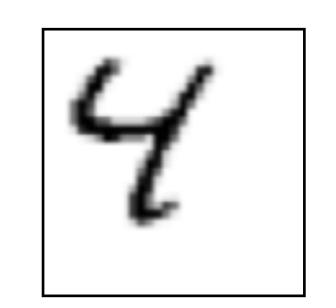








Convolutions (to the rescue)



For pixel (i,j):

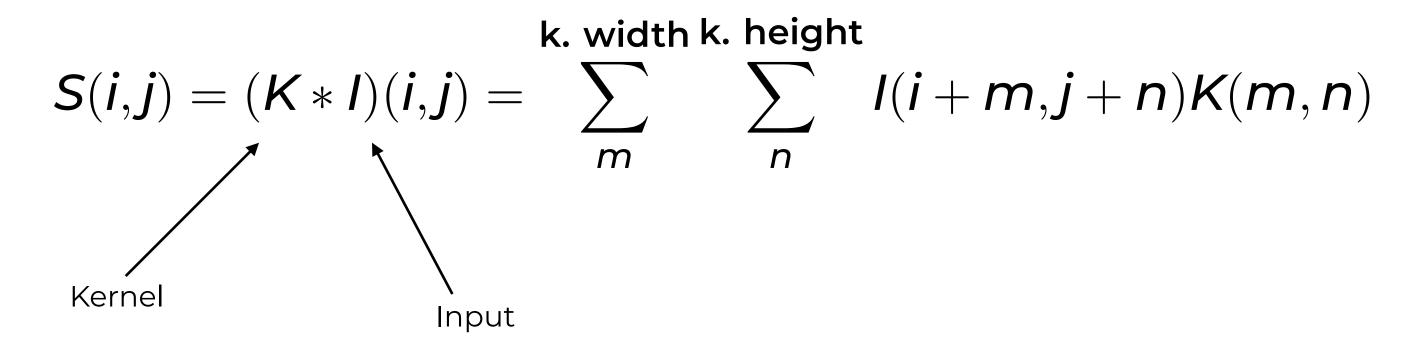
$$S(i,j) = (K*I)(i,j) = \sum_{m} \sum_{n} I(i+m,j+n)K(m,n)$$
Kernel

Dot product between "the kernel and the region"

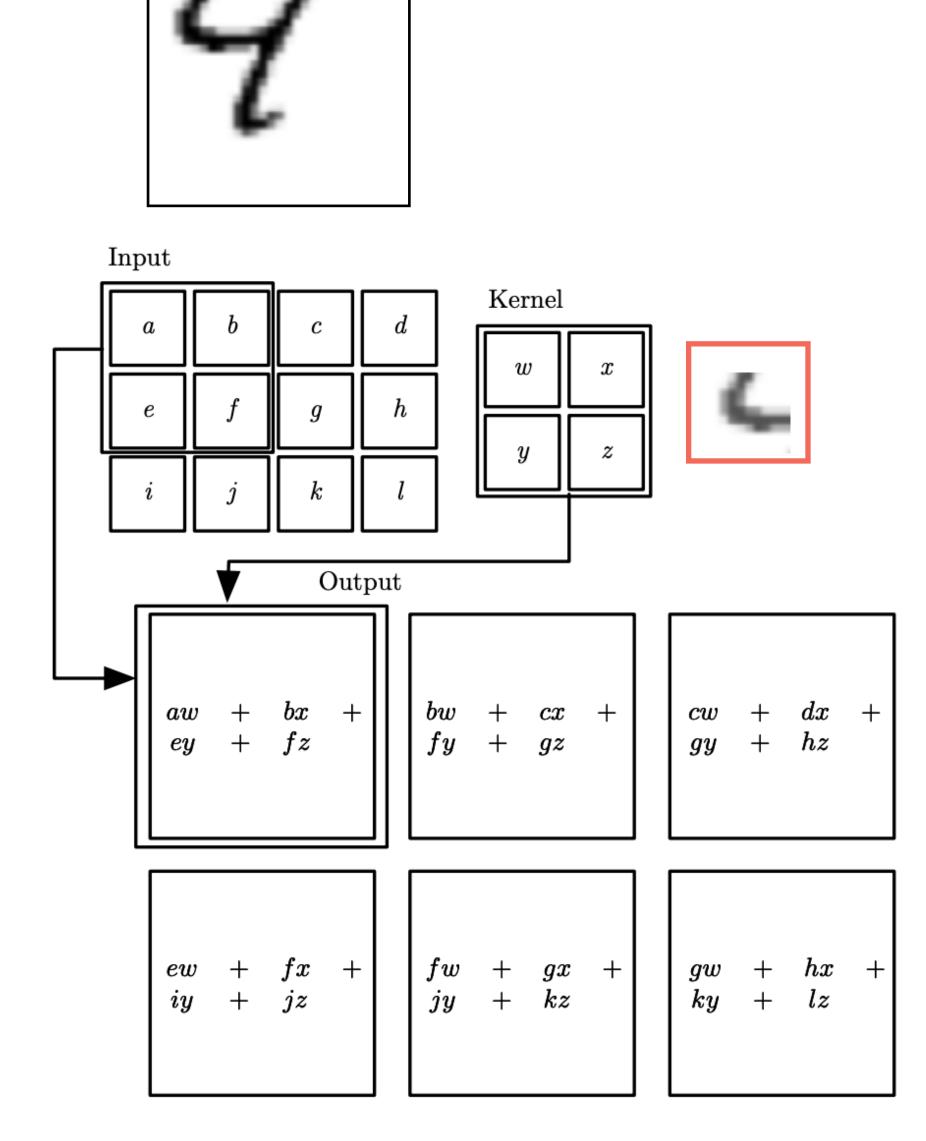


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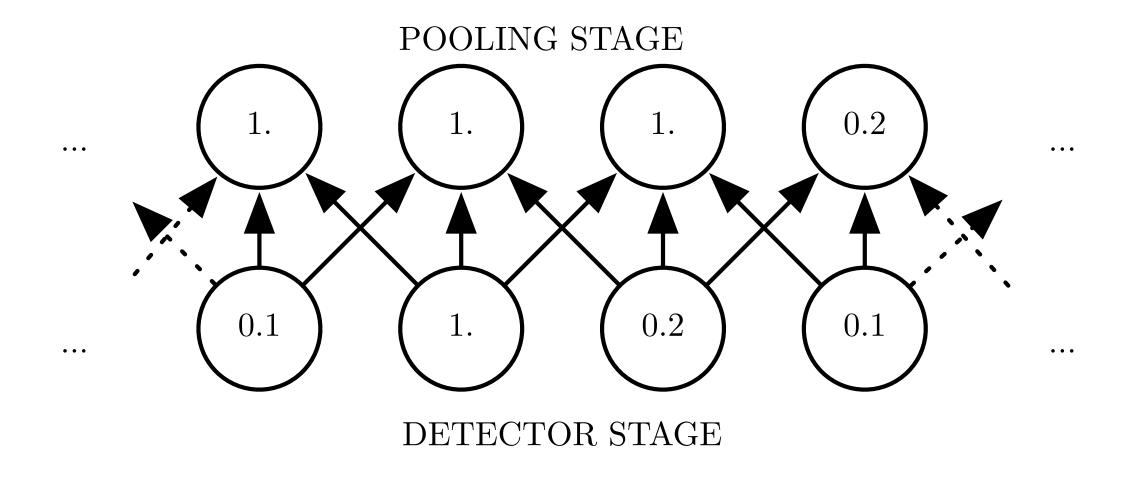


Pooling

- Make the representation invariant to small translations in the input
 - "Pool" the value of neighbour units
 - E.g., max-pooling takes the max from its input.

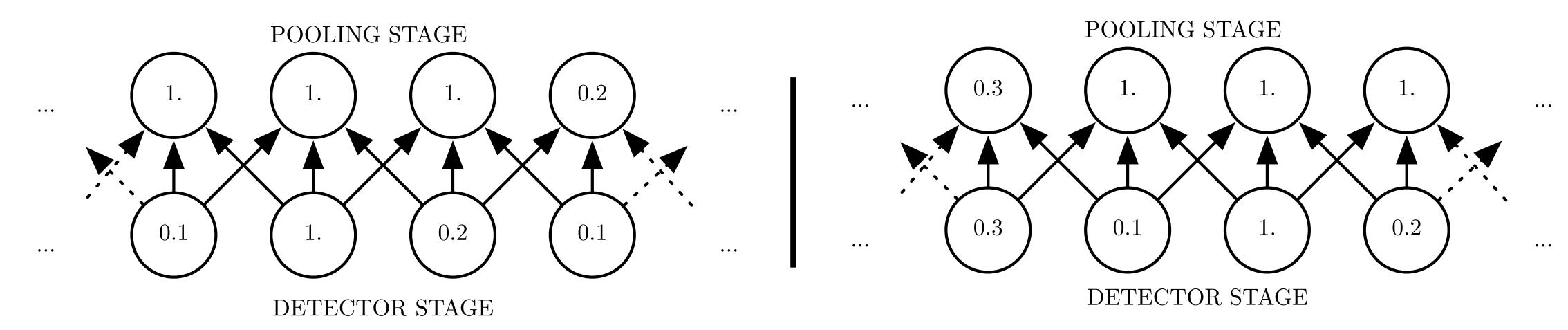
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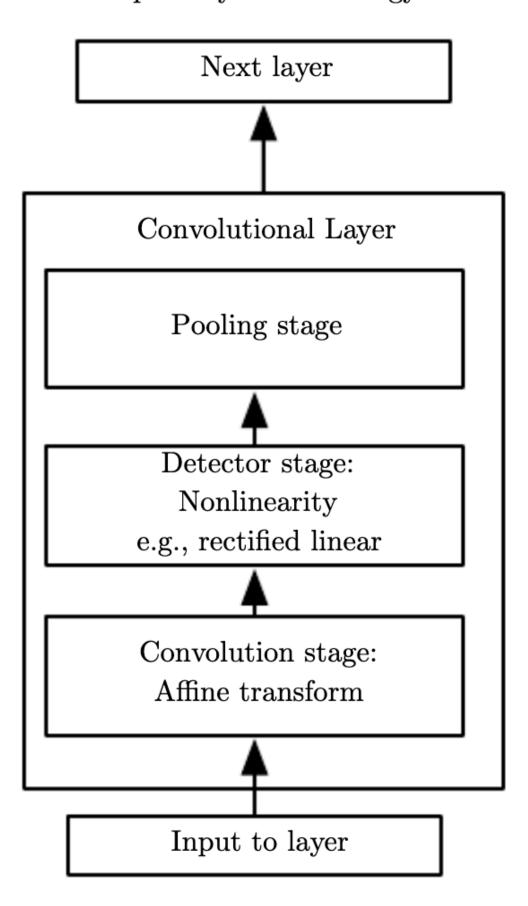
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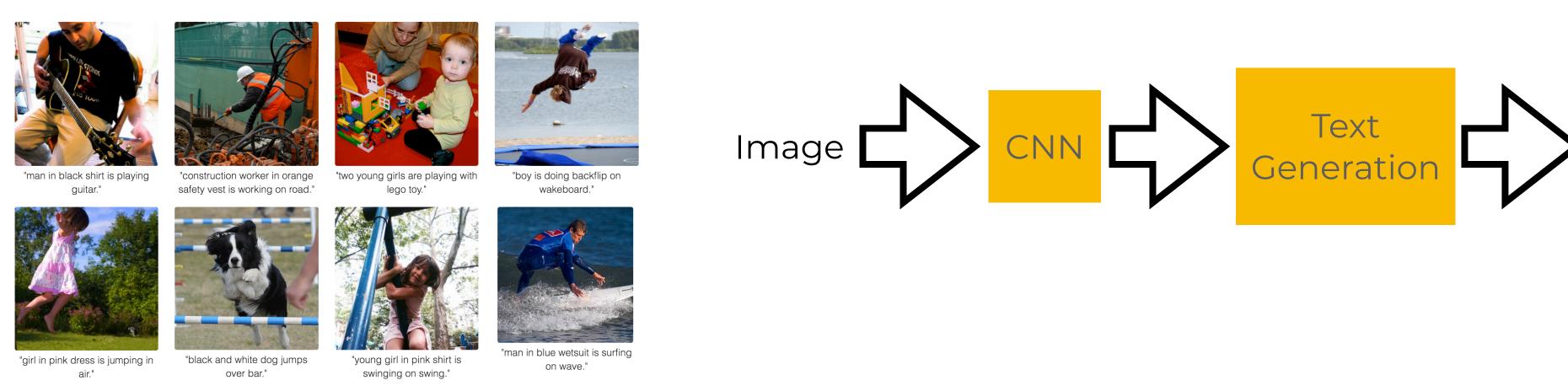
Putting it all together

Complex layer terminology



CNNs can be used as modules inside larger networks

Image Captioning



[https://cs.stanford.edu/people/karpathy/cvpr2015.pdf]

Visual Question Answering

Is the umbrella upside down?



Image CNN Text Generation Answer Understanding

Caption