

# Encoder/Decoder architecture

Two RNN's

- Encoder: takes input sequence  $\mathbf{x}$
- Decoder: creates output sequence  $\hat{\mathbf{y}}$

RNN's process sequences using the "loop architecture"

Consider the task of

- constructing the *next* element  $\hat{\mathbf{y}}_{(t)}$  of sequence  $\mathbf{y}$
- conditioned on some input sequence  $\mathbf{x} = \mathbf{x}_{(1)} \dots \mathbf{x}_{(t')}$

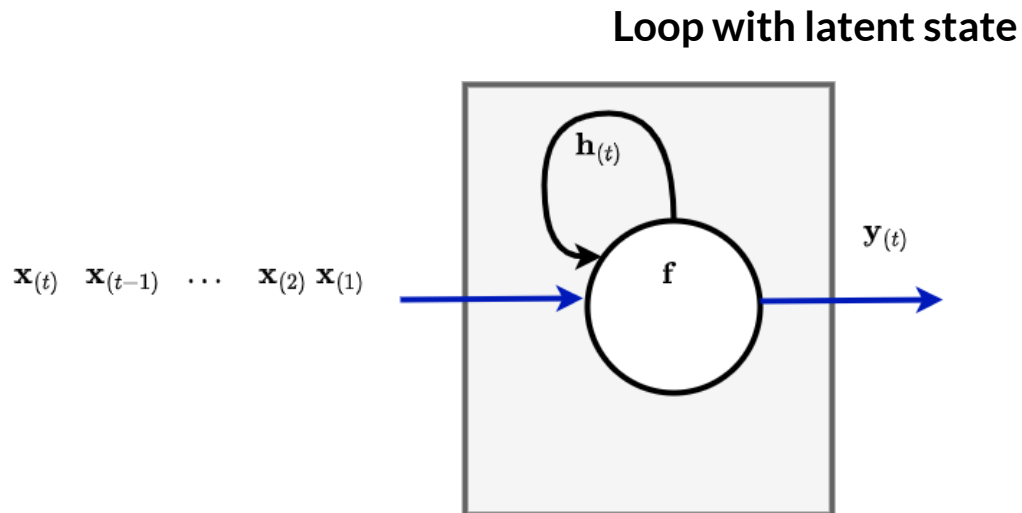
$$p(\hat{\mathbf{y}}_{(t)} | \mathbf{x}_{(1)} \dots \mathbf{x}_{(t)})$$

# RNN Loop architecture

- Uses a "latent state" that is updated with each element of the sequence, then predict the output

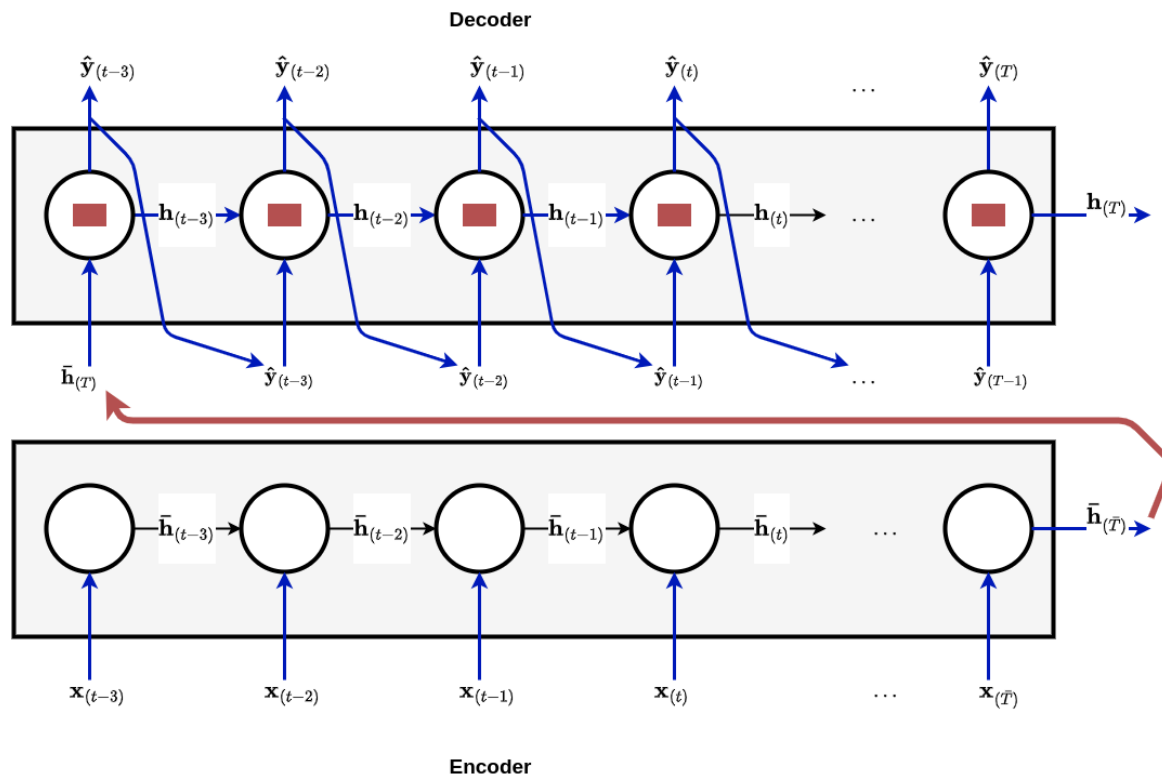
$p(\mathbf{h}_{(t)} | \mathbf{x}_{(t)}, \mathbf{h}_{(t-1)})$     latent variable  $\mathbf{h}_{(t)}$  encodes  $[\mathbf{x}_{(1)} \dots \mathbf{x}_{(t)}]$

$p(\hat{\mathbf{y}}_{(t)} | \mathbf{h}_{(t)})$     prediction contingent on latent variable



# Original Encoder/Decoder architecture

RNN Encoder/Decoder without Attention  
Bottleneck



## Critique

- bottleneck
  - *all* information about input  $\mathbf{x}$  passes through out of Encoder (red line)
  - and must be carried over to every iteration of the Decoder loop (red box)
- loop architecture for Encoder and Decoder
  - dependency: horizontal line carrying latent state across time

# Cross-Attention: removing the bottleneck

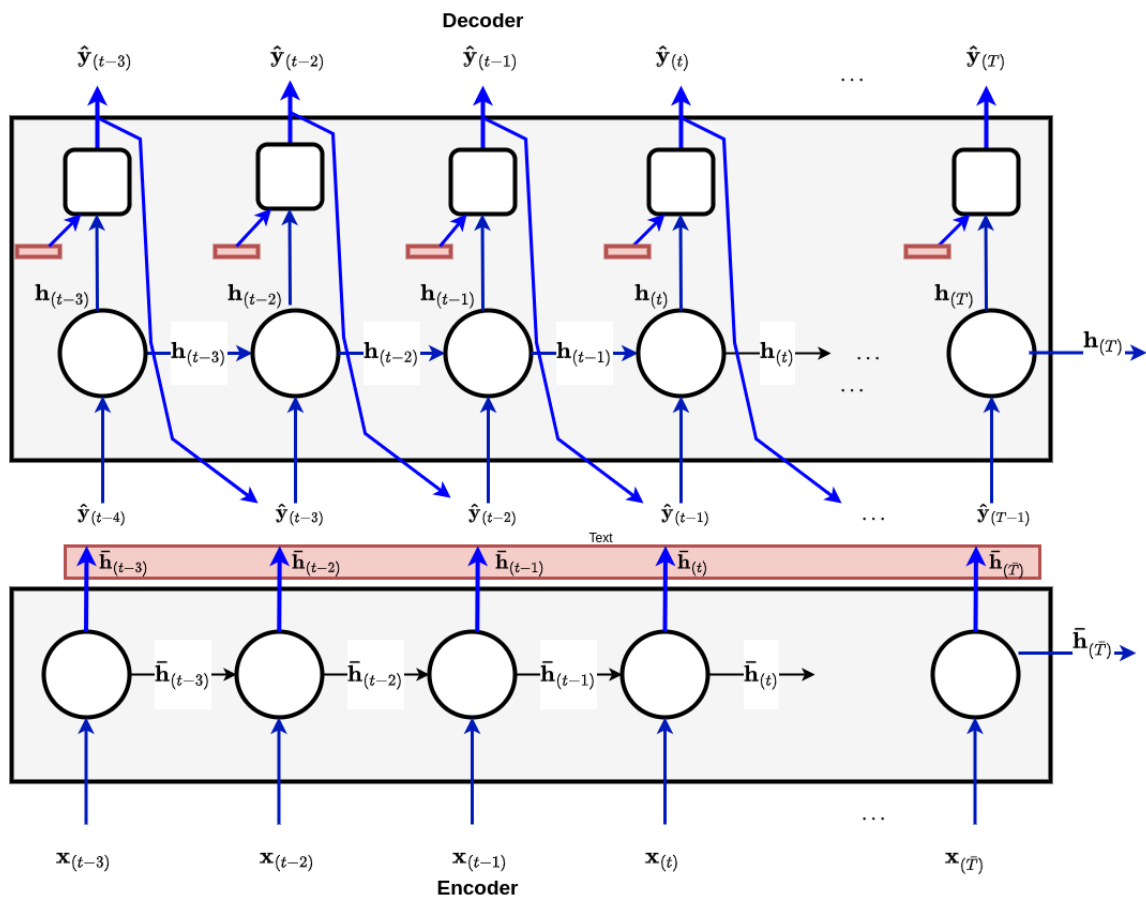
We removed the bottleneck via *Cross Attention*

- Decoder has *direct access* to **all** outputs (i.e., Latent states) of the Encoder
  - each Encoder output is proxy for a prefix of the input

The pink box is the sequent of Encoder outputs

$$\bar{\mathbf{h}}_{(1:\bar{T})}$$

## RNN Encoder/Decoder with Cross Attention



# Encoder Self-Attention: removing the Encoder loop

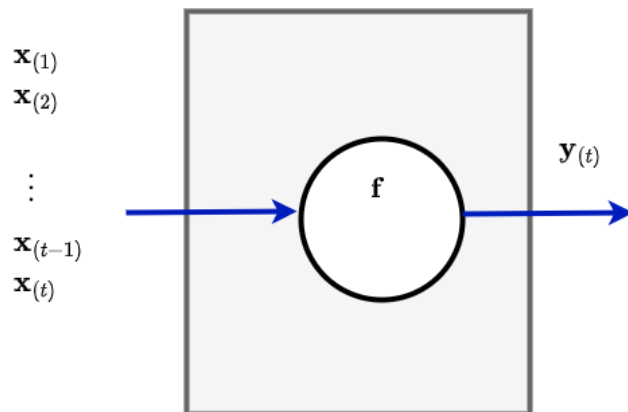
There is an alternative to the loop architecture for processing sequences

- the direct function approach

The alternative to the loop was to create a "direct function"

- Taking a **sequence**  $\mathbf{x}_{(1..t)}$  as input
- Outputting  $\hat{\mathbf{y}}_{(t)}$

**Direct function**





Can output *all* elements of sequence  $\hat{\mathbf{y}}$  *simultaneously*

- each output position is independent of previous output
- only dependent on input

We removed the "loop" architecture of the Encoder by using the direct function approach

- the mechanism enabling each position of the Encoder output to *attend* to the entire sequence  $x$  is called *Self-Attention*
  - Notice: no dependency arrow between circles in the Encoder
- Encoder output is a direct function of **all** positions in the input
  - all Encoder output positions can be computed *in parallel*

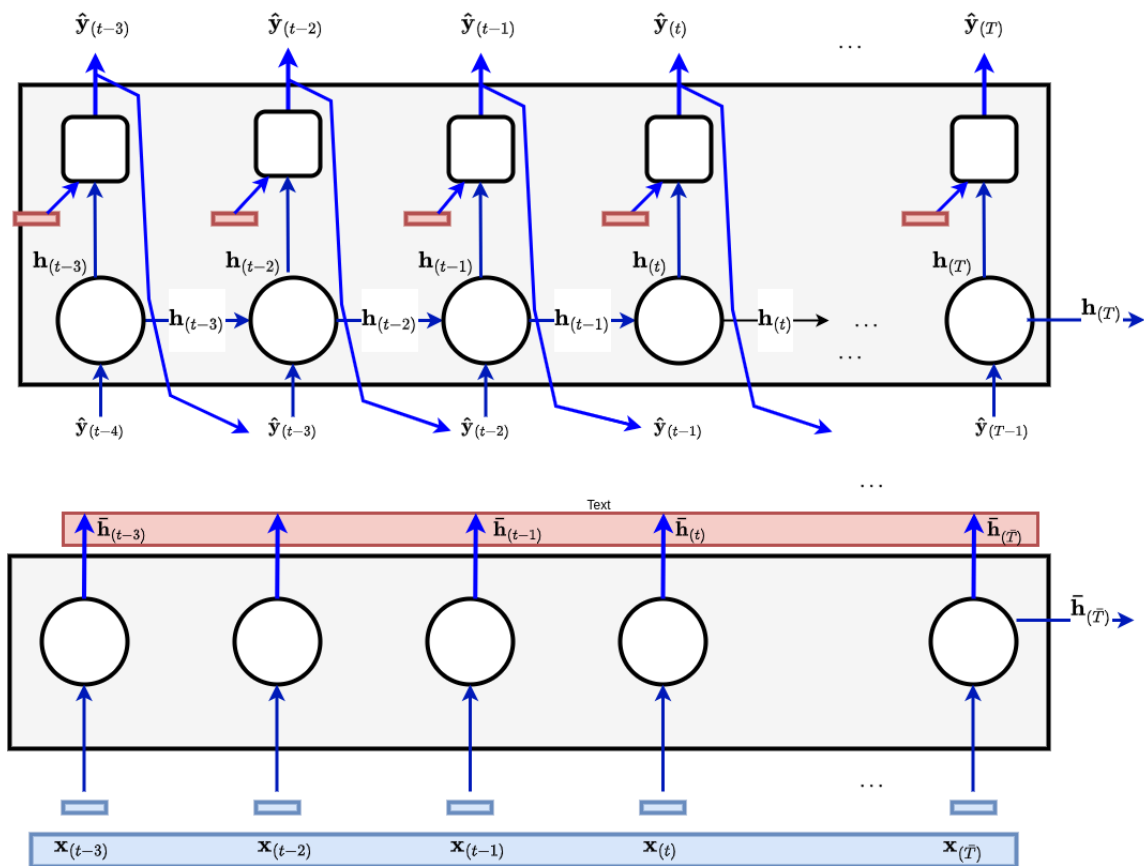
The blue box represents the *entire* input sequence

$$\mathbf{x}_{(1:\bar{T})}$$

We no longer refer to the Encoder output as a Latent state

- no more loop !

# RNN Encoder/Decoder with Cross Attention/Decoder Self Attention



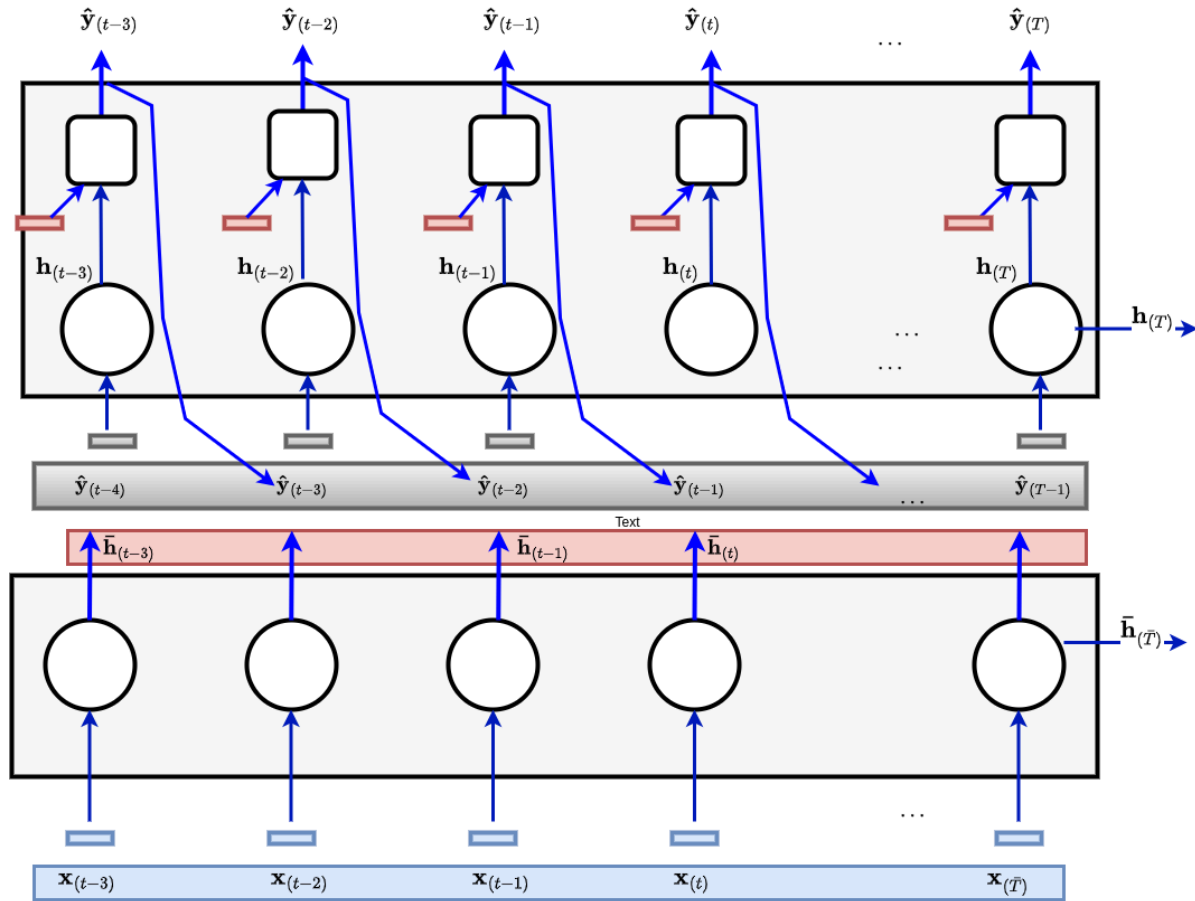
# Decoder Masked Self Attention: removing the Decoder loop

Finally we remove the loop architecture for the Decoder as well using Self-Attention

The grey box represents the *entire* output sequence

$$\hat{\mathbf{y}}_{(1:T)}$$

# RNN Encoder/Decoder with Cross Attention and Self Attention (Encoder/Decoder)



Now

- the output sequence  $\hat{\mathbf{y}}$  is built iteratively (auto-regressively)
- units work in parallel
- each iteration outputs *all* positions

$$\hat{\mathbf{y}}_{(1:T)}$$

- including ones whose full inputs have not been defined yet!
- $\hat{\mathbf{y}}_{(t)}$  is not defined until iteration  $t$

This is confusing !

The point is we don't output position  $t$  to the user until iteration  $t$

We certainly don't want  $\hat{\mathbf{y}}_{(t)}$  to change on iterations  $t' > t$

- don't want future outputs  $\hat{\mathbf{y}}_{(t')}$  for  $t' \geq t$  to affect  $\hat{\mathbf{y}}_{(t)}$
- $\hat{\mathbf{y}}_{(t)}$  depends *only* on  $\hat{\mathbf{y}}_{(1:t-1)}$

We can ensure this by using **Masked Self Attention**

- position  $t$  can only access positions  $t' < t$   
 $\hat{\mathbf{y}}_{(1:t-1)}$

This means that outputs after iteration  $t$  *can't effect*  $\hat{\mathbf{y}}_{(t)}$

In [2]: `print("Done")`

Done



