University of Antwerp

Artificial Neural Networks

[2500WETANN]

José Oramas

Modeling Sequences with Neural Networks

José Oramas

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Today's Lecture – Outline

- **Intro/Recap - Sequence Modeling**

  → [Algorithmically] How to approach the problem

- **Sequence Modeling with Recurrent Architectures**

  → RNNs, LSTMs, GRUs, etc.

- **Predictions from Sequences & Sequence Generation**

- **Transformers and Attention Mechanisms**

Recap: Supervised Image Recognition Task

Given: an input image *x*

Do: predict a label *ŷ*

(out of a set of class labels)

- **Training data**

$$\{x, y\}_i$$

– **Model**

$$\hat{y} \approx f_\theta(x)$$

– **Loss**

$$L(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$$

– **Optimization**

$$\theta* = arg\ min_\theta\ L(\theta)$$

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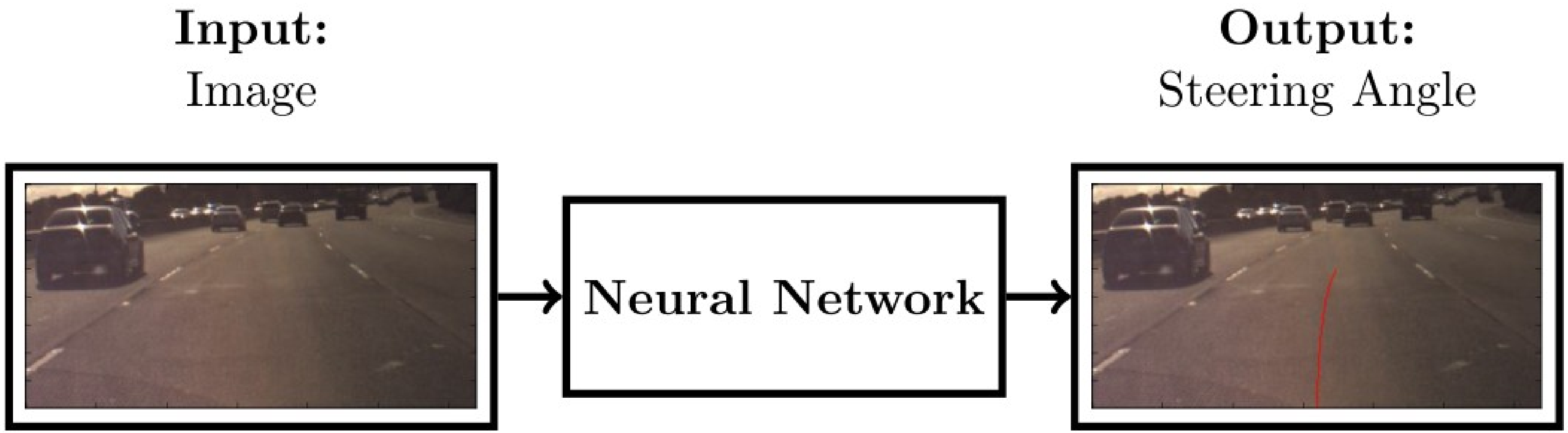
Now: Consider the Following Problem

Autonomous Driving

– **Given:** an input video x *(sequence of images)*

– **Do:** predict a label $\hat{y}$ *(out of a set of action class labels)*



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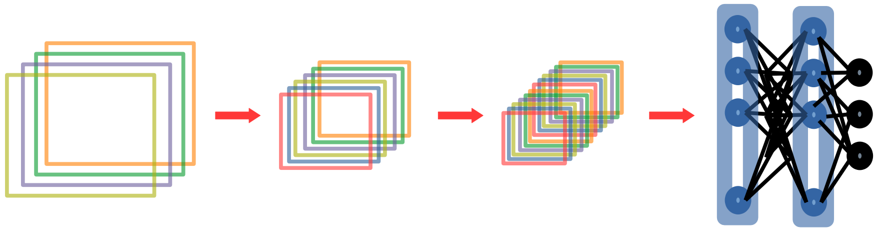
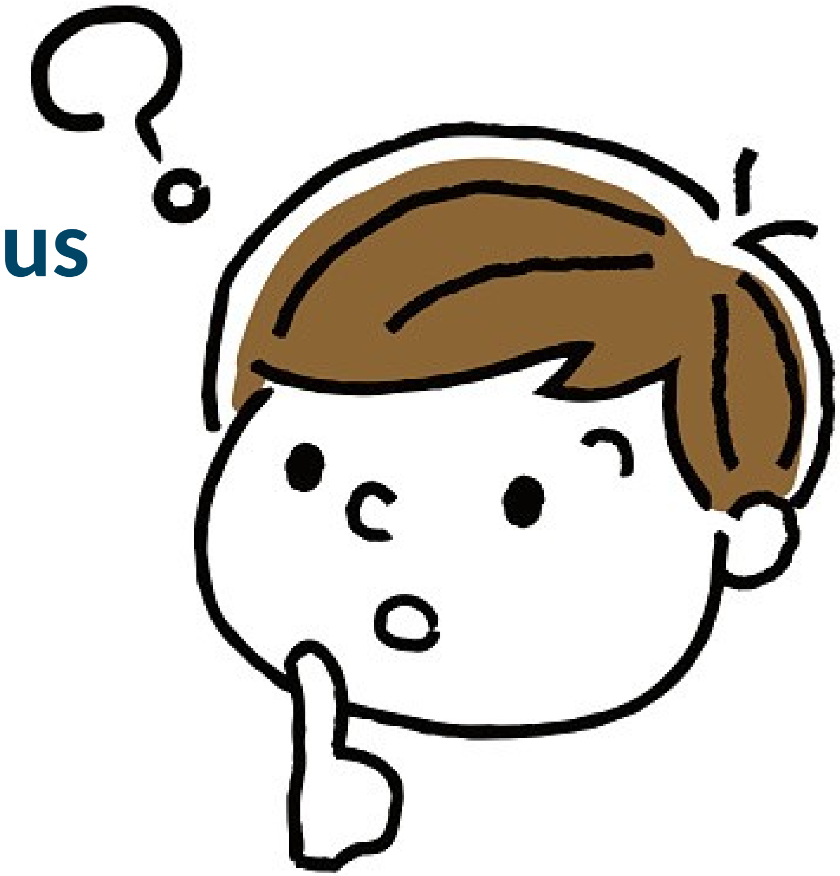
Ok, but…

Can’t we use the previous architectures for that ?





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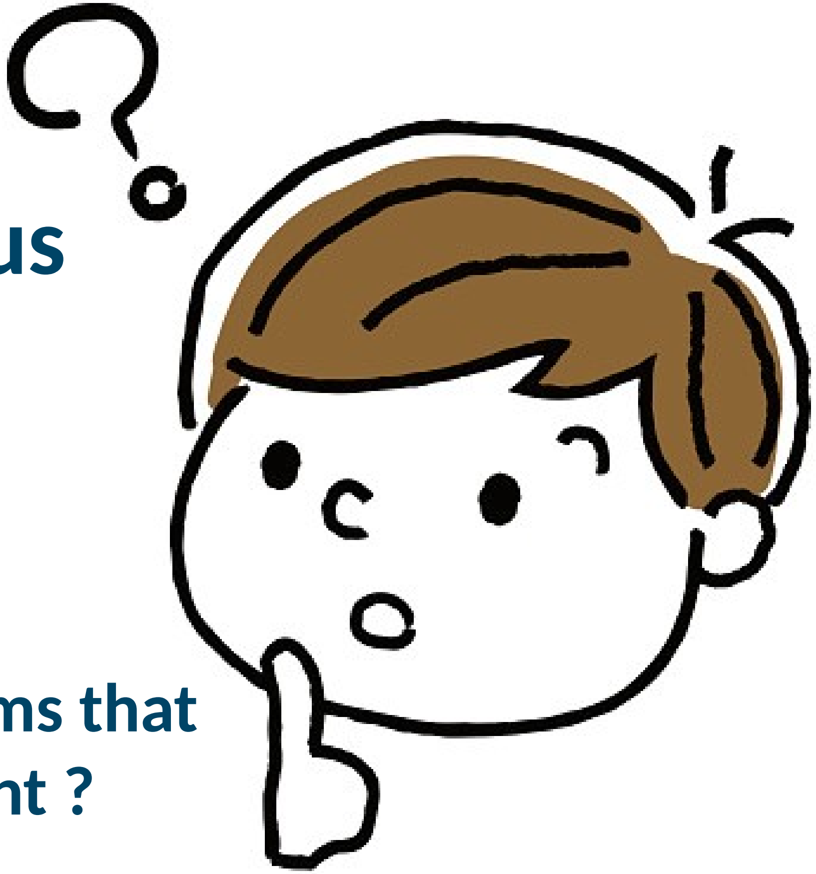
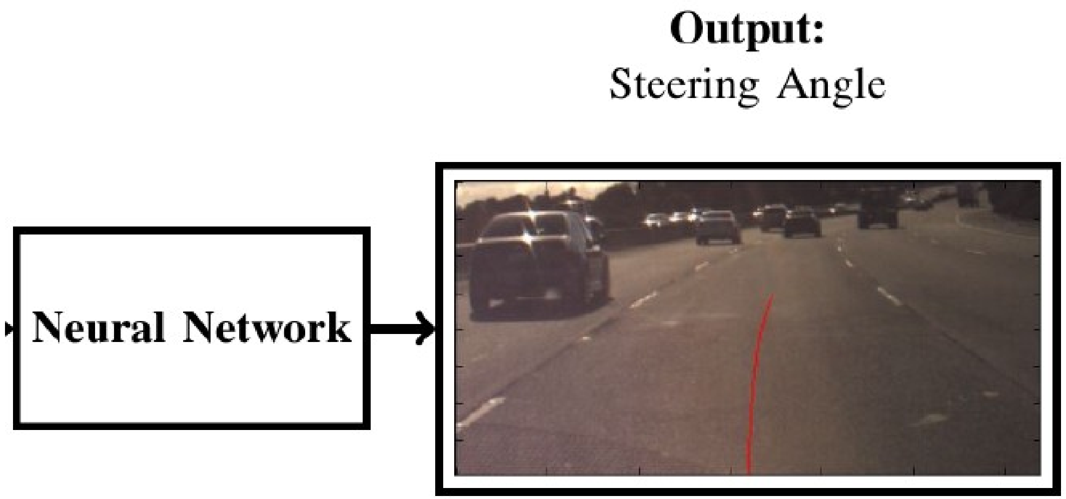


and …

Are there any other problems that we need to take into account ?

Autonomous Navigation Task

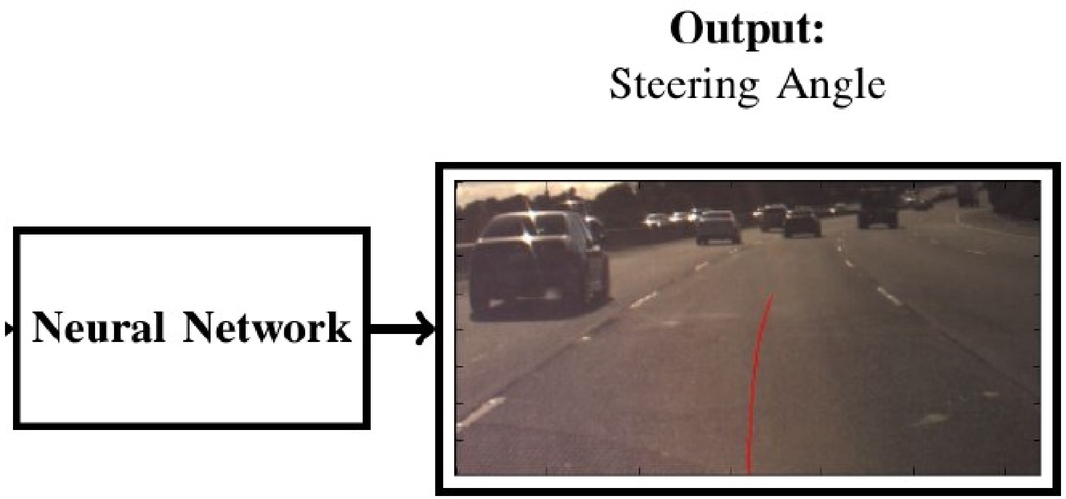
Stacking Elements from the Sequence

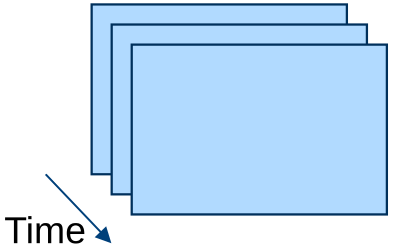


[Heylen et al., 2018]

Autonomous Navigation Task

Stacking Elements from the Sequence





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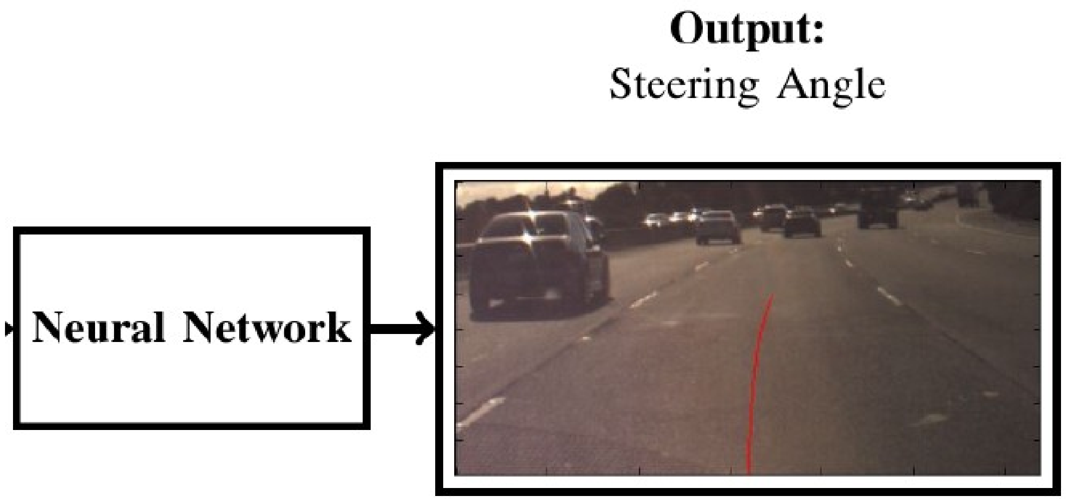
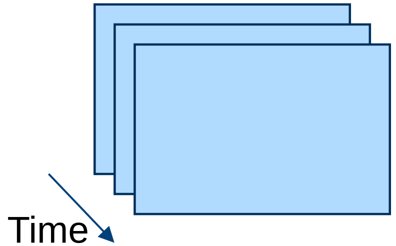
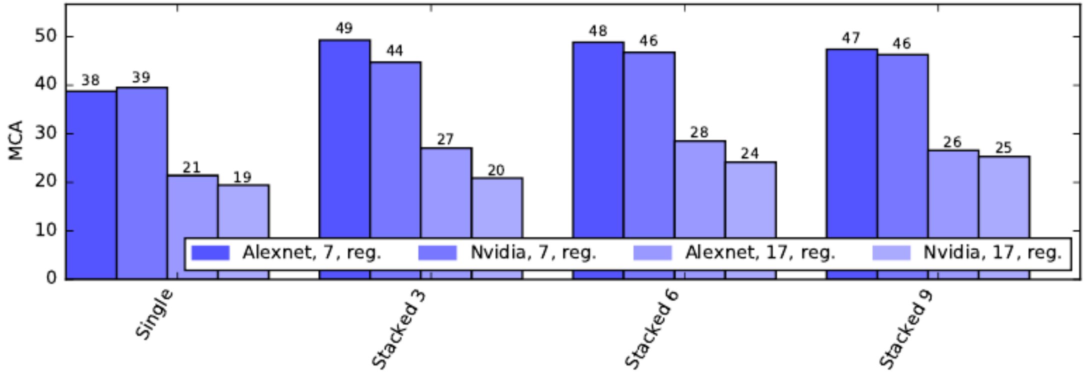
Autonomous Navigation Task

Stacking Elements from the Sequence







[Heylen et al., 2018]

Observations

- Considering sequence helps
- Reduced gains as we go further… why?

Modeling Data Sequences

[How to do it... in theory]

Modeling Data Sequences [in theory]

Some Foundations

- Supervised Learning

- Data

$$\{x, y\}_i$$

– Model

$$\hat{y} \approx f_\theta(x)$$

– Loss

$$L(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$$

– Optimization

$$\theta^* = arg\ min_\theta\ L(\theta)$$

Modeling Data Sequences [in theory]

Some Foundations

Supervised Learning

- Data

$$\{x, y\}_i$$

– Model

$$\hat{y} \approx f_\theta(x)$$

– Loss

$$L(\theta) = \sum_{i=1}^{N} l(f_\theta(x_i), y_i)$$

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Modeling Sequences

- Data

$$\{x\}_i$$

– Model

$$p(x) \approx f_\theta(x)$$

– Loss

$$L(\theta) = \sum_{i=1}^{N} log\ p(f_\theta(x_i))$$

– Optimization

$$\theta^* = arg\ max_\theta\ L(\theta)$$

Modeling Data Sequences

[How to do it... in practice]

Modeling Data Sequences [in theory]

Lets consider the following sequence

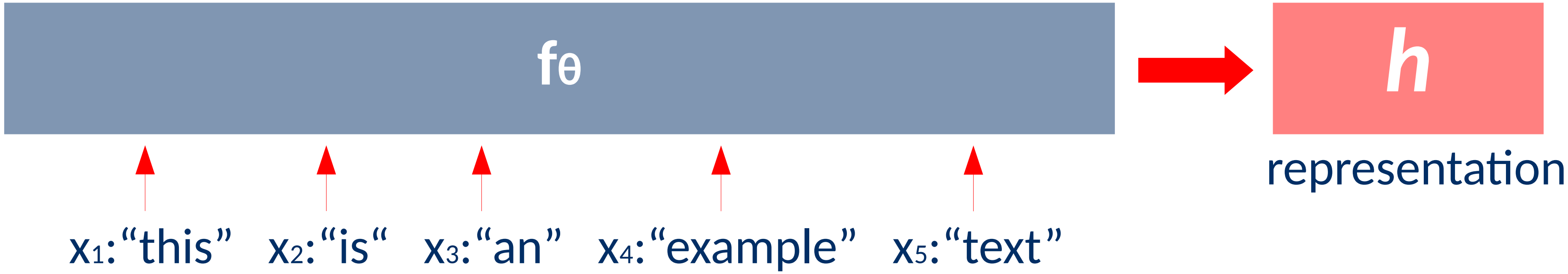
- **Idea:** Let’s focus on natural language → text

[“this” , “is“ , “an” , “example” , “text” , “sequence”]

Modeling Data Sequences [in practice]

1. Describing/Vectorizing the Context

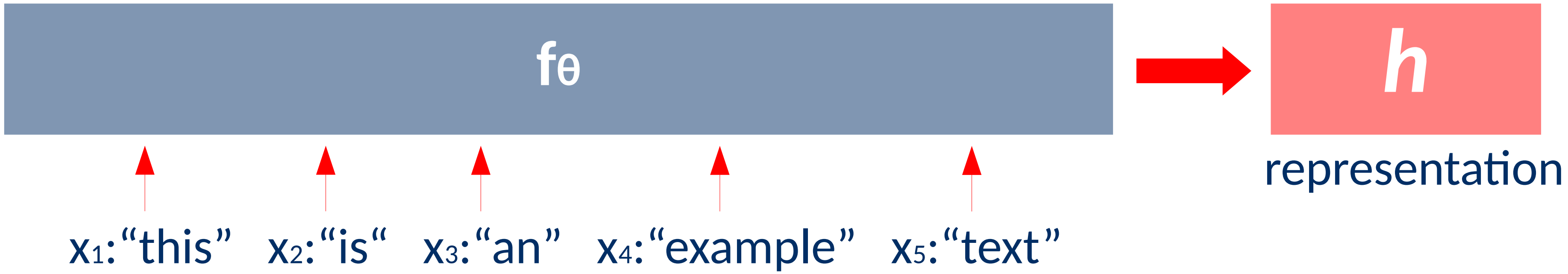
- **Idea:** Learn how to represent a sub-sequence



Modeling Data Sequences [in practice]

1. Describing/Vectorizing the Context

- **Idea:** Learn how to represent a sub-sequence



Desirable properties for f_θ

- Ranked → order matters
- Variable Length
- Learnable → differentiable
- Small changes, large effects → non-linear

Modeling Data Sequences [in practice]

2. Modeling Conditional Probabilities

- **Idea:** Predicting the next element given the context

- **Objective:** $p(x_t|h) \approx p(x_t|x_1, \ldots, x_{t-1})$

Modeling Data Sequences [in practice]

2. Modeling Conditional Probabilities

- **Idea:** Predicting the next element given the context

- **Objective:** $p(x_t|h) \approx p(x_t|x_1, \ldots, x_{t-1})$

Desirable properties for g_θ

- Output a distribution over vocabulary
- Small changes, large effects → non-linear

Recurrent Architectures

[RNNs, LSTMs, GRUs, etc.]

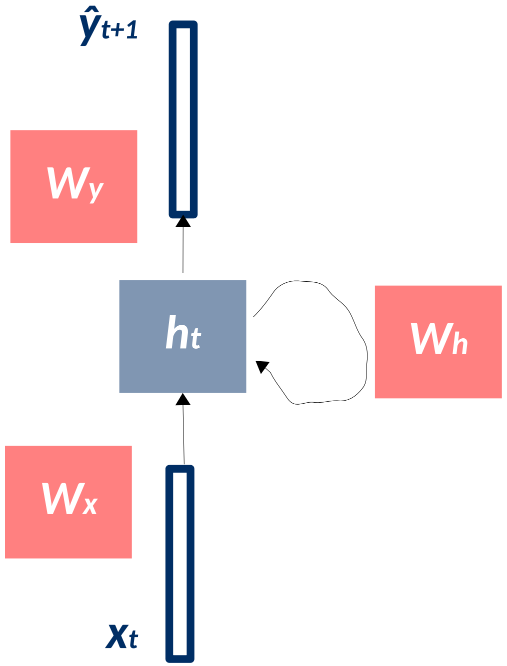
Recurrent Neural Networks

[The Most Popular Architecture]

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

- **Idea:** Use a persistent state ***h*** that encodes past observations (context)



Defined by three equations

$$\boxed{\begin{aligned} h_t &= \tanh(\ W_h h_{t-1} + W_x x_t\ ) \\ p(y_{t+1}) &= softmax(\ W_y h_t\ ) \\ L_\theta(y,\hat{y})_t &= -y_t \log \hat{y}_t \end{aligned}}$$

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

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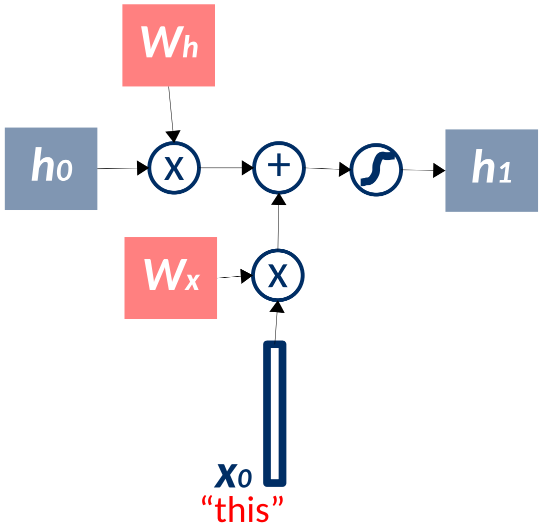

$$h_t = \tanh(\ W_h h_{t-1} + W_x x_t\ )$$

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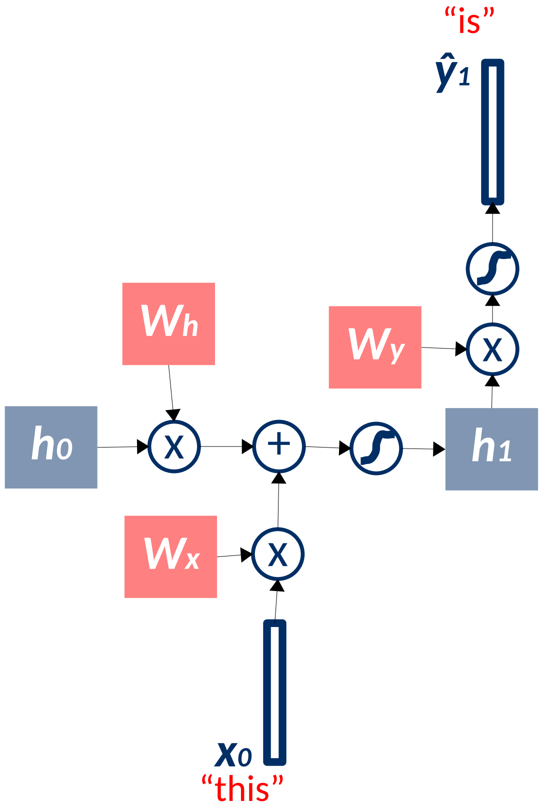
Provide Neural Networks with Memory

- **Idea:** Use a persistent state ***h*** that encodes past observations (context)



The probability of next element is obtained from the state ***h***

$$p(y_{t+1}) = softmax(\ W_y h_t\ )$$

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

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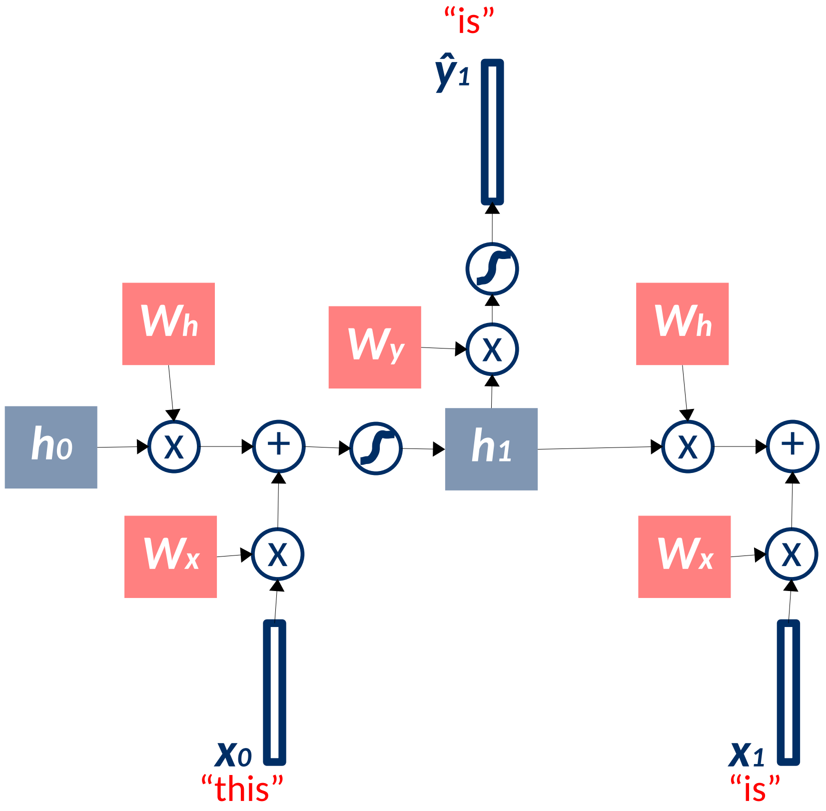
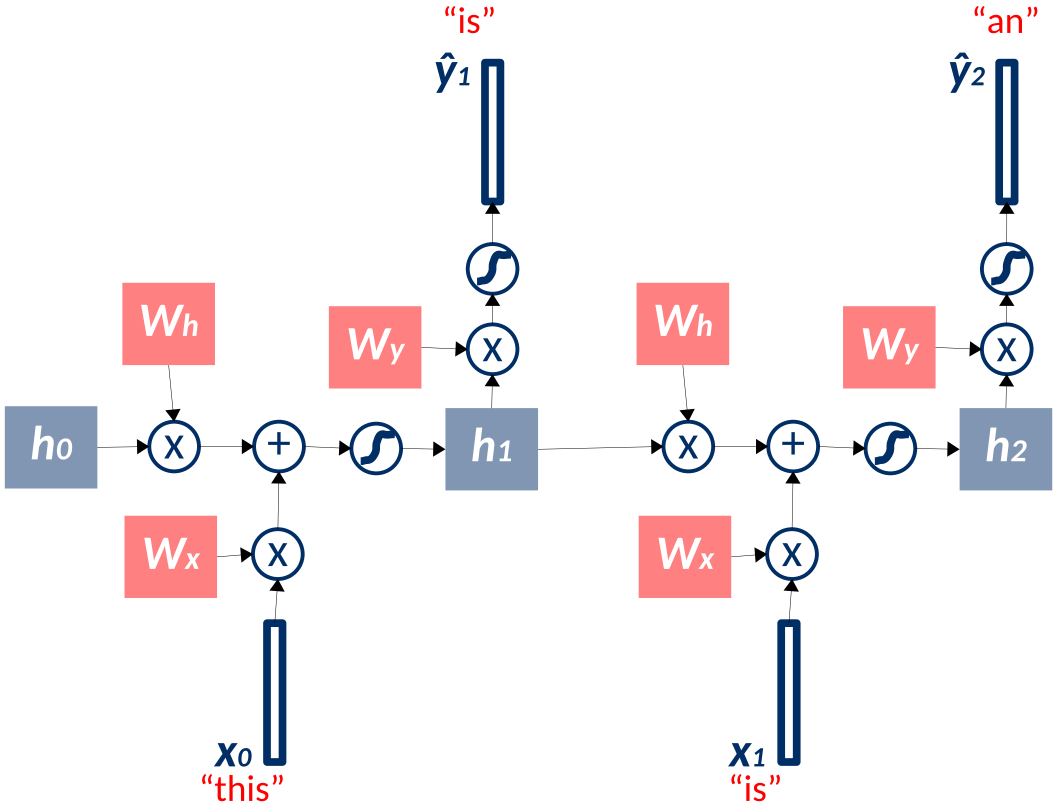


Input the next element $\boldsymbol{x_1}$ from the sequence

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

- **Idea:** Use a persistent state ***h*** that encodes past observations (context)

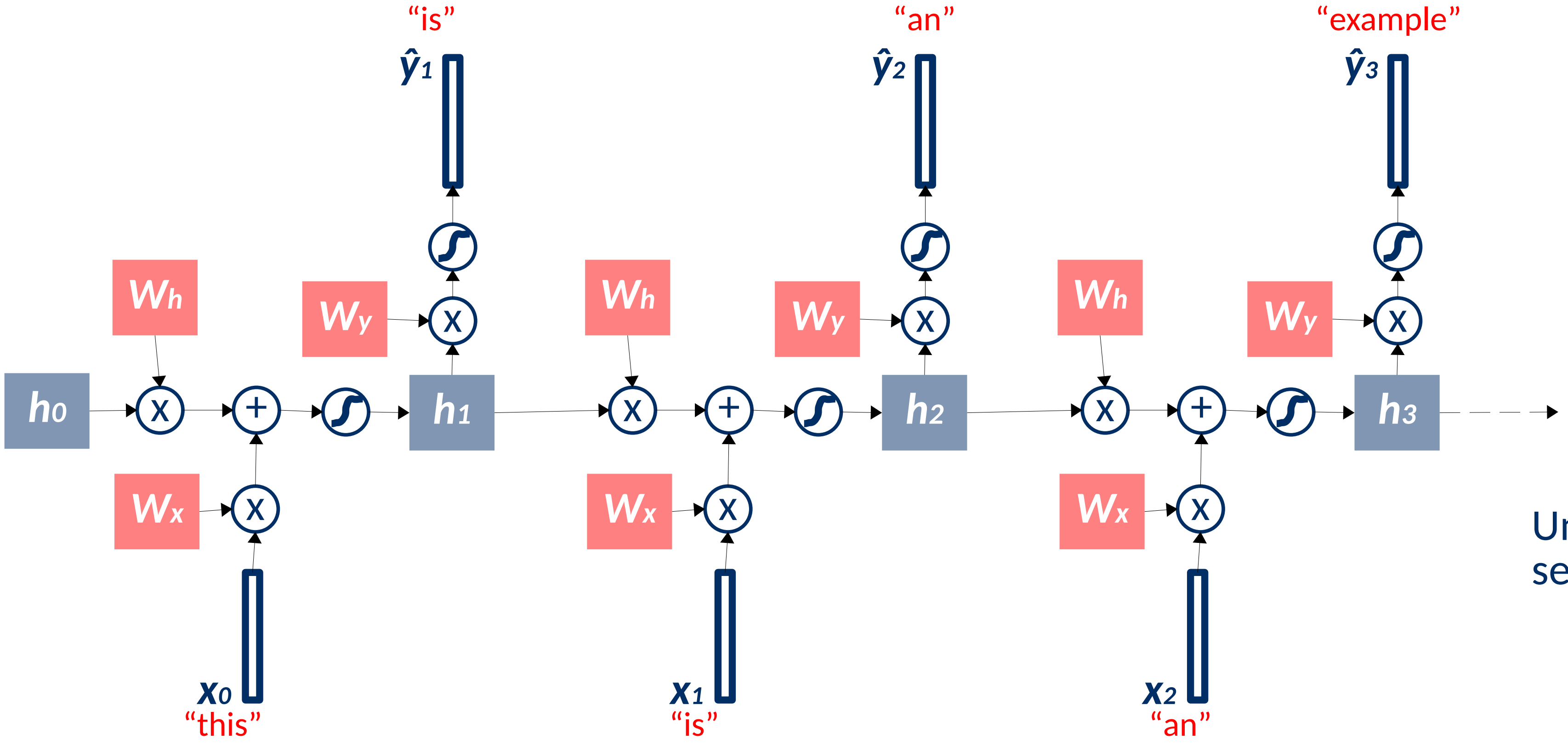


Keep going

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

- **Idea:** Use a persistent state ***h*** that encodes past observations (context)

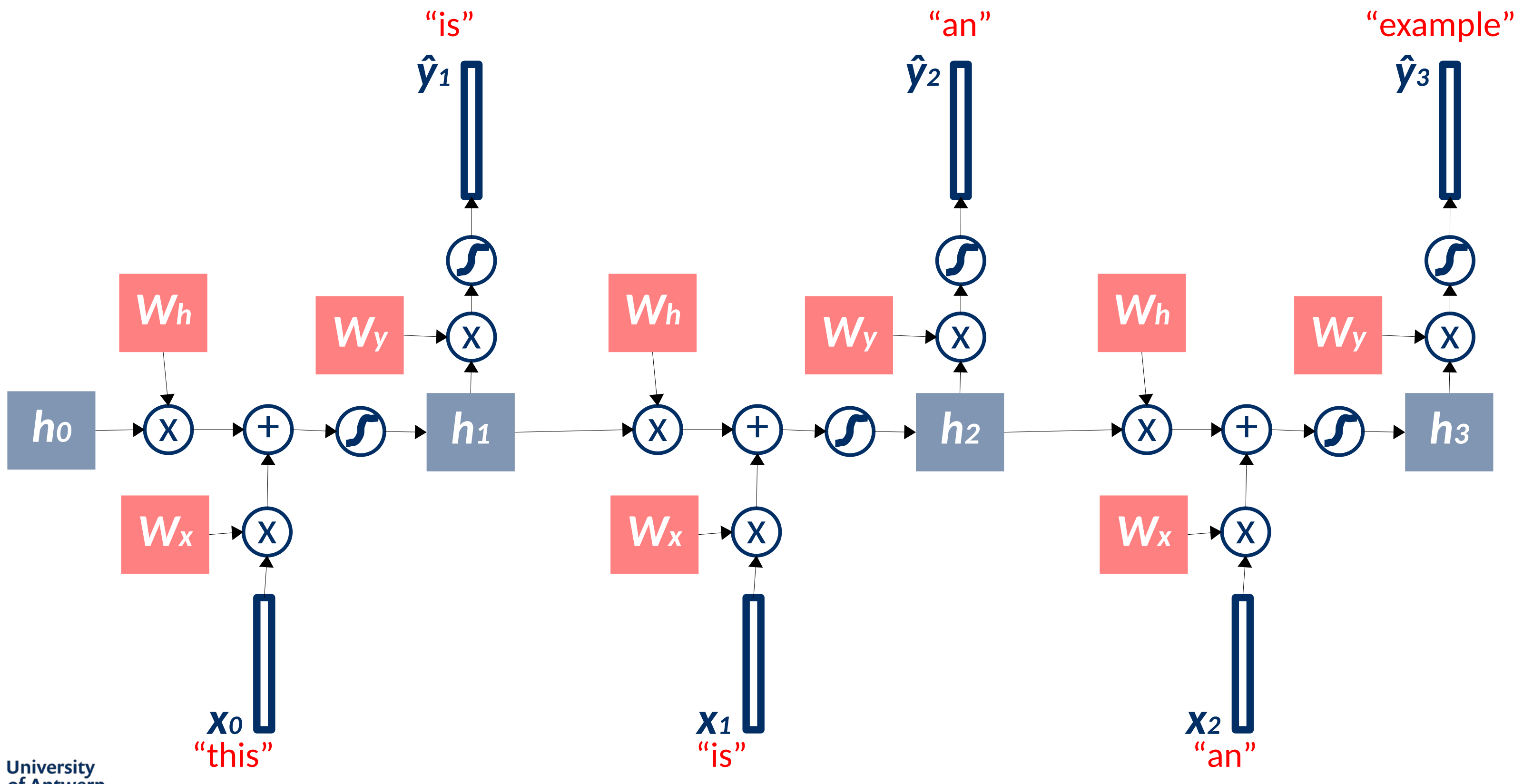


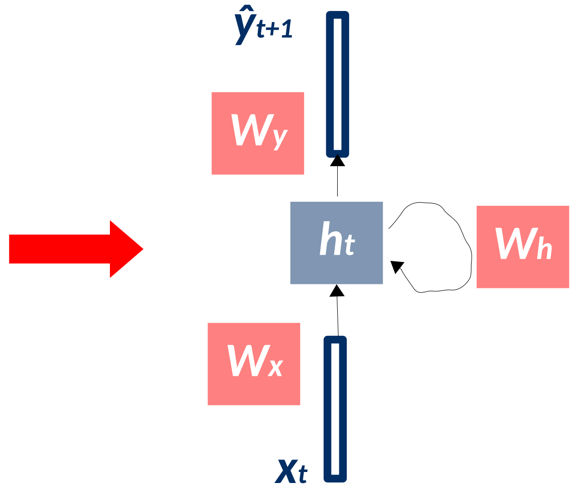
Until the whole sequence is pushed

Recurrent Neural Networks (RNNs) [Elman, 1991]

Provide Neural Networks with Memory

- **Idea:** Use a persistent state ***h*** that encodes past observations (context)

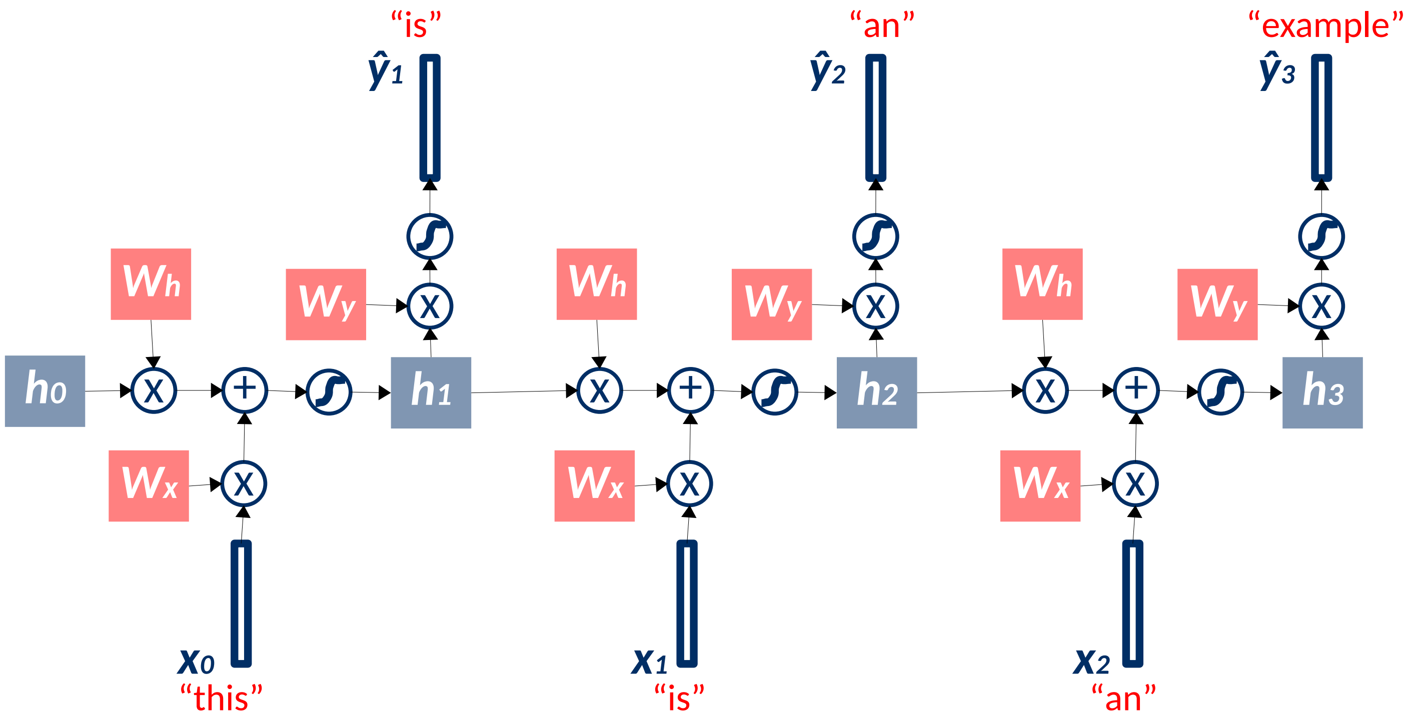




Recurrent Neural Networks (RNNs) [Elman, 1991]

Learning | Training

- **Idea:** Formulate the next-word prediction as a classification problem
- Number of classes = vocabulary_size → Use the cross-entropy loss.



Recurrent Neural Networks (RNNs) [Elman, 1991]

Learning | Training

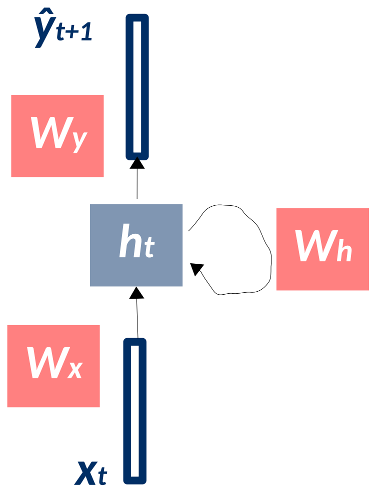
- **Idea:** Formulate the next-word prediction as a classification problem
- Number of classes = vocabulary_size → Use the cross-entropy loss.

Given a sequence of ***T*** elements:

For one element ***t*** → $L_\theta(y, \hat{y})_t = -y_t \log \hat{y}_t$

For the sequence → $L_\theta(y, \hat{y}) = -\sum_{t=1}^{T} y_t \log \hat{y}_t$

Trainable parameters → $\theta = \{W_x, W_h, W_y\}$



Recurrent Neural Networks (RNNs) [Elman, 1991]

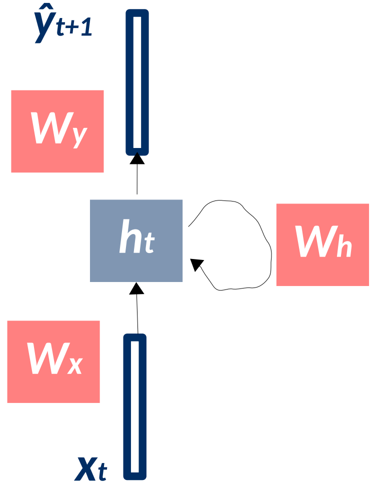
Back-Prop. - Differentiation wrt. the parameters $\theta = \{W_x, W_h, W_y\}$

$$\boxed{\begin{aligned} h_t &= \tanh(\ W_h h_{t-1} + W_x x_t\ ) \\ p(y_{t+1}) &= softmax(\ W_y h_t\ ) \\ L_\theta(y, \hat{y})_t &= -y_t \log \hat{y}_t \end{aligned}}$$

Differentiating wrt. *W_y*

$$\frac{\partial L_{\theta,t}}{\partial W_y} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial W_y}$$

$$= (y_t - \hat{y}_t) h_t$$



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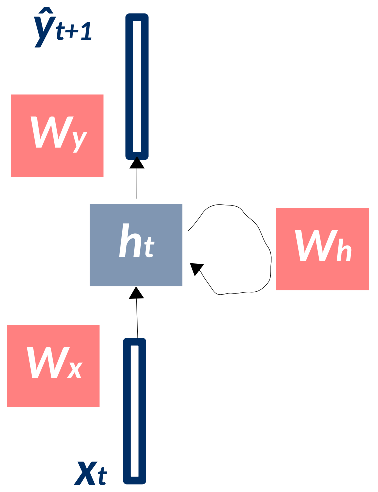
Differentiating wrt. W_h

$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$



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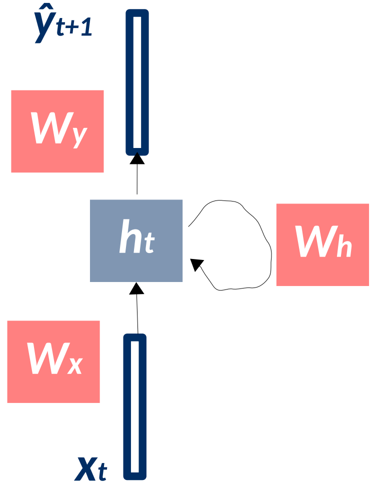
Differentiating wrt. *Wh*

$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$

$$\frac{\partial h_t}{\partial W_h} = \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W_h}$$



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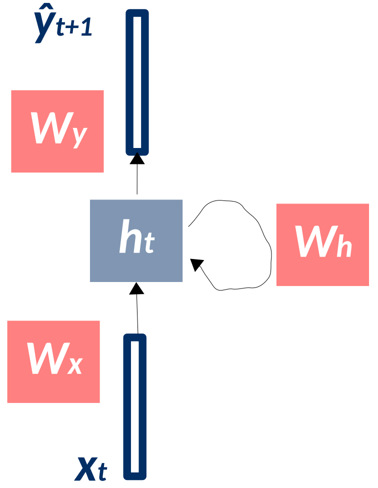


Differentiating wrt. *Wh*

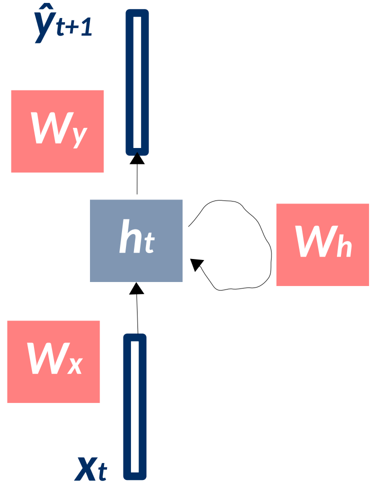
$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$

$$\begin{aligned} \frac{\partial h_t}{\partial W_h} &= \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W_h} \\ &= \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}} \left[\frac{\partial h_{t-1}}{\partial W_h} + \frac{\partial h_{t-1}}{\partial h_{t-2}} \frac{\partial h_{t-2}}{\partial W_h} \right] \end{aligned}$$

Recurrent Neural Networks (RNNs) [Elman, 1991]

Back-Prop. - Differentiation wrt. the parameters $\theta = \{W_x, W_h, W_y\}$

$$\boxed{\begin{aligned} h_t &= \tanh(\ W_h h_{t-1} + W_x x_t\ ) \\ p(y_{t+1}) &= softmax(\ W_y h_t\ ) \\ L_\theta(y, \hat{y})_t &= -y_t \log \hat{y}_t \end{aligned}}$$



Differentiating wrt. W_h

$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$

$$\begin{aligned} \frac{\partial h_t}{\partial W_h} &= \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W_h} \\ &= \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}} \left[\frac{\partial h_{t-1}}{\partial W_h} + \frac{\partial h_{t-1}}{\partial h_{t-2}} \frac{\partial h_{t-2}}{\partial W_h} \right] \\ &= \sum_{k=1}^{t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W_h} \end{aligned}$$

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Back-Prop. - Differentiation wrt. the parameters $\theta = \{W_x, W_h, W_y\}$

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Differentiating wrt. *Wh*

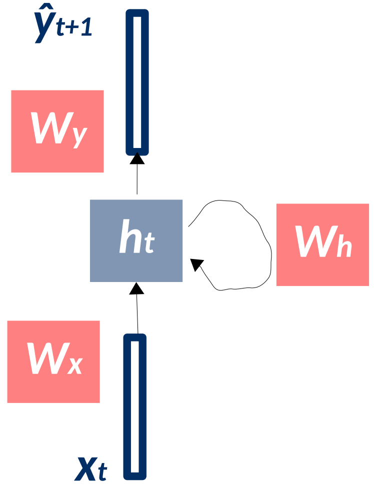
$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t}\frac{\partial \hat{y}_t}{\partial h_t}\frac{\partial h_t}{\partial W_h}$$

$$\frac{\partial h_t}{\partial W_h} = \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}}\frac{\partial h_{t-1}}{\partial W_h}$$

$$= \frac{\partial h_t}{\partial W_h} + \frac{\partial h_t}{\partial h_{t-1}}\left[\frac{\partial h_{t-1}}{\partial W_h} + \frac{\partial h_{t-1}}{\partial h_{t-2}}\frac{\partial h_{t-2}}{\partial W_h}\right]$$

$$= \sum_{k=1}^{t} \frac{\partial h_t}{\partial h_k}\frac{\partial h_k}{\partial W_h}$$

Back-propagation through time



Recurrent Neural Networks (RNNs) [Elman, 1991]

Back-Prop. - Differentiation wrt. the parameters $\theta = \{W_x, W_h, W_y\}$

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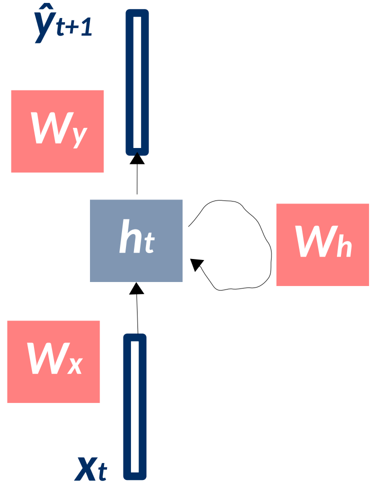
$$L_\theta(y, \hat{y})_t = -y_t \log \hat{y}_t$$

Differentiating wrt. *W_h*

$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$



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Recurrent Neural Networks (RNNs) [Elman, 1991]

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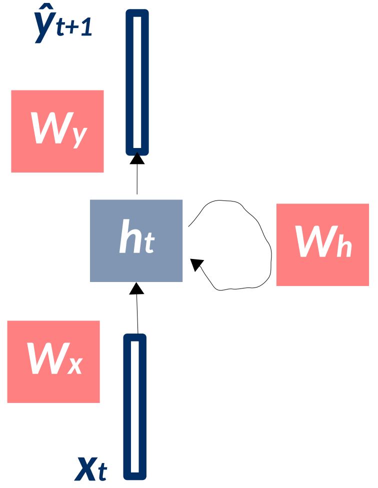

Differentiating wrt. *Wh*

$$\frac{\partial L_{\theta,t}}{\partial W_h} = \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h}$$

$$= \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \sum_{k=1}^{t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W_h}$$

Recurrent Neural Networks (RNNs) [Elman, 1991]

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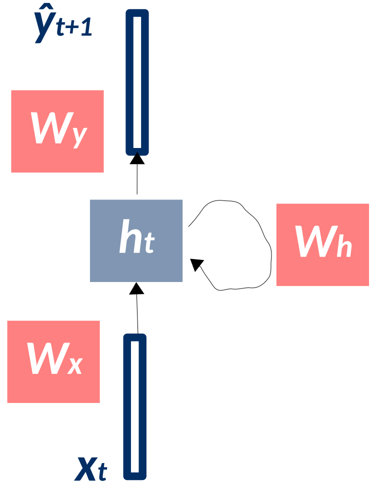
$$\boxed{\begin{aligned} &h_t = \tanh(\ W_h h_{t-1} + W_x x_t\ ) \\ &p(y_{t+1}) = softmax(\ W_y h_t\ ) \\ &L_\theta(y, \hat{y})_t = -y_t \log \hat{y}_t \end{aligned}}$$



Differentiating wrt. *Wh*

$$\begin{aligned} \frac{\partial L_{\theta,t}}{\partial W_h} &= \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W_h} \\ &= \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \sum_{k=1}^{t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W_h} \\ &= \sum_{k=1}^{t} \frac{\partial L_{\theta,t}}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial W_h} \end{aligned}$$

Recurrent Neural Networks (RNNs) [Elman, 1991]

Summarizing

- + Good at modeling sequences of variable length
- + Trainable via Back-Prop. → differentiable

- – Suffer from vanishing gradients for long sequences

Long Short-Term Memory Networks

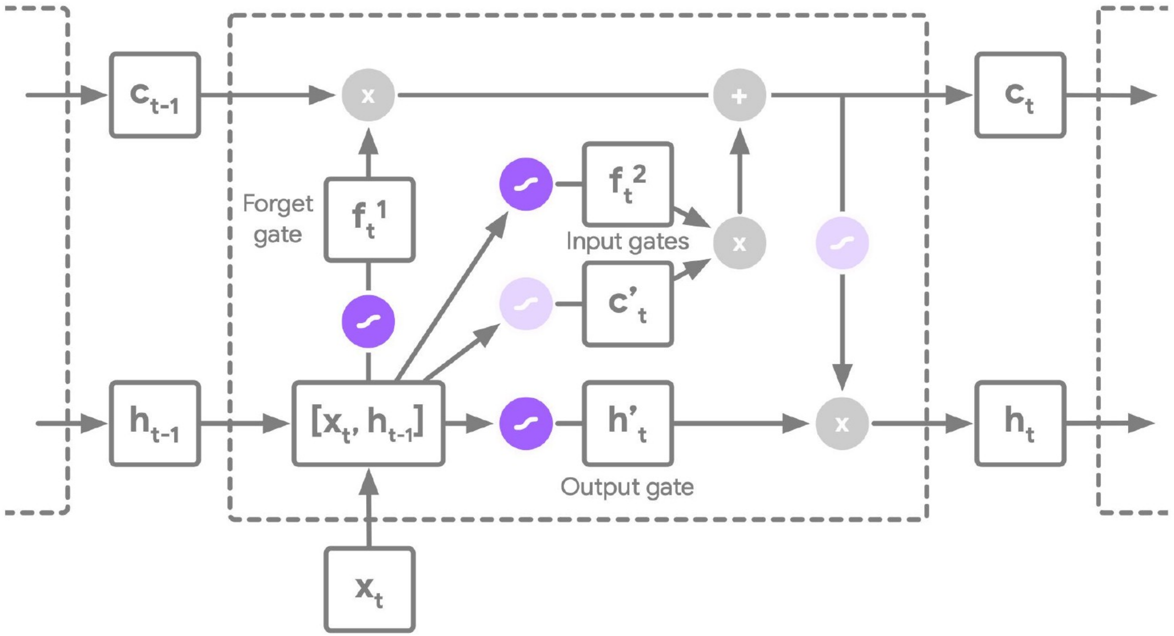
[RNNs with Extra Memory]

Long Short-Term Memory Networks (LSTMs)

[Hochreiter & Jurgen , 1997]

Provide the capability of choosing what to remember/forget

- **Idea:** Provide special gates to control the flow of “memories”

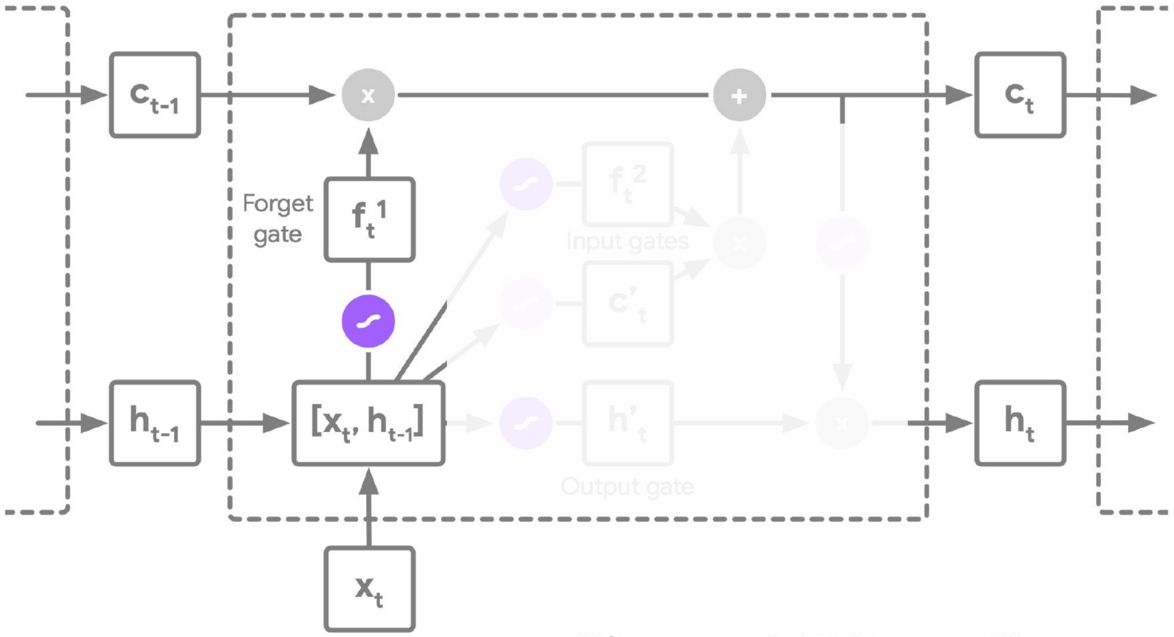


Long Short-Term Memory Networks (LSTMs)

[Hochreiter & Jurgen , 1997]

Provide the capability of choosing what to remember/forget

- f_1: Forget Gate



regulate what information to keep/ignore

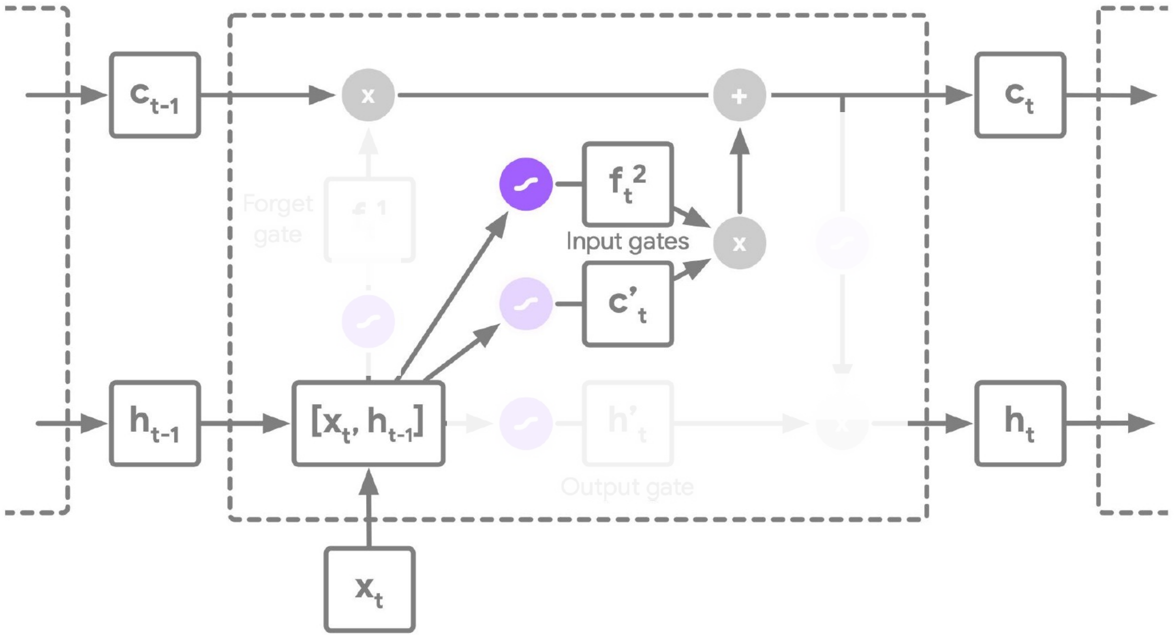
$$f_t^1 = \sigma(\ W_{f^1} \cdot [h_{t-1}, x_t] + b_{f^1}\ )$$

Long Short-Term Memory Networks (LSTMs)

[Hochreiter & Jurgen , 1997]

Provide the capability of choosing what to remember/forget

- f2: Input Gate



Decides what information to update

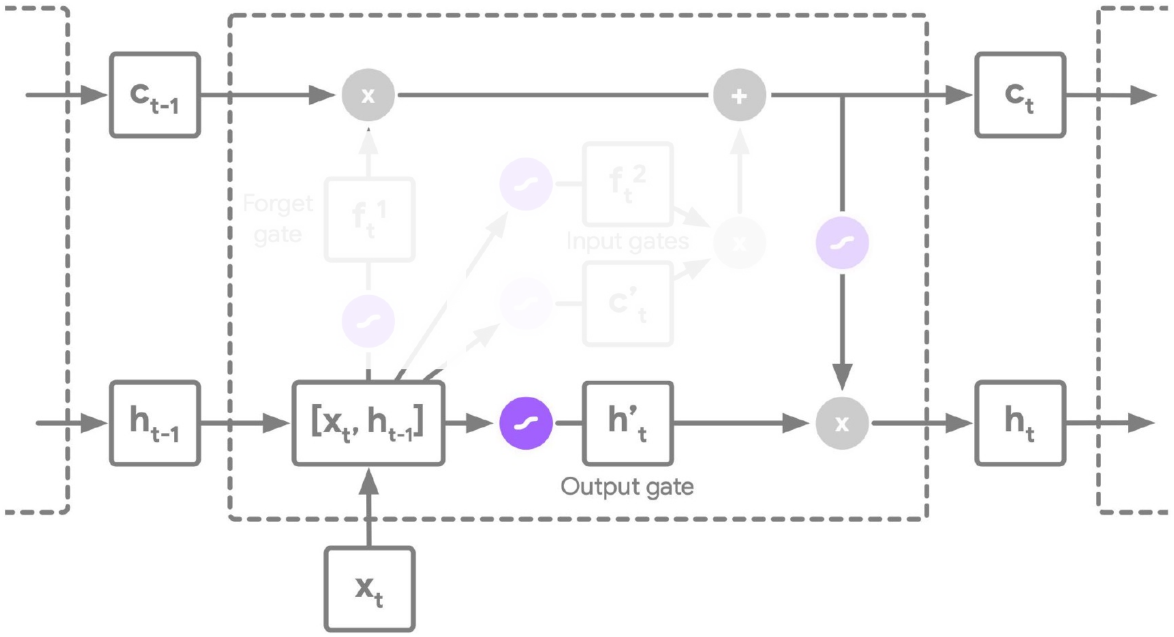
$$= \sigma(\ W_{f^2} \cdot [h_{t-1}, x_t] + b_{f^2}\ ) \odot \tanh(\ W_{c'}[h_{t-1}, x_t] + b_{c'}\ )$$

Long Short-Term Memory Networks (LSTMs)

[Hochreiter & Jurgen , 1997]

Provide the capability of choosing what to remember/forget

- h’t: Output Gate



$$= \sigma(\; W_{h'_t} \cdot [h_{t-1}, x_t] + b_{h'_t} \;) \odot \tanh(\; c_t \;)$$

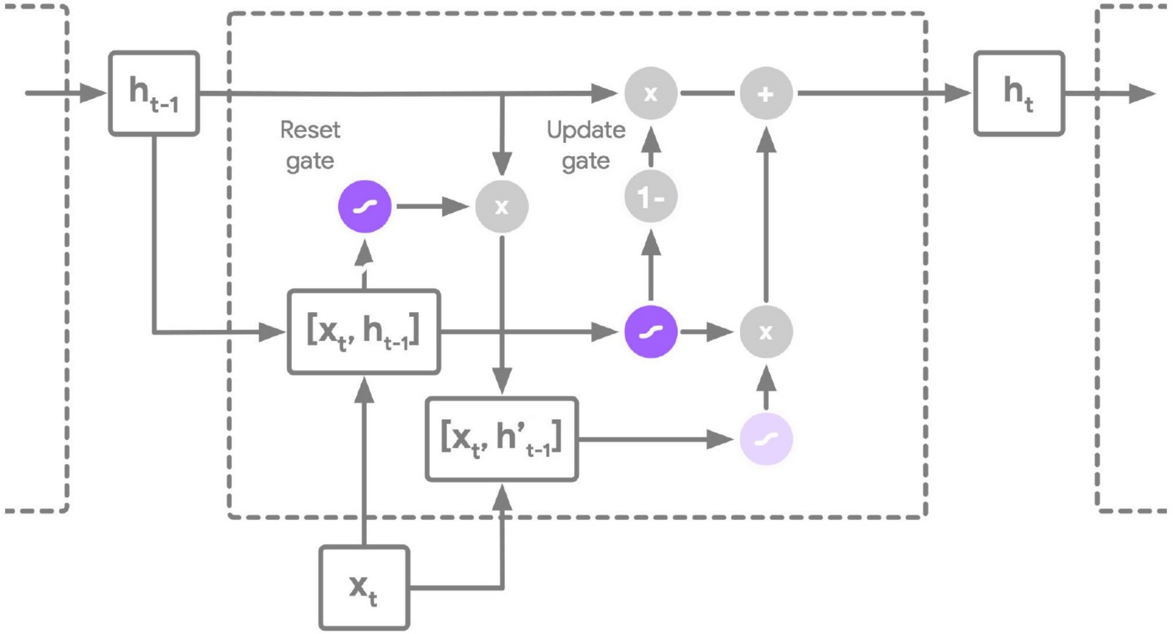
Gated Recurrent Units

[A Simplified LSTM]

Gated Recurrent Units (GRUs) [Cho et al. , 2014]

A Simplifed LSTM Network

- **Idea:** Provide special gates to control the flow of “memories”



LSTMs and GRUs

Summarizing

- **+ Good at modeling sequences of variable length**
- **+ Trainable via Back-Prop. → differentiable**

- **+ Capable of handling long sequences**

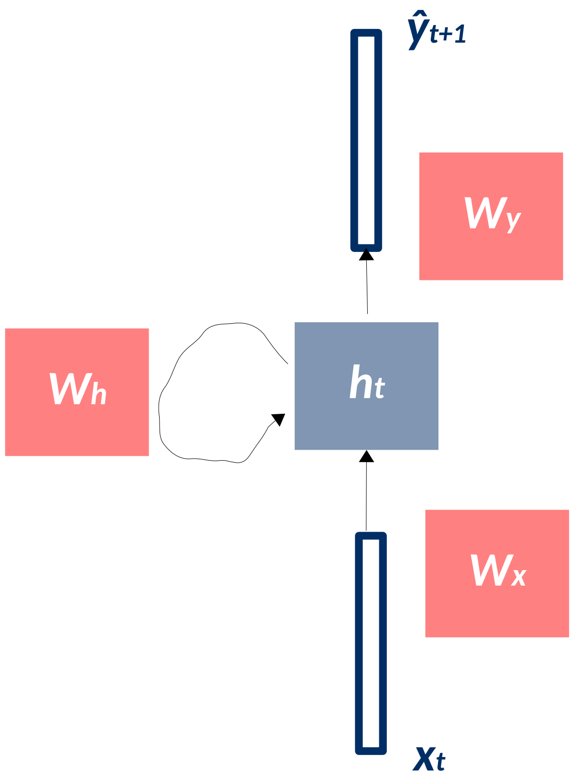
  (robust to vanishing/exploding gradients)

Predictions from Sequences

Predictions from Sequences

Training Classifiers/Regressors from Sequences

- 1) Attach a related head (classification, regression, etc.) to the *persistent* state
- 2) Measure the loss wrt. the prediction task



Predictions from Sequences

Training Classifiers/Regressors from Sequences

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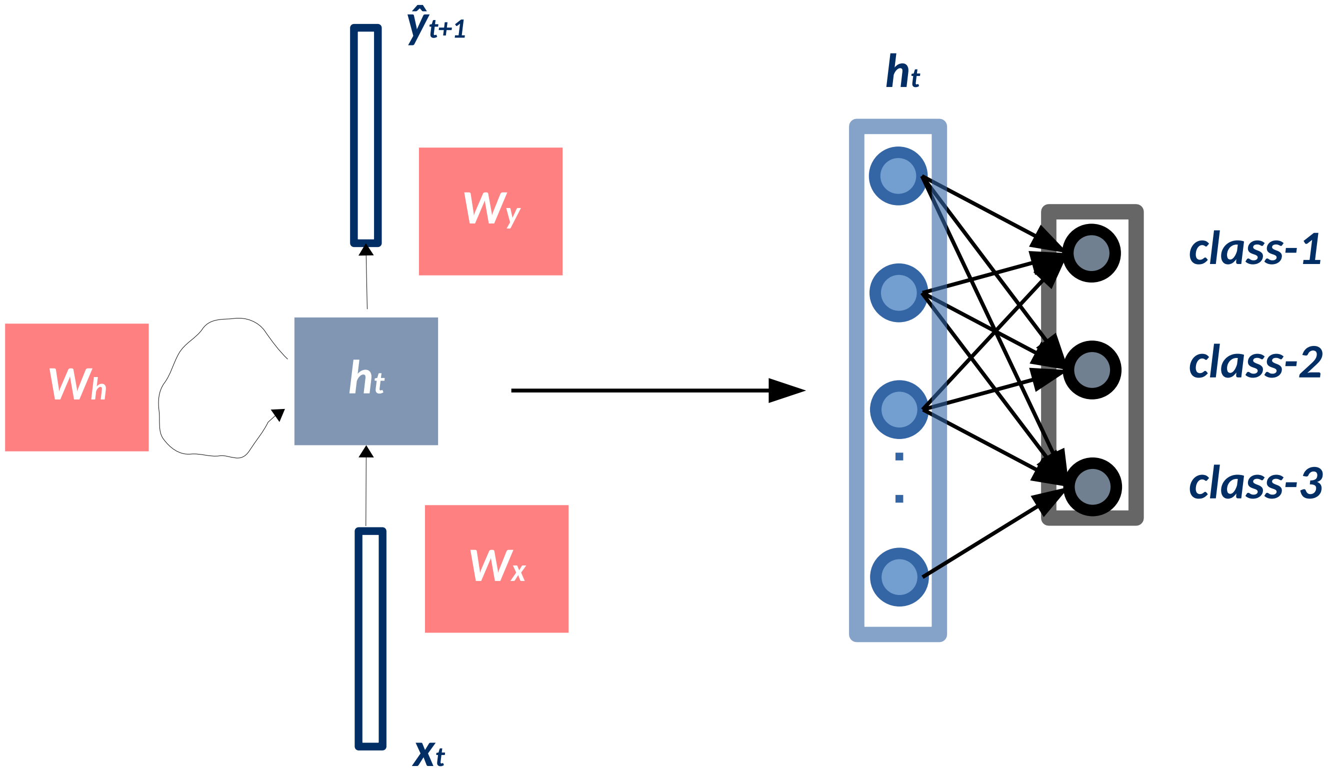
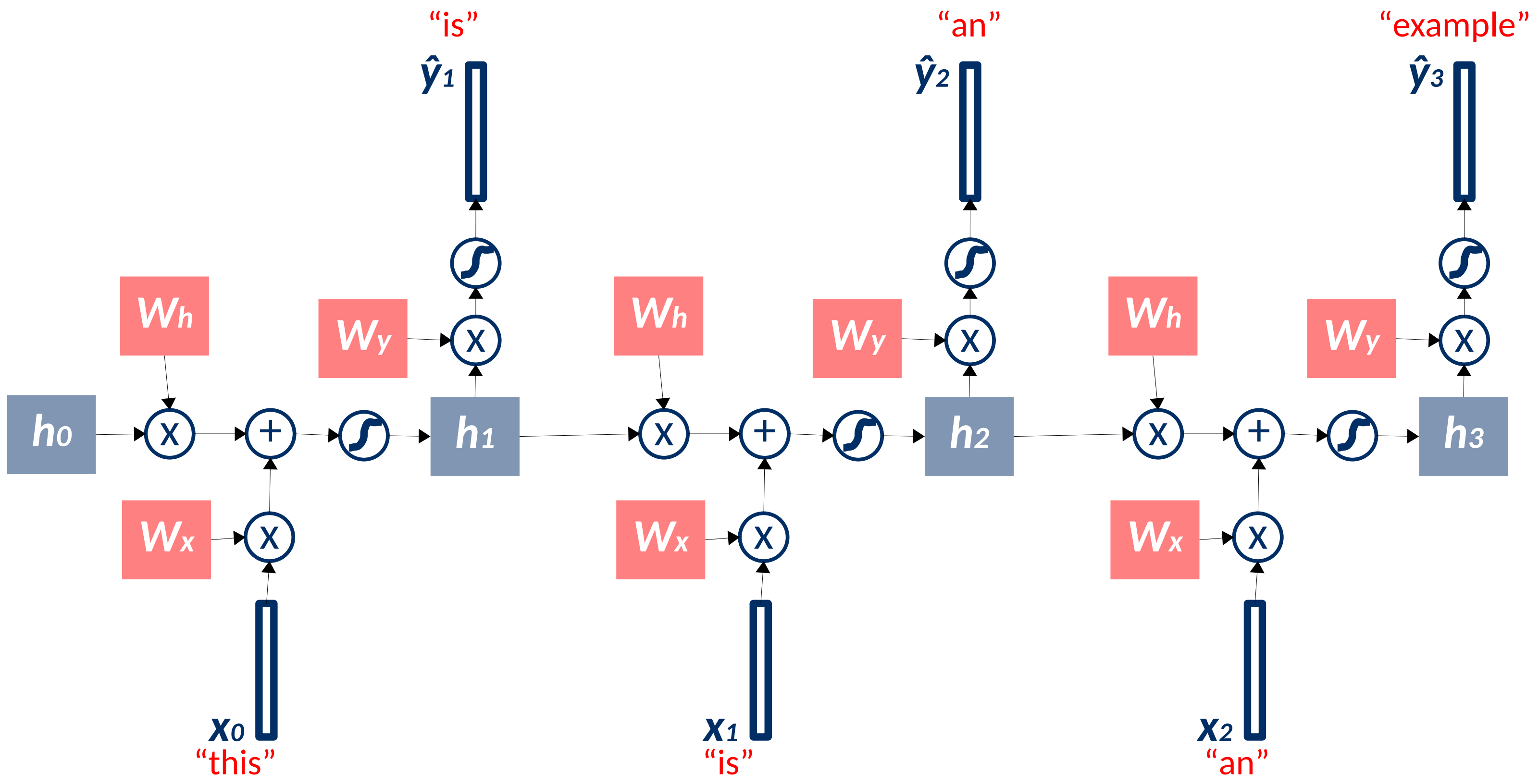


Generating Sequences

Generating Sequences

Sample the next best element from the predicted distribution

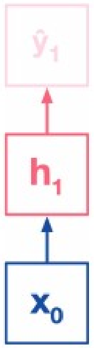
- **Idea:** Use the predicted element $\hat{y}_t$ as input in the next iteration



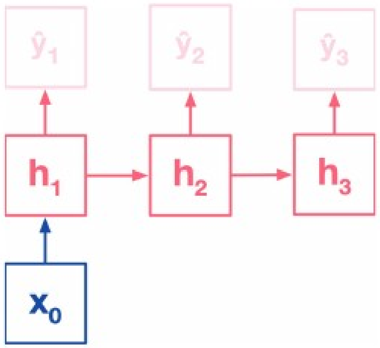
Generating Sequences

Several options are possible – beyond text sequences

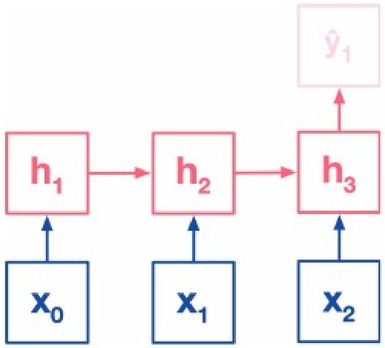
- **Idea:** Different ways to define inputs, context and outputs



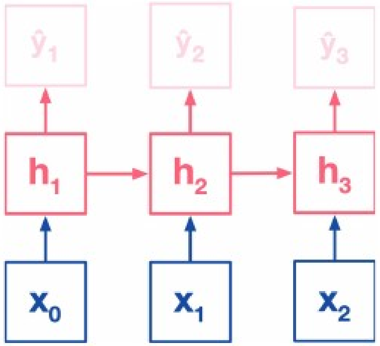
One to one



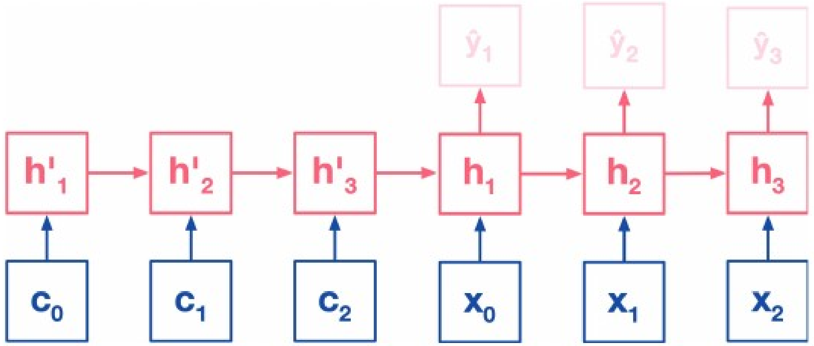
One to many



Many to one



Many to many



Many to many

Some Applications

- Language Translation
- Speech-to-Text
- Contextual Search
- Image Captioning

Break

[Let’s meet again in 15 mins.]

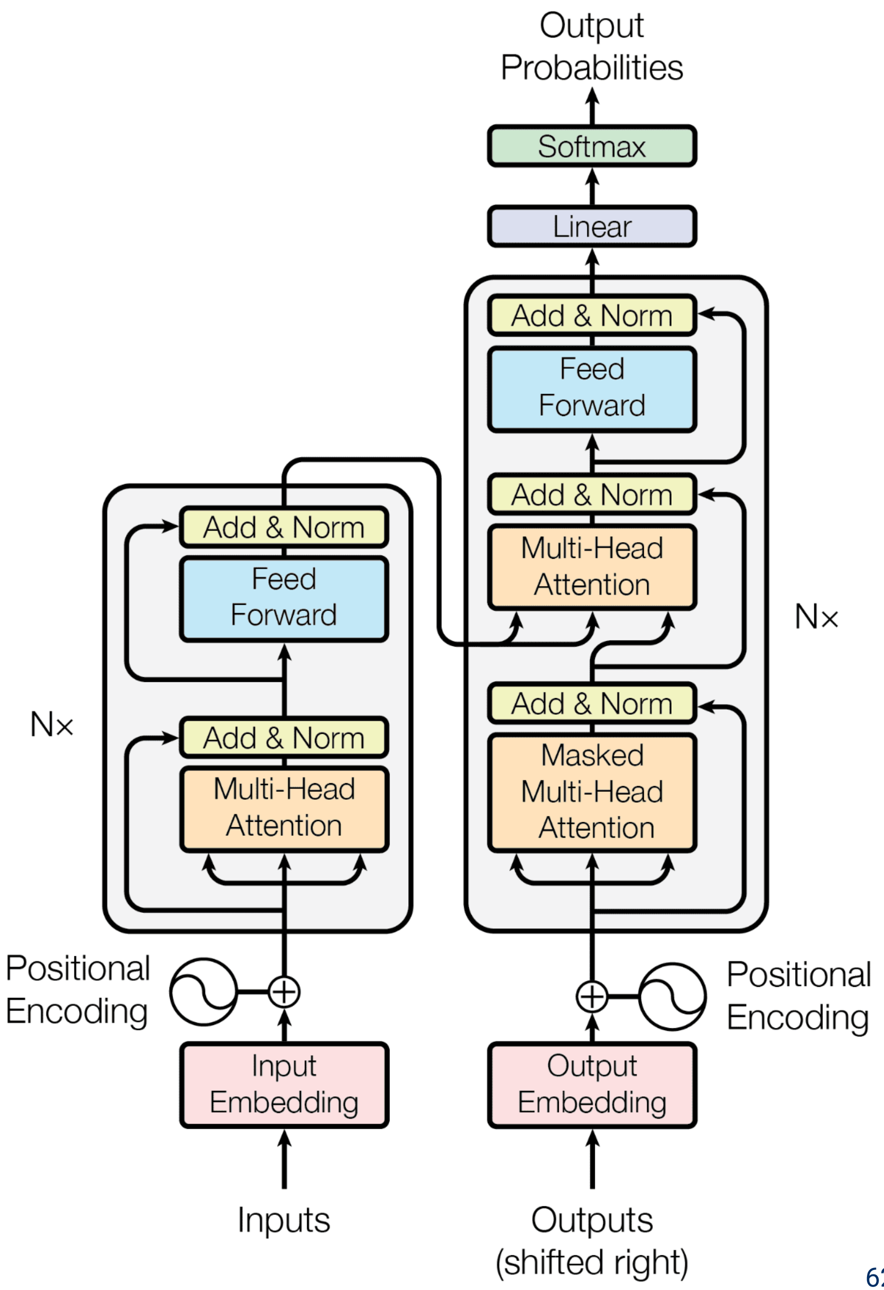
Transformers

Transformers [Vaswani et al., 2017]

Some specs

- Removed Recurrence components
- Based solely on the attention mechanism
- Originally addressed translation tasks

  [English-German | English-French]

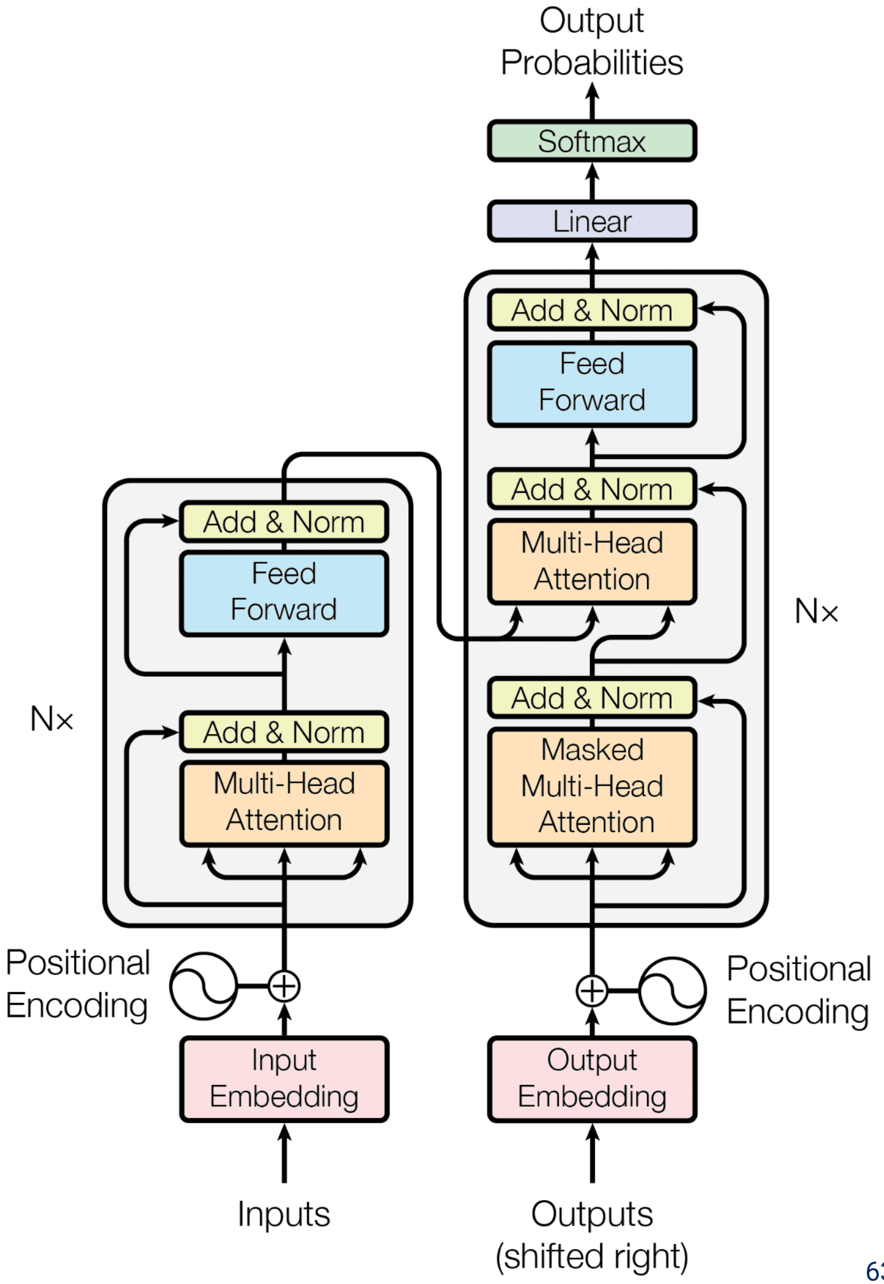


Transformers [Vaswani et al., 2017]

Some specs

- Removed Recurrence components
- Based solely on the attention mechanism
- Originally addressed translation tasks
  [English-German | English-French]

Scary-looking yes, difficult not
Let's follow Thomas' presentation



Modeling Data Sequences with Transformers

Lets consider the following sequence

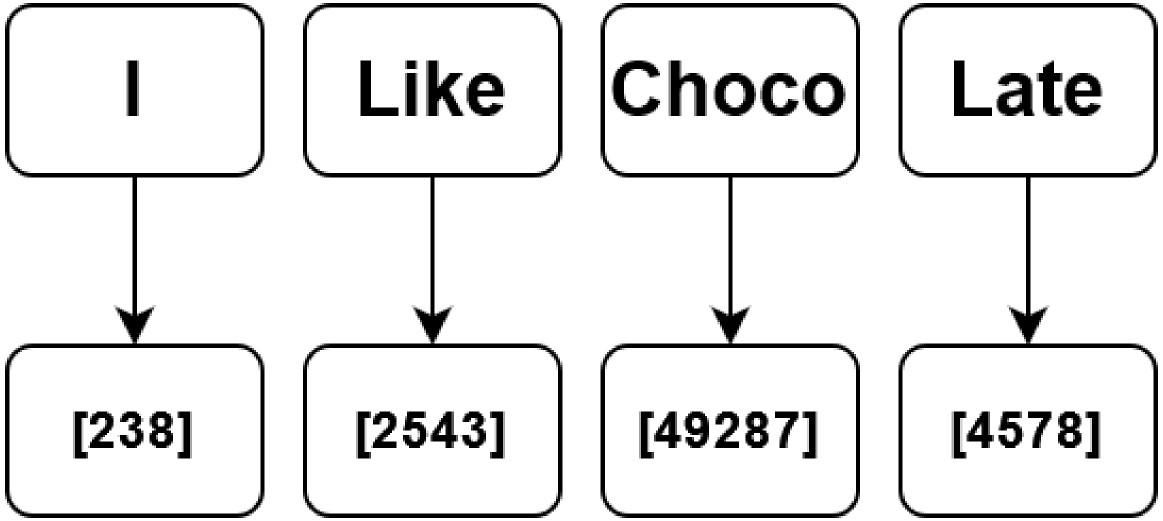
“I like chocolate”

[Dooms, 2024]

Modeling Data Sequences with Transformers

Tokenization: defining granular unit of processing

- Break the input into smaller units (*tokens*)
- Different levels of codification possible (character, word, etc.)



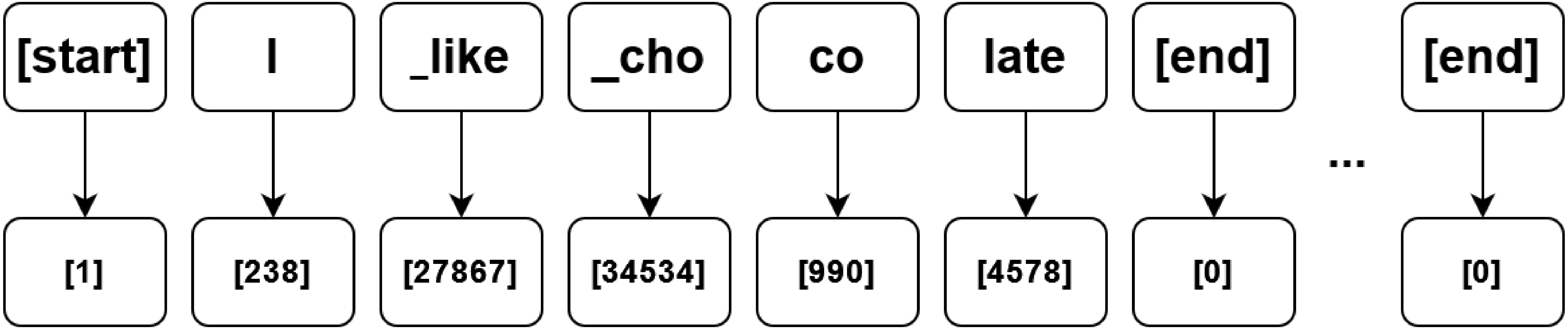
[Dooms, 2024]

Modeling Data Sequences with Transformers

Tokenization: defining granular unit of processing

- Break the input into smaller units (*tokens*)
- Different levels of codification possible (character, word, etc.)

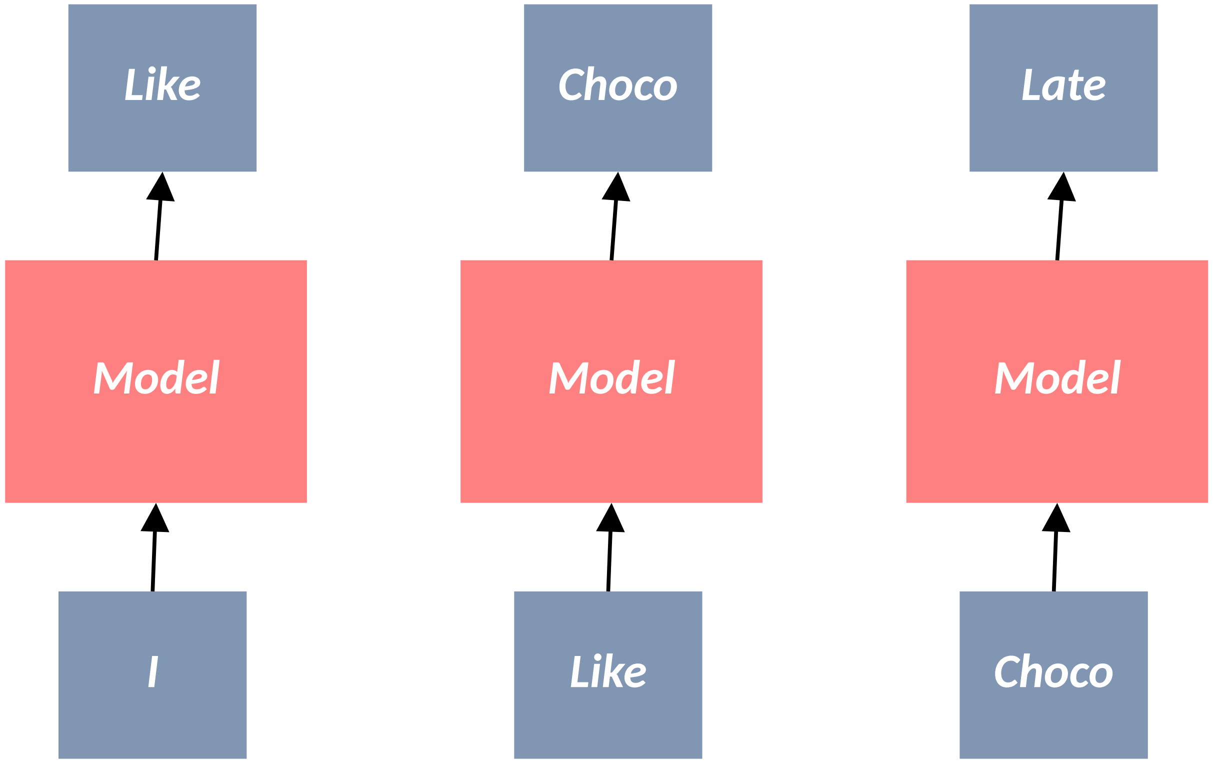
**In reality it is not that straight-forward*



[Dooms, 2024]

Modeling Data Sequences with Transformers

Predicting the next element (token)

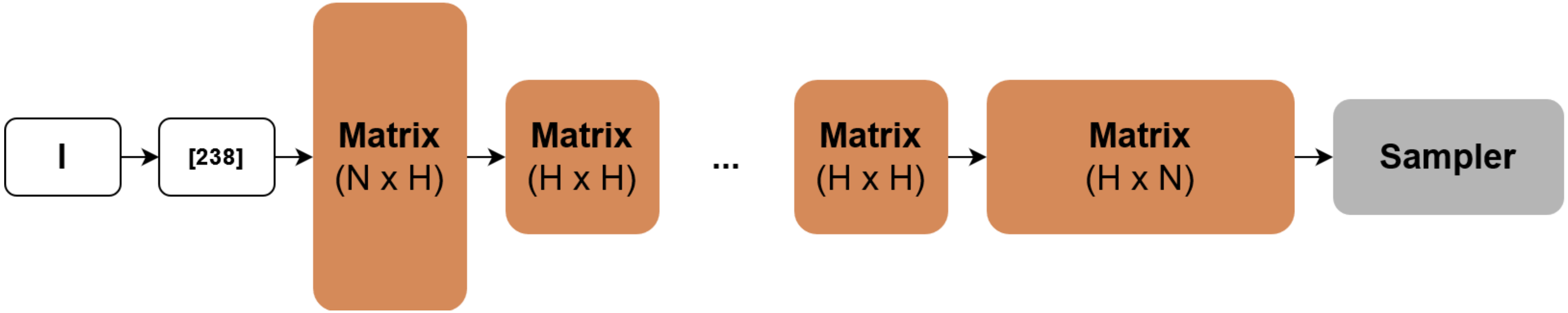


[Dooms, 2024]

Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)



[Dooms, 2024]

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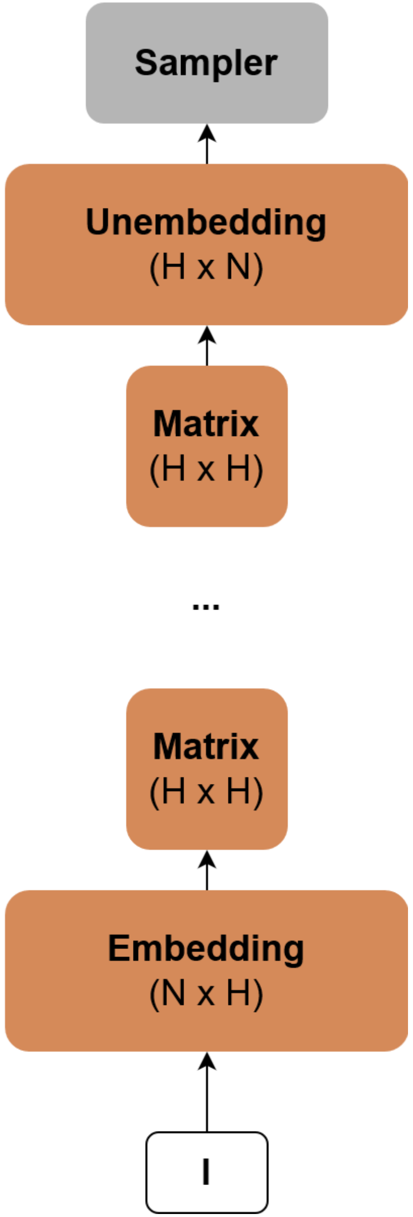
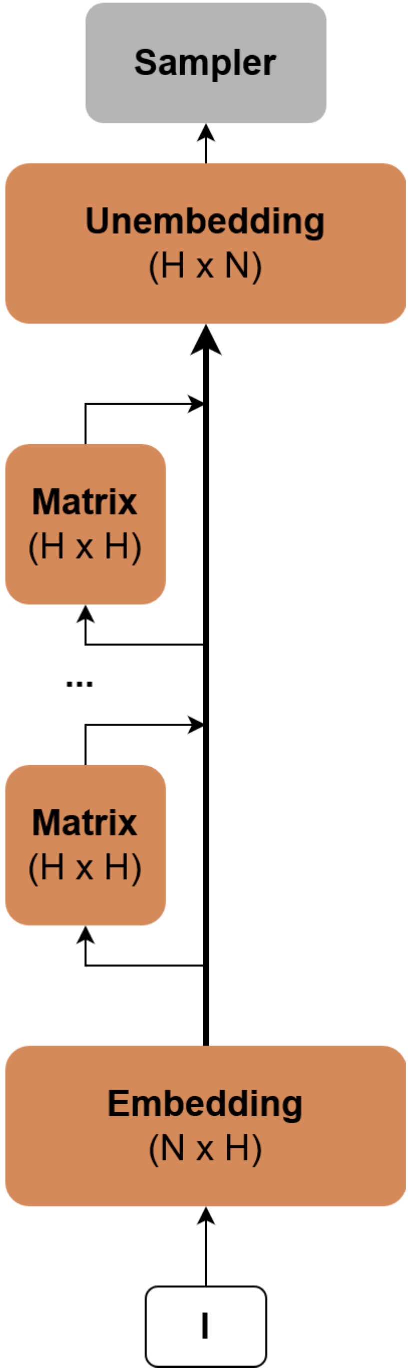


[Dooms, 2024]

Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)
- Using residual layers (**why?**)



[Dooms, 2024]

Sequence Modelling with Transformers

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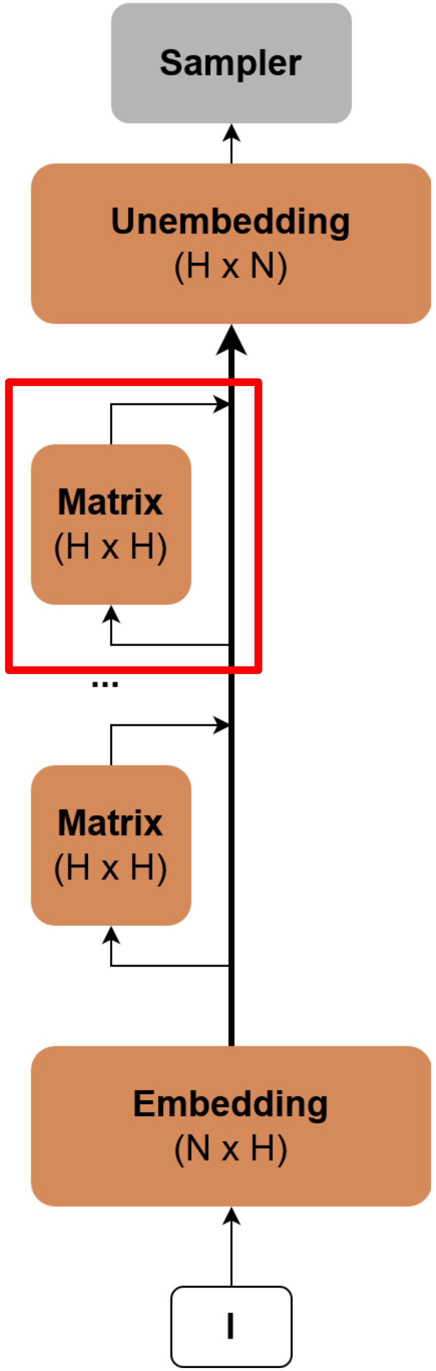


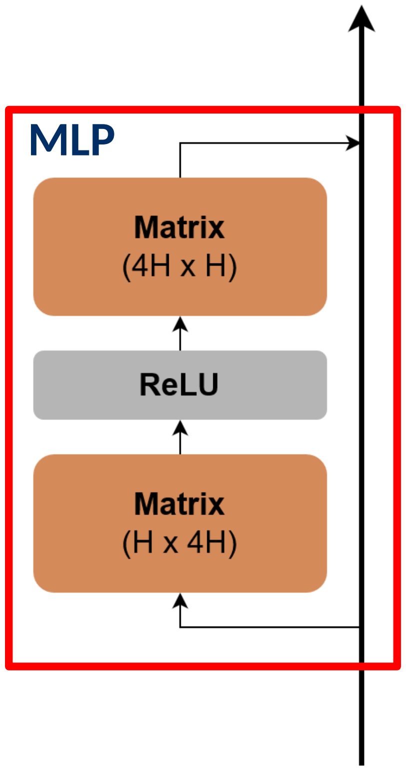
University of Antwerp

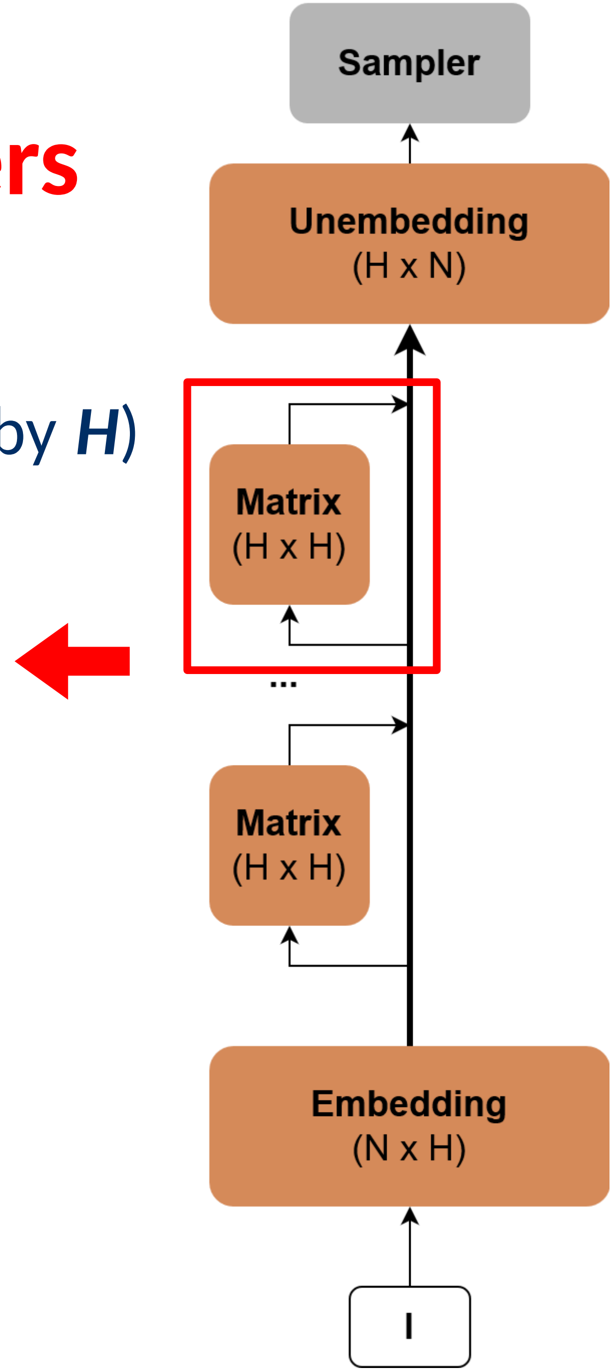
[Dooms, 2024]

Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)
- Using residual layers - MLP





[Dooms, 2024]

Sequence Modelling with Transformers

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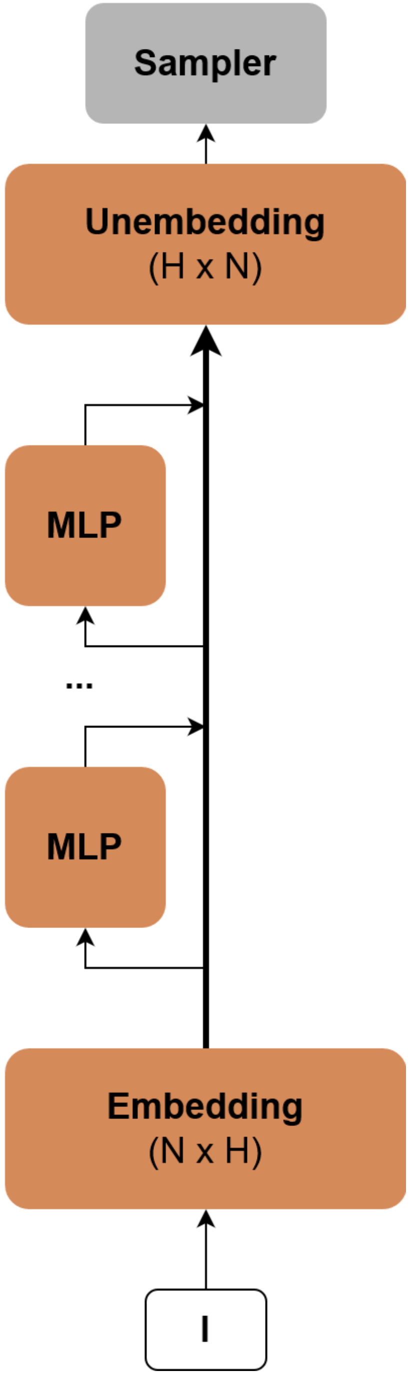


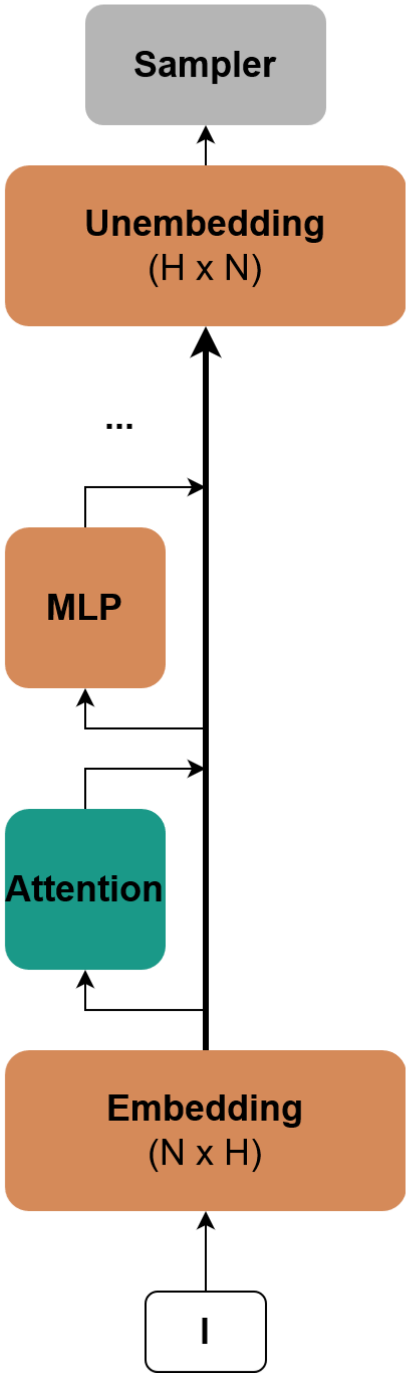
University of Antwerp

[Dooms, 2024]

Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)
- Using residual layers - MLP
- Add an [self] attention layer



[Dooms, 2024]

Sequence Modelling with Transformers

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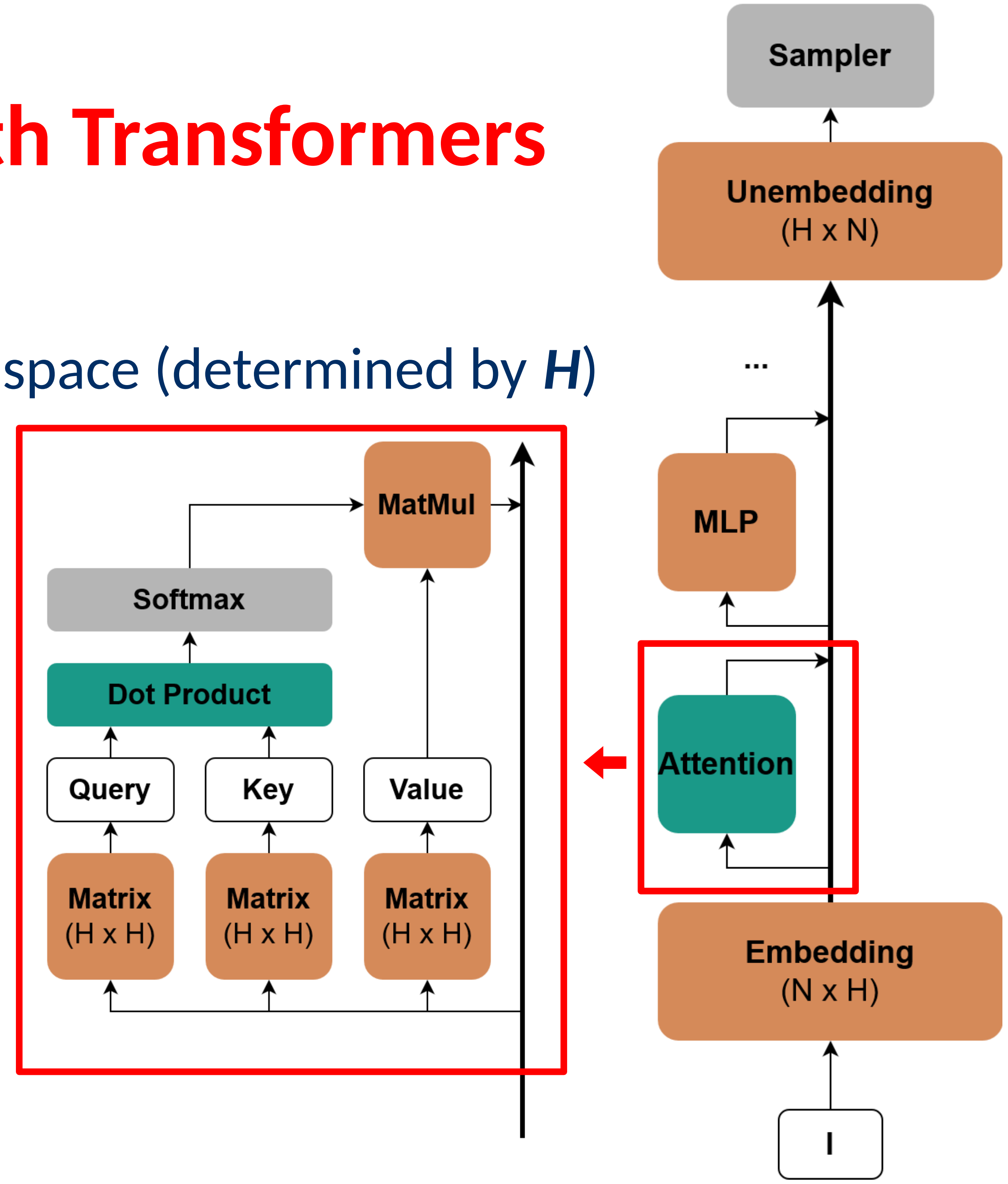


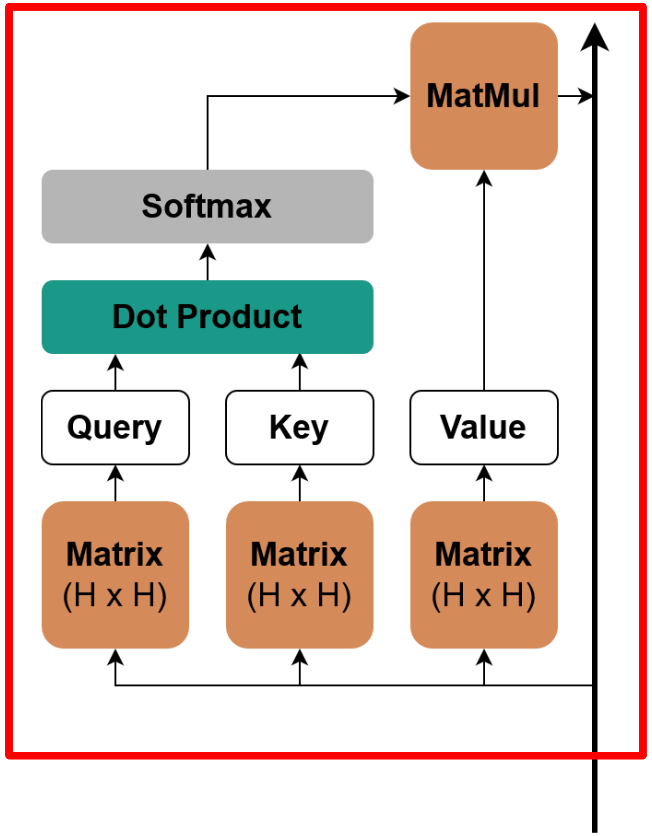
[Dooms, 2024]

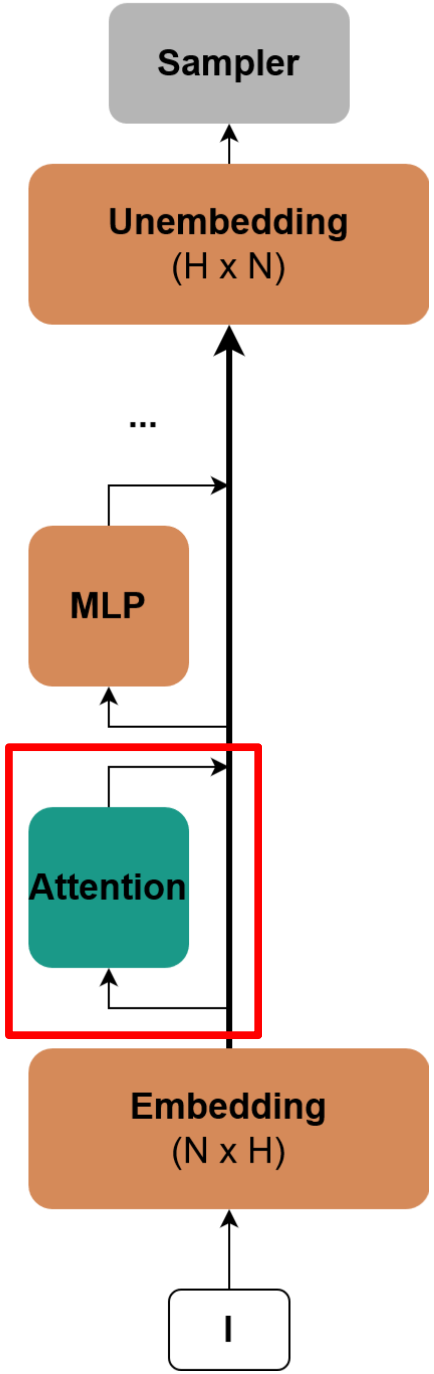
Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)
- Using residual layers - MLP
- Add an [self] attention layer

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

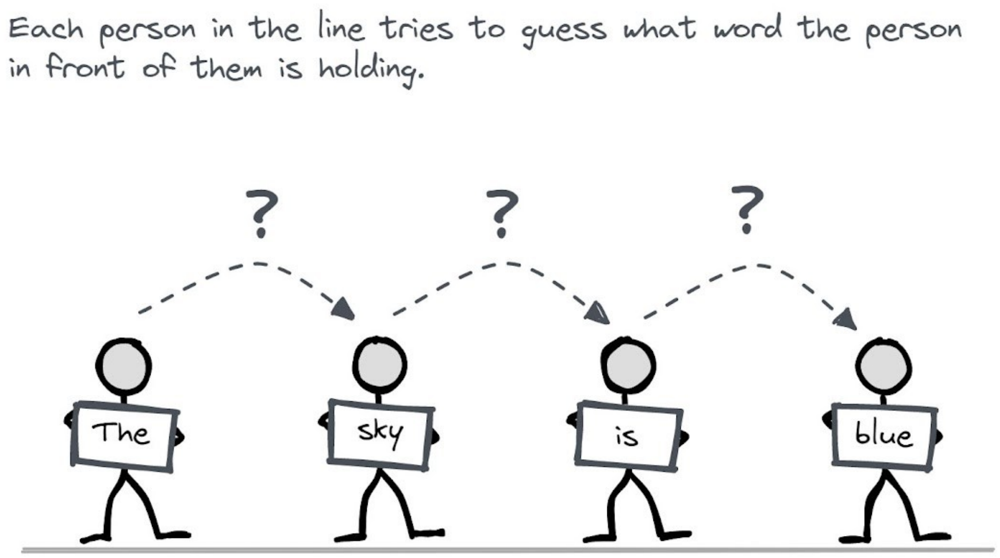




[Dooms, 2024]

Sequence Modelling with Transformers

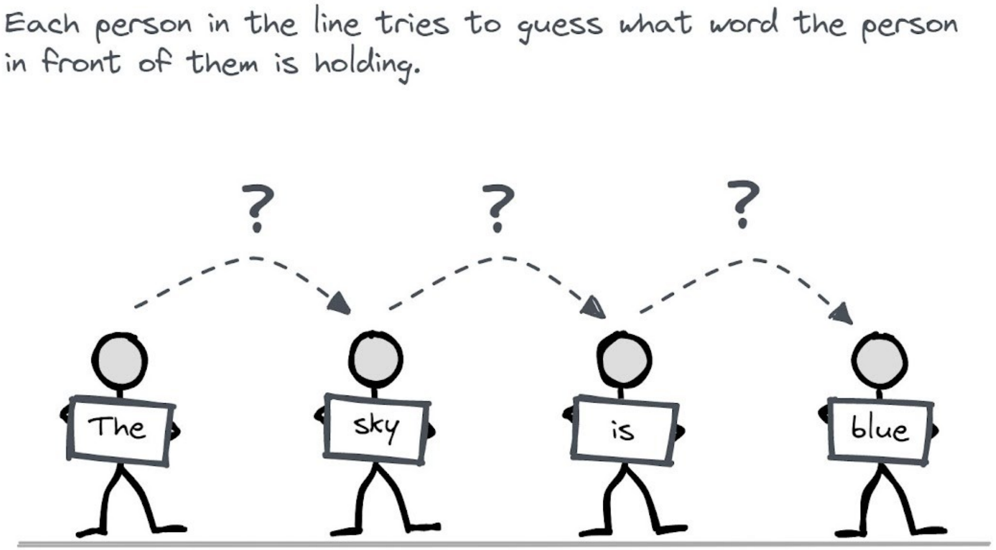
Attention Mechanism – An Intuition

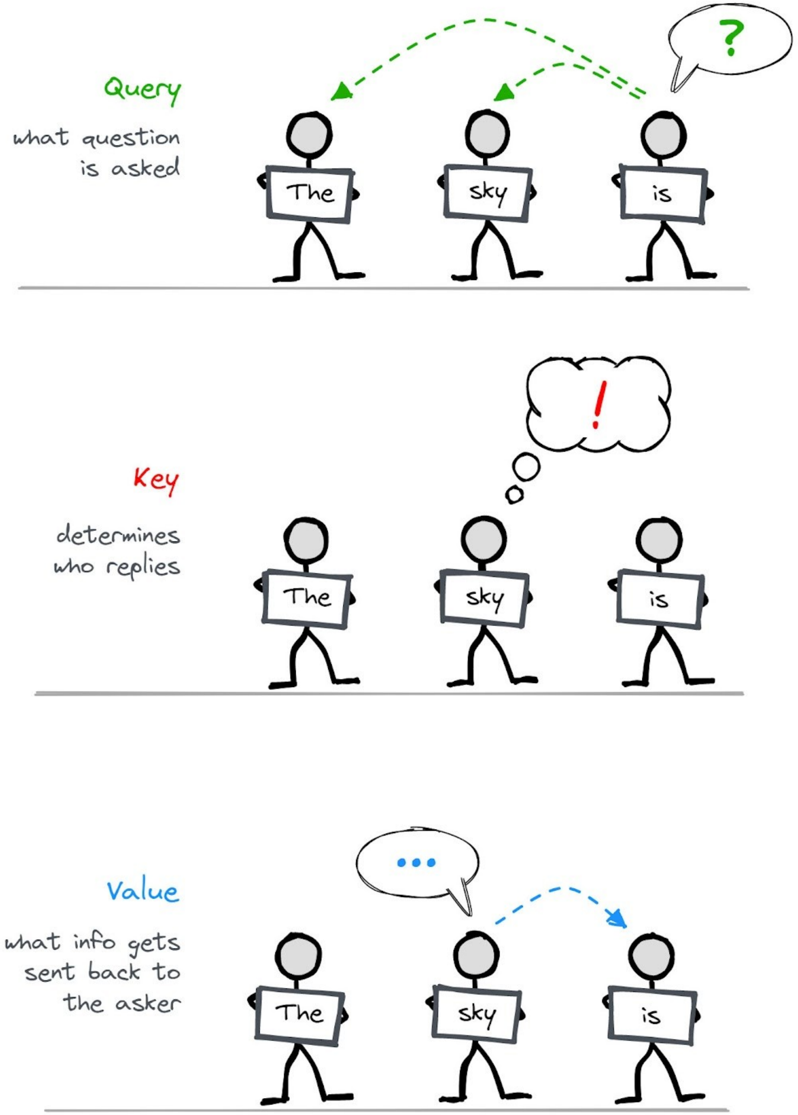


[Dooms, 2024]

Sequence Modelling with Transformers

Attention Mechanism – An Intuition



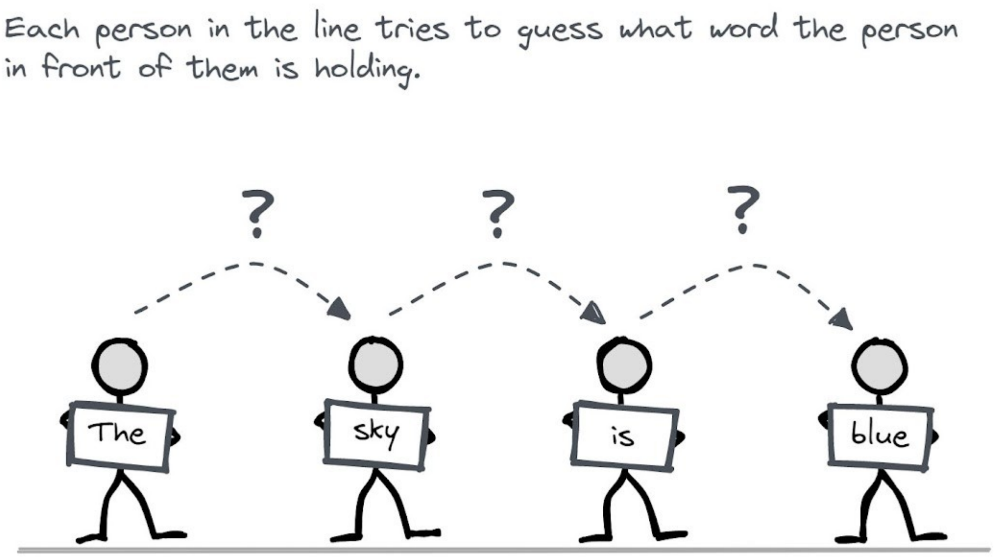


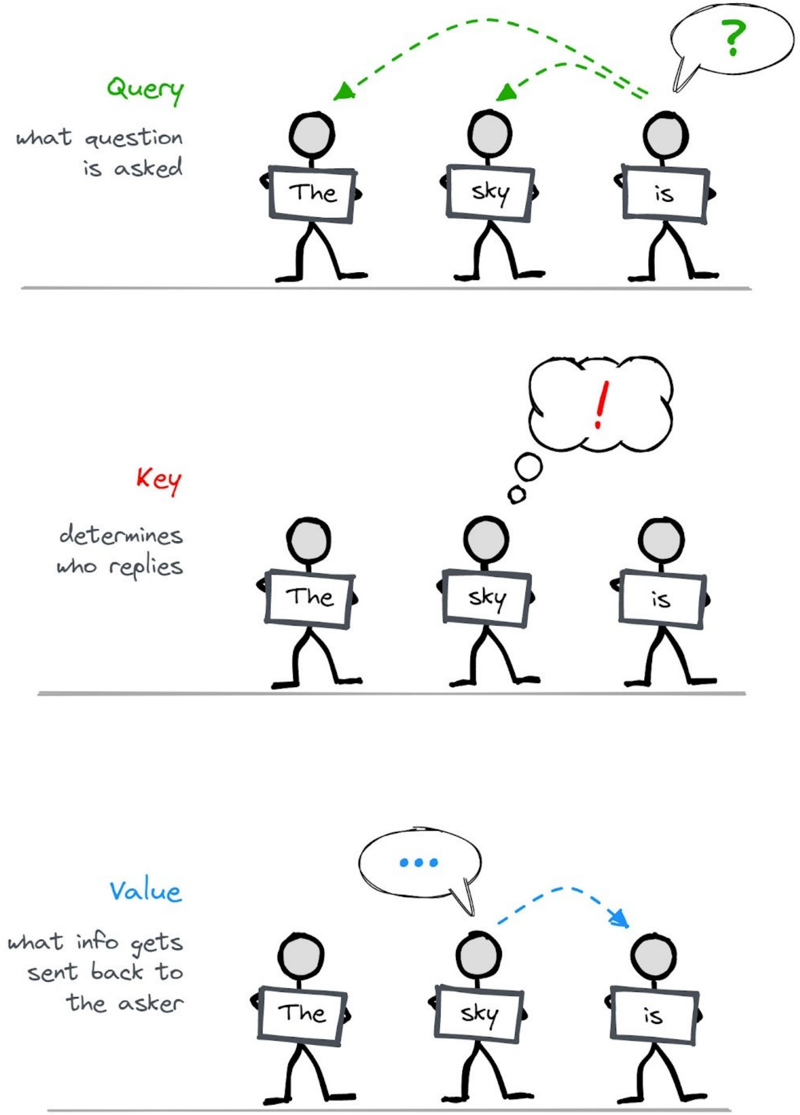
[Dooms, 2024]

Sequence Modelling with Transformers

Attention Mechanism – An Intuition

- Q → the question
- K → critical element to focus on
- V → the information to be forwarded





[Dooms, 2024]

Sequence Modelling with Transformers

Attention Mechanism – An Intuition

- Q → the question
- K → critical element to focus on
- V → the information to be forwarded

A database Analogy

	Query = 5	Values	Output
Key = 1	0	1	0
Key = 5	1	2	2
Key = 3	0	3	0
Key = 4	0	4	0
Key = 5	1	5	5
			7

[Dooms, 2024]

Sequence Modelling with Transformers

Attention Mechanism – An Intuition

- Q → the question
- K → critical element to focus on
- V → the information to be forwarded

A database Analogy

	Query = 5	Values	Output
Key = 1	0.125	1	0.125
Key = 5	1	2	2
Key = 3	0.25	3	0.75
Key = 4	0.5	4	2
Key = 5	1	5	5
			9.875

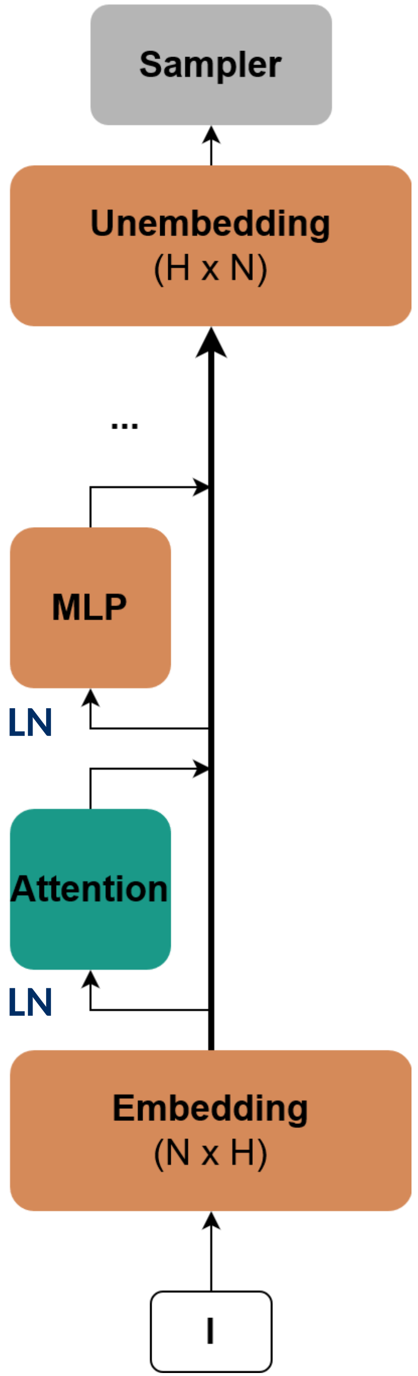
Like convolution but with dynamic weight (query-key similarity)

[Dooms, 2024]

Sequence Modelling with Transformers

A Very Popular Recipe

- Moving to a lower dimensional space (determined by ***H***)
- Using residual layers - MLP
- Add an [self] attention layer
- Add some intermediate normalization



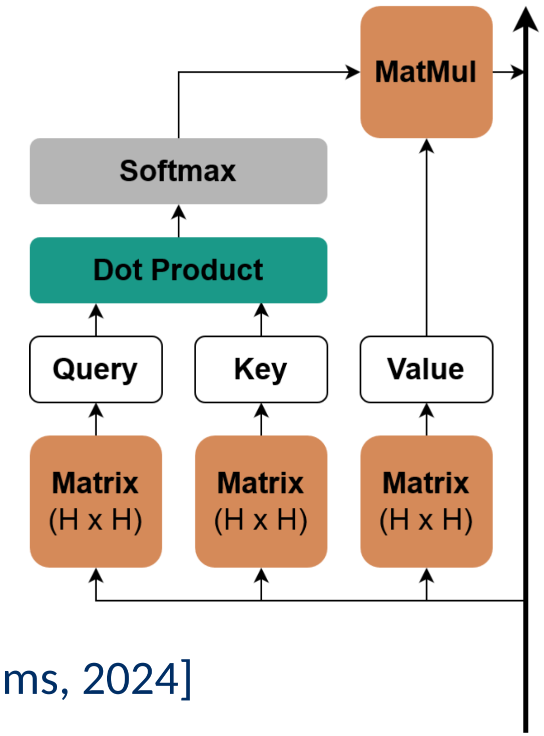
[Dooms, 2024]

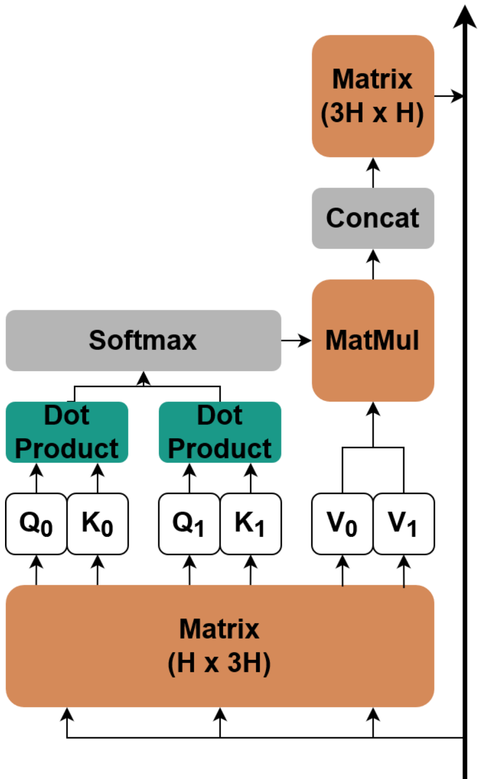
Sequence Modelling with Transformers

Single vs. Multi-head Attention

- Single: Each layer ask one question via the single QKV matrices.
- Multi: Split the QKV matrices into smaller ones → ask more/simpler questions

Single-head Attention





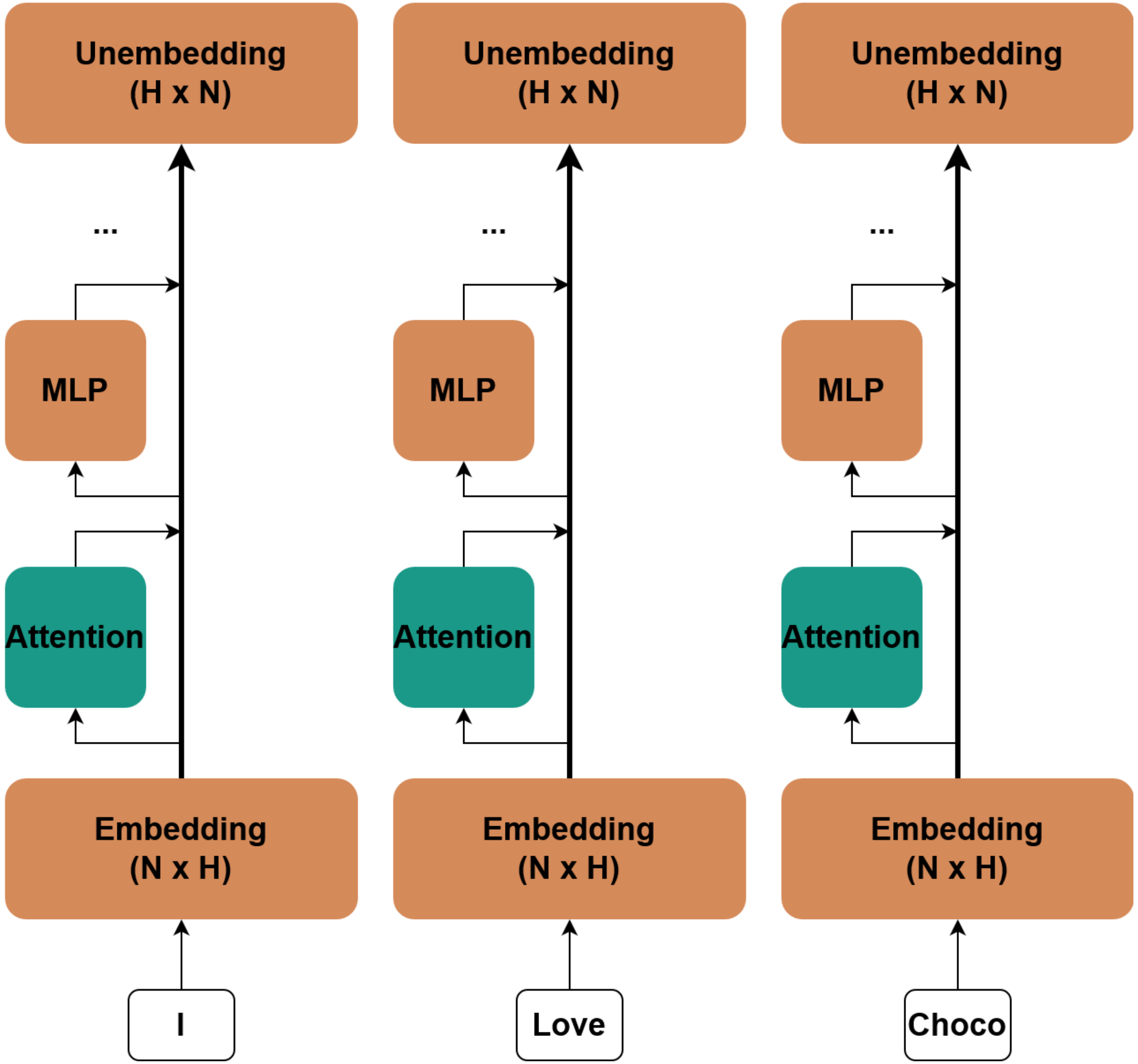
Multi-head Attention

[Dooms, 2024]

Sequence Modelling with Transformers

Strengths: Communication

- Depth: more specialized and structured
- Through attention: across tokens



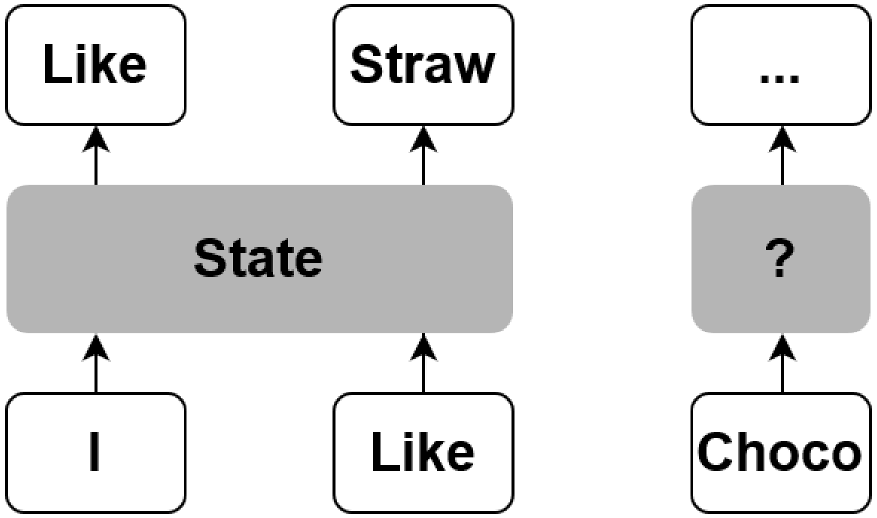
[Dooms, 2024]

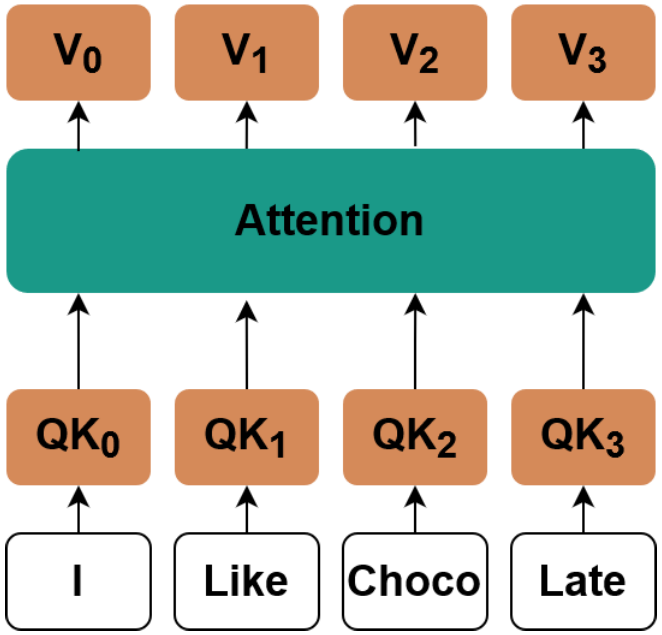
RNNs VS Transfomers

Context Sources

- Information from memory vs. tokens (error propagation)

  → Sentence vs. Word -based



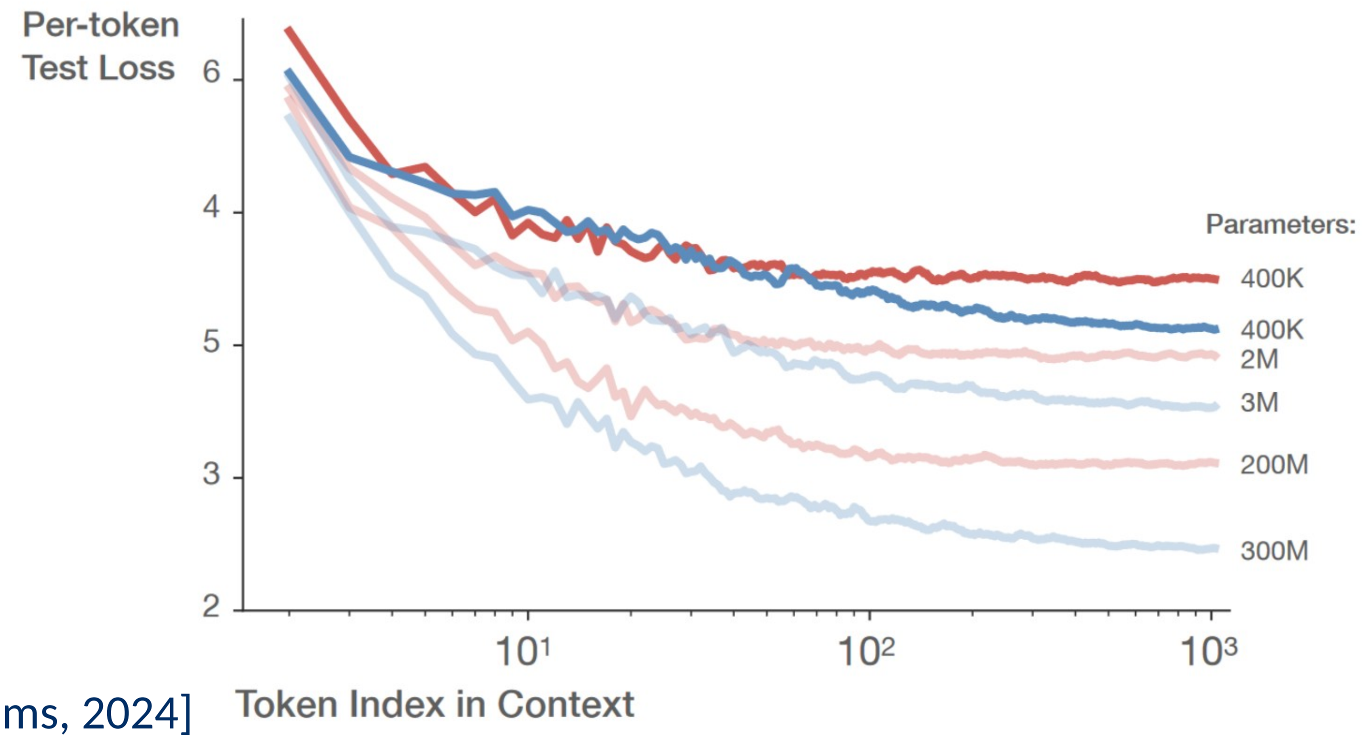


[Dooms, 2024]

RNNs VS Transfomers

Performance / size trade-off

- Higher performance as # of considered tokens increases
- Better use of parameters



[Kaplan, 2020]

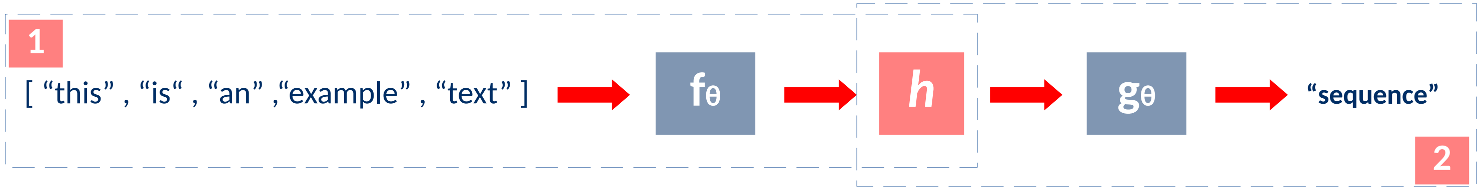
[Dooms, 2024]

Summarizing

[Finally :D]

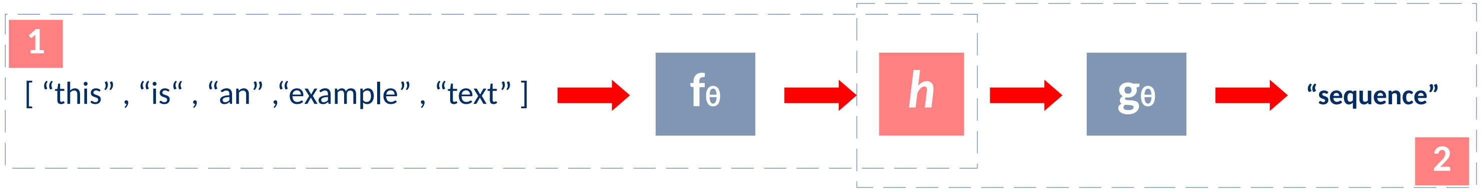
Summarizing

- **Two Step-Approach**
  1. **Model Context**
  2. **Predict Next Element given Context**



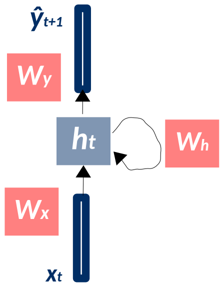
Summarizing

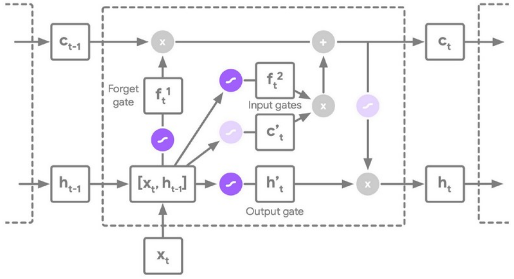
- **Two Step-Approach**
    1. Model Context
    2. Predict Next Element given Context

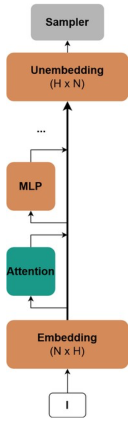


- **Serveral architectures with different capabilities**

    RNNs | LSTMs | GRUs | Transformers

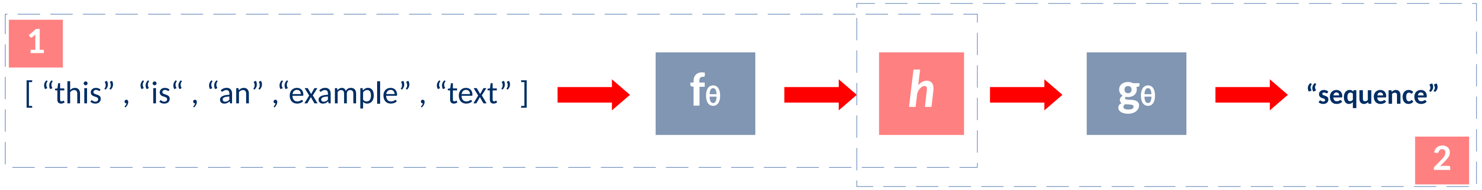






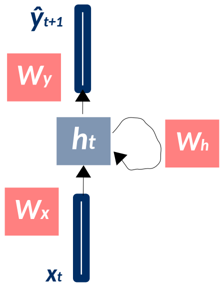
Summarizing

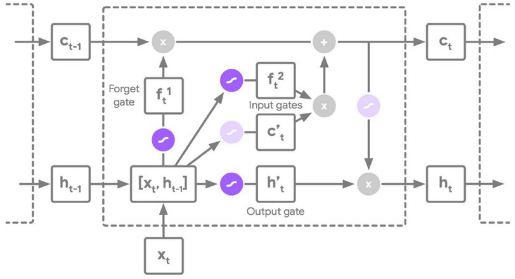
- **Two Step-Approach**
  1. Model Context
  2. Predict Next Element given Context

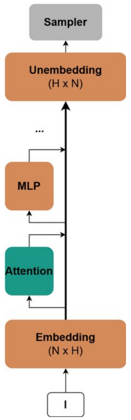


- **Serveral architectures with different capabilities**

  RNNs | LSTMs | GRUs | Transformers

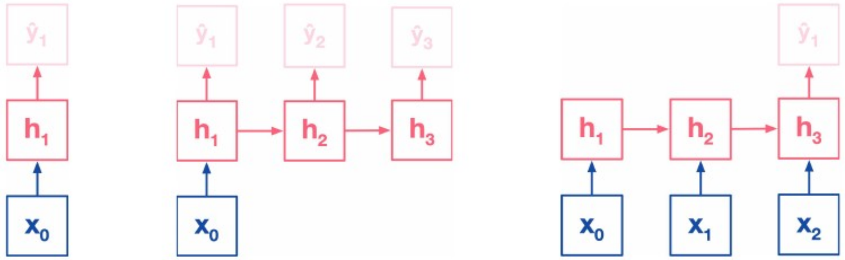






- **High Flexibility towards different problems**

  one-to-one | many-to-one | many-to-many …



References

- K. Cho, B. van Merrienboer, Gulcehre, Caglar, D. Bahdanau; F. Bougares, H. Schwenk; Y. Bengio (2014). "**Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation"**. arXiv:1406.1078.

- Elman, J. L. (1990). **Finding Structure in Time. Cognitive Science,** 14(2), 179–211. https://doi.org/10.1207/s15516709cog1402_1

- S. Hochreiter and J. Schmidhuber. 1997. **Long Short-Term Memory**. Neural Comput. 9, 8 (November 15, 1997), 1735–1780. DOI:https://doi.org/10.1162/neco.1997.9.8.1735

- **The Recurrent Neural Network - Theory and Implementation of the Elman Network and LSTM**

  https://pabloinsente.github.io/the-recurrent-net

- **Understanding LSTM Networks** - COlah's Blog

  http://colah.github.io/posts/2015-08-Understanding-LSTMs/

References

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Modeling Sequences with Neural Networks

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