Week 3: Deep Networks and Sequence Models

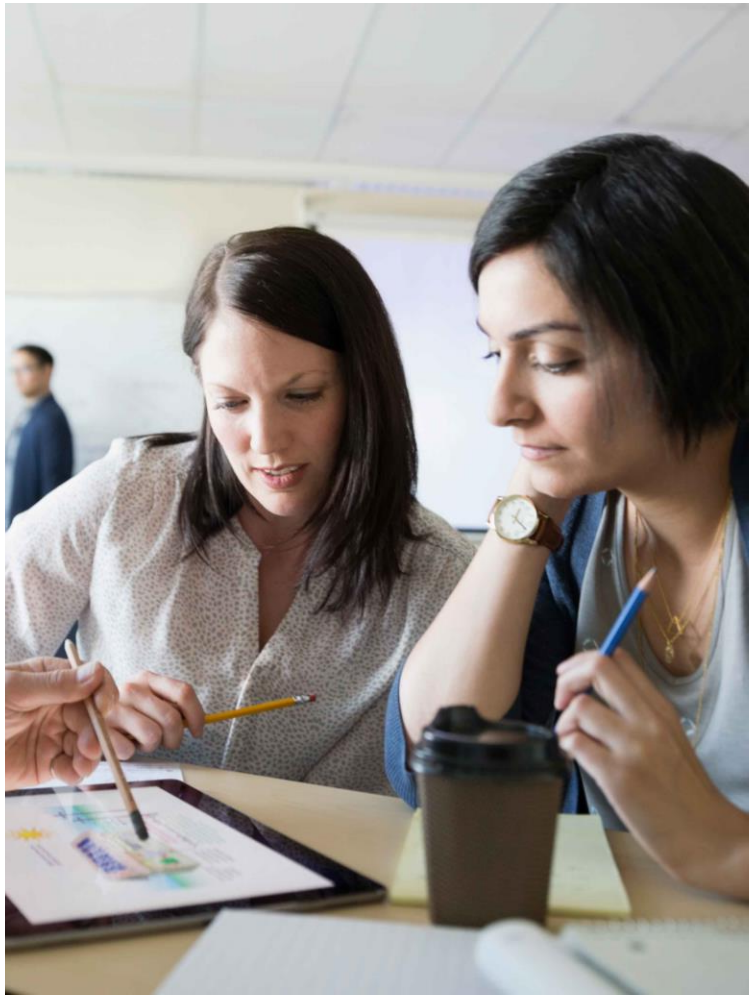
Unit 1: The Need for Deeper Networks

The Need for Deeper Networks
What we covered in the last week

Experiment setup for developing machine learning applications

Classifying structure data with TensorFlow estimators

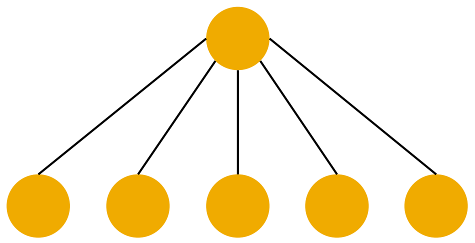
TF serving and architectures for deep learning



The Need for Deeper Networks
Motivation

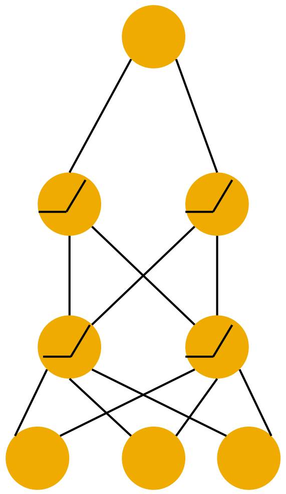
Limitations of shallow networks

- Shallow, wide networks are good at memorization
- Generalize poorly on new data



Capability of deeper networks

- Global features are learnt as a combination of local features along the depth of the network
- Less prone to memorization, better generalization



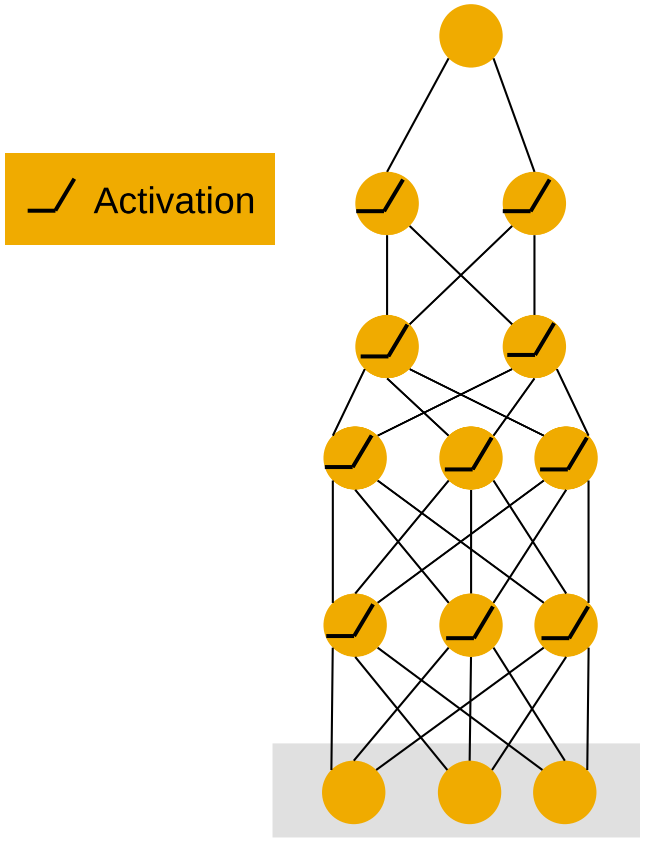
The Need for Deeper Networks

Need for non-linearity

Deep networks without non-linearity behave like a single-layer network

Complex data cannot be separated with linear transformations

Non-linear activations can map input into a hyperspace where they are linearly separable



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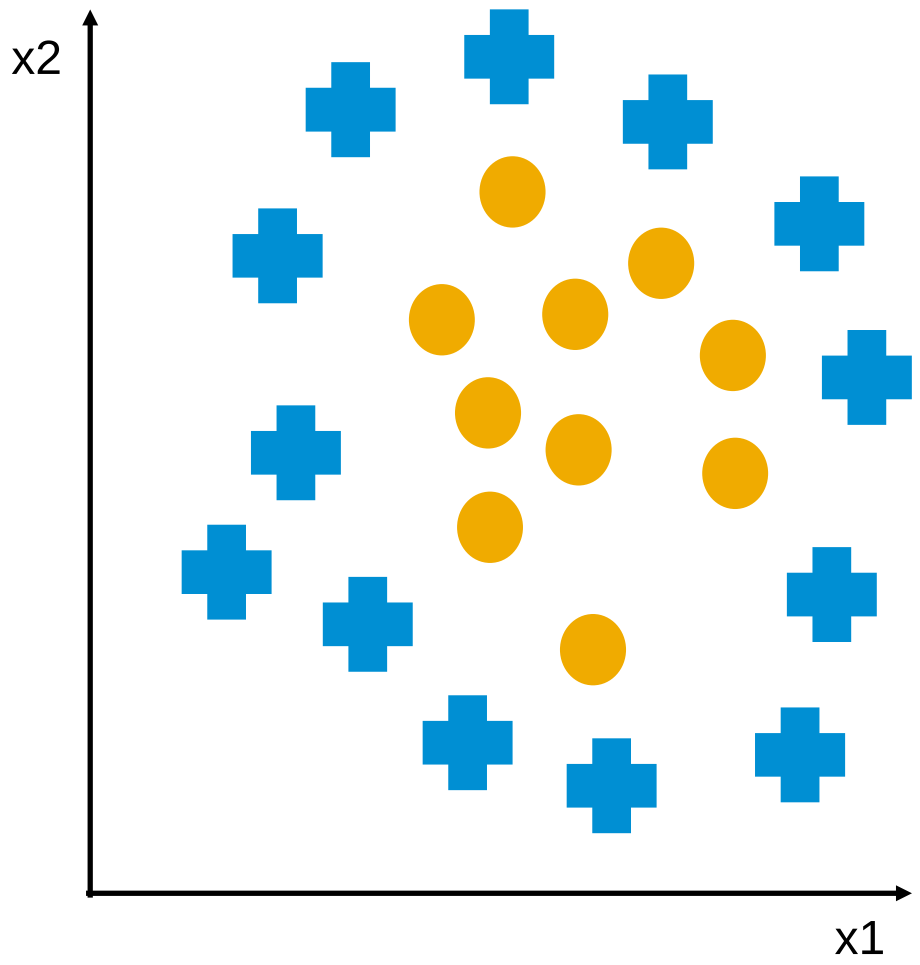


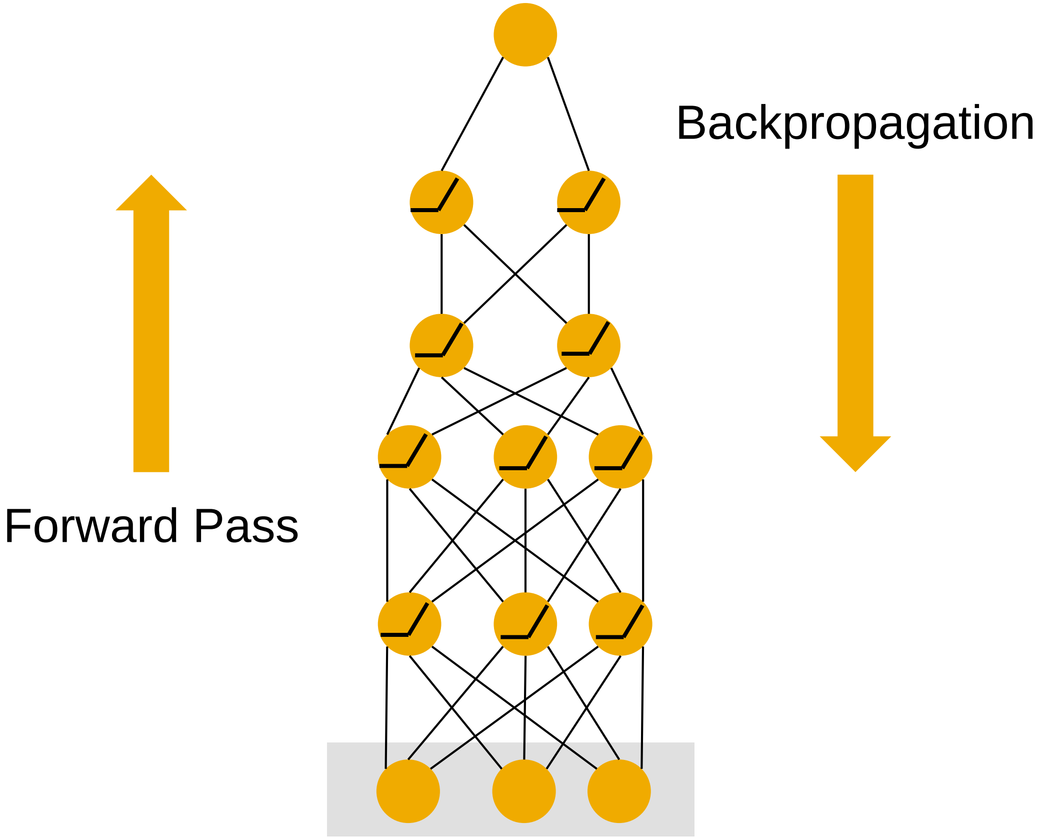
The Need for Deeper Networks
Learning process

Forward pass

- Calculates scores based on weights of hidden nodes

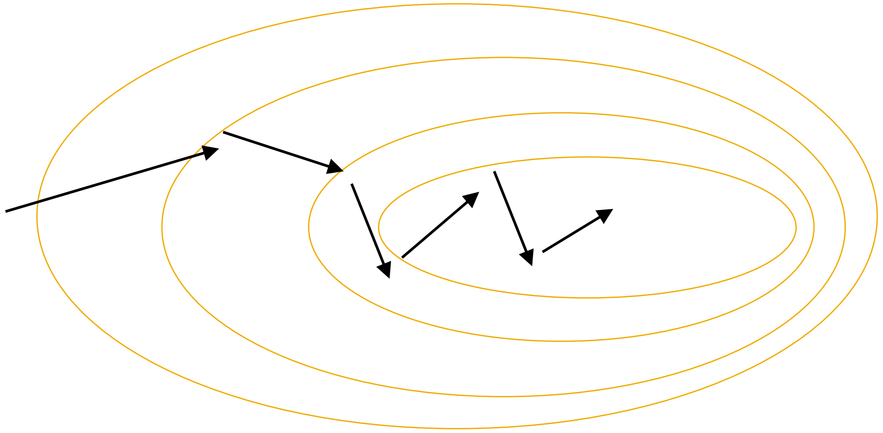
Backpropagation

- Calculates error contributed by each neuron after each batch is processed
- Weights are modified based on error calculated



The Need for Deeper Networks

Learning objectives

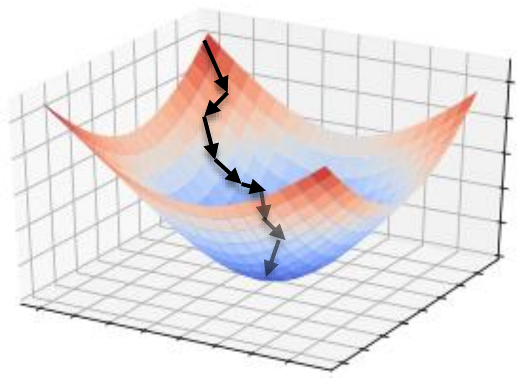


Loss and cost function

- Loss is computed on a single training example
- Cost is defined as average loss over all training data

Softmax

- A classifier that converts scores to probabilities for each class



Stochastic gradient descent (SGD)

- An optimizer commonly used for parameter updates
- Mini-batch of data to minimize the objective function

1.1	1.03	0.97	0.91	0.86	0.81	0.77	0.74	0.71	0.7	0.69	0.7	0.71	0.74	0.77	0.81	0.86	0.91	0.97	1.03
1.03	0.96	0.9	0.83	0.77	0.72	0.68	0.64	0.62	0.6	0.59	0.6	0.62	0.64	0.68	0.72	0.77	0.83	0.9	0.96
0.97	0.9	0.82	0.76	0.69	0.64	0.59	0.55	0.52	0.5	0.49	0.5	0.52	0.55	0.59	0.64	0.69	0.76	0.82	0.9
0.91	0.83	0.76	0.68	0.62	0.55	0.5	0.46	0.43	0.41	0.4	0.41	0.43	0.46	0.5	0.55	0.62	0.68	0.76	0.83
0.86	0.77	0.69	0.62	0.54	0.48	0.42	0.37	0.34	0.31	0.31	0.31	0.34	0.37	0.42	0.48	0.54	0.62	0.69	0.77
0.81	0.72	0.64	0.55	0.48	0.41	0.34	0.29	0.25	0.23	0.22	0.23	0.25	0.29	0.34	0.41	0.48	0.55	0.64	0.72
0.77	0.68	0.59	0.5	0.42	0.34	0.28	0.22	0.18	0.16	0.15	0.16	0.18	0.22	0.28	0.34	0.42	0.5	0.59	0.68
0.74	0.64	0.55	0.46	0.37	0.29	0.22	0.17	0.12	0.1	0.09	0.1	0.12	0.17	0.22	0.29	0.37	0.46	0.55	0.64
0.71	0.62	0.52	0.43	0.34	0.25	0.18	0.12	0.08	0.05	0.04	0.05	0.08	0.12	0.18	0.25	0.34	0.43	0.52	0.62
0.7	0.6	0.5	0.41	0.31	0.23	0.16	0.1	0.05	0.02	0.01	0.02	0.05	0.1	0.16	0.23	0.31	0.41	0.5	0.6
0.69	0.59	0.49	0.4	0.31	0.22	0.15	0.09	0.04	0.01	0	0.01	0.04	0.09	0.15	0.22	0.31	0.4	0.49	0.59
0.7	0.6	0.5	0.41	0.31	0.23	0.16	0.1	0.05	0.02	0.01	0.02	0.05	0.1	0.16	0.23	0.31	0.41	0.5	0.6
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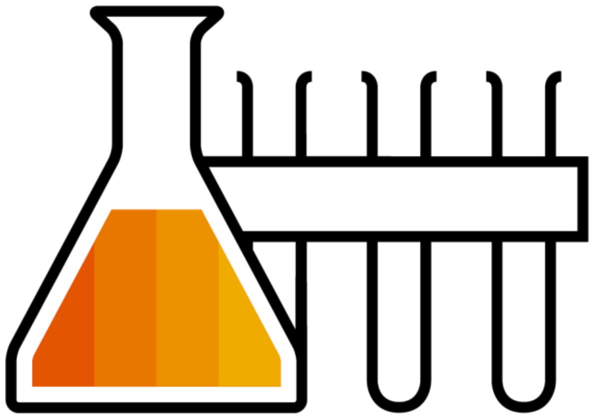
The Need for Deeper Networks
Classification example

Classification with Fashion MNIST

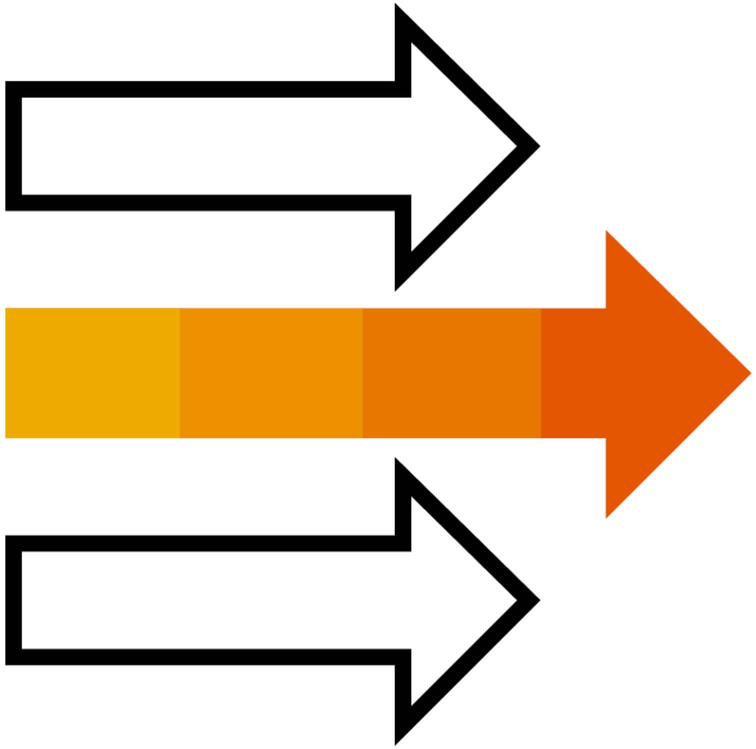
- Develop a simple single-layer neural network
- Evaluate performance on Fashion MNIST
- Add more layers and evaluate improvement



The Need for Deeper Networks
Coming up next

Introduction to sequence models

How to process sequence data



Week 3: Deep Networks and Sequence Models

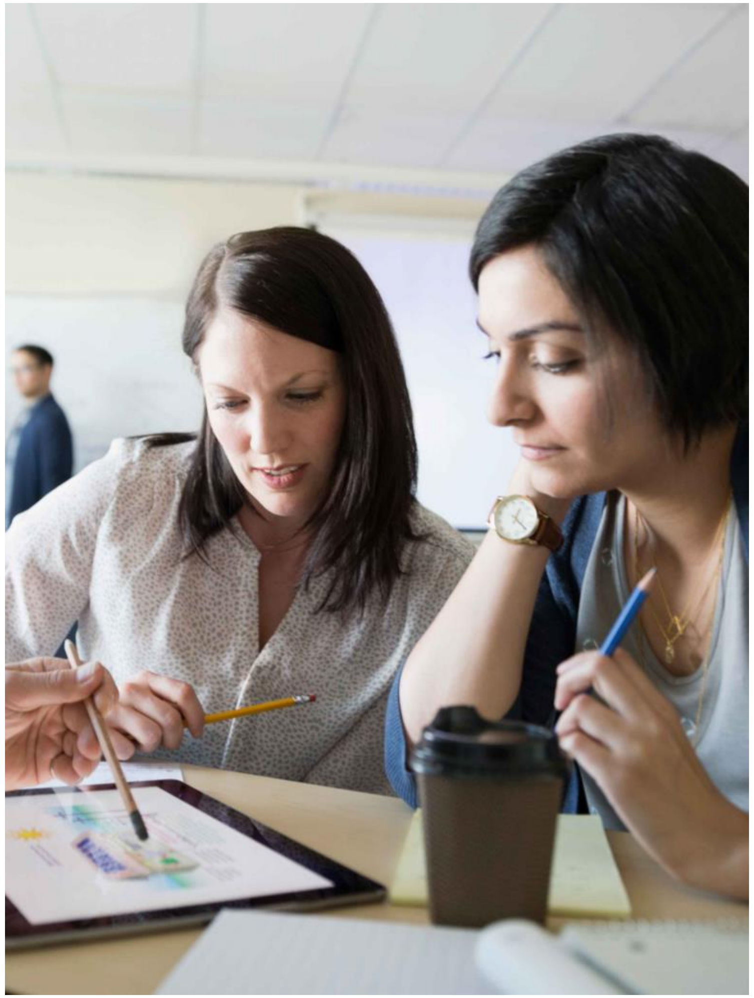
Unit 2: Introduction to Sequence Models

Introduction to Sequence Models

What we covered in the last unit

Deep networks

Deep feed-forward networks

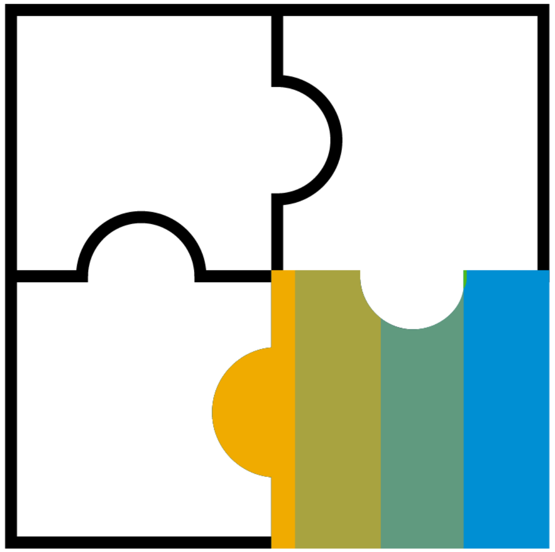


Introduction to Sequence Models

Overview

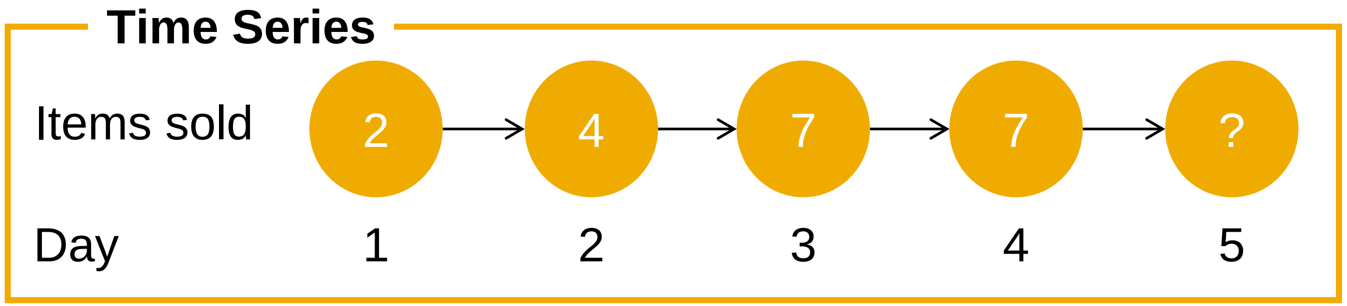
Content:

- Sequence data
- Sequence models
- Applications of sequence models



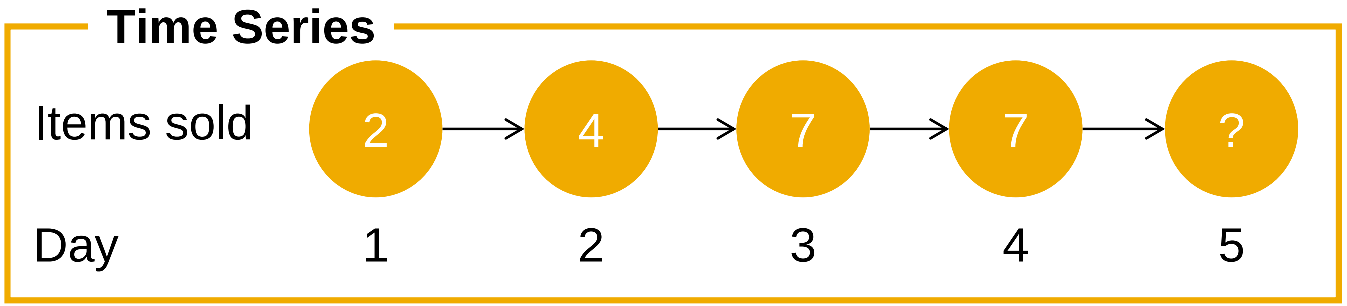
Introduction to Sequence Models

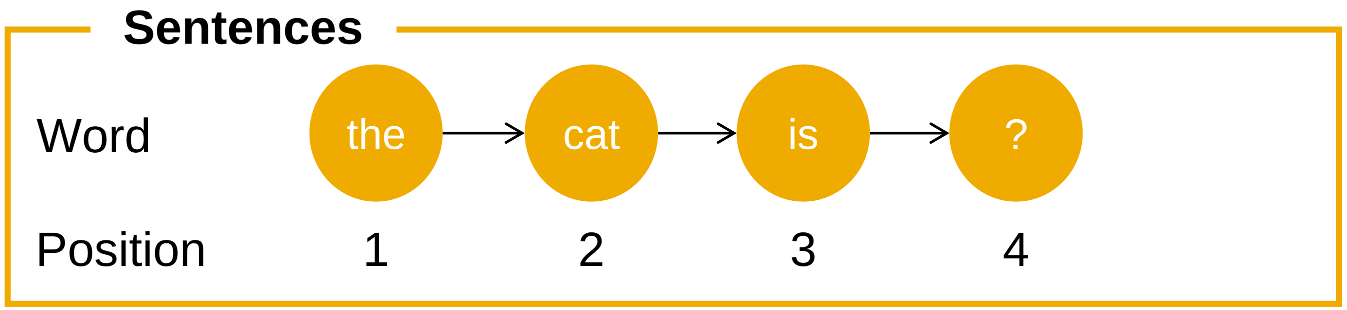
Sequence data



Introduction to Sequence Models

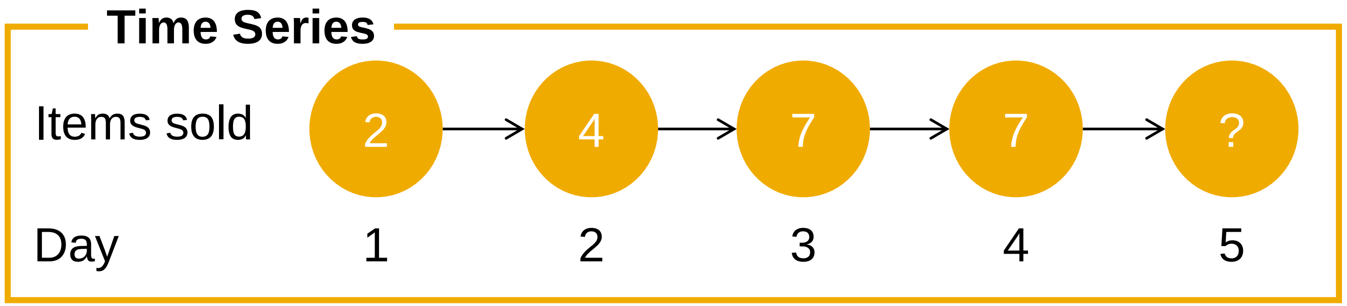
Sequence data

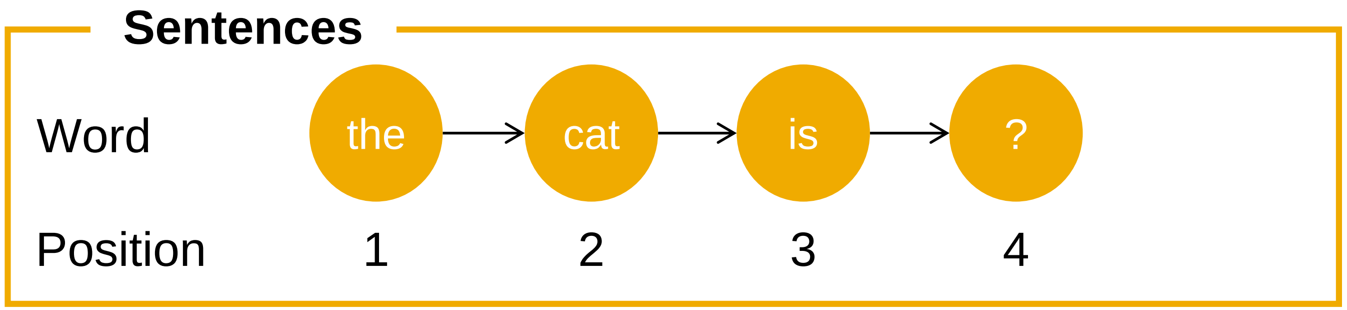




Introduction to Sequence Models

Sequence data





Characteristics:

- Ordered elements
- Number of elements can vary

Introduction to Sequence Models

What decides the next element?

- Time series
  - External factors: weather, competing products, etc.
  - Internal factors: previous values
- Sentences
  - External factors: paragraph, conversation context, etc.
  - Internal factors: previous words
- Primary focus is on *internal factors*
  - Previous elements determine the next element, up to noise
  - Mathematically: $e_{t+1} = f(e_1, e_2, \dots, e_t) + \epsilon$

error in the prediction
(unexplained noise)

Introduction to Sequence Models

Inferring the next word in a sentence

- Given a fixed vocabulary V and present words $w_1, w_2, \ldots, w_t$,
  - Compute the probability of each candidate next word x in V given $w_1, w_2, \ldots, w_t$
  - Equivalently compute $P(x \mid w_1, w_2, \ldots, w_t)$ for each x in V
  - Set w_{t+1} to x with maximal conditional probability
  - Mathematically: $w_{t+1} = \arg\max_{x \in V} P(x \mid w_1, w_2, \ldots, w_t)$

Introduction to Sequence Models

Inferring the next word in a sentence – Traditional approaches

- n-gram models
  - Infer w_{t+1} based on a fixed number n of previous words (e.g., hidden Markov models)

Introduction to Sequence Models

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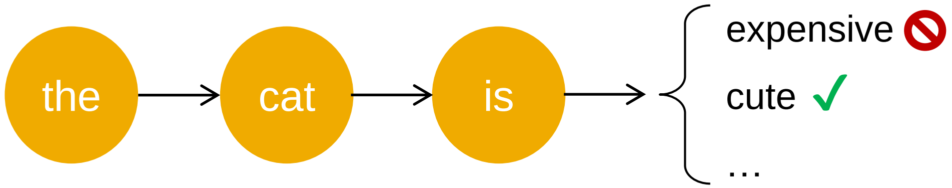

- Issue: the parameter n is restrictive and somewhat arbitrary

Introduction to Sequence Models

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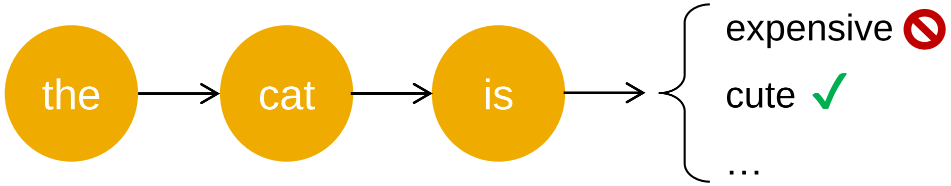

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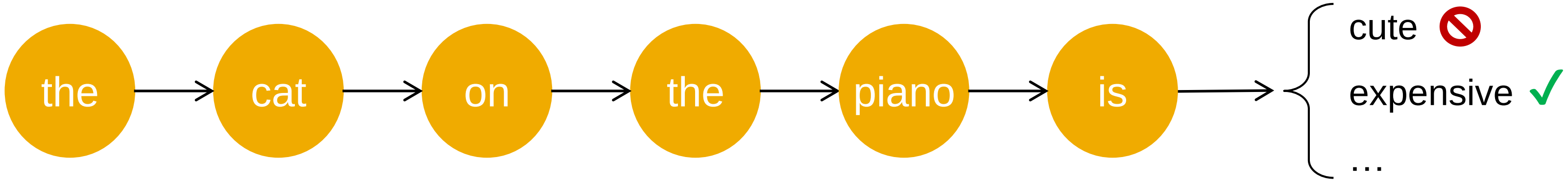

Introduction to Sequence Models

Inferring the next word in a sentence – Traditional approaches

- Bag of words
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  - Example: assume the dictionary consists of words "the", "cat", "nice", "caught", "jump"

	the	**cat**	**nice**	**caught**	**jump**
the cat is nice	1	1	1	0	0
the cat caught the mouse	2	1	0	1	0

Introduction to Sequence Models

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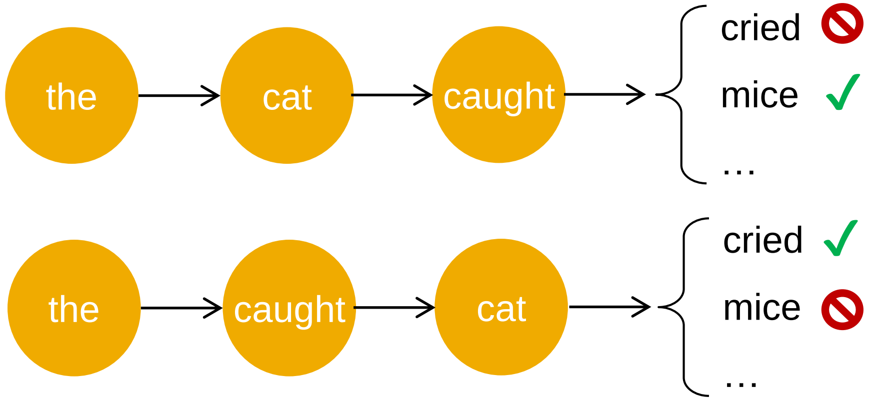
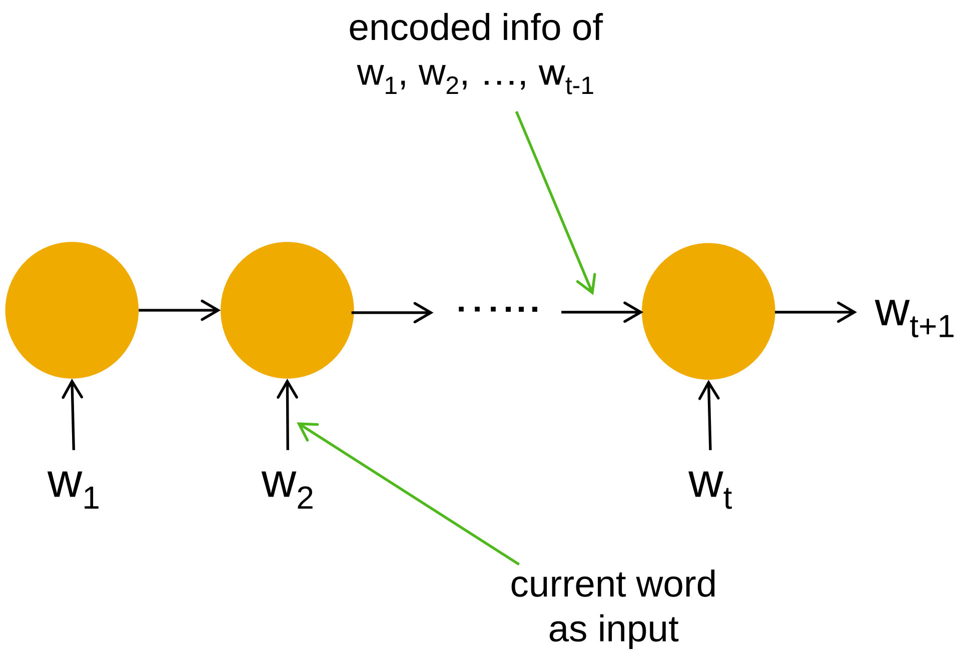
- Issue: the ordering is lost and hence the semantics of words



Introduction to Sequence Models

Sequence models



Introduction to Sequence Models

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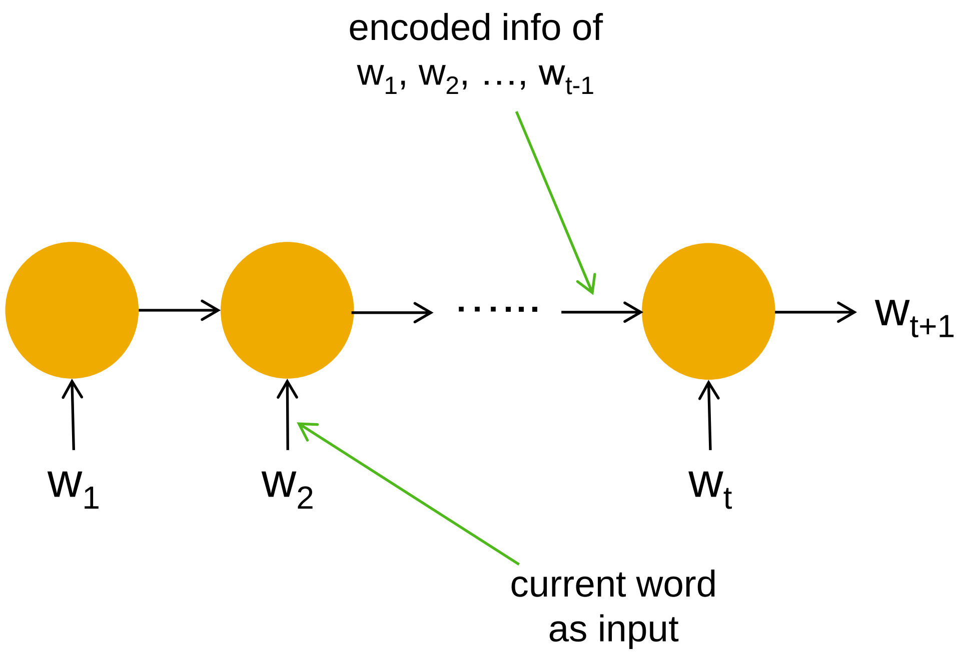


Motivation:

We change

$$w_{t+1} = f(w_1, w_2, \ldots, w_{t-1}, w_t)$$

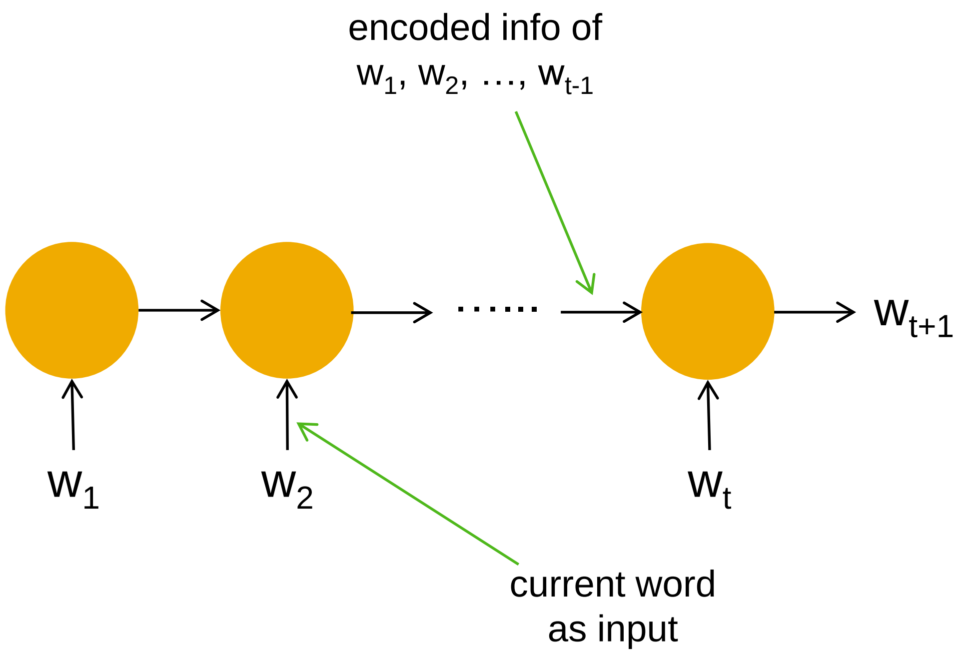
to

$$w_{t+1} = f(h, w_t)$$

where h is the encoded info of $w_1, w_2, \ldots, w_{t-1}$

Introduction to Sequence Models

Sequence models



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where h is the encoded info of $w_1, w_2, \ldots, w_{t-1}$

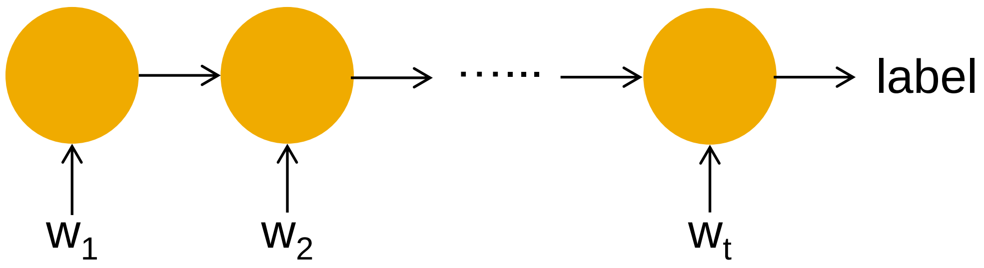
Remarks: When h can be expressed as a fixed-length feature vector:

- The function f can be learned in a similar way across different positions/states
- Sentences with different lengths are handled consistently

Introduction to Sequence Models

Other applications of sequence models – Sequence classification

- Text classification



Introduction to Sequence Models

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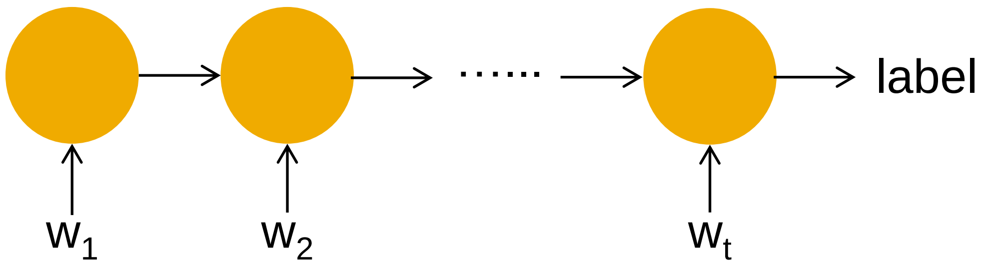
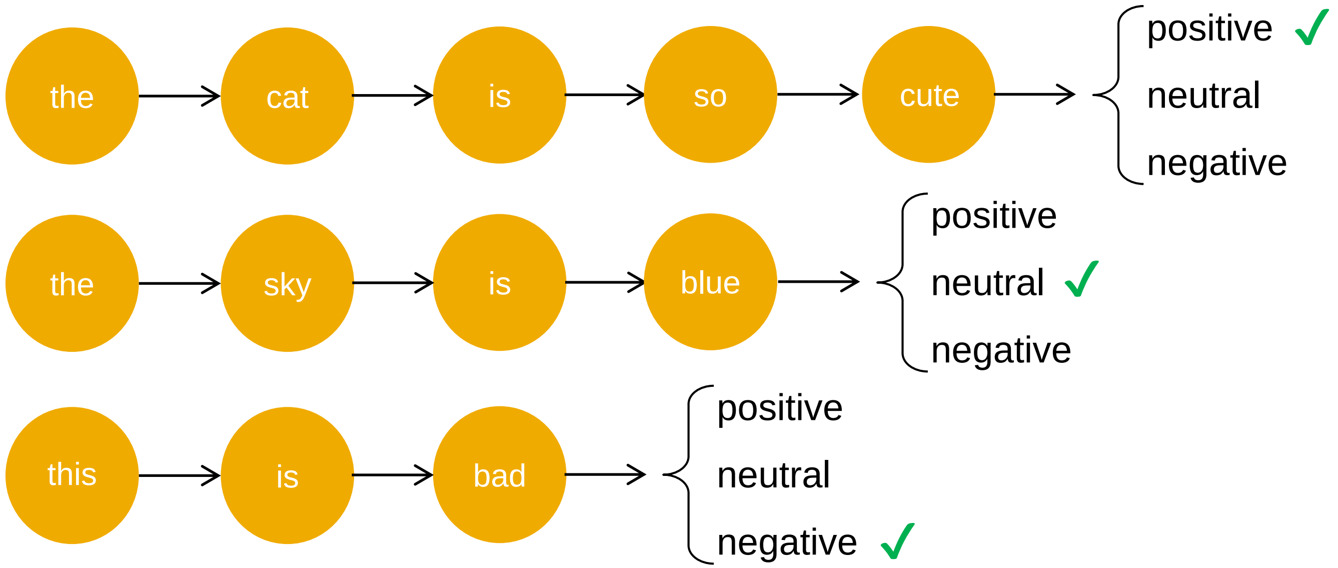


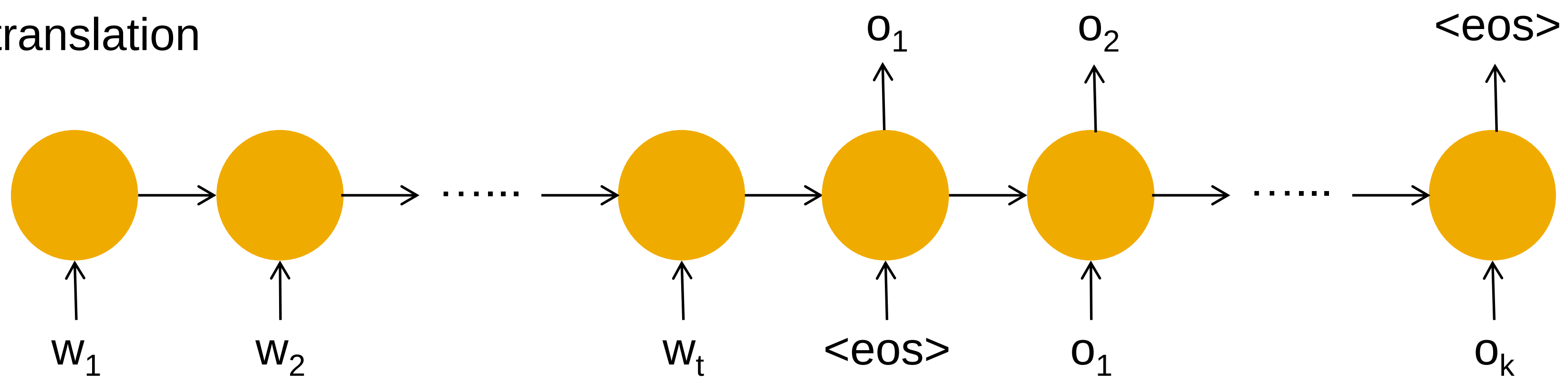
- Example: Sentiment analysis



Introduction to Sequence Models

Other applications of sequence models – Sequence to sequence

- Machine translation



Introduction to Sequence Models

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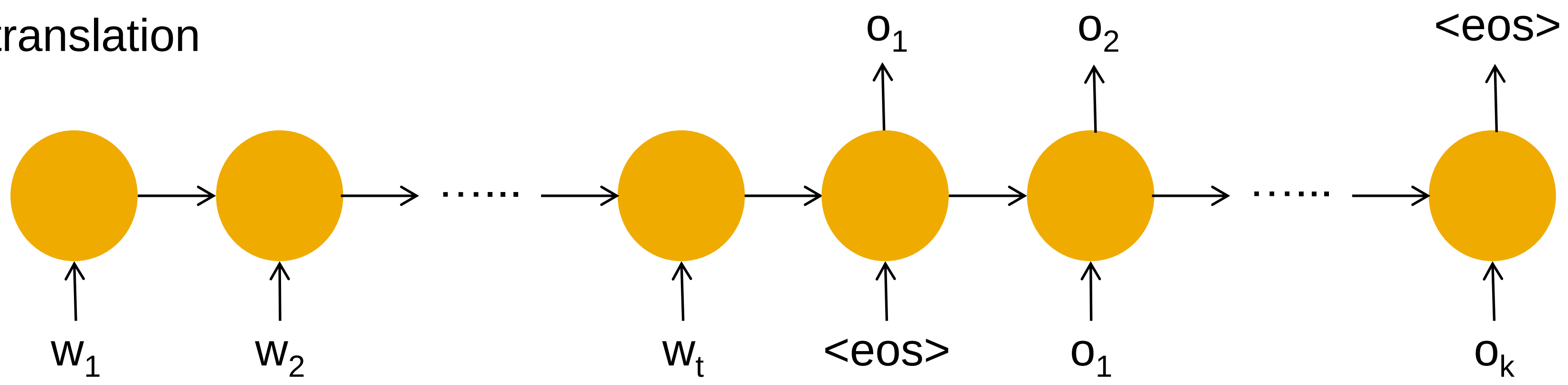
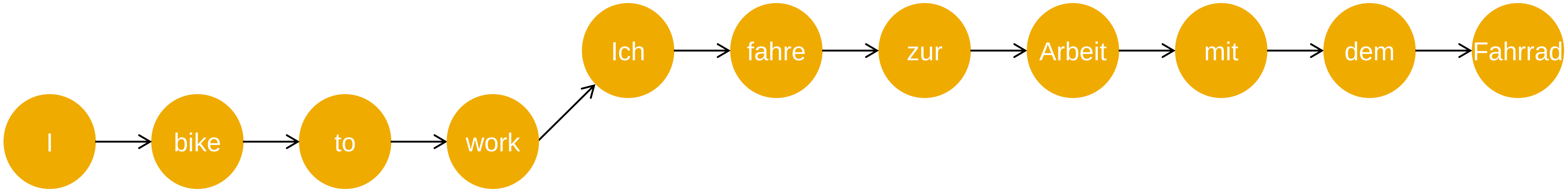


- Example: English to German translation



Introduction to Sequence Models

Word representations

- Words need to be represented numerically, as dense vectors, for easy computation
- The representation needs to capture semantic information about the words
- How to achieve this is explained in the next lecture

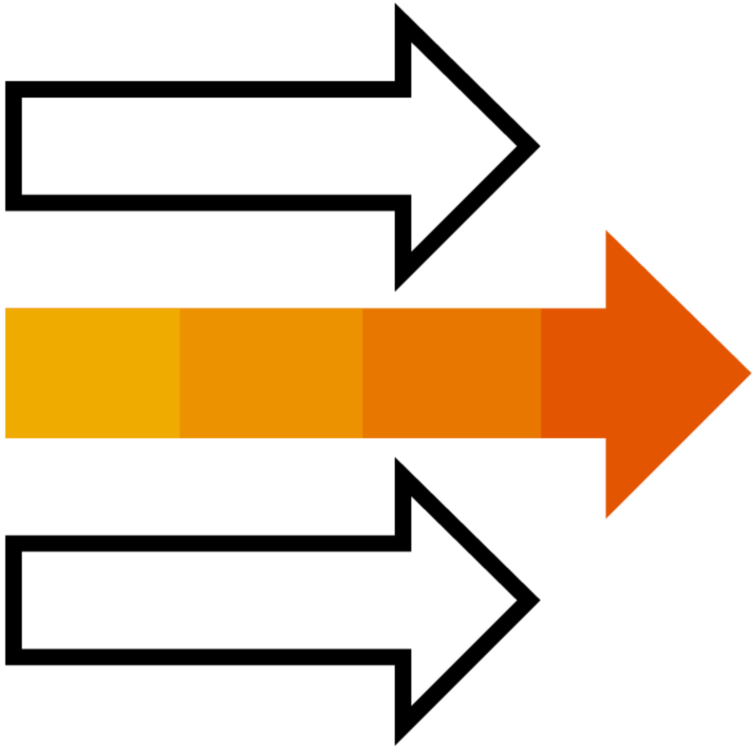
Introduction to Sequence Models

Coming up next

Vector representations of words

Distributed representations

Word2Vec



Week 3: Deep Networks and Sequence Models

Unit 3: Representation Learning for NLP

Run Simple

openSAP
open.sap.com

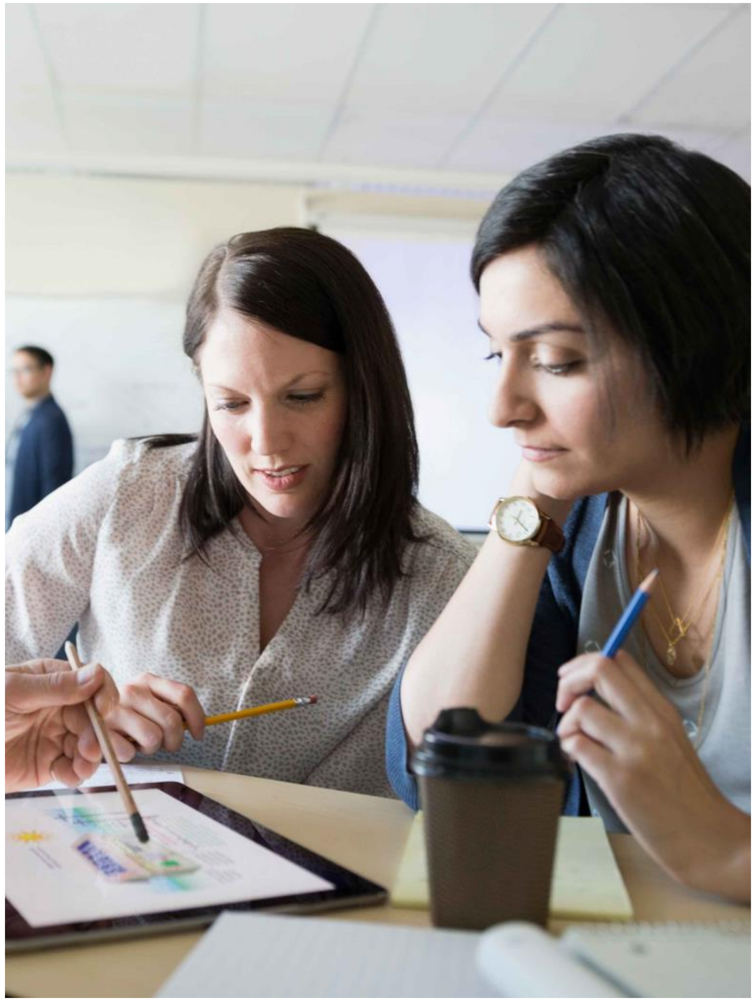
Representation Learning for NLP

What we covered in the last unit

Sequential data

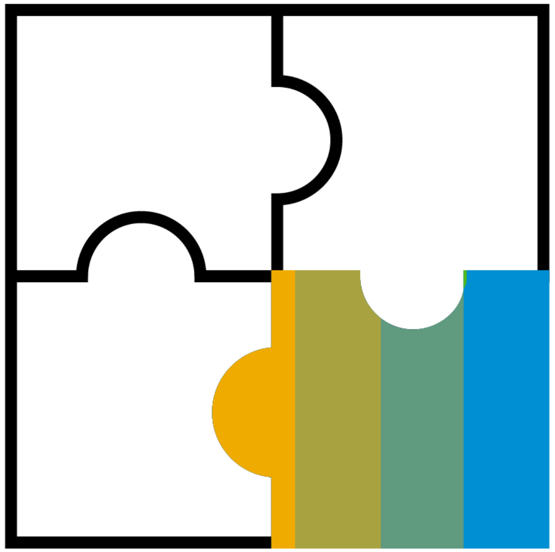
Sequence models

Applications of sequence models



Representation Learning for NLP
Overview

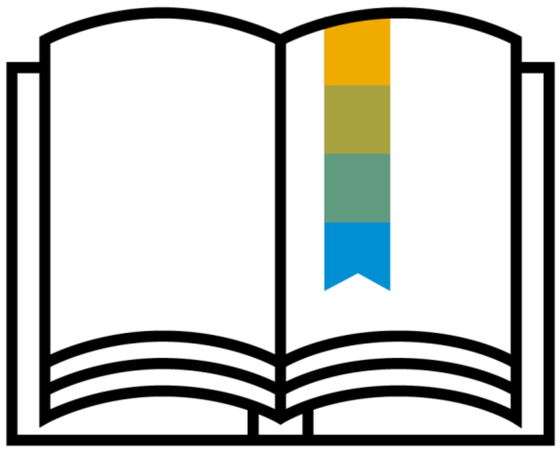
Content:
- Vector representations of words
- Distributed representations
- Word2Vec



Representation Learning for NLP

How do we represent natural language?

- Machine learning applications in natural language processing (NLP) are, for example,
  - Text classification
  - Language modeling
  - Sentiment analysis
  - Machine translation
  - Document summarization
  - Caption generation
- NLP tasks require a meaningful representation of text as input
- An input text can be thought of as a sequence where the units composing the sequence can either be characters, words, or even full documents



Representation Learning for NLP

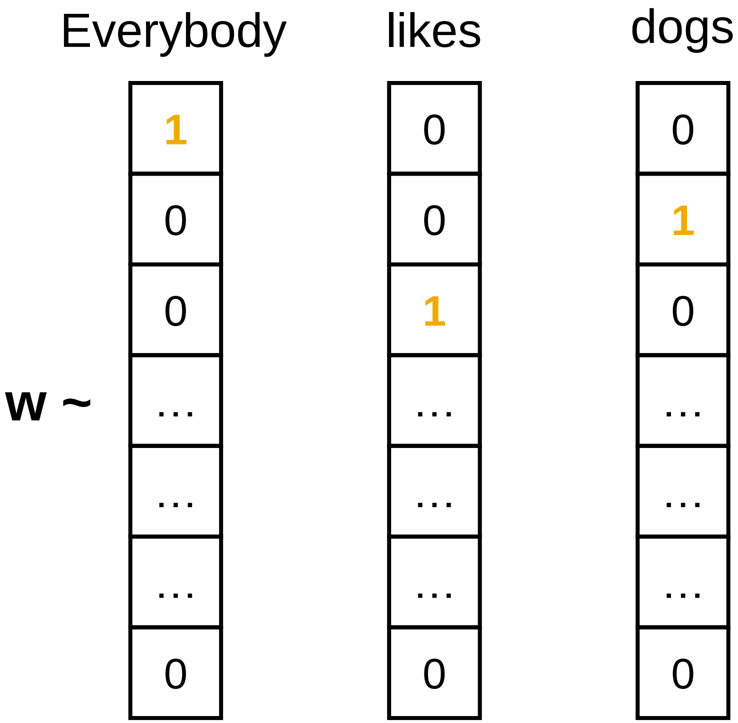
Vector representation of words

One-hot encoding

- Definition: Given a vocabulary **V**, every word is converted to a vector in $\mathbb{R}^{|V| x 1}$ that is 0 for all indices but 1 at the index of the respective word represented

- Example:

  “*Everybody likes dogs and hates bananas.*”



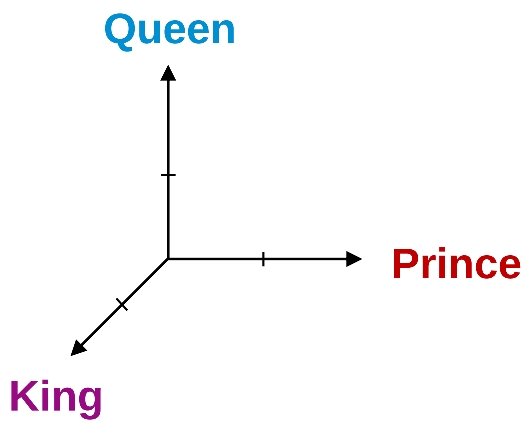
Representation Learning for NLP

Vector representation of words

One-hot representation

- Straightforward implementation
- Meaning of word is not encoded in representation
- Vector dimensionality scales with vocabulary size

$$\begin{bmatrix}1\\0\\0\\0\end{bmatrix}^T \times \begin{bmatrix}0\\1\\0\\0\end{bmatrix} = 0$$



Easy implementation

- Straightforward implementation

Missing semantics

- Meaning of word is not encoded in representation

High dimensionality

- Vector dimensionality scales with vocabulary size

Representation Learning for NLP

Vector representation of words

Distributed Representations

- Instead of storing all information in one dimension, we distribute the meaning across a fixed number of dimensions
- Encodes semantic and syntactic features of words
- Reduces the necessary number of dimensions
- Wouldn't it be great to have an algorithm that learns those representations from unstructured text?

	Queen	Woman	King	Prince	
Femininity	0.99	0.99	0.01	0.02	
Masculinity	0.01	0.01	0.99	0.92	…
Royalty	0.99	0.99	0.99	0.81	
Age	0.67	0.53	0.75	0.22	

Representation Learning for NLP

Distributed representation of words

Representations of words based on distributional similarity

"You shall know a word by the company it keeps"
(Firth, 1957)

- Represent a word based on neighboring words
- Word representations are defined through their context
- Words occurring in similar contexts should have similar representations

My neighbor has trees in his yard.

My neighbor has bushes in his yard.

The trunks of trees have many rings.

~~The trunks of bushes have many rings.~~

Representation Learning for NLP

Word2Vec: skip-gram

Skip-Gram Model

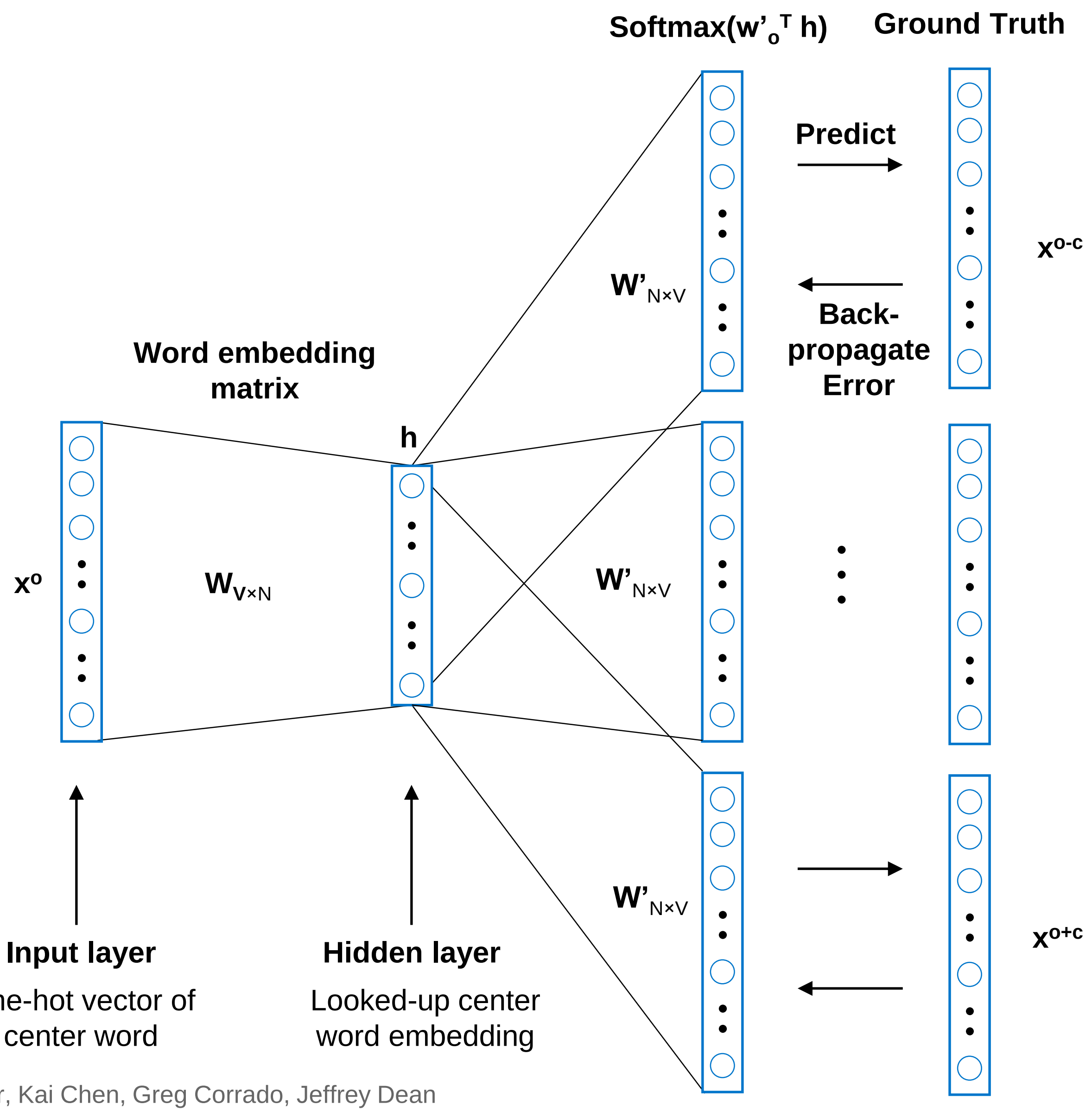
- For each word in a corpus, predict the neighboring words in a context window of length **c**

Everybody likes dogs and hates bananas.

Everybody likes dogs and hates bananas.

Everybody likes dogs and hates bananas.

V: Vocabulary size
$\mathbf{x}^i$: one-hot vector for word i in V
N: size of embedding space
W: Word embedding matrix W ϵ V×N
w: Word embedding w ϵ 1×N
W': Word embedding matrix W ϵ N×V
C: Context window



Word2Vec: Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, Jeffrey Dean *(2013). Distributed Representations of Words and Phrases and their Compositionality.*

Representation Learning for NLP

Word2Vec: CBOW

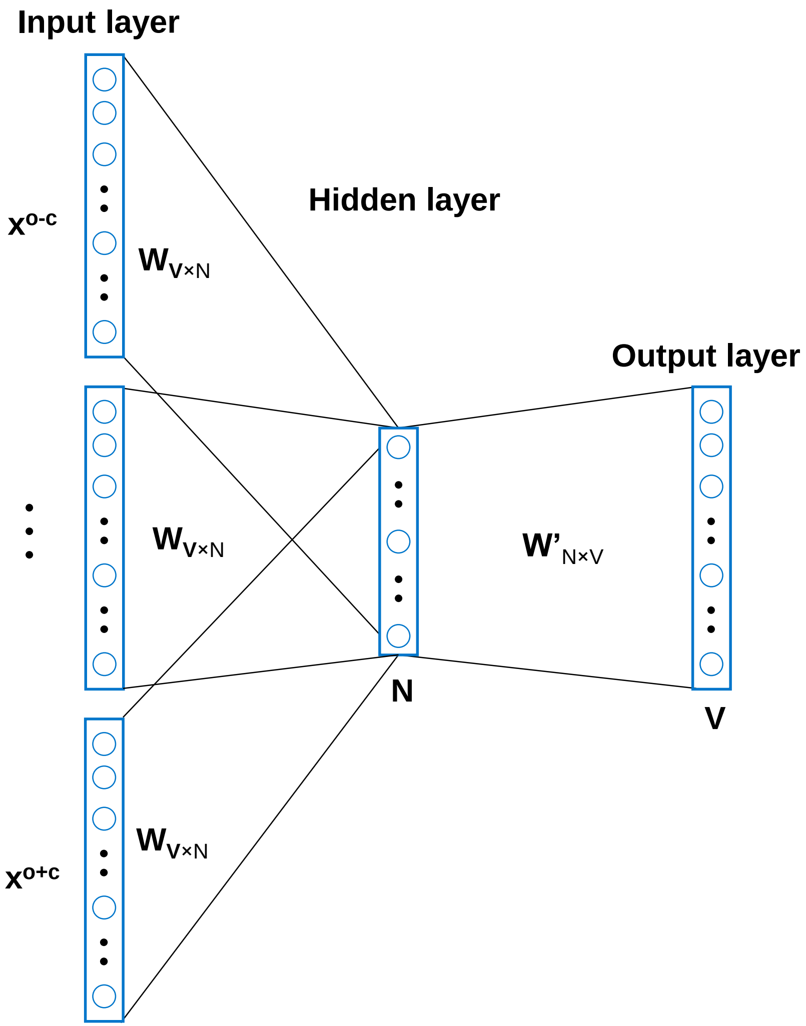
Continuous Bag of Words Model

- Predict the output word based on the neighboring words in a context window of length c

Everybody likes dogs and hates bananas.

Everybody likes dogs and hates bananas.

Everybody likes dogs and hates bananas.



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Representation Learning for NLP

Word2Vec captures similarity of words…

Word similarity

- Closest vectors in terms of (cosine) distance according to GoogleNews-vectors (trained on about 100 billion words)
- Excluded plurals for illustration

red	reddish	banana	two	parrot	PS4
yellow	brownish	pineapple	three	parrots	PSP2
blue	yellowish	mango	four	macaw	SONY NGP
purple	pinkish	papaya	five	parakeet	Wii2
orange	grayish	coconut	six	cockatiel	PS3

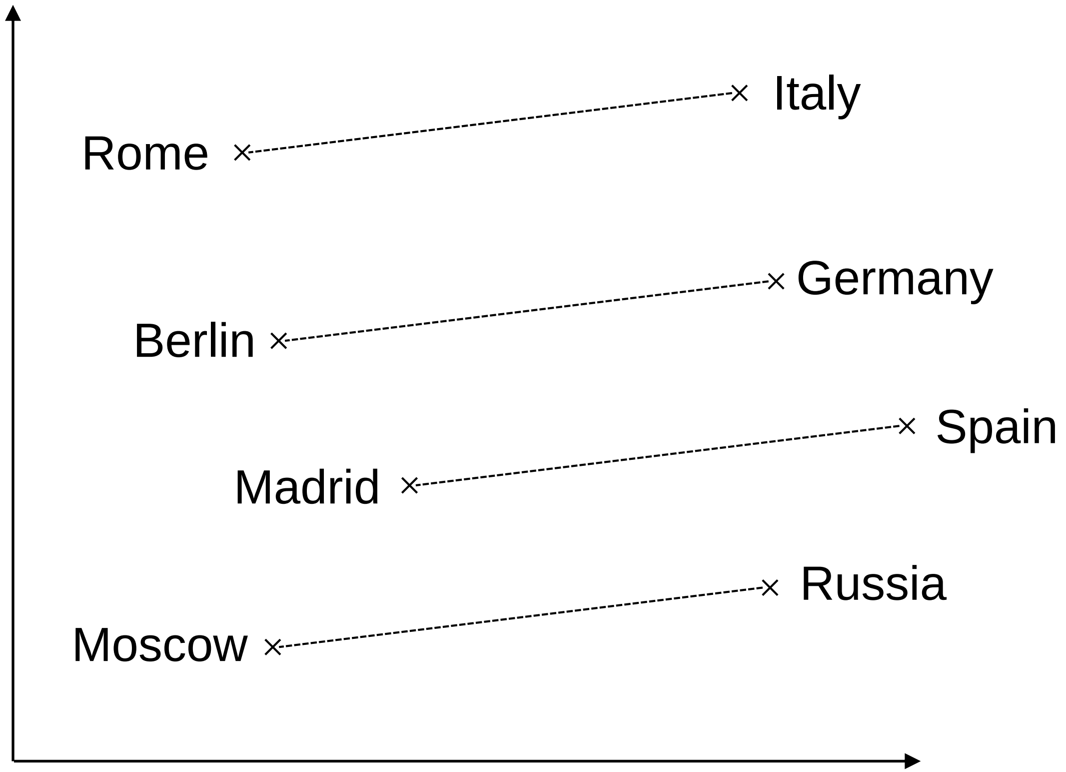
word2vec: https://code.google.com/archive/p/word2vec/

Representation Learning for NLP

…and beyond

Word analogies

- Trained on a large corpus, the distance of distributed representations encodes certain semantic concepts
- This can be e.g. gender, capital city
- Rome relates to Italy, as Berlin relates to Germany
- This applies for different languages



v(Rome) – v(Italy) + v(Berlin) ~

v(King) – v(Man) + v(Woman) ~

v(Building) – v(Architect) + v(Software) ~

Word2Vec: Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, Jeffrey Dean *(2013). Distributed Representations of Words and Phrases and their Compositionality.*

Representation Learning for NLP

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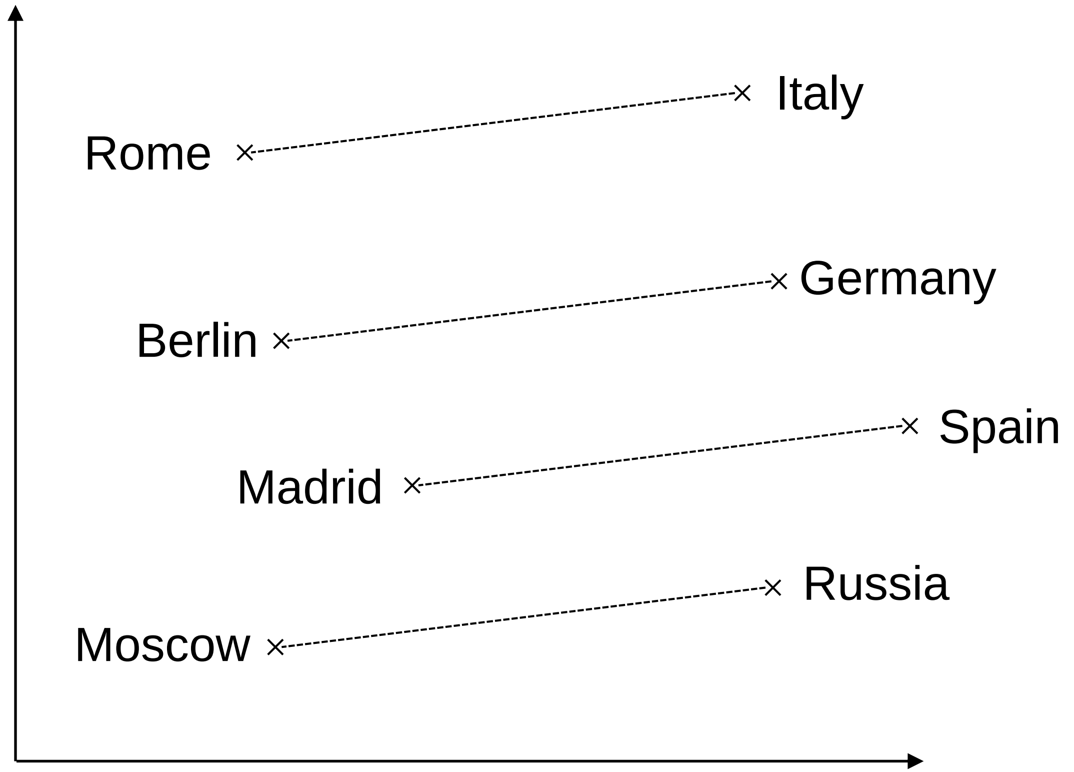

v(Rome) – v(Italy) + v(Berlin) ~ v(Germany)

v(King) – v(Man) + v(Woman) ~

v(Building) – v(Architect) + v(Software) ~

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Representation Learning for NLP

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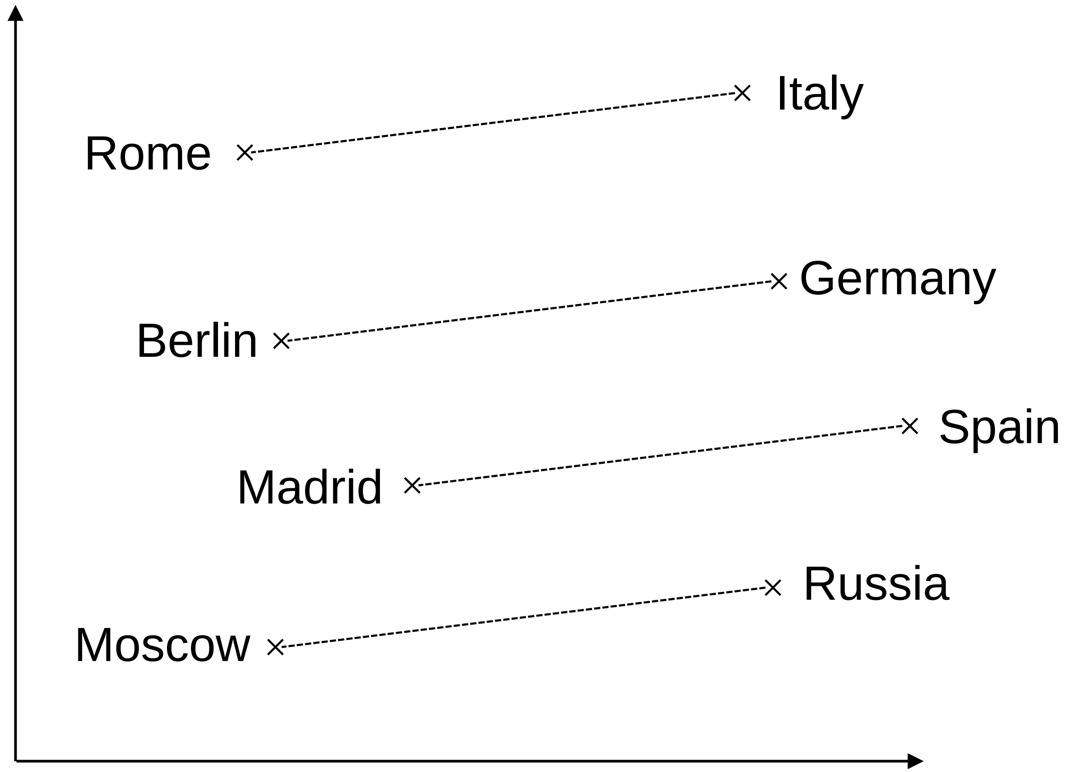

v(Rome) – v(Italy) + v(Berlin) ~ v(Germany)

v(King) – v(Man) + v(Woman) ~ v(Queen)

v(Building) – v(Architect) + v(Software) ~

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Representation Learning for NLP

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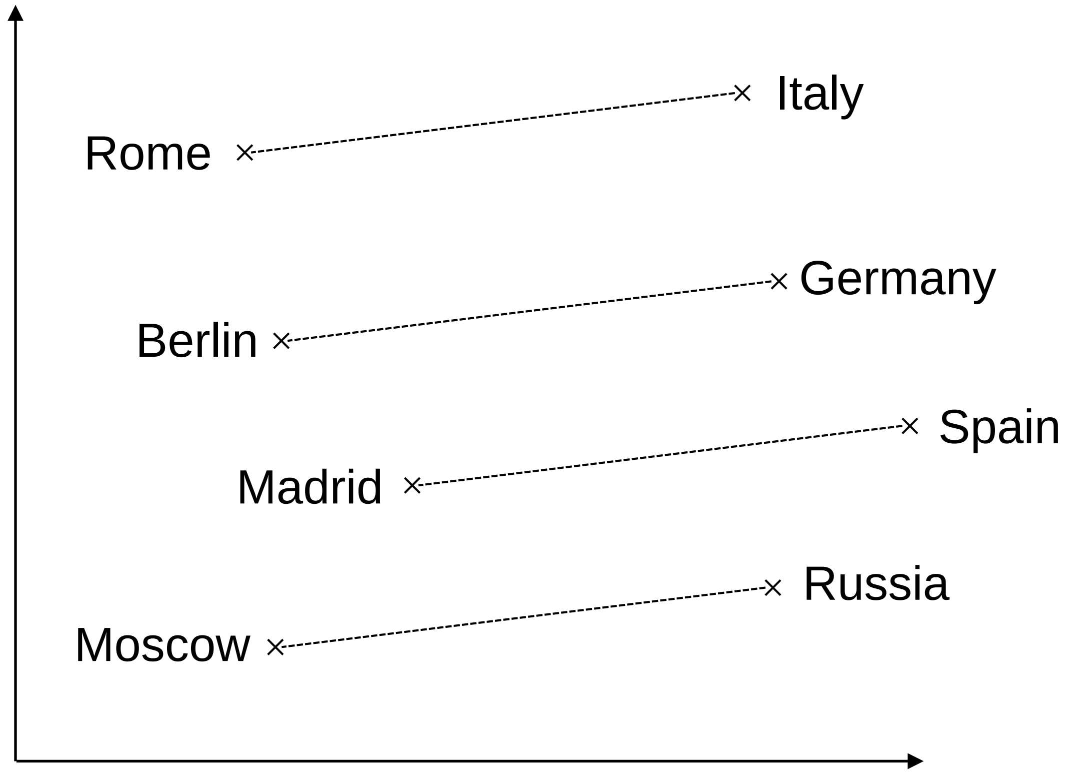


v(Rome) – v(Italy) + v(Berlin) ~ v(Germany)

v(King) – v(Man) + v(Woman) ~ v(Queen)

v(Building) – v(Architect) + v(Software) ~ v(Programmer)

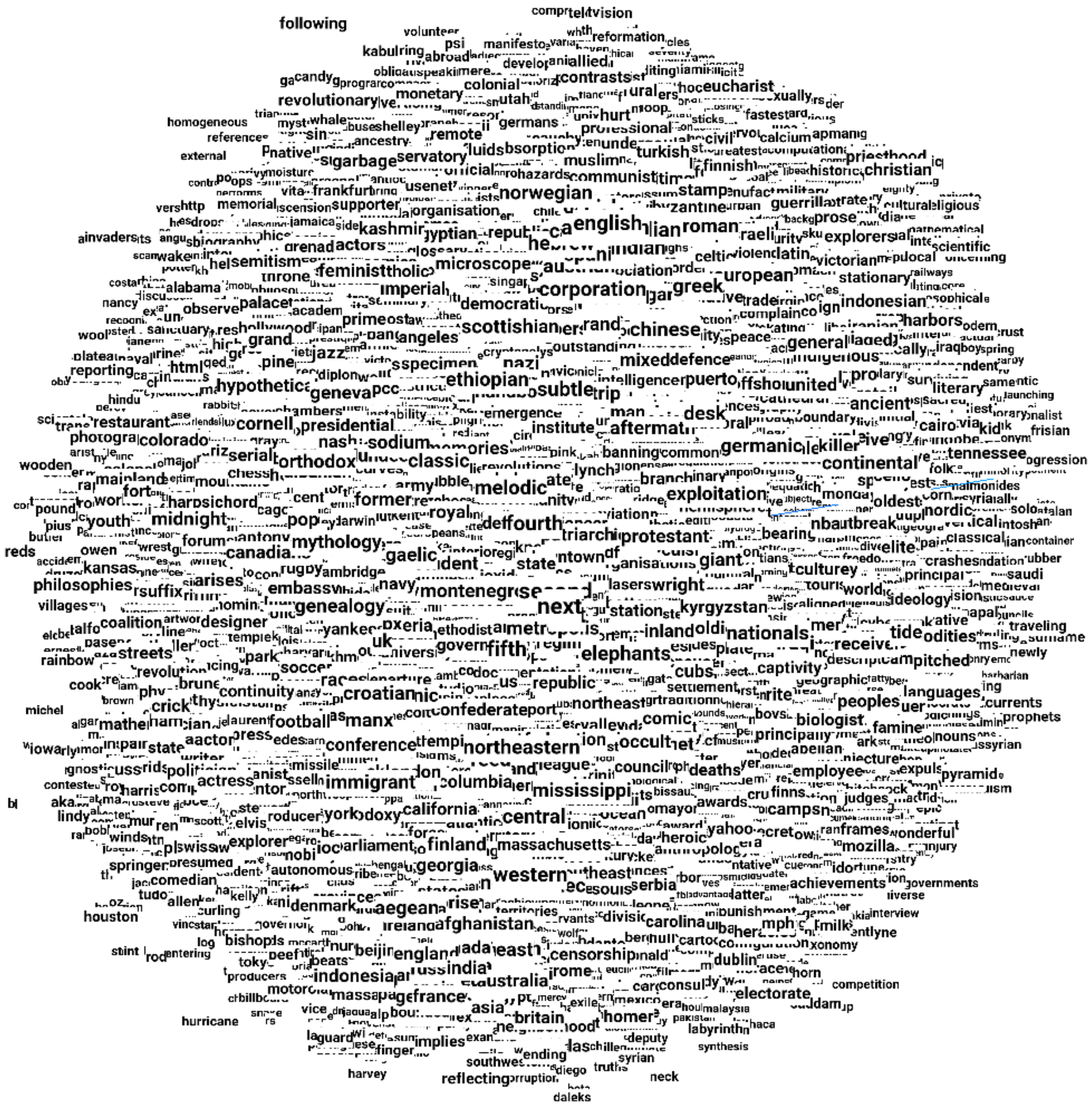
Word2Vec: Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, Jeffrey Dean *(2013). Distributed Representations of Words and Phrases and their Compositionality.*

Representation Learning for NLP

Vector representation for words

Demo in TensorBoard

- Show visualization of embeddings in TensorBoard, either by t-SNE or PCA
- 10,000 word vectors with dimensionality of 128
- Reduced to d = 3 for visualization



Representation Learning for NLP
Outlook

Adaptations of the Word2Vec algorithm

- Doc2Vec
- DNA2Vec
- Product2Vec
- App2Vec
- Emoji2Vec

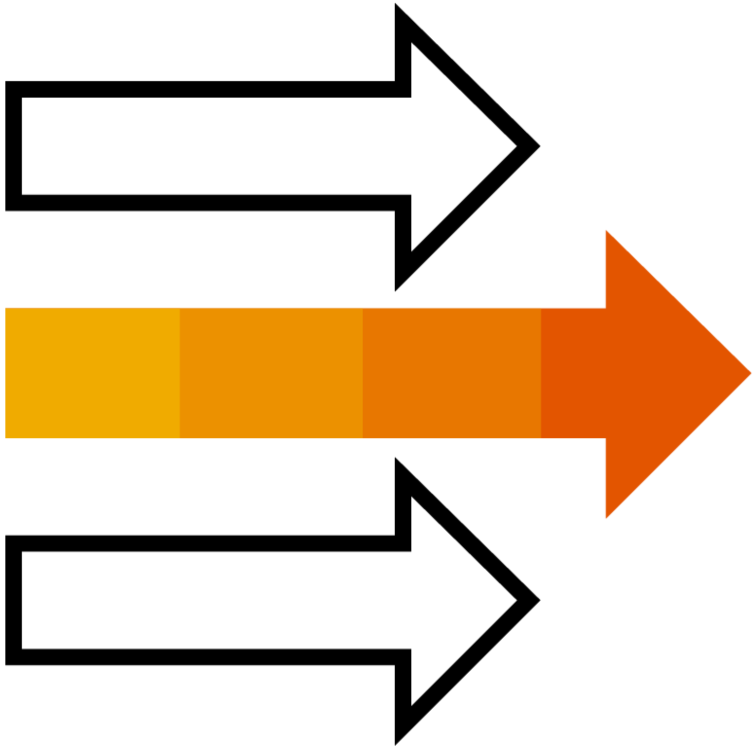
Word2Vec and its implementations are versatile algorithms for creating fixed-size embeddings of input features

Representation Learning for NLP

Coming up next

Basic Recurrent Neural Networks (RNNs)

- Types of sequences
- Basic RNN cell structure
- Problems with training RNNs



Thank you.

Contact information:

open@sap.com

Week 3: Deep Networks and Sequence Models

Unit 4: Basic RNNs in TensorFlow

Run Simple

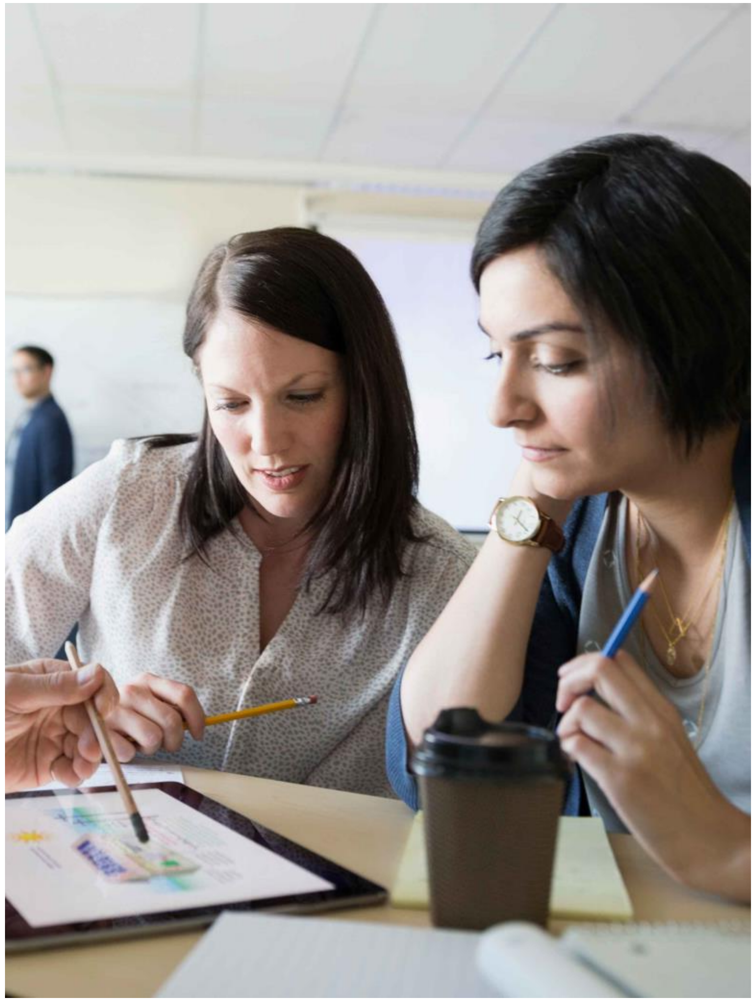
openSAP
open.sap.com

Basic RNNs in TensorFlow

What we covered in the last unit

Representation Learning for NLP

- Vector representation of words
- Distributed representations

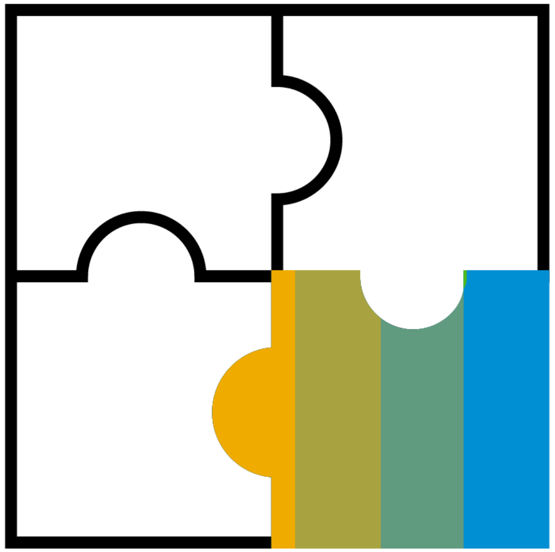


Basic RNNs in TensorFlow

Overview

Content:

- Recap: Sequence types
- Basic RNN cells
- Training RNNs

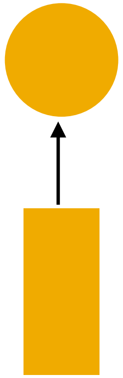


Basic RNNs in TensorFlow

Sequence types

Example:
Height

Parent’s height → Child’s height



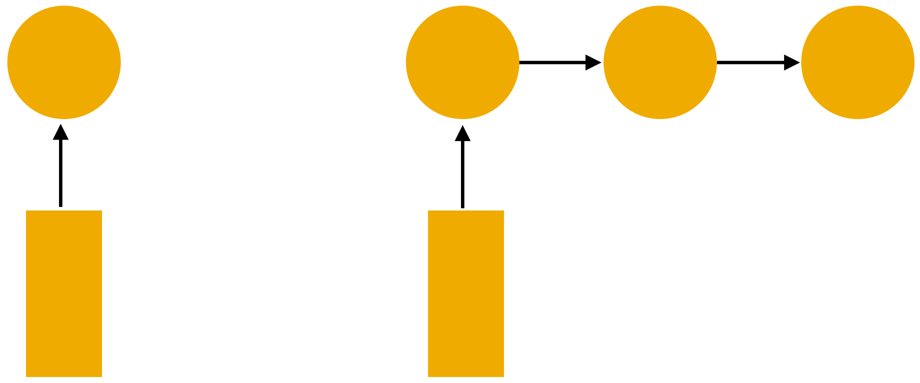
One-to-One

Basic RNNs in TensorFlow

Sequence types

Example:
Image captioning

Image → Sequence of words



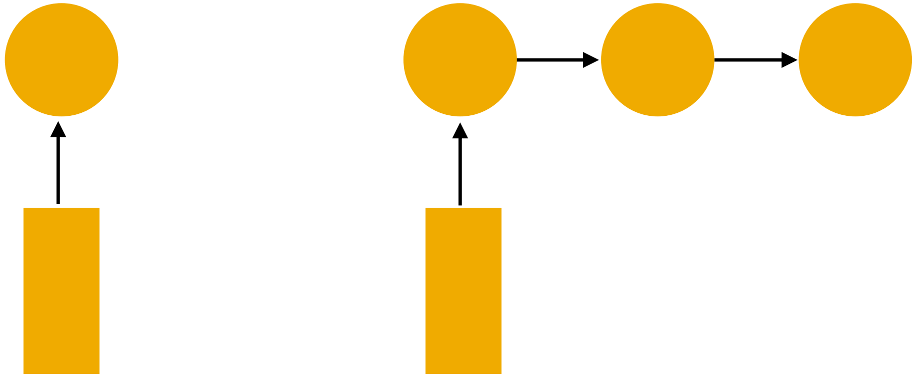
One-to-One **One-to-Many**

Basic RNNs in TensorFlow

Sequence types

Example:
Sentiment Analysis

Sequence of words → Sentiment



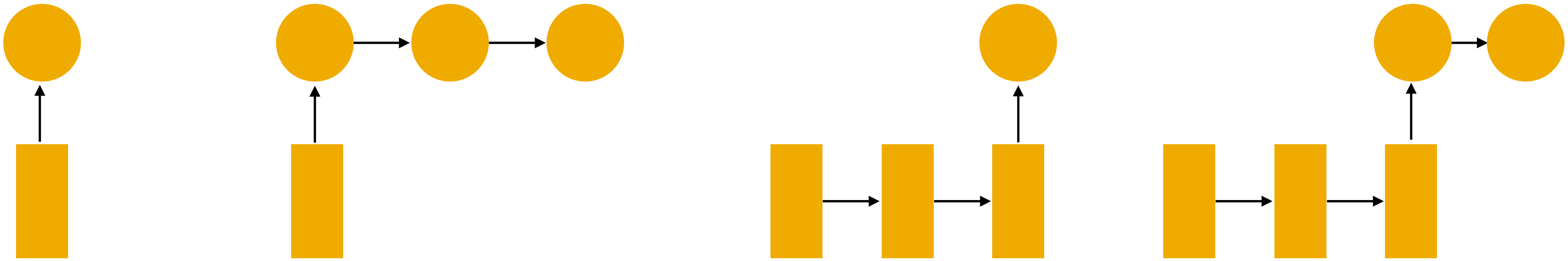
One-to-One **One-to-Many** **Many-to-One**

Basic RNNs in TensorFlow

Sequence types

Example:
Machine Translation

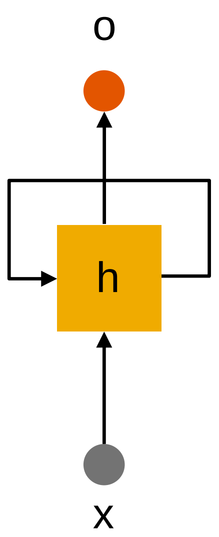
Sequence of words →
Sequence of words



One-to-One **One-to-Many** **Many-to-One** **Many-to-Many**

Basic RNNs in TensorFlow

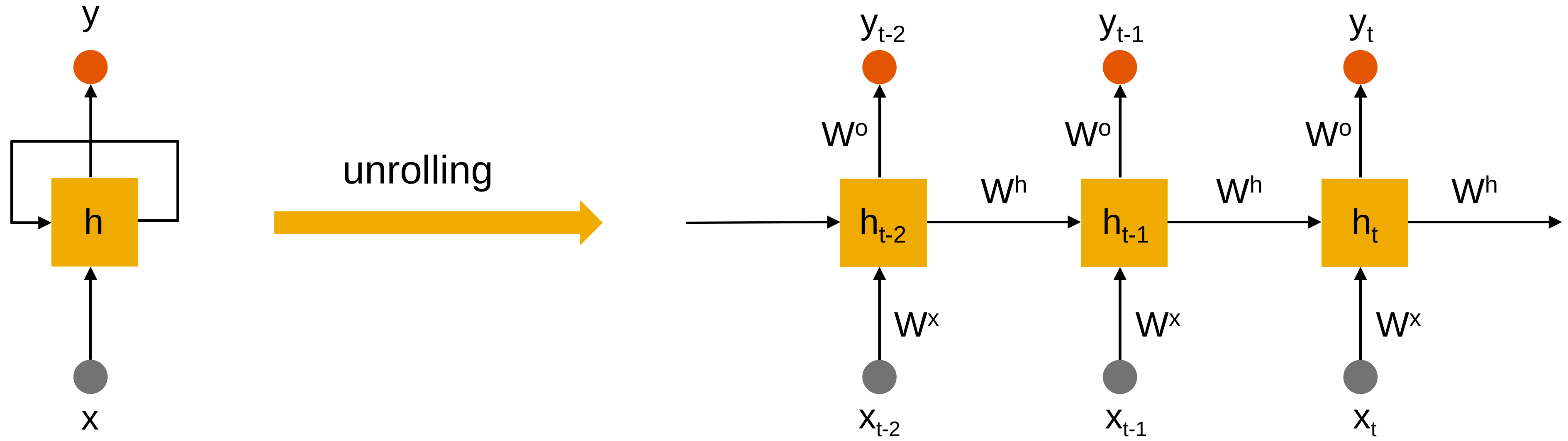
Understanding recurrent neural networks (RNNs)



- *'Recurrent'* implies that weights are shared across time steps

Basic RNNs in TensorFlow

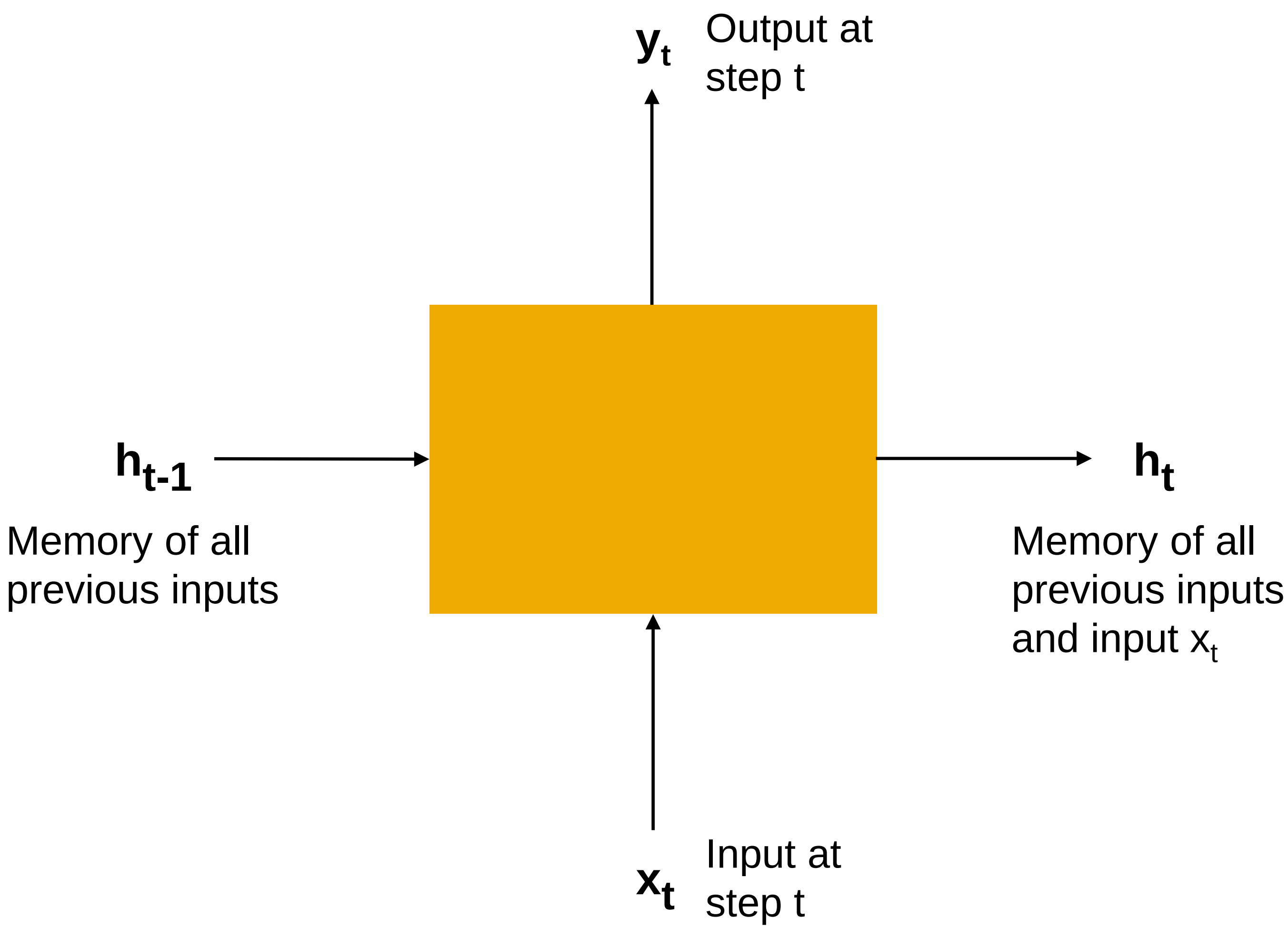
Understanding recurrent neural networks (RNNs)



- *'Recurrent'* implies that weights are shared across time steps
- The network is unrolled in time
- The same weight matrix is applied at each time step

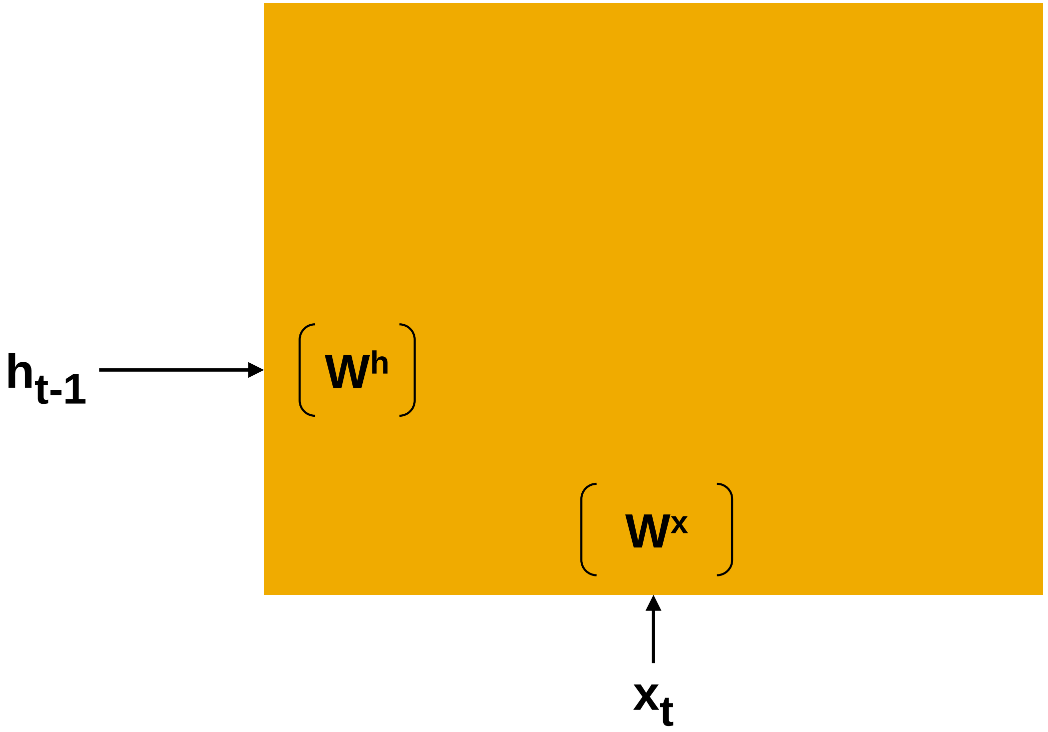
Basic RNNs in TensorFlow

Understanding an RNN cell



Basic RNNs in TensorFlow

Understanding an RNN cell



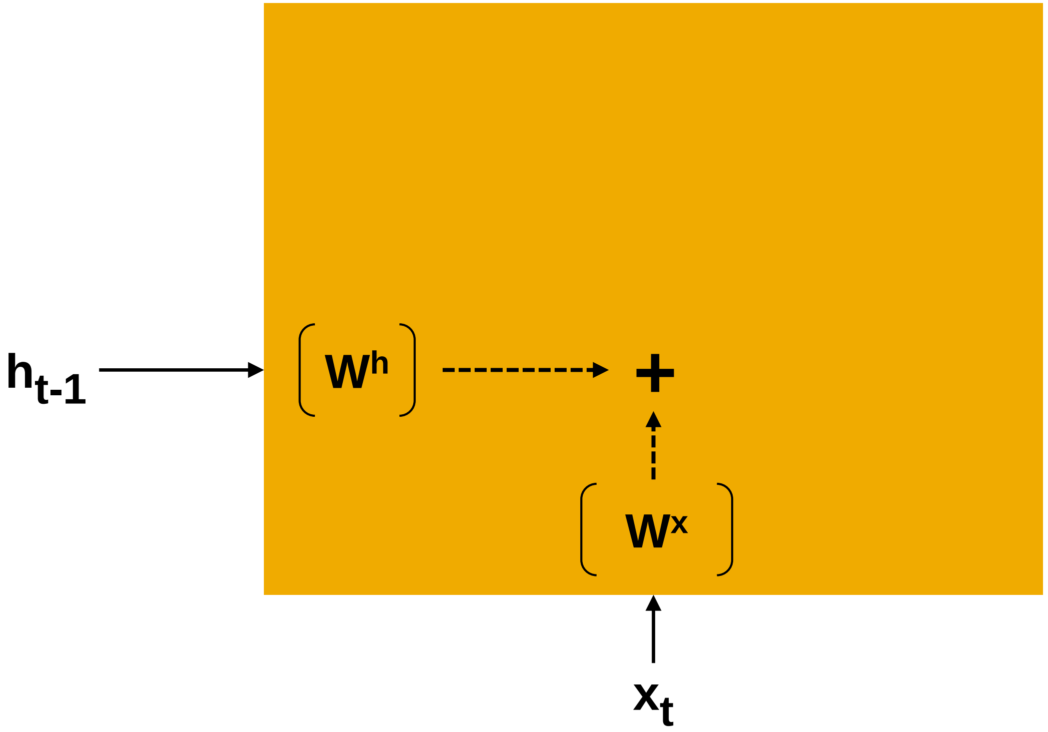
- x_t = input at step t
- h_{t-1} = memory of all previous inputs until t-1
- W^h = weight parameters for hidden state h_t
- W^x = weight parameters for input x_t

- Calculation of the hidden state h_t:

$$W^h h_{t-1} \quad W^x x_t$$

Basic RNNs in TensorFlow

Understanding an RNN cell



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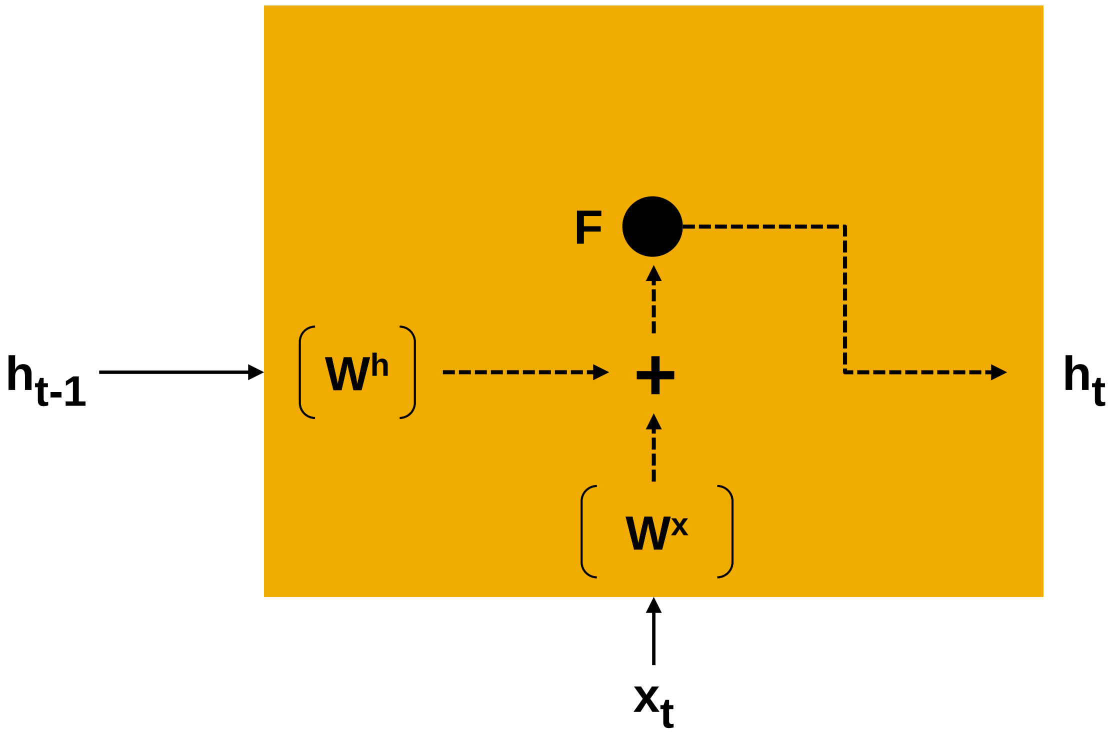
- Calculation of the hidden state h_t:

$$\boldsymbol{W^h h_{t-1} + W^x x_t}$$

Basic RNNs in TensorFlow

Understanding an RNN cell



- x_t = input at step t
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- W^h = weight parameters for hidden state h_t
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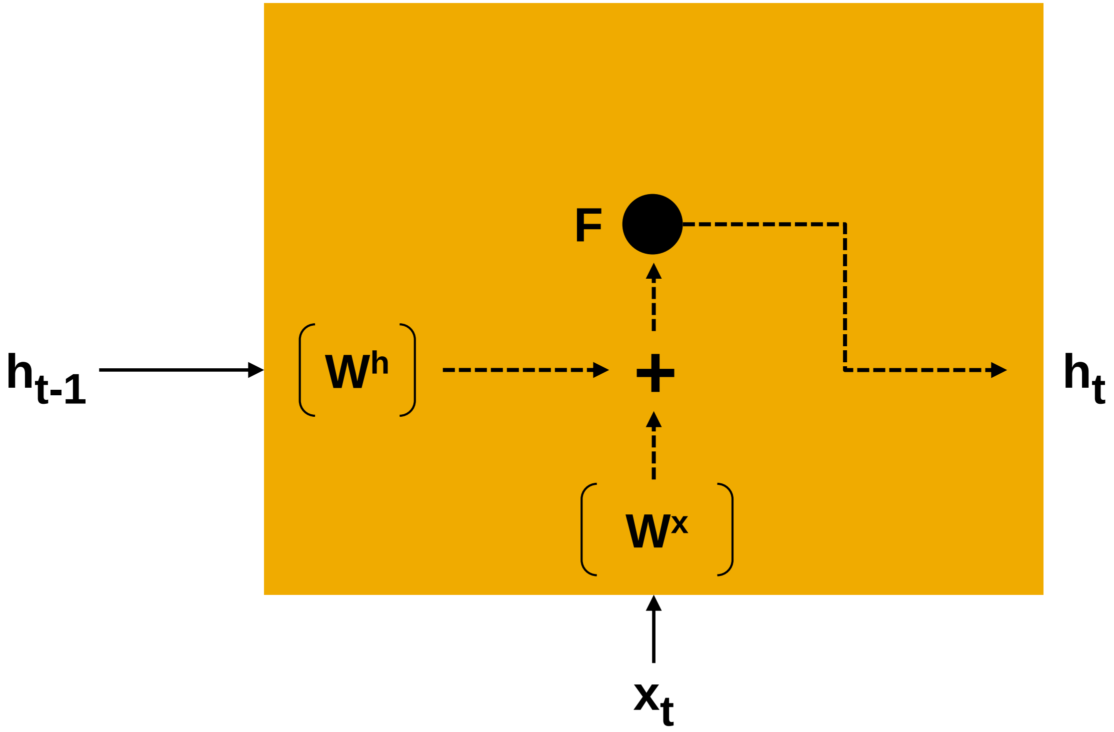
- **F** = activation function e.g. tanh

- Calculation of the hidden state h_t:

$$\boldsymbol{h_t = F(W^h h_{t-1} + W^x x_t)}$$

Basic RNNs in TensorFlow

Understanding an RNN cell



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- W^h = weight parameters for hidden state h_t
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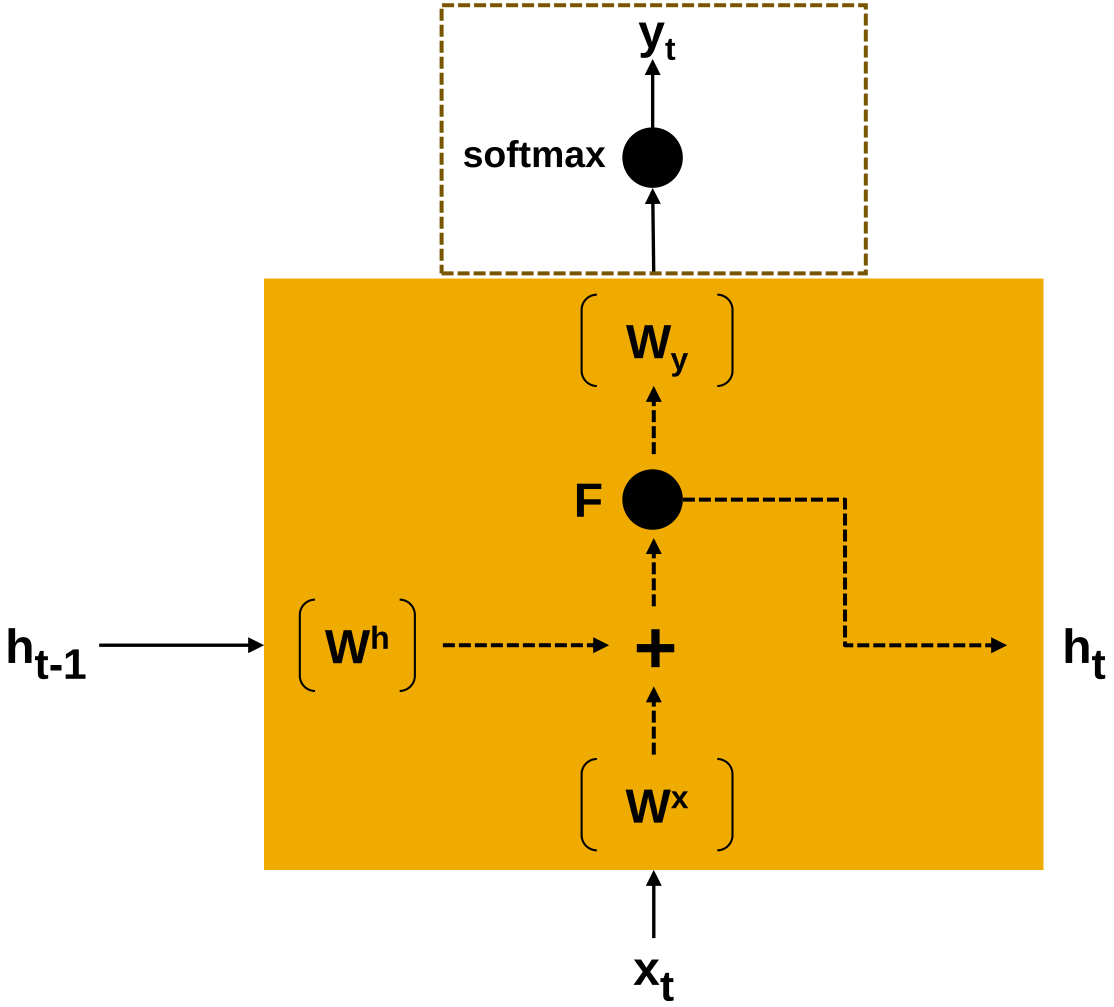
- **F** = activation function e.g. tanh

- Apply the same operation at each time step:

$$\begin{aligned} h_t &= F(W^h h_{t-1} + W^x x_t) \\ &= F(W^h F(W^h h_{t-2} + W^x x_{t-1}) + W^x x_t) \\ &\dots \end{aligned}$$

Basic RNNs in TensorFlow

Understanding an RNN cell



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- $\mathbf{W^h}$ = weight parameters for hidden state h_t
- $\mathbf{W^x}$ = weight parameters for input x_t
- **F** = activation function e.g. tanh
- $\mathbf{W^y}$ = weight parameters for hidden → output
- $\mathbf{o_t}$ = output at step t

- Calculation of the hidden state h_t:

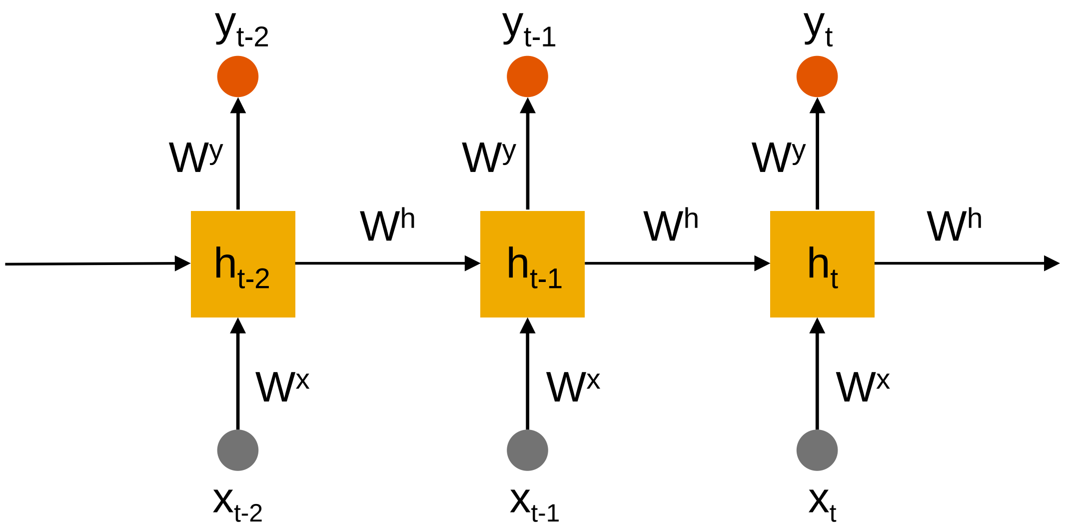
$$h_t = F(W^h h_{t-1} + W^x x_t)$$

- Calculation of the output o_t:

$$y_t = softmax(W^o h_t)$$

Basic RNNs in TensorFlow

Understanding an RNN cell

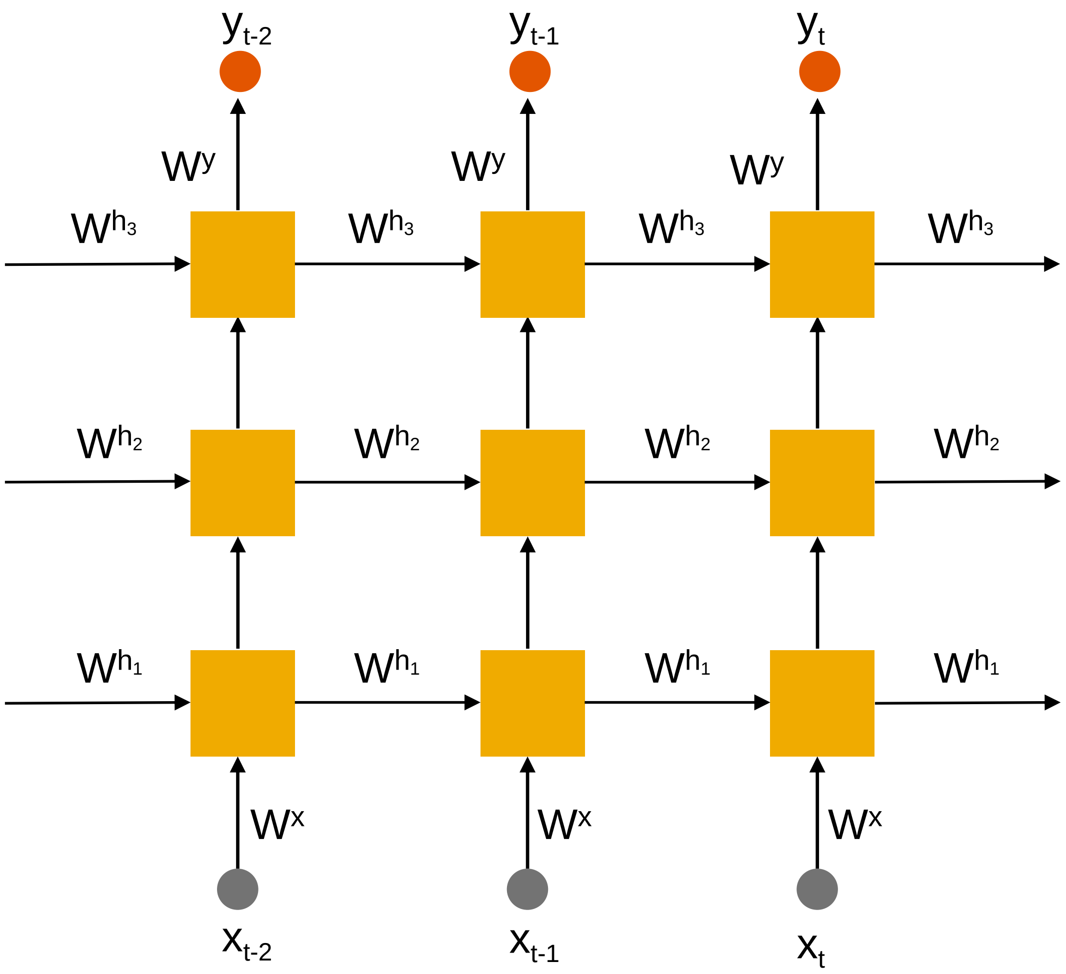


Takeaway

- We use the same weight parameters for all t
- Output depends on all previous inputs (h_{t-1}) and the current input x_t
- Calculating the output means matrix multiplication of the same matrices over and over again

Basic RNNs in TensorFlow

Getting deep with RNNs



Basic RNNs in TensorFlow
Training of RNNs

Example problem: Predict the last word in a sentence

Case 1: Short sequence:

Tom was cooking pasta. Jenny walked in. Both ate *pasta*.

Case 2: Long sequence:

Tom was cooking pasta in the kitchen. Jenny walked in. They talked about what happened during the day. Then she asked him what he was cooking. Tom replied that he was cooking *pasta*.

Basic RNNs in TensorFlow

Training of RNNs

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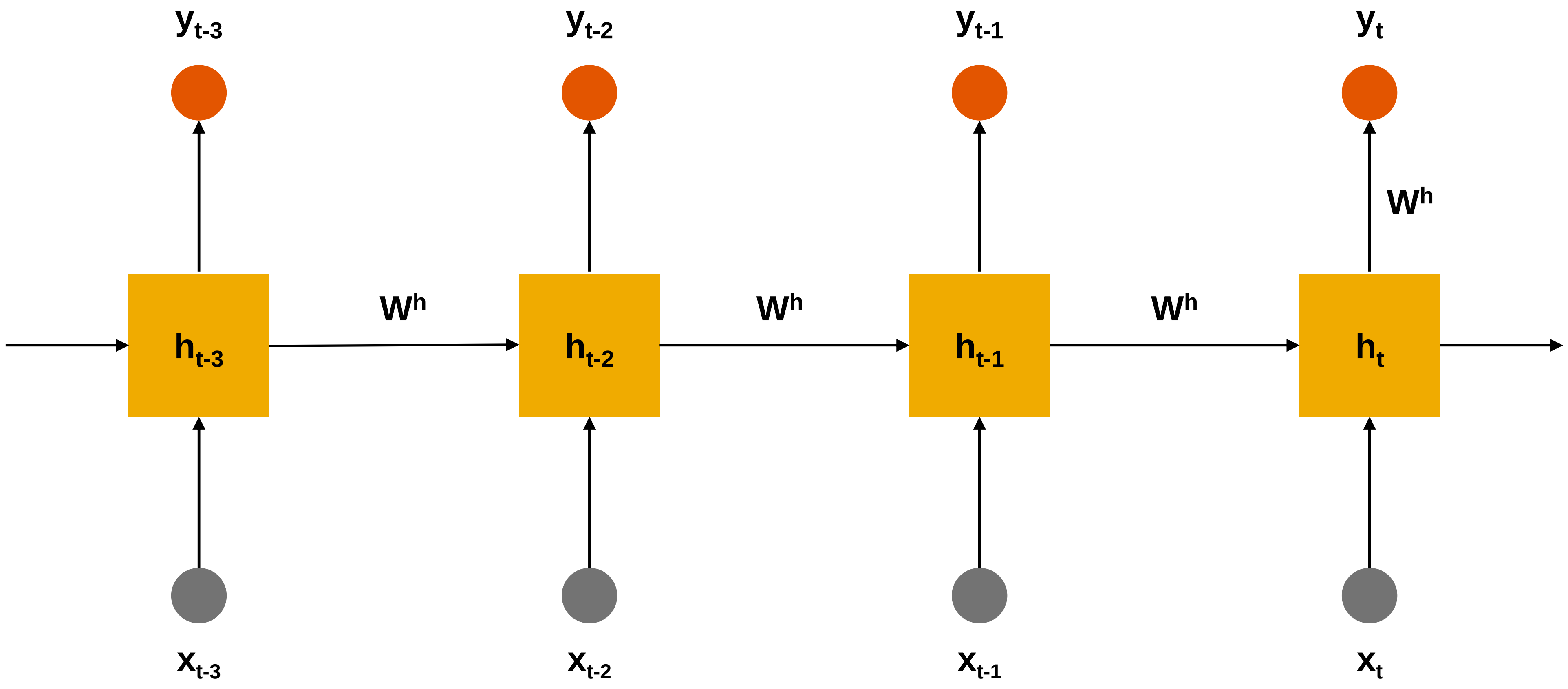
Vanilla RNNs are poor at modeling long-term dependency

Basic RNNs in TensorFlow
Training of RNNs



Basic RNNs in TensorFlow

Vanishing gradient problem in detail

- Our main problem: The same operation (matrix multiplication followed by activation function) is repeated over and over

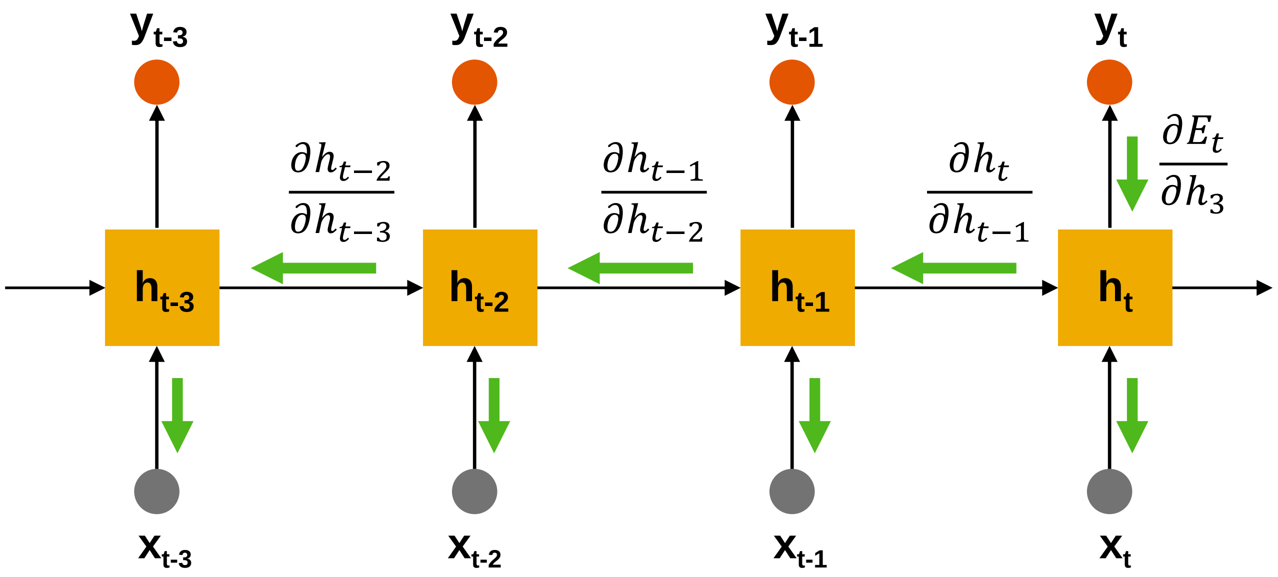
- Example: A Simpler RNN without nonlinear activation and input:

$$\boldsymbol{h_t} \sim \boldsymbol{W^h h_{t-1}}$$

$$\boldsymbol{h_t} \sim (\boldsymbol{W^h})^{\color{red}{t}} \boldsymbol{h_0}$$

- with t as our last time step

Gradient: Rate of change of cost function with respect to each parameter



Basic RNNs in TensorFlow

Vanishing gradient problem in detail

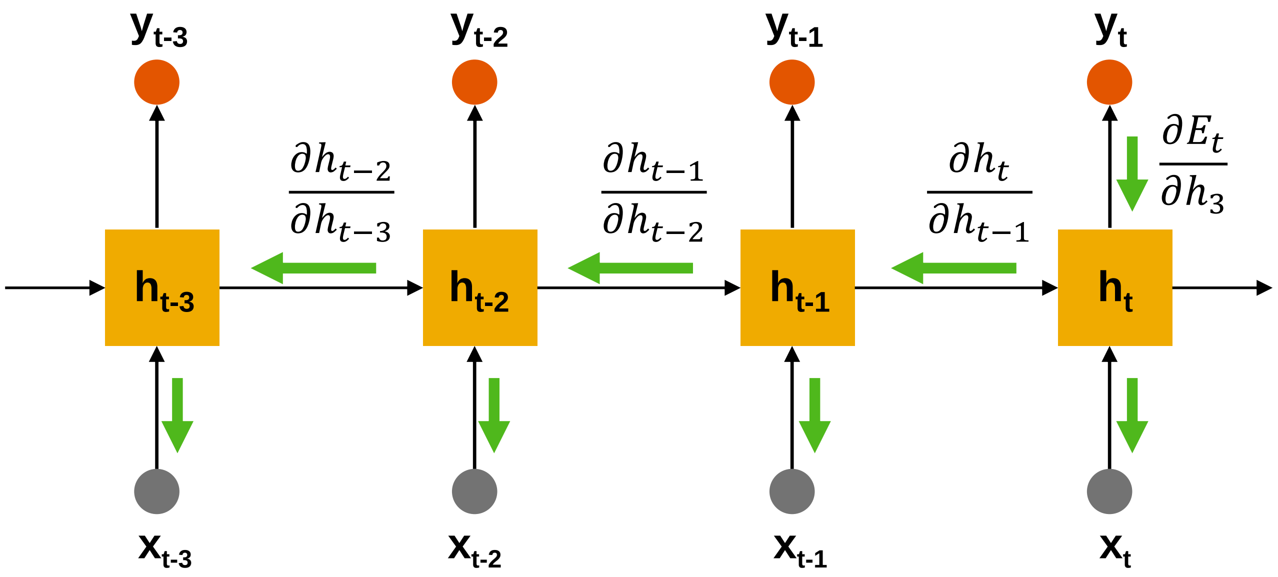
- We can factorize W via eigendecomposition:

$$\boldsymbol{W^h} = \boldsymbol{Q\Lambda Q^{-1}}$$

$$\boldsymbol{h_t} \sim \boldsymbol{Q\Lambda^t Q^{-1}}$$

- Eigenvalues are raised to the power of t
- Any eigenvalue smaller than one becomes zero
- Any eigenvalue larger than one will explode

Gradient: Rate of change of cost function with respect to each parameter

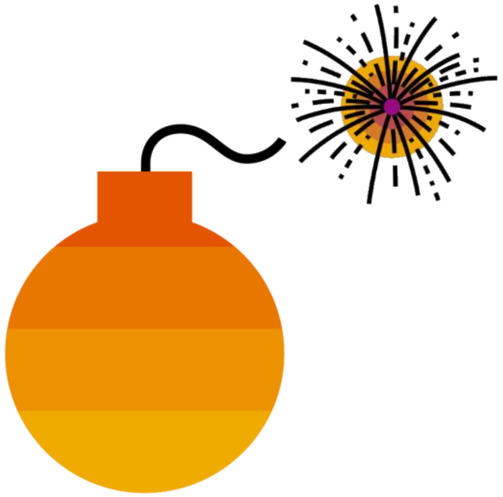


Basic RNNs in TensorFlow

Vanishing gradient problem in detail

- The same applies for backpropagating the error:

Case 1: Exploding gradient



Basic RNNs in TensorFlow

Vanishing gradient problem in detail

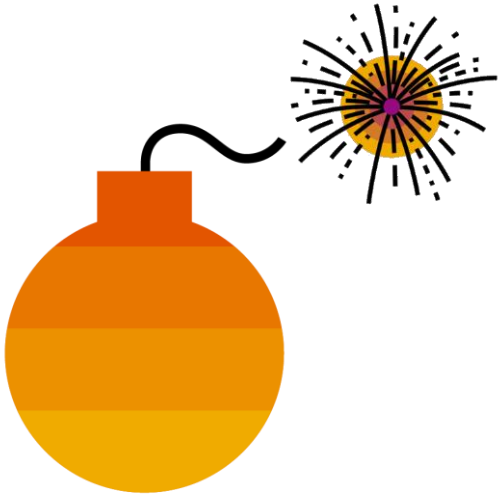
- The same applies for backpropagating the error:

Case 1: Exploding gradient → Gradient clipping

Scales the gradient if its norm gets big

if gradient_norm > threshold:

    gradient = (threshold / gradient_norm) gradient



Basic RNNs in TensorFlow

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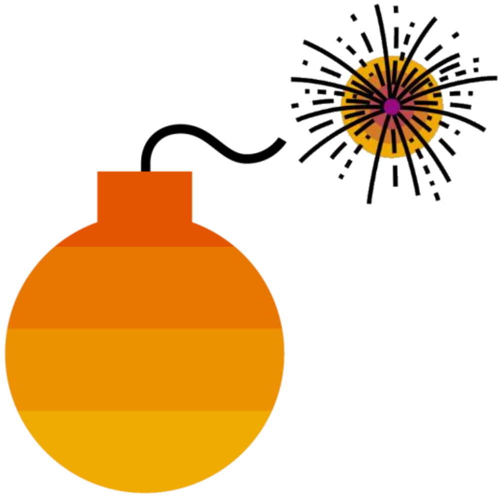

Case 1: Exploding gradient $\rightarrow$ Gradient clipping

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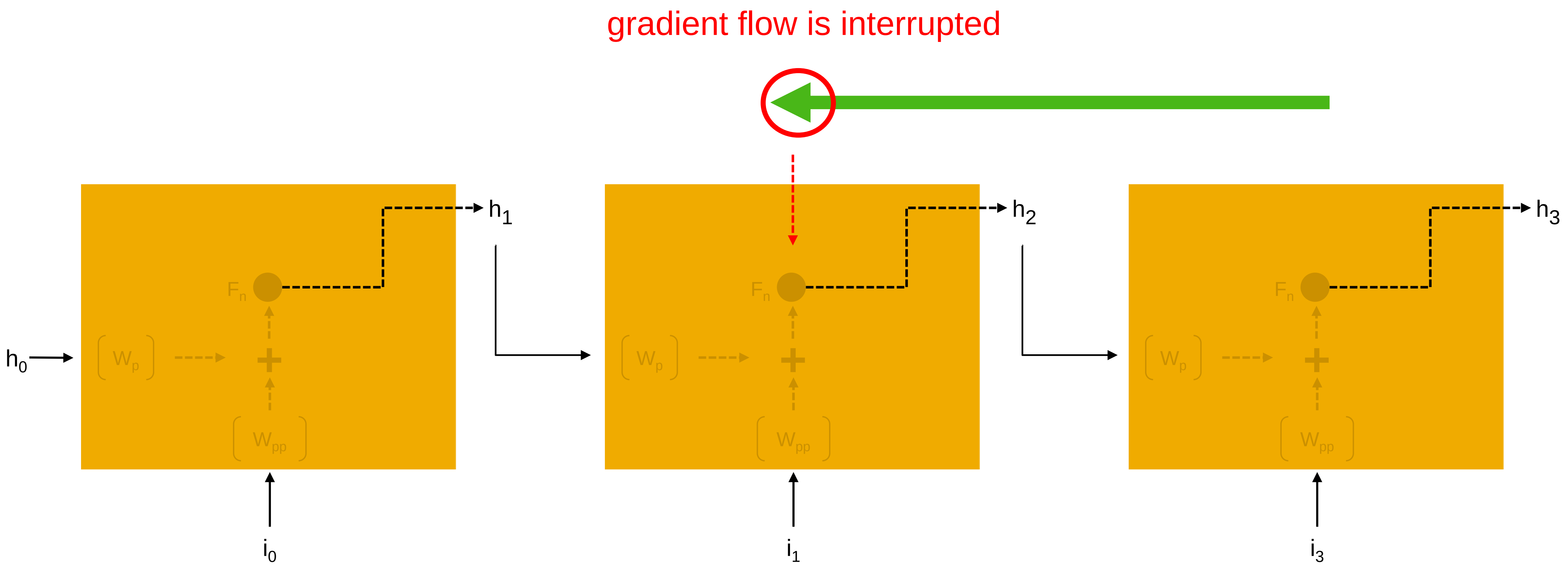
Case 2: Vanishing gradient

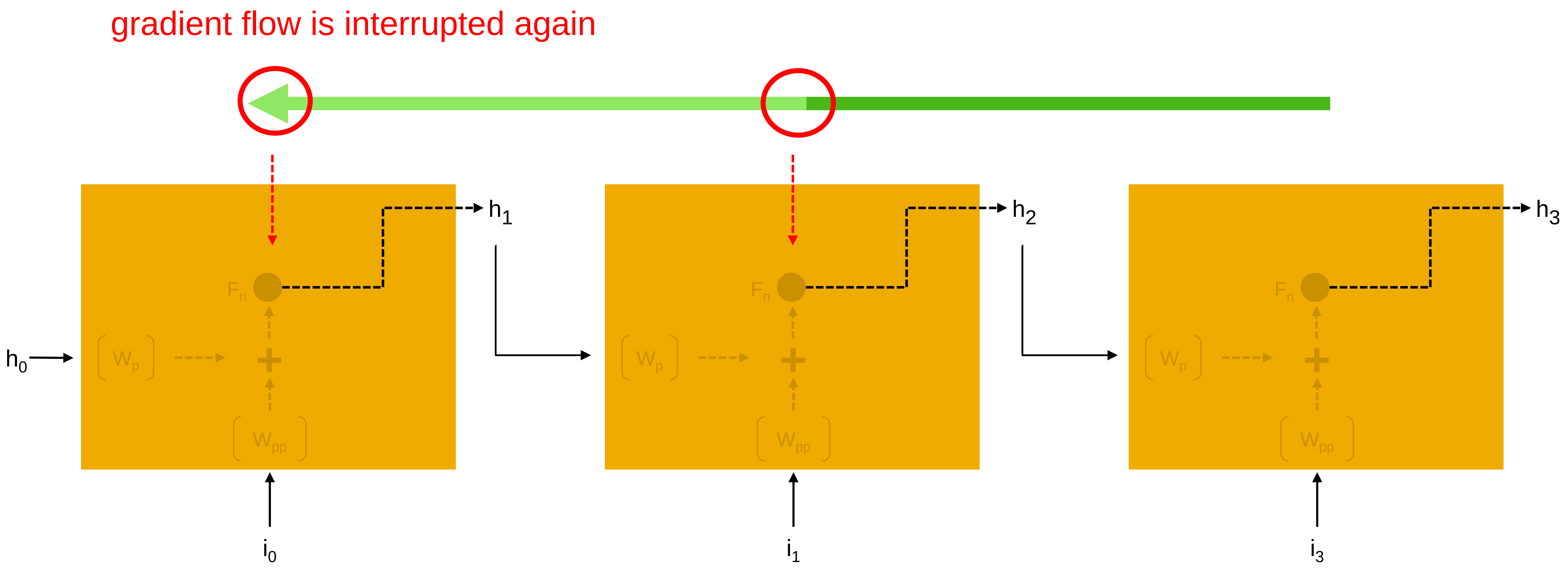
Basic RNNs in TensorFlow

Vanishing gradient problem in detail



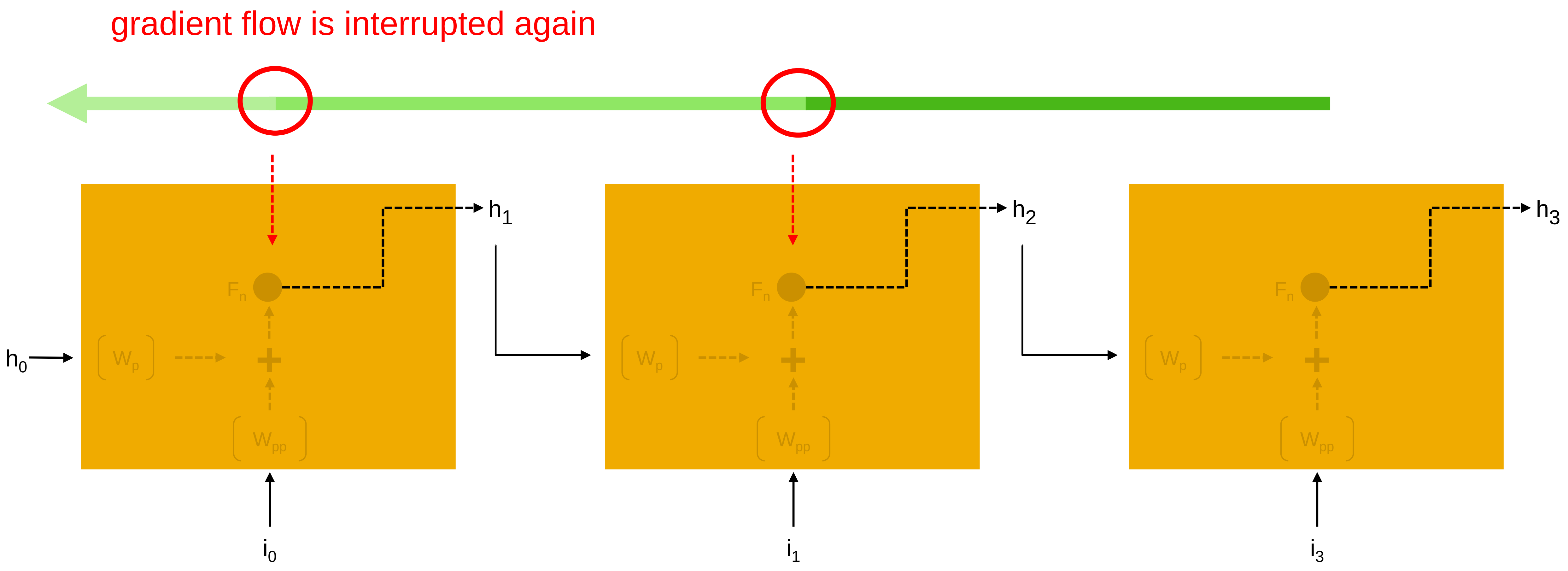
Basic RNNs in TensorFlow

Vanishing gradient problem in detail



Basic RNNs in TensorFlow

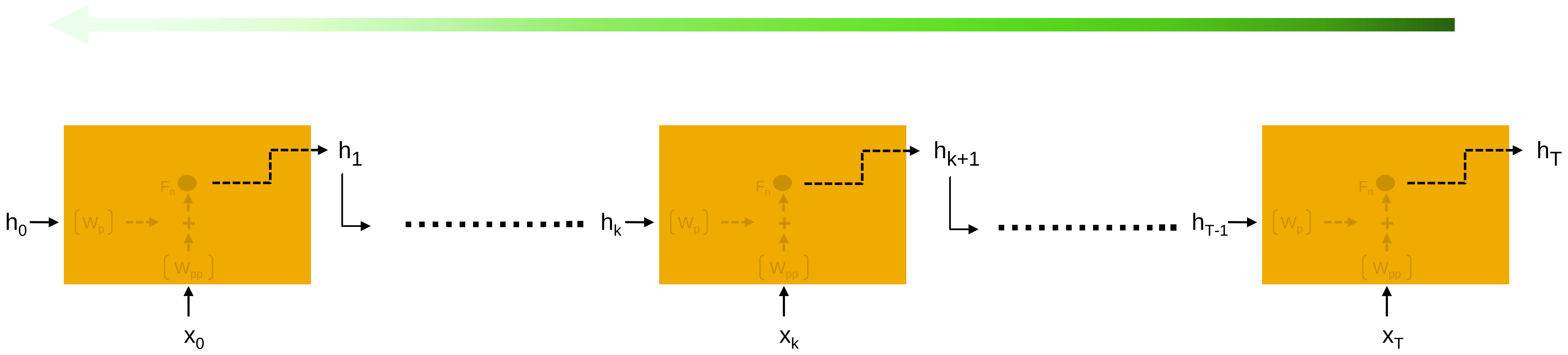
Vanishing gradient problem in detail



Basic RNNs in TensorFlow

Vanishing gradient problem in deep network

small gradient flow is interrupted at each step, thus making learning difficult large



Basic RNNs in TensorFlow

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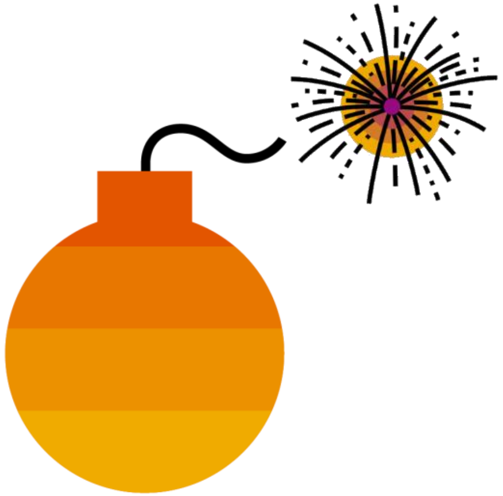
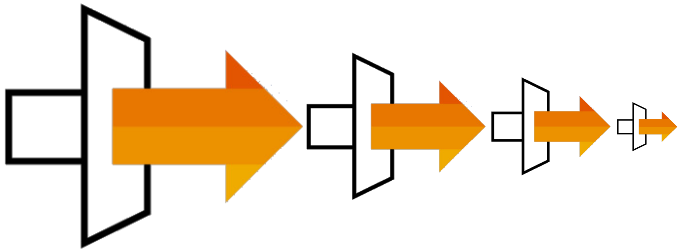


Case 2: Vanishing gradient



Basic RNNs in TensorFlow

Vanishing gradient problem in detail

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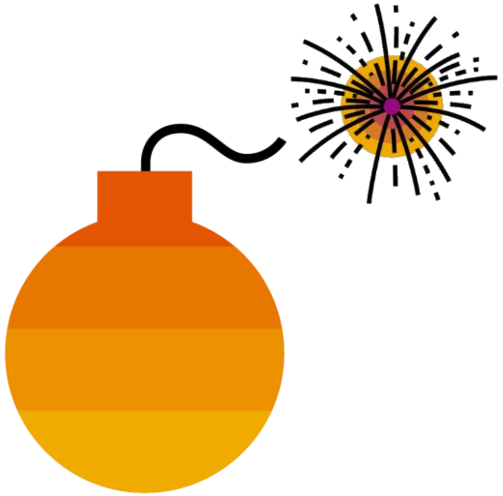
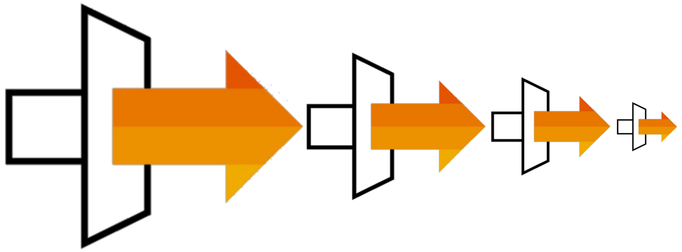


Case 2: Vanishing gradient → Change RNN architecture

This is the subject of our next unit!

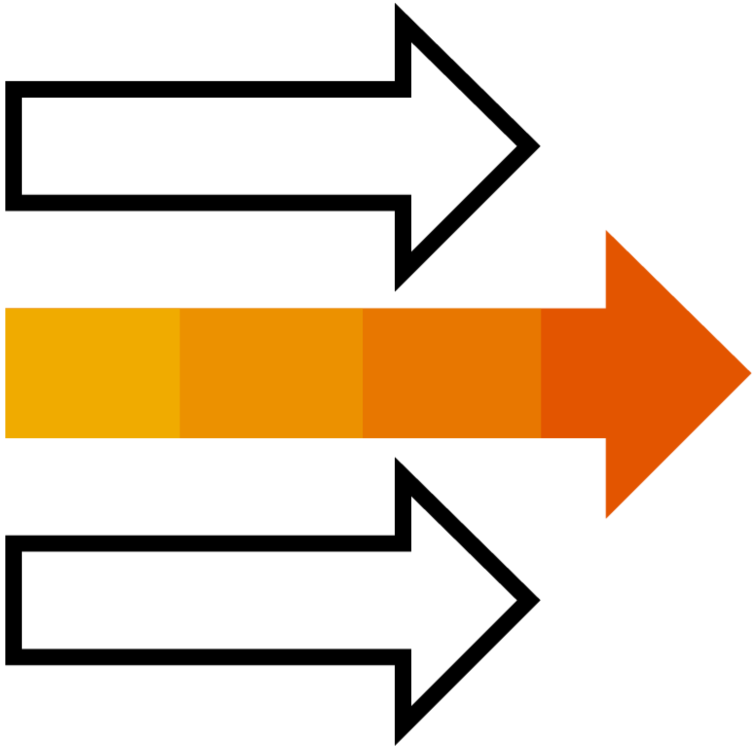


Basic RNNs in TensorFlow

Coming up next

Introduction to Long Short-Term Memory and Gated Recurrent Networks

- Vanilla LSTM cell structure
- Solution to vanishing gradient problem
- Further simplification in LSTM using GRU



Thank you.

Contact information:

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Week 3: Deep Networks and Sequence Models

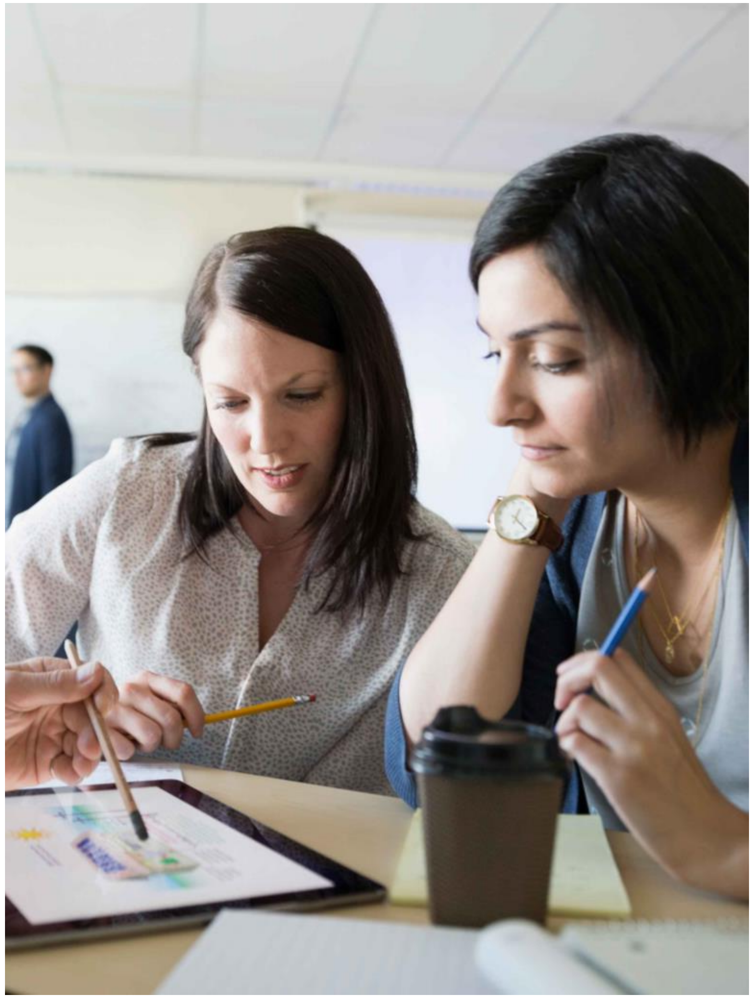
Unit 5: Introduction to LSTM, GRU

Introduction to LSTM, GRU

What we covered in the last unit

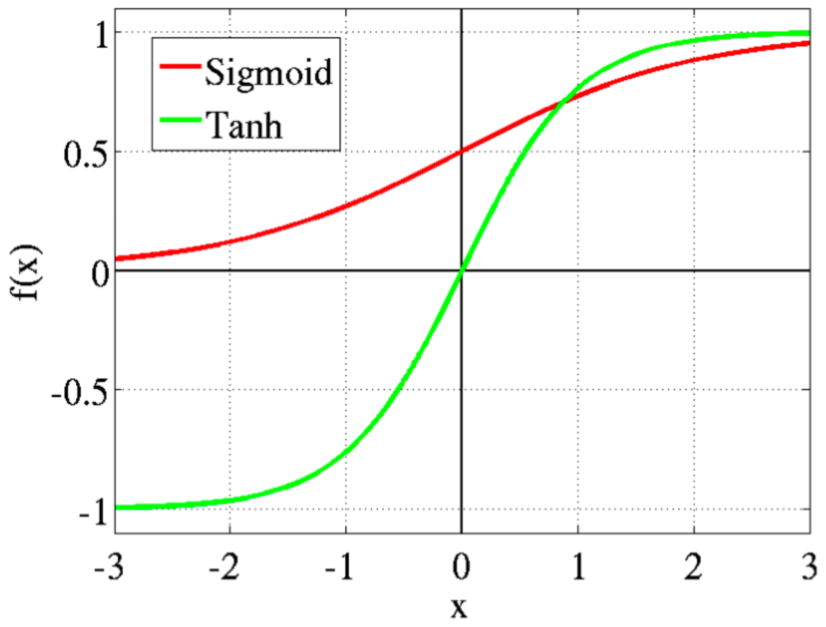
Basic Recurrent Neural Network in TensorFlow

- Types of sequences
- Basic RNN cell structure
- Problems with RNN



Introduction to LSTM, GRU

Activation functions



- Sigmoid functions map values to the range (0,1)

$$Sig(x) = \frac{e^x}{e^x + 1}$$

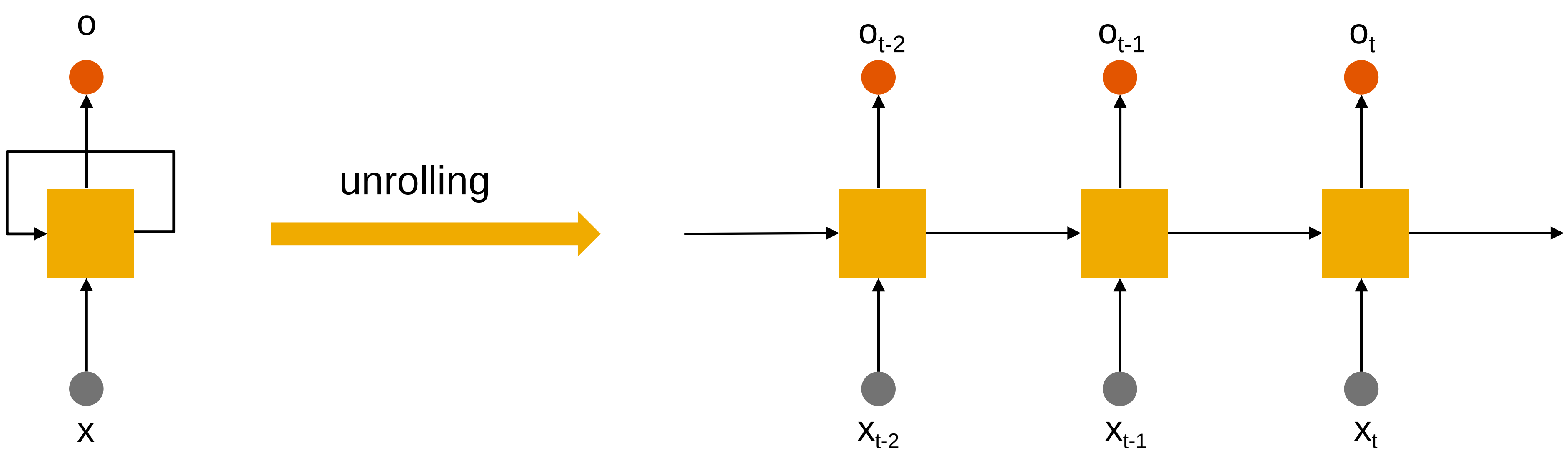
$$\forall x:\ 0 \leq Sig(x) \leq 1$$

- tanh is also bounded like a sigmoid, but is zero-centered (improves statistical properties of layer output)

$$-1 \leq tanh(x) \leq 1$$

Introduction to LSTM, GRU

Introduction to long short-term memory networks (LSTMs)



End-to-end architecture to model the sequence remains the same, but the cell structure changes

Introduction to LSTM, GRU

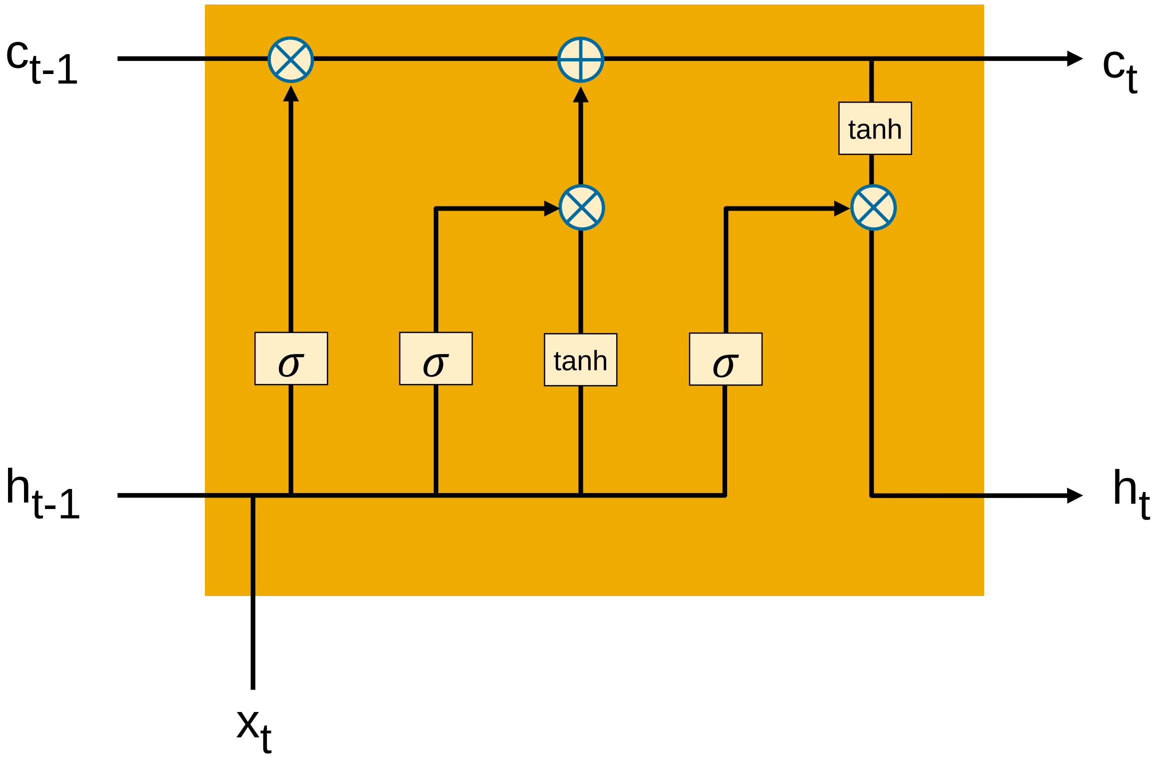
Introduction to long short-term memory networks (LSTMs)

The three main components of an LSTM cell:

- The **memory cell** captures long-term information
- The **working memory** captures short-term information
- **Gates** regulate the information exchange between the memory cell and working memory

Introduction to LSTM, GRU

LSTM cell structure



LSTM:

- Decide whether current input matters
- Decide which part of the memory to forget
- Decide what to output at the current time

LSTM: Sepp Hochreiter, Jürgen Schmidthuber *(1997). Long Short-Term Memory.*

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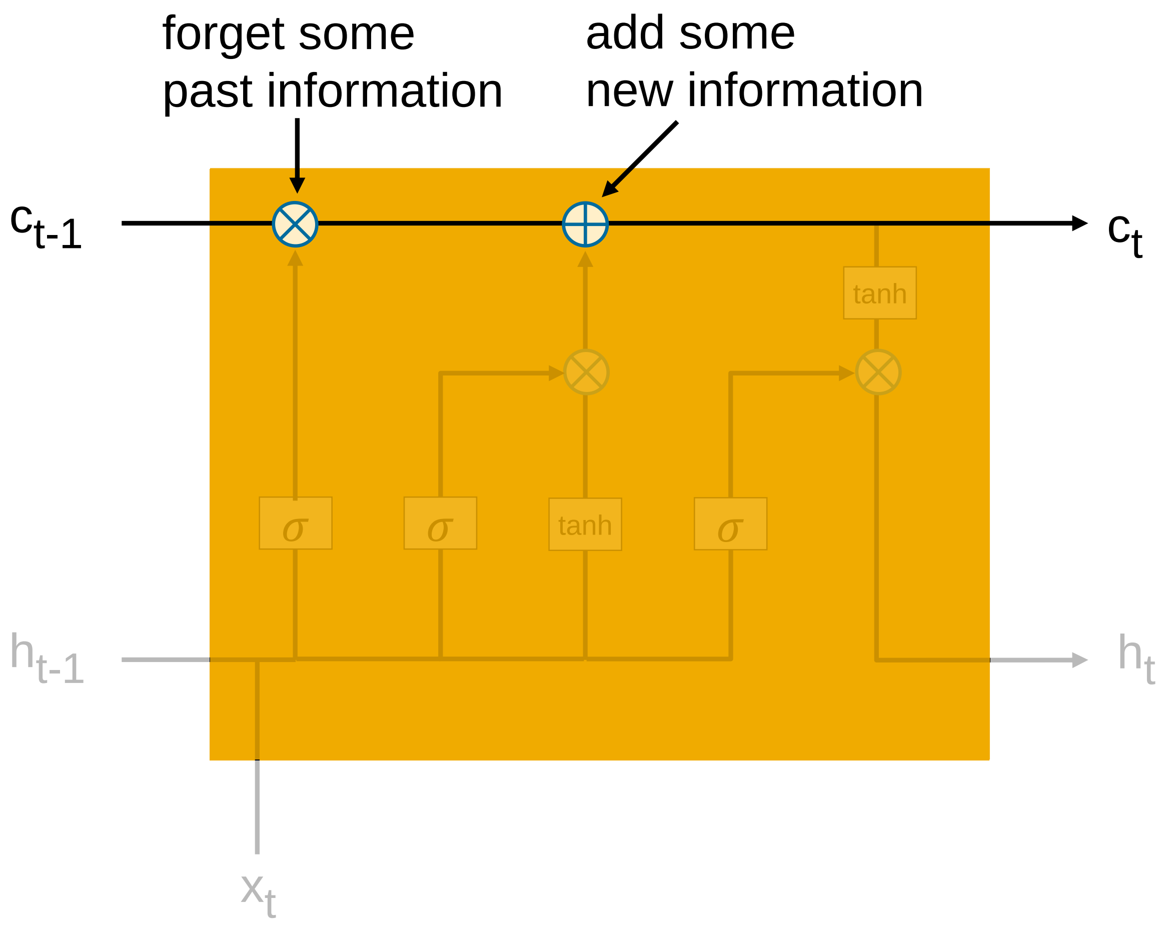
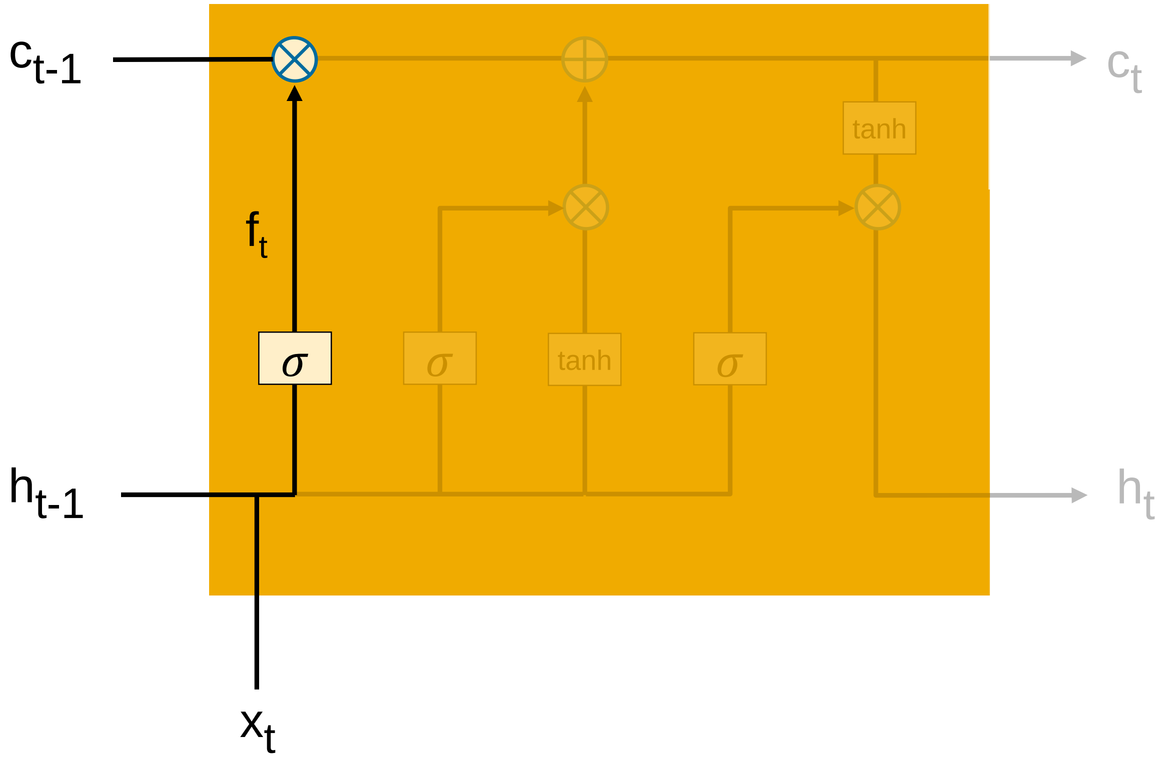
LSTM cell structure – Memory cell



- Captures long-term dependency
- Element-wise operation
- Gradients can flow freely without suppression

Introduction to LSTM, GRU

LSTM cell structure – Forget gate

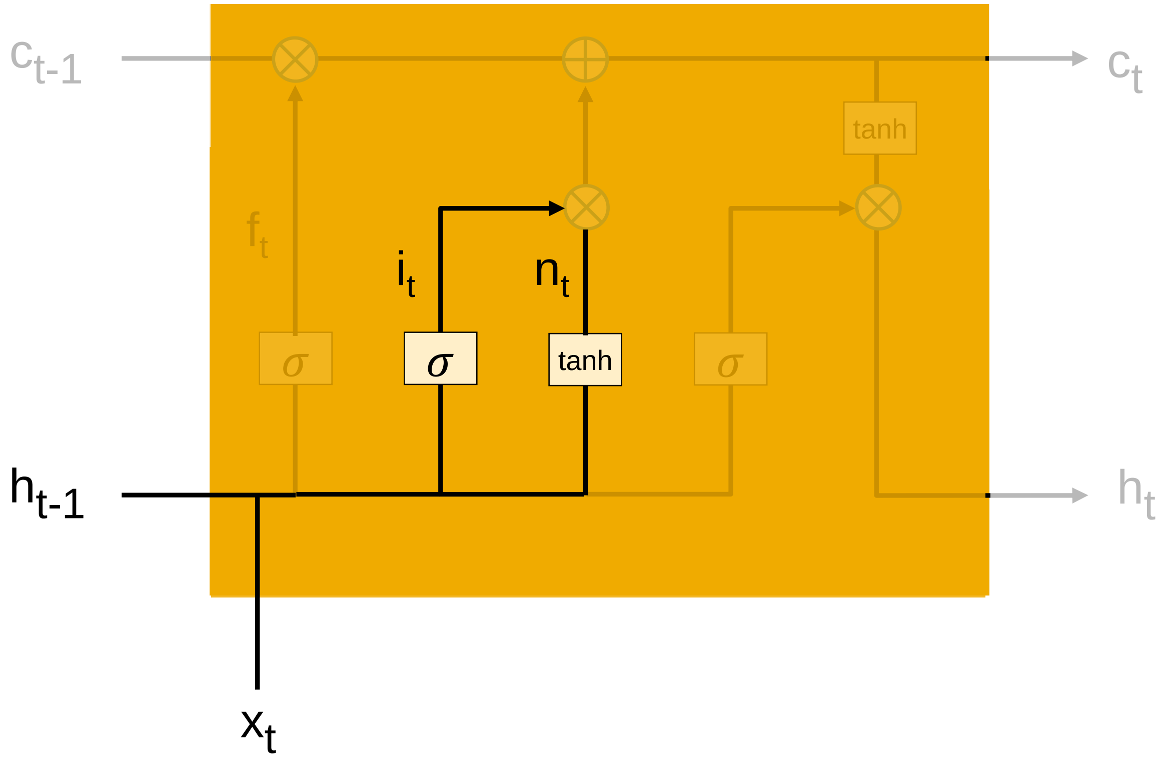


$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

- Based on the past sequence and current input, a **forget regulator (f_t)** is created
- It dampens certain elements of c_{t-1}
- As a result, some past information is forgotten
- This helps in remembering only the important part of a sequence

Introduction to LSTM, GRU

LSTM cell structure – Input gate



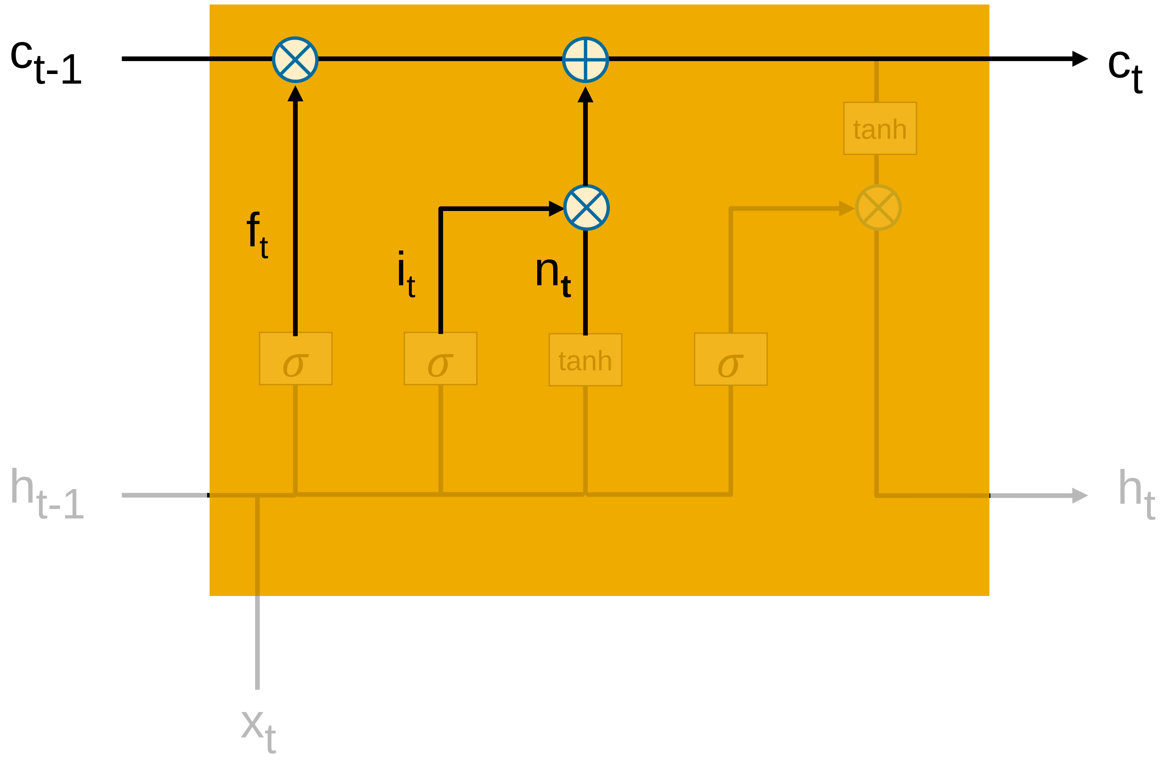
$$i_t = \sigma(W_i\,[h_{t-1}, x_t] + b_i)$$

$$\mathbf{n_t} = tanh(W_n\,[h_{t-1}, x_t] + b_n)$$

- $\mathbf{n_t}$ contributes new information from the current input
- $\mathbf{i_t}$ acts as an **input regulator**
- It suppresses some new information which is not relevant for the long-term update

Introduction to LSTM, GRU

LSTM cell structure – Updating the memory cell



$$c_t = f_t * c_{t-1} + i_t * n_t$$

- After all updates in the memory cell, we get new long-term information in $\mathbf{c_t}$
- The inputs to c_t are between 0 and 1, but the elements can be unbounded because of addition to each element over multiple steps

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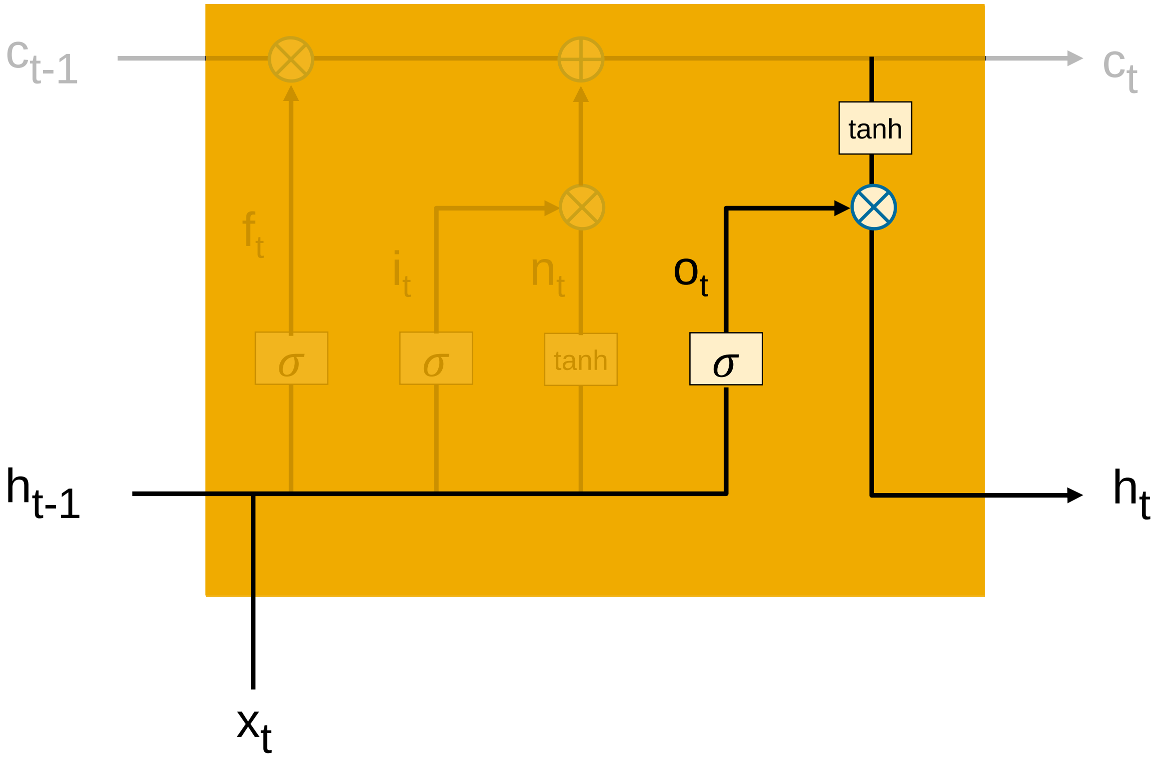
LSTM cell structure – Output gate



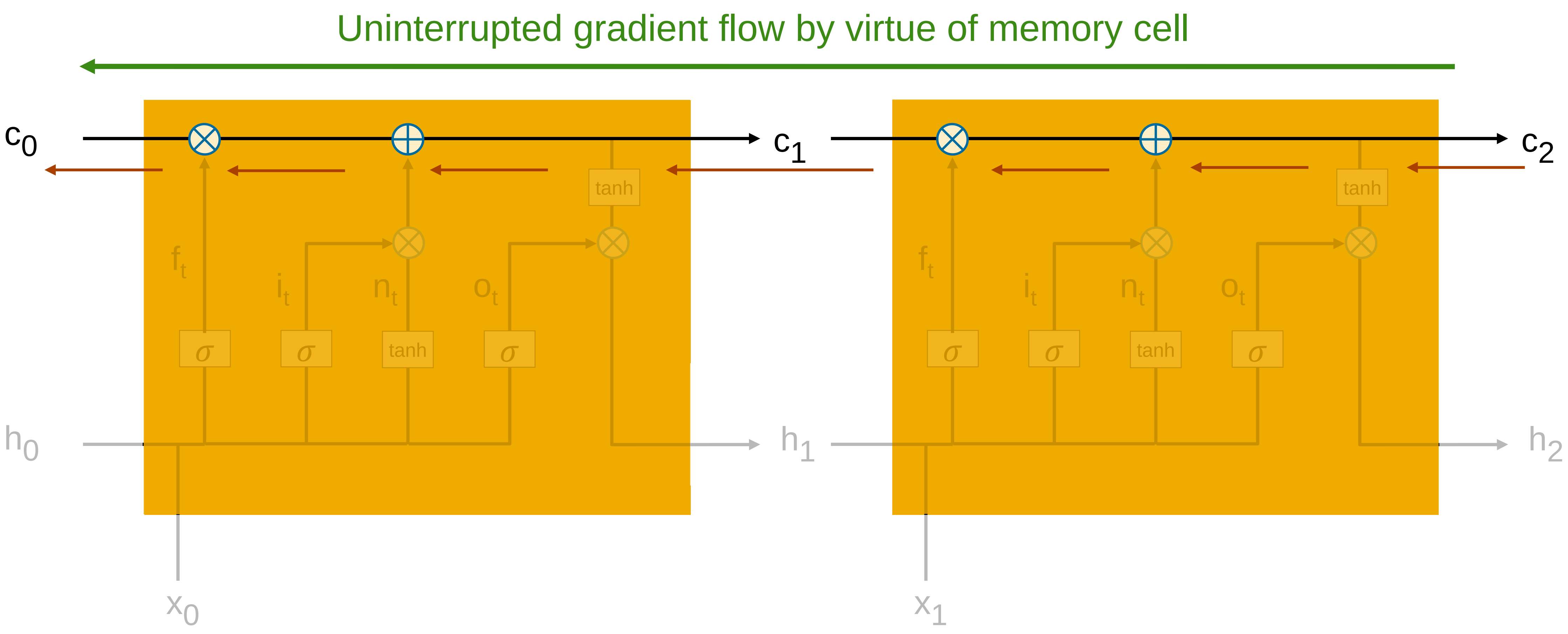
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * tanh(c_t)$$

- Computation of new short-term information
- Since c_t is unbounded, we again bound it with an activation function, in this case tanh
- **o_t** acts as an **output regulator**
- It decides what fraction of long-term information is considered for generating current working memory

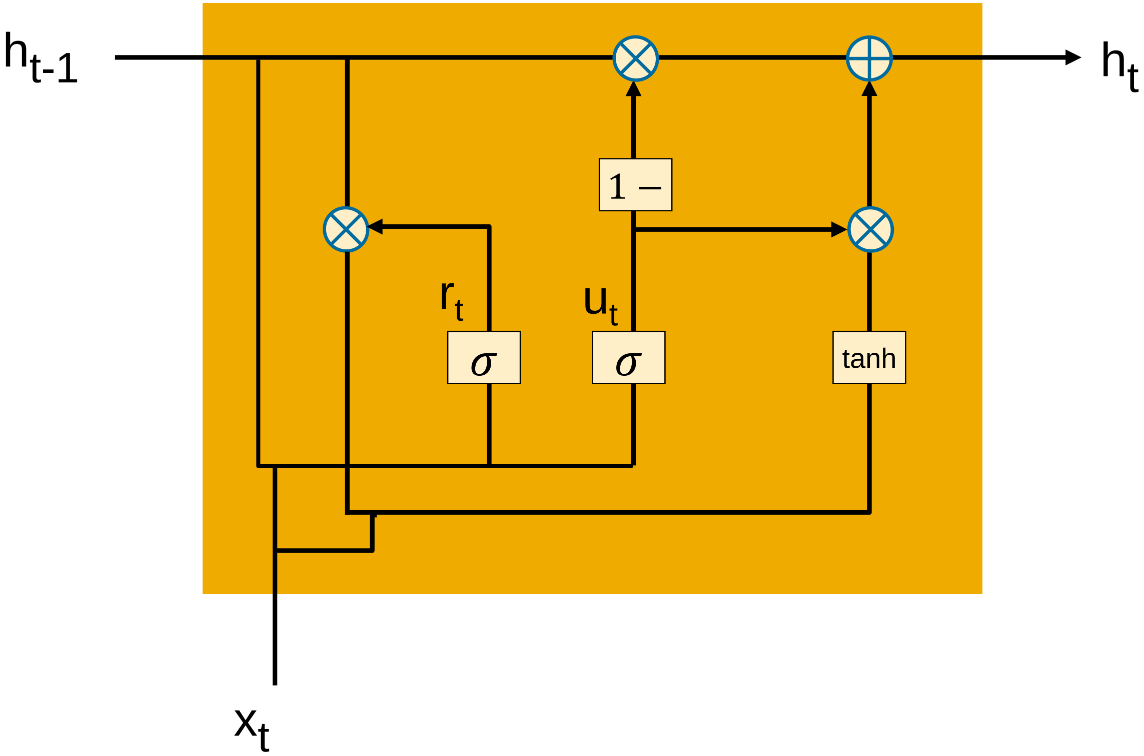
Introduction to LSTM, GRU

LSTM cell structure and the vanishing gradient



Introduction to LSTM, GRU

Gated recurrent unit (GRU) – Another variant of RNN



- Simplifies the standard LSTM cell
- Combines forget and input gate

$$u_t = \sigma(W_u[h_{t-1}, x_t])$$

$$r_t = \sigma(W_r[h_{t-1}, x_t])$$

$$n_t = tanh(W_r[h_{t-1}, x_t]\, r_t)$$

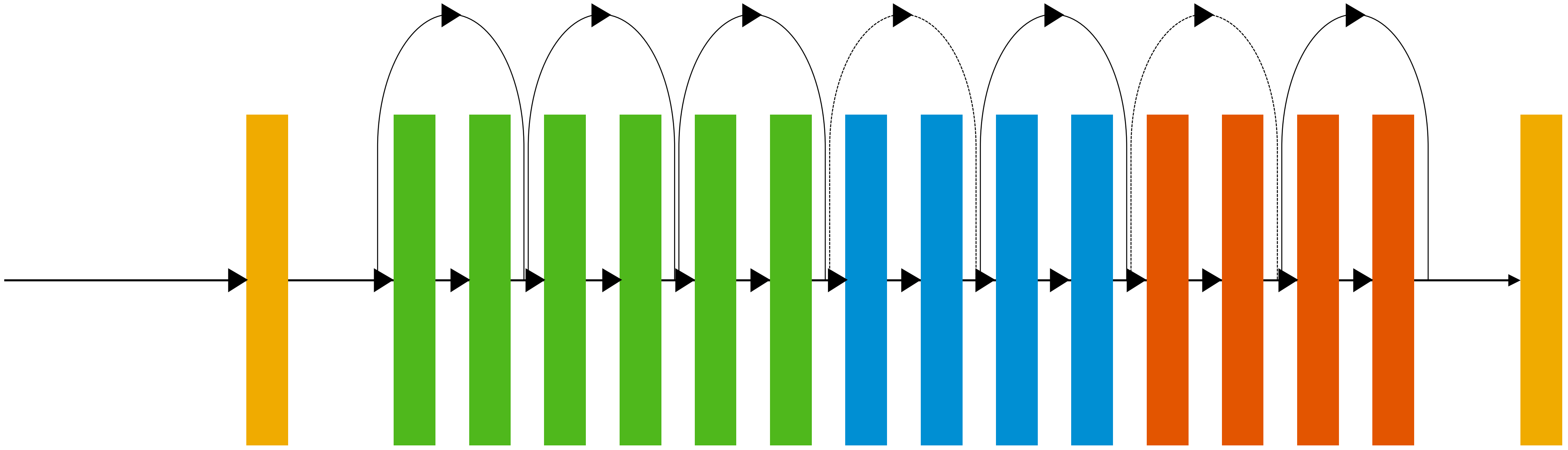
$$h_t = u_t h_{t-1} + (1-u_t)\, n_t$$

- r_t **regulates** the information in previous state
- u_t **regulates** the new information and forgettable information simultaneously

GRU: Junyoung Chung Caglar Gulcehre, KyungHyun Cho, Yoshua Bengio *(Dec, 2014). Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling.*

Introduction to LSTM, GRU

Vanilla LSTM cell structure



A similar idea is used in other state-of-the-art networks like ResNet

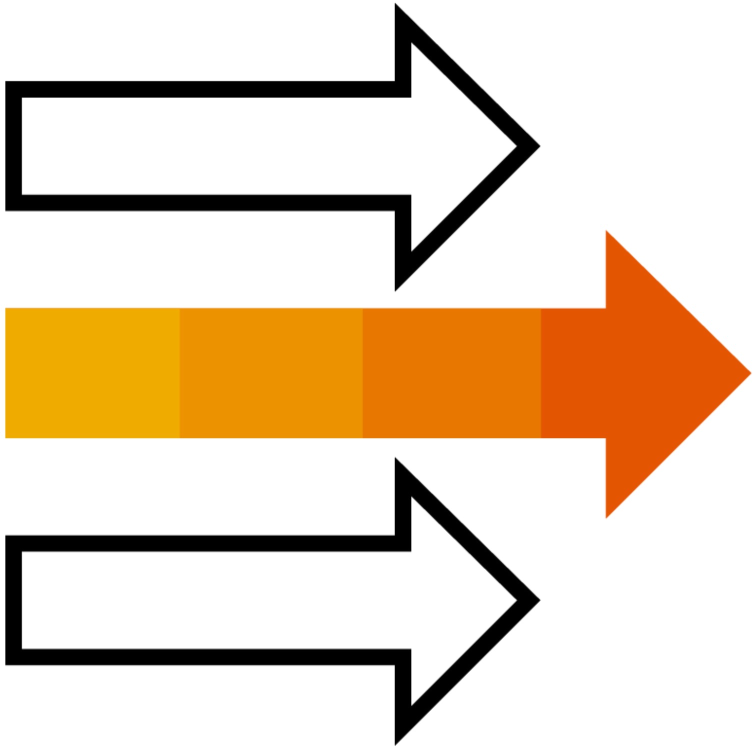
ResNet: Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun *(Dec, 2015). Deep Residual Learning for Image Recognition.*

Introduction to LSTM, GRU

Coming up next

Convolutional Networks

- Introduction to CNNs
- CNN architecture
- Accelerating deep CNN training
- Applications of CNNs



Thank you.

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