RNN: recurrent neural networks (part 2)

More advance stuff: for the very brave (or the very patient!)

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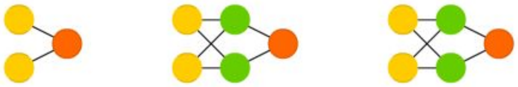

A sip of NLP

RNNs for natural language processing

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NLP: language models

audio sequence (e.g. voice)

newspaper article

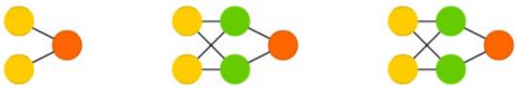
received email

webpage

speech/text recognition

input “x” → model → output “y”

: what was written/said/recorded in the input text?



NLP: language models

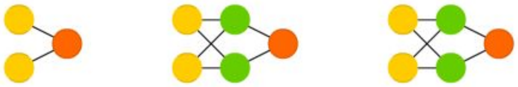
Speech recognition:

- The red dear is a ruminant
- The red deer is a ruminant

P(The red dear is a ruminant) =

P(The red deer is a ruminant) =

The objective of a language model is to estimate the probabilities of all sentences in a large corpus of text data



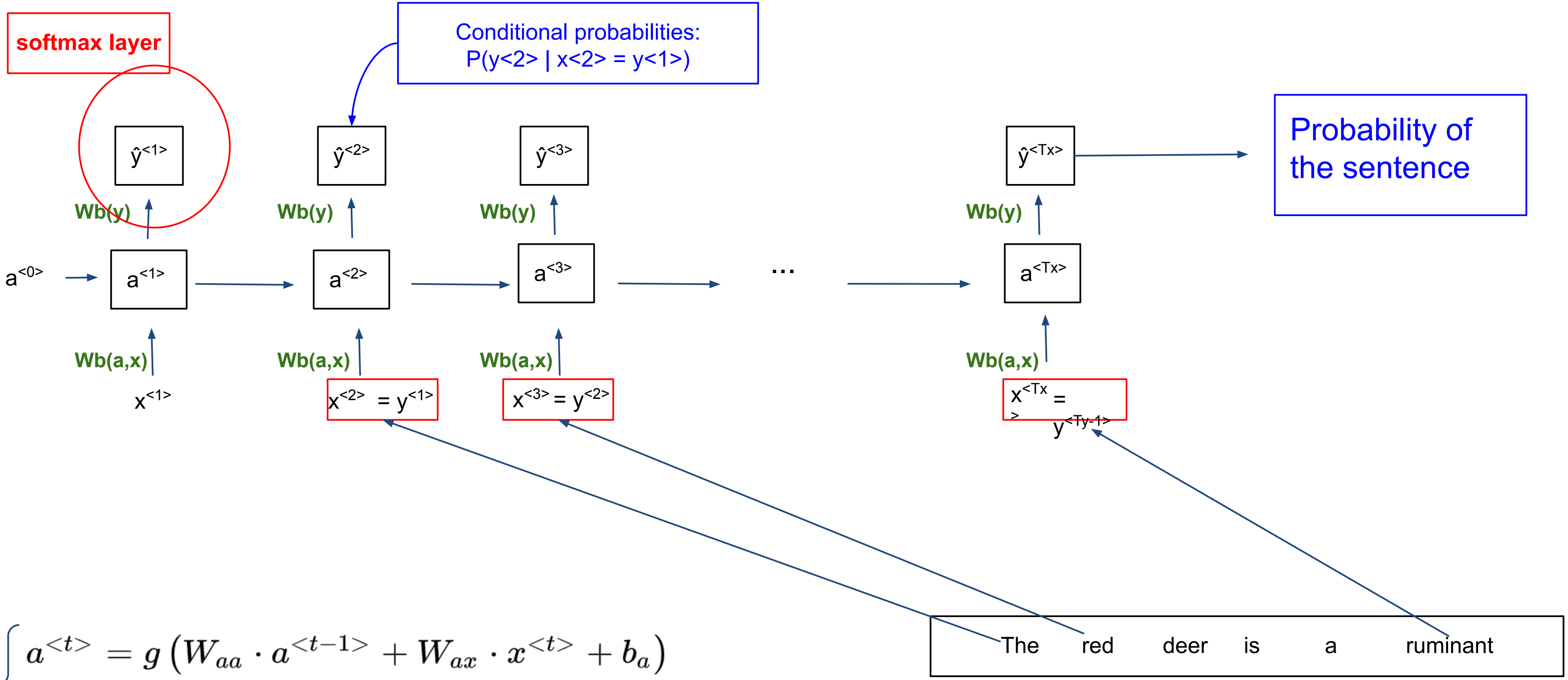
RNN models for speech/text recognition

1. **Training set**: large corpus of English texts
2. **Input text/speech**: e.g. “The red deer is a ruminant”
3. **Tokenization**: split the text in tokens (words)

The	red	deer	is	a	ruminant

Target sentence (training set) whose probability we want to model

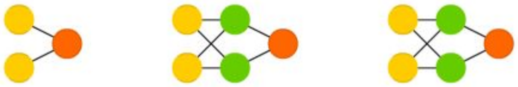
RNN models for speech/text recognition



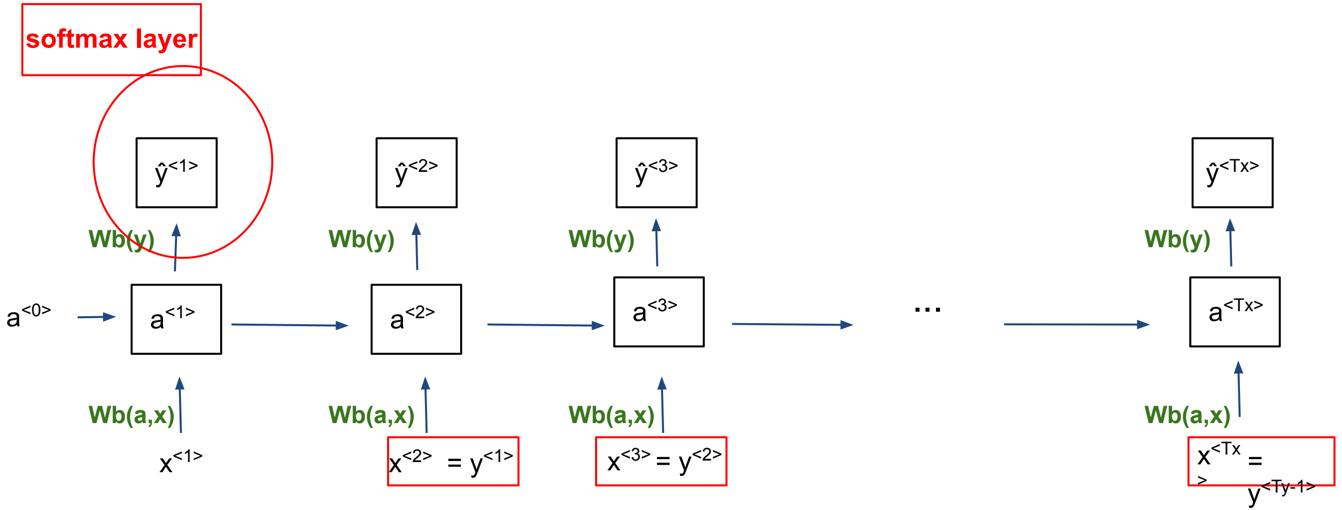
$$\begin{cases} a^{<t>} = g\left(W_{aa} \cdot a^{<t-1>} + W_{ax} \cdot x^{<t>} + b_a\right) \\ \hat{y}^{<t>} = g\left(W_{ya} \cdot a^{<t>} + b_y\right) \end{cases}$$

RNN models for speech/text recognition

- in each step, the layer will take some set of the preceding words (directly or through activation) and will calculate the conditional probability of the next word
- the RNN thus learns one word at a time, from left to right, until the probability of the input sentence is calculated
- this is then replicated for all sentences in the large corpus of text data → **LLM**
- this will take a lot of resources to train (CPU time, input data, memory storage)
- however, after training the RNN on a large set of text data, the RNN will be able to calculate the probability of a new sentence: $\mathbf{P(y^{<1>}, y^{<2>}, y^{<3>}) = P(y^{<1>}) * P(y^{<2>} \mid y^{<1>}) * P(y^{<3>} \mid y^{<1>}, y^{<2>})}$



RNN models for speech rec. - loss function



$$\begin{cases} \mathcal{L}(\hat{y}^{<t>}, y^{<t>}) = -\sum_i y_i^{<t>} \cdot \log(\hat{y}_i^{<t>}) \\ L = \sum_t \mathcal{L}^{<t>}(\hat{y}^{<t>}, y^{<t>}) \end{cases}$$

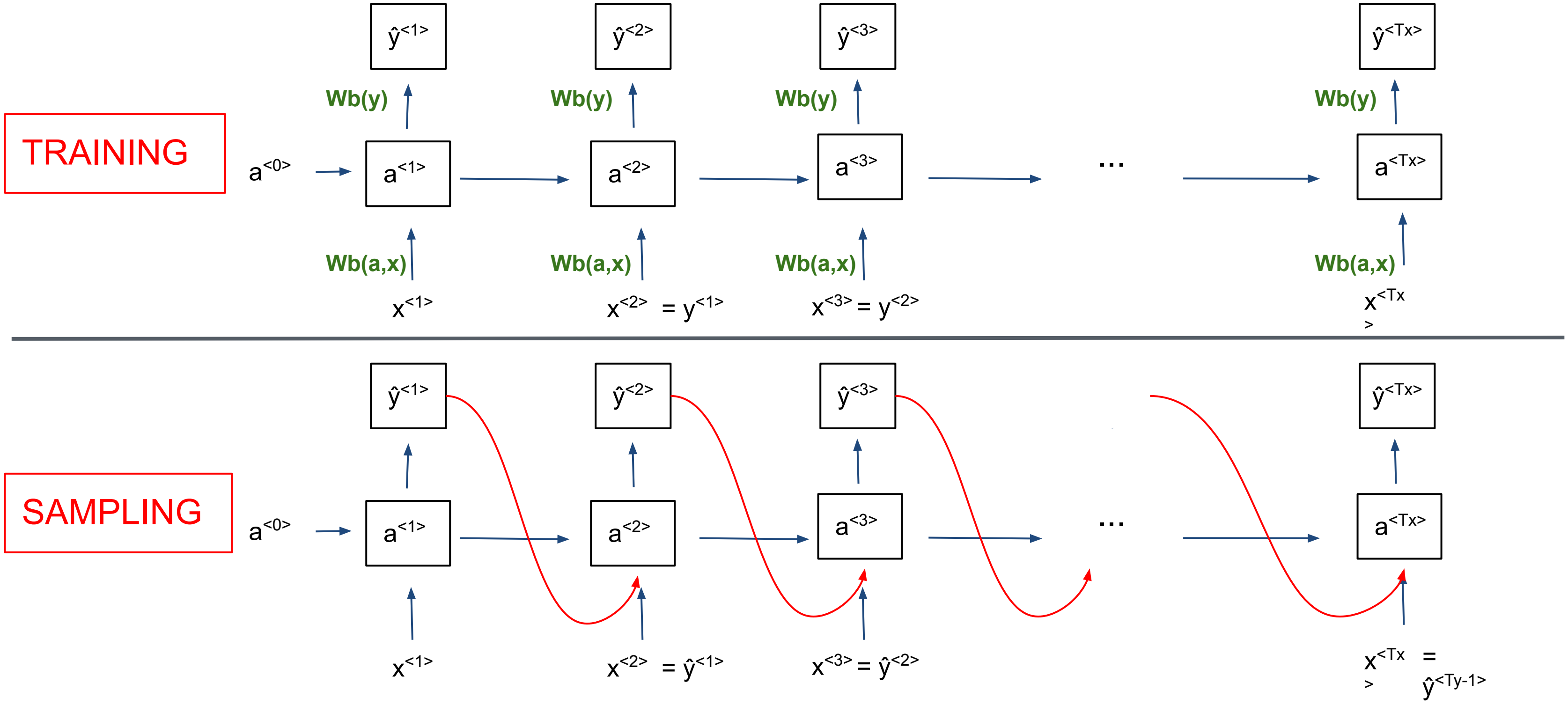
(softamx loss function)

We need to calculate the probability of a very large number of “classes” →softmax!

Trained RNN for sequence models

- speech recognition, machine translation, sequence generation → examples of **sequence models**
- we saw how to **train a RNN for a sequence model**: architecture, loss, trained output (conditional probabilities of sequences of words)
- with a **trained sequence model** you can then **sample new sequences** (e.g. sequence/text generation)

Sampling new sequences from a trained RNN



Sampling new sequences from a trained RNN

- sampling words
- sampling characters from the alphabet (sequence of characters/letters instead of words):
  - no worries about unknown word tokens, UNK (→ sequences of characters with zero prob.)
  - much longer sequences → not good at capturing relationships between early parts and later parts of the sequence
  - more computationally expensive
- music notes

Generating text: early examples

News

President enrique peña nieto, announced sench's sulk former coming football langston paring.

"I was not at all surprised," said hich langston.

"Concussion epidemic", to be examined.

The gray football the told some and this has on the uefa icon, should money as.

Shakespeare

The mortal moon hath her eclipse in love.

And subject of this thou art another this fold.

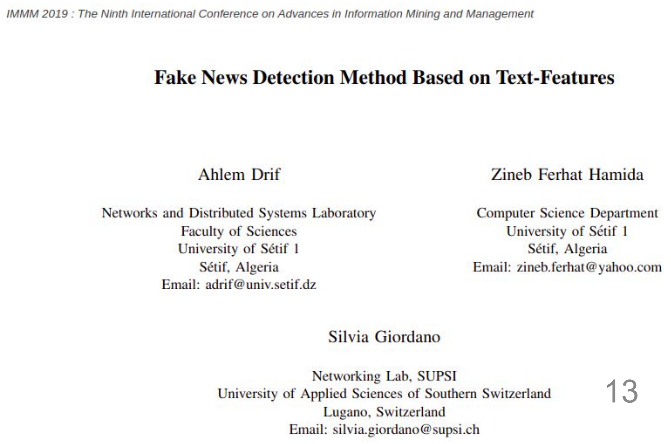
When besser be my love to me see sabl's.

For whose are ruse of mine eyes heaves.

From Andrew Ng

Generating text

- there are much more sophisticated RNN models for text generation:
  - https://www.theguardian.com/commentisfree/2020/sep/08/robot-wrote-this-article-gpt-3
  - The A.I. Tribune
- also applications to detect fake news
  - "Fake news detection: A hybrid CNN-RNN based deep learning approach", *Nasir, Khan and Varlamis, 2021*
- and now, the current LLMs explosion (ChatGPT etc.)


IMMM 2019 : The Ninth International Conference on Advances in Information Mining and Management

Fake News Detection Method Based on Text-Features

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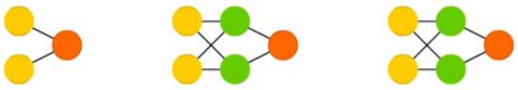

Vanishing gradients

A problem of memory loss

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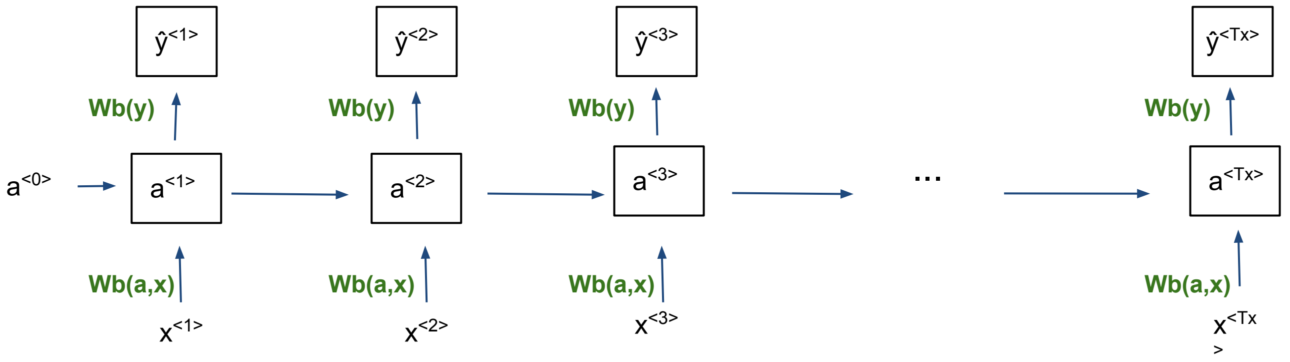
Vanishing gradients with basic RNN

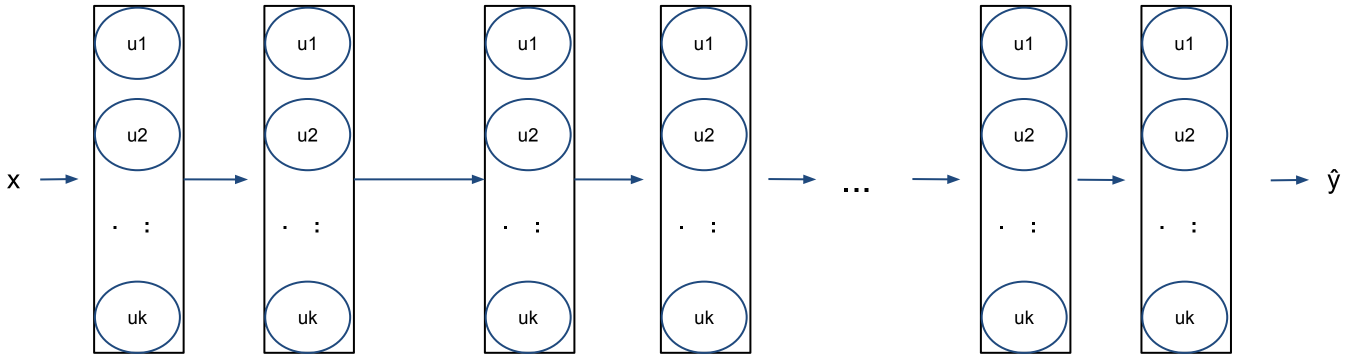
The red deer, living in the woods, grazing on ... and mating during … at temperate latitudes … is a ruminant
The red deers, living in the woods, grazing on ... and mating during … at temperate latitudes … are ruminants

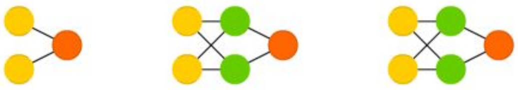


The basic RNN model is not good at capturing **distant relationships** in the sequence

Vanishing gradients with basic RNN

- problem with very deep NNs (and **RNNs are very very deep NNs**!)
- in a deep NN backprop has difficulties to have an effect on the early layers of the network (won't affect the weights) → **loss of memory!**





Why do gradients vanish?

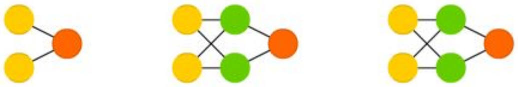
Some basic intuition:

- a deep NN can be thought of as a series of matrix products;
- simplifying further:

$$\mathbf{W}^L \quad \text{(with L = n. of layers)}$$

- when you combine many features (x_i), the coefficients (weights) will tend (have) to be small:

$$\mathbf{w_1 * x_1 + w_2 * x_2 \ldots w_m * x_m} \quad \text{(with m = n. of features)}$$



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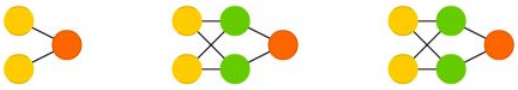
many small weights (-1 < w < 1), **many layers** (exponent) → **vanishing gradients**



Gated Recurrent Unit (GRU)

Memory pills!

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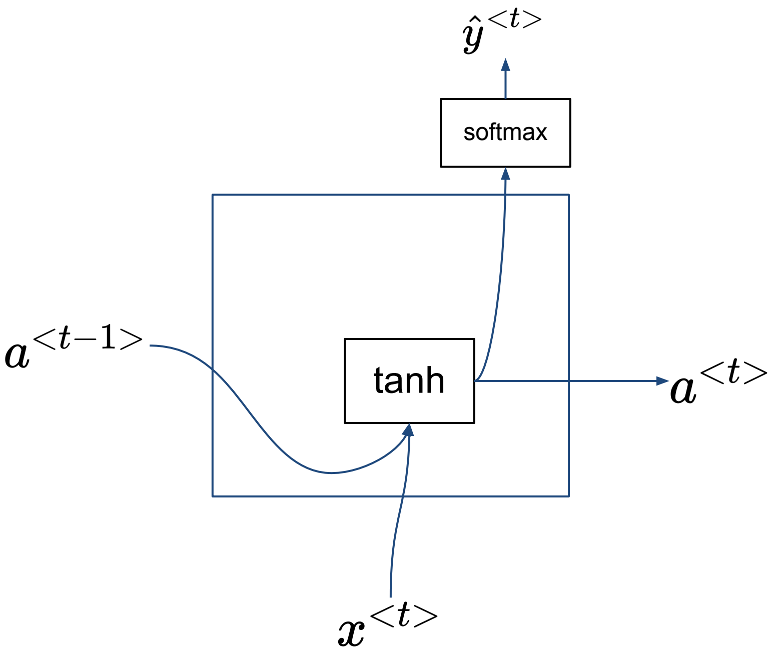
RNN unit



$$
\begin{cases}
a^{<t>} = g\left(W_{aa} \cdot a^{<t-1>} + W_{ax} \cdot x^{<t>} + b_a\right) \\
\hat{y}^{<t>} = g\left(W_{ya} \cdot a^{<t>} + b_y\right)
\end{cases}
$$

RNN unit - GRU (gated recurrent unit)

c = memory cell (e.g. remember deer/deers)

$$c^{<t>} = a^{<t>}$$

[update or not update?]

$$\tilde{c}^{<t>} = \tanh\left(W_{cc} \cdot c^{<t-1>} + W_{cx} \cdot x^{<t>} + b_c\right)$$

<u>Introducing the gate</u>

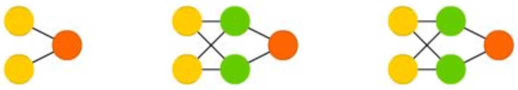
$$\Gamma_u = \sigma\left(W_{uu} \cdot c^{<t-1>} + W_{ux} \cdot x^{<t>} + b_u\right)$$

RNN unit - GRU (gated recurrent unit)

- in a GRU unit we calculate a value $\mathbf{c}^{\sim<t>}$
- we may then potentially **update** the value in the memory cell by replacing $\mathbf{c}^{<t>}$ **with** $\mathbf{c}^{\sim<t>}$
- the value of the **gate** $\boldsymbol{\Gamma}_{\mathbf{u}}$ will decide whether or not $\mathbf{c}^{<t>}$ will be updated

This is the key part of GRU!

The red deer, living in the woods, grazing on ... and mating during … at temperate latitudes … is a ruminant



RNN unit - GRU (gated recurrent unit)

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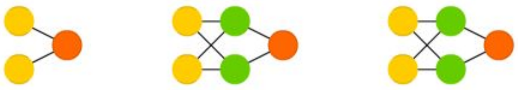
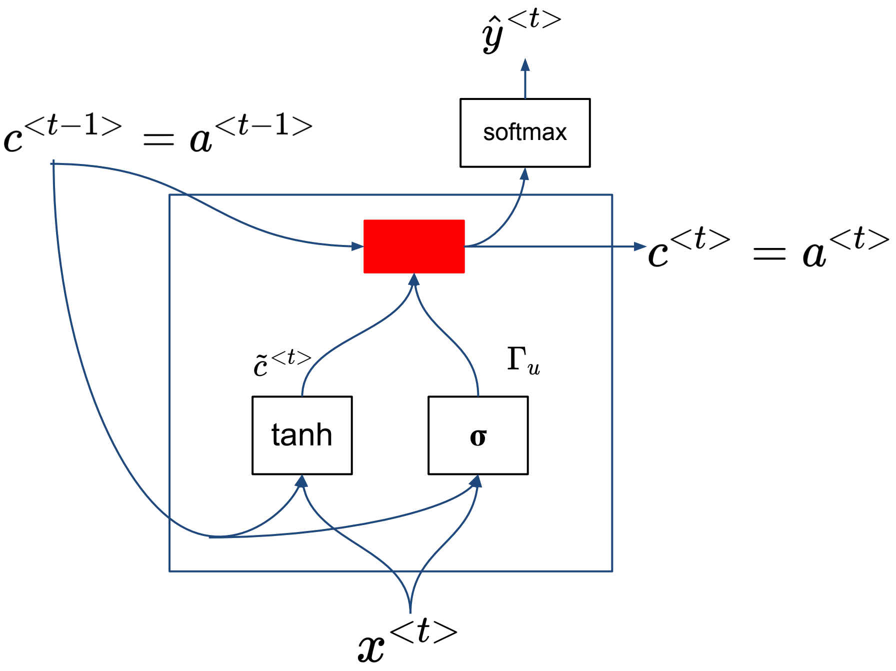
$$\boxed{c^{<t>} = \Gamma_u \cdot \tilde{c}^{<t>} + (1 - \Gamma_u) \cdot c^{<t-1>}}$$

The red deer, living in the woods, grazing on ... and mating during … at temperate latitudes … is a ruminant



RNN unit - GRU (schematic representation)



c = memory cell (e.g. remember deer/deers)

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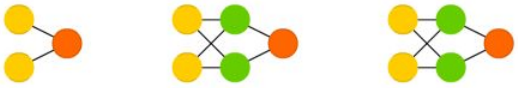
$$\boxed{c^{<t>} = \Gamma_u \cdot \tilde{c}^{<t>} + (1 - \Gamma_u) \cdot c^{<t-1>}}$$

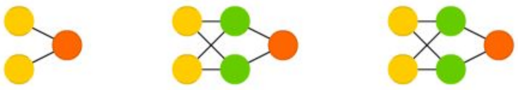
GRU units

- good at learning when to update $c^{<t>}$ and then keep it constant until used
- Γ_u very close to zero → $c^{<t>} \approx c^{<t-1>}$ across many layers → reduced problems with vanishing gradients (intuition: GRU reduces the number of matrix multiplications through the network - if needed)
- GRU units / layers can learn long-range dependencies in sequences
- $c^{<t>}$ can be a vector (usually is) → multiple memory cells to “remember” multiple things (e.g. singular/plural, past/present, context etc.)
- full GRU units are more complex and include one additional gate (reset), i.e. Γ_r for the relevance (weight) of elements in the sequence (Γ_r would be used in the calculation of $c^{\sim<t>}$, the candidate replacement for $c^{<t>}$
- by balancing the reset and update gates GRUs capture short-term and long-term dependencies in the sequence



DNN units

GRU unit: were we doing linear regression inside this unit?



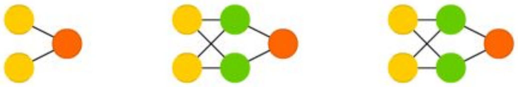
DNN units

GRU unit: were we doing linear regression inside this unit? → **NO!**

- Dense layers: “linear regression”
- CNN layers: convolutions
- Simple RNN: linear combination of the features + activations ”from the past”
- RNN+GRU layers: gate/relevance/update calculations
- RNN+LSTM: (we’ll see in a while)
- etc.

<u>With DNN you need</u>:

- “invent” some calculations
- repeat it thousands of times
- let the NN learn the parameters
- and … “bam”, the job is done! ;-)



Long-Short Term Memory (LSTM) Unit

More memory pills!

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GRU unit vs LSTM unit

$$\tilde{c}^{<t>} = \tanh\left(W_c[\Gamma_r \cdot c^{<t-1>}, x^{<t>}] + b_c\right)$$

$$\Gamma_u = \sigma\left(W_{uu} \cdot c^{<t-1>} + W_{ux} \cdot x^{<t>} + b_u\right)$$

$$\Gamma_r = \sigma\left(W_{rr} \cdot c^{<t-1>} + W_{rx} \cdot x^{<t>} + b_r\right)$$

$$c^{<t>} = \Gamma_u \cdot \tilde{c}^{<t>} + (1 - \Gamma_u) \cdot c^{<t-1>}$$

$$a^{<t>} = c^{<t>}$$

$$\tilde{c}^{<t>} = \tanh\left(W_c[a^{<t-1>}, x^{<t>}] + b_c\right)$$

$$\Gamma_u = \sigma\left(W_{uu} \cdot a^{<t-1>} + W_{ux} \cdot x^{<t>} + b_u\right)$$

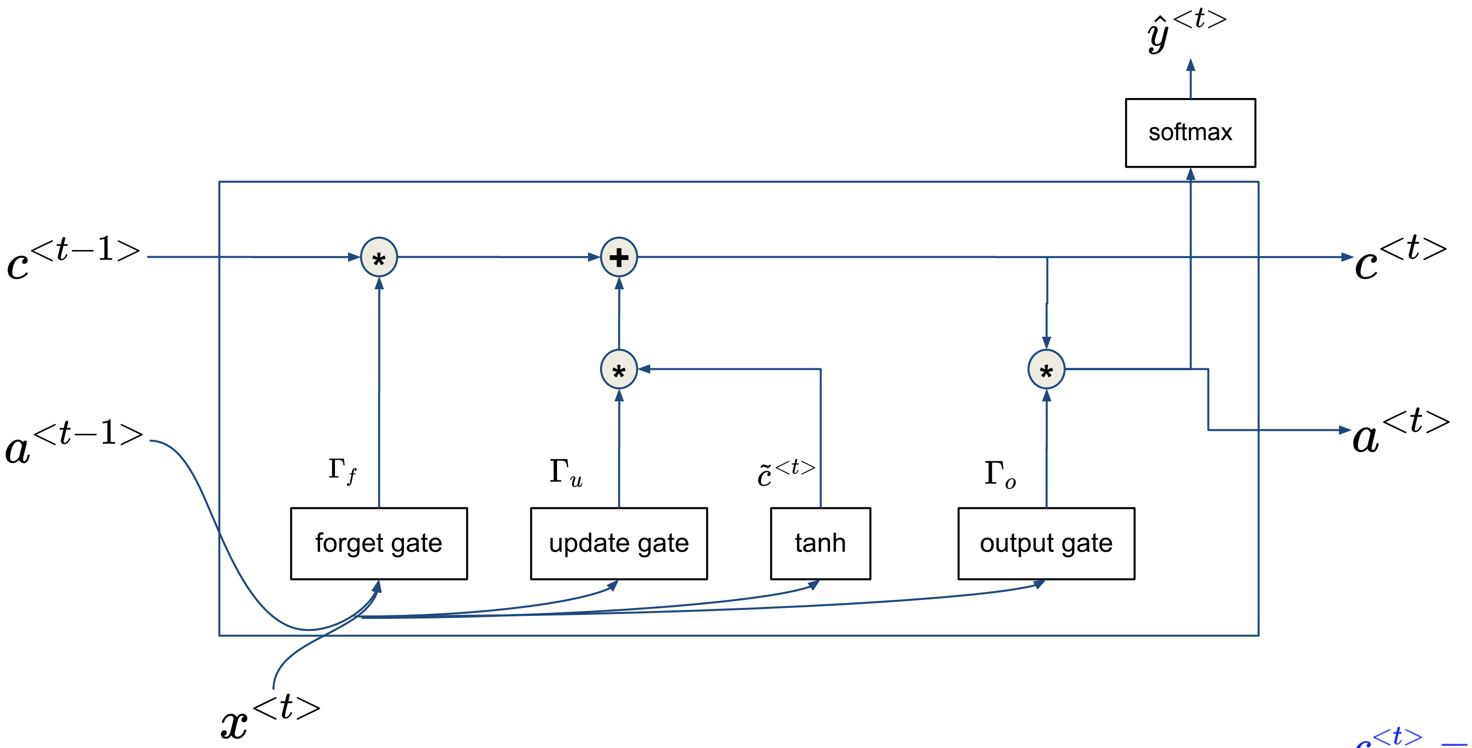
$$\Gamma_f = \sigma\left(W_{ff} \cdot a^{<t-1>} + W_{fx} \cdot x^{<t>} + b_f\right)$$

$$\Gamma_o = \sigma\left(W_{oo} \cdot a^{<t-1>} + W_{ox} \cdot x^{<t>} + b_o\right)$$

$$c^{<t>} = \Gamma_u \cdot \tilde{c}^{<t>} + \Gamma_f \cdot c^{<t-1>}$$

$$a^{<t>} = \Gamma_o \cdot \tanh(c^{<t>})$$

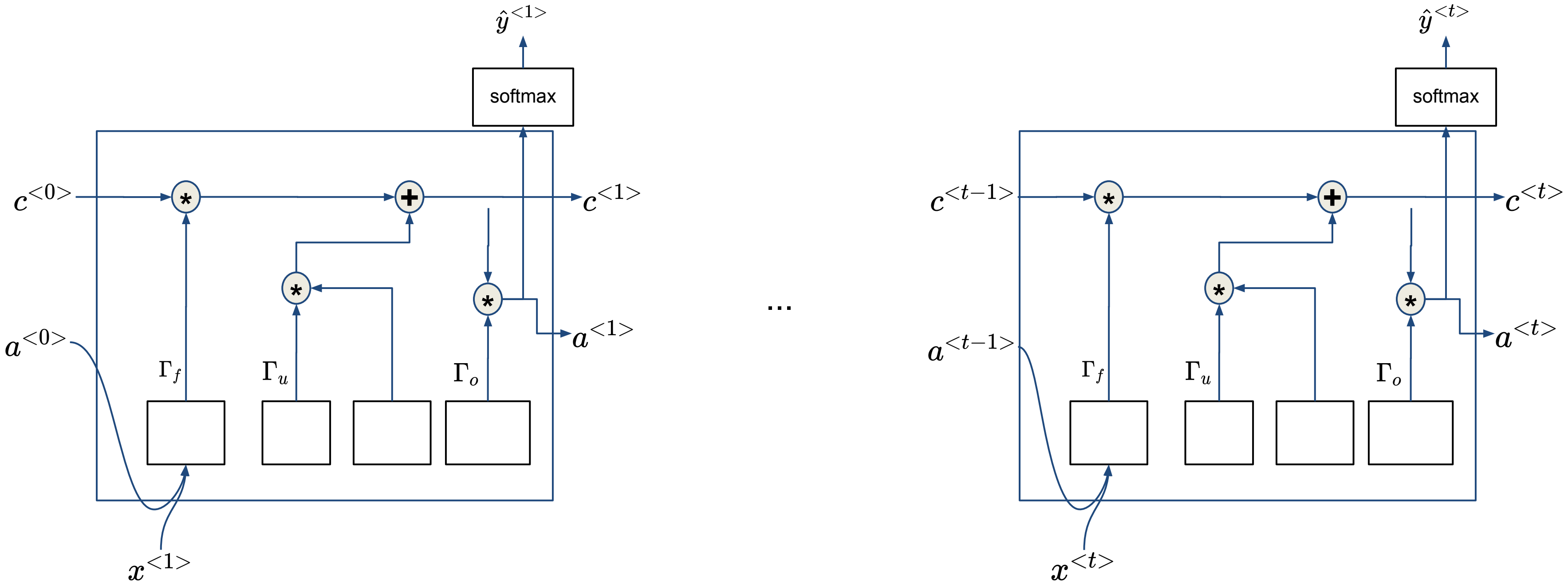
LSTM unit - schematic representation



$$c^{<t>} = \Gamma_u \cdot \tilde{c}^{<t>} + \Gamma_f \cdot c^{<t-1>}$$

$$a^{<t>} = \Gamma_o \cdot \tanh(c^{<t>})$$

LSTM units: with the memory flow



LSTM vs GRU - take #2

- LSTM (introduced in 1997): pass memory info (cell state) alongside (but separately) the hidden state (activation)
- GRU (introduced in 2014): gets rid of cell state, and pass memory info intermingled with the activation (hidden state)
- GRU perform fewer tensor operations → fewer parameters, faster calculations
- We showed GRU before LSTM for illustration purposes (GRU simpler to explain)

Bidirectional RNN

Back from the future!

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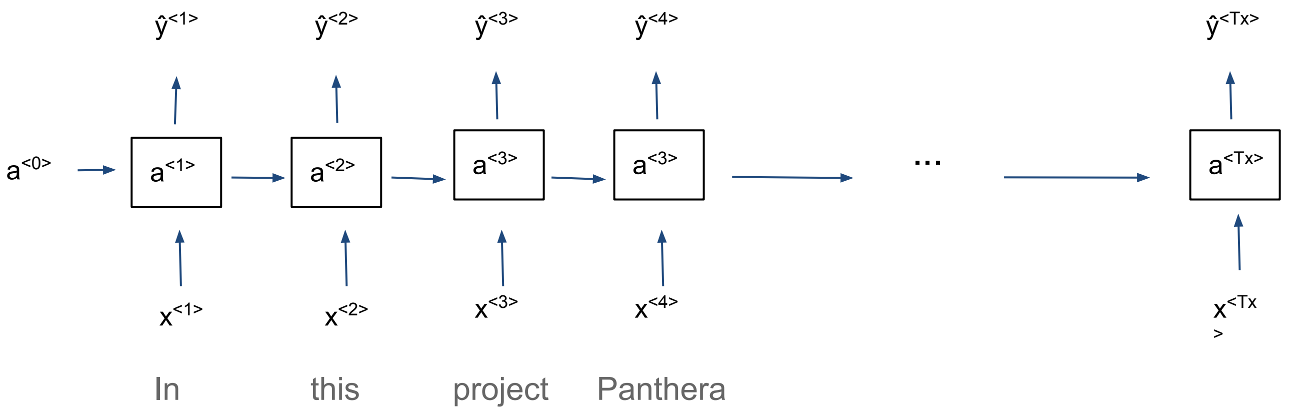
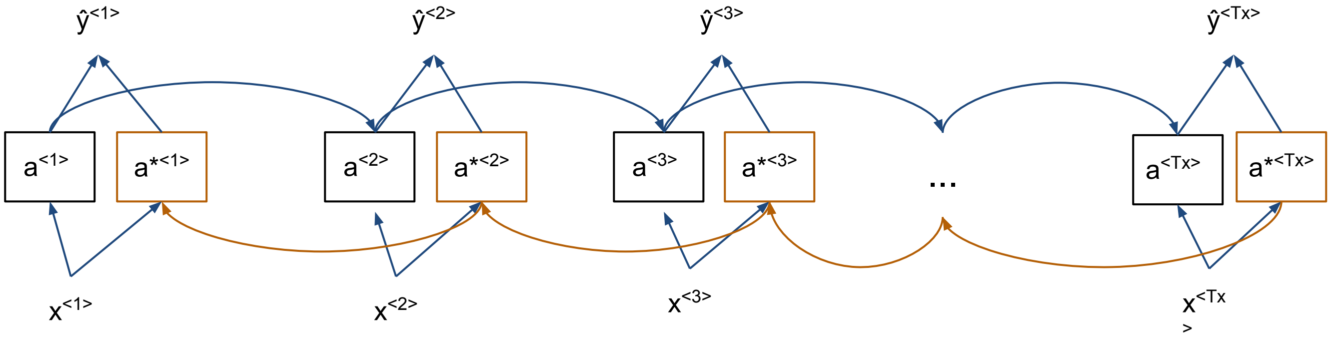
Using information from the “future”

“In this project Panthera leo samples are used”

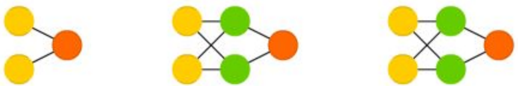
“In this project Panthera Corporation is the leading partner”



Using information from the "future"



- acyclic graph
- the **forward sequence** starts from $a^{<1>}$ … to $a^{<Tx>}$ (as usual)
- the **backward sequence** will begin from the end ($a^{*<Tx>}$) and move from right to left



Pros and cons of bidirectional RNN

- uses information from past, present and future (early and late parts of the sequence)
- making predictions anywhere in the middle of a sequence
- bidirectional RNN + LSTM units → common choice in NLP problems

- you need to process the entire sequence before making predictions (e.g. in speech recognition you need to wait for the person to finish talking) [→ more sophisticated models are needed]
- computationally expensive

Deep RNN

Not complex enough? Let's stack RNN layers!

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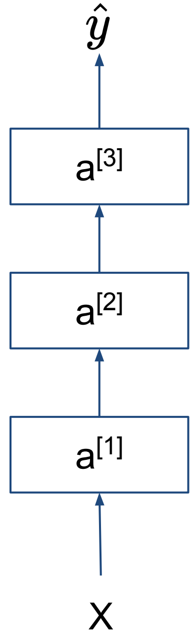
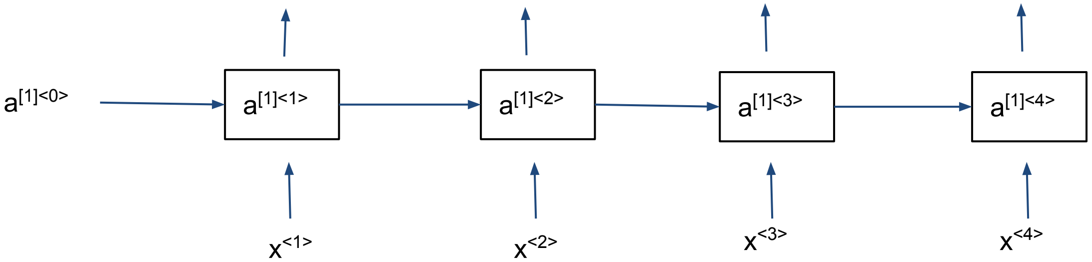
Deep RNN

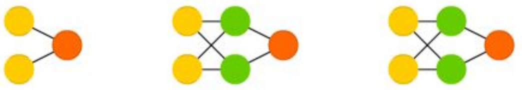
Standard multilayer NN



Basic RNN model

- <t>: time dimension (each element of the sequence) → units inside (standard, GRU, LSTM: multiple units/nodes per <t>)
- [l]: layers (stack of RNN layers)

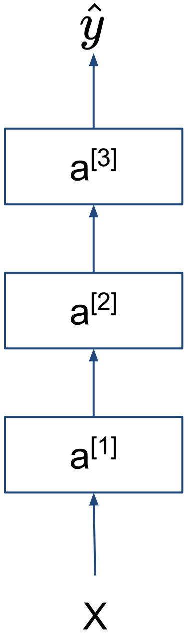


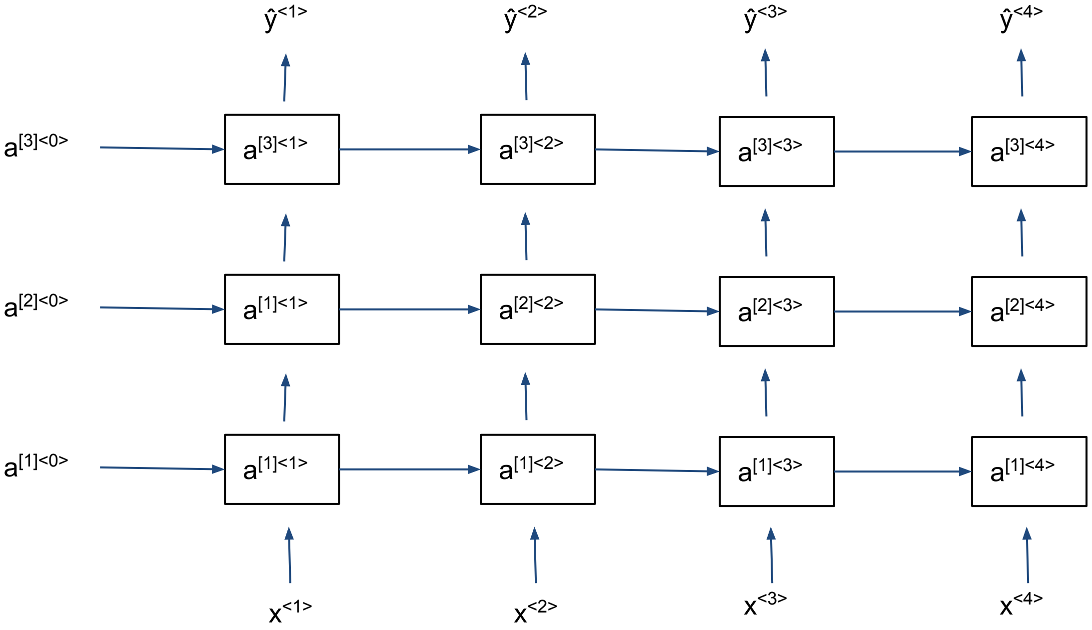


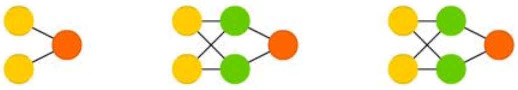
Deep RNN

Multilayer RNN model

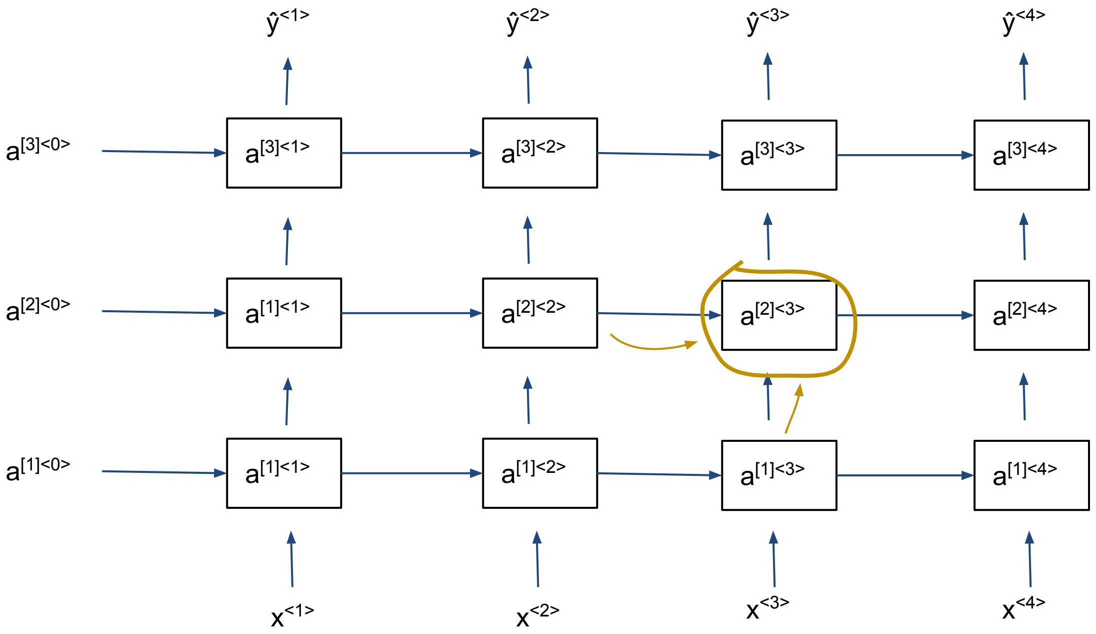
Standard multilayer NN







Deep RNN - example calculation



From basic RNN models

$$a^{<t>} = g\left(W_a[a^{<t-1>}, x^{<t>}] + b_a\right)$$

RNN models

- demonstration

  → day4_code02 RNN-1 architectures.ipynb (GRU, LSTM layers)

  → day5_code02 RNN-2 architectures.ipynb (advanced forecasting)

  → day5_code03 RNN-3 text-sequence-data.ipynb