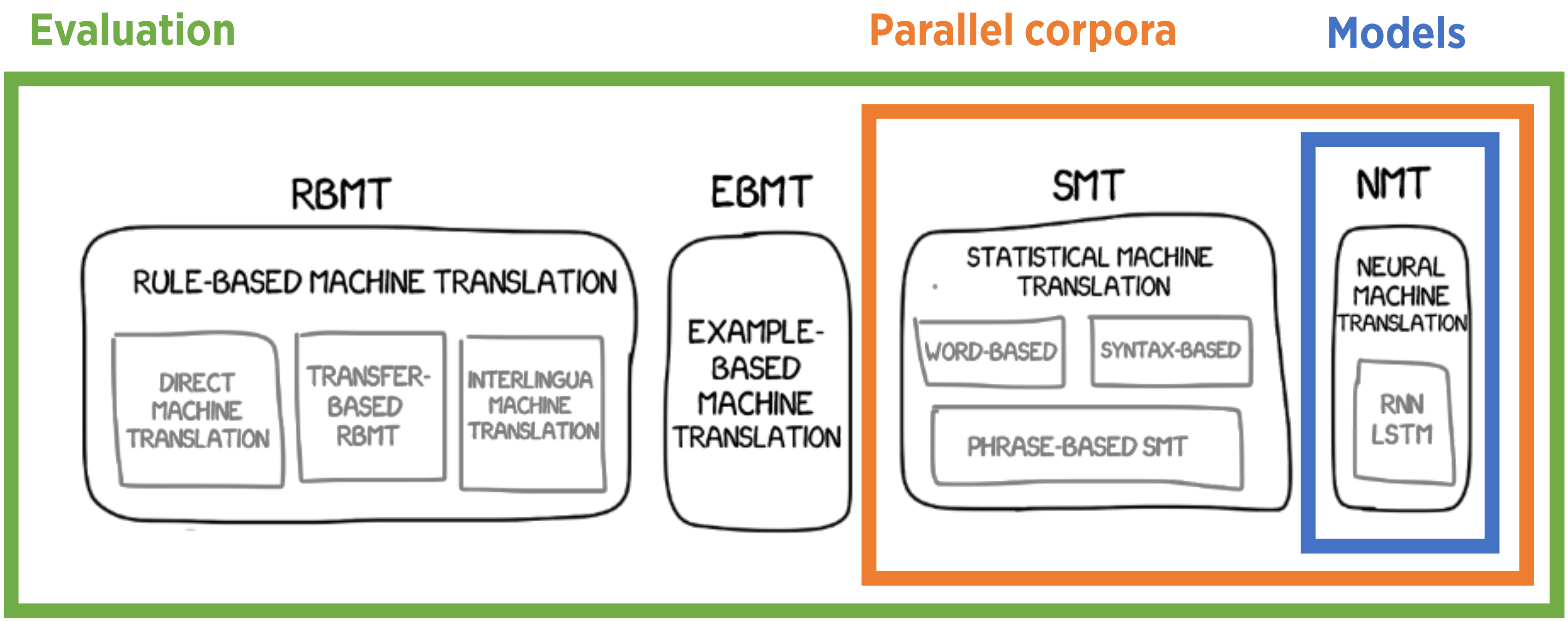
Machine Translation

Session 5: Neural Networks

Sharid Loáiciga — May 20th 2020

Slides credits: Yves Scherrer



Today: A crash course in neural networks…

Linear models

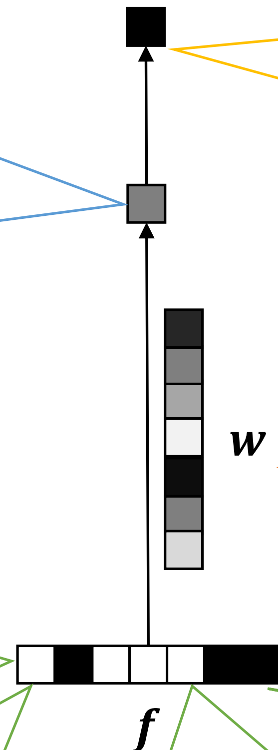
- Example: Determine if a word has negative sentiment

3. Compute a score S according to the following formula:

$$S(x) = \sum_{i=0}^{n} w_i \cdot f_i(x)$$

4. Apply a threshold function to get a yes/no answer:

$$\hat{y} = \begin{cases} 1, & S(x) \geq 0 \\ 0, & S(x) < 0 \end{cases}$$



2. Get a weight for each feature that tells how important it is for the task.
(Let's assume it is given.)

1. Represent the word as a list of features.
Each feature is on or off.

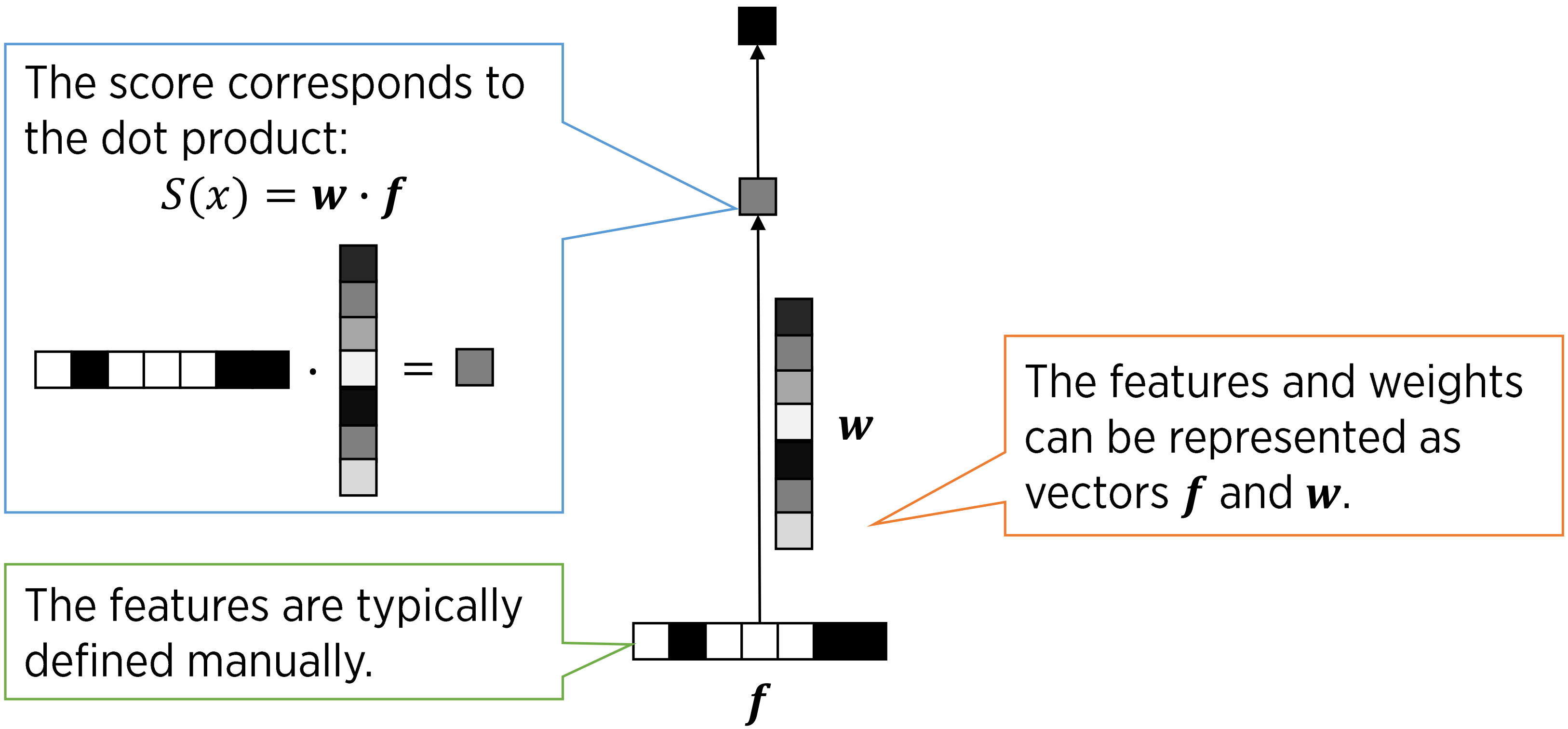
word = 'annoying'

word ends with '-ly'

word contains 'o'

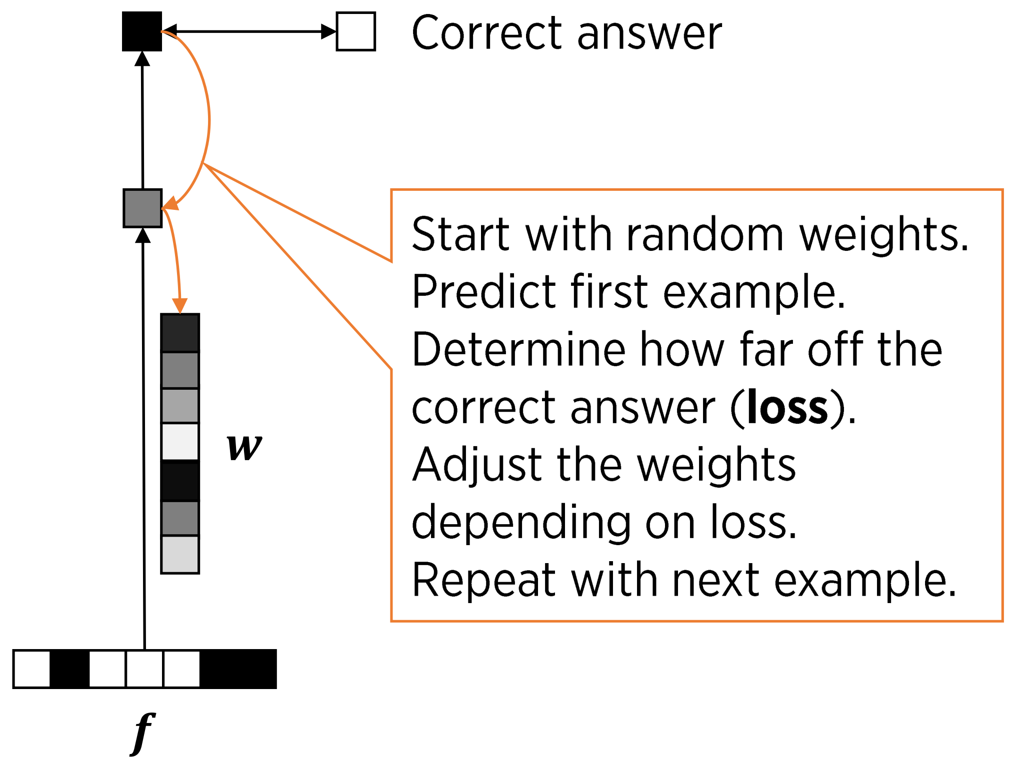
Linear models

- Example: Determine if a word has negative sentiment



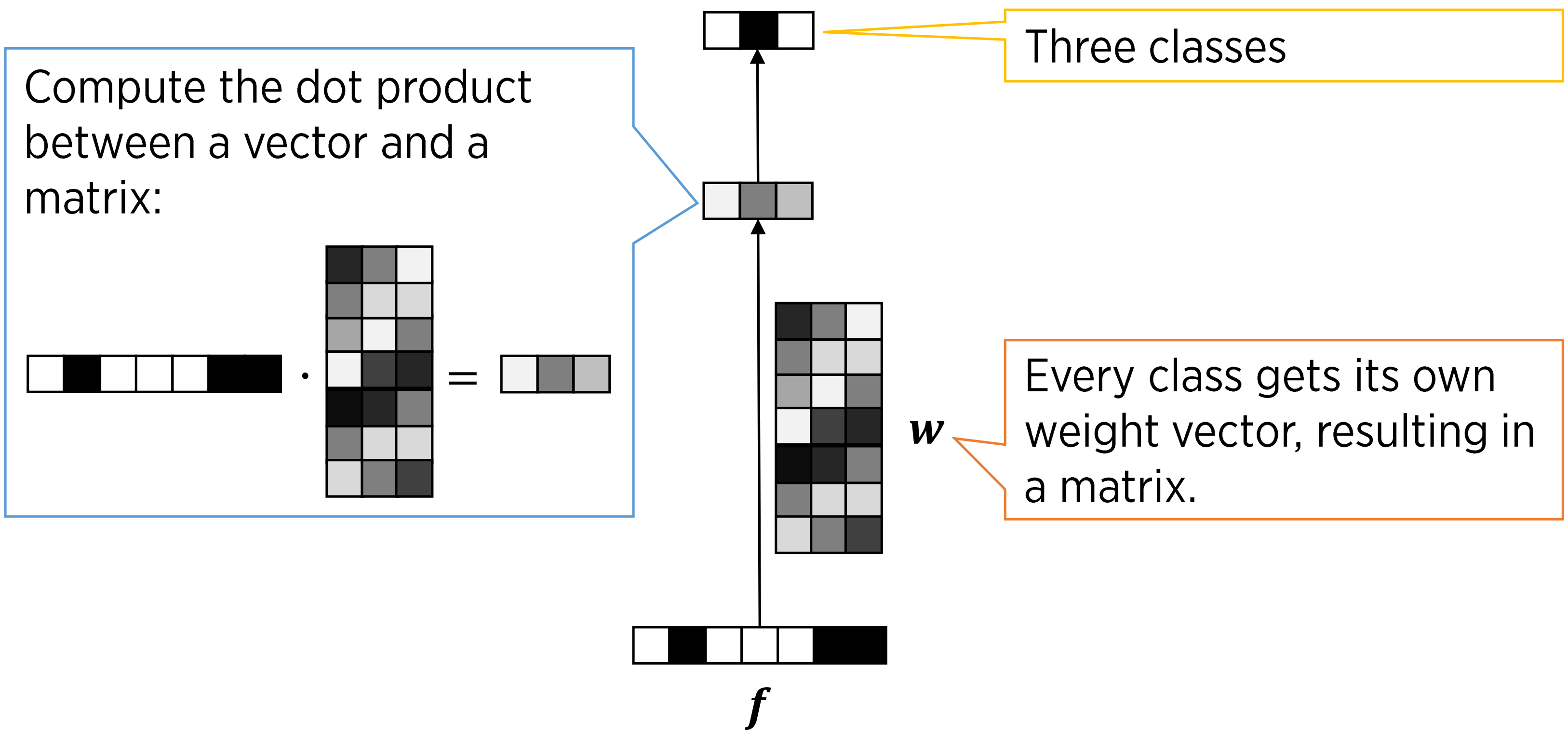
Linear models
Training

- Example: Determine if a word has negative sentiment



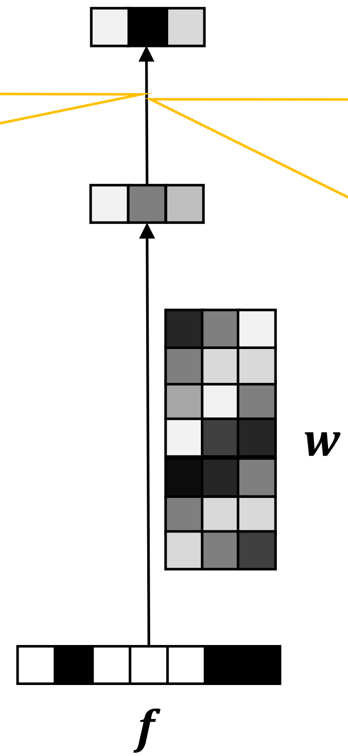
Linear models
Multi-class prediction

- Example: Determine the dominant sentiment of a word



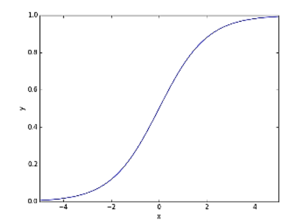
Sigmoid functions

- Example: Determine the dominant sentiment of a word



This part is also called **activation function**.

Threshold functions are not always practical. Use a different type of S-shaped (“sigmoid”) function:

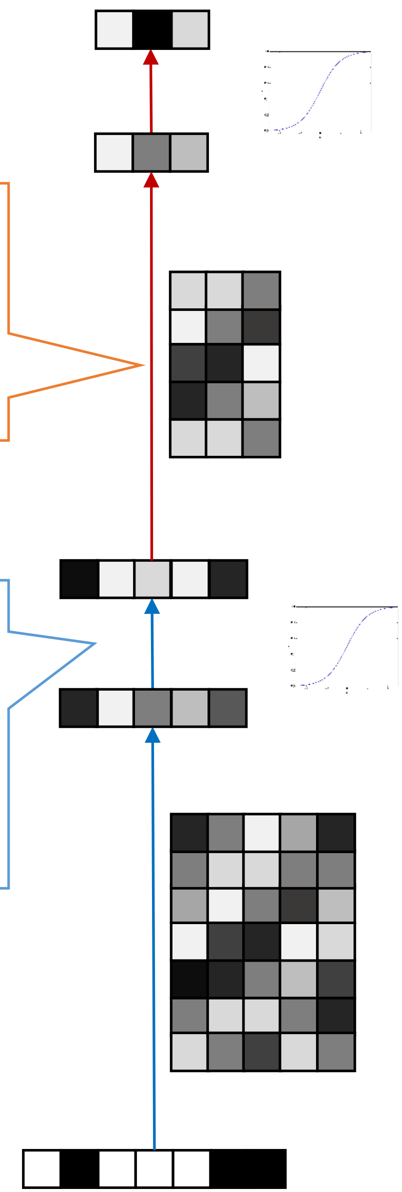


Two-step classification

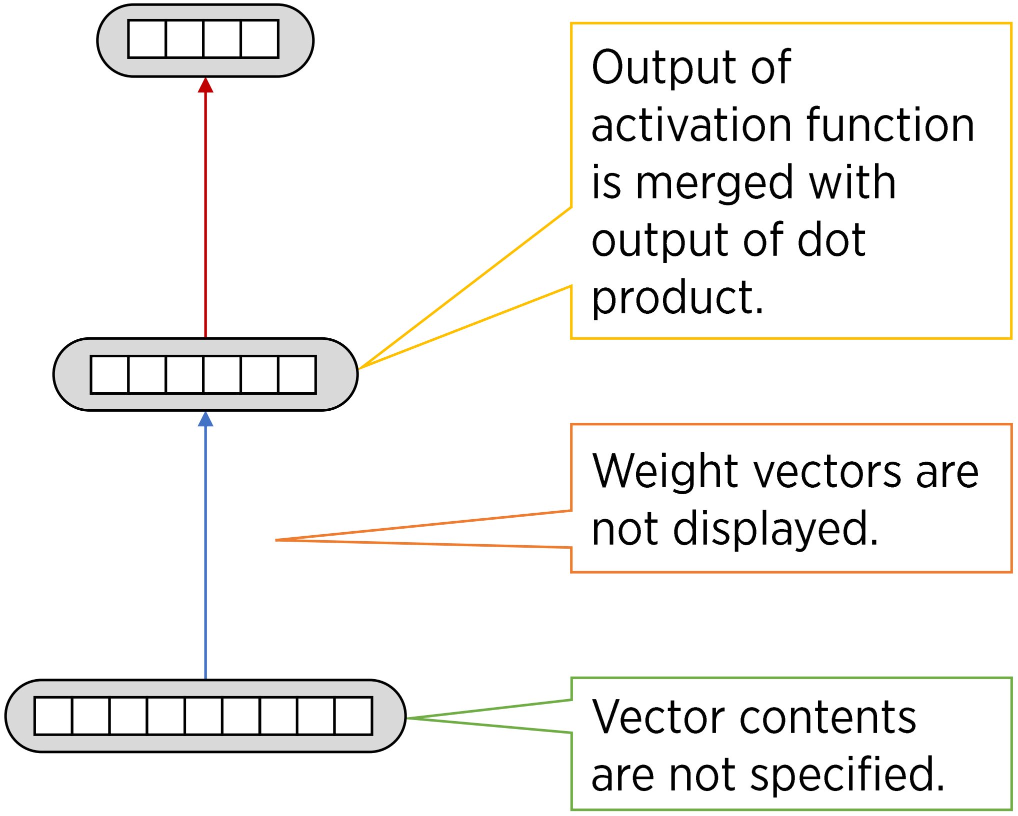
- Idea:
  - Partition the vocabulary into e.g. 100 word classes
  - Base the sentiment decision on the word class
- Let’s use the output of the first model as the input features of the second model

Both weight matrices can be trained in a single pass: **backpropagation**

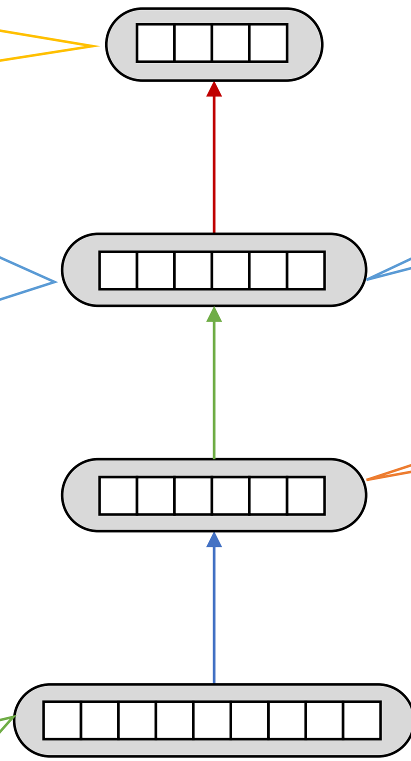
This is a **hidden layer**.
Models with hidden layers are called **neural networks**.



A more compact representation



Neural networks



The size of the prediction vector is defined by the number of classes.

Several hidden layers can be added.
Neural networks with more than one hidden layer are called **deep models**.

The size of the input vector is defined by the number of distinct words in the training corpus.

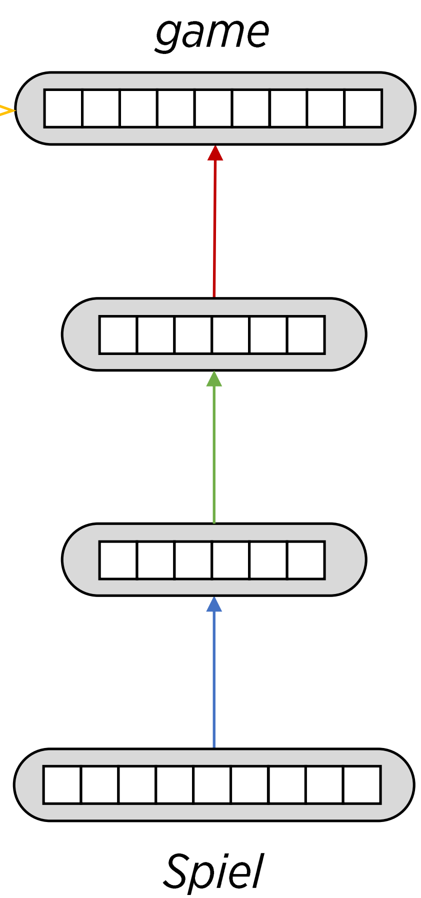
The size of the hidden layer vectors and the number of hidden layers can be freely chosen.

The first hidden layer is generally defined as the **embedding layer**.

We usually don't bother about the input features. Every word is represented by exactly one active feature. This is called **one-hot encoding**.

What about MT?

The prediction vector will be very large: one value per target word.



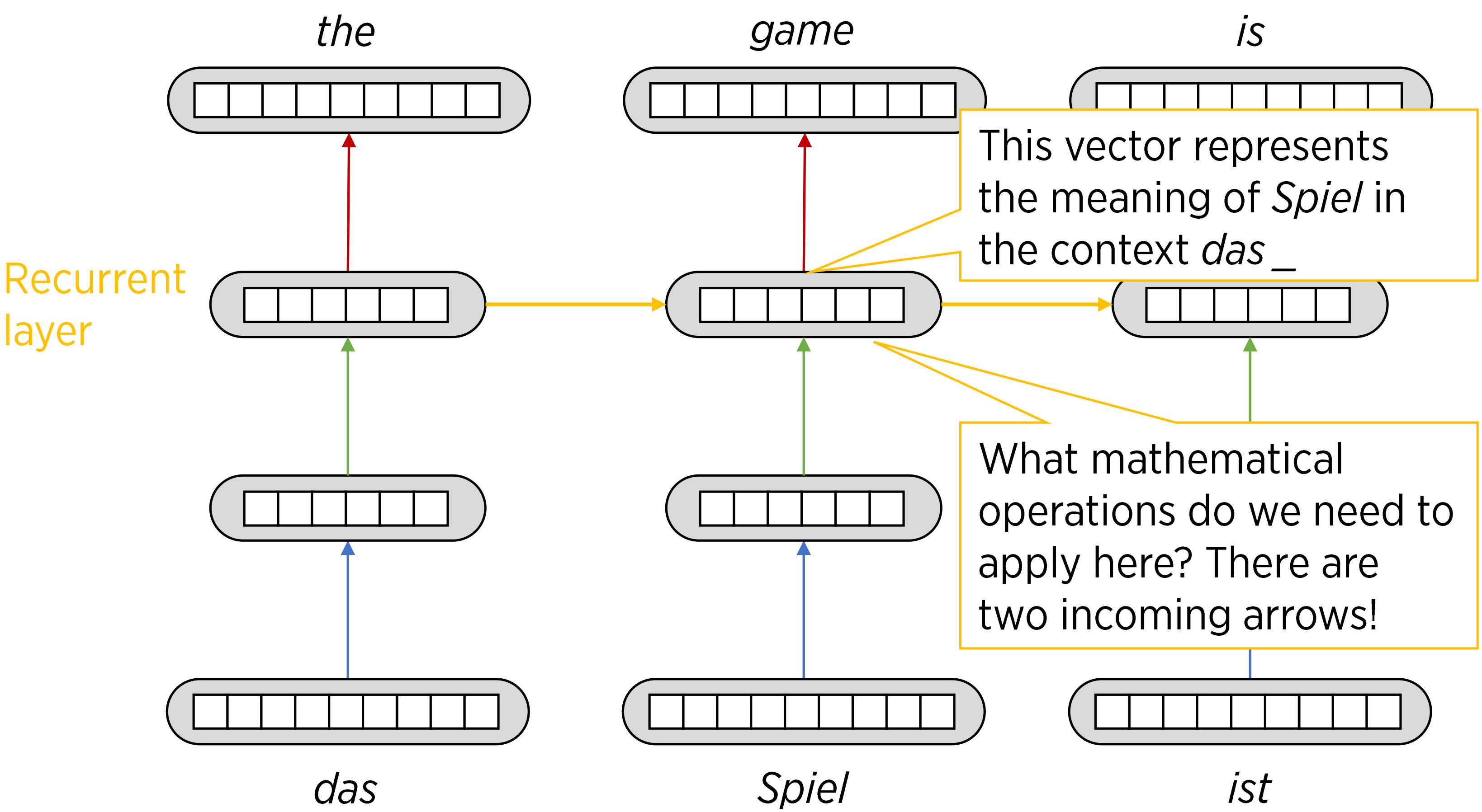
This model processes each word in isolation. It is just a sophisticated dictionary.

NLP is full of sequential data:

- Words in sentences
- Characters in words
- Sentences in text

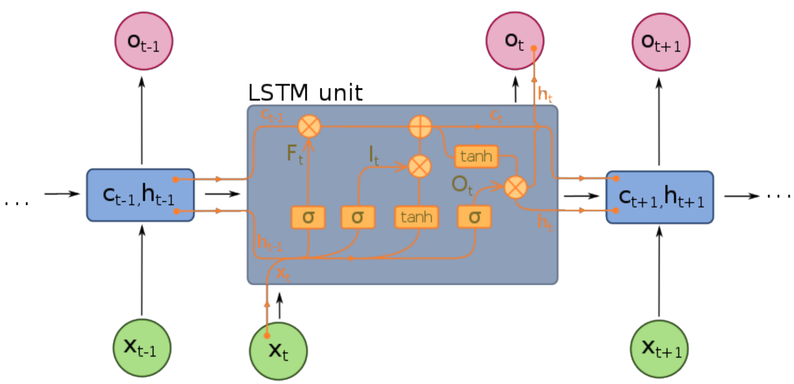
Models should take that into account.

Recurrent neural networks

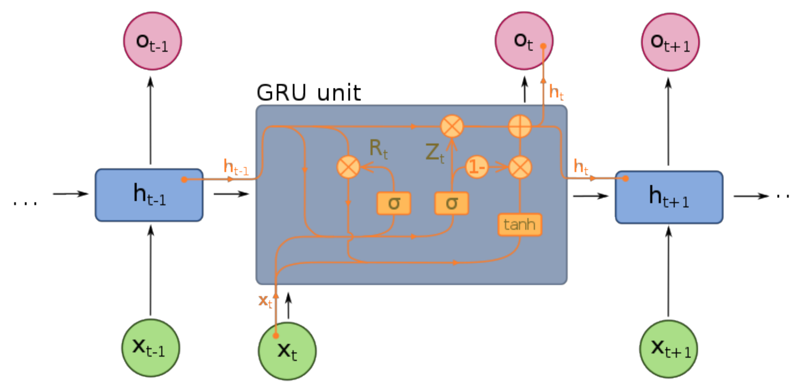


Recurrent neural networks

- Plain RNN:
  - Input vector dot product + context vector dot product
- Long-short-term memory (LSTM):

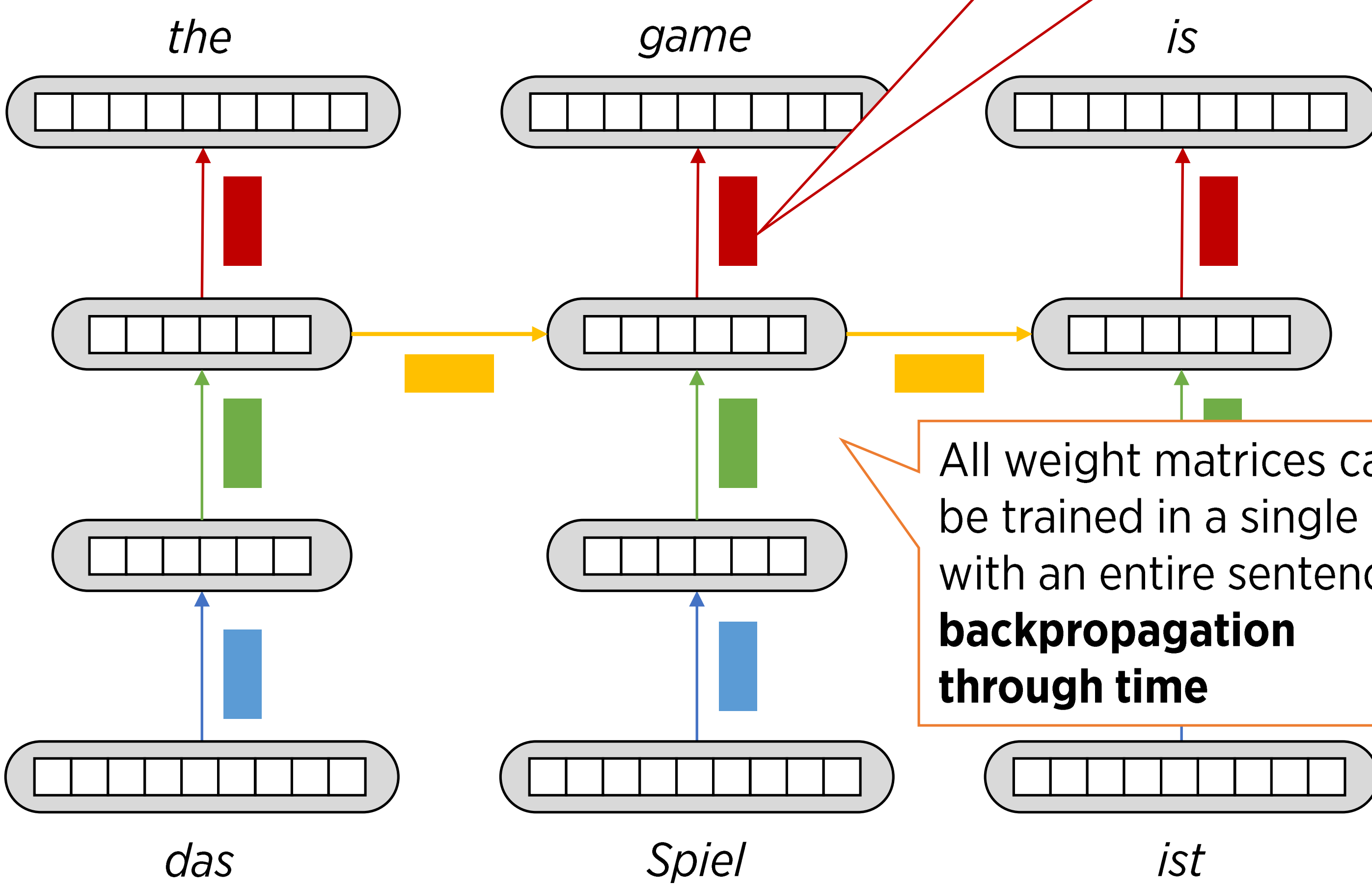


- Gated recurrent unit (GRU):



Illustrations: https://en.wikipedia.org/wiki/Recurrent_neural_network

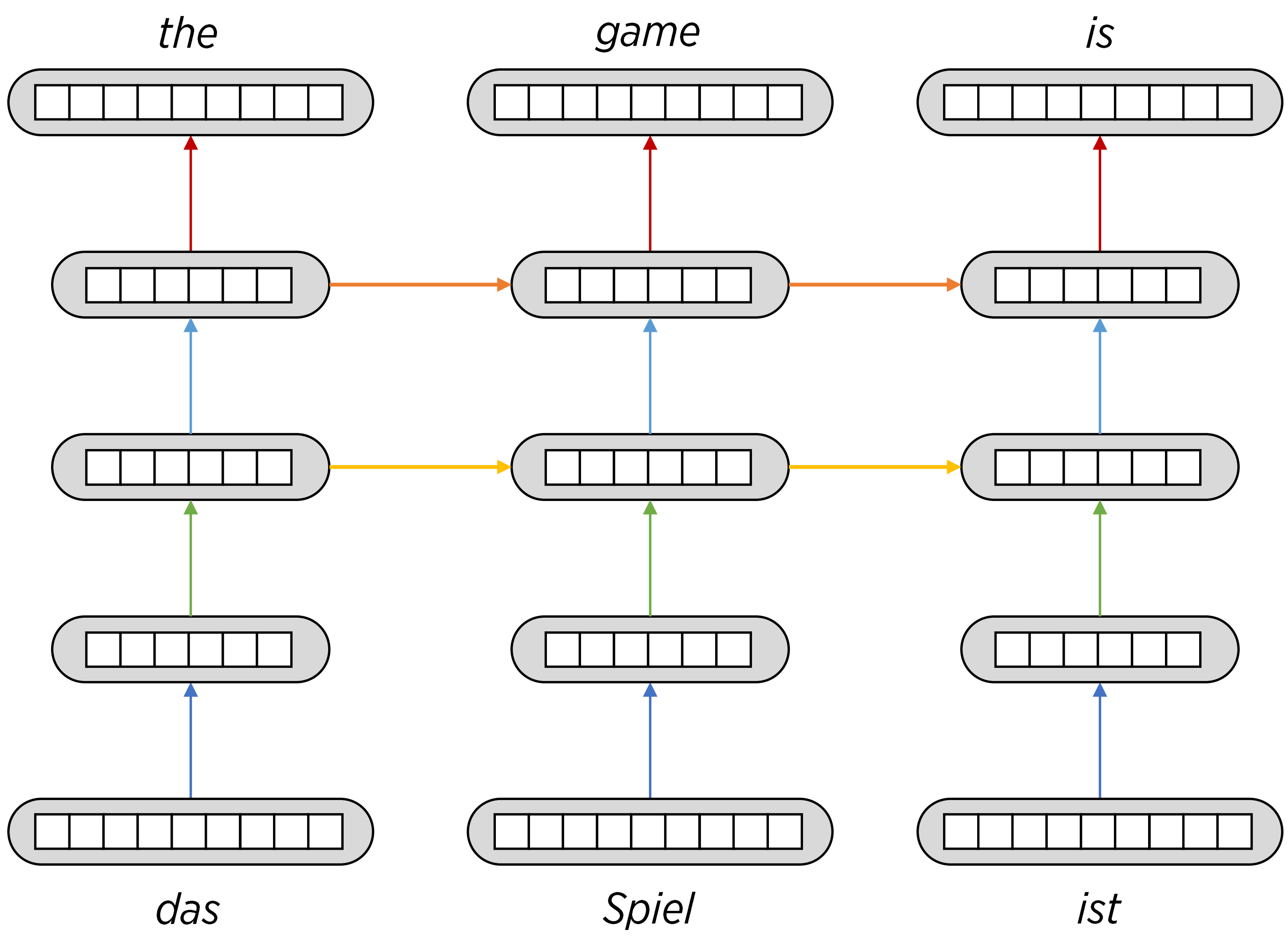
Parameter tying



The weight matrices are the same for all words.

All weight matrices can be trained in a single pass with an entire sentence: **backpropagation through time**

Multiple recurrent layers



Recurrent neural networks

- What is the problem with this approach for machine translation?

Recurrent neural networks

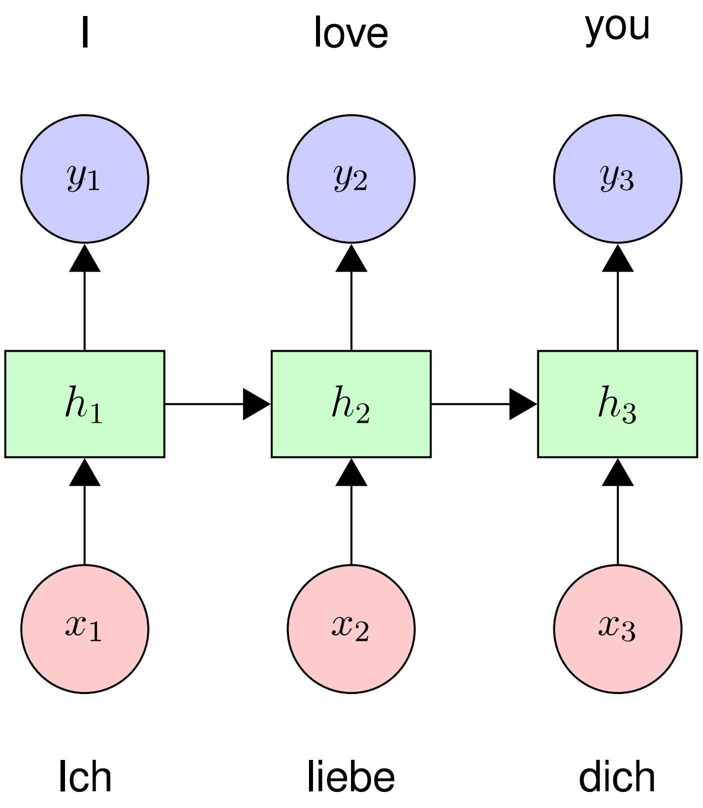


Illustration: Rico Sennrich

Recurrent neural networks

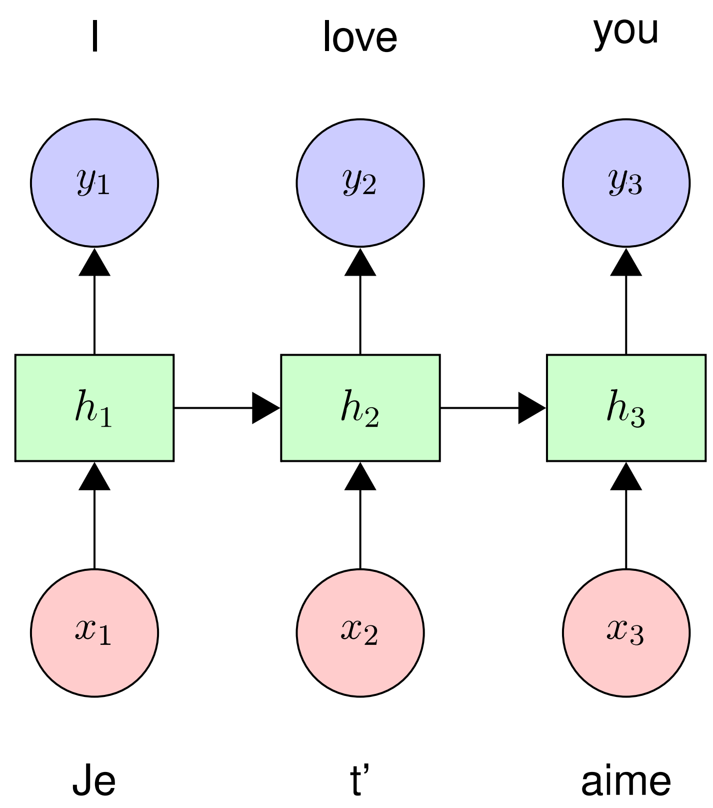


Illustration: Rico Sennrich

Recurrent neural networks

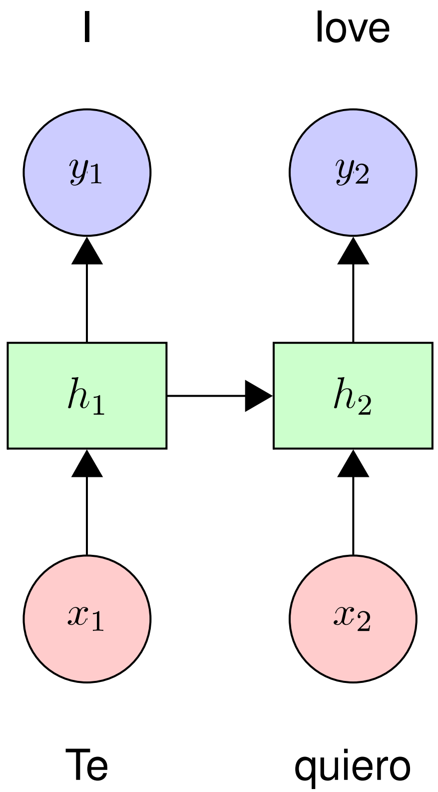


Illustration: Rico Sennrich

Architectures for machine translation

- RNNs are good for **sequence labeling** tasks
  - Part-of-speech tagging, …
  - Each word corresponds to exactly one output label
  - This doesn't work for machine translation

- Let's try a different approach…
- **Language modeling**: predict the next word
  - For each word there is exactly one next word (except when the sentence is finished…)

Traditional language models

- A sentence T of length n is a sequence $w_1 \dots w_n$
- Sentence probability:

$$p(T) = p(w_1, \dots, w_n)$$

- Chain rule:

$$p(T) = \prod_{i=1}^{n} p(w_i | w_1, \dots, w_{i-1})$$

- Markov assumption (n-gram model):

$$p(T) = \prod_{i=1}^{n} p(w_i | w_{i-k}, \dots, w_{i-1})$$

Sequential data
Long-distance dependencies

- Agreement in number, gender, etc.
  - **He** does not have very much confidence in **himself**.
  - **She** does not have very much confidence in **herself**.
- Selectional preference
  - The **reign** has lasted as long as the life of the **queen**.
  - The **rain** has lasted as long as the life of the **clouds**.
- Coreference
  - The trophy would not fit in the brown suitcase because it was too **big**.
  - The trophy would not fit in the brown suitcase because it was too **small**.

Examples: Graham Neubig

Language models

- Traditional language models need really large n-gram sizes to cover long distance dependencies
  - See examples
- We can use RNNs for language modeling
  - The hidden layers keep track of the previous words – potentially back to the beginning of the sentence
  - No hard cutoff after n characters

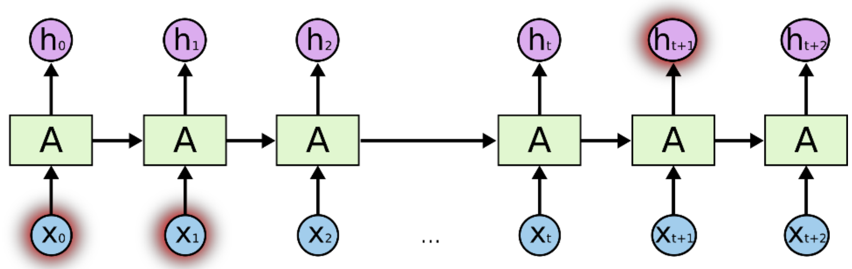
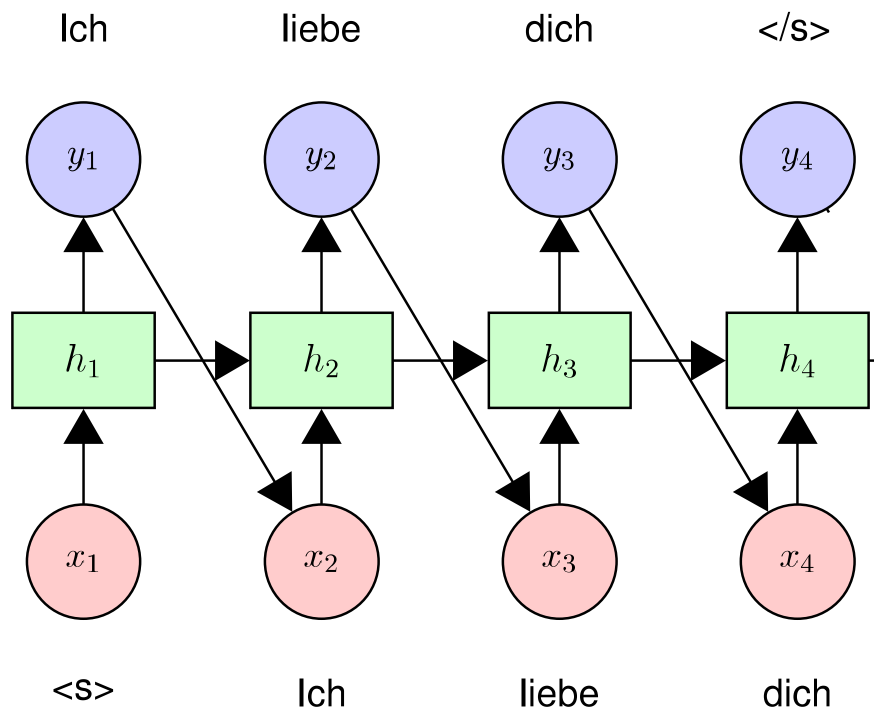


Illustration: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN language models



How does this relate to MT?

- Language models generate text
- **Conditioned language models** do not just generate text – they generate text according to some specification

Input	Output (Text)	Task
Document	Short description	Summarization
Question	Answer	Question answering
Image	Text	Image captioning
Speech signal	Transcription	Speech recognition
English text	Japanese text	Machine translation

Slide: Graham Neubig

Conditioned language models

- Suppose we have:
  - a source sentence S of length m: $x_1, \ldots, x_m$
  - a target sentence T of length n: $y_1, \ldots, y_n$
- Translation probability:

$$p(T|S) = p(y_1, \ldots, y_n | x_1, \ldots, x_m)$$

- Chain rule:

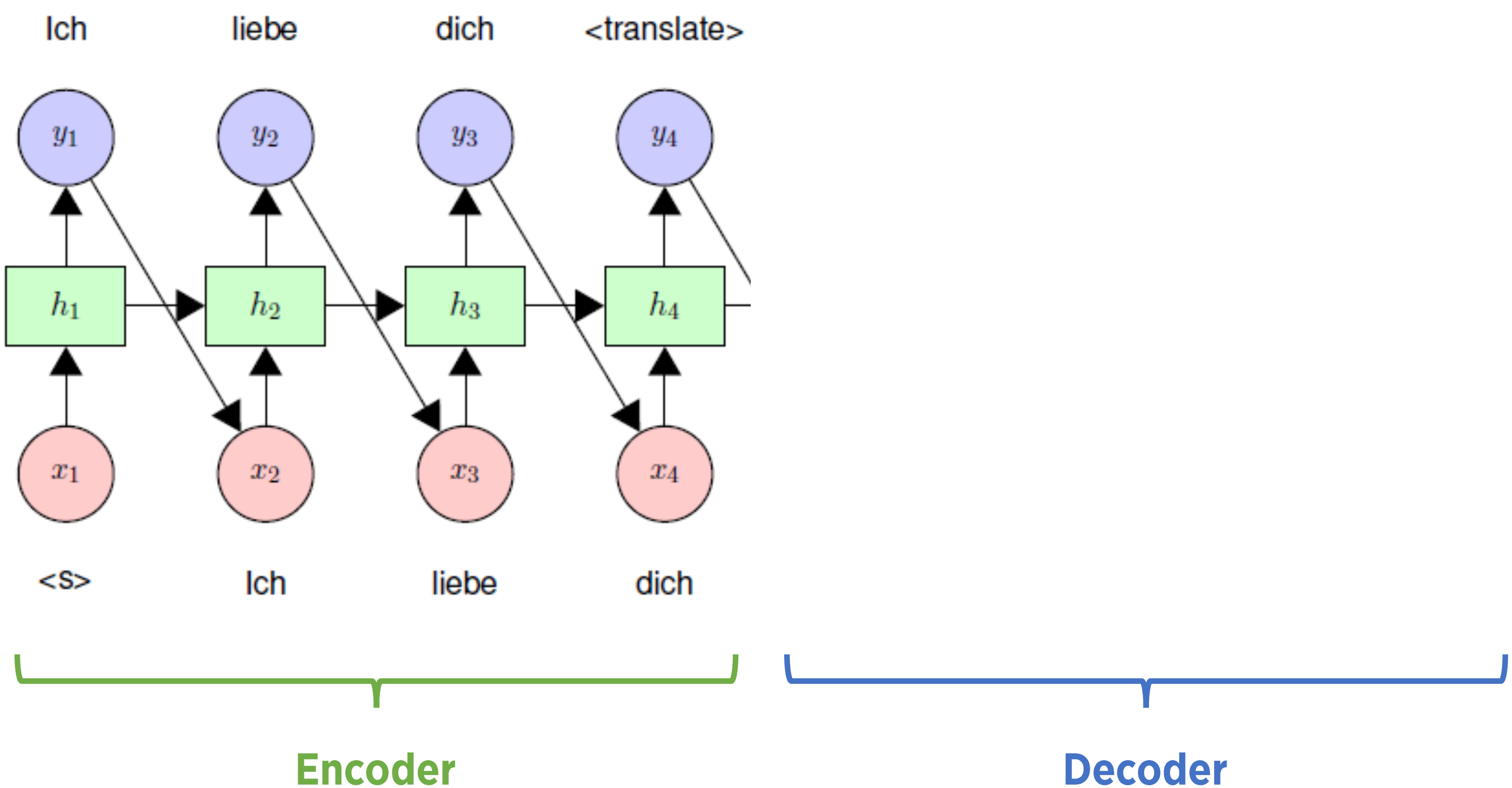
$$p(T|S) = \prod_{i=1}^{n} p(y_i | x_1, \ldots, x_m, y_1, \ldots, y_{i-1})$$

- Let's just treat the sentence pair T, S as one long sequence…

Conditioned language models

This type of RNN is called **encoder-decoder model**.

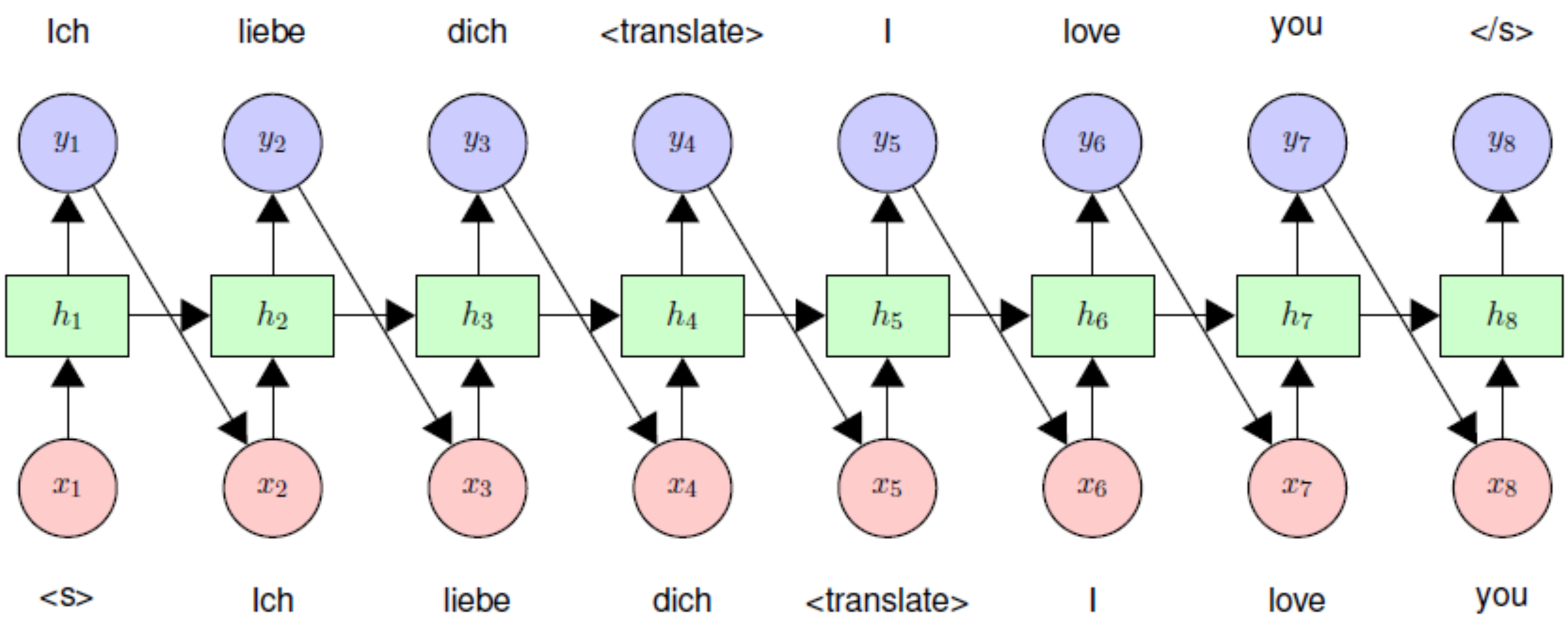
No restrictions on output order and length.
The model will decide by itself when "it is done".



Conditioned language models

We are making the task harder than it needs to be.
We do not really care about the source sentence.

Any potential problem with this approach?

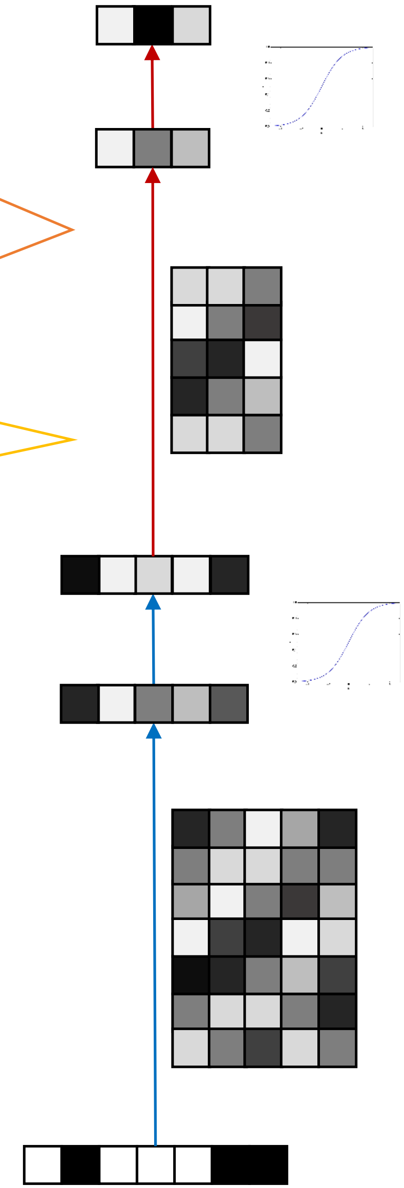


Practical considerations

Computing

Training:
- Forward pass
- Loss computation
- Backward pass

Prediction:
- Forward pass



- A lot of computations as networks grow bigger
  - But quite simple computations
  - Can be parallelized easily
- Solution:
  - Perform computations on GPU

Graphics processing units

- Very efficient at manipulating computer graphics and image processing

CPU, like a motorcycle

Quick to start, top speed not shabby

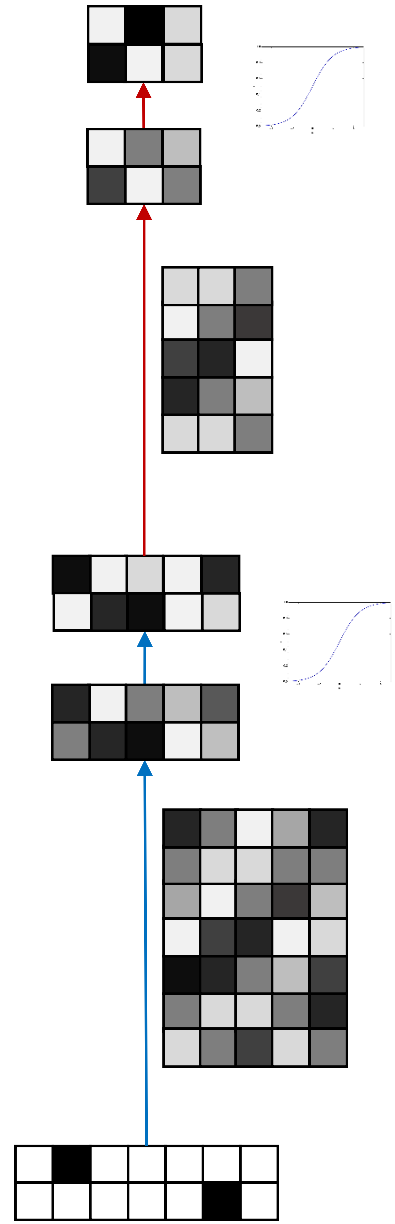
GPU, like an airplane

Takes forever to get off the ground, but super-fast once flying

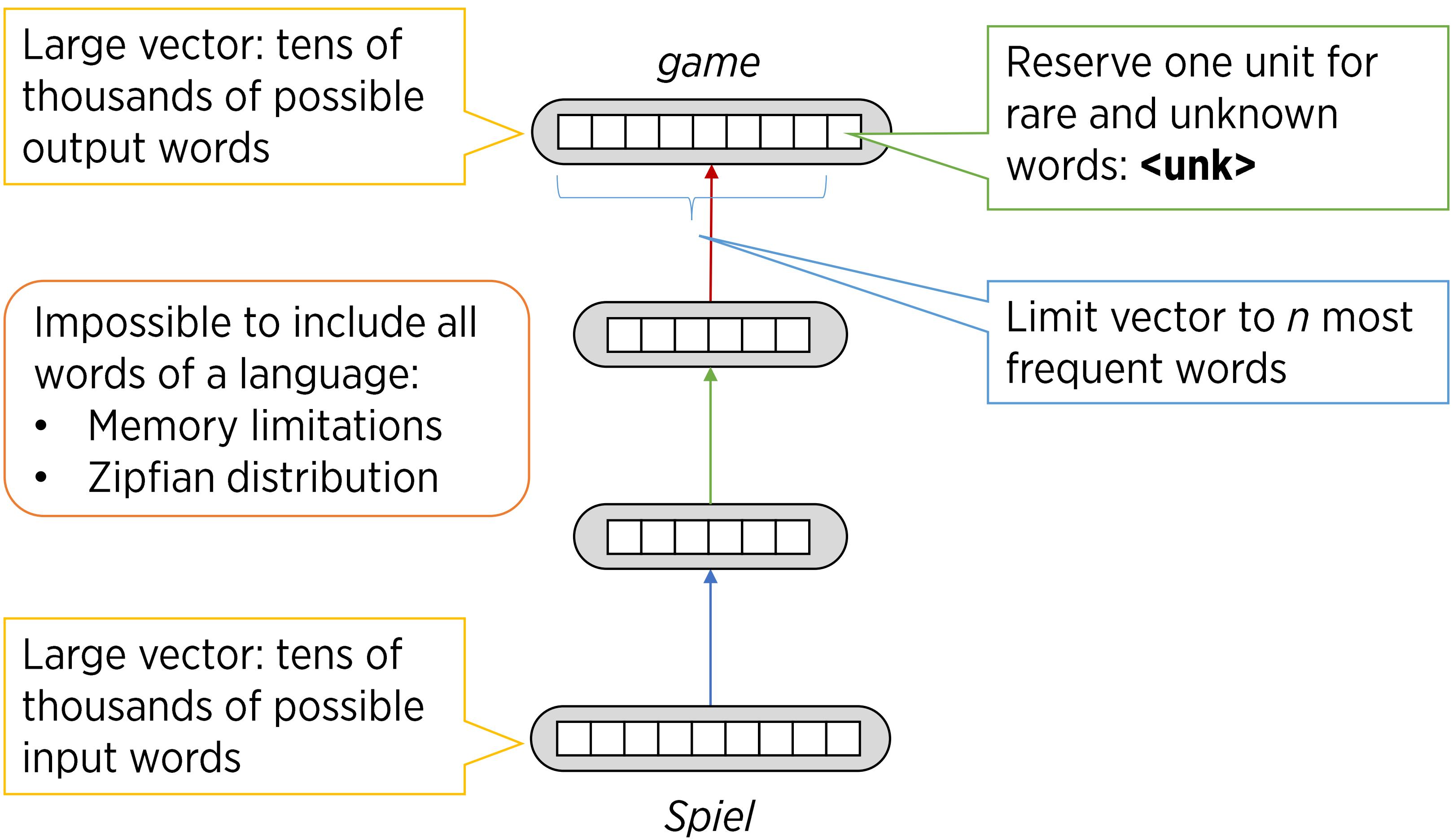
Illustration: Graham Neubig, Wikipedia images

Minibatching

- Run several examples (words / sentences) through the network at the same time
  - Increased parallelization, thus speed
  - Fewer weight updates during training, thus more stable
  - Increased memory requirements
- Minibatch size determined according to above criteria



Large vocabularies



Large vocabularies

We'll talk about better solutions later...

- Examples English – Czech:
  - The author Stephen Jay Gould died 20 years after diagnosis.
    Autor <unk> <unk> <unk> zemřel 20 let po <unk>.
  - As the Reverend Martin Luther King Jr. said fifty years ago:
    Jak řekl reverend Martin <unk> King <unk> před padesáti lety:
  - Her 11-year-old daughter, Shani Bart, said it felt a "little bit weird" [..] back to school.
    Její <unk> dcera <unk> <unk> řekla, že je to "trochu divné", [..] vrací do školy.

Decisions...

- **Model architecture:**
  - Source/target vocabulary size
  - Number, sizes of hidden layers
  - Type of recurrent layers
  - Directionality of recurrent layers
- **Training:**
  - Initialization of weight matrices
  - Minibatch size
  - Learning and optimization algorithms
  - Number of epochs/iterations, stopping criterion

Readings

- Mikel Forcada (2017): *Making sense of neural machine translation.* Translation Spaces 6(2).

- Philipp Koehn (2017): *Neural machine translation*. Appendix chapter for SMT book.
  - PDF available online, link on Moodle
  - Sections 13.1 – 13.4