Análisis de textos

Métodos estadísticos avanzados

Estratos de procesamiento en aprendizaje automático

|	
Significado comunicado por el escritor	Objetivo de predicción
↑	↑
Análisis pragmático	Predicción
↑	↑
Análisis semántico	Atención / resumen
↑	↑
Análisis sintáctico	Mezcla de embeddings
↑	↑
Análisis léxico	Token embeddings
↑	↑
Tokenización	Tokenización
↑	↑
Texto	Texto
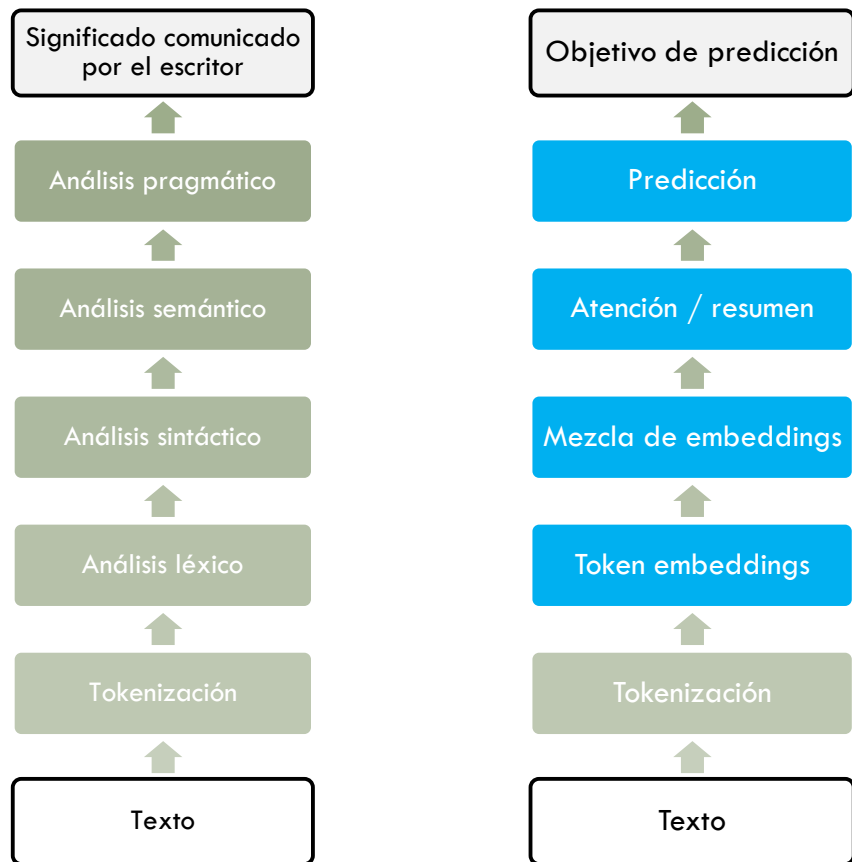
➢ En la práctica los niveles léxico, sintáctico y semántico están muy interrelacionados, y no es sencillo analizarlos por separado.

➢ Por ello en métodos actuales de análisis de texto se emplean modelos de aprendizaje automático, principalmente redes neuronales profundas, para obtener:

   ➢ Representaciones de palabras (tokens)
   ➢ Representaciones de frases/textos, mezclando las representaciones de palabras.

➢ Filosofía: no tratar de resolver el problema de lenguaje de forma general, sino solo el problema concreto que nos interesa (objetivo de predicción).

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Redes neuronales para Análisis de Textos

What is really a neural network?

A neural network can be thought as an arbitrary directed acyclic graph (DAG) of operations, from an input vector x to an output vector $\hat{y}$. Each operation has some parameters to be tuned to minimize a loss function.

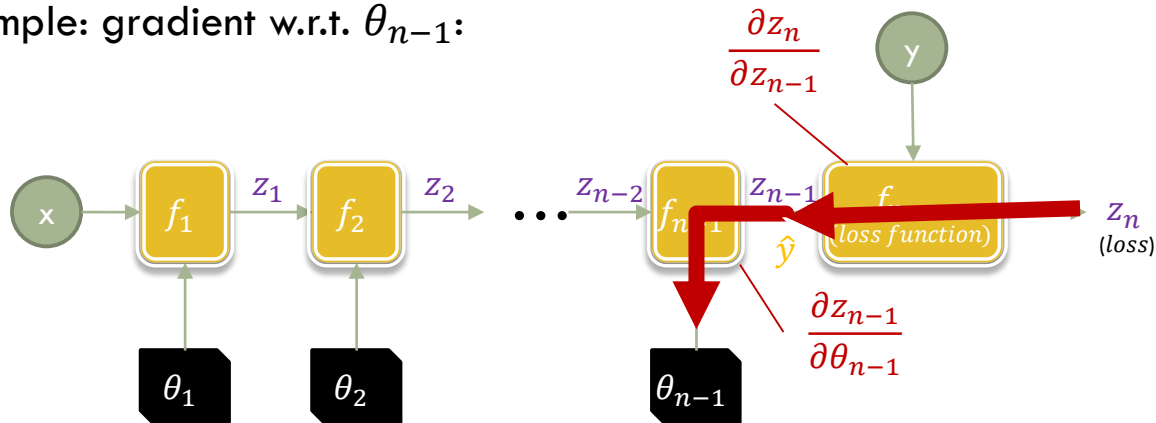Example: MLP with a single hidden layer
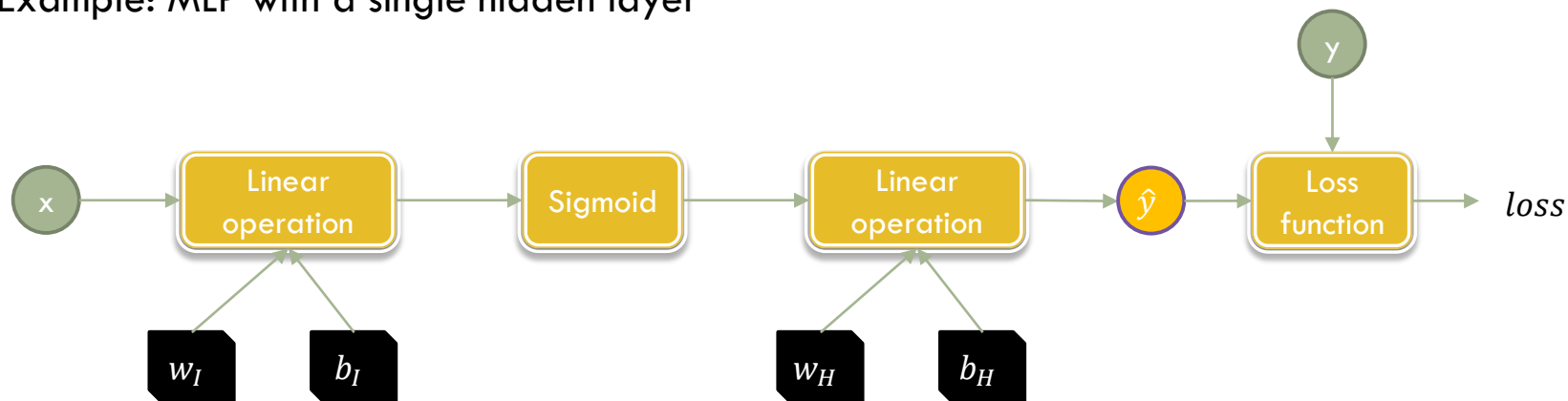
What is backpropagation doing?

Visually, backpropagation travels the network backwards from $loss$ to θ_i. Each function in the path adds a partial derivative of its output with respect to its input.
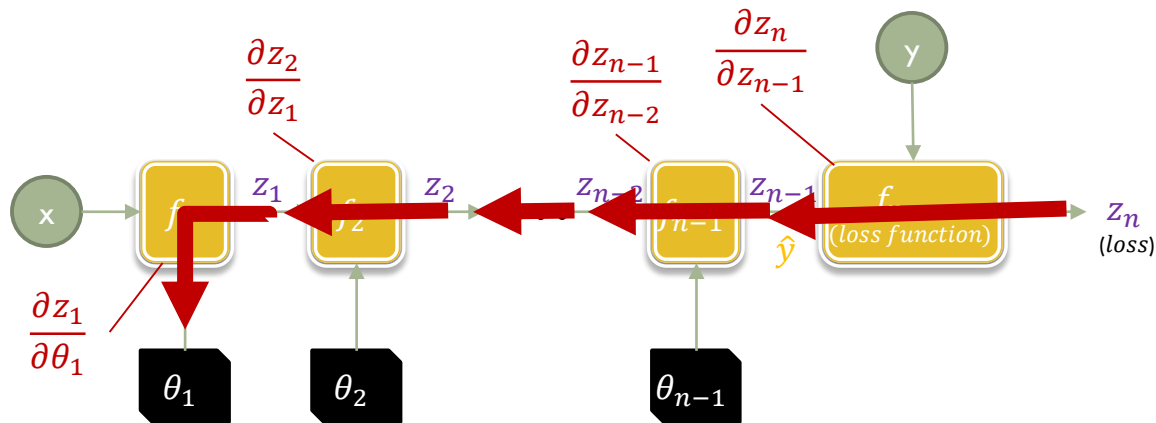
Example: gradient w.r.t. θ_{n-1}:

$$\frac{\partial F}{\partial \theta_{n-1}} = \frac{\partial z_n}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial \theta_{n-1}}$$
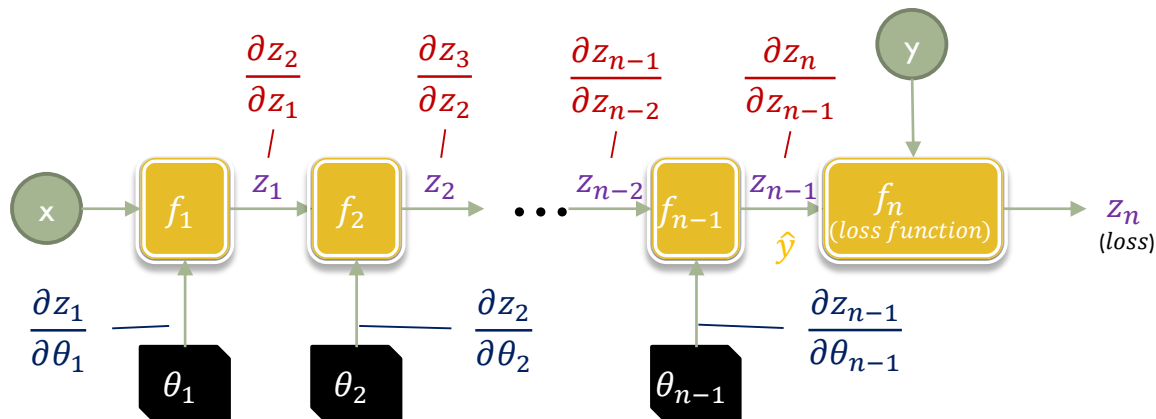
What is backpropagation doing?

Another example: gradient w.r.t. θ_1:

$$\frac{\partial F}{\partial \theta_1} = \frac{\partial z_n}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \quad \dots \quad \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial \theta_1}$$

Important observations about backpropagation

$$\frac{\partial F}{\partial \theta_{n-1}} = \frac{\partial z_n}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial \theta_{n-1}}$$

$$\frac{\partial F}{\partial \theta_{n-2}} = \frac{\partial z_n}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \frac{\partial z_{n-2}}{\partial \theta_{n-2}}$$
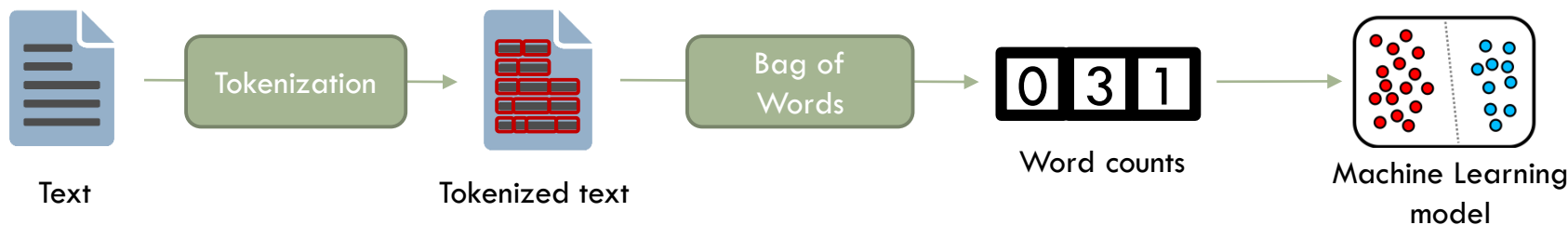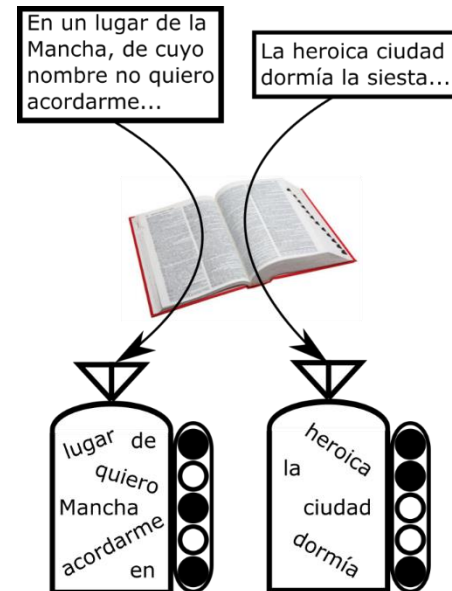
$$\frac{\partial F}{\partial \theta_{n-3}} = \frac{\partial z_n}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \frac{\partial z_{n-2}}{\partial z_{n-3}} \frac{\partial z_{n-3}}{\partial \theta_{n-3}}$$

- ➢ Terms in the form $\frac{\partial z_i}{\partial z_{i-1}}$ can be reused throughout $\frac{\partial F}{\partial \theta_i}$ computations $\forall\, i$ → efficient computation of derivatives for all network parameters.

- ➢ We can add any function f_i to a neural network, as long as we can compute every partial derivate of each output w.r.t. each input.

- ➢ Layers closer to the input → more terms in gradient calculation

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Basic feature generation: bag of words

- Build a dictionary of tokens in the training data (V tokens)

- Assign numbers $1 \ldots V$ to each token

- Encode each token as an all-zeros vector of length V, except for a 1 in the position corresponding to the token number

- Encode documents as sum of their tokens vectors (bag of words)

- Use the encoded data as inputs to the model.

Index	Token
5	.
12	the
19	cat
20	dog
…	…
288	eat
827	run
…	…

En un lugar de la Mancha, de cuyo nombre no quiero acordarme…

La heroica ciudad dormía la siesta…

lugar de quiero Mancha acordarme en

heroica la ciudad dormía

Text → Tokenization → Tokenized text → Bag of Words → Word counts → Machine Learning model

0 3 1

Word counts

Better token representations representations

- Bag of words one-hot vectors work, but lack semantic meaning
- All words are equally apart in vector space, regardless of their meaning (semantics) or function (syntax)

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

- Are there better encodings for words?

- Even more: can we learn them automatically?

Deep Learning text processing pipeline

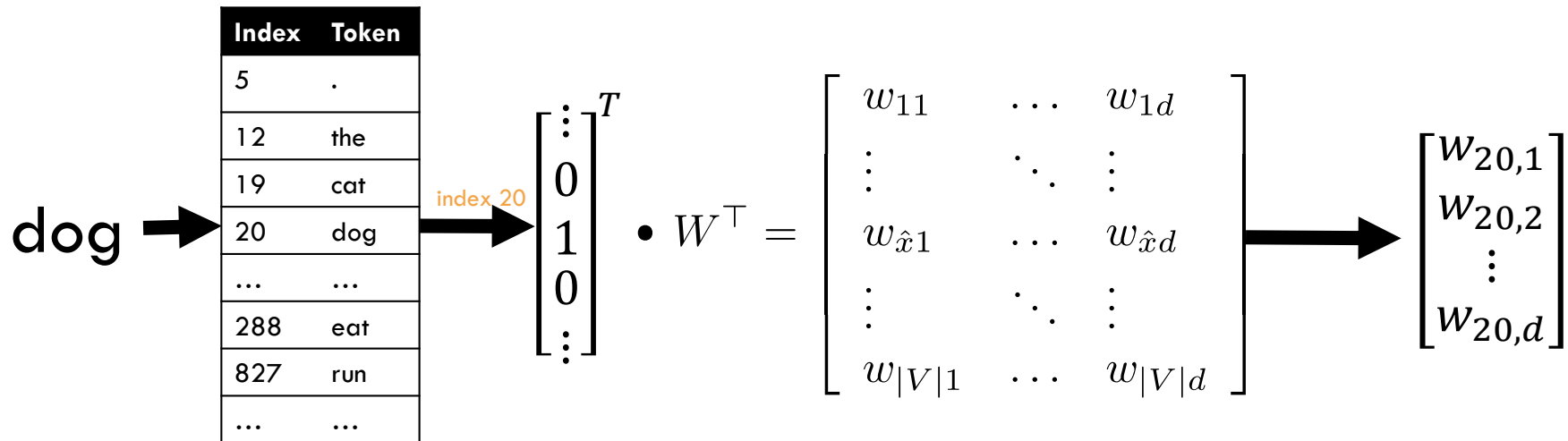Let the neural network do the feature engineering!

Text ⟶ Tokenizer ⟶ List of tokens ⟶ Deep Learning model
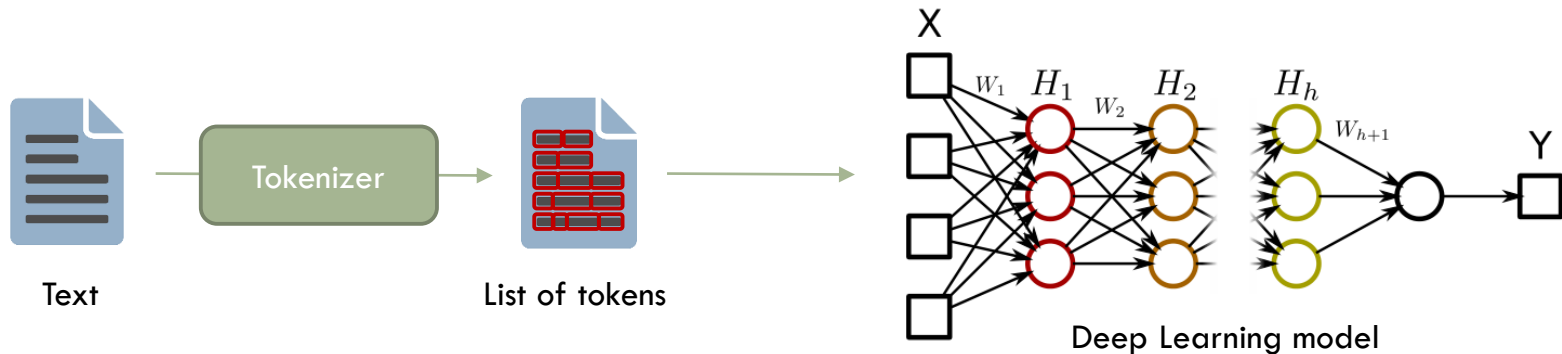
But there are two issues:

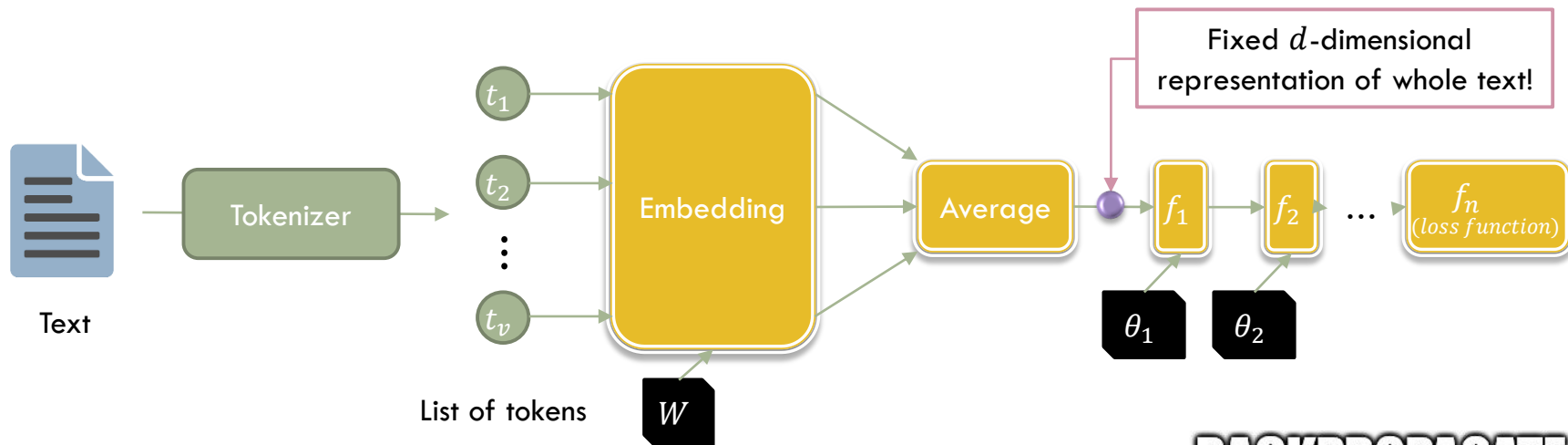X Inputs to a neural network must be numbers, not strings!

X Each text in a dataset might have different number of tokens

Automatically computing features for tokens

➤ Encode each token as in bag-of-words (one-hot) of length N

➤ Multiply this vector by an embedding matrix $W \in \mathbb{R}^{Vxd}$

  ➤ For a one-hot vector with a 1 in the i-th entry, this operation returns the i-th row of W

 ➤ $d \equiv$ embedding dimension. $[50, 300]$ usually works well.

$$\text{dog} \rightarrow \begin{array}{|c|c|}\hline \textbf{Index} & \textbf{Token} \\\hline 5 & . \\\hline 12 & \text{the} \\\hline 19 & \text{cat} \\\hline 20 & \text{dog} \\\hline \dots & \dots \\\hline 288 & \text{eat} \\\hline 827 & \text{run} \\\hline \dots & \dots \\\hline \end{array} \xrightarrow{\text{index 20}} \begin{bmatrix} \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix}^T \bullet W^\top = \begin{bmatrix} w_{11} & \dots & w_{1d} \\ \vdots & \ddots & \vdots \\ w_{\hat{x}1} & \dots & w_{\hat{x}d} \\ \vdots & \ddots & \vdots \\ w_{|V|1} & \dots & w_{|V|d} \end{bmatrix} \rightarrow \begin{bmatrix} w_{20,1} \\ w_{20,2} \\ \vdots \\ w_{20,d} \end{bmatrix}$$

The Continuous Bag of Words model (CBoW)

Fixed d-dimensional representation of whole text!

- Apply the same embedding matrix W to every token in the sentence

- Average across tokens to obtain a fixed-length vector

- Use backpropagation to learn both network parameters θ_i and token representations W
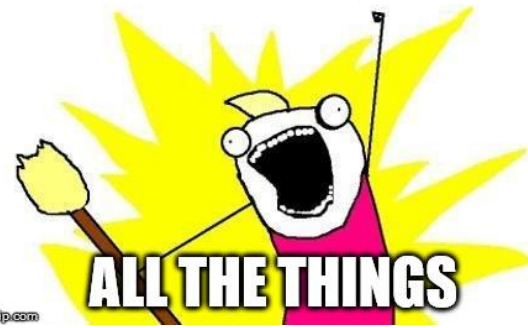
CBoW performance

✓ Many practical text problems can be solved with CBoW

BUT…

X Good word representations (embeddings W) can only be learned effectively when using large training datasets.

→ solution: language models

X CBoW does not take into account word order. This might be relevant for harder problems: translation, subtle meaning, …

→ solution: mixing models

Language models

Language Models

Objective: build a model that given a sentence, returns the probability of that sentence appearing in the language.

$$p(X) = p(x_1, x_2, \ldots, x_T)$$

Unsupervised learning problem: we just need large amounts of text to do it. No labels required!
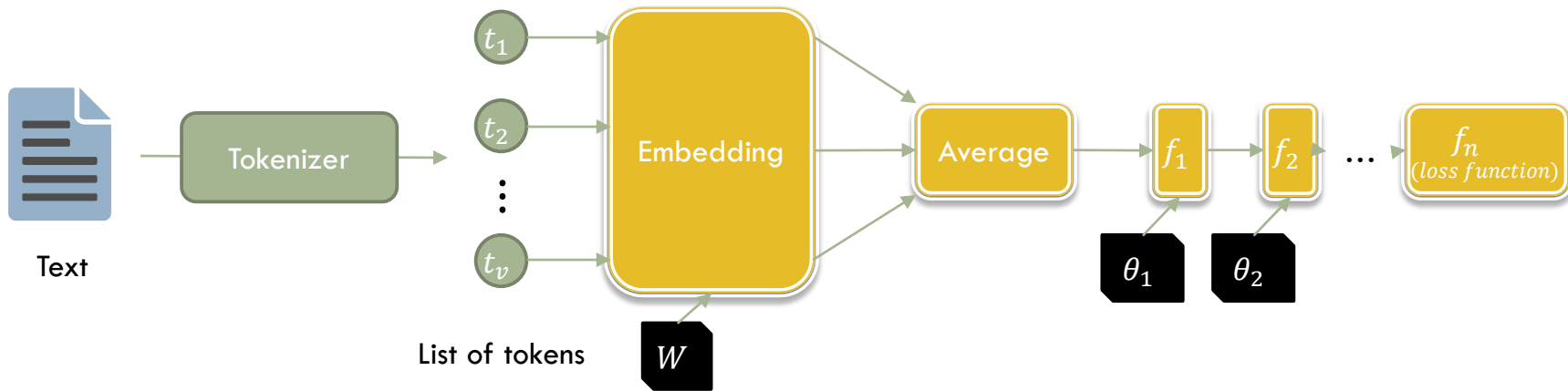
✓ Wikipedia

✓ Twitter

✓ Webscrapping

✓ Any text source!

But… how do we learn $p(x_1, x_2, \ldots, x_T)$?

Autoregressive Language Models

Using the definition of condicional probability

$$p(X) = p(x_1, x_2, \ldots, x_T) = p(x_1)p(x_2|x_1) \ldots p(x_T|x_1, \ldots, x_{T-1}) = \prod_{t=1}^{T} p(x_t|x_{<t})$$

The unsupervised problem is now a supervised classification problem: predict next word in the sentence → use CBoW!
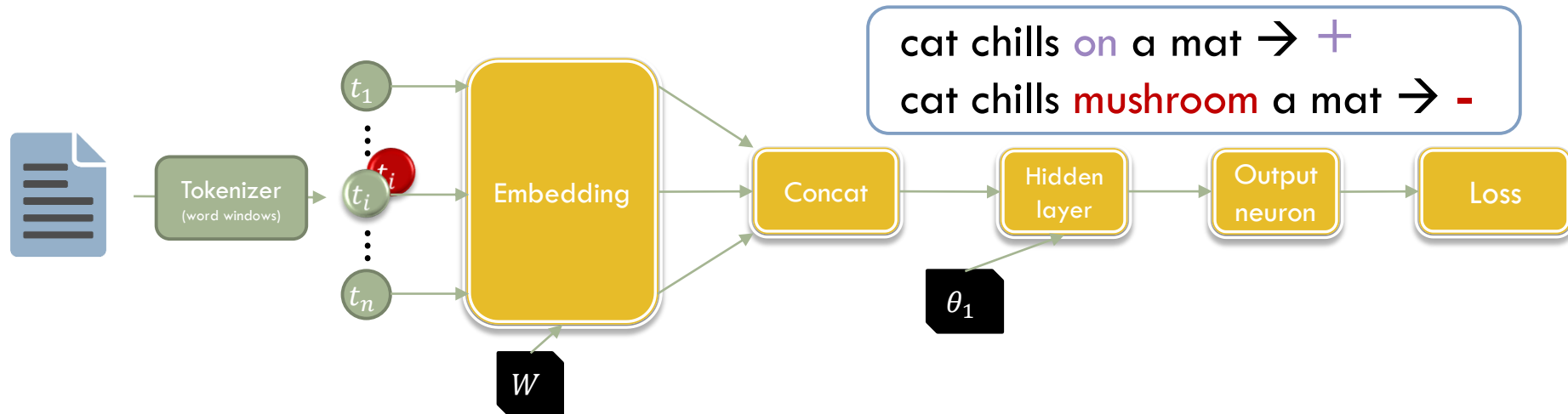
Language model example: word2vec

For each n-word window in the text, create 2 training examples:

- ➤ Positive example: concatenate all R vectors encoding the n words
- ➤ Negative example: equal to positive, but changing the central word to another random word in the training data

The language model tries to tell apart real language "sentences" from noisy ones

cat chills on a mat → +

cat chills mushroom a mat → -

Socher, Bengio, Manning: Deep Learning for NLP (without Magic): http://www.socher.org/index.php/DeepLearningTutorial/DeepLearningTutorial

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word2vec: learned embeddings

➢ Closest words to 'france'

Word	Cosine distance
spain	0.678515
belgium	0.665923
netherlands	0.652428
italy	0.633130
switzerland	0.622323
luxembourg	0.610033
portugal	0.577154
russia	0.571507
germany	0.563291
catalonia	0.534176

➢ Some k-means clusters

```
carnivores 234        acceptance 412
carnivorous 234       argue 412
cetaceans 234         argues 412
cormorant 234         arguing 412
coyotes 234           argument 412
crocodile 234         arguments 412
crocodiles 234        belief 412
crustaceans 234       believe 412
cultivated 234        challenge 412
danios 234            claim 412
```

word2vec: semantic algebra

King ⊖ man ⊕ woman ⊜ queen

Obama ⊖ USA ⊕ Russia ⊜ Putin

paella ⊖ Spain ⊕ Italy ⊜ risotto

Cristiano ⊖ Madrid ⊕ Barcelona ⊜ Messi

Language model example: fasttext

✓ word2vec produces better word representations

X But ignores the inner structure of words (morphology). This is relevant in languages with complex morphology: spanish, german, …

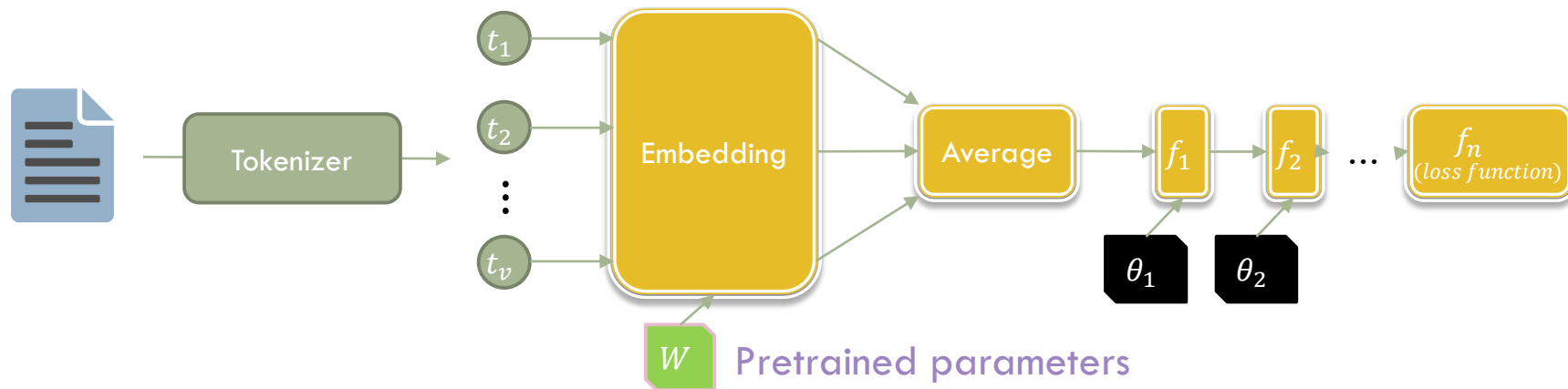The fasttext model proposes an improvement by learning a vectors for subwords (character n-grams). The vector representing a token is the sum of its subword vectors, plus a special "subword" representing the whole token.

where   =   <wh   +   whe   +   her   +   ere   +   re>   +   <where>
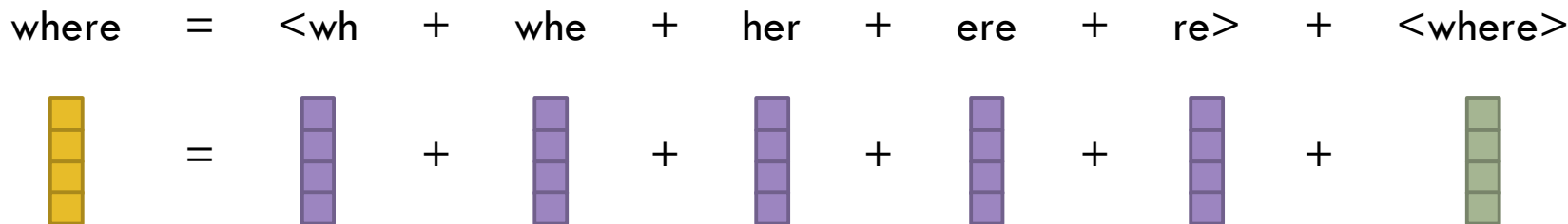
Efficient implementations allow learning a more precise language model with extremely large corpora: Common Crawl.

Bojanowski et al – Enriching Word Vectors with Subword Information

Using language models in supervised models

✓ When training data is scarce, initializing the network embeddings with the pretrained parameters from a language model can be very effective
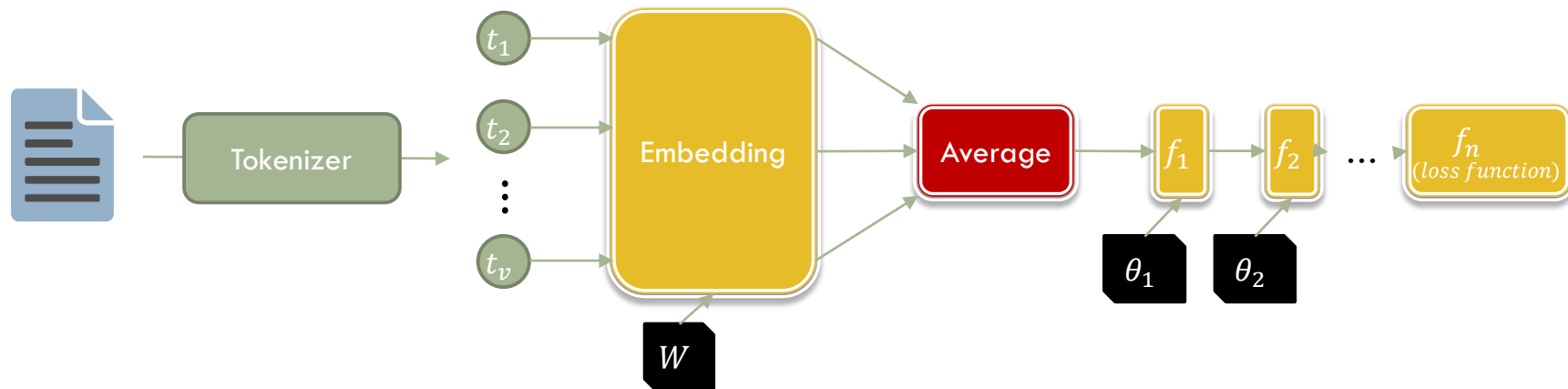

word2vec: https://code.google.com/p/word2vec/

Spanish Billion Words Corpus and Embeddings: http://crscardellino.me/SBWCE/

FastText: https://fasttext.cc/

Mixing models

Better token combinations

In some problems word ordering is very important. We can't just take the average of word representations!

I had my car cleaned

$\neq$
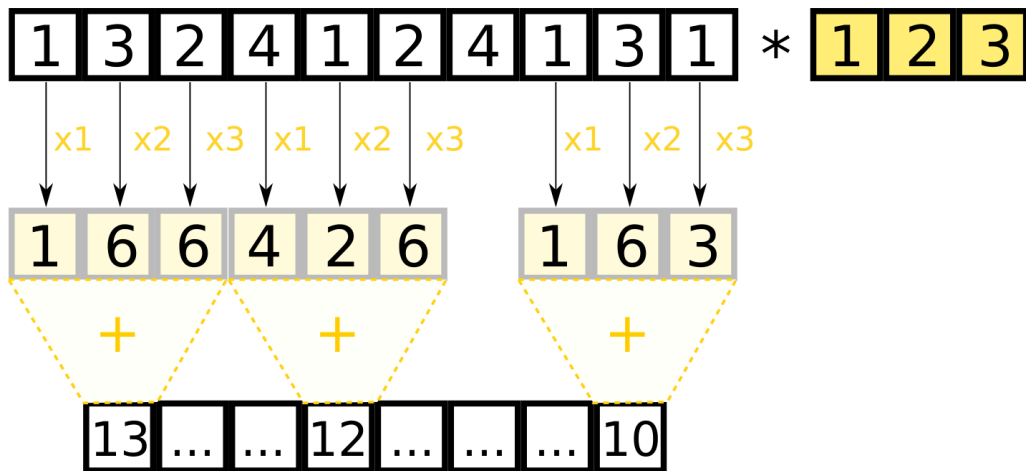
I had cleaned my car

break the end

$\neq$

end the break

Me río en el baño

$\neq$

Me baño en el río

One-dimensional convolutions

- Operation between continuous functions
$$(x * z)(t) = \int_{-\infty}^{+\infty} x(a)\, z(t-a)\, \mathrm{d}a$$

- For discrete signals
$$(x * z)_i = \sum_{j=-\infty}^{+\infty} x_j\, z_{i-j}$$

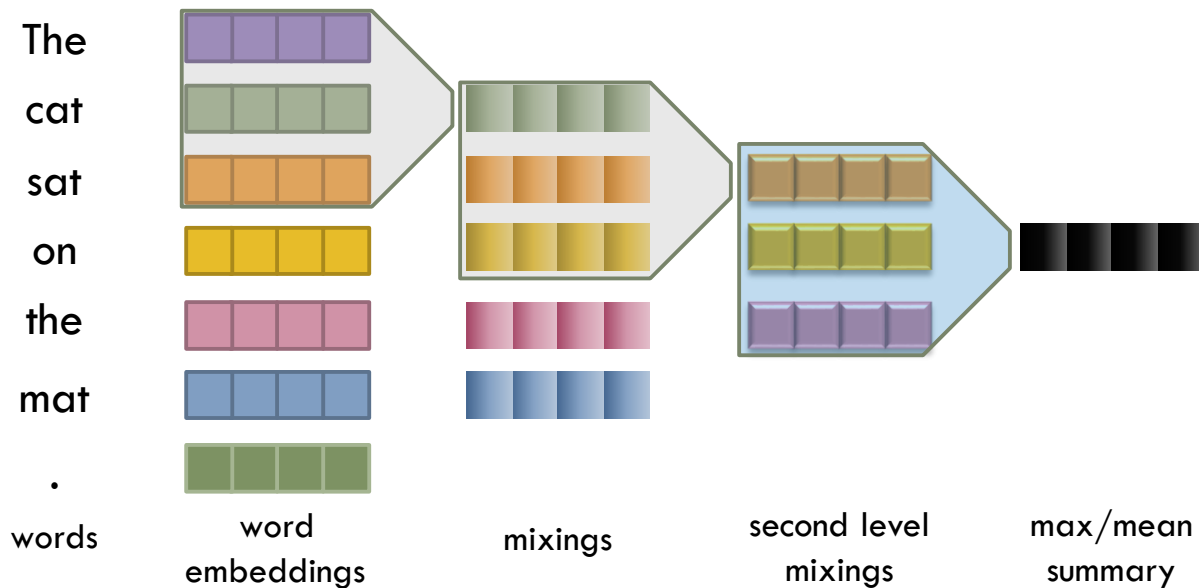- Applies a small layer of weights over each portion of the input

Convolutions over embeddings

Convolutions are helpful to mix the representation of a word with the representation of neighboring words.

By stacking convolutions a more broad mixing can be obtained.

After a number of convolutions, the mean or max values are taken to obtain a single vector that sums up the whole input document.
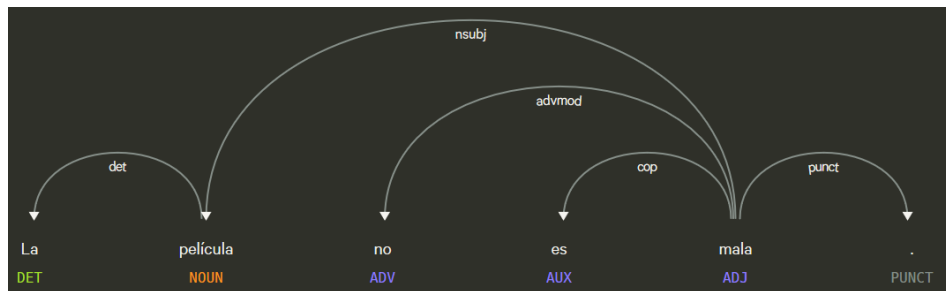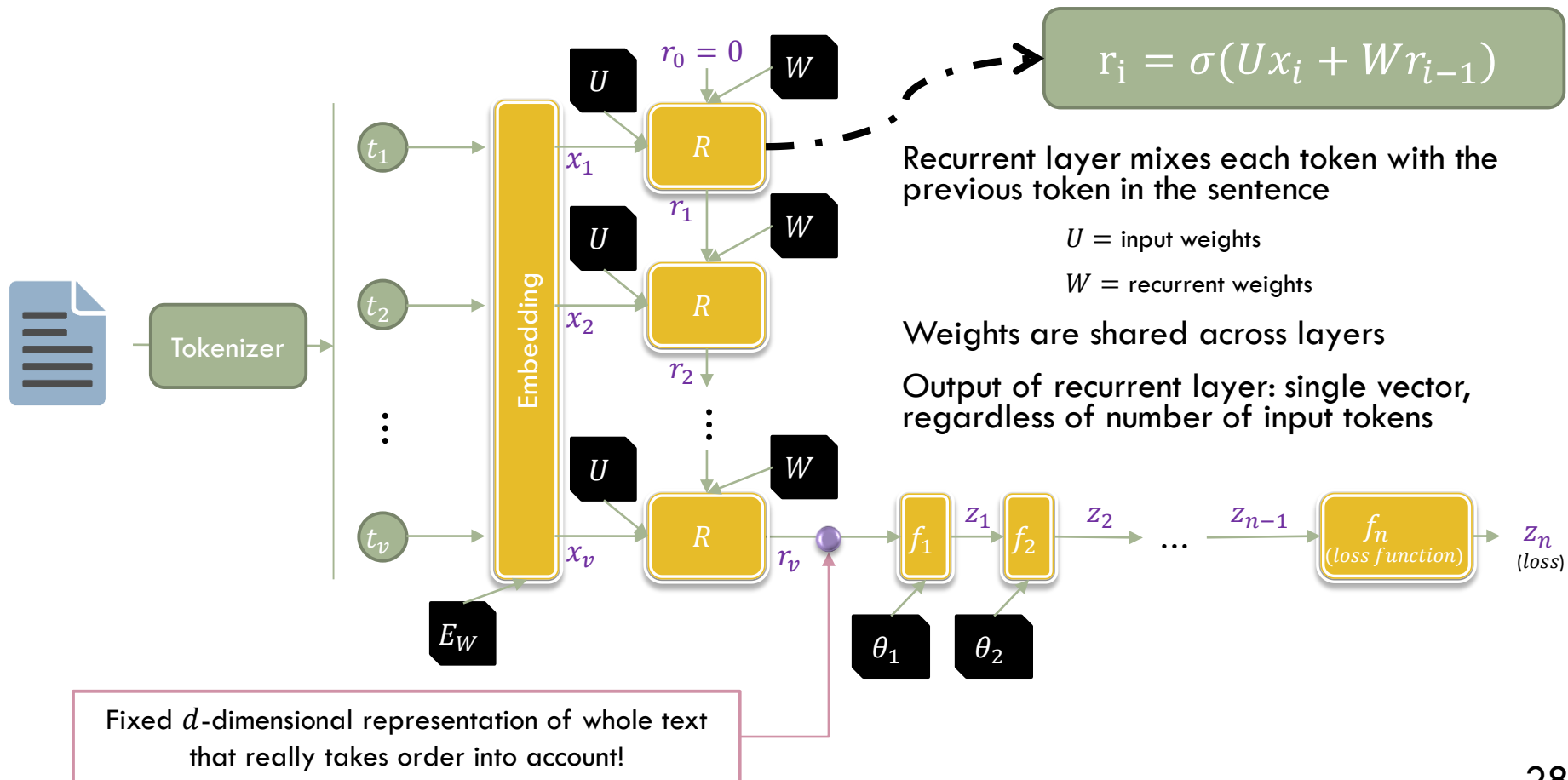
Stacked convolutions: network diagram

Fixed d-dimensional representation of whole text that takes order (somewhat) into account!
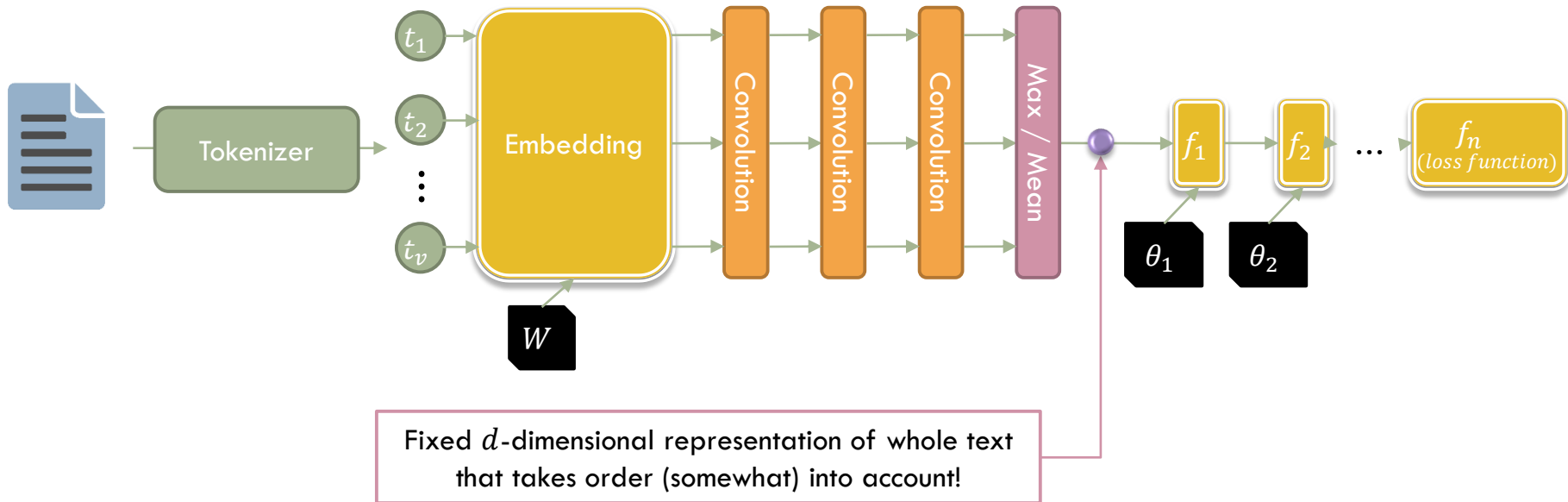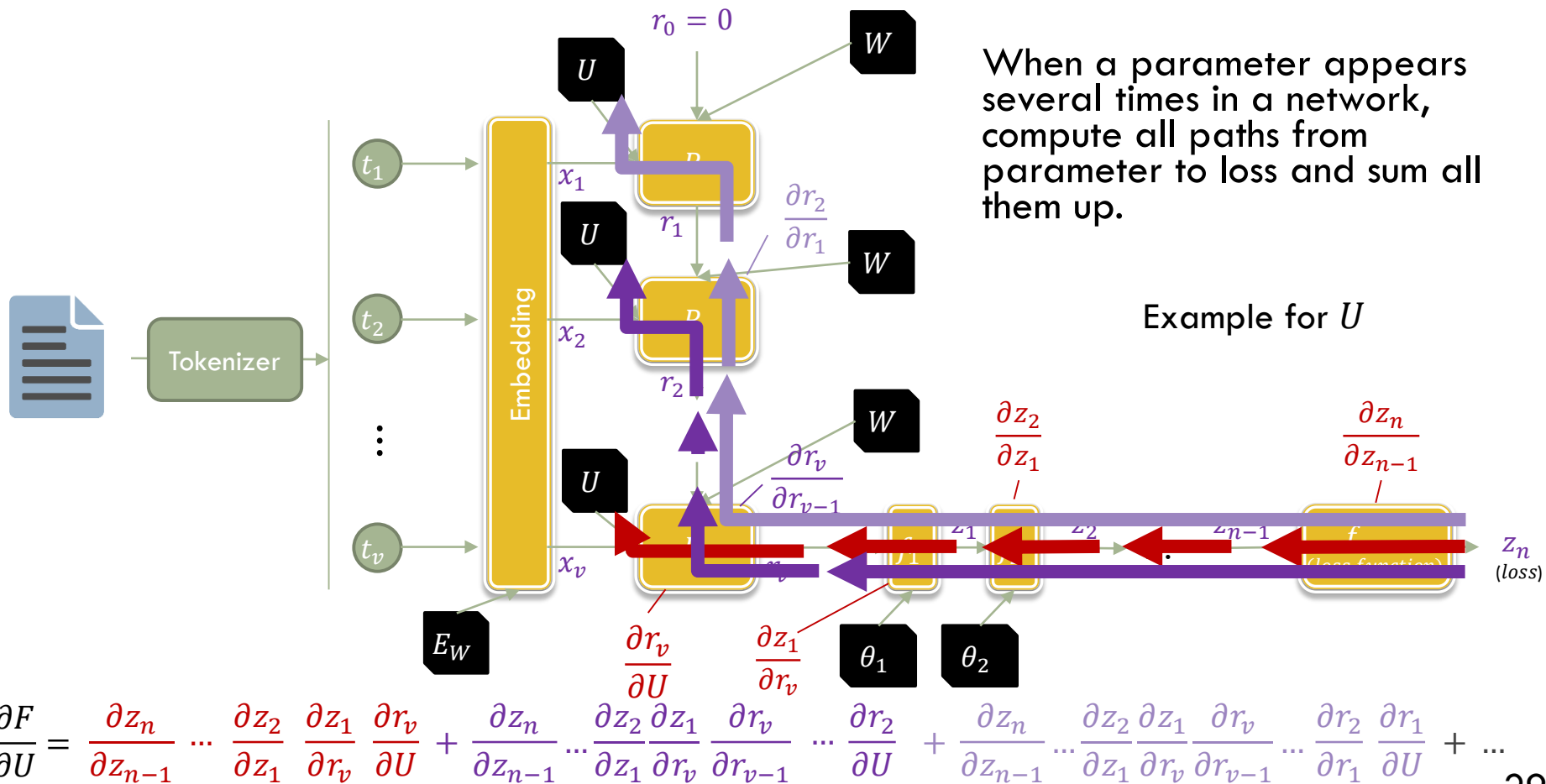
Aplicación: análisis morfosintáctico con ML

➢ Objetivo: dado un texto tokenizado, generar sus clases morfológicas y árbol de dependencias

➢ Aproximación para el problema

    ➢ Embeddings

    ➢ Modelos convolucionales de mezcla

    ➢ Capa final de la red que para cada token predice su clase morfológica, padre en el árbol y tipo de relación con el padre

➢ Recursos

    ➢ spaCy: https://spacy.io/

Better token combinations: recurrent layers

$$r_i = \sigma(Ux_i + Wr_{i-1})$$

Recurrent layer mixes each token with the previous token in the sentence

$U =$ input weights

$W =$ recurrent weights

Weights are shared across layers

Output of recurrent layer: single vector, regardless of number of input tokens

Fixed d-dimensional representation of whole text that really takes order into account!

Backpropagation with recurrent layers

When a parameter appears several times in a network, compute all paths from parameter to loss and sum all them up.

Example for U

$$\frac{\partial F}{\partial U} = \frac{\partial z_n}{\partial z_{n-1}} \dots \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial r_v} \frac{\partial r_v}{\partial U} + \frac{\partial z_n}{\partial z_{n-1}} \dots \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial r_v} \frac{\partial r_v}{\partial r_{v-1}} \dots \frac{\partial r_2}{\partial U} + \frac{\partial z_n}{\partial z_{n-1}} \dots \frac{\partial z_2}{\partial z_1} \frac{\partial z_1}{\partial r_v} \frac{\partial r_v}{\partial r_{v-1}} \dots \frac{\partial r_2}{\partial r_1} \frac{\partial r_1}{\partial U} + \dots$$

Problems when training recurrent layers

Even though recurrent networks have a small number of weights compared to deep networks, because they unfold over each input token they behave like deep networks

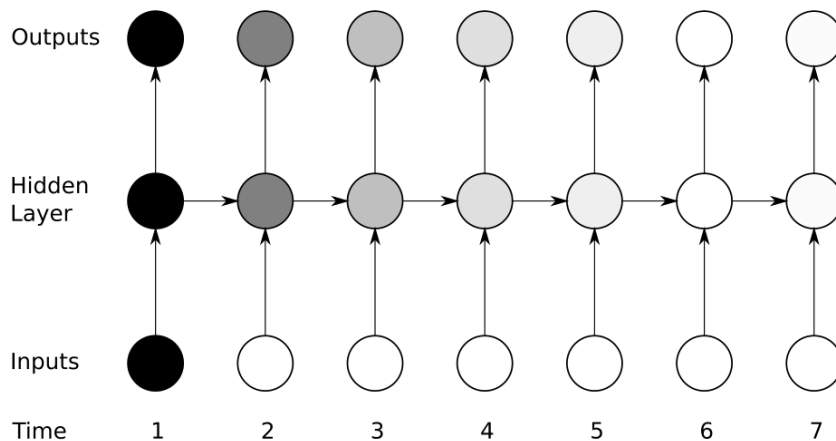In particular, they suffer from severe vanishing gradients!

Figure 4.1: **The vanishing gradient problem for RNNs.** The shading of the nodes in the unfolded network indicates their sensitivity to the inputs at time one (the darker the shade, the greater the sensitivity). The sensitivity decays over time as new inputs overwrite the activations of the hidden layer, and the network 'forgets' the first inputs.

Dealing with vanishing gradients

- To deal with vanishing gradients, many approaches have been proposed
  - Smarter weights initialization
  - Rectified Linear Units
  - Non-gradient based methods (e.g. discrete error propagation)

- The most successful aproach, which also improves over the classic RNN design are Long-Short Term Memory (LSTM) Networks
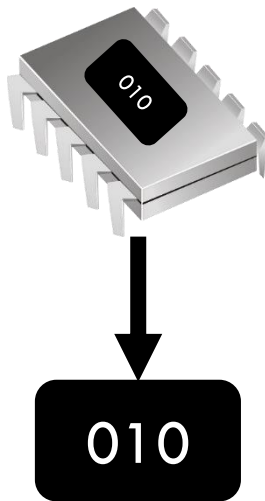
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About memories

To understand LSTM units, firts suppose a minimal data-storing device. In order to be usable it requires a minimal set of operations
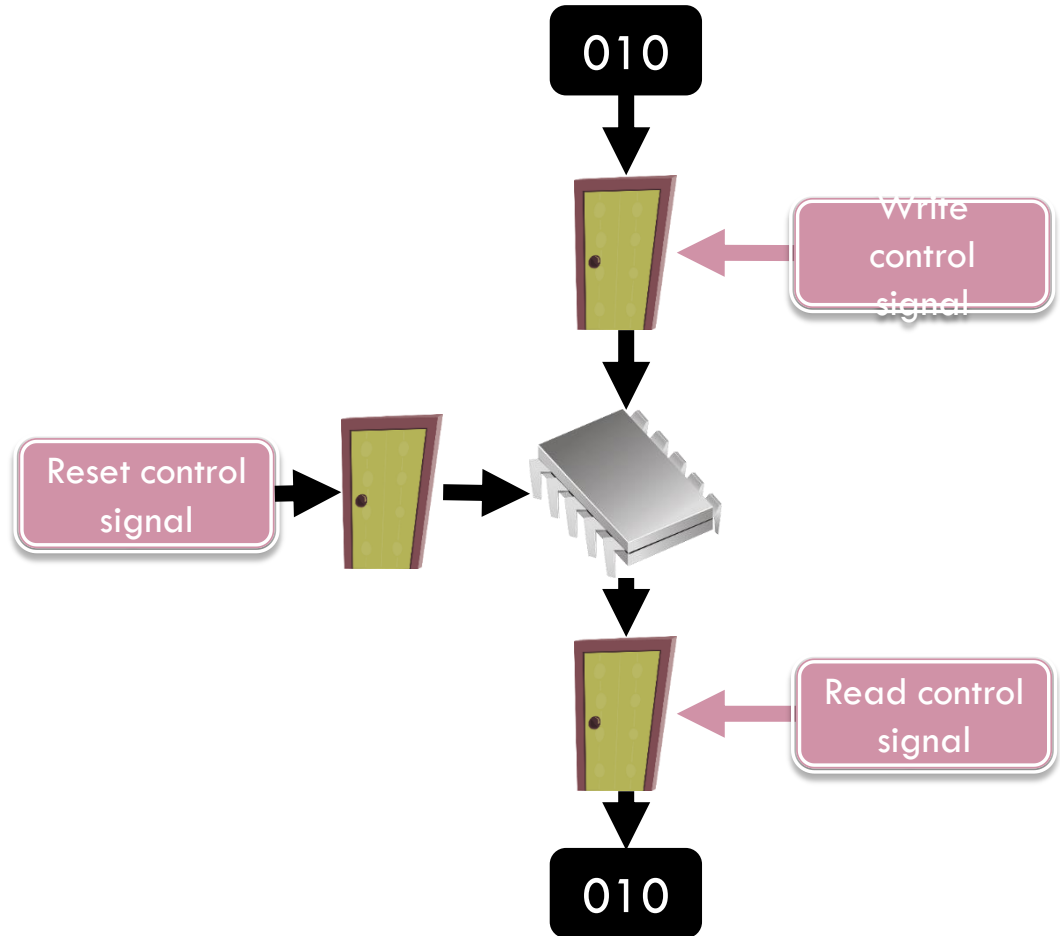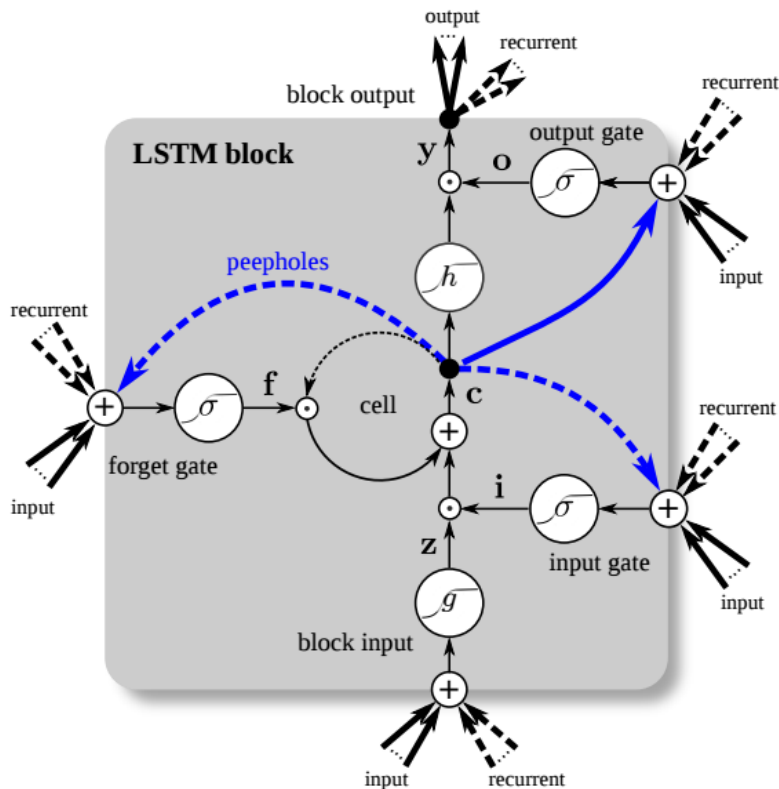
Write
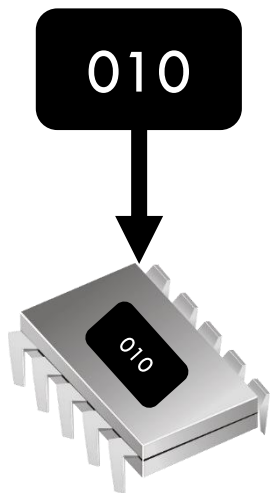
Read

Reset
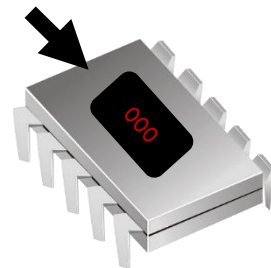
Gated memories

The three operations can be combined, together with some gates that open/close the execution of each operation.

Such gates can regulated through control signals.

This can be implemented into an artificial neuron!

010

Write control signal

Reset control signal

Read control signal

010

The Long-Short Term Memory unit

Cell: memory storage, keeps a value C_t for future use

Input gate: combines unit inputs to modify the value stored in the cell

Forget gate: attenuates the value stored in the cell

Output gate: combines unit input with cell value to produce the output

All gates receive inputs from previous layer + recurrent inputs from this layer

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Advantages of LSTMs

Input gates: the network can decide when an input is important enough to be memorized

Reset gates: the network can decide when a memory is no longer useful

Output gates: the network can decide when to release a particular memory to compute the current network output

A memorized value can be retained indefinitely
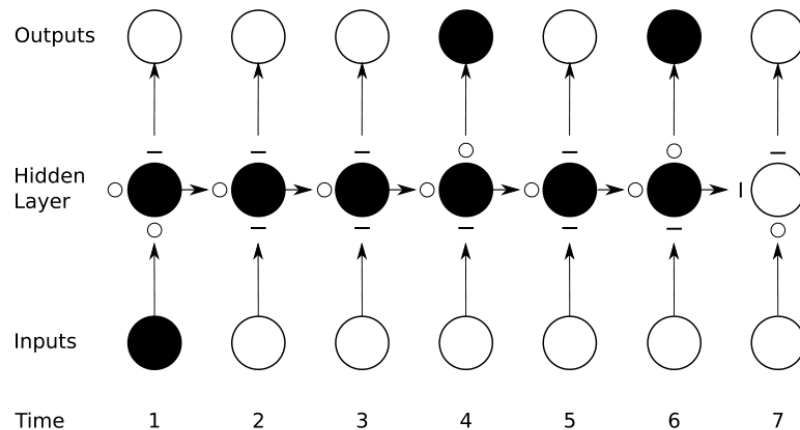
➤ Thus, no vanishing gradients!

Figure 4.4: **Preservation of gradient information by LSTM.** As in Figure 4.1 the shading of the nodes indicates their sensitivity to the inputs at time one; in this case the black nodes are maximally sensitive and the white nodes are entirely insensitive. The state of the input, forget, and output gates are displayed below, to the left and above the hidden layer respectively. For simplicity, all gates are either entirely open ('O') or closed ('—'). The memory cell 'remembers' the first input as long as the forget gate is open and the input gate is closed. The sensitivity of the output layer can be switched on and off by the output gate without affecting the cell.

Graves - Supervised Sequence Labelling with Recurrent Neural Networks
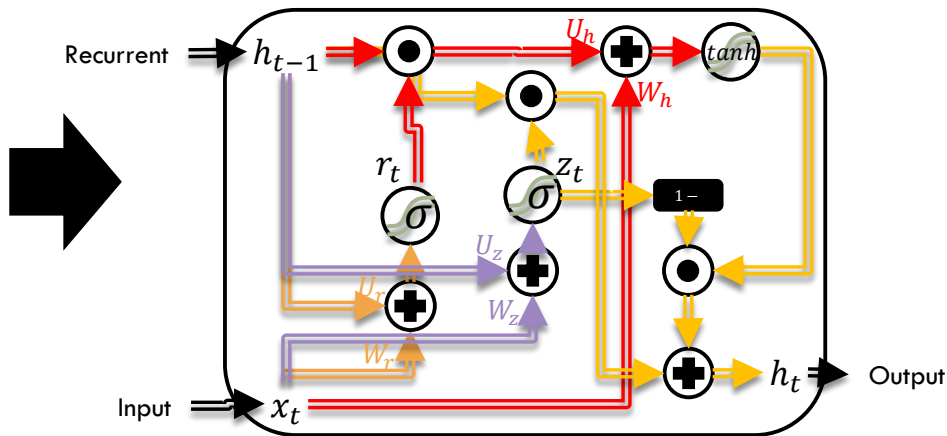
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Recurrent network with LSTM
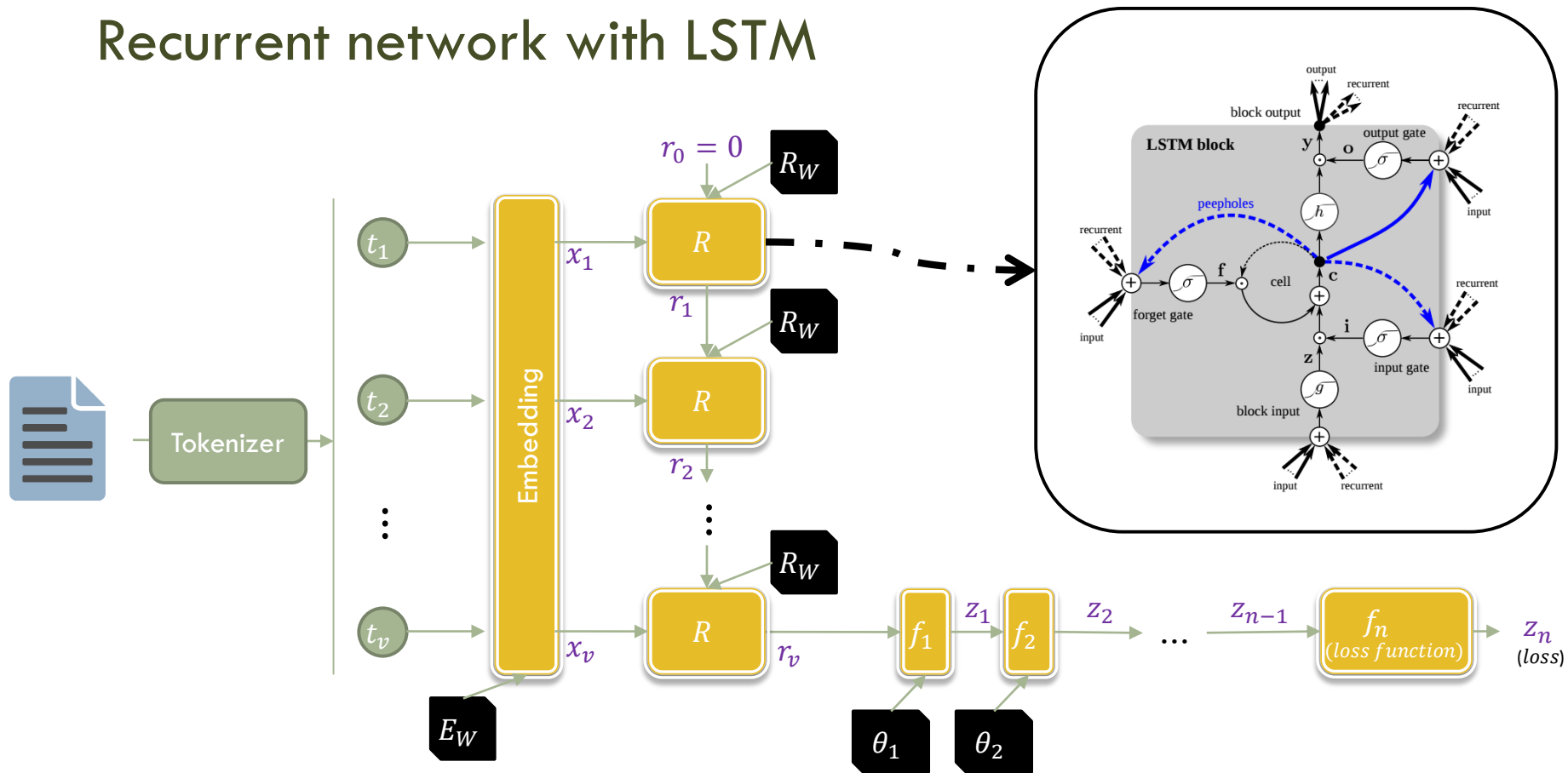
Gated Recurrent Units (GRU)
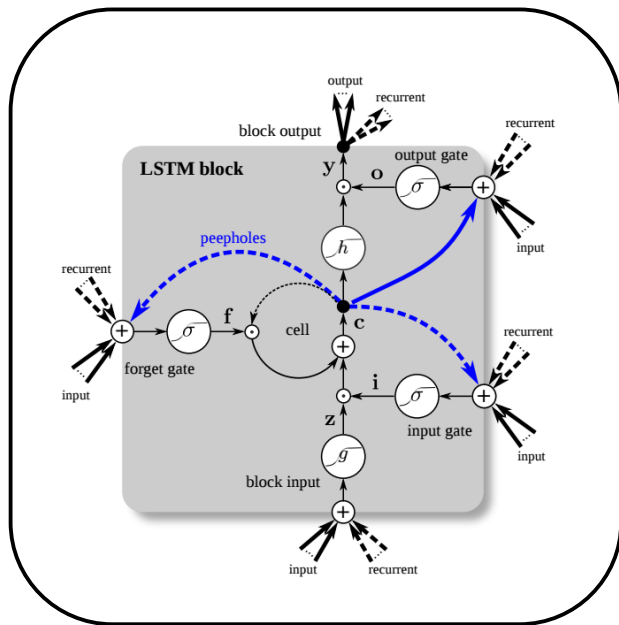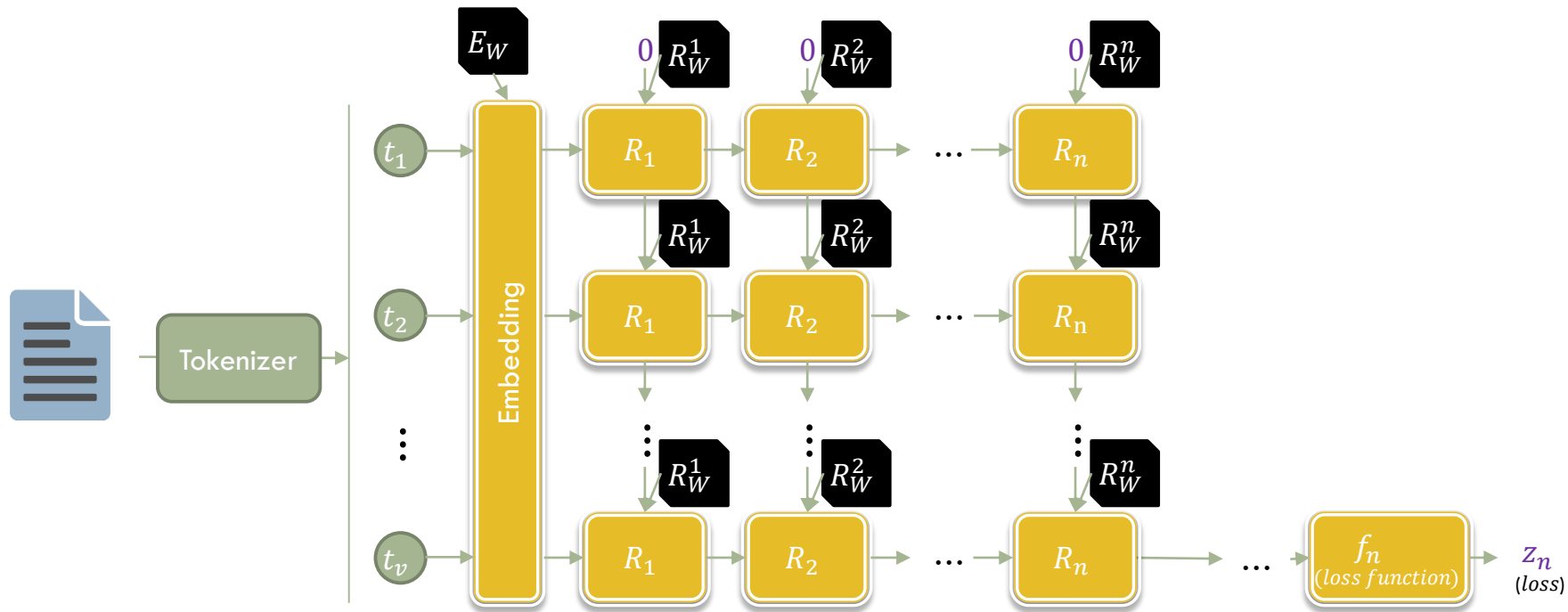

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$
$$h_t = z_t \circ h_{t-1} + (1 - z_t) \circ tanh(W_h x_t + U_h(r_t \circ h_{t-1}) + b_h)$$

- Simplified version of the LSTM cell
  - Combine "write" and "reset" gates into a single "update" gate. No "read" gate: output values h_t are the memory values themselves
- Lower computational cost
- Works better than LSTM in smaller datasets

Cho et al - Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation

Colah – Understanding LSTM Networks - http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Stacked LSTM

- As with other kind of layers, LSTM layers can be stacked on top of one another
- Each LSTM layer mixes the outputs of the previous layer
- Refined mixings of the observed sequences

Bidirectional LSTM (BiLSTM)
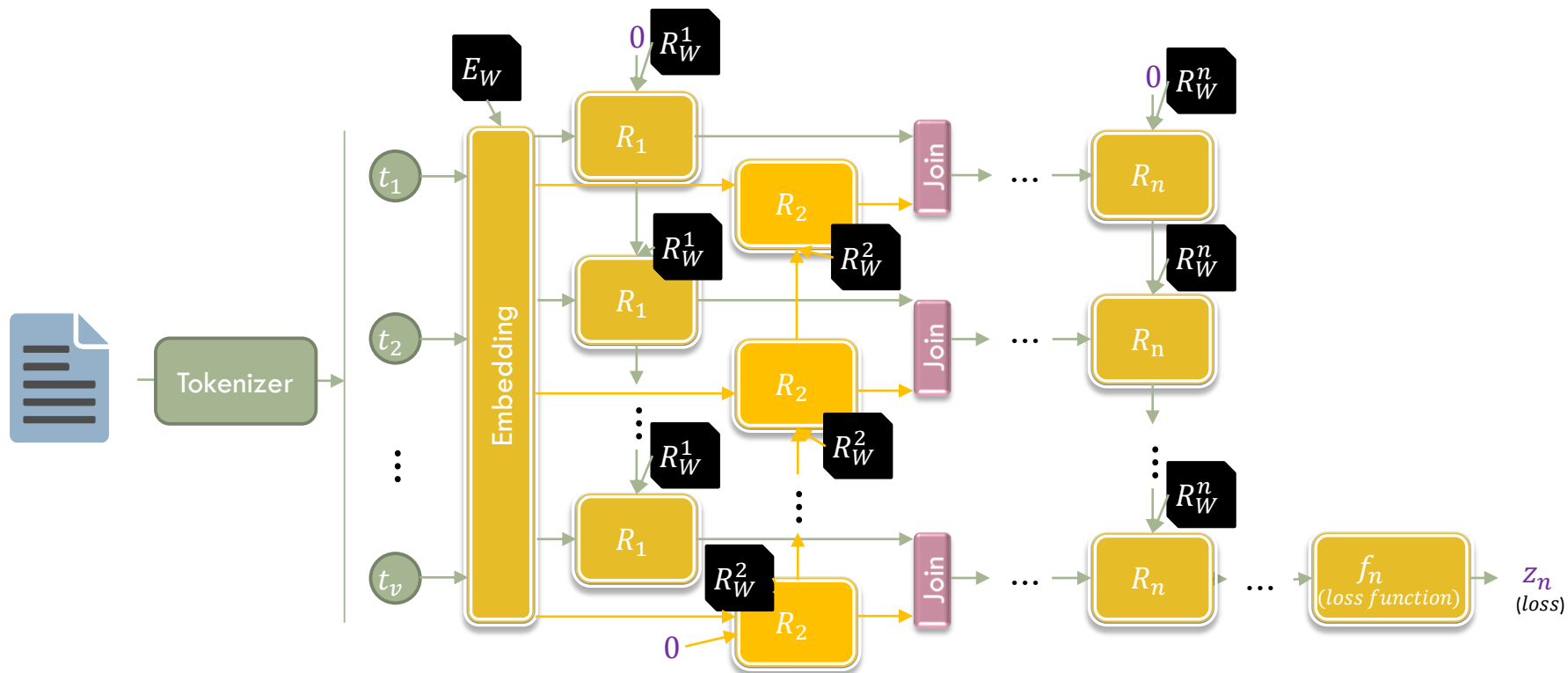
- Follow the Embedding with two LSTM layers, reading data in opposite directions
- Join the outputs of both layers (concat, mean), and propagate to next layers
- Better mixings of the observed sequences

Example: simple language generation

Train a 3-layered LSTM to predict the next character in a given text

Predict using the previous 100 characters of the text

Then generate new texts from the network!

Shakespeare

PANDARUS:

Alas, I think he shall be come approached and the day

When little srain would be attain'd into being never fed,

And who is but a chain and subjects of his death,

I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,

Breaking and strongly should be buried, when I perish

The earth and thoughts of many states.

Lovecraft

his squalid mother and grandfather in this respect was thought very notable until the horror of 1980, but the old tombs and sense of stone of the one had a hard connection which he had been there where the present horror started at the cry of the last the room of the sea. The neighbourhood of the hall it was to meet a catch of marine many of the room seemed to be indeed to see a marvellous ground of a trace of of the space we can see their specimens; and so the death of the sea some of the…

Movie Titles

Better Story<END>

Last Company<END>

The Love Balls: Part 2<END>

The Salence Truth of Boys<END>

Really Case to Disaster<END>

Ana House Thief<END>

The Secret of the Cast<END>
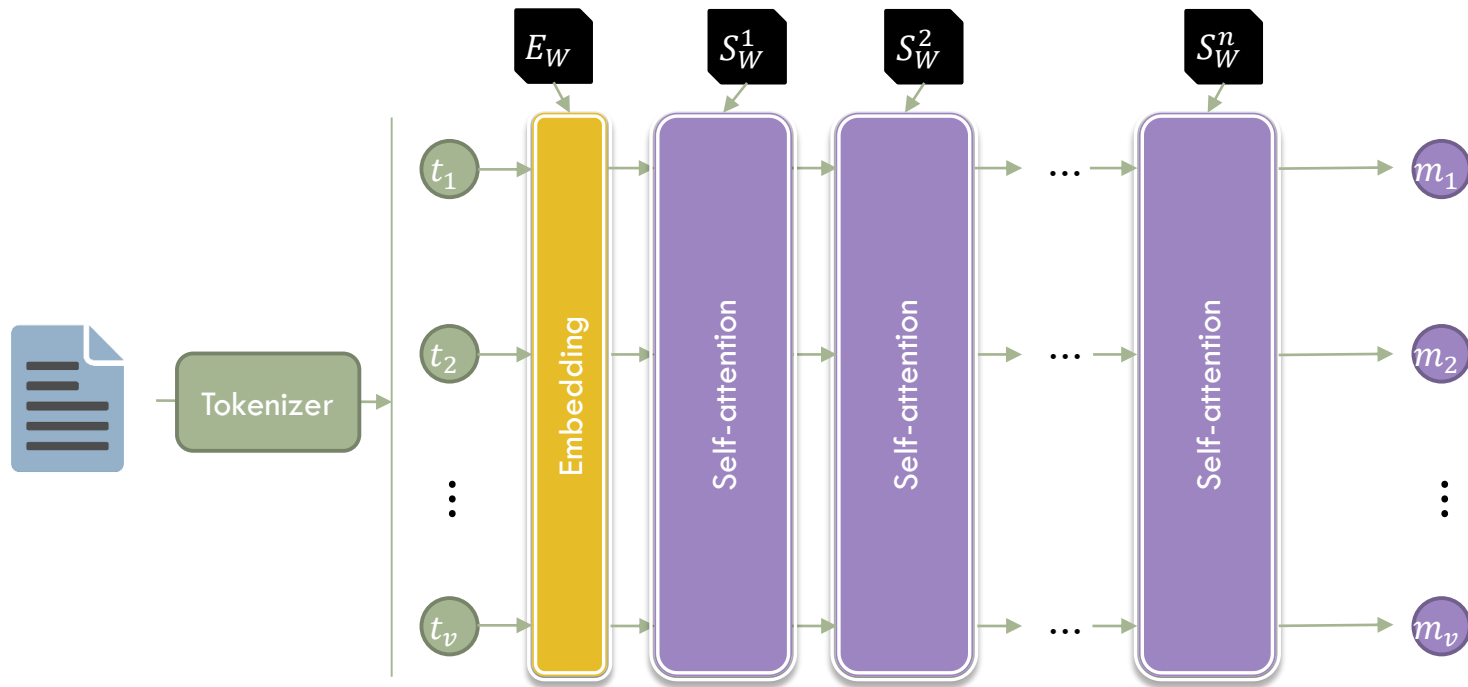
The Countdust of Story<END>

We We Travele<END>

The Tale of the Trome<END>

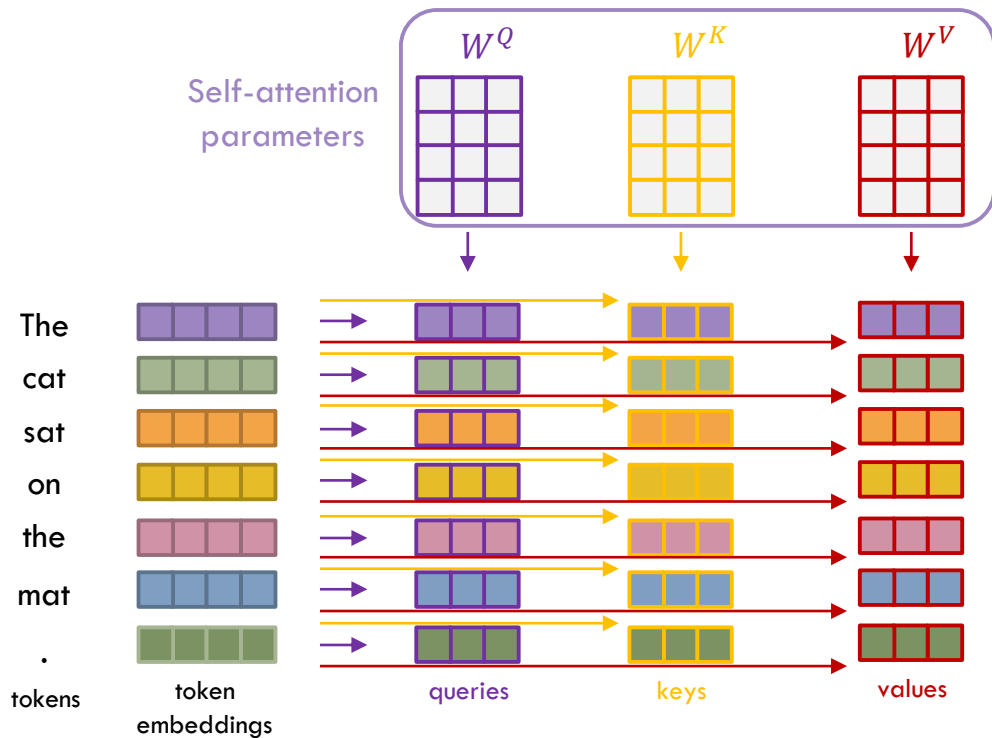The Vecyme That White Edition<END>

All Bedroom<END>

Alive a Fall<END>

Self-attention

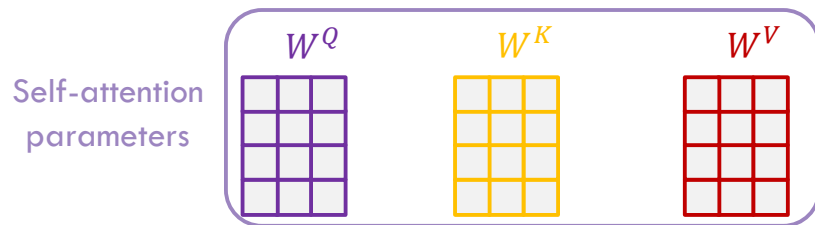

- Improving over recurrent networks, the self-attention layer mixes the representation of every token in the document with every other token, and produces a new embedding for each token.
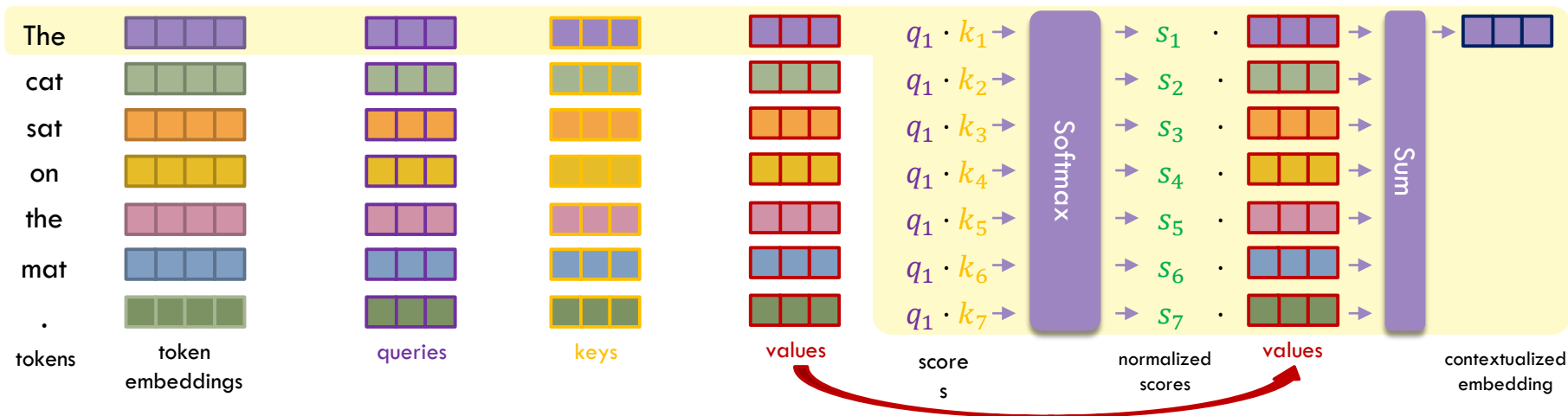- Contextualized embeddings.

Self-attention in detail

- Multiply each token embedding by matrices W^Q, W^K and W^V to produce a query, key and value vector for each token.
- Query vectors: what this token is "looking for" in other tokens
- Key vectors: what this token "can offer" to other tokens
- Relevance score: how aligned is a query vector for a token with the key vector of another token ($q_i \cdot k_j$)
  - High relevance scores mean this pair of tokens must be mixed.
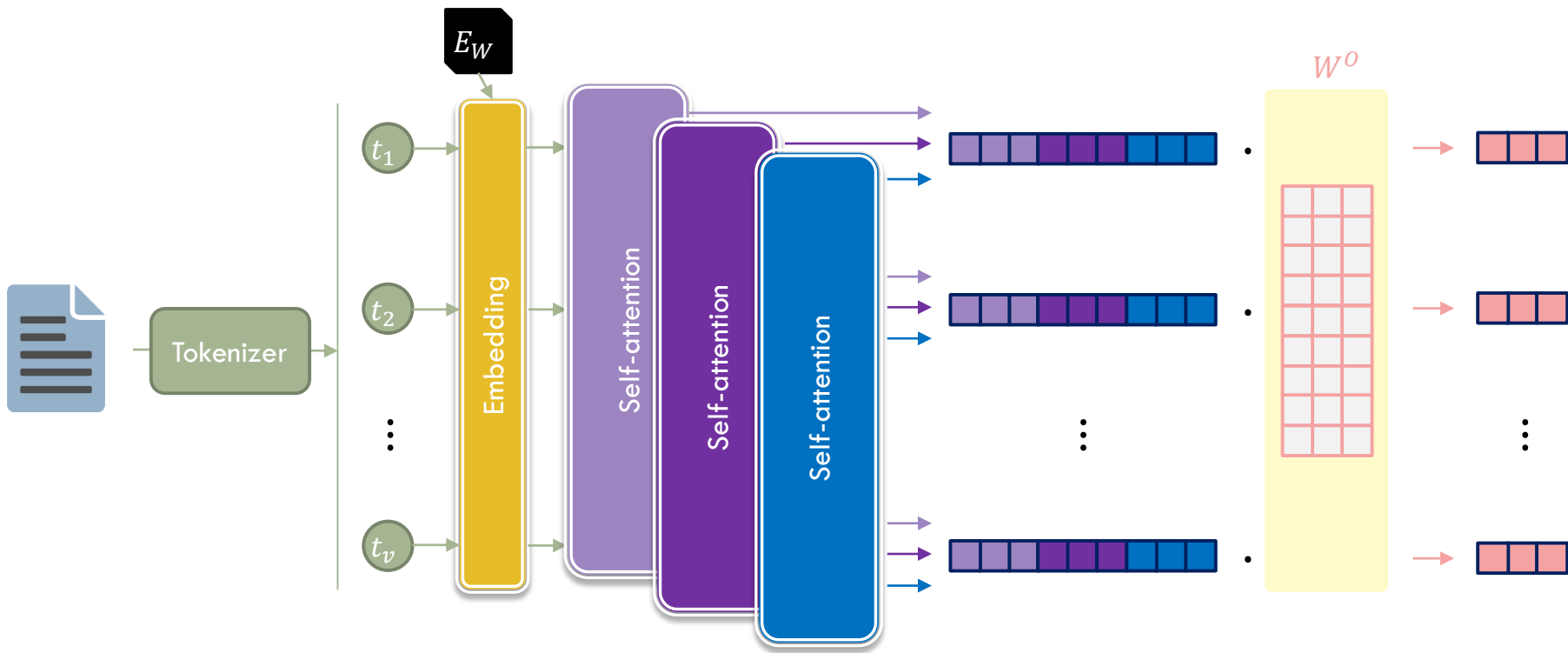- New embeddings will be produced by mixing value vectors weighted by scores.

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

Vaswani et al – Attention is All You need

Self-attention scores for a token

- The contextualized embedding for each token mixes value vectors from all words, weighted by query · key scores.
- Flow for first token:

Self-attention parameters

W^Q W^K W^V

The

cat

sat

on

the

mat

.

tokens

token embeddings

queries

keys

values

$q_1 \cdot k_1 \rightarrow s_1 \cdot$
$q_1 \cdot k_2 \rightarrow s_2 \cdot$
$q_1 \cdot k_3 \rightarrow s_3 \cdot$
$q_1 \cdot k_4 \rightarrow s_4 \cdot$
$q_1 \cdot k_5 \rightarrow s_5 \cdot$
$q_1 \cdot k_6 \rightarrow s_6 \cdot$
$q_1 \cdot k_7 \rightarrow s_7 \cdot$

Softmax

scores

normalized scores

Sum

values

contextualized embedding

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

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Multi-headed self-attention

- Multiple self-attention blocks can be used in parallel, similarly to multiple convolutional kernels.
- For n blocks (heads) n contextualized embeddings are obtained for each token.
- Concatenate embeddings and mix using an output matrix W^O to recover a single embedding per token.
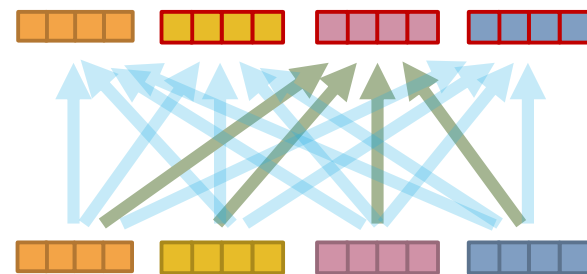
Summary of mixing models

Mixing model	Operation	Sensitive to tokens relative ordering?	Sensitive to tokens absolute position in the document?
Convolutional	Mix each token with neighbouring tokens	✓	✗
Recurrent	Mix each token with new representation of previous token	✓	✓
Self-attention	Mix each token with every other token	✗	✗
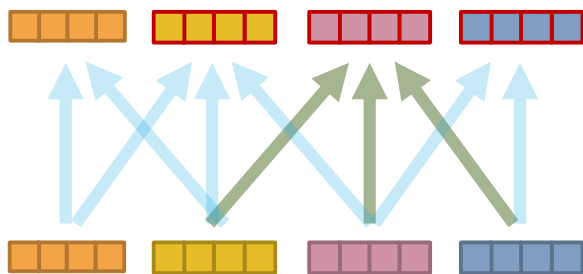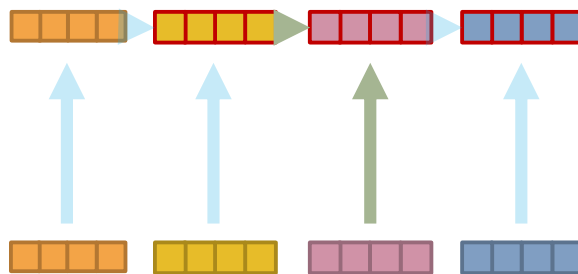
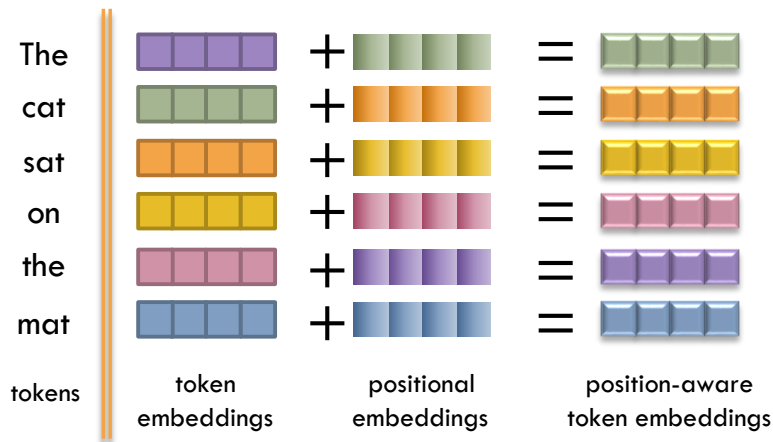Convolutional   Recurrent   Self-attention
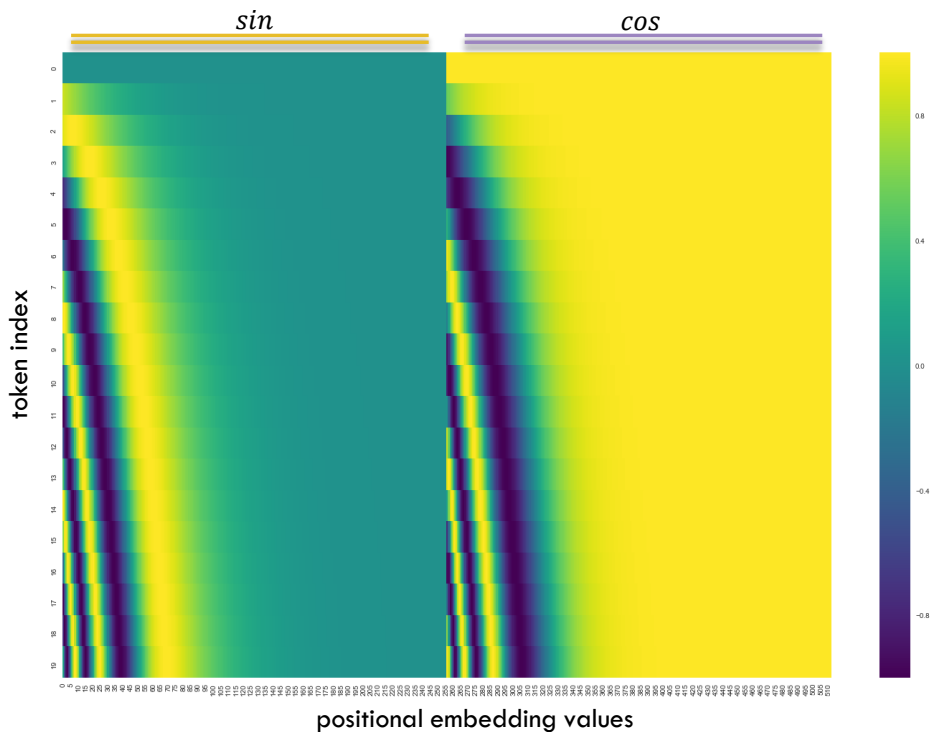
Positional embeddings

Self-attention and convolutional mixings can be made aware of tokens relative and absolute positions by introducing positional embeddings.


The cat sat on the mat

| tokens | token embeddings | positional embeddings | position-aware token embeddings |

Positional embeddings values are computed as sin and cos of the position of the word in the document. Each embedding dimension i accounts for a sinusoid of a different frequency, normalized by maximum document length. Positional embeddings have the same size d_{model} has token embeddings.

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{maxlen^{\left(\frac{2i}{d_{model}}\right)}}\right) \qquad PE_{(pos,2i+1)} = \cos\left(\frac{pos}{maxlen^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

token index

positional embedding values

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

Vaswani et al – Attention is All You need

The Transformer

An architecture combining all the topics covered so far is the Transformer, which produces state-of-the-art results in complex tasks such as language translation. A Transformer stacks several blocks in the form:
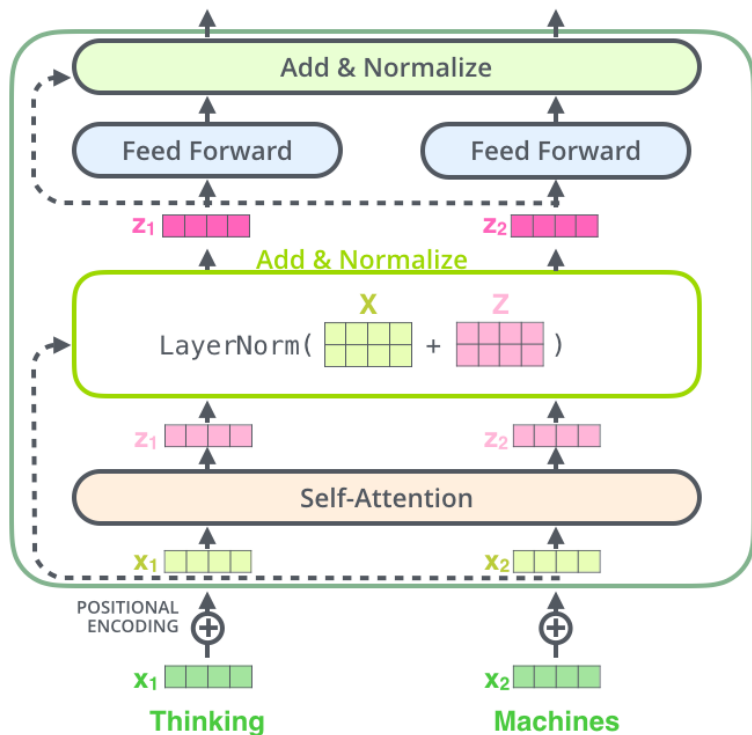
- Token + positional embeddings (in first block)
- Multi-head self-attention
- Residual block with Layer Normalization
- A small Feed Forward network: Dense + ReLU + Dense. This network is applied at each position, separately and identically.
  - This is equivalent to Conv + ReLU + Conv with kernel size 1
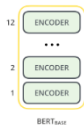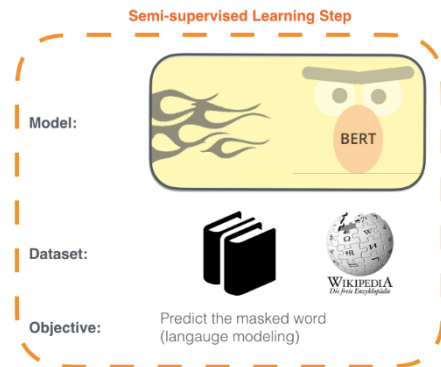- Residual block with Layer Normalization

Large Language Models
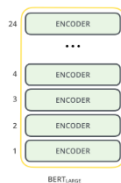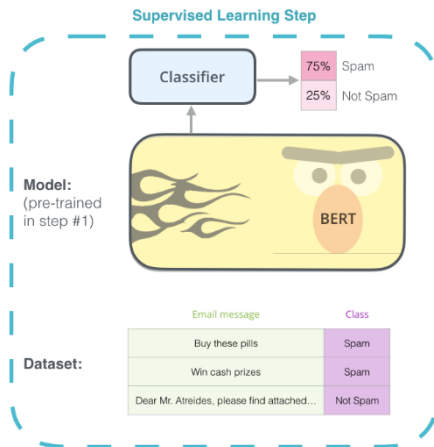
Large Language models: BERT

It is possible to train very large language models that provide us with not only better token representations, but with a whole stack of layers able to produce contextualized embeddings. The Bidirectional Encoder Representations for Transformers (BERT) model is a stack of Transformers that does this:

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).
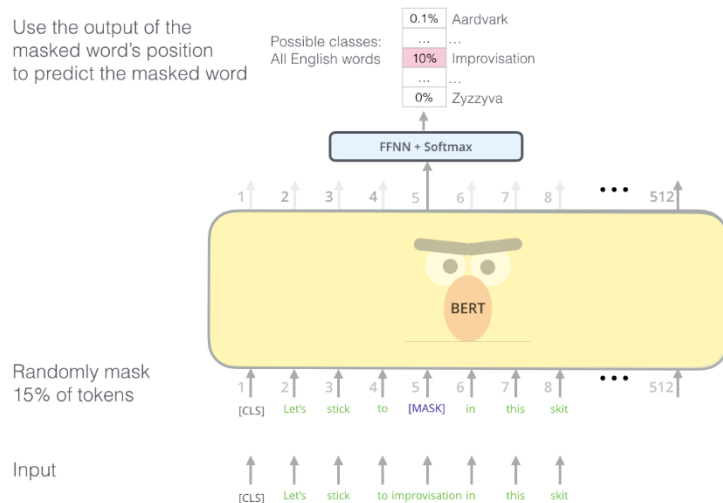
The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step

Model:

Dataset:

Objective: Predict the masked word (language modeling)

2 - Supervised training on a specific task with a labeled dataset.

Supervised Learning Step

Classifier → 75% Spam / 25% Not Spam

Model: (pre-trained in step #1)

Dataset:

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached...	Not Spam

BERT_BASE

BERT_LARGE

Use the output of the masked word's position to predict the masked word

Possible classes: All English words

0.1%	Aardvark
...	...
10%	Improvisation
...	...
0%	Zyzzyva

FFNN + Softmax

Randomly mask 15% of tokens

[CLS] Let's stick to [MASK] in this skit

Input

[CLS] Let's stick to improvisation in this skit

Jay Allamar – The Illustrated BERT, ELMo an co - https://jalammar.github.io/illustrated-bert/

Devlin et al – BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT pre-trained models: https://github.com/google-research/bert

Large Language models: BERT as transfer learning

BERT can be used as a transfer learning tool, to obtain better embeddings for our documents. We can then train a small network on BERT outputs for our particular problem.

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA
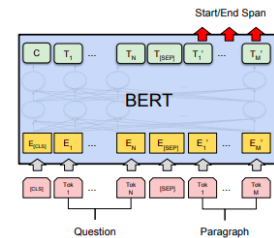
(c) Question Answering Tasks: SQuAD v1.1
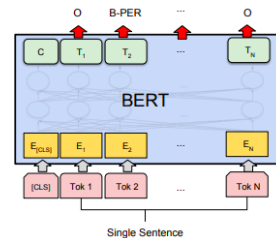
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER
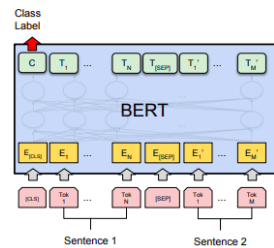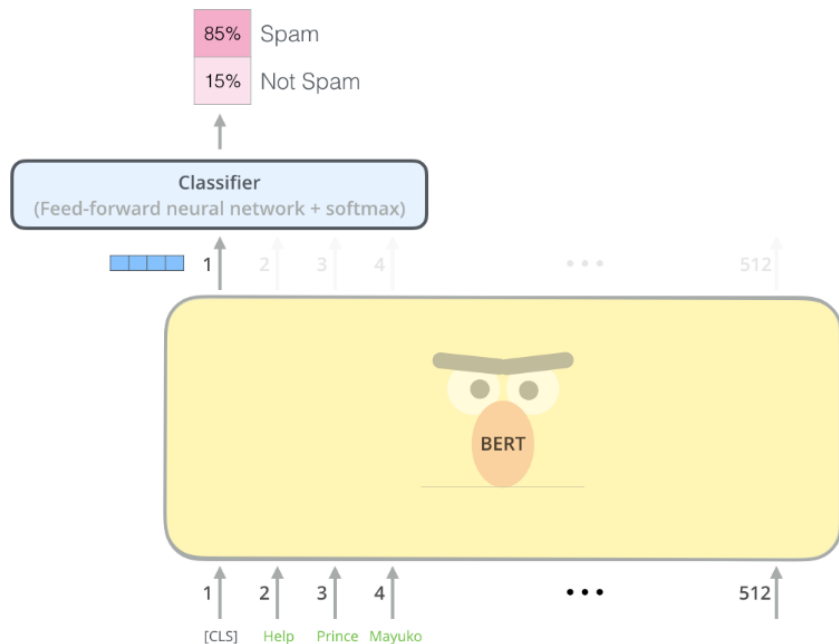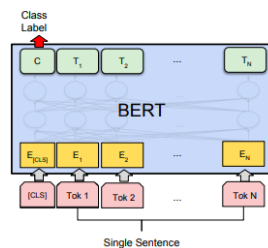
Jay Allamar – The Illustrated BERT, ELMo an co - https://jalammar.github.io/illustrated-bert/

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BERT pre-trained models: https://github.com/google-research/bert

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them — they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pérez, "In South America, such incidents seem to be quite common."

However, Pérez also pointed out that it is likely that the only way of knowing for sure if unicorns are indeed the descendants of a lost alien race is through DNA. "But they seem to be able to communicate in English quite well, which I believe is a sign of evolution, or at least a change in social organization," said the scientist.

Large Language models: GPT-2

DATASET	METRIC	OUR RESULT	PREVIOUS RECORD	HUMAN
Winograd Schema Challenge	accuracy (+)	**70.70%**	63.7%	92%+
LAMBADA	accuracy (+)	**63.24%**	59.23%	95%+
LAMBADA	perplexity (-)	**8.6**	99	~1-2
Children's Book Test Common Nouns (validation accuracy)	accuracy (+)	**93.30%**	85.7%	96%
Children's Book Test Named Entities (validation accuracy)	accuracy (+)	**89.05%**	82.3%	92%
Penn Tree Bank	perplexity (-)	**35.76**	46.54	unknown
WikiText-2	perplexity (-)	**18.34**	39.14	unknown
enwik8	bits per character (-)	**0.93**	0.99	unknown
text8	bits per character (-)	**0.98**	1.08	unknown
WikiText-103	perplexity (-)	**17.48**	18.3	unknown

GPT-2 is an even larger Transformer model, up to 48 layers, trained on Internet texts extracted from Reddit. Produces a very accurate language model. Currently not open-sourced to prevent malicious uses.
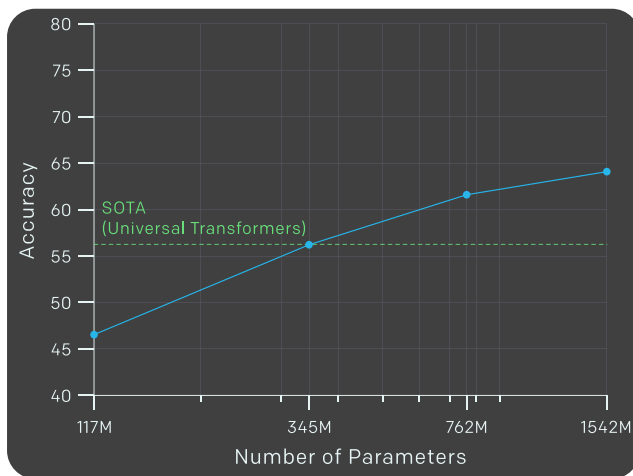
Performance in LAMBADA language modelling task

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

BERT Large

Table 2. Architecture hyperparameters for the 4 model sizes.

OpenAI - Better Language Models and their implications - https://blog.openai.com/better-language-models

Racford et al – Language Models are Unsupervised Multitask Learners
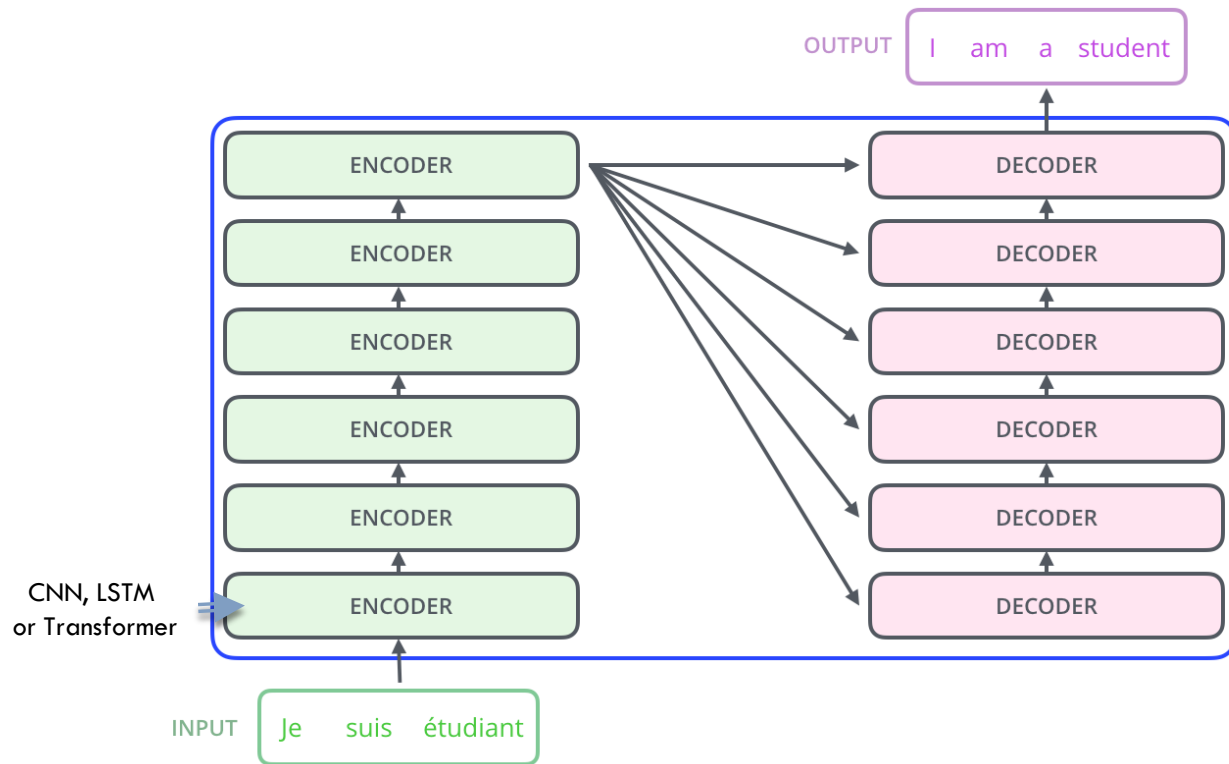
Sequence to Sequence Learning

Sequence to sequence learning
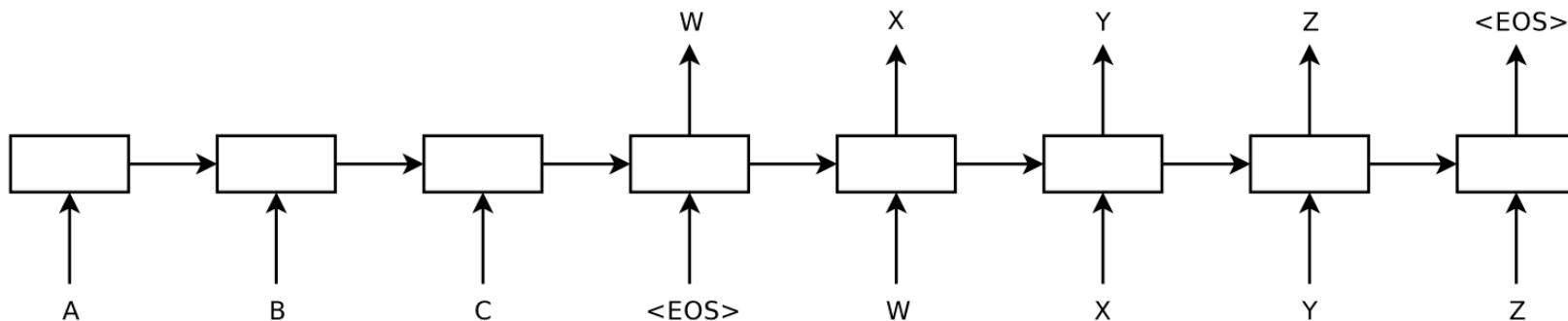
- The model reads the input sequence A + B + C and produces W + X + Y + Z as output
- After an special input <EOS> is received the hidden state of the network is used as input to the decoder network
- The decoder network generates one sequence element at a time, which is fed back as input to produce the next element
- The decoder stops once the special character <EOS> is generated

Sutskever et al: Sequence to Sequence Learning with Neural Networks

Example: Machine Translation

Encoder-Decoder architecture with Transformers

Mix encoder outputs with translation so far

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

Vaswani et al – Attention is All You need
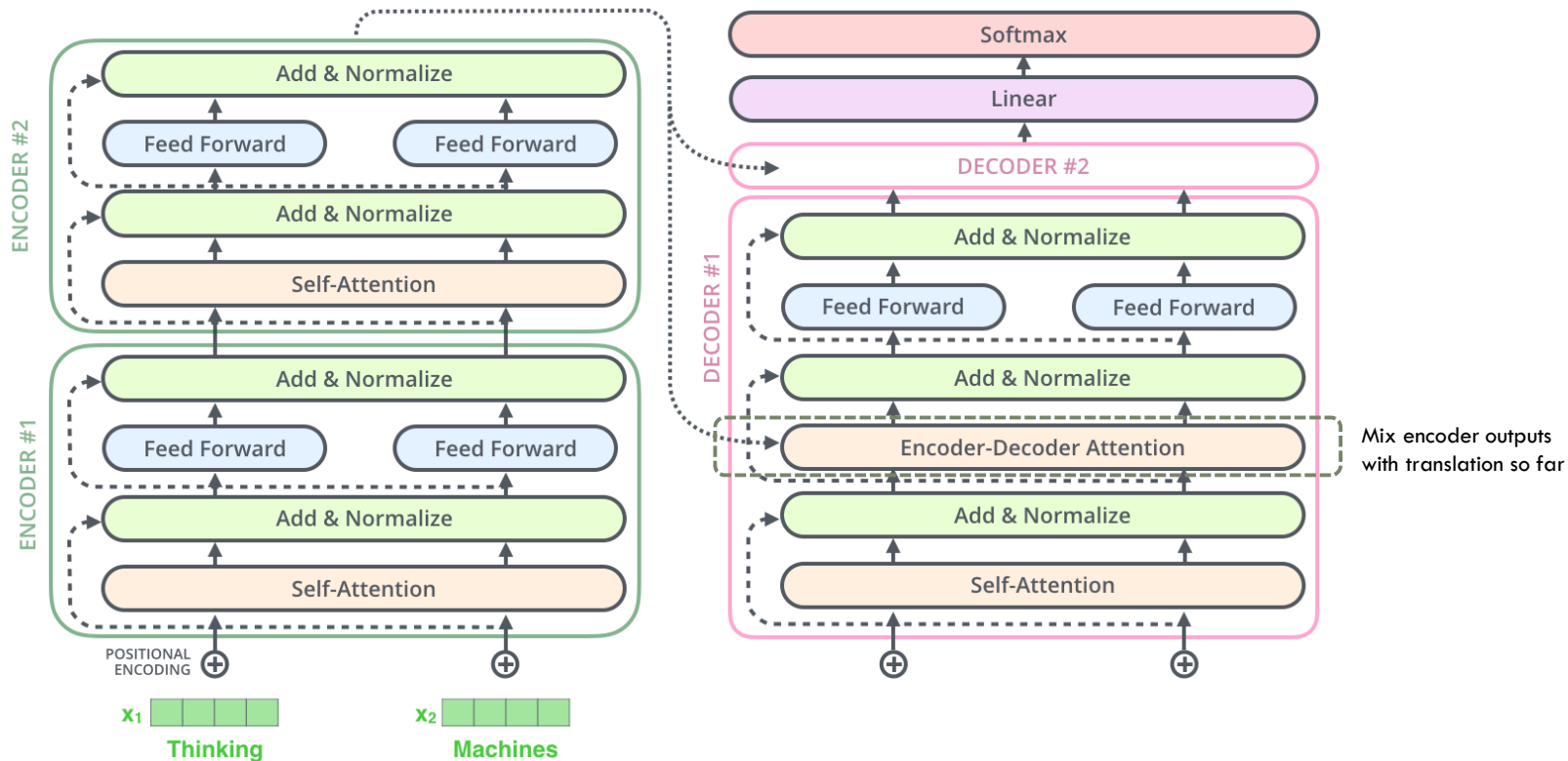
Encoder-Decoder architecture: first decoding step

Decoding time step: ① 2 3 4 5 6   OUTPUT

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

Vaswani et al – Attention is All You need
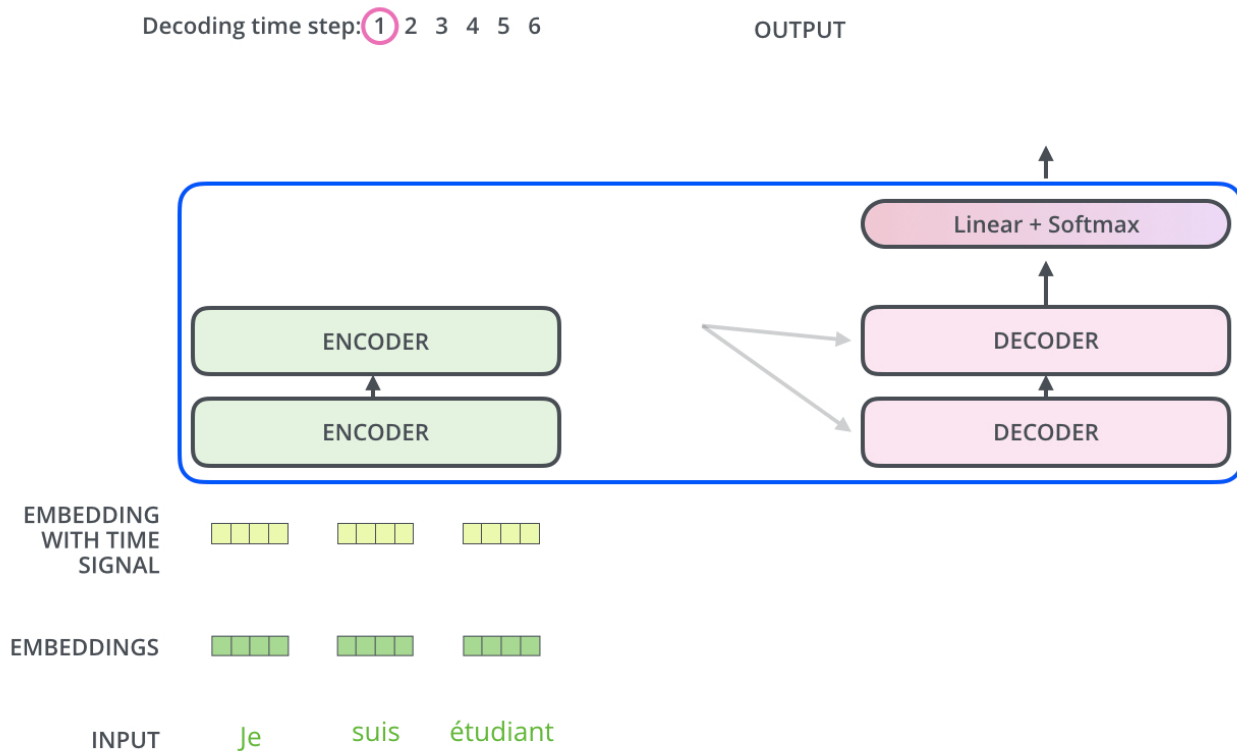
Encoder-Decoder architecture: next decoding steps

Decoding time step: 1 ②3 4 5 6   OUTPUT   I

K encdec   V encdec   Linear + Softmax

ENCODERS   DECODERS

EMBEDDING WITH TIME SIGNAL

EMBEDDINGS

INPUT   Je   suis   étudiant   PREVIOUS OUTPUTS   I

Jay Allamar – The Illustrated Transformer - https://jalammar.github.io/illustrated-transformer/

Vaswani et al – Attention is All You need
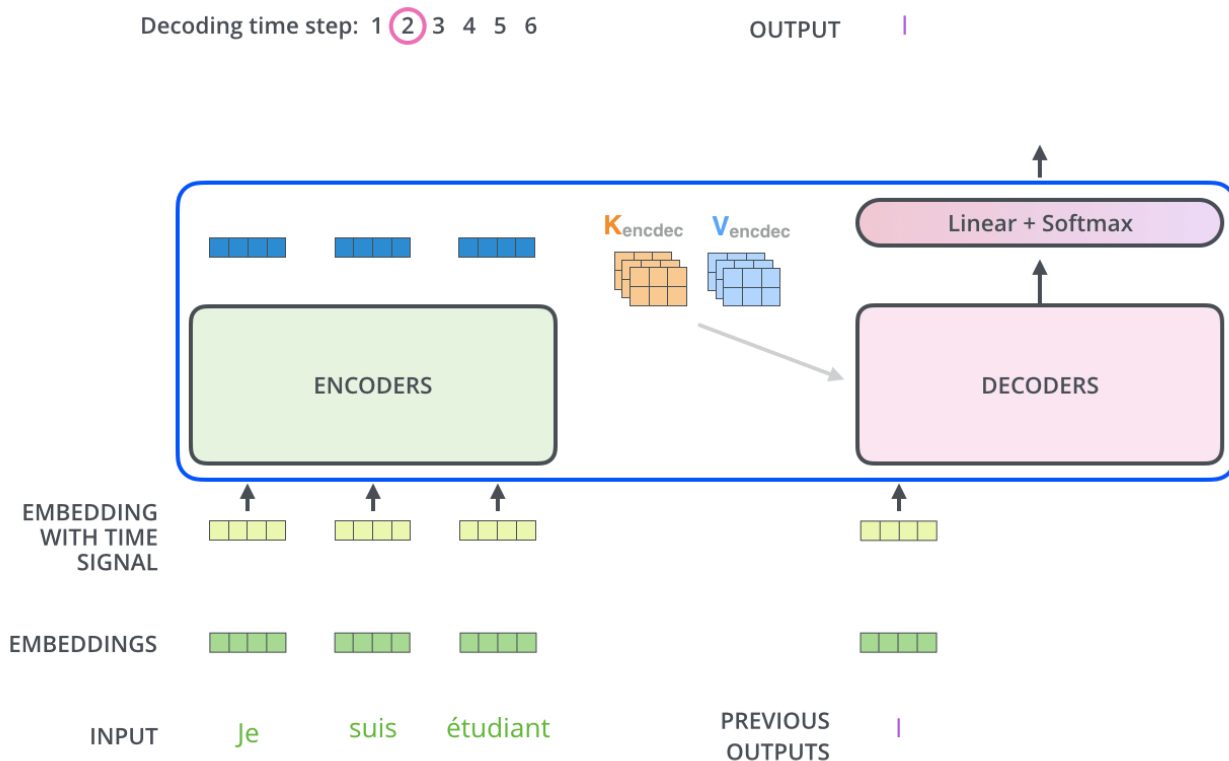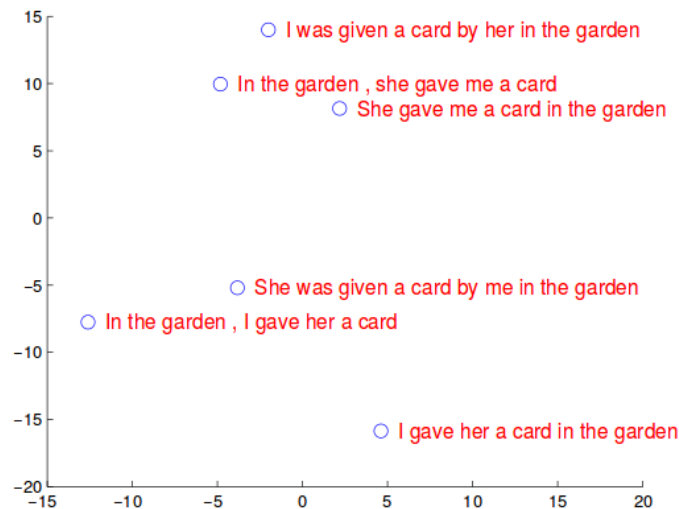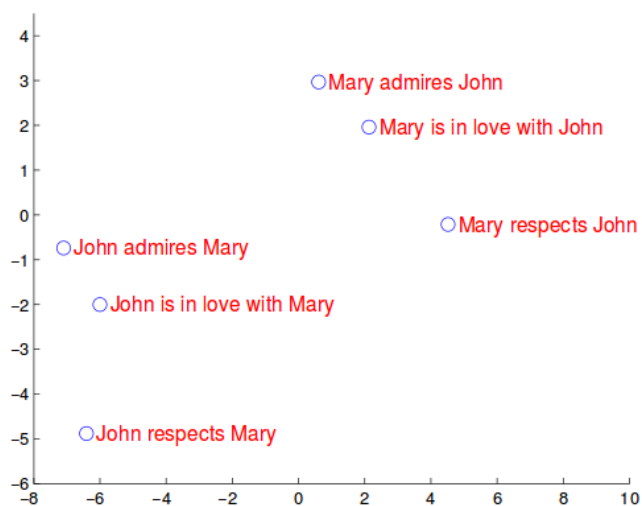
Sequence to sequence learning

Figure 2: The figure shows a 2-dimensional PCA projection of the LSTM hidden states that are obtained after processing the phrases in the figures. The phrases are clustered by meaning, which in these examples is primarily a function of word order, which would be difficult to capture with a bag-of-words model. Notice that both clusters have similar internal structure.

Aplicación: traducción automática

➢ **Objetivo**: dado un texto en un idioma conocido, traducirlo a otro idioma dado

➢ **Aproximación** para el problema

  ➢ Embeddings, Transformers, modelos grandes de lenguaje (tipo BERT)

  ➢ Modelo sequence-to-sequence que pase de la secuencia de un idioma a otro

➢ **Recursos**

  ➢ Corpus alineado del parlamento Europeo: http://www.statmt.org/europarl/

Language translation is one of the ways we can give people the power to build community and bring the world closer together. It can help people connect with family members who live overseas, or better understand the perspective of someone who speaks a different language. We use machine translation to translate text in posts and comments automatically, in order to break language barriers and allow people around the world to communicate with each other.

https://code.facebook.com/posts/289921871474277/transitioning-entirely-to-neural-machine-translation/

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Aplicación: respuesta de preguntas sobre texto

➢ Objetivo: dado un texto que presente detalles sobre un tema concreto, y una pregunta sobre ese tema, marcar en el texto dónde está la respuesta a la pregunta.

➢ Aproximación para el problema

  ➢ Modelos grandes de lenguaje (tipo BERT)

  ➢ Modelo sequence-to-sequence que reciba el texto de la pregunta y del texto, y para cada token del texto indique si forma parte de la respuesta o no

➢ Recursos

  ➢ The Stanford Question Answering Dataset https://rajpurkar.github.io/SQuAD-explorer/

European Union law is a body of treaties and legislation, such as Regulations and Directives, which have direct effect or indirect effect on the laws of European Union member states. The three sources of European Union law are primary law, secondary law and supplementary law. The main sources of primary law are the Treaties establishing the European Union. Secondary sources include regulations and directives which are based on the Treaties. The legislature of the European Union is principally composed of the European Parliament and the Council of the European Union, which under the Treaties may establish secondary law to pursue the objective set out in the Treaties.

What is European Union Law?
Ground Truth Answers: a body of treaties and legislation a body of treaties and legislation, such as Regulations and Directives, which have direct effect or indirect effect on the laws of European Union member states a body of treaties and legislation, such as Regulations and Directives a body of treaties and legislation, such as Regulations and Directives
Prediction: a body of treaties and legislation

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