Semantic representations

Sahar Ghannay

sahar.ghannay@lisn.upsaclay.fr

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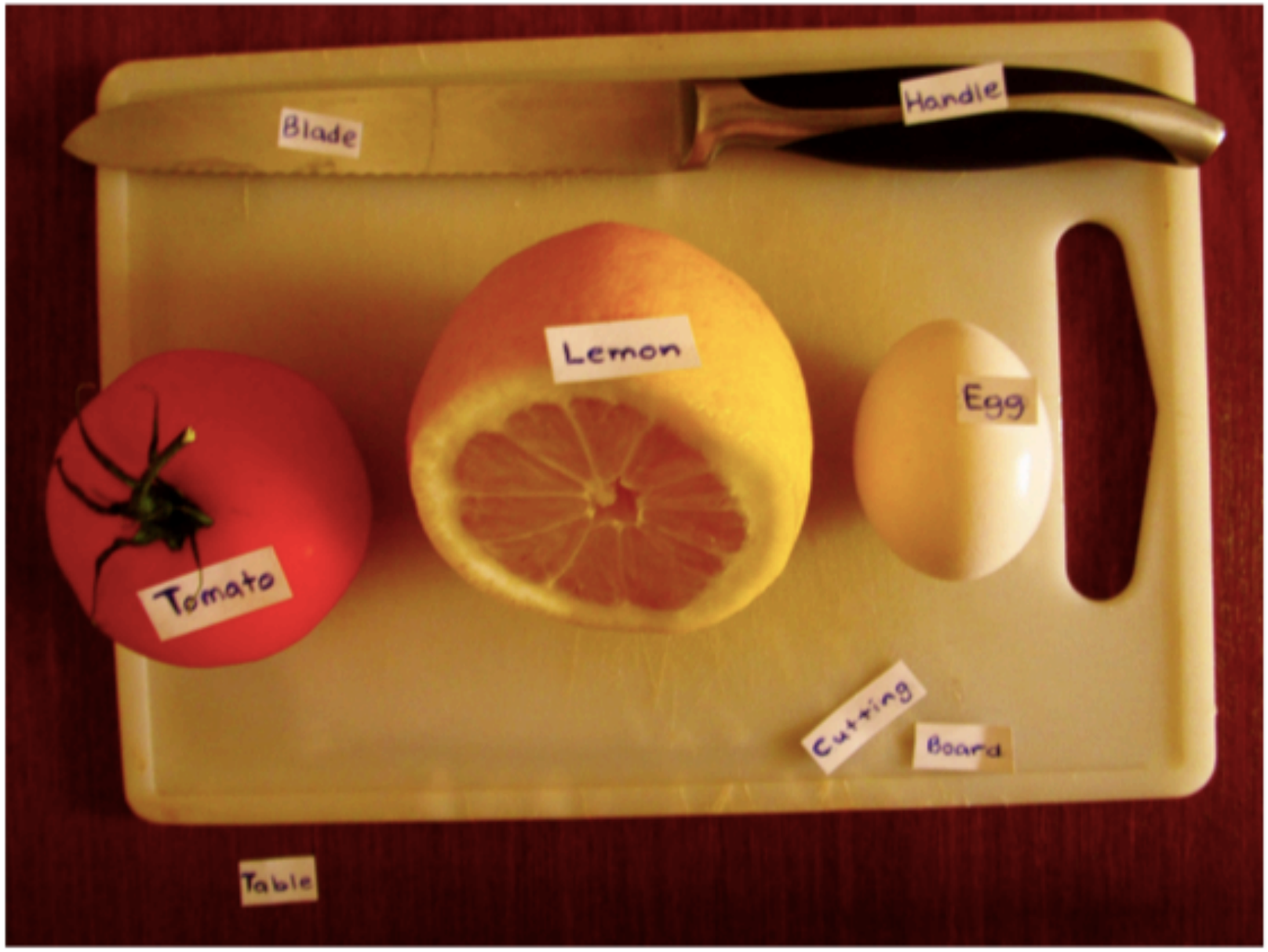
Introduction

Looking for meaning: what are we talking about? What is the meaning?

- Definition in a dictionary:
  - what is meant by a word, text, concept, or action.
- For an application:
  - The same, but restricted to the concepts needed for the application

Looking for meaning: what are we talking about? What is the meaning?



Semantic analysis in linguistic technology

- Information extraction
  - Analyzing texts to obtain information for a specific application:
    - Example: Named entity recognition
- Semantic textual similarity
- Natural language understanding
- *Etc.*

Semantic analysis in linguistic technology
Named Entity recognition

- Named entity recognition:
  - Seeks to locate and classify named entities (names of people/places/ organisations, dates) mentioned in unstructured text into pre-defined categories such as person, organizations, locations, time, ….

Semantic analysis in linguistic technology
Named Entity recognition

✤ Exemple :

On the invitation of the Festival de Cannes, the Italian actress Monica Belucci has agreed to play the role of Mistress of the Opening and Closing Ceremonies of the 70th festival de Cannes to be held from 17 to 28 May 2017, under the presidency of Spanish filmmaker Pedro Almodovar. […] Monica Bellucci's friendship with the Festival de Cannes goes back a long way: in 2000, she walked up the steps for the first time to present *Under Suspicion* by Stephen Hopkins.

Semantic analysis in linguistic technology
Named Entity recognition

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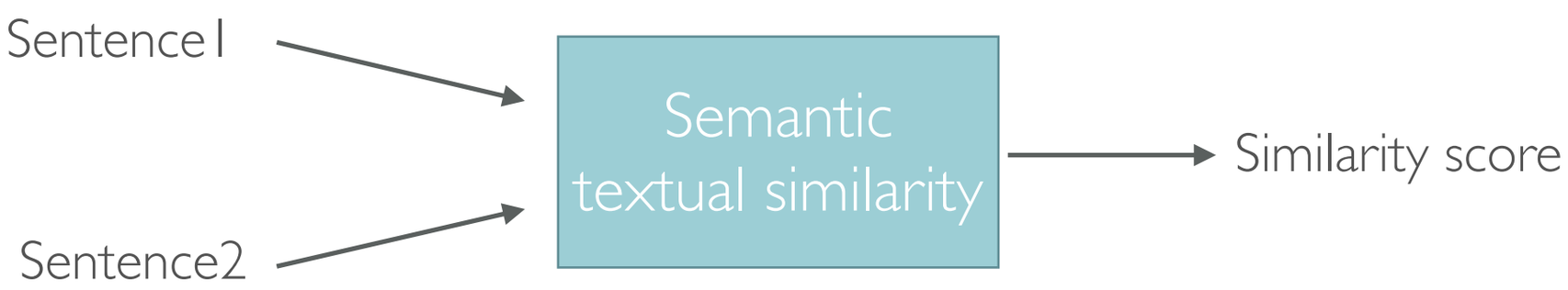
PERSON, ORGANIZATION, LOCATION, DATE

Semantic analysis in linguistic technology
Semantic textual similarity

- SemEval 2017 task 5

Exemple de paire de phrases

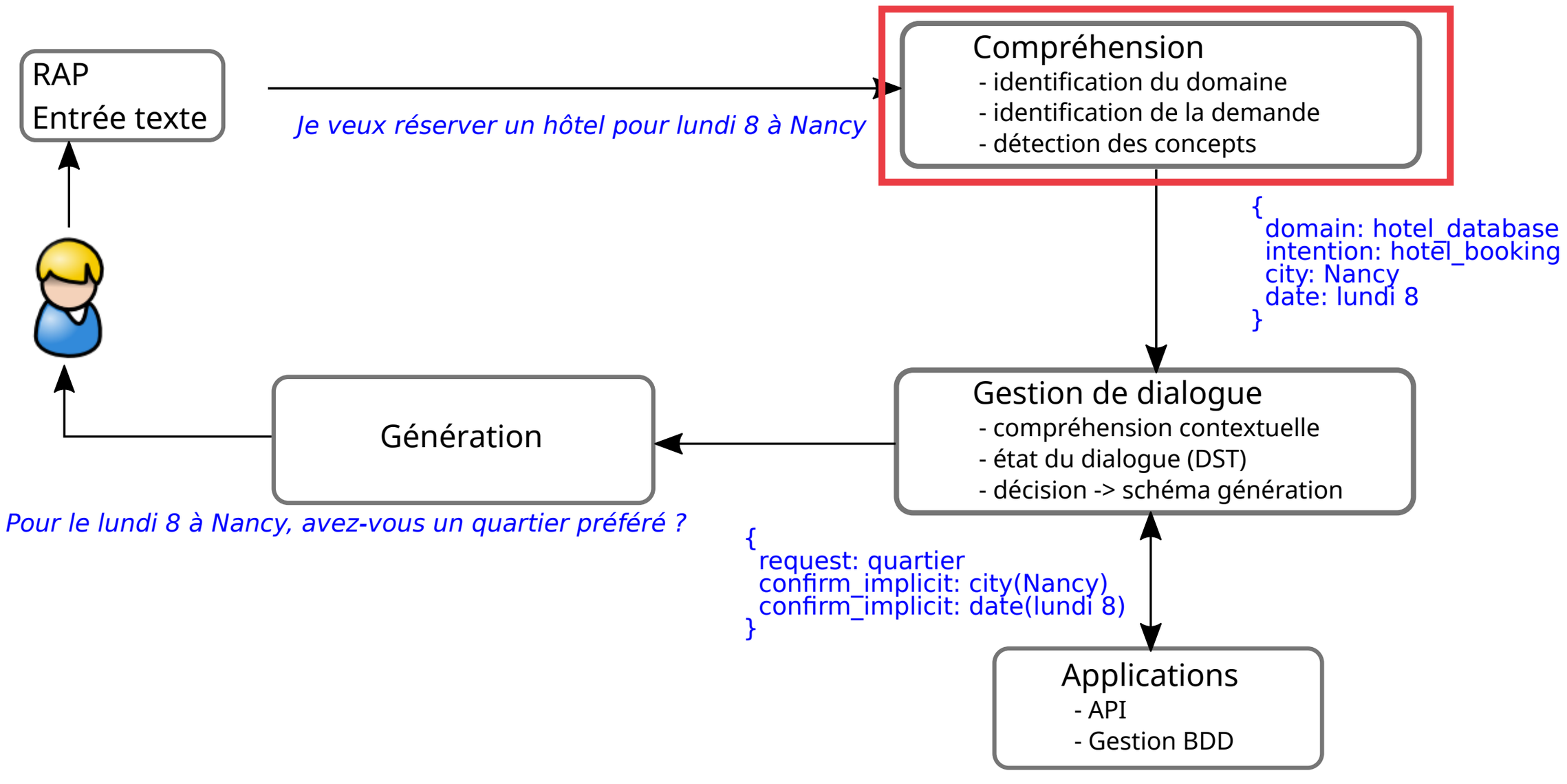
Three men are playing chess.	Two men are playing chess.
A man is playing the cello.	A man seated is playing the cello.
Some men are fighting.	Two men are fighting.



➡ **Evaluate how these sentences are close on a scale of 1 to 5**

Semantic analysis in linguistic technology
Natural/Spoken language understanding

Système orienté tâche



Semantic analysis in linguistic technology
Natural/Spoken language understanding

- Natural language understanding system (NLU):
  - Can be considered as a system that translates a sequence of words to one or more actions:
    1. Associate the sequence of words in the input of the system to intermediate semantic language often called **concepts**.
       - A concept is a class of words dealing with the same subject and sharing common properties.
         - For example, the words hotel and room can all correspond to the concept of "accommodation" in a tourism application.
    2. Translate the concepts obtained into actions or responses during a sentence interpretation step to respond to the entry request.

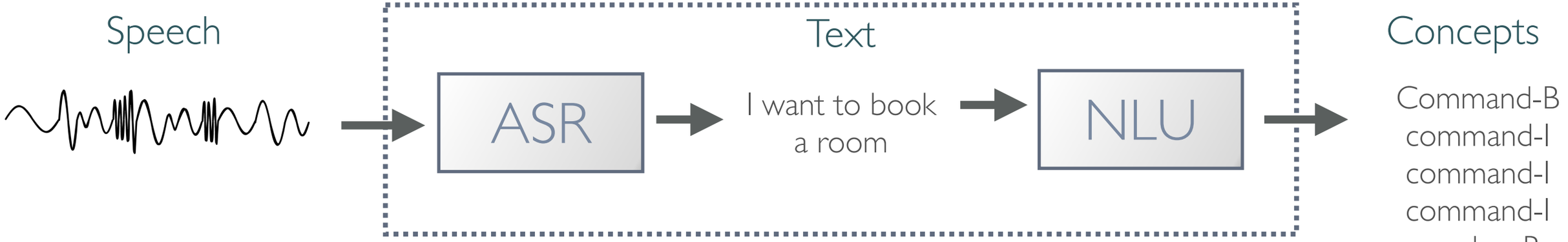
- Example:

Hyp	I	want	to	book	a	room
Concept	command				number	object
Label	command-B	command-I	command-I	command-I	number-B	object-B
Valeur	Booking				I	room

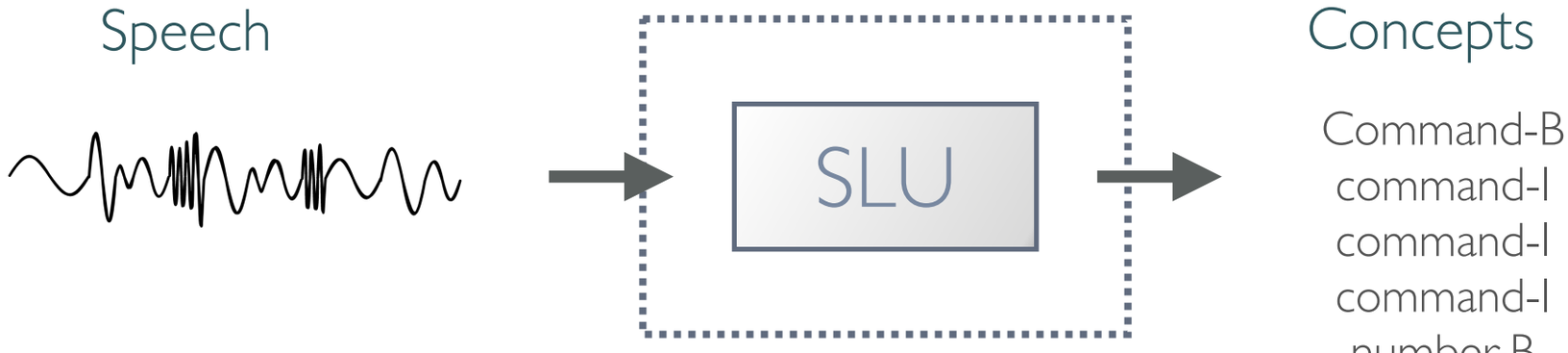
Semantic analysis in linguistic technology
Natural/Spoken language understanding

- Spoken language understanding system (SLU):
  - SLU refers to natural language processing tasks related to semantic extraction from the speech signal, like named entity recognition from speech, call routing, slot filling task in a context of human-machine dialogue…

Conventional SLU



End-to-end SLU

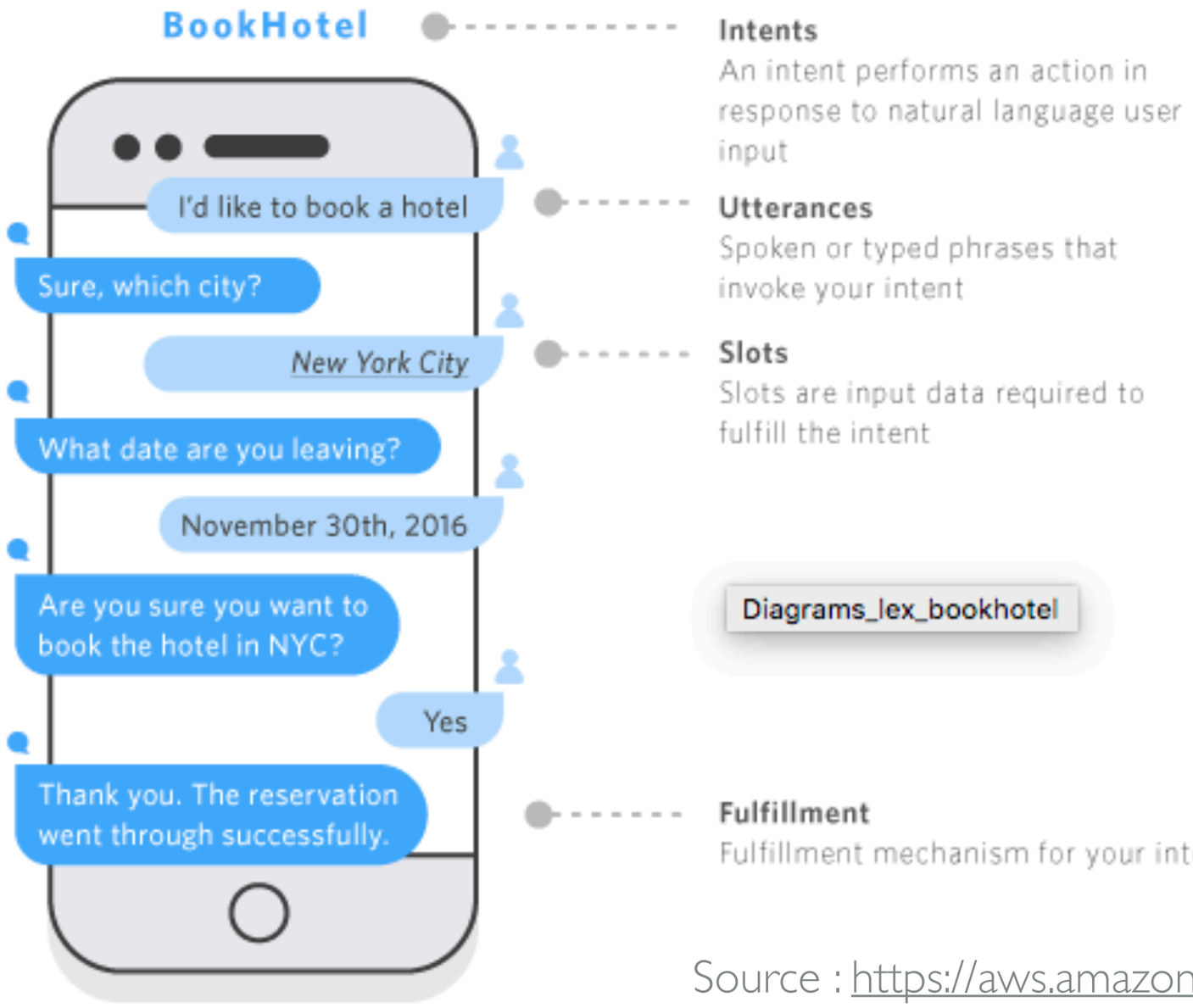


Semantic analysis in linguistic technology
Natural/Spoken language understanding

- NLU/SLU is an important module in a dialogue system
  - Provides direct human-machine interaction
  - Allows the computer to understand human languages

Semantic analysis in linguistic technology
Natural language understanding

✤ Example : Amazon Lex



Source : https://aws.amazon.com/fr/lex/details/

Recent approaches

- Recent approaches for :
  - Information extraction
    - Named entity recognition
  - Semantic textual similarity
  - Natural/Spoken language understanding
  - *Etc.*

➡ Are based on **deep learning approaches**

Deep Learning

Deep Learning

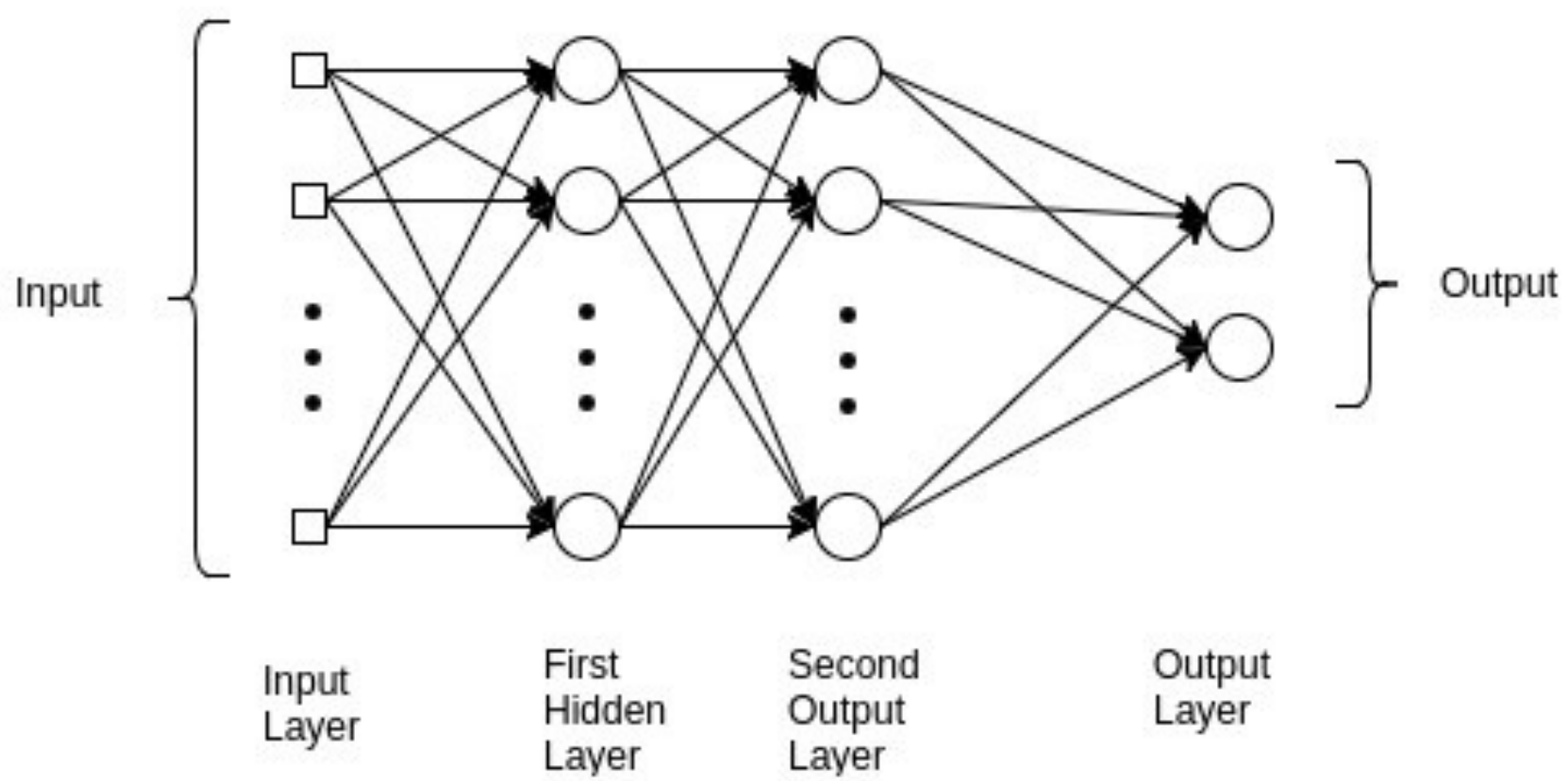
- Deep learning: part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised
- Deep learning architectures: Deep Neural Network(DNN), recurrent neural networks, convolutional neural networks, transformers, …

Machine learning

- Machine learning:
  - The study of computer algorithms that improve automatically through experience
  - Based on statistical approaches to give the systems the ability to "learn" from data, in order to make predictions or decisions without being explicitly programmed to do so
  - It is seen as a subset of artificial intelligence (IA)

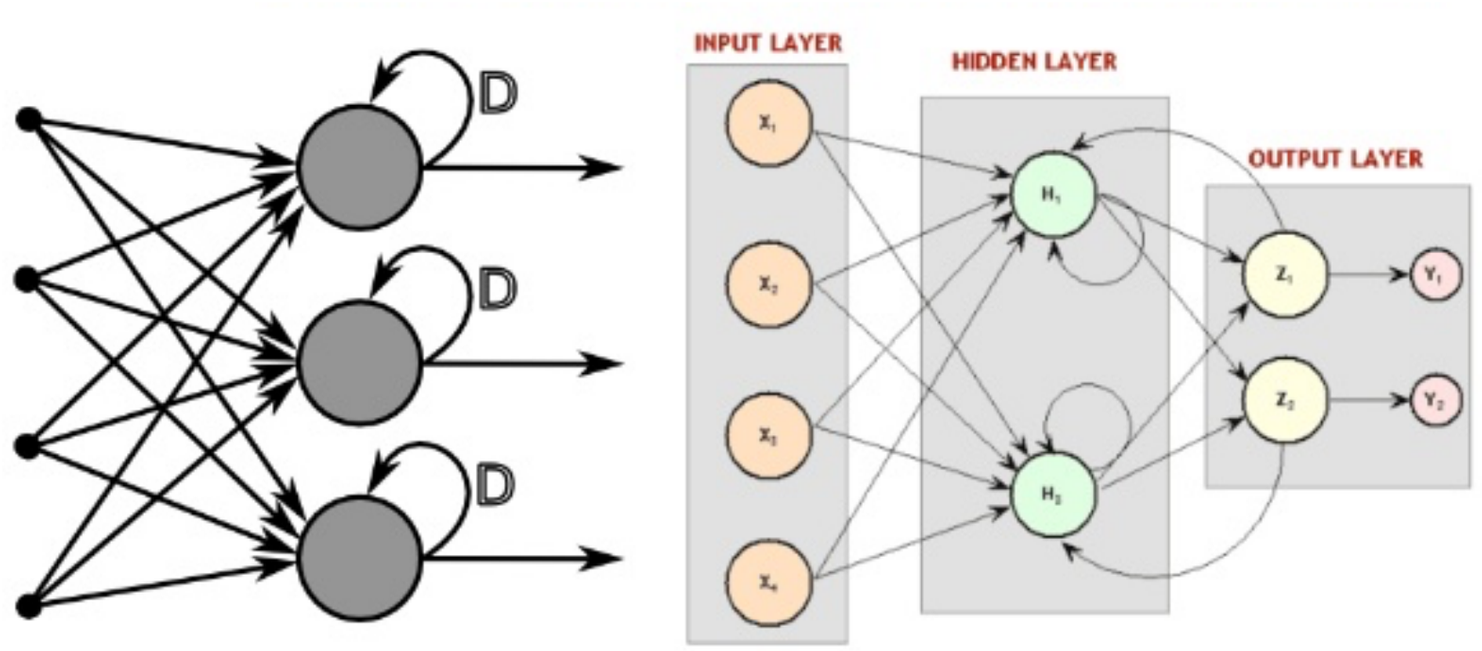
Neural network architectures

- Multilayer perceptron
  - Is a class of feedforward artificial neural network, wherein connections between the nodes do *not* form a cycle



Neural network architectures

- Recurrent neural network (RNN)
  - Is a type of neural network that contains loops, allowing information to be stored within the network
  - Use their reasoning from previous experiences to inform the upcoming events
  - ➡ During training, gradients may explode (tend to infinity) or vanish (tend to zero) because of temporal depth



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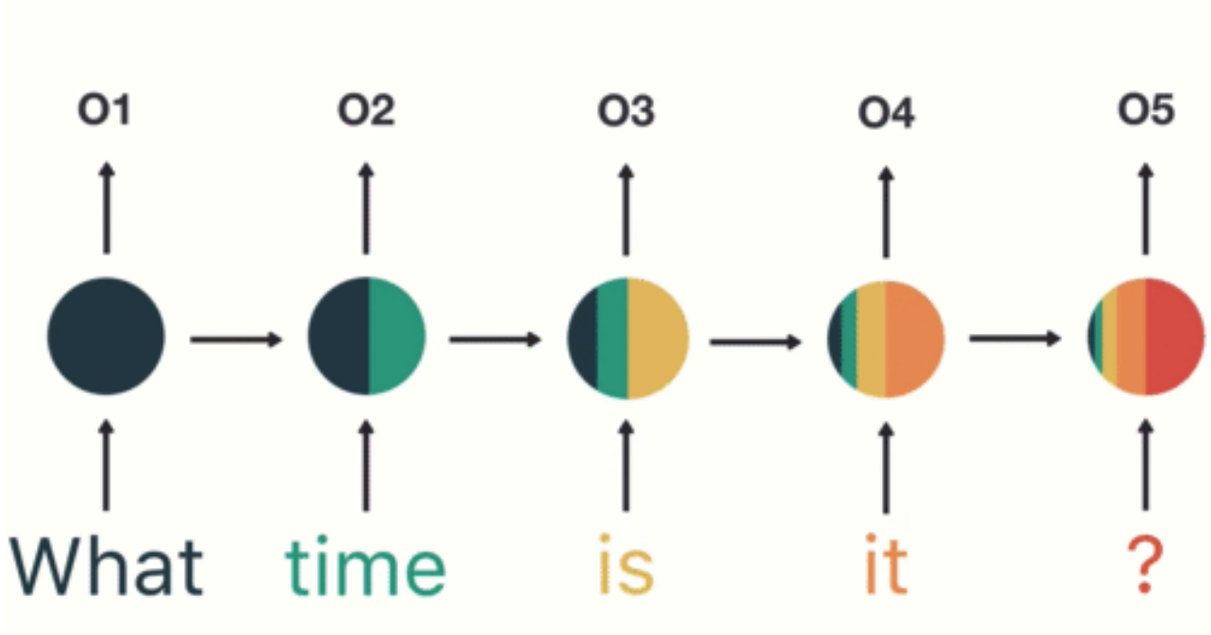
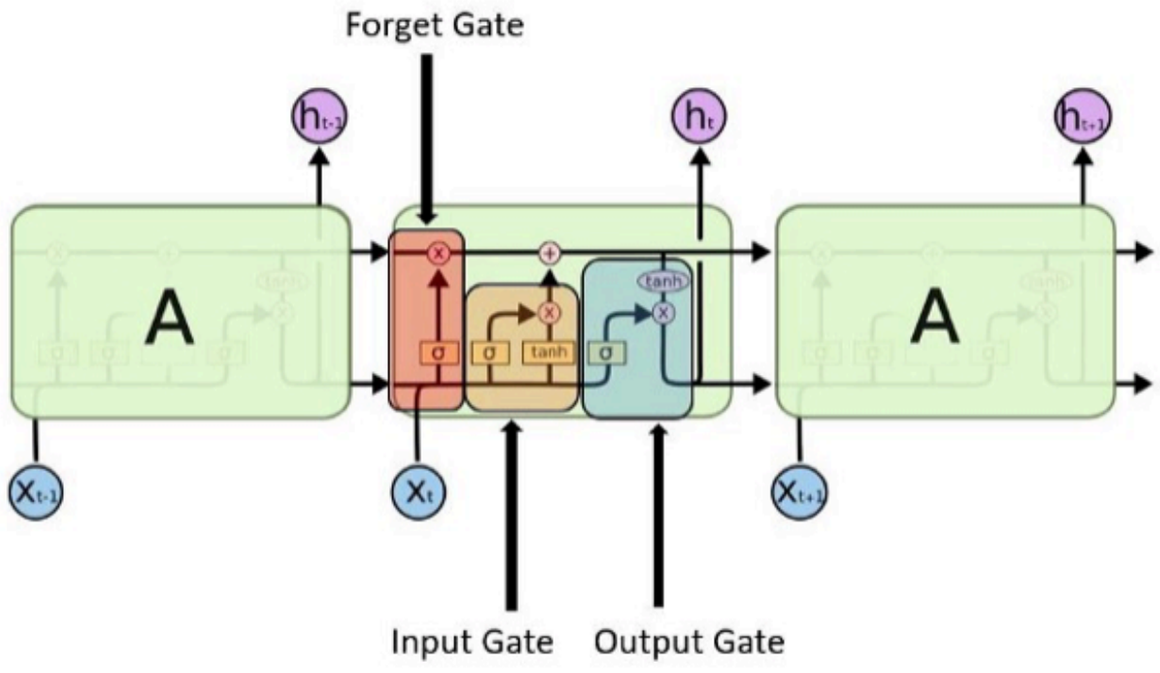


Source: Michael Nguyen / Learned Vector

Neural network architectures

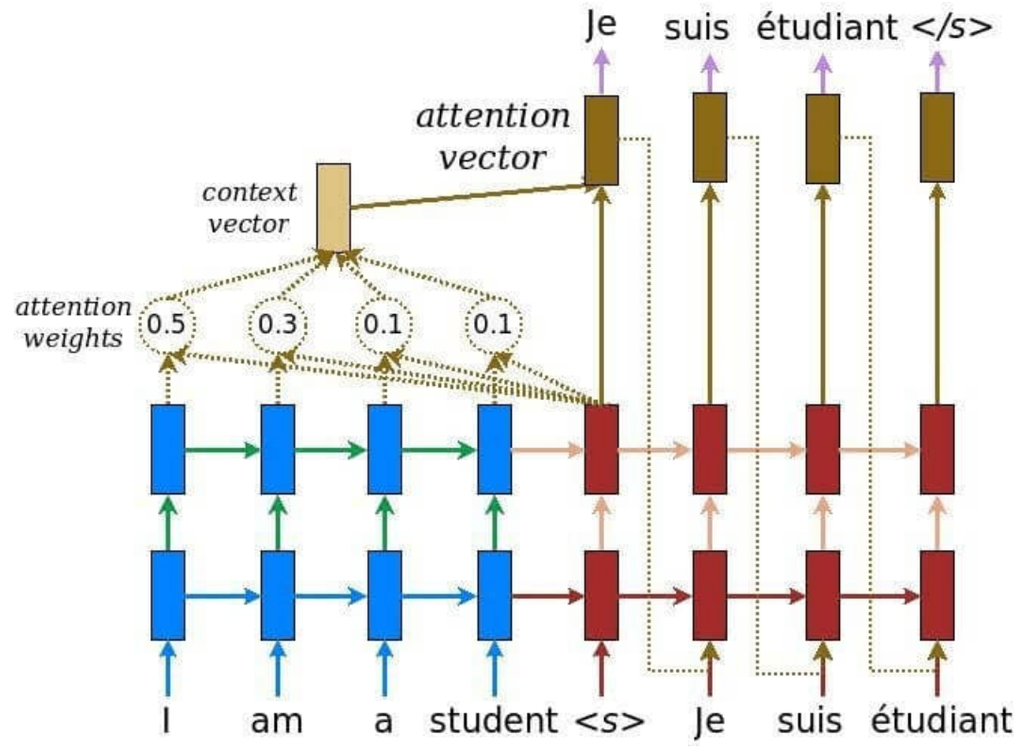
- LSTM (log short term memory)
  - Is a special kind of RNN's, capable of learning long-term dependencies.
  - Solve vanishing gradient problem
  - LSTM's have skills to remember the information for a long periods of time.
  - LSTMs' core component is the memory cell
    - can maintain its state over time, consisting of an explicit memory and gating units.
    - Gating units regulate the information flow into and out of the memory.



Neural network architectures

✤ Attention mechanism

- The mechanism's role is determine the importance of each word in the input sentence, then to extract additional context around each word
- In attention when the model is trying to predict the next word it searches for a set of positions in a source sentence where the most relevant information is concentrated.
- The model then predicts next word based on context vectors associated with these source positions and all the previous generated target words.

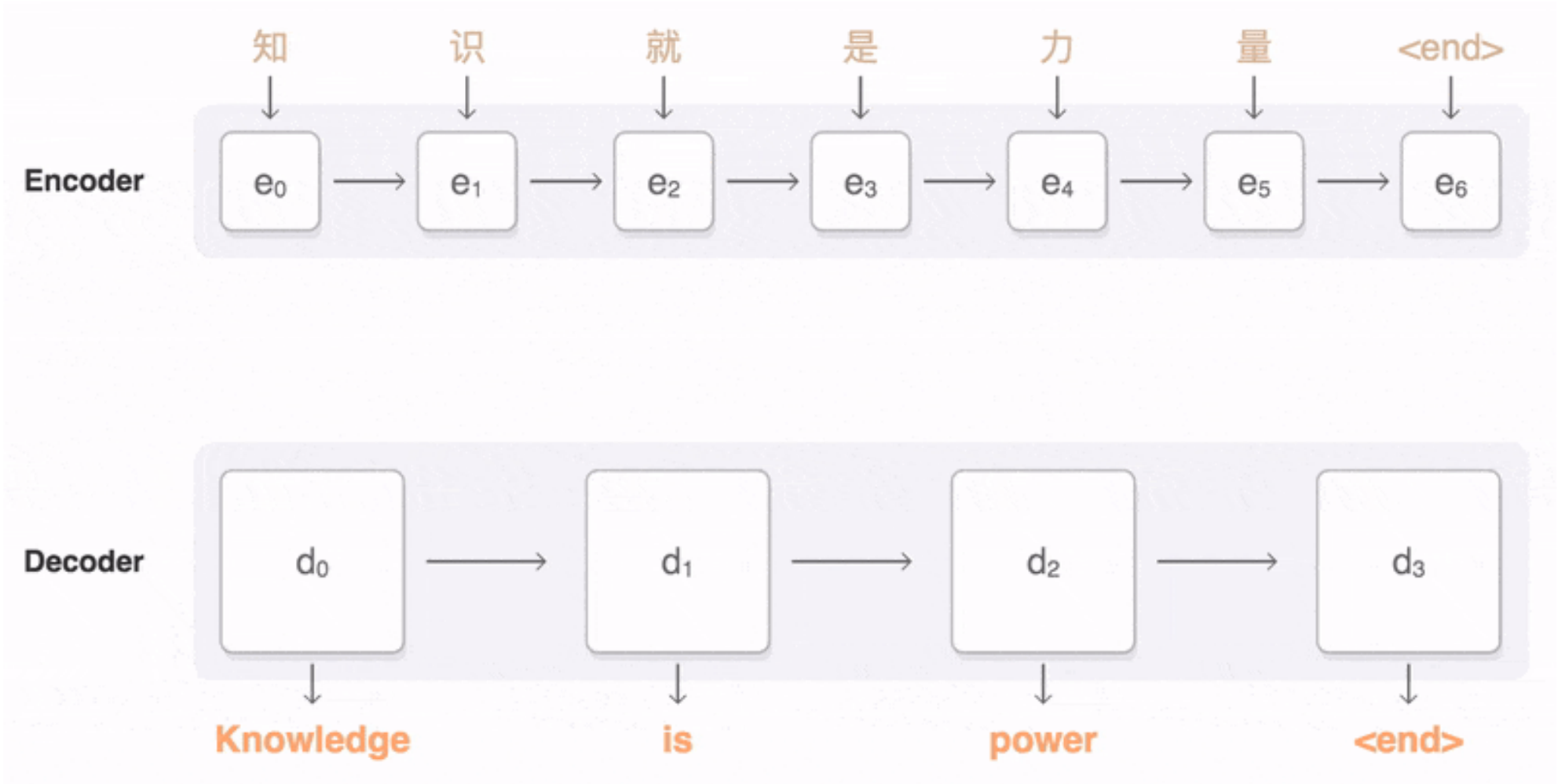


Source: TensorFlow seq2seq tutorial

—> Dzmitry Bahdanau, et al. in their paper "Neural Machine Translation by Jointly Learning to Align and Translate"

Neural network architectures

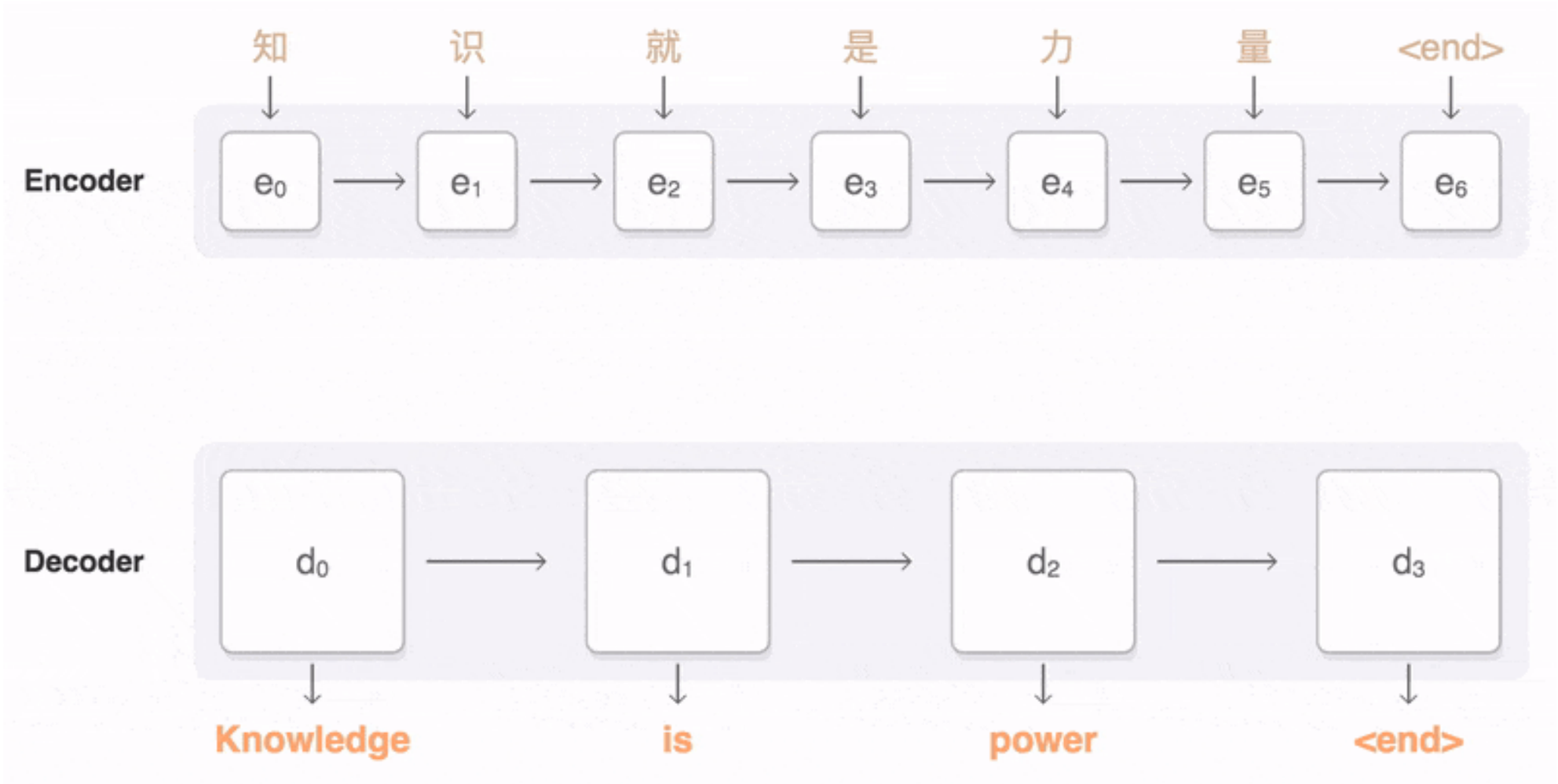
✤ Attention mechanism



Source: Google seq2seq

Neural network architectures

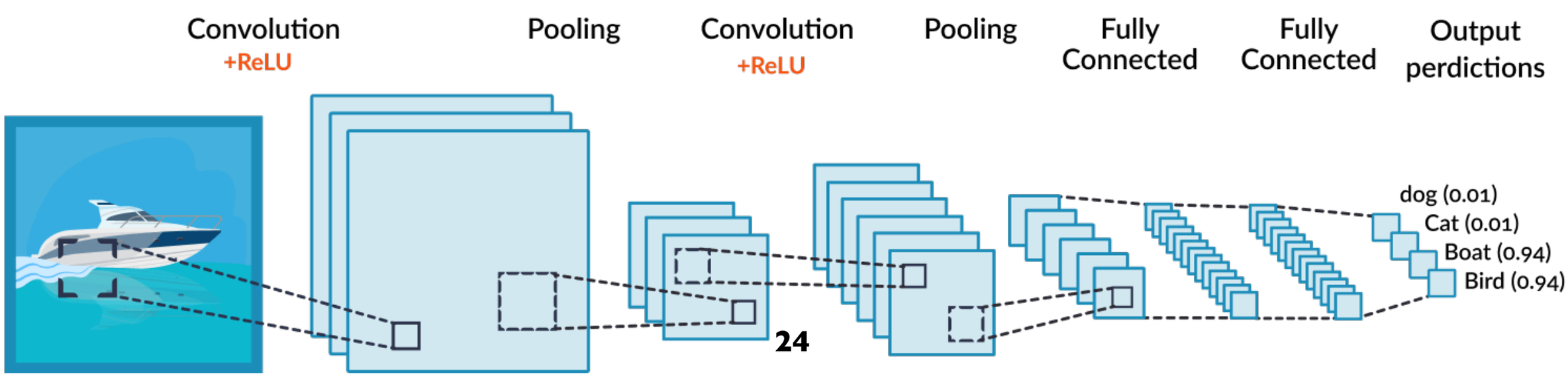
✤ Attention mechanism



Source: Google seq2seq

Neural network architectures

- Convolution neural network
  - is the foundation of most computer vision technologies.
  - uses two basic operations:
    - convolution using multiple filters is able to extract features (feature map) from the data set, through which their corresponding spatial information can be preserved.
    - pooling, also called subsampling, is used to reduce the dimensionality of feature maps from the convolution operation.
      - max pooling and average pooling are the most common pooling operations used in the CNN.



Neural network architectures

✤ Transformers

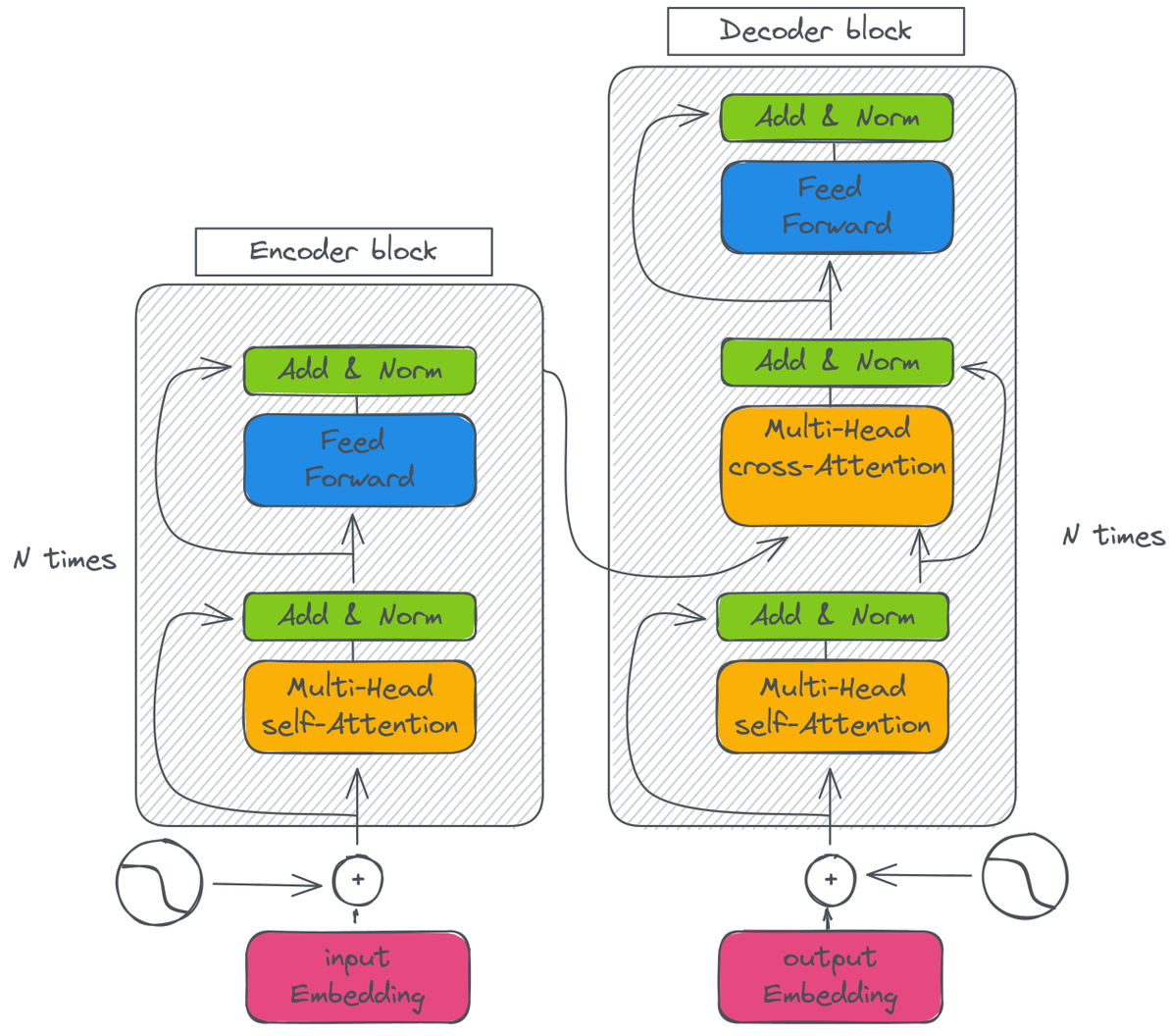
- ✦ A Neural Network for language model (not only) named transformer
  → "Attention is all you need", Vaswani et al. 2017
- ✦ A sequence transduction model based entirely on attention, replacing the recurrent layers most commonly used in encoder-decoder architectures with multi-headed self-attention
- ✦ The original Model is composed of
  - An attention mechanism
  - An encoder that transform input sequence into a same size sequence of representation
  - A decoder to generate text from encoded information and previous generated sequence

  ➡ Encoder and decoder models, each containing repeated neural blocks

Neural network architectures

✤ Transformers

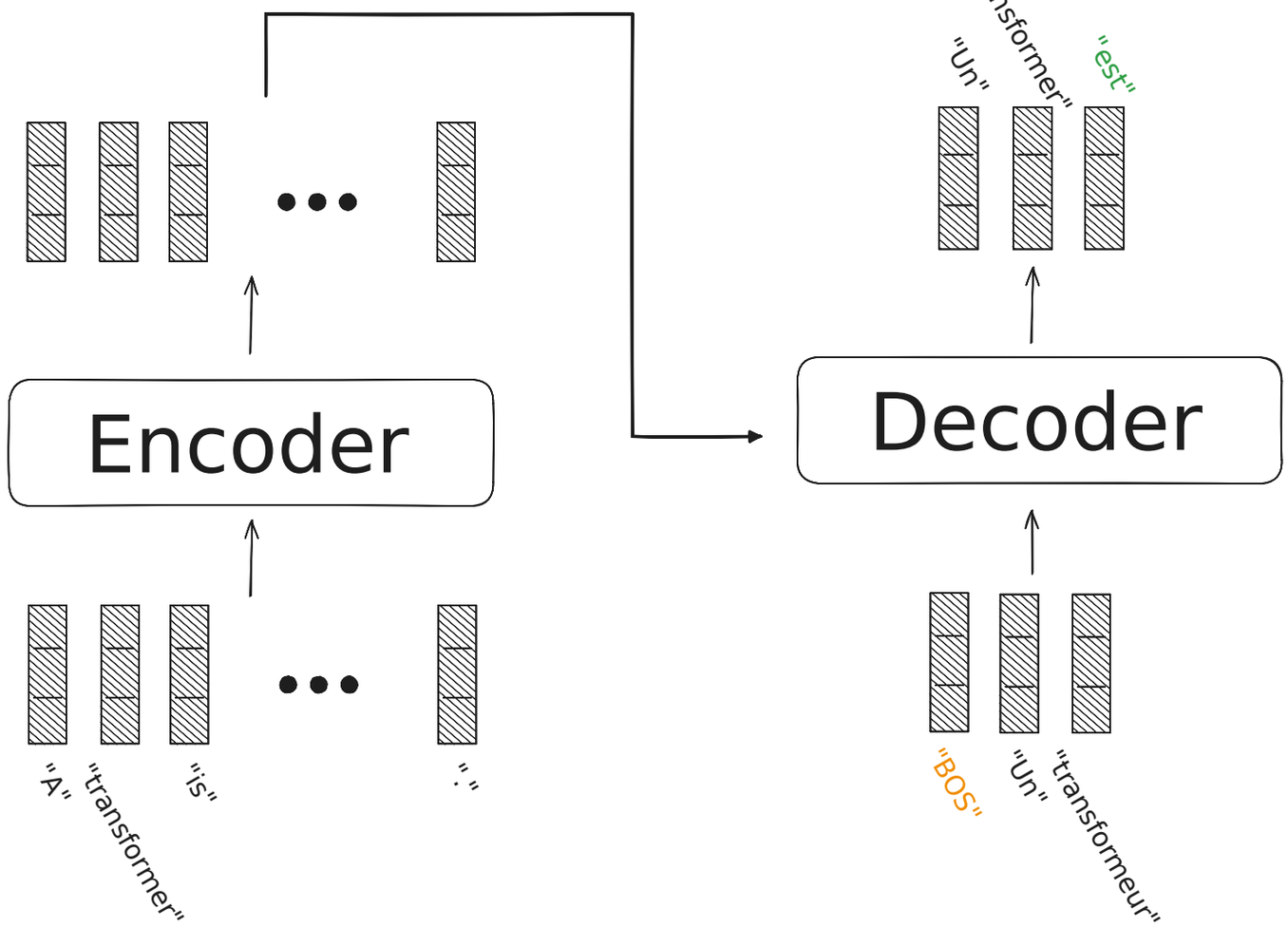
- ✦ The main characteristics are:
  - Non sequential: sentences are processed as a whole rather than word by word.
  - Self Attention: this is the newly introduced 'unit' used to compute similarity scores between words in a sentence.
  - Positional embeddings: another innovation introduced to replace recurrence. The idea is to use fixed or learned weights which encode information related to a specific position of a token in a sentence.



Neural network architectures

✤ Transformers architectures : Encoder-decoder

- ✦ The encoder transform input data and forward it to the decoder.
- ✦ The decoder generate a content (depending on the task trained for and the input)
- ✦ Task: machine translation, ..

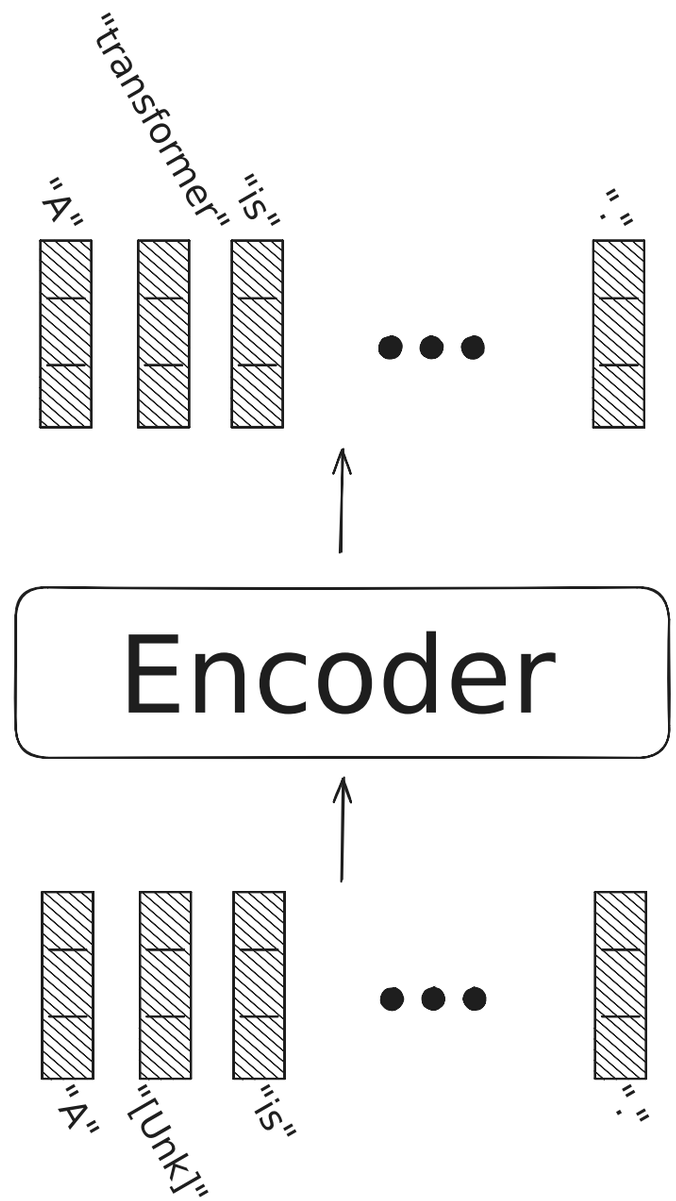


Neural network architectures

✤ Transformers architectures : Encoder only

- ✦ The encoder transform input data to create a representation that fit the task.

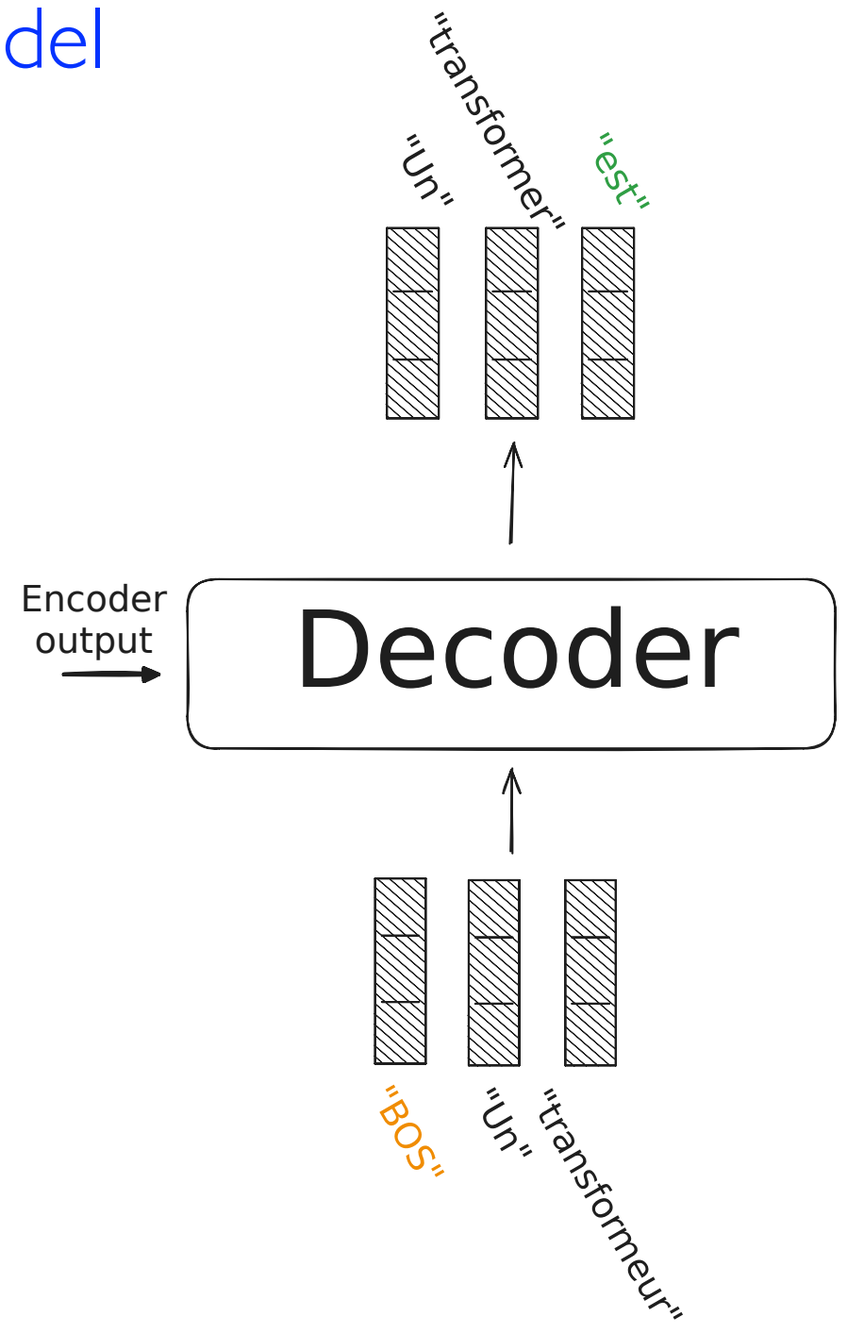
→ Some approaches relies only on encoder (classification, Bert model…)



Neural network architectures

✤ Transformers architectures : Decoder model

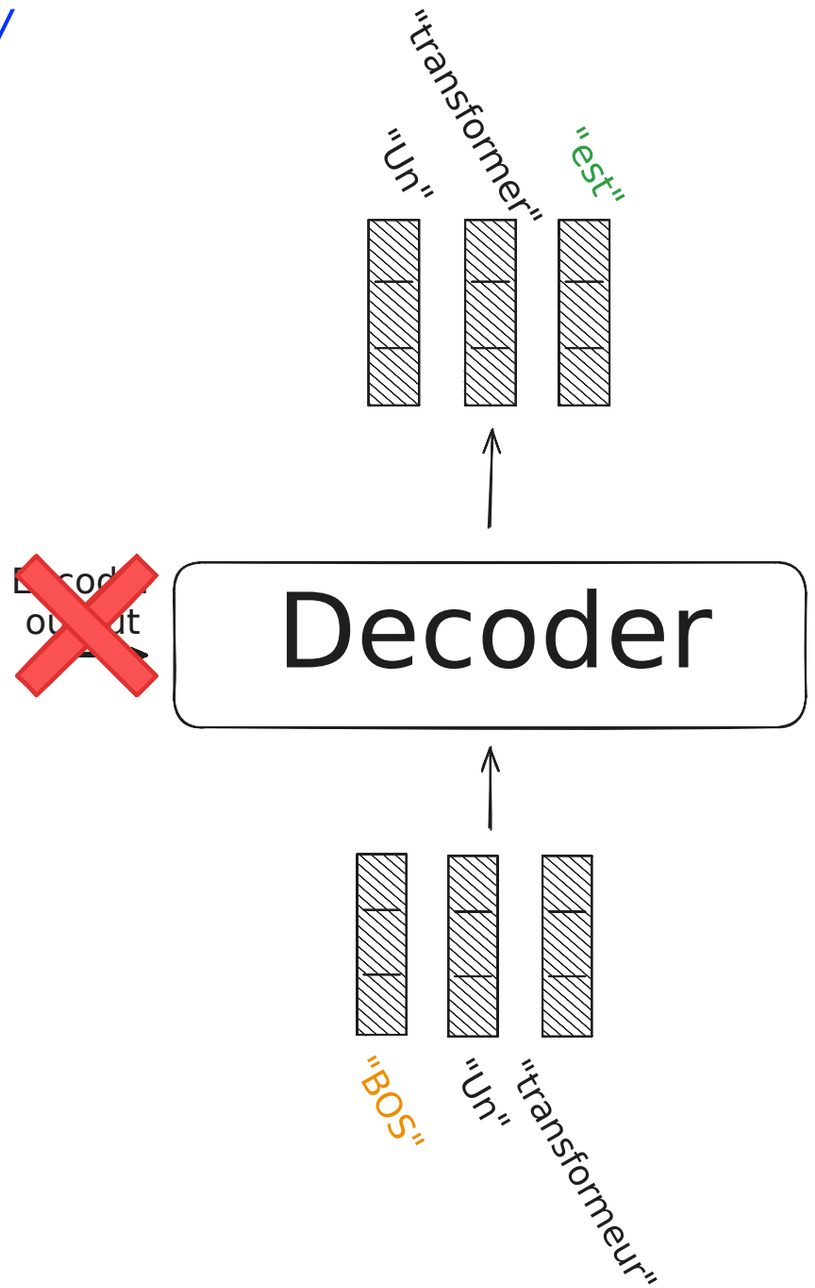
- ✦ The decoder process the encoder output embeddings and generate sequentially text. It models P(y|x) where y is the ouput sequence and x the input sequence
- ➨ Transformer input size is the same as ouput



Neural network architectures

✤ Transformers architectures : Decoder only

- ✦ Some approaches relies only on decoder
  In this case, the decoder is feed with an input text (e.g prompt, question,...)

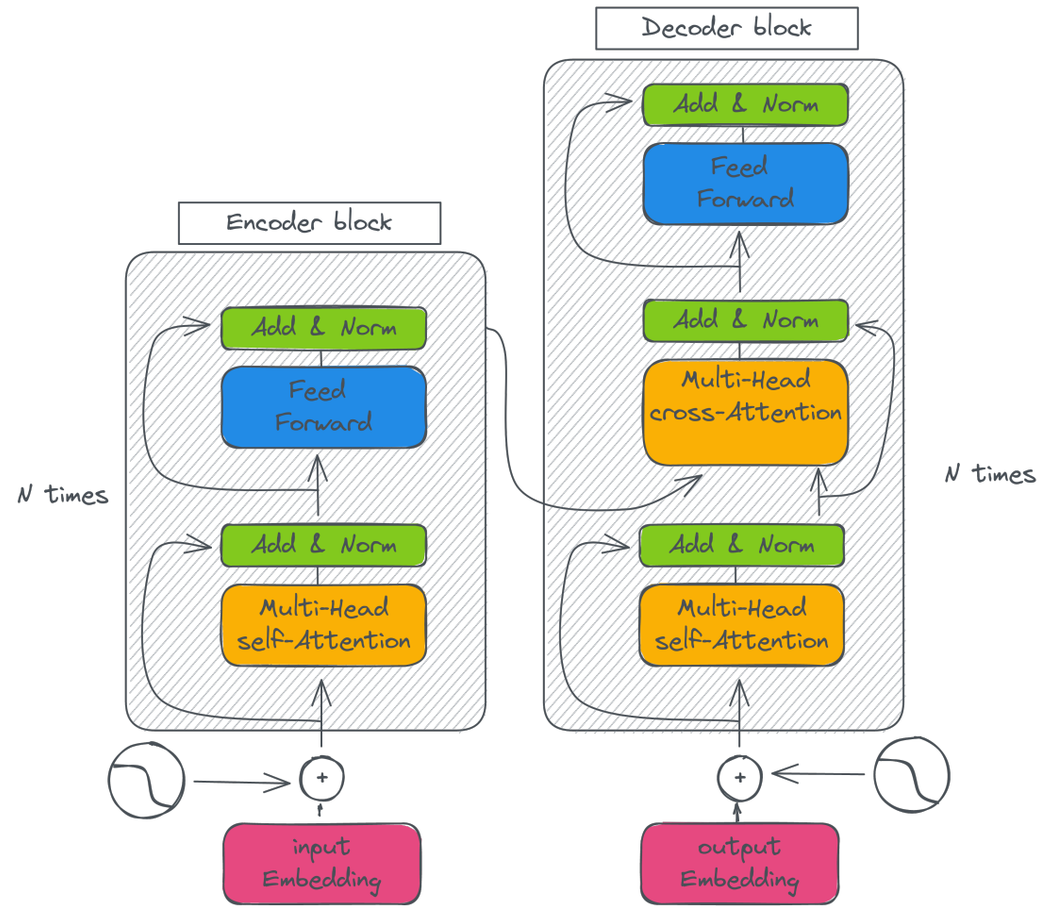


Neural network architectures

✤ Transformers

The different parts of the architceture

- ✦ Input/token embeddings (and tokenization)
- ✦ Self and Cross Attention
- ✦ Multilayer perceptron (Feed Forward)
- ✦ Add and Normalisation
- ✦ Transformer classification head (not described in this part)



Attention Is All You Need

Neural network architectures

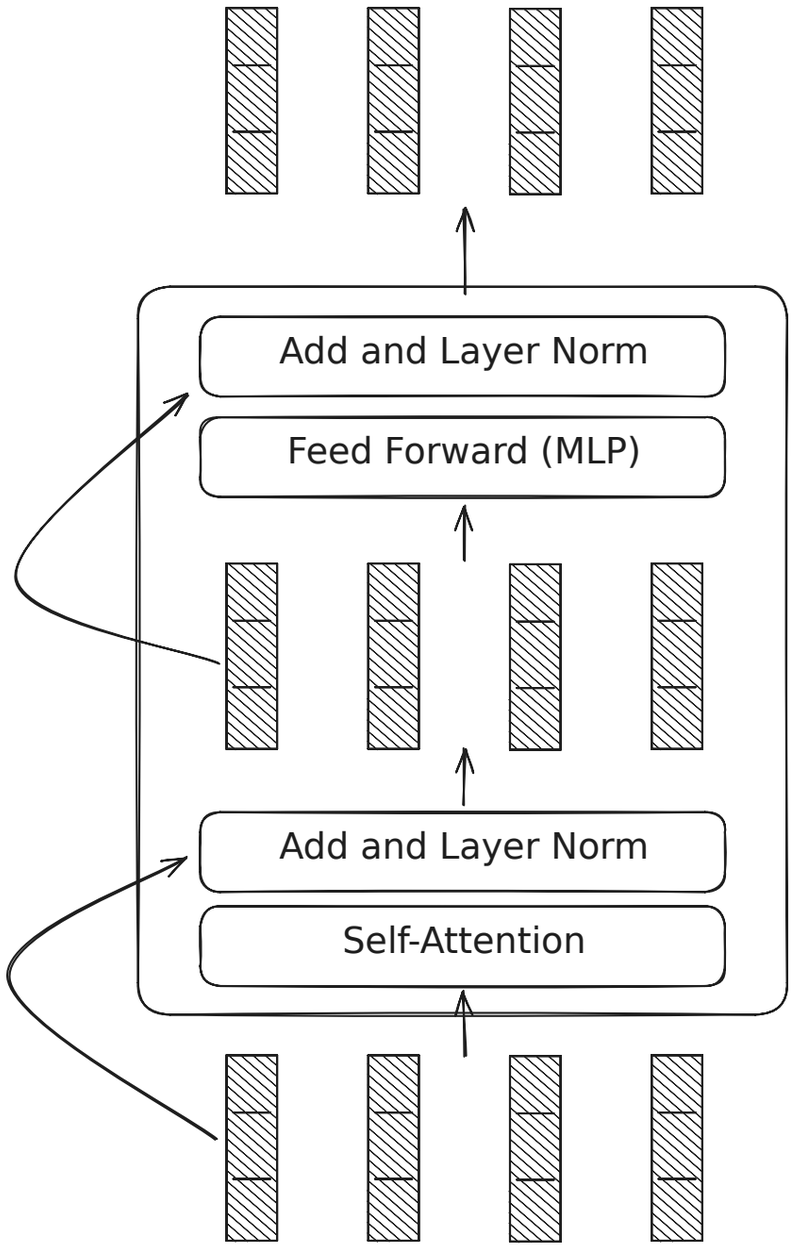
- Transformers

Encoder Block

Each block is repeated N× (emprically)

1. Information goes through a self-attention layer

2. Information goes through an MLP (Feed-Forward network)



Neural network architectures

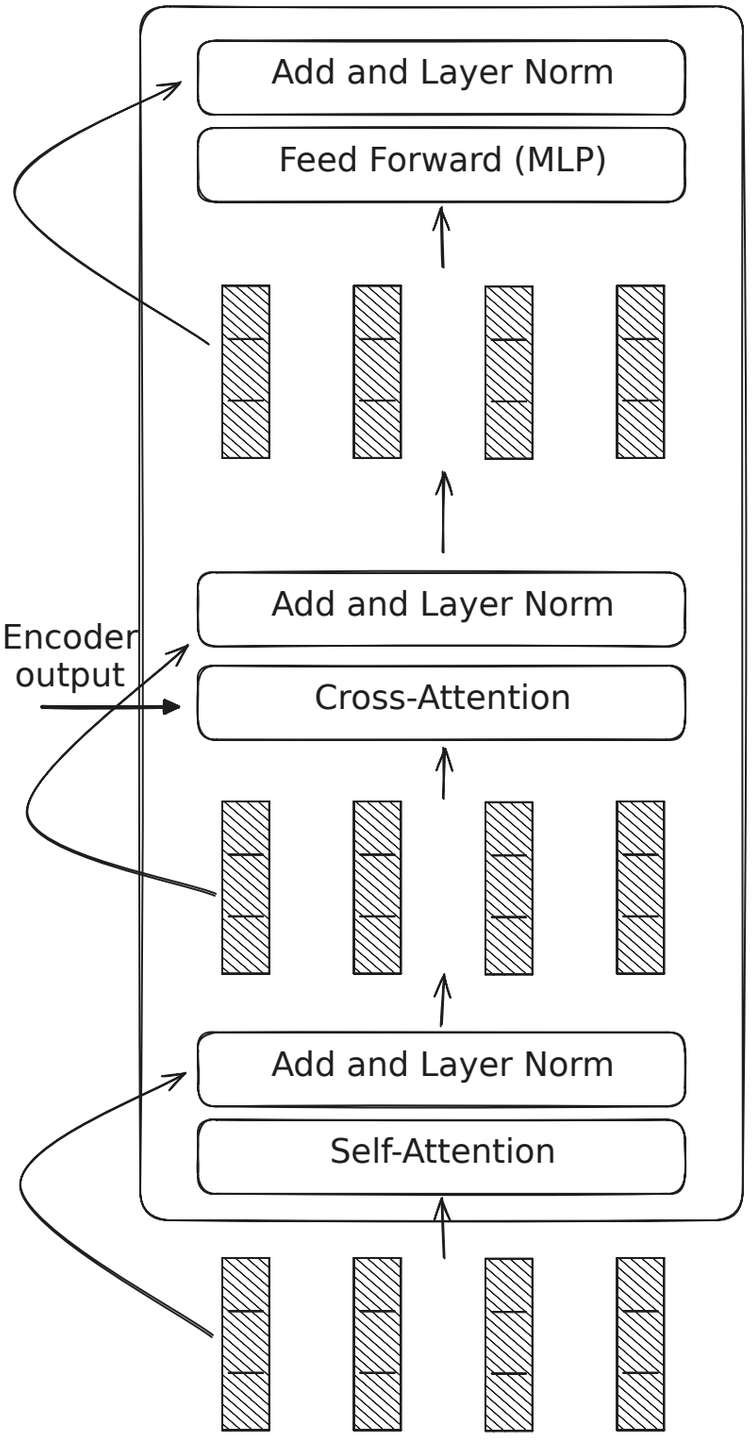
- Transformers

Decoder Block

Each block is repeated N× (empirically)

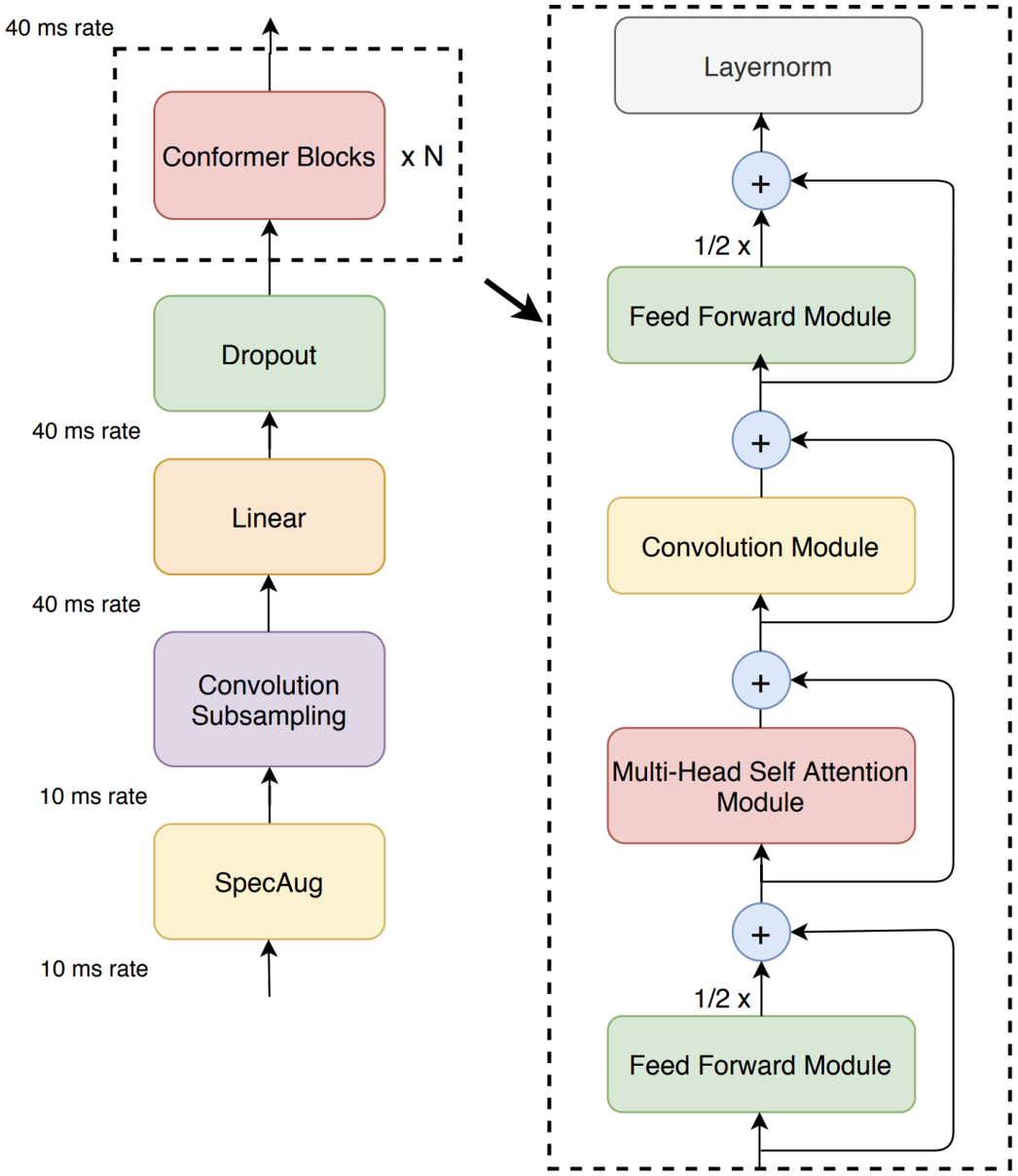
1. cross-attention layer
2. self-attention layer
3. MLP (Feed-Forward network)

→ For the decoder onl there is no cross attention layer



Neural network architectures

- Conformer: Convolution-augmented Transformer for Speech Recognition
  - In the first half of 2020, researchers at Google combined convolution neural networks to exploit local features with transformers to model the global context
  - Conformer comprises of two macaron-like feed-forward layers with half-step residual connections sandwiching the multi-headed self-attention and convolution modules. This is followed by a post layernorm.



Conformer encoder model architecture [Gulati et al 2020]

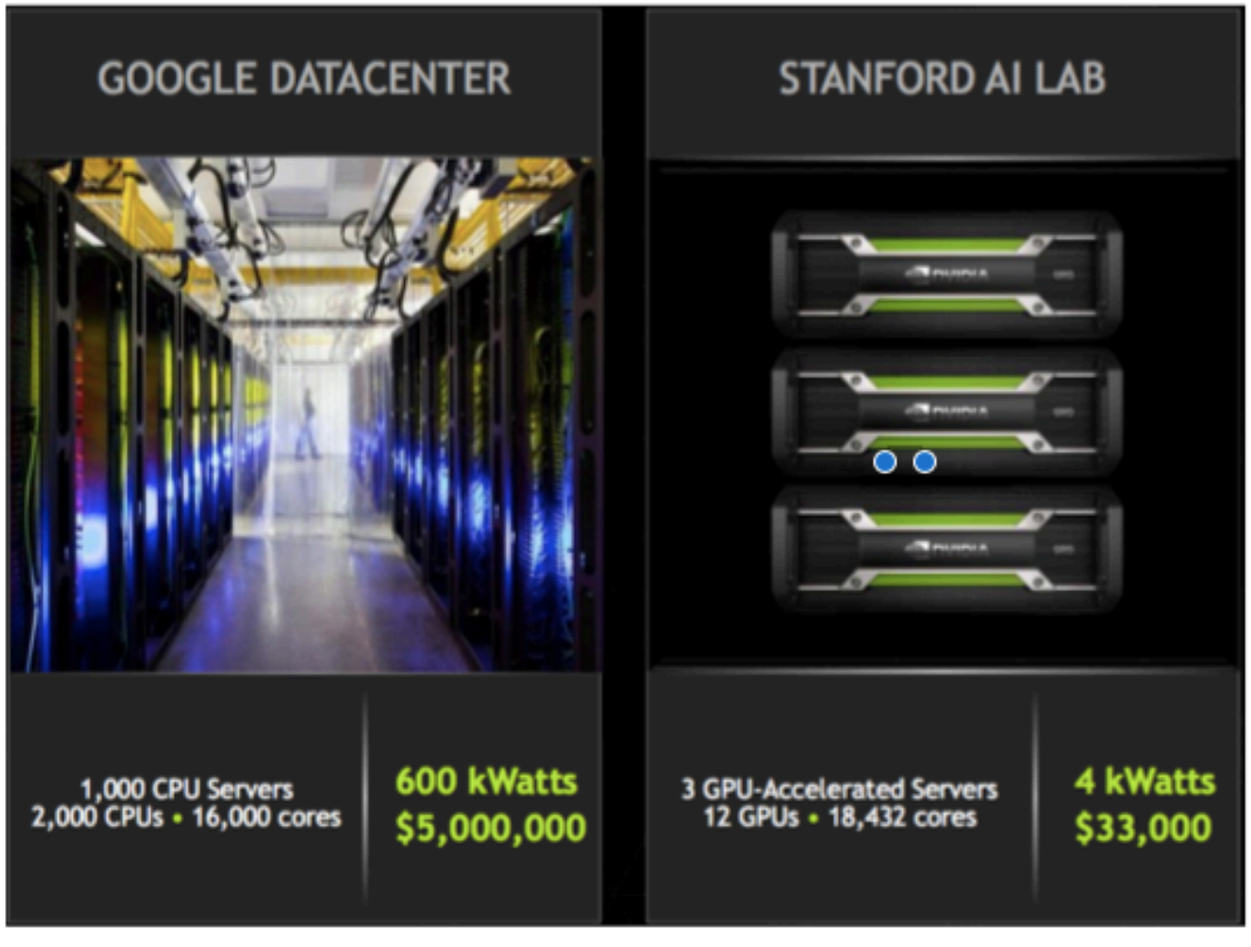
Why DNNs Work Better Now?

DNN and computing power

- Why did DNNs not work so well before, when neural networks have been experimented since the 1980s for acoustic modeling?
- A first element of response:
  - DNNs are particularly well suited to graphics cards (GPUs) that achieve phenomenal computing power ...

DNN and computing power

- ... at a very competitive price!
  ➡ This makes accessible reasonable training time and therefore feasible experiments.



DNN and data

- Availability of large amount of data
  - i.e. text, images, audio published via news sites, social media, collaborative platforms, smartphones, etc.

DNN and learning algorithms

- A third answer comes from the progress made by researchers for training DNNs:
  - best learning algorithms (pre-training RBM, SDAE, learning rate dynamique,...)
  - New architectures (transformers, attention mechanism, LSTM, GRU…)
    - ➡ use continuous representations able to encode different types of hidden relations (syntactic, semantic, contextual,..)

Continuous word
representations

WORD REPRESENTATIONS

1. One hot:

- Example : Merci ID=3, vocabulary=10 words

$Merci$:

0	0	1	0	0	0	0	0	0	0

- Difficulty:
  - can not detect the relationships between words
  - Vector size depends on vocabulary size

WORD REPRESENTATIONS

2. Continuous word representations:

- Capture relationships between words
- Different approaches have been studied in the NLP (Natural language processing) community:
  - Clustering
  - distributional word representations
  - Distributed word representations (neural) (known by: word embeddings, continuous word representations)

CONTINUOUS WORD REPRESENTATIONS

CONTINUOUS WORD REPRESENTATIONS

- Clustering (Brown *et al.*1992) :
  - Grouping words into clusters (group) based on their contexts (bigrams)
  - Disadvantage: does not consider the use of words in a larger context

CONTINUOUS WORD REPRESENTATIONS

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- Distributional word representations exp. PMI (Pointwise Mutual Information):
  - Known as *Count based models* ou *global matrix factorization*
  - Use of word co-occurrence matrix
  - The word is represented by a vector in which each entry is a measure of association between the word and a particular context
  - Disadvantage: very high dimensional sparse vector (most elements are zero) (same vocabulary size)

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  - Low dimensional dense vector with real values

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Continuous word representations

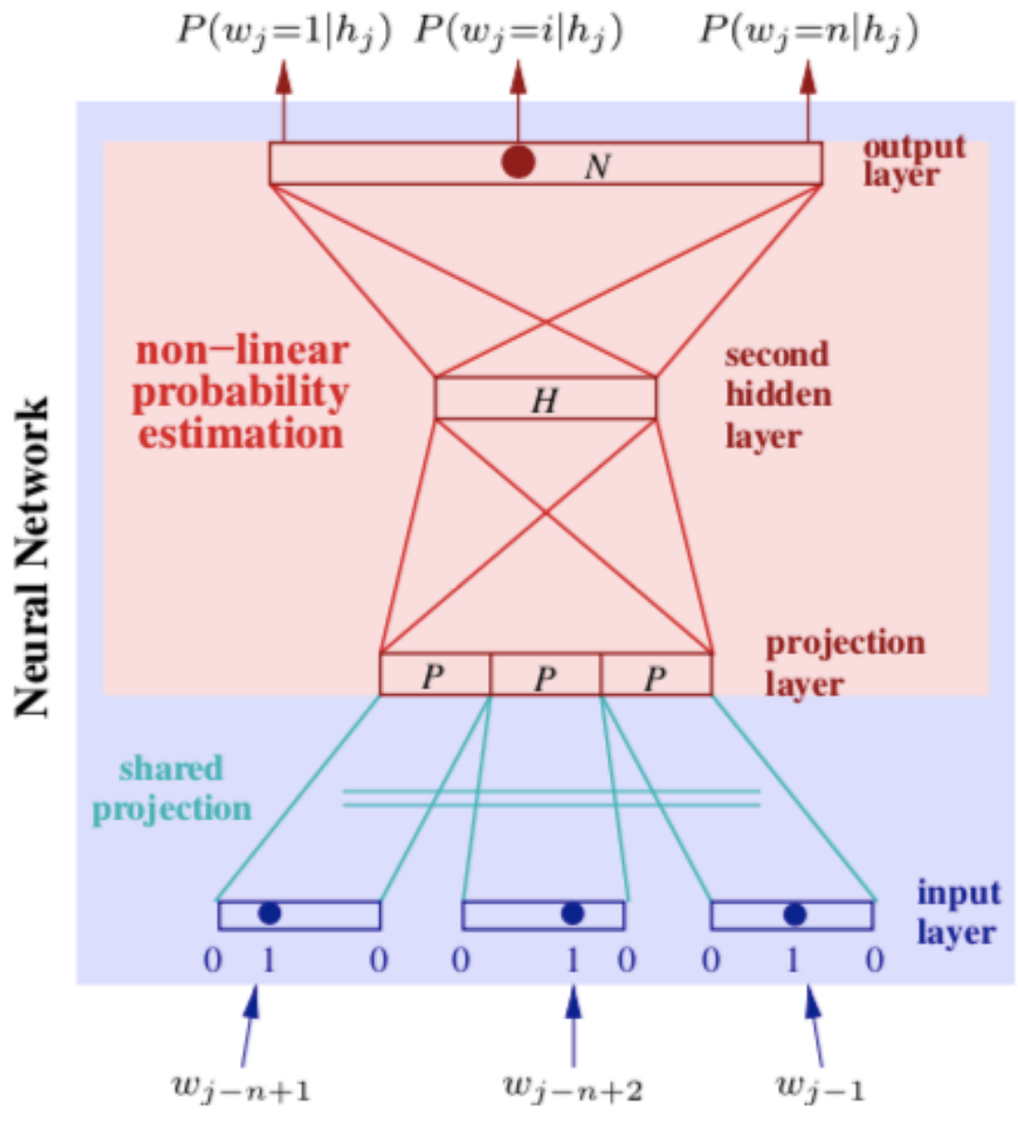
Continuous word representations

- Why dense vectors?:
  - Short vectors can be easily used in machine learning (less weight to optimize)
  - Dense vectors can generalize better
  - *etc.*

CONTINUOUS WORD REPRESENTATIONS

Word embeddings :

- Introduced through neural language models training [Y.Bengio *et al.* 2003, H.Schwenk *et al.* 2006]



CONTINUOUS WORD REPRESENTATIONS

Word embeddings :

- Introduced through neural language models training [Y.Bengio *et al.* 2003, H.Schwenk *et al.* 2006]
- it involves a mathematical embedding from a space with many dimensions per word to a continuous vector space with a much lower dimension, so as to preserve semantic, syntactic similarities, etc

$$R : Words = \{W_1, ..., W_n\} \rightarrow Vectors = \{R(W_1), ..., R(W_n)\} \subset R^d$$

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- If the word vectors are close to each other in terms of distance, the words must be semantically or syntactically close.

$$R(W_1) \approx R(W_n) \rightarrow W_1 \approx W_n$$

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$$R(W_1) \approx R(W_n) \rightarrow W_1 \approx W_n$$

- Each dimension represents a latent characteristic of the word, which can capture syntactic and semantic properties.

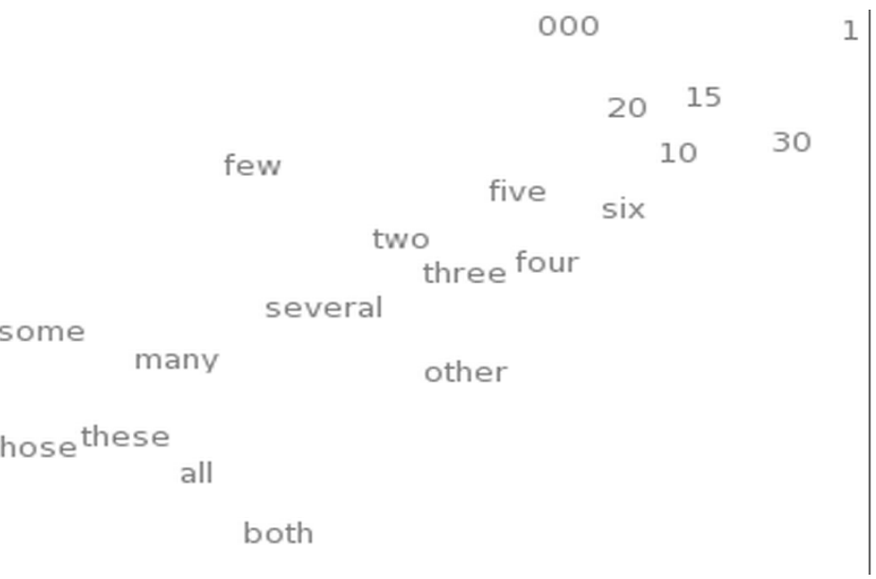
CONTINUOUS WORD REPRESENTATIONS

Word embeddings visualisation:

2D t-SNE visualizations of word embeddings. Left: Number Region; Right: Jobs Region [J.Turian *et al* . 2010]

CONTINUOUS WORD REPRESENTATIONS

Word embeddings visualisation:



2D t-SNE visualizations of word embeddings. Left: Number Region; Right: Jobs Region [J.Turian *et al* . 2010]

FRANCE	JESUS	XBOX
AUSTRIA	GOD	AMIGA
BELGIUM	SATI	PLAYSTATION
GERMANY	CHRIST	MSX
ITALY	SATAN	IPOD
GREECE	KALI	SEGA
SWEDEN	INDRA	PSNUMBER
NORWAY	VISHNU	HD
EUROPE	ANANDA	DREAMCAST
HUNGARY	PARVATI	GEFORCE
SWITZERLAND	GRACE	CAPCOM

What words have embeddings closest to a given word? [R.Collobert *et al* . 2011]

CONTINUOUS WORD REPRESENTATIONS

Word embeddings :

- Efficient for many tasks [R. Collobert et al 2011], [M. Bansal 2014] et [J.Turian et al 2010]:
  - Named entity recognition
  - Part of speech tagging
  - Natural language understanding
  - Question answering
  - etc.

Continuous word representations
Recent approaches

- Context-independent (static) word embeddings:
  - The occurrences of the same word have the same representation
  - Skipgram, CBOW, Glove, w2vf-deps, fasttext
- Contextual word embeddings:
  - Each occurrence of the word has a different representation calculated based on its context
  - Internal representations of words are a function of the entire input sentence
  - Exemple : ELMo, BERT, GPT-2

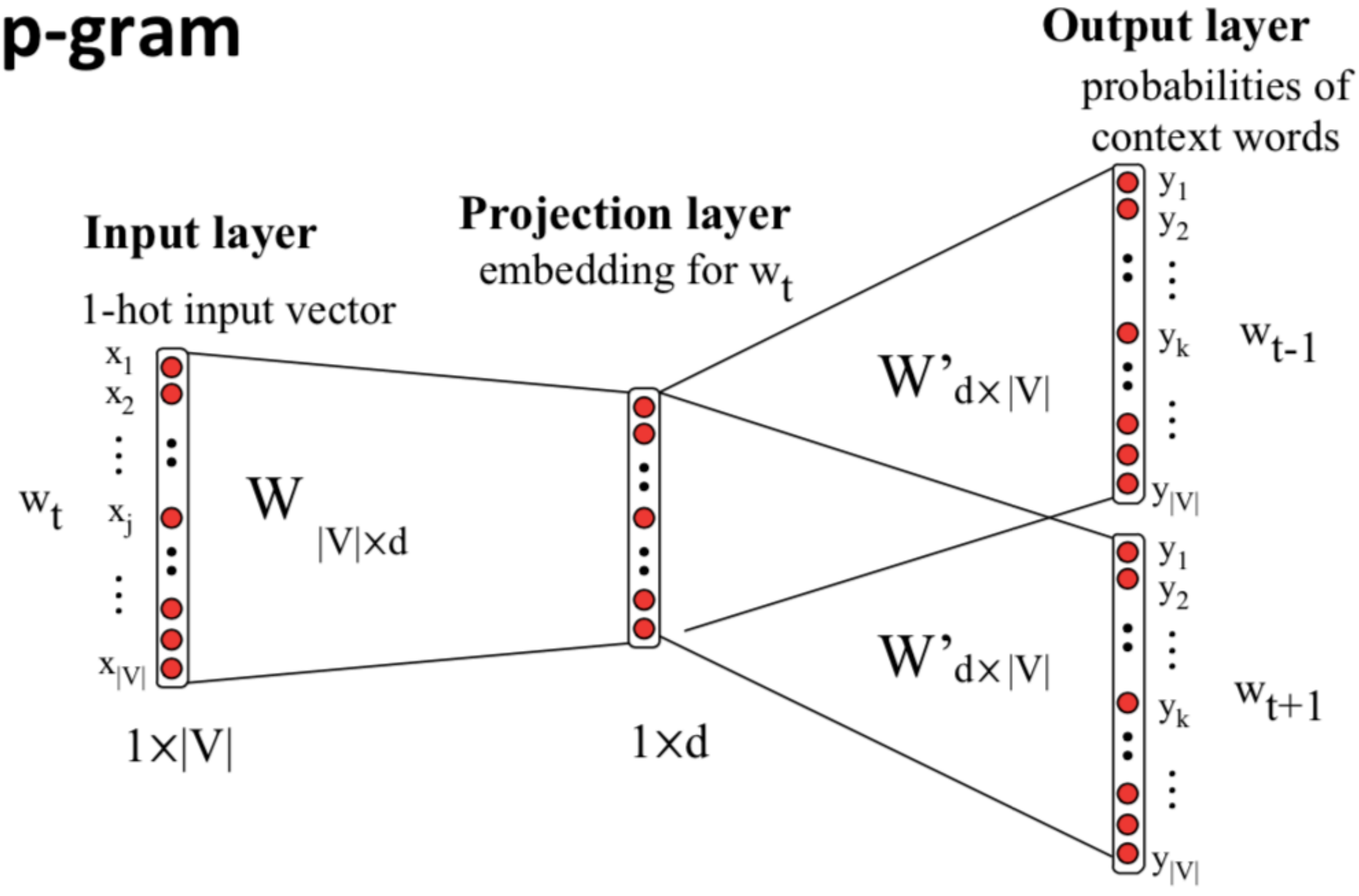
Continuous word representations
Context-independent

Skip-gram (Mikolov et al. 2013a) and CBOW (Mikolov et al. 2013a)

- Learn word embeddings as part of the word prediction process.
  - Inspired by neural language models.

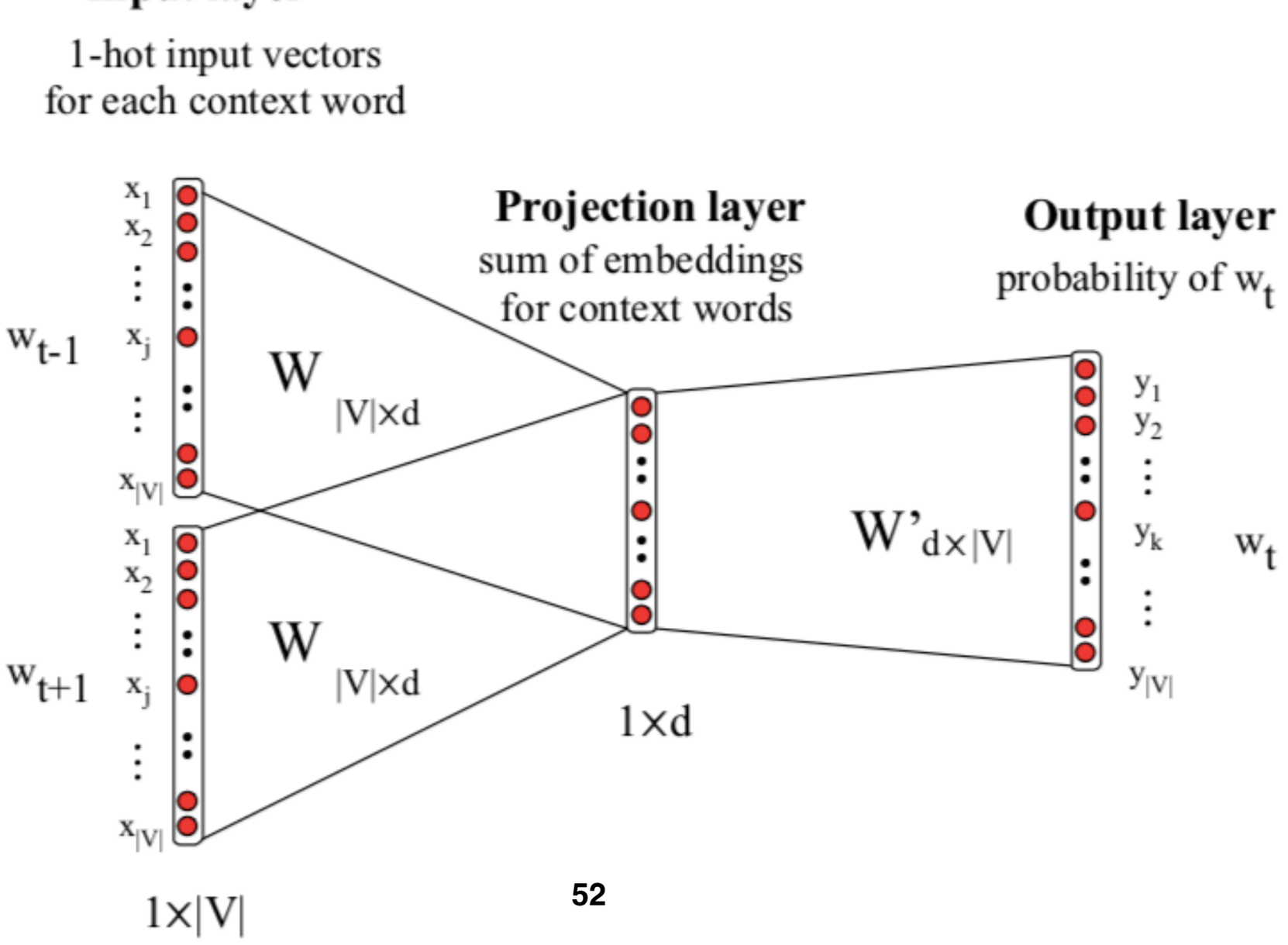
CONTINUOUS WORD REPRESENTATIONS CONTEXT-INDEPENDENT

Skip-gram



CONTINUOUS WORD REPRESENTATIONS
CONTEXT-INDEPENDENT

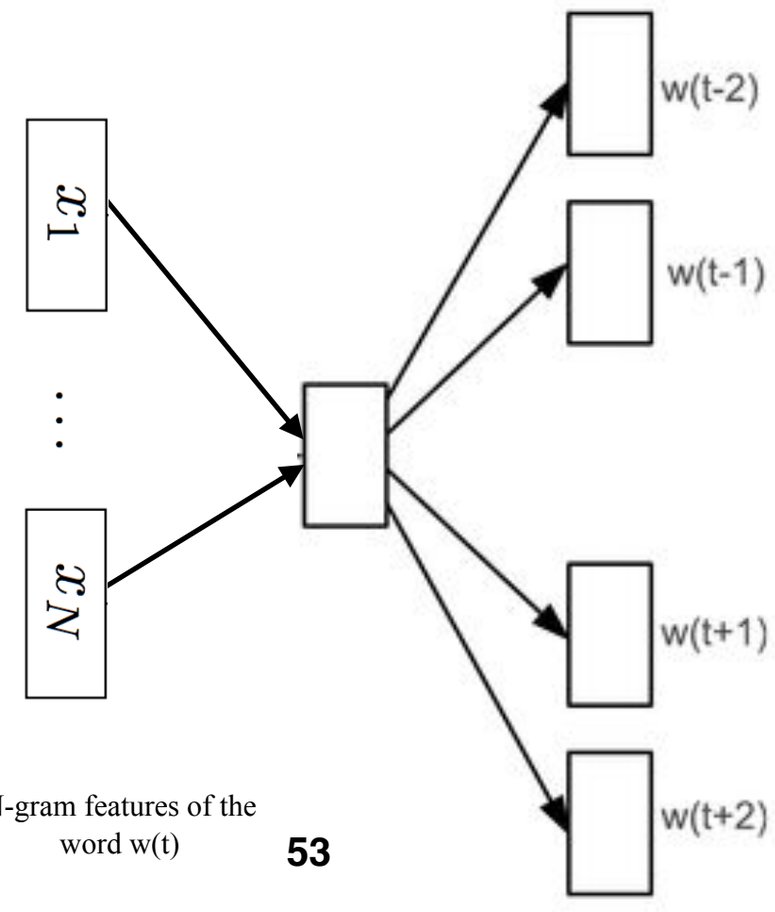
CBOW (Continuous Bag of Words)



CONTINUOUS WORD REPRESENTATIONS
CONTEXT-INDEPENDENT

FastText (P. Bojanowski et al. 2017)

- Learn word embeddings as part of the word prediction process based on the skipgram architecture
  - Takes into account the morphological information of a word represented in the form of character ngrams
  - Each word is represented as the sum of representations of its characters n grams.
  - Computes word representations for words that do not appear in the training data, which is not the case for other approaches (word2vec)

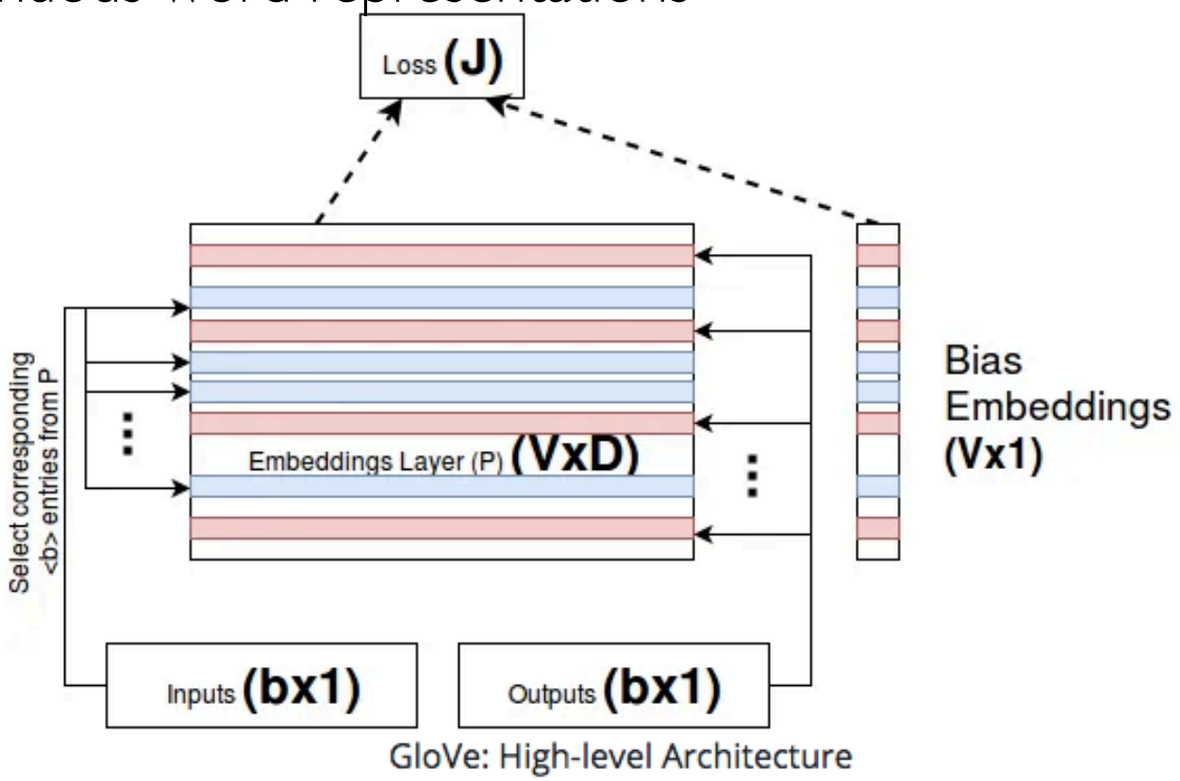


N-gram features of the word w(t)

Continuous word representations Context-independent

Glove (J. Pennington et al 2014)

- Count based approach
- Based on the analysis of the co-occurrences of words in the corpus
  - Co-occurence matrix construction: use of siding window
  - Estimation of continuous word representations

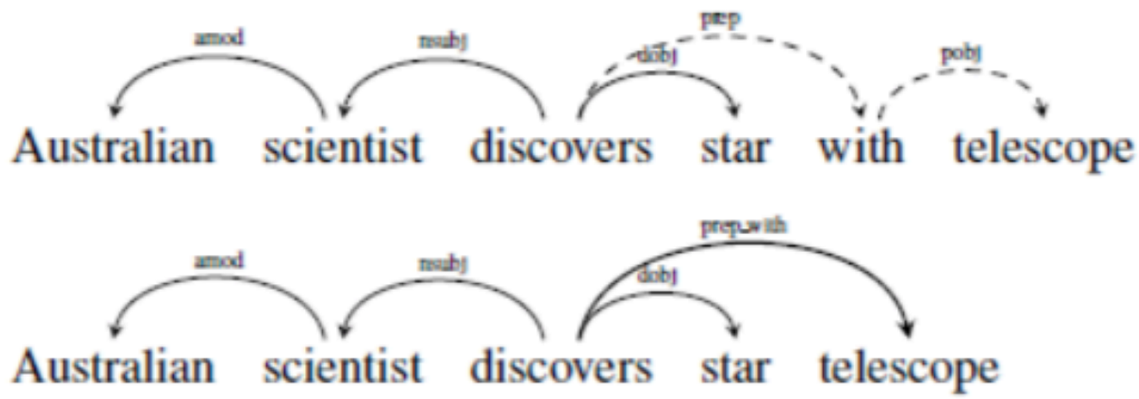


GloVe: High-level Architecture

CONTINUOUS WORD REPRESENTATIONS
CONTEXT-INDEPENDENT

w2vf-deps : dependency based word embeddings (O. Levy *et al.* 2014)

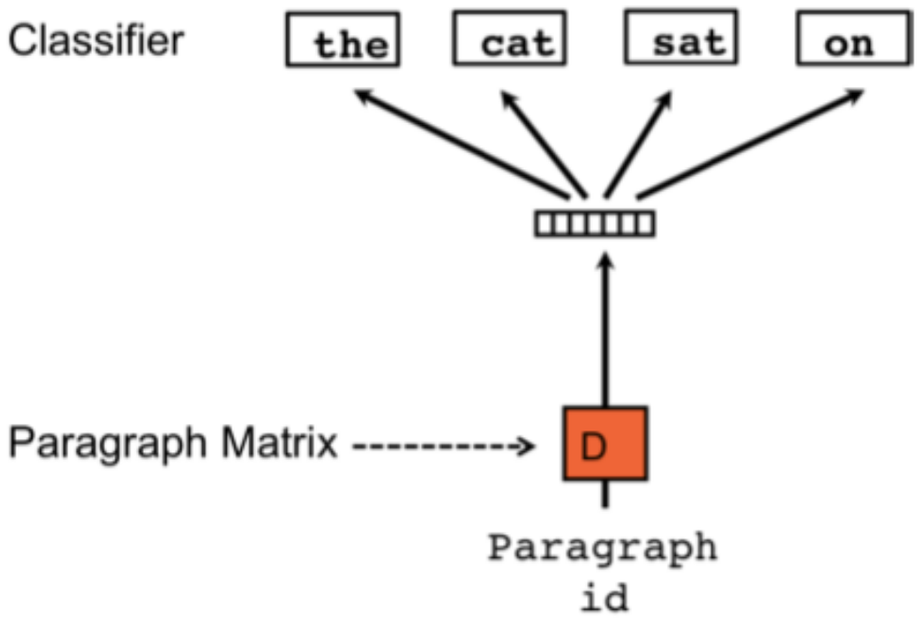
- Generalization of the skip-gram model with negative samples
- Use syntactic relationships (root words, dependency between root word and dependent words) to extract words in context
  - capture relations between distant words: can not be detected in a small context window



WORD	CONTEXTS
australian	scientist/amod^{-1}
scientist	australian/amod, discovers/nsubj^{-1}
discovers	scientist/nsubj, star/dobj, telescope/prep_with
star	discovers/dobj^{-1}
telescope	discovers/prep_with^{-1}

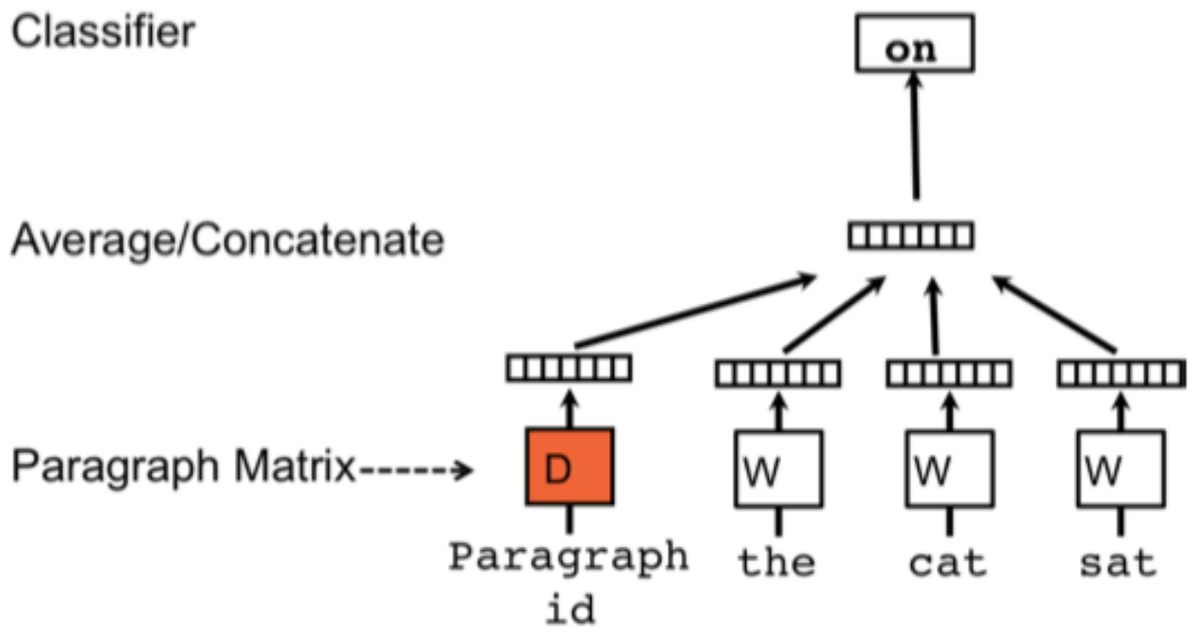
CONTINUOS DOCUMENT REPRESENTATIONS

Distributed bag of words



(Mikolov et al. 2013b)

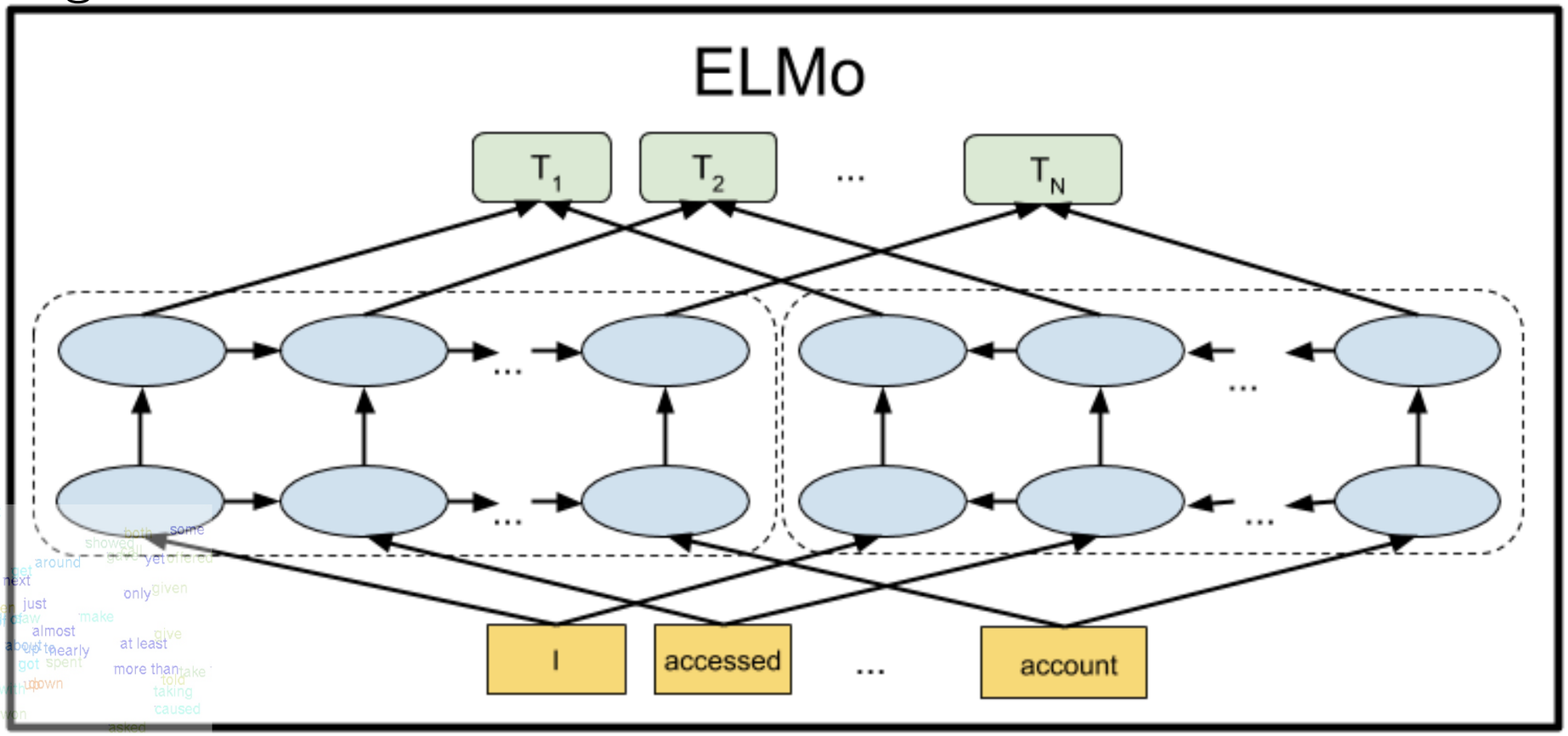
Distributed Memory model



Continuous word representations Contextual

ELMo (Embeddings from Language Models)(Peters, et al, 2018)

- Learn word embeddings by creating bidirectional language models
- Creates contextualized representations of each token by concatenating the internal states of a 2-layer biLSTM trained on a bidirectional language modeling task

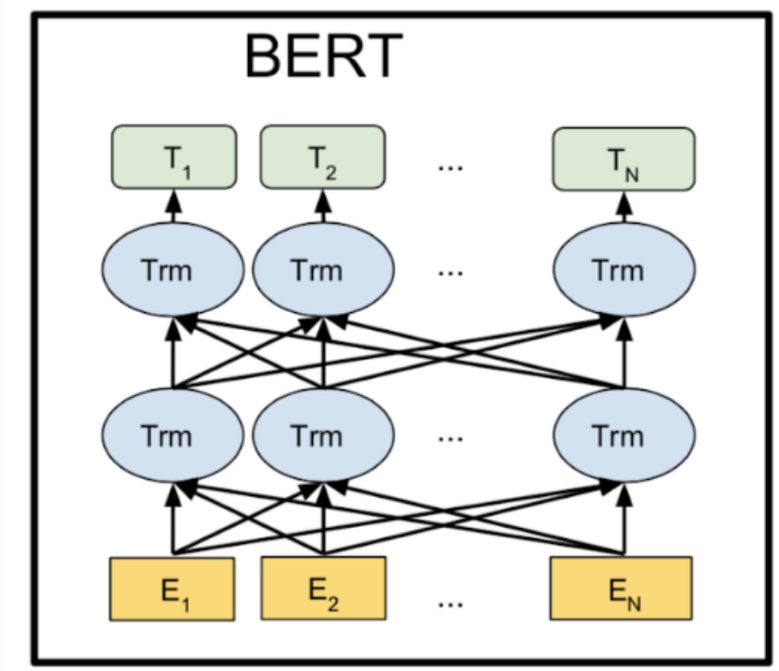


CONTINUOUS WORD REPRESENTATIONS CONTEXTUAL

TRANSFORMER BASED MODELS

BERT (Bidirectional Encoder Representations from Transformers)(Devlin, et al., 2019)

- it's a bidirectional transformer pre-trained using a combination of masked language modeling objective and next sentence prediction on a large corpus.
- Each transformer layer of 12- layer creates a contextualized representation of each token by attending to different parts of the input sentence



CONTINUOUS WORD REPRESENTATIONS CONTEXTUAL

TRANSFORMER BASED MODELS:

Encoder only

- BERT
- RoBerta
- Reformer
- FlauBERT
- CamemBERT
- Electra*
- MobileBERT
- Longformer

Decoder only

- Transformer-XL
- XLNet
- GPT series
- DialoGPT

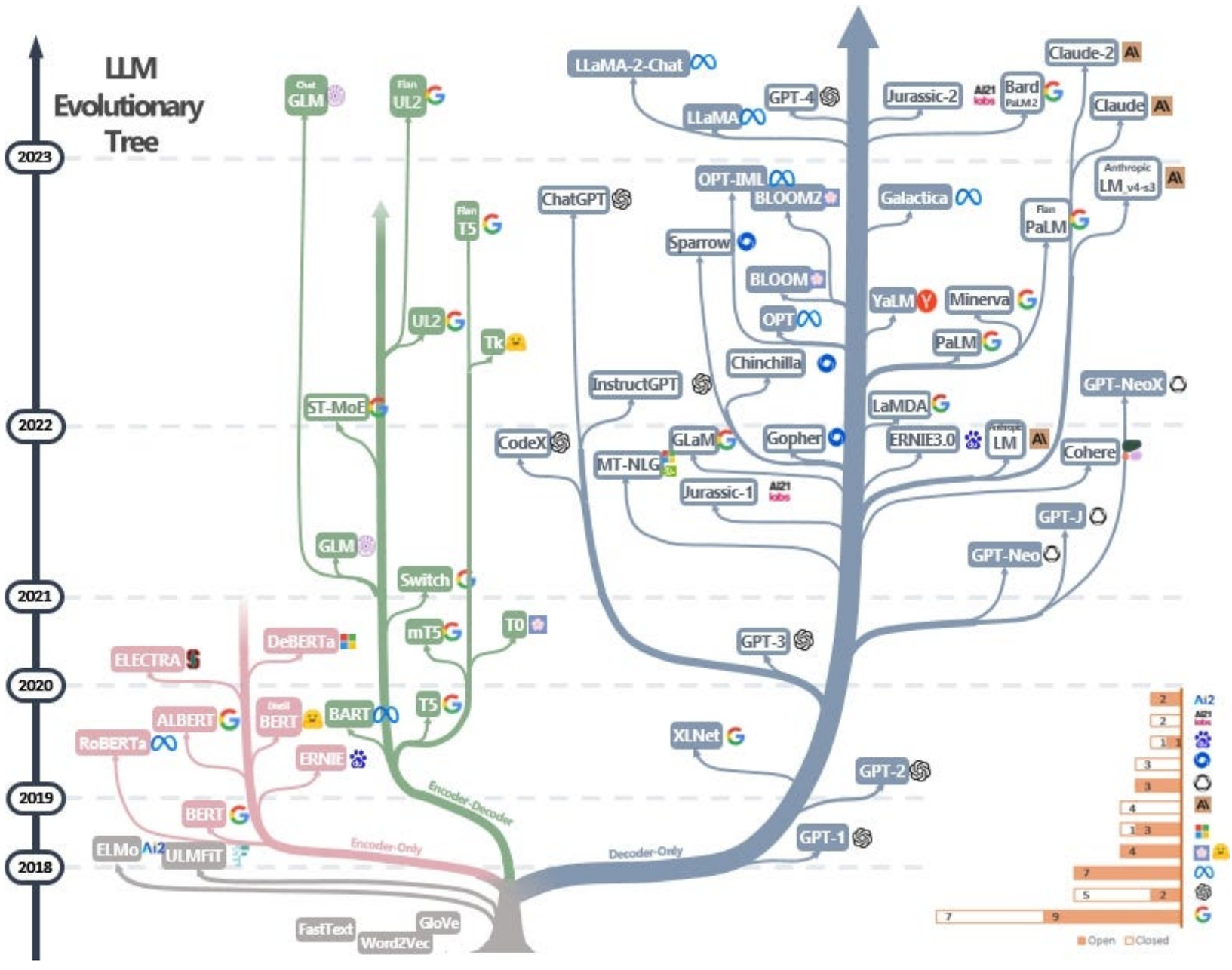
Encoder + Decoder

- Transformer
- XLM
- T5
- BART
- XLM-RoBerta
- Pegasus
- mBART

Continuous word representations

Contextual

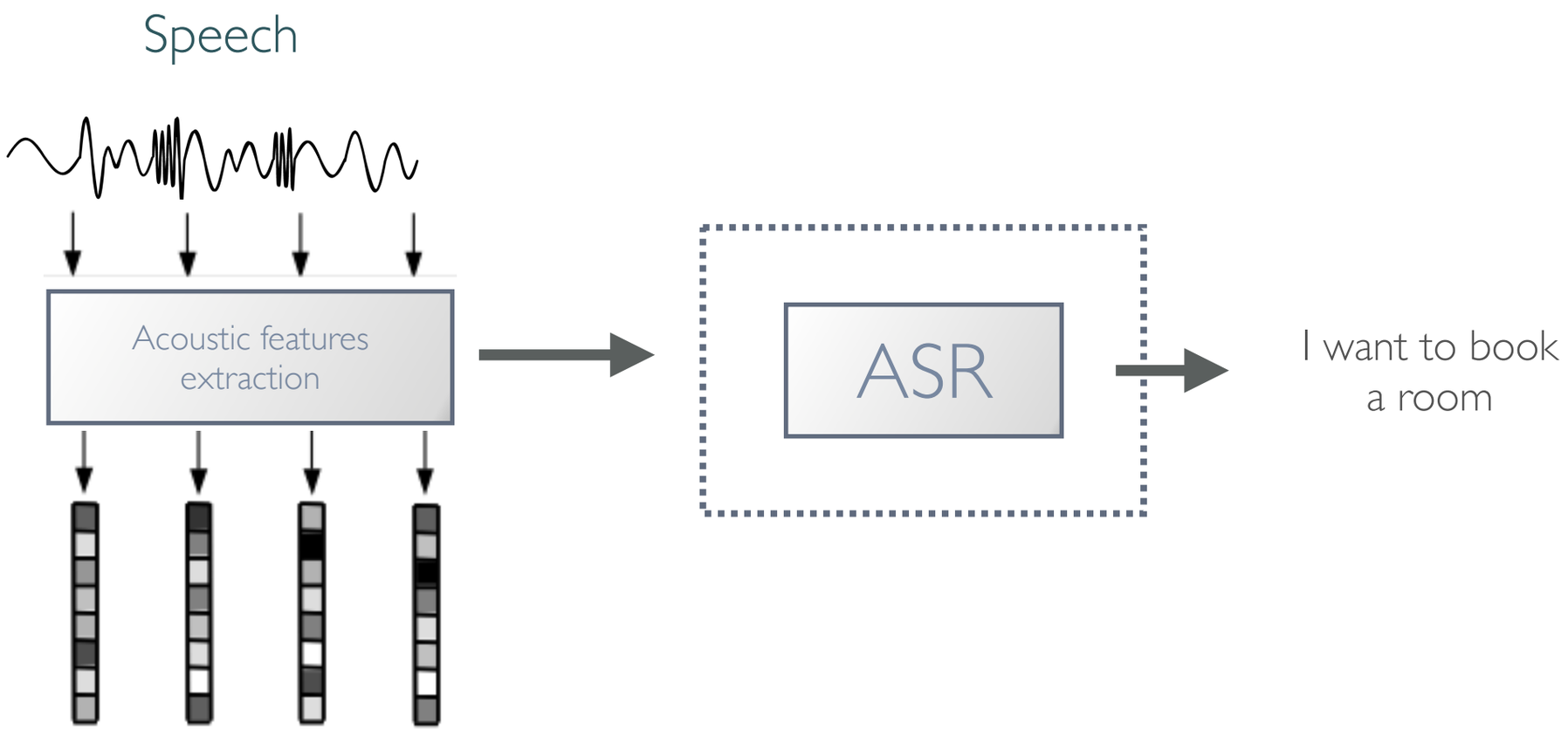
Large language models Evolution



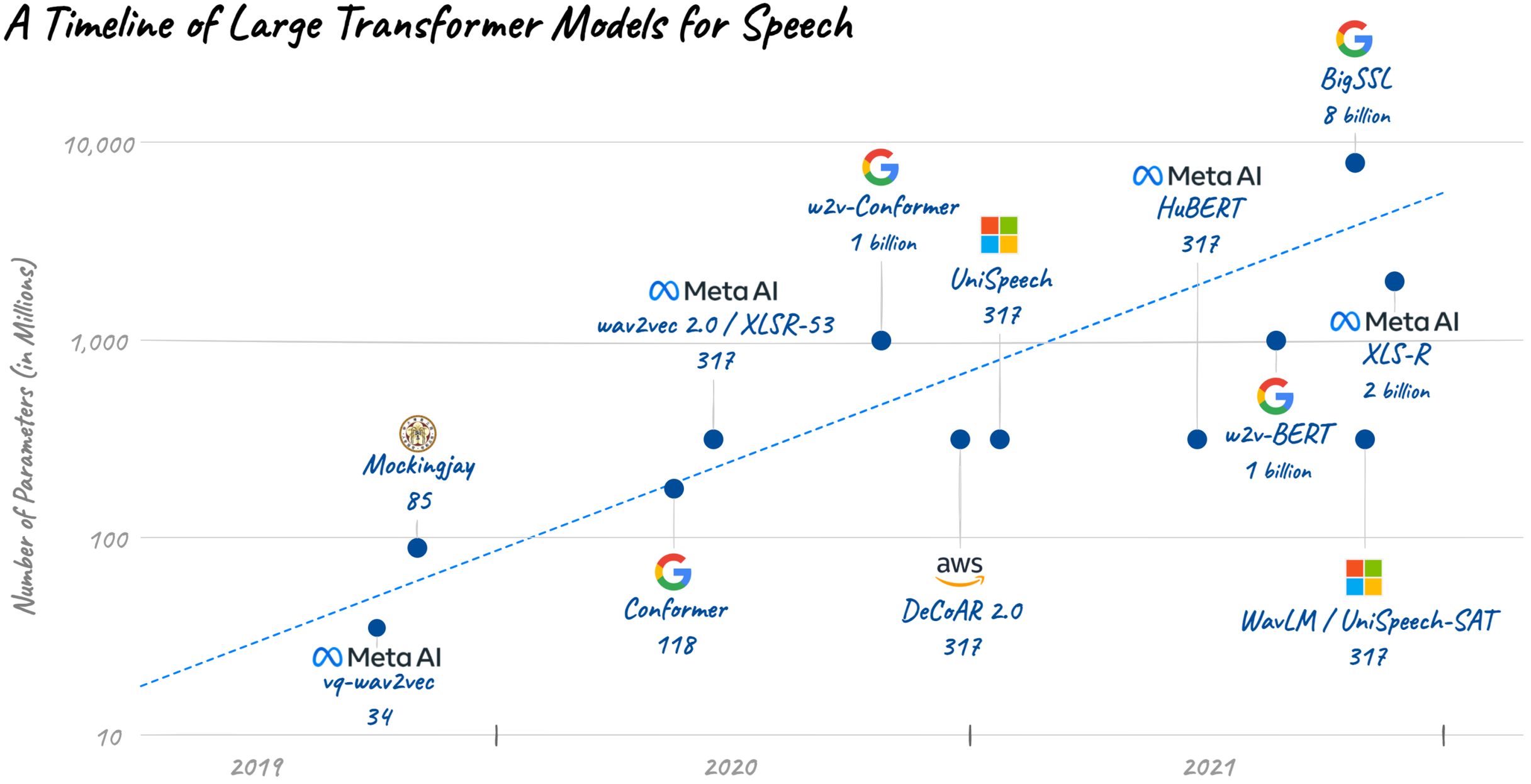
The evolutionary tree of modern LLMs traces the development of language models in recent years [Yang, Jingfeng, et al., 2024]

WHAT A BOUT SPEECH REPRESENTATION?

- Traditional hand-crafted approaches for acoustic features extraction (parameterization) are: Mel-frequency cepstral coefficients (MFCCs), FBANKs, Short-Term Fourier Transform (STFT)…
- With the advent of **self-supervised learning**, other approaches have emerged, allowing direct encoding of the speech signal through neural learning.
  - The parameterization thus becomes adaptable to the task, by optimizing the parameters of very dense neural speech encoders.



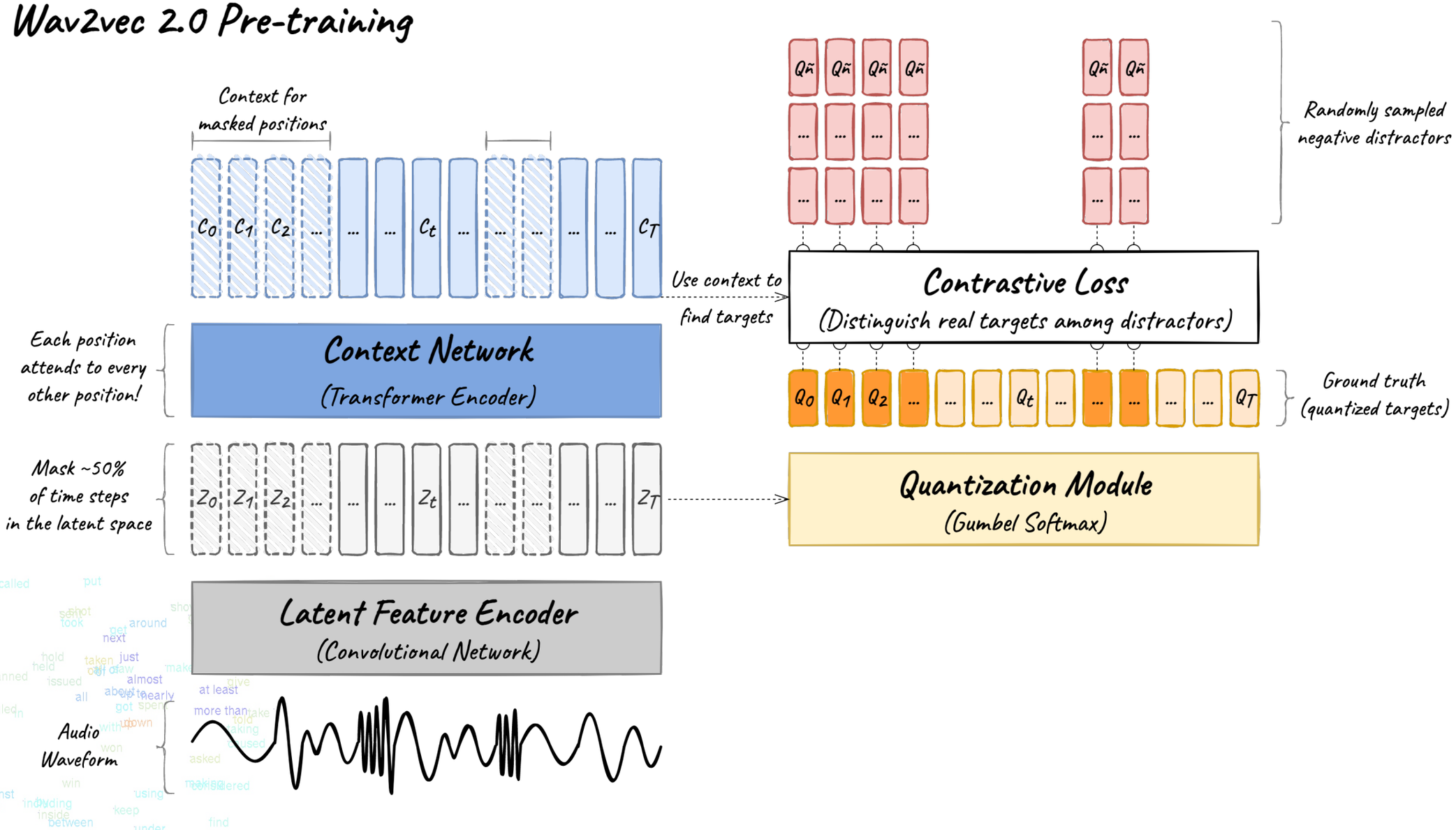
Continuous representations for speech Contextual



Source: https://jonathanbgn.com/2021/12/31/timeline-transformers-speech.html

Continuous representations for speech Contextual

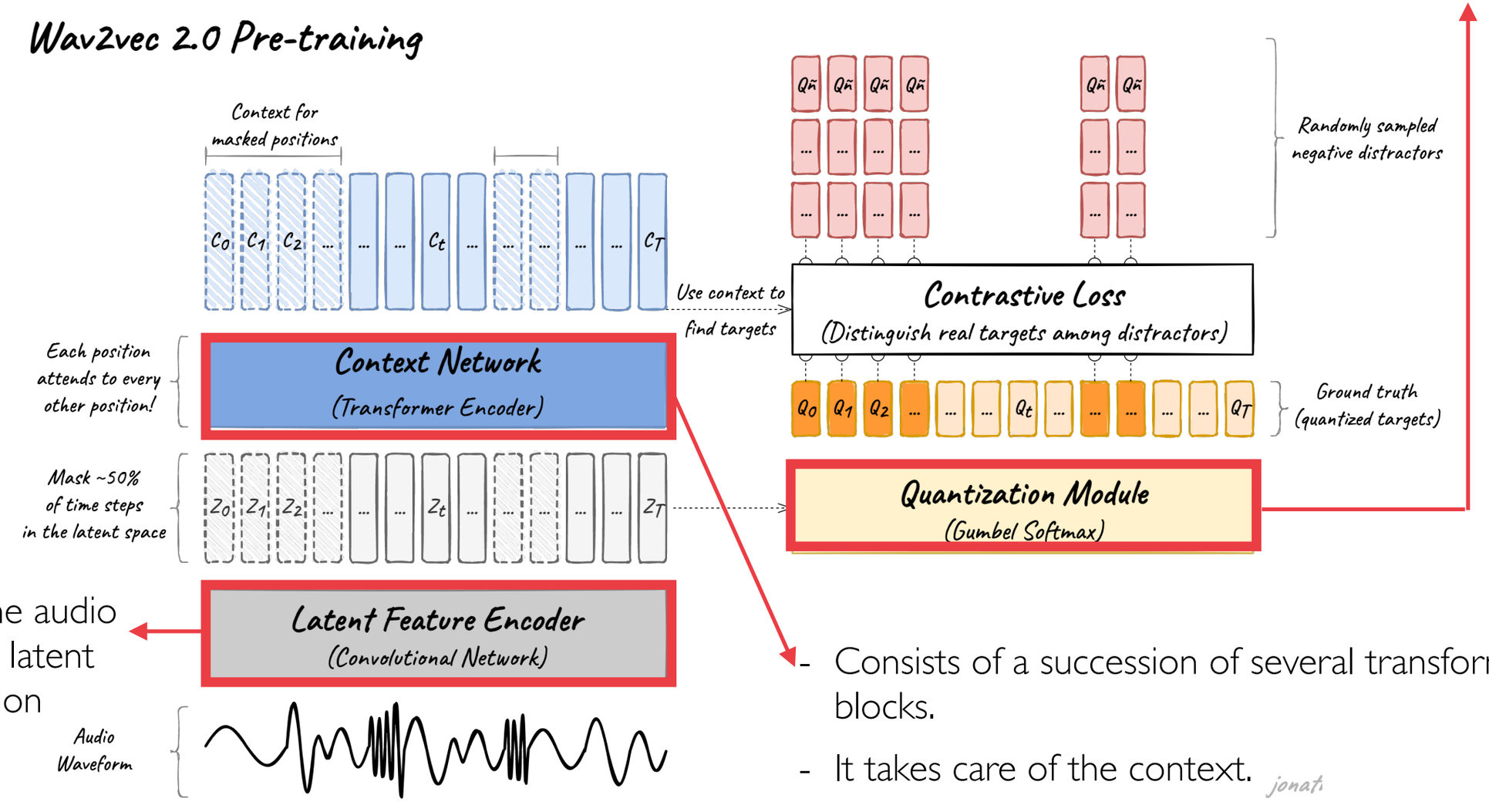
Wav2vec 2.0 (baevski *et al.*, 2020) is a model pre-trained through self-supervision. It takes raw audio as input and computes contextual representations that can be used as input for speech recognition systems.



CONTINUOUS REPRESENTATIONS FOR SPEECH CONTEXTUAL

Wav2vec 2.0 (baevski *et al.*, 2020)

- It contains three main components:



- Converts the audio signal into a latent representation

- Is used to map the values from a continuous space into a finite set of values in a discrete space

- Consists of a succession of several transformer encoder blocks.
- It takes care of the context.

Évaluation

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

1. Natural language processing tasks (NLP)

- Part-of-speech tagging (POS): syntactic roles (noun, adverb, etc.)
- Chunking (CHK): syntactic constituent (noun phrase, verb phrase, etc.)
- Named Entity recognition (NER): person, company, etc.
- Mention detection (MENT): begin, inside, and outside
- Spoken language understanding task (SLU)

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

2. Word semantic similarity (Kiela et al., 2015)

CONTINUOUS WORD REPRESENTATIONS EVALUATION TASKS

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- Is based on an idea that the distances between words in an embedding space could be evaluated through the human heuristic judgments on the actual semantic distances between these words
  - e.g., the distance between *cup* and *mug* defined in an continuous interval {0,1} would be 0.8 since these words are synonymous, but not really the same thing.
- The assessor is given a set of pairs of words and asked to assess the degree of similarity for each pair.
- The distances between these pairs are also collected in a word embeddings space, and the two obtained distances sets are compared.
- The more similar they are, the better are embeddings

CONTINUOUS WORD REPRESENTATIONS EVALUATION TASKS

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W1	W2	score
m11	m21	s1
m12	m22	s2
m13	m23	s3

→

SimCos
cos1
cos2
cos3

→

rank_score	rank_SimCos
2	9
12	1
1	30

→ Score rho

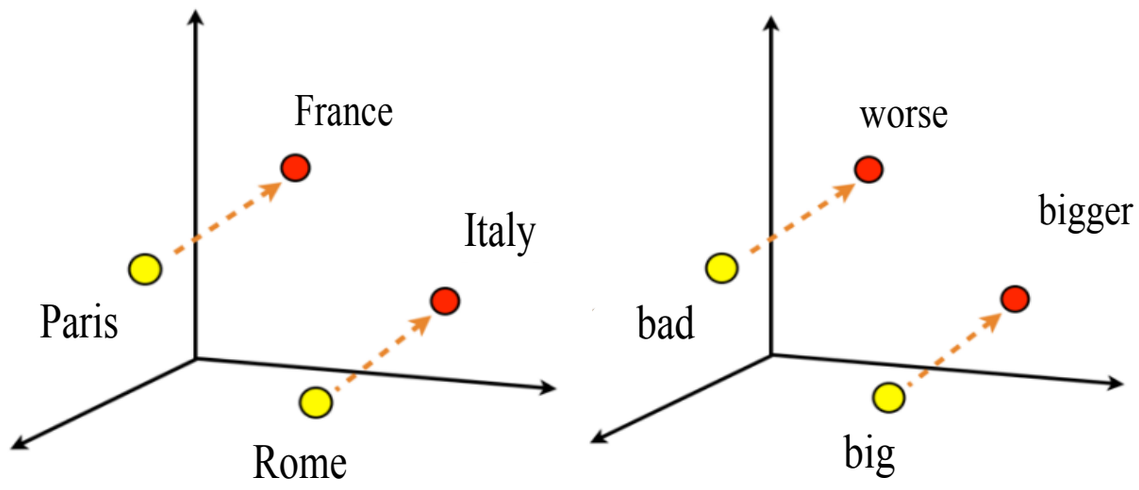
Continuous word representations Evaluation tasks

- Is based on the idea that arithmetic operations in a word vector space could be predicted by humans:
  - given a set of three words, a, a* and b, the task is to identify such word b* that the relation b:b* is the same as the relation a:a*.
  - For instance, one has words a=Paris, a*=France, b=Rome.
  - Then the target word would be Italy since the relation a:a* is capital:country, so one needs to find the capital of which country is *Rome*

1.

Semantic: Paris:France → Rome:?

Syntactic: bad:worse → big:?



CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

3. Word analogy

- Is based on the idea that arithmetic operations in a word vector space could be predicted by humans:
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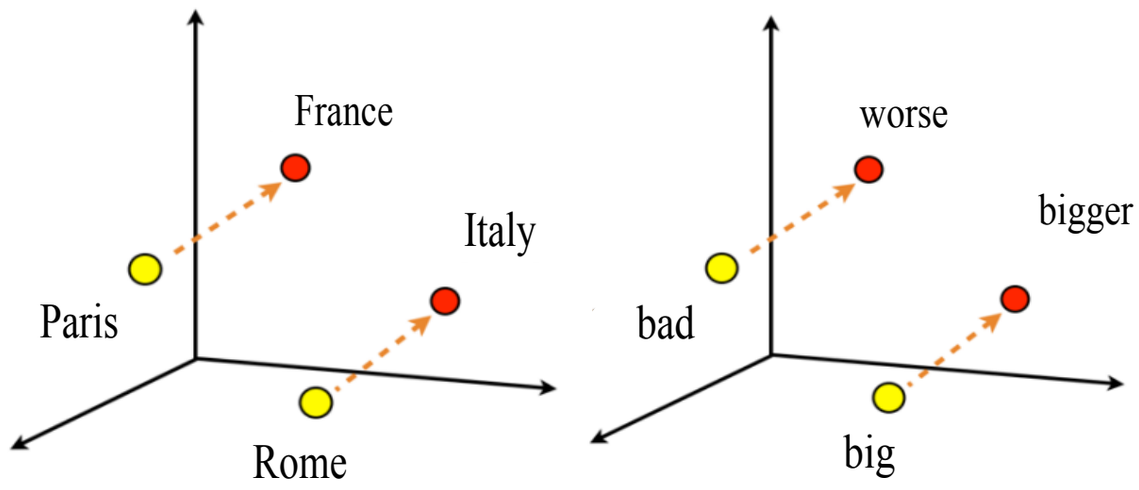
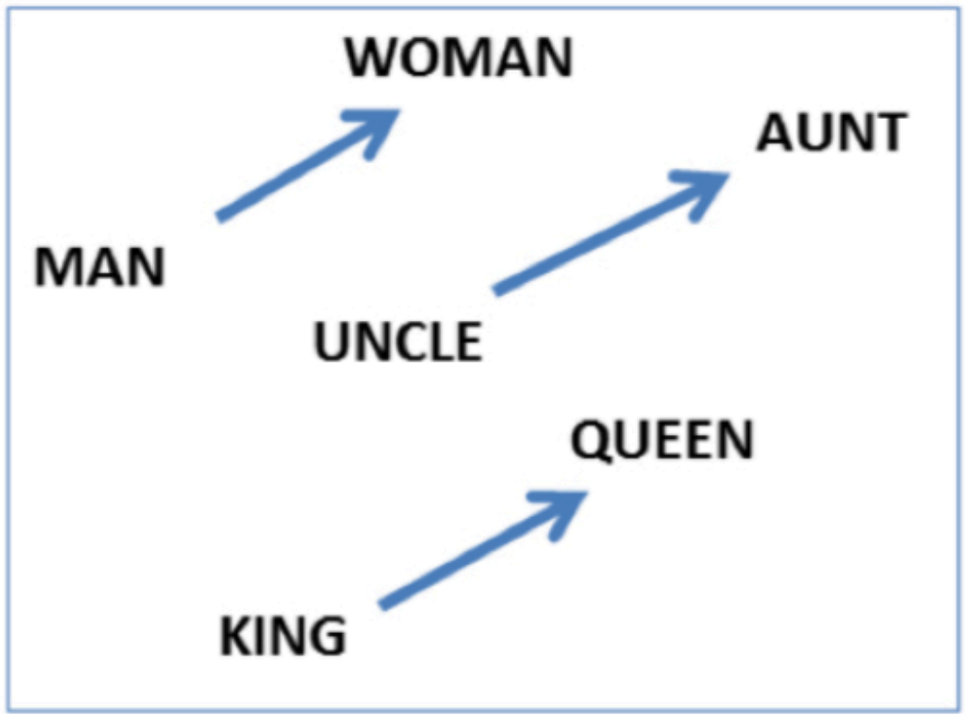
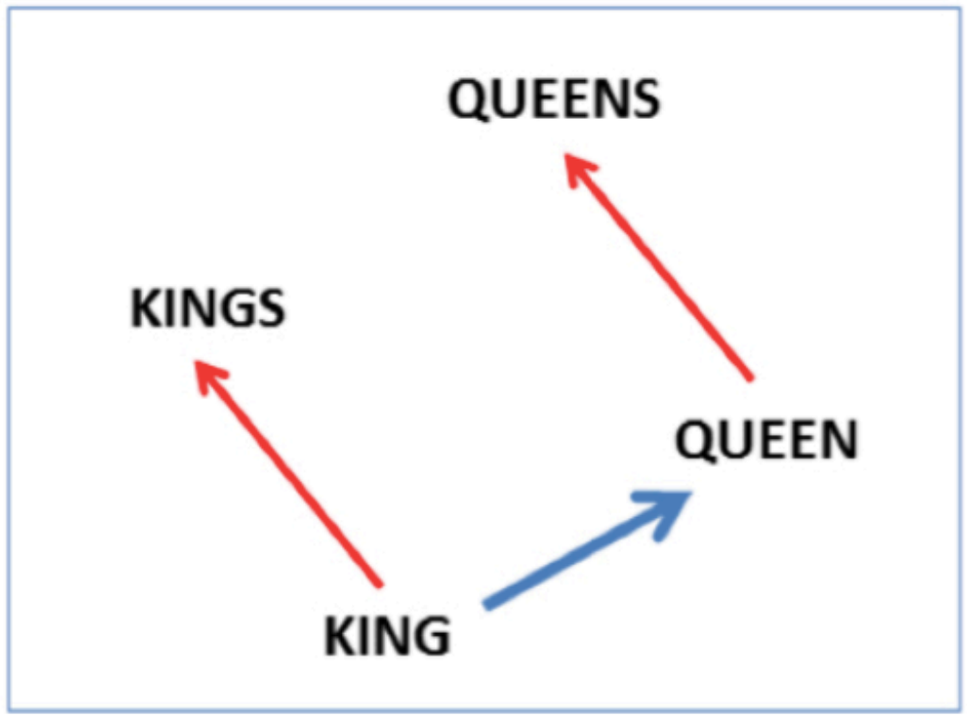


Continuous word representations
Evaluation tasks

vector(*'king'*) - vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')





CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

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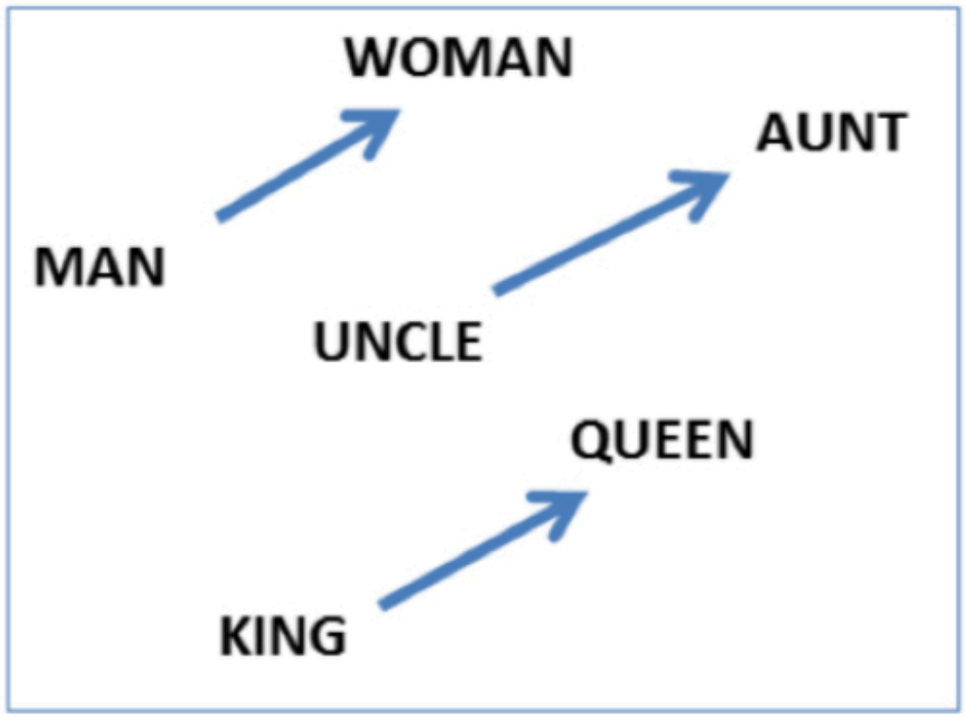

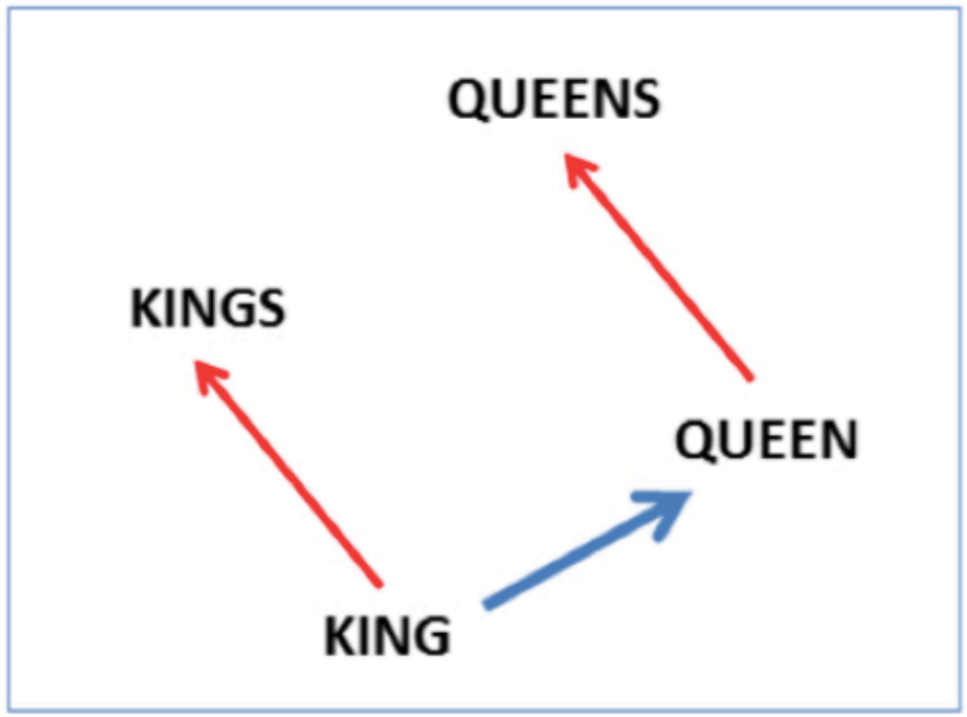

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

Evaluation data

- Word embeddings:
  - data: corpus Gigaword (english)
  - Vocabulary: 239k words
  - Parameters:

Embeddings	Ngram	Dim.	Neg.
CBOW	5	200	5
Skip-gram			5
GloVe			-
w2vf-deps	-		5

- Analogy task
  - Questions:
    - 8869 semantic
    - 10675 syntactic

- Similarity task:
  - Data:
    - WordSim353
    - RW (2034)
    - MEN (3000)

- NLP tasks
  - Data:

Task	Benchmark	Train	Dev	Test
POS	Penn Treebank	958k	34k	58k
CHK	CoNLL 2000	191k	21k	47k
NER	CoNLL 2003	205k	52k	47k
MENT	Ontonotes	736k	102k	105k

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

Embeddings	NLP				Similarity			Analogy
	POS	CHK	NER	MENT	WS353	RW	MEN	
	Acc.	F1			Spearman's rank rho			Acc.
Skip-gram	96,43	0,896	0,776	0,578	0,558	0,502	0,662	62,30
w2v-deps	96,66	0,920	0,793	0,580	0,523	0,435	0,557	42,70
GloVe	95,79	0,869	0,764	0,544	0,533	0,410	0,660	65,50

[Ghannay, et al., 2016]

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

Embeddings	NLP				Similarity			Analogy
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w2v-deps	96,66	0,920	0,793	0,580	0,523	0,435	0,557	42,70
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[Ghannay, et al., 2016]

➡These embeddings carry different information

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

TASK-DEPENDENT DATA VS OUT OF DOMAIN DATA

QUANTITATIVE EVALUATION

	task-dependent					Out-of-domain				
Bench.	**ELMo**	**FastText**	**GloVe**	**Skip-gram**	**CBOW**	**ELMo**	**FastText**	**GloVe**	**Skip-gram**	**CBOW**
M2M	88.89	72.13	**92.54**	88.87	89.39	91.14	93.01	91.77	**93.19**	92.13
ATIS	**94.38**	85.72	92.95	90.84	91.87	94.93	95.52	95.35	95.62	**95.77**
SNIPS	78.68	76.35	**87.40**	82.10	83.94	90.29	**94.85**	93.90	94.43	94.05
SNIPS70	53.06	38.19	**63.65**	47.11	49.76	75.19	79.75	78.68	78.90	**80.13**
MEDIA	80.26	71.73	**82.66**	80.01	79.57	**86.42**	85.30	85.11	85.95	86.06

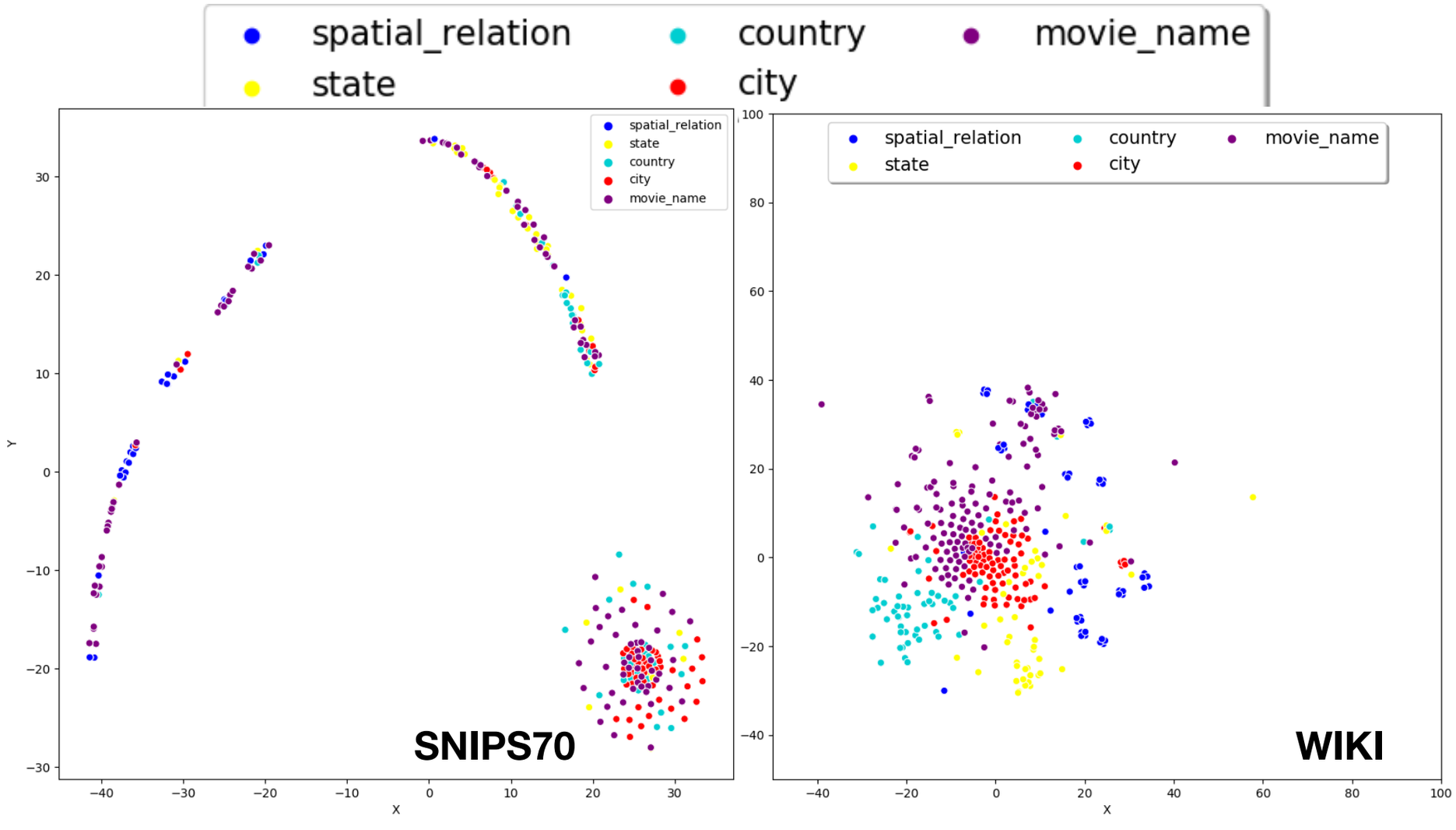
Tagging performance of different word embeddings trained on task-dependent corpus (ATIS, MEDIA, M2M, SNIPS or SNIPS70) and on huge and out of domain corpus (WIKI English or French) on all benchmark corpora in terms of F1 using conlleval scoring script (in %)

[Ghannay, et al., 2020]

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

TASK-DEPENDENT DATA VS OUT OF DOMAIN DATA

Qualitative evaluation: CBOW

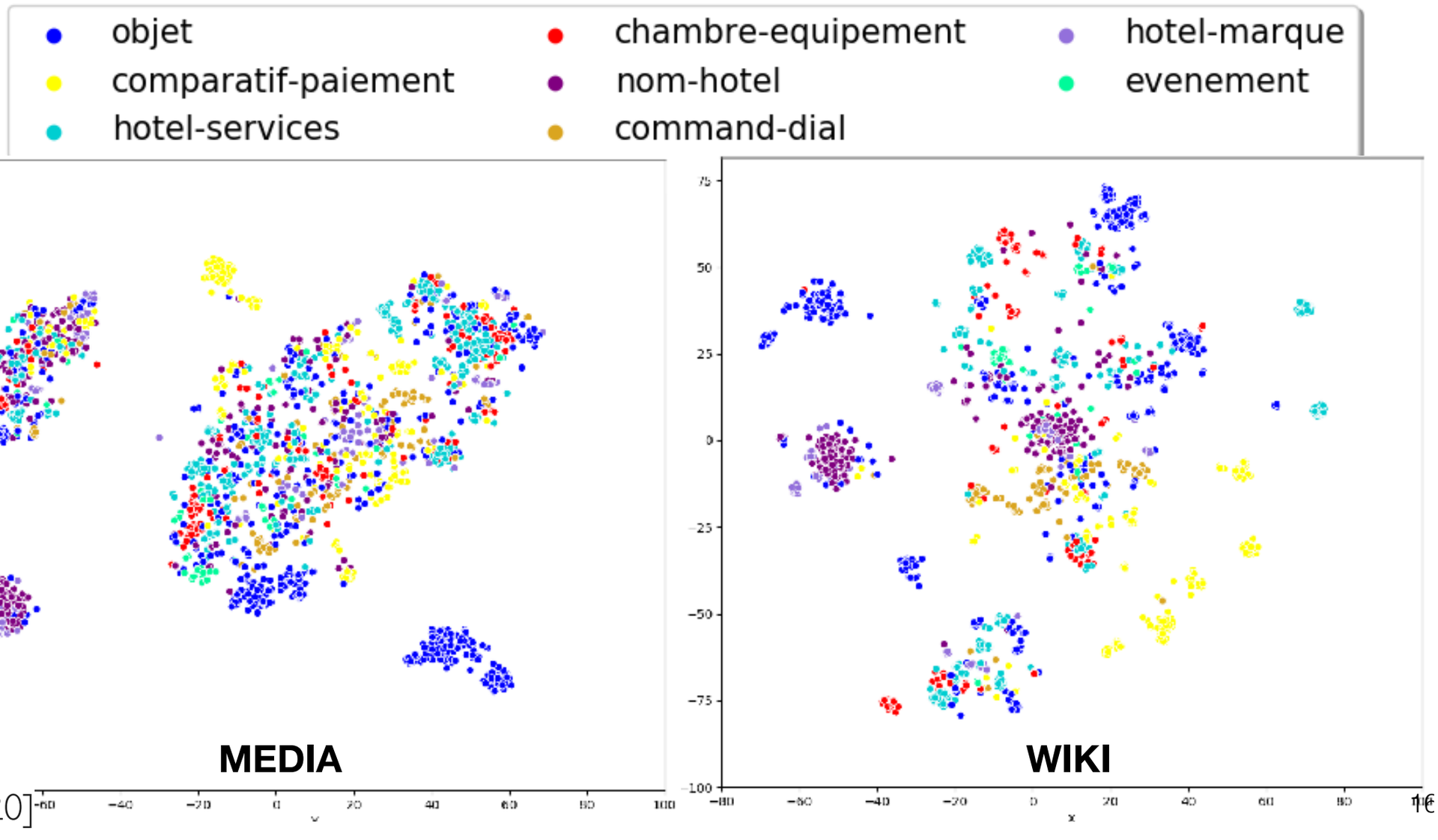


[Ghannay, et al., 2020]

CONTINUOUS WORD REPRESENTATIONS
EVALUATION TASKS

TASK-DEPENDENT DATA VS OUT OF DOMAIN DATA

Qualitative evaluation: ELMo



[Ghannay, et al., 2020]

Neural Networks approaches focused on French Spoken Language Understanding: application to MEDIA Evaluation Task

- Evaluate the performance of BERT approaches on the MEDIA task through two different ways:
  - I)Fine-tune BERT on SLU task using two French models: CamemBERT and FlauBERT
  - II)Integrate the extracted BERT's contextual embeddings to the BiLSTM and BiLSTM-CNN architectures, instead of CBOW

Architecture	Embed. Training data	Embed.'s approach	F1	CER
biRNN-EDA	–	–	–	10.7
BiLSTM-CNN	WIKI	CBOW (dim=300)†	87.40	9.88
		CBOW (dim=768)	86.80	10.11
FineTune BERT (i)	oscar 138 GB	CamemBERT-base	89.18	7.93
	ccnet 135 GB	CamemBERT-base	**89.37**	**7.56**
	heterogeneous corpus 71 GB	FlauBERT-base	89.04	8.13
BiLSTM	ccnet 135GB (ii)	CamemBERT-base (dim=768)	86.59	10.45
BiLSTM-CNN		CamemBERT-base (dim=768)	87.15	10.11

[Ghannay, et al., 2020a]

Neural Networks approaches focused on French Spoken Language Understanding: application to MEDIA Evaluation Task

➡I)CamemBERT base model trained on ccnet data achieves the best results

- 29.35% of relative improvement in terms of CER reduction in comparison to the baseline (biRNN-EDA)
- outperforms BiLSTM-CNN system and improves the prediction of some tags: "nom, chambre-fumeur, objet, …'
- Achieves comparable results to FlauBERT base model

➡II) the use of CamemBERT contextual embeddings achieves competitive results in comparison to CBOW embeddings whatever the architecture used (BiLSTM or BiLSTM-CNN)

- the results with BiLSTM and BiLSTM-CNN architectures reveals the importance of character embeddings, even when they are combined with contextual embeddings.

[Ghannay, et al., 2020a]

Tools

Tools available to build the embeddings

- Word2vec Mikolov: https://github.com/tmikolov/word2vec
- W2vf-deps Levy: https://levyomer.wordpress.com/2014/04/25/dependency-based-word-embeddings/
- Glove Pennington: https://nlp.stanford.edu/projects/glove/
- Fasttext: https://fasttext.cc/docs/en/support.html
- ELMo: allennlp https://github.com/allenai/allennlp/blob/master/tutorials/how_to/elmo.md
- BERT: https://pypi.org/project/bert-embedding/
- wav2vec 2.0: https://ai.facebook.com/blog/wav2vec-20-learning-the-structure-of-speech-from-raw-audio/
- Python library: gensim

Sitography/cknowledgment

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  - Dan Jurafsky: Vector Sementic, Standford university
  - Yannick Estève: Semantics, Avignon université
  - Sophie Rosset, LISN, CNRS :
    - https://sophierosset.github.io/docs/eidi-dhm.pdf
    - https://bigdataspeech.github.io/EN/
- Tutorials:
  - https://ahmetozlu93.medium.com/long-short-term-memory-lstm-networks-in-a-nutshell-363cd470ccac
  - https://missinglink.ai/guides/convolutional-neural-networks/convolutional-neural-network-tutorial-basic-advanced/

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Practical session

Lectures: https://saharghannay.github.io/files/Cours_Master_EN.pdf

PS: https://saharghannay.github.io/courses/cours1/example1/