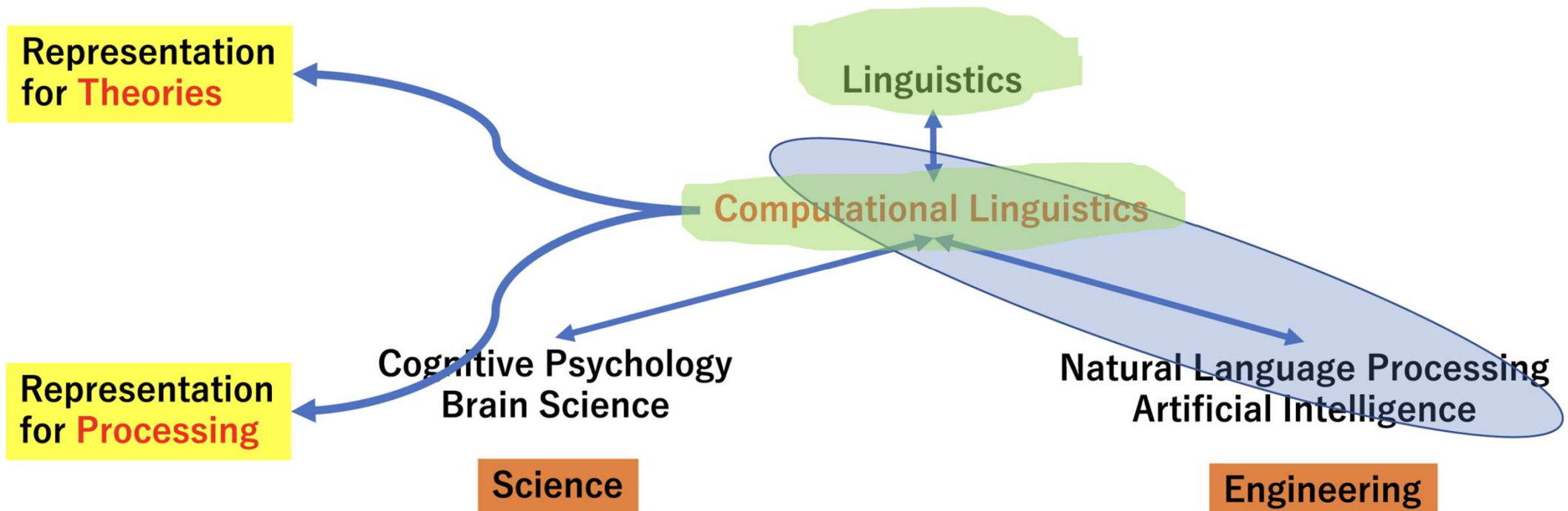


Natural Language Processing basics

NLP approaches

- Empirical - Statistical
 - Machine Learning – Corpora
 - Unsupervised
 - + Annotation - Supervised
 - Vector space models; Word embeddings
 - Neural Networks
 - Shallow parsing
- Rationalistic - Grammar-based
 - Parsing
 - Knowledge-based
 - Ontologies
 - Knowledge graphs



Linguistics – the science that studies natural language

- Phonetics and phonology
- Morphology - lexicons
- Syntax - grammars
- Semantics – knowledge bases, ontologies, semantic spaces, embeddings
- Pragmatics and discourse

Grammars (Syntax)

- Regular, Context Free, Context Dependent, General (Chomsky's hierarchy)
- Dependency
- GPSG
- HPSG
- LFG
- (L)TAG

Corpus linguistics

- Empirical approach (based on datasets, not on rationalism)
- Based on corpora
- It may or not use computational techniques
- Introduced by John Sinclair (without NLP)

Corpus-Corpora

Collection(s) of naturally-occurring language text, chosen to characterize a state or variety of a language.
(John Sinclair, 1991)

Oxford Text Archive

A repository of full-text literary and linguistic resources.
Thousands of texts in more than 25 languages.

Important notice: November 2021
The Bodleian Libraries are currently undertaking a review of the Oxford Text Archive, including its policies, technologies and content (both textual content and contextual website content). The OTA will therefore not be taking any new deposits until further notice.

Search

Advanced Search

Subject	Date range	Collections
Great Britain (11821)	2000-present (39)	Core Collection
Broadsides (4897)	1900-1999 (611)	Early English Books Online (Phase 1)
Sermons, English (4029)	1800-1899 (829)	Early English Books Online (Phase 2)
Bible. (3156)	1700-1799 (7353)	ECCO - Eighteenth Century Collections Online
England and Wales. (2169)	1600-1699 (22656)	Evans Early American Imprints
Church of England (2146)	1500-1599 (2965)	Jonathan Swift Archive
Society of Friends (1801)	0-1499 (297)	Legacy Collection
Catholic Church (1623)	BCE (142)	OTA Guides

<https://ota.ox.ac.uk/documents/creating/dlc/chapter1.htm>

Zipf's law – law of corpora

- A corpus of general text should satisfy a number of constraints, for example, Zipf's law (<https://www.youtube.com/watch?v=fCn8zs912OE>), which is specific to any language
- Other constraints should be satisfied
- It is an **instance of a power law** (Barabasy), which reflect natural properties of social networks and phenomena (e.g. the number of friends in a social networks)

Types of corpora

- Raw vs annotated
- Speech vs text
- General vs. specific
- Parallel corpora

Examples of general language corpora

- British National Corpus (BNC)
<http://www.natcorp.ox.ac.uk/>
- Corpus of Contemporary American English (COCA)
<https://corpus.byu.edu/coca/>
- Open American National Corpus (OANC)
<http://www.anc.org/>
- CoRoLa - Corpus de referință pentru limba română contemporană
http://89.38.230.23/corola_sound_search/

For various NLP learning tasks are many corpora (textual datasets)

See the Linguistic Data Consortium - <https://www ldc.upenn.edu/>

Text structuring

- Tokenization (at the level of words)
- Bracketing (syntactical structures)
- Text segmentation
- Coreference resolution
- Discourse
- Rhetoric schema identification

Text annotation (in corpora)

- Syntactic
 - Part of speech – ex. noun, verb, ...
 - “Bracketing” – syntactical structures
 - Treebanks – parsing trees
- Semantic – senses for words
- Pragmatic
 - Anaphoric annotation
 - Speech act annotation
- Discourse
- Rhetoric

Annotation languages

- SGML
- XML
- TEI
(Text Encoding Initiative - <https://tei-c.org/>)
- Others

Machine learning with corpora

- Hidden Markov Models
- Naïve Bayes
- Support Vector Machines
- ...
- Neural Networks

Deep Neural Networks for NLP

Natural Language Processing with Deep Neural Networks

- Convolutional Neural Networks
- Recurrent Neural Networks (RNN)
 - Long Short-Term Memory (LSTM)
 - Bi-directional LSTM
 - Gated Recurrent Units (GRU)
 - Encoder-Decoder
 - Encoder-Decoder with Attention
- Transformers (Bert, GPT-2, GPT-3, GPT3.5, GPT4, ChatGPT...)

Natural Language Generation with Deep Neural Networks

- Deep Neural Networks
 - For example, **ChatGPT**
- Training with a corpus of literature
- Generating new texts in the “style” of the learned corpus

Pre-processing for DNN

- Tokenization
- Embedding

Language specific features considered in NLP with DNN

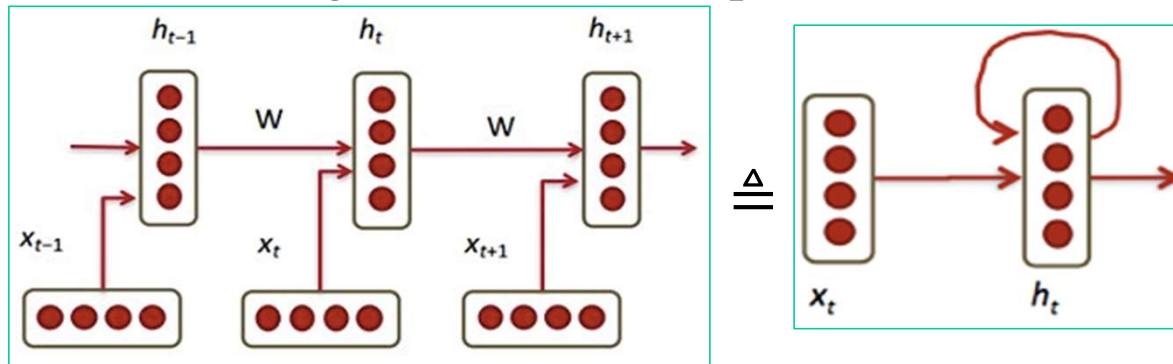
- Syntactic structures, meaning (semantics and pragmatics), and discourse are statistically learned from raw corpora
- Time sequencing
- Long distance dependencies

Recurrent Neural Networks (RNNs)

Main RNN idea for text:

Condition on **all previous words**

Use same set of weights at all time steps $h_t = \sigma(W^{(hh)}h_{t-1} + W^{(hx)}x_t)$

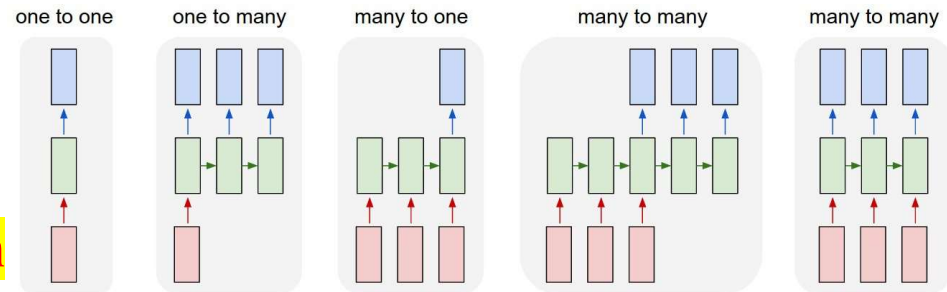


**Feed
Backward
Network**

<https://pbs.twimg.com/media/C2j-8j5UsAACgEK.jpg>

😊 Stack them up, Lego fun!

😞 **Vanishing gradient problem**



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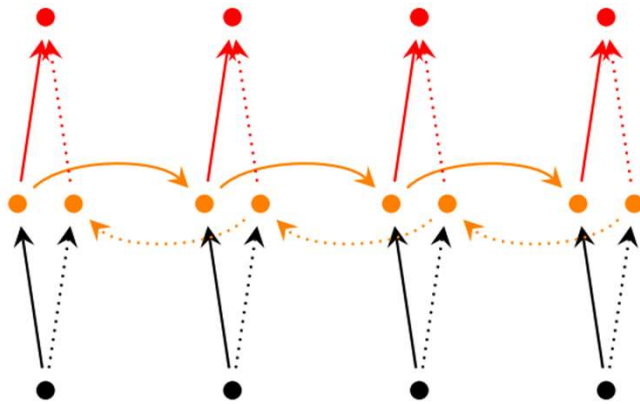
Ismini Lourentzou

<https://discuss.pytorch.org/uploads/default/original/1X/6415da0424dd66f2f5b134709b92baa59e604c55.jpg>

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Bidirectional RNNs

Main idea: incorporate both left and right context
output may not only depend on the **previous** elements in the sequence, but also **future** elements.



$$\vec{h}_t = \sigma(\vec{W}^{(hh)}\vec{h}_{t-1} + \vec{W}^{(hx)}x_t)$$

$$\overleftarrow{h}_t = \sigma(\overleftarrow{W}^{(hh)}\overleftarrow{h}_{t+1} + \overleftarrow{W}^{(hx)}x_t)$$

$$y_t = f\left(\begin{bmatrix} \vec{h}_t \\ \overleftarrow{h}_t \end{bmatrix}\right)$$

past and future around a single token

<http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/>

two RNNs stacked on top of each other

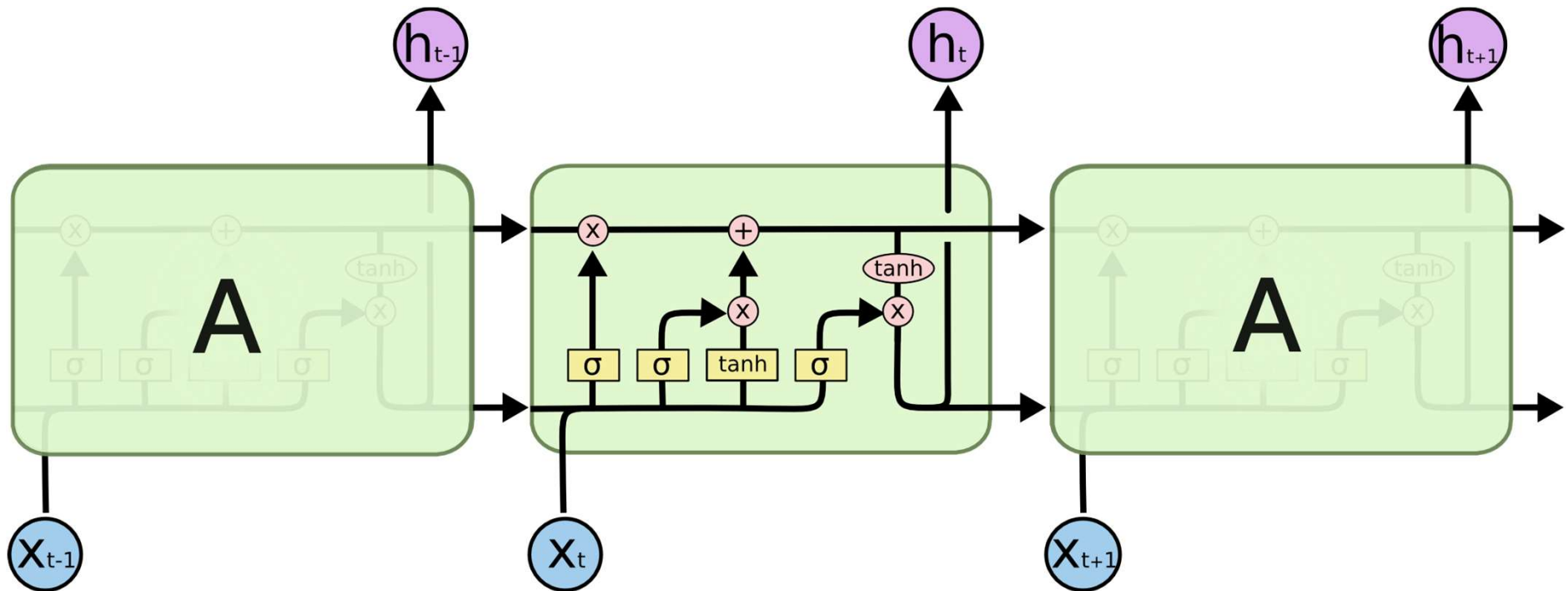
output is computed based on the hidden state of both RNNs $\begin{bmatrix} \vec{h}_t \\ \overleftarrow{h}_t \end{bmatrix}$

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Long-Short Term Memory (LSTM)

- a special kind of RNN, capable of learning long-term dependencies
- some information is forgotten



Gated Recurrent Units (GRUs)

Simpler case of LSTM

Main idea:

keep around memory to capture **long dependencies**

Allow error messages to flow at **different strengths** depending on the inputs

Standard RNN computes hidden layer at next time step directly

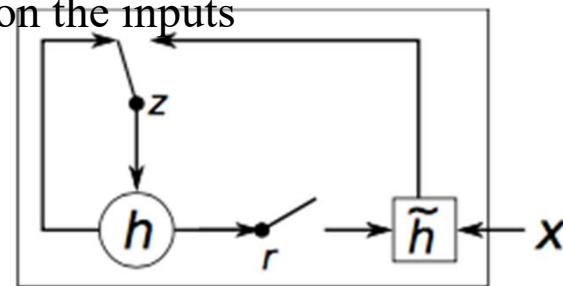
$$h_t = \sigma(W^{(hh)}h_{t-1} + W^{(hx)}x_t)$$

Compute an update gate based on current input word vector and hidden state

$$z_t = \sigma(U^{(z)}h_{t-1} + W^{(z)}x_t)$$

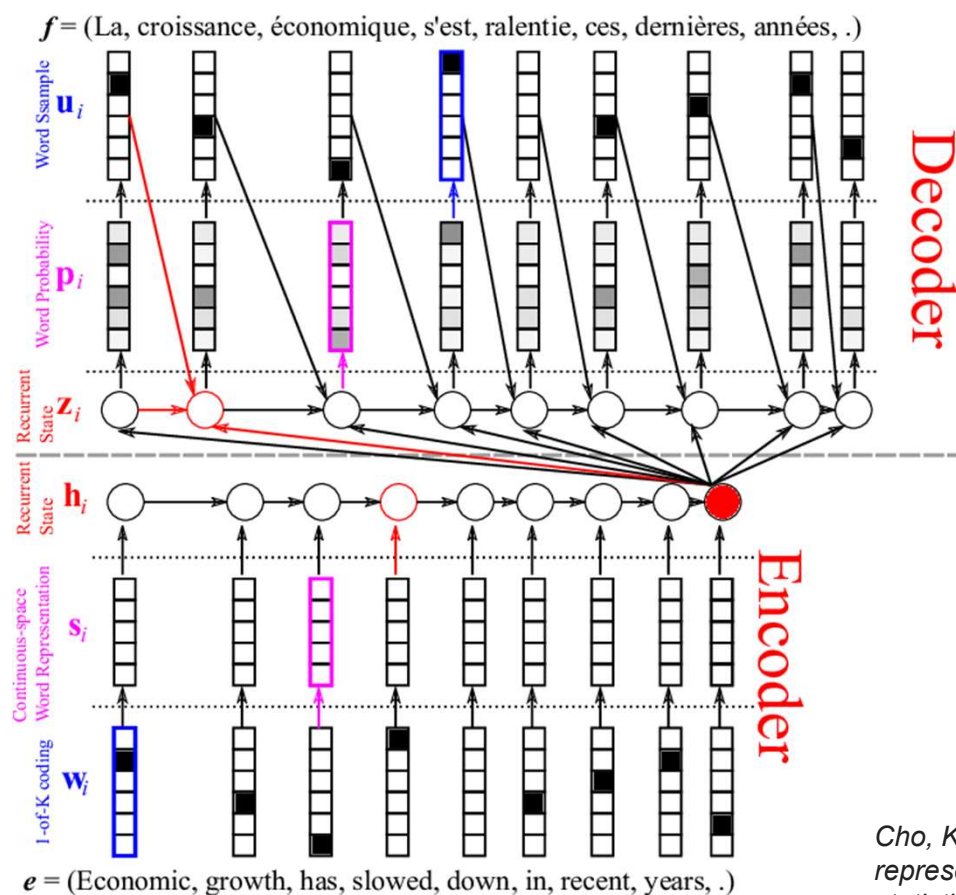
Controls how much of past state should matter now

If z close to 1, then we can copy information in that unit through many steps!



<http://www.wildml.com/2015/10/recurrent-neural-network-tutorial-part-4-implementing-a-grulstm-rnn-with-python-and-theano/>

Sequence2Sequence or Encoder-Decoder model



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Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." EMNLP 2014

25

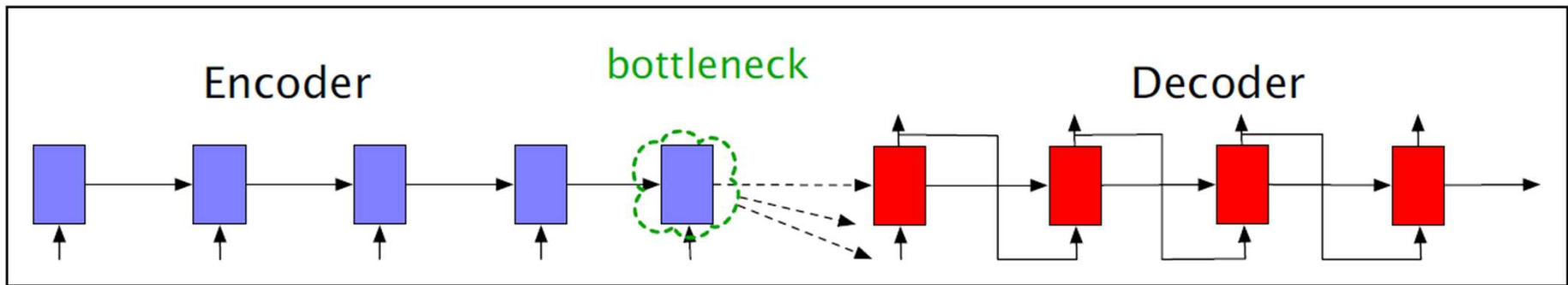
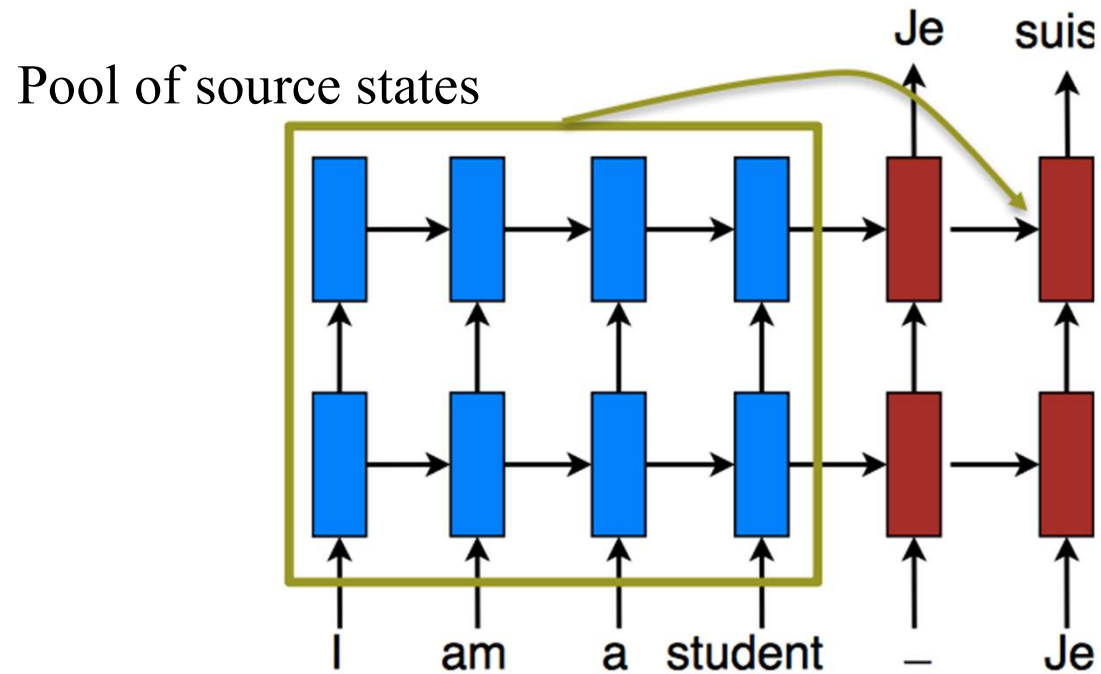


Figure 9.21 Requiring the context c to be only the encoder's final hidden state forces all the information from the entire source sentence to pass through this representational bottleneck.

(Jurafsky & Martin, 2024)

Attention Mechanism



Bahdanau D. et al. "Neural machine translation by jointly learning to align and translate." ICLR (2015)

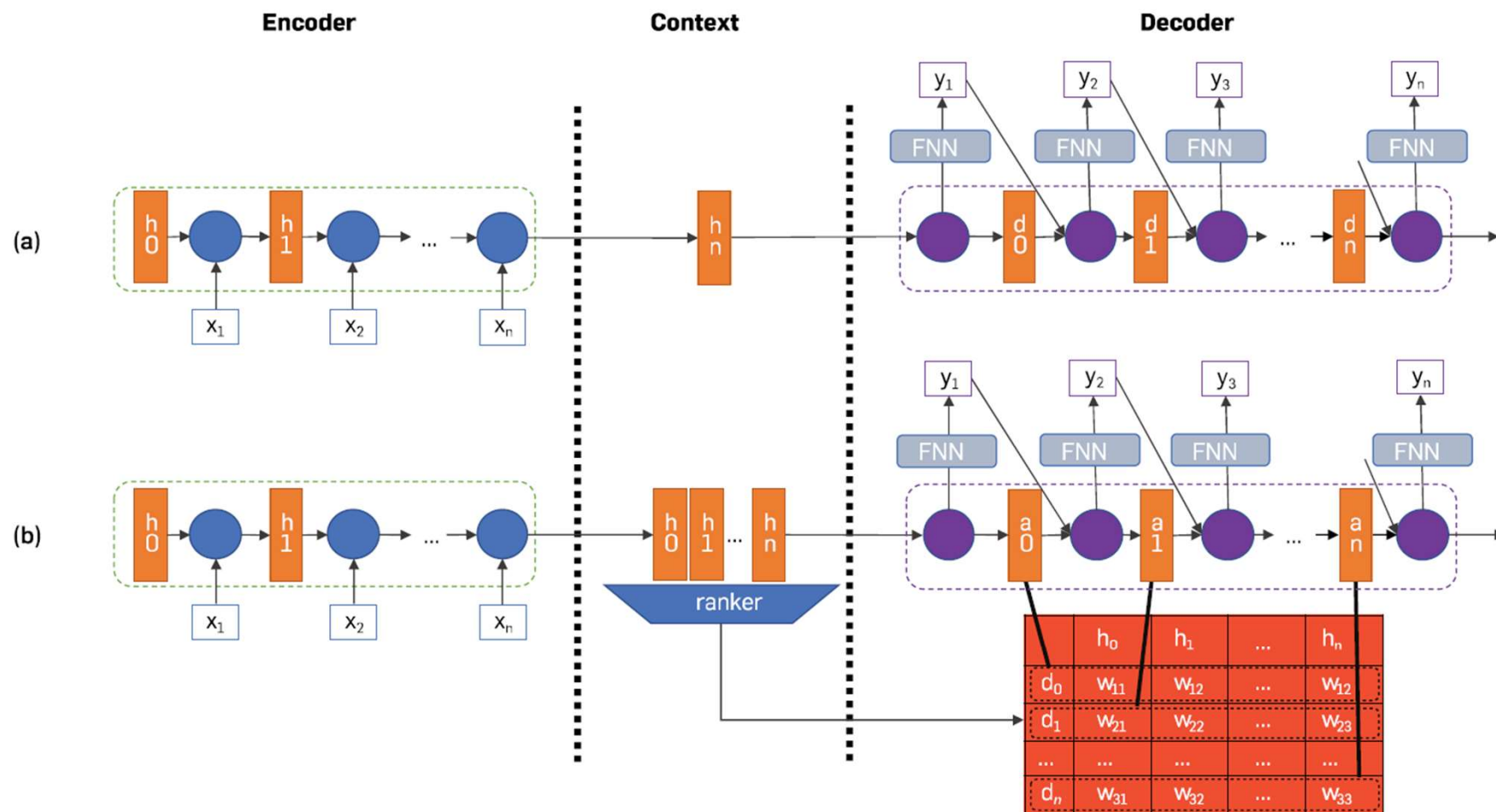
Main idea: retrieve as needed

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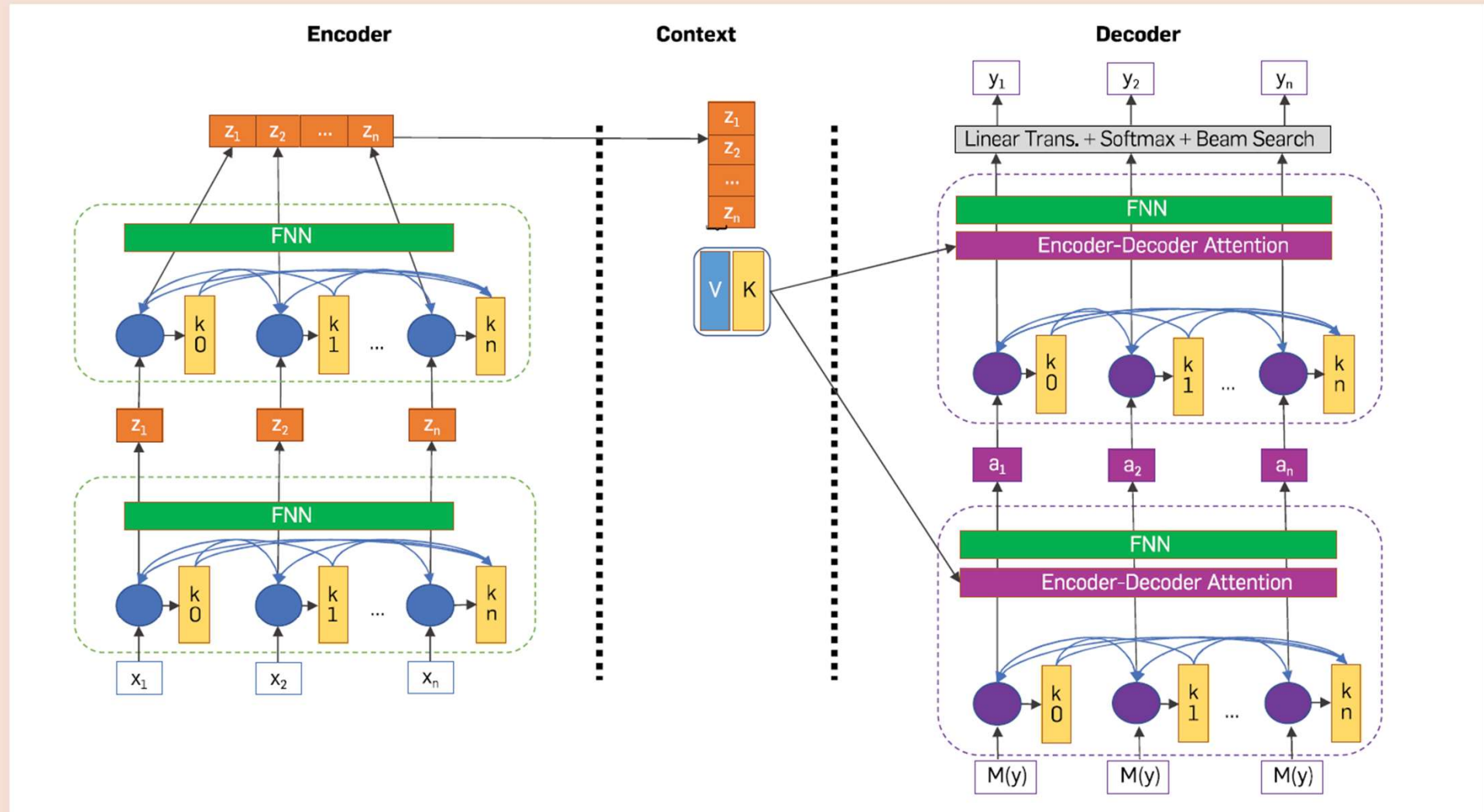
27

Figure 1. Difference between encoder-decoder methods (a) without and (b) with attention. Notice that the circles represent the same set of weights changing at different timesteps.

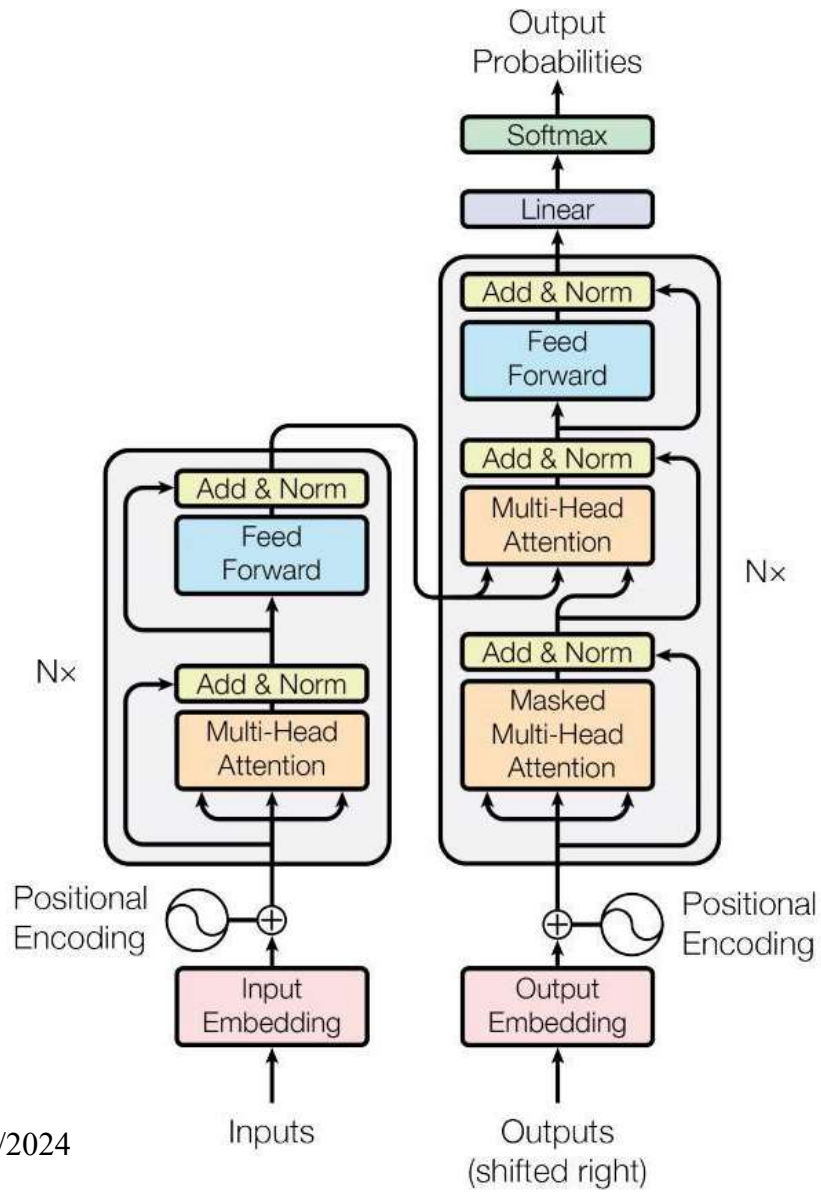


(Souza dos Reis et al, 2021, <https://cacm.acm.org/research/transformers-aftermath/>)

Figure 2. An example of Transformers composed of two encoders and two decoders. Notice that the decoders receive the context—projected in two vectors v and k —from the topmost encoder.

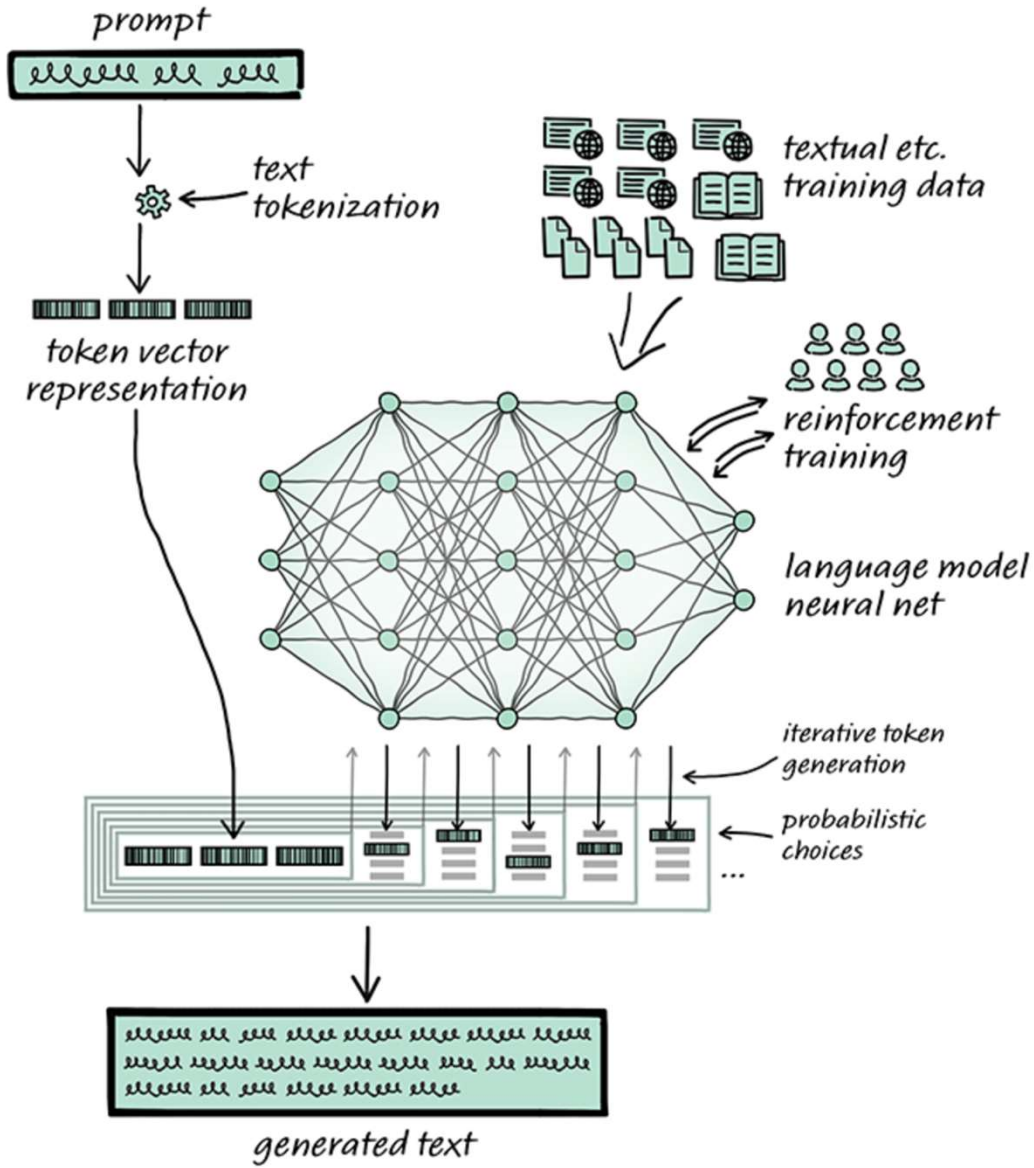


(Souza dos Reis et al, 2021, <https://cacm.acm.org/research/transformers-aftermath/>)



Attention is all you needs!

Transformer

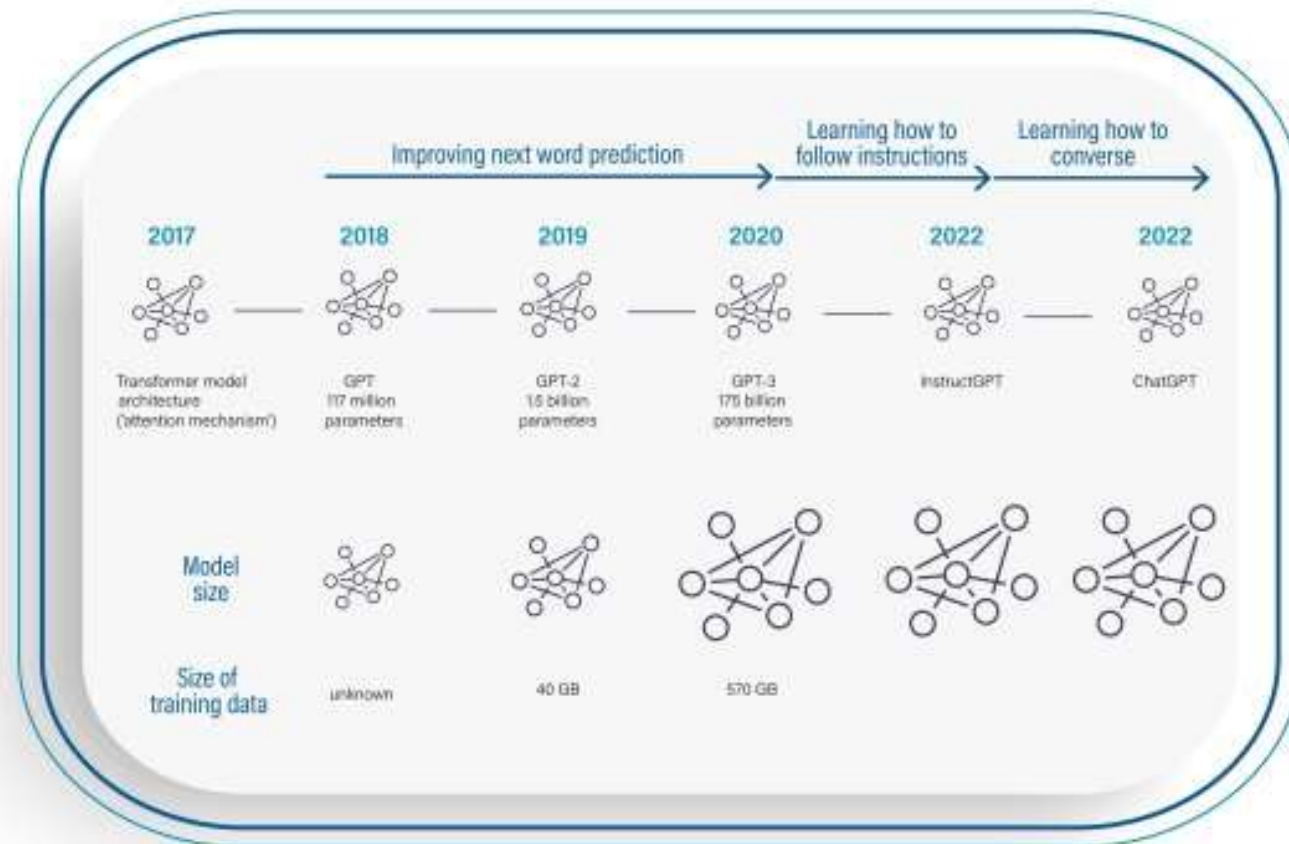


ChatGPT (Chat Generative Pretraining Transformer)

**Is a Large Language Model
(LLM)**

<https://writings.stephenwolfram.com/2023/01/wolframalpha-as-the-way-to-bring-computational-knowledge-superpowers-to-chatgpt/>

Evolution of Large Language Models (ChatGPT)



ChatGPT has a number of neurons comparable to a human brain

- 100 billion neurons
- over 100 layers
- 100 trillion synapses

<https://medium.com/@fenjiro/chatgpt-gpt-4-how-it-works-10b33fb3f12b3/7/2024>

- Human Brain - 100 billion neurons and 10× more glial cells.

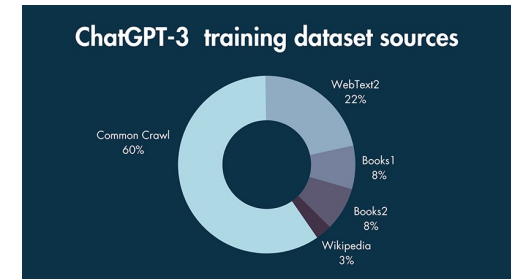
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2776484/>

Training of ChatGPT

- Some ChatGPT commentators have estimated that if ChatGPT was to be trained on a single NVIDIA Tesla V100 'Graphics Processing Unit' (GPU) that it would take around 355 years to complete ChatGPT's training on its training dataset.
- OpenAI reportedly used 1,023 A100 GPUs to train ChatGPT, so **it is possible that the training process was completed in as little as 34 days.**
- The costs of training ChatGPT is estimated to be just under \$5 million dollars.

<https://lambdalabs.com/blog/demystifying-gpt-3>

Training of ChatGPT



- **60%** of ChatGPT-3's dataset was based on a filtered version of what is known as 'common crawl' data, which consists of web page data, metadata extracts and text extracts from over 8 years of web crawling.
- **22%** of ChatGPT-3's dataset came from 'WebText2', which consists of Reddit posts that have three or more upvotes.
- **16%** of ChatGPT-3's dataset come from two Internet-based book collections. These books included fiction, non-fiction and also a wide range of academic articles.
- **3%** of ChatGPT-3's dataset comes from the English-language version of Wikipedia.
- **93%** of ChatGPT-3's data set was in English