

Learning General Language Processing Agents

Dani Yogatama

Language and Intelligence

A uniquely human ability that is a **core component** of our intelligence, independent of the surface forms it manifests in (Hockett, 1960).

ହାଲ୍ ପର୍ଶେନ୍ଦେତ୍ଜେ **Halo**

Aloha こんにちは Sveiki ଶ୍ଲୋ

Ciao Ahoj **Hello** Сайн уу
ନମସ୍କାର

KAMUSTA Γειά σου 여보세요 Salve

Здравствуйте مرحبا Merhaba

Hej 你好 Hola xin chào

Language and Intelligence

A primary medium through which we **acquire** new skills and knowledge (+visual perception).



Language and Intelligence

The **most effective** form of communication to **transmit** information and knowledge to others.

(Language for communication; Wittgenstein, 1953; Austin, 1975)



Language and Intelligence

A mechanism with which we **formulate our thought process**. (Language for thinking; Spelke, 2003)



Language and Intelligence

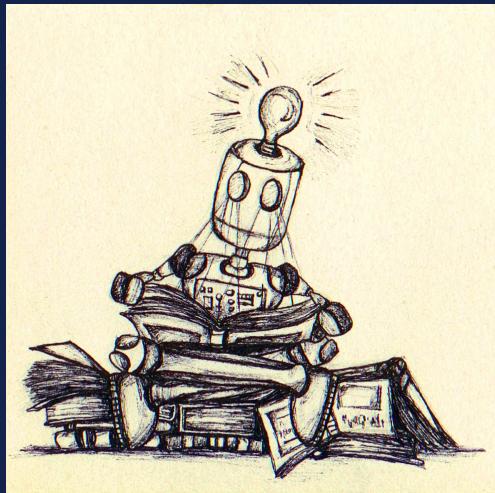
Language is key to **human intelligence** and is important for
artificial intelligence.

General Linguistic Intelligence

The ability to **acquire, store, and reuse** knowledge (about a language's lexicon, syntax, semantics, and pragmatic conventions) to **adapt** to new tasks **quickly without forgetting** old ones.

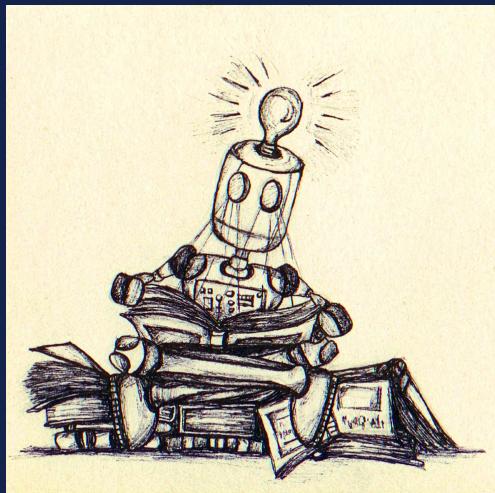
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Aloha こんにちは Sveiki שָׁלוּם
Ciao Ahoj Hello Сайн уу
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KAMUSTA Γειά σου 여보세요 Salve
Здравствуйте اب حرم Merhaba
Hej 你好 Hola xin chào



The State of Natural Language Processing

State-of-the-art models are based on increasingly larger transformers.

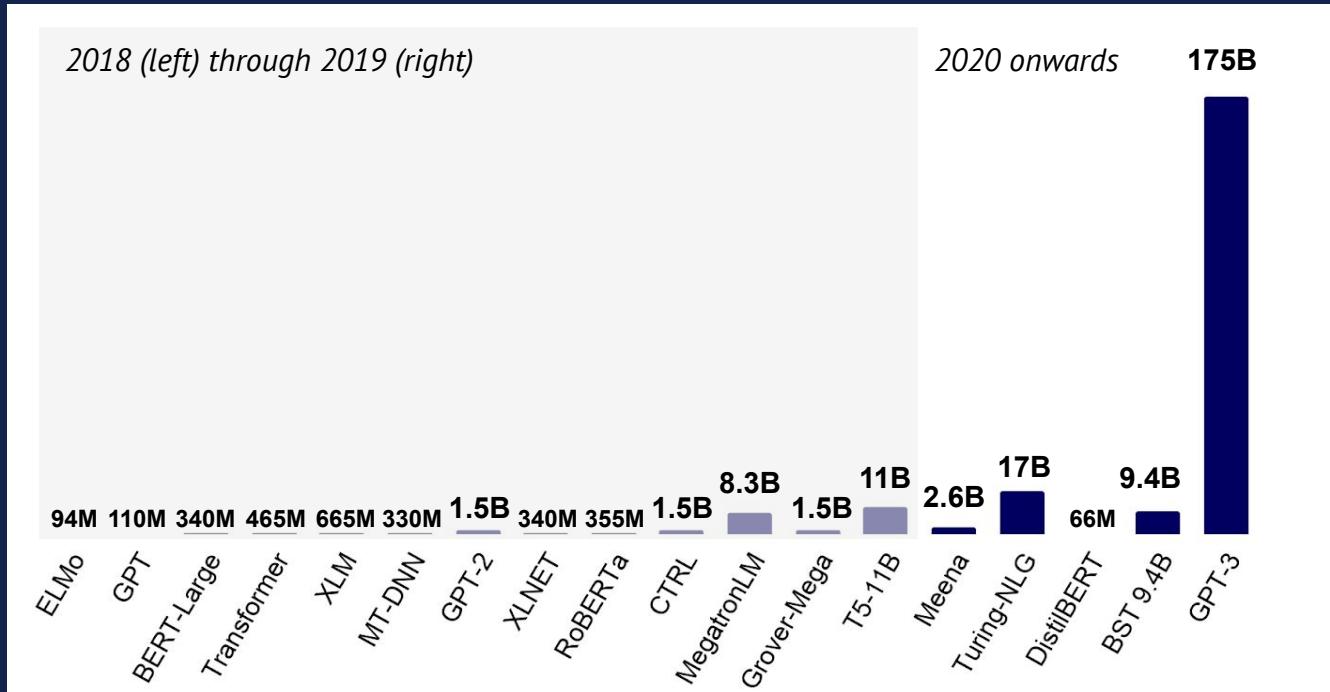
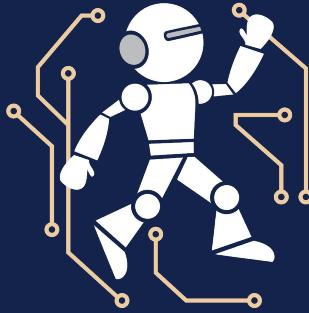


Figure taken from [State of AI Report 2020](#).

Challenges: Human Learning vs. Machine Learning



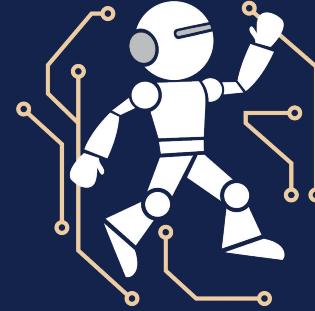
	Machine
Acquisition	Large datasets (representation learning)
Task Training	Large datasets (supervised fine tuning)
Linguistic knowledge	Dataset specific
Generalization	Forget previous tasks given a new task

Challenges: Human Learning vs. Machine Learning



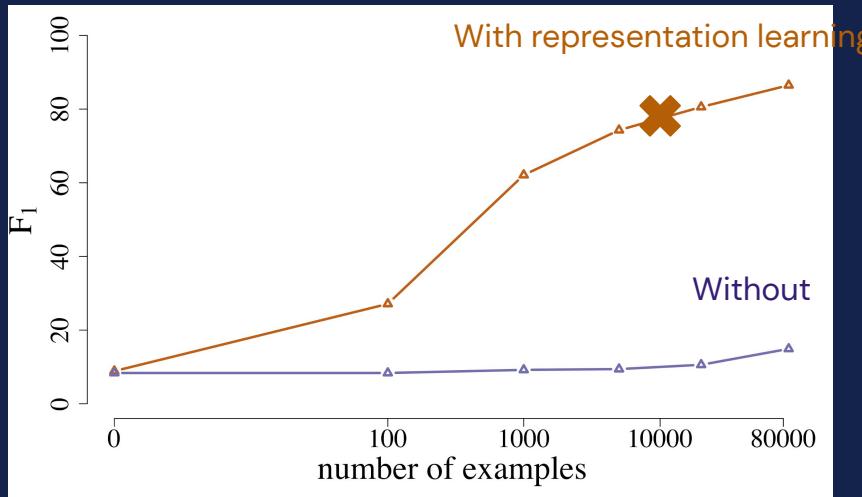
Human	
``Large'' datasets	Acquisition
Few examples	Task Training
Dataset agnostic	Linguistic knowledge
Generalizable to new tasks	Generalization

Challenges: Human Learning vs. Machine Learning



Human		Machine
“Large” datasets	Acquisition	Large datasets (representation learning)
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Dataset agnostic	Linguistic knowledge	Dataset specific
Generalizable to new tasks	Generalization	Forget previous tasks given a new task

The State of Natural Language Processing

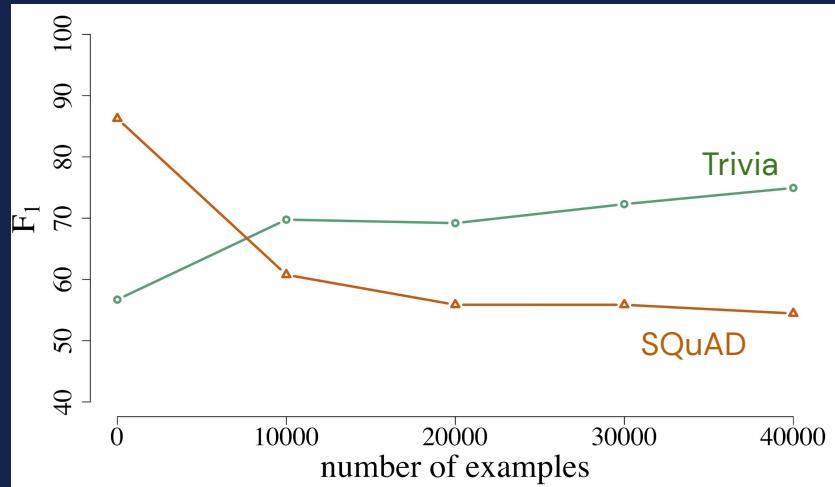
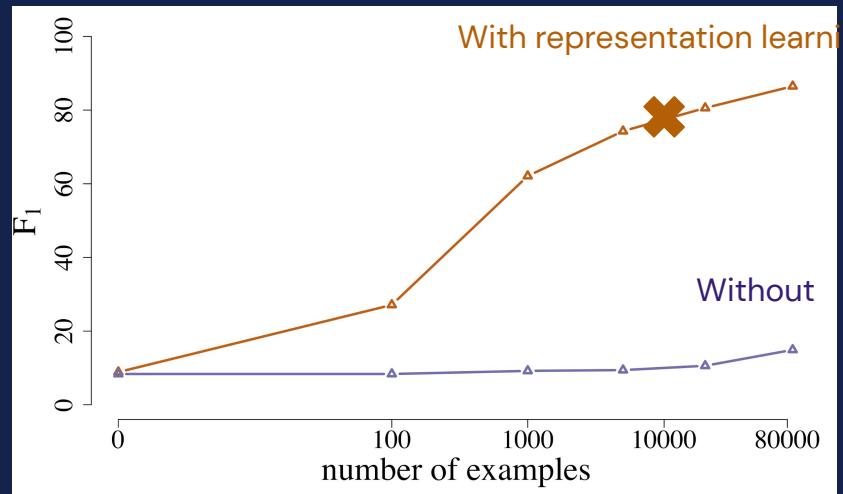


Yogatama et al., arXiv 2019

Model: BERT, Devlin et al. 2019

QA dataset: SQuAD, Rajpurkar et al., 2016

The State of Natural Language Processing



Yogatama et al., arXiv 2019

Model: BERT, Devlin et al. 2019

QA dataset: SQuAD, Rajpurkar et al., 2016

QA dataset 2: Trivia, Joshi et al., 2017

Research Areas



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Research Areas



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Training Paradigms

Model Architectures

Research Areas



A language model that continually **learns in an efficient way** to perform multiple complex tasks in many languages.

Training Paradigms

Better Representation Learning

Yogatama and Smith, ACL 2014

Yogatama et al., ACL 2015

Yogatama and Smith; ICML 2015

Kong, de Masson d'Autume, Ling, Yu, Dai, Yogatama; ICLR 2020

Model Architectures

Research Areas



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Training Paradigms

Generative Training

Yogatama et al., TACL 2014

Yogatama et al., arXiv 2017

Kong, Melis, Ling, Yu, and Yogatama, ICLR 2018

Cao and Yogatama, arXiv 2020

Model Architectures

Research Areas



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Training Paradigms

Few-shot and Transfer Learning

Yogatama and Mann, AISTATS 2014

Yogatama et al., EMNLP 2015

Artetxe, Ruder, Yogatama, ACL 2020

Model Architectures

Research Areas



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Training Paradigms

Model Architectures

Memory Networks

[Yogatama et al., ICLR 2017](#)

[Yogatama et al., ICLR 2018](#)

[de Masson d'Autume, Ruder, Kong, Yogatama, NeurIPS 2019](#)

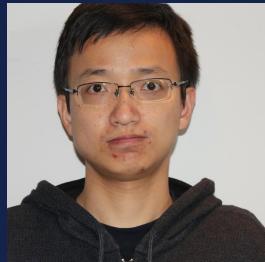
[Yogatama et al., TACL 2021](#)

This Talk

- A framework for self-supervised language representation learning methods.
Kong et al., ICLR 2020
- Semiparametric (memory-augmented) language models.
Yogatama et al., TACL 2021

A Mutual Information Maximization Perspective of Language Representation Learning

Kong et al., ICLR 2020



Lingpeng



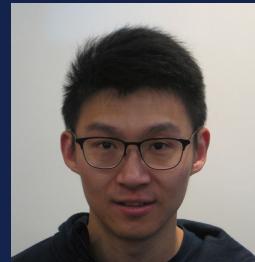
Cyprien



Wang



Lei



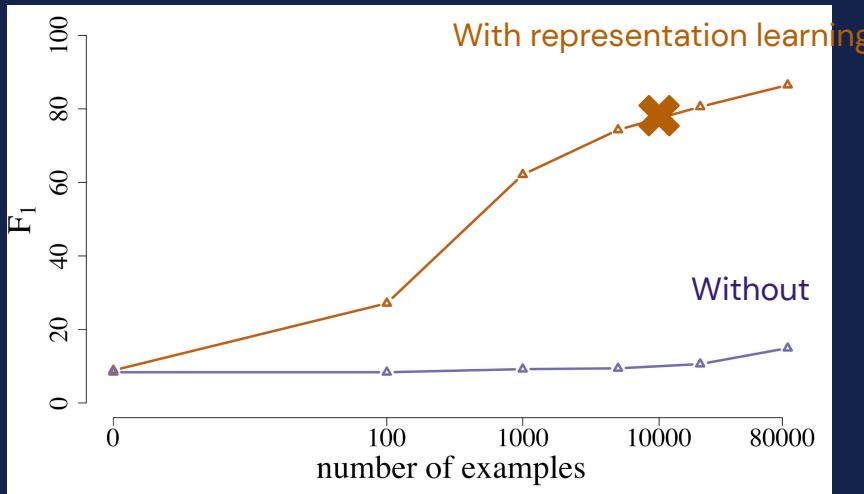
Zihang



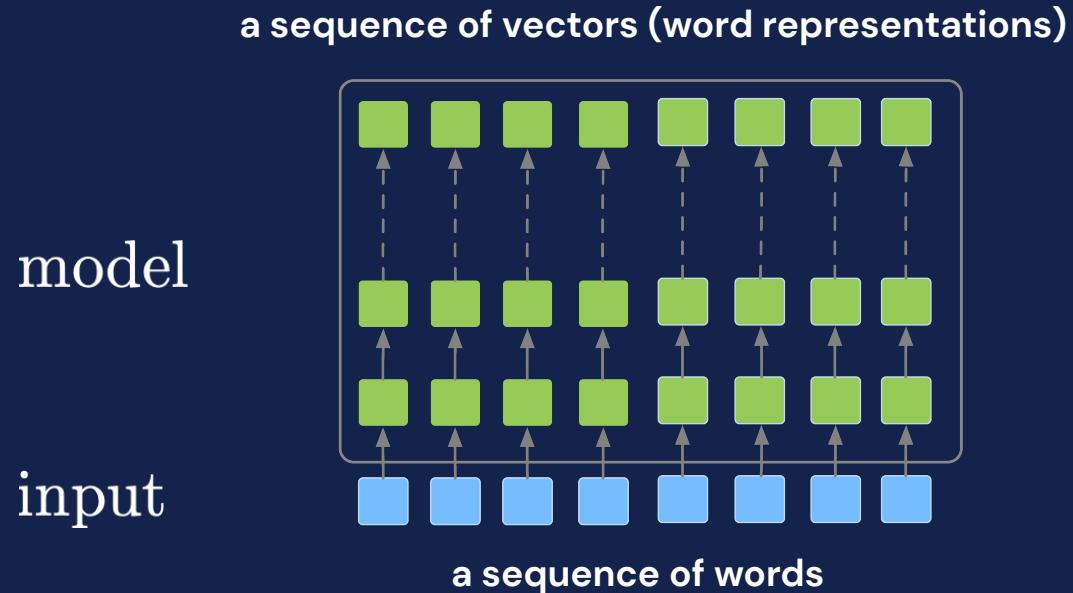
Dani

Text Representations

Good representations facilitate more efficient transfer.

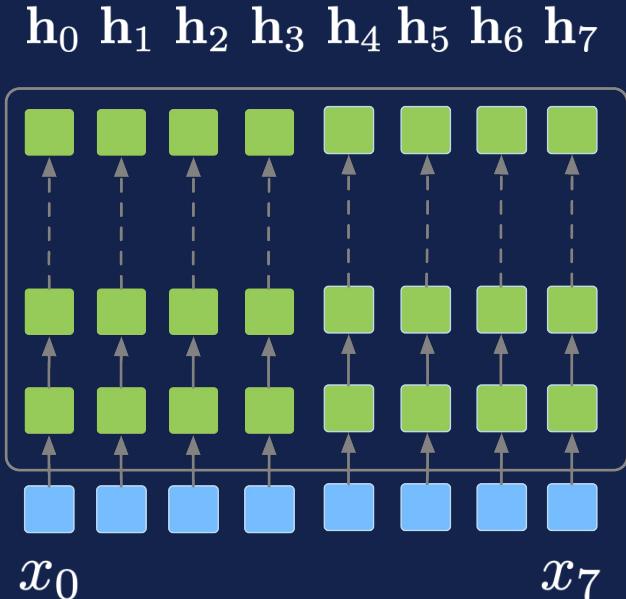


Text Representations



Text Representations

model
input



$$f(x_0, x_1, \dots, x_t) \rightarrow \mathbf{h}_0, \mathbf{h}_1, \dots, \mathbf{h}_t$$

Text Representations



<https://twitter.com/SmithaMilli/status/837153616116985856/>

Bag of words

Word embeddings

Contextual word embeddings

Skip gram, Mikolov et al., 2013.
GloVe, Pennington et al., 2014.

ELMo, Peters et al., 2018.
BERT, Devlin et al., 2019.

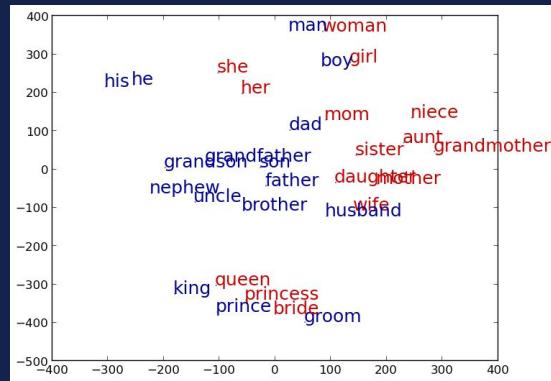


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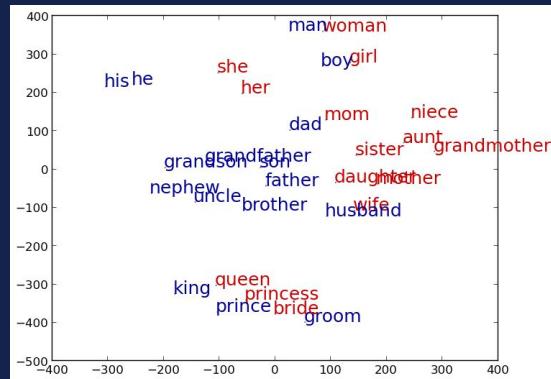


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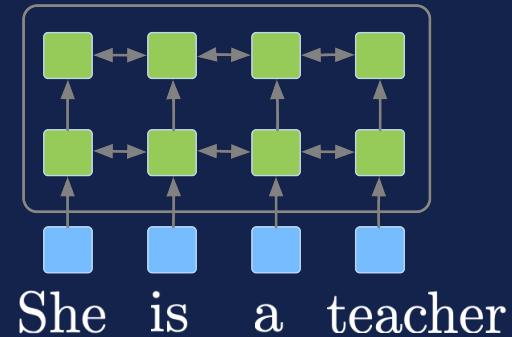
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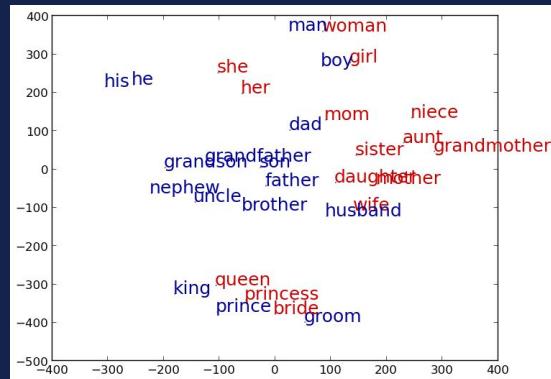
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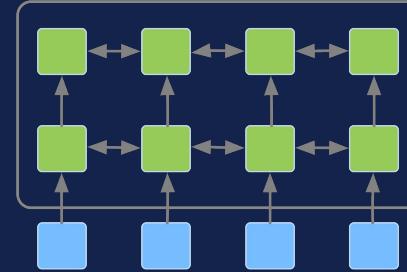
Representation learning started showing promise ~8 years ago.



Word embeddings

Skip gram, Mikolov et al., 2013.

GloVe, Pennington et al., 2014.



She is a teacher

Contextual word embeddings

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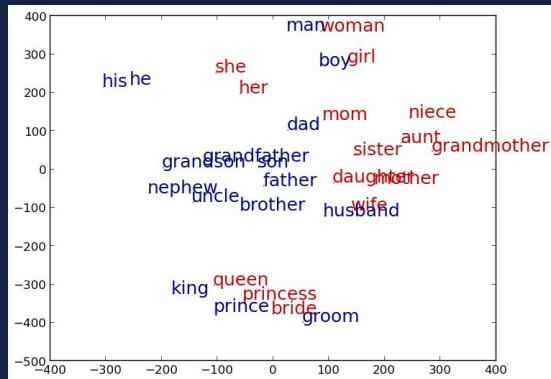


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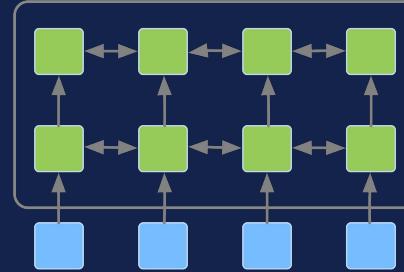
Bag of words



Word embeddings

Skip gram, Mikolov et al., 2013.
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What has been the main driver of progress so far?



She is a teacher

Contextual word embeddings

ELMo, Peters et al., 2018.
BERT, Devlin et al., 2019.



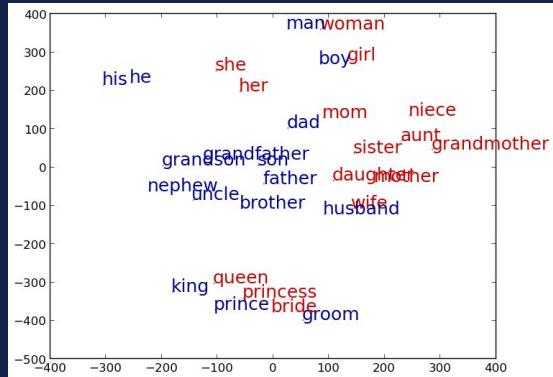
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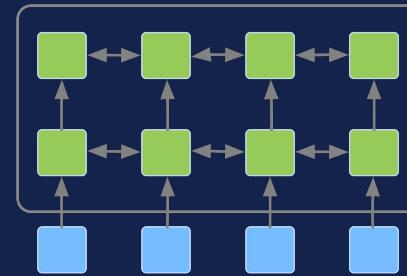
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Contrastive Learning

Main assumption: representations should capture similarity ([Arora et al., 2019](#)).

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Contrastive Learning

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Human learning is continual.

Advances in ML have driven progress in NLP.
Logistic regression can be used for classification.
Transformer uses self attention.

There are many direct flights between London and Tokyo.
London Heathrow Terminal 5 is closed for maintenance.

Contrastive Learning with InfoNCE

Main assumption: representations should capture similarity (Arora et al., 2019).

$$I(A, B) \geq \mathbb{E}_{p(A, B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp f_{\theta}(a, b)}{\exp f_{\theta}(a, b) + \sum_{c \neq b} \exp f_{\theta}(a, c)} \right] \right]$$

InfoNCE objective
Logeswaran and Lee, 2018
van den Oord, et al., 2019

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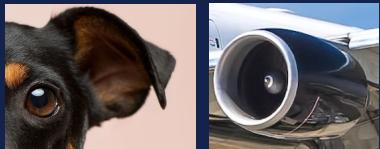
High when **a** and **b** go together

Contrastive Learning with InfoNCE

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InfoNCE objective
Logeswaran and Lee, 2018
van den Oord, et al., 2019



Low when **a** and **c** do not go together



Contrastive Learning with InfoNCE

$$\mathbb{E}_{p(A,B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp f_{\theta}(a,b)}{\exp f_{\theta}(a,b) + \sum_{c \neq b} \exp f_{\theta}(a,c)} \right] \right]$$

The University of Waterloo is located in Canada

Contrastive Learning with InfoNCE

$$\mathbb{E}_{p(A,B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp[f_{\theta}(a,b)]}{\exp f_{\theta}(a,b) + \sum_{c \neq b} \exp f_{\theta}(a,c)} \right] \right]$$

a *b*

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Contrastive Learning with InfoNCE

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a *b* *a*

The University of Waterloo is located in Canada

Contrastive Learning with InfoNCE

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a

b

The University of Waterloo is located in Canada

Contrastive Learning with InfoNCE

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a

b

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$$f_{\theta}(a,b) = g_{\psi}(b)^{\top} g_{\omega}(a)$$

Contrastive Learning with InfoNCE

$$\mathbb{E}_{p(A,B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp f_{\theta}(a,b)}{\exp f_{\theta}(a,b) + \sum_{c \neq b} \exp f_{\theta}(a,c)} \right] \right]$$

a *b*

The University of Waterloo is located in Canada

Tokyo
London
dog
cat

$$f_{\theta}(a, b) = g_{\psi}(b)^{\top} g_{\omega}(a)$$

Contrastive Learning with InfoNCE

$$\mathbb{E}_{p(A,B)} \left[\boxed{\mathbb{E}_{p(C)}} \left[\log \frac{\exp f_{\theta}(a,b)}{\exp f_{\theta}(a,b) + \sum_{c \neq b} \exp f_{\theta}(a,c)} \right] \right]$$

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The University of Waterloo is located in Canada

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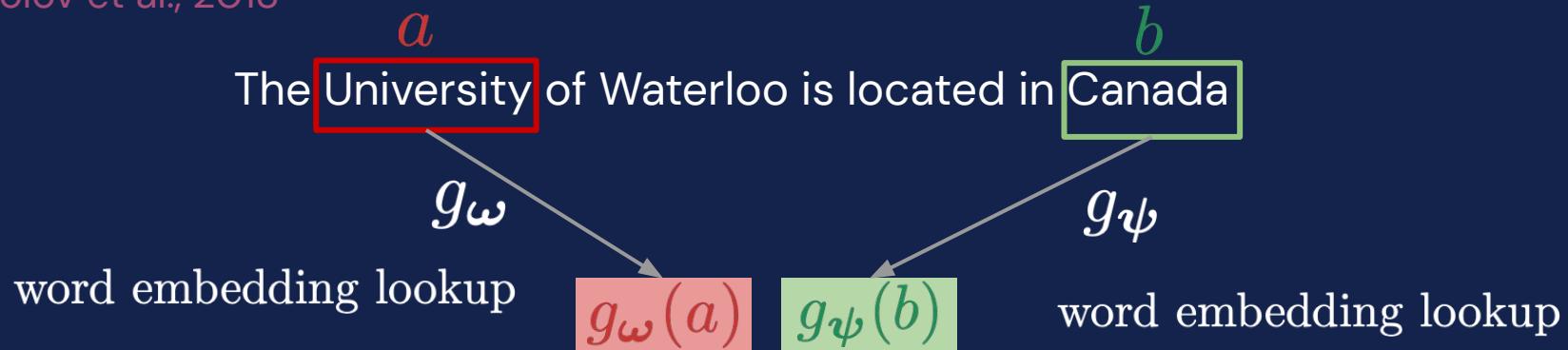
Skip-gram

Mikolov et al., 2013

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Skip-gram

Mikolov et al., 2013



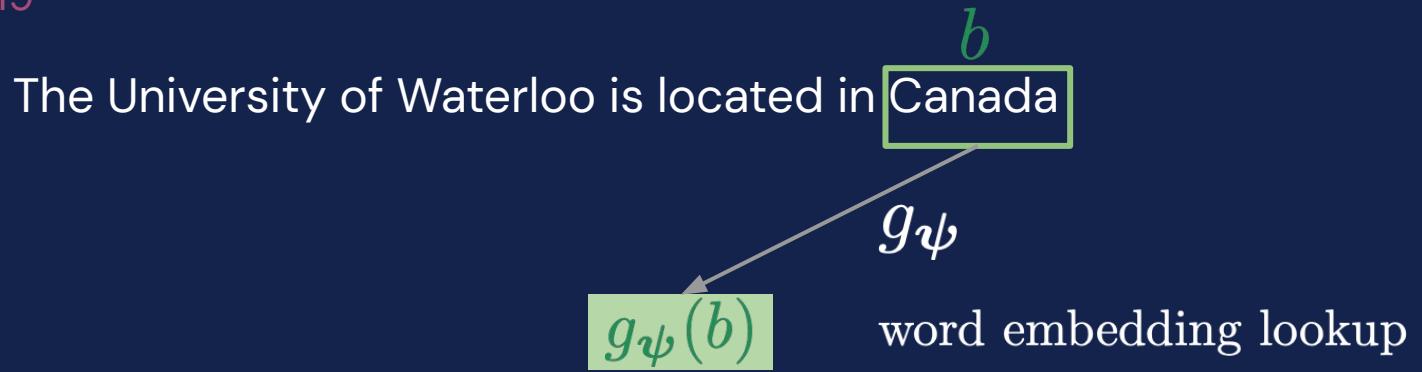
BERT

Devlin et al., 2019

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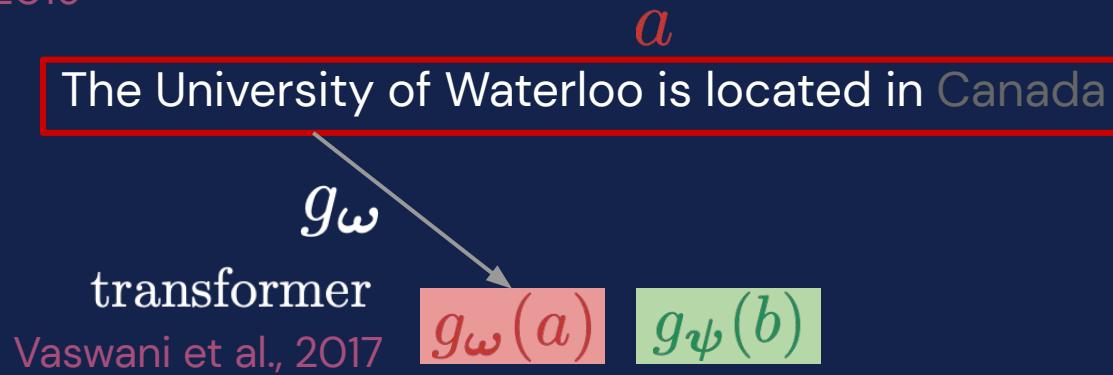
BERT

Devlin et al., 2019



BERT

Devlin et al., 2019



Why is this interesting?

- A framework that unifies classical and modern word embedding methods.

		a	b	g_{ω}	g_{ψ}
Mikolov et al., 2013	Skip-gram	word	word	lookup	lookup
Devlin et al., 2019	BERT	context	word	transformer	lookup
Yang et al., 2019	XLNet	context	word	TXL++	lookup

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- Provides connections to methods used in other domains (vision, speech).

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- Provides connections to methods used in other domains (vision, speech).
- Facilitates exchanges of ideas on how to improve representation learning models.

Model

Deep InfoMax (DIM; [Hjelm et al., 2019](#))



Model

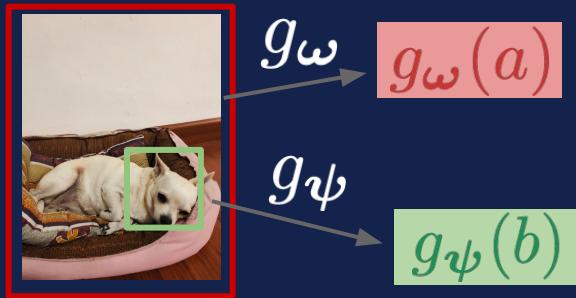
Deep InfoMax (DIM; Hjelm et al., 2019)



$$g_{\omega} \rightarrow g_{\omega}(a)$$

Model

Deep InfoMax (DIM; Hjelm et al., 2019)



Model

Deep InfoMax (DIM; Hjelm et al., 2019)



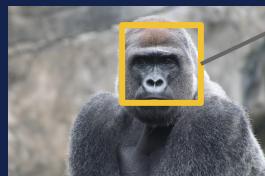
$$g_{\omega} \rightarrow g_{\omega}(a)$$

$$g_{\psi} \rightarrow g_{\psi}(b)$$



$$g_{\psi} \rightarrow g_{\psi}(c_1)$$

$$g_{\psi} \rightarrow g_{\psi}(c_2)$$



Model

Deep InfoMax (DIM; Hjelm et al., 2019)



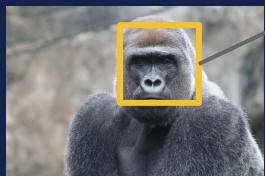
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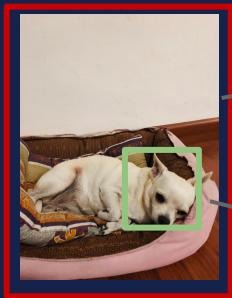
$$g_{\psi} \rightarrow g_{\psi}(c_2)$$



$$\mathcal{I}_{\text{DIM}} = \mathbb{E}_{p(A,B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp[g_{\omega}(a)^\top g_{\psi}(b)]}{\exp[g_{\omega}(a)^\top g_{\psi}(b)] + \sum_{c \neq b} \exp[g_{\omega}(a)^\top g_{\psi}(c)]} \right] \right]$$

Model

Deep InfoMax (DIM; Hjelm et al., 2019)



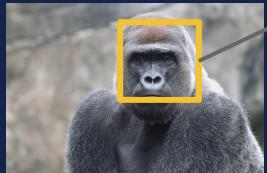
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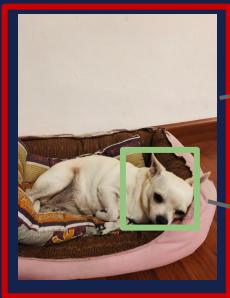
$$g_{\psi} \rightarrow g_{\psi}(c_2)$$



UWaterloo is located in Canada

Model

Deep InfoMax (DIM; Hjelm et al., 2019)



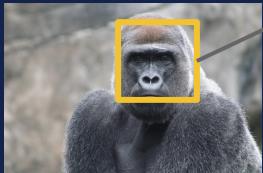
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$$g_{\psi} \rightarrow g_{\psi}(c_1)$$

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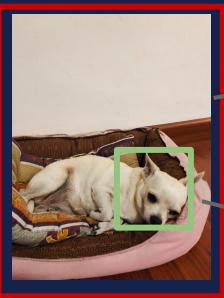


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$$\begin{array}{l} g_{\psi} \\ \text{transformer} \\ \downarrow \\ g_{\psi}(b) \end{array}$$

Model

Deep InfoMax (DIM; Hjelm et al., 2019)



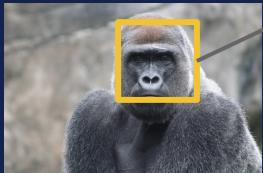
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$$g_{\psi} \rightarrow g_{\psi}(c_1)$$

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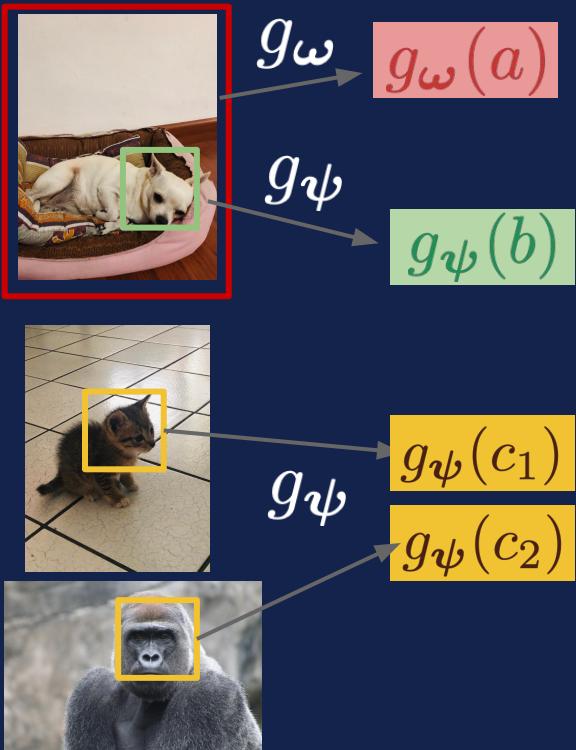
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g_{ω}
transformer

$$g_{\omega}(a) \quad g_{\psi}(b)$$

Model

Deep InfoMax (DIM; Hjelm et al., 2019)



UWaterloo is located in Canada

$g_{\omega}(a)$ $g_{\psi}(b)$

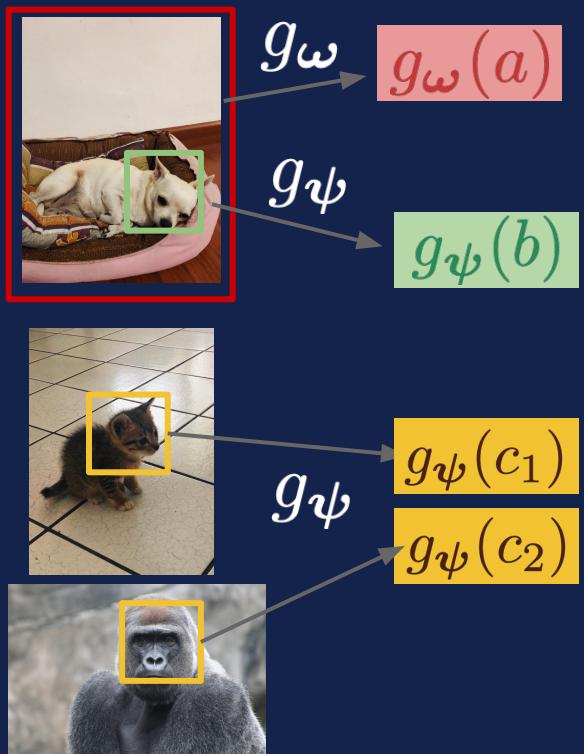
Starcraft II is a fun game

Cristiano Ronaldo scores an own goal

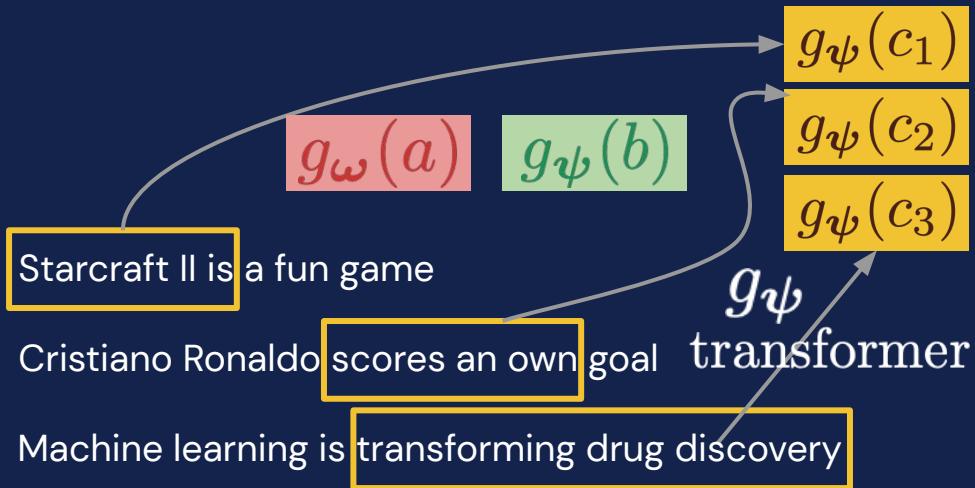
Machine learning is transforming drug discovery

Model

Deep InfoMax (DIM; Hjelm et al., 2019)

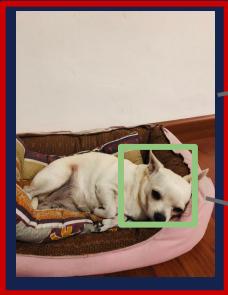


UWaterloo is located in Canada



Model

Deep InfoMax (DIM; Hjelm et al., 2019)



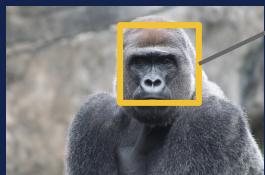
$$g_{\omega} \rightarrow g_{\omega}(a)$$

$$g_{\psi} \rightarrow g_{\psi}(b)$$



$$g_{\psi} \rightarrow g_{\psi}(c_1)$$

$$g_{\psi} \rightarrow g_{\psi}(c_2)$$



$$\mathcal{I}_{\text{DIM}} = \mathbb{E}_{p(A,B)} \left[\mathbb{E}_{p(C)} \left[\log \frac{\exp[g_{\omega}(a)^\top g_{\psi}(b)]}{\exp[g_{\omega}(a)^\top g_{\psi}(b)] + \sum_{c \neq b} \exp[g_{\omega}(a)^\top g_{\psi}(c)]} \right] \right]$$

UWaterloo is located in Canada

$g_{\omega}(a)$ $g_{\psi}(b)$

$$\begin{bmatrix} g_{\psi}(c_1) \\ g_{\psi}(c_2) \\ g_{\psi}(c_3) \end{bmatrix}$$

Starcraft II is a fun game

Cristiano Ronaldo scores an own goal

Machine learning is transforming drug discovery

Experiments

Question answering on SQuAD ([Rajpurkar et al., 2016](#)).

		F1
Small Model	BERT	90.9
	Ours	91.4
Large Model	BERT	92.7
	Ours	93.1

F1 scores (0-100), higher is better.

BERT: [Devlin et al., 2019](#).

Takeaways

- It is possible to transfer ideas across domains when designing self-supervised tasks.
- Progress in language representation learning has largely been driven by advances in model architectures (and training objectives).

Adaptive Semiparametric Language Models

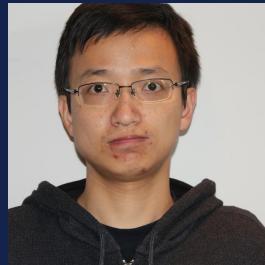
Yogatama et al., TACL 2021



Dani



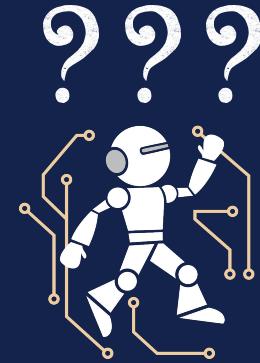
Cyprien



Lingpeng

Background

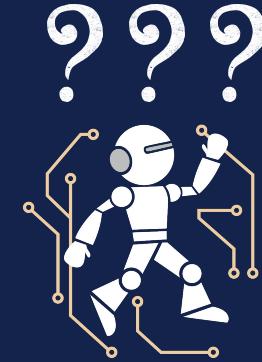
Why does a model forget?



Background

Why does a model forget?

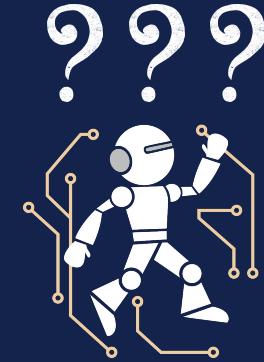
- Incoherent text generations.
- Hallucinating answers in open-domain QA.
- Performance degradation over time.



Background

Why does a model forget?

- Incoherent text generations.
- Hallucinating answers in open-domain QA.
- Performance degradation over time.



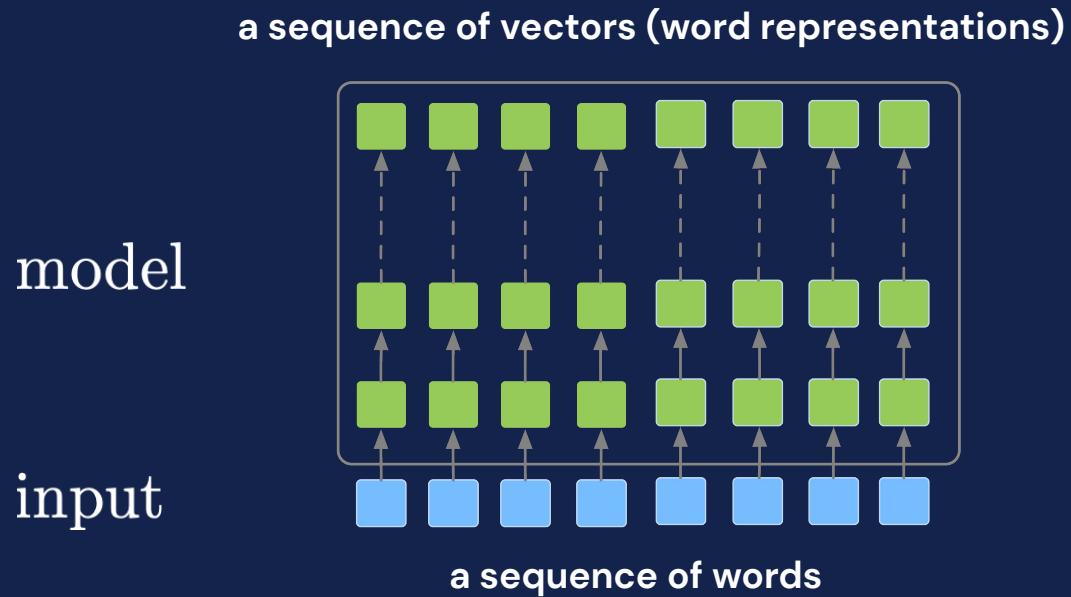
Inability to deal with long-term context

Background

Knowledge is implicitly represented in the weights of a parametric neural network.

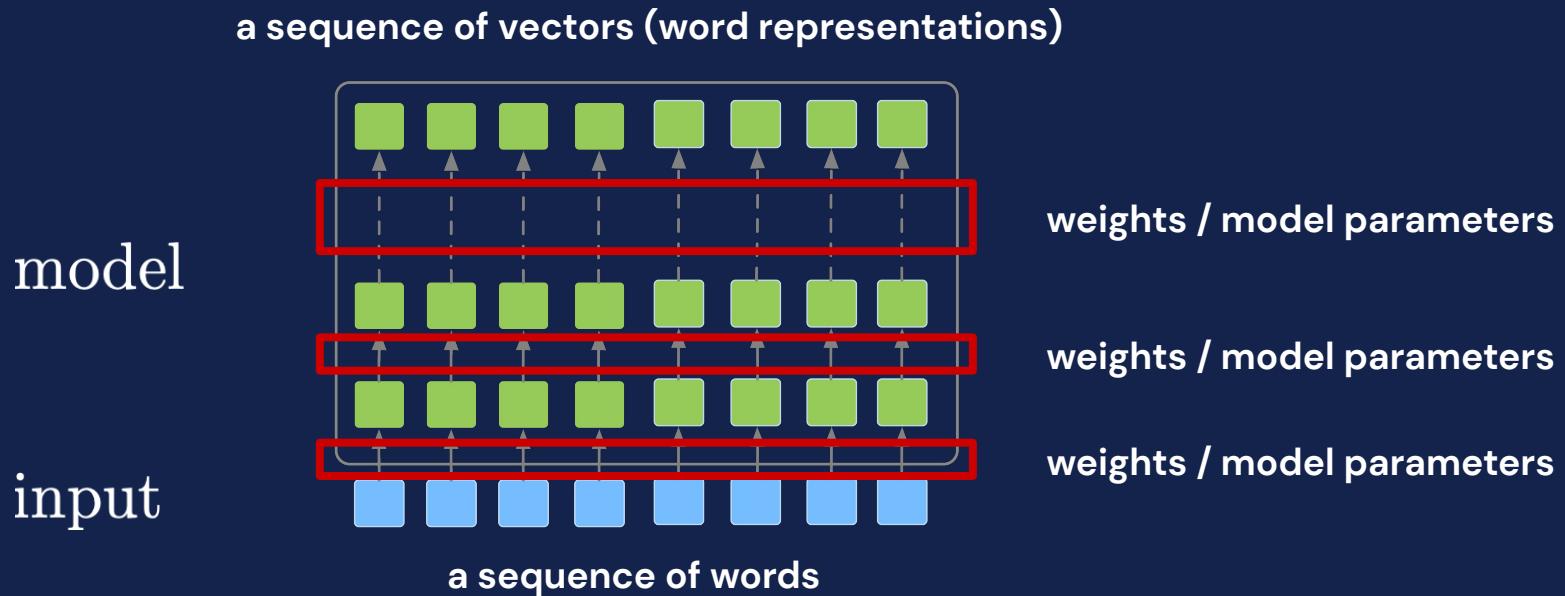
Background

Knowledge is implicitly represented in the weights of a parametric neural network.



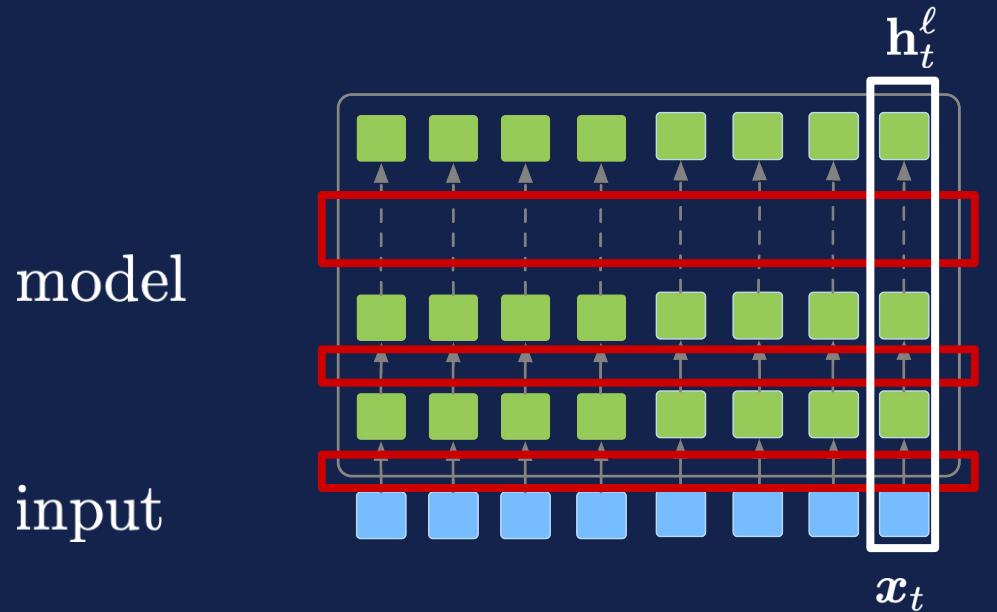
Background

Knowledge is implicitly represented in the weights of a parametric neural network.



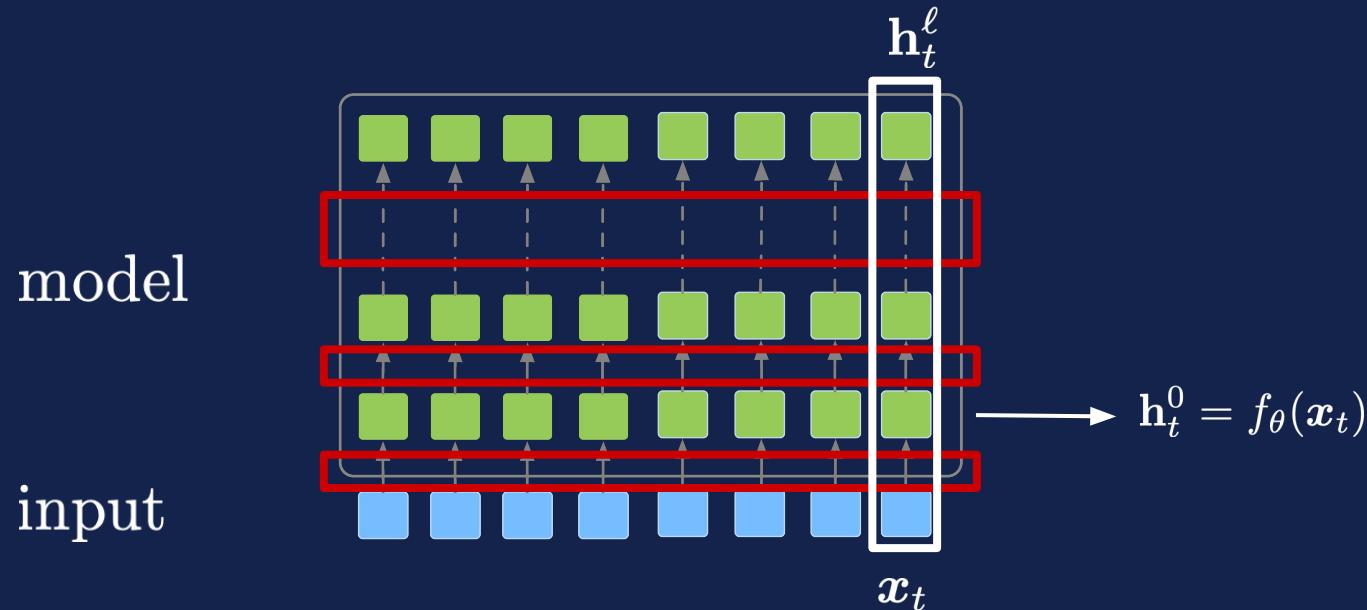
Background

Knowledge is implicitly represented in the weights of a parametric neural network.



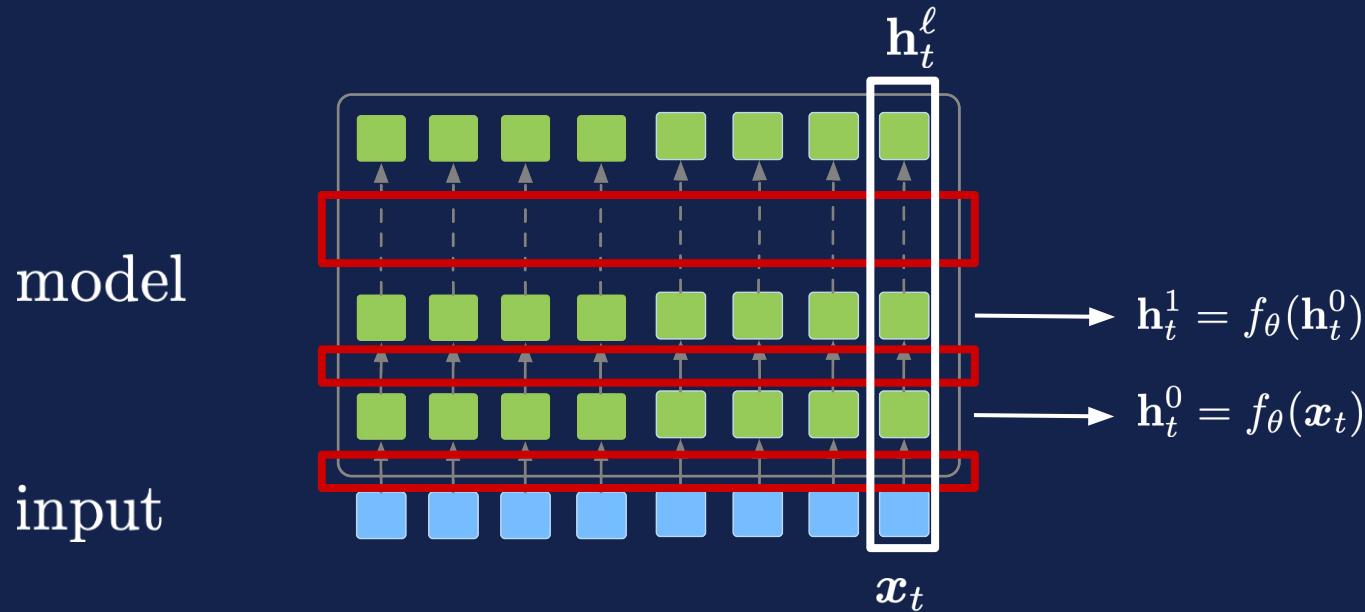
Background

Knowledge is implicitly represented in the weights of a parametric neural network.



Background

Knowledge is implicitly represented in the weights of a parametric neural network.



Background

Knowledge is implicitly represented in the weights of a parametric neural network.

Interpretations via cloze-style questions (Petroni et al., 2020) or prompts (Brown et al., 2020).

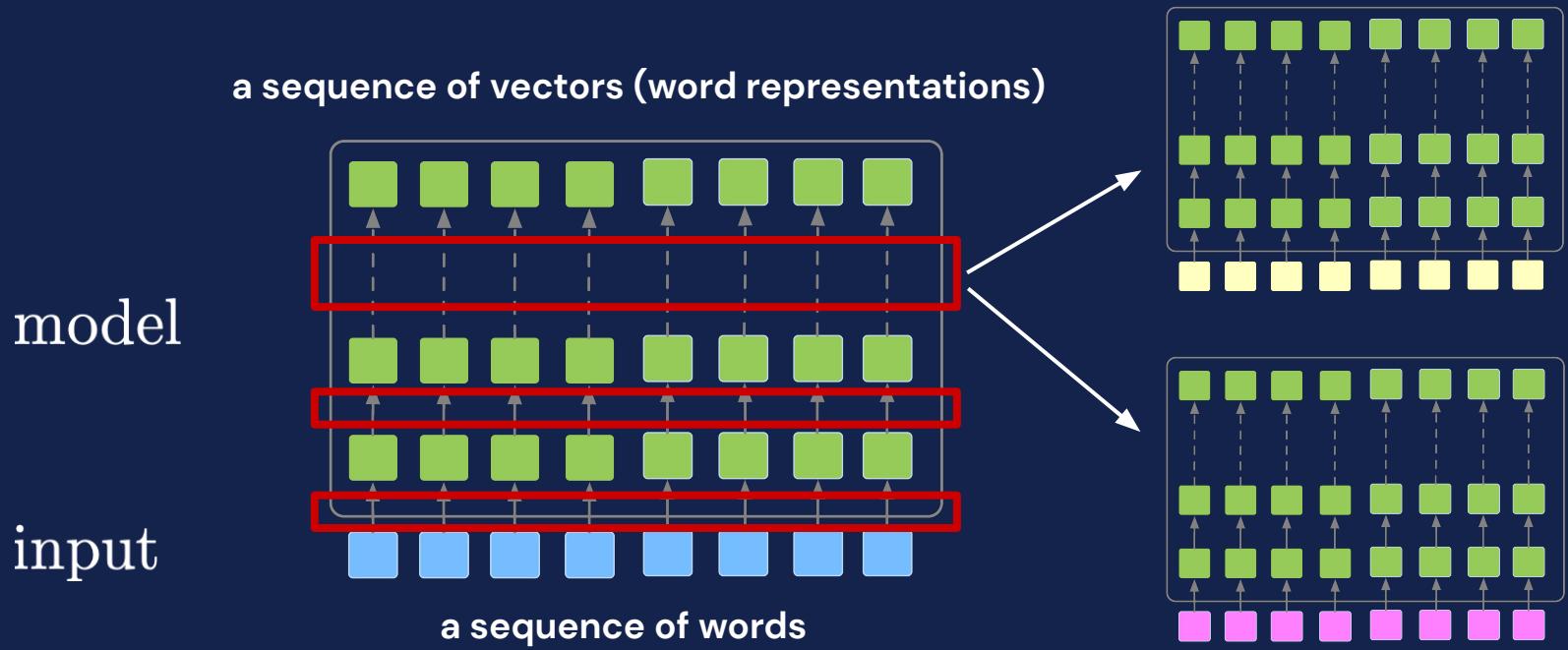
Dante was born in [MASK].

Q: Where was Dante born in?

A:

Background

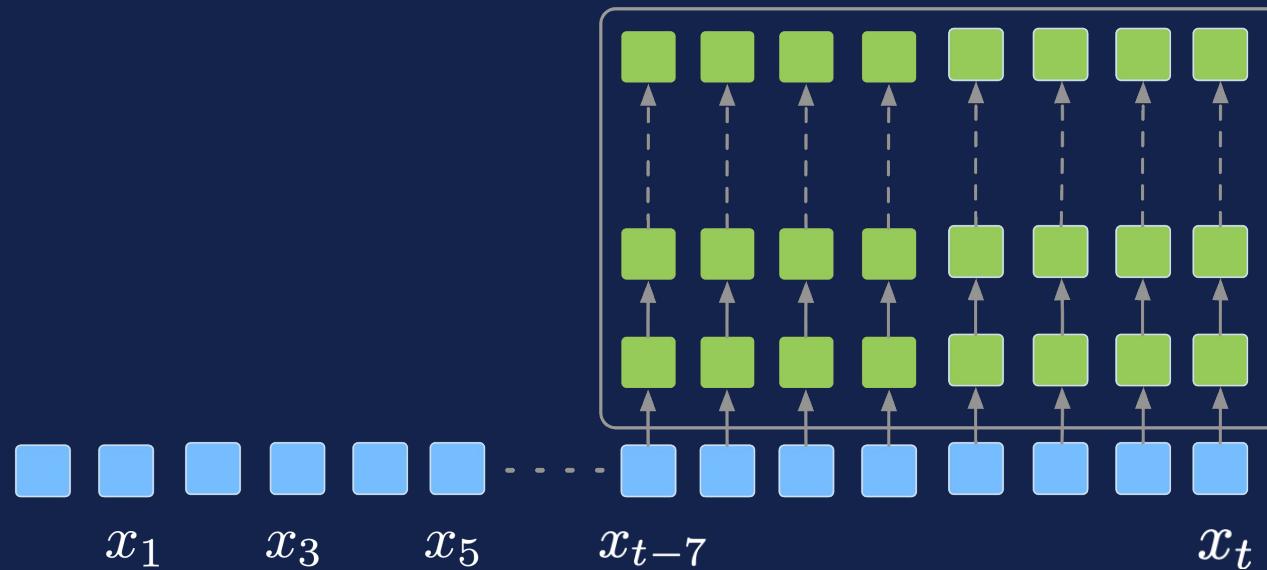
Knowledge is implicitly represented in the weights of a parametric neural network.



Update weights with new knowledge → changes affect all examples (sequences).

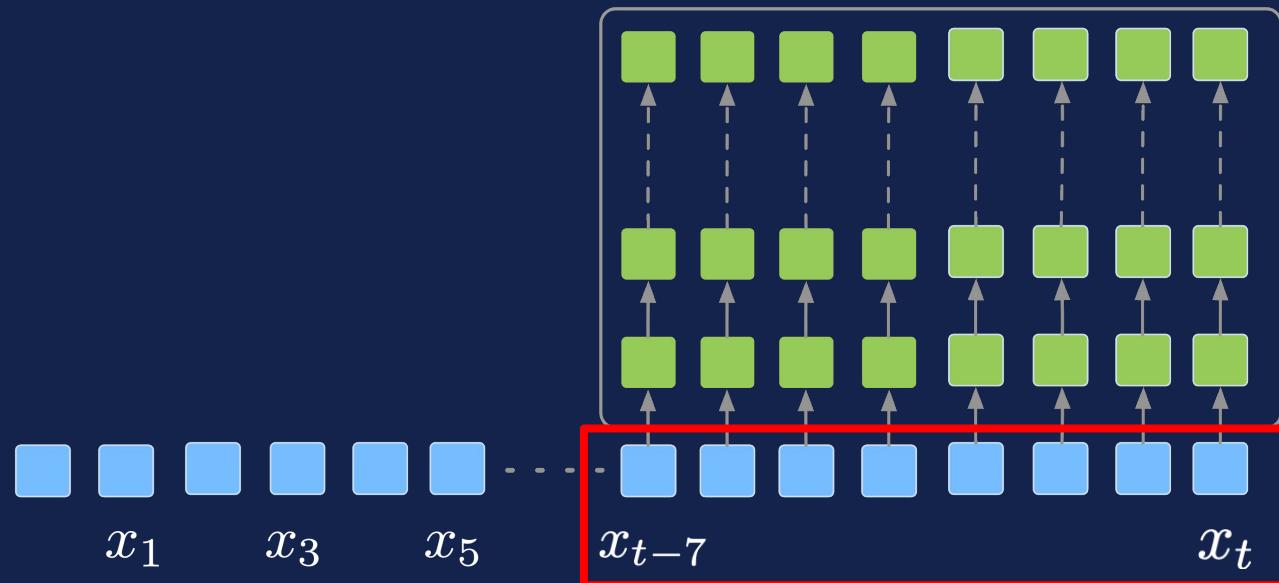
Background

Transformers, no matter how large, are limited by the input sequence length.



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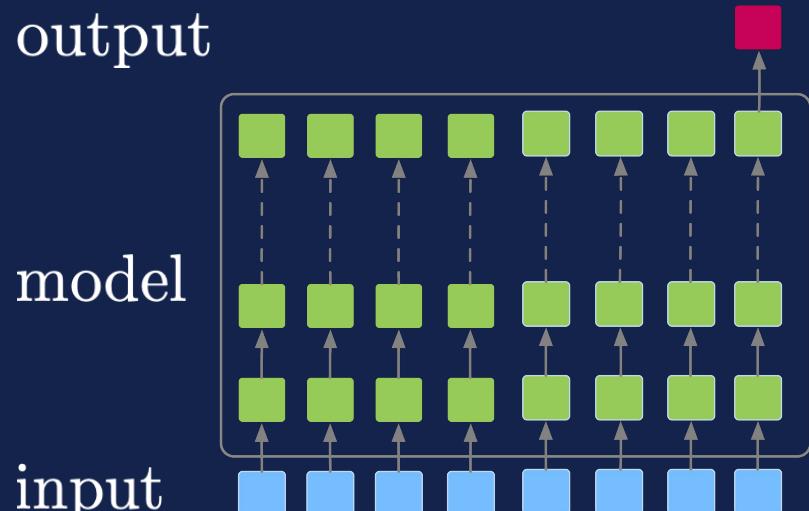


Semiparametric Language Models

Separation of computation and storage as an architectural bias.

Semiparametric Language Models

Separation of computation and storage as an architectural bias.

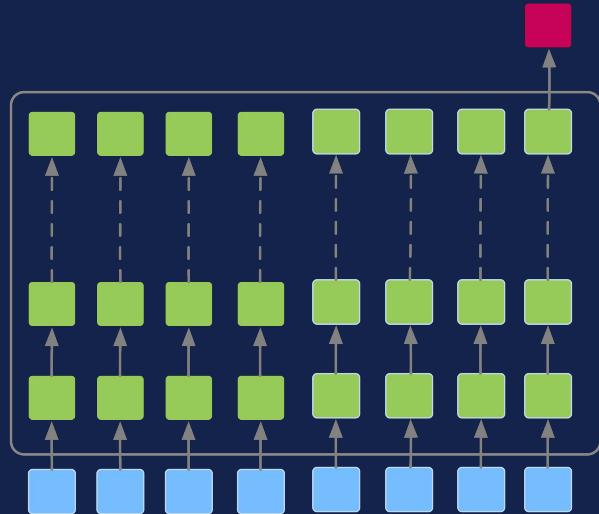


Computation: a neural network

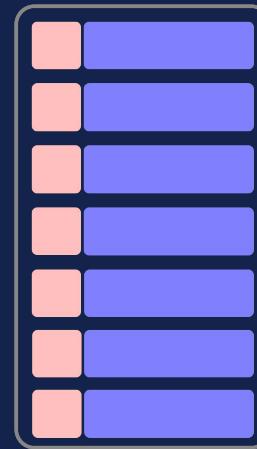
Semiparametric Language Models

Separation of computation and storage as an architectural bias.

output



Computation: a neural network



Memory (storage): a key-value database

Problem Setup

University of Waterloo Wikipedia

The University of Waterloo (commonly referred to as Waterloo, UW, or UWaterloo) is a public research university with a main campus in Waterloo, Ontario, Canada. The main campus is on 404 hectares of land adjacent to **Uptown**

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Current context

Problem Setup

University of Waterloo Wikipedia

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Current context

Extended short-term context

Problem Setup

University of Waterloo Wikipedia

The University of Waterloo (commonly referred to as Waterloo, UW, or UWaterloo) is a public research university with a main campus in Waterloo, Ontario, Canada. The main campus is on 404 hectares of land adjacent to Uptown Waterloo and Waterloo ???

Current context

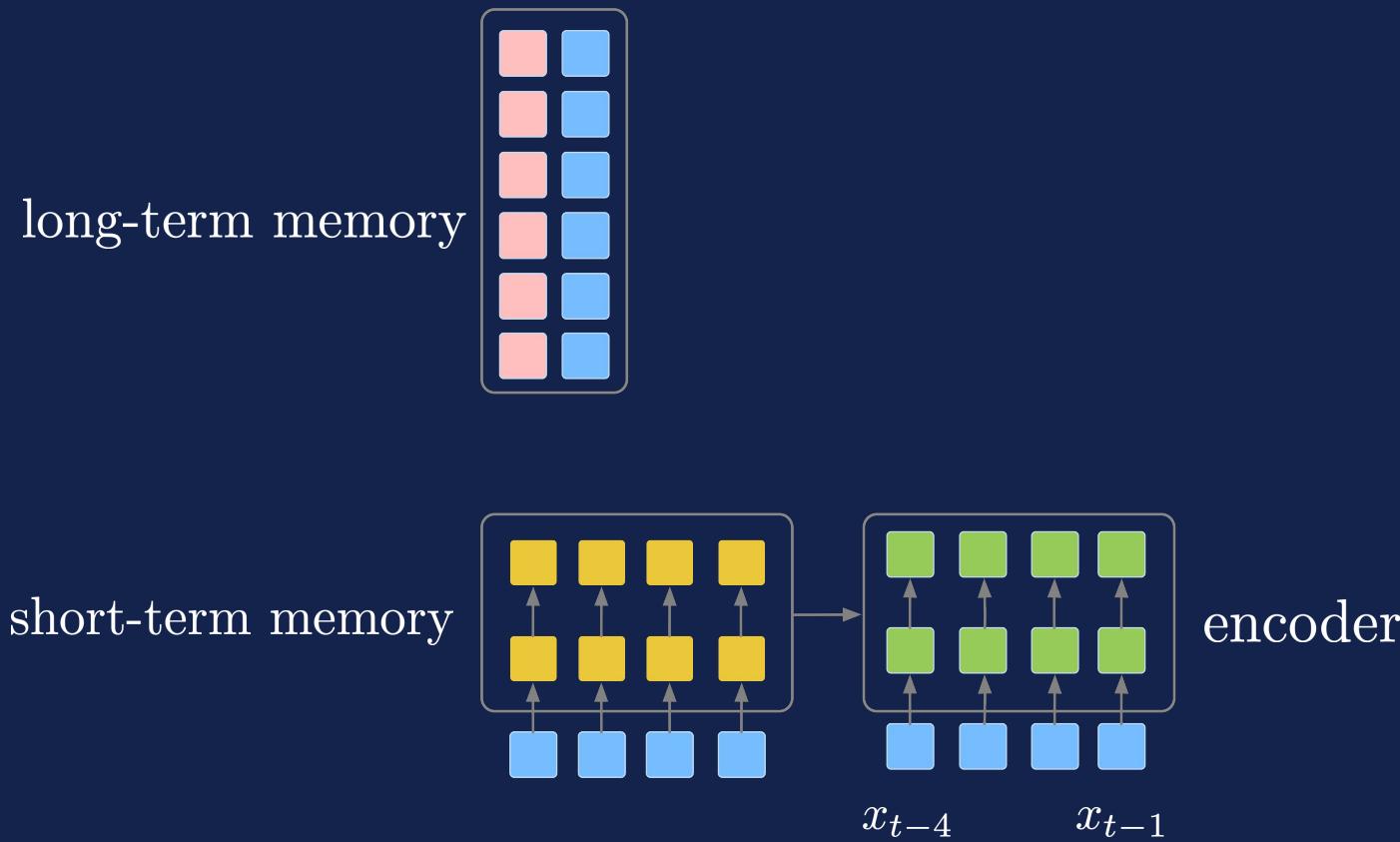
Extended short-term context

Long-term context

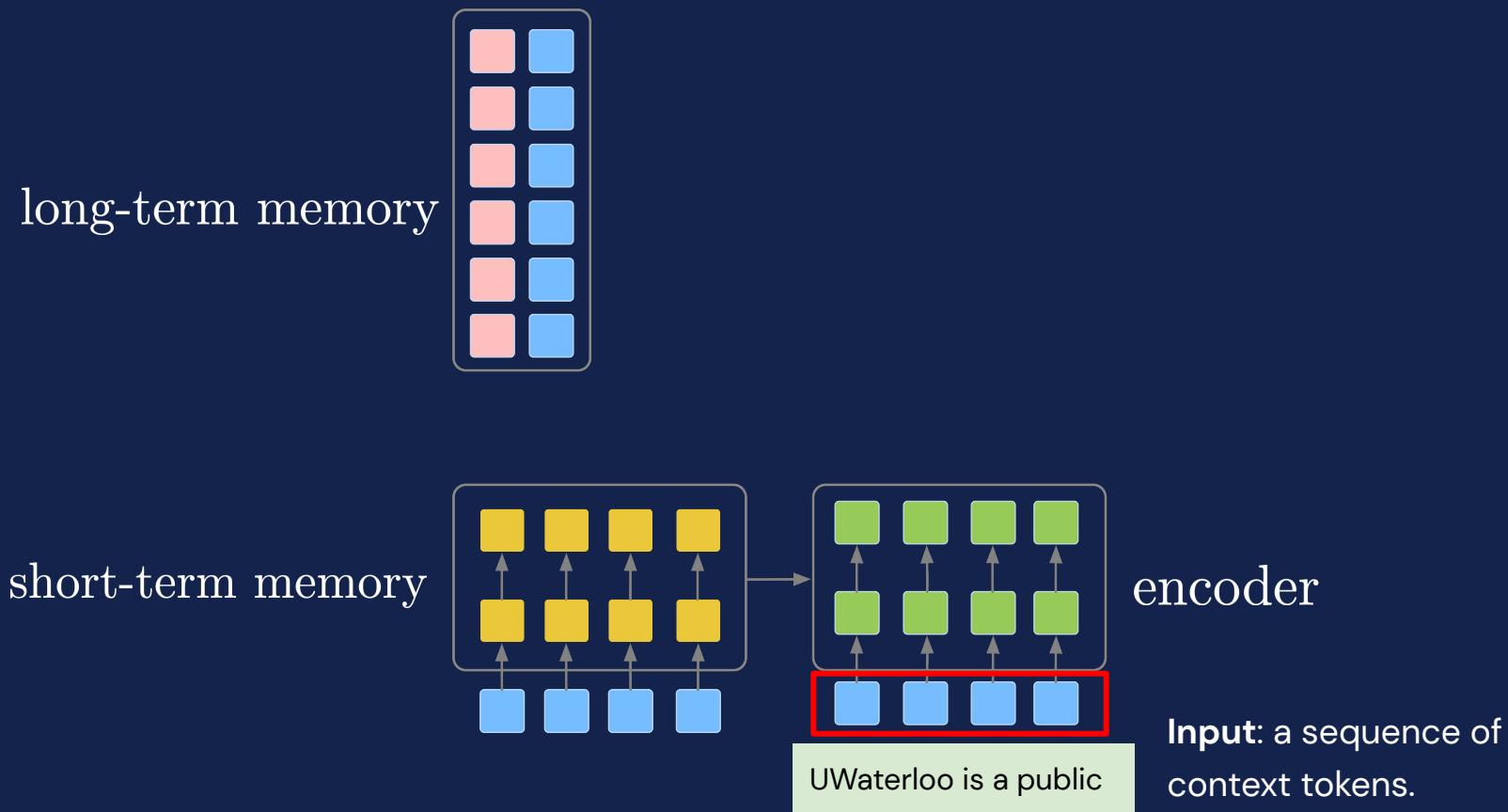
Waterloo Park Wikipedia

Waterloo Park is an urban park situated in Waterloo, Ontario, Canada.

Language Model

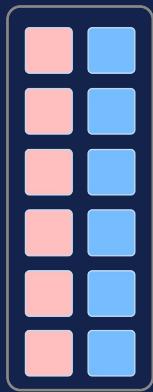


Language Model

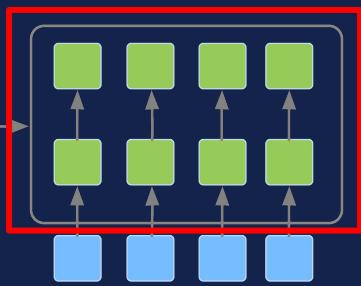
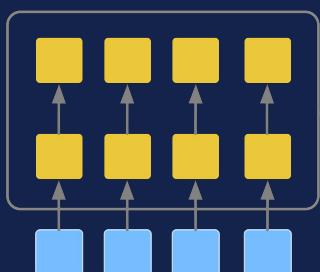


Language Model

long-term memory



short-term memory

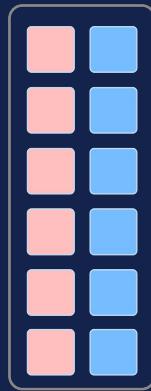


Encoder: transformer
(Vaswani et al., 2017)
encoder

UWaterloo is a public

Language Model

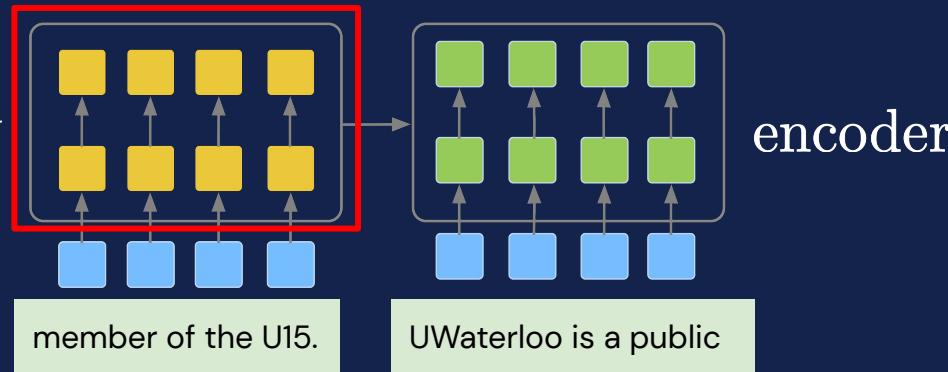
long-term memory



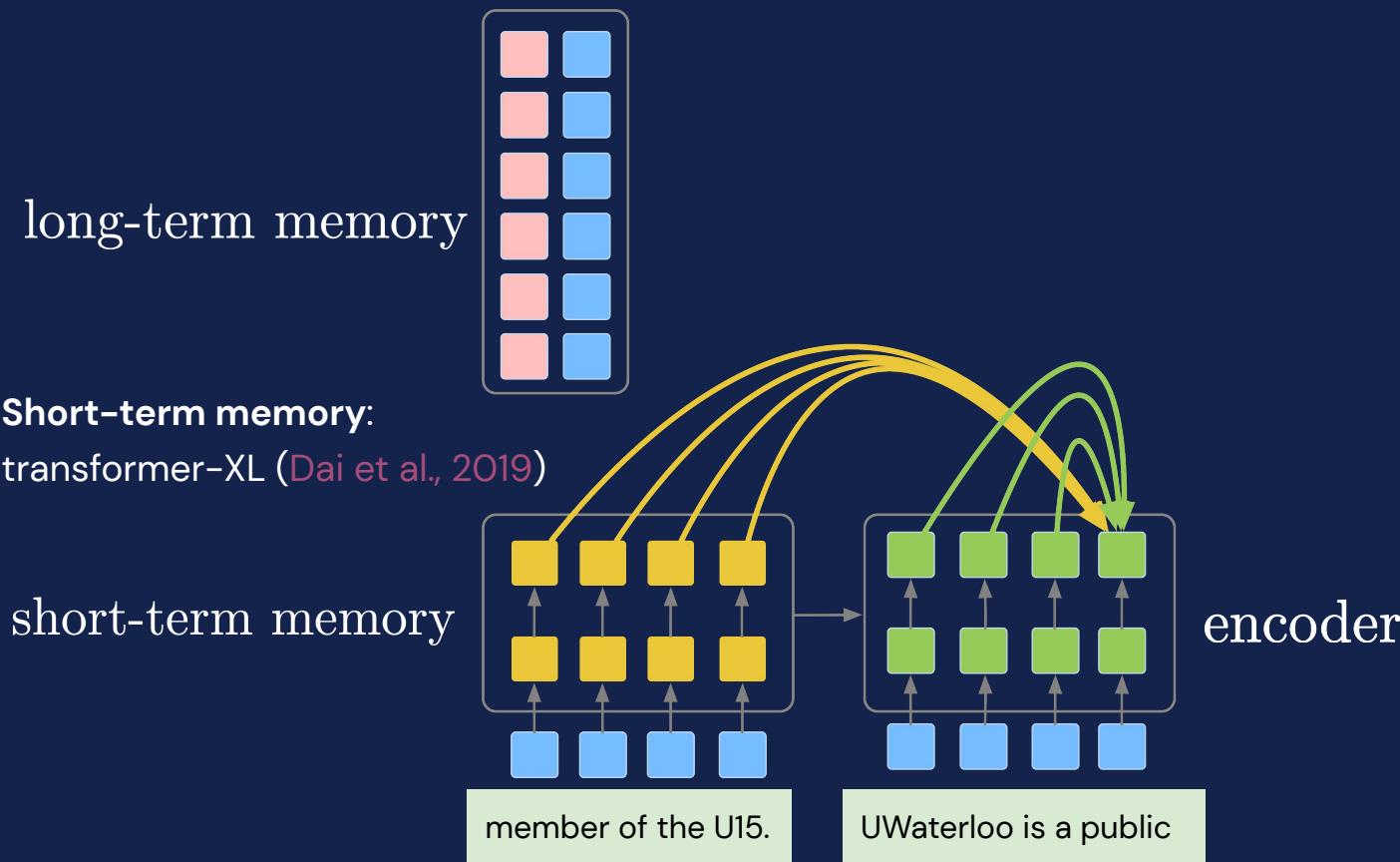
Short-term memory:

transformer-XL (Dai et al., 2019)

short-term memory



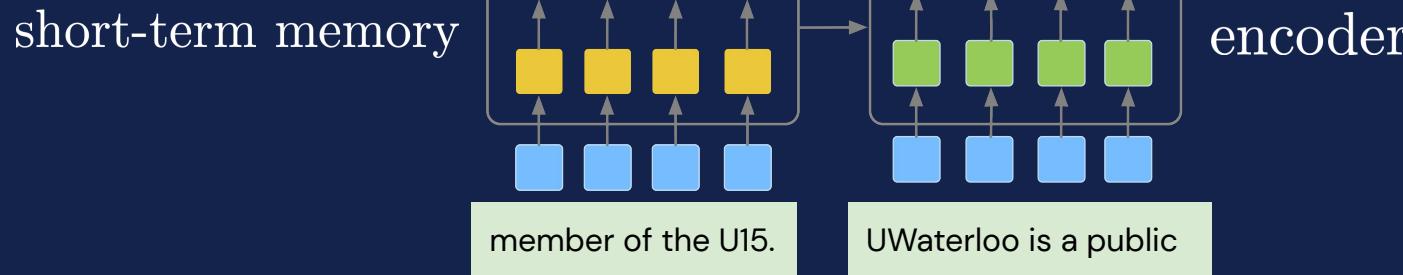
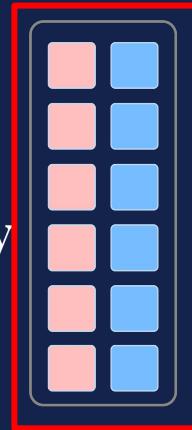
Language Model



Language Model

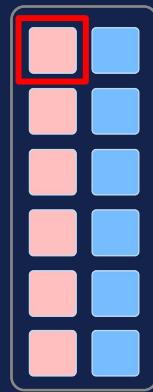
Long-term memory:
key-value database

long-term memory



Language Model

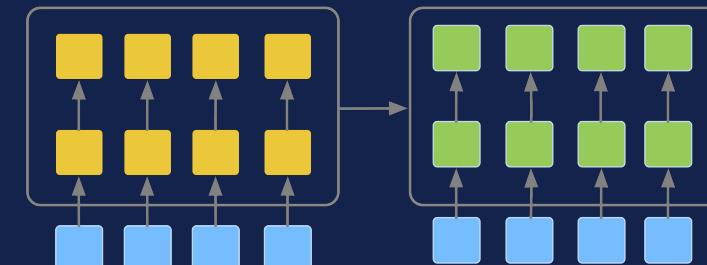
long-term memory



Key: compressed long-term context

Canada is a country in the northern part of North

short-term memory



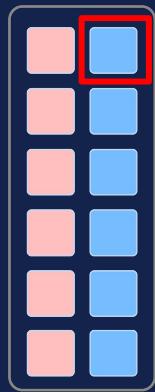
encoder

member of the U15.

UWaterloo is a public

Language Model

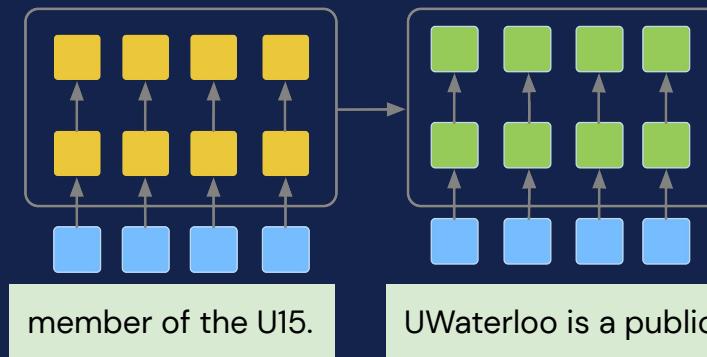
long-term memory



America

Value: output token for the respective context

short-term memory

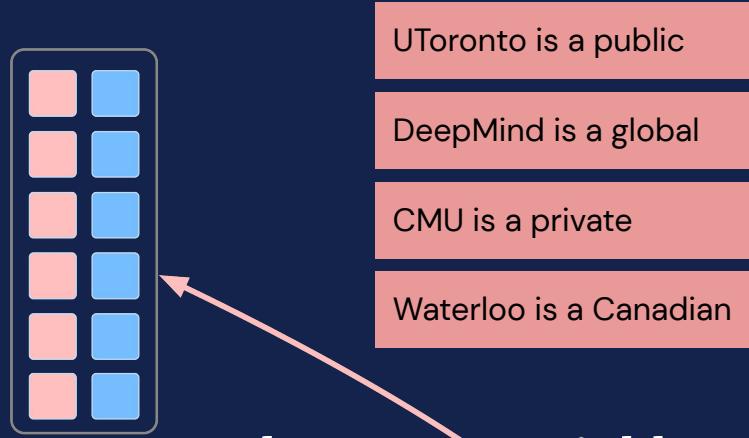


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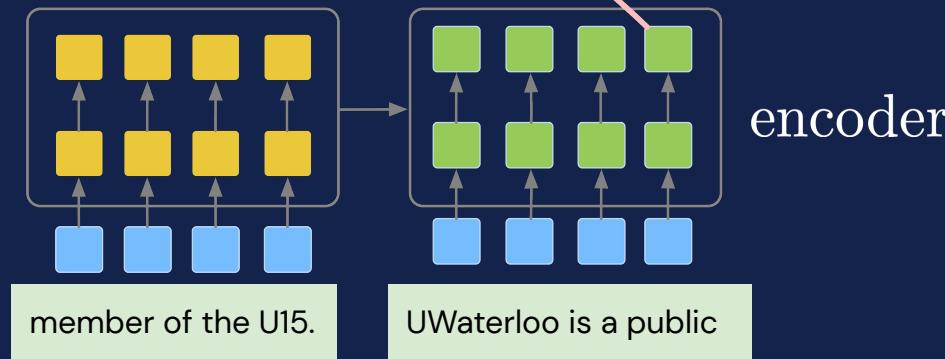
Language Model

long-term memory



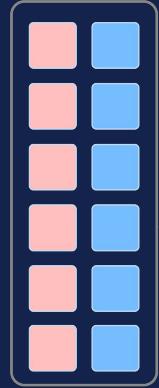
k -nearest neighbors

short-term memory



Language Model

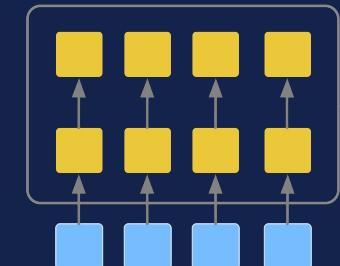
long-term memory



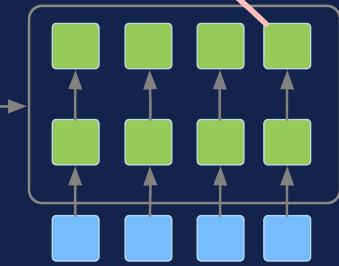
UToronto is a public	research
DeepMind is a global	research
CMU is a private	university
Waterloo is a Canadian	province

k -nearest neighbors

short-term memory



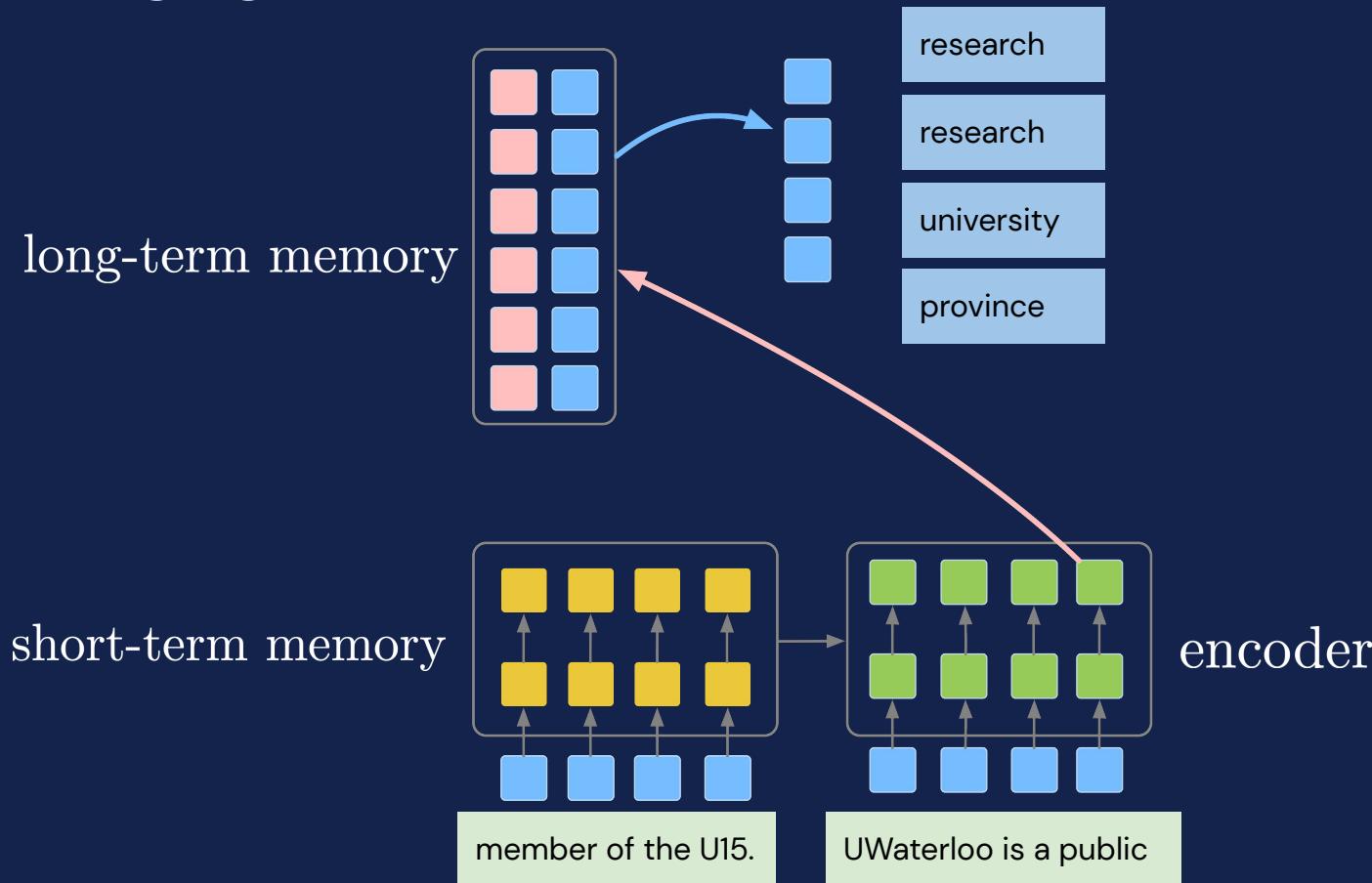
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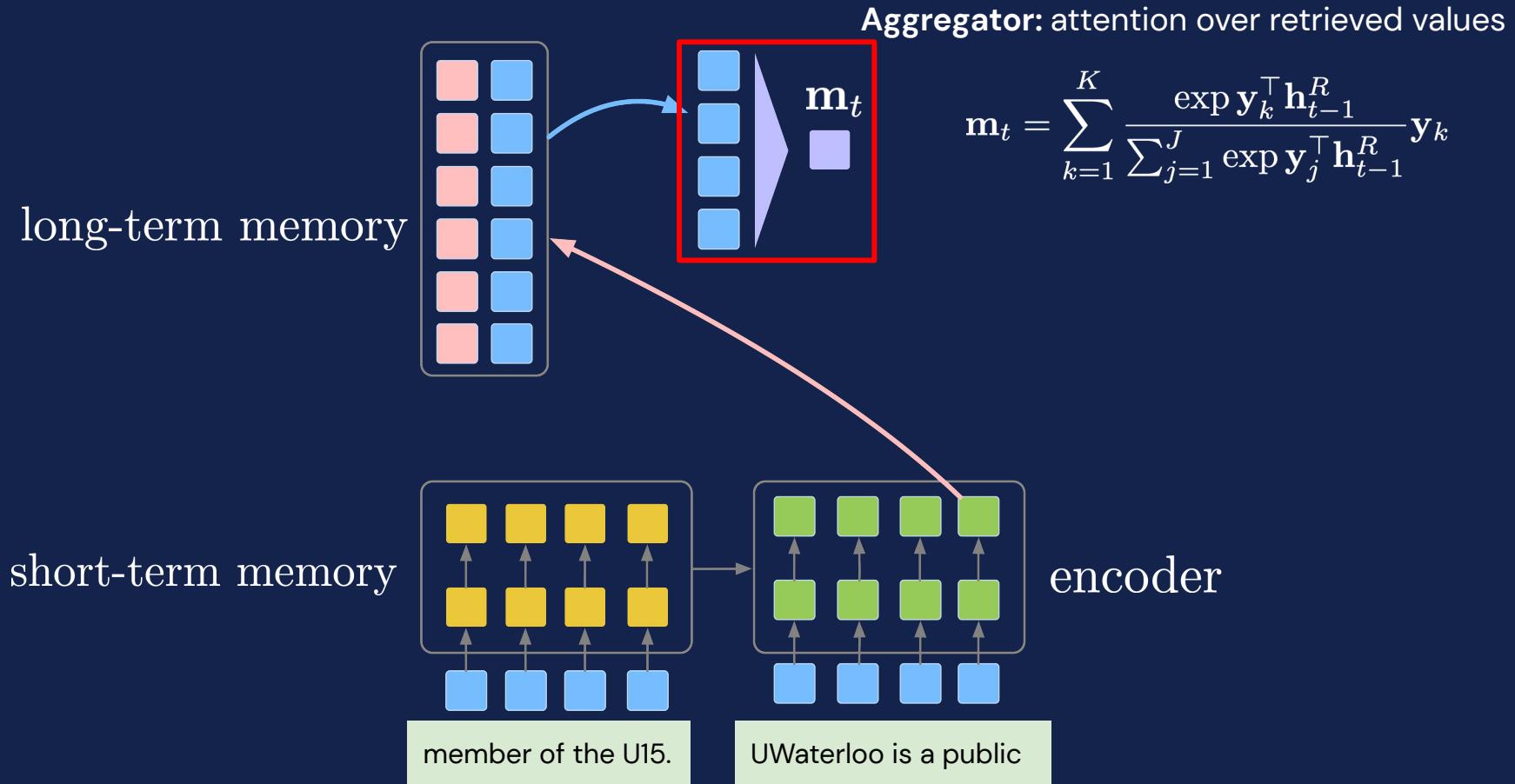
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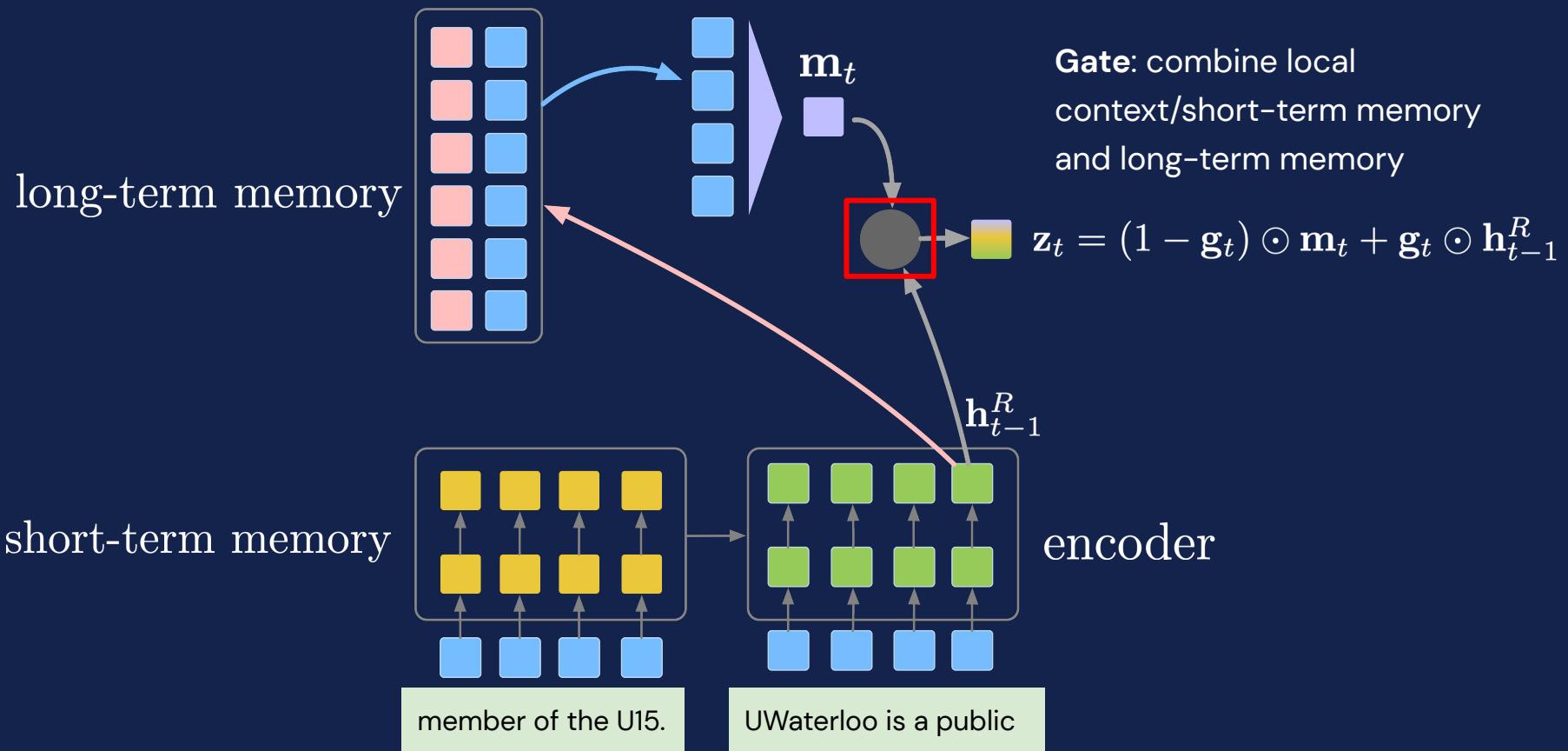
Language Model



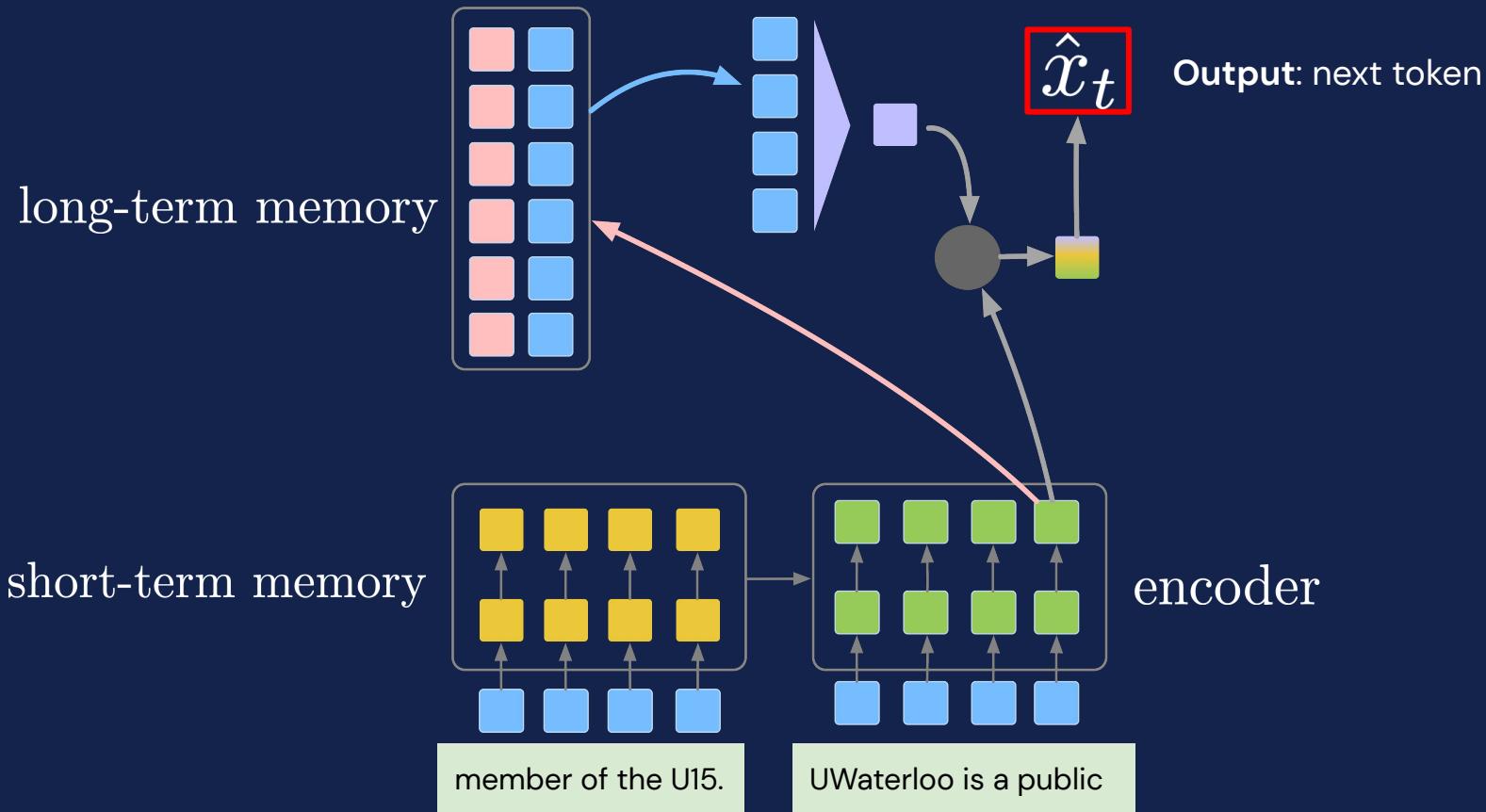
Language Model



Language Model



Language Model



Experiments

- Word-level language modeling.
 - WMT 2019 English: <http://www.statmt.org/wmt19/>.
- Character-level language modeling.
 - enwik8: <http://prize.hutter1.net>.

Experiments

Perplexity (1-inf), lower is better

	Base	TXL	kNN-LM	Ours
WikiText-103	21.8	19.1	18.0	17.6*
WMT	16.5	15.5	15.2	14.1

Transformer: Vaswani et al., 2017

Transformer-XL: Dai et al., 2019

kNN-LM: Khandelwal et al., 2020

Experiments

BPC (0-inf), lower is better

	Base	TXL	kNN-LM	Ours
enwik8	1.05	1.01	1.02	1.00

Transformer: Vaswani et al., 2017

Transformer-XL: Dai et al., 2019

kNN-LM: Khandelwal et al., 2020

Analysis

What's in the long-term memory?

Elizabeth Warren on Friday proposed \$20 trillion in spending over the next decade to provide health care for every American without raising taxes on the middle class.

Analysis

What's in the long-term memory?

For

Perhaps
Like
Elizabeth Warren

on Friday proposed \$ 20 trillion in

spending over the next decade to provide health care

every American without raising taxes on the middle class

Analysis

What's in the long-term memory?

For Warren
Warren
Perhaps Warren
Like Warren
Elizabeth Warren on Friday proposed \$20 trillion in

spending over the next decade to provide health care

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Analysis

What's in the long-term memory?

For Warren &
Perhaps Warren may
Like Warren has
Elizabeth Warren ,
spending over the next decade to provide health care
every American without raising taxes on the middle class

Analysis

What's in the long-term memory?

For Warren & Wednesday briefly a 5 billion to
Warren may Tuesday praised wiping 16 trillion in
Perhaps Warren has Sunday stood breaking 10 billion for
Like Warren , Monday defended using 166 trillion in
Elizabeth Warren on Friday proposed \$ 20 trillion in

spending over the next decade to provide health care

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Analysis

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For Warren & Wednesday briefly a 5 billion to
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grants in 10 course eight . fight even care
funding over the next three . upgrade them cover
funds over 10 next five in improve American -
, over a next 10 , invest a insur.
spending over the next decade to provide health care

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Analysis

What's in the long-term memory?

For	Warren	&	Wednesday	briefly	a	5	billion	to
	Warren	may	Tuesday	praised	wiping	16	trillion	in
Perhaps	Warren	has	Sunday	stood	breaking	10	billion	for
Like	Warren	,	Monday	defended	using	166	trillion	in
Elizabeth	Warren	on	Friday	proposed	\$	20	trillion	in
grants	in	10	course	eight	.	fight	even	care
funding	over	the	next	three	.	upgrade	them	cover
funds	over	10	next	five	in	improve	American	-
,	over	a	next	10	,	invest	a	insur.
spending	over	the	next	decade	to	provide	health	care
more	community	as	the	rates	.	the	middle	class
everyone	child	,	a	taxes	on	the	wealthy	class
some	baby	,	co	taxes	.	the	middle	class
every	American	by	triggering	taxes	on	all	middle	class
every	American	without	raising	taxes	on	the	middle	class

Takeaway and Limitation

- A language model that adaptively combines local context, short-term memory, and long-term memory.

Takeaway and Limitation

- A language model that adaptively combines local context, short-term memory, and long-term memory.
- Retrieving from long-term memory is expensive.

	CPUs	Hours
WikiText-103	1,000	6
WMT	9,000	18
enwik8	1,000	8

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Training Paradigms

Model Architectures

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

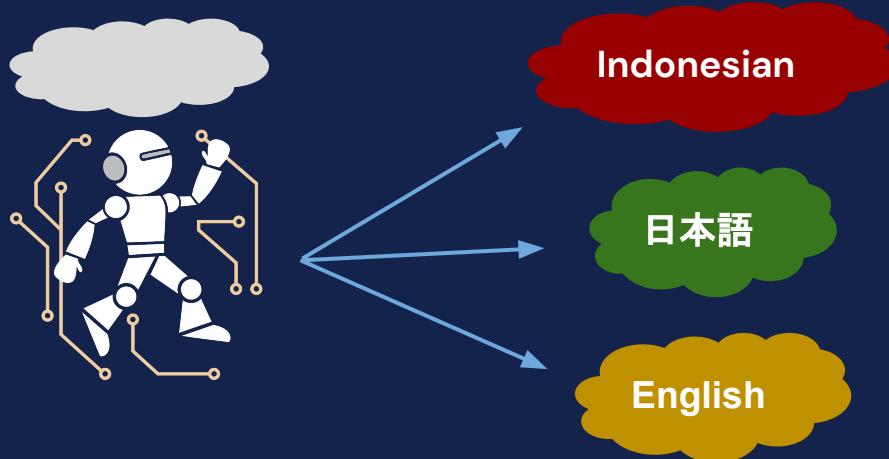
Training Paradigms

Model Architectures

Future Directions



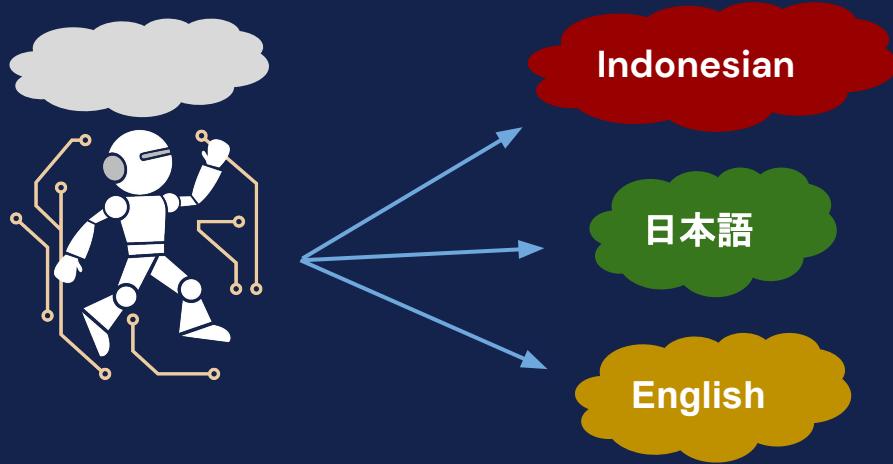
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Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Learning cross-lingual
transferable representations

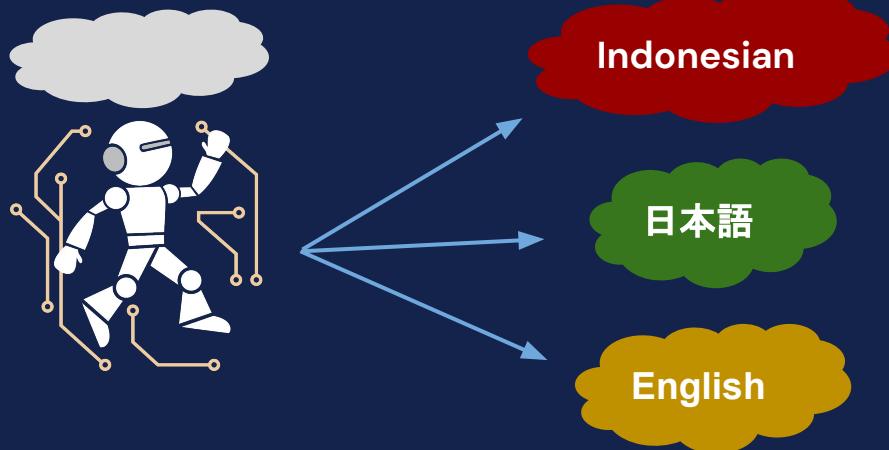
Artetxe et al., ACL 2020



Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



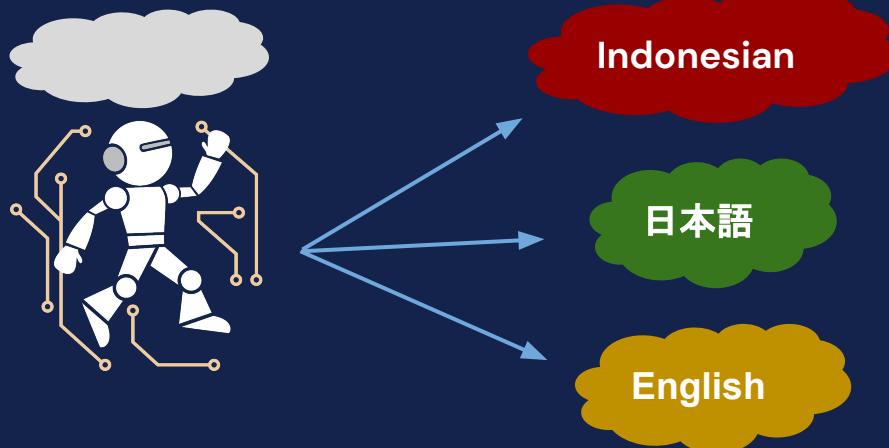
Distributionally Robust Optimization

$$\min_{\theta} \sup_q \mathbb{E}_{(x,y) \sim q} \mathcal{L}_{\theta}(x, y)$$

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Distributionally Robust Optimization

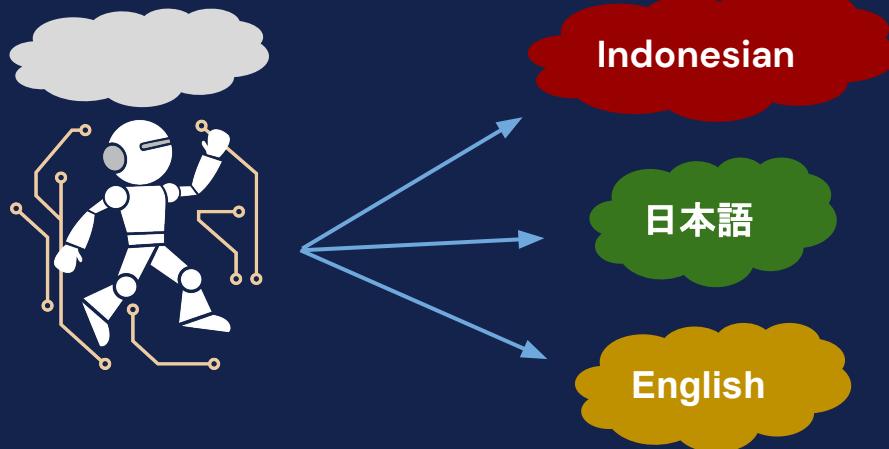
$$\min_{\theta} \sup_q \mathbb{E}_{(x,y) \sim q} \mathcal{L}_{\theta}(x, y)$$

Language

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Distributionally Robust Optimization

$$\min_{\theta} \sup_q \mathbb{E}_{(x,y) \sim q} \mathcal{L}_{\theta}(x, y)$$

Ensuring that a language model works equally well across languages (important for fairness)

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Training Paradigms

Model Architectures

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

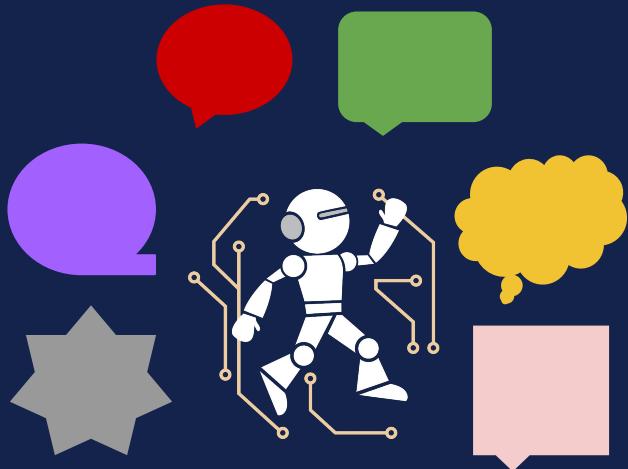
Training Paradigms

Model Architectures

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

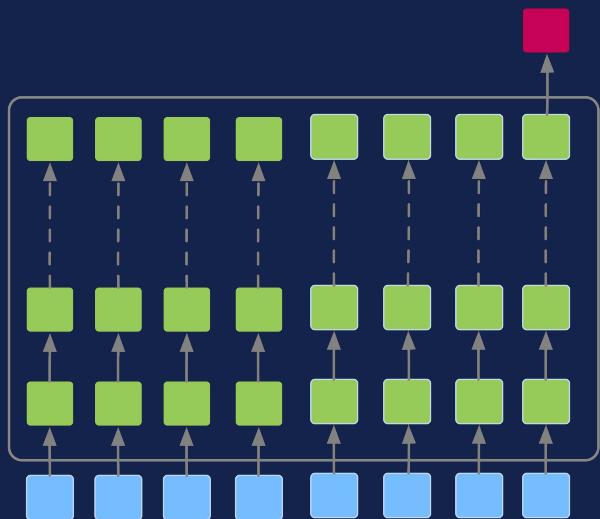


Integration of data from various sources and modalities.

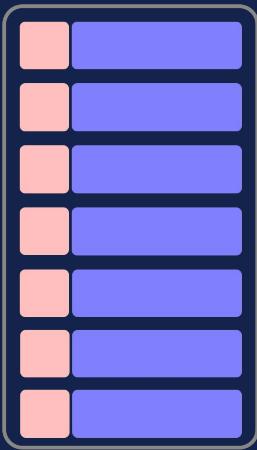
Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Computation

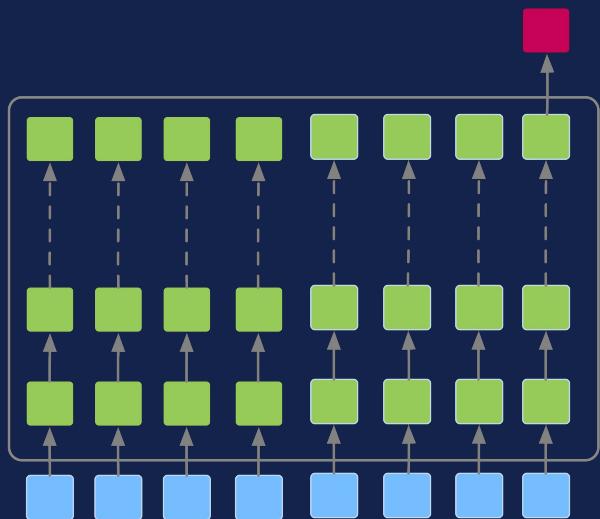


Storage

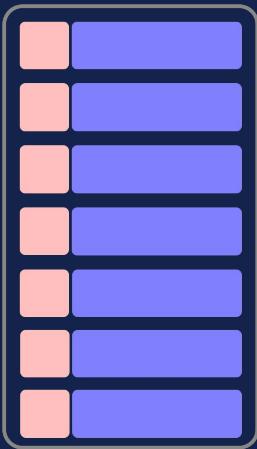
Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Computation



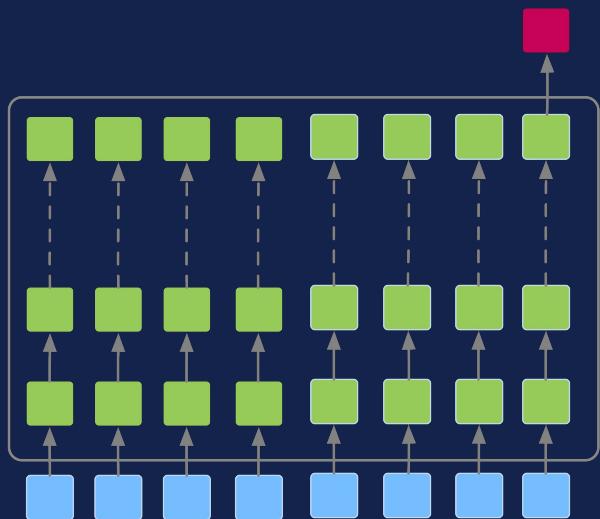
Storage



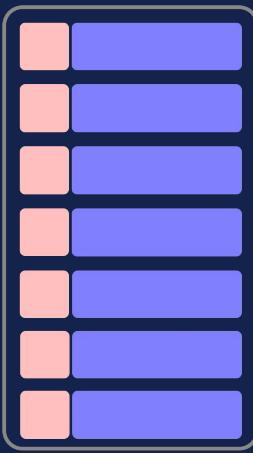
Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Computation



Storage

A screenshot of a profile page for Cristiano Ronaldo. At the top, there is a grid of five small images showing him in various poses. Below the images, his name "Cristiano Ronaldo" is displayed in a large, bold black font, followed by the subtitle "Portuguese footballer". A link "cristianoronaldo.com" is provided. In the bottom right corner of the profile area, there is a "More images" button with a camera icon. The main content area contains the following biographical information:

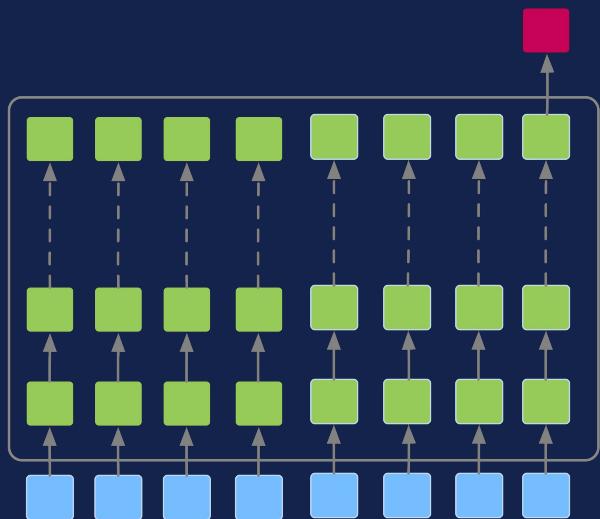
- Born: 5 February 1985 (age 36 years), Hospital Dr. Nélio Mendonça, Funchal, Portugal
- Height: 1.87 m
- Partner: Georgina Rodríguez (2017–)
- Salary: 31 million EUR (2019)
- Children: Cristiano Ronaldo Jr., Alana Martina dos Santos Aveiro, Eva Maria Dos Santos, Mateo Ronaldo
- Current teams: Juventus F.C. (#7 / Forward), Portugal national football team (#7 / Forward)

At the bottom right of the slide, there is a small "Wikipedia" logo.

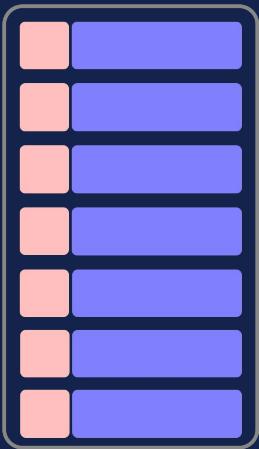
Future Directions



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Computation



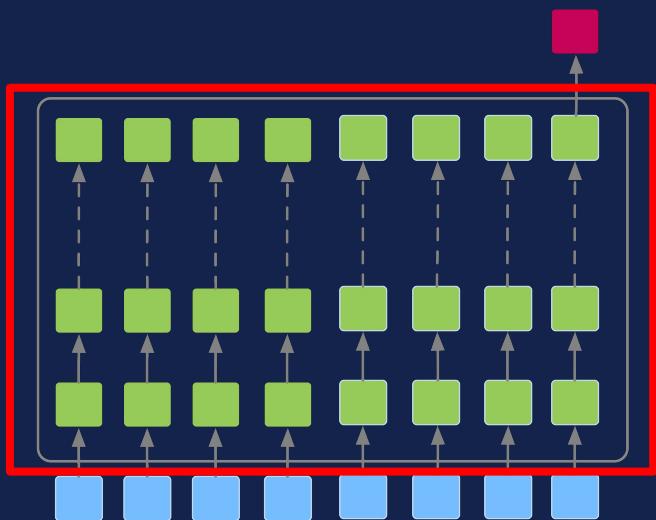
Storage

↑ computational efficiency

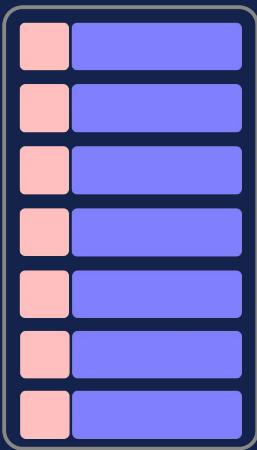
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Computation



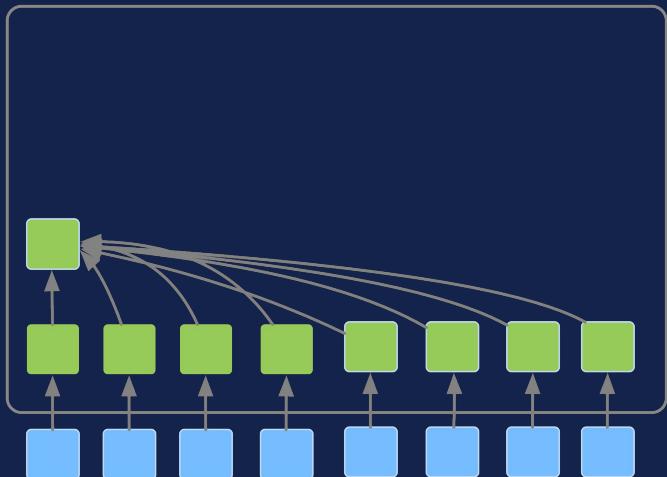
Storage

↑ computational efficiency

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Random Feature Attention

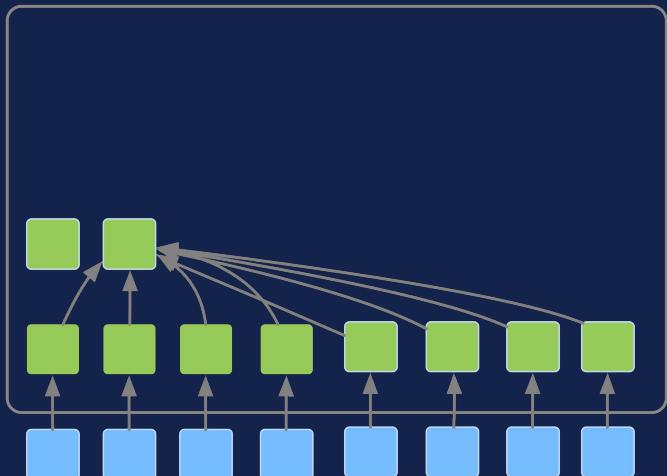
Peng et al., ICLR 2021



Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Random Feature Attention

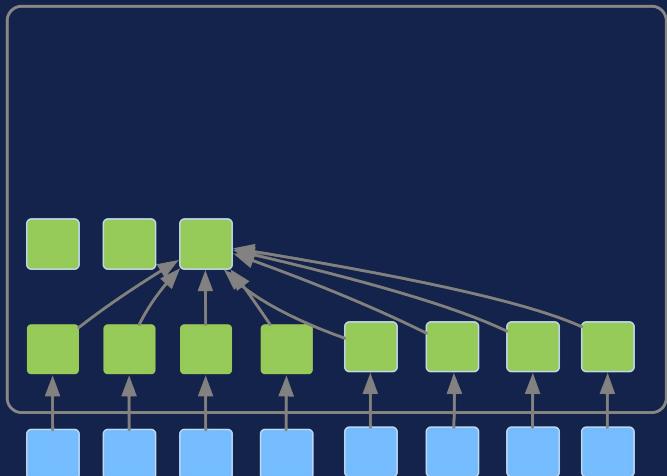
Peng et al., ICLR 2021



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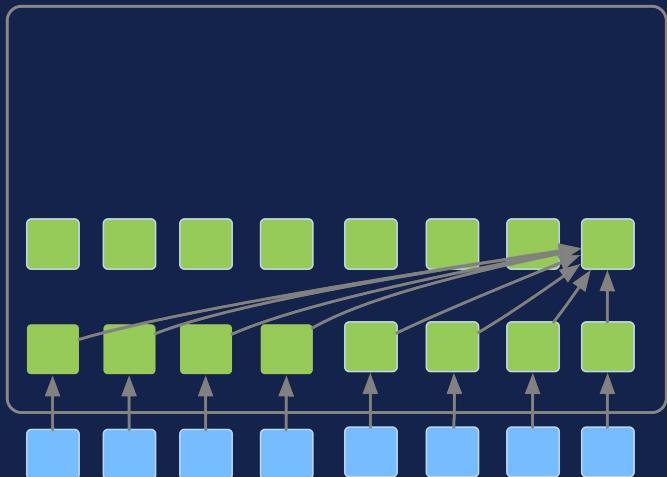
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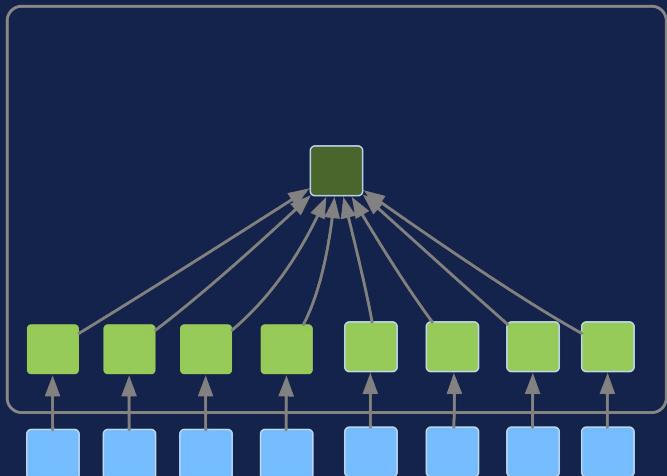
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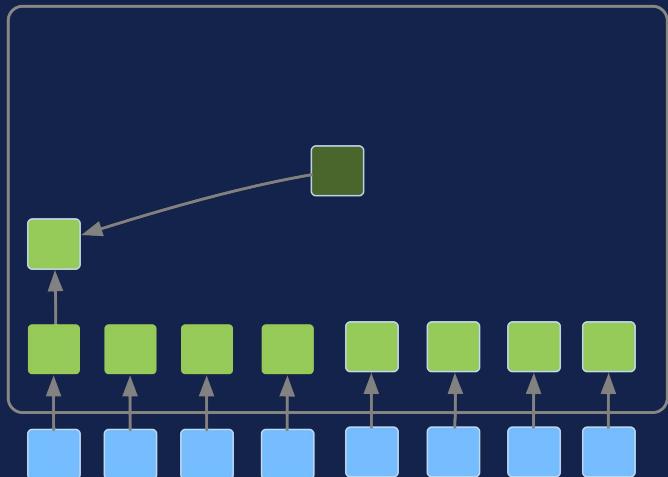
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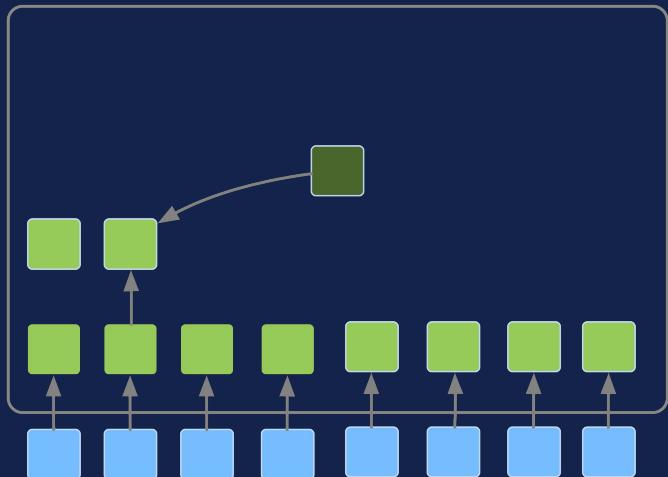
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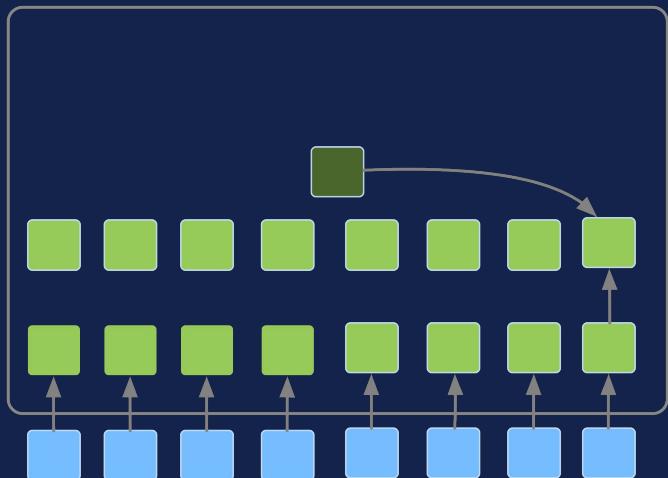
Peng et al., ICLR 2021



Future Directions



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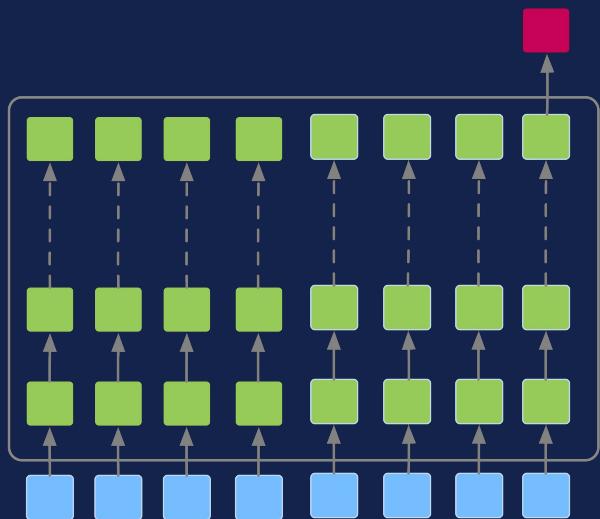
Peng et al., ICLR 2021



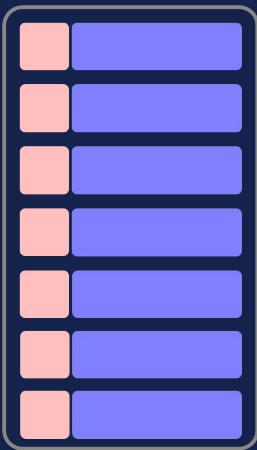
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Computation



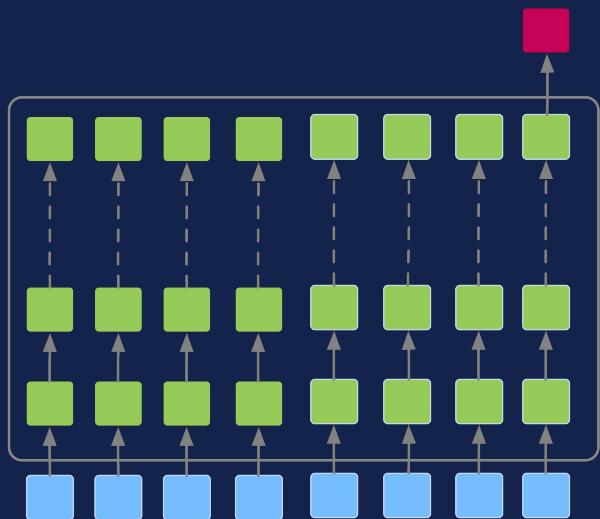
Storage

↑ computational efficiency

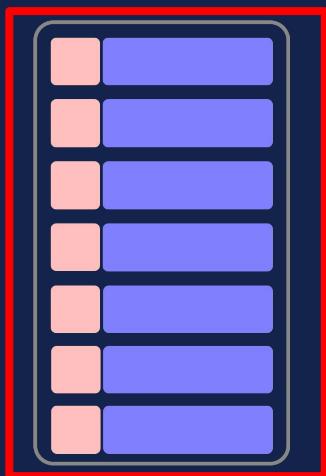
Future Directions



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Computation



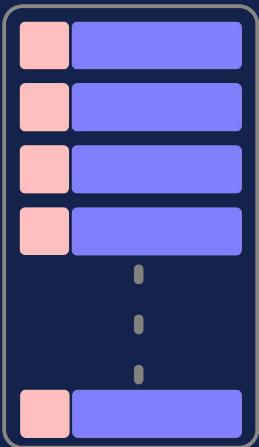
Storage

↑ computational efficiency

Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Storage

Learning to what to remember and forget

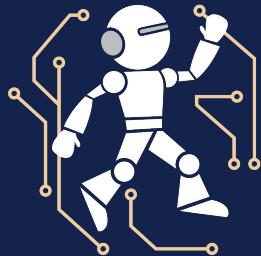


Constant-size memory

Future Directions



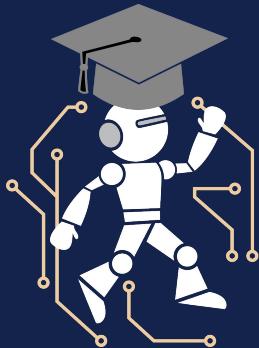
A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



Future Directions



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.



tack გნორჩაჲალითჟიოს Danke
ありがとうございました Salamat
grazie **Thank you** multumesc நன்றி
ধন্যবাদ Terima kasih Dankie 감사합니다 Merci
Спасибо شکرا جزیلا σας ευχαριστώ
teşekkür ederim 谢謝 cảm ơn bạn

<https://dyogatama.github.io>
dyogatama@google.com

Challenges: Human Learning vs. Machine Learning



Human	
``Large'' datasets	Acquisition
Few examples	Task Training
Dataset agnostic	Linguistic knowledge
Generalizable to new tasks	Generalization

Experiments

Perplexity (1-inf), lower is better

	Base	TXL	kNN-LM	Ours
WikiText-103	21.8	19.1	18.0	17.6*
WMT	16.5	15.5	15.2	14.1

Transformer: Vaswani et al., 2017

Transformer-XL: Dai et al., 2019

kNN-LM: Khandelwal et al., 2020

This Talk

- Episodic memory in lifelong language learning.
de Masson d'Autume et al., NeurIPS 2019
- A framework for self-supervised language representation learning methods.
Kong et al., ICLR 2020

Episodic Memory in Lifelong Language Learning

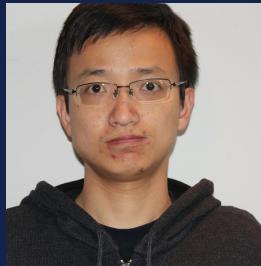
de Masson d'Autume et al., NeurIPS 2019



Cyprien



Sebastian



Lingpeng



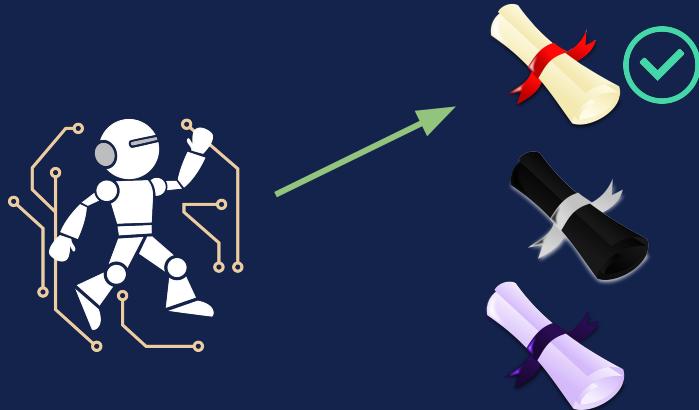
Dani

Background

- A model should be able to reuse knowledge from related tasks to learn a new task faster.
- Current models not only fail to do this, they **catastrophically forget** previously learned tasks (McCloskey and Cohen, 1989; Ratcliff, 1990).

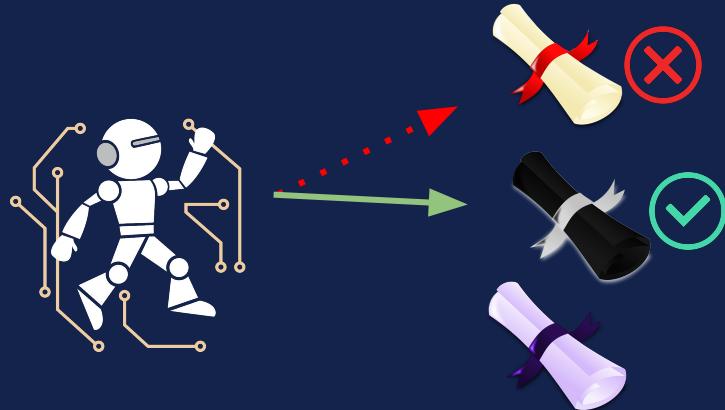
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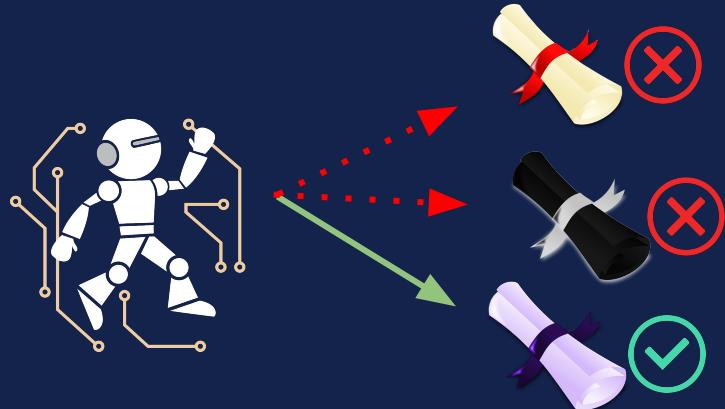
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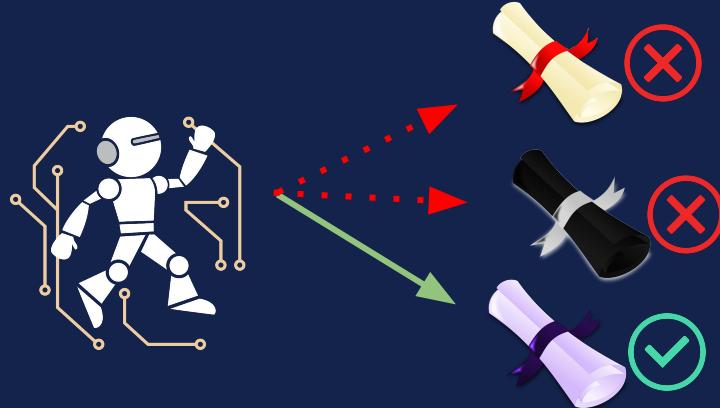
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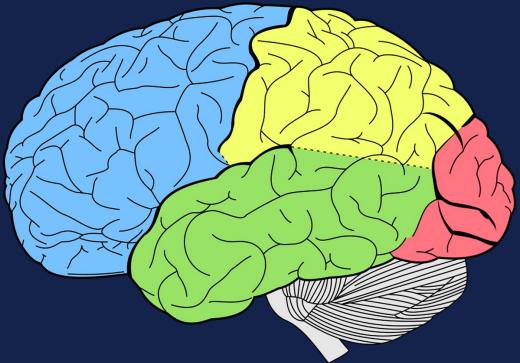
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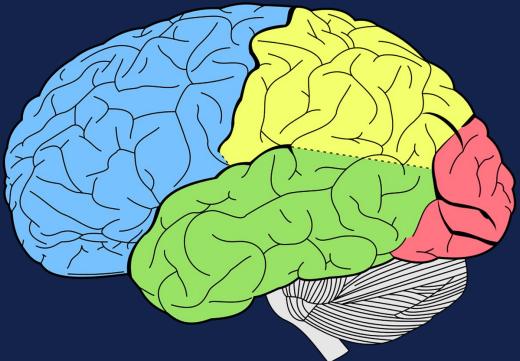
Hypothesis: episodic memory mitigates catastrophic forgetting in language learning.

On Memory-Augmented Neural Networks



Episodic memory is a type of long-term memory of **events** and **experiences**. It is often associated with a module that stores training examples in neural networks..

On Memory-Augmented Neural Networks

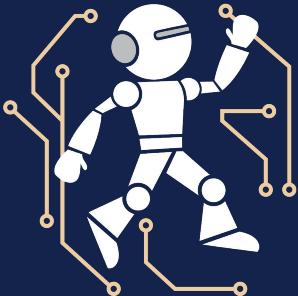


Episodic memory is a type of long-term memory of **events** and **experiences**. It is often associated with a module that stores training examples in neural networks..

Contrast this with short-term **working memory** in LSTMs ([Hochreiter and Schmidhuber, 1997](#)) and DNCs ([Graves et al., 2016](#)) that e.g., remembers context.

See [Yogatama et al., ICLR 2018](#) for comparisons of working memory models for language models.

Problem Setup



Training



TriviaQA: Joshi et al., 2017

Tanker leaks 6,000 tons of oil after running aground

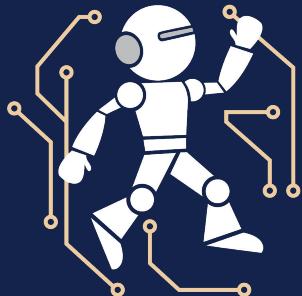
The Independent, Friday 16 February 1996
A massive anti-pollution operation was underway last night after a 147,000-ton super tanker ran aground off Milford Haven, West Wales. [...]

Which super-tanker ran aground near Milford Haven in 1996?



Problem Setup

SQuAD: Rajpurkar et al., 2016



Training

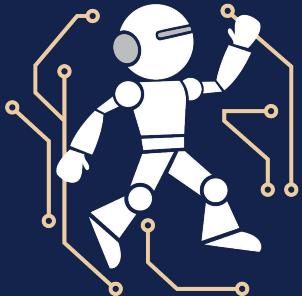


Computational Complexity Theory.
Computational complexity theory is a branch of the theory of computation in theoretical computer science that focuses on classifying computational problems according to their inherent difficulty [...]

What branch of theoretical computer science deals with broadly classifying computational problems by difficulty and class of relationship?



Problem Setup



Training



QuAC: Choi et al., 2018

Augusto Pinochet --- Intellectual life ...

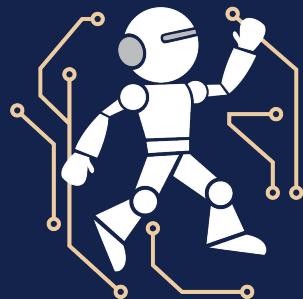
Pinochet was publicly known as a man with a lack of culture. This image was reinforced by the fact [...]

Was he known for being intelligent? No, Pinochet was publicly known as a man with a lack of culture.

Why did people feel that way?



Problem Setup



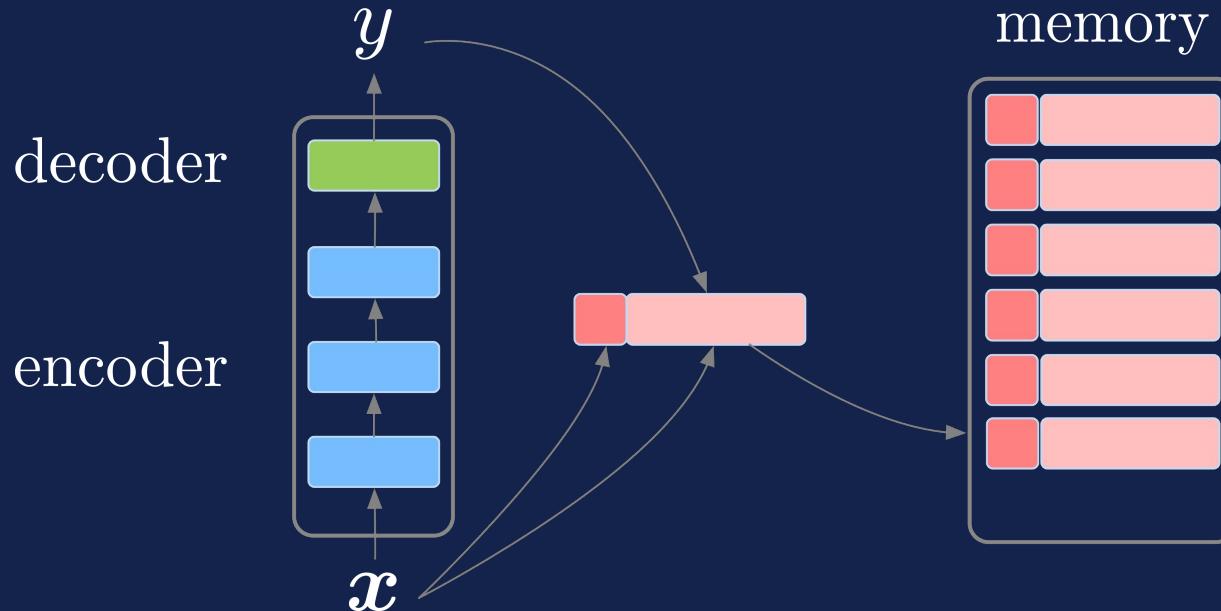
Training



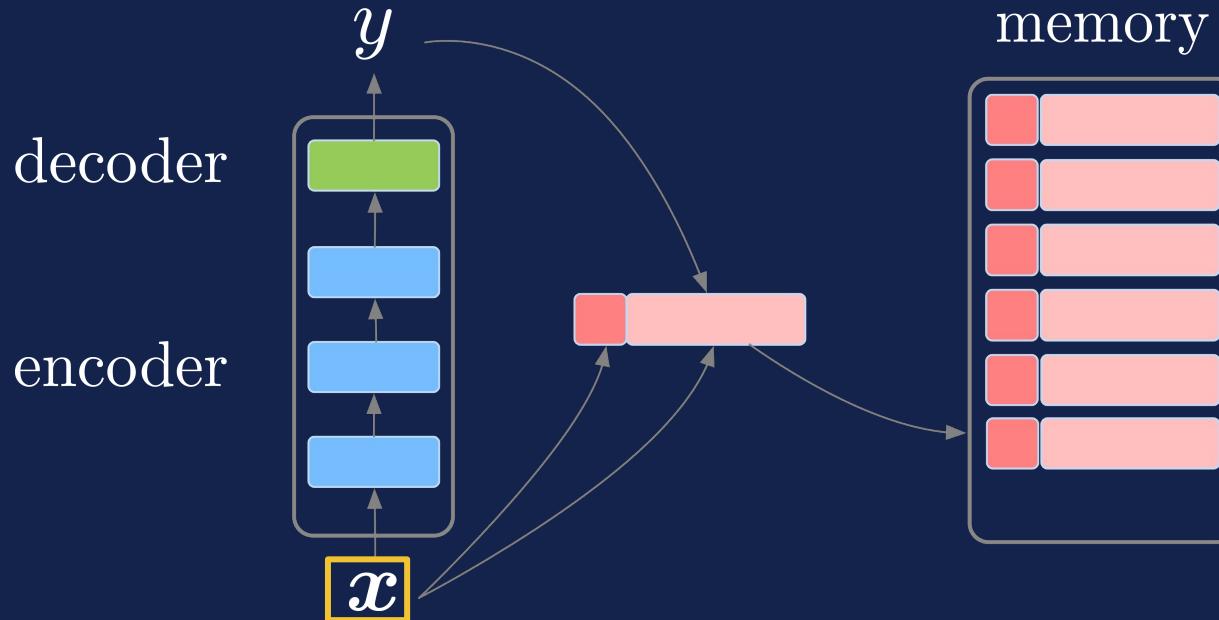
Test



Question Answering Model

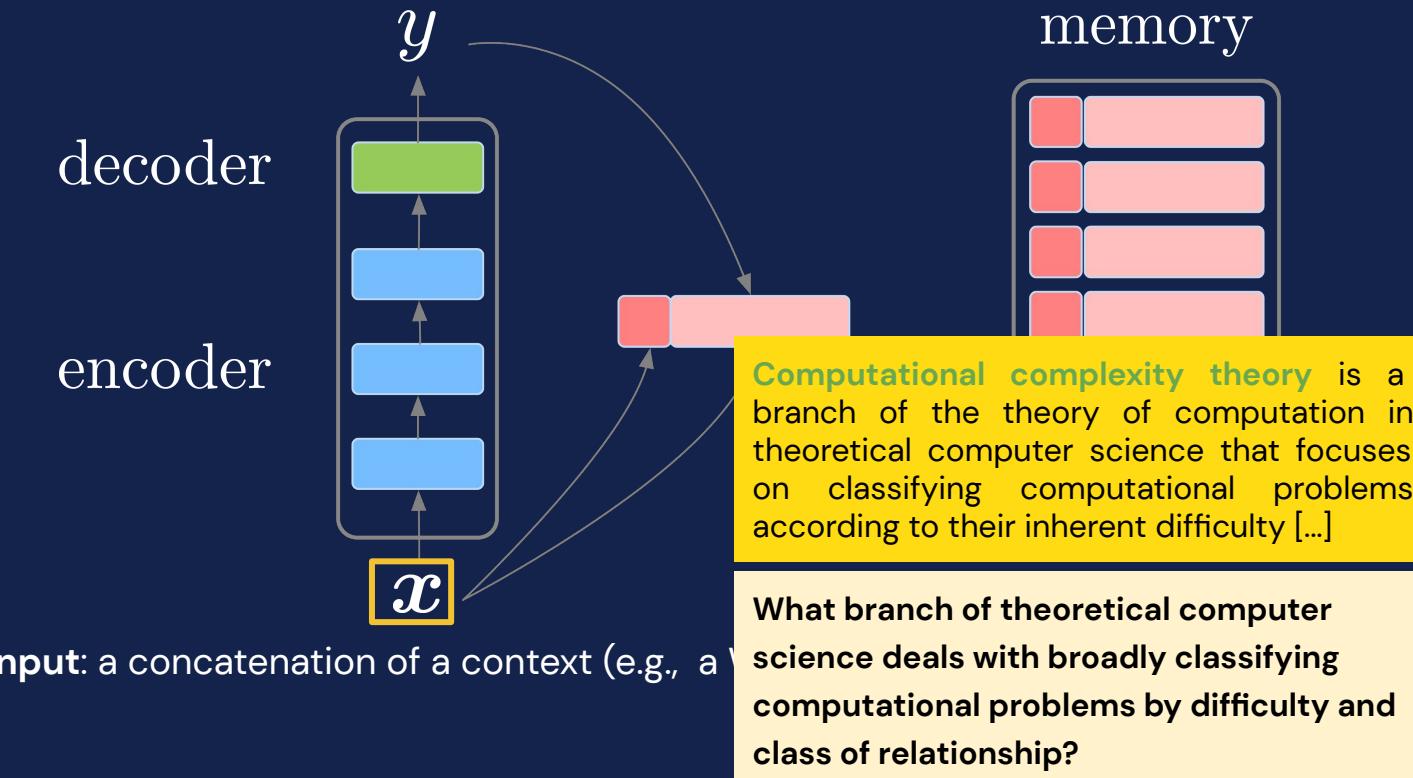


Question Answering Model



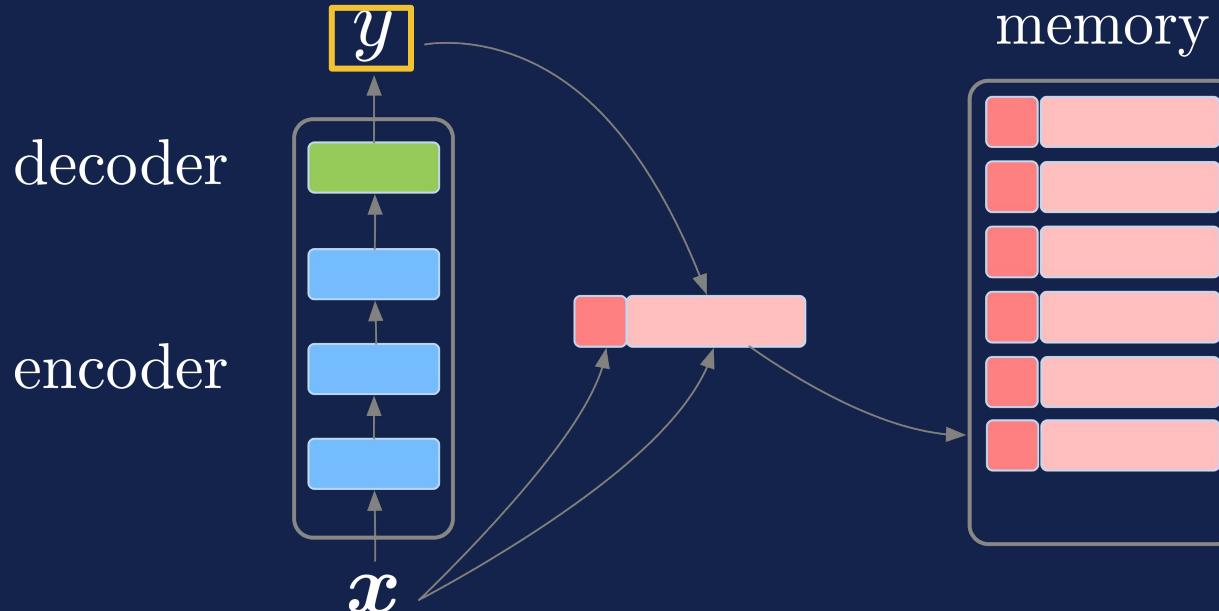
Input: a concatenation of a context (e.g., a Wikipedia article) and a question.

Question Answering Model



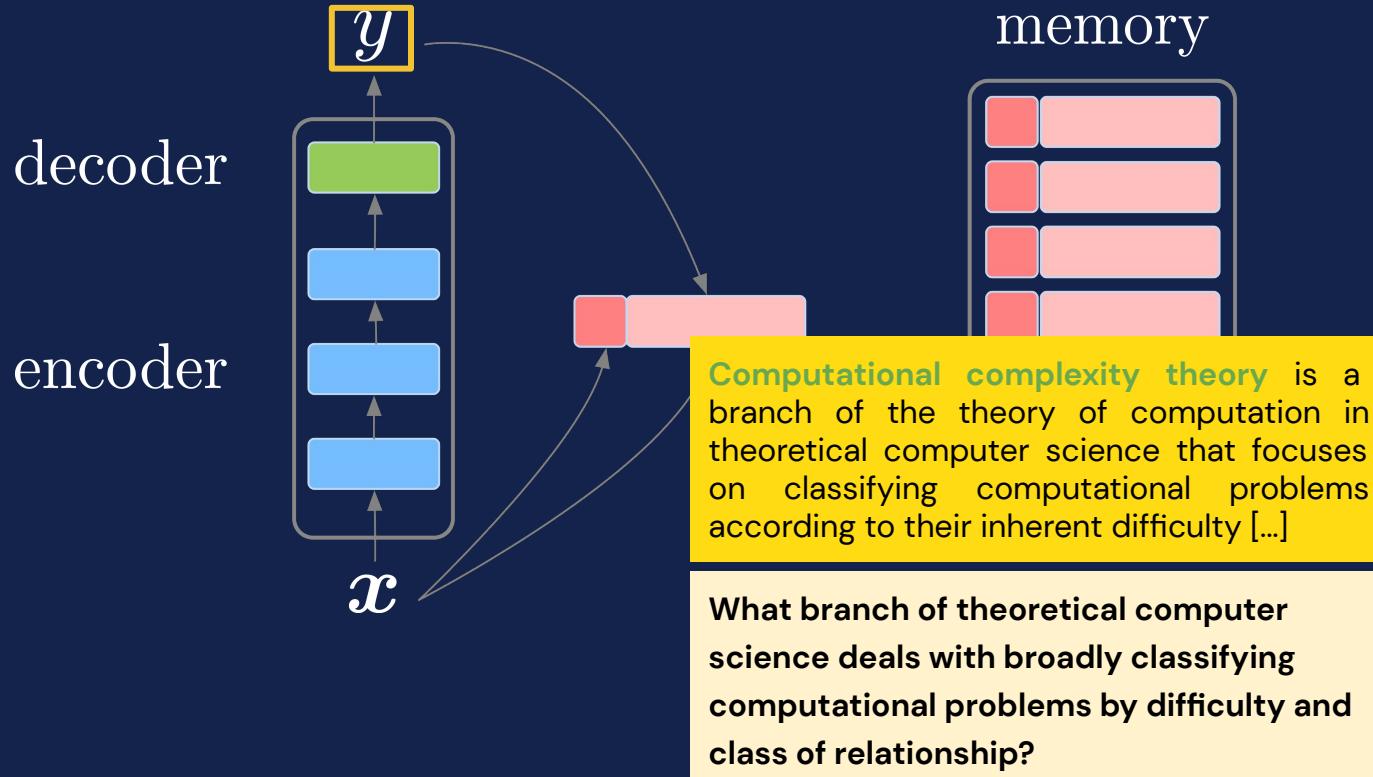
Question Answering Model

Output: an answer, predicted as start and end indices of the answer in the context.

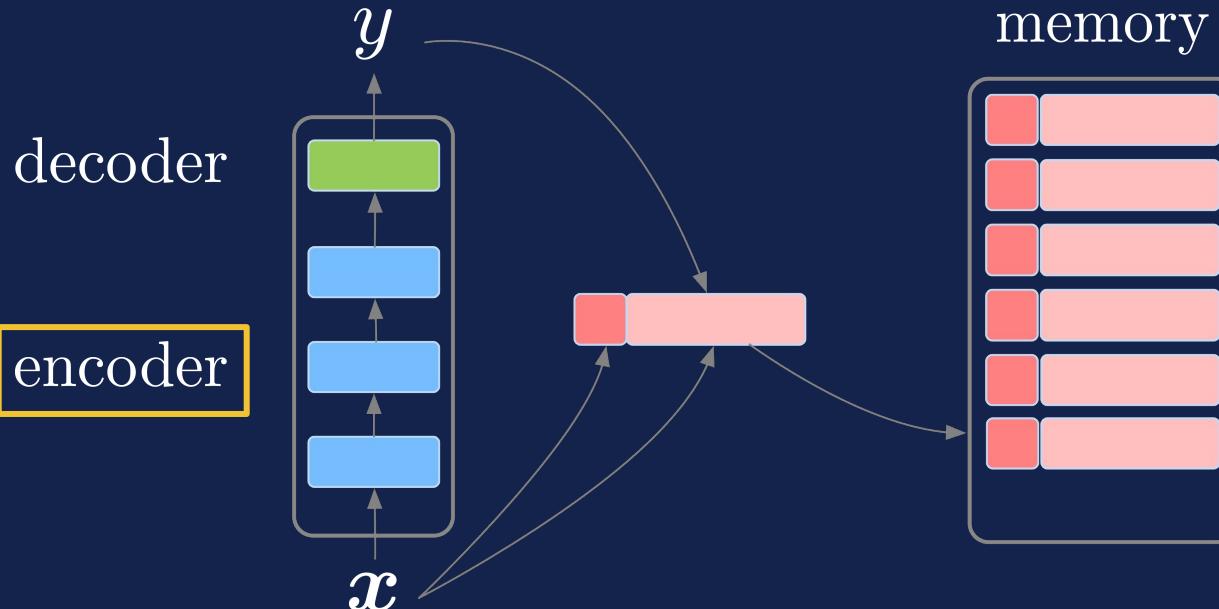


Question Answering Model

Output: an answer, predicted as start and end indices of the answer in the context.



Question Answering Model



Encoder: a large neural network, e.g., ELMo

(Peters et al., 2018), BERT (Devlin et al., 2019), XLNet

(Yang et al., 2019).

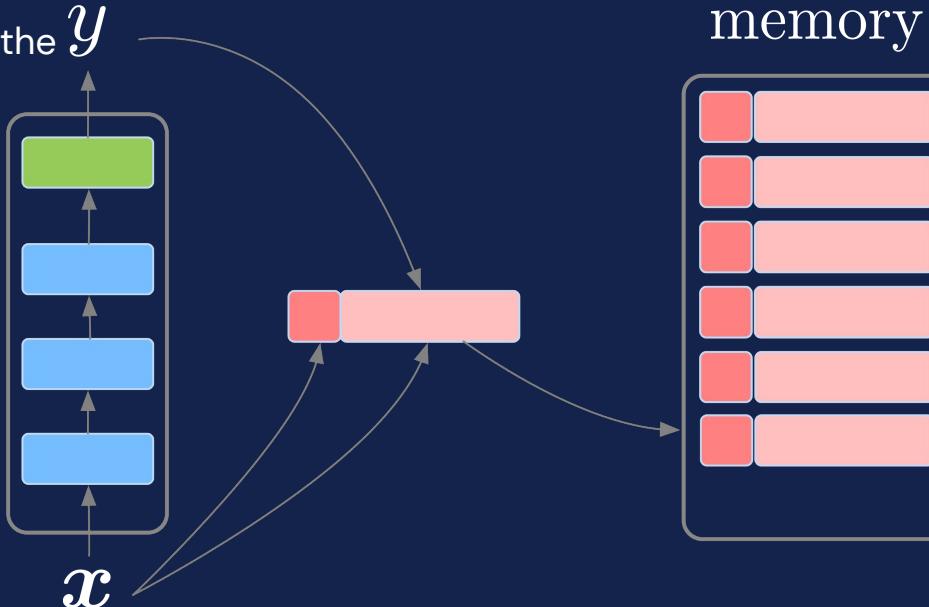
Question Answering Model

Decoder: a linear function

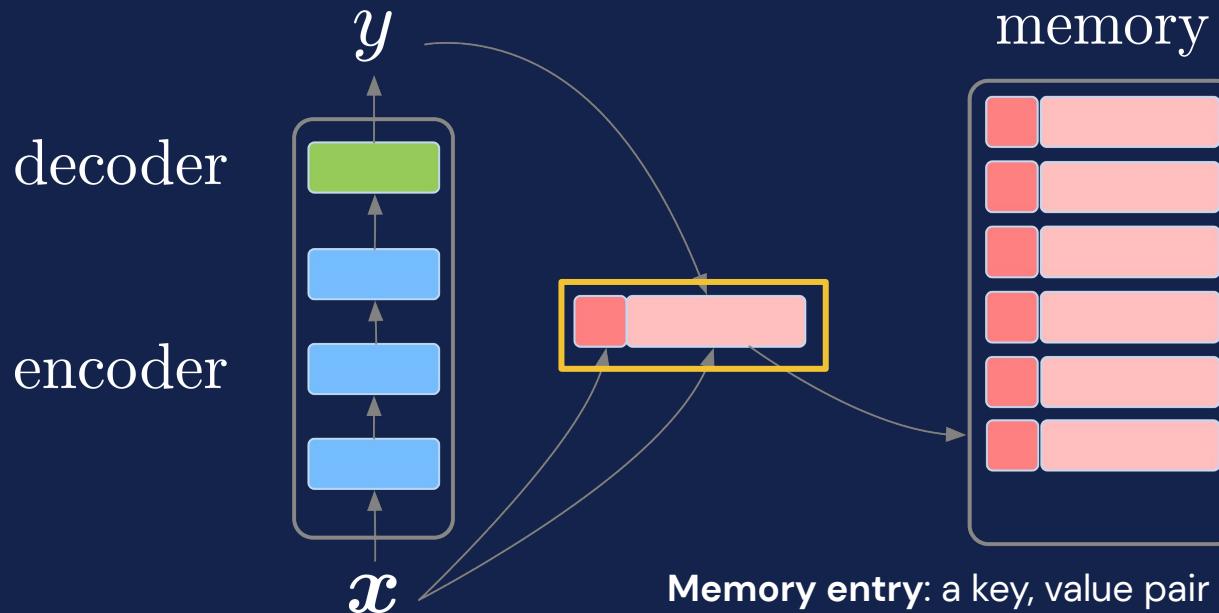
that predicts start and end
indices of the answer in the y
context.

decoder

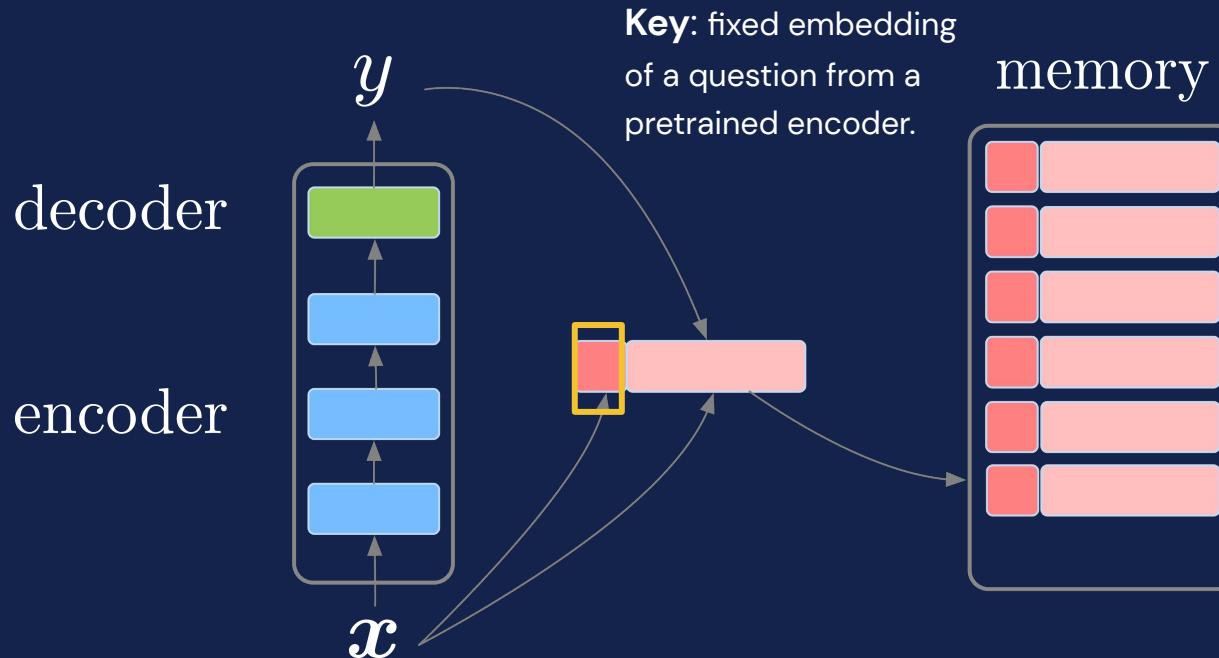
encoder



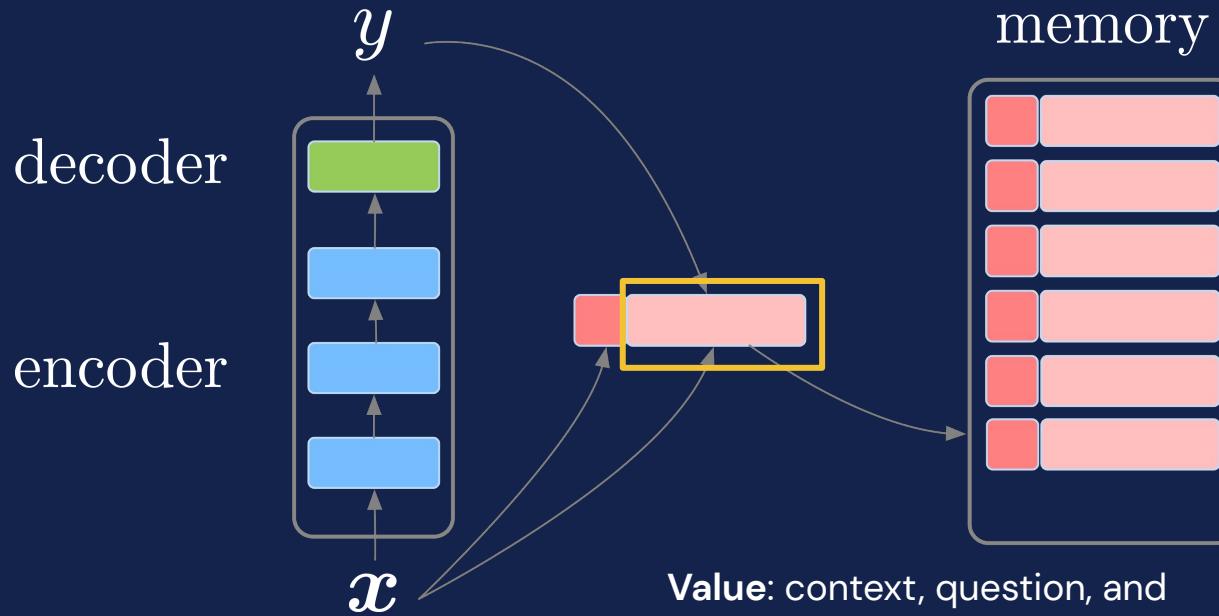
Question Answering Model



Question Answering Model

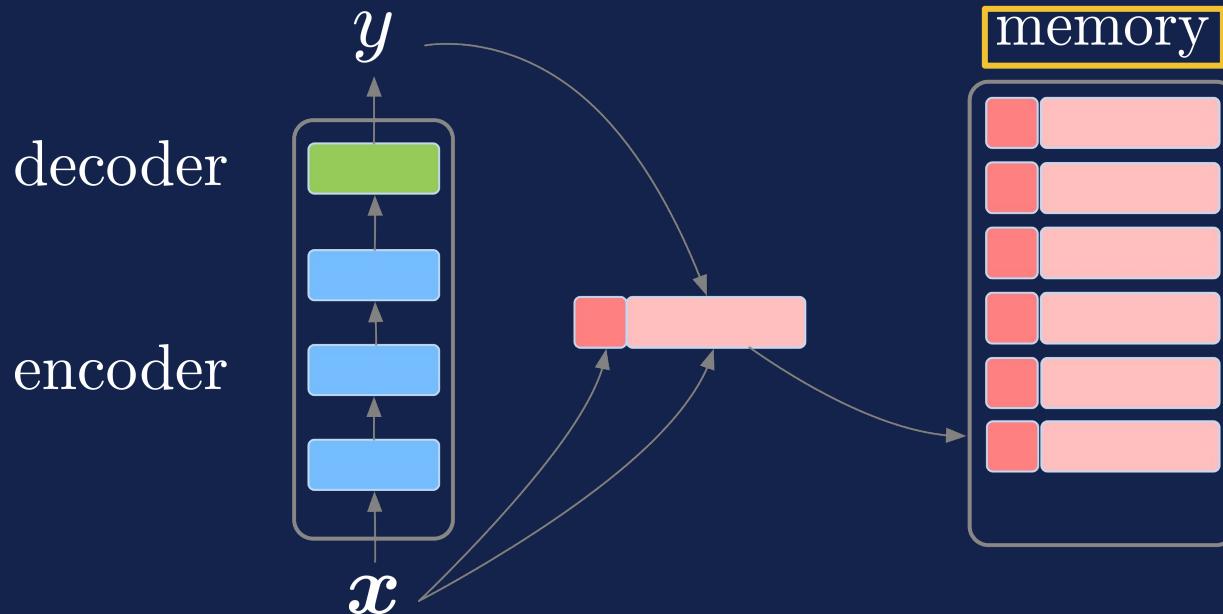


Question Answering Model



Question Answering Model

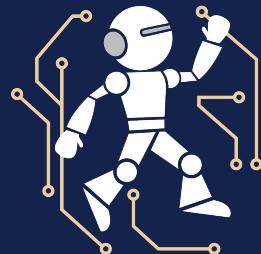
Memory: stores memory entries



Training



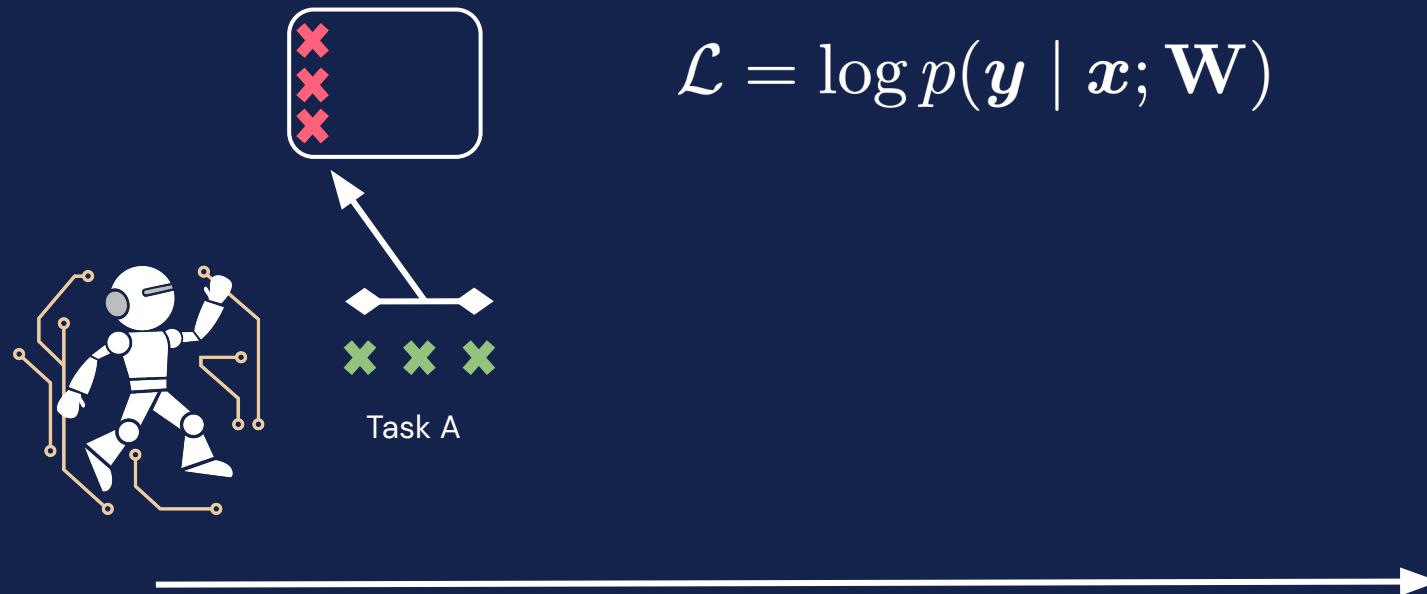
$$\mathcal{L} = \log p(\mathbf{y} \mid \mathbf{x}; \mathbf{W})$$



Task A

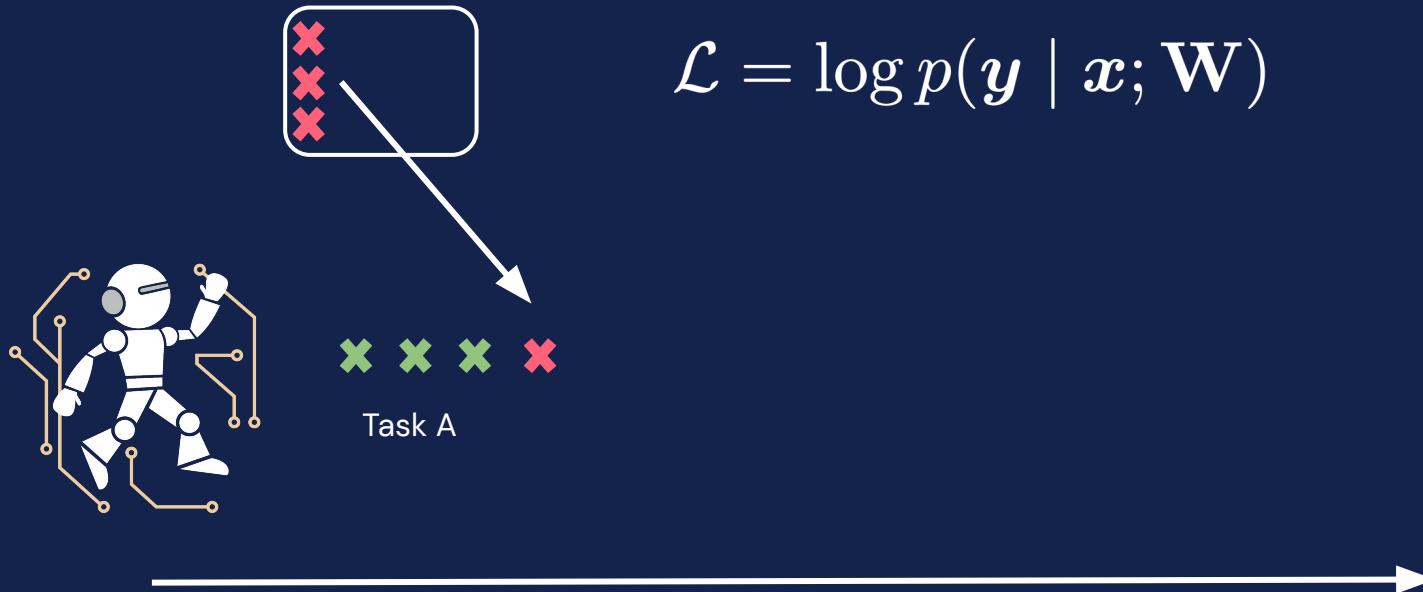


Training



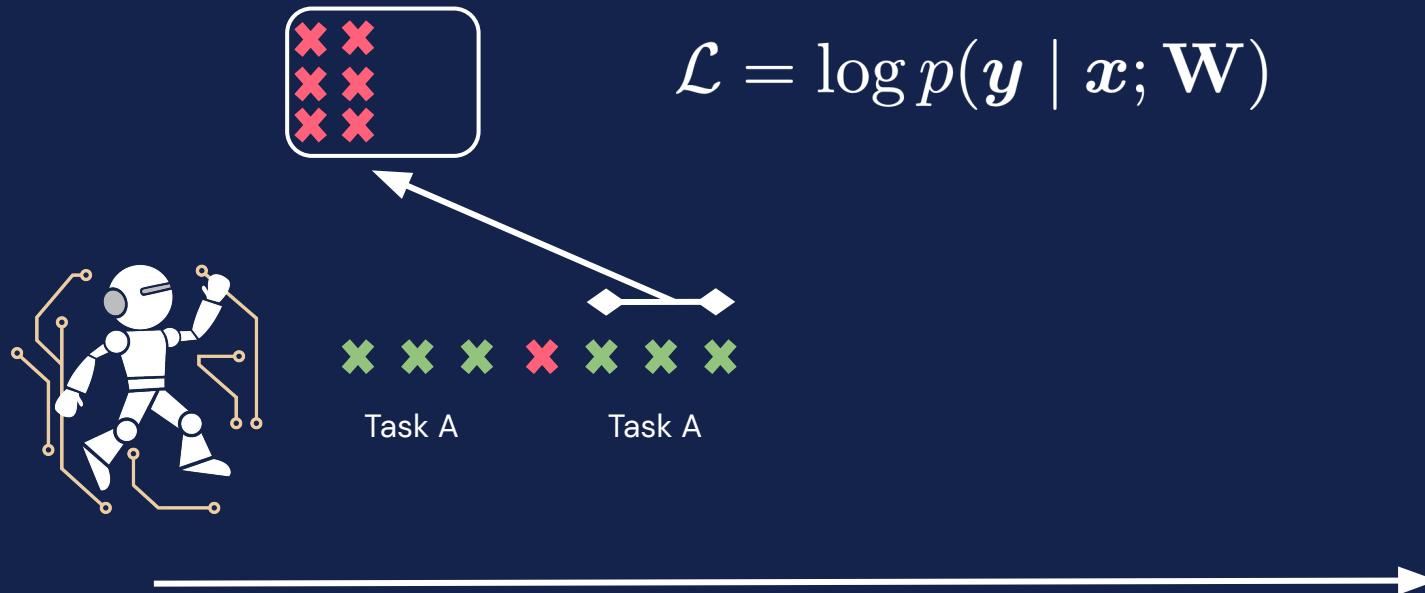
Training

Sparse experience replay: retrain on randomly sampled examples from the memory at a 1% rate.



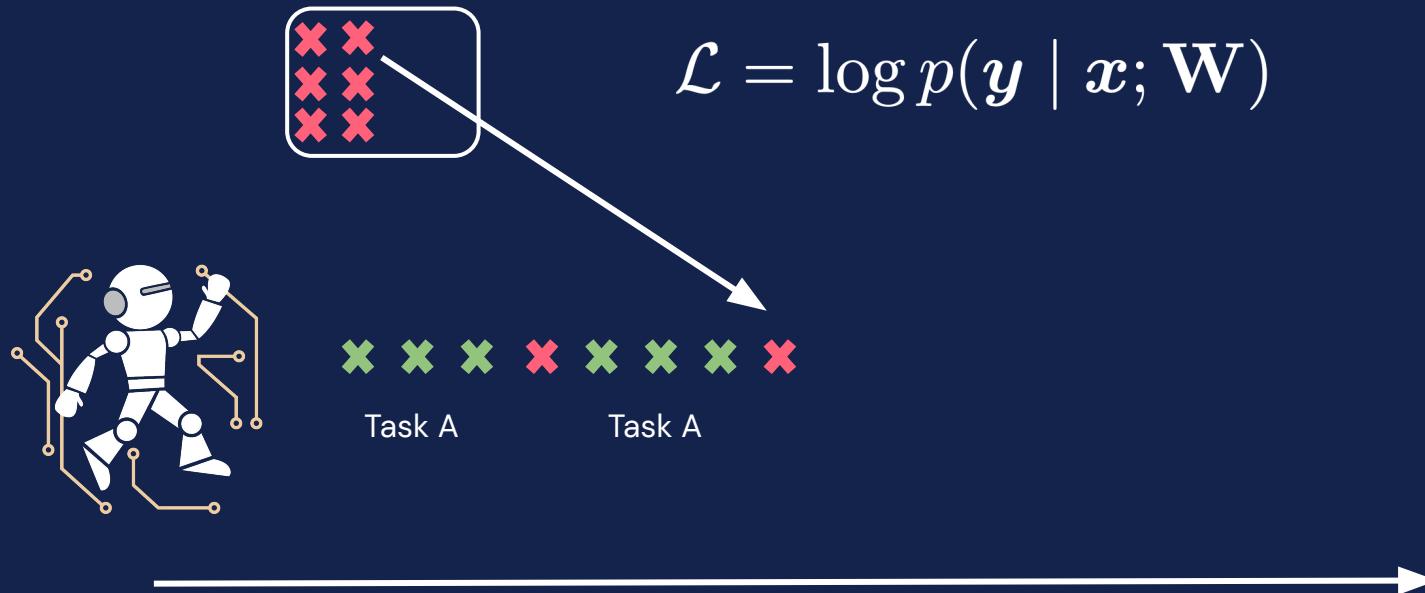
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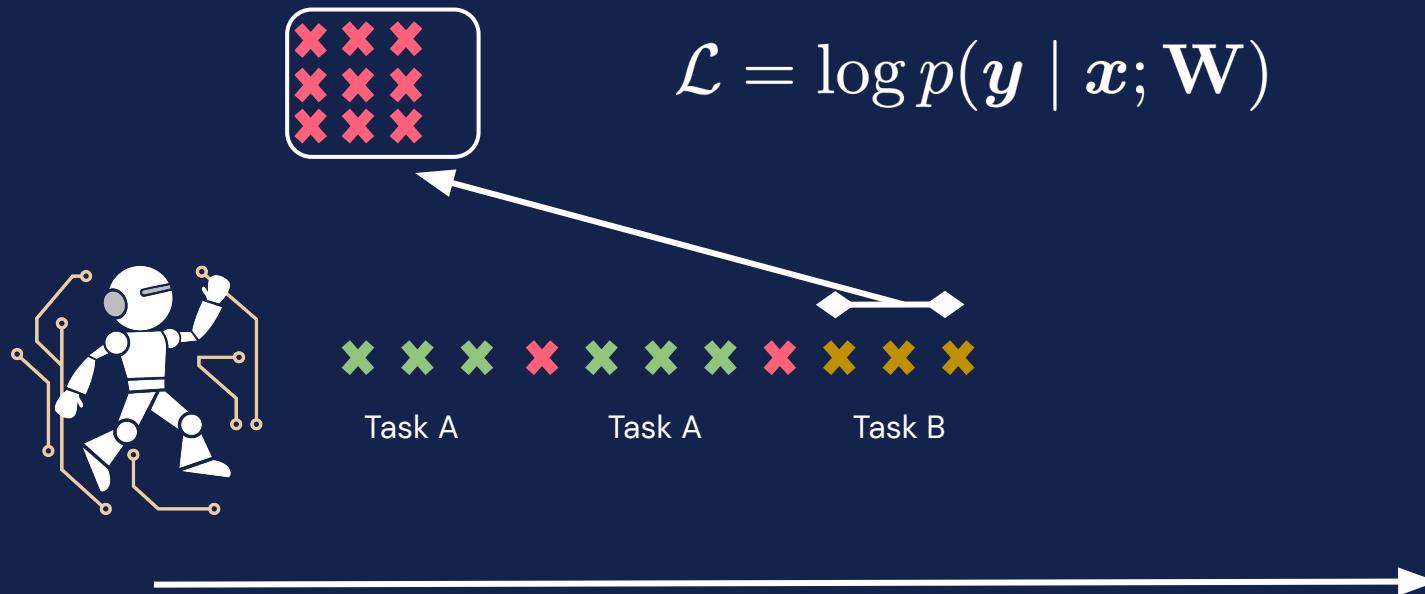
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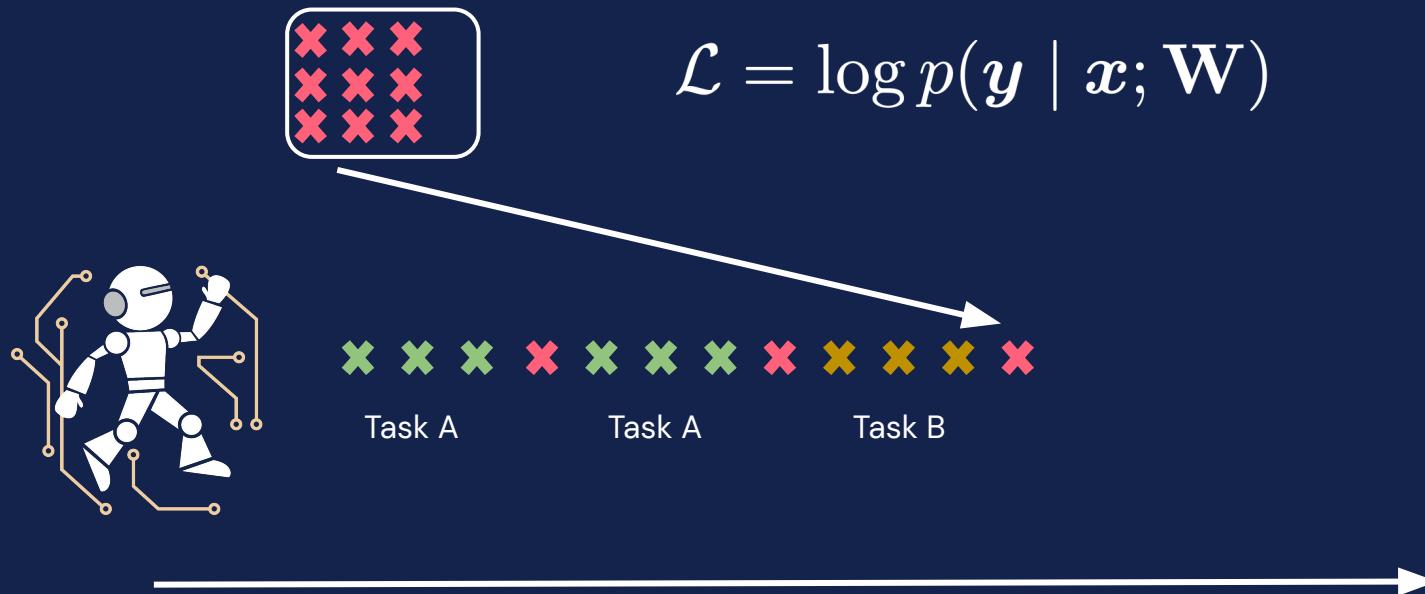
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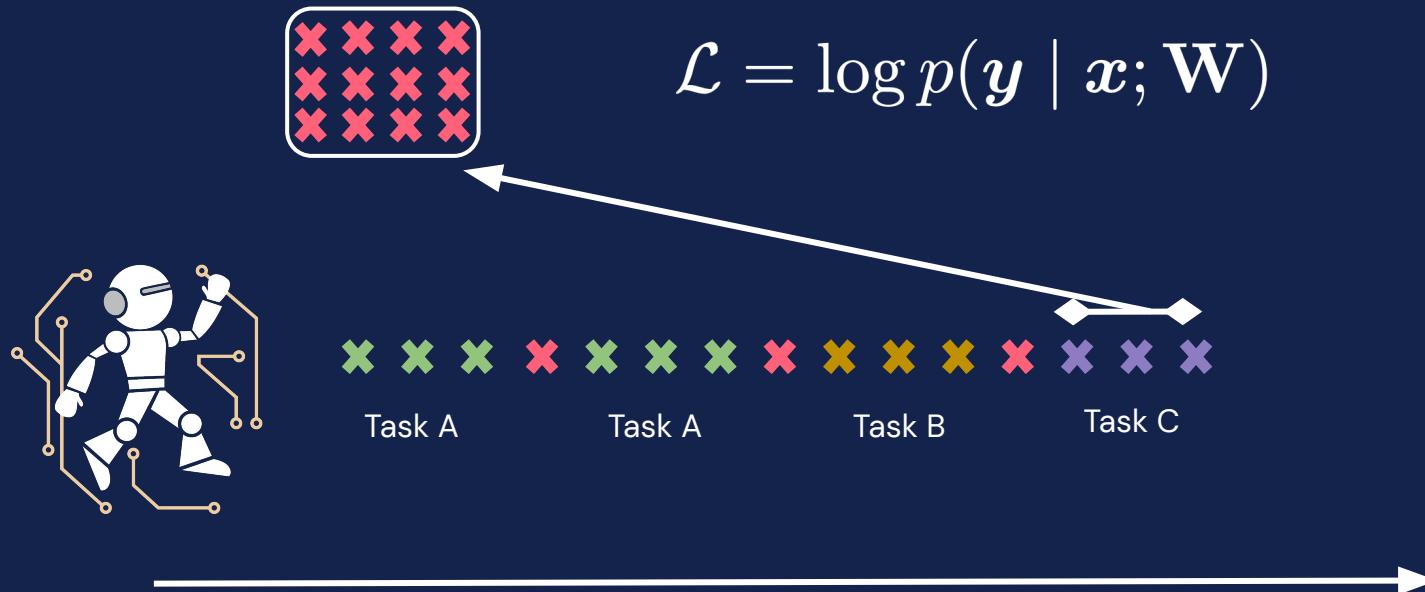
Training

Sparse experience replay: retrain on randomly sampled examples from the memory at a 1% rate.



Training

Sparse experience replay: retrain on randomly sampled examples from the memory at a 1% rate.



Inference (Prediction)

Local adaptation (Sprechmann et al., 2018).



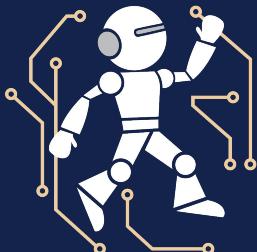
Inference (Prediction)

Local adaptation (Sprechmann et al., 2018).



Normans. The Normans (Norman: Nourmands; French: Normands; Latin: Normanni) were the people who in the 10th and 11th centuries gave their name to Normandy, a region in France. [...]

In what country is Normandy located?



Task A

Task A

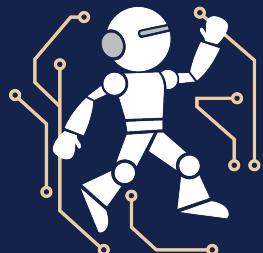
Task B

Task C



Inference (Prediction)

Local adaptation (Sprechmann et al., 2018).



K nearest
neighbors
retrieval

Normans. The Normans (Norman: Nourmands; French: Normands; Latin: Normanni) were the people who in the 10th and 11th centuries gave their name to Normandy, a region in France. [...]

In what country is Normandy located?

In what area of France is Calais located?

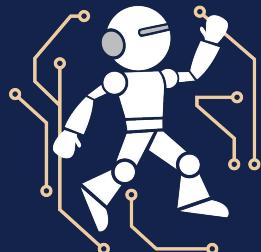
In what country is St John's located?

In what country is Spoleto located?

In what part of Africa is Palermo located?

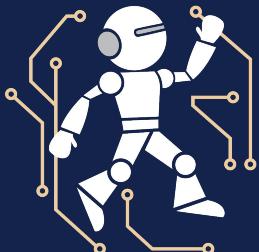
Inference (Prediction)

Local adaptation (Sprechmann et al., 2018).



Inference (Prediction)

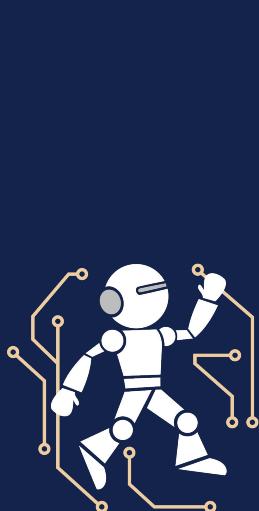
Local adaptation (Sprechmann et al., 2018).



$$\mathbf{W}_i = \arg \min_{\tilde{\mathbf{W}}} \lambda \|\tilde{\mathbf{W}} - \mathbf{W}\|_2^2 - \sum_{k=1}^K \alpha_k \log p(y_i^k \mid \mathbf{x}_i^k; \tilde{\mathbf{W}})$$

Inference (Prediction)

Local adaptation (Sprechmann et al., 2018).

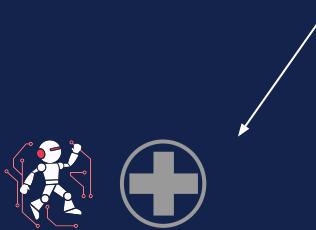


K nearest
neighbors
retrieval



Make a copy
of itself

Retrain the copy
on the retrieved
examples



Use the retrained
copy to predict

Experiments

- Four question answering datasets.
 - SQuAD: Rajpurkar et al., 2016.
 - TriviaQA-Web: Joshi et al., 2017.
 - TriviaQA-Wiki: Joshi et al., 2017.
 - QuAC: Choi et al., 2018.
- The contexts come from **different domains** (e.g., Wikipedia articles, web pages).
- The questions are posed in **different styles** (e.g., information seeking, trivia questions).

Experiments

F1 scores (0-100), higher is better

	Enc-Dec	A-GEM	MbPA	Ours
QA	53.1	56.2	60.3	62.4

A-GEM: Chaudhry et al., 2019

MbPA: Sprechmann et al., 2018

Takeaways and Limitations

- Episodic memory allows a language model to deal with changes in data distribution.

Takeaways and Limitations

- Episodic memory allows a language model to deal with changes in data distribution.
- Linear **space complexity** in the number of examples, **constant** is more realistic.

% of stored examples in memory	10%	100%
Performance	61.5	62.0

Memory in Humans

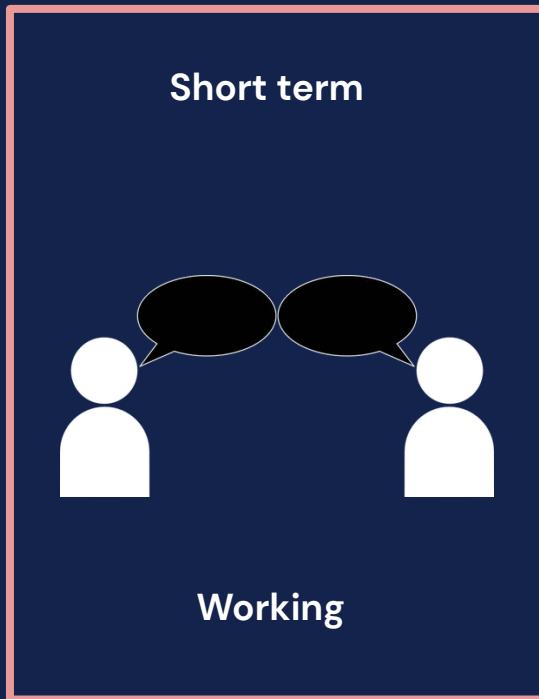
Human language processing is facilitated by specialized memory systems.

(Tulving, 1985; Rolls, 2000; Eichenbaum, 2012)

Memory in Humans

Human language processing is facilitated by specialized memory systems.

(Tulving, 1985; Rolls, 2000; Eichenbaum, 2012)

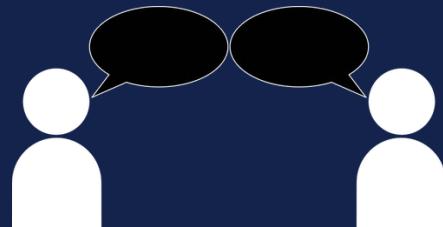


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Short term



Working

Long term

Implicit



ML is fun

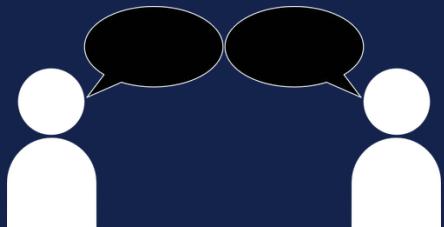
Procedural

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Semantic



Episodic

Memory in AI

Short term	Long term
LSTM (Hochreiter and Schmidhuber, 1997)	Memory Networks (Weston et al, 2015)
Differentiable Neural Computers (Graves et al, 2016)	Never-Ending Language Learning (Mitchell et al, 2015)
Reformer (Kitaev et al., 2020)	Matching Networks (Vinyals et al, 2016)
Transformer XL (Dai et al., 2019)	REALM (Guu et al, 2020)

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Stack LSTM

Yogatama et al., ICLR 2018

Memory-based Parameter Adaptation ++

de Masson d'Autume, Ruder, Kong, Yogatama, NeurIPS 2019

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A language model with short-term and long-term memory.

Future Directions



A language model that continually **learns in an efficient way** to perform **multiple complex tasks** in many languages.

Generative Models

Future Directions



A language model that continually **learns in an efficient way** to perform **multiple complex tasks** in many languages.

Modelling Latent Skills for Multitask Language Generation Cao and Yogatama, arXiv 2020



Kris



Dani

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Memory

Future Directions



A language model that **continually learns** in an efficient way to perform multiple **complex tasks** in many languages.

Adaptive Semiparametric Language Models

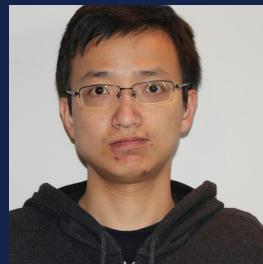
Yogatama et al., TACL 2021



Dani



Cyprien



Lingpeng

Future Directions



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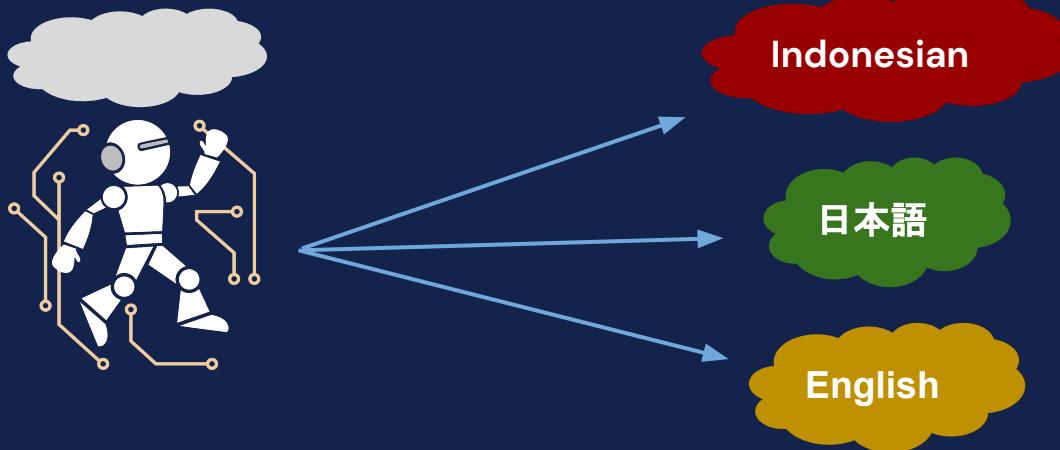
Representation Learning

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Representation Learning

On the Crosslingual Transferability of Monolingual Representations

Artetxe et al., ACL 2020



Mikel



Sebastian



Dani

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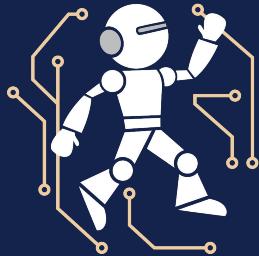


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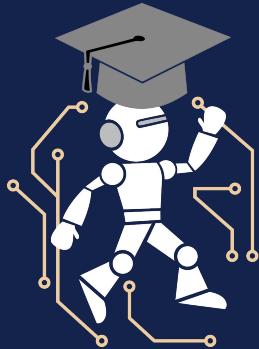


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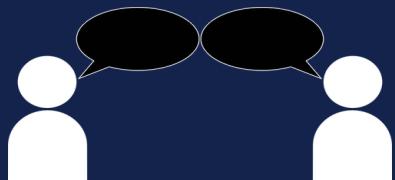


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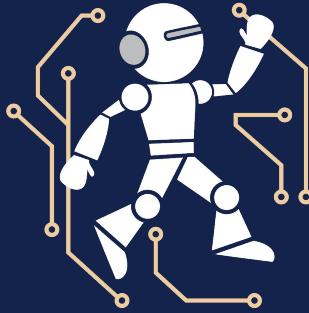


Semantic



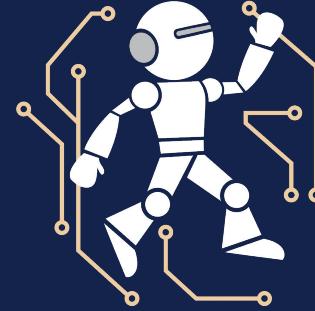
Episodic

Challenges: Human Learning vs. Machine Learning



	Machine
Acquisition	Large datasets (representation learning)
Task Training	Large datasets (supervised fine tuning)
Linguistic knowledge	Dataset specific
Generalization	Forget previous tasks given a new task

Challenges: Human Learning vs. Machine Learning



Human		Machine
“Large” datasets	Acquisition	Large datasets (representation learning)
Few examples	Task Training	Large datasets (supervised fine tuning)
Dataset agnostic	Linguistic knowledge	Dataset specific
Generalizable to new tasks	Generalization	Forget previous tasks given a new task

Research Areas



A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Research Areas



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Yogatama and Mann; AISTATS 2014

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Reasoning, interactions with other modalities, robustness, fairness, and others.

Experiments

Perplexity (1-inf), lower is better

	Base	TXL	kNN-LM	Ours
WikiText-103	21.8	19.1	18.0	17.6*
WMT	16.5	15.5	15.2	14.1

$$\lambda p_{k\text{NN}}(x_t \mid \mathbf{x}_{<t}) + (1 - \lambda)p_{\text{LM}}(x_t \mid \mathbf{x}_{<t})$$

kNN-LM: Khandelwal et al., 2020