Toward General Linguistic Intelligence

Dani Yogatama

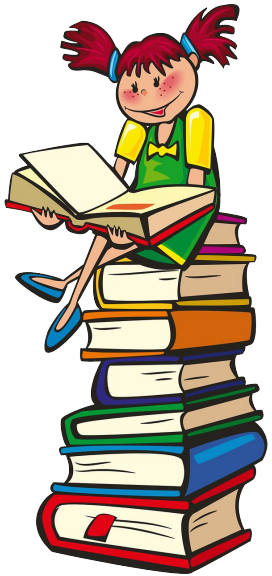
DeepMind

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).

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) from textual data to **adapt to new tasks quickly without forgetting old ones**.

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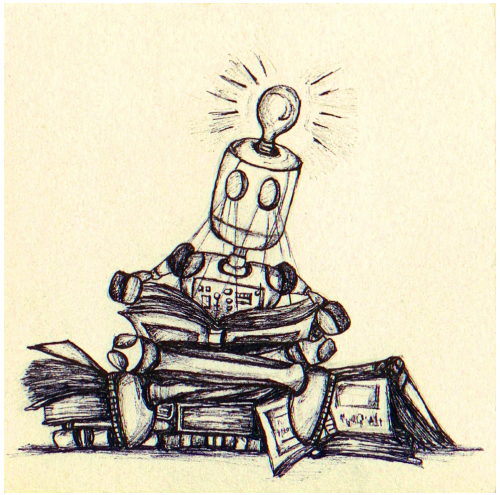

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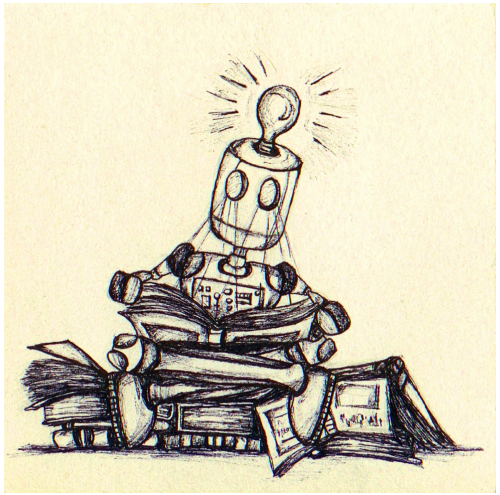
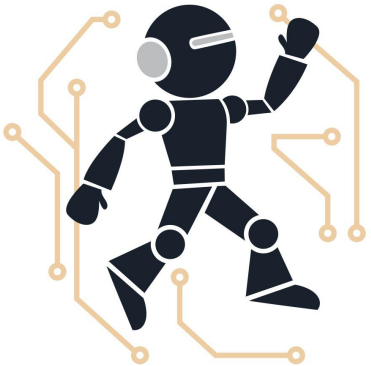


Challenges: Human Learning vs. Machine Learning

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

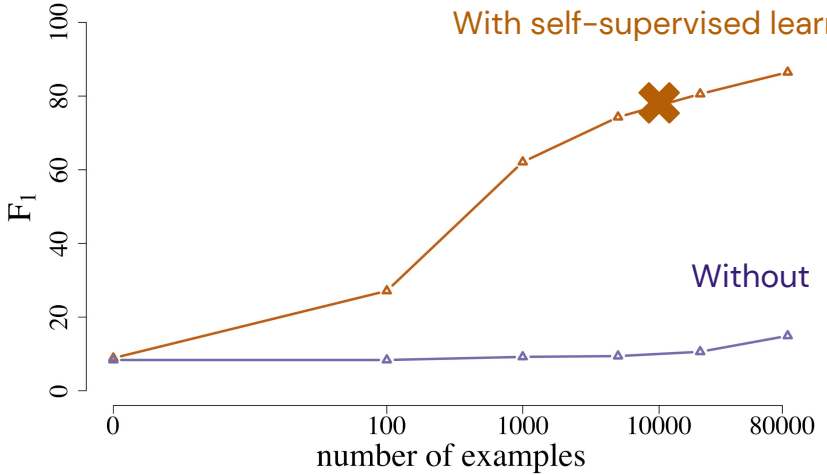
Challenges: Human Learning vs. Machine Learning



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

The State of Natural Language Processing

- Current models still require many in-domain training examples.



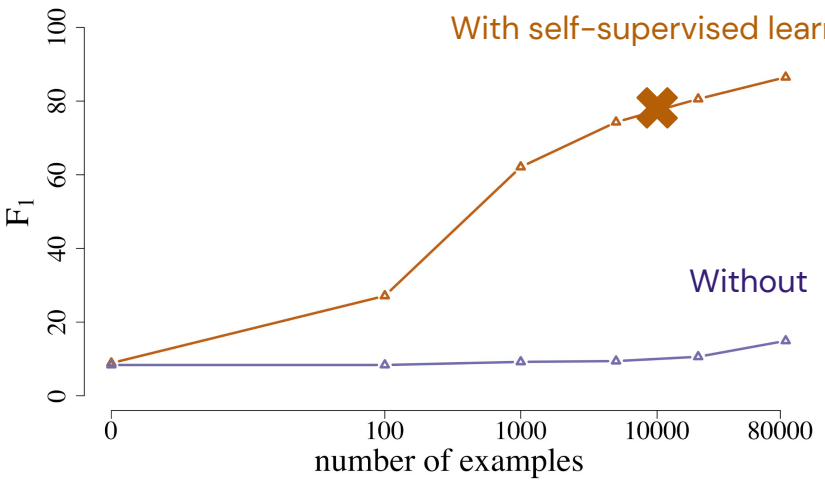
Yogatama et al., arXiv 2019

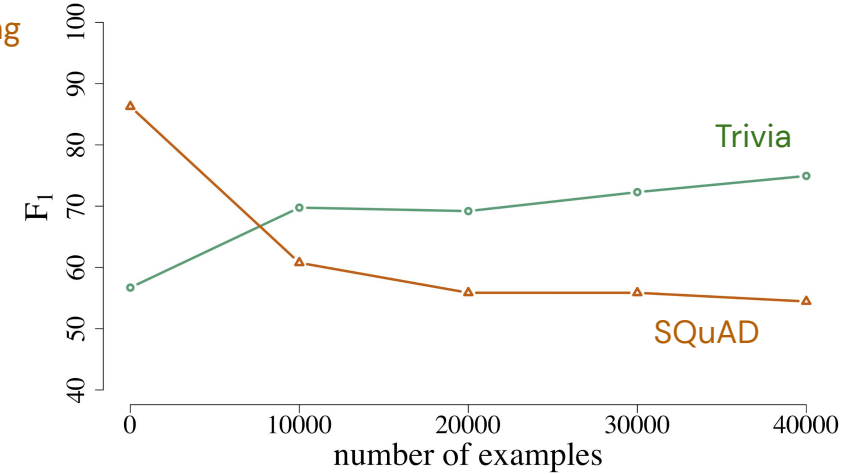
Model: BERT, Devlin et al. 2019

QA dataset: SQuAD, Rajpurkar et al., 2016

The State of Natural Language Processing

- Current models still require many in-domain training examples.
- They overfit to a specific dataset (task) and often forget.





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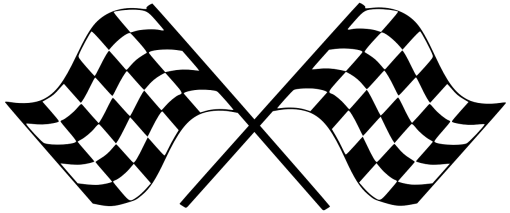
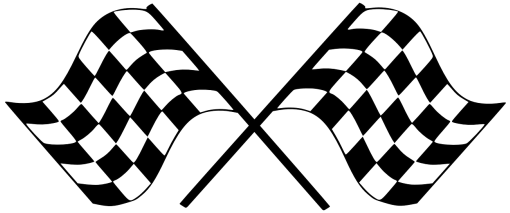
QA dataset 2: Trivia, Joshi et al., 2017

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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Yogatama and Mann; AISTATS 2014

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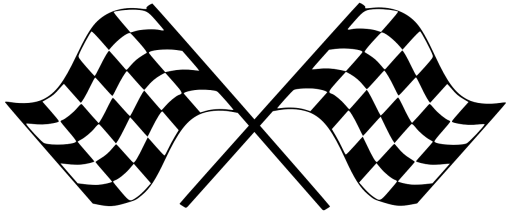

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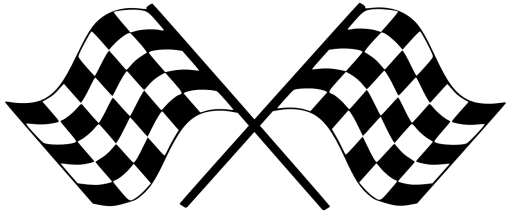

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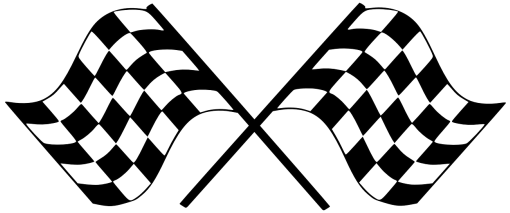

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+

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

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

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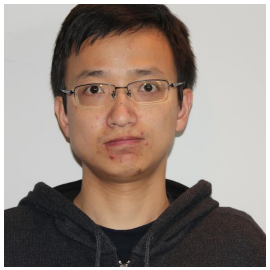
Cyprien

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 (McCloseky and Cohen, 1989; Ratcliff, 1990).

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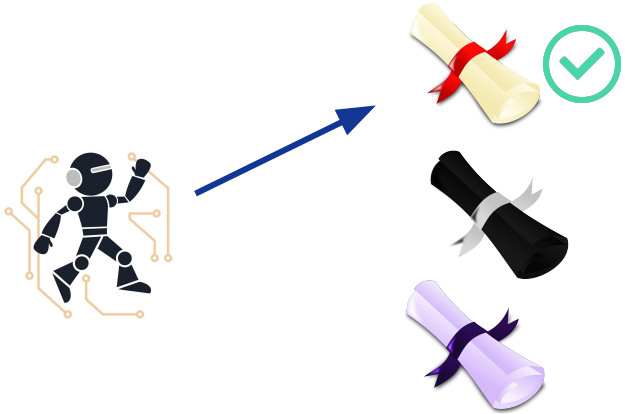

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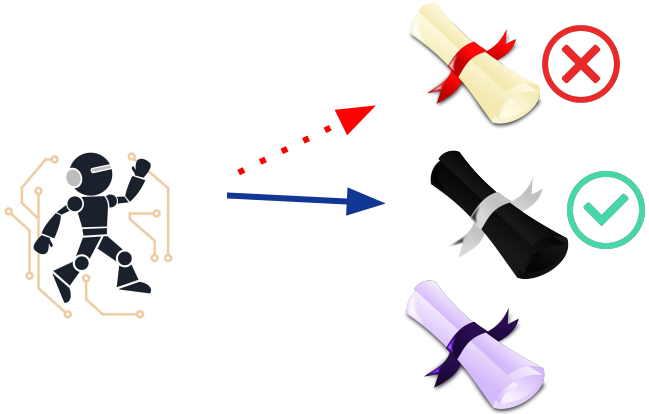

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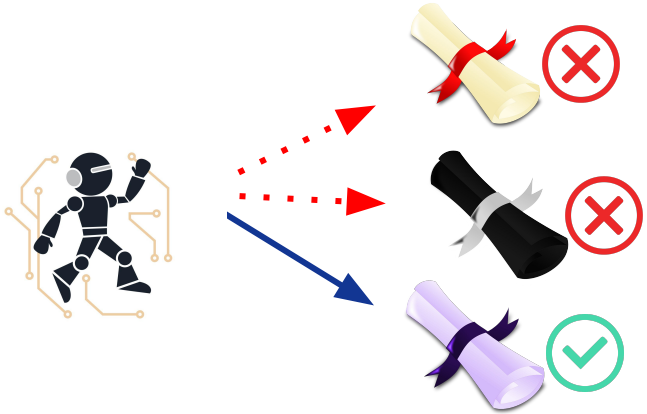

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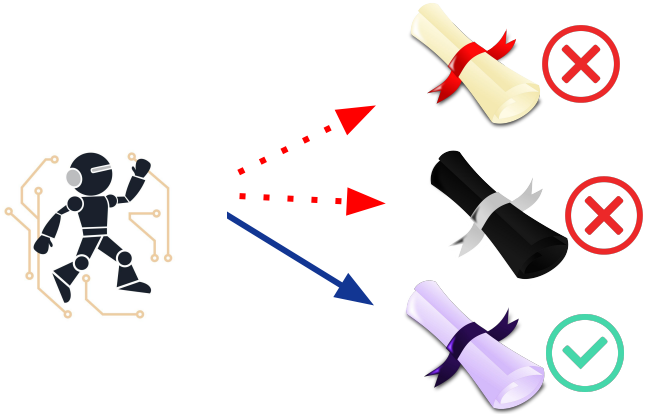
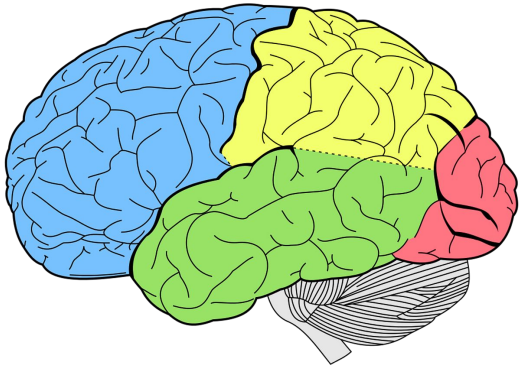


Hypothesis: episodic memory mitigates catastrophic forgetting in language learning.

On Memory-Augmented Neural Networks



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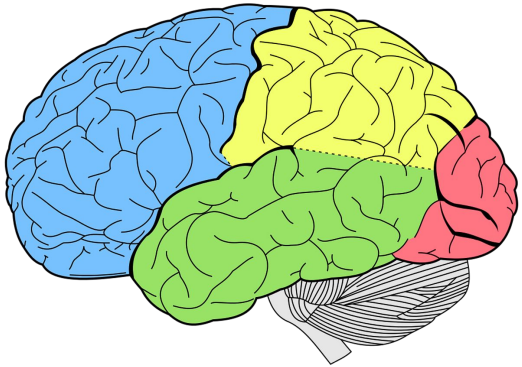

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Contrast this with short-term **working memory** in LSTMs (Hochreiter and Schmidhuber, 1997) and DNCs (Graves et al., 2016) that e.g., remembers context.

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

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?

Training

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

Problem Setup

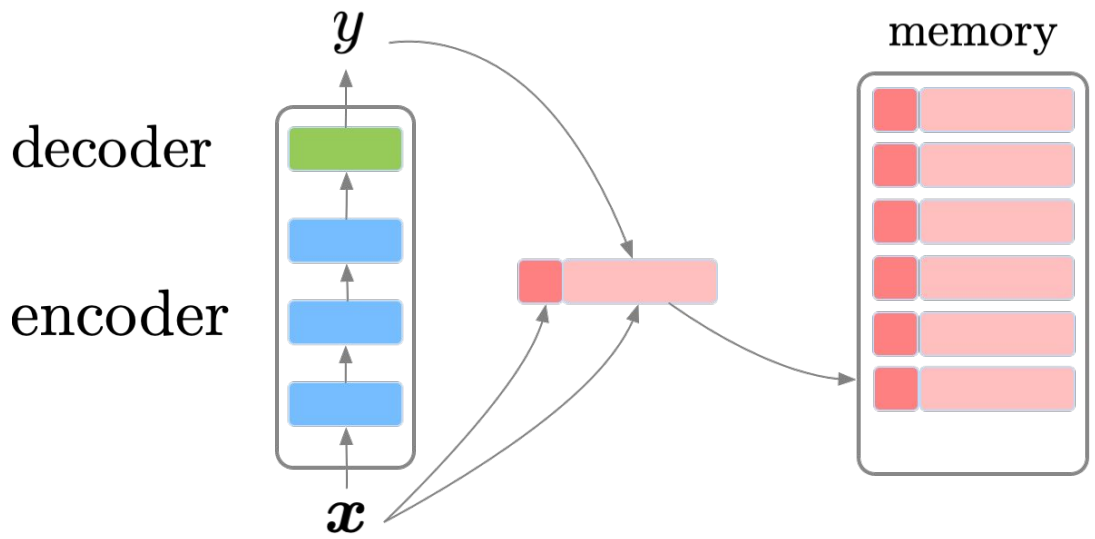
Training

Never-Ending Language Learning

Mitchell et al., 2015

Test

Question Answering Model



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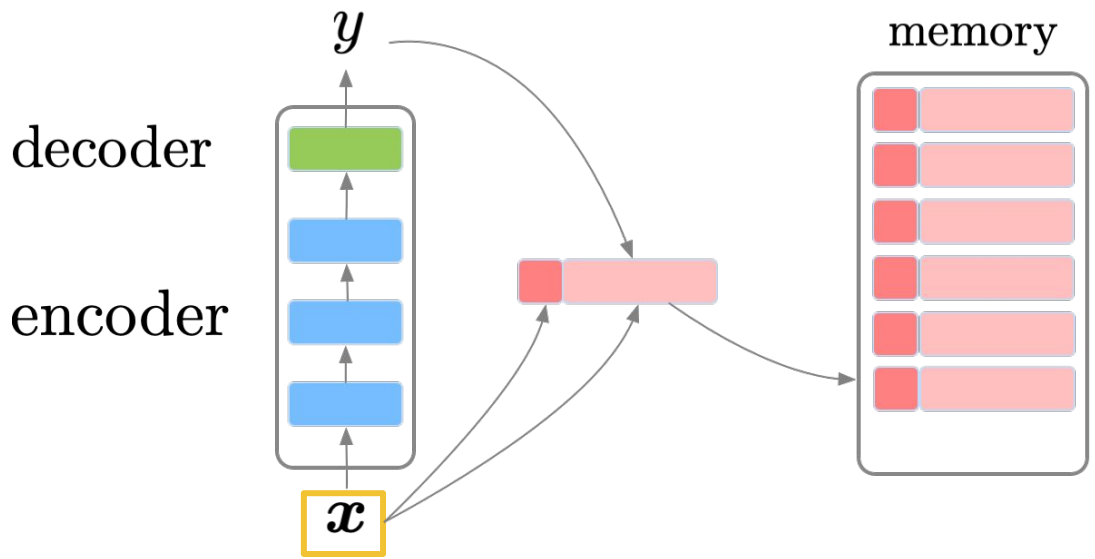
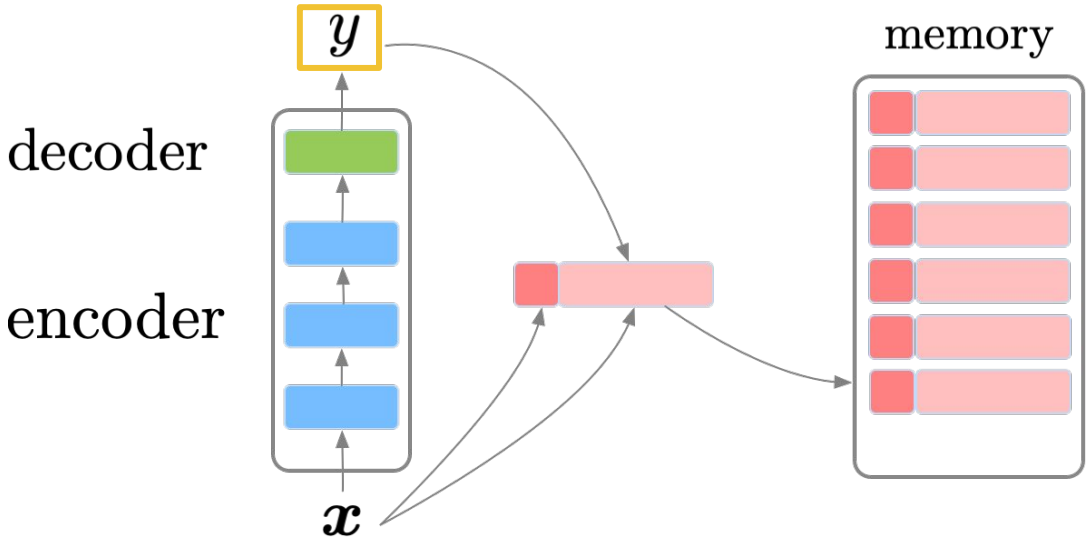


Input: a concatenation of context (e.g., a Wikipedia article) and question.

Question Answering Model

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



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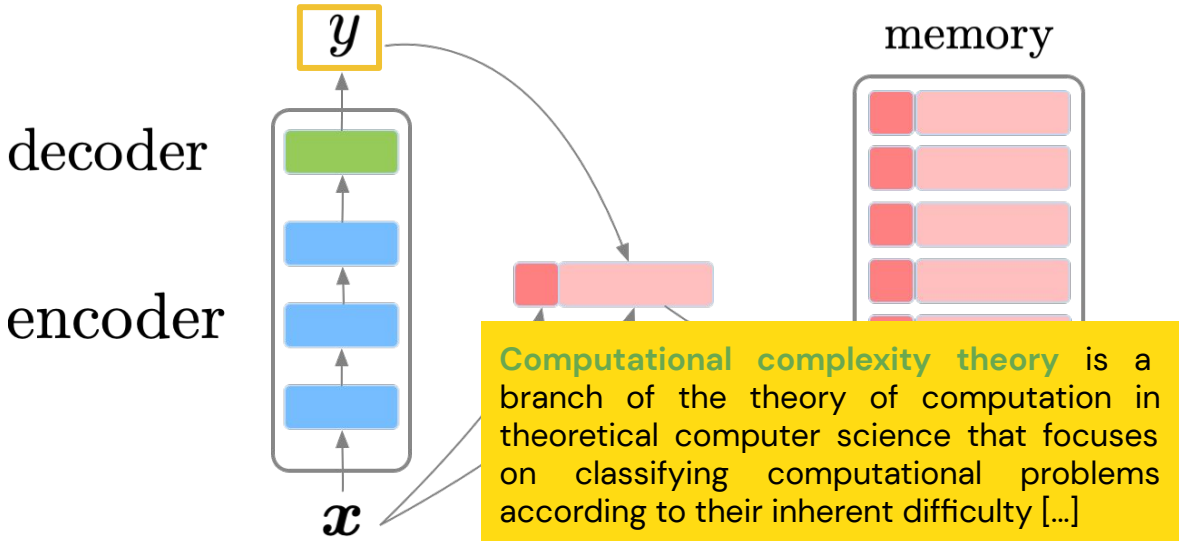

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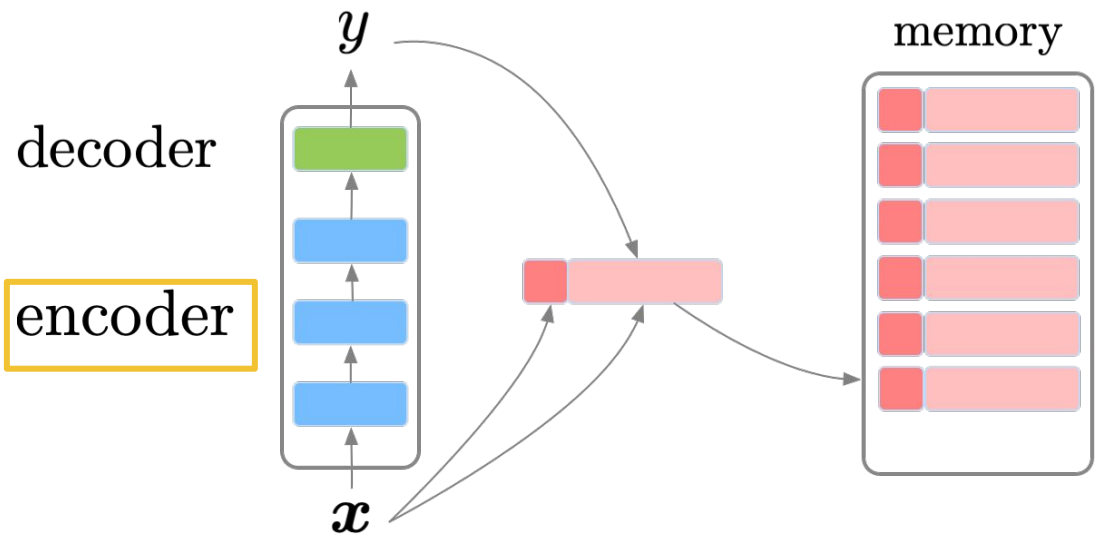
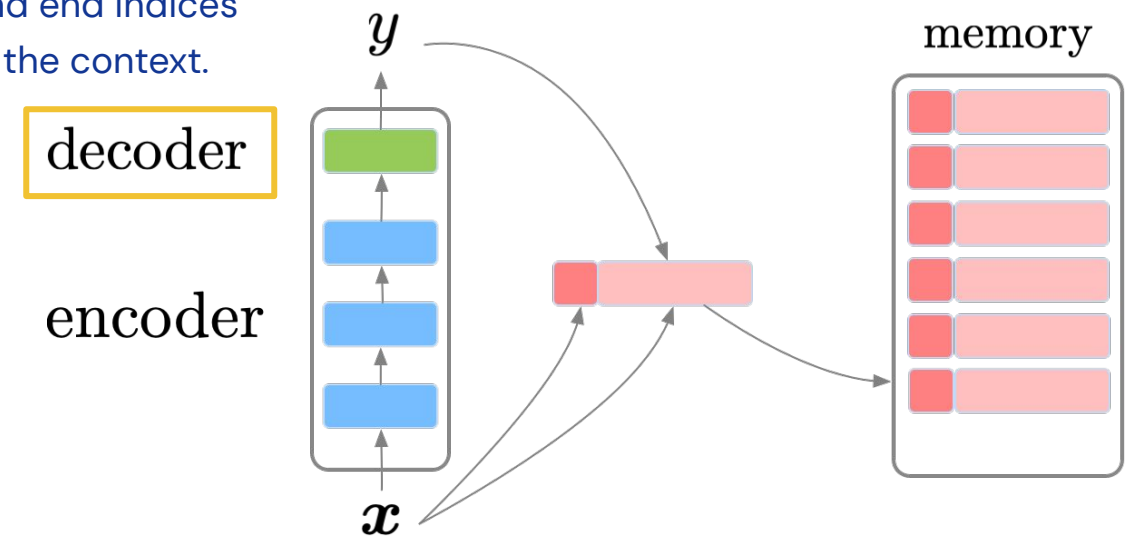


Encoder: a large neural network, e.g., ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), XLNet (Yang et al., 2019).

Question Answering Model

Decoder: a linear function that predicts start and end indices of the answer in the context.



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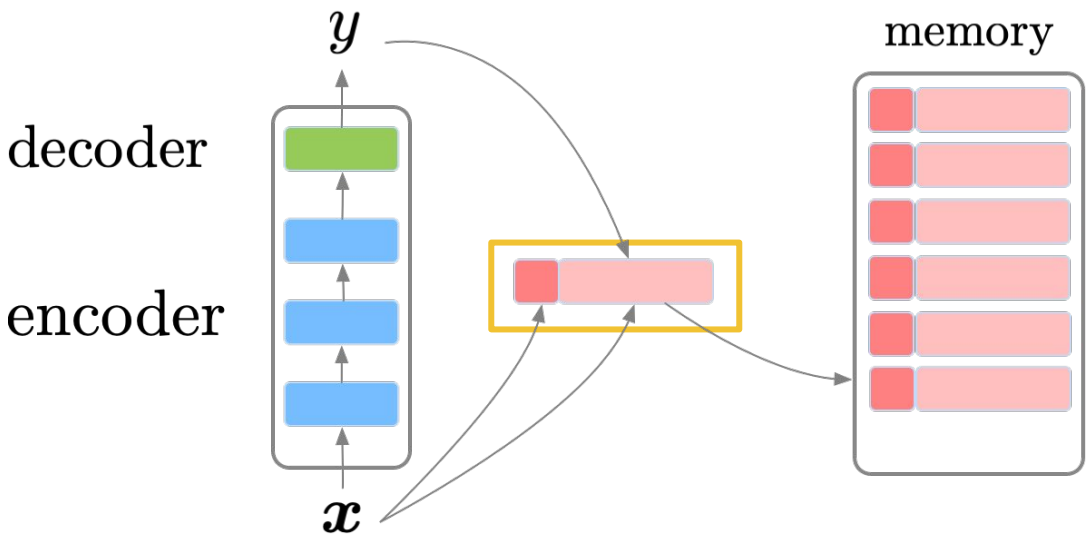
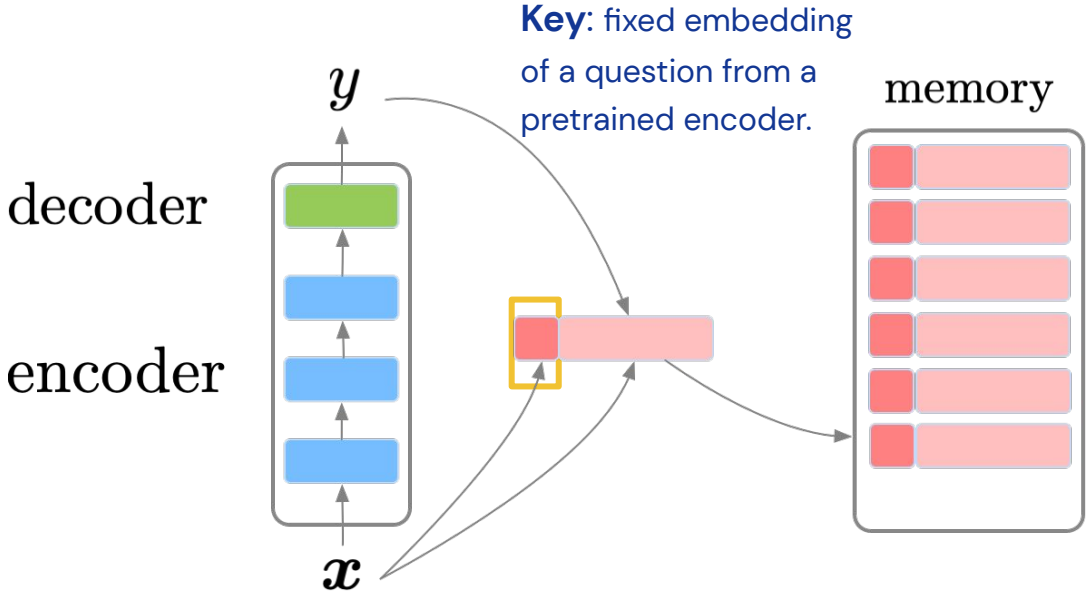


Memory entry: a key, value pair

Question Answering Model



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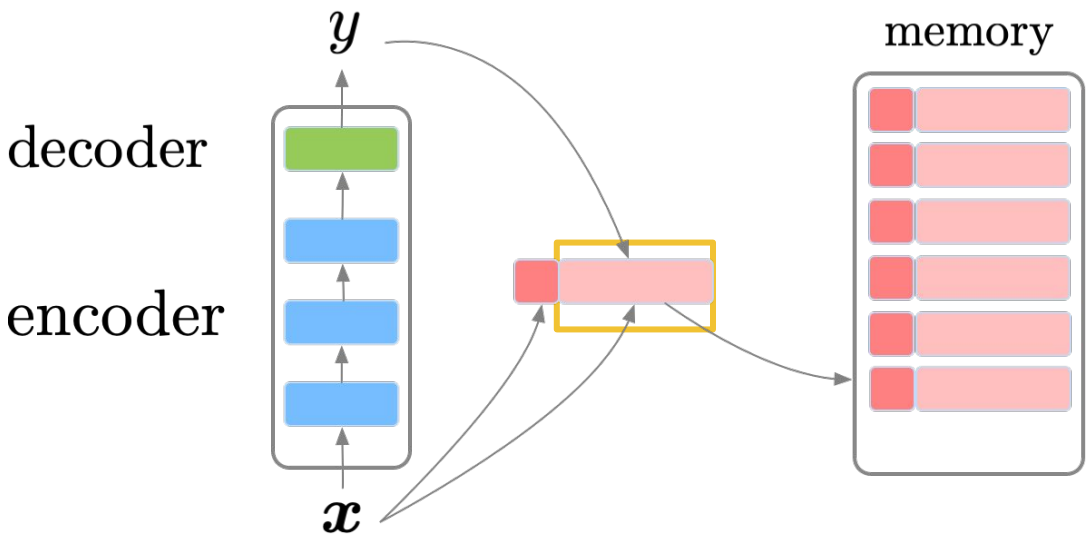
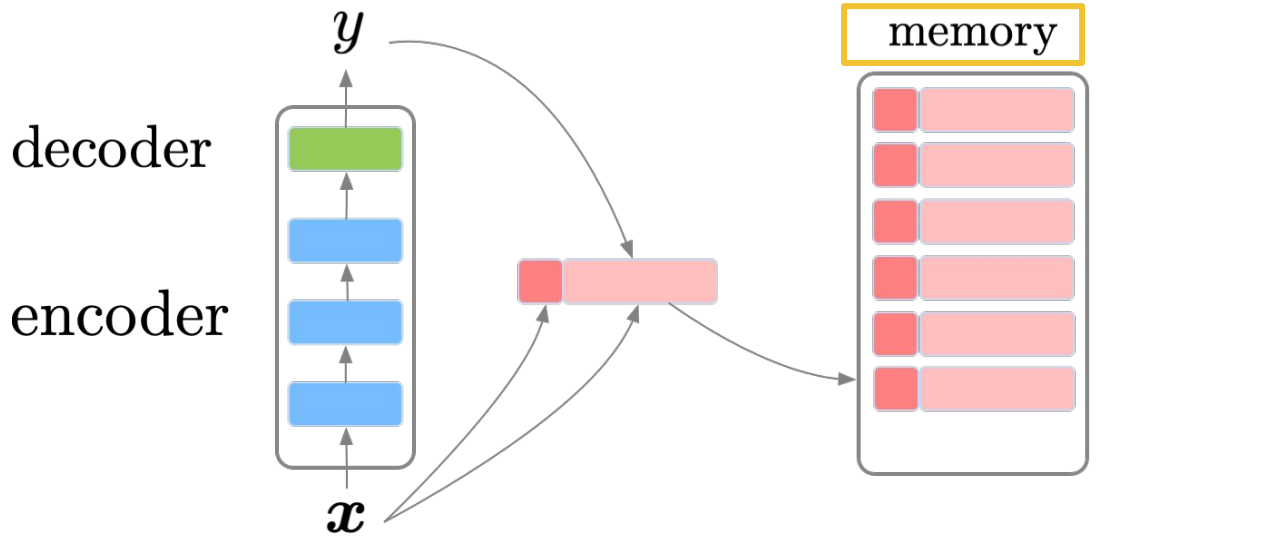


Value: context, question, and answer in textual forms (strings).

Question Answering Model

Memory: stores memory entries



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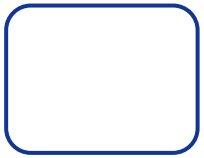
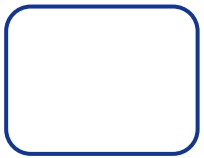


$$\mathcal{L} = \log p(\boldsymbol{y} \mid \boldsymbol{x}; \mathbf{W})$$

Task A

Training

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



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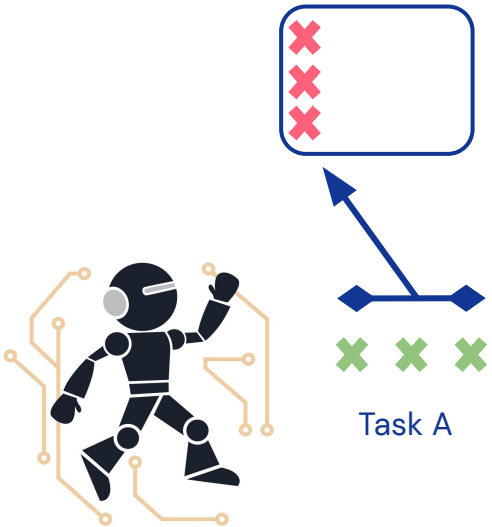

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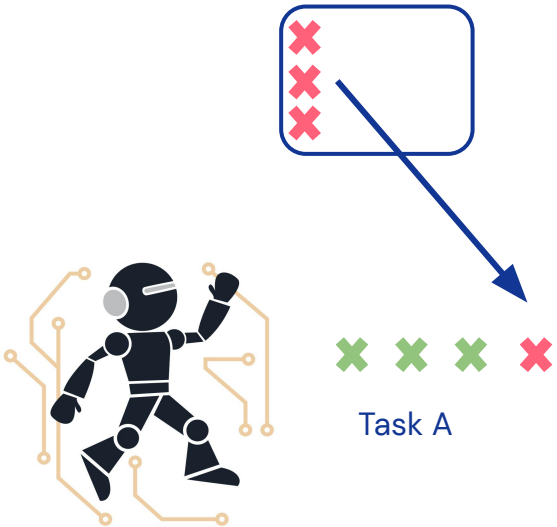

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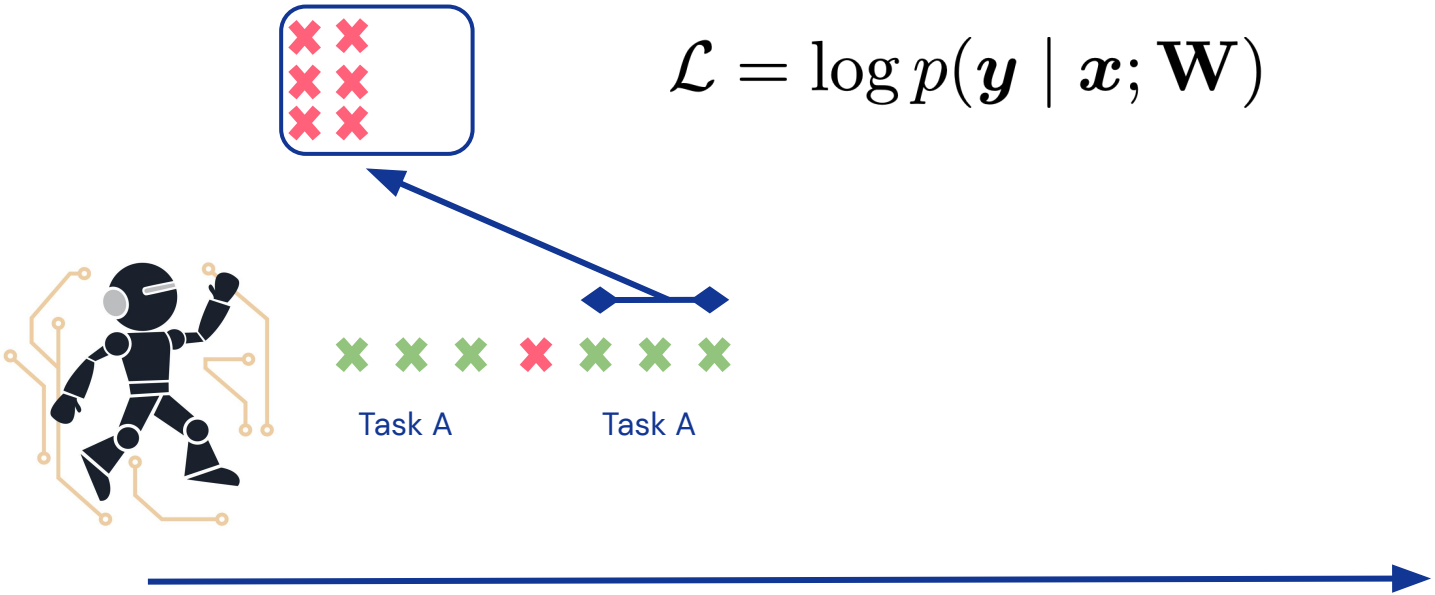

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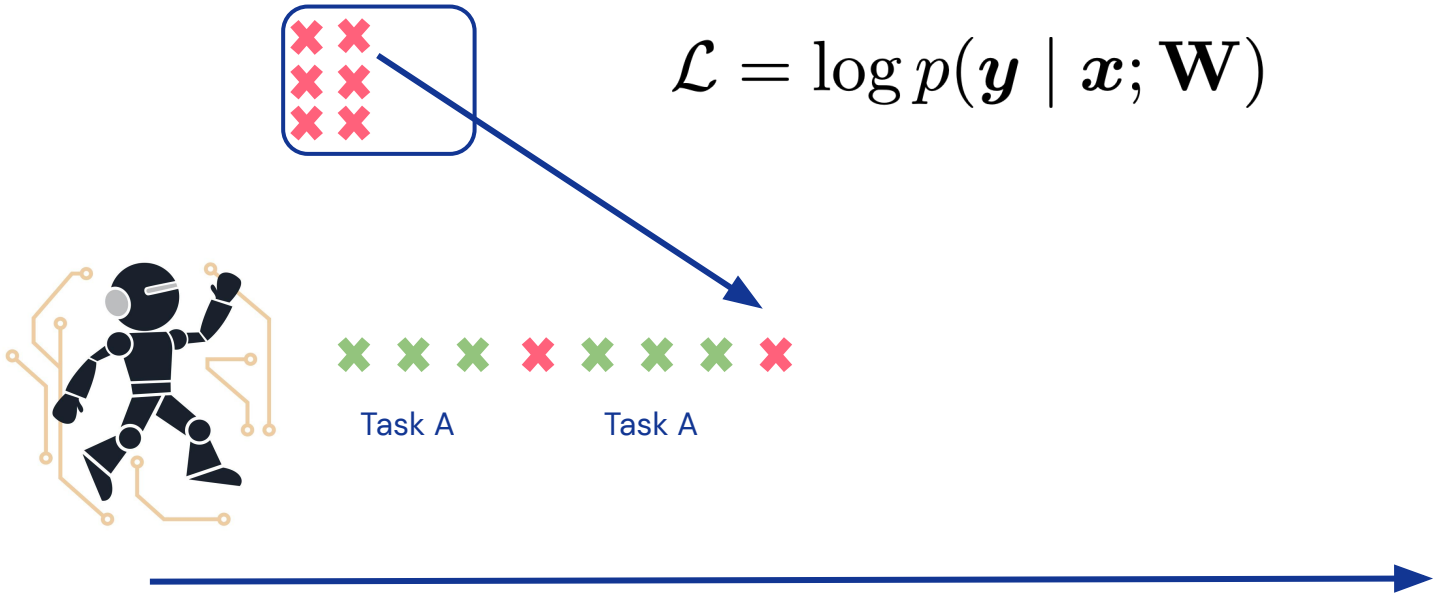

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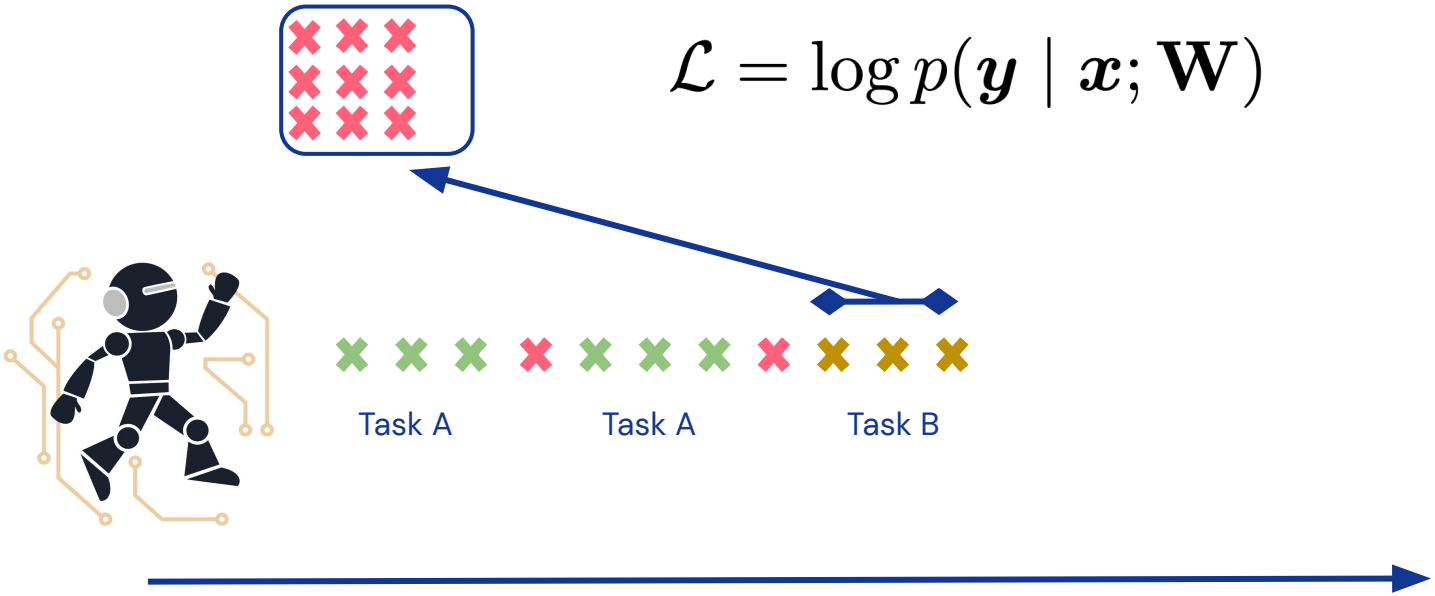

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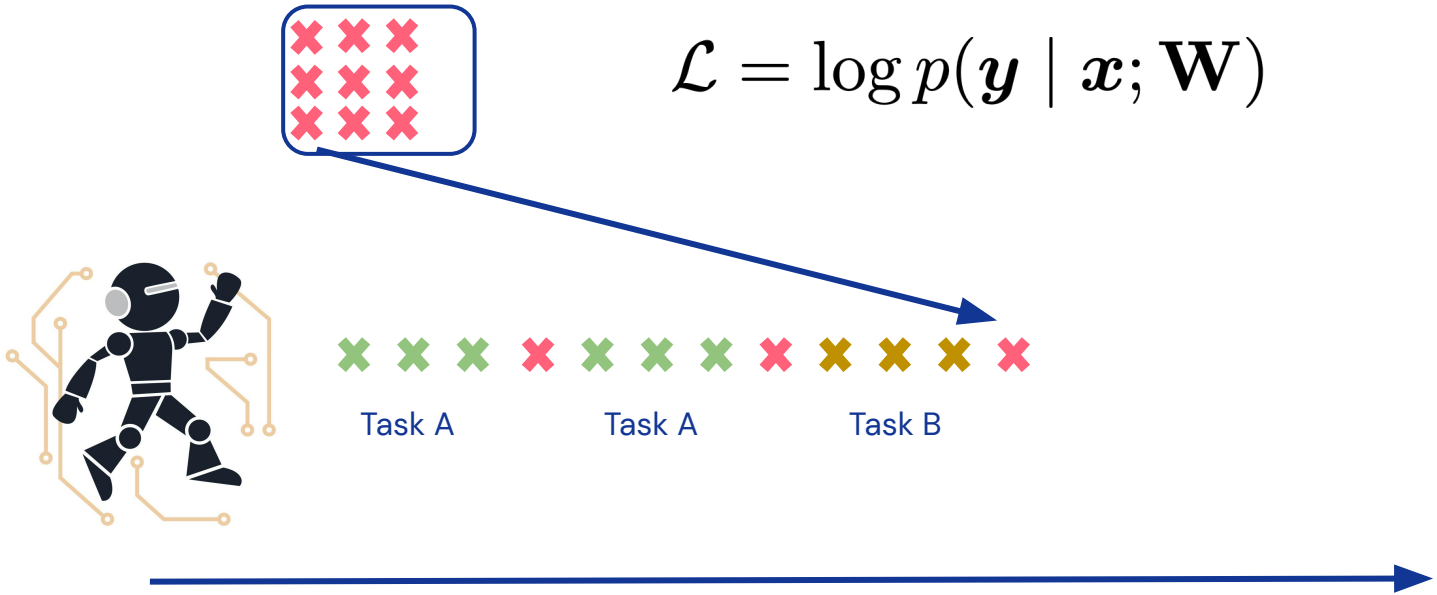

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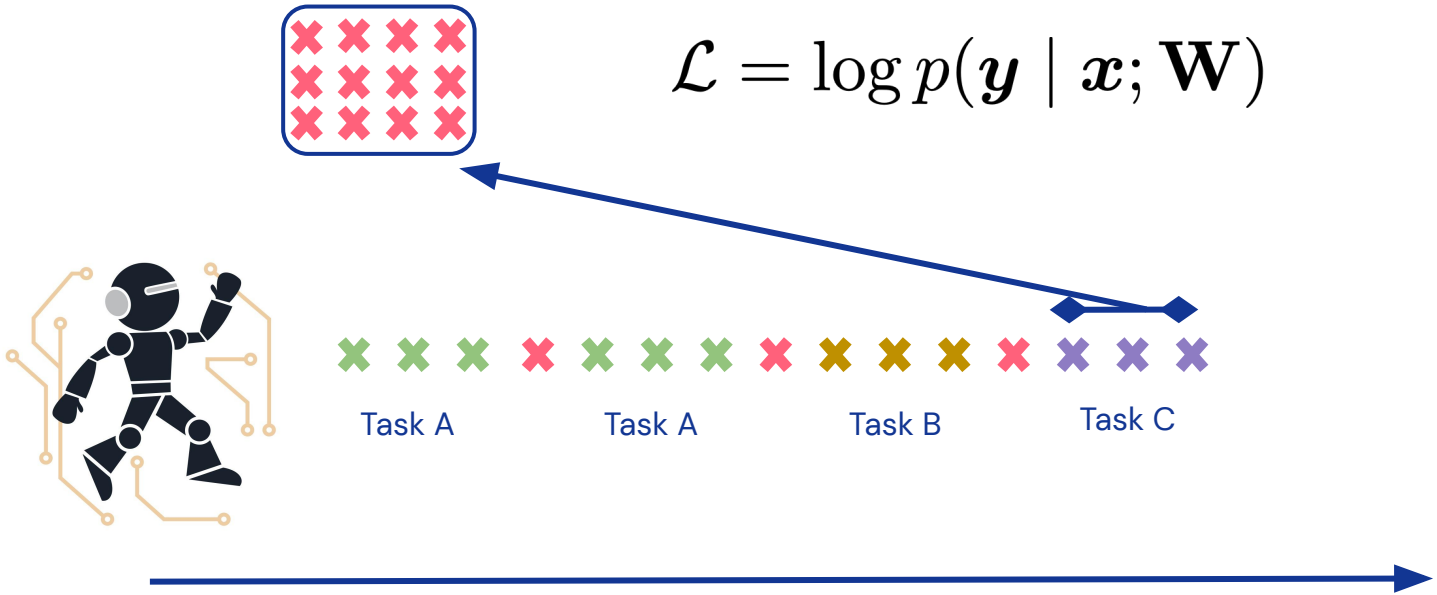
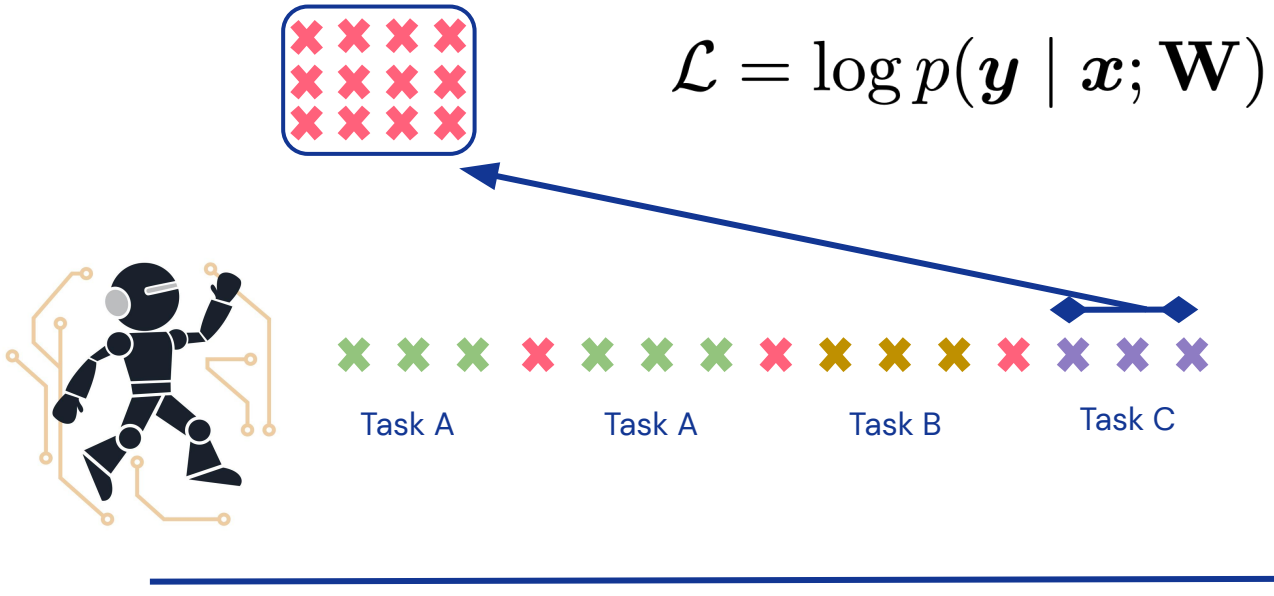


Training

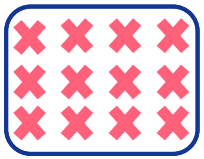
***Sparse* experience replay**: retrain on randomly sampled examples from the memory at a 1% rate.

Related to **memory consolidation** in human learning.



Inference (Prediction)

Local adaptation similar to MbPA (Sprechmann et al., 2018).



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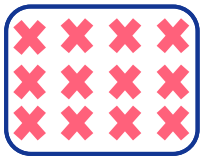

Normans. The Normans (Norman: Nourmands; French: Normands; Latin: Normanni) were the people who in the 10th and 11th centuries gave their name to Normandy, a region in France. [...]

In what country is Normandy located?

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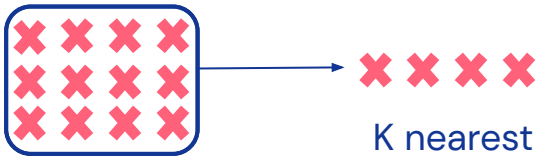


K nearest neighbors retrieval

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?

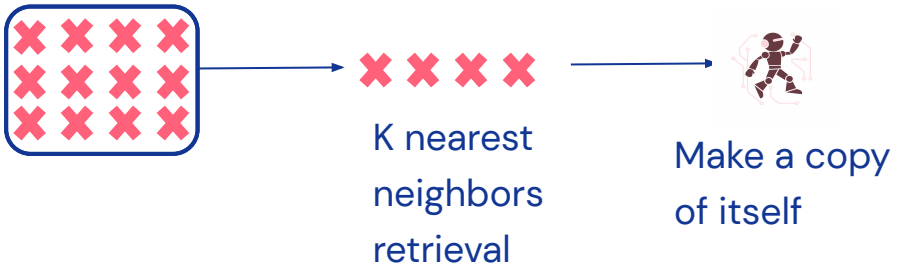
In what country is St John's located?

In what country is Spoleto located?

In what part of Africa is Palermo located?

Inference (Prediction)

Local adaptation similar to MbPA (Sprechmann et al., 2018).



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Local adaptation similar to MbPA (Sprechmann et al., 2018).

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

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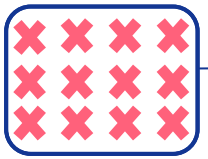

K nearest neighbors retrieval

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	Multitask (upper bound)
QA	53.1	56.2	60.3	**62.4**	67.8

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.

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- Linear **space complexity** in the number of examples, **constant** is more realistic.

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

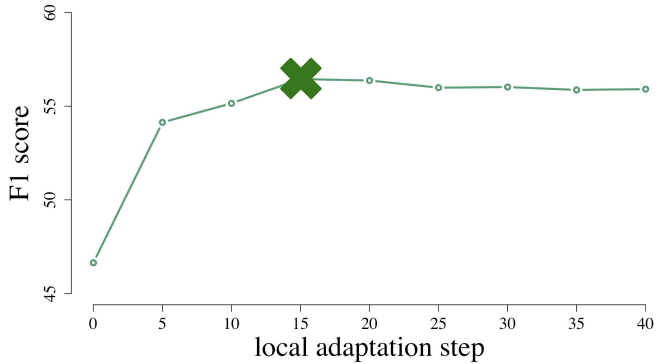
Takeaways and Limitations

- 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.

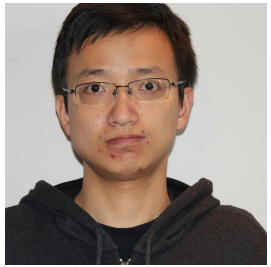
% of stored examples in memory	10%	100%
Performance	61.5	62.0

- Local adaptation at inference time is **computationally expensive**.



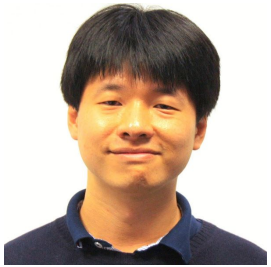
A Mutual Information Maximization Perspective of Language Representation Learning

Kong et al., ICLR 2020

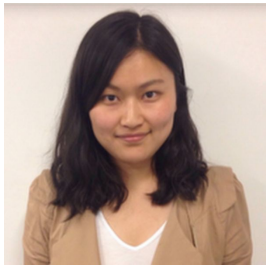


Lingpeng

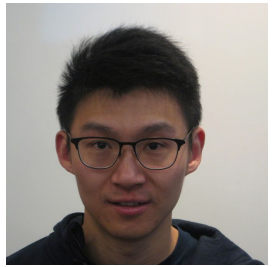
Cyprien



Wang



Lei

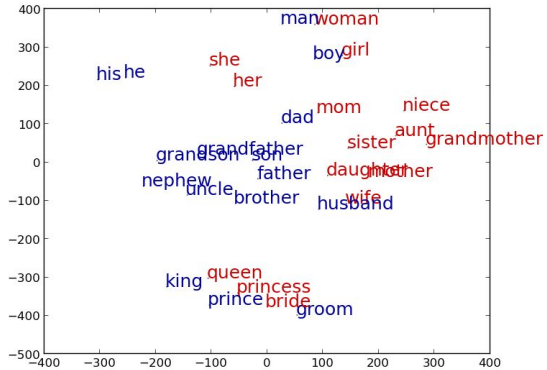


Zihang

Dani

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.

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Text Representations

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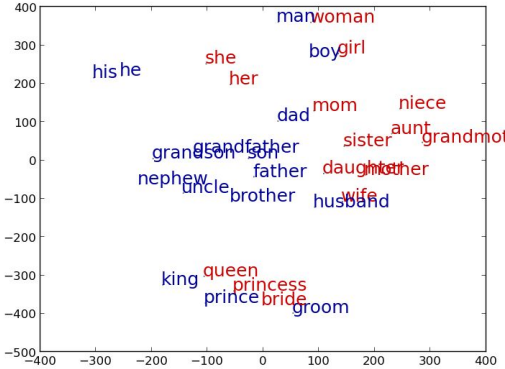

Hypothesis: these methods are different instances of one framework.

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Contrastive Learning

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

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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).

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

InfoNCE objective

Logeswaran and Lee, 2018

van den Oord, et al., 2019

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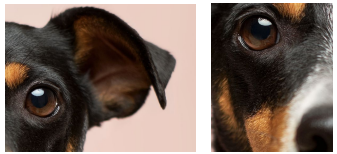

High when **a** and **b** go together

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

Contrastive Learning with InfoNCE

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Carnegie Mellon University is located in Pittsburgh

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Tokyo
London
dog
cat

a Carnegie Mellon University is located in b Pittsburgh

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Harvard University is located in Cambridge

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Tokyo
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Skip-gram

Mikolov et al., 2013

Carnegie Mellon University is located in Pittsburgh

Skip-gram

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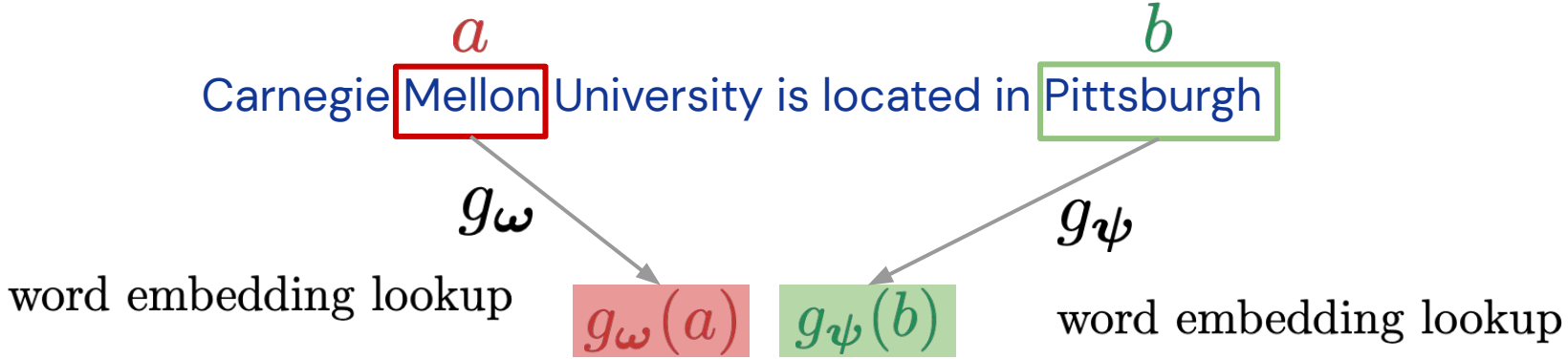

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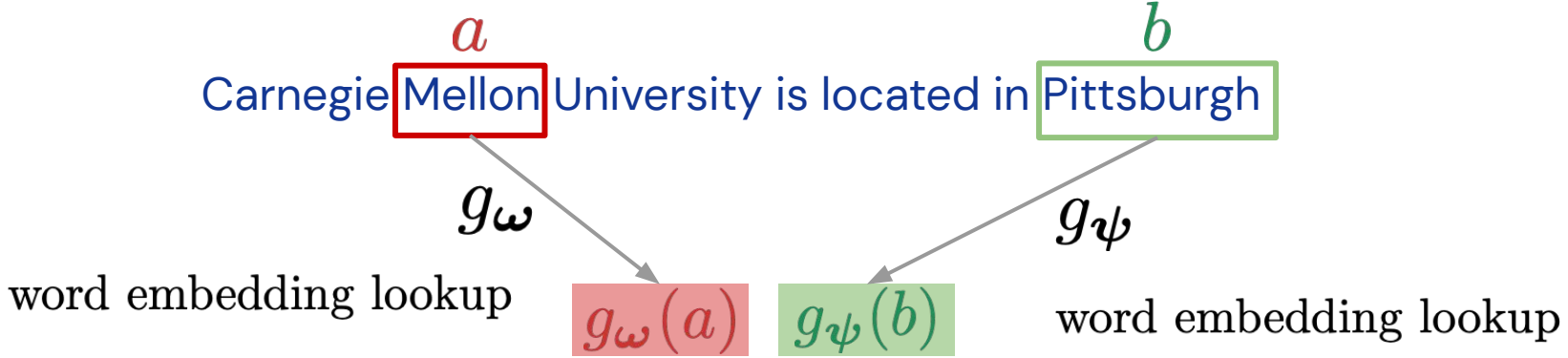

Noise Contrastive Estimation for learning word embeddings (Mnih and Kavukcuoglu, 2013)

BERT

Devlin et al., 2019

Carnegie Mellon University is located in Pittsburgh

BERT

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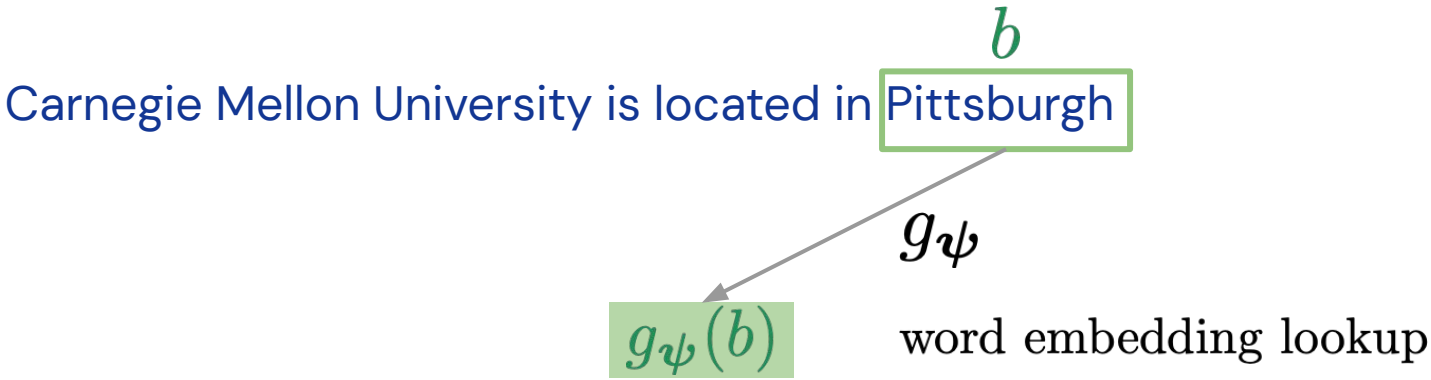

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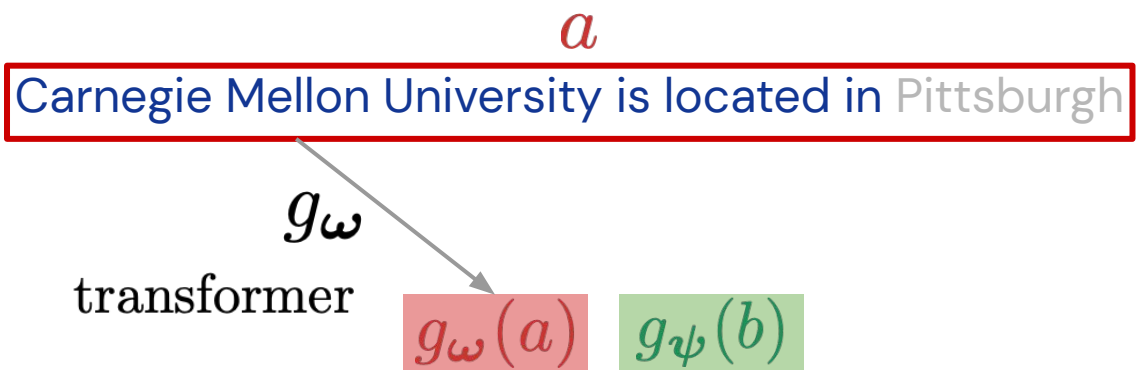

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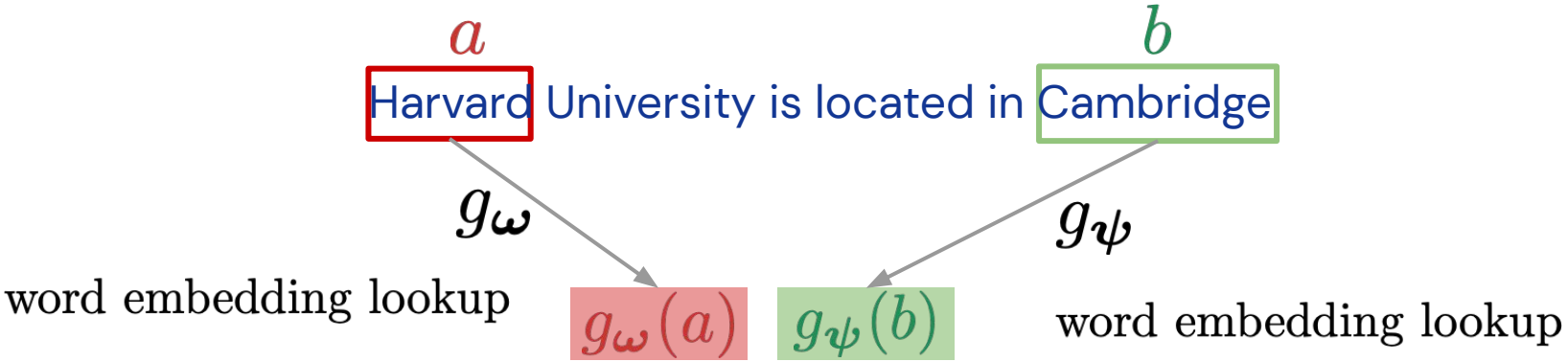

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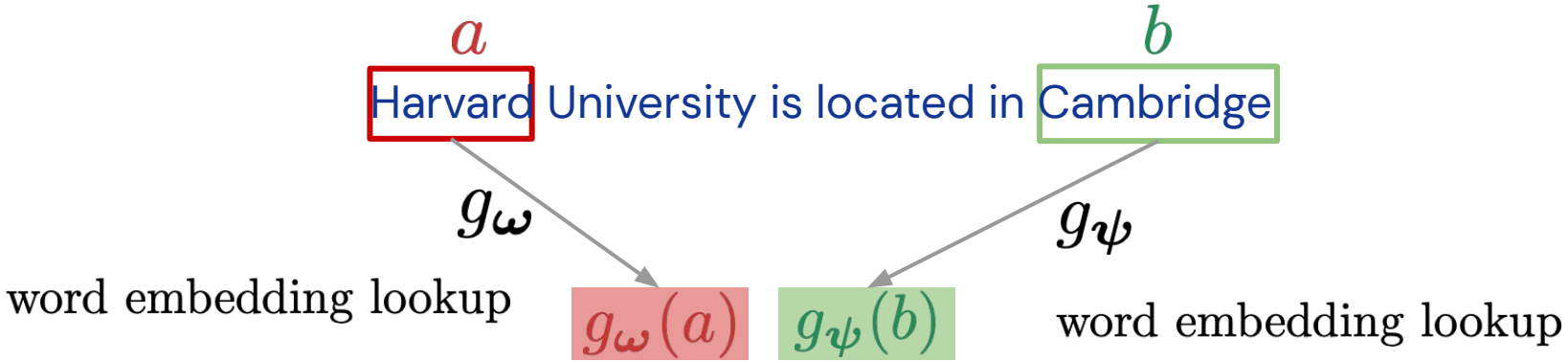

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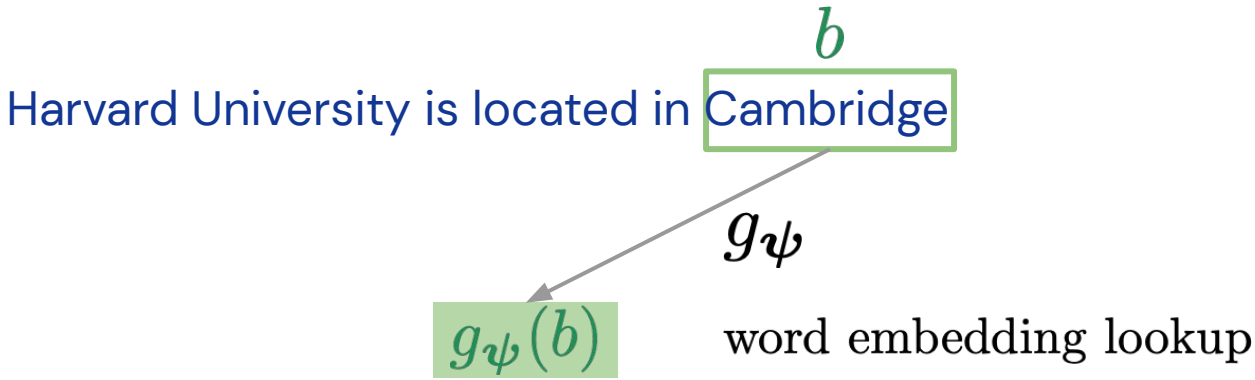

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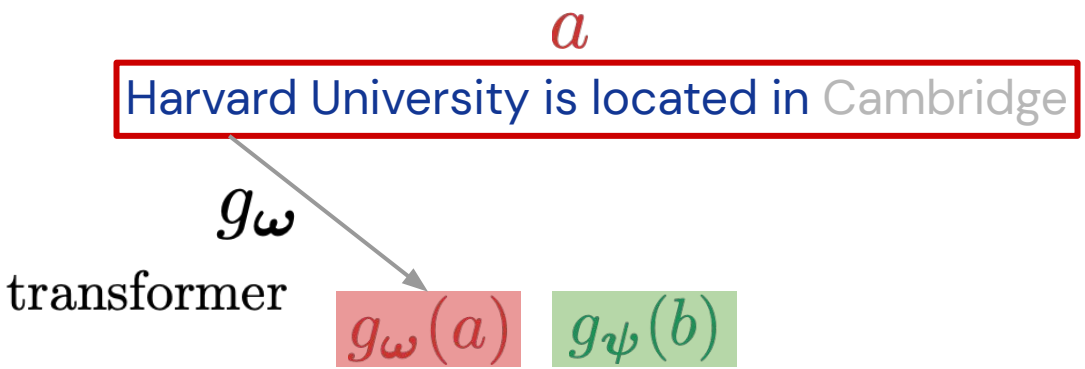

Why is this interesting?

- 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
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- Connections to representation learning methods used in other domains (vision, speech).

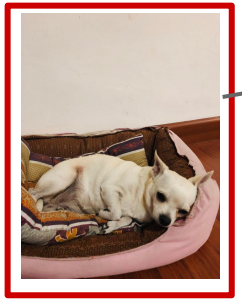
- A better understanding on how to construct new self-supervised tasks.

Model

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

Model

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



g_ω

$g_\omega(a)$

Model

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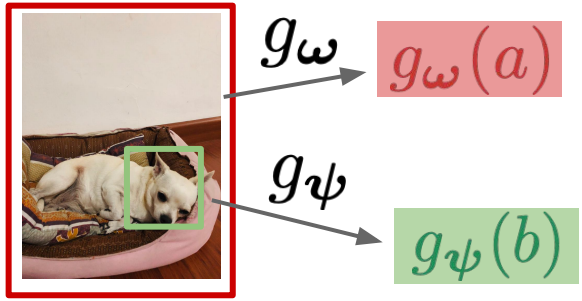

Model

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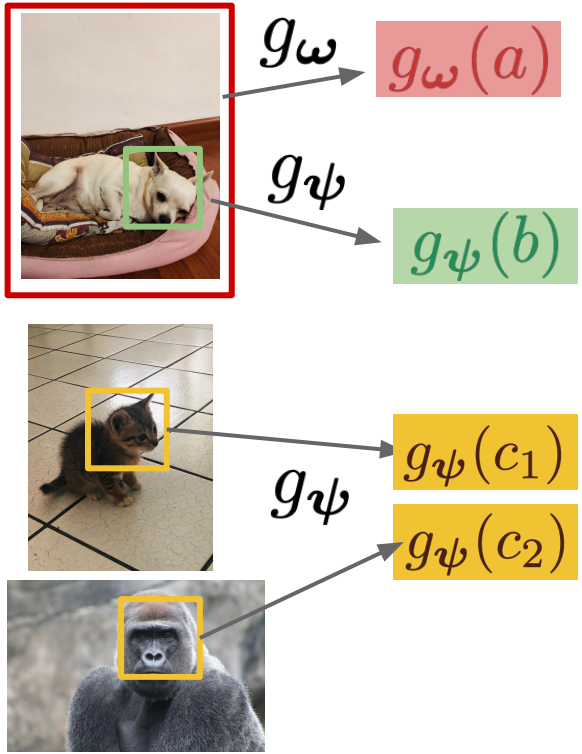

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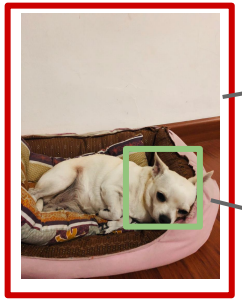
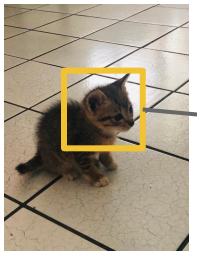
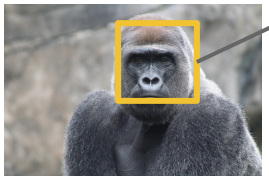


g_ω $g_\omega(a)$

g_ψ $g_\psi(b)$



g_ψ $g_\psi(c_1)$ $g_\psi(c_2)$



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

Model

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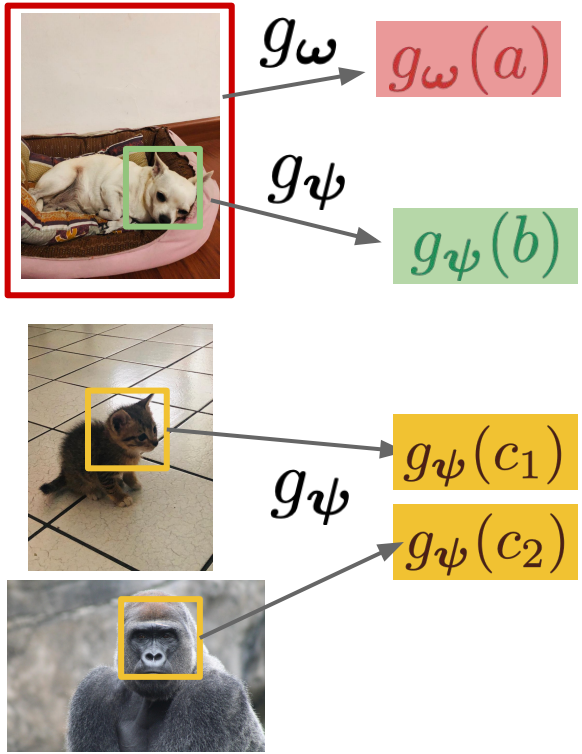

Carnegie Mellon University is located in Pittsburgh

Model

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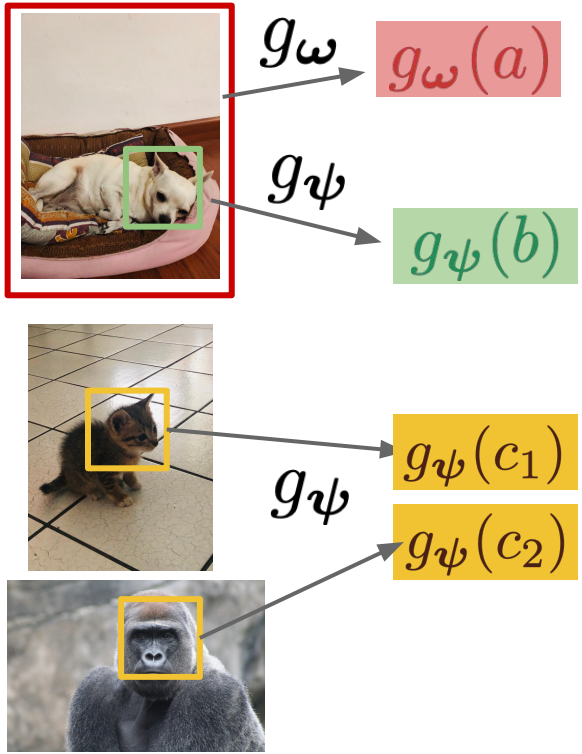

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g_ψ
transformer

$g_\psi(b)$

Model

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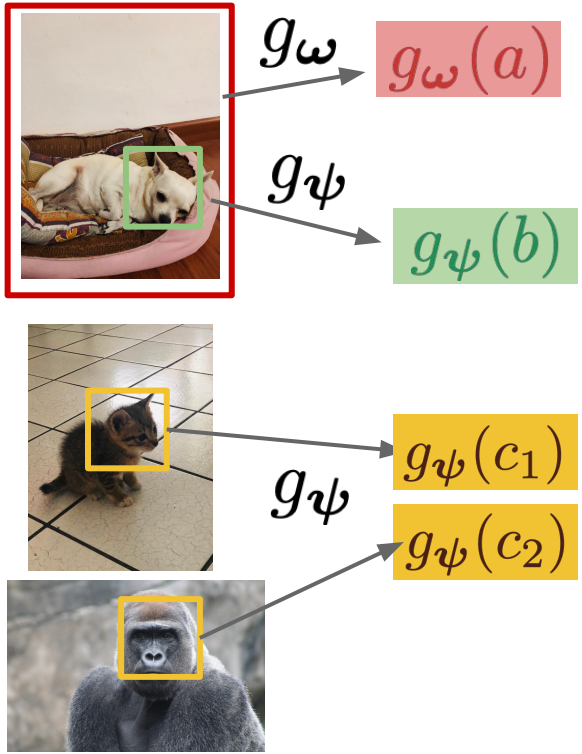

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g_ω
transformer

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

Model

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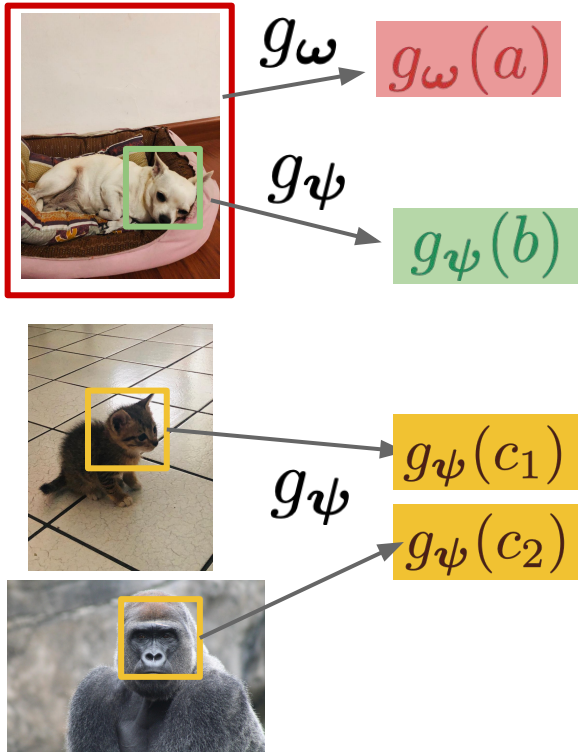

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$g_\omega(a)$ $g_\psi(b)$

Starcraft II is a fun game

Cristiano Ronaldo scores an own goal

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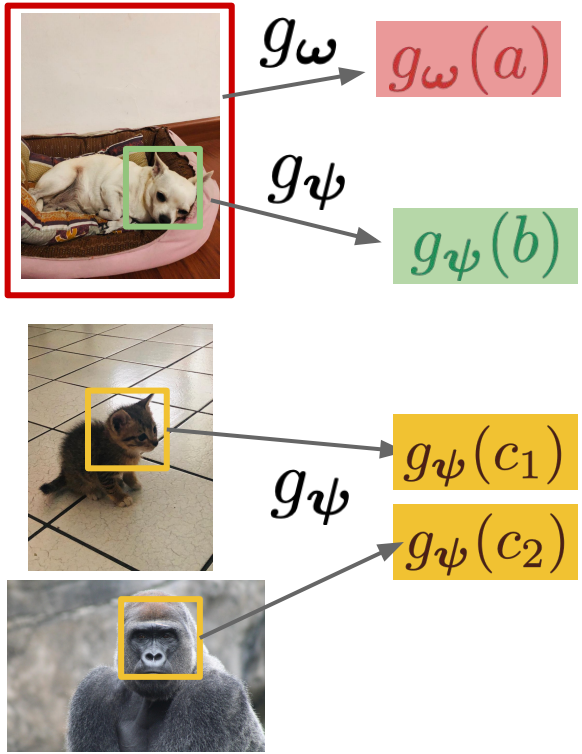

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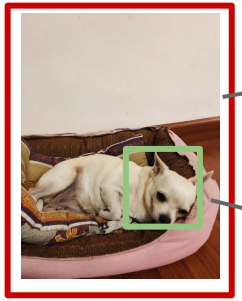

g_ω $g_\omega(a)$

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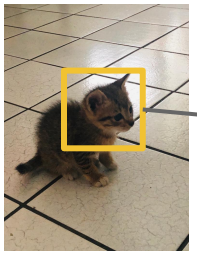

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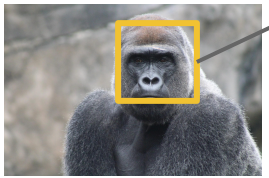

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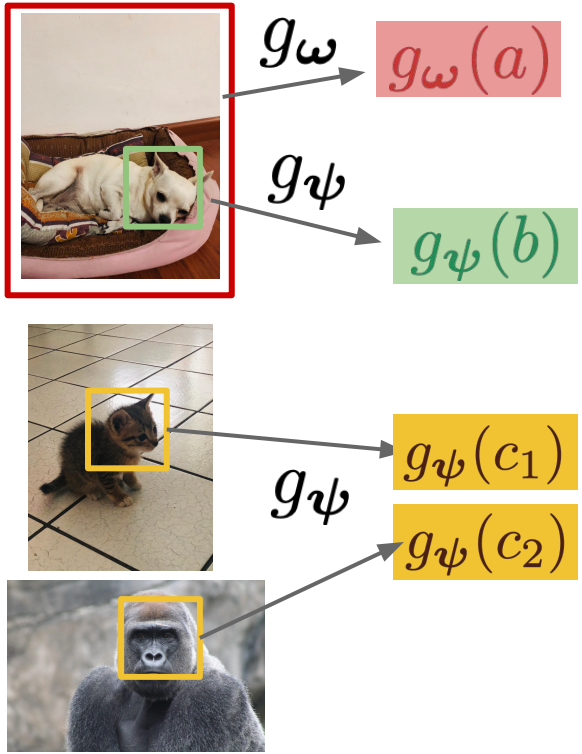

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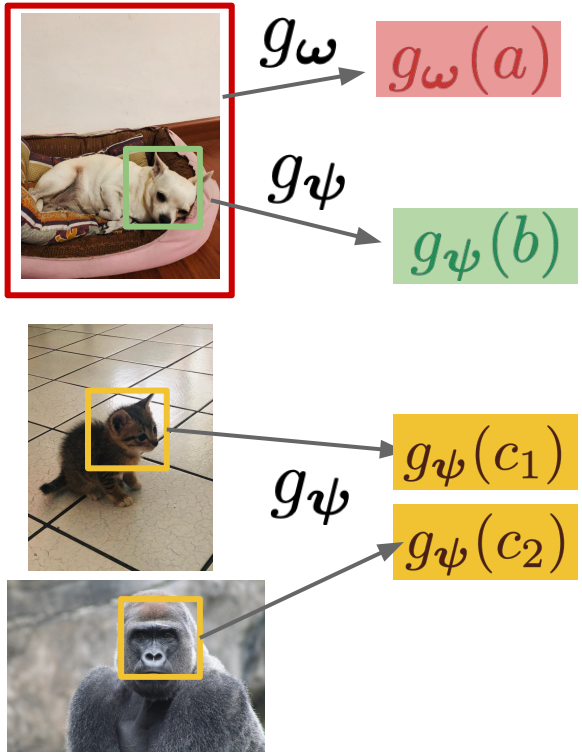

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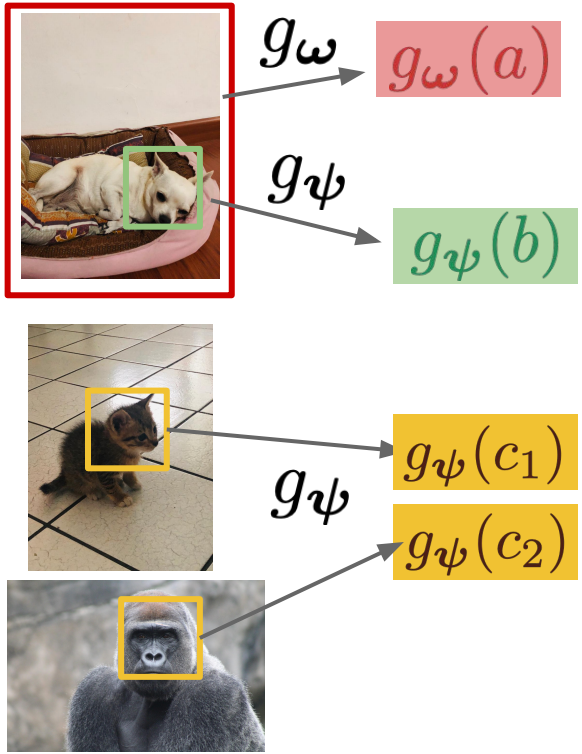

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g_ψ
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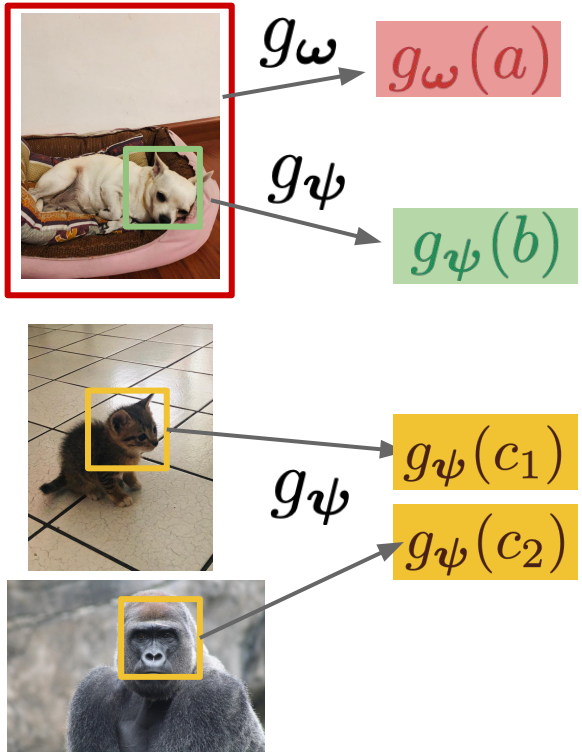

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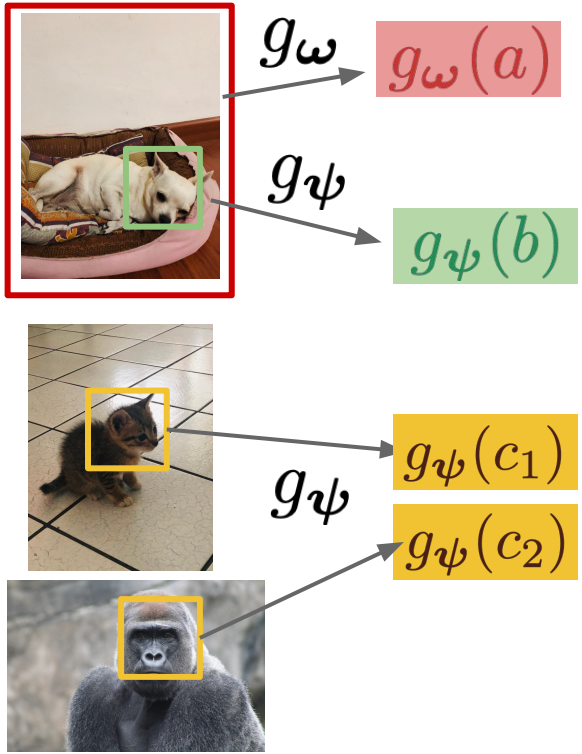

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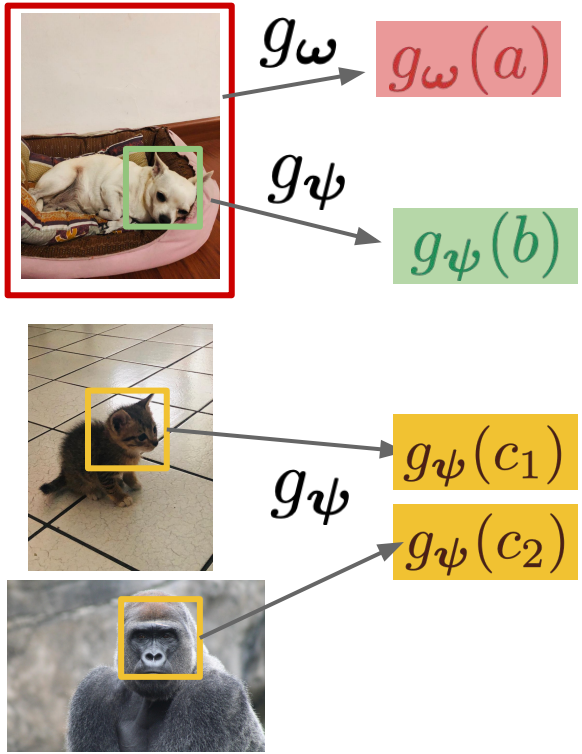

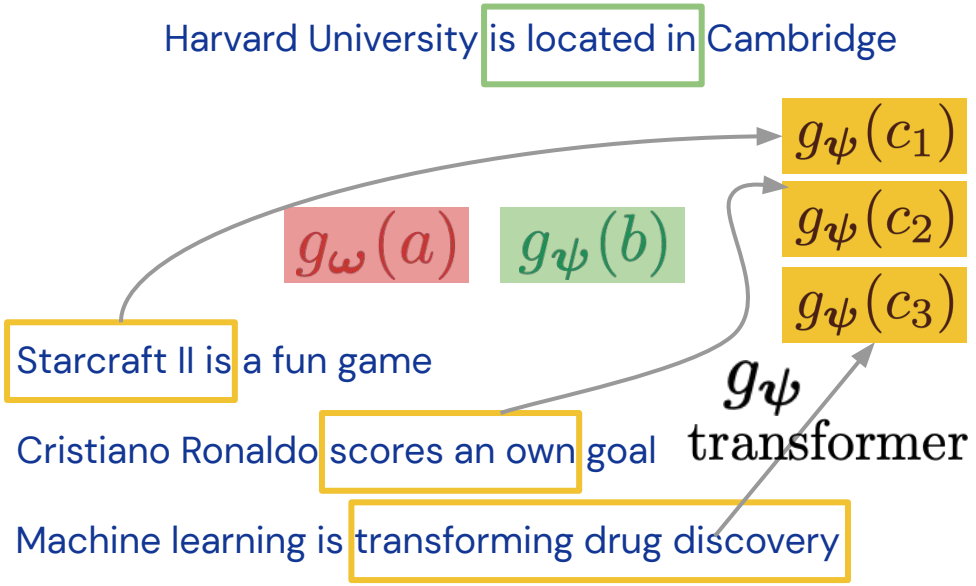

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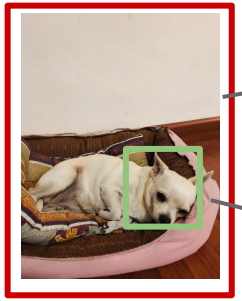

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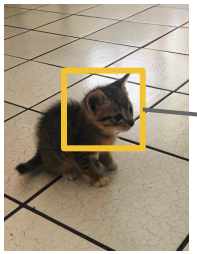

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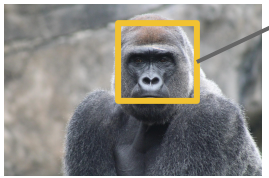

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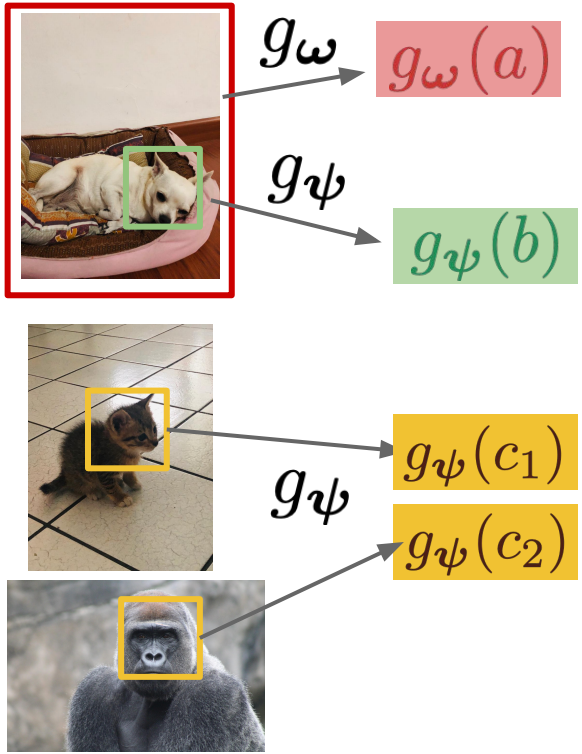

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Experiments

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 score (0–100), higher is better.

BERT: Devlin et al., 2019.

$$\mathcal{I}_{\text{BERT}} = \lambda_{\text{MLM}} \mathcal{I}_{\text{MLM}}$$
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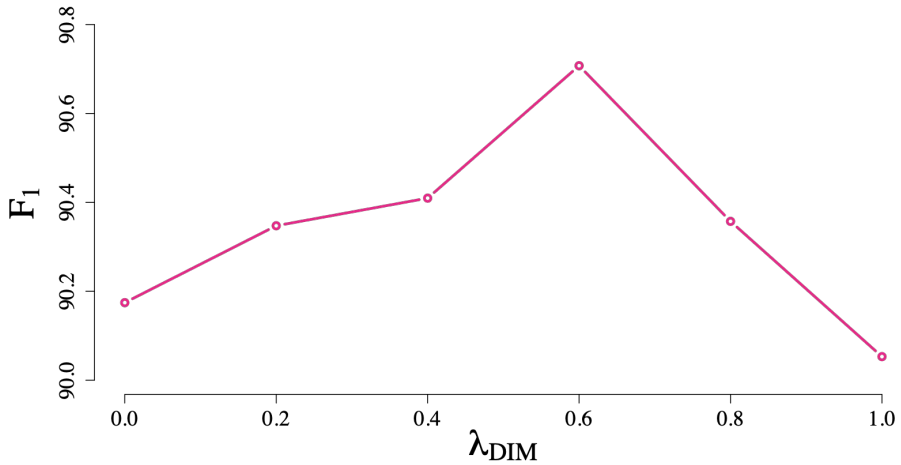

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Takeaways and Limitations

- Progress in language representation learning has largely been driven by advances in model architectures.

- It is possible to transfer ideas across domains when designing self-supervised tasks.

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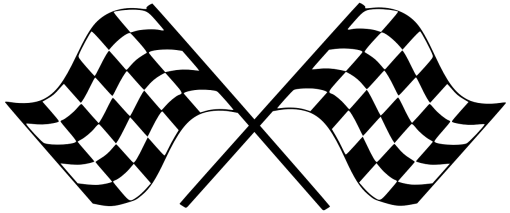
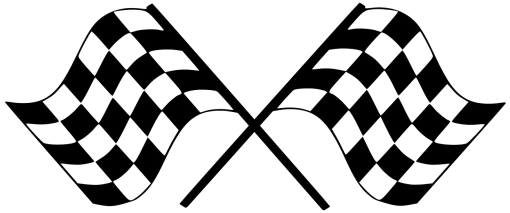
- It is possible to transfer ideas across domains when designing self-supervised tasks.
- All variants of existing models, fail to incorporate **global context** (they rely on local views).

Future Directions



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

Future Directions



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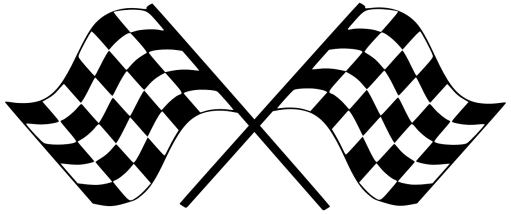
Generative Models

Future Directions



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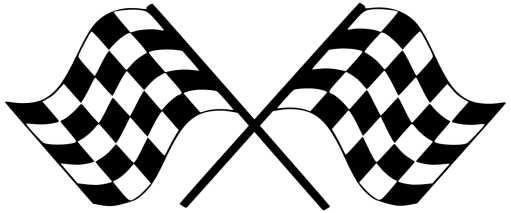

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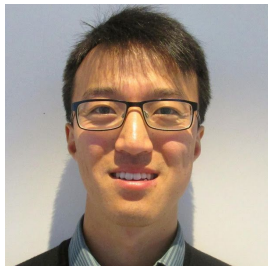
Generative Models

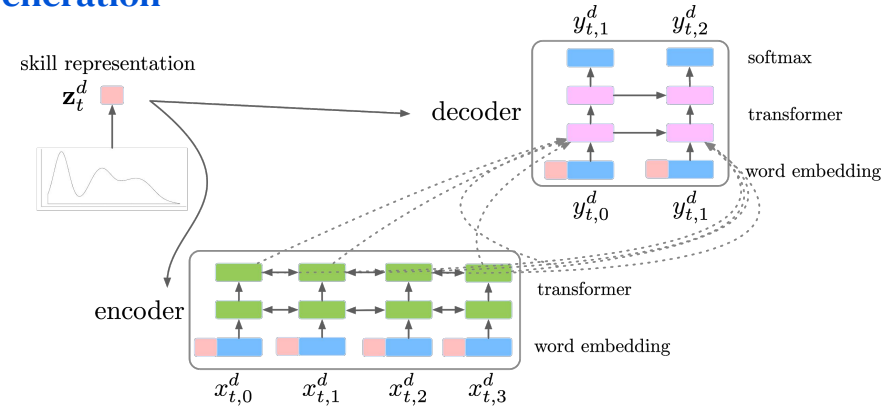
Modelling Latent Skills for Multitask Language Generation

Cao and Yogatama, arXiv 2020



Kris

Dani



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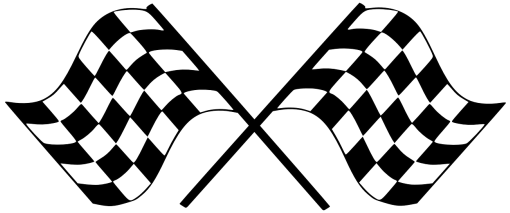

Memory

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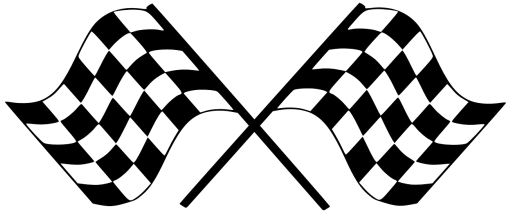
Future Directions



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Memory

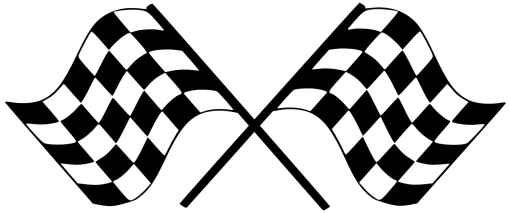
Working

Procedural

Semantic

Episodic

Future Directions



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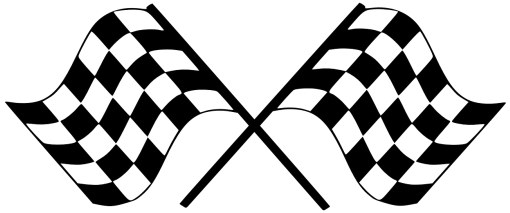

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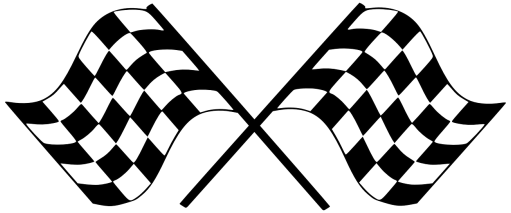
Representation Learning

Future Directions



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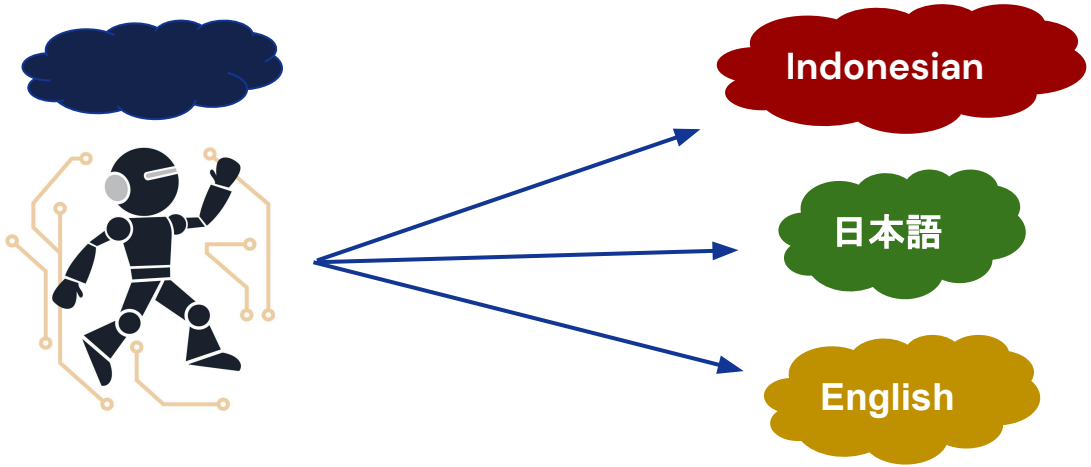
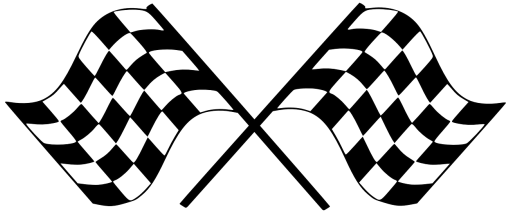


Future Directions

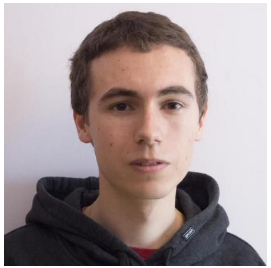


A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Representation Learning

On the Crosslingual Transferability of Monolingual Representations

Artetxe et al., arXiv 2019

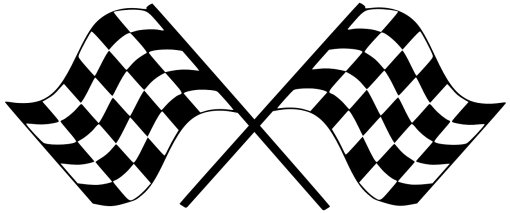


Mikel

Sebastian

Dani

Future Directions



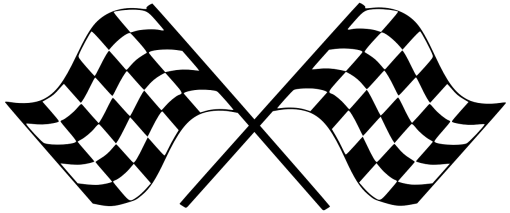
A language model that continually learns in an efficient way to perform multiple complex tasks in many languages.

Memory

Representation Learning

Generative Models

Future Directions



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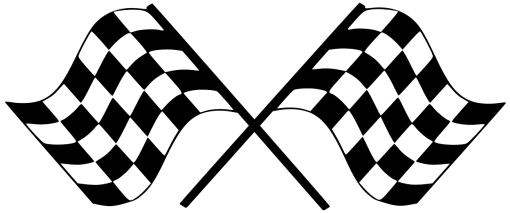
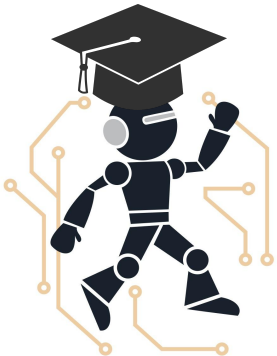
Memory	Representation Learning	Generative Models

Future Directions



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

Memory | Representation Learning | Generative Models



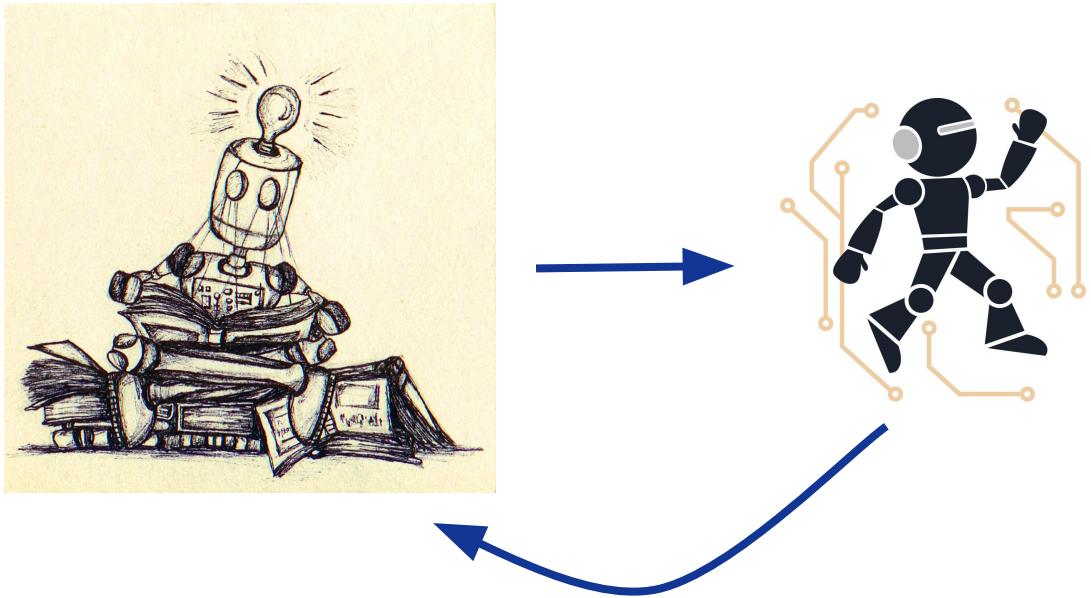
https://dyogatama.github.io

dyogatama@google.com

DeepMind

General Linguistic Intelligence

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

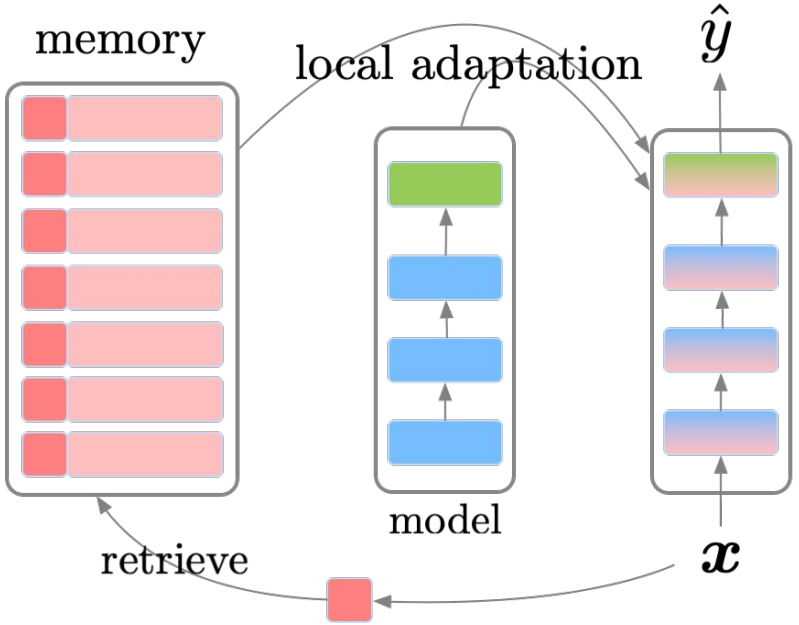


Future Directions

- The future is generative (models).
  - Elegantly deal with multiple tasks (McCann et al., 2018; Radford et al., 2019).
  - Approach their asymptotic error faster (Yogatama et al., arXiv 2017).
  - Crucial to imagination and planning (Weber et al., 2017).

Inference (Prediction)

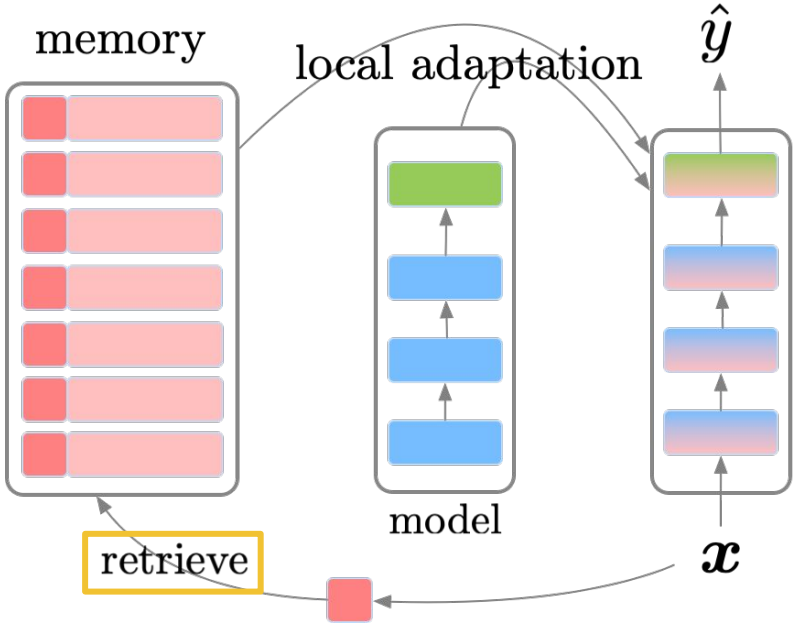
Local adaptation similar to MbPA (Sprechmann et al., 2018).



Inference (Prediction)

Local adaptation similar to MbPA (Sprechmann et al., 2018).

Query: in what country is normandy located
(17.48) in what area of france is calais located
(20.37) in what country is st john s located
(22.76) in what country is spoleto located
(23.12) in what part of africa is congo located
(23.83) on what island is palermo located



Inference (Prediction)

Local adaptation similar to MbPA (Sprechmann et al., 2018).

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

Query: in what country is normandy located
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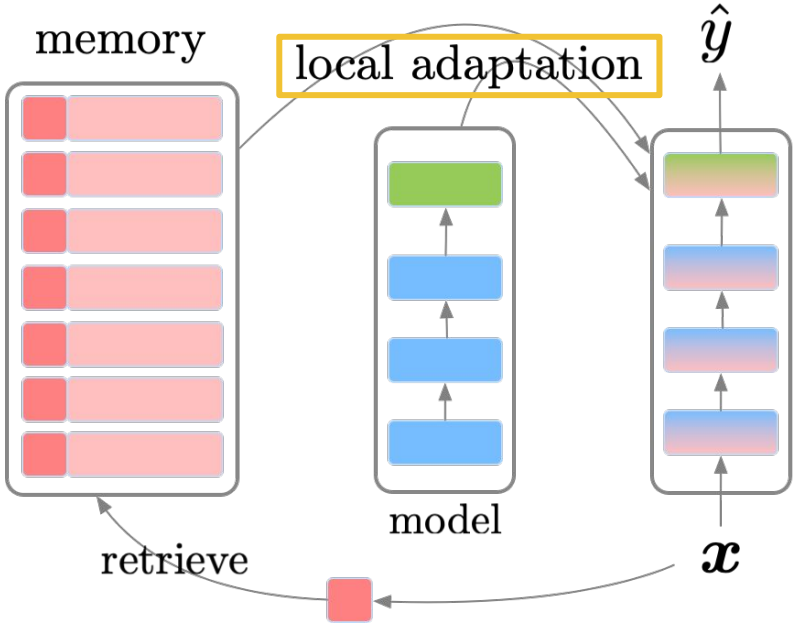
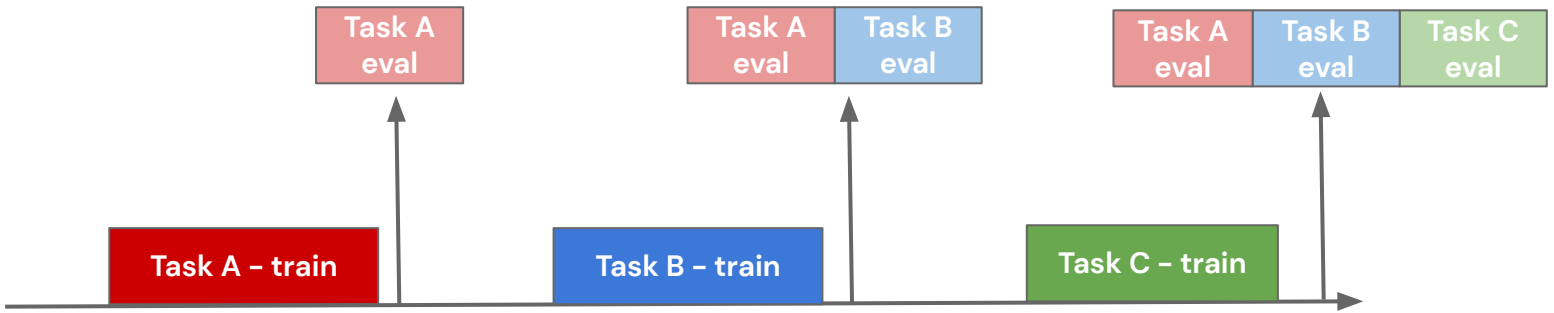


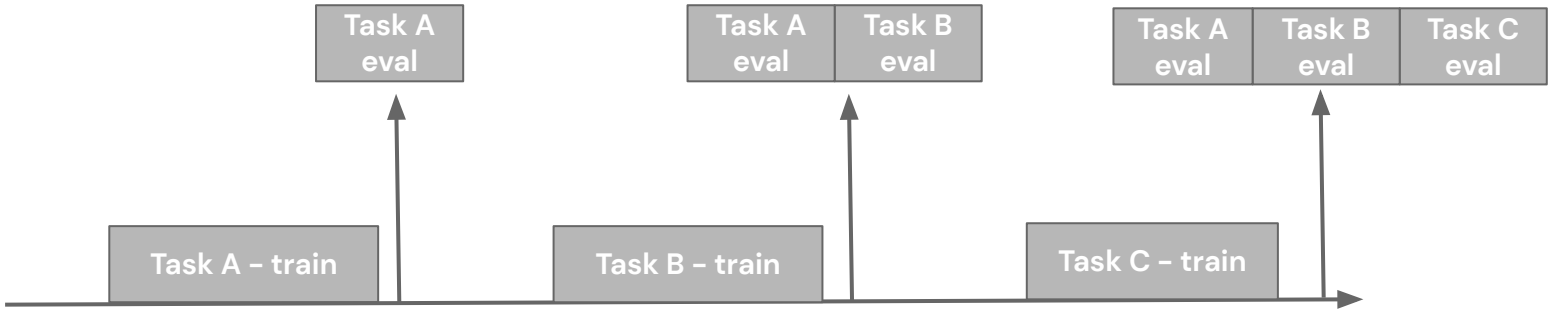
Problem Setup



Standard setup, models know which task an example belongs to.

Never-Ending Language Learning, Mitchell et al., 2015

Problem Setup



Our more difficult and realistic setup.

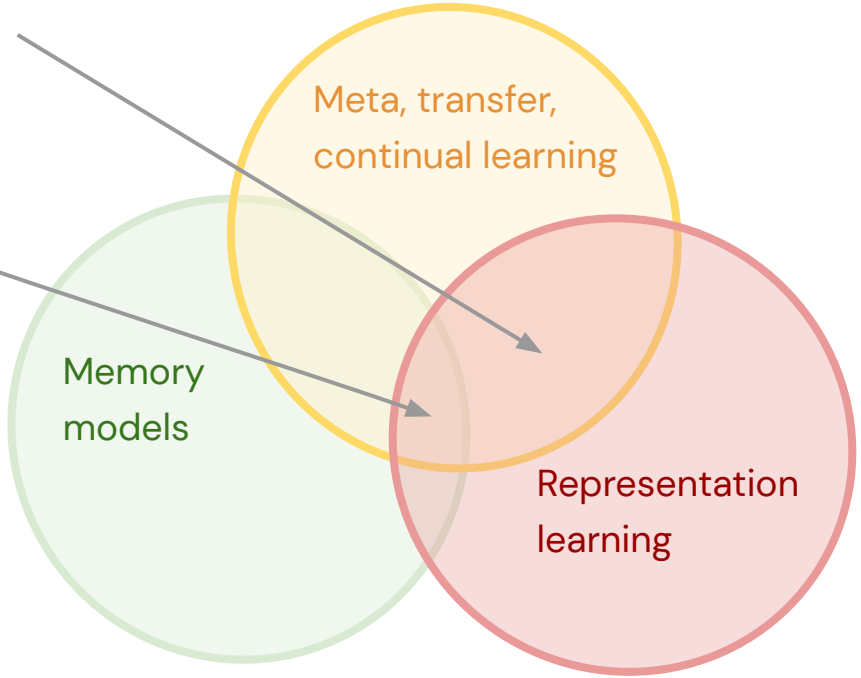
This Talk

- Episodic memory in lifelong language learning.

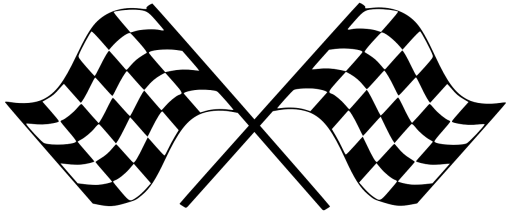
  de Masson d'Autume et al., NeurIPS 2019

- A framework for self-supervised language representation learning methods.

  Kong et al., ICLR 2020



Research Areas

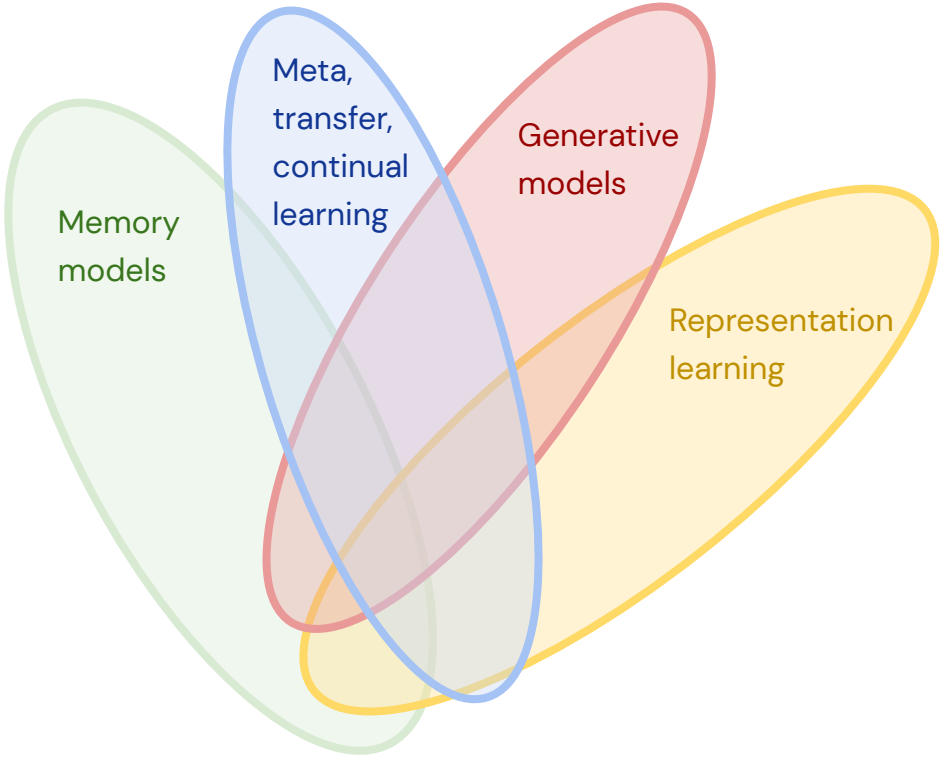


A universal language model that continually learns to perform multiple tasks in many languages.

- Semi-parametric models/memory-augmented neural networks.
  Yogatama and Mann; AISTATS 2014; Yogatama et al., ICLR 2018; de Masson d'Autume; NeurIPS 2019
- Architectural advances and structural biases for self-supervised representation learning.
  Yogatama and Smith; ACL 2014; ICML 2015; Yogatama et al., ICLR 2017; Maillard et al., JNLE 2019
- Generative language models.
  Yogatama et al., TACL 2014; Yogatama et al., arXiv 2017; Kong et al., ICLR 2018.

Reasoning (Dhingra et al., 2020), interactions with other modalities (Baltrusaitis et al., 2019), robustness (Huang et al., EMNLP 2019), fairness (Manzini et al., 2019), and others

Future Directions



Frontiers of NLP