Toward General Linguistic Intelligence

Dani Yogatama

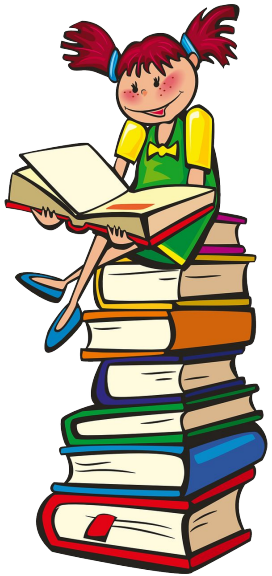
DeepMind

Language and Intelligence

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

Language and Intelligence

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



Language and Intelligence

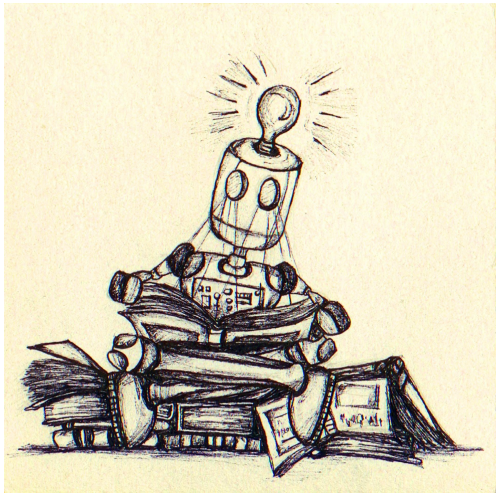
The most effective form of communication to transmit information and knowledge to others.

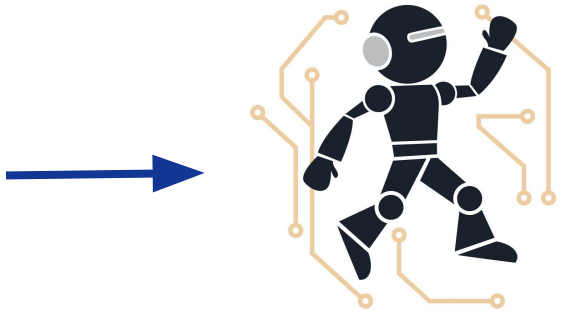
Language and Intelligence

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**.





Challenges: Human Learning vs. Machine Learning

- ``Large'' datasets → sample efficient.
- Mostly task agnostic.
- Generalizable to new tasks.

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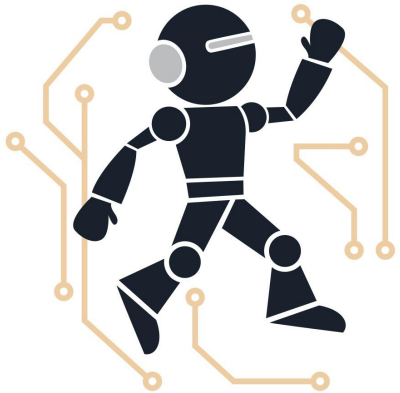
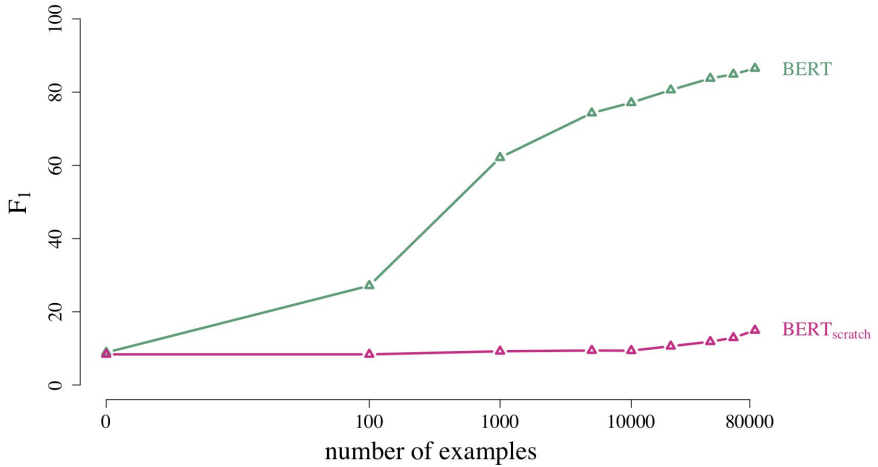


- Large datasets (self-supervised learning) → large datasets (supervised fine tuning).
- Problem specific.
- Forget previous tasks given a new task.

The State of Natural Language Processing

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



Yogatama et al., arXiv 2019

BERT model: Devlin et al. 2019

SQuAD dataset: Rajpurkar et al., 2016

Trivia dataset: Joshi et al., 2017

The State of Natural Language Processing

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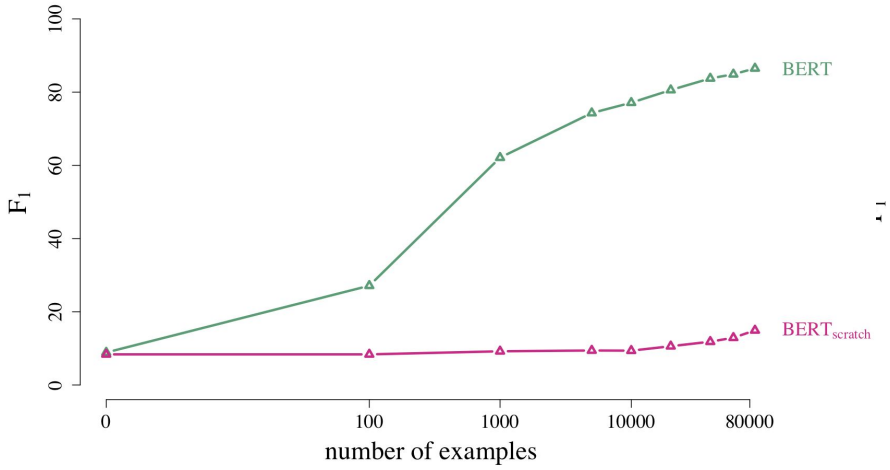
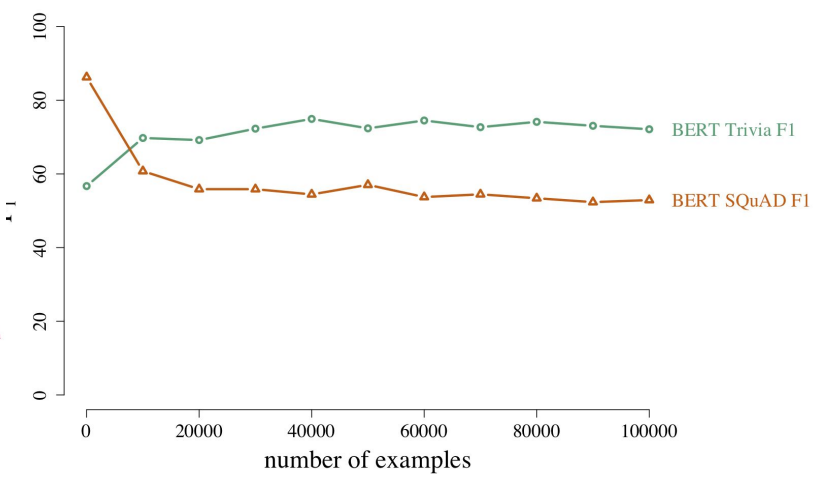
- They overfit to a specific dataset (task) and often forget.





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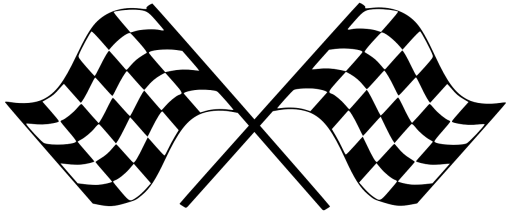
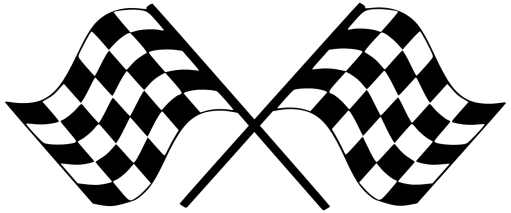
Research Areas



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

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.
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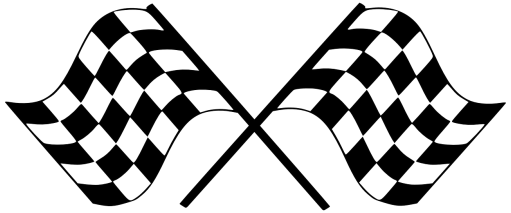

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Reasoning, interactions with other modalities, robustness, fairness, and others.

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.

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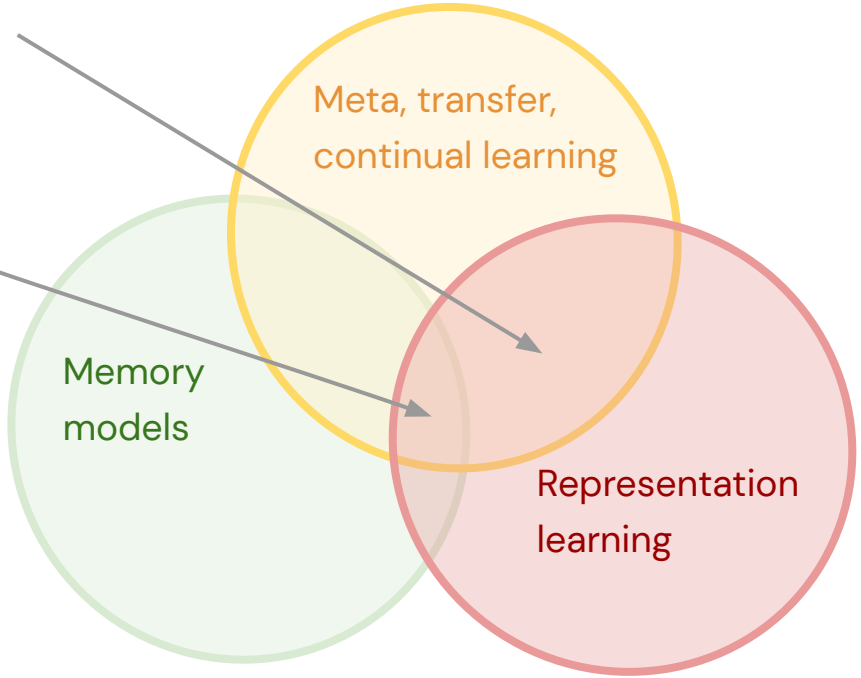
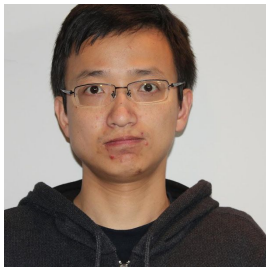


Episodic Memory in Lifelong Language Learning

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

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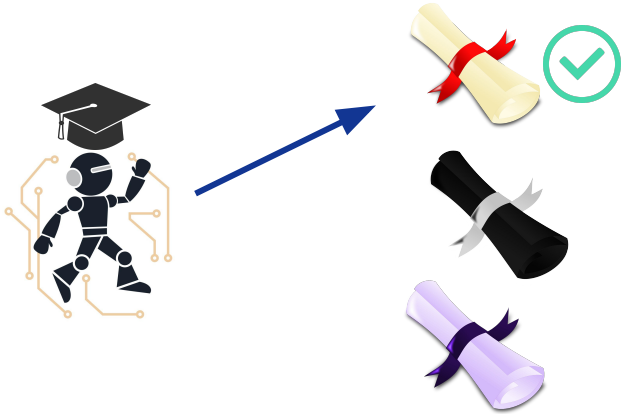

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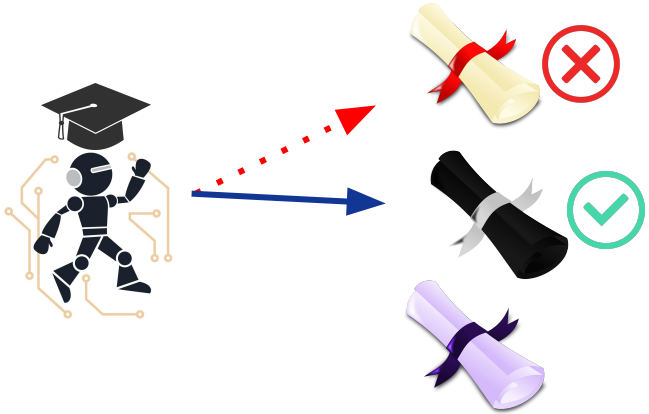

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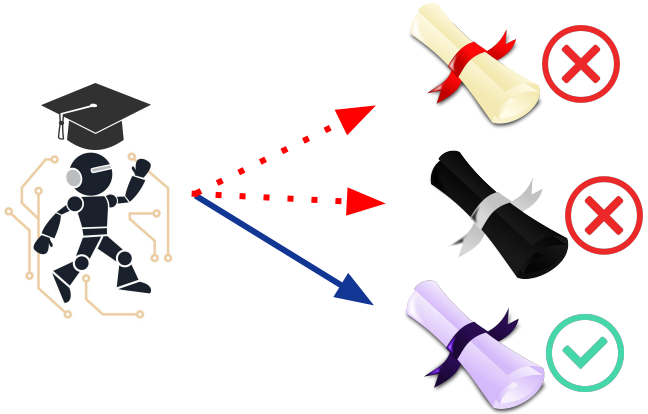

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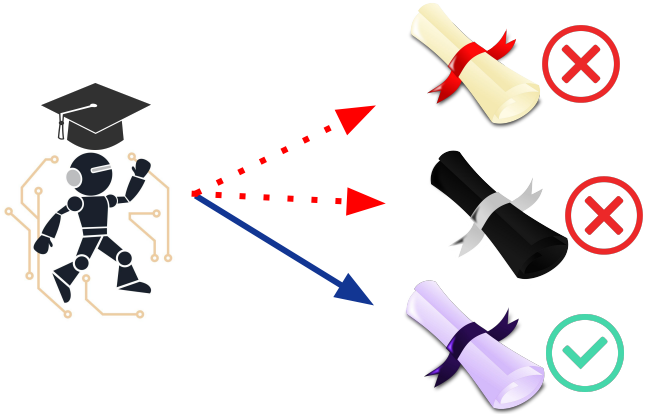
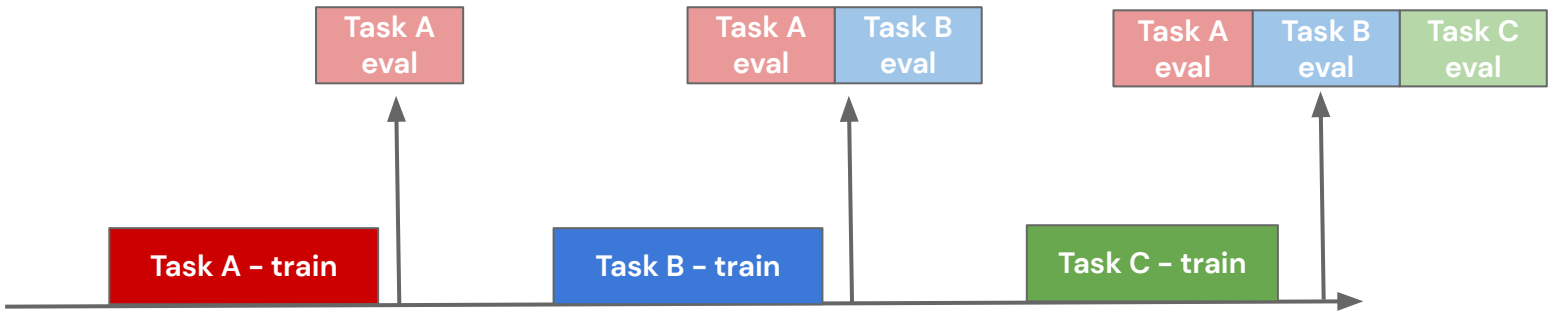


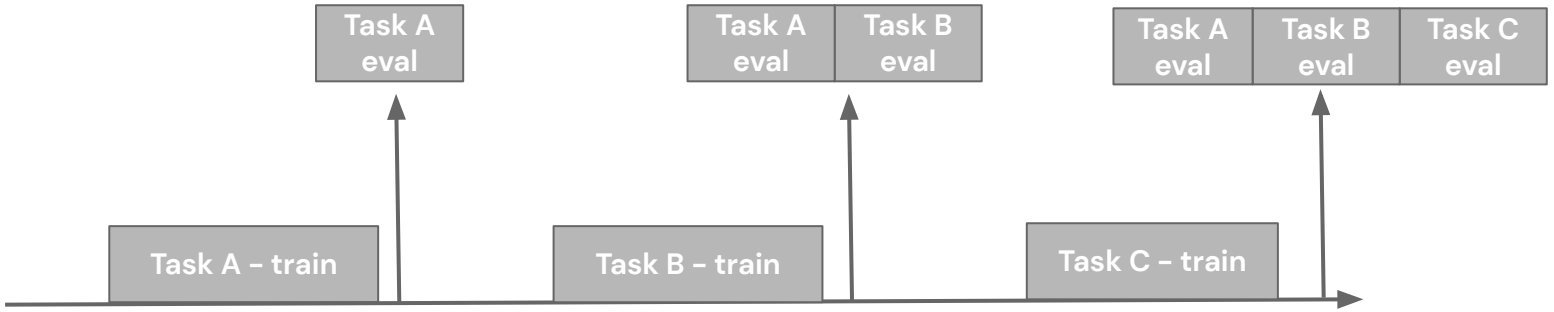
Hypothesis: episodic memory mitigates catastrophic forgetting in language learning.

Problem Setup



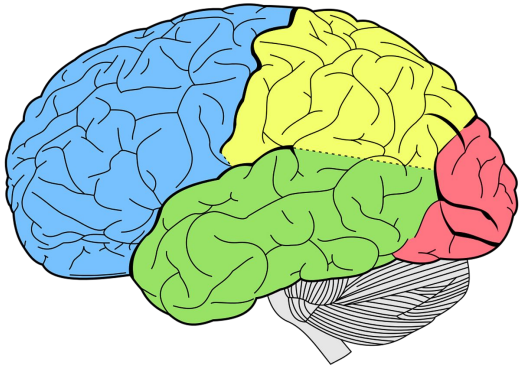
Standard setup, models know which task an example belongs to.

Problem Setup



Our more difficult and realistic setup.

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..

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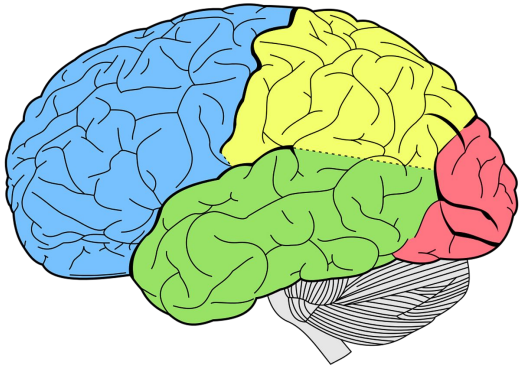
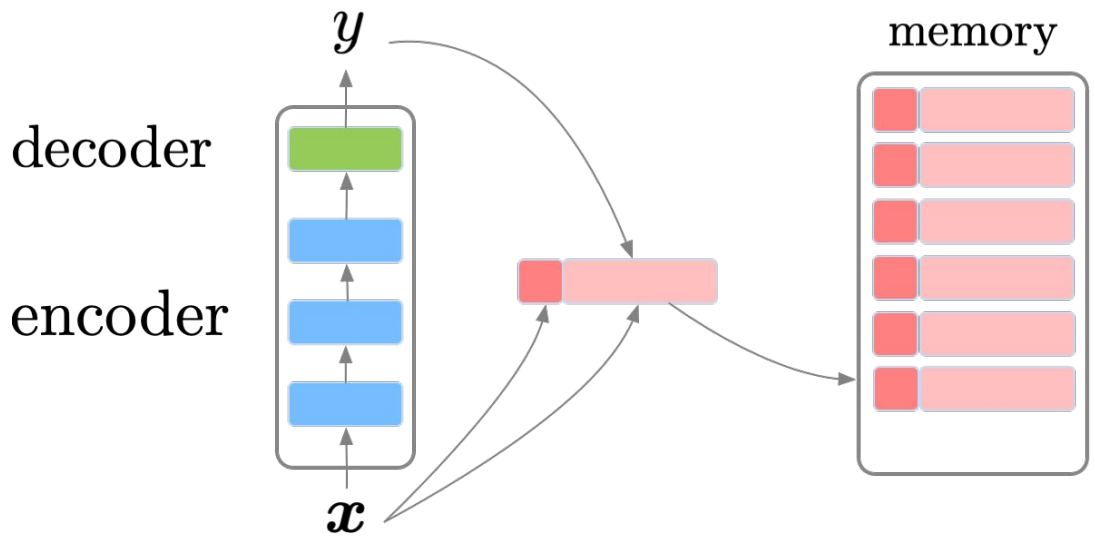


Episodic memory is a type of long-term memory of events and experiences. It is often associated with a module that stores training examples in neural networks..

Contrast this with a short-term (working) memory in e.g., LSTMs (Hochreiter and Schmidhuber, 1997) , stack-augmented networks (Joulin and Mikolov, 2015; Grefenstette et al., 2015), or DNCs (Graves et al., 2016).

See **Yogatama et al., ICLR 2018** for comparisons in the context of language models.

Question Answering Model



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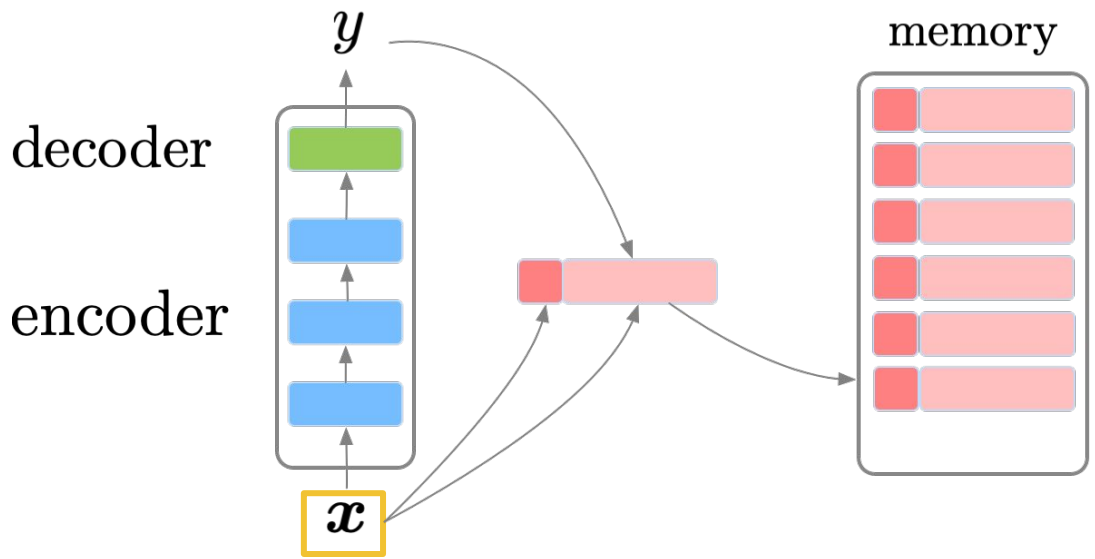
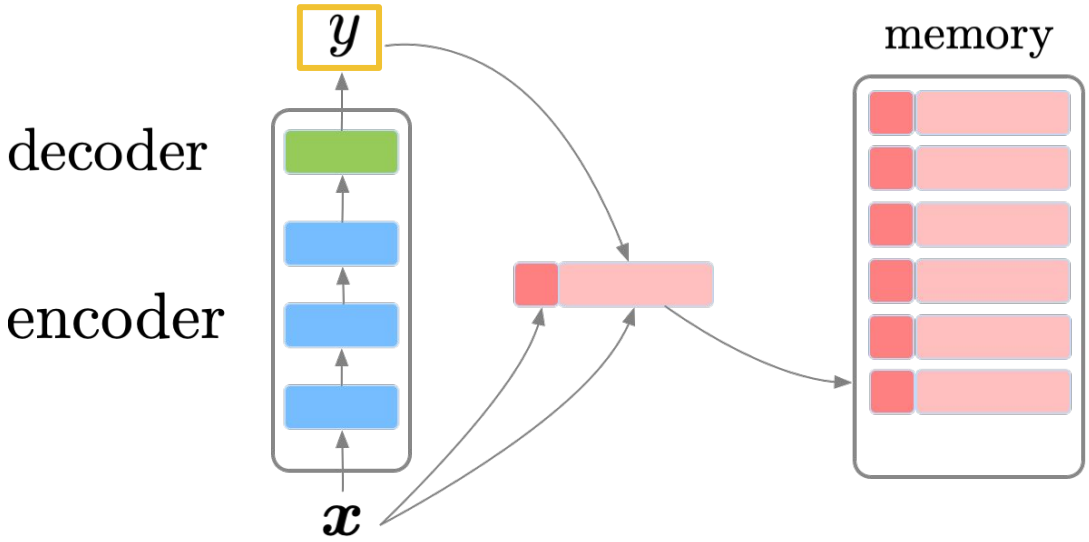


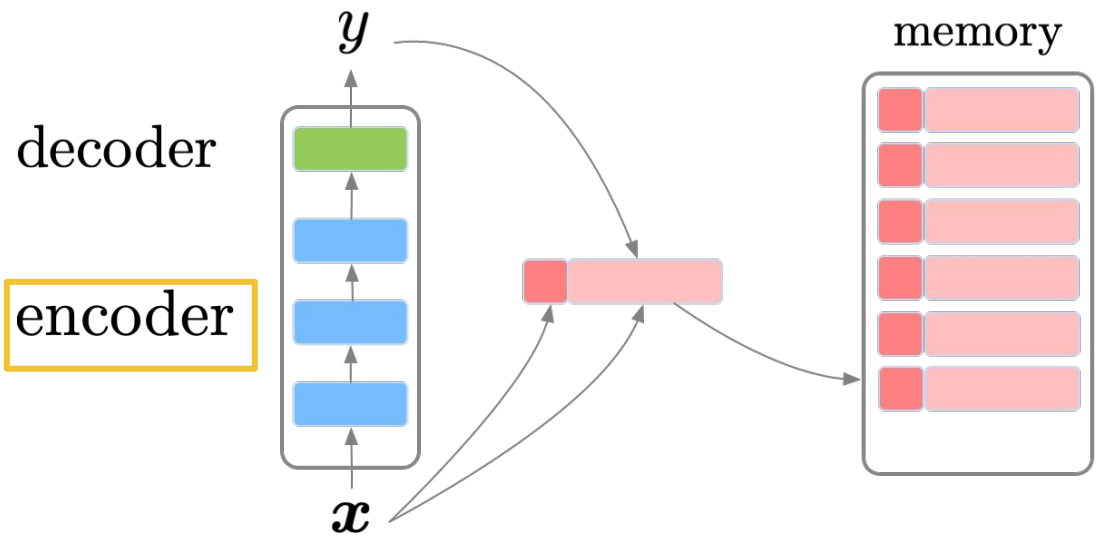
Input: a concatenation of context (e.g., a Wikipedia article) and question.

Question Answering Model

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



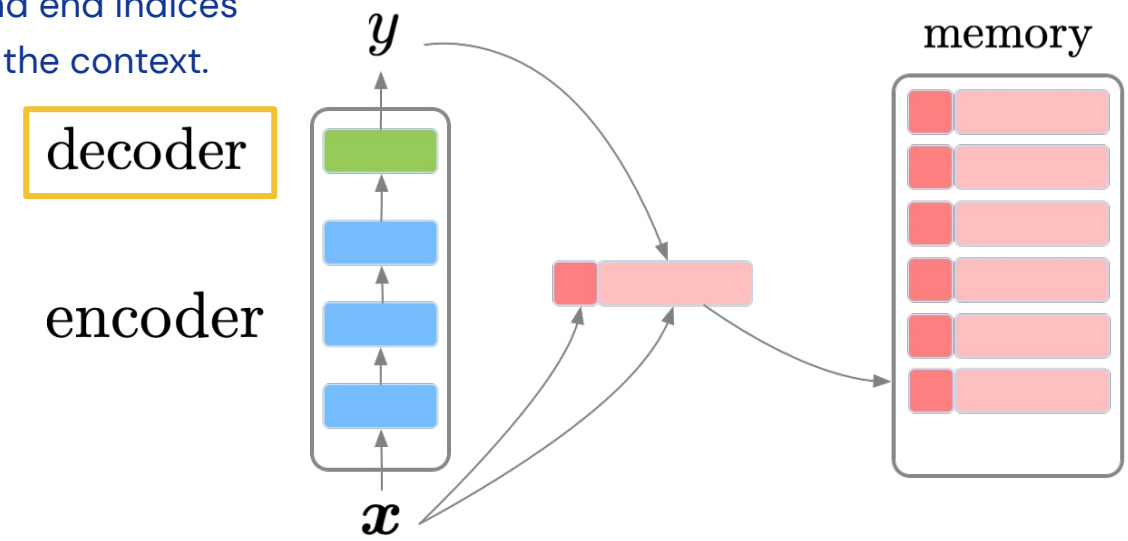
Question Answering Model



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 context.



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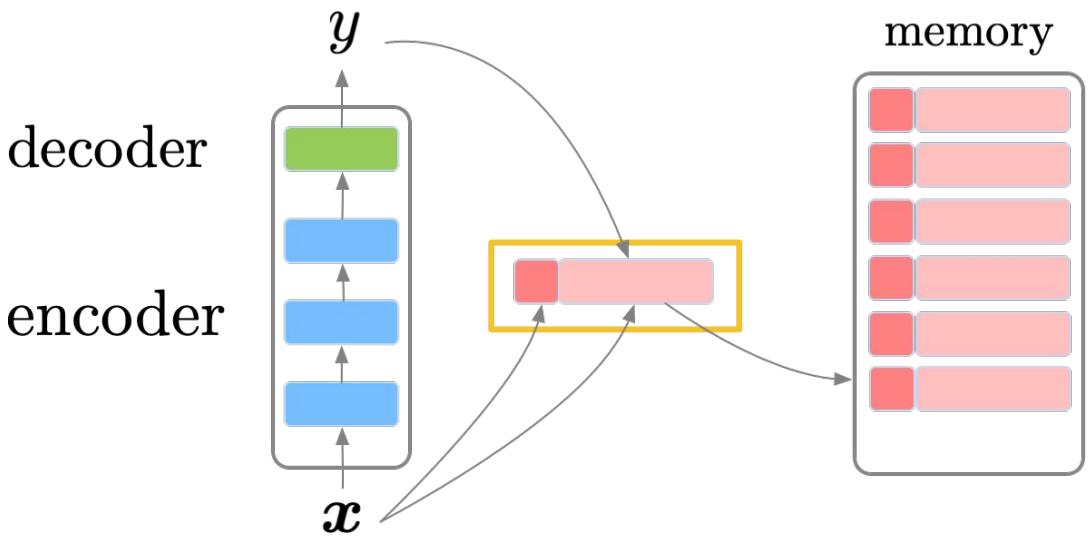
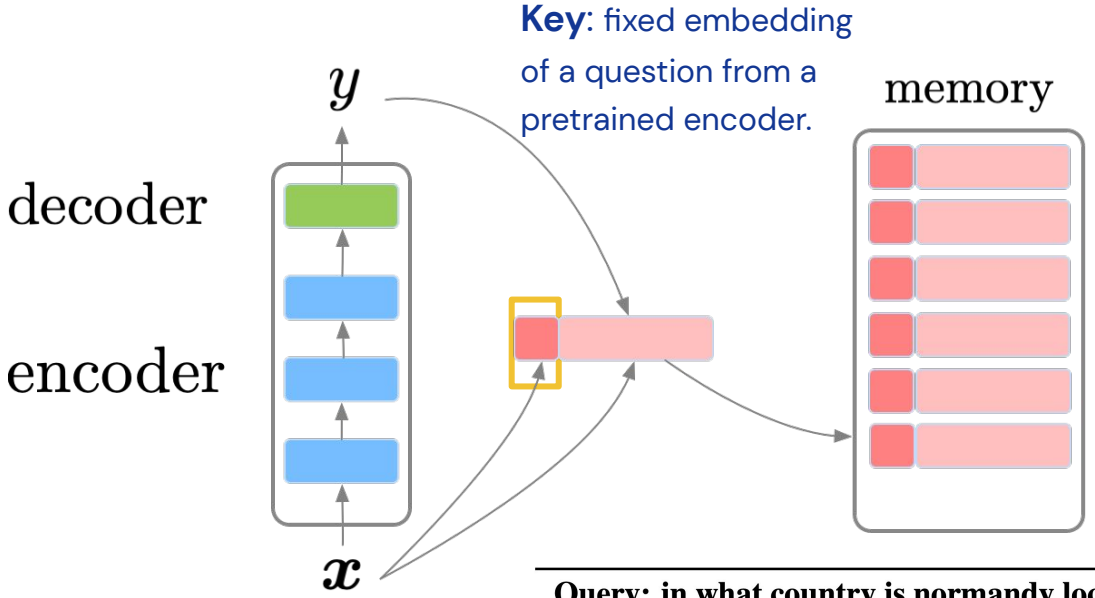


Memory entry: a key, value pair

Question Answering Model



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
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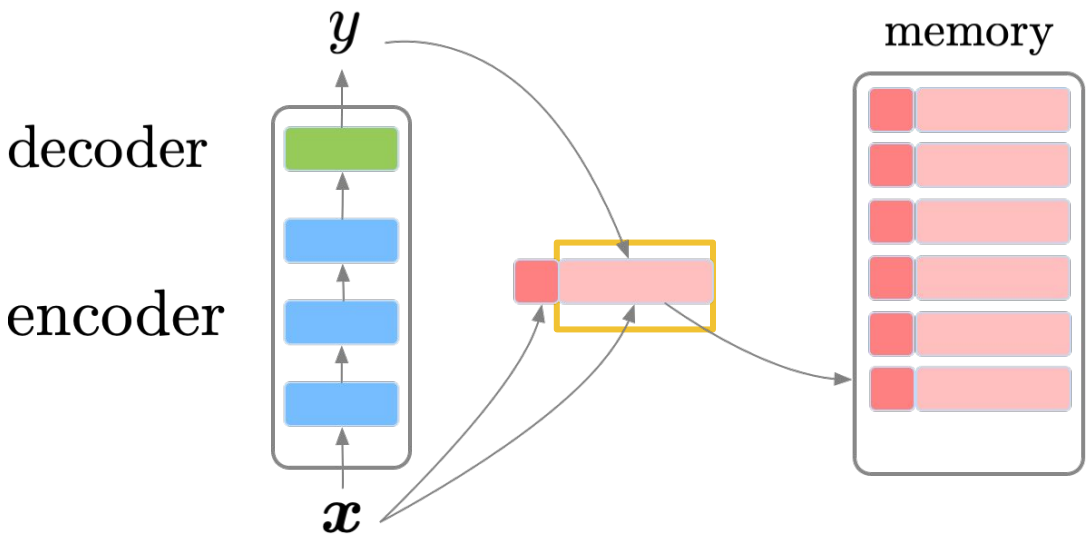
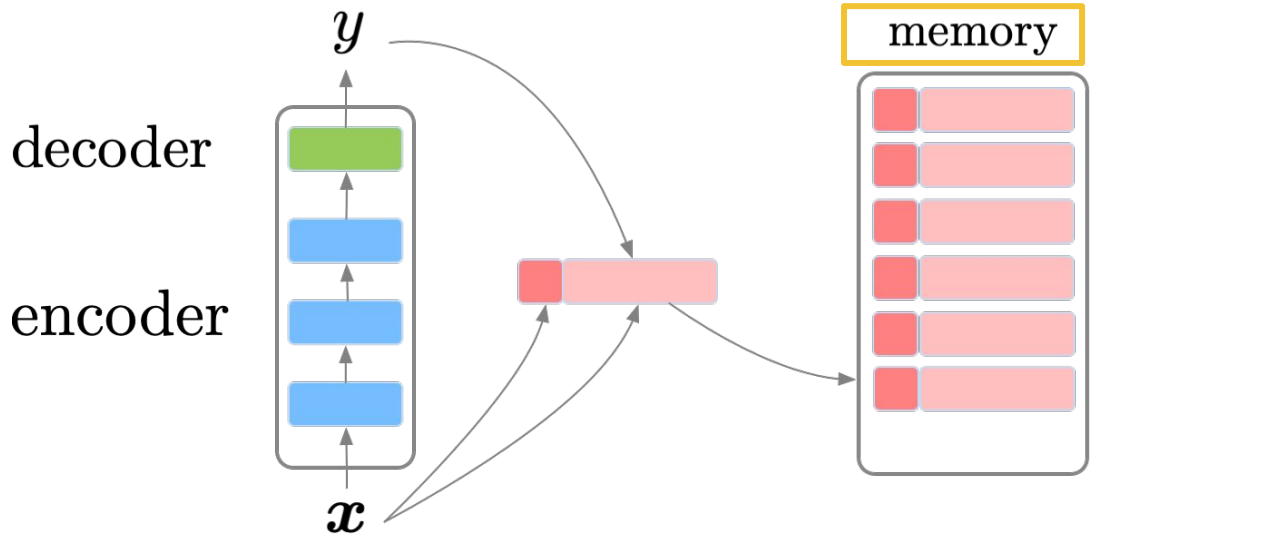


Value: context, question, and answer in textual forms (strings).

Question Answering Model

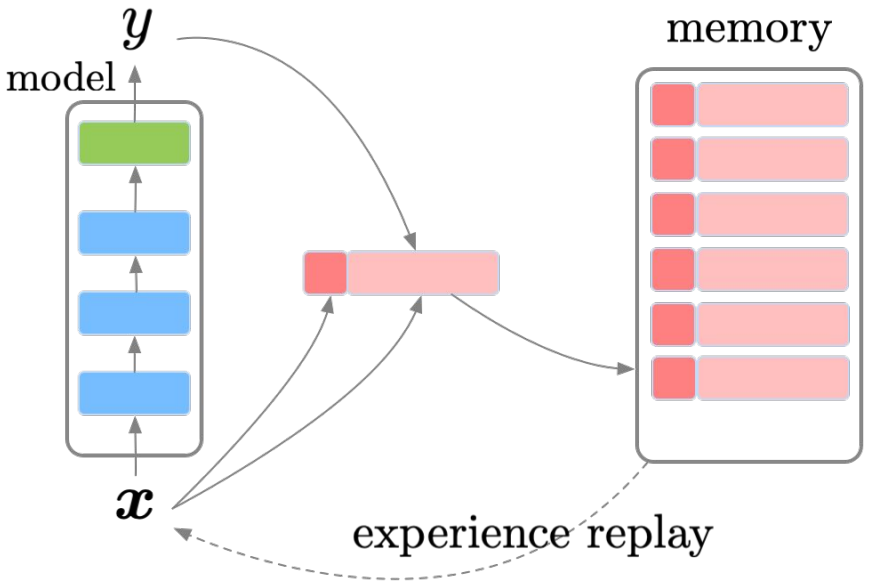
Memory: stores memory entries



Training

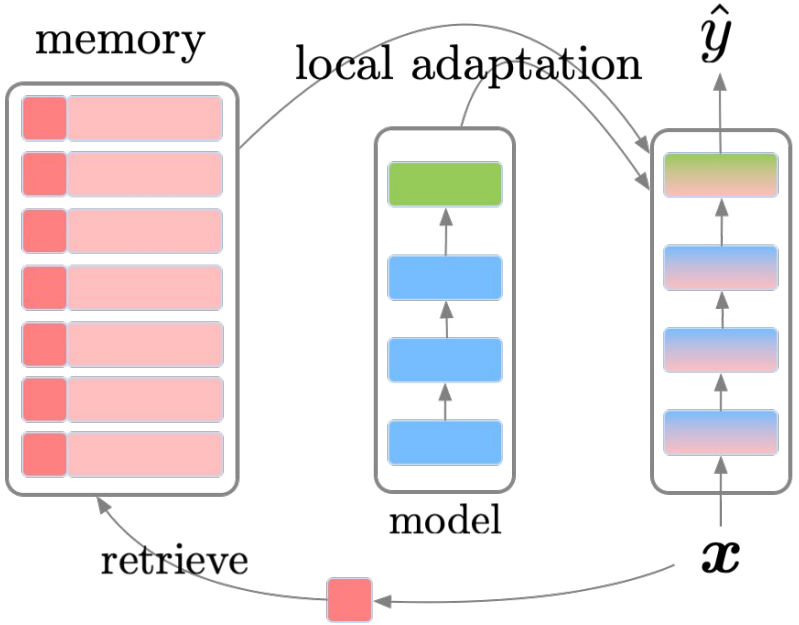
***Sparse* experience replay**: retrain on randomly sampled examples from the memory at a 1% rate.

Related to memory consolidation in human learning.



Inference (Prediction)

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



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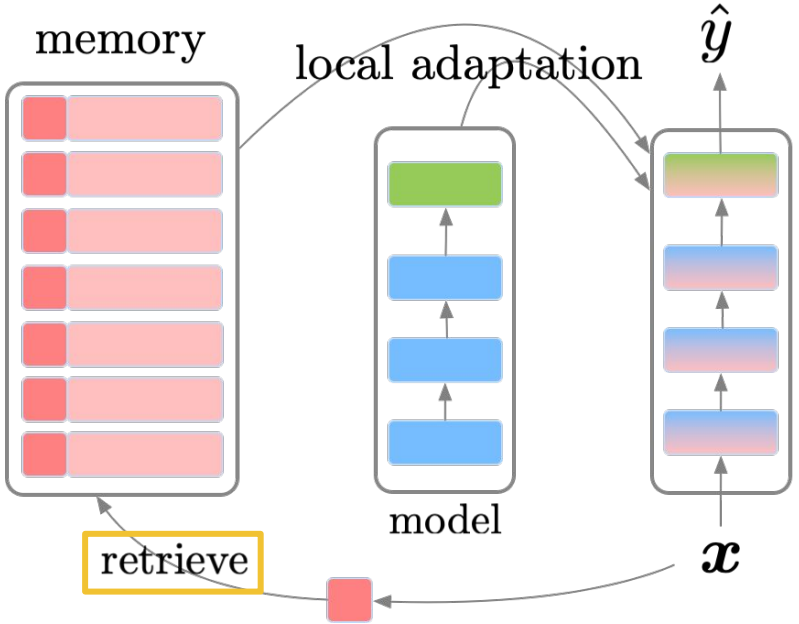

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$$\mathbf{W}_i = \arg\min_{\tilde{\mathbf{W}}} \lambda \|\tilde{\mathbf{W}} - \mathbf{W}\|_2^2 - \sum_{k=1}^{K} \alpha_k \log p(y_i^k \mid \boldsymbol{x}_i^k; \tilde{\mathbf{W}})$$

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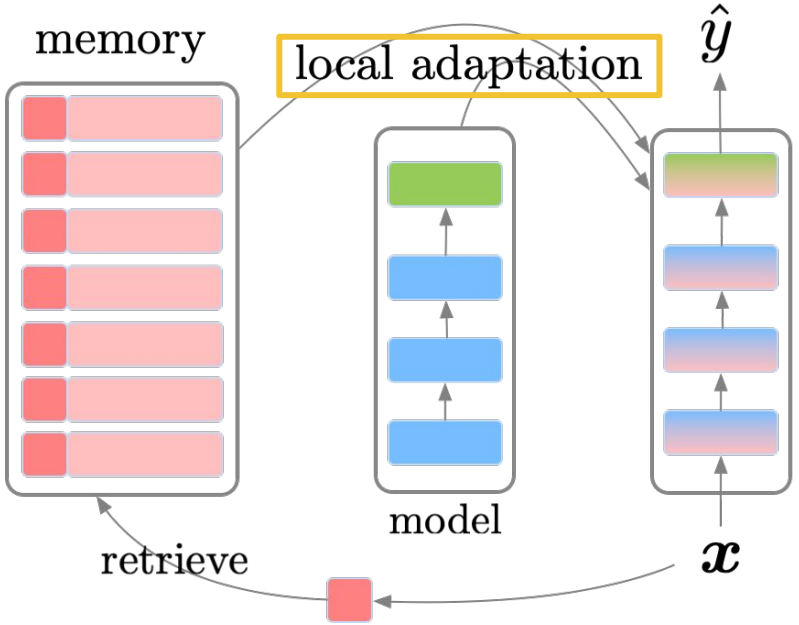

Experiments

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

A-GEM: Chaudhry et al., 2019

MbPA: Chaudhry et al., 2019

Takeaways and Limitations

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

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

10%	50%	100%
67.6	70.3	70.6

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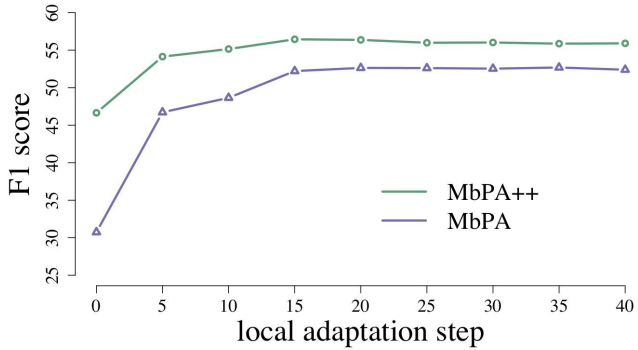
- Local adaptation at inference time is **computationally expensive**.



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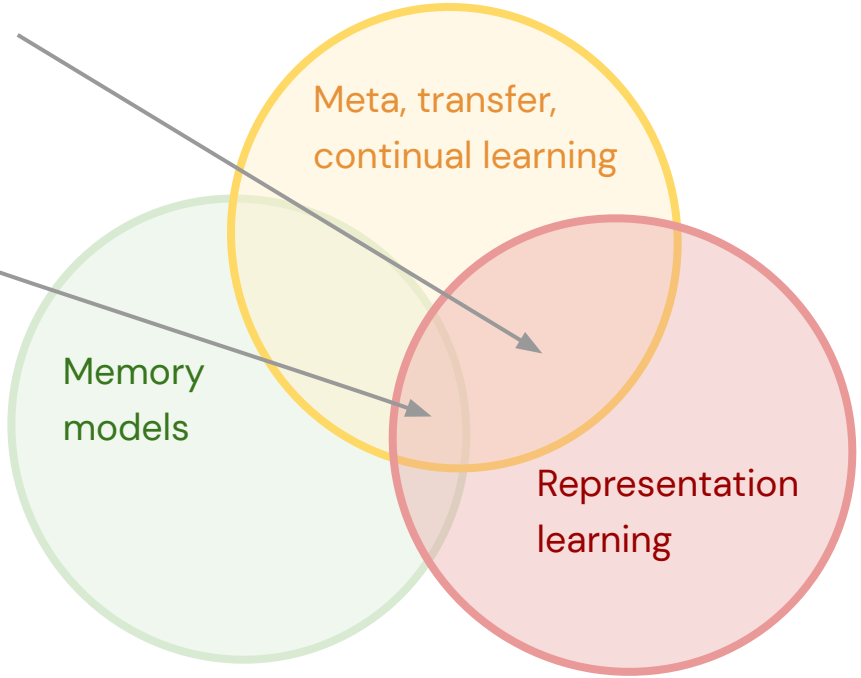
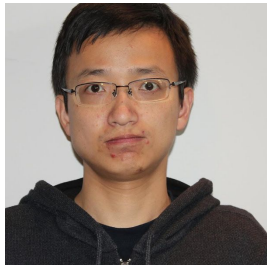
- A framework for self-supervised language representation learning methods.

  Kong et al., ICLR 2020

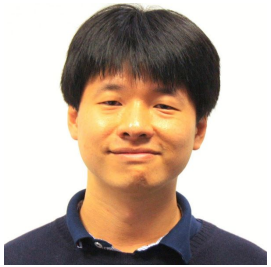


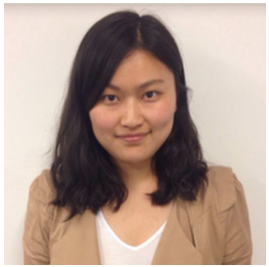
A Mutual Information Maximization Perspective of Language Representation Learning

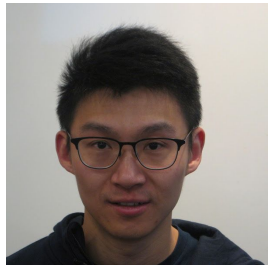
Kong et al., ICLR 2020


Lingpeng


Cyprien


Wang

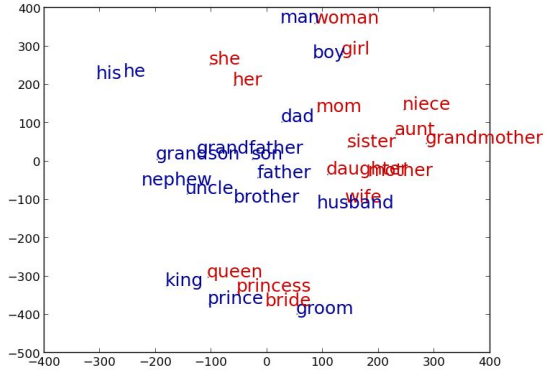

Lei


Zihang


Dani

Background

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



Skip gram, Mikolov et al., 2013.

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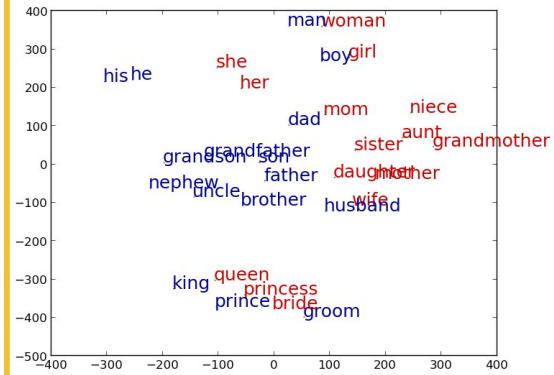

Hypothesis: these methods are different instantiations of one framework.

Skip gram, Mikolov et al., 2013.

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Mutual Information and InfoNCE (Contrastive Learning)

InfoNCE (Logeswaran and Lee, 2018; van den Oord, et al., 2019) is a bound on mutual information.

$$I(A, B) \geq \mathbb{E}_{p(A,B)} \left[\mathbb{E}_{q(\tilde{\mathcal{B}})} \left[\log \frac{\exp f_{\boldsymbol{\theta}}(a, b)}{\sum_{\tilde{b} \in \tilde{\mathcal{B}}} \exp f_{\boldsymbol{\theta}}(a, \tilde{b})} \right] \right]$$

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Pittsburgh + negative samples (other words) drawn from a proposal distribution

a b

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Skip-gram

Mikolov et al., 2013

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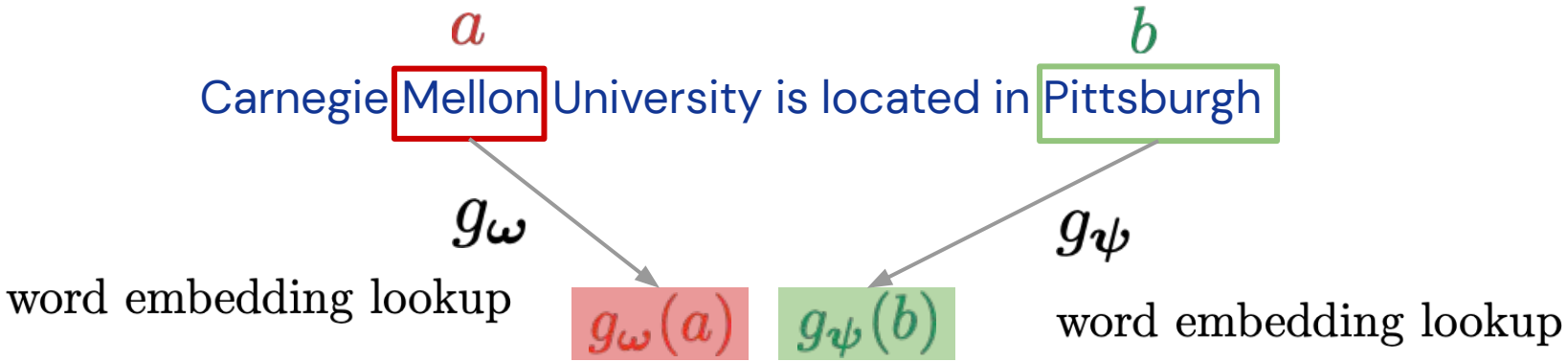
Skip-gram

Mikolov et al., 2013



BERT

Devlin et al., 2019

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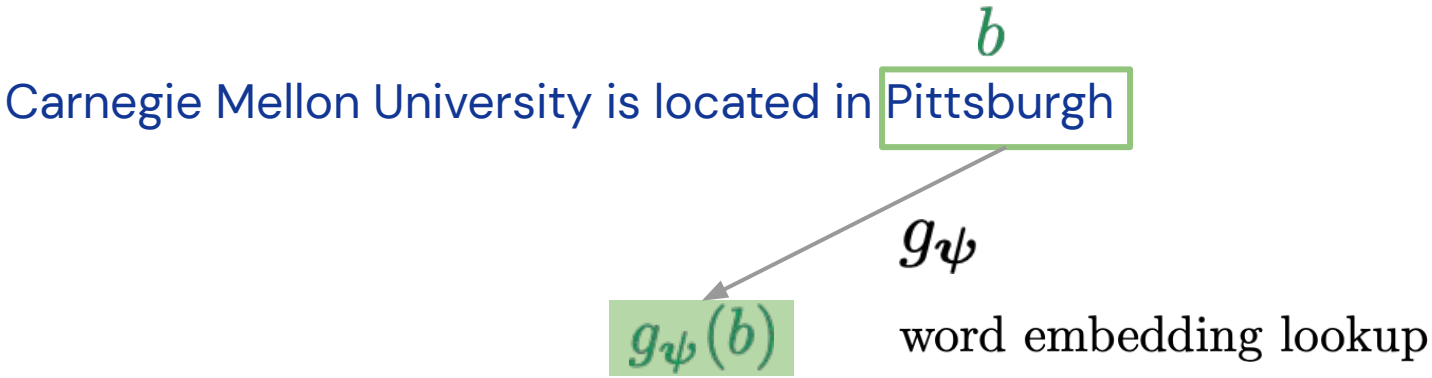
BERT

Devlin et al., 2019



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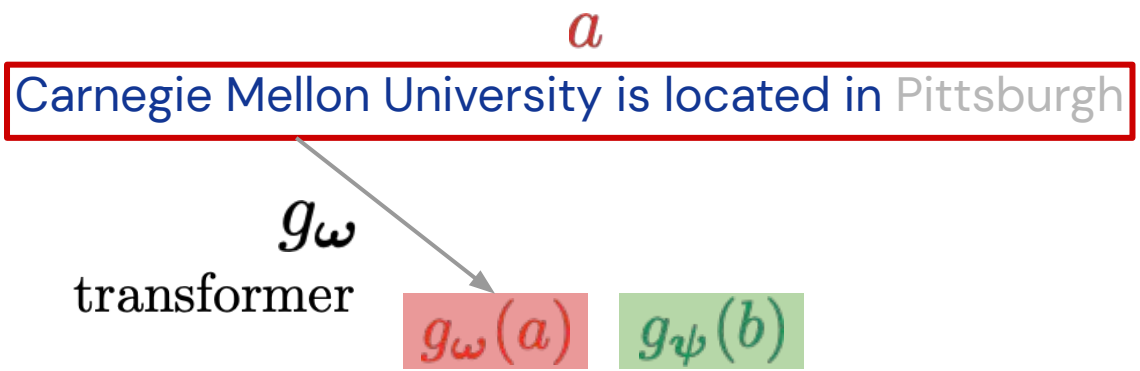

Why is this interesting?

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

	a	b	g_ω	g_ψ
Skip-gram	word	word	lookup	lookup
BERT-MLM	context	word	transformer	lookup
XLNet	context	word	TXL++	lookup

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

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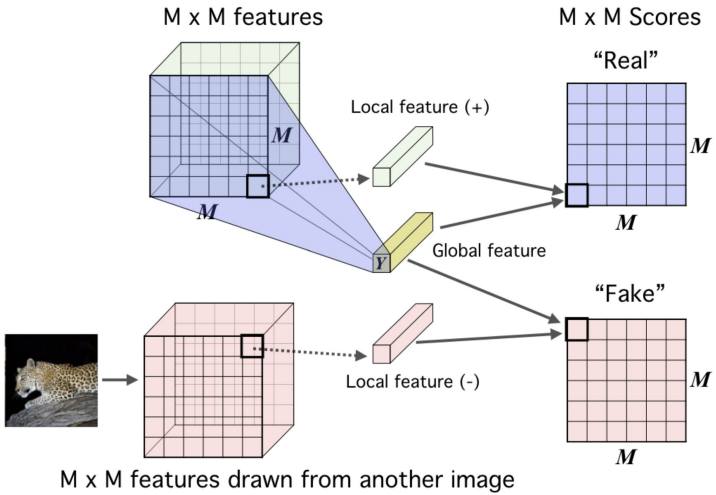
- Connections to representation learning methods used in other domains (vision, speech).

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

InfoWord

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



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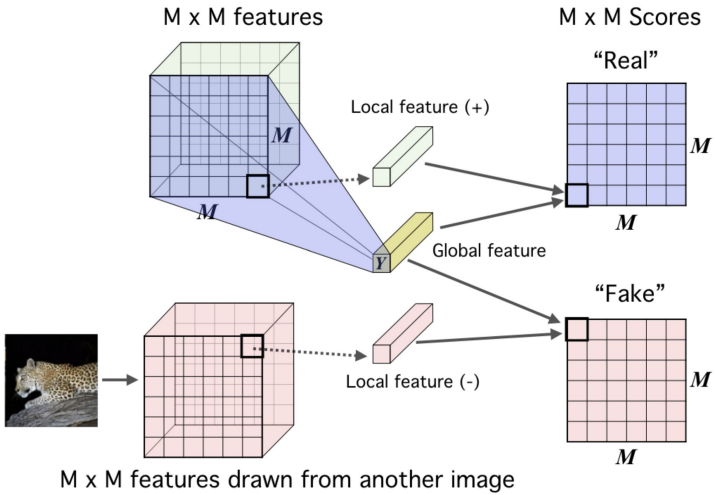

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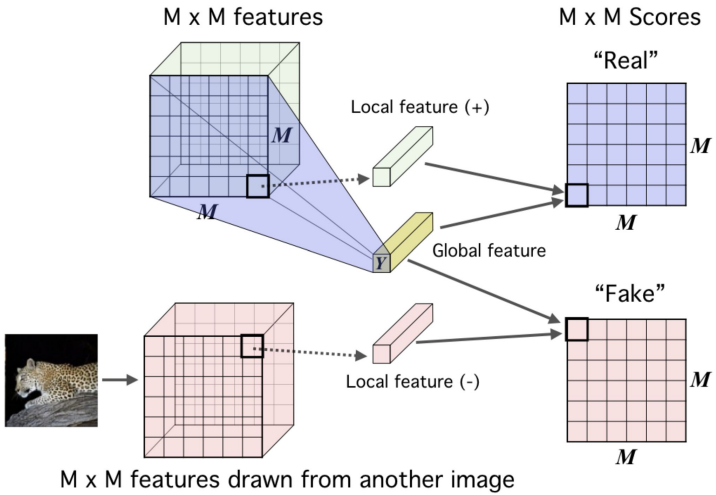

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g_ψ

transformer

$g_\psi(b)$

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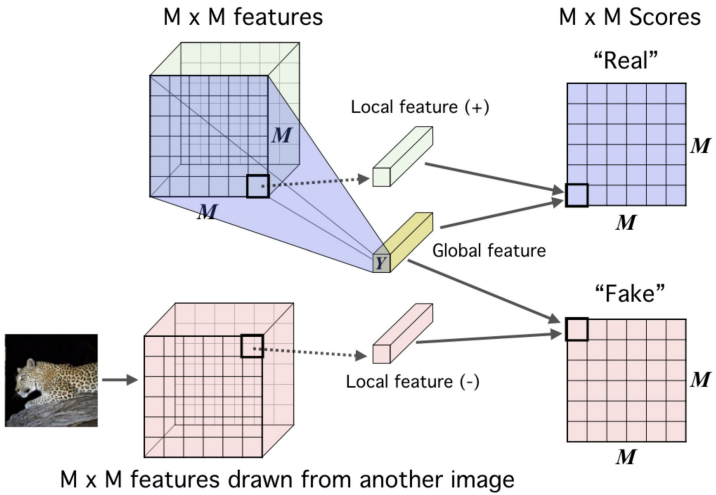

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g_ω
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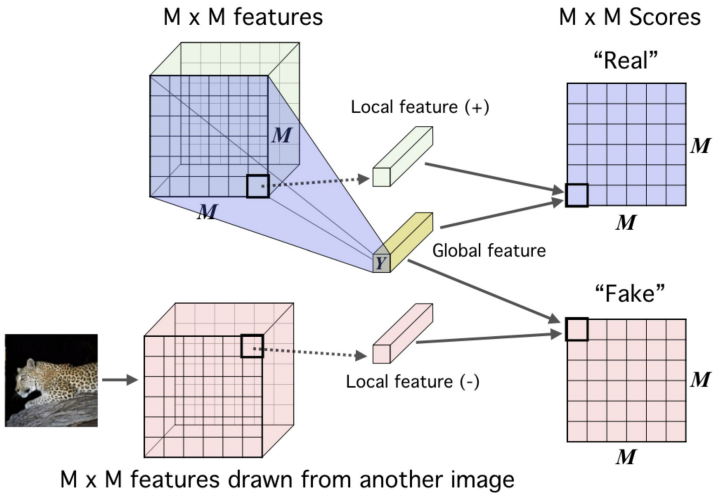

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$g_\omega(a)$ $g_\psi(b)$

Starcraft II is a boring game

Cristiano Ronaldo scores an own goal

Machine learning is transforming drug discovery

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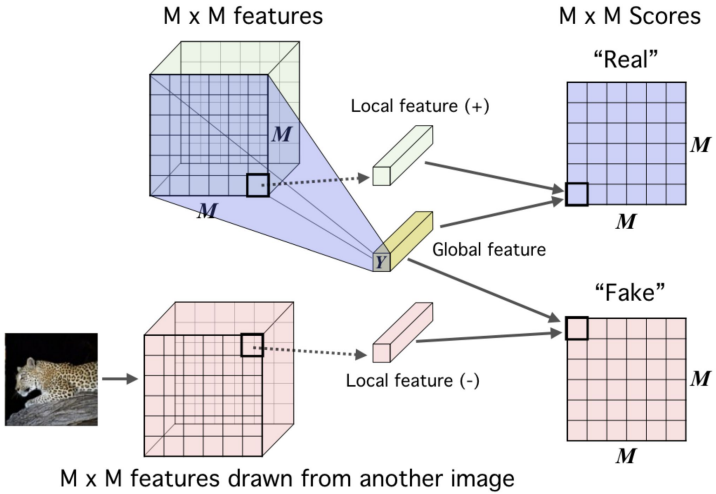

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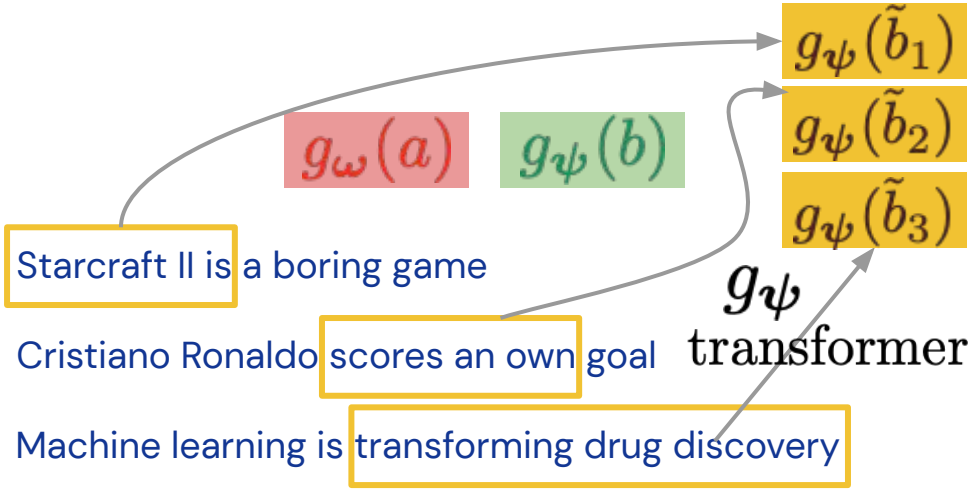

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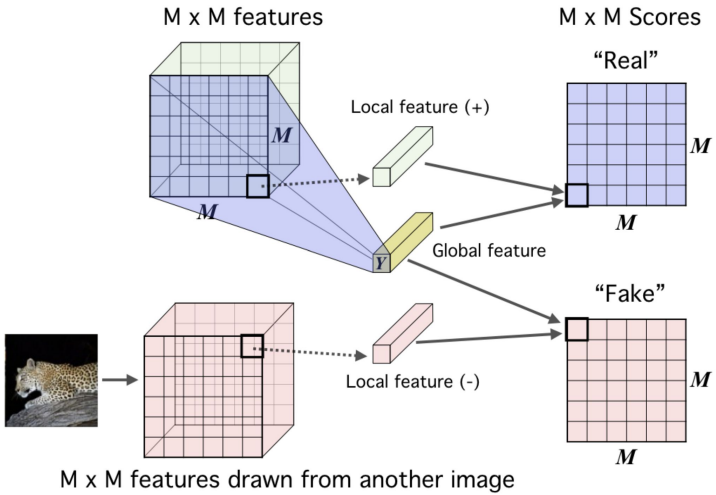

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$g_\omega(a)$ $g_\psi(b)$ $g_\psi(\tilde{b}_1)$ $g_\psi(\tilde{b}_2)$ $g_\psi(\tilde{b}_3)$

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$$\mathcal{I}_{\text{DIM}} = \mathbb{E}_{p(\hat{\boldsymbol{x}}_{i:j}, \boldsymbol{x}_{i:j})} \left[g_\omega(\hat{\boldsymbol{x}}_{i:j})^\top g_\omega(\boldsymbol{x}_{i:j}) - \log \sum_{\tilde{\boldsymbol{x}}_{i:j} \in \tilde{\mathcal{S}}} \exp(g_\omega(\hat{\boldsymbol{x}}_{i:j})^\top g_\omega(\tilde{\boldsymbol{x}}_{i:j})) \right]$$

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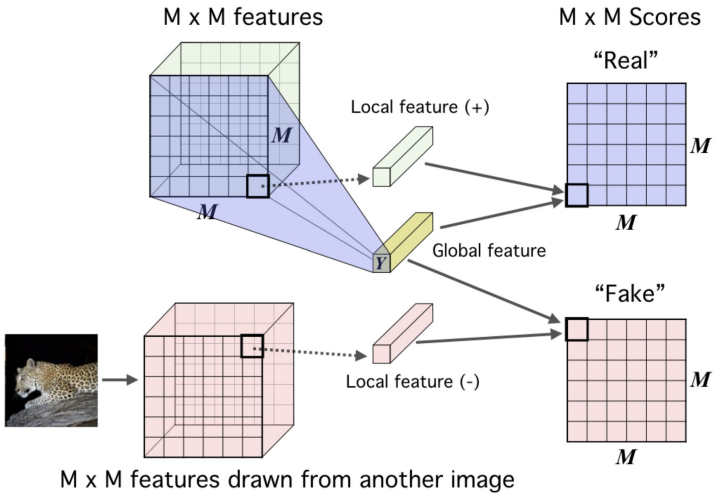

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$$\mathcal{I}_{\text{INFOWORD}} = \lambda_{\text{MLM}}\mathcal{I}_{\text{MLM}} + \lambda_{\text{DIM}}\mathcal{I}_{\text{DIM}}$$

Experiments

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

		F1	Exact Match
BASE	BERT	90.9	84.4
	InfoWord	**91.4**	**84.7**
LARGE	BERT	92.7	86.6
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F1 and exact match scores (0-100), higher is better

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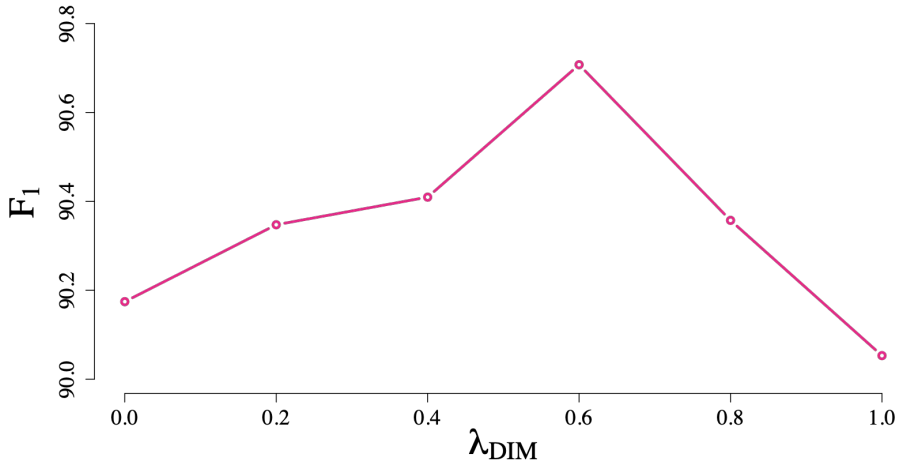

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Takeaways and Limitations

- 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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- 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.
- All variants of existing models, fail to incorporate **global context** (they rely on local views).

Future Directions

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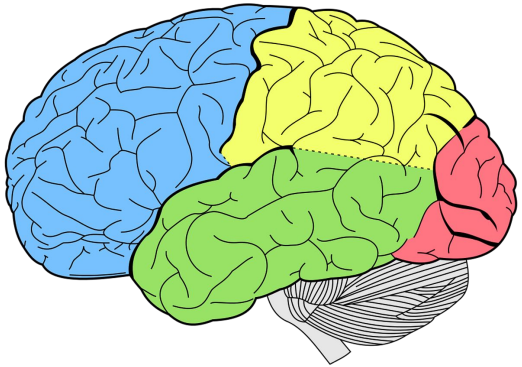
- Semi-parametric models: a combination of a big parametric neural network with non-parametric memory modules (cache, stacks, memory blocks).
  - Human memory has specialized systems for different functions.
  - Important for reasoning.



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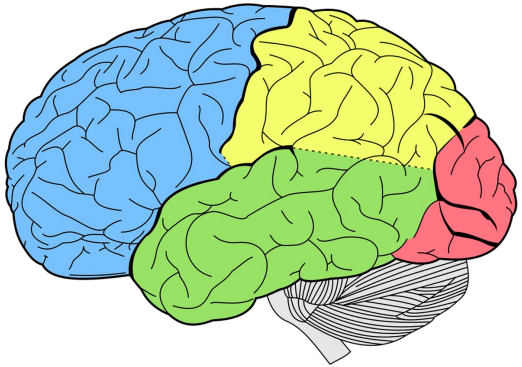
→ Learning what to remember and forget/compress, integration of modules.



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- The future is generative (models).
  - Elegantly deal with multiple tasks (McCann et al., 2018; Radford et al., 2019).
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→ Hierarchical models for efficient out-of-distribution generalization.

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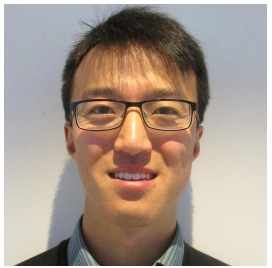
→ Hierarchical models for efficient out-of-distribution generalization.

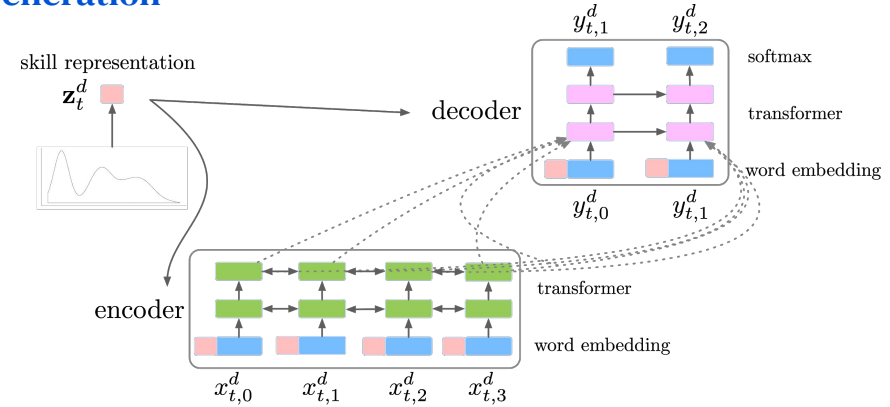
Modelling Latent Skills for Multitask Language Generation

Cao and Yogatama, arXiv 2020



Kris

Dani



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  - Humans acquire language with a mechanism that is independent of the language.
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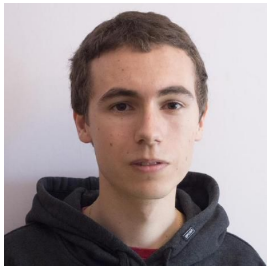
On the Crosslingual Transferability of Monolingual Representations

Artetxe et al., arXiv 2019



Mikel

Sebastian

Dani

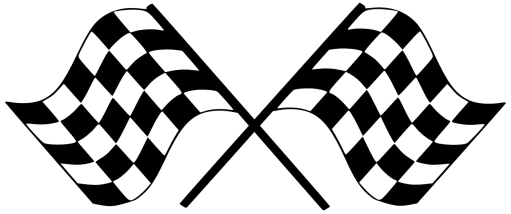
	Average (11 langs.)
Multilingual Training	65.7
Monolingual Training + Transfer	66.8

Thank you!

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

DeepMind

Research Areas

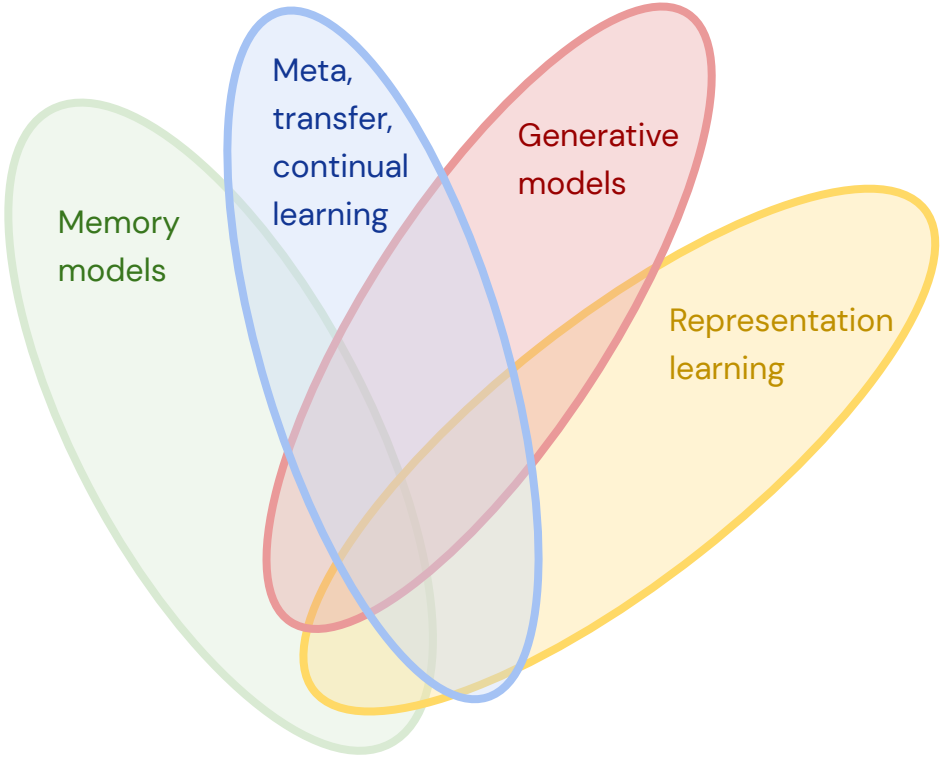


A universal language model that continually learns to perform multiple tasks in many languages.

- 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