DeepMind

Deep Learning for Language Understanding

Plan for this Lecture

01
Background:
deep learning and language

02
The Transformer

03
Unsupervised and transfer learning with BERT

04
Grounded language learning at DeepMind: towards language understanding in a situated agent

What is not covered in this lecture

01

Recurrent networks

- Seq-to-seq models and neural MT
- Speech recognition or synthesis

02

Many NLP tasks and applications

- Machine comprehension
- Question answering
- Dialogue

03

Grounding in image/video

- Visual question-answering or captioning
- CLEVR and visual reasoning
- Video captioning

1 Background: Deep learning and language

Google Cloud Text-to-Speech now has 187 voices and 95 WaveNet voices

Microsoft's Chinese-English translation system achieves human parity

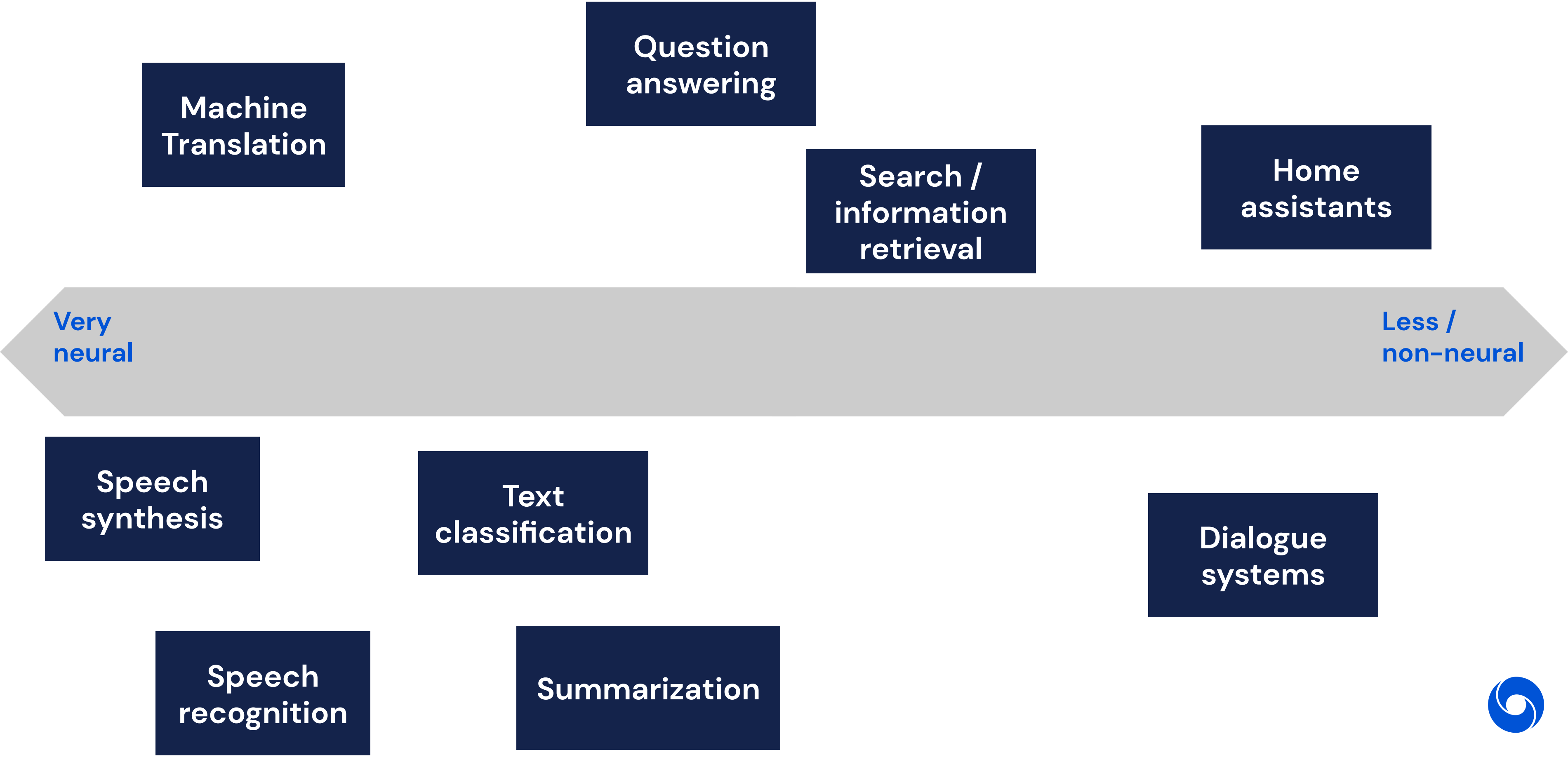
A China-US research team at software powerhouse Microsoft has developed an AI-powered system that can translate Chinese news articles into English as well as humans do.

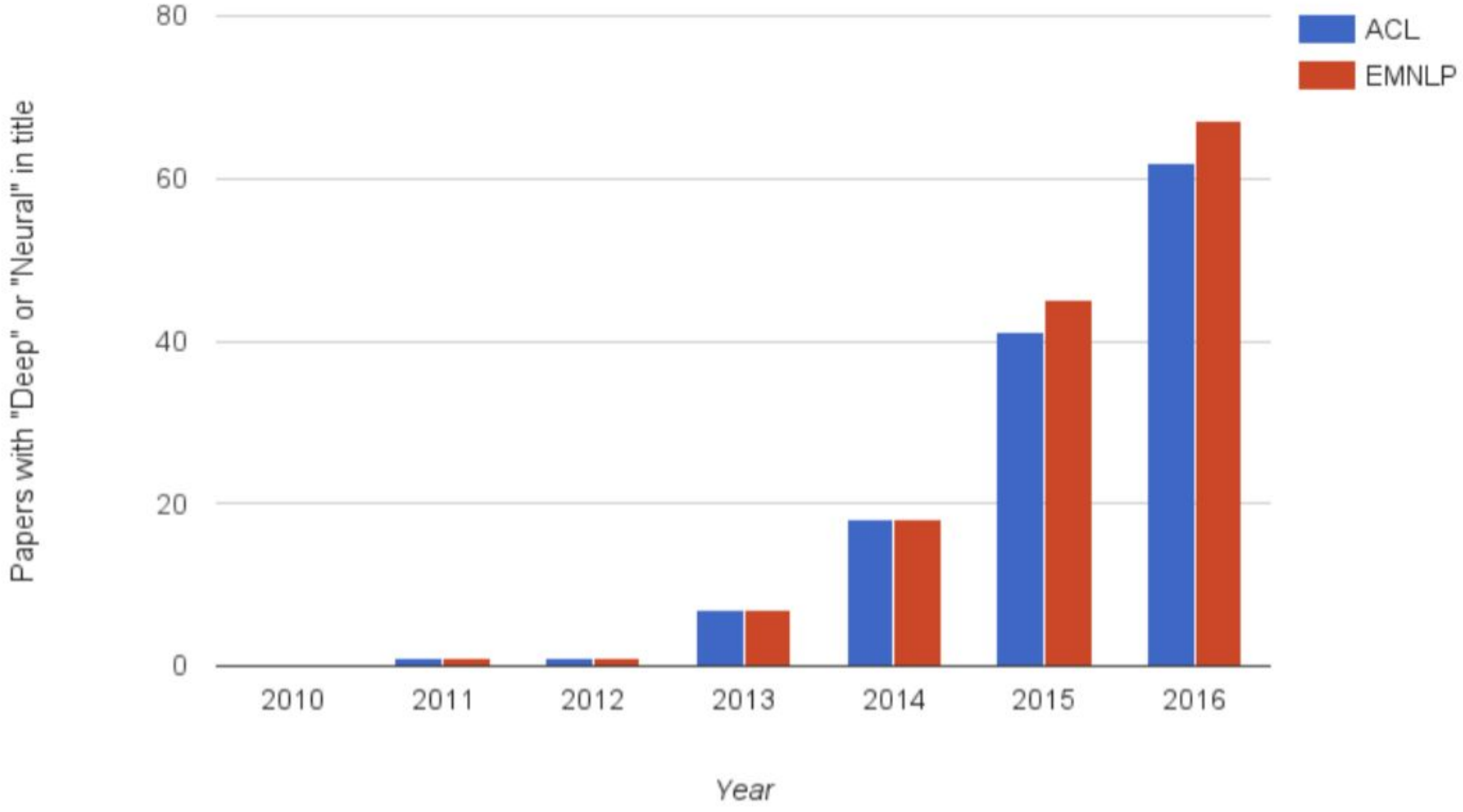
INNOVATION / AI

OpenAI's GPT2 Now Writes Scientific Paper Abstracts

A string of tweets demonstrates the transformer neural network's incredible capabilities.

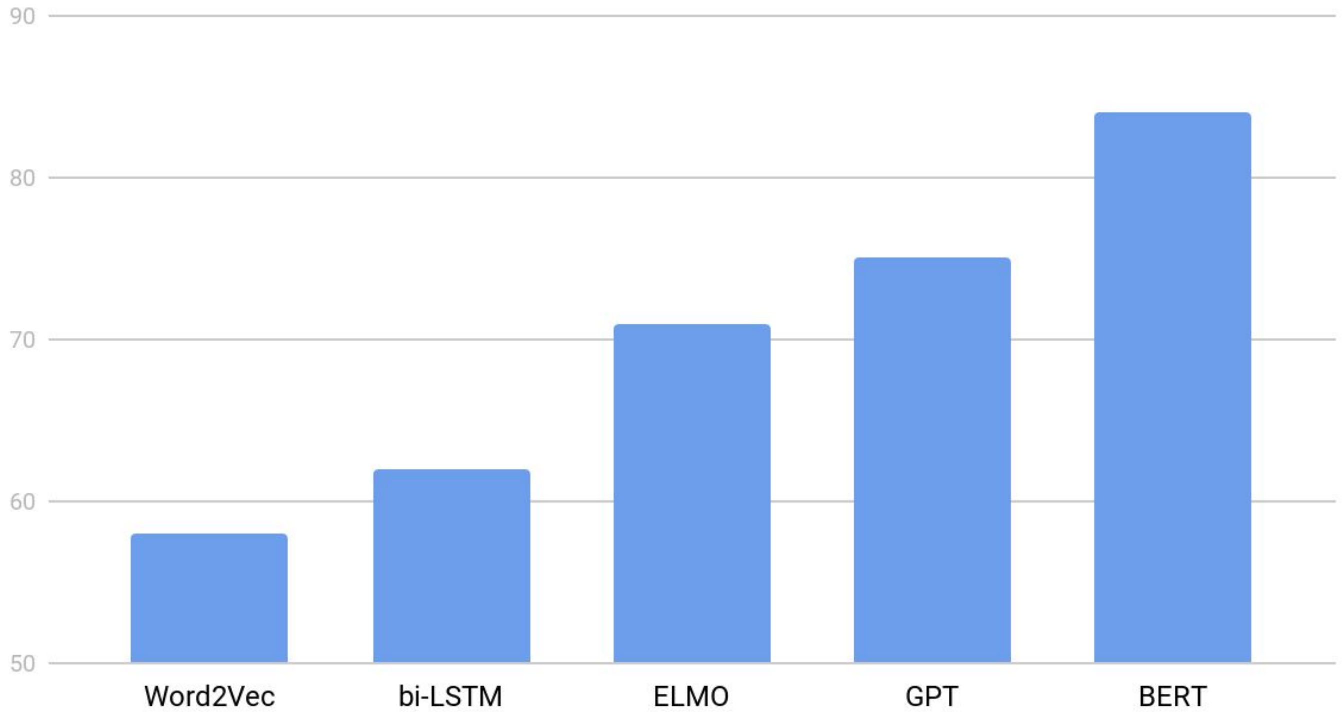
Google brings in BERT to improve its search results


Question answering
Machine Translation
Search / information retrieval
Home assistants
Very neural
Less / non-neural
Speech synthesis
Text classification
Dialogue systems
Speech recognition
Summarization



80
60
40
20
0
Papers with "Deep" or "Neural" in title
ACL
EMNLP
2010
2011
2012
2013
2014
2015
2016
Year

Performance on GLUE benchmark (11 tasks) 2018-19



Why is Deep Learning such an effective tool for language processing?

Why is Deep Learning such an effective tool for language processing?

Can it be improved?

Some things about language...

1. Words are not discrete symbols

- Did you see the look on her **face**$_1$?
- We could see the clock **face**$_2$ from below
- It could be time to **face**$_3$ his demons
- There are a few new **faces**$_4$ in the office today

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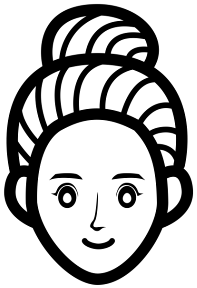

Created by Chananan from Noun Project

Face 1

- The most important side (of the head)
- Represents you / yourself
- Used to inform / communicate
- Points forward when you address/confront something

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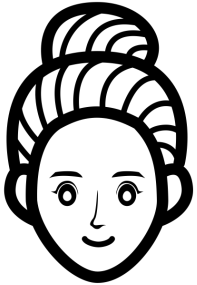

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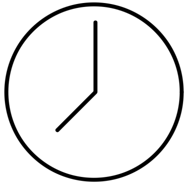
Face 2

- The most important side (of the head)
- Used to inform / communicate



Created by Neha Tyagi
from Noun Project

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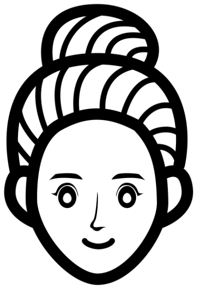

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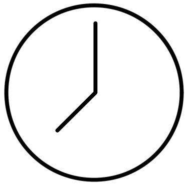

Created by Neha Tyagi
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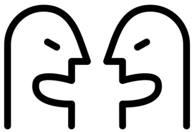
Face 3

- Points forward when you address/confront something



Created by Yu luck
from Noun Project

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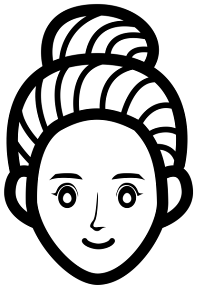

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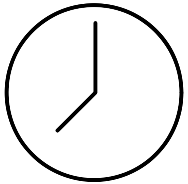
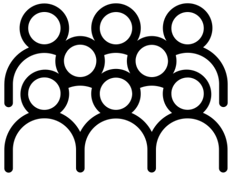


Created by Neha Tyagi from Noun Project

Face 4

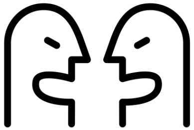
- Represents you / yourself



Created by Dániel Aczél from Noun Project

Face 3

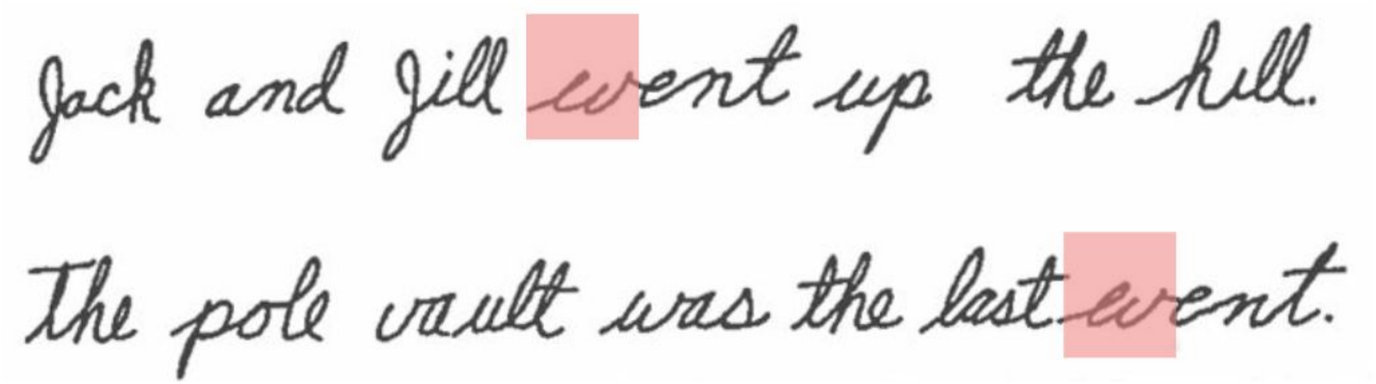
- Points forward when you address/confront something



Created by Yu luck from Noun Project

1. Words are not discrete symbols

2. Disambiguation depends on context



Rumelhart, D. E. (1976). Toward an interactive model of reading

12

ABC

14

1. Words are not discrete symbols

2. Disambiguation depends on context

3. Important interactions can be non-local

The man who ate the pepper sneezed

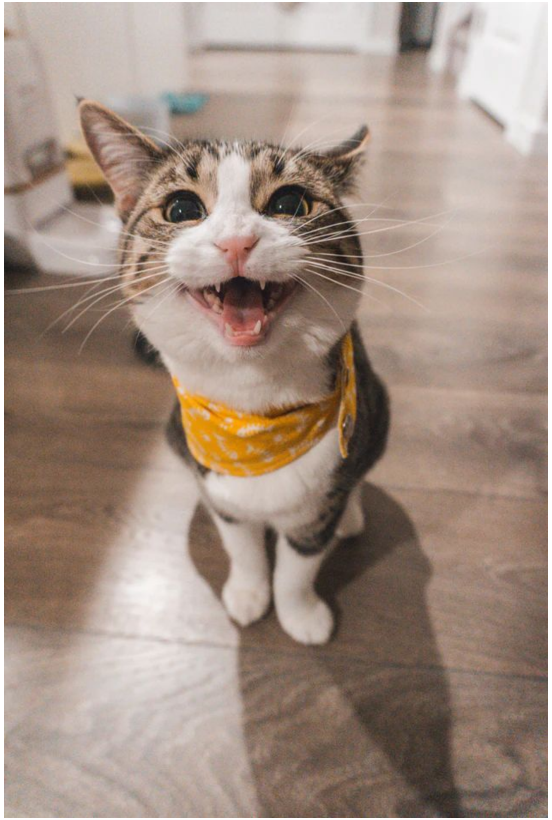
The man who ate the pepper sneezed

The man who ate the pepper sneezed

But note:

The cat who bit the dog barked

The man who ate the pepper sneezed



The cat who bit the dog barked

1. Words are not discrete symbols

2. Disambiguation depends on context

3. Important interactions can be non-local

4. How meanings combine depends on those meanings




PET

brown
white
black

FISH

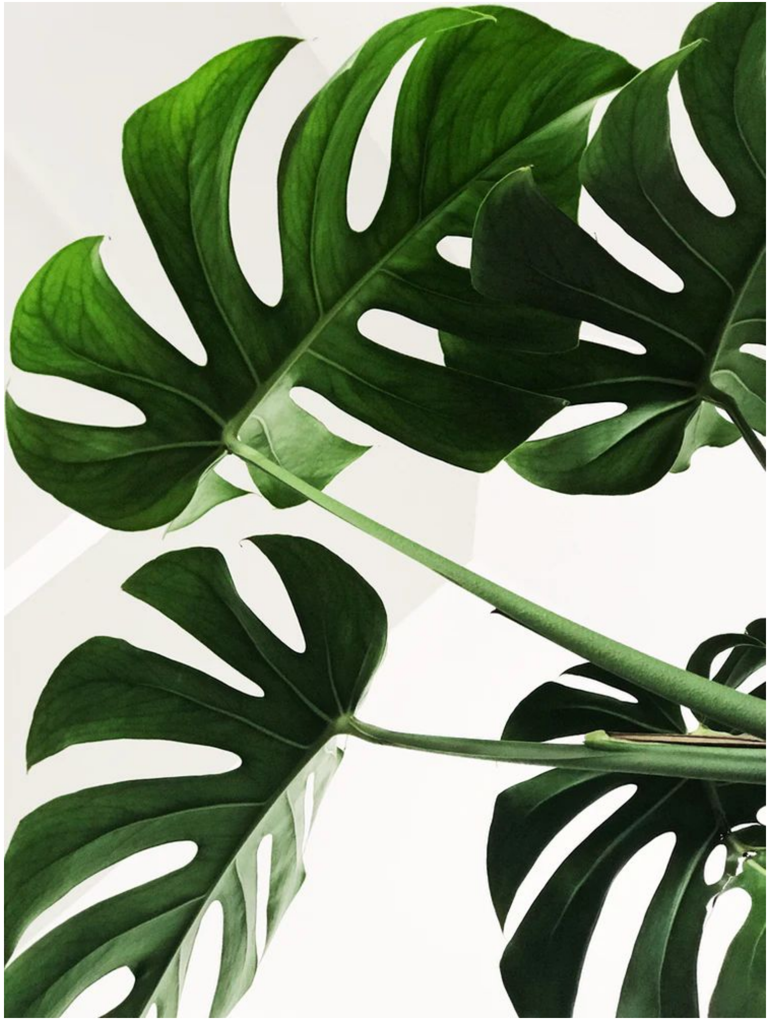
silver grey

PET

brown
white
black

PET FISH

Orange
Green
Blue
Purple
Yellow



PLANT

Green
Leaves
Grows

CARNIVORE

Eats meat
Sharp teeth

CARNIVOROUS PLANT

Green
Leaves
Grows
Sharp teeth
Eats insects

1. Words have many related senses

2. Disambiguation depends on context

3. Important interactions can be non-local

4. How meanings combine depends on those meanings

2 The Transformer

Vaswani et al. 2018

Attention Is All You Need

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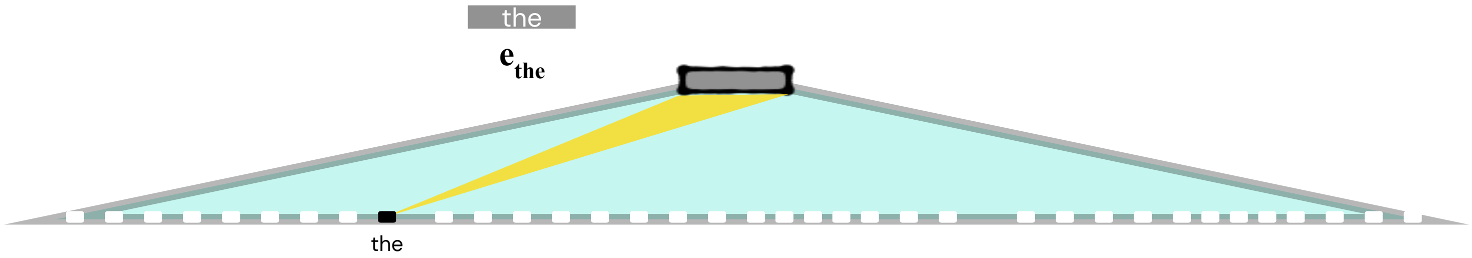
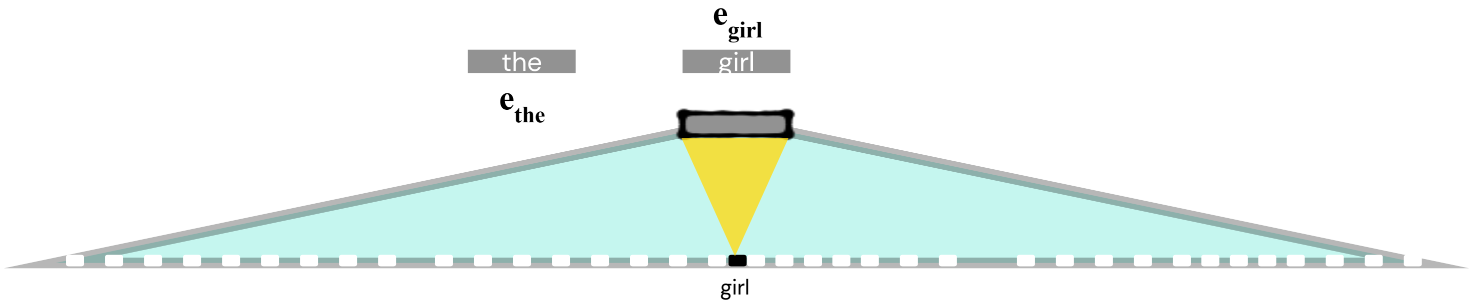
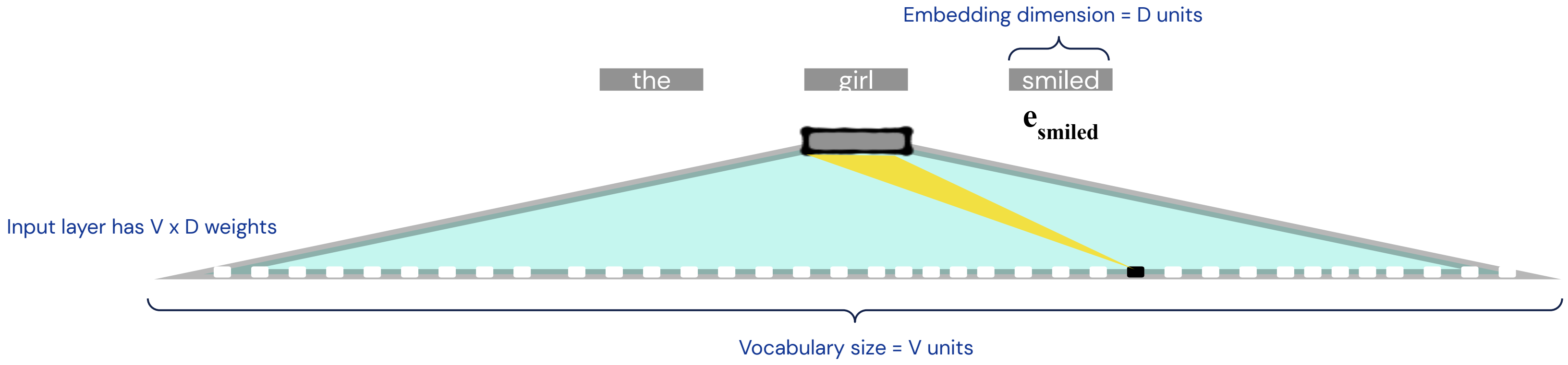
Distributed representations of words



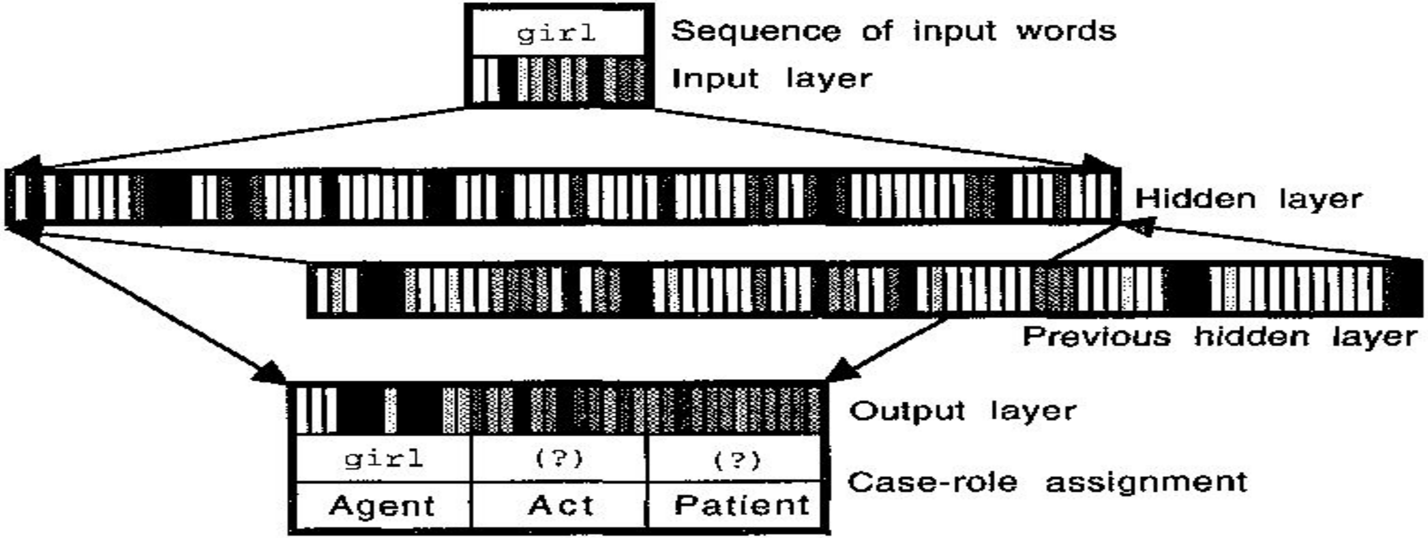
Distributed representations of words



Distributed representations of words

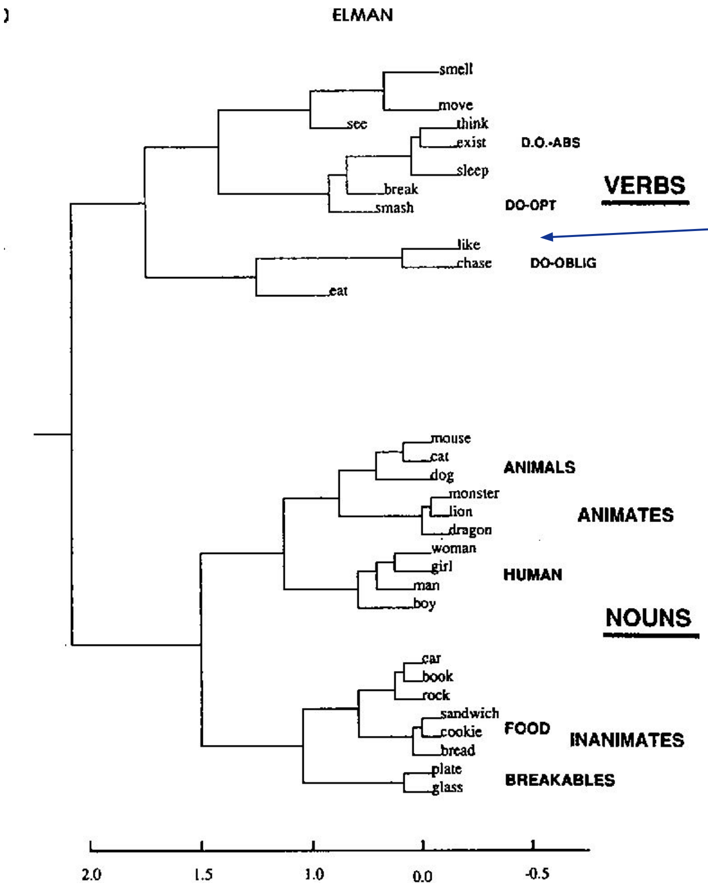


The Transformer builds on solid foundations



Mikkulainen & Dyer, 1991

Emergent semantic and syntactic structure in distributed representations



Early **contextual** word embeddings

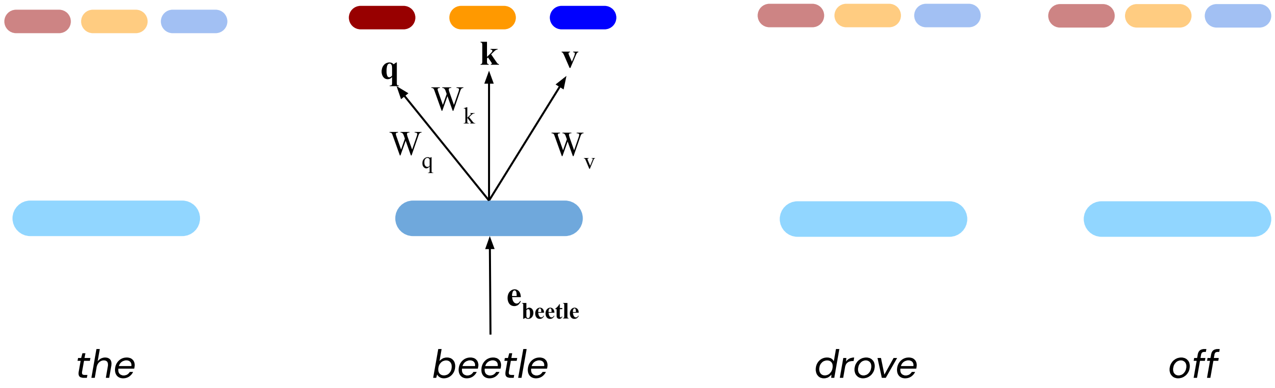
Elman,
Finding Structure in Time,
1990

The Transformer: Self-attention over word input embeddings

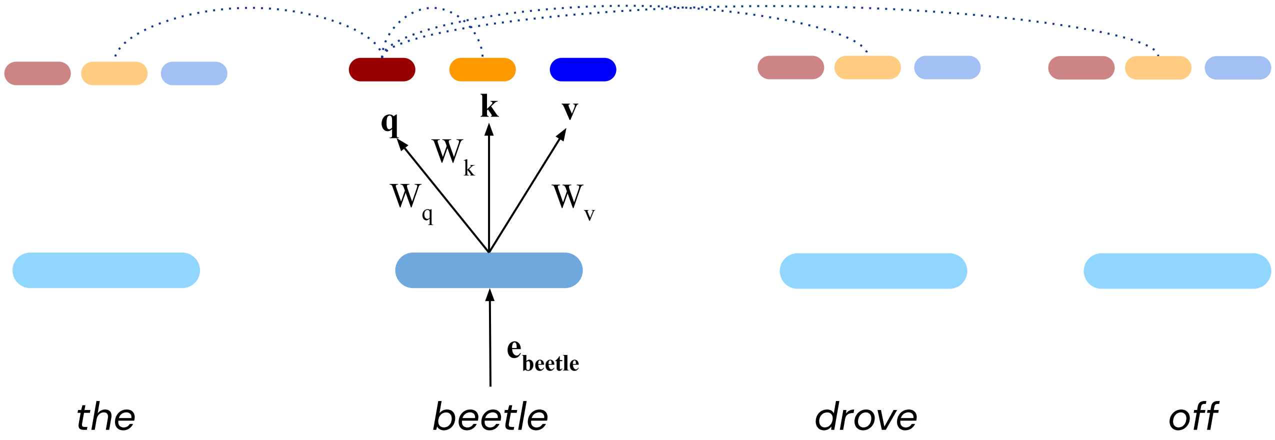
$$\mathbf{q} = \mathbf{e}_{beetle}\ W_q$$

$$\mathbf{k} = \mathbf{e}_{beetle}\ W_k$$

$$\mathbf{V} = \mathbf{e}_{beetle}\ W_v$$

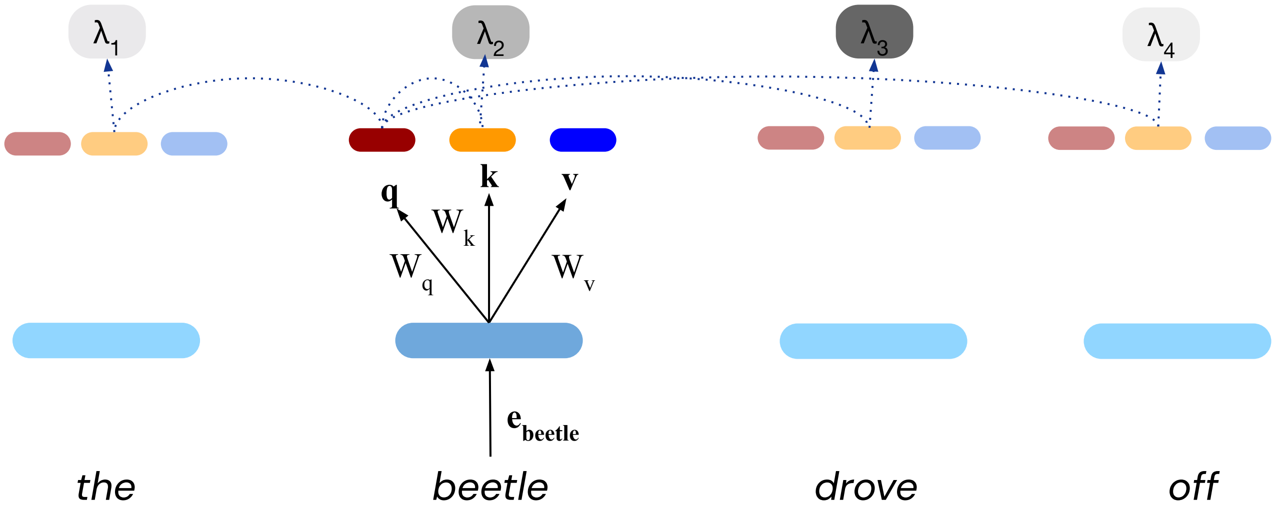


Self-attention over word input embeddings



Self-attention over word input embeddings

$$\lambda_i = \frac{e^{\mathbf{q}\cdot\mathbf{k_i}}}{\sum_{i=1}^{4} e^{\mathbf{q}\cdot\mathbf{k_i}}}$$



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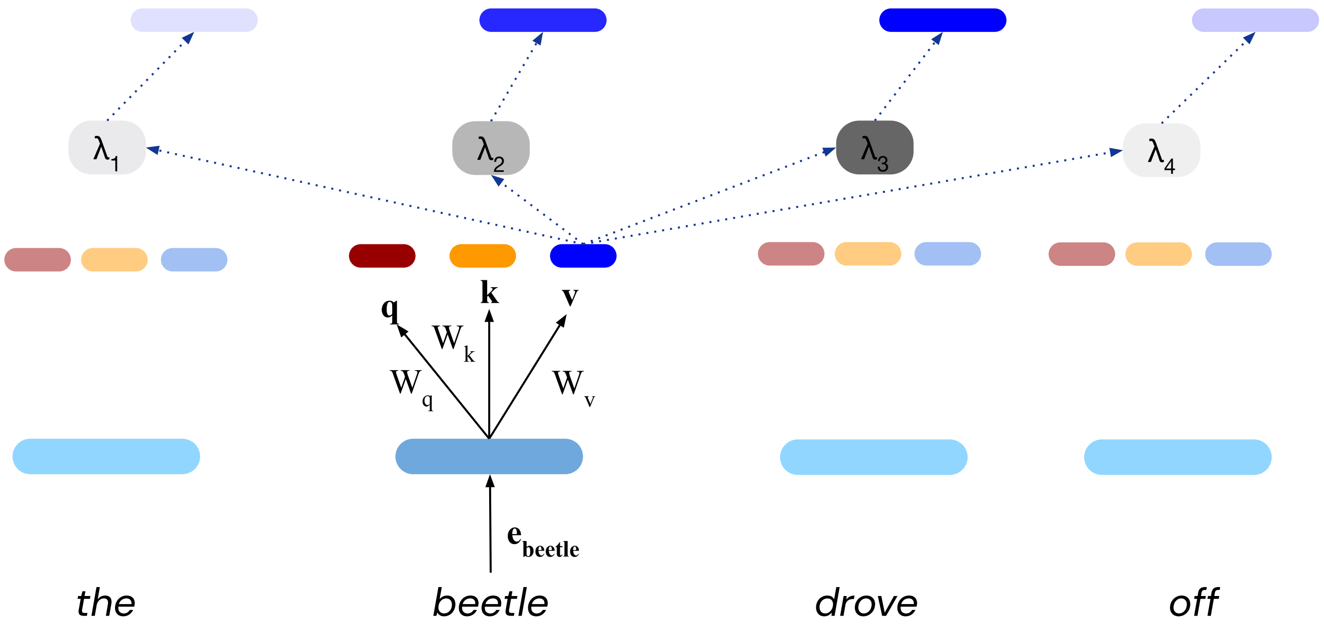
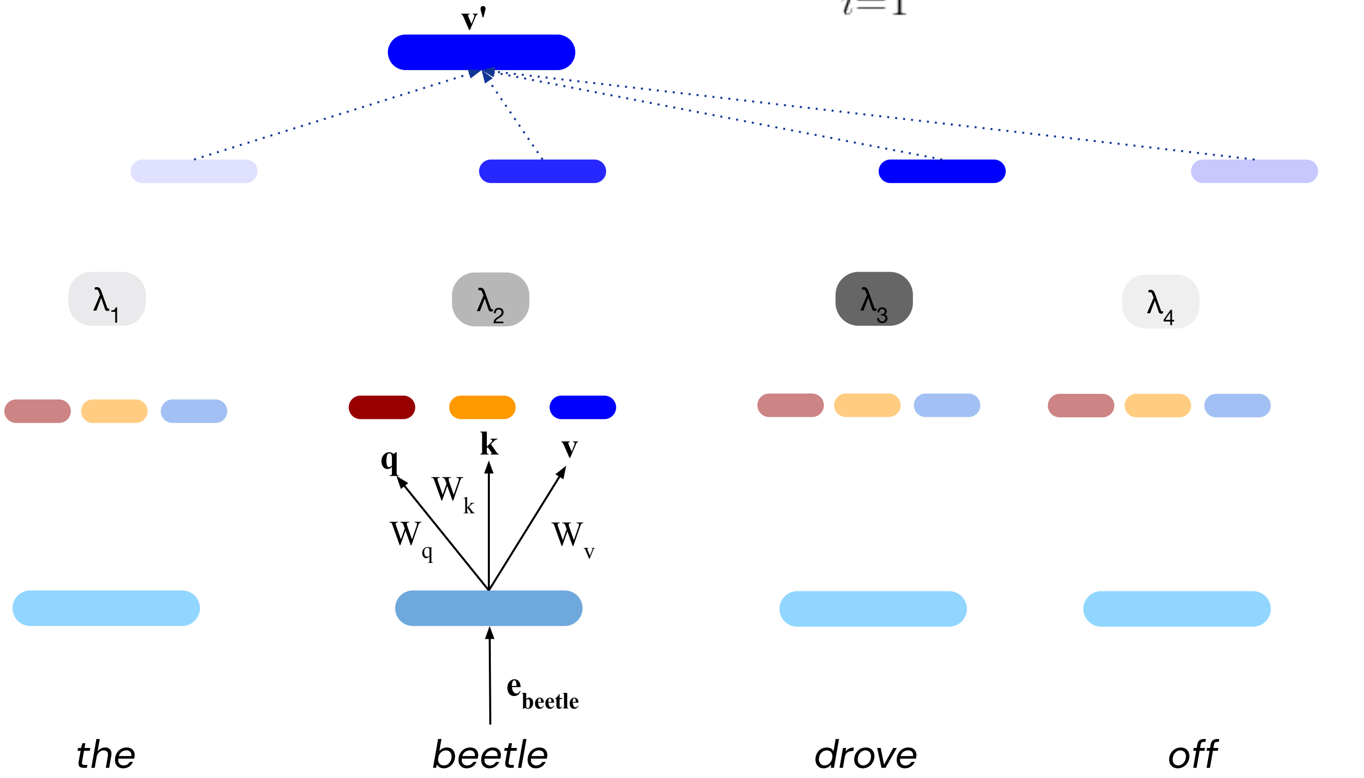
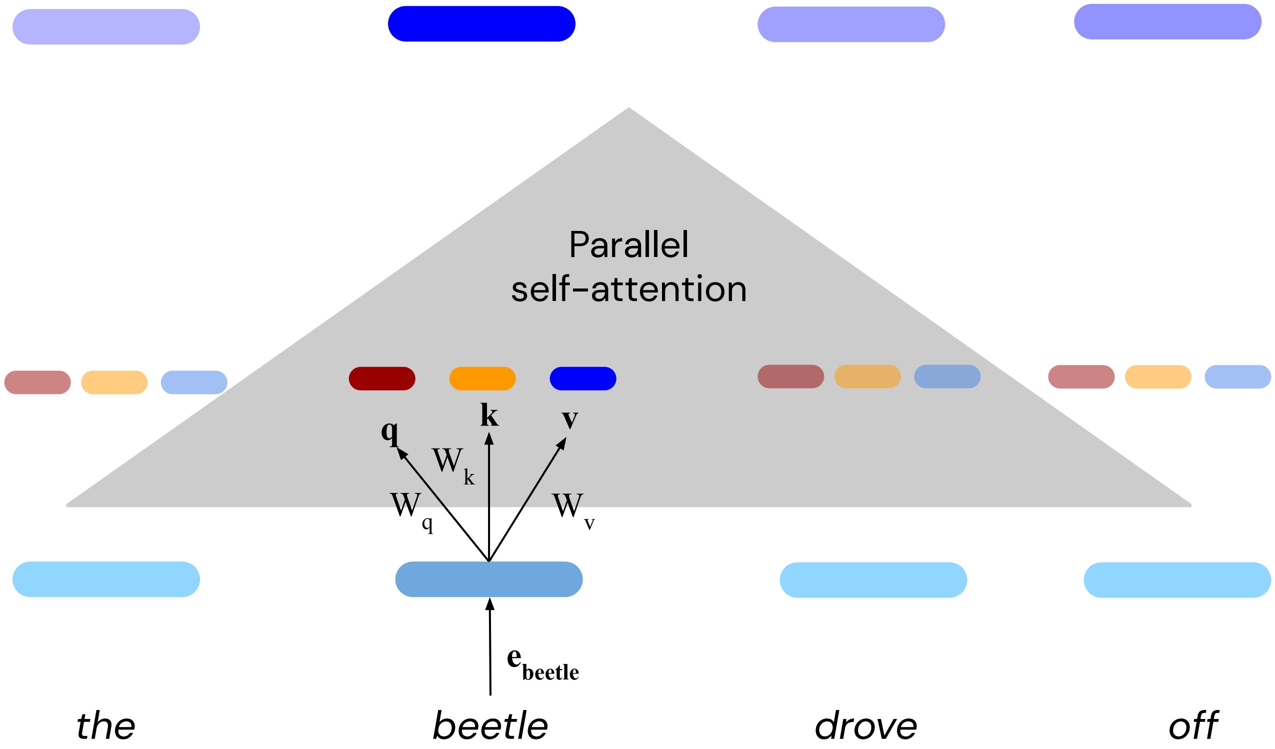


Self-attention over word input embeddings

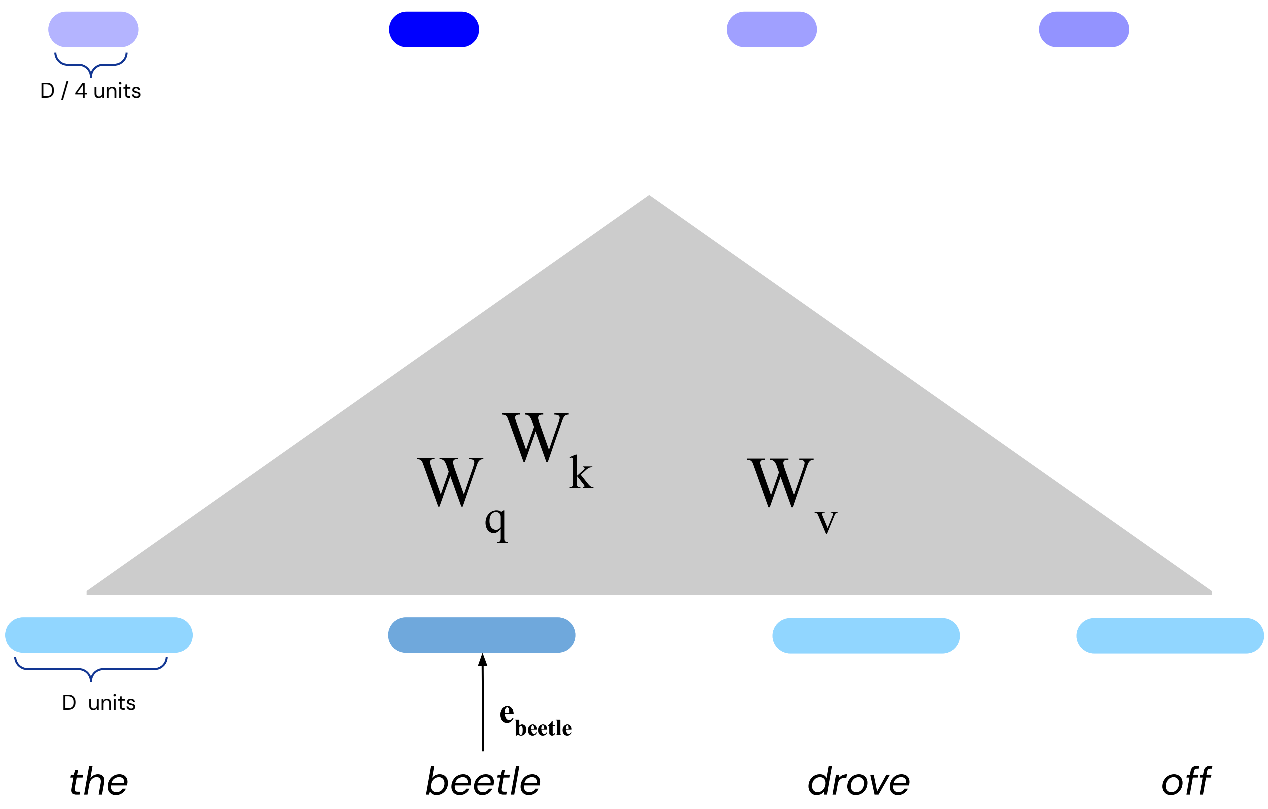
$$\mathbf{v}' = \sum_{i=1}^{4} \lambda_i \mathbf{v}_i$$



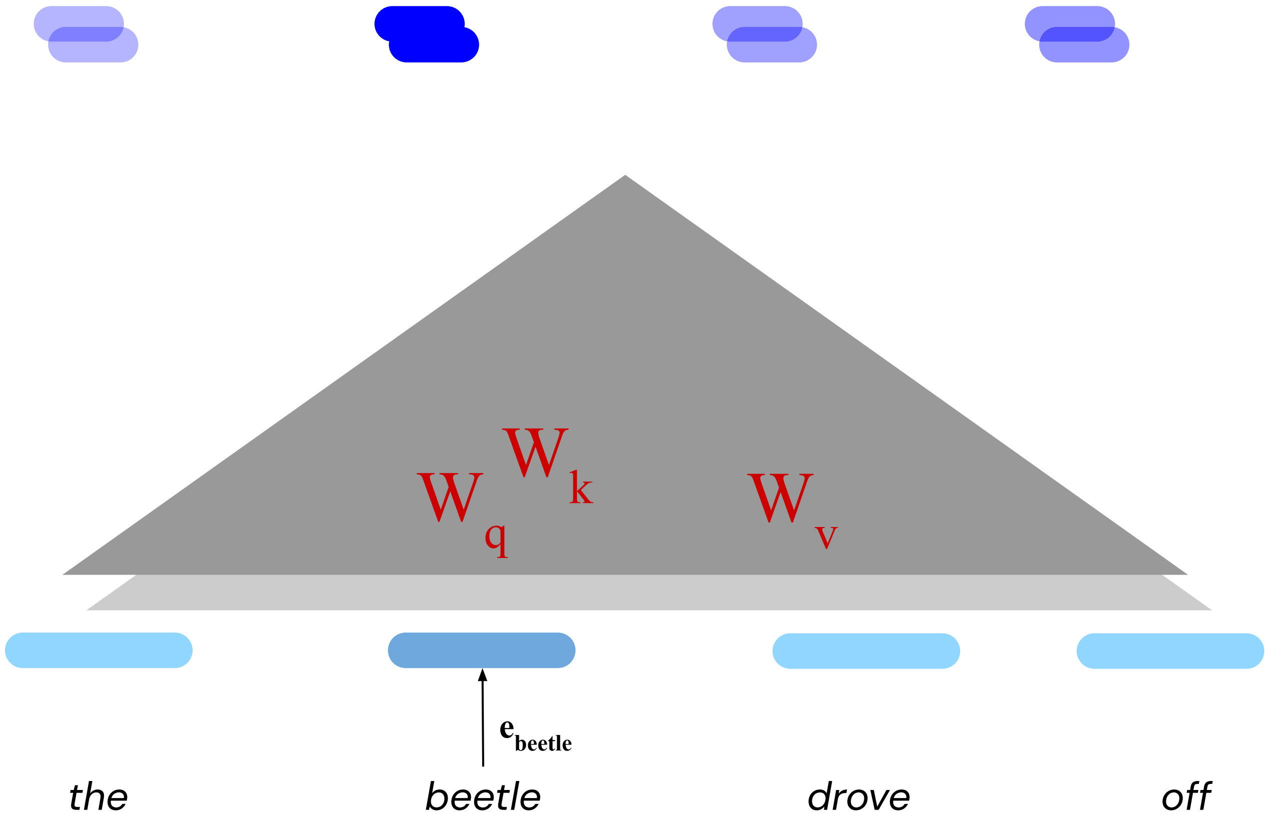
Compute self-attention for all words in input (in parallel)



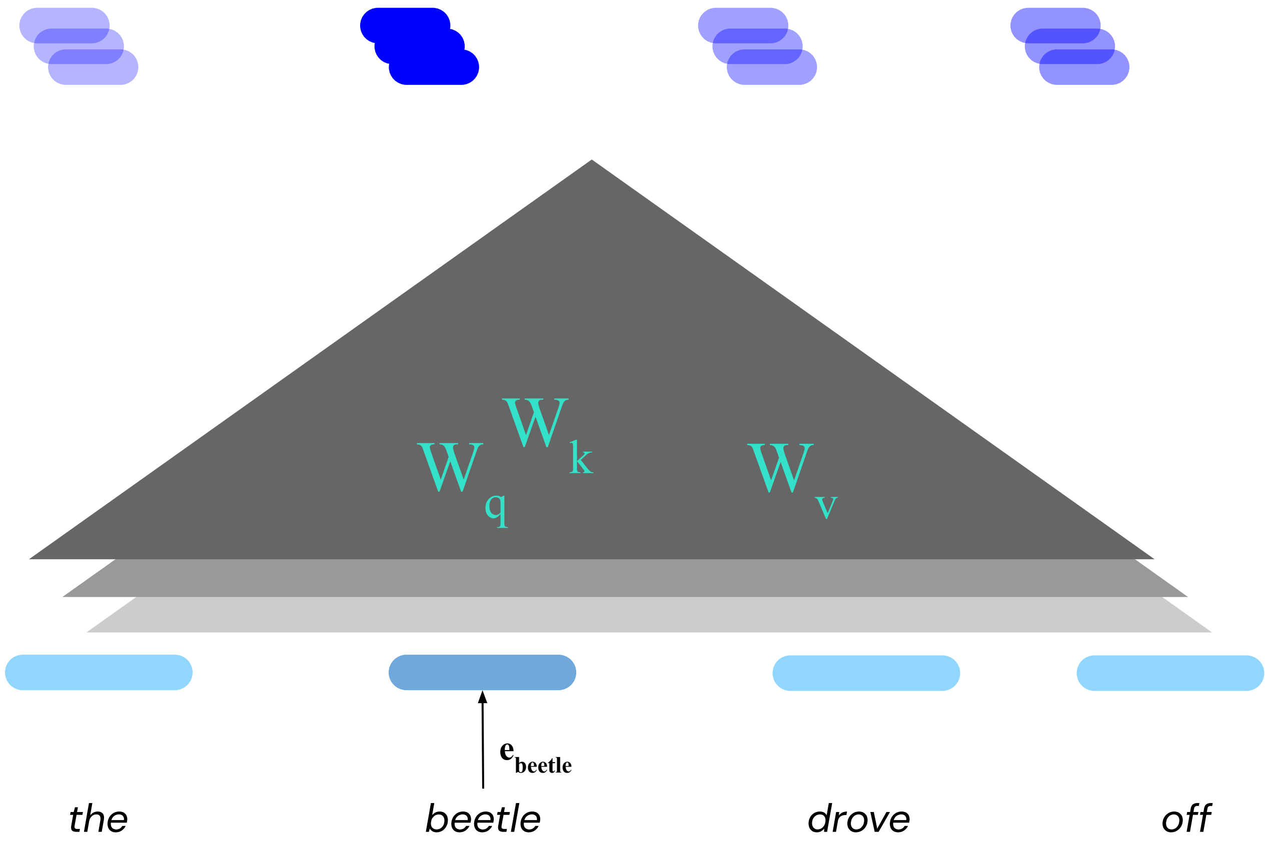
Multi-head self-attention (H = 4)



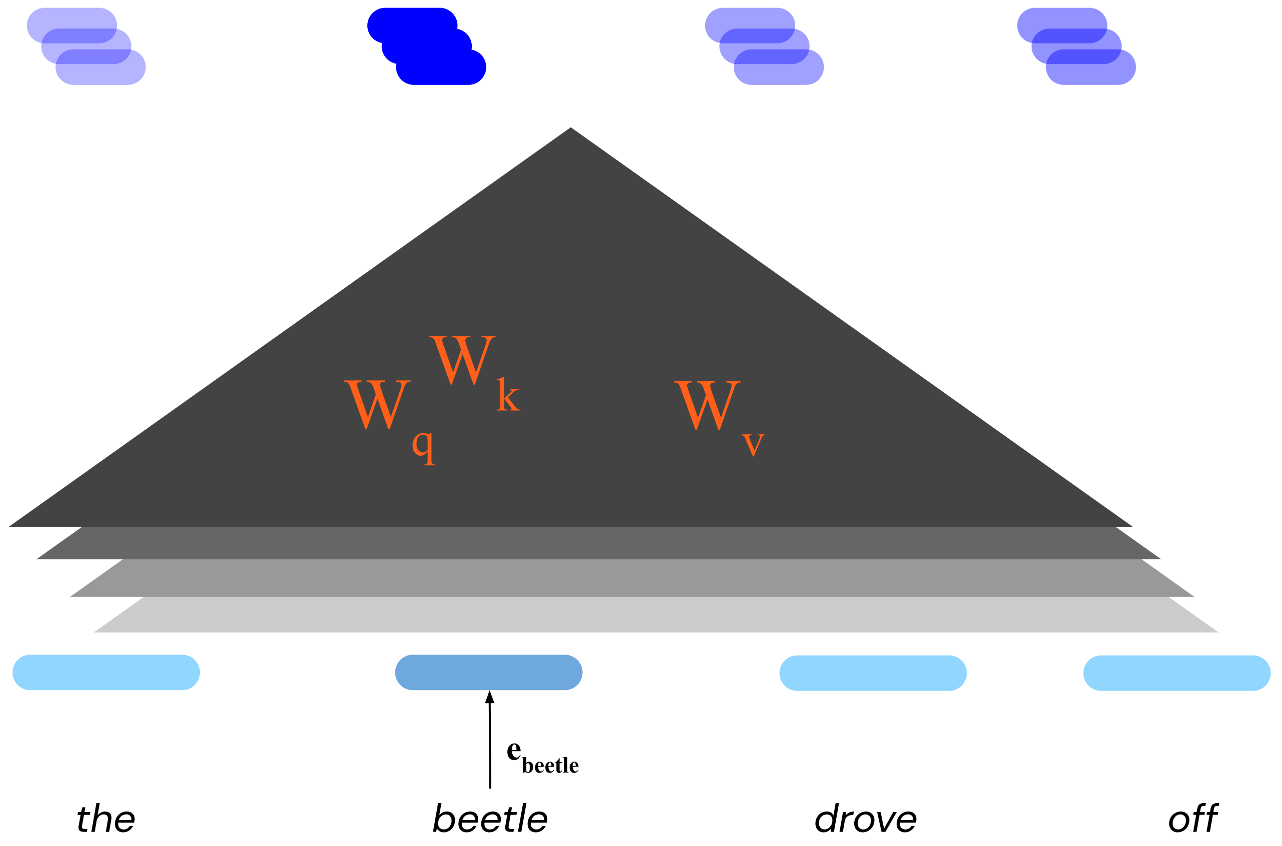
Multi-head self-attention (H = 4)

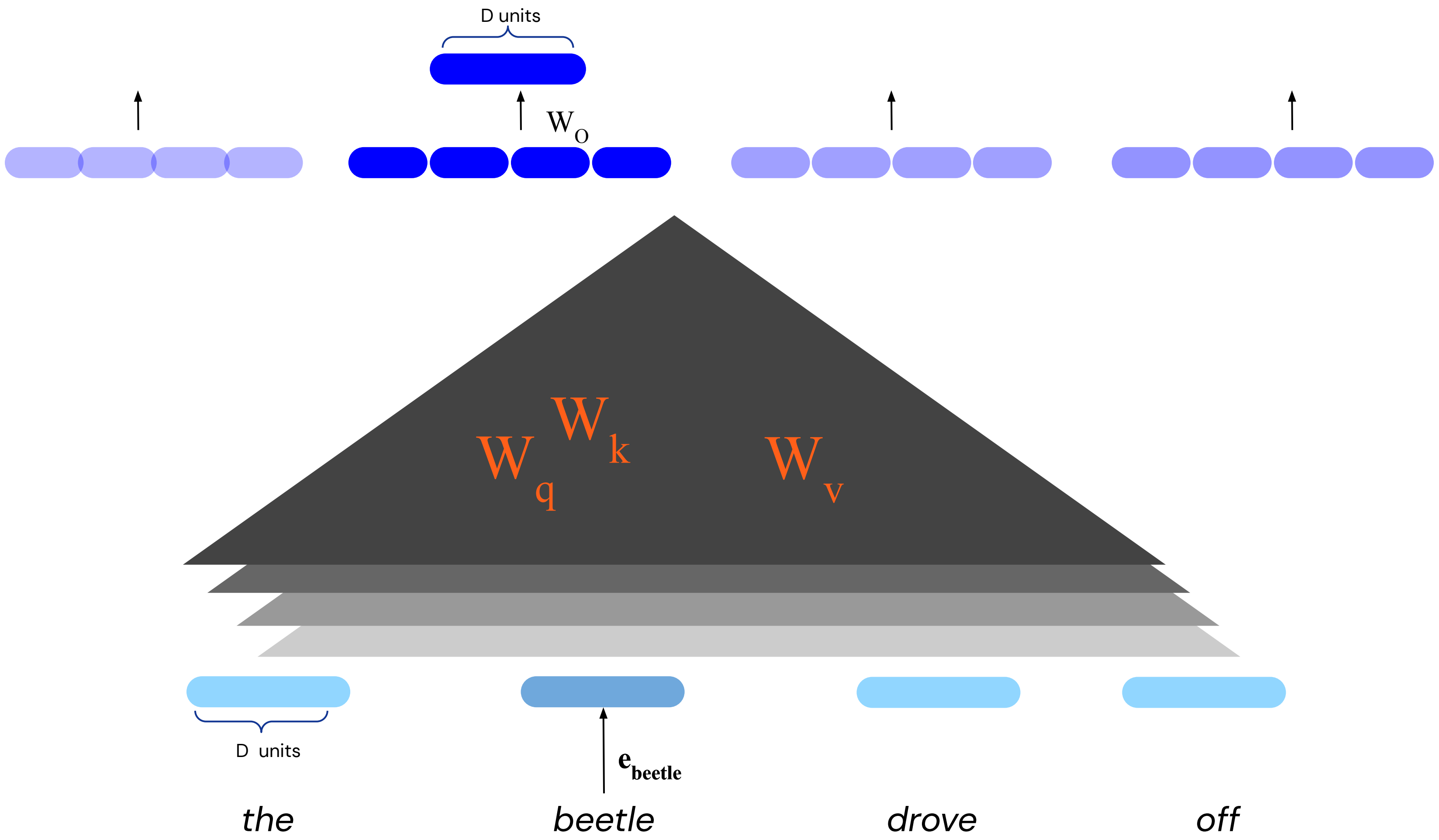


Multi-head self-attention (H = 4)



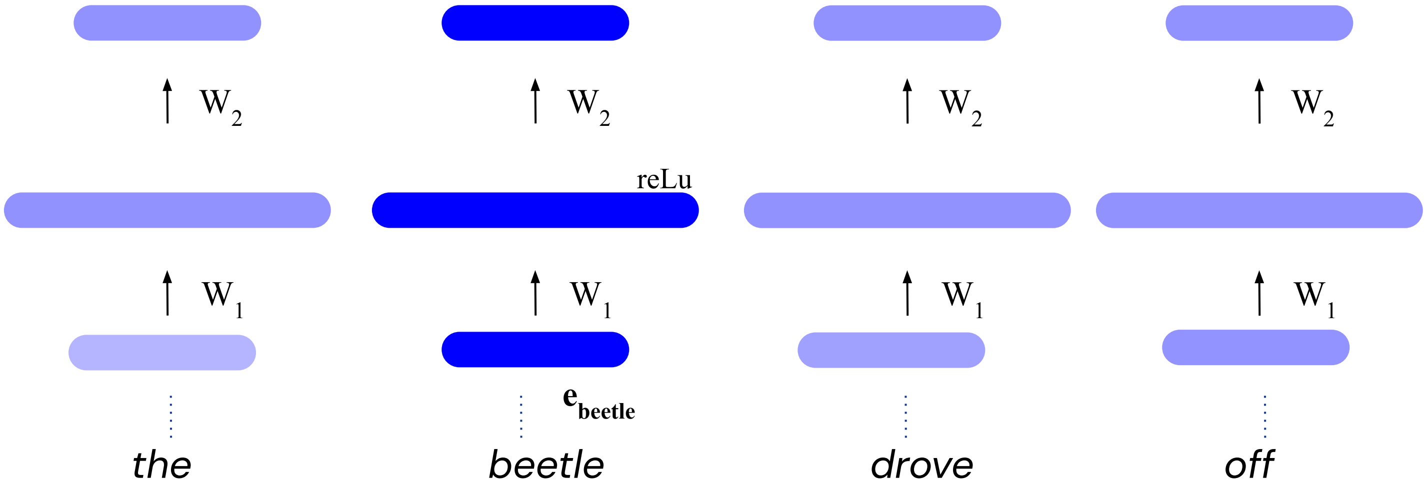
Multi-head self-attention (H = 4)



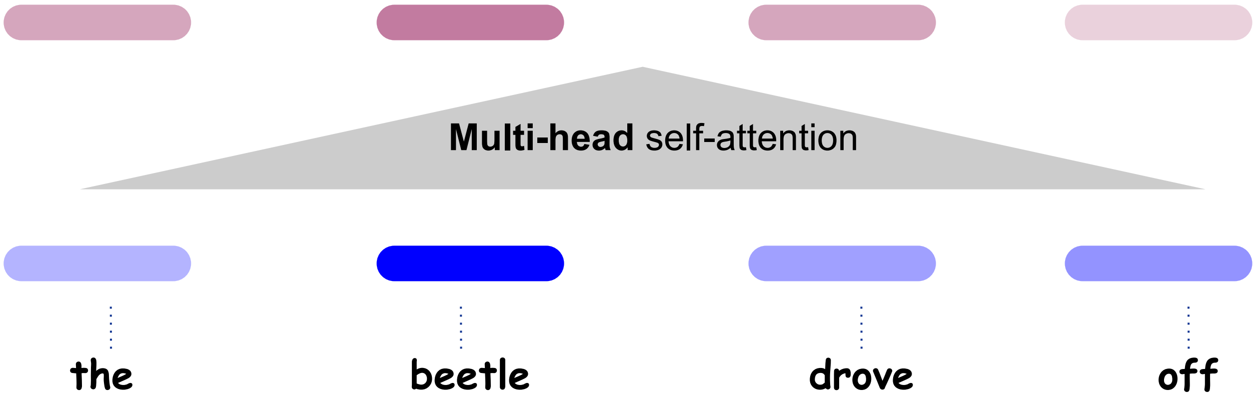


D units
W_O
W_q
W_k
W_v
D units
e_{beetle}
the
beetle
drove
off

Feedforward Layer



A complete Transformer block



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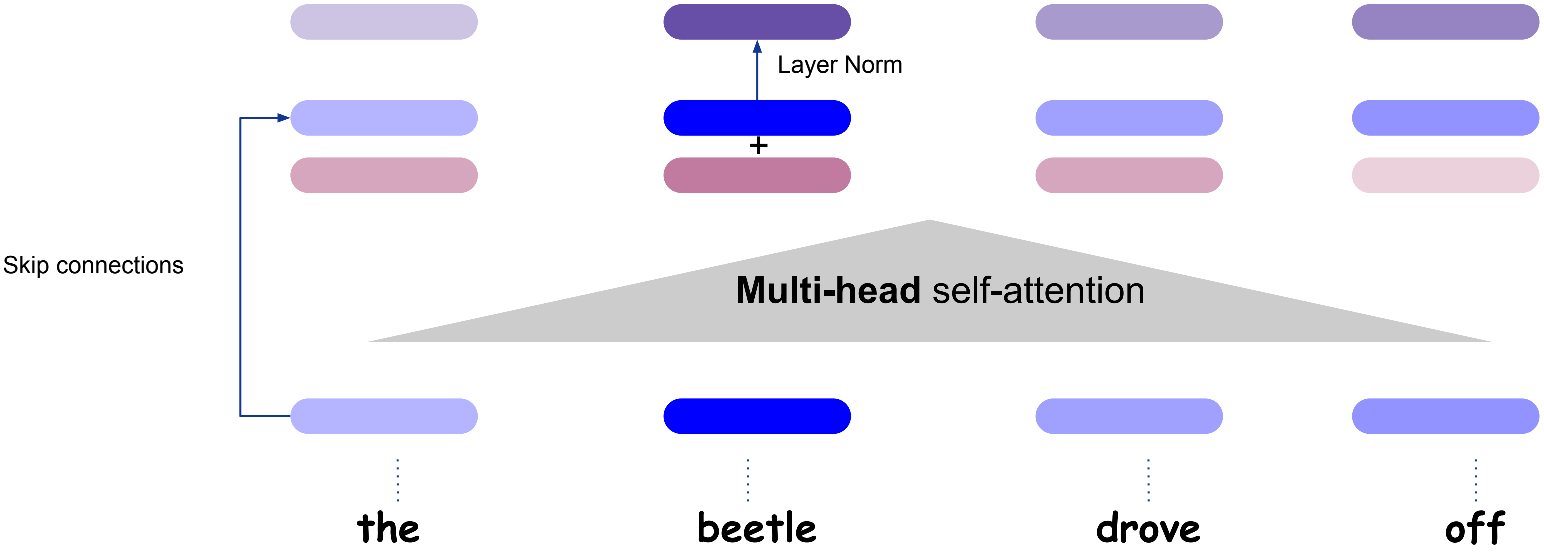

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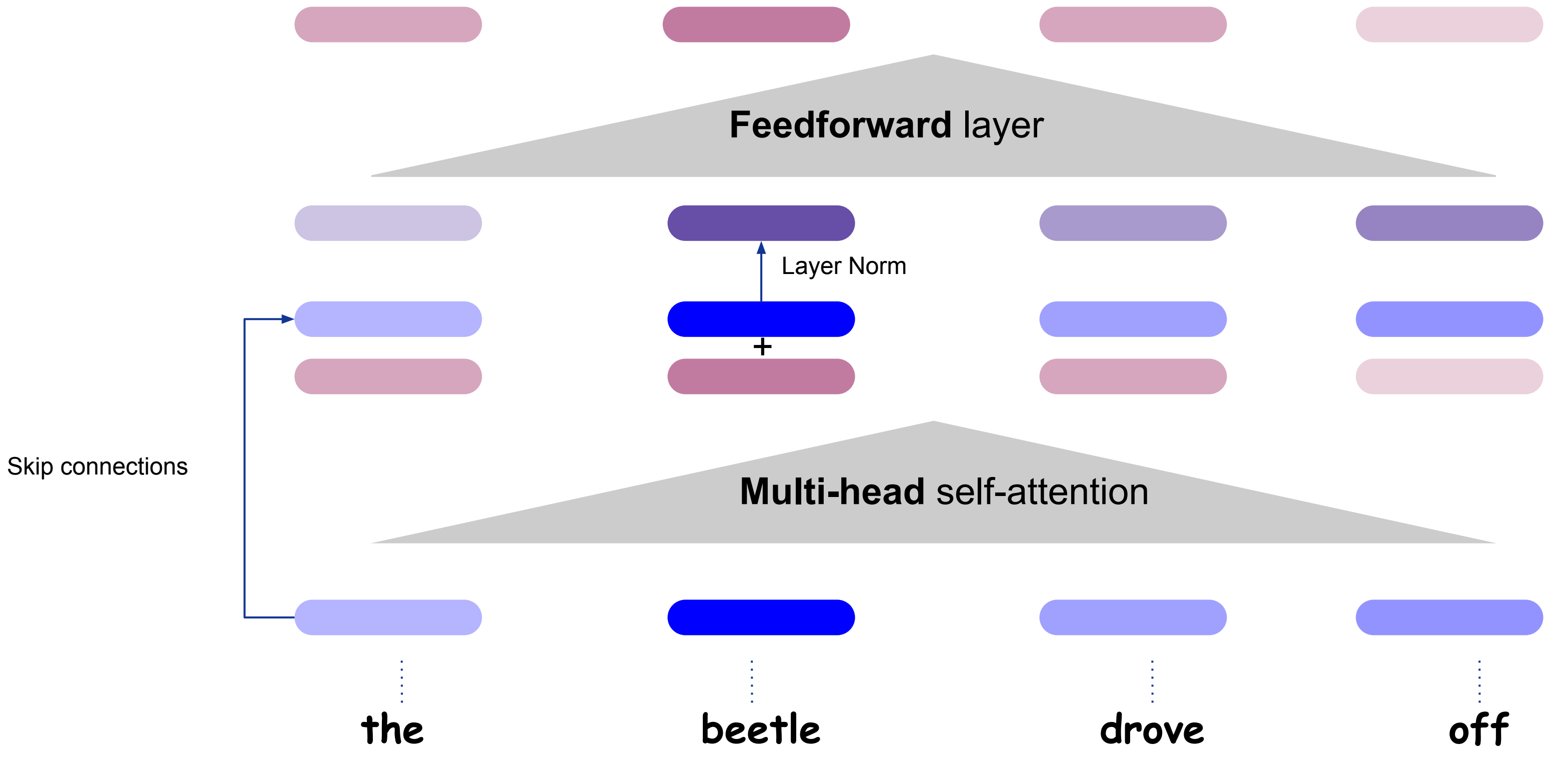
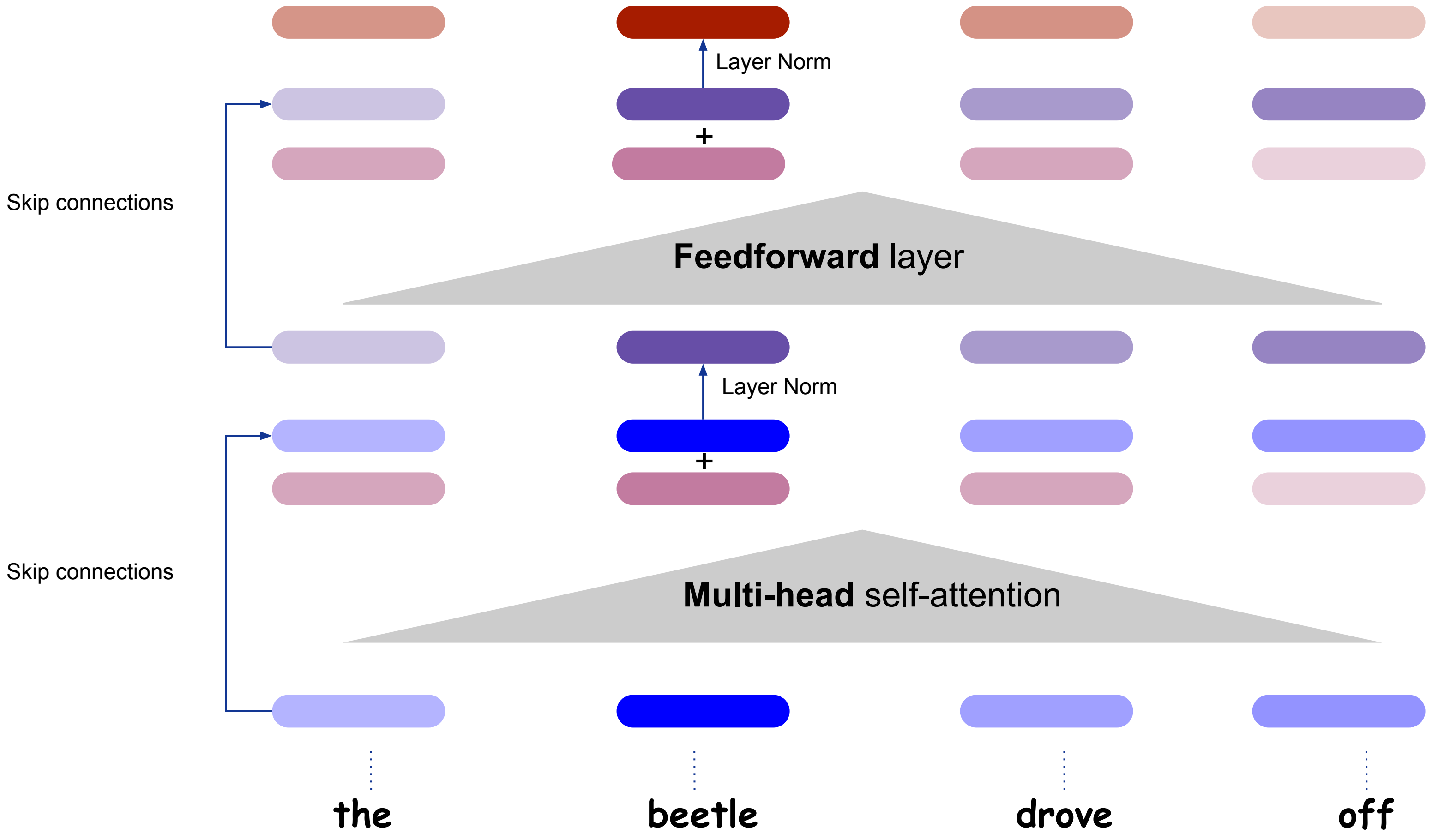
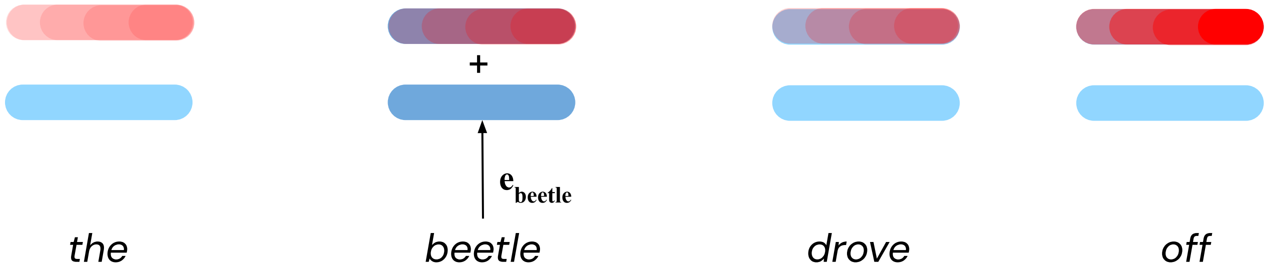


Skip-connections - for "top-down" influences



The Transformer: Position encoding of words

- Add fixed quantity to embedding activations
- The quantity added to each input embedding unit ∈ [-1, 1] depends on:
  - The dimension of the unit within the embedding
  - The (absolute) position of the words in the input



1. Words are not discrete symbols

2. Disambiguation depends on context

3. Important interactions can be non-local

4. How meanings combine depends on those meanings

1. Words are not discrete symbols

Multi-head processing

Distributed representations

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1. Words are not discrete symbols

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Distributed representations

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Self-attention

Multiple layers

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Multiple layers

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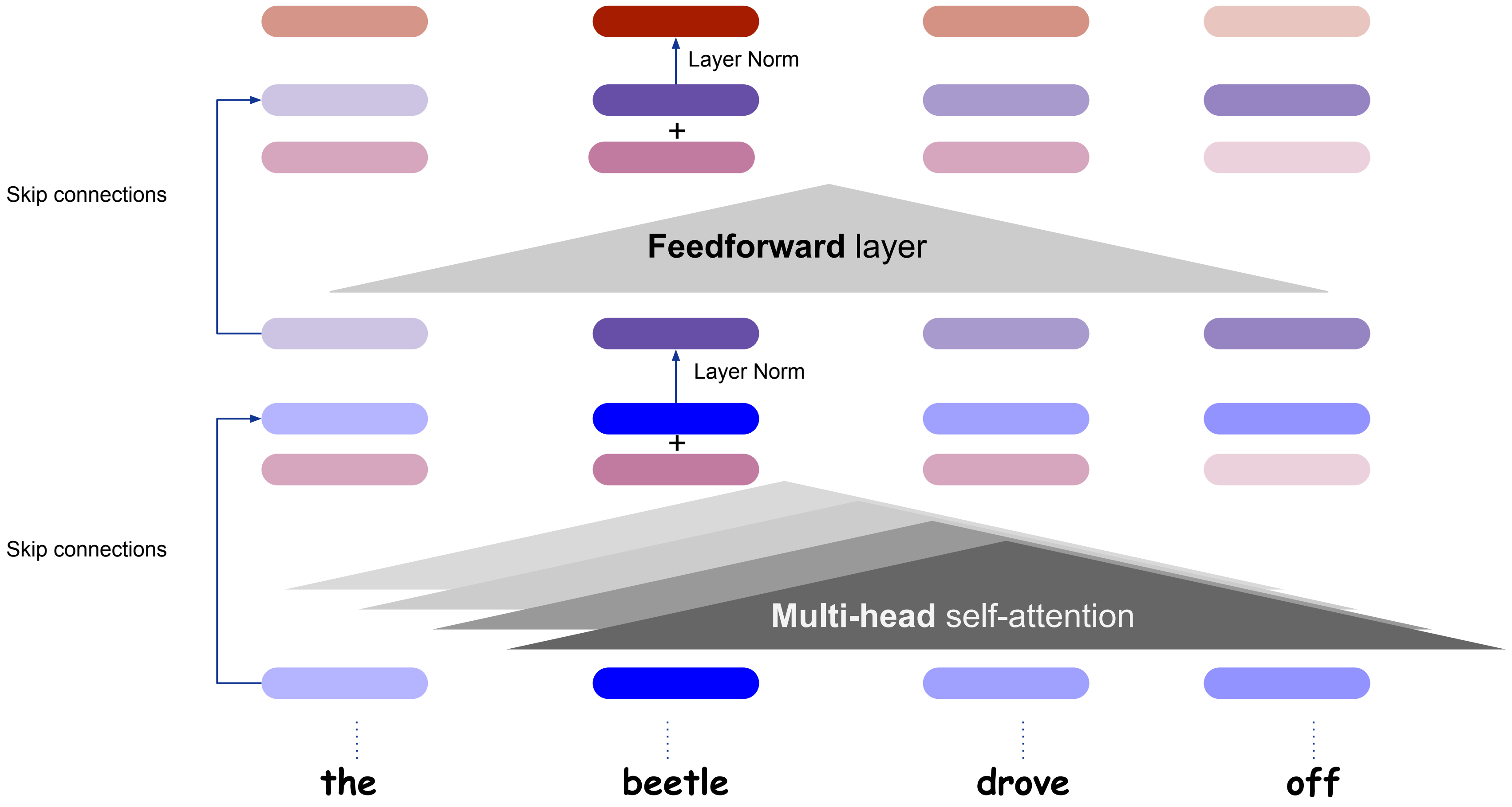
Skip connections

Distributed representations

Skip-connections - for "top-down" influences



3 Unsupervised Learning With Transformers (BERT)

Time flies like an arrow

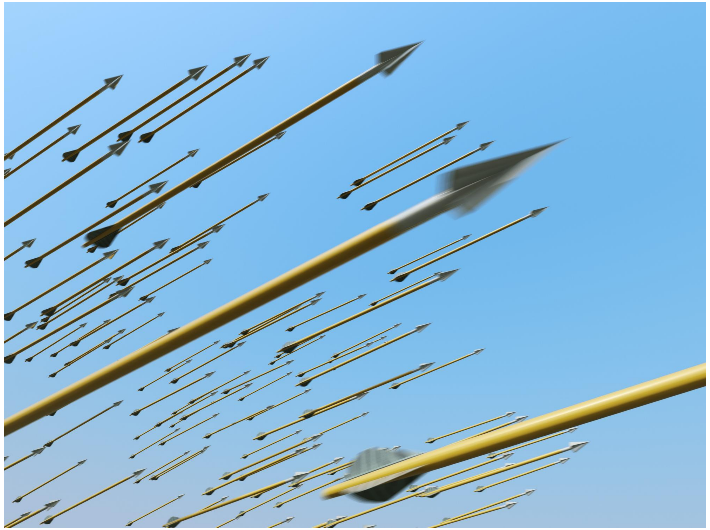
Time flies like an arrow

Fruit flies like a banana

Time flies like an arrow

John works like a trojan

The trains run like clockwork



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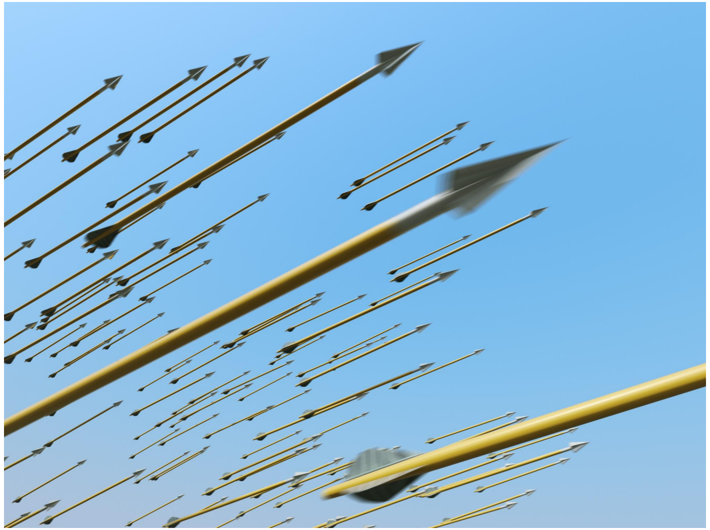


Fruit flies like a banana

Fido likes having his tummy rubbed

Grandma likes a good cuppa

1. Words have many related senses

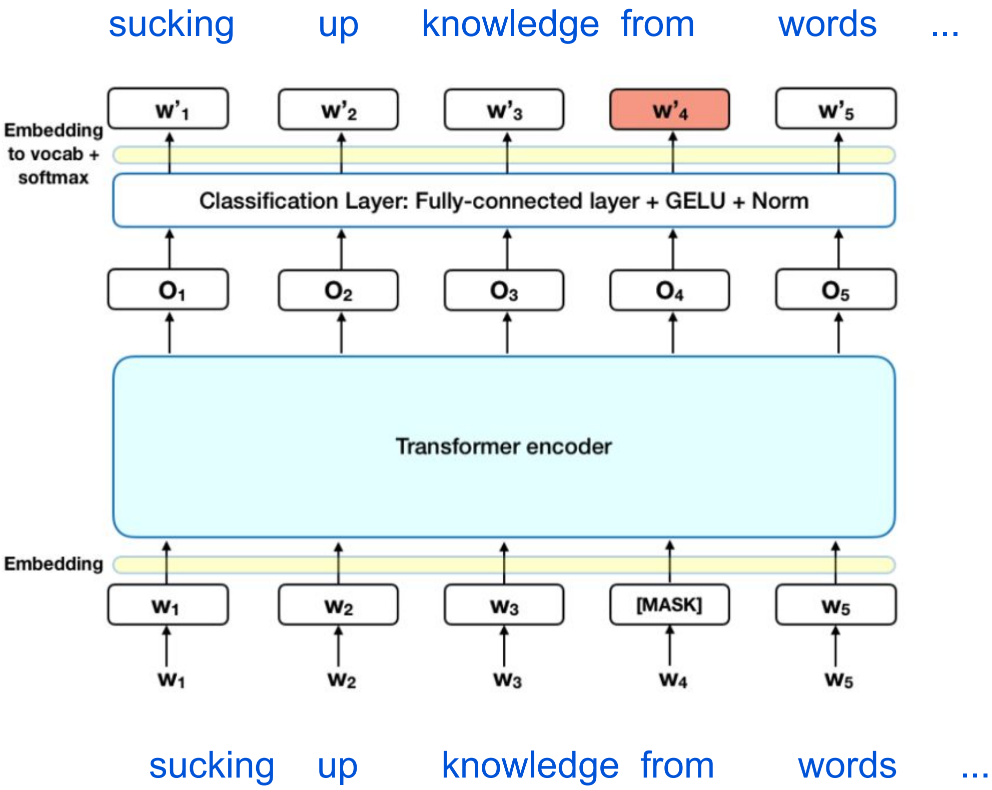
2. Disambiguation depends on context

3. Relevant context can be non-local

4. 'Composition' depends on what words mean

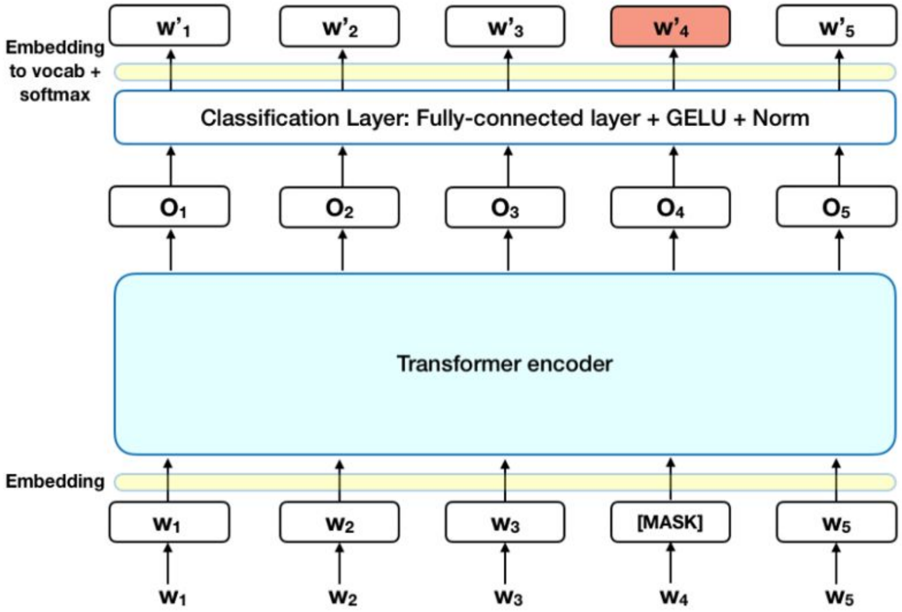
5. Understanding is balancing input with knowledge

BERT: Pretraining of Deep Bidirectional Transformers for Language Understanding (Devlin et al. 2019)



Masked language model pretraining

knowledge



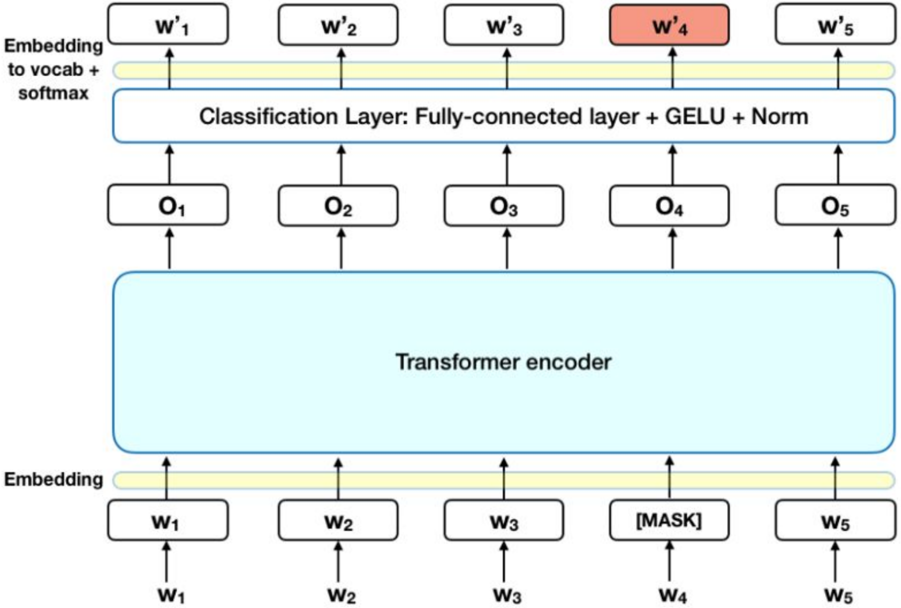
sucking up _[MASK]_ from words ...

15% of words masked - predict them!

BERT (Devlin et al. 2019)

Masked language model pretraining

knowledge



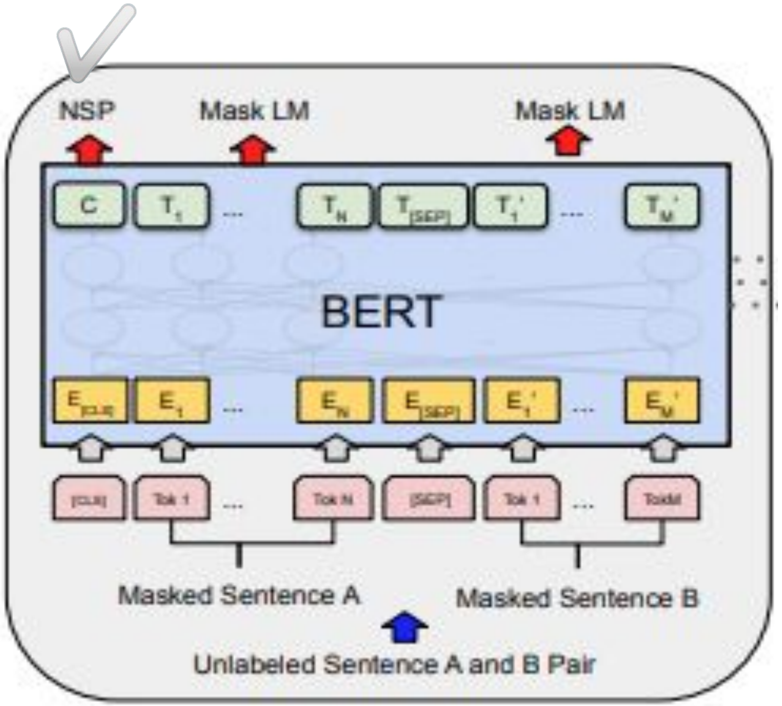
sucking up **knowledge** from words ...

15% of words masked - predict them!

10% of these instances - leave word in place

BERT (Devlin et al. 2019)

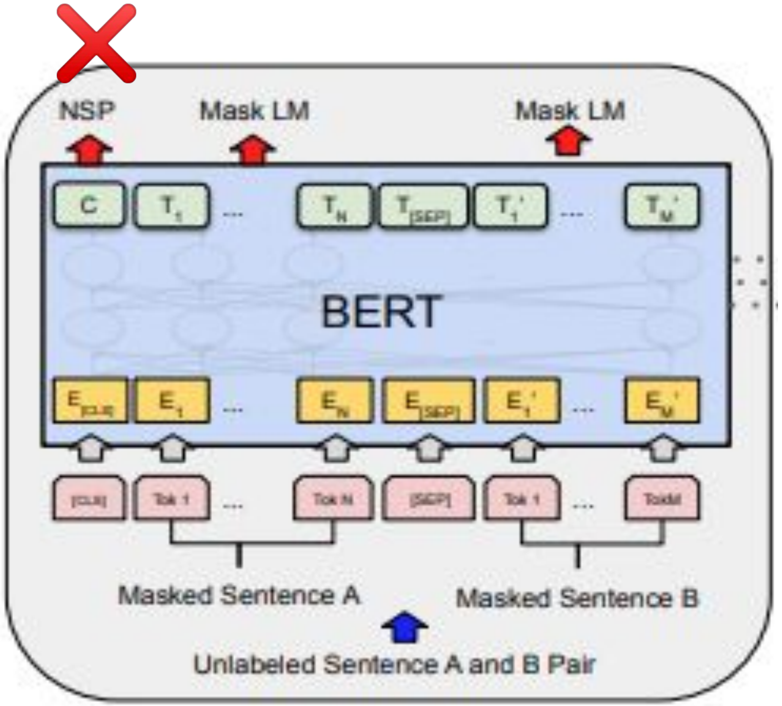
Next sentence prediction pretraining



[CLS] Sid went outside . _[SEP]_ It began to rain .

BERT (Devlin et al. 2019)

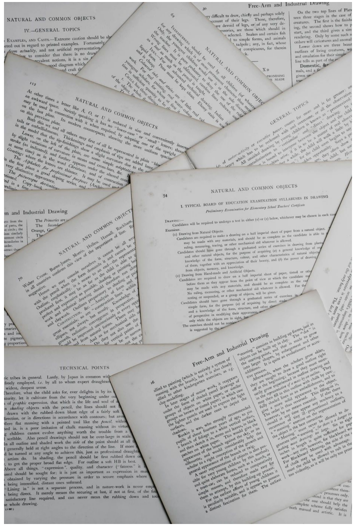
Next sentence prediction pretraining

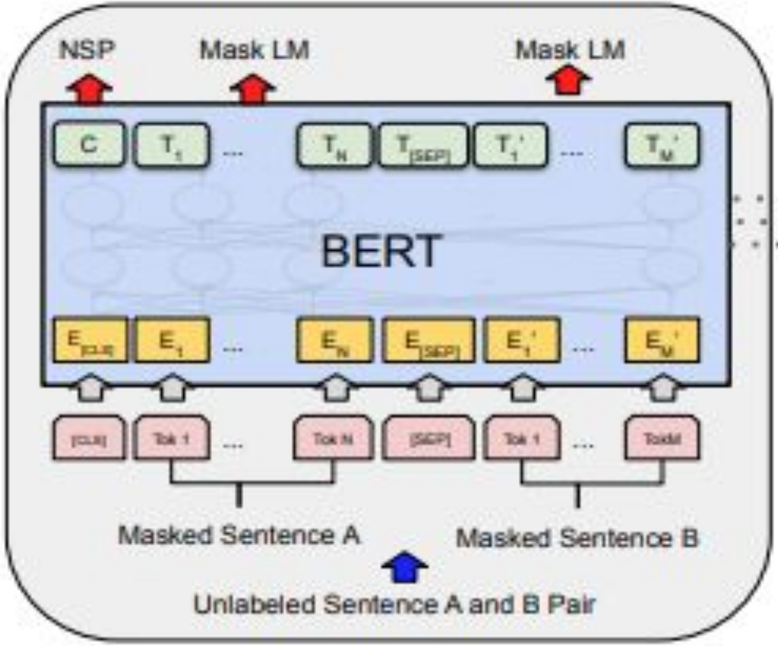


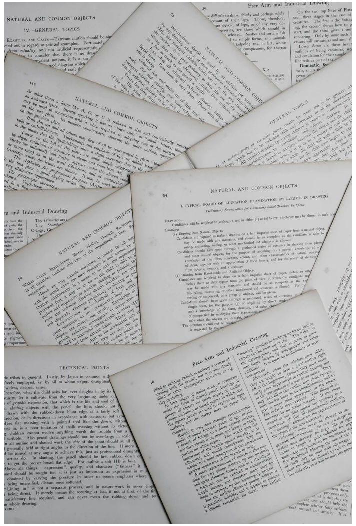
[CLS] Sid went outside . _[SEP]_ Unfortunately it wasn't
.

BERT (Devlin et al. 2019)

BERT pretraining



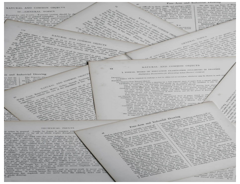


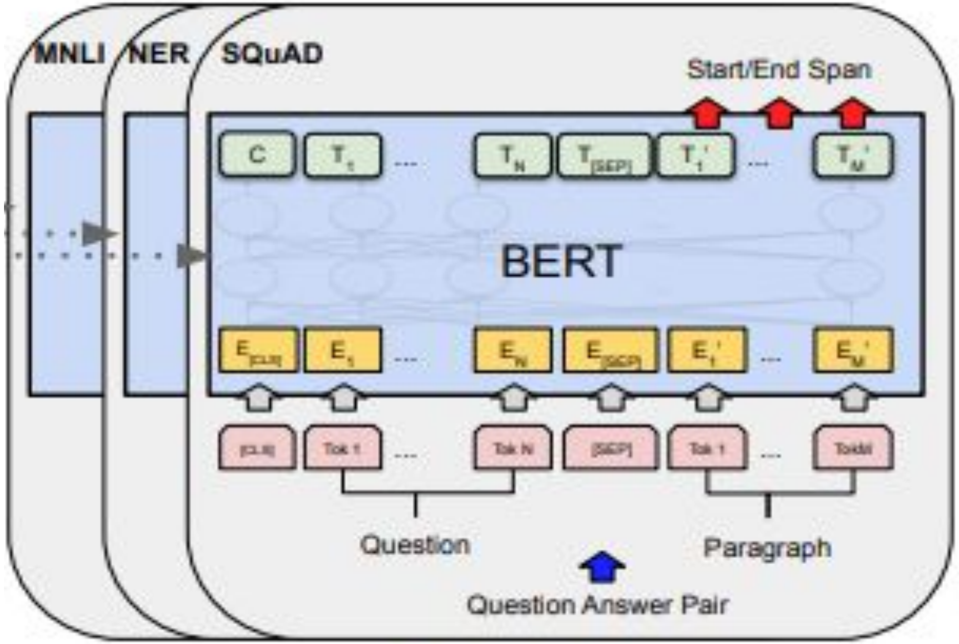


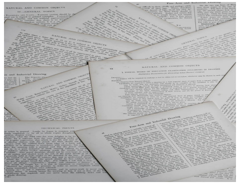
[CLS] Masses of text . _[SEP]_ From the internet .

BERT (Devlin et al. 2019)

BERT fine-tuning



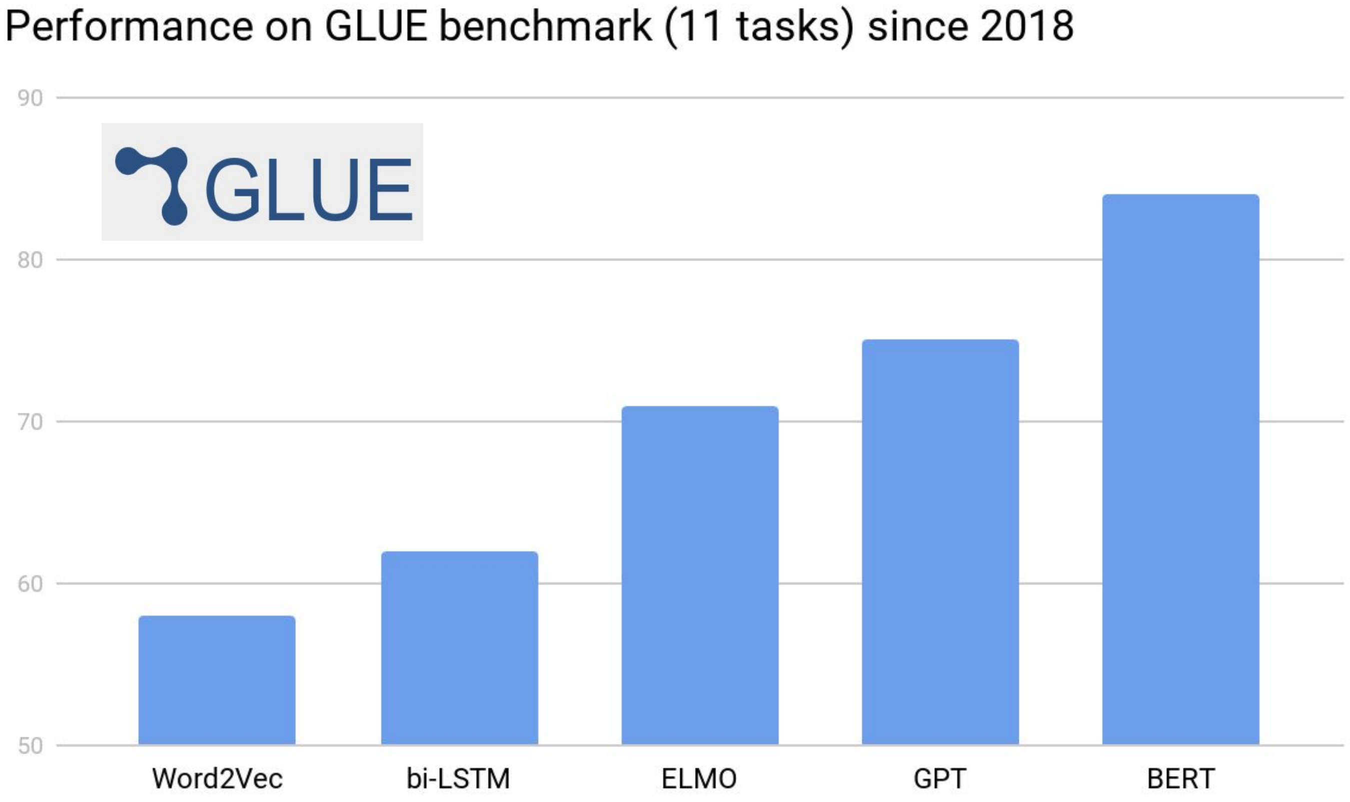




[CLS] A small amount of . _[SEP]_ Task-specific data

BERT (Devlin et al. 2019)

BERT supercharges transfer learning



1. Words have many related senses

2. Disambiguation depends on context

3. Relevant context can be non-local

4. 'Composition' depends on what words mean

5. Understanding is balancing input with knowledge

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Transfer with unsupervised learning

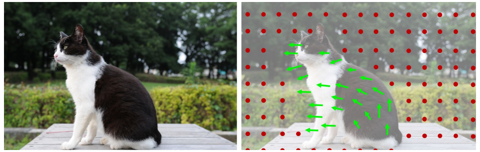
4 Extracting language-relevant knowledge from the environment

Building a multi-sensory understanding of the world

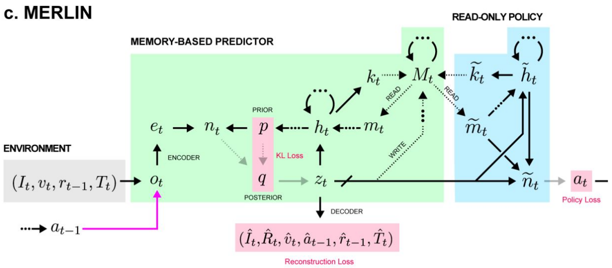
Language

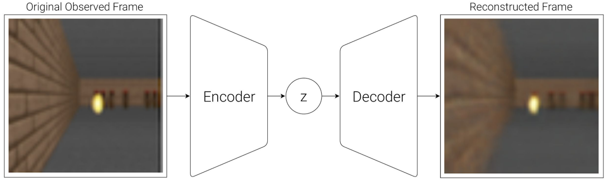
http://jalammar.github.io/illustrated-bert

Vision



Actions





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Knowledge aggregation from prediction

Helmholtz

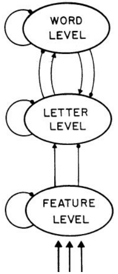
William James

H. Barlow
Cortex as a model builder.

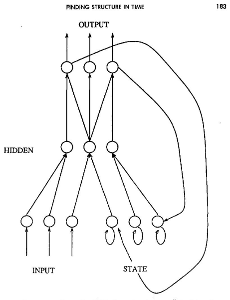
P. Elias
Predictive coding

U. Neisser
Analysis by synthesis

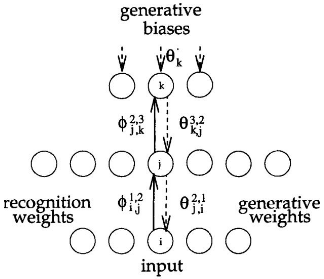
McClelland and Rumelhart
Interactive activation model



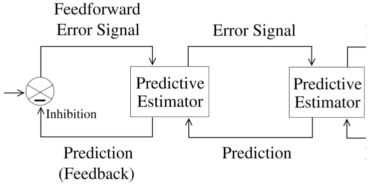
J. Elman
Finding structure in time



Dayan and Hinton
Helmholtz machine



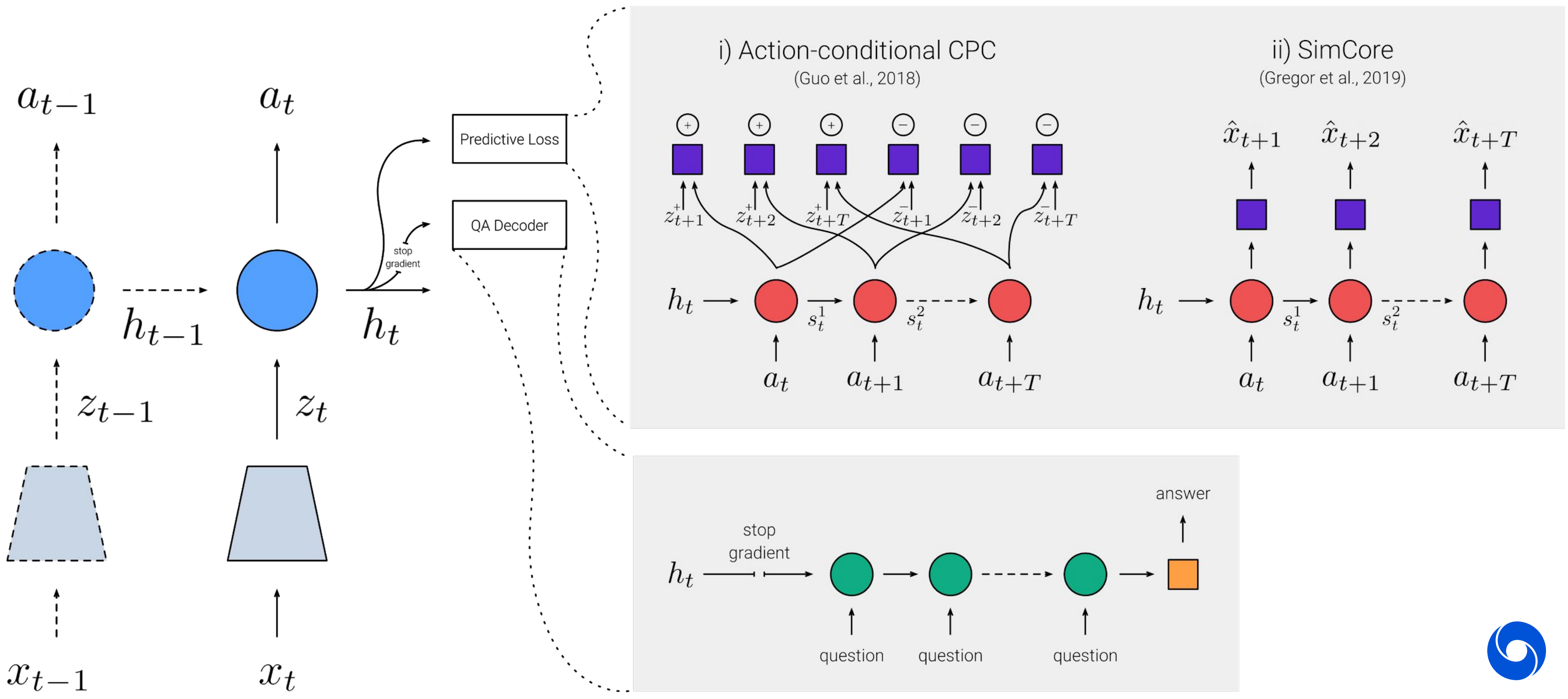
Rao and Ballard



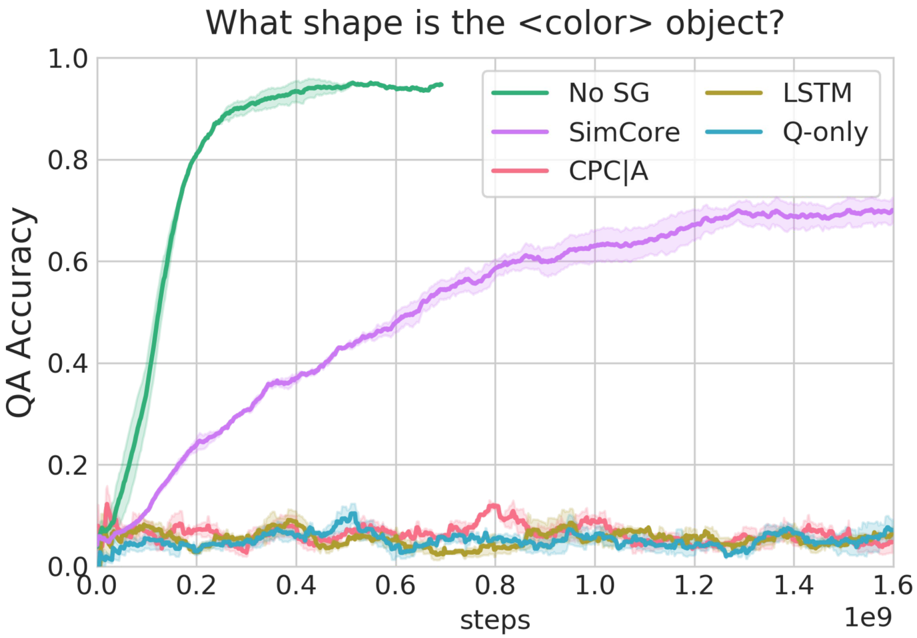
Questions to diagnose knowledge acquisition

Question type	Template	# QA pairs
Attribute	What is the color of the <`shape`>?	500
	What shape is the <`color`> object?	500
Count	How many <`shape`> are there?	200
	How many <`color`> objects are there?	40
Exist	Is there a <`shape`>?	100
Compare + Count	Are there the same number of <`color1`> objects as <`color2`> objects?	180
	Are there the same number of <`shape1`> as <`shape2`>?	4900
Relation + Attribute	What is the color of the <`shape1`> near the <`shape2`>?	24500
	What is the <`color`> object near the <`shape`>?	25000

Predictive agents



Results



Oracle:

- Without stop-gradient

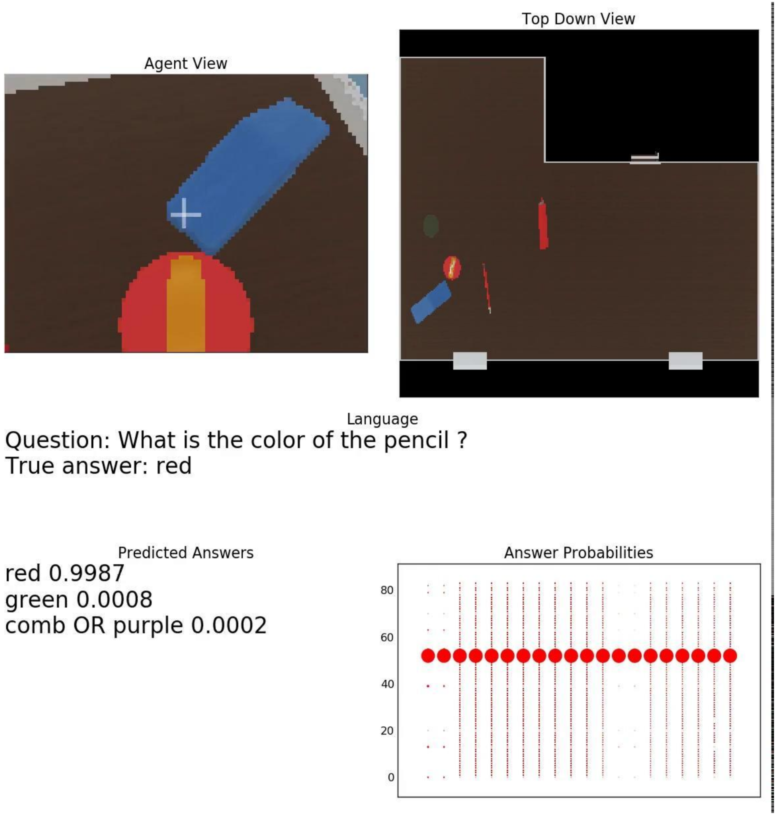
Baselines:

- Question only
- LSTM

Predictive Models:

- SimCore
- CPC|A

Results


Agent View
Top Down View
Language
Question: What is the color of the pencil ?
True answer: red
Predicted Answers
red 0.9987
green 0.0008
comb OR purple 0.0002
Answer Probabilities
80
60
40
20
0

To conclude

1. Words have many related senses

2. Disambiguation depends on context

3. Relevant context can be non-local **and non linguistic**

4. 'Composition' depends on what words mean

5. Understanding requires background knowledge....

not always from language

Transformers

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Transformers
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Self-supervised / unsupervised learning
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Transformers

Embodied learning

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not always from language

Fast-mapping

Goal-directed dialogue

Understanding intentions

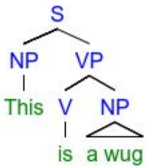
Social learning

Event cognition

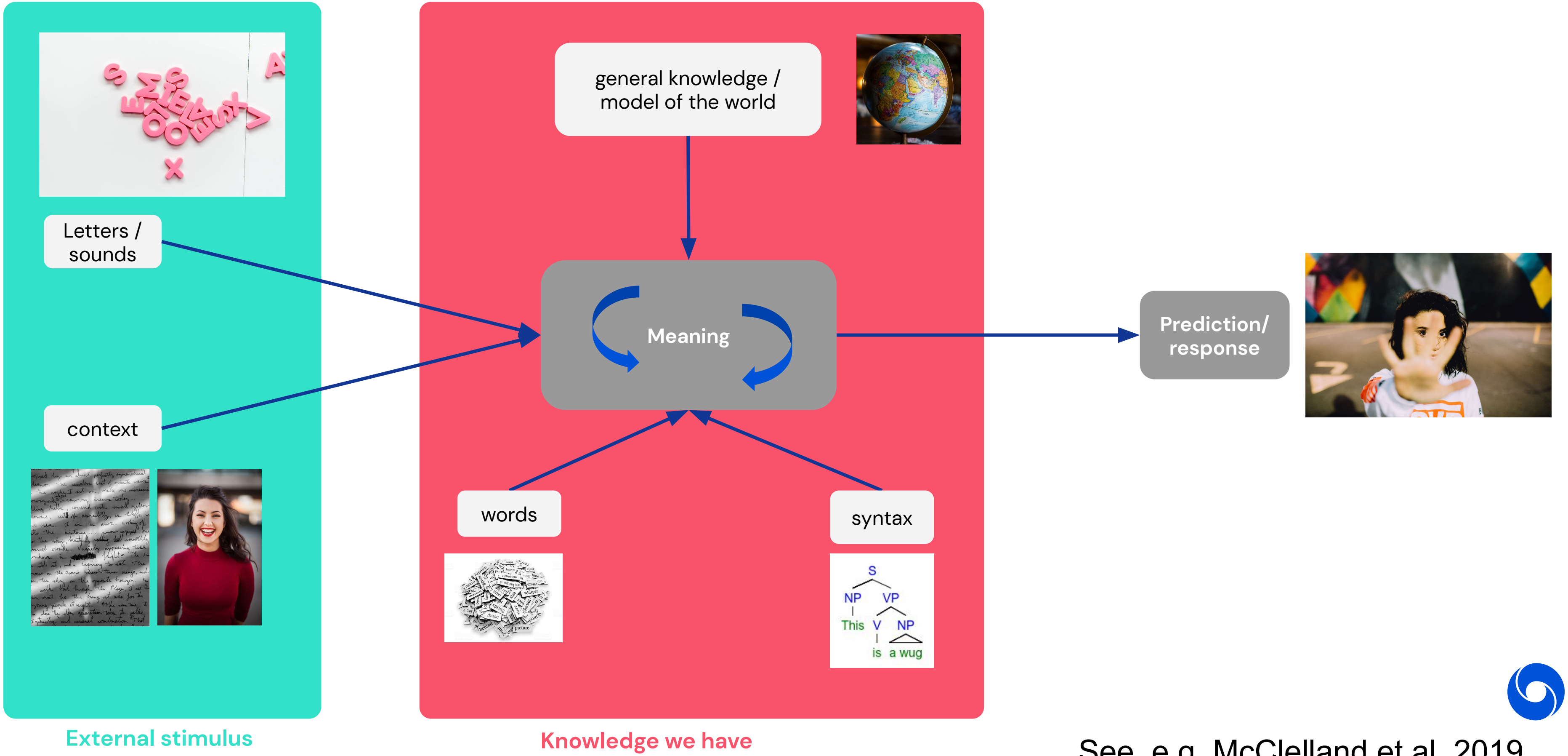
The 'pipeline' view of language processing

$$\left(\exists x\left((\forall y\, Q(x,y,z)) \wedge (\forall z\, R(z,x,f(x+y,x)))\right)\right)$$

letters → words → Syntax → Meaning → Prediction/ response



An alternative sehematic model of language processing



See. e.g. McClelland et al. 2019

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Hill et al. ICLR 2020

Robust Instruction-Following in a Situated Agent via Transfer Learning from Text
Hill et al. Under review

Probing emergent semantic knowledge in predictive agents via question answering
Carnevale et al. Under review