

Language Model Programming: Lecture 1

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August 2024



Leiden Institute of
Advanced Computer
Science

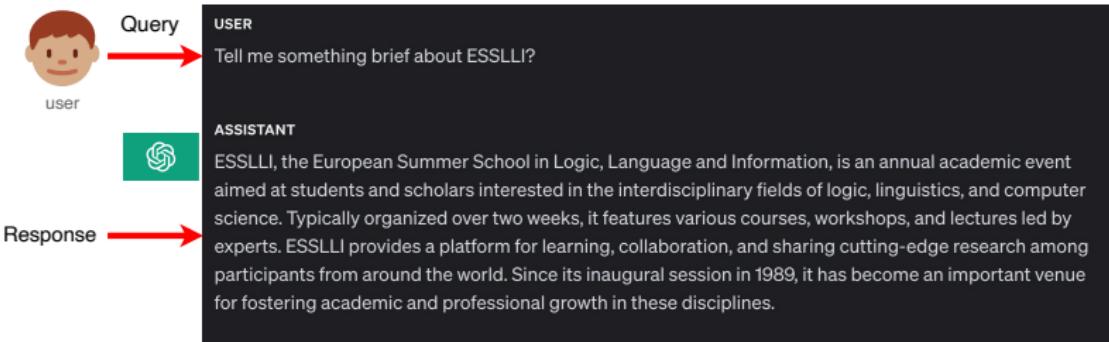


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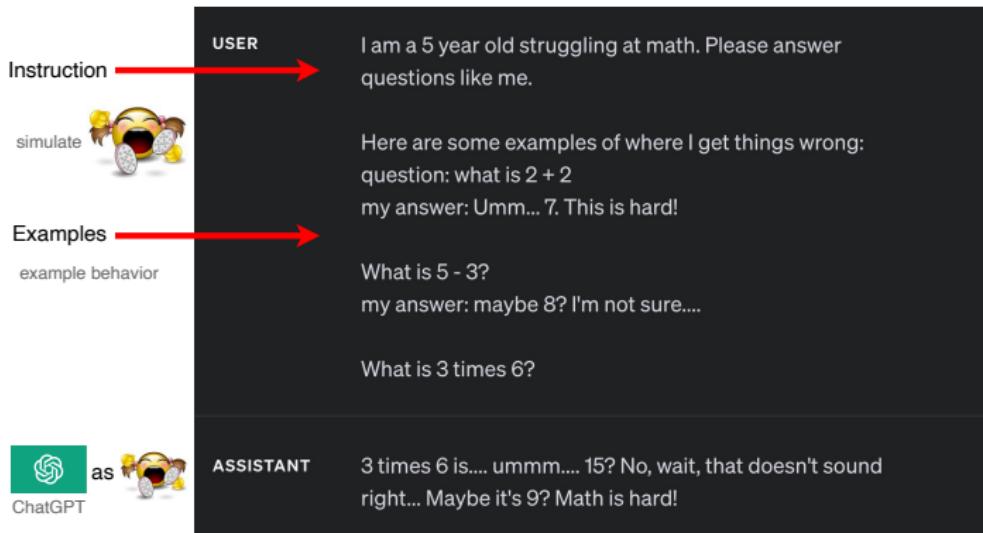
Course Overview

Language Model Programming

Language models today



In-context learning: learning through examples



In-context learning: learning through examples

<p>Instruction</p> 	<p>USER</p> <p>I am a 5 year old struggling at math. Please answer questions like me.</p>
<p>simulate example behavior</p>	<p>Here are some examples of where I get things wrong: question: what is $2 + 2$ my answer: Umm... 7. This is hard!</p> <p>What is $5 - 3$? my answer: maybe 8? I'm not sure....</p> <p>What is 3 times 6?</p>
<p>Examples</p>  as  ChatGPT	<p>ASSISTANT</p> <p>3 times 6 is.... ummm.... 15? No, wait, that doesn't sound right... Maybe it's 9? Math is hard!</p>

Traditional learning coupled with **in-context learning** (no parameter updates, just new examples added to input)

Abilities far exceed expectations...



user



Response

USER
Write me a song about the ESSLLI summer school in the style of 1990s American hip-hop music

ASSISTANT

Verse 1:
Yo, it's summertime, classes in session,
Rollin' up to ESSLLI, ain't no need for second guessin',
In the city or the campus, we takein' over,
Linguistics, logic, AI, four-leaf clover,

Kriss Kross, baggy jeans, we keep it fresh,
Knowledge in our minds, bringin' out the best,
From syntax to semantics, breakin' down the code,
In the 90s hip-hop scene, let the story unfold,

Chorus:
ESSLLI, summer school vibes,
Where the future and the past, they collide,
Gettin' schooled in the summer heat,
Rockin' to the beat, ESSLLI, can you feel the feat?

Verse 2:
Professors droppin' wisdom like bombs from the mic,
Mix it up like A Tribe Called Quest, phat and tight,
Logic seminars as deep as Wu-Tang Clan,

Learnin' more in two weeks than a lifetime span,

Peep the nightlife, cities come alive,
Student jams, open mics, the essence survive,
Connections

Abilities far exceed expectations...



USER

Write me a short function in Python that decides if a number is prime.



ASSISTANT

Certainly! Here's a short Python function that checks if a number is prime:

```
```python
def is_prime(n):
 if n <= 1:
 return False
 if n <= 3:
 return True
 if n % 2 == 0 or n % 3 == 0:
 return False
 i = 5
 while i * i <= n:
 if n % i == 0 or n % (i + 2) == 0:
 return False
 i += 6
 return True
```

```

Executable code



```
# Example usage:
print(is_prime(11)) # Output: True
print(is_prime(15)) # Output: False
...
```

```

# Integrating language models into complex systems

The screenshot shows the "ML Experiment Execution Engine" interface. It displays two steps of a "Machine learning experiment".

**Step 1:**

- Query:** Implement an encoder-only model using transformers that can do multiple-choice QA.
- System thought:** To implement an encoder-only model for multiple-choice question answering (QA) using the transformers library from Hugging Face, I'll first outline the steps in Python. This will involve loading a pre-trained encoder model, perhaps something like BERT or RoBERTa, and then adapting it to handle multiple-choice QA tasks. The model will receive a question and several possible answers as input and will have to select the most likely answer. I will use the `transformers` library for this purpose.
- Action (execute):**

```
from transformers import AutoModelForMultipleChoice, AutoTokenizer\n\nmodel_name = 'bert-base-uncased'\n\n# Load model and tokenizer\ntokenizer = AutoTokenizer.from_pretrained(model_name)\nmodel = AutoModelForMultipleChoice.from_pretrained(model_name)\n\nprint("Model and tokenizer loaded successfully.")
```
- Observation:**
  - Details:** Model and tokenizer loaded successfully.

**Step 2:**

- Running step 2**
- System thought:** The model and tokenizer have been successfully loaded. Next, I need to write a function that takes a question and a list of possible answers, formats them correctly for the model input, and then uses the model to predict the most likely answer. This function will use the tokenizer to encode the inputs and the model to get logits for each possible answer. Finally, it will select the answer with the highest logit as the predicted answer.
- Action (execute):**

```
def predict_answer(question, choices):\n inputs = tokenizer([question] * len(choices), choices, padding=True, return\n outputs = model(**inputs)
```

# Integrating language models into complex systems

The screenshot shows a user interface for "ML Experiment Execution Engine". On the left, there's a sidebar with icons for "Machine learning experiment" (a person icon) and "Model generated code" (a green square icon). Below these are two sections: "Step 1" and "Step 2".

**Step 1:** A "Query" field contains the text: "Implement an encoder-only model using transformers that can do multiple-choice QA". Below it, a "Running step 1" section shows a "System thought" block:

```
system thought : To implement an encoder-only model for multiple-choice question answering (QA) using the transformers library from Hugging Face, I'll first outline the steps in Python. This will involve loading a pre-trained encoder model, perhaps something like BERT or RoBERTa, and then adapting it to handle multiple-choice QA tasks. The model will receive a question and several possible answers as input and will have to select the most likely answer. I will use the transformers library for this purpose.
```

Below this is an "Action (execute)" block containing Python code:

```
from transformers import AutoModelForMultipleChoice, AutoTokenizer
model_name = 'bert-base-uncased'

Load model and tokenizer
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForMultipleChoice.from_pretrained(model_name)

print("Model and tokenizer loaded successfully.")
```

Under "Observation", there's a "Details" section with the message: "Model and tokenizer loaded successfully." followed by a checkmark icon.

**Step 2:** A "Running step 2" section shows a "System thought" block:

```
system thought : The model and tokenizer have been successfully loaded. Next, I need to write a function that takes a question and a list of possible answers, formats them correctly for the model input, and then uses the model to predict the most likely answer. This function will use the tokenizer to encode the inputs and the model to get logits for each possible answer. Finally, it will select the answer with the highest logit as the predicted answer.
```

Below this is an "Action (execute)" block containing Python code:

```
def predict_answer(question, choices):
 inputs = tokenizer([question] * len(choices), choices, padding=True, return_outputs = model(**inputs)
```

The right side of the interface shows a Jupyter notebook titled "jupyter - automated\_ml\_notebook.ipynb (Checkpoint, 23 minutes ago)". It displays the same code blocks and output as the main interface, with a red arrow pointing to the "Model and tokenizer loaded successfully" message in the notebook's output area.

## Experiment automation

# Integrating language models into complex systems

The screenshot shows the "ML Experiment Execution Engine" interface with two main sections: "Step 1" and "Step 2".

**Step 1:**

- Query:** "I want to implement an encoder-only model using transformers that can do multiple-choice QA."
- Action (execute):**

```
from transformers import AutoModelForMultipleChoice, AutoTokenizer\n\nmodel_name = 'bert-base-uncased'\n\n# Load model and tokenizer\ntokenizer = AutoTokenizer.from_pretrained(model_name)\nmodel = AutoModelForMultipleChoice.from_pretrained(model_name)\n\nprint("Model and tokenizer loaded successfully!")
```
- Observation:**
  - Running step 1
  - Model and tokenizer loaded successfully.

**Step 2:**

- System thought:** To implement an encoder-only model for multiple-choice question answering (MCQA) using the transformers library from Hugging Face, I'll first outline the steps in Python. This will involve loading a pre-trained encoder model, perhaps something like BERT or RoBERTa, and then adapting it to handle multiple-choice QA tasks. The model will receive a question and several possible answers as input and will have to select the most likely answer. I will use the transformers library for this purpose.
- Action (execute):**

```
def predict_answer(question, choices):\n inputs = tokenizer(question + '\n' + '\n'.join(choices),\n padding=True,\n return_tensors='pt')\n\n outputs = model(**inputs)
```
- Observation:**
  - Running step 2

On the right side of the interface, there is a Jupyter notebook titled "automated\_ml\_notebook.ipynb" showing the execution of the same code. A red arrow points to the output of the first cell, which shows the model and tokenizer were loaded successfully. Another red arrow points to the second cell, which contains the definition of the `predict_answer` function.

## Experiment automation

- Looks a lot like conventional programming, can we make the connection more precise?

# Integrating language models into complex systems

The screenshot shows the ML Experiment Execution Engine interface. It displays two steps of a machine learning experiment:

- Step 1:** A "Machine learning experiment" card with a "ChatGPT" icon. The "Query" field contains: "Implement an encoder-only model using transformers that can do multiple-choice QA". The "Action (execute)" field shows Python code for loading a BERT-base-uncased model and tokenizer from the transformers library.
- Step 2:** A "Running step 2" card with a "Details" section showing the output: "Model and tokenizer loaded successfully." An icon of a wrench and screwdriver is shown below it.

To the right, a Jupyter notebook titled "automated\_ml\_notebook.ipynb" is open. It shows the execution of the code from Step 1, resulting in the successful loading of the model and tokenizer. The notebook also includes a function definition for predicting answers based on a question and a list of choices.

## Experiment automation

- **Model programming:** How modeling components are assembled, how they interact, and the language of how this is specified.

# Problems are still easy to find



USER

Name me a country that is physically located  
between the Czech Republic and France



ASSISTANT

Germany is a country that is physically located  
between the Czech Republic and France.

# Problems are still easy to find



USER

Name me a country that is physically located between the Czech Republic and France



ASSISTANT

Germany is a country that is physically located  
between the Czech Republic and France.



USER

Is Germany physically located between the Czech Republic and France?



ASSISTANT

No, Germany is not physically located between the Czech Republic and France. The Czech Republic is located to the east of Germany, while France is located to the west of Germany. Germany shares borders with both countries, but it is not geographically situated between them.

# Problems are still easy to find



USER

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No, Germany is not physically located between the Czech Republic and France. The Czech Republic is located to the east of Germany, while France is located to the west of Germany. Germany shares borders with both countries, but it is not geographically situated between them.

Models can be wildly inconsistent, hallucinate, prompting is unstable (different results based on small changes).

# Problems are still easy to find



USER

Is Germany physically located between the Czech Republic and France?



ASSISTANT

Yes, Germany is physically located between the Czech Republic and France. The Czech Republic is to the east of Germany, while France is to the west.



USER

Are you sure



ASSISTANT

I apologize for the mistake in my previous response. Germany is not physically located between the Czech Republic and France. The Czech Republic is to the east of Germany, while France is to the west of Germany. Thank you for pointing that out.

Models have been improving fast, sort of...

# Problems are still easy to find



USER

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ASSISTANT

Germany is a country that is physically located  
between the Czech Republic and France.



USER

Is Germany physically located between the Czech Republic and France?

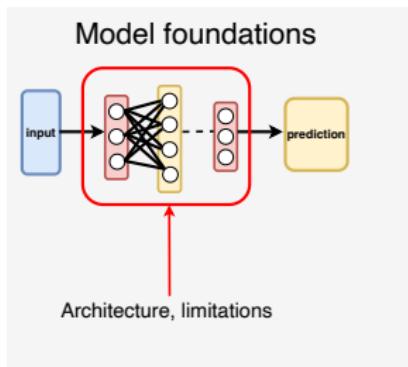


ASSISTANT

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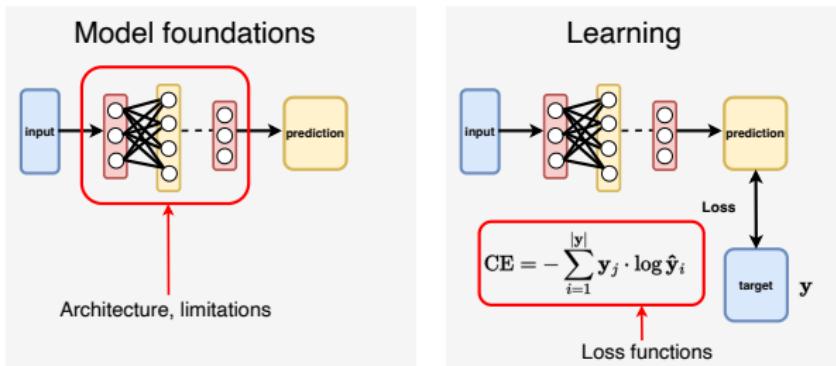
- ▶ Can programming techniques be useful here? constraint programming, probabilistic and logical programming...

# The landscape of NLP research



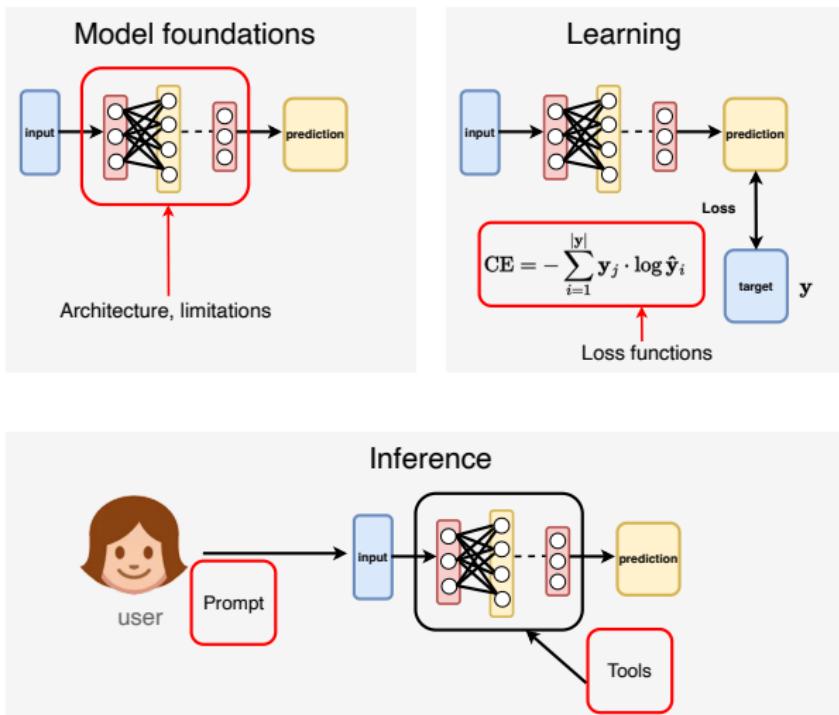
**What model to use?** What kinds of computational problems can models solve? Limitations

# The landscape of NLP research



How to train and tune models? Can we design novel loss functions, constraints? (image adapted from <https://www.v7labs.com/blog/pytorch-loss-functions>).

# The landscape of NLP research



**How to use models?** Decoding with constraints, advanced prompting strategies, coupling with tools.

# Where programming comes in

Model foundations

The diagram illustrates a neural network architecture. It starts with a blue 'input' box on the left, which has an arrow pointing to a red-bordered box labeled 'Model foundations'. Inside this box is a central layer of nodes (represented by circles) connected to both an input layer (pink rectangles) and an output layer (yellow rectangle labeled 'prediction'). A dashed arrow points from the output layer to the right. Below the 'Model foundations' box is a red arrow pointing upwards, labeled 'Architecture, limitations'.

RASPy

```
def flip():
 length = (key(1) == query(1)).value(1)
 flip = {key(length - indices - 1) == query(indices)}; value(tokens)
 return flip
flip()
```

Input h e l l o

Layer 1

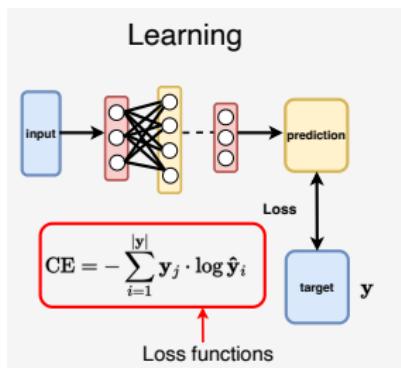
1	1	1	1	1	1
1					
1					
1					
1					
5	5	5	5	5	5

Layer 2

0	1	2	3	4	h
4					
3					
2					
1					
0	o	l	l	e	h

Final o l l e h

# Where programming comes in



```
1 // File path_planner.scl
2 type actor(x: i32, y: i32), goal(x: i32, y: i32), enemy(x: i32, y: i32)
3
4 const UP = 0, DOWN = 1, RIGHT = 2, LEFT = 3
5 rel safe_cell(x, y) = range(0, 5, x), range(0, 5, y), not enemy(x, y)
6 rel edge(x, y, x, yp, UP) = safe_cell(x, y), safe_cell(x, yp), yp == y + 1
7 // Rules for DOWN, RIGHT, and LEFT edges are omitted...
8
9 rel next_pos(p, q, a) = actor(x, y), edge(x, y, p, q, a)
10 rel path(x, y, x, y) = next_pos(x, y, _)
11 rel path(x1, y1, x3, y3) = path(x1, y1, x2, y2), edge(x2, y2, x3, y3, _)
12 rel next_action(a) = next_pos(p, q, a), path(p, q, r, s), goal(r, s)
```

Fig. 3. The logic program of the PacMan-Maze application in Scallop.

# Where programming comes in

```
●●●
@lmql.query
def meaning_of_life():
 """
 # top-level strings are prompts
 "Q: What is the answer to life, the \
 universe and everything?"

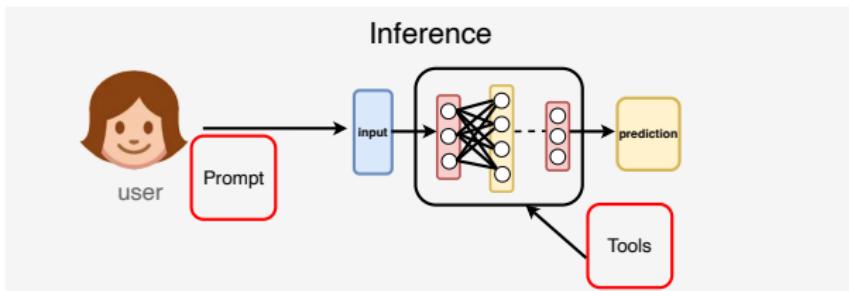
 # generation via (constrained) variables
 "A: [ANSWER]" where \
 len(ANSWER) < 120 and STOPS_AT(ANSWER, ".")

 # results are directly accessible
 print("LLM returned", ANSWER)

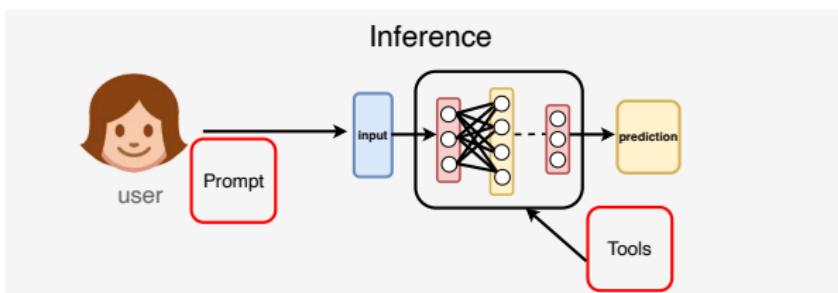
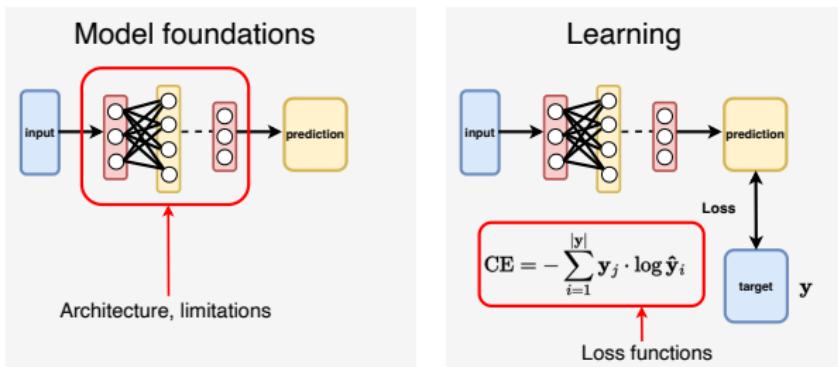
 # use typed variables for guaranteed
 # output format
 "The answer is [NUM: int]"

 # query programs are just functions
 return NUM
 ...

 # so from Python, you can just do this
meaning_of_life() # 42
```



# Thematic overview



**warning:** will only cover a small space, is a broad landscape, focus on underlying techniques and applications.

# Schedule

Kyle

- ▶ **Lecture 1:** Language model basics and background, symbolic programming of transformers.
- ▶ **Lecture 2:** Declarative programming for model training and semantic loss, logic background.
- ▶ **Lecture 3:** Declarative models of inference, SAT methods for model inference, tractable inference for logic/probabilistic reasoning.

Gijs

- ▶ **Lecture 4:** Model prompting and imperative programming, applications to constrained decoding.
- ▶ **Lecture 5:** More on constrained decoding, applications.

# Code examples and useful libraries

```
1 ### installation via pip
2 ### "pip install install z3-solver python-sat torch datasets
3 # transformers sympy PySDD pylon-lib numpy problog"
4
5 ### neural network
6 import torch ## tensor computation, deep learning
7 import transformers ### transformer models
8
9 ### solvers and theorem provers
10 import z3-solver ## z3 solver
11 import pysat ## python interface to sat solvers
12 import problog ### probabilistic logic programming
13
14 ### other useful utilities
15 import sympy # symbolic computation in python
16 import pysdd # knowledge compilation
17 import numpy ## numerical computation in python
18 import datasets ## huggingface datasets
```

# Language modeling primer

## What are language models?

- ▶ Machine learning models that **assign probabilities to sequences**.

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e.g.,  $t = \text{Germany}$  is between Czechia and France

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e.g.,  $t = \text{Germany}$  is between Czechia and France

$$\underbrace{p(w_1, w_2, \dots, w_m)}_{\text{joint distribution}} = \prod_{j=1}^m p(\underbrace{w_j}_{\text{next word}} \mid \underbrace{w_1, \dots, w_{j-1}}_{\text{previous words}})$$

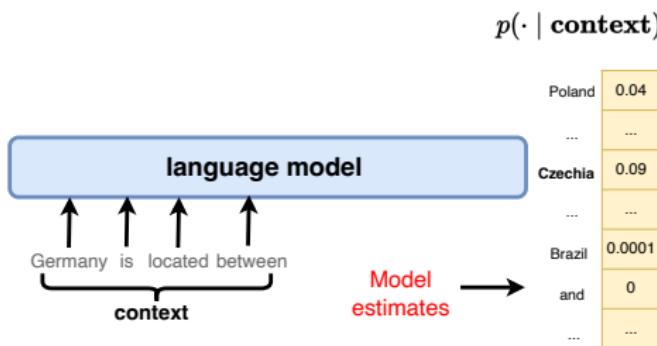
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Language models **generate**



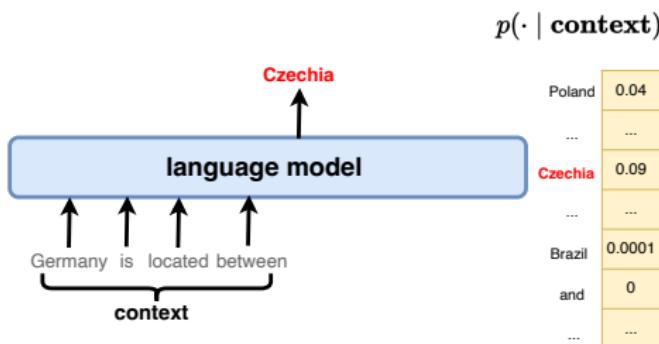
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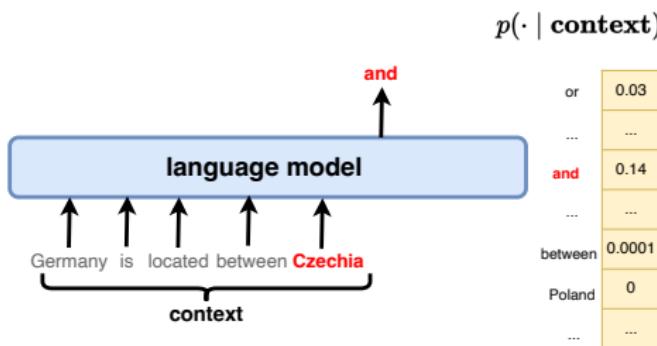
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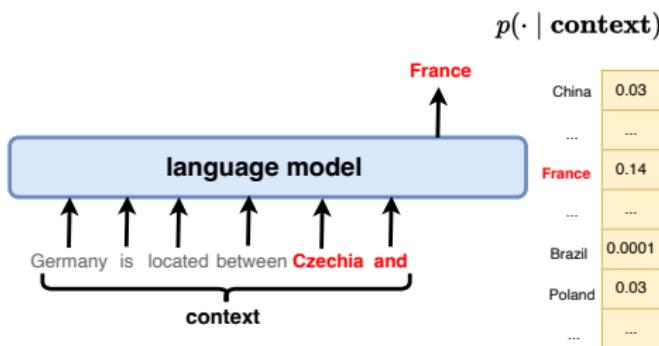
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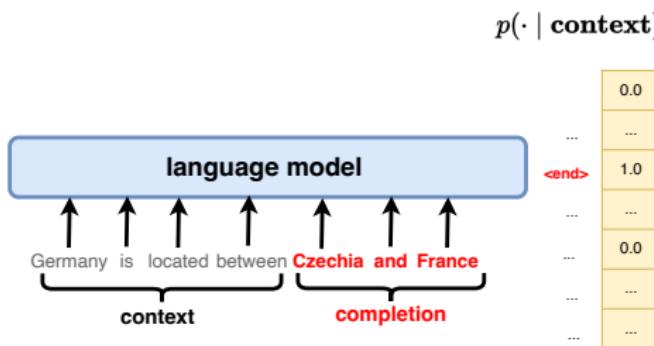
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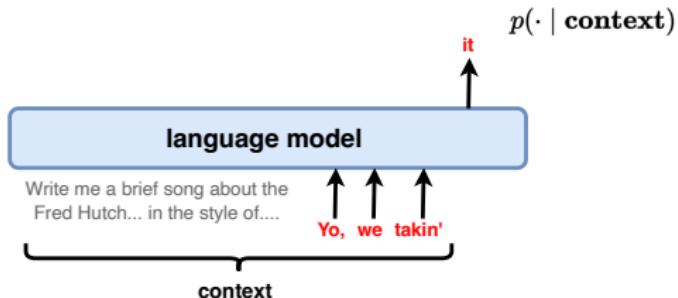
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Language models **generate**



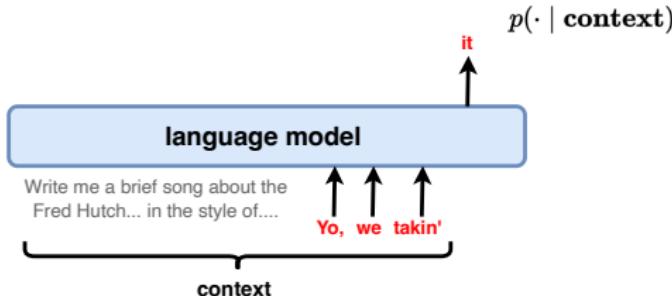
# What are language models?

Sequence modeling is not a new problem.



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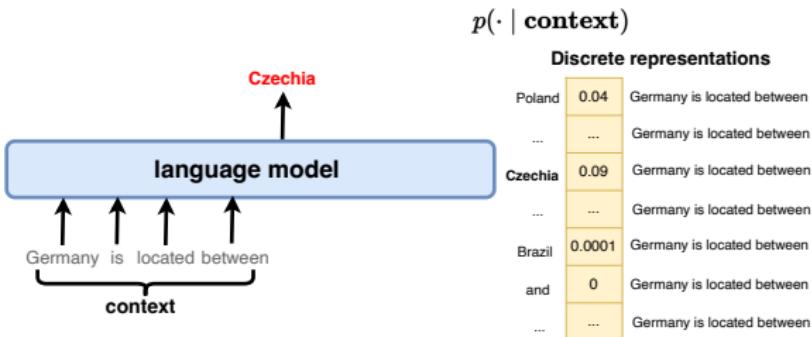
## Text documents

TaskFirst pose the question:Here are four triangles. What do all of these triangles have in common? What makes them different from the figures that are not triangles? What is true for some but not all of these triangles? ##IMAGE0## If students come up with a statement that is true about all of the triangles that they see but not true of all triangles in general, the teacher should ask students if they can imagine a triangle without that attribute. For example, if a student says, "All of the triangles are white on the inside," the teacher can ask, "Would it be possible for a triangle to have a different color on the inside?" When the class comes up with an attribute that is truly shared by all triangles, then the class can complete the sentence frame: All triangles \_\_\_\_\_, but only some triangles \_\_\_\_\_. When the students have written (or composed) their sentences based on the sentence frames, the class can write the definition of a triangle together:A triangle is a closed shape w

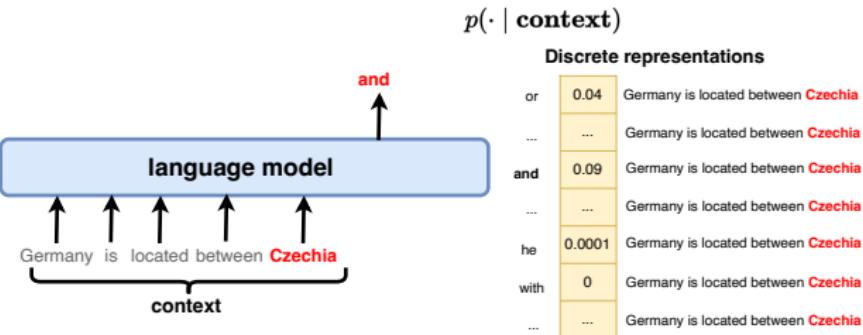
## Biological sequences

```
ATG GAT TTT GGT GTT TGT CTT CTG CCT GTG TGG GTT GAT GGT TTG GAG GGT
GCG GAG TAG CCG GCA GCG GAT GAG CGG CGC CGG TCC GTC GCA GCG GGA GGA
GGA CCC ATG
GAA GCG GAA GGC GCT GCC CGC CGC CGG GGT CCA CGC CGT GAG GCC ATC GAG
GGA GGC GGT GGC GAC CCA CCA ACA CGC GAT GCC AGT TTG ACC GGC AGC CGC GGG
CGA CGA CGG
CTT GCC AAA GGC CGG GGC TGC CGG GCG GGC CGG GCT CTG GTG GAG GAG GGC
CGA GAG GAA CTT GGC TTC CGA CGC CGC CAC CTG GCG GGC TGC GGA GCG GCC CTG
CGT GGA CGC
ACT CGG CGT GGC CGC GAG GCG GAG ATG TGC CGC GCG CGT GAG GAC GGC ATC
GCC AGC GAA CTG GAG GTG CGC AGA TGG TGC CGG GAT GAG CGG TGC CGC GGC CTG
GCC CCT
```

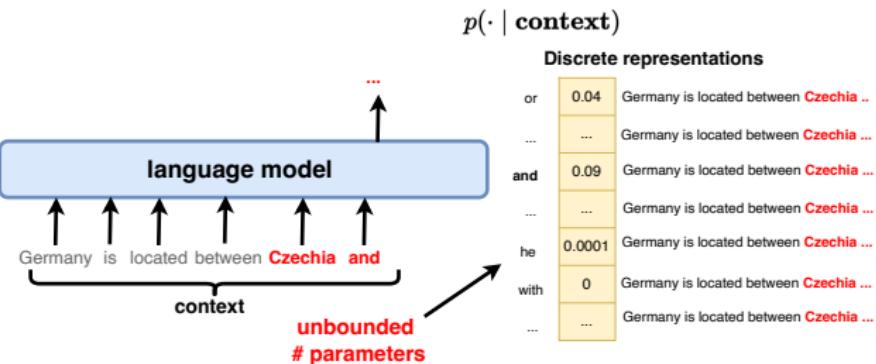
# The problem with traditional solutions



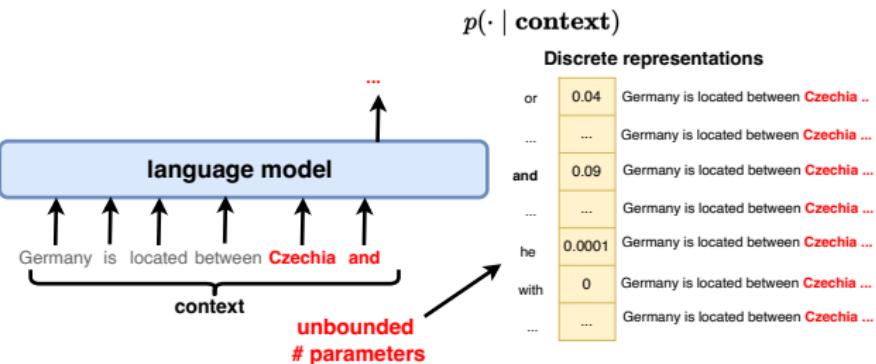
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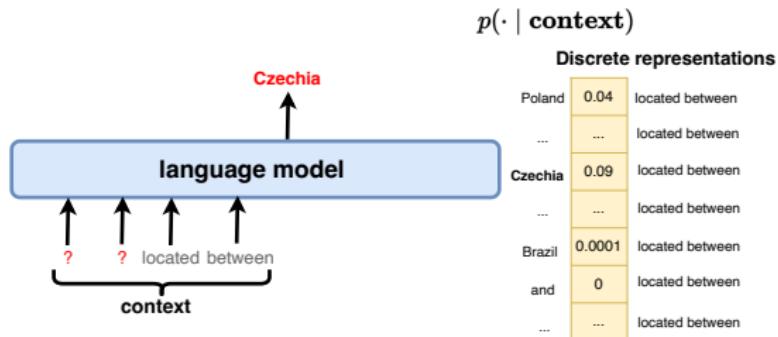


# The problem with traditional solutions



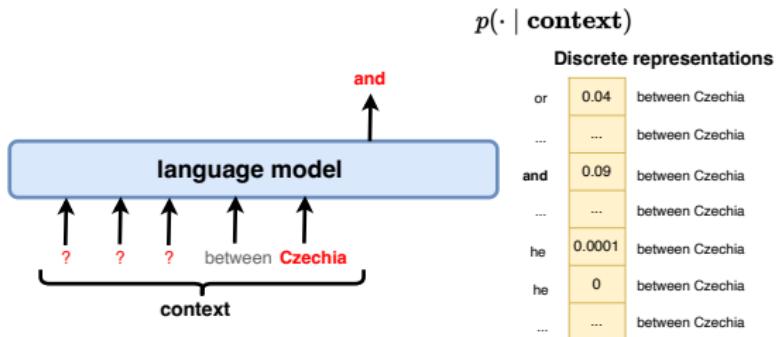
Make models tractable through **independence** or **Markov** assumptions;  
limit the allowable context.

# The problem with traditional solutions



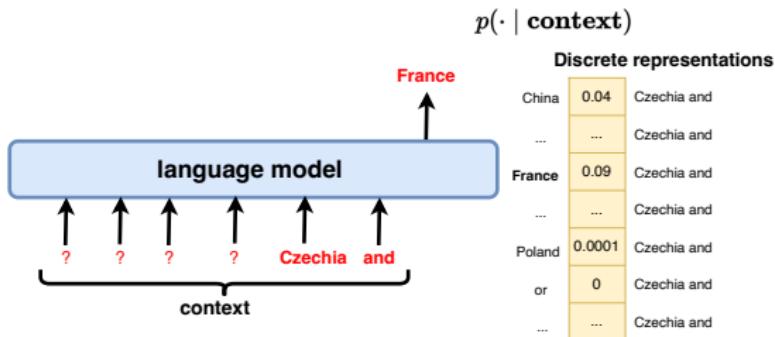
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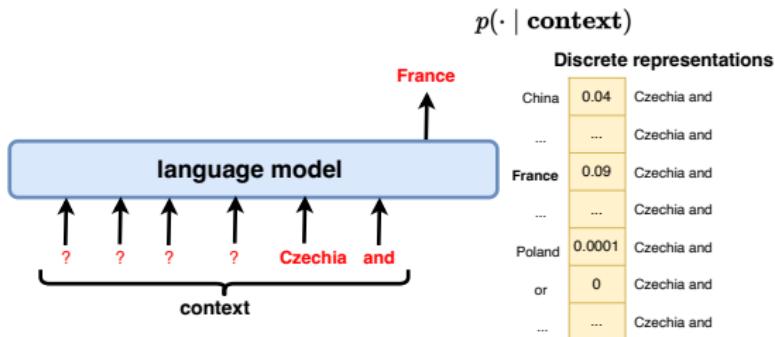
Make models tractable through **independence** or **Markov** assumptions;  
limit the allowable context.

# The problem with traditional solutions



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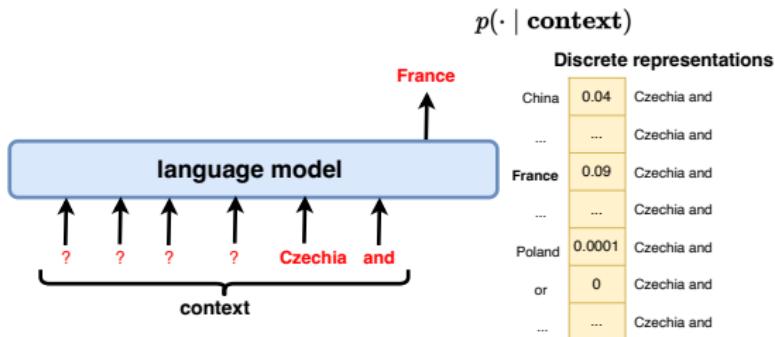
# The problem with traditional solutions



Make models tractable through **independence** or **Markov** assumptions;  
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Even limited to 2 previous words and a vocabulary of 100,000 words, results in  $10^{15}$  (**quadrillion**) probability parameters.

# The problem with traditional solutions

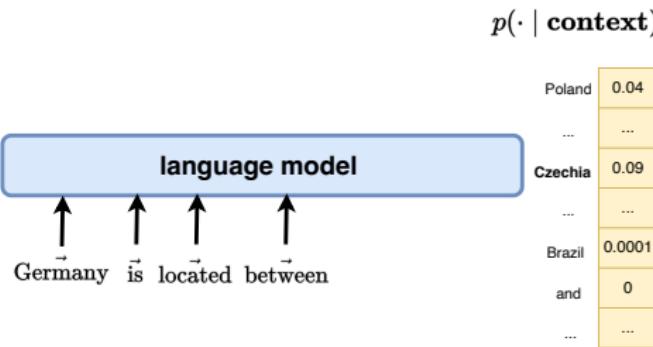


Make models tractable through **independence** or **Markov** assumptions;  
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**Do not** faithfully model these joint probability distributions!

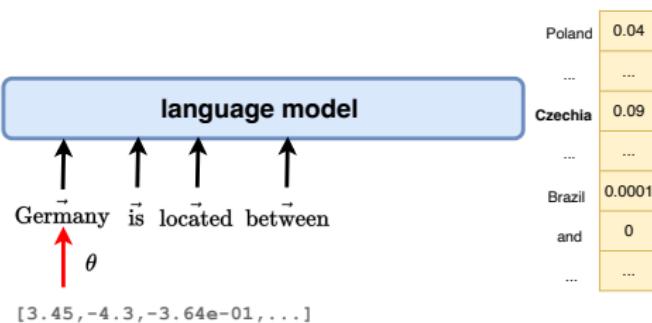
# Moving from the discrete to the continuous

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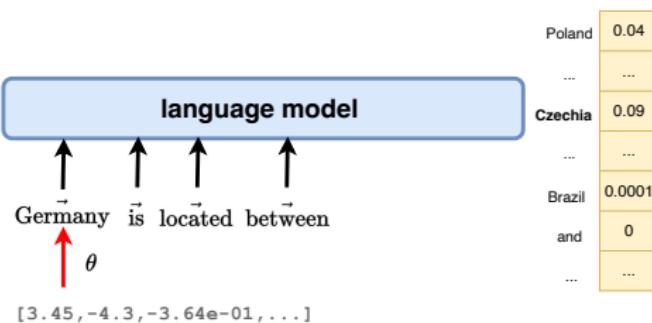
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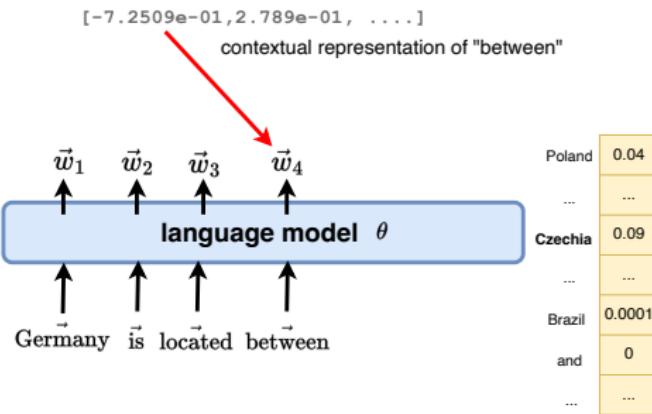
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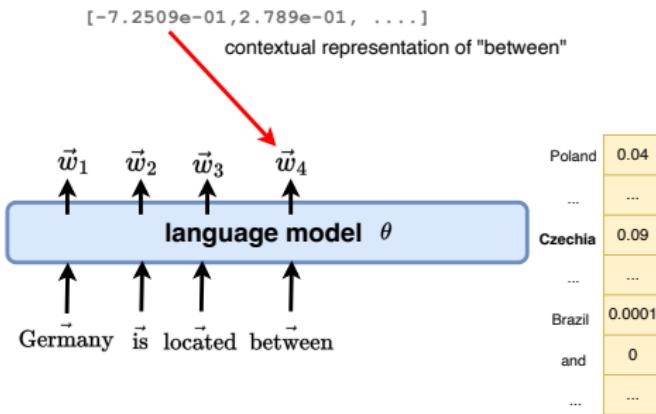
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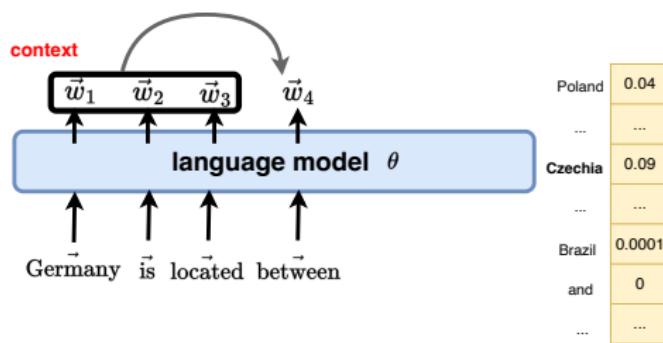
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How information flows / contextual representations are built, relates to the **model architecture**. Popular: **transformer architecture**.

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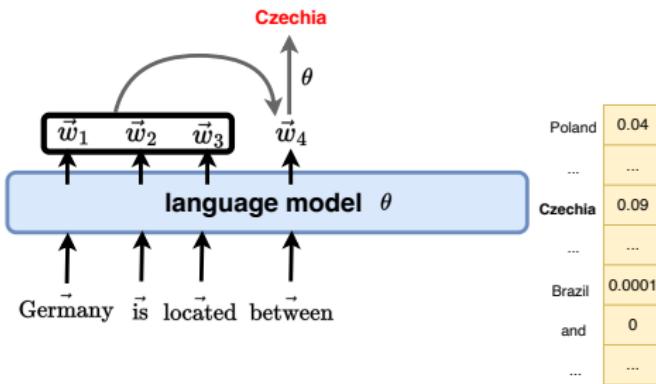
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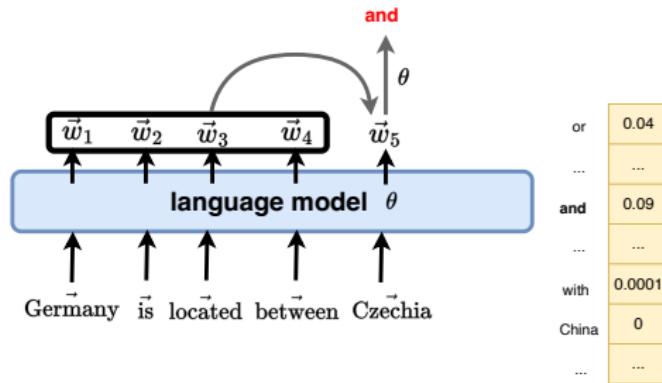
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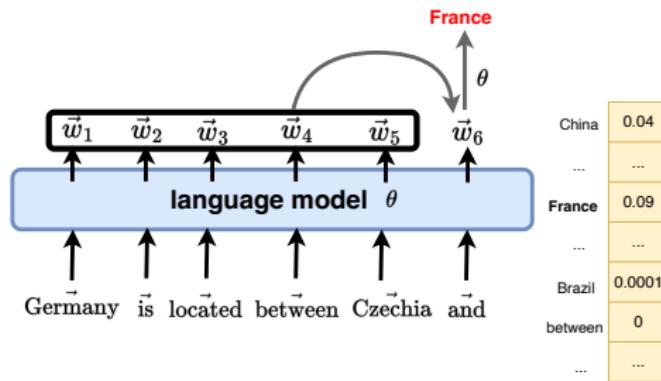
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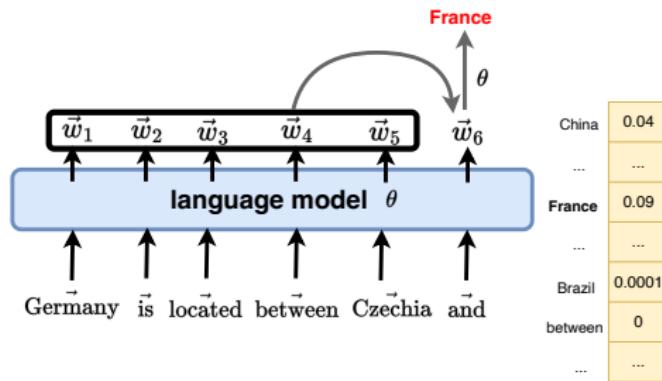
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# Moving from the discrete to the continuous

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**Fundamental problem:** learning these underlying representations.

It took time to get this right...

It took time to get this right...

<b>Input:</b>	I come from <u>Tunisia</u> .
<b>Reference:</b>	<u>チュニジア</u> の 出身です。 Chunisia no shusshindesu.
<b>System:</b>	(I'm from <u>Tunisia</u> .) ノルウェー の 出身です。 Noruue- no shusshindesu. (I'm from <u>Norway</u> .)
	Target translation Mistake

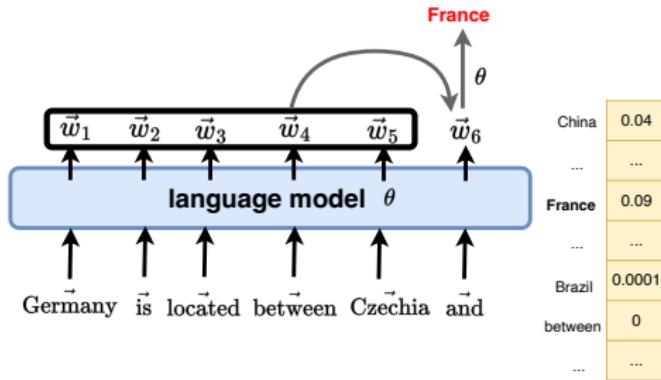
Figure 1: An example of a mistake made by NMT  
on low-frequency content words.

It took time to get this right...

Table 2: Errors from the RNN.

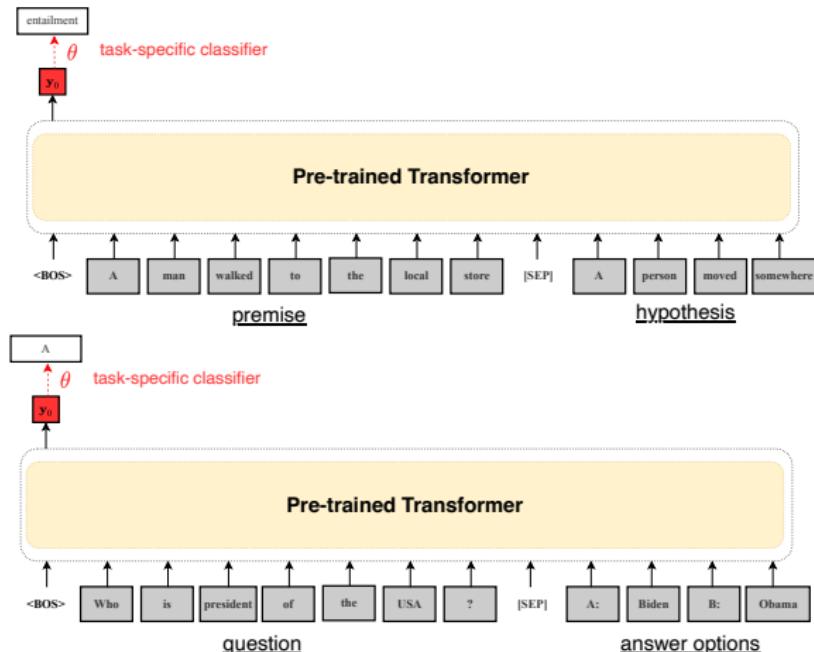
Input	Correct	Prediction
2 mA	two milliamperes	two million liters
11/10/2008	the tenth of november	the tenth of october
1/2 cc	two thousand eight	two thousand eight
18:00:00Z	half a c c	one minute c c
	eighteen hours zero minutes and zero seconds z	eighteen hundred cubic minutes

# (Pre-)Training in a nutshell



- ▶ Estimate parameters  $\theta$  from signal you get from *auto-completing* example data. Straightforward to get lots of **data for free**.

# Model Fine-tuning



**Fine-tuning:** customizing models to target tasks using additional parameters; **idea:** bootstrap off of pre-training knowledge.

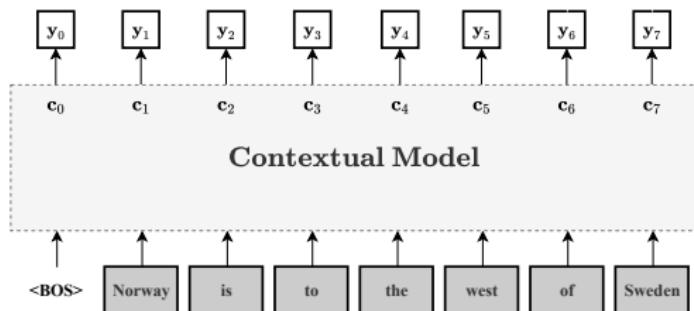
# Contextual models and transformers

## Contextual Models

- ▶ **Role:** assign continuous vectors representations  $\mathbf{y}_j \in \mathbb{R}^d$  to elements in a sequence that capture their meaning of those elements in context.

# Contextual Models

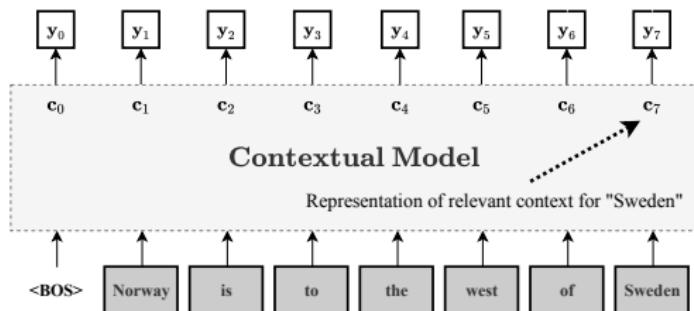
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**Operationally:** neural network models, often large and opaque.

# Contextual Models

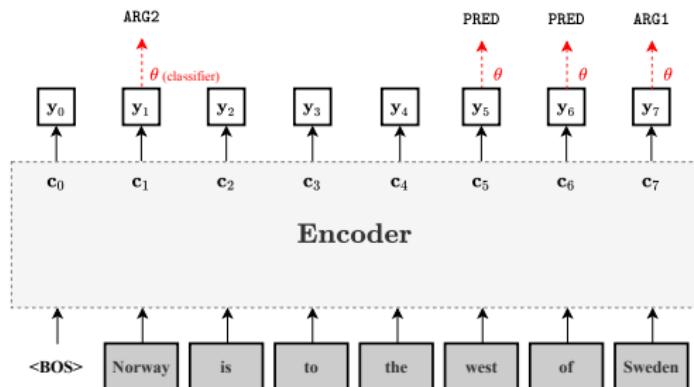
- **Role:** assign continuous vectors representations  $\mathbf{y}_j \in \mathbb{R}^d$  to elements in a sequence that capture their meaning of those elements in context.



**Semantics:**  $y_7$  captures the meaning of *Sweden* grounded in this particular sentential context, output of a compositional procedure.

# Contextual Models

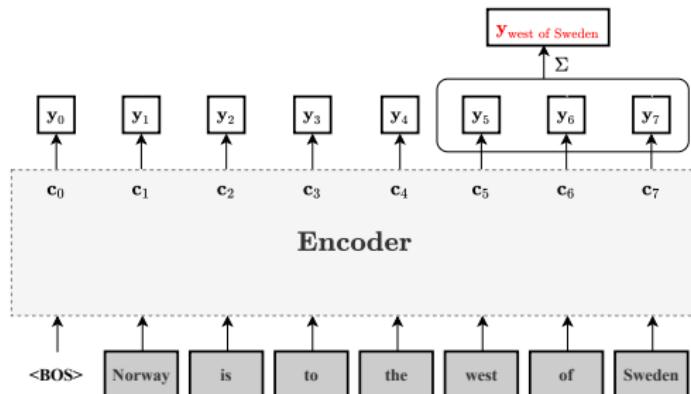
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**Why?** Build representations that allow you make predictions, **success:** learned representations that effectively solve problems.

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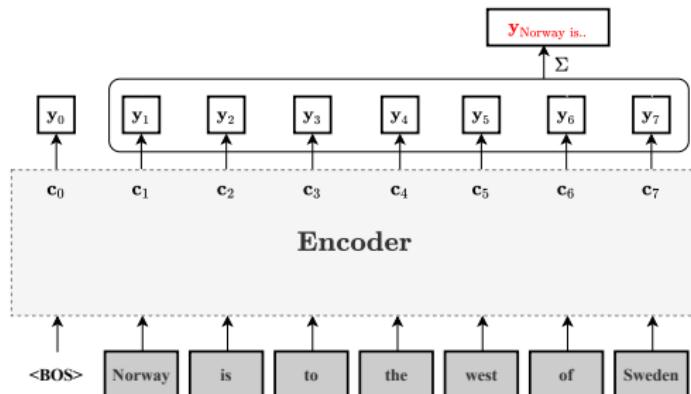
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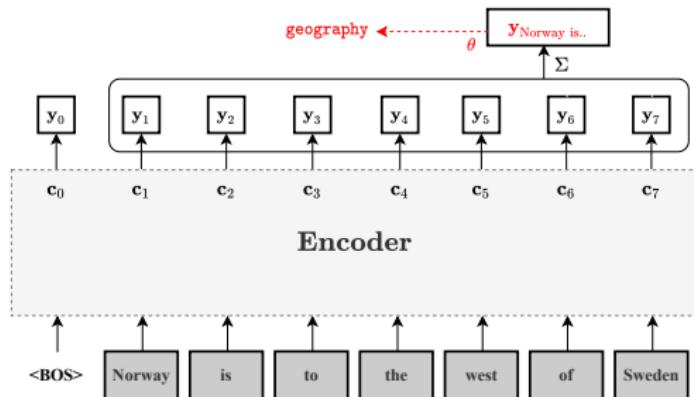
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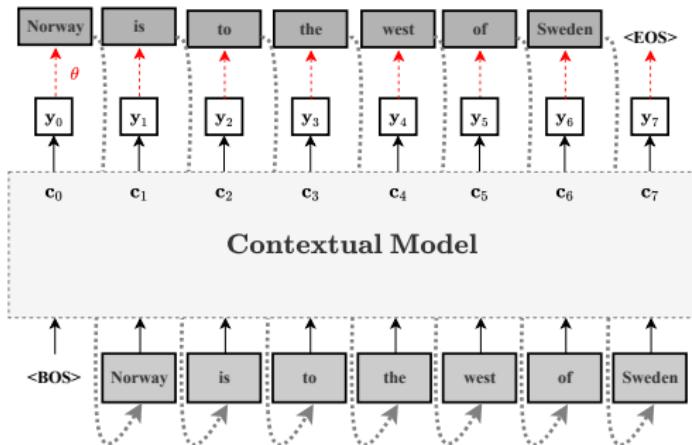
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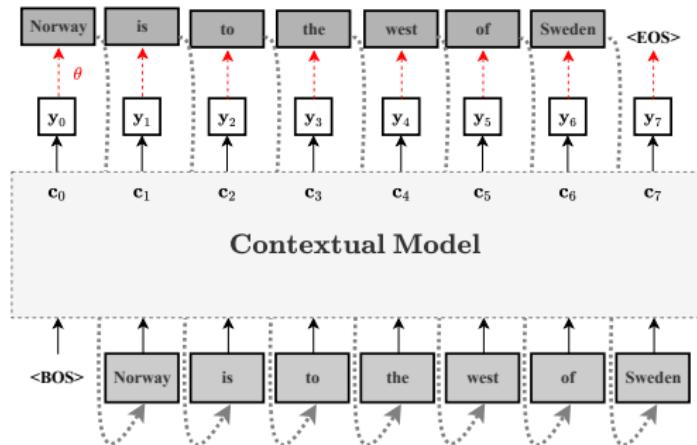
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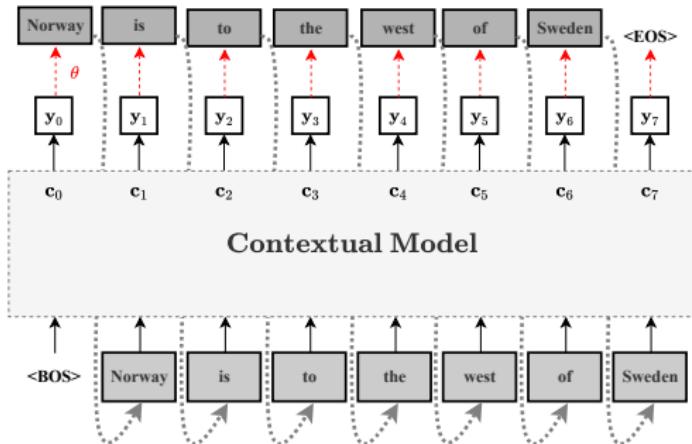
- **Role:** assign continuous vectors representations  $\mathbf{y}_j \in \mathbb{R}^d$  to elements in a sequence that capture their meaning of those elements in context.



as LMs:  $p(w_j | w_1, \dots, w_{j-1}) = p(w_j | c_{j-1})$ , Important: Can condition on full contexts, faithfully model complex joint probability distributions

# Contextual Models

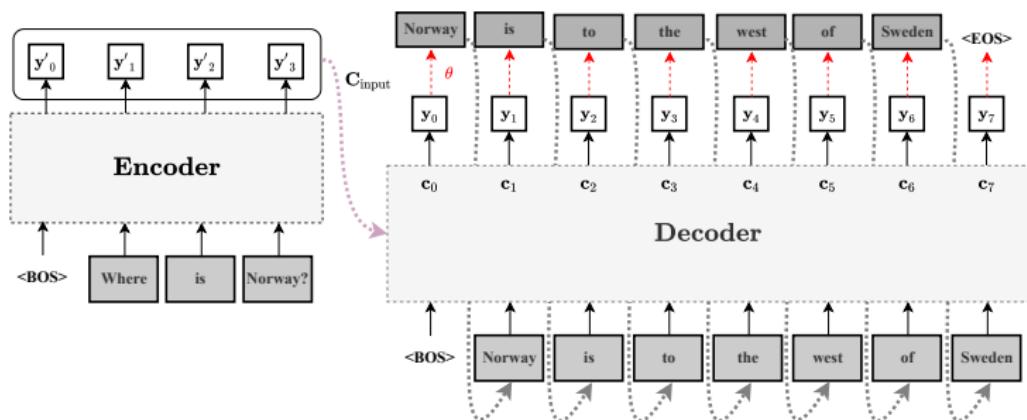
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**Model Architectures:** how information is processed, internal representations are constructed. **Common:** RNNs, Transformers.

# Contextual Models

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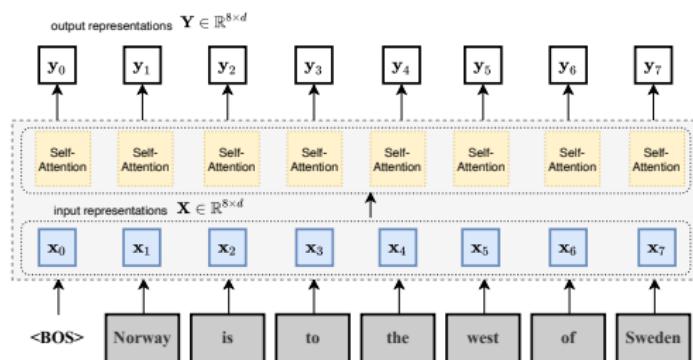


**Text2Text models:** estimate  $p(y^{\text{output}} | x^{\text{input}})$ , natural way to express many language understanding problems.

# Transformers and attention

# Self-Attention: Simple Encoder Example

**Attention:** Mechanism for building contextual representations (see [Vaswani et al. \(2017\)](#)).

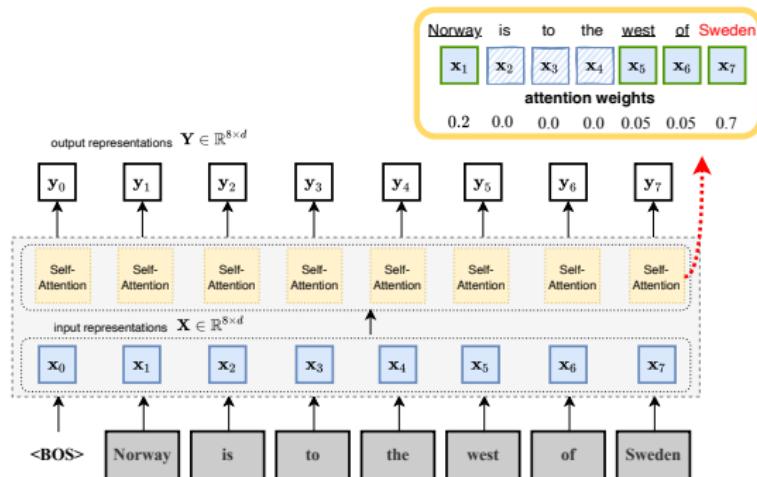


# Self-Attention: Embeddings Representations

```
1 import torch ## to install: pip install pytorch
2
3 ### word embedding parameters and matrix E
4 E = torch.nn.Embedding(
5 embedding_dim=768, ##<--- dimensionality
6 num_embeddings=3000, ##<--- # words
7)
8
9 ##e.g., Representation of our Input
10 X = E(torch.tensor([
11 0, # <BOS>
12 1, # Norway
13 2, # is
14 3, # to
15 4, # the
16 5, # west
17 6, # of
18 7, # Sweden
19])) ### => matrix 7 * 768
20
21 x1 = X[1] ##-> initial representation of Norway
22 print(x1)
23 ##### [-1.1344e+00, -3.0359e-01, 7.3585e-02,]
```

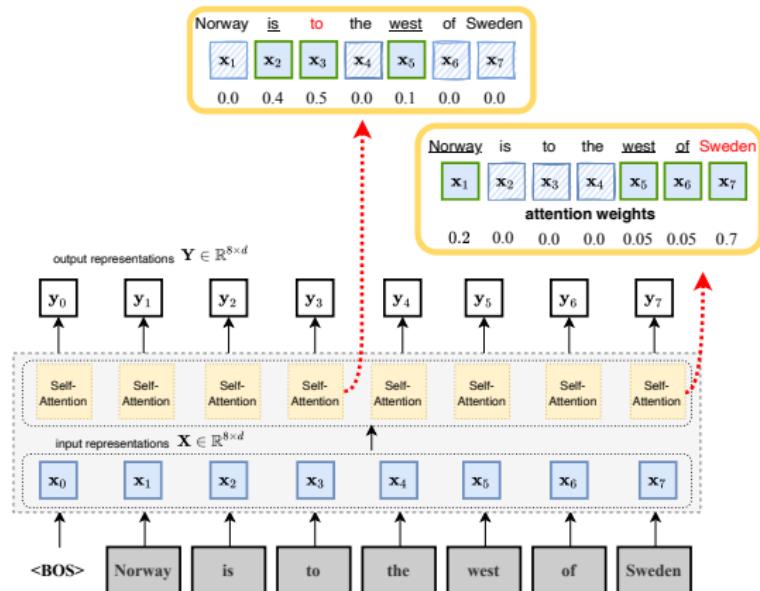
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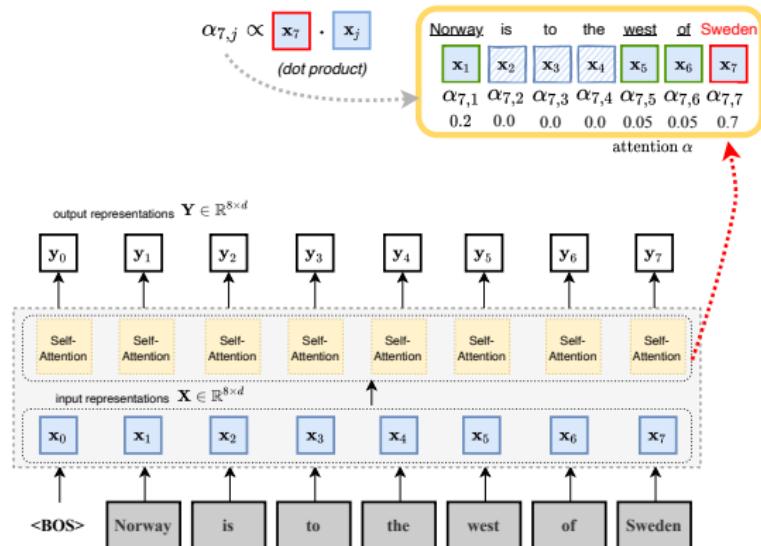
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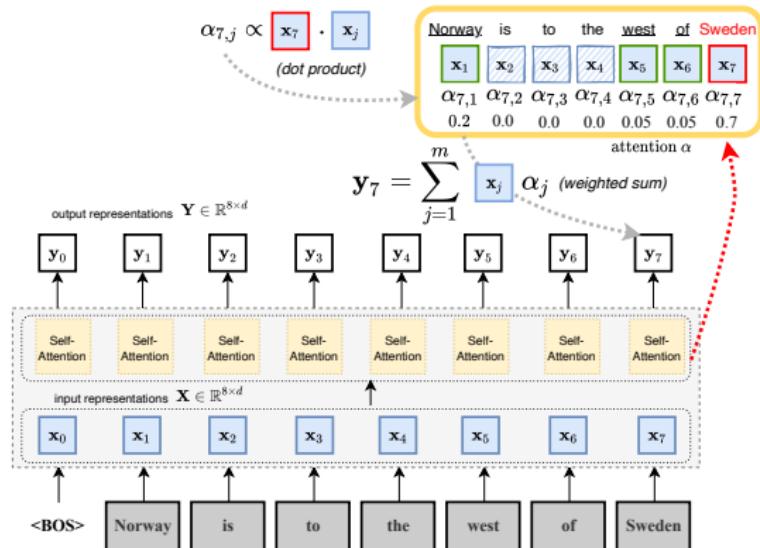
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# Self-Attention: Computing Final Representations

The full computation

$$\alpha'_{i,j} = \mathbf{x}_i \cdot \mathbf{x}_j \quad \text{dot product}$$

$$\alpha_{i,j} = \frac{e^{\alpha'_{i,j}}}{\sum_j e^{\alpha'_{i,j}}} \quad \text{softmax}$$

$$\mathbf{y}_i = \sum_j \alpha_{i,j} \mathbf{x}_j \quad \text{weighted sum}$$

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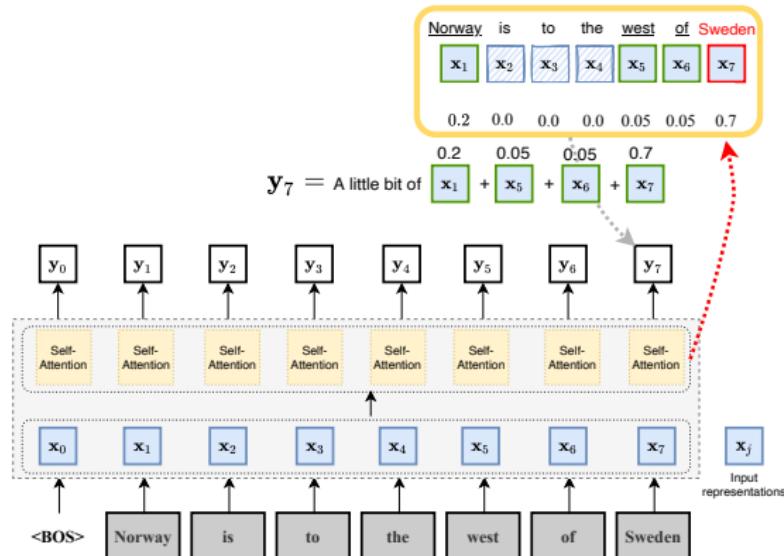
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```
1 ## Input representations (again),
2 X = torch.tensor([0,1,2,3,4,5,6,7])
3
4 ### raw weights (dot product / matrix multiplication)
5 raw_Alpha = torch.matmul(X,X.transpose(0,1))
6 ### normalized via softmax, probability distribution
7 alpha = raw_Alpha.softmax(dim=-1)
8 ### Final self attention representations
9 Y = torch.matmul(alpha,X)
10 ### self attention representation of 'Norway'
11 y1 = Y[1]
```

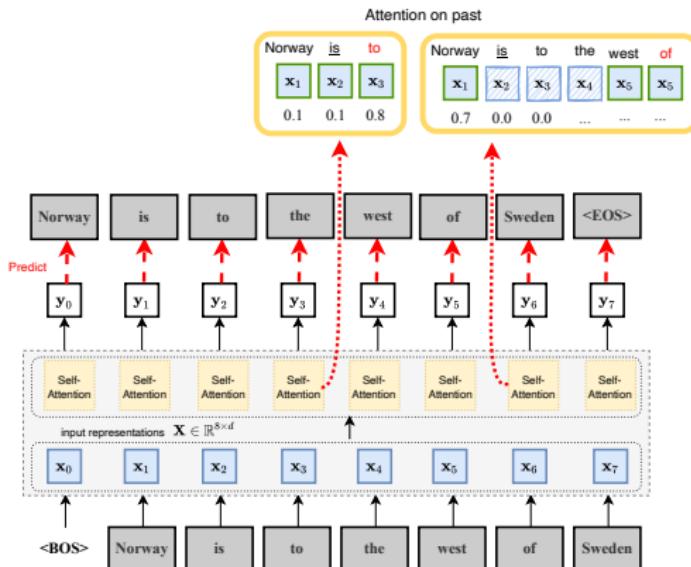
# Self-Attention: Intuition

**Attention:** A kind of brute-force looking around and aggregation of contextual information.



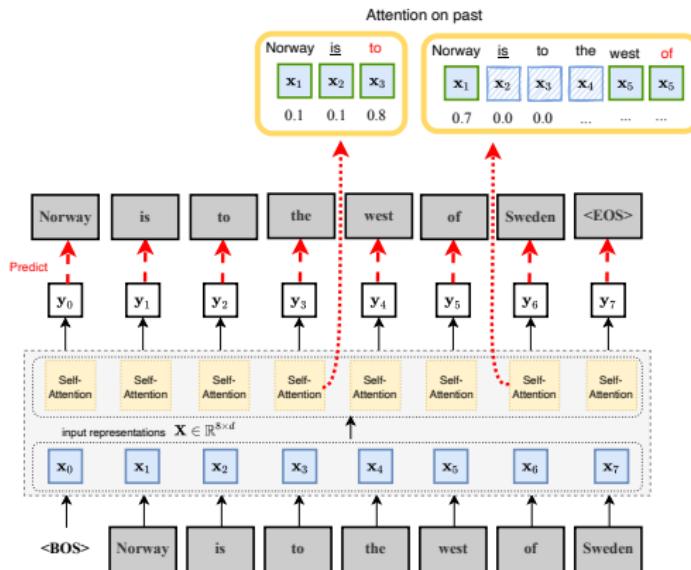
# Attention in Other Contexts

**Decoders:** Attention limited to past context, allows for generation (step-by-step prediction of next word).



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**Note:** No independence assumptions, full context.

# Causal Attention

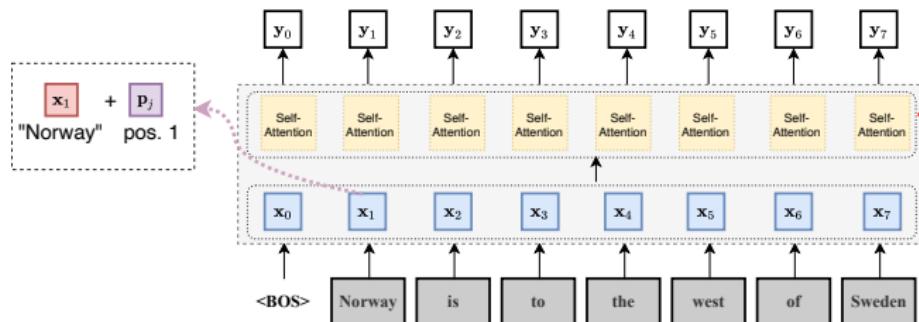
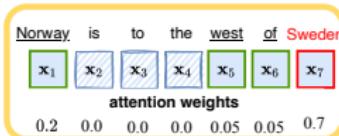
- ▶ Implementing causal attention, involves adding a **mask**.

```
1 import torch
2 ## Input representations (again),
3 X = E(torch.tensor([0,1,2,3,4,5,6,7]))
4
5 ### raw weights (dot product / matrix multiplication)
6 raw_Alpha = torch.matmul(X,X.transpose(0,1))
7
8 ### causal mask
9 mask = torch.triu_indices(8, 8, offset=1)
10 raw_Alpha[:, mask[0], mask[1]] = float('-inf')
11
12 ### normalized via softmax, probability distribution
13 alpha = raw_Alpha.softmax(dim=-1)
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# An important detail: positional information

- Word embeddings so far do not encode position information.

$$\begin{aligned} \mathbf{x}_j & \quad \mathbf{E} \in \mathbb{R}^{|words| \times d} \text{ (word embeddings)} \\ \mathbf{p}_j & \quad \mathbf{P} \in \mathbb{R}^{p \times d} \quad \text{(position embeddings)} \\ \mathbf{x}_j & = \mathbf{x}_{id} + \mathbf{p}_j \end{aligned}$$



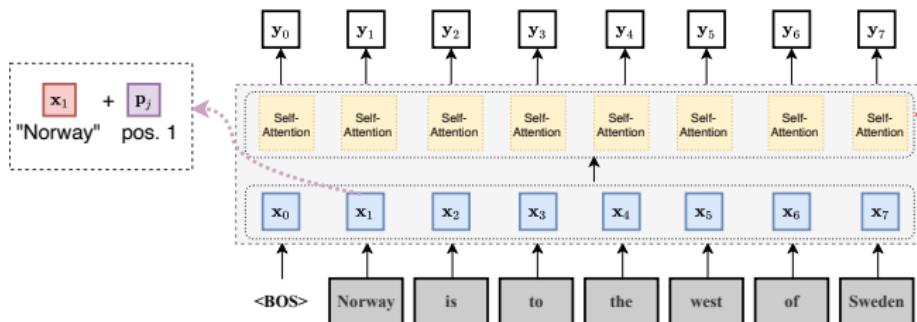
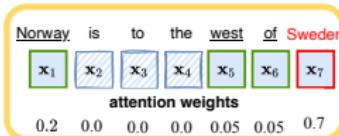
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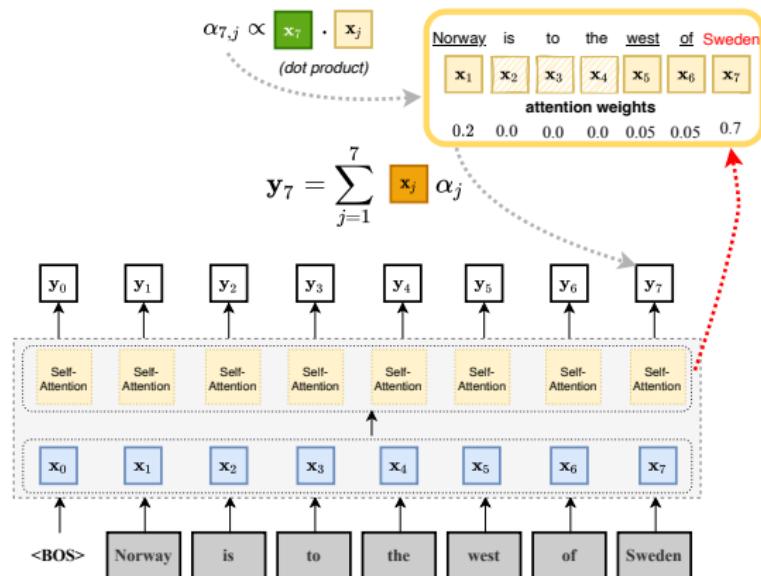
$$\mathbf{x}_j = \mathbf{x}_{id} + \mathbf{p}_j$$



**Note:** we can add any additional information we want, many variations.

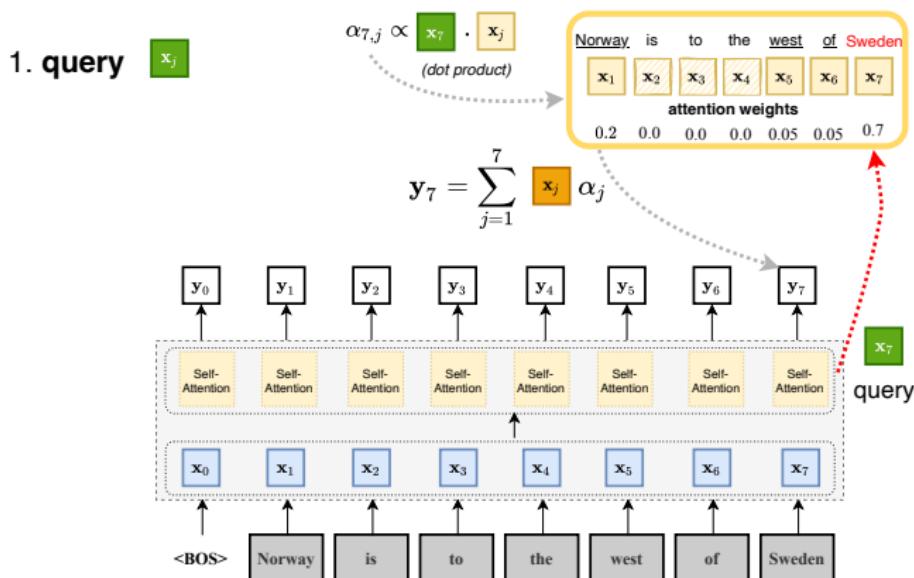
# More Parameters: Keys, Queries and Values

- ▶ Three components in our computation.



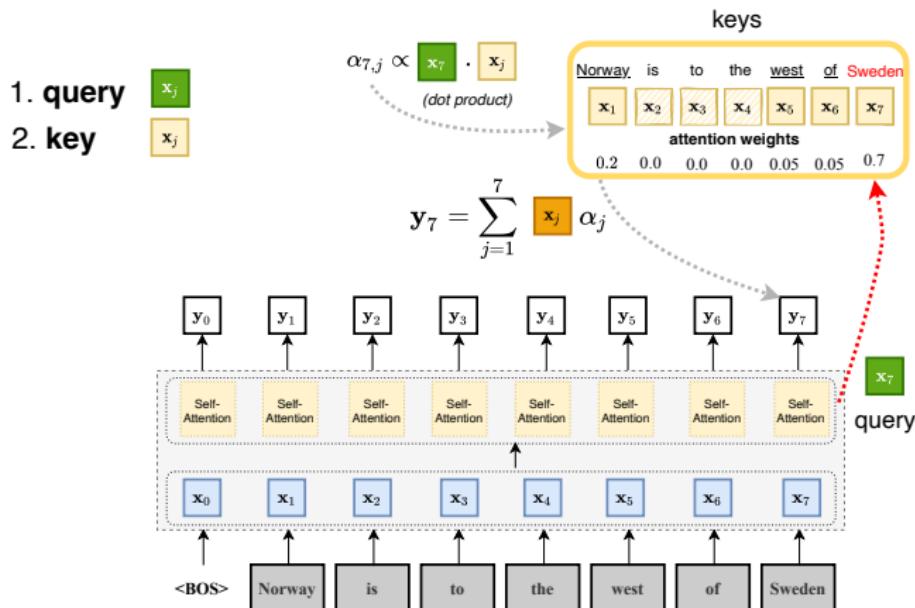
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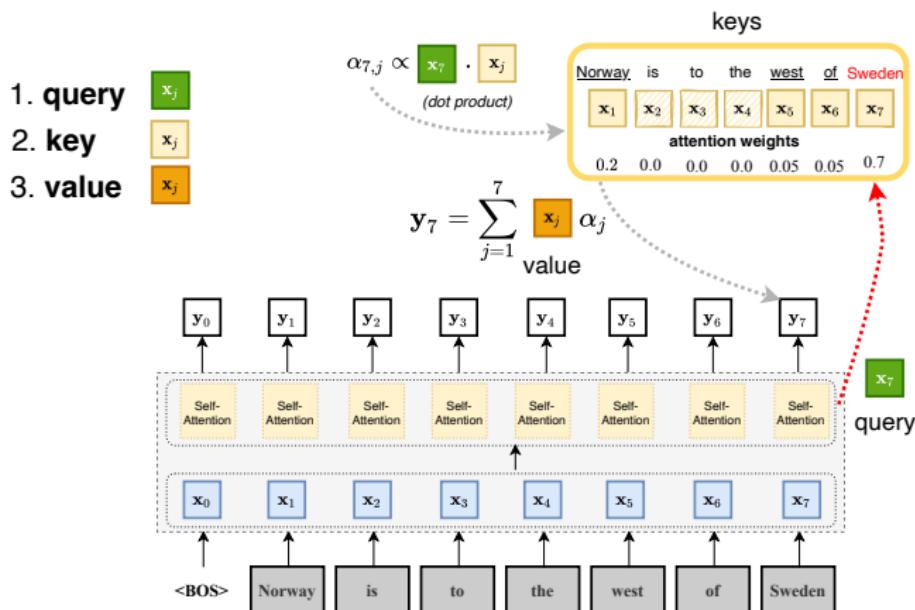
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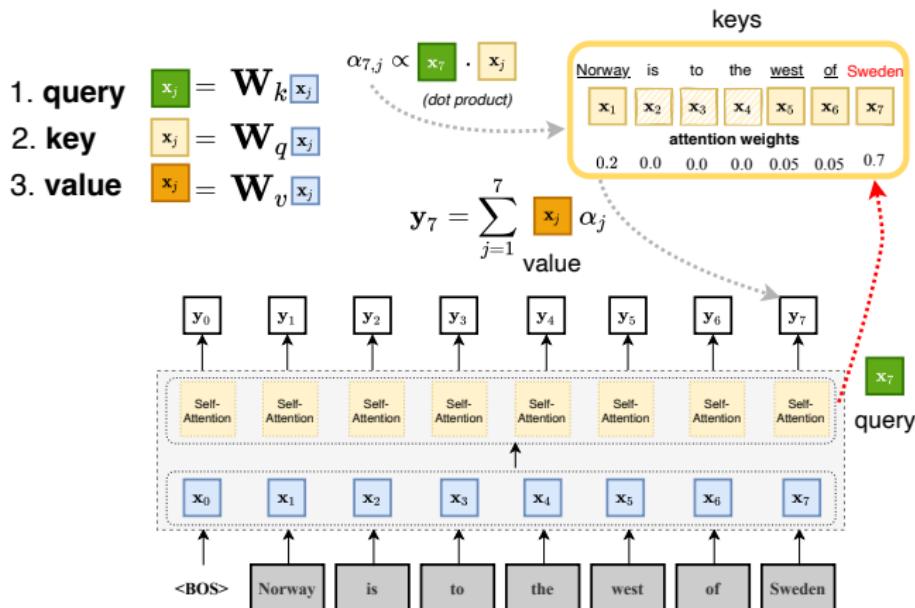
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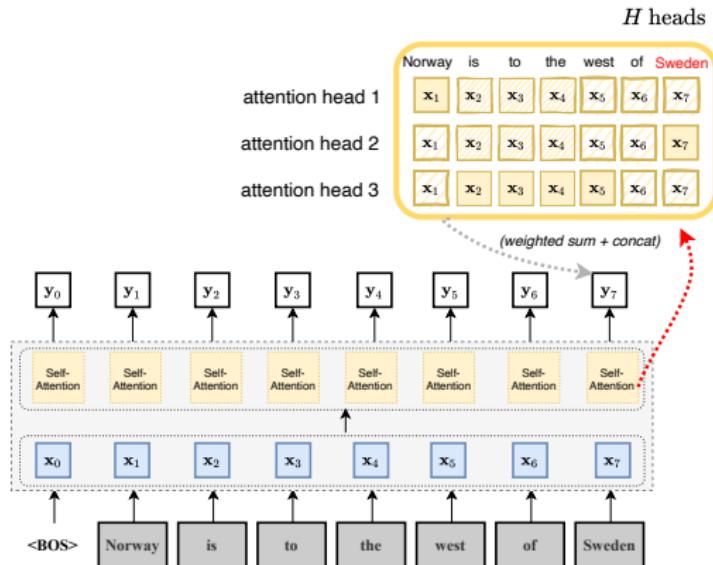
# More Parameters: Keys, Queries and Values

Another few additional lines of PyTorch

```
1 ## Input representations (again),
2 X = E(torch.tensor([0,1,2,3,4,5,6,7]))
3 D = 768
4
5 ### key, value, query parameters (linear layer)
6 W_k = torch.nn.Linear(D, D, bias=False)
7 W_q = torch.nn.Linear(D, D, bias=False)
8 W_v = torch.nn.Linear(D, D, bias=False)
9
10 key_rep = W_k(X) #<-- rep. of X as keys
11 query_rep = W_q(X) #<-- rep. of X as queries
12 value_rep = W_v(X) #<-- rep of X as values
13
14 ### sample computation with parameters applied over 'X'
15 alpha = torch.matmul(
16 query_rep,
17 key_rep.transpose(0,1)
18).softmax(dim=-1)
19
20 ### same as before
21 Y = torch.matmul(alpha,value_rep)
```

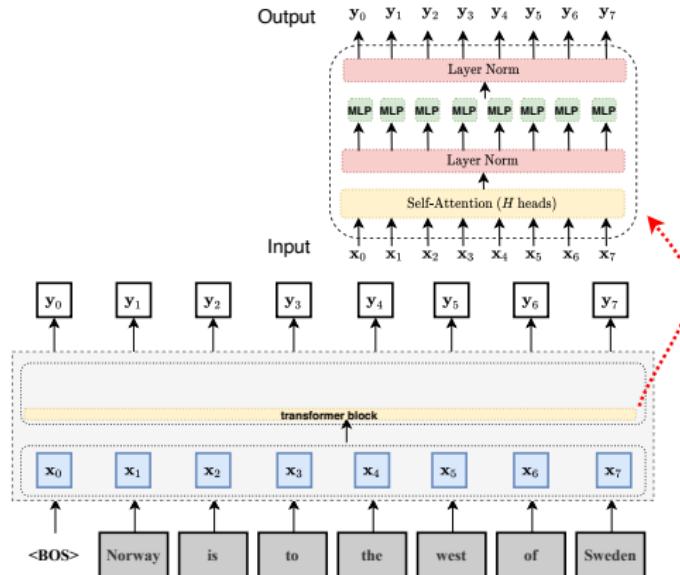
# Multi-headed Attention

- ▶ Allows the model to simultaneously focus on multiple parts of input.



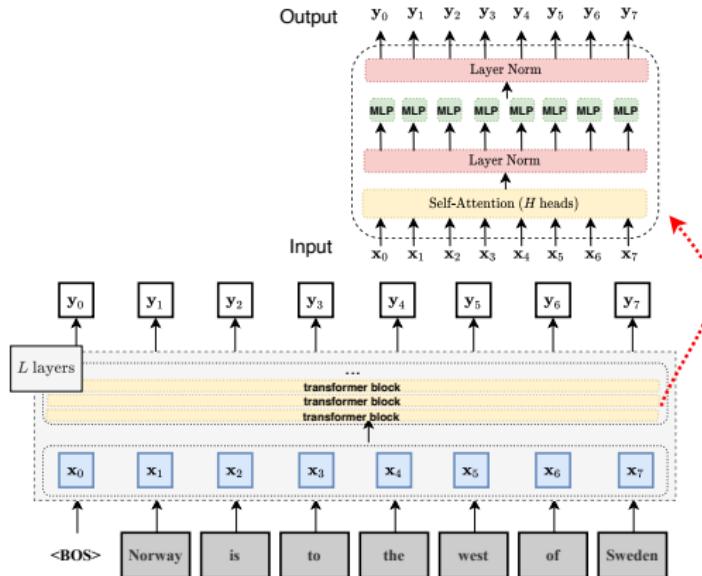
# Transformer Blocks and Multiple Layers

- ▶ Current models are a bit more complex and multi-layered.



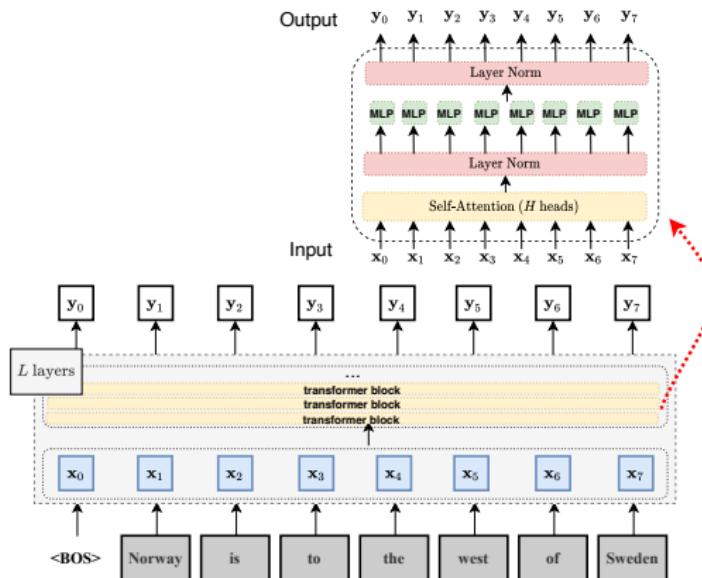
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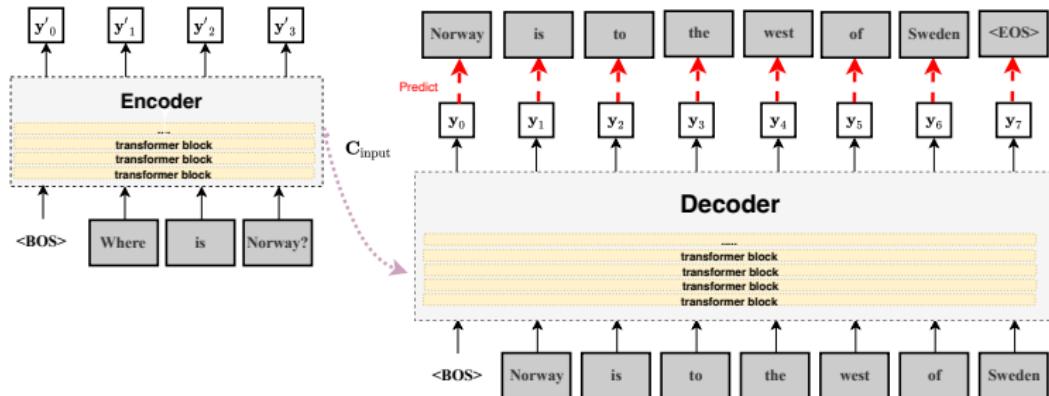
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**BERT** (Devlin et al., 2019):  $L = 24$  layers each with  $H = 16$  heads,  $340M$  parameters, embedding dimension=1024

# Transformer Blocks and Multiple Layers

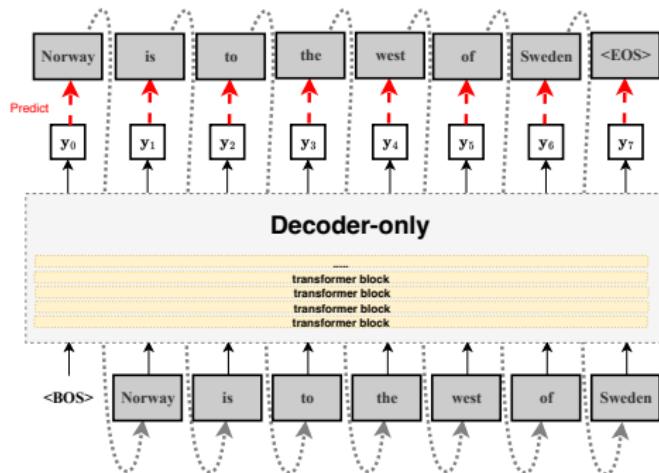
- ▶ Current models are a bit more complex and multi-layered.



T5 model ([Raffel et al., 2020](#)), text2text architecture: **encoder** and **decoder**, 24 layers, 128 heads, cross-attention (11B parameters).

# Transformer Blocks and Multiple Layers

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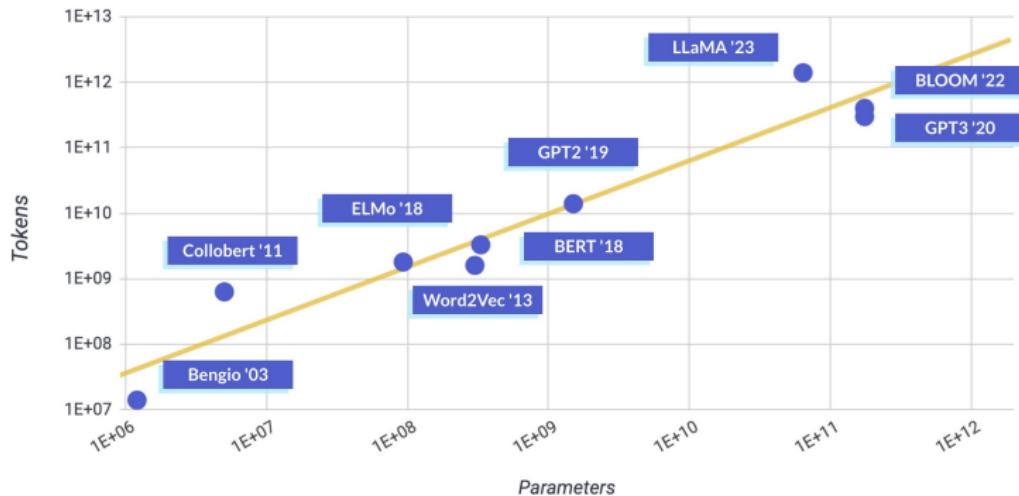
**GPT3** (Brown et al., 2020):  $L = 96$  layers each with  $H = 96$  heads ( $175B$  parameters), embedding dimension=12288

## A typical transformer block

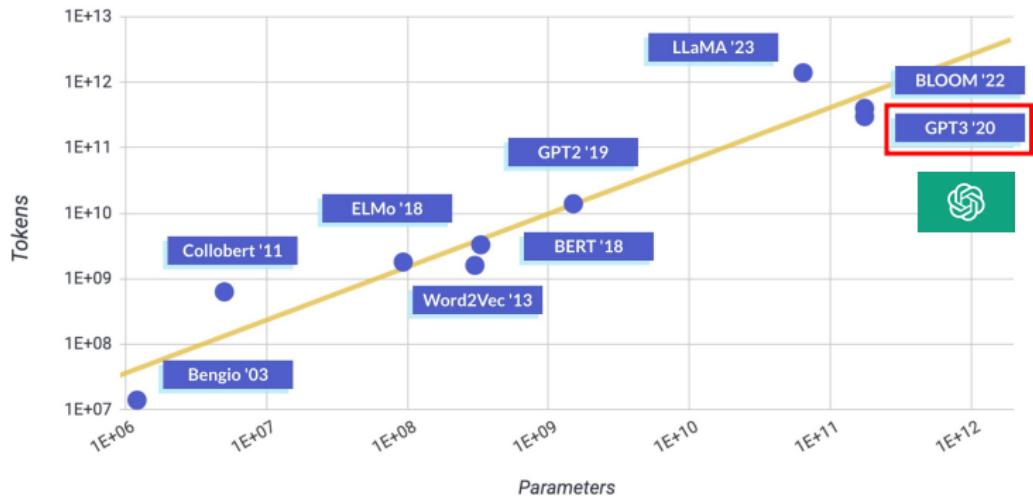
```
1 ## nanoGPT: https://github.com/karpathy/nanoGPT
2 class Block(nn.Module):
3
4 def __init__(self, config):
5 super().__init__()
6 self.ln_1 = LayerNorm(config.n_embd,
7 bias=config.bias
8)
9 self.attn = CausalSelfAttention(config)
10 self.ln_2 = LayerNorm(config.n_embd,
11 bias=config.bias
12)
13 self.mlp = MLP(config)
14
15 def forward(self, x):
16 x = x + self.attn(self.ln_1(x))
17 x = x + self.mlp(self.ln_2(x))
18 return x
```

## The nature of their training

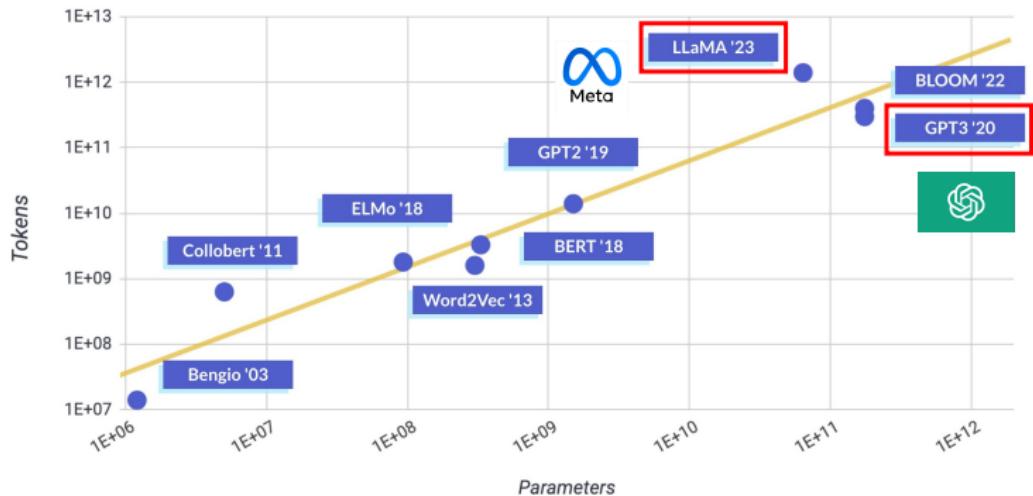
# Model and data scale: a glance



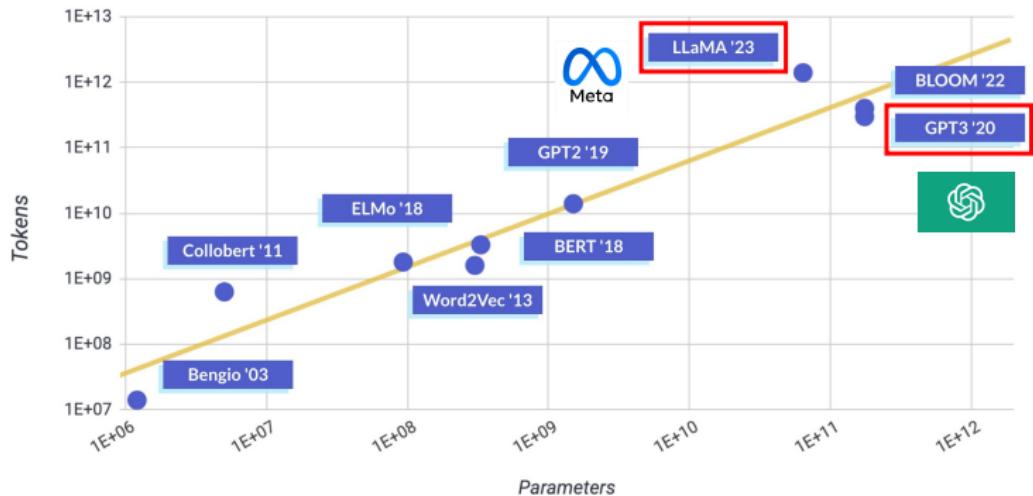
# Model and data scale: a glance



# Model and data scale: a glance



# Model and data scale: a glance

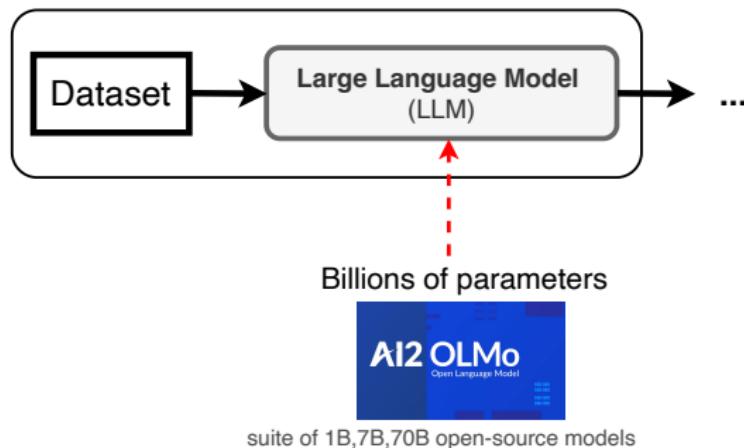


- ▶ Industry is currently dominating, we know increasingly less about what these models are and how they are trained.

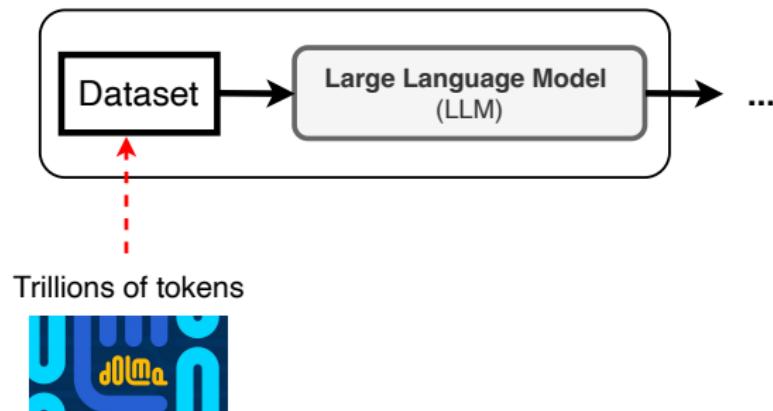
# Open Language Model (OLMo) project at AI2



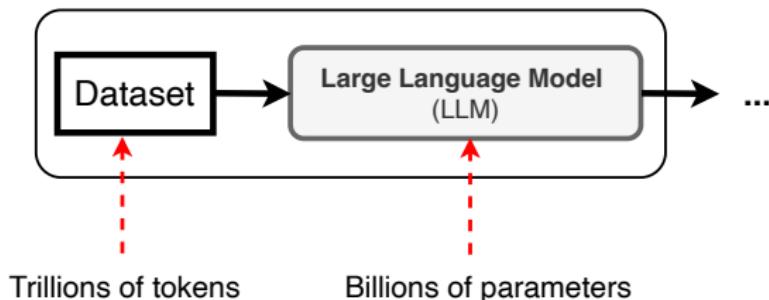
# Open Language Model (OLMo) project at AI2



# Open Language Model (OLMo) project at AI2



# Open Language Model (OLMo) project at AI2



# Where does the data come from?

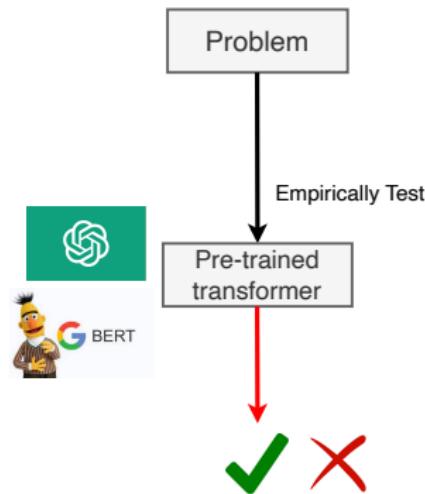
Doc Type	UTF-8 bytes (GB)	Documents (millions)	Unicode words (billions)
web pages	9,022	3,370	1,775
code	1,043	210	260
web pages	790	364	153
social media	339	377	72
STEM papers	268	38.8	50
books	20.4	0.056	4.0
encyclopedic	16.2	6.2	3.7
	<b>11,519</b>	<b>4,367</b>	<b>2,318</b>

What can models do? What do they know?

## What can models do? Different approaches

Problem

# What can models do? Different approaches



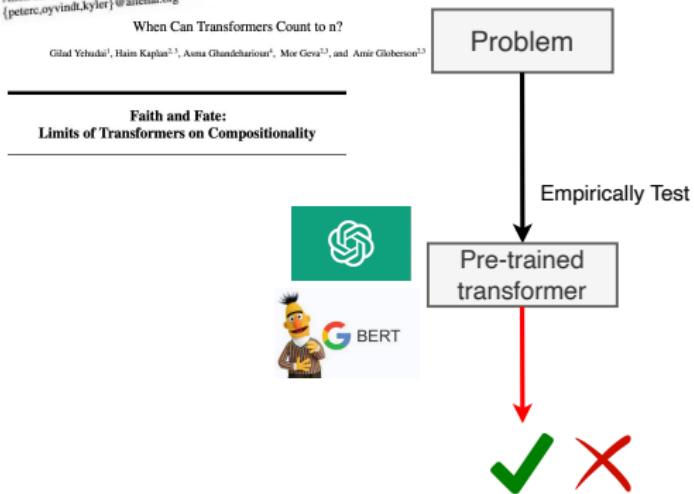
# What can models do? Different approaches

**Transformers as Soft Reasoners over Language**

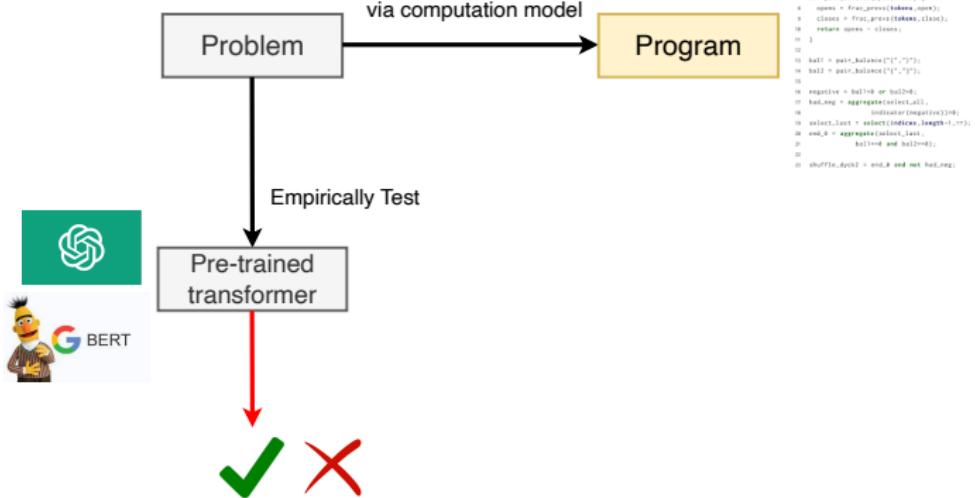
Peter Clark, Oyvind Tafjord, Kyle Richardson  
Allen Institute for AI, Seattle, WA  
[{peterc,oyvindt,kyler}@allenai.org](mailto:{peterc,oyvindt,kyler}@allenai.org)

Can Transformers Reason About Effects of Actions?  
Pratikay Baralaj, Oliver Hinsz, Max Lee, Arman Mirzaei, Kunal Patel,  
Eric C. Stachowiak, Naman Doshi, and Pratik Choudhary  
Arizona State University, Microsoft, New Mexico State University<sup>1,2</sup>  
[pbaralaj@cs.asu.edu](mailto:pbaralaj@cs.asu.edu), [ohinsz@allenai.org](mailto:ohinsz@allenai.org), [mllee@asu.edu](mailto:mllee@asu.edu), [amir.mirzaei@nmsu.edu](mailto:amir.mirzaei@nmsu.edu), [erics@cs.asu.edu](mailto:erics@cs.asu.edu), [kunal.patel@microsoft.com](mailto:kunal.patel@microsoft.com), [naman.doshi@nmsu.edu](mailto:naman.doshi@nmsu.edu)

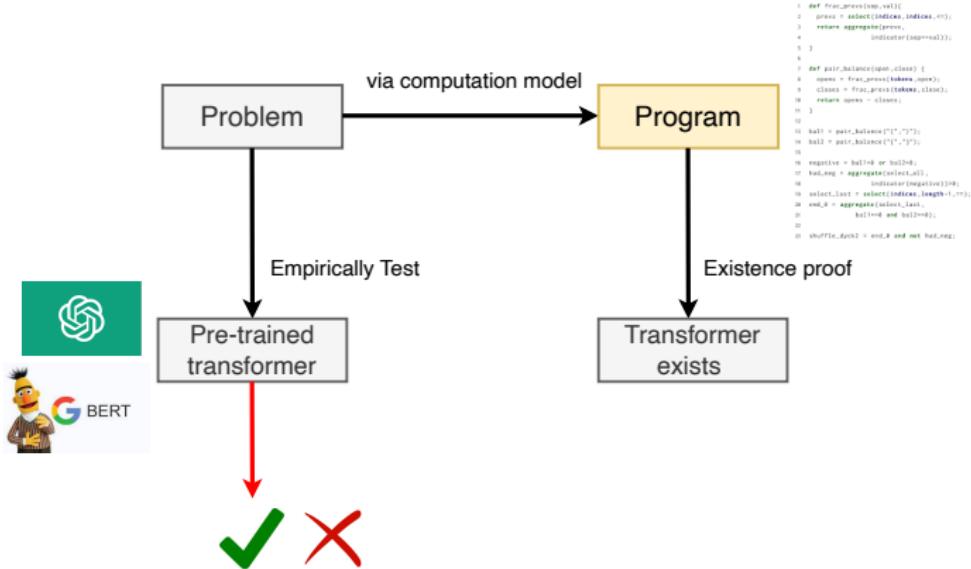
When Can Transformers Count to n?  
Giliad Yehudai<sup>1</sup>, Haim Kaplan<sup>2,3</sup>, Asma Ghandeharioun<sup>4</sup>, Mor Geva<sup>2,3</sup>, and Amir Globerson<sup>2,3</sup>



# What can models do? Different approaches



# What can models do? Different approaches



# Thinking like a transformer

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## Thinking Like Transformers

---

Gail Weiss<sup>1</sup> Yoav Goldberg<sup>2,3</sup> Eran Yahav<sup>1</sup>

- ▶ Rasp (*Restricted Access Sequence Processing Language*): a symbolic functional language for expressing transformer computation.

# Thinking like a transformer

```
1 class SimpleBlock(nn.Module):
2 def __init__(self, config):
3 super().__init__()
4 self.attn = SelfAttention(config)
5 self.mlp = MLP(config)
6
7 def forward(self, x):
8 x = x + self.attn(x) #<--- looking around
9 x = x + self.mlp(x) #<--- element-wise
10 # | residual
11 return x
```

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```

Conditions on information processing

# Thinking like a transformer

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- ▶ Each transformation on  $x$  must produce an object of the same size

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## Conditions on information processing

- ▶ Each transformation on  $x$  must produce an object of the same size
- ▶ Information across positions can only be shared via attention.

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11 return x
```

## Conditions on information processing

- ▶ Each transformation on  $x$  must produce an object of the same size
- ▶ Information across positions can only be shared via attention.
- ▶ Other transformations are element-wise, must have a way to pass around old information.

# Thinking like a transformer: reversing a string

## Reversing a string

```
text: ["this", "is", "my", "text", "</s>"]
pos: [0, 1, 2, 3, 4]
```

```
reverse ["<s>", "text", ..., "this"]
```

# Thinking like a transformer: reversing a string

## Reversing a string

```
text: ["this", "is", "my", "text", "</s>"]
pos: [0, 1, 2, 3, 4]
```

length

[4, 4, 4, 4, 4]



end symbol

# Thinking like a transformer: reversing a string

## Reversing a string

```
text: ["this", "is", "my", "text", "</s>"]
pos: [0, 1, 2, 3, 4]
```



```
length [4, 4, 4, 4]
length - pos [4, 3, 2, 1, 0]
```

# Thinking like a transformer: reversing a string

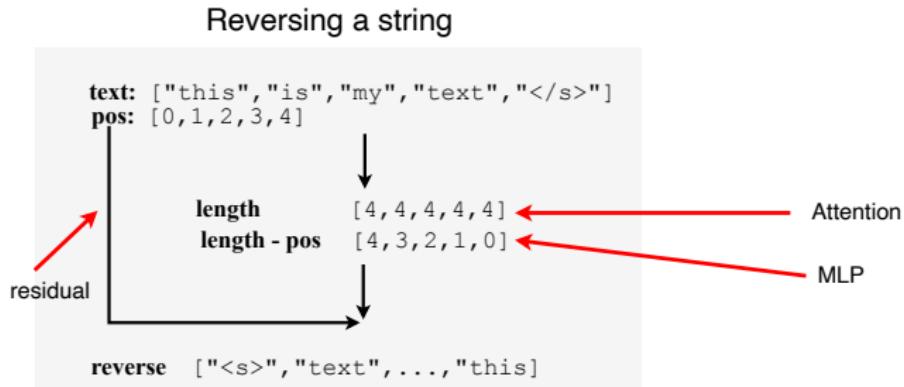
## Reversing a string

```
text: ["this", "is", "my", "text", "</s>"]
pos: [0, 1, 2, 3, 4]
```

length [4, 4, 4, 4, 4]  
length - pos [4, 3, 2, 1, 0]

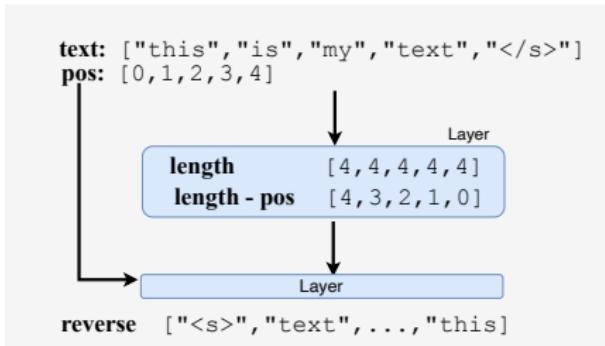
```
reverse ["<s>", "text", ..., "this"]
```

# Thinking like a transformer: reversing a string



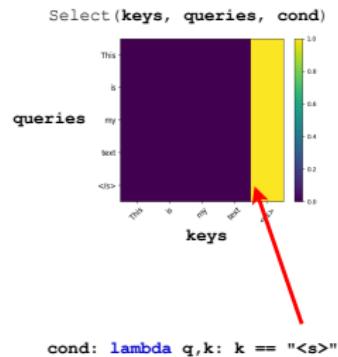
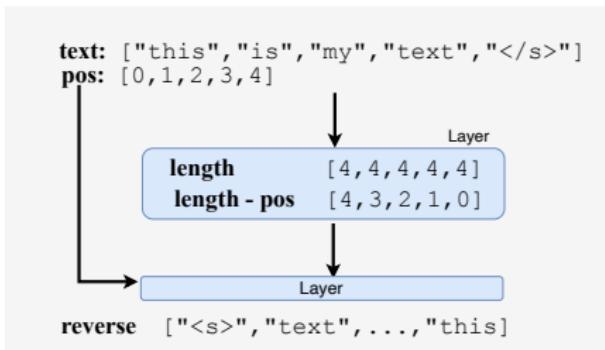
# Thinking like a transformer: reversing a string

## Reversing a string



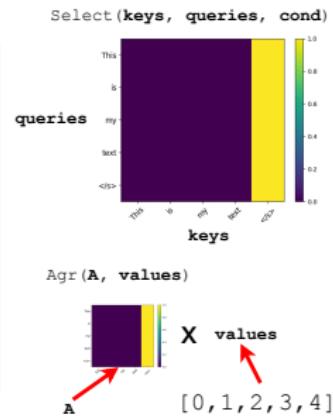
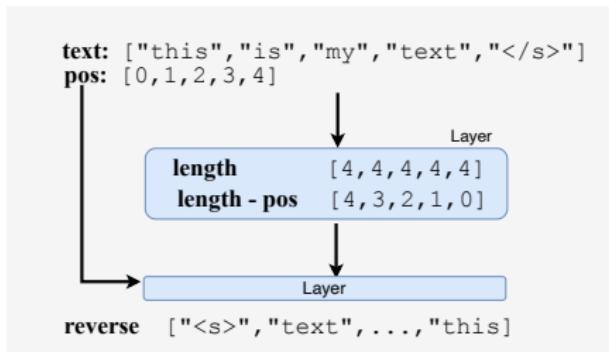
# Thinking like a transformer: reversing a string

## Reversing a string

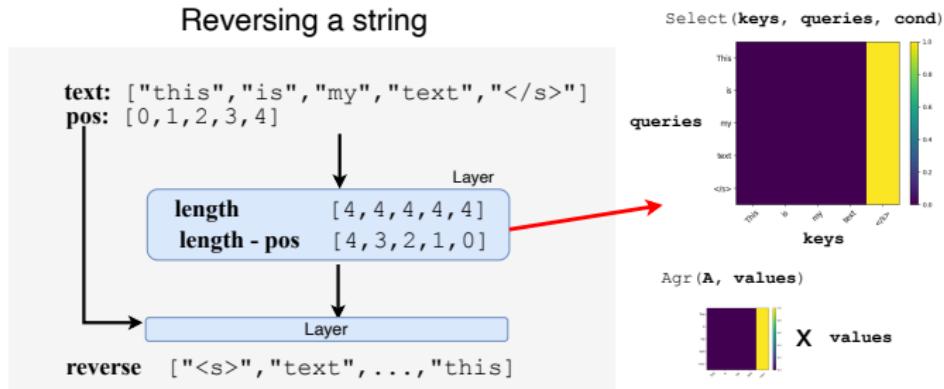


# Thinking like a transformer: reversing a string

## Reversing a string

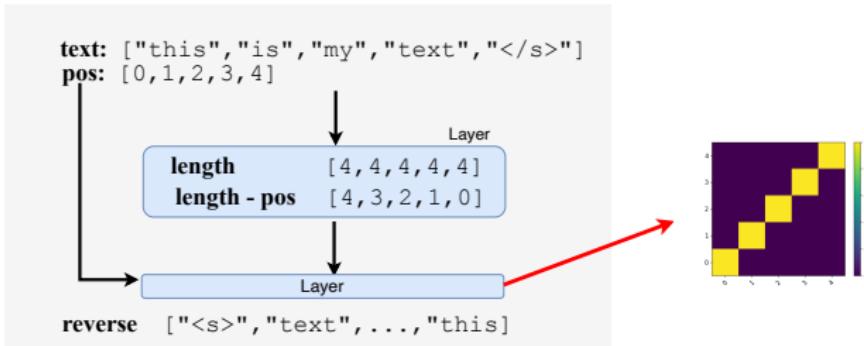


# Thinking like a transformer: reversing a string



# Thinking like a transformer: reversing a string

## Reversing a string



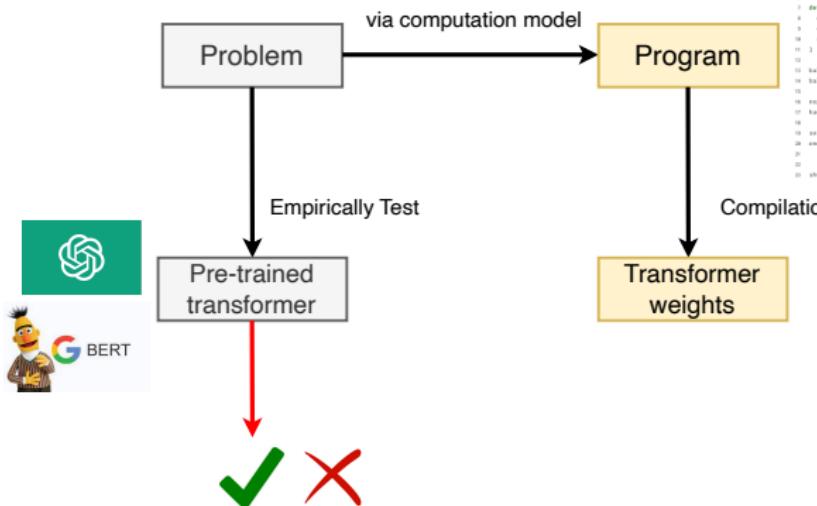
# A small implementation of Rasp

```
1 ## credits: https://github.com/apple/ml-np-rasp
2 import numpy as np
3
4 def indices(x):
5 return np.arange(len(x), dtype=int)
6 def select(k,q,pred):
7 s = len(k)
8 A = np.zeros((s, s), dtype=bool)
9 for i in range(s):
10 for j in range(s): A[i,j] = pred(q[i],k[j])
11 return A
12 def sel_width(A):
13 return np.dot(A, np.ones(len(A))).astype(int)
14 def aggr(A, v):
15 out = np.dot(A, v)
16 norm = sel_width(A)
17 out = np.divide(out,norm,where=(norm != 0))
18 return out.astype(int)
```

# A small implementation of Rasp

```
1 pos = indices(tokens)
2 EOS = 0
3
4 ##### layer 1
5 # attn layer
6 length = aggr(
7 select(tokens,tokens,lambda q,k : k == EOS),
8 pos
9)
10 targets = length - pos #<--- MLP
11
12 ##### layer 2
13 output = aggr(
14 select(pos,targets,lambda k,v: k == v),
15 tokens
16)
```

# The bigger picture now



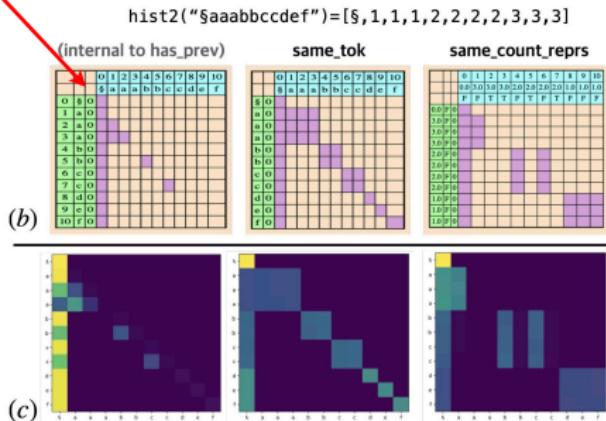
```
1 def frac_percent(samp, val):
2 presamp = select(samp, indices, val);
3 return aggregate(presamp,
4 indicator(samp==val));
5
6
7 def pair_balance(pair, class):
8 opens = frac_percent(pair[0], class);
9 closes = frac_percent(pair[1], class);
10 return opens - closes;
11
12 half1 = pair_balance(["1","2"]);
13 half2 = pair_balance(["1","3"]);
14 negative = half1 >= half2 >
15 half1 == aggregate(select_all,
16 indicator(pair[0]==0));
17 select_list = [None]*len(pair)-1;
18 end_0 = aggregate(select_list,
19 half1 <= half2 >
20 half1!=0 and half2!=0);
21
22 shuffle(end_0, half1 >= half2 and not half1==0);
```

# Does a transformer implement my algorithm?

```
1 same_tok = select(tokens,tokens,==);
2 hist = selector_width(
3 same_tok,
4 assume_bos = True);
5
6 first = not has_prev(tokens);
7 same_count = select(hist,hist,==);
8 same_count_reprs = same_count and
9 select(first,True,==);
10
11 hist2 = selector_width(
12 same_count_reprs,
13 assume_bos = True);
```

Rasp program

Target attention



Language	Layers	Heads	Test Acc.	Attn. Matches?
Reverse	2	1	99.99%	✓
Hist BOS	1	1	100%	✓
Hist no BOS	1	2	99.97%	✓
Double Hist	2	2	99.58%	✓
Sort	2	1	99.96%	✗
Most Freq	3	2	95.99%	✗
Dyck-1 PTF	2	1	99.67%	✓
Dyck-2 PTF <sup>8</sup>	3	1	99.85%	✗

## Tracr: Compiled Transformers as a Laboratory for Interpretability

---

David Lindner<sup>†</sup>  
Google DeepMind

János Kramář  
Google DeepMind

Sebastian Farquhar  
Google DeepMind

Matthew Rahtz  
Google DeepMind

Thomas McGrath  
Google DeepMind

Vladimir Mikulik<sup>†</sup>  
Google DeepMind

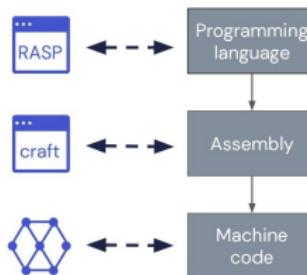


Figure 3: Tracr translates RASP to Craft and then to model weights, analogous to how programming languages are first translated to assembly then to machine code.

## Learning Transformer Programs

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Princeton University

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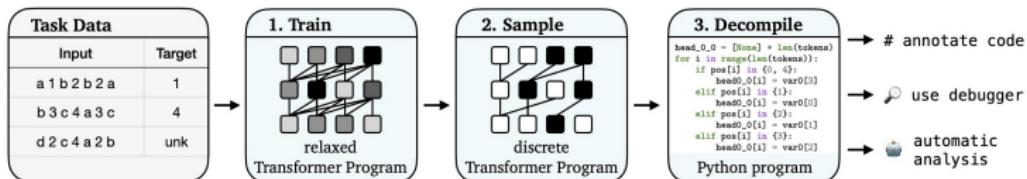


Figure 1: We design a modified Transformer that can be trained on data and then automatically discretized and converted into a human-readable program. The program is functionally identical to the Transformer, but easier to understand—for example, using an off-the-shelf Python debugger.

# Conclusions

- ▶ **covered today:** Language modeling basics, transformer architecture and model training.

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- ▶ Rasp: symbolic programming language for describing computation in transformers.
  - Useful tool for interpretability and proving properties of transformer abilities.

**Next lecture:** Declarative approaches to model training.

Thank you.

## References I

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- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.