Language Model Programming: Lecture 1

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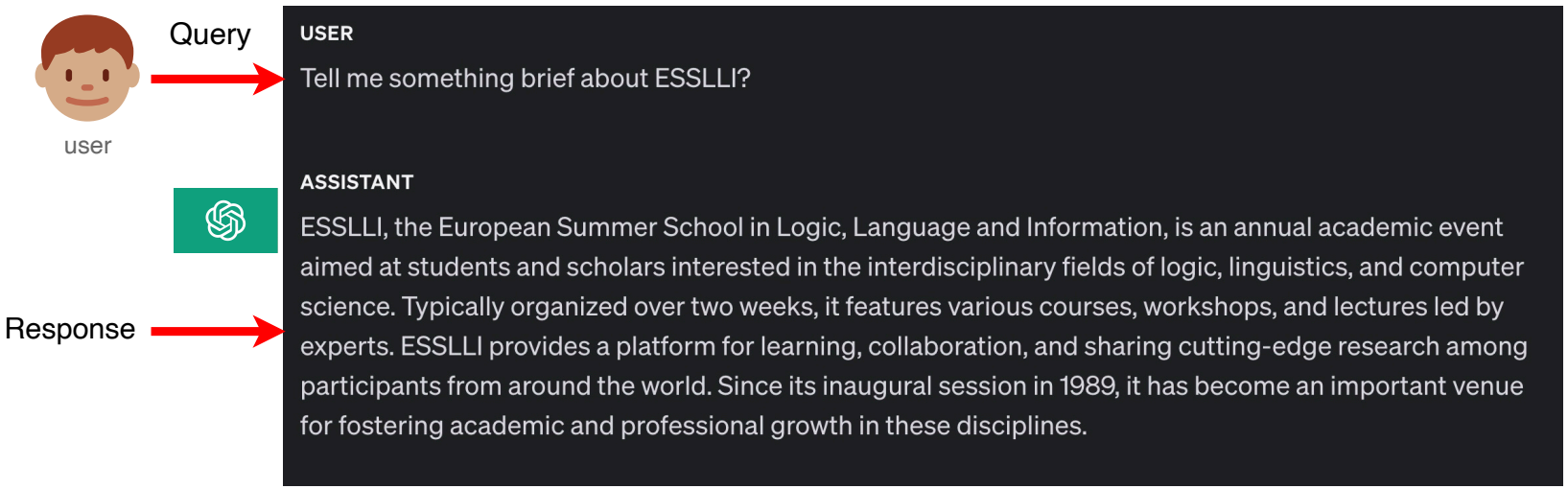
Course Overview

Language Model Programming

Language models today



In-context learning: learning through examples

Instruction

simulate 

Examples

example behavior

 as 

ChatGPT

USER

I am a 5 year old struggling at math. Please answer questions like me.

Here are some examples of where I get things wrong:
question: what is 2 + 2
my answer: Umm... 7. This is hard!

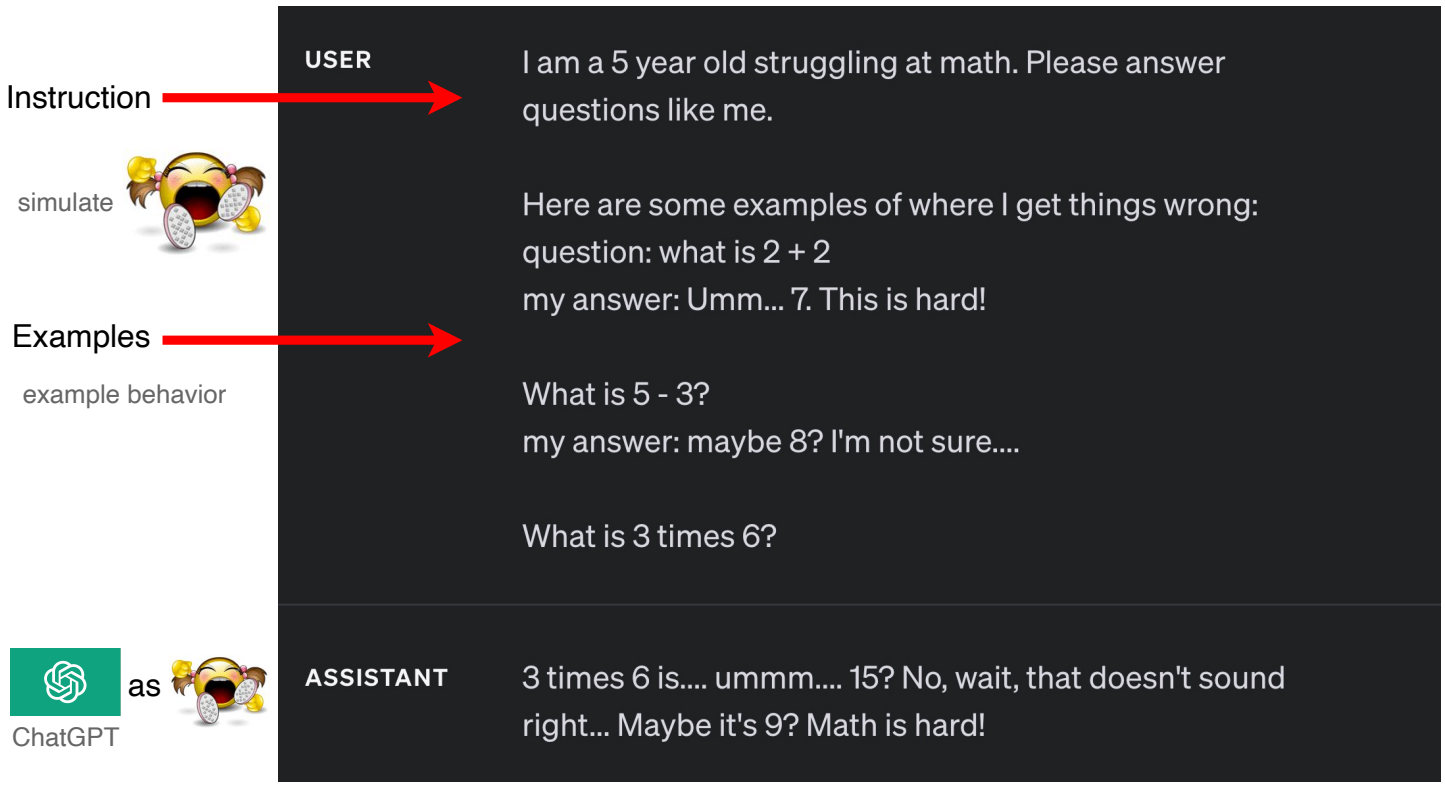
What is 5 - 3?
my answer: maybe 8? I'm not sure....

What is 3 times 6?

ASSISTANT

3 times 6 is.... ummm.... 15? No, wait, that doesn't sound right... Maybe it's 9? Math is hard!

In-context learning: learning through examples



Traditional learning coupled with **in-context leaning** (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,

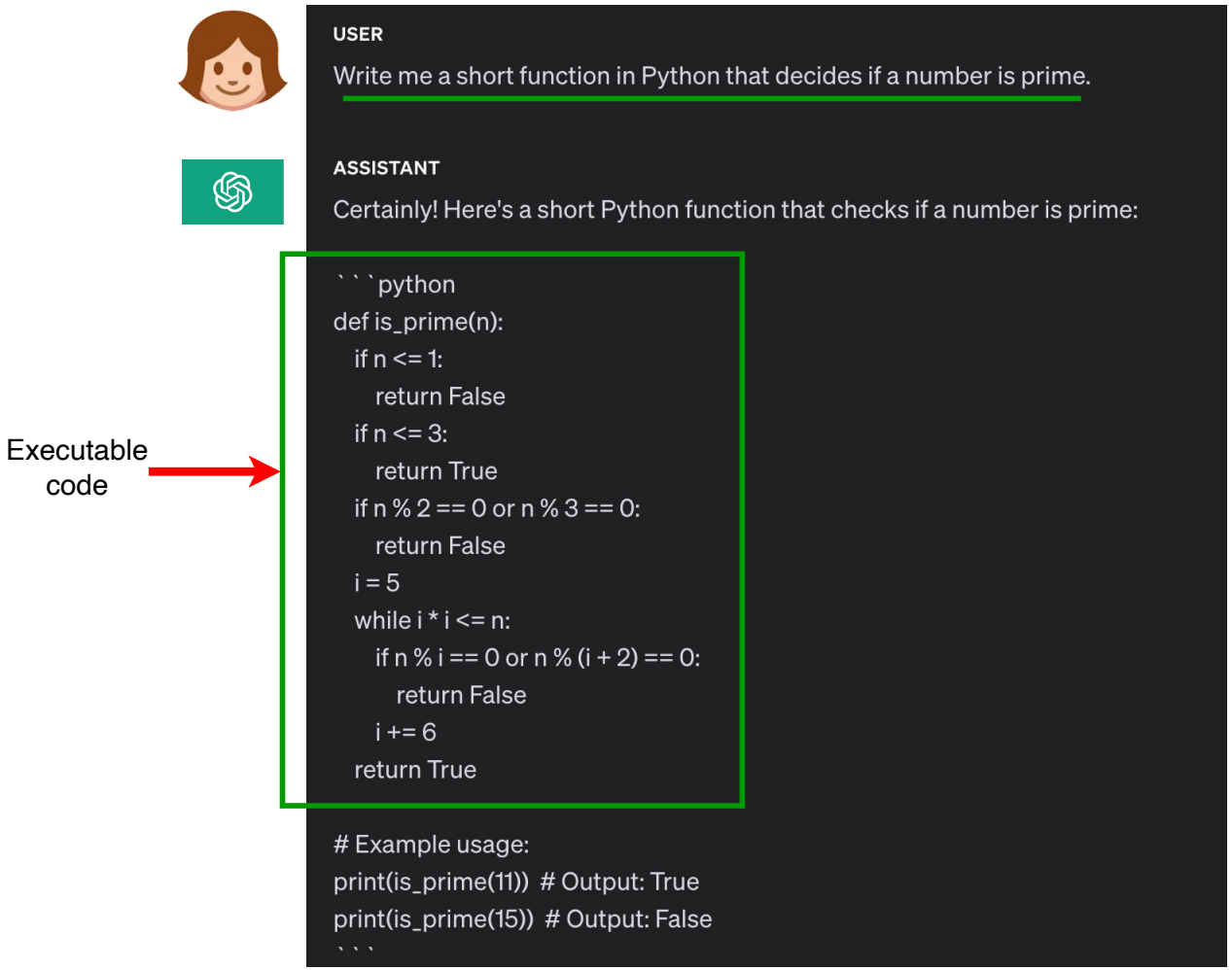
Kriss Kross, baggy jeans, we keep it fresh,
Knowledge in our minds, bringin' out the best,
From syntax to semantics, breakin' down the code,
In the 90s hip-hop scene, let the story unfold,

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?

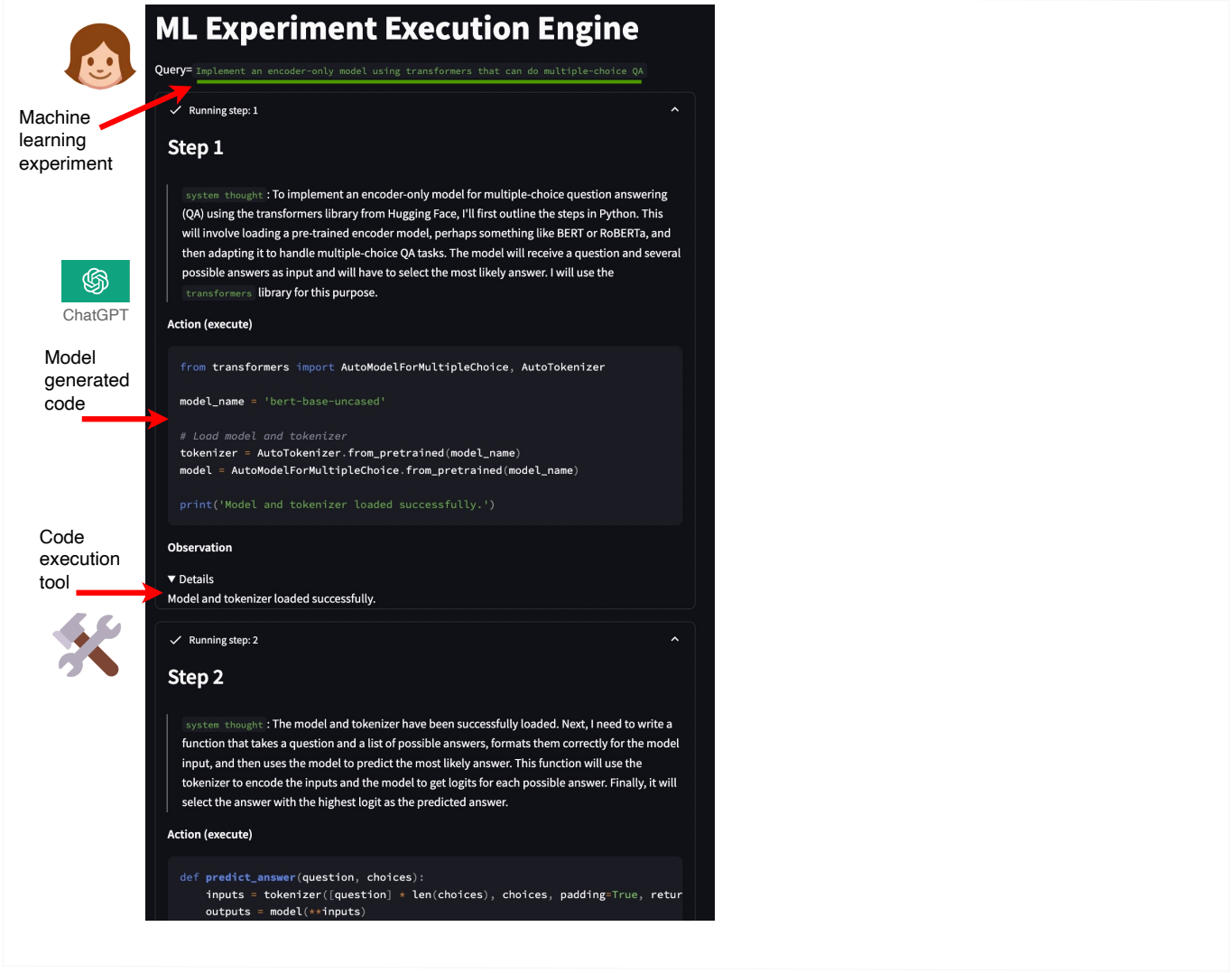
Verse 2:
Professors droppin' wisdom like bombs from the mic,
Mix it up like A Tribe Called Quest, phat and tight,
Logic seminars as deep as Wu-Tang Clan,
Learnin' more in two weeks than a lifetime span,

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

Abilities far exceed expectations...



Integrating language models into complex systems



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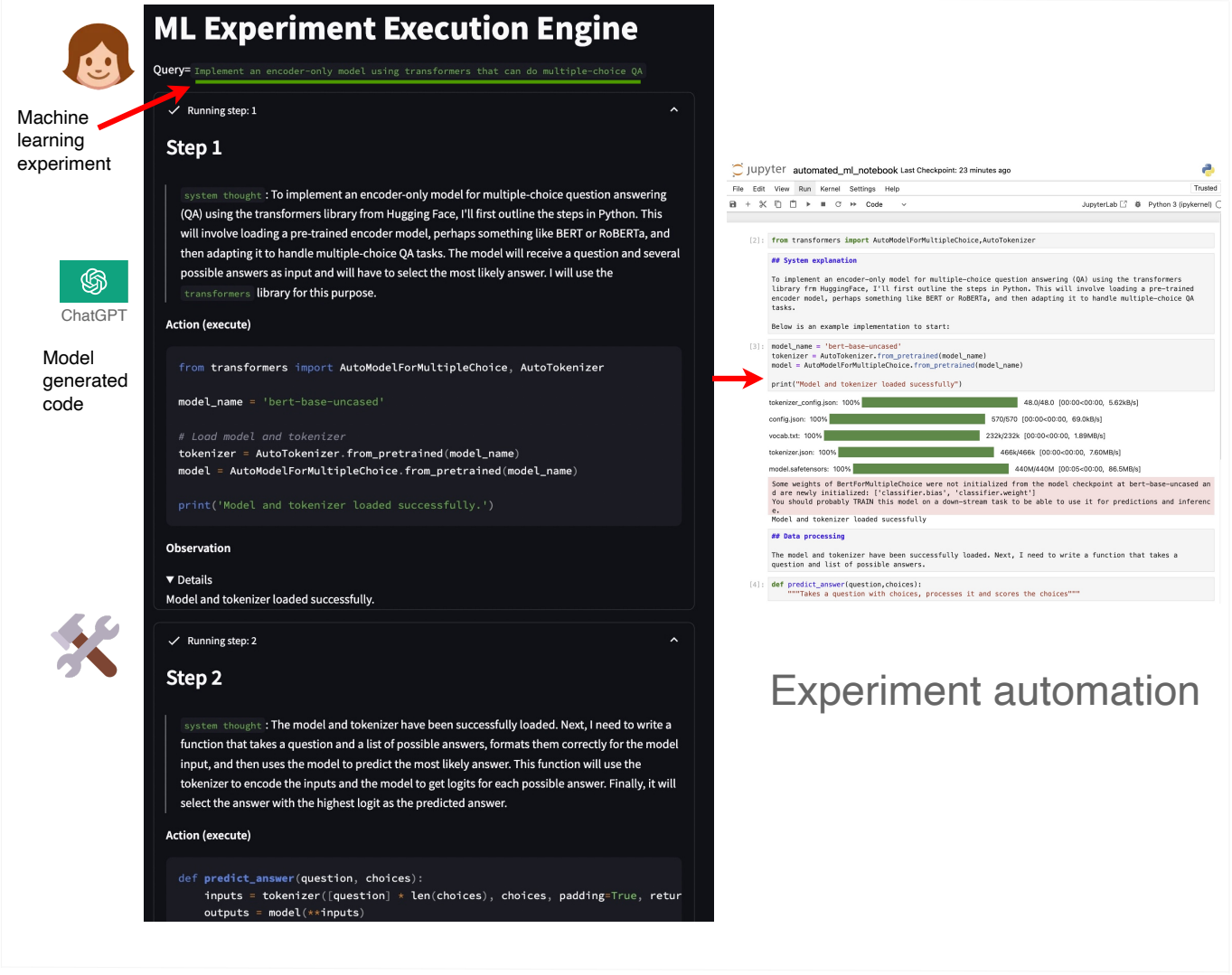

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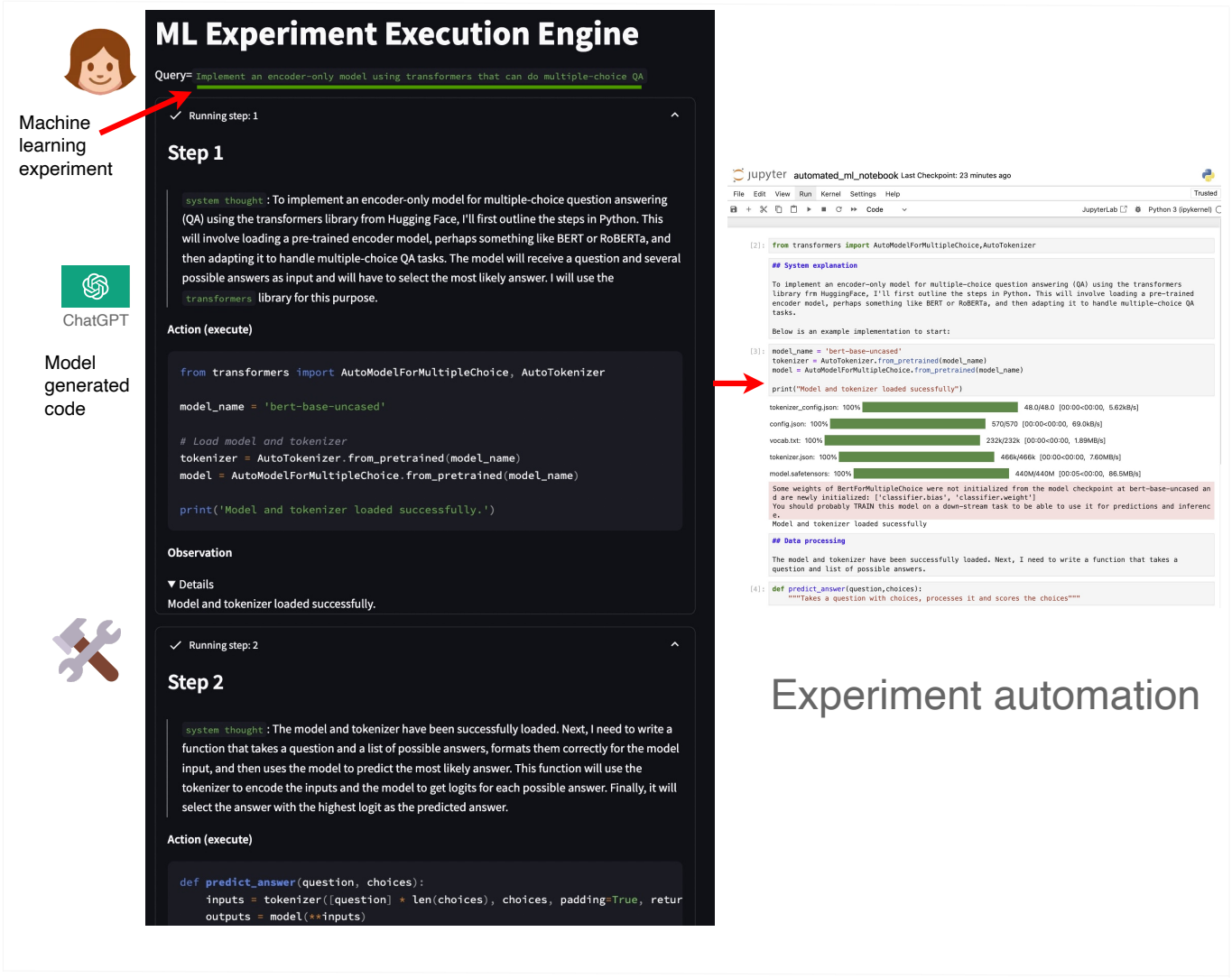
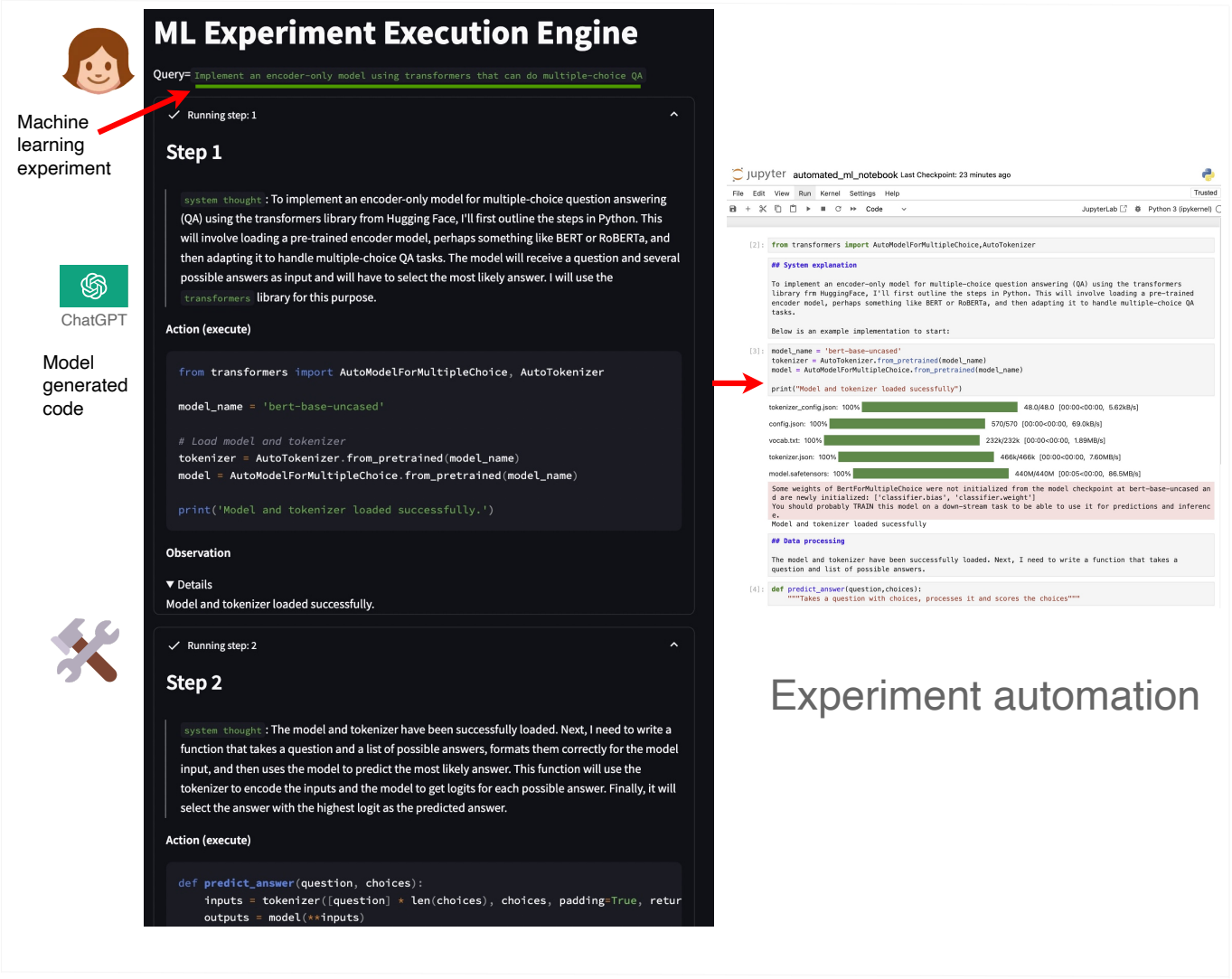


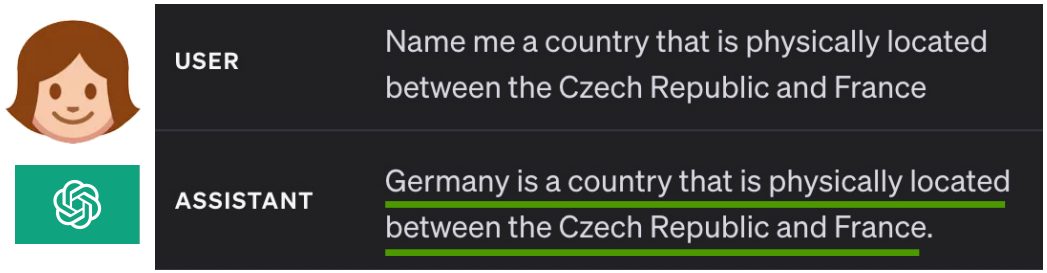
- Looks a lot like conventional programming, can we make the connection more precise?

Integrating language models into complex systems



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

Problems are still easy to find



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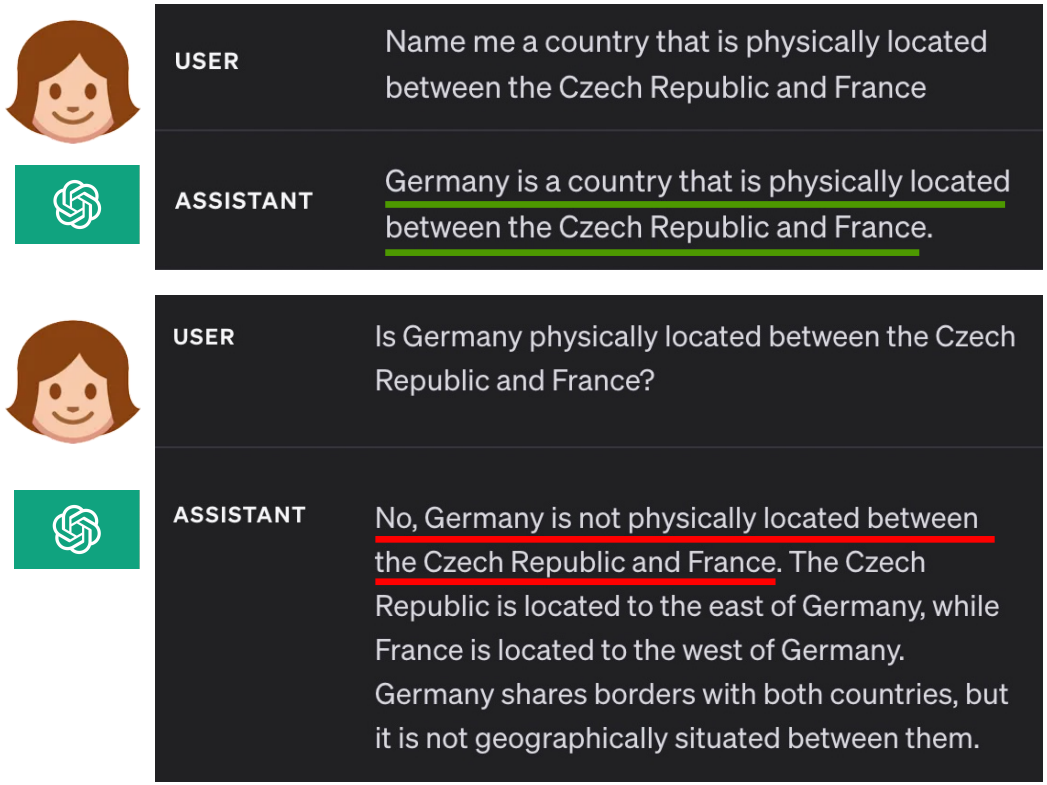

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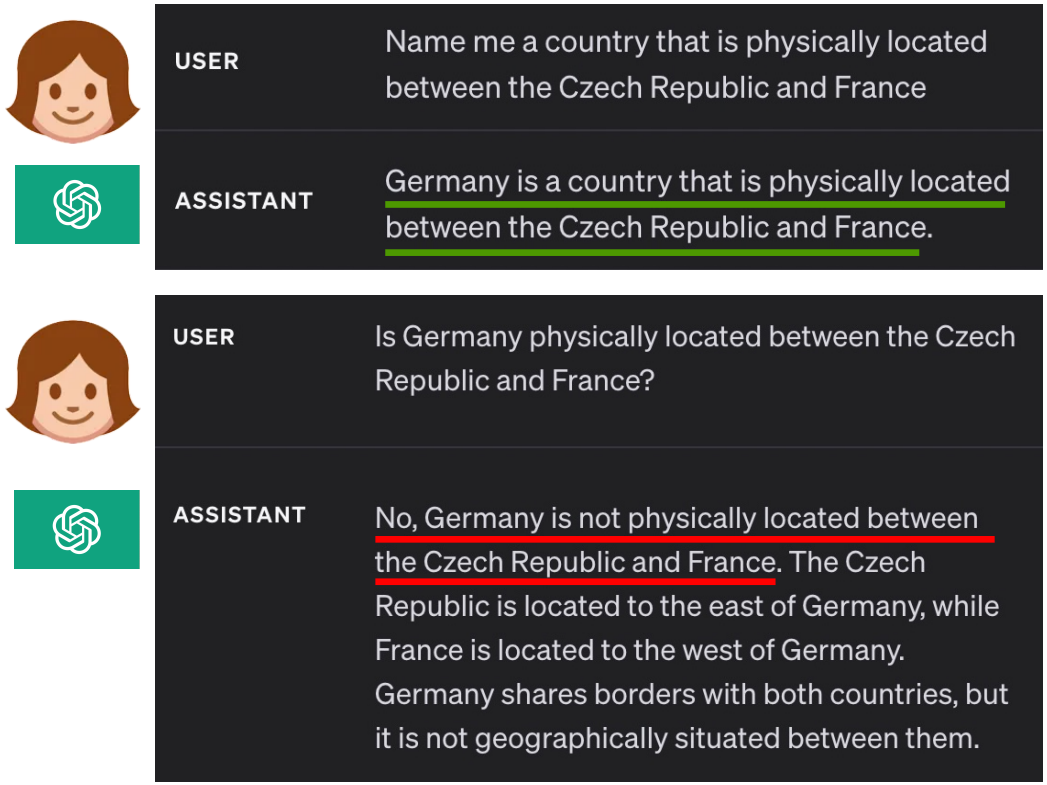
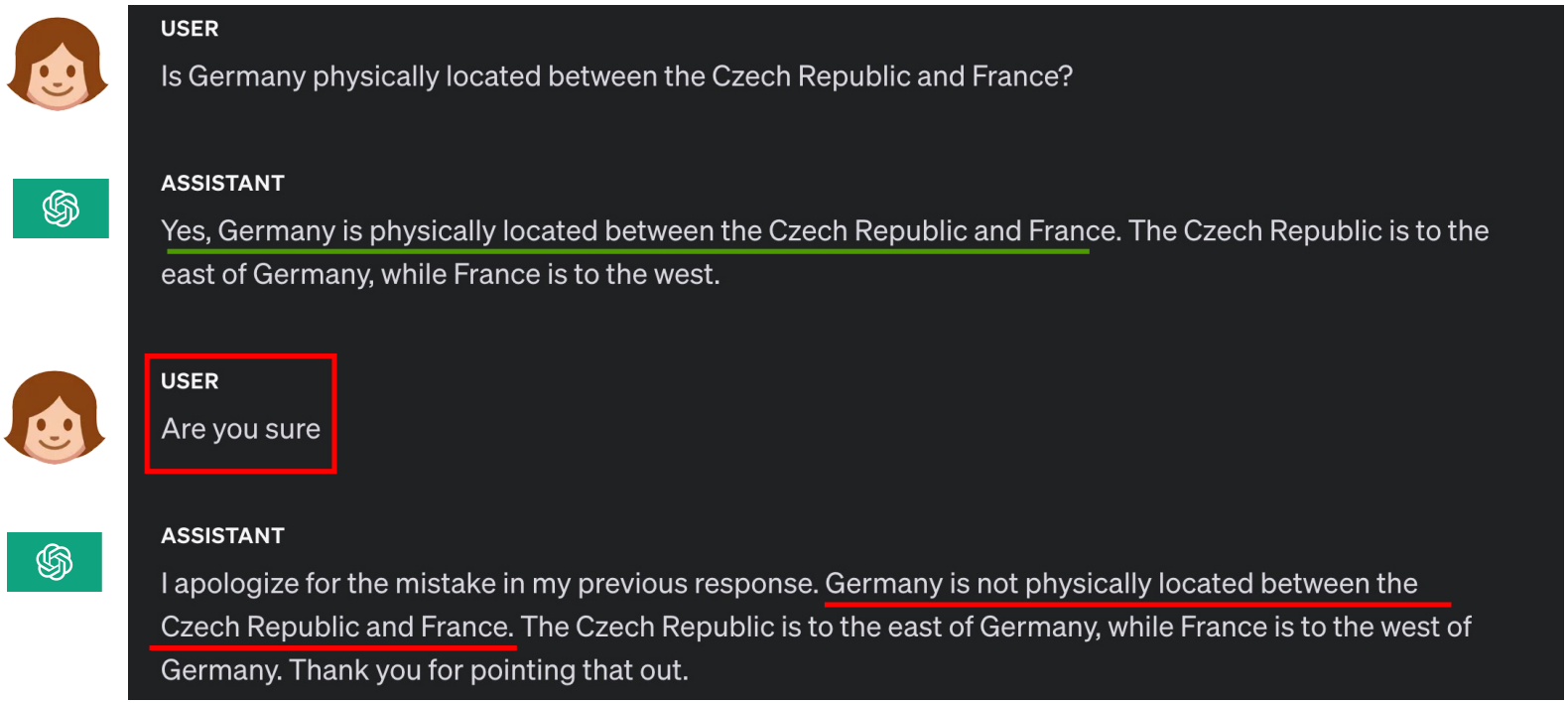


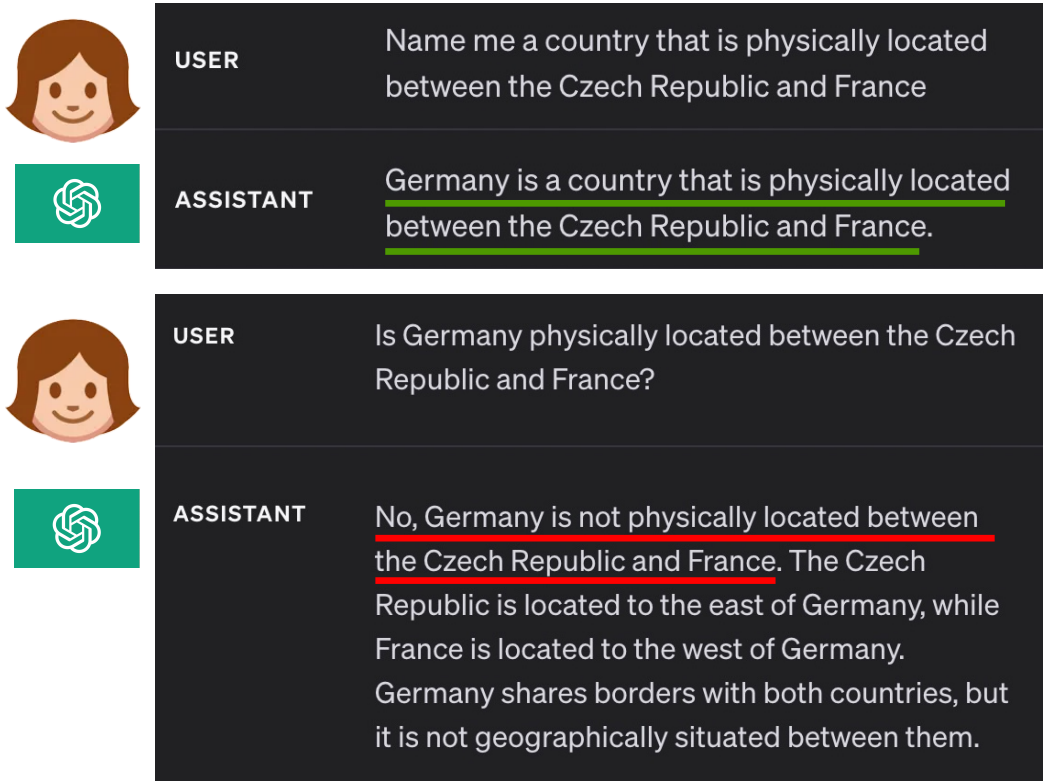
Models can be wildly inconsistent, hallucinate, prompting is unstable (different results based on small changes).

Problems are still easy to find



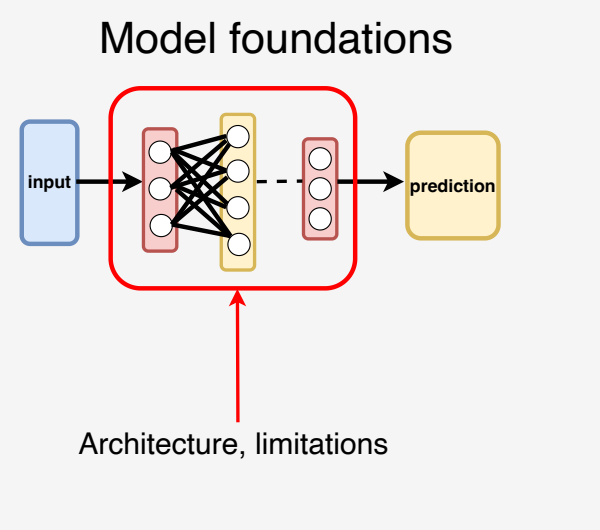
Models have been improving fast, sort of...

Problems are still easy to find



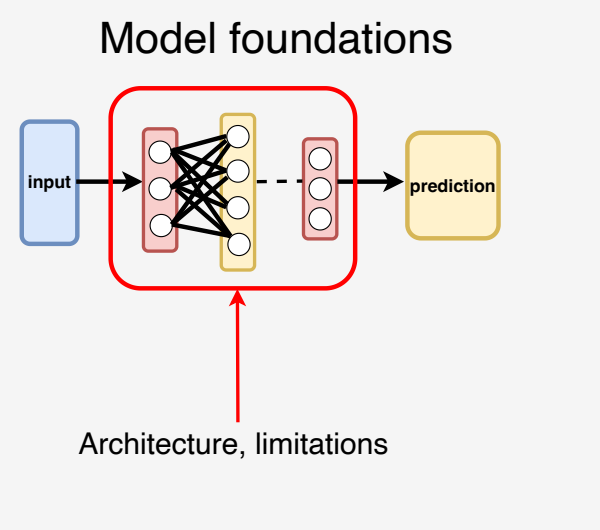
- Can programming techniques be useful here? constraint programming, probabilistic and logical programming...

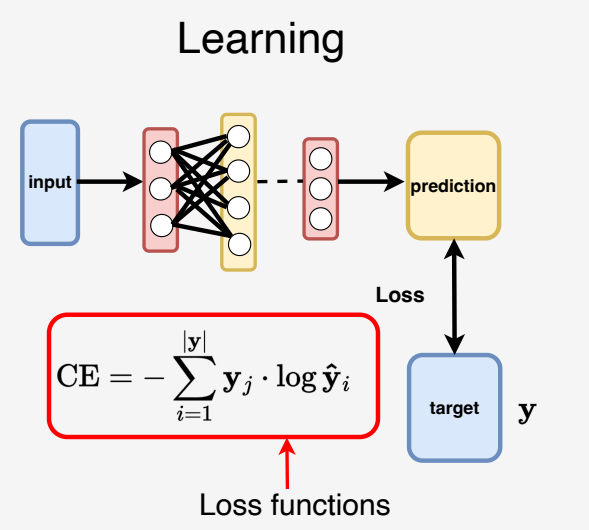
The landscape of NLP research



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

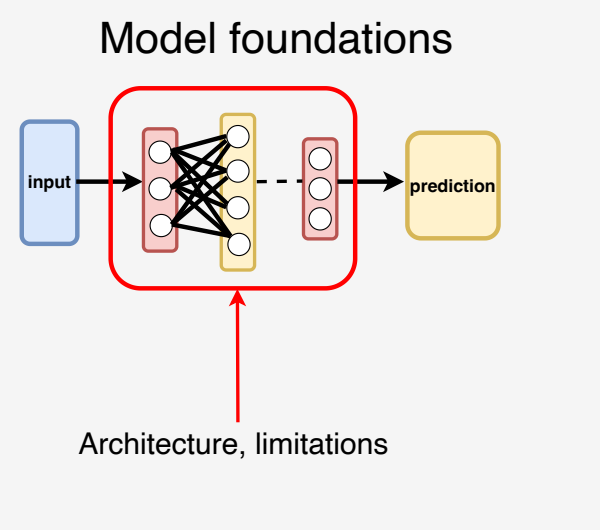
The landscape of NLP research

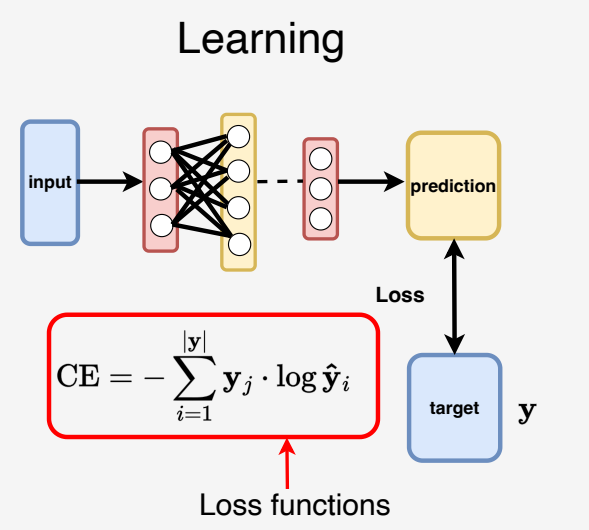


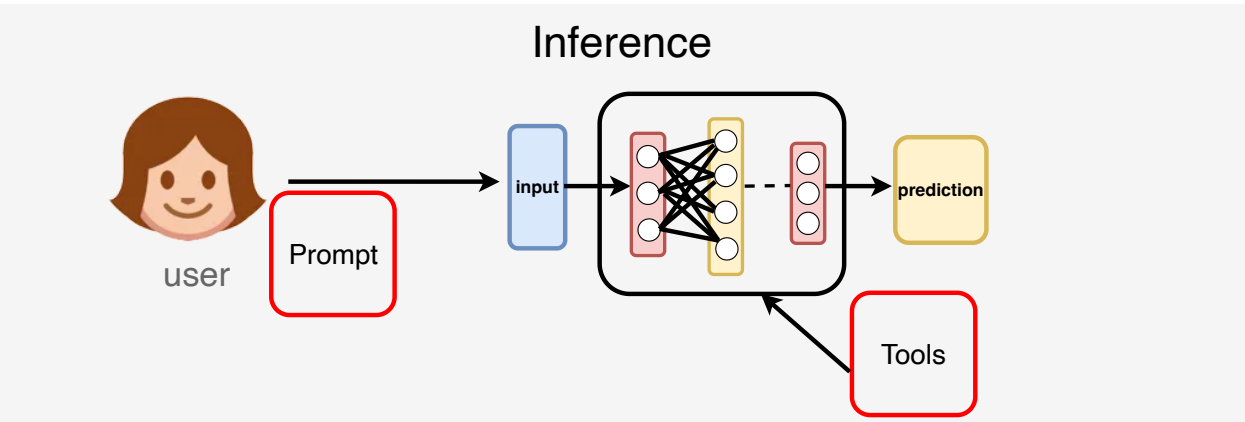


How to train and tune models? Can we design novel loss functions, background constraints?

The landscape of NLP research

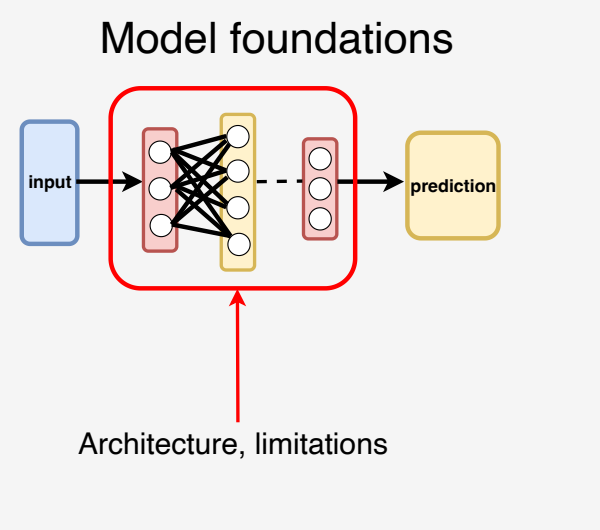






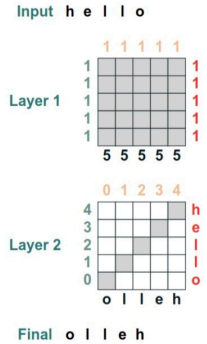
How to use models? Decoding with constraints, advanced prompting strategies, coupling with tools.

Where programming comes in



RASPy

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



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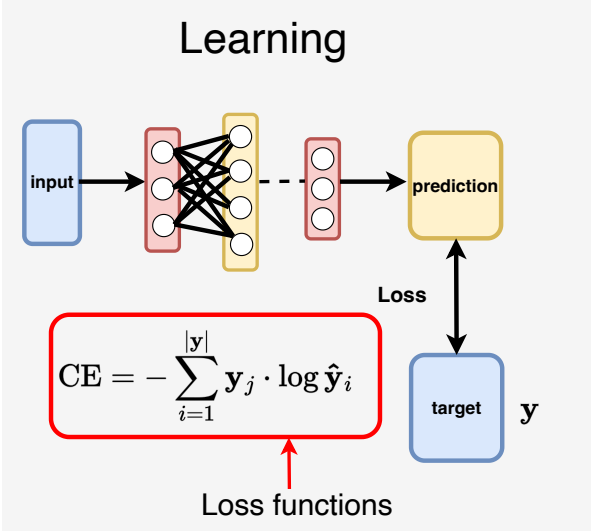
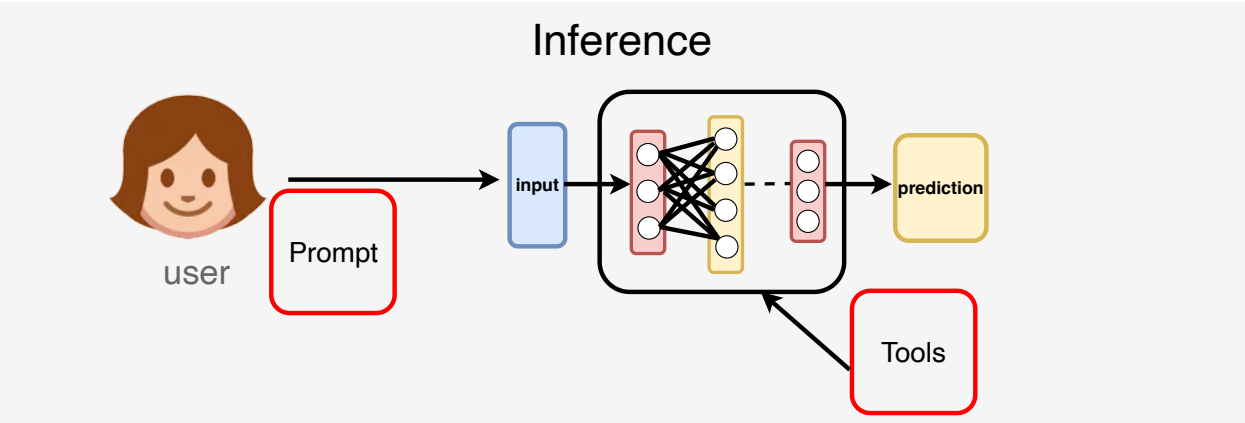



```
1  // File path_planner.scl
2  type actor(x: i32, y: i32), goal(x: i32, y: i32), enemy(x: i32, y: i32)
3
4  const UP = 0, DOWN = 1, RIGHT = 2, LEFT = 3
5  rel safe_cell(x, y) = range(0, 5, x), range(0, 5, y), not enemy(x, y)
6  rel edge(x, y, x, yp, UP) = safe_cell(x, y), safe_cell(x, yp), yp == 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)
```

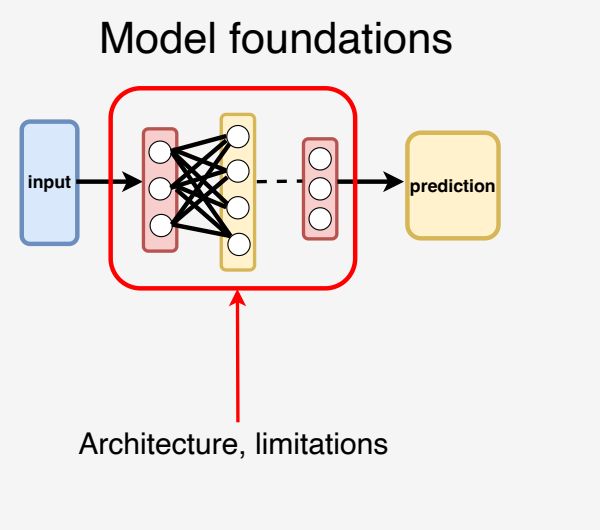
Fig. 3. The logic program of the PacMan-Maze application in Scallop.

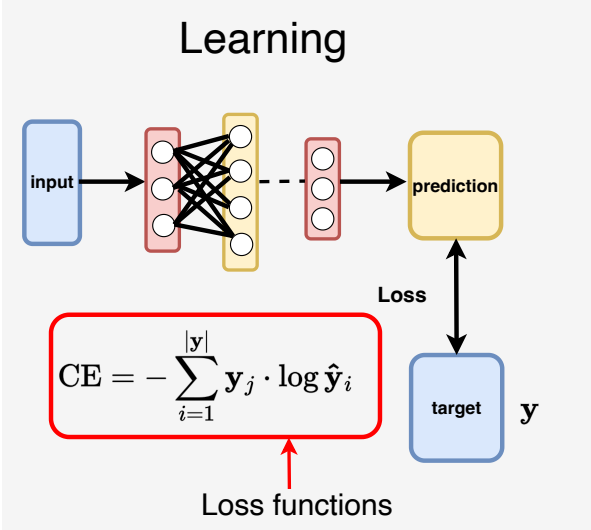
Where programming comes in

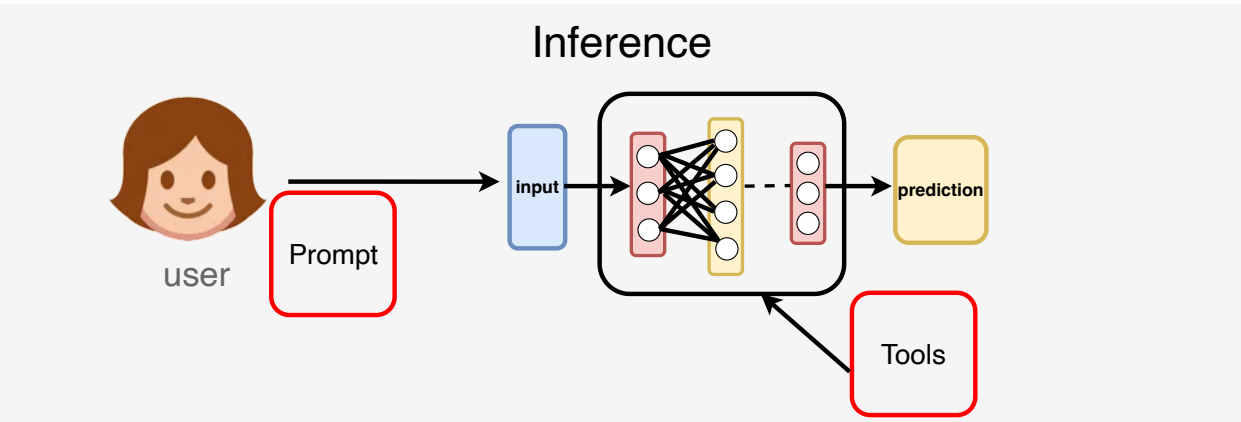
```
@lmql.query
def meaning_of_life():
    '''lmql
    # top-level strings are prompts
    "Q: What is the answer to life, the \
     universe and everything?"

    # 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

```
### installation via pip
### "pip install install z3-solver python-sat torch datasets
# transformers sympy PySDD pylon-lib numpy problog"

### neural network
import torch  ## tensor computation, deep learning
import transformers ### transformer models

### solvers and theorem provers
import z3-solver ## z3 solver
import pysat ## python interface to sat solvers
import problog ### probabilistic logic programming

### other useful utilities
import sympy # symbolic computation in python
import pysdd  # knowledge compilation
import numpy ## numerical computation in python
import datasets ## huggingface datasets
```

Language modeling primer

What are language models?

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

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

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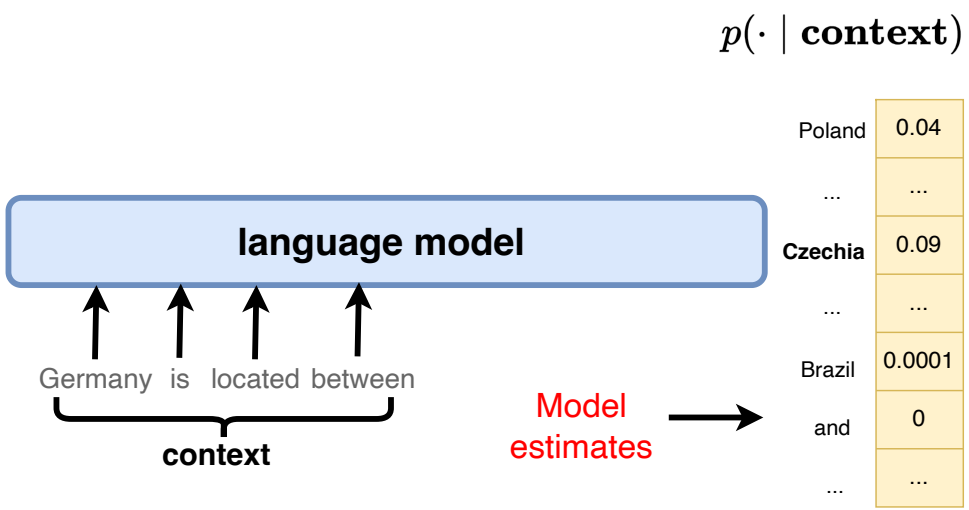

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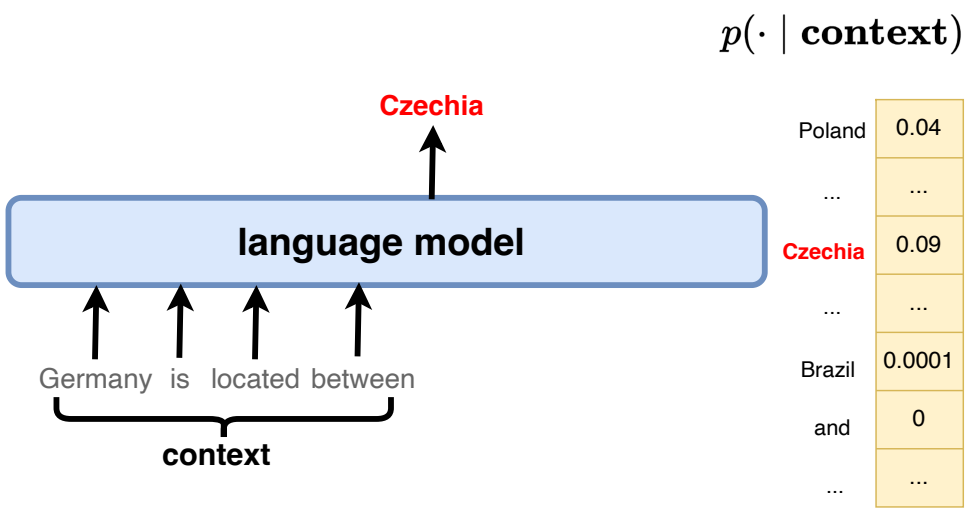

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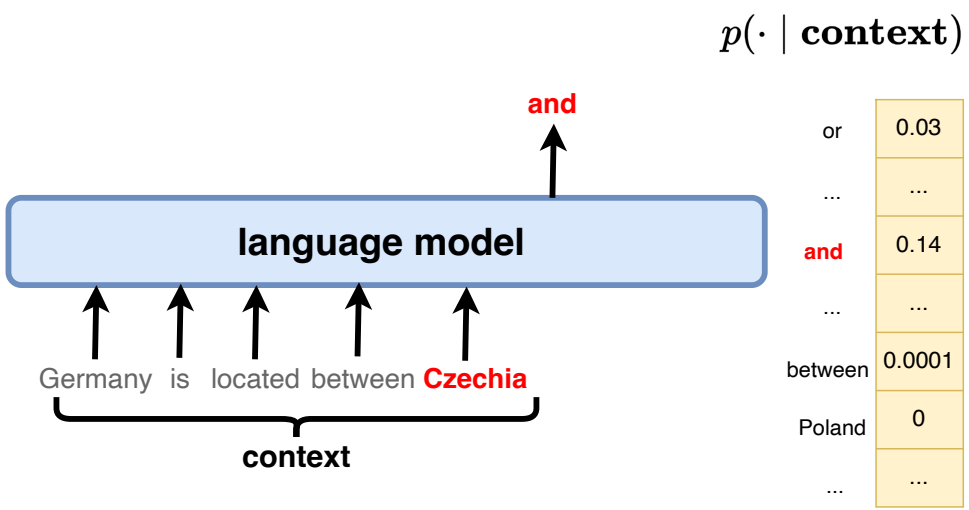

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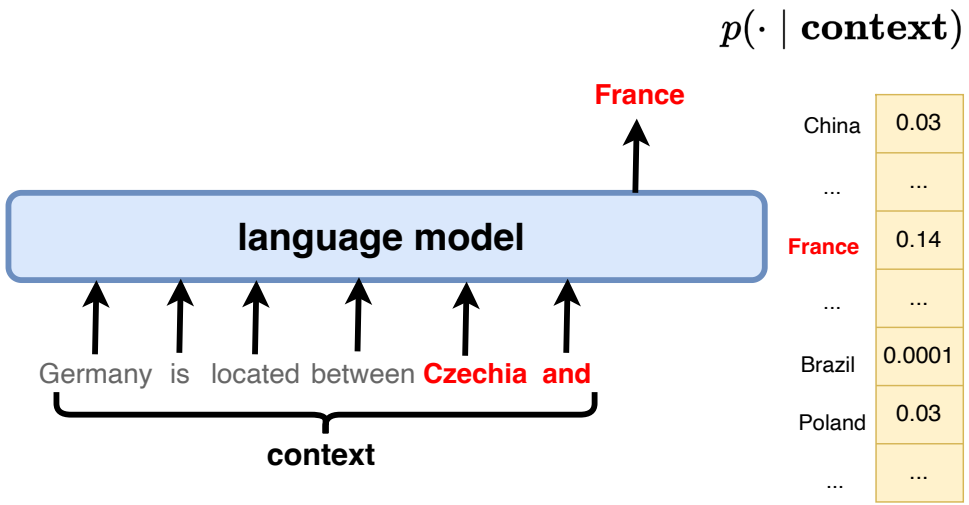

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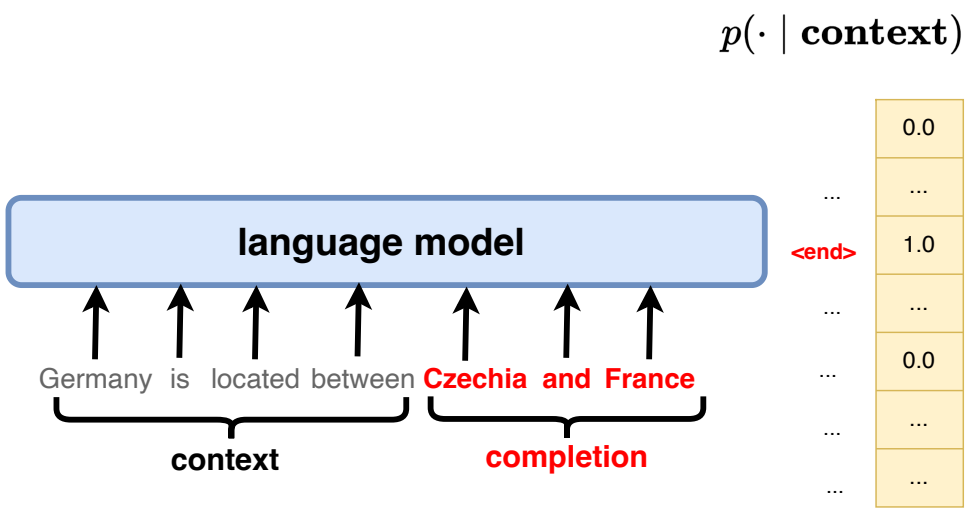
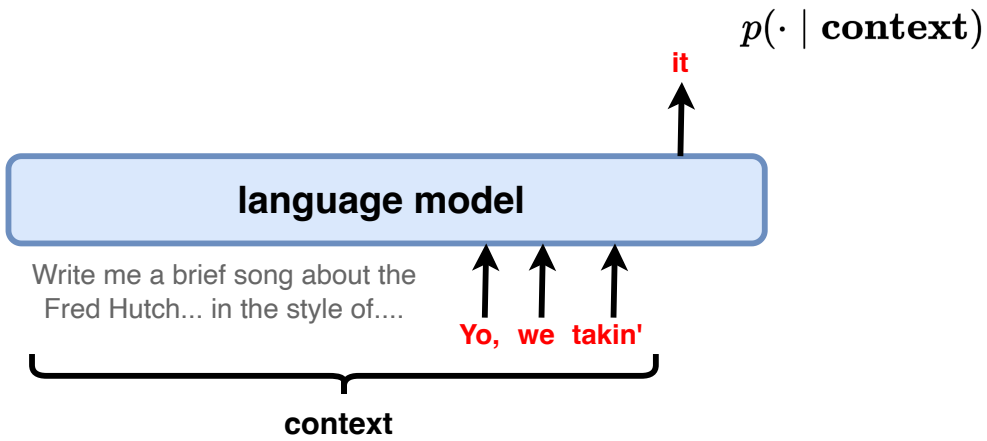


What are language models?

Sequence modeling is not a new problem.



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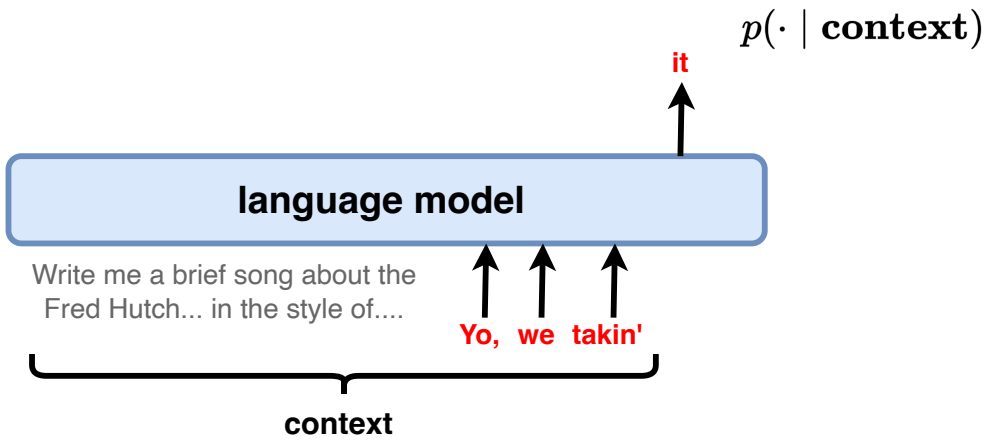


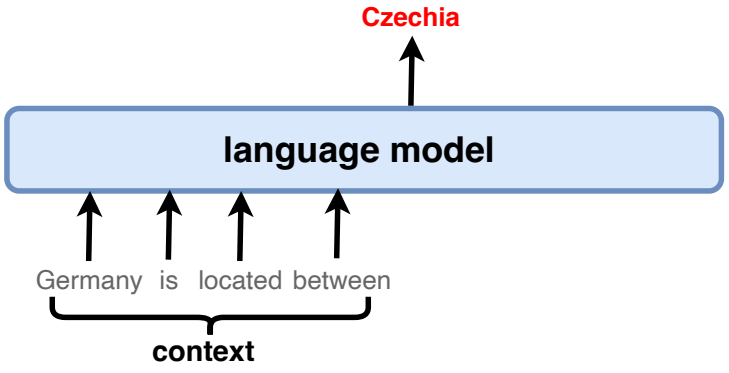
Text documents

```
TaskFirst pose the question:Here are four tr
iangles. What do all of these triangles have
 in common? What makes them different from t
he figures that are not triangles? What is t
rue for some but not all of these triangles?
###IMAGE0###If students come up with a state
ment 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 insid
e," the teacher can ask, "Would it be possib
le 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 tr
iangles, then the class can complete the sen
tence frame:  All triangles __________, but
 only some triangles _________________.  Whe
n the students have written (or composed) th
eir sentences based on the sentence frames,
the class can write the definition of a tria
ngle together:A triangle is a closed shape w
```

Biological sequences

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

The problem with traditional solutions

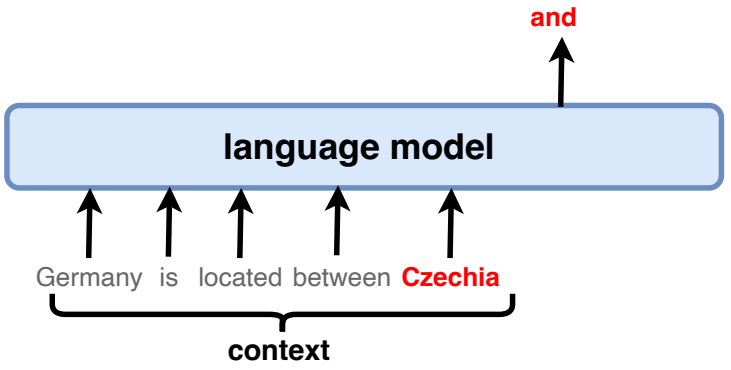


$p(\cdot \mid \textbf{context})$

Discrete representations

Poland	0.04	Germany is located between
...	...	Germany is located between
Czechia	0.09	Germany is located between
...	...	Germany is located between
Brazil	0.0001	Germany is located between
and	0	Germany is located between
...	...	Germany is located between

The problem with traditional solutions



$$p(\cdot \mid \textbf{context})$$

Discrete representations

or	0.04	Germany is located between **Czechia**
...	...	Germany is located between **Czechia**
and	0.09	Germany is located between **Czechia**
...	...	Germany is located between **Czechia**
he	0.0001	Germany is located between **Czechia**
with	0	Germany is located between **Czechia**
...	...	Germany is located between **Czechia**

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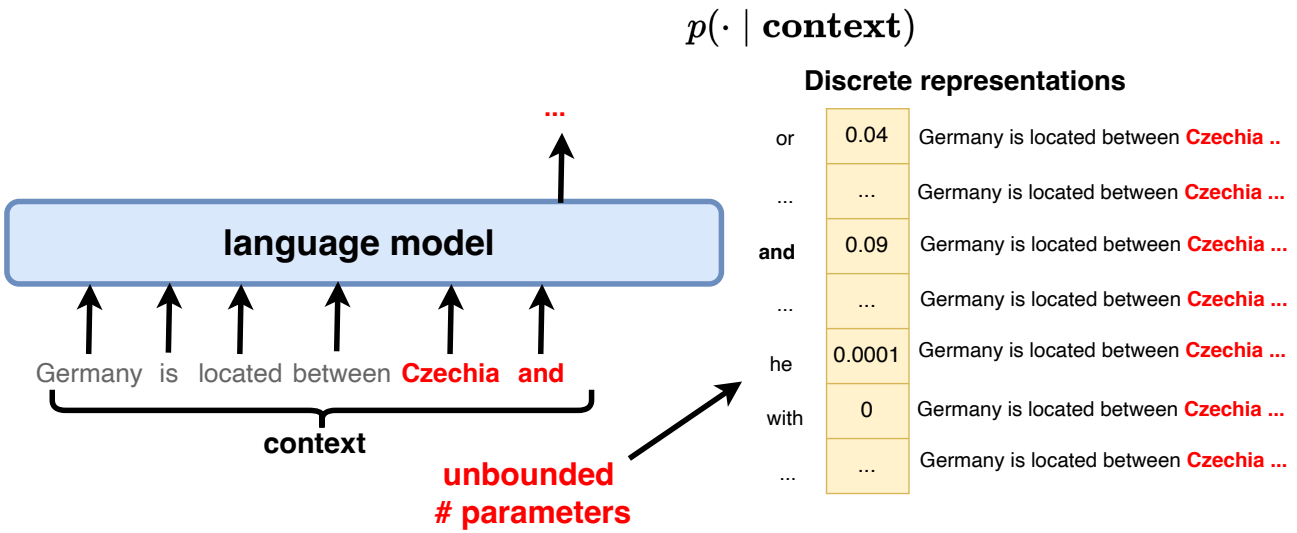

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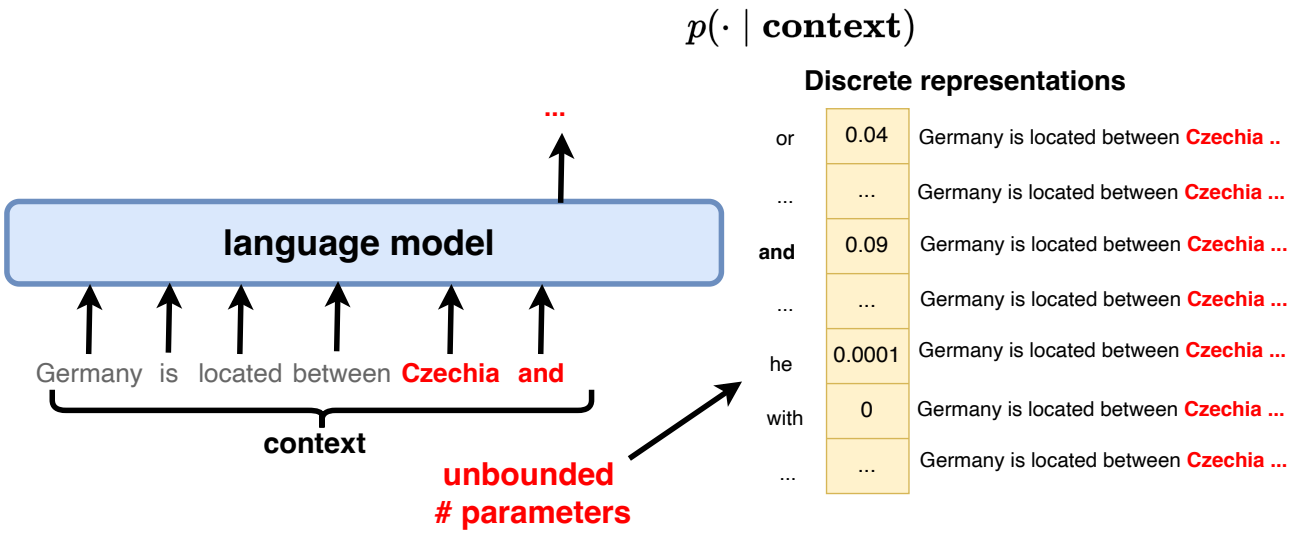

Make models tractable through **independence** or **Markov** assumptions; limit the allowable context.

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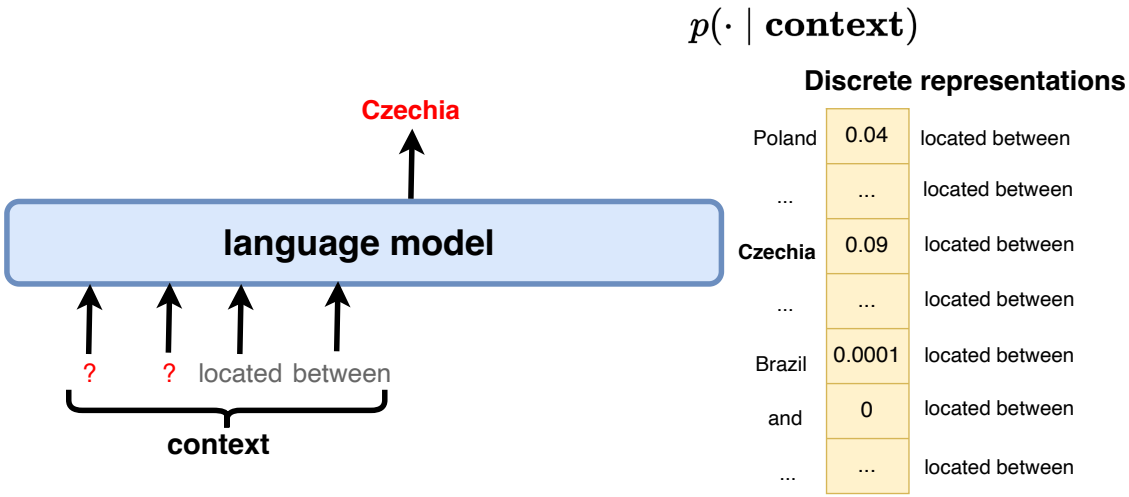

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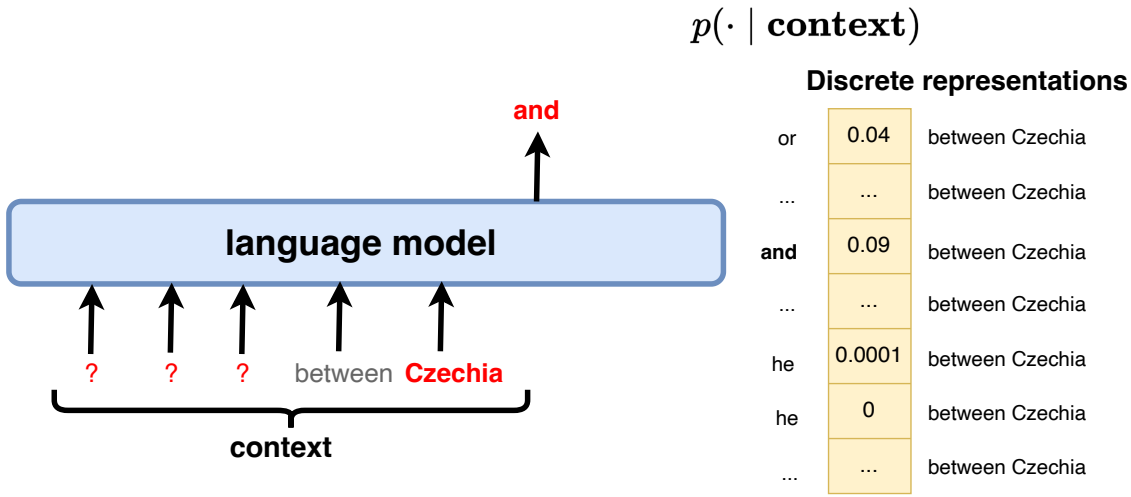

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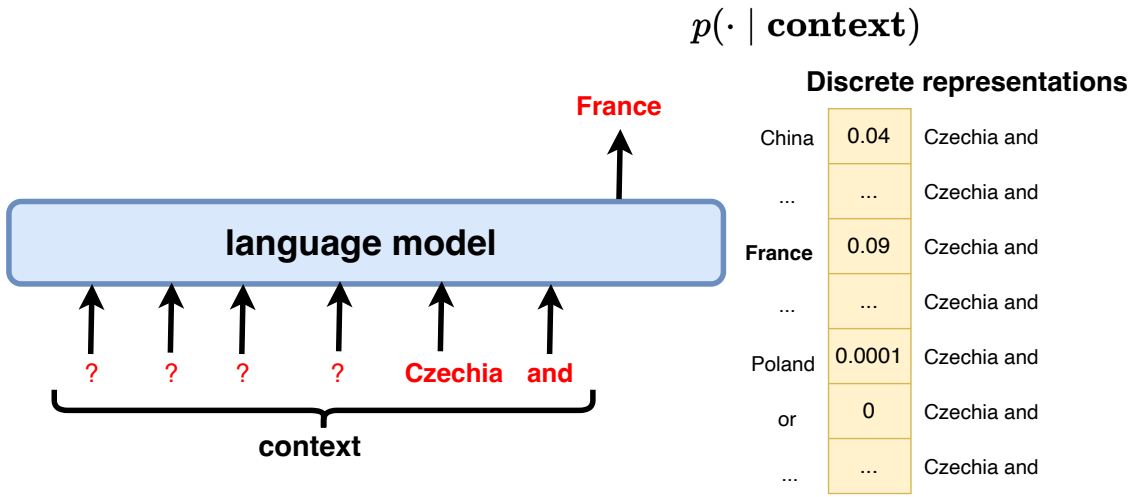

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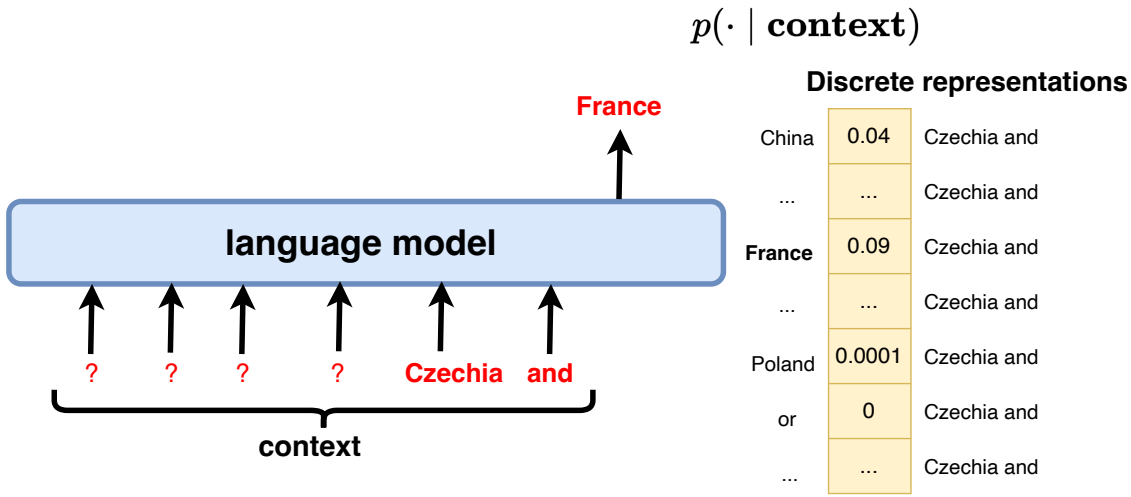
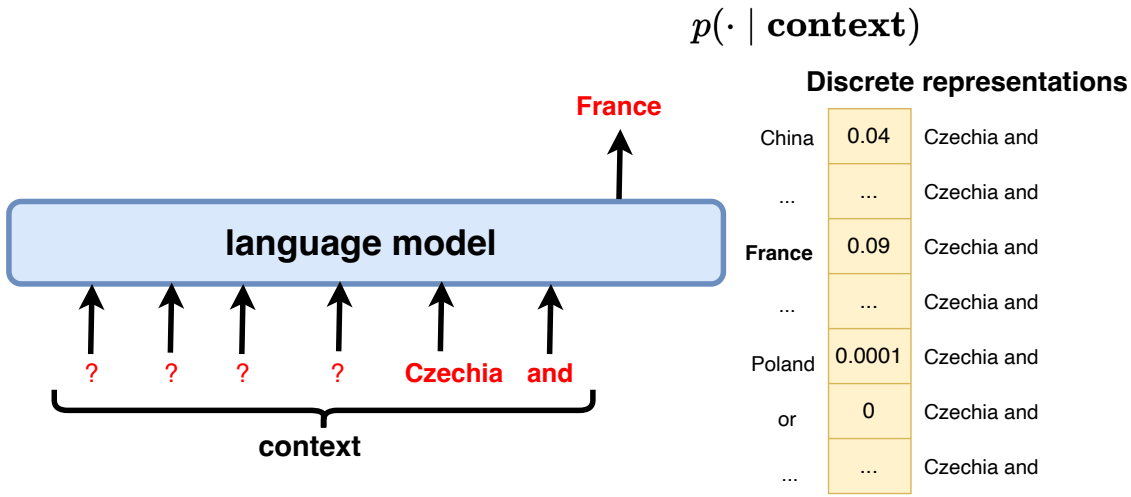


Make models tractable through **independence** or **Markov** assumptions; limit the allowable context.

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



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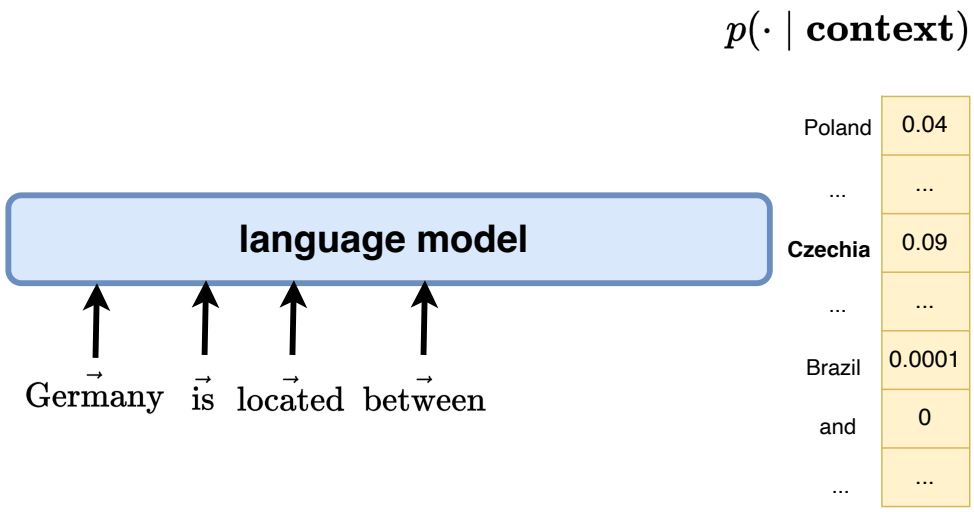
Do not faithfully model these joint probability distributions!

Moving from the discrete to the continuous

- Modern deep learning systems operate in the continuous space.



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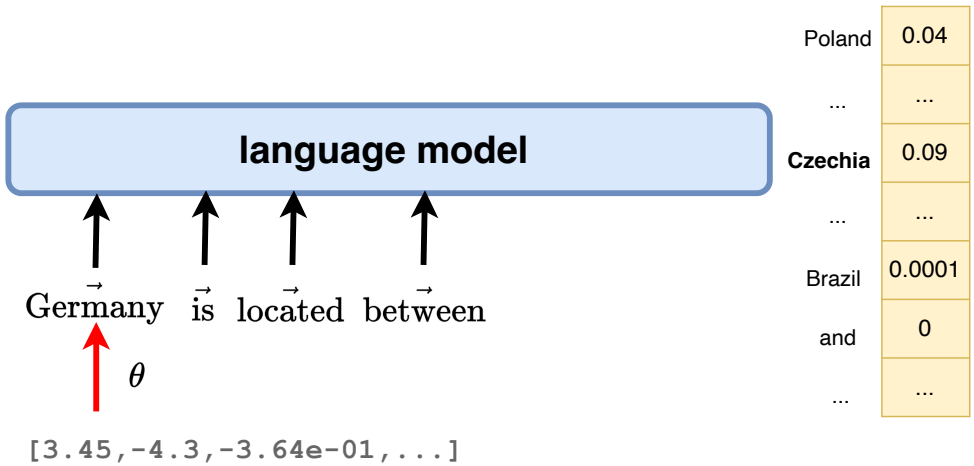

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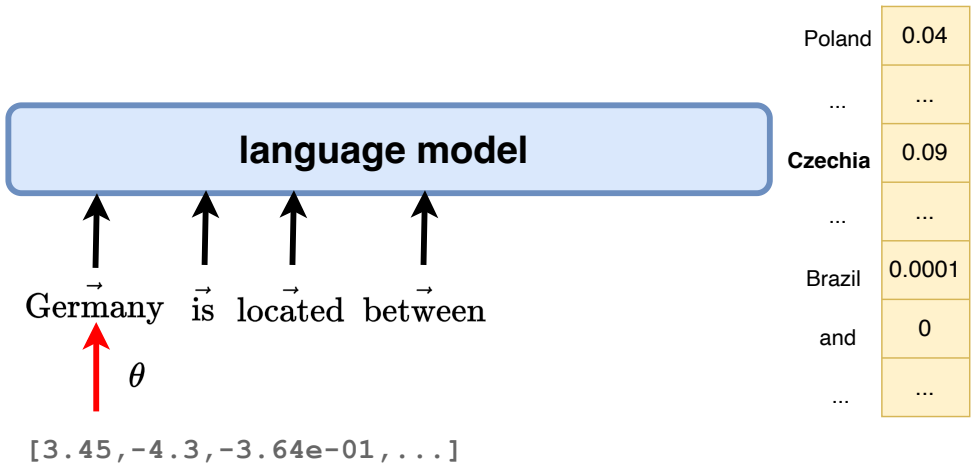

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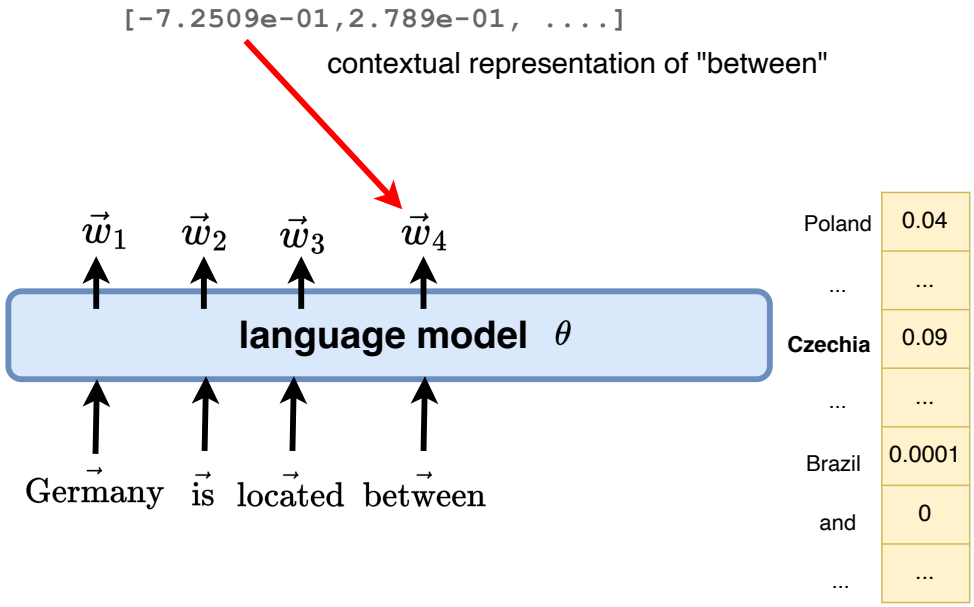

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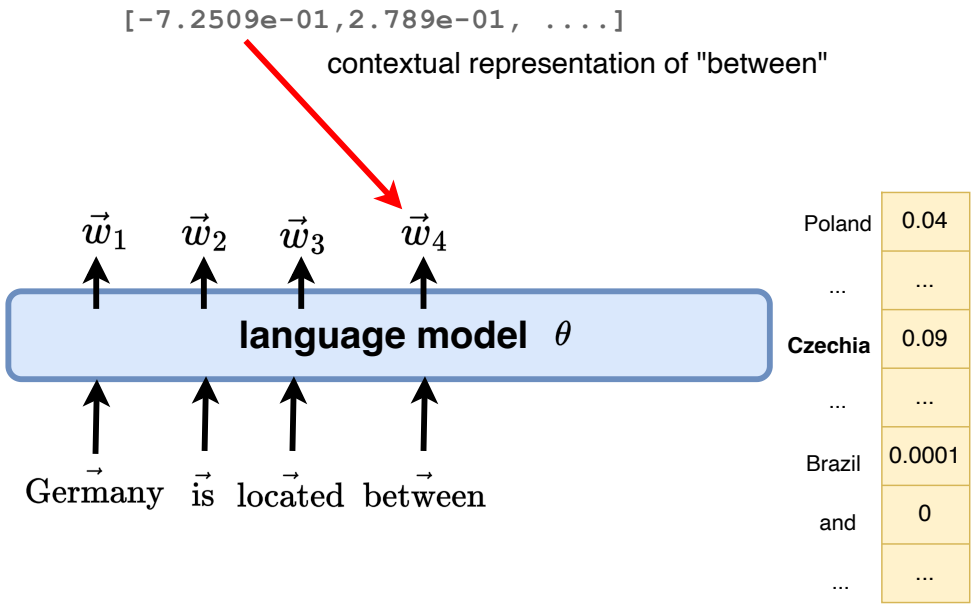

How information flows / contextual representations are built, relates to the **model architecture**. Popular: **transformer architecture**.

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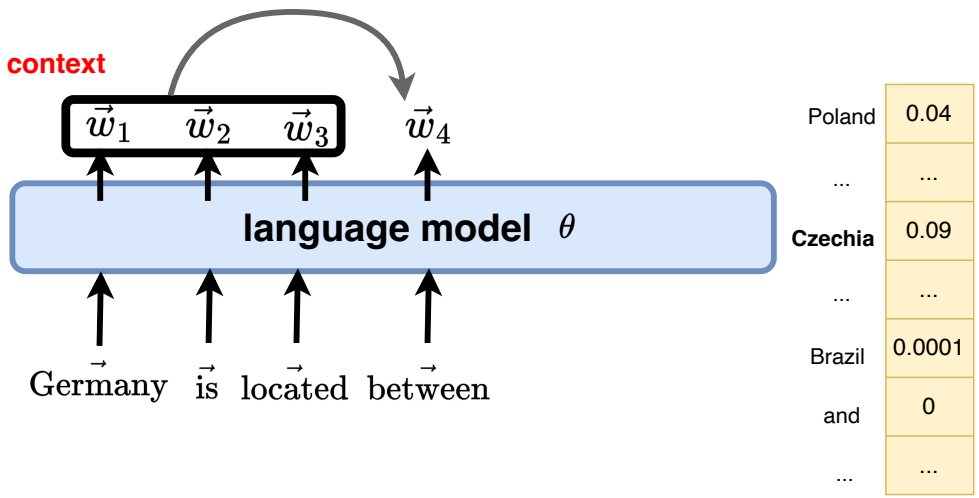

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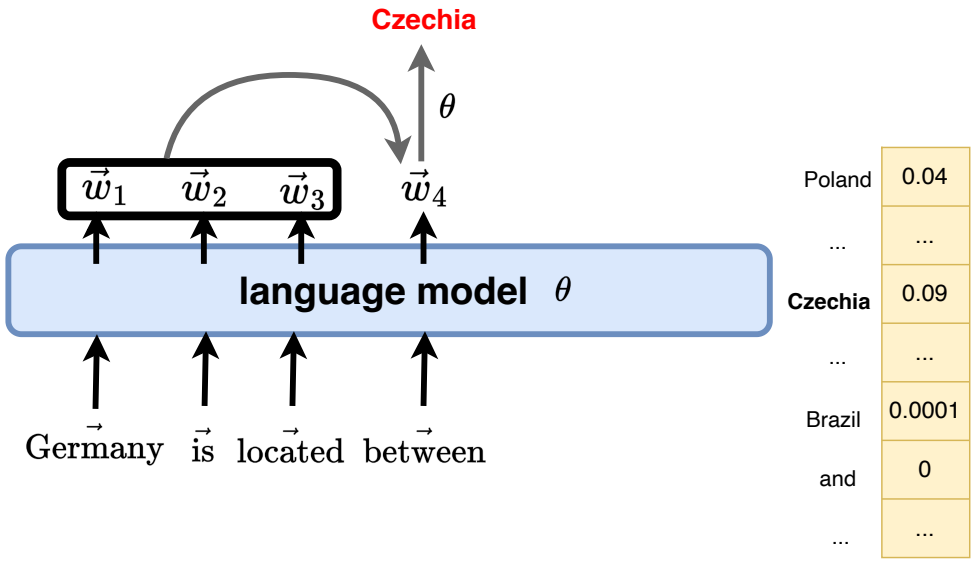

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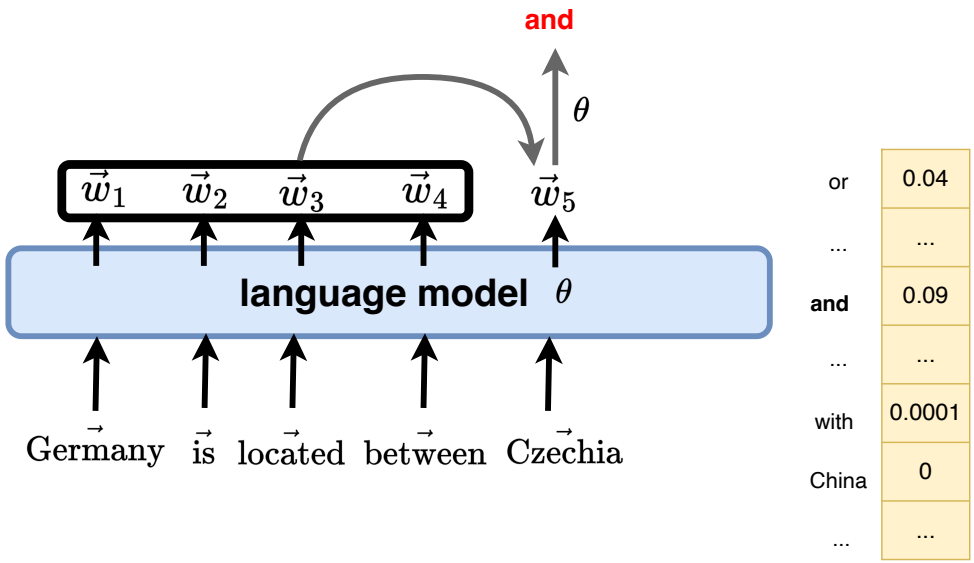

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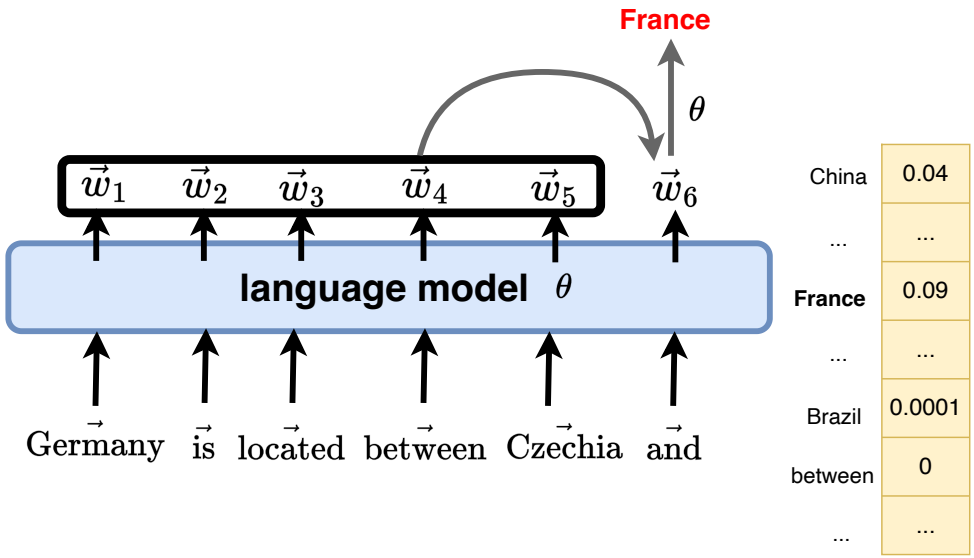

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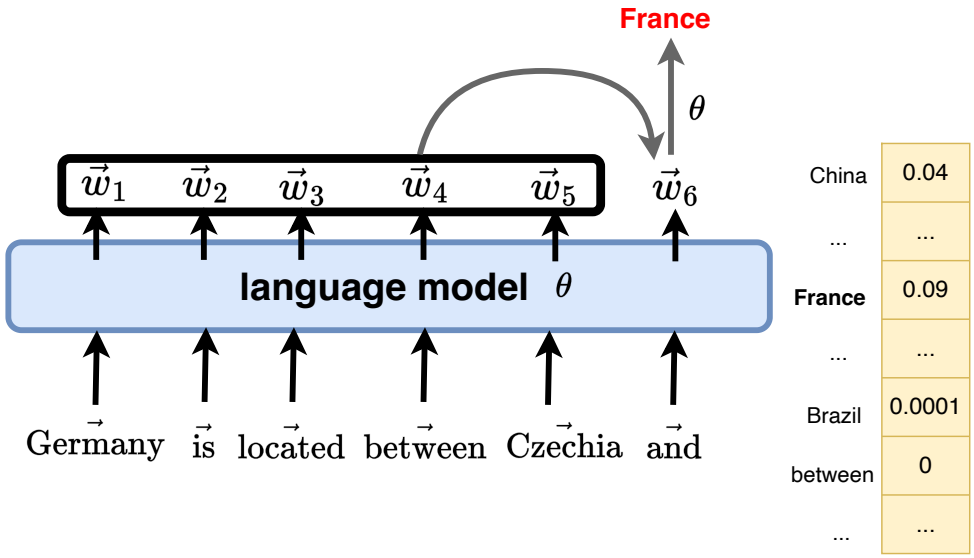

Fundamental problem: learning these underlying representations.

It took time to get this right...

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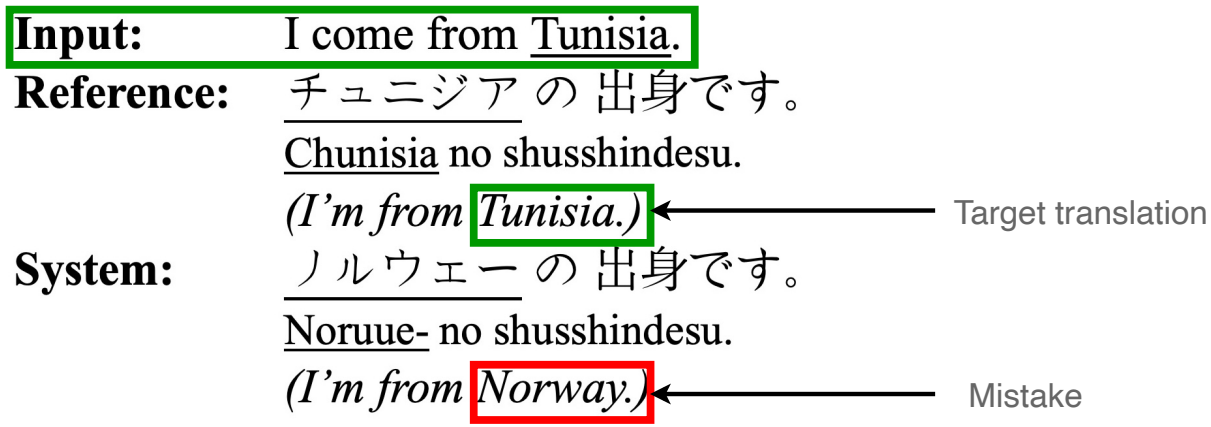


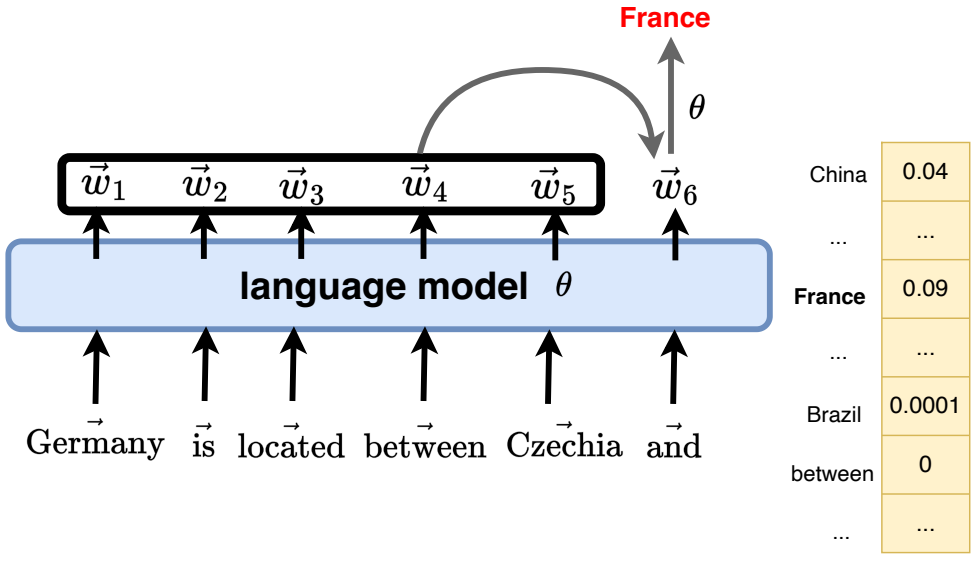
Figure 1: An example of a mistake made by NMT on low-frequency content words.

It took time to get this right...

Table 2: *Errors from the RNN.*

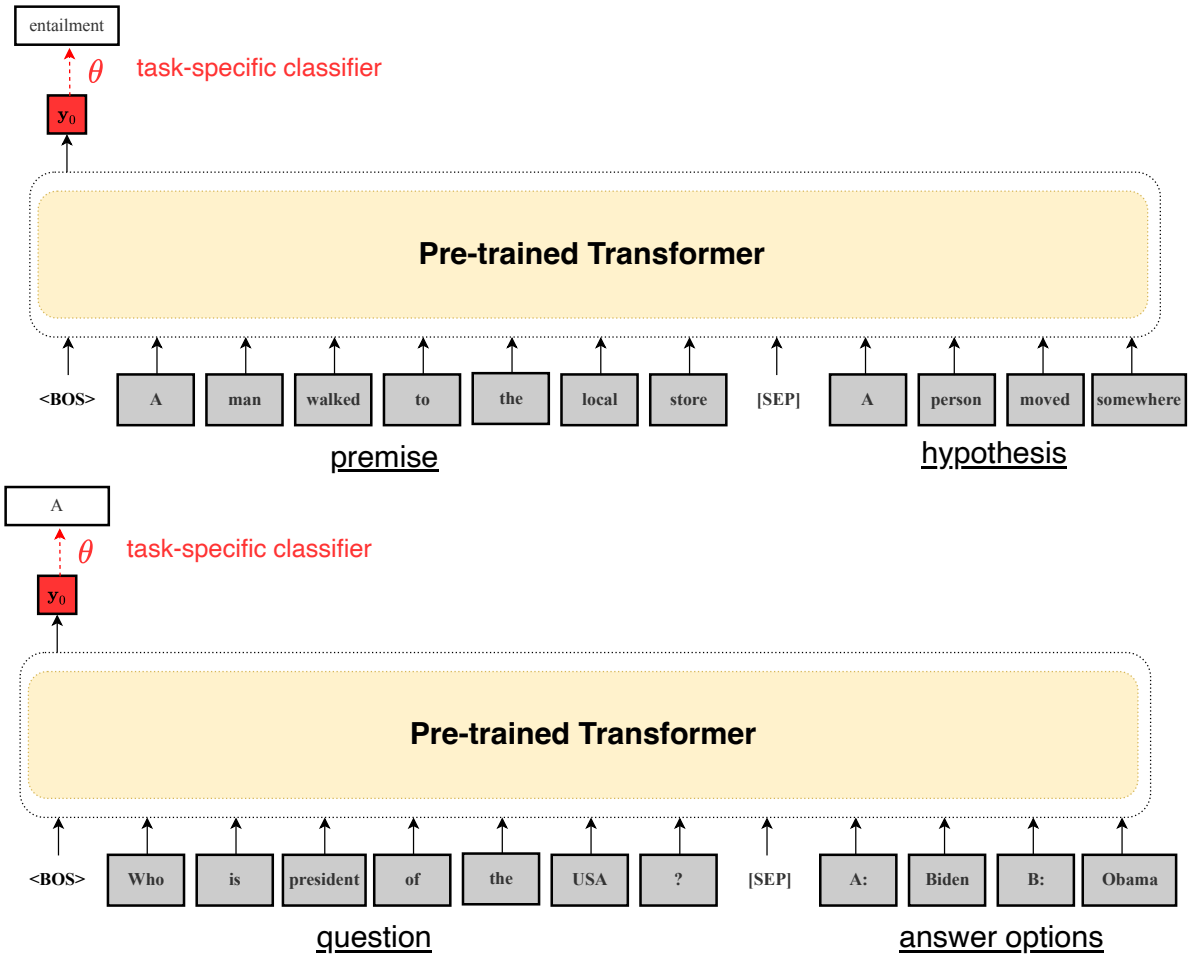
Input	Correct	Prediction
2 mA	two milliamperes	two million liters
11/10/2008	the tenth of november two thousand eight	the tenth of october two thousand eight
1/2 cc	half a c c	one minute c c
18:00:00Z	eighteen hours zero minutes and zero seconds z	eighteen hundred cubic minutes

(Pre-)Training in a nutshell



- Estimate parameters θ 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.

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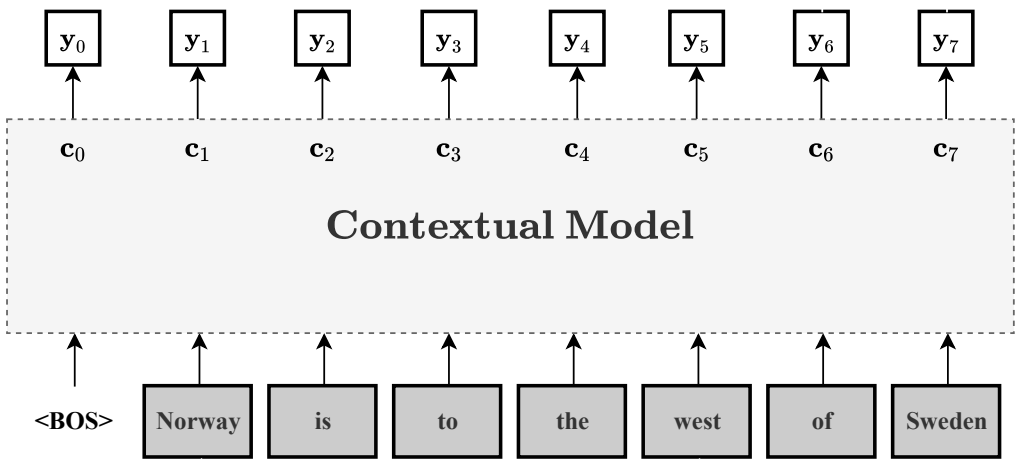

Operationally: neural network models, often large and opaque.

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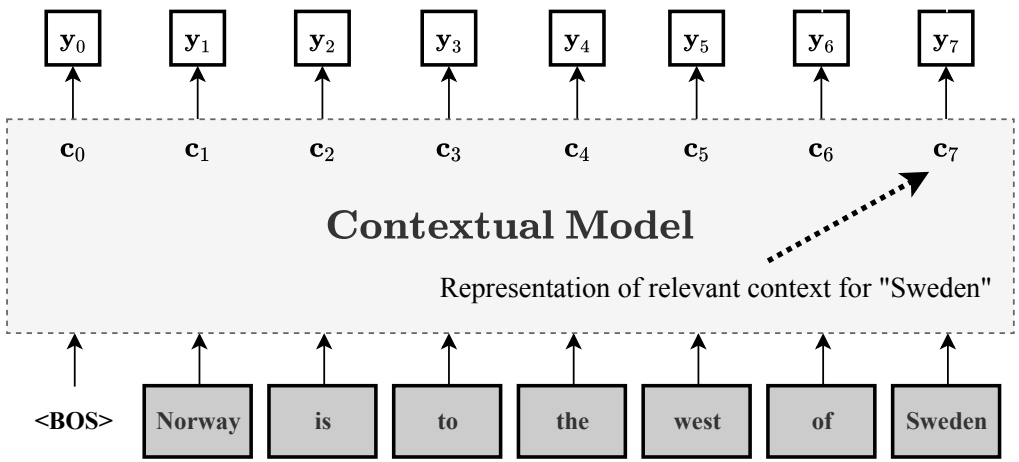

Semantics: $\mathbf{y}_7$ captures the meaning of *Sweden* grounded in this this particular sentential context, output of a compositional procedure.

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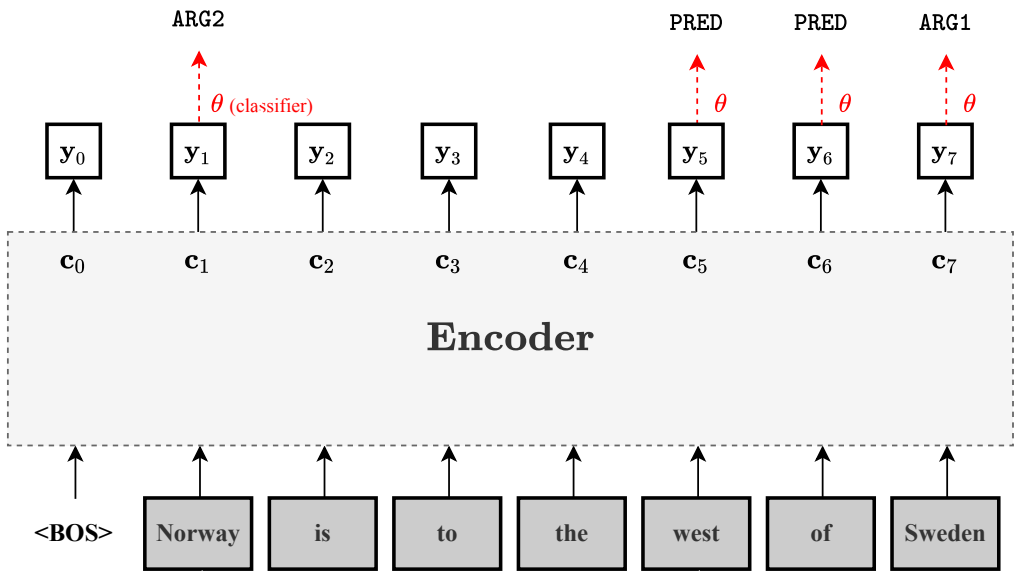

Why? Build representations that allow you make predictions, **success**: learned representations that effectively solve problems.

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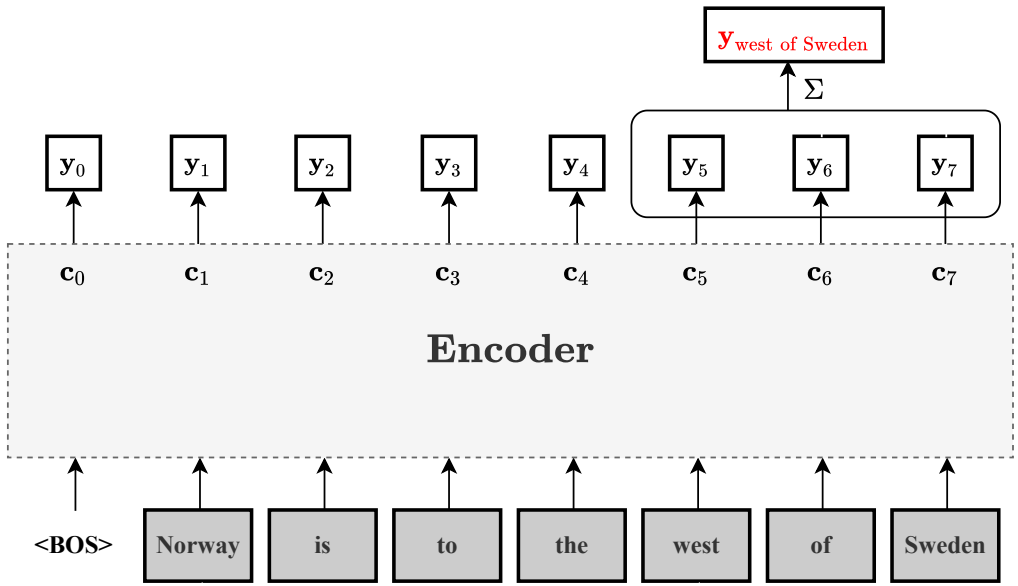

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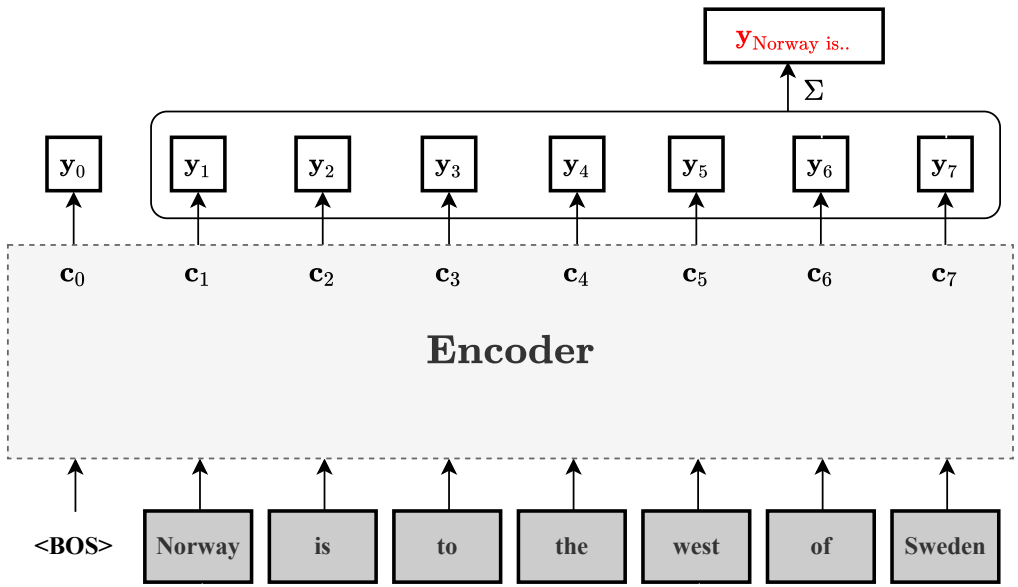

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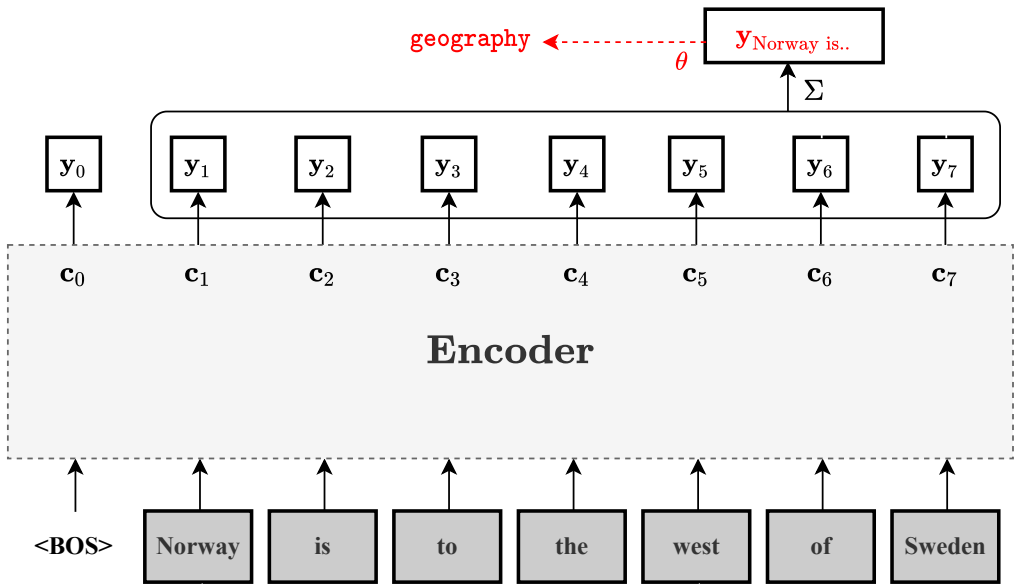

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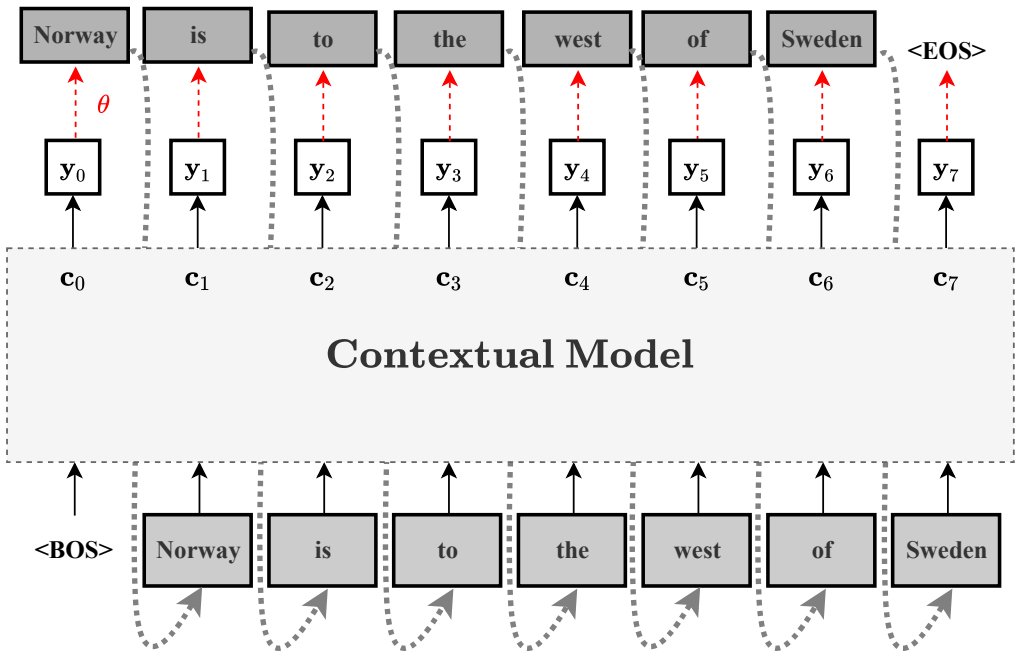

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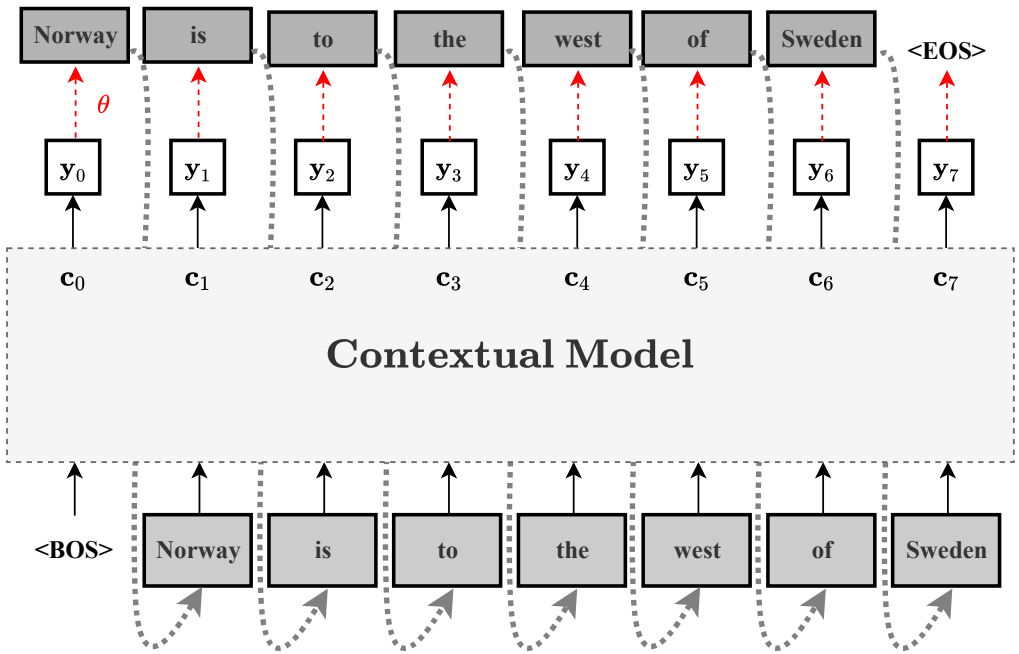

as LMs: $p(w_j \mid w_1, \ldots, w_{j-1}) = p(w_j \mid \mathbf{c}_{j-1})$, **Important:** Can condition on full contexts, *faithfully* model complex joint probability distributions

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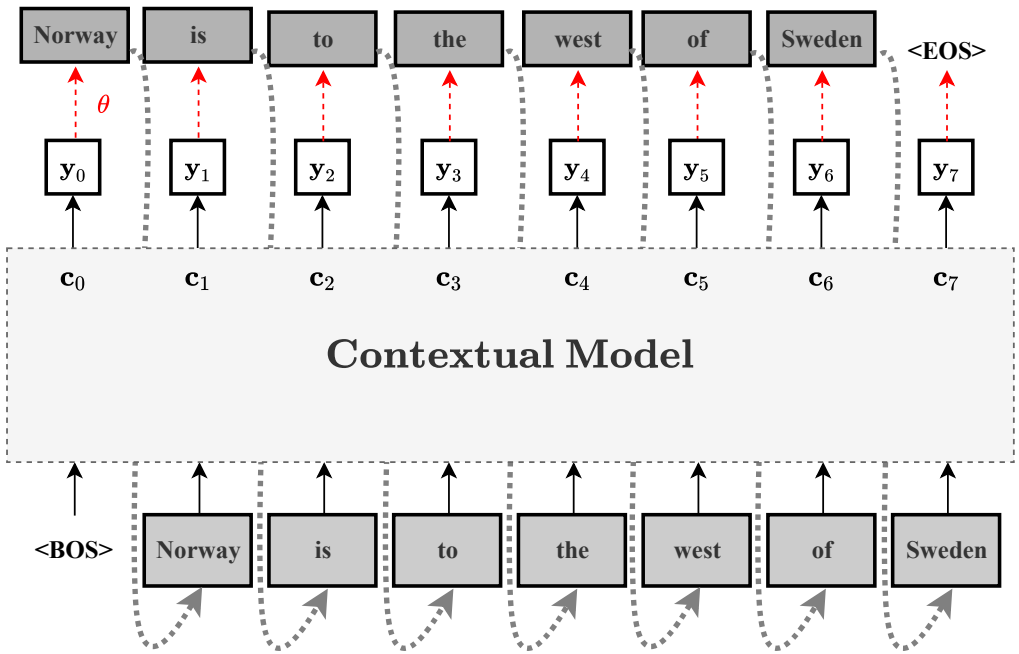

Model Architectures: how information is processed, internal representations are constructed. **Common**: RNNs, Transformers.

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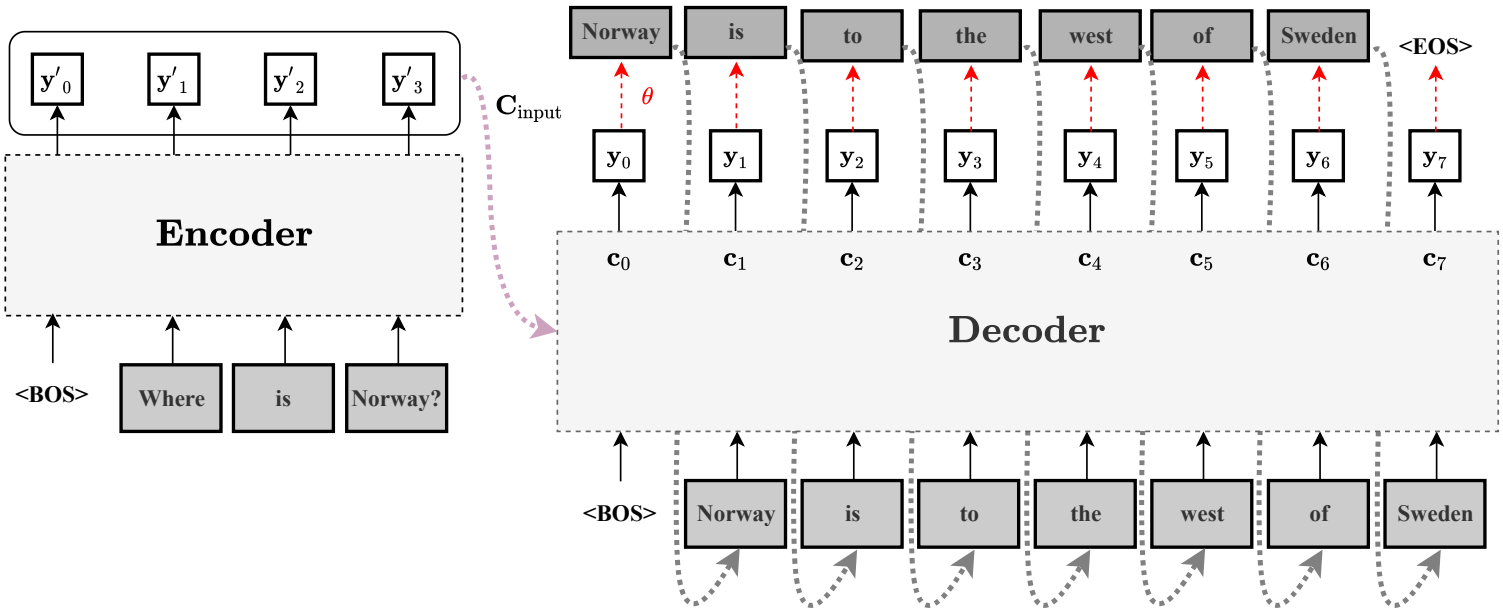
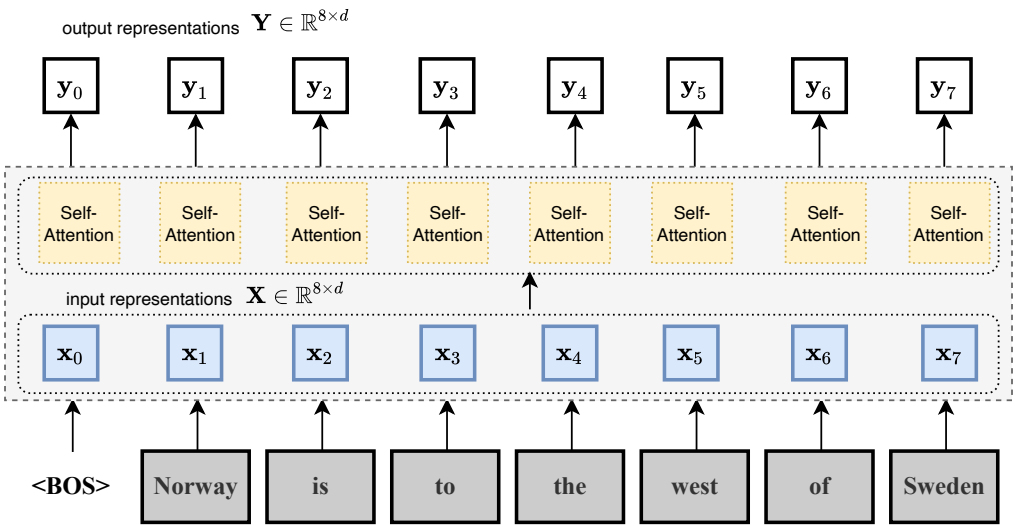


Text2Text models: estimate $p(y^{\text{output}} \mid x^{\text{input}})$, natural way to express many language understanding problems.

Transformers and attention

Self-Attention: Simple Encoder Example

Attention: Mechanism for building contextual representations (see Vaswani et al. (2017)).



Self-Attention: Embeddings Representations

```
import torch ## to install: pip install pytorch

### word embedding parameters and matrix E
E = torch.nn.Embedding(
    embedding_dim=768,  ##<--- dimensionality
    num_embeddings=3000, ##<--- # words
)

##e.g., Representation of our Input
X = E(torch.tensor([
        0, # <BOS>
        1, # Norway
        2, # is
        3, # to
        4, # the
        5, # west
        6, # of
        7, # Sweden
])) ### => matrix 7 * 768

x1 = X[1] ##-> initial representation of Norway
print(x1)
###=> [-1.1344e+00, -3.0359e-01,  7.3585e-02, .....]
```

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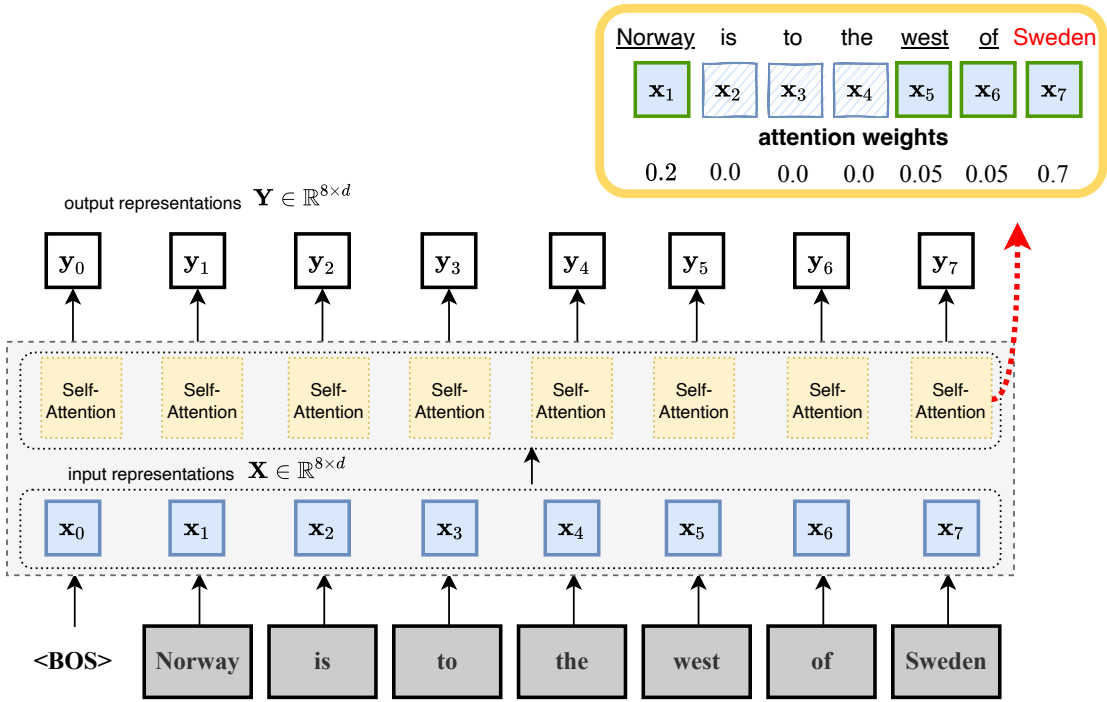

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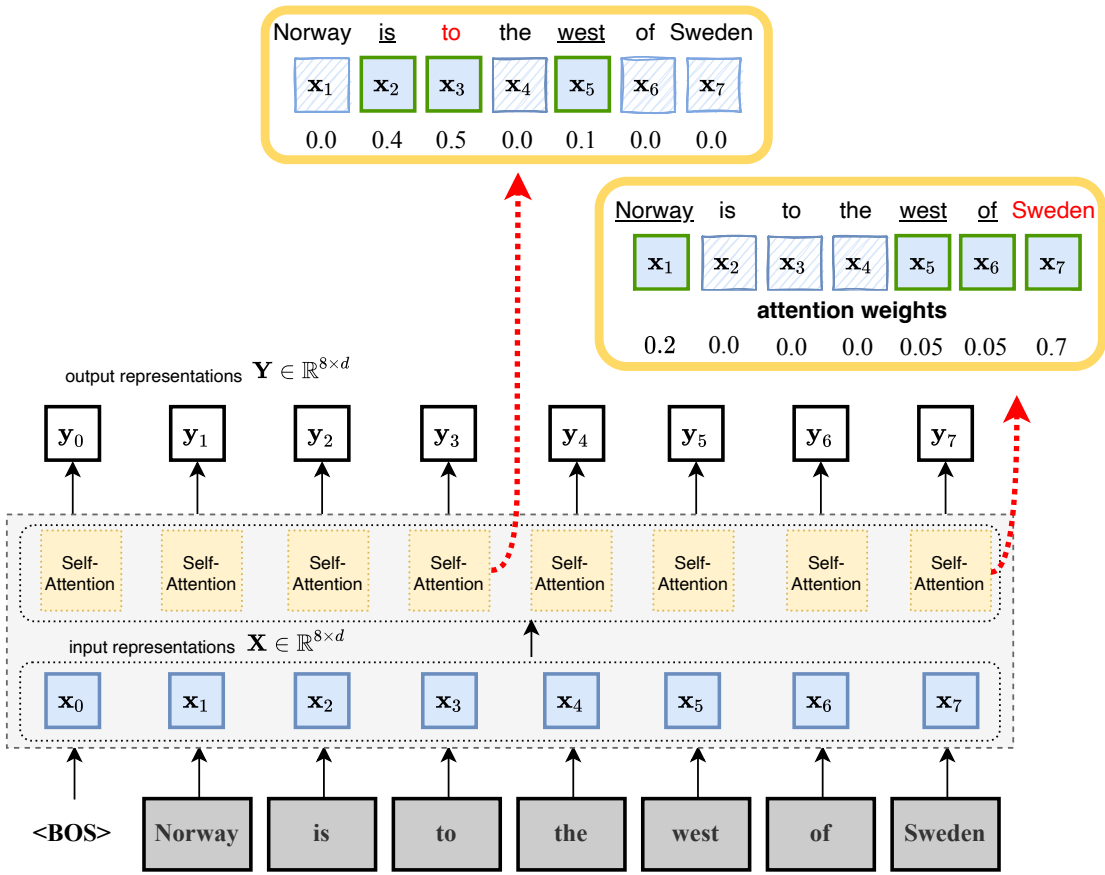

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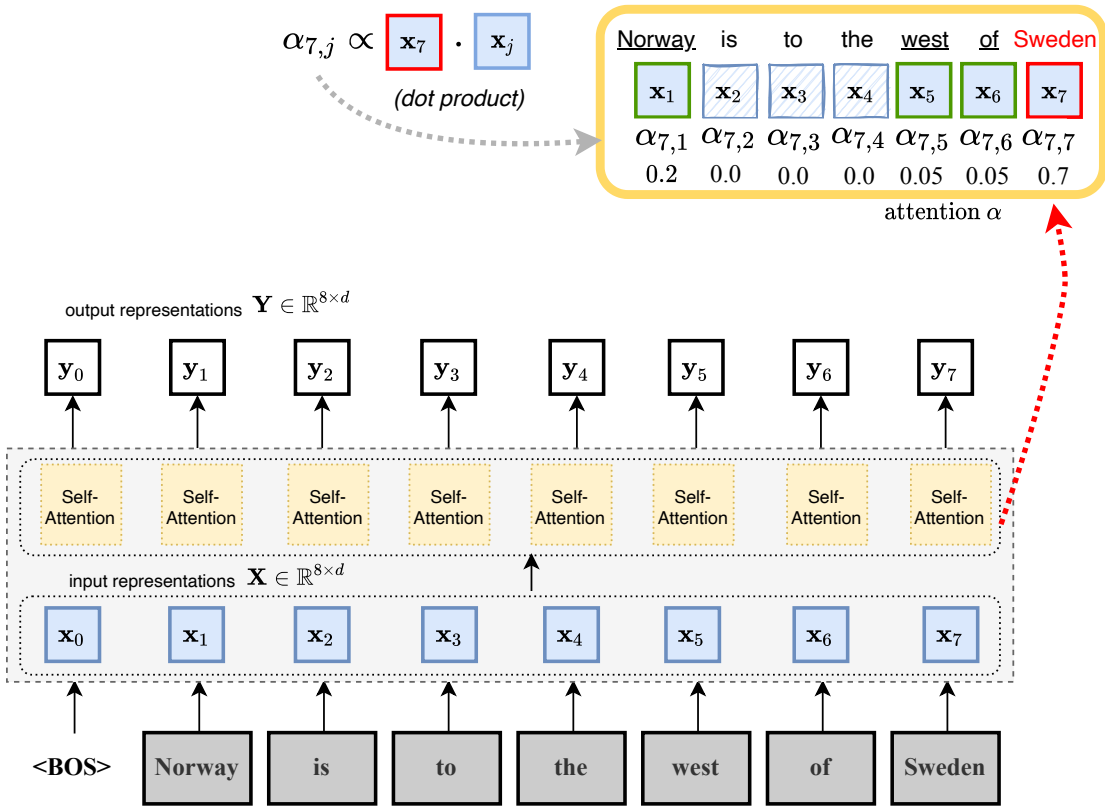

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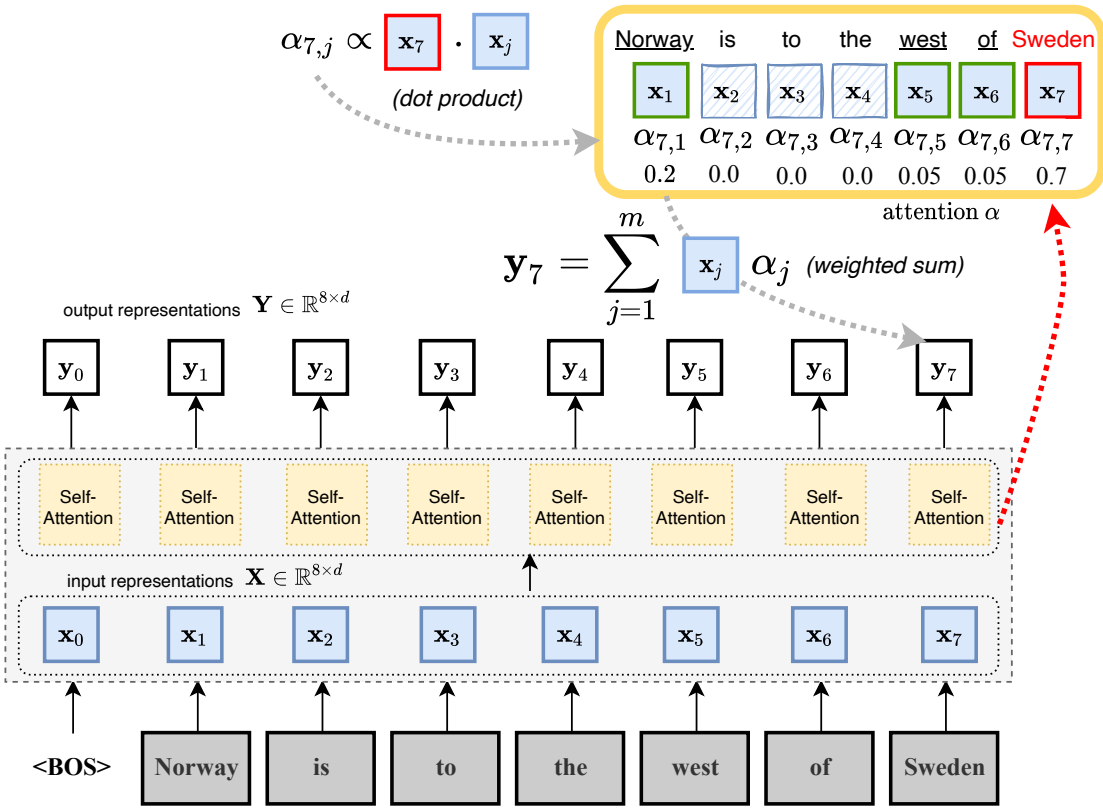

Self-Attention: Computing Final Representations

The full computation

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

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

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

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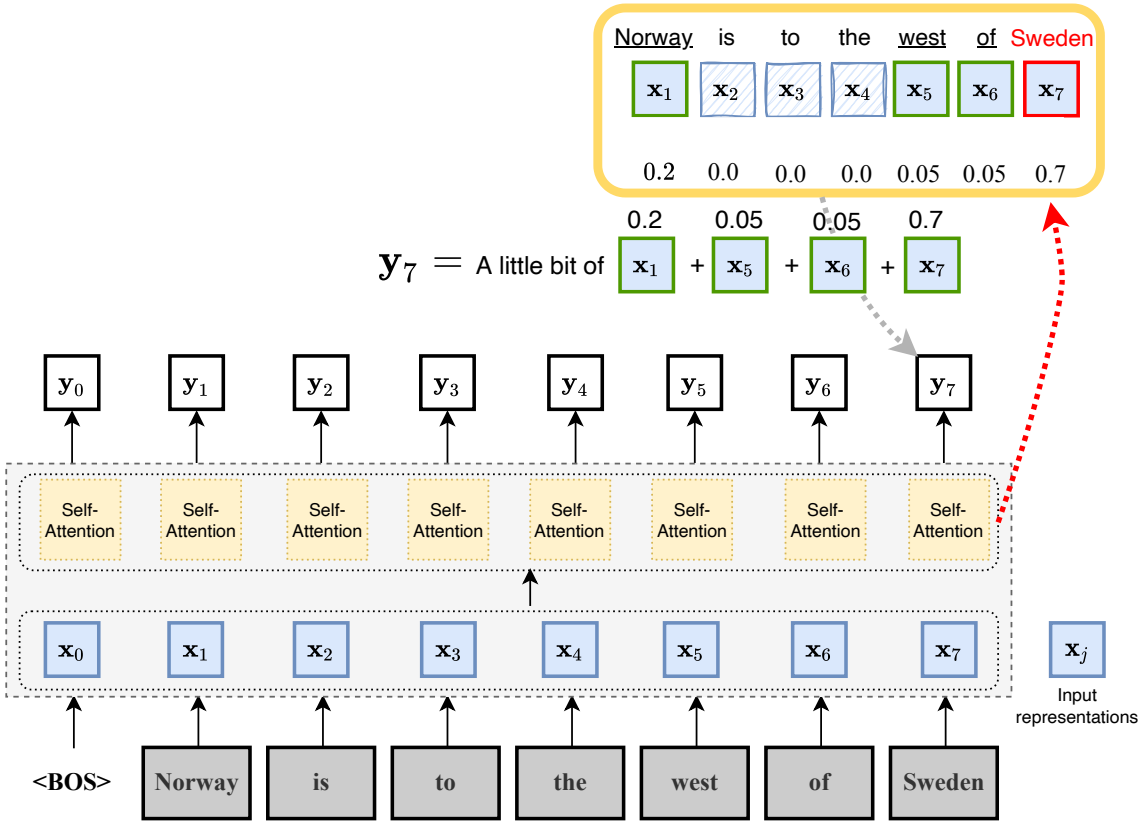
```
## Input representations (again),
X = E(torch.tensor([0,1,2,3,4,5,6,7]))

### raw weights (dot product / matrix multiplication)
raw_Alpha =  torch.matmul(X,X.transpose(0,1))
### normalized via softmax, probability distribution
alpha =  raw_Alpha.softmax(dim=-1)
### Final self attention representations
Y =  torch.matmul(alpha,X)
### self attention representation of 'Norway'
y1 = Y[1]
```

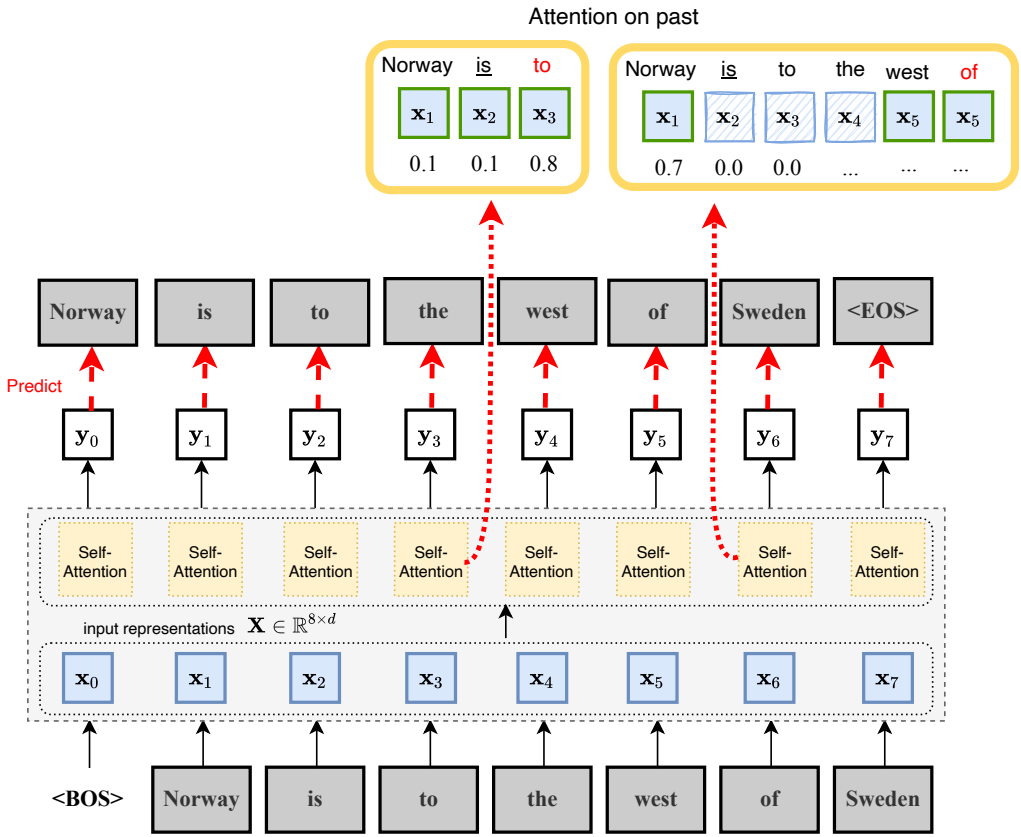
Self-Attention: Intuition

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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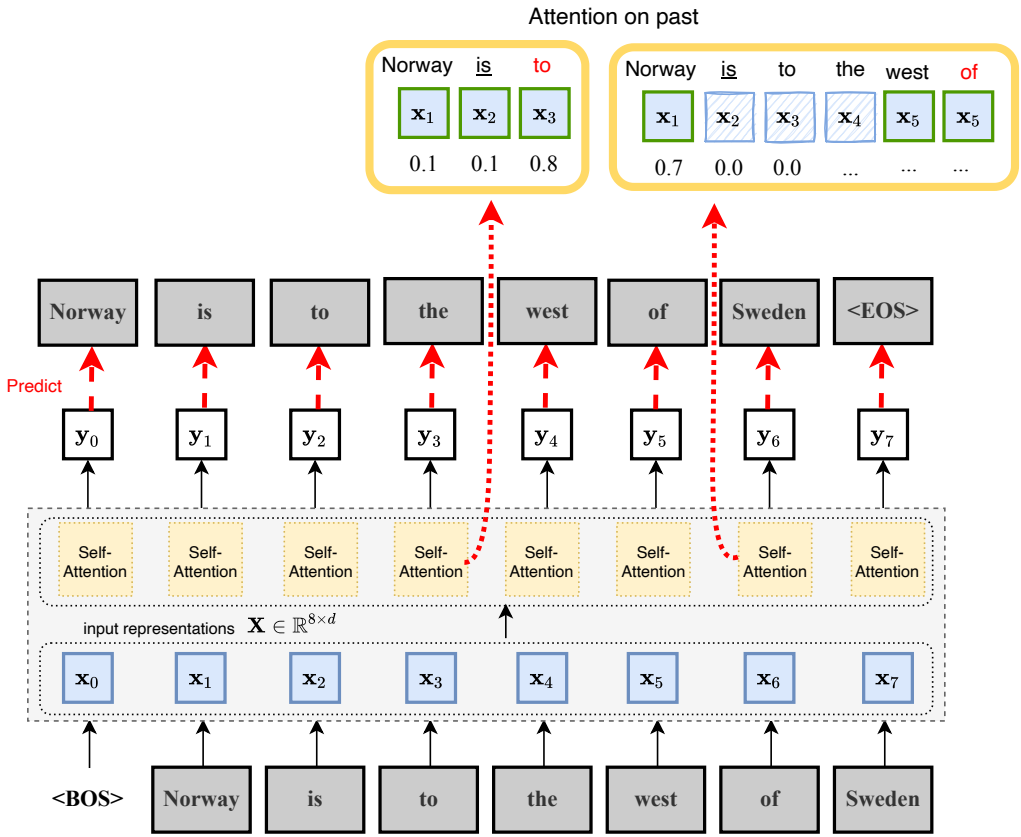


Note: No independence assumptions, full context.

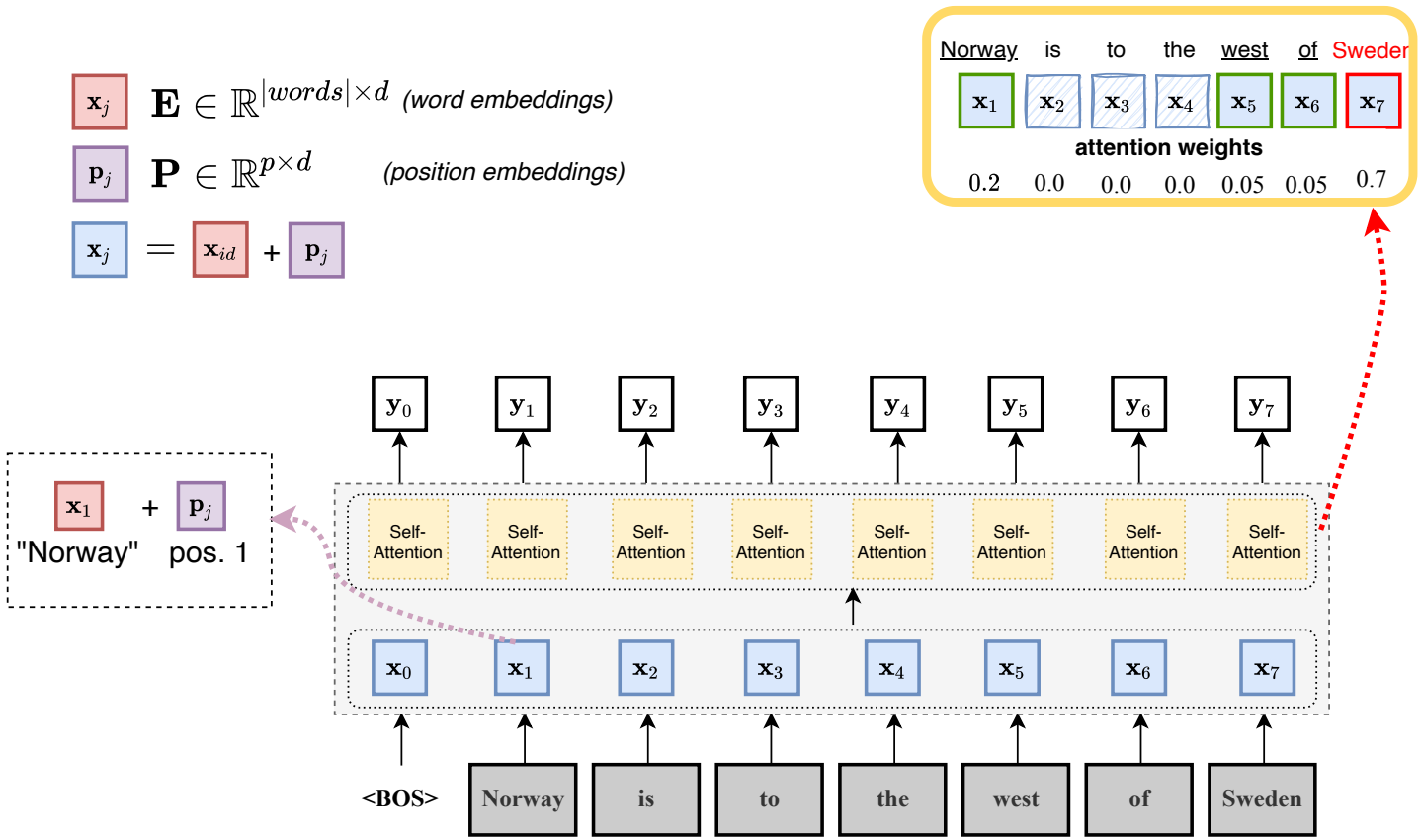
Causal Attention

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

```
import torch
## Input representations (again),
X = E(torch.tensor([0,1,2,3,4,5,6,7]))

### raw weights (dot product / matrix multiplication)
raw_Alpha =  torch.matmul(X,X.transpose(0,1))

### causal mask
mask = torch.triu_indices(8, 8, offset=1)
raw_Alpha[:, mask[0], mask[1]] = float('-inf')

### normalized via softmax, probability distribution
alpha =  raw_Alpha.softmax(dim=-1)
### Final self attention representations
Y =  torch.matmul(alpha,X)
### self attention representation of 'Norway'
y1 = Y[1]
```

An important detail: positional information

- Word embeddings so far do not encode position information.



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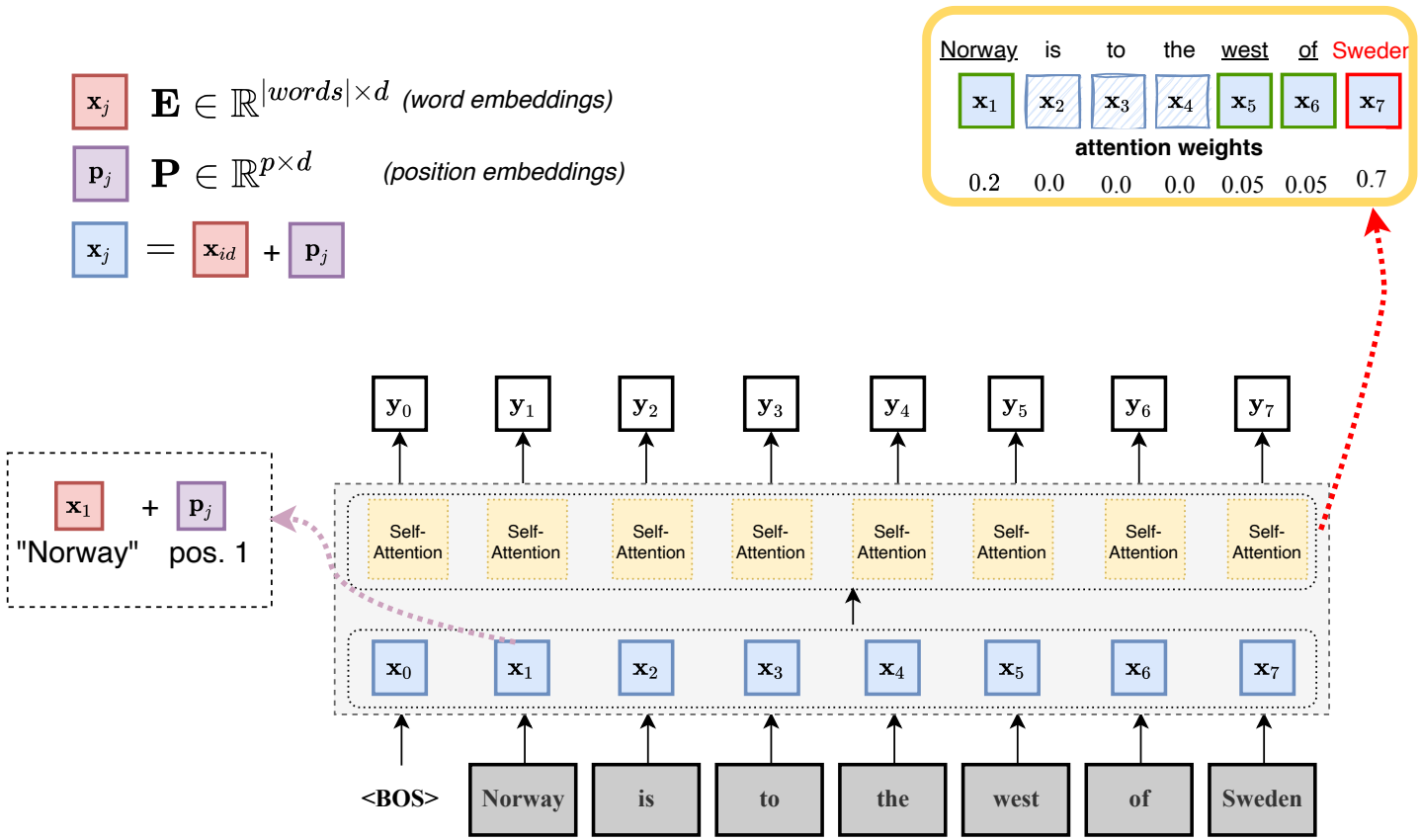
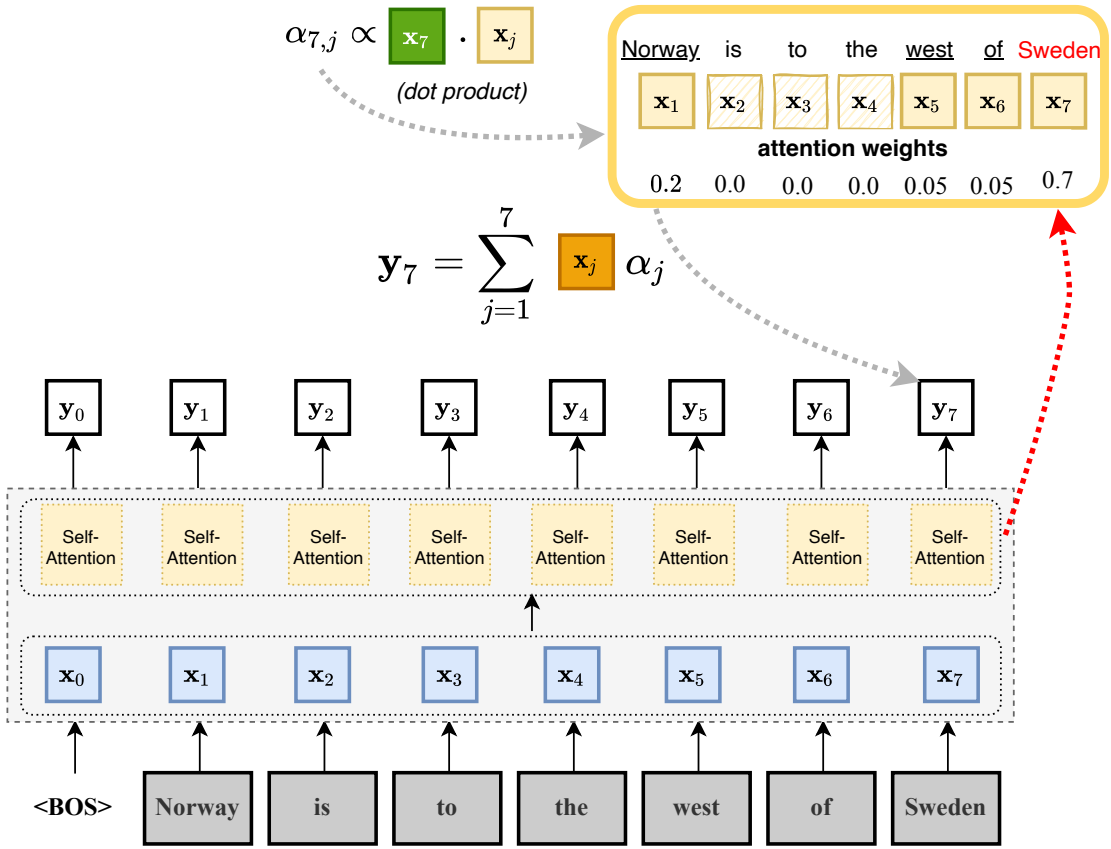


Note: we can add any additional information we want, many variations.

More Parameters: Keys, Queries and Values

- Three components in our computation.



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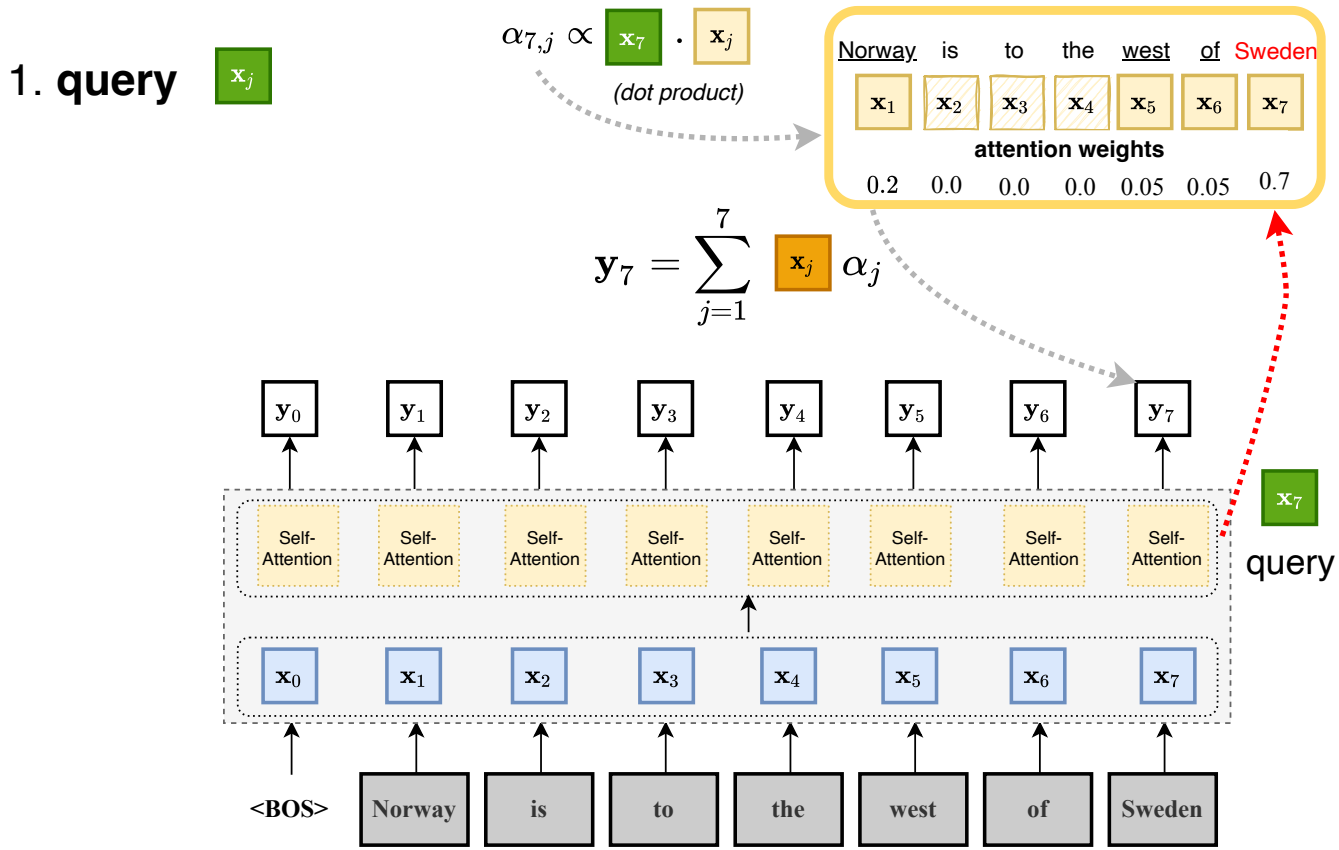

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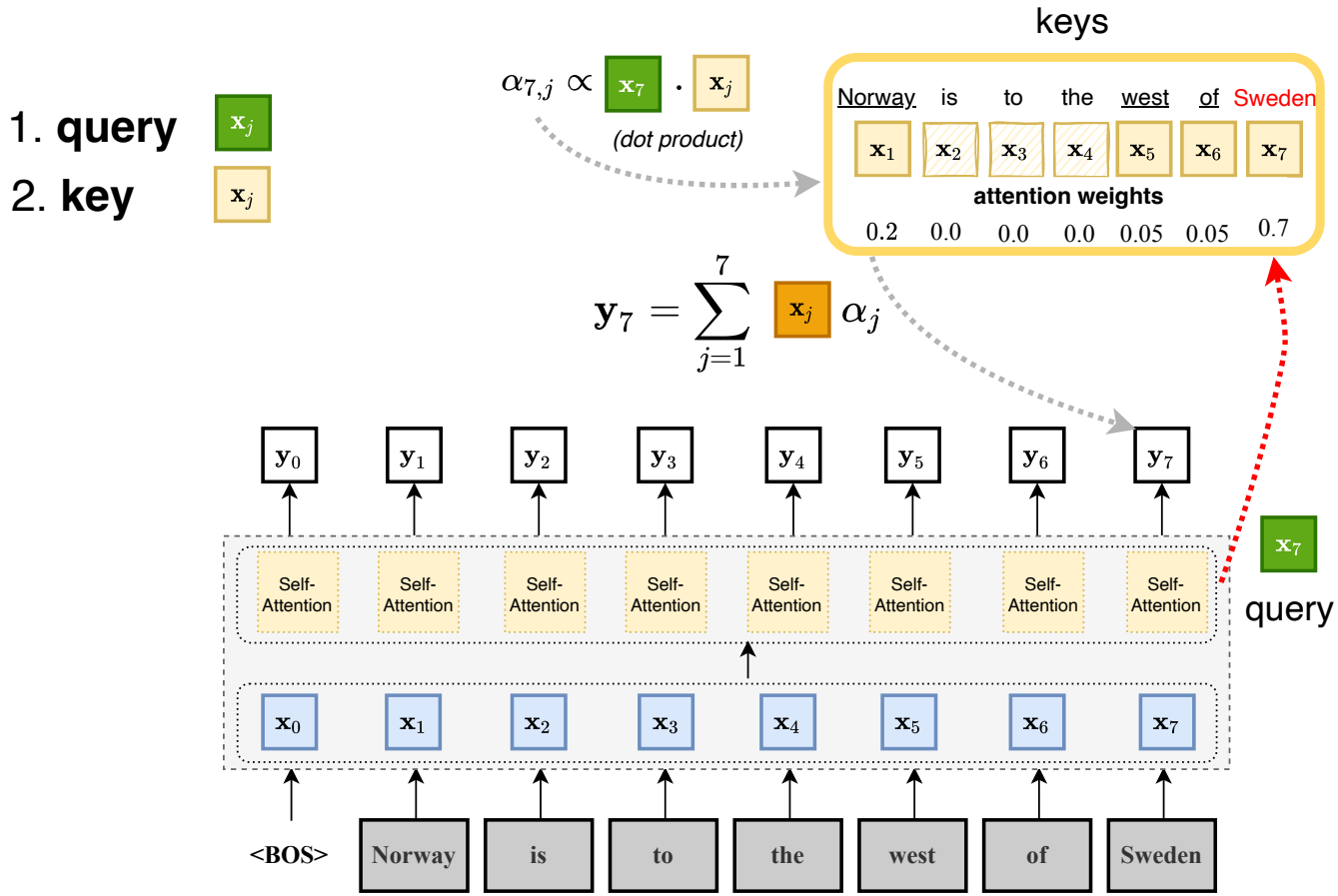

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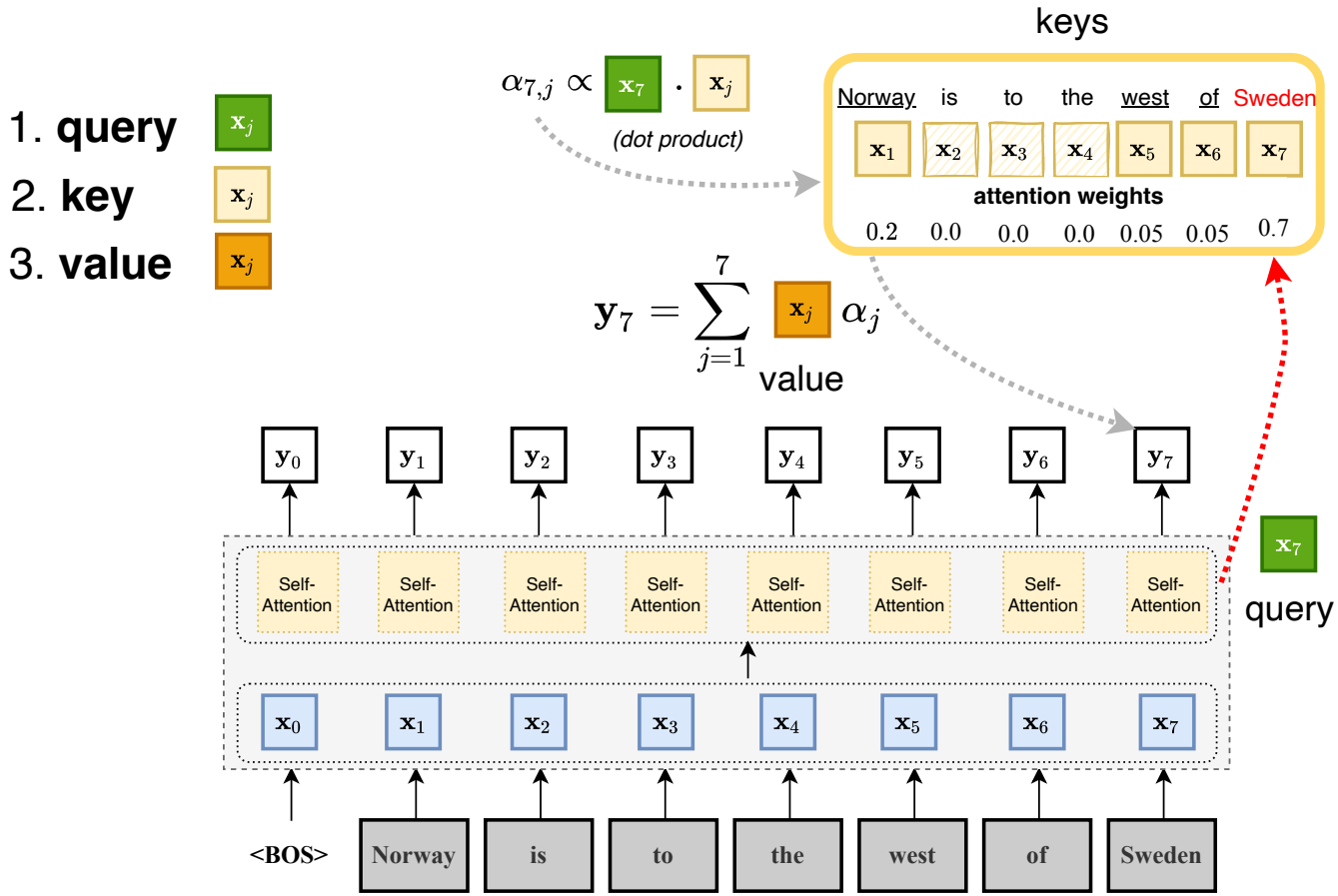

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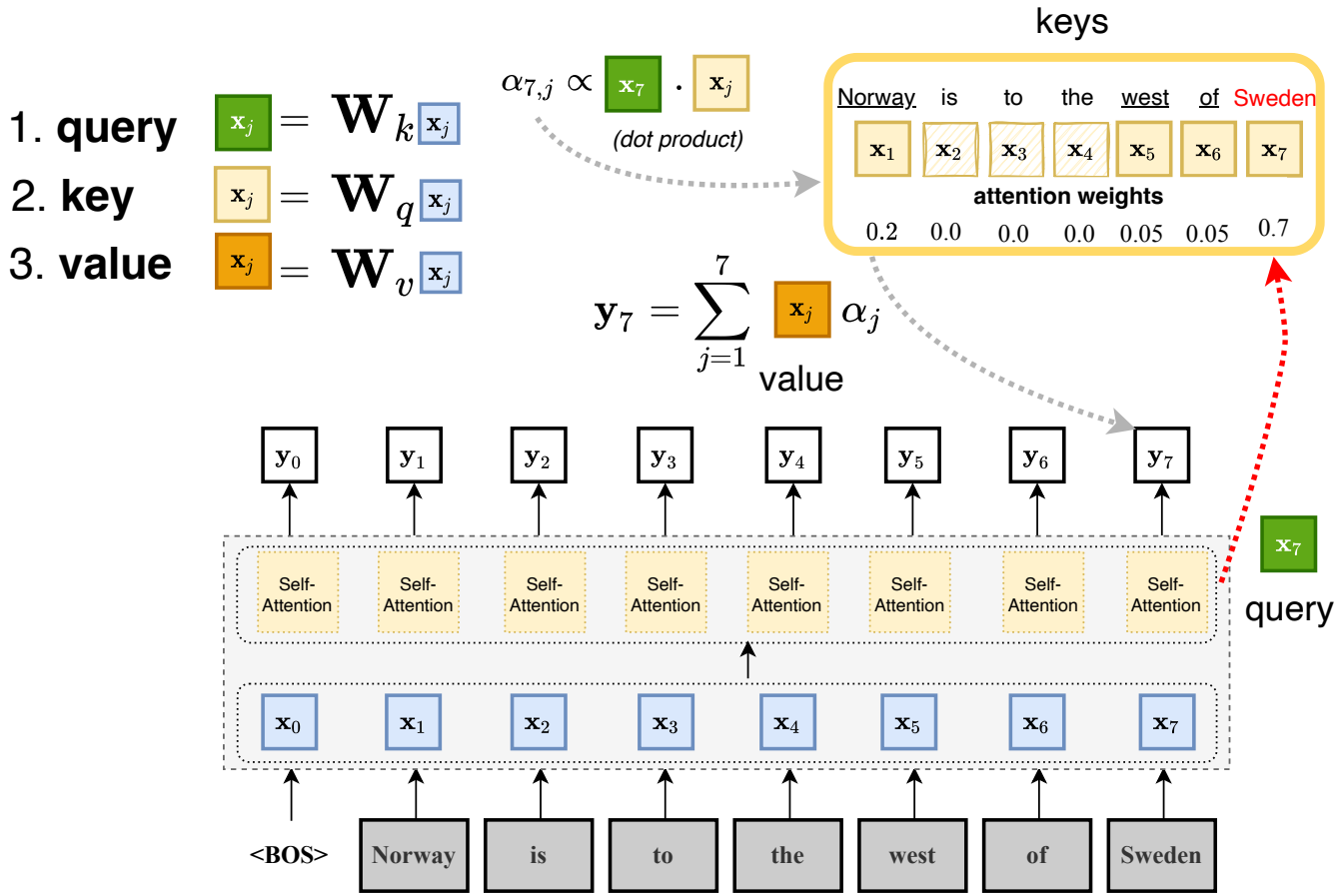


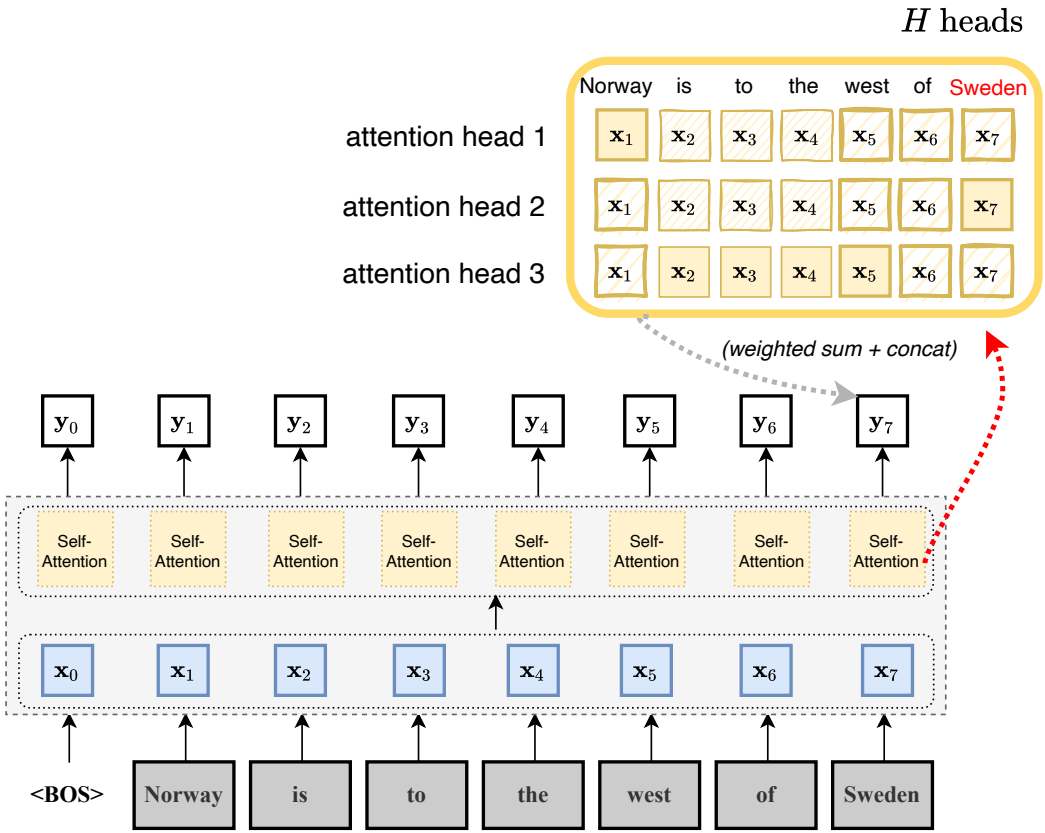
More Parameters: Keys, Queries and Values

Another few additional lines of PyTorch

```
## Input representations (again),
X = E(torch.tensor([0,1,2,3,4,5,6,7]))
D = 768

### key, value, query parameters (linear layer)
W_k   = torch.nn.Linear(D, D, bias=False)
W_q   = torch.nn.Linear(D, D, bias=False)
W_v   = torch.nn.Linear(D, D, bias=False)

key_rep    = W_k(X)  #<-- rep. of X as keys
query_rep  = W_q(X) #<-- rep. of X as queries
value_rep  = W_v(X) #<-- rep of X as values

### sample computation with parameters applied over `X`
alpha = torch.matmul(
   query_rep,
   key_rep.transpose(0,1)
).softmax(dim=-1)

### same as before
Y = torch.matmul(alpha,value_rep)
```

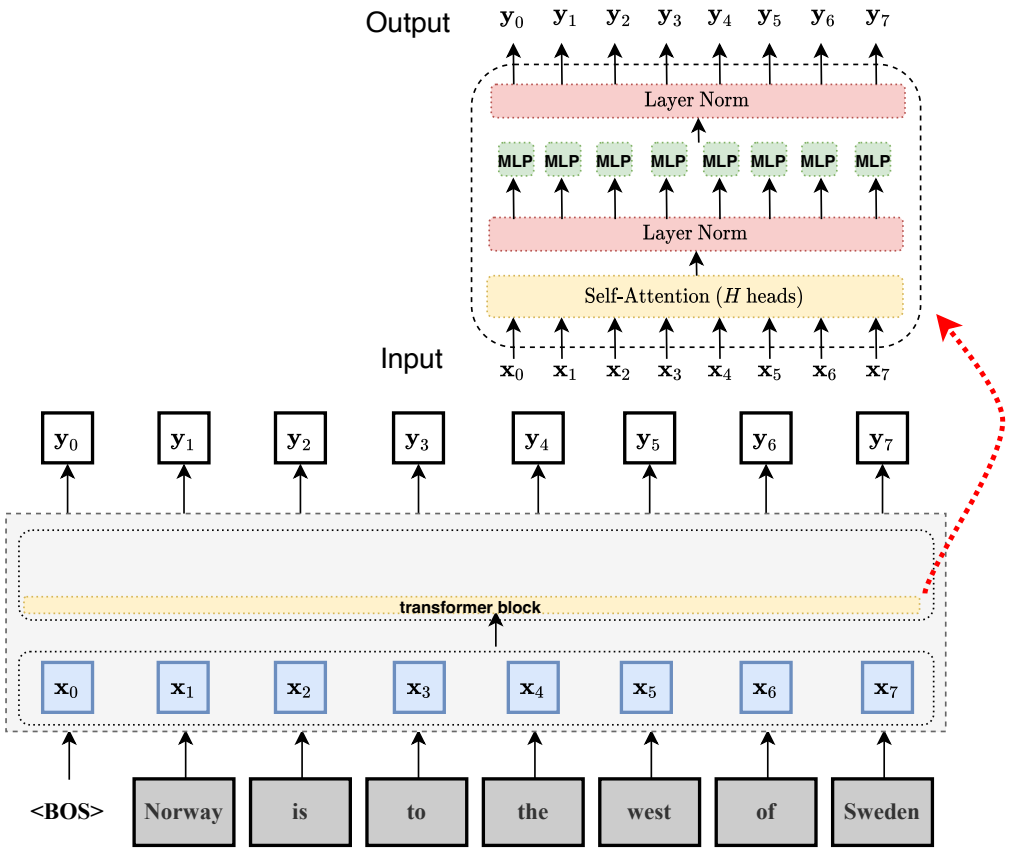
Multi-headed Attention

- 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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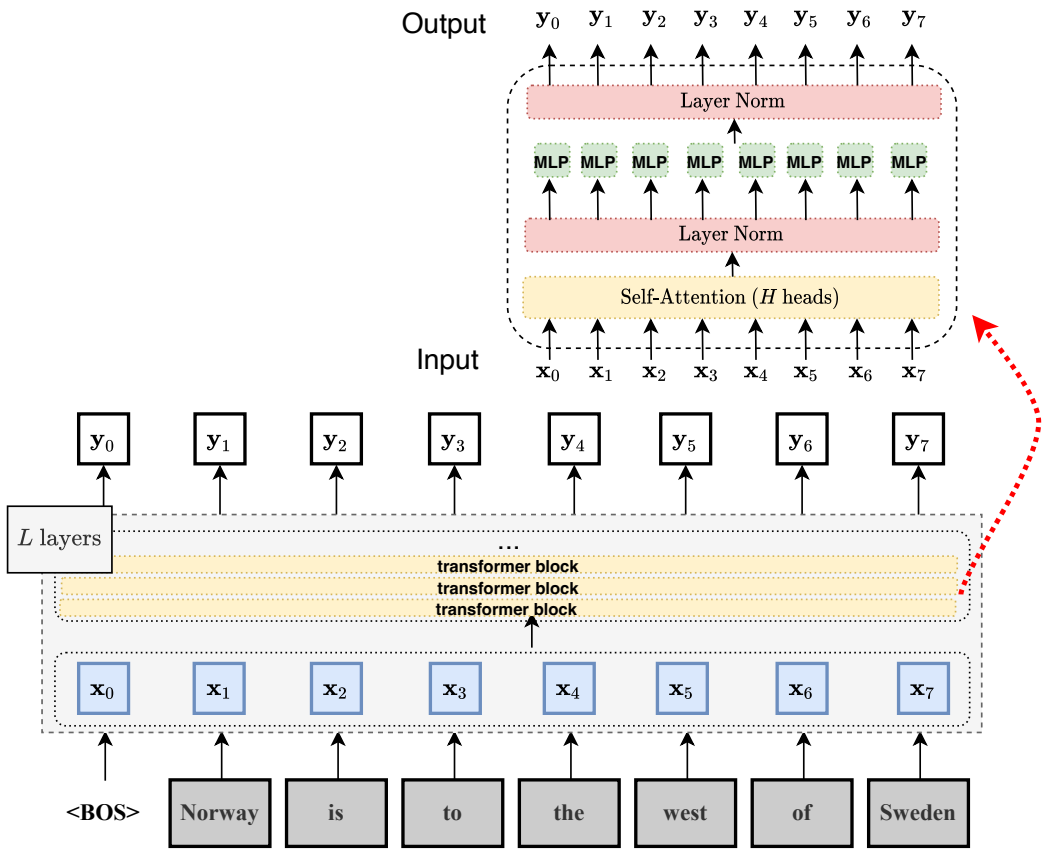

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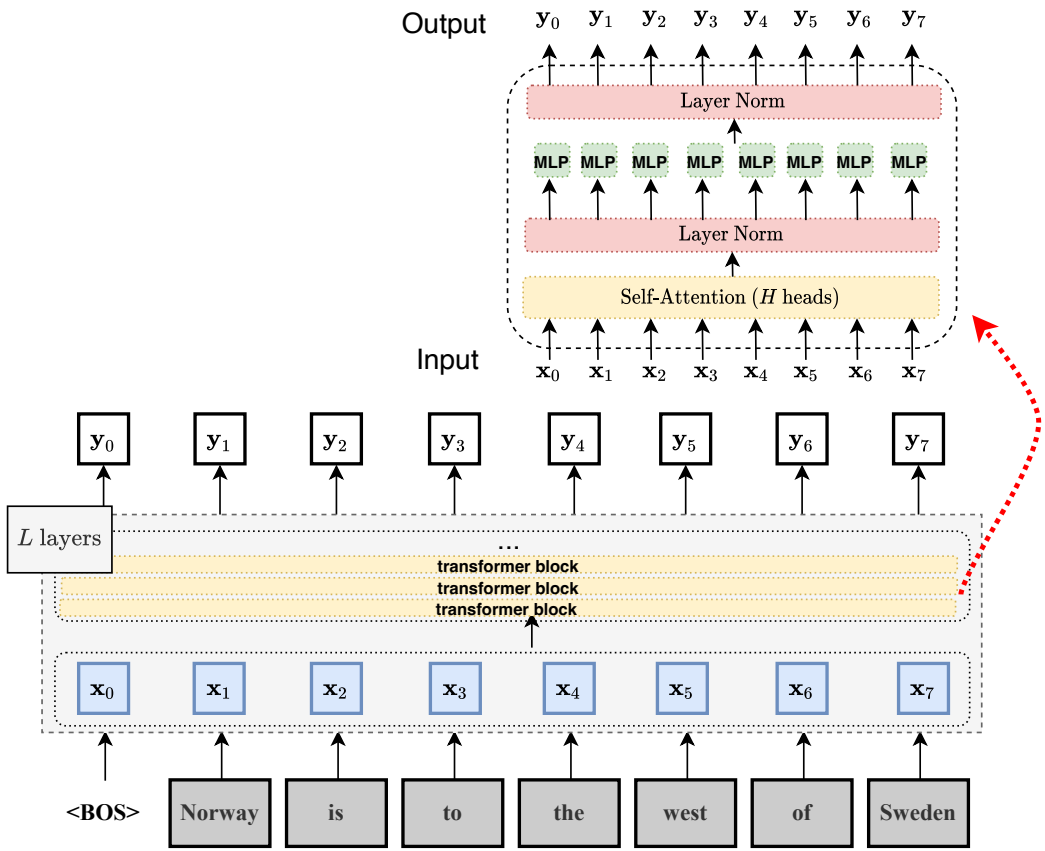

BERT (Devlin et al., 2019): $L = 24$ layers each with $H = 16$ heads, *340M* parameters, embedding dimension=1024

Transformer Blocks and Multiple Layers

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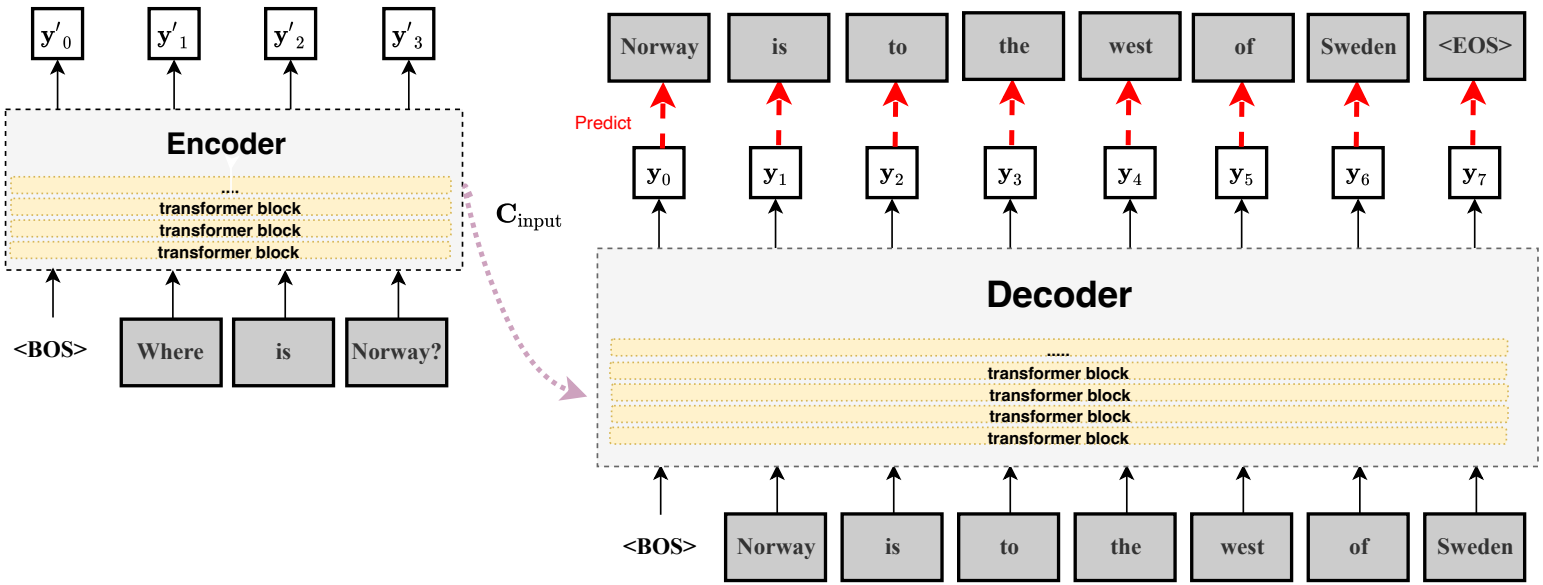
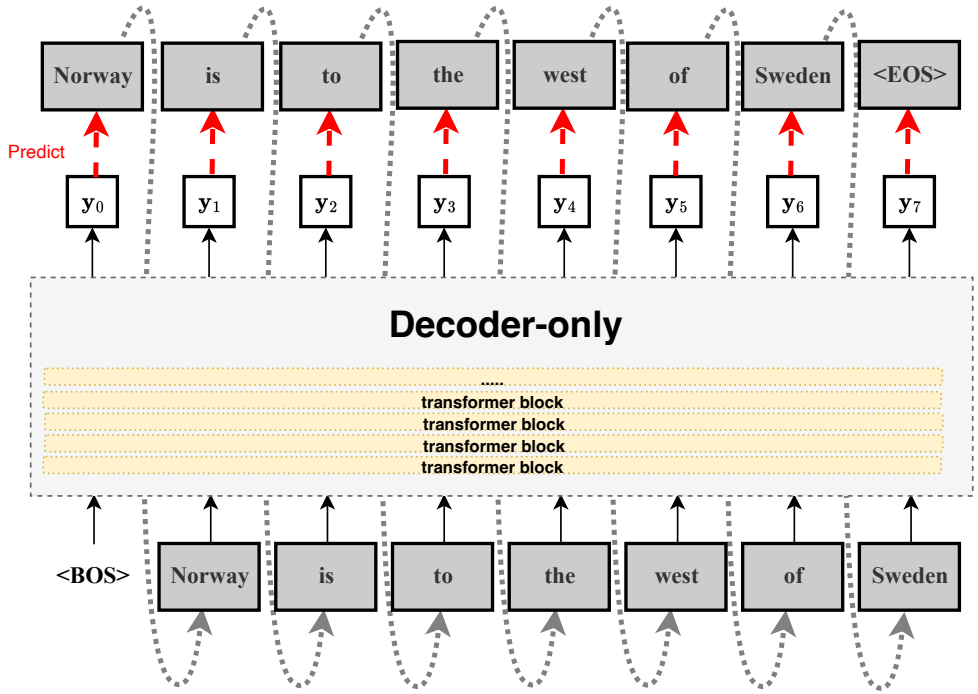


T5 model (Raffel et al., 2020), text2text architecture: **encoder** and **decoder**, 24 layers, 128 heads, cross-attention (11B parameters).

Transformer Blocks and Multiple Layers

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



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

A typical transformer block

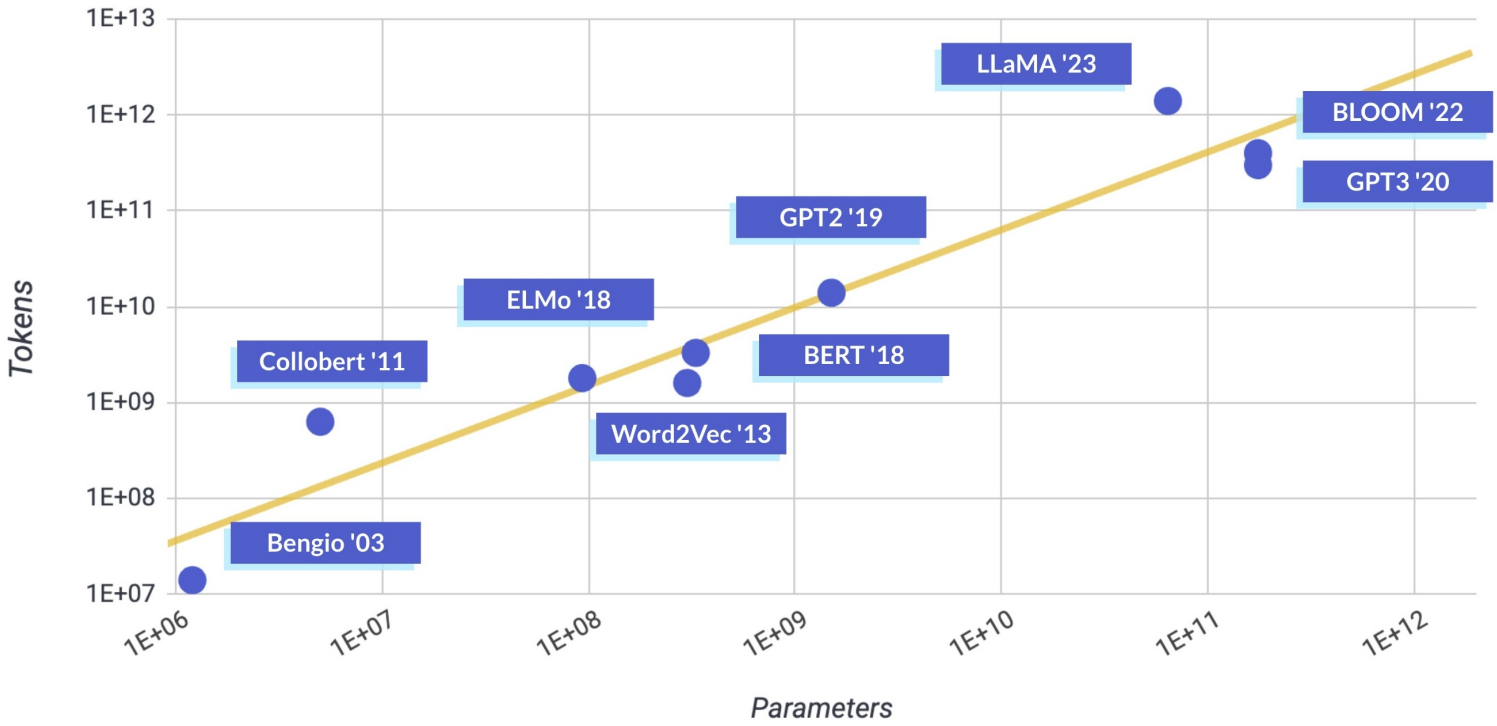
```python
## nanoGPT: https://github.com/karpathy/nanoGPT
class Block(nn.Module):

    def __init__(self, config):
        super().__init__()
        self.ln_1 = LayerNorm(config.n_embd,
                bias=config.bias
        )
        self.attn = CausalSelfAttention(config)
        self.ln_2 = LayerNorm(config.n_embd,
                bias=config.bias
        )
        self.mlp = MLP(config)

    def forward(self, x):
        x = x + self.attn(self.ln_1(x))
        x = x + self.mlp(self.ln_2(x))
        return x
```

The nature of their training

Model and data scale: a glance



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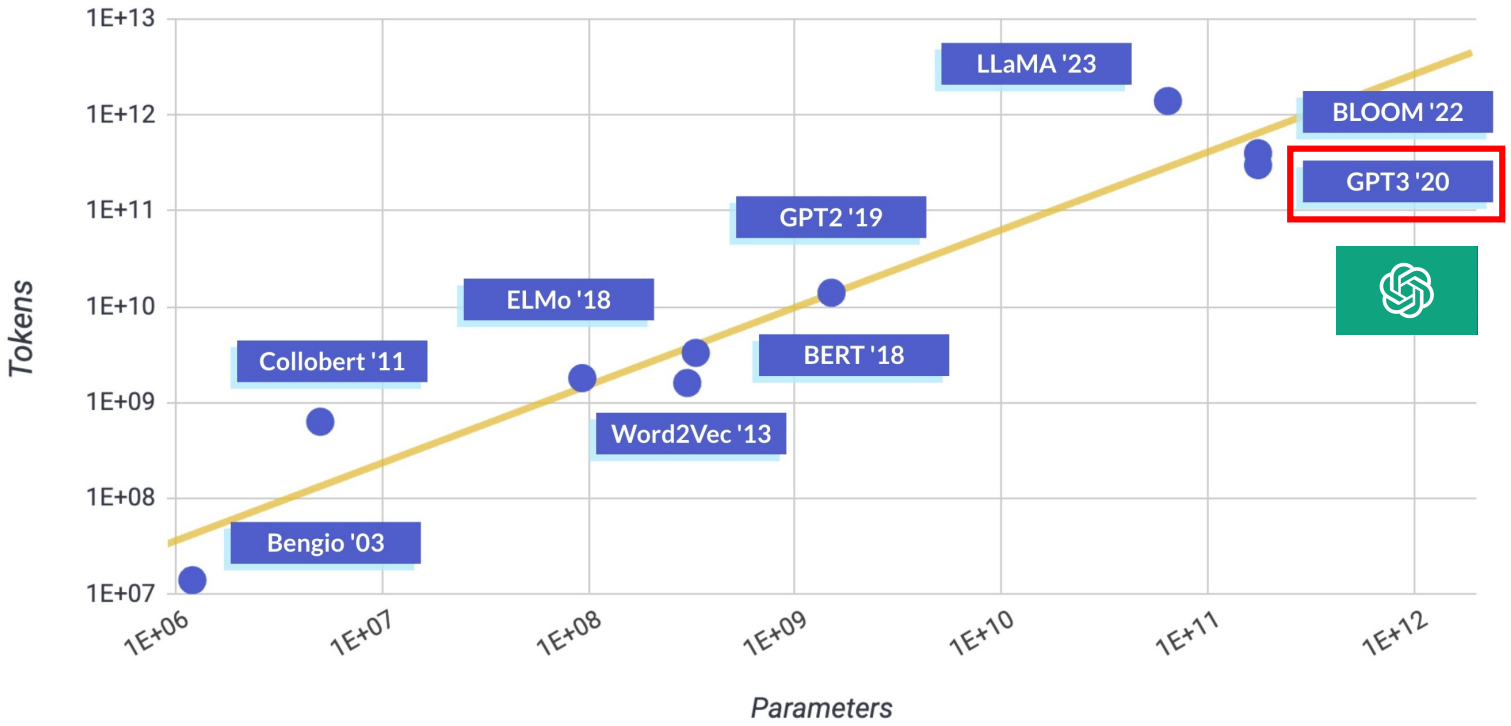

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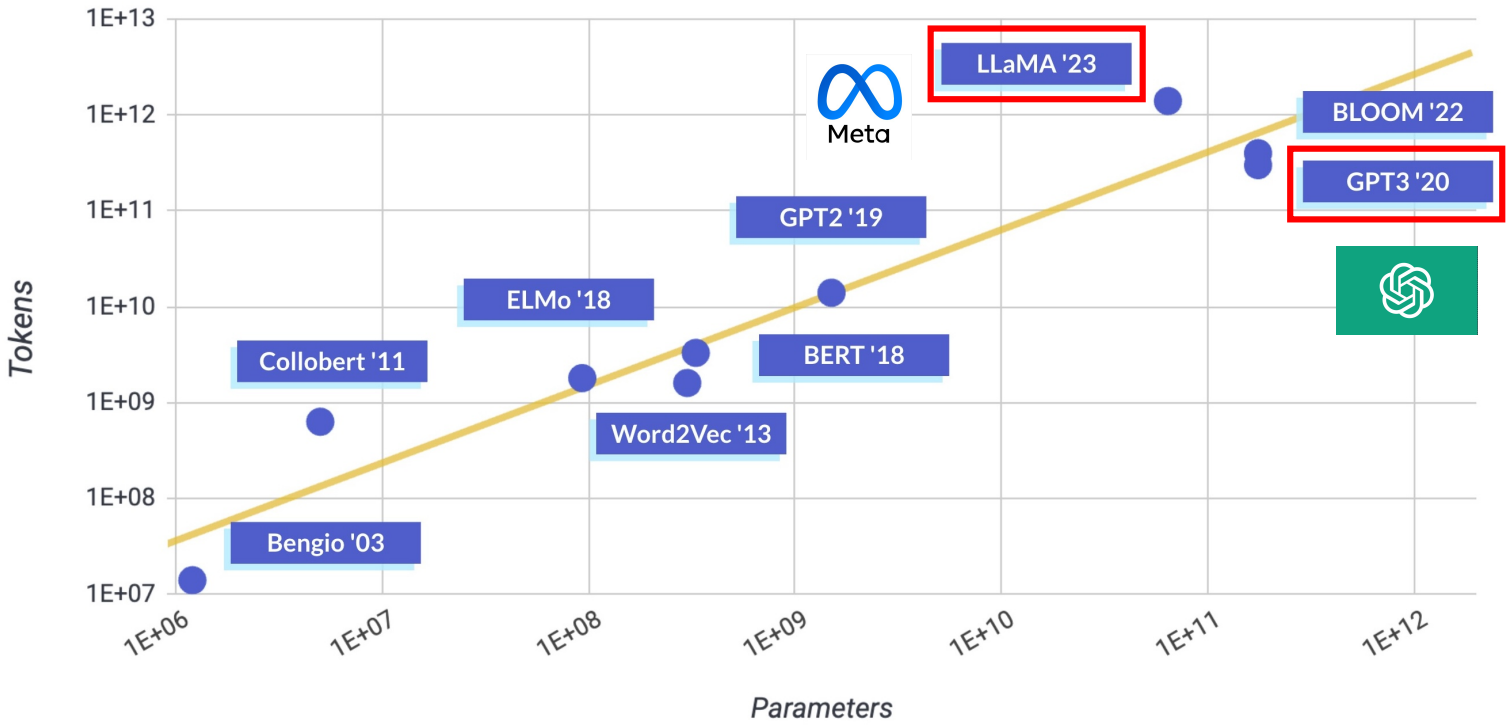

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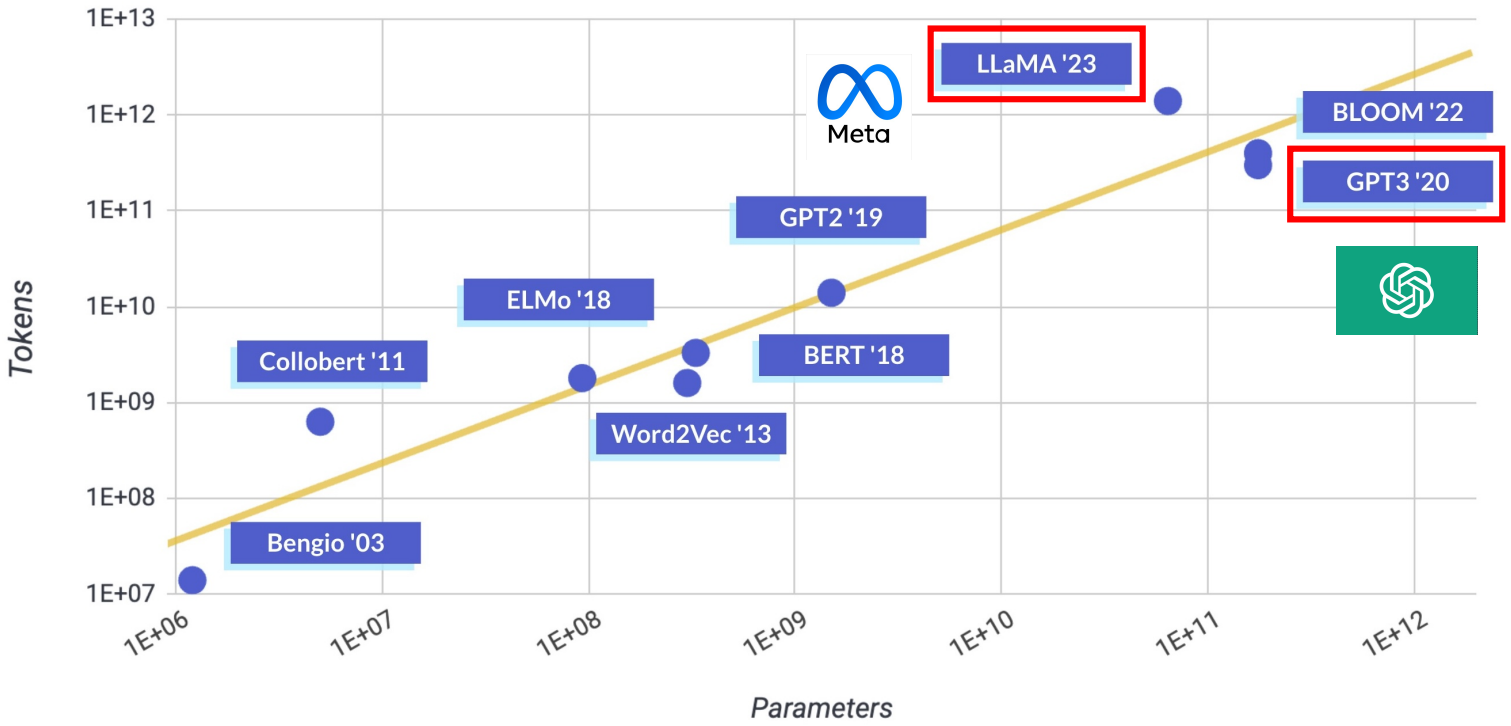

- Industry is currently dominating, we know increasingly less about what these models are and how they are trained.

Open Language Model (OLMo) project at AI2

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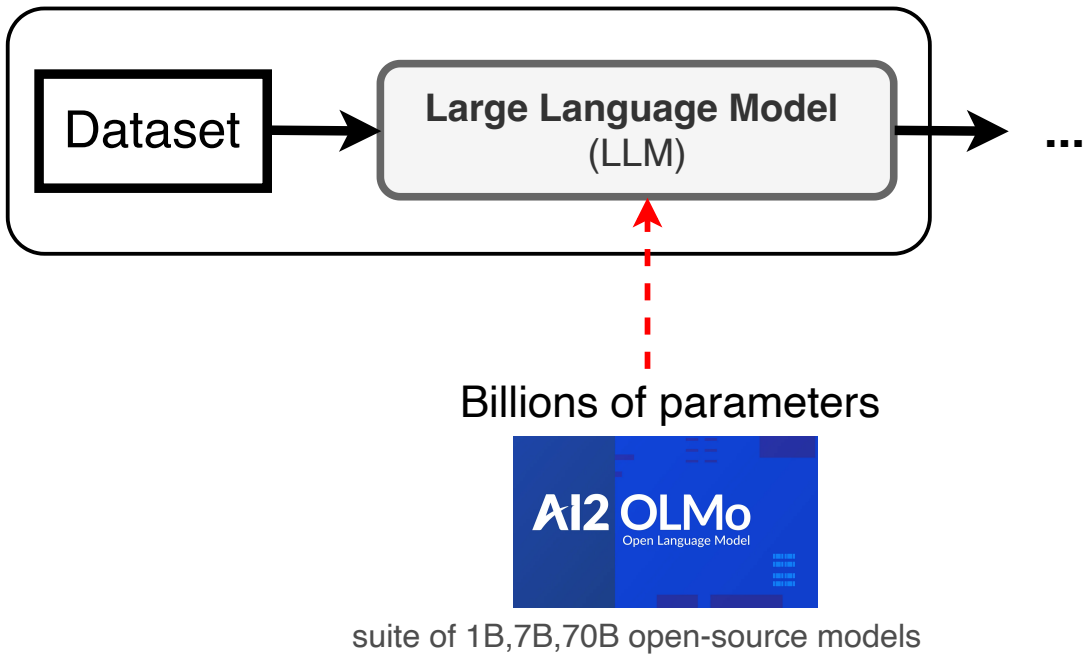

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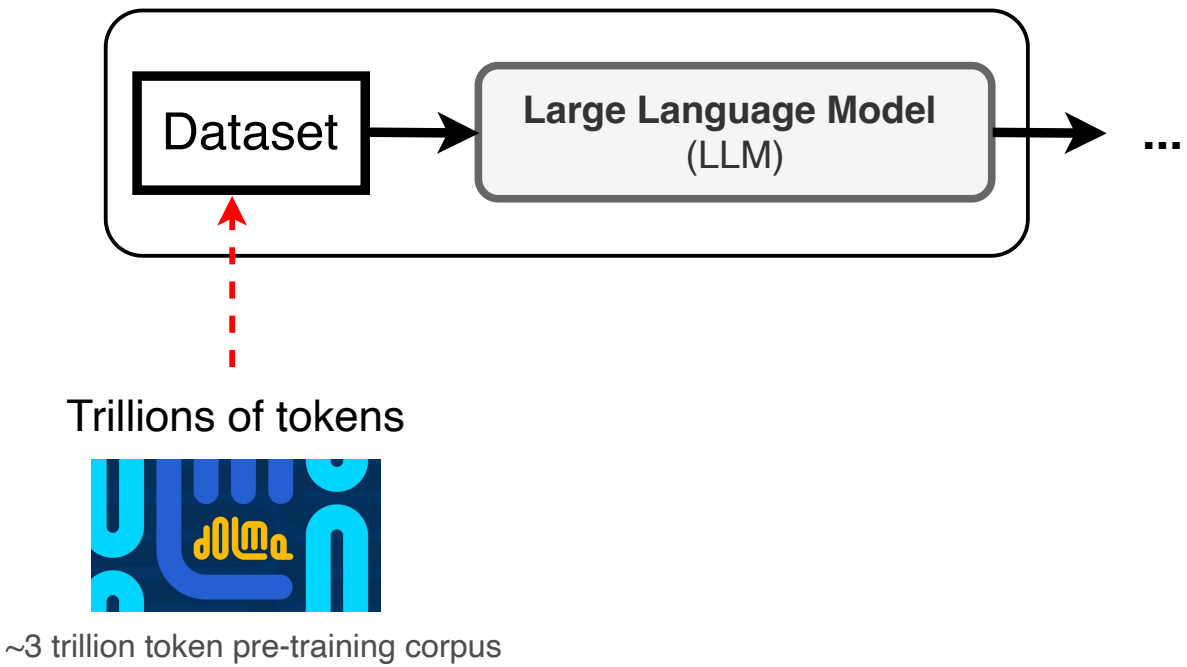

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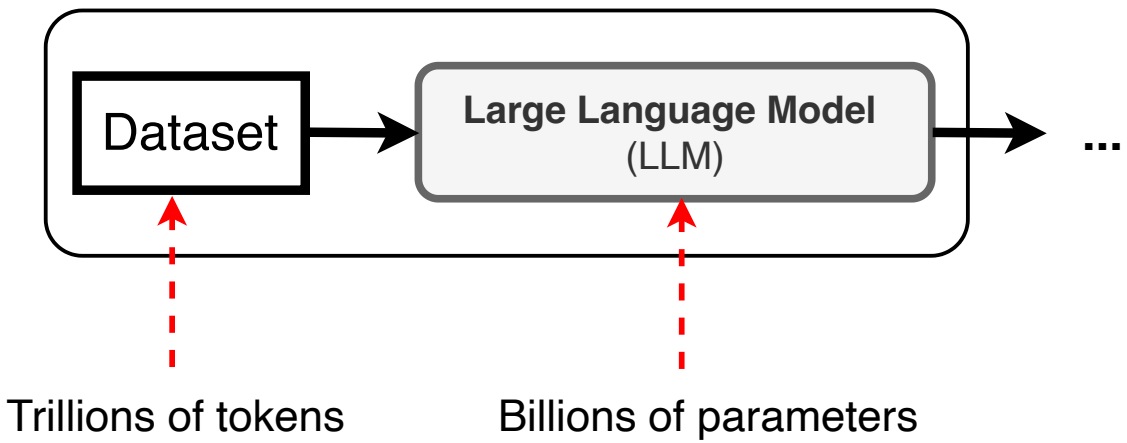

Where does the data come from?

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
	11,519	**4,367**	**2,318**

What can models do? What do they know?

What can models do? Different approaches

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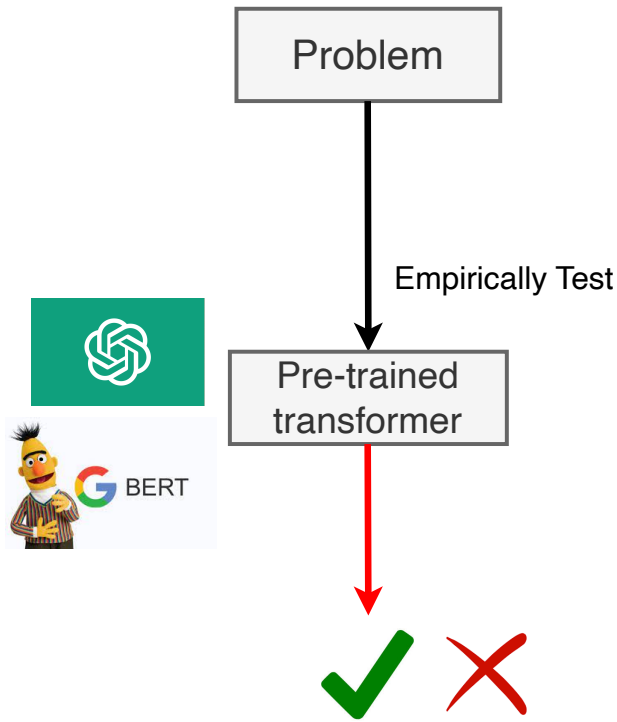
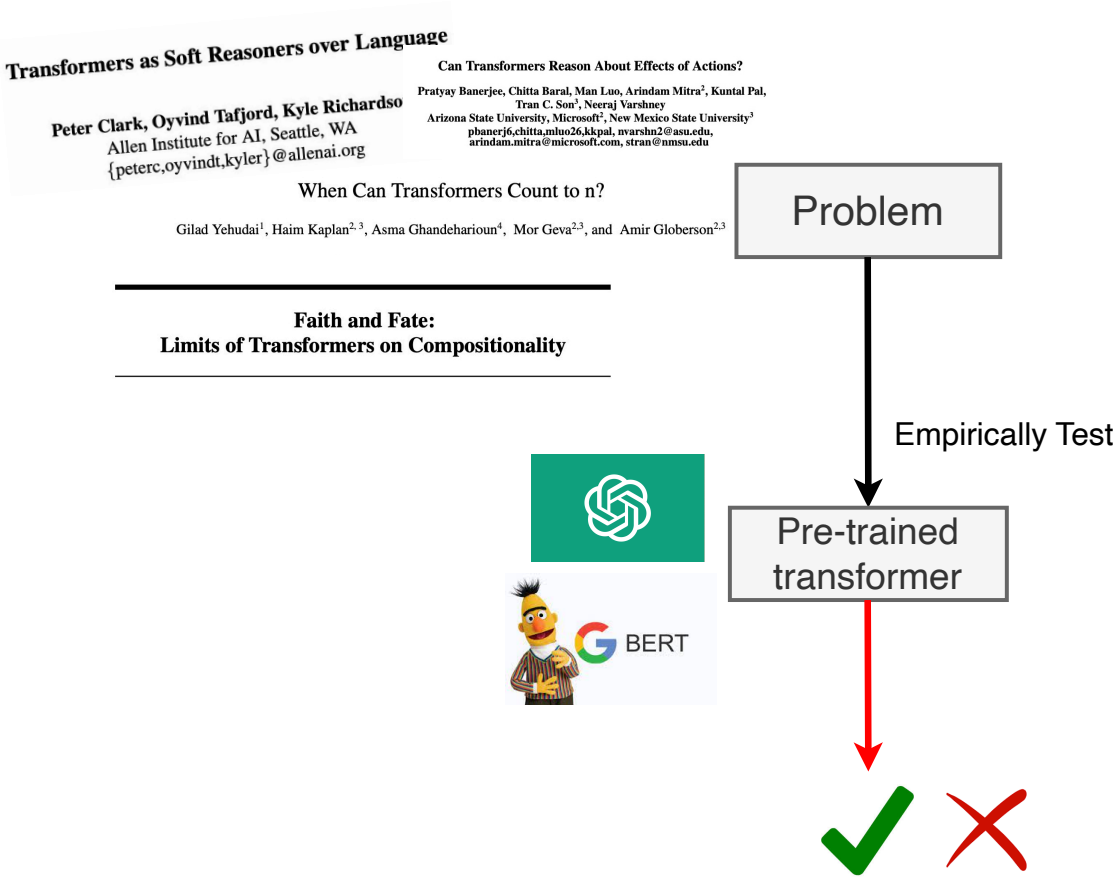


What can models do? Different approaches



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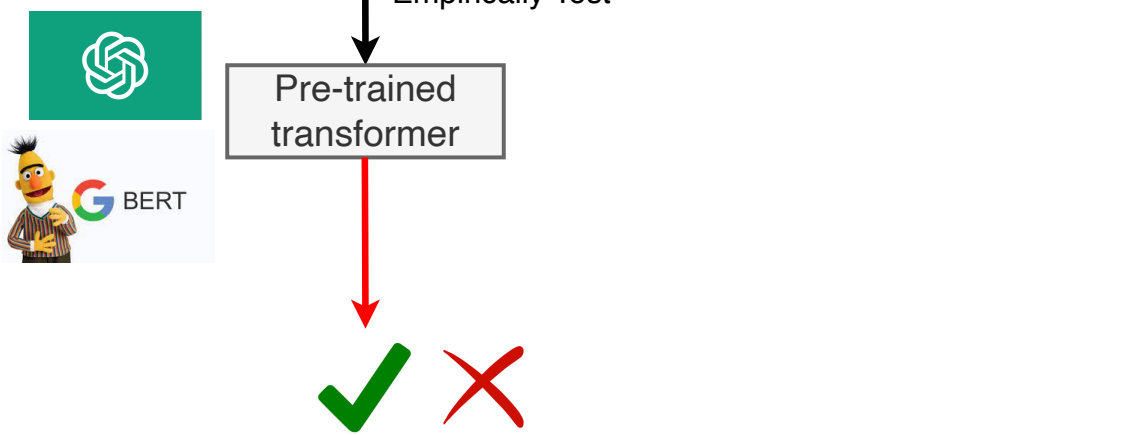
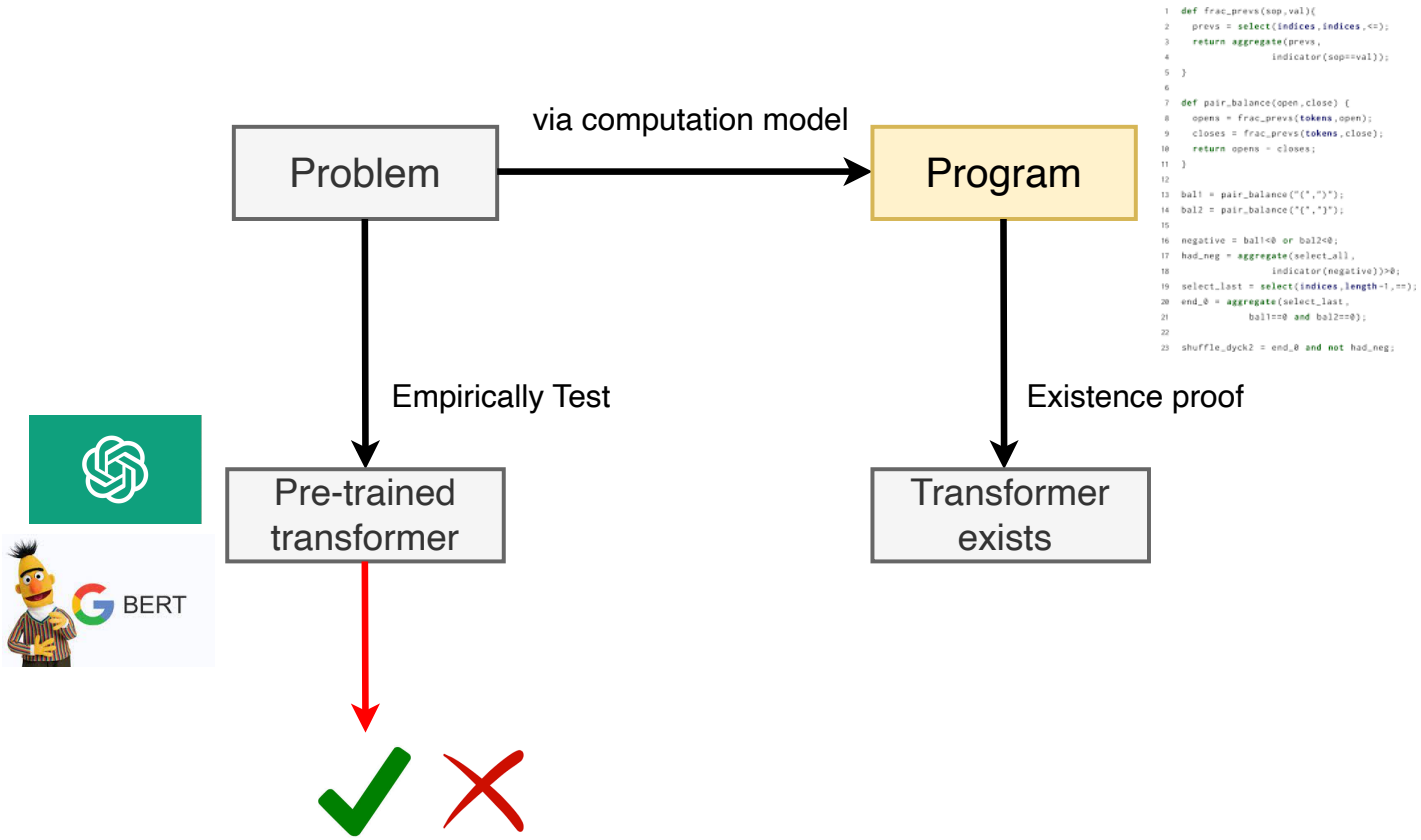



```
def frac_prevs(sop,val){
  prevs = select(indices,indices,<=);
  return aggregate(prevs,
                   indicator(sop==val));
}

def pair_balance(open,close) {
  opens = frac_prevs(tokens,open);
  closes = frac_prevs(tokens,close);
  return opens - closes;
}

bal1 = pair_balance("(",")");
bal2 = pair_balance("[","]");

negative = bal1<0 or bal2<0;
had_neg = aggregate(select_all,
                    indicator(negative))>0;
select_last = select(indices,length-1,==);
end_0 = aggregate(select_last,
                  bal1==0 and bal2==0);

shuffle_dyck2 = end_0 and not had_neg;
```

What can models do? Different approaches



Thinking like a transformer

Thinking Like Transformers

Gail Weiss [1] **Yoav Goldberg** [2 3] **Eran Yahav** [1]

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

Thinking like a transformer

```python
class SimpleBlock(nn.Module):
    def __init__(self, config):
        super().__init__()
        self.attn = SelfAttention(config)
        self.mlp = MLP(config)

    def forward(self, x):
        x = x + self.attn(x) #<--- looking around
        x = x + self.mlp(x) #<--- element-wise
        #   | residual
        return x
```

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Conditions on information processing

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

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- Information across positions can only be shared via attention.

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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.
- Other transformations are element-wise, must have a way to pass around old information.

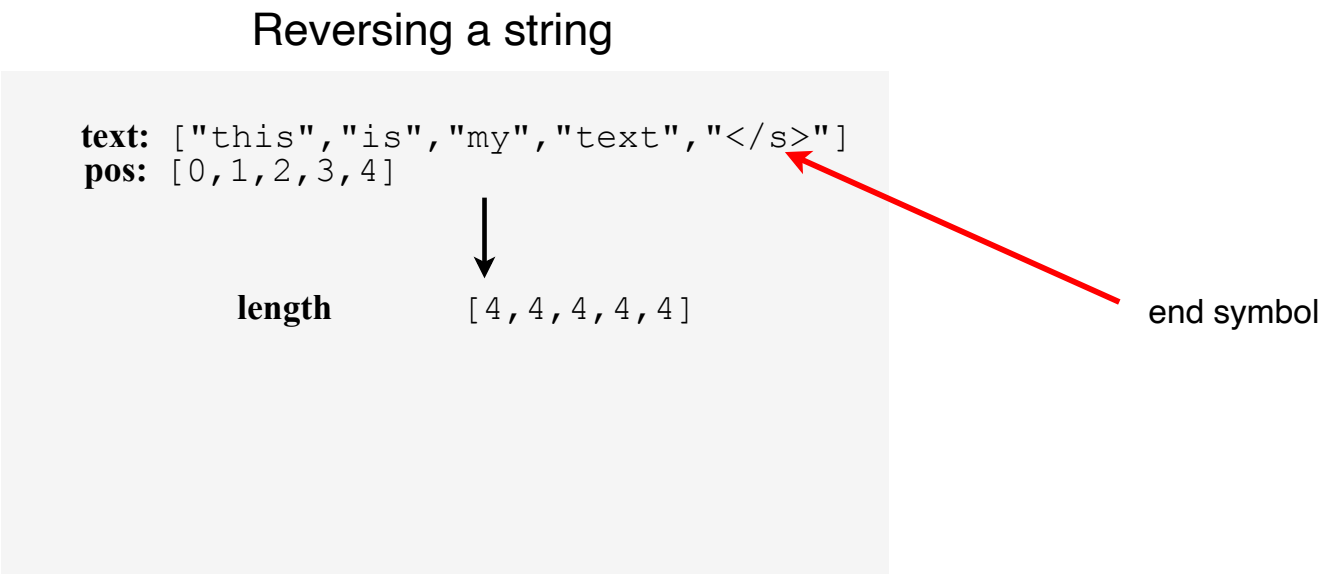
Thinking like a transformer: reversing a string

Reversing a string

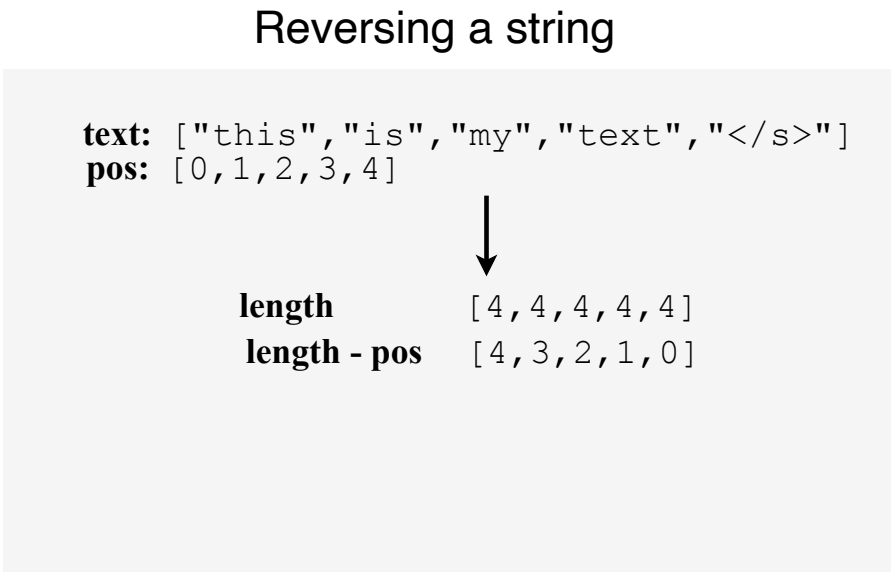
text: ["this","is","my","text","</s>"]
pos: [0,1,2,3,4]

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

Thinking like a transformer: reversing a string



Thinking like a transformer: reversing a string



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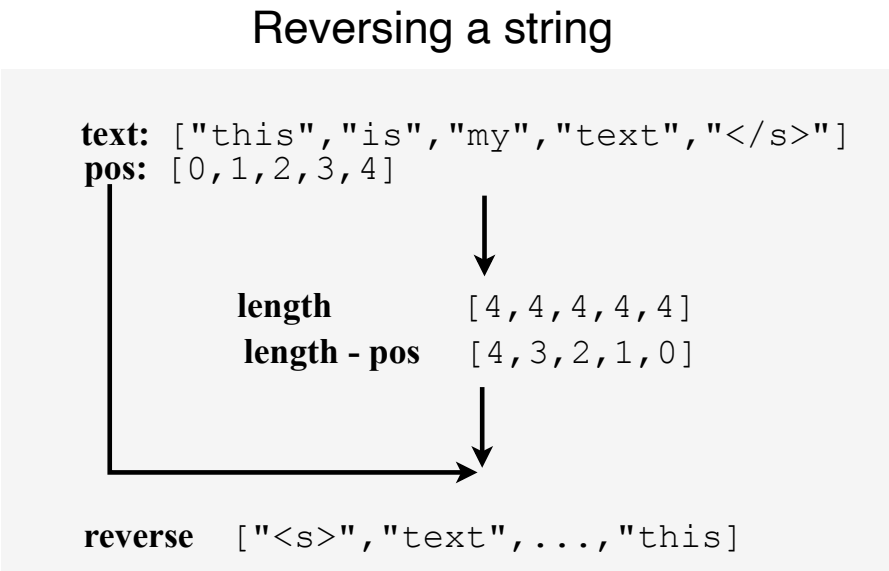

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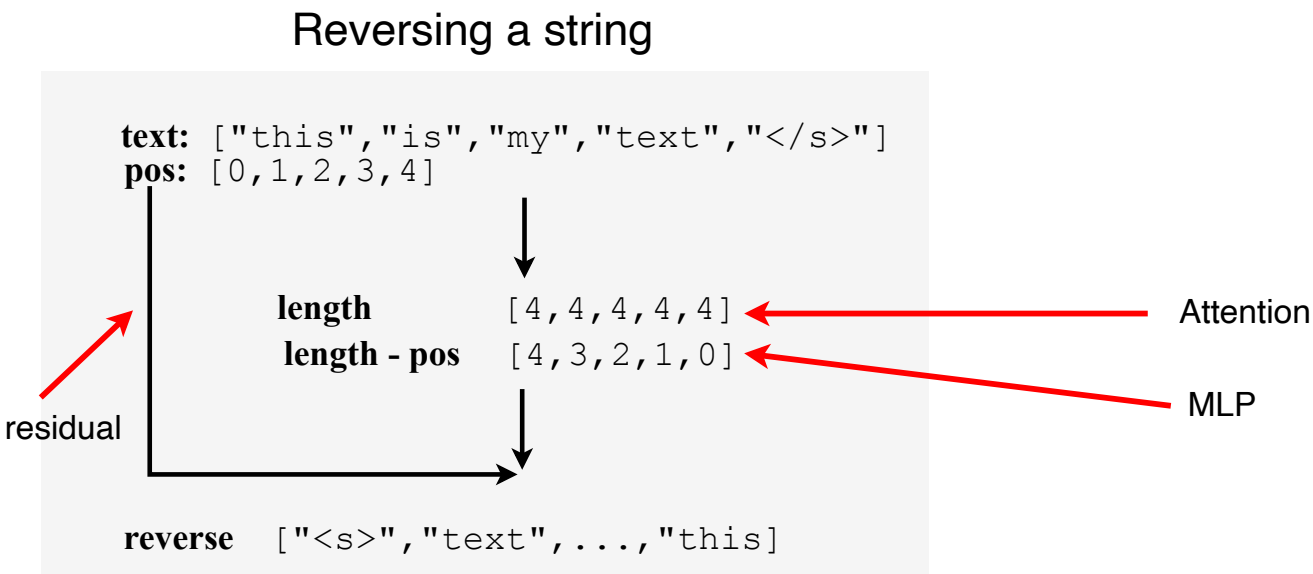

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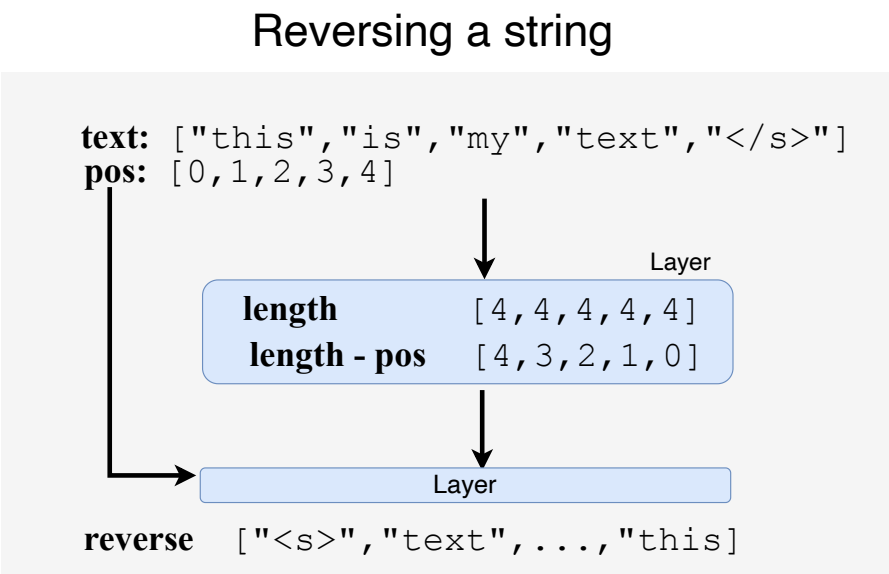

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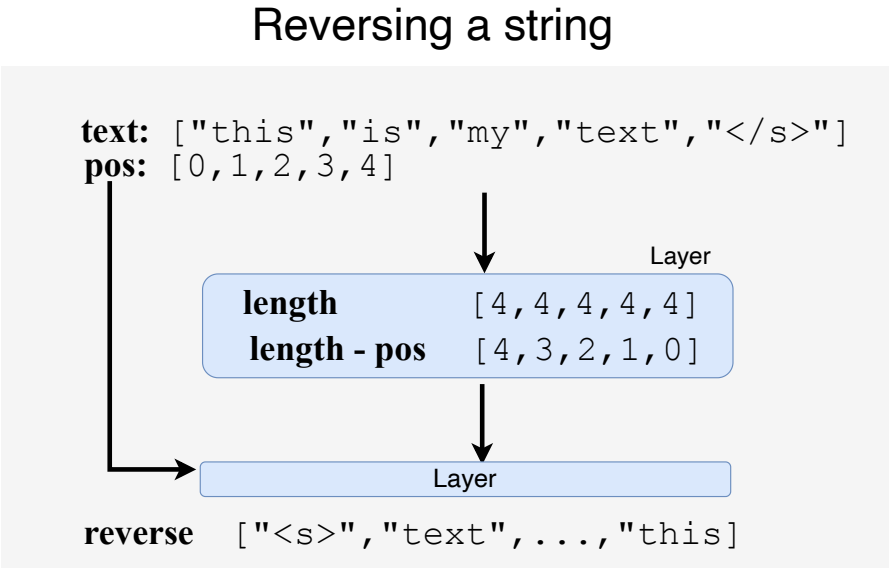

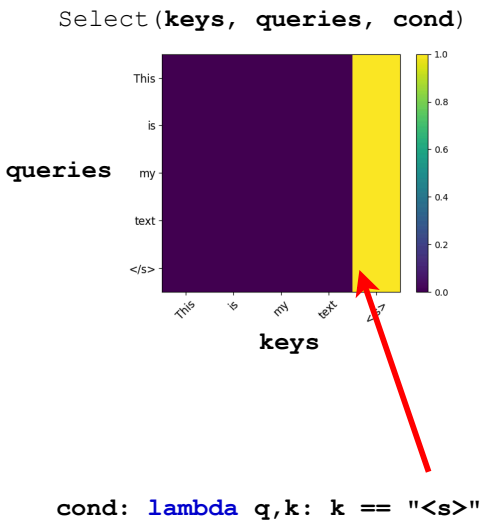

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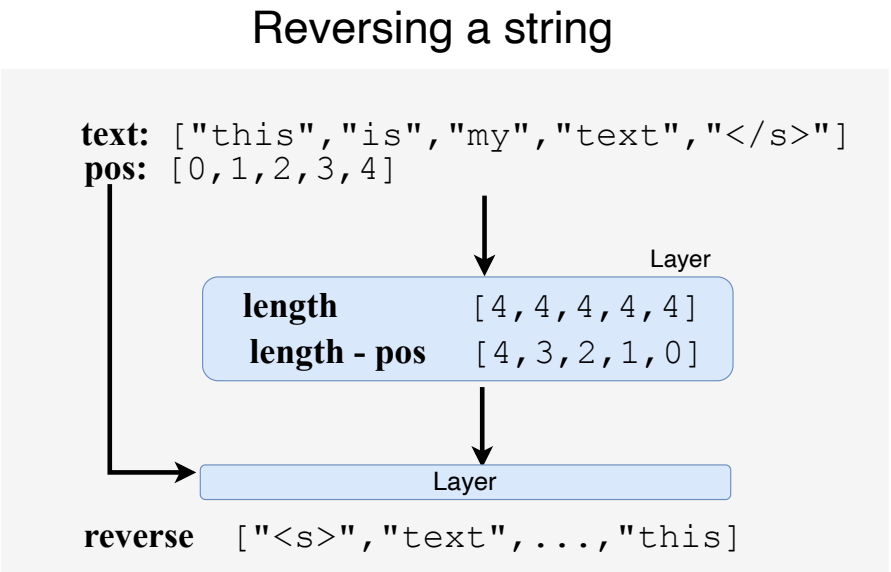
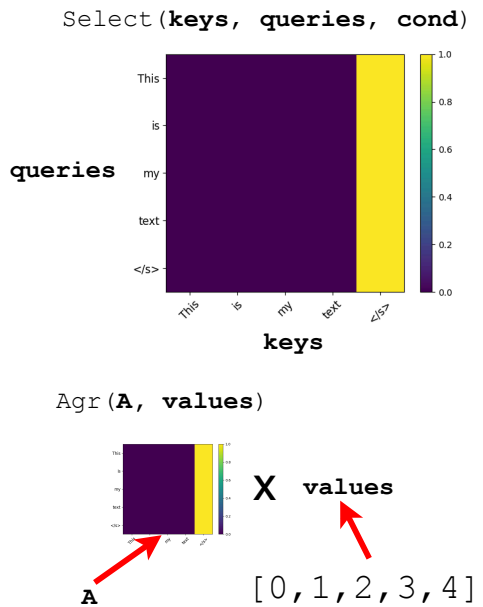
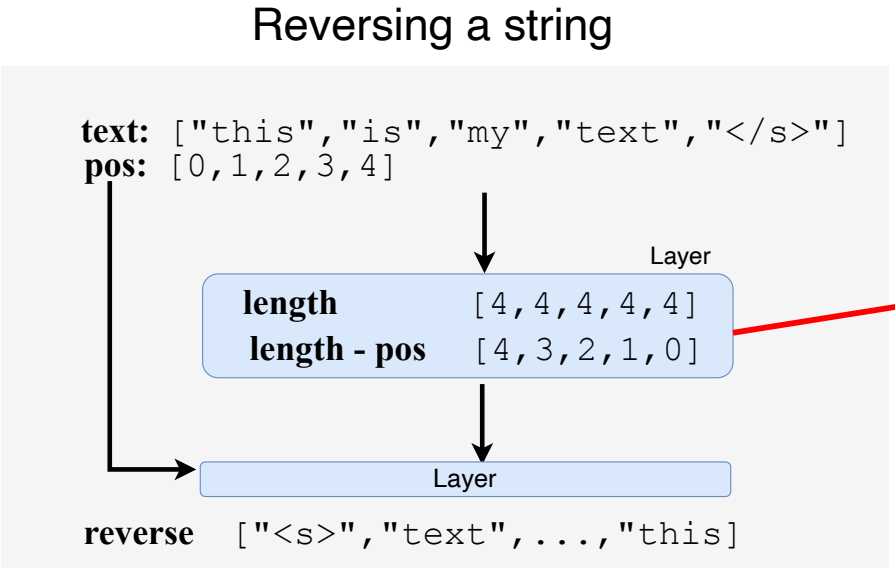
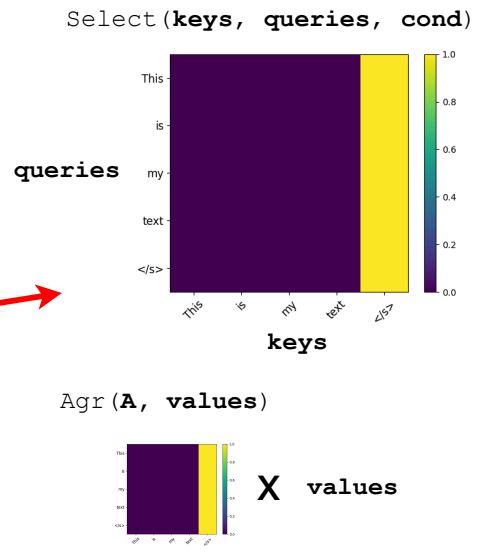




Thinking like a transformer: reversing a string





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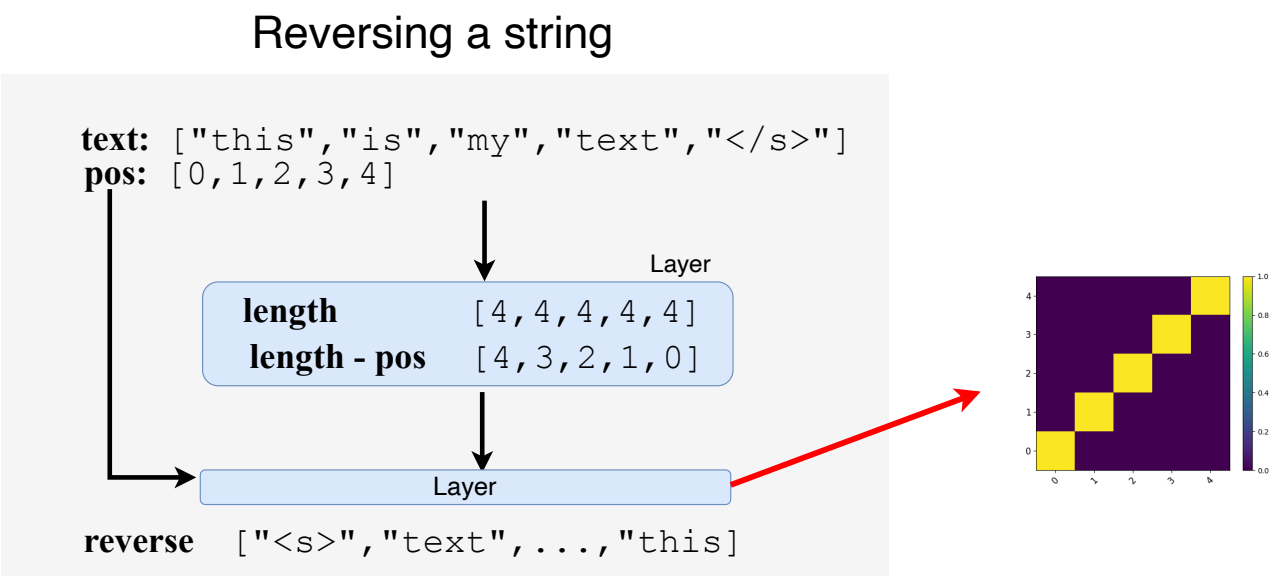


A small implementation of Rasp

```
## credits: https://github.com/apple/ml-np-rasp
import numpy as np

def indices(x):
    return np.arange(len(x), dtype=int)
def select(k,q,pred):
    s = len(k)
    A = np.zeros((s, s), dtype=bool)
    for i in range(s):
        for j in range(s): A[i,j] = pred(q[i],k[j])
    return A
def sel_width(A):
    return np.dot(A, np.ones(len(A))).astype(int)
def aggr(A, v):
    out = np.dot(A, v)
    norm = sel_width(A)
    out = np.divide(out,norm,where=(norm != 0))
    return out.astype(int)
```

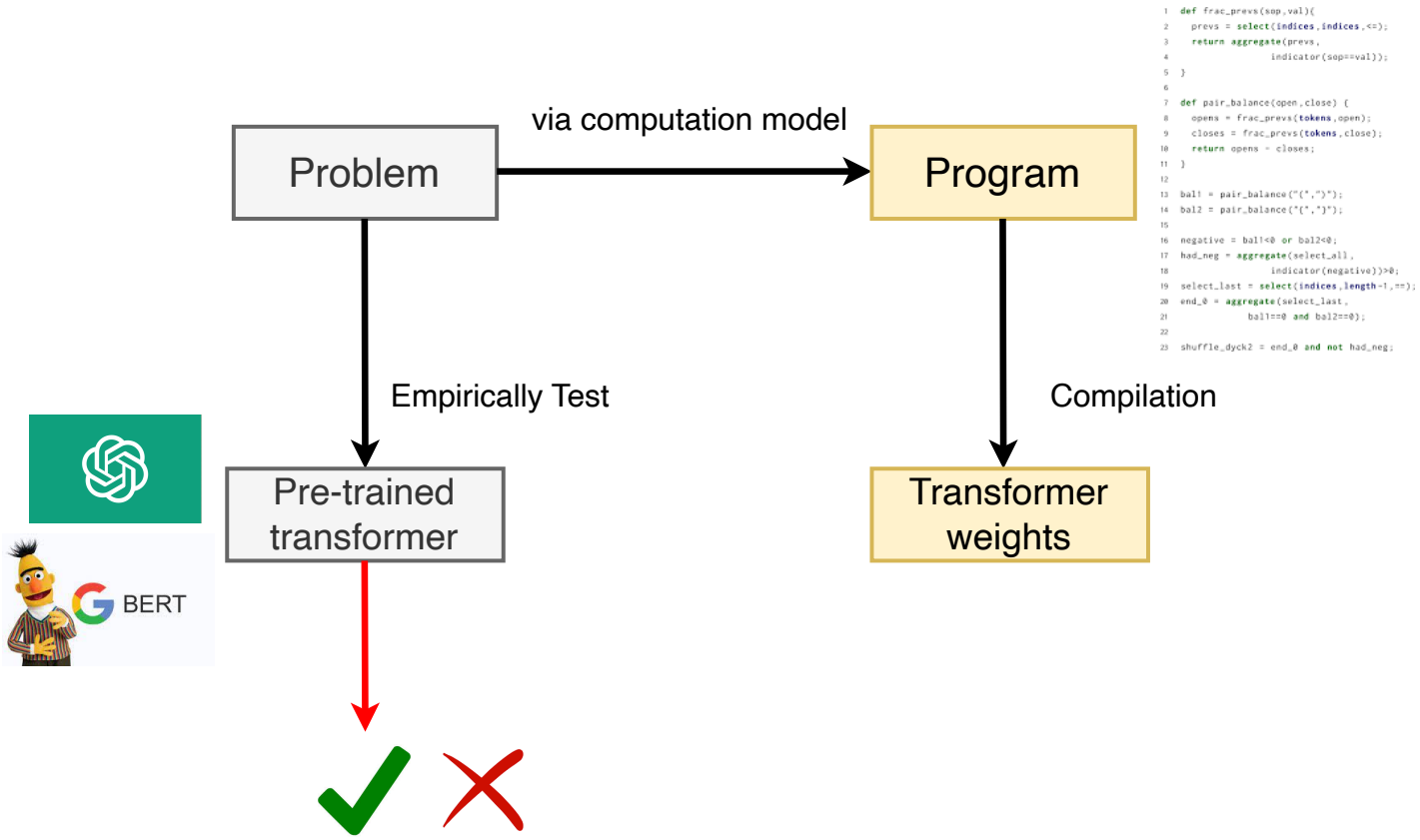
A small implementation of Rasp

```
pos = indices(tokens)
EOS = 0

#### layer 1
# attn layer
length = aggr(
 select(tokens,tokens,lambda q,k : k == EOS),
 pos
)
targets = length - pos #<--- MLP

#### layer 2
output = aggr(
 select(pos,targets,lambda k,v: k == v),
 tokens
)
```

The bigger picture now

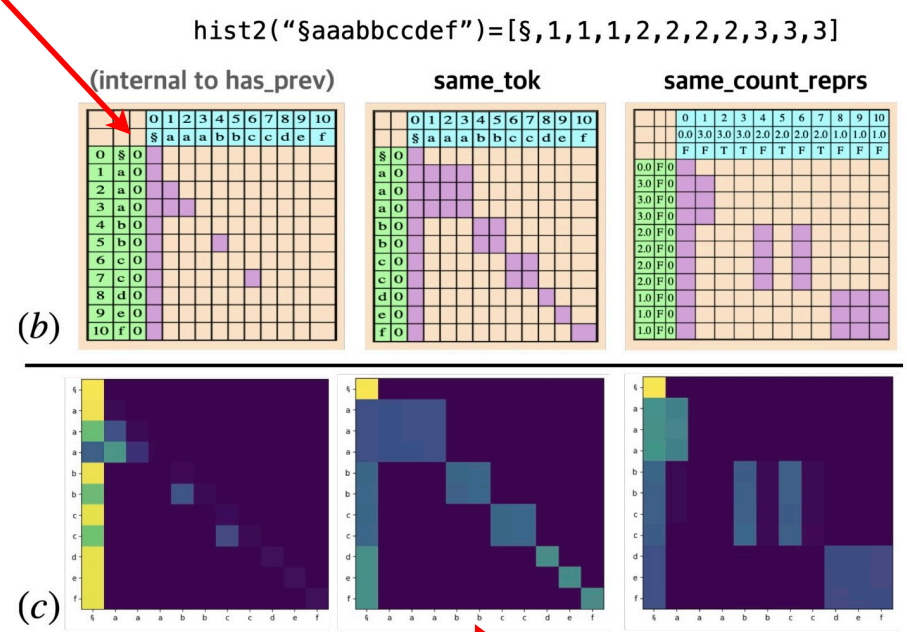


Does a transformer implement my algorithm?

Target attention

```
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);
```

(a)



Rasp program

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 [8]	3	1	99.85%	✗

Real transformer attention patterns

Recent efforts

Tracr: Compiled Transformers as a Laboratory for Interpretability

David Lindner[†] Google DeepMind
János Kramár Google DeepMind
Sebastian Farquhar Google DeepMind
Matthew Rahtz Google DeepMind
Thomas McGrath Google DeepMind
Vladimir Mikulik[†] Google DeepMind

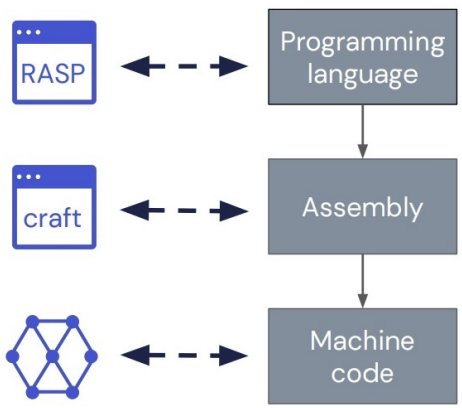


Figure 3: `Tracr` translates RASP to `Craft` and then to model weights, analogous to how programming languages are first translated to assembly then to machine code.

Recent efforts

Learning Transformer Programs

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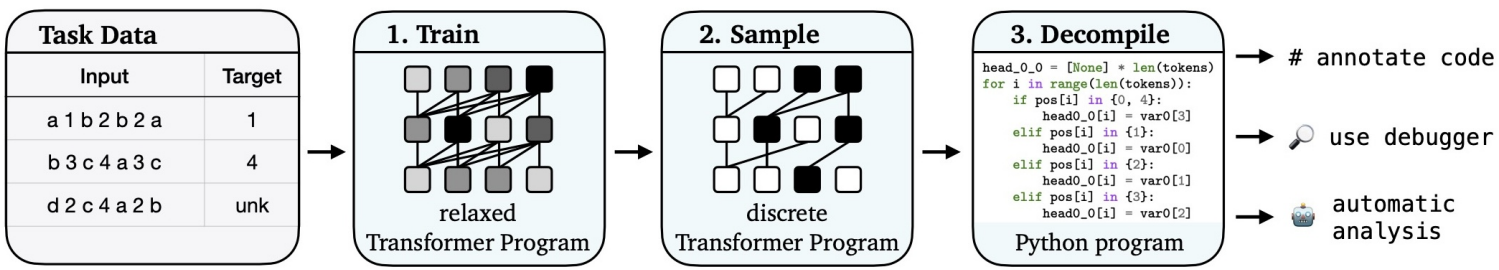

Figure 1: We design a modified Transformer that can be trained on data and then automatically discretized and converted into a human-readable program. The program is functionally identifical to the Transformer, but easier to understand—for example, using an off-the-shelf Python debugger.

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Next lecture: Declarative approaches to model training.

Thank you.

References I

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