CS 760: Machine Learning
Language Models

University of Wisconsin-Madison

Outline

- **Language Models & NLP**
  - RNNs, word embeddings, attention
- **Transformer Model**
  - Properties, architecture breakdown
- **Transformer-based Models**
  - BERT, GPTs, Foundation Models

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Language Models: Word Embeddings

- One way to encode words: one-hot vectors
  - Want something smarter…

Distributional semantics: account for relationships

- Representations should be close/similar to other words that appear in a similar context

Dense vectors:

$$\text{dog} = \begin{bmatrix} 0.13 & 0.87 & -0.23 & 0.46 & 0.87 & -0.31 \end{bmatrix}^T$$

$$\text{cat} = \begin{bmatrix} 0.07 & 1.03 & -0.43 & -0.21 & 1.11 & -0.34 \end{bmatrix}^T$$

AKA **word embeddings**

Training **Word Embeddings**

Many approaches (very popular 2010-present)

- Word2vec: a famous approach
- Write out a likelihood

Windows of length 2a

$$L(\theta) = \prod_{t=1}^{T} \prod_{-a \leq j \leq a} P(w_{t+j}|w_t, \theta)$$

Our word vectors (weights)

All positions

Training **Word Embeddings**

- Word2vec likelihood $$L(\theta) = \prod_{t=1}^{T} \prod_{-a \leq j \leq a} P(w_{t+j}|w_t, \theta)$$

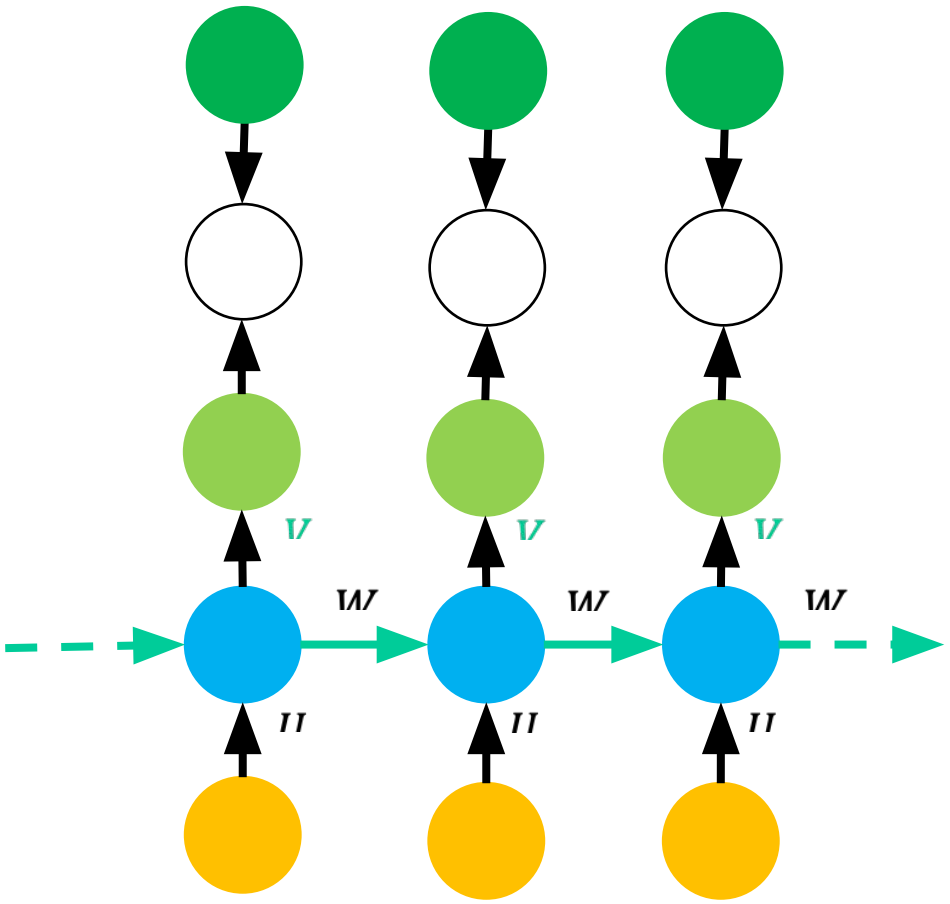
- Expression for the probability:

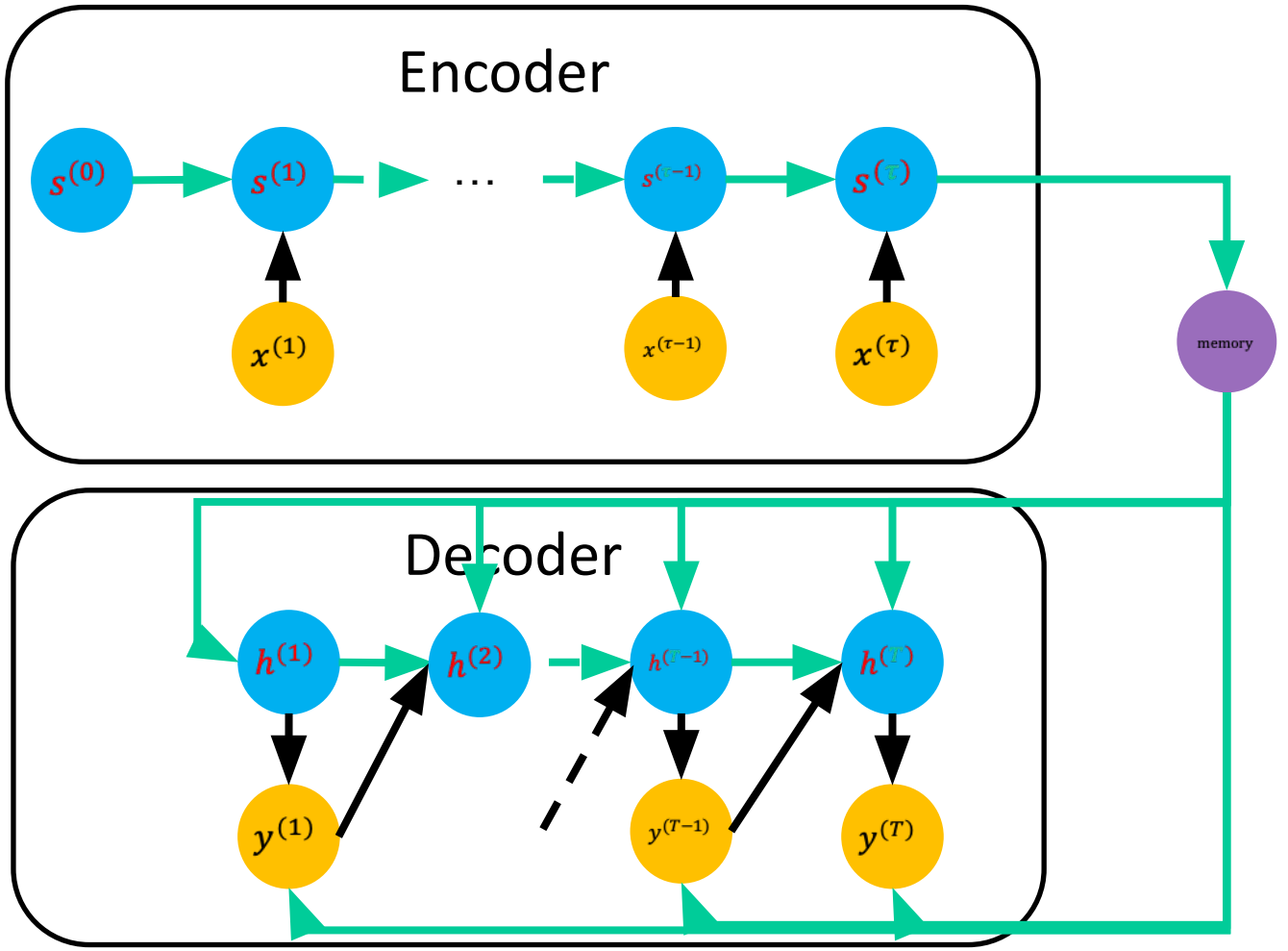
$$P(w'|w, \theta) = \frac{\exp((\theta_{w',o})^{\mathsf{T}} \theta_{w,c})}{\sum_{v \in V} \exp((\theta_{v,o})^{\mathsf{T}} \theta_{w,c})}$$

  - $\theta_{w,o}$: occurrence vector for word w
  - $\theta_{w,c}$: context vector for word w

Language Models: RNN Review

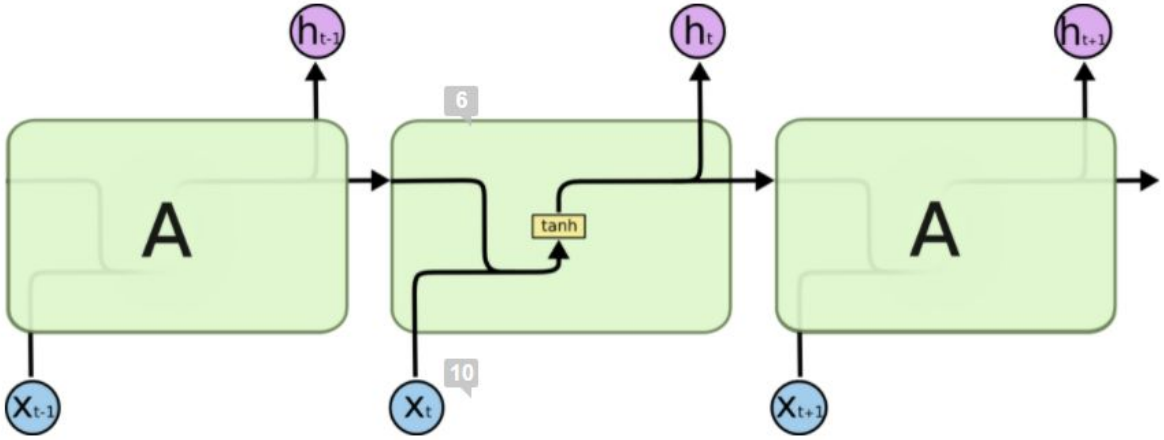
- Classical RNN model / Encoder-Decoder variant:



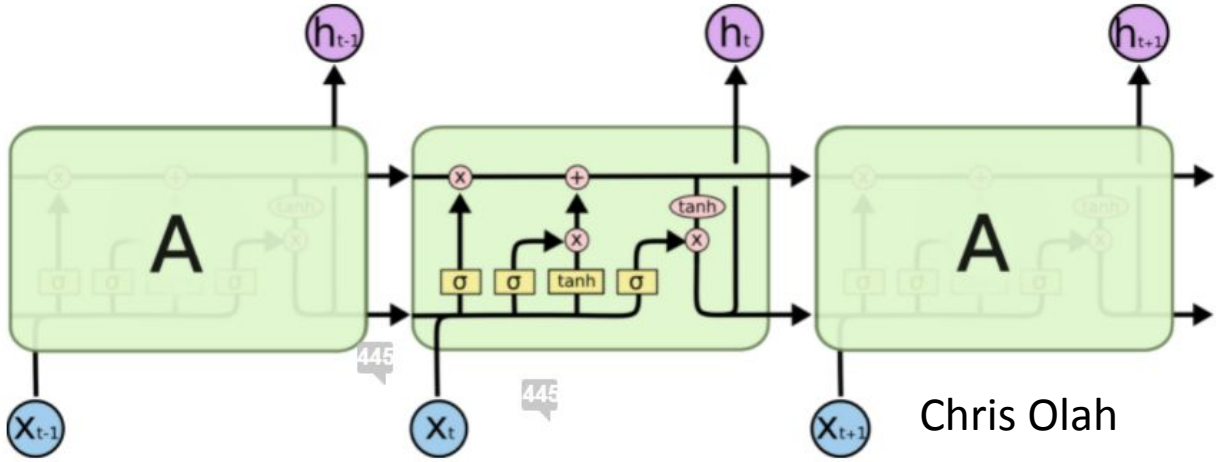


Language Models: LSTM Review

- RNN: can write structure as:



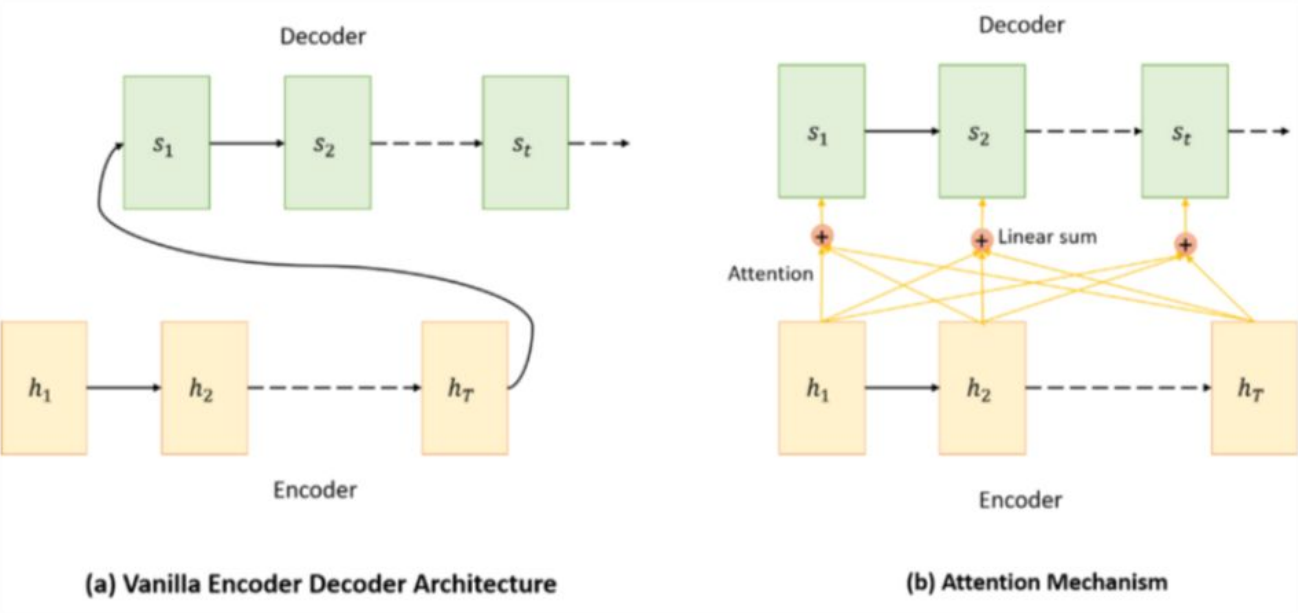
- Long Short-Term Memory: deals with problem. Cell:



Chris Olah

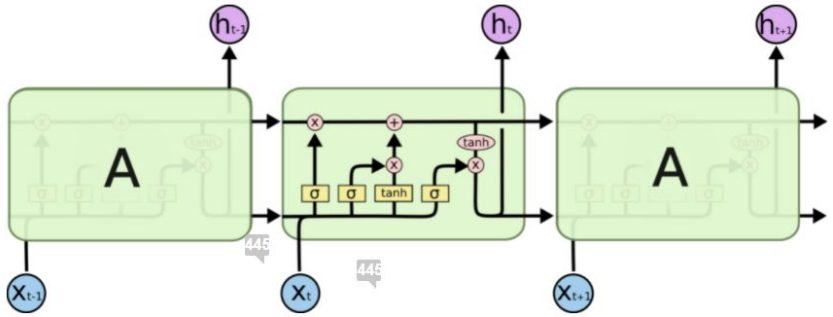
Language Models: Attention

- One challenge: dealing with the hidden state
  - Everything gets compressed there
  - Might lose information
- Solution: **attention** mechanism
  - Similar to residual connections in ResNets!

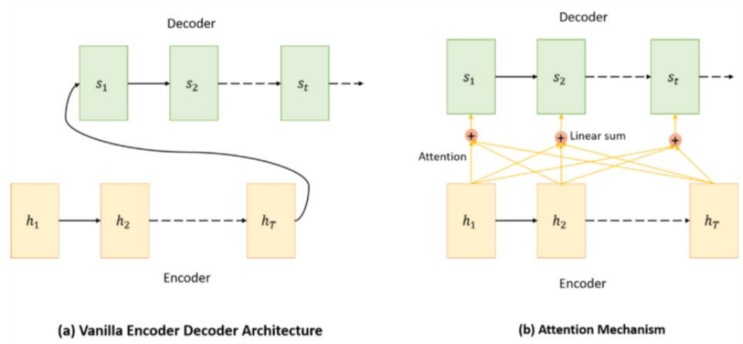


Language Models: Putting it All Together

- Before 2017: best language models
  - Use encoder/decoder architectures based on **RNNs**
  - Use **word embeddings** for word representations
  - Use attention mechanisms



$$\text{dog} = \begin{bmatrix} 0.13 & 0.87 & -0.23 & 0.46 & 0.87 & -0.31 \end{bmatrix}^T$$



(a) Vanilla Encoder Decoder Architecture

(b) Attention Mechanism

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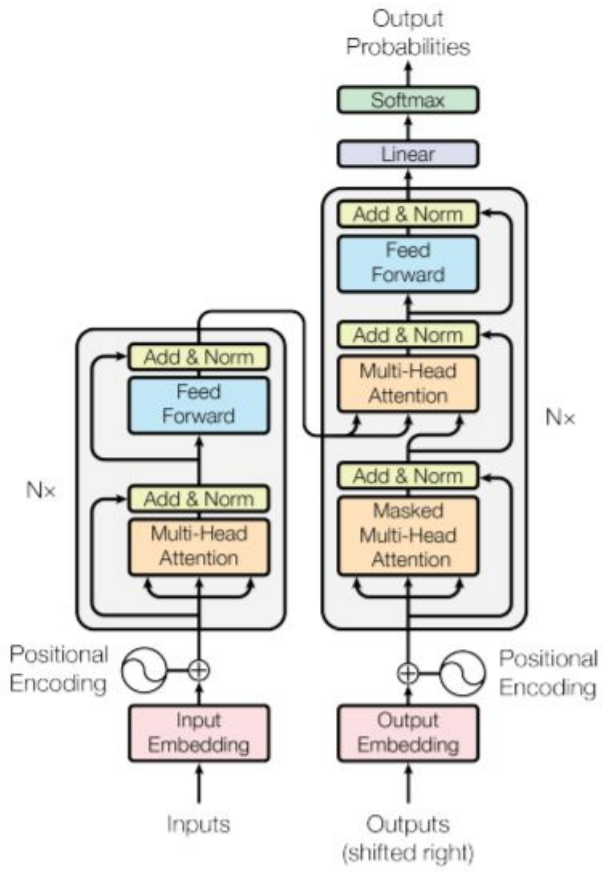
Transformers: Idea

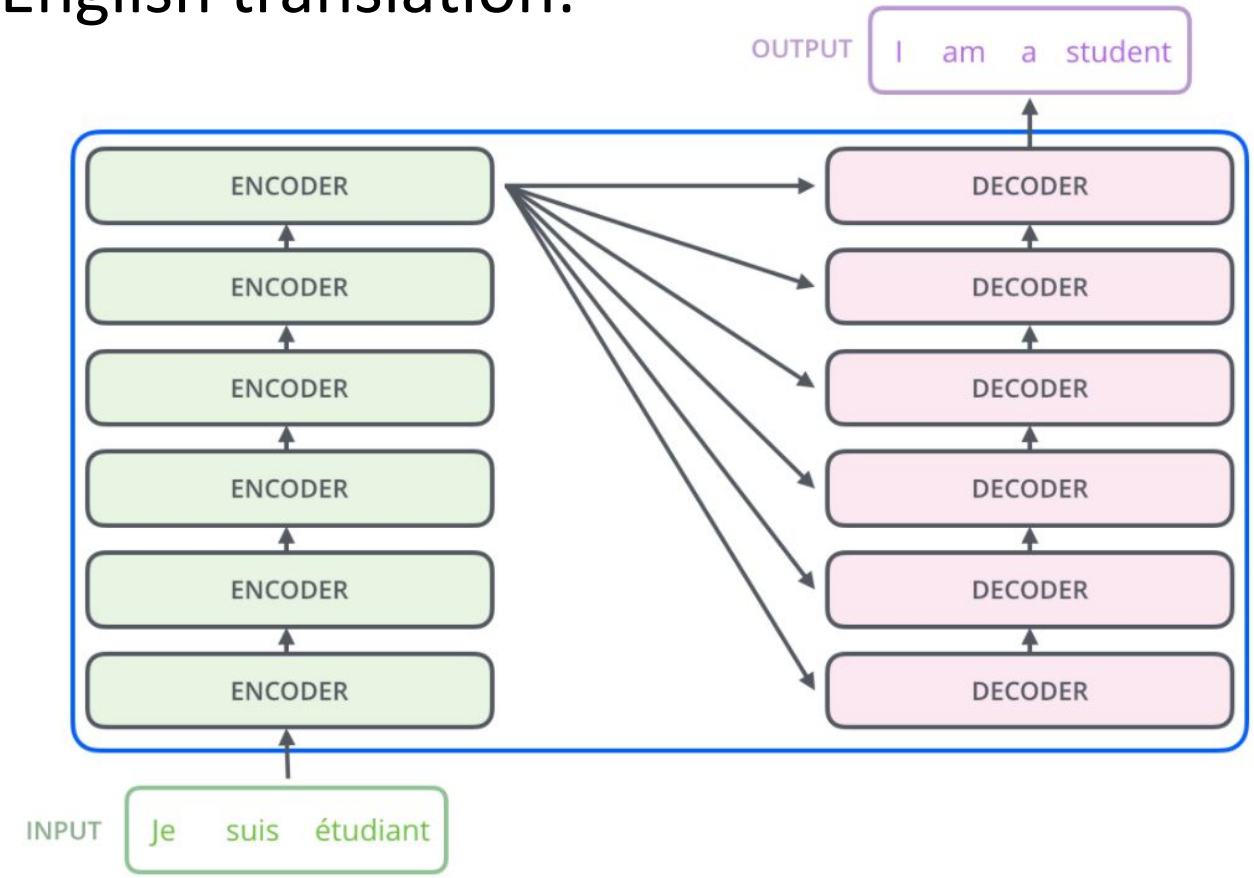
- Initial goal for an architecture: encoder-decoder
  - Get **rid of recurrence**
  - Replace with **self-attention**



Vaswani et al. ‘17

Transformers: Architecture

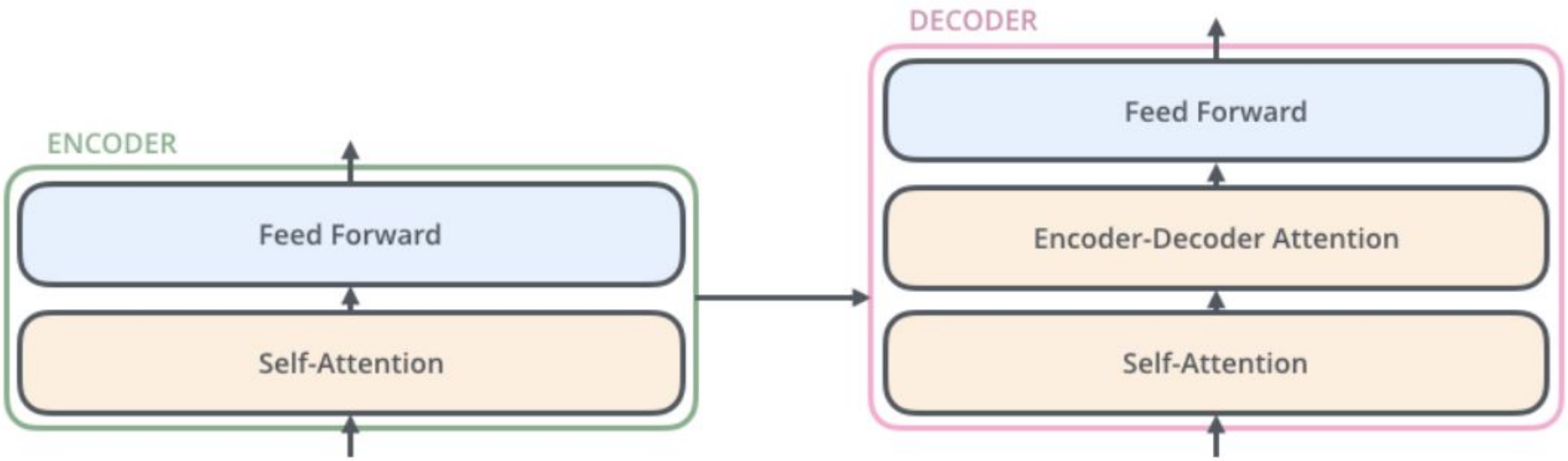
- Sequence-sequence model with **stacked** encoders/decoders:
  - For example, for French-English translation:



Excellent resource: https://jalammar.github.io/illustrated-transformer/

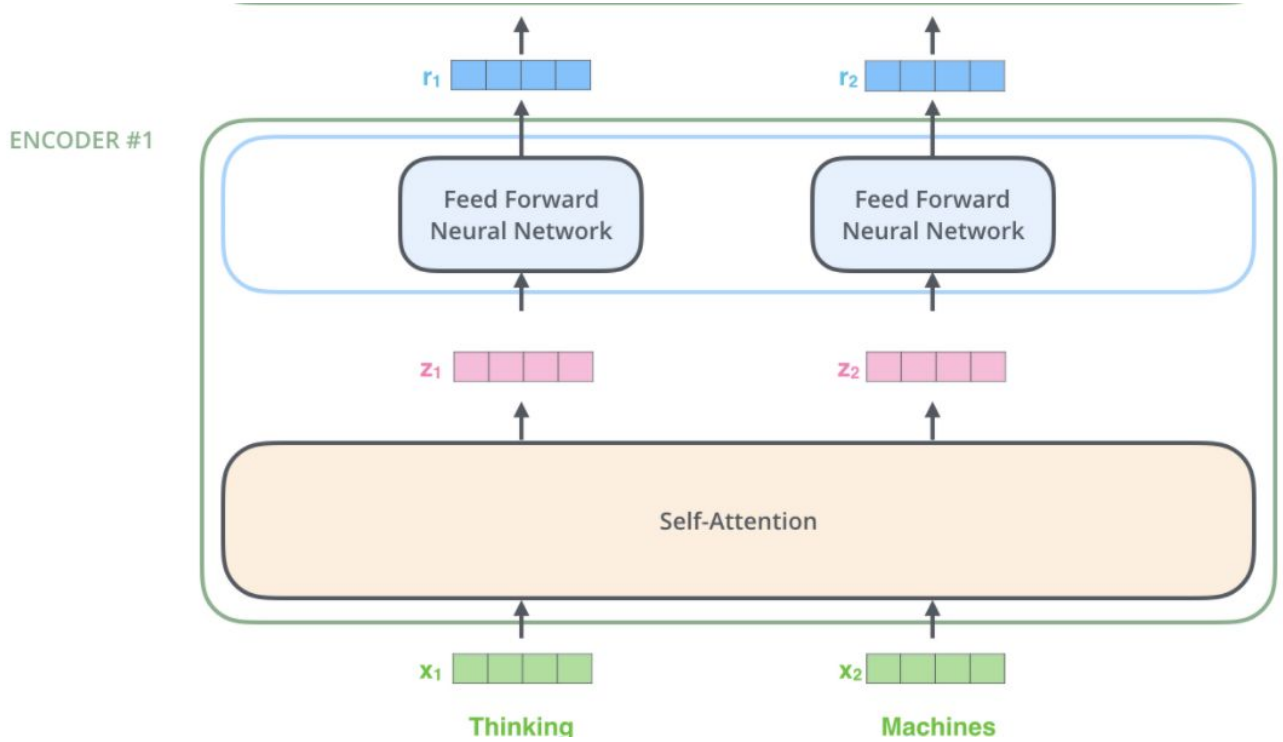
Transformers: Architecture

- Sequence-sequence model with **stacked** encoders/decoders:
  - What's inside each encoder/decoder unit?



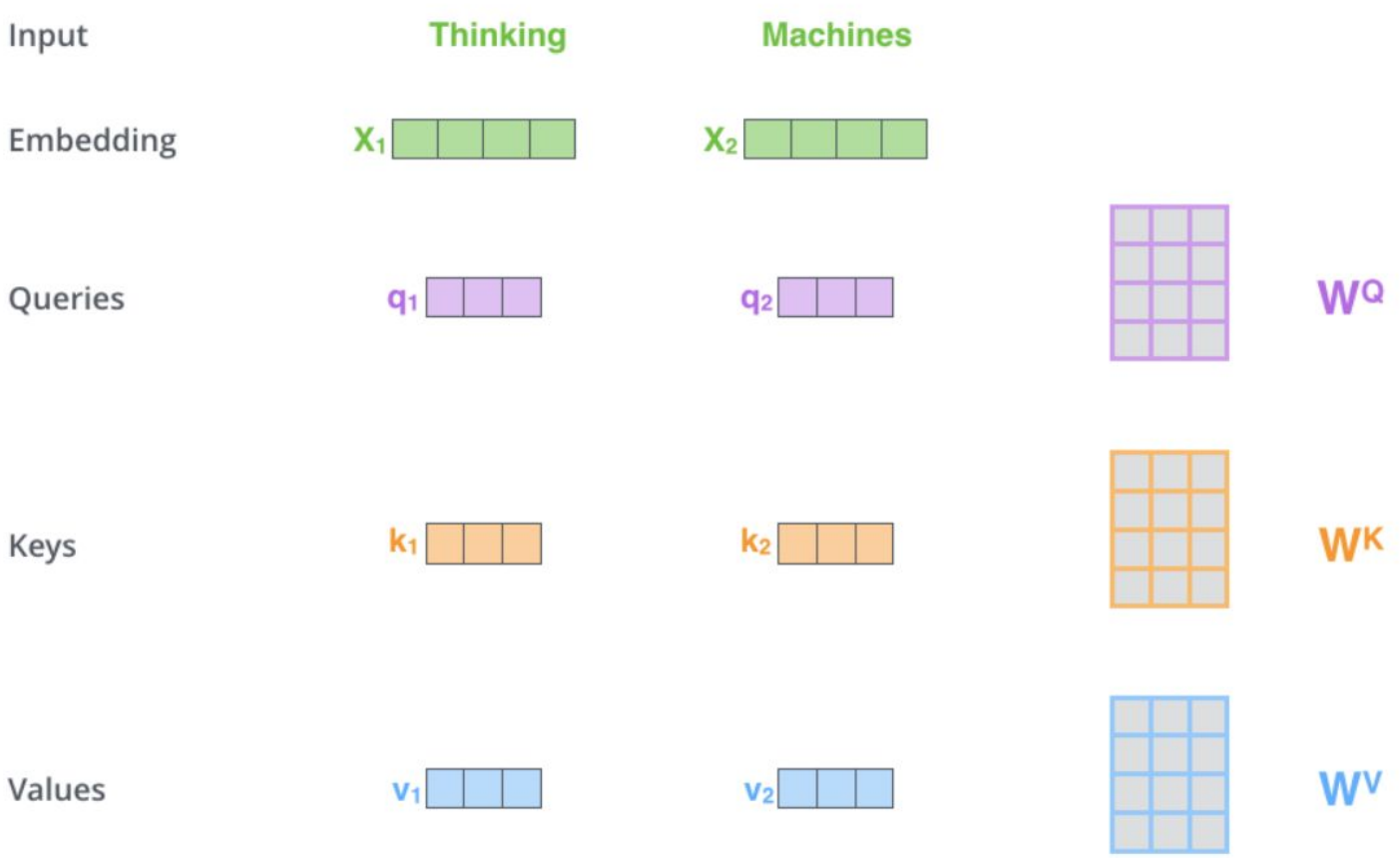
Transformers: Inside an Encoder

- Let's take a look at the encoder. Two components:
  - 1. **Self-attention** layer
  - 2. **Feedforward nets**



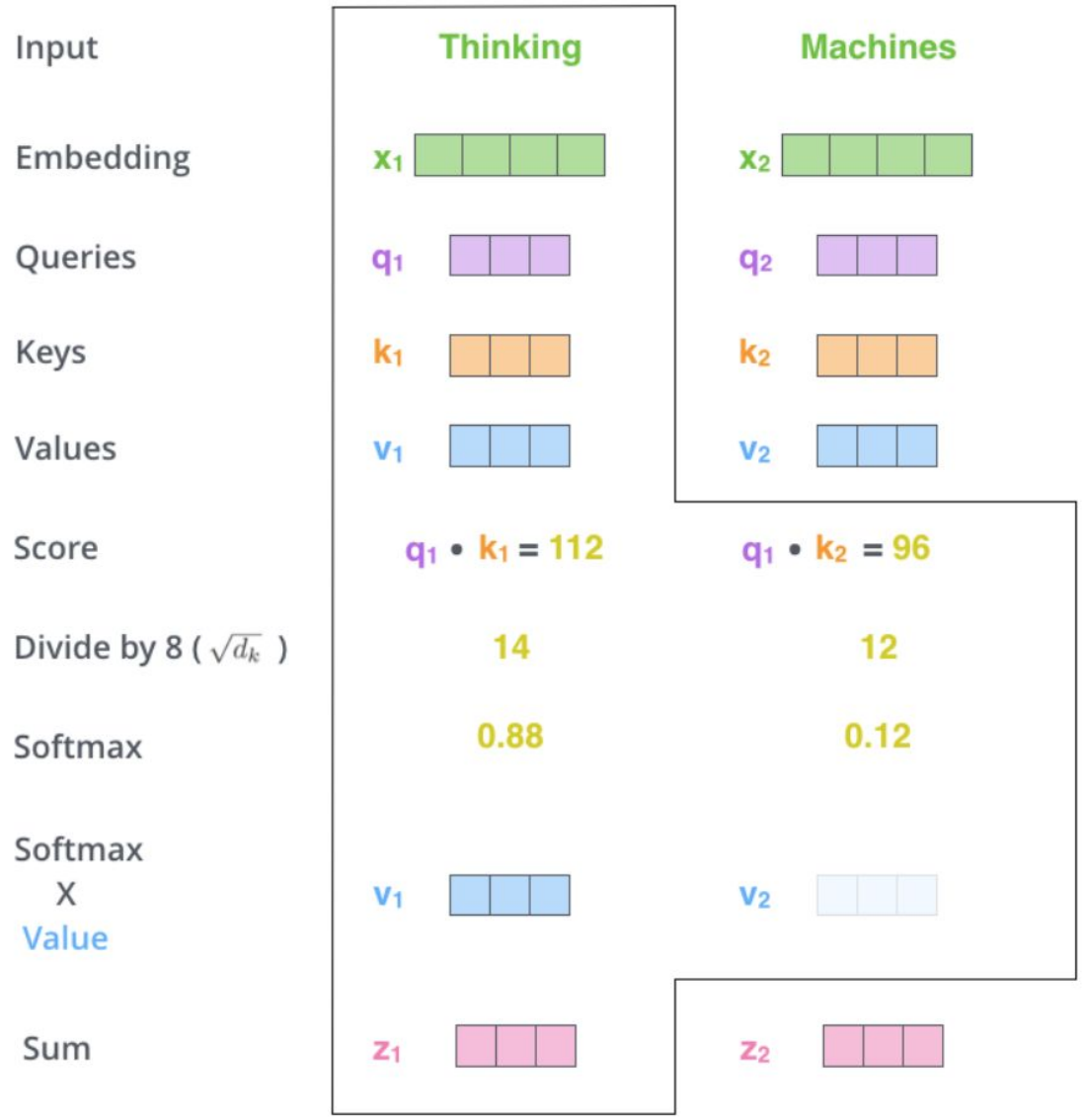
Transformers: Self-Attention

- Self-attention is the key layer in a transformer stack
  - Get 3 vectors for each embedding: **Query**, **Key**, **Value**



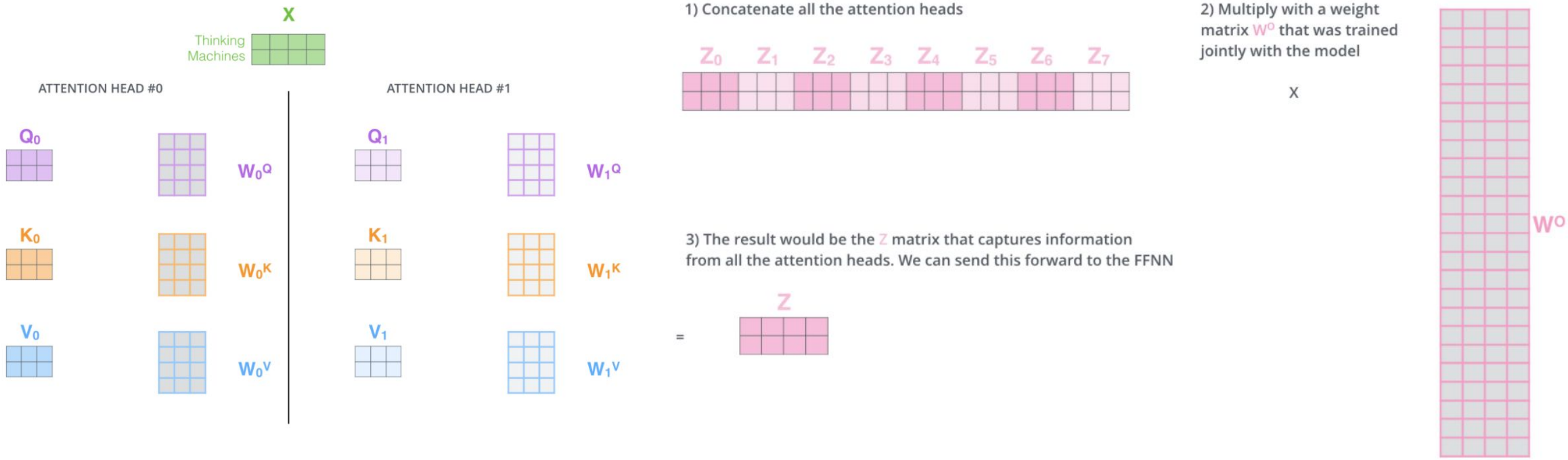
Transformers: Self-Attention

- Self-attention is the key layer in a transformer stack
  - Illustration. Recall the three vectors for each embedding: **Query**, **Key**, **Value**
  - The sum values are the outputs of the self-attention layer
  - Send these to feedforward NNs



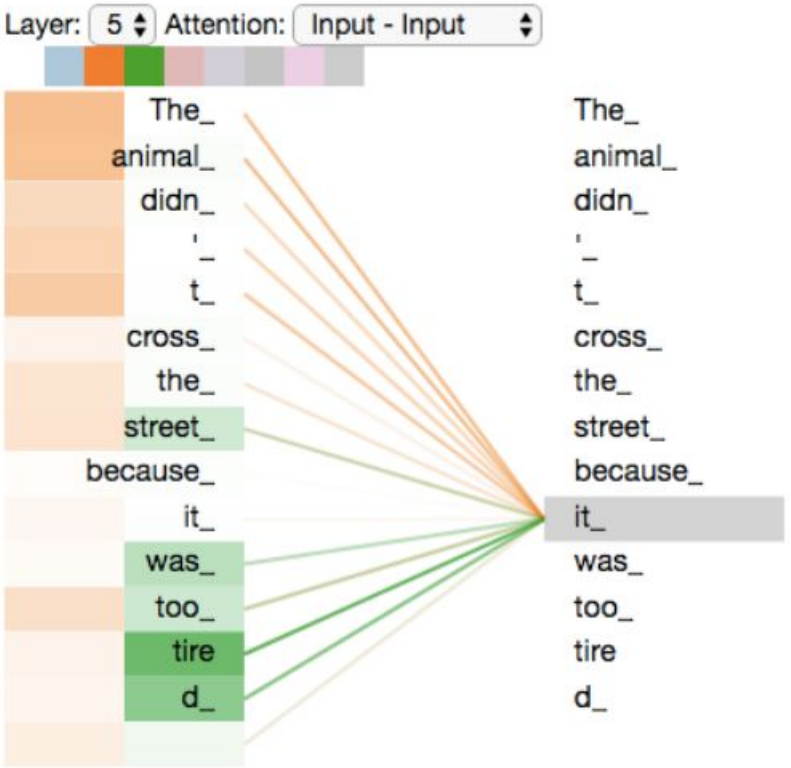
Transformers: Multi-Headed Attention

- We can do this multiple times in parallel
  - Called multiple heads
  - Need to combine the resulting output sums



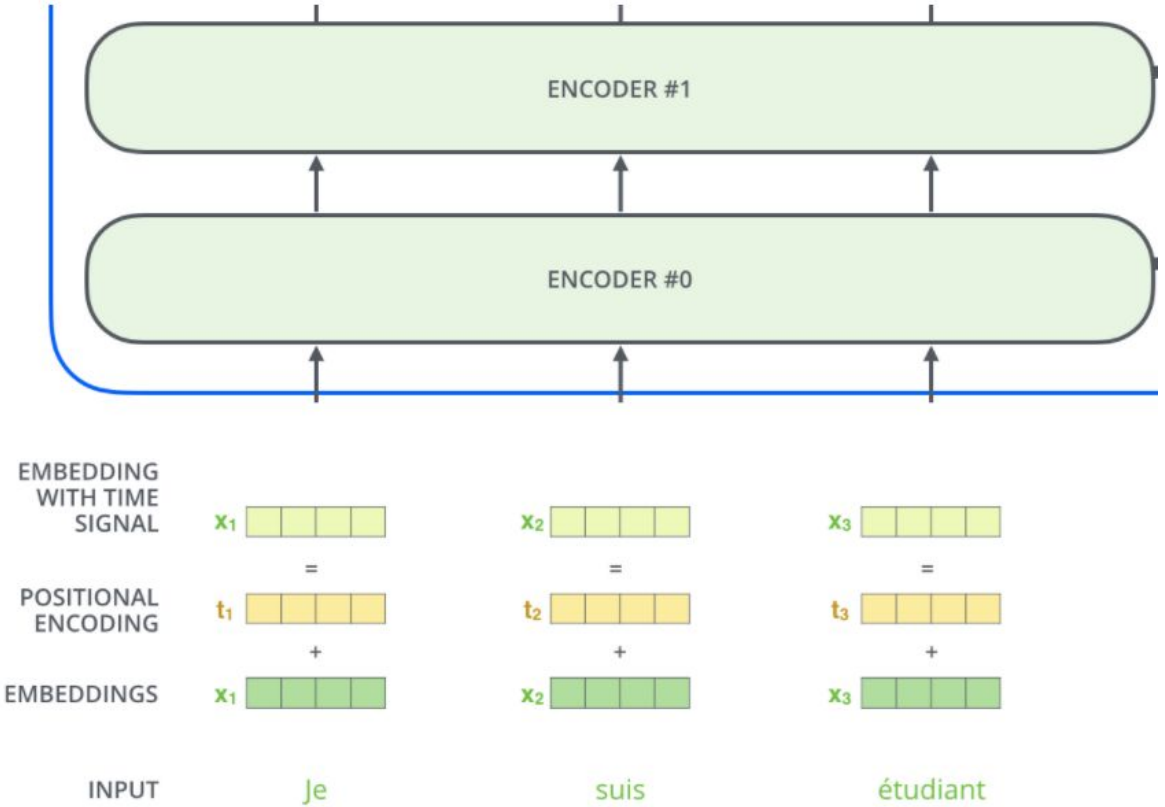
Transformers: Attention Visualization

- Attention tells us where to focus the information
  - Illustration for a sentence:



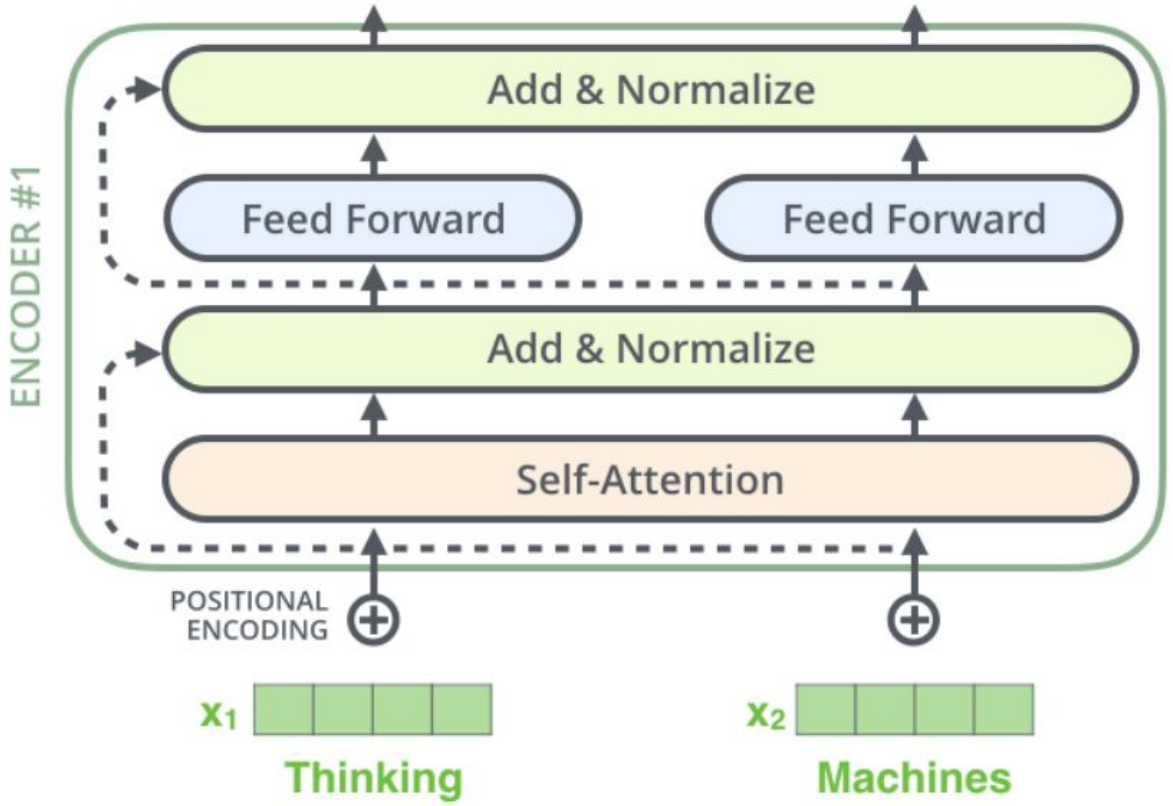
Transformers: Positional Encodings

- One thing we haven't discussed: the order of the symbols/elements in the sequence
  - Add a vector containing a special positional formula's embed



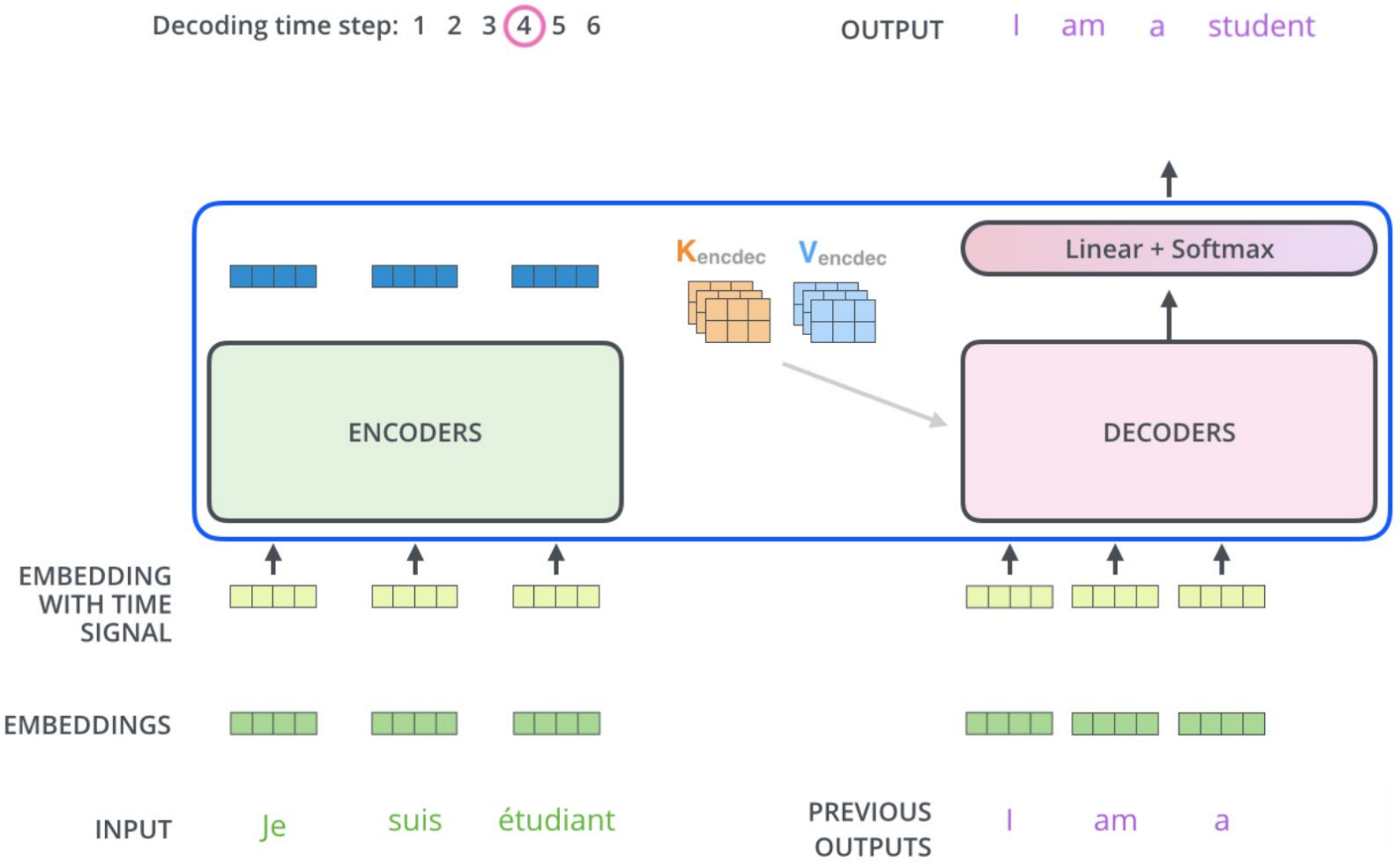
Transformers: More Tricks

- Recall a big innovation for ResNets: residual connections
  - And also layer normalizations
  - Apply to our encoder layers



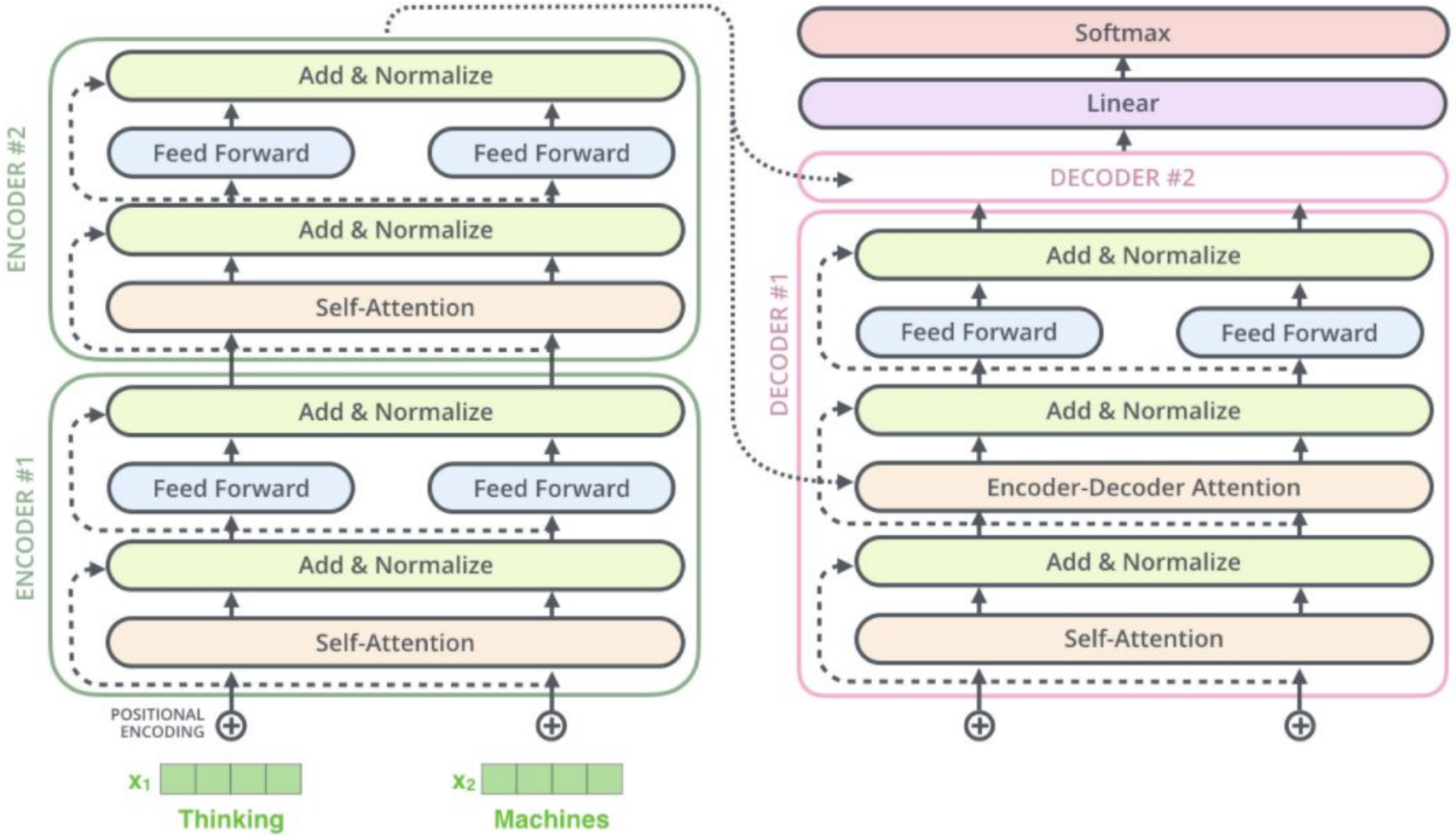
Transformers: Decoder

- Similar to encoders (see blog post for more details).
- E.g. Generating a translation



Transformers: Putting it All Together

- What does the full architecture look like?



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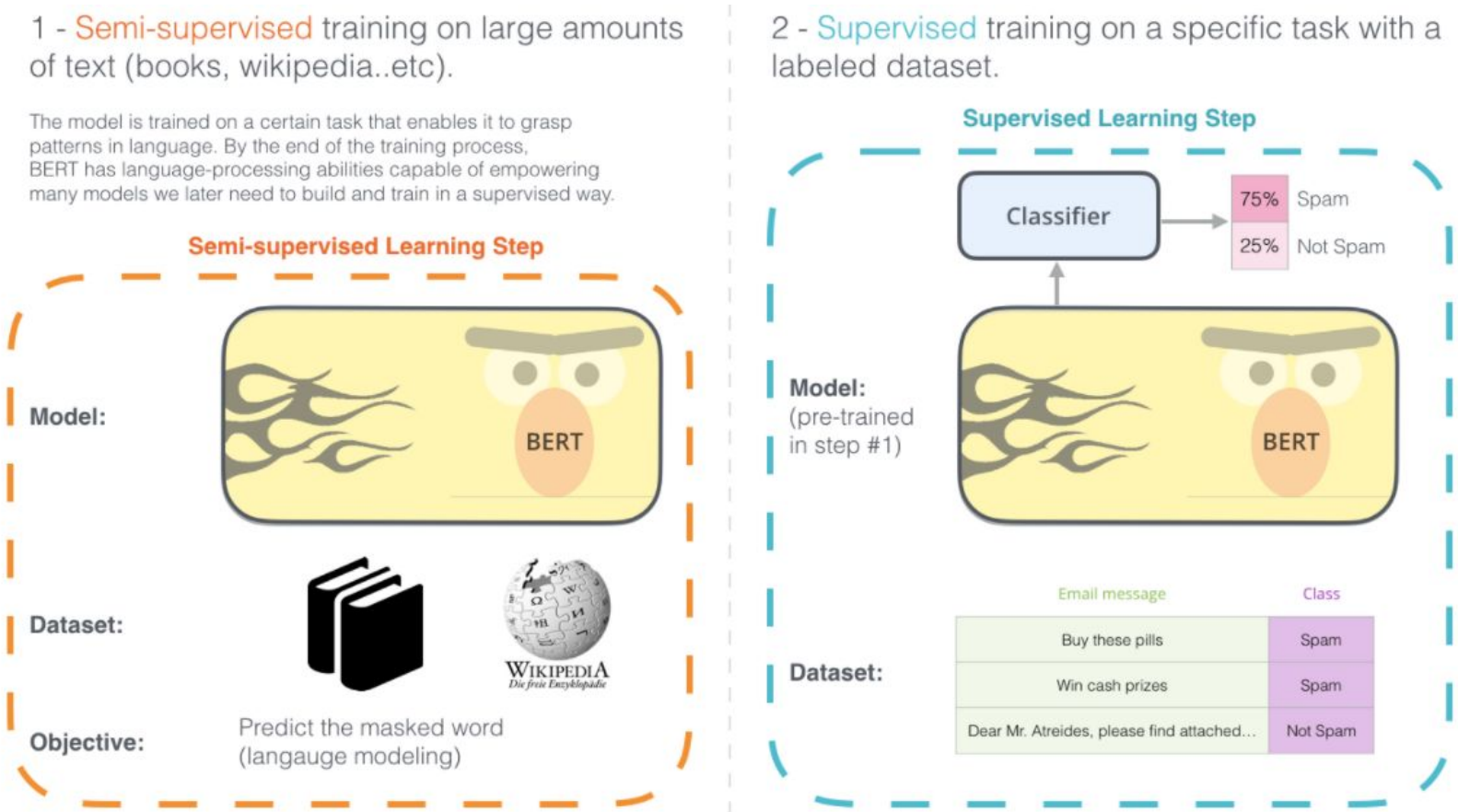
Transformer-Based Models: **BERT**

- Semi-supervised learning + Transformers
  - Semi-supervised learning to learn embeddings in encoder



BERT: Concepts

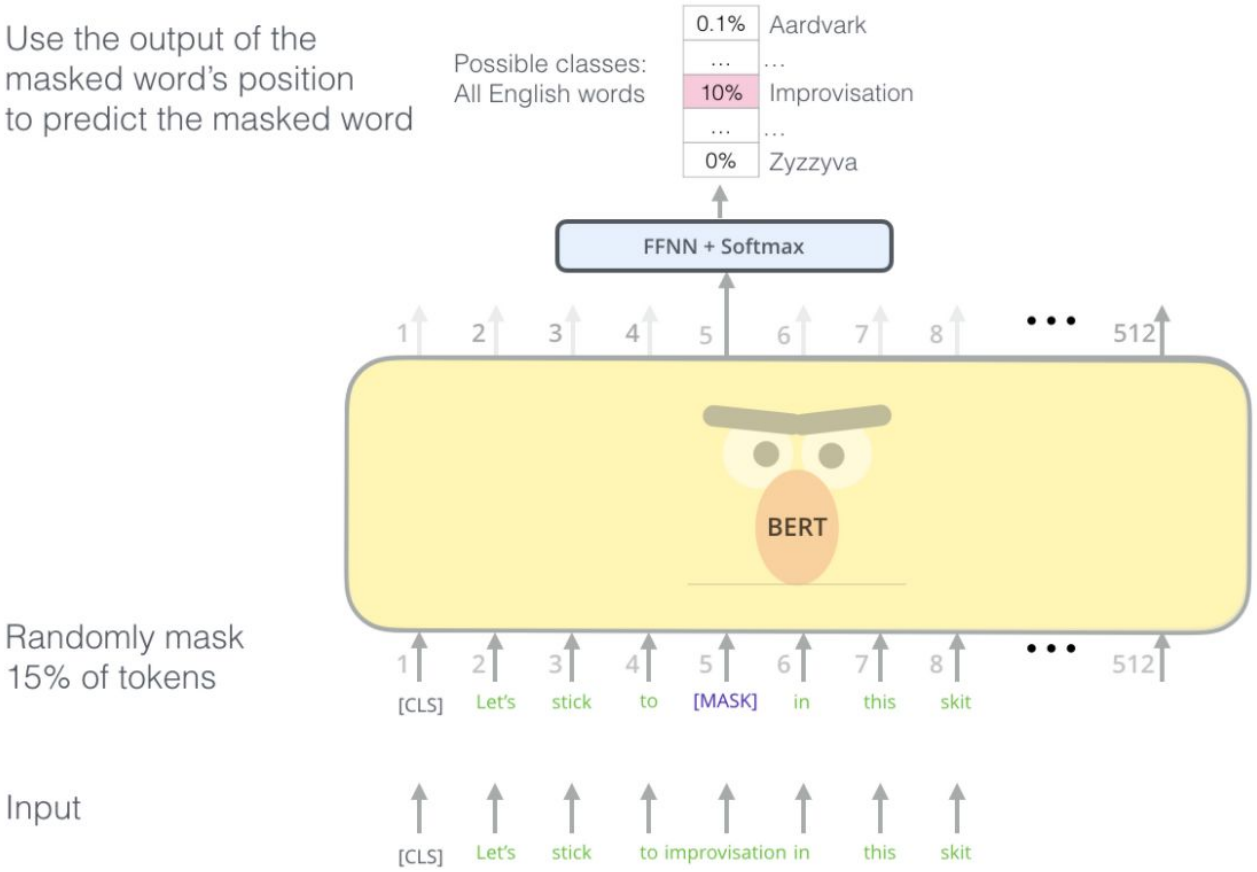
- What makes BERT work? A bunch of ideas:
  - 1. Use the **Transformer** architecture
  - 2. **Pre-training** on corpora using pretext tasks
    - Then fine-tune for a particular task
  - 3. **Scale**: BERT-Large has 340 million parameters

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Results: Devlin et al, BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

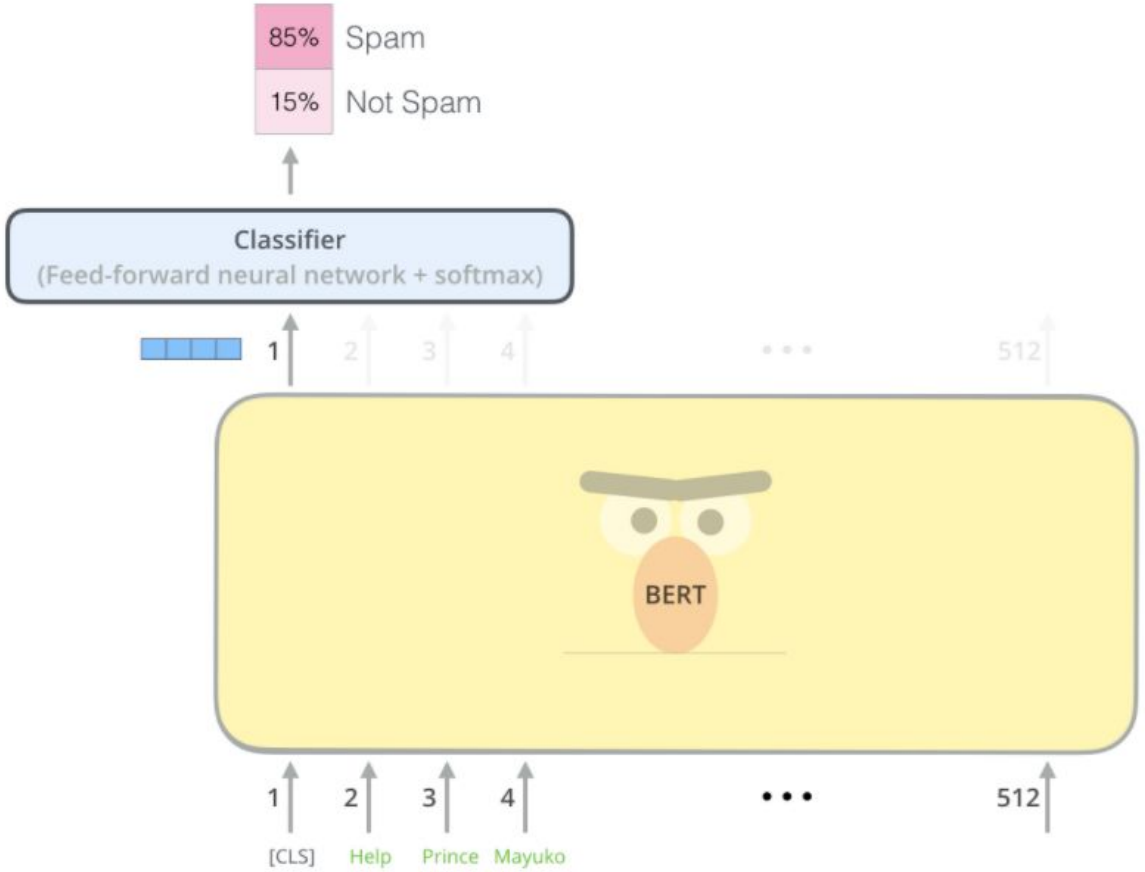
BERT: Training

- BERT is trained on a simple tasks on a huge amount of data:
  - Recall our pretext tasks in self-supervised learning
  - **Masked word prediction:**



BERT: Classification

- Then, fine-tune on a particular task
  - Example: **binary classification**, spam VS not spam

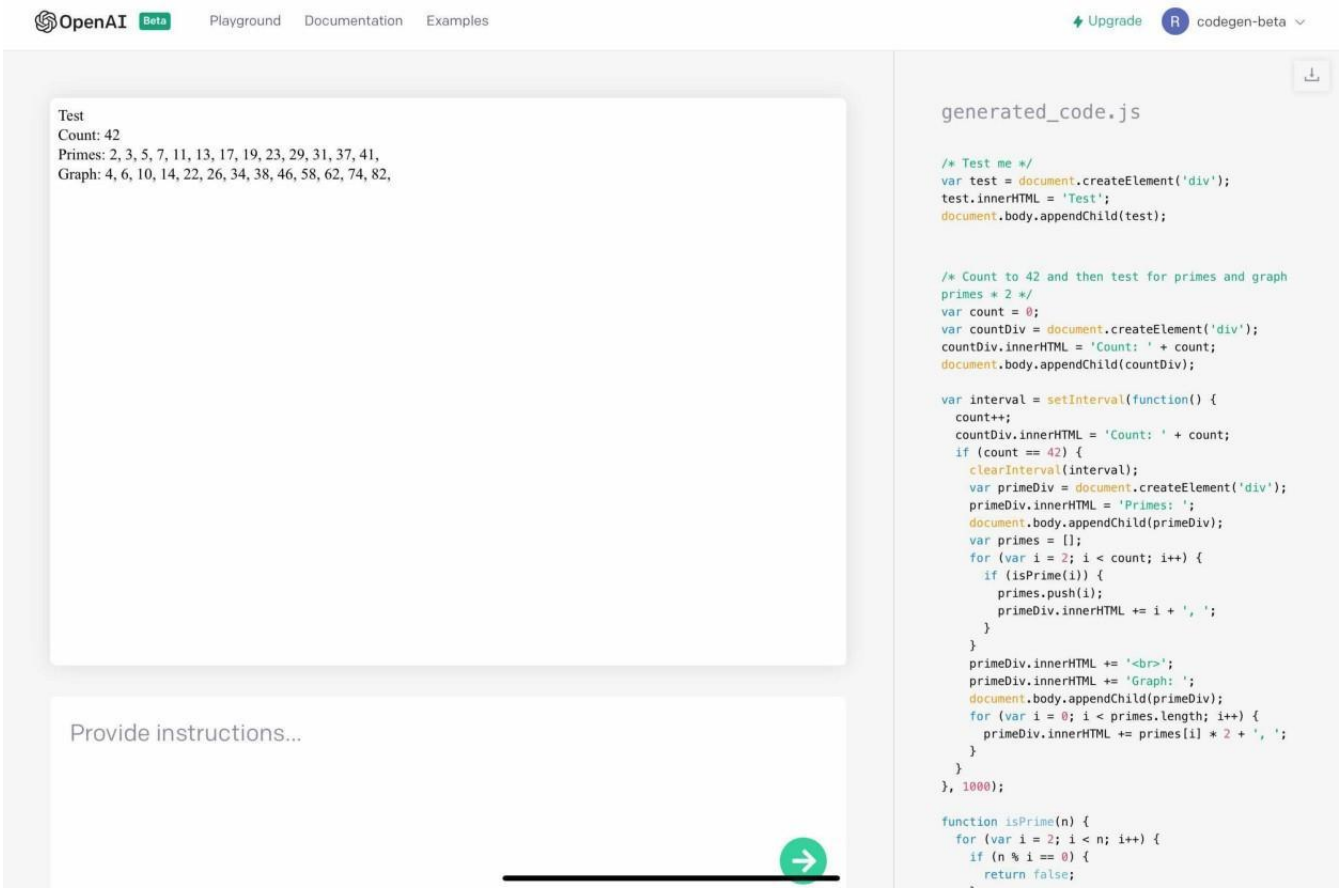


GPT Series of Models

- **GPT**: **G**enerative **P**re-trained **T**ransformer
  - Also built on top of transformer model architecture
  - Essentially the decoder part only
- Goal: generate text (possibly from a **prompt**)
- Scale: huge!
  - GPT-3: 175 billion parameters

Codex

- Codex: a variant of GPT-3 based on source code
  - Outputs code. Ex: show primes



Russell Foltz-Smith

DALL-E

- Create images from text
  - Prompt: “an armchair in the shape of an avocado. . . .”

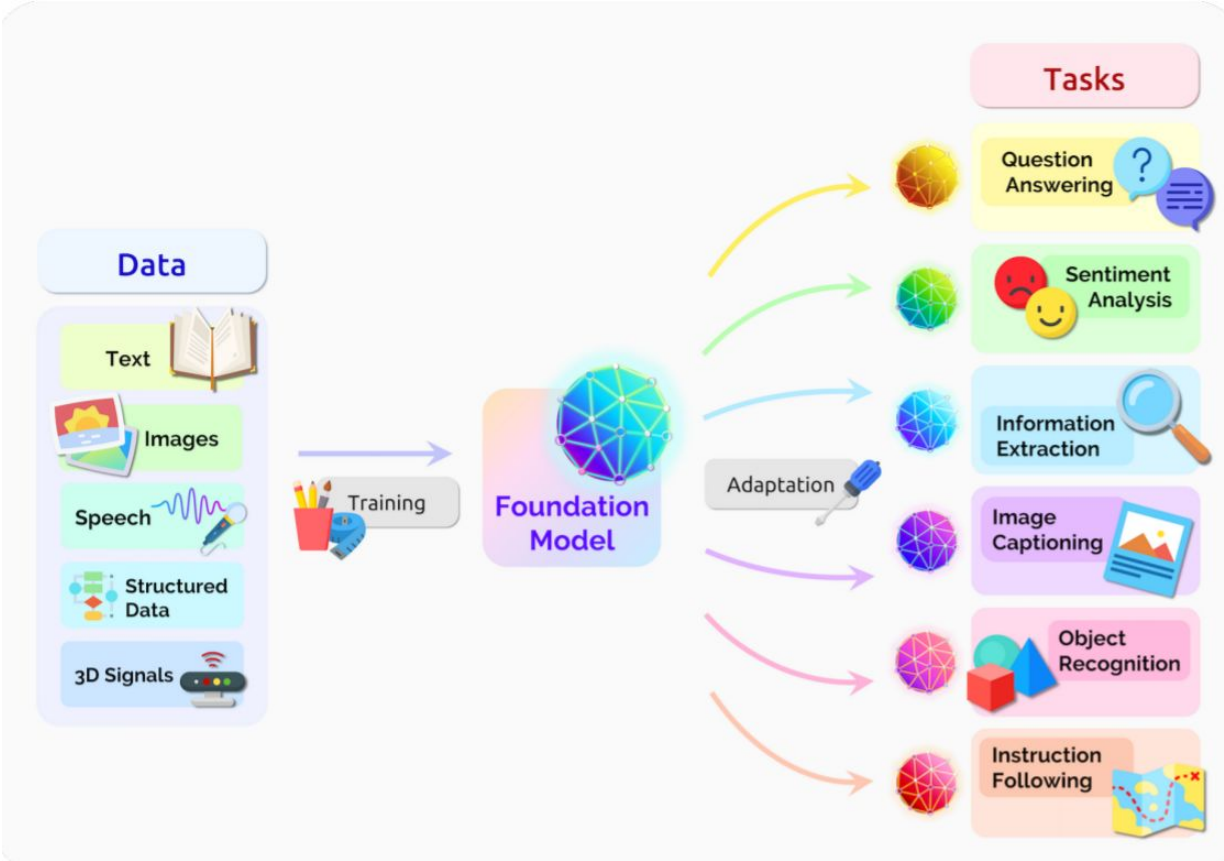
https://openai.com/blog/dall-e/

- Note: several online demos. Try it yourself!

https://huggingface.co/stabilityai/stable-diffusion-3.5-large

Foundation Models

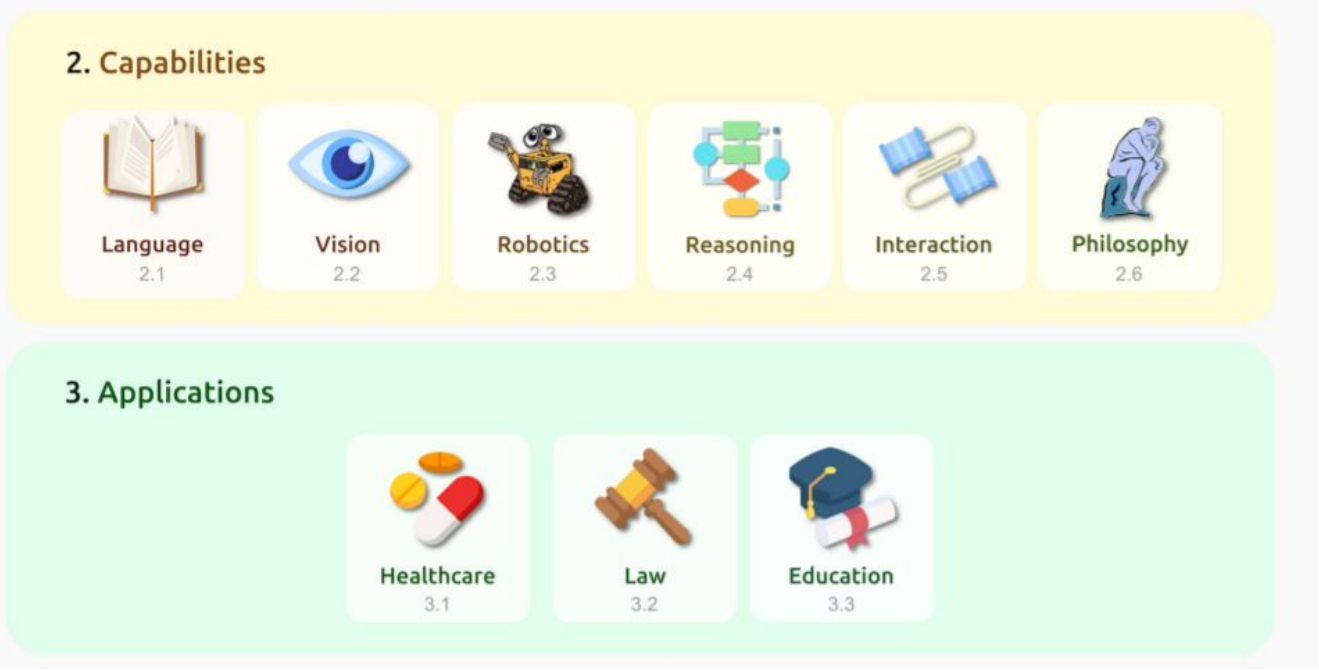
- Many more large scale models
  - Not just focused on text



Bommasani et al, “On the Opportunities and Risks of Foundation Models”

Conclusion

- "Foundation" models based on transformers and beyond
  - Huge, expensive to train, challenging in various ways… but
  - Remarkably powerful for a vast number of tasks.
  - AGI??



Bommasani et al, "On the Opportunities and Risks of Foundation Models"

Thanks Everyone!

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