Lecture 10: More about Transformers and Pretraining

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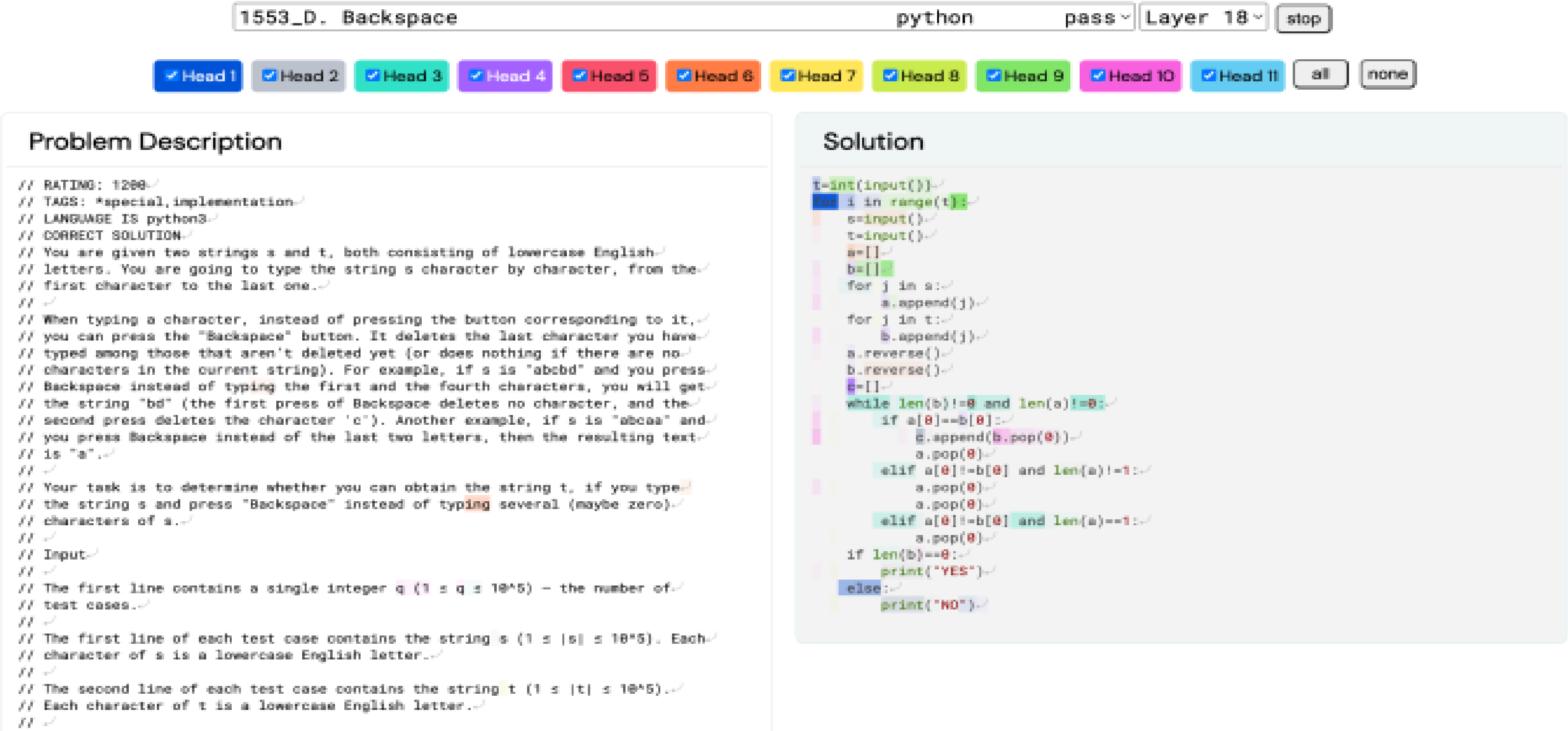
Breaking (Transformer) news

- AlphaCode (a pre-trained Transformer-based code generation model) achieved a top 54.3% rating on Codeforces programming competitions



More Breaking (Transformer) news

- Pre-trained Transformer-based theorem prover sets new state-of-the-art (41.2% vs. 29.3%) on a collection of challenging math Olympiad questions (miniF2F)

PROBLEM 1

Adapted from AMC12 2000 Problem 5

Prove that if $|x-2|=p$, where $x<2$, then $x-p=2-2p$.

FORMAL | INFORMAL

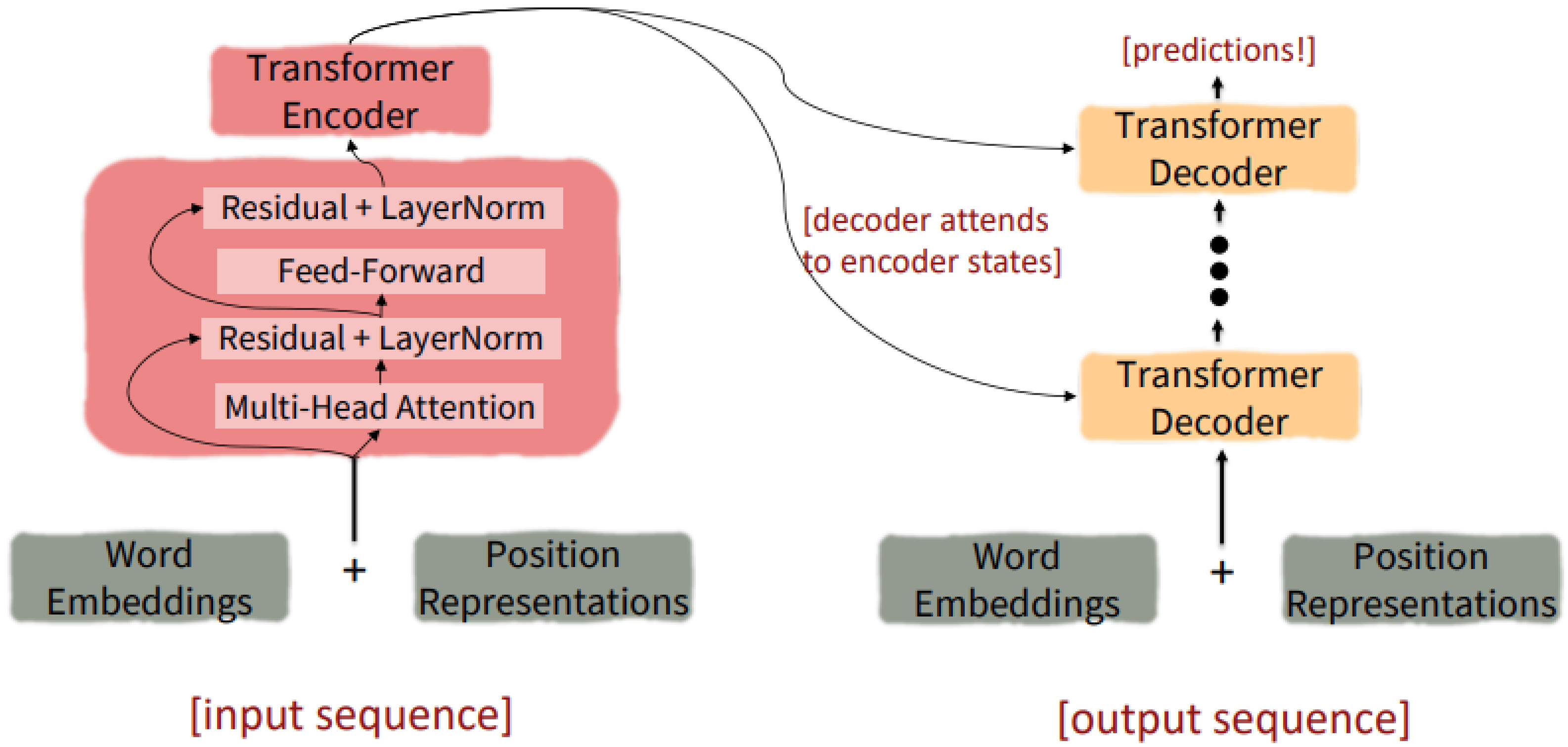
```
theorem amc12_2000_p5         -- ← theorem name
  (x p : ℝ)                   -- ← the statement we want
  (h₀ : x < 2)                --   to prove
  (h₁ : abs (x - 2) = p) :
  x - p = 2 - 2 * p :=
begin                         -- ← formal proof starts here
  -- This first tactic requires that the prover invent
  -- the term: `abs (x - 2) = -(x - 2)`.
  have h₂ : abs (x - 2) = -(x - 2), {
    apply abs_of_neg,
    linarith,
  },
  rw h₁ at h₂,
  -- At this stage the remaining goal to prove is:
  -- `x - p = 2 - 2 * p` knowing that `p = -(x - 2)`.
  linarith,
end
```

Lecture plan

1. Quick review of Transformer model
2. Brief note on subword modeling
3. Motivating model pretraining from word embeddings
4. Model pretraining three ways
    1. Decoders
    2. Encoders
    3. Encoder-Decoders

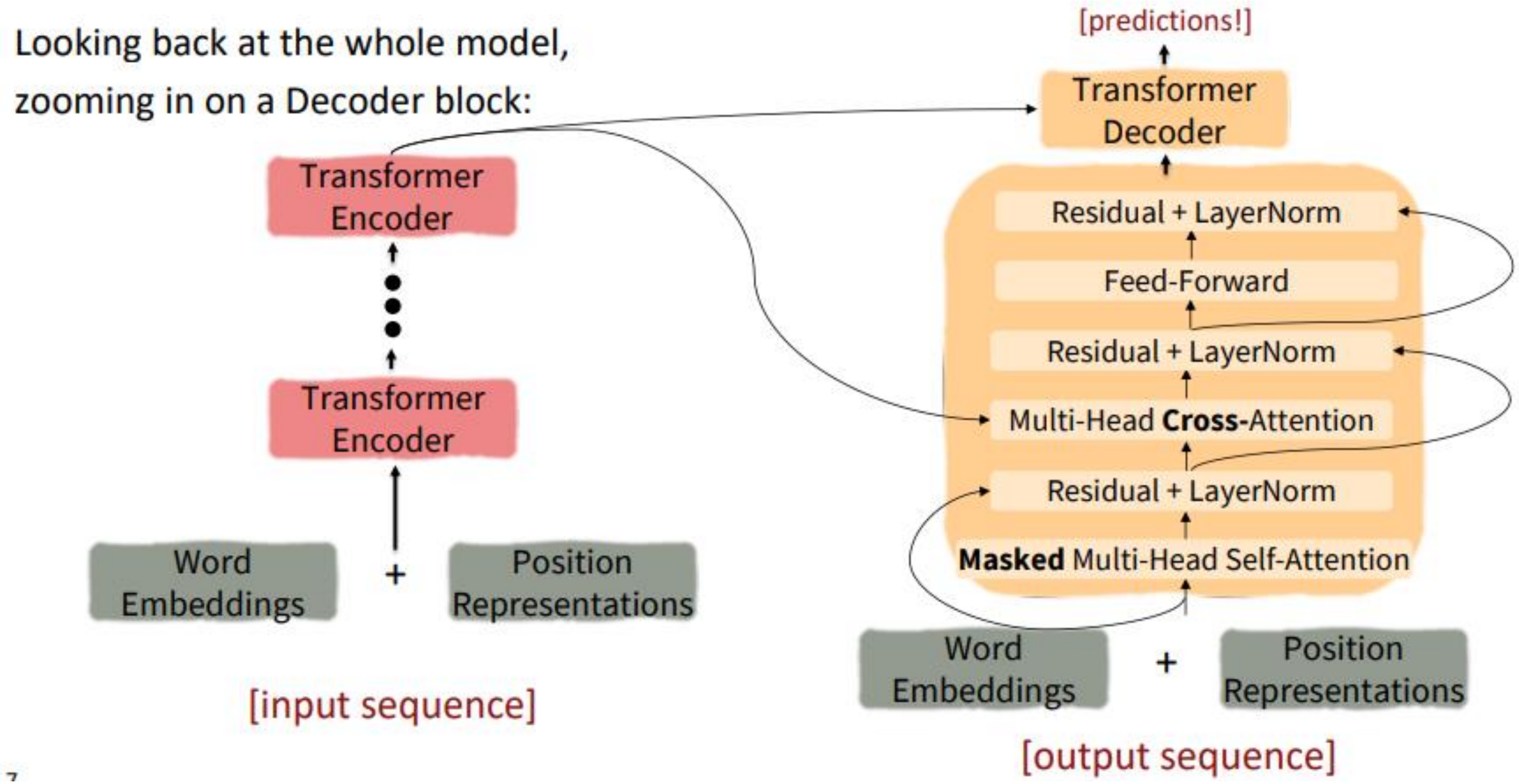
1. Quick review of Transformer model

Looking back at the whole model, zooming in on an Encoder block:



1. Quick review of Transformer model

Looking back at the whole model,
zooming in on a Decoder block:



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2. Brief note on subword modeling

- We assume a fixed vocab of tens of thousands of words, built from the training set. All novel words seen at test time are mapped to a single UNK
- However, finite vocabulary assumptions make even less sense in many languages
- Example
  - low, lower, lowest, strong, stronger, strongest – low, strong, er, est
  - Our goal is to save sequences of characters which appear with high frequency, let see BPE algorithm!

2. Brief note on subword modeling

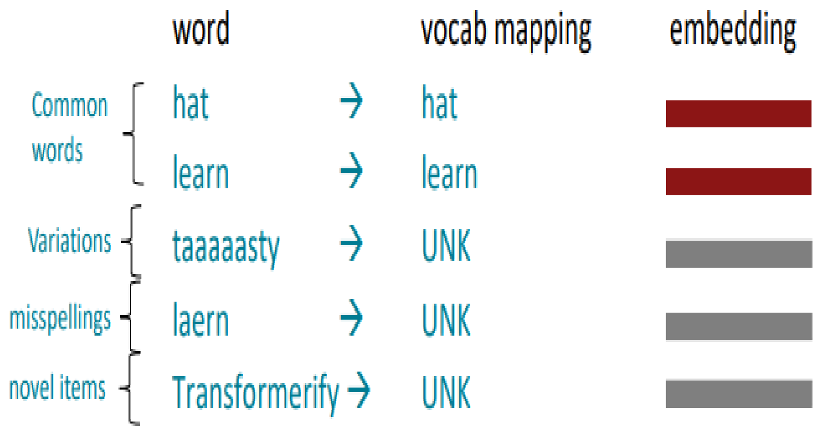
- Subword modeling in NLP encompasses a wide range of methods for reasoning about structure below the word level (parts of words, characters, bytes)
  - The dominant modern paradigm is to learn a vocabulary of parts of words (subword tokens)
  - At training and testing time, each word is split into a sequence of known subwords
- BPE (Byte-Pair Encoding)
  - Start with a vocabulary containing only characters and an "end-of-word" symbol
  - Using a corpus of text, find the most common pair of adjacent characters "a,b"; add subword "ab" to the vocab
  - Replace instances of the character pair with the new subword, repeat until desired vocab size

2. Brief note on subword modeling

- BPE example:
    - ("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
    - vocab: h u g p n b s
    - ("h" "u" "g", 10), ("p" "u" "g", 5), ("p" "u" "n", 12), ("b" "u" "n", 4), ("h" "u" "g" "s", 5)
    - "u" followed by "g" occurs 10+5+5=20 times, "ug" is add to the vocabulary
    - vocab: h u g p n b s ug
    - ("h" "ug", 10), ("p" "ug", 5), ("p" "u" "n", 12), ("b" "u" "n", 4), ("h" "ug" "s", 5)
    - "u" followed by "n" occurs 12+4=16 times, "un" is add to the vocabulary
    - vocab: vocab: h u g p n b s ug un
    - "h" followed by "ug" occurs 10+5=15 times, "hug" is add to the vocabulary
    - vocab: vocab: h u g p n b s ug un hug
    - ("hug", 10), ("p" "ug", 5), ("p" "un", 12), ("b" "un", 4), ("hug" "s", 5)
    - *repeat until desired vocab size*

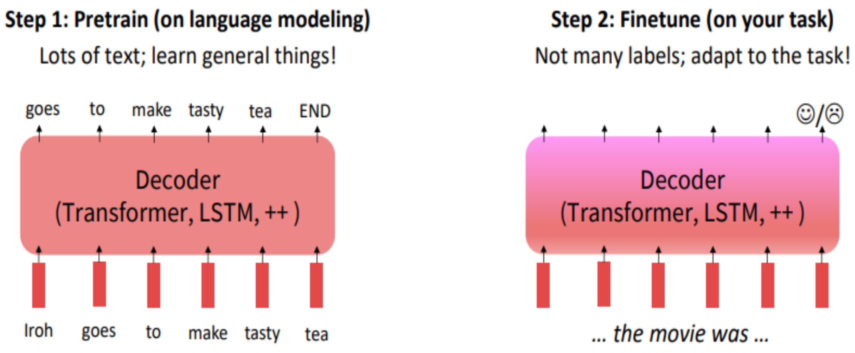
2. Brief note on subword modeling

- Result



3. Motivating model pretraining from word embeddings

- Recall the language modeling task:
  - Model $P(w_t \mid w_{1:t-1})$, the probability distribution over words given their past contexts
  - There's lots of data for this (In English)
- Pretraining through language modeling
  - Train a neural network to perform language modeling on a large amount of text
  - Save the network parameters
- Pretraining can improve NLP applications by serving as parameter initialization



4.1 Pretraining decoders

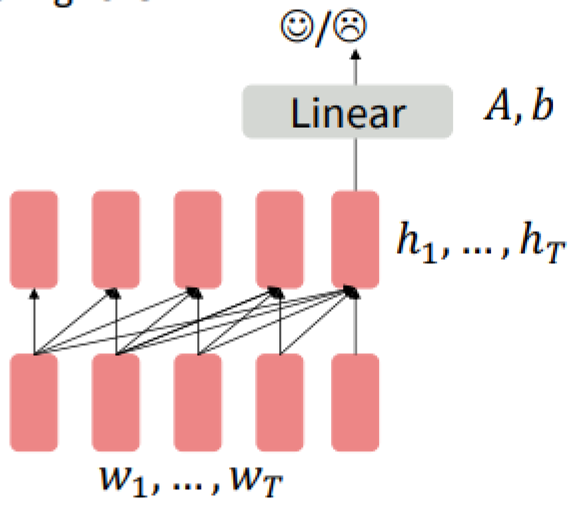
When using language model pretrained decoders, we can ignore that they were trained to model $p(w_t|w_{1:t-1})$.

We can finetune them by training a classifier on the last word's hidden state.

$$h_1, \dots, h_T = \text{Decoder}(w_1, \dots, w_T)$$
$$y \sim Ah_T + b$$

Where A and b are randomly initialized and specified by the downstream task.

Gradients backpropagate through the whole network.



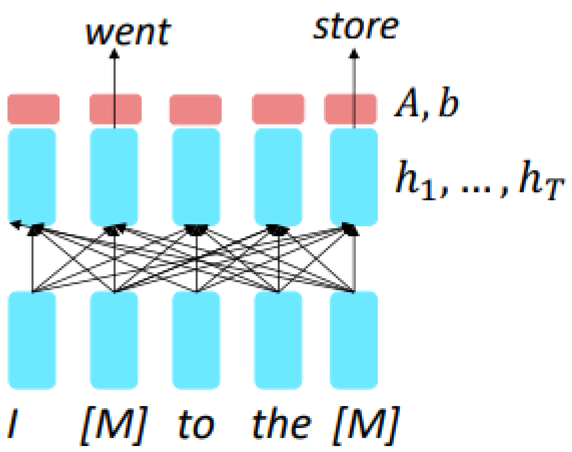
[Note how the linear layer hasn't been pretrained and must be learned from scratch.]

4.2 Pretraining encoders

So far, we've looked at language model pretraining. But **encoders get bidirectional context,** so we can't do language modeling!

Idea: replace some fraction of words in the input with a special [MASK] token; predict these words.

Only add loss terms from words that are "masked out." If $\tilde{x}$ is the masked version of x, we're learning $p_\theta(x|\tilde{x})$. Called **Masked LM**.

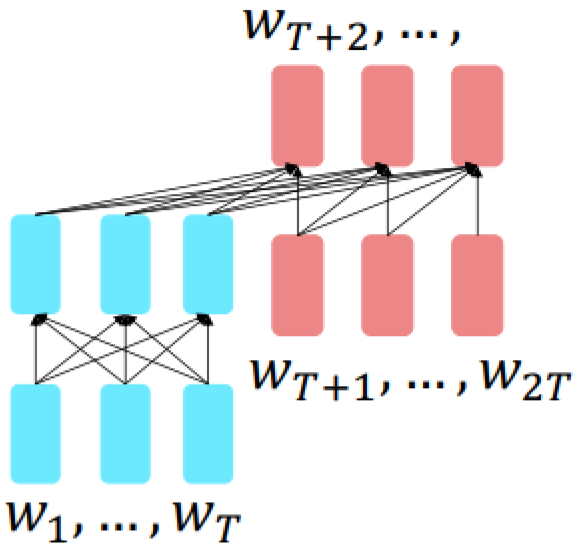


4.3 Pretraining encoder-decoders

For **encoder-decoders**, we could do something like **language modeling**, but where a prefix of every input is provided to the encoder and is not predicted.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$
$$h_{T+1}, \dots, h_2 = Decoder(w_1, \dots, w_T, h_1, \dots, h_T)$$
$$y_i \sim Aw_i + b, i > T$$

The **encoder** portion benefits from bidirectional context; the **decoder** portion is used to train the whole model through language modeling.



THANK YOU

Any question?