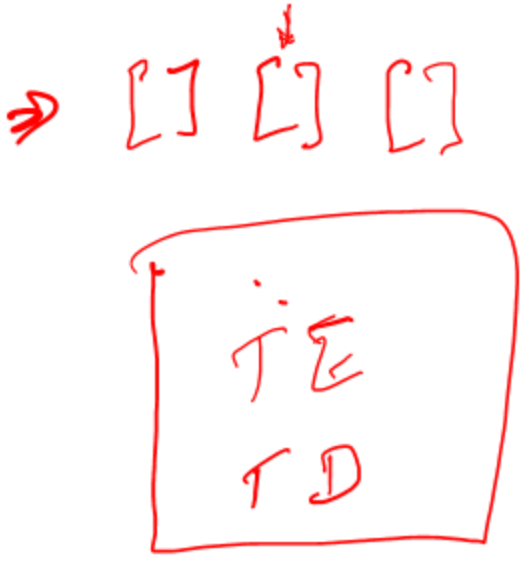
AI Module: Transformer Models

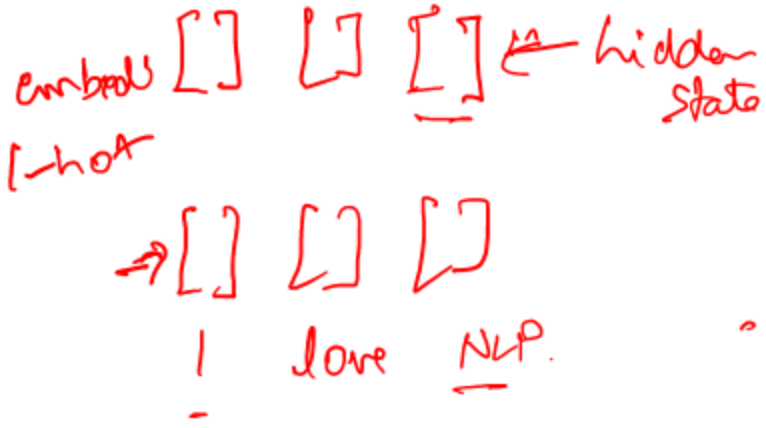
Deepak Subramani
Assistant Professor
Dept. of Computational and Data Science
Indian Institute of Science Bengaluru

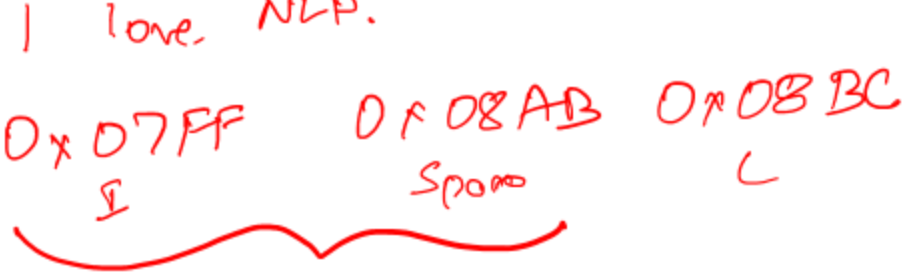
Outline for Week 03

- Part 01: BERT Models for Discriminative Tasks (NLU)
  - BERT and friends – the essential foundational model for text tasks
  - How is BERT trained?
  - What can BERT be used for with examples
  - Assignment on BERT
- Part 02: Transformer Decoder
  - Intro to Neural Machine Translation
  - Masked attention
  - Understanding Decoder through animations
  - Assignment on decoder and NMT

Recap of Transformer Encoder







Byte Pair encoding

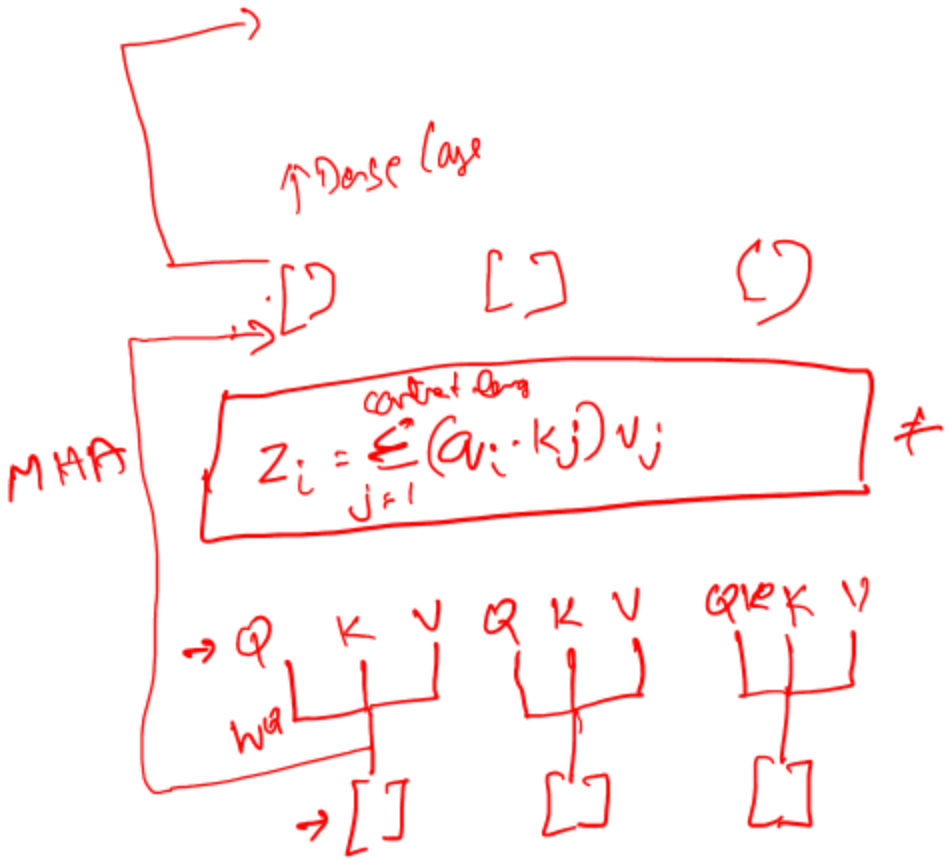
Byte Pair

- Reddit
- wiki
- Youtube comments
- Multilingual

256 characters UTF8

257

258


Dense layer
MHA
$z_i = \sum_{j=1}^{} (q_i \cdot k_j) v_j$
Q K V
Q K V
Q K V

Recap of Transformer Encoder

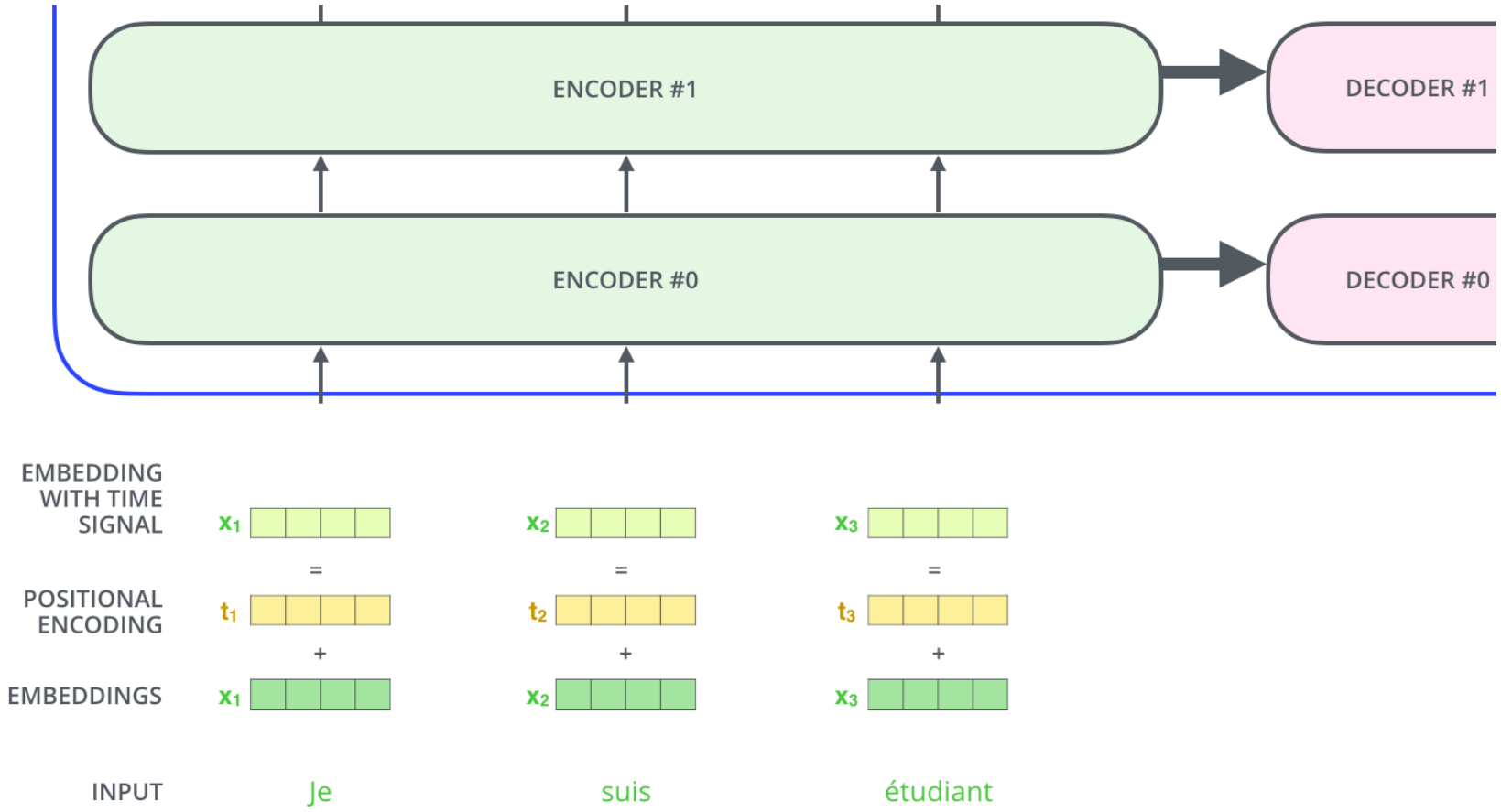


Image source: https://jalammar.github.io/illustrated-transformer/

Language Models

- Language Model (LM) is a probabilistic model of the natural language
- It understands the statistical relationship between words and can be used to fill missing words and complete sentences
- Language Models are trained by artificially introducing missing words and creating sentence completion tasks
- This procedure is called as “Pretraining” as the LM so learnt can be used with fine tuning for other particular tasks
- Large Language Models are usually transformer based neural models with a large number of parameters that are pretrained on a large number of tokens using masked model pretraining

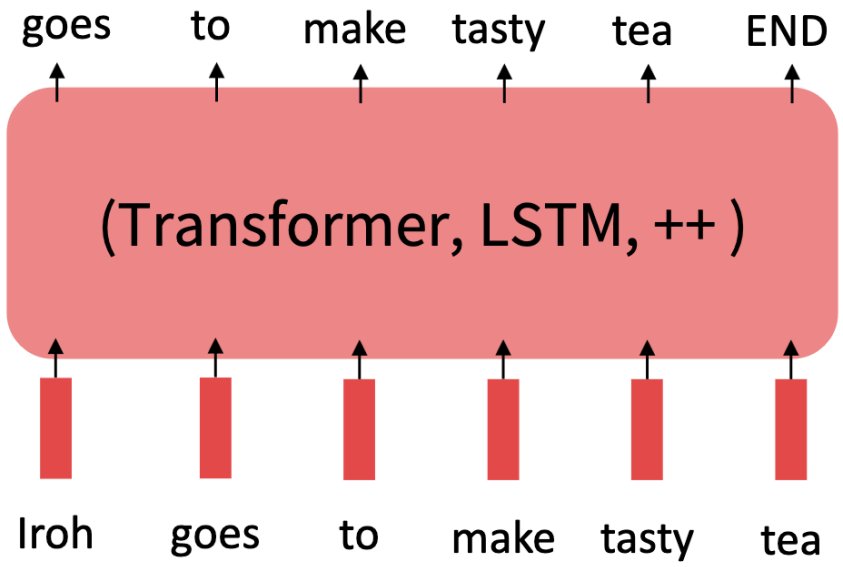
What is learned through pretraining?

- IISc is located in _____, India. [Trivia]
- He put ___ fork down on the table. [syntax]
- Naruto is the hokage of the village and _____ feels responsible for all the inhabitants. [coreference]
- I went to the ocean to see the fish, turtles, seals, and _____. [lexical semantics/topic]
- Miyazaki has created a complete, complex world with this film, and it's certainly a magical journey. The movie was ___. [sentiment]
- San went into the kitchen to make some tea. Standing next to San, Ashitaka pondered his destiny. Ashitaka left the _____. [some reasoning]

Pretraining and Finetuning

Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



Step 2: Finetune (on your task)

Not many labels; adapt to the task!

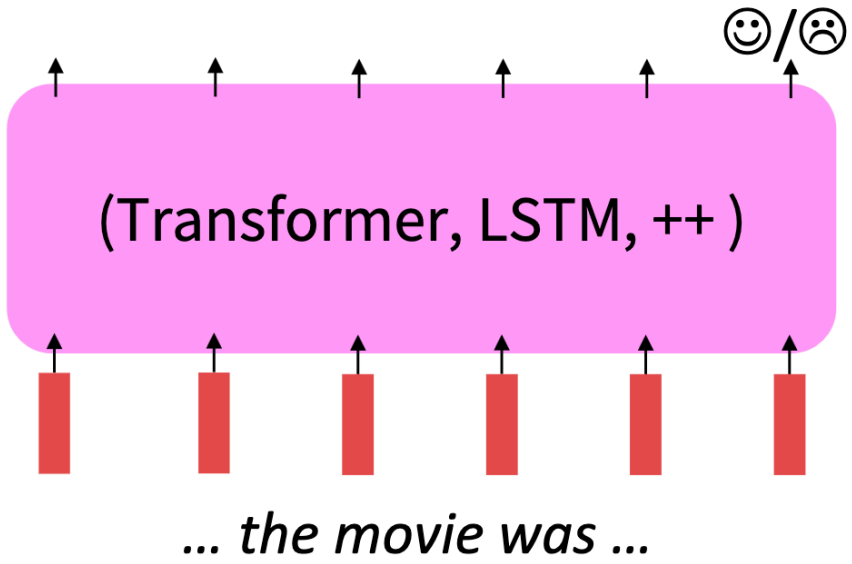


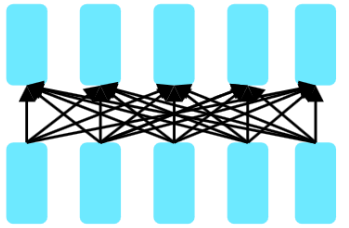
Image source: https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture9-pretraining.pdf

Gradient Descent

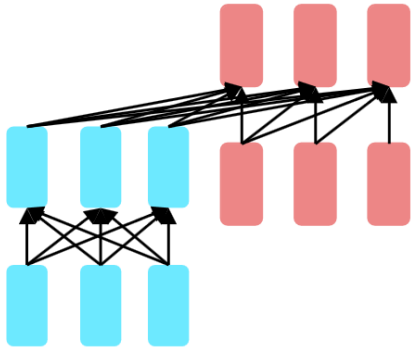
- Pretraining provides parameters, $\hat{\theta}$ by minimizing the pre-training loss.
- Finetuning approximates $min_\theta \mathcal{L}_{finetune}(\theta)$, starting at $\hat{\theta}$.
- The pretraining may matter because stochastic gradient descent sticks (relatively) close to $\hat{\theta}$ during finetuning.
  - Finetuning local minima near $\hat{\theta}$ tend to generalize well.
  - Gradients of finetuning loss near $\hat{\theta}$ propagate nicely.

Types of pre-trained LMs

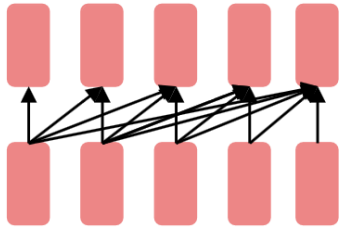
- Encoder only: bidirectional context
- Encoder-decoder: combining goodness of both
- Decoder only: doesn't have bidirectional context.



Encoders



Encoder-Decoders

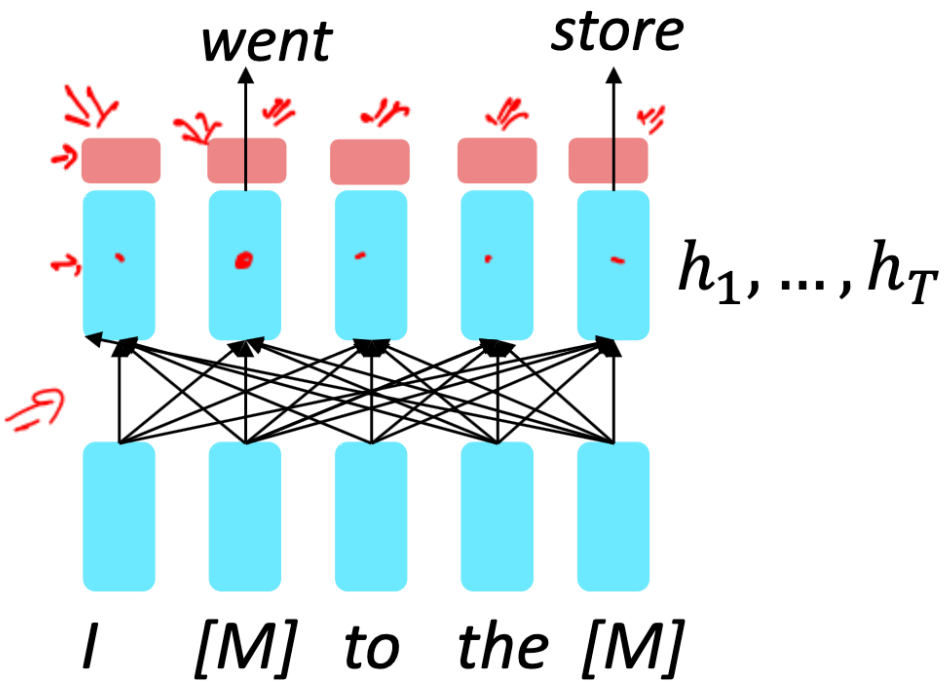


Decoders

Image source: https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture9-pretraining.pdf

Pretraining Encoders

- Encoders have bidirectional context.
- Masked Language Model:
  - A small percentage of the input tokens are masked at random,
  - The model is trained to predict the masked tokens.
- The final hidden states (encoded representations) corresponding to masked tokens are fed into an output SoftMax over the entire vocabulary.



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Devlin et al., 2018

Bidirectional Encoder Representations from Transformers (BERT) pre-training with Masked Language Modeling (MLM)

- Mask 15% of the WordPiece tokens in each sequence at random.
- The model only predicts masked words.
- Mismatch between pre-training and fine-tuning, since the [MASK] token does not appear during fine-tuning.
- Predict a random 15% of (sub)word tokens.
  - Replace input word with [MASK] 80% of the time.
  - Replace input word with a random token 10% of the time.
  - Leave input word unchanged 10% of the time.

Devlin et al., 2018

BERT - MLM

- Unlabelled sentence: my dog is hairy.
- Random masking: 4-th token (which corresponds to hairy)
  - 80% of the time: Replace the word with the [MASK] token, e.g., my dog is hairy → my dog is [MASK].
  - 10% of the time: Replace the word with a random word, e.g., my dog is hairy → my dog is apple. (Random replacement is just 10% of 15%. Empirically, this doesn't seem to affect model's understanding capability).
  - 10% of the time: Keep the word unchanged, e.g., my dog is hairy → my dog is hairy. The purpose of this is to bias the representation towards the actual observed word.

Devlin et al., 2018

BERT - MLM

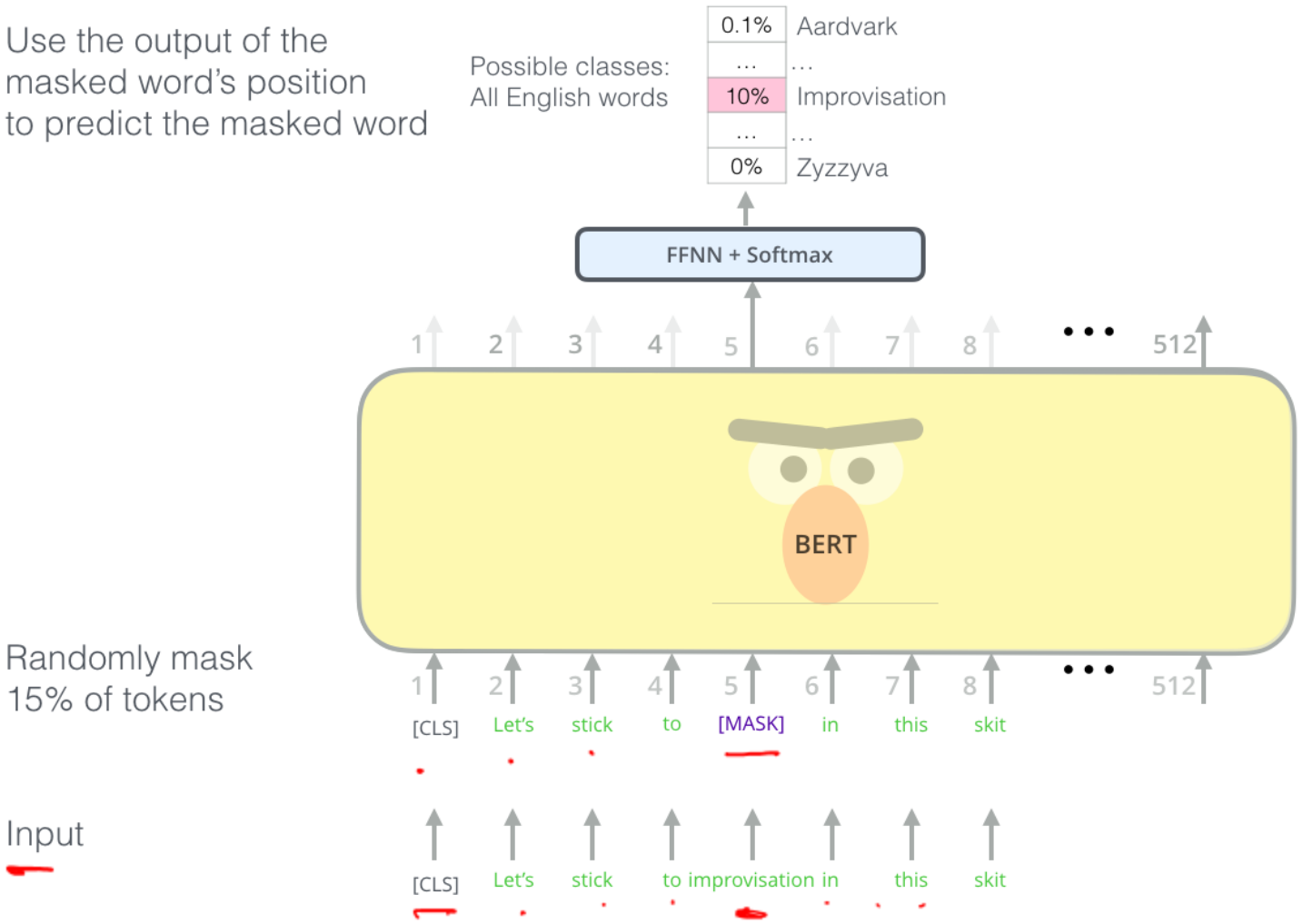

Image source: https://jalammar.github.io/illustrated-bert/

BERT - Specifics

- Two models were released:
  - BERT-base: 512 sequence length , 12 layers, 768-dim hidden states, 12 attention heads, 110 million parameters.
  - BERT-large: 512 sequence length , 24 layers, 1024-dim hidden states, 16 attention heads, 340 million parameters.
- Trained on:
  - BooksCorpus (800 million words).
  - English Wikipedia (2,500 million words).
- Pretraining is expensive and impractical on a single GPU.
  - BERT was pretrained with 64 TPU chips for a total of 4 days.

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6

① while downloading the dataset from internet

② which should not go as part of Model training

③ Isn't keeping the word unchanged

9

5/20

Input

① while [MASK] the dataset from internet

80%.

② which should not go as part of [OVERALL] traini

10%.

✓ ③ Isn't [keeping] the wor

10%

Output

2nd token downloadin

15% of 20 is 3 tokens

Output 8% tow Model

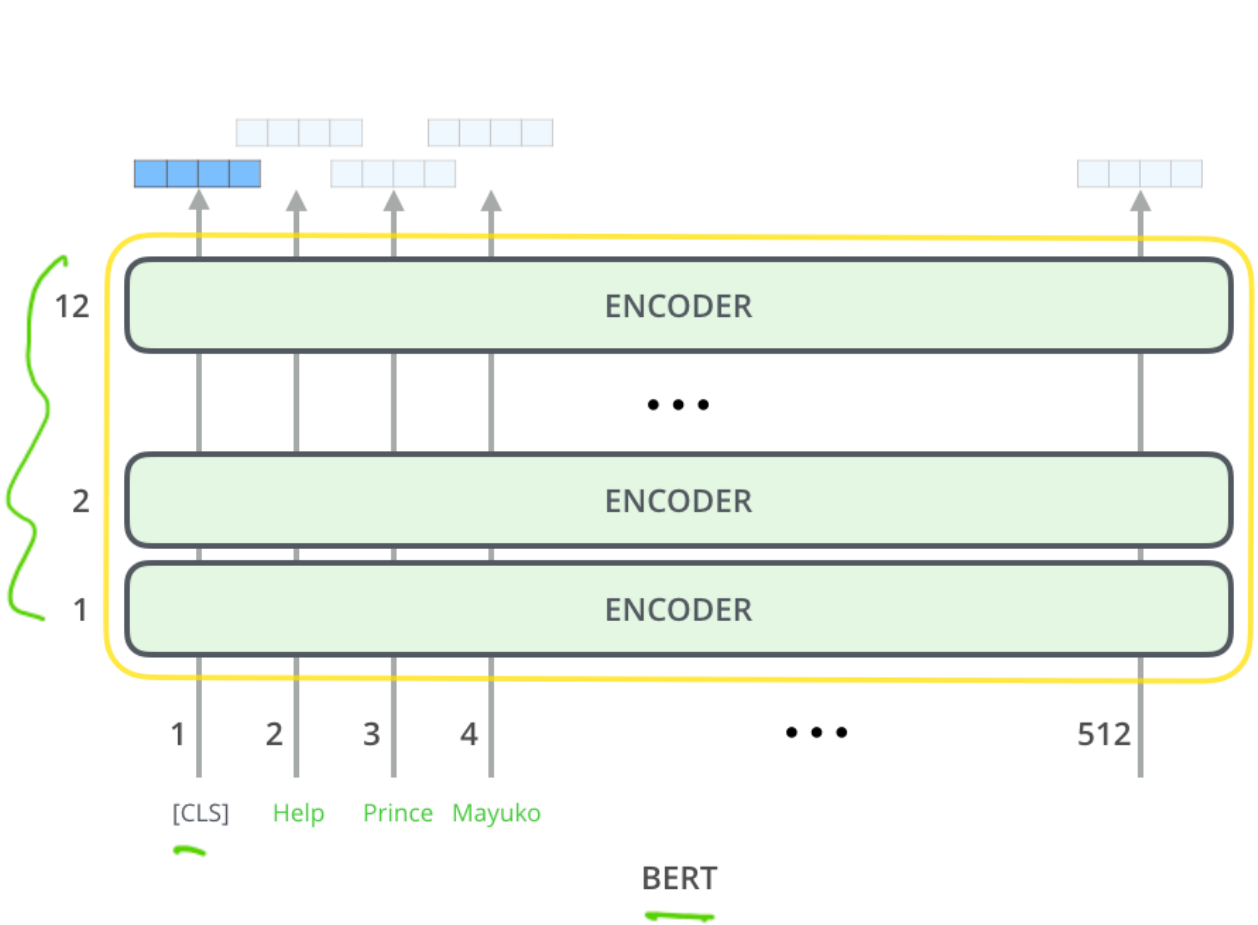
Output

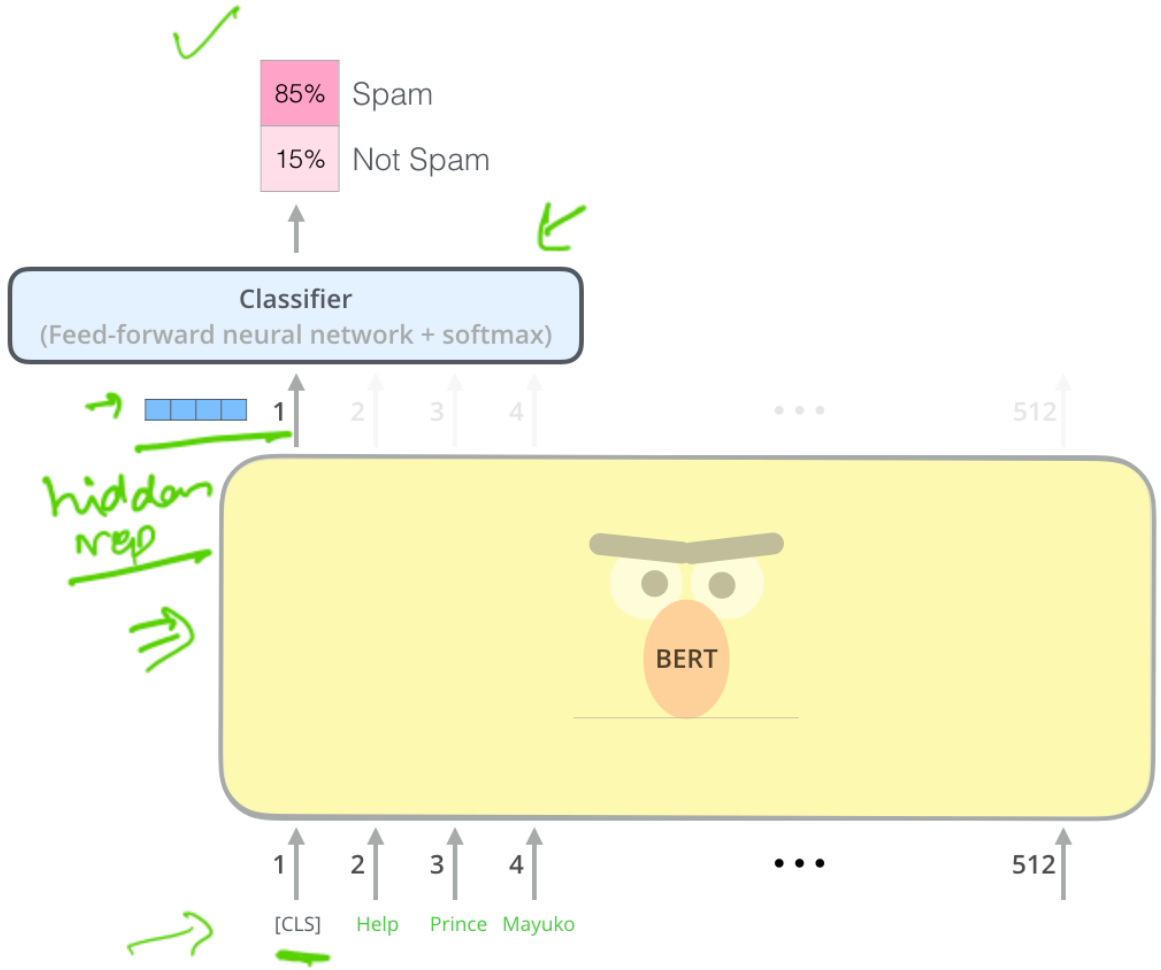
2nd keeping

BERT Finetuning

- For each task, task-specific inputs and outputs are plugged into BERT and all the parameters are finetuned end-to-end.
- At the input, sentence A and sentence B from pre-training are analogous to hypothesis-premise pairs in entailment, question-passage pairs in question answering etc.
- At the output, the token representations are fed into an output layer for token level tasks, such as sequence tagging or question answering, and the [CLS] representation is fed into an output layer for classification, such as entailment or sentiment analysis.

BERT for Text Classification





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BERT Tasks

A
It is cloudy outside [SEP]
It is going to rain
B

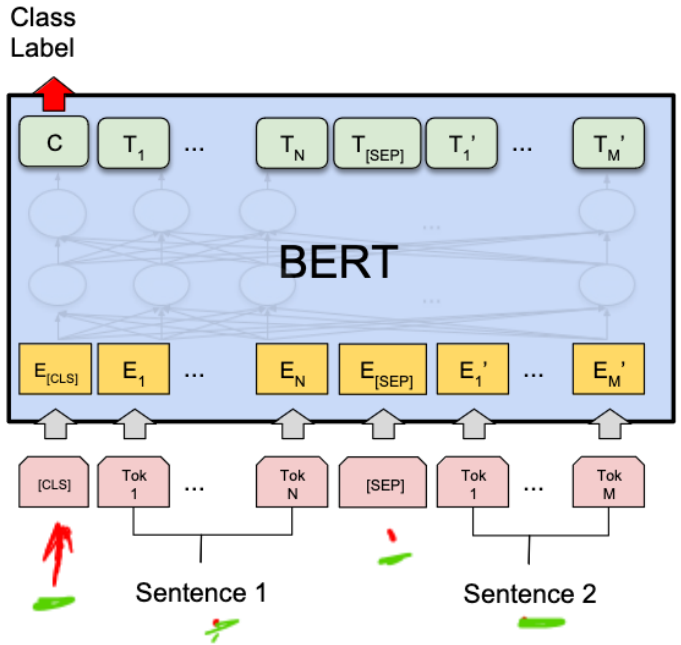
- MNLI (Multi-Genre Natural Language Inference):
  - large-scale, crowdsourced entailment classification task.
  - the goal is to predict whether the second sentence is an entailment, contradiction, or neutral with respect to the first one.
- QQP (Quora Question Pairs):
  - binary classification task where the goal is to determine if two questions asked on Quora are semantically equivalent.
- QNLI (Question Natural Language Inference):
  - version of the Stanford Question Answering Dataset which has been converted to a binary classification task.
  - positive examples are (question, sentence) pairs with the correct answers, and negative examples are pairs with no correct answer.

BERT Tasks

- SST-2 (The Stanford Sentiment Treebank):
  - binary single-sentence classification task consisting of sentences extracted from movie reviews with human annotations of their sentiment.
- CoLA (The Corpus of Linguistic Acceptability)
  - binary single-sentence classification task.
  - the goal is to predict whether an English sentence is linguistically “acceptable” or not.
- STS-B (The Semantic Textual Similarity Benchmark)
  - collection of sentence pairs drawn from news headlines and other sources.
  - annotated with a score from 1 to 5 denoting how semantic similarity.

BERT Tasks

- MRPC (Microsoft Research Paraphrase Corpus):
  - sentence pairs automatically extracted from online news sources, with human annotations for whether the sentences in the pair are semantically equivalent.
- RTE (Recognizing Textual Entailment)
  - binary entailment task like MNLI, but with much less training data.



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

Sentence 1: It is hot. I need fan. Why is AC not working? This is frustrating.

NLP Pipeline

Pipelines generally consist of

1. Tokenizer: Convert raw text to tokens
2. Model: Take tokens to output of your task
3. Post-processing: Enhance the output

Look for a finetuned BERT for your task. See HuggingFace library for all the finetuned models for each task.

https://huggingface.co/transformers/v3.2.0/pretrained_models.html

BERT and Friends

- RoBERTa – train BERT for longer and remove NSP
- SpanBERT: Masking contiguous spans of words makes the pretraining harder and more useful

- Most straightforward way is to finetune every parameter

- Researchers have tried to finetune only some part of the model also

BERT Additional Material

- Original BERT Paper was pre-trained on NSP task in addition to MLM
- Later it was shown that MLM pre-training is sufficient and NSP is not improving the pre-trained model's performance
- In the next three slides, we provide the details of NSP for your reference.

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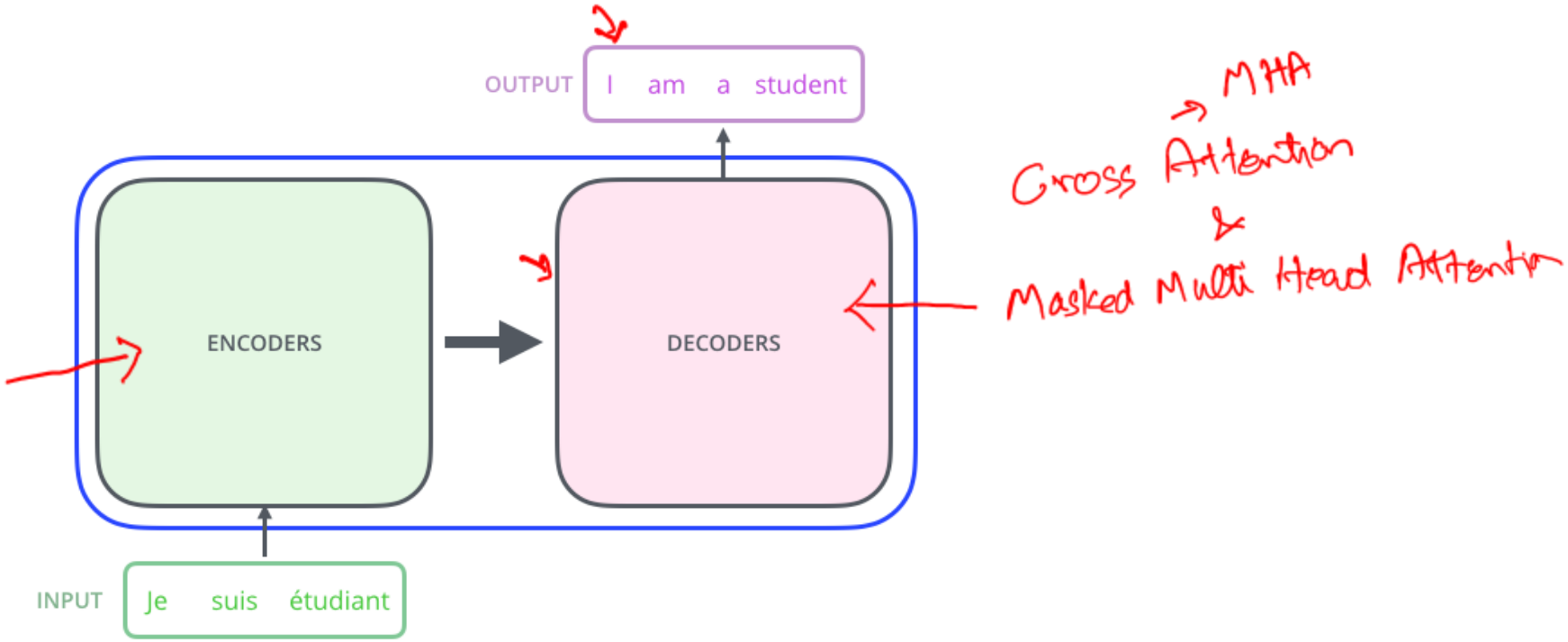
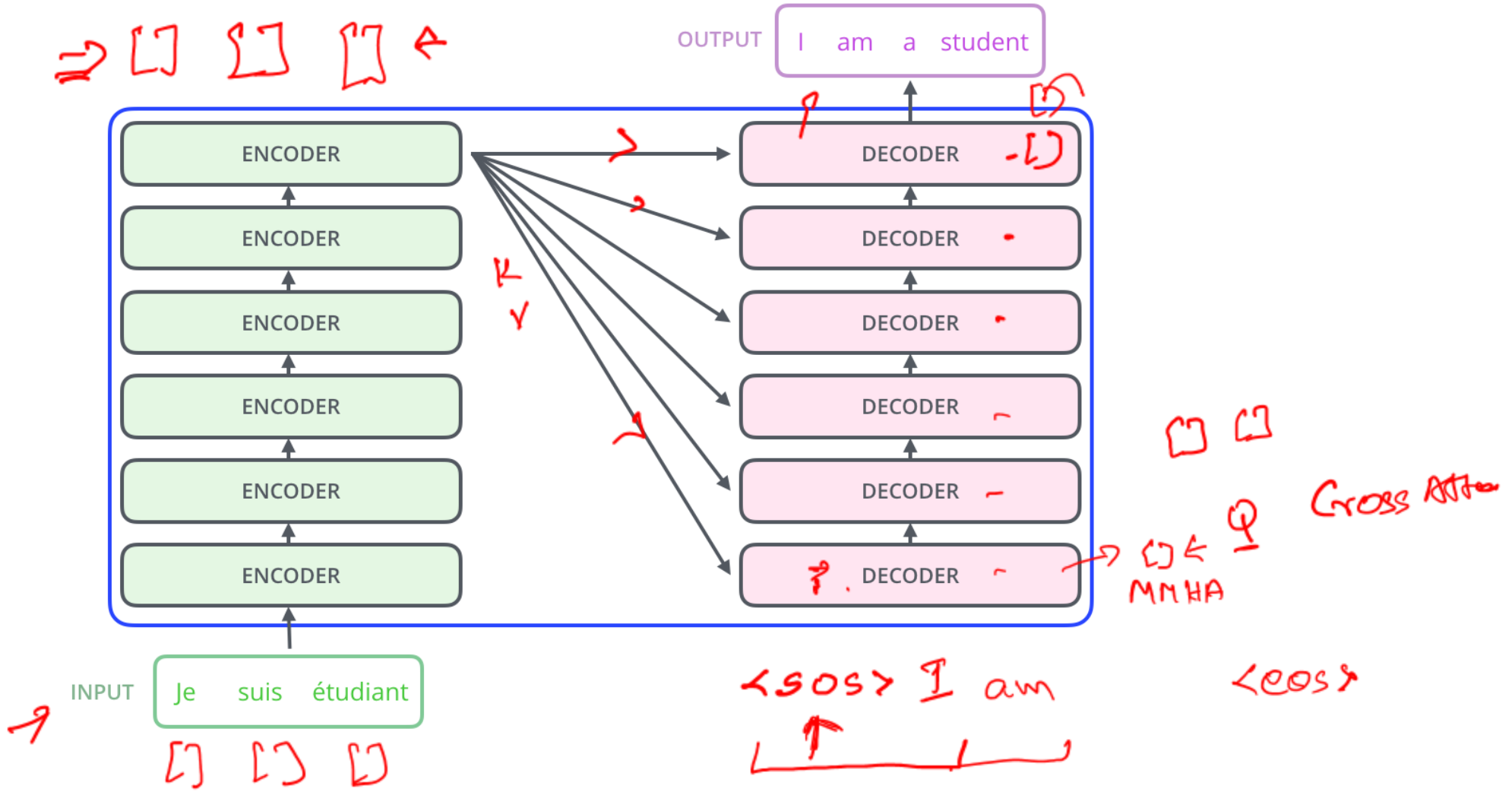
Neural Machine Translation



Full Picture



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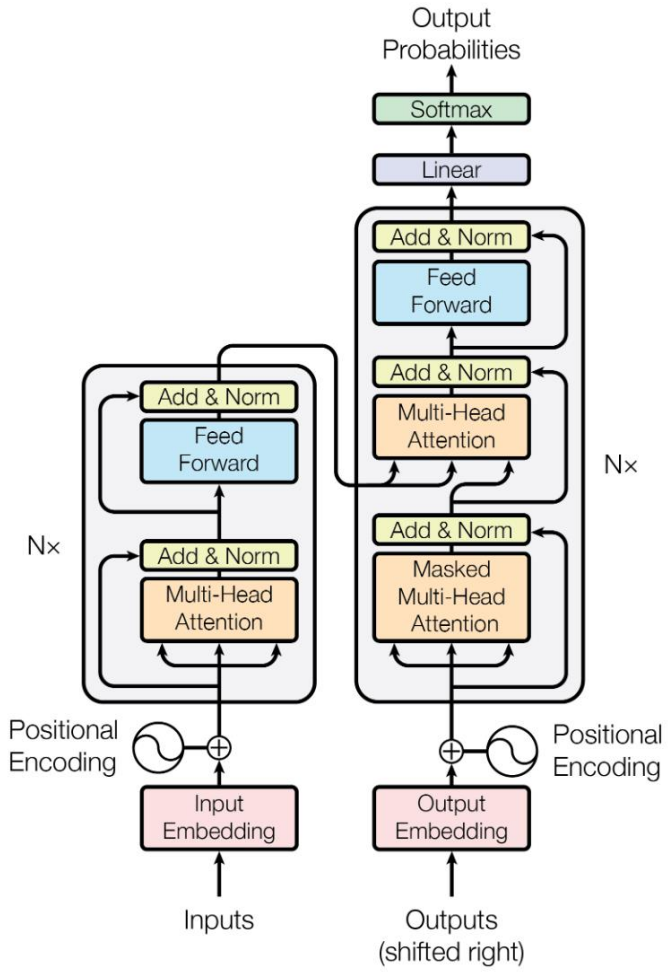
Neural Machine Translation Model

- The decoder input is shifted by one step, i.e., the decoder is given as input the word that it *should* have output at the previous step.
- For first prediction, the input is <SOS> token and decoder ends the sentence with <EOS> token.
- During inference, as the target sentence is not available the word that it output at the previous step is fed to the decoder.

NMT with Transformer: High Level

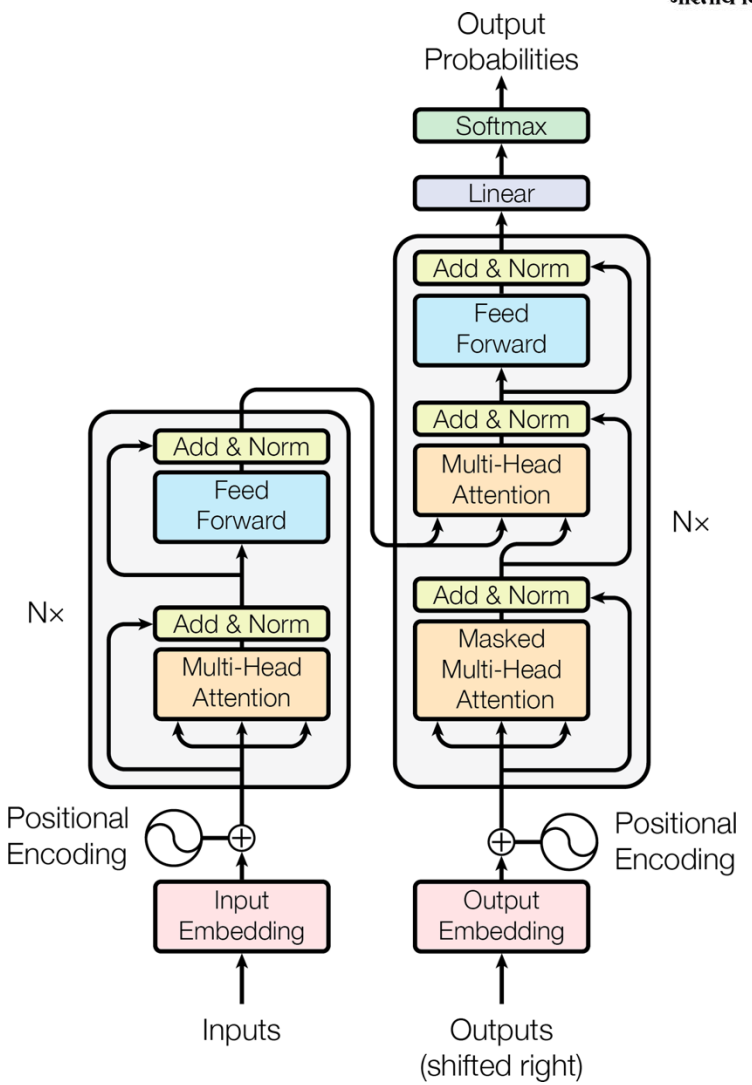
- This is a NMT model with 6 encoders and 6 decoders.
- Each encoder has a self-attention layer followed by a feedforward layer. Residual connection and layer normalization is applied in both the layers.
- Each decoder has an additional attention layer that takes in encoder output. Also, masked attention is used in Decoder to prevent attending to subsequent positions.



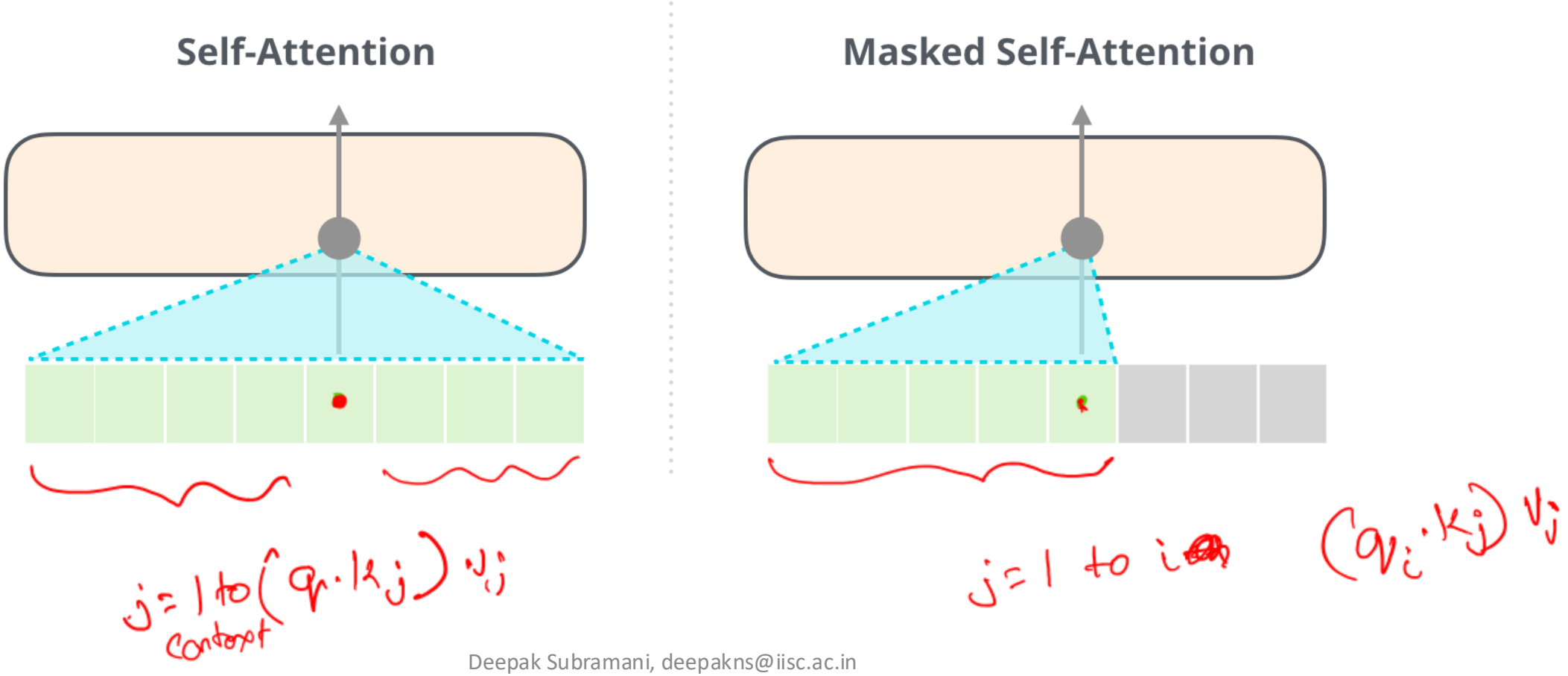
Vaswani et al., 2017, Attention Is All You Need

Sequence-to-Sequence using Transformers

- Right part of the figure – Decoder
  - The target sequence is shifted to the right by one and a <sos> is added
  - Output embedding is done similar to input embedding for the target language
  - Positional embedding is also added
- After embedding, a masked multi-head attention is used
  - A causal mask is used so that the output sequence doesn't use attention with tokens in later positions (at step n, it should not use tokens at n+1 onwards)
- After the masked MHA, the next multihead attention uses query=masked MHA output, key=value=encoder output
- The same encoder output is fed into all the decoder units in the right stack



Masked Self-Attention



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Masked Self-Attention

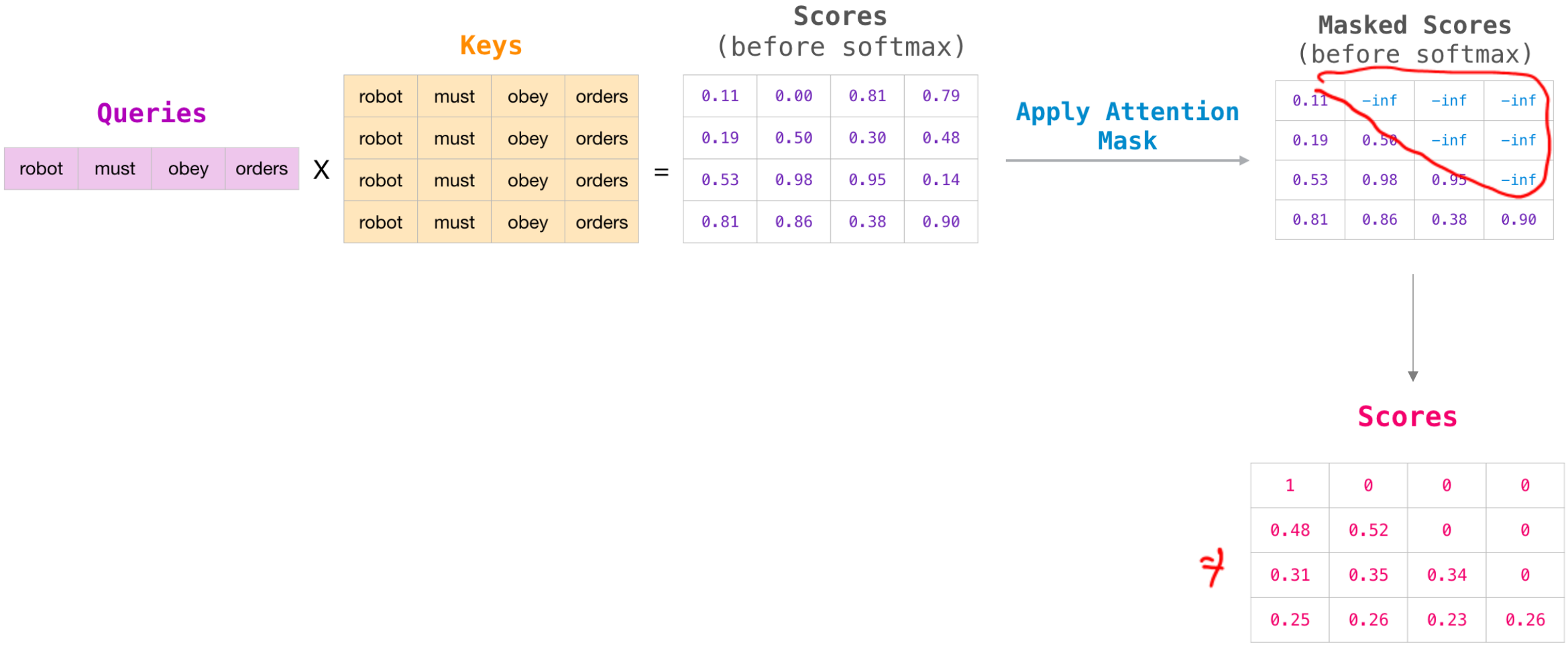
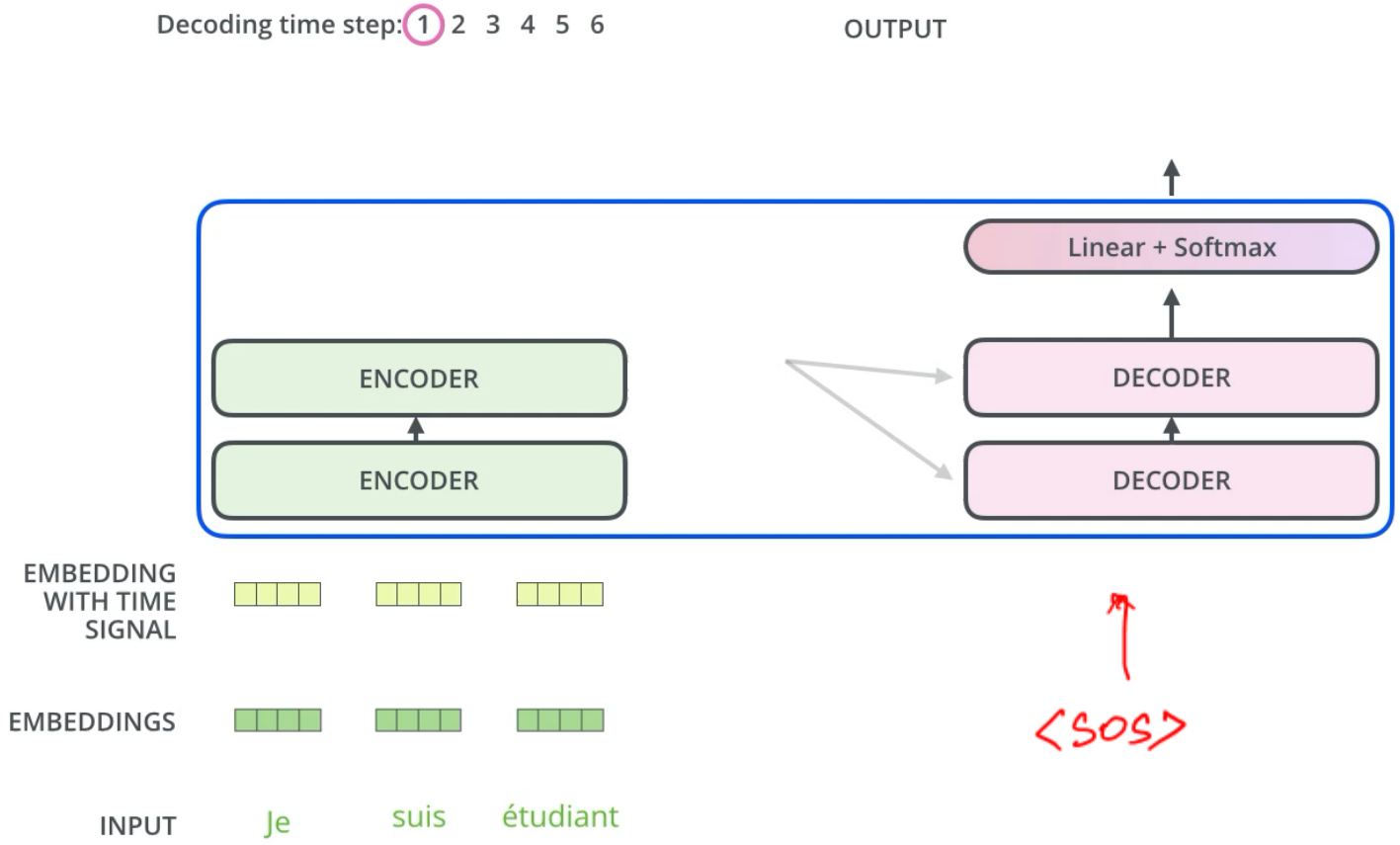


Image source: https://jalammar.github.io/illustrated-gpt2/

Seq2seq using Transformers: Decoder



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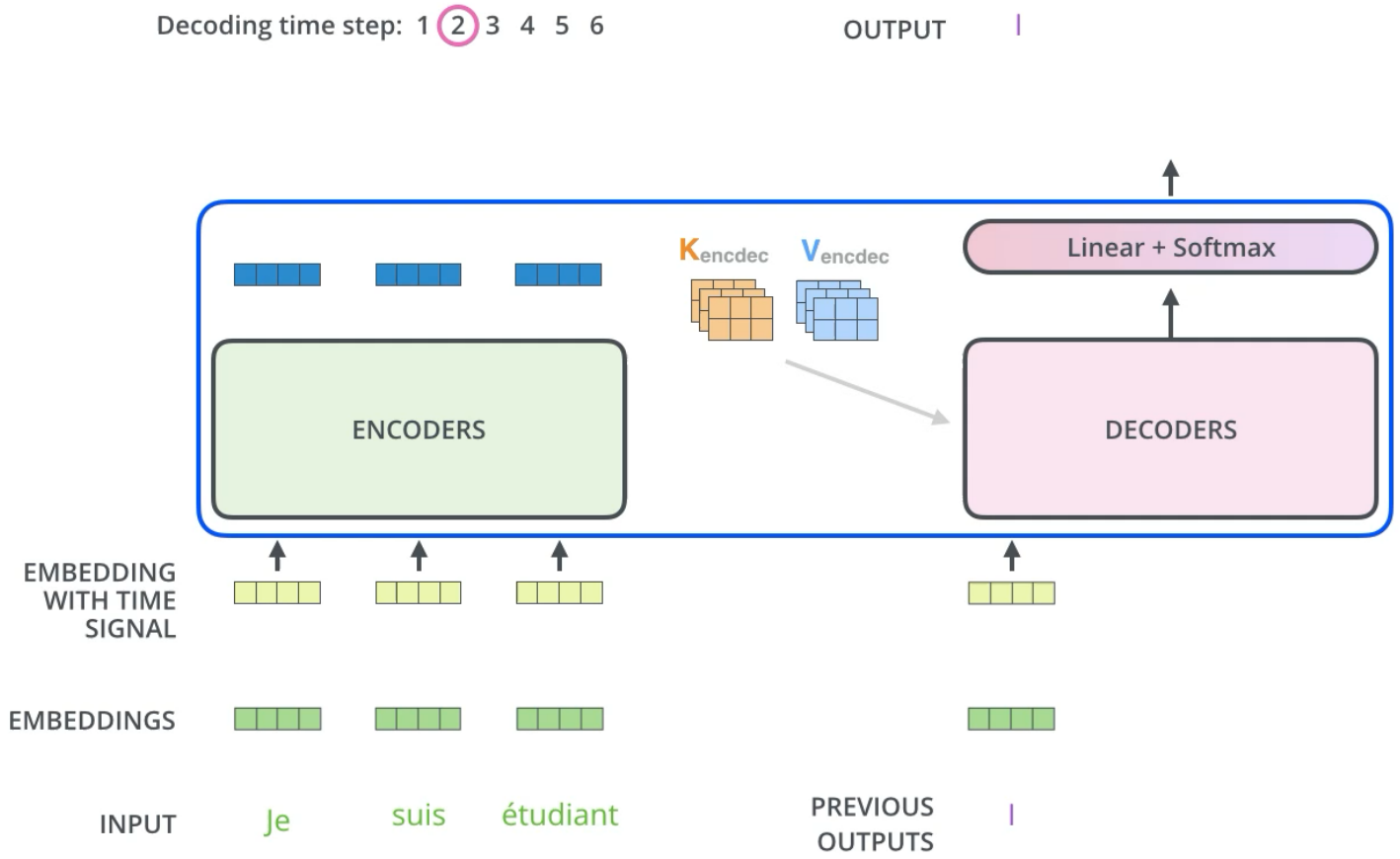
Seq2seq using Transformers: Decoder



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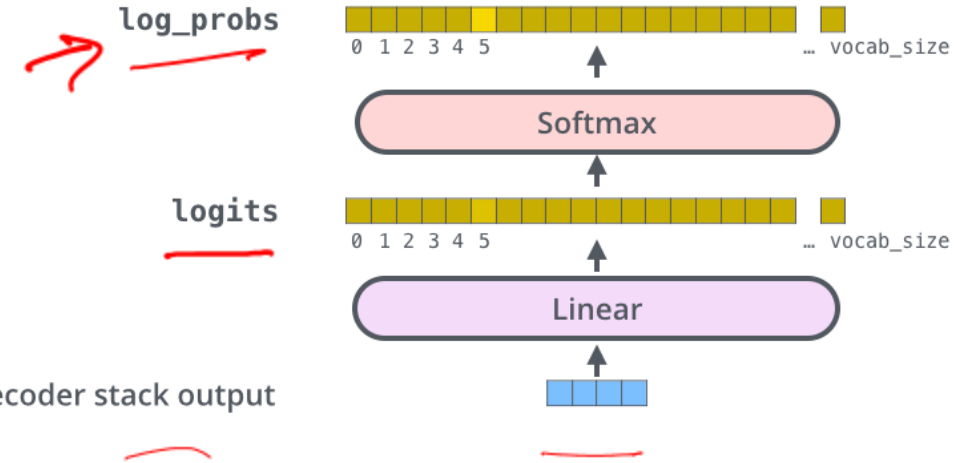
Final Layer and Output

Which word in our vocabulary is associated with this index?

am

Get the index of the cell with the highest value (argmax)

5



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Beam Search

NLU → BERT → Classification

NLG → GPT → ROUGE / BLEU

Loss Function

<sos> I am

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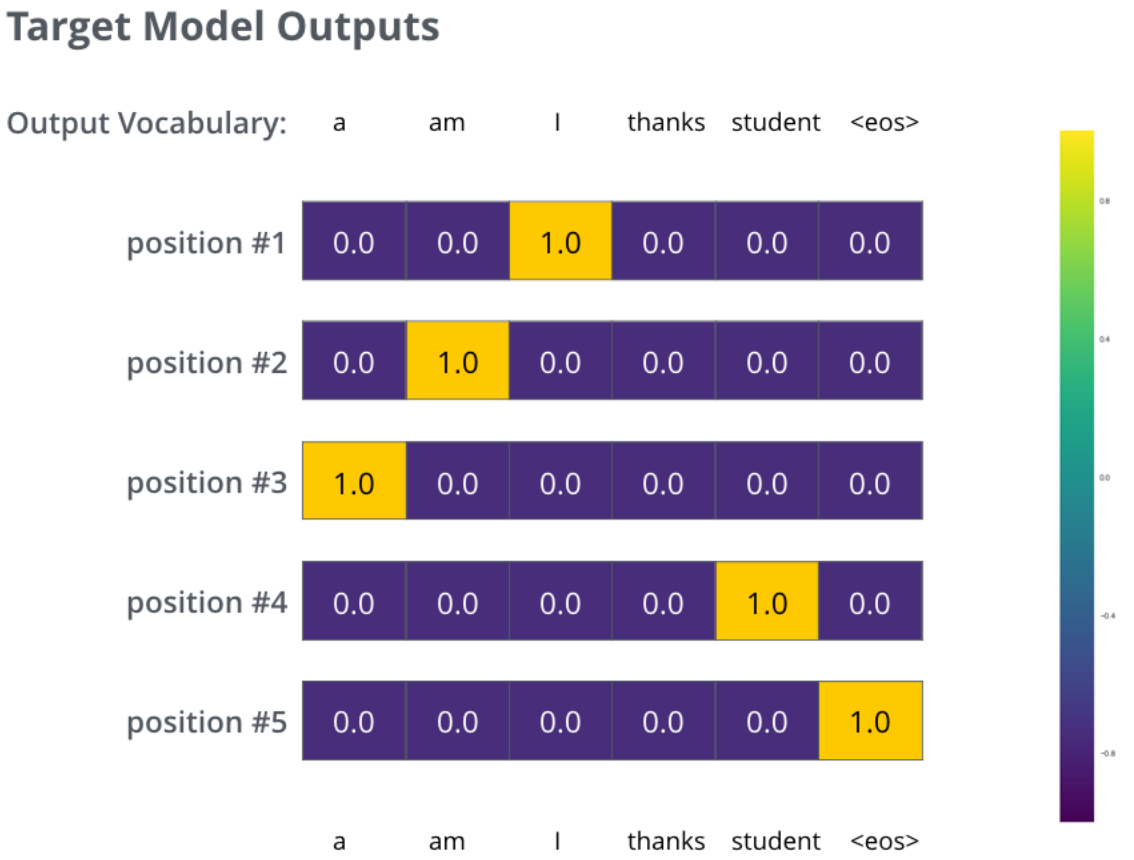
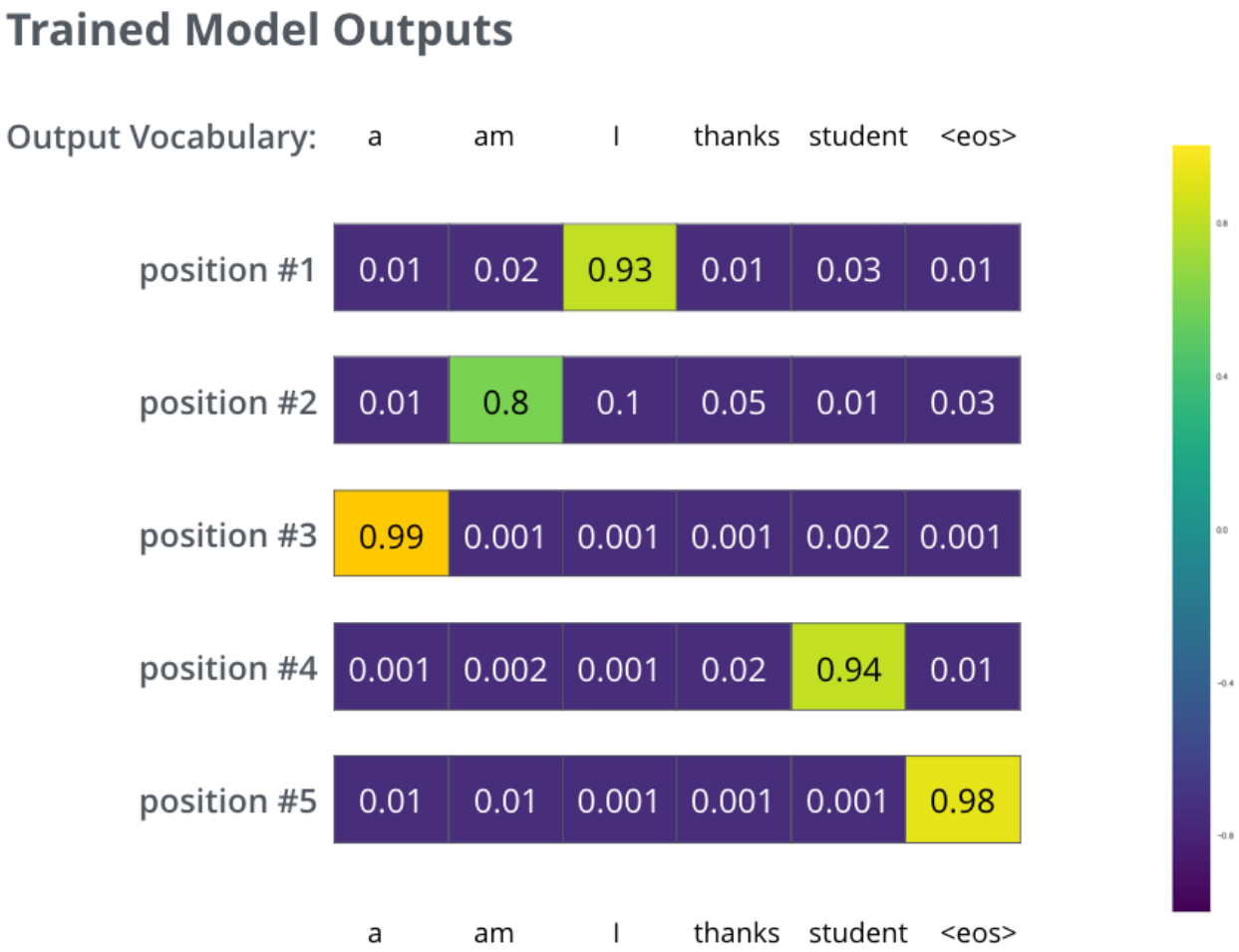
Cross Entropy Loss





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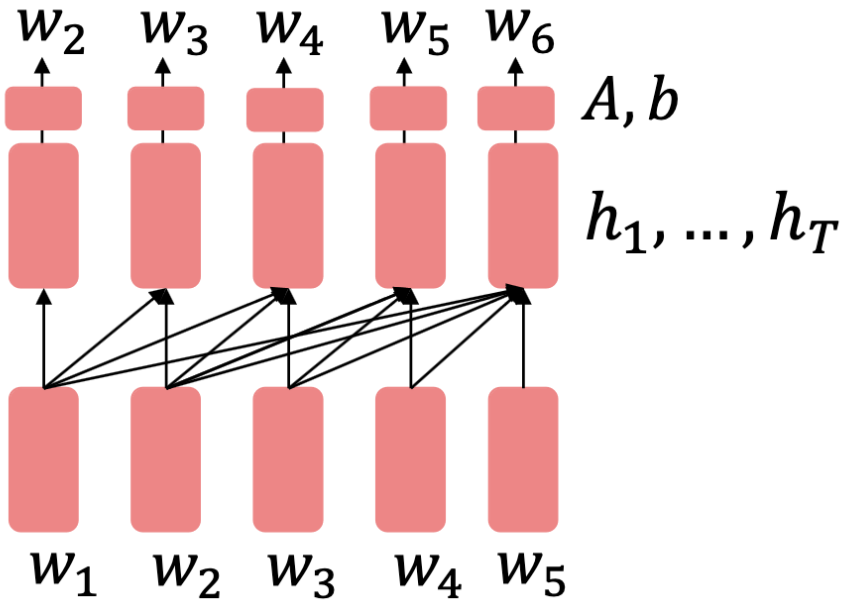
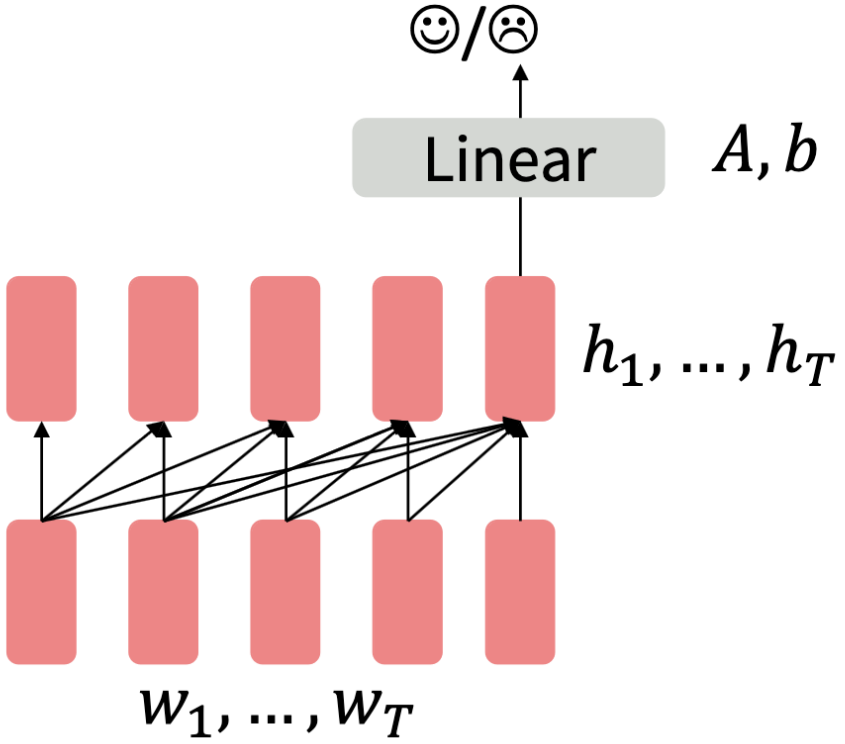
Decoders Pretraining

- Decoders generate the next word given its previous words.





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Types of pre-trained LMs

- Encoder only: BERT and friends
- Encoder-decoder: Flan T5 Model
- Decoder only: GPT

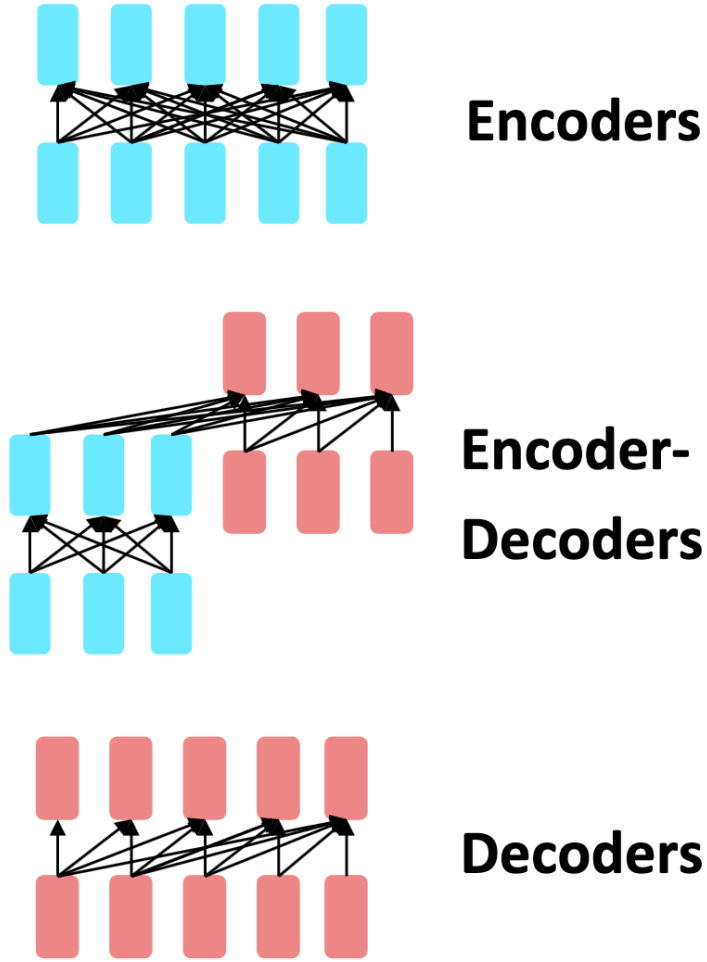


Image source: https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture9-pretraining.pdf

Evaluation Metrics

- Text Classification
  - Accuracy, Precision, Recall, F1 Score
  - Area Under the Curve (AUC) –
    - Combines true positives vs false positives as threshold for prediction is varied.
    - Used to measure the quality of a model independent of prediction threshold, and
    - to find the optimal prediction threshold for a classification task.
- Language Translation and other seq2seq tasks
  - BLEU - bilingual evaluation understudy.
    - Captures the amount of n-gram overlap between the output sentence and the reference ground truth sentence.
    - Has many variants
    - Been adapted to text to text tasks such as paraphrase generation and summarization.
  - METEOR – Advanced BLEU
    - Allows synonyms and stemmed words to be matched with the reference word
- Summarization Tasks
  - ROUGE – Measures Recall
    - Evaluate how many words a model can recall in a summary.
- Language Models
  - Perplexity – Cross entropy in next word prediction task

→ I am a student.

I am the student.

Word Piece Tokenization – Byte Pair Encoding

- ("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
  - Split: ("h" "##u" "##g", 10), ("p" "##u" "##g", 5), ("p" "##u" "##n", 12), ("b" "##u" "##n", 4), ("h" "##u" "##g" "##s", 5)
- The most frequent pair is ("##u", "##g") (present 20 times), but the individual frequency of "##u" is very high, so its score is not the highest (it's 1 / 36).
- All pairs with a "##u" actually have that same score (1 / 36), so the best score goes to the pair ("##g", "##s") — the only one without a "##u" — at 1 / 20, and the first merge learned is ("##g", "##s") -> ("##gs").
- Continue merging until we reach the desired vocabulary size

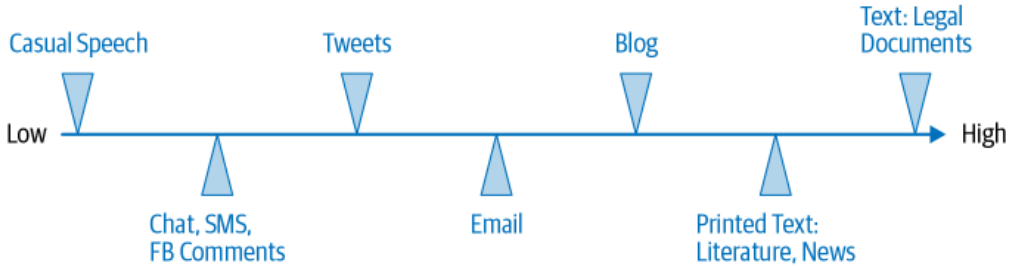
Additional Material

Miscellaneous Points

- Social Media Data
- Evaluation Metrics
- Other NLP Tasks
- Chat Bots
- Speech Modeling

Subword Embeddings

- When dealing with Social Media Text Data (SMTD), we will have OOV tokens when using standard vocabulary
- Hence, subword embeddings are more popular for SMTD
- OSU Twitter NLP Tool: https://github.com/aritter/twitter_nlp/tree/master
- NLTK Tweet Special Tokenizer
- Twikenizer – can handle abusive hidden words https://pypi.org/project/twikenizer/



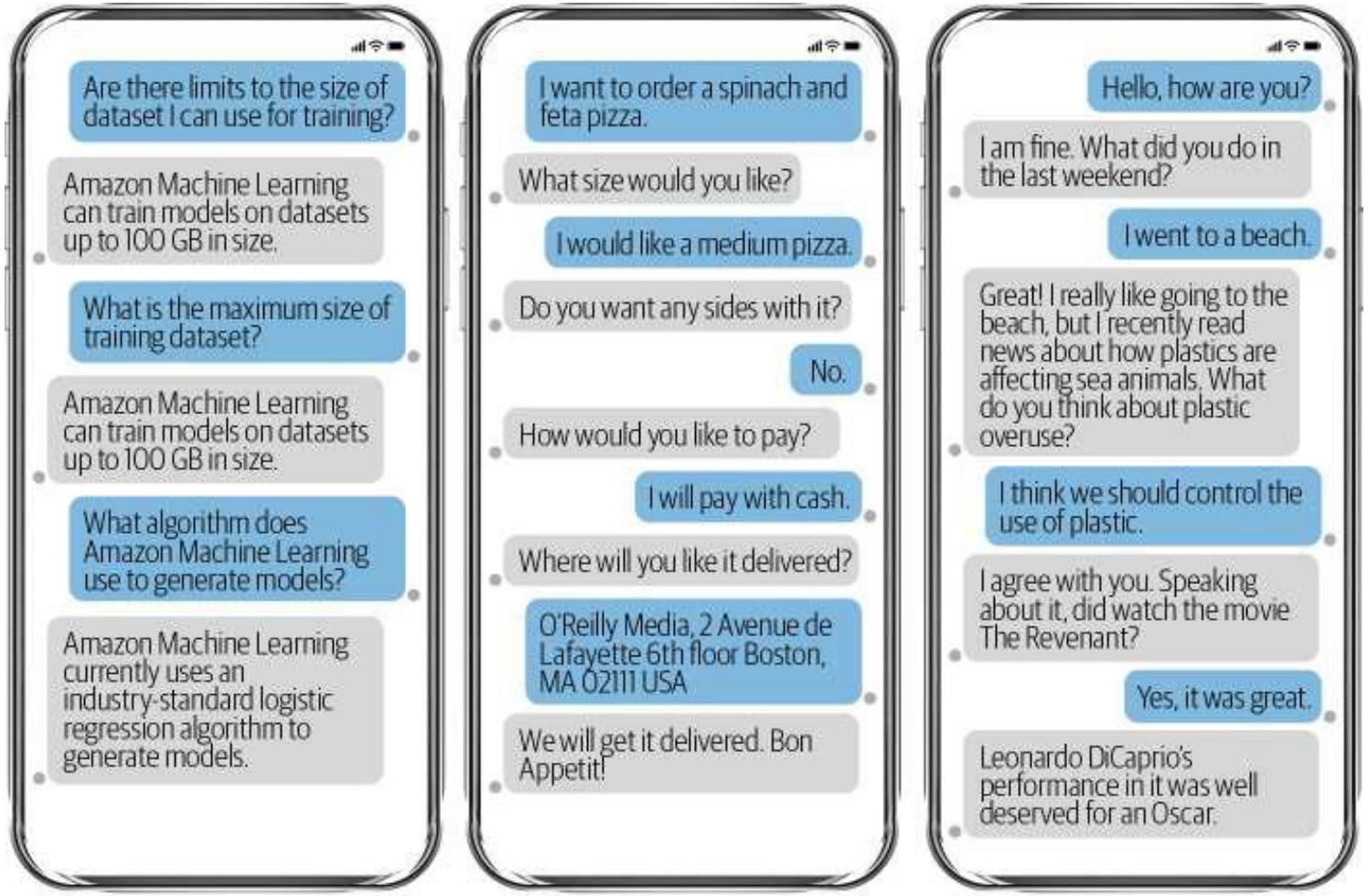
Other NLP Tasks

- Information Extraction
  - Key phrase Extraction (KPE)
  - Named Entity Recognition (NER)
  - Named Entity Linking (NEL)
  - Relationship Extraction
- Chatbots
- Topic Modeling –
  - Generally done with Latent Dirichlet Allocation (LDA) and not DL. LDA is a special case of Naïve Bayes with an assumption of Dirchlet Process prior

Attention Mechanism Video

https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Chatbots



RASA Chatbot Framework

Understand intent, take action based on rules

Deepak Subramani, deepakns@iisc.ac.in

NLP task	Use	Nature of data
Search	Find relevant content for a given user query.	World wide web/large collection of documents
Topic modeling	Find topics and hidden patterns in a set of documents.	Large collection of documents
Text summarization	Create a shorter version of the text with the most important content	Typically a single document
Recommendations	Showing related articles	Large collection of documents
Machine translation	Translate from one language to another	A single document
Question answering system	Get answers to queries directly instead of a set of documents.	A single document or a large collection of documents

Top NLP Libraries

- NLTK - tokenization, lemmatization, stemming, parsing, POS tagging, etc. This library has tools for almost all NLP tasks. Supports large number of languages
- Spacy – The main competitor for NLTK. These two libraries can be used for the same tasks. Limited language support
- Gensim – Topic and vector space modelling, document similarity
- Polyglot – similar to NLTK and has support for a large number of languages. But slow and not enough support.

Automatic Speech Recognition Models

- https://openai.com/research/whisper
- Wave 2 Vec 2
- HuBERT
- Neural Speech Models – Textless Speech Models