01. BERT

Why was BERT way ahead of its time?

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Because it was a masked language model even during pre-covid days!

Source: Ramsri Goutham

CS 1671/2071
Human Language Technologies

Session 13: BERT

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March 24, 2025

University of Pittsburgh | School of Computing and Information

Course logistics

- Project progress report is **due this Thu Mar 27**. See the project website for instructions
  - **Part 1:** Data statistics and exploratory data analysis (EDA)
  - **Part 2:** A result from baseline/initial approach
  - **Part 3:** Proposal on how to use LLMs for your task
  - **Part 4:** Open questions and challenges
- I will let you know when we have a class OpenAI API account to use ($150 total). In the meantime look into using Gemini free credits or other LLMs

Course logistics

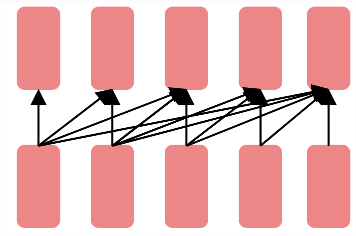
- In-person exam will be **next Wed Apr 2**
  - One page of double-sided notes will be permitted
  - Review session is next Mon Mar 31 during class
- Homework 3 will be released today or tomorrow. Will be on LLM prompting and will be **due Apr 10**

Lecture overview: BERT

- Notebook from last time: finetuning GPT-2 on Shakespeare plays
- Subword tokenization
- BERT and masked language modeling
- Finetuning BERT for classification and sequence labeling
- Notebook for this time: finetuning BERT for text classification

Review: Describe encoder, decoder, and encoder-decoder architectures

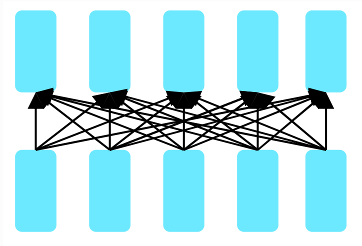
Three architectures for large language models



Decoders

GPT, Claude,

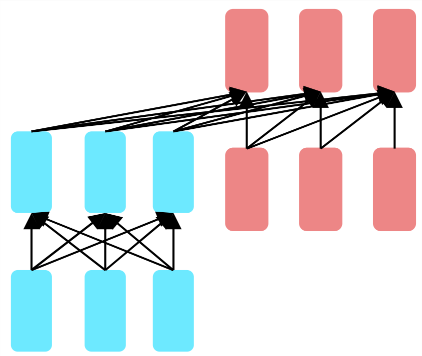
Llama, Mixtral



Encoders

BERT family,

RoBERTa



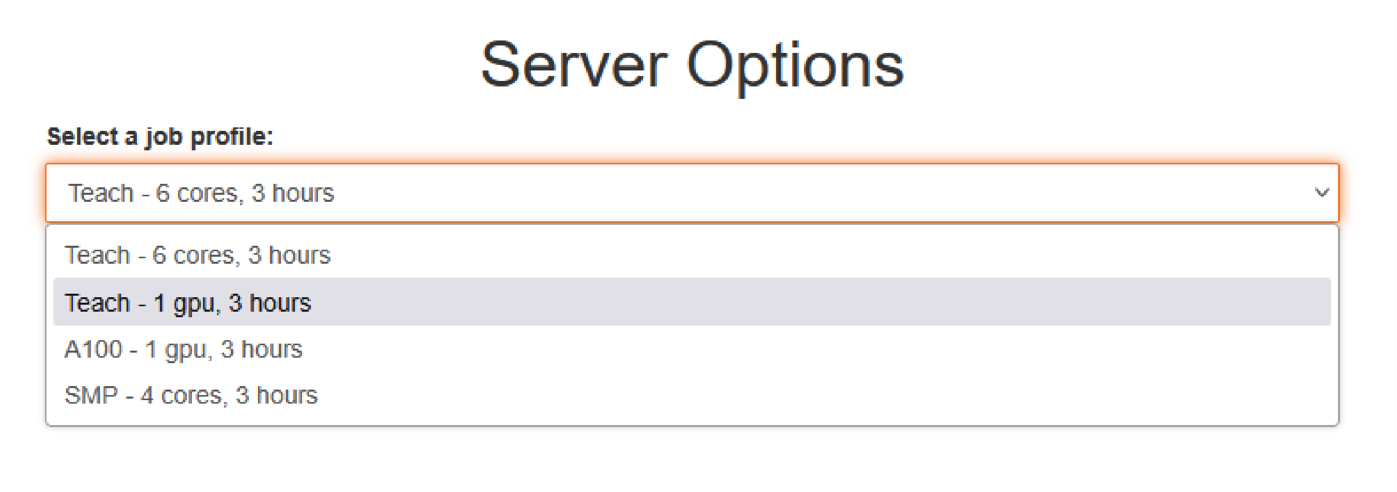
Encoder-decoders

Flan-T5, Whisper

Slide adapted from Jurafsky and Martin

Notebook from last time: finetune GPT-2 on Shakespeare

- Click on this nbgitpuller link or find the link on the course website
- **Important difference from normal:** Open a 'Teach – 1 gpu, 3 hours' server



- Open **session17_gpt2_shakespeare.ipynb**

Subword tokenization

Subword tokenization

- LLMs generally use **subword tokenization**
- E.g. byte pair encoding (BPE)

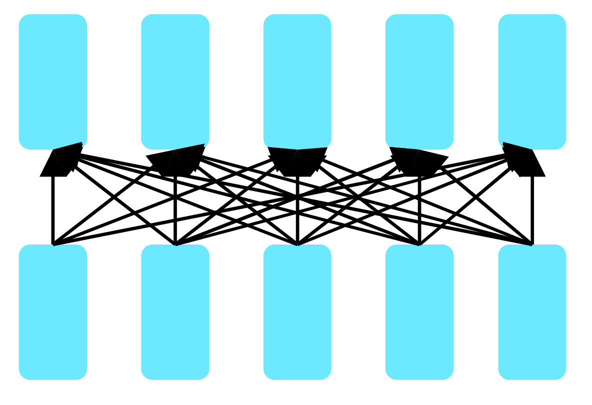
- Merges frequently seen sequences of characters together into tokens
- Repeat:
  - Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', 'B')
  - Add a new merged symbol 'AB' to the vocabulary
  - Replace every adjacent 'A' 'B' in the corpus with 'AB'.
  - Until *k* merges have been done.
- Allows them to generalize to unseen words, handle misspellings, novel words

Slide adapted from Jurafsky & Martin

Transformer encoder: BERT family

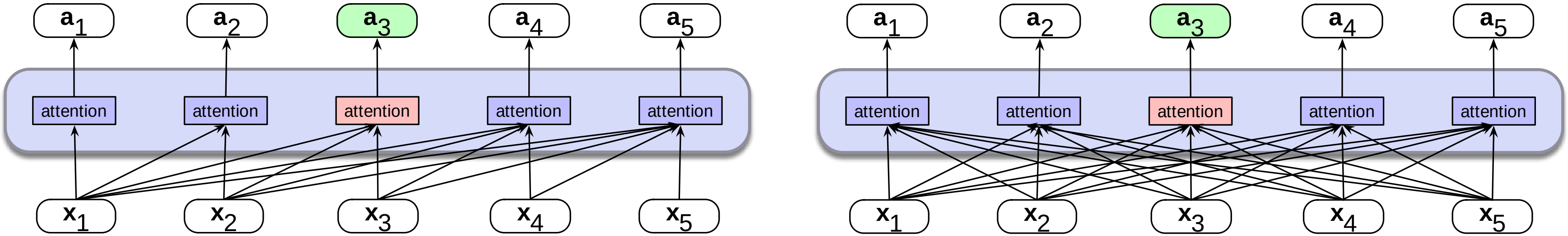
Encoders

- So far, we've looked at (causal, left-to-right) language model pretraining
- But what about tasks where we want to peek at future tokens?
- Encoders can access bidirectional context
- Map sequences of input embeddings to sequences of output embeddings that have been contextualized using information from the entire sequence
- No "masking" of future words in self-attention



Slide adapted from John Hewitt, Jurafsky and Martin

Bidirectional Self-Attention



a) A causal self-attention layer

b) A bidirectional self-attention layer

Slide adapted from Jurafsky and Martin

Pretraining encoders: masked language modeling

- BERT (Devlin et al. 2019) is pretrained with 2 objectives
  - Masked language modeling
  - Next sentence prediction (not as important, covered in class)

The Cloze Task

- The cloze task comes from psycholinguistics (the branch of linguistics and cognitive science that uses experimental methods to study how language works in human brains).
- It is a fill-in-the-blank task:

  He drove the yellow ______ into the front of our house.

- Subjects are presented with these frames and asked to fill in the missing words
- This allows experimenters to assess what a speaker understands about grammar, semantics, etc.
- According to the original BERT paper, this task provided the inspiration for BERT's masked language modeling (MLM) training task.
- But compare various kinds of denoising algorithms.

Slide credit: David Mortensen

MLM training in BERT

15% of the tokens are randomly chosen to be part of the masking .

Example: "Lunch was **delicious**", if delicious was randomly chosen:

Three possibilities:

1. 80%: Token is replaced with special token [MASK]

   Lunch was **delicious** -> Lunch was **[MASK]**

2. 10%: Token is replaced with a random token (sampled from unigram prob)

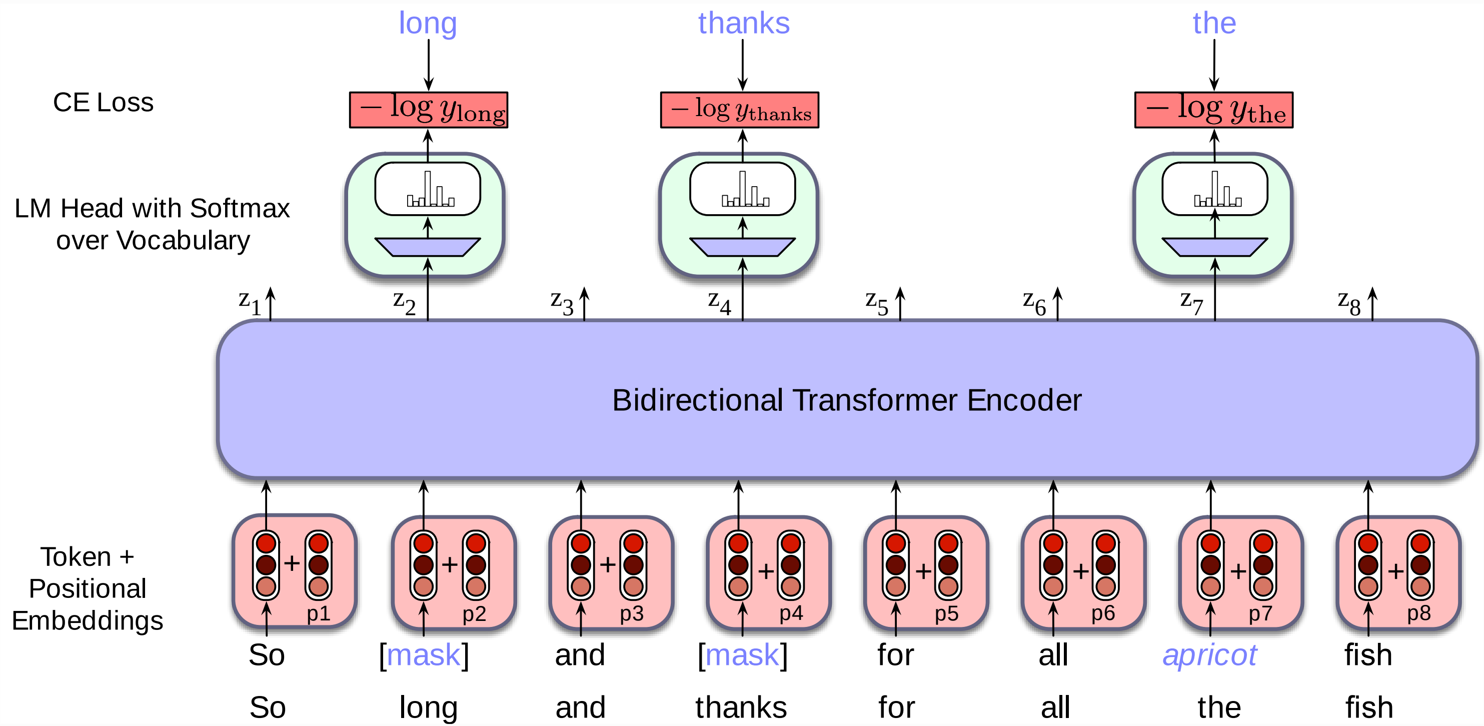
   Lunch was **delicious** -> Lunch was **gasp**

3. 10%: Token is unchanged

   Lunch was **delicious** -> Lunch was **delicious**

Slide adapted from Jurafsky and Martin

In detail



Slide adapted from Jurafsky and Martin

BERT: Bidirectional Encoder Representations from Transformers

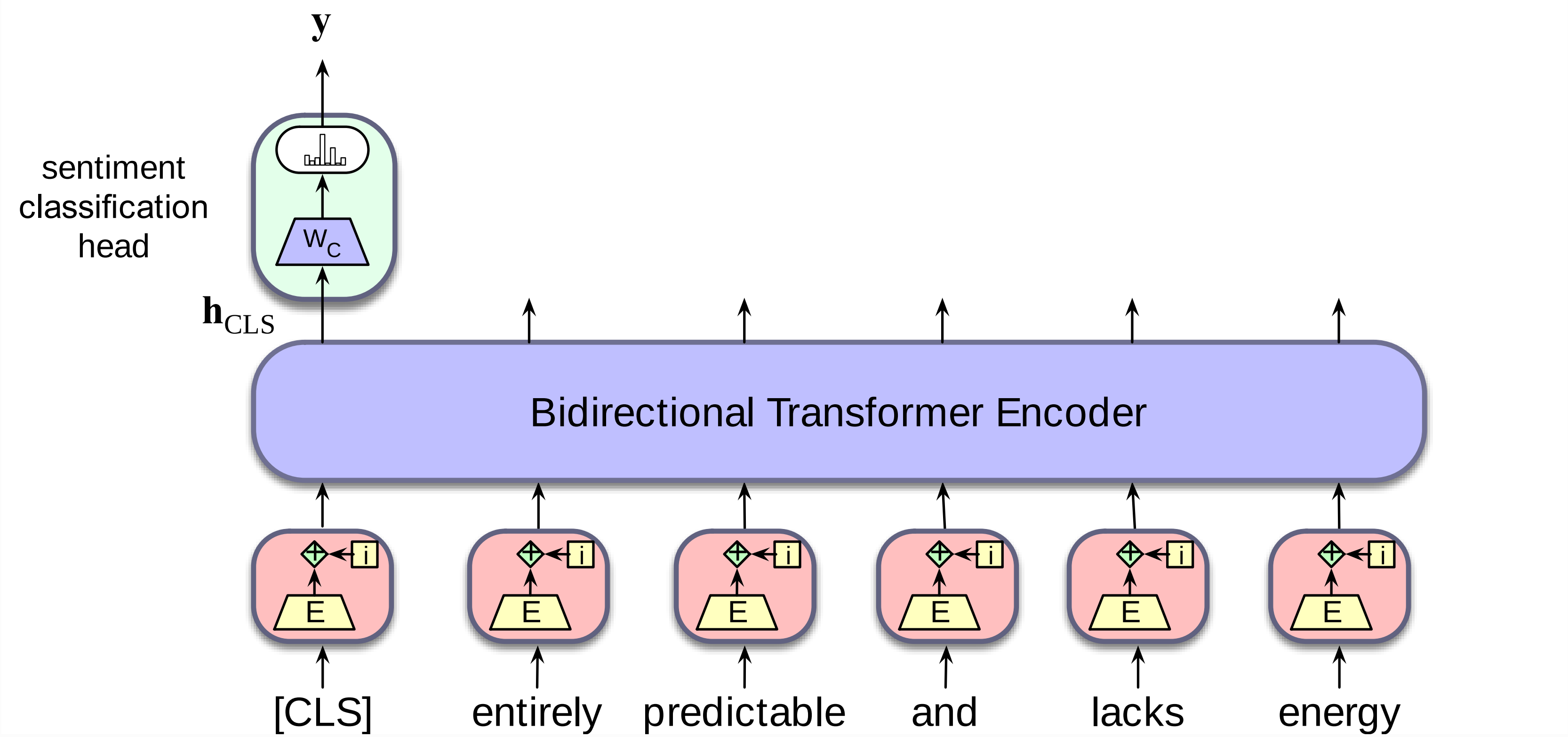
Details about BERT

- Two models were released:
    - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
    - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- 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.
      (TPUs are special tensor operation acceleration hardware)
- Finetuning is practical and common on a single GPU
    - "Pretrain once, finetune many times."

Slide adapted from John Hewitt

Finetuning BERT for classification and sequence labeling

Finetuning for classification



Slide adapted from Jurafsky and Martin

Fine-tuning for sequence labeling (new task!)

- Assign a label from a small fixed set of labels to each token in the sequence.
  - Named entity recognition
  - Part of speech tagging
    - Assign a part of speech (like NOUN, VERB, or ADJECTIVE) to every word in a sentence
- Labels depend not just on the word being classified, but labels of surrounding words
  - E.g. “States” is more likely to be part of a named entity if it follows the word “United”

Slide adapted from Jurafsky and Martin

Named Entity Recognition

- A **named entity** is anything that can be referred to with a proper name: a person, a location, an organization
- **Named entity recognition (NER):** find spans of text that constitute proper names and tag the type of the entity

Type	Tag	Sample Categories	Example sentences
People	PER	people, characters	**Turing** is a giant of computer science.
Organization	ORG	companies, sports teams	The **IPCC** warned about the cyclone.
Location	LOC	regions, mountains, seas	**Mt. Sanitas** is in **Sunshine Canyon**.
Geo-Political Entity	GPE	countries, states	**Palo Alto** is raising the fees for parking.

Slide adapted from Jurafsky and Martin

Named Entity Recognition

Citing high fuel prices, [$_{\text{ORG}}$ **United Airlines**] said [$_{\text{TIME}}$ **Friday**] it has increased fares by [$_{\text{MONEY}}$ **$6**] per round trip on flights to some cities also served by lower-cost carriers. [$_{\text{ORG}}$ **American Airlines**], a unit of [$_{\text{ORG}}$ **AMR Corp.**], immediately matched the move, spokesman [$_{\text{PER}}$ **Tim Wagner**] said. [$_{\text{ORG}}$ **United**], a unit of [$_{\text{ORG}}$ **UAL Corp.**], said the increase took effect [$_{\text{TIME}}$ **Thursday**] and applies to most routes where it competes against discount carriers, such as [$_{\text{LOC}}$ **Chicago**] to [$_{\text{LOC}}$ **Dallas**] and [$_{\text{LOC}}$ **Denver**] to [$_{\text{LOC}}$ **San Francisco**].

Slide adapted from Jurafsky and Martin

BIO tagging [Ramshaw and Marcus 1995]

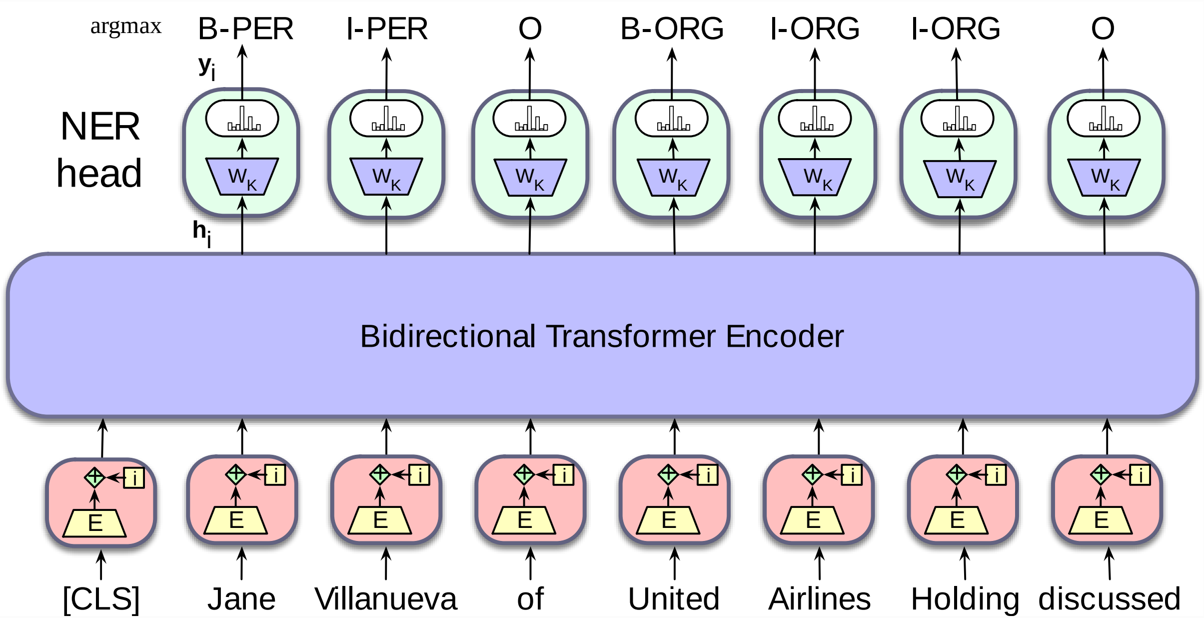
- A method that lets us turn a segmentation task (finding boundaries of entities) into a classification task

[PER Jane Villanueva] of [ORG United Airlines Holding] discussed the [LOC Chicago] route.

Words	BIO Label
Jane	B-PER
Villanueva	I-PER
of	O
United	B-ORG
Airlines	I-ORG
Holding	I-ORG
discussed	O
the	O
Chicago	B-LOC
route	O
.	O

Slide adapted from Jurafsky & Martin

Sequence labeling



$$\mathbf{y_i} = \mathrm{softmax}(\mathbf{h_i^L W_K})$$
$$\mathbf{t_i} = \mathrm{argmax}_k(\mathbf{y}_i)$$

Slide adapted from Jurafsky and Martin

Conclusion

- LLMs use subword tokenization like BPE to learn to recognize parts of words (subword tokens). This enables them to handle words they haven't seen before
- BERT is an encoder transformer model that produces an output embedding for every input token
- BERT is pretrained on the task of masked language modeling, learning to predict masked words in the middle of sentences
- BERT is often finetuned for:
  - Classification
  - Sequence labeling, which are tasks like named entity recognition where a label is predicted for every word

Coding activity: finetune BERT for text classification

Notebook for this class: finetune BERT for politeness classification

- Click on this nbgitpuller link or find the link on the course website
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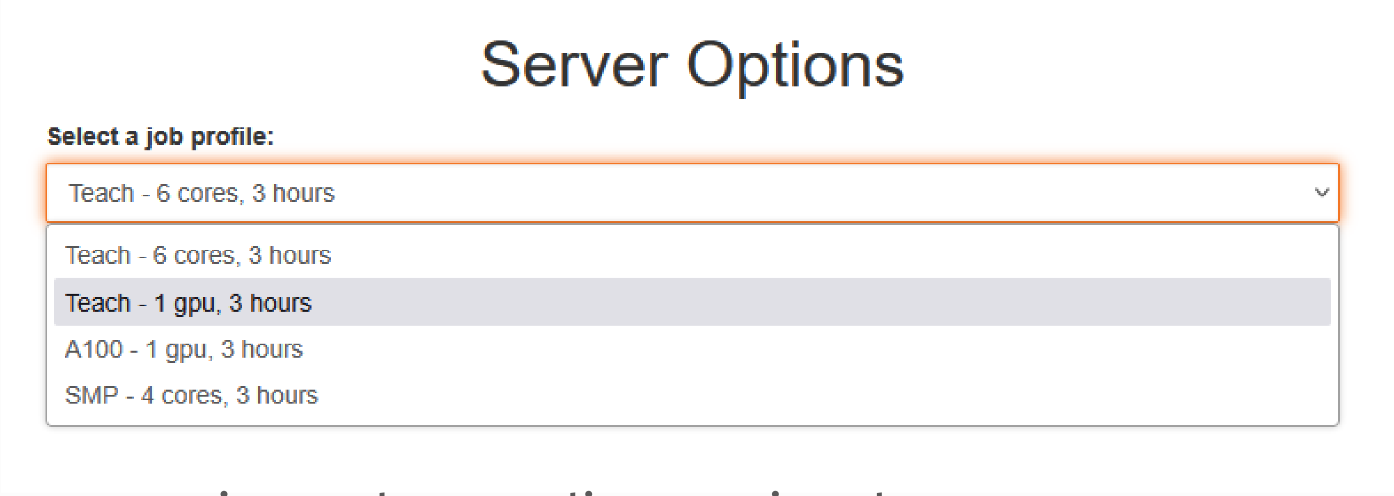

- Open **session18_bert_politeness.ipynb**