Pretraining and Finetuning

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Logistics

- Section will be in-person, starting at 4:55pm.
  - Review and Q&A about the lecture recording.
  - Lab material.
- Online midterm next week
- Spring break no lecture
- Project: start early! Proposal due after spring break

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Representation learning

What are good representations?

- Enable a notion of distance over text (word embeddings)
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negative the food is good but doesn't worth an hour wait

Simple features (e.g. BoW) require complex models.
Good features only need simple models (e.g. linear classifier) .

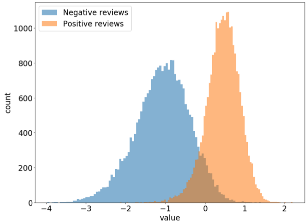

Figure: Sentiment neuron [Radford et al., 2017]

Representation learning

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- Learning with small data: fine-tuning on learned representations
- Transfer learning: one representation for many tasks
- Metric learning: get a similarity metric for free

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Training a neural network on any task gives us a representation good for *that task*.

But on which task can we learn good *general* representations?

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Word guessing entails lots of tasks related to language understanding!

Self-supervised learning

Key idea: predict parts of the input from the rest

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Approach:

- **Pretrain**: train a model using self-supervised learning objectives on large data.
- **Finetune**: update part or all of the parameters of the pretrained model (which provides an initialization) on supervise data of a task.

A bit of history

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- Pretrain a Transformer model and finetune on supervised tasks
  - GPT [Radford et al., 2018], BERT [Devlin et al., 2018]
- Scale the pretrained model to larger sizes
  - GPT-2 (1.5B), T5 (11B), GPT-3 (175B), PaLM (540B)
  - We will talk about 100B+ models in the third module

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All models are transformer based.

Encoder models

An encoder takes a sequence of tokens and output their contextualized representations:

$$h_1, \ldots, h_n = \mathrm{Encoder}(x_1, \ldots, x_n)$$

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How do we train $\mathrm{Encoder}$?

- Use any supervised task: $y = f(h_1, \dots, h_n)$
- Use self-supervised learning: predict a word from its neighbors

Masked language modeling

Learning objective:

$$\max \sum_{x \in \mathcal{D}, i \sim p_{\text{mask}}} \log p(x_i \mid x_{-i}; \theta)$$

- x_{-i}: noisy version fo x where x_i is corrupted
- p_{mask}: mask generator

BERT: objective

- **Masked language modeling**:
  - Randomly sample 15% tokens as prediction targets
  - Replace the target tokens in the input by either `[MASK]` (10%) or a random token (10%), or leave it unchanged
    cats are cute $\rightarrow$ cats `[MASK]`/is/are cute
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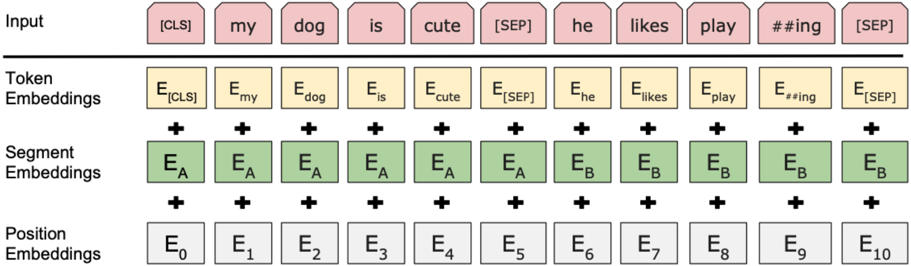
- **Next sentence prediction**: predict whether a pair of sentences are consecutive

$$\max \sum_{x \sim \mathcal{D}, x_n \sim p_{\text{next}}} \log p(y \mid x, x_n; \theta)$$

  - x_n: either the sentence following x or a randomly sampled sentence
  - y: binary label of whether x_n follows x
  - Later work has shown that this objective is not necessary

BERT: architecture



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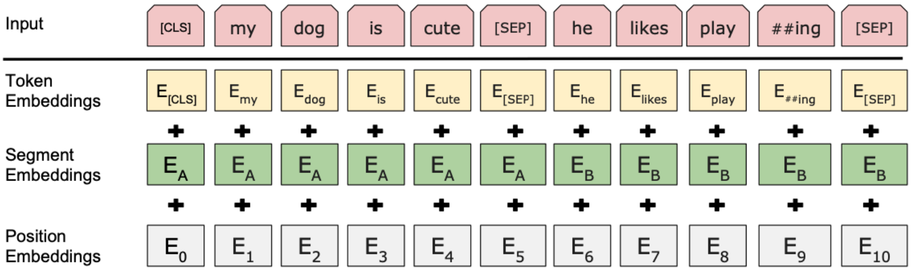

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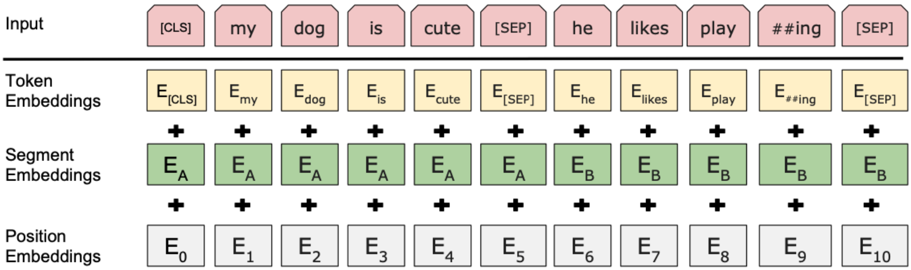

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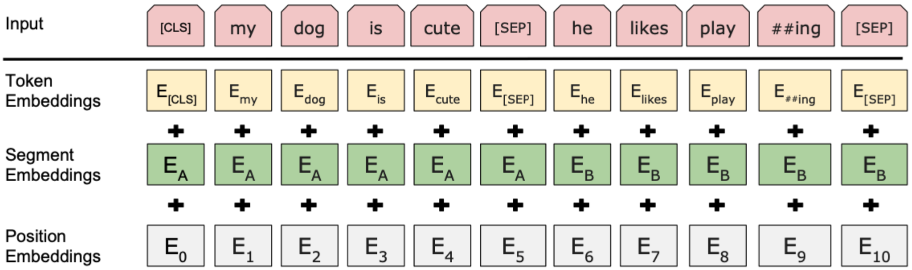

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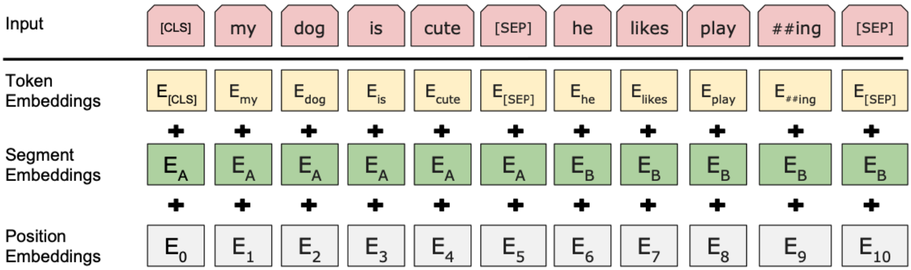

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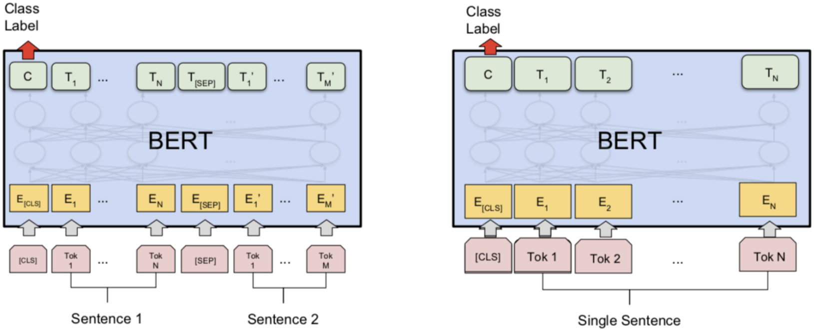
- `[CLS]`: first token of all sequences; used for next sentence prediction
- Distinguish two sentences in a pair: `[SEP]` and segment embedding
- Learned position embedding
- 12 (base; 110M params) or 24 (large; 340M params) layer Transformer

Finetuning BERT

Classification tasks: Add a linear layer (randomly initialized) on top of the `[CLS]` embedding

$$p(y \mid x) = \mathrm{softmax}(W h_{\texttt{[CLS]}})$$



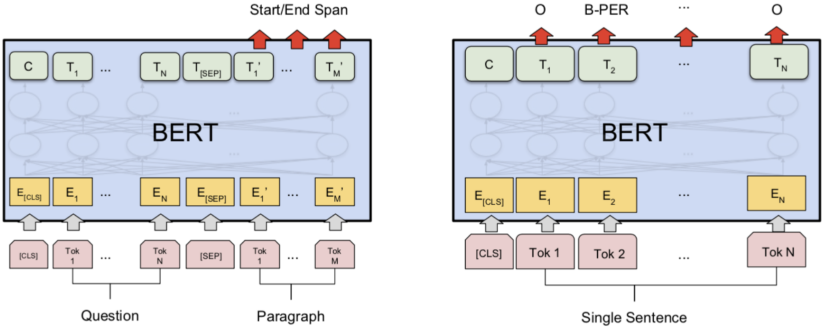
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

Finetuning BERT

Sequence labeling tasks: Add linear layers (randomly initialized) on top of every token

$$p(y_i \mid x) = \mathrm{softmax}(Wh_i)$$



(c) Question Answering Tasks:
SQuAD v1.1

(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

Finetuning BERT

- Finetune all parameters (both the newly added layer and the pretrained weights)
- Use a small learning rate (e.g., 1e-5)
- Train for a small number of epochs (e.g, 3 epochs)
- Led to SOTA results on many NLU tasks
- Not straightforward to use on text generation tasks

Encoder-decoder models

An encoder-decoder model encodes input text to a sequence of contextualized representations, and decodes a sequence of tokens autoregressively.

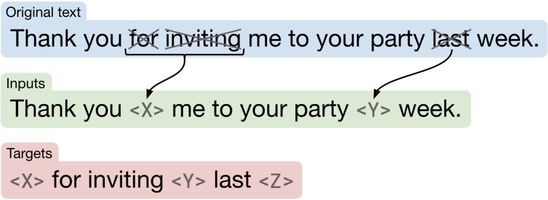
$$
\begin{aligned}
h_1, \ldots, h_n &= \mathrm{Encoder}(x_1, \ldots, x_n) \\
s_1, \ldots, s_m &= \mathrm{Decoder}(y_0, \ldots, y_{m-1}, h_1, \ldots, h_n) \\
p(y_i \mid x, y_{<i}) &= \mathrm{softmax}(W s_i)
\end{aligned}
$$

How do we train the encoder-decoder?

- Use any supervised task, e.g., machine translation
- Use self-supervised learning: predict text spans from their neighbors

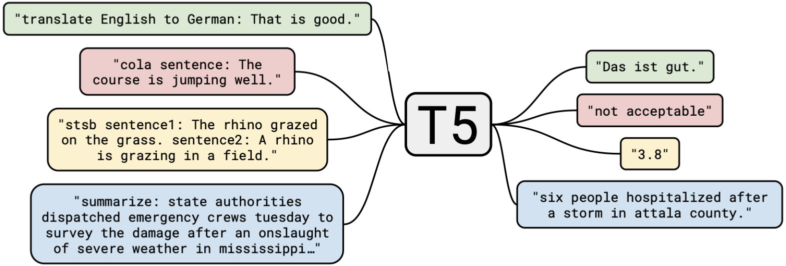
Masked language modeling using an encoder-decoder

Input: text with corrupted spans
Output: recovered spans



T5

- First train on unlabele data by **masked language modeling**
  - Predict corrupted spans as a sequence
- Then continue training by **supervised multitask learning**
  - Formulate tasks as text-to-text format
  - Use a prefix to denote the task
  - Mixing examples from different datasets when constructing batches



- Jointly training with the two objectives works slightly worse

Finetuning T5

- Formulate the task in text-to-text format
- Fine-tune all parameters (similar to BERT fine-tuning)
- Advantages over encoder models: unified modeling of many different tasks

Efficient pretraining

An obvious downside of pretrained models is that they are quite expensive to train!

How can we make them more efficient?

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Idea 1: reducing the number of parameters smartly

Example: ALBERT (a lite BERT) [Lan et al., 2020]

- **Parameter sharing**:
  - Share feedforward network weights across layers
  - Share self-attention weights across layers
  - ALBERT: share all params across layers

Efficient pretraining

Idea 2: design harder learning objectives

ALBERT: Inter-sentence coherence loss

- Motivation: the next sentence prediction task is too easy
- Design hard negative examples
- Input: take two consecutive sentences, swap their order randomly
- Output: predict if they are in natural order

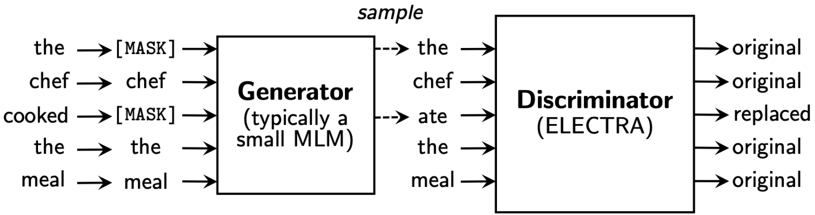
  I went home. SEP *I slept.* +1

  I slept. SEP *I went home.* -1
- What is needed to perform this task well?

Efficient pretraining

Idea 2: design harder learning objectives

ELECTRA [Clark et al., 2020]: discriminate from true vs guessed tokens



- First train the generator for n steps using the MLM objective.
- Freeze generator weights. Then train the discriminator using the sequence classification objective.
- The discriminator and generator share weights except for the input token embeddings.

Efficient pretraining

ELECTRA result:

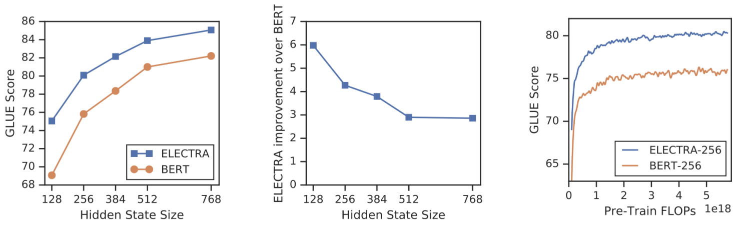


Figure: Finetuning result on the GLUE benchmark

- Larger improvement at smaller model sizes
- Faster training
- An effective approach if you don't have large compute for pretraining

What are these models trained on?

Both quantity and quality are important

- Wikipedia: encyclopedia articles (clean, single domain)
- Toronto Books Corpus: e-books (diverse domain)
- WebText (40GB): content submitted to Reddit with a vote ≥ 3 (diverse, bias)
- CommonCrawl (20TB): scraped HTML with markers removed (diverse, large, noisy, bias)
  - A cleaned version: C4 (750GB)

Summary

Lots of learning happens from just observing the world (data).

- Self-supervised learning: benefits from large data and compute
  - Basic: predict parts from other parts based on the structure of data (works beyond text)
  - Advanced: design hard negatives to improve efficiency
- Finetuning: adapt pretrained models to downstream tasks on a small amount of labeled data