Outline

Deep Learning

Final Assignment: Emotion Analysis with DistilBERT

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Outline

What is Emotion Analysis

- A more comprehensive version of *Sentiment Analysis*.
- Instead of neutral, negative and positive, it focuses on emotions.
- These two sentences are considered positive for sentiment analysis
  - "This milkshake is good."
  - "I am loving this milkshake already."
- An emotion analysis model will say that the second sentence has a stronger positive emotion than the first.

What is DistilBERT

- *DisbilBERT* is a state of the art language model based on transformers.
- Smaller and faster than *BERT*
  - As it's pretrained on massive amounts of data
- Commonly used in sentiment analysis via fine-tuning, such as sentiment prediction.
- With an appropriate setup, it is able to detect nuances.
  - Irony, sarcasm, slang, etc.

Context: LTSM

- Before Transformers, we have *LTSM*, but it suffers from two problems.
  1. The model sequentially looks at every word on the input.
     - Passed in and generated sequentially.
     - Long words, longer processing.
  2. Not truly bidirectional.
     - Uses simple concatenation and analyses words separately.
     - True meaning of words lost slightly.

Context: Transformers

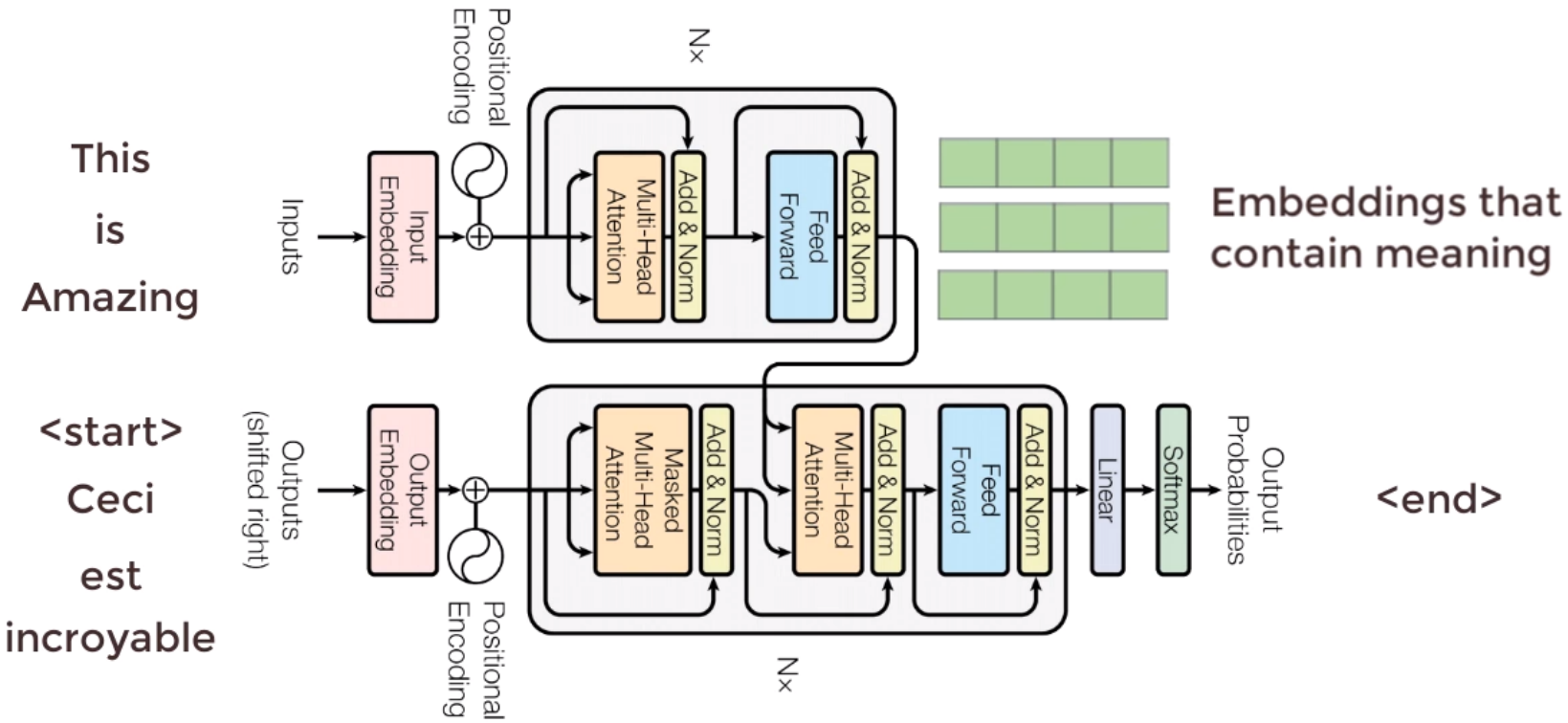
- *Transformers* solve both issues.
  1. Process words simultaneously
     - Is therefore faster
  2. Deeply bidirectional.
     - Able to learn from both directions simultaneously

Context: Transformers

- *Transformers* have two components:
  1. Encoder
     - Takes each word simultaneously.
     - Generates embeddings (the meanings) simultaneously, being vectors.
  2. Decoder
     - Takes what the encoder generated, and uses to generate text (translation, for instance).

Context: Transformers

A basic transformer model for English-French translation.[1]



[1] https://youtu.be/xI0HHN5XKDo?t=120

Context: Transformers

- The benefits of this is that we can actually see a separation in tasks.
  1. Encoder
     - For the translation example, this one knows what is English and context.
  2. Decoder
     - Knows how English words relate to French words.
- Both of them know some bit of language.
- Due to this, we can modify each side.
  - Focus on decoders, we get *GPT*
  - Focus on encoders, we get *BERT*

Context: Transformers

- Transformers can be used for translation, but we can utilize BERT to do other things
  - Such as emotion analysis.
- Training BERT can involve two things in three passes.
  - Pre-training
    - **M**asked **L**anguage **M**odeling.
    - **N**ext **S**entence **P**rediction.
  - Fine-tuning
- We'll be skipping the fine details this for time, since someone has done it before me (and better).

What is DistilBERT

- *DistilBERT* is a variant of BERT, focusing on memory-efficiency and speed, while maintaining the accuracy of BERT (within a margin of error). Released in 2019 by HuggingFace.

Why DistilBERT

- The foundational problems regarding Transformer-based models is that it keeps growing larger.

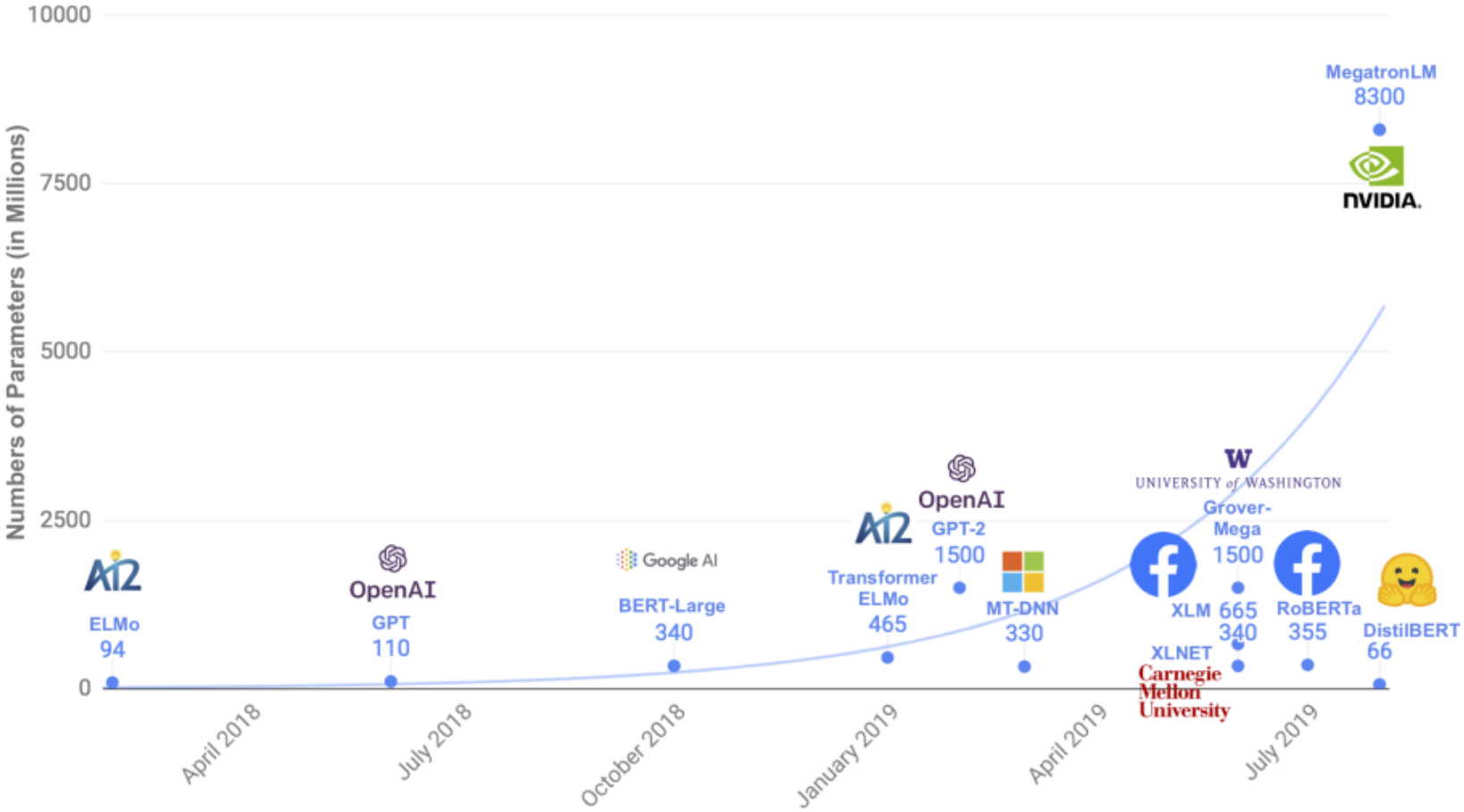


Figure 1: **Parameter counts of several recently released pretrained language models.**

[1] https://arxiv.org/abs/1910.01108, page 1

How did DistilBERT work

- How it did it was:
  1. Knowledge distillation was utilized, based on the original BERT model.
  2. Using triple loss, able to make a 40% smaller Transformer, pre-trained through distillation. While being 60% faster at inference time.
     - Cross-Entropy
     - Distillation Loss
     - Cosine Embedding Loss

Knowledge Distillation[1]

- A compression technique introduced in 2006 by [2] in which a small model is trained to reproduce the behavior of a larger model (or models).
- This is one of the main components of *DistilBERT*.

[1] Often called "teacher-student" learning, we'll call it like so.

[2] Caruana et al. In 2015, Geoffrey et al. utilized this in deep learning

Knowledge Distillation (cont.)

- In DistilBERT, the original BERT is seen as the teacher.
- The student has two objectives:
  1. Minimize cross entropy between the student's prediction and the one-hot empirical distribution of the training labels.
  2. Minimize KL divergence between the student's and teacher's prediction.

Knowledge Distillation (cont.)

- The teacher might assign small probabilities to incorrect answers, manifesting how the teacher generalizes.

From Hinton's paper[1]:

An image of a BMW, for example, may only have a very small chance of being mistaken for a garbage truck, but that mistake is still many times more probable than mistaking it for a carrot.

[1] https://arxiv.org/abs/1503.02531

Knowledge Distillation (cont.)

- Because of this, the student can learn all the probabilities from the teacher.
- But minimizing the KL divergence has a problem: The student doesn't learn much from the incorrect answers.
- Meaning, a well-trained teacher produces a very sharp distribution with high probability on a correct answer, and the rest are improbable.
- This will render distillation loss useless.

Knowledge Distillation (cont.)

- One of the solutions is to use softmax-temperature.

$$q_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

- $T = 1$: Standard softmax formula.
- $T > 1$: Probability distribution is softer, giving more weights to incorrect answers.
- This is the same temperature T to the student and teacher at training time.
- The teacher (trained and frozen) produced adjusted probability estimates which the student should learn.
- $T = 1$ is set at inference time for the student to produce the standard softmax outputs.

Other tricks

- In BERT, there are 12 encoder blocks that alternate multi-head self-attention and feed-forward layers.
- DistilBERT cuts that in half, making 6.
- BERT's weights are reused to initialize DistilBERT, providing a massive speed benefit.

Other tricks

- The 768-dimensional embedding vectors are kept since removing it doesn't do that much of a difference.
- The same dimensionality allowed the use of *cosine-distance loss between DistilBERT and BERT*.
  - To align directions of the the hidden vectors of the student and teacher.

The training

- Within the same corpus of BERT[1].
- DistilBERT is trained on 8 16GB NVIDIA V100 GPUs for 90 hours.
- For comparison, Facebook/Meta's RoBERTa model took one day on **1024 32GB V100s**.

[1] English Wikipedia and Toronto Book Corpus

The results

- DistilBERT was able to keep ahead with the original BERT.

Table 1: **DistilBERT retains 97% of BERT performance.** Comparison on the dev sets of the GLUE benchmark. ELMo results as reported by the authors. BERT and DistilBERT results are the medians of 5 runs with different seeds.

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

[1]

- DistilBERT was also faster for on device computation, 71% faster on an iPhone 7 Plus, running a question-answering model.

[1] https://arxiv.org/abs/1910.01108, page 3

The results

- An ablation study[1] showed that the Masked Language Modeling had little impact.

Table 4: **Ablation study.** Variations are relative to the model trained with triple loss and teacher weights initialization.

Ablation	**Variation on GLUE macro-score**
$\emptyset$ - L_{cos} - L_{mlm}	-2.96
L_{ce} - $\emptyset$ - L_{mlm}	-1.46
L_{ce} - L_{cos} - $\emptyset$	-0.31
Triple loss + random weights initialization	-3.69

[2]

- Meaning that the student learns from the teacher than the training data.

[1] Remove a part of the model to see what contributes the most

[2] `https://arxiv.org/abs/1910.01108`, page 4

Anything to talk about?