Machine Learning for Natural Language Processing

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Outline of the course

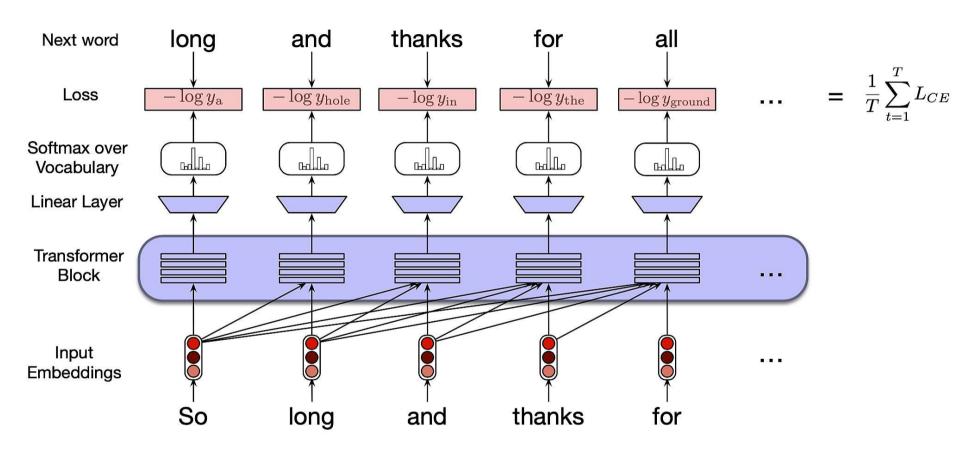
Lectures (6 x 3h)

- Lecture #1: Introduction and representation of words
 Notions: morphology, tokens, lemmas, POS, word net, word embedding
 Hands-on: manipulate basic pipelines and visualize word embeddings
- Lecture #2: Representation of documents
 Notions: vocabulary, Zipf's curse, bag of words, Bayes, RNN, BERT
 Hands-on: basic neural network classifiers
- Lecture #3: Language models
 Notions: ngrams, LSTM, bi-LSTM, language generation
 Hands-on: train a small LM and generate text
- Lecture #4: Transformers and large language models Notions: encoder/decoder, transformers, fine-tuning Hands-on: visualize embeddings, fine-tune a LLM

Large language models



Causal transformers as (generative) language models (aka GPT)



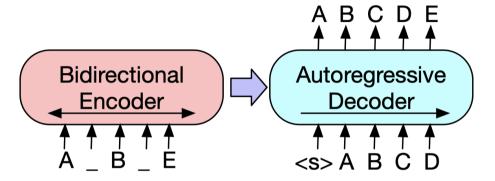
borrowed again from Jurafsky and Martin's book

⇒ can be used for language generation exactly as recurrent networks

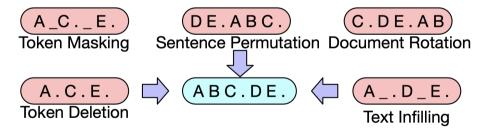


Encoder/decoder as a denoising auto-encoder

Pre-train a model that encodes a noisy version of the input and decodes the correct output



combining various input corruption mechanisms...



Lewis et al., 2019. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension.

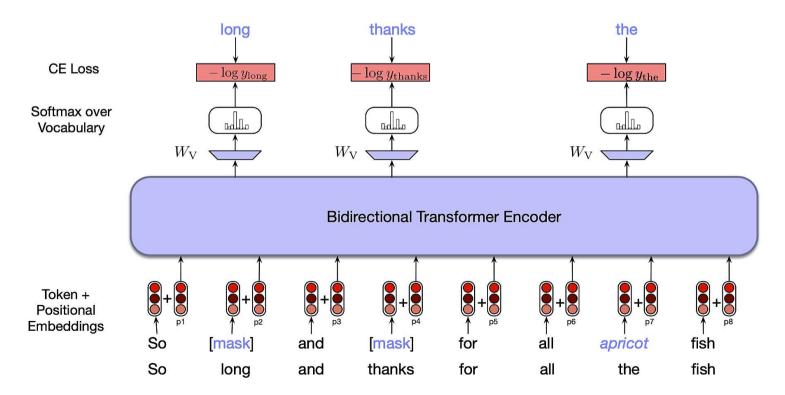
See https://huggingface.co/docs/transformers/en/model_doc/bart



Turning the encoder into a language models (aka BERT)

Randomly mask or modify words and train networks to precit the actual word from the contextual embedding of the modified tokens:

→ Original BERT trained on 3.3B tokens, 15% are modified: 80% are actually masked, 10% randomly replaced, 10% left unchanged; training the LM objective function only on the 15% modified tokens.

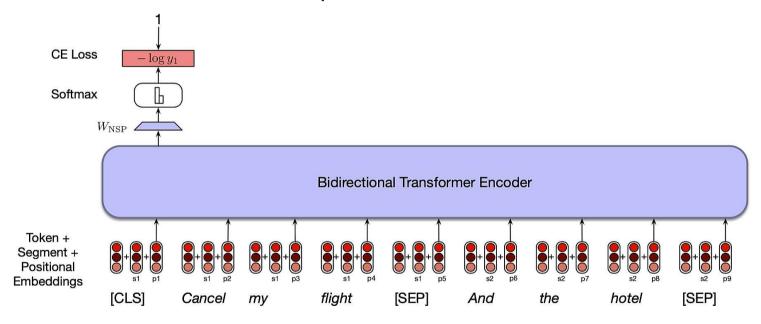




Pushing BERT one-step further with next sentence prediction

Many tasks look at two sentences (pieces of text as input), e.g., for natural language inference (entailment), measuring semantic proximity, summarization, etc.

Train BERT with two sentences to predict whether one follows the other or not

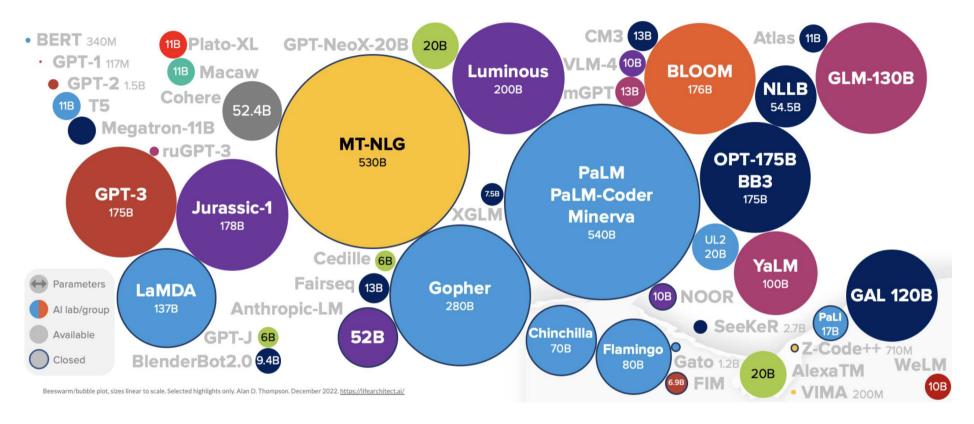


borrowed again from Jurafsky and Martin's book

Full BERT training combines masked LM and next sentence prediction (from modified sentences)



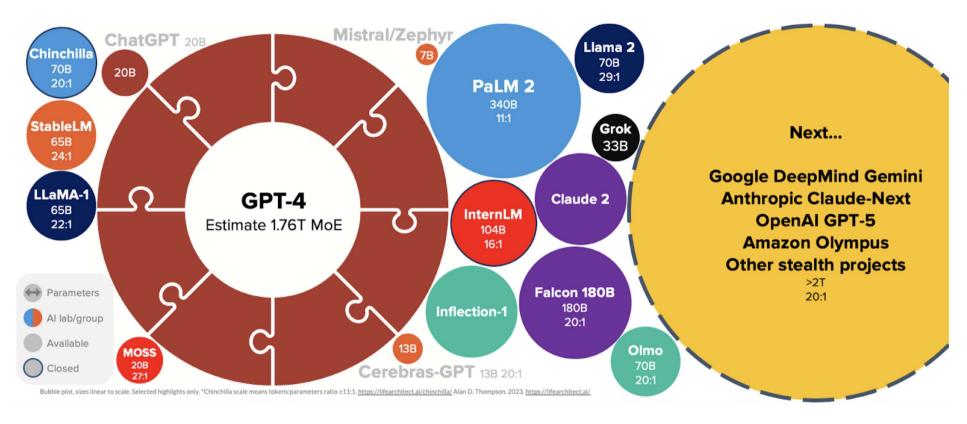
The transformer pre-trained model frenzy



copied from https://lifearchitect.ai/timeline



The transformer pre-trained model frenzy (more)

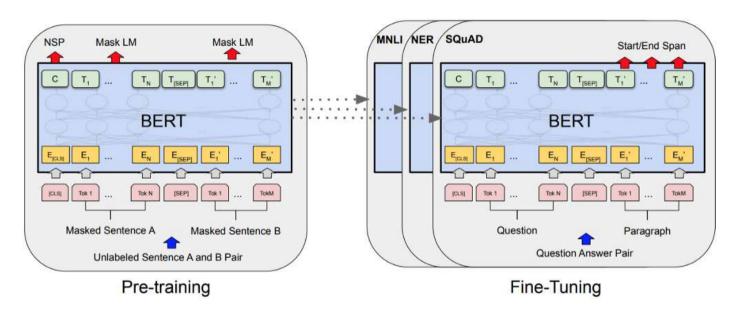


copied from https://lifearchitect.ai/timeline



Transfer learning: the BERT case

Add a classifier on top of a pre-trained transformer language model and retrain the whole stuff



Jacob Devlin et al. 2018. BERT: Pre-training of deep bidirectional transformers for language understanding

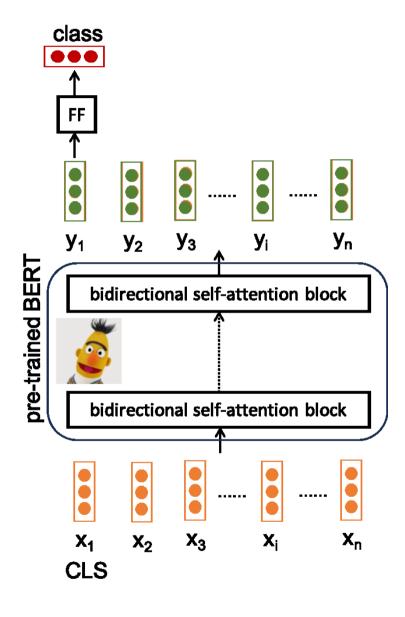
BERT's classification *head* depending on the task:

Classification
Comparison
Tagging

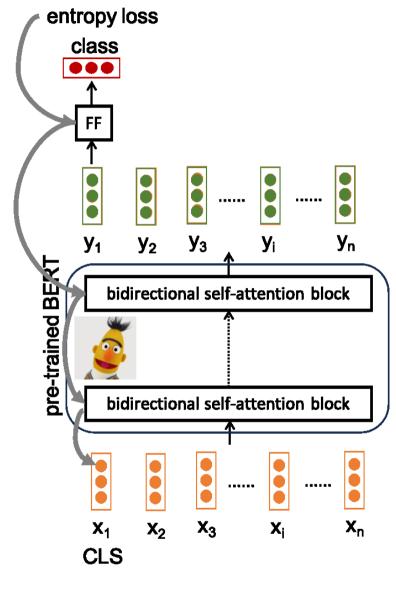
one sentence, embedding of the [CLS] token for classification two sentences, embedding of the [CLS] token for classification one sentence, contextual embeddings of tokens used in tagger



BERT transfer learning for document classification



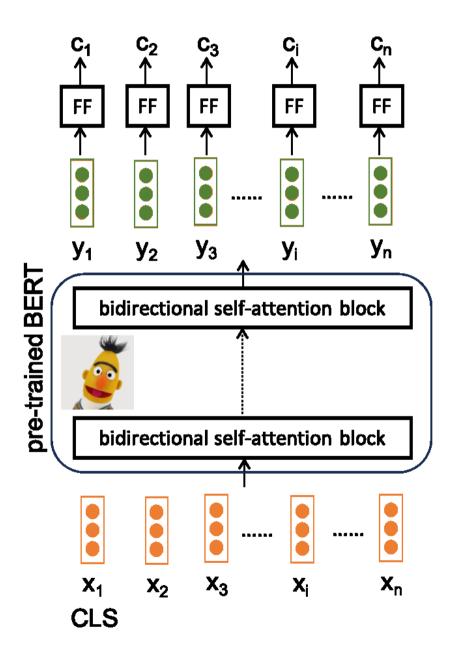




training

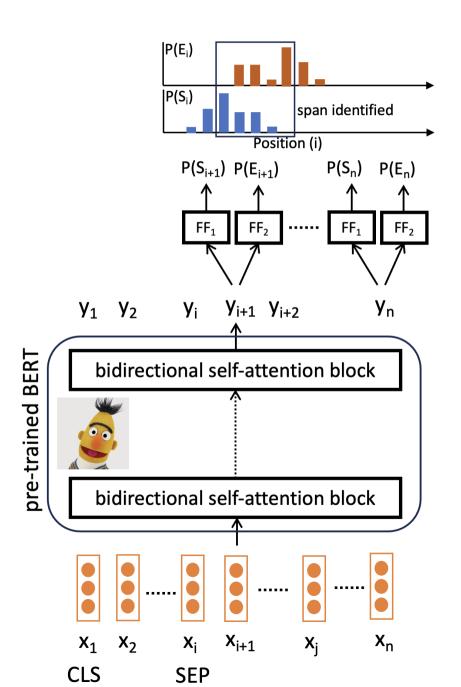


BERT transfer learning for token classification



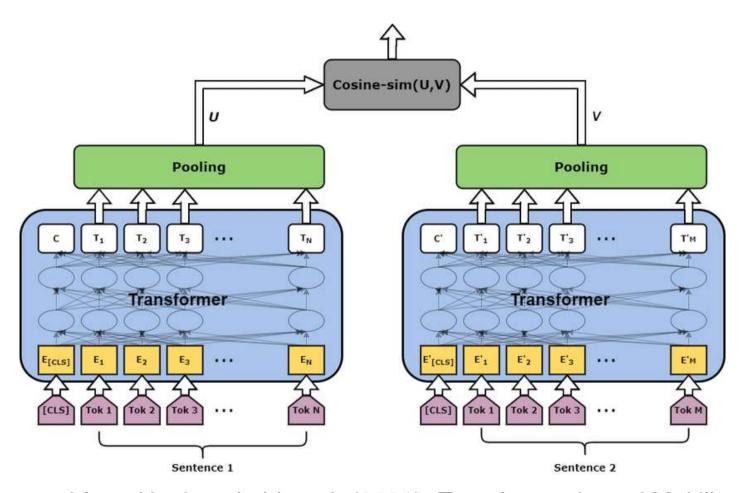


BERT transfer learning for span detection (QA)





Sentence BERT: transfer learning for document representation

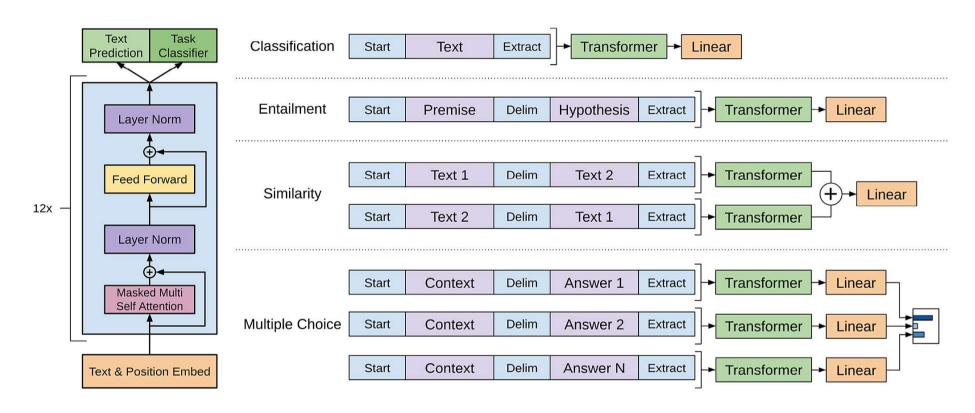


Borrowed from Hettiarachchi et al. (2021). Transformer-based Multilingual Socio-political and Crisis Event Detection.



Transfer learning: the GPT case

Add a classifier on top of a pre-trained transformer language model and retrain the whole stuff



Alex Radford et al. 2018. Improving Language Understanding by Generative Pre-Training



Other line of thoughts

- embedding spans rather than tokens
 - ▷ SpanBERT, GliNER, etc.
- retrieval augmented generation (RAG)
- prompt engineering has become increasingly popular
 - prompting models to classify, extract knowledge, etc.

This is just the begining of the NLP journey!!!!





