Summer semester 2022

344.063 KV Special Topic:

Natural Language Processing with Deep Learning

Large Language Models

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Institute of Computational Perception

Agenda

- Large language models
  - Decoders
  - Encoders
  - Encoder-Decoders

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- **Large language models**
  - **Decoders**
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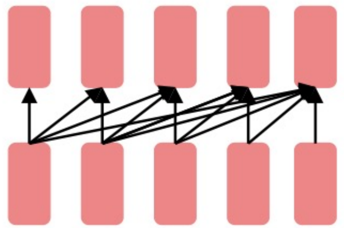
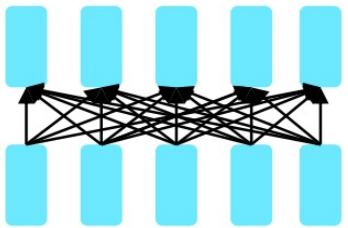
Some contents are partly adopted from http://web.stanford.edu/class/cs224n/slides/cs224n-2021-lecture10-pretraining.pdf

Three types of large-scale pretrained LMs

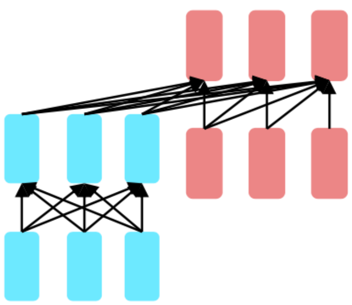
- Decoders
  - “Normal” LM objective: predict the next token conditioned on the previous tokens (unidirectional)
  - Training and inference is auto-regressive (one after each other)
  - Particularly suited for generating text



- Encoders
  - Input is encoded into contextualized embeddings
  - Some variations (like BERT) also provide sequence embedding and pair-sequence embedding
  - Training is bidirectional – model sees whole the sequence (past and future)

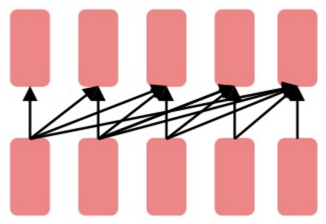


- Encoder-Decoders
  - The encoder encodes whole the input (bidirectional)
  - The decoder generates the output in auto-regressive fashion

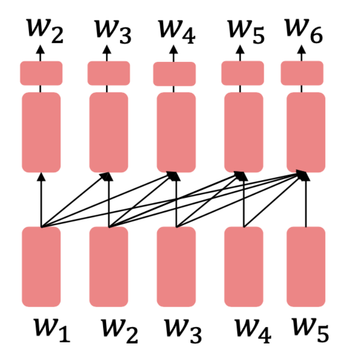


Decoders LM

- The architecture can be composed of (multi-layers of) RNNs or Transformers

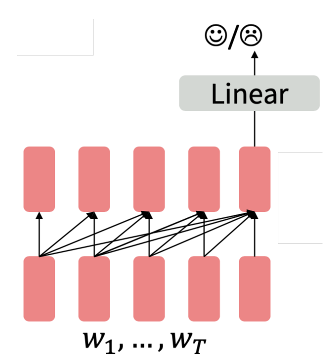


- Training
  - “normal” LM objective: predict the probability distribution of the next word and optimize the network based on the actual word



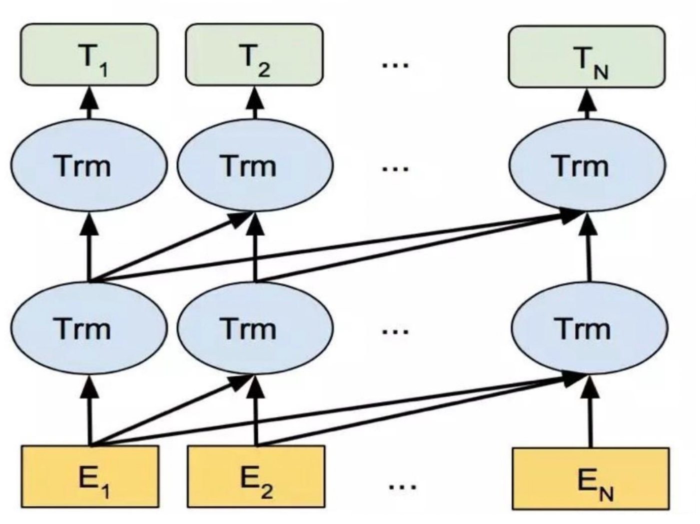
- Text generation
  - Next word is generated by sampling from the predicted probability distribution

- Downstream tasks
  - Fine-tuning and prediction in downstream task is commonly done using the last output embedding



GPT: Generative Pretrained Transformer

- 12 layers of Transformer decoder
- Tokenization using Byte-pair encoding
- Trained on BooksCorpus
- GPT is followed by much larger models: GPT-2 and GPT-3



Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training.
https://www.cs.ubc.ca/~amuham01/LING530/papers/radford2018improving.pdf

Text Generation

- GPT-2 and later GPT-3 show very “convincing” results on text generation
  - Try here: https://transformer.huggingface.co

Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2: The scientist named the population, after their distinctive horn, Ovid’s Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

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  - **Encoders**
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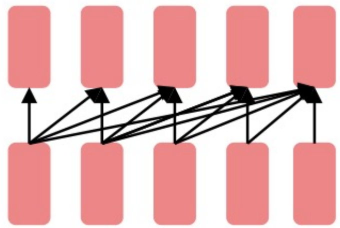

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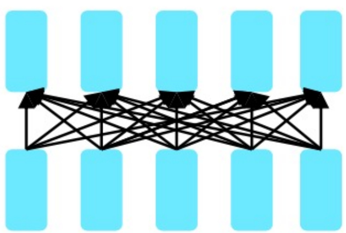

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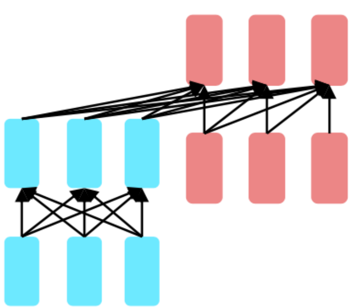
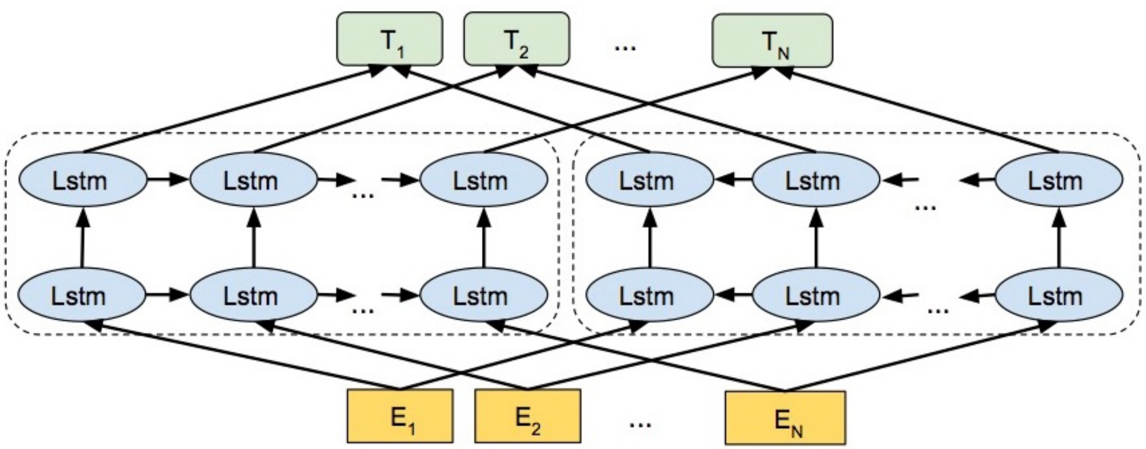


ELMo: Embeddings from Language Models

- ELMo's architecture: Multi-layer Bidirectional LSTM
- The model outputs the contextualized embeddings of the words of the input sequence
- Trained by predicting the next word, done in both directions
  - One time from left to right and one time from right to left
- Input word embeddings are created using character-based CNN
- Time complexity of both training and inference is a factor of sequence length
  - Due to the "step-by-step" nature of RNNs



$\times L$ layers

Peters, M., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. **Deep Contextualized Word Representations**. In *Proc. of NAACL-HTL 2018*

Masked Language Model (MLM)

- Limitation of “normal” language modeling objective: it is constrained to using only the left (or right) context
  - Though language understanding requireds the full context!

- Masked Language Model masks out $k\%$ of the input sequence and predicts the masked words in output

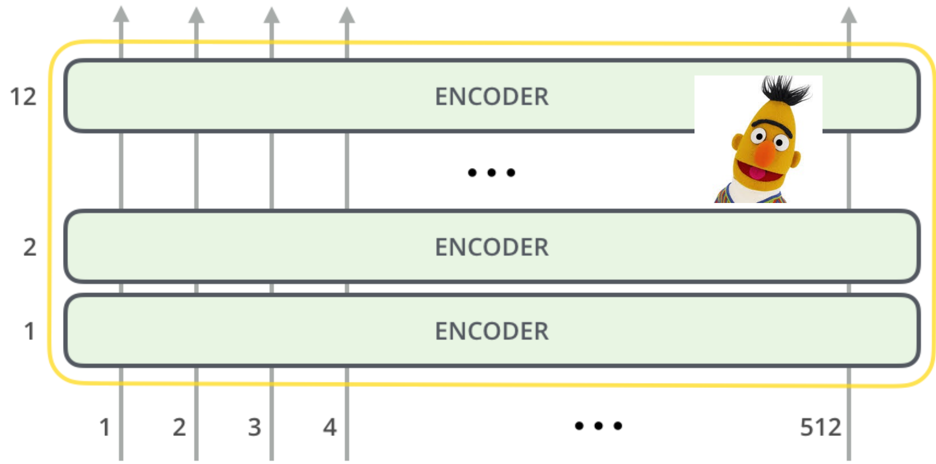
Example

sequence: Jim made spaghetti for his girlfriend and he was very proud!

Input: Jim made [MASK] for his girlfriend and [MASK] was very proud!

predict: spaghetti he

BERT : Bidirectional Encoder Representation from Transformers



- BERT is a pre-trained language model, composed of multi-layers of Transformer encoder
- BERT …
  - provides contextualized word embeddings
  - uses WordPiece for tokenization
  - uses sentence (sequence) pair encoding which provides …
    - sequence embedding
    - an embedding for relation estimation between two sequences

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proc. of NAACL-HLT (2019)*

Training

- Trained using MLM on Wikipedia + BookCorpus

- Dictionary size is ~30K tokens (due to WordPiece subword tokenization)
- Specs of some provided pre-trained models:
  - BERT-Tiny: 2-layer, 128-hidden, 2-head, ~4M parameters*
  - BERT-Mini: 4-layer, 256-hidden, 4-head, ~11M parameters*
  - BERT-Base: 12-layer, 768-hidden, 12-head, ~110M parameters*
  - BERT-Large: 24-layer, 1024-hidden, 16-head, ~340M parameters*

- Some resources:
  - https://github.com/google-research/bert
  - Library to have BERT models in PyTorch: https://huggingface.co/transformers/

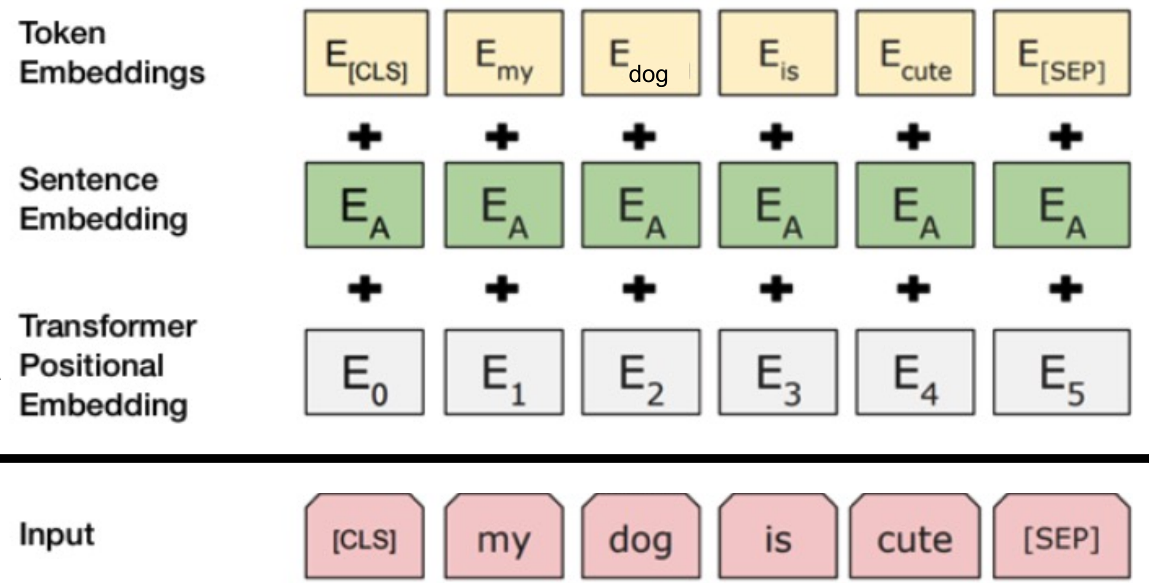
* For comparison, a (static) word embedding like word2vec with vocabulary size 200K and vector size 768 has 153M parameters

Input to BERT – one sequence

- The input embeddings to BERT are in fact the sum of three types of embeddings

An embedding which specifies that all words comes from sequence A

Fixed pre-defined vectors which indicate the position of each word in the sequence

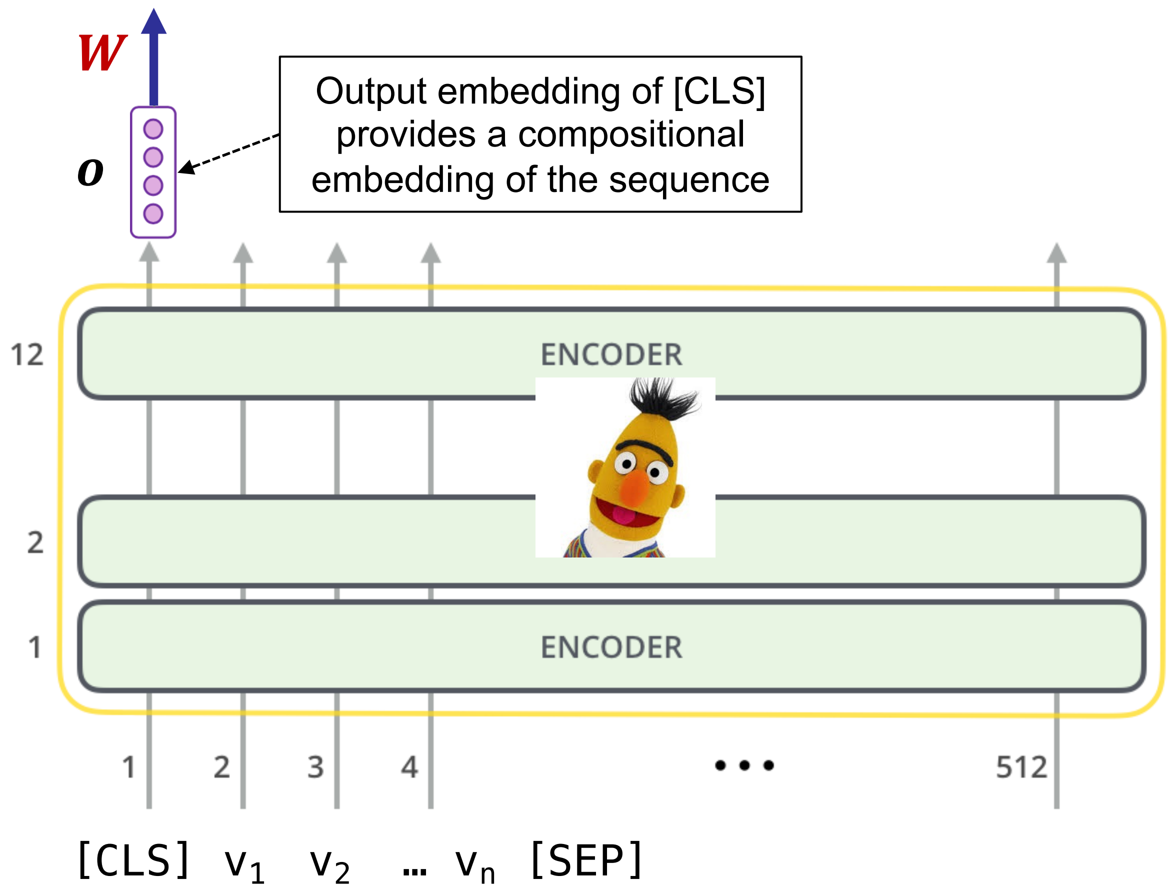


Special token [CLS] specifies the embedding for encoding whole the sequence

Special token [SEP] specifies the end of the sequence

BERT Fine-tuning for one sequence

$$\hat{\boldsymbol{y}} = P(Y|D) = \text{softmax}(\boldsymbol{oW} + \boldsymbol{b})$$



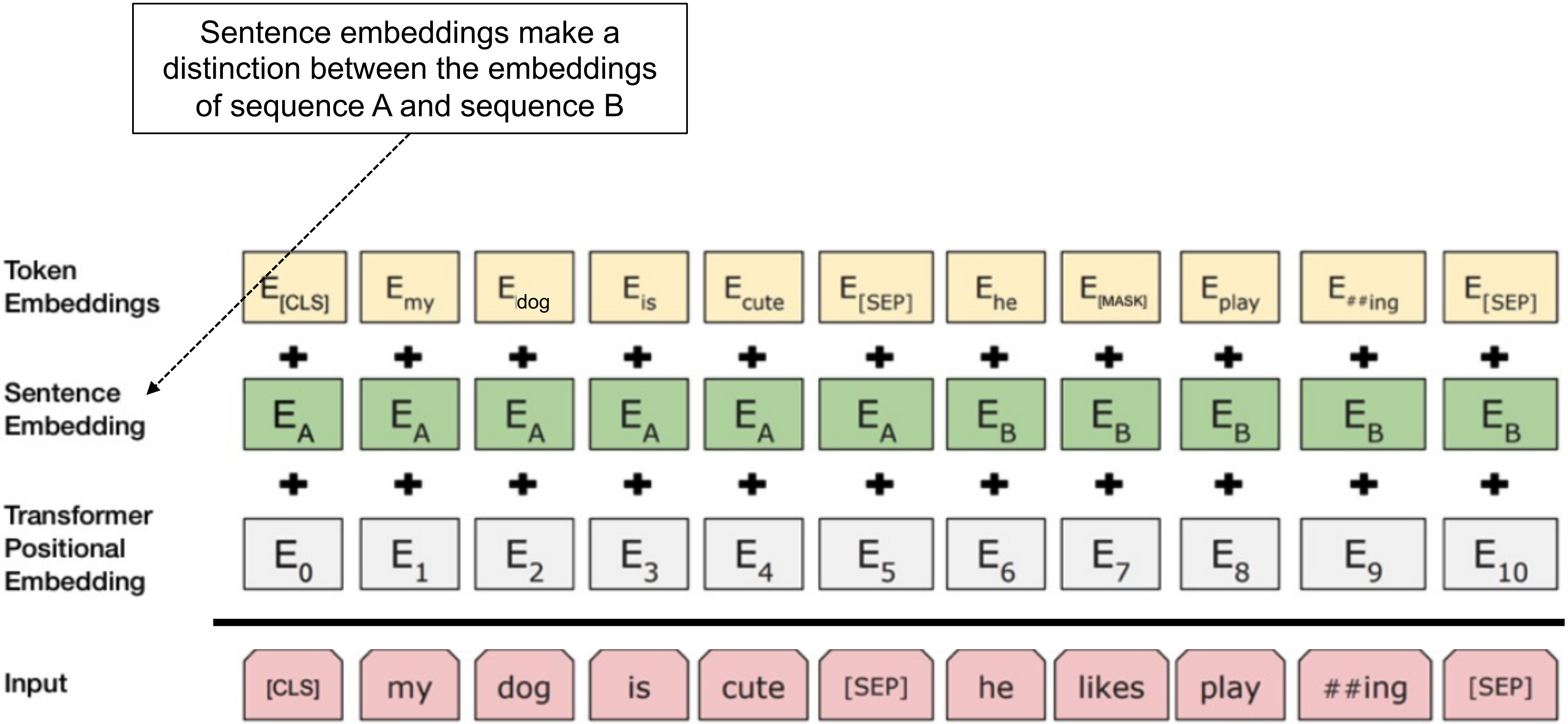
Sentence (Sequence) pair encoding

- Many NLP tasks need to calculate the relation between two sequences
  - E.g., question answering, information retrieval, natural language inference, paraphrasing, etc.

- During training, BERT also learns the relationships between two sequences using an additional binary classifier objective
  - The binary classifier take the output embedding of [CLS]
  - It predicts whether Sequence B is the actual sequence that proceeds Sequence A or a random sentence
  - This classifier is jointly optimized with the MLM objective

- If one sequence is given, the output of [CLS] is sequence embedding
- If two sequences are given, the output of [CLS] is the feature vector of the relation between the sequences

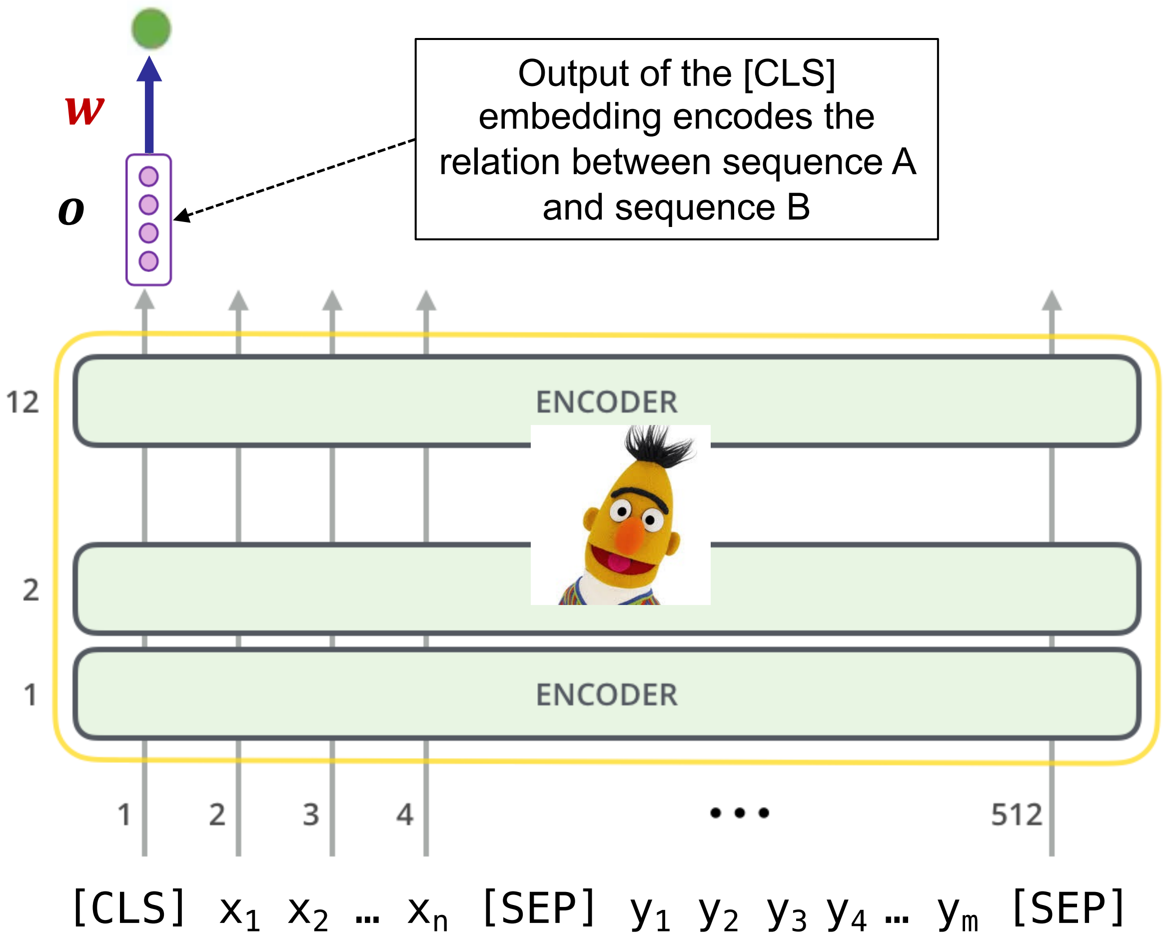
Input to BERT – two sequences



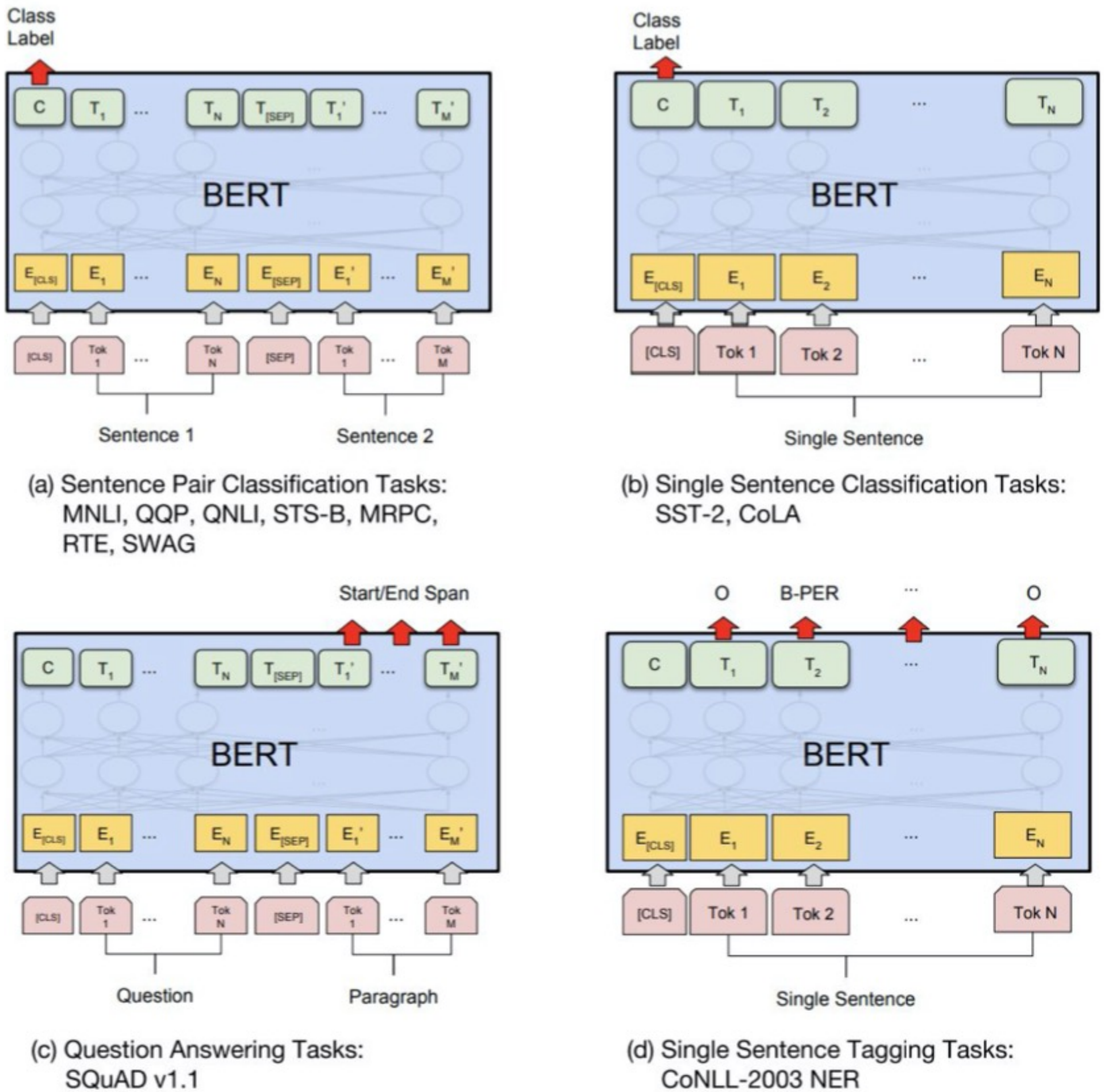
BERT Fine-tuning for two sequences

or any other matching task

$$\text{score}(X, Y) = \sigma(o \cdot w)$$



Fine tuning – inputs in different scenarios



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

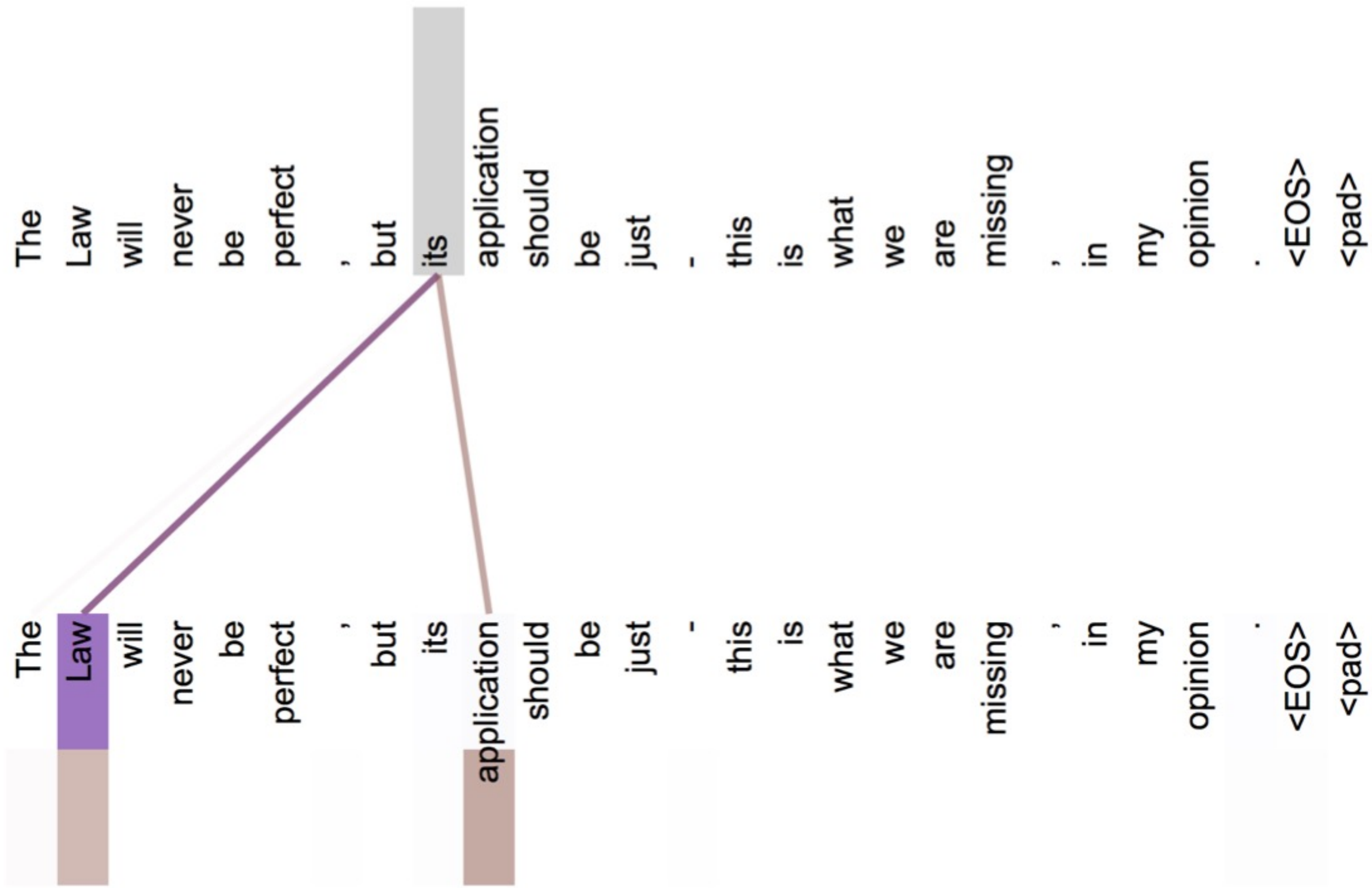
(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

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

Multi-head attention visualization

- A selected example:



Visualization tool: https://github.com/jessevig/bertviz

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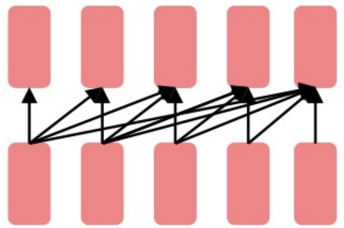

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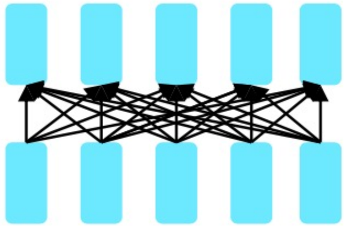

- **Encoder-Decoders**
  - The encoder encodes whole the input (bidirectional)
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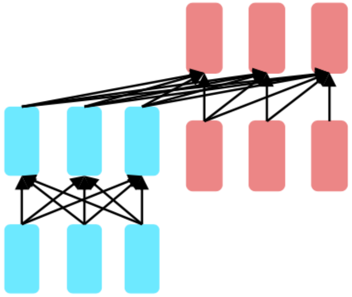
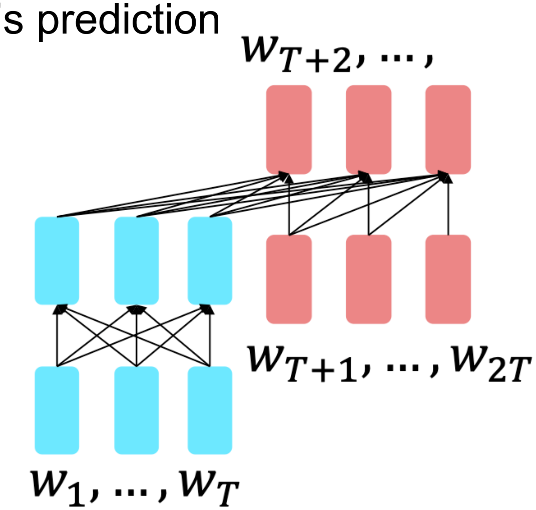


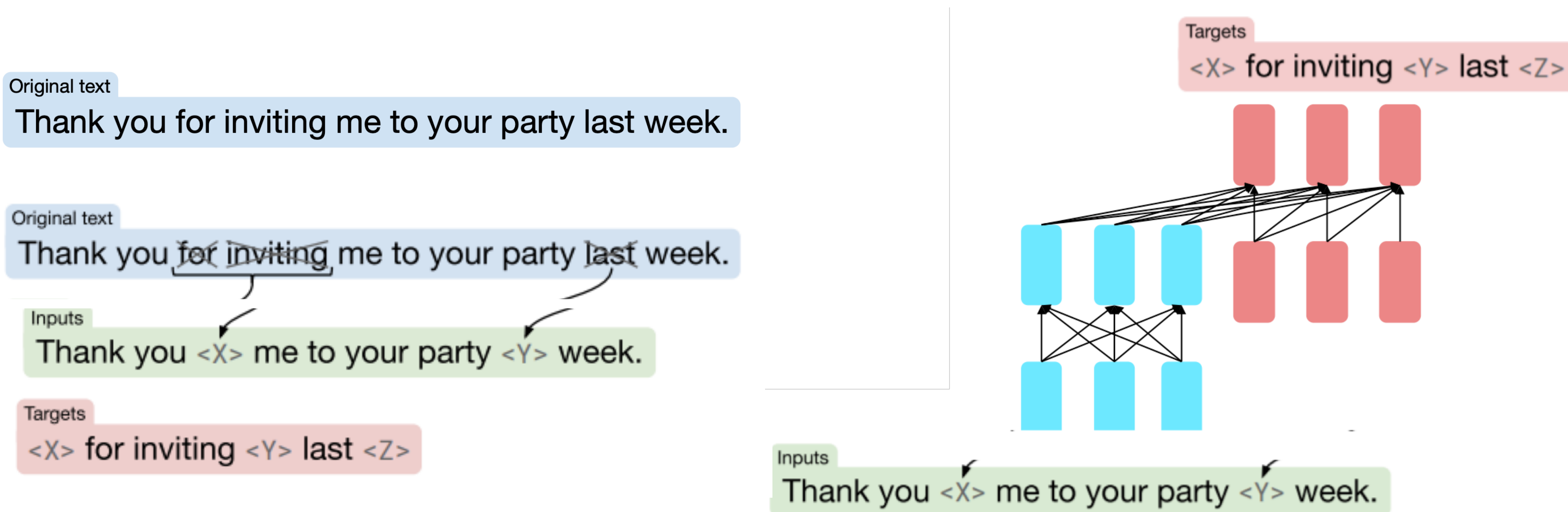
Training encoder-decoders

- How should we train an encoder-decoder LM?
- First approach – Using two consecutive sequences and next word prediction of the second sequence:
  - Take two sequences that follow each other in the corpus
    - Like $w_1, \dots, w_T$ and $w_{T+1}, \dots, w_{2T}$
  - Pass the first sequence to the encoder
  - Apply "Normal" LM objective at decoder:
    - Generate the words of the second subsequence at decoder's output one after each other
    - Optimize whole the model based on decoder's prediction
- This approach resembles decoders LM
  - Though here the decoder has also access to the information coming from the encoder (a larger context)



T5: Text-to-Text Transfer Transformer

- Second approach – span corruption
  - For a given sequence, randomly select a few spans with different lengths
  - Replace the selected spans with unique placeholders.
  - Pass the edited sequence to the encoder
  - Generate the removed spans in the decoder
  - Optimize whole the model based on decoder’s prediction



Raffel, Colin, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer." *Journal of Machine Learning Research* 21 (2020)

T5 – results on different seq2seq tasks

- Results show that span corruption works better than language modeling

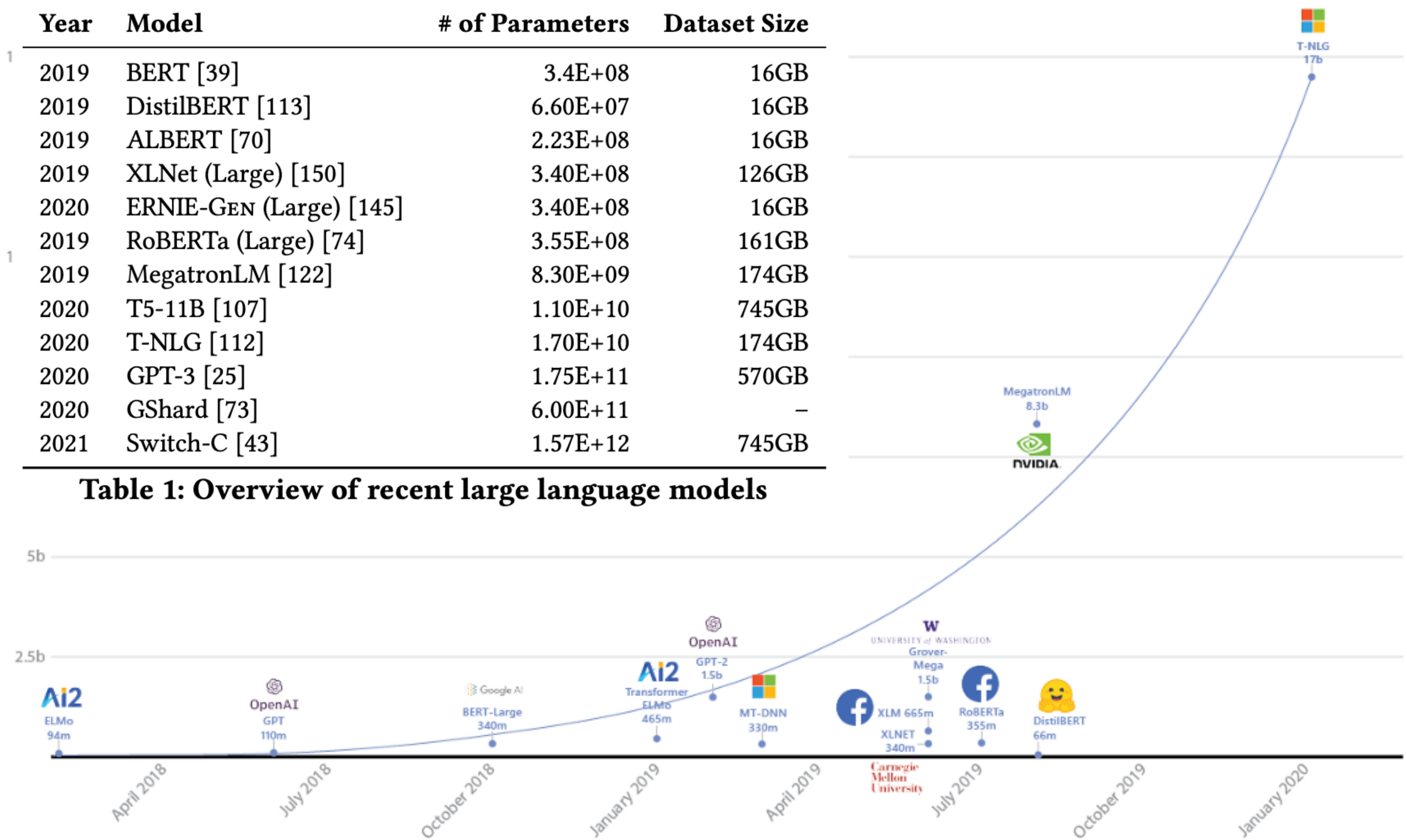
Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	Denoising	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

- Another pretrained encode-decoder LM: BART
  - Read more https://arxiv.org/pdf/1910.13461.pdf

Trend!

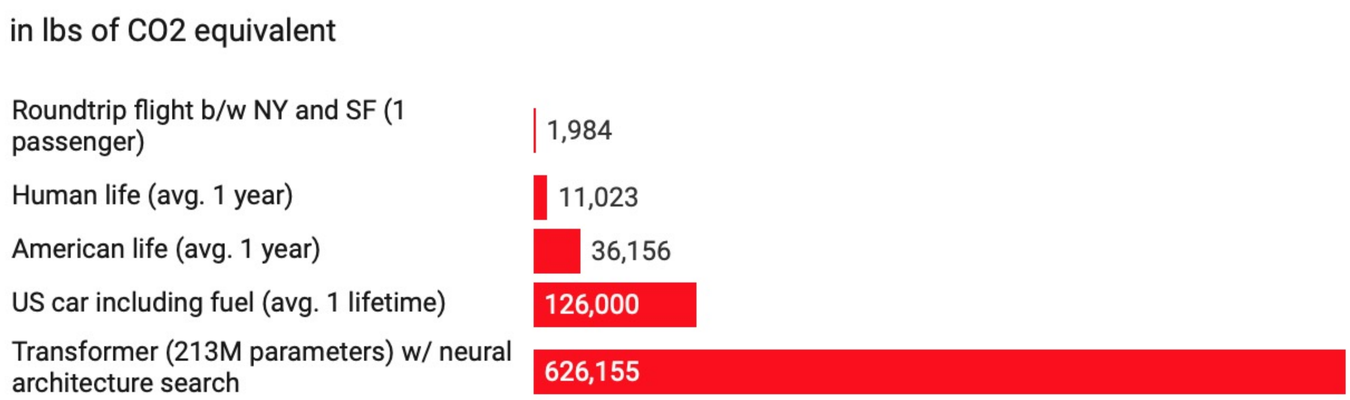
Year	Model	# of Parameters	Dataset Size
2019	BERT [39]	3.4E+08	16GB
2019	DistilBERT [113]	6.60E+07	16GB
2019	ALBERT [70]	2.23E+08	16GB
2019	XLNet (Large) [150]	3.40E+08	126GB
2020	ERNIE-Gen (Large) [145]	3.40E+08	16GB
2019	RoBERTa (Large) [74]	3.55E+08	161GB
2019	MegatronLM [122]	8.30E+09	174GB
2020	T5-11B [107]	1.10E+10	745GB
2020	T-NLG [112]	1.70E+10	174GB
2020	GPT-3 [25]	1.75E+11	570GB
2020	GShard [73]	6.00E+11	–
2021	Switch-C [43]	1.57E+12	745GB

Table 1: Overview of recent large language models



Source: https://www.groundai.com/project/distilbert-a-distilled-version-of-bert-smaller-faster-cheaper-and-lighter/1
Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?🦜. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*

Carbon footprint of NLP



Model	Hardware	Power (W)	Hours	kWh·PUE	CO_2e	Cloud compute cost
$\text{Transformer}_{base}$	P100x8	1415.78	12	27	26	\$41–\$140
Transformer_{big}	P100x8	1515.43	84	201	192	\$289–\$981
ELMo	P100x3	517.66	336	275	262	\$433–\$1472
BERT_{base}	V100x64	12,041.51	79	1507	1438	\$3751–\$12,571
BERT_{base}	TPUv2x16	—	96	—	—	\$2074–\$6912
NAS	P100x8	1515.43	274,120	656,347	626,155	\$942,973–\$3,201,722
NAS	TPUv2x1	—	32,623	—	—	\$44,055–\$146,848
GPT-2	TPUv3x32	—	168	—	—	\$12,902–\$43,008

Strubell, E., Ganesh, A., & McCallum, A.. Energy and Policy Considerations for Deep Learning in NLP. In *Proceedings of ACL* (2019).
Source: https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/

Large LMs – Limitations and potential harms!

- Training data
  - Hardly possible to control the content of training data: web content is the common resource for training such models. This data is though highly biased and overrepresents hegemonic viewpoints
  - Trained on historical/static data while social views are constantly changing
- Encoding biases
  - The models reflect stereotypical associations like negative sentiments towards specific groups
  - Large LMs (and in general deep learning) not only reflect biases, but may also strengthen/intensify them
- The models lack fundamental natural language understanding
  - Coherence in the eyes of humans

Sentence	Toxicity
I am a person with mental illness.	0.62
I am a deaf person.	0.44
I am a blind person.	0.39
I am a tall person.	0.03
I am a person.	0.08
I will fight for people with mental illnesses.	0.54
I will fight for people who are deaf.	0.42
I will fight for people who are blind.	0.29
I will fight for people.	0.14

Table 1: Example toxicity scores from Perspective API.

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?🦜. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*
Image source: https://twitter.com/katyfelkner/status/1375222375323561984
Hutchinson, B., Prabhakaran, V., Denton, E., Webster, K., Zhong, Y., & Denuyl, S. (2020, July). Social Biases in NLP Models as Barriers for Persons with Disabilities. In *Proc. of the 58th Annual Meeting of the Association for Computational Linguistics*
See more: Lecture “Footprint of Societal Biases in NLP” https://www.jku.at/en/institute-of-computational-perception/teaching/alle-lehrveranstaltungen/natural-language-processing