Transformer-based Encoders.

Masked language models based on the Transformer architecture.

BERT and related models.

Agenda: BERT and related models

Tokenization strategies

- *BPE*
- *WordPiece*
- *SentencePiece*

Agenda: BERT and related models

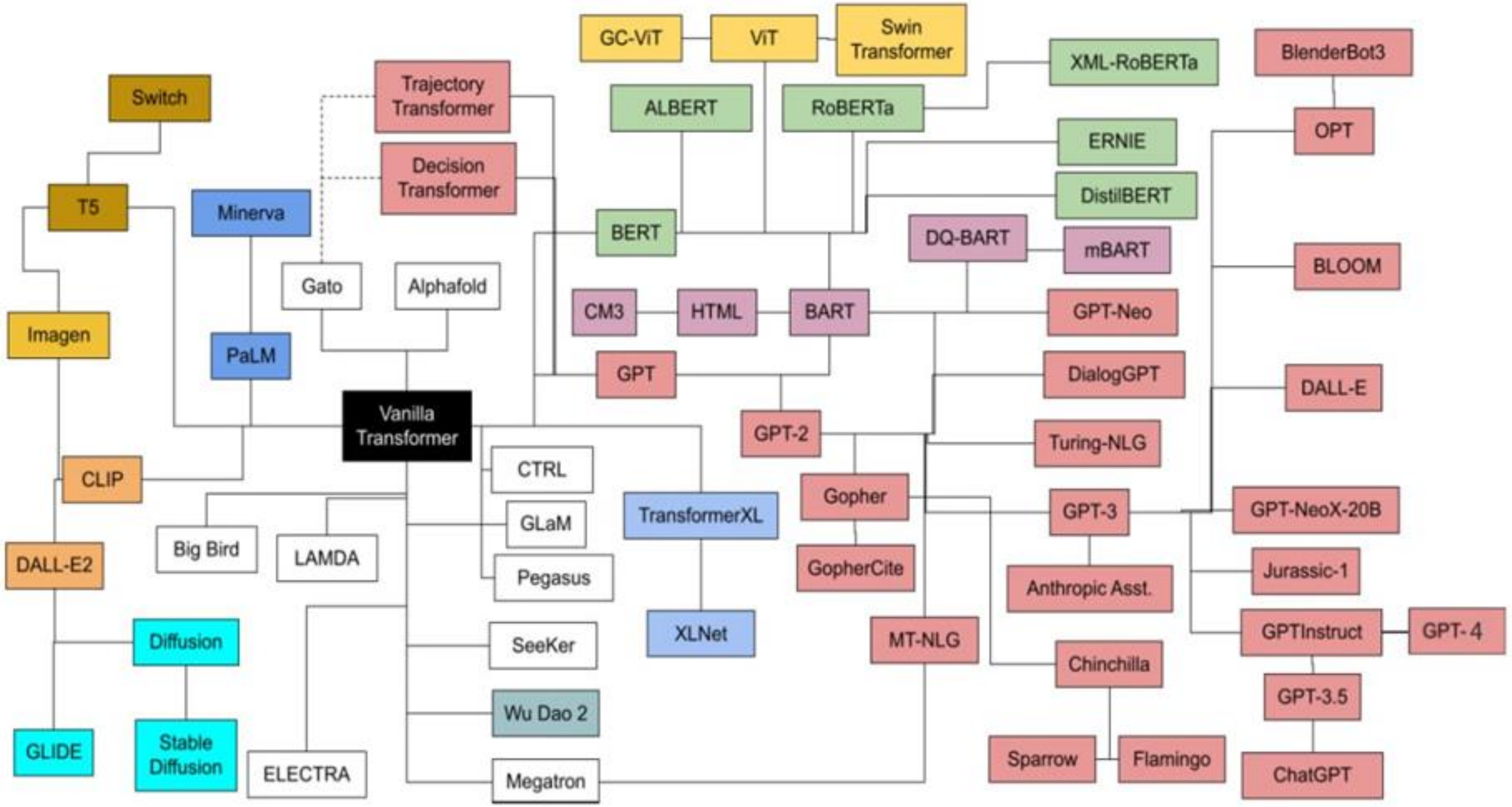
Tokenization strategies

- *BPE*
- *WordPiece*
- *Unigram*
- *SentencePiece*

Popular encoder-based models:

- *BERT*
- *RoBERTa*
- *XLM-R*

Transformer model Zoo



Transformer Family Tree

Amatriain, Xavier. "Transformer models: an introduction and catalog." arXiv preprint arXiv:2302.07730 (2023).

Options for a pre-trained model

- The pretrained models vary by many parameters
    - *training corpus*
    - *vocabulary*
    - *pretraining task*
    - *architecture and model size*
    - *training hyperparameters*

Options for a pre-trained model

- The pretrained models vary by many parameters
  - *training corpus*
  - *vocabulary*
  - *pretraining task*
  - *architecture and model size*
  - *training hyperparameters*
- How to choose the best pretrained model for a downstream task?
  - *Mostly experimentally*
  - *By similarity of pretraining corpus and task to the target problem*

Tokenization strategies

How to split a text to pieces

An extreme: traditional linguistically-motivated tokenization (*“by word”*)

- *It leads to unlimited vocabularies*
  - *A typical transformer model has limited vocabulary*
    - *It has to learn the matrix of input embeddings (but this can be fixed with e.g. FastText)*
    - *It has to predict distribution of the next (or missing) word*
  - *Out-of-vocabulary words have to be replaced with e.g. <UNK> token*
- *Many words are very rare => difficult to learn good representations*

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```
>>> list('cat'.encode('utf-8'))
[99, 97, 116]
>>> list('кот'.encode('utf-8'))
[208, 186, 208, 190, 209, 130]
>>> list('貓'.encode('utf-8'))
[232, 178, 147]
```

<u>Another extreme: split by character (or even by Unicode byte)</u>

- *Small vocabularies (not for all scripts), but very long texts*
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Compromise: subword embeddings

Byte-pair encoding

The goal is compression: encode the text corpus into the shortest possible sequence of tokens, with the fixed vocabulary size

BPE is a simple greedy algorithm:

- Start with the vocabulary of characters (or Unicode bytes)
- Merge the most frequent bigram into a new token
  - in practice, mergers across word boundaries are usually prohibited
  - space is often prepended to the next word
- Repeat for N times

Result:

- For frequent words, there are special tokens
- Rare words are represented by word pieces

```
vocab = {'l o w </w>' : 5, 'l o w e r </w>' : 2,
         'n e w e s t </w>':6, 'w i d e s t </w>':3}
num_merges = 10
for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
  print(best)
```

r ·	→	r·
l o	→	lo
lo w	→	low
e r·	→	er·

Figure 1: BPE merge operations learned from dictionary {'low', 'lowest', 'newer', 'wider'}.

Sennrich et al, 2015, [Neural Machine Translation of Rare Words with Subword Unit]
Gage, 1994, **A new algorithm for data compression**

WordPiece

Very similar to BPE

The difference: ***it is probabilistic***

- *BPE chooses the pair A+B with maximal frequency (equivalently, P(A,B))*
- *WordPiece chooses the pair with **maximal gain**: P(A,B) / [P(A) * P(B)]*
    - *By doing this, it maximizes likelihood of a 1-gram language model on the corpus*

Schuster et al., 2012 [Japanese and Korean Voice Search]

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During inference, go from left to right, and pick the longest existing token on each step.

This algorithm is used in BERT

- Tokens that do not start a word are prepended with ##
  - E.g. *Мама мыла раму => М ##ама мы ##ла р ##ам ##у*

Schuster et al., 2012 [Japanese and Korean Voice Search]

Unigram tokenizer

- Start with a large vocabulary
  - *Associate it with a unigram language model*

$$P(\mathbf{x}) = \prod_{i=1}^{M} p(x_i),$$

$$\forall i\ x_i \in \mathcal{V},\ \sum_{x \in \mathcal{V}} p(x) = 1,$$

$$\mathbf{x}^* = \arg\max_{\mathbf{x} \in \mathcal{S}(X)} P(\mathbf{x}),$$

$$\mathcal{L} = \sum_{s=1}^{|D|} \log(P(X^{(s)})) = \sum_{s=1}^{|D|} \log\Big(\sum_{\mathbf{x} \in \mathcal{S}(X^{(s)})} P(\mathbf{x})\Big)$$

- Repeatedly decrease the vocabulary
  - *For each subword, compute the reduction in likelihood in it is dropped*
  - *Drop the k% of subwords with minimal reduction in quality*

Kudo, 2018, [Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates]

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  - *For each subword, compute the reduction in likelihood in it is dropped*
  - *Drop the k% of subwords with minimal reduction in quality*
- **Result:** probabilistic vocabulary

Kudo, 2018, [Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates]

SentencePiece

This algorithm does not use pre-tokenization

- *It makes the algorithm useful for scripts that do not use spaces (e.g. Japanese)*

It performs lossless tokenization (preserves spaces and other details)

- *Space is escaped as "_" and treated as an ordinary character*

Uses BPE algorithm under the hood

Kudo et al., 2018, [SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing]()

Is there the best tokenizer?

- Vocabulary size matters much more than the algorithm
- Vocabulary contents matters a lot
  - Most of the words might be useless for the target domain
- When you use a pre-trained model, the tokenizer comes with it 🤷‍♂️
- For a new model, **SentencePiece is a good idea**
  - *Reversible tokenization is a good idea for models that generate text*
  - *Subword regularization is a good idea with noisy texts*

BERT

BERT

BERT = **B**idirectional ***Encoder*** **R**epresentations from **T**ransformers

Presented in NAACL (June, 2019), best long paper award

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

[v1] Thu, 11 Oct 2018 00:50:01 UTC (227 KB)
[v2] Fri, 24 May 2019 20:37:26 UTC (309 KB)

Results on the GLUE benchmark

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
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BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\mathrm{BERT}_{\mathrm{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
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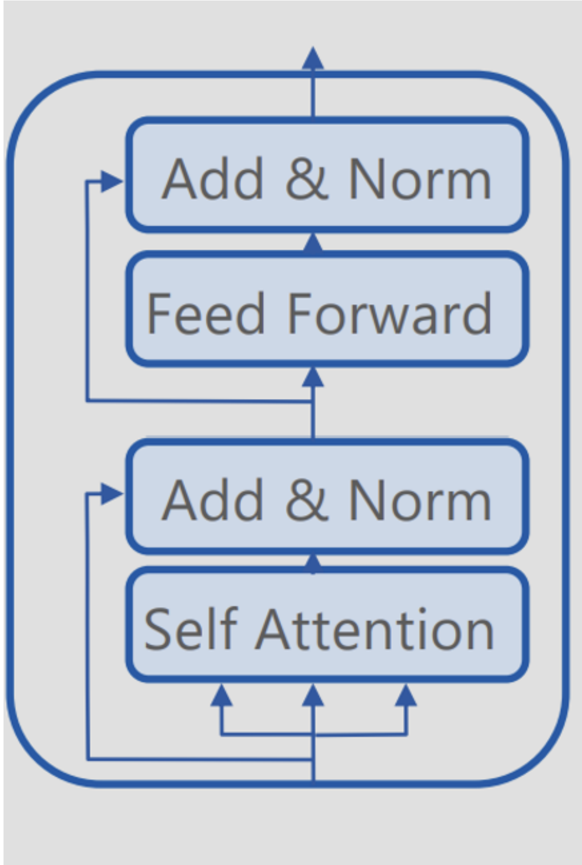
BERT architecture

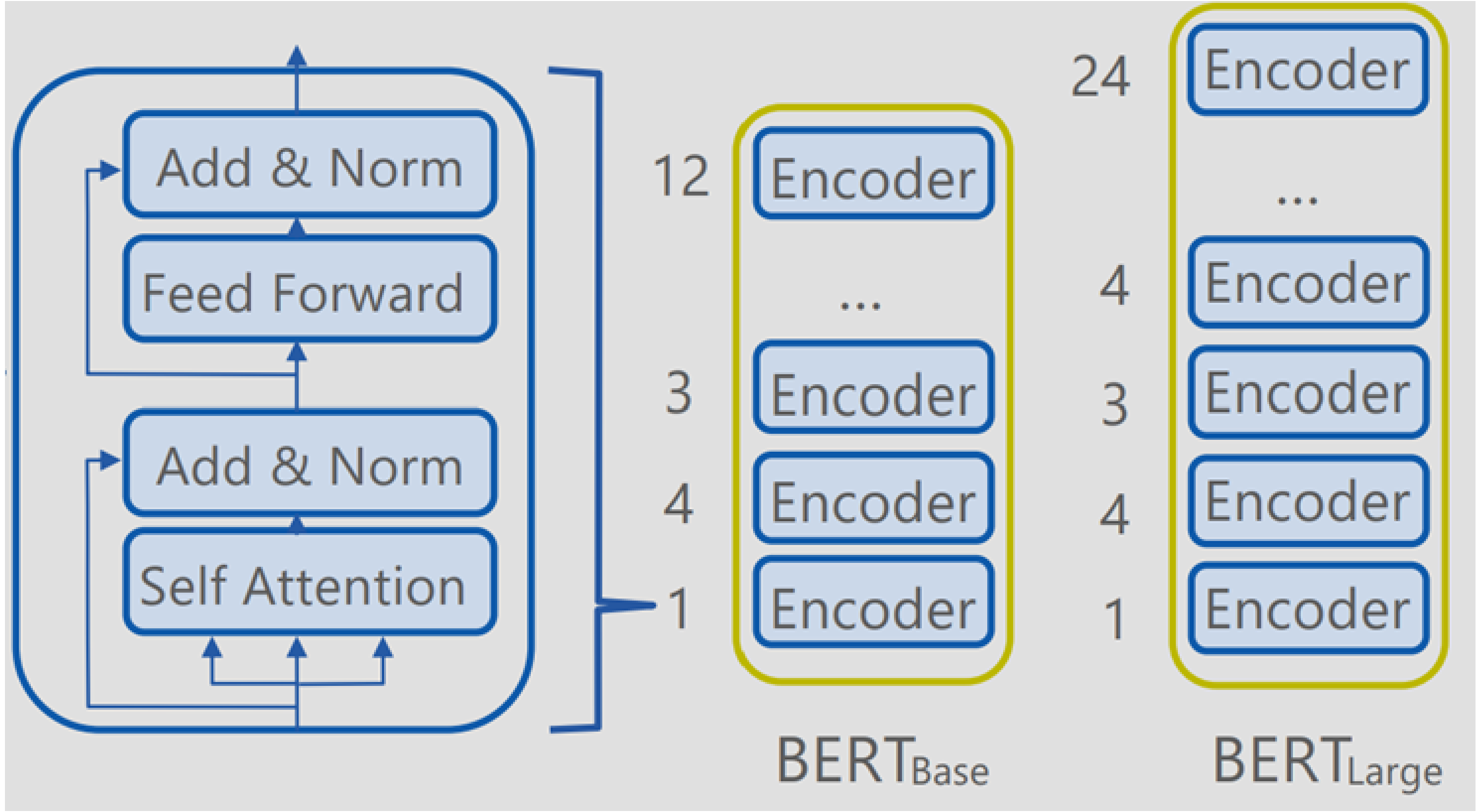
The model is based on **Encoder part** of Transformer



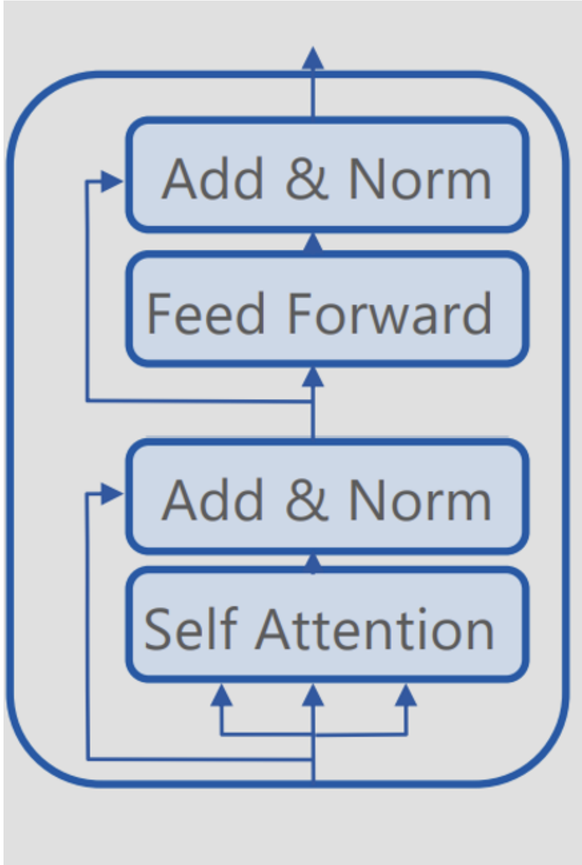
BERT architecture

The model is based on **Encoder part** of Transformer

Two main configurations: base & large

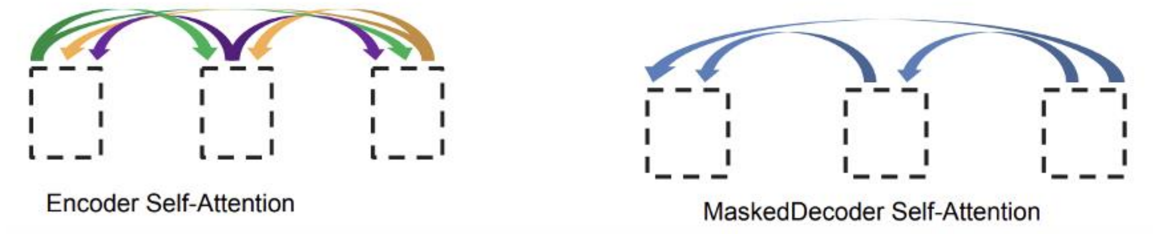


Recap: *What is the key difference between Encoder & Decoder?*



Recap: *What is the key difference between Encoder & Decoder?*

Answer: in decoder we use Masked Self-Attention, which prohibits looking into the future, while in Encoder all tokens interact with each other.



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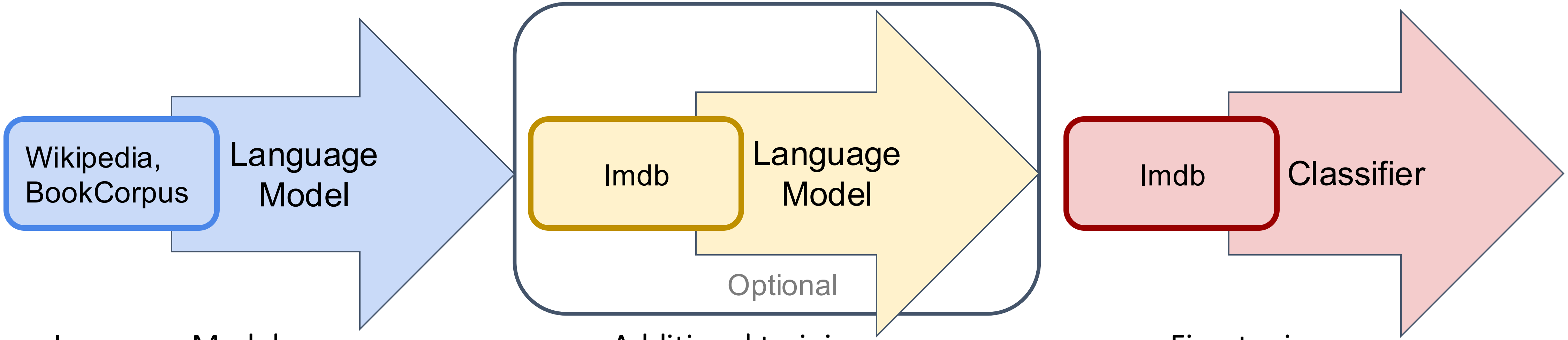
Answer: in decoder we use *Masked Self-Attention*, which prohibits looking into the future, while in Encoder *all tokens interact with each other*.

⇩

Being an Encoder BERT ”looks” at all context tokens (left & right)

General scheme for using BERT



Language Model Pre-training (MLM, Next Sentence prediction)

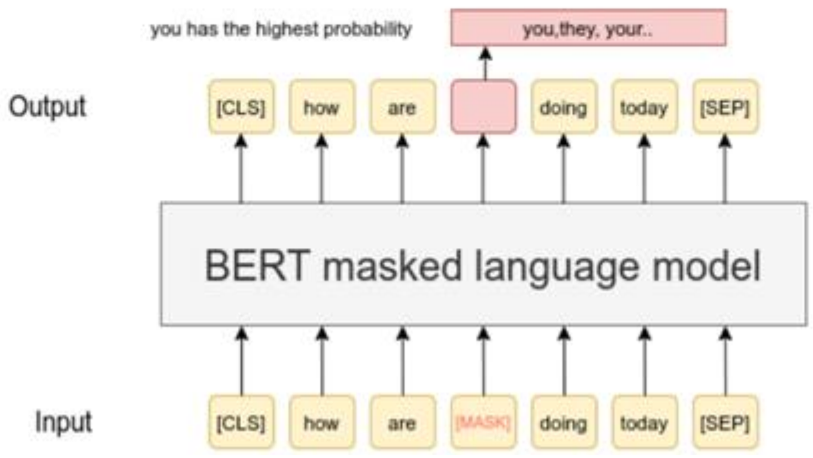
Additional training of the model on the data of the target domain

Fine-tuning on a downstream task

BERT pre-training

Two pre-training tasks:

- Masked Language Modeling Task (**MLM**)
- Next Sentence Prediction (**NSP**)



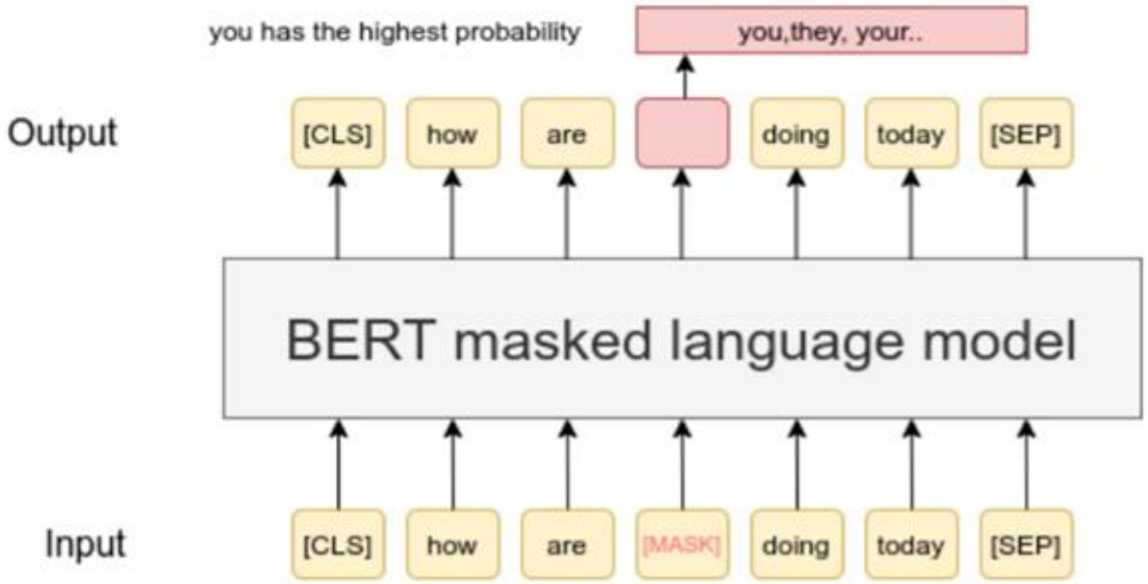
Sentence A = `The man went to the store.`
Sentence B = `He bought a gallon of milk.`
Label = `IsNextSentence`

Sentence A = `The man went to the store.`
Sentence B = `Penguins are flightless.`
Label = `NotNextSentence`

BERT pre-training

Masked Language Modeling Task (**MLM**): mask k% of the input words and then predict the masked words (usually k=15%)

- *Too little masking: Too expensive to train*
- *Too much masking: Not enough content*



Masked LM objective

<u>Problem</u>: don’t want masking for downstream tasks, but only outputs from masked timesteps affect MLM loss
=> bad representations for all other timesteps?

<u>Solution</u>: CE on (some) non-masked timesteps also

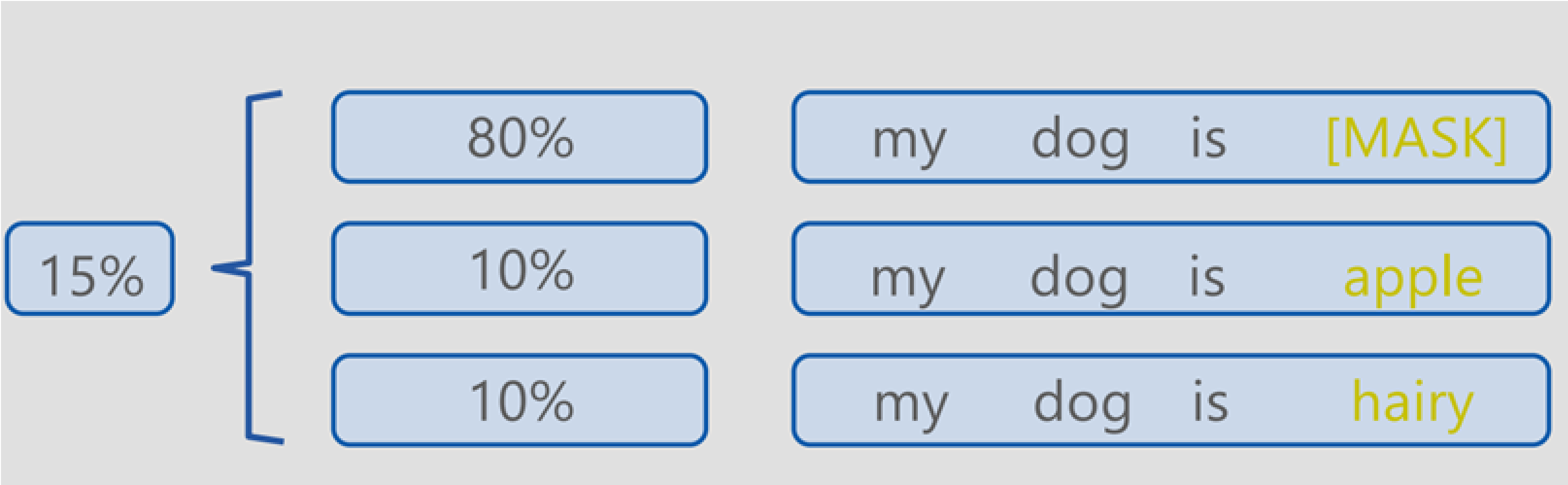
<u>Problem</u>: can learn simply to copy non-masked timesteps without even looking at context

<u>Solution</u>: replace non-masked timesteps with random words sometimes

This is **denoising autoencoder**: replace some tokens from a text fragment with random tokens / [MASK] token and try to reconstruct initial fragment!

MLM Task

- 80 % of time, replace with [MASK]
- 10% of time, replace with random words
- 10% of time keep same



Next Sentence Prediction (NSP) objective

Input 2 sentences: A,B; predict if B is next sentence after A

- *Sample B following A (with p=0.5) or random sentence from the corpus*
- *Learn to extract relations between 2 sentences (for tasks like paraphrase detection, NLI)*

NSP was shown to worsen results in the following research (too simple objective?)

- More difficult alternative: always sample 2 adjacent sentences and predict their order

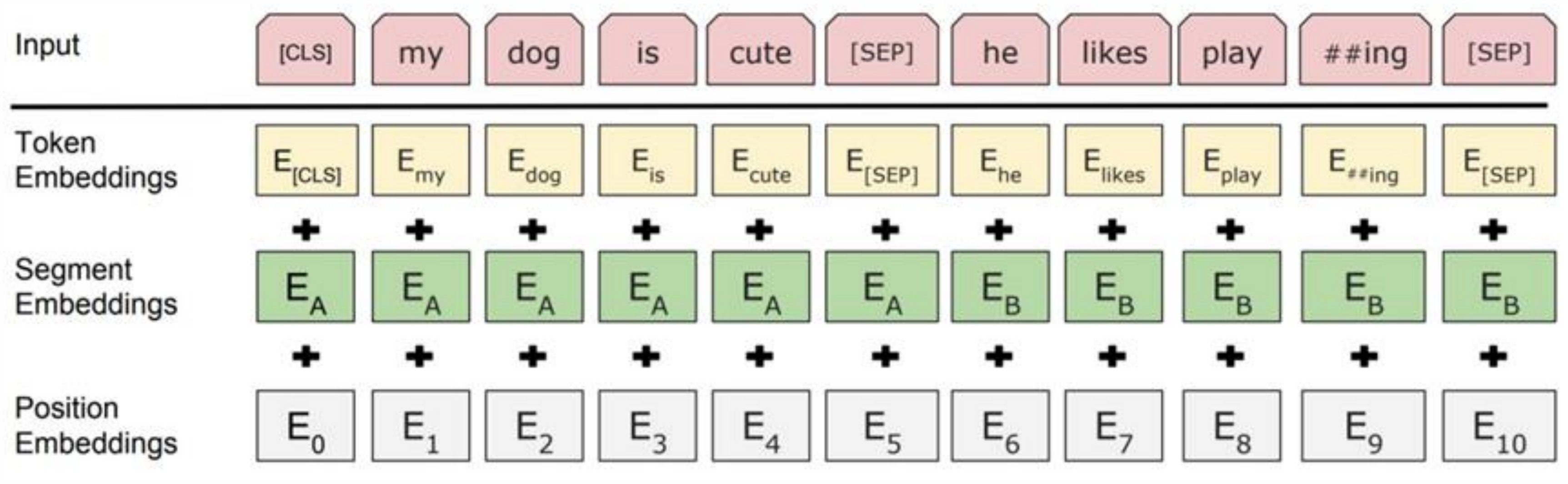
Sentence A = `The man went to the store.`	**Sentence A** = `The man went to the store.`
Sentence B = `He bought a gallon of milk.`	**Sentence B** = `Penguins are flightless.`
Label = `IsNextSentence`	**Label** = `NotNextSentence`

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.
Slides. https://nlp.stanford.edu/seminar/details/jdevlin.pdf

How to get sentence embedding from BERT?

- [CLS] - CLS token embedding from the last layer
- [MEAN] - averaging the word vectors on the last layer
- [MAX] - componentwise maximum of word vectors on the last layer (maxpooling)

Inputs



- Use 30,000 WordPiece vocabulary on input.
- Each token is sum of three embeddings
- Single sequence is much more efficient.

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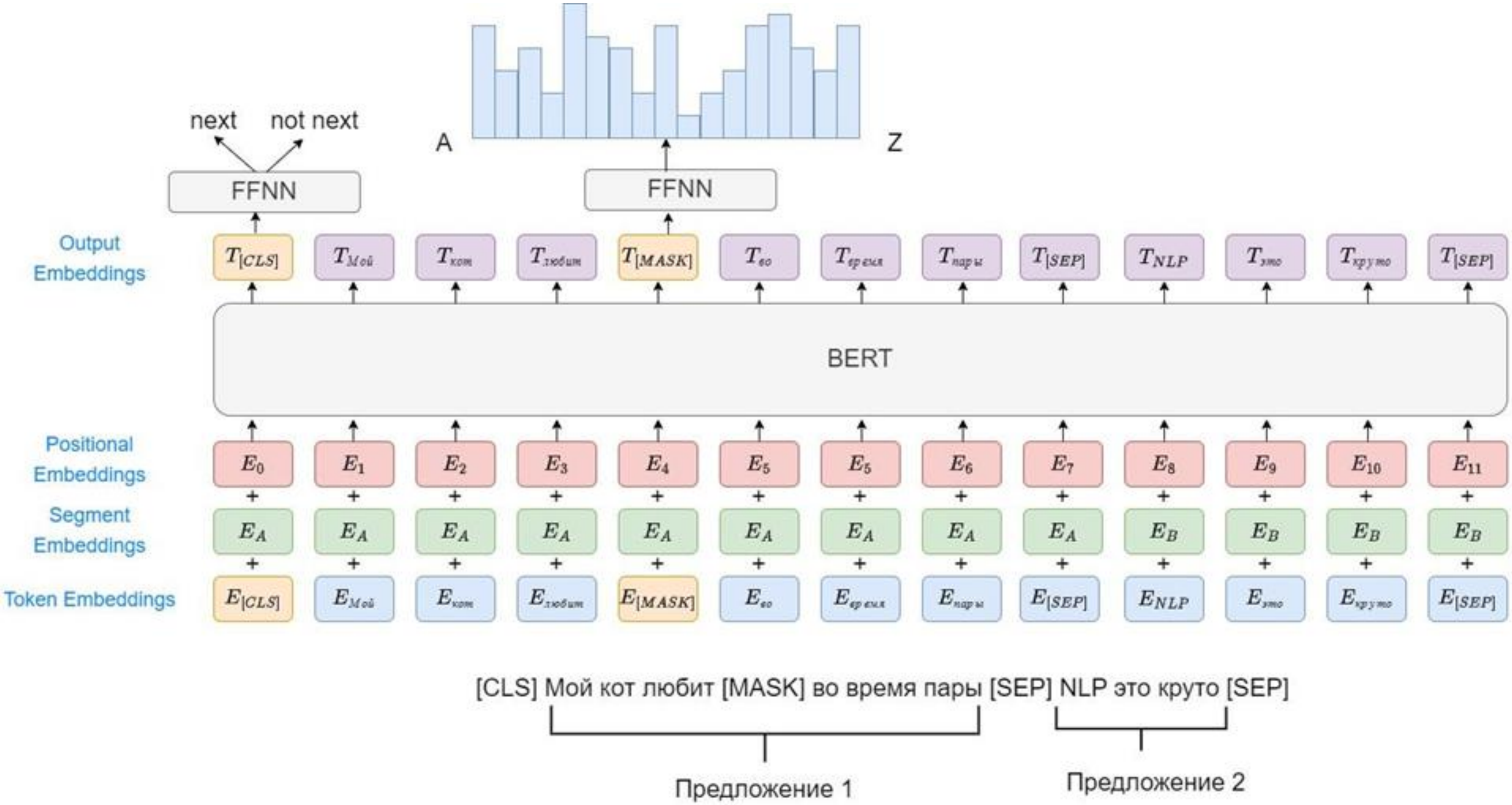
MLM and NSP together

$$\mathcal{L}_{\text{MLM}} = -\frac{1}{|M|}\sum_{i\in M}\log P(x_i|x_{\setminus M}) \qquad \mathcal{L}_{\text{total}} = \mathcal{L}_{\text{MLM}} + \mathcal{L}_{\text{NSP}}$$



BERT Pre-training

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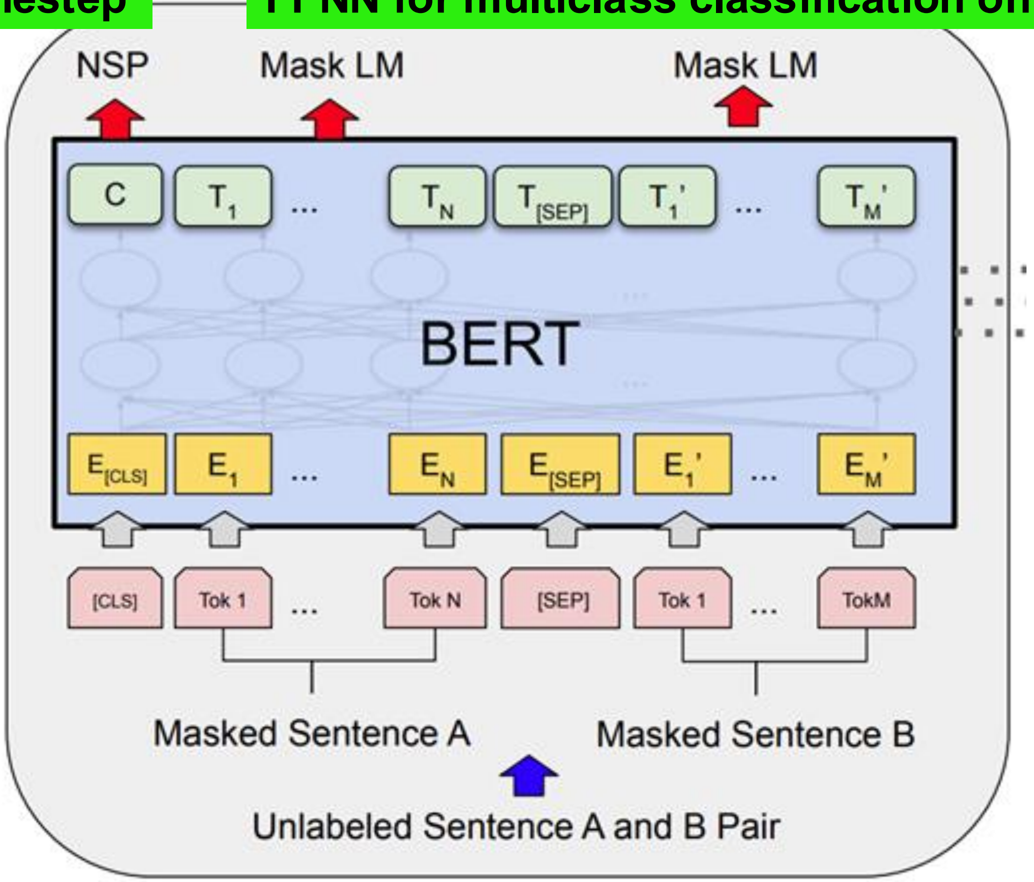
FFNN for binary classification on 1st timestep

FFNN for multiclass classification on each timestep



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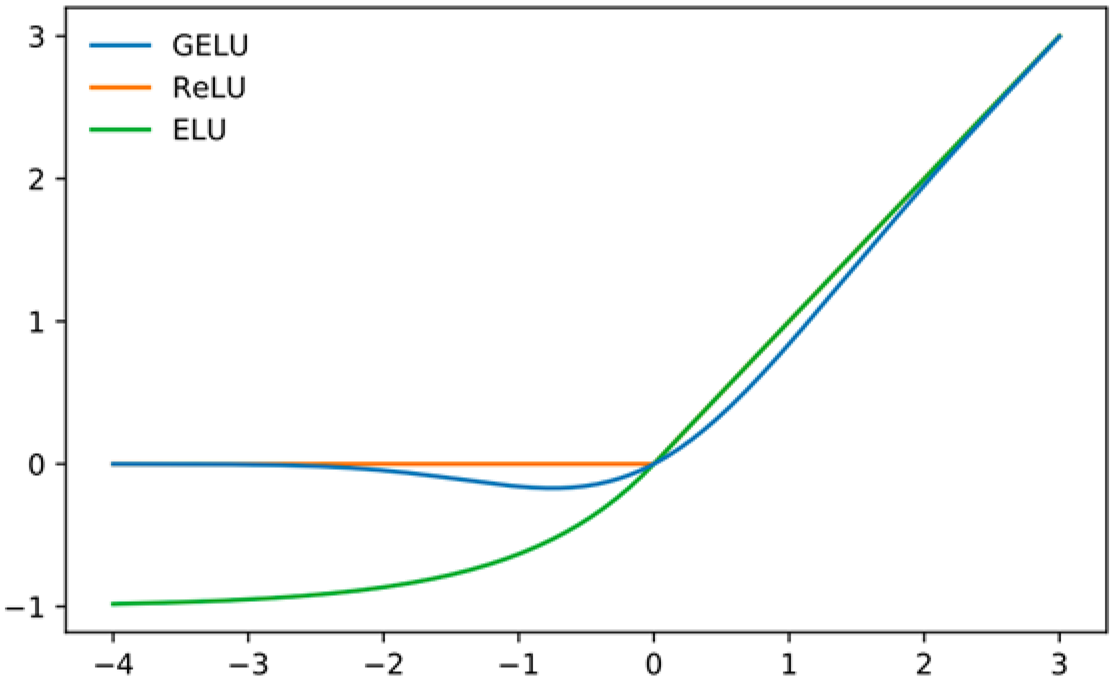
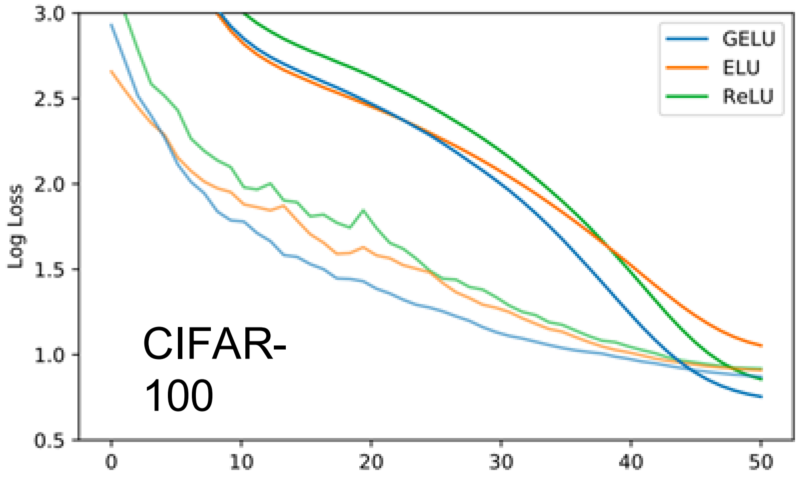
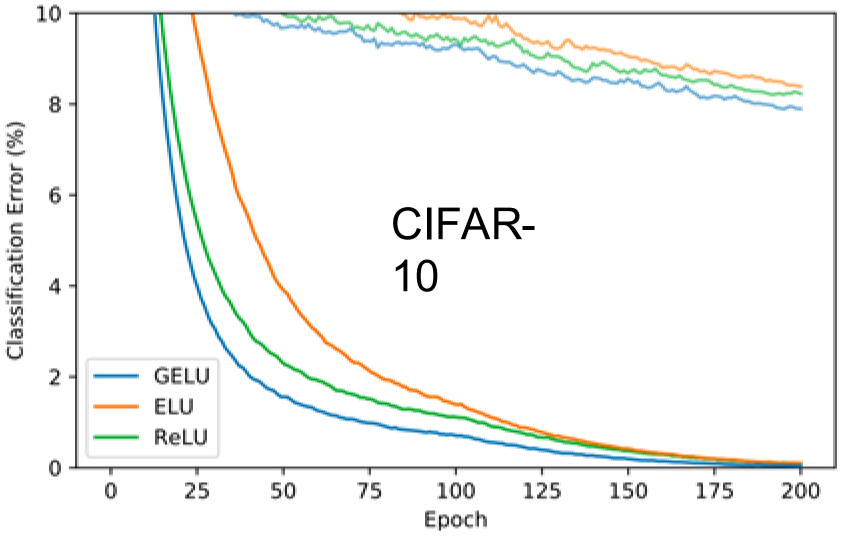
GELU activation







both GPT and BERT changed ReLU to GELU

Hendrycks and Gimpel. Gaussian Error Linear Units, 2016

BERT Pre-training details

- Data: Wikipedia (2.5B words) + BookCorpus (800M words)
- Batch Size: 131,072 words (1024 sequences * 128 length or 256 sequences * 512 length)
- Training Time: 1M steps (~40 epochs)
- Optimizer: AdamW, 1e-4 learning rate, linear decay
- `BERT-Base`: 12-layer, 768-hidden, 12-head
- `BERT-Large`: 24-layer, 1024-hidden, 16-head
- Trained on 4x4 or 8x8 TPU slice for 4 days

+10k steps lr warmup

110M params

340M params

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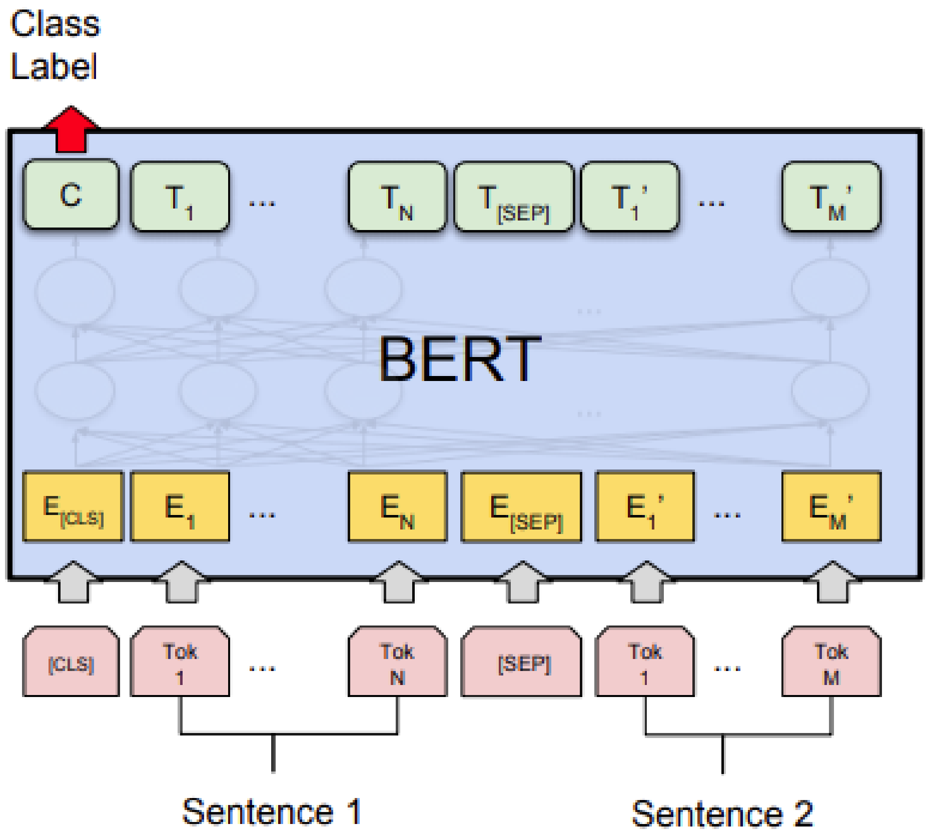
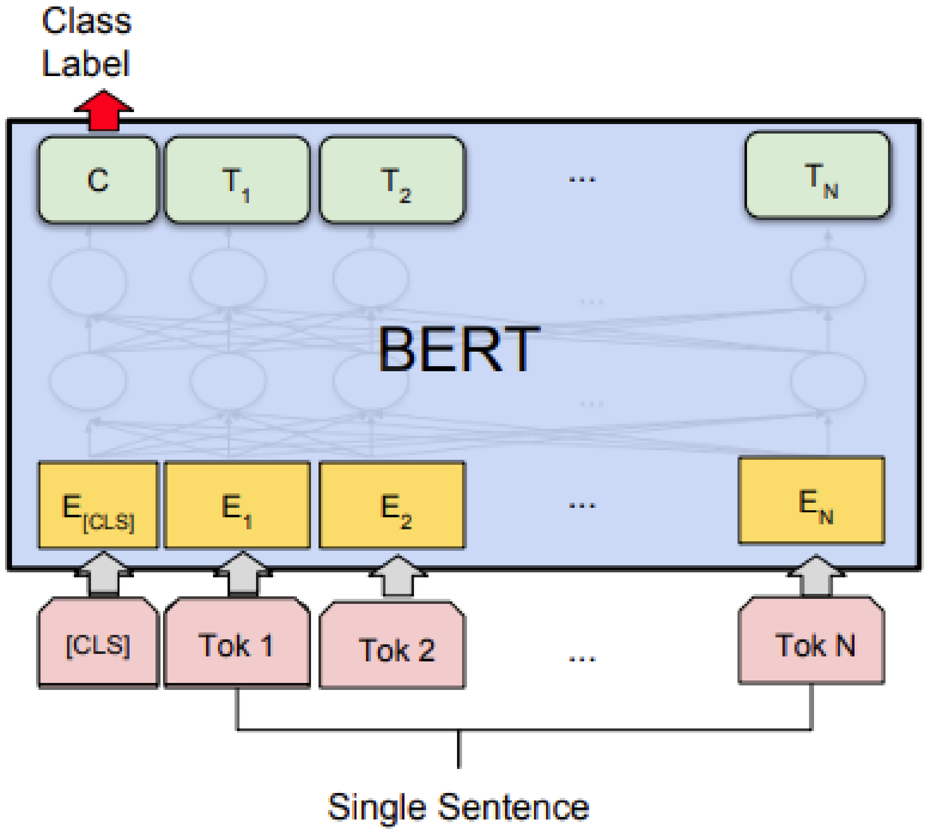
BERT Fine-tuning



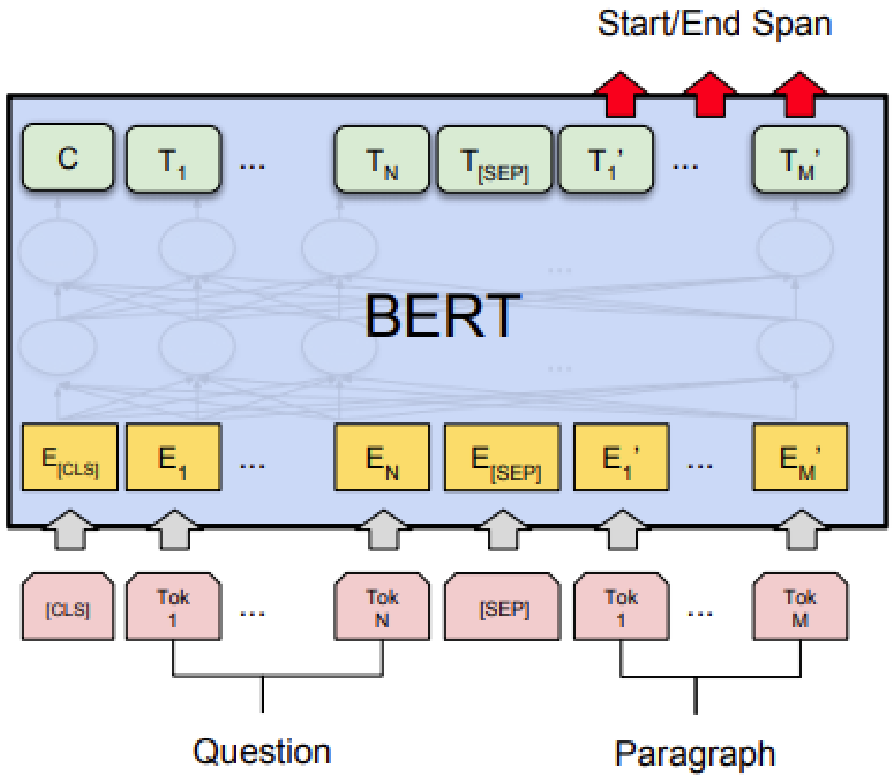
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



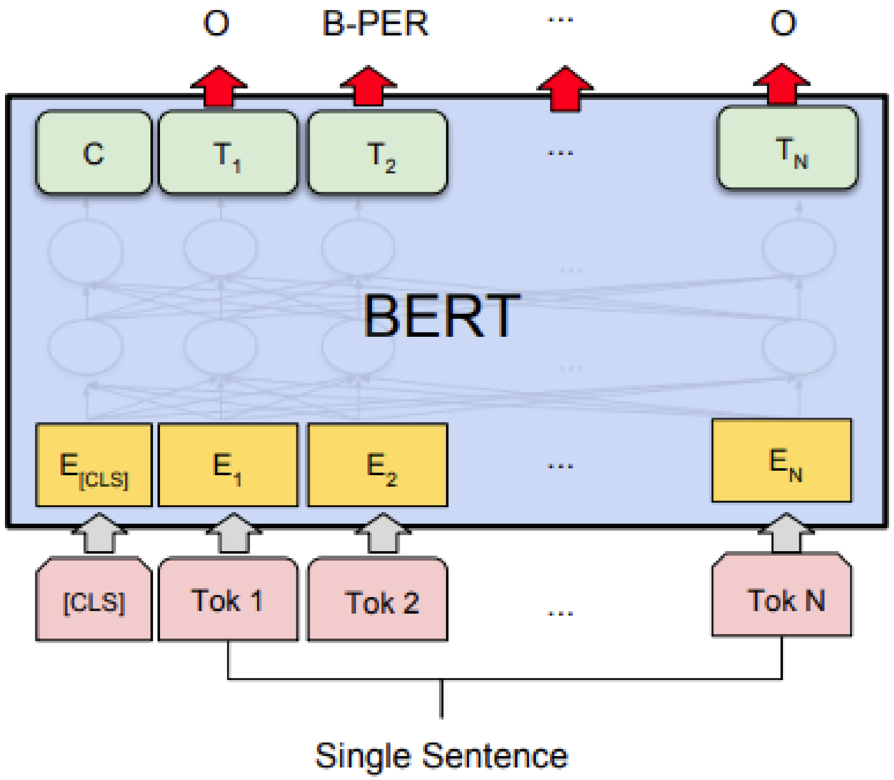
(b) Single Sentence Classification Tasks: SST-2, CoLA

Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT Fine-tuning



(c) Question Answering Tasks:
SQuAD v1.1



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

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SQuAD 1.1 Results

What was another term used for the oil crisis?
Ground Truth Answers: first oil shock shock shock first oil shock shock
Prediction: shock

The 1973 oil crisis began in October 1973 when the members of the Organization of Arab Petroleum Exporting Countries (OAPEC, consisting of the Arab members of OPEC plus Egypt and Syria) proclaimed an oil embargo. By the end of the embargo in March 1974, the price of oil had risen from US$3 per barrel to nearly $12 globally; US prices were significantly higher. The embargo caused an oil crisis, or "shock", with many short- and long-term effects on global politics and the global economy. It was later called the "first oil shock", followed by the 1979 oil crisis, termed the "second oil shock."

- Only new parameters: Start vector and end vector.
- Softr … itions.

$$P_i = \frac{e^{S \cdot T_i}}{\sum_j e^{S \cdot T_j}}$$

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar et al. '16)	82.304	91.221
1 Oct 05, 2018	BERT (ensemble) *Google AI Language* https://arxiv.org/abs/1810.04805	**87.433**	**93.160**
2 Oct 05, 2018	BERT (single model) *Google AI Language* https://arxiv.org/abs/1810.04805	85.083	91.835
2 Sep 26, 2018	nlnet (ensemble) *Microsoft Research Asia*	85.954	91.677
5 Sep 09, 2018	nlnet (single model) *Microsoft Research Asia*	83.468	90.133
3 Jul 11, 2018	QANet (ensemble) *Google Brain & CMU*	84.454	90.490

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BERT secrets

- Very large model & lots of compute
- Moderately large corpora (3.2B words)
- Deep bidirectional contextualized word representation (seeing all words when encoding each word in each layer)

ULMfit	GPT	BERT	GPT-2
Jan 2018	June 2018	Oct 2018	Feb 2019
Training:	Training	Training	Training
1 GPU day	240 GPU days	256 TPU days	~2048 TPU v3 days according to a reddit thread
		~320–560 GPU days	
fast.ai	OpenAI	Google AI	OpenAI

Christopher Manning. Cs224n/Ling284 slides.Lecture 13.

RuBERT

Pre-Trained on the Russian-language texts

Created by SberAI

- Tokenizer: bpe
- Dict size: 120 138
- Training Data Volume 30 GB

Base: https://huggingface.co/ai-forever/ruBert-base

Large: https://huggingface.co/ai-forever/ruBert-large

Conclusion

- A new paradigm in NLP: fine-tune large pre-trained model for particular tasks (Transfer learning)
- The pretrained model already knows a lot about language
- The use of pre-trained models opens up new perspectives: less data, higher quality indicators, less fine-tuning time

BERT ”relatives”

- mBERT
- RoBERTa
- XLM-RoBERTa (aka XLM-R)
- Electra
- DeBERTa
- and many-many others!

RoBERTa

RoBERTa

- RoBERTa: **R**obustly **o**ptimized **BERT a**pproach, 2019
- Was not accepted to ICLR-2020 due to the limited novelty and despite of SOTA results on GLUE, SQuAD, RACE
- Google sub-optimally selected optimization hyperparameters / decisions and trained BERT poorly, so Facebook fixed it
  => much better than BERT

RoBERTa: A Robustly Optimized BERT Pretraining Approach

Yinhan Liu[*§] **Myle Ott**[*§] **Naman Goyal**[*§] **Jingfei Du**[*§] **Mandar Joshi**[†]
Danqi Chen[§] **Omer Levy**[§] **Mike Lewis**[§] **Luke Zettlemoyer**[†§] **Veselin Stoyanov**[§]

[†] Paul G. Allen School of Computer Science & Engineering,
University of Washington, Seattle, WA
{mandar90,lsz}@cs.washington.edu

[§] Facebook AI
{yinhanliu,myleott,naman,jingfeidu,
danqi,omerlevy,mikelewis,lsz,ves}@fb.com

https://arxiv.org/abs/1907.11692

Dynamic Masking

- BERT: data was duplicated 10 times and perturbed (masked, etc.) before training for 40 epochs

  => inputs/targets are seen 4 times

- RoBERTa: randomly perturbs inputs during training.
  - No need to duplicate large datasets
  - More diverse data when training more epochs
  - Natural (like dropout)
  - Similar or better results

Masking	SQuAD 2.0	MNLI-m	SST-2
reference	76.3	84.3	92.8
Our reimplementation:			
static	78.3	84.3	92.5
dynamic	78.7	84.0	92.9

Table 1: Comparison between static and dynamic masking for $\text{BERT}_{\text{BASE}}$. We report F1 for SQuAD and accuracy for MNLI-m and SST-2. Reported results are medians over 5 random initializations (seeds). Reference results are from Yang et al. (2019).

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Inputs and NSP

- **segment-pair+NSP (BERT)**: a pair of text fragments, combined length is <=512
- **sentence-pair+NSP**: a pair of sentences, much shorter than 512 => dynamic batch size to obtain same number of tokens in a batch
- **full-sentences (no NSP)**: a sequence of whole sentences taken continuously from the corpus while length is <=512. Insert special symbol for document boundaries.
- **doc-sentences (no NSP)**: similarly to previous, but examples do not cross document boundaries. Increase batch size dynamically to obtain same number of tokens in a batch as in full-sentences.

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Inputs and NSP

Doc-sentences is best. But results in variable size batch.

=> Full-sentences is used for all other experiments.

Sentences are worse than text fragments
(cannot learn long-range deps?)

Removing NSP helps (contrary to BERT paper)

Model	SQuAD 1.1/2.0	MNLI-m	SST-2	RACE
Our reimplementation (with NSP loss):				
SEGMENT-PAIR	90.4/78.7	84.0	92.9	64.2
SENTENCE-PAIR	88.7/76.2	82.9	92.1	63.0
Our reimplementation (without NSP loss):				
FULL-SENTENCES	90.4/79.1	84.7	92.5	64.8
DOC-SENTENCES	90.6/79.7	84.7	92.7	65.6
$\text{BERT}_{\text{BASE}}$	88.5/76.3	84.3	92.8	64.3
$\text{XLNet}_{\text{BASE}}$ (K = 7)	–/81.3	85.8	92.7	66.1
$\text{XLNet}_{\text{BASE}}$ (K = 6)	–/81.0	85.6	93.4	66.7

Table 2: Development set results for base models pretrained over BOOKCORPUS and WIKIPEDIA. All models are trained for 1M steps with a batch size of 256 sequences. We report F1 for SQuAD and accuracy for MNLI-m, SST-2 and RACE. Reported results are medians over five random initializations (seeds). Results for $\text{BERT}_{\text{BASE}}$ and $\text{XLNet}_{\text{BASE}}$ are from Yang et al. (2019).

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Inputs and NSP

- Compare different batch sizes for the fixed number of epochs (different number of steps).
- => bsz=2K (8x larger than in BERT) is better even with 8x less training steps; bsz=8K is worse (too few steps?)

bsz	steps	lr	ppl	MNLI-m	SST-2
256	1M	1e-4	3.99	84.7	92.7
2K	125K	7e-4	**3.68**	**85.2**	**92.9**
8K	31K	1e-3	3.77	84.6	92.8

Table 3: Perplexity on held-out training data (*ppl*) and development set accuracy for base models trained over BOOKCORPUS and WIKIPEDIA with varying batch sizes (*bsz*). We tune the learning rate (*lr*) for each setting. Models make the same number of passes over the data (epochs) and have the same computational cost.

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Subwords

- BERT: *30K character level BPE* (WordPiece) vocabulary, heuristic preprocessing and tokenization.
- RoBERTa: **50K byte-level BPE**, no preprocessing or tokenization (much simpler and more universal, but slightly worse results for some tasks in the prelimiary experiments)
  - *Too many unicode characters (~140K), a significant part of which occurs in a diverse corpora, can occupy a large part of the vocabulary leaving too few space for words and large parts of words. The model can degenerate to character level model.*
  - *Byte-level BPE starts from bytes, not unicode symbols. With 50K vocabulary it can encode any input string without using <unk> token.*
  - *Still looks at unicode character categories to prevent merging different categories (otherwise, wastes vocabulary: dog. dog! dog?)*

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Data

- BERT→RoBERTa: 16GB→**160GB**
- 16GB from BERT: BookCropus + En Wikipedia
- 76GB CC-News – En part of CommonCrawl News
- 38GB OpenWebText – crawled URLs from Reddit with >=3 upvotes
- 31GB Stories – subset of CommonCrawl matching story-like style of Winograd schemas

- Training large models: 4days on 64 TPU chips[13]→
  1 day on 1024 V100 GPUs

Figures from Devlin et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, 2018

BERT→**RoBERTa**

- 10x larger dataset
- 32x larger batch size and longer training
  - but 2x less steps
- Dynamic masking
- Removed Next sentence prediction loss and segment-pairs input format
- 30k WordPiece→**50k byte-level BPE vocabulary**
- Careful selection of optimization hyperparameters for pre-training and fine-tuning

GLUE test results

- Single-task finetuning (unlike some other top models);
  for RTE, STS, MRPC start fine-tuning from model fine-tuned on MNLI
- Ensemble 5-7 models per task

	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	WNLI	Avg
Single-task single models on dev										
$\text{BERT}_{\text{LARGE}}$	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-	-
$\text{XLNet}_{\text{LARGE}}$	89.8/-	93.9	91.8	83.8	95.6	89.2	63.6	91.8	-	-
RoBERTa	**90.2/90.2**	**94.7**	**92.2**	**86.6**	**96.4**	**90.9**	**68.0**	**92.4**	**91.3**	-
Ensembles on test (from leaderboard as of July 25, 2019)										
ALICE	88.2/87.9	95.7	**90.7**	83.5	95.2	92.6	**68.6**	91.1	80.8	86.3
MT-DNN	87.9/87.4	96.0	89.9	86.3	96.5	92.7	68.4	91.1	89.0	87.6
XLNet	90.2/89.8	98.6	90.3	86.3	**96.8**	**93.0**	67.8	91.6	**90.4**	88.4
RoBERTa	**90.8/90.2**	**98.9**	90.2	**88.2**	96.7	92.3	67.8	**92.2**	89.0	**88.5**

Table 5: Results on GLUE. All results are based on a 24-layer architecture. $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ results are from Devlin et al. (2019) and Yang et al. (2019), respectively. RoBERTa results on the development set are a median over five runs. RoBERTa results on the test set are ensembles of *single-task* models. For RTE, STS and MRPC we finetune starting from the MNLI model instead of the baseline pretrained model. Averages are obtained from the GLUE leaderboard.

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

Other datasets

Model	SQuAD 1.1		SQuAD 2.0	
	EM	F1	EM	F1
Single models on dev, w/o data augmentation				
$\text{BERT}_{\text{LARGE}}$	84.1	90.9	79.0	81.8
$\text{XLNet}_{\text{LARGE}}$	**89.0**	94.5	86.1	88.8
RoBERTa	88.9	**94.6**	**86.5**	**89.4**
Single models on test (as of July 25, 2019)				
$\text{XLNet}_{\text{LARGE}}$			$86.3^\dagger$	$89.1^\dagger$
RoBERTa			86.8	89.8
XLNet + SG-Net Verifier			$\mathbf{87.0}^\dagger$	$\mathbf{89.9}^\dagger$

Table 6: Results on SQuAD. † indicates results that depend on additional external training data. RoBERTa uses only the provided SQuAD data in both dev and test settings. $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ results are from Devlin et al. (2019) and Yang et al. (2019), respectively.

Model	Accuracy	Middle	High
Single models on test (as of July 25, 2019)			
$\text{BERT}_{\text{LARGE}}$	72.0	76.6	70.1
$\text{XLNet}_{\text{LARGE}}$	81.7	85.4	80.2
RoBERTa	**83.2**	**86.5**	**81.3**

Table 7: Results on the RACE test set. $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ results are from Yang et al. (2019).

SOTA among models w/o data augmentation

Figures from Liu et al. RoBERTa: A Robustly Optimized BERT Pretraining Approach, 2019

XLM-RoBERTa

XLM-R (XLM-RoBERTa)

- A single RoBERTa model trained on **2.5TB** of **filtered** texts from CommonCrawl on **100 languages**
- Shows zero-shot cross-lingual transfer ability!
- Takes best from XLM (multilingual) and RoBERTa (English) models

Unsupervised Cross-lingual Representation Learning at Scale

Alexis Conneau*   Kartikay Khandelwal*

Naman Goyal   Vishrav Chaudhary   Guillaume Wenzek   Francisco Guzmán

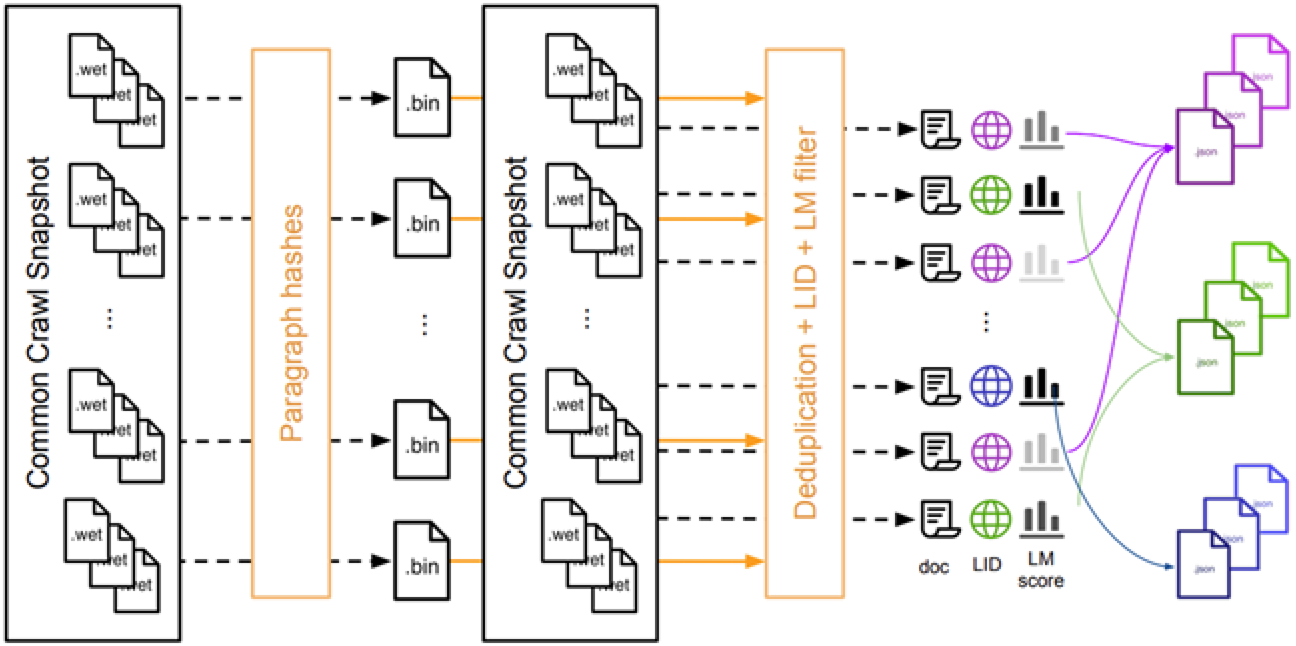
Edouard Grave   Myle Ott   Luke Zettlemoyer   Veselin Stoyanov

Facebook AI

Figures from Conneau et al. [Unsupervised Cross-lingual Representation Learning at Scale, 2020]

XLM-R data

- Build clean CommonCrawl in 100 languages with CCNet:
  - *Partially deduplicate paragraphs (also removes boilerplate)*
  - *Run lang id and filter by language*
  - *Filter by perplexity (for each language a Kneser-Ney 5-gram LM is trained on Wikipedia in this language)*



Wenzek et al. CCNet: Extracting High Quality Monolingual Datasets from Web Crawl Data, 2019

XLM-R data

- Upsampling low-resource languages
  - Alleviates bias towards high-resource languages
  - Prevents words in low-resource languages from being split into characters
  - Alpha=0.3 (0.5 in XLM):
    - Ex: English / Uzbek = 300GB / 0.7GB = 430; 4300.3=6.16
  - N is number of languages, ni is number of sentences in language i

$$q_i = \frac{p_i^\alpha}{\sum_{j=1}^N p_j^\alpha} \quad \text{with} \quad p_i = \frac{n_i}{\sum_{k=1}^N n_k}$$

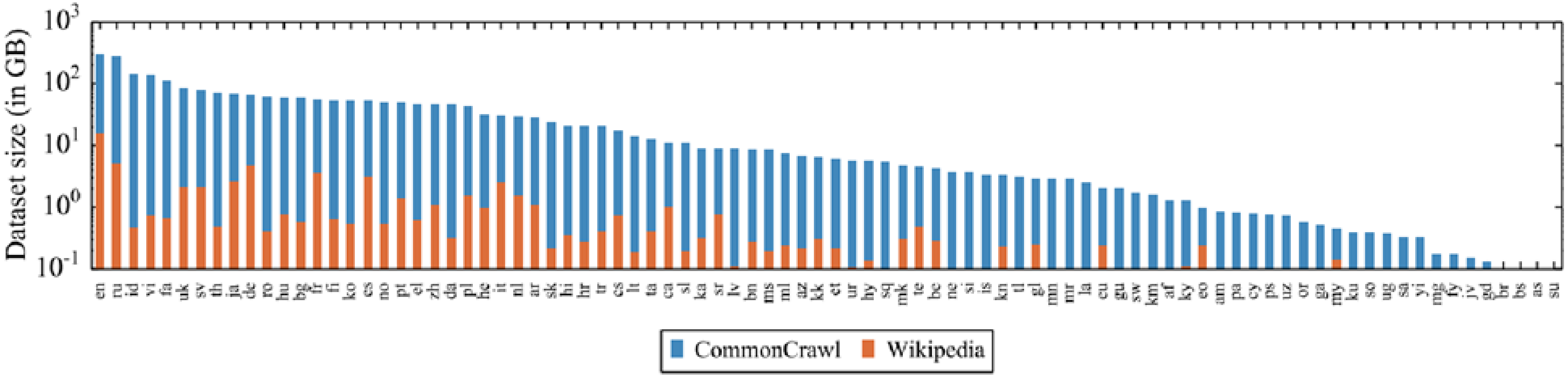


Figure 1: Amount of data in GiB (log-scale) for the 88 languages that appear in both the Wiki-100 corpus used for mBERT and XLM-100, and the CC-100 used for XLM-R. CC-100 increases the amount of data by several orders of magnitude, in particular for low-resource languages.

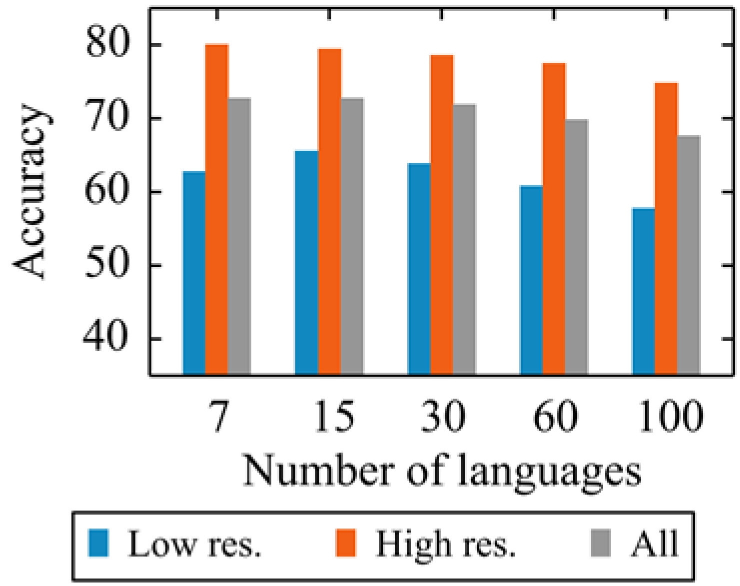
Figures from Conneau et al. Unsupervised Cross-lingual Representation Learning at Scale, 2020; Lample et al. Cross-lingual Language Model Pretraining, 2019

The curse of multilinguality

- With fixed capacity as we add more langs, the quality:
  - *When 93 langs added, acc. for 7 eval langs: 0.718→0.677*
  - *for high-res. langs decrease (capacity dilution)*
  - *for low-res. – first increases (due to cross-ling. transfer), then decreases (due to capacity dilution)*
- Increase capacity with number of languages?

For ablations: base model, pre-training on Wikipedia, fine-tuning on XNLI.

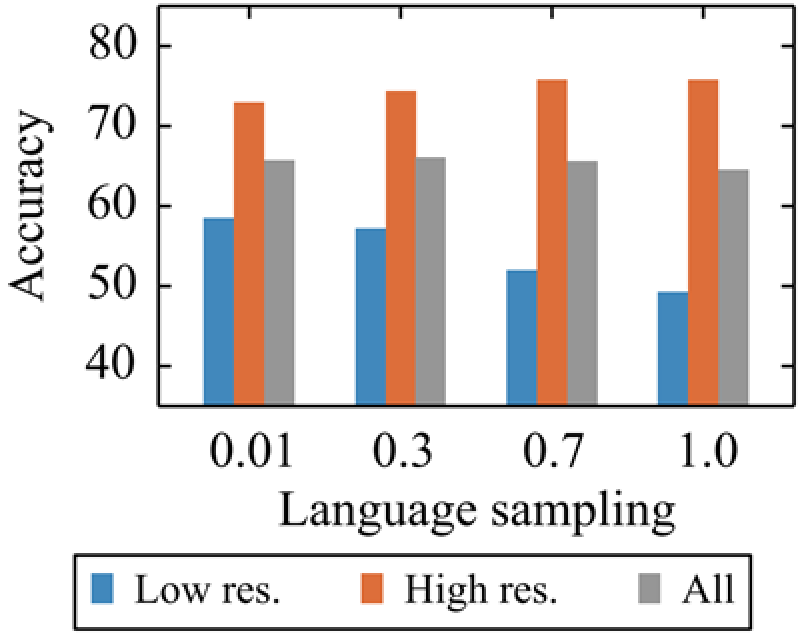
Accuracy on XNLI (zero-shot from en?)
High res.: (English + French) / 2
Low res.: (Swahili + Urdu) / 2
All: + German, Russian, Chinese



Figures from Conneau et al. Unsupervised Cross-lingual Representation Learning at Scale, 2020

The curse of multilinguality

- XLM-100 on pre-trained Wikipedia
- Upsampling helps low-res. langs a lot, but hurts high-res. langs a little
- alpha=0.3 results in best average accuracy on 7 eval. langs



Figures from Conneau et al. Unsupervised Cross-lingual Representation Learning at Scale, 2020

XLM-R large

- As BERT/RoBERTa large: 24 layers of Transformer, hidden size 1024
  - 270M/550M in base/large model
  - about half of parameters are subword embeddings
- Vocabulary: 250K subwords shared between 100 languages
  - Sentence Piece with a unigram LM directly on raw text
  - MLM pre-trained with full softmax
- 1.5M updates, bs=8192
- 500 V100 GPUs
  - How many days?
  - Compared to RoBERTa: 2x less GPUs, 3x more updates, same bs => about 1 week?

Figures from Conneau et al. Unsupervised Cross-lingual Representation Learning at Scale, 2020

XNLI accuracy (on 6/15 langs)

4 high-res | 2 high-res | Avg across 15

Model	D	#M	#lg	en	fr	es	de	sw	ur	Avg
Fine-tune multilingual model on English training set (Cross-lingual Transfer)										
Lample and Conneau (2019)	Wiki+MT	N	15	85.0	78.7	78.9	77.8	68.4	67.3	75.1
Huang et al. (2019)	Wiki+MT	N	15	85.1	79.0	79.4	77.8	69.7	66.7	75.4
Devlin et al. (2018)	Wiki	N	102	82.1	73.8	74.3	71.1	50.4	58.0	66.3
Lample and Conneau (2019)	Wiki	N	100	83.7	76.2	76.6	73.7	58.0	62.4	71.3
Lample and Conneau (2019)	Wiki	1	100	83.2	76.7	77.7	74.0	58.2	62.4	70.7
XLM-R$_{\text{Base}}$	CC	1	100	85.8	79.7	80.7	78.7	66.5	68.3	76.2
XLM-R	CC	1	100	**89.1**	**84.1**	**85.1**	**83.9**	**73.9**	**73.8**	**80.9**
Translate everything to English and use English-only model (TRANSLATE-TEST)										
BERT-en	Wiki	1	1	88.8	81.4	82.3	80.1	65.8	65.8	76.2
RoBERTa	Wiki+CC	1	1	91.3	82.9	84.3	81.2	66.7	66.8	77.8
Fine-tune multilingual model on each training set (TRANSLATE-TRAIN)										
Lample and Conneau (2019)	Wiki	N	100	82.9	77.6	77.9	77.9	66.5	62.4	74.2
Fine-tune multilingual model on all training sets (TRANSLATE-TRAIN-ALL)										
Lample and Conneau (2019)†	Wiki+MT	1	15	85.0	80.8	81.3	80.3	72.8	68.5	77.8
Huang et al. (2019)	Wiki+MT	1	15	85.6	81.1	82.3	80.9	73.8	69.6	78.5
Lample and Conneau (2019)	Wiki	1	100	84.5	80.1	81.3	79.3	69.2	67.7	76.9
XLM-R$_{\text{Base}}$	CC	1	100	85.4	81.4	82.2	80.3	73.1	73.0	79.1
XLM-R	CC	1	100	**89.1**	**85.1**	**86.6**	**85.7**	**78.0**	**78.1**	**83.6**

+14% cmp. to mBERT

Best for en, worst for other langs

Best for all langs except en

Figures from Conneau et al. Unsupervised Cross-lingual Representation Learning at Scale, 2020

XLM-R (Summary)

- Pre-training a single MLM on 100 languages:
  - requires high capacity (large vocab., hidden size)
  - requires long training with low-res. langs upsampling
- Fine-tuning multilingual MLM:
  - enables zero-shot cross-lingual transfer
  - but better translate (MT) into all target languages and fine-tune on multilingual train set

Bonus: DeBERTa

DeBERTa

- Improvements over RoBERTa:
  - Disentangle attention to content and to (relative) position of tokens
  - Incorporate absolute positions to the MLM decoder layer

- Improvements over ELECTRA:
  - Share generator embeddings with the discriminator, but not vice versa
  - Train a cross-lingual model (like XLM-R)

Published as a conference paper at ICLR 2021

DEBERTA: DECODING-ENHANCED BERT WITH DISENTANGLED ATTENTION

Pengcheng He[1], Xiaodong Liu[2], Jianfeng Gao[2], Weizhu Chen[1]
[1] Microsoft Dynamics 365 AI [2] Microsoft Research
{penhe,xiaodl,jfgao,wzchen}@microsoft.com

DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing

Pengcheng He[1], Jianfeng Gao[2], Weizhu Chen[1]
[1] Microsoft Azure AI
[2] Microsoft Research
{penhe,jfgao,wzchen}@microsoft.com

https://arxiv.org/abs/2006.03654, https://arxiv.org/abs/2111.09543

Disentangled attention

- Separate attentions for content (H) and position (P)
  - In transformers, attention often depends on position; let's simplify the job!
  - P is represented with relative position embeddings (same for all layers)
  - All attention scores are added together before softmax

$$Q = HW_q, K = HW_k, V = HW_v, A = \frac{QK^\intercal}{\sqrt{d}}$$
$$H_o = \text{softmax}(A)V$$

$$Q_c = HW_{q,c}, K_c = HW_{k,c}, V_c = HW_{v,c}, Q_r = PW_{q,r}, K_r = PW_{k,r}$$
$$\tilde{A}_{i,j} = \underbrace{Q_i^c {K_j^c}^\intercal}_{\text{(a) content-to-content}} + \underbrace{Q_i^c {K_{\delta(i,j)}^r}^\intercal}_{\text{(b) content-to-position}} + \underbrace{K_j^c {Q_{\delta(j,i)}^r}^\intercal}_{\text{(c) position-to-content}}$$
$$H_o = \text{softmax}\left(\frac{\tilde{A}}{\sqrt{3d}}\right)V_c$$

Relative position:

$$\delta(i,j) = \begin{cases} 0 & \text{for} \quad i - j \leqslant -k \\ 2k-1 & \text{for} \quad i - j \geqslant k \\ i - j + k & \text{others.} \end{cases}$$

DeBERTa: Decoding-enhanced BERT with Disentangled Attention

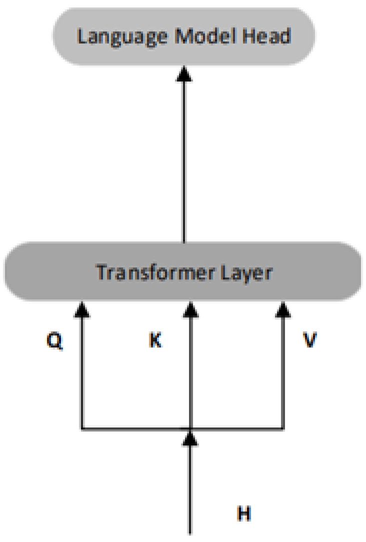
Enhanced mask decoder

How to incorporate absolute positions?

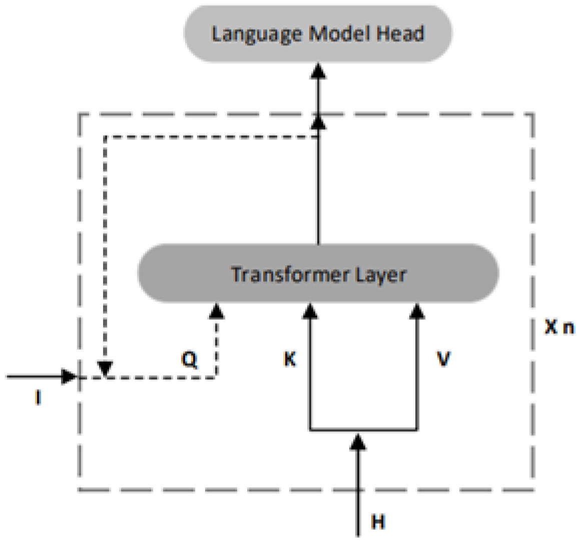
- BERT:
  - add their embeddings to the input token embeddings
- DeBERTa:
  - use their embeddings *I* as the query to the last transformer layer
  - Loop through this layer n=2 times
    - First use *I* for the queries, then the previous output of this layer

Motivation:

- Absolute positions matter most on the last layer, because syntax depends on this, and syntax matters for MLM
- "We conjecture that the early incorporation of absolute positions used by BERT might undesirably hamper the model from learning sufficient information of relative positions."



(a) BERT decoding layer



(b) Enhanced Mask Decoder

DeBERTa: Decoding-enhanced BERT with Disentangled Attention
https://github.com/microsoft/DeBERTa/blob/master/DeBERTa/apps/models/masked_language_model.py#L60

DeBERTa ablations

- Both parts of disentangled attention and EMD increase the quality

- -EMD is the DeBERTa base model without EMD.
- -C2P is the DeBERTa base model without the content-to-position term ((c) in Eq. 4).
- -P2C is the DeBERTa base model without the position-to-content term ((b) in Eq. 4). As XLNet also uses the relative position bias, this model is close to XLNet plus EMD.

Model	MNLI-m/mm Acc	SQuAD v1.1 F1/EM	SQuAD v2.0 F1/EM	RACE Acc
BERT$_{base}$ Devlin et al. (2019)	84.3/84.7	88.5/81.0	76.3/73.7	65.0
RoBERTa$_{base}$ Liu et al. (2019c)	84.7/-	90.6/-	79.7/-	65.6
XLNet$_{base}$ Yang et al. (2019)	85.8/85.4	-/-	81.3/78.5	66.7
RoBERTa-ReImp$_{base}$	84.9/85.1	91.1/84.8	79.5/76.0	66.8
DeBERTa$_{base}$	**86.3/86.2**	**92.1/86.1**	**82.5/79.3**	**71.7**
-EMD	86.1/86.1	91.8/85.8	81.3/78.0	70.3
-C2P	85.9/85.7	91.6/85.8	81.3/78.3	69.3
-P2C	86.0/85.8	91.7/85.7	80.8/77.6	69.6
-(EMD+C2P)	85.8/85.9	91.5/85.3	80.3/77.2	68.1
-(EMD+P2C)	85.8/85.8	91.3/85.1	80.2/77.1	68.5

Scale invariant fine-tuning

- This is an additive regularization loss used at fine-tuning
  - Add a small adversarial noise to the normalized input embeddings
  - Penalize for changes in the distribution
  - This loss induces smoothness
- Adds ≈1 accuracy point

$$\min_\theta \mathcal{F}(\theta) = \mathcal{L}(\theta) + \lambda_s \mathcal{R}_s(\theta),$$

$$\mathcal{R}_s(\theta) = \frac{1}{n}\sum_{i=1}^{n} \max_{\|\tilde{x}_i - x_i\|_p \le \epsilon} \ell_s(f(\tilde{x}_i;\theta), f(x_i;\theta)),$$

$$\ell_s(P,Q) = \mathcal{D}_{\mathrm{KL}}(P\|Q) + \mathcal{D}_{\mathrm{KL}}(Q\|P);$$

Model	CoLA Mcc	QQP Acc	MNLI-m/mm Acc	SST-2 Acc	STS-B Corr	QNLI Acc	RTE Acc	MRPC Acc	Avg.
DeBERTa$_{large}$	70.5	92.3	91.1/91.1	96.8	92.8	95.3	88.3	91.9	90.00
DeBERTa$_{900M}$	71.1	92.3	91.7/91.6	**97.5**	92.0	95.8	93.5	93.1	90.86
DeBERTa$_{1.5B}$	72.0	92.7	91.7/91.9	97.2	92.9	96.0	93.9	92.0	91.17
DeBERTa$_{1.5B}$+SiFT	**73.5**	**93.0**	**92.0/92.1**	97.5	**93.2**	**96.5**	**96.5**	**93.2**	**91.93**

Table 12: Comparison results of DeBERTa models with different sizes on the GLUE development set.

DeBERTa: Decoding-enhanced BERT with Disentangled Attention
SMART: Robust and Efficient Fine-Tuning for Pre-trained Natural Language Models through Principled Regularized Optimization
https://github.com/microsoft/DeBERTa/blob/master/DeBERTa/sift/sift.py

SuperGLUE results

- Some more tricks for scaling the model to 1.5B parameters
  - Share projection matrices for relative position embeddings
  - Add a convolution layer to enhance the word embeddings with subword information
- As a result of all hacks, DeBERTa was the first model to surpass the average human scores on the SuperGLUE benchmark

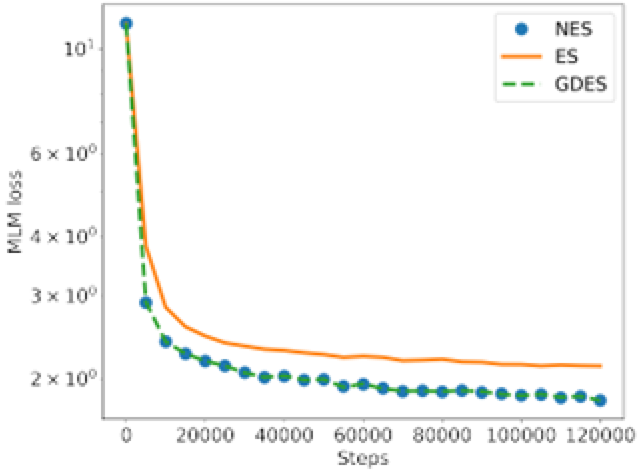
Model	BoolQ Acc	CB F1/Acc	COPA Acc	MultiRC F1a/EM	ReCoRD F1/EM	RTE Acc	WiC Acc	WSC Acc	Average Score
RoBERTa$_{large}$	87.1	90.5/95.2	90.6	84.4/52.5	90.6/90.0	88.2	69.9	89.0	84.6
NEXHA-Plus	87.8	94.4/96.0	93.6	84.6/55.1	90.1/89.6	89.1	74.6	93.2	86.7
T5$_{11B}$	91.2	93.9/96.8	94.8	88.1/63.3	94.1/93.4	92.5	76.9	93.8	89.3
T5$_{11B}$+Meena	**91.3**	**95.8/97.6**	97.4	88.3/63.0	94.2/93.5	92.7	**77.9**	95.9	90.2
Human	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	89.8
DeBERTa$_{1.5B}$+SiFT	90.4	94.9/97.2	96.8	**88.2/63.7**	**94.5/94.1**	**93.2**	76.4	**95.9**	89.9
DeBERTa$_{Ensemble}$	90.4	95.7/97.6	**98.4**	88.2/63.7	94.5/94.1	93.2	77.5	95.9	**90.3**

Table 5: SuperGLUE test set results scored using the SuperGLUE evaluation server. All the results are obtained from https://super.gluebenchmark.com on January 6, 2021.

DeBERTaV3

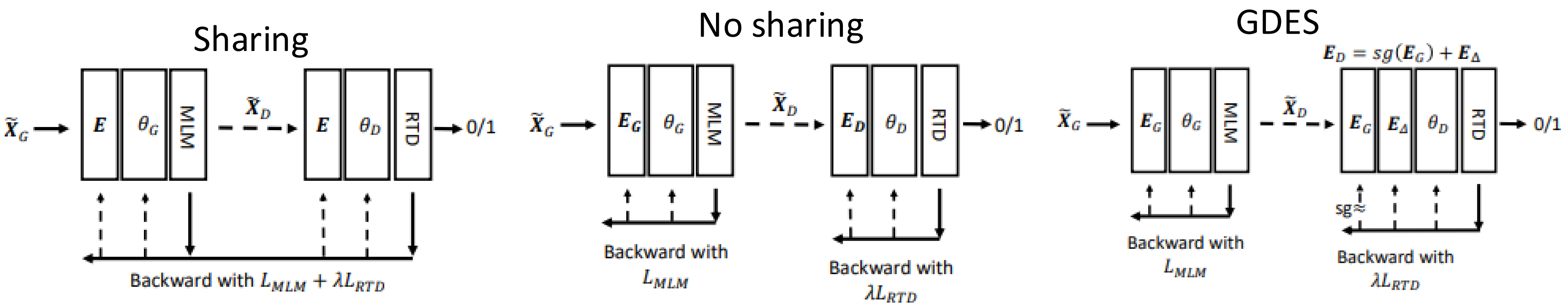
- ELECTRA-like discriminative pretraining is better than MLM
- ELECTRA shares generator and discriminator embeddings
  - this is suboptimal for the generator
    - Generator pulls embeddings of semantically similar words together, while discriminator pulls them apart
  - However, embeddings with impact from the MLM task improve the discriminator performance on downstream tasks
- We want to share embeddings only in one direction (generator → discriminator)

NES: no embedding sharing
ES: shared embeddings
GDES: a new method for partially sharing them



DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing

Gradient-Disentangled Embedding Sharing



- Solution: in discriminator, learn only a matrix that is added to the generator embeddings
- This improves performance
  - We have better good generator, and weights from it are shared with the discriminator

Model	MNLI-m/mm Acc	SQuAD v2.0 F1/EM
$BERT_{base}$ [9]	84.3/84.7	76.3/73.7
$ELECTRA_{base}$ [8]	85.8/-	-/-
$DeBERTa_{base}$ [4]	86.3/86.2	82.5/79.3
$DeBERTa{+}RTD_{base}$		
① ES	88.8/88.4	86.3/83.5
② NES	88.3/87.9	85.3/82.7
③ GDES	**89.3/89.0**	**87.2/84.5**

Results

- DeBERTaV3 = DeBERTa architecture with ELECTRA training (with GDES)
- Outperforms DeBERTa and ELECTRA on various model sizes

Model #Train	CoLA Mcc 8.5k	QQP Acc 364k	MNLI-m/mm Acc 393k	SST-2 Acc 67k	STS-B Corr 7k	QNLI Acc 108k	RTE Acc 2.5k	MRPC Acc 3.7k	Avg.
BERT$_{large}$	60.6	91.3	86.6/-	93.2	90.0	92.3	70.4	88.0	84.05
RoBERTa$_{large}$	68.0	92.2	90.2/90.2	96.4	92.4	93.9	86.6	90.9	88.82
XLNet$_{large}$	69.0	92.3	90.8/90.8	**97.0**	92.5	94.9	85.9	90.8	89.15
ELECTRA$_{large}$	69.1	92.4	90.9/-	96.9	92.6	95.0	88.0	90.8	89.46
DeBERTa$_{large}$	70.5	92.3	91.1/91.1	96.8	92.8	95.3	88.3	91.9	90.00
DeBERTaV3$_{large}$	**75.3**	**93.0**	**91.8/91.9**	96.9	**93.0**	**96.0**	**92.7**	**92.2**	**91.37**

Table 3: Comparison results on the GLUE development set.

Model	Vocabulary Size(K)	Backbone #Params(M)	MNLI-m/mm ACC	SQuAD v2.0 F1/EM
Base models:12 layers,768 hidden size,12 heads				
BERT$_{base}$	30	86	84.3/84.7	76.3/73.7
RoBERTa$_{base}$	50	86	87.6/-	83.7/80.5
XLNet$_{base}$	32	92	86.8/-	-/80.2
ELECTRA$_{base}$	30	86	88.8/-	-/80.5
DeBERTa$_{base}$	50	100	88.8/88.5	86.2/83.1
DeBERTaV3$_{base}$	128	86	**90.6/90.7**	**88.4/85.4**
Small models:6 layers,768 hidden size,12 heads				
TinyBERT$_{small}$	30	44	84.5/-	77.7/-
MiniLMv2$_{small}$	30	44	87.0/-	81.6/
BERT$_{small}$	30	44	81.8/-	73.2/-
DeBERTaV3$_{small}$	128	44	**88.2/87.9**	**82.9/80.4**
XSmall models:12 layers,384 hidden size,6 heads				
MiniLMv2$_{xsmall}$	30	22	86.9/-	82.3/
DeBERTaV3$_{xsmall}$	128	22	**88.1/88.3**	**84.8/82.0**

DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing

Multilingual DeBERTa

- Train the model on the CC100 dataset (as XLM-R)
- Vocabulary from mT5 (250K tokens)
- Pretrain like XLM-R, but for 0.5M steps instead of 1.5M
- Result: SOTA on the XNLI dataset

Model	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
Cross-lingual transfer																
XLM	83.2	76.7	77.7	74.0	72.7	74.1	72.7	68.7	68.6	72.9	68.9	72.5	65.6	58.2	62.4	70.7
$mT5_{base}$	84.7	79.1	80.3	77.4	77.1	78.6	77.1	72.8	73.3	74.2	73.2	74.1	70.8	69.4	68.3	75.4
$XLM\text{-}R_{base}$	85.8	79.7	80.7	78.7	77.5	79.6	78.1	74.2	73.8	76.5	74.6	76.7	72.4	66.5	68.3	76.2
$mDeBERTa_{base}$	**88.2**	**82.6**	**84.4**	**82.7**	**82.3**	**82.4**	**80.8**	**79.5**	**78.5**	**78.1**	**76.4**	**79.5**	**75.9**	**73.9**	**72.4**	**79.8**
Trasnlate train all																
XLM	84.5	80.1	81.3	79.3	78.6	79.4	77.5	75.2	75.6	78.3	75.7	78.3	72.1	69.2	67.7	76.9
$mT5_{base}$	82.0	77.9	79.1	77.7	78.1	78.5	76.5	74.8	74.4	74.5	75.0	76.0	72.2	71.5	70.4	75.9
$XLM\text{-}R_{base}$	85.4	81.4	82.2	80.3	80.4	81.3	79.7	78.6	77.3	79.7	77.9	80.2	76.1	73.1	73.0	79.1
$mDeBERTa_{base}$	**88.9**	**84.4**	**85.3**	**84.8**	**84.0**	**84.5**	**83.2**	**82.0**	**81.6**	**82.0**	**79.8**	**82.6**	**79.3**	**77.3**	**73.6**	**82.2**

Table 6: Results on XNLI test set under cross-lingual transfer and translate train all settings.

DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing

Conclusions

- With BERT, large pretrained transformers have conquered most NLP benchmarks
- After BERT, there were many improvements to the idea of a pretrained transformer encoder
    - But since RoBERTa, most such improvements have been rather tiny
- With XLM-R and similar models, such models went multilingual
- In the next lecture, we will discuss fine-tuning BERT in detail