Post-BERT Era

BERT-based architectures

Learning goals

- Understand the developments of the post-BERT era
- Get to know different self-supervised objectives
- Understand how to tackle BERTs critical shortcomings

SUCESSORS OF BERT

October 2018 - BERT

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BERT (and its successors) rely on the **Masked Language Modelling objective** during pre-training on huge unlabelled corpora of text.

10/2018

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10/2018 → 07/2019

July 2019 - RoBERTa

Liu et al., 2019 concentrate on improving the original BERT architecture by (1) careful hyperparameter tuning (2) abandoning the additional Next Sentence Prediction objective (3) increasing the pre-training corpus *massively*.

Other approaches now more and more concentrate on improving, down-scaling or understanding BERT. A new research direction called **BERTology** emerges.

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Ultimately, they are able to improve the performance of BERT by scaling up the smaller and more efficient model.

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October 2019 - DistilBERT

Sanh et al., 2019 employed the concept of 'model distillation' to create a smaller BERT-type model (contrary to the current trend of building ever larger models).

DistilBERT shows an impressive performance when fine-tuned on downstream tasks despite only exhibiting half the size of the ordinary BERT-BASE model.

ROBERTA – PRE-TRAINING IMPROVEMENTS

Robustly **o**ptimizied **BERT a**pproach ▸ Liu et al., 2019

Short summary:

- Change of the `MASK`ing strategy
  $\rightarrow$ BERT masks the sequences once before pre-training
  $\rightarrow$ RoBERTa uses dynamic `MASK`ing
  $\rightarrow$ RoBERTa sees the same sequence `MASK`ed differently
- RoBERTa **does not use** the additional NSP objective during pre-training
- Authors claim that BERT is seriously "undertrained"
  - 160 GB pre-training corpus instead of 13 GB
  - Pre-training is performed with larger batch sizes (8k)
- Training on full-length sequences only (512 tokens)

ROBERTA – THE ARCHITECTURE

Architectural differences:

- Architecture (layers, heads, embedding size) identical to BERT
- 50k token BPE vocabulary instead of 30k
- Model size differs (due to the larger embedding matrix)
  $\Rightarrow \sim$ 125M (360M) for the BASE (LARGE) variant

Performance differences:

	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**	-

▸ Source: Liu et al., 2019

Note: Liu et al. (2019) report the accuracy for QQP while Devlin et al. (2019) report the F1 score (cf. results displayed in chapter 6.2.3); XLNet: see next Chapter.

DYNAMIC VS. STATIC MASKING

Static Masking (BERT):

- Apply `MASK`ing procedure to pre-training corpus once
- (additional for BERT: Modify the corpus for NSP)
- Train for approximately 40 epochs

Dynamic Masking (RoBERTa):

- Duplicate the training corpus *ten* times
- Apply `MASK`ing procedure to each duplicate of the pre-training corpus
- Train for 40 epochs
- Model sees each training instance in ten different "versions" (each version four times) during pre-training

DYNAMIC VS. STATIC MASKING

- **BERT:**

The	quick	brown	[MASK]	jumps	over	the	[MASK]	dog	.

The	quick	brown	[MASK]	jumps	over	the	[MASK]	dog	.

⋮

The	quick	brown	[MASK]	jumps	over	the	[MASK]	dog	.

- **RoBERTa:**

The	quick	brown	[MASK]	jumps	over	the	[MASK]	dog	.

The	[MASK]	brown	fox	[MASK]	over	the	lazy	dog	.

[MASK]	quick	[MASK]	fox	jumps	over	the	lazy	dog	.

⋮

[MASK]	quick	brown	fox	jumps	over	the	lazy	[MASK]	.

DYNAMIC VS. STATIC MASKING

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).

Source: Liu et al., 2019

NO NEXT SENTENCE PREDICTION

- Described as important part of the pre-training process in BERT
- ▸ Liu et al., 2019 report that it hurts performance

→ Especially for QNLI, MNLI, and SQuAD 1.1

- Conduct experiments in multiple settings:
  - SEGMENT-PAIR+NSP
    (Exactly like BERT)
  - SENTENCE-PAIR+NSP
    (Like BERT, but with natural sentences)
  - FULL-SENTENCES
    (No NSP, inputs may cross document boundaries)
  - DOC-SENTENCES
    (No NSP, only sentences from one document)

NO NEXT SENTENCE PREDICTION

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).

▸ Source: Liu et al., 2019

Note: XLNet: see next Chapter.

BATCH SIZE

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.

▸ Source: Liu et al., 2019

FURTHER CHANGES IN PRE-TRAINING

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7
$\text{XLNet}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	94.0/87.8	88.4	94.4
+ additional data	126GB	2K	500K	94.5/88.8	89.8	95.6

Table 4: Development set results for RoBERTa as we pretrain over more data (16GB $\rightarrow$ 160GB of text) and pretrain for longer (100K $\rightarrow$ 300K $\rightarrow$ 500K steps). Each row accumulates improvements from the rows above. RoBERTa matches the architecture and training objective of $\text{BERT}_{\text{LARGE}}$. Results for $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ are from Devlin et al. (2019) and Yang et al. (2019), respectively. Complete results on all GLUE tasks can be found in the Appendix.

▸ Source: Liu et al., 2019

Note: XLNet: see next Chapter.

ALBERT

A Lite BERT ‣ Lan et al., 2019

Short summary:

- Major change to the architecture
  $\rightarrow$ Size of embedding layer independent from hidden layer
  (rember in Transformer/BERT: $E = H$)
  $\rightarrow$ Saves memory and compute
- Parameter sharing across layers
- Substitution of the NSP objective during pre-training

ARCHITECTURAL CHANGES

Disentanglement of E and H

- WordPiece-Embeddings (size E)
  - first layer of the model
  - each token is initially mapped to this embedding
  - context-independent
- In Transformer/BERT:
  - $H = E$
  - down-project E to keys, queries and values of size H/A
  - concatenate resulting embeddings from all A heads
  - results in hidden layer representation of size H
- **Question:** What are the implications?

ARCHITECTURAL CHANGES

Thoughts / Implications

- WordPiece-Embeddings (size E)
  - required representational capacity?
  - probably could be limited w/o loosing much
- Hidden-Layer-Embedding (size H)
  - required representational capacity?
  - depending on how polysemous a word/token might be
  - difficult to say "one size fits all"
  - probably might be better to rather increase this, compared to the WordPiece embeddings

$\rightarrow$ *Setting $E = H$ does not allow us to pursue these considerations*

ARCHITECTURAL CHANGES

Disentanglement solves this

- Hidden-Layer-Embeddings (size H) context-dependent
  $\rightarrow$ providing more capacity makes more sense here
- Setting $H >> E$ enlargens model capacity in the hidden layers without increasing the size of the embedding matrix
- $O(V \times H) > O(V \times E + E \times H)$ if $H >> E$

CROSS-LAYER PARAMETER SHARING

- Pre-trained transformer-based models are deep stacks of identically parametrized layers and thus have many parameters
- Sharing them as a way to gain parameter efficiency
- Two different places in the network, where sharing can be done
  - Attention parameters
  - FFN parameters
- Ablation studies:
  - both
  - both individually
  - none

CROSS-LAYER PARAMETER SHARING

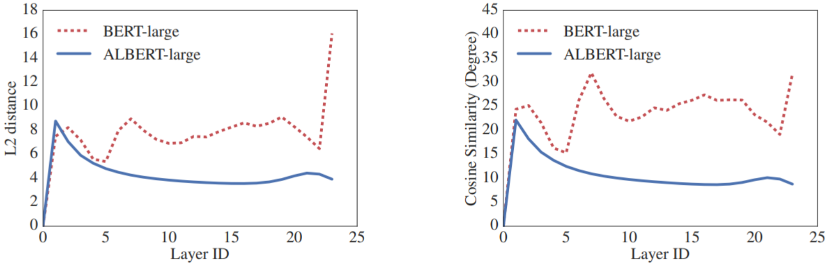
Model		Parameters	SQuAD1.1	SQuAD2.0	MNLI	SST-2	RACE	Avg
ALBERT base E=768	all-shared	31M	88.6/81.5	79.2/76.6	82.0	90.6	63.3	79.8
	shared-attention	83M	89.9/82.7	80.0/77.2	84.0	91.4	67.7	81.6
	shared-FFN	57M	89.2/82.1	78.2/75.4	81.5	90.8	62.6	79.5
	not-shared	108M	90.4/83.2	80.4/77.6	84.5	92.8	68.2	82.3
ALBERT base E=128	all-shared	12M	89.3/82.3	80.0/77.1	82.0	90.3	64.0	80.1
	shared-attention	64M	89.9/82.8	80.7/77.9	83.4	91.9	67.6	81.7
	shared-FFN	38M	88.9/81.6	78.6/75.6	82.3	91.7	64.4	80.2
	not-shared	89M	89.9/82.8	80.3/77.3	83.2	91.5	67.9	81.6

Table 4: The effect of cross-layer parameter-sharing strategies, ALBERT-base configuration.

Source: Lan et al., 2019

- (Drastic) reduction of model size (more for sharing FFN weights)
- Sharing parameters hurts performance
  - Worse for models with larger E
  - Worse for sharing FNN compared to Attention weights
  - **Question: Why? What is the intuition here?**

CROSS-LAYER PARAMETER SHARING



▸ Source: Lan et al., 2019

- Distince/Similarity of input and output embeddings per layer
- Smoother transitions for ALBERT models

CHANGES IN PRE-TRAINING

Substitution of the NSP objective

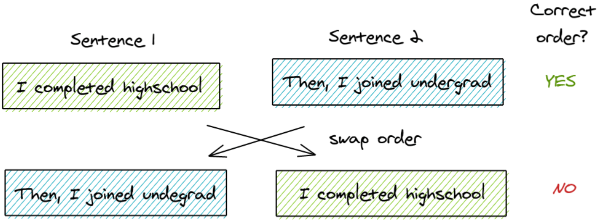
- Previous works questioned the usefulness of NSP

$\rightarrow$ Lan et al. assume that this is due to lacking difficulty

- Introduction of *Sentence-Order Prediction* (SOP) as a new pre-training task
- Positive examples created alike to those from NSP (take two consecutive sentences from the same document)
- Negative examples: Just swap the ordering of sentences

CHANGES IN PRE-TRAINING

Illustration:



▸ Source: Amit Chaudhary

Effectiveness:

SP tasks	Intrinsic Tasks MLM	NSP	SOP	Downstream Tasks SQuAD1.1	SQuAD2.0	MNLI	SST-2	RACE	Avg
None	54.9	52.4	53.3	88.6/81.5	78.1/75.3	81.5	89.9	61.7	79.0
NSP	54.5	90.5	52.0	88.4/81.5	77.2/74.6	81.6	**91.1**	62.3	79.2
SOP	54.0	78.9	86.5	**89.3/82.3**	**80.0/77.1**	**82.0**	90.3	**64.0**	**80.1**

Table 5: The effect of sentence-prediction loss, NSP vs. SOP, on intrinsic and downstream tasks.

▸ Source: Lan et al., 2019

CHANGES IN PRE-TRAINING

$n - gram$ **masking for the MLM task**

- During pre-training BERT single tokens are masked
- Lan et al. mask up to three consecutive tokens
- Choice of n:

$$p(n) = \frac{1/n}{\sum_{k=1}^{N} 1/k}$$

PERFORMANCE

Performance differences:

Model		Parameters	SQuAD1.1	SQuAD2.0	MNLI	SST-2	RACE	Avg	Speedup
BERT	base	108M	90.4/83.2	80.4/77.6	84.5	92.8	68.2	82.3	4.7x
	large	334M	92.2/85.5	85.0/82.2	86.6	93.0	73.9	85.2	1.0
ALBERT	base	12M	89.3/82.3	80.0/77.1	81.6	90.3	64.0	80.1	5.6x
	large	18M	90.6/83.9	82.3/79.4	83.5	91.7	68.5	82.4	1.7x
	xlarge	60M	92.5/86.1	86.1/83.1	86.4	92.4	74.8	85.5	0.6x
	xxlarge	235M	**94.1/88.3**	**88.1/85.1**	**88.0**	**95.2**	**82.3**	**88.7**	0.3x

▸ Source: Lan et al., 2019

Notes:

- In General: Smaller model size (because of parameter sharing)
- Nevertheless: Scale model up to almost similar size (`xxlarge` version)
- Strong performance compared to BERT