

# Post-BERT Era

## BERT-based architectures



### Learning goals

- changes to the pre-training objectives
- dynamic masking
- architectural details of BERT & Co.

# SUCCESSORS OF BERT

## October 2018 - BERT

BERT (**Devlin et al., 2018**) is a bidirectional contextual embedding model purely relying on Self-Attention by using multiple **Transformer encoder** blocks.

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

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## 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 optimized **BERT** approach ▶ Liu et al., 2019

## Short summary:

- Change of the MASKing strategy
  - BERT masks the sequences once before pre-training
  - RoBERTa uses dynamic MASKing
  - RoBERTa sees the same sequence MASKed 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)  
⇒ ~ 125M (360M) for the BASE (LARGE) variant

## Performance differences:

	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	WNLI	Avg
<i>Single-task single models on dev</i>										
BERT <sub>LARGE</sub>	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-	-
XLNet <sub>LARGE</sub>	89.8/-	93.9	91.8	83.8	95.6	89.2	63.6	91.8	-	-
RoBERTa	<b>90.2/90.2</b>	<b>94.7</b>	<b>92.2</b>	<b>86.6</b>	<b>96.4</b>	<b>90.9</b>	<b>68.0</b>	<b>92.4</b>	<b>91.3</b>	-

► 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 MASKing 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 MASKing 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]	.
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# DYNAMIC VS. STATIC MASKING

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

Table 1: Comparison between static and dynamic masking for BERT<sub>BASE</sub>. 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
<i>Our reimplementation (with NSP loss):</i>				
SEGMENT-PAIR	90.4/78.7	84.0	92.9	64.2
SENTENCE-PAIR	88.7/76.2	82.9	92.1	63.0
<i>Our reimplementation (without NSP loss):</i>				
FULL-SENTENCES	90.4/79.1	84.7	92.5	64.8
DOC-SENTENCES	90.6/79.7	84.7	92.7	65.6
BERT <sub>BASE</sub>	88.5/76.3	84.3	92.8	64.3
XLNet <sub>BASE</sub> (K = 7)	-/81.3	85.8	92.7	66.1
XLNet <sub>BASE</sub> (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 BERT<sub>BASE</sub> and XLNet<sub>BASE</sub> 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	<b>3.68</b>	<b>85.2</b>	<b>92.9</b>
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	<b>94.6/89.4</b>	<b>90.2</b>	<b>96.4</b>
BERT <sub>LARGE</sub>						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7
XLNet <sub>LARGE</sub>						
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 BERT<sub>LARGE</sub>. Results for BERT<sub>LARGE</sub> and XLNet<sub>LARGE</sub> 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
  - Size of embedding layer independent from hidden layer (remember in Transformer/BERT:  $E = H$ )
  - 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 losing 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

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

# ARCHITECTURAL CHANGES

## Disentanglement solves this

- Hidden-Layer-Embeddings (size  $H$ ) context-dependent  
→ providing more capacity makes more sense here
- Setting  $H \gg E$  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  $H \gg E$

# 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

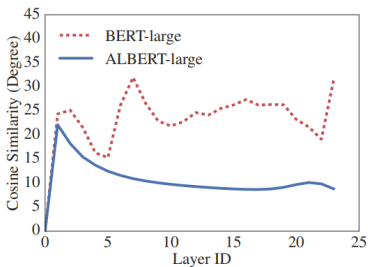
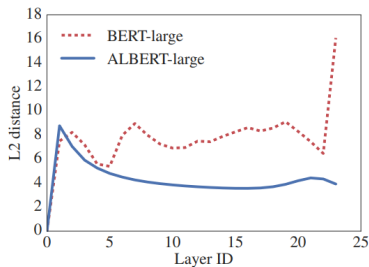
	Model	Parameters	SQuAD1.1	SQuAD2.0	MNLI	SST-2	RACE	Avg
ALBERT base $E=768$	all-shared	31M	88.6/81.5	79.2/76.6	82.0	90.6	63.3	79.8
	shared-attention	83M	89.9/82.7	80.0/77.2	84.0	91.4	67.7	81.6
	shared-FFN	57M	89.2/82.1	78.2/75.4	81.5	90.8	62.6	79.5
	not-shared	108M	90.4/83.2	80.4/77.6	84.5	92.8	68.2	82.3
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

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

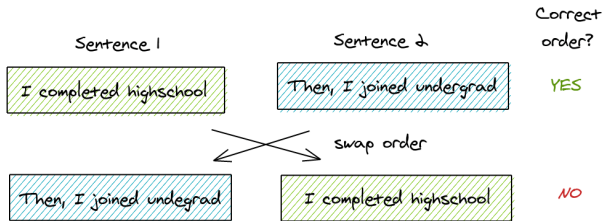
# CHANGES IN PRE-TRAINING

## Substitution of the NSP objective

- Previous works questioned the usefulness of NSP
- 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			Downstream Tasks					
	MLM	NSP	SOP	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	<b>91.1</b>	62.3	79.2
SOP	54.0	78.9	86.5	<b>89.3/82.3</b>	<b>80.0/77.1</b>	<b>82.0</b>	90.3	<b>64.0</b>	<b>80.1</b>

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	<b>94.1/88.3</b>	<b>88.1/85.1</b>	<b>88.0</b>	<b>95.2</b>	<b>82.3</b>	<b>88.7</b>	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