RoBERTa: A Robustly Optimized BERT Pretraining Approach

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Abstract

本篇論文在做的事情: 重新train 一個 優化版的Bert

相關資料: a replication study of BERT pretraining (Devlin et al. , 2019) that carefully measures the impact of many key hyperparameters and training data size

緣起: BERT was significantly undertrained, and can match or exceed the performance of every model published after it

重點及目標: hyperparameter choices have significant impact on the final results

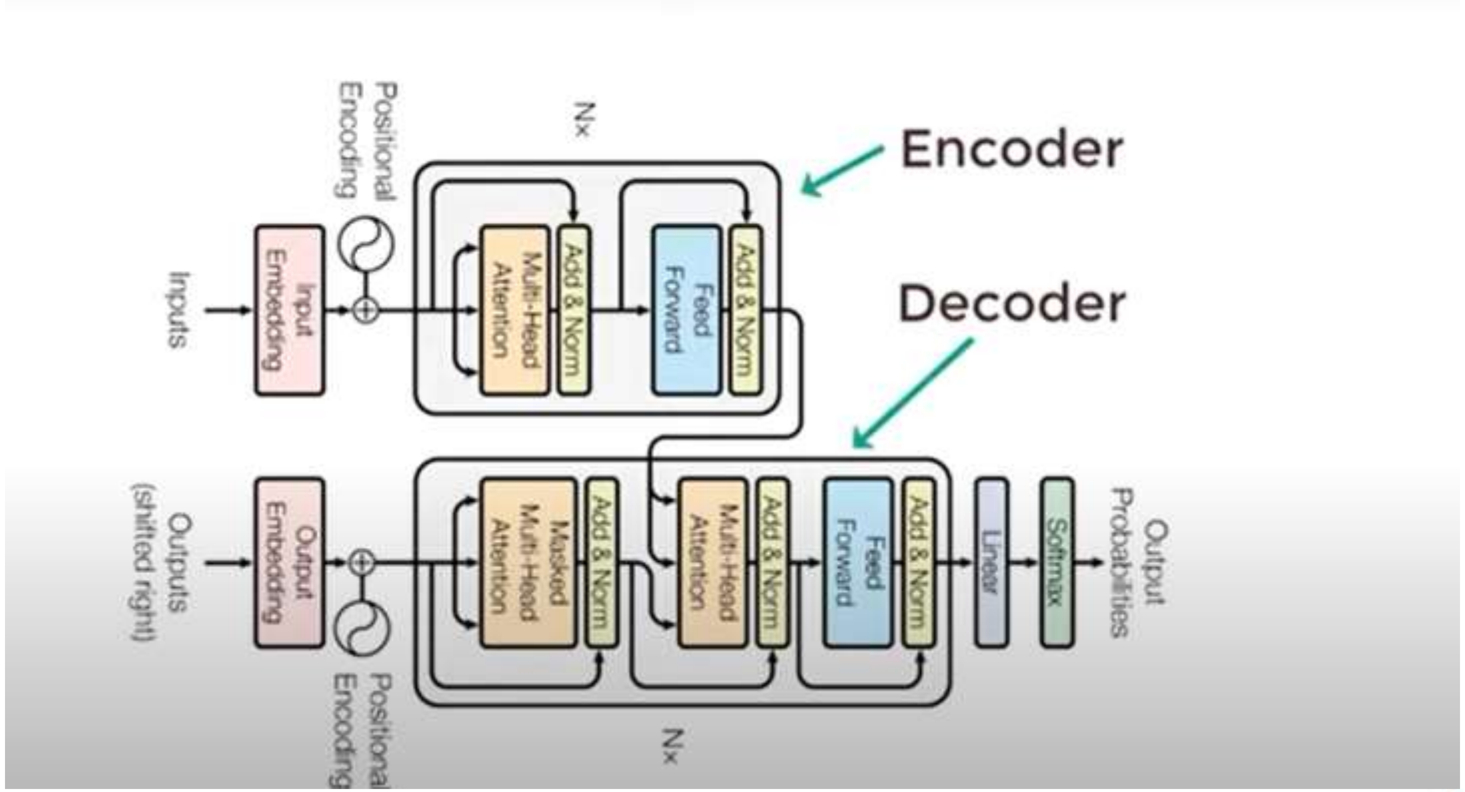
評分標準: GLUE, RACE and SQuAD

結果: highlight the importance of previously overlooked design choices, and raise questions about the source of recently reported improvements

Background

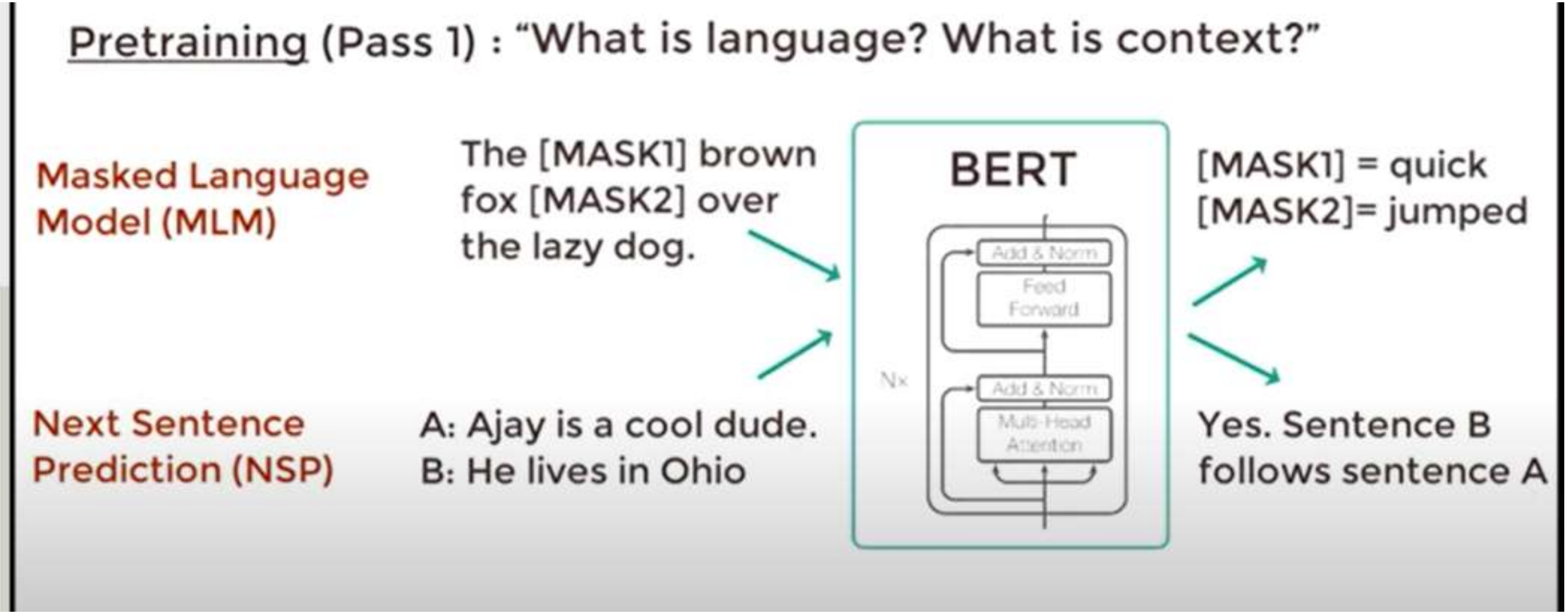
1. Architecture
2. Training Objectives
3. Optimization
4. Data

Architecture



Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *North American Association for Computational Linguistics (NAACL).*

Training Objectives



Optimization

Optimizer: Adam

Activation Function: GEL

Dan Hendrycks and Kevin Gimpel. 2016. Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*.

Data

BOOKCORPUS (Zhu et al., 2015) plus English WIKIPEDIA, which totals 16GB of uncompressed text

Tranining Procedure Analysis

1. static vs dynamic tasking
2. Input format and next sentence prediction
3. Training with large batches
4. Text Encoding (Byte-Pair Encoding(BPE))

static vs dynamic tasking

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

Model Input Format and Next Sentence Prediction

NSP: Next Sentence Prediction Loss

1.SEGMENT-PAIR+NSP (用片段TRAIN)使用NSP LOSS

2.SENTENCE-PAIR+NSP (用句子TRAIN)使用NSP LOSS

3.FULL-SENTENCES不使用NSP LOSS

4.DOC-SENTENCES不使用NSP LOSS

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

Training with large batches

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

Text Encoding (Byte-Pair Encoding(BPE))

Subword Tokenization: Byte Pair Encoding – YouTube

[1909.03341] Neural Machine Translation with Byte-Level Subwords (arxiv.org)

RoBERTa

Overall Result

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

GLUE

General Language Understanding Evaluation (GLUE)

https://gluebenchmark.com/

- Corpus of Linguistic Acceptability (CoLA)
- Stanford Sentiment Treebank (SST-2)
- Microsoft Research Paraphrase Corpus (MRPC)
- Quora Question Pairs (QQP)
- Semantic Textual Similarity Benchmark (STS-B)
- Multi-Genre Natural Language Inference (MNLI)
- Question-answering NLI (QNLI)
- Recognizing Textual Entailment (RTE)
- Winograd NLI (WNLI)

GLUE also has Chinese version (https://www.cluebenchmarks.com/)

Glue Result

	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	WNLI	Avg
Single-task single models on dev										
$\mathrm{BERT}_{\mathrm{LARGE}}$	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-	-
$\mathrm{XLNet}_{\mathrm{LARGE}}$	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**

SQuAD Introduction and Result

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[†]	89.1[†]
RoBERTa			86.8	89.8
XLNet + SG-Net Verifier			**87.0**[†]	**89.9**[†]

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Sample question and answer pairs for a passage from the SQuAD dataset. Image credits to Rajpurkar et al., the original creators of the dataset.

RACE Introduction and Result

ReAding Comprehension Dataset From Examinations

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**

Passage: Do you love holidays but hate gaining weight? You are not alone. Holidays are times for celebrating. Many people are worried about their weight. With proper planning, though, it is possible to keep normal weight during the holidays. The idea is to enjoy the holidays but not to eat too much. You don't have to turn away from the foods that you enjoy.

Here are some tips for preventing weight gain and maintaining physical fitness:

Don't skip meals. Before you leave home, have a small, low-fat meal or snack. This may help to avoid getting too excited before delicious foods.

Control the amount of food. Use a small plate that may encourage you to "load up". You should be most comfortable eating an amount of food about the size of your fist.

Begin with soup and fruit or vegetables. Fill up beforehand on water-based soup and raw fruit or vegetables, or drink a large glass of water before you eat to help you to feel full.

Avoid high-fat foods. Dishes that look oily or creamy may have large amount of fat. Choose lean meat . Fill your plate with salad and green vegetables. Use lemon juice instead of creamy food.

Stick to physical activity. Don't let exercise take a break during the holidays. A 20-minute walk helps to burn off extra calories.

Questions:

What is the best title of the passage?

Options:

A. How to avoid holiday feasting

B. Do's and don'ts for keeping slim and fit.

C. How to avoid weight gain over holidays.

D. Wonderful holidays, boring experiences.