Dive into Deep Learning for NLP

4. Contextual Representations

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gluon-nlp.mxnet.io

13:15-14:15	Natural Language Processing and Deep Learning Basics
14:15-14:25	Break
14:25-15:15	Context-free Representations with Word Embeddings
15:15-15:55	Machine Translation and Sequence Generation
15:55-16:35	Contextual Representations with BERT
16:35-16:45	Break
16:45-17:15	Model Deployment with TVM

Context Matters: Retail Bank or River Bank?

1. I jog along the **bank** of Duwamish River every day.

2. I went to the **bank** to open a savings account.

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With word embedding, the vector representing “**bank**” is the **same** in both sentences

Can we have representations that depend on the **context**?

Representations

- Context-free representation
  - CBOW/Skip-gram
  - FastText
- Contextual representation
  - ELMo: Embedding from Language Model
  - **BERT: Bidirectional Embedding Representation from Transformers**

BERT

Bidirectional Embedding from Transformers

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General Language Understanding Evaluation (GLUE Benchmark)

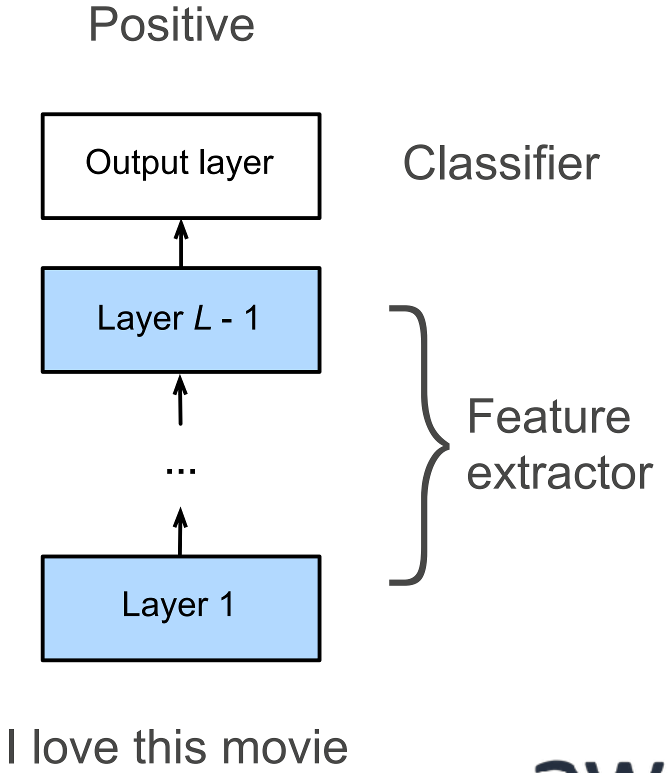
Including datasets for:

- acceptability
- sentiment
- paraphrase
- sentence similarity
- natural language inference

Model	Avg Score
CBOW	58.6
BERT	80.5

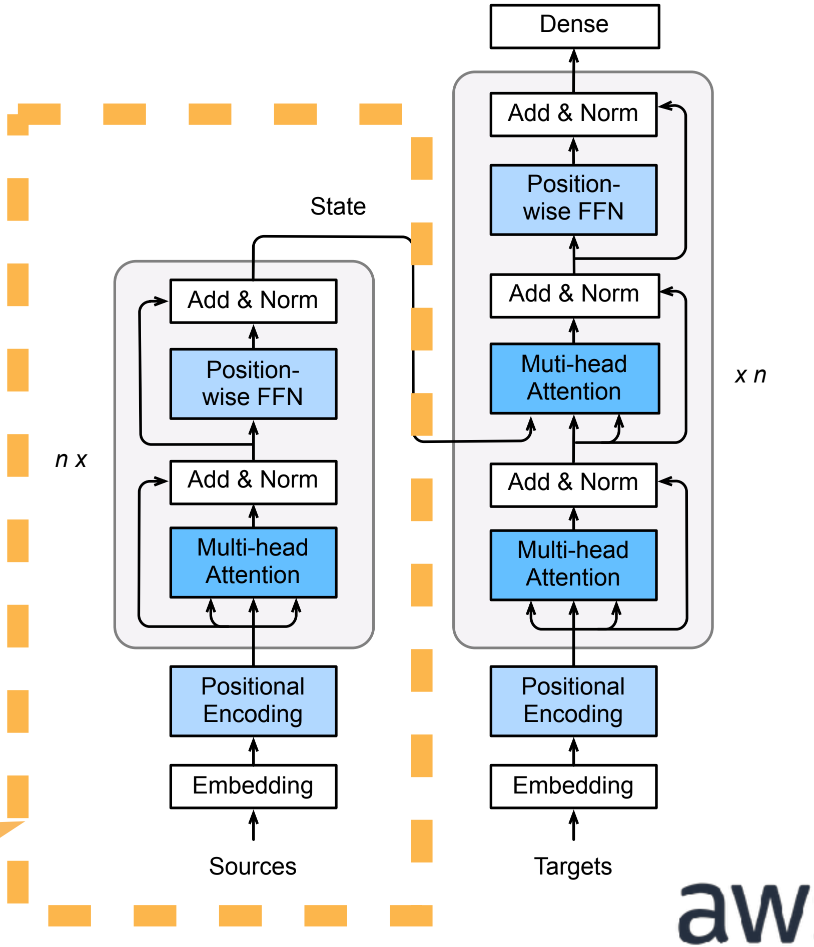
BERT

1. Pre-training: learn contextual representation on large scale corpus
2. Fine-tuning: add a simple output layer on BERT and fine-tune with the task at hand



BERT Architecture

- A (big) Transformer encoder
- BERT Base
  - # blocks = 12
  - # parameters = 110M
- BERT Large
  - # blocks = 24
  - # parameter = 340M



BERT

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BERT Pre-training

- Pre-training tasks:
    - masked language modeling
    - next sentence prediction
- Dataset: Wikipedia and BooksCorpus (>3B words)

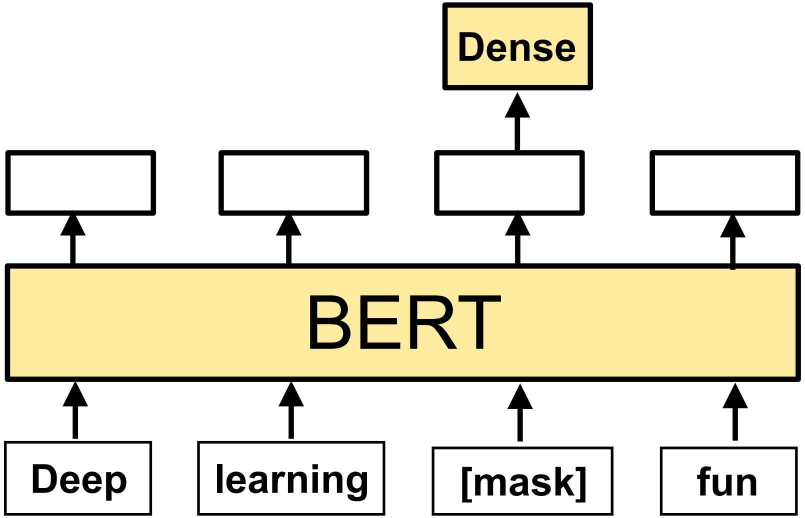
Pre-training Task 1: Masked Language Model

Original sentence:

Deep learning is fun.

Masked sentence:

Deep learning [mask] fun.



$$loss = -\log p(is \,|\, deep, learning, [mask], fun)$$

Pre-training Task 2: Next Sentence Prediction

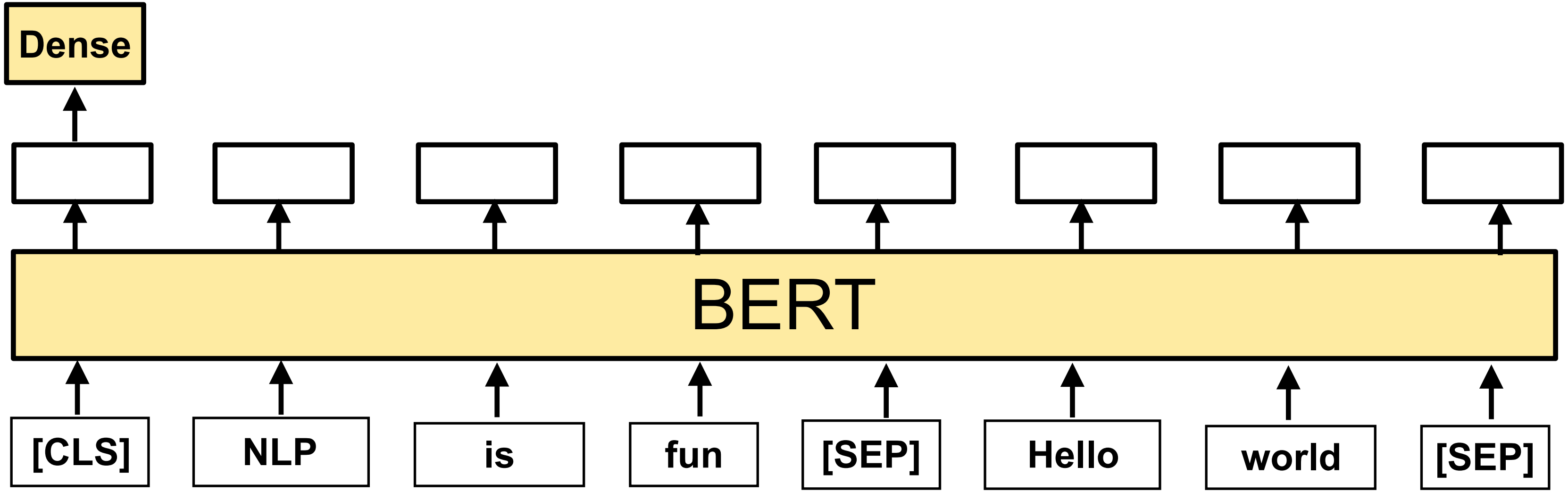
- Each example is a pair of sentences

is_next_sentence: NLP is fun. GluonNLP is awesome.

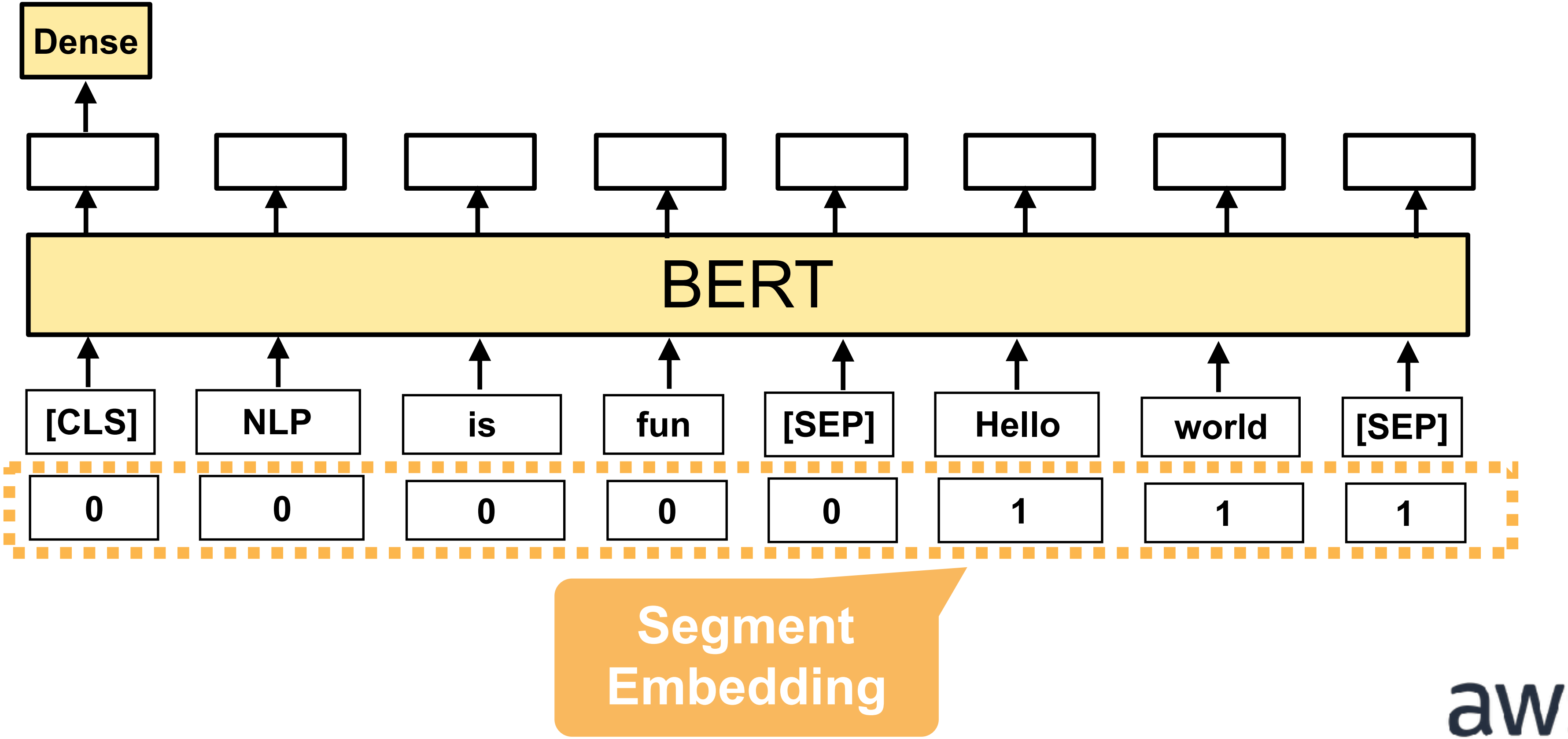
not_next_sentence: NLP is fun. Hello world.

- Sentence level binary classification

Pre-training Task 2: Next Sentence Prediction

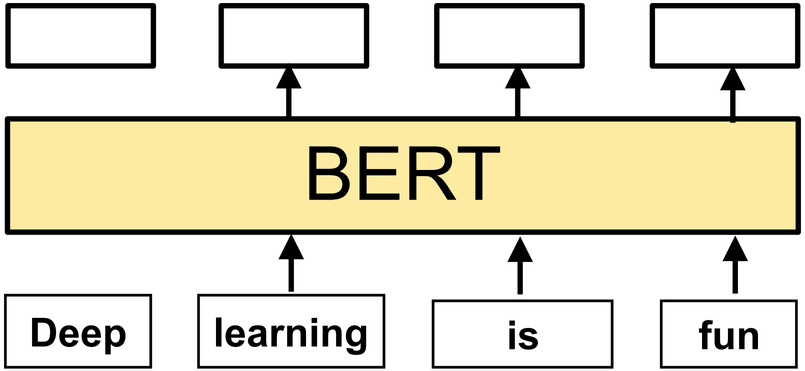


Pre-training Task 2: Next Sentence Prediction



BERT Fine-tuning

- BERT returns a (contextual) feature vector for each token
- Different fine-tuning tasks use a different set of vectors



Fine-tuning: Sentence Classification

Input: This movie is great

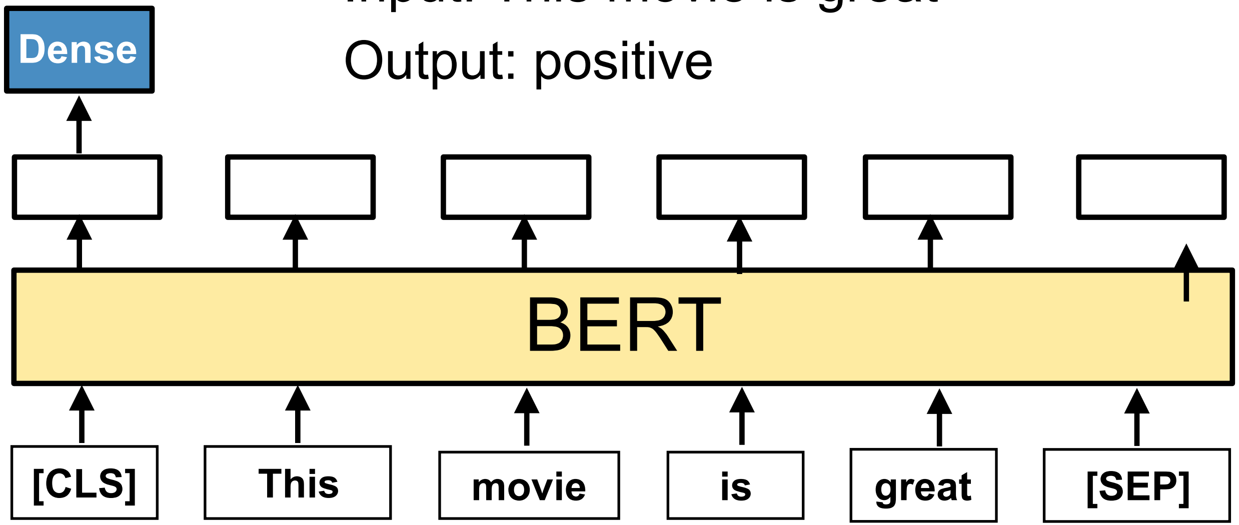
Output: positive

Fine-tuning: Sentence Classification

Feed the [CLS] token vector into a dense output layer.

Input: This movie is great

Output: positive



Fine-tuning: Sentence Pair Classification

Input_0: The processor was announced in San Jose at the Forum.

Input_1: The processor was unveiled at the Forum in San Jose.

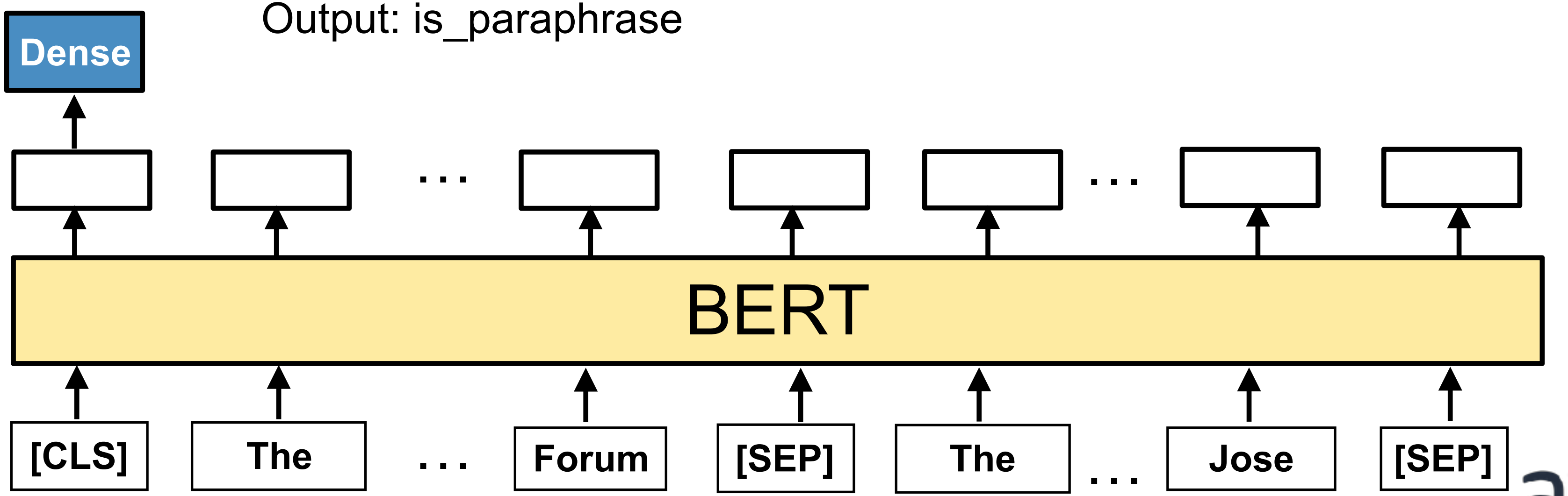
Output: is_paraphrase

Fine-tuning: Sentence Pair Classification

- Feed the [CLS] token vector into a dense output layer.

Input_0: The processor was announced in San Jose at the Forum.
Input_1: The processor was unveiled at the Forum in San Jose.

Output: is_paraphrase



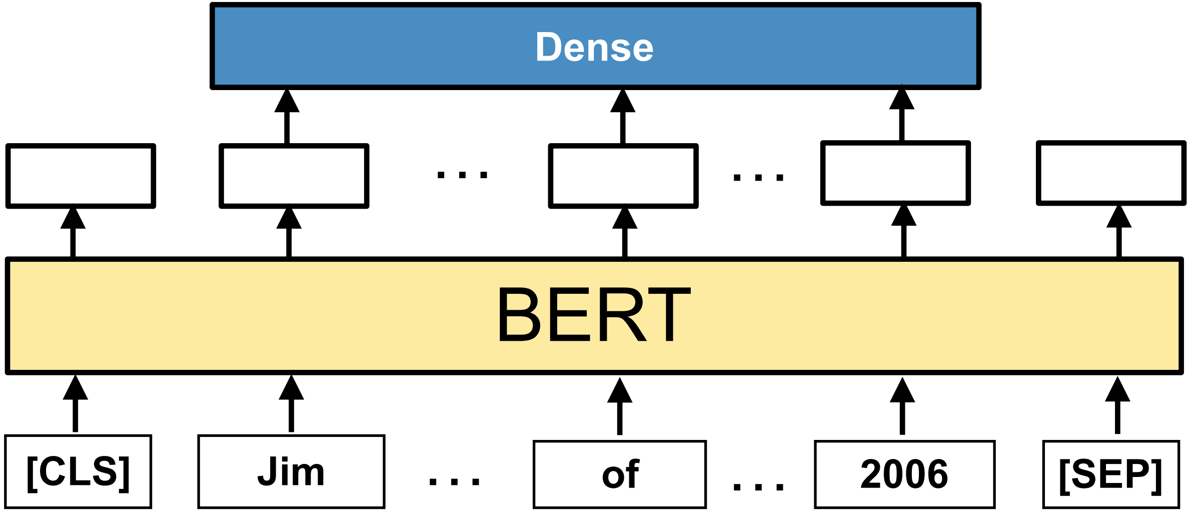
Fine-tuning: Named Entity Recognition

Input:	Jim	bought	3000	shares	of	Amazon	in	2006.
Output:	[person]					[organization]		[time]

Fine-tuning: Named Entity Recognition

- Feed each non-special token vector into a dense output layer

Input: Jim bought 3000 shares of Amazon in 2006.
Output: [person] [organization] [time]



Fine-tuning: Question Answering

Given a question and a description text, find the answer, which is a text segment in the description

Input_0: AMLC 2019 is held in Seattle
Input_1: Where is AMLC held
Output: Seattle

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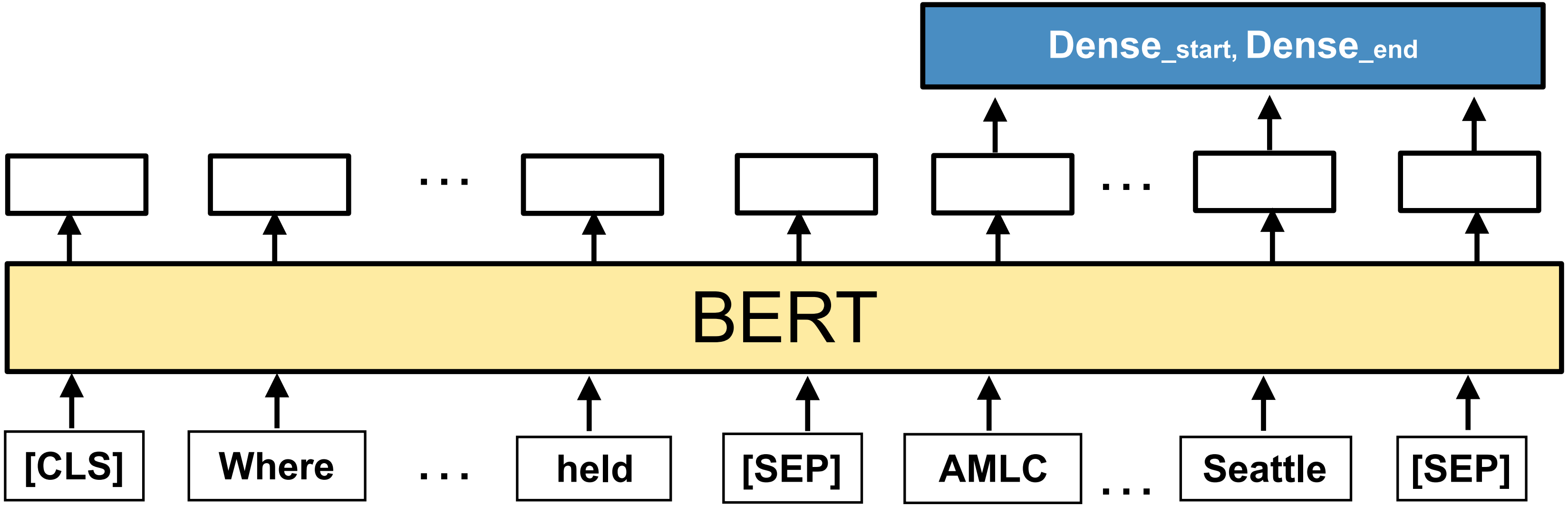
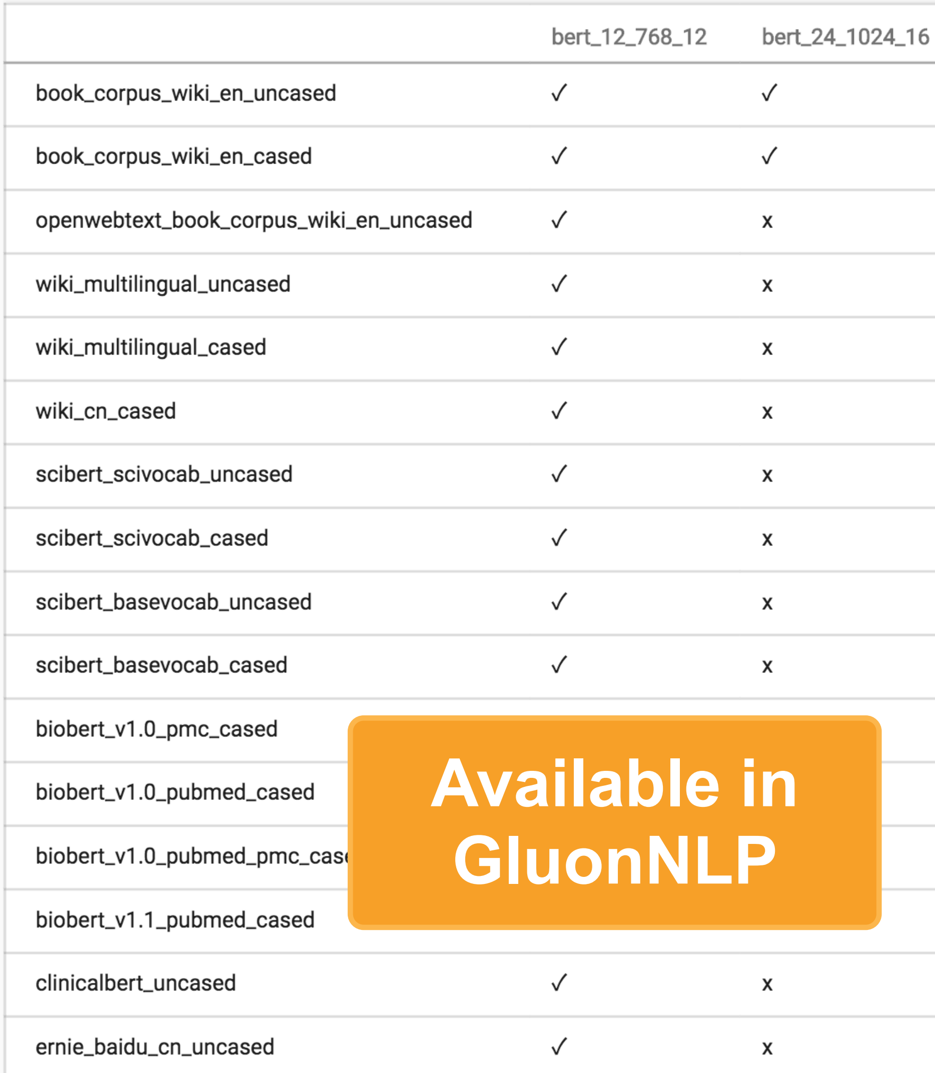


BERT in GluonNLP

```
from gluonnlp import model

model.get_model(
    “bert_12_768_12”,
    dataset_name=“wiki_cn_cased”
)
```

w.amazon.com?BERT



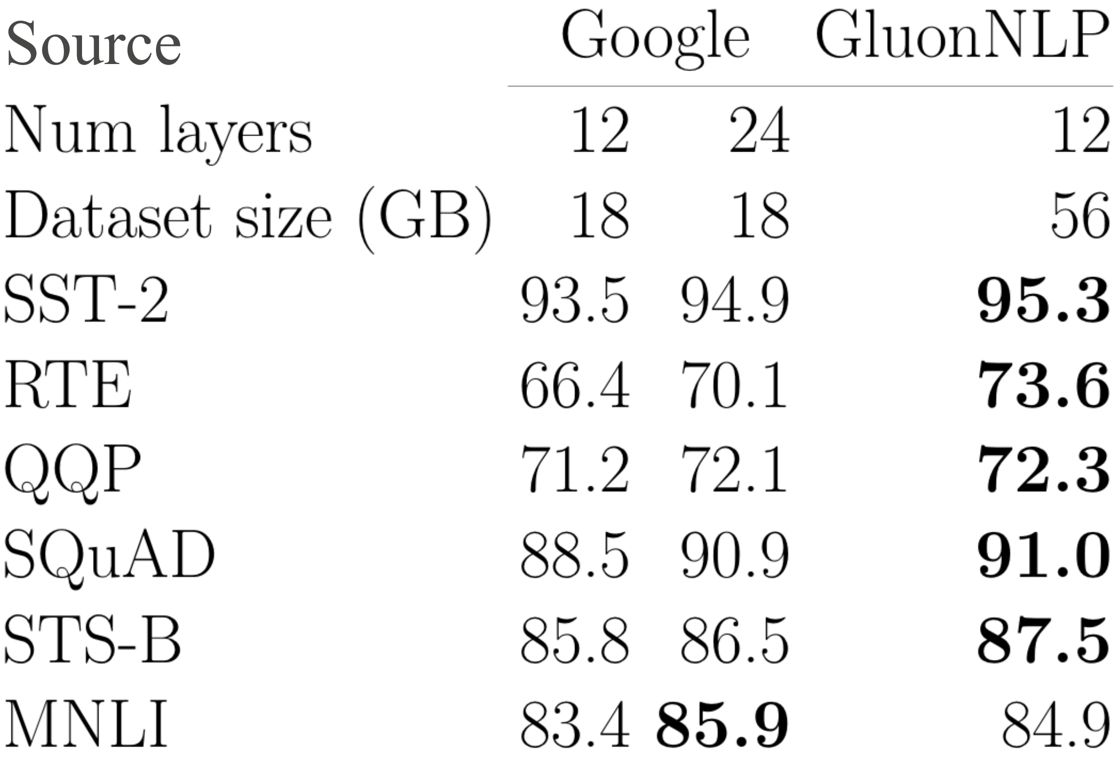
	bert_12_768_12	bert_24_1024_16
book_corpus_wiki_en_uncased	✓	✓
book_corpus_wiki_en_cased	✓	✓
openwebtext_book_corpus_wiki_en_uncased	✓	x
wiki_multilingual_uncased	✓	x
wiki_multilingual_cased	✓	x
wiki_cn_cased	✓	x
scibert_scivocab_uncased	✓	x
scibert_scivocab_cased	✓	x
scibert_basevocab_uncased	✓	x
scibert_basevocab_cased	✓	x
biobert_v1.0_pmc_cased		
biobert_v1.0_pubmed_cased		
biobert_v1.0_pubmed_pmc_case		
biobert_v1.1_pubmed_cased		
clinicalbert_uncased	✓	x
ernie_baidu_cn_uncased	✓	x

Available in GluonNLP

gluon-nlp.mxnet.io

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectiona
arXiv preprint arXiv:1810.04805 (2018).

BERT in GluonNLP



Source	Google		GluonNLP
Num layers	12	24	12
Dataset size (GB)	18	18	56
SST-2	93.5	94.9	**95.3**
RTE	66.4	70.1	**73.6**
QQP	71.2	72.1	**72.3**
SQuAD	88.5	90.9	**91.0**
STS-B	85.8	86.5	**87.5**
MNLI	83.4	**85.9**	84.9

BERT inference with GluonNLP

float32 inference

- BERT Base sentence classifier on Yahoo answers dataset
- with 4 cores on c5.12xlarge (out of 48 vCPUs)

Package	max_length	latency (ms)	accuracy
mxnet-mkl=1.4.1	256	178.04	74.6
latest mxnet	256	75.39	74.6

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int8 inference (coming soon)

- 1.7x latency reduction, 2.2x model size reduction
- <1% accuracy drop

Demo: BERT for Question Answering

04_contextual_representation/
question_answering.ipynb