Project: Part II Natural Language Processing with Disaster Tweets



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Data Description

Goal

Predicting whether a given tweet is about a real disaster or not

Necessity

- > Twitter has become an important communication channel in times of emergency
- ➤ The ubiquitousness of smartphones enables people to announce an emergency they're observing in real-time
- But it's not always clear whether a person's words are actually announcing a disaster

Data format

- > Train.csv: the training set
 - Including id, text, location, keyword, and target
- > Test.csv: the test set
 - Including id, text, location, keyword
- Sample_submission.csv: a sample submission file in the correct format



On plus side LOOK AT THE SKY LAST NIGHT IT WAS ABLAZE



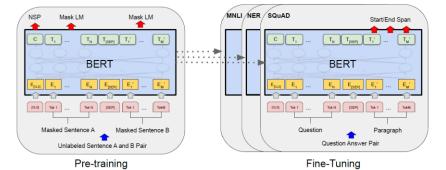
12:43 AM · Aug 6, 2015 · Twitter for Android



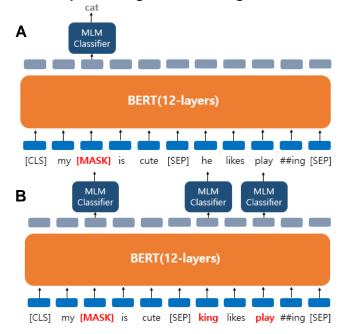
Baseline Model 1

BERT

- Goal
 - Natural language processing
- Architecture
 - Transformer encoder 12 or 24 layers
 - Word embedding with context
 - Pre-training
 - Using massive data without labels
 - Masked language model (MLM)
 - » Text random masking
 - Next sentence prediction (NSP)
 - » Train with randomly concatenated sentences
 - Fine-tuning
 - Using additional tasks with labels
 - Single text classification
 - » ex) emotion classification
 - Tagging
 - Question answering



Overall pre-training and fine-tuning architecture



Example of pre-training (A) MLM (B) NSP



Results 1

Implementation environment

- Hardware
 - 64GB of RAM
 - GPU with 16GB of RAM
- > Software
 - Anaconda environment (local)
 - Python: 3.9.7

Model

- Pre-trained BERT
 - Epoch: 3

Result

- Learning time: 7m
- 95.21 % accuracy for the training (+ 40.41 %)
 - Baseline model: 54.8 %
- > 83.39 % accuracy for the validation (+ 27.29 %)
 - Baseline model: 56.1 %



Baseline Model 2

DistilBERT

- Goal
 - **Smaller parameter counts**
 - **Faster speed**
- Architecture
 - Student model
 - Remove NSP training
 - Remove token-type embedding
 - Reduced to Layer 1/2
 - **Distillation**
 - Soft target loss (L_{ce})
 - » Comparison between teacher and student model's soft target
 - Hard target loss (L_{mlm})
 - » Masked language model's loss
 - Cosine embedding loss (L_{cos})
 - » Aligning teacher and student model's hidden vector
- Results
 - 40% size, 160% speed, 97% capability $_{\text{Fig. 5}}$ The specific architecture of the benchmark knowledge distillation (Hinton et al., 2015).



Figure 1: Parameter counts of several recently released pretrained language models.





Results 2

Implementation environment

- Hardware
 - 64GB of RAM
 - GPU with 16GB of RAM
- > Software
 - Anaconda environment (local)
 - Python: 3.9.7
- Model
 - Pre-trained DistilBERT
 - Epoch: 3
- Result
 - Learning time: 1m 30s
 - 90.39 % accuracy for the training (+ 35.59 %)
 - Baseline model: 54.8 %
 - > 85.04 % accuracy for the validation (+ 28.94 %)
 - Baseline model: 56.1 %
 - BERT: 83.39 %

```
Epoch 1/3
accuracy: 0.7724
Epoch 1: val loss improved from inf to 0.36113, saving model to
mycheckpoint
452/452 [=========== ] - 33s 63ms/step - loss:
0.5037 - accuracy: 0.7724 - val loss: 0.3611 - val accuracy: 0.8583
Epoch 2/3
accuracy: 0.8555
Epoch 2: val loss did not improve from 0.36113
452/452 [============ ] - 26s 58ms/step - loss:
0.3502 - accuracy: 0.8555 - val loss: 0.3755 - val accuracy: 0.8504
Epoch 3/3
accuracy: 0.9041
Epoch 3: val loss did not improve from 0.36113
0.2553 - accuracy: 0.9039 - val loss: 0.4381 - val accuracy: 0.8504
```