BERT FOR SQuAD 2.0: SIZE ISN'T EVERYTHING

A BETTER BERT-BASE PERFORMS ALMOST AS WELL AS BASELINE BERT-LARGE

CS224
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Background

This project adapts pre-trained models of Bidirectional Encoder Representations from Transformers (BERT) to the NLP task of answer span prediction ("QA") on the Stanford Question Answering Dataset (SQuAD 2.0). The original BERT implementation ("origBERT") achieved SOTA performance of 88.5 F1 on a SQuAD 1.1 dataset with 100,000+ answerable context-question tuples. However, when origBERT is used on the much more challenging SQuAD 2.0 dataset, released subsequently with 50,000+ additional questions with no answer, performance drops to **73.1 F1 baseline for this project.**

Objective

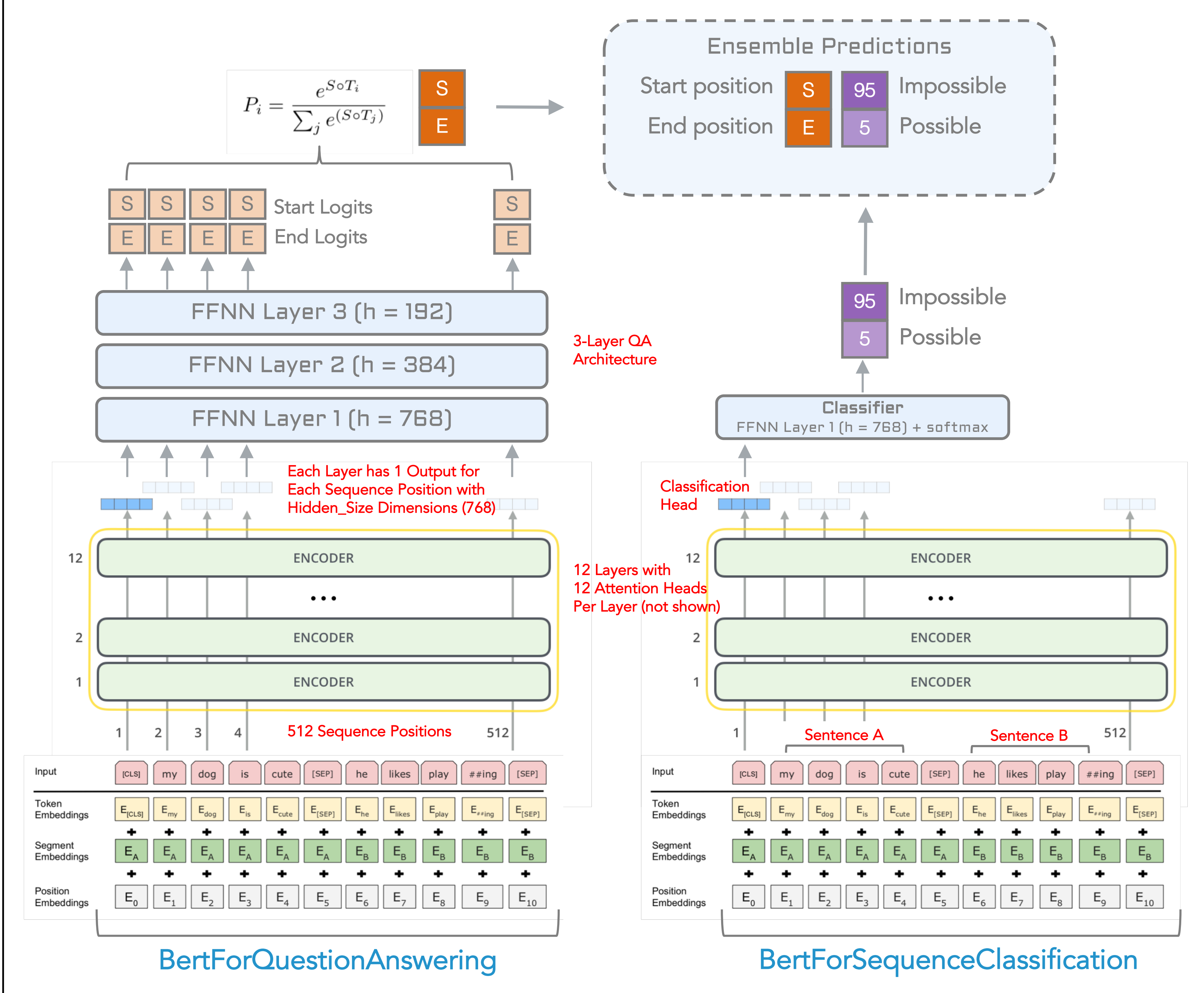
Improve the fine-tuning procedure for BERT-base and BERT-large models to perform better than origBERT on SQuAD 2.0 measured by F1 above baseline of 73.1.

Approach

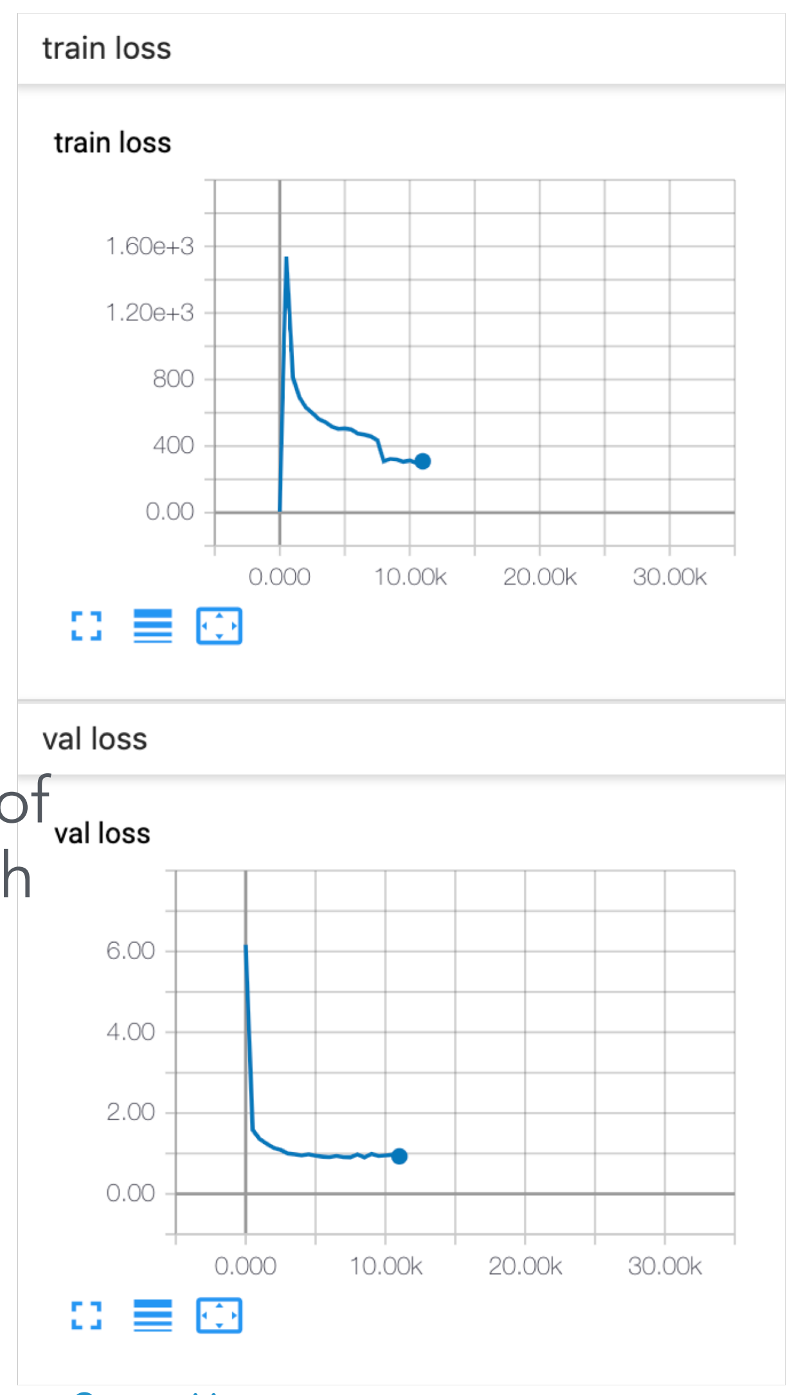
I considered but ruled out potential improvements to the pre-trained BERT models and underlying Transformer architecture because pre-training much more compute time than fine-tuning. Instead, I narrowed my exploration to the following potential improvements to the fine-tuning process used in origBERT:

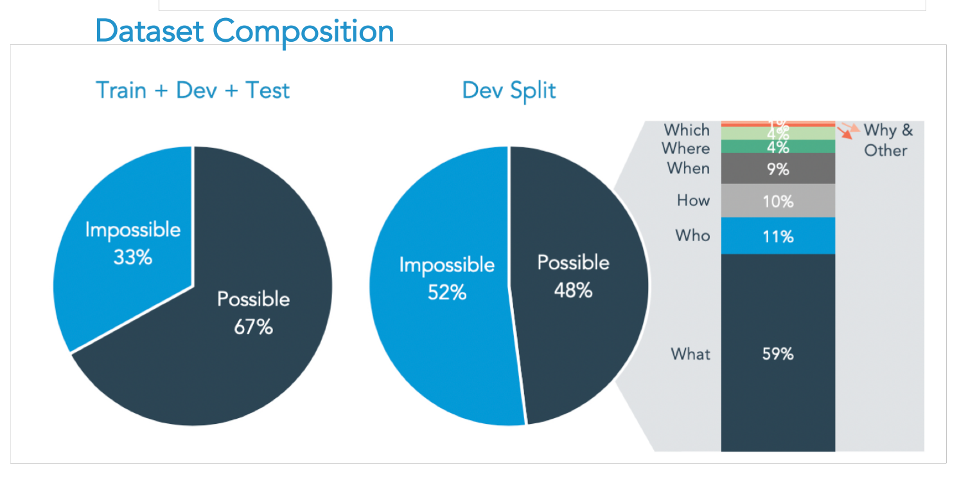
- **Deeper QA architecture** I started with a task-specific architecture that can learn more powerful relationships than the single FFNN in origBERT.
- **Concatenate multiple BERT output layers** In origBERT, only the hidden-states of the last encoding layer are fed into the QA.
- **Weighted cost function** Impossible vs Possible classes are unbalanced in the entire dataset (33/67) and between the Train and Dev splits.
- **Ensemble two different BERT models** I trained a second class of model with its sole objective being the binary classification of whether an input sequence is_impossible. I then ensemble the results of the QA and BSC model as illustrated below.
- **Train on larger and/or balanced QA Dataset** I tried to add examples from the TriviaQA dataset to either increase the size of or balance the classes within the SQuAD 2.0 training data split.

Predictive Models


$P_i = \frac{e^{S \cdot T_i}}{\sum_j e^{(S \cdot T_j)}}$
S
E
Ensemble Predictions
Start position S 95 Impossible
End position E 5 Possible
Start Logits
End Logits
FFNN Layer 3 (h = 192)
FFNN Layer 2 (h = 384)
FFNN Layer 1 (h = 768)
3-Layer QA Architecture
95 Impossible
5 Possible
Classifier
FFNN Layer 1 (h = 768) + softmax
Each Layer has 1 Output for Each Sequence Position with Hidden_Size Dimensions (768)
Classification Head
ENCODER
12 Layers with 12 Attention Heads Per Layer (not shown)
512 Sequence Positions
Sentence A
Sentence B
Input
Token Embeddings
Segment Embeddings
Position Embeddings
[CLS] my dog is cute [SEP] he likes play ##ing [SEP]
BertForQuestionAnswering
BertForSequenceClassification

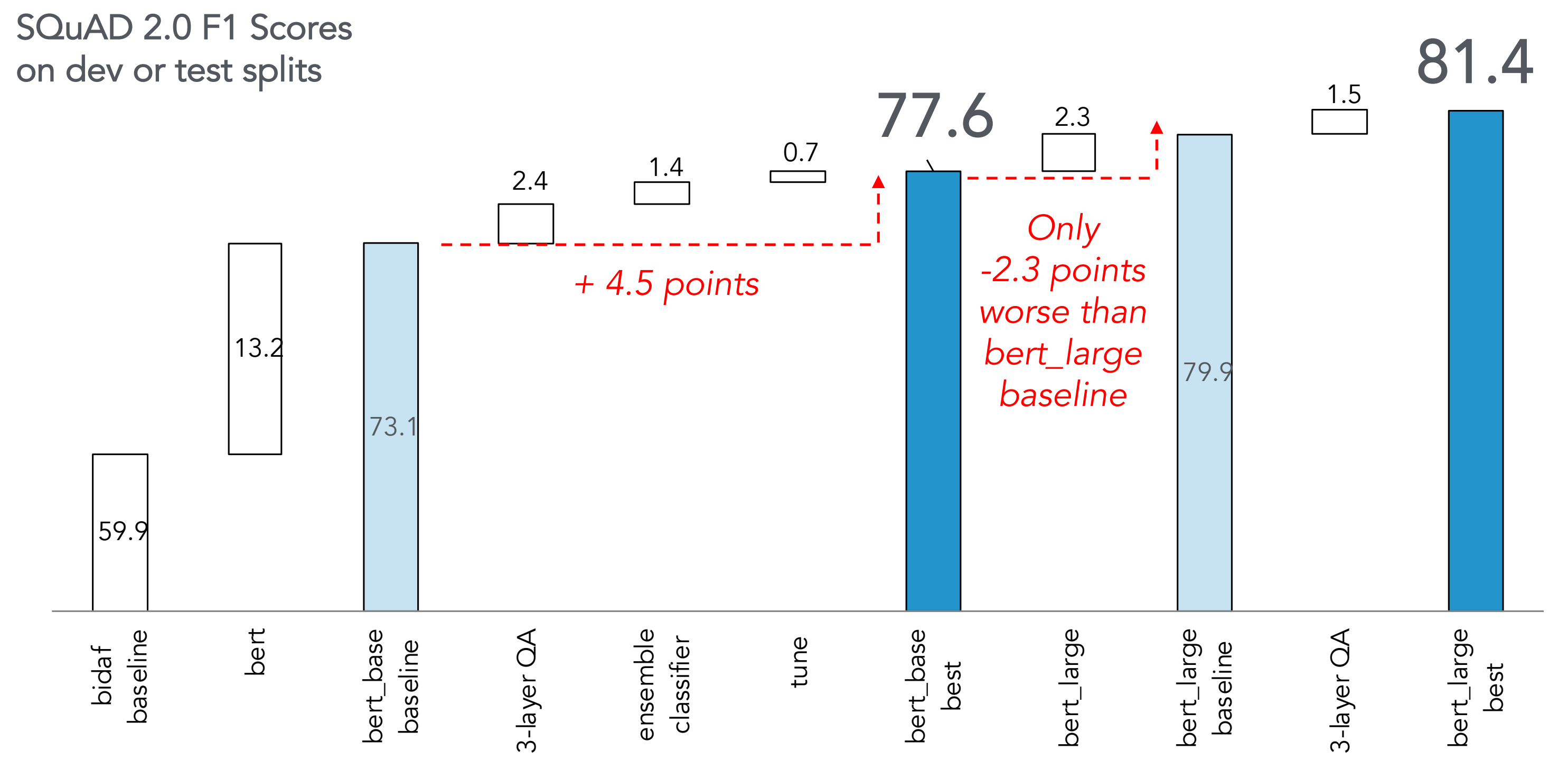
Output:	• BSQ: Yhat ∈ ℤ {0, +1} • BQA: Yhat ∈ ℤ {0, …, 384)
Loss Fn:	BSQ: Weighted CrossEntropy BQA: CrossEntropy
Fine-Tune:	SQuAD 2.0 Two models: • BSQ binary classify impossible • BQA predict start-end positions of answer span in context paragraph
Pre-Train Learning:	• 40 epochs , 256 batch size • 10% dropout, GeLU • Adam, α=1e-4, beta1=0.9, beta2=0.999, L2 decay 0.01
Pre-Train:	BooksCorpus & English Wikipedia Two unsupervised tasks: • Masked Language Model • Next Sentence Predection
Input:	Packed pair of A/B sentences up to max_seq_length=384





Results

BERT-base improved by 4.5 points to 77.6 F1. Notably, this is only 2.3 points below the origBERT-large baseline performance, which is 3x larger and considerably more expensive to train. **Maximum F1 of 81.4** achieved with a 3-layer QA BERT-large model.



Discussion

- The 6.8 point increase from BERT-base to **BERT-large** is driven by the increased power of a model with 340M vs 110M parameters rather than by any improvements I made. But it was not trivial to train BERT-large models. This capability allowed me to explore the effects of BERT model size, batch size, training epochs, and task-specific QA architecture.
- **3-layer QA** architecture produces a 2.4 point improvement. Increasing QA depth to 6 layers resulted in very little incremental improvement (+0.05).
- **Overfitting** was in issue in all models, and required careful monitoring of test-validation splits, checkpointing and early stopping when val loss began to diverge.
- **Concatenating** BERT's last 4 encoding layers for input to QA hurt performance by (-0.5 F1) so I stuck with the last-layer only.
- **Ensembling two different BERT models**, one for binary classification of impossible questions, improved performance by 1.4 F1. Using a **weighted cost function** for the binary classifier helped correct the class imbalance between q's.
- I tried to add **TriviaQA examples** to the train dataset, but was unable to replicate the origBERT results.
- **Tuning hyperparameters,** including max_query_length, null_score_threshold, and test-val checkpoint early stopping, improved performance by an additional 0.7 F1.

Sources

- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.
- Jay Alammar, The Illustrated BERT, ELMo, and Co. (Graphics) https://jalammar.github.io/illustrated-bert/ … AND MANY OTHERS…See References in accompanying project paper.