FASTFUSIONNET:  
NEW STATE-OF-THE-ART FOR DAWNBENCH SQUAD

A TECHNICAL REPORT

Felix Wu, Boyi Li, Lequn Wang  
Cornell University  

Ni Lao  
SayMosaic Inc.  

John Blitzer  
Google Inc.  

Kilian Q. Weinberger  
Cornell University

ABSTRACT

In this technical report, we introduce FastFusionNet, an efficient variant of FusionNet [12]. FusionNet is a high performing reading comprehension architecture, which was designed primarily for maximum retrieval accuracy with less regard towards computational requirements. For FastFusionNets we remove the expensive CoVe layers [21] and substitute the BiLSTMs with far more efficient SRU layers [19]. The resulting architecture obtains state-of-the-art results on DAWNBench [5] while achieving the lowest training and inference time on SQuAD [25] to-date. The code is available at https://github.com/felixgwu/FastFusionNet.

1 Introduction

Recently, machine reading comprehension, or question answering, has received a significant amount of attention in the field of natural language processing. Reading comprehension tasks focus on an agent’s ability to read a piece of text and subsequently answer questions about it. An array of reading comprehension datasets have been released in the past years including WikiQA [37], SQuAD [25], SQuAD v2 [26], TriviaQA [13], SearchQA [8], NarrativeQA [17], CoQA [27], QuAC [4], and Natural Questions [18]. SQuAD is one of the most popular datasets, where a model is presented with a question-context pair and asked to highlight a span in the context as the answer to the question. Figure 1 shows some examples from SQuAD dataset.

Q: How many Americans are richer than more than half of all citizens?  
According to PolitiFact the top 400 richest Americans “have more wealth than half of all Americans combined.” According to ...

Q: What philosophy of thought addresses wealth inequality?  
Neoclassical economics views inequalities in the distribution of income as arising from differences in value added by labor, capital and land. Within labor ...

Q: What is the term that describes the difference between what higher paid and lower paid professionals earn?  
... Thus, in a market economy, inequality is a reflection of the productivity gap between highly-paid professions and lower-paid professions.

Figure 1: Question/Answer samples from SQuAD [25]

Although automatic reading comprehension systems have recently reached super-human performance by some benchmarks [7] (with the help of unsupervised pre-training on large-scale datasets), less attention has been paid to their computational efficiency, which is a crucial aspect in the context of training and deploying such models in real world applications. Coleman et al. [5] introduce DAWNBench, a benchmark suite for end-to-end deep learning training and inference. While many teams have shown interest in the image classification tracks, only few (ParlAI and Google) have participated in the question answering tracks. The ParlAI [22] team has successfully reduced the training time of the model to 27 minutes, while maintaining a decent retrieval accuracy (F1 score greater than or equal to 75%).
In this technical report, we analyze the inference bottlenecks of FusionNet [12] and introduce FastFusionNet that tackles them. In our experiments, we show that FastFusionNet achieves new state-of-the-art training and inference time on SQuAD based on the metrics of DAWNBench.

2 Background

2.1 Efficient Sequence Encoding

The sequential nature of Recurrent Neural Networks (RNNs) makes them inherently slow, even on parallel computing devices. Consequently, a series of methods have been proposed to either reduce the sequential computation within RNNs or substitute them with alternative building blocks. Yu et al. [38] propose LSTM-Jump, in which LSTMs [10] are trained to predict the number of tokens to skip. Seo et al. [29] propose skim-RNN for sentiment analysis and question answering, which has a special RNN unit combining big and small RNN cells. Bradbury et al. [1] introduce Quesi-RNNs that combines convolution with sequential pooling to reduce the sequential. Lei et al. [19] invent Simple Recurrent Unit (SRU) a fast RNN variant, which will be explained further in subsection 2.2. Their second version [20] is more accurate but a little less efficient. To the best of our knowledge, SRU is the most efficient RNN variant, so we choose it as our preferred building block throughout this manuscript.

Other lines of work replace RNNs with convolution layers [6, 9, 14, 35, 36, 39, 40] or self-attention [30, 31, 33, 39]. Shen et al. [30] introduce bidirectional block self-attentions (Bi-BloSA) that split a sequence into blocks and compute intra-block and inter-block self-attention that significantly reduces computation and memory footprint compared to the popular multi-head self-attention [33]. Wu et al. [36] propose lightweight and dynamic convolutions as efficient alternatives to self-attentions with comparable performance.

2.2 Simple Recurrent Unit

The key idea behind Simple Recurrent Unit (SRU) [19, 20] is to separate the matrix multiplications (the bottleneck) from the recurrence. To be specific, SRU replaces the matrix multiplication style recurrence to a vector summation style recurrence. As a consequence, the matrix multiplication can be done in parallel at once. The complete architecture is:

\[
\begin{align*}
\tilde{x}_t &= Wx_t \\
f_t &= \sigma(W_f x_t + b_f) \\
r_t &= \sigma(W_r x_t + b_r) \\
c_t &= f_t \odot c_{t-1} + (1 - f_t) \odot \tilde{x}_t \\
h_t &= r_t \odot \tanh(c_t) + (1 - r_t) \odot x_t
\end{align*}
\]

where \(x_t\) is the input at the time step \(t\), \(c_t\) is the hidden state and \(h_t\) is the output. All blue computations can be performed through simple parallel matrix multiplication followed by parallel element-wise function operators, and are therefore maximally efficient on modern CUDA hardware. The only sequential operation is the update to \(c_t\), which is a highly efficient vector operation. The final update to \(h_t\) is again fully parallel.

2.3 DrQA

DrQA [2] is one of the simplest reading comprehension model, which employs a variety of features including pre-trained word vectors, term frequencies, part-of-speech tags, name entity relations, and the fact that whether a context word is in the question or not, encodes the features with RNNs, and predicts the start and end of an answer with a PointerNet-like module [34].

3 Analysis of FusionNet

FusionNet [12] is reading comprehension model built on top of DrQA by introducing Fully-aware attention layers (context-question attention and context self-attention), contextual embeddings [21], and more RNN layers. Their proposed fully-aware attention mechanism uses the concatenation of layers of hidden representations as the query and the key to compute attention weights, which shares a similar intuition as DenseNet [11]. FusionNet was the state-of-the-art reading comprehension model at the time of writing (Oct. 4th 2017).

Figure 2 provides an analysis of the individual components of FusionNet that the contextual embedding layer, i.e. CoVe [21], with several layers of wide LSTMs, takes up to 35.5% of the inference time while only contributing a 1.1% improvement of F1 Score (from 82.5% to 83.6%) Huang et al. [12]. Additionally, the LSTM layers contribute to 58.8%
Figure 2: The time spent on different components of FusionNet during inference. Note that we have to block CUDA threads to time each component, which may not reflect the real inference time when we remove the components and forward the whole model without blocking.

Figure 3: Inference time in log-scale of SRU [19], GRU [3], LSTM [10], QANet Encoder [39], and 5-layer CNN w/ GLU [6, 35]. We time a 5-layer CNN since it matches the performance of one layer SRU.

4 FastFusionNet

Here we introduce FastFusionNet which addresses the inference bottlenecks of FusionNet [12]. There are two differences compared to FusionNet: i) the CoVe [21] layers are removed and ii) each BiLSTM layer is replaced with two BiSRU layers.

We closely follow the implementation of Huang et al. [12] described in their paper except for the changes above. Following Huang et al. [12], the hidden size of each SRU is set to 125, resulting in a 250-d output feature of each BiSRU regardless of the input size. In the following explanation, we use \([A; B]\) to represent concatenation in the feature dimension. \(\text{Attn}(Q, K, V)\) represents the attention mechanism taking the query \(Q\), the key \(K\), and the value \(V\) as inputs. Assuming \(O\) being the output, we have \(O_i = \sum_j \alpha_{ij} V_j, \alpha_{ij} = \frac{\exp(\alpha_{ij})}{\sum_k \exp(\alpha_{ik})}, \alpha_{ij} = \text{ReLU}(WQ)^\top \text{ReLU}(WK)\).

Input Features. Following Chen et al. [2], we use 300-d GloVe [24] vectors, term-frequency, part-of-speech (POS) tags, and named entity recognition (NER) tags as features for each word in the context or the question. We fine-tune the embedding vector of the padding token, the unknown word token, and the top 1000 most frequent words in the training set. Like others [12] we use a randomly initialized the trainable embedding layer with 12 dimensions for POS tags and 8 dimensions for NER. We use question matching features proposed by Chen et al. [2] as well, which contains a hard version and a soft version.

The hard version contains 3 binary features indicating where a context word's original form, lower case form, or lemmatized form appears in the question, respectively. The soft version uses a trainable attention module that learns to represent each context word as a mixture of question words. Overall, the \(i\)-th context token is represented as \(C_i\), which has 624 dimensions, and the \(j\)-th question token is represented as a 300-d \(Q_j\) glove vector.

We have the context features \(C \in \mathbb{R}^{n \times 624}\) and question features \(Q \in \mathbb{R}^{m \times 300}\) where \(m\) and \(n\) are the length of the question and context, respectively. Specifically,

\[
C^{\text{soft\_match}} \leftarrow \text{Attn}(C^{\text{GloVe}}, Q^{\text{GloVe}}, Q^{\text{GloVe}}),
\]

\[
C^{\text{In}} \leftarrow [C^{\text{GloVe}}; C^{\text{TF}}; C^{\text{POS}}; C^{\text{NER}}; C^{\text{soft\_match}}; C^{\text{hard\_match}}],
\]

\[
Q^{\text{In}} \leftarrow Q^{\text{GloVe}},
\]

where \(C \in \mathbb{R}^{n \times 624}, C^{\text{GloVe}} \in \mathbb{R}^{n \times 300}, C^{\text{TF}} \in \mathbb{R}^{n \times 1}, C^{\text{POS}} \in \mathbb{R}^{n \times 12}, C^{\text{NER}} \in \mathbb{R}^{n \times 8}, C^{\text{hard\_match}} \in \mathbb{R}^{n \times 3},\) and \(Q = Q^{\text{GloVe}} \in \mathbb{R}^{m \times 300}\).
Low-level encoding Layer. We apply 2-layer BiSRU on $C^l$ and $Q^l$ to obtain lower-level representations $C^l$ and $Q^l$ respectively. That is,

$$
C^l \leftarrow \text{BiSRU}(\text{BiSRU}(C^l)),$$
$$Q^l \leftarrow \text{BiSRU}(\text{BiSRU}(Q^l)),$$

where $C^l \in \mathbb{R}^{n \times 250}$, $Q^l \in \mathbb{R}^{m \times 250}$.

High-level Encoding Layer consists of another 2-layer BiSRU to obtain high-level representations $C^h$ and $Q^h$. In other words,

$$C^h \leftarrow \text{BiSRU}(\text{BiSRU}(C^l)),$$
$$Q^h \leftarrow \text{BiSRU}(\text{BiSRU}(Q^l)),$$

where $C^h \in \mathbb{R}^{n \times 250}$, $Q^h \in \mathbb{R}^{m \times 250}$.

The Question Understanding Layer is another 2-layer BiSRU combining $Q^l$ and $Q^h$ into $Q^u$, i.e.

$$Q^u \leftarrow \text{BiSRU}(\text{BiSRU}([Q^l; Q^h])),$$

where $Q^u \in \mathbb{R}^{m \times 250}$.

The Question-Context Attention Layer is a fully-aware attention module [12] which takes the history (concatenation of GloVe, low-level, and high-level features) of each context word and question words as query and key for three attention modules, and represents each context word as three different vectors: $C^f$ (weighted sum of $Q^f$'s), $C^h$ (weighted sum of $Q^h$'s), and $C^u$ (weighted sum of $Q^u$'s). Another 2-layer SRU processes the concatenation of all previous context word vectors $C^f, C^h, \hat{C}^f, \hat{C}^h$, and $C^u$ into $C^v$. To be specific,

$$C^{His} \leftarrow [C^{GloVe}; C^{CoVe}; C^f; C^h],$$
$$Q^{His} \leftarrow [Q^{GloVe}; Q^{CoVe}; Q^f; Q^h],$$
$$\hat{C}^f \leftarrow \text{Attn}(C^{His}, Q^{His}, Q^f),$$
$$\hat{C}^h \leftarrow \text{Attn}(C^{His}, Q^{His}, Q^h),$$
$$\hat{C}^u \leftarrow \text{Attn}(C^{His}, Q^{His}, Q^u),$$
$$C^v \leftarrow \text{BiSRU}(\text{BiSRU}([C^f; C^h; \hat{C}^f; \hat{C}^h; \hat{C}^u])),$$

where $\hat{C}^f, \hat{C}^h, \hat{C}^u, C^v \in \mathbb{R}^{n \times 250}$.

The Context Self-Attention Layer is another fully-aware attention module that treats the history of words (GloVe vectors, $C^i_1, C^i_2, C^i_3, C^i_4, C^i_5, C^i_6$, and $C^i_7$) as the key and also as query to produce a new vector of each context word $\hat{C}^i_1$ from the input $C^i_1$. The last 2-layer SRU processes the concatenation of $\hat{C}^i_1$ and $\hat{C}^i_2$ into $C^v_1$, i.e.

$$C^{His2} \leftarrow [C^{GloVe}; C^{CoVe}; C^f; C^h; \hat{C}^f; \hat{C}^h; \hat{C}^u; C^v],$$
$$\hat{C}^v \leftarrow \text{Attn}(C^{His2}, C^{His2}, C^v),$$
$$C^v \leftarrow \text{BiSRU}(\text{BiSRU}([C^v; \hat{C}^v])),$$

where $\hat{C}^v, C^v \in \mathbb{R}^{n \times 250}$.

Answer Prediction Layer. This layer predicts the positions of the start and end of the answer span using the final representations of the context $C^v$ and the question $Q^v$. This layer first combines all question vectors into a weighted sum $q = \sum_{j=1}^{m} \alpha_j Q^v_j$ using a single trainable parameter $v \in \mathbb{R}^{250}$, where $\alpha_j = \frac{\exp(v^\top Q^v_j)}{\sum_{j=1}^{m} \exp(v^\top Q^v_j)}$. As a next step it predicts the probability that the $i^{th}$ word denotes the start of the answer span as $s_i = \frac{\exp(q^\top W_1 C^v_i)}{\sum_{i=1}^{n} \exp(q^\top W_1 C^v_i)}$, using a bilinear soft-max model. Subsequently, it summarizes the context with the start prediction and produces $z = \sum_{i=1}^{n} s_i C^v_i$. 

A Technical Report
| Time to F1 ≥ 75.0% | Model | Framework | Hardware |
|-------------------|-------|-----------|----------|
| 0:18:46           | FastFusionNet (4 epochs) | PyTorch v0.3.1 | 1 GTX-1080 Ti |
| 0:23:06           | FusionNet [12] (2 epochs) | PyTorch v0.3.1 | 1 GTX-1080 Ti |
| 0:27:07           | DrQA (ParlAI) [22] | PyTorch v1.0.0 | 1 RTX-2080 |
| 0:29:24           | FusionNet without CoVe (3 epochs) [12] | PyTorch v0.3.1 | 1 GTX-1080 Ti |
| 0:45:56           | QANet [39] | TensorFlow v1.8 | 1 TPUv2 |
| 0:50:21           | DrQA (ParlAI) [22] | PyTorch v1.0.0 | 1 T4 / GCP |
| 0:56:43           | DrQA (ParlAI) [22] | PyTorch v1.0.0 | 1 P4 / GCP |
| 1:00:35           | DrQA (ParlAI) [22] | PyTorch v0.4.1 | 1 V100 |
| 1:22:33           | BERT-base [7] (1 epoch fine-tuning) | TensorFlow v1.11.0 | 1 GTX-1080 Ti |
| 7:38:10           | BiDAF[5, 28] | TensorFlow v1.2 | 1 K80 |

Table 1: DAWNBench Training Track

It then produces a refined question vector $\hat{q}$ with one step of GRU [1], using the original question vector $q$ as the hidden memory and $z$ as the input, i.e. $\hat{q} = \text{GRUCell}(z, q)$. Similarly, a bi-linear module is applied to get the end predicted probability $e_i = \exp(\hat{q}^T W^C u_i) / \sum_{k=1}^n \exp(\hat{q}^T W^C u_k)$. The product of the respective start and end probabilities becomes the score of an answer span. However, we only consider answers with no more than 15 words and do a exhaustive search to find the best span.

5 Experiments

5.1 Experimental Setup

We conduct our experiments on the SQuAD dataset, which contains 87K, 10K, and 10K context-question pairs for training, development, and test. Like the other models submitted to the DAWNBench, we use the publicly available development set to evaluate the performance and the efficiency of our model. All of the experiments are conducted on a single Nvidia GTX-1080 Ti GPU. We use PyTorch [25] 0.3.1 to implement our model. We use single precision floating-point in our implementation. Arguably, using half-precision floating-point may further improve our results. Our implementation is based on two open source code bases: We follow their data pre-processing procedure.

Training procedure. We train the model for 100 epochs to ensure convergence; however, the model stops improving after 60 epochs. The other hyper-parameters are borrowed from Lei et al. [19]. We do not tune the hyper-parameters. We use batch size 32 for training. We use Adam optimizer [15] with $\alpha = 0.001$ and clip the $\ell_2$-norm of the gradients to 20 before each update. The SQuAD dataset is tokenized and tagged by the SpaCy package [2]. We apply variational dropout [16] to sequential features and normal dropout [32] to others. Following [2], dropout rate for input embeddings is set to 0.4. We also dropout all inputs of LSTMs and attentions with probability 0.4. For SRUs, we follow [19] using dropout rate 0.2. We do not use learning rate decay or weight decay for simplicity.

5.2 DAWNBench Results

We report the performance of our FastFusionNet on DAWNBench [5]. We consider three baselines: i) FusionNet ii) FusionNet without CoVe, and iii) BERT-base. For BERT-base, we use the open source code [3]. Our FastFusionNet reaches F1 75% in 4 epochs and achieves at F1 82.5% at the end which matches the reported F1 82.5% of FusionNet without CoVe on SQuAD development set[12].

The training time track aims to minimize the time to train a model up to at least 75% F1 score on SQuAD development set. Table 1 shows that our FastFusionNet reaches F1 75.0% within 20 minutes (after 4 epochs), which gives a 45% speedup compared to the winner DrQA (ParlAI) on the leaderboard. Notably, we use an Nvidia GTX-1080 GPU which is about 22% slower than their Nvidia RTX-2080 GPU. When controlling the generation of GPUs and comparing our model with a DrQA (ParlAI) trained on an Nvidia V100, our model achieves a 3.1× speedup. Compared to FusionNet, FastFusionNet is 23% faster to reach 75% F1 score; however, in terms of the training time per epoch, it is in fact 2.6× as fast as FusionNet.

https://github.com/hitvoice/DrQA and https://github.com/momohuang/FusionNet-NLI
https://spacy.io/ We use version 1.9.0
https://github.com/google-research/bert
A T E C H N I C A L  R E P O R T

1-example Latency | Model (F1 ≥ 75%) | Framework | Hardware
---|---|---|---
7.9 ms | FastFusionNet (F1 82.5%) | PyTorch v0.3.1 | 1 GTX-1080 Ti
22.3 ms | BERT-base (F1 88.5%) | TensorFlow v1.11.0 | 1 GTX-1080 Ti
32.6 ms | FusionNet without CoVe [12] (F1 82.5%*) | PyTorch v0.3.1 | 1 GTX-1080 Ti
45.5 ms | FusionNet [12] (F1 83.6%*) | PyTorch v0.3.1 | 1 GTX-1080 Ti
100.0 ms | BiDAF (F1 77.3%) | TensorFlow v1.2 | 16 CPU
590.0 ms | BiDAF (F1 77.3%) | TensorFlow v1.2 | 1 K80
638.1 ms | BiDAF (F1 77.3%) | TensorFlow v1.2 | 1 P100

Table 2: DAWN-Bench Inference Track. *: We use the F1 score reported by Huang et al. [12] here since our re-implementation is about 0.5% F1 score worse.

The inference time track evaluates the average 1-example inference latency of a model with an F1 score at least 75%. Our FastFusionNet reduces the 1-example latency down to 7.9 ms, which is 2.8× as fast as a BERT-base and 12.7× over BiDAF. FastFusionNet achieves a 5.8× speedup over the original FusionNet.

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