Low Rank Factorization for Compact Multi-Head Self-Attention

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Abstract
Effective representation learning from text has been an active area of research in the fields of NLP and text mining. Attention mechanisms have been at the forefront in order to learn contextual sentence representations. Current state-of-art approaches in representation learning use single-head and multi-head attention mechanisms to learn context-aware representations. However, these approaches can be largely parameter intensive resulting in low-resource bottlenecks. In this work we present a novel multi-head attention mechanism that uses low-rank bilinear pooling to efficiently construct a structured sentence representation that attends to multiple aspects of a sentence. We show that the proposed model is more effective than single-head attention mechanisms and is also more parameter efficient and faster to compute than existing multi-head approaches. We evaluate the performance of the proposed model on multiple datasets on two text classification benchmarks including: (i) Sentiment Analysis and (ii) News classification.

1 Introduction
Learning effective language representation is important for a variety of text analysis tasks including sentiment analysis, news classification, natural language inference and question answering. Language representations can be learned via supervised or unsupervised approaches. Supervised learning using neural networks commonly entails learning intermediate sentence representations usually using an attention mechanism followed by a task specific layer. For text classification tasks; this is usually a fully connected layer followed by an N-way softmax layer where N is the number of classes.

Learning unsupervised language representations has made substantial progress in recent years with the introduction of new techniques for language modeling combined with deep models like ELMo [20], ULMFit [10], BERT [5] and GPT-2 [21]. These methods have enabled transfer of learned representations via pre-training to downstream tasks. Although these models work well on a variety of tasks there are two major limitations: 1) they are computationally expensive to train and 2) they usually have a large number of parameters that greatly increases the model size and memory requirements. For instance, the multilingual BERT-base Cased model has 110M parameters, the small GPT-2 model has 117M parameters [21] and the RoBERTa model was trained on 160GB of data [16]. It is natural to see how task specific training (ELMo) or fine-tuning (BERT, GPT-2) can be limiting when the training data and computational resources are scarce. Further, running inference on and storing such models can also be difficult in low resource scenarios such as IoT devices or low-latency use cases. Hence, supervised learning for task-specific architectures which are trained from scratch, especially where domain specific training data is available are useful. They are light-weight and easy to deploy. In this work we focus on learning compact attention-based supervised language representations with text classification as the downstream task.

As outlined above, modern neural networks have a large number of parameters. Computation at attention layers in these networks can get prohibitive. Especially, multi-head attention mechanisms [15, 8, 23] (multiple attention distributions over a given sentence) that form an integral part of many state-of-the-art architectures for NLP tasks [23, 5] can be expensive to compute. We argue that the attention layer giving rise to multiple attentions in these methods is over-parameterized. In this work, we propose a novel low-rank factorization based multi-head attention mechanism (LAMA), which is computationally cheaper than prior approaches and sometimes exceeds the performance of state-of-the-art
baselines.

Contrary to previous approaches [15] [8] that are based on the additive attention mechanism [1], LAMA is based on the multiplicative attention [17] which replaces the additive attention by the dot product attention for faster computation. We further introduce a bilinear projection while computing the dot product to capture similarities between a global context vector and each word in the sentence. The function of the bilinear projection is to capture nuanced context dependent word-importance as corroborated by previous works [2]. Next, we use a low-rank formulation of the bilinear projection matrix based on hadamard product [12] [27] to compress the attention layer and speed up the computation of multiple attention distributions for each word. We leverage this approach to decompose a single bilinear matrix to produce multiple attentions between the global context vector and each word as opposed to having a different learned vector [15] or matrix [28]. We evaluate our model by performing experiments on multiple datasets spanning two different tasks namely Sentiment Analysis and Text Classification. We find that our model restores or in some cases outperforms state-of-the-art approaches with fewer parameters for efficient computation.

The rest of the paper is organized as follows: In the next section (§2), we discuss connections with the related work, followed by the description of the proposed model (§3). Next we describe the experiments and the datasets (§4), followed by results and discussion (§5), before concluding (§6).

2 Related Work

Spearheaded by their success in neural machine translation [1] [17] attention mechanisms are now ubiquitously used in problems such as question answering [9] [22] [7], text summarization [19] [2] and training large language models [5] [21]. In sequence modeling, attention mechanisms allow the decoder to learn which part of the sequence it should “attend” to based on the input sequence and the output it has generated so far [1]. A special case of attention known as self-attention [15] or intra attention [20] is used for text classification tasks such as sentiment analysis and natural language inference.

Models have been proposed that compute multiple attention distributions over a single sequence of words. Multi-view networks [8] use a different set of parameters for each view which leads to an increase in the number of parameters. Lin et al. [15] use the additive attention mechanism and modify it to produce multiple attentions to obtain a matrix sentence embedding. Recently proposed multi-head attention (also known as scaled dot product attention) has been shown to be very effective in machine translation [25] and pretraining [5]. In this work we propose a more parameter efficient way to compute multiple attentions. The score between the context vector and the word hidden representation is computed using a bilinear projection matrix followed by an approach inspired by multi-modal low rank bilinear pooling [12] to factorize the matrix into two low rank matrices to compute multiple attention distributions over words. Contrary to Guo et al. [8] we use matrix factorization to alleviate the problem of increasing parameters with increasing views and our approach uses fewer parameters than [15] to compute multiple attentions and performs superior to their approach. Low-rank factorization has been a popular approach to reduce the size of the hidden layers [3] [21]. In this work we use Hadamard product formulation of the product of two low-rank matrices to compactify the attention layer.

3 Proposed Model

A document (review or a news article) is first tokenized and converted to a word embedding via a lookup into a pretrained embedding matrix. The embedding of each token is encoded via a bi-GRU sentence encoder to get a contextual annotation of each word. The LAMA attention mechanism then obtains multiple attention distributions over those words by computing an alignment score of their hidden representation with a word-level context vector. Sum of the word representations weighted by the scores from multiple attention distributions then forms a matrix sentence embedding. The matrix embedding is then flattened and passed onto downstream layers (either a classifier or another encoder depending on the task). Since we model all tokens in the text together without using any hierarchical structure, without loss of generality the terms sentence and document are used interchangeably in the rest of the paper. Capital bold letters indicate matrices, small bold letters indicate vectors and small letters indicate scalars.

3.1 Sequence Encoder We use the GRU [1] RNN as the sequence encoder. GRU uses a gating mechanism to track the state of the sequences. There are two types of gates: the reset gate $r_t$ and the update gate $z_t$. The update gate decides how much past information is kept and how much new information is added. At time $t$, the GRU computes its new state as:

\[
h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}
\]

and the update gate $z_t$ is updated as:

\[
z_t = \sigma(W_z \ast x_t + U_z \ast h_{t-1} + b_z)
\]
The RNN candidate state $\tilde{h}_t$ is computed as:

\begin{equation}
\tilde{h}_t = tanh(W_h x_t + r_t \odot (U_h h_{t-1} + b_h))
\end{equation}

Here $r_t$ is the reset gate which controls how much the past state contributes to the candidate state. If $r_t$ is zero, then it forgets the previous state. The reset gate is updated as follows:

\begin{equation}
r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)
\end{equation}

Consider a document $D_i$ containing $T$ words. $D_i = \{w_1, ..., w_t, ..., w_T\}$. Let each word be denoted by $w_t$, $t \in [0, T]$ where every word is converted to a real valued word vector $x_t$ using the pre-trained embedding matrix $W_e = R^{d \times |V|}$, $x_t = W_e w_t$, $t \in [1, T]$ where $d$ is the embedding dimension and $V$ is the vocabulary. The embedding matrix $W_e$ is fine-tuned during training. Note that we have dropped the subscript $i$ as all the derivations are for the $i^{th}$ document and it is assumed implicit in the following sections.

We encode the document using a bi-directional GRU (bi-GRU) that summarizes information in both directions along the text to get a contextual annotation of a word. In a bi-GRU the hidden state at time step $t$ is represented as a concatenation of hidden states in the forward and backward direction. The forward GRU denoted by $GRU$ processes the sentence from $w_1$ to $w_T$ whereas the backward GRU denoted by $\overline{GRU}$ processes it from $w_T$ to $w_1$.

\begin{equation}
x_t = W_e w_t
\end{equation}

\begin{equation}
\overrightarrow{h}_t = \overline{GRU}(x_t, h_{(t-1)}, \theta)
\end{equation}

\begin{equation}
\overleftarrow{h}_t = \overline{GRU}(x_t, h_{(t+1)}, \theta)
\end{equation}

Here the word annotation $h_t$ is obtained by concatenating the forward hidden state $\overrightarrow{h}_t$ and the backward hidden state $\overleftarrow{h}_t$.

### 3.2 Single-Head Attention

To alleviate the burden of remembering long term dependencies from GRUs we use the global attention mechanism [17] in which the sentence representation is computed by attending to all words in the sentence. Let $h_t$ be the annotation corresponding to the word $x_t$. First we transform $h_t$ using a one layer Multi-Layer Perceptron (MLP) to obtain its hidden representation $u_t$. We assume Gaussian priors with 0 mean and 0.1 standard deviation on $W_w$ and $b_w$.

\begin{equation}
u_t = tanh(W_w h_t + b_w)
\end{equation}

Next, to compute the importance of the word in the current context we calculate its relevance to a global context vector $c$.

\begin{equation}
f_t = c^T W_i u_t
\end{equation}

Here, $W_i \in R^{2h \times 2h}$, is a bilinear projection matrix which is randomly initialized and jointly learned with other parameters during training. $h$ is the dimension of the GRU hidden state and $u_t$ & $c$ are both of dimension $2h \times 1$ since we’re using a bi-GRU. The mean of the word embeddings provides a good initial approximation of the global context of the sentence. We initialize $c = \frac{1}{T} \sum_{t=1}^T w_t$ which is then updated during training. We use a bilinear model because they are more effective in learning pairwise interactions. The attention weight for the word $x_t$ is then computed using a softmax function where summation is taken over all the words in the document.

\begin{equation}
\alpha_t = \frac{\exp(f_t)}{\sum_{t'} \exp(f_{t'})}
\end{equation}

### 3.3 LAMA

The attention distribution above usually focuses on a specific component of the document, like a special set of trigger words. So it is expected to reflect an aspect, or component of the semantics in a document. This type of attention is useful for smaller pieces of texts such as tweets or short reviews. For larger reviews there can be multiple aspects that describe that review. For this we introduce a novel way of computing multiple heads of attention that capture different aspects.

Suppose $m$ aspects are to be extracted from a sentence, we need $m$ alignment scores between each word hidden representation $u_t$ and the context vector $c$. To obtain an $m$ dimensional output $f_t$, we need to learn $m$ weight matrices given by $W = [W_1, ..., W_m] \in R^{m \times 2h \times 2h}$ as demonstrated in previous works. Although this strategy might be effective in capturing pairwise interactions for each aspect it also introduces a huge number of parameters that may lead to overfitting.

| Notation | Meaning |
|----------|---------|
| $N$      | Corpus size |
| $T$      | # of words tokens in a sample |
| $m$      | # of aspects |
| $f_t$    | alignment score |
| $\alpha_t$ | word hidden representation |
| $u_t$    | attention weight |
| $c$      | global context vector |
| $h$      | GRU hidden state dimension |
and also incur a high computational cost especially for a large $m$ or a large $h$. To address this, the rank of matrix $W$ can be reduced by using low-rank bilinear method to have less number of parameters [12] [23]. Consider one aspect; the bilinear projection matrix $W_i$ in Eq. 3.8 is factorized into two low rank matrices $P$ & $Q$.

\begin{align}
  f_t &= c^T PQ^T u_t = \sum_{d=1}^{k} c^T p_d q_d^T u_t = \mathbb{1}^T (P^T c \circ Q^T u_t)
\end{align}

where $P = [p_1,...,p_k] \in \mathbb{R}^{2h \times k}$ and $Q = [q_1,...,q_k] \in \mathbb{R}^{2h \times k}$ are two low-rank matrices, $\circ$ is the Hadamard product or the element-wise multiplication of two vectors, $\mathbb{1} \in \mathbb{R}^k$ is an all-one vector and $k$ is the latent dimensionality of the factorized matrices.

To obtain $m$ scores, by Eq. 3.10, the weights to be learned are two three-order tensors $P = [P_1,...,P_m] \in \mathbb{R}^{2h \times k \times m}$ and $Q = [Q_1,...,Q_m] \in \mathbb{R}^{2h \times k \times m}$ accordingly. Without loss of generality $P$ and $Q$ can be re-formulated as 2-D matrices $P \in \mathbb{R}^{2h \times km}$ and $Q \in \mathbb{R}^{2h \times km}$ respectively with simple reshape operations. Setting $k = 1$, which corresponds to rank-1 factorization. Eq. 3.10 can be written as:

\begin{align}
  f_t &= \tilde{P}^T c \circ \tilde{Q}^T u_t
\end{align}

This brings the two feature vectors $u_t, h_t \in \mathbb{R}^{2h}$, the word hidden representation and $c \in \mathbb{R}^{2h}$, the global context vector in a common subspace and are given by $u_t$ and $\hat{c}$ respectively. $f_t \in \mathbb{R}^m$ now is a multi-head alignment vector for the word $x_t$. For computing attention for one head, this is equivalent to replacing the projection matrix $W_i$ in Eq. 3.8 by the outer product of vectors $\tilde{P}_i$ and $\tilde{Q}_i$ - rows of the matrices $\tilde{P}$ and $\tilde{Q}$ respectively and rewriting it as the Hadamard product. As a result each row of matrices $\tilde{P}_i$ and $\tilde{Q}_i$ represent the vectors for computing the score for a different head.

The multi-head attention vector $\alpha_t \in \mathbb{R}^m$ is obtained by computing a softmax function along the sentence length:

\begin{align}
  \alpha_t &= \frac{\exp(f_t)}{\sum_{t'} \exp(f_{t'})}
\end{align}

Before computing softmax, similar to [12] [23] to further increase the model capacity we apply the $\tanh$ nonlinearity to $f_t$. Since element-wise multiplication is introduced the values of neurons may vary a lot so we apply an $l_2$ normalization layer across the $m$ dimension. Although $l_2$ is not strictly necessary since both $c$ and $u_t$ are in the same modality empirically we do see improvement after applying $l_2$. Each component $k$ of $\alpha_t$ is the contribution of the word $x_t$ to the $k^{th}$ aspect.

Let $H = (h_1,h_2,...,h_T)$ be a matrix of all word annotations in the sentence; $H \in \mathbb{R}^{T \times 2h}$. The attention matrix for the sentence can be computed as:

\begin{align}
  A &= \text{softmax}(l_2(\tanh(\tilde{P}^T C_g \circ \tilde{Q}^T H^T)))
\end{align}

where, $C_g \in \mathbb{R}^{2h \times T}$ is $c$ repeated $T$ times, once for each word, $l_2(x) = \frac{x}{\|x\|}$ and $\text{softmax}$ is applied row-wise. $A \in \mathbb{R}^{m \times T}$ is the attention matrix between the sentence and the global context with each row representing attention for one aspect.

Given $A = [\alpha_1,\alpha_2,...,\alpha_T]$, the multi-head attention matrix for the sentence; $A \in \mathbb{R}^{m \times T}$. The sentence representation for an aspect $j$ given by $\alpha_j = \{\alpha_{j1},\alpha_{j2},..\alpha_{jT}\}$ can be computed by taking a weighted attention matrix.
sum of all word annotations.

\[(3.14) \quad s_j = \sum_{k=1}^{T} h_k \ast \alpha_{jk} \]

Similarly, sentence representation can be computed for all heads and is given in a compact form by:

\[(3.15) \quad S = AH \]

Here \(S \in \mathbb{R}^{m \times 2h}\) is a matrix sentence embedding and contains as many rows as the number of heads. Each row contains an attention distribution for a new aspect. It is flattened by concatenating all rows to obtain the document representation \(d\). From the document representation, the class probabilities are obtained as follows.

\[(3.16) \quad \hat{y} = \text{softmax}(W_d + b_c) \]

Loss is computed using cross entropy.

\[(3.17) \quad l = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) \]

where \(C\) is the number of classes and \(\hat{y}_c\) is the probability of the class \(c\). The final training loss is given by:

\[(3.18) \quad L = \sum_{d} l \]

The summation is taken over all the documents in a mini-batch. We use the mini-batch stochastic gradient descent algorithm \[11\] with momentum and weight decay for optimizing the loss function and the backpropagation algorithm is used to compute the gradients. Fig. 1 illustrates a schematic of the model architecture. A single document and its flow through various model components is shown. The middle block illustrates the proposed attention mechanism for one word \(w_t\) of the document.

3.3.1 Hyperparameters We use a word embedding size of 100. The embedding matrix \(W_e\) is pretrained on the corpus using word2vec. All words appearing less than 5 times are discarded. The GRU hidden state is set to \(h = 50\), MLP hidden state to 512 and apply a 0.4 dropout to the hidden layer. We use a batch size of 32 for training and an initial learning rate of 0.05. For early stopping we use patience = 5.

3.3.2 Computational Efficiency for Attention Other variables such as input sentence length and dimension of the hidden state representations held constant, the computational complexity depends on the attention layer. Here, we show how the proposed model LAMA compares to the self attentive network (SAN) \[15\] with respect to the number of parameters needed to compute an attention matrix for a sentence. In SAN the attention matrix \(A\) can be computed as:

\[(3.19) \quad A = \text{softmax}(W_s tanh(W_s H^T)) \]

where, \(H\) is a matrix of word annotations with the shape \(T\)-by-\(2h\), \(W_{s1}\) is \(d_a\)-by-\(2h\) and \(W_{s2}\) is \(m\)-by-\(2h\) where \(m\) is the number of aspects. So the total number of parameters needed to be learned are \(2d_a + 2hm\). For the proposed model, to compute the attention matrix given by Eq. 3.13 the parameters to be learned are matrices \(\tilde{P}, Q\) and the context vector \(c\). So the total number of parameters required are \(2hm + 2hm\). Comparing the above terms the reduction factor is \(\frac{d_a + m}{2m}\). Even though, both are \(O(m)\) the parameter savings come from the constant factor. For \(m << d_a\), reduction factor is \(\frac{d_a}{2m}\). For the Transformer model \[23\], the multi-head attention in one layer is given by:

\[(3.20) \quad \text{Multihead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_m)W_O \]

where the projections are parameter matrices \(W_i^Q \& W_i^K \in \mathbb{R}^{d_{model} \times d_k}\), \(W_i^V \in \mathbb{R}^{d_{model} \times d_v}\) and \(W_O \in \mathbb{R}^{md_v \times d_{model}}\). In the self-attention case, all of \(Q, K\), and \(V\) are the input representations from the previous layer. The number of parameters required to compute the multi-head attention in Eq. 3.20 are \(O(m^2)\). It should be noted that even though the attention computation in Transformer is an order of magnitude higher, it does not contain any GRU layers. So the overall complexity depends on the choice of the input layer such as convolutional or recurrent layers.

4 Experiments

We evaluate the performance of the proposed model on two tasks with five different datasets. Table 2 gives an overview of the datasets and their statistics.

4.1 Sentiment Analysis For the sentiment analysis task we pick two datasets - the YELP Ratings dataset and the IMDB Movie Sentiment Dataset.
4.1 Yelp The Yelp dataset consists of 2.7M Yelp reviews and user ratings from 1 to 5. Given a review as input the goal is to predict the number of stars the user who wrote that review assigned to the corresponding business store. We treat the task as 5-way text classification where each class indicates the user rating. We randomly selected 500K review-star pairs as training set, 4,000 for the dev set, and 4,000 for test set. Reviews were tokenized using the Spacy tokenizer. 100-dimensional word embeddings were trained from scratch on the train dataset using the gensim software package.

Multi-head attention capturing multiple aspects is more useful for classifying ratings that are more subjective i.e. longer reviews where people express their experiences in detail. We create a subset of the YELP dataset containing all longer reviews i.e. reviews containing longer than 118 tokens which we found to be the mean length of the reviews in the dataset. The training set consists of 175,844 reviews, the dev set consists of 1,416 reviews and the test set consists of 1,378 reviews. The goal is to predict the ratings from the above subset of the Yelp dataset. We refer to this dataset as Yelp-L (Yelp-Long) in the rest of the paper since it consists of all longer reviews. We hypothesize that having multi-head attention would benefit in this setting where more intricate foraging of information from different parts of the text is required to make a prediction. The model hyperparameters and training settings remain the same as the above.

4.1.2 Movie Reviews The large Movie Review dataset contains movie reviews along with their associated binary sentiment polarity labels. It contains 50,000 highly polar reviews (score ≤ 4 out of 10 for negative reviews and score >= 7 out of 10 for positive reviews) split evenly into 25K train and 25K test sets. The overall distribution of labels is balanced (25K pos and 25K neg). In the entire collection, no more than 30 reviews are allowed for any given movie because reviews for the same movie tend to have correlated ratings. Further, the train and test sets contain a disjoint set of movies, so no significant performance is obtained by memorizing movie-unique terms and their associated with observed labels. From the training set we randomly set aside 1000 reviews for validation. We refer to this dataset as IMDB in the rest of the paper.

4.2 News Classification For this task we selected two datasets.

4.2.1 News Aggregator This dataset contains headlines, URLs, and categories for news stories collected by a web aggregator between March 10th, 2014 and August 10th, 2014. News categories included in this dataset include business; science and technology; entertainment; and health. Different news articles that refer to the same news item (e.g., several articles about recently released employment statistics) are also categorized together. Given a news article the task is to classify it into one of the four categories. Training dataset consists of 151,328 articles and test dataset consists of 32,428. The average token length is 352.

4.2.2 Reuters This dataset is taken from Reuters-21578 Text Categorization Collection. This is a collection of documents that appeared on Reuters newswire in 1987. The documents were assembled and indexed with categories. We evaluate on the Reuters8 dataset consisting of news articles about 8 topics including acq, crude, earn, grain, interest, money-fx, ship, trade.

4.3 Comparative Methods We use supervised and unsupervised baselines for comparison. For supervised methods we use simple average of word embeddings (AVG) and the recently proposed BERT model as our baseline. We use a pretrained BERT implementation and finetune it with a task-specific classifier. This finetuning is performed for 10 epochs using the ADAM optimizer with a learning rate of 5e-6.

Among supervised methods we use a variety of models with and without attention as our baselines. We use a bi-GRU model with maxpooling referred as BiGRU as a baseline. We use a convolutional neural network with max-over-time pooling as another baseline. We refer to this as CNN in the paper.

Among attention-based multi-head models we use the Self Attention Network proposed in. We refer to this baseline as SAN. Following the original paper we have used 30 attention heads and MLP hidden size of 512 for this baseline. Encoder of the Transformer model is another multi-head attention mechanism that is used as a baseline. For this baseline we use one encoder layer and 16 attention heads. We use $d_{model} = 1024$ such that $d_{model}/heads = 64$ as used their paper. For our attention-based models we performed a grid search to identify the optimal number of attention heads to get the best performance.

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1. https://www.yelp.com/dataset challenge
2. https://spacy.io/
3. https://radimrehurek.com/gensim/
5 Results

Table 3 shows the accuracy of the baselines and the proposed model. Numbers highlighted in bold represent best performing models in supervised and unsupervised categories respectively. The proposed model with context (LAMA+ctx) outperforms the SAN model \([15]\) on all tasks from 3.3% (Reuters) to 8.2% (IMDB).

Extrapolating the attention over larger chunks of text we get uniform attention to all words, which is equivalent to no attention or equal preference for all words which is what a simple BiGRU model does (in a contextual setting and average of word embeddings in a non-contextual setting). We note that this model outperforms LSTM model by 2.0% (News), 22.4% (Reuters) 9.8% (Yelp) and 9.4 % (Yelp-L) and 2.7 % (IMDB).

Our models outperform the Transformer Encoder on all tasks except the Reuters dataset where both models perform on par. When compared to finetuned pretrained language models such as BERT we find that performance of both models is similar except the YELP-L dataset where BERT outperforms LAMA.

If we consider the non-contextual baseline of average of word embeddings we see an improvement of 1.4% (News), 22.4% (Reuters) 9.8% (Yelp), 11.4% (Yelp-L) and 3.0% (IMDB) which proves that contextual dependencies captured by LSTM or CNN models are indeed important for the tasks.

Compared to CNN models we see an improvement of 1% (News), 1.4% (Reuters) and 3.3% (Yelp) and 3.0 % (IMDB). On the Yelp-L dataset our model and CNN perform similarly. This maybe because of the ability of CNNs to capture local context using multiple fixed sized kernels and our model’s ability to capture phrase-level context.

5.1 Contextual Attention Weights To verify that our model captures context dependent word importance, we plot the distribution of the attention weights of the positive words ‘amazing’, ‘happy’ and ‘recommended’ and negative words ‘poor’, ‘terrible’ and ‘worst’ from the test split of the Yelp data set as shown in Figure \([2]\). We plot the distribution when conditioned on the ratings of the review. It can be seen from Figure \([2]\) that the weight of positive words concentrates on the low end in the reviews with rating 1 (blue line). As the rating increases, the weight distribution shifts to the right. This indicates that positive words play a more important role for reviews with higher ratings. The trend is opposite for the negative words where words with negative connotation have lower attention weights for reviews with rating 5 (purple line). However, there are a few exceptions. For example, it is intuitive that ‘amazing’ gets a high weight for reviews with high ratings but it also gets a high weight for reviews with rating 2 (orange line). This is because, inspecting the Yelp dataset we find that ‘amazing’ occurs quite frequently with the word ‘not’ in the reviews with rating 2; ‘above average but not amazing’, ‘was ok but not amazing’. Our model captures this phrase-level context and assigns similar weights to ‘not’ and ‘amazing’, ‘not’ being a negative word gets a high weight for lower ratings and hence so does ‘amazing’. Similarly, other exceptions such as ‘terrible’ for rating 4 can be explained due to the fact that customers might dislike one aspect of a business such as their service but like another aspect such as food.

To further illustrate context-dependent word importance Table 4 lists top attended keywords for Yelp and Reuters datasets. It can be seen that certain words that often occur in pairs such as ‘would recommend’, ‘very
5.2 Why Multiple Heads

Having a structured embedding with multiple rows, provides for more contextual representations. To verify this we evaluate the model performance as we vary the number of attention heads $m$ from 1 to 25. Specifically, we plot the validation accuracy vs. epochs for different values of $m$, for the Yelp-L and IMDB datasets. We vary $m$ from 1 to 20 to get 5 models with $m = 1$, $m = 5$, $m = 10$, $m = 15$ and $m = 20$. The plots are shown in Figure 3. From the figure we can see that for the Yelp-L dataset model performance peaks for $m = 15$ and then starts falling for $m = 20$. We can clearly see a significant difference between $m = 1$ and $m = 20$, showing that having a multi-aspect attention mechanism helps. For the IMDB dataset model with $m = 15$ performs the best whereas model with $m = 1$ performs the worst although performances for $m = 5, 15, 20$ are similar to each other for this task.

5.3 Attentional Unit Efficiency

In this section we compare the number of trainable parameters in the attention layer of three multi-head attention mechanisms (§3.3.2): the proposed model (LAMA), Self-Attentive network (SAN) and the Transformer Encoder (TE). Fig. 4 shows the increase in number of parameters (y-axis) when the number of attention heads are increased from 1 to 40.

5.4 Convergence Analysis

We plot the training loss per epoch for the three attention-based models (SAN, TE and LAMA). As can be seen LAMA converges faster on average and to a smaller optimum.
6 Conclusion
In this paper we presented a novel compact multi-head attention mechanism and illustrated its effectiveness on text classification benchmarks. The proposed method computes multiple attention distributions over words which leads to contextual sentence representations. The results showed that this mechanism performed better than several other approaches including non-contextual unsupervised baselines such as average of word embeddings, contextual baselines such as LSTM-based methods and CNNs and also other attention mechanisms with fewer parameters. We further demonstrated the computational superiority of our approach in comparison to prior multi-aspect mechanisms in computing attentions and hence is more amenable in low-resource scenarios. An important research question concerns with the discernibility of different attention heads with respect to each other for better interpretability. One of the obstacles in learning attention in an unsupervised way is that there is no implicit mechanism to impose structure on different rows; although it merits further research.

References

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