CAM: A Combined Attention Model for Natural Language Inference

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***Abstract*—Natural Language Inference (NLI) is a fundamental step towards natural language understanding. The task aims to detect whether a premise entails or contradicts a given hypothesis. NLI contributes to a wide range of natural language understanding applications such as question answering, text summarization and information extraction. Recently, the public availability of big datasets such as Stanford Natural Language Inference (SNLI) and SciTail, has made it feasible to train complex neural NLI models. Particularly, Bidirectional Long Short-Term Memory networks (BiLSTMs) with attention mechanisms have shown promising performance for NLI. In this paper, we propose a Combined Attention Model (CAM) for NLI. CAM combines the two attention mechanisms: intra-attention and inter-attention. The model first captures the semantics of the individual input premise and hypothesis with intra-attention and then aligns the premise and hypothesis with inter-sentence attention. We evaluate CAM on two benchmark datasets: Stanford Natural Language Inference (SNLI) and SciTail, achieving 86.14% accuracy on SNLI and 77.23% on SciTail. Further, to investigate the effectiveness of individual attention mechanism and in combination with each other, we present an analysis showing that the intra- and inter-attention mechanisms achieve higher accuracy when they are combined together than when they are independently used.**

***Keywords*-Natural Language Inference, Deep Learning, Attention Mechanism, Big datasets, SNLI dataset, SciTail dataset.**

I. Introduction

Natural Language Inference (NLI), also known as Recognizing Textual Entailment (RTE), is a fundamental step towards natural language understanding. NLI is the task of determining whether a sentence called hypothesis can be inferred from a given sentence called the premise. From the algorithmic perspective, NLI is a multi-class classification problem. The three classes are Entailment (inferred to be true), Contradiction (inferred to be false) and Neutral (truth value unknown).

Many solutions have been proposed for solving NLI since its inception in 2004 [1]. Traditional approaches to NLI range from machine learning based [2], lexical and semantic similarity based [3], [4], to the methods that extracts structured information such as discourse commitments [5] and predicate-argument [6]. Formal reasoning [7] and natural logic [8] methods are also applied to NLI. However, traditional approaches require extensive feature engineering. Moreover, these approaches do not generalise well because of the complexity and domain dependence nature of feature engineering task.

Machine learning has been a dominant approach to NLI [9]. However, the machine learning research for NLI is severely limited in performance by the lack of gold-standard premise-hypothesis pairs [10]. The field has renewed prosperity by the recent introduction of big datasets such as Stanford Natural Language Inference (SNLI) [10] and SciTail [11]. The public availability of these big datasets has made it feasible to train complex neural network models for NLI. Recurrent Neural Networks (RNNs), particularly bidirectional LSTMs (BiLSTMs) [12] in combination with attention mechanisms [13] have shown state-of-the-art results on the SNLI dataset [14].

Attention mechanisms have shown promising performance for complex natural language understanding sequence modelling tasks such as machine translation [15], [16], dialogue generation [17], machine comprehension [18] and natural language inference [19]. Attention mechanisms allow RNNs to automatically search for the most relevant parts of an input sequence and assigns weights to those parts. These weights are used for creating the attention-weighted representation of the input sequence [13].

The two broad categories of attention in research literature are: intra-attention and inter-attention. The intra-attention mechanism, known as self-attention [20], involves applying attention to the input sentence itself. During training, the model learns to assign higher weight to those parts of the input sentence which are important to its semantics. The

attention-weighted sentence representations thus generated also capture the global context of the sentence [21].

In inter-attention mechanism, attention is applied between the input sentences. The attention-weighted sentence representation of one sentence is generated based on the contents of another sentence. In the sentence representation, the information that is important with respect to other sentences is assigned higher weights.

Attention mechanism has helped in achieving state-of-the-art performance for NLI task [19]. However, the current models that employ only intra-attention [21], [22] do not utilize information from another sentence. The models utilizing inter-attention [23], [24] do not exploit contexts in individual sentences. This paper proposes, a Combined Attention Model (CAM) which employs intra-attention in conjunction with inter-attention to utilize the benefits from both the mechanisms.

Our experiments on the SNLI and SciTail dataset show that intra- and inter-attention mechanisms work constructively and achieve higher accuracy when they are combined together in the same model than using them independently. By combining the intra- and inter-attention mechanism we achieve an accuracy of 86.14% on SNLI and 77.23% on SciTail datasets. The model performs exceptionally well on SciTail outperforming the prominent ESIM model [14] and decomposable attention model [25] by 6.6% and 4.9% respectively.

II. Related Work

Attention mechanism is an essential constituent of the state-of-the-art NLI models [14], [19], [26].

The intra-attention based model proposed by Liu et al. [21], applies attention to premise and hypothesis itself in order to identify the parts of sentences that are important to sentence semantics. Average pooling is first applied to the outputs of word-level BiLSTM and then intra-attention mechanism is employed to replace average pooling on the same sentence for better sentence representation. The authors applied various input strategies and achieved the maximum accuracy of 85.0%. Shen et al. [22], proposed a directional self attention network for sentence encoding. The model relies exclusively on the proposed directional self-attention mechanism to produce the context aware representations for the words in the sentence. The proposed multi-dimensional attention encodes the full sentence into the final sentence representation.

Rocktäschel et al. [23] first applied inter-attention to NLI models. The model is based on word-by-word attention and reasons entailment or contradiction over aligned word- and phrase-pairs. The eminence of inter-attention for NLI task is further established in the state-of-the-art models of Chen et al. [14], Tay et al. [19], Parikh et al. [25] and Ghaeini et al. [26]. The key idea of modeling inter-sentence attention is to soft-align the sub-phrases of premise and hypothesis. Tay et al. [19] and Parikh et al. [25] employs standard projection layer with ReLU activation function whereas Chen et al. [14] and Ghaeini et al. [26] utilize the similarity between the output hidden states of BiLSTMs of premise and hypothesis.

The closest work to our research is that by Parikh et al. [25]; they augmented inter-attention with intra-attention gaining 0.5% in accuracy by employing feed-forward neural-network at both the intra- and inter-attention layers. Our model fundamentally differs from the model proposed by Parikh et al. [25] both at the intra- and inter-attention layers. They have employed feed-forward neural-network at both the intra- and inter-attention layers. However, we used inner-attention mechanism [21] for intra-attention and dot attention mechanism [16] at the inter-attention layers.

Parikh et al. [25] have shown the effectiveness of using combined attention mechanisms, however, the possibility of using different attention mechanisms at intra- and inter-attention layers has not been explored to the best of our knowledge. We experimented with various combinations of attention mechanisms at intra- and inter-attention layer and found that not all combined attention mechanisms work constructively to achieve competitive accuracy for NLI task. We explored the possibility of employing inner-attention [21] and word-attention [27] at the intra-attention layer in combination with each of the dot, general and concate attention mechanisms [16] at inter-attention layer. We achieved the highest accuracy for the proposed combination of inner-attention and dot attention mechanisms. Furthermore, with each attention mechanism at intra- and inter-attention layers we experimented with the feed-forward neural network of [25], however that did not further improve the accuracy of our model.

III. Proposed Model

The proposed model combines intra-attention and inter-attention for modeling the interaction between premise-hypothesis pairs. Fig. 1 demonstrates the high-level view of the proposed NLI model. The layered architecture is composed of the following layers: input encoding, intra-attention, inter-attention, composition and pooling.

In our notations, given the word sequence of premise $\mathbf{a} = (a_1, \ldots, a_n)$ and hypothesis $\mathbf{b} = (b_1, \ldots, b_m)$ with lengths n and m respectively. Each a_i, $b_j \in \mathbb{R}^r$, is a word embedding of r-dimensional, which can be initialized with pre-trained embeddings vectors, such as Glove [28] or Word2Vec [29].

A. Input Encoding Layer

We utilize BiLSTMs to encode the input premise and hypothesis sentences. The BiLSTM processes the input sequence in forward and backward directions to incorporate contextual information at each time step of processing a word in the input sequence. The hidden state output at any time step is the concatenation of forward and backward

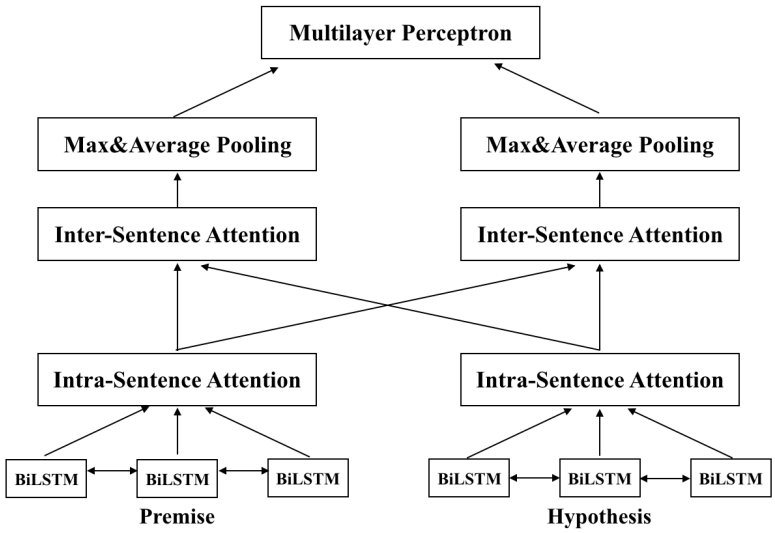


Figure 1: A high level view of our Combined Attention Model (CAM).

hidden states. The $\bar{a} \in \mathbb{R}^{n \times 2d}$ and $\bar{b} \in \mathbb{R}^{m \times 2d}$ in Equation (1) and (2) respectively, represents the $2d$-dimensional representation for each word in the premise and hypothesis. Where d is the dimension of hidden states of LSTMs.

$$\bar{a}_i = \text{BiLSTM}(a, i) \forall i \in [1, \ldots, n] \tag{1}$$

$$\bar{b}_j = \text{BiLSTM}(b, j) \forall i \in [1, \ldots, m] \tag{2}$$

B. Intra-Attention Layer

This layer applies intra-attention [21] to premise and hypothesis sentence independently. Through attention weights, the intra-attention layer emphasizes the words important to the semantics of the input sentence. The attention-weighted sentence representation thus generated represent a more accurate and focused sentence representations of the input sentence. The attention-weighted sentence representation is generated according to Equations $(3) - (5)$

$$M = \tanh\left(W^y Y + W^h R_{avg} \otimes e_L\right) \tag{3}$$

$$\alpha = softmax\left(w^T M\right) \tag{4}$$

$$r = Y \alpha^T \tag{5}$$

where W^y and W^h are trained projection matrices, Y is the matrix of hidden output vectors of the BiLSTM layer, R_{avg} is obtained from the average pooling of Y, $e_L \in \mathbb{R}^L$ is a vector of 1s, w^T is the transpose of trained parameter vector w, α is a vector of attention weights and r is the attention-weighted sentence representation. The attention-weighted sentence representation generated for premise and hypothesis is denoted as r_p and r_h respectively.

C. Inter-Attention Layer

The inter-attention layer uses soft alignment to associate relevant sub-components between the attention weighted representations of premise and hypothesis. The inter-attention layer, first, computes the unnormalized attention weights as a similarity of hidden states of intra-attention weighted representations premise and hypothesis following Equation (6).

$$e_{ij} = r_{pi}^T r_{hj} \tag{6}$$

Next, for each word in the intra-attention weighted representation of the premise, the relevant semantics based on hypothesis, is extracted following Equation (7). Similarly, this is done for hypothesis according to Equation (8).

$$\tilde{r}_{pi} = \sum_{j=1}^{m} \frac{\exp(e_{ij})}{\sum_{k=1}^{m} \exp(e_{ik})} r_{hj} \tag{7}$$

$$\tilde{r}_{hj} = \sum_{i=1}^{n} \frac{\exp(e_{ij})}{\sum_{k=1}^{n} \exp(e_{kj})} r_{pi} \tag{8}$$

$\tilde{r}_p$ represents the content in r_p which are relevant based on r_h. Similarly, $\tilde{r_h}$ represents the content in r_h which are important with respect to r_p. We enrich the collected inference information through the element-wise multiplication of the tuples $(r_p, \tilde{r}_p)$ and $(r_h, \tilde{r}_p)$ as shown in Equations (9) and (10).

$$f_p = \tilde{r_p} \odot r_p \tag{9}$$

$$f_h = \tilde{r_h} \odot r_h \tag{10}$$

D. Pooling Layer

To facilitate the classification of the relationship between premise and hypothesis, a relation vector is formed from the average and max pooling of the encoding of premise

and hypothesis generated previously by inter-attention layer in Equations (9) and (10). Pooling is performed according to Equations (11) and (12).

$$\begin{aligned} \mathrm{v}_{p,avg} &= \text{average } \{f_p, i\}_{i=1}^{n} \\ \mathrm{v}_{p,max} &= \max \{f_p, i\}_{i=1}^{n} \end{aligned} \tag{11}$$

$$\begin{aligned} \mathrm{v}_{h,avg} &= \text{average}\{f_h, i\}_{i=1}^{m} \\ \mathrm{v}_{h,max} &= \max\{f_h, i\}_{i=1}^{m} \end{aligned} \tag{12}$$

where $v_{p,avg}$ and $v_{p,max}$ represents the fixed length vector for premise sentences resulting from the average and max pooling over $\{f_p, i\}_{i=1}^{n}$. Similarly, the fixed length representations is generated for hypothesis according to Equation (12).

E. Classification Layer

To classify the relationship between premise and hypothesis, we feed the concatenation of vectors obtained from Equations (11) and (12) to a multilayer perceptron (MLP) classifier. Specifically, the classifier input is composed as in Equation (13).

$$F_{relation} = [\mathrm{v}_{p,avg}; \mathrm{v}_{p,max}; \mathrm{v}_{h,avg}; \mathrm{v}_{h,max}] \tag{13}$$

The MLP classifier consists of a hidden layer with $tanh$ activation and a three-way $softmax$ output layer. The network is then trained in an end-to-end manner with the standard multi-class cross entropy loss.

IV. Experiments

A. Data

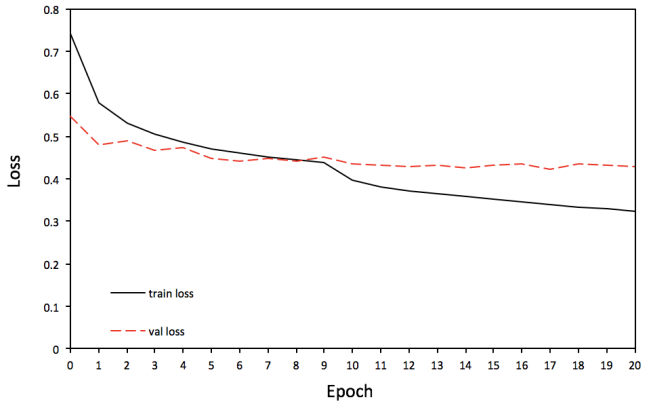
The datasets used for evaluating our model are SNLI [30] and SciTail [11]. For both the datasets, we used the standard train/dev/test splits.

SNLI contains $570,152$ human annotated premise-hypothesis pairs with the entailment, contradiction, neutral and $-$ labels. The label '-' indicates a lack of consensus from the human annotators. We discard the premise-hypothesis pairs with this label. The final train/dev/test sets consists of $549,367/9,842/9,824$ samples respectively.

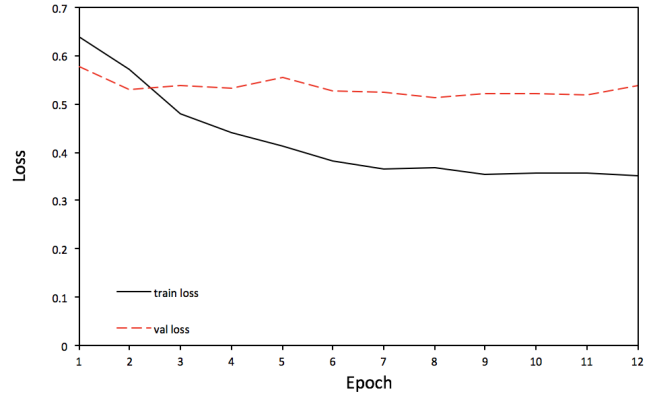
SciTail is derived from Science question-answering task. It contains $27,026$ premise-hypothesis pairs classified into entailment and neutral classes. The train/dev/test splits contains $23,596/1,304/2,126$ samples respectively.

B. Parameters

We use pre-trained 300-*D* Glove 840*B* vectors to initialize the word embeddings [28]. The out-of-vocabulary (OOV) words are initialized by uniform distribution between [-0.05, 0.05]. The hidden states of all the layers for SciTail and SNLI datasets are set to 100 and 300 respectively. Adam optimizer [31] with an initial learning rate of 0.001 is used. Dropout with the rate of 0.4 is applied only to the input of BiLSTM layer for SNLI and to each feed forward connection with dropout rate 0.3 for SciTail dataset. We tuned the batch size amongst [32, 256, 512] and L2 regularization amongst [1e-4, 1e-5]. Each model is optimized on development set for the best performance. The validation and training loss across epochs for the best parameters are depicted in Fig. 2(a) for SNLI and in Fig. 2(b) for SciTail.



(a) SNLI



(b) SciTail

Figure 2: Validation versus training loss of CAM for SNLI and SciTail.

C. Results on SNLI

Table I shows the performance of different models on SNLI benchmark. The first row presents the lexical classifier by Bowman et al. [30]. Sentence encoding based models are shown in the second group (from row 2 to 9) of Table I. Bowman et al. [30] used LSTMs to generate sentence encoding of premise and hypothesis. The sentence encodings are then fed to a multilayer perceptron to identify the relationship between premise and hypothesis. Following this strategy various sentence encoders are proposed, as shown in the second group of models in Table I.

The third group of models (from row 10 to 18) used inter-attention mechanism to align the sub-phrases between premise and hypothesis. Peters et al. [40] holds the cur-

Table I: Accuracies of the models on SNLI.

Models	Accuracy	
	Train	Test
Lexical Classifier [30]	99.7	78.2
100D LSTM [30]	84.8	77.6
300D LSTM [32]	83.9	80.6
1024D GRU [33]	98.8	81.4
300D Tree-based CNN [34]	83.3	82.1
600D BiLSTM (intra-attention) [21]	84.5	84.2
300D Directional self-attention network [22]	91.1	85.6
600D Gumbel TreeLSTM [35]	93.1	86.0
Distance-based Self-Attention Network [36]	89.6	86.3
100D LSTMs word-by-word attention [23]	85.3	83.5
100D Deep Fusion LSTM [37]	85.2	84.6
600D BiLSTM (intra-attention with diversing input) [21]	85.9	85.0
50D Stacked TC-LSTMs [24]	86.7	85.1
300D MMA-NSE (attention) [38]	86.9	85.4
300D LSTMN (deep attention fusion) [39]	87.3	85.7
200D Decomposable attention (intra-attention) [25]	90.5	86.8
600D ESIM + 300D TreeLSTM [14]	93.5	88.6
ESIM + ELMo [40]	91.6	88.7
300D Combined attention mechanism (CAM, our approach)	90.5	**86.1**

rent state-of-the-art performance on SNLI among the inter-attention, non-ensemble models. Embeddings from Language Models (ELMo) word embeddings of Peters et al. [40], when used with ESIM model of Chen et al. [14] improved the accuracy from 88.6% to 88.7%.

Among the models employing inter-sentence attention, our model (Combined Attention Model (CAM)) achieves a competitive accuracy of 86.14% on the SNLI dataset. Our model outperforms the previous models proposed by Rocktäschel et al. [23], Liu et al. [37], Liu et al. [21], Liu et al. [24], Munkhdalai and Yu [38] and Cheng et al. [39]. CAM achieves higher accuracy than the intra-attention with diversing input model of Liu et al. [21] by 1.4%.

D. Results on SciTail

SciTail dataset contains the labelled data for the classes of NLI - neutral and entailment. The NLI, thus transforms into binary classification task. Table II shows our empirical results on SciTail dataset. The low accuracies of the state-of-the-art ESIM [14] and decomposable attention model [25] suggest that SciTail is a difficult dataset to model. The performance gain of CAM over the strong ESIM and decomposable attention model is 6.6% and 4.9% in terms of accuracy.

E. Ablation Analysis

We evaluate the effectiveness of individual components of our model on SciTail and SNLI datasets. Table III depicts the results. For SciTail, both of our intra-attention-only and inter-attention-only models outperforms the models of Parikh et al. [25] and Chen et al. [14] by a large margin, as detailed below.

Table II: Accuracies of the models on SciTail. The model accuracies are reported from [11] except for CAFE which is reported from [19]

Models	Test Accuracy
Majority class	60.3
NGram	70.6
ESIM	70.6
DGEM w/o edges	70.8
Decomposable attention	72.3
DGEM	77.3
CAFE	83.3
CAM (our approach)	**77.23**

Table III: Ablation analysis for SCI and SNLI datasets

Models	Test Accuracy(%)	
	SciTail	**SNLI**
Combined Attention	**77.23**	**86.14**
Intra-attention-only	75.49	80.27
Inter-attention-only	76.06	85.04

When we remove inter-attention mechanism from CAM, the intra-attention-only model has an accuracy of 75.49% and outperforms the decomposable attention model of Parikh et al. [25] and ESIM model of Chen et al. [14] (please refer Table II for the model accuracy of Parikh et al. [25] and Chen et al. [14]) by 3.1% and 4.9% respectively.

When we remove the intra-attention mechanism from CAM, the inter-attention-only model achieves an accuracy of 76.06%. The inter-attention-only model improves over the accuracy of decomposable attention of Parikh et al. [25] by

3.76% and by 5.46% over the ESIM model of Chen et al. [14]. CAM performs comparatively with DGEM model of Khot et al. [11].

For SNLI, the intra-attention-only model does not perform well and it achieves an accuracy of 80.27%. However, the inter-attention-only model achieves an accuracy of 85.04%, which is higher than the word-by-word attention model of Rocktäschel et al. [23] by 1.5% and deep fusion LSTM model of Liu et al. [37] by 0.4%. The inter-attention-only model performs competitively with the intra-attention with diversing input model of Liu et al. [21]

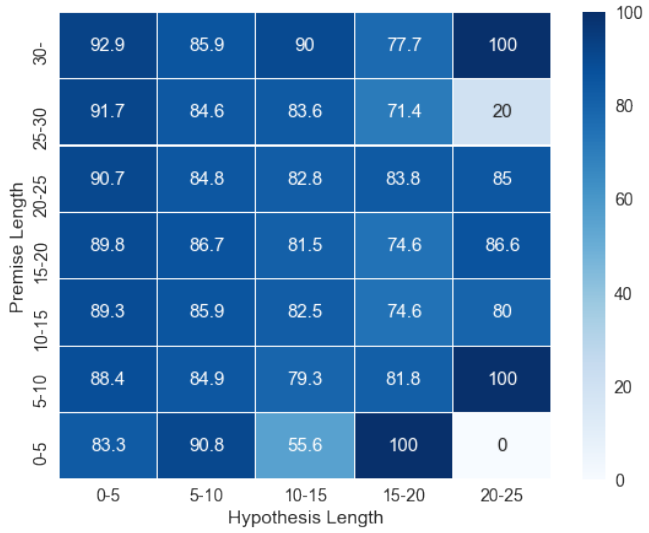
It is worth to note that SciTail dataset contains longer premise and hypothesis than SNLI dataset [11]. The results of the ablation analysis for SciTail suggest that for long sentences, it is crucial to first capture the semantics of the input sentence by intra-attention mechanism. The results on both of the datasets suggest that intra-attention and inter-attention work constructively and achieve high accuracy when they are combined.

V. Qualitative Analysis

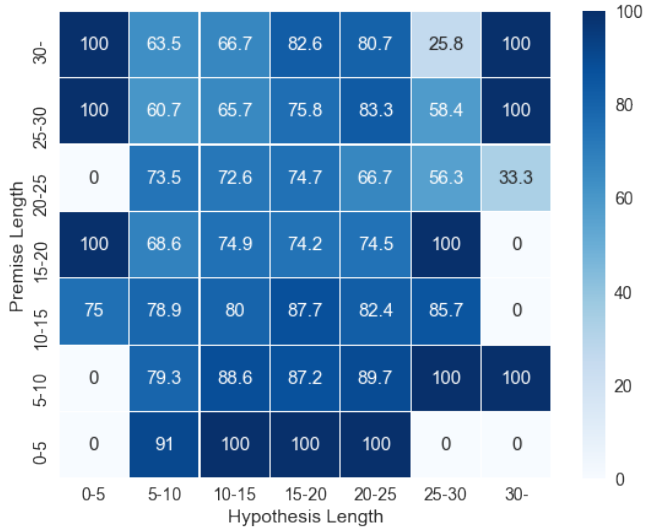
We semantically and syntactically analysed the premise-hypothesis pairs of test set that are correctly classified and the pairs that are misclassified by our model. The semantic analysis suggest that our model effectively learns to reason between premise and hypothesis and do not depend on the word overlap between them. Table IV and Table V illustrates some of the correctly and misclassified examples from the SciTail dataset.

The test case 1 in the Table IV, suggests that the model correctly learns to reason that hydrogen is the most abundant element in the universe without this being explicitly stated in the premise sentence. Similarly, for the text case 2, for the premise-hypothesis pair to be correctly classified, the model must learn the numerical reasoning by which it can conclude that - 98 percent of the matter is the most" of the universe. Text case 3 is an interesting example where our model excels. The test case have a high degree of word overlap, however the model do not get confused and correctly identifies that hypothesis is neutral to premise. For the misclassified text cases of Table V, we observed that premise-hypothesis pairs are generally syntactically and semantically intricate and contains ambiguous words.

To understand the effectiveness of CAM for premise and hypothesis sentences of varying lengths (word count), we evaluate the accuracy of the model when hypothesis and premise lengths vary in the intervals 0-5, 10-15, 15-20, 20-25, 25-30 and greater than 30 words. The results are reported in Fig. 3. For both SNLI and SciTail datasets, the result suggests that for all the premise length intervals, the model is very effective for hypothesis lengths greater than 10 words. The accuracy of 0% shows that no test case exist in that interval of premise-hypothesis length.



(a) SNLI



(b) SciTail

Figure 3: CAM accuracy for varying premise and hypothesis lengths.

VI. Further Analysis

To investigate the effectiveness of each attention mechanism individually and in combination with each other, we further analyse the performance of each model in Table III. Fig. 4 present the result of the analysis.

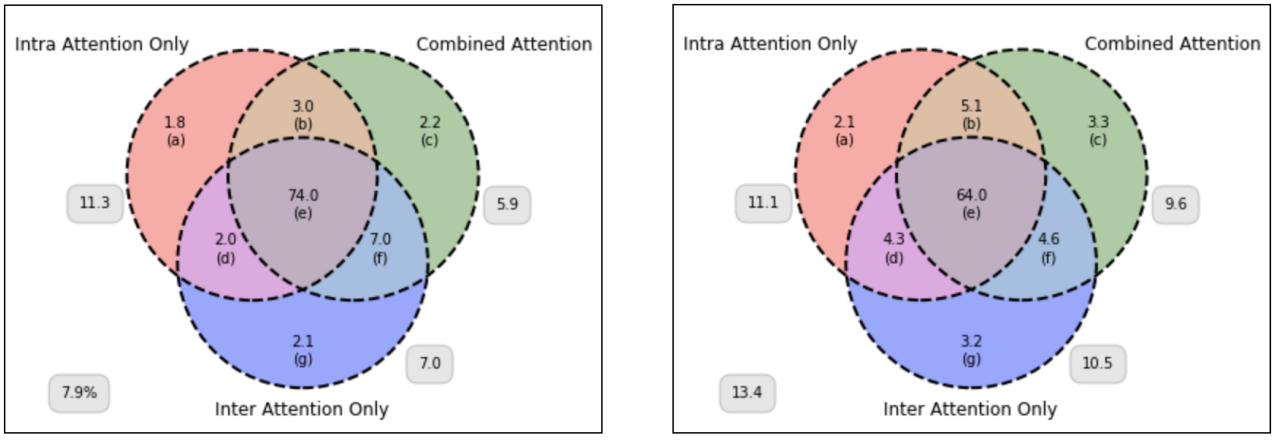
For SNLI: The three models correctly classified 74% the test samples (central region (e) Fig. 4(a)). Combined attention model outperforms each of the individual attention mechanism by correctly classifying 2.2% of test cases individually (region(c) in Fig. 4(a)) as compared to 1.8% of intra-attention only and 2.1% of inter-attention only model. The inter-attention model and combined attention

Table IV: Correctly classified test cases from SciTail dataset.

S.No	Premise\Hypothesis Pair	Correct Test Label
1.	Helium is the second most abundant element in the known universe, after hydrogen.\The element hydrogen is the most abundant in the universe.	Entailment
2.	The reality is that plasmas make up over 98% of the matter in the universe.\Plasma matter makes up most of the universe.	Entailment
3.	A convex lens is a lens that is thicker in the middle than at its edges.\A concave lens is thicker at the edges than it is in the middle.	Neutral

Table V: Misclassified test cases from SciTail dataset.

S.No	Premise\Hypothesis Pair	Correct Test Label
1.	In the terminology of engineering mechanics, statics is the study of forces on structures, and dynamics is the study of forces on structures in motion.\Dynamics is the study of how forces affect the motion of objects.	Entailment
2.	Our digestive system requires that our food is chewed by teeth, go through the esophagus, stomach, intestine and many associate organs.\Esophagus, stomach, intestines are the structures that make up the digestive system in the human body.	Entailment



(a) SNLI

(b) SciTail

Figure 4: Venn diagram showing the percent of test samples correctly classified by each model in Table III. The central overlapped region depicts the percent of correctly classified test samples by all the three models. The label adjoining each attention model shows the percent of test cases incorrectly classified by the individual model. The label at the left bottom shows the percent of test samples incorrectly classified by all the models. For instance, for SNLI (Fig. (a)) the three models classified 74.0% of test cases correctly. The combined attention model individually misclassified 5.9% of test cases and all the three models misclassified 7.9% of test cases.

model correctly classify 7.0% of test samples whereas intra-attention and combined attention correctly classify 3.0% of test samples. This suggests that inter attention is crucial for the high performance on SNLI. The intra-attention and inter-attention correctly classifies 2.0% of test samples. There are 7.9% test samples which cannot be classified correctly by any of the three models.

For SciTail: The three models correctly classified 64% of test cases (central region, Fig. 4(b)). Similar to SNLI, the combined attention model gets the highest percent (3.3%) of test samples classified correctly. Unlike for SNLI, the intra-attention-only and combined attention models agree on a larger number of test cases (5.1%) than the inter-attention-only and combined attention model, which agree on 4.6% of test cases. Given the fact that SciTail is difficult to model [19], the result suggest that capturing the semantics of individual sequence first with intra-sentence attention is crucial for modeling complex datasets. Moreover, a significant number of test samples (13.4%) are not classified correctly by any of the model. This further indicates the high complexity SciTail.

Linguistic analysis of the test samples in each region of Fig. 4 is an interesting investigation to understand the behaviour of each model. Particularly, it is interesting to

analyze syntax and semantics of the premise-hypothesis pairs, which are incorrectly classified by the intra-attention-only and inter-attention-only models but correctly classified by combined attention model. Region (c) in Fig. 4 depicts these test cases. A preliminary linguistic observation on the syntactic structure of premise-hypothesis pairs in this region suggest that for longer premises (word count > 20) the combined attention model predicts the test classes correctly more often than the intra-attention-only and inter-attention-only models.

VII. Conclusions

In this paper, we proposed a natural language inference model called Combined Attention Model (CAM), that benefits from intra-attention and inter-attention mechanisms. Experiments on two benchmark datasets: SNLI and SciTail demonstrate that CAM performs competitively to the previous models. CAM achieves an accuracy of 86.14% on SNLI and 77.23% on SciTail. We show that, CAM performs particularly effectively on the hard to model SciTail dataset and outperforms the state-of-the-art ESIM by 6.6% and decomposable attention models by 4.9%. Further, the results of ablation analysis shows that the intra-attention and inter-attention mechanism work constructively and achieve higher accuracy when they are combined together in the same model than when they are independently used.

In future work, we will further investigate the linguistic structure of the benchmark datasets, such as SNLI and SciTail to understand the effectiveness of CAM on these datasets. The analysis will pave the way for further improvements to our model. Another interesting line of research is to investigate the effectiveness of incorporating syntactic information such as part-of-speech tags and parse trees into the input sentences. We believe those linguistic features would further benefit the model to capture some semantic aspects of the sentences.

References

[1] I. Dagan and O. Glickman, "Probabilistic textual entailment: Generic applied modeling of language variability," 2004.

[2] B. MacCartney, T. Grenager, M.-C. de Marneffe, D. Cer, and C. D. Manning, "Learning to recognize features of valid textual entailments," in *Proceedings of the Main Conference on Human Language Technology Conference of the North American Chapter of the Association of Computational Linguistics*, ser. HLT-NAACL '06. Stroudsburg, PA, USA: Association for Computational Linguistics, 2006, pp. 41–48. [Online]. Available: https://doi.org/10.3115/1220835.1220841

[3] V. Jijkoun, M. de Rijke *et al.*, "Recognizing textual entailment using lexical similarity," in *Proceedings of the PASCAL Challenges Workshop on Recognising Textual Entailment*. Citeseer, 2005, pp. 73–76.

[4] M. Heilman and N. A. Smith, "Tree edit models for recognizing textual entailments, paraphrases, and answers to questions," in *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 2010, pp. 1011–1019.

[5] A. Hickl, "Using discourse commitments to recognize textual entailment," in *Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1*. Association for Computational Linguistics, 2008, pp. 337–344.

[6] R. Wang and Y. Zhang, "Recognizing textual relatedness with predicate-argument structures," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 2-Volume 2*. Association for Computational Linguistics, 2009, pp. 784–792.

[7] J. Bos and K. Markert, "Recognising textual entailment with logical inference," in *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2005, pp. 628–635.

[8] B. MacCartney, *Natural language inference*. Stanford University, 2009.

[9] I. Androutsopoulos and P. Malakasiotis, "A survey of paraphrasing and textual entailment methods," *J. Artif. Int. Res.*, vol. 38, no. 1, pp. 135–187, May 2010. [Online]. Available: http://dl.acm.org/citation.cfm?id=1892211.1892215

[10] S. R. Bowman, G. Angeli, C. Potts, and C. D. Manning, "A large annotated corpus for learning natural language inference," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 632–642.

[11] T. Khot, A. Sabharwal, and P. Clark, "Scitail: A textual entailment dataset from science question answering," in *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, New Orleans, Louisiana, USA, February 2-7, 2018*, 2018. [Online]. Available: https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/17368

[12] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[13] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," *arXiv preprint arXiv:1409.0473*, 2014.

[14] Q. Chen, X. Zhu, Z.-H. Ling, S. Wei, H. Jiang, and D. Inkpen, "Enhanced lstm for natural language inference," in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, vol. 1, 2017, pp. 1657–1668.

[15] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Advances in Neural Information Processing Systems*, 2017, pp. 6000–6010.

[16] M.-T. Luong, H. Pham, and C. D. Manning, "Effective approaches to attention-based neural machine translation," *arXiv preprint arXiv:1508.04025*, 2015.

[17] L. Shang, Z. Lu, and H. Li, "Neural responding machine for short-text conversation," *arXiv preprint arXiv:1503.02364*, 2015.

[18] M. Seo, A. Kembhavi, A. Farhadi, and H. Hajishirzi, "Bidirectional attention flow for machine comprehension," *arXiv preprint arXiv:1611.01603*, 2016.

[19] Y. Tay, L. A. Tuan, and S. C. Hui, "A compare-propagate architecture with alignment factorization for natural language inference," *arXiv preprint arXiv:1801.00102*, 2017.

[20] Z. Lin, M. Feng, C. N. d. Santos, M. Yu, B. Xiang, B. Zhou, and Y. Bengio, "A structured self-attentive sentence embedding," *arXiv preprint arXiv:1703.03130*, 2017.

[21] Y. Liu, C. Sun, L. Lin, and X. Wang, "Learning natural language inference using bidirectional lstm model and inner-attention," *arXiv preprint arXiv:1605.09090*, 2016.

[22] T. Shen, T. Zhou, G. Long, J. Jiang, S. Pan, and C. Zhang, "Disan: Directional self-attention network for rnn/cnn-free language understanding," *arXiv preprint arXiv:1709.04696*, 2017.

[23] T. Rocktäschel, E. Grefenstette, K. M. Hermann, T. Kocisky, and P. Blunsom, "Reasoning about entailment with neural attention," in *International Conference on Learning Representations (ICLR)*, 2016.

[24] P. Liu, X. Qiu, Y. Zhou, J. Chen, and X. Huang, "Modelling interaction of sentence pair with coupled-lstms," in *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2016, pp. 1703–1712.

[25] A. P. Parikh, O. Täckström, D. Das, and J. Uszkoreit, "A decomposable attention model for natural language inference," *arXiv preprint arXiv:1606.01933*, 2016.

[26] R. Ghaeini, S. A. Hasan, V. Datla, J. Liu, K. Lee, A. Qadir, Y. Ling, A. Prakash, X. Z. Fern, and O. Farri, "Dr-bilstm: Dependent reading bidirectional lstm for natural language inference," *arXiv preprint arXiv:1802.05577*, 2018.

[27] Z. Yang, D. Yang, C. Dyer, X. He, A. Smola, and E. Hovy, "Hierarchical attention networks for document classification," in *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2016, pp. 1480–1489.

[28] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 2014, pp. 1532–1543.

[29] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," *arXiv preprint arXiv:1301.3781*, 2013.

[30] S. R. Bowman, G. Angeli, C. Potts, and C. D. Manning, "A large annotated corpus for learning natural language inference," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 632–642. [Online]. Available: http://www.aclweb.org/anthology/D15-1075

[31] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *CoRR*, vol. abs/1412.6980, 2014. [Online]. Available: http://arxiv.org/abs/1412.6980

[32] S. R. Bowman, J. Gauthier, A. Rastogi, R. Gupta, C. D. Manning, and C. Potts, "A fast unified model for parsing and sentence understanding," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, vol. 1, 2016, pp. 1466–1477.

[33] I. Vendov, R. Kiros, S. Fidler, and R. Urtasun, "Order-embeddings of images and language," May 2016.

[34] L. Mou, R. Men, G. Li, Y. Xu, L. Zhang, R. Yan, and Z. Jin, "Natural language inference by tree-based convolution and heuristic matching," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, vol. 2, 2016, pp. 130–136.

[35] J. Choi, K. M. Yoo, and S. goo Lee, "Learning to compose task-specific tree structures." AAAI, 2017.

[36] J. Im and S. Cho, "Distance-based self-attention network for natural language inference," *arXiv preprint arXiv:1712.02047*, 2017.

[37] P. Liu, X. Qiu, J. Chen, and X. Huang, "Deep fusion lstms for text semantic matching," in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, vol. 1, 2016, pp. 1034–1043.

[38] T. Munkhdalai and H. Yu, "Neural tree indexers for text understanding," in *Proceedings of the conference. Association for Computational Linguistics. Meeting*, vol. 1. NIH Public Access, 2017, p. 11.

[39] J. Cheng, L. Dong, and M. Lapata, "Long short-term memory-networks for machine reading," in *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, 2016, pp. 551–561.

[40] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, "Deep contextualized word representations," *CoRR*, vol. abs/1802.05365, 2018. [Online]. Available: http://arxiv.org/abs/1802.05365