Attentive Convolution

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Abstract

In NLP, convolution neural networks (CNNs) have benefited less than recurrent neural networks (RNNs) from attention mechanisms. We hypothesize that this is because attention in CNNs has been mainly implemented as *attentive pooling* (i.e., it is applied to pooling) rather than as *attentive convolution* (i.e., it is integrated into convolution). Convolution is the differentiator of CNNs in that it can powerfully model the higher-level representation of a word by taking into account its *local fixed-size* context in input text t^x. In this work, we propose an attentive convolution network, *AttentiveConvNet*. It *extends the context scope* of the convolution operation, deriving higher-level features for a word not only from local context, but also from information extracted from nonlocal context by the *attention mechanism commonly used in RNNs*. This nonlocal context can come (i) from parts of the input text t^x that are distant or (ii) from a second input text, the context text t^y. In an evaluation on sentence relation classification (textual entailment and answer sentence selection) and text classification, experiments demonstrate that AttentiveConvNet has state-of-the-art performance and outperforms RNN/CNN variants with and without attention. All code will be publicly released.

1 Introduction

Natural language processing (NLP) has benefited greatly from the resurgence of deep neural networks (DNNs), due to their high performance with less need of engineered features. A standard DNN consists of a series of non-linear transformation layers, each producing a fixed-dimensional hidden representation. For tasks like machine translation that

have large input spaces, this paradigm must encode the entire input text in one hidden state, resulting in an information bottleneck; systems cannot encode all input information in this bottleneck, but do not know how to select the subset that is needed for correct subsequent decisions. In response, attention mechanisms are commonly used to perform a soft-selection over hidden representations; this mechanism scales with input size, dynamically picking only that information that is important for each step (e.g., of the translation process). Attention is roughly a variable-length memory model and has shown to be important for good performance on many tasks.

Convolution neural networks (CNNs, LeCun et al. (1998)) and recurrent neural networks (RNNs, Elman (1990)) are two important types of DNNs. Most work on attention has been done for RNNs. Attention-based RNNs typically take three types of input to make a decision at current step: (i) the current input state, (ii) a representation of local context (computed unidirectionaly or bidirectionally, Rocktäschel et al. (2016)) and (iii) the attention-weighted sum of hidden states corresponding to nonlocal context (e.g., the hidden states of the encoder in neural machine translation (Bahdanau et al., 2015a)). An important question therefore is whether CNNs can benefit from such an attention mechanism as well and how. This is our *technical motivation*.

Our second motivation is natural language understanding (NLU). *Attentive convolution is needed for NLU tasks*. We distinguish two main cases: intertext and intratext. *Intertext* means that, in addition to the input text t^x, there is a second input text t^y over which we compute attention. Consider the SNLI textual entailment examples in Table 1; here the input text t^x is the hypothesis and the context text t^y is

textual entailment example	
premise	three bikers stop in town
hyp$_1$	a group of bikers are in the street
hyp$_2$	the bikers did n't stop in the town
sentiment analysis example	

With the 2017 NBA All-Star game in the books I think we can all agree that this was definitely one to *remember*. Not because of the three-point shootout, the dunk contest, or the game itself but because of the *ludicrous* trade that occurred after the festivities.

Table 1: Examples for inter- and intratext attention.

the premise. Intuitively, a system in this task should match "three bikers" and "in town" in the premise with "a group of bikers" and "in the street" in hyp$_1$, respectively; and match "three bikers" and "stop" in the premise with "the bikers" and "did n't stop" in hyp$_2$, respectively. Thus, cross-text, i.e., intertext, phrase matching is important and we cannot just match words, we also need to take their contexts into account. *Intratext* means that we compute attention over the input text t^x; so the same text takes the roles of both input text t^x and context text t^y. Consider the sentiment analysis examples in Table 1. In addition to taking into consideration local contexts (as most sentiment analysis systems do), "remember" (per default a neutral word) can only be interpreted as enhancing negativity here if it is related to the distant phrase "ludicrous".

A convolutional filter in conventional CNNs models mutual dependencies within a local context window, but *ignores both intertext and intratext context*. Attentive pooling CNNs (Yin and Schütze, 2015; dos Santos et al., 2016) also do intertext modeling, but they perform the phrase matching after the convolution process, so that *no rich intertext and intratext context is available to convolutional filters*.

In this work, we propose attentive convolution networks, AttentiveConvNets. In the intratext case (text classification in our example), AttentiveConvNets extend the local context window of standard CNNs to cover the entire input text t^x. In the intertext case (sentence relation identification in our example), AttentiveConvNets extend the local context window to cover a second input text t^y, the context text. Our formalization is the same for intertext and intratext. So we will use t^a from now on to refer to

the text over which we compute attention. t^a is t^y for intertext and t^x for intratext.

For a convolution operation over a window in t^x like (*left*$_\text{context}$, *target*, *right*$_\text{context}$), we first compare the representation of *target* with all hidden states in t^a to get an attentive context representation *att*$_\text{context}$, then CNN derives a higher-level representation for *target*, denoted as *target*$^\text{new}$, by integrating *target* with three pieces of context: *left*$_\text{context}$, *right*$_\text{context}$ and *att*$_\text{context}$. We can *have two interpretations for this attentive convolution*. (i) For intratext, a higher-level word representation *target*$^\text{new}$ is learned by considering local (i.e., *left*$_\text{context}$ and *right*$_\text{context}$) as well as nonlocal (i.e., *att*$_\text{context}$) context. (ii) For intertext, representation *target*$^\text{new}$ is generated to denote the cross-text aligned phrases (*target*, *att*$_\text{context}$) in context *left*$_\text{context}$ and *right*$_\text{context}$.

We apply AttentiveConvNets to two sentence relation identification tasks, SNLI textual entailment (Bowman et al., 2015) and question-aware answer sentence selection on SQUAD (Rajpurkar et al., 2016), and on the large-scale Yelp sentiment classification task (Lin et al., 2017). AttentiveConvNet outperforms competitive DNNs with and without attention and gets state-of-the-art on the three tasks.

Overall, we make the following contributions:

- This is the first work that enables CNNs to acquire the attention mechanism commonly employed in RNNs.

- We distinguish and build flexible modules – attention source, attention focus and attention beneficiary – to greatly advance the expressivity of attention mechanisms in CNNs.

- AttentiveConvNet provides a new way to broaden the originally constrained scope of filters in conventional CNNs. Broader and richer context comes from either external inputs (intertext) or internal inputs (intratext).

- AttentiveConvNet shows its superiority over competitive DNNs with and without attention.

2 Related Work

In this section we discuss attention-related DNNs in NLP, the most relevant work for our paper.

2.1 RNNs with Attention

Graves (2013) and Graves et al. (2014) first introduced a differentiable attention mechanism that allows RNNs to focus on different parts of the input. This idea has been broadly explored in RNNs. We now summarize three bodies of relevant NLP work.

Sequence-to-sequence text generation. This category follows $Encoder(source) \longrightarrow Decoder(target)$. The attention mechanism in Seq2Seq learning allows an RNN decoder to directly access information about the input each time before it emits a symbol.

Bahdanau et al. (2015b) bring the attention idea into neural machine translation (NMT), extending the basic encoder-decoder by automatically aligning the current decoding hidden state with each source hidden state, then all source hidden states are weight-averaged as a *context vector*. The model then predicts a target word based on the context vector and the previously generated target words. Luong et al. (2015) extend this "global" attention (Bahdanau et al., 2015b) and propose a type of "local" attention for NMT – focusing on a subset of the source positions per target word. Libovický and Helcl (2017) further extend the attention mechanism for multimodal translation: multiple input sources, single target. Kim et al. (2017) generalize soft-selection attention by specifying possible structural dependencies among source elements in a soft manner.

Other work on text generation includes response generation in social media (Shang et al., 2015), document reconstruction (Li et al., 2015) and document summarization (Nallapati et al., 2016).

Machine comprehension. This category follows a function $f(text_{doc}, text_{question}) \longrightarrow text_{answer}$. Hermann et al. (2015) provide reading comprehension datasets "CNN" and "Daily Mail" and develop a class of attention based RNNs that learn to read real documents and answer complex questions. For a (document, question) pair, the system predicts *which token* in the document answers the question. The key contribution is the attention mechanism; it supports learning a compact joint representation for the (document, question) pair.

Kumar et al. (2016) and Xiong et al. (2016) present dynamic memory networks (DMNs) for modeling question answering for bAbI. DMN is still

a recurrent attention process over question representation, fact representations in the document and previous memory episode.

Wang and Jiang (2017) present the first attention based RNN for SQUAD (Rajpurkar et al., 2016) in which the input is a (document, question) pair, output is a *text span* in the document as the answer. Other attentive RNNs for SQUAD include Dynamic Coattention Networks (Xiong et al., 2017), Bi-Directional Attention Flow (BIDAF) (Seo et al., 2017), Recurrent Span Representations (Lee et al., 2016), Document Reader (Chen et al., 2017a), Reasoning Network (Shen et al., 2017), Ruminating Reader (Gong and Bowman, 2017), Mnemonic Reader (Hu et al., 2017), R-Net (Wang et al., 2017a).

We define **sentence relation classification** as $f(text_x, text_y) \longrightarrow class$. Rocktäschel et al. (2016) employ neural word-to-word attention similar to Bahdanau et al. (2015b) and Hermann et al. (2015) for SNLI (Bowman et al., 2015). The difference is that attention is not used to generate words, but to obtain a text-pair representation from fine-grained cross-text alignments. Wang and Jiang (2016) propose match-LSTM, an extension of (Rocktäschel et al., 2016)'s attention. Cheng et al. (2016) present a new machine reader that equips an LSTM with a memory tape instead of a memory cell to store the past information and adaptively use it without severe information compression. Other work on attentive matching includes Multi-Perspective Matching (Wang et al., 2017b) and Enhanced LSTM (Chen et al., 2017b).

Miao et al. (2016) present Neural Answer Selection Model (NASM) based on LSTM and attention to identify the correct sentences answering a factual question from a set of candidate sentences. NASM applies an attention model to focus on the words in the answer sentence that are prominent for predicting the answer matched to the current question.

2.2 CNNs with Attentive Pooling

In NLP, there is little work on attention-based CNNs; two exceptions are (Yin et al., 2016) and (dos Santos et al., 2016). These two papers mainly implement the attention *in pooling*, i.e., the convolution is not affected. Specifically, their systems work on two input sentences, each with a set of hidden states generated by a convolution layer, then each sentence

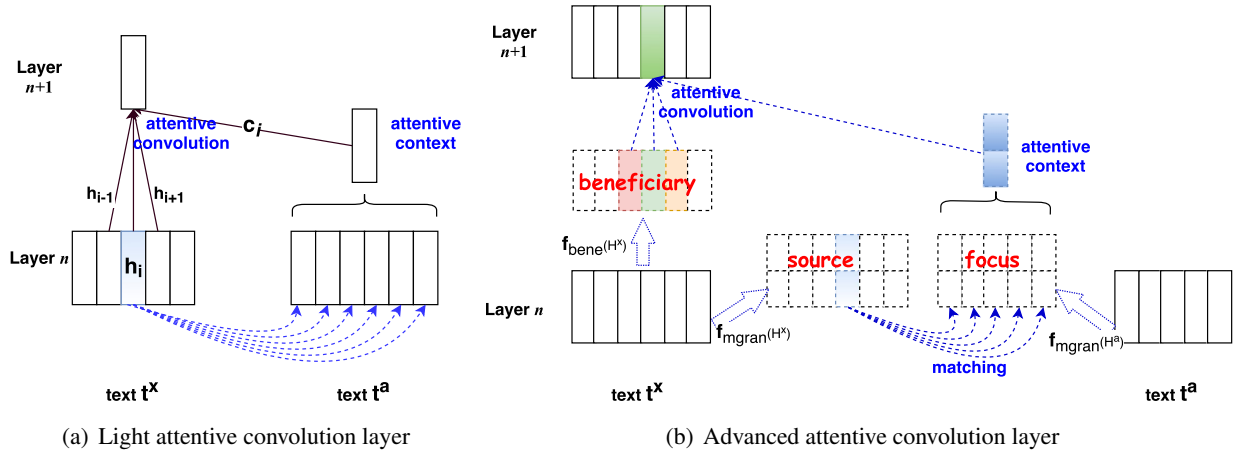(a) Light attentive convolution layer (b) Advanced attentive convolution layer

Figure 1: Attentive convolution layer

will learn a weight for every hidden state by comparing this hidden state with all hidden states in the other sentence, finally each input sentence obtains a representation by a weighted mean pooling over all its hidden states. *The core component – weighted mean pooling – was referred to as "attentive pooling"*, aiming to yield the sentence representation.

In contrast to attentive convolution, attentive pooling *does not connect the hidden states* of cross-text aligned phrases directly and in a fine-grained manner *to the final decision making*, *only the matching scores* contribute to the final weighting in mean pooling. This important distinction between attentive convolution and attentive pooling is further discussed in Section 4.1 (see paragraph "**Analysis**").

Inspired by the attention mechanisms in RNNs, we assume that it is the hidden states of aligned phrases rather than their matching scores that can better contribute to the representation learning and decision making. Hence, our attentive convolution work differs from attentive pooling in that it uses attended hidden states from extra context (intertext) or broader context range (intratext) to participate in the convolution. In experiments, we will show its superiority.

2.3 Attention in Other DNN Architectures

Parikh et al. (2016) address SNLI by accumulating fine-grained word-by-word alignments, computed by feedforward neural networks.

Vaswani et al. (2017)'s Transformer uses self-attention (Cheng et al., 2016; Lin et al., 2017), dispensing with recurrence and convolutions entirely.

3 AttentiveConvNet Model

We use bold uppercase, e.g., $\mathbf{H}$, for matrices; bold lowercase, e.g., $\mathbf{h}$, for vectors; bold lowercase with index, e.g., $\mathbf{h}_i$, for columns of $\mathbf{H}$; and non-bold lowercase for scalars.

For our system, we assume that at a certain layer, AttentiveConvNet represents text t ($t \in \{t^x, t^a\}$) as a sequence of hidden states $\mathbf{h}_i \in \mathbb{R}^d$ ($i = 1, 2, \ldots, |t|$), forming feature map $\mathbf{H} \in \mathbb{R}^{d \times |t|}$, where d is the dimensionality of hidden states. Each hidden state $\mathbf{h}_i$ has its left context $\mathbf{l}_i$ and right context $\mathbf{r}_i$. In concrete CNN systems, context $\mathbf{l}_i$ and $\mathbf{r}_i$ can cover multiple adjacent hidden states, we set $\mathbf{l}_i = \mathbf{h}_{i-1}$ and $\mathbf{r}_i = \mathbf{h}_{i+1}$ for simplicity in following description.

We now describe light and advanced versions of AttentiveConvNet. Recall that AttentiveConvNets aim to compute a representation for t^x in a way that convolution filters encode not only local context, but also attentive context over t^a.

3.1 Light AttentiveConvNet

Figure 1(a) shows the light version of AttentiveConvNet. It differs in two key points – (i) and (ii) – both from the basic convolution layer that models a single piece of text and from the Siamese CNN that models two text pieces in parallel. (i) A matching process by an energy function[1] determines how relevant each hidden state in text t^a is to the current hidden state $\mathbf{h}_i^x$ in t^x. We then compute an average

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[1]Similar to Bordes et al. (2014), we use this term broadly to refer to any semantic matching function.

of the hidden states in t^a, weighted by the matching scores, to get the attentive context $\mathbf{c}_i^x$ for $\mathbf{h}_i^x$. (ii) Convolution for position i in t^x integrates hidden state $\mathbf{h}_i^x$ with *three sources of context*: left context $\mathbf{h}_{i-1}^x$, right context $\mathbf{h}_{i+1}^x$ and attentive context $\mathbf{c}_i^x$.

Attentive Context Vector Generation. First, an energy function $f_e(\mathbf{h}_i^x, \mathbf{h}_j^a)$ in matching process generates a matching score $e_{i,j}$ between a hidden state in t^x and a hidden state in t^a by (i) dot product:

$$e_{i,j} = (\mathbf{h}_i^x)^T \cdot \mathbf{h}_j^a \quad (1)$$

or (ii) bilinear form:

$$e_{i,j} = (\mathbf{h}_i^x)^T \mathbf{W}_e \mathbf{h}_j^a \quad (2)$$

(where $\mathbf{W}_e \in \mathbb{R}^{d \times d}$) or (iii) additive projection:

$$e_{i,j} = (\mathbf{v}_e)^T \cdot \tanh(\mathbf{W}_e \cdot \mathbf{h}_i^x + \mathbf{U}_e \cdot \mathbf{h}_j^a) \quad (3)$$

where $\mathbf{W}_e, \mathbf{U}_e \in \mathbb{R}^{d \times d}$ and $\mathbf{v}_e \in \mathbb{R}^d$.

Given the matching scores, the attentive context $\mathbf{c}_i^x$ for hidden state $\mathbf{h}_i^x$ is the weighted average of all hidden states in t^a:

$$\mathbf{c}_i^x = \sum_j \text{softmax}(\mathbf{e}_i)_j \cdot \mathbf{h}_j^a \quad (4)$$

We refer to the concatenation of attentive contexts $[\mathbf{c}_1^x; \ldots; \mathbf{c}_i^x; \ldots; \mathbf{c}_{|t^x|}^x]$ as the feature map $\mathbf{C}^x \in \mathbb{R}^{d \times |t^x|}$ for t^x.

Attentive Convolution. A position i in t^x at layer n has hidden state $\mathbf{h}_i^{x,n}$, left context $\mathbf{h}_{i-1}^{x,n}$, right context $\mathbf{h}_{i+1}^{x,n}$ and attentive context $\mathbf{c}_i^{x,n}$. Attentive convolution then generates the higher-level hidden state at position i at layer $n+1$:

$$\mathbf{h}_i^{x,n+1} = \tanh(\mathbf{W} \cdot [\mathbf{h}_{i-1}^{x,n}, \mathbf{h}_i^{x,n}, \mathbf{h}_{i+1}^{x,n}, \mathbf{c}_i^{x,n}] + \mathbf{b}) \quad (5)$$

$$= \tanh(\mathbf{W^1} \cdot [\mathbf{h}_{i-1}^{x,n}, \mathbf{h}_i^{x,n}, \mathbf{h}_{i+1}^{x,n}] + \mathbf{W^2} \cdot \mathbf{c}_i^{x,n} + \mathbf{b}) \quad (6)$$

where $\mathbf{W} \in \mathbb{R}^{d \times 4d}$ is the concatenation of $\mathbf{W}^1 \in \mathbb{R}^{d \times 3d}$ and $\mathbf{W}^2 \in \mathbb{R}^{d \times d}$, $\mathbf{b} \in \mathbb{R}^d$.

As Equation 6 shows, Equation 5 can be achieved by summing up the results of two separate and parallel convolution steps before the non-linearity. The first is still standard convolution-without-attention over feature map $\mathbf{H}^{x,n}$ by filter width 3 over window ($\mathbf{h}_{i-1}^{x,n}$, $\mathbf{h}_i^{x,n}$, $\mathbf{h}_{i+1}^{x,n}$). The second is convolution on the feature map $\mathbf{C}^{x,n}$, i.e., the attentive context, with filter width 1, i.e., over each $\mathbf{c}_i^{x,n}$. Finally sum up the results element-wise and add bias term and non-linearity. This divide-and-conquer makes the attentive convolution easy to implement in practice with no need to create a new feature map, as required

role	text
premise	Three firefighter **come out** of subway station
hypothesis	Three firefighters **putting out** a fire **inside** of a subway station

Table 2: Multi-granular alignments required in textual entailment

in Equation 5, to integrate $\mathbf{H}^{x,n}$ and $\mathbf{C}^{x,n}$.

Our experiments show that this light version of AttentiveConvNet works much better than the basic CNN. The following two considerations show that there is space to improve its expressivity.

(i) *Higher-level or more abstract representations are required in subsequent layers.* We find that directly forwarding the hidden states in t^x or t^a to the matching process is less optimal in some tasks. Pre-learning some more higher-level or abstract representations helps in subsequent learning phase.

(ii) *Multi-granular alignments are preferred in some text pair modeling cases.* Table 2 shows another example from SNLI. On the unigram level, "out" in premise matches with "out" in hypothesis perfectly, while "out" in premise is contradictory to "inside" in hypothesis. But considering their context – "come out" in premise and "putting out a fire" in hypothesis – clearly indicates they are not semantically equivalent. And the ground truth conclusion for this pair is "neutral", i.e., the hypothesis is possibly true. Therefore, matching should be conducted across phrase granularities.

We now present advanced AttentiveConvNet. It is more expressive and modular, based on the two foregoing considerations (i) and (ii).

3.2 Advanced AttentiveConvNet

Adel and Schütze (2017) distinguish between **focus** and **source** of attention. The *focus* of attention is the layer of the network that is reweighted by attention weights. The *source* of attention is the information source that is used to compute the attention weights. Adel and Schütze (2017) showed that increasing the scope of the attention source is beneficial. Here we further extend this principle to define **beneficiary** of attention – the feature map (labeled "beneficiary" in Figure 1(b)) that is contextualized by *the attentive context* (labeled "attentive context" in Figure 1(b)). In light attentive convolutional layer (Figure 1(a)), the source of attention is hidden states in text t^x, the focus of attention is hidden states of text t^a, the ben-

eficiary of attention is again the hidden states of t^x, i.e., it is identical to the source of attention.

We now try to distinguish these three concepts further to promote the expressivity of an attentive convolutional layer. We call it "advanced AttentiveConvNet", see Figure 1(b). It differs from the light version in three ways: (i) *attention source* is learned by function $f_{\mathrm{mgran}}(\mathbf{H}^x)$, feature map $\mathbf{H}^x$ of t^x acting as input; (ii) *attention focus* is learned by function $f_{\mathrm{mgran}}(\mathbf{H}^a)$, feature map $\mathbf{H}^a$ of t^a acting as input; (iii) *attention beneficiary* is learned by function $f_{\mathrm{bene}}(\mathbf{H}^x)$, $\mathbf{H}^x$ acting as input. Both functions $f_{\mathrm{mgran}}()$ and $f_{\mathrm{bene}}()$ are based on a *gated convolutional function* $f_{\mathrm{gconv}}()$:

$$\overline{\mathbf{o}}_i = \tanh(\mathbf{W}_h \cdot \mathbf{i}_i + \mathbf{b}_h) \qquad (7)$$

$$\mathbf{g}_i = \mathrm{sigmoid}(\mathbf{W}_g \cdot \mathbf{i}_i + \mathbf{b}_g) \qquad (8)$$

$$f_{\mathrm{gconv}}(\mathbf{i}_i) = \mathbf{g}_i \cdot \mathbf{u}_i + (1 - \mathbf{g}_i) \cdot \overline{\mathbf{o}}_i \qquad (9)$$

where $\mathbf{i}_i$ is a composed representation, denoting a generally defined input phrase $[\cdots, \mathbf{u}_i, \cdots]$ of arbitrary length with $\mathbf{u}_i$ as the central unigram-level hidden state, the gate $\mathbf{g}_i$ sets a trade-off between the unigram-level input $\mathbf{u}_i$ and the temporary output $\overline{\mathbf{o}}_i$ at the phrase-level. We elaborate these modules in the remainder of this subsection.

Attention Source. First, we present a general instance of generating source of attention by function $f_{\mathbf{mgran}}(\mathbf{H})$, learning word representation in multi-granulary context. In our system, we consider granularities one and three, corresponding to uni-gram hidden state and tri-gram hidden state. For the uni-hidden state case, it is a gated convolution layer:

$$\mathbf{h}^x_{\mathrm{uni},i} = f_{\mathrm{gconv}}(\mathbf{h}^x_i) \qquad (10)$$

For tri-hidden state case:

$$\mathbf{h}^x_{\mathrm{tri},i} = f_{\mathrm{gconv}}([\mathbf{h}^x_{i-1}, \mathbf{h}^x_i, \mathbf{h}^x_{i+1}]) \qquad (11)$$

Finally, the overall hidden state at position i is the concatenation of $\mathbf{h}_{\mathrm{uni},i}$ and $\mathbf{h}_{\mathrm{tri},i}$:

$$\mathbf{h}^x_{\mathrm{mgran},i} = [\mathbf{h}^x_{\mathrm{uni},i}, \mathbf{h}^x_{\mathrm{tri},i}] \qquad (12)$$

i.e., $f_{\mathbf{mgran}}(\mathbf{H}^x) = \mathbf{H}^x_{\mathrm{mgran}}$.

Such kind of comprehensive hidden state can encode the semantics of multigranular spans at a position, such as "out" and "come out of". Gating here implicitly enables cross-granular alignments in subsequent attention mechanism as it sets highway connection (Srivastava et al., 2015) between the input granularity and the output granularity.

Attention Focus. For simplicity, we use the same architecture for the *attention source* (just introduced) and for the *attention focus*, t^a; i.e., for the attention focus: $f_{\mathbf{mgran}}(\mathbf{H}^a) = \mathbf{H}^a_{\mathrm{mgran}}$. See Figure 1(b). Thus, the focus of attention will participate in the matching process as well as be reweighted to form an attentive context vector. We leave exploring different architectures for attention source and focus for future work.

Another benefit of multi-granular hidden states in attention focus is to keep structure information in context vector. In standard attention mechanisms in RNNs, all hidden states are average-weighted as a context vector, the order information is missing. In CNNs, bigger-granular hidden states keep the local order or structures to boost the attentive effect.

Attention Beneficiary. In our system, we simply use $f_{\mathbf{gconv}}()$ over uni-granularity to learn a more abstract representation over the current hidden representations in $\mathbf{H}^x$, so that

$$f_{\mathrm{bene}}(\mathbf{h}^x_i) = f_{\mathrm{gconv}}(\mathbf{h}^x_i) \qquad (13)$$

Subsequently, the *attentive context vector* $\mathbf{c}^x_i$ is generated based on *attention source* feature map $f_{\mathrm{mgran}}(\mathbf{H}^x)$ and *attention focus* feature map $f_{\mathrm{mgran}}(\mathbf{H}^a)$, according to the description in the light attentive convolutional layer. Then attentive convolution is conducted over *attention beneficiary* feature map $f_{\mathrm{bene}}(\mathbf{H}^x)$ and the attentive context vectors $\mathbf{C}^x$ to get higher-layer feature map $\mathbf{H}^{x,n+1}$ for text t^x. *A symmetrical process can be carried out for the text t^y as well to form a two-way attentional system.* This is the architecture we use for sentence relation classification below.

3.3 Analysis

AttentiveConvNet consists of three modules; each can be flexibly built. In addition, we can do (max, mean etc.) pooling over the output feature map of the attentive convolution layer, or stack new attentive convolution layers to form deep architectures.

Compared to the standard attention mechanism in RNNs, AttentiveConvNet has a similar energy function and a similar process of computing context vectors, but differs in three ways. (i) The discrimination of attention source, focus and beneficiary improves expressivity. (ii) In CNNs, the surrounding hidden states for a concrete position are

available, so the attention matching is able to encode the left context as well as the right context. In RNNs however, it needs bidirectional RNNs to yield both left and right context representations. (iii) As attentive convolution can be implemented by summing up two separate convolution steps, it means this architecture provides the attentive representations, as well as representations computed without the use of attention. This trick is helpful in practice to use richer representations for better performance. In contrast, such a clean modular separation of representations computed with and without attention is harder to realize in attention-based RNNs.

Prior attention mechanisms explored in CNNs mostly involve attentive pooling (Yin et al., 2016; dos Santos et al., 2016), i.e., the weights of the post-convolution pooling layer are determined by attention. These weights come from energy function between hidden states of two text pieces. However, a weight value is not informative enough to tell the relationships between aligned objects. Consider a textual entailment sentence pair for which we need to determine whether "inside $\longrightarrow$ outside" holds. The cosine similarity of these two words is high, e.g., $\approx .7$ in word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014). On the other hand, cosine similarity between "inside" and "in" is lower: .31 in word2vec, .46 in glove. Apparently, the higher number .7 does not mean "outside" is more likely than "in" to be entailed by "inside". Instead, joint representations for aligned phrases [$\mathbf{h}_{\text{inside}}$, $\mathbf{h}_{\text{outside}}$], [$\mathbf{h}_{\text{inside}}$, $\mathbf{h}_{\text{in}}$] are more informative and enable fine-grained reasoning. This illustrates why attentive context vectors participating in the convolution operation are expected to be more effective than the post-convolution attentive pooling.

Inter-text attention & intra-text attention. Figures 1(a)-1(b) depict the modeling for two text pieces t^x and t^y. This is a common application of attention mechanism in literature; we call it inter-text attention. But AttentiveConvNet can also be applied to model a single text input, i.e., intra-text attention. As the sentiment analysis example in Table 1 shows, a text piece can contain informative points at different locations; conventional CNNs' ability to model nonlocal dependency is limited due to fixed-size filter widths. In AttentiveConvNet, we can set $t^a = t^x$. The attentive context vector then accumulates all re-

lated parts together for a given position. In other words, our intra-text attentive convolution is able to connect all related spans together to form a comprehensive decision. *This is a new way to broaden the scope of conventional filter widths: a filter now covers not only the local window, but also those spans that are related yet beyond the scope of the window.*

4 Experiments

We evaluate *intertext attention* on *sentence relation classification* (textual entailment and answer sentence selection) and *intratext attention* on *"single-text" classification*.

All experiments share a **common setup**. The input is represented using 300-dimensional publicly available GloVe embeddings; OOVs are randomly initialized. The architecture consists of the following seven layers in sequence: embedding, attentive convolution, max-pooling, composition, hidden 1, hidden 2 and logistic regression. The input to logistic regression is the concatenation of the outputs of the previous three layers: composition, hidden 1 and hidden 2. We use AdaGrad (Duchi et al., 2011) for training. Embeddings are fine-tuned during training.

The natural settings for sentence relation and single-text classification are intertext and intratext, respectively. For sentence relation, we also test using *both intertext and intratext*, referred to as "advanced&intra-attention" in the tables. We always report "light" and "advanced" AttentiveConvNet performance and compare against three types of baselines: (i) w/o-attention, (ii) with-attention: RNNs with attention and attentive pooling CNNs and (iii) prior state of the art, *typeset in italics*.

4.1 Textual Entailment

Dataset: Stanford Natural Language Inference (SNLI, Bowman et al. (2015)), split 549,367 / 9,842 / 9,824 into train/dev/test; sentence relation classes: entailment, contradiction, neutral. **Setup:** dropout of .1 for the output of each layer, learning rate .02, hidden size 300 across layers, batch size 50, filter width 3. In this task, the architecture is "Siamese" up to the max-pooling layer for the two inputs t^x and t^y. Let $\mathbf{r}^z$ be the output of max-pooling for input t^z. The composition layer concatenates $\mathbf{r}^x$, $\mathbf{r}^y$ and $\mathbf{r}^x \odot \mathbf{r}^y$ (where $\odot$ is dot product) and passes this

	Systems	acc
w/o attention	bi-CNN	80.3
	bi-LSTM (Bowman et al., 2015)	77.6
	Tree-CNN (Mou et al., 2016)	82.1
	NES (Munkhdalai and Yu, 2017)	84.8
with attention	W-by-W attention (Rocktäschel)	83.5
	Self-Attentive (Lin et al., 2017)	84.4
	Match-LSTM (Wang & Jiang)	86.1
	Decompose Attention (Parikh)	86.8
	LSTMN (Cheng et al., 2016)	*89.1*
	ABCNN (Yin et al., 2016)	83.7
	APCNN (dos Santos et al., 2016)	83.9
Attentive ConvNet	light	86.3
	advanced	87.8
	advanced&intra-attention	88.4
	ensemble	**89.3**

Table 3: Performance comparison on SNLI test

on as input to hidden layer 1.

Baselines: (i) w/o-attention. **bi-CNN**: Siamese CNN, very similar to AttentiveConvNet, but without attention; **bi-LSTM** (Bowman et al., 2015): Siamese LSTM; **Tree-CNN** (Mou et al., 2016): Siamese CNN over dependency trees of sentences; **NSE**: Neural Semantic Encoders (Munkhdalai and Yu, 2017); (ii) with-attention. **Word-by-Word Attention** (Rocktäschel et al., 2016), the first work that employs standard attention mechanism in RNN system in this task, and its enhanced variants: **Match-LSTM** (Wang and Jiang, 2016) and the state-of-the-art **LSTMN** (Cheng et al., 2016); **Self-Attentive** (Lin et al., 2017), an intra-sentence attention model; **Decompose Attention** (Parikh et al., 2016), the first work that achieves fine-grained cross-sentence alignments and reasoning without convolutional or recurrent components. Attentive pooling CNNs: **ABCNN** (Yin et al., 2016) and **APCNN** (dos Santos et al., 2016).

Results. In Table 3, AttentiveConvNet outperforms bi-CNN, its w/o-attention equivalent, by $\geq$ $6 = 86.3 - 80.3$. This shows the effectiveness of attentive convolution. The AttentiveConvNet ensemble[2] outperforms all prior with-attention work:

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[2] The ensemble uses five copies of AttentiveConvNet-advanced&intra-attention system with different parameters, trained over different minibatches. In testing, we forward the same minibatch to each copy, average the output probabilities and pick the highest-probability label.

W-by-W attention (Rocktäschel et al., 2016), Self-Attentive (Lin et al., 2017), Match-LSTM (Wang and Jiang, 2016) and LSTMN (Cheng et al., 2016). The single system advanced&intra-attention outperforms three of these baselines and is close to LSTMN (89.1 vs. 88.4).

Analysis. As attentive pooling CNN baselines, we use ABCNN and APCNN. As we discussed in related work, in attentive pooling, information flows through attention weights rather than through attentive context vectors. Attentive context vectors are much more informative than attention weights when making decisions based on aligned phrases. Take the following SNLI pair as an example. Premise: "A couple is eating *outside* at a table and he is pointing at something"; Hypothesis: "A couple is eating *inside* at a table and he is pointing at something". They only differ by a single word: *outside* vs. *inside*. However, *outside* and *inside* have cosine similarity $\approx .7$ for word2vec and GloVe. There are two problems for ABCNN and APCNN. (i) Attentive pooling has an implicit assumption that hidden states that are better matched should be highly weighted. In above example, all words except for the contradictory pair "outside" / "inside" can find the best match with cosine similarity 1.0 since all are identical words. This means these identical words will be more highly weighted than "outside" / "inside" in the respective text representation. However, it is apparent that "outside" / "inside" are more decisive than other words in this instance. *Attentive convolution* takes the hidden states of "outside" and "inside" (not their uninformative similarity) directly as input. This capability is needed here to make the correct decision. (ii) Attentive pooling essentially is a weighted average operation. Each text representation is therefore an unordered sum of all hidden states. This makes it less sensitive to distinguish the relationships of individual, aligned hidden state pairs. *Attentive convolution* instead relies on both the two aligned hidden states and their context hidden states to make fine-grained judgment.

Recall that in Section 3.2 we implemented unigram-level and trigram-level hidden states for multigranular alignments and proposed a gating mechanism to achieve alignment across granularities. Therefore, apart from above overall performance, we also evaluate the contributions of fol-

Systems	acc
AttentiveConvNet (advanced+intra-attention)	88.7
w/o tri-hidden	88.4
w/o uni-hidden	87.3
w/o gate	88.2

Table 4: Ablation test on SNLI dev

lowing *three key architecture settings* of Attentive-ConvNet: (i) tri-hidden states in attention source and attention focus; (ii) uni-hidden states in attention source and attention focus; (iii) convolution gates in attention source, focus and beneficiary learning. Table 4 reports the ablation test of AttentiveConv-Net (advanced&intra-attention) on SNLI dev. Each component is found contributing to overall performance; uni-hidden states show especially big benefit compared to tri-hidden states. This hints that unigram level alignment is already strong information. This is consistent with the basic rationale of previous work (Parikh et al., 2016) and it is why we do not stack another attentive convolution layer.

4.2 Answer Sentence Selection

We create an answer sentence selection benchmark based on SQUAD (Rajpurkar et al., 2016), referred to as *SQUAD-AnSS*, as follows. A SQUAD instance has the form (passage, question, answer) where answer is a subsequence of passage. We split each passage into sentences. The sentence containing the answer is labeled positive, the other sentences negative. As SQUAD only releases train and dev publicly (not test), we use 105,980 question-sentence pairs derived from squad-dev as *test* set. We derive 448,307 question sentence pairs from squad-train and split them into *train* (400,000) and *dev* (48,307).

Most work on SQUAD processes the entire input paragraph, then detects the answer span in this long sequence. SQUAD-AnSS is a stepping stone towards an alternative approach: first rank sentences, then detect the answer span in the top-ranked sentence. Our performance is almost 90% (Table 5), suggesting that this approach is promising.

Setup. We treat this task as a ranking problem: rank the predicted probability of a positive pair higher than that of a negative pair by a margin (set to .85). We use precision at 1 for evaluation since only the top-1 sentence is used in our SQUAD application scenario. Other hyperparameters: learning rate

	Systems	p@1
w/o attention	WordC1	68.87
	WordC2	79.59
	CDSSM (Shen et al., 2014)	67.21
	bi-CNN	77.94
	Bi-GRU (Tang et al., 2017)	78.14
with attention	*Sentence-Rank*	*86.00*
	ABCNN (Yin et al., 2016)	84.72
	APCNN (dos Santos et al., 2016)	84.14
Attentive ConvNet	light	87.42*
	advanced	88.27*
	advanced&intra-att	**88.54***

Table 5: System comparison on SQUAD-AnSS. Significant improvements over state of the art are marked with ∗ (test of equal proportions, p < .05).

.02, batch size 30. The composition layer outputs $[\mathbf{r}^x, \mathbf{r}^y, \mathbf{r}^x \odot \mathbf{r}^y]$ as for textual entailment.

Baselines. (i) w/o-attention. Two feature engineering methods: **WordC1** (word cooccurrence normalized by answer sentence length) and **WordC2** (word cooccurrence normalized by question length); three DNN systems: **CDSSM** (Shen et al., 2014), **bi-CNN** and **Bi-(directional) GRU** (Tang et al., 2017). (ii) with-attention. Two attentive pooling CNNs (**ABCNN** and **APCNN**) and the state-of-the-art system **Sentence-Rank** (Wang et al., 2017a).

Results and Analysis. AttentiveConvNet outperforms all prior systems. It is 3 points above the attentive pooling CNNs and up to 2.54 above the state-of-the-art. We attribute the success of AttentiveConv-Net to two factors. (i) A question-sentence match is more easily and effectively detected by matching of some local core phrases rather than global semantic matching. This is widely-recognized in literature. E.g., WordC2, the simple method with overlapping features, is even more effective than Tang et al. (2017)'s Bi-GRU (note that GRU systems are widely developed to learn global semantics of text); this indicates that the surface overlap is already very effective to downweight lots of negative sentence candidates. CNNs are the DNNs with most strength in deriving robust local features. (ii) Attentive convolution enables fine-grained cross-text phrase matching with consideration of surrounding context so that more effective reasoning can be achieved.

	Systems	acc
w/o attention	Paragraph Vector	58.43
	Lin et al. BiLSTM	61.99
	Lin et al. CNN	62.05
	MultichannelCNN (Kim)	*64.62*
with attention	CNN+internal attention	61.43
	Lin et al. RNN Self-Att.	64.21
Attentive ConvNet	light	66.75
	advanced	**67.36**[*]

Table 6: System comparison on Yelp. Significant improvements over state of the art are marked with [*] (test of equal proportions, $p < .05$).

4.3 Text Classification

We evaluate sentiment analysis on Yelp (Lin et al., 2017): 500K/2000/2000 review-star pairs in train/dev/test. Most text instances in this dataset are long: 25%, 50%, 75% percentiles are 46, 81, 125 words, respectively. The task is five-way classification: one to five stars. The measure is accuracy.

Setup. The composition layer passes the output $\mathbf{r}^x$ of max-pooling through without modification. Hyperparameters: learning rate .01, hidden size 500 across layers, dropout .1, batch size 10.

Baselines. (i) w/o-attention. Three baselines from Lin et al. (2017): **Paragraph Vector** (Le and Mikolov, 2014) (unsupervised sentence representation learning), **BiLSTM** and **CNN**. We also reimplement **MultichannelCNN** (Kim, 2014), recognized as a simple, but surprisingly strong sentence modeler. (ii) with-attention. **RNN Self-Attention** (Lin et al., 2017) is directly comparable to AttentiveConvNet: it also uses intra-text attention. We also reimplement **CNN+internal attention** (Adel and Schütze, 2017), an intra-text attention idea similar to, but less complicated than (Lin et al., 2017).

Results and Analysis. Table 6 shows that AttentiveConvNet outperforms the w/o-attention baselines. More importantly, it outperforms the two self-attentive models: CNN+internal attention (Adel and Schütze, 2017) and RNN Self-Attention (Lin et al., 2017). Adel and Schütze (2017) generate an attention weight for each CNN hidden state by a linear transformation of the same hidden state, then compute weighted average over all hidden states as the text representation. Lin et al. (2017) extend that idea by generating *a group of* attention weight vectors,
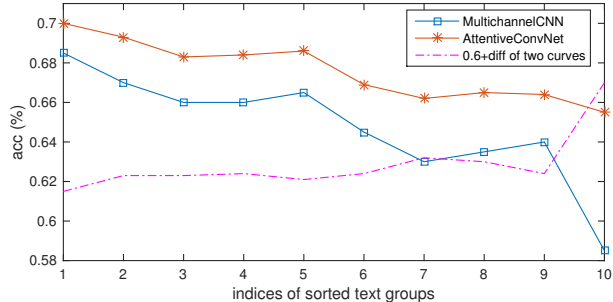

Figure 2: AttentiveConvNet vs. MultichannelCNN.

then RNN hidden states are averaged by those diverse weighted vectors, allowing extracting different aspects of the text into multiple vector representations. Both works are essentially weighted mean pooling, similar to the attentive pooling in (Yin et al., 2016; dos Santos et al., 2016).

Next, we compare AttentiveConvNet with MultichannelCNN for different length ranges. We sort the 2000 test instances by length, then split them into 10 groups, each consisting of 200 instances. Figure 2 shows performance of AttentiveConvNet vs. MultichannnelCNN.

We observe that AttentiveConvNet consistently outperforms MultichannelCNN, the strongest baseline system, for all lengths. Furthermore, the improvement over MultichannelCNN generally increases with length. This is evidence that AttentiveConvNet is more effectively modeling long text. This is likely due to AttentiveConvNet's capability to encode broader context in its filters.

5 Summary

We presented AttentiveConvNet, the first work that enables CNNs to acquire the attention mechanism commonly employed in RNNs. AttentiveConvNet combines the strengths of CNNs with the strengths of the RNN attention mechanism. On the one hand, it makes broad and rich context available for prediction, either context from external inputs (intertext) or internal inputs (intratext). On the other hand, it can take full advantage of the strengths of convolution: it is more order-sensitive than attention in RNNs and local-context information can be powerfully and efficiently modeled through convolution filters. Our experiments demonstrate that AttentiveConvNet performs better than prior DNNs with and without attention.

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