Neural Semantic Encoders

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Abstract

We present a memory augmented neural network for natural language understanding: Neural Semantic Encoders (NSE). NSE has a variable sized encoding memory that evolves over time and maintains the understanding of input sequences through read, compose and write operations. NSE can access multiple and shared memories depending on the complexity of a task. We demonstrated the effectiveness and the flexibility of NSE on five different natural language tasks, natural language inference, question answering, sentence classification, document sentiment analysis and machine translation where NSE achieved state-of-the-art performance when evaluated on publically available benchmarks. For example, our shared-memory model showed an encouraging result on neural machine translation, improving an attention-based baseline by approximately 1.0 BLEU.

1 Introduction

Recurrent neural networks (RNNs) have been extremely successful for modeling sequences [1]. Particularly, RNNs equipped with internal short memories, such as long short-term memories (LSTMs) [2] have achieved a notable success in sequential tasks [3, 4]. LSTMs are powerful because it learns to control its short term memories. However, the short term memories in LSTMs are a part of the training parameters. This imposes some practical difficulties in training and modeling long sequences with LSTMs.

Recently several studies have explored ways of extending the neural networks with an external memory [5–7]. Unlike LSTMs, the short term memories and the training parameters of such a neural network are no longer coupled and can be adapted. In this paper we introduce Neural Semantic Encoders (NSE), a class of memory augmented neural networks, for natural language understanding (NLU). NSE has a variable sized encoding memory and naturally supports semantic compositionality. The encoding memory evolves over time and maintains a mental image of input sequence through read, compose and write operations. NSE is flexible. It can read from and write to a set of relevant encoding memories simultaneously or multiple NSEs can access a shared encoding memory. The size of the memory can be altered depending on the input length, i.e., we use a larger memory for long sequences and a smaller memory for short sequences. Our models are robust and suitable for practical NLU tasks and can be trained easily by any gradient descent optimizer.

We evaluate our models on five different real tasks. For four of them, our models set new state-of-the-art results. Our results suggest that a model with the shared memory between encoder and decoder is a promising approach for sequence transduction problems such as machine translation and abstractive summarization. In particular, we observe that the attention-based neural machine translation can be further improved by shared-memory models.

1 By access we mean changing the memory states by the read, compose and write operations.
Figure 1: High-level architectures of the Neural Semantic Encoders. NSE reads and writes its own encoding memory in each time step (a). MMA-NSE accesses multiple relevant memories simultaneously (b).

2 Related Work

One of the pioneering work that attempts to extend deep neural networks with an external memory is Neural Turing Machines (NTM) [5]. NTM implements a centralized controller and a fixed-sized random access memory. The controller uses attention mechanisms to access the memory. NTM performed well on copying and sorting sequences.

Although the RNNSearch model proposed in [8] has no explicitly designed external memory, it can be seen as a variation of memory augmented networks due to its ability to read the historic output states of RNNs with soft attention. The work of [9] combines the soft attention with Memory Networks (MemNNs) [6]. Although MemNNs are designed with non-writable memories, it constructed layered memory representations and showed promising results on both artificial and real question answering tasks. Another variation of MemNNs is Dynamic Memory Network [10] which is equipped with an episodic memory and seems to be flexible in different settings.

The aforementioned models including our Neural Semantic Encoders use the attention mechanism to access the external memory. Unlike NTM, the memory size of our model is not fixed beforehand and is adapted for a particular input. Our model is robust; therefore it is practical in real settings. NTM addresses some algorithmic tasks while our model and MemNNs focus on language tasks. Unlike MemNNs, the encoding memory of NSE is readable and writable. In summary, NSE is flexible and can access to multiple and shared memories simultaneously.

Other related work includes Neural Program-Interpreters [11], which learns to run sub-programs and to compose them for high-level programs. It uses execution traces to provide the full supervision. Researchers have also explored ways to add unbounded memory to LSTMs [7]. The memory bank is accessed through data structure such as stack and queue.

Most of aforementioned memory augmented neural networks have been tested on algorithmic artificial tasks whereas in this paper we tested NSE on a wide range of real natural language applications.

3 Proposed Approach

We consider supervised tasks where the training set consists of \( N \) examples \( \{X^i, Y^i\}_{i=1}^N \), where the input \( X^i \) is a sequence \( w_1^i, w_2^i, \ldots, w_T^i \) of tokens while the output \( Y^i \) can be either a single target or a sequence. We transform each input token \( w_t \) to its word embedding \( x_t \).

Our Neural Semantic Encoders (NSE) have four main components: read, compose and write modules and an encoding memory \( M \in \mathbb{R}^{k \times l} \) with a variable number of slots, where \( k \) is the embedding dimension and \( l \) is the length of the input sequence. Each memory slot vector \( m_t \in \mathbb{R}^k \) corresponds to the vector representation of information about word \( w_t \) in memory. In particular, the memory is initialized by the embedding vectors \( \{x_t\}_{t=1}^l \) and is evolved over time, through read, compose and write operations. Figure 1(a) illustrates the architecture of NSE.
3.1 Read, Compose and Write

NSE performs the three main operations in every time step. After initializing the memory slots with the corresponding input representations, NSE processes an embedding vector $x_t$ and retrieves a memory slot $m_{r,t}$ that is semantically associated with the current input word $w_t$. The slot location $r$ (ranging from 1 to $l$) is defined by a key vector $z_t$ which the read module emits by attending over the memory slots. The compose module implements a composition operation that combines the memory slot with the current input. The write module then transforms the composition output to the encoding memory space and writes the resulting new representation into the slot location of the memory. Instead of composing the raw embedding vector $x_t$, we use the hidden state $o_t$ produced by the read module at time $t$.

Concretely, let $e_l \in R^l$ be a vector of ones and given a read function $f_L^{LSTM}$, a composition $f_c^{MLP}$ and a write $f_w^{LSTM}$ NSE in Figure 1(a) computes the key vector $z_t$, the output state $h_t$, and the encoding memory $M_t$ in time step $t$ as:

\begin{align}
  o_t &= f_L^{LSTM}(x_t) \\
  z_t &= \text{softmax}(o_t^T M_{t-1}) \\
  m_{r,t} &= z_t^T M_{t-1} \\
  c_t &= f_c^{MLP}(o_t, m_{r,t}) \\
  h_t &= f_w^{LSTM}(c_t) \\
  M_t &= M_{t-1}(1 - z_t \otimes e_l) + h_t z_t \otimes e_l
\end{align}

where $1$ is a matrix of ones, $\otimes$ denotes the outer product which duplicates its left vector $l$ times to form a matrix. The read function $f_L^{LSTM}$ sequentially maps the word embeddings to the internal space of the memory $M_{t-1}$. Then Equation 2 looks for the slots related to the input by computing semantic similarity between each memory slot and the hidden state $o_t$. We calculate the similarity by the dot product and transform the similarity scores to the fuzzy key vector $z_t$ by normalizing with softmax function. Since our key vector is fuzzy, the slot to be composed is retrieved by taking weighted sum of the all slots as in Equation 3. This process can also be seen as the soft attention mechanism [8]. In Equation 4 and 5, we compose the retrieved slot with the current hidden state and map the resulting vector to the encoder output space. Finally, we write the new representation to the memory location pointed by the key vector in Equation 6. First the slot that was retrieved is erased and then the new representation is located. NSE performs this iterative process until all words in the input sequence is read. The encoding memories $\{M\}_{t=1}^T$ and output states $\{h\}_{t=1}^T$ are further used for the tasks.

With the encoding memory, NSE maintains a mental image of the input sequence. The memory is initialized with the raw embedding vector at time $t = 0$. We term such a freshly initialized memory a baby memory. As NSE reads more input content in time, the baby memory evolves and refines the encoded mental image.

The read $f_L^{LSTM}$, the composition $f_c^{MLP}$ and the write $f_w^{LSTM}$ functions are neural networks and are the training parameters in our NSE. As the name suggests, we use LSTMs and multi-layer perceptron (MLP) in this paper. Since NSE is fully differentiable, it can be trained with any gradient descent optimizer.

3.2 Shared and Multiple Memory Accesses

For sequence to sequence transduction tasks like question answering, natural language inference and machine translation, it is beneficial to access other relevant memories in addition to its own one.

NSE can easily be extended, so that it is able to read from and write to multiple memories simultaneously or multiple NSEs are able to access a shared memory. Figure 1(b) depicts a high-level architectural diagram of a multiple memory access-NSE (MMA-NSE). The first memory (in green) is the shared memory accessed by more than one NSEs. Given a shared memory $M^n \in R^{k \times n}$ that has been encoded by processing a relevant sequence with length $n$, MMA-NSE with the access to one relevant memory is defined as
\[ o_t = f^{LSTM}_r(x_t) \]  \hspace{1cm} (7)
\[ z_t = \text{softmax}(o_t^T M_{t-1}) \] \hspace{1cm} (8)
\[ m_{r,t} = z_t^T M_{t-1} \] \hspace{1cm} (9)
\[ z_t^n = \text{softmax}(o_t^T M_{t-1}^n) \] \hspace{1cm} (10)
\[ m_{r,t}^n = z_t^n M_{t-1} \] \hspace{1cm} (11)
\[ c_t = f^{MLP}_c(o_t, m_{r,t}, m_{r,t}^n) \] \hspace{1cm} (12)
\[ h_t = f^{LSTM}_w(c_t) \] \hspace{1cm} (13)
\[ M_t = M_{t-1}(1 - z_t \otimes e_t) + h_t z_t \otimes e_t \] \hspace{1cm} (14)
\[ M_t^n = M_{t-1}^n(1 - z_t^n \otimes e_t) + h_t z_t^n \otimes e_t \] \hspace{1cm} (15)

and this is almost the same as standard NSE. The read module now emits the additional key vector \( z_t^n \) for the shared memory and the composition function \( f^{MLP}_c \) combines more than one slots.

In MMA-NSE, the different memory slots are retrieved from the shared memories depending their encoded semantic representations. They are then composed together with the current input and written back to their corresponding slots. Note that MMA-NSE is capable of accessing a variable number of relevant shared memories once a composition function that takes dynamic inputs is chosen.

## 4 Experiments

We describe in this section experiments on five different tasks, in order to show that NSE can be effective and flexible in different settings. We report results on natural language inference, question answering (QA), sentence classification, document sentiment analysis and machine translation. All five tasks challenge a model in terms of language understanding and semantic reasoning.

The models are trained using Adam [12] with hyperparameters selected on development set. We re-scale the gradients if their norm is above 15. We chose two one-layer LSTMs for read/write modules on the tasks other than QA on which we used two-layer LSTMs. The pre-trained 300-D Glove 840B vectors and 100-D Glove 6B vectors [13] were obtained for the word embeddings. The word embeddings are fixed during training. The embeddings for out-of-vocabulary words were set to zero vector. We crop or pad the input sequence to a fixed length. A padding vector was inserted when padding. The models were regularized by using dropouts and an \( L^2 \) weight decay [4].

### 4.1 Natural Language Inference

The natural language inference is one of the main tasks in language understanding. This task tests the ability of a model to reason about the semantic relationship between two sentences. In order to perform well on the task, NSE should be able capture sentence semantics and be able to reason relation between the sentence pairs, i.e., whether premise-hypothesis pairs are entailment, contradictory, or neutral. We conducted experiments on the Stanford Natural Language Inference (SNLI) dataset [14], which consists of 549,367/9,842/9,824 premise-hypothesis pairs for train/dev/test sets and target label indicating their relation.

Following the setting in [15] NSE output for each sentence was input to a MLP, whose input layer computes the concatenation \( [h_p^0; h_h^0] \), absolute difference \( h_p^0 - h_h^0 \) and elementwise product \( h_p^0 \cdot h_h^0 \) of the two sentence representations. In addition, the MLP has a hidden layer with 1024 units with ReLU activation and a softmax layer. We set the batch size to 128, the initial learning rate to 3e-4 and \( L_2 \) regularizer strength to 3e-5, and train each model for 40 epochs. The write/read neural nets and the last linear layer were regularized by using 30% dropouts.

Table 1 compares the results of our models with the previous methods on the task. The classifier with handcrafted features extracts a set of lexical features. The next group of models are based on

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2Code for the experiments and NSEs will be available at http://anonymized upon publication.
3http://nlp.stanford.edu/projects/glove/
4More detail on hyper-parameters can be found in code.

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Table 1: Training and test accuracy on natural language inference task. $d$ is the word embedding size and $|\theta|_M$ the number of model parameters.

| Model                                           | $d$  | $|\theta|_M$ | Train | Test  |
|-------------------------------------------------|------|--------------|-------|-------|
| Classifier with handcrafted features [14]      | -    | -            | 99.7  | 78.2  |
| LSTMs encoders [14]                            | 300  | 3.0M         | 83.9  | 80.6  |
| Dependency Tree CNN encoders [16]              | 300  | 3.5M         | 83.3  | 82.1  |
| SPINN-NP encoders [15]                         | 300  | 3.7M         | 89.2  | 83.2  |
| NSE                                            | 300  | 3M           | 86.2  | 84.6  |
| MMA-NSE                                        | 300  | 3M           | 87.1  | 84.8  |
| LSTMs attention [17]                           | 100  | 242K         | 85.4  | 82.3  |
| LSTMs word-by-word attention [17]              | 100  | 252K         | 85.3  | 83.5  |
| MMA-NSE attention                              | 300  | 3.18M        | 86.9  | 85.4  |
| mLSTM word-by-word attention [18]              | 300  | 1.9M         | 92.0  | 86.1  |
| LSTMsN with deep attention fusion [19]         | 450  | 3.4M         | 89.5  | 86.3  |
| Decompositional attention model [20]           | 200  | 582K         | 90.5  | 86.8  |

sentence encoding. While most of the sentence encoder models rely solely on word embeddings, the dependency tree CNN and the SPINN-NP models make use of sentence parser output. The SPINN-NP model is similar to NSE in spirit that it also explicitly computes word composition. However, the composition in the SPINN-NP is guided by supervisions form a dependency parser. NSE outperformed the previous sentence encoders on this task. The MMA-SNE further slightly improved the result, indicating that reading the premise memory is helpful while encoding the hypothesis.

The last set of methods designs inter-sentence relation with parameterized soft attention [8]. Our MMA-NSE attention model is similar to the LSTMs attention model. Particularly, it attends over the premise encoder outputs $\{h^p_t\}_{t=1}^T$ in respect to the final hypothesis representation $h^h_1$ and constructs an attentively blended vector of the premise. This model obtained 85.4% accuracy score. The best performing model performs phrase matching by using the attention mechanism for the task.

4.2 Answer Sentence Selection

Answer sentence selection is an integral part of the open-domain question answering. For this task, a model is trained to identify the correct sentences that answer a factual question, from a set of candidate sentences. We experiment on WikiQA dataset constructed from Wikipedia [21]. The dataset contains 20,360/2,733/6,165 QA pairs for train/dev/test sets.

We used two-layer LSTMs with 512 hidden units for the read/write modules. The MLP setup used in the language inference task is kept same, except that we now replace the softmax layer with a sigmoid layer and model the following conditional probability distribution.

$$p_{\theta}(y = 1|h^q_1, h^a_1) = \text{sigmoid}(o^{QA})$$

where $h^q_1$ and $h^a_1$ are the question and the answer encoded vectors and $o^{QA}$ denotes the output of the hidden layer of the MLP. We trained the MMA-NSE attention model to minimize the sigmoid cross entropy loss. MMA-NSE first encodes the answers and then the questions by accessing its own and the answer encoding memories. In our preliminary experiment, we found that the multiple memory access and the attention over answer encoder outputs $\{h^a_t\}_{t=1}^T$ are crucial to this problem. Following previous work, we adopt MAP and MRR as the evaluation metrics for this task.

We set the batch size to 4 and the initial learning rate to 1e-5, and train the model for 10 epochs. We used 40% dropouts after word embeddings and no $l_2$ weight decay. The word embeddings are pre-trained 300-D Glove 840B vectors. For this task, a linear mapping layer transforms the 300-D word embeddings to the 512-D LSTMs inputs.

Table 2 presents the results of our model and the previous models for the task. The classifier with handcrafted features is a SVM model trained with a set of features. The Bigram-CNN model is a simple convolutional neural net. While the LSTMs and LSTM attention models outperform the

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5 We used trec_eval script to calculate the evaluation metrics
6 Inclusion of simple word count feature improves the performance by around 0.15-0.3 across the board
previous best result by nearly 5-6% by implementing deep LSTMs with three hidden layers, the NASM improves it further and sets a strong baseline by combining variational auto-encoder with the soft attention. In the NASM, they adopt the deep LSTMs and introduced a latent stochastic attention mechanism. Our MMA-NSE attention model exceeds the NASM by approximately 1% on MAP and 0.8% on MRR for this task.

4.3 Sentence Classification

We evaluated NSE on the Stanford Sentiment Treebank (SST) [27]. This dataset comes with standard train/dev/test sets and two subtasks: binary sentence classification or fine-grained classification of five classes. We trained our model on the text spans corresponding to labeled phrases in the training set and evaluated the model on the full sentences.

The sentence representations were passed to a two-layer MLP for classification. The first layer of the MLP has ReLU activation and 1024 or 300 units for binary or fine-grained setting. The second layer is a softmax layer. The read/write modules are two one-layer LSTMs with 300 hidden units and the word embeddings are the pre-trained 300-D Glove 840B vectors. We set the batch size to 64, the initial learning rate to 3e-4 and $l_2$ regularizer strength to 3e-5, and train each model for 25 epochs. The write/read neural nets and the last linear layer were regularized by 50% dropouts.

Table 3 compares the result of our model with the state-of-the-art methods on the two subtasks. Most best performing methods exploited the parse tree provided in the treebank on this task with the exception of the DMN. The DNM (Dynamic Memory Network) model is a memory-augmented network. Our model outperformed the DNM and set the state-of-the-art results on both subtasks.

4.4 Document Sentiment Analysis

We evaluated our models for document-level sentiment analysis on two publically available large-scale datasets: the IMDB consisting of 335,018 movie reviews and Yelp 13 consisting of 348,415 restaurant reviews. Particularly, we used the pre-split datasets of [31]. Each document in the datasets is associated with human ratings and we used these ratings as gold labels for sentiment classification.

We stack a NSE or LSTMs on the top of another NSE for document modeling. The first NSE encodes the sentences and the second NSE or LSTMs takes sentence encoded outputs and constructs document representations. The document representation is given to a output softmax layer. The whole network is trained jointly by backpropagating the cross entropy loss. We used one-layer LSTMs with 100
Table 4: Results of document-level sentiment classification. MSE: mean squared error.

| Model                                  | Yelp 13 | IMDB |
|----------------------------------------|---------|------|
|                                        | Accuracy | MSE  | Accuracy | MSE  |
| Classifier with handcrafted features [31] | 59.8    | 0.68 | 40.5     | 3.36 |
| Paragraph Vector [31]                  | 57.7    | 0.86 | 34.1     | 4.69 |
| CNN [31]                               | 59.7    | 0.76 | 37.6     | 3.30 |
| Conv-GRNN [31]                         | 63.7    | 0.56 | 42.5     | 2.71 |
| LSTM-GRNN [31]                         | 65.1    | 0.50 | 45.3     | 3.00 |
| NSE-NSE [31]                           | 66.6    | 0.48 | **48.3** | **1.94** |
| NSE-LSTMs                              | 67.0    | **0.47** | 48.1 | 1.98 |

hidden units for the read/write modules and the pre-trained 100-D Glove 6B vectors on this task. We set the batch size to 32, the initial learning rate to 3e-4 and $l_2$ regularizer strength to 1e-5, and train each model for 50 epochs. The write/read neural nets and the document-level NSE/LSTMs were regularized by 15% dropouts and the softmax layer by 20% dropouts. For this task, we create document buckets by considering the number of sentences per document, i.e., documents with the same number of sentences were put together in one bucket. The buckets were shuffled and updated per epoch. We did not use curriculum scheduling [32], although it is observed to help sequence training.

Table 4 shows our results. We report the two performance metrics: accuracy and MSE. The best results on the task were previously obtained by Conv-GRNN and LSTM-GRNN, which are also stacked models. These models learn the sentence representations with a CNN or LSTMs and combine them for document representation using a gated recurrent neural network (GRNN). Our models are able to outperform the previous state-of-the-art in terms of both accuracy and MSE, by approximately 2-3%. All systems tend to show poor results on the IMDB dataset. That is, the IMDB dataset contains longer documents than the Yelp 13 and it has 10 classes while the Yelp 13 dataset has five classes to distinguish. The stacked NSEs (NSE-NSE) performed slightly better than the NSE-LSTMs on the IMDB dataset. This is possibly due to the encoding memory of the document level NSE that preserves the long dependency in documents with a large number of sentences.

### 4.5 Machine Translation

Lastly, we conducted a controlled experiment to see the effectiveness of models for neural machine translation (NMT). The NMT problem is mostly defined within the encoder-decoder framework [33, 3, 34]. The encoder provides the semantic and syntactic information about the source sentence to the decoder and the decoder generates the target sentences by conditioning on this information and its partially produced translation. For an efficient encoding, the attention-based NTM was introduced [8].

For this task, we implemented three different NTM models. The first model is a baseline model and similar to the one proposed in [8] (RNNSearch). This model (LSTMs-LSTMs) has two LSTMs for the encoder/decoder and has the soft attention neural net, which attends over the source sentence and constructs a focused encoding vector for each target word. The second model is an NSE-LSTMs encoder-decoder which encodes the source sentence with NSE and generates the targets with the LSTM network by using the NSE output states and the attention network. The last model is an NSE-NSE setup, where the encoding part is the same as the NSE-LSTMs while the decoder NSE now uses the output state and has an access to the encoder memory, i.e., the encoder and the decoder NSEs access a shared memory. The memory is encoded by the first NSEs and then read/written by the decoder NSEs.

We used the English-German translation corpus from the IWSLT 2014 evaluation campaign [35]. The corpus consists of sentence-aligned translation of TED talks. The data was pre-processed and lowercased with the Moses toolkit [9]. We merged the dev2010 and dev2012 sets for development and the tst2010, tst2011 and tst2012 sets for test data. Sentence pairs with length longer than 25 words.

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7 The average number of sentences and words in a document for IMDB: 14, 152 and Yelp 13: 9, 326
8 https://github.com/moses-smt/mosesdecoder
9 We modified `prepareData.sh` script: https://github.com/facebookresearch/MIXER
Table 5: BLEU scores for English-German translation task.

| Model                      | Train | Dev  | Test |
|----------------------------|-------|------|------|
| Baseline LSTMs-LSTMs       | 28.06 | 17.96| 17.02|
| NSE-LSTMs                  | 28.73 | 17.67| 17.13|
| NSE-NSE (Shared memory access) | 29.89 | **18.53** | **17.93** |

were filtered out. This resulted in 110,439/4,998/4,793 pairs for train/dev/test sets. We kept the most frequent 25,000 words for the German dictionary. The English dictionary has 51,821 words. The 300-D Glove 840B vectors were used for embedding the words in the source sentence whereas a lookup embedding layer was used for the target German words. Note that the word embeddings are usually optimized along with the NMT models. However, for the evaluation purpose we in this experiment do not optimize the English word embeddings. Besides, we do not use a beam search to generate the target sentences.

The LSTM encoder/decoders have two layers with 300 units. The NSE read/write modules are two one-layer LSTMs with the same number of units as the LSTM encoder/decoders. This ensures that the number of parameters of the models is roughly the equal. The models were trained to minimize word-level cross entropy loss and were regularized by 20% input dropouts and the 30% output dropouts. We set the batch size to 128, the initial learning rate to 1e-3 for LSTMs-LSTMs and 3e-4 for the other models and $l_2$ regularizer strength to 3e-5, and train each model for 40 epochs. We report BLEU score for each models.

Table 5 reports our results. The baseline LSTMs-LSTMs encoder-decoder (with attention) obtained 17.02 BLEU on the test set. The NSE-LSTMs improved the baseline slightly. Given this very small improvement of the NSE-LSTMs, it is unclear whether the NSE encoder is helpful in NMT. However, if we replace the LSTMs decoder with another NSE and introduce the shared memory access to the encoder-decoder model (NSE-NSE), we improve the baseline result by almost 1.0 BLEU. The NSE-NSE model also yields an increasing BLEU score on dev set. Although it is not a major improvement, the result is encouraging because this model shows that the attention-based NMT systems can be taken one step further by a shared-memory encoder-decoder model. In addition, memory-based NMT systems should perform well on translation of long sequences by preserving long term dependencies.

5 Conclusion

We evaluated the effectiveness and the flexibility of Neural Semantic Encoders on five tasks. We studied shared and multiple memory accesses within the framework of NSE. Choosing a memory access in consideration of the problem addressed has been shown to be useful. For instance allowing NSE to access premise encoded memory when processing hypothesis for natural language inference or to access answer encoded memory when reading question for QA yielded performance improvements whereas sharing a single encoded memory between encoder and decoder was helpful in machine translation. We believe our NSE models scratch the surface of the memory access patterns and possibilities of memory augmented neural networks for natural language understanding. NSE can be extended so it learns to select and access a relevant subset from a memory set. Unsupervised variations of NSE have yet to be explored. For example, NSE can be trained to produce encoding memory and representation vector of entire sentences or documents by borrowing the idea of skip-gram model.

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10 We computed the BLEU score with *multi-bleu.perl* script of the Moses toolkit
