Scaffolding Networks for Teaching and Learning to Comprehend
Asli Celikyilmaz, Li Deng, Lihong Li, Chong Wang
Microsoft Research

Abstract—In scaffolding teaching, students are gradually asked questions to build background knowledge, clear up confusions, learn to be attentive, and improve comprehension. Inspired by this approach, we explore methods for teaching machines to learn to reason over text documents through asking questions about the past information. We address three key challenges in teaching and learning to reason: 1) the need for an effective architecture that learns from the information in text and keeps it in memory; 2) the difficulty of self-assessing what is learned at any given point and what is left to be learned; 3) the difficulty of teaching reasoning in a scalable way. To address the first challenge, we present the Scaffolding Network, an attention-based neural network agent that can reason over a dynamic memory. It learns a policy using reinforcement learning to incrementally register new information about concepts and their relations. For the second challenge, we describe a question simulator as part of the scaffolding network that learns to continuously question the agent about the information processed so far. Through questioning, the agent learns to correctly answer as many questions as possible. For the last challenge, we explore training with reduced annotated data. We evaluate on synthetic and real datasets, demonstrating that our model competes well with the state-of-the-art methods, especially when less supervision is used.

I. INTRODUCTION

Instructional scaffolding teaching [1, 2] is a process through which a teacher adds support for students to enhance learning. A common method in scaffolding teaching is to repeatedly question students to check for understanding, which systematically builds on students’ experiences and knowledge. In this paper, we present a modular neural network architecture that imitates scaffolding teaching and teaches machines to read and comprehend text by iteratively asking questions. The Scaffolding Network (as sketched in Figure 1) combines several desirable features into a single, effective network: it can iteratively learn to track the information in text one sentence at a time; it can generate questions from the text via a question simulator; it learns to answer these questions based on the reward signal it receives from an agent that repeatedly interacts with the text and the simulator. By scaffolding questions about the previous memory, it improves comprehension.

In the literature, the machine reading and comprehension is mostly taken as a cloze-style question answering (QA) task. Especially the neural-network-based approaches learn to selectively attend to different parts of the input text relevant to a target question. They squash the input text into a vector representation, e.g., [3, 4, 5], and use the answer as the output signal in a supervised learning setting. The key challenge is to understand the relation(s) between different parts of the text and do reasoning about the related facts. Similar to [6, 7, 8], our model receives the input text in sequences of smaller segments (e.g., sentences). Unlike previous work, our network does not just focus on answering a target question, but rather sequentially encode the text while repeatedly refreshing its memory and generating questions about the recent past. This way, it learns to keep track of the new information in each sentence, building up on previous memory, thus improve comprehension. This is similar to the scaffolding teaching, in which teachers typically break up learning a skill into discrete parts and check to see if students have understood the concepts in previous parts.

Our main contribution is a novel reading comprehension architecture and an associated algorithm that iteratively learns to map hidden facts in sentences into state representation. It uses an attention network while keeping the representation of the previous sentences of the text in memory. The second module, the question simulator, generates question-answer pairs related to the text processed so far along with their answers based on the error signal it receives from the network. Contrary to earlier work, we do not provide the final question and its answer (true labels) until after all the sentences are encoded through scaffold questioning. To reduce the dependency on the training data labels, we evaluate our model on data by reducing the training data labels and instead use the generated question-answer pairs as the labels. In a sense, scaffolding network can be self-trained with these auxiliary questions. Nevertheless, labels from training data improve learning to answer different types of questions, possibly more complex than the generated question-answers. The third module, the agent, produces scores for the set of possible answers to the posed question given the current state representation. The agent receives a limited (partial) information about the state of the world (no prior information as entities, slots or relations between them are provided) and learns to encode them given previous memory. Therefore, we adopt a reinforcement learning (RL) framework, and use agent’s reward as the learning signal. The scaffolding agent aims to maximize its rewards that it obtains upon answering generated questions. Using Deep Q-Learning [9, 10] (DQN), the agent learns a policy in the form of an action-value function to evaluate the merit of the predicted answer to generated question. Action-value function is parameterized with the scaffolding network using the answers to questions as a feedback.

We evaluate the Scaffolding Network (SN) on story-based reasoning and question/answering datasets including a travel-log data, bAbI QA [11], bAbI dialog set and DSTC2 dialog datasets [12] in the supervised learning setting. In most of the experiments, when all labels are used, our SN competes well with the state-of-the-art. We also demonstrate that it shows promising results on reasonings tasks that require learning
II. The Scaffolding Network

Similar to approaches that use dialog modeling for comprehension tasks [6], the SN agent interactively learns to parse the input text and register the information into the memory by interacting with a question simulator. Unlike these systems, where a simulator and agent take turns and the agent asks clarifying questions to get more information, the information that the our agent needs is readily available in the text, but is mostly hidden. Our agent’s interaction with the simulator is implicit and agent’s goal is to learn to track information in text while continuously trying to answer a generated question.

Consider that the network shown in Figure 1 is encoding the shown input text. Each sentence is processed through this network one at a time. For instance, the figure shows that at time \( t=3 \) the network is reading the sentence “the bathroom is south of the kitchen”. First, the question simulator samples a sentence from the first \( t-1 \) sentences and generates a question along with an answer (e.g., if sentence 2 is sampled, the generated question can be "the garden is west of the ?" with kitchen being the answer) (path 1-6). Then, the network encodes the current sentence together with the generated question and the dynamic memory into a concatenated hidden state representation (path 7). The attention network identifies new information in the current sentence relative to the dynamic memory (flow 8) and updates the memory (flow 9). The network concatenates all this information (flow 10) into a vector representation and sends to the policy network (flow 11), which produces a reward for answering the question (flow 12). Thus, the goal in scaffold questioning is to reinforce the registering of key hidden facts (e.g., kitchen’s location relative to the garden and bathroom) with as little external supervision as possible. If the corpus is equipped with question-answer pairs about the text, they are also encoded when the end of text is reached. The reward is positive when the agent answers correctly, and negative when a wrong answer is predicted. By trial-and-error exploration, the network learns to keep track of the hidden states within the text. We provide the details of SN modules below and the pseudo-code for training the network end-to-end in Algorithms 1 and 2 in Appendix-A.

A. Input Encoder Module

The training data \( D_{train} \) is a collection of passages. Each passage, denoted \( \mathcal{X} \), consists of a sequence of sentences: \( \mathcal{X} = \{x_1, \ldots, x_T\} \). The network is trained using one sentence at a time, \( x_t = (w_{t,1}, \ldots, w_{t,n}) \), represented as a sequence of \( n \) words, used as the input units. Each word \( w_{t,i} \) is represented with embedding \( e_{t,i} \), yielding a sequence of embedding vectors \( e_t = (e_{t,1}, \ldots, e_{t,n}) \). The embedding vector at time \( t \) is used as input to an long short-term memory (LSTM) [13] model to obtain \( H_t \in \mathbb{R}^{d \times n} \), which is a matrix of hidden states of each word \( H_t = (h_{t,1}, \ldots, h_{t,n}) \), and \( d \) indicates the size of the hidden layers. We also inject the previous context into the LSTM. This is crucial for our network, as the network may be asked questions about previous context. To do this, the information accumulated from the previous sentence after processing the last state, \( \tilde{H}_{t-1} \), is used as the initial state of the LSTM that processes the current sentence. The last hidden state \( h_{t,n} \) of the current sentence is used to update the dynamic memory.

B. Question-Sentence Encoder

Similar to the input encoder, each word \( a_i \) in a question \( x_q = (a_1 \cdots a_n) \), be it generated by the question simulator or provided in the corpus, is encoded by first mapping onto embedding vectors \( e^q_i = (e^q_{i,1}, \ldots, e^q_{i,n}) \), and then using LSTM to get the hidden vectors. The final rolled hidden state \( h^q_{t,n} \) is a fixed length vector representing each question at time \( t \). The similarity of a question \( x^q_t \) at time \( t \) to the current sentence \( x_t \) as well as the previous memory is computed by a linear combination of the output of the last hidden state of the question LSTM \( h^q_{t,n} \), hidden-state representation of the previous memory \( \tilde{H}_{t-1} \), and the current sentence word embeddings \( e_t \) as follows:

\[
\tilde{e}_t \leftarrow e_t + h^q_t \odot I^q \\
\tilde{e}_{t,0} \leftarrow \tilde{H}_{t-1} \odot h^q_t \\
o_t \leftarrow \text{LSTM}(\tilde{e}_{t,0}, \tilde{e}_t),
\]

where \( I^q \in \mathbb{R}^n \) is a vector of 1s that we use to merge the encoded question vector with the embedding vector of each word in the sentence, \( e_t \). Element-wise product (\( \odot \)) of the question and the previous memory is used as the initial state \( \tilde{e}_{t,0} \) of the question-sentence encoder. The non-linear combination of the question and sentence, \( o_t \), ensures encoding of the information in sentence \( t \), in relation to the question and the previous memory, as part of the state representation.

C. Attention Network

The goal of the attention network is two-folds: (i) learn to detect new information in the current sentence in relation to the information extracted in previous sentences using soft attention, (ii) learn to build a dynamic memory to store the previous memory and current information using a gating function. To achieve these goals, the attention network receives two inputs: the hidden states of each word of the current sentence \( t \), \( H_t = (h_{t,1}, \ldots, h_{t,n}) \) and the last hidden state from the previous time step, \( \tilde{H}_{t-1} \).

Soft Attention. [14] learns an entailment relation between two sentences (a premise and a hypothesis text) by word-by-word soft attention to encourage reasoning over entailment of pairs of words or phrases. We implement a similar soft attention mechanism. Rather than learning entailment relations, we aim to learn dissimilarities between the previous sentences (premises) and the current sentence (the hypothesis) to track and encode the new information in the current sentence into states. Weaker attention indicates that the information in the current sentence compared to the memory (e.g., a new entity present in the current sentence) is different and should be tracked in state representation. The attentive network produces intermediate attention representation \( m_t \) as a non-linear combination of the
previous sentence’s last hidden state \( \tilde{h}_{t-1} \) and hidden states of each word in the current sentence \( h_{t,i} \in H_t \):

\[
\mathbf{m}_t \leftarrow \phi(W^w H_t + W^h \tilde{h}_{t-1} \otimes \mathbf{I}_n),
\]

where \( W^w \) and \( W^h \) are weight matrices to be learned, and the output product \( W^h \tilde{h}_{t-1} \otimes \mathbf{I}_n \) repeats the previous sentence hidden state \( \tilde{h}_{t-1} \) \( n \) times. \( \phi \) is the activation function; in our experiments, we used the hyperbolic tangent (tanh) activation function. Each column \( \mathbf{m}_{t,i} \) of the output attention matrix \( \mathbf{m}_t \) (as in Figure 1) is the un-normalized attention of the \( i \)th word of sentence \( x_t \).

Dynamic Memory. After encoding the sentence with attention, the network determines how much information to carry over to the next sentence using a gating function:

\[
g_t \leftarrow \phi(W^c h_t + W^p \tilde{h}_{t-1}),
\]

\[
\tilde{h}_t \leftarrow h_t + g_t \otimes \tilde{h}_{t-1}.
\]

In the above, \( W^c \) and \( W^p \) are weight matrices to be learned. They represent the weights associated with the current sentence and the previous memory at time \( t - 1 \). \( h_t \) is the last hidden state of the current sentence LSTM model. We choose hyperbolic tangent for the activation \( \phi \). In the experiments, we compare the effectiveness of our gating function to simpler memory update functions, i.e., summation: \( \tilde{h}_t = \tilde{h}_{t-1} + h_t \) and moving average: \( \tilde{h}_t = (\tilde{h}_{t-1} + h_t)/2 \).

D. Question Simulator

Instead of a human proving question-answers as a teacher, our question simulator is designed to ask scaffolding questions to the agent. Its goal is to reinforce tracking of the information as states and learning the relations between the information extracted from sentences. To generate questions, we use two types of methods:

Rule-Based Simulator: The rule-based question simulator randomly selects a sentence among the sentences that have been processed so far. Similar to [15], it randomly samples one word (we omit stop words) as the answer (\( a_t \)), and replaces it with an unknown word ‘unk’ (“the documents are released to the press” \( \rightarrow \) “the documents are released to unk?”). Such questions represent what is known as wh-questions, such as “who are the documents released to?”. The generated question is processed through an LSTM to obtain the last hidden state vector \( h_t \) and is sent to the question-sentence encoder.

Reward-Driven Simulator: Our RL agent encodes the internal state of sentences by iteratively learning to correctly answer questions. With no signal from the agent, the rule-based agent may unnecessarily generate questions that the model has already learnt to correctly answer. We propose rather an intelligent simulator that learns to generate questions based on the reward it receives from the agent. To achieve this, we first select a candidate sentence from those already processed so far.
The candidate sentence words are converted into embedding vectors, then processed through an LSTM layer to obtain unrolled hidden states of its words \( H_q = (h_{q,1}, \ldots, h_{q,n}) \). We learn a mapping (parameterized by \( \beta \)) from hidden states to a probability distribution \( p_t \) over words in the selected sentence, so that

\[
p_t(a_t) \propto \exp(\beta^T h_{t+1}^q),
\]

The \( p_t(a_t) \) is the probability that the word \( a_t \) is chosen from the candidate words \( \{a_1, \ldots, a_n\} \) normalized over all candidate words, and we define \( p_t = [p_t(a_1) \ldots p_t(a_n)] \) as the probability vector. Among all words, a candidate answer \( a_t^* \) is sampled from this distribution. The generated question is then formed by replacing the candidate answer with an unknown word ‘unk’. The generated question is processed through the same LSTM to obtain the last hidden state vector and is sent to the question-sentence encoder (as shown in Figure 1). The question word probabilities \( p_t \) are concatenated to the input state representation so the scaffolding is trained with the simulator end-to-end. Under this model, the simulator will learn to sample among answer candidates, for which the model has yielded negative reward in the past. When the question-answer pairs are provided in corpus (i.e, at the end of the text), the provided question follows through the question-generation path (1-6) in Figure 1 to obtain the word probabilities \( p_t \) skipping the answer sampling step. Then the provided answer is used as the target answer.

E. Scaffolding Deep Q-Network Agent

We pose the task of learning to reason through questioning into a problem well suited for an RL problem. State. At each time step \( t \), the agent observes the current state \( s_t \in S \), which, for the rule-based simulator, consists of the output of the question-sentence encoder \( (o_t) \) and the attention vector \( (m_t) \): \( s_t = [o_t; m_t] \). For the reward-driven simulator, the state also includes the question word probabilities \( (p_t) \); that is, \( s_t = [o_t; m_t; p_t] \). This is similar to [16], in which our agent attempts to understand the text not only from encoding the question and sentence together with the dynamic memory, but also from encoding the generated question, which includes some hidden information about the candidate answer. Action. At each time step, the agent selects an action \( a_t \) from a finite set of actions \( A = \{1, \ldots, K\} \). In our task, an action corresponds to an answer, which is an entity from a task-specific entity set. The agent selects an answer, then collects the corresponding reward. The agent’s action affects the next operations of the whole network, including whether the next sentence from the input text is to be read, and how the question generator samples question-answer pairs; this in turn affects the next state, \( s_{t+1} \), observed by the RL agent. Reward. A negative reward is provided when the agent answers the question wrong, and positive when correct. For a wrong answer at time \( t \), the question simulator generates a new question, the \( t \)th sentence is encoded with the new question and are sent to the agent. Then the agent samples an answer and collects reward. This process continues until the agent gets a correct answer or a maximum of \( \Gamma \) trials are exhausted. The reward at terminal is a larger positive number which is proportional to the number of correctly answered questions given the sentences in the input text.

Policy. We learn the optimal policy through a Deep Q-Network, or DQN. As the forward activation, the agent first interacts with each sentence over a sequence of discrete steps until the end of text is reached. At each time step, it observes the current state \( s_t \), and chooses an action/answer \( a_t \) to the generated question according to a policy \( \pi : S \rightarrow \mathcal{A} \). The agent receives a reward \( r_t \) and observes a new state \( s_{t+1} \), continuing to read sentences until the end of text. The Q-function for the policy \( \pi \) measures, for each state-action pair \((s, a)\), the expected cumulative discounted reward if the agent chooses \( a \) in state \( s \) and then follows \( \pi \) thereafter:

\[
Q^\pi(s, a) = \mathbb{E}_\pi \left[ \sum_{i=0}^T \gamma^i r_{t+i} | s_t = s, a_t = a \right],
\]

where \( \gamma \) is the discount factor. An optimal policy \( \pi^* \) has a Q-function, denoted \( Q^* \), that uniformly dominates every other policy’s Q-function. During learning, \( \epsilon \)-greedy exploration is used with \( \epsilon = 0.1 \) which decays over time.

Learning Double DQN: Back Propagation. In standard Deep Q-learning [10], given an optimal policy \( Q^* \), at any time-step \( t \), the agent’s optimal move is to choose action \( a^* = \arg \max_a Q^*(s, a) \). For reasoning tasks, the action space is large and state space is continuous, so we approximate the Q-function by a 2-layered deep-learning model \( Q(s, a; \theta) \), where \( \theta \) are parameters to be learned. As commonly done, we represent experiences as tuples of transitions, \( ((s_t, a_t, r_t, s_{t+1}) \in D_c) \). Using a greedy policy, we aim to improve the value function by minimizing the squared error between the current prediction and one-step look ahead prediction. With stochastic approximation, we train the q-function. We use experience reply [10] by maintaining a buffer of experiences and training on randomly selected mini-batches of experiences. As proposed in [10], we also use the target network to compute the training targets \( y_t \). We implement double deep q-learning (D-DQN) [17] for the scaffolding agent policy learning to eliminate over-optimism during learning. In D-DQN, two value functions, \( \theta \) and \( \theta' \) are learnt by alternating their use. One of the value functions is used to determine the greedy policy, and the other value function is used to determine its value. (see Appendix-A for implementation details)

III. RELATED WORK

One of the challenges in reading comprehension is to learn to represent document structure to do a proper reasoning. Neural Readers have recently seen considerable success, specifically in cloZE form question answering tasks. Most early work applied single turn-reasoning utilizing an attention mechanism to emphasize some sections of a document which are relevant to a query and proposed different network structures [18]. [19], [3], [4], [20]. While they do reasonably well in representing the similarity relations between a passage and a question, they fail short on the reasoning capabilities because it is harder to keep track of relations between encoded knowledge with such architecture. For reasoning tasks, we must design a network that can extract information from different parts of the text and track in memory, as shown in Section II-C.
The second and arguably the most important challenge is to evaluate the efficacy of the model on doing a fair reasoning. Several recent work has simulated this by combining the facts in a query with the new information from previous iterations to do multi-turn reasoning [15, 21, 22, 5, 23] for more complex stories which require deeper reasoning. Most work are based on memory networks [11] or RNNs with attention components, e.g. Gated Attention Reader [24], Iterative Alternative Reader [5], Fine-Grained Gating [25], Chunk Extraction [26], Dynamic Co-Attention Networks [27] etc.

Similar to our work, others receive the text in sequences of sentences and encode them separately. [6] considers dialog modeling approach, in which an agent iteratively asks additional questions about relevant missing facts, so it learns to correctly answer the target question. Unlike their approach, our agent does not ask questions, but rather a question simulator module, implicitly acting as a teacher, repeatedly questions the agent about the hidden facts to strength its memory network. [28]’s dialog-based learning approach gets feedback from a teacher and various correction types and imitates such signals in order to learn to answer questions. [8] encodes the labeled question together with each sentence separately to identify question related facts. The goal of these earlier studies is to highlight relevant facts about the questions by using the question-answer pairs in the corpus as the supervised signal. Unlike them, our goal is not to search for clues about a given question, but, to learn to encode the given text to do reasoning later. The closest to our work is the Recurrent Entity Networks [7], in which the authors try to learn the internal state representation of each sentence and store in memory by parallel recurrent units with tied weights using gating functions. Similar to ours, their goal is to learn to represent a story into states to later do reasoning. Unlike their work, we use scaffolding to imitate the student teaching experience using RL. In the experiments we use some these models to compare against the scaffolding networks.

IV. EXPERIMENTAL SETUP

We evaluated our SNs on a set of reasoning tasks with synthetic and real datasets. Our goal is to show that a reward-based question simulator as a teacher in a self-training setting is fundamental to reasoning about facts that may be partially observable. Even with reduced labeled data, the scaffolding can learn to do reasoning well on complex tasks, reducing the dependence on humans as teachers.

A. Training the Scaffolding Network

If no validation data is provided, we withhold 10% of the data for hyper-parameter tuning. We use hidden size of 100 for small datasets (~1K training data) and 128 for the rest of the datasets. The weights in the input and output units were initialized with zero mean and standard deviation of $1/\sqrt{d}$. L2 weight decay of 0.001 is used for all weights. All models are trained with ADAM [29] with initial learning rates set by a grid search over $\{0.1, 0.01\}$. We varied the epochs at training by 100-500 epochs. For each experiment, we assign a reward of -1 for answering a question wrong, +1 when correct. At the last sentence, we provide +5 for correct answer plus a reward proportional to the number of correct answers, e.g., if there are 10 sentences in text, and 3 of the questions are correctly answered (including the last labeled question) the reward at terminal is $r_T = 5 + 3$. As large variance in performance can be observed on some tasks [30], we repeat each training 5-10 times with different random initializations and choose the best model based on validation performance and report test results of the best model.

Our benchmark models use multi-hop/multi-layer memory networks and show promising improvements compared to single hop/layer counterparts. For a fair comparison, we also used 2-layer LSTMs for the question simulator and the question-sentence encoder. We obtain two last hidden states from the two layer question simulator, $h_q^{\text{LSTM}}, h_q^{\text{LSTM}}$. The first one is used as an input to the first LSTM of the question-sentence encoder same as in Equation 1 and 2. The second one is linearly combined with the unrolled output of the first LSTM, $o_t^1$, and sent to the second LSTM as follows:

$$ o_t^2 \leftarrow o_t^1 + h_q^{\text{LSTM}} \otimes I^q $$

$$ o_t^2 \leftarrow \text{LSTM}(o_t^2) $$

The state is then represented as: $s = [o_t^2; m_t]$ and $s = [o_t^2; m_t; p_t]$ with the reward driven simulator. We get slight improvements with 2-layered SN and use in all experiments.

B. Datasets

Travel Log datasets. Travel log dataset is a collection of text documents about travel narratives. Our goal in creating these datasets is to measure the ability of our scaffolding network in reasoning tasks which require learning relations between multiple facts. Each text is constructed by placing a traveler agent in a town defined by a 9×9 grid, which is full of attractions. The agent starts randomly in one location and wanders around the town by randomly choosing a direction to the next move (i.e., north, west, south, east) and logs each move. As agent moves to a new direction, logs any attraction nearby with respect to the current location (e.g. there is a museum on my left). End of each log, a question is asked about the location of a randomly chosen attraction, (e.g., what is north of the museum?). The task is to find the correct answer, which can only be inferred from the text by tracing the traveler’s steps. The complexity of the task increases as the number of attractions in town is increased. Five different cities of log datasets are generated by varying the number of attractions, i.e., complexity of the reasoning task. Each dataset contains 1000 training and test logs. (Samples from log data can be found in Appendix-B.)

bAbI story-based QA datasets. bAbI dataset is a collection of 20 question answering datasets [11] of different tasks. A task consists of a text in the form of sequence of sentences followed by a question whose answer is a word or set of words from the text. The task is to answer the question correctly, both of which are available at training time, but the answer is to be predicted at test time. Two sets of the QA datasets are used: one of them has 10,000 training problems per task and the other has 1,000 per task.
bAbI Dialog datasets. Goal oriented dialog datasets \cite{21} with 5 different tasks of completing a restaurant reservation conversational dialog system between a user and a system. The datasets (T1,...,T5) are synthetically generated based on knowledge based consisting of 7 facts which define restaurants (e.g., such as location and price range). These tasks test the capacity of end-to-end dialog systems with various goals (e.g., request phone-number, address, etc.) A different set of test sets, named out-of-vocabulary (OOV), are also used to test the capability of a system to deal with entities not appearing in training data.

DSTC-2 Dialog datasets. This dataset \cite{32} is provided with real human-bot conversations, in restaurant domain, and derived from second Dialog State Tracking Challenge \cite{33}. Sample conversations are provided in Appendix-C.

For the QA datasets, the scaffolding RL agent uses all the vocabulary (after stop words are removed) as its action space. Some tasks include "yes/no" questions, so we added "yes" and "no" to our action space. For the dialog tasks, the input text is defined by taking the utterances \( c_1^{u}, c_2^{u}, c_2^{s}, \ldots, c_{t-1}^{u}, c_{t-1}^{s} \) (alternating between the user \( c_1^{u} \) and the system response \( c_1^{s} \), while the \( c_2^{s} \) is the question and the goal is to predict the response \( c_2^{s} \). The answers are comprised of multiple words. Similar to \cite{12}, we define an action \( a_i \) as the \( i \)th response in the candidate set \( C \) such that \( a_i \in C \). The set of candidate responses includes all possible bot utterances and API calls.

V. Experimental Results

A. Results on Supervised Setting

I. Travel-Log Datasets. We start with studying our model’s comprehension capability on learning the relations between multiple facts in text logs. To make the tasks harder, we gradually increase the number of attractions. We compare the performance of \texttt{LSTM}, \texttt{End-to-End Memory Networks (MemNN)} \cite{30} and \texttt{Scaffolding Networks with Reward Driven Simulator (SN-RD)}.

Table I shows results. For each model we repeated the experiment 5 times and report the best performance. The scaffolding models outperform almost all the benchmark models, except for the simplest task with 5 attractions. The \texttt{LSTM}s performed poorly. \texttt{MemNN} performed similarly to the scaffolding models for simpler tasks (#attractions \( \leq 10 \)). Although, the performance of all models drop as the complexity increase, our scaffolding agent is both more accurate and more robust on complex tasks. As shown Appendix-B, Table 3, the question simulator learns to ask the questions that would challenge the agent. This teaches the agent to learn to encode the correct facts and relations.

II. QA and Dialog Datasets. We compare our approach to recently published work mentioned in the related work: \texttt{End-to-End Memory Networks (MemNN)} \cite{30}, \texttt{Query Reduction Networks (QRN)} \cite{8}, \texttt{Dynamic memory Networks (DMN)} \cite{21}, \texttt{Recurrent Entity Networks (EntNet)} \cite{27}, \texttt{End-to-End Goal Oriented Dialog (N2N)} \cite{12} (This approach is same as the \texttt{MemNN} models except dialog features are used). For fair comparison with benchmark models, we show the 2-layer results of \texttt{QRN} (their best model on bAbI and dialog data). We list the results of our \texttt{SNs} with rule based question simulator (\texttt{SN-RB}), and with reward driven question simulator (\texttt{SN-RD}).

Performance results are summarized in Table II for story based QA datasets (top table), both of our \texttt{SN} models are ranked in top tier among the best reported models based on the mean error over 20 tasks. \texttt{SNs} are trained with a goal of interactively learning to encode the sentences in input text first, then to answer labeled questions. In that sense, the scaffolding model results are promising and comparable to state-of-the-art. In addition, some of these tasks are more challenging requiring multiple steps of reasoning and incremental knowledge contemplation. Although our models do not outperform baselines in the overall, the scaffolding agent shows promising improvements over the baselines especially for complex tasks requiring deeper reasoning, e.g., positional and size reasoning, and the tasks including lists, as detailed in Appendix-D. The model with the reward driven question simulator \texttt{SN-RD} shows slight improvement over the rule based \texttt{SN-RB} suggesting that reward-driven simulator can learn to tackle with the reasoning tasks better.

Following previous work, we expand the state representation with 7 additional features, each focusing on one of the 7
We predict the labels for the removed data, and training with the rest (100-% labeled data, add them back even with reduced labeled data). Then we predict the labels for the removed m% data, add them back to the training data, re-train and repeat the process.

In Figure 2, we demonstrate the self-training results on bAbI QA Task 9,14,17 and DSTC-2 dialog tasks. We repeated the experiments 10 times and report the best results. Our models show promising results. Even when scaffolding models’ error rate is same or higher than the memory networks when 100% labeled data is used (Task 9 and 14), removing the labels does not affect the scaffolding models’ performance as much as the memory networks due to the self-training property of the reward-driven scaffold questioning.

C. Analysis on the Gating Function

The gating functions in Equation 5 and 6 enable the amount of information flow as each sentence is processed, hence the scaffolding network learns to control the dynamic memory. With enough training and scaffolding through questioning, our hope is that it learns to keep track of the new but hidden facts as well as register and strengthen/weaken their relations. To visualize this, using our scaffolding agent we compare our gating function to other much simpler memory transferring methods between sentences, i.e., (i) summing the current and past memory, (ii) moving average of current and past memory (as explained in Section II-C).

Figure 3 demonstrates the training success rate in accuracy over the number of episodes for Task-2 of bAbI QA data. In each episode we report average success rates of 100 randomly sampled train instances, i.e., 100 different [story,question,answer] pairs. Our gating function can learn to keep more rich information for the reasoning tasks.

VI. CONCLUSIONS

Summary. We take a step towards teaching machines to comprehend by introducing an RL framework that simulates instructional scaffolding teaching. We found that by integrating the strengths of neural attention models and deep Q-networks we can repeatedly check and update the agent about the information it encodes in sequential order. We additionally found after using a reward based question simulator that enables self-supervision, the network can continue to comprehend text even with reduced labeled data.

Limitations and Future Work. Our results reveal the promise of scaffolding teaching of text based learning functions.
Our model is far from perfect, and more work is needed to explore the processes humans use to learn to comprehend. Future work could use an adversarial training agent for generating questions about a story using the reward signal from another encoder agent. We hope to show results on larger datasets.
REFERENCES

[1] Y. Kim, “Scaffolding through questions in upper elementary esl learning,” Literacy Teaching and Learning, vol. 15, no. 1–2, pp. 109–137, 2010.

[2] K. Hogan and M. Pressley, Scaffolding student learning: Instructional approaches and issues. Cambridge, MA: Brookline Books, 1997.

[3] R. Kaldec, M. Schmid, O. Bajgar, and J. Kleindienst, “Text understanding with the attention sum reader network,” in arXiv Preprint arXiv:1603.01547, 2016.

[4] S. Kobayashi, R. Tian, N. Okazaki, and K. Inui, “Dynamic entity representations with max-pooling improves machine reading,” in NAACL-HLT, 2016.

[5] A. Sordoni, P. Bachman, and Y. Bengio, “Iterative alternating neural attention for machine reading,” in arXiv Preprint, 2016.

[6] X. Guo, T. Klinger, C. Rosenbaum, J. P. Bigus, M. Campbell, B. Kawass, K. Talampapula, and G. Tesauru, “Learning to query, reason and answer question on ambiguous texts,” in ICLR, 2017.

[7] M. Henaff, J. Weston, A. Szlam, A. Bordes, and Y. LeCun, “Tracking the world state with recurrent entity networks,” in ICLR, 2017.

[8] M. Seo, S. Min, A. Farhadi, and H. Hajishirzi, “Query-reduction networks for question answering,” in ICLR, 2017.

[9] K. K. S. D. G. A. I. W. D. Mnih, V., “Playing atari with deep reinforcement learning,” in arXiv preprint arXiv:1312.5602, 2013.

[10] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, I. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, and H. Hassabis, “Human-level control through deep reinforcement learning,” Nature, vol. 518, pp. 529–533, 2015.

[11] J. Weston, A. Bordes, S. Chopra, and T. Mikolov, “Towards Al-complete question answering: A set of prerequisite toy tasks,” in ICLR, 2016.

[12] A. Bordes and J. Weston, “Learning end-to-end goal-oriented dialog,” in arXiv Preprint arXiv:1605.07683, 2016.

[13] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[14] T. Rocktaschel, E. Grefenstette, K. M. Hermann, T. Kocisky, and P. Blunsom, “Reasoning about entailment with neural attention,” in ICLR, 2016.

[15] F. Hill, A. Bordes, S. Chopra, and J. Weston, “The Goldilocks principle: Reading children’s books with explicit memory represenations,” in ICLR, 2016.

[16] J. He, J. Che, X. He, J. Gao, L. Li, L. Deng, and M. Ostendorf, “Deep reinforcement learning with a natural language action space,” in ACL, 2016.

[17] A. G. Hado Van Hasselt and D. Silver, “Deep reinforcement learning with double Q-learning,” in AAAI, 2015.

[18] D. Chen, J. Bolton, and C. D. Manning, “A thorough examination of the cnn / daily mail reading comprehension task,” in ACL, 2016.

[19] K. Moritz, H. Tommas, Kocisky, E. Grefenstette, L. Espeholt, W. Kay, M. Suleyman, and P. Blunsom, “Teaching machines to read and comprehend,” in NIPS, 2015.

[20] A. Trischler, Z. Ye, X. Yuan, and K. Suleman, “Natural language comprehension with the epireader,” in CoRR, abs/1606.02270, 2016.

[21] M. Weissm, “Separating answers from queries for neural reading comprehension,” in arXiv preprint arXiv:1607.03316, 2016.

[22] Y. Cui, Z. Chen, S. Wei, S. Wang, T. Liu, and G. Hu, “Attention-over-attention neural networks for reading comprehension,” in CoRR, abs/1607.04423, 2016.

[23] C. Xiong, V. Zhong, and R. Socher, “Dynamic co-attention networks for question answering,” in ICLR 2017, 2017.

[24] J. Weston, “Dialog based language learning,” in arXiv preprint arXiv:1604.06045v7, 2016.

[25] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in 3rd International Conference for Learning Representations, San Diego, 2015.

[26] S. Sukhbaatar, A. Szlam, J. Weston, and R. Fergus, “End-to-end memory networks,” in NIPS, 2015.
APPENDIX

Appendix-A: Training Scaffolding Agent with Double DQN - Implementation Details

The scaffolding network can use a rule-based or a reward driven question simulator. In Algorithm 1 below, we provide the details of the forward activation of the scaffolding network training using the reward-driven question simulator. Algorithm 1 focuses on the forward activation step where the experiences are stored and used by the q-network for training a policy. We use Double DQN (D-DQN) framework to train the scaffolding agent policy as presented in Algorithm 2. So, in Algorithm 1 we refer to Algorithm 2 that shows the pseudo code for policy learning.

As the network encodes each sentence from the input text of \(1, \ldots, T\) sentences, the question simulator sub-module of the scaffolding network generates one question. The corpora we use in this work include training and test datasets where the instances include list of tuples, i.e., (input text; question; answer). The corpora used in this work include training and test datasets where the instances include list of tuples, i.e., (input text; question; answer). The corpora used in this work include training and test datasets where the instances include list of tuples, i.e., (input text; question; answer). The corpora used in this work include training and test datasets where the instances include list of tuples, i.e., (input text; question; answer). The corpora used in this work include training and test datasets where the instances include list of tuples, i.e., (input text; question; answer).

Algorithm 1 Forward Activation in Scaffolding Network

\textbf{Training with Reward Driven Question Simulator}

\begin{itemize}
  \item \textbf{Input:} Input text \(X=\{x^1, \ldots, x^T\}\) of \(T\) sentences
  \item \textbf{Output:} State representation \(s_t \in S\) to be used by the D-DQN
  \item \textbf{Parameters:} 3-different LSTM weights; attention sub-module weights: \(\{W^x, W^h\}\); gating function weights: \(\{W^C, W^P\}\); q-network parameters: \(\{\theta_Q, \theta'_Q\}\); reward-driven simulator weights over fixed length question vector: \(\beta\)
\end{itemize}

(Once at the beginning of the training) Initialize replay memory \(D_e\) and empty the initial dynamic memory vector \(\tilde{h}_0\)

\textbf{Initialize all weights randomly. Set} \(r_0 = 1, \Gamma\) \textbf{max trials}

\textbf{for} \(t = 1 \text{ to } T\) \textbf{do}

- process LSTM\((e_t)\) on sentence \(t\)'s word embeddings \(e_t\) to obtain hidden states \(h_{t,i}\) for each word

  \textbf{(attention encoding)}

- execute attention \(m_{t,i} \sim \phi(h_{t-1}, h_{t,i})\) on each word using the dynamic memory from \((t-1)\) to obtain attention vector of the sentence \(t, m_t\)

- \(\gamma = 0\) (trial constant for the agent)

\textbf{while} \(r_t < 0 \text{ or } \gamma < \Gamma\) \textbf{do}

  \textbf{(question simulator)}

- sample a candidate sentence \(x_q \sim \{x_1, \ldots, x_{t-1}\}\)

- process question LSTM\((e_q)\) on candidate sentence words to obtain hidden states \(h^q_{t,i} \in h^q_{t}\) of each word

- compute answer probabilities \(p_t \propto \sigma(\beta^T h^q_t)\)

- sample \(a^*_t \sim P(a|h^q_t)\) as the target variable

- generate question based on the selected answer, obtain embedding vectors, \(e_q\), and process the question LSTM to obtain the last hidden state \(h^q_t\)

  \textbf{(question-sentence encoding)}

- process Equation 1 and 2 to obtain joint query and sentence encodings

- process LSTM\((\tilde{e}_t, 0, \tilde{e}_t)\) to obtain question-sentence encoding \(o_{t,i} \in o_t\) for each word

  \textbf{(q-network)}

- concatenate the question-sentence, attention and candidate answer probabilities into current state representation: \(s_t = [m_t; a_t; p_t]\)

- run policy \(\pi_{\theta, \theta'}\) on \(\{s_t = [m_t; o_t; p_t]; a^*_t\}\) and observe reward \(r_t\) using Algorithm 2

- \(\gamma = \gamma + 1\)

\textbf{end while}

- calculate gate value \(g_t\) using Equation 5 and update dynamic memory \(\tilde{h}_t\) using Equation 6

\textbf{end for}
Algorithm 2 Training Scaffolding Agent with D-DQN

0: function: \textit{train } Q(.,.;.) network

\textbf{Input:} \( Q \) (D-DQN), the \( T \) number of input sentences in text, input text \( \mathcal{X} = \{x^1, ..., x^T\} \) of \( T \) sentences, experience replay memory \( D_e \)

\textbf{Output:} Learnt parameters \( \theta_Q, \theta'_Q, \epsilon \) for greedy exploration

\begin{algorithm}
\begin{algorithmic}
\For {\( t = 1 \) \text{ to } \( T \)}
\State Select randomly among parameters \( \theta_Q \leftarrow \{ \theta_Q, \theta'_Q \} \)
\State process input \( x_t \) using Algorithm 1 to obtain \( s_t \)
\State With probability \( \epsilon \) select random answer \( a_t \); otherwise, select answer \( a_t = \max a' Q(s_t, a'; \theta_Q) \)
\State Using the answer \( a_t \), observe reward \( r_t \) and successor state \( s_{t+1} \) based on the answer being correct (read next sentence or stay on encoding the current one with a different generated question from the question simulator)
\State Store transition \( (s_t, a_t, r_t, s_{t+1}) \) in \( D_e \)
\State Sample random mini-batch \( (s_\mu, a_\mu, r_\mu, s_{\mu+1}) \) transitions from \( D_e \)
\State Set \( y_\mu \leftarrow \begin{cases} r_\mu & \text{for terminal } s_{\mu+1} \\ r_{\mu+1} + \Theta & \text{for non-terminal } s_{\mu+1} \end{cases} \)
\State where \( \Theta = \gamma \max_a' Q(s_{\mu+1}, \arg\max_a Q(s_{\mu+1}, a; \theta_Q); \theta'_Q) \)
\State Perform a gradient descent step (SGD): \( \theta_Q \leftarrow \theta_Q + \alpha (y_\mu - Q(s_\mu, a_\mu; \theta + Q)) \nabla Q(\theta'_Q) \)
\EndFor
\end{algorithmic}
\end{algorithm}
Appendix-B : Details of the Travel Log Experiments

The traveler is placed on a 9×9 grid town of 81 distinct locations with a list of attractions in randomly chosen locations. At each time step, the traveler’s next direction is chosen at random among 4 possible actions, e.g., north, south, east, west. If the selection puts the traveler off the grid, a new legal direction is chosen at random. Below we provide a sample travel log where the attractions are highlighted.

1 moving to south
2 moving to west
3 there is a tower on my south
4 moving to south
5 i am at the tower
6 the museum is on my west
7 moving to west
8 i am at the museum
9 there is a tower on my east
10 moving to north
11 there is a tower on my south
12 continuing on north
13 there is a palace on my west
14 moving to west
15 i am at the palace
16 moving to north
17 on my west is a park
18 moving to west
19 i am at the park
20 moving to north
21 Question:What is west of the museum? Answer:palace

We use the following rules to generate the log data. The traveler visits each attraction only once. If the randomly chosen next direction takes the traveler to an attraction previously visited, a new random direction is chosen. If all the 4 directions contain attractions that are visited before, the log terminates. Once the traveler is in a new location, she looks at 4 immediate directions to log attractions. If there is no attraction, she continues on the next direction. Otherwise randomly chooses one attraction to log. We randomly generate different town layouts by varying the number of attractions, e.g., {5,10,15,20,25} and evaluate the performance of the models in the experiments.

We use all the words in the vocabulary except a list of stop words. The list of attractions and 4 different directions are used as the output space. If the attraction is a multi-word expression, we combine all the words. The question simulator of the scaffolding agent only uses the sentences that contain the location of the attractions to generate questions. During training, it samples a candidate sentence, then samples a possible answer from the words of this sentence that are either attractions or one of the four possible directions. For instance, the simulator selects sentence 17 above as candidate sentence to generate the question. Then it either picks west or park as candidate answer to generate on my 'unk' is a park ? with west as target answer.

In Table III we demonstrate the output of the scaffolding network over a single log data selected from the travel log test dataset. The questions and answers generated by the question simulator and the rewards observed based on agent’s response are shown in each column. At any given time, as the network reads a sentence, the question generator samples a candidate sentence from the previously observed sentences. Then, using the reward-driven question generation, it samples a candidate answer from the words of the sampled sentence (see Section 2.4 for details.) This candidate answer is used as the target output for the current turn. Then, the current sentence, generated question and dynamic memory are encoded into state representation and sent to the agent. The agent runs through the policy and selects an answer, observes a reward as shown in the table. The agent’s decision determines if a next sentence should be read or the same sentence is encoded with a new question generated by the question simulator. If the reward is negative, the agent reads the same sentence, the question simulator samples a new sentence to generate a new question. This is to ensure that the agent learns to encode the information in the so far processed text by learning to correctly answer questions posed to it. At each trial, the agent’s decision changes the dynamic memory as well as the encoding of the next states. This step continues until a positive reward is observed, or a maximum of \( \Gamma \) trials are exhausted. In this example, we use \( \Gamma = 3 \). If the reward is positive it continues to read the next sentence. With the reward-driven approach the simulator asks questions that the agent didn’t get right in the past, helping it to learn to better encode the objects and relations through iteration.

Appendix-C : Example Dialog from the DSTC-2 Dataset

| Turn | User Utterance (U) / System Response (S) |
|------|------------------------------------------|
| 1    | (U) <SILENCE>                           |
| 2    | (U) i want a moderately priced restaurant that serves gastropub food |
| 3    | (U) canapes food                        |
| 4    | (U) it doesn't matter                   |
| 5    | api-call canapes R-location moderate    |
| 6    | (U) <SILENCE>                           |
| 7    | (U) gastropub food                      |
| 8    | (U) i want a gastropub restaurant       |
| 9    | (U) what is the address                 |
| 10   | (U) The phone number of the cow pizza kitchen and bar is on the-cow-pizza-kitchen-and-bar-address |
| 11   | (U) what is the area                    |
| 12   | (U) thank you goodbye                  |
|      | (S) you are welcome                     |
TABLE III: An example output from scaffolding network inference over a single travel log from the travel-log test data. The questions and answers generated at inference time are shown. The action taken by the agent is the selected answer to the generated question. The agent collects reward based on the expected answer. There are 5 unique attractions observed in this log: {museum, tourist center, school, coffee-shop, park} and 4 directions: {east, north, south, west}. The bolded question at line 19 is the labeled question (not generated by the simulator).

| Sentences in Travel Log | Generated Question | Simulator Selected | Agent Selected Answer | Reward |
|-------------------------|--------------------|--------------------|-----------------------|--------|
| 1: i am at the museum   | i am at the ‘unk’? | museum             | museum                | 1      |
| 2: there is a school on my east | there is a school on my ‘unk’? | east            | east                  | 1      |
| 3: moving to east       | i am at the ‘unk’? | museum             | east                  | -1     |
| 4: the museum is on my east | i am at the ‘unk’? | museum             | east                  | -1     |
| 5: the museum is on my east | there is a ‘unk’ on my east? | school         | school                | 1      |
| 6: moving to south      | there is a ‘unk’ on my east? | school         | school                | -1     |
| 7: there is a tourist center on my east | i am at the ‘unk’? | museum             | museum                | 1      |
| 8: moving to east       | there is a ‘unk’ on my east? | tourist center   | tourist center        | 1      |
| 9: moving to east       | i am at the ‘unk’? | museum             | east                  | -1     |
| 10: on my north is a tourist center | there is a ‘unk’ on my east? | school         | museum                | -1     |
| 11: continuing on east  | on my north is a ‘unk’? | tourist center   | tourist center        | 1      |
| 12: i am now at the coffee shop | on my ‘unk’ is a tourist center? | north         | north                 | 1      |
| 13: moving to north     | there is a school on my ‘unk’? | north         | north                 | -1     |
| 14: museum is on my north now | there is a school on my ‘unk’ | east         | east                  | 1      |
| 15: moving to east      | museum is on my ‘unk’? | north         | north                 | 1      |
| 16: school is in the north | museum is on my ‘unk’? | north         | north                 | -1     |
| 17: moving to south     | ‘unk’ is on my north now? | museum         | school                 | -1     |
| 18: i arrived the park  | ‘unk’ is on my north now? | school         | school                 | 1      |
| 19: **what is east of tourist center** | | | | 5+16 |
Appendix-D: Additional Results on bAbI Tasks

We provide some additional experiment results on the bAbI tasks to better understand the influence of (i) reward based answer selection for question generation versus rule-based answer selection, (iii) the degree of self-supervision, and (ii) the amount of training data. The results are presented in Table 4, 5, 6 and 7.

In most of these tasks, the scaffolding networks, SNs, either follow the best reported result or perform better. Based on the overall mean error measure for the 1K and 10K babi tasks, the reward driven SN model, SN-RD, competes well against the best performing EntNet and QRN models.
TABLE IV: Error Rates on bAbI Tasks with 10K Samples. Previous work include: End-to-End Memory Networks (MemN2N) [30], Query Reduction Networks (QRN) [8], Dynamic memory Networks (DMN) [21], Recurrent Entity Networks (EntNet) [7], as well as our Scaffolding Network with rule based simulator (SN-RB), and Scaffolding Network with reward driven question simulator (SC-RD). Best performing models are bolded.

| TASK | MemN2N | DMN | QRN | EntNet | SN-RB | SC-RD |
|------|--------|-----|-----|--------|-------|-------|
| 1: 1 SUPPORTING FACT | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 2: 2 SUPPORTING FACT | 0.3 | 0.30 | 0.4 | 0.1 | 1.2 | 0.5 |
| 3: 3 SUPPORTING FACT | 2.1 | 1.10 | 0.4 | 4.1 | 4.0 | 4.5 |
| 4: 2 ARGUMENT RELATIONS | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 5: 3 ARGUMENT RELATIONS | 0.8 | 0.5 | 0.5 | 0.3 | 0.5 | 0.5 |
| 6: YES/NO QUESTIONS | 0.1 | 0.0 | 0.0 | 0.2 | 0.8 | 0.8 |
| 7: COUNTING | 2.0 | 2.4 | 1.0 | 0.0 | 0.0 | 0.0 |
| 8: LISTS/SETS | 0.9 | 0.0 | 1.4 | 0.5 | 0.3 | 0.0 |
| 9: SIMPLE NEGATION | 0.3 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 |
| 10: INDEFINITE KNOWLEDGE | 0.0 | 0.0 | 0.0 | 0.06 | 0.1 | 0.01 |
| 11: BASIC CO-REFERENCE | 0.0 | 0.0 | 0.0 | 0.3 | 0.0 | 0.0 |
| 12: CONJUNCTION | 0.0 | 0.2 | 0.0 | 0.0 | 0.0 | 0.0 |
| 13: COMPOUND CO-REFERENCE | 0.0 | 0.0 | 0.0 | 1.3 | 2.6 | 0.04 |
| 14: TIME REASONING | 0.2 | 0.2 | 0.2 | 0.0 | 8.2 | 8.0 |
| 15: BASIC DEDUCTION | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 16: BASIC INDUCTION | 51.8 | 45.3 | 49.4 | 0.20 | 15.0 | 17.5 |
| 17: POSITIONAL REASONING | 18.6 | 4.2 | 0.9 | 0.50 | 0.2 | 0.6 |
| 18: SIZE REASONING | 5.3 | 2.1 | 1.6 | 0.3 | 0.7 | 0.5 |
| 19: PATH FINDING | 2.3 | 0.0 | 36.1 | 2.3 | 1.7 | 3.5 |
| 20: AGENT’S MOTIVATION | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

Failed Tasks (> 5% error): 3 | 1 | 2 | 0 | 2 | 1
Mean Error: 4.2 | 2.8 | 4.6 | 0.5 | 1.7 | 1.5

TABLE V: Error Rates on Babi Tasks with 1K Samples. The same benchmark models from Table IV are used. Best performing models as well as the best SN models that compete well with the best performing models are bolded.

| TASK | MemN2N | DMN | QRN | EntNet | SN-RB | SC-RD |
|------|--------|-----|-----|--------|-------|-------|
| 1: 1 SUPPORTING FACT | 0.0 | 1.3 | 0.0 | 0.7 | 0.0 | 0.3 |
| 2: 2 SUPPORTING FACT | 8.3 | 72.3 | 0.7 | 56.4 | 52.9 | 45.5 |
| 3: 3 SUPPORTING FACT | 40.3 | 73.3 | 5.7 | 69.7 | 45.3 | 39.3 |
| 4: 2 ARGUMENT RELATIONS | 2.8 | 26.9 | 0.0 | 1.4 | 0.03 | 0.0 |
| 5: 3 ARGUMENT RELATIONS | 13.1 | 25.6 | 1.1 | 4.6 | 3.9 | 2.5 |
| 6: YES/NO QUESTIONS | 7.6 | 28.5 | 0.9 | 30.0 | 25.4 | 27.6 |
| 7: COUNTING | 17.3 | 21.9 | 9.6 | 22.3 | 13.3 | 12.5 |
| 8: LISTS/SETS | 10.0 | 21.9 | 5.6 | 19.2 | 3.4 | 4.3 |
| 9: SIMPLE NEGATION | 13.2 | 42.9 | 0.0 | 31.5 | 24.0 | 22.0 |
| 10: INDEFINITE KNOWLEDGE | 15.1 | 23.1 | 0.0 | 15.6 | 10.2 | 9.0 |
| 11: BASIC CO-REFERENCE | 0.9 | 4.3 | 0.0 | 8.0 | 0.1 | 0.5 |
| 12: CONJUNCTION | 0.2 | 3.5 | 0.0 | 0.8 | 0.0 | 0.5 |
| 13: COMPOUND CO-REFERENCE | 0.4 | 7.8 | 0.0 | 9.0 | 4.0 | 4.9 |
| 14: TIME REASONING | 1.7 | 61.9 | 0.8 | 62.9 | 5.6 | 4.2 |
| 15: BASIC DEDUCTION | 0.0 | 47.6 | 0.0 | 57.8 | 46.6 | 45.0 |
| 16: BASIC INDUCTION | 1.3 | 54.4 | 53.0 | 53.2 | 51.6 | 54.6 |
| 17: POSITIONAL REASONING | 51.0 | 44.1 | 34.4 | 46.4 | 31.8 | 31.6 |
| 18: SIZE REASONING | 11.1 | 9.1 | 7.9 | 8.8 | 4.3 | 4.5 |
| 19: PATH FINDING | 82.8 | 90.8 | 78.7 | 90.4 | 88.2 | 87.5 |
| 20: AGENT’S MOTIVATION | 0.0 | 2.2 | 0.2 | 2.6 | 1.5 | 1.7 |

Failed Tasks (> 5% error): 11 | 16 | 7 | 15 | 11 | 10
Mean Error: 13.6 | 33.2 | 9.9 | 29.6 | 20.6 | 19.9
TABLE VI: Error Rates on Babi Dialog and DSTC2 dialog datasets [12] no match features are used. Previous work include: End-to-End Goal Oriented Dialog (N2N) [12], Query Reduction Networks (QRN) [8], as well as our Scaffolding Network with rule based simulator (SC-RB), and Scaffolding Network with reward driven question simulator.)

| Task                        | N2N | QRN | SN-RB | SN-RD |
|-----------------------------|-----|-----|-------|-------|
| 1: Issuing API Calls        | 0.1 | 0.0 | 0.0   | 0.5   |
| 2: Updating API Calls       | 0.0 | 0.01| 0.0   | 0.0   |
| 3: Displaying Options       | 25.1| 12.6| 18.7  | 22.6  |
| 4: Providing Extra Information | 40.5| 14.3| 14.8  | 14.2  |
| 5: Conducting Full Dialogs  | 3.9 | 0.6 | 2.0   | 3.4   |
| Average Error Rates (%)     | 13.9| 5.5 | 7.1   | 8.1   |

**TABLE VII: Error Rates on Babi Dialog and DSTC2 dialog datasets with match features.** The same bechmark models are used as in Table VI

| Task                        | N2N | QRN | SN-RB | SN-RD |
|-----------------------------|-----|-----|-------|-------|
| 1: Issuing API Calls        | 0.0 | 0.0 | 4.7   | 2.0   |
| 2: Updating API Calls       | 1.7 | 0.0 | 5.0   | 4.7   |
| 3: Displaying Options       | 25.1| 25.1| 7.4   | 7.9   |
| 4: Providing Extra Information | 0.0 | 0.0 | 0.0   | 0.0   |
| 5: Conducting Full Dialogs  | 6.6 | 2.0 | 5.0   | 5.2   |
| Average Error Rates (%)     | 6.7 | 5.4 | 4.4   | 4.0   |

**TABLE VII: Error Rates on Babi Dialog and DSTC2 dialog datasets with match features.** The same bechmark models are used as in Table VI

| Task                        | N2N | QRN | SN-RB | SN-RD |
|-----------------------------|-----|-----|-------|-------|
| 1: Issuing API Calls        | 3.5 | 0.0 | 4.5   | 2.7   |
| 2: (OOV) Updating API Calls | 5.5 | 5.8 | 10.0  | 10.0  |
| 3: (OOV) Displaying Options | 24.8| 24.9| 16.9  | 18.0  |
| 4: (OOV) Providing Extra Information | 0.0 | 0.0 | 0.0   | 0.1   |
| 5: (OOV) Conducting Full Dialogs | 22.3| 20.6| 22.6  | 20.0  |
| Average Error Rates (%)     | 11.2| 10.3| 10.8  | 10.1  |

6: DSTC2 Dialog

| Task                        | N2N | QRN | SN-RB | SN-RD |
|-----------------------------|-----|-----|-------|-------|
| 1: (OOV) Issuing API Calls  | 59.0| 51.3| 52.7  | 51.3  |