Query-Regression Networks for Machine Comprehension

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Abstract

We present Query-Regression Network (QRN), a variant of Recurrent Neural Network (RNN) that is suitable for end-to-end machine comprehension. While previous work [18, 22] largely relied on external memory and global softmax attention mechanism, QRN is a single recurrent unit with internal memory and local sigmoid attention. Unlike most RNN-based models, QRN is able to effectively handle long-term dependencies and is highly parallelizable. In our experiments we show that QRN obtains the state-of-the-art result in end-to-end bAbI QA tasks [21].

1 Introduction

Machine comprehension (MC) is the task of obtaining the answer to a natural language question given a sequence of natural language sentences (story) [16, 14]. We are particularly interested in the task of end-to-end MC, where (1) external language resources, such as lexicon or dependency parser, are not provided, and (2) the only supervision during training is the answer to the question. This task becomes particularly challenging when answering a question requires logical reasoning by selecting relevant facts from a large pool of sentences and combining them in a correct order to answer the question.

While Recurrent Neural Network (RNN) and its variants, such as Long Short-Term Memory (LSTM) [8] and Gated Recurrent Unit (GRU) [4], are popular choices for modeling sequential data, Weston et al. [21] have shown that RNN-based models perform poorly on end-to-end MC, largely because RNN’s internal memory is inherently unstable over a long term. Hence, recent approaches in this literature have mainly relied on global attention mechanism and shared external memory [20, 18, 13, 10, 22]. The attention mechanism allows the models to focus on a single sentence in each layer, and the models can sequentially read multiple relevant sentences from the memory with multiple layers. However, the biggest drawback of the vanilla attention mechanism is that it is insensitive to the time step (memory address) of the sentences when accessing them. End-to-end Memory Network [18] attempts to resolve this problem by adding time-dependent variable to the sentence representation at each time step (address) of the memory. Dynamic Memory Network [10, 22] combines RNN and attention mechanism together to incorporate time dependency into the model.

Our proposed model, Query-Regression Network (QRN), is a single recurrent unit that addresses the long-term dependency problem of most RNN-based models by simplifying the recurrent update, while taking the full advantage of RNN’s capability to model sequential data (Figure 1). QRN considers the sentences (story) as a sequence of state-changing triggers, and QRN transforms (regresses) the original question (query) to an easier-to-answer query as it observes each trigger through time. For instance, consider the question-story pair in Figure 1b. The original question, “Where is the apple?” cannot be directly answered by any single sentence from the story. Hence, after observing the first sentence “Sandra got the apple there.”, QRN transforms the original question to “Where

¹Code is available at: github.com/seominjoon/qrn
is Sandra?”, which is presumably easier to answer. This mechanism is akin to logic regression in situation calculus \[15\]. QRN is distinct from previous approaches \[20, 18, 13, 10, 22\] in that it does not have memory access controller (circle nodes in Figure \[2\]) and the query regression in our model is performed **locally**, so it can better encode locality information. We experimentally demonstrate that the local query regression is effective for handling the time dependency and the long-term dependency problems. We also show that, unlike most RNN-based models, QRN can be parallelized over time by computing regressed queries directly from local input queries and sentence vectors. In fact, the parallelizability of QRN implies that QRN does not suffer from the vanishing gradient problem of RNN, hence effectively addressing the long-term dependency.

### 2 Model

In the task of end-to-end MC, the input is a story as a sequence of sentences and a question in natural language. The output is the predicted answer to the question in natural language (e.g. “garden” in Figure \[1\]). The only supervision provided during training is the answer to the question.

**Notation.** We use lowercase, boldface letters to denote column vectors (e.g. \( x \)), and uppercase, boldface letters (e.g. \( W \)) to denote matrices. Non-boldface italic letters denote scalar values (e.g. \( t, T, d \)), and boldface italic letters denote non-numerical objects such as a sentence (e.g. \( x \)). \( \top \) is used to denote vector or matrix transpose. Scalar and vector functions will be denoted by non-boldface and boldface lowercase Greek letters (e.g. \( \alpha, \rho \)), respectively. \( [:] \) is the concatenation of vectors across row, and \( [\cdot] \) is the concatenation of vectors across column. \( \langle \cdot \rangle \) denotes a sequence. A subscript denotes time step \((t)\) in the story, and a superscript denotes the layer index \((k)\) of the network. A superscript with parenthesis (e.g. \( W^{(z)}, W^{(h)} \)) indicates that the weight matrix or vector is used to compute the value in the parenthesis (e.g. \( z, h \)).

Let \( \langle x_1, \ldots, x_T \rangle \) denote the sequence of sentences, where \( T \) is the number of sentences in the story, and let \( q \) denote the question. Let \( y \) denote the predicted answer, and \( \hat{y} \) denote the true answer. Our proposed system for end-to-end MC task can be divided into three modules, as shown in Figure \[1\]: right: input module, QRN, and output module.

**Input module.** Input module maps each sentence \( x_t \) and the question \( q \) to \( d \)-dimensional vector space, \( x_t \in \mathbb{R}^d \) and \( q_t \in \mathbb{R}^d \). We adopt a previous solution for the input module, as will be discussed in Section \[5\].

**QRN.** QRN uses the sentence vectors and the question vector from the input module to obtain the predicted answer in vector space, \( \hat{y} \in \mathbb{R}^d \). The details of QRN module is explained throughout this section \[2.1 \ 2.2\].

**Output module.** Output module maps \( \hat{y} \) obtained from QRN to a natural language answer \( \hat{y} \). Similarly to the input module, we adopt a standard solution for the output module, to be discussed in Section \[5\].

In short, QRN can be considered as a variant of RNN with two inputs, two outputs, and a hidden state (regressed query), all of which operate in vector space. We first formally define the base model of a QRN unit, and then we explain how we connect the input and output modules to it. We also present a few variations to the network that can improve QRN’s performance. In Section \[3\] we show that QRN can be parallelized over time, giving computational advantage over most RNN-based models by one order of magnitude.

#### 2.1 QRN Unit

As an RNN-based model, QRN is a single recurrent unit that updates its hidden state (regressed query) through time and layers. A QRN unit accepts two inputs (local query vector \( q_t \in \mathbb{R}^d \) and sentence vector \( x_t \in \mathbb{R}^d \)), and two outputs (regressed query vector \( \hat{q} \in \mathbb{R}^d \), which is similar to the hidden state in RNN, and the sentence vector \( x_t \) from the input without modification). The local query vector is not necessarily identical to the original query (question) vector \( q \). In order to compute the outputs, we use update gate function \( \alpha : \mathbb{R}^d \times \mathbb{R}^d \rightarrow [0, 1] \) and regress function \( \rho : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d \). Intuitively, the update gate function measures the relevance between the sentence and the local query,
where $z_t$ is the scalar update gate, $\tilde{h}_t$ is the candidate regressed query, and $h_t$ is the final regressed query at time step $t$, $\sigma(\cdot)$ is sigmoid activation, $\tanh(\cdot)$ is hyperbolic tangent activation (applied element-wise), $W^{(z)} \in \mathbb{R}^{1 \times d}$, $W^{(h)} \in \mathbb{R}^{d \times 2d}$ are weight matrices, $b^{(z)} \in \mathbb{R}$, $b^{(h)} \in \mathbb{R}^d$ are bias terms, $\circ$ is element-wise vector multiplication, and $[\cdot]$ is vector concatenation along the row. As a base case, $h_0 = 0$. Here we have explicitly defined $\alpha$ and $\rho$, but they can be any arbitrary differentiable functions in general.

The update gate is similar to the global attention mechanism [18, 22] in that it measures the similarity between the sentence (a memory slot) and the query. However, a significant difference is that the update gate is computed using sigmoid function on the current memory slot only (hence internally embedded within the unit), whereas the global attention is computed using softmax function over the entire memory (hence globally defined). The update gate can be rather considered as local sigmoid attention.

We just showed the single-layer case of QRN, but QRN with multiple layers is able to perform reasoning over multiple facts more effectively, as shown in the example of Figure 1b. In order to stack several layers of QRN, the outputs of the current layer are used as the inputs to the next layer. That is, using superscript $k$ to denote the current layer’s index (assuming 1-based indexing), we let $q^k_{t+1} = h^k_t$. Note that $x_t$ is passed to the next layer without any modification, so we do not put a layer index on it. Figure 1a depicts the schematic structure of a QRN unit, and Figure 1b demonstrates how layers are stacked.

**Connecting input and output modules.** Figure 1c depicts how QRN is connected with the input and output modules. In the first layer of QRN, $q^1_t = q$ for all $t$, where $q$ is obtained from the input module by processing the natural language question input $q$. $x_t$ is also obtained from $x_t$ by the same input module. The output at the last time step in the last layer is passed to the output module. That is, $\hat{y} = h^K$, where $K$ represent the number of layers in the network. Then the output module gives the predicted answer $\hat{y}$ in natural language.
2.2 Variations

Here we introduce a few variations of QRN, and later in our experiments, we test QRN’s performance with and without each of these variations.

Reset gate. Inspired by Gated Recurrent Unit (GRU) [4], we found that it is useful to allow the QRN unit to reset (nullify) the candidate regressed query (i.e., $\tilde{h}_t$) when necessary. For this we use reset gate function $\beta : \mathbb{R}^d \times \mathbb{R}^d \rightarrow [0, 1]$, which can be defined similarly to the update gate function:

$$r_t = \beta(x_t, q_t) = \sigma(W^{(r)}(x_t \circ q_t) + b^{(r)})$$

(4)

where $W^{(r)} \in \mathbb{R}^{1 \times d}$ is a weight matrix, and $b^{(r)} \in \mathbb{R}$ is a bias term. Then Equation 3 can be rewritten as

$$h_t = z_t r_t \tilde{h}_t + (1 - z_t) h_{t-1}.$$  

(5)

Note that we do not use the reset gate in the last layer.

Vector gates. As in LSTM [8] and GRU [4], update and reset gates can be vectors instead of scalar values for fine-controlled gating. For vector gates, we modify the row dimension of weights and biases in Equation 1 and 4 from 1 to $d$. Then we obtain $x_t, r_t \in \mathbb{R}^d$ (instead of $z_t, r_t \in \mathbb{R}$), and these can be element-wise multiplied ($\circ$) instead of being broadcasted in Equation 3 and 5.

Bi-direction. So far we have only shown the forward direction definition of $h_t$. That is, at each time step $t$, we assumed that QRN only needs to look at past sentences, and does not need to know about the future. However, often times, query answers can depend on future sentences. For instance, consider a sentence “John dropped the football.” at time $t$. Then, even if there is no mention about the “football” in the past (at time $t < t$), it can be implied that “John” has the “football” at the current time $t$. In order to incorporate the future dependency, we obtain $\tilde{h}_t$ and $\bar{h}_t$ in both forward and backward directions, respectively, using Equation 3 and then we add them together to get $q_t$ for the next layer. That is,

$$q_t^{k+1} = \tilde{h}^k_t + \bar{h}^k_t$$

(6)

for layer indices $1 \leq k \leq K - 1$. Note that the variables $W^{(z)}, b^{(z)}, W^{(h)}, b^{(h)}$ are shared between the two directions (the variables of the reset gate are not shared).

3 Parallelization

An important advantage of QRN is that the recurrent updates in Equation 3 and 4 can be computed in parallel across time. This is in contrast with most RNN-based models that cannot be parallelized, where computing the hidden state at time $t$ explicitly requires the previous hidden state. On the other hand, in QRN, the final regressed queries ($h_t$) can be written as a factor over candidate regressed queries ($\tilde{h}_t$), without looking at the previous regressed query. Here we primarily show that the query update in Equation 3 can be parallelized by rewriting the equation with matrix operations. The extension to Equation 4 is straightforward. The proof will also give an intuition how QRN with vector gates can be parallelized as well. The recursive definition of Equation 3 can be explicitly written as

$$h_t = \sum_{i=1}^{t} \left[ \prod_{j=i+1}^{t} (1 - z_j) \right] z_i \tilde{h}_i = \sum_{i=1}^{t} \exp \left\{ \sum_{j=i+1}^{t} \log (1 - z_j) \right\} z_i \tilde{h}_i$$

(7)

where $\exp(\cdot)$ and $\log(\cdot)$ are exponential and logarithm functions, respectively. Let $b_i = \log(1 - z_i)$ for brevity. Then we can rewrite Equation 7 as the following equation:

$$\begin{pmatrix}
\tilde{h}_1 \\
\tilde{h}_2 \\
\vdots \\
\tilde{h}_T \\
\end{pmatrix} = \exp \left( \begin{pmatrix}
0 & -\infty & -\infty & \cdots & -\infty \\
-b_2 & 0 & -\infty & \cdots & -\infty \\
-b_2 + b_3 & b_3 & 0 & \cdots & -\infty \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
-b_2 \sum_{j=2}^{T} b_j & b_3 \sum_{j=3}^{T} b_j & b_3 \sum_{j=4}^{T} b_j & \cdots & 0 \\
\end{pmatrix} \right) \begin{pmatrix}
z_1 \tilde{h}_1 \\
z_2 \tilde{h}_2 \\
z_3 \tilde{h}_3 \\
\vdots \\
z_T \tilde{h}_T \\
\end{pmatrix}$$

(8)
Let $H = [h_1^T; \ldots; h_T^T]$ be a $T$-by-$d$ matrix where the transposes ($^T$) of the column vectors $h_t$ are concatenated across row. We similarly define $\tilde{H}$ from $\tilde{h}_t$. Also, let $z = [z_1; \ldots; z_T]$ and $b = [0; b_2; \ldots; b_T]$ be column vectors (note that we use 0 instead of $b_1$). Then Equation 8 is equivalent to

$$H = [L \circ \exp (L [B \circ L'])] [Z \circ \tilde{H}]$$

(9)

where $L, L' \in \mathbb{R}^{T \times T}$ are lower and strictly lower triangular matrices of 1’s, respectively, $\circ$ is element-wise multiplication, and $B$ is a matrix where $T$ $b$’s are tiled across the column, i.e. $B = [b, \ldots, b] \in \mathbb{R}^{T \times T}$, and similarly $Z = [z, \ldots, z] \in \mathbb{R}^{T \times d}$. All implicit operations are matrix multiplications. With reasonable $N$ (batch size), $d$ and $T$ (e.g. $N, d, T = 100$), matrix operations in Equation 9 can be comfortably computed in most modern GPUs.

4 Related Work

Previous solutions to question answering use open information extraction or textual semantic parsing to query or create a knowledge base [3, 19, 9, 2, 6, 17]. Here, we primarily describe the most related approaches, which use deep neural networks for end-to-end machine comprehension. Figure 2 shows the comparison between QRN and other relevant models.

QRN is inspired by RNN-based models with gating mechanism, such as LSTM [8] and GRU [4]. As QRN is designed for sequential data with query, its unit accepts two inputs (query and sentences) instead of one input. While GRU and LSTM use the previous hidden state and the current input to obtain the current hidden state, QRN only uses the current two inputs to obtain the regressed query (equivalent to hidden state). We conjecture that this not only gives computational advantage via parallelization, but also makes training easier, i.e., avoiding vanishing gradient (which is critical for long-term dependency), overfitting (by simplifying the model), and converging to local minima. The advantage of QRN over other RNN-based models is experimentally shown in Table 1, where LSTM performs very poorly.

End-to-end Memory Network (MemN2N) [18] (and Neural Reasoner [13]) uses external memory with multi-layer attention mechanism to focus on sentences that are relevant to the question. There are two key differences between the model and QRN. First, MemN2N summarizes the entire memory in each layer to control the attention in the next layer, as indicated by circle nodes in Figure 2b. This is in contrast with QRN which does not have any controller node, as shown in Figure 2a. Instead, QRN is able to focus on relevant sentences through the update gate that is internally embodied within its unit. Second, MemN2N adds time-dependent trainable weights to the sentence representations to model the time dependency of the sentences (as discussed in Section 1). QRN does not need such additional weights as its inherent RNN architecture allows QRN to effectively model the time dependency.

Improved Dynamic Memory Network (DMN+) [22] uses the hybrid of the attention mechanism and the RNN architecture to model the sequence of sentences. It consists of two distinct GRUs, one for the time axis (rectangle nodes in Figure 2c) and one for the layer axis (circle nodes in Figure 2c). Note that the update gate of the GRU for the time axis is replaced with external softmax attention weights. DMN+ uses the time-axis GRU to summarizes the entire memory in each layer, and then the layer-axis GRU controls the attention weights in each layer. In contrast, QRN is simply a single recurrent unit without any controller node.

Memory Networks [20] and Dynamic Memory Networks [10] are earlier models that inspired MemN2N and DMN+, respectively. However, they are strongly supervised (i.e. during training they are given what facts are relevant to the question), where QRN is only supervised by the answers to the questions. So we do not make a direct comparison against them.

While Mitra and Baral [12] and Lee et al. [11] have shown near-perfect accuracies in bAbI QA dataset, they are largely rule-based (requiring human efforts), they use different models for different tasks, and/or they use external language resources such as dependency parser. So we do not consider them as end-to-end machine comprehension systems.
5 Experiments

5.1 Data

Following previous neural architecture models in end-to-end machine comprehension [18, 22, 13], we test our model on bAbI question answering (QA) dataset [21]. bAbi dataset is composed of 20 different tasks, each of which has 1,000 (1k) synthetically-generated story-question pair. A story can be as short as two sentences and as long as 200+ sentences. A system is tested on getting the correct answers to the questions, and the authors of the dataset define that a system passes a task if its error rate is no more than 5%. Most answers are single-words, and some of them are lists (e.g. “football, apple”). Answering questions in each task requires selecting a set of relevant sentences and applying a different kinds of logical reasoning over them. See Table 1 for the complete list of the 20 tasks.

bAbi dataset also provides 10k dataset (for each task), which was originally intended for evaluating how much more training data (than 1k) does a system need to pass each task. Since DMN+ [22] only reports on the 10k dataset, we report our result on it as well for a fair comparison. We also report how much more training data (than 1k) does a system need to pass each task. Since DMN+ [22] only release their code. Following MemN2N [18] and DMN+, QRN is only supervised by question answers. Hence we do not compare QRN against Memory Networks [20] and DMN [10], which require strong supervision of supporting facts during training.

5.2 Model Details

Input Module. In the input module, we are given sentences $x_t$ and a question $q$, and we want to obtain their vector representations, $x_t, q \in \mathbb{R}^d$. We use a trainable embedding matrix $A \in \mathbb{R}^{d \times V}$ to encode the one-hot vector of each word $x_{tj}$ in each sentence $x_t$ into a $d$-dimensional vector $x_{tj} \in \mathbb{R}^d$. Then the sentence representation $x_t$ is obtained by Position Encoder [20]: $x_t = \sum_j l_j \circ x_{tj}$ where $k$-th element of the vector $l_j \in \mathbb{R}^d$ is $(1 - j / J) - (k / d)(1 - 2j / J)$ (assuming 1-based indexing), where $J$ is the number of words in $x_t$. Note that the order of words affects $x_t$. The same encoder with the same embedding matrix is also used to obtain the question vector $q$ from $q$.

Output Module. In the output module, we are given the vector representation of the predicted answer $\hat{y}$ and we want to obtain the natural language form of the answer, $y$. We use a V-way single-layer softmax classifier to map $\hat{y}$ to a $V$-dimensional sparse vector, $\hat{v} = \text{softmax} (W^{(v)} \hat{y}) \in \mathbb{R}^V$, where $W^{(v)} \in \mathbb{R}^{V \times d}$ is a weight matrix. Then the final answer $y$ is simply the argmax word in $\hat{v}$. For 10k dataset, we instead use $\hat{v} = \text{softmax} (W^{(v)} \hat{y}; q)$ (hence $W^{(v)} \in \mathbb{R}^{V \times 2d}$). To handle questions with multiple-word answers, we simply consider each of them as a single word that contains punctuations such as space and comma, and put it in the vocabulary. Although not explored, an

\[\text{Code obtained from: }\text{github.com/therne/dmn-tensorflow}\]
Table 1: bAbI QA dataset [21] error rates (%) of QRN and previous work: LSTM [21], End-to-end Memory Networks (N2N [18]), and Dynamic Memory Networks (DMN+ [22]). For QRN, a number (1, 2, 3, 6) indicates the number of layers, ‘r’ indicates that the reset gate is used, ‘v’ indicates that the gates were vectorized, and ‘b’ indicates that the query updates were bi-directional.

**Training.** We withheld 10% of the training for development. d was set to 50 for all QRN models. Batch sizes of 32 and 128 were used for 1k and 10k datasets, respectively. The weights in the input and output modules were initialized with zero mean and the standard deviation of $1/\sqrt{d}$. Weights in the QRN unit were initialized using techniques by Glorot and Bengio [7], and were tied across the layers. Forget bias of 2.5 was used for update gates (no bias for reset gates). L2 weight decay of 0.001 was used for all weights. The loss function is the cross entropy between v and the one-hot vector of the true answer. The loss is minimized by stochastic gradient descent for 150 epochs, and the learning rate was controlled by AdaGrad [5] with the initial learning rate of 0.5. Since the model was sensitive to the weight initialization, we repeated each training procedure 10 times (50 times for 10k) with the new random initialization of the weights and reported the result on the test data with the lowest loss on the development data.

### 5.3 Results

Table 1 reports the results of our model (QRN) and previous work on bAbI QA. Most notably, in 1k data, the average accuracy of QRN’s ‘2rvb’ (2 layers + reset gate + vector gates + bi-direction) model outperforms that of MemNN2N (PE+LS+LW+joint model) by 5.3%, and the task-wise accuracies of the QRN model are equal or higher than those of MemNN in 19 tasks, only losing in Task 16. Also, the QRN’s ‘3rb’ model passes 5 more tasks than MemNN2N.

In 10k dataset, the average accuracy of QRN’s 10k ‘2rvb’ (2 layers + reset gate + vector gates + bi-direction) model outperforms that of MemNN2N (PE+LS+LW+RN* model) by 1.0%. It is also comparable to that of DMN+, differing only by 0.3%, even though our model is simpler and faster to train than DMN+. The same QRN model also sets the state of the art in Tasks 5, 7, and 17.

**Ablations.** We tested four types of ablations (also discussed in Section 2.2): number of layers (1, 2, 3, or 6), reset gate (r), gate vectorization (v), and bi-directional query update (b). We show a subset of combinations of the ablations in Table 1, other combinations performed poorly and/or did not give interesting observations. According to the ablation results, we can infer that:

- When the number of layers is only one, the model lacks reasoning capability. When there are too many layers (6), it seems correctly training the model becomes increasingly difficult.
Where is Sandra? In order to obtain these, we place a decoder on the input question embedding \( q \) (machine comprehension on real data such as MCTest [16] and SQuAD [14]).

Each time step, and its internal representation, in the form of updated query, is interpretable. We question answering when the size of stories grows. Lastly, QRN is able to answer questions after regressing queries and Query-Regression Network (QRN) answers machine comprehension questions by storing local facts that tell who has the "apple", and in the second layer, we see high update gate values on those.

Figure 3: Consider the Task 2 example (top left): in the first layer, we see high update gate values on "Sandra picked up the apple there.", "Sandra dropped the apple.", "Sandra travelled to the bathroom.", and "Daniel went to the hallway.". At \( t = 2 \), as "Sandra dropped the apple.", the apple is no more relevant to Sandra. We obtain "Where is Daniel?" at time \( t = 3 \), and it is propagated until \( t = 5 \), where we observe a sentence (fact) that can be used to answer the query. In this case, the regress function \( \gamma \) is trained so that it outputs the answer to the query ("garden") instead of another regressed query.

We also visualize the (scalar) magnitudes of update and reset gates on story sentences, as shown in Figure 3. Consider the Task 2 example (top left): in the first layer, we see high update gate values on facts that tell who has the “apple”, and in the second layer, we see high update gate values on those that tell where that person went to. We also see that the forward reset gate at \( t = 2 \) in the first layer \( r^{1}_{1} \) is low, which is signifying that “apple” no more belongs to “Sandra”.

### Parallelization.

We implemented QRN with and without parallelization in TensorFlow on a single Titan X GPU to quantify the computational gain of the parallelization. For QRN without parallelization, we used the RNN library provided by TensorFlow. QRN with parallelization gave 6.2 times faster training and testing than QRN without parallelization on average. We expect that the speedup can be even higher for datasets with longer sentences.

### Interpretations.

One of the advantages of QRN is that the intermediate query updates are interpretable. Figure 1 shows intermediate local queries (\( q^{k}_{i} \)) interpreted in natural language, such as “Where is Sandra?”. In order to obtain these, we place a decoder on the input question embedding \( q \) and add its loss for recovering the question to the classification loss (similarly to Peng et al. [13]). We then use the same decoder to decode the intermediate queries. This helps us understand the flow of information in the networks. In Figure 1, the question “Where is apple?” is transformed into “Where is Sandra?” at \( t = 1 \). At \( t = 2 \), as “Sandra dropped the apple.”, the apple is no more relevant to Sandra. We obtain “Where is Daniel?” at time \( t = 3 \), and it is propagated until \( t = 5 \), where we observe a sentence (fact) that can be used to answer the query. In this case, the regress function \( \gamma \) is trained so that it outputs the answer to the query ("garden") instead of another regressed query.

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## 6 Conclusion

Query-Regression Network (QRN) answers machine comprehension questions by storing local queries and regressing them as QRN observes state-changing sentences. While an RNN-based model, QRN is effective for encoding long-term dependencies between sentences. In addition, it is simpler than previous work [18][22] and is highly parallelizable, making them a suitable choice for large-scale question answering when the size of stories grows. Lastly, QRN is able to answer questions after each time step, and its internal representation, in the form of updated query, is interpretable. We have experimentally shown that QRN is capable of learning to perform different kinds of reasoning over multiple facts in bAbI QA dataset. Future work involves using QRN for language modeling and machine comprehension on real data such as MCTest [16] and SQuAD [15].
References

[1] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, et al. Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv preprint arXiv:1603.04467*, 2016.

[2] Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. Semantic parsing on freebase from question-answer pairs. In *EMNLP*, 2013.

[3] Qingqing Cai and Alexander Yates. Large-scale semantic parsing via schema matching and lexicon extension. In *ACL*, 2013.

[4] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. In *EMNLP*, 2014.

[5] John Duchi, Elad Hazan, and Yoram Singer. Adaptive subgradient methods for online learning and stochastic optimization. *JMLR*, 12, 2011.

[6] Anthony Fader, Luke S. Zettlemoyer, and Oren Etzioni. Paraphrase-driven learning for open question answering. In *ACL*, 2013.

[7] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *JMLR*, 2010.

[8] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[9] Mohammad Javad Hosseini, Hannaneh Hajishirzi, Oren Etzioni, and Nate Kushman. Learning to solve arithmetic word problems with verb categorization. In *EMNLP*, 2014.

[10] Ankit Kumar, Ozan Irsoy, Jonathan Su, James Bradbury, Robert English, Brian Pierce, Peter Ondruska, Ishaan Gulrajani, and Richard Socher. Ask me anything: Dynamic memory networks for natural language processing. In *ICML*, 2016.

[11] Moontae Lee, Xiaodong He, Wen tau Yih, Jianfeng Gao, Li Deng, and Paul Smolensky. Reasoning in vector space: An exploratory study of question answering. In *ICLR*, 2016.

[12] Arindam Mitra and Chitta Baral. Addressing a question answering challenge by combining statistical methods with inductive rule learning and reasoning. In *AAAI*, 2016.

[13] Baolin Peng, Zhendong Lu, Hang Li, and Kam-Fai Wong. Towards neural network-based reasoning. *arXiv preprint arXiv:1508.05508*, 2015.

[14] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*, 2016.

[15] Raymond Reiter. *Knowledge in Action*. MIT Press, 1st edition, 2001.

[16] Matthew Richardson, Christopher JC Burges, and Erin Renshaw. Mctest: A challenge dataset for the open-domain machine comprehension of text. In *EMNLP*, 2013.

[17] Minjoon Seo, Hannaneh Hajishirzi, Ali Farhadi, Oren Etzioni, and Clint Malcolm. Solving geometry problems: Combining text and diagram interpretation. In *EMNLP*, 2015.

[18] Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. End-to-end memory networks. In *NIPS*, 2015.

[19] Wen tau Yih, Ming-Wei Chang, Xiaodong He, and Jianfeng Gao. Semantic parsing via staged query graph generation: Question answering with knowledge base. In *ACL*, 2015.

[20] Jason Weston, Sumit Chopra, and Antoine Bordes. Memory networks. In *ICLR*, 2015.

[21] Jason Weston, Antoine Bordes, Sumit Chopra, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. In *ICLR*, 2016.

[22] Caiming Xiong, Stephen Merity, and Richard Socher. Dynamic memory networks for visual and textual question answering. In *ICML*, 2016.