Question answering and machine comprehension with neural attention

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Two End-to-End Question Answering Systems with Neural Attention

• Bidirectional Attention Flow (BiDAF)
  • On Stanford Question Answering Dataset and CNN/DailyMail Cloze Test

• Query-Reduction Networks (QRN)
  • On bAbI QA and dialog, DSTC2 datasets
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Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi's Stadium in the San Francisco Bay Area at Santa Clara, California. As this was the 50th Super Bowl, the league emphasized the "golden anniversary" with various gold-themed initiatives, as well as temporarily suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as "Super Bowl L"), so that the logo could prominently feature the Arabic numerals 50.

Q: Which NFL team represented the AFC at Super Bowl 50?

A: Denver Broncos
Why Neural Attention?

Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi's Stadium in the San Francisco Bay Area at Santa Clara, California. As this was the 50th Super Bowl, the league emphasized the "golden anniversary" with various gold-themed initiatives, as well as temporarily suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as "Super Bowl L"), so that the logo could prominently feature the Arabic numerals 50.

Q: Which NFL team represented the AFC at Super Bowl 50?

Allows a deep learning architecture to focus on the most relevant phrase of the context to the query in a **differentiable manner**.
Our Model: Bi-directional Attention Flow (BiDAF)

Barak Obama is the president of the U.S.

Who leads the United States?
(Bidirectional) Attention Flow
Char/Word Embedding Layers

- Output Layer
- Modeling Layer
- Attention Flow Layer
- Phrase Embed Layer
- Word Embed Layer
- Character Embed Layer

- Start
- End

LSTM

Dense + Softmax
LSTM + Softmax

Context2Query and Context2Query
Attention

Query2Context and Context2Query

Dense + Softmax

Word Embedding

GLOVE

Character Embedding
Character and Word Embedding

- Word embedding is fragile against unseen words
- Char embedding can’t easily learn semantics of words
- Use both!
- Char embedding as proposed by Kim (2015)
Phrase Embedding Layer
Phrase Embedding Layer

- **Inputs**: the char/word embedding of query and context words
- **Outputs**: word representations aware of their neighbors (phrase-aware words)

- Apply bidirectional RNN (LSTM) for both query and context
Attention Layer
Attention Layer

• **Inputs**: phrase-aware context and query words
• **Outputs**: query-aware representations of context words

• **Context-to-query attention**: For each (phrase-aware) context word, choose the most relevant word from the (phrase-aware) query words
• **Query-to-context attention**: Choose the context word that is most relevant to any of query words.
Context-to-Query Attention (C2Q)

Q: Who leads the United States?

C: Barak Obama is the president of the USA.

For each context word, find the most relevant query word.
Query-to-Context Attention (Q2C)

While Seattle's weather is very nice in summer, its weather is very rainy in winter, making it one of the most gloomy cities in the U.S. LA is ...

Q: Which city is gloomy in winter?
Modeling Layer

Output Layer

Modeling Layer

Attention Flow Layer

Phrase Embed Layer

Word Embed Layer

Character Embed Layer

Start

End

Dense + Softmax

LSTM + Softmax

Query2Context and Context2Query

Attention

Context

Query

Character Embedding

GLOVE

Char - CNN
Modeling Layer

• **Attention layer**: modeling interactions between query and context

• **Modeling layer**: modeling interactions within (query-aware) context words via RNN (LSTM)

• **Division of labor**: let attention and modeling layers solely focus on their own tasks

• We experimentally show that this leads to a better result than intermixing attention and modeling
Output Layer
Training

• Minimizes the negative log probabilities of the true start index and the true end index

\[ L(\theta) = -\frac{1}{N} \sum_{i}^{N} \log(p_{y_i}^1) + \log(p_{y_i}^2) \]

\( y_i^1 \) True start index of example i

\( y_i^2 \) True end index of example i

\( p^1 \) Probability distribution of start index

\( p^2 \) Probability distribution of stop index
Previous work

• Using neural attention as a controller (Xiong et al., 2016)
• Using neural attention within RNN (Wang & Jiang, 2016)
• Most of these attentions are uni-directional

• BiDAF (our model)
  • uses neural attention as a layer,
  • Is separated from modeling part (RNN),
  • Is bidirectional
Image Classifier and BiDAF

VGG-16

BiDAF (ours)
Stanford Question Answering Dataset (SQuAD) (Rajpurkar et al., 2016)

- Most popular articles from Wikipedia
- Questions and answers from Turkers
- 90k train, 10k dev, ? test (hidden)
- Answer must lie in the context
- Two metrics: Exact Match (EM) and F1
SQuAD Results (http://stanford-qa.com) as of 12pm Today

Test Set Leaderboard

Since the release of our dataset (and paper), the community has made rapid progress! Here are the ExactMatch (EM) and F1 scores of the best models evaluated on the test and development sets of v1.1.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Model</th>
<th>Test EM</th>
<th>Test F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BiDAF (ensemble) Allen Institute for AI &amp; University of Washington</td>
<td>73.3</td>
<td>81.1</td>
</tr>
<tr>
<td></td>
<td>(Seo et al. ’16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Dynamic Coattention Networks (ensemble) Salesforce Research</td>
<td>71.6</td>
<td>80.4</td>
</tr>
<tr>
<td></td>
<td>(Xiong &amp; Zhong et al. ’16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>r-net (ensemble) Microsoft Research Asia</td>
<td>72.1</td>
<td>79.7</td>
</tr>
<tr>
<td>4</td>
<td>r-net (single model) Microsoft Research Asia</td>
<td>68.4</td>
<td>77.5</td>
</tr>
<tr>
<td>5</td>
<td>BiDAF (single model) Allen Institute for AI &amp; University of Washington</td>
<td>68.0</td>
<td>77.3</td>
</tr>
<tr>
<td></td>
<td>(Seo et al. ’16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Multi-Perspective Matching (ensemble) IBM Research</td>
<td>68.2</td>
<td>77.2</td>
</tr>
</tbody>
</table>
## SQuAD Results

<table>
<thead>
<tr>
<th></th>
<th>EM</th>
<th>F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford(^1) (baseline)</td>
<td>40.4</td>
<td>51.0</td>
</tr>
<tr>
<td>IBM(^2)</td>
<td>62.5</td>
<td>71.0</td>
</tr>
<tr>
<td>CMU(^3)</td>
<td>62.5</td>
<td>73.3</td>
</tr>
<tr>
<td>Singapore Management(^4) (ensemble)</td>
<td>67.9</td>
<td>77.0</td>
</tr>
<tr>
<td>IBM Research (ensemble)</td>
<td>68.2</td>
<td>77.2</td>
</tr>
<tr>
<td>Salesforce Research(^6) (ensemble)</td>
<td>71.6</td>
<td>80.4</td>
</tr>
<tr>
<td>Microsoft Research Asia (ensemble)</td>
<td>72.1</td>
<td>79.7</td>
</tr>
<tr>
<td>Ours (ensemble)</td>
<td><strong>73.3</strong></td>
<td><strong>81.1</strong></td>
</tr>
</tbody>
</table>

1: Rajpurkar et al. (2016)  
2: Yu et al. (2016)  
3: Yang et al. (2016)  
6: Xiong et al. (2016)
Ablations on dev data
Interactive Demo

http://allenai.github.io/bi-att-flow/demo
There are 13 natural reserves in Warsaw—among others, Bielany Forest, Kabaty Woods, Czerniaków Lake. About 15 kilometres (9 miles) from Warsaw, the Vistula river’s environment changes strikingly and features a perfectly preserved ecosystem, with a habitat of animals that includes the otter, beaver, and hundreds of bird species. There are also several lakes in Warsaw—mainly the oxbow lakes, like Czerniaków Lake, the lakes in the Łazienki or Wilanów Parks, Kamionek Lake. There are lot of small lakes in the parks, but only a few are permanent—the majority are emptied before winter to clean them of plants and sediments.

Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi’s Stadium in the San Francisco Bay Area at Santa Clara, California. As this was the 50th Super Bowl, the league emphasized the "golden anniversary" with various gold-themed initiatives, as well as temporarily suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as "Super Bowl L"), so that the logo could prominently feature the Arabic numerals 50.
Embedding Visualization at Word vs Phrase Layers

Opening in May 1852 at the state may not aid. Of these may be more effect and may result in the state may not aid.

from 28 January to 25 but by September had been debut on May 5.
How does it compare with feature-based models?

Questions answered correctly by our BiDAF model and the more traditional baseline model
CNN/DailyMail Cloze Test (Hermann et al., 2015)

**Context**
The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the “Top Gear” host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon “to an unprovoked physical and verbal attack.” …

**Query**
Producer X will not press charges against Jeremy Clarkson, his lawyer says.

**Answer**
Oisin Tymon

- Cloze Test (Predicting Missing words)
- Articles from CNN/DailyMail
- Human-written summaries
- Missing words are always entities
- CNN – 300k article-query pairs
- DailyMail – 1M article-query pairs
## CNN/DailyMail Cloze Test Results

<table>
<thead>
<tr>
<th>Model</th>
<th>CNN val</th>
<th>CNN test</th>
<th>DailyMail val</th>
<th>DailyMail test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attentive Reader (Hermann et al., 2015)</td>
<td>61.6</td>
<td>63.0</td>
<td>70.5</td>
<td>69.0</td>
</tr>
<tr>
<td>MemNN (Hill et al., 2016)</td>
<td>63.4</td>
<td>6.8</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>AS Reader (Kadlec et al., 2016)</td>
<td>68.6</td>
<td>69.5</td>
<td>75.0</td>
<td>73.9</td>
</tr>
<tr>
<td>Stanford AR (Chen et al., 2016)</td>
<td>68.6</td>
<td>69.5</td>
<td>75.0</td>
<td>73.9</td>
</tr>
<tr>
<td>DER Network (Kobayashi et al., 2016)</td>
<td>71.3</td>
<td>72.9</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Iterative Attention (Sordoni et al., 2016)</td>
<td>72.6</td>
<td>73.3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>EpiReader (Trischler et al., 2016)</td>
<td>73.4</td>
<td>74.0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GAReader (Dhingra et al., 2016)</td>
<td>73.0</td>
<td>73.8</td>
<td>76.7</td>
<td>75.7</td>
</tr>
<tr>
<td>AoA Reader (Cui et al., 2016)</td>
<td>73.1</td>
<td>74.4</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ReasoNet (Shen et al., 2016)</td>
<td>72.9</td>
<td>74.7</td>
<td>77.6</td>
<td>76.6</td>
</tr>
<tr>
<td>BiDAF (Ours)</td>
<td><strong>76.3</strong></td>
<td><strong>76.9</strong></td>
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<td><strong>79.6</strong></td>
</tr>
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<td>69.4</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
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<td>79.1</td>
<td>78.1</td>
</tr>
</tbody>
</table>
Some limitations of SQuAD

<table>
<thead>
<tr>
<th>Reasoning</th>
<th>Description</th>
<th>Example</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lexical variation (synonymy)</td>
<td>Major correspondences between the question and the answer sentence are synonyms.</td>
<td>Q: What is the Rankine cycle sometimes <strong>called</strong>? Sentence: The Rankine cycle is sometimes <strong>referred</strong> to as a practical Carnot cycle.</td>
<td>33.3%</td>
</tr>
<tr>
<td>Lexical variation (world knowledge)</td>
<td>Major correspondences between the question and the answer sentence require world knowledge to resolve.</td>
<td>Q: Which <strong>governing bodies</strong> have veto power? Sen.: <strong>The European Parliament and the Council of the European Union</strong> have powers of amendment and veto during the legislative process.</td>
<td>9.1%</td>
</tr>
<tr>
<td>Syntactic variation</td>
<td>After the question is paraphrased into declarative form, its syntactic dependency structure does not match that of the answer sentence even after local modifications.</td>
<td>Q: What Shakespeare scholar is <strong>currently on the faculty</strong>? Sen.: <strong>Current faculty include</strong> the anthropologist Marshall Sahlins, ..., Shakespeare scholar David Bevington.</td>
<td>64.1%</td>
</tr>
<tr>
<td>Multiple sentence reasoning</td>
<td>There is anaphora, or higher-level fusion of multiple sentences is required.</td>
<td>Q: What collection does <strong>the V&amp;A Theatre &amp; Performance galleries</strong> hold? Sen.: <strong>The V&amp;A Theatre &amp; Performance galleries</strong> opened in March 2009. ... They hold the UK’s biggest national collection of material about live performance.</td>
<td>13.6%</td>
</tr>
<tr>
<td>Ambiguous</td>
<td>We don’t agree with the crowd-workers’ answer, or the question does not have a unique answer.</td>
<td>Q: What is the main goal of criminal punishment? Sen.: <strong>Achieving crime control via incapacitation and deterrence</strong> is a major goal of criminal punishment.</td>
<td>6.1%</td>
</tr>
</tbody>
</table>
Two Question Answering Systems with Neural Attention

• Bidirectional Attention Flow (BiDAF)
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• Query-Reduction Networks (QRN)
  • On bAbI QA and dialog datasets
Reasoning Question Answering

Task 1: Single Supporting Fact
Mary went to the bathroom.
John moved to the hallway.
Mary travelled to the office.
Where is Mary? A: office

Task 2: Two Supporting Facts
John is in the playground.
John picked up the football.
Bob went to the kitchen.
Where is the football? A: playground

Task 3: Three Supporting Facts
John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A: office

Task 4: Two Argument Relations
The office is north of the bedroom.
The bedroom is north of the bathroom.
The kitchen is west of the garden.
What is north of the bedroom? A: office
What is the bedroom north of? A: bathroom
Dialog System

U: Can you book a table in Rome in Italian Cuisine

S: How many people in your party?

U: For four people please.

S: What price range are you looking for?
Dialog task vs QA

• Dialog system can be considered as QA system:
  • Last user’s utterance is the query
  • All previous conversations are context to the query
  • The system’s next response is the answer to the query

• Poses a few unique challenges
  • Dialog system requires tracking states
  • Dialog system needs to look at multiple sentences in the conversation
  • Building end-to-end dialog system is more challenging
Our approach: Query-Reduction

Reduced query:

Where is the apple?
Where is Sandra?
Where is Sandra?
Where is Daniel?
Where is Daniel?
Where is Daniel? → garden

Q: Where is the apple?
A: garden
Query-Reduction Networks

• Reduce the query into an easier-to-answer query over the sequence of state-changing triggers (sentences), \textit{in vector space}

\[
x_1 \quad q_1^2 \quad x_2 \quad q_2^2 \quad x_3 \quad q_3^2 \quad x_4 \quad q_4^2 \quad x_5 \quad q_5^2
\]

\[
\begin{align*}
h_1^1 & \rightarrow h_1^2 \quad \emptyset \quad h_2^2 \quad \emptyset \quad h_3^2 \quad \emptyset \quad h_4^2 \quad \emptyset \quad h_5^2 \rightarrow \hat{y} \\
x_1 & \quad q_1^1 \quad x_2 & \quad q_2^1 \quad x_3 & \quad q_3^1 \quad x_4 & \quad q_4^1 \quad x_5 & \quad q_5^1 \\
&Sandra got \ the \ apple \ there. \quad Sandra \ dropped \ the \ apple \ there. \quad Daniel \ took \ the \ apple \ there. \quad Sandra \ went \ to \ the \ hallway. \quad Daniel \ journeyed \ to \ the \ garden. \quad \text{Where is the apple?}
\end{align*}
\]
QRN Cell

\[ z_t = \alpha(x_t, q_t) \]

\[ \tilde{h}_t = \rho(x_t, q_t) \]

\[ h_t = z_t \tilde{h}_t + (1 - z_t)h_{t-1} \]
Characteristics of QRN

• Update gate can be considered as local attention
  • QRN chooses to consider / ignore each candidate reduced query
  • The decision is made locally (as opposed to global softmax attention)

• Subclass of Recurrent Neural Network (RNN)
  • Two inputs, hidden state, gating mechanism
  • Able to handle sequential dependency (attention cannot)

• Simpler recurrent update enables *parallelization* over time
  • Candidate hidden state (reduced query) is computed from inputs only
  • Hidden state can be explicitly computed as a function of inputs
Parallelization

\[ z_t = \alpha(x_t, q_t) \]
\[ \tilde{h}_t = \rho(x_t, q_t) \]

\[ h_t = z_t \tilde{h}_t + (1 - z_t) h_{t-1} \]

Can be explicitly expressed as the geometric sum of previous candidate hidden states

\[ h_t = \sum_{i=1}^{t} \left[ \prod_{j=i+1}^{t} 1 - z_j \right] z_i \tilde{h}_i \]
Parallelization

- \( x_1 \) -> \( q_1^1 \) -> \( h_1^1 \) -> \( q_1^2 \) -> \( h_2^1 \) -> \( q_2^2 \) -> \( h_3^1 \) -> \( q_3^2 \) -> \( h_4^1 \) -> \( q_4^2 \) -> \( h_5^1 \) -> \( \hat{y} \)

- Sandra got the apple there.
- Sandra dropped the apple.
- Daniel took the apple there.
- Sandra went to the hallway.
- Daniel journeyed to the garden.
- Where is Sandra?
- Where is Daniel?

\( q \)
Characteristics of QRN

• Update gate can be considered as local attention
• Subclass of Recurrent Neural Network (RNN)
• Simpler recurrent update enables *parallelization* over time

QRN sits between neural attention mechanism and recurrent neural networks, taking the advantage of both paradigms.
bAbI QA Dataset

- 20 different tasks
- 1k story-question pairs for each task (10k also available)
- Synthetically generated
- Many questions require looking at multiple sentences
- For end-to-end system supervised by answers only
What’s different from SQuAD?

• Synthetic
• More than lexical / syntactic understanding
• Different kinds of inferences
  • induction, deduction, counting, path finding, etc.
• Reasoning over multiple sentences
• Interesting testbed towards developing complex QA system (and dialog system)
bAbI QA Results (1k)

<table>
<thead>
<tr>
<th>Model</th>
<th>Avg Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM</td>
<td>50</td>
</tr>
<tr>
<td>DMN+</td>
<td>30</td>
</tr>
<tr>
<td>MemN2N</td>
<td>15</td>
</tr>
<tr>
<td>GMemN2N</td>
<td>10</td>
</tr>
<tr>
<td>QRN (Ours)</td>
<td>5</td>
</tr>
</tbody>
</table>

Avg Error (%)
bAbI QA Results (10k)

<table>
<thead>
<tr>
<th>Model</th>
<th>Avg Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MemN2N</td>
<td>4.0</td>
</tr>
<tr>
<td>DNC</td>
<td>3.8</td>
</tr>
<tr>
<td>GMemN2N</td>
<td>3.5</td>
</tr>
<tr>
<td>DMN+</td>
<td>2.8</td>
</tr>
<tr>
<td>QRN (Ours)</td>
<td>0.5</td>
</tr>
</tbody>
</table>
Dialog Datasets

• bAbI Dialog Dataset
  • Synthetic
  • 5 different tasks
  • 1k dialogs for each task

• DSTC2* Dataset
  • Real dataset
  • Evaluation metric is different from original DSTC2: response generation instead of “state-tracking”
  • Each dialog is 800+ utterances
  • 2407 possible responses
bAbI Dialog Results (OOV)
DSTC2* Dialog Results

Avg Error (%)

MemN2N  GMemN2N  QRN (Ours)
bAbI QA Visualization

<table>
<thead>
<tr>
<th>Task 2: Two Supporting Facts</th>
<th>Layer 1</th>
<th>Layer 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$z^1$</td>
<td>$\tau^1$</td>
</tr>
<tr>
<td>Sandra picked up the apple there.</td>
<td>0.95</td>
<td>0.89</td>
</tr>
<tr>
<td>Sandra dropped the apple.</td>
<td>0.83</td>
<td>0.05</td>
</tr>
<tr>
<td>Daniel grabbed the apple there.</td>
<td>0.88</td>
<td>0.93</td>
</tr>
<tr>
<td>Sandra travelled to the bathroom.</td>
<td>0.01</td>
<td>0.18</td>
</tr>
<tr>
<td>Daniel went to the hallway.</td>
<td>0.01</td>
<td>0.24</td>
</tr>
<tr>
<td>Where is the apple?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$z^l = \text{Local attention (update gate) at layer } l$
## DSTC2 (Dialog) Visualization

### Task 6 DSTC2 dialog

<table>
<thead>
<tr>
<th>Dialog</th>
<th>Layer 1</th>
<th>Layer 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$z^1$</td>
<td>$\overrightarrow{r}^1$</td>
<td>$\overleftarrow{r}^1$</td>
</tr>
<tr>
<td>Spanish food.</td>
<td>0.84</td>
<td>0.07</td>
</tr>
<tr>
<td>You are looking for a Spanish restaurant right?</td>
<td>0.98</td>
<td>0.02</td>
</tr>
<tr>
<td>Yes.</td>
<td>0.01</td>
<td>1.00</td>
</tr>
<tr>
<td>What part of town do you have in mind?</td>
<td>0.20</td>
<td>0.73</td>
</tr>
<tr>
<td>I don’t care.</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>What price range would you like?</td>
<td>0.72</td>
<td>0.46</td>
</tr>
</tbody>
</table>

I don’t care. API CALL Spanish R-location R-price

$z^l = $ Local attention (update gate) at layer $l$
Conclusion

• Presented two novel approaches for QA tasks using neural attention

• **Bidirectional Attention Flow**: using attention as a layer, on both directions (context to query, query to context)

• **Query-reduction Networks**: a sequential model that takes advantage of both attention and RNN for reasoning over multiple sentences
Thanks!
Why do we need attention?

• RNN has long-term dependency problem
  • Vanishing gradients (Pascanu et al., 2013)
  • Inherently unstable over a long period of time (Weston et al., 2016)
• Attention provides shortcut access to relevant information
  • Directly retrieves the context vector from a distant location
• Critical to most modern sequence models
  • Machine translation
  • Question answering, machine comprehension
Neural Attention in Sequence Modeling

- Apply RNN on context vectors
- Apply RNN on query vectors
  - At each time step, use neural attention to soft-select a single context vector
  - Use the selected context vector, along with current query vector and current hidden state, to obtain the next hidden state

(Bahdanau et al., 2015)