Adding semantic robustness to dialog agents

Felipe Salvatore
https://felipessalvatore.github.io/

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IME-USP: Instituto de Matemática e Estatística - Universidade de São Paulo

Research problem

- Create a set of tasks that incorporate logic reasoning to boost performance of the current dialog agents.
- Perform a stress test in the existing *neural network based end-to-end dialog systems*.
- Integrate linguistic reasoning with visual references to create a new set of visual question answering (VQA) tasks.
- Define new models to achieve better results in the tasks proposed above.

Background

Neural network based language model

We call language model a probability distribution over sequences of tokens in a natural language.

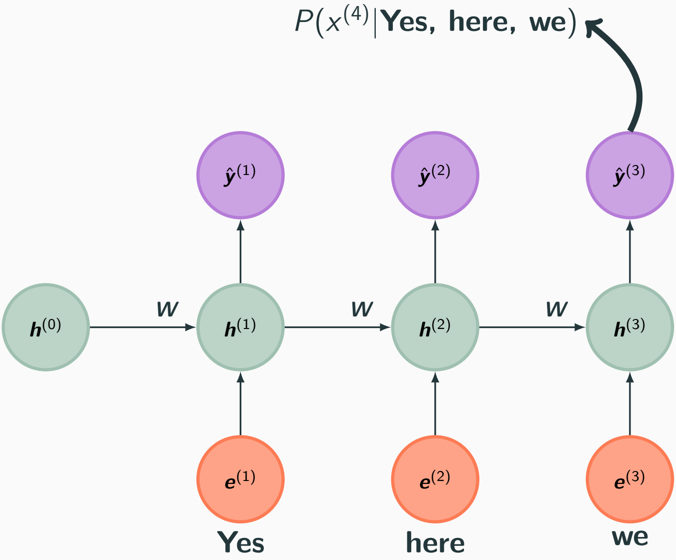
$$P(x_1, x_2, x_3, x_4) = p \tag{1}$$

Since [7], we use a Recurrent Neural Network (RNN) to estimate the probability distribution

$$P(x_n = \text{word}_{j^*} | x_1, \dots, x_{n-1}) \tag{2}$$

for any $(n-1)$-sequence of words $x_1, \dots, x_{n-1}$.

Neural network based language model



GRU: Gated Recurrent Units

$$\widetilde{\boldsymbol{h}}^{(t)} = tahn(\boldsymbol{W}(\boldsymbol{h}^{(t-1)} \odot \boldsymbol{r}^{(t)}) + \boldsymbol{U}\boldsymbol{x}^{(t)} + \boldsymbol{b}) \tag{3}$$

$$\boldsymbol{r}^{(t)} = \sigma(\boldsymbol{W}_r\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r\boldsymbol{x}^{(t)} + \boldsymbol{b}_r) \tag{4}$$

$$\boldsymbol{u}^{(t)} = \sigma(\boldsymbol{W}_u\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u\boldsymbol{x}^{(t)} + \boldsymbol{b}_u) \tag{5}$$

$$\boldsymbol{h}^{(t)} = \boldsymbol{u}^{(t)} \odot \widetilde{\boldsymbol{h}}^{(t)} + (1 - \boldsymbol{u}^{(t)}) \odot \boldsymbol{h}^{(t-1)} \tag{6}$$

LSTM: Long Short Term Memory

$$\boldsymbol{f}^{(t)} = \sigma(\boldsymbol{W}_f \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_f \boldsymbol{x}^{(t)} + \boldsymbol{b}_f) \tag{7}$$

$$\boldsymbol{i}^{(t)} = \sigma(\boldsymbol{W}_i \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_i \boldsymbol{x}^{(t)} + \boldsymbol{b}_i) \tag{8}$$

$$\boldsymbol{o}^{(t)} = \sigma(\boldsymbol{W}_o \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_o \boldsymbol{x}^{(t)} + \boldsymbol{b}_o) \tag{9}$$

$$\tilde{\boldsymbol{c}}^{(t)} = tahn(\boldsymbol{W} \boldsymbol{h}^{(t-1)} + \boldsymbol{U} \boldsymbol{x}^{(t)} + \boldsymbol{b}) \tag{10}$$

$$\boldsymbol{c}^{(t)} = \boldsymbol{f}^{(t)} \odot \boldsymbol{c}^{(t-1)} + \boldsymbol{i}^{(t)} \odot \tilde{\boldsymbol{c}}^{(t)} \tag{11}$$

$$\boldsymbol{h}^{(t)} = \boldsymbol{o}^{(t)} \odot tanh(\boldsymbol{c}^{(t)}) \tag{12}$$

Sequence-to-sequence

- $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(n)}$, source sentence
- $\boldsymbol{y}^{(1)}, \ldots, \boldsymbol{y}^{(m)}$, target sentence
- f_{enc} (the *encoder*), a RNN
- f_{dec} (the *encoder*), a language model

$$\boldsymbol{s} = f_{enc}(\boldsymbol{x}^{(n)}, \boldsymbol{h}^{(n-1)}) \tag{13}$$

$$\tilde{\boldsymbol{h}}^{(t)} = f_{dec}(\boldsymbol{y}^{(t)}, \tilde{\boldsymbol{h}}^{(t-1)}) \tag{14}$$

$$p(y_t | y_1, \ldots, y_{t-1}, x_1, \ldots, x_n) = softmax(\boldsymbol{W}_s \tilde{\boldsymbol{h}}^{(t)} + \boldsymbol{b}_s) \tag{15}$$

Attention

$$\boldsymbol{a}_{ts} = \frac{exp(score(\tilde{\boldsymbol{h}}^{(t)}, \boldsymbol{h}^{(s)}))}{\sum_j exp(score(\tilde{\boldsymbol{h}}^{(t)}, \boldsymbol{h}^{(j)}))} \tag{16}$$

$$score(\tilde{\boldsymbol{h}}^{(t)}, \boldsymbol{h}^{(s)}) = \begin{cases} \tilde{\boldsymbol{h}}^{(t)}.^{\top} \boldsymbol{h}^{(s)} \\ \tilde{\boldsymbol{h}}^{(t)}.^{\top} \boldsymbol{W}_a \boldsymbol{h}^{(s)} \\ \boldsymbol{v}_a^{\top} tahn(\boldsymbol{W}_a[\tilde{\boldsymbol{h}}^{(t)}; \boldsymbol{h}^{(s)}]) \end{cases} \tag{17}$$

$$\boldsymbol{c}^{(t)} = \sum_s \boldsymbol{a}_{ts} \boldsymbol{h}^{(s)} \tag{18}$$

$$\tilde{\boldsymbol{h}}_{out}^{(t)} = tahn(\boldsymbol{W}_c[\boldsymbol{c}^{(t)}; \boldsymbol{h}^{(t)}]) \tag{19}$$

$$p(y_t | y_1, \ldots, y_{t-1}, x_1, \ldots, x_n) = softmax(\boldsymbol{W}_s \tilde{\boldsymbol{h}}_{out}^{(t)} + \boldsymbol{b}_s) \tag{20}$$

Attention

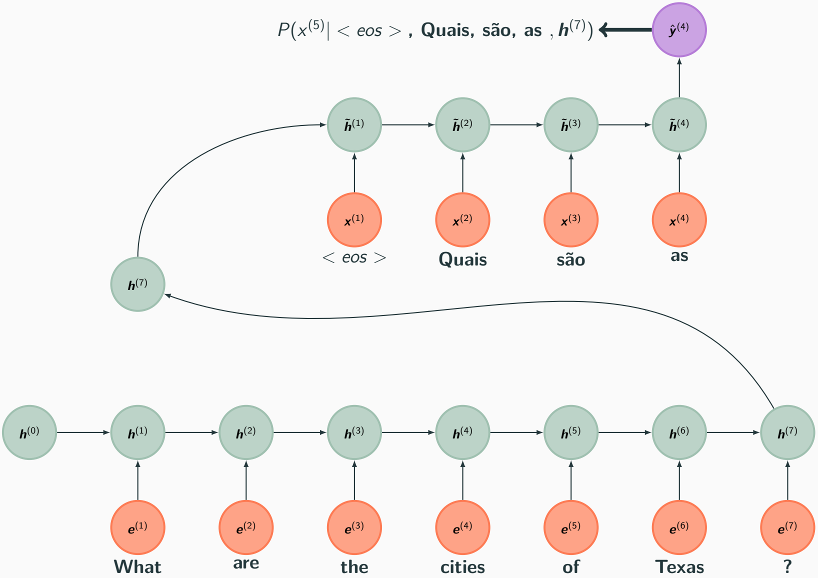
$$f(\boldsymbol{Q}, \boldsymbol{K}_i) = \begin{cases} \boldsymbol{Q}.^\top \boldsymbol{K}_i & \text{dot} \\ \boldsymbol{Q}.^\top \boldsymbol{W}_a \boldsymbol{K}_i & \text{general} \\ \boldsymbol{W}_a[\boldsymbol{Q}; \boldsymbol{K}_i] & \text{concat} \\ \boldsymbol{v}_a.^\top tahn(\boldsymbol{W}_a \boldsymbol{Q} + \boldsymbol{U}_a \boldsymbol{K}_i) & \text{perceptron} \end{cases} \tag{21}$$

$$\begin{bmatrix} f(\boldsymbol{Q}, \boldsymbol{K}_1) \\ f(\boldsymbol{Q}, \boldsymbol{K}_2) \\ \vdots \\ f(\boldsymbol{Q}, \boldsymbol{K}_n) \end{bmatrix} \xrightarrow{\text{softmax}} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

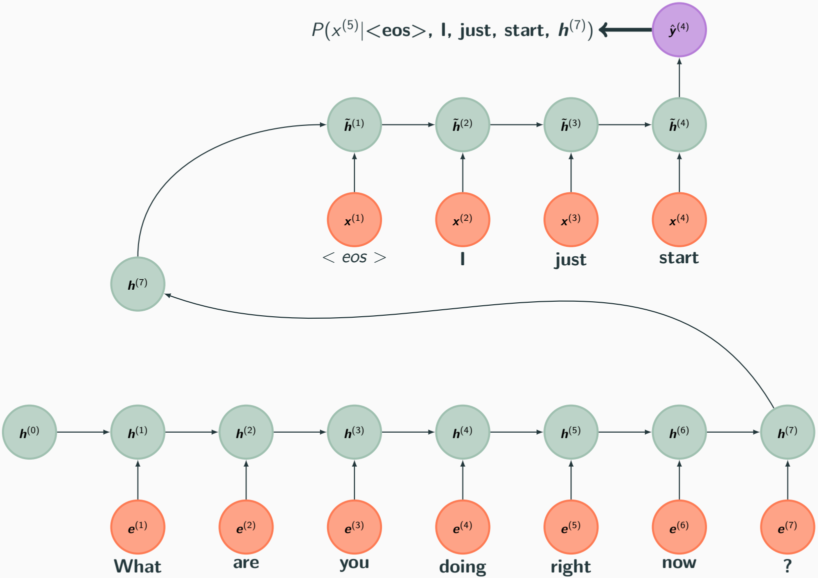
$$Attention(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \sum_i \boldsymbol{a}_i \boldsymbol{V}_i \tag{22}$$

Neural network based dialog systems

Seq2seq applied to translation



Seq2seq applied to dialog [8]



MemNN

- $U_1, \ldots, U_n$ context
- q question
- a answer

We have $k = 1, \ldots, K$ memory layers:

- $\{\boldsymbol{m}^{(k)}{}_i\}$, memory vectors
- $\boldsymbol{u}^{(k)}$, input vector
- $\boldsymbol{p}^{(k)}$, match between $\boldsymbol{u}^{(k)}$ and each $\boldsymbol{m}_i^{(k)}$
- $\{\boldsymbol{c}^{(k)}{}_i\}$, another representation of the context $U_1, ..., U_n$
- $\boldsymbol{o}^{(k)}$, output.
- $\hat{\boldsymbol{a}} = softmax(\boldsymbol{W}(\boldsymbol{o}^K))$, candidate answer

How to evaluate dialogs?

Human evaluation [5]

In the first trial, we asked the following questions to the users, for each response:

1. How appropriate is the response overall? (overall, scale of 1-5)
2. How on-topic is the response? (topicality, scale of 1-5)
3. How specific is the response to some context? (specificity, scale of 1-5)
4. How much background information is required to understand the context? (background, scale of 1-5)

1. Adequacy: the meaning equivalence between the generated and control sentence.
2. Fluency: the syntactic correctness of the generated sequence.
3. Readability: efficacy of the generated sentence in a particular context.

BLEU (bilingual evaluation understudy)

$$P_n = \frac{\text{number of } n\text{-grams in both } \hat{y} \text{ and } y}{\text{number of } n\text{-grams appearing in } \hat{y}} \tag{23}$$

$$BP = \begin{cases} 1 & \text{if } len(\hat{y}) > len(y) \\ \exp\left(1 - \frac{len(y)}{len(\hat{y})}\right) & \text{otherwise} \end{cases} \tag{24}$$

$$BLEU = BP \ \exp\left(\frac{1}{N}\sum_{n=1}^{N} \log P_n\right) \tag{25}$$

METEOR (Metric for Evaluation of Translation with Explicit ORdering)

$$P = \frac{\text{number of unigrams in both } \hat{y} \text{ and } y}{\text{number of unigrams appearing in } \hat{y}} \tag{26}$$

$$R = \frac{\text{number of unigrams in both } \hat{y} \text{ and } y}{\text{number of unigrams appearing in } y} \tag{27}$$

$$F_{mean} = \frac{10PR}{R + 9P} \tag{28}$$

$$METEOR = F_{mean}(1 - penalty) \tag{29}$$

ROUGE (Recall Oriented Understudy for Gisting Evaluation)

$$P_{lcs} = \frac{lcs(\hat{y}, y)}{len(\hat{y})} \tag{30}$$

$$R_{lcs} = \frac{lcs(\hat{y}, y)}{len(y)} \tag{31}$$

$$ROUGE_L = \frac{(1 + \beta^2) P_{lcs} R_{lcs}}{R_{lcs} + \beta^2 P_{lcs}} \tag{32}$$

where β is usually set to favour recal ($\beta = 1.2$).

Problems [4]

metric	Spearman	p-value	Pearson	p-value
BLEU	0.34	< 0.01	0.14	0.17
METEOR	0.19	0.06	0.19	0.05
ROUGE	0.12	0.22	0.1	0.34

Table 1: Correlation between automatic metrics and human judgments based on dialog generated on Twitter

metric	Spearman	p-value	Pearson	p-value
BLEU	0.12	0.23	0.11	0.26
METEOR	0.06	0.53	0.14	0.16
ROUGE	0.05	0.59	0.06	0.53

Table 2: Correlation between automatic metrics and human judgments based on dialog generated on Ubuntu

Creating simplified tasks as tests

bAbI [9]

One solution is to create a set of QA synthetic tasks to test different capabilities of a dialog agent.

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

Task 5: Three Argument Relations
Mary gave the cake to Fred.
Fred gave the cake to Bill.
Jeff was given the milk by Bill.
Who gave the cake to Fred? A: Mary
Who did Fred give the cake to? A: Bill

Task 6: Yes/No Questions
John moved to the playground.
Daniel went to the bathroom.
John went back to the hallway.
Is John in the playground? A:no
Is Daniel in the bathroom? A:yes

ParlAI

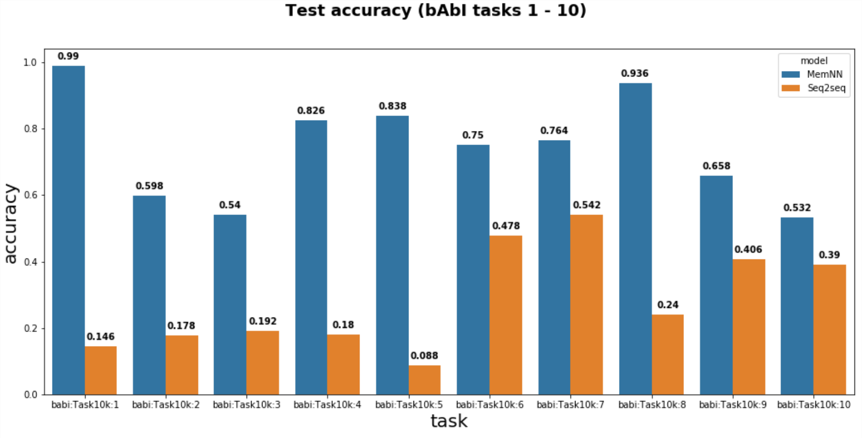
`https://github.com/facebookresearch/ParlAI`

"ParlAI (pronounced 'par-lay') is a framework for dialog AI research, implemented in Python.

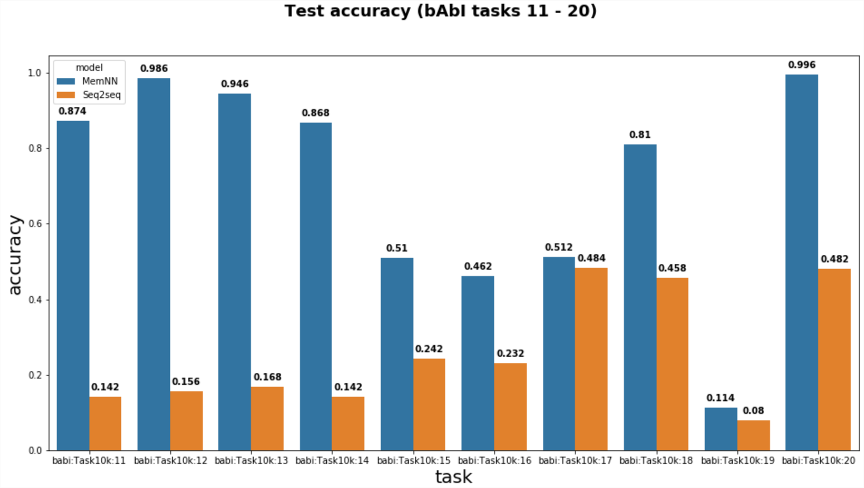
Its goal is to provide researchers:

- a unified framework for sharing, training and testing dialog models
- many popular datasets available all in one place, with the ability to multi-task over them
- seamless integration of Amazon Mechanical Turk for data collection and human evaluation"

Sanity check experiments



Sanity check experiments



Entailment-QA

bAbI: task 15

Basic Deduction

Task 15: Basic Deduction
Sheep are afraid of wolves.
Cats are afraid of dogs.
Mice are afraid of cats.
Gertrude is a sheep.
What is Gertrude afraid of? A:wolves

$$
\begin{gathered}
P^1 \text{ are afraid of } Q^1 \\
P^2 \text{ are afraid of } Q^2 \\
P^3 \text{ are afraid of } Q^3 \\
P^4 \text{ are afraid of } Q^4 \\
c^1 \text{ is a } P^1 \\
c^2 \text{ is a } P^2 \\
c^3 \text{ is a } P^3 \\
c^4 \text{ is a } P^4 \\
\text{What is } c^j \text{ afraid of? } \text{A: } Q^j
\end{gathered}
$$

bAbI: task 16

Basic Induction

Task 16: Basic Induction

Lily is a swan.
Lily is white.
Bernhard is green.
Greg is a swan.
What color is Greg? A:white

$$
\begin{gathered}
c^1 \text{ is a } P^1 \\
c^1 \text{ is } C^1 \\
c^2 \text{ is a } P^2 \\
c^2 \text{ is } C^2 \\
c^3 \text{ is a } P^3 \\
c^3 \text{ is } C^3 \\
c^4 \text{ is a } P^4 \\
c^4 \text{ is } C^4 \\
c \text{ is a } P^j \\
\text{What color is } c\text{? A: } C^j
\end{gathered}
$$

Entailment-QA

1. **Boolean Connectives**
2. **First-Order Quantifiers**
3. **Synonymy**
4. **Antinomy**
5. **Hypernymy**
6. **Active/Passive voice**

Entailment-QA: task 1

- Entailment (s_1 implies s_2)
  - $\underbrace{P^1 a^1 \wedge \cdots \wedge P^n a^n}_{s_1}, \underbrace{P^j a^j}_{s_2}$
  - $\underbrace{P^j a^j}_{s_1}, \underbrace{P^1 a^1 \vee \cdots \vee P^n a^n}_{s_2}$
  - $\underbrace{Pa}_{s_1}, \underbrace{\neg\neg Pa}_{s_2}$
- Not entailment (s_1 does not imply s_2)
  - $\underbrace{P^j a^j}_{s_1}, \underbrace{P^1 a^1 \wedge \cdots \wedge P^n a^n}_{s_2}$
  - $\underbrace{P^1 a^1 \vee \cdots \vee P^n a^n}_{s_1}, \underbrace{P^j a^j}_{s_2}$
  - $\underbrace{Pa}_{s_1}, \underbrace{\neg Pa}_{s_2}$

Entailment-QA: task 1

Ashley is fit

Ashley is not fit

The first sentence implies the second sentence? A: no

Avery is nice and Avery is obedient

Avery is nice

The first sentence implies the second sentence? A: yes

Elbert is handsome or Elbert is long

Elbert is handsome

The first sentence implies the second sentence? A: no

Entailment-QA: task 2

- Entailment
    - $\forall x Px, Pa$
    - $Pa, \exists x Px$
- Contradiction
    - $\forall x Px, \neg Pa$
    - $\forall x Px, \exists x \neg Px$
- Neutral
    - Pa, Qa
    - $\forall x Px, \neg Qa$

Entailment-QA: task 2

Every person is lively

Belden is lively

What is the semantic relation? A: entailment

Every person is short

There is one person that is not short

What is the semantic relation? A: contradiction

Every person is beautiful

Abilene is not blue

What is the semantic relation? A: neutral

Entailment-QA: task proxy

SICK (Sentences Involving Compositional Knowledge) [6]

Relatedness score	Example
1.6	A: "*A man is jumping into an empty pool*" B: "*There is no biker jumping in the air*"
2.9	A: "*Two children are lying in the snow and are making snow angels*" B: "*Two angels are making snow on the lying children*"
3.6	A: "*The young boys are playing outdoors and the man is smiling nearby*" B: "*There is no boy playing outdoors and there is no man smiling*"
4.9	A: "*A person in a black jacket is doing tricks on a motorbike*" B: "*A man in a black jacket is doing tricks on a motorbike*"

Table 1: Examples of sentence pairs with their gold relatedness scores (on a 5-point rating scale).

Entailment label	Example
ENTAILMENT	A: "*Two teams are competing in a football match*" B: "*Two groups of people are playing football*"
CONTRADICTION	A: "*The brown horse is near a red barrel at the rodeo*" B: "*The brown horse is far from a red barrel at the rodeo*"
NEUTRAL	A: "*A man in a black jacket is doing tricks on a motorbike*" B: "*A person is riding the bicycle on one wheel*"

Table 2: Examples of sentence pairs with their gold entailment labels.

Entailment-QA: task proxy

There is no dog leaping in the air

A dog is leaping high in the air and another is watching

What is the semantic relation? A: contradiction

A man is exercising

A baby is laughing

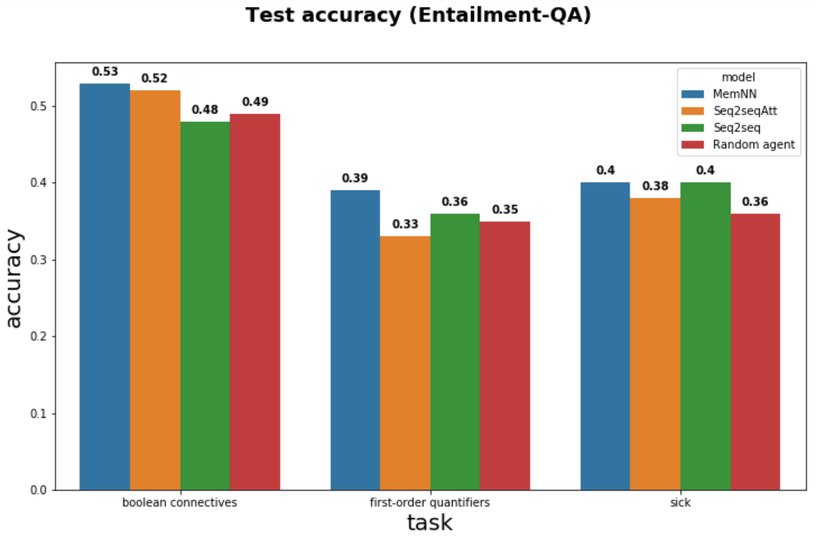
What is the semantic relation? A: neutral

Some dogs are playing in a river

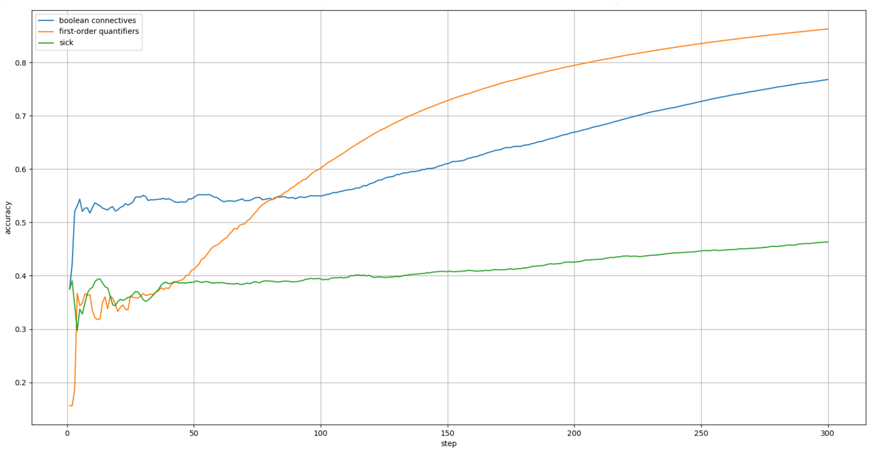
Some dogs are playing in a stream

What is the semantic relation? A: entailment

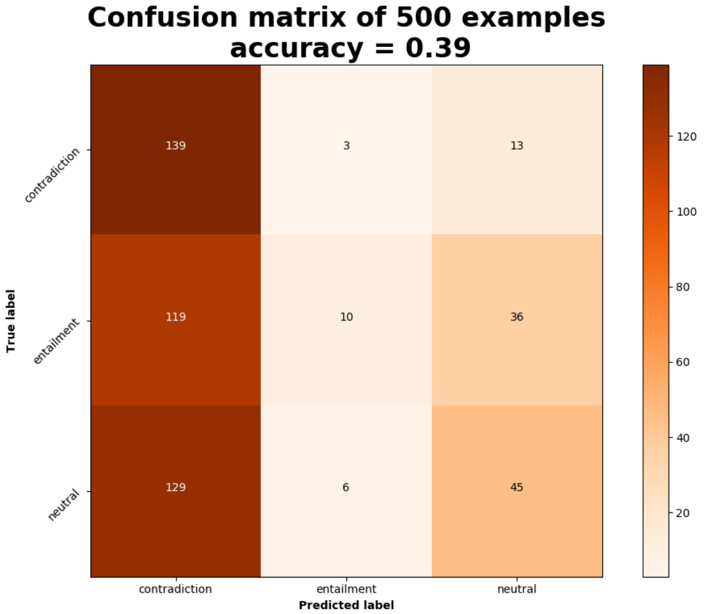
Preliminary Results



Preliminary Results



Preliminary Results



Future Steps

- Try to overcome the reported overfitting problem.
- Finish the Entailment-QA corpus.
- Explore new models not mentioned here, like Dynamic Memory Networks [3] and Memory Attention and Composition (MAC) cell [2].
- Create a visual version of the Entailment-QA to test logical inference with images.
- Check the reinforcement learning on dialog.
- Review the literature on the theory of comparing models [1].

Schedule

Activity	2016		2017		2018		2019		2020
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st
Courses									
Teaching Assist. (PAE)									
Bibliographic Review									
Software Implementation									
Qualification Writing									
Qualification Exam									
Finishing Entailment-QA task									
Visual Entailment-QA task									
Improve Training									
Adding new models									
Reinforcement Learning Methods									
Model Comparison Theory									
Thesis Writing									
Thesis Defense									

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