Improving task for dialog system: a proposal

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Abstract

Using the available dataset SICK (Sentence Involving Compositional Knowledge), we introduce a set of new question answering tasks **Entailment-QA** to measure how well a dialog system deals with abstract semantic knowledge. These tasks force the dialog agent to struggle with distinct notions that are at the intersection of text understanding and reasoning: boolean connectives, first-order quantifiers, synonymy/antinomy/hypernymy resolution, and paraphrase. Experimental results indicate that the current dialog systems present difficulties in solving these tasks.

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Chapter 1

Introduction

One of the main goals in NLP is to build agents capable of *understanding language and reasoning*, i.e., agents capable of carrying a conversation as if they were human. This goal is as old as the field of *artificial intelligence* itself [21], and it is a very ambitious one. We shall call this kind of agents "dialog systems".

But if we think more carefully about this subject, we will recognize that there is not a single type of conversation. A dialog between strangers in an elevator, a conversation between one psychologist and his patient, a salesman offering a service to a possible client, a scientific exchange in a conference; all these events can be classified as "dialog" but they present very different *dynamics* and *goals*. As a way of refining the analysis, the NLP literature on dialog made the distinction between *goal-driven dialog systems* and *non-goal-driven dialog systems*; the former includes *chatbots*, normally used in the industry for technical support services or information acquisition; the latter is a term used to refer to any conversational agent with no explicit purpose.

Each paradigm presents its advantages and disadvantages: on the one hand goal-driven dialog systems are useful systems but they demand a precise understanding (of the goal at hand) and there are not so much available data to train such systems. On the other hand, non-goal-driven dialog systems produce, at best, chit-chat conversation. Although we have have a lot of available data to train such models (movie legends, social media conversations, etc.), it is not so easy to justify its relevancy.

Moreover, there is a central difference between these two paradigms: *the evaluation metric*. More precisely, *there is no good quantitative metric to compare non-goal-driven agents*, and as a consequence *there is also no stan-*

dardized benchmark. Given this limitations one alternative approach was proposed by [24]: developed a series of synthetic tasks in the form of question answering (QA) to test different capabilities of the competing models. Each task tries to assert one prerequisite to *full language understanding*.

Following this research decision, here we propose to expand the work done in [1, 24] by *adding new testbeds for complex semantic relationships*: **Entailment-QA**. The motivation behind this expansion is to guarantee that an end-to-end machine learning model can perform *complex linguistic inferences*. So far we have been focusing on two kinds of inferences: the ones defined by *logical operators* and others defined by *word knowledge*.

1.1 Motivation

Logic is not important by itself. But it can help us build agents capable of distinguishing between sentences that have a real informational content from sentences that do not. An intelligent agent should distinguish between *meaningful* and *nonsensical* speech. To do that the agent can make use of background knowledge, but it can also point out *gaps in the speech's rationality*. Although this importance, logical reasoning is one area that is often neglected by Conversational AI researchers. This Ph.D. proposal tries to address this deficiency.

We often see a discussion inside the artificial intelligence community between deep learning specialist and the classical IA researcher. This discussion can have a non-productive outcome: we heard that the former's engineering methodology is a kind of unscientific alchemy and that the results from the later has been made irrelevant by big data and deep models. Here we are trying to find a productive middle ground: combining the rich tradition of certain themes of classical AI (like logic reasoning) with the models and techniques of the deep learning community.

1.2 Objectives

The goal of this proposal is twofold: propose a new set of synthetic tasks in the same lines as [24] in order to help evaluating and building dialog systems that present reasonable text reasoning capabilities; and proposing new models for these tasks. Hence, we have defined the following specific objectives:

- Create a set of tasks that explicitly make use of complex logical forms.
- Perform a stress test in the existing models regarding linguistic reasoning.
- 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.

1.3 Organization

Chapter 2 exposes the theory that is the basis for the research. Chapter 3 presents the models for dialog and our proposed task to evaluate logical reasoning. Chapter 4 describe the proposed methodology. And chapter 5 discuss the possible results of this research.

Chapter 2

Background

2.0.1 Neural network

A neural network is a non-linear function $f(\boldsymbol{x};\theta)$. It is defined by a collection of parameters $\boldsymbol{\theta}$ and a collection of non-linear transformations. It is usual to represent f as a compositions of functions:

$$\begin{aligned} f(\boldsymbol{x};\theta) &= f^{(2)}(f^{(1)}(\boldsymbol{x};\boldsymbol{W}_1,\boldsymbol{b}_1);\boldsymbol{W}_2,\boldsymbol{b}_2) \quad (2.1) \\ &= softmax(\boldsymbol{W}_2(\sigma(\boldsymbol{W}_1\boldsymbol{x}+\boldsymbol{b}_1))+\boldsymbol{b}_2) \quad (2.2) \end{aligned}$$

The output of these intermediary functions are referred as *layers*. So in the example above, $\boldsymbol{x}$ (the output of the identity function) is the *input layer*, $f^{(1)}(\boldsymbol{x};\boldsymbol{W}_1,\boldsymbol{b}_1)$ is the *hidden layer* and $f^{(2)}(f^{(1)}(\boldsymbol{x};\boldsymbol{W}_1,\boldsymbol{b}_1);\boldsymbol{W}_2,\boldsymbol{b}_2)$ is the *output layer*. Since each layer is a vector, we normally speak about the *dimension* of a layer. For historical reasons we also say that each entry on a layer is a *node* or a *neuron*. Models with a large number of hidden layers are called *deep models*, for this reason the name *deep learning* is used.

A neural network is a function approximator: it can approximate any Borel measurable function from one finite dimensional space to another with any desired nonzero amount of error. This theoretical result is know as the *universal approximation theorem*[3]. Without entering in the theoretical concepts, it suffice to note that the family of Borel mensurable functions include all continuous functions on a closed and bounded subset of $\mathbb{R}^n$.

Different deep learning architectures are used in NLP: **convolutional architectures** have a good performance in tasks were it is required to find a linguistic indicator regardless of its position (e.g., document classification, short-text categorization, sentiment classification, etc); high quality word embeddings can be achieved with models that are a kind of **feedforward neural network** [12]. But for a variety of works in natural language we want to capture regularities and similarities in a text structure. That is way **recurrent** and **recursive** models have been widely used in the field. Here we are focused on generative models and since recurrent models have been producing very strong results for language modeling [4], we will concentrate on them.

2.1 RNN

Recurrent Neural Network is a family of neural network specialized in sequential data $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_\tau$. As a neural network, a RNN is a parametrized function that we use to approximate one hidden function from the data. As before we can take the simplest RNN as a neural network with only one hidden layer. But now, what make RNNs unique is a recurrent definition of one of its hidden layer:

$$\boldsymbol{h}^{(t)} = g(\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}; \boldsymbol{\theta}) \tag{2.3}$$

$\boldsymbol{h}^{(t)}$ is called *state*, *hidden state*, or **cell**.

Is costumerely to represent a RNN as a ciclic graph 2.1

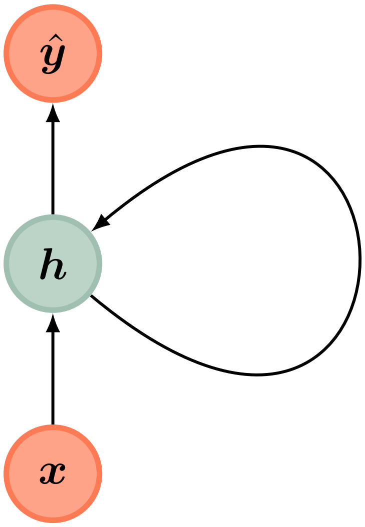


Figure 2.1: Ciclic representation

This recurrent equation can be unfolded for a finite number of steps τ. For example, when $\tau = 3$:

$$\begin{aligned}
\boldsymbol{h}^{(3)} &= g(\boldsymbol{h}^{(2)}, \boldsymbol{x}^{(3)}; \boldsymbol{\theta}) && (2.4)\\
&= g(g(\boldsymbol{h}^{(1)}, \boldsymbol{x}^{(2)}; \boldsymbol{\theta}), \boldsymbol{x}^{(3)}; \boldsymbol{\theta}) && (2.5)\\
&= g(g(g(\boldsymbol{h}^{(0)}, \boldsymbol{x}^{(1)}; \boldsymbol{\theta}), \boldsymbol{x}^{(2)}; \boldsymbol{\theta}), \boldsymbol{x}^{(3)}; \boldsymbol{\theta}) && (2.6)\\
& && (2.7)
\end{aligned}$$

Hence for any finite step τ we can describe the model as a DAG 2.1.

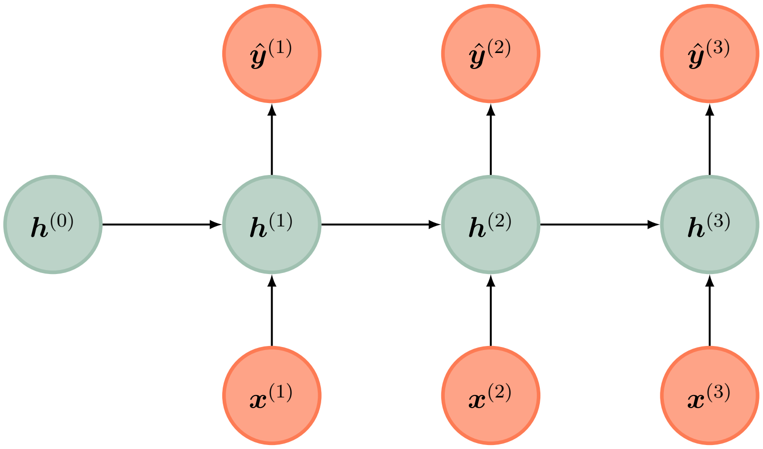


Figure 2.2: Unfolded computational graph

Using a concrete example consider the following model define by the equations:

$$f(\boldsymbol{x}^{(t)}, \boldsymbol{h}^{(t-1)}; \boldsymbol{V}, \boldsymbol{W}, \boldsymbol{U}, \boldsymbol{c}, \boldsymbol{b}) = \hat{\boldsymbol{y}}^{(t)} \tag{2.8}$$

$$\hat{\boldsymbol{y}}^{(t)} = softmax(\boldsymbol{V}\boldsymbol{h}^{(t)} + \boldsymbol{c}) \tag{2.9}$$

$$\boldsymbol{h}^{(t)} = g(\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}; \boldsymbol{W}, \boldsymbol{U}, \boldsymbol{b}) \tag{2.10}$$

$$\boldsymbol{h}^{(t)} = \sigma(\boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} + \boldsymbol{b}) \tag{2.11}$$

Using the graphical representation the model can be view as:

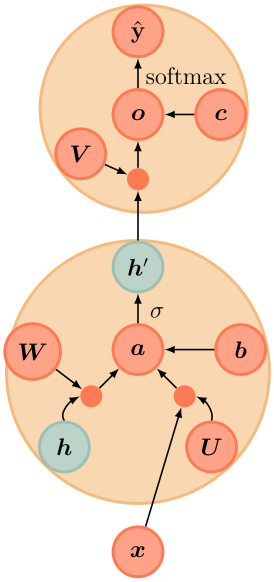


Figure 2.3: Graph of a RNN

!!! explicar como funciona o treinamento !!!
An RNN with a loss function:

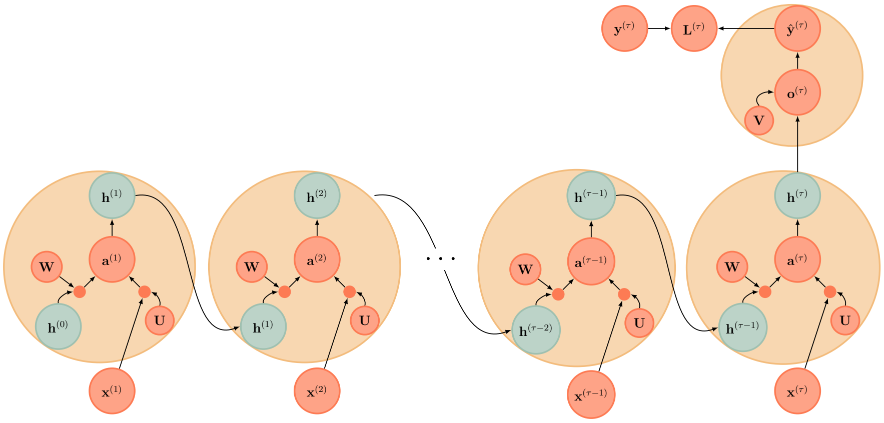


Figure 2.4: The computational graph to compute the training loss of a RNN

2.2 GRU

To capture long-term dependencies on a RNN the authors of the paper [2] proposed a new architecture called **gated recurrent unit** (**GRU**). This model was constructed to make each hidden state $\boldsymbol{h}^{(t)}$ to adaptively capture dependencies of different time steps. It work as follows, at each step t one candidate for hidden state is formed:

$$\widetilde{\boldsymbol{h}}^{(t)} = tahn(\boldsymbol{W}(\boldsymbol{h}^{(t-1)} \odot \boldsymbol{r}^{(t)}) + \boldsymbol{U}\boldsymbol{x}^{(t)} + \boldsymbol{b}) \tag{2.12}$$

where $\boldsymbol{r}^{(t)}$ is a vector with values in $[0,1]$ called a **reset gate**, i.e., a vector that at each entry outputs the probability of reseting the corresponding entry in the previous hidden state $\boldsymbol{h}^{(t-1)}$. Together with $\boldsymbol{r}^{(t)}$ we define an **update gate**, $\boldsymbol{u}^{(t)}$. It is also a vector with values in $[0,1]$. Intuitively we can say that this vector decides how much on each dimension we will use the candidate update. Both $\boldsymbol{r}^{(t)}$ and $\boldsymbol{u}^{(t)}$ are defined by $\boldsymbol{h}^{(t-1)}$ and $\boldsymbol{x}^{(t)}$; they also have specific parameters:

$$\boldsymbol{r}^{(t)} = \sigma(\boldsymbol{W}_r\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r\boldsymbol{x}^{(t)} + \boldsymbol{b}_r) \tag{2.13}$$

$$\boldsymbol{u}^{(t)} = \sigma(\boldsymbol{W}_u\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u\boldsymbol{x}^{(t)} + \boldsymbol{b}_u) \tag{2.14}$$

At the end the new hidden state $\boldsymbol{h}^{(t)}$ is defined by the recurrence:

$$\boldsymbol{h}^{(t)} = \boldsymbol{u}^{(t)} \odot \widetilde{\boldsymbol{h}}^{(t)} + (1 - \boldsymbol{u}^{(t)}) \odot \boldsymbol{h}^{(t-1)} \tag{2.15}$$

Note that the new hidden state combines the candidate hidden state $\widetilde{\boldsymbol{h}}^{(t)}$ with the past hidden state $\boldsymbol{h}^{(t-1)}$ using both $\boldsymbol{r}^{(t)}$ and $\boldsymbol{u}^{(t)}$ to adaptively copy and forget information.

It can appear more complex, but we can view the GRU model just as a refinement of the standard RNN with a new computation for the hidden state. Let $\boldsymbol{\theta} = [\boldsymbol{W}, \boldsymbol{U}, \boldsymbol{b}]$, $\boldsymbol{\theta}_u = [\boldsymbol{W}_u, \boldsymbol{U}_u, \boldsymbol{b}_u]$ and $\boldsymbol{\theta}_r = [\boldsymbol{W}_r, \boldsymbol{U}_r, \boldsymbol{b}_r]$; and $\text{aff}(\boldsymbol{\theta})$ be the following operation:

$$\text{aff}(\boldsymbol{\theta}) = \boldsymbol{W}\boldsymbol{h} + \boldsymbol{U}\boldsymbol{x} + \boldsymbol{b} \tag{2.16}$$

With similar definitions for $\text{aff}(\boldsymbol{\theta}_u)$ and $\text{aff}(\boldsymbol{\theta}_r)$. Figure 2.3 shows the hidden state of the GRU model for time step t. If compared with Figure 2.1 we can see that the basic structure is the same, just the way of computing the hidden state $\boldsymbol{h}^{(t)}$ has changed.

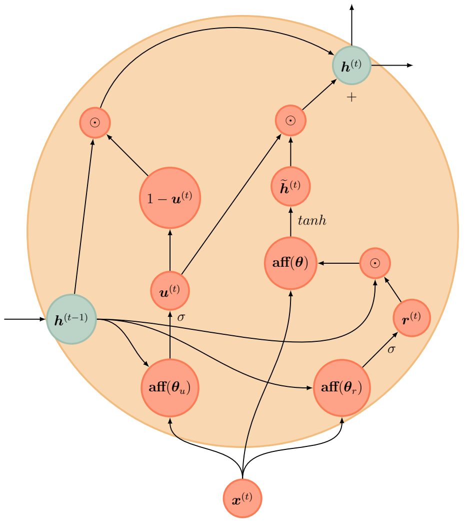


Figure 2.5: GRU hidden cell

2.3 LSTM

Long short-term memory (LSTM) is one of the most applied versions of the RNN family of models. Historically it was developed before the GRU model, but conceptually we can think in the RNN as an expansion of the model presented in the last session. Because of notation differences they can look different. LSTM is based also with parametrized gates; in this case three: the **forget gate**, $\boldsymbol{f}^{(t)}$, the **input gate**, $\boldsymbol{i}^{(t)}$, and the **output gate**, $\boldsymbol{o}^{(t)}$. There gates are defined only by $\boldsymbol{h}^{(t-1)}$ and $\boldsymbol{x}^{(t)}$ with specific parameters:

$$\boldsymbol{f}^{(t)} = \sigma(\boldsymbol{W}_f\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_f\boldsymbol{x}^{(t)} + \boldsymbol{b}_f) \tag{2.17}$$

$$\boldsymbol{i}^{(t)} = \sigma(\boldsymbol{W}_i\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_i\boldsymbol{x}^{(t)} + \boldsymbol{b}_i) \tag{2.18}$$

$$\boldsymbol{o}^{(t)} = \sigma(\boldsymbol{W}_o\boldsymbol{h}^{(t-1)} + \boldsymbol{U}_o\boldsymbol{x}^{(t)} + \boldsymbol{b}_o) \tag{2.19}$$

Intuitively $\boldsymbol{f}^{(t)}$ should control how much informative be discarded, $\boldsymbol{i}^{(t)}$ controls how much information will be updated, and $\boldsymbol{o}^{(t)}$ controls how munch each component should be outputted. A candidate cell, $\tilde{\boldsymbol{c}}^{(t)}$ is formed:

$$\tilde{\boldsymbol{c}}^{(t)} = tahn(\boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} + \boldsymbol{b}) \tag{2.20}$$

and a new cell $\tilde{\boldsymbol{c}}^{(t)}$ is formed by forgetting some information of the previous cell $\tilde{\boldsymbol{c}}^{(t-1)}$ and by adding new values from $\tilde{\boldsymbol{c}}^{(t)}$ (scaled by the input gate)

$$\boldsymbol{c}^{(t)} = \boldsymbol{f}^{(t)} \otimes \boldsymbol{c}^{(t-1)} + \boldsymbol{i}^{(t)} \otimes \tilde{\boldsymbol{c}}^{(t)} \tag{2.21}$$

The new hidden state, $\boldsymbol{h}^{(t)}$, is formed by filtering $\boldsymbol{c}^{(t)}$:

$$\boldsymbol{h}^{(t)} = \boldsymbol{o}^{(t)} \otimes tanh(\boldsymbol{c}^{(t)}) \tag{2.22}$$

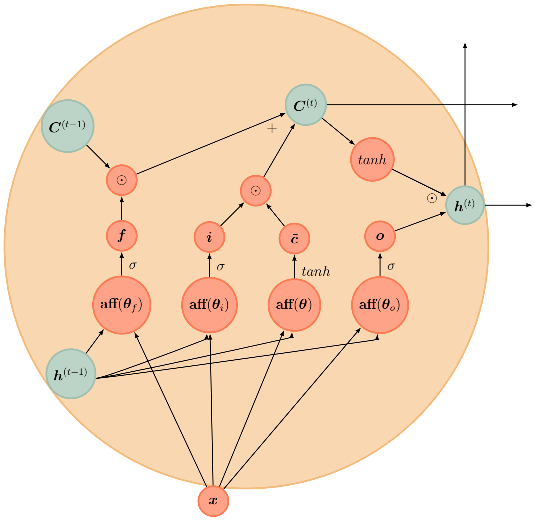


Figure 2.6: LSTM hidden cell

2.4 Language model

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

$$P(x_1, x_2, x_3, x_4) = p$$

This model is used for different nlp tasks such as speech recognition, machine translation, text auto-completion, spell correction, question answering, summarization and many others.

The classical approuch to a languange model was to use the chain rule and a markovian assumptiom, i.e., for a specific n we assume that:

$$P(x_1, \ldots, x_T) = \prod_{t=1}^{T} P(x_t|x_1, \ldots, x_{t-1}) = \prod_{t=1}^{T} P(x_t|x_{t-(n+1)}, \ldots, x_{t-1}) \quad (2.23)$$

This gave raise to models based on n-gram statistics. The choice of n yields different models; for example *Unigram* language model ($n = 1$):

$$P_{uni}(x_1, x_2, x_3, x_4) = P(x_1)P(x_2)P(x_3)P(x_4) \quad (2.24)$$

where $P(x_i) = count(x_i)$.

Bigram language model ($n = 2$):

$$P_{bi}(x_1, x_2, x_3, x_4) = P(x_1)P(x_2|x_1)P(x_3|x_2)P(x_4|x_3) \quad (2.25)$$

where

$$P(x_i|x_j) = \frac{count(x_i, x_j)}{count(x_j)}$$

Higher n-grams yields better performance. But at the same time higher n-grams requires a lot of memory[5].

Since [13] the approach has change, instead of using one approach that is specific for the language domain, we can use a general model for sequential data prediction: a RNN.

So, our learning task is to estimate the probability distribution

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

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

We start with a corpus C with T tokens and a vocabulary $\mathbb{V}$.

Example: **Make Some Noise** by the Beastie Boys.

Yes, here we go again, give you more, nothing lesser
Back on the mic is the anti-depressor
Ad-Rock, the pressure, yes, we need this
The best is yet to come, and yes, believe this
...

- $T = 378$
- $|\mathbb{V}| = 186$

The dataset is a collection of pairs $(\boldsymbol{x}, \boldsymbol{y})$ where $\boldsymbol{x}$ is one word and $\boldsymbol{y}$ is the immediately next word. For example:

$(\boldsymbol{x}^{(1)}, \boldsymbol{y}^{(1)}) =$ (Yes, here).

$(\boldsymbol{x}^{(2)}, \boldsymbol{y}^{(2)}) =$ (here, we)

$(\boldsymbol{x}^{(3)}, \boldsymbol{y}^{(3)}) =$ (we, go)

$(\boldsymbol{x}^{(4)}, \boldsymbol{y}^{(4)}) =$ (go, again)

$(\boldsymbol{x}^{(5)}, \boldsymbol{y}^{(5)}) =$ (again, give)

$(\boldsymbol{x}^{(6)}, \boldsymbol{y}^{(6)}) =$ (give, you)

$(\boldsymbol{x}^{(7)}, \boldsymbol{y}^{(7)}) =$ (you, more)

$\ldots$

Notation

- $\boldsymbol{E} \in \mathbb{R}^{d,|\mathbb{V}|}$ is the matrix of word embeddings.
- $\boldsymbol{x}^{(t)} \in \mathbb{R}^{|\mathbb{V}|}$ is one-hot word vector at time step t.
- $\boldsymbol{y}^{(t)} \in \mathbb{R}^{|\mathbb{V}|}$ is the ground truth at time step t (also an one-hot word vector).

The language model is similar as the RNN described above. It is defined by the following equations:

$$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)} \tag{2.26}$$

$$\boldsymbol{h}^{(t)} = \sigma(\boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{e}^{(t)} + \boldsymbol{b}) \tag{2.27}$$

$$\hat{\boldsymbol{y}}^{(t)} = softmax(\boldsymbol{V}\boldsymbol{h}^{(t)} + \boldsymbol{c}) \tag{2.28}$$

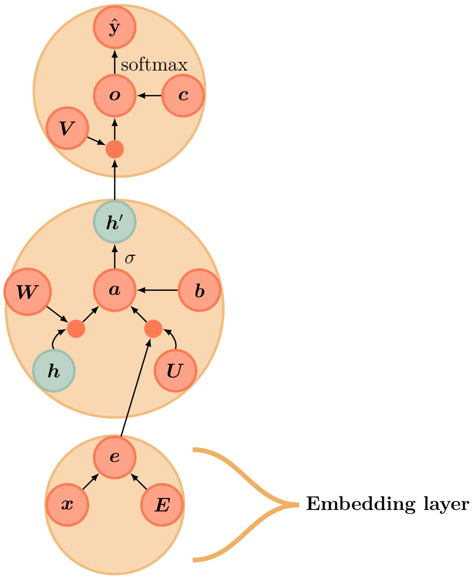


Figure 2.7: Simple language model

At each time t the point-wise loss is:

$$\begin{aligned} L^{(t)} &= CE(\boldsymbol{y}^{(t)}, \hat{\boldsymbol{y}}^{(t)}) && (2.29)\\ &= -\log(\hat{\boldsymbol{y}}_{j^*}) && (2.30)\\ &= -\log P(x^{(t+1)} = \text{word}_{j^*} | x^{(1)}, \ldots, x^{(t)}) && (2.31) \end{aligned}$$

The loss L is the mean of all the point-wise losses

$$L = \frac{1}{T}\sum_{t=1}^{T} L^{(t)} \tag{2.32}$$

Evaluating a language model. We can evaluate a language model using a *extrinsic evaluation*: How our model perform in a NLP task such as text auto-completion. Or a *intrinsic evaluation*: Perplexity (PP) can be thought as the weighted average branching factor of a language.

Given $C = x_1, x_2, \ldots, x_T$, we define the perplexity of C as:

$$\begin{aligned} PP(C) &= P(x_1, x_2, \ldots, x_T)^{-\frac{1}{T}} && (2.33) \\ & && (2.34) \\ &= \sqrt[T]{\frac{1}{P(x_1, x_2, \ldots, x_T)}} && (2.35) \\ & && (2.36) \\ &= \sqrt[T]{\prod_{i=1}^{T} \frac{1}{P(x_i|x_1, \ldots, x_{i-1})}} && (2.37) \end{aligned}$$

we can relate Loss and Perplexity:

Since

$$\begin{aligned} L^{(t)} &= -\log P(x^{(t+1)}|x^{(1)}, \ldots, x^{(t)}) && (2.38) \\ &= \log(\frac{1}{P(x^{(t+1)}|x^{(1)}, \ldots, x^{(t)})}) && (2.39) \\ & && (2.40) \end{aligned}$$

We have that:

$$\begin{aligned} L &= \frac{1}{T}\sum_{t=1}^{T} L^{(t)} && (2.41) \\ &= \log\left(\sqrt[T]{\prod_{i=1}^{T} \frac{1}{P(x_i|x_1, \ldots, x_{i-1})}}\right) && (2.42) \\ &= \log(PP(C)) && (2.43) \end{aligned}$$

So another definition of perplexity is

$$2^L = PP(C) \tag{2.44}$$

2.5 Seq2seq

fsdfdsfdsf

2.6 Atention

fksdhfjsdgjf

2.7 Memory Networks

fksdhfjsdgjf

Chapter 3

Dialog Systems

Techniques to generate dialog fall under the broader field of text generation. There a variety of different tasks of text generation like automatic journalism and automatic summarization. In this chapter, we will review the basic techniques to produce text (in the dialog context) and to evaluate the generated text

3.1 Using neural networks to generate dialog

Sequence to sequence (seq2seq) models are originally formulated to improve the automatic translation task [20]. The authors of [22] proposed to use this model to simplify the dialog generation problem as a simple *context-to-response mapping*. Since then the field of dialog generation was revolutionized.

As we have seen, a seq2seq model encodes the source sentence in a vector $\boldsymbol{h}$ and uses this vector to initiate a language model. This can be used to model a dialog as follows: suposse we have recorded two agents A and B. We will use this dialog as the training data for our model. The model will try to predict how B would respond. Let $\boldsymbol{s} = s_1, s_2, \ldots, s_n$ be an utterance from A and $\boldsymbol{x} = x_1, x_2, \ldots, x_m$ be the response from B (both $\boldsymbol{s}$ and $\boldsymbol{x}$ are a sequence of words). $\boldsymbol{s}$ is input to an encoder network, which is a RNN. The encodes summarizes the input utterance into a vector, say $\boldsymbol{h}$, and this vector is used to initiate the decoder model, which is another RNN. And the decoder takes as input $\boldsymbol{x}$ and at each time t the model tries to predict the word $t+1$ using $x_1, x_2, ..., x_{t-1}, \boldsymbol{h}$. This became a multiclass classification task, and we train the model by minimizing the cross entropy loss.

After we training we can use the same model to generate a new dialog: the agent A gives an utterance and we use the encoder model to summarize this uterance in a vector h as before, but now we use the probability distribution learned by the decoder model (initialized by $\boldsymbol{h}$) to sample words until it generates an end-of-speech <eos> token (or until a upper bound for the uterance size is reached). This approach lead to interesting results, for example in [22] after they have trained the model on the OpenSubtitles dataset (a dataset compose of subtitles from different movies) they sample some results of the human-model interaction:

- **Human**: What is moral ?
- **Machine**: What empowered humanity , what intellectual the essence is.
- **Human**: What is immoral ?
- **Machine**: The fact that you have a child .
- **Human**: What is morality ?
- **Machine**: What is altruism ?
- **Human**: What is the definition of altruism ?
- **Machine**: If you don ’t believe in god , then you don ’t know .
- **Human**: Ok ... so what is the definition of morality ?
- **Machine**: Well , the truth is , you’re not a believer in god almighty .
- **Human**: Tell me the definition of morality , I am quite upset now !
- **Machine**: I ’m not ashamed of being a philosopher!

The model is clearly learning some interesting responses, but it is clear to see that some answers are generic (for example, answer the question ‘What is morality ?’ with another question ‘What is altruism ?’). We can also see that the model lacks coherence on the responses.

Nevertheless the seq2seq model presents a good basis for more complex models. For example, take the hierarchical recurrent encoder-decoder architecture (HRED) proposed by Sordoni et al. [17]. In this setting a dialogue is viewed as a sequence of utterances $D = \langle U_1, \ldots, U_M \rangle$ involving two interlocutors such that each U_i contains a sequence of N_i tokens, $U_i = \langle w_{i,1}, \ldots, w_{i,N_i} \rangle$. Each $w_{i,j}$ is a random variable that taking values in the $V \cup A$ where V is the vocabulary and A is the set of *speech acts* (for example 'pause' and 'end of turn' are speech acts). In this case the learning task is the same as the one in language modeling: we want to estimate of the probability of one token (speech acts included) conditioned on the previously tokens:

$$P(w_{i,j} | w_{i,1}, \ldots, w_{i,j-1}, U_1, \ldots U_{i-1}) \tag{3.1}$$

The different dialogues $\langle U_1, \ldots, U_M \rangle$ will serve as a corpus. In this paper the authors use a **Hierarchical Recurrent Encoder-Decoder model(HRED)**, i.e., a model based on three RNNs: an *encoder* RNN, a *context* RNN and a *decoder* RNN. To understand the workings of this model, suppose we have the following dialog:

- (U_1) Mom, I don't feel so good.

- (U_2) What's wrong?

- (U_3) I feel like I'm going to pass out.

First the encoder RNN will encode the sentence U_1 in a vector $\boldsymbol{U}_1$, then the context RNN will compute a hidden state, say $\boldsymbol{C_1}$ using $\boldsymbol{U}_1$ and all past sentences in the dialog. After that the decoder RNN will use U_2 as an input to predict the next word using $\boldsymbol{C_1}$. The same procedure is repeated for U_2. Figure x shows the computational graph of this process.

Note that in this model the prediction is conditioned on the hidden state of the context RNN.

3.2 How to evaluate dialogs?

In the seminal paper by Alan Turing [21] it is proposed a game to evaluate a dialog system. The idea behind the game was simple: three players A, B and

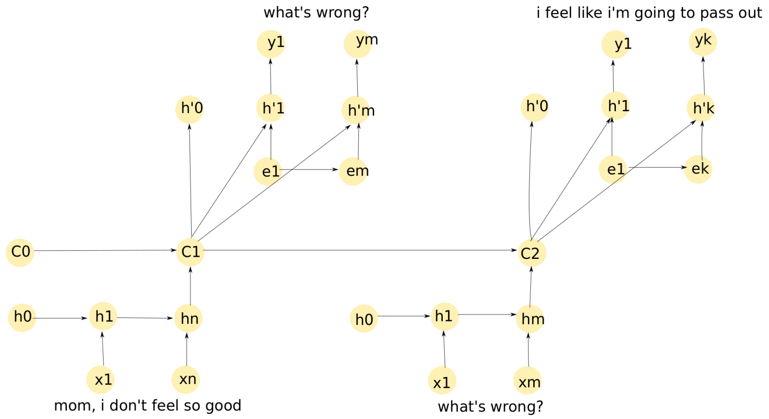


Figure 3.1: HRED model

C can interact only by nonpersonal communication. C knows that he will interact with a dialog system (A) and a person (B), but he does not know which is which. C should exchange some conversation both with A and B; after some time he should guess who is the dialog system and who is the human. The goal of A is to be as human as possible in order to fool C; and the goal of B is to help C come to the right answer.

This is the famous *Turing Test*. If the dialog system wins this game we say that *it has passed the Turing Test*. For many people this is the holy grail of artificial intelligence. We disagree with that. [Give your oppion about that]

3.2.1 Human evaluation

The most basic form to check if a generated sentence is sound is by using human evaluations. Hence is normal to see researches making use of crowdsourced judges (using services like Amazon Mechanical Turk). These judges can say that a generated sentence is just good or bad, in an informal way. But we can also use a more rigorous score system.

In [19] the authors enumerate three criteria to judge a generated sentence:

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.

3.2.2 Automatic evaluation

Because of the problems presented in using human judges, you can find in the literature the use of automatic metrics from the field of machine translation and automatic summarization.

BLUE

One popular metric for automatic translation is called BLUE (bilingual evaluation understudy) [15]. It compares n-grams of the candidate translation with the n-grams of the reference translation and counts the number of matches. Let s be a source sentence $\hat{y}$ the hypothesis translation and y a reference translations produced by a professional human translator.

To define the BLUE score for each translation we need to define first the n-gram precision p_n:

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

We also define a brevity penalty (BP) for translations that are too short. Let $len(a)$ be the length of the sentence a, we define BP as:

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

Hence, the BLEU score is define as:

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

There are some details about the definition above: to avoid computing $\log 0$ all precisions are smoothed to ensure that they are positive (one technique of smoothing is to use a small positive value to replace any $p_n = 0$); each n-gram in the candidate $\hat{y}$ is used at most once; and since its expensive to calculate higher n-grams we usually take $N = 4$.

It is useful to see one application of this metric. For example, suppose s is the Portuguese sentence ‘Nas tardes de fazenda há muito azul demais’, y is the reference English translation ‘In the farm’s afternoons there is too much blue' and suppose we also have three models producing three distinct English translations

- $\hat{y}_1$: 'In the afternoons of the farm there is too much blue'
- $\hat{y}_2$: 'In the farm's afternoons there is a lot of blue'
- $\hat{y}_3$: 'The farm's afternoons are blue'

The table below shows all the values to compute the BLUE score for this example.

Sentence	p_1	p_2	p_3	p_4	BP	$BLUE$
$\hat{y}_1$	8/11	5/10	3/9	2/8	1	.42
$\hat{y}_2$	7/10	5/9	4/8	3/7	1	.52
$\hat{y}_3$	3/5	1/4	0	0	.45	.28

Figure 3.2: Example of calculating p_n, BP and $BLUE$ score

METEOR

The METEOR (Metric for Evaluation of Translation with Explicit ORdering) metric was created to address the weakness in BLUE [7]. This metric is based on an alignment between unigrams from the hypothesis translation $\hat{y}$ and unigrams from the reference translation y. This alignment can be based on exact matches, matching between stemmed unigrams, or matching by synonym.

After the alignment is done we compute the unigram precision P and unigram recall R as:

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

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

We them combine these values using the harmonic mean:

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

To take into account longer matches, this metric computes a penalty for the "chunkiness" of the alignment. The idea is to group the unigrams in fewest possible chunks. Here chunk is defined as a set of unigrams that are adjacent in $\hat{y}$ and in y. Hence the penalty is defined as

$$penalty = 0.5\left(\frac{c}{um}\right)^3$$

where c is the number of *chunks* and um is the number of matched unigrams. Hence the METEOR score is defined as

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

ROUGE

ROUGE, first in [26], defined in stands for (Recall Oriented Understudy for Gisting Evaluation) and it is a set of metrics for automatic summarization. Among these metrics, we will consider only the $ROUGE_L$ metric (in the same way as [9]). This one is just an F-measure based on the Longest Common Subsequence (LCS), i.e., the longest non-contiguous set of words that occurs in two sentences in the same order. So, let $lcs(a,b)$ be the lenght of the LCS between the sentences a and b, the $ROUGE_L$ metric is defined as follows:

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

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

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

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

3.2.3 The mismatch between human and automatic evaluation

Complaints about the mismatch between the automatic metrics and the human judgments are not new. In [19] the authors have observed that i) there are positive, but not strong, correlations between the scores of the automatic evaluation metrics and human judgments of adequacy; ii) there are negative correlations between the scores of the automatic metrics and human judgments of fluency. As can be seen on the table below:

Automatic metric	Adequacy	Fluency
BLEU	.039	−0.49

Figure 3.3: Correlation between $BLUE$ score and human judgments of adequacy and fluency [19]

In a more recencent paper [8], the authors trained two neural generative models a LSTM language model and HRED on two difrent datasets: the chit chat oriented Twitter dataset and the technical Ubuntu Dialogue Corpus.

After the models were training the were used to generate some sentences, these sentences were evaluated using both the automatic metrics and human judgment.

The main experiment of the paper was to test for significance of correlation between each automatic metric and human judgments. The tables below show the results from this experiment:

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 3.1: Correlation between automatic metrics and human judgments based on dialog generated on Twitter [8]

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 3.2: Correlation between automatic metrics and human judgments based on dialog generated on Ubuntu [8]

What this paper indicates is that these metrics correlate very weakly with human judgements in the non-technical Twitter domain, and not at all in the technical Ubuntu domain. This should not be seen as a final sentence to the automatic metrics, they are very useful. But in regarding dialog systems, the use of these metrics should be followed by cautiousness.

3.3 Creating simplified tasks

Given all these limitations, one interesting strategy proposed on [24] is to create a set of question answering (QA) synthetic tasks to test different capabilities of a dialog agent. QA tasks are easy to evaluate, so the difficulty lies on creating the right tasks. They should be simple, diverse, self-contained and relevant. At the same time, any adult person with no specialized knowledge should be able to achieve 100 % accuracy on each task.

With that purpose the authors of [24] have created a set of 20 simple tasks, they believe that those tasks are a 'prerequisite to full language understanding and reasoning'. Without entering in the details of each task, it was designed to cover a variety of skills: from counting to positional reasoning. By running a set of experiments with different models they observed that by using a memory network they achieve 95 % accuracy in most of the tasks (the mean performance was 93 %).

Here we will focus only in how logic, and logic relations were formulated in this framework and how it can be expanded.

3.4 The logical entailment problem inside the bAbI task

In [24], among a variety of useful tasks the authors introduce two tasks that deals with logical inference: *basic deduction* and *basic induction.* The basic deduction task offers questions of the form:

$$\begin{array}{c}
P^1 \text{ are afraid of } Q^1 \\
P^2 \text{ are afraid of } Q^2 \\
P^3 \text{ are afraid of } Q^3 \\
P^4 \text{ are afraid of } Q^4 \\
c^1 \text{ is a } P^1 \\
c^2 \text{ is a } P^2 \\
c^3 \text{ is a } P^3
\end{array}$$

c^4 is a P^4
What is c^j afraid of? A: P^j

where P^j and Q^j are animals (e.g., "cats", "mice", "wolfs", etc.) and c^j are names (e.g., "Jessica", "Gertrud", "Emily", etc.). The underlying relation under focus here is the *membership* relation: if Emily is a cat and cats are afraid of wolfs then Emily is afraid of wolfs. This task is solvable by the current models, in [24] the best accuracy for this task is 100%.

The basic induction task is composed by questions of the form:

c^1 is a P^1
c^1 is C^1
c^2 is a P^2
c^2 is C^2
c^3 is a P^3
c^3 is C^3
c^4 is a P^4
c^4 is C^4
c is a P^j
What color is c? A: C^j

Where P^j is a animal, C^j is a color, and c^j is a name. Here the agent is asked to remember the relation between animal and color, and when presented a new name of an animal in the example, the agent should infer the color using past examples. Similar to the deduction task, in [24] is reported that this task is completely solved.

These two tasks present a first step towards *a complete set of tasks to tests inference capabilities*. One aspect that is missing though is the use of logical operators such as *boolean connectives* and *first-order quantifiers*. Those operators play a big role on everyday speech, hence a natural way of expanding this work is by creating a set of tasks that make agents learn *valid logic structures*.

3.5 Entailment-QA

To highlight the speech structure we will make use of an artificial language, but, to be clear, this is just an exposition tool. We are concerned in logical structures *only used in everyday speech*.

Boolean Connectives The first task is focused only on some propositional connectives $\wedge$ (and), $\vee$ (or), $\neg$ (not). The agent is given two sentences s_1 and s_2, and he is asked if s_1 entails s_2 or not (a yes/no question). The position of the sentences is important here. We look at only six general cases:

- Entailment
  - $\underbrace{P^1a^1 \wedge \cdots \wedge P^na^n}_{s_1}, \underbrace{P^ja^j}_{s_2}$
  - $\underbrace{P^ja^j}_{s_1}, \underbrace{P^1a^1 \vee \cdots \vee P^na^n}_{s_2}$
  - $\underbrace{Pa}_{s_1}, \underbrace{\neg\neg Pa}_{s_2}$
- Not entailment
  - $\underbrace{P^ja^j}_{s_1}, \underbrace{P^1a^1 \wedge \cdots \wedge P^na^n}_{s_2}$
  - $\underbrace{P^1a^1 \vee \cdots \vee P^na^n}_{s_1}, \underbrace{P^ja^j}_{s_2}$
  - $\underbrace{Pa}_{s_1}, \underbrace{\neg Pa}_{s_2}$

Where P is a predicate and a is a name. The point here is not to demand that the agent learn complex logical forms, but to recognize which forms are sound and which are not. This should be achieved independently from the content, i.e., the different predicates and names that appear on the sentences. So from the abstract forms above we have only simple examples like:

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

First-Order Quantifiers Task 2 tries to capture the use of some basic *quantifiers*. In this dataset we are trying to predict the entailment relationship between two sentences s_1 and s_2. We say that there is a *entailment* relationship if s_1 implies s_2, we say that there is a *contradiction* if the combination of sentences s_1 and s_2 implies an absurdity and if the combination of sentences does not imply an absurdity we say that they are *neutral*. We have used six forms of logical relations for the quantifiers $\forall$ (for every) and $\exists$ (exists):

- 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
  - $\forall x Px, \neg Qa$

where P and Q are non-related predicates and a is a name. So we have examples like:

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

The tasks above force the dialog system to predict entailment independently of the specific meaning of nouns, verbs and adjectives presented on speech. To balance that we intend to design four more tasks centered on *generic semantic knowledge.*

Synonymy This task tests if a dialog system can identify paraphrase caused by synonym use. Two supporting facts are presented, the second differs from the first by one noun, verb or adjective that can be a synonym or not, e.g., "*The girl is talking into the microphone. The girl is speaking. Are the above sentences duplicate?*".

Antinomy This task consists of recognizing contradictions by antinomy use. For example, the question "*John is not an old person. John is young. Are the above sentences a contradiction?*" should be answered "no" and the question "*Susan is happy. Susan is sad and she is crying. Are the above sentences a contradiction?*" should be answered "yes".

Hypernymy When one term is a specific instance of another we say that there is a hypernymy relationship between then. For example, we say that "anthem" is a hyponym and "song" a hypernym, because anthem is a kind of song. Task 5 tests the kind of linguistic entailment caused by the use of hyponyms and hypernyms, e.g., "*A woman is eating an apple. A woman is eating a fruit. Are the above sentences duplicate?*"

Active/Passive voice Finally the last task is centered on the paraphrases originated by the changes from active to passive voice. So two supporting facts are presented, although they have a different syntactic structure, they share the same meaning. For example, "*A man is playing the piano. The piano is being played by a man. Are the above sentences duplicate?*".

It should be noted that we can formulate the notion of paraphrase as an entailment relation: if s_1 is a paraphrase of s_2, it is natural to say that s_1 implies s_2 and vice-versa. This is done in [11]. Although this approach presents no problem it can alienate some people from the machine learning community: this community normally deals with problems of similarity between sentences, there is very little datasets available centered on the notion of entailment. So although we have mentioned only paraphrase detection in tasks 3–6 the entailment relationship is present.

3.6 Approach

We will only consider *neural network based end-to-end dialog systems*, these are the most important models today [1, 9, 16, 17, 18, 23]. To organize all experiment in an unified framework we decided to use the platform ParlAI [14]. Our criteria for a *semantic robust dialog agent* is not an agent that is only tuned for the Entailment-QA tasks mentioned above, but an agent that performs well across all established tasks (like the bAbI tasks [24]) and performs reasonably on the Entailment-QA tasks 1-6. Here "reasonably" means that the agent should exceed a random agent by a significant margin.

Right now we are in the process of creating the dataset. We have already built tasks 1 (boolean connectives) and 2 (first order quantifiers). They both are composed of 10000 questions for training and 1000 for testing.

We have used the dataset SICK (Sentence Involving Compositional Knowledge) [11] as a proxy for tasks 3-6, since all the structures presented on those tasks are presented in this dataset. The SICK data is composed of a pairs of sentences and a label describing the entailment relation between the sentences. To cast this classification dataset as a question answering problem we have added a question and maintained the labels:

> A group of people are marching
>
> A group of people are walking
>
> What is the semantic relation? A: entailment
>
> 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

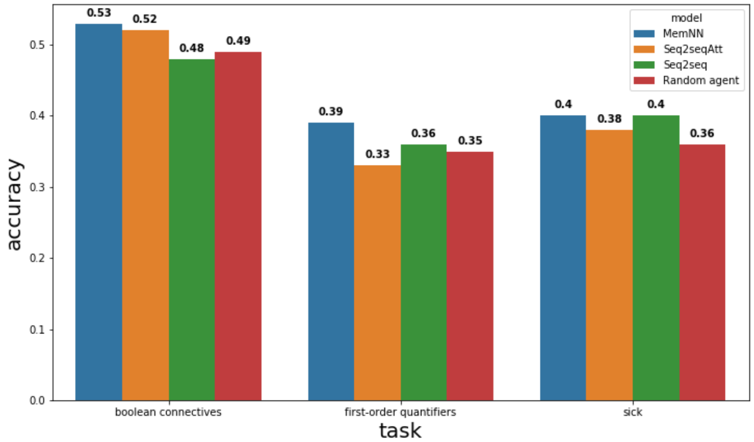
What is the semantic relation? A: entailment

This QA task is composed of 23000 questions for training and 5900 for testing.

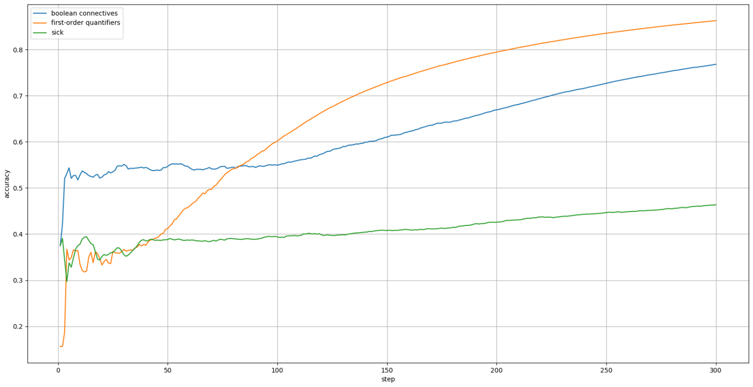
3.7 Preliminary results

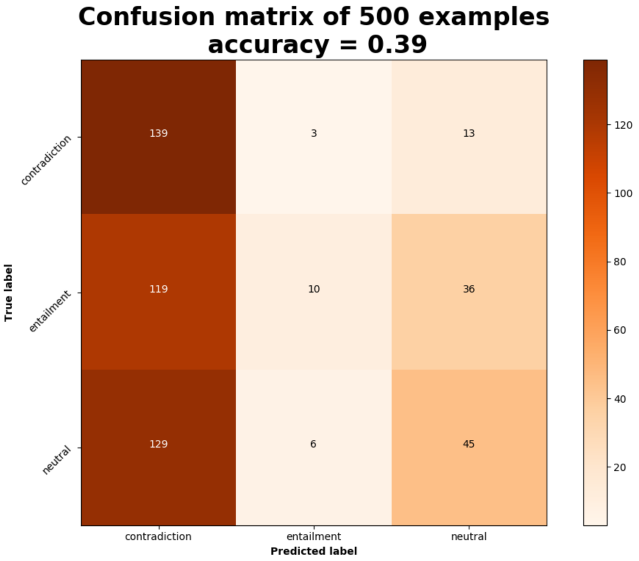
We have performed the first experiments using the sequence to sequence model [20](with and without attention: Seq2seq and Seq2seqAtt, respectively) and the memory network model (MenNN) [25].

So far these models show unsatisfactory results, as can be seen in Figure 1.



Their overall performance is only slightly better when compared to the random agent. For example, when we look at the memory model, the model that often outperform the seq2seq model on QA tasks [24], we can see that regarding tasks 1 and 2 there is an overfitting problem: the model shows high accuracy on the train dataset (75% accuracy on task 1, and 86% accuracy on task 2) as can be seen in Figure 2. But when we take a closer look at the confusion matrix of the test data, Figure 3, the results are not impressive.[1]





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[1] All the experiments and the respective results are available on GitHub: `https://github.com/felipessalvatore/DialogGym`.

3.8 KDD comments

The paper presents a high quality and very interesting research. The concept of incorporating logic reasoning to boost performance of dialogue agent is very promising and employed by the authors in a novel way. The paper is focused on logical reasoning, the area that is often neglected by Conversational AI developers. Splitting the analysis for synonymy, antinomy, hypernymy and active or passive voice is hard to find in recent academic literature. These features make it an outstanding paper.

The Entailment-QA analysis of Neural Network dialog systems on 11000 questions provides interesting results. The fact that the overall accuracy is below 50% in many cases, points out a significant issue in the current phase of conversational AI. My only concern is that the methods of the research fall outside of Artificial Intelligence (AI) / Machine Learning (ML) domain which makes the paper less relevant to the workshop.

The paper is focused on specific issues of Conversation AI, in particular on complex semantic relationships. The paper is not covering machine learning aspects of Conversation AI. Instead the authors discuss a rule-based approach in more details. The paper would be a good fit for a workshop focused on rule-based methods in Conversational AI and for a workshop focused on automatic testing methods for chatbots. Due to the limitations on the number of accepted papers, this high quality paper might not make it to the short list. I would encourage the authors to proceed with their efforts to publish the paper elsewhere or come back next time when the workshop will have enough bandwidth.

Chapter 4

Project Methodology

To address our research proposal we decided to formulate the following steps:

-
-

4.1 Work Plan

Chapter 5

Conclusion

The results so far may seen grim, but they show also a positive side: *the Entailment-QA tasks are not a set of trivial tasks that can be completely solved by the current models.* These results indicated that it is worthwhile to explore this set of task with more detail, either by improving the training using the current models or by exploring new kinds of models. One thing should be clear, we are not concern in obtaining high accuracy on these tasks only (just as a comparison, in [6] is reported an accuracy of 87% on the SICK dataset by using feature engineering techniques). The main idea is to use an end-to-end QA model to obtain good results in the Entailment-QA task without compromising the accuracy on other well established QA tasks.

Future work will explore two branches: on the one hand, we need to finish the Entailment-QA corpus to have a fine grain analysis of the result that we are seeing on the SICK corpus; on the other hand, we need to explore the different extensions for all mentioned models [10, 17] before inferring any kind of limitation of the current set of QA models.

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