Dialog state tracking, a machine reading approach using a memory-enhanced neural network

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June 30, 2016

Abstract
In an end-to-end dialog system, the aim of dialog state tracking is to accurately estimate a compact representation of the current dialog status from a sequence of noisy observations produced by the speech recognition and the natural language understanding modules. A state tracking module is primarily meant to act as support for a dialog policy but it can also be used as support for dialog corpus summarization and other kinds of information extraction from transcription of dialogs. From a probabilistic view, this is achieved by maintaining a posterior distribution over hidden dialog states composed, in the simplest case, of a set of context dependent variables. Once a dialog policy is defined, deterministic or learnt, it is in charge of selecting an optimal dialog act given the estimated dialog state and a defined reward function. This paper introduces a novel method of dialog state tracking based on the general paradigm of machine reading and proposes to solve it using a memory-enhanced neural network architecture. We evaluate the proposed approach on the second Dialog State Tracking Challenge (DSTC-2) dataset that has been converted for the occasion in order to fit the relaxed assumption of a machine reading formulation where the true state is only provided at the very end of each dialog instead of providing the state updates at the utterance level. We show that the proposed tracker gives encouraging results. Finally, we propose to extend the DSTC-2 dataset with specific reasoning capabilities requirement like counting, list maintenance, yes-no question answering and indefinite knowledge management.

1 Introduction
One of the core components of state-of-the-art and industrially deployed dialog systems is a dialog state tracker. Its purpose is to provide a compact representation
of a dialog produced from past user inputs and system outputs which is called the dialog state. The dialog state summarizes the information needed to successfully maintain and finish a dialog, such as users’ goals or requests. The precise definition of the state depends on the associated dialog task. In the simplest case of a so-called slot-filling schema, the state is composed of a predefined set of variables with a predefined domain of expression for each of them. As a matter of fact, in the recent context of end-to-end machine trainable dialog systems, state tracking remains a central element of such architectures [WGM+16]. Indeed, in the most general case, effective dialog systems tend to include a tracking mechanism which is able to accurately accumulate evidence over the sequence of turns of a dialog and must adjust the dialog state according to its observations. The goal of the dialog system is to efficiently instantiate each of these variables thereby performing an associated task and satisfying the corresponding intent of the user. Because of the reasoning capability that can be required in such task, we propose to formalize the state tracking problem as a particular instance of a machine reading problem. As far as our knowledge goes, it is the first attempt to explicitly frame the task of dialog state tracking as a machine reading problem. Following this direction, we extend the current definition of dialog state dataset by assuming the true dialog state is only available at the end of each dialog. On the other hand, such formalization allows for the implementation of approximate reasoning capability that has been shown to be crucial for any machine reading tasks [WBCM15].

Roadmap: This paper is structured as follows, Section 2 recalls the main definitions associated to transactional dialogs and describes the associated problem of statistical dialog state tracking with both the generative and discriminative approaches. At the end of this section, the current limitations of the current models in terms of necessary annotations and reasoning capabilities are addressed. Then, Section 3 depicts the proposed machine reading model for dialog state tracking and proposes to extend a state of the art dialog state tracking dataset, DSTC-2, to several simple reasoning capabilities. Section 4 illustrates the approach with experimental results obtained using a state of the art benchmark for dialog state tracking.

2 Dialog state tracking

In this section, the main definitions of a dialog state tracking task are recalled and the two main learning based approaches are described and discussed.
2.1 Main definitions

A dialog state tracking task is formalized as follows: at each turn of a dyadic dialog, the dialog agent chooses a dialog act $d$ to express and the user answers with an utterance $u$. In the simplest case, the dialog state at each turn of a given dialog is defined as a distribution over a set of predefined variables, which define the structure of the state as mentioned in [WPY05]. This classic state structure is commonly called *slot filling* or *semantic frame*. In this context, the state tracking task consists of estimating the value of a set of predefined variables in order to perform a procedure or transaction which is, in fact, the purpose of the dialog. Typically, a natural language understanding module processes the user utterance and generates an N-best list $o = \{(d_1, f_1), \ldots, (d_n, f_n)\}$, where $d_i$ is the hypothesized user dialog act and $f_i$ is its confidence score. Various approaches have been proposed to define dialog state trackers. The traditional methods used in most commercial implementations use hand-crafted rules that typically rely on the most likely result from an NLU module as described in [YDJ14] and hardly models uncertainty. However, these rule-based systems are prone to frequent errors as the most likely result is not always the correct one [Wil14]. More recent methods employ statistical approaches to estimate the posterior distribution over the dialog states allowing them to leverage on the uncertainty of the results of the NLU module.

In the simplest case where no ASR and NLU modules are employed, as in a text based dialog system as proposed in [HTY13] the utterance is taken as the observation using a so-called bag of words representation. If an NLU module is available, standardized dialog act schemas can be considered as observations as in [BAC+10]. Furthermore, if prosodic information is available from the ASR component of the dialog system as in [MR03], it can also be considered as part of the observation definition. A statistical dialog state tracker maintains, at each discrete time step $t$, the probability distribution over states, $b(s_t)$, which is the system’s belief over the state. The general process of slot-filling, transactional dialog management is summarized by the following sequence of steps. First, *intent detection* is typically an NLU problem consisting of identifying the task the user wants the system to accomplish. This first step determines the set of variables to instantiate during the second step, which is the slot-filling process. This type of dialog management assumes that a set of variables are required for each predefined intention. Second, the actual slot filling process is composed of the cyclic tasks of *information gathering* and integration, in other words – *dialog state tracking*. Finally, once all the variables have been correctly instantiated, a common practice in dialog systems is to perform a last general confirmation of the task desired by the user before finally executing the requested task. In such framework, the purpose is to estimate as early as possible in the course of a given dialog the correct instantiation of each variable.
In the following, we will assume the state is represented as a concatenation of zero-one encoding of the values for each variable defining the state. Furthermore, in the context of this paper, only the bag of words has been considered as an observation at a given turn but dialog acts or detected named entity provided by an SLU module could have also been incorporated as evidence.

Two statistical approaches have been considered for maintaining the distribution over a state given sequential NLU output. First, the discriminative approach aims to model the posterior probability distribution of the state at time \( t + 1 \) with regard to state at time \( t \) and observations \( z_{1:t} \). Second, the generative approach attempts to model the transition probability and the observation probability in order to exploit possible interdependencies between hidden variables that comprise the dialog state.

### 2.2 Generative Dialog State Tracking

A generative approach to dialog state tracking computes the belief over the state using Bayes’ rule, using the belief from the last turn \( b(s_{t-1}) \) as a prior and the likelihood given the user utterance hypotheses \( p(z_t | s_t) \), with \( z_t \) the observation gathered at time \( t \). In prior works \cite{WPY05}, the likelihood is factored and some independence assumptions are made:

\[
b_t \propto \sum_{s_{t-1}, z_t} p(s_t | z_t, d_{t-1}, s_{t-1}) p(z_t | s_{t-1}) b(s_{t-1})
\]

A typical generative model of a dialog state tracking process using a factorial hidden Markov model proposed by \cite{GJ97}. The shaded variables are the observed dialog turns and each unshaded variable represents a single variable describing the task dependent variables. In this family of approaches, scalability is considered as one of the main issues. One way to reduce the amount of computation is to group the states into partitions, as proposed in the Hidden Information State (HIS) model of \cite{GY11}. Other approaches to cope with the scalability problem in dialog state tracking is to adopt a factored dynamic Bayesian network by making conditional independence assumptions among dialog state components, and then using approximate inference algorithms such as loopy belief propagation as proposed in \cite{TY10} or a blocked Gibbs sampling as in \cite{RM11}. To cope with such limitations, discriminative methods of state tracking presented in the next part of this section aim at directly model the posterior distribution of the tracked state using a chosen parametric form.
2.3 Discriminative Dialog State Tracking

The discriminative approach of dialog state tracking computes the belief over a state via a trained parametric model that directly represents the belief \( b(s_{t+1}) = p(s_{t+1} | s_t, z_t) \). Maximum Entropy has been widely used in the discriminative approach as described in [MBW13]. It formulates the belief as follows:

\[
b(s) = P(s|x) = \eta \cdot e^{w^T \phi(x,s)}
\]

where \( \eta \) is the normalizing constant, \( x = (d^u_1, d^m_1, s_1, \ldots, d^u_t, d^m_t, s_t) \) is the history of user dialog acts, \( d^u_i, i \in \{1, \ldots, t\} \), the system dialog acts, \( d^m_i, i \in \{1, \ldots, t\} \), and the sequence of states leading to the current dialog turn at time \( t \). Then, \( \phi(.) \) is a vector of feature functions on \( x \) and \( s \), and finally, \( w \) is the set of model parameters to be learned from annotated dialog data. According to this formulation, the posterior computation has to be carried out for all possible state realizations in order to obtain the normalizing constant \( \eta \). This is not feasible for real dialog domains, which can have a large number of variables and possible variable instantiations. So, it is vital to the discriminative approach to reduce the size of the state space. For example, [MBW13] proposes to restrict the set of possible state variables to those that appeared in NLU results. Finally, deep neural models, performing on a sliding window of features extracted from previous user turns, have also been proposed in [HTY14b]. Of the current literature, this family of approaches have proven to be the most efficient for publicly available state tracking datasets.

2.4 Current limitations

Using error analysis [HTW14], several limitations have been observed in the application of the current types of inference model. On one hand, current models tend to fail at considering long-tail dependencies that can occur on dialogs as coreferences and inter-utterances informations even with the usage of recurrent network models [HTY14a]. On the other hand, reasoning capabilities, as required in machine reading applications [PD10, BSC+14, WBCM15] remain absent in these classic formalizations of dialog state tracking. In the next section, we present a model of dialog state tracking that aims at leveraging on the current advances of memory-enhanced neural networks and their approximate reasoning capabilities that seems particularly adapted to the sequential, long range dependency equipped and sparse nature of complex dialog state tracking tasks. Furthermore, this model allows to relax the hypothesis of utterance-level annotation to dialog-level annotation that corresponds to common pratices in industrial applications of transactional conversational user interfaces. Indeed, in such contexts, annotations tend to be associated with an overall dialog scale and not at the utterance one. In that context,
producing such annotation required a dedicated effort that can be tedious.

3 A Machine reading formulation of dialog state tracking

We propose to formalize the problem of dialog state tracking as a particular case of machine reading [EBC07, BSC+14]. Indeed, this task can be understood as the capability of inferring a set of latent values \( l \) associated to a set of variables \( v \) related to a given dyadic or multi-party conversation \( d \), from direct correlation and/or reasoning, using the course of exchanges of utterances, \( p(l|d,v) \). In this section, we recall the main definitions of the task of machine reading, then we mention the principal recent models of memory-enhanced neural network architectures designed to handle such tasks. Finally, we formalized the task of dialog state tracking as a machine reading problem and propose to solve it using a memory-enhanced neural architecture of inference.

3.1 Machine reading

The task of textual understanding has recently been formulated as a supervised learning problem [KIS+15, HKG+15]. The task consists in estimating the conditional probability \( p(a|d,q) \) of an answer \( a \) to a query \( q \) where \( d \) is a document. Such an approach requires a large training corpus of \{document - query - answer\} triples and until now such corpora have been limited to hundreds of examples [RBRT13]. On the other hand, in the context of dialog state tracking, state updates at an utterance level are rarely provided off-the-shelf from a production environment. So an additional effort of specific annotation is often needed in order to train a state of the art statistical state tracking model [HTW14]. In the context of dialog state tracking challenges, the dialogs are currently limited to two to three thousands of dialogs [HTW14]. In the context of human-to-human dialog systems, like personal assistance or customer care, a transactional dialog is often summarized/annotated at the end by the entire state that corresponds to the situation encountered during the dialog. Because of that, the machine reading paradigm becomes a promising formulation for the general problem of dialog state tracking. Furthermore, current approaches and available datasets for state tracking do not explicitly cover reasoning capabilities such as temporal and spatial reasoning, counting, sorting and deduction. I suggest that in the future dataset dialogs expressing such specific abilities should be developed. In this last part, several reasoning enhancements are suggested to the DSTC-2 dataset.
3.2 Memory-enhanced neural networks

Several neural network models have very recently been developed with memory capability enhancement [GWD14, JM15, SSWF15, KIS+15]. Briefly, they share the particularity of taking a discrete set of inputs \(\{x_1; \ldots; x_n\}\) that have to be stored in the memory, a query \(q\), and outputs an answer \(a\). Each of the \(x_i\), \(q\), and \(a\) contains symbols coming from a dictionary with \(V\) words. The model writes all \(x\) to the memory up to a fixed buffer size, and then it finds a continuous representation for the \(x\) and \(q\). The continuous representation is then processed via multiple hops to output a distribution over \(a\). This allows backpropagation of the error signal through multiple memory accesses back to the input during training. As mentioned in [WCB14], the main point of such family of approach is to combine the successful, mainly stochastic gradient-based, learning strategies developed in the machine learning literature for inference with a memory component that can be read and written to. In that sense, the model is trained to learn how to operate effectively with a memory component and enable it to capture more complex reasoning dynamics that other model lack. In the next section, we show how the task of dialog state tracking can be formalized as machine reading task and solved using such memory enhanced model.

3.3 Dialog reading model for state tracking

In this section, we propose to formalize dialog state tracking using the paradigm of machine reading. As far as our knowledge goes, it is the first attempt to apply this approach and develop a specific dataset format, detailed in Section 4, from an existing and publicly available dialog state tracking challenge dataset to fulfill this task. Assuming (1) a dyadic dialog \(d\), (2) a state composed with (2a) a set of variables \(v_i\) with \(i = \{1, \ldots, n\}\) and (2b) a set of corresponding assigned values \(l_i\). One can define a query \(q_{v_i} = l_i\) that corresponds to the specific instantiation of a variable to a value in the context of a dialog \(p(q_{v_i} = l_i|d)\). In such context, a dialog state tracking task consists in determining for each variable \(v_i\), \(l^* = \arg \max_{l_i \in L} P(q_{v_i} = l_i|d)\), with \(L\) the specific domain of expression of a variable \(v_i\). In additional to the actual dataset, we propose to tackle four general reasoning tasks using DSTC-2 dataset as a starting point. In such way, we leverage on the dataset of DSTC-2 to create more complex reasoning task than the ones present in the original dialogs of the dataset by performing deterministic and stochastic conversions of the corpus. Obviously, the goal is to develop resolution algorithms that are not dedicated to a specific reasoning task but inference models that will be as generic as possible.

**Single Supporting Fact:** This first task corresponds to the most classic view of dialog state tracking. It consists of questions where a previously given single
supporting fact, potentially amongst a set of other irrelevant facts, provides the answer. This kind of task was already employed in [WCB14] in the context of a virtual world. At the difference of the proper state tracking task, the true variable state is given at the end of the overall sequence. The use of the supporting fact corresponds to the same information than the one given in the original dataset. In that sense, the result obtained to such task are comparable with the state of the art approaches. Table 4 given an example of such dialog for the case of the food slot of the DSTC-2 dataset.

**Yes/No Questions** : This task tests, on some of the simplest questions possible, like confirming the value of a given slot, the ability of a model to answer true/false type questions like "Is the food italian ?". The conversion of a dialog to such format is deterministic regarding the fact that the utterances and corresponding true states are known at each utterance of a given dialog. Table 7 is an example if such conversion.

**Indefinite Knowledge** : This task tests a complex natural language construction. It tests if statements can be models in order to describe possibilities rather than certainties, as proposed in [WCB14], in our case the answer will be "maybe" to the question "Is the price-range required moderate ?". In the case of state tracking, it will allow to seamlessly deal with unknown information about the dialog state. Table 8 gives an example of such conversion.

**Counting and Lists/Sets** : This last task tests the capacity of the model to perform simple counting operations, by asking about the number of objects with a certain property, e.g. "How many area are requested ?". Similarly, the ability to produce a set of single word answers in the form of a list, e.g. "What are the area requested ?". Table 9 gives an example of such conversion.

We believe more reasoning capabilities need to be explore in the future, like spacial and temporal reasoning or deduction as suggested in [WBCM15]. However, it will probably need the development of a new dedicated ressource. Another alternative could be to develop a question-answering annotation task based on a dialog corpus where reasoning task are present. The closest work to our proposal that can be cited is [BW16]. In this paper, the authors proposes to learn a so-called end-to-end learnable dialog system to infer the answer, from a finite set of eligible answers, by the dialog system w.r.t the current list of utterances of the dialog. The authors generate 5 artificial tasks of dialog however the reasoning capabilities are not explicitly addressed and the author explicitly claim that the resulting dialog system is not satisfactory yet. Indeed, we believe that having a proper dialog state tracker where a policy is built on top can guarantee dialog achievement by properly optimizing a reward function throughout a explicitly learnt dialog policy. indeed, in the case of proper end-to-end systems, the objective function is not explicitly defined [SLCP15] and the resulting systems tend to be used in the con-
text of chat-oriented and non-goal oriented dialog systems. In the next section, we present experimental results obtained on the basis of the DSTC-2 dataset and its conversion to the four mentioned reasoning tasks.

4 Experiments

This section is organized in two parts. In a first part, the generation of a machine reading type of dataset from the publicly available DSTC-2 corpus is presented. In a section part, experimental results are provided.

4.1 A machine reading dataset of the DSTC-2 corpus

We use the DSTC-2 dialog domain [WRRB13] as a basis for evaluating the proposed approach. In this dialog corpus, the user queries a database of local restaurants by interacting with a dialog system. A dialog proceeds as follows: first, the user specifies constraints concerning the restaurant. Then, the system offers the name of a restaurant that satisfies the constraints. Finally, the user accepts the offer and requests additional information about the accepted restaurant. In this context, the dialog state tracker should be able to track several types of information that compose the state like the geographic area, the food type and the price range slots. In this paper, we restrict ourselves to tracking these variables, but our tracker can be easily setup to track others as well if they are properly specified. We adapt the dataset in order to correspond to a proper task of machine reading by only considering the annotation at a dialog-level instead of a utterance-level one. In that sense, the tracker task consists in finding the value $l^*$ as defined in Section 3.3. We present examples of a machine reading formulation of a dialog state tracking task for the slots Food in Tables 4, Area in Tables 5 and Price range in Tables 6 from the DSTC-2 dialog corpus that we have produced for this task. This three first examples are part of the One supporting fact set of the corpus in reference to [WBCM15]. In order to exhibit reasoning capability of the proposed model in the context of dialog state tracking, three other dataset have been automatically generated from the DSTC-2 corpus in order to support 3 capabilities of reasoning as mentioned in [WBCM15], (1) Yes-No question in Table 7, (2) Indefinite Knowledge in Table 8, (3) Counting in Table 9, (4) List in Table 10.

Figures 1, 2 and 3 detail the respective distributions of dialog length for each slot-specific corpus extracted from the DSTC-2 corpus to generate the examples used for the machine reading learning tasks. Table 11 recalls the domain of expression of each variables of the DSTC-2 corpus.
4.2 Experimental results

The learning protocol follows the process described in [SSWF15], we decided to use the Memory Network model for the implementation of our experiment, in the future we plan to experiment and compare the same approach with Stacked-Augmented Recurrent Neural Network [JM15] and Neural Turing Machine [GWD14] that sounds also promising for these reasoning tasks. The size the embedding has been varied for experimental purposes. Concerning the choice of hyperparameters, the number of internal hops between the memory and the decision stack has been set to 3, the learning rate $\lambda = 0.01$, the batch size to 50 and the number of epochs to 60.

Table 2 presents detailed results obtained by the proposed machine reading model for state tracking on three tracked variables of the DSTC-2 dataset formulated a so-called one supporting fact question answering task. In this context, a memory enhanced model allows to obtain competitive results with the most close, non-memory enhanced, state of the art approach of recurrent neural network.

As a second result, Table 3 presents the performance obtained for the four simple reasoning tasks. The obtained results lead us to think that memory enhanced model are a competitive alternative for the task dialog state tracking. In the future, we believe new reasoning capabilities like spacial and temporal reasoning and deduction should be exploited on the basis of a specifically designed dataset.
Table 2: One supporting fact task: Acc. obtained on DSTC2 dataset

| Variable   | Emb. size | Acc. |
|------------|-----------|------|
| Food       | 20        | 0.87 |
|            | 40        | **0.88** |
|            | 60        | 0.86 |
| Area       | 20        | **0.89** |
|            | 40        | 0.88 |
|            | 60        | 0.87 |
| PriceRange | 20        | **0.95** |
|            | 40        | 0.92 |
|            | 60        | 0.92 |
| RNN [HTY14a] |          | 0.784 |

Table 3: Reasoning tasks: Acc. on DSTC2 reasoning datasets

| Variable   | Emb. size | Yes-No | I.K. | Count. | List. |
|------------|-----------|--------|------|--------|-------|
| Food       | 20        | **0.85** | 0.79 | 0.89   | 0.41  |
|            | 40        | 0.83   | **0.84** | 0.88 | **0.42** |
|            | 60        | 0.82   | 0.82   | **0.90** | 0.39 |
| Area       | 20        | 0.86   | 0.83   | 0.94   | **0.79** |
|            | 40        | **0.90** | 0.89 | **0.96** | 0.75 |
|            | 60        | 0.88   | **0.90** | 0.95   | 0.78 |
| PriceRange | 20        | **0.93** | **0.86** | **0.93** | **0.83** |
|            | 40        | 0.92   | 0.85   | 0.90   | 0.80 |
|            | 60        | 0.91   | 0.85   | 0.91   | 0.81 |

5 Conclusion and further work

This paper describes a novel method of dialog state tracking based on the general paradigm of machine reading and solved using a memory-enhanced neural network architecture. In this context, a specific dataset format inspired from the current dataset format of machine reading tasks has been developed for the task of dialog state tracking. As far as our knowledge goes, it is the very first attempt to solve this classic problem of dialog management in such way. Beyond the experimental results presented in the previous section, the proposed approach offers several advantages compared to state of the art methods of tracking. First, the proposed method allows to perform tracking on the basis of dialog-level annotation instead of utterance-level one that is commonly admitted in academic datasets but tedious to produce in a large scale industrial environment where annotation is often per-
formed afterhand for the purpose of logging, monitoring and quality assessment. Indeed, dialog-level annotations correspond to common practices of annotation especially in personal assistance, customer care dialogs and, in a more general sense, industrial application of transactional conversational user interfaces. Second, we propose to develop reasoning capability specific dialog corpus to exhibit limitations of current models of dialog state tracking when exposed to such challenges as mentioned before. Finally, the memory enhanced inference model used in this paper seems to be able to cope with reasoning capabilities that remains nearly impossible with state of art approaches of state tracking like recurrent neural networks. In this paper, we have addressed four simple reasoning capabilities. In further work, we plan to address more complex tasks like spatial and temporal reasoning, sorting, counting or deduction and experiment with different memory enhanced inference models.

References

[BAC+10] Harry Bunt, Jan Alexandersson, Jean Carletta, Jae-Woong Choe, Alex Chengyu Fang, Koiti Hasida, Kiyong Lee, Volha Petukhova, Andrei Popescu-Belis, Laurent Romary, Claudia Soria, and David Traum. Towards an ISO standard for dialogue act annotation. In Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC’10). European Language Resources Association (ELRA), may 2010.

[BSC+14] Jonathan Berant, Vivek Srikumar, Pei-Chun Chen, Abby Vander Linden, Brittany Harding, Brad Huang, Peter Clark, and Christopher D. Manning. Modeling biological processes for reading comprehension. In Alessandro Moschitti, Bo Pang, and Walter Daelemans, editors, Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL. ACL, 2014.

[BW16] Antoine Bordes and Jason Weston. Learning end-to-end goal-oriented dialog. CoRR, 2016.

[EBC07] Oren Etzioni, Michele Banko, and Michael J. Cafarella. Machine reading. In AAAI Spring Symposium: Machine Reading. AAAI, 2007.

[GJ97] Zoubin Ghahramani and Michael I. Jordan. Factorial hidden Markov models. Machine Learning, 29(2-3):245–273, 1997.
[GWD14] Alex Graves, Greg Wayne, and Ivo Danihelka. Neural turing machines. CoRR, 2014.

[GY11] Milica Gasic and Steve Young. Effective handling of dialogue state in the hidden information state POMDP-based dialogue manager. TSLP, 7(3):4, 2011.

[HKG+15] Karl Moritz Hermann, Tomás Kociský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. CoRR, 2015.

[HTW14] Matthew Henderson, Blaise Thomson, and Jason D. Williams. The third dialog state tracking challenge. In SLT, pages 324–329. IEEE, 2014.

[HTY13] Matthew Henderson, Blaise Thomson, and Steve Young. Proceedings of the SIGDIAL 2013 Conference, chapter Deep Neural Network Approach for the Dialog State Tracking Challenge, pages 467–471. Association for Computational Linguistics, 2013.

[HTY14a] M. Henderson, B. Thomson, and S. J. Young. Robust dialog state tracking using delexicalised recurrent neural networks and unsupervised adaptation. In Proceedings of IEEE Spoken Language Technology, 2014.

[HTY14b] Matthew Henderson, Blaise Thomson, and Steve Young. Word-based dialog state tracking with recurrent neural networks. In Proceedings of SIGDial, 2014.

[JM15] Armand Joulin and Tomas Mikolov. Inferring algorithmic patterns with stack-augmented recurrent nets. CoRR, 2015.

[KIS+15] 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. CoRR, 2015.

[MBW13] Angeliki Metallinou, Dan Bohus, and Jason Williams. Discriminative state tracking for spoken dialog systems. In Association for Computer Linguistics, pages 466–475. The Association for Computer Linguistics, 2013.
[MR03] Diego H. Milone and Antonio J. Rubio. Prosodic and accentual information for automatic speech recognition. *IEEE Transactions on Speech and Audio Processing*, 11(4):321–333, 2003.

[PD10] Hoifung Poon and Pedro M. Domingos. Machine reading: A ”killer app” for statistical relational AI. In *Statistical Relational Artificial Intelligence*, volume WS-10-06 of *AAAI Workshops*. AAAI, 2010.

[RBR13] Matthew Richardson, Christopher J. C. Burges, and Erin Renshaw. MCTest: A challenge dataset for the open-domain machine comprehension of text. In *EMNLP*, pages 193–203. ACL, 2013.

[RM11] Antoine Raux and Yi Ma. Efficient probabilistic tracking of user goal and dialog history for spoken dialog systems. In *INTERSPEECH*, pages 801–804. ISCA, 2011.

[SLCP15] Iulian Vlad Serban, Ryan Lowe, Laurent Charlin, and Joelle Pineau. A survey of available corpora for building data-driven dialogue systems. *CoRR*, 2015.

[SSWF15] Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. End-to-end memory networks. In Corinna Cortes, Neil D. Lawrence, Daniel D. Lee, Masashi Sugiyama, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 2440–2448, 2015.

[TY10] Blaise Thomson and Steve Young. Bayesian update of dialogue state: A POMDP framework for spoken dialogue systems. *Computer Speech & Language*, 24(4):562–588, 2010.

[WBCM15] Jason Weston, Antoine Bordes, Sumit Chopra, and Tomas Mikolov. Towards AI-complete question answering: A set of prerequisite toy tasks. *CoRR*, 2015.

[WCB14] Jason Weston, Sumit Chopra, and Antoine Bordes. Memory networks. *CoRR*, 2014.

[WGM+16] Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Lina Maria Rojas-Barahona, Pei-Hao Su, Stefan Ultes, David Vandyke, and Steve J. Young. A network-based end-to-end trainable task-oriented dialogue system. *CoRR*, 2016.
[Wil14] Jason D. Williams. Web-style ranking and slu combination for dialog state tracking. In Proceedings of SIGDIAL. ACL Association for Computational Linguistics, June 2014.

[WPY05] Jason D. Williams, Pascal Poupart, and Steve Young. Factored partially observable markov decision processes for dialogue management. In In 4th Workshop on Knowledge and Reasoning in Practical Dialog Systems, pages 76–82, 2005.

[WRRB13] Jason Williams, Antoine Raux, Deepak Ramachandran, and Alan Black. The dialog state tracking challenge. In Proceedings of the SIGDIAL 2013 Conference, pages 404–413, Metz, France, August 2013. Association for Computational Linguistics.

[YDJ+14] Peter Z. Yeh, Benjamin Douglas, William Jarrold, Adwait Ratnarparkhi, Deepak Ramachandran, Peter F. Patel-Schneider, Stephen Laverty, Nirvana Tikku, Sean Brown, and Jeremy Mendel. A speech-driven second screen application for TV program discovery. In Carla E. Brodley and Peter Stone, editors, Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence, July 27 -31, 2014, Québec City, Québec, Canada, pages 3010–3016. AAAI Press, 2014.
6 Appendix

Table 4: **One supporting fact task**: A machine reading task formulated dialog state tracking learning example for the *Food* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|--------------------------------------------------------------------------|
| 1     | Cust  | West part of town cuban food.                                            |
| 2     | Agent | Sorry there is no cuban restaurant in the west of town.                  |
| 3     | Cust  | Ok, do you have an Italian place ?                                       |
| 4     | Agent | Prezzo is a nice restaurant in the west of town serving italian food.    |
| 5     | Cust  | Phone number.                                                            |
| 6     | Agent | You are looking for a restaurant is that right ?                         |
| 7     | Cust  | Yes.                                                                     |
| 8     | Agent | Prezzo is a nice restaurant in the west of town serving italian food.    |
| 9     | Cust  | What is the phone number ?                                               |
| 10    | Agent | The phone number of prezzo is 097 6567 865.                              |
| 11    | Cust  | Goodbye.                                                                 |

12 *What is Food ? Answer: Italian - Supporting Fact : 3*

Table 5: **One supporting fact task**: A machine reading task formulated dialog state tracking learning example for the *Area* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|--------------------------------------------------------------------------|
| 1     | Cust  | I’m looking for italian food.                                             |
| 2     | Agent | Would you like something in the cheap moderate or expensive price range ?|
| 3     | Cust  | Moderate.                                                                |
| 4     | Agent | What part of town do you have in mind ?                                  |
| 5     | Cust  | North.                                                                   |
| 6     | Agent | Sorry there is no moderate restaurant in the north of town serving italian food. |
| 7     | Cust  | Thank you good bye.                                                     |

8 *What is Area ? Answer: North - Supporting Fact : 5*
Table 6: **One supporting fact task**: A machine reading task formulated dialog state tracking learning example for the *Pricerange* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|---------------------------------------------------------------------------|
| 1     | Cust  | What kind of restaurant that serves french food.                          |
| 2     | Agent | Restaurant two two serves french food.                                    |
| 3     | Cust  | I dont care about the price range with the address.                       |
| 4     | Agent | Sure restaurant two two is on chesterton road chesterton.                 |
| 5     | Cust  | Thank you goodbye.                                                       |
| 6     |       | What is Pricerange? Answer: Dontcare - Supporting Fact : 3                |

Table 7: **Yes-No question task**: A machine reading task formulated dialog state tracking learning example for the *Area* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|---------------------------------------------------------------------------|
| 1     | Cust  | I need a moderately priced north part of town.                            |
| 2     | Agent | You are looking for a restaurant is that right.                           |
| 3     | Cust  | Yes.                                                                      |
| 4     | Agent | Golden wok is a nice restaurant in the north of town in the moderate price range. |
| 5     | Cust  | What is the address and phone number of.                                  |
| 6     | Agent | The phone number of golden wok is 987 678 65 and it is on histon road chesterton. |
| 7     | Cust  | Thank you good bye.                                                      |
| 8     |       | Is area north ? Answer: Yes - Supporting Fact : 1                         |

Table 8: **Indefinite knowledge task**: A machine reading task formulated dialog state tracking learning example for the *Food* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|---------------------------------------------------------------------------|
| 1     | Cust  | I’m looking for a cheap restaurant in north.                              |
| 2     | Agent | The royal spice is a nice restaurant in the north of town in the cheap price range. |
| 3     | Cust  | I would like the phone number.                                            |
| 4     | Agent | The phone number of royal spice is 987 678 65.                            |
| 5     | Cust  | Thank you goodbye.                                                       |
| 6     |       | Is food Indian ? Maybe - Supporting Fact : 1                              |
Table 9: **Counting task**: A machine reading task formulated dialog state tracking learning example for the *Food* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|---------------------------------------------------------------------------|
| 1     | cust  | I’d like a portuguese or brazilian restaurant.                           |
| 2     | Agent | Nandos city centre serves portuguese food.                               |
| 3     | Cust  | What is the address.                                                    |
| 4     | Agent | sure nandos city centre is on 17 - saint andrews street.                 |
| 5     | Cust  | Thank you good bye.                                                     |
| 6     |       | **How many food ? Answer: Two - Supporting Fact : 1**                    |

Table 10: **Listing task**: A machine reading task formulated dialog state tracking learning example for the *Area* slot from *DSTC2* dataset

| Index | Actor | Utterance                                                                 |
|-------|-------|---------------------------------------------------------------------------|
| 1     | Cust  | Im looking for a cheap restaurant in the west or east part of town.       |
| 2     | Agent | Thanh Binh is a nice restaurant in the west of town in the cheap price range. |
| 3     | Cust  | What is the address and post code.                                        |
| 4     | Agent | Thanh Binh is on magdalene street city centre.                            |
| 5     | Cust  | Thank you goodbye.                                                       |
| 6     |       | **What is area ? Answer: {West,East} - Supporting Fact : 1**              |

Table 11: Attention shifting example for the *PriceRange* slot from *DSTC2* dataset

| Actor  | Utterance                                                                 | Hop 1 | Hop 2 | Hop 3 | Hop 4 | Hop 5 |
|--------|---------------------------------------------------------------------------|-------|-------|-------|-------|-------|
| Cust   | Im looking for a cheap restaurant that serves chinese food                | 0.00  | 0.14  | 0.01  | 0.00  | 0.00  |
| Agent  | What part of town do you have in mind                                    | 0.02  | 0.17  | 0.05  | 0.00  | 0.00  |
| Cust   | I dont care                                                               | 0.00  | 0.00  | 0.14  | 0.00  | 0.00  |
| Agent  | Rice house serves chinese food in the cheap price range                   | 0.00  | 0.02  | 0.03  | 0.98  | 1.00  |
| Cust   | What is the address and telephone number                                  | 0.57  | 0.07  | 0.15  | 0.00  | 0.00  |
| Agent  | Sure rice house is on mill road city centre                              | 0.03  | 0.01  | 0.13  | 0.02  | 0.00  |
| Cust   | Phone number                                                              | 0.00  | 0.01  | 0.03  | 0.00  | 0.00  |
| Agent  | The phone number of rice house is 765-239-09                             | 0.37  | 0.58  | 0.45  | 0.00  | 0.00  |
| Cust   | Thank you good bye                                                       | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |

**What is the pricerange ? Answer: cheap**
Table 12: Attention shifting example for the *Food* slot from *DSTC2* dataset

| Actor  | Utterance                                                                 | Hop 1 | Hop 2 | Hop 3 | Hop 4 | Hop 5 |
|--------|---------------------------------------------------------------------------|-------|-------|-------|-------|-------|
| Cust   | The restaurant in any area that serves japanese food                      | 0.01  | 0.00  | 0.27  | 1.00  | 1.00  |
| Agent  | wagamama is a nice restaurant in the centre of town serving japanese food | 0.95  | 1.00  | 0.73  | 0.00  | 0.00  |
| Cust   | Phone number                                                              | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Agent  | Can i help you with anything else                                         | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Cust   | What is the phone number                                                  | 0.04  | 0.00  | 0.00  | 0.00  | 0.00  |
| Agent  | The phone number of wagamama is 987-765-67                                | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Cust   | Thank you goodbye                                                         | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |

*What is the food type? Answer: japanese*

Table 13: Attention shifting example for the *Area* slot from *DSTC2* dataset

| Actor   | Utterance                                                                 | Hop 1 | Hop 2 | Hop 3 | Hop 4 | Hop 5 |
|---------|---------------------------------------------------------------------------|-------|-------|-------|-------|-------|
| Cust    | Im looking for a cheap restaurant that serves chinese food                 | 0.00  | 0.18  | 0.11  | 0.04  | 0.00  |
| Agent   | What part of town do you have in mind                                     | 0.33  | 0.30  | 0.00  | 0.00  | 0.00  |
| Cust    | I dont care                                                               | 0.00  | 0.00  | 0.17  | 0.37  | 1.00  |
| Agent   | Rice house serves chinese food in the cheap price range                    | 0.01  | 0.00  | 0.00  | 0.00  | 0.00  |
| Cust    | What is the address and telephone number                                  | 0.58  | 0.09  | 0.01  | 0.00  | 0.00  |
| Agent   | Sure rice house is on mill road city centre                               | 0.03  | 0.00  | 0.00  | 0.00  | 0.00  |
| Cust    | Phone number                                                              | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
| Agent   | The phone number of rice house is 765-239-09                              | 0.02  | 0.01  | 0.00  | 0.00  | 0.00  |
| Cust    | Thank you good bye                                                        | 0.02  | 0.42  | 0.71  | 0.59  | 0.00  |

*What is the area? Answer: dontcare*