Towards Exploiting Background Knowledge for Building Conversation Systems

Nikita Moghe¹,², Siddhartha Arora¹, Suman Banerjee¹, and Mitesh M. Khapra¹,²

¹Department of Computer Science and Engineering, Indian Institute of Technology Madras
²Robert Bosch Centre for Data Science and AI (RBC-DSAI), Indian Institute of Technology Madras

{nikitavam, sidarora, suman, miteshk}@cse.iitm.ac.in

Abstract

Existing dialog datasets contain a sequence of utterances and responses without any explicit background knowledge associated with them. This has resulted in the development of models which treat conversation as a sequence-to-sequence generation task (i.e., given a sequence of utterances generate the response sequence). This is not only an overly simplistic view of conversation but it is also emphatically different from the way humans converse by heavily relying on their background knowledge about the topic (as opposed to simply relying on the previous sequence of utterances). For example, it is common for humans to (involuntarily) produce utterances which are copied or suitably modified from background articles they have read about the topic. To facilitate the development of such natural conversation models which mimic the human process of conversing, we create a new dataset containing movie chats wherein each response is explicitly generated by copying and/or modifying sentences from unstructured background knowledge such as plots, comments and reviews about the movie. We establish baseline results on this dataset (90K utterances from 9K conversations) using three different models: (i) pure generation based models which ignore the background knowledge (ii) generation based models which learn to copy information from the background knowledge when required and (iii) span prediction based models which predict the appropriate response span in the background knowledge.

1 Introduction

Background knowledge plays a very important role in human conversations. For example, to have a meaningful conversation about a movie, one uses their knowledge about the plot, reviews, comments and facts about the movie. A typical conversation involves recalling important points from this background knowledge and producing them appropriately in the context of the conversation. However, most existing large scale datasets (Lowe et al., 2015b; Ritter et al., 2010; Serban et al., 2016) simply contain a sequence of utterances and responses without any explicit background knowledge associated with them. This has led to the development of models which treat conversation as a simple sequence-to-sequence generation task and often produce output which is both syntactically incorrect and incoherent (off topic). To make conversations more coherent, there is an increasing interest in integrating structured and unstructured knowledge sources with neural conversation models. While there are already some works in this direction (Rojas-Barahona et al., 2017; Williams et al., 2016; Lowe et al., 2015a; Ghazvininejad et al., 2017) which try to integrate external knowledge sources with existing datasets, we believe that building new datasets where the utterances are explicitly linked to external background knowledge will further facilitate the development of such background aware conversation models.

With this motivation, we built a new background aware conversation dataset using crowdsourcing. Specifically, we asked workers to chat about a movie using structured and unstructured resources about the movie such as plots, reviews, comments, fact tables (see Figure 1). For every even numbered utterance, we asked the workers to consult the available background knowledge and try to construct a sentence which contains information from this background knowledge and is relevant in the current context of the conversation (akin to how humans recall things from their background knowledge and insert them appropriately in the conversation). For example, in Turn 2, Speaker 2 picked a sentence from the plot which is relevant to the current context of the conversation. Similarly, in Turn 3, Speaker 2 picked a
sentence from the movie review. We also asked the workers to suitably modify the content picked from the background knowledge, if needed, so that the conversation remains coherent. We collected around 9K such conversations containing a total of 90K utterances pertaining to about 921 movies. These conversations along with the background resources will be made publicly available1. For every utterance, we also provide information about the exact span in the resource from which this utterance was created. Lastly note that unlike existing datasets, our test set contains multiple reference responses for each test context thereby facilitating better evaluation of conversation models. We believe that this dataset will allow the community to take a fresh look at conversation modeling and will lead to the development of models which can learn to exploit background knowledge to pick appropriate responses instead of generating responses from scratch. Such a conversation strategy which produces responses from background knowledge would be useful in various domains. For example, a troubleshooting bot could exploit the information available in manuals, reviews and previous bug reports about the software. Similarly, an e-commerce bot could exploit the rich information available in product descriptions, reviews, fact tables, etc. about the product. While the proposed dataset is domain specific, it serves as a good benchmark for developing creative background-knowledge-aware models which can then be ported to different domains by building similar datasets for other domains.

We establish some initial baselines using three different paradigms to demonstrate the various models that can be developed and evaluated using this dataset. For the sake of completeness, the first paradigm is a hierarchical variant of the sequence to sequence architecture which does not exploit any background knowledge. The second paradigm is the copy-and-generate paradigm wherein the model tries to copy text from the given resources whenever appropriate and generate it otherwise. The third paradigm borrows from the span prediction based models which are predominantly being used for Question Answering (QA). These baseline results along with the dataset would hopefully shape future research in the area of background aware conversation models.

2 Related Work

There has been an active interest in building datasets (Serban et al., 2015) for training dialog systems. Some of these datasets contain transcripts of human-bot conversations (Williams et al., 2013; Henderson et al., 2014a,b) while others are created using a fixed set of natural language patterns (Bordes and Weston, 2017; Dodge et al., 2016). The advent of deep learning created

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1https://github.com/nikitacs16/Holl-E

Figure 1: A sample chat from our dataset which uses background resources. The chosen spans used in the conversation are shown in blue. The letters in the brackets denote the type of resource that was chosen - P, C, R, F and N indicate Plot, Comments, Review, Fact Table and None respectively.
interest in the construction of large-scale dialog datasets (Lowe et al., 2015b; Ritter et al., 2010; Sordoni et al., 2015) leading to the development of several end-to-end conversation systems (Shang et al., 2015; Vinyals and Le, 2015; Li et al., 2016; Serban et al., 2016) which treat dialog as a sequence generation task.

To make the output of these models more coherent, there is an increasing effort in integrating external background knowledge with these models. This is because human beings rely on background knowledge for conversations as well as other tasks (Schallert, 2002). There has been considerable work on incorporating background knowledge in the context of goal-oriented dialog datasets even before the advent of large-scale datasets for deep learning (Raux et al., 2005; Seneff et al., 1991) as well as in recent times (Rojas-Barahona et al., 2017; Williams et al., 2016; Eric et al., 2017) where datasets include small sized knowledge graphs as background knowledge. However, the conversations in these datasets are very templated and nowhere close to open conversations in specific domains such as the ones contained in our dataset.

Even in the case of open domain conversations, there are some works which have integrated external knowledge sources. Most of the entries in 2017 Amazon Alexa Prize (Ram et al., 2017) relied on background knowledge for meaningful response generation. Milabot (Serban et al., 2017a) and even the winning entry Sound­ingBoard (Liu et al., 2018) used Reddit pages, Amazon’s Evi Service, and large databases like OMDB, Google Knowledge Graph and Wikidata as external knowledge. The submission named Eigen (Guss et al., 2017) used several dialog datasets and corpora belonging to related Natural Language Processing tasks to make their responses more informative. We refer the reader to (Ram et al., 2017) for detailed analysis of these systems. In the space of academic datasets, (Lowe et al., 2015a) report results on the Ubuntu dataset using manpages as external knowledge whereas (Ghazvininejad et al., 2017) use Foursquare tips as external knowledge for social media conversations. However, unlike our work both these works do not create a new dataset where the responses are explicitly linked to a knowledge source. The infusion of external knowledge in both these works is post facto (as opposed to our work where we take a bottom-up approach and explicitly create a dataset which allows exploitation of background knowledge). Additionally, existing large-scale datasets are noisy as they are extracted from online forums which are inherently noisy. In contrast, since we use crowdsourcing, the extent of noise is reduced since there are humans in the loop who were explicitly instructed to use only clean sentences from the external knowledge sources.

We would also like to mention some existing works such as (He et al., 2017; Lewis et al., 2017; Krause et al., 2017) which have used crowdsourcing for creating conversation datasets. In fact, our data collection method is inspired by the work of (Krause et al., 2017) where the authors use self-dialogs to collect conversation data about movies, music and sports. They are referred to as self-dialogs because the same worker plays the role of both parties in the conversation. However, our work differs from (Krause et al., 2017) as we provide explicit background knowledge sources to the workers from where they can copy text with the addition of suitable prefixes and suffixes to generate appropriate coherent responses.

3 Dataset

In the following sub-sections we describe the various stages involved in collecting our dataset.

3.1 Curating a list of popular movies

We created a list of 921 movies containing (i) top 10 popular movies within the past five years, (ii) top 250 movies as per IMDb rankings, (iii) top 10 movies in popular genres, and (iv) other popular movie lists made available elsewhere on the Internet. These movies belonged to 22 different genres such as sci-fi, action, horror, fantasy, adventure, romance, etc. thereby ensuring that our dataset is not limited to a specific genre. We considered those movies for which enough background information such as plots, reviews, comments, facts, etc. were available on the Internet irrespective of whether they were box-office successes or not. Please find the respective urls in the Appendix.

3.2 Collecting background knowledge

For each movie, we collected the following background knowledge:

1. Review (R): For each movie, we asked some in-house workers to fetch the top 2 most popular reviews for this movie from IMDb using the sort
by Total Votes option. We also instructed them to avoid choosing reviews which were less than 50 words but this was typically never the case with popular reviews. 2. Plot (P): For each movie, we extracted information about the “Plot” of the movie from the Wikipedia page of the movie. Wikipedia pages of movies have an explicit section on “Plot” making it easy to extract this information using scripts.

3. Comments (C): Websites like Reddit have a segment called “official discussion page about X” (where X is a movie name) containing small comments about various aspects of movie. We identified such pages and extracted the first comment on every thread on this page. We bundled all these comments into a single text file and refer to it as the resource containing “Comments”. For a few movies, the official discussion page was not present in which case we used the review titles of all the IMDb reviews of the movie as comments. The difference between Reviews and Comments is that a Review is an opinion piece given by one person thus typically exhibiting one sentiment throughout while Comments include opinions of several people about the same movie ensuring that positive, negative and factual aspects of the movie are captured as well as some banter.

4. Meta data or Fact Table (F): For each movie, we also collected factual details about the movie, viz., box office collection, similar movies (for recommendations), awards and tag-lines from the corresponding IMDb pages and Wikipedia Infoboxes. Such information would be useful for inserting facts in the conversation, for example, “Did you know that the movie won an Oscar?”.

We included only 4 fields in our fact table instead of showing the entire Wikipedia Infobox to reduce the cognitive load on turkers who already had to read the plot, reviews and comments of the movie.

3.3 Collecting conversation starters

During our initial pilots, we observed that if we asked the workers to converse for at least 8 turns, they used a lot of the initial turns in greetings and general chit-chat before actually chatting about a movie. To avoid this, we collected opening statements using Amazon Mechanical Turk (AMT) where the task for the workers was to answer the following questions “What is your favorite scene from the movie X?”; “What is your favorite character from the movie X?” and “What is your opinion about the movie X?” (X is the movie name). We paid the workers 0.04$ per movie and showed the same movie to 3 different workers, thereby collecting 9 different opening statements for every movie. By using these statements as conversation starters in our data collection, the workers could now directly start conversing about the movie.

3.4 Collecting background knowledge aware conversations via crowdsourcing

Our aim is to create a conversation dataset wherein every response is explicitly linked to some structured or unstructured background knowledge. Creating such a dataset using dedicated in-house workers would obviously be expensive and time consuming and so we decided to use crowdsourcing. However, unlike other NLP and Vision tasks, where crowdsourcing has been very successful, collecting conversations via crowdsourcing is a bit challenging. The main difficulty arises from the fact that conversation is inherently a task involving two persons but it is hard to get two workers to synchronize and chat on AMT. We did try a few pilot experiments where we setup a server to connect two AMT workers but we found that the probability of two workers simultaneously logging in was very low. Thus, most workers logged in and left in a few seconds because no other worker joined simultaneously. Finally, we took inspiration from the idea of self chats (Krause et al., 2017) in which, the same worker plays the role of both Speaker 1 and Speaker 2 to create the chat. In the above self chat setup, we showed every worker 3 to 4 resources related to the movie, viz., plot (P), review (R), comments (C) and fact table (F). We also showed them a randomly selected opening statement from the 9 opening statements that we had collected for each movie and requested them to continue the conversation from that point. The workers were asked to add at least 8 utterances to this initial chat. While playing the role of Speaker 1, the worker was not restricted to copy/modify sentences from the background resources but was given the freedom to create (write) original sentences. However, when playing the role of Speaker 2, the worker was strictly instructed to copy/modify sentences from the shown resources such that they were relevant in the current context of the conversation. The reason for not imposing any restrictions on Speaker 1 was to ensure that the chats look more natural and
coherent. Further, Speaker 2 was allowed to add words at the beginning or end of the span selected from the resources to make the chats more coherent and natural (for example, see the prefix in utterance 2 of Speaker 2 in Figure 1). We paid the workers 40 cents for every chat. Please refer to the Appendix for the instruction screen shots.

3.5 Verification of the collected chats

Every chat that was collected by the above process was verified by an in-house evaluator to check if the workers adhered to the instructions and produced coherent chats. Since humans typically tend to paraphrase the background knowledge acquired by reading articles, one could argue that such conversations may not look very natural because of this restriction to copy/modify content from the provided resources. To verify this, we conducted a separate human evaluation wherein we asked 15 in-house evaluators to read conversations (without the background resources) from our dataset and rate them on five different parameters. Specifically, they were asked to check if the conversations were 1) **intelligible**: *i.e.*, an average reader could understand the conversation 2) **coherent**: *i.e.*, there were no abrupt context switches 3) **grammatically correct** 4) **on-topic**: *i.e.*, the chat revolved around the concerned movie with digression limited to related movies/characters/actors and 5) **natural two-person chats**: *i.e.*, the role-play setup does not make the chat look unnatural. These evaluators were post-graduate students who were fluent in English and had watched at least 100 Hollywood movies. We did not give them any information about the data creation process. We used a total of 500 chats for the evaluation and every chat was shown to 3 different evaluators. The evaluators rated the conversations on a scale of 1 (very poor) to 5 (very good). We computed inter-annotator agreement using the mean linearly weighted Cohen’s $\kappa$ (Cohen, 1968) and mean Krippendorff’s $\alpha$ (Hayes and Krippendorff, 2007). The average rating for each of the 5 parameters along with the inter annotator agreement are reported in Table 1 and are very encouraging.

### Table 1: Average human evaluation scores with standard deviations for conversations (scale 1-5). We also report mean Krippendorff’s $\alpha$ and mean Cohen’s $\kappa$

| Metric         | Rating ± SD | $\alpha$ | $\kappa$ |
|----------------|-------------|----------|----------|
| Intelligible   | 4.47 ± 0.52 | 0.70     | 0.69     |
| Coherent       | 4.33 ± 0.93 | 0.57     | 0.71     |
| Grammar        | 4.41 ± 0.56 | 0.60     | 0.69     |
| Two-person-chat| 4.47 ± 0.46 | 0.64     | 0.70     |
| On Topic       | 4.57 ± 0.43 | 0.72     | 0.70     |

3.6 Statistics

In Table 2, we show different statistics about the dataset collected using the above process. These include average number of utterances per chat, average number of words per utterance, and so on followed by the statistics of the different resources which were used as background knowledge. Please note that the # unique Plots and # unique Reviews correspond to unique paragraphs while the # unique Comments is the count of unique sentences. We observed that 41.2%, 34.6%, 16.1% and 8.1% of Speaker 2 responses came from Reviews, Comments, Plots and Fact Table respectively.

### Table 2: Statistics of the dataset

| Category               | Value   |
|------------------------|---------|
| #chats                 | 9071    |
| #movies                | 921     |
| #utterances            | 90810   |
| Average # of utterances per chat | 10.01  |
| Average # of words per utterance | 15.29  |
| Average # of words per chat | 153.07 |
| Average # of words in Plot | 186.10 |
| Average # of words in Review | 384.44 |
| Average # of words in Comments | 123.81 |
| Average # of words in Fact Table | 33.47  |
| # unique Plots         | 5157    |
| # unique Reviews       | 1817    |
| # unique Comments      | 12740   |

4 Models

We evaluate three different types of models as described below. Since these are popular existing models, we describe them very briefly below and refer the reader to the original papers for more details. Note that in this work we merge the comments, reviews, plots and facts into one single document and refer to it as background knowledge. In the rest of the paper, when we refer to a *resource* we mean this single document which is a merger of all the resources unless specified otherwise.

4.1 Generation based models

We use the standard Hierarchical Recurrent Encoder Decoder model (HRED) (Serban et al., 2016) instead of its variant (Serban et al., 2017b)
as the standard model performs only slightly poorly than the variant and is much easier to implement. It decomposes the context of the conversation as two level hierarchy using Recurrent Neural Networks (RNN). The lower RNN encodes individual utterances (sequence of words) which is then fed into the higher level RNN as a sequence of utterances. The decoder RNN then generates the output based on this hierarchical context representation.

4.2 Generate-or-Copy models

Get To The Point (GTTP) (See et al., 2017) proposed a hybrid pointer generator network for abstractive summarization that learns to copy words from the source document when required and otherwise generates a word like any sequence-to-sequence model. In the summarization task, the input is a document and the output is a summary whereas in our case the input is a \{document, context\} pair and the output is a response. Here, the context includes the previous two utterances and the current utterance. We modified the architecture to suit our task. We use an RNN to compute the representation of the document (like the original model) and introduce another RNN to compute a representation of the context by treating it as a single sequence of words. The decoder which is also an RNN then uses the document representation, context representation and its own internal state representation to compute a (i) probability score which indicates whether the next word should be copied or generated (ii) probability distribution over the vocabulary if the next word needs to be generated and (iii) probability distribution over the input words if the next word needs to be copied. These three probability distributions are then combined to produce the next word in the response.

5 Experimental Setup

In this section we describe the train-validation-test splits, the process used for creating training instances, the manner in which the models were trained using our data and the evaluation metrics.

5.1 Creating train/valid/test splits

On average we have 9.14 chats per movie. We divide the collected chats into train, validation, and test splits such that all the chats corresponding to a given movie are in exactly one of the splits. This ensures that a movie seen in the test or validation set is never seen at training time. We create the splits such that the percentage of chats in the train-validation-test set is roughly 80%-10%-10%.

5.2 Creating training instances

For each chat in the training data, we construct training instances of the form \{resource, context, response\} where the context is taken as previous two utterances and current utterance. We consider only the even numbered utterances as training examples as they are generated from the background resources thus emulating a human-bot setup. If a chat has 10 turns, we will have 5 instances. The task then is to train a model which can predict these even numbered responses. At test time the model is shown \{resource, context\} and predicts the response. Note that, HRED will ignore the resource and only use \{context, response\} as input-output pairs. BiDAF and GTTP will use \{resource, context, response\} as training data with relevant span instead of response for BiDAF.

5.3 Merging resources into a single document

As stated earlier, we simply merge all the background information to create a single document which we collectively refer to as resource. For the BiDAF model, we had to restrict the length of the resource to 256 words because we found that even on a K80 GPU with 12GB RAM, this model gives an out of memory error for longer
documents. We found this to be a severe limitation of this and other span based models (for example, R-Net (Wang et al., 2017)). We experimented with three methods of creating this resource. The first method \textit{oracle} uses the actual resource (plot or comments or reviews) from which the next response was generated as a resource. If that resource itself has more than 256 words then we truncate it from the beginning and the end such that the span containing the actual response is contained within the retained 256 words. The number of words that are discarded from the start or the end is chosen at random so that the correct spans do not end up in similar positions throughout the dataset. The next two methods \textit{mixed-short} and \textit{mixed-long} are created by merging the individual resources. We retain each resource in the merged document proportional to its length. (\textit{i.e.,} if there are 400 words in the plot, 200 words in the review and 100 in the comments, the merged resource will contain contiguous sentences from these three resources in the ratio of 4:2:1.) Further, we ensure that the merged resource contains the actual response span. In this way, we create \textit{mixed-short} with 256 words and \textit{mixed-long} with 1200 words (the maximum length of the merged resources). We will henceforth denote \textit{oracle}, \textit{mixed-long} and \textit{mixed-short} using \textit{'(o)'}, \textit{'(ms)'} and \textit{'(ml)' respectively. We report results for BiDAF(o), BiDAF (ms), GTTP (o) and GTTP (ml).

5.4 Evaluation metrics

As HRED and GTTP models are generation based models we use BLEU-4, ROUGE-1, ROUGE-2 and ROUGE-L as the evaluation metrics. For BiDAF we use the above metrics by comparing the predicted span with the reference span. For BiDAF, we also report F1 as stated in (Rajpurkar et al., 2016).

In addition to the automatic evaluation, we also collected human judgments using 100 test responses generated for every model for every setup (oracle, mixed-short, mixed-long). These evaluators had the same qualifications as the evaluators who earlier helped us evaluate our dataset. They were asked to rate the response on scale of 1 to 5 (with 1 being the least) on the following four metrics: (1) Fluency(Flu), (2) appropriateness/relevance (apt) of the response in the current context language (3) humanness (Hum) of the response, \textit{i.e.,} whether the responses look as if they were generated by a human (4) and specificity (spec) of the response, \textit{i.e.,} whether the model produced movie-specific responses or generic responses such as “This movie is amazing”. We report these results in Table 4.

5.5 Collecting multiple reference responses

One common issue with evaluating dialog systems is that existing datasets typically contain only one reference response whereas in practice several responses can be correct in a given context. To solve this to a certain extent, we collected three reference responses for every Speaker 2 utterance in our dataset (note that Speaker 2 is treated as the bot while training/testing our models). We show the previous utterances ending with Speaker 1’s response and ask workers to provide three appropriate responses from the given resources. We found that in some cases there was only one appropriate response like factual response and the workers could not provide multiple references. In this way we were able to create a multiple reference test set where 78.04% of the test instances have multiple responses. In Table 3, we report two sets of scores based on single-reference test dataset and multi-reference test dataset. While calculating the scores for multi-reference dataset, we take the maximum score over multiple reference responses.

Please refer to the Appendix section for the details of the model, hyperparameters, example of multiple references in our dataset and sample outputs produced by different models.

6 Results and Discussion

In this section, we discuss the results of our experiments as summarized in Tables 3 and 4.

\textbf{Generation based models v/s Span prediction models:} We compare the generation based models and span prediction models only based on results in the \textit{oracle} setting. Here, the span based model (BiDAF) outperforms the generation based models (HRED and GTTP). This confirms our belief that the natural language generation (NLG) capabilities of current generation based models are far from being acceptable even in case of generate-or-copy modes. This also emphasizes the importance of this data which allows building models which can exploit well-formed sentences in the background knowledge and reproduce them with minor modifications instead of generating them from scratch. While the results for BiDAF are
Table 3: Performance of the proposed models on our dataset. The figures on the left in each column indicate scores on single-reference test dataset while the figures on the right denote scores on multi-reference dataset.

| Model      | F1   | BLEU  | Rouge-1 | Rouge-2 | Rouge-L  |
|------------|------|-------|---------|---------|----------|
| HRED       | -    | -     | 5.23    | 5.38    |          |
| GTTP (o)   | 13.92| 16.46 | 30.32   | 31.6    | 17.78    |
| GTTP (ms)  | 11.05| 15.68 | 29.66   | 31.71   | 17.70    |
| GTTP (ml)  | 7.51 | 8.73  | 23.20   | 21.55   | 9.91     |
| BiDAF (o)  | 39.69| 47.18 | 39.68   | 46.49   | 33.72    |
| BiDAF (ms) | 45.73| 51.35 | 45.69   | 50.73   | 40.18    |

Table 4: Human evaluation results on the model performances.

| Model      | Hum | Apt | Flu | Spec |
|------------|-----|-----|-----|------|
| HRED       | 3.08| 2.49| 2.64| 2.06 |
| GTTP (o)   | 4.10| 3.73| 4.03| 3.33 |
| GTTP (ml)  | 2.93| 2.97| 3.42| 2.60 |
| BiDAF (o)  | 3.78| 3.71| 4.05| 3.76 |
| BiDAF (ms) | 3.41| 3.38| 3.47| 3.30 |

encouraging, we reiterate that it does not scale to longer documents (we were not able to run it in the mixed-long setting). We still need much better models as BiDAF on SQuAD dataset gives an F1 of 81.52% which is much higher than the results on our dataset. Further, note that using the predicted span as a response is not natural. This is evident from human likeliness (Hum) score of GTTP (o) being higher than both the BiDAF models. We need models which can suitably alter the span to retain the coherence of the context.

**Effect of including background knowledge:** We observe that there isn’t much difference between the performance of HRED which does not use any background knowledge when compared to GTTP (ml) which actually uses a lot of background knowledge. However, there is a substantial difference between the performance of HRED and GTTP (o) which uses only the relevant background knowledge. Further, without background knowledge, HRED learns to produce very generic responses (Spec score = 2.06). This shows that the background knowledge is important, but the models should learn to focus on the right background knowledge relevant to the current context. Alternatively, we can have a two-stage network which first predicts the right resource (plot, review, comments) from which the span should be selected and then selects the span from this chosen resource.

**Oracle vs mixed-short resource:** We observe that the performance of BiDAF (ms) is actually better than BiDAF (o) even when the resource length for both is 256 words. We would expect a poor performance for BiDAF (ms) as the resource has more noise because of the sentences from irrelevant resources. However, we speculate the model learns to regard irrelevant sentences as noise and learns to focus on sentences corresponding to the correct resource resulting in improved performance (however, this is only a hypothesis and it needs to be verified). We realize that this is clearly a poor baseline and we need better span prediction based models which can work with longer documents. At the same time, GTTP (o) and GTTP (ms) have comparable (yet poor) performance. There is no co-attention mechanism in this model which can effectively filter out noisy sentences.

**Observations from the copy-and-gen model:** We observed that this model produced sentences where on average of 82.18% (oracle) and 71.95% (mixed-long) of the tokens were copied. One interesting observation was that it easily learns to copy longer contiguous sequences one word at a time. However, as is evident from the automatic evaluation metrics, in many cases, the ‘copied’ spans are not relevant to the current context.

**Evaluating with multiple references:** When considering multiple references, the performance numbers as reported in Table 3 indeed improve. This shows the importance of having multiple references and the need to develop metrics which account for multiple dissimilar references.

7 Conclusion

We introduce a new dataset for building dialog systems which would hopefully allow the community to take a fresh look at this task. Unlike existing datasets which only contain a sequence of utterances, in our dataset each response is explic-
Itly linked to some background knowledge. This mimics how humans converse by recalling information from their background knowledge and use it appropriately in the context of the conversation. Using this dataset, we evaluated models belonging to three different paradigms, viz., generation based models, generate-or-copy models and span prediction models. Our results suggest that the NLG capabilities of existing seq-to-seq models are still far from desirable while span based models which completely bypass the process of NLG show some promise but with clear scope for improvement.

Going forward, we would like to build models which are a hybrid of span prediction models and generation models. Specifically, we would like to build models which can learn to copy a large sequence from the input instead of one word at a time. Another important aspect is to build less complex models which can handle longer documents. For example, the BiDAF model has an expensive outer product between two large matrices which makes it infeasible for long documents (because the size of these matrices grows with the length of the document). Alternately, we would like to build two-stage models which first select the correct resource from which the next response is to be generated and then generate or copy the response from the resource.

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Appendix

Model details - GTTP

Since we modified the existing architecture of Get to the Point (See et al., 2017), we now provide details of the same. In the summarization task, the input is a document and the output is a summary whereas in our case the input is a \{resource/document, context\} pair and the output is a response. Note that the context includes the previous two utterances (dialog history) and the current utterance. Since, in both the tasks, the output is a response, we provide details of the same. In the summarization task, the input is a document. In the Get to the Point (See et al., 2017), we now provide details of the same.

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Let \( N \) be the length of the document then the RNN computes representations \( h_1^r, h_2^r, \ldots, h_N^r \) for all the words in the resource (we use the superscript \( r \) to indicate resource). The final representation of the resource is then the attention weighted sum of these word representations:

\[
\begin{align*}
    e_t^r &= v^T \tanh(W_r h_t^r + U s_t + b_r) \\
    a_t^r &= \text{softmax}(e_t^r) \\
    r_t &= \sum_i a_t^r h_i^r
\end{align*}
\]

where \( s_t \) is the state of the decoder at the current time step. In addition, in our case, we also have the context of the conversation apart from the document (resource). Once again, we use an RNN to compute a representation of this context. Specifically, we consider the previous \( k \) utterances as a single sequence of words and feed these to an RNN. Let \( M \) be the total length of the context (i.e., all the \( k \) utterances taken together) then the RNN computes representations \( h_1^c, h_2^c, \ldots, h_M^c \) for all the words in the context (we use the superscript \( c \) to indicate context). The final representation of the context is then the attention weighted sum of these word representations:

\[
\begin{align*}
    f_t^c &= v^T \tanh(W_c h_t^c + V s_t + b_c) \\
    m_t^c &= \text{softmax}(f_t^c) \\
    c_t &= \sum_i m_t^c h_i^c
\end{align*}
\]

where \( s_t \) is the state of the decoder at the current time step.

The decoder then uses \( r_t \) (document representation), \( c_t \) (context representation) and \( s_t \) (decoder’s internal state) to compute a probability distribution over the vocabulary \( P_{\text{vocab}} \). In addition the model also computes \( p_{\text{gen}} \) which indicates that there is a probability \( p_{\text{gen}} \) that the next word will be generated and a probability \((1 - p_{\text{gen}})\) that the next word will be copied. We use the following modified equation to compute \( p_{\text{gen}} \)

\[
p_{\text{gen}} = \sigma(w_r^T r_t + w_c^T c_t + w_s^T s_t + w_x^T x_t + b_g) \tag{3}
\]

where \( x_t \) is the previous word predicted by the decoder and fed as input to the decoder at the current time step. Similarly, \( s_t \) is the current state of the decoder computed using this input \( x_t \). The final probability of a word \( w \) is then computed using a combination of two distributions, viz., \((P_{\text{vocab}})\) as described above and the attention weights assigned to the document words as shown below

\[
P(w) = p_{\text{gen}} P_{\text{vocab}}(w) + (1 - p_{\text{gen}}) \sum_{i: w_i = w} a_i^t \tag{4}
\]

where \( a_i^t \) are the attention weights assigned to every word in the document as computed in Equation 1. Thus, effectively, the model could learn to copy a word \( i \) if \( p_{\text{gen}} \) is low and \( a_i^t \) is high.

Example from the multiple reference test set

As seen from the Table 5, the given chat on “Secret Life of Pets” can have multiple responses for Speaker 2. Notice how Reference 1 talks against low critique scores thus emphasizing that he was totally impressed by the movie while Reference 4 has neutral opinion about the same. At the same time, Reference 3 talks about movie specific details like his favorite character while Reference 4 gives a personal opinion. All these four responses are valid given the current context.

Hyper-parameters

We describe the hyperparameters that we used for each model in this sub section. Following the original paper, we trained the HRED model using Adam (Kingma and Ba, 2014) optimizer with an initial learning rate of 0.001 on a minibatch of size 16. We used a dropout (Srivastava et al., 2014)
The Secret Life of Pets

Chat
Speaker1: What do you think about the movie?
Speaker2: I think it was comical and entertaining.
Speaker1: It delivered what was promised.

Reference 1
I agree! I’m surprised this film got such a low overall score by users.

Reference 2
My favorite character was Gidget! She was so much fun and so loyal to her friends!

Reference 3
Yes! As a Great Dane owner, I often wonder what my dogs are thinking.

Reference 4
It was full of cliches with a predictable story, but with some really funny moments.

Table 5: Multiple references for the given chat.

| Movie Name                   | The Secret Life of Pets |
|------------------------------|-------------------------|
| Chat                         |                         |
| Speaker1: What do you think about the movie? |                         |
| Speaker2: I think it was comical and entertaining. |                         |
| Speaker1: It delivered what was promised. |                         |
| Reference 1                  | I agree! I’m surprised this film got such a low overall score by users. |
| Reference 2                  | My favorite character was Gidget! She was so much fun and so loyal to her friends! |
| Reference 3                  | Yes! As a Great Dane owner, I often wonder what my dogs are thinking. |
| Reference 4                  | It was full of cliches with a predictable story, but with some really funny moments. |

with a rate of 0.25. For word embeddings we use pre-trained GloVe \cite{Pennington:2014} embeddings of size 300. For all the encoders and decoders in the model we used Gated Recurrent Unit (GRU) with 300 as the size of the hidden state. We restricted our vocabulary size to 20,000 most frequent words.

We followed the hyperparameters mentioned in the original paper and trained GTTP using Adagrad \cite{Duchi:2011} optimizer with an initial learning rate of 0.15 and an initial accumulator value of 0.1 on a minibatch of size 16. For the encoders and decoders we used LSTMs with 256 as the size of the hidden state. To avoid vanishing and exploding gradient problem we use gradient clipping with a maximum gradient norm of 2. We used early stopping based on the validation loss.

Again following the original paper, we trained BiDAF using AdaDelta \cite{Zeiler:2012} optimizer with an initial learning rate of 0.5 on a minibatch of size 32. For all encoders, we use LSTMs with 256 as the size of the hidden state. We used a dropout \cite{Srivastava:2014} rate of 0.2 across all LSTM layers, and for the linear transformation before the softmax for the answers. For word embeddings we use pre-trained GloVe embeddings of size 100. For both GTTP and BiDAF, we had to restrict context length to 65 tokens for fair comparison. Note that GTTP can scale beyond 65 tokens but BiDAF cannot.

**Sample responses produced by the models**

As seen from Table 6, HRED isn’t able to produce responses that correspond to the given movie or the given context as it lacks any notion of background knowledge associated with it. We will not consider HRED for the following discussion. In Example 1, we can clearly see that only GTTP (oracle) matches with the ground truth. The remaining three models produce varied outputs which are still relevant to the context. In Example 2, we observe that prediction based models produce appropriate recommendation because of better context-document mapping mechanisms. Both the GTTP models produce responses which are copied but irrelevant to the context. At the same time, just producing spans without any structure isn’t natural. This explains the need for hybrid models.

Data Collection Interfaces used on Amazon Mechanical Turk

As explained in the paper, we resorted to AMT for three types of data collection viz. collection of opening statements as discussed in stage 3 of the dataset collection (Figure 6), the actual chat data collection explained in stage 4 of the procedure and additional responses collected for the test dataset. We will now show the instruction screens. The html files for the same will be released along with the code.
| Movie        | Example 1 (Creed)                                                                 | Example 2 (Ted)                                                                 | Example 3 (Jaws)                                                                 |
|-------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Context     | S1: Which was the best scene in the movie according to you?                      | S2: The scene where they’re yelling at each other out the window was gold       | S1: What do you think about the characters in this movie?                        |
|             | S2: I liked the one in which Rocky trains and runs.                               | S1: Thats a similar scene from family guy. I couldn’t stop laughing.            | S2: My favorite character was Brody, he was such a fun character.                |
|             | S1: It was great when the match commences, and although Donnie takes a few hits,  | S2: I thought every scene was gold. I also couldn’t believe Liam Neeson was     | S1: I didn’t get Quint’s backstory.                                               |
|             | he defeats Leo.                                                                   | in the movie.                                                                    |                                                                                  |
|             | S2: Creed goes the distance as an exceptional crowd pleaser.                      | S1: I will love to pick something similar this evening. Do you have a           |                                                                                  |
|             | S1: I agree with grit, style and substance. There’s no other way to say it; Creed| recommendation?                                                                  |                                                                                  |
|             | is a knockout from start to finish.                                               |                                                                                  |                                                                                  |
| Ground Truth| It wholeheartedly captures what was so brilliant about the first film: the      | Yes. You can try 22 Jump Street.                                                 | Quint, aboard that ship in World War II when it was sunk by torpedoes, had       |
|             | characters.                                                                       |                                                                                  | witnessed the deaths of roughly 800 men that day, many of whom were eaten by    |
|             |                                                                                  |                                                                                  | sharks as they struggled helplessly in the water.                                |
| HRED        | yeah, but as the ark is launched, and you are right taxi driver, runs with the  | the plot is a classic in the film, it ’s not that it ’s an original and cinematic| i ’m not ashamed to admit it, mary poppins is bangin ! ! !                       |
|             | beauty, <UNK><UNK>, and <UNK><UNK>.                                                | experience.                                                                     |                                                                                  |
| BiDAF(o)    | I can’t say enough great things about writer / director Ryan Coogler.              | The Hangover                                                                    | Hooper notices the shark beginning to circle the boat, and Quint rushes out for  |
| BiDAF(ms)   |                                                                                  |                                                                                  | a look.                                                                          |
| GTTP(o)     | it wholeheartedly captures what was so brilliant about the first film: the       | $ 218,628,680 i think .                                                          | Brody is stunned and alerts quint .                                              |
|             | characters .                                                                      |                                                                                  |                                                                                  |
| GTTP(ml)    | i can’t say enough great things about writer / director ryan coogler .             | this movie had way too much product placement .                                 | Jaws’ is the original summer blockbuster                                         |

Table 6: Examples produced by various models. S1 denotes Speaker1 while S2 denotes Speaker2. ‘o’,‘ml’ and ‘ms’ represent oracle, mixed-long and mixed-short versions of the dataset respectively.
Instructions

Imagine you are chatting with a friend about the movie $(movie\_name)$. For the given conversation, fill in appropriate response by picking up a sentence from the given passage so that it fits in with the conversation. Wikipedia page about the movie can be found here.

Please keep the following rules in mind:

1. You need to provide three appropriate responses.
2. If there are two passages, try to pick one response each from either of them.
3. You can pick full sentence or a part of the sentence but do not change the order of words in the given sentence.
4. You are free to add words at the start of the sentence or at the end of the sentence to improve the quality of the response.

Example: Interstellar

Document

Honesty, it was so beautiful that I felt like I was sucked into the movie. We can feel the talent of Christopher Nolan, just by looking at the way it is filmed. The techniques he used contribute to create that visual environment in a believable way. The sound environment is just mesmerizing. It is a very important part of the movie, because some scenes take place in space, and Nolan just found the right way to use sound. The soundtrack (made by the great Hans Zimmer) is breathtaking, epic, amazing, unreal. I could find a lot more adjectives to qualify it, but you have to hear it to understand how epic they are. These two important parts (image and sound) create a stunning atmosphere. You will forget you are in a movie theater, and you will be lost in space, sucked into the adventures of this new Space Odyssey, begging for more. It is a truly unique experience.

Chat

Speaker1: What do you think about this movie?
Speaker2: It is a well-crafted movie. Loved it!

Speaker1: Christopher Nolan is a genius filmmaker.

Response

Response 1: We can feel the talent of Christopher Nolan, just by looking at the way it is filmed. Response 2: Such is the beauty of Nolan’s direction. You will forget you are in a movie theater, and you will be lost in space. Response 3: Indeed. Nolan just found the right way to use sound. The background score was beautiful.

Notice how in Response1, Speaker2 continues the appreciating Christopher Nolan, in Response2 Speaker2 is a bit exaggerating about his experience and in Response3, Speaker2 appreciates Nolan by highlighting the beauty of background score in the movie. All the above responses are apt in this conversation. The words in green are added to improve the quality of response.

Figure 2: Instruction screen for collection of multiple-responses for the same chat for the test dataset.

Figure 3: Instruction screen for chat data collection from Phase 4 of the dataset collection procedure.
For example, consider the conversation on Dunkirk

**Plot:**

The British navy requisitions civilian vessels that can get close to the beach. In Weymouth, Mr. Dawson and his son Peter set out on his boat Moonstone rather than let the navy take it. Impulsively, their teenage friend George joins them. At sea, they rescue a shell-shocked officer from a wrecked ship. When he realises that Dawson is sailing for Dunkirk, the officer demands that they turn back, and tries to wrest control of the boat; in the struggle, George suffers a head injury that renders him blind.

**Review:**

Dunkirk is edge of your seat filmmaking. Can honestly say I've never seen anything like it. A lot of people were wondering about Harry _styles & unknown cast_. They're all great but Dunkirk is not about any one soldier. Also Dunkirk is another brilliant collaboration between Nolan & HansZimmer. The way he mixes in a ticking clock with score is nail biting. DUNKIRK relies on very little dialogue. We all know what happened on that beach, but Nolan's take is worth visiting. Yes, DUNKIRK relies heavily on sound of an increasingly fast ticking clock to build suspense. Drop everything and go watch Dunkirk. It is an experience. Not a mere film.

**Comment:**

This is a very important movie, because it doesn't glamorize or glorify war.

I think the movie was brilliant.

Just awesome! Simply awesome!

Hans Zimmer did really great with the score and it really was an immersive experience

**Fact Table:**

| Tagline                        | Hope is a weapon. Survival is victory. The event that shaped our world. |
|-------------------------------|-------------------------------------------------------------------------|
| **Similar Movies**            | Saving Private Ryan  |
|                               | Interstellar  |
|                               | The Sea Wolves |

**Figure 4: Background resources for the example chat shown to the workers on AMT**

**Conversation**

Speaker1 (N): What do you think about the movie?
Speaker2 (C): I think the movie was brilliant.
Speaker1 (N): Agreed! One of the finest in this genre. (A casual sentence to start expressing your thoughts about the same.)
Speaker2 (C): I believe the best part about the movie is that it doesn't glamorize or glorify war. (picked from a review - the words I believe are inserted at the beginning to make the conversation coherent)
Speaker1 (N): Totally! Oh by the way do you remember the name of the ship headed by Mr. Dawson? (Speaker1 listens and appreciates Speaker2's thoughts and continues discussing with a new aspect, in this case small details about the movie. Speaker 1 deliberately creates a question which can be answered from the plot)
Speaker2 (P): Yes. It was Moonstone. (This can be inferred only if you read the plot)
Speaker1 (N): Right. I am always impressed by the Nolan - Hans Zimmer collaboration. (Speaker1 gets the answer, but there's no need of elaborating on Moonstone further. Hence Speaker1 talks about the people behind the movie - once again paving way for the next utterance to be picked up from the given resources)
Speaker2 (R): The way he mixes in a ticking clock with score is nail biting. (Speaker2 continues appreciating Hans Zimmer.)
Speaker1 (N): Some of the scenes seem so real, I feel I was present right there at that very moment. (Speaker1 creates a sentence which connects well to the previous utterance)
Speaker2 (R): To sum it up, it is an experience. Not a mere film (Speaker 2 intelligently picks a sentence from the resources and gives a nice conclusion about his opinion on the film.)
Speaker1 (N): That's an interesting way to put it. Can you recommend any other movies?
Speaker2 (F): You should check out Saving Private Ryan. (Based on the "Similar Movies" from the fact table, Speaker 2 recommends another movie.)

**Figure 5: Example chat shown to the workers on AMT**
Instructions

Below you have been asked 4 questions about a specific movie. Your answer to each question should begin with a specific phrase as mentioned below. You can refer to the wikipedia page of the movie here.

What was your favourite scene from the movie [MOVIE]? (click on the movie name to open the wikipedia page of the movie)
Your answer should begin with the phrase "I liked the one in which":

What do you think about the movie [MOVIE]? 
Your answer should begin with the phrase "I think it was":

Which character from the movie [MOVIE] do you like the most and why?
Your answer should begin with "My favorite character was":

Ask a question about the plot of the movie [MOVIE] which can only be answered by someone who has actually watched the movie carefully.
Your answer should begin with "Do you remember what [event/lot/...]? (for example, "Do you remember who killed Jack in the movie?")

Figure 6: Instruction screen for opening statement collection from the stage of the dataset collection procedure

References

Antoine Bordes and Jason Weston. 2017. Learning end-to-end goal-oriented dialog. *International Conference on Learning Representations*.

Jacob Cohen. 1968. Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. *Psychological bulletin*, 70(4):213.

Jesse Dodge, Andreea Gane, Xiang Zhang, Antoine Bordes, Sumit Chopra, Alexander H. Miller, Arthur Szlam, and Jason Weston. 2016. Evaluating prerequisite qualities for learning end-to-end dialog systems. *International Conference on Learning Representations*, abs/1511.06931.

John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, 12(Jul):2121–2159.

Mihail Eric, Lakshmi Krishnan, Francois Charette, and Christopher D. Manning. 2017. Key-value retrieval networks for task-oriented dialogue. In *Proceedings of the 18th Annual SIGDIAL Meeting on Discourse and Dialogue*, Saarbrücken, Germany, August 15-17, 2017, pages 37-49.

Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley. 2017. A knowledge-grounded neural conversation model. *CoRR*, abs/1702.01932.

William H. Guss, James Bartlett, Phillip Kuznetsov, and Piyush Patil. 2017. Eigen: A step towards conversational ai. *Alexa Prize Proceedings*.

Andrew F Hayes and Klaus Krippendorff. 2007. Answering the call for a standard reliability measure for coding data. *Communication methods and measures*, 1(1):77–89.

He He, Anusha Balakrishnan, Mihail Eric, and Percy Liang. 2017. Learning symmetric collaborative dialogue agents with dynamic knowledge graph embeddings. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017*, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 1766–1776.

Matthew Henderson, Blaise Thomson, and Jason D. Williams. 2014a. The second dialog state tracking challenge. In *Proceedings of the SIGDIAL 2014 Conference, The 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, 18-20 June 2014, Philadelphia, PA, USA, pages 263–272.

Matthew Henderson, Blaise Thomson, and Jason D. Williams. 2014b. The third dialog state tracking challenge. In *2014 IEEE Spoken Language Technology Workshop, SLT 2014*, South Lake Tahoe, NV, USA, December 7-10, 2014, pages 324–329.

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980.

Ben Krause, Marco Damonte, Mihai Dobre, Daniel Duma, Joachim Fainberg, Federico Fancellu, Emmanuel Kahembwe, Jianpeng Cheng, and Bonnie L. Webber. 2017. Edina: Building an open domain socialbot with self-dialogues. *Alexa Prize Proceedings*.

Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? end-to-end learning of negotiation dialogues. In *Proceedings of
the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017, pages 2443–2453.

Jiwei Li, Michel Galley, Chris Brockett, Georgios P. Spithourakis, Jianfeng Gao, and William B. Dolan. 2016. A persona-based neural conversation model. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL 2016, August 7-12, 2016, Berlin, Germany, Volume 1: Long Papers, pages 994–1003.

Yang Liu, Tim Paek, and Manasi Patwardhan, editors. 2018. Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 2-4, 2018, Demonstrations. Association for Computational Linguistics.

Ryan Lowe, Nissan Pow, Iulian Serban, Laurent Charlin, and Joelle Pineau. 2015a. Incorporating unstructured textual knowledge sources into neural dialogue systems. In Neural Information Processing Systems Workshop on Machine Learning for Spoken Language Understanding.

Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. 2015b. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In Proceedings of the SIGDIAL 2015 Conference, The 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2-4 September 2015, Prague, Czech Republic, pages 285–294.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In EMNLP, volume 14, pages 1532–1543.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100, 000+ questions for machine comprehension of text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, EMNLP 2016, Austin, Texas, USA, November 1-4, 2016, pages 2383–2392.

Ashwin Ram, Rohit Prasad, Chandra Khatri, Anu Venkatesh, Raeret Gabriel, Qing Liu, Jeff Nunn, Behnam Hedayatnia, Ming Cheng, Ashish Nagar, Eric King, Kate Bland, Amanda Wartick, Yi Pan, Han Song, Sk Jayadevan, Gene Hwang, and Art Petigruce. 2017. Conversational AI: the science behind the alexa prize. Alexa Prize Proceedings.

Antoine Raux, Brian Langner, Dan Bohus, Alan W. Black, and Maxine Eskénazi. 2005. Let’s go public! taking a spoken dialogue system to the real world. In INTERSPEECH 2005 - Eurospeech, 9th European Conference on Speech Communication and Technology, Lisbon, Portugal, September 4-8, 2005, pages 885–888.

Alan Ritter, Colin Cherry, and Bill Dolan. 2010. Unsupervised modeling of twitter conversations. In Human Language Technologies: Conference of the North American Chapter of the Association of Computational Linguistics, Proceedings, June 2-4, 2010, Los Angeles, California, USA, pages 172–180.

Lina Maria Rojas-Barahona, Milica Gasic, Nikola Mrksic, Pei-Hao Su, Stefan Ultes, Tsung-Hsien Wen, Steve J. Young, and David Vandyke. 2017. A network-based end-to-end trainable task-oriented dialogue system. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2017, Valencia, Spain, April 3-7, 2017, Volume 1: Long Papers, pages 438–449.

Diane L. Schallert. 2002. Schema theory. Literacy in America: An encyclopedia of history, theory, and practice Santa Barbara, CA, pages 556–558.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 1073–1083.

Stephanie Seneff, James R. Glass, David Goddeau, David Goodine, Lynette Hirschman, Hong C. Leung, Michael S. Phillips, Joseph Polilroni, and Victor Zue. 1991. Development and preliminary evaluation of the MIT ATIS system. In Speech and Natural Language, Proceedings of a Workshop held at Pacific Grove, California, USA, February 19-22, 1991.

Min Joon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannanah Hajishirzi. 2017. Bidirectional attention flow for machine comprehension. International Conference on Learning Representations.

Iulian Vlad Serban, Ryan Lowe, Peter Henderson, Laurent Charlin, and Joelle Pineau. 2015. A network-based end-to-end trainable task-oriented dialogue system. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 438–449.

Iulian Vlad Serban, Chinnadhurai Sankar, Mathieu Germain, Saizheng Zhang, Zhouhan Lin, Sandeep Subramanian, Taesup Kim, Michael Pieper, Sarath Chandar, Nan Rosemary Ke, Sai Mudumba, Alexandre de Brébisson, Jose Sotelo, Dendi Suhubdy, Vincent Michalski, Alexandre Nguyen, Joelle Pineau, and Yoshua Bengio. 2017a. The octopus approach to the alexa competition: A deep ensemble-based socialbot. Alexa Prize Proceedings.

Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C. Courville, and Joelle Pineau. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016, Phoenix, Arizona, USA., pages 3776–3784.
Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. 2017b. A hierarchical latent variable encoder-decoder model for generating dialogues. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA., pages 3295–3301.

Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. Neural responding machine for short-text conversation. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, ACL 2015, July 26-31, 2015, Beijing, China, Volume 1: Long Papers, pages 1577–1586.

Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. In NAACL HLT 2015, The 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Denver, Colorado, USA, May 31 - June 5, 2015, pages 196–205.

Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1):1929–1958.

Oriol Vinyals and Quoc V. Le. 2015. A neural conversational model. In Proceedings of ICML Deep Learning Workshop, 2015.

Wenhui Wang, Nan Yang, Furu Wei, Baobao Chang, and Ming Zhou. 2017. Gated self-matching networks for reading comprehension and question answering. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 189–198.

Jason D. Williams, Antoine Raux, and Matthew Henderson. 2016. The dialog state tracking challenge series: A review. D&D, 7(3):4–33.

Jason D. Williams, Antoine Raux, Deepak Ramachandran, and Alan W. Black. 2013. The dialog state tracking challenge. In Proceedings of the SIGDIAL 2013 Conference, The 14th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 22-24 August 2013, SUPELEC, Metz, France, pages 404–413.

Matthew D. Zeiler. 2012. ADADELTA: an adaptive learning rate method. CoRR, abs/1212.5701.