Key-Value Retrieval Networks for Task-Oriented Dialogue

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Abstract

Neural task-oriented dialogue systems often struggle to smoothly interface with a knowledge base. In this work, we seek to address this problem by proposing a new neural dialogue agent that is able to effectively sustain grounded, multi-domain discourse through a novel key-value retrieval mechanism. The model is end-to-end differentiable and does not need to explicitly model dialogue state or belief trackers. We also release a new dataset of 3,031 dialogues that are grounded through underlying knowledge bases and span three distinct tasks in the in-car personal assistant space: calendar scheduling, weather information retrieval, and point-of-interest navigation. Our architecture is simultaneously trained on data from all domains and significantly outperforms a competitive rule-based system and other existing neural dialogue architectures on the provided domains according to both automatic and human evaluation metrics.

1 Introduction

With the success of new speech-based human-computer interfaces, there is a great need for effective task-oriented dialogue agents that can handle everyday tasks such as scheduling events and booking hotels. Current commercial dialogue agents are often brittle pattern-matching systems which are unable to maintain the kind of flexible conversations that people desire. Neural dialogue agents present one of the most promising avenues for leveraging dialogue corpora to build statistical models directly from data by using powerful distributed representations (Bordes and Weston, 2016; Wen et al., 2016b; Dhingra et al., 2016).

Event	Time	Date	Party	Agenda
opt. appt.	10am	Thursday	sister	-
dinner	8pm	the 13th	Ana	-
opt. appt.	7pm	the 20th	Jeff	-
opt. appt.	4pm	the 13th	Alex	-
...	...	...	...	...

DRIVER: I need to find out the time and parties attending my optometrist appointment.
CAR: I have 3 appointments scheduled, with Alex, your sister, and Jeff. Which are you referring to?
DRIVER: I want to know about the one that Alex is joining me at
CAR: That optometrist appointment is at 4 pm.
DRIVER: Thanks
CAR: no problem

Figure 1: Sample dialogue from our dataset. Note some columns and rows from the knowledge base are not included due to space constraints. A dash indicates a missing value.

While this work has been somewhat successful, these task-oriented neural dialogue models suffer from a number of problems: 1) They struggle to effectively reason over and incorporate knowledge base information while still preserving their end-to-end trainability and 2) They often require explicitly modelling user dialogues with belief trackers and dialogue state information, which necessitates additional data annotation and also breaks differentiability.

To address some of the modelling issues in previous neural dialogue agents, we introduce a new architecture called the Key-Value Retrieval Network. This model augments existing recurrent network architectures with an attention-based key-value retrieval mechanism over the entries of a knowledge base, which is inspired by recent work on key-value memory networks (Miller et al., 2016). By doing so, it is able to learn how to extract useful information from a knowledge base directly from data in an end-to-end fashion, with-

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out the need for explicit training of belief or intent trackers as is done in traditional task-oriented dialogue systems. The architecture has no dependence on the specifics of the data domain, learning how to appropriately incorporate world knowledge into its dialogue utterances via attention over the key-value entries of the underlying knowledge base.

In addition, we introduce and make publicly available a new corpus of 3,031 dialogues spanning three different domain types in the in-car personal assistant space: calendar scheduling, weather information retrieval, and point-of-interest navigation. The dialogues are grounded through knowledge bases. This makes them ideal for building dialogue architectures that seamlessly reason over world knowledge. The multi-domain nature of the dialogues in the corpus also makes this dataset an apt test bed for generalizability of modelling architectures.[1]

The main contributions of our work are therefore two-fold: 1) We introduce the Key-Value Retrieval Network, a highly performant neural task-oriented dialogue agent that is able to smoothly incorporate information from underlying knowledge bases through a novel key-value retrieval mechanism. Unlike other dialogue agents which only rely on prior dialogue history for generation (Kannan et al., 2016; Eric and Manning, 2017), our architecture is able to access and use database-style information, while still retaining the text generation advantages of recent neural models. By doing so, our model outperforms a competitive rule-based system and other baseline neural models on a number of automatic metrics as well as human evaluation. 2) We release a new publicly-available dialogue corpus across three distinct domains in the in-car personal assistant space that we hope will help further work on task-oriented dialogue agents.

2 Key-Value Retrieval Networks

While recent neural dialogue models have explicitly modelled dialogue state through belief and user intent trackers (Wen et al., 2016b; Dhingra et al., 2016; Henderson et al., 2014b), we choose instead to rely on learned neural representations for implicit modelling of dialogue state, forming a truly end-to-end trainable system. Our model starts with an encoder-decoder sequence architecture and is further augmented with an attention-based retrieval mechanism that effectively reasons over a key-value representation of the underlying knowledge base. We describe each component of our model in the subsequent sections.

2.1 Encoder

Given a dialogue between a user (*u*) and a system (*s*), we represent the dialogue utterances as $\{(u_1, s_1), (u_2, s_2), \ldots, (u_k, s_k)\}$ where k denotes the number of turns in the dialogue. At the i^{th} turn of the dialogue, we encode the aggregated dialogue context composed of the tokens of $(u_1, s_1, \ldots, s_{i-1}, u_i)$. Letting $x_1, \ldots, x_m$ denote these tokens, we first embed these tokens using a trained embedding function ϕ^{emb} that maps each token to a fixed-dimensional vector. These mappings are fed into the encoder to produce context-sensitive hidden representations $h_1, \ldots, h_m$, by repeatedly applying the recurrence:

$$h_i = \text{LSTM}(\phi^{emb}(x_i), h_{i-1}) \tag{1}$$

where the recurrence uses a long-short-term memory unit, as described by (Hochreiter and Schmidhuber, 1997).

2.2 Decoder

The vanilla sequence-to-sequence decoder predicts the tokens of the i^{th} system response s_i by first computing decoder hidden states via the recurrent unit. We denote $\tilde{h}_1, \ldots, \tilde{h}_n$ as the hidden states of the decoder and $y_1, \ldots, y_n$ as the output tokens. We extend this decoder with an attention-based model (Bahdanau et al., 2015; Luong et al., 2015a), where, at every time step t of the decoding, an attention score a_i^t is computed for each hidden state h_i of the encoder, using the attention mechanism of (Vinyals et al., 2015). Formally this attention can be described by the following equations:

$$u_i^t = w^T \tanh(W_2 \tanh(W_1[h_i, \tilde{h}_t])) \tag{2}$$

$$a_i^t = \text{Softmax}(u_i^t) \tag{3}$$

$$\tilde{h}_t' = \sum_{i=1}^{m} a_i^t h_i \tag{4}$$

$$o_t = U[\tilde{h}_t, \tilde{h}_t'] \tag{5}$$

$$y_t = \text{Softmax}(o_t) \tag{6}$$

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[1] The data is available for download at https://nlp.stanford.edu/blog/a-new-multi-turn-multi-domain-task-oriented-dialogue-dataset/

where U, W_1, W_2, and w are trainable parameters of the model and o_t represents the logits over the tokens of the output vocabulary V. In (2) above, the attention logit on h_i is computed via a two-layer MLP function with a $\tanh$ nonlinearity at the intermediate layers. During training, the next token y_t is predicted so as to maximize the log-likelihood of the correct output sequence given the input sequence.

2.3 Key-Value Knowledge Base Retrieval

Recently, some neural task-oriented dialogue agents that query underlying knowledge bases (KBs) and extract relevant entities either do the following: 1) create and execute well-formatted API calls to the KB, operations which require intermediate supervision in the form of training slot trackers and which break differentiability (Wen et al., 2016b), or 2) softly attend to the KB and combine this probability distribution with belief trackers as state input for a reinforcement learning policy (Dhingra et al., 2016). We choose to build off the latter approach as it fits nicely into the end-to-end trainable framework of sequence-to-sequence modelling, though we are in a supervised learning setting and we do away with explicit representations of belief trackers or dialogue state.

For storing the KB of a given dialogue, we take inspiration from the work of (Miller et al., 2016) which found that a key-value structured memory allowed for efficient machine reading of documents. We store every entry of our KB using a *(subject, relation, object)* representation. In our representation a KB entry from the dialogue in Figure 1 such as (**event**=*dinner*, **time**=*8pm*, **date**=*the 13th*, **party**=*Ana*, **agenda**="-") would be normalized into four separate triples of the form (*dinner*, *time*, *8pm*). Every KB has at most 230 normalized triples. This formalism is similar to a neo-Davidsonian or RDF-style representation of events.

Recent literature has shown that incorporating a copying mechanism into neural architectures improves performance on various sequence-to-sequence tasks (Jia and Liang, 2016; Gu et al., 2016; Ling et al., 2016; Gulcehre et al., 2016; Eric and Manning, 2017). We build off this intuition in the following way: at every timestep of decoding, we take the decoder hidden state and compute an attention score with the key of each normalized KB entry. For our purposes, the key of an entry corresponds to the sum of the word embeddings of the subject (*meeting*) and relation (*time*). The attention logits then become the logits of the value for that KB entry. For our KB attentions, we replace the embedding of the value with a canonicalized token representation. For example, the value *5pm* is replaced with the canonicalized representation *meeting_time*. At runtime, if we decode this canonicalized representation token, we convert it into the actual value of the KB entry (*5pm* in our running example) through a KB lookup. Note that this means we are expanding our original output vocabulary to $|V| + n$ where n is the number of separate canonical key representation KB entries.

In particular, let k_j denote the word embedding of the key of our j^{th} normalized KB entry. We can now formalize the decoding for our KB attention-based retrieval. Assume that we have m distinct triples in our KB and that we are in the t^{th} timestep of decoding:

$$u_j^t = r^T \tanh(W_2' \tanh(W_1'[k_j, \tilde{h}_t])) \quad (7)$$

$$o_t = U[\tilde{h}_t, \tilde{h}_t'] + \bar{v}^t \quad (8)$$

$$y_t = \text{Softmax}(o_t) \quad (9)$$

where r, W_1', and W_2' are trainable parameters. In (8) above, $\bar{v}^t$ is a sparse vector with length $|V| + n$. Within $\bar{v}^t$, the entry for the value embedding v_j corresponding to the key k_j is equal to the logit score u_j^t on k_j. Hence, the m entries of $\bar{v}^t$ corresponding to the values in the KB are non-zero, whereas the remaining entries corresponding to the original vocabulary tokens are 0. This sparse vector contains our aggregated KB logit scores which we combine with the original logits to get a modified o_t. We then select the argmax token as input to the next timestep. This description seeks to capture the intuition that in response to the query *What time is my meeting*, we want the model to put a high attention weight on the key representation for the (*meeting*, *time*, *5pm*) KB triple, which should then lead the model to favor outputting the value token at the given timestep. We provide a visualization of the Key-Value Retrieval Network in Figure 2.

3 A Multi-Turn, Multi-Domain Dialogue Dataset

In an effort to further work in multi-domain dialogue agents, we built a corpus of multi-turn

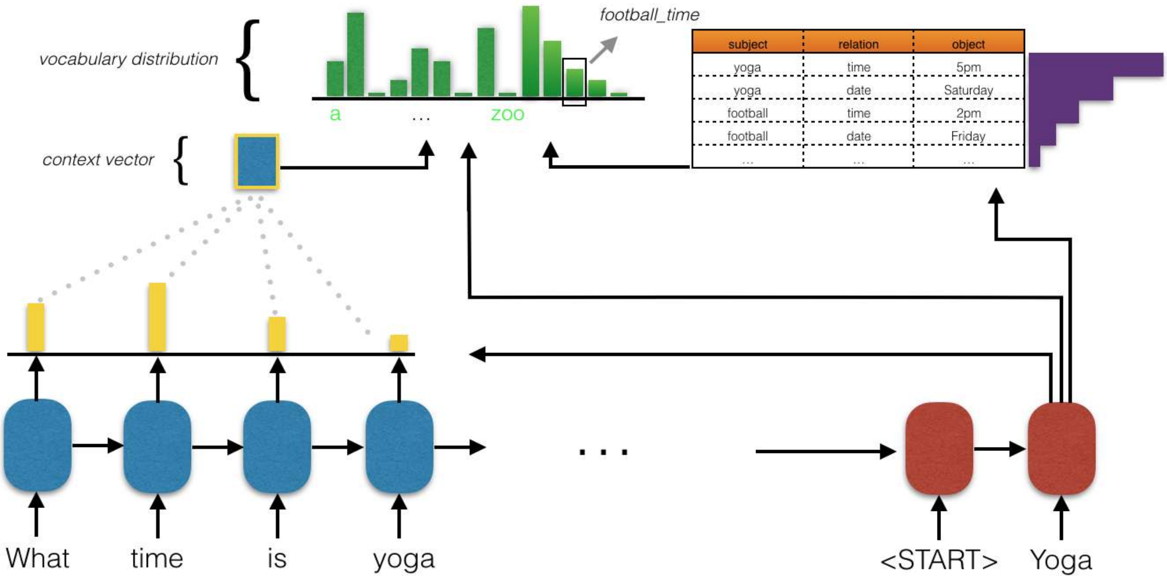

Figure 2: Key-value retrieval network. For each time-step of decoding, the cell state is used to compute an attention over the encoder states and a separate attention over the key of each entry in the KB. The attentions over the encoder are used to generate a context vector which is combined with the cell state to get a distribution over the normal vocabulary. The attentions over the keys of the KB become the logits for their associated values and are separate entries in a now augmented vocabulary that we argmax over.

dialogues in three distinct domains: calendar scheduling, weather information retrieval, and point-of-interest navigation. While these domains are different, they are all relevant to the overarching theme of tasks that users would expect of a sophisticated in-car personal assistant.

3.1 Data Collection

The data for the multi-turn dialogues was collected using a Wizard-of-Oz scheme inspired by that of (Wen et al., 2016b). In our scheme, users had two potential modes they could play: *Driver* and *Car Assistant*. In the *Driver* mode, users were presented with a task that listed certain information they were trying to extract from the *Car Assistant* as well as the dialogue history exchanged between *Driver* and *Car Assistant* up to that point. An example task presented could be: *You want to find what the temperature is like in San Mateo over the next two days*. The *Driver* was then only responsible for contributing a single line of dialogue that appropriately continued the discourse given the prior dialogue history and the task definition.

Tasks were randomly specified by selecting values (*5pm*, *Saturday*, *San Francisco*, etc.) for three to five slots (`time`, `date`, `location`, etc.), depending on the domain type. Values specified for the slots were chosen according to a uniform distribution from a per-domain candidate set.

In the *Car Assistant* mode, users were presented with the dialogue history exchanged up to that point in the running dialogue and a private knowledge base known only to the *Car Assistant* with information that could be useful for satisfying the *Driver* query. Examples of knowledge bases could include a calendar of event information, a collection of weekly forecasts for nearby cities, or a collection of nearby points-of-interest with relevant information. The *Car Assistant* was then responsible for using this private information to provide a single utterance that progressed the user-directed dialogues. The *Car Assistant* was also asked to fill in dialogue state information for mentioned slots and values in the dialogue history up to that point.

Each private knowledge base had six to seven distinct rows and five to seven attribute types. The private knowledge bases used were generated by uniformly selecting a value for a given attribute type, where each attribute type had a variable number of candidate values. Some knowledge bases intentionally lacked attributes to encourage diversity in discourse.

During data collection, some of the dialogues

	Calendar Scheduling	**Weather Information Retrieval**	**POI Navigation**
Slot Types	event, time, date, party, room, agenda	location, weekly time, temperature, weather attribute	POI name, traffic info, POI category, address, distance
# Distinct Slot Values	79	65	140

Table 1: Slots types and number distinct slot values for different domains. POI denotes point-of-interest.

Training Dialogues	2,425
Validation Dialogues	302
Test Dialogues	304
Calendar Scheduling Dialogues	1034
Navigation Dialogues	1000
Weather Dialogues	997
Avg. # of Utterances Per Dialogue	5.25
Avg. # of Tokens Per Utterance	9
Vocabulary Size	1,601
# of Distinct Entities	284
# of Entity (or Slot) Types	15

Table 2: Statistics of Dataset.

in the calendar scheduling domain did not explicitly require the use of a KB. For example, in a task such as *Set a meeting reminder at 3pm*, we hoped to encourage dialogues that required the *Car Assistant* to execute a task while asking for *Driver* clarification on underspecified information. Roughly half of the scheduling dialogues fell into this category.

While specifying the attribute types and values in each task presented to the *Driver* allowed us to ground the subject of each dialogue with our desired entities, it would occasionally result in more mechanical discourse exchanges. To encourage more naturalistic, unbiased utterances, we had users record themselves saying commands in response to underspecified visual depictions of an action a car assistant could perform. These commands were transcribed and then inserted as the first exchange in a given dialogue on behalf of the *Driver*. Roughly ∼1,500 of the dialogues employed this transcribed audio command first-utterance technique.

241 unique workers from Amazon Mechanical Turk were anonymously recruited to use the interface we built over a period of about six days. Data statistics are provided in Table 1 and slot types and values are provided in Table 2. A screenshot of the user-facing interfaces for the data collection, as well as a visual used to prompt user recorded commands, are provided in the supplementary material.

4 Related Work

Task-oriented agents for spoken dialogue systems have been the subject of extensive research effort. One line of work by (Young et al., 2013) has tackled the problem using partially observable Markov decision processes and reinforcement learning with carefully designed action spaces, though the number of distinct action states makes this approach often brittle and computationally intractable.

The recent successes of neural architectures on a number of traditional natural language processing subtasks (Bahdanau et al., 2015; Sutskever et al., 2014; Vinyals et al., 2015) have motivated investigation into dialogue agents that can effectively make use of distributed neural representations for dialogue state management, belief tracking, and response generation. Recent work by (Wen et al., 2016b) has built systems with modularly-connected representation, belief state, and generation components. These models learn to explicitly represent user intent through intermediate supervision, which breaks end-to-end trainability. Other work by (Bordes and Weston, 2016; Liu and Perez, 2016) stores dialogue context in a memory module and repeatedly queries and reasons about this context to select an adequate system response from a set of all candidate responses.

Another line of recent work has developed task-oriented models which are amenable to both supervised learning and reinforcement learning and are able to incorporate domain-specific knowledge via explicitly-provided features and model-output restrictions (Williams et al., 2017). Our model contrasts with these works in that training is done in a strictly supervised fashion via a per utterance token generative process, and the model does not need dialogue state trackers, relying instead on latent neural embeddings for accurate system response generation.

Research in task-oriented dialogue often struggles with a lack of standard, publicly available datasets. Several classical corpora have consisted of moderately-sized collections of dialogues related to travel-booking (Hemphill et al., 1990;

Bennett and Rudnicky, 2002). Another well-known corpus is derived from a series of competitions on the task of dialogue-state tracking (Williams et al., 2013). While the competitions were designed to test systems for state tracking, recent work has chosen to repurpose this data by only using the transcripts of dialogues without state annotation for developing systems (Bordes and Weston, 2016; Williams et al., 2017). More recently, Maluuba has released a dataset of hotel and travel-booking dialogues collected in a Wizard-of-Oz Scheme with elaborate semantic frames annotated (Asri et al., 2017). This dataset aims to encourage research in non-linear decision-making processes that are present in task-oriented dialogues.

5 Experiments

In this section we first introduce the details of the experiments and then present results from both automatic and human evaluation.

5.1 Details

For our experiments, we divided the dialogues into train/validation/test sets using a 0.8/0.1/0.1 data split and ensured that each domain type was equally represented in each of the splits.

To reduce lexical variability, in a pre-processing step, we map the variant surface expression of entities to a canonical form using named entity recognition and linking. For example, the surface form *20 Main Street* is mapped to *Pizza My Heart address*. During inference, our model outputs the canonical forms of the entities, and so we realize their surface forms by running the system output through an inverse lexicon. The inverse lexicon converts the entities back to their surface forms by sampling from a multinomial distribution with parameters of the distribution equal to the frequency count of a given surface form for an entity as observed in the training and validation data. Note that for the purposes of computing our evaluation metrics, we operate on the canonicalized forms, so that any non-deterministic variability in surface form realization does not affect the computed metrics.

5.2 Hyperparameters

We trained using a cross-entropy loss and the Adam optimizer (Kingma and Ba, 2015) with learning rates sampled from the interval $[10^{-4}, 10^{-3}]$. We applied dropout (Hinton et al., 2012) as a regularizer to the input and output of the LSTM. We also added an l_2 regularization penalty on the weights of the model. We identified hyperparameters by random search, evaluating on the held-out validation subset of the data. Dropout keep rates were sampled from $[0.8, 0.9]$ and the l_2 coefficient was sampled from $[3 \cdot 10^{-6}, 10^{-5}]$. We used word embeddings, hidden layer, and cell sizes with size 200. We applied gradient clipping with a clip-value of 10 to avoid gradient explosions during training. The attention, output parameters, word embeddings, and LSTM weights were randomly initialized from a uniform unit-scaled distribution in the style of (Sussillo and Abbott, 2015). We also added a bias of 1 to the LSTM cell forget gate in the style of (Pham et al., 2014).

5.3 Baseline Models

We provide several baseline models for comparing performance of the Key-Value Retrieval Network:

- **Rule-Based Model**: This model is a traditional rule-based system with modular dialogue state trackers, KB query, and natural language generation components. It first does an extensive domain-dependent keyword search in the user utterances to detect intent. The user utterances are also provided to a lexicon to extract any entities mentioned. Collectively, this information forms the dialogue state up to a given point in the dialogue. This dialogue state is used to query the KB as appropriate, and the returned KB values are used to fill in predefined template system responses.

- **Copy-Augmented Sequence-to-Sequence Network**: This model is derived from the work of (Eric and Manning, 2017). It augments a sequence-to-sequence architecture with encoder attention, with an additional attention-based hard-copy mechanism over the KB entities mentioned in the encoder context. This model does not explicitly incorporate information from the underlying KB and instead relies solely on dialogue history for system response generation. Unlike the best performing model of (Eric and Manning, 2017), we do not enhance the inputs to the encoder with additional entity type features, as we found that the

Model	BLEU	Ent. F_1	Scheduling Ent. F_1	Weather Ent. F_1	Navigation Ent. F_1
Rule-Based	6.6	43.8	61.3	39.5	40.4
Copy Net	11.0	37.0	28.1	**50.1**	28.4
Attn. Seq2Seq	10.2	30.0	30.0	42.4	17.9
KV Retrieval Net (no enc. attn.)	10.8	40.9	59.5	35.6	36.6
KV Retrieval Net	**13.2**	**48.0**	**62.9**	47.0	**41.3**
Human Performance	13.5	60.7	64.3	61.6	55.2

Table 3: Evaluation on our test data. Bold values indicate best model performance. We provide both an aggregated F_1 score as well as domain-specific F_1 scores. Attn. Seq2Seq refers to a sequence-to-sequence model with encoder attention. KV Retrieval Net (no enc. attn.) refers to our new model with no encoder attention context vector computed during decoding.

model performed worse on our data with this added mechanism. We choose this model for comparison as it is also end-to-end trainable and implicitly models dialogue state through learned neural representations, putting it in the same class of dialogue models as our key-value retrieval net. This model has also been shown to be a competitive task-oriented dialogue baseline that can accurately interpret user input and act on this input through latent distributed representation. We refer to this model as Copy Net in the results tables.

5.4 Automatic Evaluation

5.4.1 Metrics

Though prior work has shown that automatic evaluation metrics often correlate poorly with human assessments of dialogue agents (Liu et al., 2016), we report a number of automatic metrics in Table 3. These metrics are provided for coarse-grained evaluation of dialogue response quality:

- **BLEU**: We use the BLEU metric, commonly employed in evaluating machine translation systems (Papineni et al., 2002), which has also been used in past literature for evaluating dialogue systems both of the chatbot and task-oriented variety (Ritter et al., 2011; Li et al., 2016; Wen et al., 2016b). While work by (Liu et al., 2016) has demonstrated that n-gram based evaluation metrics such as BLEU and METEOR do not correlate well with human performance on non-task-oriented dialogue datasets, recently (Sharma et al., 2017) have shown that these metrics can show comparatively stronger correlation with human assessment on task-oriented datasets. We, therefore, calculate average BLEU score over all responses generated by the system, and primarily report these scores to gauge our model's ability to accurately generate the language patterns seen in our data.

- **Entity F_1**: Each human Turker's *Car Assistant* response in the test data defines a gold set of entities. To compute an entity F_1, we micro-average over the entire set of system dialogue responses and use the entities in their canonicalized forms. This metric evaluates the model's ability to generate relevant entities from the underlying knowledge base and to capture the semantics of the user-initiated dialogue flow. Given that our test set contains dialogues from all three domains, we compute a per-domain entity F_1 as well as an aggregated dataset entity F_1. We note that other work on task-oriented dialogue by (Wen et al., 2016b; Henderson et al., 2014a) have reported the slot-tracking accuracy of their systems, which is a similar but perhaps more informative and fine-grained notion of a system's ability to capture user semantics. Because our model does not have provisions for slot-tracking by design, we are unable to report such a metric and hence report our entity F_1.

5.4.2 Results

We see that of our baseline models, Copy Net has the lowest aggregate entity F_1 performance. Though it has the highest model entity F_1 for the weather domain dialogues, it performs very poorly in the other domains, indicating its inability to generalize well to multiple dialogue domains and to accurately integrate relevant entities into its responses. Copy Net does, however, have the second highest BLEU score, which is not surprising given that the model is a powerful extension to the sequence-to-sequence modelling class, which is known to have very robust language modelling capabilities.

Our rule-based model has the lowest BLEU score, which is a consequence of the fact that the naturalness of the system output is very limited by the number of diverse and distinct response templates we manually provided. This is a common issue with heuristic dialogue agents and one that could be partially alleviated through a larger collection of lexically rich response templates. However, the rule-based system has a very competitive aggregate entity F_1. This is because it was designed to accurately parse the semantics of user utterances and query the underlying KB of the dialogue, through manually-provided heuristics.

As precursors to our key-value retrieval net, we first report results of a model that does not compute an attention over the KB (referred to as Attn. Seq2Seq) and show that without computing attention over the KB, the model performs poorly in entity F_1 as its output is agnostic to the world state represented in the KB. Note that this model is effectively a sequence-to-sequence model with encoder attention. If we include an attention over the KB but do not compute an encoder attention (referred to as KV Retrieval Net no enc. attn.), the entity F_1 increases drastically, showing that the model is able to incorporate relevant entities from the KB. Finally, we combine these two attention mechanisms to get our final key-value retrieval net. Our proposed key-value retrieval net has the highest modelling performance in BLEU, aggregate entity F_1, and entity F_1 for the scheduling and navigation domains. It outperforms the rule-based aggregate entity F_1 by 4.2% and outperforms the Copy Net BLEU score by 2.2 points as well as its entity F_1 by 11%. These salient gains are noteworthy because our model is able to achieve them by learning its latent representationts directly from data, without the need for heuristics or manual labelling.

We also report human performance on the provided metrics. These scores were computed by taking the dialogues of the test set and having a second distinct batch of Amazon Mechanical Turk workers provide system responses given prior dialogue context. This, in effect, functions as an interannotator agreement score and sets a human upper bound on model performance. We see that there is a sizable gap between human performance on entity F_1 and that of our key-value retrieval net ($\sim$ 12.7%), though our model is on par with human performance in BLEU score.

5.5 Human Evaluation

We randomly generated 120 distinct scenarios across the three dialogue domains, where a scenario is defined by an underlying KB as well as a user goal for the dialogue (e.g. *find the nearest gas station, avoiding heavy traffic*). We then paired Amazon Mechanical Turkers with one of our systems in a real-time chat environment, where each Turker played the role of the *Driver*. We evaluated the rule-based model, Copy Net, and key-value retrieval network on each of the 120 scenarios. We also paired a Turker with another Turker for each of the scenarios, in order to get evaluations of human performance. At the end of the chat, the Turker was asked to judge the quality of their partner according to fluency, cooperativeness, and humanlikeness on a scale from 1 to 5. The average scores per pairing are reported in Table 4. In a separate experiment, we also had Turkers evaluate the outputs of the systems on 80 randomly selected dialogues from the test split of our dataset. Those outputs were evaluated according to correctness, appropriateness, and humanlikeness of the responses, and the scores are reported in Table 5.

We see that on real-time dialogues the key-value retrieval network outperforms the baseline models on all of the metrics, with especially sizeable performance gains over the Copy Net which is the only other recurrent neural model evaluated. We also see that human performance on this assessment sets the upper bound on scores, as expected. The results on human evaluation of test outputs show that the rule-based model provides the most correct system responses, the KV network provides the most appropriate responses, and the Copy Net gives the most humanlike responses by small margins. We should note, however, that the second regime for human evaluation is more unrealistic because it involves providing a dialogue context that is directly sampled from our dataset, whereas the first regime of real-time dialogues measures the models' abilities to adapt to new and noisier user input. This suggests that the first set of results are more meaningful and representative for assessing overall model efficacy.

Examples of dialogues conducted between our model and Turkers are included in Figure 3. Particularly noteworthy is our model's ability to seamlessly integrate world information from the underlying KBs in the respective dialogues, while

Model	Fluency	Cooperative	Humanlike
Rule-based	3.20	3.39	2.87
Copy Net	2.33	2.42	2.02
KV Ret. Net	**3.36**	**3.43**	**3.09**
Human	3.98	3.95	4.04

Table 4: Human evaluation results on realtime dialogues.

still producing very naturalistic utterances. The model is able to do this effectively across multiple domains.

POI	Category	Traffic Info	...
Civic Center	parking garage	car collision	...
Valero	gas station	road block	...
Webster Garage	parking garage	car collision	...
Trader Joes	grocery store	heavy	...
Mandarin Rts.	chinese rest.	moderate	...
...	...	...	...

DRIVER: I am looking for a gas station near me with the shortest route from me.
CAR: *the closest gas station is valero but, but there is a road block nearby.*
DRIVER: What is the next nearest gas station?
CAR: *valero is the only gas station that i can find*
DRIVER: Thanks
CAR: *here to serve.*

Event	Time	Date	Party	Agenda
swimming act.	3pm	the 11th	sister	-
dinner	7pm	the 3rd	mother	-
football	2pm	the 20th	mother	-
lab appt.	10am	the 17th	Jeff	-
...	...	...	...	...

DRIVER: car when is gonna be my next swimming activity?
CAR: *your next swimming activity is on the 11th at 3pm.*
DRIVER: who is gonna attend with me?
CAR: *your swimming activity is on the 11th, one at 3pm with sister*
DRIVER: thank you!
CAR: *you are welcome*

Figure 3: Sample dialogues from our human evaluation, conducted between a Turker and the KV Retrieval Net. In the dialogue, our model responses are italicized. Additional dialogues are included in the supplementary material.

6 Conclusion and Future Work

In this work, we have presented a novel neural task-oriented dialogue model that is able to sustain grounded discourse across a variety of domains by retrieving world knowledge represented in knowledge bases. It smoothly incorporates this world knowledge into natural-sounding system responses in an end-to-end trainable fashion, without the need to explicitly model dialogue state. Our model outperforms competitive heuristic and neural baselines on both automatic and human evaluation metrics. In addition, we have introduced a publicly available dialogue dataset across three domains in the in-car personal assistant space that we hope will help the data scarcity issue present in task-oriented dialogue research.

Model	Correct	Appropriate	Humanlike
Rule-based	**3.96**	3.57	3.28
Copy Net	3.52	3.63	**3.56**
KV Ret. Net	3.70	**3.64**	3.50

Table 5: Human evaluation of system outputs on test set.

Future work will address closing the margin between the Key-Value Retrieval Network and human performance on the various metrics. This will include developing new methods for robust handling of joint KB attributes as well as usage of the KB that requires more pragmatic understanding of the world via notions such as temporal reasoning.

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References

L. El Asri, H. Schulz, S. Sharma, J. Zumer, J. Harris, E. Fine, R. Mehrotra, and K. Suleman. 2017. Frames: A corpus for adding memory to goal-oriented dialogue systems. *http://www.maluuba.com/publications/* .

Dzimitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In *International Conference on Learning Representations (ICLR2015)*.

Christina Bennett and Alexander I. Rudnicky. 2002. The carnegie mellon communicator corpus. In *ICSLP*.

Antoine Bordes and Jason Weston. 2016. Learning end-to-end goal-oriented dialog. *arXiv preprint arXiv:1605.07683* .

Bhuwan Dhingra, Lihong Li, Xiujun Li, Jianfeng Gao, Yun-Nung Chen, Faisal Ahmed, and Li Deng.

2016. End-to-end reinforcement learning of dialogue agents for information access. *arXiv preprint arXiv:1609.00777* .

Mihail Eric and Christopher Manning. 2017. A copy-augmented sequence-to-sequence architecture gives good performance on task-oriented dialogue. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*. Association for Computational Linguistics, pages 468–473. http://aclweb.org/anthology/E17-2075.

Jiatao Gu, Zhengdong Lu, Hang Li, and Victor O.K. Li. 2016. Incorporating copying mechanism in sequence-to-sequence learning. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Berlin, Germany, pages 1631–1640. http://www.aclweb.org/anthology/P16-1154.

Caglar Gulcehre, Sungjin Ahn, Ramesh Nallapati, Bowen Zhou, and Yoshua Bengio. 2016. Pointing the unknown words. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Berlin, Germany, pages 140–149. http://www.aclweb.org/anthology/P16-1014.

C.T. Hemphill, J. J. Godfrey, and G. R. Doddington. 1990. The atis spoken language systems pilot corpus. In *Proceedings of the DARPA speech and natural language workshop*.

Matthew Henderson, Blaise Thomson, and Jason Williams. 2014a. The second dialog state tracking challenge. *15th Annual Meeting of the Special Interest Group on Discourse and Dialogue* page 263.

Matthew Henderson, Blaise Thomson, and Steve Young. 2014b. Word-based dialog state tracking with recurrent neural networks. In *Proceedings of the SIGDIAL 2014 Conference*.

Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan R. Salakhutdinov. 2012. Improving neural networks by preventing co-adaptation of feature detectors. *arXiv preprint arXiv:1207.0580* .

Sepp Hochreiter and Jurgen Schmidhuber. 1997. Long short-term memory. *Neural Computation* pages 1735–1780.

Robin Jia and Percy Liang. 2016. Data recombination for neural semantic parsing. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Berlin, Germany, pages 12–22. http://www.aclweb.org/anthology/P16-1002.

Anjuli Kannan, Karol Kurach, Sujith Ravi, Tobias Kaufman, Balint Miklos, Greg Corrado, Andrew Tomkins, Laszlo Lukacs, Marina Ganea, Peter Young, and Vivek Ramavajjala. 2016. Smart reply: Automated response suggestion for email. In *Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD) (2016).*. https://arxiv.org/pdf/1606.04870v1.pdf.

Diederik Kingma and Jimmy Ba. 2015. Adam: a method for stochastic optimization. In *International Conference on Learning Representations (ICLR2015)*.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, San Diego, California, pages 110–119. http://www.aclweb.org/anthology/N16-1014.

Wang Ling, Phil Blunsom, Edward Grefenstette, Karl Moritz Hermann, Tomáš Kočiský, Fumin Wang, and Andrew Senior. 2016. Latent predictor networks for code generation. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Berlin, Germany, pages 599–609. http://www.aclweb.org/anthology/P16-1057.

Chia-Wei Liu, Ryan Lowe, Iulian Serban, Mike Noseworthy, Laurent Charlin, and Joelle Pineau. 2016. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Austin, Texas, pages 2122–2132. https://aclweb.org/anthology/D16-1230.

Fei Liu and Julien Perez. 2016. Gated end-to-end memory networks. *arXiv preprint arXiv:1610.04211* .

Minh-Thang Luong, Hieu Pham, and Christopher D. Manning. 2015a. Effective approaches to attention-based neural machine translation. *Empirical Methods in Natural Language Processing* pages 1412–1421.

Alexander Miller, Adam Fisch, Jesse Dodge, Amir-Hossein Karimi, Antoine Bordes, and Jason Weston. 2016. Key-value memory networks for directly reading documents. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Austin, Texas, pages 1400–1409. https://aclweb.org/anthology/D16-1147.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of 40th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Philadelphia, Pennsylvania, USA, pages 311–318. https://doi.org/10.3115/1073083.1073135.

Vu Pham, Theodore Bluche, Christopher Kermorvant, and Jerome Louradour. 2014. Dropout improves recurrent neural networks for handwriting recognition. *arXiv preprint arXiv:1312.4569v2* .

Alan Ritter, Colin Cherry, and William B. Dolan. 2011. Data-driven response generation in social media. *Empirical Methods in Natural Language Processing* pages 583–593.

Sikhar Sharma, Layla El Asri, Hannes Schulz, and Jeremie Zumer. 2017. Relevance of unsupervised metrics in task-oriented dialogue for evaluating natural language generation. *arXiv preprint arXiv:1706.09799* .

David Sussillo and L.F. Abbott. 2015. Random walk initialization for training very deep feed forward networks. *arXiv preprint arXiv:1412.6558* .

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27*, Curran Associates, Inc., pages 3104–3112. http://papers.nips.cc/paper/5346-sequence-to-sequence-learning-with-neural-networks.pdf.

Oriol Vinyals, Ł ukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, and Geoffrey Hinton. 2015. Grammar as a foreign language. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28*, Curran Associates, Inc., pages 2773–2781. http://papers.nips.cc/paper/5635-grammar-as-a-foreign-language.pdf.

Tsung-Hsien Wen, David Vandyke, Milica Gasic, Nikola Mrksic, Lina. M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. 2016b. A network-based end-to-end trainable task-oriented dialogue system. *arXiv preprint arXiv:1604.04562* .

Jason D. Williams, Kavosh Asadi, and Geoffrey Zweig. 2017. Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. *arXiv preprint arXiv:1702.03274* .

Jason D. Williams, Antoine Raux, Deepak Ramachadran, and Alan Black. 2013. The dialog state tracking challenge. In *Proceedings of the SIGDIAL*. Metz, France.

Steve Young, Milica Gasic, Blaise Thomson, and Jason D. Williams. 2013. POMDP-based statistical spoken dialog systems: a review. *Proceedings of the IEEE* 28(1):114–133.

POI	Category	Address	Traffic Info	Distance
Dish Parking	parking garage	550 Alester Ave	no traffic	3 miles
Cafe Venetia	coffee or tea place	329 El Camino Real	road block nearby	4 miles
Mandarin Roots	chinese restaurant	271 Springer St	car collision nearby	3 miles
Dominos	pizza restaurant	776 Arastradero Rd	moderate traffic	6 miles
Travelers Lodge	rest stop	333 Arbol Dr	moderate traffic	4 miles

DRIVER: What is the nearest parking garage within 4 miles
that has no traffic.
CAR: *the nearest is dish parking at 550 alester ave, 3 miles away*
DRIVER: Does it have any traffic?
CAR: *there is no traffic on the route to dish parking*
DRIVER: Thanks
CAR: *you're welcome!*

Event	Time	Date	Party	Agenda	Location
dinner	5pm	the 4th	brother	-	-
meeting	1pm	the 18th	vice president	discuss company picnic	room 100
conference	11am	the 1st	HR	go over budget	room 50
meeting	4pm	the 9th	HR	onboard new members	room 100
lab appt.	6pm	the 14th	Jon	-	-
dinner	6pm	the 1st	Jon	-	-

DRIVER: When is my dinner going to be and who will be attending
CAR: *your next dinner is on the 1st at 6 pm with your jon*
DRIVER: Great, thanks.
CAR: *you're welcome!*

POI	Category	Address	Traffic Info	Distance
Dominos	pizza restaurant	776 Arastradero Rd	moderate traffic	7 miles
Stanford Express Care	hospital	214 El Camino Real	car collision nearby	1 miles
Travelers Lodge	rest stop	333 Arbol Dr	no traffic	4 miles
Coupa	coffee or tea place	394 Van Ness Ave	moderate traffic	7 miles
The Clement Hotel	rest stop	657 Ames Ave	road block nearby	6 miles
5672 barringer st.	certain address	5672 barringer st.	car collision nearby	4 miles

DRIVER: Hi, I'd like to find a coffee place near me
CAR: *we're 7 miles away from coupa but there is a moderate traffic*
DRIVER: What's the address?
CAR: *the address is 394 van ness ave, i sent it on your screen*
DRIVER: Great. Can you find me the fastest route there?
CAR: *the fastest route is for coupa.*
DRIVER: Ok, so coupa is the closest place and you have the fastest route there
CAR: *the fastest route has moderate traffic and there is a moderate traffic on the route*
do you want to go there?
DRIVER: yes
CAR: *i sent the info on your screen, drive carefully!*
DRIVER: Thanks
CAR: *you're welcome, have a great day.*

	monday	tuesday	wednesday	thursday	friday	...
los angeles	hail, 60-70f	foggy, 30-40f	cloudy, 20-30f	stormy 30-40f	drizzle, 30-50f	...
durham	rain, 80-90f	cloudy, 50-70f	misty, 40-60f	dry, 80-100f	rain, 50-70f	...
boston	overcast, 30-50f	misty, 40-60f	foggy, 40-50f	foggy, 40-50f	clear skies 20-30f	...
seattle	warm, 60-70f	foggy, 30-40f	cloudy, 20-30f	stormy, 30-40f	drizzle, 30-50f	...
fresno	clear skies, 40-60f	drizzle, 70-80f	humid, 70-90f	stormy, 60-70f	cloudy, 90-100f	...
san francisco	foggy, 40-60f	hot, 90-100f	humid, 50-70f	rain, 80-100f	misty, 20-40f	...
alhambra	dew, 30-40f	dry, 30-50f	dry, 50-60f	humid, 80-90f	snow, 60-80f	...

DRIVER: how is the weather
CAR: *what city would you like the weather for?*
DRIVER: is it foggy in seattle?
CAR: *it will not be foggy in seattle today*
DRIVER: thanks
CAR: *you're welcome!*

Figure 4: Sample dialogues from our model. Note in the weather dialogue, the current day is italicized.

Figure 5: An image provided to users to elicit unbiased audio commands for prompting more naturalistic dialogues

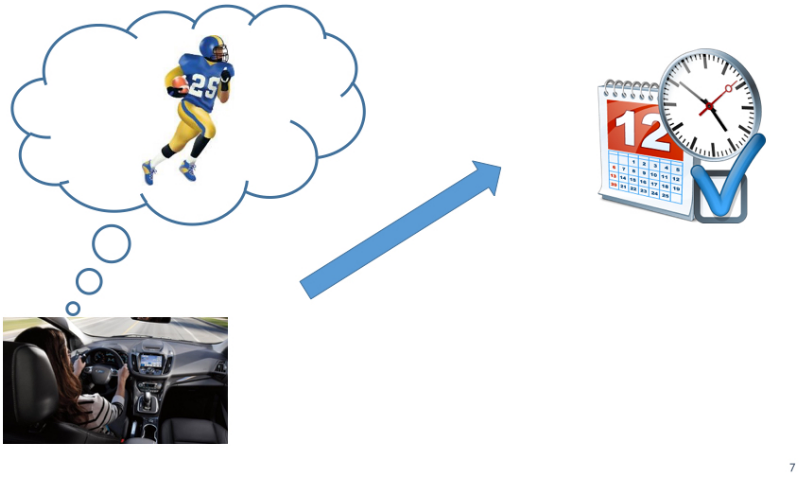


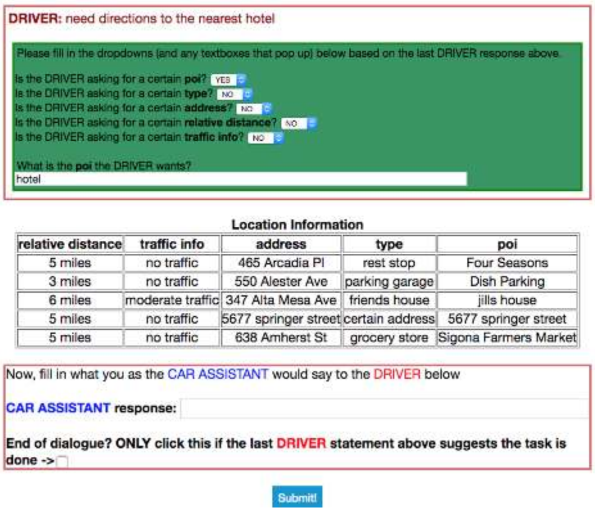
Figure 6: *Driver* mode in the wizard-of-oz collection scheme

TASK: You want to know the forecast in new york for the following period of time: today and tomorrow

DRIVER response:

tell me the temperature in new york

Figure 7: *Car Assistant* mode in the wizard-of-oz collection scheme



DRIVER: need directions to the nearest hotel

Please fill in the dropdowns (and any textboxes that pop up) below based on the last DRIVER response above.

Is the DRIVER asking for a certain **poi**? YES

Is the DRIVER asking for a certain **type**? NO

Is the DRIVER asking for a certain **address**? NO

Is the DRIVER asking for a certain **relative distance**? NO

Is the DRIVER asking for a certain **traffic info**? NO

What is the **poi** the DRIVER wants?

hotel

Location Information

relative distance	traffic info	address	type	poi
5 miles	no traffic	465 Arcadia Pl	rest stop	Four Seasons
3 miles	no traffic	550 Alester Ave	parking garage	Dish Parking
6 miles	moderate traffic	347 Alta Mesa Ave	friends house	jills house
5 miles	no traffic	5677 springer street	certain address	5677 springer street
5 miles	no traffic	638 Amherst St	grocery store	Sigona Farmers Market

Now, fill in what you as the CAR ASSISTANT would say to the DRIVER below

CAR ASSISTANT response:

End of dialogue? ONLY click this if the last DRIVER statement above suggests the task is done -> ☐