Attention Guided Dialogue State Tracking with Sparse Supervision

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Abstract
Existing approaches to Dialogue State Tracking (DST) rely on turn level dialogue state annotations, which are expensive to acquire in large scale. In call centers, for tasks like managing bookings or subscriptions, the user goal can be associated with actions (e.g. API calls) issued by customer service agents. These action logs are available in large volumes and can be utilized for learning dialogue states. However, unlike turn-level annotations, such logged actions are only available sparsely across the dialogue, providing only a form of weak supervision for DST models.

To efficiently learn DST with sparse labels, we extend a state-of-the-art encoder-decoder model. The model learns a slot-aware representation of dialogue history, which focuses on relevant turns to guide the decoder. We present results on two public multi-domain DST datasets (MultiWOZ and Schema Guided Dialogue) in both settings i.e. training with turn-level and with sparse supervision. The proposed approach improves over baseline in both settings. More importantly, our model trained with sparse supervision is competitive in performance to fully supervised baselines, while being more data and cost efficient.

1 Introduction
A task-oriented conversational system helps a user achieve a specific goal, such as booking a hotel, taxi, or a table at a restaurant (Gao et al., 2018). An essential component in dialogue systems is dialogue state tracking (DST), i.e. the accurate prediction of a user’s goal as the dialogue progresses. It is typically modelled as slot (time)-value (18:30) pairs specific to a domain (taxi). Current DST systems rely on extensive human annotation of slot-values at each dialogue turn as supervision signal for training. This is prone to annotation errors (c.f. the extensive label corrections between MultiWOZ 2.0 and 2.1 (Eric et al., 2019)) and costs a lot of time and effort to create. Furthermore, domains and services emerge continuously. Generalization to new domains using limited data is one of the most important challenges for using DST and goal-oriented conversational AI research more broadly.

We propose a novel approach of learning DST through sparse supervision signals, which can be obtained in large quantities without manual annotation. In call-centers, customer service agents handle a large number of user queries every day. The actions taken by agents while resolving user queries are reflected in logged API function calls, together with associated parameters and their values. An example API call to refund a customer for an order could be: `issue_refund(order_id, refund_method, amount)`, where `order_id` is the unique ID of the order, `refund_method` could be credit card or voucher, and `amount` is the money to be refunded. This is analogous to the notion of domain and associated slots and values in public DST datasets and represent the state of a dialogue (the goal of dialogues being to issue those API calls). However, unlike annotated dialogue states, these calls would only be available sparsely across the turns, making it challenging to learn a DST model.

Figure 1 illustrates the difference between full supervision with manual annotation, and weak supervision acquired from sparsely logged API calls. As can be seen from Figure 1a, training with full supervision provides slot labels at every turn, while in weakly supervised setting the model would have labels only for a few turns where a request is confirmed and an API call (e.g. `book_restaurant`) is issued. Irrespective of how a model is trained, during inference the dialogue state would need to be predicted at every turn (Figure 1b), to inform the response generation and resolve the task at the appropriate turn. In other words, with weak super-
Our main contributions are the following.

1. We define a novel learning setup, where labels for only a few dialogue turns are used to learn a DST model with weak supervision. Despite the challenging nature of the task, this is a practical setting that leverages large scale, robust, and cheap training data available for a new domain.

2. We propose a neural encoder-decoder architecture, named AGG, with an attention mechanism to help the model focus on small and important fractions of the input. This enables the model to achieve superior performance in the weakly supervised setting.

Our experiments on the public benchmark MultiWOZ 2.1 and Schema Guided Dialogues datasets show that under weak supervision, our proposed model achieves a joint goal accuracy improvement of 5.94% (MultiWOZ 2.1), and 4.95% (Schema Guided Dialogues) absolute over the baseline model. Further analysis shows that on MultiWOZ 2.1 dataset, using sparse supervision is comparable to training the baseline model using full supervision on 60% of the dialogues, which proves that our proposed model is particularly data efficient.

To the best of our knowledge, this is the first work to study DST in a weakly supervised setting, with sparse labels for dialogue states, that aligns well with practical applications of Conversational AI.

Figure 1: Illustration of DST training and inference procedure. (a) depicts the difference between training a model with full vs weak supervision signals. In case of weak supervision, only the labels for a few intermediate turns (in blue) are available. For full supervision, labels for all turns are available. (b) shows the inference setting for DST. The model needs to make turn level predictions irrespective of how it was trained.
2 Related Work

Multidomain DST has gained recent attention with the availability of large scale datasets such as MultiWOZ 2.0 (Budzianowski et al., 2018) and its successor MultiWOZ 2.1 (Eric et al., 2019), which focus on restaurant, train, taxi, attraction and hotel domains, and Schema Guided Dialogues Dataset (Rastogi et al., 2019).

The recent works on DST can be categorized into 1) Picklist; 2) Span prediction; and 3) Generation based models. Picklist models (Zhang et al., 2019) are used extensively in machine reading comprehension literature (Rajpurkar et al., 2016) but some slot values cannot be directly copied from source side, such as “yes or no” questions. Additionally, it becomes even harder to find an exact match if the dataset has been created by annotators writing down the slot value instead of marking the spans. To overcome the drawbacks of these two approaches, recent works (Rastogi et al., 2019; Zhang et al., 2019) adopt a hybrid approach where some slots are categorical and others are non-categorical. For categorical slots the authors use a pick-list approach and employ span-prediction for non-categorical slots.

Generation of slot values is typically based on Sequence to Sequence models that are also widely used in Machine Translation (Sutskever et al., 2014; Bahdanau et al., 2015). This approach is ontology independent, flexible, and generalizable. Wu et al. (2019) proposes a sequence to sequence style model with soft copy mechanism (See et al., 2017). Our work is built upon TRADE (Wu et al., 2019), due to its ontology free nature and flexibility to generate new values. Kumar et al. (2020) also proposes a model based on TRADE with the addition of multiple attention to model the interactions between slot and dialogue contexts. Team 2 at DSTC-8 (Lo et al., 2020) also uses a TRADE-like model on Schema Guided Dialogues Dataset. This work can be considered as complementary to (Kumar et al., 2020) and (Lo et al., 2020), since our focus is on the weak-supervision setting.

Recent research (Bingel et al., 2019) has also shown the efficacy of using weak dialogue level signals for domain transfer in DST. They pre-train a model with turn level signals on a domain and fine-tune with a dialogue-level reward signal on a target domain. In contrast, we propose to learn DST only from sparse signals available through API logs, without requiring any turn-level annotations.

3 DST with Sparse Supervision

In this section we formalize the task of DST with sparse supervision signals. For a dialogue \( D = \{u_1, a_1, u_2, a_2, \ldots, u_{n_D}, a_{n_D}\} \), we denote the agent and user utterances at turn \( j \) as \( a_j \) and \( u_j \), respectively. In a multi-domain setup, let us assume we have \( S = \{s_1, s_2, \ldots, s_N\} \) slots across all domains. For a dialogue turn \( j \), the dialogue state \( (y_j) \) is defined as a set of slot-value pairs i.e. \( y_j = \{(s_1, v_1), (s_2, v_2), \ldots, (s_N, v_N)\} \), where \( s_i \in S \) is a slot and \( v_i \in V \) is its corresponding value. Slots which have not been mentioned in the dialogue will have None as their value in the dialogue state. Given the dialogue history of agent and user utterances up to turn \( j \), the objective of a DST system is to predict the dialogue state \( y_j \) at every turn \( j \in n_D \) of the dialogue.

Existing DST systems consider this as a fully supervised problem, where every turn in the dialogue is manually annotated (set of labels \( Y_D = \{y_1, y_2, \ldots, y_{n_D}\}, |Y_D| = n_D \)). We focus on a realistic but harder setting, where supervision signals are available sparsely for only a few turns, i.e. \( |Y_D| < n_D \). Such sparse labels for intermediate turns can be obtained when an API call is invoked after the turn (as illustrated in Figure 1a). In industrial conversational systems, alignment of API calls even at intermediate turns might not be available, as these are often logged at the whole dialogue level. Such invocation logs can provide supervision only at the end of dialogue \( Y_D = \{y_{n_D}\}, |Y_D| = 1 \), pushing sparsity to the extreme.

It is important to note that training a DST model with sparse labels instead of turn-level annotations, makes this a weakly supervised task. This is due to the fact that during training, the model has supervision signals for only a few turns \((y_j \in Y_D)\), after which API calls were made. However, during inference it needs to predict the state at every turn in the dialogue \( \{\hat{y}_j, \forall j \in (1, n_D)\} \). In other words, this task requires building a model that can be trained with coarse supervision signal for multiple turns, but can make fine-grained predictions for individual turns.
4 Model Architecture

In this section we propose a model architecture for the dialogue state tracking task, as shown in Figure 2. The architecture is based on the encoder-decoder paradigm and is adapted from TRADE (Wu et al., 2019). Note that the model itself is agnostic to the learning setup (weak vs full supervision) used for the task.

4.1 Utterance Encoder

Dialogue history at turn $j$ is formed by concatenating all agent and user utterances in the dialogue from turn 1 to $j$.

$$X_j = \text{concat}(u_1, a_1, u_2, a_2, \cdots, a_{j-1}, u_j)$$

where concat represents text concatenation function. The concatenated text is then tokenized using a white space tokenizer and embedded.

We use a combination of word and character embeddings to project all tokens to a low-dimensional vector space. We concatenate 300 dimensional GloVe word embeddings (Pennington et al., 2014) and 100 dimensional character embeddings (Hashimoto et al., 2017) to represent the tokens. These embeddings are further fine-tuned during the training process.

The dialogue history is embedded as:

$$E_j = \text{embed}(X_j) \in \mathbb{R}^{T_j \times d_{emb}}$$

where $T_j$ is the number of tokens in the dialogue history and $d_{emb}$ is the embedding dimension.

For embedding domain and slot names, a separate randomly initialized embedding table is used in TRADE. In contrast, we share the embeddings among dialogue history, domain, and slot tokens by using the same embed function for all of them. This ensures common tokens such as price range have the same representation when they occur in a dialogue turn and as a slot name.

A bidirectional GRU (Cho et al., 2014) is used to get a contextualized representation of dialogue history:

$$h_t^{enc} = \text{BiGRU}(E_j[t])$$

$$H_j^{enc} = \{h_1^{enc}, h_2^{enc}, \cdots, h_T^{enc}\} \in \mathbb{R}^{T_j \times d_{hdd}}$$

where $E_j[t]$ is the embedding for the $t$th token, $h_t^{enc}$ is the hidden state of the encoder at $t$th time-step, $d_{hdd}$ is the summation of output dimensions from forward and backward GRUs, and $H_j^{enc}$ represents the encoded dialogue history after $j$ turns.

4.2 State Generator

Another GRU is used as a decoder to generate slot values in the state generator. For a dialogue turn $j$, the decoder runs $N_j$ times to predict values for all $N_j$ slots in the dialogue state.

For a slot $s_k$ in dialogue state, the average embeddings of its domain and slot name are used as input in the first time step of the decoder:

$$x_0^{dec} = \text{embed}(s_k)$$

The output from the decoder at each time step is used for generating a word as the value of the corresponding slot. The generator may use words present in vocabulary or may choose to directly copy tokens from the source side, similar to the soft-gated copy mechanism (See et al., 2017). This enables the model to predict slot values that might not have been pre-defined in the vocabulary but are present in the dialogue history.

4.3 Attention Guided Generator (AGG)

Unlike other sequence-to-sequence problems such as machine translation or summarization, in dialogue state tracking the values to be generated are usually quite short - only one or two words long on average. Therefore, the initial hidden state of the generator is of crucial importance to generate accurate slot values.

TRADE uses the last hidden state of the BiGRU in utterance encoder as initial hidden state of the decoder in state generator (shown in Figure 3a).

$$h_0^{dec} = h_T^{enc}$$

$h_T^{enc}$ contains the whole encoded dialogue history up to turn $j$ and is agnostic of slots.

A dialogue history contains many turns and not all of those are important for a particular slot. In the weakly supervised setting, this becomes even
more pronounced. In the hardest scenario, when supervision is available only for the last turn, the whole dialogue would be concatenated to create the dialogue history. This can result in a long sequence of text, where only a fraction of the information is relevant for a particular target slot.

The model must learn to identify relevant turns for a target slot during training. This is because, during real-time deployment of the model at the inference stage, the model would need to predict the slot values at turn level, although it has been trained with signals at dialogue level. Therefore, a model relying on the complete dialogue history will struggle to make predictions during inference when only part of the dialogue is given.

We propose Attention-Guided-Generator (AGG) (shown in Figure 3b), which is initialized with a slot aware dialogue history. We apply a cross-attention between the target slot embedding and encoded source tokens to learn the relevance of tokens in dialogue history for that particular slot.

\[
\alpha_{sk,t} = \text{attention}(s_k, h_{t}^{enc}) \quad (7)
\]

\[
h_{sk,0}^{dec} = \sum_{t=1}^{T_j} \alpha_{sk,t} \cdot h_{t}^{enc} \quad (8)
\]

where \(\alpha_{sk,t}\) denotes the attention weight for token \(t\) in the dialogue for slot \(s_k\), \(h_{sk,0}^{dec}\) is the initial state of the decoder for the slot \(s_k\).

The use of this slot-aware dialogue history provides a better initialization for the generator. More importantly, it also forces the model to focus only on those tokens in the dialogue history that are relevant to the slot to generate its value. This makes the prediction of values from partial input, i.e. at the turn level, more robust and accurate.

| MultiWOZ 2.1 | SGD |
|--------------|-----|
| # of domains | 7   | 16  |
| # of dialogues | 8,438 | 16,142 |
| Total # of turns | 113,556 | 329,964 |
| Avg turns per dialogue | 13.46 | 20.44 |
| # of slots | 24  | 214 |

Table 1: Dataset statistics for MultiWOZ 2.1 and Schema Guided Dialogues Dataset (SGD)

5 Experiments

5.1 Dataset

We experiment on two datasets: MultiWOZ 2.1 (Eric et al., 2019) and Schema Guided Dialogues Dataset (SGD) (Rastogi et al., 2019). MultiWOZ contains human-human written conversations spanning 7 domains. MultiWOZ 2.1 is the successor of MultiWOZ 2.0 (Budzianowski et al., 2018), which fixes noisy state annotations. SGD is a larger dataset created by defining schemas and generating dialogue structures automatically. Humans were then asked to rewrite the dialogue structures in a more fluent natural language. For MultiWOZ, the predictions are made over all the domain-slot pairs, while in SGD predictions are made over a dynamic set of slots. The detailed statistics are shown in Table 1.

Currently, there is no publicly available large dataset with API call logs, therefore we use sparse dialogue state annotations for the weak-supervision setting. In MultiWOZ dataset, only the dialogue states at the end of each dialogue are used for training to represent the hardest scenario for weak supervision, where API calls are fully characterized only at the end. SGD dataset has been annotated in a slightly different manner. If a particular service has been completed at a turn in the middle of the dialogue, say turn \(j\), then its dialogue state annotations...
Table 2: Results on MultiWOZ 2.1 for models trained with full and weak supervision. TRADE (Wu et al., 2019) refers to results reported in their paper.

| Supervision | Model   | dev SA | Joint GA | test SA | Joint GA |
|-------------|---------|--------|----------|---------|----------|
| Full        | TRADE (Wu et al., 2019) | - | - | - | 45.60 |
|             | TRADE   | 96.83 | 50.20 | 96.88 | 45.02 |
|             | AGG     | 97.22 | 52.40 | 97.25 | 47.57 |
| Weak        | TRADE   | 95.17 | 42.23 | 95.52 | 37.52 |
|             | AGG     | 96.10 | 48.03 | 96.30 | 43.46 |

Table 3: Joint GA for Weak Supervision (AGG and TRADE) and Zero-Shot Transfer Learning (TRADE) on MultiWOZ 2.1 (Kumar et al., 2020).

| Domain | Weak Supervision AGG | TRADE | Zero-Shot |
|--------|----------------------|-------|----------|
| taxi   | 42.06                | 27.41 | 59.21   |
| restaurant | 54.30   | 50.21 | 12.59   |
| hotel  | 37.56                | 31.84 | 14.20   |
| attraction | 57.25   | 46.53 | 20.06   |
| train  | 65.99                | 63.92 | 22.39   |

5.2 Implementation details

We reimplement TRADE with PyTorch in AllenNLP (Gardner et al., 2017) framework based on the open-source code ¹ and obtain results similar to the ones reported in the original paper. On MultiWOZ 2.1 dataset, we follow the settings of TRADE as in the MultiWOZ 2.0. On SGD dataset, we tokenize the dialogue history with Spacy tokenizer and preserve casing. For the encoder, one layer bidirectional GRU with 400 hidden units is used, and a dropout of 0.2 is applied to the embedding output as well as the GRU output. For the decoder, we use teacher forcing (Bengio et al., 2015) ratio of 0.5 to sample from gold and generated tokens, and greedy decoding is used due to the short length of the target sequences. Adam optimizer (Kingma and Ba, 2015) is used with an initial learning rate of 0.001. All reported numbers are produced by running with 5 random seeds and averaging their results.

5.3 Results on MultiWOZ 2.1

There are two evaluation metrics for MultiWOZ 2.1 dataset.

Slot accuracy (SA): compares the predicted value for each slot at each dialogue turn.

Joint Goal Accuracy (Joint GA): computes accuracy of the predicted dialogue state at each dialogue turn. The predicted state is considered to be correct only if all slot values are correctly predicted.

Experiment results on the test set of MultiWOZ 2.1 are shown in Table 2. Values for Slot Accuracy are quite high for all methods, since many slots have none values across the dialogue turns, therefore we focus more on the Joint goal accuracy metric. We first observe that AGG outperforms TRADE in both full and weak supervision settings comfortably, with improvements of 1.97% and 5.94% absolute, respectively.

We also note that AGG trained with weak supervision is only 4.11% lower in performance than the model trained with full supervision. This performance drop is much lower compared to TRADE when used where the gap in performance between full and weak supervision is 8.08%. This shows the effectiveness of slot aware attention in sparse settings. The low drop in performance due to weak supervision illustrates that using broadly available, inexpensive labels we can achieve performance very close to a model trained with full supervision.

Scaling to new domains: In the next set of experiments, we evaluate the efficacy of using the weak supervision approach for scaling to new domains. For a new domain, we propose to use automatically-collected sparse signals for weak supervision, instead of predicting with zero-shot learning. We compare our weakly supervised model (AGG-ws) on MultiWOZ 2.1, with a standard approach from literature, i.e. TRADE trained on turn-level signal evaluated on a new domain in zero-shot setting.

We measure Joint GA on test sets only from a single target domain. Training set contains dialogues from the other four domains with full supervision.

¹https://github.com/jasonwu0731/trade-dst
Figure 4: Attention weights (calculated from Equation 7), for a sample dialogue from MultiWOZ 2.1. Color bars under the texts represent attention weights for slot restaurant-price_range, taxi-leave_at and attraction-type.

| Supervision Type | Model    | All Services | Seen Services | Unseen Services |
|------------------|----------|--------------|---------------|-----------------|
|                  |          | Joint GA     | Average GA    | Joint GA        | Average GA      | Joint GA        | Average GA      |
| Full             | Google Baseline | 0.2337      | 0.3605        | 0.4123          | 0.6778          | 0.2000          | 0.5192          |
|                  | Team 2   | 0.3647      | 0.7438        | 0.7363          | 0.9132          | 0.2406          | 0.6850          |
|                  | TRADE    | 0.3457      | 0.6429        | 0.7133          | 0.8885          | 0.2350          | 0.5756          |
|                  | AGG      | 0.3273      | 0.6192        | 0.7196          | 0.8902          | 0.1964          | 0.5250          |
| Weak             | TRADE    | 0.2139      | 0.3766        | 0.4791          | 0.7968          | 0.1253          | 0.5000          |
|                  | AGG      | 0.2501      | 0.6261        | 0.5679          | 0.8522          | 0.1452          | 0.5474          |
leave that exploration for future work.

From the results on SGD test set as shown in Table 4, we first note that in weak supervision setting, the proposed model AGG outperforms TRADE by large margins for both Seen and Unseen Services. Furthermore, the drop in performance for training with weak vs full supervision, is consistently lower for AGG than for TRADE. This is inline with our observation from results on MultiWOZ dataset as well (in Section 5.3). On Seen Services, AGG trained with weak supervision outperforms the Google Baseline trained with full supervision. We note that with full supervision the performances of TRADE and AGG are lower than that of Team 2. One factor could be that Team 2 also uses the service and slot descriptions provided in the SGD dataset. This additional textual information possibly helps quite a bit in informing the model. However, we only use service and slot names in our models to make the learning task similar across datasets, i.e. same as MultiWOZ where such additional signals are not available.

### 5.5 Efficiency Analysis

In this subsection, we analyze the efficiency of training weakly supervised models compared to traditional fully supervised ones from time and data requirements perspective.

#### Training Time

The training time for different model variations is shown in Table 5. All models have been trained on an AWS EC2 p3.16xlarge instance which has 8 Tesla V100 GPUs. We can see that using only weak supervision, the time per epoch and time required for complete model training has reduced to nearly a quarter on both MultiWOZ 2.1 and SGD datasets.

#### Data Efficiency

We want to analyze the data efficiency of weak supervision and our model in terms of impact on performance with varying data sizes. We subsample the dialogues in MultiWOZ 2.1 and plot the result of TRADE trained with full supervision on varied dataset sizes. As Figure 5 shows, 20% of dialogues are required with turn level supervision to match the performance of a TRADE model that is trained with weak signals on the full dataset. On the other hand, AGG learns a strong model from weak state annotations that is on par with TRADE trained on 80% of dialogues annotated at every dialogue turn. This demonstrates that AGG is more data-efficient and particularly effective for weakly supervised DST.

### 6 Conclusion

In this work, we introduce a new learning setup for dialogue state tracking by effectively leveraging sparse dialogue states as weak supervision signals. We propose an encoder-decoder based approach inspired by a copy-generative model TRADE. We introduce an attention-guided generator that learns to focus on relevant parts of a dialogue for a given slot to make predictions. Experimental results on two large open-domain dialogue datasets show that training on sparse state annotations can achieve a predictive performance close to that when training on full data. This work follows the body of literature aiming to train models with fewer labeled samples. Our approach shows that, without manual annotations and using only proxy signals for weak supervision, we can train models at large scale and expand to new domains.
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