Hi-DST: A Hierarchical Approach for Scalable and Extensible Dialogue State Tracking

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Abstract
Dialogue State Tracking (DST) is a sub-task of task-based dialogue systems where the user intention is tracked through a set of (domain, slot, slot-value) triplets. Existing DST models can be difficult to extend for new datasets with larger domains/slots mainly due to either of the two reasons: i) prediction of domain-slot as a pair, and ii) dependency of model parameters on the number of slots and domains. In this work, we propose to address these issues using a Hierarchical DST (Hi-DST) model. At a given turn, the model first detects a change in domain followed by domain prediction if required. Then it decides suitable action for each slot in the predicted domains and finds their value accordingly. The model parameters of Hi-DST are independent of the number of domains/slots. Due to the hierarchical modeling, it achieves $O(|M| + |N|)$ belief state prediction for a single turn where $M$ and $N$ are the set of unique domains and slots respectively. We argue that the hierarchical structure helps in the model explainability and makes it easily extensible to new datasets. Experiments on the MultiWOZ dataset show that our proposed model achieves comparable joint accuracy performance to state-of-the-art DST models.

1 Introduction
In a goal-oriented or task-oriented dialogue system, Dialogue State Tracking (DST) refers to the problem of extracting the goal or intention shown by the user at each turn. The user’s goals are captured through a set of dialogue states which are the system’s internal representation of the ongoing conversation. DST is essential because it not only helps to understand the user’s requirement but also impacts the next dialogue generation. In this era of immersive AI, task-based dialogue systems are gaining popularity day by day. As a result, dealing with a large number of domains and slots will soon become a real problem for task-based chatbots. In this work, we propose a scalable and extensible solution framework for DST to address this forthcoming issue.

We now briefly define DST with an illustration shown in Fig 1. Let $U_t$ and $S_t$ be the user and system utterance respectively at turn $t$. Then a task-based conversation is generally expressed as $D = \{U_0, (S_1, U_1), \cdots , (S_n, U_n)\}$. Let belief state $B_t$ be the ground-truth dialogue state for turn $t$. $B_t$ represents the set of (domain, slot, slot-value) triplets that have been extracted so far till turn $t$. The task of DST is to predict $B_t$ given the dialogue history till turn $t$.

The solution framework for the DST model

Figure 1: A sample conversation from the MultiWOZ (Budzianowski et al., 2018) dataset (dialogue id PMUL3336).
can be broadly categorized into three classes - i) picklist-based, ii) generation-based, and iii) end-to-end modeling. The first two methods approach the DST problem explicitly, whereas the third class solves it as a part of end-to-end modeling of the task-based dialogue system. Picklist-based models (Mrkšić et al., 2017; Nouri and Hosseini-Asl, 2018; Zhong et al., 2018; Goel et al., 2019) find the value of a given domain-slot pair from a pre-defined candidate set. This is why these methods need access to the complete ontology of the dataset. This type of modeling can be used only when the candidate set is limited. But in reality, there are many slots (e.g., name, time, etc.) where the range of values can be indefinitely large. Generation-based approaches (Gao et al., 2019; Wu et al., 2019; Kim et al., 2020; Heck et al., 2020) solve this problem by generating the slot-value directly from the dialogue history. These methods usually formulate the slot-value prediction as a reading comprehension (Chen et al., 2017) or text summarization (See et al., 2017) task. There are hybrid models (Zhang et al., 2020) which take the advantages of both picklist and generation-based methods by choosing the slot-value prediction strategy based on the type of slot. On the other hand, end-to-end models (Hosseini-Asl et al., 2020; Wu et al., 2020; Lin et al., 2020; Mehri et al., 2020) aim to unify multiple sub-tasks of a task-oriented dialogue system using a single model. They have the advantage of being fully generative and are usually trained as a conditional or causal language model to generate the next system utterance.

Although recent progress in generation-based and end-to-end approaches has shown significant performance gain in DST, there are still some scalability and extensibility issues that need to be addressed. These issues mainly occur due to two properties - i) predicting domain and slot as a pair, ii) dependency of model parameters on number of domains and slots. All the existing DST solutions hold either of these properties and in most cases both. The first property leads to $O(|S|)$ belief state prediction time for each turn where $S$ is the set of all possible domain-slot pairs in a given dataset. In the worst case, $|S| = |M| \times |N|$ where $M$ and $N$ are the sets of unique domains and slots respectively. Since task-based chatbots are designed to work in real-time, reducing time complexity is of critical need. Ren et al. (2019) tackles this issue by predicting domain and slot sequentially and thereby reducing the time complexity to $O(N)$ using their $O(1)$ domain prediction strategy. However, their domain prediction depends on the ordering of domains which can be hard to maintain in a real setup. They also satisfy the second property due to the inclusion of the previous belief state as input. Even though this kind of auxiliary feature has been helpful in improving the joint accuracy (Kim et al., 2020; Heck et al., 2020), it makes the model difficult to extend. The end-to-end models also possess the second property because they encode the previous belief state along with dialogue history to represent a complete turn (Hosseini-Asl et al., 2020). With the growing popularity of task-based conversational systems, we can anticipate larger datasets with lots of domains and slots to be used in the future for the training and development of such systems. Since these datasets will contain a large set of unique domains and slots, scalability and extensibility will become an issue for the existing models.

In this paper, we propose a Hierarchical DST (Hi-DST) model to tackle the issues discussed above. We break the DST task into a hierarchy of four generic sub-tasks - domain change prediction, domain prediction, slot action prediction, and slot-value prediction. We adopt the triple copy strategy (Heck et al., 2020) for slot-value prediction and use the neural span-based question-answering method to extract the slot values from the utterances directly. In contrast to others, we reduce the problem of slot-value prediction to SQuAD (Rajpurkar et al., 2016) to leverage transfer learning. We keep our model parameters independent of the number of domains/slots. This is why we refrain from using any kind of auxiliary features that depend on the domain/slot set. Contributions of our work can be summarized as follows: 

- **We present Hi-DST**, a scalable and extensible DST solution that adopts hierarchical modeling without any dependency on the number of domains and slots. Hi-DST achieves $O(|M| + |N|)$ belief state prediction for each turn where $M$ and $N$ are the sets of unique domain and slot respectively.

- **We show that Hi-DST** achieves a comparable performance to existing DST models while being scalable and extensible simultaneously.

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1 Code is available at github.com/SuvodipDey/Hi-DST
• We argue that the hierarchical structure helps in the explainability of the model and makes it easily extensible to new datasets with a much larger number of domains and slots.

2 Hierarchical DST (Hi-DST)

The core idea behind our approach is to decouple the prediction of domain-slot pairs to achieve belief state prediction in $O(|M| + |N|)$ time. We also keep our model free from any kind of dependency on the number of domains and slots to make it easily extensible. We propose Hi-DST that comprises of four generic components: domain change prediction (section 2.1), domain prediction (section 2.2), slot-action prediction (section 2.3), and slot-value prediction (section 2.4). During prediction (section 2.5), we first detect any change in domain. If there is a change in domain predicted, we run domain prediction and update the set of current domain(s) that keeps track of the active domains for a given turn. We next predict the appropriate actions necessary for relevant domain-slot pairs. Finally, we extract the slot values using span-based method (Chen et al., 2017) when required. We incrementally update our predicted dialogue states at each turn to get the desired belief state. Fig. 2 shows the workflow of our proposed approach.

2.1 Domain Change Prediction

In a task-based conversation, a user can converse about multiple domains and switch between them if necessary. The objective of this component is to detect the point of domain changes. We formulate it as a ternary classification problem. A prediction of 0 represents that there is no change in domain. In this case, we use the domain set of the previous turn as current domains. Prediction 1 indicates a domain change in the current turn. Here, we need to run the domain prediction model to get the new domains. Finally, class label 2 represents a general conversation (like greeting, thanking, etc.). In this case, we do no further prediction as the user is not showing any additional intention. Basically, this model component captures the theme of a dialogue turn in an abstract way and guides the subsequent predictions accordingly.

We model this three-class classification problem using BERT (Devlin et al., 2019) finetuning. Let $S_t$ and $U_t$ be the system and user utterances at turn $t$. Then the objective of this model is to find the probability of $p(y|S_t, U_t)$ where $y \in \{0, 1, 2\}$. Let $X_t \in \mathbb{R}^d$ be the encoding of utterance pair $(S_t, U_t)$ where $d=768$ be the dimension of the BERT embedding. We compute $X_t$ by taking an average of the token embeddings of BERT’s second-last hidden layer with $([CLS]S_t[SEP]U_t)$ as input. We pass $X_t$ through a linear layer of dimension $(d \times 3)$ to find the class probabilities. We use a cross-entropy loss to update the model parameters.

2.2 Domain Prediction

The objective of this component is to find the set of relevant domains in a given user turn. We use a binary classification model to predict 1 if a given domain is relevant and 0 otherwise. Let $D$ be the set of unique domains. Then the goal of the domain prediction model is to find the probability of $p(y|S_t, U_t, d_j)$ where $y \in \{0, 1\}$, and $d_j \in D$. We run this prediction for each domain to obtain the set of current domains.

We encode a specific domain using pre-trained GloVe (Pennington et al., 2014) embedding of dimension $d_1$ followed by a linear layer and GeLu (Hendrycks and Gimpel, 2020) activation. Let $Z$ be the encoding of domain $d_j$. So, $Z = GeLu(l_1(Glove(d_j))) \in \mathbb{R}^{d_2}$ where $l_1$ is a linear layer of dimension of $(d_1 \times d_2)$.

Next, we encode the utterances using BERT. Let $G_t$ be the token representation of utterance pair $(S_t, U_t)$ generated by BERT tokenization. Let $H_t \in \mathbb{R}^{d_2 \times L}$ be the output of BERT’s second-to-last hidden layer with input $G_t$ where $L$ is the maximum sequence length and $d_2 = 768$ is the dimension of the BERT embedding. To put attention on relevant tokens, we take a linear combination of the column-vectors of $H_t$ using scaled dot-product attention (Vaswani et al., 2017). We express our fi-
nal utterance encoding as $X_t = \sum_{l=1}^L \alpha_l H_{tl}$ where $X_t \in \mathbb{R}^{d_2}$, $H_{tl} \in \mathbb{R}^{d_2}$ is the output vector of the $l$th token, and attention $\alpha = \text{softmax}(H_t^T Z / \sqrt{d_2}) \in \mathbb{R}^L$. We now concatenate $X_t$ and $Z$ and pass it through a linear classification head of dimension $(2d_2 \times 2)$ to find the class probabilities. We use a softmax classifier with cross-entropy loss. We do not update the GloVe embeddings of the domains during back propagation to extend the model easily for unseen domains.

### 2.3 Slot Action Prediction

In this component, we find the relevant slots from the predicted set of domains for a given turn. We achieve this by a slot action model that predicts suitable action for a given domain-slot pair. Let $D$ be the set of current domains at turn $t$. Let $C_i$ be the set of slots in the domain $d_i$ and $A$ be the set of actions. Then the objective of this model is to find the probability of $p(y|S_t, U_t, c_{ij}, d_i) \forall i, j$ where $y \in A$, $c_{ij} \in C_i$, and $d_i \in D$.

Based on our analysis, we define eight general and two dataset-specific actions described in Table 1. Slot-action 0 (NONE) indicates that a domain-slot pair is irrelevant. All the slot-actions between 1 and 4 indicate that the slot-value needs to be inferred rather than extracted directly from the utterances. Slot action 5 (EXT$_{usr}$) represents that the slot-value resides in the current user utterance $U_t$. Slot action 6 (EXT$_{sys}$) indicates that the slot-value is informed/recommended by the system and can be extracted from the current system utterance $S_t$. Finally, slot action 7 (REF) means that the slot-value is referred to some previous slot-value in the belief state. Besides the general actions, we have two non-trivial slot-actions specific to Multi-WOZ dataset. The first one is HTL$_{type}$ for (hotel, type, hotel) triplet. We add this action because the annotation for this triplet is inconsistent throughout the dataset (Wu et al., 2019). The second one is PPL$_1$ for triplet $(d, people, 1)$ for any domain $d$. This triplet often needs to be inferred rather than extracted directly as shown in the example in Table 1. We found that it is better to handle such dataset-specific non-trivial cases with a new slot action since these values are difficult to extract using span-based approaches.

Our slot action prediction model is very similar to the domain prediction model of Section 2.2. Instead of a domain, here we encode a domain-slot pair in a similar fashion. Here, the encoding of a given domain-slot pair $(d, c)$ can be expressed as $Z = GeLu(l_1([\text{Glove}(c); \text{Glove}(d)]))$ where $Z \in \mathbb{R}^{d_2}$ and $l_1$ is a linear layer of dimension of $(2d_1 \times d_2)$. The rest of the modeling remains the same as the domain prediction model except for the final classification head. The dimension of the final linear layer becomes $(2d_2 \times k)$ where $k$ is the number of slot actions. GloVe embedding of the domains or slots is not updated during training just like our domain prediction model.

| Label | Action | Description | Example |
|-------|--------|-------------|---------|
| 0     | NONE   | slot is irrelevant, slot-value is "None" | In "I want an expensive place to stay in the west side.", slots like Name and Parking are irrelevant. |
| 1     | REQ    | slot is requested by the user, slot-value is "?" | In "What is their address and phone number?", use has requested Address and Phone. |
| 2     | DNC    | user doesn’t care about the slot, slot-value is "don’t care" | In "I’m looking for a hotel in the west, internet is optional", slot-value for Internet will be "don’t care". |
| 3     | YES    | slot-value is "Yes" | In "I need free parking", slot-value for Parking is "Yes". |
| 4     | NO     | slot-value is "No" | In "I don’t need internet or free parking", slot-value for Parking is "No". |
| 5     | EXT$_{usr}$ | slot-value needs to be extracted from the current user utterance | $S_t$: Okay, where would you like to depart from? $U_t$: I’d like to leave from Cambridge, please. |
| 6     | EXT$_{sys}$ | slot-value needs to be extracted from the current system utterance | $S_t$: I recommend Kettle’s Yard on Castle Street which is a museum. $U_t$: Could I get the postcode for that museum? |
| 7     | REF    | the value of the slot needs to be referred | In "I’d like to go see a college that’s in the same area as the hotel", slot-value of Area refers to a previously extracted value. |
| 8     | HTL$_{type}$ | type of the hotel is "hotel" | "I also need to find a 2 star room." |
| 9     | PPL$_1$ | number of people is 1 | $S_t$: How many tickets would you like? $U_t$: Just for myself, please. |

Table 1: Description of slot actions with example.
2.4 Slot Value Prediction

The fourth and final component of Hi-DST is the slot-value prediction for a given domain-slot pair. We need slot-value prediction model for slot actions 5 (EXT_{usr}), 6 (EXT_{sys}), and 7 (REF) because for the rest it can be inferred directly. If the predicted slot-action for a given domain-slot pair is 5 and 6, we need to extract the slot-value from the current user and system utterance respectively. Whereas for slot-action 7, we have to find the reference point of the slot-value from the user utterance and then copy its value. This kind of strategy for slot-value prediction is called triple copy strategy (Heck et al., 2020) and has been shown to be beneficial for DST. We reduce these three kinds of slot-value prediction to the span-based answering problem of the SQuAD dataset (Rajpurkar et al., 2016). By doing so we can directly fine-tune the span-based neural comprehension model (Chen et al., 2017) pre-trained on SQuAD and reap the benefits of transfer learning. In the SQuAD dataset, the input is a pair of a question and context and the objective is to predict the span (start and end index) of the answer in the given context. We reduce our slot-value prediction problem to SQuAD as follows:

**Extract from User Utterance (EXT_{usr}):** For slot action 5 (EXT_{usr}), the value of a given domain slot pair is present in the current user utterance. So, we set the context to $U_t$. We generate the question by converting the given domain-slot pair into an English sentence. For example, (hotel-name) becomes “What is the name of the hotel?”, (train-destination) becomes “What is the destination of the train?”, and so on. The motivation for such question generation is to match the format of SQuAD. In this work, we use rule-based question generation like DS-DST (Zhang et al., 2020) as the set of domain-slot pairs is limited. It would be nice to have a model-based approach to handle question generation on a large scale.

**Extract from System utterance (EXT_{sys}):** In this scenario, the value of a given domain slot pair is present in the current system utterance. It occurs when the user accepts the system’s recommendation/suggestion. The reduction is absolutely similar to the earlier case except the context now being the current system utterance $S_t$. If the set of informed slots by the system at each turn is available, then we do not need to extract the slot value. Instead, we can copy the slot-value of the domain-slot pair directly from that set during prediction.

**Refer (REF):** In this case, the slot-value for a given domain-slot pair refers to a previously extracted value. Hence, our objective here is to find the appropriate reference point in the belief state of the previous turn and then copy its value. Let the reference point for a given domain slot pair $(d, s)$ be $(d^{ref}, s^{ref})$. In general, we observe that slots $s$ and $s^{ref}$ remain the same. So, the main challenge is to find the reference domain $d^{ref}$. We formulate the problem of finding the reference domain similar to the formulation of slot action 5 (EXT_{usr}) and 6 (EXT_{sys}). The context is set to be the current user utterance $U_t$. We convert a domain-slot pair into a question in a slightly different manner. For example, the REF instance shown in Table 1, we form the question as “What is the reference point of the attraction area?” and the model is trained to extract the reference domain “hotel”. There are few special cases where the original slot $s$ does not match the reference slot $s^{ref}$. For instance in the MultiWOZ dataset, slots like destination and departure refers name. In this work, we resolve these slot references manually while creating the training data for this phase, since such examples were limited in number.

2.5 Predictive Algorithm

We now briefly describe our predictive algorithm for a single conversation. Let $D$ be the set of current domain(s) that keeps track of the active domains for a given turn. Let $B$ be the set of predicted belief states. Initially, both $D$ and $B$ are empty. Before moving on to the next turn, $B$ and $D$ are updated based on the predictions made for the current turn. For each user turn $t$ with input $(S_t, U_t, D, B)$, we do the following:

- **Step 1:** Run the domain change prediction model (Section 2.1).
  - If the prediction is a general conversation (Class 2), we make $D = \emptyset$ and skip all subsequent predictions for the current turn.
  - If domain change is detected (Class 1), we go to Step 2.
  - If no change in the domain is predicted (Class 0), we do the following:
    - If the cardinality of the set of current domains ($|D|$) is 1, we directly go to the slot action prediction in Step 3.
    - Otherwise, we go to Step 2 to update $D$. It gives the model an extra chance to find
a domain when $D = \emptyset$. Whereas, it helps to remove extraneous domains in case of more than one relevant domain.

- **Step 2**: Run domain prediction model (Section 2.2) to get the set of current domains for turn $t$.

- **Step 3**: Predict slot action (Section 2.3) for each slots of the current domains. If slot action $\text{EXT}_\text{usr}$, $\text{EXT}_\text{sys}$ or $\text{REF}$ is detected, we go to Step 4. Otherwise, the slot-values are directly inferred and updated in the belief state for turn $t$.

- **Step 4**: Extract the slot-value or reference domain using span-based question-answering method (Section 2.4) and update the belief state $B$ accordingly.

The main purpose of steps 1 and 2 is to predict the relevant domains that are subsequently used for slot value prediction (wherever necessary). This is required due to our decoupling of the domain and slot predictions. We observe that in Step 4 for slot action $\text{REF}$, the model sometimes fails to find the reference domain. This occurs when the user does not explicitly mention the reference domain. For example, “Could you please book train tickets for the same group?”. In such cases, we select the most recent domain that contains the reference slot $s^{\text{ref}}$ as the reference domain $d^{\text{ref}}$.

## 3 Dataset and Experimental Setups

### 3.1 Dataset

We use the MultiWOZ dataset (Budzianowski et al., 2018) for experimentation. It is one of the largest multi-domain conversation corpus available for task-oriented dialogue systems. We perform our experiments on MultiWOZ 2.1 (Eric et al., 2020) and MultiWOZ 2.2 (Zang et al., 2020). Both the datasets are updated versions of the original MultiWOZ dataset and contain fixes to some noisy annotations. Table 2 and 3 shows some basic statistics of the dataset.

### 3.2 Evaluation Metric

Dialogue state tracking is broadly evaluated using several metrics like joint accuracy, slot accuracy, and average joint accuracy (Rastogi et al., 2020). The primary metric for DST is joint accuracy or joint goal accuracy. Joint accuracy is defined by the fraction of turns where the predicted belief state exactly matches the ground truth (Wu et al., 2019). In this work, we only use joint accuracy so that we can directly compare Hi-DST with other models.

There are a lot of instances in the MultiWOZ dataset where the labeled slot value for a given domain-slot pair is not present in the dialogues in its exact form. Rather some variant of the slot value exists like cafe jello instead of cafe jello gallery, centre instead of center, and so on. This can cause a problem for a fair evaluation of span-based slot value prediction. TripPy (Heck et al., 2020) addresses this issue using a label variant map 2 where each value is mapped to a set of variants. A match is considered if the predicted slot value exactly matches the ground truth or any of its variants. We follow the same to evaluate Hi-DST.

### 3.3 Data Preparation

We now summarize the training data generation for Hi-DST. We use the turn-level belief state rather than the cumulative one in our training process. Let $B_t$ be the set of belief state at turn $t$. Then $T_t = B_t \setminus B_{t-1}$ be the turn-level belief state for turn $t$. We ignore the turns for data preparation where $T_t = \emptyset$.

Let $D_t$ be the set of domains in $T_t$. Then for the domain change component, we compare $D_t$ and $D_{t-1}$. If there is no change, we label 0, and 1 otherwise. Annotation for general conversation is available in the MultiWOZ dataset. If this annotation is not available in a dataset, we can ignore this class and train the domain change model with only two classes. For the domain model, we label

| Domain          | Slots                                          | Conversations |
|-----------------|------------------------------------------------|---------------|
| attraction      | name, type, area                               | 33.47%        |
| hotel           | name, type, parking, area, day, stay, internet, people, stars, price | 40.1%        |
| restaurant      | name, food, area, day, time, people, price     | 45.48%        |
| taxi            | arrive, departure, leave, destination          | 18.01%        |
| train           | arrive, day, leave, destination, departure, people | 37.64%        |

Table 3: Unique domain-slot pairs for which slot-value needs to be extracted in MultiWOZ 2.1.

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1. gitlab.cs.uni-duesseldorf.de/general/dsml/trippy-public/blob/master/dataset_config/multiwoz21.json

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Table 2: Data statistics of MultiWOZ 2.1
Table 4: Class-wise performance of domain change, domain, and slot action models on MultiWOZ 2.1 dataset.

| Data | Metric | domain change model | domain model | slot action model |
|------|--------|---------------------|--------------|------------------|
| Train | Precision | 0.90 | 0.90 | 0.90 |
| Recall | 0.96 | 0.96 | 0.96 |
| F1-score | 0.96 | 0.96 | 0.96 |
| Support | 31060 | 136797 | 52238 |
| Dev | Precision | 0.96 | 0.96 | 0.96 |
| Recall | 0.98 | 0.98 | 0.98 |
| F1-score | 0.98 | 0.98 | 0.98 |
| Support | 4052 | 18206 | 7214 |
| Test | Precision | 0.96 | 0.96 | 0.96 |
| Recall | 0.98 | 0.98 | 0.98 |
| F1-score | 0.98 | 0.98 | 0.98 |
| Support | 4059 | 18646 | 7168 |

Table 5: Individual performance of slot-value prediction model on MultiWOZ 2.1 dataset.

| Data | Accuracy | Support |
|------|----------|---------|
| Train | 0.983 | 137,185 |
| Dev   | 0.979 | 18,293  |
| Test  | 0.979 | 18,551  |

Table 6: Joint accuracy comparison

| DST Model | MultiWOZ 2.1 | MultiWOZ 2.2 |
|-----------|-------------|-------------|
| SGD baseline | 43.4% | 42.0% |
| TRADE | 46.0% | 45.4% |
| TripPy (without auxiliary features) | 49.23% | - |
| DS-DST | 51.2% | 51.7% |
| SimpleTOD | 55.3% | - |
| Hi-DST (Ours) | 49.16% | 49.44% |

4 Result and Analysis

4.1 Result

We report our result on MultiWOZ 2.1 (Eric et al., 2020) and MultiWOZ 2.2 (Zang et al., 2020) dataset in Table 6. We compare our models with SGD baseline (Rastogi et al., 2020), TRADE (Wu et al., 2019), DS-DST (Zhang et al., 2020), TripPy (Heck et al., 2020), and simple-TOD (Hosseini-Asl et al., 2020). Although the performance of Hi-DST is comparable to existing models, its performance is generally lower than most of the recent models. We discuss this point in Section 4.2.4 elaborately while analyzing our method.

4.2 Analysis

We analyse Hi-DST in four different aspects: scalability (Section 4.2.1), extensibility (Section 4.2.2), explainability (Section 4.2.3), and performance analysis (Section 4.2.4).

4.2.1 Scalability

We made Hi-DST scalable by ensuring two things: i) making slot-value prediction completely rely on span-based QA, ii) decoupling the prediction of domain and slot. As a result of this kind of modeling, Hi-DST takes \(O(|M| + |N|)\) time to predict a belief state for a given user turn where \(M\) and \(N\) are the sets of domain and slot names respectively. We discuss this point in Section 4.2.4 elaborately while analyzing our method.
$T_0$: Can you help me find some attractions in the east part of town?
$S_0$: Definitely! My favorite place in the east is the Funky Fun House. It's funky and fun!
$T_1$: Can I have the number please?
$S_1$: It's 01223304705. Do you need anything else?
$T_2$: Yeah, I need a restaurant. They need to serve Indian food and be in the same area as Funky Fun House.
$S_2$: There are 4 Indian restaurants in the area. Two are moderately priced and two are expensive. Can I ask what price range you would like?
$T_3$: I would prefer one in the moderate price range.
$S_3$: May I suggest the Rajmahal located at 7 Barnwell Road Fen Ditton. $T_4$: Can I also have their phone number and postcode?
$S_4$: Sure, their phone number is 01223244955 and the postcode is cb58rg. Is there anything else I could help you with?
$T_5$: That is all I need.

Figure 3: Illustration of the working of Hi-DST.

$N$ are the sets of unique domains and slots respectively. It is to be noted that all turns do not require $O(|M| + |N|)$. It is true only for those turns where we need to update the set of current domains. Belief state prediction can take $O(|N|)$ and $O(1)$ when domain change prediction is 0 and 2 respectively. Since the number of domain changes and general dialogues in a task-based conversation is very limited, the dominating factor is $O(|N|)$. To the best of our knowledge, $O(|M| + |N|)$ is the best time complexity for dialogue state prediction without any kind of dependency on auxiliary features and domain statistics.

4.2.2 Extensibility

All four components of Hi-DST are completely independent of the number of domains and slots. So, the number of model parameters will remain the same for any dataset. This is why Hi-DST is easily extensible to datasets with a large number of domains/slots. Moreover, we convert a domain/slot using Glove embedding which is not updated during training. This property enables the model to be used in zero-shot and few-shot scenarios.

4.2.3 Explainability

As described earlier, we break the DST task into a hierarchy of generic sub-tasks. Due to this hierarchical structure, we can look at Hi-DST as a series of meaningful actions which closely resemble human-like decision-making. In Fig 3, we show the details of a Hi-DST prediction along with the confidence of each decision. Firstly, we can observe that it is human-readable and self-explanatory. Secondly, the probability score quantifies each decision and helps in debuggability. For a wrong prediction, we can easily eyeball the probability scores and find the root cause of the mistake. Thirdly, the model is capable of detecting user requests which enable the understanding of complete user intent.

4.2.4 Performance Analysis

We now do a critical analysis of our model performance. Even though having some good properties (like scalability, extensibility, and explainability), our accuracy is lower in comparison to the state-of-the-art models. There are several factors that limit the performance of Hi-DST. Firstly, most of the high-performing models don’t predict domain. We introduce an extra uncertainty in our model through domain prediction which reduces the accuracy but helps in scalability. Secondly, there are a lot of wrong and inconsistent annotations in the MultiWOZ dataset (Zang et al., 2020). These noisy annotations can have a big impact on the predictions since our model components are trained independently. Thirdly, the higher accuracy models use auxiliary features to preserve contextual information. For example, the inclusion of the previous belief state has been shown to be beneficial (Heck et al., 2020). We can observe in Table 6 that the joint accuracy of TripPy drops from 55.3% to 49.2% without the auxiliary features which is very similar to the performance of our model. Although these auxiliary features are helpful, they are dependent on the number of domains and slots which makes them difficult to extend to a new dataset with different domains and slots. Whereas, due to the generic modules and the extensible nature of Hi-DST, we can easily adapt to a new dataset. We also do not need to re-train or finetune all the components for a new dataset. For example, if a newer dataset has
the same set of domains, fine-tuning the slot-action model is enough to get a decent result.

5 Conclusion

In this work, we propose Hierarchical-DST (Hi-DST), a scalable and extensible solution framework for DST. We split the task of DST into four generic modules that not only make Hi-DST scalable and extensible for larger datasets but also improve its explainability. Hi-DST takes $O(|M| + |N|)$ time belief state prediction per user turn and achieves comparable performance to existing DST models. We discuss the performance trade-off due to the enforcement of scalability and extensibility. As future work, we want to continue our experimentation in zero-shot and few-shot scenarios and investigate the efficiency of Hi-DST in complex datasets like SGD (Rastogi et al., 2020). We would also like to explore the possibility of including additional information or auxiliary features without impacting the desirable properties of Hi-DST such as scalability, explainability etc.

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