Transforming Slot Schema Induction with Generative Dialogue State Inference

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Abstract

The challenge of defining a slot schema to represent the state of a task-oriented dialogue system is addressed by Slot Schema Induction (SSI), which aims to automatically induce slots from unlabeled dialogue data. Whereas previous approaches induce slots by clustering value spans extracted directly from the dialogue text, we demonstrate the power of discovering slots using a generative approach. By training a model to generate slot names and values that summarize key dialogue information with no prior task knowledge, our SSI method discovers high-quality candidate information for representing dialogue state. These discovered slot-value candidates can be easily clustered into unified slot schemas that align well with human-authored schemas. Experimental comparisons on the MultiWOZ and SGD datasets demonstrate that Generative Dialogue State Inference (`GenDSI`) outperforms the previous state-of-the-art on multiple aspects of the SSI task.

1 Introduction

Developing Task-Oriented Dialogue (TOD) systems presents the significant challenge of creating and maintaining a *slot schema*, where each slot defines a type of information that is critical for successfully completing the dialogue task (Budzianowski et al., 2018). Traditionally slot schemas are handcrafted, but manually defining each slot is time-consuming, especially when task domains are complicated or the functionality of the dialogue system is frequently updated. To address this, Slot Schema Induction (SSI) has been proposed to automatically generate slot schemas from unlabeled dialogue data (Chen et al., 2013; Min et al., 2020). This task facilitates the automatic analysis of dialogue structure (Qiu et al., 2022) and identifies key types of information that should be included in dialogue state representations (Min et al., 2020). By reducing the need for manual schema creation, SSI expedites developing TOD systems for new application domains, and enables continual discovery of new slot types to improve the coverage of existing slot schemata.

The core challenge of SSI is identifying which information presented in unlabeled dialogue data is important for the task domain and should be included in the dialogue state. Once the important information values are identified, a second challenge is defining a minimal set of slots that captures the different types of information the values represent. All previous work on SSI tackles these challenges in an explicit two-step process involving (1) candidate value identification and (2) inducing a slot schema by clustering candidate values into a set of slot clusters. Identifying value candidates has been explored using tagging models trained on other tasks such as NER or SRL (Min et al., 2020; Hudeček et al., 2021; Qiu et al., 2022; Wu et al., 2022), or using token attention distributions produced by a PLM to extract syntactic constituents (Yu et al., 2022). Inducing slots from value candidates has been explored using out-of-the-box clustering algorithms (Qiu et al., 2022), multi-stage clustering pipelines specific to SSI (Hudeček et al., 2021; Wu et al., 2022; Yu et al., 2022), or a neural latent variable model (Min et al., 2020).

Unlike all previous approaches to SSI, we are the first to take a generative approach to value candidate identification.[1] Candidates are identified using a dialogue state generator model, which is trained to summarize the key task-related information in a given dialogue context as a set of state values. Crucially, this state generator also creates a slot name for each value, which serves as a candidate prediction of the name of the slot the value fills. Value candidates are then clustered in conjunction with these predicted slot names to induce a uni-

[1]The code, models, and data for our approach is publicly available at `https://github.com/emorynlp/GenDSI`.

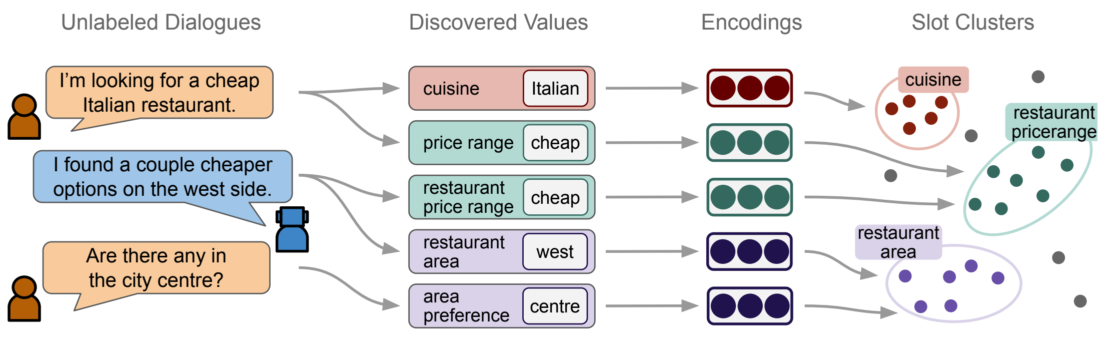

Figure 1: Overview of the `GenDSI` approach.

fied set of slots. The advantage of this approach is that the type semantics of each value candidate are concretely represented using slot name predictions, whereas previous approaches rely on the similarity of value encodings alone to cluster values into slot types. Predicting slot names has the additional benefit of enabling automatic naming of each slot cluster in the induced schema. We demonstrate the impact of these benefits by evaluating our approach on the MultiWOZ (Eric et al., 2020) and SGD (Rastogi et al., 2020) datasets. Our SSI approach produces slot schemas that better match gold reference schemas when compared to the previous state-of-the-art (SoTA) approaches.

2 Approach

Our SSI approach, Generative Dialogue State Inference (`GenDSI`), induces a slot schema consisting of a set of slot clusters from an unlabeled set of dialogues. The induction procedure is performed in three stages (Fig. 1). First, a dialogue state generator discovers value candidates for each turn in the dialogue data and jointly predicts a slot name with each value. Second, an encoding model produces a dense vector representation for each slot-value candidate. Finally, a clustering algorithm uses the encodings to filter and group candidates into a unified set of slot clusters.

Dialogue State Generator Our approach formulates the discovery of value candidates from unlabeled dialogue data as a sequence-to-sequence generation task. The input is a dialogue context $D_{*..t}$, and the output is a list of slot-value candidates $[(s_1, v_1), ..., (s_k, v_k)]$ represented by the sequence format $s_1{:}v_1; s_2{:}v_2; ...s_k{:}v_k[eos]$. Each candidate includes a value v_i that is inferred to belong to the dialogue state and a slot name prediction s_i to represent the type of v_i. To enable the model to generate slot-value pairs that discover important dialogue state information without any prior knowledge of the task domain, we fine-tune a pretrained encoder-decoder transformer on TOD data that covers a large variety of domains. Section 3 presents an evaluation of the dialogue state generator in which two different training datasets are compared.

Value Candidate Encoding Each slot-value candidate (s_i, v_i) produced by the dialogue state generator is encoded into a single dense vector representation e_i. To do this, we concatenate the slot name and value candidate with a separator to form a single token sequence $s_i{:}v_i$. We then use the SBERT encoder (Reimers and Gurevych, 2019) to independently encode each candidate sequence.

Slot Clustering Given a complete list of all slot-value candidates $[(s_1, v_1), ..., (s_n, v_n)]$ produced by the dialogue state generator across all turns of the dialogue dataset, slot-value candidates are jointly filtered and grouped by applying the HDBSCAN algorithm (McInnes et al., 2017) to the candidate encodings $[e_1, e_2, ..., e_n]$. As demonstrated in previous work (Yu et al., 2022), HDBSCAN is a suitable clustering algorithm because (1) it automatically discovers an appropriate number of slot clusters and (2) it filters out examples in low-density regions of the encoding space, which are likely to represent noisy candidates. The result is a set of slot clusters $[S_1, S_2, ..., S_k]$ where each cluster S_i is a list of values that fill the slot it represents.

3 State Generator Evaluation

Since our SSI approach relies mainly on the dialogue state generator component to infer high-quality value candidates with appropriate slot names, we first conduct an evaluation of the performance of this component when discovering slot-values from dialogues in unseen task domains.

Metrics The dialogue state generator is evaluated by human judges, since discovered slot-value candidates are generated and many surface forms can be equally correct. We recruit three university students as volunteers to evaluate two key aspects of slot value candidate inferences. (1) *Completeness* measures the proportion of dialogue turns for which all key information has been captured as slot-value candidates. (2) *Correctness* measures the proportion of slot-value candidates that accurately represent specific information in their corresponding turns. Details of metrics are presented in Appx. A. This evaluation is performed using a custom annotation software, which was developed to optimize the efficiency of the annotation work. The interface is shown in Appx. C.

To validate our human evaluation metrics, inter-annotator agreement was calculated between the three human judges at 0.43 and 0.27 Krippendorff's Alpha for Correctness and Completeness respectively. Based on a manual review of the annotation disagreements for Completeness items, we believe the lower agreement occurs because judges are required to consider more information across an entire state update compared to judging the correctness of a single slot-value pair, leading to higher annotation difficulty and thus some noisy judgements.

Data Since our goal is to train a dialogue state generator to discover slot-value candidates for unseen domains, we experiment with two domain-diverse datasets for training: SGD (Rastogi et al., 2020) and D0T (Finch and Choi, 2024). SGD is a popular TOD dataset that contains 20 domains and $16,142$ dialogues, with gold dialogue state labels. D0T is a recent dataset that was created using a fully automatic data generation method based on GPT-3.5 and GPT-4. It covers a large $1,003$ domains across $5,015$ dialogues, but it contains some noisy labels from automatic annotation.

We adapt these datasets for slot-value candidate discovery by simply training on dialogue state *updates* instead of full dialogue states, which represent only the slots that are filled by new values. This avoids training the dialogue state generator to predict empty slots, which are not useful for candidate discovery. Additionally, the special request value "?" is removed from D0T state updates. We also replace each slot name in the SGD training split with a random synonymous name from SGD-X (Lee et al., 2022), as we found this augmentation to improve performance.

Both SGD and D0T are also used as evaluation data by randomly sampling 60 turns from their test splits, each from a unique dialogue. Crucially, we *only* sample turns from domains *not* included in the training split. Since the D0T dataset has no native splits for training and testing, we randomly sample 100 domains out of the total $1,003$ to be held-out for evaluation. The D0T training split thus includes only the remaining $4,515$ dialogues.

Models We train two models using T5-3B (Raffel et al., 2020) as a base model: `T5-D0T` trained on D0T and `T5-SGD` trained on SGD. We also compare against the GPT-based automatic annotator used to create silver D0T state update labels (`GPT-D0T`). Implementation details presented in Appx. D.

	D0T			SGD		
Model	CP	CR	HM	CP	CR	HM
T5-SGD	32.3	72.6	44.7	69.3	**90.8***	78.6
GPT-D0T	93.3*	**82.0***	87.3	90.0*	84.7	87.3
T5-D0T	**95.7***	81.2*	**87.9**	**94.7**†	81.7	**87.7**

Table 1: Human evaluation of completeness (CP), correctness (CR), and their harmonic mean (HM) for each dialogue state generator. */† denote statistical significance against unstarred/all results in the same column (Agresti-Caffo, $p < 0.05$).

Results As shown in Table 1, `T5-D0T` exhibits the best overall performance, achieving approximately 81% correct slot-value inferences and completely covering all key information in 95% of turns. The fact that there was nearly zero performance drop-off on the out-of-distribution SGD evaluation demonstrates its robustness in discovering useful slot-values for new domains. As expected, `GPT-D0T` exhibits similar performance, as it generated the labels used to train `T5-D0T`; however, `GPT-D0T` is much costlier due to multiple API calls to GPT3.5 and GPT4. `T5-SGD` achieves the highest correctness score when evaluated on held-out SGD domains, but its completeness score of only 70% demonstrates it is incapable of fully adapting to unseen domains. On the out-of-distribution D0T evaluation, the performance of `T5-SGD` heavily suffers, achieving only 32% completeness and 73% correctness. This result demonstrates the difficulty of discovering state information in unseen domains, and indicates that SGD is insufficiently diverse as a training resource for this purpose.

	MultiWOZ							SGD						
		Slot			Value				Slot			Value		
Model	C	P	R	F1	P	R	F1	C	P	R	F1	P	R	F1
DSI	522	96.2	80.7	87.7	41.5	57.4	37.2	11992	-	-	**92.2**	-	-	46.2
USI	290	**100.0**	93.6	**96.7**	61.3	67.3	58.7	806	-	-	77.0	-	-	47.5
GenDSI	180	85.6	**96.8**	90.9	81.4	**70.2**	70.5	746	**92.4**	77.9	84.5	65.4	**50.0**	**48.8**
- slot names	**157**	73.9	90.3	81.3	85.2	47.7	55.3	**467**	76.4	75.6	76.0	**70.6**	36.3	37.9
+ all domains	161	85.1	**96.8**	90.6	**87.9**	68.1	**71.0**	737	90.8	**79.1**	84.5	68.0	47.2	47.7

Table 2: Schema induction results showing Precision/Recall/F1 (P/R/F1) for both induced slots and discovered values, as well as the induced Slot Count (C). Note that the optimal Slot Count would equal the gold slot counts of 31 and 82 for MultiWOZ and SGD respectively. DSI and USI results taken from Yu et al. (2022).

4 Schema Induction Evaluation

To evaluate our SSI approach, we use the benchmark defined by Yu et al. (2022) on the validation splits of MultiWOZ 2.1 (Eric et al., 2020) and SGD (Rastogi et al., 2020) datasets. This evaluation method measures the quality of an induced set of slot clusters by matching it against a gold reference slot schema.

Matching is performed automatically by computing the centroid of each induced and gold reference slot cluster using BERT encodings (Devlin et al., 2019) of their values. Each induced cluster is mapped to the gold slot whose cluster centroid is nearest by cosine similarity, or to no cluster if there is no match of 80% similarity or higher. Similarly, in order to evaluate the purity and coverage of clustered values, discovered values are matched against the gold value labels that fill each slot. This value matching is performed between the values that fill each gold slot and the discovered values of all induced clusters mapped to that slot using fuzzy string matching.

Metrics Given the mapping of induced clusters to gold slots, *Slot Precision* measures the proportion of induced clusters that were able to be matched to a gold slot, *Slot Recall* is the proportion of gold slots that were matched with at least one induced cluster, and *Slot F1* is their harmonic mean. Since multiple induced slots are allowed to map to a single gold slot, the induced *Slot Count* is also reported to measure redundancy. *Value Precision* is the average proportion of discovered values that matched to gold values, averaged across all gold slots. Similarly, *Value Recall* is the average proportion of gold values that were matched to a discovered value, and *Value F1* is the average F1 score across all gold slots. Equations defining these metrics are presented in Appx. B.

Models Our SSI approach, GenDSI, uses a T5-3B model trained on the D0T dataset. Since D0T contains some task domains that are related to travel domains appearing in MultiWOZ and SGD, we manually review and filter out 34 domains with overlap and train our dialogue state generator on all D0T dialogues in remaining domains. We also evaluate the performance when using a model trained with all D0T domains (GenDSI +all domains), which simulates extending our approach using the D0T data generation method to create synthetic training resources for target domains. Additionally, we evaluate a version of our approach where value candidates are encoded without their predicted slot names (GenDSI -slot names) to measure the benefit of concretely representing value type information. Implementation details provided are in Appx. D. Finally, we compare to two strong baselines from previous work:

- DSI (Min et al., 2020), which leverages a Part-of-Speech (POS) tagger, Named Entity Recognition (NER) tagger, and coreference resolution model to extract value candidate spans using a set of heuristic rules. Slot clusters are then assigned to value candidates using a neural latent variable model.
- USI (Yu et al., 2022), which is the SoTA SSI approach. It is a fully unsupervised SSI approach that leverages attention scores between token spans estimated using a pretrained language model to extract value candidates. A three-step hierarchical clustering procedure is then used that aims to cluster value types, then domains, then slots, using HDBSCAN.

Results As shown in Table 2, GenDSI outperforms the previous SoTA USI on almost every aspect of the SSI task. It contains fewer redundant slot clusters, superior recall of gold slots, higher cluster purity as measured by value precision, and better coverage of gold slot values. The only metric on which `GenDSI` did not outperform `USI` is slot precision on the MultiWOZ evaluation. This is because the state generator model learned to predict boolean slot values from the `D0T` dataset that represent intent types, such as greeting and requesting information, which are considered as precision errors under this evaluation since gold slots do not encode intent classes. The performance of `GenDSI -slot names` dropped considerably on all metrics other than slot count, indicating the utility of inferring concrete slot names when discovering value candidates. Surprisingly, `GenDSI +all domains` did not afford any meaningful benefit, which may indicate that our approach generalizes to new domains without the need to generate in-domain resources.

Slot Name Evaluation Our SSI approach is the first to enable automatic naming of slot clusters. Simply labeling each cluster with the most frequent candidate slot name achieves 93.5% correctly named clusters by human evaluation.

5 Conclusion

This work presents a new SoTA for SSI, demonstrating the power of a generative approach to value candidate discovery. Our dialogue state generator model shows excellent performance for discovering key dialogue state information from unlabeled dialogues without any prior knowledge of the task domain. Its ability to label discovered values with appropriate slot names provides rich type information, allowing a simple clustering method to induce a quality slot schema for unseen domains. Despite this advancement, there is still room to improve SSI. In particular, current SSI methods produce a far greater number of induced slots compared to human-defined schemas. Although our approach reduces the number of induced slots somewhat, future work should aim for SSI with minimal redundancies in induced slots to further improve the utility of SSI in practical settings.

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A State Generator Evaluation Details

To facilitate a thorough evaluation of dialogue state generators, a human evaluation measures the following two key aspects:

State Update Completeness measures the proportion of predicted state updates that humans have judged to fully capture the key information in their associated turns. Human judges are asked to read each turn within its context and make a binary decision on whether or not *any* essential information is missing in the state update such that:

$$\mathsf{CP} = \frac{1}{|\mathcal{U}|} \sum_{\forall U \in \mathcal{U}} \mathbb{I}(\textbf{complete}(U))$$

$\mathcal{U}$ is a list of all state updates across dialogues to be evaluated and $\mathbb{I}(x)$ is 1 if x is true; otherwise, 0. Note that the judges are not responsible for finding *all* missing information but identifying at least one to assess completeness for efficient evaluation.

Slot Value Correctness measures the proportion of slot-value pairs that humans have judged to accurately represent *specific* information in their corresponding turns. Judges are asked to mark each slot-value pair as correct if it makes sense and is entirely faithful to the content of the associated turn s.t.:

$$\mathsf{CR} = \frac{1}{\sum_{\forall U \in \mathcal{U}} |U|} \sum_{\forall U \in \mathcal{U}} \sum_{\forall (s,v) \in U} \mathbb{I}(\textbf{correct}(s, v))$$

Note that both the slot name s and value v must be accurate for $\mathbb{I}(\textbf{correct}(s, v))$ to be 1.

B SSI Evaluation Metrics

An SSI model produces a list of slot clusters $\hat{S} = [\hat{s_1}, \hat{s_2}, ..., \hat{s_n}]$ where each slot $\hat{s_i}$ is a cluster of values $\hat{s_i} = [\hat{v_1}, \hat{v_2}, ..., \hat{v}_{|\hat{s_i}|}]$. The quality of these slot clusters is measured by matching them against a list of gold reference slots $S = [s_1, s_2, ..., s_m]$, each of which can be similarly represented as a list of the gold value labels that fill each slot such that $s_i = [v_1, v_2, ..., v_{|s_i|}]$.

Matching is performed by assigning each induced slot $\hat{s_i}$ to one or zero gold slots, creating a mapping $M : \hat{S} \to S \oplus$ [none]. This matching is performed automatically. First, a centroid representation c_i is computed for each induced slot cluster and each gold slot cluster using the average BERT (Devlin et al., 2019) encoding of each value:

$$c_i = \frac{\sum_{v_j \in s_i} \text{BERT}(v_j)}{|s_i|}$$

Each induced cluster is mapped to the gold cluster whose centroid is closest by cosine distance, or to none if no gold centroid is within ≥ 0.8 cosine similarity.

Given the mapping M from predicted to gold slots, the evaluation metrics are calculated follows:

Slot Precision is the proportion of predicted slots that were able to be mapped to a gold slot:

$$\text{SP} = \frac{\sum_{\hat{s}_i \in \hat{S}} 1_S(M(\hat{s}_i))}{|\hat{S}|}$$

Slot Recall is the proportion of gold slots for which there is at least one corresponding predicted slot:

$$\text{SR} = \frac{|\{M(\hat{s}_i) : \hat{s}_i \in \hat{S}\} - \{\text{none}\}|}{|S|}$$

Slot F1 is calculated normally as the harmonic mean of precision and recall:

$$\text{S-F1} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Slot Count In the above Slot Precision calculation, multiple predicted clusters are allowed to be mapped to a single gold slot. This choice of formulation was made by previous work to avoid punishing the schema induction approach for inducing a finer-grained schema than what the gold schema provides, but fails to reflect the number of redundant clusters that are induced. To mitigate this, the number of induced slots is reported as an additional evaluation metric, where a lower number of induced slots is considered preferable.

Value Precision is meant to measure the purity of predicted slot clusters. It is calculated only between matched predicted clusters $\hat{S}_{matched}$ and matched gold clusters $S_{matched}$. For each gold slot with at least one match $s_i \in S_{matched}$, the proportion of predicted values in the mapped predicted slots that have a fuzzy match to some gold slot value is measured using fuzzy match boolean function f:

$$\text{VP}_{s_i} = \frac{|\{\hat{v}_{kl} : \hat{v}_{kl} \in \hat{v_k}, M(\hat{s_k}) = s_i, v_{ij} \in s_i, f(v_{ij}, \hat{v}_{kl})\}|}{|\{\hat{v}_{kl} : \hat{v}_{kl} \in \hat{v_k}, M(\hat{s_k}) = s_i\}|}$$

The final Value Precision score is an average across matched gold slots calculated in this way:

$$\text{VP} = \frac{\sum_{s_i \in S_{matched}} \text{VP}_{s_i}}{|S_{matched}|}$$

Value Recall is calculated similarly to Value Precision. For each gold slot with a mapping to one or more predicted clusters, recall is measured as the proportion of gold values that have a fuzzy match to some value in the corresponding predicted clusters:

$$\text{VR}_{s_i} = \frac{|\{v_{ij} : \hat{v}_{kl} \in \hat{v_k}, M(\hat{s_k}) = s_i, v_{ij} \in s_i, f(v_{ij}, \hat{v}_{kl})\}|}{|s_i|}$$

The final Value Recall is also averaged across matched gold slots:

$$\text{VR} = \frac{\sum_{s_i \in S_{matched}} \text{VR}_{s_i}}{|S_{matched}|}$$

C State Generator Evaluation Interface

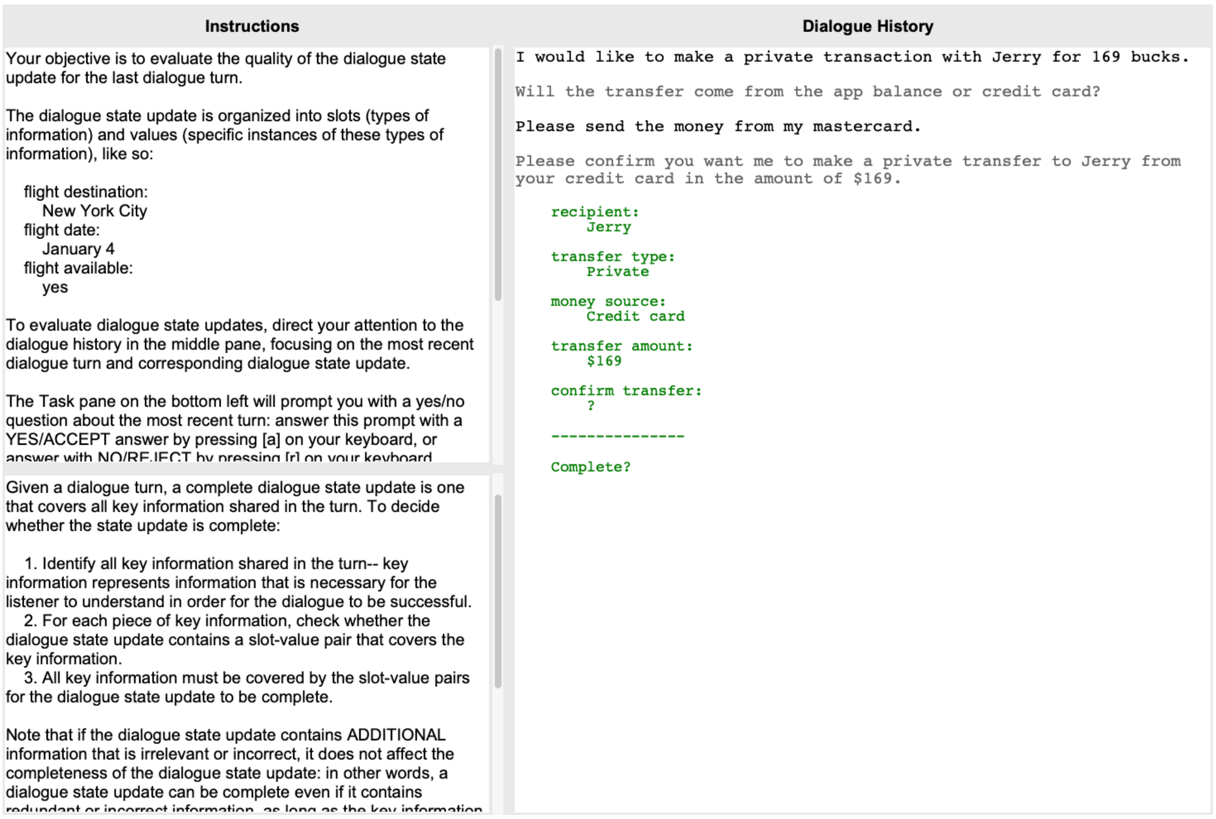
Figure 2 shows a screenshot of the interface when performing completeness annotations, and Figure 3 shows a screenshot of the interface when performing correctness annotations. Note that the application interface relies on custom keybindings (e.g. pressing the `y` or `n` keys to indicate "yes" or "no") for annotators to record their evaluation judgements.

D Implementation Details

Dialogue State Generator All dialogue state generator models were trained using the original version of T5-3B using the huggingface transformers library[2]. All training was performed using a learning rate of $1e-4$, weight decay of $5e-3$, batch size 128, and for exactly 1 epoch, using the Adam optimizer.

Slot Schema Induction All SSI models used a T5-3B dialogue state generator model trained with the configuration presented above. The `all-MiniLM-L6-v2` model from SentenceTransformers[3] was used for slot-value encoding. All HDBSCAN runs used the CUML[4] library with a a min. samples of 5, minimum cluster size 25, and cluster merge epsilon 0.3.

[2]https://huggingface.co/docs/transformers
[3]https://www.sbert.net
[4]https://docs.rapids.ai/api/cuml/stable/



Instructions

Your objective is to evaluate the quality of the dialogue state update for the last dialogue turn.

The dialogue state update is organized into slots (types of information) and values (specific instances of these types of information), like so:

```
    flight destination:
        New York City
    flight date:
        January 4
    flight available:
        yes
```

To evaluate dialogue state updates, direct your attention to the dialogue history in the middle pane, focusing on the most recent dialogue turn and corresponding dialogue state update.

The Task pane on the bottom left will prompt you with a yes/no question about the most recent turn: answer this prompt with a YES/ACCEPT answer by pressing [a] on your keyboard, or answer with NO/REJECT by pressing [r] on your keyboard

Given a dialogue turn, a complete dialogue state update is one that covers all key information shared in the turn. To decide whether the state update is complete:

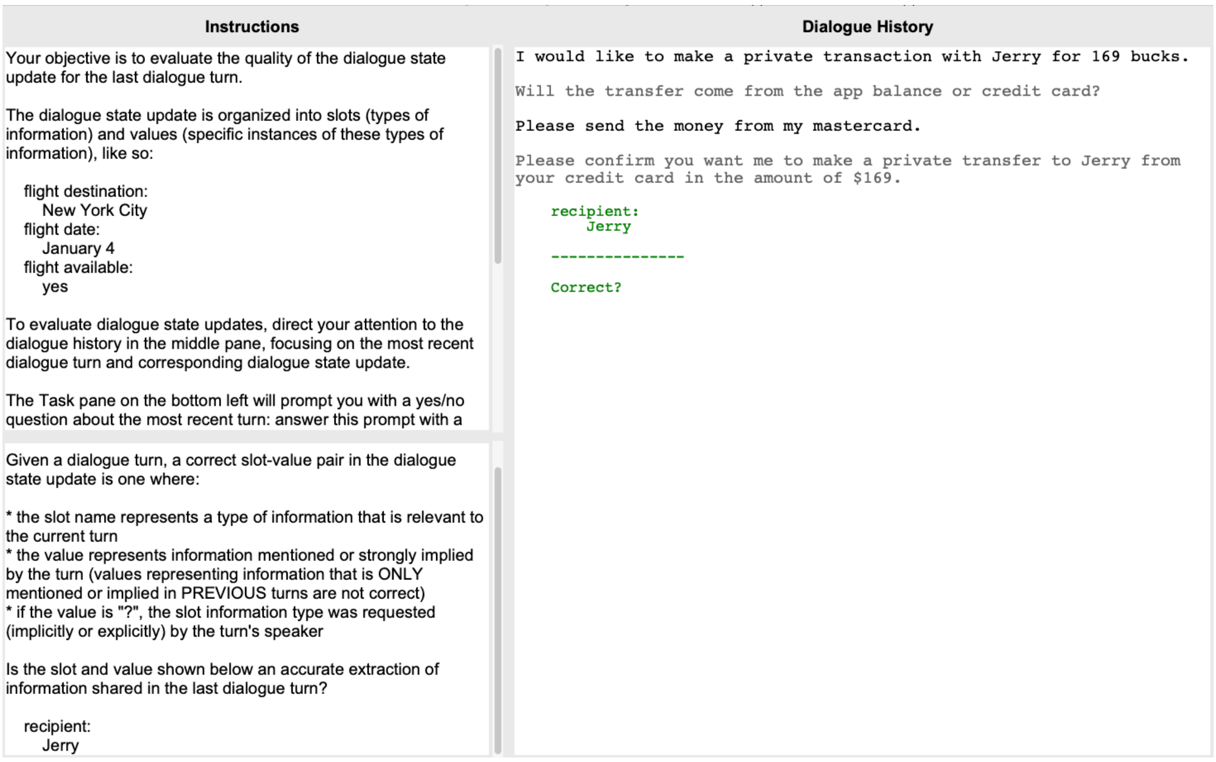
1. Identify all key information shared in the turn-- key information represents information that is necessary for the listener to understand in order for the dialogue to be successful.
2. For each piece of key information, check whether the dialogue state update contains a slot-value pair that covers the key information.
3. All key information must be covered by the slot-value pairs for the dialogue state update to be complete.

Note that if the dialogue state update contains ADDITIONAL information that is irrelevant or incorrect, it does not affect the completeness of the dialogue state update: in other words, a dialogue state update can be complete even if it contains redundant or incorrect information, as long as the key information

Dialogue History

```
I would like to make a private transaction with Jerry for 169 bucks.

Will the transfer come from the app balance or credit card?

Please send the money from my mastercard.

Please confirm you want me to make a private transfer to Jerry from
your credit card in the amount of $169.

    recipient:
        Jerry

    transfer type:
        Private

    money source:
        Credit card

    transfer amount:
        $169

    confirm transfer:
        ?

    ---------------

    Complete?
```

Figure 2: Annotation interface with instructions for human evaluation of Completeness of predicted state updates.



Instructions

Your objective is to evaluate the quality of the dialogue state update for the last dialogue turn.

The dialogue state update is organized into slots (types of information) and values (specific instances of these types of information), like so:

```
    flight destination:
        New York City
    flight date:
        January 4
    flight available:
        yes
```

To evaluate dialogue state updates, direct your attention to the dialogue history in the middle pane, focusing on the most recent dialogue turn and corresponding dialogue state update.

The Task pane on the bottom left will prompt you with a yes/no question about the most recent turn: answer this prompt with a

Given a dialogue turn, a correct slot-value pair in the dialogue state update is one where:

* the slot name represents a type of information that is relevant to the current turn
* the value represents information mentioned or strongly implied by the turn (values representing information that is ONLY mentioned or implied in PREVIOUS turns are not correct)
* if the value is "?", the slot information type was requested (implicitly or explicitly) by the turn's speaker

Is the slot and value shown below an accurate extraction of information shared in the last dialogue turn?

```
    recipient:
        Jerry
```

Dialogue History

```
I would like to make a private transaction with Jerry for 169 bucks.

Will the transfer come from the app balance or credit card?

Please send the money from my mastercard.

Please confirm you want me to make a private transfer to Jerry from
your credit card in the amount of $169.

    recipient:
        Jerry

    ---------------

    Correct?
```

Figure 3: Annotation interface with instructions for human evaluation of Correctness of predicted slot-value pairs.