BETOLD:
A Task-Oriented Dialog Dataset for Breakdown Detection
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Abstract

Task-Oriented Dialog (TOD) systems often suffer from dialog breakdowns - situations in which users cannot or do not want to proceed with the conversation. Ideally TOD systems should be able to detect dialog breakdowns to prevent users from quitting a conversation and to encourage them to interact with the system again. In this paper, we present BETOLD, a privacy-preserving dataset for breakdown detection. The dataset consists of user and system turns represented by intents and entity annotations, derived from NLU and NLG dialog manager components. We also propose an attention-based model that detects potential breakdowns using these annotations, instead of the utterances’ text. This approach achieves a comparable performance to the corresponding utterance-only model, while ensuring data privacy.

1 Introduction

Task-Oriented Dialog (TOD) systems (Zhang et al., 2020) enable users to complete specific tasks, such as booking a reservation at a restaurant. Unlike open-domain dialog systems (Huang et al., 2020), where the aim is to maximize user engagement, in TOD systems it is crucial to optimally assist a user to fulfill the task at hand. Detecting dialog breakdowns due to miscommunications potentially paves the way to intervene and rescue the dialog, improve customer satisfaction and motivate the user to continue interacting with the system (Brandtzæg and Følstad, 2018).

A dialog breakdown is often defined as a point in the dialog where the user gives up the conversation without completing the task, often due to not understanding the intended meaning of user’s utterance (Martinovski and Traum, 2003; Higashinaka et al., 2015). If conversational system engineers can understand when and why a conversation is likely to break down, they can build systems that prevent broken dialogs, or design conversational breakdown recovery strategies (Benner et al., 2021).

The Dialog Breakdown Detection Challenge (DBDC) has motivated the academic community’s interest in the breakdown detection problem, which is the goal of predicting the occurrence of a breakdown at some point in the conversation (Higashinaka et al., 2016). This challenge also came with the release of English and Japanese datasets for addressing this task. Despite the great value of these proposed datasets, they only provide the sequence of user and system utterances. Utterances are indeed useful to detect a breakdown, however, in certain contexts, especially in industry, a stakeholder may decide not to share and release the texts for privacy preserving purposes (Xu et al., 2021).

The utterances produced by a user during a task-oriented conversation often contain privacy-sensitive information. Let us consider a dialog system in a company that handles issues relating to human resources as an example. The system may receive data regarding an employee’s health status or compensation, i.e., data that a company is unwilling to share. In this paper, we demonstrate that even without access to the text of the conversation, it is still possible to identify a breakdown. In fact, traditional dialog systems often provide synthetic annotation of the user and system utterances as the intents and entities, originating from the Natural Language Understanding (NLU) and Natural Language Generation (NLG) components (Wahde and Virgolin, 2022). In particular, the NLU component classifies the user utterances into intents (book_appointment) and extracts entities (user_name="John Smith"). The NLG component consists of a closed set of possible system utterances (each defined by a unique intent), often parameterized by or supplemented with entities (e.g. "restaurant_name is open on day_of_the_week", where restaurant_name and day_of_the_week...
Table 1: Comparison of our BETOLD and other two publicly available datasets used for breakdown detection. *BD stands for “breakdown”. **User’s intent “restart” could be used as a substitute for breakdown.

In our study, we propose a simple yet effective way to automatically create a new breakdown detection dataset, given an existing TOD system. In particular, we consider a phone-call scenario, in which a customer talks to a digital assistant to schedule a service appointment for their mobile phone. In our experience, two central events indicating caller’s frustration with the current dialog state and projected outcomes are: a) hang-ups, b) requests to talk to a human agent. Therefore, we consider caller hang-ups and transfer to human requests as dialog breakdowns.

We also release a novel task-oriented dialog dataset BETOLD (Breakdown Expectation for Task-Oriented Long Dialogues) with the proposed annotation schema. The dataset contains real human-agent conversations, between customers and our modular dialog system. The system automatically annotates the user utterances with NLU intents and entities, and generates appropriate NLG responses which contain NLG intents and accompanying entities.

Finally, we propose an attention-based model, capable of taking these features into account. Our results show that, instead of relying only on the word tokens of the utterances, the use of NLU and NLG intents is sufficient to confidently predict a breakdown in a task-oriented conversation, therefore reaching satisfactory results while guaranteeing the privacy of the data.

2 Related Work

2.1 Datasets for Breakdown Detection

Only few task-oriented dialog breakdown datasets are openly available. We report the most relevant ones in Table 1. Overall, they are small and human-annotated, and with varying definitions of dialog breakdown.

The Dialogue Breakdown Detection Challenge (DBDC) offers a small dataset with 615 English conversations, annotated with system utterances that cause dialog breakdown (Higashinaka et al., 2016). It contains three classes: breakdown, possible breakdown, and no breakdown. However, no intents and entities annotations are available. Additionally, opposite to BETOLD, most of conversations in DBDC are open-domain. Another open-source alternative is the Dialog State Tracking Challenge (DSTC2) dataset, which unfortunately lacks breakdown annotations (Williams et al., 2014). However, 7 out of 2,115 conversations have an intent “Restart” which. If more prevalent, this could be used as a substitute for breakdown.

Similar to our work, Gorin et al. (1997) annotated 10,000 TODs between customers and agents. Subsequent experiments with the same dataset identified user hangup and requests to transfer to human agent as a specific learning problem, as proposed in our work (Walker et al., 2000). However, the dataset is not publicly available. Further examples of closed-source studies feature predicting in-
teraction quality from automatically extracted features (Schmitt et al., 2011) or manually-annotated features by AMT workers (Meena et al., 2015). These studies used publicly available un-annotated datasets, however the authors did not release their annotations.

2.2 Models for Breakdown Detection

The initial approaches to the breakdown identification problem focused on extracting features that can characterize a breakdown (Schmitt et al., 2011; Meena et al., 2015; Walker et al., 2000). Textual features can be used to compute similarity between the system utterance and user utterance (Meena et al., 2015), or detecting emotions from utterances and using them as indicators of a dialog breakdown (Schmitt et al., 2011; Matsumoto et al., 2022). Alternatively, dialog manager-generated tabular features such as repetitions, negations, or utterance counts can be considered as well (Walker et al., 2000; Schmitt et al., 2011).

With advent of the DBDC challenge, novel approaches have been proposed, yet limited by the available dataset features. These approaches rely solely on the textual utterances and the number of turns. They explore both traditional (Kato and Sakai, 2017; Sugiyama, 2021) and deep learning-based models (Hendriksen et al., 2021; Wang et al., 2021; Park et al., 2017). Given the sequential nature of dialogs, many models exploit sequential architectures, such as RNN or LSTM (Hendriksen et al., 2021; Wang et al., 2021; Shin et al., 2019; Lee et al., 2020), or they use an attention mechanism to determine the utterance embeddings on which to focus the attention (Park et al., 2017).

Considering the encoding of the text, different approaches have been investigated: from the use of static word embeddings such as Glove and Word2Vec (Hendriksen et al., 2021) to contextualized embeddings, e.g., BERT (Sugiyama, 2021; Shin et al., 2019).

3 A Privacy-Preserving Dataset for Breakdown Detection

3.1 Dataset Creation

The considered conversations are based on real conversations between a human and a task-oriented dialog system, with the goal of scheduling or canceling an appointment. The user interacts with the system over the phone. We considered four scenarios in which a phone call could end:

- **successful calls**: the caller hangs up after the caller’s goal has been satisfied (e.g. the agent has successfully scheduled a booking);
- **agent-initiated forwarded calls**: the agent takes the decision to forward the call (e.g. technical problems with the system);
- **user-initiated forwarded calls**: the user explicitly requests to talk to an operator, identified by the `transfer_to_human` intent. (This may include NLU misclassifications);
- **user-initiated caller hangup**: all the remaining calls.

A conversational engineer strives to avoid both user-initiated forward calls and user-initiated hangups. However, observing the data, we can see that the caller’s behavior changes depending on the number of turns. There is no way to prevent the caller from hanging up in the initial turns: This is the case when a user does not want to speak to a digital assistant at all. We report in Figure 1 the distribution of the different types of phone calls over the number of turns.

![Figure 1: Distribution of the different types of phone calls over the number of turns on a sample of 45,385 conversations.](image)

Given these considerations, we focus on user-initiated forward calls and hang-ups occurring late in the conversation. We will refer to these calls as to LUHFs (Late User-initiated Hang-ups or Forward calls), a particular class of dialog breakdowns.

LUHFs are the types of calls that we aim to predict (positive examples). We consider as late conversations all the calls that reach at least the 8th turn. On the other hand, late successful calls are the negative examples of the dataset. In particular, we sample successful calls and then truncate the conversations at a random point (still, after the
Table 2: Extract of a conversation between the system and a human. The entity values are enclosed by angular parentheses in the utterances.

| Utterance                                                                 | Intent            | Entities                      |
|--------------------------------------------------------------------------|-------------------|-------------------------------|
| S: Are you a registered customer?                                        | ask_if_current_client |                              |
| H: Uhm no                                                                 |                   | negate                        |
| S: Can I book your service appointment under the phone number ending in <1234>? | confirm_phone_number | user_phone_suffix             |
| H: Yeah that’s correct                                                    |                   | confirm                       |
| S: What is the brand, model and year of your phone device?               |                   | new_user_profile_brand_model_year |
| H: It’s a <phonepink> why 100 <2022>                                     | inform            | brand_device, year            |
| S: What is the model of phone device?                                    | ask_device_model   | model_device                  |
| H: It is <y100>                                                          | inform            |                               |
| S: What is the battery health percentage of your phone device?           | ask_for_battery_health |                             |
| H: <zero>                                                                | inform            | numeric                       |
| S: What is your first name?                                              | ask_first_name     | ask_last_name                 |
| H: My name’s <John>                                                      | inform            | client_name                   |
| S: Great, what is your last name?                                        | ask_last_name      | client_name                   |
| H: <Smith>                                                               | inform            |                               |
| S: What service does your phone device need?                             | ask_desired_service |                               |
| H: Uhm <battery replacement>                                             | inform            | type_of_repair                |

Table 2: Extract of a conversation between the system and a human. The entity values are enclosed by angular parentheses in the utterances.

“late”-call threshold). The user-initiated forward calls are also truncated from the point when the caller asks to be transferred. The ratio successful calls/LUHFs is 2:1. As a result, the dataset contains 13,524 calls (4,508 LUHFs and 9,016 not LUHFs).

Let us notice that the dataset contains noisy data because it is automatically annotated. Conversations may lead to a user-initiated forward, for example, even if there was no indication of user frustration. Similarly, a user may become irritated with the conversation but still decide to end the call. Moreover, it is worth noticing that the provided annotation is not at the utterance-level. Instead, a LUHF/not LUHF annotation refers to the overall conversation. In other words, if a conversation is a LUHF, we are not aware of at which point of the conversation a breakdown occurred. These elements make the predictions more challenging.

3.2 Dataset Features

The dialog system is composed of different modular components, including an NLU and an NLG component. The NLU provides annotations to the user’s utterances, i.e. the intent and the entities, recognized by an intent classifier and a named-entity recognition system respectively. The NLG also provides the name of the intent and the entities, uttered by the system. The NLG intents are always different from the NLU intents. On the other hand, the NLG and NLU may have some entities in common.

3.3 Dataset Anonymization for Privacy Preservation

We anonymize the original data to protect the privacy of the original conversation content. In particular, we remove natural-language text and entity values. Keeping only the intent and entity annotations guarantees the privacy of the data.

We report an example of a fictitious conversation in Table 2, reporting the utterances exchanged between the system and a human. The detected entities are enclosed by angular parentheses in the utterances. We can notice that the caller releases sensitive information, such as the name and phone number. The entities and the intents are a synthetic way to represent the utterances, and therefore to substitute the utterances with these annotations is a valid way to proceed. One may argue that, in order to not lose much information, it could be possible to keep the text and remove only the entity values. This approach would work fine only with a perfect NLU that is able to recognize all the entities in the text. As we can see from Table 2, the entity model_device is not detected the first time. Moreover, the caller may reveal other types of sensitive information that an NLU is not supposed to detect. Since the NLU is prone to these errors and may not detect an entity in the text, it is
indeed safer to remove all the textual information to preserve the privacy of the data.

| # labels | # not LUHFs | # LUHF's | # LUHs | # LUFs |
|----------|-------------|----------|--------|--------|
|          | 9016        | 4508     | 2477   | 2765   |

| # turns | min | max | avg |
|---------|-----|-----|-----|
|         | 8   | 34  | 10  |

Table 3: BETOLD dataset statistics.

Table 3 reports the main dataset statistics. The resulting privacy-preserving dataset, named BETOLD (Breakdown Expectation for Task-Oriented Long Dialogues), is available at the following link: https://github.com/telepathyai/BETOLD_dataset.

4 An Attention-based Model for LUHF Detection

The task in BETOLD dataset is to classify if a conversation between a human and the system is a LUHF or not. In this setting, it is fundamental to keep track of what happened in the past, represented by the dialog history. We therefore investigate an attention-based architecture (Vaswani et al., 2017), that has proved to perform well in several dialog-related tasks (Qin et al., 2021; Colombo et al., 2020; Zhao and Kawahara, 2019; Hori et al., 2016), including dialog breakdown detection (Park et al., 2017).

4.1 Model Architecture

A conversation between a human and the system can be represented as a sequence $x$ of $n$ tuples, where each element of a tuple represents a different feature. Here, the features include the caller name (either NLG or NLU), the intents, and the entities. The sets of possible values (also called vocabularies) of each feature are represented by $C$, $I$, and $E$ for the caller names, intents and entities respectively. The sequence $x$ is then:

$$ x = (c_1, i_1, e_1), (c_2, i_2, e_2), \ldots, (c_n, i_n, e_n) $$

where $(c_j, i_j, e_j)$ is a tuple composed of a caller name $c_j \in C$, an intent $i_j \in I$ and an entity set $e_j \in \mathcal{P}(E)$ and $j = 1, \ldots, n$. We refer to the entities as entity set, because for each tuple, we can have zero, one or more entities. The vocabulary sets $C$, $I$ and $E$ have different dimensions, to which we add an unknown symbol for unseen elements and a padding symbol.

For each of these features, the model learns embedded representations of dimension $m$. These vector representations are then summed up, obtaining a $m$-dimensional vector, which is then passed through a positional encoding layer, to keep track of the order of each element of the sequence. The resulting sequence of $m$-dimensional vectors is used as input to the Transformer encoder. The Transformer encoder is a stack of $t$ encoder layers of $l$ dimensionality. The output sequence of the Transformer encoder is averaged and the resulting vector passes through a sequence of linear layers. Finally, we apply a sigmoid function to the last layer to get the predicted score (LUHF or not LUHF). We use a weighted Binary Cross Entropy (BCE) loss to optimize.

Figure 2 shows a sketch of the proposed architecture. Each type of feature is represented in a different color.

5 Experimental Setting

5.1 Text-only Baseline

Our goal is to demonstrate that a text-free model can achieve comparable performance to a text-based model. As a consequence, we consider the text-only model to be our baseline model. The available text is represented by the user and system utterances. We use Sentence-BERT (Reimers and Gurevych, 2019) to generate a contextualized sentence representation for each utterance.

We use the same type of architecture as the proposed model to ensure a fair comparison, except that the model’s input is different, i.e. dense vector representations of text. We call this model TEXT.

5.2 Models

We compare the text-only baseline TEXT with different variants of the proposed model. To identify the single contribution of the entities and intents, we consider two variants of the model, namely INT and ENT, as the models that rely solely on intents or entities respectively. We then consider a model that combines all the features (intents, entities, and caller type (NLU or NLG)), referred to as IEC. The implementation of the models is available at
Figure 2: Sketch of the model architecture. To train the LUHF/not LUHF classifier multiple features are embedded and summed before a transformer encoder block followed by linear layers. The represented features are callers (orange, possible callers are “NLG” and “NLU”), intents (yellow, 91 intent names from NLU and NLG), and entities (blue, 41 entity names from NLU and NLG).

the following link: https://github.com/telepathylabsai/dialog_breakdown_detection.

5.3 Hyperparameter Setting

For running the experiments, we split the dataset into three parts: 80% for training, 10% for testing, and 10% for validation. We run all models for 50 epochs and then select the best model based on the validation set. We augment the training data by adding successful calls. In particular, we truncate the successful calls at random points and use them to expand the training data. We added 30% more successful calls to the overall training data. We do not perform data augmentation for the LUHFs because the LUHF annotation refers to the overall conversation and we have no hints about at which point in the conversation something went wrong.

We use grid search to determine the optimal hyperparameter configuration of the models. In particular, since we are more interested in the prediction of a LUHF rather than the prediction of a not LUHF, we select the optimal configuration based on the F1 score of the LUHF class. For the text-only model TEXT, we use the all-MiniLM-L6-v2 pre-trained model to obtain the utterance representations.1 Any document embedding model can be used to generate the utterances representations and feed the TEXT model. We run the TEXT model on the non-anonymized version of BETOLD, ensuring the same train/test/validation splits for a fair comparison. See Appendix A for further details on the hyperparameters.

6 Results

6.1 Quantitative Analysis

Table 4 reports the results of the models in terms of the F1 score for each class and the macro-averaged score. As a first remark, the models ENT and INT obtain a similar performance. This is probably due to the fact that some intents can be recognized by the entities of which they are composed. But since not all the intents are characterized by entities, the ENT model is not able to reach the same performance as the INT one.

Focusing on the IEC model, which combines the intents, entities, and caller type, we can notice that this model gets improved performance with re-

1See https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2. In a preliminary investigation, we tried different pre-trained sentence embedding models made available by Hugging Face. Here, we report the results with the best performing model.
Table 4: Results of the considered models in terms of F1 score. We report the average and the deviation of 5 independent runs with the same hyperparameter configuration.

|       | LUHF          | not LUHF       | Macro avg |
|-------|---------------|----------------|-----------|
| TEXT  | 0.798 ± 0.016 | 0.903 ± 0.005  | 0.850 ± 0.010 |
| INT   | 0.727 ± 0.018 | 0.877 ± 0.002  | 0.802 ± 0.010 |
| ENT   | 0.707 ± 0.018 | 0.867 ± 0.007  | 0.787 ± 0.011 |
| IEC   | 0.744 ± 0.008 | 0.879 ± 0.003  | 0.812 ± 0.005 |

6.2 Qualitative Analysis

In this section, we discuss some qualitative examples of the IEC model on the test set, one of a LUHF classification and one of a not LUHF misclassified as a LUHF.

Let us consider the conversation shown in Table 5. For each step of the conversation, we report the corresponding caller type (NLG or NLU), the intent, the entities, and the probability of identifying a LUHF. We filter out the first steps of the conversations due to space limitations. Let us recall that the LUHF annotation corresponds to the overall call. Therefore the model was not trained on each step of the conversation because there is no information about a breakdown occurred at a given step. We will further discuss this issue in Section 7. Nevertheless, we can still compute the probability of identifying a LUHF at each step for a conversation, by generating a synthetic dataset composed of the same conversation but incrementally truncated.

Table 5 shows that the probability of detecting a LUHF increases as the conversation progresses. However, the probability often decreases after a user input, represented by an NLU annotation. We presume that this behavior happens because a user is less likely to hang up after replying and would wait until the next utterance before deciding to hang up. For example, at step 23, a user negates the proposed date of the system. This may be a signal of a breakdown and indeed the probability of a LUHF increases at step 24. The intent time_asked_unavailable_propose_new indicates an NLG intent where a time preference proposed by the user is unavailable, therefore the system proposes a new time. This can be an additional signal for a breakdown, which in fact increases the probability of detecting a LUHF.

In Table 6, we report an example of a not LUHF that has been classified as a LUHF at the final step of the conversation. As before, we eliminated the early steps of the call, where the conversation flowed nicely. At steps 13 and 16, the probability of predicting a LUHF increases, although there are no clear indications of a breakdown. It is worth noting that in the previous example the probability of a LUHF also increased after the intent propose_date (Table 5). Many LUHFs may happen in correspondence to this intent, therefore biasing the model to believe that this intent is an indication of a breakdown.

7 Limitations

As mentioned in Section 3.1, the labels in BETOLD are automatically assigned to each conversation. Therefore, it is possible that a conversation where everything goes smoothly but suddenly the user decides to hang up is classified as LUHF. Similarly, the user may decide to reach the end of the conversation even if they are extremely unsatisfied with the call. This case is not considered a dialog breakdown.

In addition to this issue, a LUHF annotation applies to the overall call and is not an indication of what happened during at each step of the conversation. A model that generalizes well should be able to predict whether a LUHF happened at each step of the call. The process of data augmentation described in Section 5.3 is an attempt to address this issue. This is, however, limited to not LUHF calls, given that we have no guarantees on when a breakdown happened in a conversation. Instead, we are quite confident that, if a call was successful, it was also successful in the previous steps.
| Step | Caller | Intent | Entities | Probability of LUHF |
|------|--------|--------|----------|--------------------|
| 9    | NLG    | ask_for_battery_health |          | 0.002              |
| 10   | NLU    | inform  |          | 0.000              |
| 11   | NLG    | ask_first_name |          | 0.109              |
| 12   | NLU    | inform  |          | 0.002              |
| 13   | NLG    | ask_last_name |          | 0.296              |
| 14   | NLU    | inform  |          | 0.016              |
| 15   | NLG    | ask_desired_service |       | 0.344              |
| 16   | NLU    | user_initial_request | type_of_repair | 0.033              |
| 17   | NLG    | ask_additional_service |       | 0.262              |
| 18   | NLU    | inconclusive |          | 0.012              |
| 19   | NLG    | transportation_of_device | ask_to_scheduled, ask_means_of_transportation | 0.253              |
| 20   | NLU    | confirm |          | 0.014              |
| 21   | NLG    | inform_schedule_inspection | transportation_type_selection, available_slot_to_schedule | 0.269              |
| 22   | NLG    | propose_date |          | 0.033              |
| 23   | NLU    | negate  |          | 0.378              |
| 24   | NLG    | ask_time_preference | time_range_indication | 0.153              |
| 25   | NLU    | user_proposed_date | transportation_type_selection, available_slot_to_schedule, user_request_start_time | 0.922              |
| 26   | NLG    | time_asked_unavailable_propose_new |          | 0.764              |
| 27   | NLU    | negate  |          | 0.960              |
| 28   | NLG    | ask_time_preference |          |                    |

Table 5: Example of LUHF conversation correctly classified.

Figure 3 shows a density histogram of the probability by class of predicting a LUHF, averaged over all the conversation steps, for the test set conversations. As we can observe in the plot, the average probability of predicting a LUHF in a not LUHF call is low in general. We recall that we have more data available for the successful calls (the not LUHFs are two times more than the LUHFs and, in addition, we add 30% more successful calls through augmentation). Therefore, it is not surprising to see that the not LUHF distribution is more skewed towards 0 than the LUHF distribution. Moreover, the results shown in the plot correspond to the average score across many steps of the conversation. A breakdown may happen very late in the conversation, thus resulting in an overall low average score. However, this is hard to determine through an automatic investigation and would require a manual inspection.

8 Conclusions

In this paper, we proposed a simple way to automatically generate a breakdown detection dataset in task-oriented dialogs, where the breakdown labels are extracted by user-initiated events. This dataset guarantees the privacy of the data by only keeping the annotations from NLU and NLG components. We proposed an attention-based model which uses these types of annotations. As a result, we demonstrated that a model does not necessarily require textual utterances to predict a breakdown; yet, it can benefit from the NLG and NLU intents and entities, automatically provided by a classical dialog system.
We also discussed some possible limitations of the model and the dataset, connected to the annotation schema. An automatic annotation, as it often happens, results in noisy data. However, we do believe that the proposed dataset is a promising starting point, which can save resources and could be further improved through manual annotations.

As highlighted by the qualitative analysis, it is worth further investigating the results to understand which elements play a role in the detection of a LUHF. The implementation of explainability methods can be an important tool in this context (Lundberg and Lee, 2017). Given the transformer-based architecture of our proposed model, current explainability tools (Kokhlikyan et al., 2020; Attanasio et al., 2022) can enrich our investigation of the role of each attention head in the breakdown prediction. For that, gradient-based methods can give an overview of the importance of individual features as well as of the interactions.

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```markdown
| Step | Caller | Intent | Entities | Probability of LUHF |
|------|--------|--------|----------|---------------------|
| 11   | NLG    | transportation_of_device | ask_means_of_transportation, ask_to_schedule | 0.164 |
| 12   | NLU    | confirm |          | 0.005 |
| 13   | NLG    | ask_time_preference |          | 0.391 |
| 14   | NLU    | confirm |          | 0.011 |
| 15   | NLG    | inform_schedule_inspection |          | 0.005 |
| 16   | NLG    | propose_date | transportation_type_selection, available_slot_to_schedule | 0.678 |
```

Table 6: Example of not LUHF conversation misclassified as a LUHF.
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A Hyperparameter Search

We report the hyperparameter space in Table 8. Table 7 shows the optimal hyperparameters selected after the grid search approach. We train the models for 15 epochs and select the best result based on the F1 score for the LUHF class on the validation set.

B Computing Infrastructure

We ran the experiments on a machine equipped with AMD® Ryzen 9 5900hx CPU, NVIDIA GeForce RTX 3060 GPU with CUDA v11.4, Driver Version 470.141.03 and 32GB RAM.
| Parameter Description                              | Value   |
|----------------------------------------------------|---------|
| Embedded representations dimension \( l \)        | 400     |
| Transformer Encoder embeddings dimension \( m \)  | 128     |
| # layers of the Transformer Encoder \( t \)       | 3       |
| # attention heads of the Transformer Encoder       | 16      |
| Dropout ratio applied in the Transformer Encoder   | 0.01    |
| Learning Rate                                      | 0.0001  |
| Size of layers of decoding stage                   | (256, 32) |
| Optimizer                                          | Adam    |
| Number of epochs                                   | 15      |
| BCE weight for not LUHF\'s                        | 1.0     |
| BCE weight for LUHF\'s                            | 3.0     |

Table 7: Hyperparameters used for training the models.
| Parameter Description                                      | Value                                      |
|-----------------------------------------------------------|--------------------------------------------|
| Embedded representations dimension $l$                    | [256, 400, 800]                            |
| Transformer Encoder embeddings dimension $m$              | [64, 128, 256]                             |
| # layers of the Transformer Encoder $t$                   | [1, 3, 5]                                  |
| # attention heads of the Transformer Encoder              | [4, 8, 16]                                 |
| Dropout ratio applied in the Transformer Encoder           | [0.01, 0.1, 0.5]                           |
| Learning Rate                                             | [0.0001, 0.0005, 0.001]                    |
|                                                           | [(256, 32), (256, 128, 32), (256, 64), (256, 128, 64), (256, 128, 64, 32)] |
| Size of layers of decoding stage                          |                                           |
|                                                           |                                           |
| Optimizer                                                 | Adam                                       |
| Number of epochs                                           | 50                                         |
| BCE weight for not LUHF$Fs$                                | 1.0                                        |
| BCE weight for LUHF$Fs$                                    | [1.0, 3.0, 5.0, 10.0]                      |

Table 8: Hyperparameter space used for grid search.