Improved Goal Oriented Dialogue via Utterance Generation and Look Ahead

Eyal Ben-David⁎†, Boaz Carmeli* 2, Ateret Anaby-Tavor2
1Faculty of Industrial Engineering and Management, Technion, IIT
2IBM Research
eyalbd12@campus.technion.ac.il
{boazc,atereta}@il.ibm.com

Abstract

Goal oriented dialogue systems have become a prominent customer-care interaction channel for most businesses. However, not all interactions are smooth, and customer intent misunderstanding is a major cause of dialogue failure. We show that intent prediction can be improved by training a deep text-to-text neural model to generate successive user utterances from unlabeled dialogue data. For that, we define a multi-task training regime that utilizes successive user-utterance generation to improve the intent prediction. Our approach achieves the reported improvement due to two complementary factors: First, it uses a large amount of unlabeled dialogue data for an auxiliary generation task. Second, it uses the generated user utterance as an additional signal for the intent prediction model. Lastly, we present a novel look-ahead approach that uses user utterance generation to improve intent prediction in inference time. Specifically, we generate counterfactual successive user utterances for conversations with ambiguous predicted intents, and disambiguate the prediction by reassessing the concatenated sequence of available and generated utterances.

1 Introduction

Dialogue systems have emerged as a prevalent method for humans to interact with their digital surroundings (Chen et al., 2017; Ralston et al., 2019; Bocklisch et al., 2017). Consequently, goal-oriented dialogue systems have become a prominent customer-service interaction-channel for most businesses (Yan et al., 2017). However, there is still a long way to go until we reach a pervasively-integrated, fully-automated, and reliable dialogue system to serve as the preferred customer-care go-to channel (Gao et al., 2018).

A key component of these systems are information-completion processes that are mutually carried out by two actors: the user and the bot (Luo et al., 2014). The user knows her goal but is usually unaware of the various options and the optimal way to achieve it. The bot, on the other hand, has extensive knowledge of the possible options and the various ways to achieve them, but is unaware of the user’s exact goal. Via a dialogue, the two actors cooperate to achieve the user’s goal in the most effective way.

Typically, users express their intent at the beginning of the conversation, and the bot reacts with its most suitable response. Bot responses are dependent on user intents. Ultimately, an accurate bot response depends on its ability to correctly understand the intent. Bot misunderstanding of the user intent will most probably lead to an unsatisfactory response, which in turn will cause the user to react accordingly (see Figure 1). For example, the user might ask for a human agent, express negative sentiment, or rephrase her request. Therefore, the likelihood of a dialogue system to retrospectively identifying errors in its initial predicted user intent increases as the conversation progresses.

Given this observation, we hypothesise that successive user utterances provide an invaluable, yet overlooked, indication for the language un-
derstanding level expressed by the previous bot response. Thus, training a model to predict successive user utterances can help predict the user’s intent (§ 2.2, 3.2).

To validate our hypothesis, we experiment with training a text-to-text transformer model using multi-task regime that simultaneously i) generates predicted user utterances from a vast amount of unsupervised dialogue data; and ii) predicts the intent from dialogue context, enriched with successive, generated, user utterances. While earlier deep neural network models require a dedicated classification layer and parameters (Devlin et al., 2019), a text-to-text model, such as T5 (Raffel et al., 2019), solves the classification task in a generative manner. This approach allows the model to share all its parameters across the prediction and generation tasks and thus, potentially achieve better results (§ 2.3).

Having a model that is trained to generate user utterances suggests an innovative way to further improve the intent prediction by generating successive user utterances and using them as a look-ahead signal during inference (§ 3.3). Furthermore, such a model can also assist in solving the specific situation of conflicting intents. For that, one may generate counterfactual successive user utterances and use them as a look-ahead signal to disambiguate the conflicting intents (§ 6).

Our contribution is thus, two-fold. We show that i) training a text-to-text model using a multi-task regime, in which the secondary task is to predict the succeeding user utterance, further improves the main task of intent prediction, and ii) generating a successive user utterance and using it as a look-ahead signal improves prediction in inference time.

2 Related Work

2.1 Contextual Intent Prediction

Intent prediction is usually formulated as a sentence classification task. Given an utterance (e.g., “what are the details of this flight?”), a system needs to predict its intent (e.g., “flight details”). Modern approaches use neural networks to model intent prediction, using many different classification architectures such as RNNs (Ravuri and Stolcke, 2015), CNNs (Zhang et al., 2015), attention-based CNN (Zhao and Wu, 2016), and transformer-based architectures (Devlin et al., 2019). In many cases, intent prediction is modeled jointly with slot filling (Xu and Sarikaya, 2013; Chen et al., 2016; Liu and Lane, 2016; Goo et al., 2018; Chen et al., 2019).

Another way to approach this prediction task is to use more contextual knowledge, such as more dialogue turns (Feng et al., 2020). This approach was made possible thanks to the creation of public datasets for task-oriented dialogue, which contain utterance level annotations for full conversations (Budzianowski et al., 2018; Rastogi et al., 2020). While most studies in this direction seek to build a dialogue state tracking model (Liu and Lane, 2017; Nouri and Hosseini-Asl, 2018; Cheng et al., 2020), several works model it together with intent prediction (Ma et al., 2019).

In this paper, we use the dialogue context for intent prediction. Unlike previous work, we face a setup in which there are few conversations with intent-annotation, as we consider this more realistic for a system’s development phase. Furthermore, we use only dialogue utterances for prediction, without any other information (e.g., internal dialogue state tracking variables).

2.2 Modeling User-side Utterances

Modeling the user side in dialogue systems has been researched in several tasks and applications. One approach is to develop a user simulator, which is essential e.g., for training dialogue models based on reinforcement learning (RL). Naturally, the performance of the simulator directly impacts the RL policy. Within this line of work, two methods have proven particularly useful: 1) Agenda-based simulators, using rule-based software to generate a simulation (Schatzmann et al., 2006, 2007; Li et al., 2016b), and 2) data-driven simulators that learn user responses directly from a corpus (Asri et al., 2016; He et al., 2018; Kreyssig et al., 2018).

The modeling of users’ written and spoken utterances is another direction that has been extensively studied within the standard dialogue modeling framework (Kobsa and Carberry, 1989; Kobsa, 1990; Lin and Walker, 2011; Li et al., 2016a). Existing methods strive to improve users’ language consistency in conversations and generate meaningful responses in an open-domain dialog.

In this work, we use user-side modeling to improve the performance of goal-oriented dialogue systems. We rely on the hypothesis that the user conveys her intent to the bot and then implicitly reflects, in successive utterances, whether the bot correctly understood it. Our model, thus, incorporates the generation of successive user-utterances, aiming to learn from this weak-supervision signal.
2.3 Transformer-based Language Modeling

Previous research works consider two main approaches when training a language model (LM) that is based on the Transformer architecture (Vaswani et al., 2017). The first treats the model as a contextualized word embedding (CWE) (Devlin et al., 2019; Yang et al., 2019; Liu et al., 2019; Sanh et al., 2019; Martin et al., 2020). As such, it employs the model as an encoder. When fine-tuning the model, additional architecture is placed on top of the model, adjusting model’s CWE representation to a specific downstream discriminative task.

The second approach handles the task in a sequence-to-sequence manner. As such, it uses an encoder-decoder architecture (or just a decoder (Radford et al., 2019)), such that when given a context, it generates the missing tokens. Because of their generative nature, these models are commonly integrated into text generation downstream tasks (Radford et al., 2019; Anaby-Tavor et al., 2020; Rothe et al., 2020). Recently, Raffel et al. (2019) presented T5, a text-to-text transfer transformer, and showed that encoder-decoder LMs are efficient in both discriminative and generative tasks. T5 demonstrated its superiority in many tasks, eliminating the need to add task-related architecture.

In this work we follow the second approach and take advantage of the T5 unified framework, which converts all text-based language problems into a text-in text-out format. We apply T5 to the task of intent prediction under the low-supervision scenarios we encounter by enriching our supervised task with semi-supervised signals from unlabeled data.

2.4 Utterance Generation for Look Ahead

Although there is line of work on learning from user feedback (Hancock et al., 2019; Shin et al., 2019), and specifically from generating user-side utterances (Weston, 2016), ours is the first work we know of that uses generated user utterance as a look-ahead signal to improve dialogue understanding during inference.

3 Model and Methods

Dialogue representation relies on a complex data structure, composed of multiple utterances, generated alternately by two actors: user and bot. The number of utterances in a dialogue varies dramatically and so does the length of each utterance. To cope with this complexity we based our experiments on a flexible text-to-text model (T5) that supports multi-task training by design via encoder-decoder architecture and language-modeling training. In T5, all tasks are mapped into text-in text-out format. Specifically, the model resolves classification tasks by generating the predicted class’ label. The model is thus able to use the same loss function and parameter weights across different tasks, data sets, and training regimes.

Next, we explain our text-in text-out experimental method in more details.

3.1 Contextual Intent Prediction

We start by training two T5-based variants: The first, referred to as semantic utterance classification (SUC) (Tur et al., 2012) is trained on just the first user-utterance from each dialogue. This classifier serves as our baseline. The second, referred to as semantic dialogue classification (SDC), is trained on, at least, three successive dialogue utterances.

For low data regimes, we further enriched the supervised dialogue data with a weak supervision signal. To that end, we trained RoBERTa (Liu et al., 2019) and BERT (Devlin et al., 2019), two state-of-the-art classifiers, on the available supervised dataset and used them to predict the intent for unlabeled conversation. We added samples for which the two classifiers agreed on the predicted intent to the supervised train set.

To measure the model’s ability to correctly predict the intent, we constructed a full-dialogue test set. Each dialogue in this set consisted of at least three successive utterances that pertain to the same user intent. We measured the model’s accuracy by classifying one, two, and three initial utterances
from each dialogue in the dataset.

3.2 Utterance Generation

To evaluate the hypothesis that utterance generation improves intent prediction, we defined a generative task to predict (i.e., by generating) the third user utterance from a given first user utterance and successive bot response. We refer to this task as 3UG. To train the T5 model on this task, we used a vast amount of unlabeled data that was continuously logged by the dialogue system during interaction with users. Alternatively, dialogue data from user to human-agent interactions can be used in situations where data from dialogue systems does not exist.

We test results by comparing the SDC performance after training on the 3UG task to the SUC intent prediction performance. Importantly, one may notice that the SDC model takes advantage of the additional supervision signal available within the successive user utterance during training, although this utterance is not available during inference. Thus, for comparing classifier performance on real-time conversations, we experiment with complementing the first available utterance with two additional utterances as follows. First, we used the dialogue system to get the bot response i.e., the second utterance. Second, we used the T5 model already-trained on the 3UG task to generate a successive user utterance, conditioned upon the first user utterance and the bot response (see Figure 3).

We report results for these two complementary experiments in section 5.

3.3 Disambiguate Conflicting Intents

Conflicting-intents refers to situations where the classifier prediction doesn’t clearly distinguish between small set of competing intents. To solve this specific problem we experimented with a novel counterfactual approach that uses the 3UG model to generate a counterfactual user utterance for each of the conflicting intents as described in § 3.2. We then evaluated the performance by predicting the intent based on the ensemble of predictions for all look-ahead conversations, where each conversation now has three successive utterances.

3.4 Multi-task Training Regimes

We wanted to evaluate the level of intrinsic synergy between intent classification and utterance generation tasks. To accomplish this, we compared the intent prediction accuracy achieved by T5 trained on the supervised full-dialogue dataset alone, (thus performing only a classification task), to the results when the model was asked to first perform the successive utterance generation task (trained on the unsupervised dataset) and then predict the intent (trained on the supervised dataset). We also extracted an utterance reordering task out of unsupervised data, in which we shuffled dialogue utterances and train the model to correctly reorder them. We elaborate more on dialogue-related auxiliary tasks in the supplemental material.

4 Experiments

We conducted most of the experiments by fine-tuning a pre-trained T5-base model, which shares its parameters across tasks. Specifically, we fine-tuned the T5 model repeatedly using unsupervised, semi-supervised, and supervised datasets in various orders across three different datasets.

4.1 Datasets

We used the following datasets (see Table 1):

- **MultiWOZ** - a large-scale multi-domain Wizard-Of-Oz dataset for task-oriented dialogue modelling, containing over 8400 dialogues, and spanning seven domains (Budzianowski et al., 2018). This dataset contains human to human conversations, and thus does not obey any well-defined bot-side dialogue rules or learning algorithm.

- **SGD** - a schema-guided dialogue dataset, containing over 16K conversations, spanning 86 intents, and covering 16 different domains (Rastogi et al., 2018).
This dataset was created by asking crowd-sourced workers to rephrase dialogue utterances that were created by a rule-based simulator. Thus, this dataset obeys predefined dialogue rules but still reflects the language diversity and variations one expects to find in goal-oriented dialogues.

EDU - an unpublished dataset extracted from an operational goal-oriented dialogue system. It contains over 4K dialogues across 115 intents pertaining to the learning-and-education domain; out of these 4K dialogues, only 350 have intent labels. This dataset was extracted from a real customer-care dialogue system that uses an SVM-based intent classifier and a rule-based dialogue-flow software. Intent identification in this dataset depends solely on prediction from the SVM-based single-utterance classifier; the dialogue system uses additional rule-based logic to return a concrete bot response.

From the original datasets, we extracted conversations with at least three successive utterances pertaining to the same intent. We further split dialogues that expressed multiple intents into different parts, keeping those that have at least three successive utterances pertaining to a single intent as separate dialogues. This left us with 3994, 34056, and 2063 conversations pertaining to 11, 86, and 115 intents for MultiWOZ, SGD, and EDU, respectively. From these we used 1012, 1000 and 100 conversations for supervised training and 2,538, 23,128, and 1,200 conversations for unsupervised training, for the three datasets, respectively. For MultiWOZ and SGD, we mimicked the situation of unsupervised data by ignoring the available label. For EDU, we had only 350 labeled conversations, which we split into 100, 50, and 200 for the train, validation and test sets, respectively. To increase the very low amount of supervised EDU data, we further applied the weak-labeling algorithm described in § 3.1, which added an additional 513 semi-supervised conversations.

### Table 1: Intents and data-splits for the three datasets

| #Intents | MultiWOZ | SGD | EDU |
|----------|----------|-----|-----|
| Unsupervised | 2,538 | 23,128 | 1,200 |
| Supervised    | 1,012 | 1,000 | 100 |
| Weakly labeled | 0 | 0 | 513 |
| Dev          | 211 | 4933 | 50 |
| Test         | 233 | 4995 | 200 |

2019). This dataset was created by asking crowd-sourced workers to rephrase dialogue utterances that were created by a rule-based simulator. Thus, this dataset obeys predefined dialogue rules but still reflects the language diversity and variations one expects to find in goal-oriented dialogues.

### 4.2 Models and Baselines

We used SDC as our main model for researching the performance of contextual intent prediction. This involved training SDC by fine-tuning a pre-trained T5 model on the supervised data.

We then used SUC as a baseline model for the contextual intent prediction experiment. To train SUC, we fine-tuned a pre-trained T5 model with supervised data containing just the first utterance from each dialogue and the associated intent label.

To better understand the effect of the multi-task training, we further examined three SDC model variants that differ in their fine-tuning regimes: ALL, which we fine-tuned on all available datasets: the unsupervised, supervised, and semi-supervised, as described in § 3.4. PART-SDC, which we fine-tuned in two steps: first on all except for the supervised intent prediction dataset, and then on the supervised dataset. ALL-SDC, which we also fine-tuned in two steps: first on all available datasets and then, again, on the supervised intent prediction dataset.

### 4.3 Experimental Setup

Our experiments assume at least three consecutive dialogue utterances of user-bot-user relating to the same intent. We tested model’s performance in predicting the user intent as the dialogue progressed by letting it classify one, two, and three consecutive utterances from each dialogue available in the test set. We refer to these as 1-u, 2-u and 3-u test scenarios, respectively, as can be seen in Table 2. To evaluate performance, we measured intent accuracy, namely \( t/d \) where \( t \) is the number of true predictions and \( d \) is the number of samples, i.e., predictions, in the test data. In the EDU experiments, we report a model’s improvement in accuracy with respect to SUC, to avoid revealing sensitive information regarding an inner-system’s performance.

To evaluate the hypothesis that a third generated utterance serves as a good look-ahead signal during run-time, we sampled such utterances from the best-performing T5 model and used them instead of the actual utterance available in the test set. This experiment is referred to as 3-gen in Table 4. To better understand the power of the generative model to produce qualitative utterances, we experimented with the 'five times third-user-utterance’ method, referred as 3-5xg. This method generates five third-user-utterance alternatives for each two successive user-bot utterances. It then predicts the
We report the key results of our experiments in Table 2. As shown, the performance of intent classification increases significantly with dialogue progression along all datasets, even if the model was trained on just the supervised data (SDC). Specifically, MultiWoz: 93.1% → 96.6%; SGD: 68.5% → 73.6%; EDU: +1.8% → +6.3%. Moreover, training the model on all available data and all tasks (ALL-SDC) improved the results across all datasets and all test scenarios: 1-u, 2-u, and 3-u. These results clearly prove our hypothesis that generating a third utterance as a secondary task in a multi-task training regime improves intent prediction performance.

Interestingly, we observed that both SDC and ALL-SDC models outperform the baseline SUC model even when tested on the 1-u scenario, namely when tested to predict the intent from only the first utterance. This phenomenon occurs across all datasets (MultiWoz: 90.5% → 93.1% → 94.4%; SGD: 68.2% → 68.5% → 71.1%; EDU: 0.0% → +1.8% → +5.5%). This important finding clearly indicates the benefit of training text-to-text models over full conversations, even if the model is used to predict intents from just the first utterance during inference.

### Improved prediction via look-ahead

The rightmost column (3-5xg) in Table 2 reports results of the look-ahead experiment. Here, we generated five user utterances and used majority voting to choose among them. As can be observed, the generation of a third utterance improves intent prediction compared to using just the two utterances available during inference. Notably, these results hold for all datasets and all models except EDU:ALL-SDC. Interestingly, intent classification performance with the generated utterance (3-5xg column) is comparable to the one using real utterances (3-u column). More specifically, MultiWoz: 98.7% vs 98.3%; SGD: 74.6% vs 75.8%; EDU: +9.1% vs +8.2%.

### 6 Ablation Analysis

We conducted several ablation experiments to shed more light on our key results. First, we investigated the impact of various training regimes on model performance. Next, we examined the effect of conversation reordering as an auxiliary task in our multi-task training regime. Then, we assess the quality of utterances sampled from our generative models. Finally, we demonstrate the ability of our model to generate counterfactual utterances which may resolve situations of conflicting intents. To ensure compatibility with previous results, we kept all experiment details similar to what described in § 4.3.

**Tables**

Table 2: Results for three different models (SUC, SDC, ALL-SDC) on four different test scenarios (1-u, 2-u, 3-u, 3-5xg) across the three datasets.

| Model  | 1-u | 2-u | 3-u | 3-5xg |
|--------|-----|-----|-----|-------|
| MultiWoz | 90.5 | - | - | - |
| SUC | 93.1 | 95.5 | 96.6 | 96.6 |
| SDC | 94.4 | 97.2 | 98.7 | 98.3 |
| ALL-SDC | 1-u | 2-u | 3-u | 3-5xg |
| SUC | 68.2 | - | - | - |
| SDC | 68.5 | 73.2 | 73.6 | 74.0 |
| ALL-SDC | 71.1 | 74.2 | 74.6 | **75.8** |
| EDU | 1-u | 2-u | 3-u | 3-5xg |
| SUC | 0.0 | - | - | - |
| SDC | +1.8 | +1.8 | +6.3 | +5.5 |
| ALL-SDC | +5.5 | +8.2 | **+9.1** | +8.2 |

Table 3: Results from four different training regimes, tested for accuracy on one, two and three dialogue utterances across the three datasets.

| Model  | 1-u | 2-u | 3-u |
|--------|-----|-----|-----|
| MultiWoz | 93.1 | 95.5 | 96.6 |
| SDC | 94.0 | 95.7 | 97.0 |
| PART-SDC | 94.8 | 97.0 | 98.2 |
| ALL | 94.4 | 97.2 | 98.7 |
| ALL-SDC | 1-u | 2-u | 3-u |
| SDC | 68.5 | 73.2 | 73.6 |
| PART-SDC | 68.7 | 73.3 | 74.0 |
| ALL | 71.6 | 76.1 | 76.6 |
| ALL-SDC | 71.1 | 74.2 | 74.6 |
| EDU | 1-u | 2-u | 3-u |
| SDC | +1.8 | +1.8 | +6.3 |
| PART-SDC | +0.9 | +2.7 | +5.4 |
| ALL | -1.8 | +2.7 | +6.3 |
| ALL-SDC | +5.4 | +8.2 | +9.1 |
shows that fine-tuning the model in two steps, first on all but the supervised data and then on the supervised data (PART-SDC), is inferior to fine-tuning the model on all available data in a single step (ALL). Lastly, we observe that as in ALL-SDC, the two-step training regime further improves results over the ALL model when tested on three utterances, in two out of the three datasets (MultiWOZ: 98.2% → 98.7%; EDU: +6.3% → +9.1%)

**Sentence reordering importance** We studied the impact of the additional semi-supervised task (see § 3.4) on intent prediction. Notably, creating a semi-supervised dataset for the utterance reordering task is straightforward. Thus, this task can be added to any model, using any dialogue dataset.

Figure 4 shows intent-classification accuracy when training with five utterance reordering ratio alternatives (0.0, 0.1, 0.3, 0.5, 1.0) on the MultiWOZ and SGD datasets. Per the 0.0 alternative, we used all data for the utterance generation task, while per the 1.0 alternative, we used all data for the utterance reordering task. The results indicate similar trends in both datasets, showing that using a small portion (0.1) of utterance reordering data is most beneficial. The proportion parameter affects model performance, with a gap higher than 1.1% between best- and worst-performing model in both datasets.

**Look-ahead for intent prediction** Even though our main table reports results from majority voting, this was not our first approach to generation-forlook-ahead. Naively, we started our experiments with generating just a single look-ahead utterance. We report the results from this experiment in the 3-gen columns of Table 4. When this approach failed to meet the expected performance, we turned to sample several (e.g., five) times from the generative model and used majority voting to elect the predicted intent. Results of this experiment appear in the 3-5xg columns of Table 4. Notably, majority voting improves performance across most models and datasets. As a last baseline-step of our analysis, we used random generated utterances for look-ahead. The results appear in the 3-rnd column of Table 4. Clearly, the results degrade significantly across all datasets and all models, reconfirming the importance of qualitative third utterances for accurate intent prediction.

**Qualitative look-ahead utterances** To analyse the ability of the model to generate qualitative look-ahead utterances, we considered two model alternatives: PART, which was trained on all tasks but not on the supervised intent prediction, and ALL, which was trained on all tasks, intent-prediction included. We used all the above-mentioned SDC model variants to evaluate utterance quality, as indicated by the rows of Table 4. Each of these models was tested with utterances generated by both generation model alternatives (PART and ALL columns of Table 4) and under both look-ahead techniques (3-gen and 3-5xg).

Table 4 shows that ALL is a statistically stronger generative-model, outperforming PART in 15 out of 24 look-ahead experiments. In comparison, only in 2 out of the 24 experiments did the models under evaluation achieve higher accuracy when using utterances generated by the PART model. For both generative models, generating five user utterances and using majority voting to choose among them outperforms the single-generation alternative. This

|                   | 3-gen | 3-5xg | 3-rnd |
|-------------------|-------|-------|-------|
| **MultiWOZ**      |       |       |       |
| SDC               | 94.4  | 95.5  | 92.7  |
| PART-SDC          | 95.3  | 95.3  | 89.7  |
| ALL               | 96.6  | 97.9  | 92.3  |
| ALL-SDC           | 96.6  | 98.3  | 94.8  |
| **SGD**           |       |       |       |
| SDC               | 72.3  | 72.6  | 62.3  |
| PART-SDC          | 73.1  | 73.1  | 64.7  |
| ALL               | 78.9  | 75.3  | 65.8  |
| ALL-SDC           | 73.7  | 72.6  | 64.3  |
| **EDU**           |       |       |       |
| SDC               | +2.7  | +4.6  | +2.7  |
| PART-SDC          | +1.8  | +4.6  | +5.5  |
| ALL               | +3.7  | +5.5  | +1.8  |
| ALL-SDC           | +7.2  | +9.0  | +6.3  |

Figure 4: The data proportion for reordering conversations according to intent accuracy. Data is divided between utterance reordering and third utterance generation.
result is consistent with results presented in § 5, and confirms that the quality of generated utterances does not depend on the quality of the discriminative model used for intent prediction.

Solving intent conflicts with counterfactual user utterances Most goal oriented dialogue systems use specific approaches for solving ambiguity in intent prediction. For example, the bot can present the user with the conflicting intents and let her choose the right one, or it can ask a clarification question and wait for user response. Here, we suggest a novel counterfactual approach for solving intent ambiguity. In contrast to other approaches, ours doesn’t require any additional input from the user. To achieve that we use the 3UG model to generate counterfactual user utterance for each of the conflicting intents (see Figure 5). We test our approach with the following setup: (1) Fit an ALL-SDC model with an intent classification head to the SGD training set and use it to predict intent of test examples with single user-utterance; (2) Identify conflicting intents by setting a threshold bound on the last softmax layer of the ALL-SDC classifier; (3) For each conflicting intent, generate the bot’s response (second utterance). Since we do not able to generate bot responses in our experimental setup, we mimic the generation process by choosing a response utterance that is associated with the predicted intent and has the most overlapping slots with the gold response (gold slots are provided in the SGD dataset); (4) Generate the third utterance by applying the 3UG model to the first two utterances; (5) Predict the intent based on the ensemble of predictions for all look-ahead conversations, where each conversation now has three successive utterances.

While, ideally, one may detect conflicting intents by applying a threshold bound (Threshold-based conflicts), we also examine our counterfactual algorithm when given a hindsight regards conflicting intents. We examine two types of hindsight: (1) Identifying all mistaken examples and count the two top predicted intents as the conflict intents (Mistake Oracle); and (2) Identifying mistaken examples in which the second top predicted intent is the gold intent (Conflict-oracle).

In Table 5, we report experiment results. As seen, with the Conflict-oracle hindsight the algorithm fixes more than 30% of the mistakes examples. This illustrates the potential of our algorithm. To fully realize this potential one must have an intent classifier with high accuracy/confidence correlation. However, when using our classifier’s confidence, algorithm achieves modest improvement. This can be attributed to the un-calibrated nature of the used classifier and its failure, in most cases, to predict the gold intent as the second- or third–top prediction.

7 Conclusions
In this work we show how recent text-to-text models can benefit from abundant past conversation data to improve the intent prediction along the course of the dialogue. Specifically, we show that training text-to-text models to generate successive user utterances as a secondary task in a multi-task training regime improves the performance of the main intent prediction task. We further show that the real power of these generative text-to-text models, trained on vast amounts of unlabeled data, lies
in their ability to synthetically sample possible user responses and use them as a look ahead signal to improve intent prediction in inference time.

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We took further advantage of the T5 model’s ability to share parameters across tasks and defined several auxiliary dialogue-related tasks:

**Utterance reordering**: shuffle dialogue utterances and train the model to correctly reorder them.

**Conversation escalation**: predict false if the bot contains the entire conversation and true if it was eventually handled by a human agent.

**Utterance repetition**: predict true for repetitive bot utterances or rephrased user utterances, and false otherwise.

We used various weak labeling techniques to add labels to the raw dialogue data for each of these tasks. We then used these semi-supervised datasets together with the supervised full-dialogue dataset and the unsupervised dialogue data to train a T5 model to predict the user intent. We evaluated the performance gained from each of these datasets by introducing them to the T5 model in different orders and amount ratios, and measured the intent prediction accuracy.

We performed an analysis by examining the performance of additional auxiliary tasks. Table 6 presents results for the EDU and SGD datasets. For the EDU dataset, we considered all auxiliary tasks presented in §A. For SGD, we did not include utterance-repetition and conversation-escalation as this dataset does not contain these phenomena. We report intent prediction results achieved with a one-step training regime, similar to the training regime that we use to train the ALL model.

Clearly, combining all tasks together performs better than using each task separately. The gap between the ALL model and the best-performing single-task model is 1.7% for EDU and 0.4% for SGD. Furthermore, when used separately, the escalation and repetitious tasks perform sub-optimally, with measured accuracy of +1.8% and 0.0% respectively, compared to +4.6% and +3.6% achieved by the utterance generation and reordering tasks, respectively. This did not come as surprise, since these signals correlate with dialogue outcome more than with a specific user intent.

### Table 6: Model performance using various auxiliary tasks.

| Aux Task | EDU | SGD |
|----------|-----|-----|
| Utterance Generation | +4.6 | 76.2 |
| Reordering | +3.6 | 75.8 |
| Escalation | +1.8 | - |
| Repetitious | +0.0 | - |
| ALL | +6.3 | 76.6 |

### A Auxiliary Tasks

We took further advantage of the T5 model’s ability to share parameters across tasks and defined several auxiliary tasks.
Alternative Classification Models

In this analysis, we focus on a potential alternative modeling solution. As described in the main paper, we direct our modeling efforts at T5 variants (Raffel et al., 2019): through baselines and our own contributions. However, another possible modeling direction for the task could use a state-of-the-art discriminative classifier (Devlin et al., 2019; Yang et al., 2019; Liu et al., 2019).

Thus, as another baseline, we used a BERT classifier (Devlin et al., 2019), which we trained to predict the intent from three successive utterances, denoted as SDC-BERT. In Table 7, we report models’ accuracy across the three different datasets: Multiwoz, SGD, and EDU. We further tested this model under our look-ahead scenario, 3-gen, while using our trained T5 ALL model to generate the look-ahead utterances. For a complete picture, we present the results of our three T5 variants, SDC, ALL, and ALL-SDC, even though these results have already been presented in the main paper.

Our unsupervised and semi-supervised data-integration methods improved SDC performance across most training regimes; ALL and ALL-SDC outperform SDC-BERT in five out of six different setups. The performance of the T5 SDC and SDC-BERT models that use only supervised data, are on a par. In three out of six setups, the T5-based classifier outperforms BERT, and vice versa. However, looking deeper, SDC-BERT has the largest degradation when evaluated on the look-ahead scenario, with an average of 2.4% accuracy drop across all setups, compared to 1.3%, 0.8%, and 1.0% achieved by SDC, ALL, and ALL-SDC respectively.

Look-ahead is an important setup for an intent classifier because it supports intent prediction improvement while the dialogue is on-going. More research is needed to determine the best way to integrate the unsupervised and semi-supervised tasks described here with the supervised data, to improve a discriminative model’s performance. We consider SDC-BERT’s large degradation in this setup to be another incentive towards applying a unified test-to-test model, such as T5, to the task.

Hyper-Parameters, Configurations, and Experimental Details

We use a single V100 GPU with 64 GB RAM in all experiments. All T5-based models, namely SUC, SDC, ALL, and ALL-SDC share the same hyperparameters with respect to their shared architecture and to the optimization process. They all use an initialized T5-Base (Raffel et al., 2019). SDC-BERT use an initialized BERT-Base encoder (Devlin et al., 2019) and share the same optimization process as the T5-based models. Configuration details and the hyper-parameters of the training process are provided in Table 8.

All hyper-parameters were tuned on the development set. We tuned the maximal sequence lengths \{128, 256, 512\} and the batch size \{32, 64\}. We then chose the best performing set of hyperparameter according to the higher accuracy score on the appropriate development set. For all models we set the amount of training epochs to be 50, with an early stopping criteria of 7.

URLs of Code and Data

We provide here the URLs for the datasets and code we have used:
• We use code and pre-trained weights of the pre-trained \textit{BERT-Base, Uncased} (Devlin et al., 2019) and the pre-trained \textit{T5} (Raffel et al., 2019) from \texttt{huggingface}: https://github.com/huggingface/transformers

• \textit{MultiWOZ} (Budzianowski et al., 2018) conversations with intent labels are extracted from the official paper’s repository: https://github.com/budzianowski/multiwoz

• \textit{SGD} (Rastogi et al., 2019) conversations with intent labels are extracted from the official paper’s repository: https://github.com/google-research-datasets/dstc8-schema-guided-dialogue