# **AuGPT: Dialogue with Pre-trained Language Models and Data Augmentation**

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#### **Abstract**

Attention-based pre-trained language models such as GPT-2 brought considerable progress to end-to-end dialogue modelling. However, they also present considerable risks for taskoriented dialogue, such as lack of knowledge grounding or diversity. To address these issues, we introduce modified training objectives for language model finetuning, and we employ massive data augmentation via backtranslation to increase the diversity of the training data. We further examine the possibilities of combining data from multiples sources to improve performance on the target dataset. We carefully evaluate our contributions with both human and automatic methods. Our model achieves state-of-the-art performance on the MultiWOZ data and shows competitive performance in human evaluation.

# 1 Introduction

Unlike traditional task-oriented systems based on modularized pipelines (Young et al., 2013; Gao et al., 2019), end-to-end dialogue systems integrate nearly all functionality required to hold a dialogue into a single neural network (Wen et al., 2017; Eric et al., 2017; Lei et al., 2018), reducing error-propagation and data annotation requirements. While these systems are not yet ready for production use, they made considerable progress in recent years, especially with the advent of pretrained neural language models (LMs) (Devlin et al., 2019; Radford et al., 2019; Zhang et al., 2020c). Systems such as GPT-2 finetuned by Budzianowski and Vulić (2019) show that with an LM pre-trained on a large number of generaldomain dialogues without annotation, only small amounts of data are required to perform in a given task-oriented domain.

The pre-trained LMs still run enormous risks. First, solely training for response generation may

result in a lack of grounding for the responses, where the LM hallucinates words without any relation to the database. This has been addressed by multi-task training and auxiliary training objectives (Peng et al., 2020) to an extent. Second, finetuning on small datasets may reduce response diversity and fluency due to neural networks' known propensity for catastrophic forgetting (Greco et al., 2019) – the model overfits the finetuning set too tightly, "forgetting" the language modeling capabilities learned during pre-training.

This paper presents an end-to-end model for multi-domain task-oriented response generation on the MultiWOZ data (Budzianowski et al., 2018),<sup>1</sup> where we address the above problems with pretrained LMs. AuGPT is based on the DialoGPT pre-trained LM. To improve response consistency, we build upon Peng et al. (2020)'s auxiliary training objectives and introduce improvements. For higher output diversity and fluency, we apply massive training data augmentation through additional task-oriented datasets and back-translation (Sennrich et al., 2016). In addition to standard automatic evaluation, we evaluate our system in a shared task human evaluation campaign, where it reaches high performance. We also include a detailed error analysis on a sample of dialogues collected in-house by experts.

Our contributions can be summarized as follows:

- We show that augmenting data using backtranslation markedly improves performance in task-oriented settings.
- We introduce an improved dialogue consistency classification task used as an auxiliary training objective, based on subtle changes to the dialogue state (instead of replacing the

https://convlab.github.io/

state with a random one). This brings additional performance improvement.

- To further improve output diversity, we experiment with unlikelihood loss (Welleck et al., 2020; Li et al., 2020).
- We provide results for our model and comparisons to multiple baselines on MultiWOZ versions 2.0 and 2.1. To our knowledge, our system obtains state-of-the-art results for an end-to-end model on this dataset.

To advocate research transparency and reproducibility, we publish our augmented training data, source code, and pre-trained models on GitHub.<sup>2</sup>

#### 2 Related Work

While the first attempts to build generative endto-end task-oriented systems mimicked the traditional dialogue system components (Wen et al., 2017), the task was soon recast as a sequence prediction problem in a two-stage setup. A sequenceto-sequence (seq2seq) model first generates the belief state based on dialogue context, then generates the system response based on the context and the belief state (Sequicity; Lei et al., 2018). The basic recurrent seq2seq architecture (Sutskever et al., 2014) was enhanced with various attention mechanisms to support copying tokens from the context into the belief state or from the belief state onto the output (Wu et al., 2019; Shu et al., 2019). Database operations typically stay outside the model, but some approaches even include the database in the model via attention over possible entries (Eric et al., 2017; Wen et al., 2018; Madotto et al., 2018).

Recently, large-scale task-oriented datasets were proposed (Budzianowski et al., 2018; Byrne et al., 2019; Rastogi et al., 2020) to encourage research in the field of multi-domain dialogue modeling. Even though the aforementioned approaches achieved promising results on smaller domains such as Cam-Rest676 (Wen et al., 2016), their ability to generalize over multiple domains remains limited (Zhang et al., 2020b). To address this, Zhang et al. (2020a) introduce the LABES-S2S model that - in addition to a two-stage seq2seq approach - models belief states as discrete latent variables. Zhang et al. (2020b) present DAMD, a three-stage seq2seq architecture which explicitly decodes the system action. They optimize for multiple good actions given a single belief state.

The line of research that is closest to our work makes use of large pre-trained LMs based on the transformer architecture (Vaswani et al., 2017) such as GPT-2 (Radford et al., 2019) or BERT (Devlin et al., 2019). Finetuned variants of these models achieved state-of-the-art results on many NLP tasks, e.g., question answering or natural language inference (Liu et al., 2019), and they seem to be useful even in the context of dialogue systems. For example, Wu et al. (2020) propose finetuning BERT (Devlin et al., 2019) for task-oriented dialogue on multiple datasets; Zhang et al. (2020c) extended the GPT-2 LM to model open-domain chit-chat.

We follow research initiated by Budzianowski and Vulić (2019), who use GPT-2 to model multidomain task-oriented dialogues. Recently, three similar modifications to their model were proposed, namely SOLOIST (Peng et al., 2020), SimpleTOD (Hosseini-Asl et al., 2020), and the approach by Ham et al. (2020). Our work extends these models and proposes a novel training approach and data augmentation strategies based on back-translation (Edunov et al., 2018; Federmann et al., 2019).

#### 3 Method

The task-oriented setting requires the dialogue system to respond adequately to the user's input and fulfill its goal. The goal could be, e.g., booking a train or requesting restaurant details. To achieve that, the system has to process the user's input, keep track of the belief state with respect to user preferences regarding individual in-domain attributes (slots) and generate a relevant response in natural language. The system also must be able to interact with an external database to incorporate the necessary information into the generated response (see Figure 1 for an example).

Due to its excellent language modeling and language generation capabilities, we have chosen the pre-trained GPT-2 LM as our system's backbone architecture. Similarly to Budzianowski and Vulić (2019), we use the LM to model both the belief state and the response.

# 3.1 Model Representation

The training instances for an LM-based taskoriented dialogue system can be considered as tuples (c, b, d, r), where r is the system's response, c is the context (i.e., a concatenation of all previous utterances in the dialogue – both system's and user's), b is the system's belief state which is

<sup>2</sup>https://github.com/ufal/augpt/

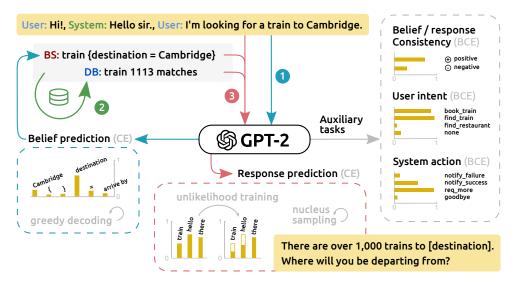


Figure 1: The architecture of AuGPT. The pipeline runs in two stages. First, a finetuned GPT-2 LM is used to predict a belief. Then the database results are obtained and everything is passed to the GPT-2 again to predict a final delexicalized response, along with possible auxiliary tasks (belief consistency, intent classification, system action classification). Unlikelihood loss is used for response prediction training.

also used for querying the database, and d are the database results.

In our case, the dialogue system handles multiple domains and the belief state is a set of pairs (domain name, domain belief), where the domain belief is an assignment of values into slots, i.e., a set of pairs (slot name, value) (see Example 1). Similarly, the database results d are a set of pairs (domain name, domain database results), where the domain database results are an ordered list of entities returned by the database. We further define the database result counts  $d_c$  denoting the number of results in d for each domain.

Ideally, we would like our system to model the probability distribution over possible responses conditioned on the context p(r|c). To simplify computation and model the interaction with an external database, this distribution can be factorized as follows:

$$\begin{split} p(r|c) &= \sum_{d} p(r|d,c) p(d|c) \\ &= \sum_{d} \sum_{b} p(r|d,b,c) p(d|b) p(b|c) \\ &= \sum_{b} p(r|\textit{Query}(b),b,c) p(b|c) \,, \end{split} \tag{1}$$

where p(d|b) is a deterministic distribution over the database results, and Query is a function returning database results.

By using this formulation and by modeling p(r|d, b, c) and p(b|c), our model would be able

to process the context, query the database, and generate the response based on the database results. However, we would face a problem with data sparsity when estimating parameters of p(r|d, b, c). The reason for the data sparsity is the relatively small size of datasets for task-oriented dialogues and the responses containing underrepresented, sometimes unique words, such as reference numbers, hotel names, etc. To maximally reuse the training samples, we choose to train our model on delexicalized responses (Wen et al., 2015) denoted  $\bar{r}$ , where slot values are replaced with placeholders. During inference, the responses are lexicalized back deterministically using both the belief state and the database results. We assume perfect lexicalization, i.e., always being able to lexicalize the response  $\bar{r}$  back based on d and b.<sup>3</sup>

Both the database lookup and the lexicalization are deterministic, and the delexicalized response  $\bar{r}$  does not depend on the database results d, but only on their counts  $d_c$ . Therefore, the distribution p(r|d,b,c) is equal to the distribution  $p(\bar{r}|d_c,b,c)$ , and by maximizing its likelihood we are achieving the goal of maximizing the likelihood of p(r|c).

We use the same language model  $\hat{p}$  to model the belief state and to generate the delexicalized prediction. That is,

$$p(\bar{r}|d_c, b, c) \approx \hat{p}(\bar{r}|d_c, b, c, \theta)$$
 (2)

$$p(b|c) \approx \hat{p}(b|\emptyset, \emptyset, c, \theta),$$
 (3)

<sup>&</sup>lt;sup>3</sup>We found in our experiments on the MultiWOZ data (see Section 4) that this assumption was almost always fulfilled.

where we denote the model's parameters as  $\theta$ .

In the MultiWOZ dataset (Budzianowski et al., 2018; Eric et al., 2020, see Section 4), responses are delexicalized by replacing concrete values with placeholder tokens of the form domain\_slot. For better generalization across domains, we chose to use only slot instead. We had noticed it was never the case that a response would involve more than one domain. Therefore, we decided to train our model to detect the active domain and used the predicted active domain during the final lexicalization. The model predicts the active domain by outputting it as the first domain in the belief state. The other domains then follow in lexicographical order. The disadvantage of this approach is that we cannot determine the active domain if the belief state is empty. However, in such a case the lexicalization would fail anyway, so the system's performance is not affected by this decision.

```
Belief state: train{ leave at=15:30,
arrive by=17:15 },
hotel { price range = cheap }
DB: train 23 matches, hotel no match
```

Example 1: String format for AuGPT's belief state and database result count.

To generate the belief state and to input the database result counts to our model, we need a string representation. To fully exploit pre-training on natural language texts, we have chosen a compact representation containing as few special tokens as possible (see Example 1).

## 3.2 Model Training

Although the parameters are shared for the belief state predictor and the delexicalized response predictor, the training objectives slightly differ. We use the cross-entropy loss for both predictions. For the response prediction, the unlikelihood loss (Welleck et al., 2020; Li et al., 2020) is used as an additional objective. The unlikelihood loss gives a penalty for each repeated token, which helps the model avoid repetitions and makes frequent words less likely, increasing the answers' diversity.

To help the model learn a better internal representation from the data, we employ additional auxiliary tasks. Similarly to Devlin et al. (2019) and Peng et al. (2020), we train a binary classifier to detect dialogue inconsistencies. In each training batch, we corrupt half of the samples by randomly

applying one or more of the following changes with the same probability:

- 1. We replace the belief state *b* with another belief state, sampled uniformly randomly from the training data.
- 2. We replace the delexicalized response  $\bar{r}$  with a different randomly chosen one. If this change is applied in combination with the first one, the delexicalized response and the belief state are taken from the same random sample.
- A different valid value is uniformly sampled for each slot in the belief state. In this case, the domain names and domain order are unchanged (i.e., the active domain is the same).

The first two changes are the same as those applied by Peng et al. (2020), whereas the third one is a new one which we find very useful in the context of multiple domains, where it is much more challenging to detect if the belief state was changed when the domain names are kept the same. The consistency detection binary classifier is trained to recognize negative samples from the positive ones based on logits of the last response token. It is represented by an affine classifier trained using binary cross-entropy (BCE).

We also experiment with additional two classifiers predicting the user intent and the system action. These are implemented as two fully-connected layers attached to the feature representations of the last context token and the last database result token, respectively. However, based on our experimental results, we decided not to use these tasks in the final model.

We train the whole pipeline by optimizing the non-weighted sum of individual component losses, i.e., cross-entropy for the belief state and the response prediction, unlikelihood loss for the response, and BCE for the consistency detection are summed in our final system.

# 3.3 Response Generation

For each user input, the system transitions through several stages before the final response is generated. First, only the previous dialogue context is passed to the LM, which greedily generates the string representation of the belief state. The belief state is then parsed and passed to the database handler. The database handler then constructs a query and returns a set of results for each domain.

We take the number of results for each domain and generate the string representation of database result counts (see Example 1). All strings are concatenated and again passed to the language model. This time, we utilize the nucleus sampling (Holtzman et al., 2020) to generate the delexicalized response. We found nucleus sampling useful for generating the response since it increases diversity, but we prefer greedy decoding for the belief state with a fixed structure. Finally, the tokens in the delexicalized response are substituted by values from the database results and the belief state. The process is illustrated in Figure 1.

# 3.4 Data Augmentation

Following its successful usage in other NLP tasks, (Konstas et al., 2017; Elder et al., 2020), we experiment with data augmentation using paraphrases, i.e., variants of training utterances with different surface forms. In our setup, we generate multiple paraphrases for each training utterance and use them to augment the training data. This way, we effectively increase the variability of the data.

Generating paraphrases is not a trivial process. Various data-driven approaches were proposed, the majority of them corpora-based (Madnani and Dorr, 2010). Recently, machine translation systems proved strong performance in generating paraphrases using the back-translation procedure (Sennrich et al., 2016; Edunov et al., 2018; Federmann et al., 2019). We take advantage of these findings and use a trained multilingual machine translation model (Macháček et al., 2020; Edunov et al., 2018) to paraphrase our data. We employ ten intermediate languages and thus obtain a set of different paraphrases for each input utterance. When training, we choose the input user utterance uniformly at random from the set of all variants of the utterance including the original one.

# 4 Experiments

We consider a series of experiments to compare our model to current state-of-the-art methods, and include human evaluation and detailed error analysis. We also carefully evaluate all proposed contributions through a series of ablation experiments.

#### 4.1 Datasets

We have used several datasets for training our system and for the final evaluation and comparison.

We use MultiWOZ 2.1, an enhanced version

of MultiWOZ 2.0 (Budzianowski et al., 2018) that reduces the amount of noise in the data; we also use the 2.0 version in additional experiments so that we can compare to previous works. The dataset contains 7 distinct domains (all related to tourist information, e.g., hotels, restaurants) and 10,438 dialogues, 7,032 of which are multi-domain.

We experiment with pre-training our model on additional datasets. For the pre-training phase, we use Taskmaster-1 (Byrne et al., 2019) and Schema-Guided Dialogue (Rastogi et al., 2020). Both Taskmaster-1 and Schema-Guided Dialogue are multi-domain, task-oriented, large dialogue corpora consisting of 12,215 and 22,825 dialogues, respectively. Taskmaster-1 was obtained using the Wizard-of-Oz and self-dialogue methods, while the collection of Schema-Guided Dialogue is somewhat artificial – humans are only employed to paraphrase machine-generated utterances.

## 4.2 Data Preprocessing

Although the MultiWOZ 2.1 dataset was collected by humans, it contains a lot of inconsistencies. We hypothesize that when using only *clean* samples which are consistent with the database, the benefit of using higher quality training data outweighs the decrease in the number of training samples. This claim is further supported by experiments (see the Ablation section). To filter the training data, we choose only those dialogues where the annotated dialogue goal corresponds with the turn-level annotated data. When using the *clean* samples, we omit about 30% of the training data.

To effectively combine all our datasets, we unified the domain-slot pairs in the belief states and the delexicalization. However, the datasets use different naming conventions (e.g., leaveAt vs. leave\_at) and different domain and slot names even though the corresponding domain-slot pairs describe the same concepts (e.g., restaurant-food vs. restaurant-type). Therefore, we created a new unified ontology and manually designed a mapping between slot names. Notably, we decided to rename some slots so they use natural language tokens, as we base our model on the GPT-2 LM which is pre-trained on natural language texts (e.g. "leaveAt"  $\rightarrow$  "leave at"). Our final ontology that unifies all three datasets contains 22 domains and 135 slots.

We use our own implementation of delexicalization, which directly produces our belief state string

	M	ultiWOZ 2	2.0	MultiWOZ 2.1			
method	inform	success	BLEU	inform	success	BLEU	
Human	91.0	82.7	_	86.3	79.1	_	
AuGPT	90.2	75.5	17.2	91.4	72.9	17.2	
SOLOIST (Peng et al., 2020)	85.5	72.9	16.5	_	_	_	
SimpleTOD (Hosseini-Asl et al., 2020)	84.4	70.1	15.1	85.0	70.5	15.2	
LABES-S2S (Zhang et al., 2020a)	_	_	_	78.1	67.1	18.3	
DAMD (Zhang et al., 2020b)	76.3	60.4	18.6	_	_	_	
MD-Sequicity (Zhang et al., 2020b)	86.6	71.6	16.8	_	_	_	

Table 1: Comparison with previous works on the MultiWOZ dataset (see Section 4.4 for a description of the metrics). *MD-Sequicity* is a variant of Lei et al. (2018)'s model, extended for a multi-domain setting.

	I			inform			turn	
method	complete	success	book	P	R	F1	succ	all
AuGPT	89.4	60.1	85.7	64.5	82.1	70.3	12.7	14.6
DAMD (Zhang et al., 2020b)	39.5	34.3	51.4	60.4	59.8	56.3	15.8	29.8
Sequicity (Lei et al., 2018)	23.1	9.8	4.1	33.0	32.7	29.9	12.2	32.6

Table 2: ConvLab evaluation comparison with other works (see Section 4.5 for a description of the metrics).

representation (see Section 3.1 and Example 1).

#### 4.3 Training Details

We implement our model in the PyTorch framework (Paszke et al., 2019). The model extends the small variant of the GPT-2 model. It consists of 12 transformer blocks with a model layer size equal to 768, having 124 million parameters in total. For all auxiliary tasks, we use a dropout of 0.1 with label smoothing 0.1. We use the AdamW optimizer (Loshchilov and Hutter, 2019). For greater training effectiveness, we employ mixed-precision training (Micikevicius et al., 2018) through PyTorch AMP. The finetuning runs for 8 epochs on the MultiWOZ 2.1 data when all the training examples are used, and for the corresponding number of minibatches if a lower number of samples is used when using only clean samples. The training takes less than one day when using 4 GPUs.

# 4.4 Corpus-based Evaluation

To compare with previous results on MultiWOZ, we evaluate the model performance with a set of corpus-based intrinsic metrics on both versions of the data. In the case of MultiWOZ 2.0, we use the original delexicalization used also by other compared methods (Peng et al., 2020; Hosseini-Asl et al., 2020; Zhang et al., 2020b). For MultiWOZ 2.1, we use our own delexicalization. We employ

the original evaluation scheme by Budzianowski et al. (2018), which provides two metrics – the inform rate and the success rate. The inform rate is the percentage of dialogues in which the system provided an appropriate entity, whereas the success rate is the percentage of dialogues in which the system outputted all the requested information. Additionally, we compute the BLEU score (Papineni et al., 2002) between the generated system utterances and the ground truth to get an approximation of the output fluency. Note that both the inform rate and the success rate are unaffected by using a different delexicalization and these metrics can be directly compared to other methods. A different delexicalization could, however, render a slightly different BLEU, but based on preliminary results, we believe this change has almost no effect.

#### 4.5 ConvLab 2 Evaluation

We use the ConvLab 2 platform (Zhu et al., 2020) for automatic evaluation. The platform includes an agent-based evaluation component, therefore we obtain results gathered from interaction between our system and the simulated user agent. We run the evaluation component 1,000 times, i.e. on 1,000 simulated conversations. The agent mimics user behavior, interacts with the system under evaluation, and computes multiple metrics, among which the most relevant are *complete*, *success* and *book* rates.

Method	Average Success	Success w/ DB	Success w/o DB	NLU score	Response appropriateness	Turns
Baseline	69.6	56.8	82.4	4.34	4.18	18.5
Winner	74.8	70.2	79.4	4.54	4.47	18.5
Our submission	72.3	62.0	82.6	4.53	4.41	17.1

Table 3: Human evaluation results obtained during the shared task using Amazon Mechanical Turk. Note that only 4 submissions outperformed the Baseline according to the average success metric.

The *complete rate* reflects the ratio of dialogues that are completed, i.e. all the user requests have been met. The *success rate* computes the percentage of dialogues which are successful, meaning the system captures correct informed entities and provides a valid booking if requested. Finally, the *book rate* is the proportion of dialogues where the system was able to book the correct entity (hotel, restaurant, train) if it was asked to. We also compute *precision*, *recall* and *F1 score* for the informed entities and the average number of turns in the dialogue.

# 4.6 Human Evaluation and Error Analysis

Thanks to our participation in a task-oriented dialogue shared task, the best one of our submissions was evaluated by human judges on the Amazon Mechanical Turk platform. The judges communicated with the agent in natural language and rated the system afterward with respect to the success/failure of the dialogue, language understanding score, and response appropriateness. Information provided by the system was additionally checked for consistency with the database, and the average of success rates given by the judges and by database grounding is used as the main metric.

In addition to the crowdsourced evaluation, we perform a detailed in-house error analysis of the model behavior based on human interactions with our final system. Expert annotators followed randomly chosen dialogue goals accompanying the MultiWOZ test set and recorded any incorrect system behavior.

## 5 Results

In this section, we first describe and discuss the quantitative results for both corpus-based and crowdsourced human evaluation. In the second part, we also perform a qualitative analysis of the model behavior.

# 5.1 Comparison to State-of-the-Art on MultiWOZ

Table 1 shows a comparison between our methods and current state-of-the-art systems, which are described in the Related Work section. Since MultiWOZ 2.1 has been released quite recently and some of the compared methods do not provide results with this version, we report results on both MultiWOZ 2.0 and MultiWOZ 2.1. As we can see, AuGPT outperforms all other approaches in terms of the inform and success metrics. However, DAMD and LABES-S2S produce higher BLEU scores. This would indicate better fluency of these models, however, one would need human evaluation to confidently claim that. One possible reason for this behavior would be our removal of some training samples (see Data Preprocessing), which may have decreased the BLEU score. Importantly, thanks to the higher success metric, we can say that our model is better at providing all the necessary information in the responses.

Table 2 shows a comparison with two other models in the ConvLab evaluation scheme with a simulated user. The compared systems were chosen because they both implement fully trainable end-to-end methods. Our system outperforms both compared systems by a wide margin. Our model is able to perform well not just in a single-turn response generation scenario, but over the course of the whole dialogue. As the example of DAMD shows, this is not always guaranteed.

#### 5.2 Human Evaluation

We show the human evaluation results in Table 3. Our model outperformed the baseline on the main average success metric (along with only half of other submissions). We did not match the winning submission in terms of average success, but we achieved the best overall success rate based on human judgments (without checking consistency with the database). This suggests that the biggest drawback of our model was the integration with database grounding. This can be caused by our

	Erroneous	BS	DB	Policy	Other
	Dialogues	Error	Error	Error	Error
All dialogues Unsuccessful dialogues	50 17	30 10	4 3	21 2	6 2

Table 4: Interactive analysis performed by human evaluators using 130 prepared dialogue goals. 17 of these dialogues contained an error that caused the dialogue to fail. We show summary statistics regarding the number of respective error sources (BS = belief state, DB = database). Note that some of the dialogues contain more than one error.

Туре	Count	Source	Description
Hallucinated values	21	BS/Policy	Used a slot value in the reply that is not grounded in the DB nor in the context
Wrong lexicalization	6	Policy	Repeats the same value in a list of choices during lexicalization
Missing information	5	Policy	Makes booking while not all information is specified
Ignored input	5	BS	Keeps asking for information that was provided
Bad domain	4	BS	Fails to focus on the correct domain
False response	4	Policy	States a different value of a slot than the value stored in DB
Repeated output	3	Policy	Repeats the same slot twice on the output
Failed booking	3	DB/Policy	Booking was unsuccessful due to DB mismatch
Other	10	BS/DB/P/Oth	(Various rare errors that could not be categorized)

Table 5: Distribution of the most common error types encountered during the human evaluation of 130 dialogues. Absolute counts of errors in the 50 erroneous dialogues are shown. The total error count is 61 as some dialogues contained multiple errors. The most likely source of the error (cf. Table 4) and a short description are given for each type.

modified delexicalization, which makes it harder in some cases to match the database properly. In addition, our model needed the smallest number of turns overall to complete the evaluation dialogues.

We note that out of 5 submitted model variants in the competition (cf. Table 6), only the model variant scoring best in the automatic evaluation was considered for human evaluation. In our case, the chosen model variant did not include additional data pre-training, which could possibly improve performance in the human evaluation scenario.

# **5.3 Detailed Error Analysis**

Our expert annotators evaluated 130 dialogues in total, 50 of which contained at least one error. However, in most cases, the system was able to recover from the errors, resulting in an overall success rate of 86.9% (i.e., 17 unsuccessful dialogues).

The purpose of this analysis was to find out what kind of errors occur during real interaction. The annotators were familiar with the model architecture and were instructed to categorize the errors according to the cause of the problem. Specifically, they identified which component caused the respective error based on the internal system state. In addition, the annotators categorized the errors into more specific types.

The overall results are given in Table 4. We

[...] user: I want to make a booking at sitar tandoori **belief:** restaurant {name = sitar tandoori} train {arrive by = 18:00, day = sunday, departure = cambridge, destination = london liverpool street, people = 1} system: What day would you like the booking for? user: the same day, 13:30 **belief:** restaurant {day = sunday, name = sitar tandoori, people = 1, time = 13:30} train {arrive by = 18:00, day = sunday, departure = cambridge, destination = london liverpool street, people = 1} system: Booking was successful. The table will be reserved for 15 minutes. Reference number is: 00000200.

Example 2: A dialogue where the system did not ask for necessary information. The user previously booked a train trip for one person (cf. the belief state in the first turn shown). When they went on to book a restaurant, the system took over the number of persons from the train ride and did not ask again.

observe that the most common reason for a failed dialogue is an error related to the belief state. Also, although policy errors happen relatively often, they rarely cause the whole dialogue to fail. We observe that we have a slightly higher number of successful dialogues compared to the 82.6% success rate (without checking database consistency) found in human evaluation (cf. Table 3). The most likely

user: I'm looking for a theatre in Cambridge belief: attraction {type = theatre} system: There are 5 theatres in Cambridge. Is there an area of town you prefer? user: no I don't care belief: attraction {type = theatre} system: I recommend Adc Theatre in the centre. Would you like more information? user: no, I'm also looking for some place to stay belief: attraction {type = theatre} system: I have 5 theatres in the centre. Do you have a price range? user: I'm looking for a place to stay belief: attraction {type = theatre} **system:** There are 5 theatres in the centre. Do you have a preference for area? **user:** I'm looking for a hotel belief: hotel {type = hotel} attraction {type = theatre} system: There are 9 hotels in the north. Do you have a price range?

Example 3: Dialogue sample with a bad domain focus and a hallucination. First, the system ignores that the user switched from searching for a theater to searching for a hotel. After accepting the new domain, the system replies with hotels "in the north" even though the user did not specify.

cause of this behavior is that our expert annotators were more motivated to recover from erroneous system behavior and finish the dialogue.

Fine-grained error types identified by annotators are given in Table 5. We now provide examples for some of the frequent types which deserve more detail. By far the most common error was hallucinated values - lack of grounding for some of the information provided (see the end of Example 2). One of the causes of this error, as in the case of this example, were hallucinations coming from the decoder. This probably stems from an imperfect delexicalization of some of the training samples. Another error type is missing information, i.e., not asking for information that is required (Example 3). In this case, the system uses information from a different domain without the user explicitly confirming this. A most probable cause of this is that most instances of the training data carry over the information. A third common error type is bad domain (see the beginning of Example 2). Here, the system does not react to the user's request for a different search (hotels instead of attractions in the example). This might be caused by a less frequent wording of the request in the given context, and usually gets resolved by rephrasing the request.

Apart from the errors, many examples of nontrivial positive behavior were found during the analuser: I am looking for a cheap *chinse* restaurant.
belief: restaurant {food = chinese, price range = cheap}
system: I have 4 cheap chinese restaurants. What area of town would you like to dine in?
user: downtown
belief: restaurant {area = centre, food = chinese, price range = cheap}
system: I have 3 cheap chinese restaurants in the centre. Would you like to book at Charlie Chan?

Example 4: A snippet from challenging yet successful dialogue. The system deals with input noise (chinse) as well as with paraphrases (downtown).

ysis. As illustrated in Example 4, the model is able to deal with paraphrases and is robust to a certain amount of noise in the data. Specifically, it handles typos, various time formats, etc. Interaction between domains is also successful in most cases – the system is able to resolve references to another domain's belief state (e.g., make a booking for the same group of people as done before in a different venue).

# 6 Ablation Study

We tested many variants of our method with different combinations of our proposed system's components to evaluate their contributions. The results are presented in Table 6. Namely, we are interested in the following components: (1) the unlikelihood loss, (2) the auxiliary tasks, (3) the data augmentation, (4) the modified consistency task and (5) unclean data filtering.

We can see that all proposed contributions which are a part of our final system have a positive effect on the system performance with respect to the primary metrics. We can see that removing either the pre-training or the back-translations decreases the BLEU score and, more importantly, the success rates. Furthermore, we notice the positive effect of using our improved consistency detection task over the one used in SOLOIST (Peng et al., 2020), which in turn scores better than no consistency detection.

Removing either the unlikelihood loss or training on all data as opposed to only "clean" samples clearly reduces performance. However, we did not notice any increase in performance when the user intent prediction and system action prediction auxiliary tasks were used (cf. Section 3.2). The reason for this behavior could be that the model learns to represent the actions well enough implicitly, without the need for these additional objectives. How-

MultiWOZ 2.1					ConvLab 2					tu	rn
method	inf	suc	BLEU	comp	suc	book	P	R	F1	suc	all
AuGPT	91.4	72.9	17.2	89.4	60.1	85.7	64.5	82.1	70.3	12.7	14.6
w/o. unlikelihood w/o. clean w/o. unlikelihood, clean w. all auxiliary	90.8 <b>91.6</b> 90.4 91.1	70.4 70.7 72.7 71.4	16.9 15.8 <b>17.5</b> 16.8	89.2 85.0 85.9 88.7	59.3 57.7 58.4 59.2	90.8 85.6 81.3 86.0	63.9 65.6 62.2 64.6	81.6 79.1 79.8 81.1	69.5 69.6 67.5 69.9	12.8 12.7 12.6 <b>12.6</b>	14.6 14.5 <b>14.1</b> 14.4
w/o. pre-training w/o. back-translations w. old consistency w/o. consistency	90.7 89.1 90.7 90.4	67.9 67.9 71.8 68.7	15.1 15.2 17.0 16.8	88.1 88.9 85.5 86.4	59.8 58.2 57.8 57.1	83.7 87.4 86.0 84.1	68.1 68.0 65.2 66.3	80.9 81.6 80.0 81.2	72.1 <b>72.2</b> 69.8 70.9	13.5 12.9 12.7 13.1	15.6 14.9 14.6 14.6

Table 6: Ablation study (inf = inform, suc = success, book = book rate; see Section 4.4 for a description of metrics). The model version with the best ConvLab 2 success rate is chosen as our best model. Variants are denoted with their respective modifications compared to the default: "w/o. unlikelihood" = unlikelihood loss was not used for training; "w/o. clean" uses all training samples as opposed to using only the ones consistent with the database; "w/o. pre-training" = the additional Taskmaster-1 and Schema-Guided datasets were not used for training; "all auxiliary" = using two additional auxiliary tasks (see the Method section for details); "w/o. consistency" = dialogue consistency task is not used; "old consistency" refers to the consistency task as defined by Peng et al. (2020) (see the Section 3.2 for details).

ever, these tasks are not a part of our final model.

## 7 Conclusions & Future Work

We present a dialogue modeling pipeline based on the pre-trained GPT-2 language model. AuGPT uses modified training objectives and employs data augmentation to increase the diversity of generated utterances. Our experiments show that the proposed approach performs better than state-ofthe-art baselines in a multi-domain scenario on the MultiWOZ dataset. We also run a series of ablation experiments to assess the individual contributions of the modifications. According to our detailed ablation study, training data augmentation using back-translation via multiple languages and a modified auxiliary training objective for dialogue consistency detection are the features that contribute most to our system's performance. Additionally, we perform a qualitative analysis of the outputs to give a better insight into our model behavior.

In the future, we plan to construct a latent representation of the belief state and optimize it jointly with the language model. We will replace the deterministic lexicalization with a trainable alternative, and possibly even integrate the database module into the model. To improve the transfer to new domains, we will learn a domain embedding and optimize it jointly with the model, unifying all datasets.

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