

JOINT SPEECH AND TEXT TRAINING FOR LLM-BASED END-TO-END SPOKEN DIALOGUE STATE TRACKING

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ABSTRACT

End-to-end spoken dialogue state tracking (DST) is made difficult by the tandem of having to handle speech input and data scarcity. Combining speech foundation encoders and large language models has been proposed in recent work as to alleviate some of this difficulty. Although this approach has been shown to result in strong spoken DST models, achieving state-of-the-art performance in realistic multi-turn DST, it struggles to generalize across domains and requires annotated spoken DST training data for each domain of interest. However, collecting such data for every target domain is both costly and difficult. Noting that textual DST data is more easily obtained for various domains, in this work, we propose jointly training on available spoken DST data and written textual data from other domains as a way to achieve cross-domain generalization. We conduct experiments which show the efficacy of our proposed method for getting good cross-domain DST performance without relying on spoken training data from the target domains.

Index Terms— dialogue state tracking, task-oriented dialogue, speech LLM, domain adaptation, joint speech-text training

1. INTRODUCTION

Task-oriented dialogue (ToD) systems are conversational agents that assist users in achieving certain defined goals such as making reservations, locating attractions, requesting information, etc. As the dialogues typically comprise multiple user-agent turns in unstructured natural language, a key component of ToD systems is dialogue state tracking (DST)—the extraction of structured domains and slots from the natural language conversation. (e.g. from conversation turn: “*Yes, it should leave on Sunday. It should leave after 13:45.*” and its context, it should extract the following domain: *train*, and slots: *train*: {*day*: *Sunday*, *departure*: *Cambridge*, *destination*: *London Liverpool Street*, *leave at*: *13:45*}).

That speech constitutes a natural and often more convenient medium of communication has prompted research in DST from spoken rather than text input [1]. This conventionally entailed cascading an automatic speech recognition (ASR) module, optional error correction modules, and text-based DST modules [2, 3]. However, recent end-to-end (E2E) methods have been developed which are trained to directly predict the dialogue states from speech [4, 5, 6, 7].

E2E methods alleviate some of the deficiencies of their cascade counterparts such as system complexity, error propagation, latency, loss of paralinguistic information and other discrepancies between spoken and written language. However, they suffer from a data scarcity problem—collecting enough spoken dialogue data for training a well-performing spoken DST model from scratch is a laborious and expensive undertaking.

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A recent E2E method [7]—which we take as a baseline in this work—tackles the data scarcity problem by using a connector module to link a pretrained speech encoder and a pretrained large language model (LLM) in order to combine the former’s robust speech modeling ability with the latter’s ability to extract complex structured information from natural language. The connector is then trained along with low-rank adapter (LoRA) [8] layers to directly predict the dialogue states encoded as a JSON string from the speech input into the encoder. While this approach proved successful, considerably outperforming previous state-of-the-art DST systems on the multi-domain SpokenWOZ [9], it struggles to generalize to domains (specifically, slot values corresponding to names of places, restaurants, etc.) other than those on which it was trained.

Given the cost and difficulty of collecting spoken DST training data for every target domain, it is necessary to develop methods that generalize to multiple domains without access to spoken training data from those domains. We note that *unpaired*¹ textual DST training data is more abundant and less costly to collect. Moreover, prior work has shown that slot-augmentation can significantly improve the performance and robustness of text-based DST systems [10, 11]. Applying such augmentation to speech input is nontrivial however. Therefore, inspired by similar joint training methods that have been utilized for other speech processing tasks [12, 13, 14, 15, 16, 17], we propose a joint training method which combines single-domain spoken DST data with cross- or multi-domain textual data for training.

In our method, we augment the LLM-based E2E speech-to-DST model with a text encoder whose input is the natural language query from the user and whose output is passed into the connector and then into the LLM to predict the dialogue states. By sharing parameters (specifically the connector and the LoRA layers in the LLM) between the speech and text pipelines and jointly training on spoken DST data from some source domain(s) and textual DST data from target domains, we aim to learn a multi-domain model capable of conducting DST in the target domain.

We conduct experiments on the SpokenWOZ [9] and Speech-Aware MultiWOZ [18] datasets, where we train on speech data from a *source* domain jointly with text from a *target* domain. These experiments show that the proposed method consistently improves cross-domain generalization across datasets and models, including scenarios where the target text forms only a small portion of some larger text corpora used for training.

2. METHODS

Our DST system is based on the E2E framework from [7], which uses a model comprising a speech encoder, a large language model and a connector module used to transform the outputs of the former

¹Note that by unpaired, here and throughout the paper, we mean DST data with no spoken utterances as opposed to text data with no DST labels.

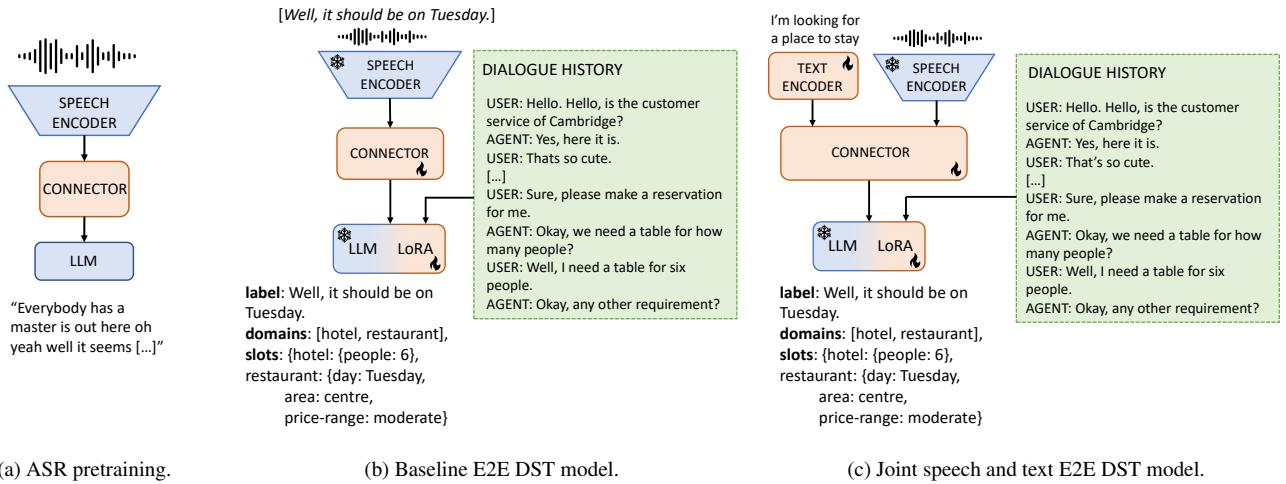


Fig. 1: E2E DST model under various training regimes.

into the embedding space of the latter (illustrated in Figure 1b). The model’s inputs are the speech corresponding to the user input at the current turn of the dialogue and the dialogue history in the form of transcriptions of user and agent turns of the dialogue with a new-line character (`\n`) inserted between turns. The speech is encoded by the tandem of the encoder and the connector, and resulting speech embeddings are prepended to the LM embeddings of the dialogue history. The resulting sequence is passed through the LLM transformer layers. The model is trained to output a single JSON string encoding a Python dictionary that contains the ASR transcription and the dialogue states, i.e., the set of active domains and corresponding slots.

2.1. Joint Speech and Text E2E DST (Multimodal DST)

We propose modifying the E2E DST model to accommodate training on not just spoken but also written task-oriented dialogues. To this end, we augment it with a text encoder which accepts as input the natural language user input of the current user turn of the dialogue. As with the speech encoder output, the text encoder output then goes through the connector, is prepended to the dialogue history and then fed into the language model to predict dialogue states.

The inclusion of the text encoder allows us to train on diverse text DST data without requiring paired spoken user utterances. We hypothesize that this would allow us to improve the model performance on spoken data from those domains. Note that the text encoder is only used to aid training and can be discarded during inference, thus incurring no additional inference cost compared to the baseline E2E DST system.

2.2. Training

Following the findings of [7], we train the model in two phases: First, we freeze the LM and pretrain the encoder and connector for ASR on diverse training data using the cross-entropy objective. Then, we introduce the text encoder and insert LoRA layers into the LM, and finetune the connector, text encoder and LoRA parameters jointly for DST from speech and text with the speech encoder and base language model frozen.

At each step of training, we feed a speech batch and a text batch through their respective encoders and train to minimize a sum of

three cross-entropy losses. In addition to the cross-entropy objectives computed from the DST on speech data and text DST on unpaired text data, we also train the model for text DST from the transcription of the speech batch.

3. EXPERIMENTS

3.1. Datasets and metrics

We conduct our experiments on two spoken dialogue state tracking datasets: SpokenWOZ (SW) [9] and Speech-aware MultiWOZ (MW) [18]. In most of our experiments, we utilize a training set from one of them as the paired speech-text data and the other as unpaired text data, e.g., training on a combination of SpokenWOZ speech and MultiWOZ text and vice versa, allowing us to measure the cross-domain performance. We also use text from DialogStudio (DS) [19] as an alternative unpaired text to measure the impact of training on unpaired DST data, which does not exactly match the target domain. For SpokenWOZ, we follow the pre-processing from [7], discarding nine corrupted conversations from the SpokenWOZ test sets, and employing Whisper-large-v3 [20] to re-transcribe the user and agent speech. We note that MultiWOZ presents an additional challenge because its validation and test sets contain data from a different city (New York) than the training set (Cambridge); therefore, we expect using MultiWOZ training text for joint training would improve the slot keys but not necessarily the values for the MultiWOZ.

For the ASR training, we use the Fisher [21], LibriSpeech [22], CommonVoice (version 17) [23] and VoxPopuli [24] datasets.

We report the joint goal accuracy (JGA) computed using the MultiWOZ evaluation script² [25]. As is standard practice in DST, before scoring, we post-process the outputs of all DST systems using fuzzy matching³ to match hypothesized slots to the closest slots by edit distance in the ontology.

3.2. Model architecture and hyper-parameters

We use WavLM [26] as the pretrained speech encoder in all our experiments, and Gemma-3-1B-it [27] as the LLM in most exper-

²github.com/Tomiinek/MultiWOZ_Evaluation

³pypi.org/project/fuzzywuzzy/

Table 1: Joint goal accuracy (%) as unpaired text data is varied on E2E model with Gemma-1B-it.

	Training Speech	Training Text	SW Val	MW Val
A1		✗	36.1	15.1
A2	SW	MW	36.3	19.0
A3		MW, DS	37.9	18.4
A4		DS	37.1	17.1
B1		✗	20.5	28.6
B2	MW	SW	30.6	24.7
B3		SW, DS	28.8	23.6
B4		DS	20.5	28.1
C1	SW	MW-train+test	38.7	23.1
C2	MW	SW-train+test	32.6	25.7
C3	MW+SW	✗	36.2	16.9
C4	MW+SW	MW-val, SW-val	55.3	42.4

iments. We also report a subset of results with Gemma-3-4B-it and Gemma-3-12B-it to quantify the impact of scaling, as well as OLMo-1B [28] to facilitate comparison with prior state-of-the-art [7] and because the openness of its training data and configuration allay risks of data contamination.

For the connector, we use a 4-layer Transformer encoder with hidden size 1024, 4 attention heads, feedforward intermediate dimensions of 4096 and sinusoidal positional encoding with maximum length set to 512. The Transformer layers are preceded by two convolutional layers with strides of 3 and 2, so that the speech input to the LLM has 8Hz. Note that text inputs from the text encoder are passed through only the Transformer and not the convolutional module of the connector.

For the text encoder, we use a Transformer encoder with identical dimensions to the connector Transformer, preceded by an input embedding layer with the same tokenizer as the respective LM.

In the ASR training phase, we use AdamW optimizer [29] for 100k steps. The learning rate is warmed up over the first 1000 steps up to a peak of 2×10^{-4} and then decayed linearly to 0.01 of the peak over the course of training.

In the finetuning phase, we use LoRA with rank and alpha 32 and train using AdamW. We warm up the learning rate to a peak of 5×10^{-5} over 1000 steps, and then decay it for up to 60k steps. We measure the JGA (in teacher-forcing mode) on the validation sets, and use it for early stopping and for selecting checkpoints. We find that training typically terminates in the first 10k steps.

3.3. Training with text data from various sources

First, we explore the impact of training with text alongside speech while varying the degree of relevance to the target test sets, and we report these in Table 1.

Comparing rows A1 to A2, we find that training on paired SpokenWOZ data with unpaired MultiWOZ training text considerably improves performance on the MultiWOZ validation set compared to the model trained with no text, reducing the JGA gap to the model trained on paired MultiWOZ data by 28.9%. In the converse case, comparing B1 to B2, we observe even larger improvements with a 64.7% reduction of the gap.

Next, we consider the case where the target text is mixed with

Table 2: Joint goal accuracy (%) on Gemma-1B-it with or without text encoder.

	Training Speech	Training Text	Text Encoder	SW Val	MW Val
A1		✗	✗	36.1	15.1
A2	SW	MW	✓	36.3	19.0
D1		MW	✗	36.1	17.4
B1		✗	✗	20.5	28.6
B2	MW	SW	✓	30.6	24.7
D2		SW	✗	28.6	24.9

DialogStudio text (rows A3 and B3). This emulates a setting where a large text corpus, including text from the target domain, is available for training, but the target domain is not necessarily known *a priori*. This slightly degrades the target set performance compared to using only target training data as the paired text, but is still considerably better than the baseline trained with no unpaired text.

Subsequently, we train using only unpaired text from DialogStudio without text from the target domain (rows A4 and B4), and observe moderate improvement over the baseline on the MultiWOZ validation set but none whatsoever on SpokenWOZ. This can be explained by the fact that the DialogStudio collection contains the MultiWOZ training data but not SpokenWOZ.

Overall, these results indicate that our proposed method enables adaptation to a target domain using only unpaired text from that domain, even when it forms only a small portion of a larger text corpus.

Finally, we report results on a set of toplines. In C1 and C2, we use as unpaired text the concatenation of the train and test sets of the target domain (while still testing on the validation set). We note that while C2 slightly outperforms B2 on SpokenWOZ (6.5%), C1 yields a more substantial relative improvement of 21.6%. This latter result shows the impact of training on text data with not just overlapping the domains but also the slot values since the MultiWOZ test and validation sets contain dialogues from the same city. In C3, we train on paired data from both SpokenWOZ and MultiWOZ, and in C2, we additionally use the text from the *validation* sets as unpaired texts. C4 massively outperforms C3 although the former is already trained on paired data from both domains. Although this last experiment is only an oracle one, it underscores the capability of our method to adapt under idealized conditions.

3.4. Mechanism of incorporating unpaired text

Although we have seen the benefits of training on unpaired text, a natural question arises as to whether and how much the text encoder actually contributes. Specifically, if the improvements are a result of simply exposing the LM to dialogue states from the target domain, we may simply finetune the LoRA parameters on the unpaired data without a text encoder at all.

Table 2 shows the results of this comparison. We observe that excluding the text encoder (D1 and D2) performs worse on the target domain than having it (A2 and B2, respectively), but it consistently improves upon the baseline with no unpaired text (A1 and B1). This indicates that while part of our improvements stem from simply exposing the LM to the target domain dialogue states, another part of it comes from improving the speech pipeline’s ability to extract these dialogue states from natural language input.

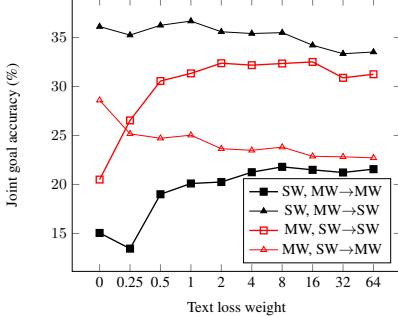


Fig. 2: Variation of JGA as text loss weight is varied. In the legend, X, Y→Z denotes a model trained on paired speech data from X and unpaired text from Y, and tested on the validation set from Z.

3.5. Text objective weighting

So far, we have always multiplied the cross-entropy objective of text training batches by a default value of 0.5. Figure 2 shows the target domain JGA as the loss weight is varied. Increasing the text weight improves the target domain performance, while degrading the source domain performance moderately (in the case of SpokenWOZ) to considerably (in the case of MultiWOZ). Thus, weighting the loss proves to be a viable way of trading off inter-domain performance as desired.

3.6. Test set performance

Finally, we report the results of experiments on the test sets in Table 3. In addition to the Gemma-3-1B-it model used in all experiments above, we also report results obtained with OLMo-1B, Gemma-3-4B-it and Gemma-3-12B-it. OLMo-1B lets us observe how well our method works on an LM from a different family and to compare with [7] where most results were from OLMo-1B. Experiments on Gemma-3-4B-it and Gemma-3-12B-it show how well our approach translates to larger and better language models. In these experiments, we keep the same LoRA rank of 32.

On OLMo-1B, our implementation of the no-text baselines outperforms the results reported in [7] (compare E0 and F0 to E5 and F5, respectively). We credit this to using more data for the ASR pre-training phase. Nevertheless, as in the Gemma-3-1B-it experiments, joint training with target domain text leads to much improved target domain performance with SpokenWOZ, especially benefiting significantly from target text training. Specifically, joint training with SpokenWOZ speech and MultiWOZ text (E6) closes 46% of the MultiWOZ performance gap between the baseline trained on MultiWOZ speech with no text (E5) and that trained on SpokenWOZ speech (F5). In the converse experiment, where we train with MultiWOZ speech and SpokenWOZ text (F6), we observe that we can recover 79% of the performance gap on SpokenWOZ between training on MultiWOZ only (F5) and actual SpokenWOZ speech (E5).

As is to be expected, we find that larger LMs generally perform better. More interestingly, the relative impact of joint text training is more pronounced the larger the LM is. In the case of the largest model in our experiment, Gemma-3-12B-it, joint training with SpokenWOZ text and MultiWOZ speech (F4) yields almost identical SpokenWOZ test set JGA as actually training on SpokenWOZ speech (E3). Similarly, we observe larger relative improvements on MultiWOZ with the larger models. Moreover, in the case of MultiWOZ, where adding SpokenWOZ text degrades the Multi-

Table 3: Test set joint goal accuracy (%) with various LLMs.

	Training Speech	LLM	Training Text	SW Test	MW Test
A1		Gemma-3-1B-it	X	35.6	14.3
A2			MW	36.3	18.4
E1		Gemma-3-4B-it	X	41.0	16.9
E2			MW	40.3	22.6
E3	SW	Gemma-3-12B-it	X	42.6	16.6
E4			MW	43.0	23.5
E0 [7]		OLMo-1B	X	32.1	-
E5			X	34.1	13.9
E6			MW	34.9	18.2
B1		Gemma-3-1B-it	X	18.9	27.1
B2			SW	30.9	23.5
F1		Gemma-3-4B-it	X	19.8	27.3
F2			SW	37.4	30.8
F3	MW	Gemma-3-12B-it	X	20.7	32.4
F4			SW	42.2	31.6
F0 [7]		OLMo-1B	X	-	18.2
F5			X	18.7	23.2
F6			SW	29.3	21.9

WOZ test set JGA for Gemma-3-1B-it (B1 vs B2), we observe that this performance degradation set decreases (F3 vs F4) or disappears (F1 vs F2) for the larger models.

On inspection of the outputs from the Gemma-3-1B-it models, we found that joint training significantly improved recall of slot keys related to names on MultiWOZ, e.g. restaurant name (41.5% higher recall), hotel name (31.8%) and attraction name (35.9%); however, the difference in recall rate of values for which the keys were correctly recalled was much lower at 5.4%, 2.6% and 19.2%. On SpokenWOZ however, we observe that the recall rates of the values are improved by 36.0%, 41.7% and 58%. This reflects the difference in the text data on which we train, as the SpokenWOZ training set contains dialogues from the same city as the test set, so that the values overlap unlike the MultiWOZ train set which contains a completely different city from the test set.

4. CONCLUSIONS

In this paper, we have proposed a joint speech and text training method for end-to-end spoken dialogue state tracking. Our method entails augmenting an LLM-based spoken DST model with a text encoder which allows the model to be trained on arbitrary textual DST data. We show empirically on the SpokenWOZ and MultiWOZ datasets that this method is able to perform spoken DST on domains for which only textual training data is available, even in the presence of other irrelevant training data. Furthermore, we show the stability of the model across various language model choices, and similar improvement trends even for stronger language models.

The approach we propose enables training multi-domain spoken DST models with speech data from only a subset of domains and only text data from the others. This work opens the possibility of future work leveraging strategies known to improve textual DST such as paraphrasing and slot augmentation [10, 11] which would otherwise be difficult to implement directly on speech input.

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