Variational Hierarchical Dialog Autoencoder for Dialogue State Tracking Data Augmentation

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Abstract

Recent works have shown that generative data augmentation, where synthetic samples generated from deep generative models are used to augment the training dataset, benefit certain NLP tasks. In this work, we extend this approach to the task of dialogue state tracking for goal-oriented dialogues, in which the data naturally exhibits a hierarchical structure over utterances and related annotations. Deep generative data augmentation for dialogue state tracking requires the generative model to be aware of the hierarchically structured data. We propose Variational Hierarchical Dialog Autoencoder (VHDA) for modeling various aspects of goal-oriented dialogues, including linguistic and underlying annotation structures. Our experiments show that our model is able to generate realistic and novel samples that improve the robustness of state-of-the-art dialogue state trackers, ultimately improving their final dialogue state tracking performances on several datasets.

1. Introduction

Data augmentation, a technique where the training set is augmented with label-preserving synthetic samples, is commonly employed in modern machine learning approaches. Data augmentation has been used extensively in visual learning pipelines (Shorten & Khoshgoftaar, 2019) and in some NLP tasks as well, such as text classification (Zhang et al., 2015), spoken language understanding (Yoo et al., 2019), machine translation (Fadaee et al., 2017). Data augmentation for NLP tasks is relatively less common because it is less straightforward.

Ideally, a data augmentation technique must synthesize (1) class-preserving and (2) realistic samples, where the latter property implies that the synthetic samples adhere to the true data distribution. Current approaches for data augmentation in NLP tasks largely revolve around thesaurus data augmentation (Zhang et al., 2015), in which words that belong to the same semantic role are substituted with one another using a preconstructed lexicon, and noisy data augmentation (Wei & Zou, 2019) where random editing operations are applied to the language space. Thesaurus data augmentation satisfies both properties of an ideal technique, but it requires a set of handcrafted semantic dictionaries, which are costly to build and maintain; whereas noisy data augmentation does not guarantee synthetic samples to be realistic. As an alternative to the two approaches, generative data augmentation (GDA) has been proposed to leverage deep generative models, such as VAEs, to delegate automatic discovery of novel class-preserving samples to machine learning (Hu et al., 2017; Yoo et al., 2019; Shin et al., 2019). In this work, we extend this line of methodologies to the task of dialogue state tracking, which pertain dialogue modeling and understanding.

Goal-oriented dialogues take place between a user and a system who communicate verbally in order to accomplish the user’s goals. However, because the user’s goals and the system’s possible actions are not transparent to each other, both parties must rely on verbal communications to infer and make appropriate actions to resolve the goals. Dialogue state tracker is a core component of goal-oriented dialogue system, allowing it to track the current status of the dialogue and make informed choices (Henderson et al., 2014a). A dialogue state typically consists of inform and request types of slot values. For example, a user might inform that the preferred food type is asian (inform(food=asian)) or might request the address of a specific restaurant (request(address)). Hence, given a user utterance, a dialogue state tracker must understand the context of the dialogue (all utterances and system acts up to the current utterance) and predict the user intents as a highly sparse multi-class classification problem. In order to generate novel samples for augmenting goal-oriented dialogues, an appropriate dialogue modeling method must be devised first.
Various approaches of deep generative dialogue models have been proposed previously, such as the Markov approach (Serban et al., 2017), which uses a sequence-to-sequence variational autoencoder (VAE) (Kingma & Welling, 2013) to predict the next utterance given a deterministic context representation, and the holistic approach (Park et al., 2018), which uses a global latent variable to encode the holistic representation of the dialogue, improving the coherence and long-term dependency resolution of generated dialogues. However, most approaches handle the linguistic features of the dialogues only and not the underlying annotation structures. A recent work (Bak & Oh, 2019) proposed a hierarchical VAE structure that also considers the speaker information, but a universal dialogue modeling architecture for encompassing all aspects (speaker, dialogue state) of goal-oriented dialogues has yet to be devised. Such model, if realized, would be able to introduce variations into the synthetic samples not only at or below the utterance level but even at the dialogue level.

In this paper, we propose a novel hierarchical and recurrent VAE structure, called Variational Hierarchical Dialog Autoencoder (VHDA), for modeling all aspects of goal-oriented dialogues to achieve generative data augmentation for dialogue state tracking. However, autoregressive VAEs are known to be at the risk of posterior collapse (Cremer et al., 2018), which is also known as the degeneracy problem, where, in some cases, the inference network fails to encode meaningful information into the root latent variable. Due to the complexity of the decoder, our proposed model is at even higher risk. To reduce the hazard, we also propose a simple but effective training policy, which is empirically demonstrated to be effective at mitigating posterior collapse, ultimately improving the data augmentation performance.

Our contributions can be summarized as follows.

- We propose a novel deep latent variable model for generating both linguistic features and underlying structures of goal-oriented dialogues, which can be used to generate novel samples and augment the original training set that improves the robustness of the resulting dialogue state trackers.
- We conduct extensive experiments on multiple goal-oriented dialogue corpora and dialogue state trackers to confirm the benefits of generative data augmentation for dialogue state tracking.
- We propose a novel training scheme for hierarchical autoregressive VAEs that reduces the risk of posterior collapse.

The rest of the paper is structured as follows. Section 2 provides the relevant background and the related work on task-oriented dialogues and deep generative dialogue models. Section 3 describes our proposed model and related training techniques. Section 4 provides details about the experimental settings and quantitative/qualitative results regarding our deep generative model and generative data augmentation. In the final section, we summarize the paper and offer our findings about the work, including limitations and future work.

### 2. Background and Related Work

**Dialogue State Tracking.** Dialogue state tracking (DST) is the task of predicting the user’s current goals and dialogue acts given the context of the dialogue. Historically, DST models relied on hand-crafted finite-state automata to emulate humans in conversations (Dybkjer & Minker, 2008) or separate SLU modules to achieve dialogue tracking using a two-stage process (Thomson & Young, 2010; Wang & Lemon, 2013; Henderson et al., 2014b). Recent approaches combine the two-stage process into one unified model to directly predict dialogue states from dialogue features (Zilka & Jurcicek, 2015; Mrkšić et al., 2017; Zhong et al., 2018; Nouri & Hosseini-Asl, 2018; Wu et al., 2019).

Among the integrated single-stage models, the earlier ones relied on delexicalization – the act of replacing entities in slots and values with generic tags using handcrafted semantic dictionaries – to improve generalization. Neural Belief Tracker (NBT) (Mrkšić et al., 2017) has been proposed to decrease reliance on handcrafted semantic dictionaries by reformulating the multi-class classification problem to multiple binary classification problems. GLAD (Zhong et al., 2018) improves upon NBT by introducing global modules (for sharing parameters among estimators for slot values) and local modules to learn slot-specific feature representations. GCE (Nouri & Hosseini-Asl, 2018) improves within the paradigm of neural belief tracking by forgoing the separation of global and local modules and letting the unified module to take slot embeddings as the condition, greatly reducing the number of parameters and improving the inference efficiency.

**Conversation Modeling.** The prominent approach for hierarchical dialogue modeling was based on the Markov assumption (Serban et al., 2017), but recent approaches have converged on utilizing global latent variables for representing the holistic properties of dialogues (Park et al., 2018; Gu et al., 2018; Bak & Oh, 2019), which preserves long term dependencies in the dialogue. In this work, we employ global latent variables to maximize the effectiveness in preserving dialogue semantics for data augmentation.

**Data Augmentation.** Transformation-based data
augmentation is widely adopted in vision learning (Shorten & Khoshgoftaar, 2019) and speech signal processing (Ko et al., 2015), while thesaurus and noisy data augmentation has been explored in NLP (Zhang et al., 2015; Wei & Zou, 2019). Recently, generative data augmentation (GDA), where samples generated from deep generative models are used for data augmentation, have gained traction in a subset of NLP tasks (Hu et al., 2017; Hou et al., 2018; Yoo et al., 2019; Shin et al., 2019). GDA can be seen as a form of unsupervised data augmentation, delegating the automatic discovery of augmentational data to machine learning without injecting external knowledge or data sources. While most works utilized VAE for the generative model, some works achieved a similar effect on simpler tasks without employing variational inference (Kurata et al., 2016; Hou et al., 2018). In contrast to unsupervised data augmentation, another line of work has explored self-supervision mechanisms as a way to fine-tune the generators for specific tasks (Tran et al., 2017; Antoniou et al., 2017; Cubuk et al., 2018). A recent work proposed reinforced noisy data augmentation framework for dialogue state tracking (Yin et al., 2019).

3. Variational Hierarchical Dialogue Autoencoder (VHDA)

In this section, we describe the proposed latent variable model for generating goal-oriented dialogue datasets complete with their annotations. To facilitate in describing our main work, we introduce a set of notations for representing dialogue-related concepts and offer a short description of the prior work that uses a hierarchical VAE structure to solely model the linguistic features (Park et al., 2018). In the rest of the section, we present details and inner workings of VHDA, which captures not only the linguistic features but also the underlying structural features simultaneously.

3.1. Notations

In this subsection, we establish a set of general notations for describing any type of goal-oriented dialogue. A goal-oriented dialogue dataset \( \mathcal{D} \) is a set of \( N \) i.i.d goal-oriented dialogue samples \( \{c_1, \ldots, c_N\} \), where each \( c \) is a sequence of dialogue turns \( (v_1, \ldots, v_T) \). Each goal-oriented dialogue turn \( v \) is a tuple of speaker information \( r \), the speaker’s goals \( g \), dialogue state \( s \), and the speaker’s utterance \( u \): \( v = (r, g, s, u) \). Each utterance \( u \) is a sequence of words \( (w_1, \ldots, w_{|u|}) \). Each set of speaker goals \( g \) and each dialogue state \( s \) are defined as a set of the smallest unit of dialogue state specification \( a \) (Henderson et al., 2014a), which is a tuple of dialogue act, slot and value defined over the space of dialogue acts \( \mathcal{A} \), slots \( \mathcal{S} \), and values \( \mathcal{V} \): \( g = \{a_1, \ldots, a_{|g|}\} \), \( s = \{u_1, \ldots, u_{|s|}\} \), where \( a_i \in (\mathcal{A}, \mathcal{S}, \mathcal{V}) \).

3.2. Variational Hierarchical Conversational RNN

Given a conversation \( c \), Variational Hierarchical Conversational RNN (VHCR) (Park et al., 2018) models the holistic features of the conversation as well as individual utterances \( u \) using a hierarchical and recurrent VAE model, as shown in Figure 1. The model introduces global-level latent variables \( z^{(c)} \) for encoding the high-level structure of the conversation, and local-level latent variables \( z^{(u)}_t \) responsible for encoding and generating utterances at each turn step \( t \). The local latent variables \( z^{(u)}_t \) are designed to be conditionally dependent on \( z^{(c)} \) and the previous observations, forming a hierarchical structure. This model is realized by the hidden variables \( h_t \) that have conditional dependence on the global information and the hidden variables from the previous timestep \( h_{t-1} \).
3.3. Proposed Model

To achieve complete modeling of goal-oriented dialogues, we propose Variational Hierarchical Dialogue Autoencoder (VHDA) to generate dialogues and their underlying dialogue annotations simultaneously (Figure 2). Similar to VHCR, we employ a hierarchical latent structure to capture both the holistic dialogue semantics using the conversation latent variables \( z^{(c)} \) and individual turn-level features \( z^{(r)} \) (speaker), \( z^{(g)} \) (goal), \( z^{(s)} \) (dialogue state), and \( z^{(u)} \) (utterance). Motivated by speech act theory, we also employ a hierarchical structure for the turn-level latent variables, in which the utterance latent variables \( z^{(u)} \) are dependent on all other latent variables within the same turn. The model is not only capable of generating linguistic features and the relevant annotations from a single model, but it is also capable of generating languages of higher quality and diversity thanks to the effect of joint learning, which we discuss in Section 4.2.2.

VHDA consists of multiple encoder modules and multiple decoder modules, each responsible for extracting features or generating a particular dialogue feature. However, multiple encoders share the same sequence-encoding architecture (but not parameters).

3.3.1. Sequence Encoder Architecture

Given a sequence of variable number of elements \( X = [x_1; \ldots; x_n]^T \in \mathbb{R}^{n \times d} \), where \( n \) is the number of elements, the goal of a sequence encoder is to extract a fixed-size representation \( h \in \mathbb{R}^d \), where \( d \) is the dimensionality of the hidden representation. For our implementation, we employ a shallow self-attention mechanism over hidden outputs of bidirectional LSTM (Hochreiter & Schmidhuber, 1997) cells produced from taking inputs from the input sequence. We also allow the attention mechanism to be queried by external variables, enabling the sequence to be attended according to more specific external factors, such as attending over a word sequence of an utterance based on a dialogue context:

\[
H = \left[ \text{LSTM}(X); \hat{\text{LSTM}}(X) \right] \in \mathbb{R}^{n \times d} \\
a = \text{softmax}(W[H;Q]^T + b) \in \mathbb{R}^n \\
h = H^T a \in \mathbb{R}^d
\]

Here, \( Q \in \mathbb{R}^{n \times d_q} \) is a collection of query vectors of dimensionality \( d_q \) that can query each element in the sequence; \( W \in \mathbb{R}^{d+q \times d} \) and \( b \in \mathbb{R}^{d+q} \) are learnable parameters for inferring the attention weights \( a \) with given hidden outputs \( H \) and query vectors \( Q \). We encapsulate above operations using the notation ENC, which takes a sequence of input vectors and query vectors and returns a fixed sized representation and is defined as follows.

\[
\text{ENC} : \mathbb{R}^{n \times d} \times \mathbb{R}^{n \times d_q} \rightarrow \mathbb{R}^d
\]

The architecture of ENC is utilized repetitively for encoding various features in dialogues that have dynamic lengths (sequences of words, sequences of dialogue acts, sequences of turns, etc.).

3.3.2. Main Architecture

Our model architecture consists of five sequence encoders (dialogue act encoder ENC\(^{(a)}\), goal encoder ENC\(^{(g)}\), dialogue state encoder ENC\(^{(s)}\), utterance encoder ENC\(^{(u)}\), and conversation encoder ENC\(^{(c)}\)), a context encoder ENC\(^{(ctx)}\), and four decoders for each dialogue feature (DEC\(^{(r)}\), DEC\(^{(g)}\), DEC\(^{(s)}\), and DEC\(^{(u)}\)), all parameterized separately. In addition to the conversational latent variables \( z^{(c)} \) and utterance latent variables \( z^{(u)} \) introduced in VHCR, our model also consists of latent variables for the speaker \( z^{(r)} \), the goal \( z^{(g)} \), and the dialogue state \( z^{(s)} \) at each dialogue turn.

Initially, the global latent variable \( z^{(c)} \) is generated from a standard Gaussian prior: \( p(z^{(c)}) = \mathcal{N}(0, I) \). At dialogue turn step \( t \), VHDA uses the context encoder ENC\(^{(ctx)}\) to encode the context information \( h_t \) using (1) the context information \( h \) encoded from the previous turn step \( t - 1 \) and (2) the information about all dialogue features (the speaker \( r \), the goal \( g \), the dialogue state \( s \), and the utterance \( u \)) at the current turn step:

\[
v_{t-1} = \left[ h_{t-1}^{(r)}; h_{t-1}^{(g)}; h_{t-1}^{(s)}; h_{t-1}^{(u)} \right] \\
h_t = \text{ENC}^{(ctx)}(h_{t-1}, v_{t-1})
\]

where \( v_t \) is the concatenation of all feature representations at the turn step \( t \). Note that context encoder ENC\(^{(ctx)}\) has a different structure than other sequence encoders in that it employs uni-directional sequence encoding and takes inputs from the previous turn step and returns hidden outputs one step at a time. Here, the hidden representations of the dialogue features \( h^{(r)} \), \( h^{(g)} \), \( h^{(s)} \), and \( h^{(u)} \) are encoded by the sequence encoders from the respective dialogue features, which we describe in subsequent subsections.

For the following step, VHDA successively generates latent variables using a series of inference networks for each turn step \( t \):

\[
p_\theta \left( z_t^{(r)} \mid v_{<t}, z^{(c)} \right) = \mathcal{N}\left( \mu_t^{(r)}, \sigma_t^{(r)} \right) \\
\vdots \\
p_\theta \left( z_t^{(u)} \mid v_{<t}, z^{(c)}, z_t^{(r)}, z_t^{(g)}, z_t^{(s)} \right) = \mathcal{N}\left( \mu_t^{(u)}, \sigma_t^{(u)} \right)
\]
A separate set of parameters, denoted by $\phi$, are implemented using multi-layer feedforward networks $f$ that predict the parameters of gaussian distribution families $f$ given all previous conditions (softplus omitted for brevity):

$$
\begin{align*}
\mu_t^{(r)}, \sigma_t^{(r)} &= f^{(r)}(h_t, z^{(c)}) \\
&\vdots \\
\mu_t^{(u)}, \sigma_t^{(u)} &= f^{(u)}(h_t, z^{(c)}, z_t^{(r)}; z_t^{(s)}).
\end{align*}
$$

We use the reparameterization trick (Kingma & Welling, 2013) to allow the samples of latent variables to be computed with standard backpropagation during training and optimization.

### 3.3.3. Approximate Posterior Networks

A separate set of parameters, denoted by $\phi$, approximates posterior distributions of all latent variables from evidence. The global latent variables $z^{(c)}$ are estimated using the conversation encoder based on hidden representations of all dialogue features.

$$
q_\phi(z^{(c)}|v_1, \ldots, v_T) = \mathcal{N}(\mu^{(c)}, \sigma^{(c)})
$$

The rest of the turn-level latent variables are estimated similarly conditioned on conversation latent variables $z^{(c)}$ and turn-level hidden factors $h_t$:

$$
q_\phi(z_t^{(r)}|v_{<t}, z^{(c)}, h_t^{(r)}) = \mathcal{N}(\mu_t^{(r)}, \sigma_t^{(r)})
$$

The rest of the turn-level latent variables are estimated similarly conditioned on conversation latent variables $z^{(c)}$ and turn-level hidden factors $h_t$:

$$
q_\phi(z_t^{(u)}|v_{<t}, z^{(c)}, \ldots, h_t^{(u)}) = \mathcal{N}(\mu_t^{(u)}, \sigma_t^{(u)})
$$

### 3.3.4. Common Encoder Networks

Apart from the recognition networks, common encoders are responsible for encoding dialogue features from their respective feature spaces to hidden representations that can be understood by the recognition and decoder networks. Hence the parameters are shared across the recognition and decoder networks. Specifically, each dialogue feature of $h^{(r)}$, $h^{(g)}$, $h^{(s)}$, and $h^{(u)}$ is encoded by the respective sequence encoder. For speaker information $h^{(r)}$, the encoding mechanism is achieved by a speaker embedding matrix $W^{(r)} \in \mathbb{R}^{n(r) \times d(r)}$, where $n(r)$ is the number of participants and $d(r)$ is the dimensionality of the speaker embedding. Assuming that the speaker information is given as a one-hot encoded vector, the speaker embedding is obtained by $W^{(r)} r$.

For goal representation $h^{(g)}$ and dialogue state (or act) representation $h^{(s)}$, the encoding takes place over two-steps. In the first step, given a set of dialogue state specifications $g = \{a_1, \ldots, a_{|g|}\}$ or $s = \{a_1, \ldots, a_{|s|}\}$, a common dialogue act encoder $ENC(a)$ encodes each dialogue act specification into a fixed size hidden representation $h^{(a)}$. In the second step, the hidden representations of dialogue act specifications $h^{(a)}$ are encoded by the respective encoder into a fixed size representation for the goal or the dialogue state:

$$
\begin{align*}
&h^{(g)} = ENC(g) \left( \left[ ENC(a) \left( a_1^{(g)} \right); \ldots; ENC(a) \left( a_{|g|}^{(g)} \right) \right] \right) \\
&h^{(s)} = ENC(s) \left( \left[ ENC(a) \left( a_1^{(s)} \right); \ldots; ENC(a) \left( a_{|s|}^{(s)} \right) \right] \right)
\end{align*}
$$

The encoding of a dialogue act specification is realized by treating it as a sequence of tokens delimited by appropriate special words. Additionally, we use GloVe embeddings to obtain hints about the general token semantics. The utterances are encoded in a similar fashion, in which we apply the utterance encoder $ENC(u)$ over arrays of word embeddings:

$$
\begin{align*}
&h^{(u)} = ENC(u) \left( [w_1; \ldots; w_{|u|}] \right)
\end{align*}
$$

### 3.3.5. Realization Networks

During the decoding step, the series of decoder networks successively decodes the latent variables into their respective feature spaces, with each successive decoding taking all latent variables up to the previous hierarchical level as inputs. Each decoder network is also conditioned on the global latent variable $z^{(c)}$ and the turn-level hidden variable $h_t$.

$$
\begin{align*}
&p_\theta \left( r_t | v_{<t}, z^{(c)}, z_t^{(r)} \right) = DEC(r) \left( h_t, z^{(c)}, z_t^{(r)} \right) \\
&\vdots \\
&p_\theta \left( u_t | v_{<t}, z^{(c)}, \ldots, z_t^{(u)} \right) = DEC(u) \left( h_t, z^{(c)}, \ldots, z_t^{(u)} \right)
\end{align*}
$$

### 3.3.6. Hierarchically-scaled Dropout Scheme

The common techniques for alleviating the inference collapse problem include (1) annealing the KL-divergence term weight during the initial stage of training and (2) employing word dropouts on the decoder inputs (Bowman et al., 2016). In a recent work, utterance-level dropouts were shown to be more effective than word
Comparison of data augmentation results between VHDA with and without explicit goal tracking.

Table 1. Results of data augmentation using VHDA for dialogue state tracking on various datasets and state trackers. Note that we report results of data augmentation using VHDA for dialogue state tracking on various datasets and state trackers. Note that we report information on the neural belief tracker (Henderson et al., 2017) and DSTC2 (Zhong et al., 2018), which are competitive dialogue state trackers based on the neural belief tracker (Mrkšić et al., 2017) paradigm. The baseline state trackers are modified to perform more stably over random seeds (GLAD+ and GCE+). Specifically, we enrich the word embeddings with subword information (Bojanowski et al., 2017) and apply dropout on word embeddings (dropout rate of 0.2). Additionally, we conduct experiments on a simpler architecture that shares a similar architecture with GCE but does not employ self-attention for each sequence encoder (RNN).

4.1.1. DATASETS

We conduct experiments on four state tracking corpora: WoZ2.0 (Wen et al., 2017), DSTC2 (Henderson et al., 2014a), MultiWoZ (Budzianowski et al., 2018), and DialEdit (Manuvinakurike et al., 2018). These corpora are chosen such that experiments cover various dialogue domains (restaurant booking, hotel reservation, and image editing). Note that, because MultiWoZ dataset is a multi-domain corpora, we extract single-domain dialogue samples for two largest domains (hotel [MultiWoZ-H] and restaurant [MultiWoZ-R]).

4.1.2. DIALOGUE STATE TRACKERS

For baseline dialogue state trackers, we use GLAD (Zhong et al., 2018) and GCE (Nouri & Hosseini-Asl, 2018), which are competitive dialogue state trackers based on the neural belief tracker (Mrkšić et al., 2017) paradigm. The baseline state trackers are modified to perform more stably over random seeds (GLAD+ and GCE+). Specifically, we enrich the word embeddings with subword information (Bojanowski et al., 2017) and apply dropout on word embeddings (dropout rate of 0.2). Additionally, we conduct experiments on a simpler architecture that shares a similar architecture with GCE but does not employ self-attention for each sequence encoder (RNN).

4.1.3. EVALUATION MEASURES

Joint goal accuracy, or Goal for short, measures the ratio of the number of turns whose goals have been correctly iden-
We conduct experiments to explore the effect of augmenting state tracking datasets using synthetic samples generated from VHDA and report the results on various datasets and trackers as shown in Table 1. Results show that generative data augmentation for dialogue state tracking is a viable strategy for improving existing DST models without modifying the trackers and only augmenting the dataset using synthetic samples from our model. Regardless of the tracker model and the dataset, improvements were observed at a statistically significant level. Note that, due to the high-variance nature of the joint-goal metric, some of the improvements with relatively larger margins (e.g., GCE on MultiWoZ restaurant dataset) had weaker statistical significance.

4.2. Effect of Joint Goal Tracking

Since user goals can be inferred from turn-level informative dialogue acts, it may seem redundant to incorporate goal modeling into our model. To verify its effectiveness, we train a variant of VHDA, where the goal tracking latent variables are removed from the generator. The results (Table 2) show that VHDA without explicit goal tracking suffers in joint goal accuracy but performs better in turn request accuracy at certain times. We conjecture that explicit goal tracking helps the model to reinforce the long-term goals of the dialogue participants; however, the model does so in the minor expense of short-term state tracking, which exhibits as decreases in request tracking performance.

4.2.3. Effect of Dropout Schemes

To demonstrate that the effectiveness of hierarchically-scaled dropout scheme, we compare the data augmentation results with other policies. Along with the data augmentation results, we also report the KL-divergence term of the global latent variables \(z^{(c)}\) on the test set (Table 3). The experimental results support our hypothesis that the regularization measures drastically reduces the risk of inference collapse, maintaining the magnitude of the KL-divergence term at higher-levels, while achieving better data augmentation results.

4.3. Language Evaluation

To gain deeper insight into the generation capability of VHDA, we compare the language quality and diversity of generated dialogues with those generated by VHCR. Following the evaluation protocol employed by previous work (Bak & Oh, 2019; Wen et al., 2017), we use ROUGE-L f1-score (Lin, 2004) to evaluate the linguistic quality and utilize utterance-level unigram cross-entropy (Serban et al., 2017) (with respect to the training corpus distribution) to evaluate diversity. Results (Table 4) show that our model generates utterances of higher quality and comparable or higher diversity compared to the previous state-of-the-art model on conversation modeling. This supports our hypothesis that joint learning of dialogue structures improves the generation quality of utterances, thereby increasing the chance of generating novel samples that strengthen the resulting trackers.

4.4. \(z^{(c)}\)-interpolation

We conduct \(z^{(c)}\)-interpolation experiments to demonstrate that our model is able to generalize the dataset space and learn to decode plausible samples from unseen latent space. The generated sample (Table 5) show that our model is able to maintain coherence while generalizing key dialogue features, such as the user goal and the dialogue length, to generate novel dialogues. Specifically, since the user’s goal in the first anchor point is to look for a Mediterranean restaurant and the second anchor point is Indian restaurant (both not shown), the midpoint between the two latent variables results in a novel dialogue with no specific preference for

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1 We posit that, regarding the high-variance nature, conducting larger number of trials should improve the statistical confidence; however, our experiments were constrained by limited computational resources relative to the large number of combinations.
Table 5. A sample generated from the midpoint between two latent variables in the $\mathbf{z}^{(c)}$ space encoded from two anchor data points.

| Speaker | Utterance | Goal | Turn Act |
|---------|-----------|------|----------|
| 1 User  | i want to find a cheap restaurant in the north part of town. | inform(area=north) | inform(price range=cheap) |
|         | | inform(area=north) | inform(price range=cheap) |
| 2 Wizard | what food type are you looking for? | request(slot=food) |
| 3 User  | any type of restaurant will be fine. | inform(area=north) | inform(food=dontcare) |
|         | | inform(food=dontcare) | inform(price range=cheap) |
| 4 Wizard | the <place> is a cheap indian restaurant in the north. would you like more information? | inform(area=north) | inform(food=dontcare) |
|         | | inform(food=dontcare) | inform(price range=cheap) |
| 5 User  | what is the number? | request(slot=phone) | inform(area=north) |
|         | | inform(area=north) | inform(food=dontcare) |
|         | | inform(food=dontcare) | inform(price range=cheap) |
| 6 Wizard | <place>’s phone number is <number>. is there anything else i can help you with? | inform(area=north) | inform(food=dontcare) |
|         | | inform(food=dontcare) | inform(price range=cheap) |
| 7 User  | no thank you. goodbye. | inform(area=north) | inform(food=dontcare) |
|         | | inform(food=dontcare) | inform(price range=cheap) |

food type ($\text{food}=\text{dontcare}$).

5. Conclusion

We proposed a novel hierarchical and recurrent VAE-based architecture to accurately capture the semantics of fully annotated goal-oriented dialogue corpora. To reduce the risk of inference collapse while maximizing the generation quality, we devised and employed a simple but effective technique to scale the decoder dropout rates according to the depth in the hierarchy. Through extensive experiments, we showed that our proposed model VHDA was able to achieve significant improvements for various competitive dialogue state trackers and corpora. With recent trends in goal-oriented dialogue systems gravitating towards end-to-end approaches (Lei et al., 2018), we wish to explore a self-supervised variational generative model with knowledge-base management. We would also like to explore the benefits of dialogue synthesis beyond data augmentation and towards user simulation and the assistance of corpora construction.

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