Event Representation with Sequential, Semi-Supervised Discrete Variables

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Abstract
Within the context of event modeling and understanding, we propose a new method for neural sequence modeling that takes partially-observed sequences of discrete, external knowledge into account. We construct a sequential, neural variational autoencoder that uses a carefully defined encoder, and Gumbel-Softmax reparameterization, to allow for successful backpropagation during training. We show that our approach outperforms multiple baselines and the state-of-the-art in narrative script induction on multiple event modeling tasks. We demonstrate that our approach converges more quickly.

1 Introduction
For the many wide and varied tasks—from semantic hashing (Zhang and Zhu, 2019) to labeled sequence transduction (Zhou and Neubig, 2017)—that can make use of reliable, external, discrete, knowledge, actually utilizing that knowledge can lead to sizeable task improvements. When the external knowledge is neither sufficiently reliable nor present, a natural question arises: how can our models utilize the knowledge that is present?

Generative probabilistic models provide a framework for doing so: external knowledge is a random variable, which can be observed or latent, and the data/observations are generated (explained) from it. Knowledge that is discrete, sequential, or both—such as relevant for many NLP tasks—complicates the development of neural generative models.

In this paper, we provide a successful approach for utilizing partially-observed, discrete, sequential external knowledge within a neural generative model. We specifically examine event sequence modeling augmented by semantic frames. Frames (Minsky, 1974, i.a.) are a semantic representation designed to capture the common and general knowledge we have about events, situations, and things. They have been effective in providing crucial information for modeling events and understanding the meaning (Peng and Roth, 2016; Ferraro et al., 2017; Padia et al., 2018; Zhang et al., 2020); our work shows how frame knowledge can be further utilized. Though we focus on frames, this work is equally applicable to other types of external, discrete, sequential knowledge.

Consider the following three events, preceded by their corresponding frames, in brackets:

\[
\begin{align*}
\text{[Event]} & \quad \text{crash occurred at station.} \\
\text{[Impact]} & \quad \text{train collided with train.} \\
\text{[Killing]} & \quad \text{killed passengers and injured.}
\end{align*}
\]

We can see that tokens like crash, station and killed from the first and third events play a role in predicting [Impact] in the second event. On the other hand, the [Event] and [Impact] frames can help predict the word killed in the third event. To successfully predict the unobserved frames, beyond capturing the frame to frame connections, the model should take to account all the information from the observed data as well, see Fig. 1. Overall, we see that the frames help summarize the events and can be used as guidance for the latent variables to represent the data.

A number of efforts have leveraged frame in-
duction for event modeling (Cheung et al., 2013; Chambers, 2013; Ferraro and Van Durme, 2016; Kallmeyer et al., 2018; Ribeiro et al., 2019). These methods are restricted to explicit connections between events and their corresponding frames; they do not offer a way to capture all the possible connections between the observed events and frames. Weber et al. (2018b) proposed a hierarchical attention structure (HAQAE) that corrects for this. The HAQAE structure is meant to capture sequential event structure via tree-based latent variables; vector quantization (Van Den Oord et al., 2017) allows an unsupervised learning algorithm.

In this work, we study the effect of tying discrete, sequential latent variables to partially-observable, noisy (imperfect) semantic frames. Like HAQAE, our semi-supervised model is a bidirectional autoencoder, with a structured collection of latent variables separating the encoder and decoder, and attention mechanisms on both the encoder and decoder. Rather than applying vector quantization, we adopt a Gumbel-Softmax (Jang et al., 2017) ancestral sampling method to easily switch between the observed frames and latent ones; this both easily permits semi-supervised learning, improved performance across multiple event modeling tasks, and faster training convergence. Our contributions are:

- We demonstrate how to learn a VAE that contains sequential, discrete, and partially-observed latent variables.
- We show that adding partially-observed, external, semantic frame knowledge to our structured, neural generative model leads to improvements over the current state-of-the-art on recent core event modeling tasks. In addition to outperforming the state-of-the-art, our approach leads to faster training convergence.
- We show that our semi-supervised model, though developed as a generative model with our proposed method, can outperform a discriminatively trained model with full supervision.

2 Related Work

Sequential event modeling, as in this paper, can be viewed as a type of script or schema induction (Schank and Abelson, 1977). Mooney and DeJong (1985) provided an early analysis of explanatory schema generating system to process narratives, and Pichotta and Mooney (2016) applied an LSTM-based model to predict the sequential event arguments. Modi (2016) proposed a feed-forward neural network model for event sequences that was able to incrementally predict randomly missing events. Weber et al. (2018a) proposed a tensor-based composition method that maximizes the similarity between co-occurring events; Ding et al. (2019) used a similar strategy to construct a low-rank tensor embedding for commonsense knowledge, e.g., the intentions in an event.

Previous work has also examined how to incorporate or learn various forms of semantic representations while modeling events. Cheung et al. (2013) introduced a non-neural, HMM-based model that explained event sequences via latent frames; they encoded inertia in their model to encode inertia to improve consistency and coherence in the frame sequence. Materna (2012), Chambers (2013) and Bamman et al. (2013) provided structured graphical models to learn event models over syntactic dependencies; Ferraro and Van Durme (2016) unified and generalized these approaches to capture varying levels of semantic forms and representation. Kallmeyer et al. (2018) proposed a Bayesian network based on latent variable probabilistic context free grammars that assumes there is a hierarchical dependency between tokens, roles, syntactic dependencies and frames. Ribeiro et al. (2019) provided an analysis of clustering predicates and their arguments to infer semantic frames in unsupervised settings.

With the advent of variational autoencoders and attention networks (Kingma and Welling, 2013; Bahdanau et al., 2014), a recent line of research was motivated in this direction. Works such as Bisk et al. (2019) suggested using recurrent neural networks with attention to capture the abstract and concrete script representations. Weber et al. (2018b) came up with a recurrent autoencoder model (HAQAE), which used vector-quantization to learn hierarchical dependencies among discrete latent variables and an observed event sequence. Kiyomaru et al. (2019) suggested generating next events using a conditional VAE-based seq2seq model.

In another thread of research, Chen et al. (2018) introduced three different methods to incorporate labels in conjunction with latent variables, but unlike Weber et al. (2018b), their model’s latent variables are conditionally independent and do not form a hierarchy. Sønderby et al. (2016) pro-
posed a sequential latent structure with Gaussian latent variables. Liévin et al. (2019), similar to our model structure, provided an analysis of hierarchical relaxed categorical sampling but for the unsupervised settings. Kingma et al. (2014) is one of the earliest frameworks that generalized VAEs to the semi-supervised setup, but they assume that the dataset can be split into observed and unobserved samples and they have defined separate loss functions for each case; in our work, we allow portions of a sequence to be latent. The previous work of (Teng et al., 2020) characterized the semi-supervised VAEs from the sparsity perspective. (See Mousavi et al. (2019) for an in-depth study of well-received sparse models).

Of the approaches that have been developed for handling discrete latent variables in a neural model (Vahdat et al., 2018a,b; Lorberbom et al., 2019, i.a.), we use the Gumbel-Softmax reparameterization (Jang et al., 2017; Maddison et al., 2019). For handling discrete latent variables in a neural model (Vahdat et al., 2018a,b; Lorberbom et al., 2019, i.a.), we use the Gumbel-Softmax reparameterization (Jang et al., 2017; Maddison et al., 2019). This approximates a discrete draw with logits \( \pi \) as \( \text{softmax}(\frac{\pi + \tau}{\tau}) \), where \( g \) is a vector of Gumbel(0,1) draws and \( \tau \) is an annealing temperature that allows targeted behavior; its ease, customizability, and efficacy are big advantages.

3 Method

In this section, we formalize our problem and introduce the necessary notations. Then, we proceed to explain in detail the model structure.

We begin by defining each document as a sequence of \( M \) events, where each event represents a 4-tuple, including the verb, subject, object and modifier. Each document is a sequence of \( T \) words \( w = \{w_t\}_{t=1}^{T} \), where \( T = 4M \) and each \( w_t \) is from a vocabulary of size \( V \).

Let \( F \) be the total number of unique frames. We define the latent frames for all the events as \( f = \{f_m\}_{m=1}^{M} \), with \( f_m \in \{0, 1\}^F \) in one-hot encoded representation (we approximate this with a Gumbel-Softmax representation for learning and inference).

The joint probability for our model factorizes as

\[
p(w, f) = \prod_{t=1}^{T} p(w_t|f, w_{<t}) \prod_{m=1}^{M} p(f_m|f_{m-1}).
\]

(1)

Inference for this model requires marginalization over the latent variables, in which for the cases that \( F \gg 1 \), maximizing the likelihood is intractable. We follow amortized variational inference (Kingma and Welling, 2013) as an alternative approach and use ancestral sampling technique to evaluate it. We define the variational distribution as

\[
q(f|w; I) = \prod_{m=1}^{M} q(f_m|f_{m-1}, I_m, w),
\]

where \( I = \{I_m\}_{m=1}^{M} \) denotes our external information, in which for the observed frame values, \( I_q \) is one-hot encoded and otherwise we set \( I_m = \mathbf{0} \). (For simplicity we omit the \( I_m \) notation when possible.) We optimize the evidence lower bound (ELBO):

\[
\mathcal{L} = \mathbb{E}_{q(f|w)} \log p(w|f) + \mathbb{E}_{q(f|w)} \log \frac{p(f)}{q(f|w)}.
\]

(2)

For now, we restrict our attention to the first term, which is the reconstruction part and calls for an autoencoder structure (Fig. 2). We describe these in the next sections, along with our semi-supervised training procedure (§3.4).

3.1 Encoder

The reconstruction term relies on the frame samples given by the encoder. Alg. 1 gives a detailed description of the encoder’s aligning and sampling method, which is specifically designed to take the observed frames into account in a way that does not affect back-propagation and learning.
Algorithm 1 Encoder: The following algorithm shows how we compute the next frame $f_m$ given the previous frame $f_{m-1}$. We compute and return a hidden frame representation $\gamma_m$, and $f_m$ via a continuous Gumbel-Softmax reparametrization.

**Input:** previous frame $(f_{m-1} = f')$, $f' \in \mathbb{R}^F$

- current frame observation $(I_m)$,
- frames embeddings $E^F \in \mathbb{R}^{F \times d_e}$,
- encoder RNN hidden states $H \in \mathbb{R}^{T \times d_h}$.

**Parameters:** $U_{in} \in \mathbb{R}^{d_h \times d_e}$, $U_{out} \in \mathbb{R}^{T \times d_e}$

**Output:** $f_m$, $\gamma_m$

1. $e'_m = f'^T E^F$  
2. $\alpha \leftarrow \text{Softmax}(HU_{in}e'_m) \triangleright \text{Attn. Scores}$
3. $c_m \leftarrow \alpha^T H \triangleright \text{Context Vector}$
4. $\gamma_m \leftarrow U_{out}(\text{tanh}(U_{in}e'_m) + \text{tanh}(c_m))$
5. $\gamma'_m \leftarrow \gamma_m + \|\gamma_m\|_2 I_m \triangleright \text{Observation}$
6. $q(f_m|f_{m-1}) \leftarrow \text{GumbelSoftmax}(\gamma_m)$
7. $\gamma_m \leftarrow \text{Softmax}(\gamma_m)$
8. $f_m \sim q(f_m|f_{m-1}) \triangleright f_m \in \mathbb{R}^F$

As we mentioned before, the HAQAE model applies vector quantization, in which the encoder’s discrete outputs are selected based on a nearest neighbor matching using an embedding matrix. While effective for completely latent settings, vector quantization makes it difficult to incorporate observed values for the latent variables since forced nearest neighbor computation and reconstruction loss used complicate backpropagation. A simple way to bypass this problem is drawing the $f_m \in \mathbb{R}^F$ vectors from a Gumbel-Softmax distribution (Jang et al., 2017). Since each drawn $f_m$ is a simplex vector, a learnable frame embedding matrix $E^F \in \mathbb{R}^{F \times d_e}$ provides a richer representation for frames. Each row $e_m$ of $E^F$ indicates the embedding for a frame type; $d_e$ is the embedding dimension. We obtain the frame representation in embedding space by calculating $e_m = f_m^T E^F$.

Our encoder (Alg. 1) proceeds iteratively over each of the $M$ events as follows: given the previous frame $f_{m-1}$, and the encoder RNN hidden states $H \in \mathbb{R}^{T \times d_h}$, the model calculates the similarity between $e_{f_{m-1}}$ and $H$ rows (line 2). After deriving the attention scores, the weighted average of hidden states namely the context vector summarizes the role of tokens in predicting the frame $f_m$ (line 3).

Given the context vector and previous frame embedding, we begin to construct the logits for Gumbel-Softmax without considering the observed frame, $I_m$ (line 4). Since our model defines a chain of variables—some of which may be observed and some of which may be latent—care must be taken to preserve the gradient flow within the network. We note that an initial strategy of solely using $I_m$ instead of $f_m$ (whenever $I_m$ is observed) is not sufficient to ensure gradient flow. To correct for this, we incorporate the observed information given by $I_m$ by adding this information to the output of encoder logits before drawing $f_m$ samples (line 5). This remedy motivates the encoder to softly increase the importance of the observed frames during the training. Finally, a sample for $f_m$ is drawn from the Gumbel-Softmax distribution (line 8).

As a result of our encoding, we can compute $T^F$, a contextual token-to-frame soft clustering matrix as $T^F \text{ = tanh}(H)U_{out}^T$ for each document; this clustering is useful for analyzing and interpreting the model and its predictions (c.f. Table 3).

3.2 Decoder

Our decoder (Alg. 2) must be able to reconstruct the input event token sequence from the inferred frame embeddings. We compute these embeddings as $E^M = fE^F \in \mathbb{R}^{M \times d_e}$, where $f$ is computed from Alg. 1 and $E^F$ are learnable frame embeddings. At each time step $t$, we align the decoder RNN hidden state $h_t$ with $E^M$ rows (line 1). After calculating the scores for each frame embedding, we obtain the context vector (line 3), which will be used in conjunction with the hidden states to generate $w_t$ token (line 6). As with the encoder, we can compute a frame-to-word soft-clustering $M^V = \text{tanh}(E^M)W_{out}^T$ contextualized in part based on the inferred frames; this clustering is useful for analyzing and interpreting the model and its predictions (c.f. §3.3, Table 3).

3.3 Attention Description

In this section, we explain the rationale behind deriving $T^F$ from Alg. 1 and $M^V$ from Alg. 2. For simplicity we focus on the decoder, though an analogous discussion applies for the encoder.

In contrast with a bi-linear attention mechanism (Luong et al., 2015) that first concatenates $W_{in}h_t$ and $e^M$, and then proceeds to calculate the output, we have used the addition instead of concatenation with the goal of separating the role of each term. Observe that this separation leads to interpretable soft clusters in describing the connection both within and between the frames and tokens, c.f. Table 3. Here we will provide an intuitive explanation behind this modification. We refer to the
Algorithm 2 Decoder: To (re)generate each token in the event sequence, we compute an attention $\alpha^M$ over the sequence of frame random variables $f$ (from Alg. 1). This attention weights each frame’s contribution to generating the current word.

**Input:** $E^M \in \mathbb{R}^{M \times d_e}$ (computed as $FE^F$) 
**decoder hidden state** $h_t \in \mathbb{R}^{d_h}$ 

**Parameters:** $W_{in} \in \mathbb{R}^{d_e \times d_h}$, $W_{out} \in \mathbb{R}^{V \times d_e}$ 

**Output:** $w_t$

1. $\alpha^M \leftarrow E^M W_{in} h_t$
2. $\alpha^M \leftarrow \text{Softmax}(\alpha^M)$ \hspace{2em} \text{Attn. Scores}
3. $c_t \leftarrow E^M \alpha^M$ \hspace{2em} \text{Context Vector}
4. $g \leftarrow W_{out} (\tanh(W_{in} h_t) + \tanh(c_t))$
5. $p(w_t|f; h_t) \propto \exp(g)$
6. $w_t \sim p(w_t|f; h_t)$

During the decoding process of a recurrent latent topic model called Topic-RNN (Dieng et al., 2016), in Topic-RNN, individual tokens are autoregressively drawn from the contribution of $h_t$ and topic information: $p(w_t|h_t, \theta, \beta) \propto \exp(f(h_t) + g(\beta \theta))$, where $\theta$ is a categorical distribution over topic choice and $\beta$ is a collection of topics, which provides a soft clustering over words via distributions over the vocabulary. Finally, $f$ and $g$ are two linear functions.

In our model, the attention output function is analogous to topic-RNN strategy, where our $W_{out} (\tanh(W_{in} h_t))$ stands in for $f(h_t)$, and similarly, the following approximations hold:

$$\tanh(E^M) W_{out} \approx \beta, \quad \alpha^M \approx \theta.$$

Our qualitative analyses support the notion that these approximations let our model learn reasonable soft cluster of verbs into frame-based “topics.” However, we leave the development of any theoretical guarantees for future work.

### 3.4 Training Process

So far, we have described the encoder and decoder structures. We now shift our focus to analyze the different terms in ELBO.

In Eq. (2), we apply a chain of ancestral sampling to approximate the reconstruction term:

$$L_w = \mathbb{E}_{q(f|w)} \log p(f) - \mathbb{E}_{q(f|w)} \log q(f|w). \tag{4}$$

The uniform assumption for $p(f)$ allows us to neglect the first term. We utilize the probability vectors $\gamma_m$ from the encoder to approximate the second term (see Alg. 1, line 7)

$$L_q = -\mathbb{E}_{q(f|w)} \log q(f|w) \approx -\sum_m \gamma_m^+ \log \gamma_m.$$

We can see that $L_q$ encourages the entropy of the variational distribution to be high which makes it hard for the encoder to distinguish the true frames from the wrong ones. We follow the KL annealing method (Bowman et al., 2015) and add a fixed and constant regularization coefficient $\alpha_q$ to decrease the effect of this term. We additionally draw further inspiration from Kingma et al. (2014); Chen et al. (2018); Ye et al. (2020) and motivate the variational distribution to classify the true frames. We introduce the classification loss as $L_c = \sum_{I_m > 0} \bar{I}_m \log \gamma_m$. Finally, our objective function is

$$L = L_w + \alpha_r L_r + \alpha_c L_c. \tag{5}$$

### 4 Experimental Results

We test the performance of our model on a portion of the Concretely Annotated Wikipedia dataset (Ferraro et al., 2014), which is a dump of English Wikipedia that has been annotated with the outputs of more than a dozen NLP analytics; we use this as it has readily-available FrameNet annotations provided via SemaFor (Das et al., 2014). Our training data has 457k documents, our validation set has 16k documents, and our test set has 21k documents. More than 99% of the frames are concentrated in the first 500 most common frames, so we set $F = 500$. Nearly 15% of the events
did not have any frame, many of which were due to auxiliary/modal verb structures; as a result, we did not include them. For all the experiments, the vocabulary size \((V)\) is set as \(40k\) and the number of events \((M)\) is 5; this is to maintain comparability with HAQAE. For the documents that had more than 5 events, we extracted the first 5 events that had frames. For both the validation and test datasets, we have set \(I_m = 0\) for all the events; frames are only observed during training.

Documents are fed to the model as a sequence of events with verb, subj, object and modifier elements. The events are separated with a special separating \(<TUP>\) token and the missing elements are represented with a special \(\text{NONE}\) token. In order to facilitate semi-supervised training and examine the impact of frame knowledge, we introduce a user-set value \(\epsilon\); in each document, for event \(m\), the true value of the frame is preserved in \(I_m\) with probability \(\epsilon\), while with probability \(1 - \epsilon\) we set \(I_m = 0\). This \(\epsilon\) is set and fixed prior to each experiment. For all the experiments we set \(\alpha_r\) and \(\alpha_c\) as 0.1.

**Setup** We optimized our parameters using the Adam optimizer with initial learning rate \(10^{-3}\) and early stopping (lack of validation performance improvement for 10 iterations). The encoder takes as input a sequence of events by their pretrained Glove 300 embeddings. We utilized gradient clipping at 5.0 to prevent exploding gradients. We have not used drop out or batch norm on any layer. We have used two layers of Bi-directional GRU cells with a hidden dimension of 512 for both the encoder and decoder modules. We implemented the model with Pytorch.\(^1\) Models were trained using a single TITAN RTX GPU, though we note that neither our models nor baselines required the full memory of the GPU (e.g., our models used roughly 6GB of GPU memory for a batch of 100 documents).

**Baselines** In our experiments, we compare our proposed methods against the following methods:

- **RNNLM**: We report the performance of a sequence to sequence language model with the same structure used in our own model. A Bi-directional GRU cell with two layers and hidden dimension of 512 and gradient clipping at 5. Similar to our own model we have used Glove 300 embeddings to represent words.

- **RNNLM+ROLE** (Pichotta and Mooney, 2016): This model has the same structure as RNNLM, but the role for each token (verb, subject, object, modifier) as a learnable embedding vector is concentrated to the token embeddings and then it is fed to the model. The embedding dimension for roles is 300.

- **HAQAE** (Weber et al., 2018b) This work is the most similar to ours. The core differences are that our model supports partially-observed frame sequences (i.e., semi-supervised learning); the linear-chain connection among the event variables in our model is simpler than the tree-based and hierarchical structure in HAQAE; our attention mechanism is based on addition rather than concatenation; and our handling of latent discrete variables is based on the Gumbel-Softmax reparametrization, rather than vector quantization. All the other parameters are the same.

| Model          | \(\epsilon\) | Valid PPL | Test PPL |
|----------------|-------------|-----------|----------|
| RNNLM          | -           | 62.79     | 61.67    |
| RNNLM+ROLE     | -           | 66.36     | 64.46    |
| HAQAE          | -           | 24.92     | 21.68    |
| Ours \(^\star\) | 0.0         | 40.34     | 36.76    |
| Ours           | 0.2         | 38.03     | 33.34    |
| Ours           | 0.4         | 37.90     | 33.45    |
| Ours           | 0.5         | 36.06     | 31.47    |
| Ours           | 0.7         | 23.09     | 20.38    |
| Ours           | 0.8         | 22.83     | 19.97    |
| Ours           | 0.9         | 22.17     | 19.45    |

Table 1: Validation and test per-word perplexities (lower is better). Recall that \(\epsilon\) is the (average) percent of frames observed during training though during evaluation no frames are observed. We always outperform RNNLM and RNNLM+ROLE, and outperform HAQAE when automatically extracted frames are sufficiently available during training \((\epsilon \in \{0.7, 0.8, 0.9\})\).

\(^1\)Our code will be available upon publication.
HAQAE for $\epsilon \in \{0.7, 0.8, 0.9\}$. This suggests that while the tree-based latent structure can be helpful when external, semantic knowledge is not sufficiently available during training, a simpler linear structure can be successfully guided by that knowledge when it is available. Finally, recall that the external frame annotations we use are automatically provided: there is no human supervision or curation of the actual frames that were used during training. This suggests that our model does not require perfectly, curated annotations. These observations support the hypothesis that frame observations, in conjunction with latent variables, provide a benefit to event modeling.

**Inverse Narrative Cloze** This task has been proposed by Weber et al. (2018b) to evaluate the ability of models to classify the legitimate sequence of events over detractor sequences. For this task, we have created two Wikipedia-based datasets from our validation and test datasets, each with 2000 samples. For each of the samples, we have six options in which the seeds (first events) are the same and only one of the options represents the actual sequence of events. All the options have a fixed size of 6 events and the one that has the lowest perplexity is selected as the correct one. We also consider two NYT inverse narrative cloze datasets that are publicly available. All the models are trained on the Wikipedia dataset and then tested on either Wiki or NYT as appropriate.

Table 2 presents the results for this task. Our method tends to achieve a superior classification score over all the baselines, even for small $\epsilon$. Our model also gives performance improvement on the NYT validation and test datasets. We observe that the inverse narrative cloze scores for the NYT datasets is almost independent from the $\epsilon$. Since the models are trained on the Wikipedia dataset, the reason for the flat results on NYT, can be summarized as the different structure of the datasets. Note that while our model’s perplexity improved monotonically as $\epsilon$ increased, we do not see monotonic changes, with respect to $\epsilon$, for this task. By examining computed quantities from our model, we observed both that a high $\epsilon$ resulted in very low entropy attention and that frames very often attended to the verb of the event—it learned this association despite never being explicitly directly to. While this is a benefit to localized next word prediction (i.e., perplexity), it is detrimental to inverse narrative cloze. On the other hand, lower $\epsilon$ resulted in slightly higher attention entropy, suggesting that less peaky attention allows the model to capture more of the entire event sequence and improve global coherence.

**Inferred frames and tokens** To illustrate the effectiveness of our proposed attention mechanism, in Table 3 we have reported the most likely frames given tokens from the encoder (top), and tokens given frames matrices from the decoder (bottom). These results demonstrate that the frames in the encoder (top) mostly attend to the verbs and similarly the decoder utilizes expected and reasonable frames to predict the next verb. Note that we have not restricted the frames and tokens connection: the attention mechanism makes the ultimate decision for these connections.

### 4.2 Classification Metrics

Although the nature of our approach is a generative model, we want to make sure the latent nodes are capable of leveraging the frame information to finally utilize them in the decoder. We approach this by assessing the ability of one single latent node to classify the frame for an event. In doing so, we repurpose the Wikipedia language modeling dataset into a new training data set with 1,643,656 samples, validation with 57,261 samples and test with 75903 samples. We used 500 frame labels for this task. Each sample is a single event. We fixed the number of latent nodes to be one. We use RNNLM and RNNLM+ROLE as baselines, where

| Model          | $\epsilon$ | Wiki Valid | Wiki Test | NYT Valid | NYT Test |
|----------------|------------|------------|-----------|-----------|----------|
| RNNLM          | 0.0        | 20.33      | 20.44     | 17.65     | 17.45    |
| RNNLM+ROLE     | 0.2        | 20.32      | 20.18     | 17.60     | 18.20    |
| HAQAE          | 0.4        | 27.80      | 26.05     | 20.15     | 22.35    |
| Ours 0.0       | 0.7        | 37.00      | 43.00     | 28.70     | 28.25    |
| Ours 0.2       | 0.8        | 47.50      | 48.55     | 30.45     | 29.40    |
| Ours 0.4       | 0.5        | 43.75      | 43.75     | 28.75     | 30.40    |
| Ours 0.8       | 0.7        | 43.75      | 43.75     | 28.75     | 30.40    |
| Ours 0.9       | 0.8        | 37.15      | 36.75     | 29.15     | 29.40    |
| Ours 0.5       | 0.9        | 35.95      | 36.45     | 30.00     | 29.60    |

Table 2: Inverse Narrative Cloze scores (higher is better), using 500 frames and 5 clauses. All of the models are trained with Wiki and then tested on either Wiki or NYT as appropriate.
Table 3: Results for the outputs of the attention layer, the upper table shows the $T^F$ and the bottom table shows the $F^V$, when $\epsilon = 0.7$. Each row shows the top 5 words for each clustering.

| Model     | $\epsilon$ | Valid Acc | Valid Prec | Valid f1  | Test Acc | Test Prec | Test f1  |
|-----------|-------------|-----------|------------|-----------|----------|-----------|----------|
| RNNLM     | -           | 0.89      | 0.72       | 0.66      | 0.88     | 0.70      | 0.65     |
| RNNLM + ROLE | 0.90       | 0.90      | 0.78       | 0.73      | 0.89     | 0.77      | 0.71     |
| Ours      | 0.00        | 0.00      | 0.00       | 0.00      | 0.00     | 0.00      | 0.00     |
| Ours      | 0.20        | 0.66      | 0.23       | 0.22      | 0.67     | 0.23      | 0.22     |
| Ours      | 0.40        | 0.76      | 0.34       | 0.33      | 0.76     | 0.34      | 0.32     |
| Ours      | 0.50        | 0.78      | 0.42       | 0.39      | 0.78     | 0.44      | 0.38     |
| Ours      | 0.70        | 0.84      | 0.64       | 0.61      | 0.83     | 0.63      | 0.61     |
| Ours      | 0.80        | 0.86      | 0.75       | 0.74      | 0.85     | 0.75      | 0.75     |
| Ours      | 0.90        | 0.87      | 0.81       | 0.79      | 0.87     | 0.81      | 0.79     |

Table 4: Accuracy, macro precision and macro F1-score.

we added a linear classifier layer followed by the softplus function on top of the bidirectional GRU last hidden vectors and a dropout of 0.15 on the logits. We trained all the models with the aforementioned training dataset, and tuned the hyper parameters on the validation dataset.

We trained the RNNLM and RNNLM+ROLE in a purely supervised way, whereas our model mixed supervised (discriminative) and unsupervised (generative) training. The baselines observed all of the frame labels in the training set; our model only observed frame values in training with probability $\epsilon$, which it predicted from $\gamma_m$. The parameters leading to the highest accuracy were chosen to evaluate the classification on the test dataset. The results for this task are summarized in Table 4. Our model with larger $\epsilon$ tends to achieve better performance in terms of macro precision and macro F1-score.

**Training Speed** Our experiments show that our proposed approach is much faster than the existing HAQAE model. For fairness, we have used the same data-loader, batch size as 100, learning rate as $10^{-3}$ and Adam optimizer. In Fig. 3, on average each iteration takes 0.2951 seconds for HAQAE and 0.2958 seconds for our model. From Fig. 3 we can see that for sufficiently high values of $\epsilon$ our model is converging both better, in terms of negative log-likelihood (NLL), and faster—though for small $\epsilon$, our model still converges much faster. The reasons for this can be boiled down to utilizing Gumbel-Softmax rather than VQ-VAE, and also injection information in the form of frames jointly.

5 Conclusion We utilized external information in a semi-supervised, VAE setting. We demonstrated how to do semi-supervised learning when sequential, discrete latent variables are only partially observed. We used Gumbel-Softmax and a modified attention computation to learn a semi-supervised VAE that can outperform the state-of-the-art and be highly effective as an event language model (low perplexity), predictor of how an initial event may progress (improved inverse narrative cloze), and a task-based classifier (outperforming the baselines with strong F1 in a 500-class classification task).
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