VARIATIONAL TEMPLATE MACHINE FOR DATA-TO-TEXT GENERATION

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ABSTRACT

How to generate descriptions from structured data organized in tables? Existing approaches using neural encoder-decoder models often suffer from lacking diversity. We claim that an open set of templates is crucial for enriching the phrase constructions and realizing varied generations. Learning such templates is prohibitive since it often requires a large paired `<table,description>` corpus, which is seldom available. This paper explores the problem of automatically learning reusable "templates" from paired and non-paired data. We propose the *variational template machine* (VTM), a novel method to generate text descriptions from data tables. Our contributions include: *a)* we carefully devise a specific model architecture and losses to explicitly disentangle text template and semantic content information, in the latent spaces, and *b)* we utilize both small parallel data and large raw text without aligned tables to enrich the template learning. Experiments on datasets from a variety of different domains show that VTM is able generate more diversely while keeping a good fluency and quality.

1 INTRODUCTION

Generating text descriptions from structured data (data-to-text) is an important task with many practical applications. Data-to-text have been used to generate different kinds of texts, such as weather reports (Angeli et al., 2010), sports news (Mei et al., 2016; Wiseman et al., 2017) and biographies (Lebret et al., 2016; Wang et al., 2018b; Chisholm et al., 2017). Figure 1 gives an example of data-to-text task. We take an infobox [1] as the input and output a brief description about the information in the table. There are several recent methods utilizing neural encoder-decoder frameworks to generate text description from data tables (Lebret et al., 2016; Bao et al., 2018; Chisholm et al., 2017; Liu et al., 2018).

Although current table-to-text models could generate high quality sentences, the diversity of these output sentences are not satisfactory. We find that *templates* are crucial in increasing the variations of sentence structure. For example, Table 1 gives three descriptions with their templates for the given table input. Different templates control the sentence arrangement, thus vary the generation. Some related works (Wiseman et al., 2018; Dou et al., 2018) employ the semi-Markov hidden model to extract templates from the table-text pairs, then induce generation, which leads to interpretable table-to-text generation and makes the output more diverse.

We argue that templates can be better considered for generating more diverse outputs. First, it is non-trivial to sample different templates for obtaining different output utterances. Directly adopting variational auto-encoders (VAEs, Kingma & Welling (2013)) in table-to-text only enable to sample in the latent space. VAEs always generate irrelevant outputs, which may change the table content instead of sampling templates but fix table contents. This may harm the quality of output sentences. To address the above problem, if we can directly sample in the template space, we may get more diverse outputs while keeping the good quality of output sentences.

Additionally, we can hardly obtain promising sentences by sampling in the template space, if the template space is less informative. Namely, no matter encoder-decoder models or VAE-based models, they all require abundant parallel table-text pairs during the training, and constructing high-

[1] An infobox is a table containing attribute-value data about certain subject. It is mostly used on Wikipedia pages.

Table:	**name**[nameVariable], **eatType**[pub], **food**[Japanese], **priceRange**[average], **customerRating**[low], **area**[riverside]
Template1:	[name] is a [food] restaurant, it is a [eatType] and it has an [priceRange] cost and [customerRating] rating. it is in [area].
Sentence1:	nameVariable is a Japanese restaurant, it is a pub and it has an average cost and low rating. it is in riverside.
Template2:	[name] has an [priceRange] price range with a [customerRating] rating, and [name] is an [food] [eatType] in [area].
Sentence2:	nameVariable has an average price range with a low rating, and nameVariable is an Japanse pub in riverside.
Template3:	[name] is a [eatType] with a [customerRating] rating and [priceRange] cost, it is a [food] restaurant and [name] is in [area].
Sentence3:	nameVariable is a pub with a low rating and average cost, it is a Japanese restaurant and nameVariable is in riverside.

Table 1: An example: generating sentences based on different templates.

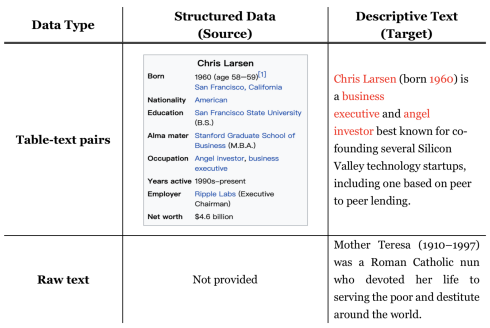

Figure 1: Two types of data in the data-to-text task: Row 2 presents an example of table-text pairs; Row 3 shows a sample of raw text, whose table input is missing and only sentence is provided.

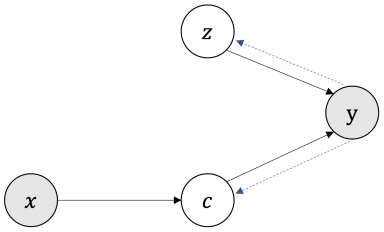

Figure 2: The graphical model of VTM: $\boldsymbol{z}$ is the latent variable from template space, and $\boldsymbol{c}$ is the content variable. $\boldsymbol{x}$ is the corresponding table for the table-text pairs. $\boldsymbol{y}$ is the observed sentence. The solid lines depict the generative model and the dashed lines form the inference model.

quality parallel dataset is often labor-intensive. With limited table-sentence pairs, a VAE model cannot guarantee an informative template space. In such case, how to fully utilize raw sentences (without table annotation) to enrich the latent template space is under study.

In this paper, to address the above two problems, we propose the *variational template machine* (VTM) for data-to-text generation, which enables generating diverse outputs while preserving the output sentence quality. Particularly, we introduce two latent variables, representing *template* and *content*, to control the generation. The two latent variables are disentangled, and thus we can generate diverse outputs by directly sampling in the template space. Moreover, we propose a novel approach for semi-supervised learning in the VAE framework, which could fully exploit the raw sentences for enriching the template space. Inspired by back-translation (Sennrich et al., 2016; Burlot & Yvon, 2018; Artetxe et al., 2018), we design a variational back-translation process. Instead of training a sentence-to-table back generation model, the content latent variable is taken as the representation of table. And the inference network for the content latent variable is taken as the backward generator to help training the forward generative model of pair-wise data. Auxiliary losses are introduced to ensure the learning of meaningful and disentangled latent variables.

Experimental results on Wikipedia biography dataset (Lebret et al., 2016) and sentence planning dataset (Reed et al., 2018) show that our model can generate texts with more diversity while keeping a good fluency quality. In addition, training together with large amount of raw text, VTM is able to improve the generation performance compared with learning only from paired data. Besides, ablation studies show the effectiveness of the auxiliary losses on the disentanglement of template and content spaces.

2 PROBLEM FORMULATION AND NOTATIONS

As a data-to-text task, we have **table-text pairs** $\mathcal{D}_p = \{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^N$, where $\boldsymbol{x}_i$ is the table input, and $\boldsymbol{y}_i$ is the sentence output.

Following the description scheme of Lebret et al. (2016), table $\boldsymbol{x}$ can be viewed as a set of K records of field-position-value triples, i.e., $\boldsymbol{x} = \{(f, p, v)_i\}_{i=1}^K$, where f is the field, p is the index of value v in the field f. For example, we denote item *"Name: John Lennon"* as two corresponding records: (*Name, 1, John*) and (*Name, 2, Lennon*). For each triple, we first embed field, position and value as d-dim vectors $e_p, e_f, e_v \in \mathbb{R}^d$. Then, the representation of the record is obtained by $h_i = \textbf{tanh}(W[e_f, e_p, e_v]^T + b), \quad i = 1...K$, where $W \in \mathbb{R}^{d_t \times d}$ and $b \in \mathbb{R}^{d_t}$ are parameters. Finally, we exert a max-pooling over all the field-position-value triple records and get the finally presentation of the table, denote as $f_{enc}(x)$:

$$h = \textbf{MaxPool}_i\{h_i; i = 1...K\} = f_{\text{enc}}(x)$$

In addition to the table-text pairs, we also have **raw texts** with table input missing, denote as $\mathcal{D}_r = \{\boldsymbol{y}_i\}_{i=1}^M$, usually, $M \gg N$.

3 VARIATIONAL TEMPLATE MACHINE

As shown in the graphical model in Figure 2, our VTM modifies the vanilla VAE model by introducing two independent latent variables $\boldsymbol{z}$ and $\boldsymbol{c}$, representing **template** latent variable and **content** latent variable respectively. $\boldsymbol{c}$ models the content information in the table, while $\boldsymbol{z}$ models the sentence template information. Target sentence y is generated by both content and template variables. The two latent variables are disentangled, which makes it possible to generate diverse and relevant sentences by sampling template variable and retraining the content variable. Considering two data types presented in Figure 1, the generation process for the content latent variable $\boldsymbol{c}$ is different.

- For a given table-text pair $(x, y) \in \mathcal{D}_p$, the content is observable from table x. As a result, $\boldsymbol{c}$ is assumed to be deterministic given table x, whose prior is defined as a delta distribution $p(c|x) = \delta(c = f_{\text{enc}}(x))$. The marginal log-likelihood is:

$$\begin{aligned} \log p_\theta(y|x) &= \log \int_z \int_c p_\theta(y|x, z, c) p(z) p(c|x) \text{dcdz} \\ &= \log \int_z p_\theta(y|x, z, c = f_{\text{enc}}(x)) p(z) \text{dz}, (x, y) \in \mathcal{D}_p. \end{aligned} \tag{1}$$

- For raw text $y \in \mathcal{D}_n$, the content is unobservable with the absence of table x. As a result, the content latent variable c should be sampled from prior of Gaussian distribution $\mathcal{N}(0, I)$. The marginal log-likelihood is:

$$\log p_\theta(y) = \log \int_z \int_c p_\theta(y|z, c) p(z) p(c) \text{dcdz}, y \in \mathcal{D}_n. \tag{2}$$

In order to make full use of both table-text pair data and raw text data, the above marginal log-likelihood should be optimized jointly:

$$\mathcal{L}(\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}_p}[\log p_\theta(y|x)] + \mathbb{E}_{y\sim\mathcal{D}_r}[\log p_\theta(y)]. \tag{3}$$

Directly optimizing Equation 3 is intractable. Following the idea of variational inference (Kingma & Welling, 2013), a variational posterior $q_\phi(\cdot)$ is constructed as an inference model (dashed lines in Figure 2) to approximate the true posterior. Instead of optimizing the marginal log-likelihood in Equation 3, we maximize the evidence lower bound (ELBO). In Section 3.1 and 3.2, the ELBO of table-text pairwise data and raw text data are discussed, respectively.

3.1 LEARNING FROM TABLE-TEXT PAIR DATA

In this section, we will show the learning loss of table-text pair data. According to the aforementioned assumption, the content variable $\boldsymbol{c}$ is observable and follows a delta distribution centred in the hidden representation of the table x.

ELBO objective. Assuming that the template variable $\boldsymbol{z}$ only relies on the template of target sentence, we introduce $q_\phi(z|y)$ as an approximation of the true posterior $p(z|y,c,x)$,

The ELBO loss of Equation 1 is written as

$$\mathcal{L}_{\text{ELBO}_p}(x,y) = -\mathbb{E}_{q_{\phi_z}(z|y)} \log p_\theta(y|z, c = f_{\text{enc}}(x), x) + D_{\text{KL}}(q_{\phi_z}(z|y)\|p(z)), \quad (x,y) \in \mathcal{D}_p.$$

The variational posterior $q_{\phi_z}(z|y)$ is assumed as a multivariate Gaussian distribution $\mathcal{N}(\mu_{\phi_z}(y), \Sigma_{\phi_z}(y))$, while the prior $p(z)$ is taken as a normal distribution $\mathcal{N}(0, I)$.

Preserving-Template Loss. Without any supervision, the ELBO loss alone does not guarantee to learn a good template representation space. Inspired by the work in style-transfer (Hu et al., 2017b; Shen et al., 2017; Bao et al., 2019; John et al., 2018), an auxiliary loss is introduced to embed the template information of sentences into template variable $\boldsymbol{z}$.

With table, we are able to roughly align the entities in sentence with the records in the table. By replacing these entities with a special token *<ent>*, we can remove the content information from sentences and get the sketchy sentence template, denote as $\tilde{y}$. We devise the preserving-template loss $\mathcal{L}_{\text{pt}}$ to ensure that the latent variable z only contains the information of the template.

$$\mathcal{L}_{\text{pt}}(x,y,\tilde{y}) = -\mathbb{E}_{q_{\phi_z}(z|y)} log p_\eta(\tilde{y}|z) = -\mathbb{E}_{q_{\phi_z}(z|y)} \sum_{t=1}^{m} \log p_\eta(\tilde{y}_t|z, \tilde{y}_{<t})$$

where m is the length of the $\tilde{y}$, and η denotes the parameters of the extra template generator. $\mathcal{L}_{\text{pt}}$ is trained via parallel data. In practice, due to the insufficient amount of parallel data, template generator p_η may not be well-learned. However, experimental results show that this loss is sufficient to provide a guidance for learning a template space.

3.2 Learning from Raw Text Data

Our model is able to make use of a large number of raw data without table since the content information of table could be obtained by the content latent variable.

ELBO objective. According to the definition of generative model in Equation 2, the ELBO of raw text data is

$$\log p_\theta(y) \geq \text{ELBO} = \mathbb{E}_{q_\phi(z,c|y)} \log \frac{p_\theta(y,z,c)}{q_\phi(z,c|y)}, \quad y \in \mathcal{D}_n$$

With the mean field approximation (Xing et al., 2003), $q_\phi(z,c|x)$ can be factorized as: $q_\phi(z,c|y) = q_{\phi_z}(z|y)q_{\phi_c}(c|y)$. We have:

$$\begin{aligned}\mathcal{L}_{\text{ELBO}_r}(y) = &- \mathbb{E}_{q_{\phi_z}(z|y)q_{\phi_c}(c|y)} \log p_\theta(y|z,c) \\ &+ D_{\text{KL}}(q_{\phi_z}(z|y)||p(z)) + D_{\text{KL}}(q_{\phi_c}(c|y)||p(c)), \quad y \in \mathcal{D}_n.\end{aligned}$$

In order to make use of template information contained in raw text data effectively, the parameters of generation network $p_\theta(y|z,c)$ and posterior network $q_{\phi_z}(z|y)$ are shared for pairwise and raw data. In decoding process, for raw text data, we use content variable c as the table embedding for the missing of table x. Variational posterior for c is deployed as another multivariate Guassian $q_{\phi_c}(c|y) = \mathcal{N}(\mu_{\phi_c}(y), \Sigma_{\phi_c}(y))$. Both $p(z)$ and $p(c)$ are taken as normal distribution $\mathcal{N}(0, I)$.

Preserving-Content Loss. In order to make the posterior $q_{\phi_c}(c|y)$ correctly infers the content information, the table-text pairs are used as the supervision to train the recognition network of $q_{\phi_c}(c|y)$. To this end, we add a preserving-content loss

$$\mathcal{L}_{\text{pc}}(x,y) = -\mathbb{E}_{q_{\phi_c}(c|y)}\|c - h\|^2 + D_{\text{KL}}(q_{\phi_c}(c|y)||p(c)), \quad (x,y) \in \mathcal{D}_p,$$

where $h = f_{\text{enc}}(x)$ is the embedding of table obtained by the table encoder. Minimizing $\mathcal{L}_{\text{pc}}$ is also helpful to bridge the gap of c between pairwise (taking $c = h$) and raw training data (sampling from $q_\phi(c|y)$). Moreover, we find that the first term of $\mathcal{L}_{\text{pc}}$ is equivalent to (1) make the mean of $q_\phi(c|y)$ closer to h; (2) minimize the trace of co-variance of $q_\phi(c|y)$. The second term serves as a regularization. Detailed explanations and proof are referred in supplementary materials.

Algorithm 1 Training procedure

Input: Model parameters $\phi_z, \phi_c, \theta, \eta$
Parallel data $\mathcal{D}_p = \{(\boldsymbol{x}, \boldsymbol{y})_i\}_{i=1}^N$; non-parallel data $\mathcal{D}_r = \{\boldsymbol{y}_j\}_{j=1}^M$; $M \gg N$
Procedure TRAIN($\mathcal{P}, \mathcal{R}$):
1: Update $\phi_z, \phi_c, \theta, \eta$ by gradient descent on $\mathcal{L}_{\text{ELBO}_p} + \mathcal{L}_{\text{MI}} + \mathcal{L}_{\text{pt}} + \mathcal{L}_{\text{pc}}$
2: Update ϕ_z, ϕ_c, θ by gradient descent on $\mathcal{L}_{\text{ELBO}_n} + \mathcal{L}_{\text{MI}}$
3: Update $\phi_z, \phi_c, \theta, \eta$ by gradient descent on $\mathcal{L}_{tot}$

3.3 MUTUAL INFORMATION LOSS

As introduced by previous works (Chen et al., 2016; Zhao et al., 2017; 2018), adding mutual information term to ELBO could alleviate KL collapse effectively and improve the quality of variational posterior. Adding mutual information terms directly imposes the association of content and template latent variables with target sentences. Besides, theoretical proof[2] and experimental results show that introducing mutual information bias is necessary in the presence of preserving-template loss $\mathcal{L}_{\text{pt}}(\boldsymbol{x}^p, \boldsymbol{y}^p)$.

As a result, in our work, the following mutual information term is added to objective

$$\mathcal{L}_{\text{MI}}(y) = -I(z, y) - I(c, y).$$

3.4 TRAINING PROCESS

The final loss of VTM is made up of the ELBO losses and extra losses:

$$\begin{aligned}\mathcal{L}_{tot}(x^p, y^p, y^n) = \mathcal{L}_{\text{ELBO}_p}(x^p, y^p) + \mathcal{L}_{\text{ELBO}_r}(y^n) + \lambda_{\text{MI}}(\mathcal{L}_{\text{MI}}(y^p) + \mathcal{L}_{\text{MI}}(y^n)) \\ + \lambda_{\text{pt}}\mathcal{L}_{\text{pt}}(x^p, y^p) + \lambda_{\text{pc}}\mathcal{L}_{\text{pc}}(x^p, y^p), \qquad (x^p, y^p) \in \mathcal{D}_p, y^n \in \mathcal{D}_n.\end{aligned}$$

λ_{MI}, λ_{pt} and λ_{pc} are hyperparameters with respect to auxiliary losses.

The training procedure is shown in Algorithm 1. The parameters of generation network θ and posterior network $\phi_{z,c}$ could be trained jointly by both table-text pair data and raw text data. In this way, a large number of raw text data can be used to enrich the generation diversity.

4 EXPERIMENT

4.1 DATASETS AND BASELINE MODELS

Dataset. We perform the experiment on WIKI (Lebret et al., 2016; Wang et al., 2018b) and SPNLG(Reed et al., 2018)[3]. Two datasets come from two different domains. The former contains $728,321$ sentences of biographies from Wikipedia. The latter depicts restaurants, and it expands the E2E dataset[4] into a total of $204,955$ utterances with more varied sentence structures and instances. To simulate the environment that large amount of raw texts provided, we just use part of the table-text pairs from two datasets, leaving the most of the instances as raw texts. Concretely, for two datasets, we initially keep the ratio of table-text pairs to raw texts as 1:10. And as for WIKI dataset, in addition to the data from *WikiBio*, it also contains the biographical descriptions of people[5] from external *Wikipedia Person and Animal* Dataset (Wang et al., 2018a). The statistics for the number of table-text pairs and raw texts in the training, validation and test sets are shown in Table 2. For WIKI dataset, we evaluate the generation quality of different models based on BLEU-4, NIST, ROUGE-L (F-score). For SPNLG, we use BLEU-4, NIST, METEOR, ROUGE-L (F-score), and CIDEr. We directly use the same automatic evaluation script from E2E NLG Challenge[6]. The diversity of generation is evaluated by self-BLEU (Zhu et al., 2018). The lower self-BLEU the model receives, the more diversely it generates.

Baseline models. We reimplement the following models as baselines:

[2]Proof can be found in Appendix C
[3]https://nlds.soe.ucsc.edu/sentence-planning-NLG
[4]http://www.macs.hw.ac.uk/InteractionLab/E2E/
[5]https://eaglew.github.io/patents/
[6]https://github.com/tuetschek/e2e-metrics

	Train		Valid		Test
Dataset	#table-text pair	#raw text	#table-text pair	#raw text	#table-text pair
WIKI	84,150	841,507	72,831	42,874	72,831
SPNLG	14,906	149,058	20,495	/	20,496

Table 2: Dataset statistics in our experiments.

Methods	BLEU	NIST	ROUGE	Self-BLEU
Table2seq-beam	26.74	5.97	48.20	92.00
Table2seq-sample	21.75	5.32	42.09	36.07
Temp-KN	11.68	2.04	40.54	73.14
VTM	25.22	5.96	45.36	74.86
-$\mathcal{L}_{pc}$	22.16	4.28	40.91	80.39
VTM-noraw	21.59	5.02	39.07	78.19
-$\mathcal{L}_{\text{MI}}$	21.30	4.73	40.99	79.45
-$\mathcal{L}_{\text{MI}}$-$\mathcal{L}_{\text{pt}}$	16.20	3.81	38.04	84.45

Table 3: Results for WIKI dataset. All the metrics are significant under 0.05 significance level.

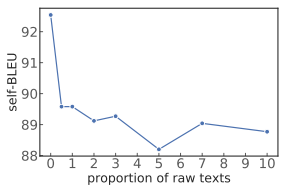

Figure 3: Self-BLEU and the proportion of raw texts.

- **Table2seq**: Table2seq model first encodes the table into a hidden representation then generates the sentence based on it. For a fair comparison, we apply the same table-encoder architecture as in Section 2 and the same LSTM generator with attention mechanism as our model. The model is only trained on pair-wise data. During the generation, different beam size is applied (**Table2seq-beam**). And we also implement the decoder with forward sampling (namely **Table2seq-sample**).
- **Temp-KN**: Template-KN model first generates a template according to the interpolated 5-gram Kneser-Ney (KN) language modeled over sentence templates, then replaces the special token for field with the corresponding words from the table.

The parameters of the VTM are tuned based on the lowest ELBO on the validation set in all the experiments. Word embeddings are randomly initialized with 300-dimension. During training, we use Adam optimizer (Kingma & Ba, 2014) with initial learning rate as 0.001. Details on hyperparameters are listed in Appendix D.

4.2 EXPERIMENTAL RESULTS ON WIKI DATASET

Quantitative analysis. According to the results in Table 3, we find that our variational template machine (VTM) can generally produce sentences with more diversity under a promising performance in terms of BLEU metrics. As for the baseline model, Table2seq with beam search algorithm (Table2seq-beam), which is only trained on parallel data, generates the most fluent sentences, but its diversity is rather poor. Besides, although the sampling decoder gets the lowest self-BELU, it actually sacrifices the fluency at the cost. For template-based model, although Temp-KN receives the lowest self-BLEU score, it fails to generate fluent sentences.

Ablation study. To study the effectiveness of the auxiliary loses and the augmented raw texts, we progressively remove the auxiliary losses and raw data in the ablation study. We are able to reach the conclusions as following.

- Without the preserving-content loss $\mathcal{L}_{\text{pc}}$, the model has a relative decline in generation quality. This implies that, by sharing the same inference model with parallel data, preserving-content loss provides an effective instruction for raw training data to learn the content space.
- VTM-noraw is the model trained without using raw data. Only the loss functions in Section 3.1 are optimized. Comparing with VTM-noraw, we find VTM gets a substantial improvement in generation quality. More importantly, there is also a decline in self-BLEU, which proves that VTM can generate more diversely. As explained previously, raw data indeed plays a valuable role in improving both generation quality and diversity, which is often neglected by previous studies.
- After removing the mutual information loss and preserving-template loss from VTM-noraw, we find that the generation quality and diversity continuously declines, which proves the effect of two losses during the training.

Table	**name**[Jack Ryder], **country**[Australia], **fullname**[John Ryder], **nickname**[the king of Collingwood], **birth_date**[8 August 1889], **birth_place**[Collingwood, Victoria, Australia], **death_date**[4 April 1977], **death_place**[Fitzroy, Victoria, Australia], **club**[Victoria], **testdebutyear**[1920 england], **aritcle_title**[Jack Ryder (cricketer)]
Reference	John "Jack" Ryder, mbe (8 August 1889 – 3 April 1977) was a cricketer who played for Victoria and Australia.
Table2seq-sample	**1:** john Ryder (8 August 1889 – 3 April 1977) was an Australian cricketer . **2:** john Ryder Ryder (8 August 1889 – 3 April 1977) was an Australian cricketer . **3:** john Ryder Ryder (8 August 1889 – 3 April 1977) was an Australian cricketer who played for gloucestershire cricket club in 1912 . **4:** john Ryder (8 August 1889 – 3 April 1977) was an Australian cricketer . **5:** john Ryder oliveira (8 August 1889 – 3 April 1977) was an Australian test cricketer who played against great Britain with international cricket club .
Temp-KN	**1:** jack Ryder (born August 8, 1889) is a former professional cricketer) . **2:** "jack" Ryder (born August 8, 1889) is a former professional cricketer) who played in the national football league. **3:** jack Ryder (born 8 August 1889 in Collingwood, Victoria,) is a former professional cricketer) . **4:** Jack Ryder (born August 8, 1889, in Collingwood, Victoria, Australia) is a former professional football player who is currently a member of the united states . **5:** jack Ryder (born August 8, 1889) is a former professional cricketer) .
VTM-noraw	**1:** John Ryder (8 August 1889 – 4 April 1977) was an Australian cricketer. **2:** Jack Ryder (born August 21, 1951 in Melbourne, Victoria) was an Australian cricketer. **3:** John Ryder (21 August 1889 – 4 April 1977) was an Australian cricketer. **4:** Jack Ryder (8 March 1889 – 3 April 1977) was an Australian cricketer. **5:** John Ryder (August 1889 – April 1977) was an Australian cricketer.
VTM	**1:** John Ryder (8 August 1889 – 4 April 1977) was an Australian cricketer. **2:** John Ryder (born 8 August 1889) was an Australian cricketer. **3:** Jack Ryder (born August 9, 1889 in Victoria, Australia) was an Australian cricketer. **4:** John Ryder (August 8, 1889 – April 4, 1977) was an Australian rules footballer who played for Victoria in the Victorian football league (VFL). **5:** John Ryder, also known as the king of Collingwood (8 August 1889 – 4 April 1977) was an Australian cricketer.

Table 4: An example of the generated text by our model and the baselines on WIKI dataset.

Case study. Table 4 shows an example of sentences generated by different models. On the other hand, although forward sampling enables the Table2seq model to generate diversely, some details may be not correct, for example, club name in Sentence 3. Due to the property of sampling, without raw data, VTM-noraw can generate texts with altered templates, like different expressions for birth date and death date, while preserving some readability. Finally, our VTM further diversify the expression structures, that other models cannot produce, such as "[*fullname*], also known as [*nickname*] ([*birth_date*] – [*daeth_date*]) was a [*country*] [*article_name_4*]." (Sentence 5). This may imply that raw sentences not in the parallel dataset additionally expand the template space.

4.3 EXPERIMENTAL RESULTS ON SPNLG DATASET

Methods	**BLEU**	**NIST**	**METEOR**	**ROUGE**	**CIDEr**	**Self-BLEU**
Table2seq-beam	40.61	6.31	38.67	56.95	3.74	97.14
Table2seq-sample	34.97	5.68	35.46	52.74	3.00	65.69
Temp-KN	6.45	0.45	12.53	27.60	0.23	37.85
VTM	40.04	6.25	38.31	56.48	3.64	88.77
-$\mathcal{L}_{pc}$	39.58	6.24	38.30	56.24	3.69	87.20
VTM-noraw	39.94	6.22	38.42	56.72	3.66	88.92
-$\mathcal{L}_{\text{MI}}$	38.33	6.02	37.77	55.92	3.51	96.55
-$\mathcal{L}_{\text{MI}}$-$\mathcal{L}_{\text{pt}}$	39.63	6.24	38.35	56.36	3.70	92.54

Table 5: Result for SPNLG data set. Under the 0.05 significance level, VTM gets significantly higher results in all the fluency metrics than all the baselines except Table2seq-beam.

Table 5 shows the results for SPNLG dataset, same conclusions can be drawn as in the WIKI experiments for both the **quantitative analysis** and **ablation study**. Since the SPNLG dataset is much simpler than WIKI dataset, Table2seq model can learn to generate well even if training samples is less than test samples. Still, VTM is able to produce sentences with the commensurate quality as Table2seq-beam and more diversity. Moreover, the automatic evaluation results of VTM-noraw-$\mathcal{L}_{\text{MI}}$-$\mathcal{L}_{\text{pt}}$ empirically show that preserving-template loss may be a hinder if we only add it during the training, as illustrated in Section 3.3.

Experiment on the diversity under different proportions of raw data. In order to show how much raw data may contribute to the whole model, we also train the model under different proportions of raw data in training data. We gradually add raw sentences in the training set, train the model and test based on the same test set. Specifically, we control the ratio of raw sentences to the table-text pairs under 0.5:1, 1:1, 2:1, 3:1, 5:1, 7:1 and 10:1 respectively. And Figure 3 shows, the self-BLEU rapidly decreases even adding a small number of raw data, and continuously decreases until the ratio equals 5:1. It becomes smoother as more raw texts added.

Case study. From Table 6 in Appendix E, we can draw almost the same the conclusion for Table2seq model. Despite template-like structures vary much in a forward sampling model, the information in sentences may be wrong. For example, Sentence 3 says that the restaurant is a Japanese place. Notably, VTM produces correct texts with more diversity of templates and with different number of sentences and aggregation operations. For example, "[*name*] is a [*food*] place in [*area*] with a price range of [*priceRange*]. It is a [*eatType*]." (Sentence 1, two sentences, "with" aggregation), "[*name*] is a [*eatType*] with a price range of [*priceRange*]. It is in [*area*]. It is a [*food*] place." (Sentence 2, three sentences, "with" aggregation), "[*name*] is a [*food*] restaurant in [*area*] and it is a [*food*]." (Sentence 4, one sentence, "and" aggregation).

5 Related Work

Data-to-text Generation. Data-to-text generation aims to produce summary for the factual structured data, such as numerical table. Neural language models have made distinguished progress by generating sentences from the table in an end-to-end style. Jain et al. (2018) proposed a mixed hierarchical attention model to generate weather report from the standard table. Gong et al. (2019) proposed a hierarchical table-encoder and a decoder with dual attention. Although encoder-decoder models can generate fluent sentences, they are criticized for deficiency in sentence diversity. Other works focused on controllable and interpretable generation by introducing templates as latent variables. Wiseman et al. (2018) designed a Semi-HMM decoder to learn discrete templates representation, and Dou et al. (2018) created a platform, Data2TextStudio, equipped with a Semi-HMMs model, to extract template and generate from table input in an interactive way.

Semi-supervised Learning From Raw Data. It is easier to acquire raw text than to get structured data, and most neural generators cannot make the best use of raw text, universally. Ma et al. (2019) proposed that encoder-decoder framework may fail when not enough parallel corpus is provided. In the area of machine translation, back-translation have been proved to be an effective method to utilize monolingual data (Sennrich et al., 2016; Burlot & Yvon, 2018).

Latent Variable Generative Model. Deep generative models, especially variational autoencoders (VAE) (Kingma & Welling, 2013) have shown a promising performance in generation. Bowman et al. (2016) showed that a RNN-based VAE model can produce diverse and well-formed sentences by sampling from the prior of continuous latent variable. Recent works explored methods to learn disentangled latent variables (Hu et al., 2017a; Zhou & Neubig, 2017; Bao et al., 2019). For instance, Bao et al. (2019) devised multi-task losses adversarial losses to disentangle the latent space into syntactic space and semantic space. Motivated by the idea of back-translation and variational inference, VTM model proposed in this work can not only fully utilize the non-parallel text corpus, but also learn a disentangled representation for template and content.

6 Conclusion

In this paper, we propose Variational Template Machine (VTM) based on a semi-supervised learning approach in the VAE framework. Our VTM not only builds disentangled spaces for template and content to contribute in diverse generation based on templates, but also exploits raw texts without tables to expand the template space. Experimental results on two datasets show that VTM outperforms the VAE model in terms of both generation quality and diversity, and it can achieve a commensurate quality in generation, as well as promote the diversity by a large margin.

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A EXPLANATION FOR PRESERVING-CONTENT LOSS

The first term of $-\mathcal{L}_{\text{pc}}(x, y)$ is equivalent to:

$$\begin{aligned}
\mathbb{E}_{q_c(c|x)}||c-h||^2 &= \mathbb{E}_{q_c(c|x)} \sum_{i=1}^{K} (c_i - h_i)^2 \\
&= \sum_{i=1}^{K} \mathbb{E}_{q_c(c|x)} (c_i - h_i)^2 \\
&= \sum_{i=1}^{K} [(\mathbb{E}(c_i - h_i))^2 + \text{var}(c_i)] \\
&= \sum_{i=1}^{K} [(E(c_i) - h_i)^2 + \text{var}(c_i)] \\
&= \sum_{i=1}^{K} [(\mu_i - h_i)^2 + \Sigma_{ii}] \\
&= ||\mu - h||^2 + tr(\Sigma)
\end{aligned}$$

When we minimize it, we jointly minimize the distance between mean of approximated posterior distribution, and the trace of the co-variance matrix.

B PROOF FOR ANTI-INFORMATION PROPERTY OF ELBO

Consider the KL divergence over the whole dataset (or a mini-batch of data), we have

$$\begin{aligned}
\mathbb{E}_{x\sim p(x)}[D_{\text{KL}}(q(z|x)\|p(x))] =& \mathbb{E}_{q(z|x)p(x)}[\log q(z|x) - \log p(z)] \\
=& -H(z|x) - \mathbb{E}_{q(z)} \log p(z) \\
=& -H(z|x) + H(z) + D_{\text{KL}}(q(z)\|p(z)) \\
=& I(z, x) + D_{\text{KL}}(q(z)\|p(z))
\end{aligned}$$

where $q(z) = \mathbb{E}_{x\sim\mathcal{D}}(q(z|x))$ and $I(z, x) = H(z) - H(z|x)$. Since KL divergence can be viewed as a regularization term in ELBO loss, When ELBO is maximized, the KL term is minimized, and mutual information between x and latent z, $I(z, x)$ is minimized. This implies that z and x eventually become more independent.

C PROOF FOR THE PRESERVING-TEMPLATE LOSS WHEN POSTERIOR COLLAPSE HAPPENS

When posterior collapse happens, $D_{\text{KL}}(q(z|y)||p(z)) \approx 0$,

$$\begin{aligned}
\mathcal{L}_{pt}(Y, \tilde{Y}) =& \mathbb{E}_{\tilde{y}\sim p(\tilde{y}), y\sim p(y)} \mathbb{E}_{z\sim q(z|y)} \log p_\eta(\tilde{y}|z) \\
=& \mathbb{E}_{\tilde{y}\sim p(\tilde{y})} \mathbb{E}_{z\sim p(z)} \log p_\eta(\tilde{y}|z) \\
=& \int_{\tilde{y}} p(\tilde{y}) \int_z p(z) \log p_\eta(\tilde{y}|z) \text{dz d}\tilde{y} \\
=& \int_z p(z) \int_{\tilde{y}} p(\tilde{y}) \log p_\eta(\tilde{y}|z) \text{dz d}\tilde{y} \\
=& \mathbb{E}_z \mathbb{E}_{\tilde{y}}[\log p_\eta(y)|z] = \mathbb{E}_{\tilde{y}} \log p_\eta(y)
\end{aligned}$$

During the back-propagation,

$$|| \bigtriangledown_z \mathcal{L}_{pt}(Y, \tilde{Y})|| = 0$$

thus, ϕ_z is not updated.

D IMPLEMENTATION DETAILS

For the model trained on WIKI dataset, the the dimension of latent template variable is set as 100, and the dimension of latent content variable is set as 200. The dimension of the hidden for table is 300. During the tuning, we find that there is a trade-off between the generation quality and diversity. For the hyperparameters of total loss $\mathcal{L}_{tot}$, we set $\lambda_{\text{MI}} = 0.5$, $\lambda_{\text{pt}} = 1.0$ and $\lambda_{\text{pc}} = 0.5$.

For the model trained on SPNLG dataset, the dimension of latent template variable is set as 64, and the dimension of latent content variable is set as 100. The dimension of the hidden for table is also 300. For the hyperparameters of total loss $\mathcal{L}_{tot}$, we set $\lambda_{\text{MI}} = \lambda_{\text{pt}} = \lambda_{\text{pc}} = 1.0$.

E CASE STUDY ON SPNLG EXPERIMENT

Table	**name**[nameVariable], **eatType**[pub], **food**[French], **priceRange**[20-25], **area**[riverside]
Reference	nameVariable is a French place with a price range of 20-25. It is in riverside. It is a pub.
Table2seq-sample	**1:** nameVariable is a pub with a price range of 20-25. It is a French restaurant in riverside. **2:** nameVariable is a French restaurant in riverside with a price range of 20-25. nameVariable is a pub. **3:** nameVariable is a pub with a price range of 20-25 and nameVariable is a French restaurant in riverside. **4:** nameVariable is a pub with a price range of 20-25, also it is in riverside. it is a Japanese place. **5:** nameVariable is a pub with a average rating and it is a French place in riverside.
Temp-KN	**1:** nameVariable is in riverside, also it is in riverside. **2:** nameVariable is a French restaurant. **3:** nameVariable is the best restaurant. **4:** nameVariable is in riverside, and nameVariable is in [location]. **5:** nameVariable is in. Its a French restaurant and it is in [location] with food and, even if nameVariable is [food_qual], it is the best place.
VTM-noraw	**1:** nameVariable is a pub with a price range of 20-25. It is a French place in riverside. **2:** nameVariable is a pub with a price range of 20-25. it is a pub. It is in riverside. **3:** nameVariable is a French place in riverside with a price range of 20-25. It is a pub. **4:** nameVariable is a French place in riverside with a price range of 20-25. It is a pub. **5:** nameVariable is a French place in riverside with a price range of 20-25. It is a pub.
VTM	**1:** nameVariable is a French place in riverside with a price range of 20-25. It is a pub. **2:** nameVariable is a pub with a price range of 20-25. It is in riverside. It is a French place. **3:** nameVariable is a French pub in riverside with a price range of 20-25, and it is a pub. **4:** nameVariable is a French restaurant in riverside and it is a pub. **5:** nameVariable is a French place in riverside with a price range of 20-25. It is a pub.

Table 6: An example of the generated text by our model and the baselines on SPNLG dataset.