Select and Attend: Towards Controllable Content Selection in Text Generation

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Abstract

Many text generation tasks naturally contain two steps: content selection and surface realization. Current neural encoder-decoder models conflate both steps into a black-box architecture. As a result, the content to be described in the text cannot be explicitly controlled. This paper tackles this problem by decoupling content selection from the decoder. The decoupled content selection is human interpretable, whose value can be manually manipulated to control the content of generated text. The model can be trained end-to-end without human annotations by maximizing a lower bound of the marginal likelihood. We further propose an effective way to trade-off between performance and controllability with a single adjustable hyperparameter. In both data-to-text and headline generation tasks, our model achieves promising results, paving the way for controllable content selection in text generation.

1 Introduction

Many text generation tasks, e.g., data-to-text, summarization and image captioning, can be naturally divided into two steps: content selection and surface realization. The generations are supposed to have two levels of diversity: (1) content-level diversity reflecting multiple possibilities of content selection (what to say) and (2) surface-level diversity reflecting the linguistic variations of verbalizing the selected contents (how to say) (Reiter and Dale, 2000; Nema et al., 2017). Recent neural network models handle these tasks with the encoder-decoder (Enc-Dec) framework (Sutskever et al., 2014; Bahdanau et al., 2015), which simultaneously performs selecting and verbalizing in a black-box way. Therefore, both levels of diversity are entangled within the generation. This entanglement, however, sacrifices the controllability and interpretability, making it difficult to specify the content to be conveyed in the generated text (Qin et al., 2018; Wiseman et al., 2018).

With this in mind, this paper proposes decoupling content selection from the Enc-Dec framework to allow finer-grained control over the generation. Table 1 shows an example. We can easily modify the content selection to generate text with various focuses, or sample multiple paraphrases by fixing the content selection.

Table 1: Headline generation examples from our model. We can generate text describing various contents by sampling different content selections. The selected source word and its corresponding realizations in the text are highlighted with the same color.

| Source Sentence: The sri lankan government on Wednesday announced the closure of government schools with immediate effect as a military campaign against tamil separatists escalated in the north of the country. |
|-----------------------------------------------|
| Selected : sri lankan, closure, schools         |
| Text : sri lanka closes schools.               |

| Selected : sri lankan, Wednesday, closure, schools |
| Text : sri lanka closes schools on Wednesday. |

| Selected : sri lankan, closure, schools, military campaign |
| Text : sri lanka shuts down schools amid war fears. |

| Selected : sri lankan, announced, closure, schools |
| Text : sri lanka declares closure of schools. |

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\textsuperscript{1}The source code is available on https://github.com/chin-gyou/controllable-selection
discrepancy when integrating them together.

2. **Soft-select**: Learn a soft mask to filter useless information (Mei et al., 2016; Zhou et al., 2017). However, the mask is deterministic without any probabilistic variations, making it hard to model the content-level diversity.

3. **Reinforce-select**: Train the selector with reinforcement learning (Chen and Bansal, 2018), which has high training variance and low diversity on content selection.

In this paper, we treat the content selection as latent variables and train with amortized variational inference (Kingma and Welling, 2014; Mnih and Gregor, 2014). This provides a lower training variance than Reinforce-select. The selector and generator are co-trained within the same objective, the generations are thus more faithful to the selected contents than Bottom-up methods. Our model is task-agnostic, end-to-end trainable and can be seamlessly inserted into any encoder-decoder architecture. On both the data-to-text and headline generation task, we show our model outperforms others regarding content-level diversity and controllability while maintaining comparable performance. The performance/controllability trade-off can be effectively adjusted by adjusting a single hyperparameter in the training stage, which constrains an upper bound of the conditional mutual information (CMI) between the selector and generated text (Alemi et al., 2018; Zhao et al., 2018). A higher CMI leads to stronger controllability with a bit more risk of text disfluency.

In summary, our contributions are (1) systematically studying the problem of controllable content selection for Enc-1Dec text generation, (2) proposing a task-agnostic training framework achieving promising results and (3) introducing an effective way to achieve the trade-off between performance and controllability.

2 Background and Notation

Let $X, Y$ denote a source-target pair. $X$ is a sequence of $x_1, x_2, \ldots, x_n$ and can be either some structured data or unstructured text/image depending on the task. $Y$ corresponds to $y_1, y_2, \ldots, y_m$ which is a text description of $X$. The goal of text generation is to learn a distribution $p(Y|X)$ to automatically generate proper text.

The Enc-1Dec architecture handles this task with an encode-attend-decode process (Bahdanau et al., 2015; Xu et al., 2015). The encoder first encodes each $x_i$ into a vector $h_i$. At each time step, the decoder pays attentions to some source embeddings and outputs the probability of the next token by $p(y_t|y_{1:t-1}, C_t)$. $C_t$ is a weighted average of source embeddings:

$$C_t = \sum_i \alpha_{t,i} h_i$$

$$\alpha_{t,i} = \frac{e^{f(h_i, d_t)}}{\sum_j e^{f(h_j, d_t)}}$$

$d_t$ is the hidden state of the decoder at time step $t$. $f$ is a score function to compute the similarity between $h_i$ and $d_t$ (Luong et al., 2015).

3 Content Selection

Our goal is to decouple the content selection from the decoder by introducing an extra content selector. We hope the content-level diversity can be fully captured by the content selector for a more interpretable and controllable generation process. Following Gehrmann et al. (2018); Yu et al. (2018), we define content selection as a sequence labeling task. Let $\beta_1, \beta_2, \ldots, \beta_n$ denote a sequence of binary selection masks. $\beta_i = 1$ if $h_i$ is selected and 0 otherwise. $\beta_i$ is assumed to be independent from each other and is sampled from a bernoulli distribution $B(\gamma_i)^2$. $\gamma_i$ is the bernoulli parameter, which we estimate using a two-layer feedforward network on top of the source encoder.

Text are generated by first sampling $\beta$ from $B(\gamma)$ to decide which content to cover, then decode with the conditional distribution $p_{\theta}(Y|X, \beta)$. The text is expected to faithfully convey all selected contents and drop unselected ones. Fig. 1 depicts this generation process. Note that the selection is based on the token-level context-aware embeddings $h$ and will maintain information from the surrounding contexts. It encourages the decoder to stay faithful to the original information instead of simply fabricating random sentences by connecting the selected tokens. For each source-target pair, the ground-truth selection mask is unknown, so training is challenging. In the following session, we discuss several training possibilities and introduce the proposed model in detail.

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2Devlin et al. (2019) have shown that excellent performance can be obtained by assuming such conditionally independence given a sufficiently expressive representation of $x$, though modelling a richer inter-label dependency is for sure beneficial (Lei et al., 2016; Nallapati et al., 2017).
3.1 Bottom-up

The most intuitive way is training the content selector to target some heuristically extracted contents. For example, we can train the selector to select overlapped words between the source and target (Gehrmann et al., 2018), sentences with higher tf-idf scores (Li et al., 2018) or identified image objects that appear in the caption (Wang et al., 2017). A standard encoder-decoder model is independently trained. In the testing stage, the prediction of the content selector is used to hard-mask the attention vector to guide the text generation in a bottom-up way. Though easy to train, Bottom-up generation has the following two problems: (1) The heuristically extracted contents might be coarse and cannot reflect the variety of human languages and (2) The selector and decoder are independently trained towards different objectives thus might not adapt to each other well.

\( \beta \) as Latent Variable: Another way is to treat \( \beta \) as a latent variable and co-train selector and generator by maximizing the marginal data likelihood. By doing so, the selector has the potential to automatically explore optimal selecting strategies best fit for the corresponding generator component.

With this in mind. We design \( p_\theta(Y | X, \beta) \) by changing the original decoder in the following way: (1) We initialize hidden states of the decoder from a mean pooling over selected contents to inform the decoder which contents to cover and (2) Unselected contents will be prohibited from being attended to:

\[
d_0 = \text{MLP} \left( \frac{1}{n} \left( \sum_i^n \beta_i h_i \right) \right)
\]

\[
\alpha_{t,i} = \frac{e^{f(h_t, d_i)} \beta_i}{\sum_j e^{f(h_t, d_j)} \beta_j}
\]

Since computing the exact marginal likelihood \( \log \mathbb{E}_{\beta \sim B(\gamma)} p_\theta(Y | X, \beta) \) requires enumerating over all possible combinations of \( \beta \) (complexity \( O(2^n) \)), we need some way to efficiently estimate the likelihood.

3.2 Soft-Select

Soft-select falls back on a deterministic network to output the likelihood function’s first-order Taylor series approximation expanded at \( \mathbb{E}_{\beta \sim B(\gamma)} \):

\[
\log \mathbb{E}_{\beta \sim B(\gamma)} p_\theta(Y | X, \beta) \\
\approx \log[p_\theta(Y | X, \gamma)] + \mathbb{E}_{\beta \sim B(\gamma)} (\beta - \gamma)p_\theta(Y | X, \gamma) \\
= \log p_\theta(Y | X, \gamma)
\]

By moving the expectation into the decoding function, we can deterministically compute the likelihood by setting \( \beta_i = \gamma_i \), reducing complexity to \( O(1) \). Each attention weight will first be “soft-masked” by \( \gamma \) before being passed to the decoder. Soft-select is fully differentiable and can be easily trained by gradient descent. However, this soft-approximation is normally inaccurate, especially when \( B(\gamma) \) has a high entropy, which is common in one-to-many text generation tasks. The gap between log \( \mathbb{E}_{\beta \sim B(\gamma)} p_\theta(Y | X, \beta) \) and \( \log p_\theta(Y | X, \mathbb{E}_{\beta \sim B(\gamma)}) \) will be large (Ma et al., 2017; Deng et al., 2018). In practice, this would lead to unrealistic generations when sampling \( \beta \) from the deterministically trained distribution.

3.3 Reinforce-Select

Reinforce-select (RS) (Ling and Rush, 2017; Chen and Bansal, 2018) utilizes reinforcement learning to approximate the marginal likelihood. Specifically, it is trained to maximize a lower bound of the likelihood by applying the Jensen inequality:

\[
\log \mathbb{E}_{\beta \sim B(\gamma)} p_\theta(Y | X, \beta) \geq \mathbb{E}_{\beta \sim B(\gamma)} \log p_\theta(Y | X, \beta)
\]

The gradient to \( \gamma \) is approximated with Monte-Carlo sampling by applying the REINFORCE algorithm (Williams, 1992; Glynn, 1990). To speed up convergence, we pre-train the selector by some distant supervision, which is a common practice in reinforcement learning. REINFORCE is unbiased but has a high variance. Many research have proposed sophisticated techniques for variance reduction (Mnih and Gregor, 2014; Tucker et al., 2017; Grathwohl et al., 2018). In text generation, the high-variance problem is aggravated because there exists multiple valid selections. Accurately estimating the likelihood becomes difficult. Another
issue is its tendency to avoid stochasticity (Raiko et al., 2015), which we will show in Sec 5.2 that it results in low content-level diversity.

3.4 Variational Reinforce-Select

We propose Variational Reinforce-Select (VRS) which applies variational inference (Kingma and Welling, 2014) for variance reduction. Instead of directly integrating over \( B(\gamma) \), it imposes a proposal distribution \( q_{\phi} \) for importance sampling. The marginal likelihood is lower bounded by:

\[
\log \mathbb{E}_{\beta \sim B(\gamma)} p_{\theta}(Y|X, \beta) = \log \mathbb{E}_{\beta \sim q_{\phi}} \frac{p_{\theta}(Y, \beta|X)}{q_{\phi}(\beta)} \geq \mathbb{E}_{\beta \sim q_{\phi}} \log \frac{p_{\theta}(Y, \beta|X)}{q_{\phi}(\beta)} = \mathbb{E}_{\beta \sim q_{\phi}} \log p_{\theta}(Y|X, \beta) - KL(q_{\phi}||B(\gamma))
\]

By choosing a proper \( q_{\phi} \), the bound will be improved and the variance can be largely reduced compared with REINFORCE. If \( q_{\phi} \) equals the posterior distribution \( p_{\theta}(\beta|X,Y) \), the bound is tight and the variance would be zero (Mnih and Rezende, 2016). We define \( q_{\phi}(\beta|X,Y) \) as a mean-field distribution parameterized by a set of global parameters \( \phi \) to approach the true posterior distribution. \( \phi \), \( \theta \) and \( \gamma \) are simultaneously trained by minimizing the last term of Eq. 3. \( q_{\phi}(\beta|X,Y) \) also allows us to further perform posterior inference: Given an arbitrary text \( Y \) for a source \( X \), we can infer which source contents are included in \( Y \) (An example is given in Appendix C).

In Eq.3, the KL divergence term can be computed analytically. As for the independence assumption, it can be summed over each individual \( \beta_i \). The likelihood term is differentiable to \( \theta \) but not to \( \phi \), we estimate the gradient to \( \phi \) in Eq 3 by applying the REINFORCE estimator:

\[
\nabla_{\phi} \mathbb{E}_{\beta \sim q_{\phi}} \log p_{\theta}(Y|X, \beta) = \mathbb{E}_{\beta \sim q_{\phi}} \nabla_{\phi} \log q_{\phi}(\beta|X,Y) (\log p_{\theta}(Y|X, \beta) - B)
\]

\( B \) is the control variate (Williams, 1992). The optimal \( B \) would be (Weaver and Tao, 2001):

\[
B^* = \mathbb{E}_{\beta \sim q_{\phi}} \log p_{\theta}(Y|X, \beta)
\]

which we set as a soft-select approximation:

\[
B = \log p_{\theta}(Y|X, \beta) - KL(q_{\phi}||B(\gamma))
\]

We estimate Eq. 3.4 with a single sample from \( q_{\phi} \) for efficiency. Though multiple-sample could potentially further tighten the bound and reduce the variance (Burda et al., 2016; Lawson et al., 2018; Tucker et al., 2019), it brings significant computational overhead, especially in text generation tasks where the whole sentence needs to be decoded.

3.5 Degree of Controllability

In practice, when treating content selection as latent variables, the model tends to end up with a trivial solution of always selecting all source tokens (Shen et al., 2018a; Ke et al., 2018). This behavior is understandable since Eq. 2 strictly masks unselected tokens. Wrongly unselecting one token will largely deteriorate the likelihood. Under the maximum likelihood (MLE) objective, this high risk pushes the selector to take a conservative strategy of always keeping all tokens, then the whole model degenerates to the standard Enc-Dec and the selection mask loses effects on the generation. Usually people apply a penalty term to the selecting ratio when optimizing the likelihood:

\[
\mathcal{L} + \lambda |(\bar{\gamma} - \alpha)|
\]

\( \mathcal{L} \) is the MLE loss function, \( \bar{\gamma} \) is the mean of \( \gamma \) and \( \alpha \) is the target selecting ratio. This forces the selector to select the most important \( \alpha \) tokens for each source input instead of keeping all of them.

In our VRS model, we can easily adjust the degree of controllability by limiting an upper bound of the conditional mutual information (CMI) \( I(\beta, Y|X) \) (Zhao et al., 2018). Specifically, we can change our objective into:

\[
\max_{\phi, \theta, \gamma} \mathcal{L} = \max_{\phi, \theta, \gamma} \mathbb{E}_{\beta \sim q_{\phi}} \log p_{\theta}(Y|X, \beta) - \lambda KL(q_{\phi}||B(\gamma)) - \epsilon)
\]

\( \lambda \) is a fixed lagrangian multiplier. Eq. 5 can be proved equal to maximum likelihood with the constraint \( I(\beta, Y|X) = \epsilon \) given proper \( \lambda \) (Alemi et al., 2018). A higher \( \epsilon \) indicates \( \beta \) has more influences to \( Y \) (higher controllability) while always safely selecting all tokens will lead \( I(\beta, Y|X) = 0 \). It is preferred over Eq. 4 because (a) CMI directly considers the dependency between the selection and multiple-possible text while limiting the ratio aims at finding the single most salient parts for each source. (b) Unlike CMI, limiting the ratio is coarse. It considers only the total selected size and ignores its internal distribution.

\(^{3}\)We also tried adding a coverage constraint to ensure the decoder covers all the selected tokens (Wen et al., 2015; Wang et al., 2019), but we find it brings no tangible help since a higher CMI can already discourage including redundant tokens into the selection.
Algorithm 1 Variational Reinforce-Select (VRS)

Parameters: $\theta, \phi, \gamma$

$pretrain \leftarrow$ TRUE

repeat
  Sample $X, Y$ from the corpus;
  Encode $X$ into $(h_1, h_2, \ldots, h_n)$;
  if $pretrain$ then
    Update $\phi$ with distant supervision;
    Update $\theta, \gamma$ by $\nabla_{\theta, \gamma}$ Eq. 3;
  else
    Update $\theta, \gamma, \phi$ by $\nabla_{\theta, \gamma, \phi}$ Eq. 5;
  end if
  $pretrain \leftarrow$ FALSE if Eq. 3 degrades until convergence and $pretrain$ is False

In practice, we can set $\epsilon$ to adjust the degree of controllability we want. Later we will show it leads to a trade-off with performance. The final algorithm is detailed in Algorithm 1. To keep fairness, we train RS and VRS with the same control variate and pre-training strategy.

4 Related Work

Most content selection models train the selector with heuristic rules (Hsu et al., 2018; Li et al., 2018; Yu et al., 2018; Gehrmann et al., 2018; Yao et al., 2019; Moryossef et al., 2019), which fail to fully capture the relation between selection and generation. Mei et al. (2016); Zhou et al. (2017); Lin et al. (2018); Li et al. (2018) “soft-select” word or sentence embeddings based on a gating function. The output score from the gate is a deterministic vector without any probabilistic variations, so controlling the selection to generate diverse text is impossible. Very few works explicitly define a bernoulli distribution for the selector, then train with the REINFORCE algorithm (Ling and Rush, 2017; Chen and Bansal, 2018), but the selection targets at a high recall regardless of the low precision, so the controllability over generated text is weak. Fan et al. (2018) control the generation by manually concatenating entity embeddings, while our model is much more flexible by explicitly defining the selection probability over all source tokens.

Our work is closely related with learning discrete representations with variational inference (Wen et al., 2017; van den Oord et al., 2017; Kaiser et al., 2018; Lawson et al., 2018), where we treat content selection as the latent representation. Limiting the KL-term is a common technique to deal with the “posterior collapse” problem (Kingma et al., 2016; Yang et al., 2017; Shen et al., 2018b). We adopt a similar approach and use it to further control the selecting strategy.

5 Experiments

For the experiments, we focus on comparing (1) Bottom-up generation (Bo.Up.), (2) soft-select (SS), (3) Reinforce-select (RS) and (4) Variational-Reinforce-select (VRS) regarding their performance on content selection. SS and RS are trained with the selecting ratio constraint in Eq. 4. For the SS model, we further add a regularization term to encourage the maximum value of $\gamma$ to be close to 1 as in Mei et al. (2016). We first briefly introduce the tasks and important setup, then present the evaluation results.

5.1 Tasks and Setup

We test content-selection models on the headline and data-to-text generation task. Both tasks share the same framework with the only difference of source-side encoders.

Headline Generation: We use English Gigaword preprocessed by Rush et al. (2015), which pairs first sentences of news articles with their headlines. We keep most settings same as in Zhou et al. (2017), but use a vocabulary built by byte-pair-encoding (Sennrich et al., 2016). We find it speeds up training with superior performance.

Data-to-Text Generation: We use the Wikibio dataset (Lebret et al., 2016). The source is a Wikipedia infobox and the target is a one-sentence biography description. Most settings are the same as in Liu et al. (2018), but we use a bi-LSTM encoder for better performance.

Heuristically extracted content: This is used to train the selector for bottom up models and pre-train the RS and VRS model. For wikibio, we simply extract overlapped words between the source and target. In Gigaword, as the headline is more abstractive, we select the closest source word for each target word in the embedding space. Stop words and punctuations are prohibited from being selected.

Choice of $\alpha/\epsilon$: As seen in Sec 3.5, we need to set the hyperparameter $\alpha$ for RS/SS and $\epsilon$ for
Table 2: Diversity of content selection. The % effect of selector is defined as the ratio of unique generation and mask, which reflects the rate that changing the selector will lead to corresponding changes of the generated text.

VRS. $\alpha$ corresponds to the selecting ratio. We set them as $\alpha = 0.35$ for Wikibio and 0.25 for Gigaword. The value is decided by running a human evaluation to get the empirical estimation. To keep comparison fairness, we tune $\epsilon$ to make VRS select similar amount of tokens with RS. The values we get are $\epsilon = 0.15n$ for Wikibio and $\epsilon = 0.25n$ for Gigaword. $n$ is the number of source tokens.

5.2 Results and Analysis

Ideally we would expect the learned content selector to (1) have reasonable diversity so that text with various contents can be easily sampled, (2) properly control the contents described in the generated text and (3) not hurt performance. The following section will evaluate these three points in order.

Diversity: We first look into the diversity of content selection learned by different models. For each test data, 50 selection masks are randomly sampled from the model’s learned distribution. Greedy decoding is run to generate the text for each mask. We measure the entropy of the selector, proportion of unique selection masks and generated text in the 50 samples. We further define the “effect” of the selector as the ratio of sampled unique text and mask. This indicates how often changing the selection mask will also lead to a change in the generated text. The results are averaged over all test data. Following Rush et al. (2015) and Lebret et al. (2016), we measure the quality of generated text with ROUGE-1, 2, L F-score for Gigaword and ROUGE-4, BLEU-4, NIST for Wikibio. As there is only one reference text for each source, we report an oracle upper bound of these scores by assuming an “oracle” that can choose the best text among all the candidates (Mao et al., 2015; Wang et al., 2017). Namely, out of each 50 sampled text, we pick the one with the maximum metric score. The final metric score is evaluated on these “oracle” picked samples. The intuition is that if the content selector is properly trained, at least one out of the 50 samples should describe similar contents with the reference text, the metric score between it and the reference text should be high. Table 2 lists the results. We can have the following observations:

- RS model completely fails to capture the content-level diversity. Its selector is largely deterministic, with a lowest entropy value among all models. In contrast, the selector from SS, VRS and Bo.Up. have reasonable diversity, with over 90% and 75% unique selection masks for Gigaword and Wikibio respectively.

- The selector from VRS has the strongest effect to the generator, especially on the Gigaword data where modifying the content selection changes the corresponding text in more than 95% of the cases. RS has the lowest effect value, which indicates that even with the selecting ratio constraint, its generator still ignores the selection mask to a large extent.

- The oracle metric score of VRS is much higher than the other two. This is beneficial when people want to apply the model to generate a few candidate text then hand-pick the suitable one. VRS has more potential than the other three to contain the expected text. SS performs worst. The gap between the
soft approximation and the real distribution, as mentioned before, indeed results in a large drop of performance.

In short, compared with others, the content selector of VRS is (1) diverse, (2) has stronger effect on the text generation and (3) with a larger potential of producing an expected text.

**Controllability:** We have shown the content selector of VRS is diverse and has strong effect on the text generation. This section aims at examining whether such effect is desirable, i.e., whether the selector is able to properly control the contents described in the text. We measure it based on the self-bleu metric and a human evaluation.

The self-bleu metric measures the controllability by evaluating the “intra-selection” similarity of generated text. Intuitively, by fixing the selection mask, multiple text sampled from the decoder are expected to describe the same contents and thereby should be highly similar to each other. The decoder should only model surface-level diversity without further modifying the selected contents. With this in mind, for each test data, we randomly sample a selection mask from the selector’s distribution, then fix the mask and run the decoder to sample 10 different text. The self-BLEU-1 score (Zhu et al., 2018) on the sampled text is reported, which is the average BLEU score between each text pair. A higher self-BLEU score indicates the sampled text are more similar with each other. The results are shown in Table 3. We can see generations from VRS have a clearly higher intra-selection similarity. SS performs even worse than RS, despite having a high effect score in Table 2. The selector from SS affects the generation in an undesirable way, which also explain why SS has a lowest oracle metric score though with a high score on content diversity and effect.

| Method  | Fluency | intra-consistency | inter-diversity |
|---------|---------|------------------|-----------------|
| Reference | 0.96 | - | - |
| Enc-Dec | 0.83 | - | - |
| Bo.Up. | 0.46 | 0.48 | 0.61 |
| SS | 0.27 | 0.41 | 0.54 |
| RS | 0.78 | 0.39 | 0.47 |
| VRS | 0.74 | 0.72 | 0.87 |

Table 4: Human evaluation on fluency, intra-consistency and inter-diversity of content selection on DUC 2004.

We further run a human evaluation to measure the text-content consistency among different models. 100 source text are randomly sampled from the human-written DUC 2004 data for task 1&2 (Over et al., 2007). Bo.Up, SS, RS and VRS are applied to generate the target text by first sampling a selection mask, then run beam search decoding with beam size 10. We are interested in seeing (1) if multiple generations from the same selection mask are paraphrases to each other (intra-consistent) and (2) if generations from different selection masks do differ in the content they described (inter-diverse). The results in Table 4 show that VRS significantly outperforms the other two in both intra-consistency and inter-diversity. RS has the lowest score on both because the selector has very weak effects on the generation as measured in the last section. Bo.Up and SS lay between them. Overall VRS is able to maintain the highest content-text consistency among them.

| Method | R-1 | R-2 | R-L | %Word |
|--------|-----|-----|-----|-------|
| Zhou et al. (2017) | 36.15 | 17.54 | 33.63 | 100 |
| Enc-Dec | 35.92 | 17.43 | 33.42 | 100 |
| SS | 20.35 | 4.78 | 16.53 | 24.82 |
| Bo.Up | 28.17 | 10.32 | 26.68 | 24.54 |
| RS | 35.45 | 16.38 | 32.71 | 25.12 |
| VRS(ϵ = 0)-pri | 36.42 | 17.81 | 33.86 | 78.63 |
| VRS(ϵ = 0.25)-pri | 34.26 | 15.11 | 31.69 | 78.66 |
| VRS(ϵ = 0)-post | 37.14 | 18.03 | 34.26 | 78.66 |
| VRS(ϵ = 0.25)-post | 56.72 | 33.24 | 51.88 | 24.53 |

Table 5: Gigaword best-select results. Larger ϵ leads to more controllable selector with a bit degrade of performance. (-post) means selecting from the posterior \(q_\phi(\beta|X,Y)\). (-pri) is from the prior \(B(γ_i)\).

**Performance & Trade-off:** To see if the selector affects performance, we also ask human annotators to judge the text fluency. The fluency score is computed as the average number of text being judged as fluent. We include generations from the standard Enc-Dec model. Table 4 shows the best fluency is achieved for Enc-Dec. Imposing
Table 6: Wikibio best-select results.

| Method         | R-4 | B-4 | NIST | %Word |
|----------------|-----|-----|------|-------|
| Liu et al. (2018) | 41.65 | 44.71 | 100  |
| Enc-Dec        | 42.07 | 44.80 | 9.82 | 100   |
| SS            | 5.10  | 5.73  | 0.24 | 35.12 |
| Bo.Up         | 8.07  | 9.52  | 0.42 | 38.79 |
| RS            | 42.64 | 45.08 | 10.01| 34.53 |
| VRS(ϵ = 0)-pri| 43.01 | 46.01 | 10.24| 84.56 |
| VRS(ϵ = 0.15)-pri | 42.13 | 44.51 | 9.84 | 34.04 |
| VRS(ϵ = 0)-post| 43.84 | 46.60 | 10.27| 85.34 |
| VRS(ϵ = 0.15)-post| 49.68 | 52.26 | 11.48| 34.57 |

Table 5/6 further measure the metric scores on Gigaword/Wikibio by decoding text from the best selection mask based on the selector’s distribution (set $\beta_i = 1$ if $B(\gamma_i) > 0.5$ and 0 otherwise). We include results from VRS model with $\epsilon = 0$, which puts no constraint on the mutual information. We further report the score by generating the best selection mask from the learned posterior distribution $q_{\phi}(\beta|X,Y)$ for VRS model. Two current SOTA results from Zhou et al. (2017) and Liu et al. (2018) and the proportion of selected source words for each model are also included. We have the following observations:

- As the value of $\epsilon$ decreases, the performance of VRS improves, but the selector loses more controllability because the model tends to over-select contents (over 75% source words selected). The text-content consistency will become low.
- Increasing $\epsilon$ sacrifices a bit performance, but still comparable with SOTA. Especially on Wikibio where the performance drop is minor. The reason should be that Wikibio is relatively easier to predict the selection but Gigaword has more uncertainty.

- Increasing $\epsilon$ improves the accuracy of the posterior selection. This would be useful when we want to perform posterior inference for some source-target pair.
- Setting $\epsilon = 0$ can actually outperform SOTA seq2seq which keeps all tokens, suggesting it is still beneficial to use the VRS model even if we do not care about the controllability.

Figure 2: Negative log likelihood (NLL), selection entropy and self-BLEU as $\epsilon$ changes. NLL and self-BLEU on Wikibio are added by 1 for better visualization. Lower NLL suggests higher performance. Higher entropy/self-BLEU means higher diversity/controllability.

Figure 2 visualizes how changing the value of $\epsilon$ affects the negative log likelihood (NLL), entropy of the selector and self-BLEU score, which roughly correlates with performance, diversity and controllability. NLL is evaluated based on the lower bound in Eq 3 (Sohn et al., 2015). We can see as $\epsilon$ increases, the performance decreases gradually but the content selection gains more diversity and controllability. In practice we can tune the $\epsilon$ value to achieve a trade-off.

**Generation Example:** Figure 3 shows some examples from Gigaword. As can be seen, decodings from the VRS model are largely consistent with each other, in most cases only replacing one or two words with corresponding synonyms. Samples are able to faithfully convey all selected contents. In contrast, generations from SS. Bo.Up. and RS are unpreditable, differing in both selected
In this paper, we tackle the unaddressed problem of controllable content selection in text generation. We propose a general framework based on variational inference that can be potentially applied to arbitrary tasks. On both the headline generation and data-to-text tasks, our model outperforms state-of-the-art models regarding the diversity and controllability of content selection. We further introduce an effective way to achieve a performance/controllability trade-off, which can be easily tuned to meet specific requirement.

6 Conclusion

In this paper, we tackle the unaddressed problem of controllable content selection in text generation. We propose a general framework based on variational inference that can be potentially applied to arbitrary tasks. On both the headline generation and data-to-text tasks, our model outperforms state-of-the-art models regarding the diversity and controllability of content selection. We further introduce an effective way to achieve a performance/controllability trade-off, which can be easily tuned to meet specific requirement.

Acknowledgments

We thank anonymous reviewers for valuable comments, thank Aditya Mogadala, Shun Kiyono, Thomas Melachlan and other members of the LIAT team at RIKEN AIP for useful discussions. Xiaoyu Shen is supported by IMPRS-CS fellowship. The work of J. Suzuki was partly supported by JSPS KAKENHI Grant Number JP19104418 and AIRPF Grant Number 30AI036-8. This work is also partially funded by DFG collaborative research center SFB 1102.

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A Performance/Controllability trade-off

The trade-off between performance and interpretability has been a long-standing problem in feature selection (Jackson, 1998; Haury et al., 2011). The trade-off exists because it is usually very difficult to accurately find the exact features needed to make the prediction. Safely keeping more features will almost always lead to better performance. Some models do succeed in achieving superior performance by selecting only a subset of the input. However, they mostly still target at the recall of the selection (Hsu et al., 2018; Chen and Bansal, 2018; Shen et al., 2018a), i.e., to select all possible content that might help predict the target. The final selected contents reduce some most useful information from the source, but they still contain many redundant contents (same like our VRS-($\epsilon = 0$) as in Table 6 and 5). This makes them unsuitable for controllable content selection. In text generation, a recent work from Moryossef et al. (2019) shows they could control the contents by integrating a symbolic selector into the neural network. However, their selector is tailored by some rules only for the RDF triples. Moreover, even based on their fine-tuned selector, the fluency they observe is still slightly worse than a standard seq2seq.

We assume the content selector is the major battle if we want a model that can achieve controllability without sacrificing the performance. We can clearly observe in Table 6 that the performance drop in Wikibio is marginal compared with Gigaword. The reason should be that the selection on Wikibio is much easier than Gigaword. The biography of a person almost always follow some simple patterns, like name, birthday and profession, but for news headlines, it can contain information with various focuses. In our two tasks, due to the independence assumption we made on $\beta_i$ and the model capacity limit, the content selector cannot fully fit the true selecting distribution, so the trade-off is necessary. Improving the selector with SOTA sequence labelling models like Bert (Devlin et al., 2019) would be worth trying.

There are also other ways to improve. For example, we could learn a ranker to help us choose the best contents (Stent et al., 2004). Or we could manually define some matching rules to help rank the selection (Cornia et al., 2018). In Table 2, we show the VRS model achieves very high metric scores based on an oracle ranker, so learning a ranker should be able to improve the performance straightforwardly.

Source: The sri lankan government on Wednesday announced the closure of government schools with immediate effect as a military campaign against tamil separatists escalated in the north of the country.
Reference: sri lanka closes schools as war escalates .
b1: sri lanka shuts schools as war escalates .
b2: sri lanka closes schools as violence escalates .
b3: sri lanka shuts schools as fighting escalates .
b4: sri lanka closes schools as offensive expands .
b5: sri lanka closes schools as war continues .

Figure 4: Posterior inference example. Highlighted words are selected contents according to the posterior distribution $q_\phi(\beta|X,Y)$. b1-b5 are decoded by fixing the selected contents.

B Example from Wikibio

To see how we can manually control the content selection, Figure 5 shows an example from Wikibio, the model is mostly able to form a proper sentence covering all selected information. If the selector assigns very high probability to select some content and we force to remove it, the resulting text could be unnatural (as in summary 4 in Figure 5 because the model has seen very few text without containing the birthday information in the training corpus). However, thanks to the diversity of the content selector as shown in the previous section, it is able to handle most combinatorial patterns of content selection.

C Posterior inference

Figure 4 further provides an example of how we can perform posterior inference given a provided text. Our model is able to infer which source contents are covered in the given summary. With the inferred selection, we can sample multiple paraphrases describing the same contents. As seen in Table 6 and 5, the metric scores are remarkably high when decoding from the posterior inferred selections (last three rows), suggesting the posterior distribution is well trained. The posterior inference part could be beneficial for other tasks like content transfer among text (Wang et al., 2019; Prabhumoye et al., 2019). The described source contents can be first predicted with the posterior inference, then transferred to a new text.
| Personal information |
|----------------------|
| **Full name**        | Dillon Douglas Sheppard |
| **Date of birth**    | 27 February 1979 (age 39) |
| **Place of birth**   | Durban, South Africa |
| **Height**           | 1.80 m (5 ft 11 in) |
| **Playing position** | Left-winger |

| Club information     |
|----------------------|
| **Current team**     | Bidvest Wits |
| **Number**           | 29 |

Selected Content: Dillon Douglas Sheppard, 27 February 1979, Left-winger
Summary 1: Dillon Douglas Sheppard, born 27 February 1979, is a football (soccer) left-winger.

Selected Content: Dillon Douglas Sheppard, 27 February 1979, South Africa, Left-winger
Summary 2: Dillon Douglas Sheppard, born 27 February 1979, is a South African football (soccer) left-winger.

Selected Content: Dillon Douglas Sheppard, 27 February 1979, South Africa, Left-winger, Bidvest Wits
Summary 3: Dillon Douglas Sheppard, born 27 February 1979, is a South African football (soccer) left-winger who plays for Bidvest Wits.

Selected Content: Dillon Douglas Sheppard, Left-winger, Bidvest Wits
Summary 4: Dillon Douglas Sheppard, born, is a football (soccer) left-winger who plays for Bidvest Wits.

Figure 5: Example of content selection in Wikibio. Summary 4 is unnatural because we force to remove the birthday content which the selector assigns very high probability to select.
| Vocabulary          | Gigaword                                | WikiBio                  |
|--------------------|-----------------------------------------|--------------------------|
| Word Embedding     | Built with byte-pair segmentation with size 30k | Built by keeping the most frequent 20k tokens |
| Size                | 300. Initialized with Glove (Pennington et al., 2014). | OOVs are randomly initialized from a normal distribution |
| Inputs             | Sequence of source word embeddings      | Sequence of concatenation of source table field, value, position and reverse position embeddings (Lebret et al., 2016) |
| Source Encoder     | Single-layer Bi-LSTM with hidden size 512 | Single-layer Bi-LSTM with hidden size 500 |
| Target Decoder     | Single-layer LSTM with hidden size 512   | Single-layer LSTM with hidden size 500 |
| Drop out rate      | 0.3 for both encoder and decoder        |                           |
| Decoding Method    | Beam search with beam size 5            | Greedy decoding. UNK words are replaced with the most attended source token as in Liu et al. (2018) |
| Mini-batch size    | 256                                     | 128                      |
| Optimizer          | Adam, $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$, weight decay = $1.2 \times 10^{-6}$, gradient clipping in [-5,5] | 0.0005 |
| Initial Learning Rate |                                         |                          |
| Prior Selector     | $B(\gamma_i) = \sigma(\text{MLP}(h_i))$. MLP is a multi-layer perceptron. $h_i$ comes from the encoder hidden state |                           |
| Posterior Selector | $q_{\phi}(\beta_i | X, Y) = \sigma(\text{MLP}([h_i \circ e(y)]))$. $\circ$ means concatenation |                           |

Table 7: Detailed settings of our experiment. $e(y)$ in the posterior selector is an encoded representation of the ground-truth text. We use a bi-LSTM encoder. The last hidden state is treated as the representation for the text.