Preventing Posterior Collapse in Sequence VAEs with Pooling

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Abstract
Variational Autoencoders (VAEs) hold great potential for modelling text, as they could in theory separate high-level semantic and syntactic properties from local regularities of natural language. Practically, however, VAEs with autoregressive decoders often suffer from posterior collapse, a phenomenon where the model learns to ignore the latent variables, causing the sequence VAE to degenerate into a language model. Previous works attempt to solve this problem with complex architectural changes or costly optimization schemes. In this paper, we argue that posterior collapse is caused in part by the encoder network failing to capture the input variabilities. We verify this hypothesis empirically and propose a straightforward fix using pooling. This simple technique effectively prevents posterior collapse, allowing the model to achieve significantly better data log-likelihood than standard sequence VAEs. Compared to the previous SOTA on preventing posterior collapse, we are able to achieve comparable performances while being significantly faster.

1 Introduction
Variational Autoencoders (VAEs) (Kingma and Welling, 2014) are a class of latent variable models that allow tractable sampling through the decoder network and efficient approximate inference via the recognition network. Bowman et al. (2016) proposed an adaptation of VAEs for text in the hope that the latent variables could capture global features while the decoder RNN can model the low-level local semantic and syntactic structures. VAEs have been applied to many NLP-related tasks, such as language modeling, question answering (Miao et al., 2016), text compression (Miao and Blunsom, 2016), semi-supervised text classification (Xu et al., 2017), controllable language generation (Hu et al., 2017), and dialogue response generation (Wen et al., 2017; Zhao et al., 2017; Park et al., 2018). However, in practice sequence VAE training can be brittle; the latent variable is often completely ignored while the model degenerates into a regular language model. This phenomenon occurs when the inferred posterior distribution collapses onto the prior completely and is commonly referred to as posterior collapse (Bowman et al., 2016).

Previous work that attempts to address posterior collapse mostly falls into two categories. The first line of work analyzes the problem from an optimization perspective (Alemi et al., 2018) and proposes to solve the issue with costly optimization schemes (He et al., 2019; Liu et al., 2019). The other one focuses on improving the architectural designs for different model components, particularly for the decoders (Semeniuta et al., 2017; Yang et al., 2017; Dieng et al., 2019) and the choice of approximate posteriors (Kim et al., 2018; Xu and Durrett, 2018).

In this paper, we analyze the issue from the perspective of the encoder networks. We argue that posterior collapse is caused in part by overly similar feature representations of input data produced by the RNN encoders. Since the parameters of the approximate posteriors are produced by feeding the feature vectors to a shared linear transformation, representations that are close to each other in the feature space would lead to the approximate posteriors for each sentence concentrating in a small region in the space of approximate posteriors. This makes the latent variables for different input somewhat indistinguishable from each other. During training, since the decoder cannot differentiate the input data based on their latent variables, the optimization would try to maximize the ELBO objective by pushing the approximate posterior to the prior to avoid paying the cost of KL divergence, thus causing posterior collapse.
We show that such issues do play a role when applying VAEs to text, and demonstrate that simple pooling operations can be leveraged to alleviate posterior collapse without major modifications to the standard VAE formulation and optimization process. Our findings also point to a new direction which suggests that more can be done to improve sequence VAEs by designing better encoders, as doing so would allow us to address the issue while avoiding paying the hefty price that comes with costly optimization schemes or losing on the expressive power by intentionally weakening the decoders (Semeniuta et al., 2017; Yang et al., 2017). This paper is structured as follows. We present the preliminaries regarding the ELBO objective, sequence VAE models, and detailed description of posterior collapse. Then we present our argument about how certain undesired properties of RNNs could contribute to posterior collapse, and show that simple operations like pooling could be employed to mitigate such issues. In the experiments section, we present evidence to support our argument and quantitative results to show that our method is able to effectively prevent posterior collapse while achieving significantly better-estimated log likelihood on unseen data. We design additional experiments to show that the approximate posteriors can capture useful information about the data. Following that, we briefly discuss some other work for solving posterior collapse in related work. We conclude our discussion with an overview of this paper followed with a discussion about potential future work.

2 Preliminaries

2.1 VAE Formulation

Variational autoencoders were initially proposed by Kingma and Welling (2014). Compared to the standard autoencoders, VAEs introduce an explicitly parameterized latent variable $z$ over data $x$. Instead of directly maximizing the log likelihood of data, VAEs are trained to maximize the Evidence Lower Bound (ELBO) on log likelihood:

$$\log p_{\theta}(x) \geq \mathbb{E}_{q_{\phi}(z|x)}[\log p_{\theta}(x|z)] - D_{KL}(q_{\phi}(z|x)|p_{\theta}(z)) = \mathcal{L}(\theta, \phi; x)$$

where $p_{\theta}(z)$ is the prior distribution, $q_{\phi}(z|x)$ is typically referred to as the recognition model (encoder), and $p_{\theta}(x|z)$ is the generative model (decoder). Note that we will use these terms interchangeably throughout this paper.

The ELBO objective $\mathcal{L}(\theta, \phi; x)$ consists of two terms. The first one is the reconstruction term $\mathbb{E}_{q_{\phi}(z|x)}[\log p_{\theta}(x|z)]$, which trains the generative model to reconstruct input data $x$ given its latent variable $z$. The second term is the KL divergence from $q_{\phi}(z|x)$ to $p_{\theta}(x)$, which acts as a regularizer and penalizes the approximate posteriors produced by recognition model for deviating from the prior distribution too much. Note that in practice, rather than maximizing the ELBO, we often train VAEs to minimize the negative ELBO $-\mathcal{L}(\theta, \phi; x)$ instead for the convenience of optimization.

In a standard VAE, the prior is typically assumed to be an isotropic Gaussian with no learnable parameters, i.e. $p_{\theta}(z) = \mathcal{N}(0, I)$. The approximate posterior for $z$ is defined as a multivariate Gaussian distribution with diagonal covariance matrix whose parameters are functions of $x$, thus $q_{\phi} = \mathcal{N}(\mu_{\phi}(x), \sigma_{\phi}^2(x))$ with $\phi$ being the parameters of recognition model. Such assumptions ensure that both the forward and backward passes can be performed efficiently during training, and the KL regularizer can be computed analytically.

2.2 Sequence VAEs

Inspired by Kingma and Welling (2014), Bowman et al. (2016) proposed an adaptation of variational autoencoders for generative text modeling, dubbed the Sequence VAEs (SeqVAEs). Neural language models (Mikolov et al., 2010) typically predict each token $x_t$ conditioned on the history of previously generated tokens:

$$p(x) = \prod_{t=1}^{T} p(x_t|x_1, x_2, ..., x_{t-1})$$

Rather than directly modeling the above factorization of sequence $x$, Bowman et al. (2016) specified a generative process for input sequence $x$ that is conditioned on some latent variable $z$:

$$p(x|z) = \prod_{t=1}^{T} p(x_t|x_1, x_2, ..., x_{t-1}, z)$$

where the marginal distribution $p(x)$ could in theory be recovered by integrating out the latent variable. The hope is that latent variable $z$ would be able to capture certain holistic properties of sentences, such as topic, style and other high-level syntactic and semantic features.
Given the sequential nature of natural language, autoregressive architectures such as RNNs are the ideal choice for parameterizing the encoder and the decoder in SeqVAEs. Specifically, the encoder first reads the entire sentence $x$ in order to produce feature vector $h$ for the sequence. The feature vector is then fed to some linear transformation to produce the mean and covariance of approximate posterior. Latent code $z$ is sampled from the approximate posterior and then passed to the decoder network to reconstruct the original sentence $x$.

2.3 Posterior Collapse

An alternative interpretation for VAEs is to view them as a regularized version of the standard autencoders. The reconstruction term in the ELBO objective encourages the latent code $z$ to convey meaningful information in order to reconstruct $x$. On the other hand, the KL divergence term constantly tries to penalize $q_\phi(z|x)$ for deviating from $p_\theta(z)$ too much, preventing the model from simply memorizing each data point. This creates the possibility of an undesirable local optimum in which the approximate posterior becomes nearly identical to the prior distribution, namely $q_\phi(z|x) = p_\theta(z)$ for all $x$.

Such a degenerate solution is commonly known as posterior collapse and is often signalled by the close-to-zero KL term in the ELBO objective during training. When optimization reaches the collapsed solutions, the approximate posterior resembles the prior distribution and conveys no useful information about the corresponding data $x$, which defeats the purpose of having a recognition model. In this case, the decoder would have no other choice but to ignore the latent codes.

Posterior collapse is particularly prevalent when applying VAEs to text data. To address this issue, Bowman et al. (2016) proposed to gradually increase the weight of the KL regularizer from a small value to 1 following a simple annealing schedule. However, in practice, this method alone is not sufficient to prevent posterior collapse (Xu et al., 2017). Other solutions have been proposed to address this problem, which we will discuss in more details in Section 4.

3 Importance of Feature Dispersion

3.1 Issues with Last Hidden States

In sequence VAEs, the encoder RNN processes the input sentence $x = [x_1, x_2, ..., x_n]$ one word at a time to produce a series of hidden states $h = [h_1, h_2, ..., h_n]$. Under the typical architecture, the last hidden state $h_n$ is taken as the feature vector to compute the mean and variance parameters of the approximate posterior, as shown on the left side of Figure 1, thus:

$$
q_\phi(z|x) = \mathcal{N}(\mu_\phi(x), \sigma_\phi^2(x))
$$

s.t.  $\mu_\phi(x) = W_1 \ast h_n + b_1$

$$
\sigma_\phi^2(x) = \exp(W_2 \ast h_n + b_2)
$$

where $W_1, b_1$ and $W_2, b_2$ are the linear layer parameters for mean and log-variance respectively.

However, using the last hidden state as feature representation could be problematic as RNNs, including their variants such as LSTMs and GRUs, are known to have issues retaining information further back in history. As a result, the last hidden state $h_n$ tends to be dominated by later words in the input sequence. We hypothesize that such tendencies of RNNs would create a feature space with insufficient dispersion when only $h_n$ is utilized.

As a result, when used to compute the parameters for approximate posteriors, vectors from such a feature space would result in posterior distributions that are concentrated in a small region of the posterior space, with high chances of overlap for different input data. Under this circumstance, latent codes sampled from different approximate posteriors would look somewhat similar to each other and thus provide very little useful information to the decoder. Since no useful information could be conveyed by the latent variables, the optimization would push approximate posteriors towards the prior to maximize the overall ELBO objective, thus causing training to reach undesirable local optimum that is posterior collapse.

3.2 Increasing Encoder Feature Dispersion

Following our intuition, we aim to find a better alternative for generating feature vectors for a sequence $x = [x_1, x_2, ..., x_n]$ other than $h_n$. Ideally, we would like to make use of information contained in all hidden states rather than just the last one. Thus, we would like the feature vector $h_x$ for sequence $x$ to be:

$$
h_x = \text{aggregate}([h_1, h_2, ..., h_n])
$$

where aggregate is some function that takes a sequence of vectors of variable lengths and produces a single combined representation.
Figure 1: Left: The typical architecture of recognition model for a sequence VAE in which only the last hidden state $h_n$ from encoder RNN is used as feature representation to compute the mean $\mu$ and variance $\sigma^2$ parameters of approximate posteriors $q_\phi(z|x)$. Right: Our proposed modification of how the feature vector $h_x$ for sequence $x$ is computed. Specifically, $h_x$ is now computed by performing pooling over the temporal dimension of all hidden states $h = [h_1, h_2, ..., h_n]$ output by RNN encoder, which is then used to compute parameters $\mu$ and $\sigma^2$ as usual.

In order to avoid adding more parameters to the model, we choose to experiment with various pooling functions. Since the attention mechanism is the prevalent method for many NLP-related tasks, pooling is not as widely used in NLP as in Computer Vision. However, there have been some successful applications of pooling in NLP, such as multi-task learning (Collobert and Weston, 2008) and learning pretrained universal sentence encoders (Conneau et al., 2017), and in some cases has shown superior performance over attention-based methods, particularly in settings where the size of the dataset is limited.

In the context of sequence VAE models, we perform pooling over the temporal dimension of hidden states $h = [h_1, h_2, ..., h_n]$ produced by the encoder RNN, as illustrated on the right side of Figure 1. We experiment with three variations of the pooling functions, first two of which are the commonly used average pooling (AvgPool) and max pooling (MaxPool). The last one performs max pooling based on the absolute values of each element while preserving the signs of the pooled elements, which we refer to as sign-preserved absolute pooling (AbsPool).

Specifically, for the $k$-th dimension of feature vector $h_x^k$, average pooling computes it by taking the mean of the $k$-th dimension across all hidden states, i.e. $h_x^k = \frac{1}{n} \sum_{i=1}^{n} h_i^k$. On the other hand, max pooling computes $h_x^k$ by taking the maximum value along $k$-th dimension, namely $h_x^k = \max(h_1^k, h_2^k, ..., h_n^k)$. For sign-preserved absolute pooling, $h_x^k$ is computed by taking the $h_i^k$ whose absolute value is the largest. Note that the sign of the selected $h_i^k$ is not modified in this case.

Note that there are other alternatives for the aggregate function. One option is to jointly learn a self-attention module to perform the aggregation (Yang et al., 2016). We also experimented with the attention-based approach and found that it is outperformed by the pooling-based methods. We suspect that it could be due to the fact that the attention mechanism adds a significant amount of parameters to the model and causes it to overfit more easily, thus creating more complications to the already challenging optimization problem.

4 Related Work

Prior work that aim to address posterior collapse roughly fall into the following two categories. The first line of work tries to analyze this issue from the optimization perspective. The other one focuses on the aspect of architectural design of the model.

Bowman et al. (2016) initially proposed to use a simple annealing schedule that starts with a small value and gradually increases to 1 for the KL term in the ELBO objective at the beginning of train-
Figure 2: Feature space visualizations for a typical sequence VAE and one plus pooling. For the regular SeqVAE, feature representations for all sequences have collapsed to a very small region in feature space. With pooling, the occupied region in feature space appears to be dense with variations preserved along each axis to various degrees.

...However in practice, this trick along is not sufficient to prevent posterior collapse. Later, Higgins et al. (2017) proposed $\beta$-VAEs for which the weight for KL term is considered as a hyperparameter and is usually set to be smaller than 1. Doing so could generally avoid posterior collapse, but at the cost of worse estimated NLLs. Most recently, Liu et al. (2019) proposed that posterior collapse is caused by the approximate posterior $q_\phi(z|x)$ lagging behind the intractable true posterior $p_\theta(z|x)$ during training, thus proposes to always train the encoder till convergence before updating to the generative model. The proposed architectural changes mainly focus on the decoder network and the choice of distributions of approximate posteriors. Semeniuta et al. (2017) and Yang et al. (2017) argued that posterior collapse was caused by the powerful autoregressive decoders and proposed to intentionally weaken the decoder, forcing it to rely more on the latent variables to reconstruct the input, which also leads to worse estimated data likelihood. Deng et al. (2019) proposed to add skip connections from the latent variables to lower layers of the decoder and proved that doing so increases the mutual information between data and latent codes. On the other hand, Kim et al. (2018) and Xu and Durrett (2018) argued that using multivariate Gaussian is inherently flawed and advocated for augmenting the amortized approximate posteriors with instance-based inference, or using completely different probability distributions for both the prior and approximate posterior. Additionally, Wang and Wang (2019) tried to address the limitation of the Gaussian assumption by transforming the latent variables with flow-based models and minimizing the Wasserstein distance between the marginal distribution and the prior directly.

5 Experiments

In this section, we first present evidence to support our hypothesis. Next, we report quantitative results on two text modelling benchmarks. We design additional experiments to gain more insights about various models and pooling operations.

5.1 Settings

We evaluate all models on two benchmark datasets for text modelling: Yahoo and Yelp (Yang et al., 2017). Both datasets consist of train, valid, and test partitions of 100k, 10k, and 10k sentences, with average sentence lengths of 78.76 for Yahoo and 96.01 for Yelp respectively.

Following the experiment settings from previous work (Kim et al., 2018; He et al., 2019), we employ a single-layer LSTM with 1024 hidden units for both the encoder and decoder with a latent space of 32 dimensions, unless specifically mentioned otherwise. For all models, we use an isotropic Gaussian $\mathcal{N}(0, I)$ as the prior and the recognition model parameterizes a multivariate Gaussian with diagonal covariance matrix. We use standard SGD with early stopping.
Figure 3: Pairwise cosine similarities between feature vectors and KL divergences for the validation sets. Notice that for regular SeqVAE models, the cosine similarities among different sequences remain at a higher level as the training progresses. As a result, the KL term quickly collapses to close to zero. On the other hand, pooling is able to maintain the dispersion in the feature space, thus helping to avoid posterior collapse.

5.2 Visualizing the Feature Space

Aiming to verify our intuition proposed in Section 3.1, we train two sequence VAE models whose encoders are parameterized by an LSTM with only three hidden units on the Yelp dataset, one with max pooling and the other one without. Although clearly not the optimal architectures, doing so would enable us to visualize the feature spaces produced by the encoders explicitly.

Figure 2 visualizes the feature spaces for the validation set. Notice that the standard sequence VAE maps all sentences to a very concentrated region in the feature space. On the other hand, the model with pooling can produce feature representations that are densely distributed with variabilities preserved to different degrees along each dimension. This verifies our intuition that posterior collapse is caused in part by overly similar feature representations produced by the encoders, which in turn lead to indistinguishable latent codes among different input sequences.

For the full models, since we are unable to visualize high dimensional spaces without losing information, we monitor the pairwise cosine similarities between feature vectors for sequences from the validation set. Figure 3 shows the average pairwise cosine similarities and the average KL divergence for both benchmark datasets during training.

Observe that for the regular sequence VAEs, the average pairwise cosine similarities among samples in the validation set remain at a higher level compared to the pooling models. As the training goes on, KL divergence is quickly pushed to take on small values by the optimization and gradually approach to zero, signalling the occurrence of posterior collapse. Whereas for the models equipped with pooling, the cosine similarities are kept at a lower level, suggesting more dispersive and diverse feature space. As a result, the KL terms plateaus at non-zero values.

5.3 Results

We performed experiments with various models on Yahoo and Yelp datasets. We report the approximate negative log likelihood (NLL) es-
| Model                      | Yahoo | Yelp |
|---------------------------|-------|------|
|                          | NLL   | NLL  | KL  | MI | AU | NLL | NLL  | KL  | MI | AU |
| LSTM-LM*                  | 328.0 | –    | –   | –  | –  | 358.1| –    | –   | 0.3| 0.3| 1  |
| SeqVAE                    | 328.6 | 0.0  | 0.0 | 0.0| 0  | 358.1| 0.3  | 0.8| 1  |
| SeqVAE + WordDrop         | 330.7 | 5.4  | 3.0 | 6  | 362.2| 1.0  | 0.8 | 1  |
| SkipVAE                   | 328.1 | 4.5  | 2.4 | 11 | 357.4| 2.5  | 1.5 | 4  |
| WAE-RNF**                 | 339.0 | 3.0  | –   | –  | –  | 362.2| 0.3  | 0.8| 1  |
| SeqVAE + Cyclical         | 328.6 | 0.0  | 0.0 | 0  | 358.4| 0.4  | 0.3 | 1  |
| SeqVAE + Aggressive       | 326.7 | 5.7  | 2.9 | 15 | 355.9| 3.8  | 2.4 | 11 |
| SeqVAE + AvgPool          | 327.8 | 2.4  | 1.6 | 5  | 357.5| 1.6  | 1.2 | 5  |
| SeqVAE + AbsPool          | 327.4 | 3.6  | 2.4 | 8  | 356.6| 2.0  | 1.7 | 7  |
| SeqVAE + MaxPool          | 327.2 | 3.7  | 2.5 | 9  | 356.0| 3.1  | 2.2 | 8  |
| iVAE                      | –     | 309.5| 8.0 | 4.4| 32 | –   | 348.2| 7.6| 4.6| 32 |
| iVAEMI                    | –     | 309.1| 11.4| 10.7|32| –   | 348.7| 11.6| 11.0|32 |

Table 1: Experiment results on the Yahoo and Yelp datasets. For the LSTM-LM*, we report the exact negative log likelihood. For the WAE-RNF**, we only show the results on Yahoo reported by Wang and Wang (2019) as their experiments on Yelp were conducted on a different version of the dataset. Also note that the estimated negative log likelihood in iVAE (Fang et al., 2019) cannot be directly compared with the estimated NLL from previous methods since iVAE uses a lower bound on the typical negative ELBO, which could under-estimate its NLL comparing to other methods. For this reason, we use NLL for NLL estimated from negative ELBO in previous methods, and use NLL for iVAE. For a more detailed explanation of the difference, please refer to Section B of the appendix.

|         | Yahoo | Yelp |
|---------|-------|------|
|         | Hours | Updates | Hours | Updates |
| aggr.   | 14.55 | 608k    | 18.62| 625k   |
| pool.   | 5.06  | 199k    | 6.00 | 196k   |

Table 2: Computation costs of aggressive training vs model with pooling. The cost of aggressive training is nearly triple that of a simple architecture change.

Ultimately what we want from a model is lower negative log likelihood (with non-zero KL divergence) since that is a direct indication of how well our models capture the data distribution.

We compare our models with the following methods from the existing literature: SkipVAE (Dieng et al., 2019), WAE-RNF (Wang and Wang, 2019) which make modifications to decoders or variational distributions; and Cyclical Annealing (Liu et al., 2019), Aggressive Training (He et al., 2019) which aim to prevent posterior collapse with new optimization schemes. Additionally, we train two baseline SeqVAE models: one only with KL annealing; and the other with both KL annealing and Word Dropout as in Bowman et al. (2016). All models, including various models from the literature, are trained following a simple linear KL annealing schedule at early stage of training except for the model trained with the cyclical annealing schedule.

Note that recently Fang et al. (2019) proposed a variation of sequence VAEs that utilizes implicit distributions as their choice of variational posteriors, which they named implicit VAE (iVAE). At the first glance, their model achieved impressive results and improved upon the previous state-of-
the-state by a large margin. However, it is worth mentioning that their claimed results NLL is in fact a lower bound on the true NLL of the data and thus cannot be directly compared to the results of other models (see Section B in the appendix).

Table 1 shows the experiment results of various models. We observe that pooling can effectively prevent posterior collapse while achieving significantly lower estimated NLLs compared to standard sequence VAEs, with max pooling offering the best performances for both datasets. Applying heavy word dropout leads to non-zero KL term but also worse log likelihood, suggesting the model has also converged to a different undesirable local optimum. Although better than the baseline model, average pooling provides the least amount of improvement compared to the other two methods. The gap is noticeably more significant on Yelp, which aligns our intuition that average pooling is likely to produce less dispersion over longer sequences due to the central limit theorem.

We also see that our methods outperform both SkipVAE and WAE-RNF, which suggests that certain proposed architectural changes might not be necessary to improve upon the original sequence VAE models with Gaussian distributions. Liu et al. (2019) reported promising results for text modelling on the relatively simple Penn Tree Bank (PTB) dataset with their proposed cyclical annealing schedule. However as we can see the success is not carried over when applying their method to more complex data. Aggressive training gives the best estimated NLLs on both datasets, our methods are able to achieve comparable performances, particularly on the more challenging Yelp dataset where the average sequence length is much longer, while being significantly more computationally efficient, as shown in Table 2.

5.4 Comparison with Aggressive Training

From Table 1, we see that pooling and aggressive training are able to offer much bigger improvements to the standard sequence VAE models compared to other baseline models. To better understand the connections between these two methods, we again monitor the pairwise cosine similarities averaged over the validation set as the training progresses, which is illustrated in Figure 4.

We observe that for both aggressive training and max pooling, the average pairwise cosine similarities among feature representations produced by the encoder are kept at a lower level as opposed to the baseline model, which indicates that aggressive training is also able to increase the dispersion in feature space. Therefore the effectiveness of aggressive training could also be attributed in part to our main intuition, with the difference that aggressive training achieves the same effect by adopting a more costly optimization scheme which triples the compute costs comparing to our method.

5.5 Importance of KL Annealing

As mentioned previously, the experiment results of various models presented in Section 5.3 were achieved with KL annealing, which is necessary to achieve the best possible data log likelihood. As a matter of fact, it is often used together with the proposed algorithms in order to achieve the best possible results. To illustrate the importance of KL annealing, we compare the estimated NLLs of SkipVAE, Aggressive Training, and MaxPool when trained without and with KL annealing.

As shown in Table 3, KL annealing is indeed rather important and necessary if we want a model
| Dataset | Pool. | Origin | Shuffle | Diff. |
|---------|-------|--------|---------|------|
| Yahoo  | None  | 328.6  | 328.7   | 0.1  |
|         | Avg   | 327.8  | 328.0   | 0.2  |
|         | Abs   | 327.4  | 327.7   | 0.3  |
|         | Max   | 327.2  | 327.3   | 0.1  |
| Yelp    | None  | 358.1  | 358.1   | 0.0  |
|         | Avg   | 357.5  | 357.8   | 0.3  |
|         | Abs   | 356.6  | 356.8   | 0.2  |
|         | Max   | 356.0  | 356.7   | 0.7  |

Table 4: Estimated negative log likelihoods on test data. Results in the Shuffle column are computed by randomly permuting the input to the encoders.

that better captures the data distribution. Note that in most cases, the gap for estimated NLLs between whether using it or not is rather significant, suggesting that KL annealing might be able to help the model to better explore during early stage of learning and eventually reach better local optimum. Additional research is needed to better understand the effects of KL annealing in optimizing variational models and why it is so crucial for reaching a better local optimum of ELBO.

5.6 Does Order Matter?

One concern that arises regarding pooling is that it could destroy order information contained in the hidden states. If this was indeed the case, then the model would merely learn to encode nothing more than bag-of-words representations of the input sequences in the latent space. To examine this hypothesis, we evaluate all trained models under a setting where input sequences to the encoder RNNs are randomly permuted. If the hypothesis holds, the effects of such permutations on performance should be limited for models with pooling.

Table 4 compares the estimated NLLs of various models evaluated on the original and the shuffled input. We observe that on both datasets, models with pooling are at least just as negatively impacted by the permutations as the standard model, showing that the latent space clearly captures information beyond simply bag of words. Interestingly, the estimated NLLs evaluated on permuted input are still much lower than that of the baseline model evaluated on the original input sequences. This suggests that pooling might potentially help the models to capture high-level global features that are equivariant with respect to word order.

6 Conclusion

In this paper, we analyze posterior collapse from the perspective of encoder features. We argue that the problem is caused in part by overly similar representations produced by the encoders, which in turn, lead to nearly indistinguishable samples from the approximate posteriors. Since the latent variables convey no useful information about the data, optimization will push the approximate posteriors towards prior to minimize the KL term and the overall ELBO objective, eventually causing approximate posteriors to collapse completely onto the prior.

We verify this hypothesis and propose a simple architectural change that utilizes pooling operations, which can effectively prevent the model from reaching collapsed solutions while achieving significantly lower estimated NLLs without additional computation costs.

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Appendix

A Text Classification

To see whether the latent codes from improved unsupervised learning lead to better downstream task performance, we train a set of classifiers on the Yelp dataset, which comes with labels for all
sentences, with labels from 1 to 5 representing the scores for restaurant reviews. For sequence $x$, we take the mean and variance produced by the recognition models, concatenate them together and use as the feature $\tilde{h}_x$ for a 3-layer MLP followed by a softmax activation layer, i.e. $\tilde{h}_x = [\mu_x, \sigma^2_x]$. The parameters of the recognition models are kept frozen, only the parameters of the MLPs are optimized with the supervised signals.

As a supervised baseline, we train a 1-layer bi-LSTM followed 3-layer MLP of the same size. The number of parameters for the bi-LSTM is kept roughly comparable to the LSTM used to parameterized recognition models in SeqVAEs. Note that the baseline has more learnable parameters. The baseline has more learnable parameters. The implication is that the estimated NLL from Fang et al. (2019) cannot be directly compared with previous methods. We provide an overview of the work by Fang et al. (2019), followed with a detailed analysis of the caveat regarding their method and why their experimental results for NLL are not to be directly compared to previous works.

The model proposed by Fang et al. (2019) is a variation of the sequence VAEs that utilizes implicit distributions as their choice for variational posteriors instead of the commonly used Gaussian distributions. The key idea is rooted on the dual form of KL divergence based on the Fenchel duality theorem (Dai et al., 2018):

$$D_{KL}(q(\phi | x) | p(\phi)) = \max_{v \in F_+} \mathbb{E}_{z \sim q_{\phi}(\phi)}[v(x, z)] - \mathbb{E}_{z \sim p}[\exp(v(x, z))] + 1$$

where $v(x, z)$ is an auxiliary dual function in function space $F_+$ which contains all positive functions.

The dual form would enable us to compute the KL term using samples from the approximate posterior and the prior rather than analytically in the Gaussian case. Fang et al. (2019) reported experimental results on text modelling which improved upon the previous state-of-the-art by very large margins on standard benchmark datasets. Please refer to Section 5.1 of their paper for more details.

The caveat is that the equality between the true $D_{KL}(q(\phi | x) | p(\phi))$ and its dual form only holds if the dual function was the optimal one in the defined function space. For their implementation, Fang et al. (2019) use a fixed-capacity neural network to parameterize the dual function $v(x, z)$, which only covers a small subset of the function space. This automatically renders the corresponding $\overline{D}_{KL}(q(\phi | x) | p(\phi))$ computed using the dual form a lower bound on the true value of the KL term. Additionally, their parameterized $v(x, z)$ is jointly trained with the rest of the model; in practice there is no guarantee that the optimization would be able to find the optimal function in even this small subset of the function space.

Therefore we have the following inequality:

$$\overline{D}_{KL}(q(\phi | x) | p(\phi)) \leq D_{KL}(q(\phi | x) | p(\phi))$$

| Model                          | Accuracy |
|--------------------------------|----------|
| bi-LSTMs                       | 59.92%   |
| SeqVAE (Yelp)                  | 26.19%   |
| SeqVAE + MaxPool (Yelp)        | 53.40%   |
| SeqVAE + MaxPool (Yahoo)       | 40.67%   |

Table 5: Test accuracies on Yelp. Our models with unsupervised pre-trained encoders are able to achieve reasonable performances compared to the fully supervised baseline.

\section{Caveat About Implicit VAEs}

In this section, we show why the negative ELBO used as objective function and evaluation criteria from Fang et al. (2019) is a lower bound on the negative ELBO of typical VAEs. The implication is that the estimated NLL from Fang et al. (2019) cannot be directly compared with previous methods. We provide an overview of the work by Fang et al. (2019), followed with a detailed analysis of the caveat regarding their method and why their experimental results for NLL are not to be directly compared to previous works.

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Therefore we have the following inequality:

$$\overline{D}_{KL}(q(\phi | x) | p(\phi)) \leq D_{KL}(q(\phi | x) | p(\phi))$$
Adding the reconstruction error to both sides:

\[-\mathcal{L}(x) = -\mathbb{E}_{q_{\phi}(z|x)}[\log p_{\theta}(x|z)] + D_{KL}(q_{\phi}\|p)\]
\[\leq -\mathbb{E}_{q_{\phi}(z|x)}[\log p_{\theta}(x|z)] + D_{KL}(q_{\phi}\|p)\]
\[= -\mathcal{L}(x)\]

In other words, the negative ELBO \(-\mathcal{L}(x)\) that we obtain using the dual form is in fact also a lower bound on the true negative ELBO \(-\mathcal{L}(x)\). In the most extreme case, \(-\mathcal{L}(x)\) could even be sitting below the true negative log-likelihood of the data, which would be problematic as it is meaningless to minimize a lower bound on the NLLs.

The same reasoning also applies to their evaluation. Since the results claimed in Fang et al. (2019) were computed using the learned dual function \(v\), their reported negative ELBOs and in turn their estimated NLLs are a lower bound on the true NLLs of the data, thus \(\text{NLL} \leq \text{NLL}\). Given the tools that we currently have in learn theory, it is not trivial, if not impossible, to quantify the exact gap between this lower bound and the true negative log-likelihoods. Therefore it is unfair to compare their reported lower bound on NLLs with the exact results of other models that follow the Gaussian assumption with analytical solutions to the KL terms.

We choose to present the reported results of implicit VAEs for the sake of completeness in terms of comparison. However we would like to point out this caveat of their method and their evaluation so that progress that is made in this direction can be assessed appropriately.