Probabilistic Natural Language Generation with Wasserstein Autoencoders

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Abstract

Probabilistic generation of natural language sentences is an important task in NLP. Existing models such as variational autoencoders (VAE) for sequence generation are extremely difficult to train due to the issues associated with the Kullback-Leibler (KL) loss collapsing to zero. One has to implement various heuristics such as KL weight annealing and word dropout in a carefully engineered manner to successfully train a text VAE. In this paper, we propose the use of Wasserstein autoencoders (WAE) for probabilistic natural language sentence generation. We show that sequence-to-sequence WAEs are more robust towards hyperparameters and can be trained in a straightforward manner without the need for any weight annealing. Empirical evidence shows that the latent space learned by WAEs exhibits properties of continuity and smoothness as in VAEs, while simultaneously achieving much higher BLEU scores for sentence reconstruction.

1 Introduction

Natural language generation in the deep learning regime typically involves building a recurrent neural network (RNN) that predicts the most probable next word given previous words (Mikolov et al., 2010, 2011). Such RNN architecture can be further conditioned on some source information, for example, an input sentence, resulting in a sequence-to-sequence (Seq2Seq) model (Sutskever et al., 2014).

Traditionally, natural language generation is accomplished in a deterministic fashion. That is to say, the Seq2Seq model uses a deterministic neural network to encode an input sentence to some hidden representations, from which it then decodes an output sentence using another neural network.

Bowman et al. (2016) propose to use variational autoencoders (Kingma and Welling, 2014, VAE) to map an input sentence onto a probabilistic continuous latent space, making it possible to generate sentences from a distribution. In many applications, such probabilistic natural language generation is desired. For example, in an open-domain dialog system, the information of an utterance and its response is not necessarily a one-to-one mapping. Multiple plausible responses are suitable for a given input. Probabilistic natural language generation makes the dialog system more diversified and more meaningful (Serban et al., 2017; Bahuleyan et al., 2018). Besides, probabilistic modeling of the hidden representations serves as a way of posterior regularization (Zhang et al., 2016), facilitating linear interpolation (Bowman et al., 2016) or manipulation of the latent representation (Hu et al., 2017).

However, training VAEs for sequence generation in NLP is extremely difficult, in contrast to VAEs in the image domain (Kingma and Welling, 2014; Kulkarni et al., 2015). The training of VAE requires that given an input sentence, the posterior of the latent space is close to its prior, where closeness is measured by the Kullback-Leibler (KL) divergence. An important observation of Seq2Seq VAEs is that the KL term tends to vanish to zero during training (Bowman et al., 2016; Yang et al., 2017), resulting in an ineffective latent space. To alleviate the problem, Bowman et al. (2016) propose several heuristics, including performing word dropout and annealing the weight of the KL loss. These heuristics have a variety of parameters that must further be tuned, e.g. word drop rate, annealing strength, schedule, and the beginning and...
end time steps of annealing. In practice, one needs to carefully engineer this training procedure, and the resulting protocol differs from one study to another (Zhou and Neubig, 2017; Xu et al., 2017; Bahuleyan et al., 2018). Therefore, training VAEs for text generation is considered to be difficult.

In this paper, we address the problem of stochastic encoding in VAE combined with autoregressive decoders, and propose to use Wasserstein autoencoders (Tolstikhin et al., 2018, WAE) for probabilistic generation of natural language sentences. WAE modifies VAE in that it requires the integration of the posterior distribution to be close to its prior, where the closeness is measured based on empirical samples. In this way, we could simply use a deterministic encoder, but still retain probabilistic properties. This is particularly useful for natural language generation as it circumvents the difficult-to-train variational latent space.

Experimental results show that the sentences generated by WAE exhibit properties of continuity and smoothness as in VAE, while achieving a much higher reconstruction performance. More importantly, WAE is robust to hyperparameters and much easier to train, without having to anneal the penalty term.

2 Probabilistic Sequence Generation

In this section, we describe probabilistic sequence generation in detail. We first start from the base model, deterministic autoencoder, in Subsection 2.1. Then we describe variational and Wasserstein autoencoders in Subsections 2.2 and 2.3, respectively.

2.1 Base Model: Deterministic Autoencoder

A deterministic autoencoder (DAE) encodes a sentence as input using a recurrent neural network (RNN) and then decodes the same sentence by another RNN, illustrated in Figure 1a. In our work, we use long short term memory (LSTM) as the RNN transition (Hochreiter and Schmidhuber, 1997).

For the encoder, the hidden state of the last word is represented as the latent space of the input sentence $x$. The latent representation is denoted as $z$. We feed $z$ to the decoder RNN which predicts one word at a time using a softmax layer $p(x_t|z, x_{<t}) = \text{softmax}(W h_t^{(de)} + b)$, where $W$ and $b$ are parameters, and $h_t^{(de)}$ is the hidden state at time step $t$ of the decoder. The training objective for DAE is the cross-entropy loss, given by

$$ J = - \sum_{n=1}^{N} \sum_{t=1}^{N} \log p(x_t^{(n)}|z^{(n)}, x_{<t}^{(n)}) $$  (1)

where superscript $(n)$ denotes the $n$th data point.

In DAE, the latent space is encoded and then decoded in a deterministic way. That is to say, there is no probabilistic modeling of the hidden space. The data points may be projected onto an arbitrary manifold in the hidden space (Figure 1b), which is not suitable for probabilistic natural language generation.

2.2 Variational Autoencoder

The variational autoencoder (VAE), proposed in Kingma and Welling (2014), extends DAE by imposing a prior distribution $p(z)$ on the latent variable $z$, which is typically set to the standard normal $\mathcal{N}(0, 1)$. Given an input sentence $x$, we would like to model the posterior of $z$ by another normal distribution, $q(z|x) = \mathcal{N}(\mu_{post}, \sigma_{post})$, where $\mu_{post}$ and $\sigma_{post}$ are the output of the encoder.

In the training of VAE, $z$ is sampled from $q(z|x)$, and the training objective is to optimize the (expected) reconstruction loss similar to Equation (1), while being regularized by the KL divergence between $q(z|x)$ and $p(z)$, given by

$$ J = \sum_{n=1}^{N} \left[ - \mathbb{E}_{z^{(n)} \sim q} \sum_{t=1}^{N} \log p(x_t^{(n)}|z^{(n)}, x_{<t}^{(n)}) + \lambda_{\text{VAE}} \cdot \text{KL}(q(z^{(n)}|x^{(n)})||p(z)) \right] $$  (2)
where $\lambda_{\text{VAE}}$ is a hyperparameter balancing the two terms.

Since VAEs penalize the divergence of $z$’s posterior from its prior, it serves as a way of posterior regularization, making it possible to generate sentences from the continuous latent space (Bowman et al., 2016).

However, as argued by Tolstikhin et al. (2018), the two objectives in (2) are contradictory to each other. VAE pushes the posterior of $z$ given any input $x^{(n)}$ to be close to its prior, i.e., every blue ellipse in Figure 1c should be close to the red one. This makes perfect reconstruction impossible.

We would also like to provide another intuitive explanation of why VAE is especially difficult to train in NLP. Generating a sentence (a sequence of words) is an auto-regressive process, i.e., future words depend on previous words, and the total loss is the sum of the loss of all words. During backpropagation, the decoder RNN is easy to train (except for the first few steps) due to its auto-regressiveness and exact gradient. On the other hand, the training of the encoder is much harder because this involves stochastic sampling in the latent space (refer Figure 2.2). If the reconstruction loss and KL loss in (2) are not properly balanced, VAE might simply fit $z$’s posterior to its prior and learn a language model for the decoder. In this case, the KL loss is minimized to zero. The reconstruction loss may be comparatively high for the first few words, but is reasonably low for future words due to auto-regressiveness. This is precisely what we observe for the “KL collapse” problem.

Existing optimization tricks of KL annealing and word dropout alleviate the problem from different points of view. KL annealing makes latent space less stochastic at the beginning of the training, so that we can propagate gradient better to the encoder. Word dropout randomly substitutes a word on the decoder side with a special token <UNK>, which diminishes the auto-regressiveness of the decoding process. In short, stochastic sampling from the latent space is generally not desired for the auto-regressive decoder.

### 2.3 Wasserstein Autoencoder

In this section, we seek a non-stochastic encoder for probabilistic sentence generation. A recently proposed alternative to VAE is the Wasserstein autoencoder (Tolstikhin et al., 2018, WAE).

Generally, WAE imposes a constraint that the marginal posterior of $z$ should be the same as its prior, i.e., $q(z) \triangleq \sum_x q(z|x)p(x) \approx p(z)$. By contrast, VAE requires that $q(z|x)$ should be close to $p(z)$ for every input sentence $x$.

For computational purposes, WAE relaxes the above constraint by penalizing some distance between $q(z|x)$ and $p(z)$. In particular, Maximum Mean Discrepancy (MMD) is used to measure the distance, defined as

$$\text{MMD} = \left\| \int k(z, \cdot) dP(z) - \int k(z, \cdot) dQ(z) \right\|_{\mathcal{H}_k}$$

where $\mathcal{H}_k$ refers to the reproducing kernel Hilbert space defined by the kernel $k$, which is often chosen as the inverse multiquadratic kernel $k(x, y) = \frac{C}{C + \|x - y\|_2^2}$ for high-dimensional multivariate normal distributions.

One benefit of MMD is that it can be estimated with empirical samples:

$$\hat{\text{MMD}} = \frac{1}{N(N-1)} \sum_{n \neq m} k(z^{(n)}, z^{(m)}) + \frac{1}{N(N-1)} \sum_{n \neq m} k(\tilde{z}^{(n)}, \tilde{z}^{(m)}) - \frac{1}{N^2} \sum_{n, m} k(z^{(n)}, \tilde{z}^{(m)})$$

where $z^{(n)}$ is a sample from the prior $p(z)$; $\tilde{z}^{(n)}$ is a sample from the marginal posterior $q(z^{(n)})$.

Tolstikhin et al. (2018) further suggest to use a deterministic function to encode the hidden representation as $\tilde{z}^{(n)} = f_{\text{encoder}}(x^{(n)})$, where $x^{(n)}$ is a data sample. In summary, the training objective of Wasserstein autoencoder is

$$J = -\sum_{n=1}^{N} \sum_{t=1}^{|x^{(n)}|} \log p(x_t^{(n)} | \tilde{z}^{(n)}, x_{<t}^{(n)}) + \lambda_{\text{WAE}} \hat{\text{MMD}}$$

(4)
where \( \lambda_{\text{WAE}} \) balances the MMD penalty and the reconstruction loss.\(^1\)

Although the Wasserstein autoencoder itself is not new to this paper, we have successfully applied WAE with a deterministic autoencoder to Seq2Seq scenarios.

Our paper also makes the point that non-stochastic encoding is particularly desired for the Seq2Seq model due to its auto-regressiveness. WAE circumvents the stochastic modeling of \( z \) by working with its marginal posterior, where the marginalization is taken over input \( x \) with a deterministic transformation from \( x \) to \( z \). We will show in the following section that WAE not only improves the performance but also stabilizes the training of probabilistic generation.

3 Experiments

3.1 Dataset and Settings

This section describes the autoencoding experiments carried out with the three models under comparison. In our study, we used a subset (100k sentences) of the Stanford Natural Language Inference (SNLI) dataset (Bowman et al., 2015) as the corpus, with a train/validation/test split of 90k/5k/5k, respectively.

The neural model is a single-layer RNN with 100d LSTM units for both encoder and decoder. For the DAE and WAE, the output of the encoder LSTM at the final timestep is set to be the latent vector \( z \). For the VAE, the encoder output is first transformed to obtain two separate vectors, \( \mu_{\text{post}} \) and \( \sigma_{\text{post}} \), both of which are of 100 dimensions. The latent vector is then computed as \( z = \mu_{\text{post}} + \epsilon \circ \sigma_{\text{post}}, \) where \( \epsilon \sim \mathcal{N}(0, I) \), where \( \circ \) refers to element-wise product.

We adopt 300d pretrained word embeddings (Mikolov et al., 2013), with a vocabulary of 20k most frequent words in the corpus. All models were trained with the Adam optimizer (Kingma and Ba, 2014) with \( \beta_1 = 0.9, \beta_2 = 0.999 \), and a constant learning rate of 0.001.

VAE training details. VAE is notoriously difficult to train in the Seq2Seq setting. We adopt several tricks to stabilize the training: (1) The coefficient \( \lambda_{\text{VAE}} \) was annealed in a sigmoid manner. We monitored the value of \( \lambda \cdot \text{KL} \) and stopped annealing once it reached its peak value. (2) For word dropout, we started with no dropout, and gradually increased the dropout rate by 0.05 every epoch until 0.5.

Besides, we also show the performance of a VAE trained without annealing, that is, the KL weight remains a constant throughout the training. In this case, we only tuned the strength of the KL term as measured by the coefficient \( \lambda_{\text{VAE}} \).

3.2 Overall Results

We compare WAE with DAE and VAE in terms of multiple metrics. Table 1 shows the overall results. We tabulate the results with two variants of WAE, setting \( \lambda_{\text{WAE}} \) to be 3.0 and 10.0, respectively. In this subsection, we focus on the setting in Tolstikhin et al. (2018) where \( \lambda_{\text{WAE}} = 10.0 \).

Reconstruction. We begin by analyzing the reconstruction performance of the three autoencoders. This is evaluated by calculating the BLEU scores of reconstructed sentences with respect to the groundtruth sentences.

We see that DAE achieves the best BLEU score (73.66). This is not surprising because DAE directly optimizes the maximum likelihood of data, which can be viewed as a surrogate of word prediction accuracy. VAE and WAE have additional penalty that departs from the goal of reconstruction. However, we see WAEs achieve very close results (72.72 and 68.82), whereas VAE is much worse (31.77). This is because VAE pushes every posterior to its prior, from which it is theoretically impossible to reconstruct the data.

Generating sentences from the latent space. In this part, we evaluate the quality of probabilistic sentence generation. For WAE and VAE, we sample a latent vector \( z \) from the prior \( \mathcal{N}(0, I) \) and then decode a sentence. Although there is no probabilistic modeling of the latent space in DAEs, we nevertheless draw samples from \( \mathcal{N}(0, I) \), which could serve as a non-informative prior.

The first evaluation metric we used is the negative log-likelihood (NLL) of sentences to show the fluency of generated sentences. NLL is evaluated with a tri-gram language model trained on WMT18 English corpus.\(^2\) Since the NLL metric here is not computed by any related neural network, it would be a fair metric to compare DAE,
Table 1: Overall performance of the Wasserstein autoencoder (WAE) compared with the deterministic autoencoder (DAE) and the variational autoencoder (VAE). For Entropy and AvgLen, the closer to corpus statistics, the better.

|               | BLEU | NLL  | UnigramKL | Entropy | AvgLen |
|---------------|------|------|-----------|---------|--------|
| Corpus        | -    | 9.92 | -         | 5.65    | 9.7    |
| DAE           | 73.66| 13.71| 0.180     | 5.94    | 13.3   |
| VAE           | 31.77| 11.52| 0.125     | 4.95    | 9.1    |
| WAE ($\lambda_{\text{WAE}} = 3.0$) | 72.72| 12.04| 0.078     | 5.52    | 10.0   |
| WAE ($\lambda_{\text{WAE}} = 10.0$) | 68.82| 11.74| 0.079     | 5.54    | 9.9    |

Figure 3: Learning curves of the KL term in the VAE loss function ($\lambda \cdot$KL) for different values of $\lambda$, and the variant where $\lambda$ is annealed.

Table 1: Overall performance of the Wasserstein autoencoder (WAE) compared with the deterministic autoencoder (DAE) and the variational autoencoder (VAE). For Entropy and AvgLen, the closer to corpus statistics, the better.

From Table 1, we see that this time VAE has the best performance among the models. The lowest NLL score (11.52) shows that it generates the most fluent sentences (although not as fluent as humans, i.e., the corpus NLL of 9.92). WAE is slightly worse (12.04 and 11.74), but still comparable. DAE yields an NLL score of 13.3, significantly worse than both VAE and WAE. This shows that the latent space of DAE is less regularized, which makes DAE not suitable for sampling a sentence from the latent space. On the other hand, VAE and WAE probabilistically model the latent space, resulting in more fluent generated sentences.

Next, we evaluate how close the generated sentences are to the corpus distribution. Ideally, we would like to evaluate population sentence distributions, but it is infeasible to measure due to the sparseness of the sentence space. As a surrogate, we work with corpus-level unigram distributions, i.e., we measure the KL divergence between the generated and the true unigram distributions. This is milder than the (intractable) sentence distribution, as a zero KL of unigram distributions is a necessary but not sufficient condition for a zero KL of sentence distributions. A good generative model should be able to produce sentences that come from a similar distribution as the original corpus. We also report the entropy and average length (AvgLen) of sentences as auxiliary metrics.

These statistics consistently support the fact that WAEs generate sentences closest to the corpus, while being robust with respect to the hyperparameter $\lambda_{\text{WAE}}$. DAE is the worst due to its lack of probabilistic modeling, as expected.

**Case Study.** Next, we qualitatively analyze the learnt latent space. Table 2 shows sentences generated by randomly sampling points in the latent space for the three models, along with sample sentences from the training set. Since both WAEs are of equal quality, we use the one with $\lambda_{\text{WAE}} = 10.0$ for reporting purposes. The sentences generated by the VAE tend to be slightly better than the
the family is walking away from the pond.
the little kids all play and jump around inside the inflatable toy.
two people are outside talking to each other.
a girl learns to play softball.
the man flying an airplane.

| Training Samples | WAE |
|------------------|-----|
| a child in a sky suit and white skirt. | two women are standing on a busy street outside a fair. |
| a tourists is having fun on a sunny day | the wheel is on all girl. |
| women kneeling in front of a bus station. | |

| DAE | VAE |
|-----|-----|
| a road dressed with a biker is lying all wide his foot. | a woman wearing white shorts climbs the stairs. |
| the gray is pole changing three occupied to her beach-goers play. | the band is performing for a concert |
| a woman wearing white shorts climbs the stairs. | a dog is sleeping. |
| a lady approaches a bored while older school is at a stool. | guy is watching others work |
| middle stage jump that leads to hug her barefoot girl. | two boys are trying to figure out. |

Table 2: Sentences generated by random sampling for different models.

WAE. In some cases, the WAE generates new sentences that seem to be less accurate. The DAE produces sentences that are visibly longer and also meaningless which is expected since there is no learnt latent space.

3.3 The Difficulty of Training

In this part, we compare the difficulty of training VAE and WAE.

It is a common practice that training Seq2Seq VAEs involve KL annealing and word dropout, which further consists of hacks for tuning hyperparameters. We conducted an experiment of training VAE without KL annealing. In Figure 3, we present the KL loss (weighted by $\lambda_{VAE}$) during the training process for different values of $\lambda_{VAE}$. The KL loss is believed to be an important diagnostic measure to indicate if the latent space is “variational” (Yang et al., 2017; Higgins et al., 2017; Burgess et al., 2017). We see that if the penalty is too large, KL simply collapses to zero, ignoring the entire input. On the other hand, if the KL penalty is too small, the model tends to become more deterministic and the KL term does not play an important role in the training. This is expected since in the limit of $\lambda_{VAE}$ to 0, the model ignores the KL term and becomes a deterministic autoencoder. Moreover, empirically, such a model does not exhibit interesting properties such as random sampling for probabilistic sequence generation (Bowman et al., 2016).

In contrast, WAEs for sequence-to-sequence models are trained without any additional optimization strategies such as annealing. WAEs are also robust to their hyperparameters, as the results are comparable when $\lambda_{WAE} = 10.0$ and $\lambda_{WAE} = 3.0$.

4 Conclusion

In this paper, we propose the use of Wasserstein autoencoders (WAEs) for probabilistic natural language sentence generation. The WAE is compared to existing generation models, specifically the variational autoencoder (VAE) and the deterministic autoencoder (DAE). Based on quantitative and qualitative evaluation, we observe that the latent space learnt by WAE produces sentences of similar quality and fluency as that of VAE. In contrast to VAE, which is extremely difficult to train due to issues associated with the KL loss collapsing to zero, we show that a Seq2Seq WAE is much more robust to its hyperparameters and can be trained in a straightforward manner.

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