Representation Learning in Sequence to Sequence Tasks: Multi-filter Gaussian Mixture Autoencoder

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Abstract

Heterogeneity of sentences exists in sequence to sequence tasks such as machine translation. Sentences with largely varied meanings or grammatical structures may increase the difficulty of convergence while training the network. In this paper, we introduce a model to resolve the heterogeneity in the sequence to sequence task. The Multi-filter Gaussian Mixture Autoencoder (MGMAE) utilizes an autoencoder to learn the representations of the inputs. The representations are the outputs from the encoder, lying in the latent space whose dimension is the hidden dimension of the encoder. The representations of training data in the latent space are used to train Gaussian mixtures. The latent space representations are divided into several mixtures of Gaussian distributions. A filter (decoder) is tuned to fit the data in one of the Gaussian distributions specifically. Each Gaussian is corresponding to one filter so that the filter is responsible for the heterogeneity within this Gaussian. Thus the heterogeneity of the training data can be resolved. Comparative experiments are conducted on the Geo-query dataset and English-French translation. Our experiments show that compares to the traditional encoder-decoder model, this network achieves better performance on sequence to sequence tasks such as machine translation and question answering.

1 Introduction

Semantic parsing comprises translating sentences into various kinds of formal representations, with the goal of executing these to compute a result in the context of an environment such as a knowledge base. It generally converts natural languages into machine-understandable representations. The representations should preserve the meanings of the words/sentences. Semantic parsing can be applied to many aspects such as machine translation, question answering, automated reasoning, and code generation. Generally, an encoder-decoder model is used for semantic parsing.

The encoder-decoder model is one of the techniques for semantic parsing. The encoder-decoder model is a technique of applying recurrent neural networks to sequence-to-sequence prediction problems. It was originally developed for machine translation problems. Then, the model achieves good performances at other related sequence-to-sequence prediction problems.

However, the encoder-decoder model lacks the potential on generating representations. Then, an autoencoder is introduced for representation learning. An autoencoder is a type of deep neural network that is trained in a supervised manner. It is used to reconstruct the input in a pre-defined way(Kramer, 1991). Internally, it has a hidden layer that used to represent the input(Goodfellow et al., 2016). In between the encoder and decoder, there is a latent space. In the latent space, words or sentences are typically represented by low-dimensional vectors, where the words or sentences with similar meanings are close to each other. Thus, better results may be obtained by analyzing the data on the latent space, such as the distance between vectors (sentence similarities).

Because of these properties, autoencoder is commonly used in representation learning. Representation learning, also known as feature learning, is a set of techniques that allows a system to automatically determine the representations needed for feature detection or classification from raw data(Bengio et al., 2014).

In sequence to sequence tasks, an autoencoder is a model where its inputs and outputs are the same. This technique is known as self-supervised learning, where the input data is the target data. One goal for self-supervised learning is to learn the representations of the input data.

1Code: https://github.com/yunhaoyang234/MGMAE
The representations are the outputs of the encoder, lying in the latent space. Latent space refers to an abstract multi-dimensional space containing feature values that cannot be interpreted directly. Instead, the values in the latent space are meaningful internal representations that are encoded from some externally observed data. The latent space intends to provide data that is machine recognizable/understandable to a computer through a quantitative spatial representation or modeling.

Latent space can be considered as a set of hidden features or internal representations over the input data, thus a small variation in the latent space may be caused by a large difference in the input data. The process of learning a latent space is to tune the parameters within the encoder and decoder to obtain a better representation of the data. A well-learned latent space would help the machine learning model better understanding the features and easily identifying the principal components of the data.

2 Related Work

Encoder-decoder network is one of the classical model for solving sequence to sequence tasks such as machine translation. In machine translation, an encoder on the language can create inner representations and a decoder then unveil these coding into desired output(Cvetko, 2020). The purpose of machine translation relevant tasks is to obtain a semantic isomorphism (eg. similar syntax structure). If the semantic qualities of the input can be condensed to be an intermediate representation that is also good for the syntactic unfolding in the next stage, then this intermediate representation is the modular link between the input and the target output(Oshri and Khandwala, 2015).

Encoder-decoder network in sequence to sequence problems generally utilizes deep recurrent neural networks and train the networks in a supervised manner(Sherstinsky, 2020). This approach is a general end-to-end approach to sequence learning that makes minimal assumptions on the sequence structure. The method applies a multilayered Long Short-Term Memory (LSTM)(Hochreiter and Schmidhuber, 1997) encoder to map the input sequence to a vector of fixed dimensionality (hidden layer dimension), and then an LSTM decoder is used to construct the target sequence from the vector(Sutskever et al., 2014).

Another approach is Convolutional Autoencoder(Kalchbrenner et al., 2014). The network uses Dynamic k-Max Pooling, a global pooling operation over linear sequences. The encoder consists of a set of one-dimensional convolution layers that reduce the dimension of the input data. The decoder consists of a set of transposed one-dimensional convolution layers that are symmetric to the layers in the encoder. The decoder is designed for reconstructing the input data based on the lower-dimensional vectors extracted from the latent space.

In addition to the ordinary supervised learning approach, some research develops an autoencoder structure to exploit sequence representations in an unsupervised fashion. Research has explored this approach for machine translation, under the utilization of pre-trained cross-lingual word embedding, they seek to exploit a language-independent multilingual sentence representation to easily generalize to a new language(Mullov et al., 2021).

Autoencoder is often used to learn the representations of the raw input, which the representations preserve or exploit useful features. Several researches have utilized autoencoder for representation learning(Li et al., 2021), specifically for series data(Kortmann et al., 2021). Research has shown that latent space representations generated from autoencoder can better indicate the key attributes of the input data(Yang and Whinston, 2021). Thus the learned representations can be used as a starting stage for the sequence to sequence tasks.

Since the latent space representations can better demonstrate the features of the raw input, the representations can also be divided into different groups where each group consists of homogeneous data. There are some researches exploring hierarchical structures on the latent space to obtain richer representations(Goyal et al., 2017; Bouchacourt et al., 2018). There are several other researches performing clustering or learning a mixture model within the latent space encoding, including Hard K-means Clustering (Yang et al., 2017), Soft K-means Clustering (Jabi et al., 2019), Gaussian Mixture Model VAE(Dilokthanakul et al., 2016). These researches have shown that dividing latent space can improve the quality of the representations in some aspects. Another research utilizes this conclusion to develop a multi-filter Gaussian-mixture variational autoencoder. Where the latent space is trained as a mixture of Gaussians, then each Gaussian is corresponding to a filter that is used for
decoding. The experiments have shown that the multi-filter structure does enhance the performance in Camera ISP (Yang et al., 2021).

3 Methodology

The architecture is inspired by the Patch Subspace Variational Autoencoder (PS-VAE) for Camera ISP (Yang et al., 2021). There is an autoencoder to learn the representations of the inputs, and several filters to decode the representations in a defined way. A Gaussian mixture model is used to determine which filter the input goes. This model is denoted by Multi-filter Gaussian Mixture Autoencoder (MGMAE). A visualization of MGMAE is in Figure 1.

3.1 Representation Learning via Autoencoder

One direction of generating representations that preserve the semantic meaning is being able to reconstruct the generated vector back into its original text. This can be done by utilizing an autoencoder.

The autoencoder consists of a similar structure with the encoder-decoder model. The encoder takes in a sequence of inputs and returns a sequence of outputs and a final hidden state. It consists of an embedding layer that transforms the input text into an embedded vector, a bidirectional long short-term memory classifier that generates the outputs and hidden states. The decoder executes one step of computation at a time until reaching the "End of Sentence" token or hitting the maximum sentence length. The input for each step is the output from the previous decoding step. At the first step, the start-of-sentence token is fed into the decoder as the beginning of the decoding sequence. The first hidden state of the decoder is the final hidden state from the encoder. The decoder consists of a long short-term memory network, a linear layer that converts the output from hidden dimension to output dimension, and a LogSoftmax layer. A dot product attention mechanism (Luong et al., 2015) is appended to the decoder, after the LSTM network. The attention weights are computed using the hidden state \( \tilde{h} \) generated by the LSTM network and the sequence of the encoder’s outputs \( h \).

To train the autoencoder, a Negative Likelihood Loss is utilized to update gradients. The outputs of the decoder are gone through a LogSoftmax layer and then used to compute the Negative Likelihood Loss:

\[
L(x, y) = \{l_1, ..., l_N\}^T, \quad l_n = -w_{yn}x_{n, yn} \tag{1}
\]

where \( x \) is the output tensor and \( y \) is the label tensor.

After the autoencoder is fine tuned, the encoder is utilized to generate representations. The final hidden state outputted from the encoder is considered the representation of the input sequence. The space where the representations laying in is denoted as the latent space.

3.2 Gaussian Mixture Model on Latent Space

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities (Reynolds, 2015). GMM parameters are estimated from the training data using the iterative expectation-maximization (EM) algorithm. The Gaussian mixture model is a weighted sum of \( M \) component Gaussian densities:

\[
p(x|\lambda) = \sum_{i=1}^{M} w_i g(x|\mu_i, \Sigma_i) \tag{2}
\]

in equation 2, \( x \) is the vector from the latent space, which is the output from the encoder. The latent space dimension is denoted \( L \). \( w_i \) for \( i = 1, ..., M \) are the mixture weights, \( M \) is the number of Gaussian mixtures, as well as the number of filters in the multi-filter model. The component Gaussian densities are computed by:

\[
g(x|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{L/2}} \sqrt{\det{\Sigma_i}} \exp\left(\frac{-\frac{1}{2}d^T\Sigma_i^{-1}d}{2}\right) \tag{3}
\]

where \( d = x - \mu_i \), \( \mu_i \) and \( \Sigma_i \) are the mean vector and covariance matrix respectively. The mean and covariance are represented by the notation \( \lambda = \{\mu_i, \Sigma_i, w_i\} \).

3.3 Multi-filter Decoding

MGMAE has a certain number of filters for decoding purposes. Each filter shares an identical structure with the decoder in the autoencoder. The filters are designed for constructing the target outputs from the representations in the latent space. For instance, the filters generate answers in the question answering system or construct target language in machine translation.

The Gaussian mixture model has divided the data into \( k \) clusters, where each cluster is a Gaussian
distribution. Based on the clustering result, we set up \( k \) filters that each cluster is associated with one filter. All the filters are identical in network structure but their parameters are independent. Each filter is trained only using the data assigned to its corresponding cluster. The loss used to train the filters is the Negative Likelihood Loss. The losses for each filter are computed separately and their gradients are updated separately as well. While during the testing stage, only the samples classified into the corresponding cluster will go through this filter.

In this way, we can form Gaussian mixture groups and construct a set of feature-specific filters that resolves the heterogeneity in each group.

4 Experiments and Results

In order to demonstrate the effectiveness of the multi-filter Gaussian Mixture architecture, some comparative experiments are conducted. The experiments are run on two types of sequence to sequence tasks: question answering and machine translation. The goal of the experiments is to show that the multi-filter architecture does achieve better performance compare to the ordinary encoder-decoder model. Thus we can prove the effectiveness of our multi-filter Gaussian mixture model.

4.1 Question Answering in Geo-query

First, the model is tested on solving question answering problems. This set of experiments uses the Geo-query dataset (Zelle and Mooney, 1996) that includes geographical questions and answers. There are two metrics for evaluation: the token level accuracy, and the denotation accuracy. The token level accuracy is based on simple token-level comparison against the reference logical form. And the denotation accuracy is the percentage of denotation match, as in (Jia and Liang, 2016) and (Liang et al., 2011).

In the comparative experiment, the models are trained and tested under the same environment settings. The training set consists of 480 question-answer pairs and the development set consists of 120 pairs for testing purpose. All the models are tuned in 10 epochs, with word-embedding dimension 150, hidden dimension (which is the latent space dimension) 200, learning rate 0.001, dropout rate 0.2, and the LSTM network in the encoder is set to bidirectional. Under this experimental setting, several MGMAEs are evaluated, from single-filter MGMAE to four-filter MGMAE. Thus we can explore how the number of filters affects the performance and what should be the optimal number of filters. In addition, The MGMAEs are compared with the ordinary encoder-decoder model to show
whether there is any enhancement. Experiment for each model is conducted five times and the averaged results are shown in Table 1.

Table 1: Performance comparison between the original encoder-decoder model and MGMAEs in different number of filters.

| Filter Number | Token Denotation |
|---------------|------------------|
| 1             | 74.2 43.6        |
| 2             | 77.9 48.6        |
| 3             | 76.5 45.1        |
| 4             | 73.6 42.5        |
| Enc-Dec       | 77.4 43.8        |

The results have shown how the number of filters affects performance. On the Geo-query dataset, two-filter MGMAE achieves the best performance, then the accuracies decrease when the number of filters increases. The single-filter MGMAE does not work as well as the ordinary encoder-decoder model, since the encoder in MGMAE is only trained by the input data, while the encoder in the encoder-decoder model is tuned by the input-output sequences. However, the two-filter MGMAE significantly improves the performance and gains better results compared to the encoder-decoder model. Which indicates the effectiveness of the multi-filter architecture. Figure 2 shows the latent space representations for the training samples. The left figure clearly indicates that two Gaussians superbly separate the samples, thus we get the best result for two-filter MGMAE. By contrast, three Gaussians do not well divide the samples, which may result in cluster misassignment in the test data and thus deprecate the performance.

![Figure 2: latent space clustering in Geo-query training data. The left figure shows the clustering result for two Gaussian mixtures, the right figures shows the result for three mixtures.](image)

4.2 Machine Translation

To justify the performance of our MGMAE in machine translation tasks, we use the English-French sentence pairs from Tab-delimited Bilin- gual Sentence Pairs as the training and testing dataset. In this set of experiments, models in both control group and experimental group are trained and tested using this dataset. Since this is a set of comparative experiments, we concentrates on comparing the results from different models under the same experimental settings, rather than tuning hyper-parameters to achieve the best performance.

To evaluate and compare the results, BLEU (bilingual evaluation under study) score is utilized. BLEU score is a quick and inexpensive metric for evaluating the quality of text which has been machine-translated from one natural language to another (Papineni et al., 2002). To compute BLEU score, first we use the test corpus’ reference length $r$ and candidate translation corpus’s length $c$ to calculate the brevity penalty:

$$BP = \exp(1 - r/c)$$

then, the BLEU score is computed by:

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

where $p_n$ is the N-gram precision. In the experiments, we use $N = 4$ and uniform weights $w_n = 1/4$.

Table 2: Performance comparison between the original encoder-decoder model and MGMAEs in machine translation. The table shows the average BLEU score ($\pm$ standard deviation) across five identical experiments.

| Filter Number | BLEU    |
|---------------|---------|
| 1             | 41.7 (±2.4) |
| 2             | 44.1 (±5.7) |
| 3             | 42.9 (±4.4) |
| 4             | 39.7 (±6.3) |
| Enc-Dec       | 42.4 (±1.9) |

In this set of experiments, we use a training set consists of 10,000 bilingual sentence pairs and the development set consists of 2,000 pairs for evaluation. All the models are tuned under the same experimental settings: a bidirectional LSTM in the encoder, LSTMs in the decoder and filters, with word-embedding dimension 150, hidden dimension 200, and dropout rate 0.2. The models are optimized in 20 epochs with a learning rate of 0.001.

Table 2 indicates that our MGMAE can perform better than the encoder-decoder model as long as
we choose the correct number of filters. Two-filter and three-filter MGMAE attain some good accuracies, this is revealed in Figure 3 as well. Two-filter MGMAE works the best and its latent space is well divided. The filters are trained by a group of clearly defined features and tested by the samples consists of highly similar features. Clusters in the four-filter model are mixed up, which increases the possibility of misclassification, thus the samples may be assigned to the wrong filter.

Figure 3: latent space clustering in Bilingual Pairs training data. The figures from top left to bottom right present the latent space clustering results for one, two, three, and four Gaussian mixtures respectively.

5 Discussion and Future Direction

The experiments demonstrate that our MGMAE is able to enhance the performance on sequence to sequence tasks. One of the key component that significantly affect the performance is the number of filters in the MGMAE. To determine the optimal number of mixtures for the GMM parameter, we use Silhouette Coefficient to evaluate the clustering performance given a specific number of mixtures.

Table 3 presents how the Silhouette coefficient related to the model’s performance. We can observe a positive relationship between the Silhouette coefficient and the Token-level accuracy, Denotation accuracy, and BLEU score. This indicates that the quality of the Gaussian mixture is positively related to the prediction accuracies of the model. A better clustering result means the data is clearly separable under a certain number of clusters. Then, each filter can be trained using a fixed set of unique features with less overlapping to the features in other clusters. Thus we can obtain better outcomes.

An advantage of our model is that the MGMAE is trained to generate representations only by using the input data, which means the representations are independent of the target output data. Therefore, this model may be applied to tasks such as multi-lingual translation which translates from one language to multiple languages. In such tasks, the autoencoder and representations are only trained once, then we only need to optimize the parameters in the filters for multiple tasks.

5.1 Future Research

A future direction is extending this approach to probability distributions other than Gaussian distribution, such as Exponential mixture model (Mosler and Seidel, 2001) or Poisson mixture model (Burda et al., 2012). Instead of assuming all the samples are normally distributed, different mixture models are selected based on the distribution of latent space representations of the training data.

Another potential improvement is applying soft-clustering to the representations, replacing hard-clustering (what we are doing in this paper). During predictions, instead of output a discrete result, the mixture model can return posterior probabilities of each component given the data. The posterior probabilities are considered the weights to assign filters. The representations $R$ are decoded by all the filters and the outputs $P$ are integrated based on the posterior probability $Pr(i|G)$, rather than using one filter with highest probability to decode.

$$P = \sum_i Pr(i|G) \cdot f_i(R) \quad (6)$$

where $G$ is the input to the Gaussian mixture model and $P(i|G)$ is the posterior probability that the representation is in cluster $i$, and $f_i$ is the decoding function in the filter that corresponding to cluster $i$. This may largely reduce the consequence of misclassifying clusters.

6 Conclusion

We introduce a Multi-filter Gaussian Mixture Autoencoder for solving sequence to sequence problems. Our MGMAE resolves the heterogeneity of the data by divide samples into relatively homogeneous groups and utilizing multiple filters so that each filter is corresponding to one group. In this approach, each filter concentrates on a smaller set of features. Based on the results from the two sets of comparative experiments, we concluded that the multi-filter architecture is able to enhance the performance in question answering and machine translation.
Table 3: Silhouette Coefficient vs. model’s performance in Geo-query question-answering and Bilingual Sentence Pairs (English to French) datasets.

| Filter Number | Geo Silhouette | Geo Token | Geo Denotation | En-Fr Silhouette | En-Fr BLEU |
|---------------|----------------|-----------|----------------|-----------------|------------|
| 2             | 43.7           | 78.1      | 49.4           | 26.4            | 44.2       |
| 3             | 31.5           | 75.8      | 44.7           | 21.6            | 41.0       |
| 4             | 22.3           | 73.2      | 42.2           | 17.3            | 38.5       |
| 5             | 19.7           | 71.6      | 39.4           | 15.7            | 34.6       |
| 6             | 18.9           | 68.4      | 32.7           | 15.4            | 34.7       |

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