Latent Diffusion for Language Generation

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Introduction

- This paper tries to explore and analyse the applicability of diffusion models in natural language generation.
- By training encoder-decoder language models, we try to learn high-quality language autoencoders which can provide good latent spaces of language to be used by diffusion models

Goal

- Demonstrate the effectiveness of latent diffusion models in generating natural language
- Reproduce results comparable to the reference models
- Try different approaches to improve the performance of the learnt diffusion model on a variety of metrics.
- Understand and explain the impact of the modifications based on existing literature about diffusion models

References

- https://arxiv.org/pdf/2212.09462
- https://github.com/AnujSinghal21/IPR-latent-diffusion

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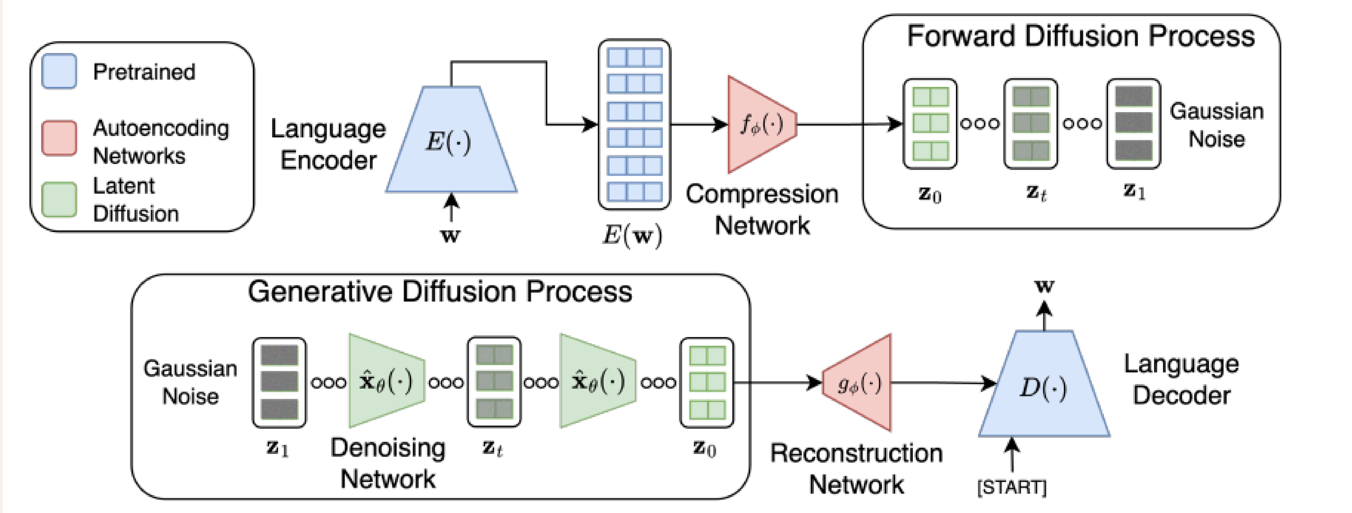
Methodology

The model consists of two primary components: a high-quality language autoencoder with a compact latent space, and a continuous diffusion model.

Language Autoencoder

The language autoencoder is built on top of BART with only the added autoencoding modules being trained on the dataset



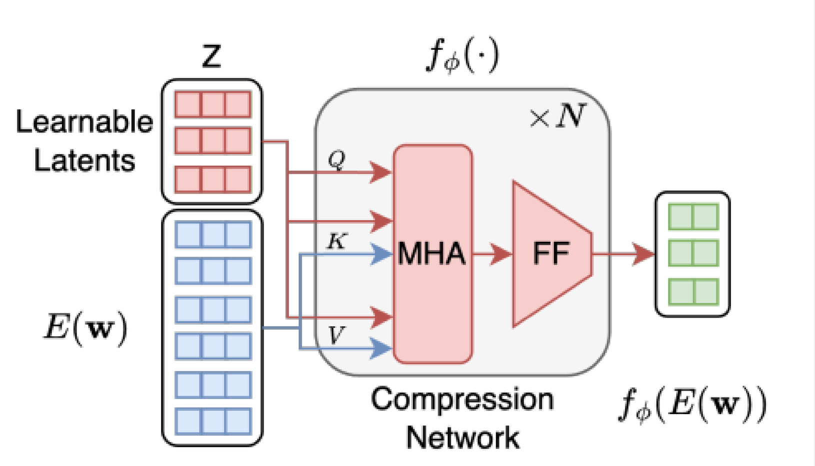


Figure 2: Architecture of our Compression Network.

Compression Network

This network is based on a combination of multi-head attention (MHA) and feedforward (FF) layers

Reconstruction Network

The compressed representation is projected to the appropriate dimensionality, and position embeddings are added before passing it through a transformer model

Results and Conclusion

- The model's performance is comparable to reference on widely used score for language generation
- The model's evaluation was still improving so we believe that training for further time should lead to the desired results
- Further, the suggested improvements slightly improve some of the metrics, although the improvement is not drastic, it gives hope that the performance can be improved

Metric	Achieved Value	Reference Value
Unique Word Count	1173	1236
2-gram Repetition	0.263	0.244
3-gram Repetition	0.048	0.042
4-gram Repetition	0.009	0.008
Diversity	0.695	0.718
Perplexity	39.22	20.37
Memorization	0.328	0.370
MAUVE Score	0.768	0.901

Table 1: Comparison of Achieved Metrics with Reference Values