TransFusion: Generating Long, High-Fidelity Time Series using Diffusion Models with Transformer

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Abstract

The generation of high-quality, long-sequence time-series data is essential due to its wide range of applications. In the past, standalone recurrent and convolutional neural network-based generative adversarial network (GAN) has been used to synthesize time-series data. However, they are not adequate for generating long sequences of time-series data due to limitations in their architecture. Furthermore, GANs are well known for their training instability and mode collapse problem. To address this, we propose TransFusion, a diffusion and transformer-based generative model to generate high-quality long-sequence time-series data. We have stretched the sequence length to 384, and generated high-quality synthetic data. To our knowledge, this is the first work done with data of this sequence length. Also, we introduce a new evaluation metric to evaluate the quality of the synthetic data by using post-hoc classification method. We evaluate TransFusion with a wide variety of visual and empirical metrics, and TransFusion outperforms the previous state-of-the-art with a significant margin.

Introduction

Research Challenges

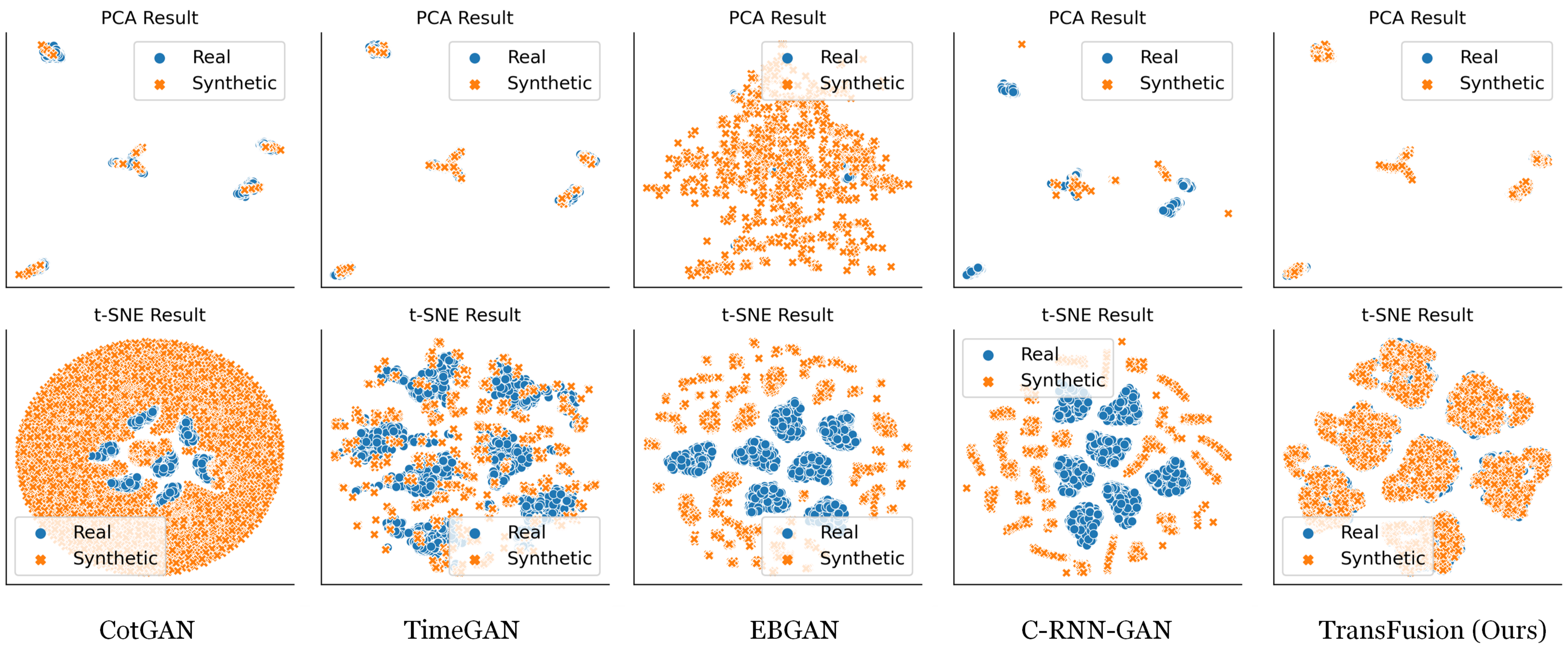
- How can we generate long and high-fidelity time-series data?
- How can we evaluate long-sequenced synthetic time-series data?
- How can we overcome the mode-collapse problem of generative models?

Motivation

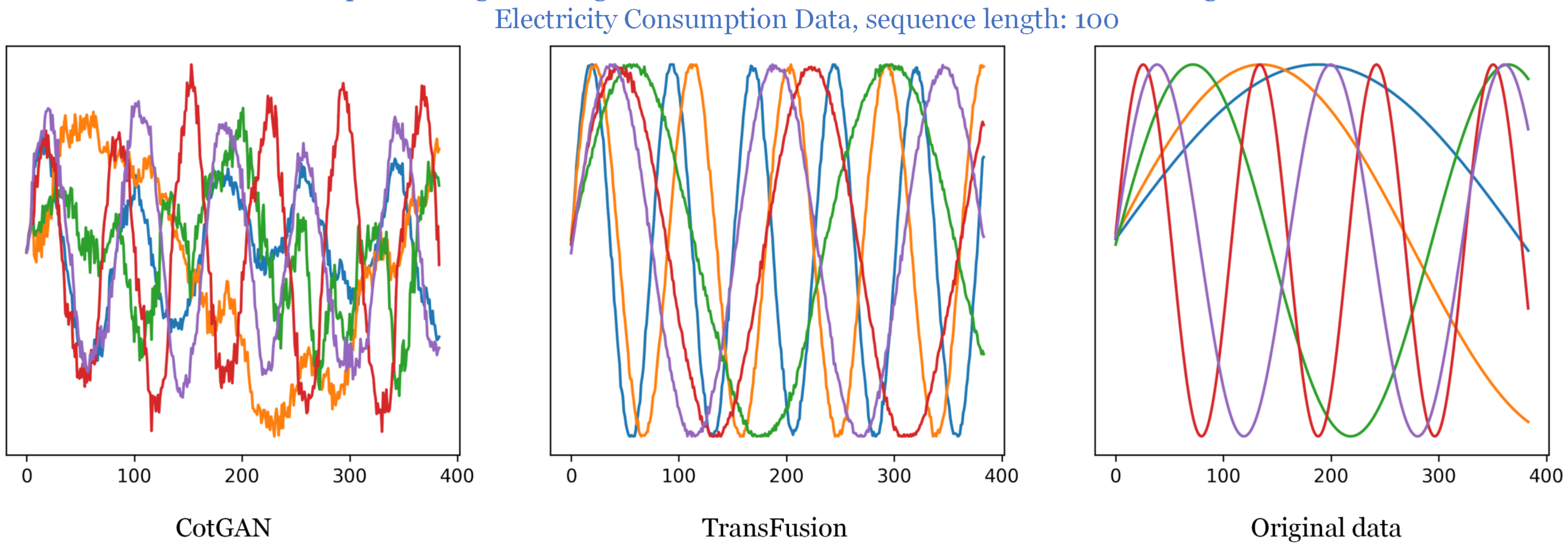
- Long-sequenced time-series data gives more information than the short-sequenced data.
- Most time-series generative models are Generative Adversarial Networks (GAN) [1, 3] and training GAN is challenging as well as it prones to mode-collapse problem.
- Transformer architecture can capture long-term dependencies.

Our Contributions

- We introduce **TransFusion**, a Transformer and diffusion based generative model, that can generate long-sequenced high-fidelity time series data. Transformer allows us to capture long-term dependencies. And diffusion process overcomes the mode-collapse problem.
- We propose a new post-hoc classifier-based evaluation metric called **Long Discriminative Score (LDS)**. In the metric, we train a classifier (transformer-based architecture) in a supervised manner with the original and synthetic data labeled as real and fake, respectively, then test the classifier's performance with the held-out data and measure the classification error. Again, Transformer architecture allows us to use this metrics with longer-sequenced time series data.



PCA and t-SNE plots of original and generated data from TransFusion and other SOTA generative models on Electricity Consumption Data, sequence length: 100

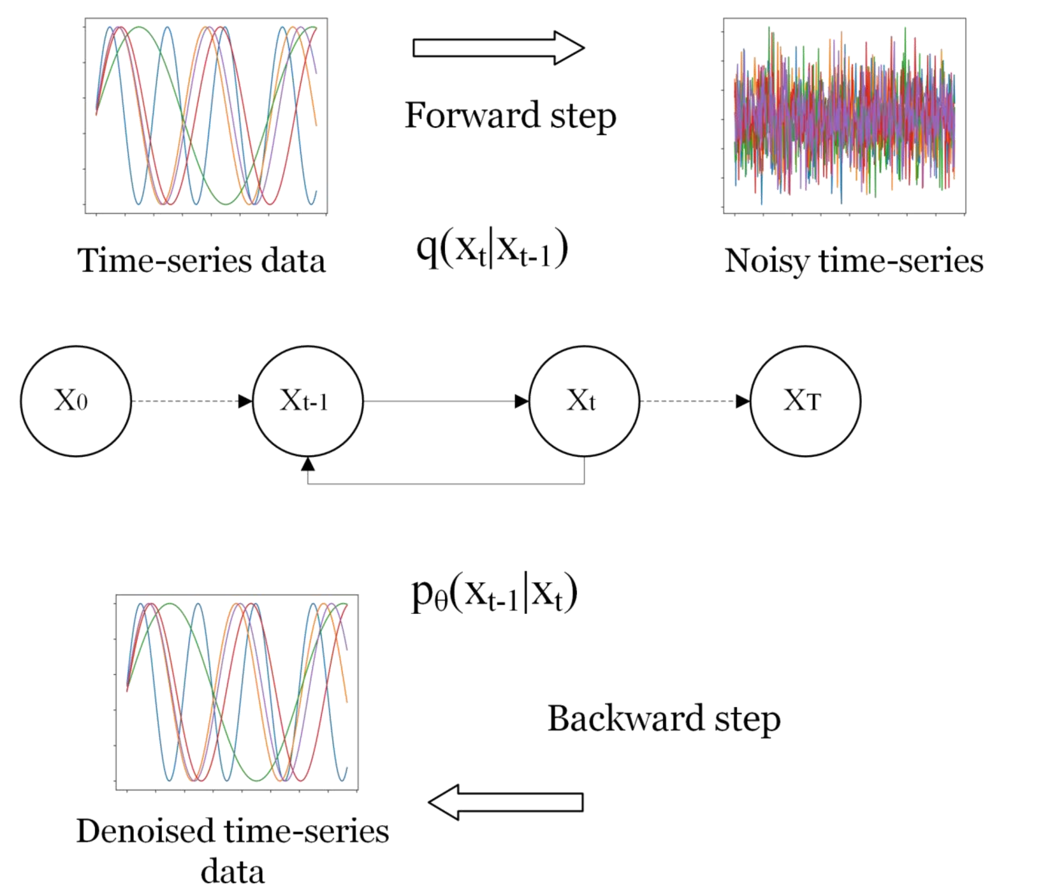


Generated samples of sine wave using CotGAN, TransFusion and comparing with original data, sequence length 384

Method

Transfusion works in two steps [2]:

- **Forward step**: We add noise to the data until the data become pure Gaussian noise.
- **Backward step**: We use a Transformer-Encoder [4] based neural network to denoise the data and approximate the original data distribution.



TransFusion workflow

Results

- We use four benhmarking datasets (stock price, sinusoidal wave, air-quality data, and, electricity consumption data).
- We compare the quality of generated data with four generative models in terms of Fidelity, Diversity.
- Visual Evaluation
  - PCA & t-SNE Plots
- Empirical Evaluation
  - **Fidelity**: LDS, Jenson Shanon Divergence (JSD), **α**-precision [5]
  - **Diversity**: **β**-recall [5]
  - **Check mode collapse**: Coverage [5]

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References

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Poster

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