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

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Abstract

The generation of high-quality, long-sequenced time-series data is essential due to its wide range of applications. In the past, standalone Recurrent and Convolutional Neural Network-based Generative Adversarial Networks (GAN) were used to synthesize time-series data. However, they are inadequate for generating long sequences of time-series data due to limitations in the architecture. Furthermore, GANs are well known for their training instability and mode collapse problem. To address this, we propose TransFusion, a diffusion, and transformers-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 the best of our knowledge, this is the first study that has been done with this long-sequence length. Also, we introduce two evaluation metrics to evaluate the quality of the synthetic data as well as its predictive characteristics. We evaluate TransFusion with a wide variety of visual and empirical metrics, and TransFusion outperforms the previous state-of-the-art by a significant margin.

Introduction

Research Challenges

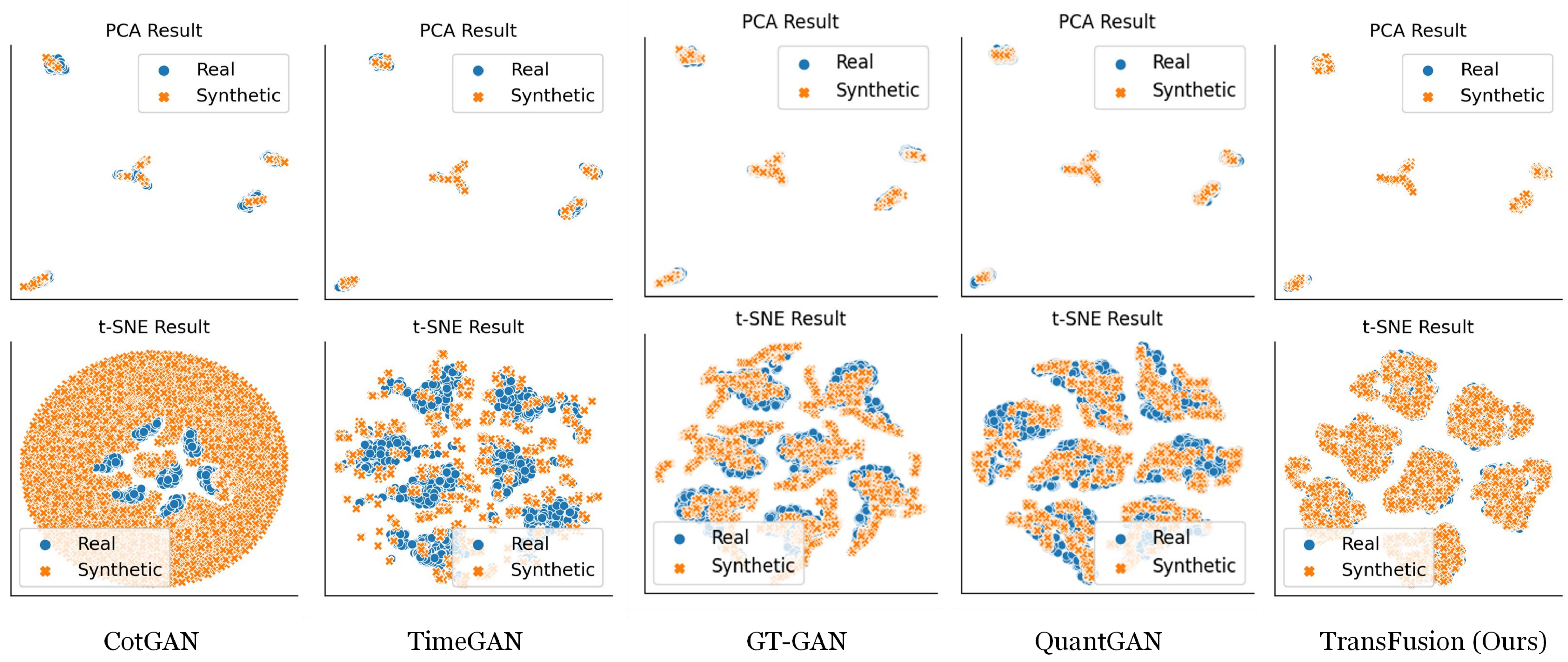
- How can we generate long and high-fidelity time-series data?
- How can we evaluate long-sequenced synthetic time-series data?
- How can we overcome the mode-collapse problem of generative models?

Motivation

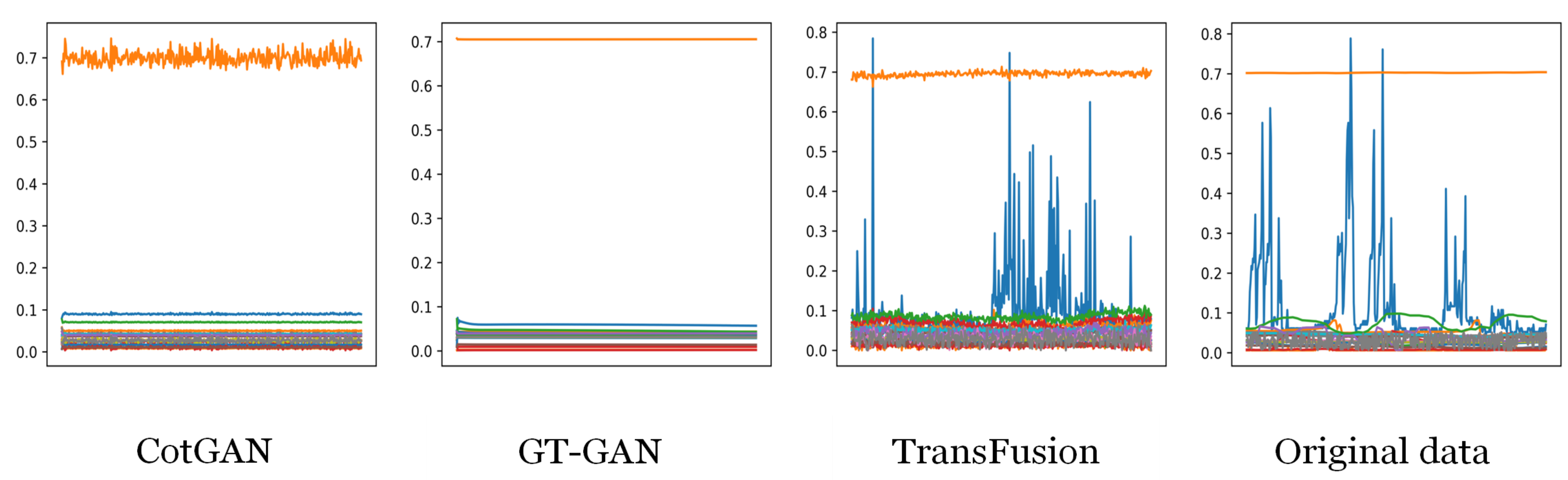
- Long-sequenced time-series data gives more information than the short-sequenced data.
- Most time-series generative models are Generative Adversarial Networks (GAN) [1, 3] and training GAN is challenging as well as it prones to mode-collapse problem.
- Transformer architecture can capture long-term 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 two evaluation metrics, **Long Discriminative Score (LDS)** & **Long Sequenced Predictive Score (LPS)**, which can distinguish original and synthetic data and provide an overview of the synthetic data's performance over sequence prediction task, respectively. LDS and LPS are both based on Transformers architecture, so it can capture long-term dependencies. This allows the evaluation metrics to work with long-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

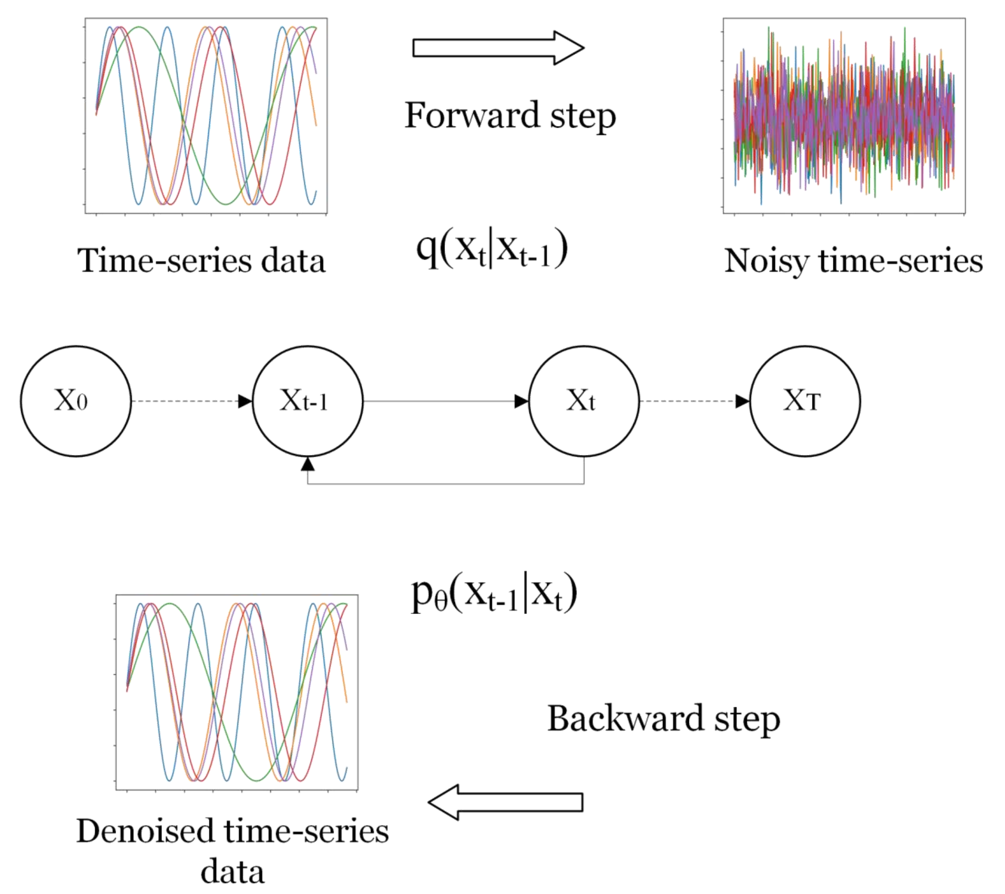


Generated samples of Electricity Consumption data using CotGAN, GT-GAN & TransFusion and comparing with original data, sequence length 384

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 benchmarking 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, Jensen-Shannon Divergence (JSD), **α**-precision [5]
  - **Diversity**: **β**-recall [5]
  - **Check mode collapse**: Coverage [5]
  - **Predictive Analysis**: LPS, +5 Steps Ahead

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Poster

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