

# **Generative Adversarial Networks for Time Series**

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### **Evaluation Metrics for GAN**





Evaluation metrics ensure that synthetic data closely resembles real data in terms of realism and feature distribution.

- Qualitative evaluation: Human visual inspection of the generated data.
- Quantitative evaluation: Use of metrics associated with statistical measures used for time series analytics

### **Evaluation Metrics Used**





#### 1. Discriminative Score:

- A recurrent neural network (RNN) is trained to distinguish between real and GAN-generated synthetic time-series data.
- The metric evaluates how well the RNN performs by measuring the difference between its accuracy and 50%, indicating how distinguishable the synthetic data is from real data.

Time- GAN 4

### **Evaluation Metrics Used**





#### 2. Predictive Score:

- A recurrent neural network (RNN) is trained using synthetic data to predict the next step in a time series.
- The metric evaluates how well this model performs on real data by calculating the mean absolute error (MAE), indicating the accuracy of the synthetic data in replicating real-world patterns.

Time- GAN 5

# **Frequently used Metrics**





#### **Distance-Based Evaluation Metrics:**

- **Euclidean Distance**: Measures the straight-line distance between corresponding points in real and synthetic datasets.
- Kullback-Leibler (KL) Divergence: Quantifies how much one probability distribution diverges from a second, expected probability distribution.
- Wasserstein Distance: Also known as Earth Mover's Distance, it measures the minimum effort required to transform the distribution of synthetic data into that of the real data.

#### **Similarity-Based Evaluation Metrics:**

- Cosine Similarity: Compares the orientation of the vectors in a multi-dimensional space.
- Jaccard Similarity: Compares the similarity between two sets by dividing the intersection of the sets by the union of the sets.

T- GAN 6

# **Other Frequently used Metrics**





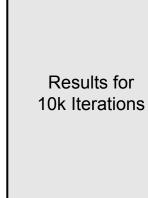
- 1. **Inception Scores (IS)**: Calculated by generating synthetic data samples and passing them through a pre-trained neural network (typically an Inception model) to classify the samples. The score evaluates two key aspects: Confidence and Diversity.
- 2. **Fréchet Distances**: Measure the similarity between two distributions by calculating the Wasserstein distance, commonly used to compare real and generated data distributions.
- 3. **Fréchet Inception Distances (FID)**: Compare the distributions of real and generated data by calculating the Fréchet Distance between feature representations extracted from a pre-trained Inception model, capturing both the quality and diversity of the generated data.

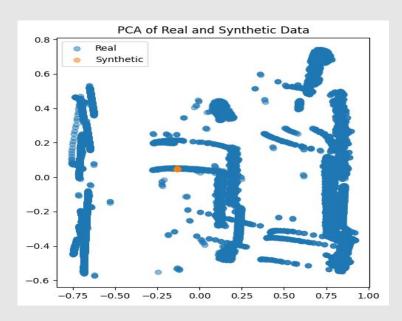
T- GAN 7

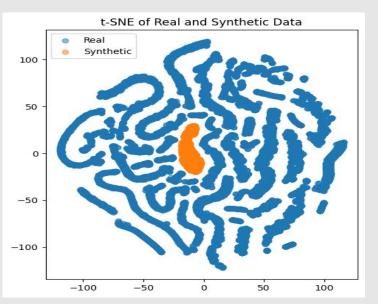
# **Transformer GAN - Evaluation Results**







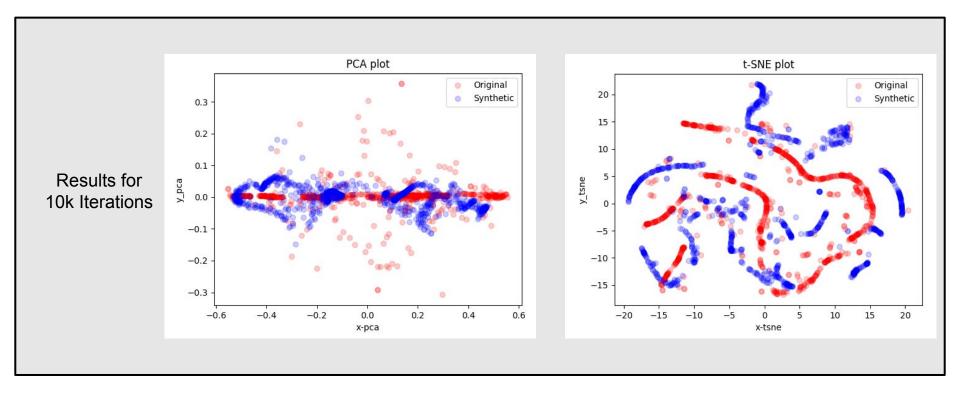




## **TimeGAN - Results for LSTM**



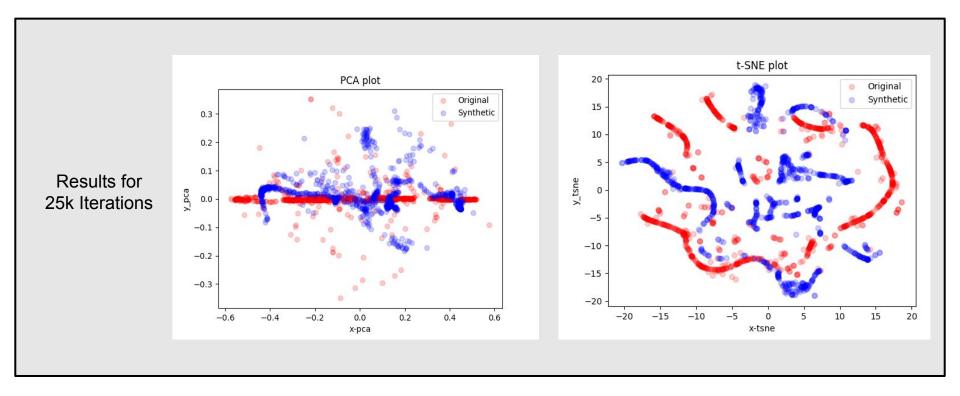




## **TimeGAN - Results for LSTM**



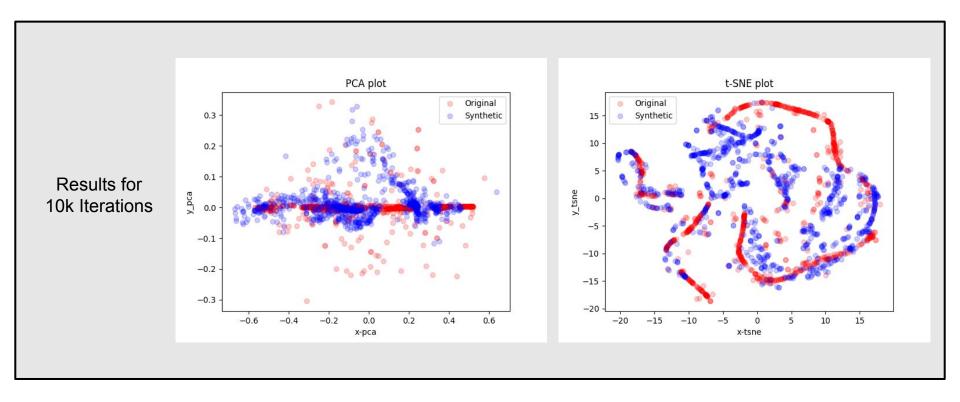




## **TimeGAN - Results for GRU**







# **Way Forward**





- 1. Comparing the results of TimeGAN, TransformerGAN and WGAN by a common evaluation metric.
- 2. **Implementing a common evaluation metric** for time series data and which is suitable for the provided CNC dataset.
- 3. Develop simple and **interactive visualizations** to compare the real and generated time-series data.

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# **Generative Adversarial Networks for Time Series**

## **Thank You For Your Attention!**

