Generating Private and Fair Long-Sequenced Longitudinal Healthcare Records

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Abstract
Generating long-sequenced longitudinal healthcare records is critical as it has numerous potential applications. Long-sequenced longitudinal data allow us to better understand and find patterns from the data. However, privacy concerns make it challenging to share the data, and real-world data is not bias-free. Generative Adversarial Networks (GAN) [1, 3] and training GAN is challenging as well as it prone to mode-collapse problem. Transformers architecture can capture long-term dependencies.

Introduction
Overview
This project is part of an ongoing PhD study. In the PhD study, we aim to propose methods for generating high-quality and long-sequenced time series data and maintaining privacy and fairness in the model. Also, we aim to propose methods to evaluate the quality of synthetic long-sequence time-series data.

Overall Research Challenges

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 prone to mode-collapse problem.
- Transformers architecture can capture long-term dependencies.

Evaluation
- We use two benchmarking healthcare datasets (MIMIC-III & MIMIC-IV).
- We use Gender as the sensitive attribute.
- 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
- Fairness Evaluation
  - Demographic Parity
  - Predictive Parity
- Privacy Evaluation
  - AUROC
  - LDS
  - Authenticity [5]

Why Private and Fair Synthetic Data
- Private synthetic healthcare data can improve the quality of research and development without compromising patient’s privacy.
- Fair synthetic healthcare data can mitigate the bias issue in the real data.

Our Contribution
- Our model is capable of generating long-sequenced longitudinal healthcare records.
- Generates fair and private data.
- We add fairness penalty to ensure fair data generation.
- Usage of Diffusion and Transformers overcome the mode-collapse problem of generative models.

Method
Our proposed model works in the following steps:
- Diffusion Forward step: We add noise to the data until the data become pure Gaussian noise.
- Diffusion Backward step: We use a Transformer-Encoder [4] based neural network to denoise the data and approximate the original data distribution.
- Adding fairness penalty: We add fairness penalty to the diffusion backward step to ensure fair data generation.
- Train in DP manner: We also train the whole process in differential privacy (DP) manner to ensure private data generation.

References

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