>>> **Privacy-Preserving Data Generation:**
>>> Towards Generating Privacy-Preserving, Synthetic and
Useful Time Series ECG Data for Anomaly Detection
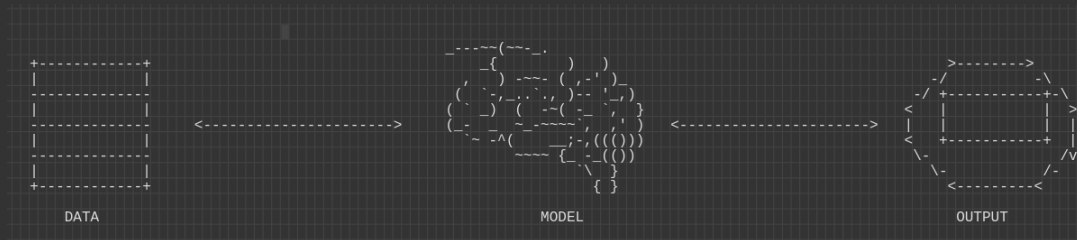
KTH x RISE

Sijun John Tu

March 11, 2024

>>> **Outline**

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● ● ●   **Figure:** High-level machine learning pipeline

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DATA   MODEL   OUTPUT

>>> Anomaly detection using privacy-preserving, synthetic time series data

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$ Solution:
- Promising solution: `synthetic data` with privacy guarantees!
- Synthetic data with `differential private` (DP) guarantees is a promising solution to ensure privacy independent of downstream task.

$ BUT:
- `Privacy-Utility-Tradeoff`: Commonly, a gain in privacy results in a loss of utility.
- For `anomaly detection` this might not be the case (?).

Figure: Structure of Experiment pipeline
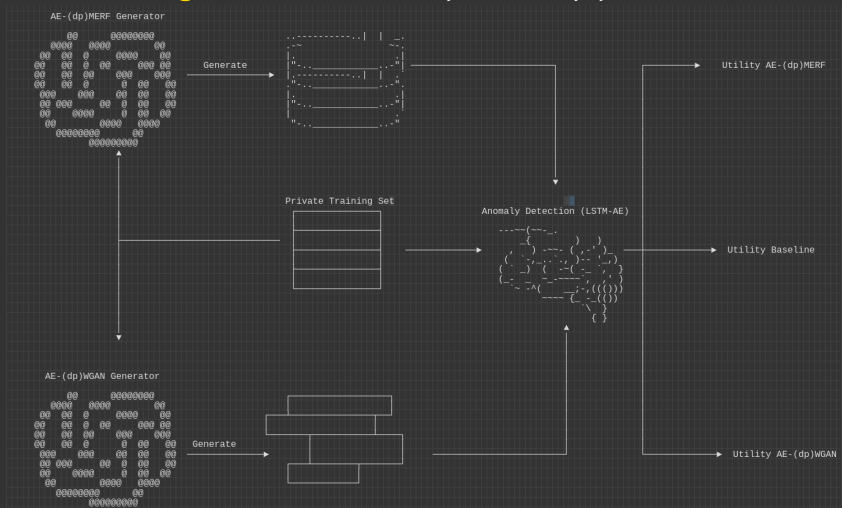
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5. **Contaminate** training data with anomalous heartbeats and repeat.

>>> **Outline**

1. Project introduction

2. Dataset: MITBIH ECG data

3. Privacy-preserving Time Series Data Generation

4. Results
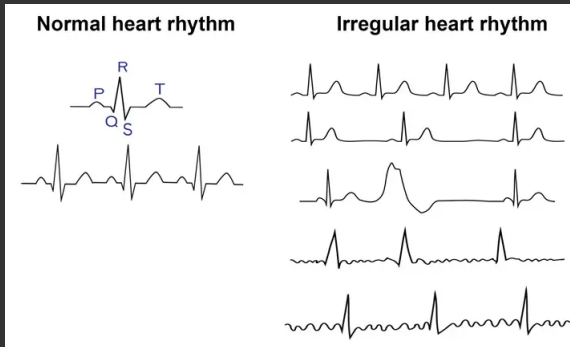
5. Summary

6. References

>>> Heartbeat Arrhythmia

Figure: Different heartbeat arrhythmias [1]

_____

[1]source: https://www.parkwayshenton.com.sg/health-plus/article/arrhythmia-guide

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- $ Given an anomalous heartbeat the model should give **higher reconstruction error**.
- $ Based on an optimal **threshold** for that error we classify this heartbeat as either regular or anomalous.

Two reasons for this semi-supervised approach: high class imbalancy and no need for labelling.

Model is a LSTM-AE that is `trained only on regular, private samples` with the goal to reconstruct normal samples. The classification is made based on the reconstruction error.
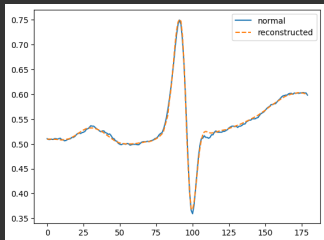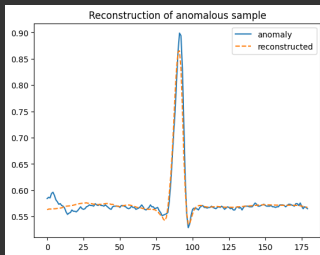

Figure: reconstruction on normal sample

Figure: reconstruction on anomalous sample

>>> **Outline**

1. Project introduction

2. Dataset: MITBIH ECG data

3. **Privacy-preserving Time Series Data Generation**

4. Results

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6. References

Idea. Hide the influence of one particular sample on the output of the model by adding randomness.

>>> Review: Differential Privacy

Idea. Hide the influence of one particular sample on the output of the model by adding randomness.

Definition (Differential Privacy)

A randomised algorithm $\mathcal{M}$ is (ϵ, δ)- differentially private if for all set of outcomes $S \subset ran\mathcal{M}$ and for all databases x, y, such that they **only differ in one element**, we have

$$\mathbb{P}(\mathcal{M}(x) \in S) \leq e^{\epsilon} \cdot \mathbb{P}(\mathcal{M}(y) \in S) + \delta \quad , \tag{1}$$

where the probability is taken over the randomness of $\mathcal{M}$.

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where the probability is taken over the randomness of $\mathcal{M}$.

Informally. Replacing one record in the data will not change the outcome of algorithm $\mathcal{M}$ *too much* (specified via privacy budget ϵ). The lower ϵ the stricter the privacy guarantees.

$ Gaussian mechanism
- Add Gaussian noise to output of some function.
- For a given function $f : \mathbb{N}^{|\mathcal{X}|} \longrightarrow \mathbb{R}^d$, privacy parameters $\epsilon \in (0,1)$ and $\delta > 0$ define the gaussian mechanism $F(x)$ as follows:

$$F(x) = f(x) + \xi \quad , \tag{2}$$

where $\xi \sim \mathcal{N}(0, \sigma^2 I)$ and $\sigma \geq \frac{2\Delta f}{\epsilon} \ln(\frac{1.25}{\delta})$ to satisfy DP.

$ DP-SGD
- DP version for training neural networks
- Add noise to gradients while training
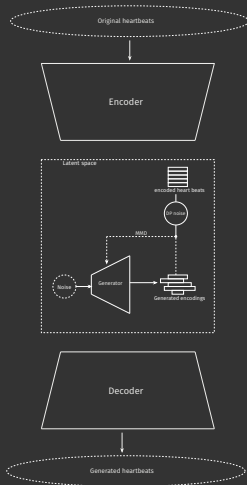
Figure: AE-(dp)MERF architecture

1. Encode dataset X: $X^{enc} = Enc(X)$
2. Generate encodings by sampling from Gaussian noise: $\widetilde{X}^{enc} = Gen(z)$
3. Train generator via loss maximum mean discrepancy (MMD) loss:
$MMD(X^{enc}, \widetilde{X}^{enc}) = \|\frac{1}{m}\sum_{i=1}^{m}\hat{\Phi}(x_i^{enc}) - \frac{1}{m}\sum_{j=1}^{m}\hat{\Phi}(\tilde{x}_j^{enc})\|_{\mathcal{H}}^2$
where $\hat{\Phi}(x) \in \mathbb{R}^D$ and $\hat{\Phi}_j(x) = \sqrt{\frac{2}{D}}cos(\omega_j^T x)$.
4. Decode generated encodings:
$\widetilde{X} = Dec(\widetilde{X}^{enc})$

We are making AE-MERF differentially private by adding noise to the loss function:

$$MMD(X^{enc}, \widetilde{X}^{enc}) = ||\frac{1}{m}\sum_{i=1}^{m}\hat{\Phi}(x_i^{enc}) - \frac{1}{m}\sum_{j=1}^{m}\hat{\Phi}(\tilde{x}_j^{enc})||_{\mathcal{H}}^2 \quad . \tag{3}$$

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where $\xi \sim \mathcal{N}(0, \sigma^2 I)$

>>> AE-(dp)WGAN: Architecture

1. Encode dataset X: $X^{enc} = Enc(X)$
2. Generate encodings by sampling from Gaussian noise: $\widetilde{X}^{enc} = Gen(z)$
3. Discriminator learns to distinguish between real and fake samples.
4. Train Discriminator and Generator jointly.
5. Decode generated encodings: $\widetilde{X} = Dec(\widetilde{X}^{enc})$
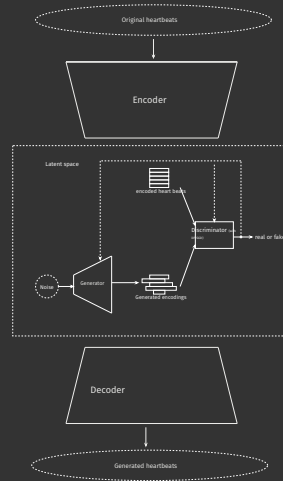
Figure: Architecture of AE-(dp)WGAN

>>> Outline
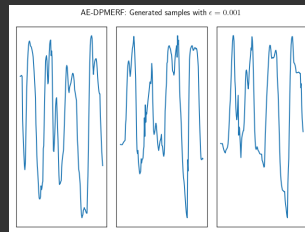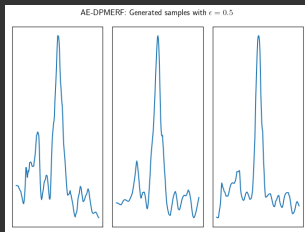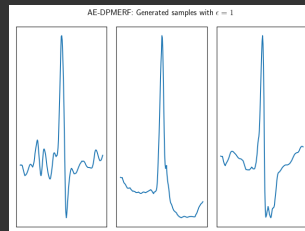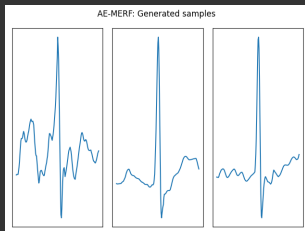
Figure: AE-(dp)MERF generated samples
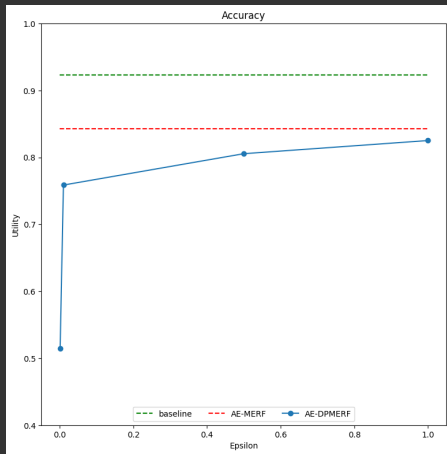
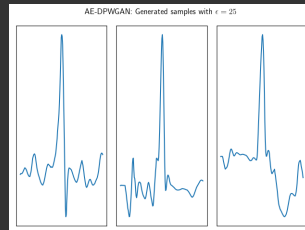**Figure:** Results of AE-(DP)MERF with different privacy budgets (lower epsilon means higher privacy)
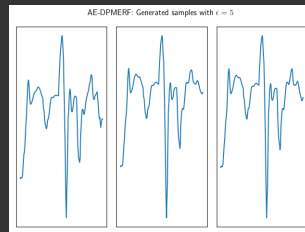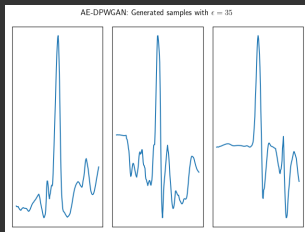
Figure: AE-(dp)WGAN generated samples

Figure: Results of AE-(dp)WGAN with different privacy budgets (lower epsilon means higher privacy)
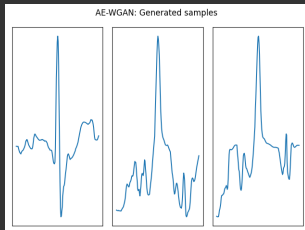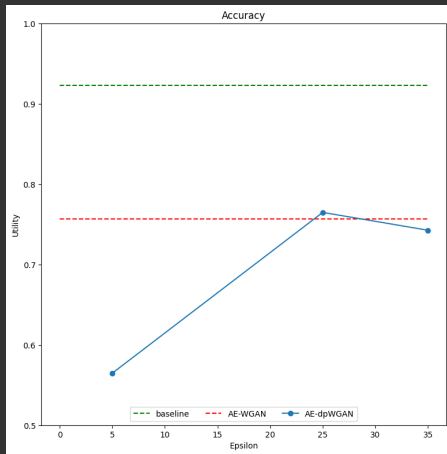
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$ BUT: Adding **privacy does not further degrade the utility** for anomaly detection too much until too much noise is added.

>>> Contamination

We `contaminate` the train set that only consists of regular samples with 1%, 2%, 5% anomalous samples (the percentage of heartbeat arrhythmias is estimated to be around max. 5%).

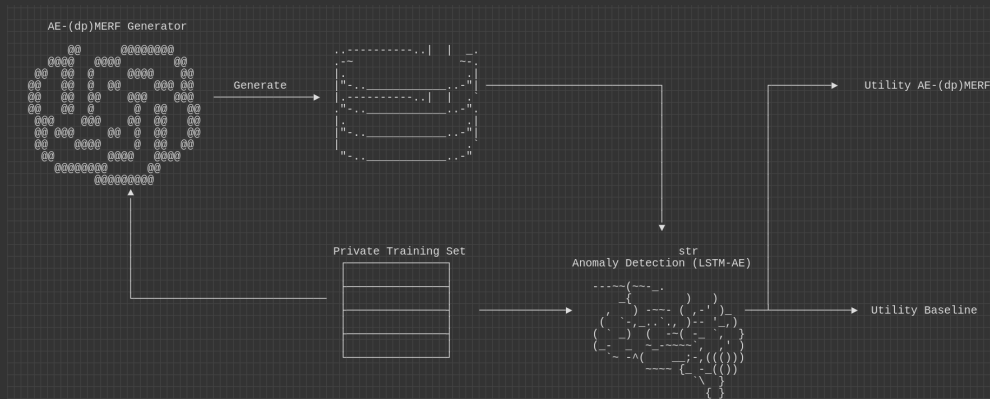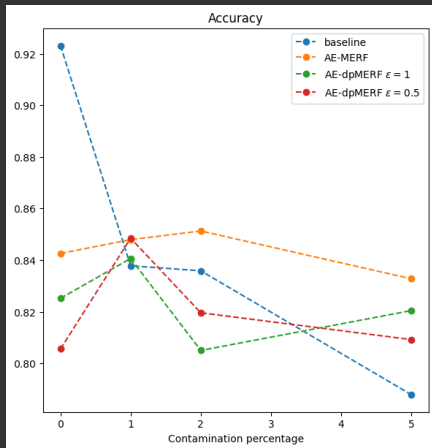**Figure:** Structure of Contamination Experiment

Figure: Contaminated training set: AE-(DP)MERF

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$ **Baseline model**
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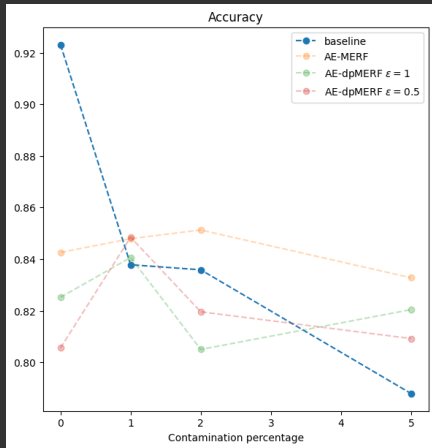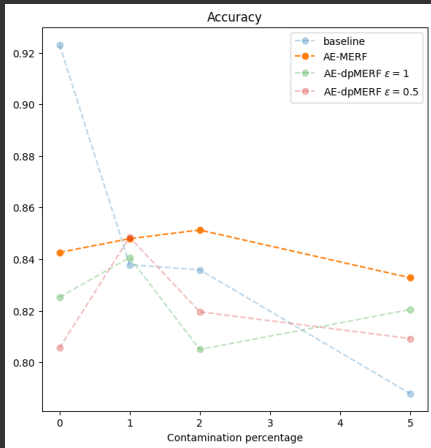**Figure:** Contaminated training set: AE-(DP)MERF

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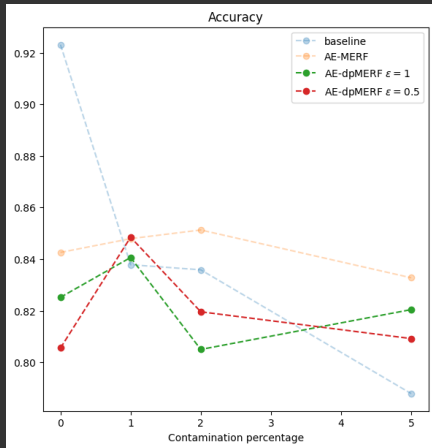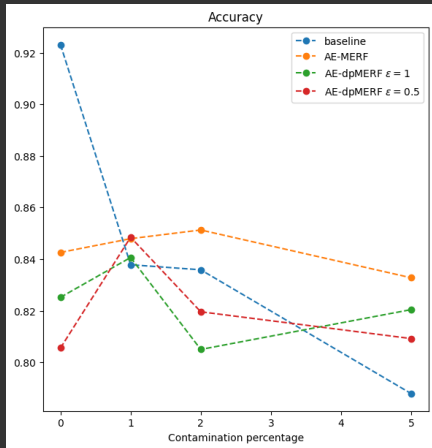$ Utility of **AE-dpMERF** generated samples first increases and then decrease when contamination is too high.

Figure: Contaminated training set: AE-(DP)MERF

$ **Baseline model**
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$ Utility of synthetic data is
higher than baseline model

Hypothesis: Noise added during data generation and DP noise can have a **regularising effect** on the synthetic data which counteracts the contamination.

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$ We tested two different `DP times series data generation` models on the MITBIH ECG data set.

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$ We measured the `utility` of the synthetic data via the downstream task of anomaly detection (heartbeat arrhythmia).

$ We investigated the `robustness` of the data generation by `contaminating` the data set with anomalous samples.

>>> Main Findings

$ AE-(dp)MERF works better than GAN based approach.

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$ The `Privacy-Utility-Tradeoff is more nuanced` and depends on the use case. For anomaly detection, privacy and utility can go hand in hand.

$ Synthetic data and DP can add `robustness`.

>>> **Future Work**

$ Test with `other time series data`.

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$ Work with `other use cases`, e.g. classification, regression.

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$ Further investigate `robustness`.

$ Verify theoretical privacy guarantees with empirical tests, e.g. `membership inference attacks`.

Thank you Aflsono, Apslotsuo, Hna, Sihahd!

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- Ang, Yihao et al. (2023). TSGBench: Time Series Generation Benchmark. arXiv: 2309.03755 [cs.LG].
- Dwork, Cynthia, Aaron Roth, et al. (2014). "The algorithmic foundations of differential privacy". In: Foundations and Trends® in Theoretical Computer Science 9.3–4, pp. 211–407.
- Harder, Frederik, Kamil Adamczewski, and Mijung Park (2020). "Differentially Private Mean Embeddings with Random Features (DP-MERF) for Simple & Practical Synthetic Data Generation". In: CoRR abs/2002.11603. arXiv: 2002.11603. URL: https://arxiv.org/abs/2002.11603.
- Hu, Yuzheng et al. (2023). SoK: Privacy-Preserving Data Synthesis. arXiv: 2307.02106 [cs.CR].
- Pei, Hengzhi et al. (2021). "Towards Generating Real-World Time Series Data". In: Proceedings of the 2021 IEEE International Conference on Data Mining (ICDM).
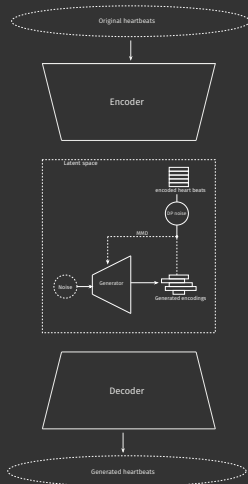
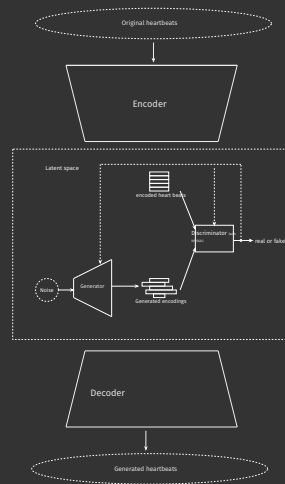Figure: AE-(dp)MERF architecture

Figure: Architecture of AE-(dp)WGAN

>>> Gaussian Mechanism

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$$F(x) = f(x) + \mathcal{N}(0, \sigma^2) \qquad (5)$$

where the variance is calibrated by the sensitivity of f and the given privacy level, such that $\sigma \geq \frac{2\Delta f}{\epsilon} \ln(\frac{1.25}{\delta})$

>>> Performance metrics

$ Accuracy measures the overall percentage of correct classifications:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad . \tag{6}$$

$ Precision looks only on the samples that are labelled as anomalies and computes the percentages of correctly detected anomalies:

$$Precision = \frac{TP}{TP + FP} \quad . \tag{7}$$

$ Recall looks at all true anomalies and computes the percentage of correctly detected anomalies

$$Recall = \frac{TP}{TP + FN} \quad . \tag{8}$$

$ F1 computes the an average of Precision and Recall

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad . \tag{9}$$
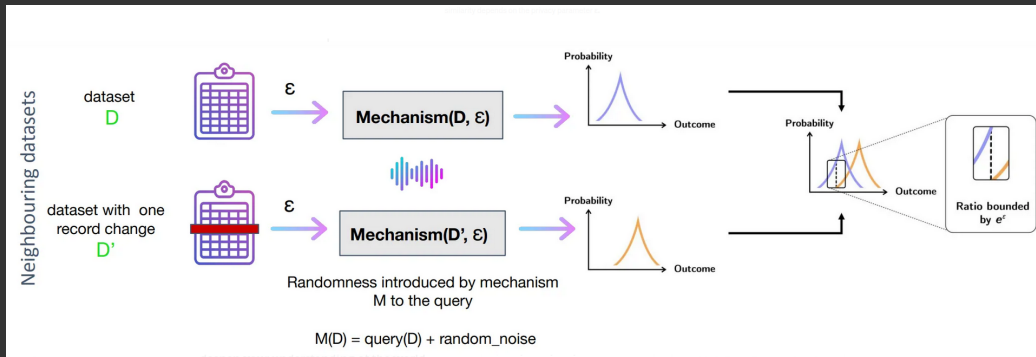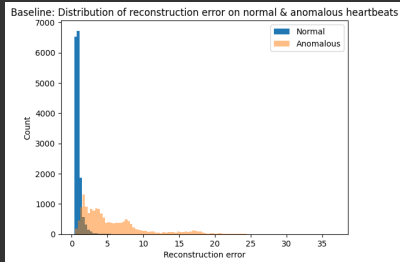
>>> DP Illustrated

Figure: Illustration of DP[2]

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[2]taken from: https://medium.com/dsaid-govtech/protecting-your-data-privacy-with-differential-privacy-an-introduction-abee1d7fcb63

Figure: Distribution of reconstruction error on regular & anomalous samples

We can clearly see a `difference in error distribution` for regular and anomalous samples. We choose the `threshold that maximises the classification` accuracy.

AE-(dp)MERF

$ AE-(dp)MERF is based on DP-MERF (best state of the art generator for tabular data).

```
>>> Models
```

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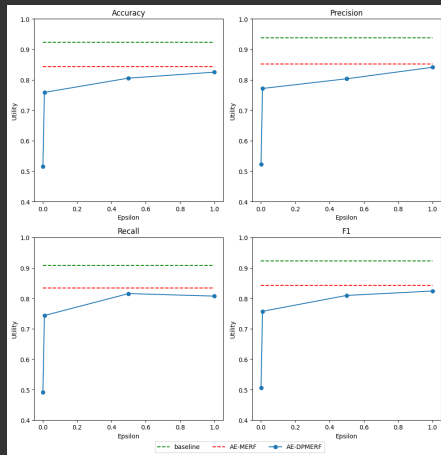- $ No private counterpart, hence we will implement our own private version.

Figure: Results of AE-(DP)MERF with different privacy budgets (lower epsilon means higher privacy)

Figure: Results of AE-(dp)WGAN with different privacy budgets (lower epsilon means higher privacy)

Figure: Contaminated training set: AE-(DP)MERF

$ **Baseline model** performance degrades with increasing contamination percentage.

$ **AE-MERF** generated samples retain stable utility.

$ Utility of **AE-dpMERF** generated samples first increases and then decrease when contamination is too high.

$ Utility of synthetic data is higher than baseline model