>>> 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 7, 2024

>>> Outline

1. Project introduction
2. Dataset: MITBIH ECG data
3. Privacy-preserving Time Series Data Generation
4. Results
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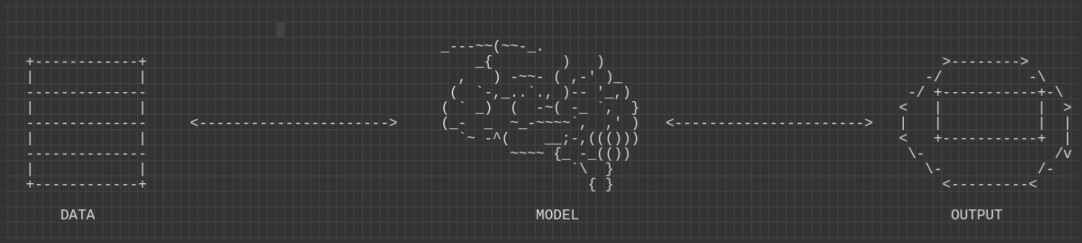
>>> Machine Learning Pipeline

Figure: High-level machine learning pipeline



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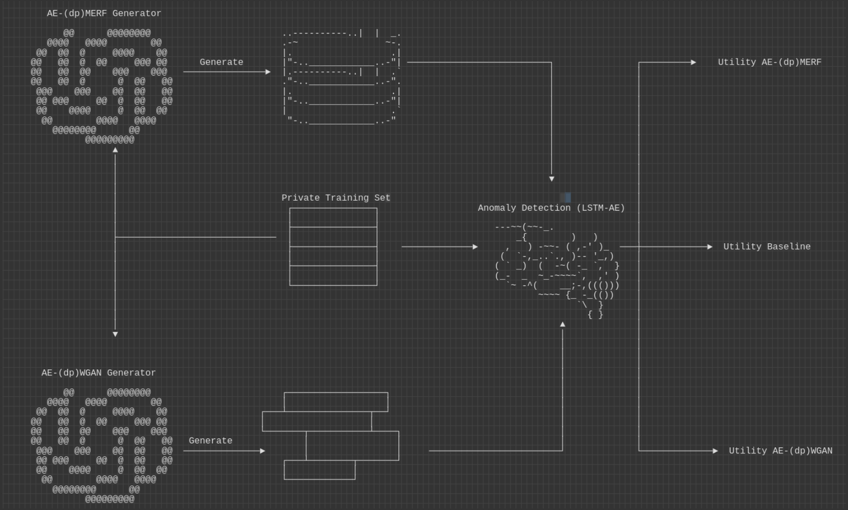
Goal: generate useful and privacy-preserving ECG data for anomaly detection (heartbeat arrhythmia).

>>> Structure

Figure: Structure of Experiment pipeline



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5. `Contaminate` training data with anomalous heartbeats and repeat.

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>>> Heartbeat Arrhythmia

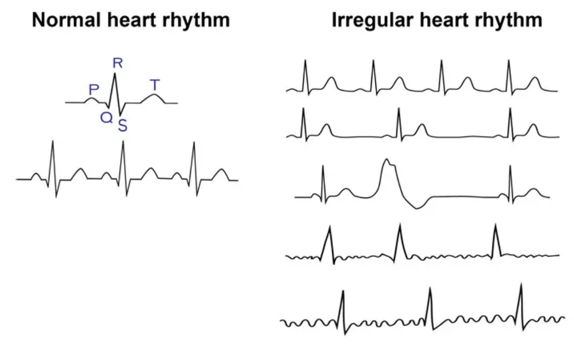

Figure: Different heartbeat arrhythmias [1]

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

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- $ 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.

>>> Baseline Model

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.

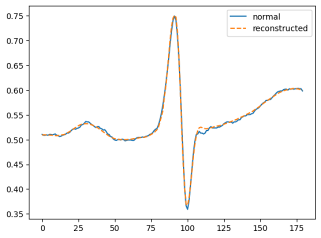

Figure: reconstruction on normal sample

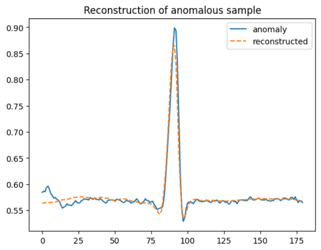

Figure: reconstruction on anomalous sample

>>> Classification based on Reconstruction Error

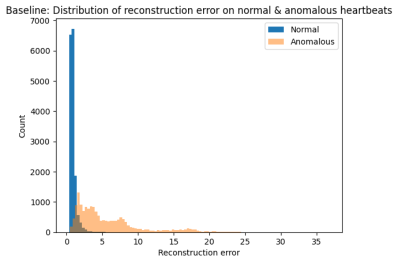

Figure: Distribution of reconstruction error on regular & anomalous samples

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

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>>> Review: Differential Privacy

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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.

>>> Examples of DP mechanism

$ 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:

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

where the variance is calibrated to satisfy DP.

$ DP-SGD

- DP version for training neural networks
- **Add noise to gradients** while training

>>> **Models**

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AE-(dp)WGAN

- $ Model based on GAN network, which are commonly used in image generation.
- $ Based on RTSGAN, which delivers state of the art performance for time series data.
- $ No private counterpart, hence we will implement our own private version.

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>>> AE-(dp)MERF

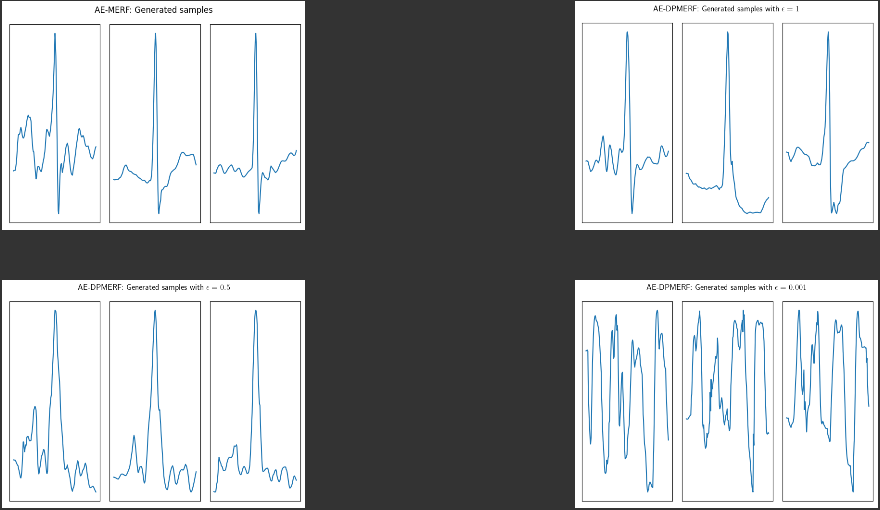


Figure: AE-(dp)MERF generated samples

>>> AE-(DP)MERF

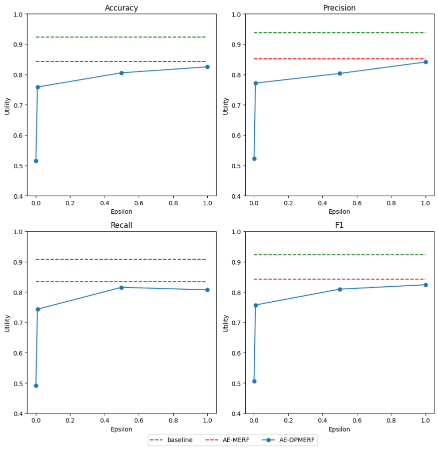
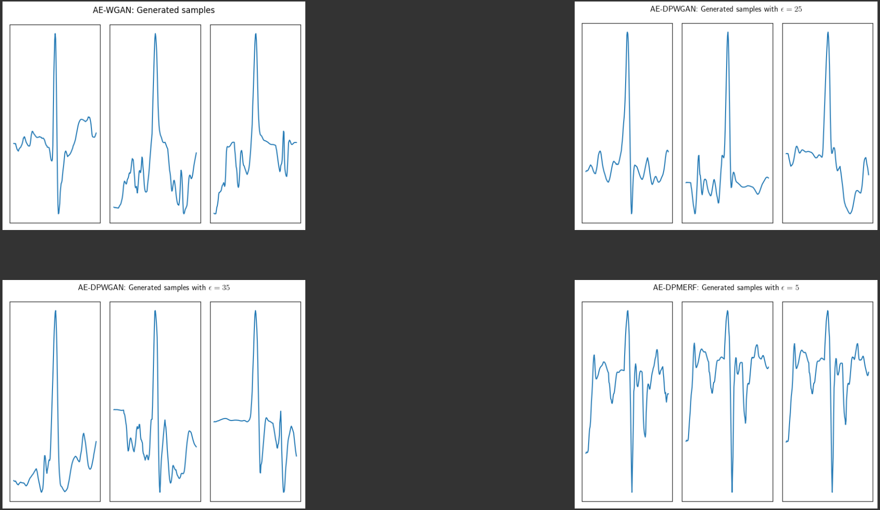


Figure: Results of AE-(DP)MERF with different privacy budgets (lower epsilon means higher privacy)

\>>> AE-(dp)WGAN



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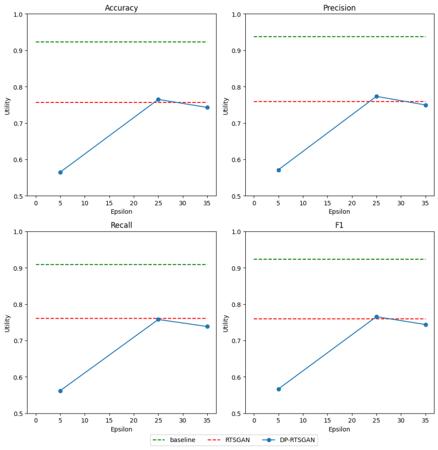

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- $ AE-(dp)MERF can work in **lower epsilon ranges**, which translates to **stronger privacy guarantees**.
- $ **AE-(dp)WGAN gives worse utility** and can only work with meaningless privacy budgets ϵ.
- $ We lose utility when **replacing original data with non-private synthetic** data.
- $ 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%).

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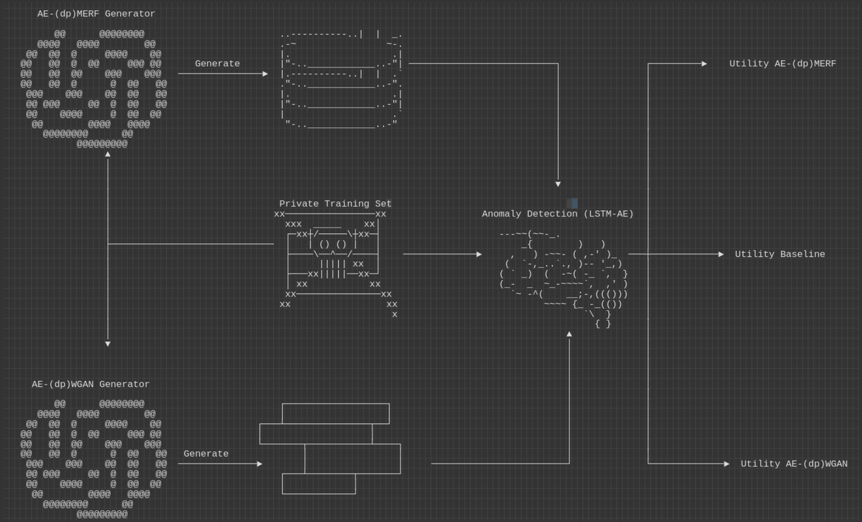

Figure: Structure of Contamination Experiment

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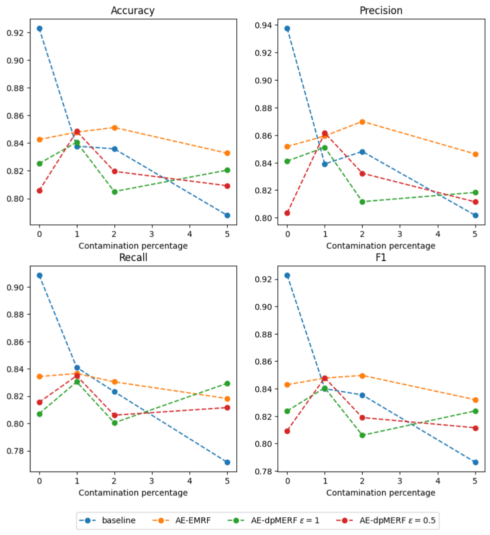

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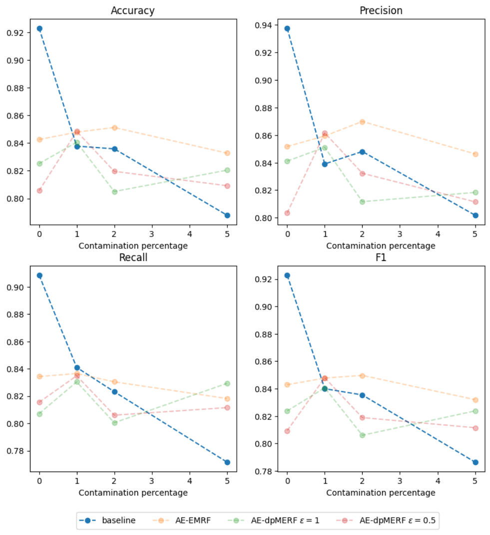

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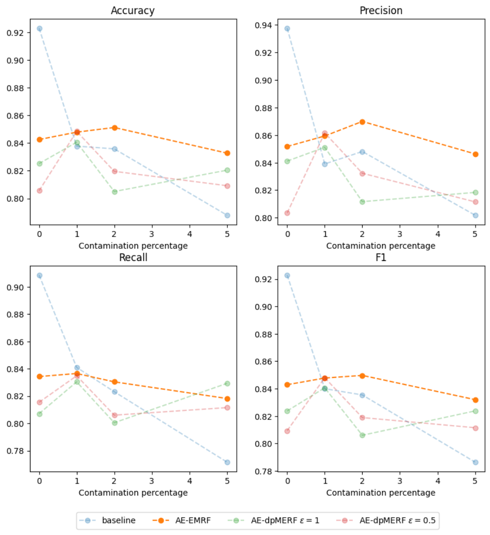

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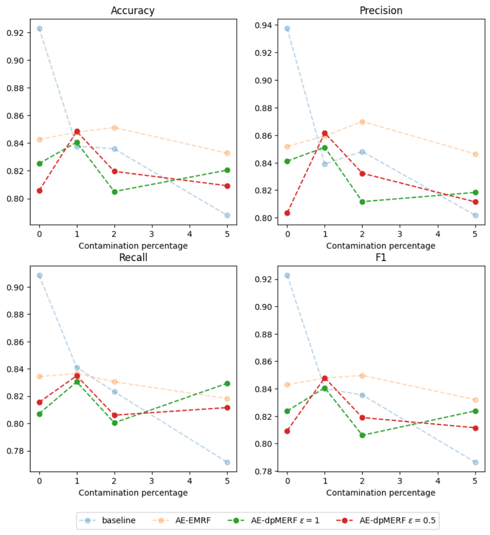

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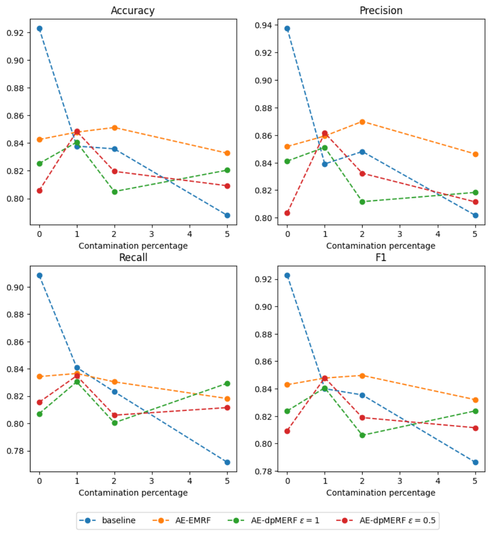

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- $ We measured the `utility` of the synthetic data via the downstream task of anomaly detection (heartbeat arrhythmia).
- $ We investigated the `robustness` of the data generation by `contaminating` the data set with anomalous samples.

>>> Main Findings

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

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

\>>> Privacy-Preserving Acknowledgement

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].
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- 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).

>>> BACKUP

>>> Model Architecture

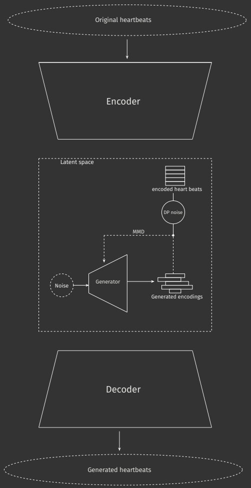

Figure: AE-(dp)MERF architecture

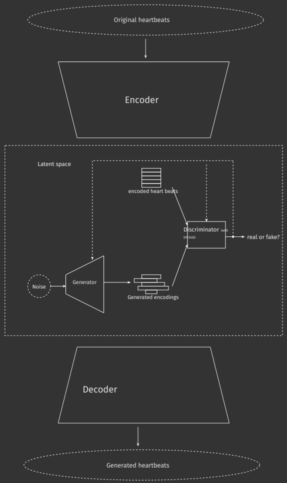

Figure: Architecture of AE-(dp)WGAN

>>> Gaussian Mechanism

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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:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad . \tag{4}$$

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

$$Precision = \frac{TP}{TP + FP} \quad . \tag{5}$$

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

$$Recall = \frac{TP}{TP + FN} \quad . \tag{6}$$

- $ F1 computes the an average of Precision and Recall

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \quad . \tag{7}$$

>>> DP Illustrated

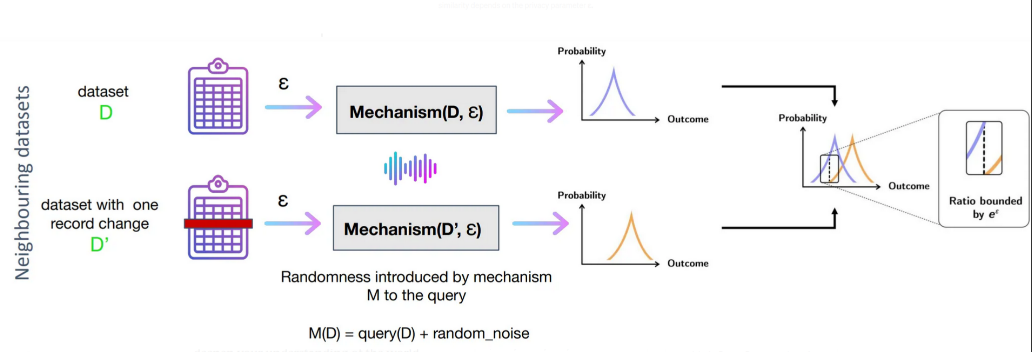
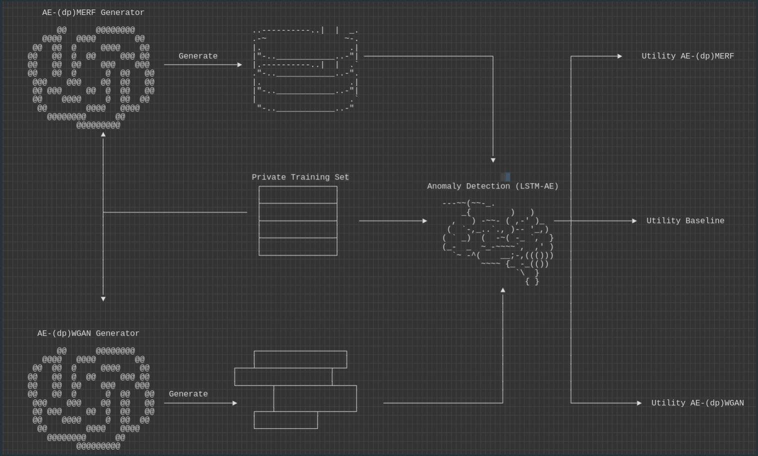


Figure: Illustration of DP[2]

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

Terminal


AE-(dp)MERF Generator
Generate
Utility AE-(dp)MERF
Private Training Set
Anomaly Detection (LSTM-AE)
Utility Baseline
AE-(dp)WGAN Generator
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>>> asd

AE-(dp)MERF Generator