Evaluating the Privacy-Preserving Capabilities of Generated Synthetic Data

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Objective: Evaluate the privacy-preservation of SOTA generative models in synthesizing financial data for ML research.

Generative Models: Banksformer, CTGAN, TVAE, DoppelGANger

Dataset: Czech 1M transactions dataset with account, type, opteration, amount, k_symbol

Privacy Evaluation Summary

Privacy Metrics: Measured k-anonymity, l-diversity, and t-closeness, where the synthetic datasets maintained lower k-anonymity and l-diversity. Banksformer showed the closest distribution proximity.

Re-identification Risk: likelihood of tracing an individual back to their original data from the generated data via comparing frequency distributions. DoppelGANger and Banksformer exhibited higher re-identification risks as distributions don't closely match the real ones.

Attribute Disclosure Risk: potential for sensitive information about individuals to be inferred from a dataset. Al synthetic datasets exhibited lower risk as they don't retain the same attribute relationships.

Membership Inference Attacks: determine if an individual's data was used in the training set of a model. Results revealed that Banksformer and DoppelGANger are highly susceptible to these attacks.

Centre for Management of Technology & Entrepreneurship

Balancing Utility and Privacy

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Objectives

Evaluate the privacy-preservation of state-of-the-art generative models in synthesizing financial datasets

Investigate the trade-offs between data utility and privacy across different synthetic data generation techniques

Generative Models

CTGAN

Generating tabular data that mimic real distributions, addressing challenges of imbalanced and sparse data

DoppelGANger

Dual mechanism with MLPs and RNNs, generating metadata and time-series data while preventing mode collapse

TVAE

Triplet-based Variational Autoencoder, enhances data representation in latent space to capture complex relationships

Banksformer

A transformer-based approach for generating sequence data, focusing on temporal dynamics and patterns

Dataset: Czech transactions

Over 1M Transactions from 4500 accounts

Timestamps from Jan 1, 1993 to December 31, 1998

Features: account, type, operation, amount, k_symbol

Privacy Metrics

01

K-Anonymity

each individual is indistinguishable from at least **k–1** others for every identifiable attribute set

02

L-Diversity

for every group of individuals, there are at least **l** diverse values for each sensitive attribute

03

T-Closeness

distribution of a sensitive attribute is no further than **t** from the dist of the attribute in the entire dataset

Results

- Real data maintained high k-anonymity and l-diversity, synthetic data had low
- T-closeness varied significantly: Banksformer showed closer distribution proximity compared to others

Re-identification Risk

The likelihood that an individual's data in a synthetic dataset can be traced back to that individual in the original dataset

Frequency Dists

Compare the frequency distributions of categorical variables between the real and synthetic

Kolmogorov-Smirnov (KS) Test

Similarity between the distribution of numerical variables, quantifying the max discrepancy between their cumulative distribution functions

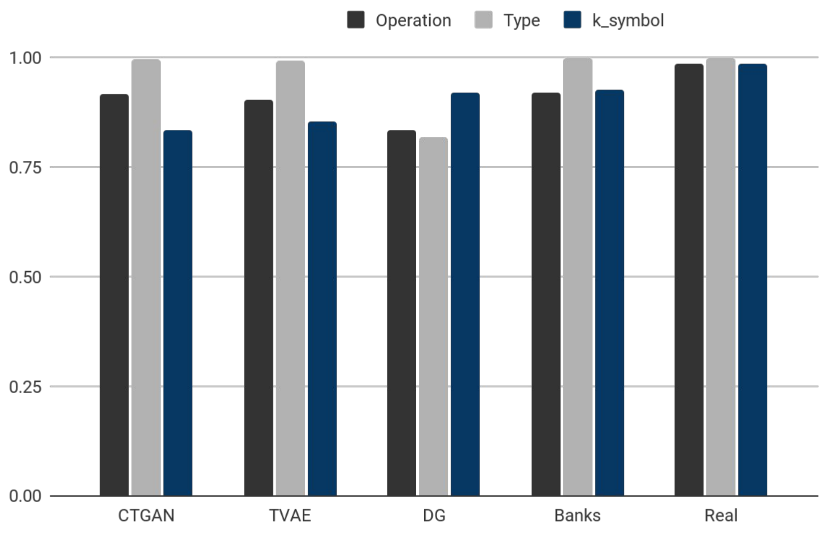
Results

- DoppelGANger and Banksformer exhibited higher re-identification risks
  - significant discrepancies in both categorical and numerical
- CTGAN and TVAE provide a more balanced approach
  - close categorical similarities, diverse numerical distributions
  - better balance between privacy and utility

Attribute Disclosure Risk

Potential for sensitive information about individuals to be inferred from a dataset

- Random Forest classifiers to predict sensitive attributes based on other data attributes



Results

Models trained on synthetic data typically yielded lower prediction accuracies, indicating that the synthetic data doesn't retain the same attribute relationships

Membership Inference Attacks

Combine Data

Real and synthetic combined and labelled: creates a dataset that reflects potential knowledge an attacker might possess

Attack Models

Binary classifiers trained to differentiate between real and fake

- logistic regression, Naive Bayes, Random Forest, XGBOOST, GBM, and a feedforward neural network

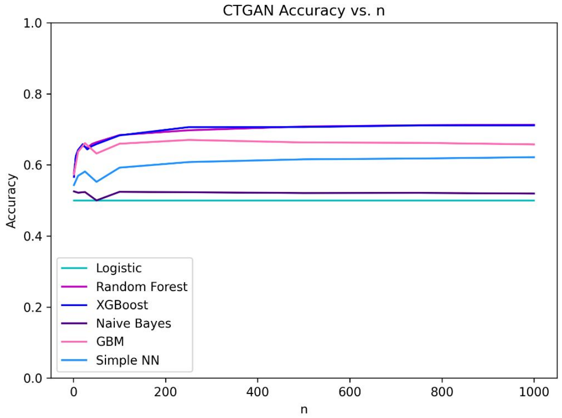
Performance Metrics

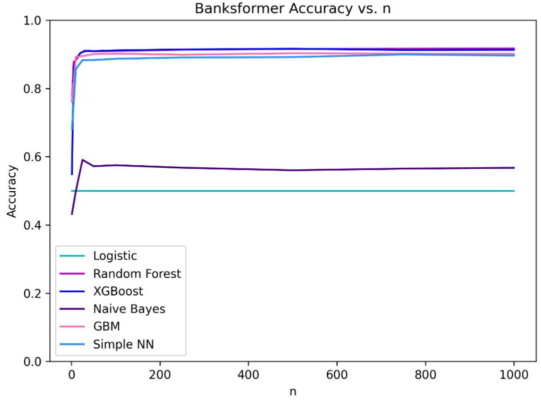
Balanced accuracy, precision, recall, and F1 scores using 5-fold cross-validation

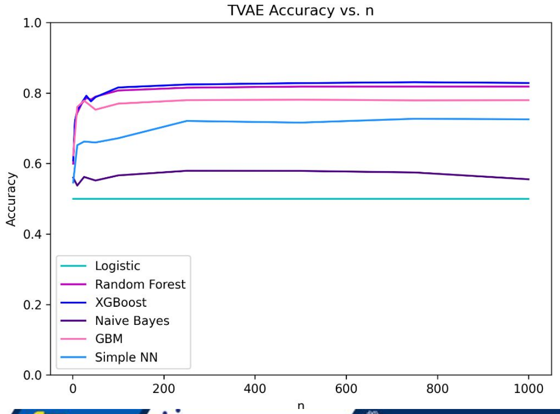
Different Splits

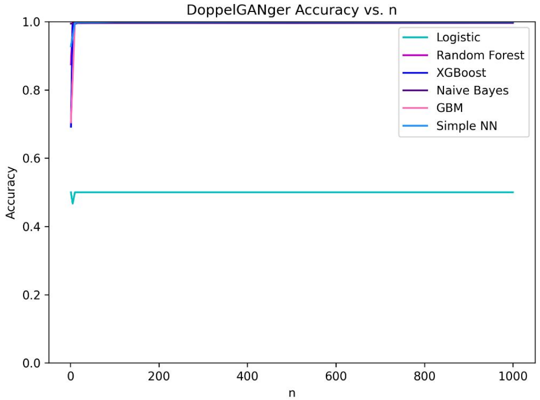
Varying n, the number of accounts to which an attacker has access to labels = 1, 10, 25, 50, 100, 250, 500, 750, 1000

Membership Inference Attack Results









- As n increases, accuracies converged
- Logistic Regression overfit: predits 1 class → balanced accuracy of around 50%
- Banksformer and DoppelGANger: high accuracies → significant privacy concerns
- CTGAN and TVAE: better resistance to attacks, with accuracies closer to the ideal 50%

Conclusions

Generative Model Effectiveness

CTGAN and TVAE showed better results in protecting privacy

Banksformer and DoppelGANger exhibited vulnerabilities that could lead to privacy breaches

Data Utility and Privacy Balance

Further development and refinement of generative models are required to enhance their ability to produce useful yet non-revealing datasets

Further Research

Integration of differential privacy or encryption techniques directly into the data generation process and the exploration of the trade-off between utility and privacy

Thanks!