_Privacy-Aware Data Integration

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Overview

Data privacy as a topic has entered the mainstream conscious. Years of negligent data storage, leading to breaches, and inappropriate sharing have made the public reluctant to share their data. In addition, this caused legislators to enact restrictions in the use and handling of data.

Data, through analysis, has a large utilitarian and economic value. It is, therefore, imperative, that workflows for data sanitation and responsible sharing are created, compliant with current regulations. Those will, in turn, help curb reluctance of sharing data.

Data Release Types

Data releases can be broadly split into 2: datasets and and the results of analyses of the data.

Publishing the results of an analysis (models, statistics, census data) lowers the possible exposure of the participants but limits the usability of the data to the questions answered by the release. However, since the information output is limited it is easier to protect the data using a tool such as Differential Privacy.

A more general data release, such as a dataset, allows for answering any arbitrary question. This larger scope raises questions about which information should be kept in the data, and how it should be evaluated in terms of privacy and accuracy.

Ensuring Privacy and Accuracy

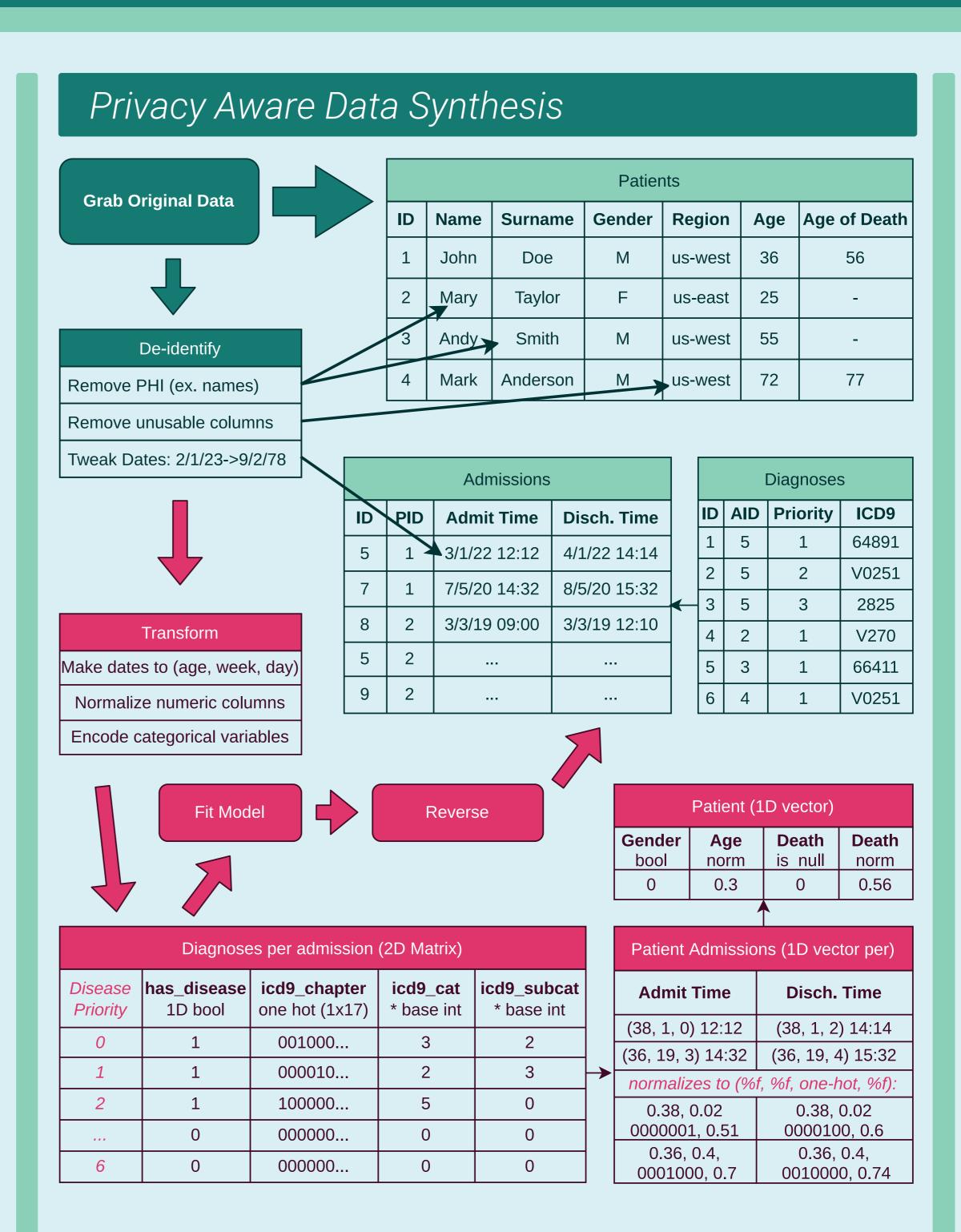
In order to ensure that a data release meets accuracy and privacy requirements, two approaches are used.

First, when modeling the data, great care is taken to create a compressed representation (a dense bayesian network or a small neural network with transfer learning). This limits the information extracted from the data, lowering the noise added. Then, Differential Privacy is applied to the model, which mathematically bounds the privacy and accuracy output.

The end result is **benchmarked** by measuring the **deviation of queries**, the behavior of **models**, and a suite of **marginal metrics** (statistics based).

Future goals

Test viability of Differential Privacy in Data Synthesis, create multiple models for synthesizing multimodal data, and create a suite of viable metrics for that data.



Testing of Synthetic Data

CS	X^2	р	KS	KS
lang	0.01	0.89	age	0.02
ethn	0.03	0.7	death	0.05

KL	diag	meds
age	0.8	0.78
death	0.7	0.5

AVG err: select avg(age) from patients select count(*) from diagnoses group by icd9 limit 20

p

0.78

0.68

Train classifiers, Test accuracy:

↑ accuracy_{real data} = ↑ quality accuracy_{train data} > accuracy_{test data} = ↓ privacy





