GENERATING SYNTHETIC LONGITUDINAL DATA DEC. 1, 2021 | 11AM EDT

Presented by



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Generating Synthetic Longitudinal Data

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The Synthesis Process





- The source datasets can be as small as 100 or 150 patients. We have developed generative modeling techniques that will work for small datasets.
- The source datasets can be very large then it becomes a function of compute capacity that is available.
- It is not necessary to know how the synthetic data will be analyzed to build the generative models. The generative models capture many of the patterns in the source data.





Synthetic Data

COU1A	AGECAT	AGELE70	WHITE	MALE	BMI
United States	2	1	1	1	33.75155
United States	2	1	1	0	39.24707
United States	1	1	1	0	26.5625
United States	4	1	1	1	40.58273
United States	5	0	0	1	24.42046
United States	5	0	1	0	19.07124
United States	3	1	1	1	26.04938
United States	4	1	1	1	25.46939



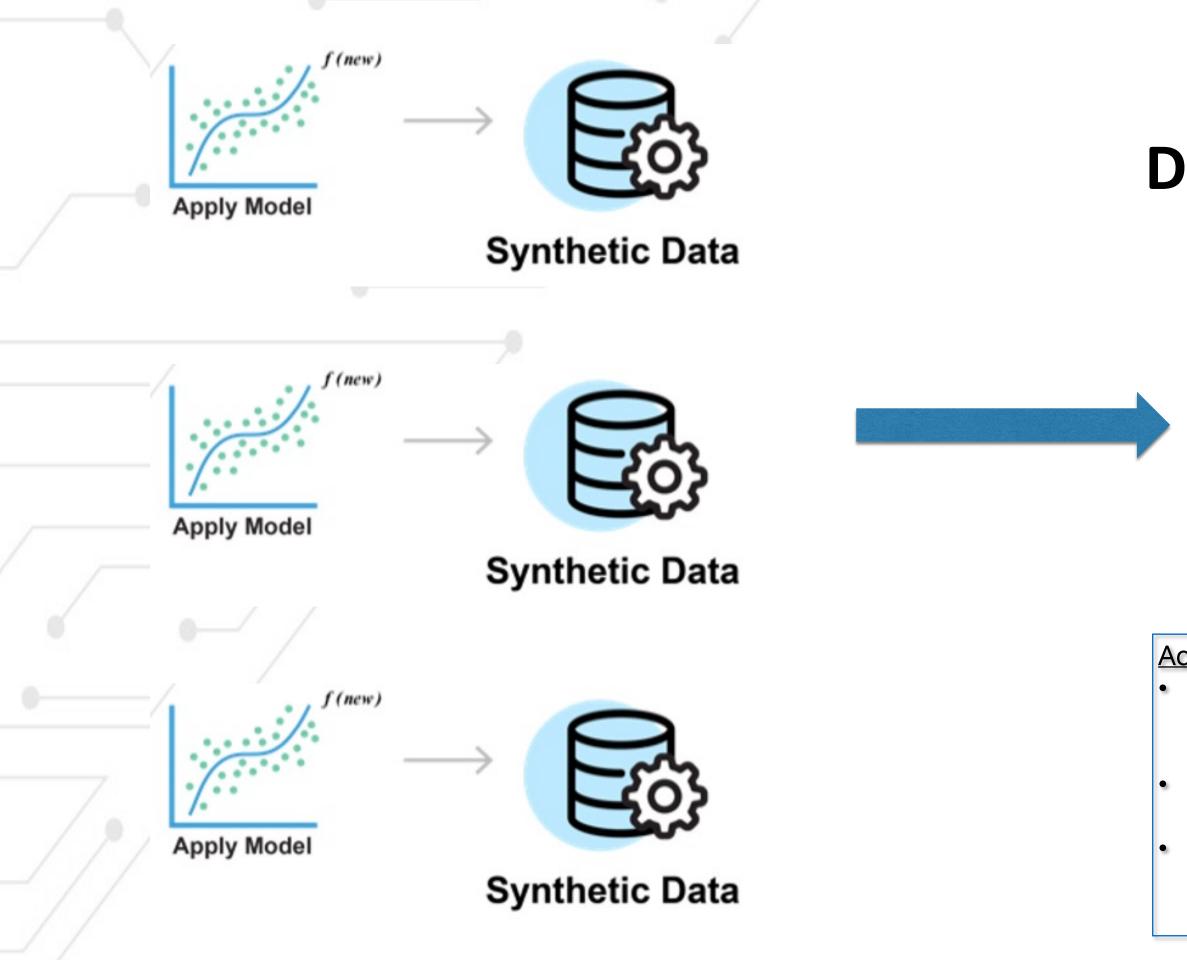








A simulator exchange allows data to be made available without sharing actual data



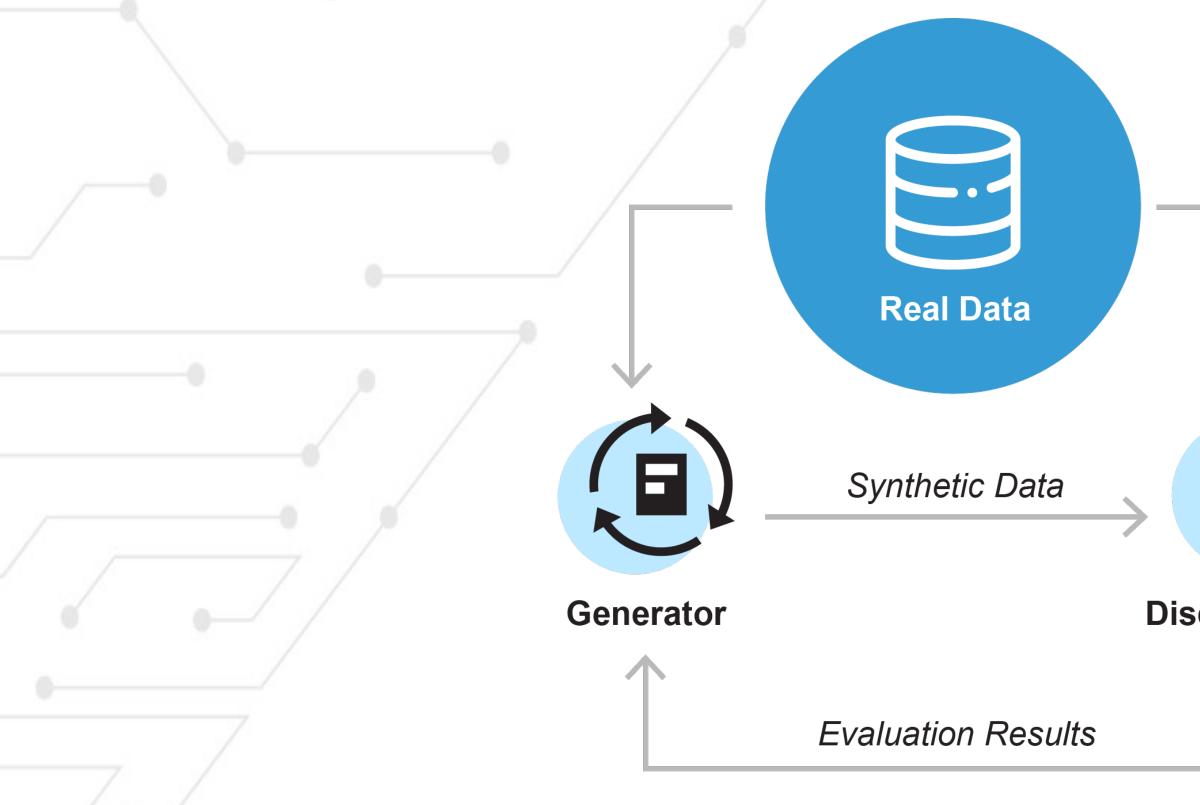
Data Consumers

Additional Clarifications

- The simulators would not be given to the data consumers they would only have access to them through an interface.
- This access would be monitored and throttled to reduce the risk of attacks on the models.
- Data consumers would also need to agree to terms of use around the access to the simulators.



Training a generative model often uses a discriminator







Discriminator





The synthesis of longitudinal data requires a different approach

- Features & Cohorts:
 - Define features on the raw longitudinal data and then synthesize the tabular feature dataset
 - Define a cohort on the raw longitudinal data and then synthesize the • tabular cohort dataset
- Raw Longitudinal:
 - Fully vs partially synthetic data
 - For RWD we use a hybrid approach of sequential synthesis and recurrent neural network architectures to synthesize these – full synthesis



Two synthesis strategies for raw **longitudinal data**

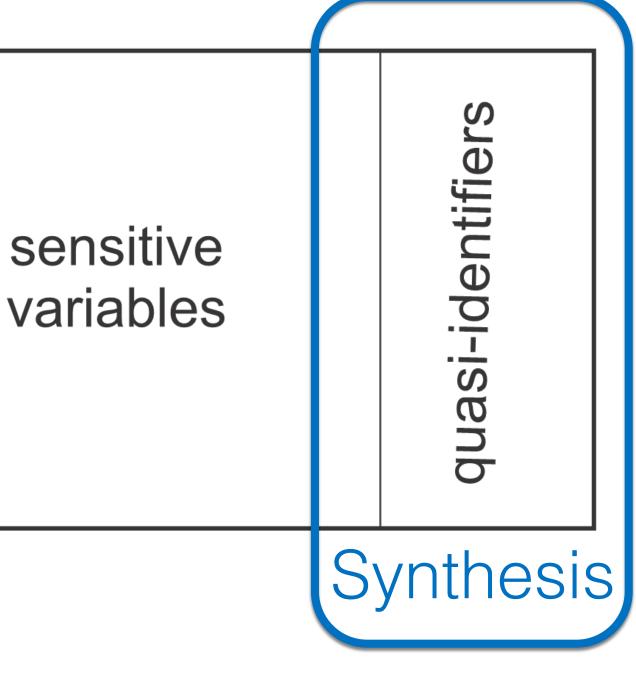
quasi-identifiers

Full Synthesis Synthesize all variables

sensitive variables

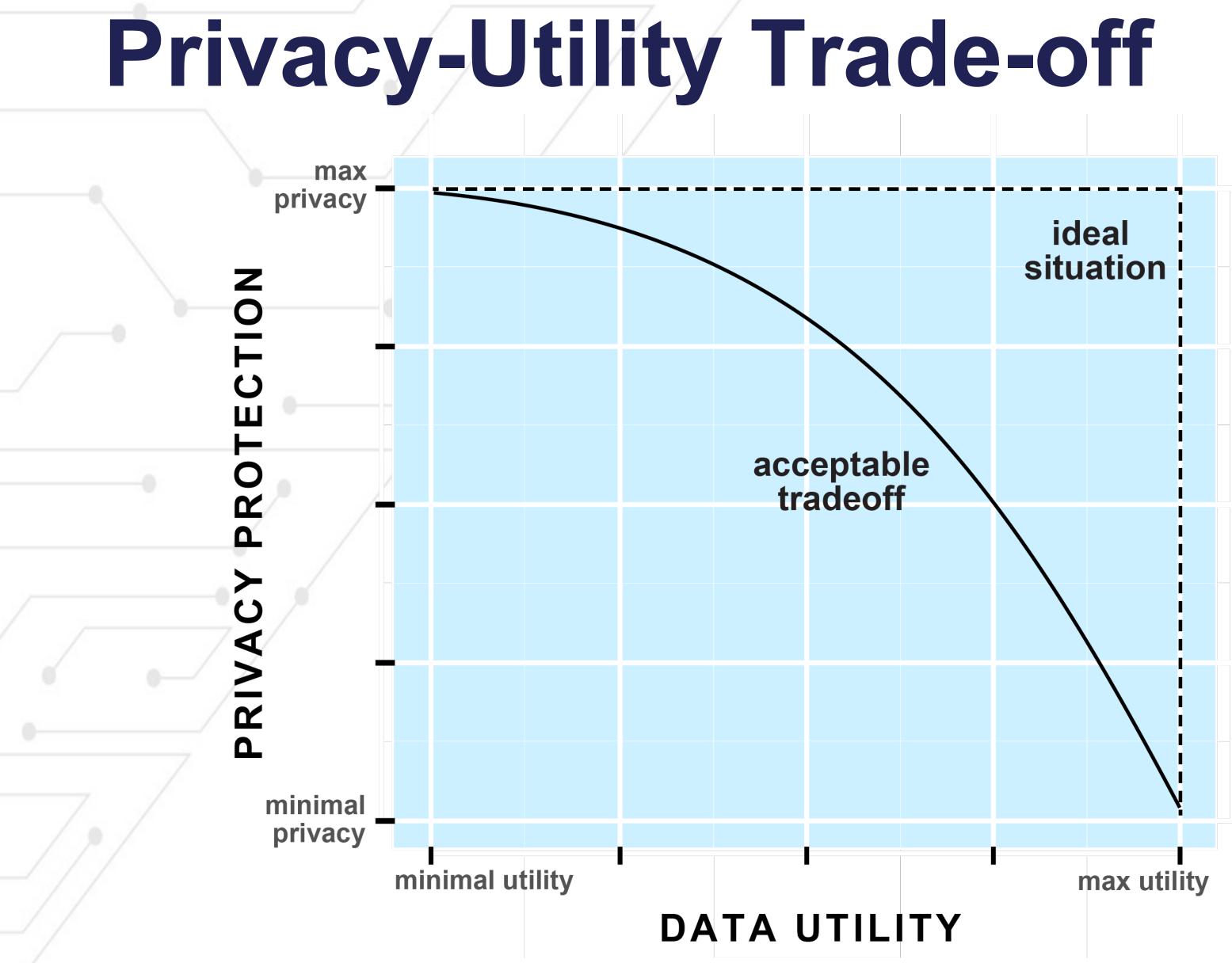
Synthesis

Partial Synthesis Synthesize quasi-identifiers



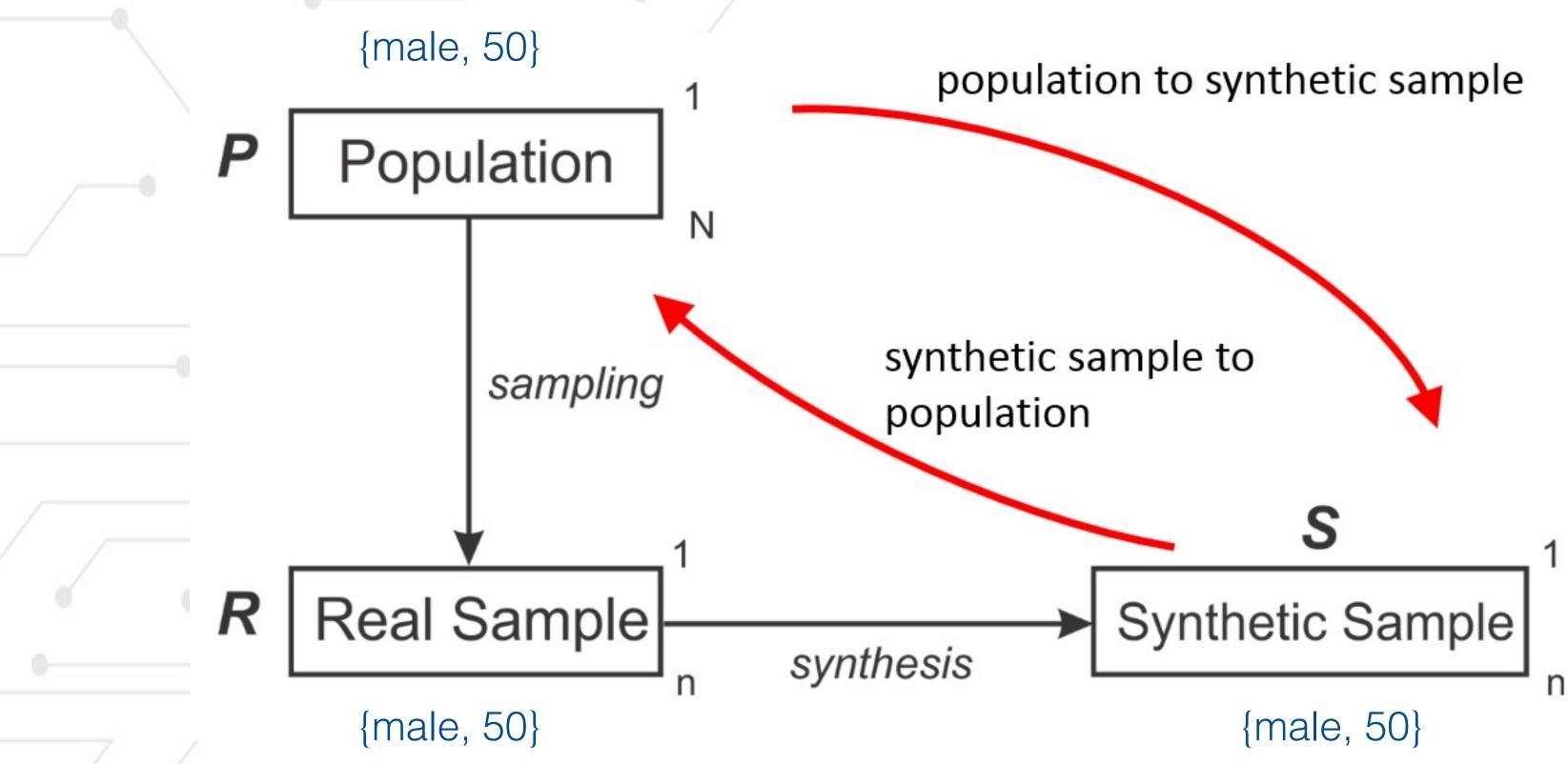








Identity Disclosure Model







Evaluations of (re-)identification risks show that it is low in multiple studies across multiple datasets

Dataset	Fully Synthetic Data	
Washington Hospital Data (Discharge)	0.0197	
Canadian COVID-19 Data (Public Health)	0.0086	

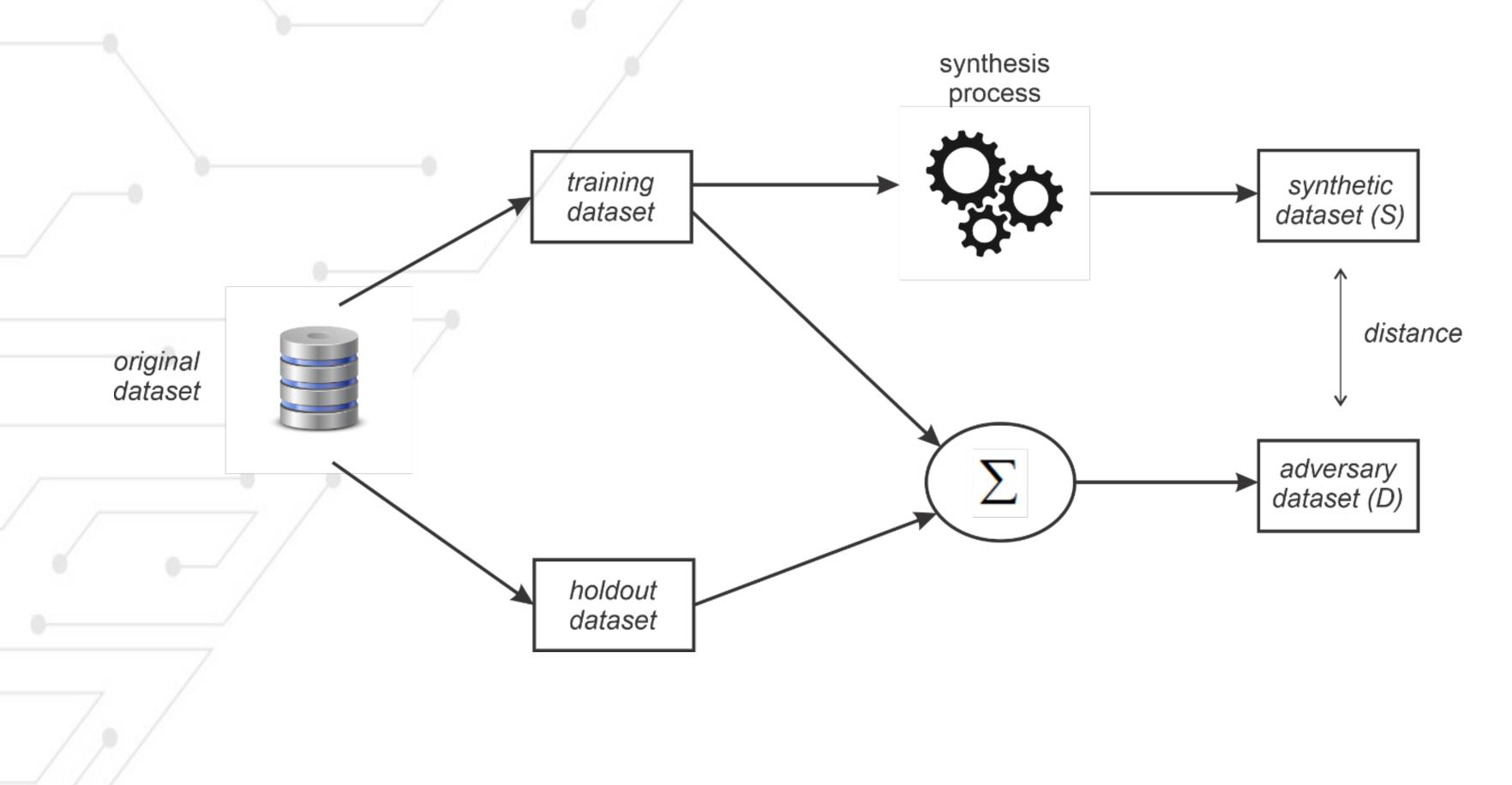
A commonly used risk threshold = 0.09

Original Data 0.098

0.034

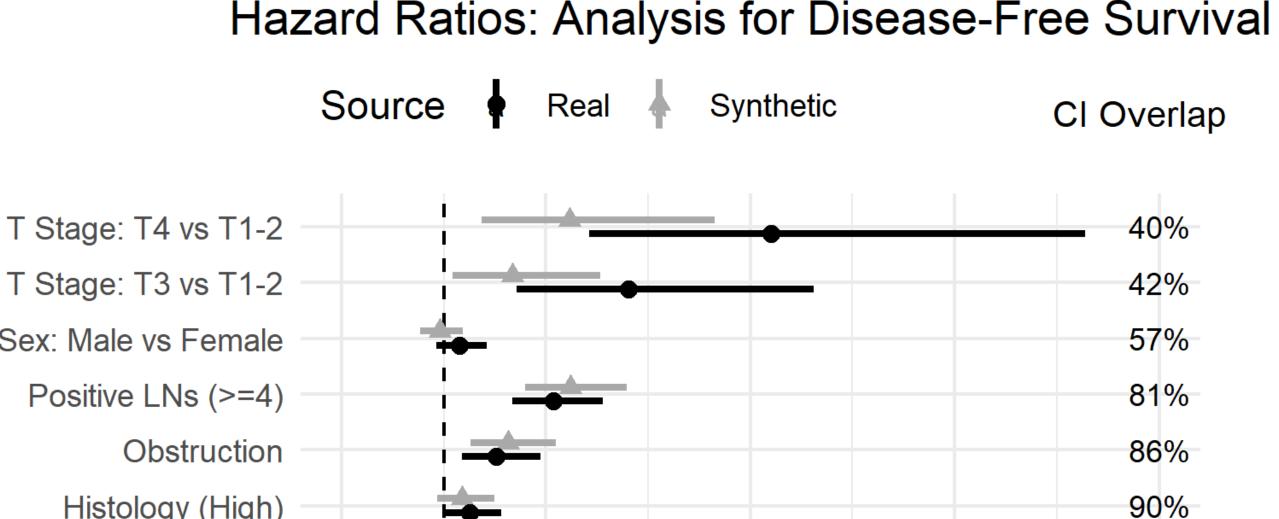


Membership disclosure: is the distance between S and D predictive of which records are in the training dataset





Comparing real and synthetic data: Adjusted model of impact of bowel obstruction on DFS



T Stage: T3 vs T1-2 Sex: Male vs Female Positive LNs (>=4) Obstruction Histology (High) ECOG: 1-2 vs 0 BMI: 25-30 vs <25 BMI: >30 vs <25 Age: 40-69 vs <40 Age: >=70 vs <40

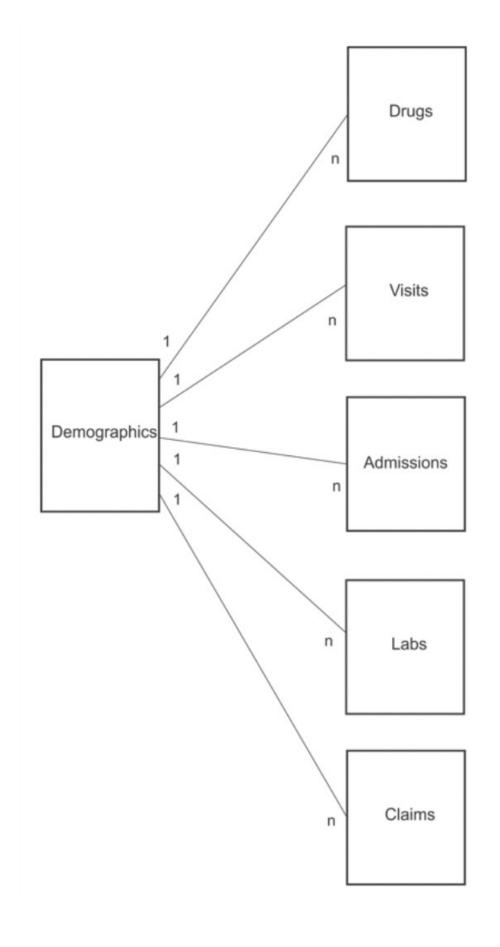
0

CI Overlap

	40%
	42%
	57%
	81%
	86%
	90%
	89%
	89%
	91%
	99%
	88%
6	8



Longitudinal Data Model



Demographics
Age
Sex
Time to last day of follow-up available
Comorbidity score (elixhauser)

Drugs
Dispensed amount quantity
Relative dispensed time in days
Dispensed day supply quantity
Morphine use (binary)
Oxycodone use (binary)
Antidepressant use (binary)

Visits (ED)
Relative admission time in days
Problem code 1
Problem code 2
Resource intensity weights

Admissions (Hospital)	
Relative time admitted in days	
LOS	
Diagnosis code 1	
Diagnosis code 2	
Resource intensity weight	

Lab

Test name

Test result (integer)

Relative time in days lab taken

Claims

Primary diagnosis code

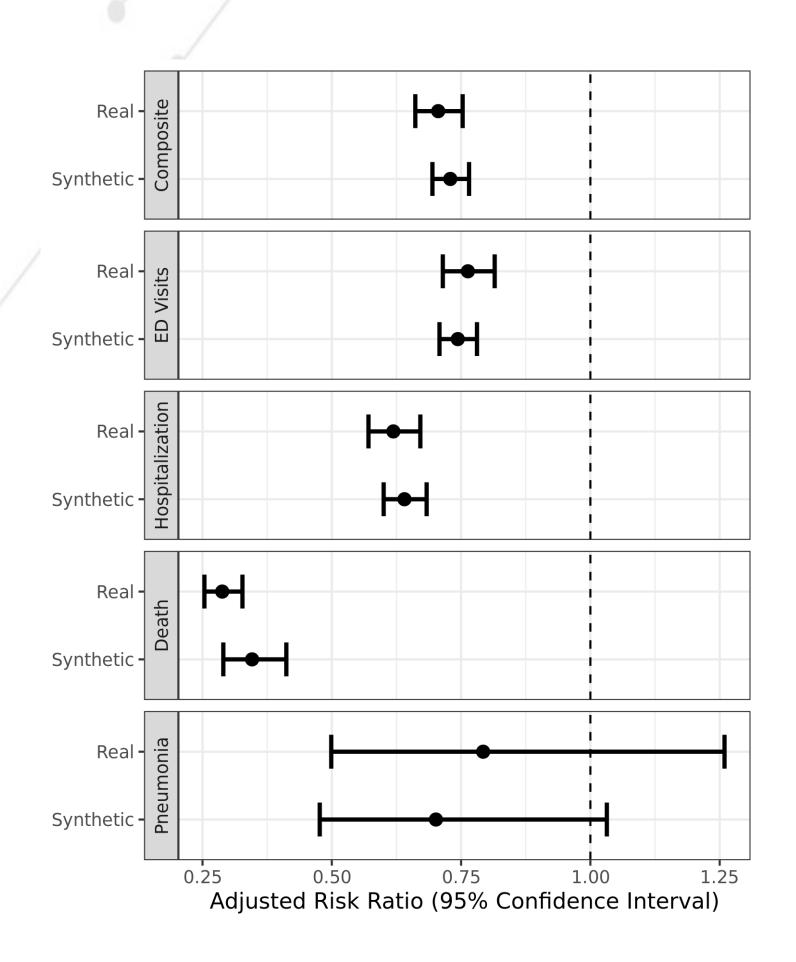
Provide specialty

Relative service event start date



Adjusted Cox Regression

Note: Adjusted estimates include the following co-variates: age, sex, antidepressant use, Elixhauser score, ALT, eGFR, HCT; Opioid 1 served as the reference group





One way to classify utility metrics is as broad and narrow

broad metrics

These are generic metrics that are easy to calculate when the generative model is built and synthetic data are synthesized. They are only useful if they are predictive of workload-specific metrics.

→ narrow metrics

These are workload-specific and are what is of most interest to the data users. However, all the possible workloads will not be known in advance and therefore we have to consider representative workloads when developing and evaluating utility metrics.



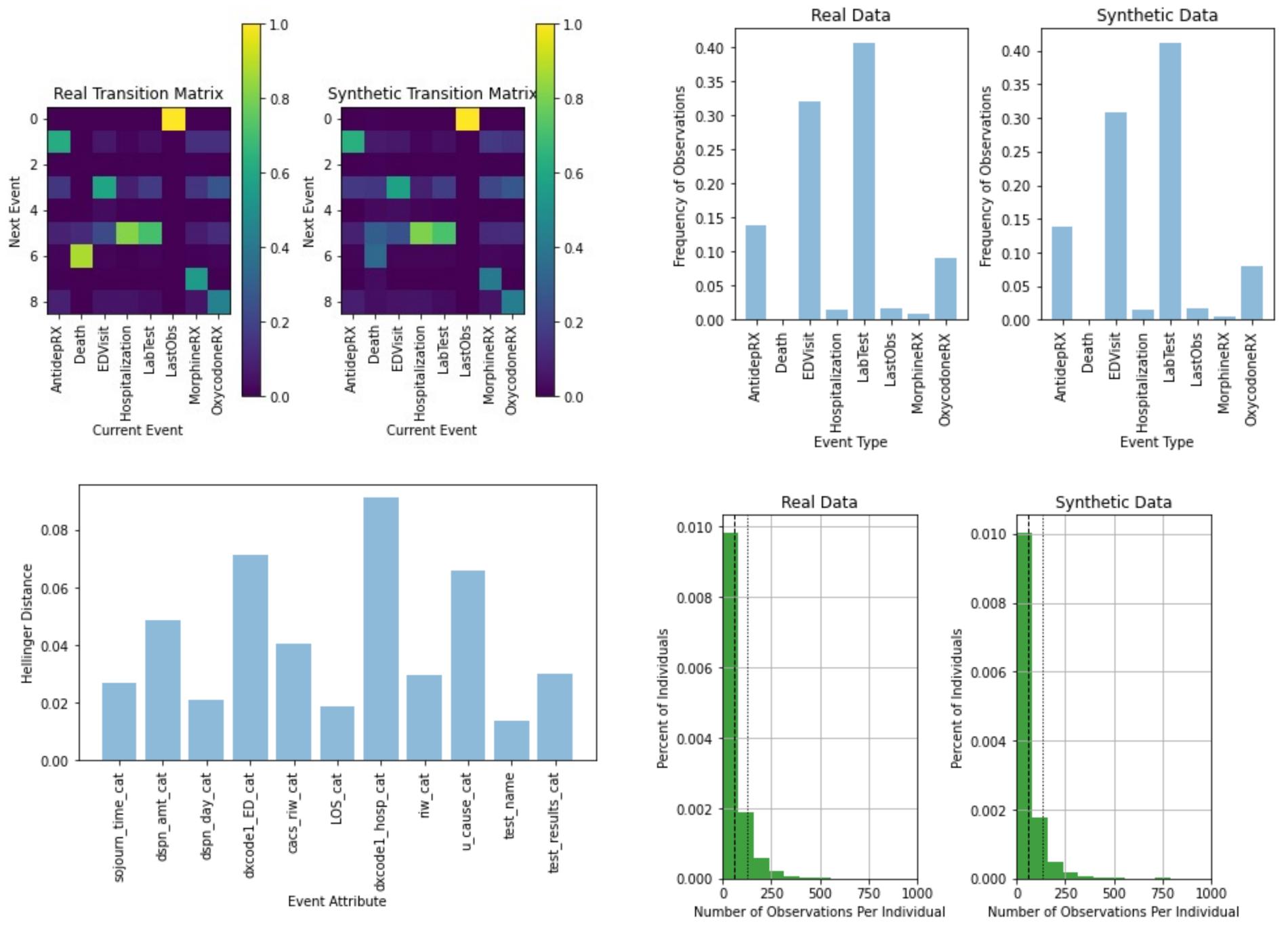
Examples of Broad Metrics

- Comparison of the number of events per patient
 - Number of certain types of events (e.g., prescriptions) per patient
 - Limit the above to a certain time interval
- Comparison of the overall frequency of events
- Comparisons of event distributions across classes of events using univariate distribution comparison metrics
- Evaluation of the k-order transition matrices among events

or classes of events

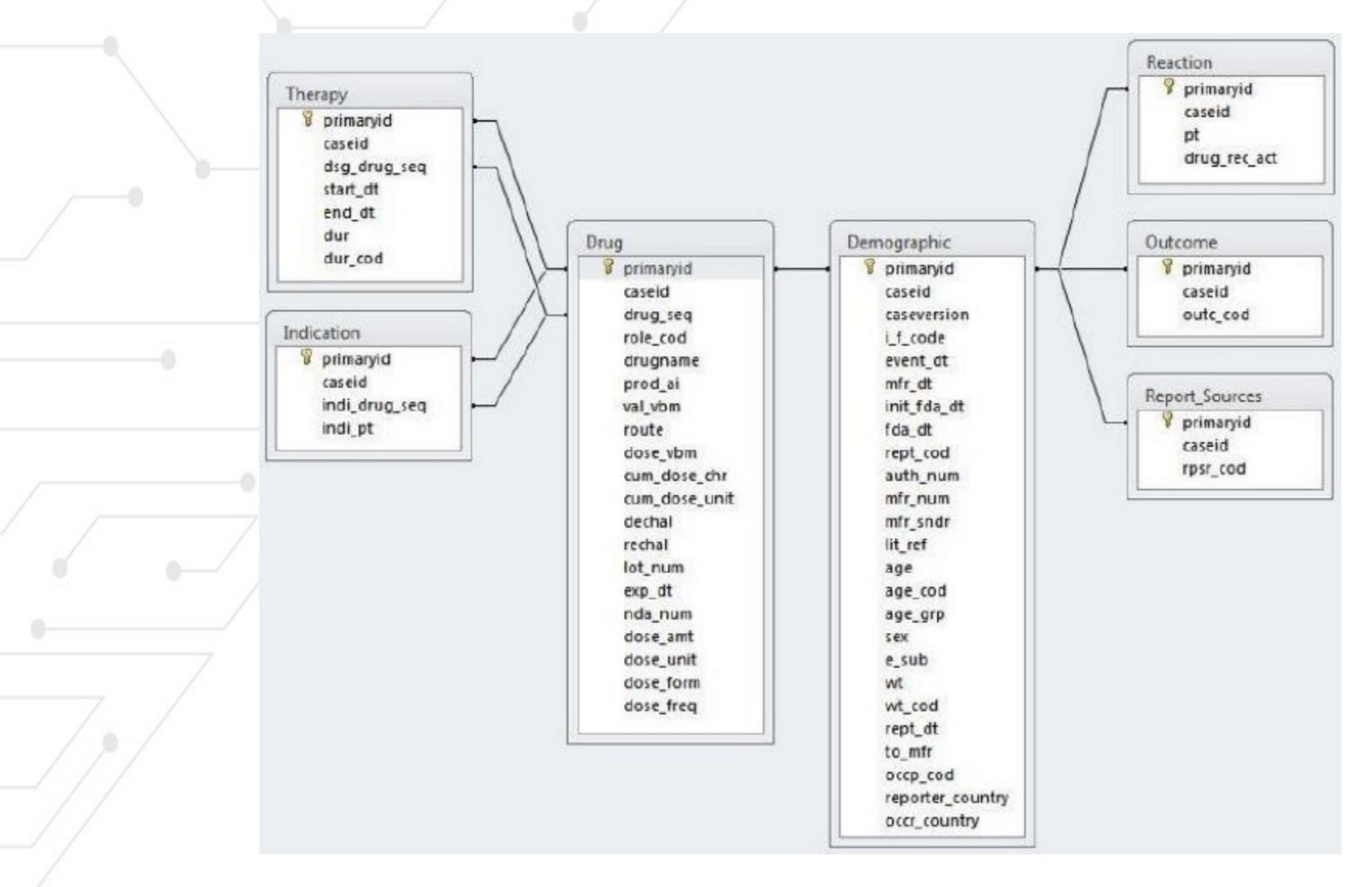




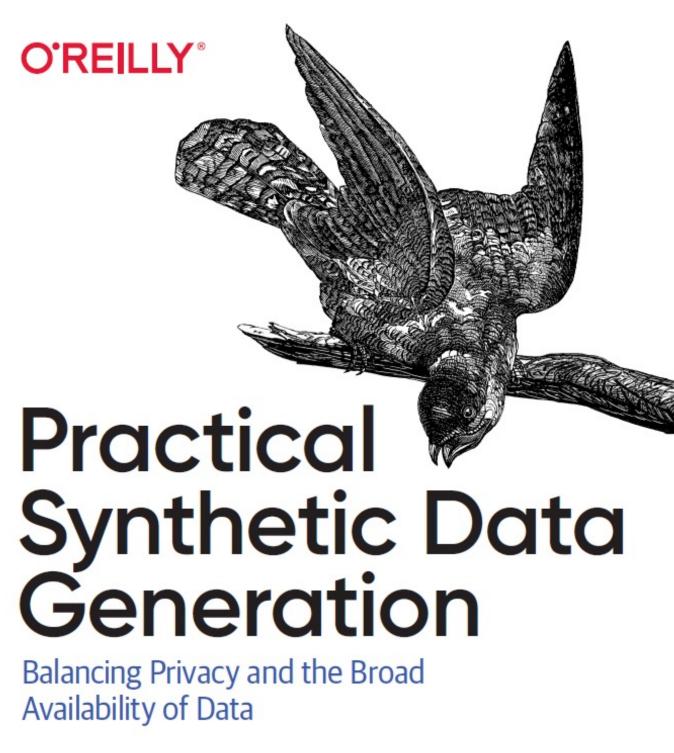




Hierarchical datasets require a different approach







Khaled El Emam, Lucy Mosquera & **Richard Hoptroff**

Introductory Book on Data Synthesis

Published in 2020





Use Case: Analyzing **Longitudinal Hospital Discharge** Data



Roles

Claire (Researcher)

Claire is a researcher who is interested in assessing high-cost hospitalizations with lengths of stay greater than 5 days.

Claire puts in a request for access to data to the data provider





Alice represents the data provider and is authorized to access personal health information. She has a computing background and works in the IT department supporting the data scientists and researchers.

Alice

She receives data requests from users for research purposes





Use Case

Alice can provide synthetic data for Clare for research

purposes as:

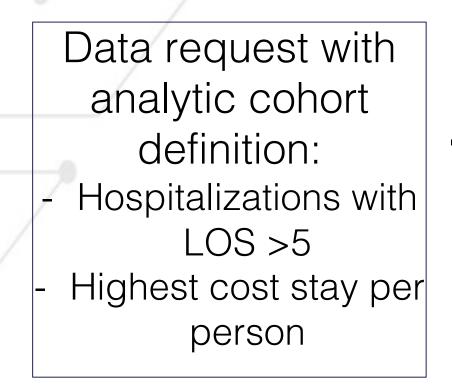
1) A specified cohort of key features 2) Raw longitudinal data

We will illustrate both these use cases





Case 1: Synthesis of a Cohort



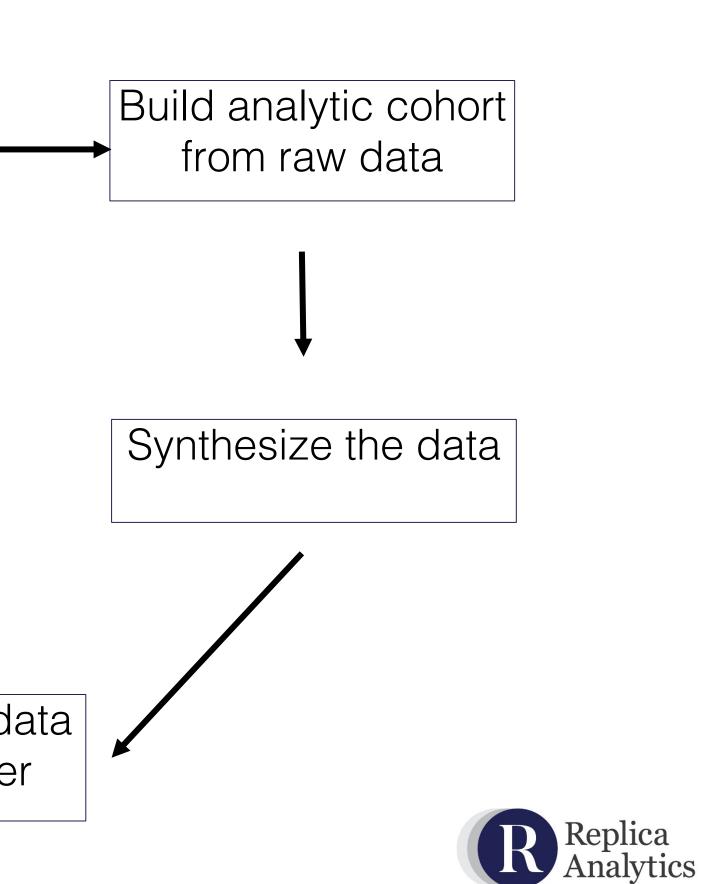


Conduct analysis

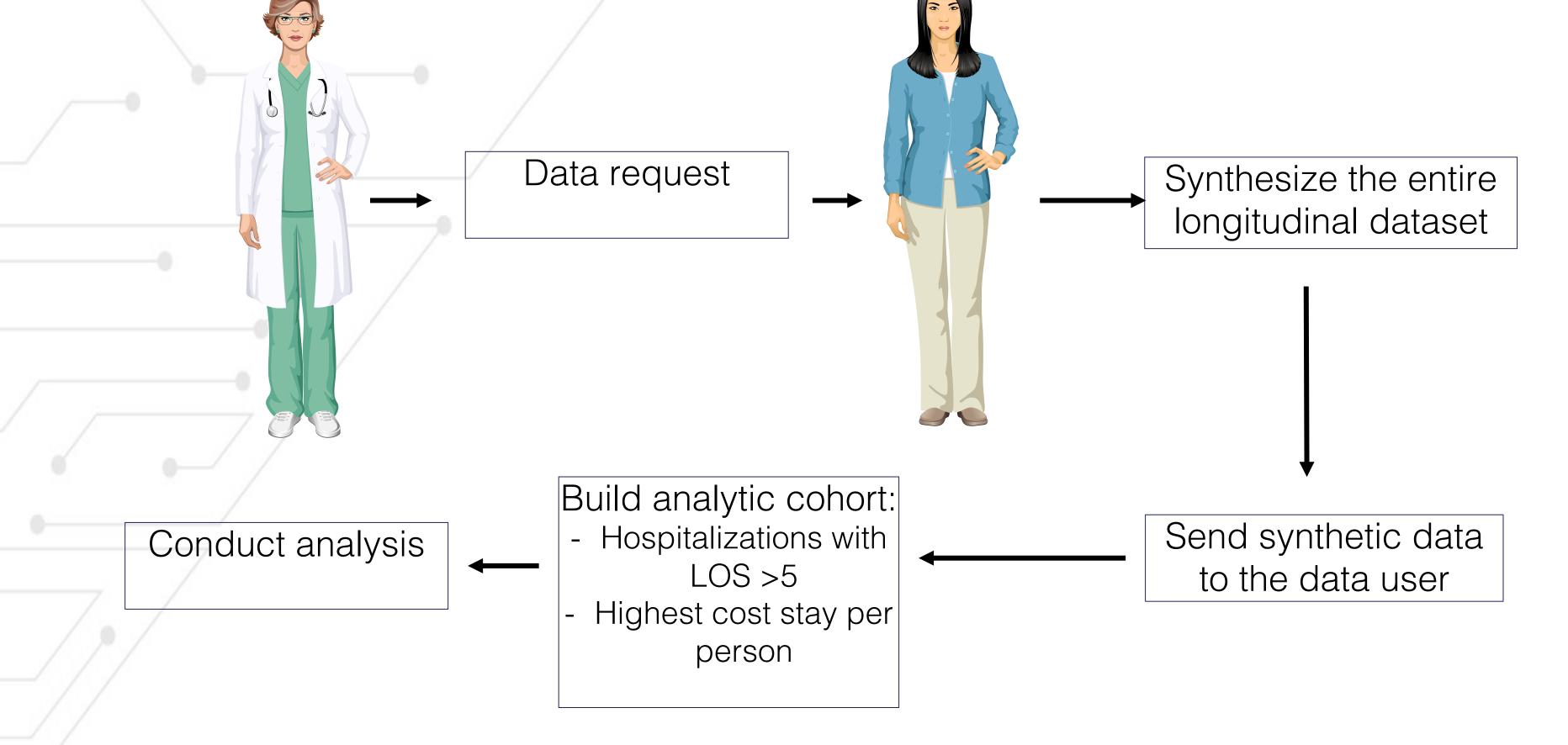


Send synthetic data to the data user





Case 2: Synthesis of Raw Longitudinal Data









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synthesis: <u>https://bit.ly/2TXI0Jy</u>

Read our introductory report and book on the topic

