### Practical Considerations for Synthetic Data Generation

Khaled El Emam kelemam@ehealthinformation.ca

10<sup>th</sup> November 2021

# Training a generative model often uses a discriminator





### Discriminator





## **Two Synthesis Strategies**

quasi-identifiers

### **Full Synthesis** Synthesize all variables

sensitive variables

### **Synthesis**

Se Va



### Partial Synthesis Synthesize quasiidentifiers

ensitive ariables	quasi-identifiers	
	Synthesis	
	Electro	onic lth

Information

Laboratory

# **Privacy-Utility Trade-off**







# **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



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

Hazard Ratio



### 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 a	dmission time in days
Pr	oblem code 1
Pr	oblem code 2
Resourc	ce 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





## Hierarchical datasets require a different approach







## **SDG References**

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