



Synthetic Data Generation – OSIM 5

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Why synthetic data?

- Lack of benchmark datasets for research
- Privacy concerns for data sharing
- Data from commercial vendors is not easily accessible



Different needs!



Less realistic data may be sufficient

Realistic, patient level data is needed





Classification of synthetic data

Algorithm



Knowledge
based

Data Driven

Data Source



Patient
Level Data

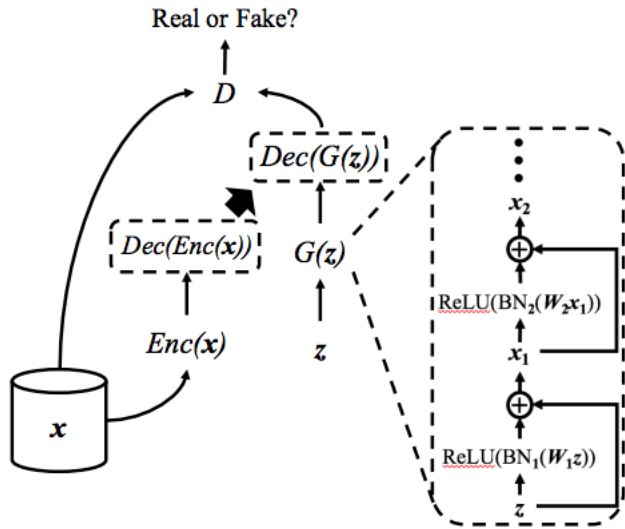
Population
Level
Statistics



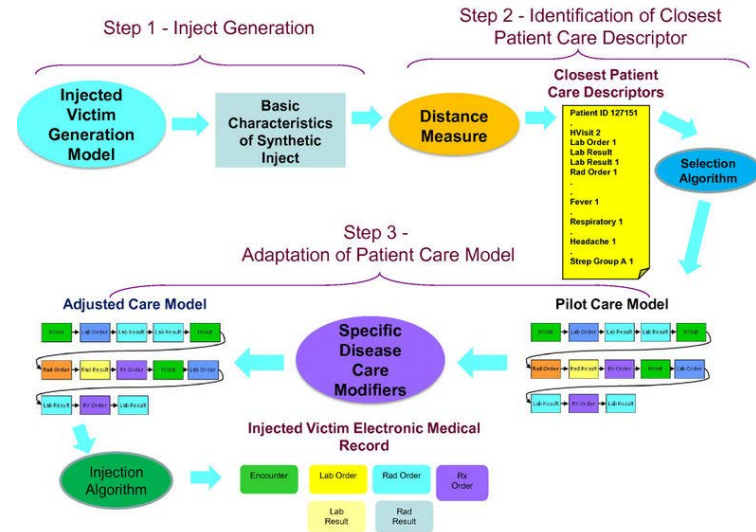
Some available generators



Other research



Choi E, Biswal S, Malin B, Duke J, Stewart WF, Sun J. Generating Multi-label Discrete Patient Records using Generative Adversarial Networks.



Anna L Buczak, Steven Babin and Linda Moniz. Data-driven approach for creating synthetic electronic medical records



OSIM

- Simulated datasets modeled on real observational data sources
- Contain synthetic persons with condition and drug occurrences
- Based on random sampling from probability distributions
- Probability distributions defined on relationships between the actual conditions and drugs
- Originally implemented for OMOP v1 and v2¹

¹ Richard E Murray, Patrick B Ryan, and Stephanie J Reisinger. Design and Validation of a Data Simulation Model for Longitudinal Healthcare Data. AMIA Annu Symp Proc. 2011; 2011: 1176–1185.



Overview

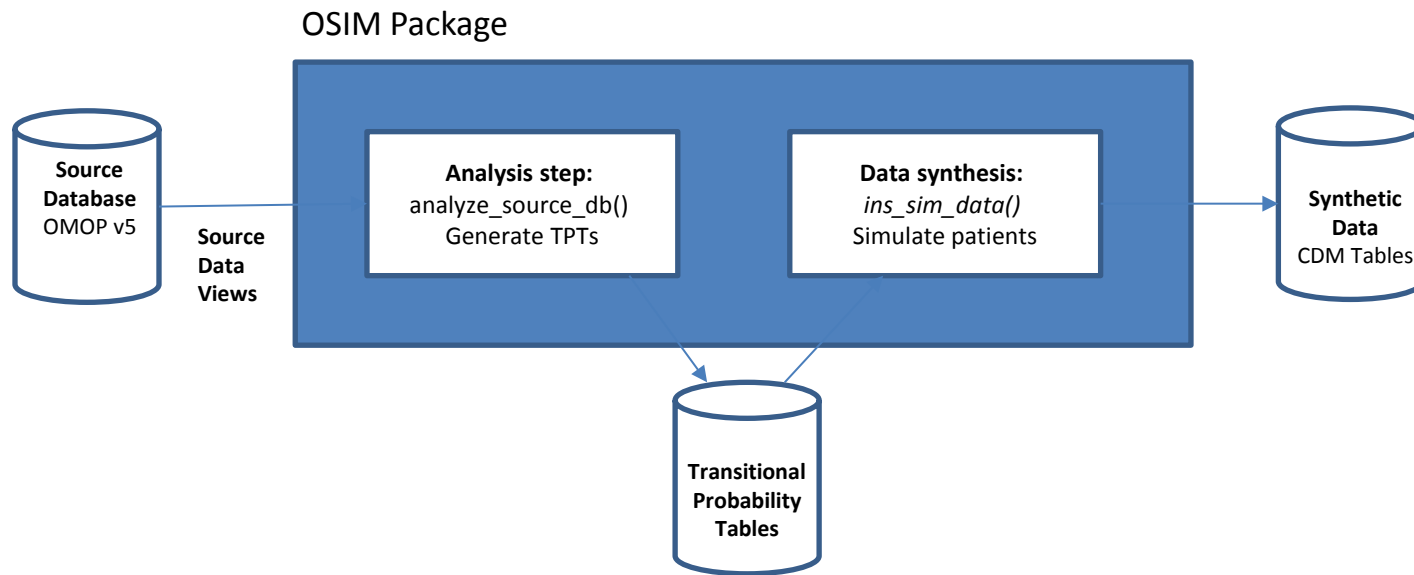


Figure 1. Process flow for OSIM

Analysis

- Preliminary analysis of OMOP CDM data source to record characteristics
- **analyze_source_db()**: generates 18 tables that document transitional probabilities

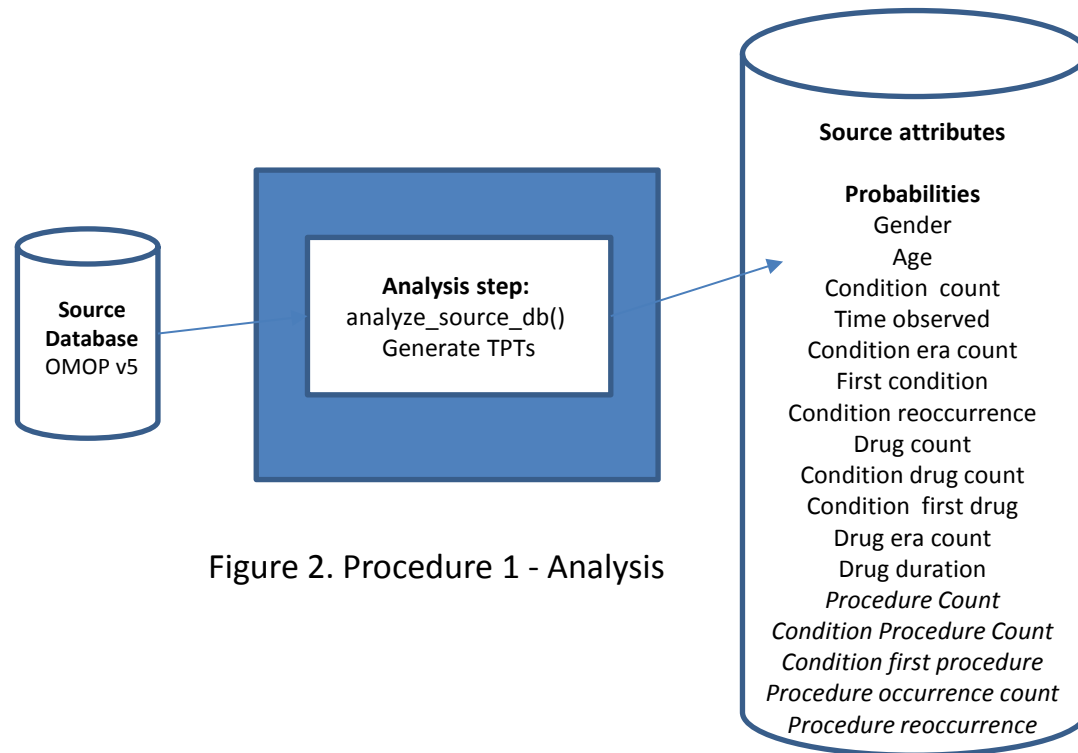


Figure 2. Procedure 1 - Analysis



Analysis

- **src_db_attributes:** Number of persons, drug eras & condition eras, min & max dates
- **gender_prob:** $P(\text{gender concept id})$
- **age_at_obs_prob:** $P(\text{age at obs} \mid \text{gender concept id})$
- **cond_count_prob:** $P(\text{cond concept count} \mid \text{gender concept id, age at obs})$
- **time_obs_prob:** $P(\text{time observed} \mid \text{gender concept id, age at obs, cond count bucket})$
- **first_cond_prob:** $P(\text{condition2 concept id, delta days} \mid \text{gender concept id, age range, cond count bucket, time remaining, condition1 concept id})$
- **cond_era_count_prob:** $P(\text{cond era count} \mid \text{condition concept id, cond count bucket, time remaining})$

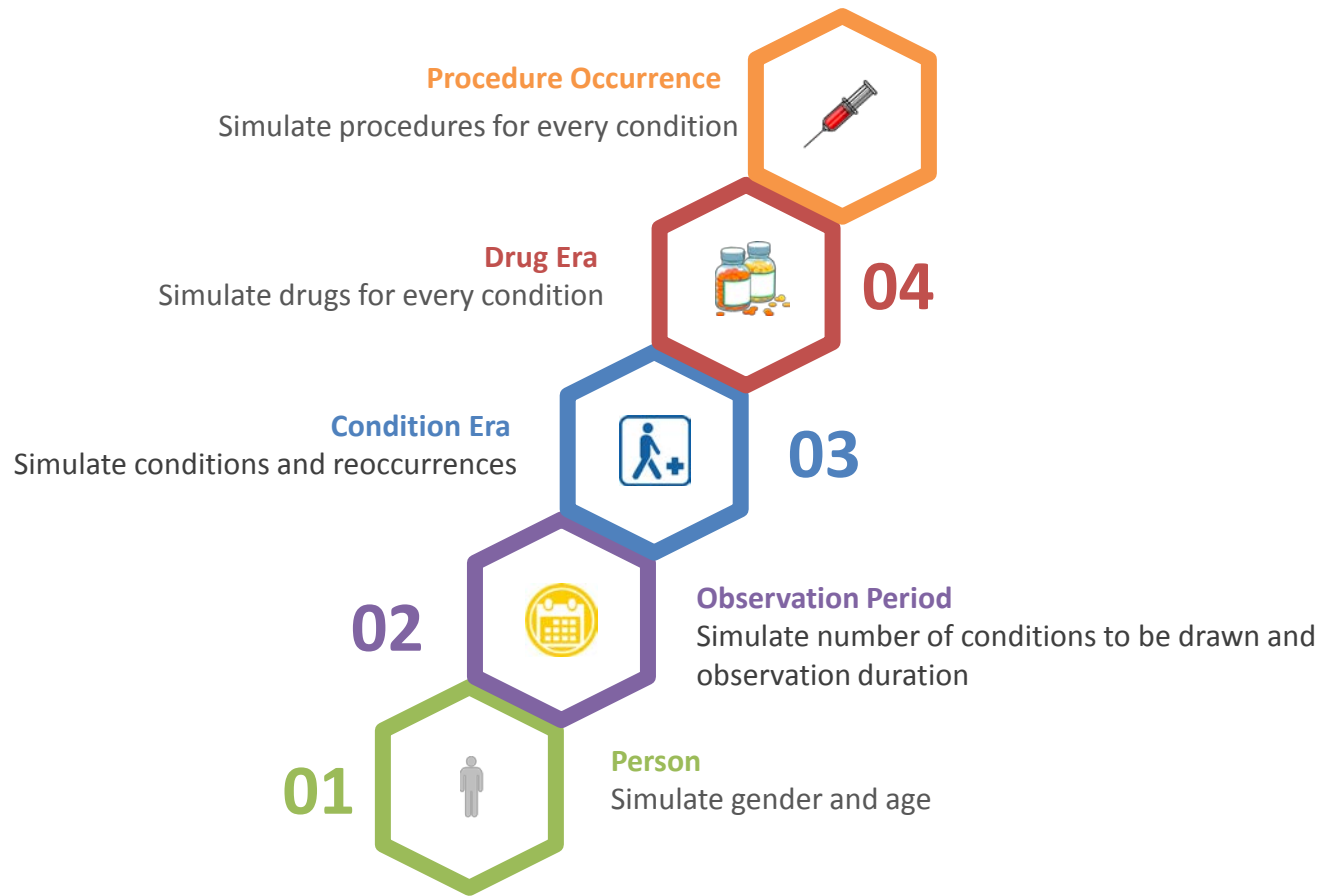


Analysis

- **cond_reoccur_prob:** $P(\text{delta days} \mid \text{condition concept id, age range, time remaining})$
- **drug_count_prob:** $P(\text{drug count} \mid \text{gender concept id, age range, cond count bucket})$
- **cond_drug_count_prob:** $P(\text{drug draw count} \mid \text{condition concept id, interval bucket, age range, drug count bucket, cond count bucket})$
- **cond_first_drug_prob:** $P(\text{drug concept id, delta days} \mid \text{condition concept id, interval bucket, gender concept id, age range, condition count bucket, drug count bucket, day cond count})$
- **drug_era_count_prob:** $P(\text{drug era count, total exposure} \mid \text{drug concept id, drug count bucket, condition count bucket, age range, time remaining})$
- **drug_duration_prob:** $P(\text{total duration} \mid \text{drug concept id, time remaining, drug era count, total exposure})$
- **5 additional tables for procedure occurrence generation**



Data Generation





Data Generation: Person, Observation Period

- Person: Random draw for gender & age

Gender:

osim_gender_prob
P(gender concept id)

Age:

osim_age_at_obs_prob
P(age at obs | gender concept id)

- Observation Period: Random draw for condition count and observation duration

Condition Count:

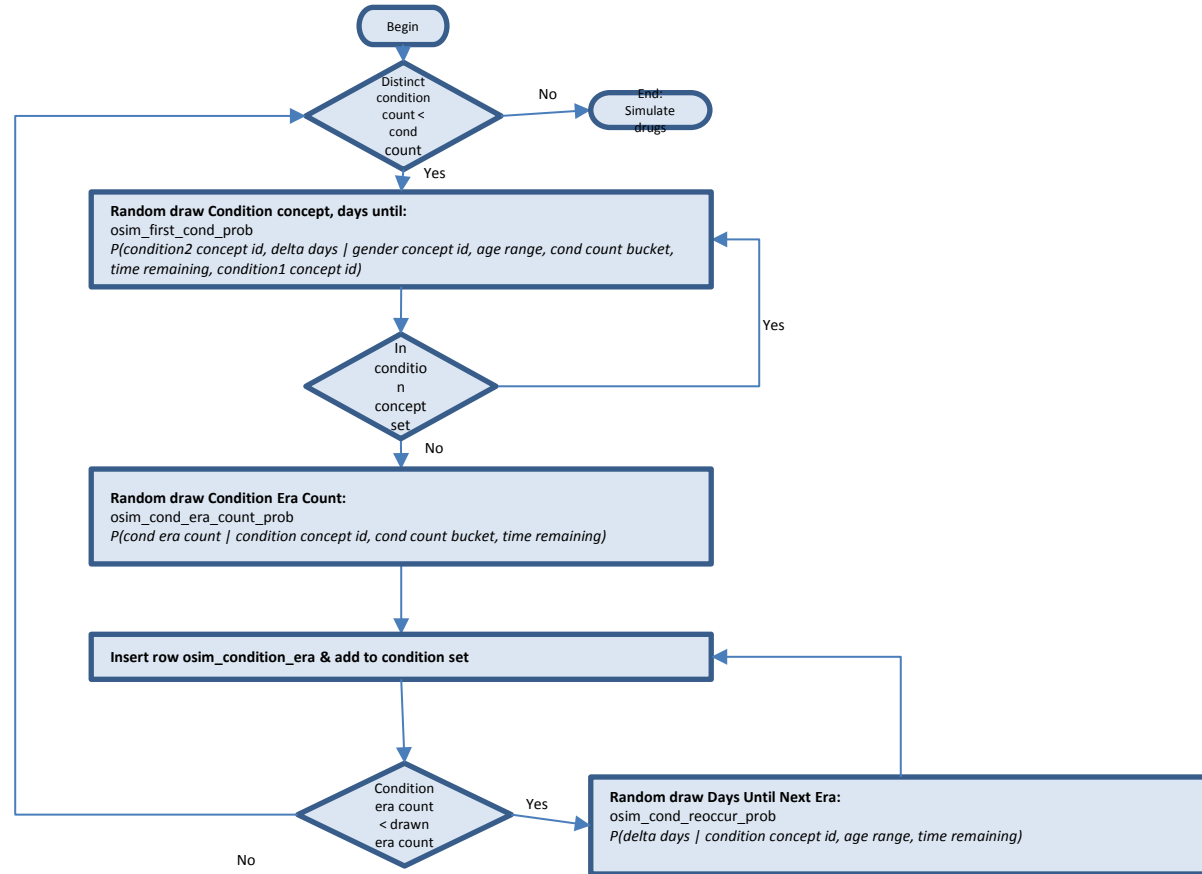
osim_cond_count_prob
P(cond count | gender concept id, age at obs)

Observation period:

osim_time_obs_prob
P(time observed | gender, age, cond count)

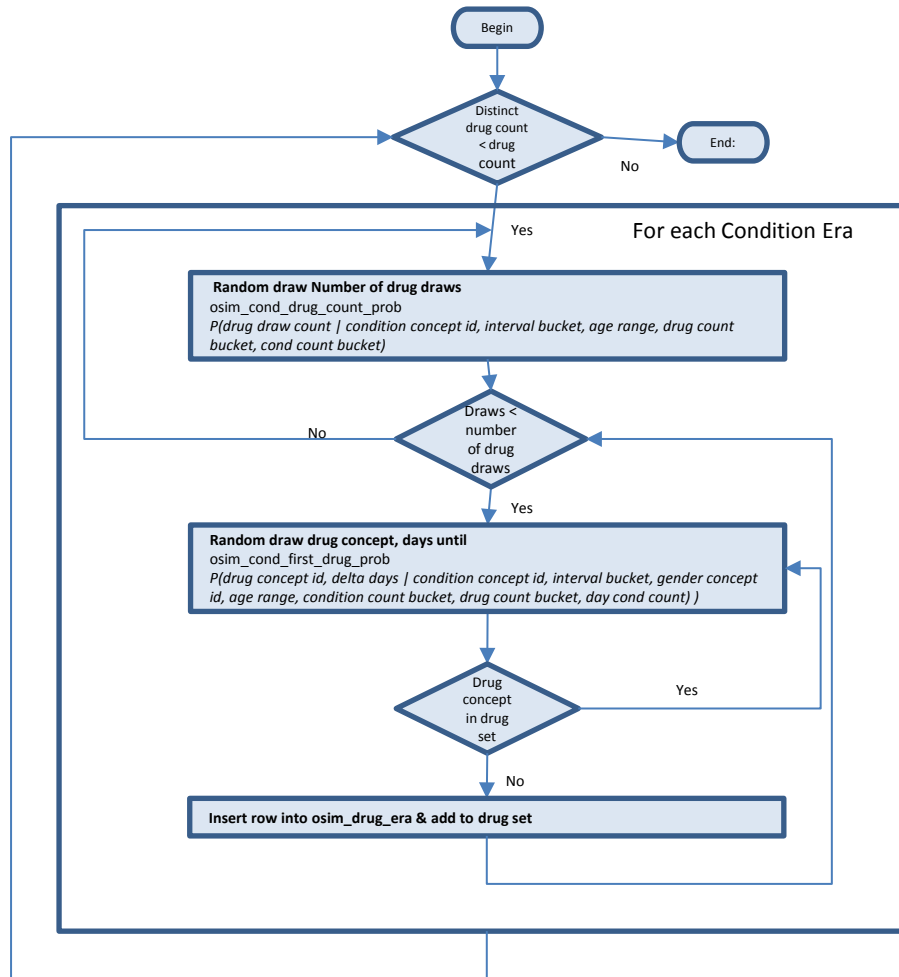


Data Generation: Condition Era





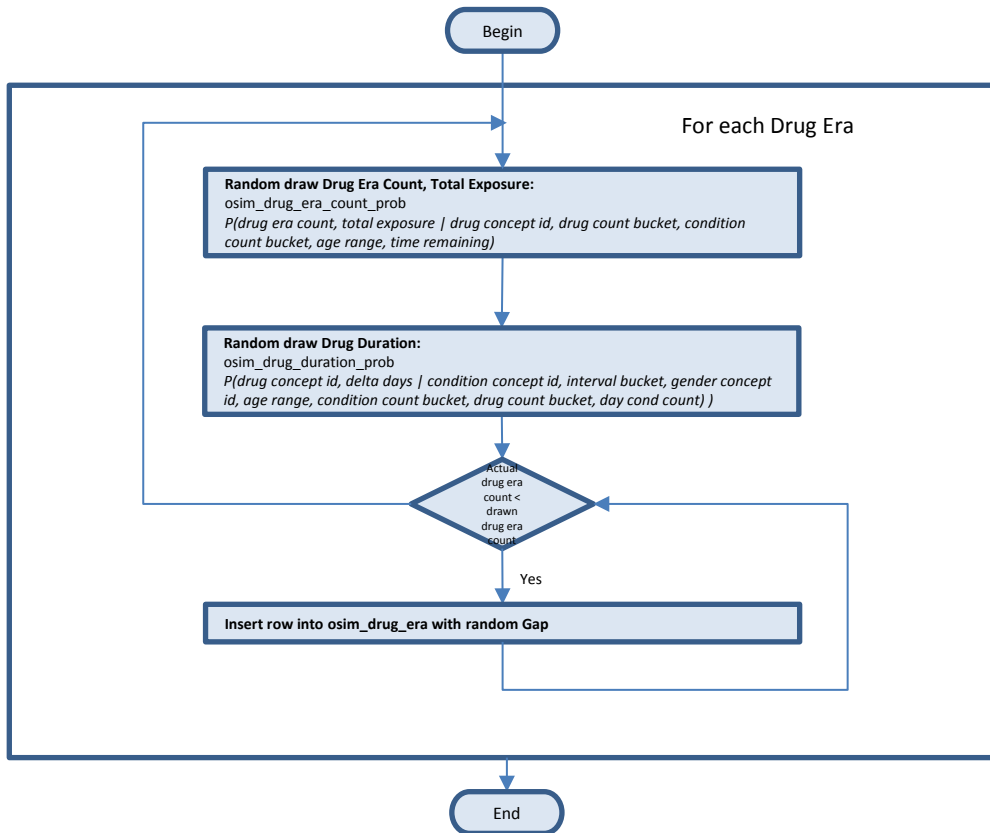
Data Generation: Drug Era



Simulate first occurrence drug eras



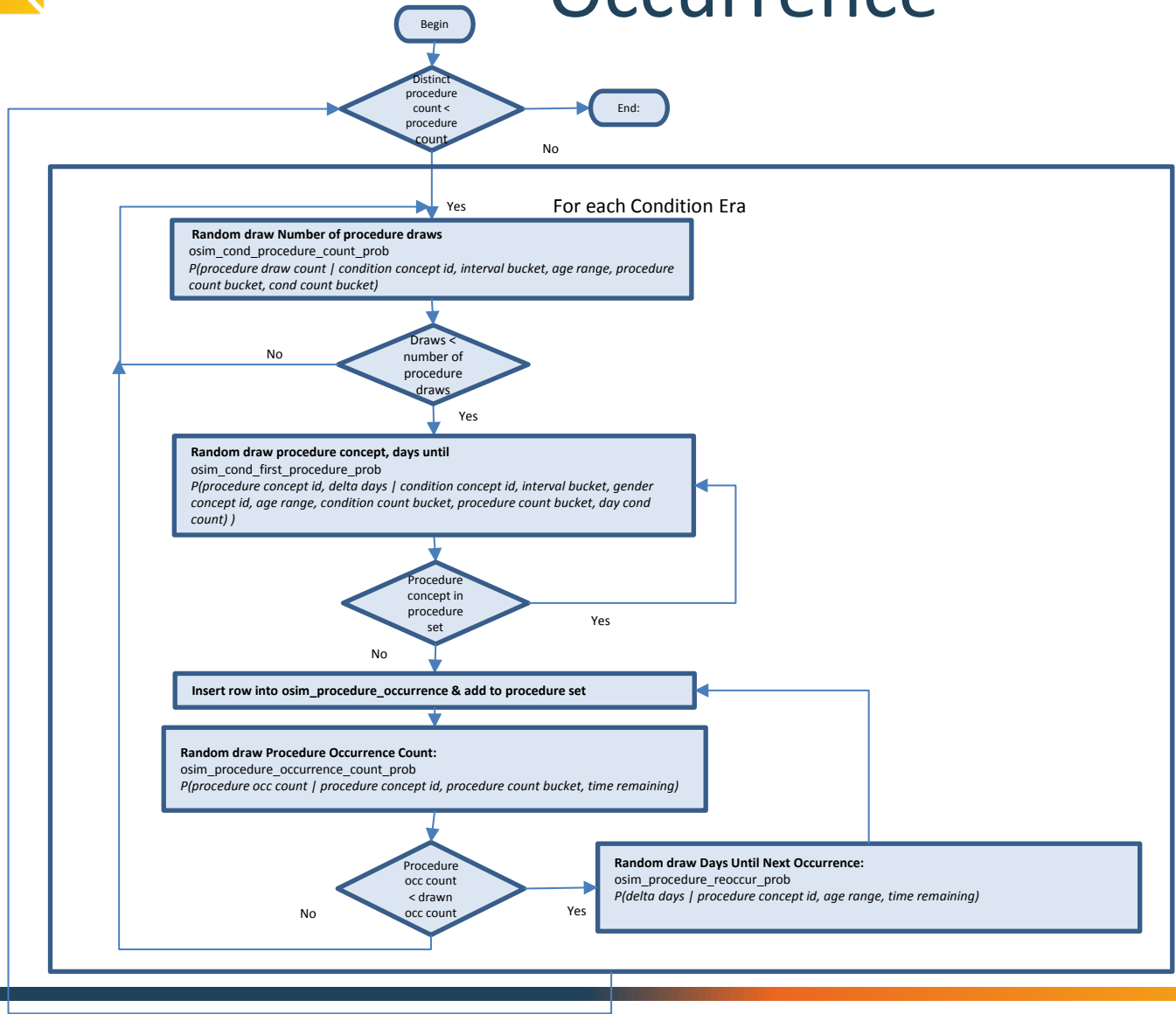
Data Generation: Drug Era



Simulate subsequent drug eras



Data Generation: Procedure Occurrence





Data Generation: Some Potential Issues

- **Procedure Re-occurrence**
- **Explore Visits:** Generate visits first, and for each visit generate conditions, drugs, procedures
- **Drugs & Procedures Relationship:** Currently assumed that condition to procedure relationship encompasses the drugs - procedures relationship, which may not always be the case



Version 2 -> Version 5

- Uses OMOP CDM v5 format as data source
 - Current only available in PostgreSQL
 - Persistence
 - Procedure Occurrence
 - Cohort Generation
-

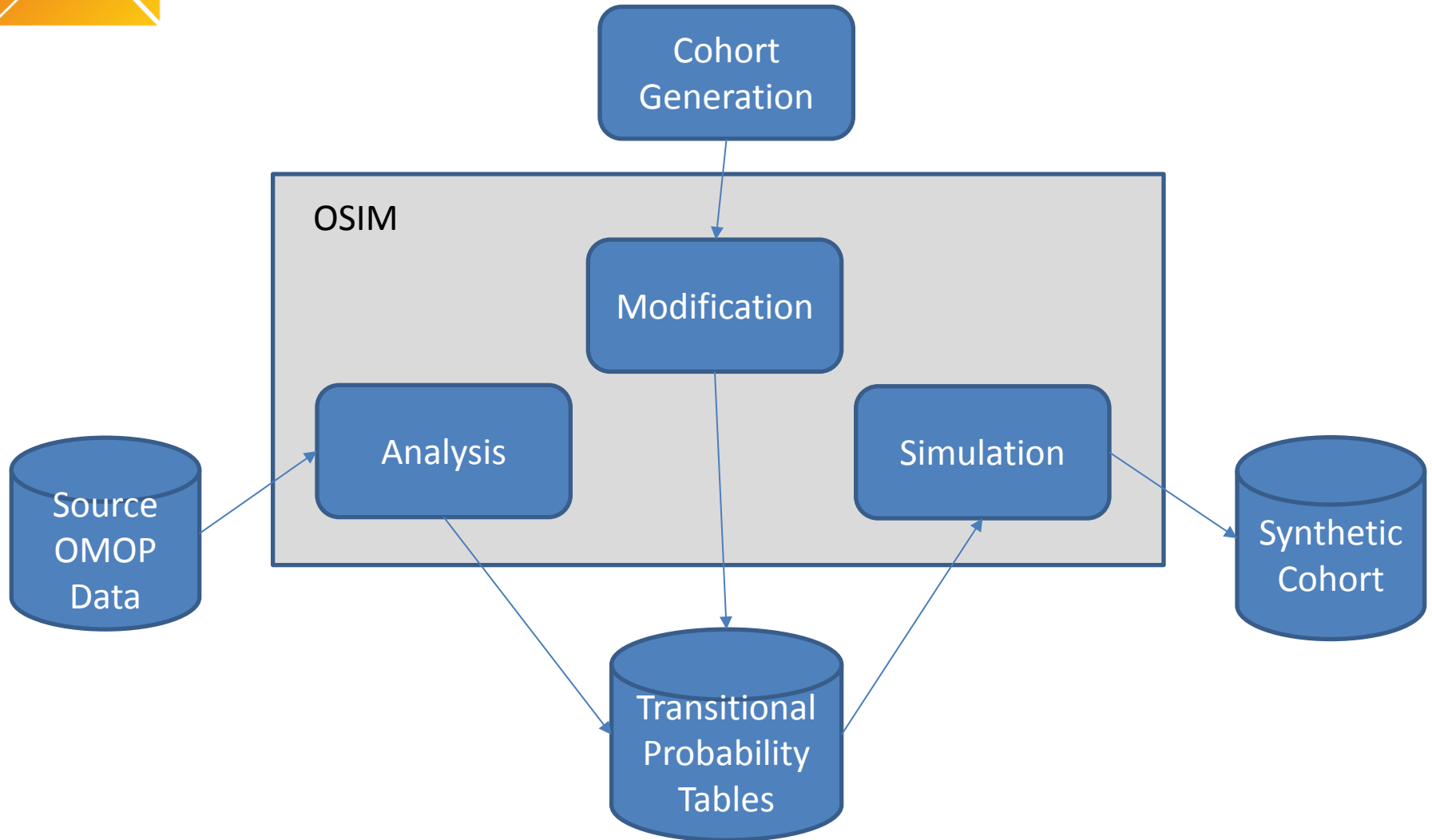


Next Steps

- Generate data in visits
- Include Observations & Measurements in synthetic data
- Challenges
 - Condition each subsequent visit on the previous visits drugs & conditions
 - Complex relationships between condition, observation & measurement
 - Cannot be easily modeled based on existing probability framework



Next Steps: Cohort Generation





Datasets Available!

- Pilot v5 datasets are available for SynPUF and Mimic
- Currently without procedure occurrence – person, observation period, drug era and condition era available
- Datasets for Truven, including procedure occurrence, will be available soon

	Mimic	Synpuf	Truven
Source Patients	46520	2,326,856	81,826,982
Synthetic Patients Available	10,000	10,000	In Progress!



Things to remember!

- OSIM **approximates** the true complex relationships between conditions, drugs and disease progression
- The simulated data has some **missing fields** like race, ethnicity, etc.
- Data simulation for measurements, observations, and other CDM tables is not currently implemented
- Models **population level similarities**, so analyses results on a real dataset may be worse



Some resources

OSIM

- **OSIM v2:** <ftp://ftp.ohdsi.org/osim2/>
- **OSIM v5:** <https://github.com/OHDSI/OSIM-v5>
- **Design and Validation of a Data Simulation Model for Longitudinal Healthcare Data:**
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3243118/>
- **Pilot Datasets:** <https://github.gatech.edu/HDAP/synthetic-datasets>

Other synthetic data generators

- **Synthea:** <https://github.com/synthetichealth/synthea>
- **PatientGen:** <https://mihin.org/services/patient-generator/>
- **Medgan:** <https://github.com/mp2893/medgan>



Questions?

