

**OBSERVATIONAL
MEDICAL
OUTCOMES
PARTNERSHIP**

**OSIM2 Training Session I
Model overview**

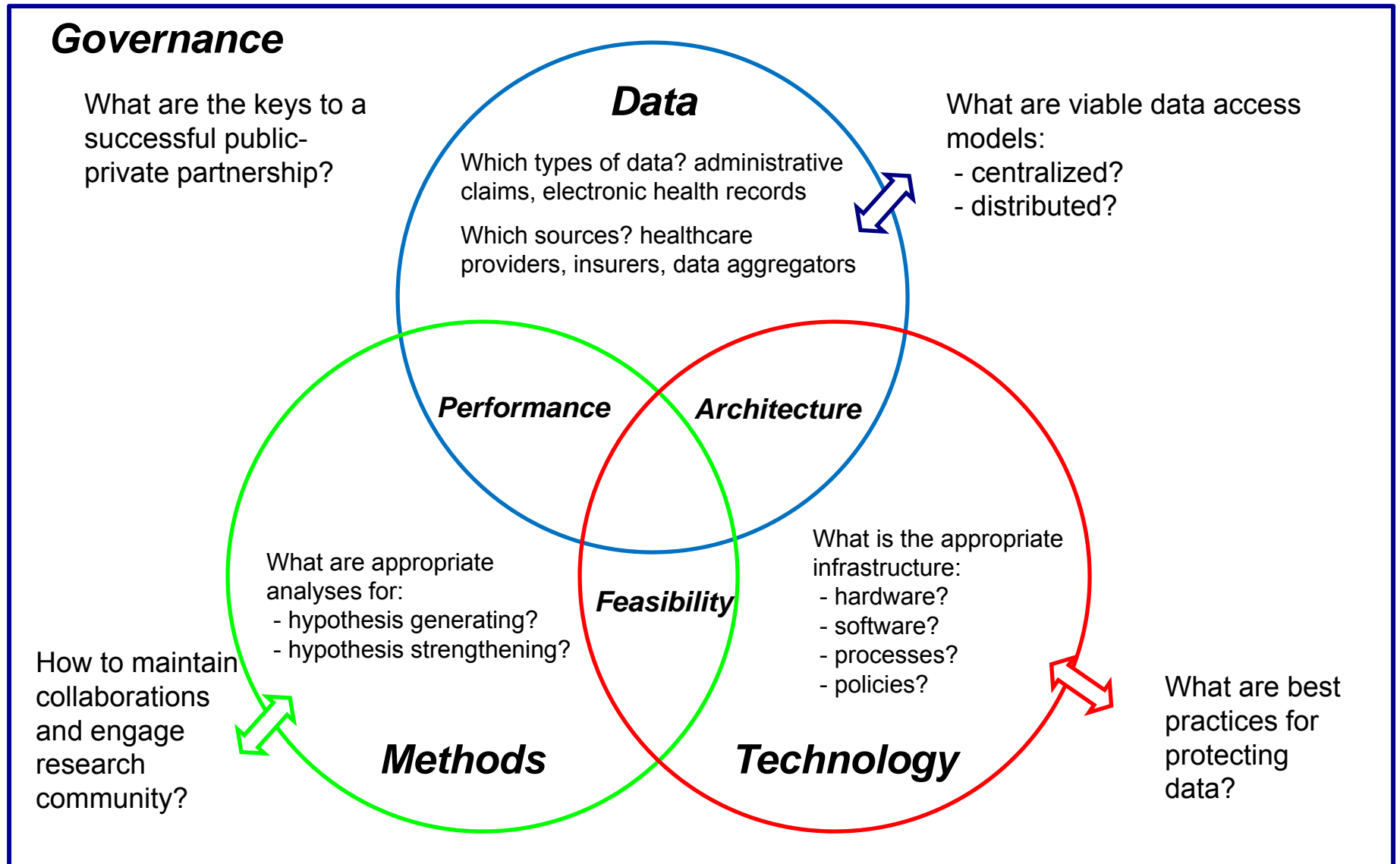
February 25, 2011
Washington, DC

Patrick Ryan, Johnson & Johnson, OMOP
Steph Reisinger, United BioSource Corp.
Rich Murray, United BioSource Corp.

Agenda for the Day

- Session I – Overview and Conceptual Model
 - Introduction to Simulation
 - Conceptual Simulation Model
 - Review of Simulation Results and Deliverables
- Session II – Technical Review
 - Architecture
 - Program Execution
 - Review of Program Modules

Outstanding questions for active surveillance



Observational Medical Outcomes Partnership

Established to inform the appropriate use of observational healthcare databases for active surveillance by:

- **Conducting methodological research** to empirically evaluate the performance of alternative methods on their ability to identify true drug safety issues
- **Developing tools and capabilities** for transforming, characterizing, and analyzing disparate data sources
- **Establishing a shared resource** so that the broader research community can collaboratively advance the science

Session I Agenda

- Introduction and Context
- OSIM2 Conceptual Design
- OSIM2 Validation
- Uses of Simulated Data
- Limitations
- OSIM2 Deliverables
- Summary and Discussion
- Transition to Session II

INTRODUCTION / CONTEXT

Context for Simulated Data

“The OMOP partnership will conduct a two-year initiative to research methods that are feasible and useful to analyze existing healthcare databases to identify and evaluate safety and benefit issues of drugs already on the market”

source: omop.fnih.org

Method Evaluation Requirements:

- Characterize Individual Method Performance
- Compare Performance Among Methods

Objective Measures for:

- Sensitivity
- Specificity
- Positive and Negative Predictive Value

'Ground truth' for Monitoring Health Outcomes of Interest (HOI)

Outcome	Drug									
	ACE Inhibitors	Amphotericin B	Antibiotics: erythromycins, sulfonamides, tetracyclines	Antiepileptics: carbamazepine, phenytoin	Benzodiazepines	Beta blockers	Bisphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema										
Aplastic Anemia										
Acute Liver Injury										
Bleeding										
Hip Fracture										
Hospitalization										
Myocardial Infarction										
Mortality after MI										
Renal Failure										
GI Ulcer Hospitalization										

Legend	Total
True positive' benefit	2
True positive' risk	9
Negative control'	44

Limitations of Observational Data for Supporting Methods Evaluation

Observational Data	Simulated Data
Data is “noisy” (confounding)	Model both adverse drug reactions and confounding
Data capture process provides further distortion	Simulate data capture process
Limited gold standards for objective measurement	Known characteristics provide “truth” for measurement
Access limited & expensive	Data freely & widely available
Disparate data formats / coding schemes	Use of Common Data Model mitigates format issues

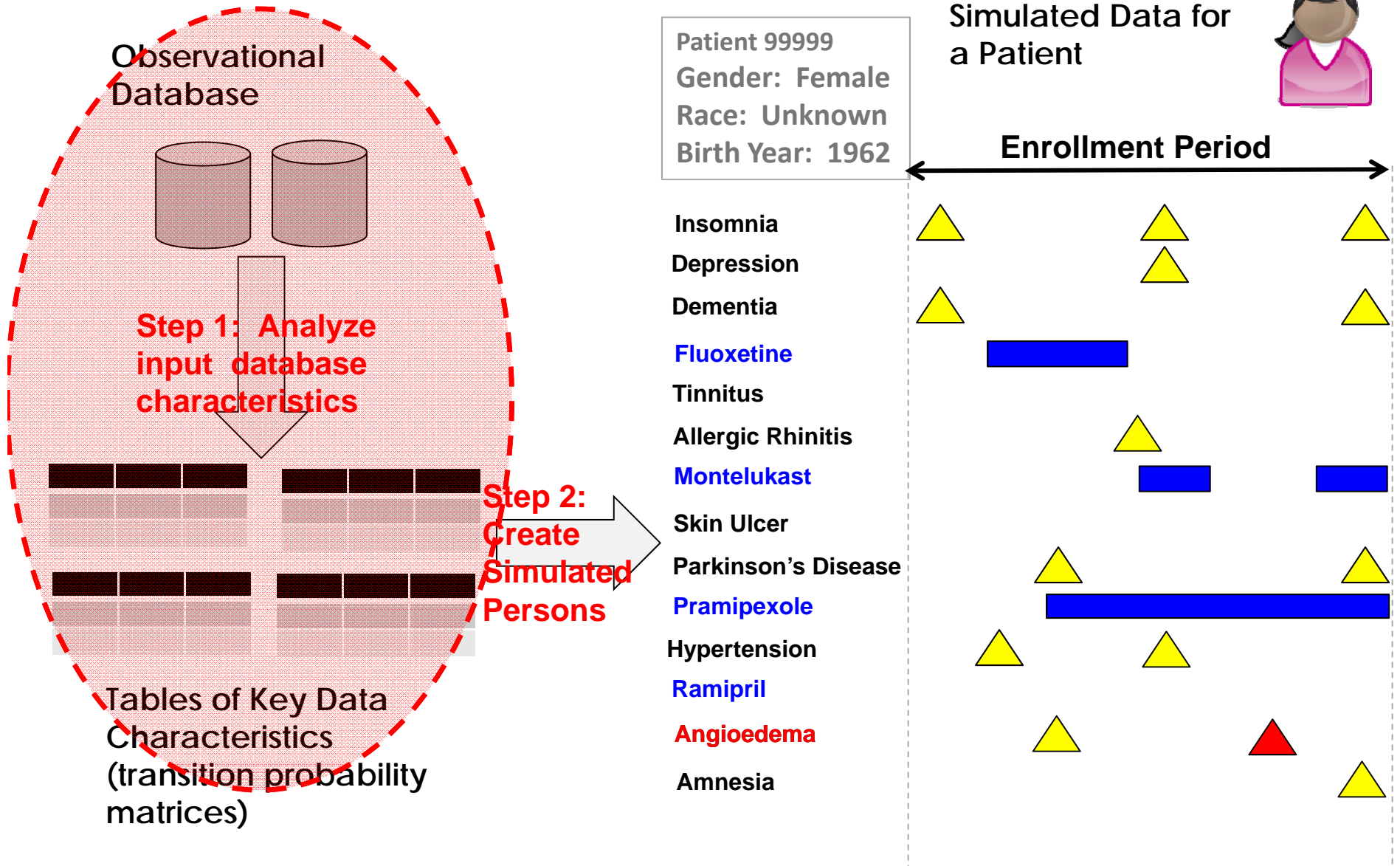
Simulated data, with known properties and characteristics, can facilitate systematic evaluation & comparison among methods providing objective gold standard

Observational Medical Dataset Simulator

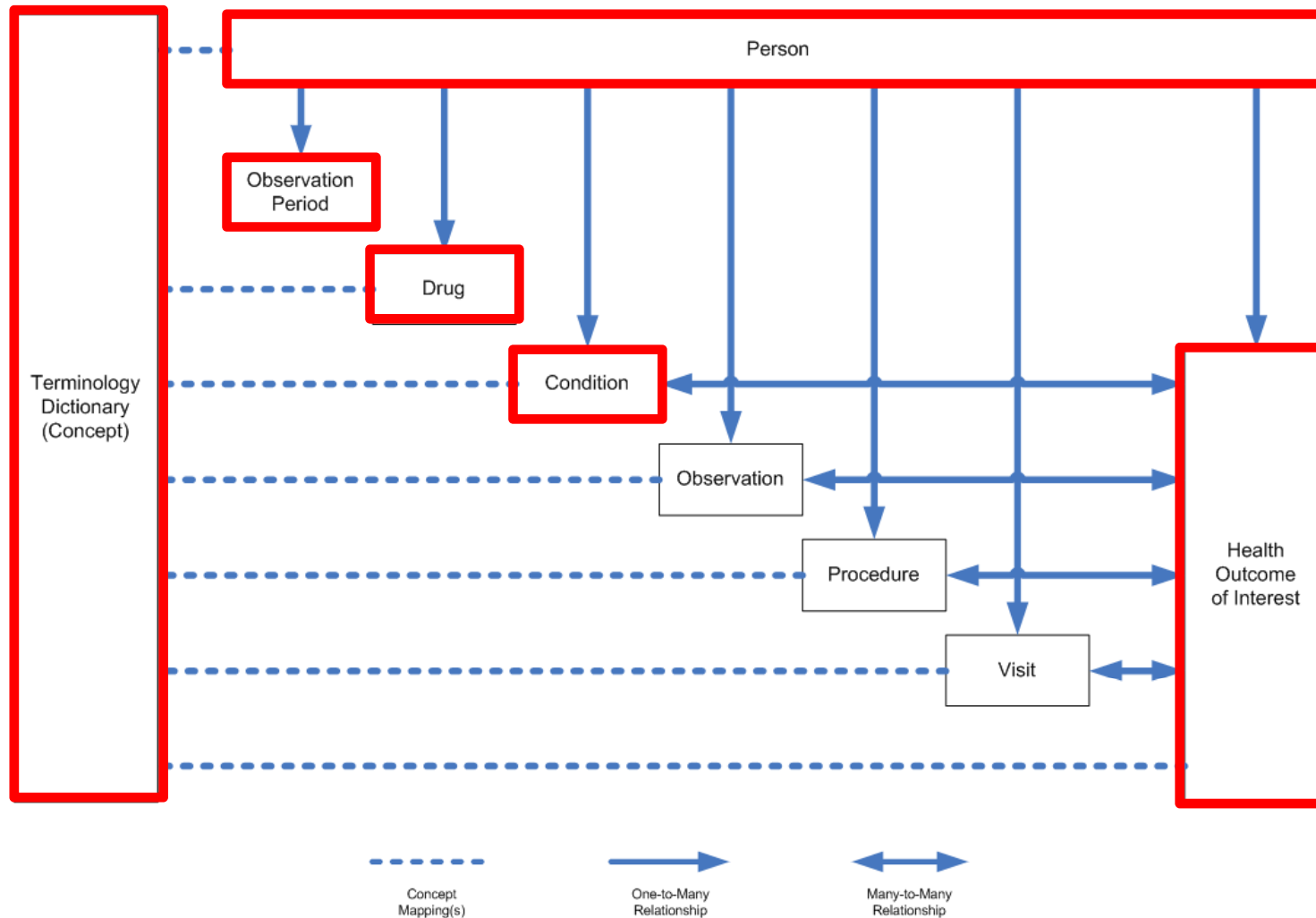
- **Goal: construct large-scale, high-fidelity, simulated database to complement ‘real’ data experiments for methodological research**
- **OSIM (1 and 2)**
 - Developed to address need for objective Method evaluation criteria
 - Open source software application
 - File of simulated persons with drug exposures and condition occurrences
 - Input parameters mimic characteristics of real observational data
 - **Provide known “Ground Truth” for developing methods**

OSIM2 CONCEPTUAL DESIGN

Conceptual OSIM2 Simulation Process

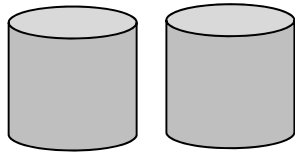


OMOP Common Data Model Domains Within OSIM2 Simulation



Database

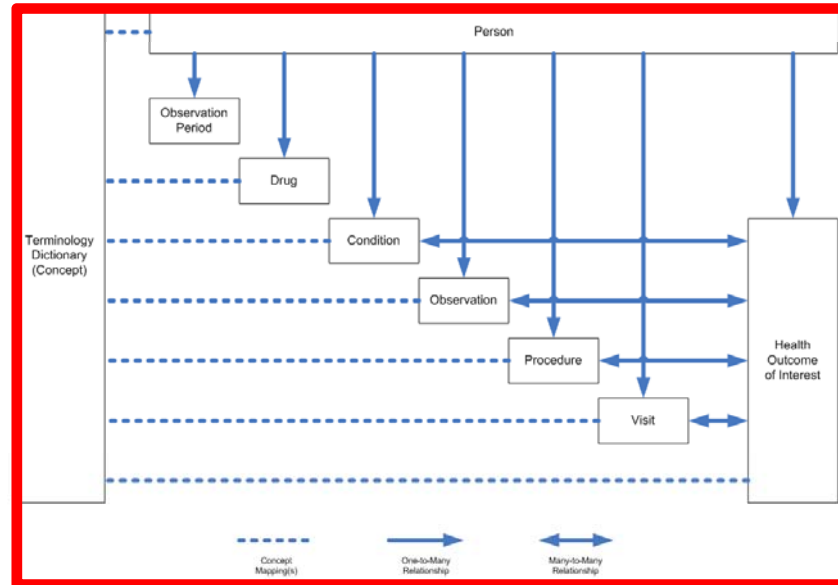
Real Observational Database



**Step 1: Analyze
input database
characteristics**



Transition probability
matrices

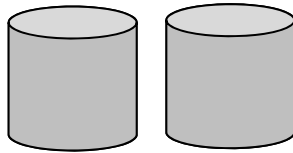


Overall Database Characteristics

- Person count
- Earliest date of observation
- Latest date of observation

Person

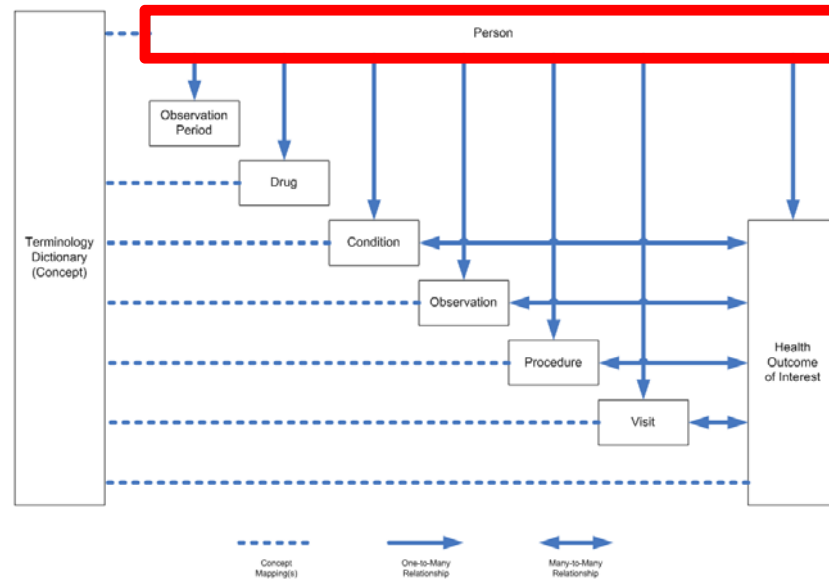
Real Observational Database



**Step 1: Analyze
input database
characteristics**



Transition probability
matrices



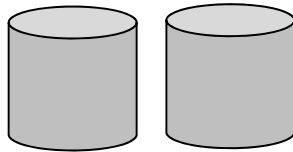
Person Characteristics

- Gender
- Age

Extract full empirical
distributions from 'real data' to
construct multinomial distribution

Observation Period

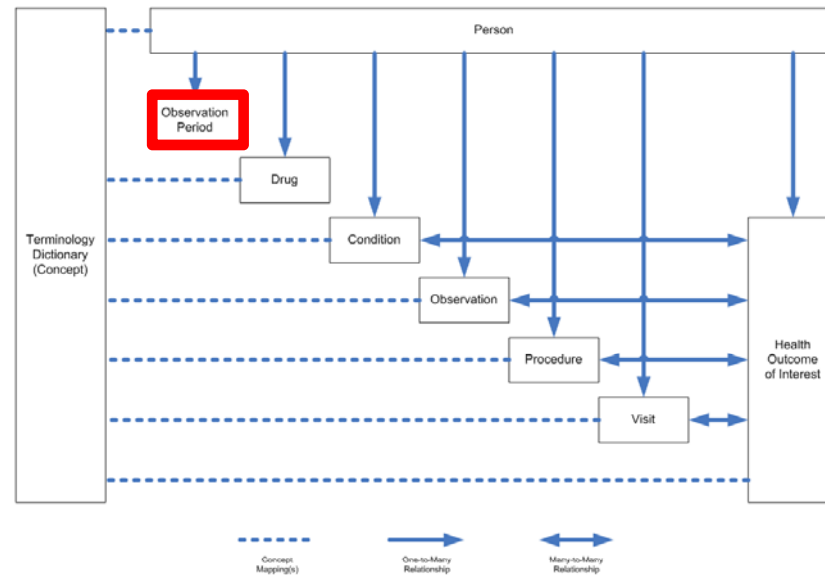
Real Observational
Database



**Step 1: Analyze
input database
characteristics**



Transition probability
matrices

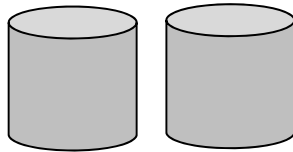


Observation Period Characteristics

- Observation Period Length

Condition

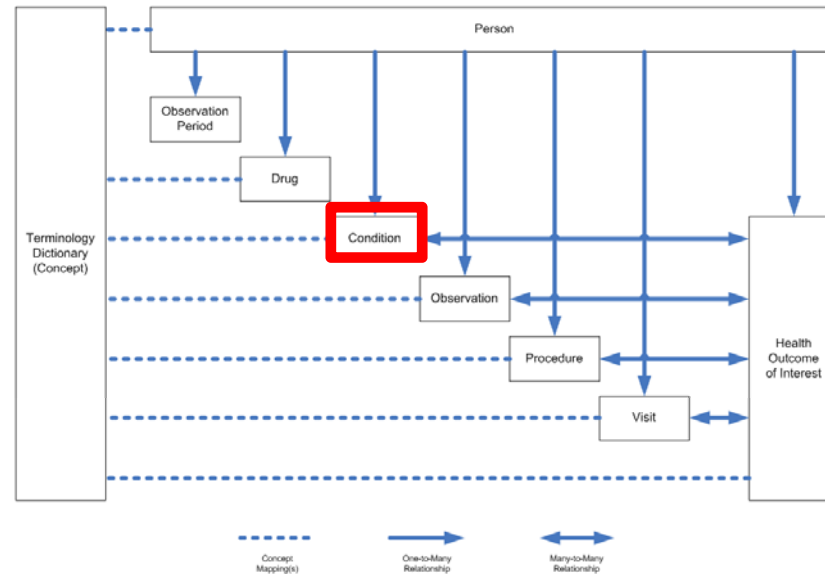
Real Observational Database



**Step 1: Analyze
input database
characteristics**



Transition probability
matrices

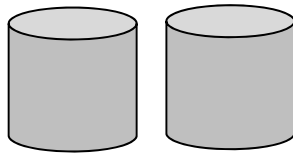


Condition Characteristics

- Distinct Condition Count
- Number of Condition Records
- Condition to Next Condition Transition and Time between
- Time between Re-occurring Conditions

Drug

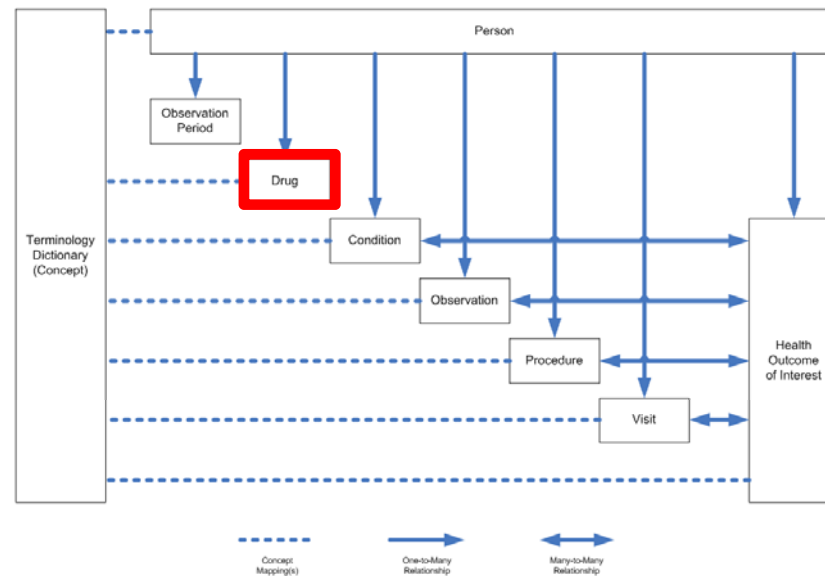
Real Observational Database



**Step 1: Analyze
input database
characteristics**



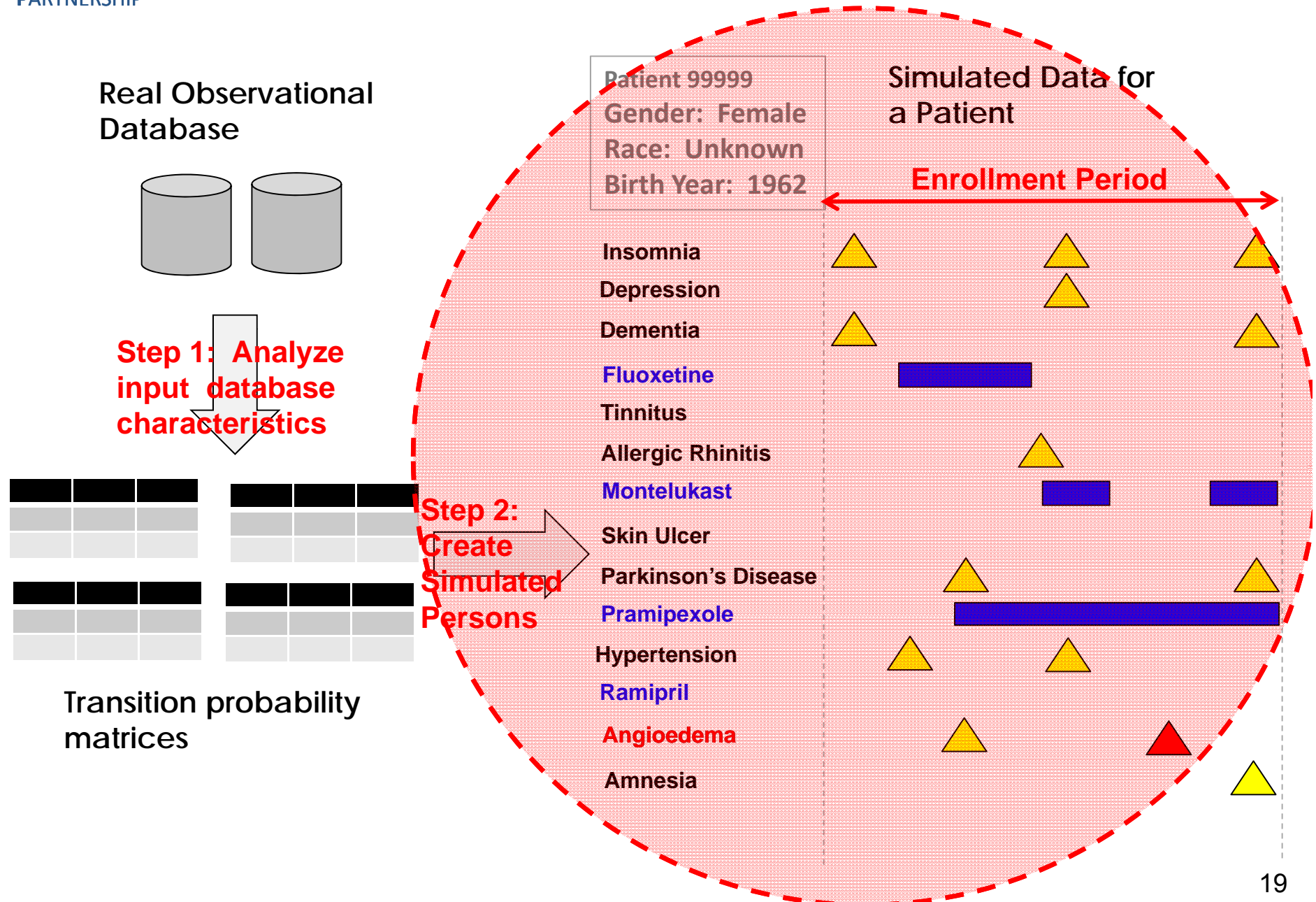
Transition probability
matrices



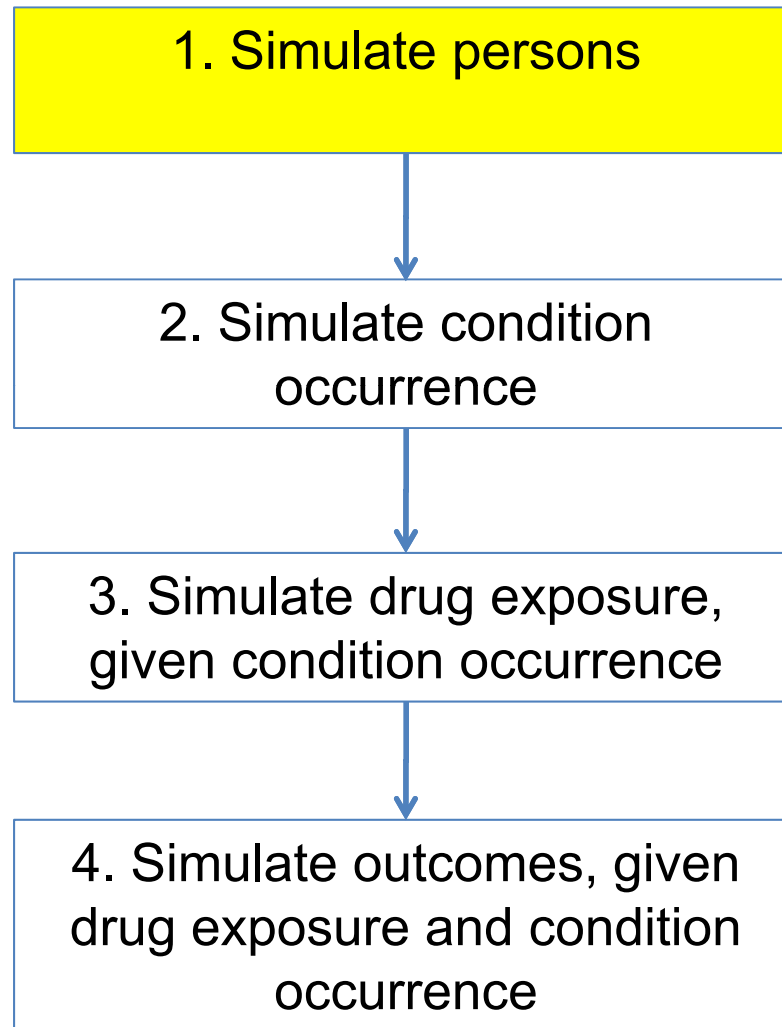
Drug Characteristics

- Distinct Drug Count
- Number of Drug Records
- Total Length of Exposure
- Time from first exposure to last exposure
- Number of drugs following condition
- Condition to Drug Transition and Time Between

Conceptual Simulation Process



Creating Simulated Data



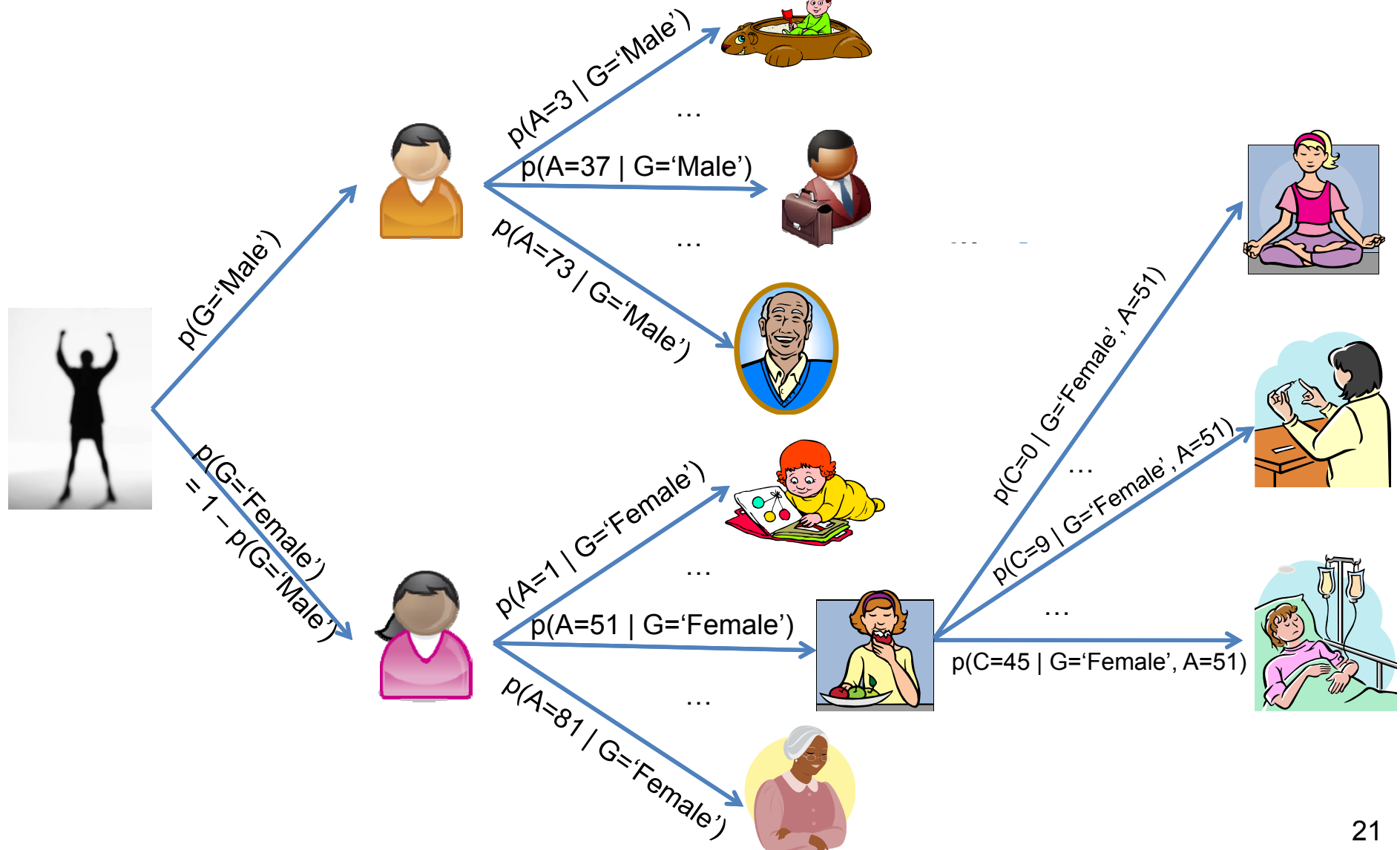
The 'birth' of a OSIM2 'person'

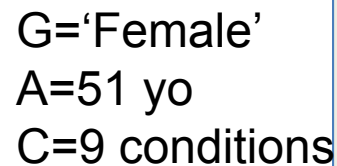
Create a new
'person'

Give the person a
Gender G

Give the person a
Age A

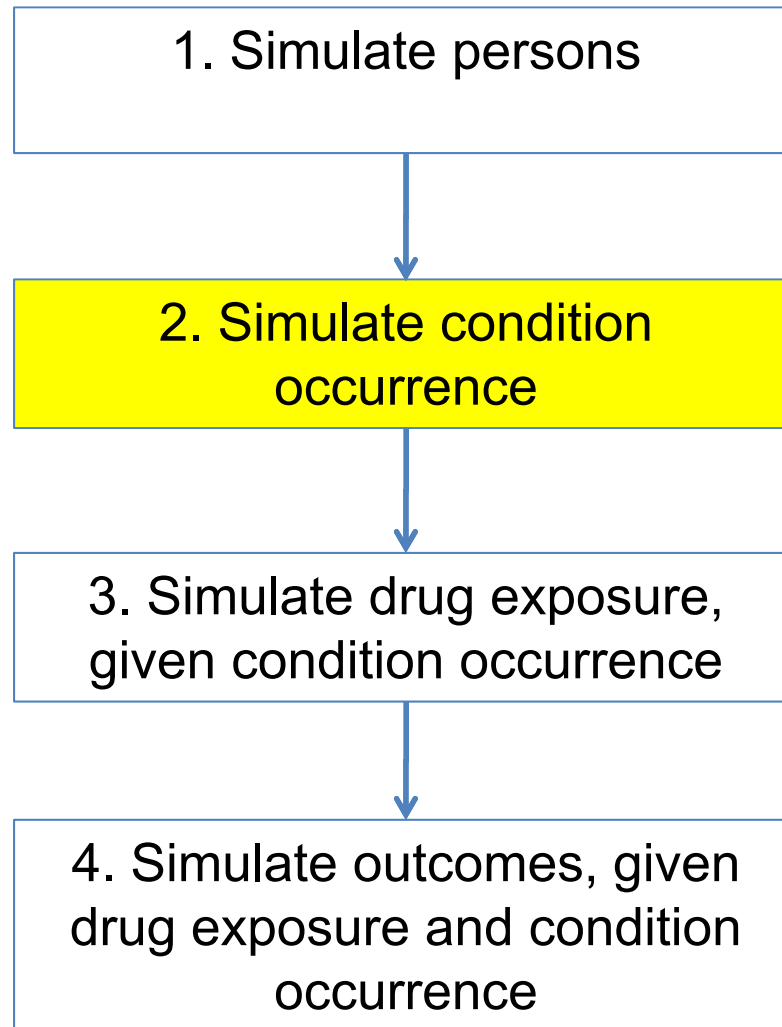
Give the person
Conditions C





When will the persons record start?
 $\text{Start} = \text{Unif}(\text{DBStart}, (\text{DBEnd} - \text{TR}))$

Creating Simulated Data



We need to give this person 9 conditions...
what should she get first?



G='Female'
A=51 yo
C=9 conditions
TR=24 mo

Diabetes mellitus type 2

Essential hypertension

Hyperlipidemia

Depressive disorder

Asthma

Gastroesophageal reflux disorder

$p(C1=c \mid G='Female', AR=21-55yo, CR=8-25, TR=24 \text{ mo})$

When should the person get the first condition?

$p(TR=t \mid G='Female', AR=21-55yo, CR=8-25, TR=24 \text{ mo}, C1=c)$

AR: Age range {<6, 6-14, 15-20, 21-55, 56-70, 70+}

CR: comorbidity range {<3, 3-7, 8-25, 25+}

TR: time remaining in database, 6mo intervals

'c' can be any condition
observed as a first diagnosis
within that person strata

Her first condition was 'Diabetes' ...
what should she get next?



G='Female'
A=51 yo
C=9 conditions
TR=18 mo
C1='Diabetes
mellitus type 2'

Diabetes mellitus type 2

Essential hypertension

Hyperlipidemia

Congestive heart failure

Acute myocardial infarction

Closed fracture of pelvis

$p(C2=c \mid C1='Diabetes\ mellitus\ type\ 2', G='Female',$
 $AR=21-55yo, CR=8-25, TR=18\ mo)$

When should the person get the next condition?

$p(TR=t \mid C1='Diabetes\ mellitus\ type\ 2', C2=c,$
 $G='Female', AR=21-55yo, CR=8-25, TR=24\ mo)$

'c' can be any condition
observed as after the
prior diagnosis within
that person strata

Her next condition was 'Essential hypertension' ...
what should she get next?



Diabetes mellitus type 2

Essential hypertension

Hyperlipidemia

Congestive heart failure

Acute myocardial infarction

Closed fracture of pelvis

G='Female'
A=51 yo
C=9 conditions
TR=18 mo
C1='Diabetes
mellitus type 2'
C2='Essential
hypertension'

$p(C3=c \mid C2='Essential hypertension', G='Female',$
 $AR=21-55yo, CR=8-25, TR=18 mo)$

NOTE: $p(C3=c)$ does not
depend on $C1='Diabetes'$

More generally,

$p(C_n=x \mid C_{n-1}=y, G, AR, CR, TR, C_{1..n-1} \neq x)$
 $p(TR_n=t \mid C_n=x, C_{n-1}=y, G, AR, CR, TR)$

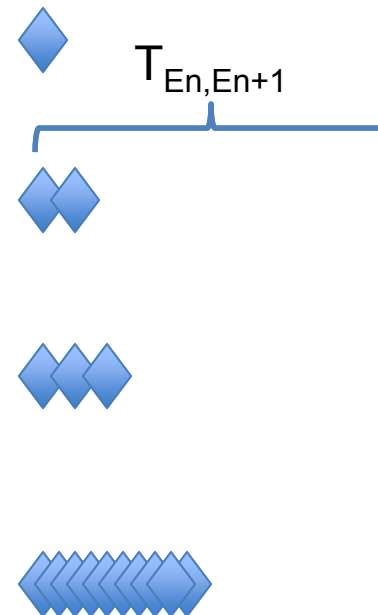
She had the condition 'Diabetes', so how should diagnosis codes be recorded in her database record?



G='Female'
A=51 yo
C=9 conditions
TR=18 mo
C1='Diabetes
mellitus type 2'

1 record
2 records
3 records
...
10 records

TR=18mo



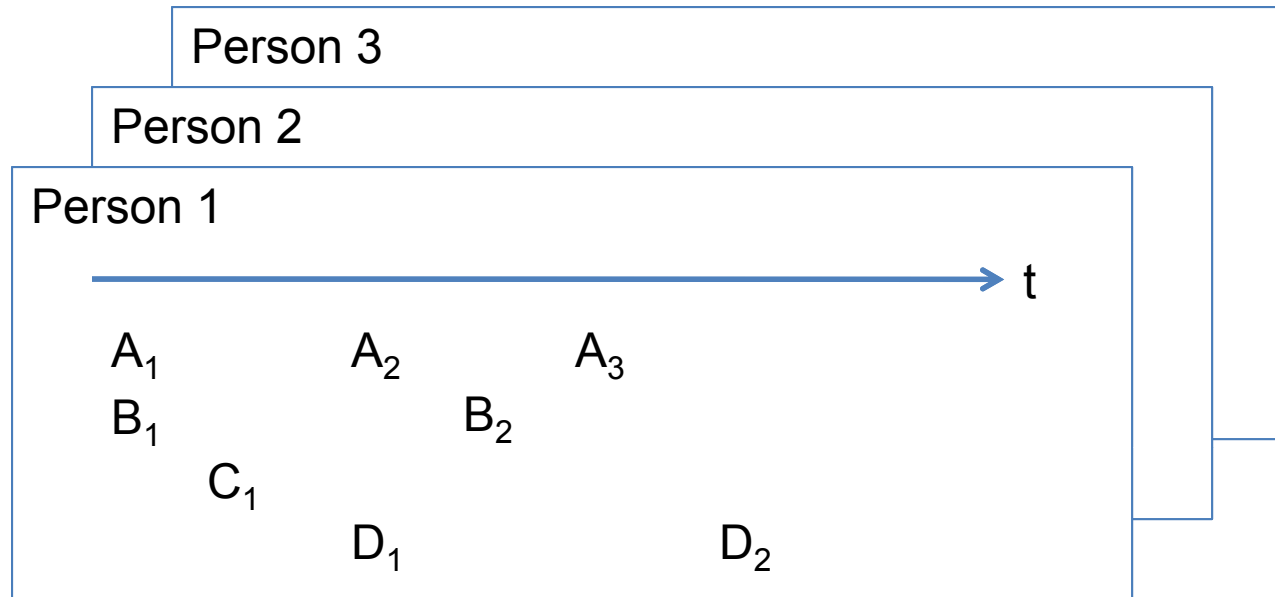
$p(E=e \mid C=\text{'Diabetes mellitus type 2'}, CR=8-25, TR=18 \text{ mo})$

Time between records

$p(T_{En,En+1}=t \mid C=\text{'Diabetes mellitus type 2'}, AR=21-55yo, TR=18 \text{ mo})$

E: Era count

Condition data patterns to model



Transitions between occurrences:

Person 1: $A_1 \rightarrow B_1 \rightarrow C_1 \rightarrow A_2 \rightarrow D_1 \rightarrow B_2 \rightarrow A_3 \rightarrow D_2$

Person 2: $A_1 \rightarrow D_1 \rightarrow C_1 \rightarrow D_2 \rightarrow A_2$

Person 3: B_1

Transitions between conditions:

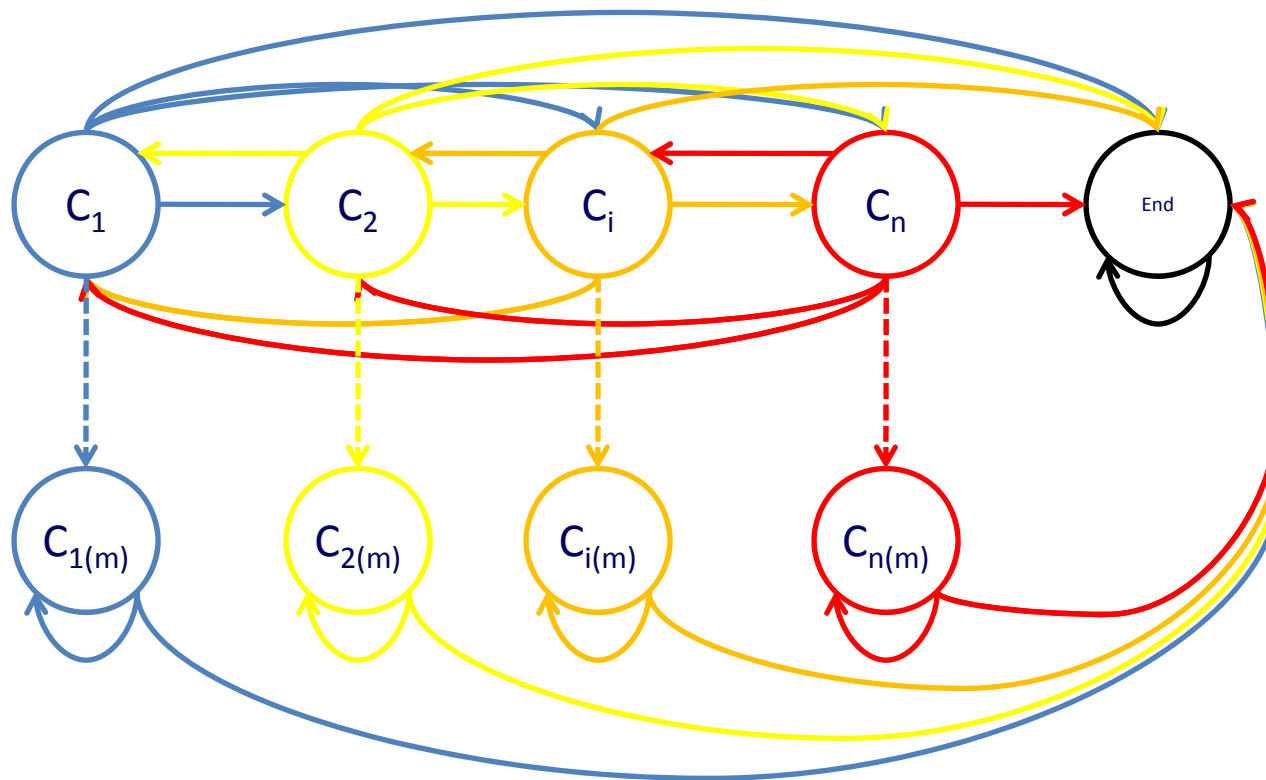
$A \rightarrow B \rightarrow C \rightarrow D$

$A \rightarrow D \rightarrow C$

B

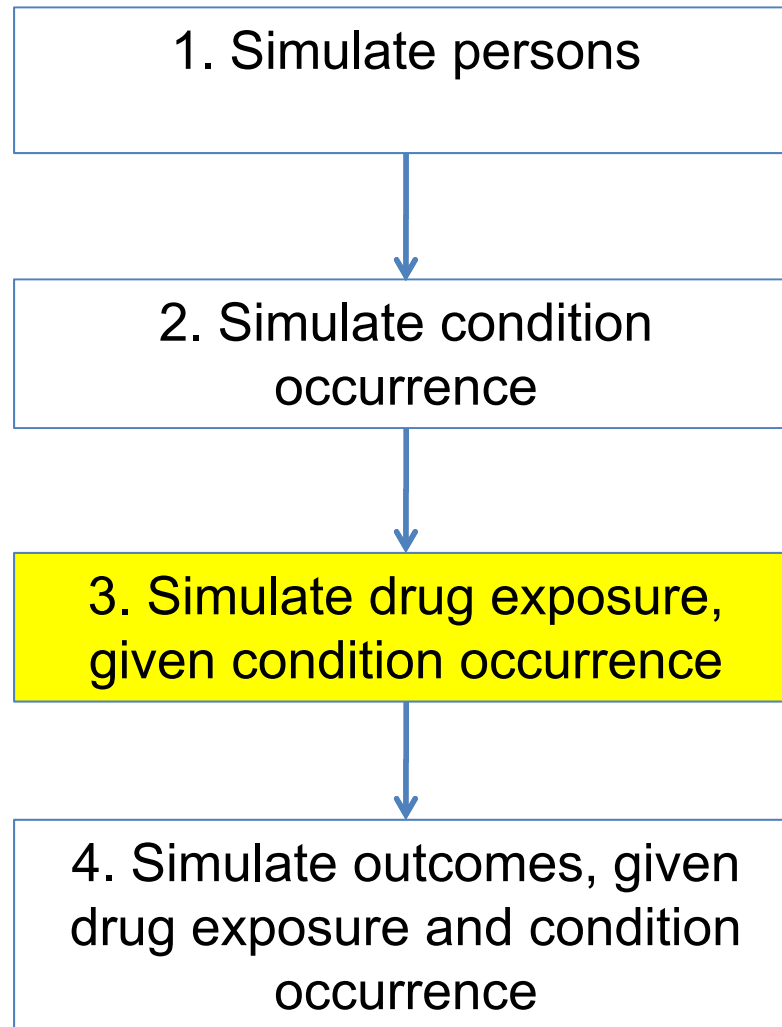
- 'Conditions' are recorded observations about a disease in a given individual.
- One 'condition' can have multiple 'occurrences' if it is recorded
- Conditions can be indications, comorbidities, outcomes, and/or adverse events.
- In real data, we infer the type of condition based on its temporal relationship with other observations, such as drug exposure.
- In simulated data, we can explicitly separate background condition prevalence from drug-related effects

First-order Markov model for incident conditions



- C_1 - C_n : reflect all incident conditions in the database
- $C_{i(m)}$: reflects the m number of occurrences of condition C in the database
- $p_{ij} = \Pr(C_{k+1}=j | C_k=i, C_1..C_k \neq j) = \Pr(C_{k+1}=j | C_1=C_1, C_2=C_2, \dots, C_k=C_k)$
- Time-homogenous : probabilities are independent of k
- Null recurrent: condition j cannot be revisited
- p_{ij} can be estimated from real data based on frequency of condition co-occurrence
- Model replicated within age * gender * condition count strata

Creating Simulated Data

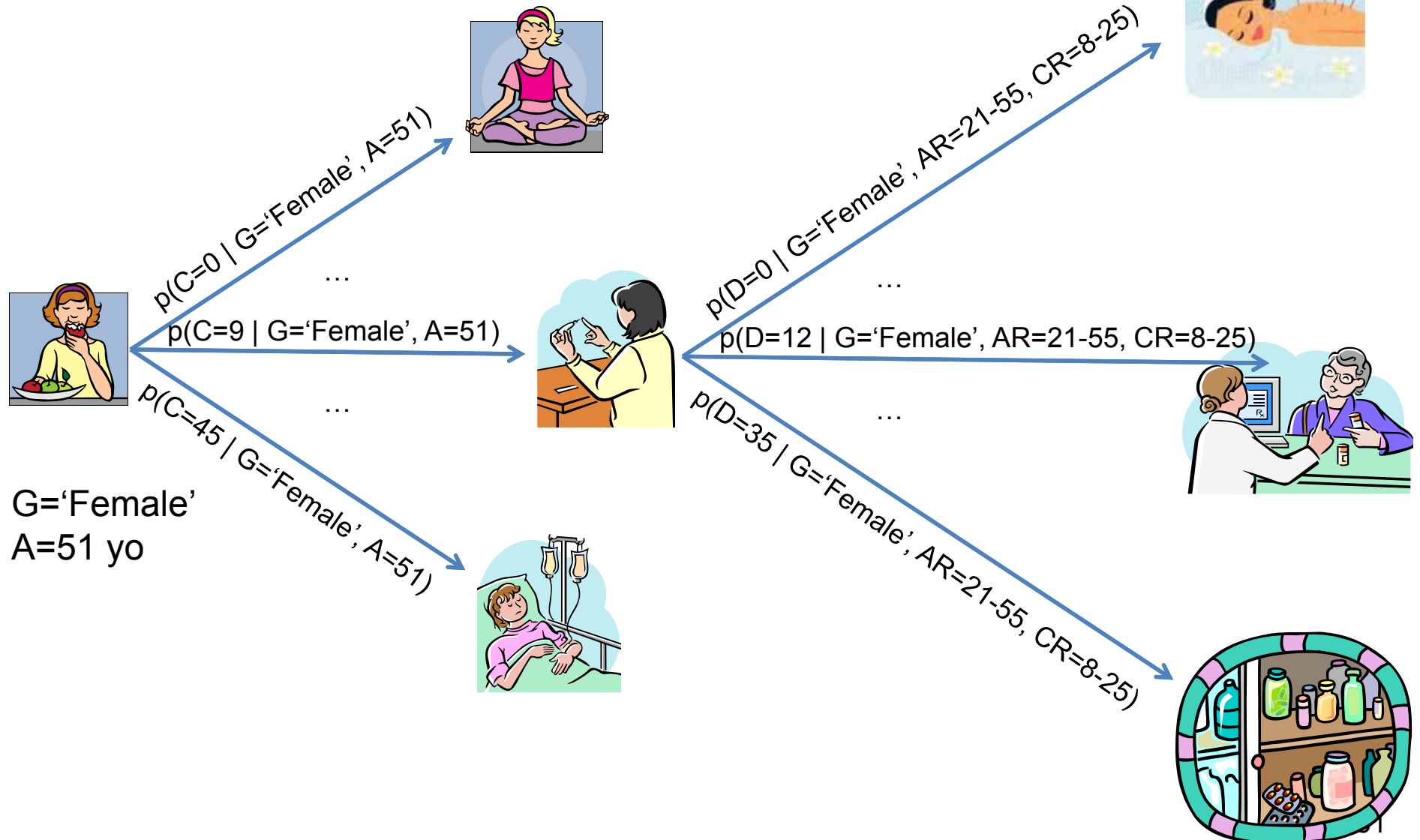


Create a new
'person'

'Treating' our OSIM2 population

Give the person
Conditions C

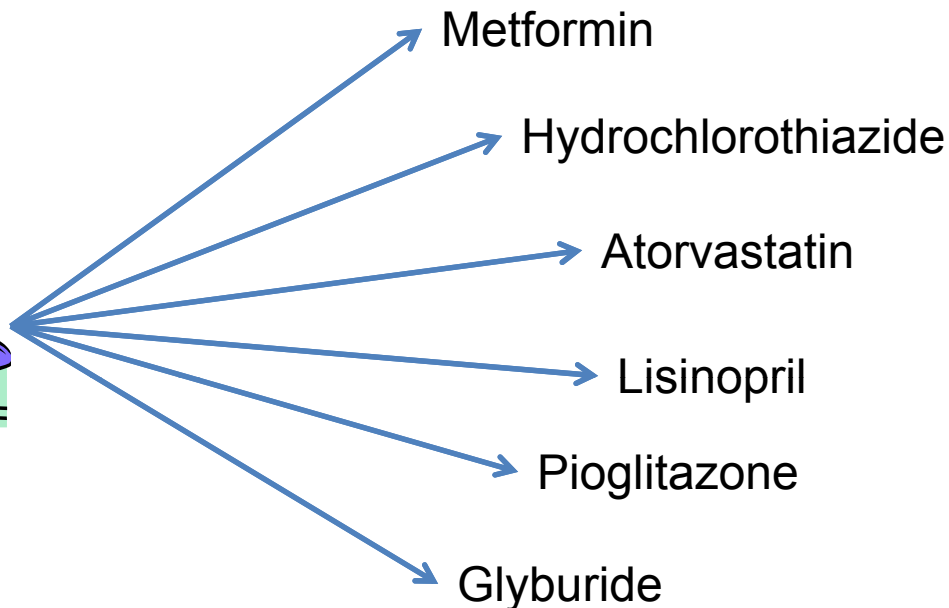
Give the person
Drugs D



Her first condition was 'Diabetes' ...
what subsequent drug(s) get recorded?



G='Female'
A=51 yo
C=9 conditions
D=12 drugs
C1='Diabetes
mellitus type 2'



NOTE: 'd' needn't be an indicated treatment for 'c', as model is empirically driven based on d-c co-occurrence in real data

$p(N=n \mid C1='Diabetes\ mellitus\ type\ 2',$
 $AR=21-55yo, CR=8-25, DR= 8-25, IR=1\ wk)$

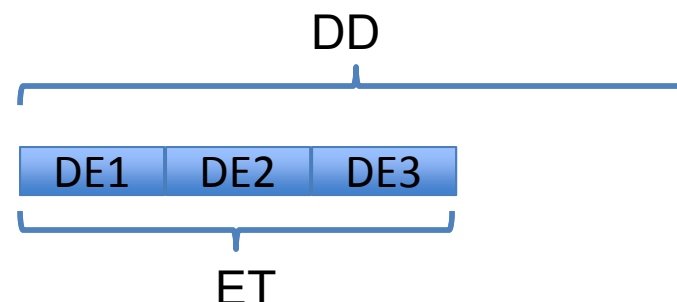
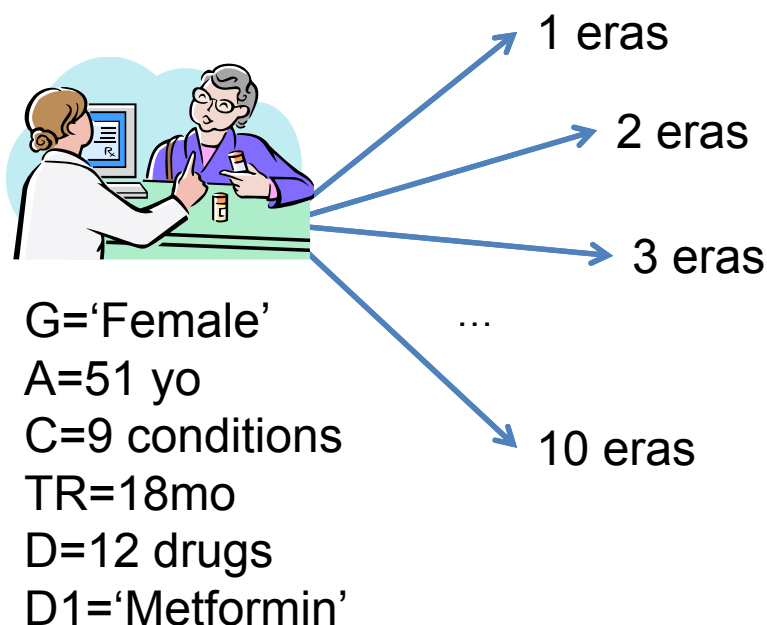
$p(D_i=d \mid C1='Diabetes\ mellitus\ type\ 2', G='Female',$
 $AR=21-55yo, CR=8-25, DR= 8-25, IR=1\ wk, N \geq i)$

N: number of drugs to select for condition
DR: drug count range {<3, 3-7, 8-25, 25+}
IR: interval range, time between C1 and C2

'd' can be any generic ingredient observed within that person strata 32

She gets the drug 'Metformin', so how should prescription eras be recorded in her database record?

TR=18mo



How many distinct periods of exposure?

$p(\text{DE}=\text{de} \mid \text{D1}=\text{'Metformin'}, \text{CR}=8-25, \text{DR}=8-25, \text{AR}=21-55, \text{TR}=18 \text{ mo})$

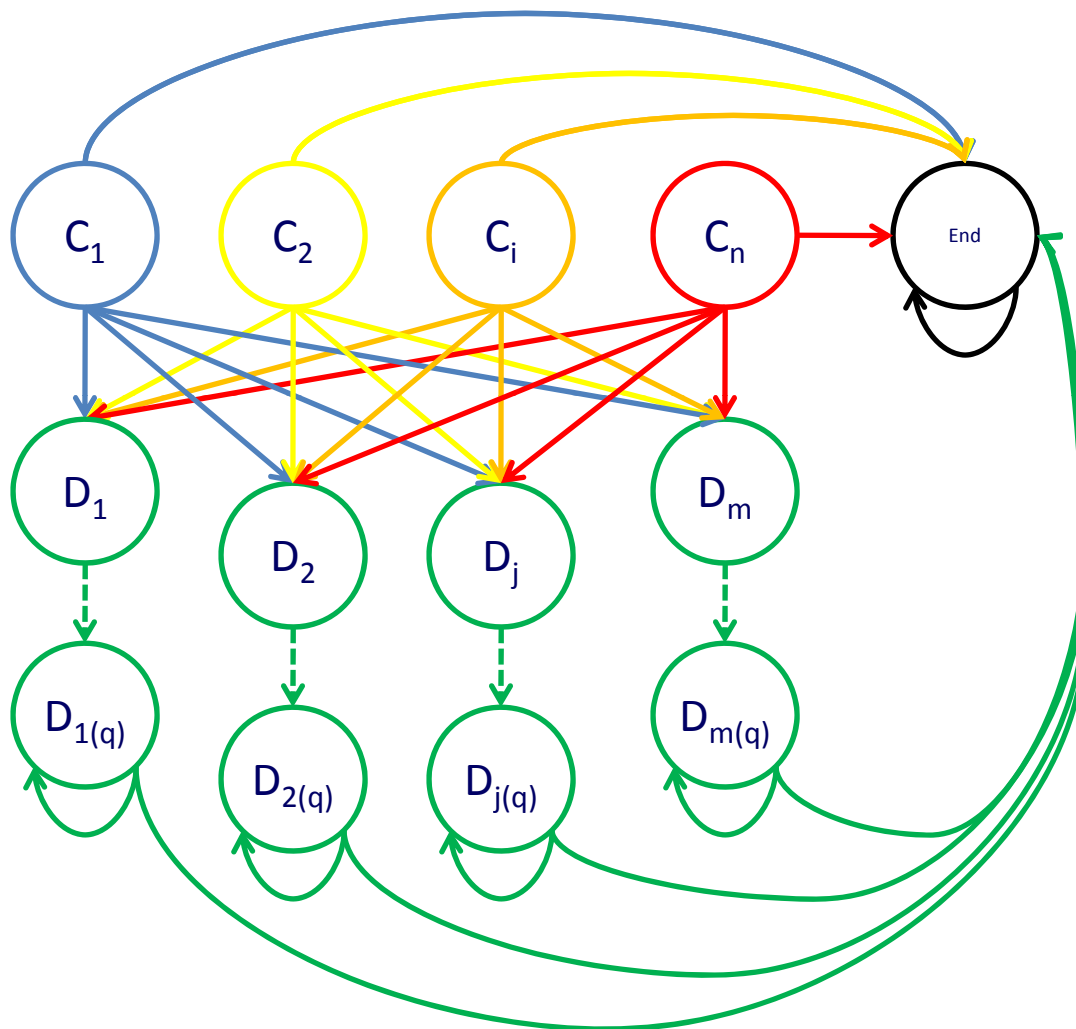
What's the total length of exposure?

$p(\text{ET}=\text{et} \mid \text{D1}=\text{'Metformin'}, \text{CR}=8-25, \text{DR}=8-25, \text{AR}=21-55, \text{TR}=18 \text{ mo})$

What's the duration during with the exposure takes place?

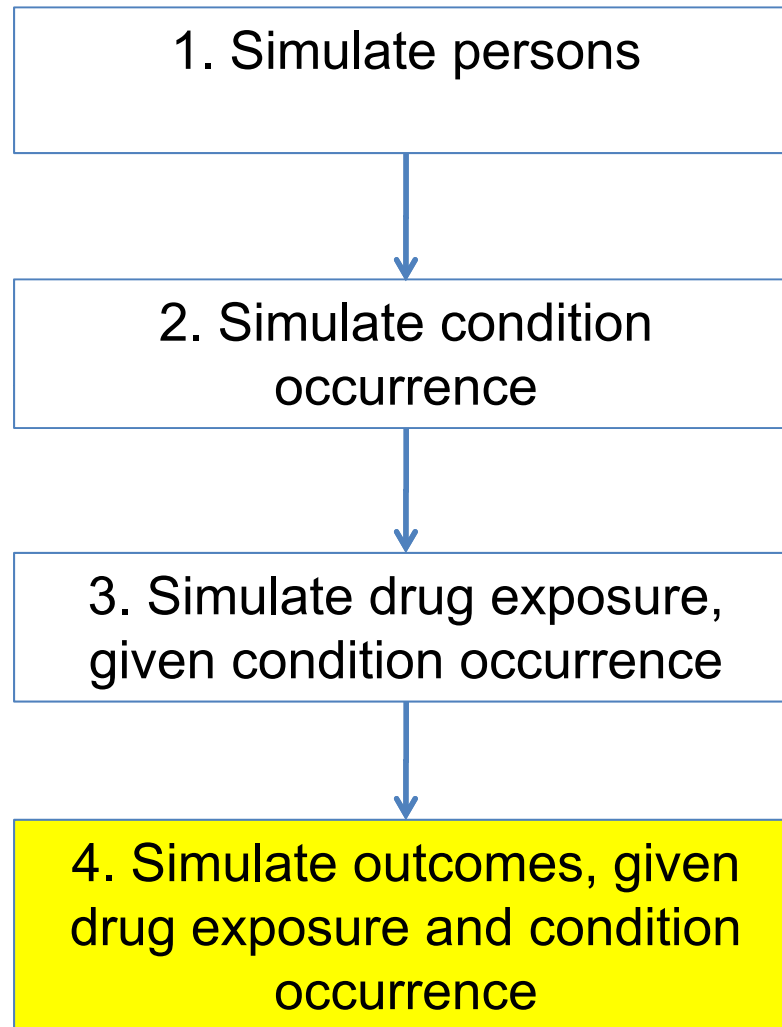
$p(\text{DD}=\text{dd} \mid \text{D1}=\text{'Metformin'}, \text{TR}=18 \text{ mo}, \text{DE}, \text{ET})$

Modeling drug exposure given conditions



- C_1-C_n : reflect all conditions in the database
- D_1-D_m : reflect all drugs in the database
- $D_{i(q)}$: reflect the q number of occurrences of drug D_i in the database
- $p_{ij} = \Pr(D_{k+1}=j | C_k=i, D_1..D_k \neq j)$
- p_{ij} can be estimated from real data based on frequency of condition/drug co-occurrence
- Model replicated within age * gender * condition count * drug count strata
- Model preserves conditional independence between drugs and subsequent conditions

Creating Simulated Data



Definition: **Simulated Signals**

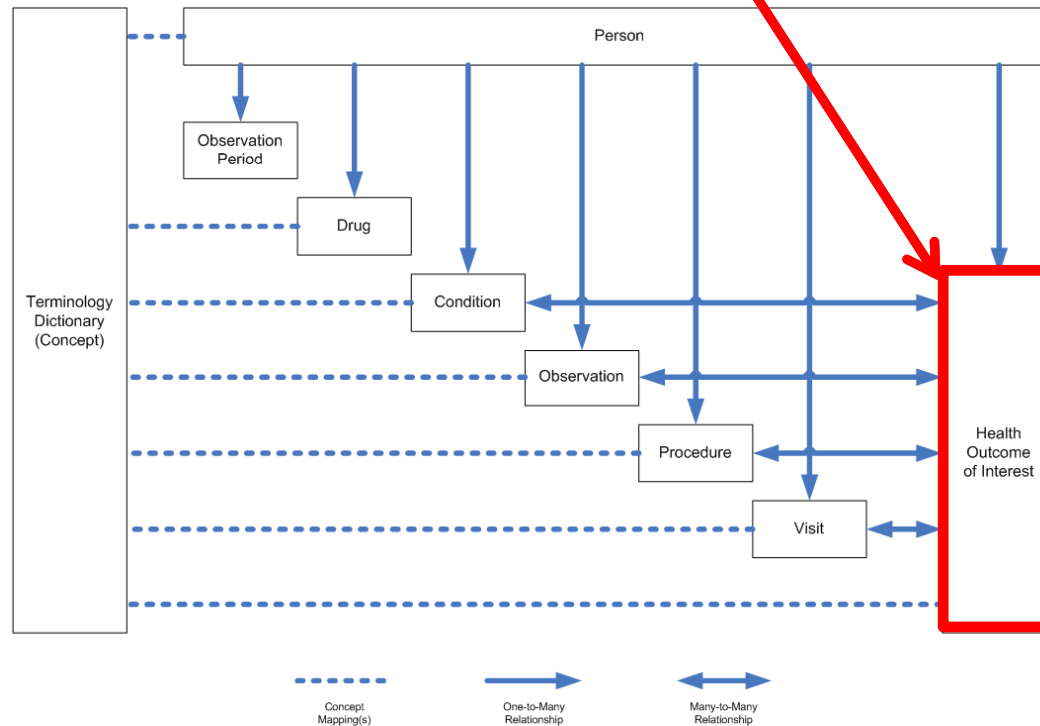
- **Algorithmically introduce known relationships between a drug and an outcome**
- **Conditions are added to or removed from baseline simulation**
 - Add conditions → drug adverse event
 - Remove conditions → beneficial effect
- **Relative Risk**
 - Multiplier applied to background rate to simulate the drug / outcome effect

Simulated Signals

Drug										
Outcome	ACE inhibitors	Amphotericin B	Antibiotics: oxymetazoline, sulfonamides, tetracyclines	Antiepileptics: carbamazepine, phenytoin	Benztolazepam	Beta blockers	Biphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema										
Aplastic Anemia										
Acute Liver Injury										
Bleeding										
Hip Fracture										
Hospitalization										
Myocardial Infarction										
Mortality after MI										
Renal Failure										
GI Ulcer Hospitalization										

Legend	Total
True positive/ benefit	2
True positive/ risk	9
Negative control	44

Inject "known" Drug / Outcome Relationships into Baseline Simulation Results



Attributes of a Simulated Signal

Attribute	Parameters
Outcome Definition	Drug and Condition Pair
Type of Outcome	Risk Benefit
Strength of Association	Relative Risk within specified timeframe
Exposure Relationship	First Exposure : Outcomes added to (or removed from) first exposure Any Exposure : Outcomes added to (or removed from) any exposure
Time to Event Relationship	Acute / Delayed : Outcomes randomly added (or removed) within a user specified risk window after exposure Insidious : Outcomes randomly added (or removed) starting at a random date after exposure Accumulative : Outcomes randomly added (or removed) starting at a random date after exposure with accumulating probability over time
Time at Risk	Risk Window Start : Minimum days after exposure start Risk Window End : Maximum days after exposure start

Simulated HOIs

Outcome	ACE Inhibitors	Amphotericin B	Antibiotics: erythromycins, sulfonamides, tetracyclines	Antiepileptics: carbamazepine, phenytoin	Benzodiazepines	Beta blockers	Bisphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Aplastic Anemia	True positive' risk	Negative control'	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Acute Liver Injury	Negative control'	Negative control'	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Bleeding	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	True positive' risk
Hip Fracture	Negative control'	Negative control'	Negative control'	Negative control'	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Hospitalization	True positive' benefit	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Myocardial Infarction	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	True positive' risk	True positive' risk	Negative control'	Negative control'
Mortality after MI	Negative control'	Negative control'	Negative control'	Negative control'	True positive' benefit	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
Renal Failure	Negative control'	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'
GI Ulcer Hospitalization	Negative control'	Negative control'	Negative control'	Negative control'	Negative control'	True positive' risk	Negative control'	Negative control'	Negative control'	Negative control'

Legend

True positive' benefit
True positive' risk
Negative control'

Total

2
9
44

Relative Risk: 3.0

Onset: First Exposure

Time at Risk: Between 0-30 days after exposure

Simulated HOIs

Outcome	ACE Inhibitors	Amphotericin B	Antibiotics: erythromycins, sulfonamides, tetracyclines	Antiepileptics: carbamazepine, phenytoin	Benzodiazepines	Beta blockers	Bisphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema										
Aplastic Anemia										
Acute Liver Injury										
Bleeding										
Hip Fracture										
Hospitalization										
Myocardial Infarction										
Mortality after MI										
Renal Failure										
GI Ulcer Hospitalization										

Legend

	True positive' benefit
	True positive' risk
	Negative control'

Total

2
9
44

Relative Risk: 1.5

Onset: Insidious

Time at Risk: Starting at least 1 day after exposure

Simulated HOIs

Outcome	ACE Inhibitors	Amphotericin B	Antibiotics: erythromycins, sulfonamides, tetracyclines	Antiepileptics: carbamazepine, phenytoin	Benzodiazepines	Beta blockers	Bisphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema	True positive' risk	Negative control'								
Aplastic Anemia				True positive' risk						
Acute Liver Injury			True positive' risk							
Bleeding										True positive' risk
Hip Fracture					True positive' risk					
Hospitalization	True positive' benefit									
Myocardial Infarction							True positive' risk	True positive' risk		
Mortality after MI						True positive' benefit				
Renal Failure		True positive' risk								
GI Ulcer Hospitalization							True positive' risk			

Legend

True positive' benefit
True positive' risk
Negative control'

Total

2
9
44

Relative Risk: 0.8

Onset: Accumulative

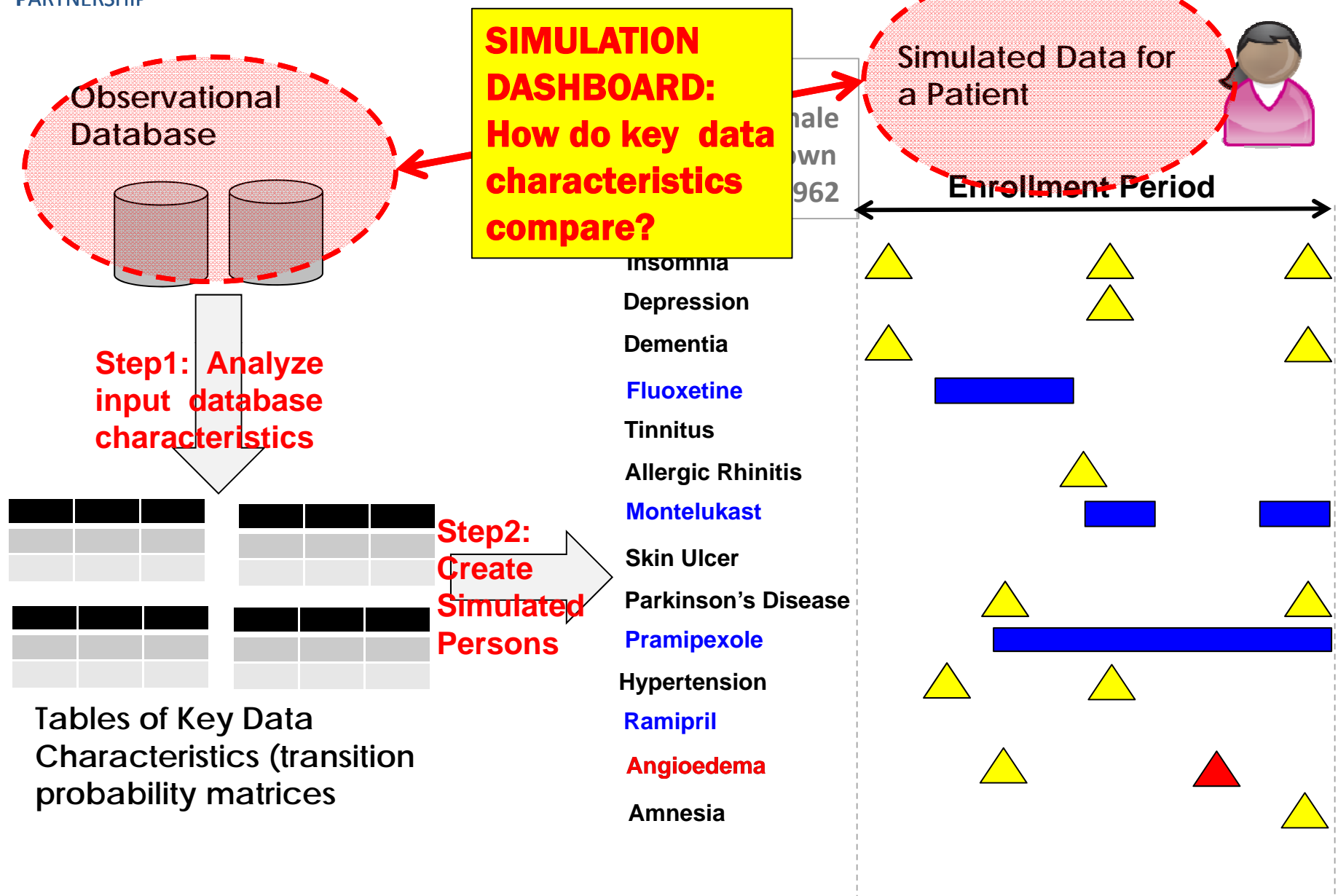
Time at Risk: Starting at least 1 day after exposure

Simulated signals to model the OMOP HOI experiment

Outcome type	Drug concept name	Health Outcome of Interest	Relative risk	Outcome risk type	Risk Window Start	Risk Window End
risk	ACE Inhibitors	Angioedema	3	first exposure	0	30
risk	Antiepileptics	Aplastic Anemia	2.5	first exposure	15	90
risk	Antibiotics	Acute Liver Injury	1.3	any exposure	1	45
risk	Amphotericin B	Renal Failure	5	insidious	0	
risk	Warfarin	Bleeding	2	insidious	0	
risk	Benzodiazapines	Hip Fracture	1.8	accumulative	3	
risk	Tricyclic antidepressants	Myocardial Infarction	1.2	accumulative	60	
risk	Bisphosphonates	GI Ulcer Hospital- ization	1.25	insidious	1	
benefit	ACE Inhibitors	Hospitalization	0.8	accumulative	1	
benefit	Beta blocker	Mortality after MI	0.75	first exposure	1	180

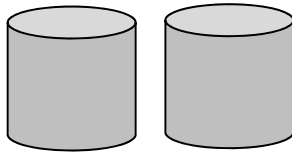
OSIM2 SIMULATION VALIDATION

OSIM2 Simulation Performance



Simulation Summary Statistics

Observational Database



Simulated Data



Thomson MSLR	
Person Count:	1,229,321
Condition Records:	25,228,245
Avg. Condition Records per Person	20.5
Drug Records:	16,350,306
Avg. Drug Records per Person	13.3

Simulated Data	
Person Count:	1,000,000
Condition Records:	22,062,495
Avg. Condition Records per Person	22
Drug Records:	12,160,304
Avg. Drug Records per Person	12.1

Run Time

Step 1 Analyze: 5:13

Step 2 Simulate: 20:18

Total File Size

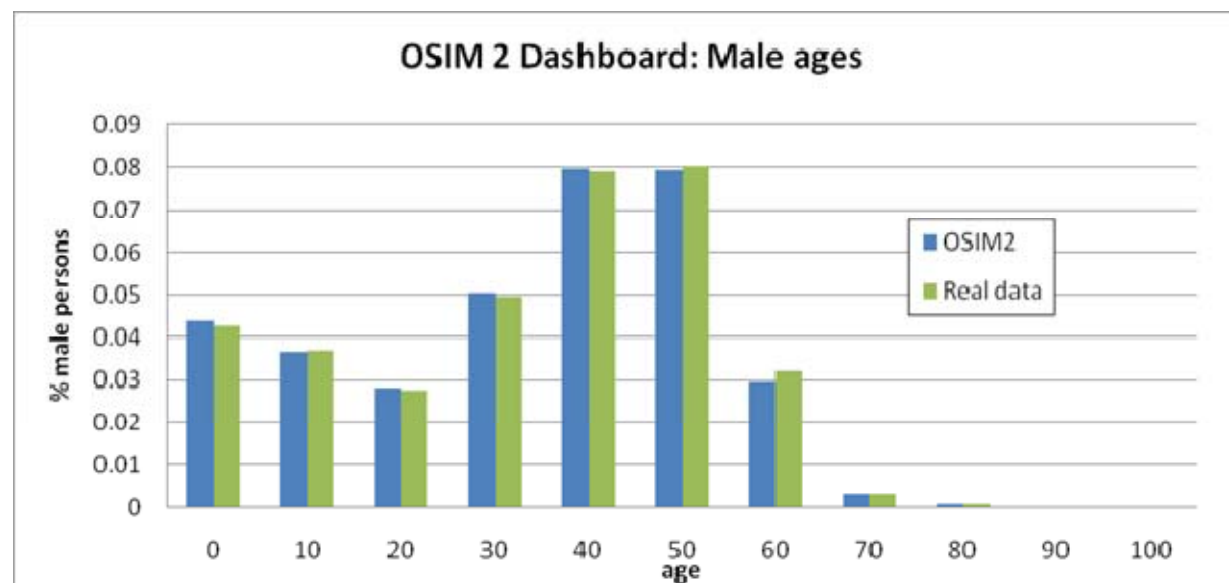
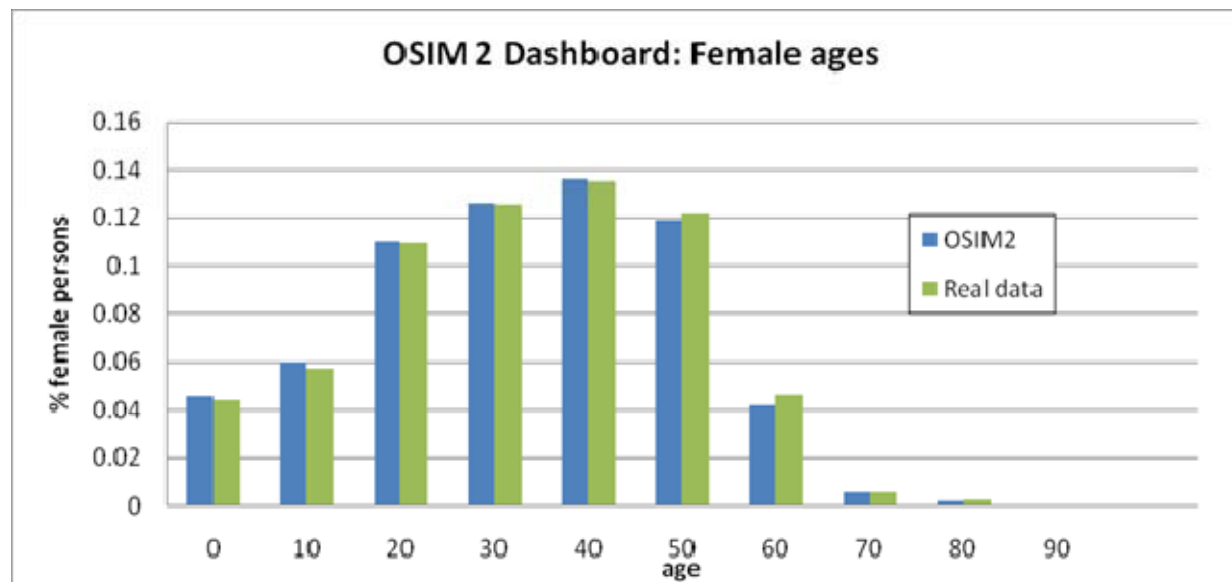
Transition Matrices: 3.9 GB

Simulated Data: 1.25 GB

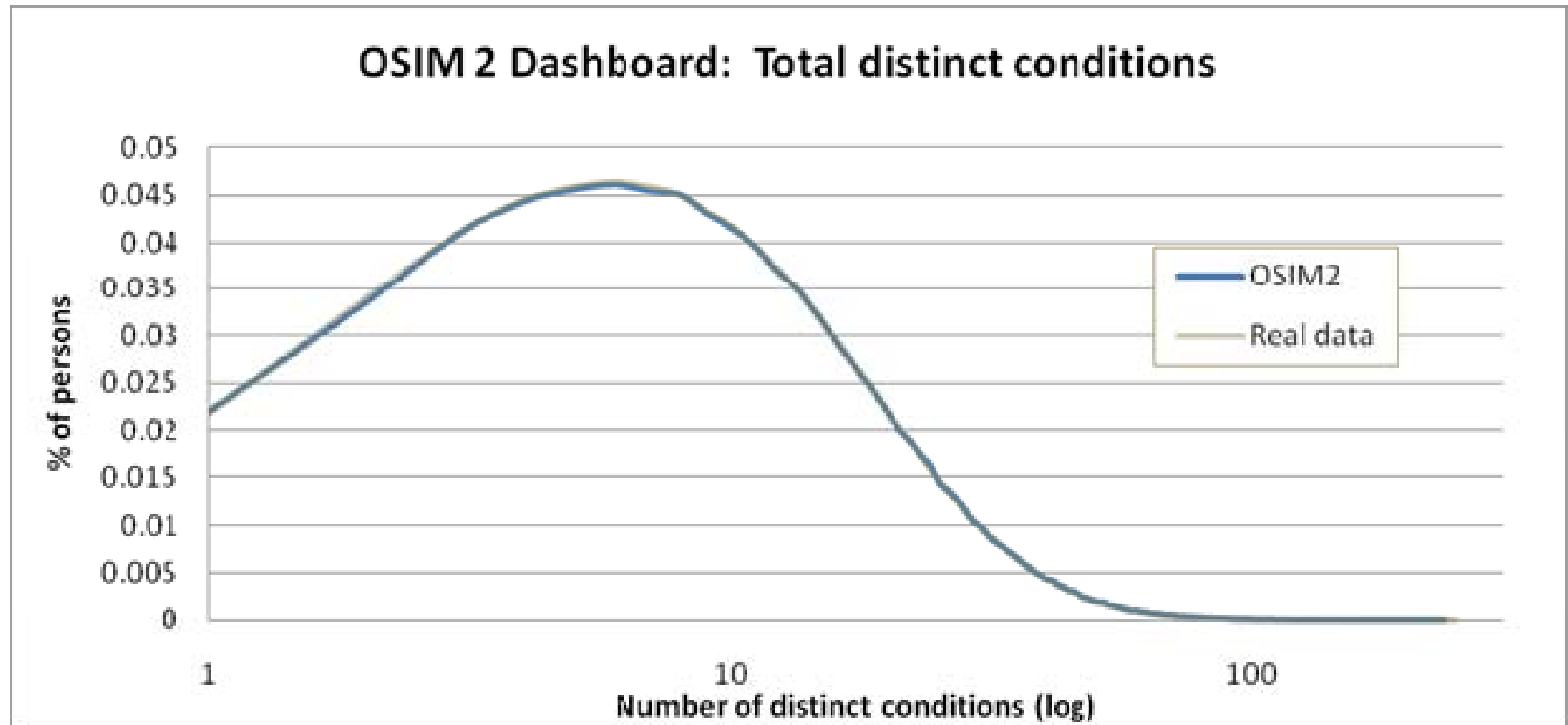
Model validation through test cases: Dashboard analyses

- Validate key characteristics of simulation modeling reality with sufficient precision
- Person
 - Age, gender distributions
 - Observation period length
- Condition
 - Number of comorbidities per person
 - Prevalence of each condition
 - Co-occurrence between conditions
 - Timing between and within conditions
- Drug
 - Number of exposures per person
 - Prevalence and of each drug
 - Total number and length of exposure
 - Co-occurrence between conditions and drugs
 - Co-occurrence between drugs
 - Timing between and within drugs

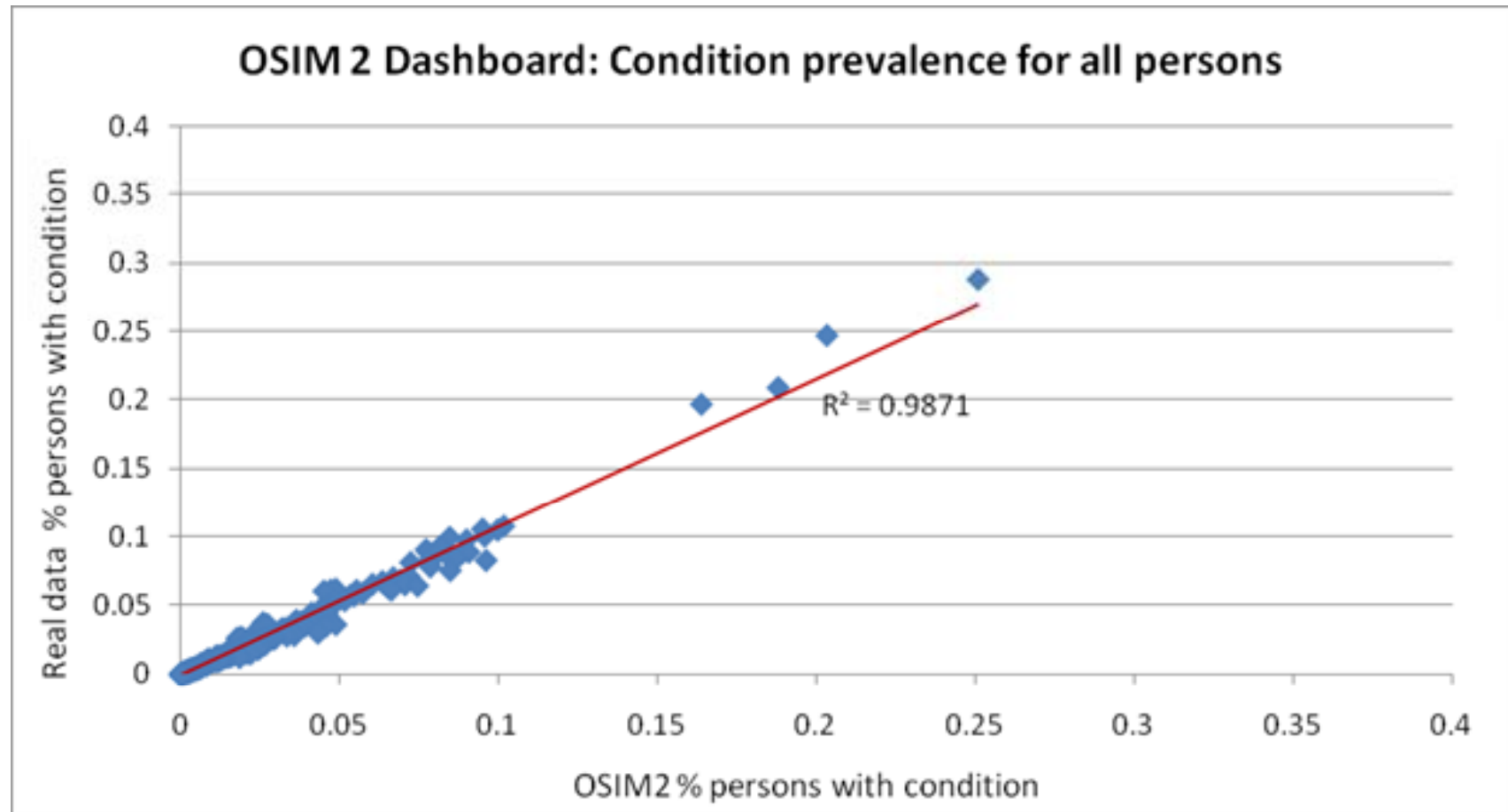
Simulation Dashboard (OSIM2 v MSLR): Age by gender



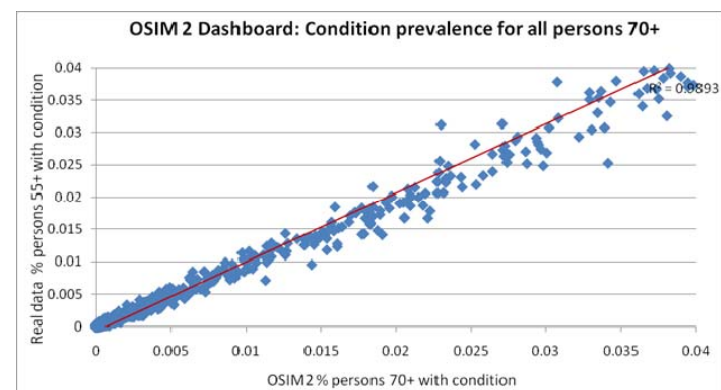
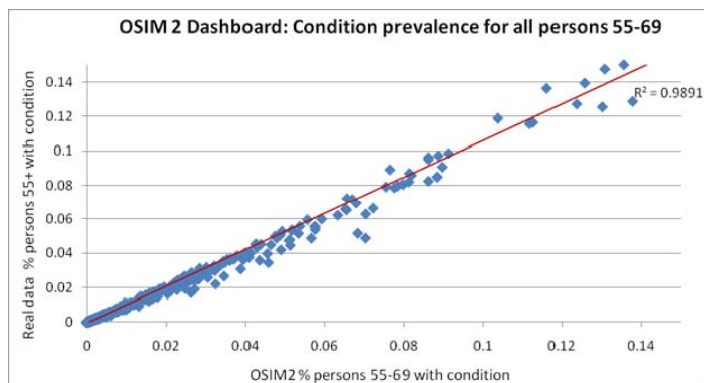
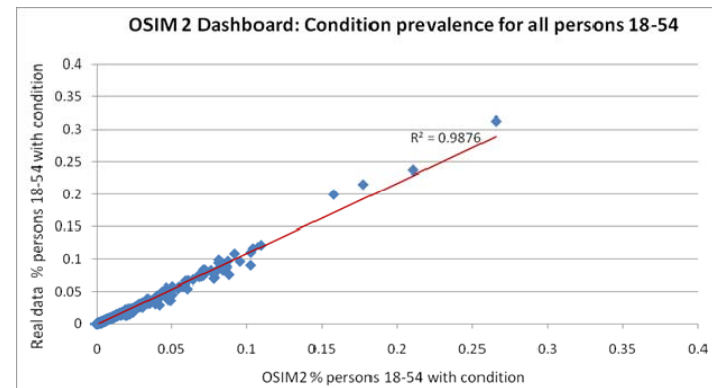
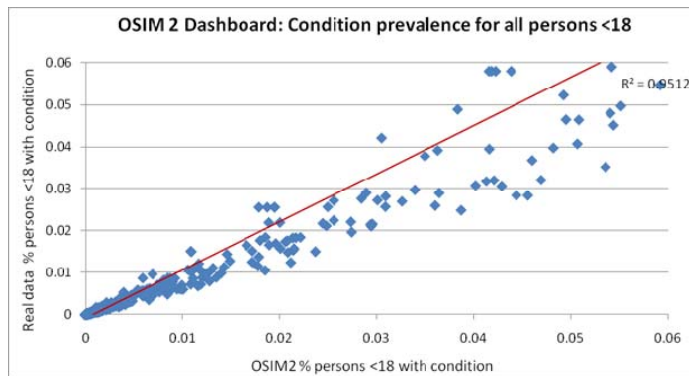
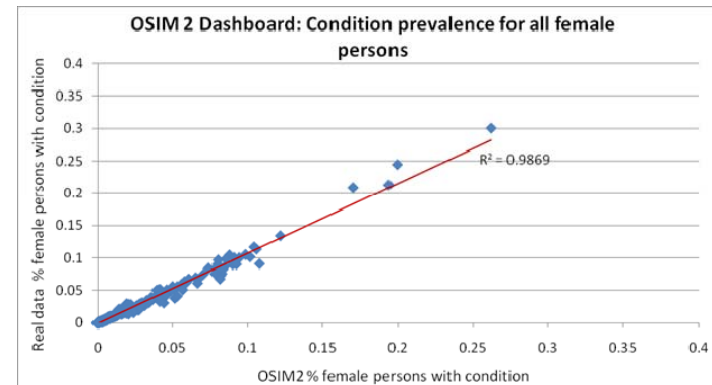
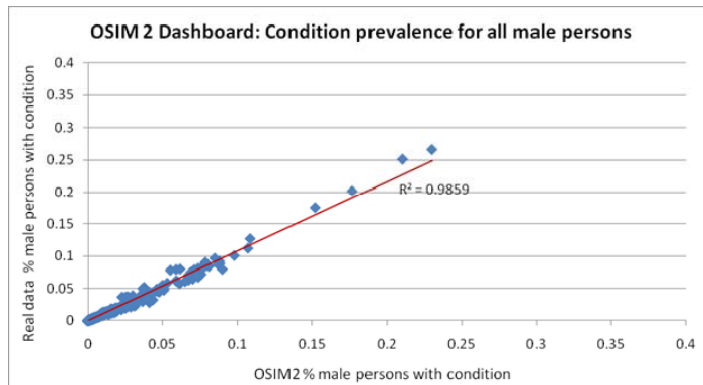
Simulation Dashboard (OSIM2 v MSLR): Condition Eras



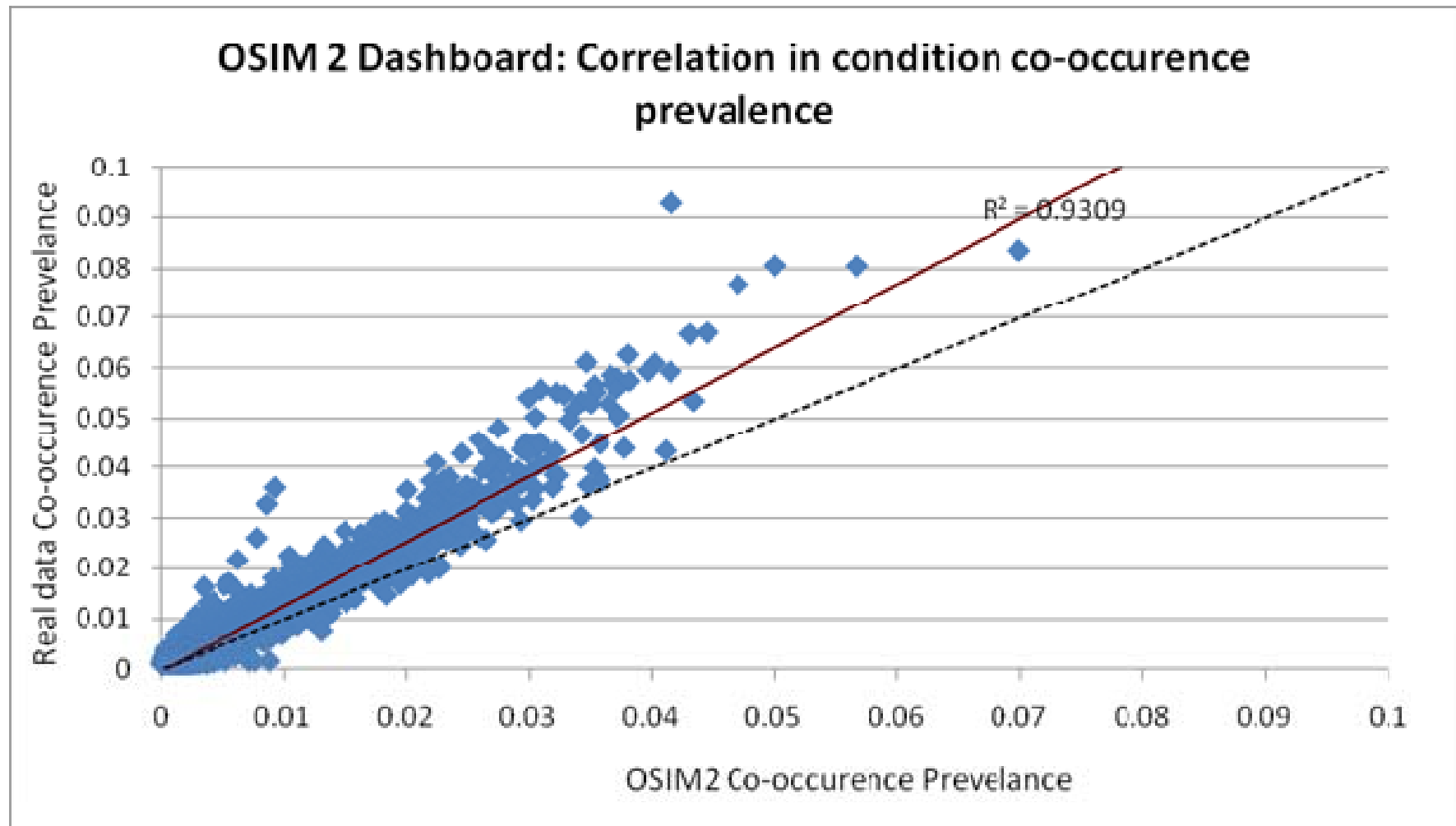
Simulation Dashboard (OSIM2 v MSLR): Condition Prevalence



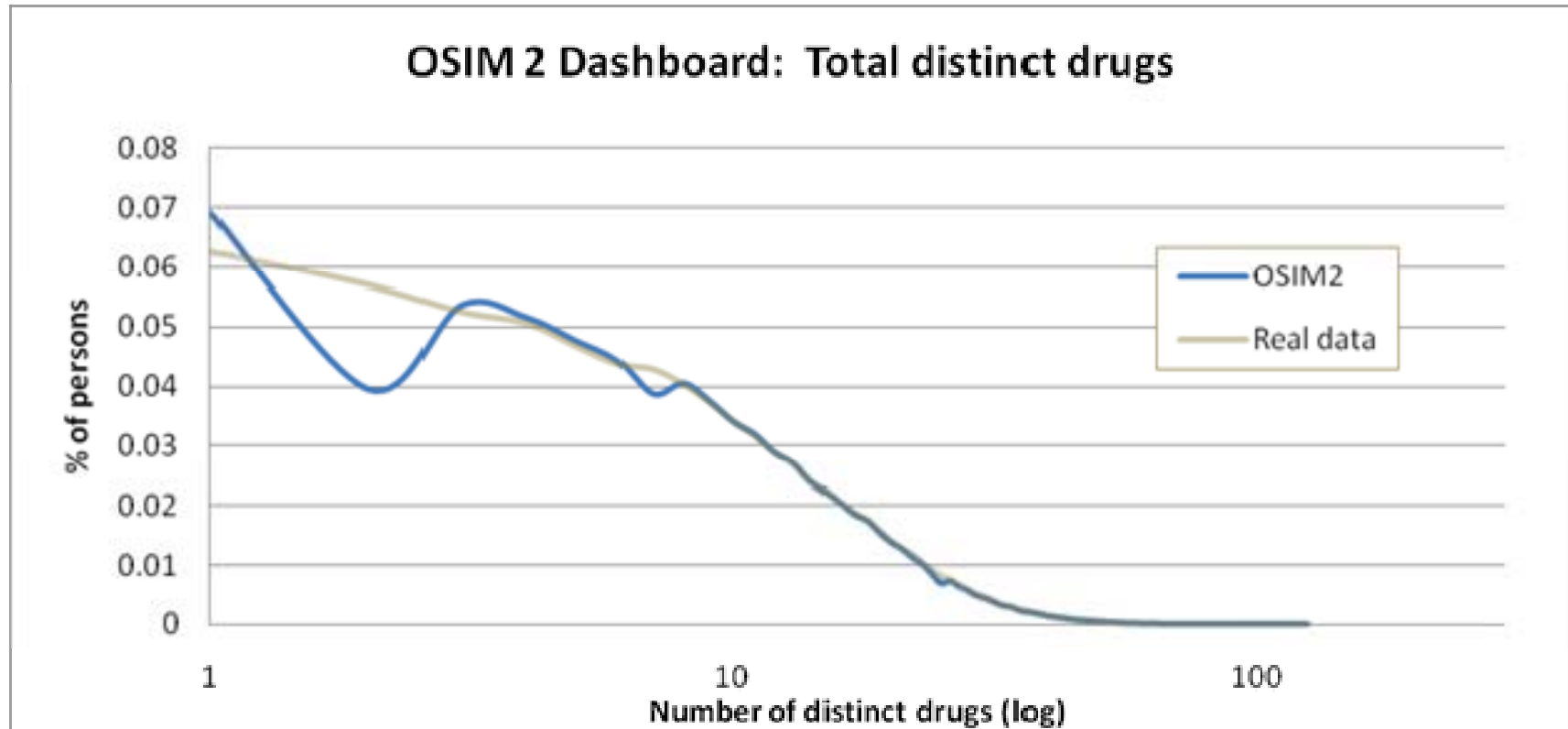
Simulation Dashboard (OSIM2 v MSLR): Condition Prevalence Stratified



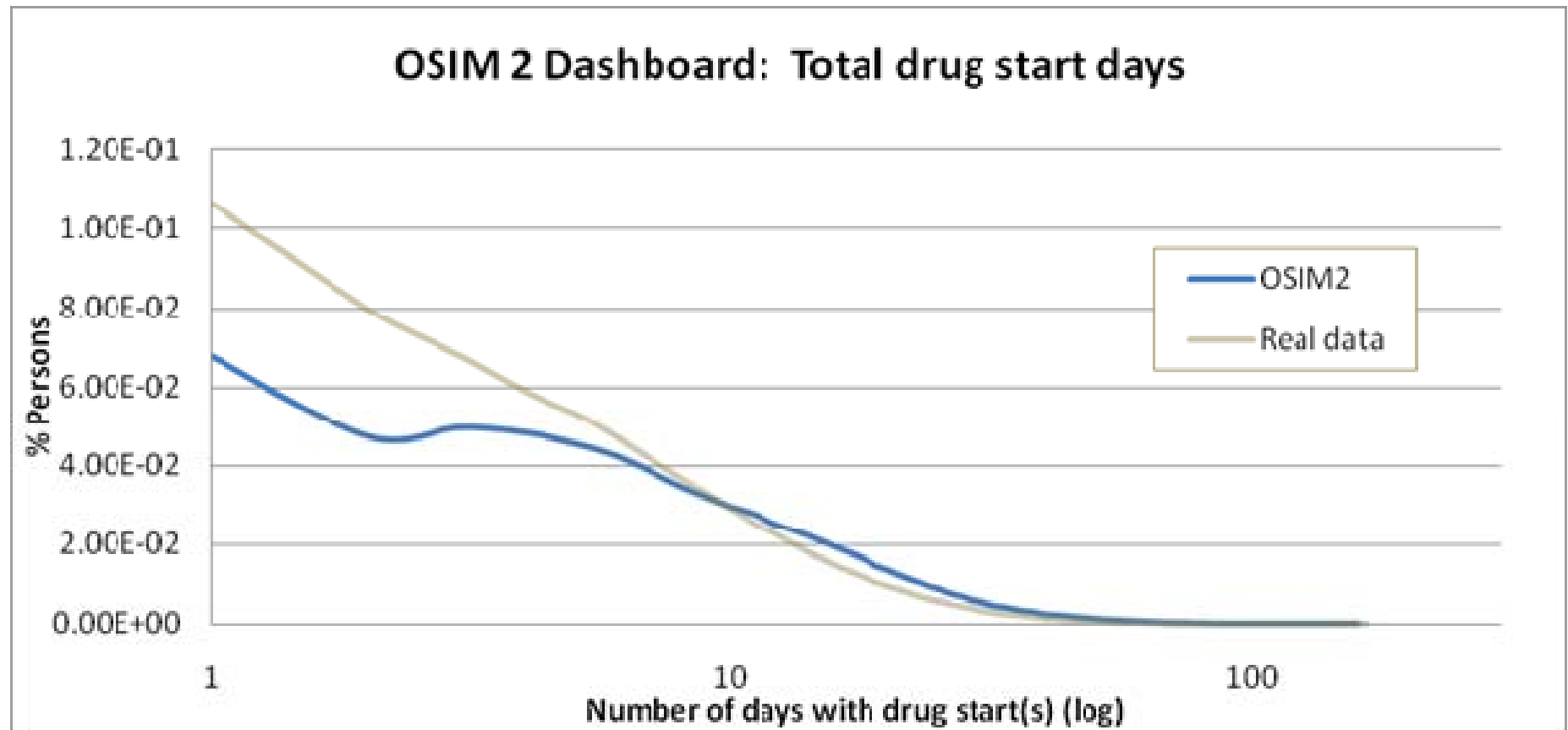
Simulation Dashboard (OSIM2 v MSLR): Condition Co-Occurrence



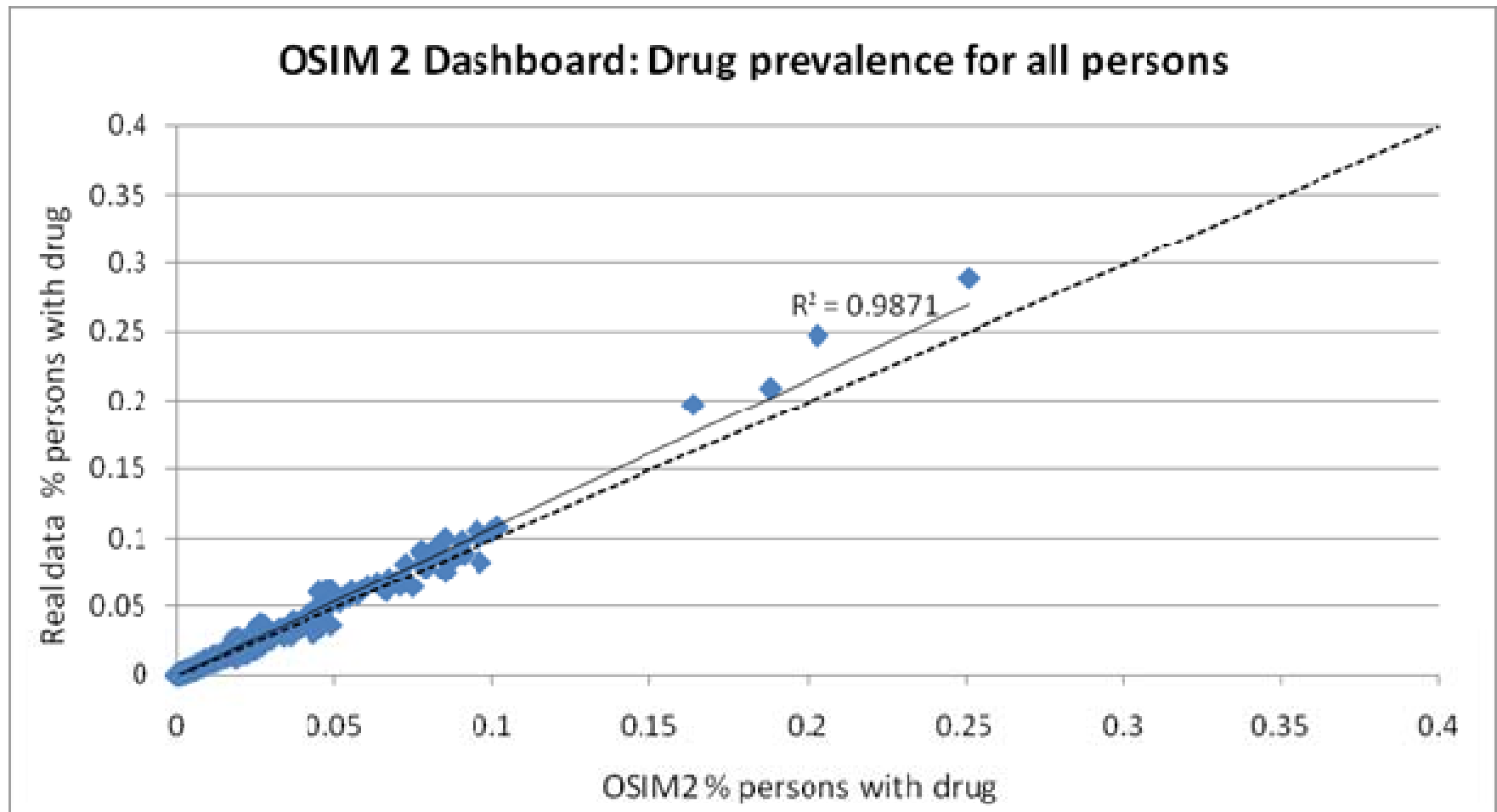
Simulation Dashboard (OSIM2 v MSLR): Distinct Drugs



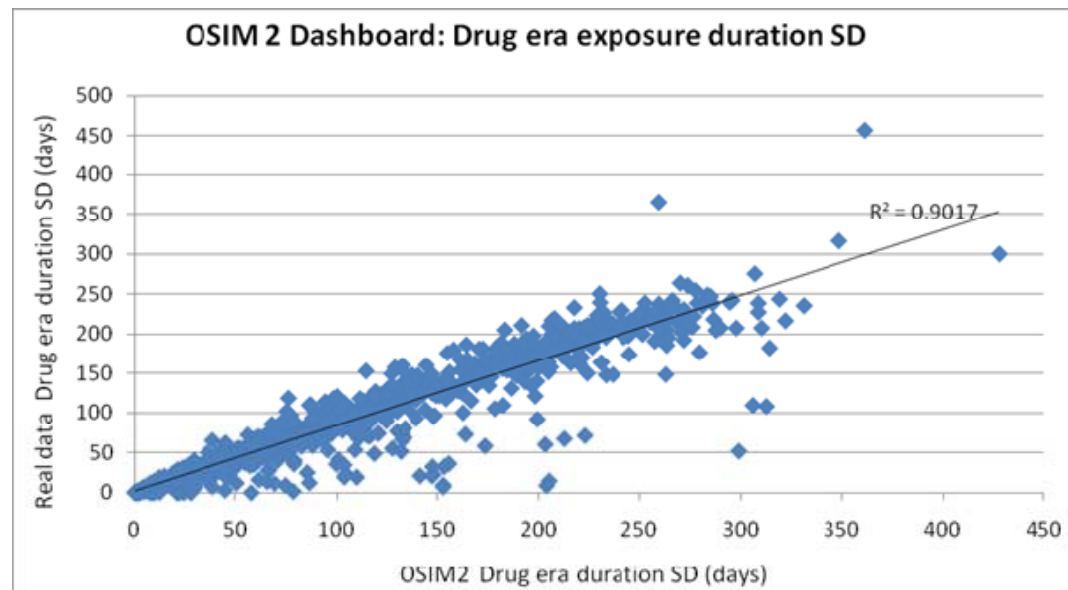
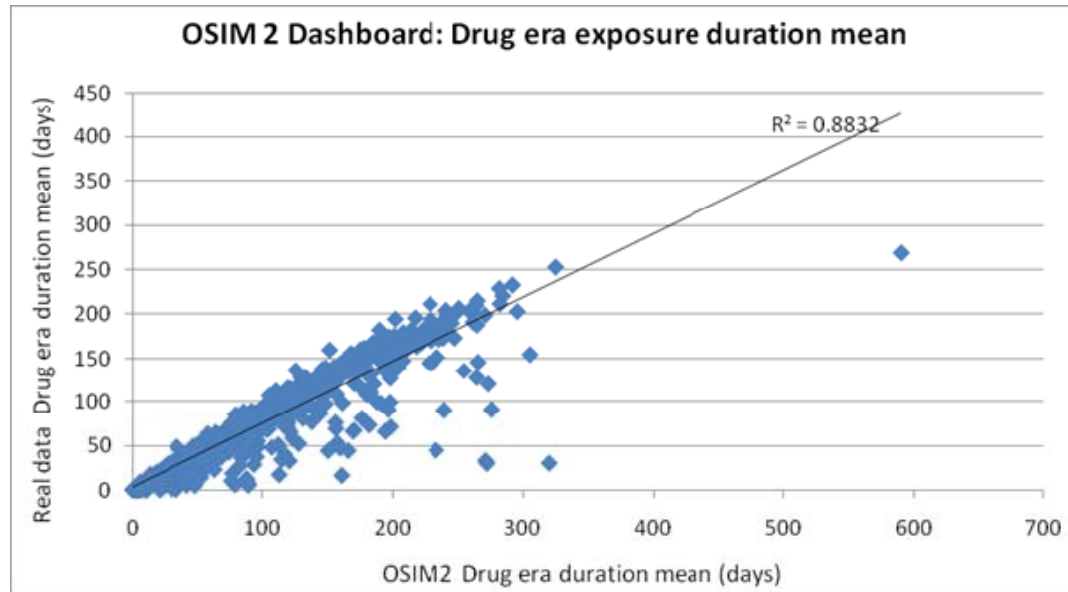
Simulation Dashboard (OSIM2 v MSLR): Days with Drug Starts



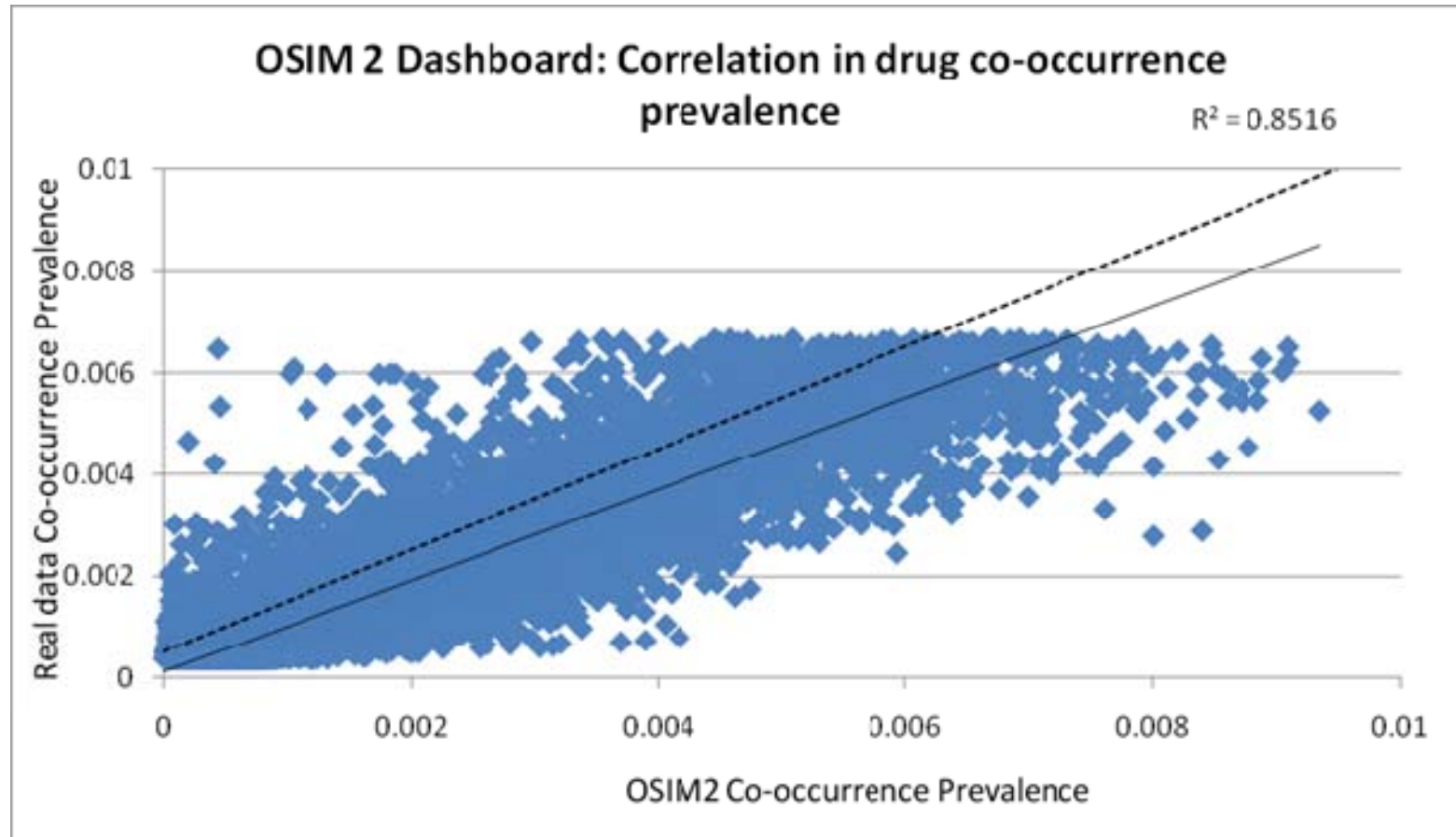
Simulation Dashboard (OSIM2 v MSLR): Drug Prevalence



Simulation Dashboard (OSIM2 v MSLR): Drug Exposure Duration



Simulation Dashboard (OSIM2 v MSLR): Drug Co-Occurrence

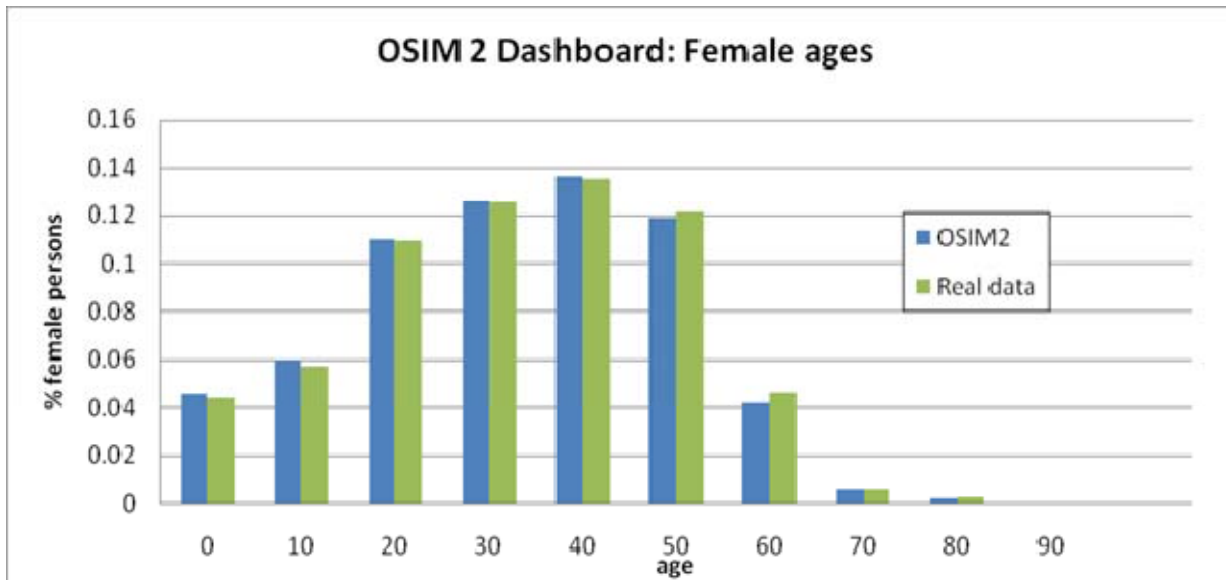


USES OF SIMULATED DATA

How do we use simulated data?

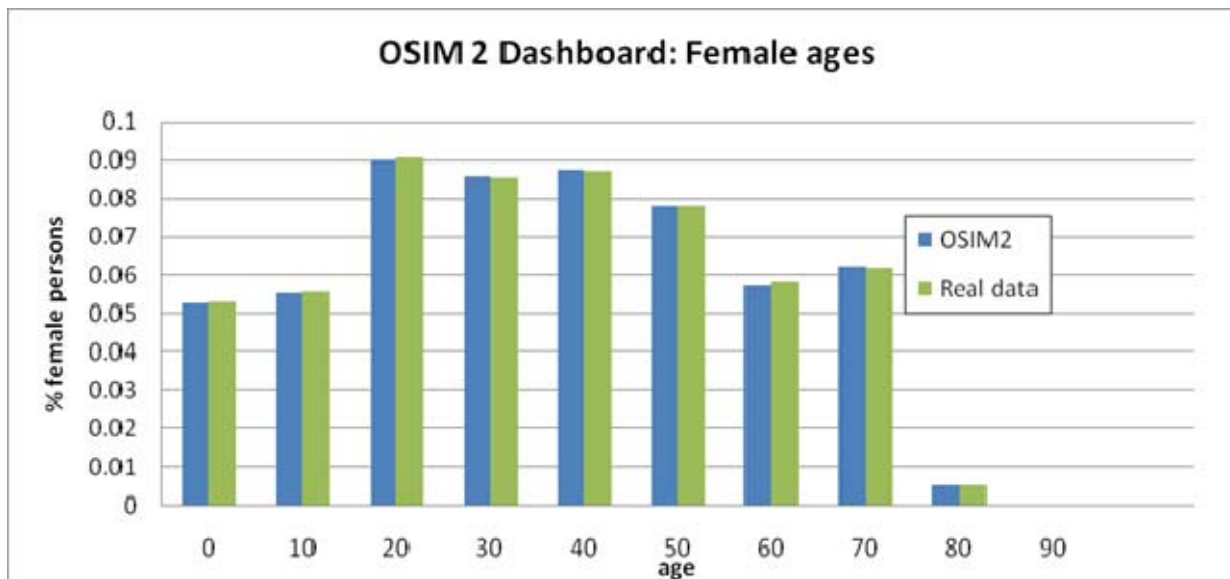
- **Experiments to understand characteristics of real data**
- **Software validation**
- **Methods development**
- ...

Uses of Simulated Data: Experiments to Understand Characteristics of Real Data



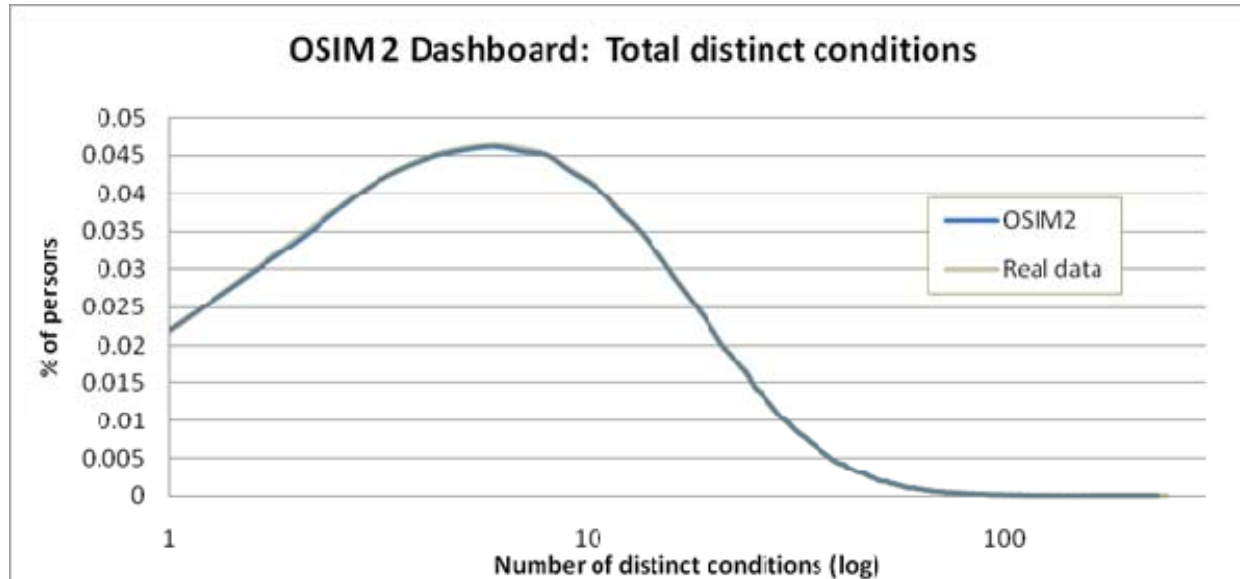
**Claims Data Simulation
(MSLR)**

Female Ages



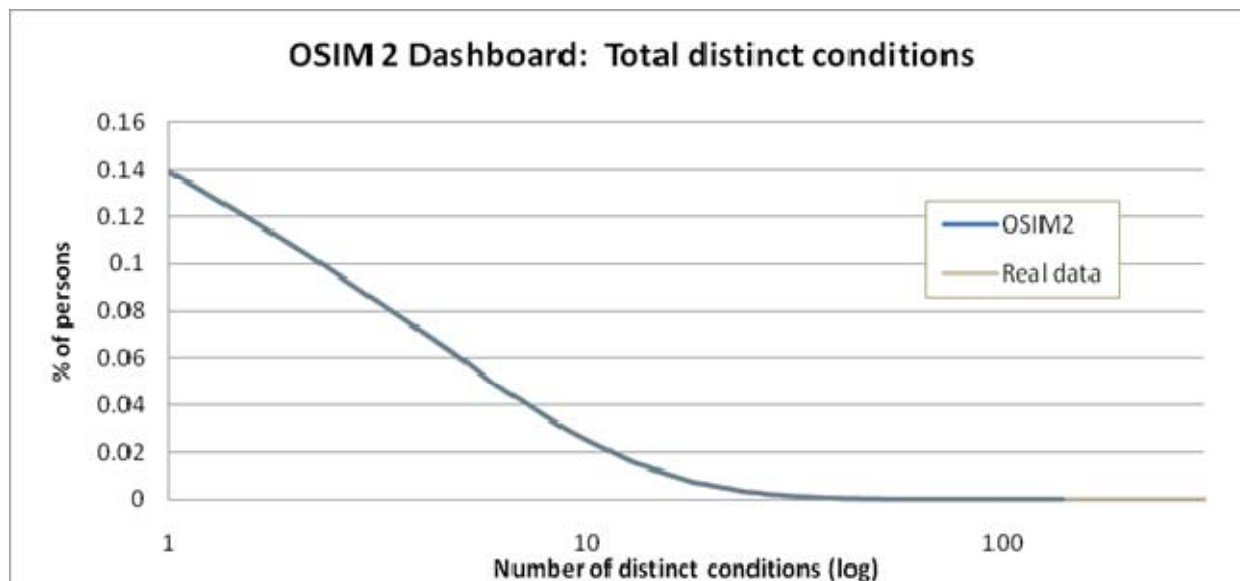
**EMR Data
Simulation (GE)**

Uses of Simulated Data: Experiments to Understand Characteristics of Real Data



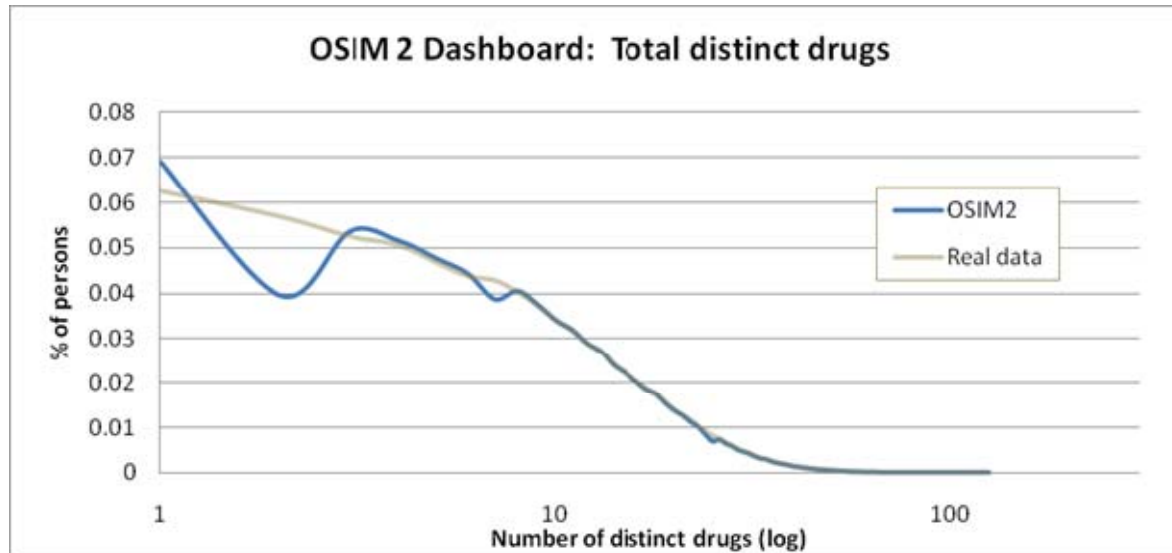
**Claims Data Simulation
(MSLR)**

**Total Distinct
Conditions**



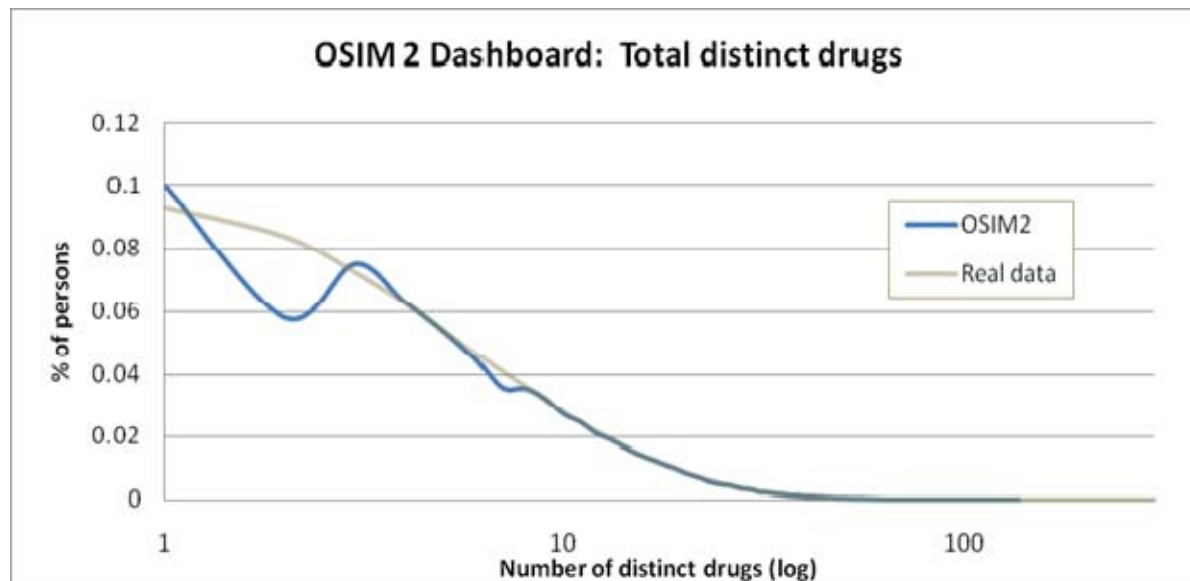
**EMR Data
Simulation (GE)**

Uses of Simulated Data: Experiments to Understand Characteristics of Real Data



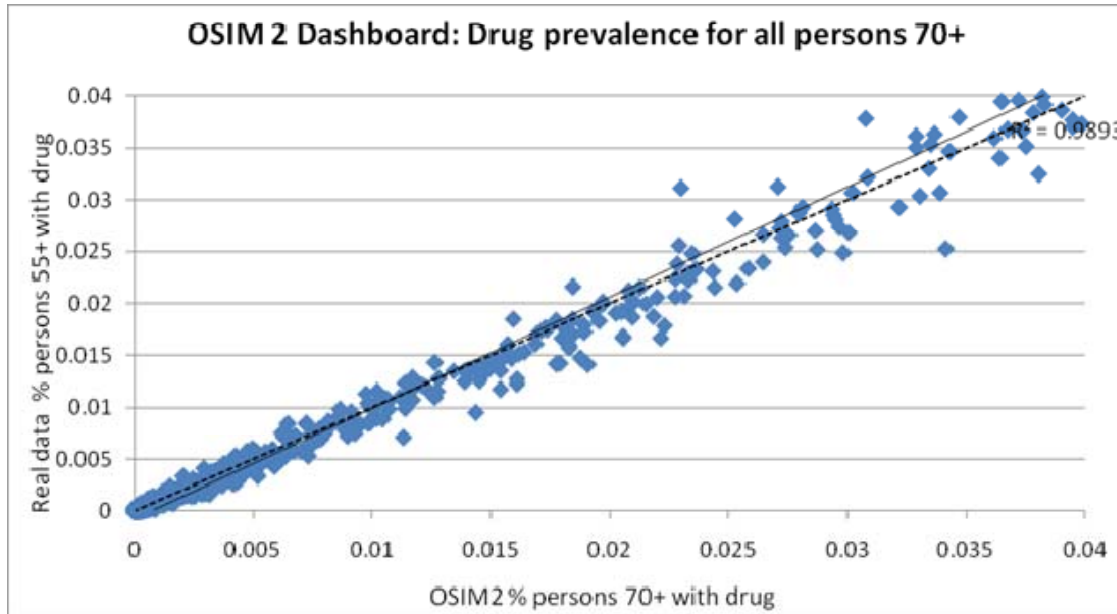
**Claims Data Simulation
(MSLR)**

**Total Distinct
Drugs**



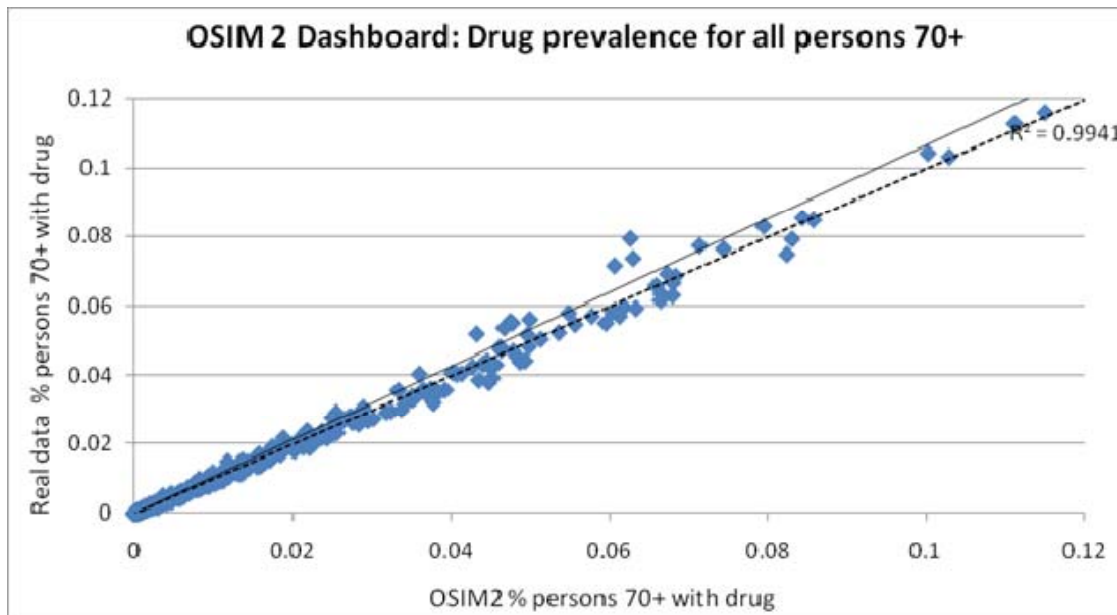
**EMR Data
Simulation (GE)**

Uses of Simulated Data: Experiments to Understand Characteristics of Real Data



**Claims Data Simulation
(MSLR)**

**Drug
Prevalence for
Persons > 70**



**EMR Data
Simulation (GE)**

Uses of Simulated Data: Software Validation and Training

- Software development
 - Identify sets of simulated patients with characteristics to test key features (analytic method, etc.)
 - Develop test cases and expected results
 - Regression test each software release to ensure results are consistent
- Training
 - Inexpensive source of Data
 - Train users on functions / analytic methods where results are expected / known
 - Mitigates issues of “unexpected results” during training phase

Uses of Simulated Data: Methods Development

Method Evaluation Requirements:

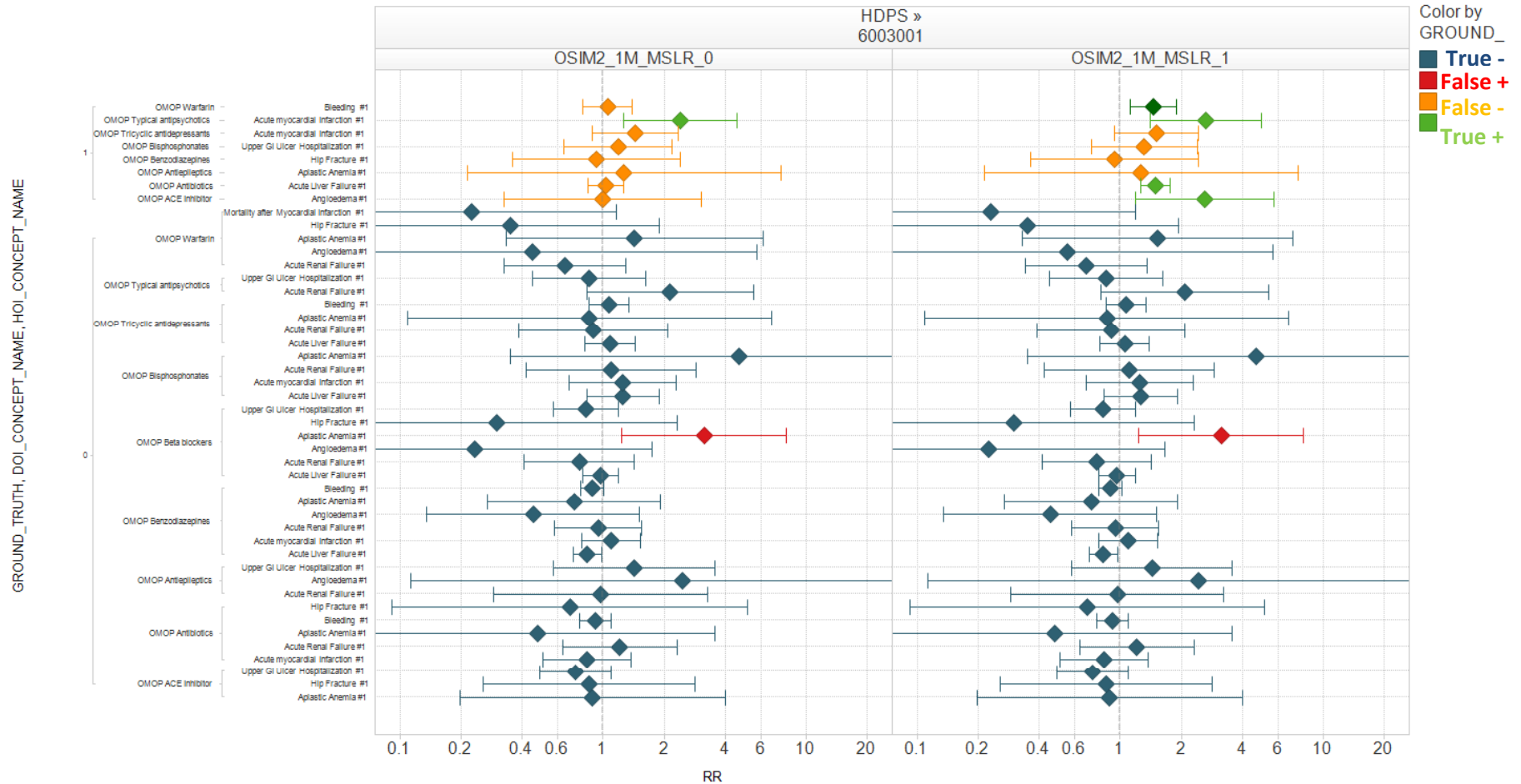
- Characterize Individual Method Performance
- Compare Performance Among Methods

Objective Measures for:

- Sensitivity
- Specificity
- Positive and Negative Predictive Value

Method performance pre/post signal

Drug-outcome pair estimates

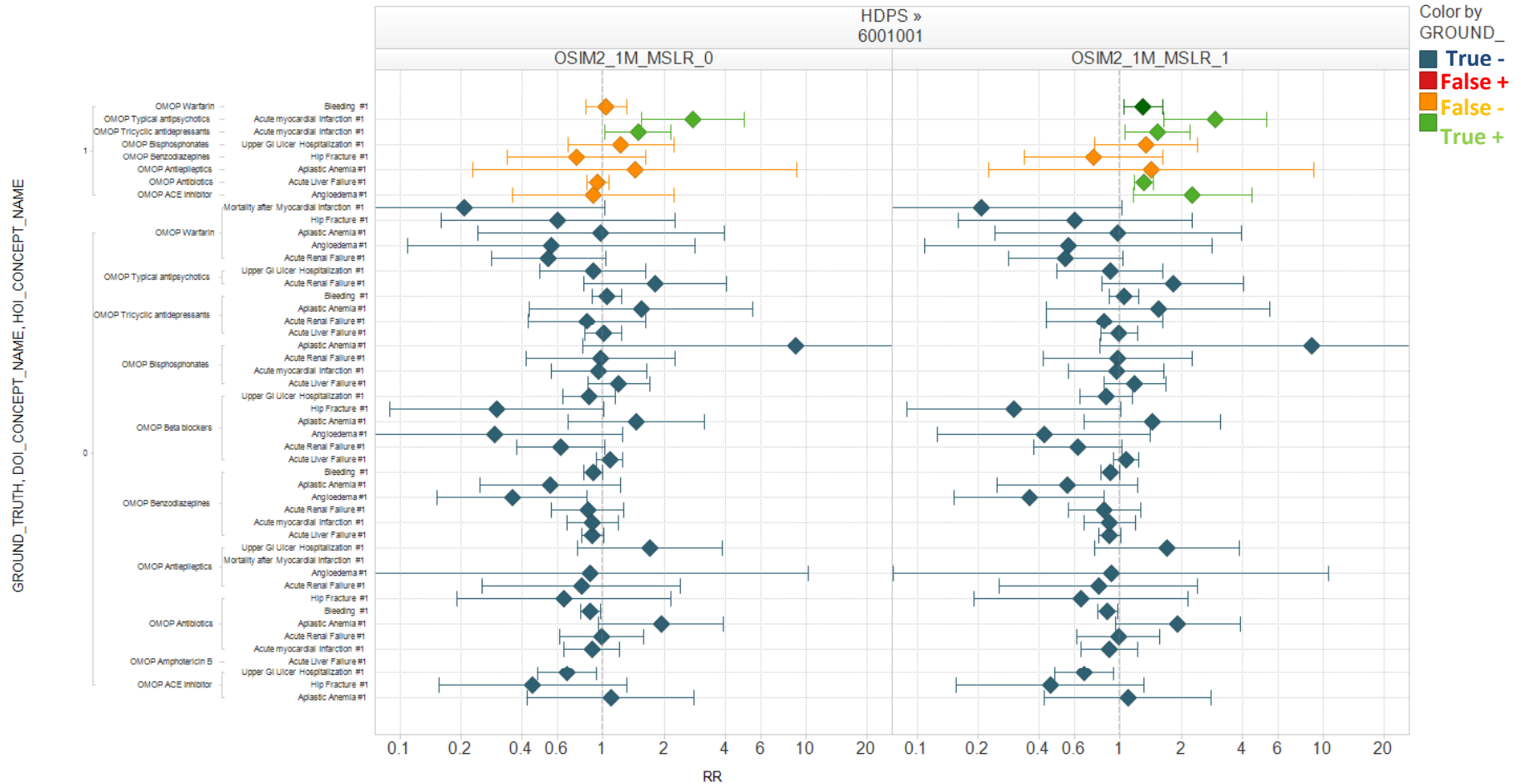


Method reference

ANALYSIS...	METHOD...	OUTPUT_FILE...	RUN_NAME	PARAM_SETTINGS
6003001	HDPS	hdps_NAME_MH_wo180ce9999swn30tf100tn200tc100pg5pd30pc30ip0.t	HDPS_HOI_RUN_3	COVARIATE_ELIGIBILITY_DAYS: 9999; ~~~SURVEILLANCE_WINDOW_DAYS: -30; ~~~TOP_CONFOUNDERS: 100; ~~~NUMBER_OF_GROUPS_BY_PROPENSITY_SCORE: 5; ~~~OUTPUT_METRIC: MH; ~~~COMPARATOR_DRUG: 3; ~~~

Method performance pre/post signal

Drug-outcome pair estimates

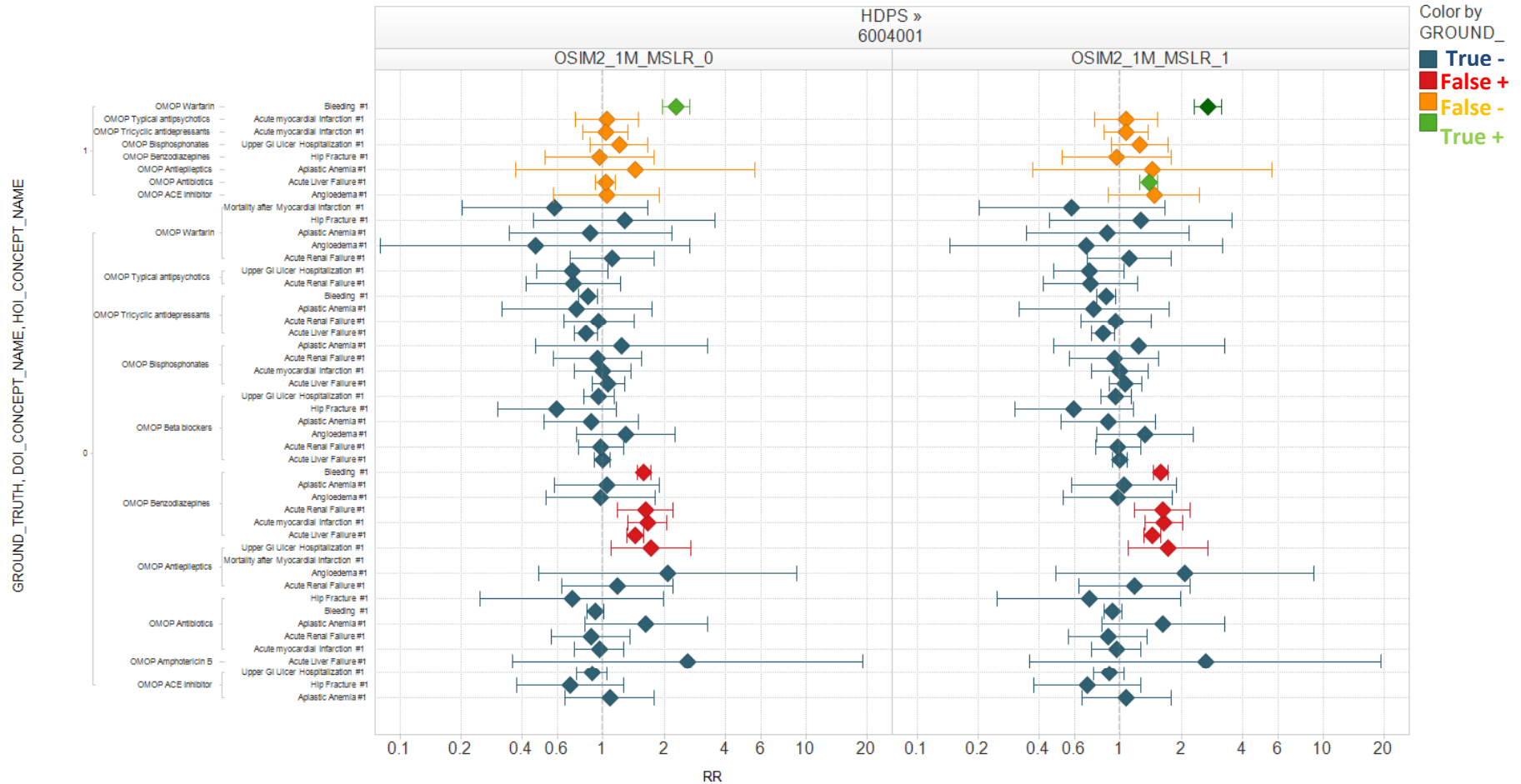


Method reference

ANALYSIS...	METHOD...	OUTPUT_FILE...	RUN_NAME	PARAM_SETTINGS
6001001	HDPS	hdps_NAME_MH_wo180ce30swn30tf100tn200tc100pg5pd30pc30ip0.txt	HDPS_HOI_RUN_1	COVARIATE_ELIGIBILITY_DAYS: 30; ~~~SURVEILLANCE_WINDOW_DAYS: -30; ~~~TOP_CONFOUNDERS: 100; ~~~NUMBER_OF_GROUPS_BY_PROPENSITY_SCORE: 5; ~~~OUTPUT_METRIC: MH; ~~~COMPARATOR_DRUG: 3; ~~~

Method performance pre/post signal

Drug-outcome pair estimates

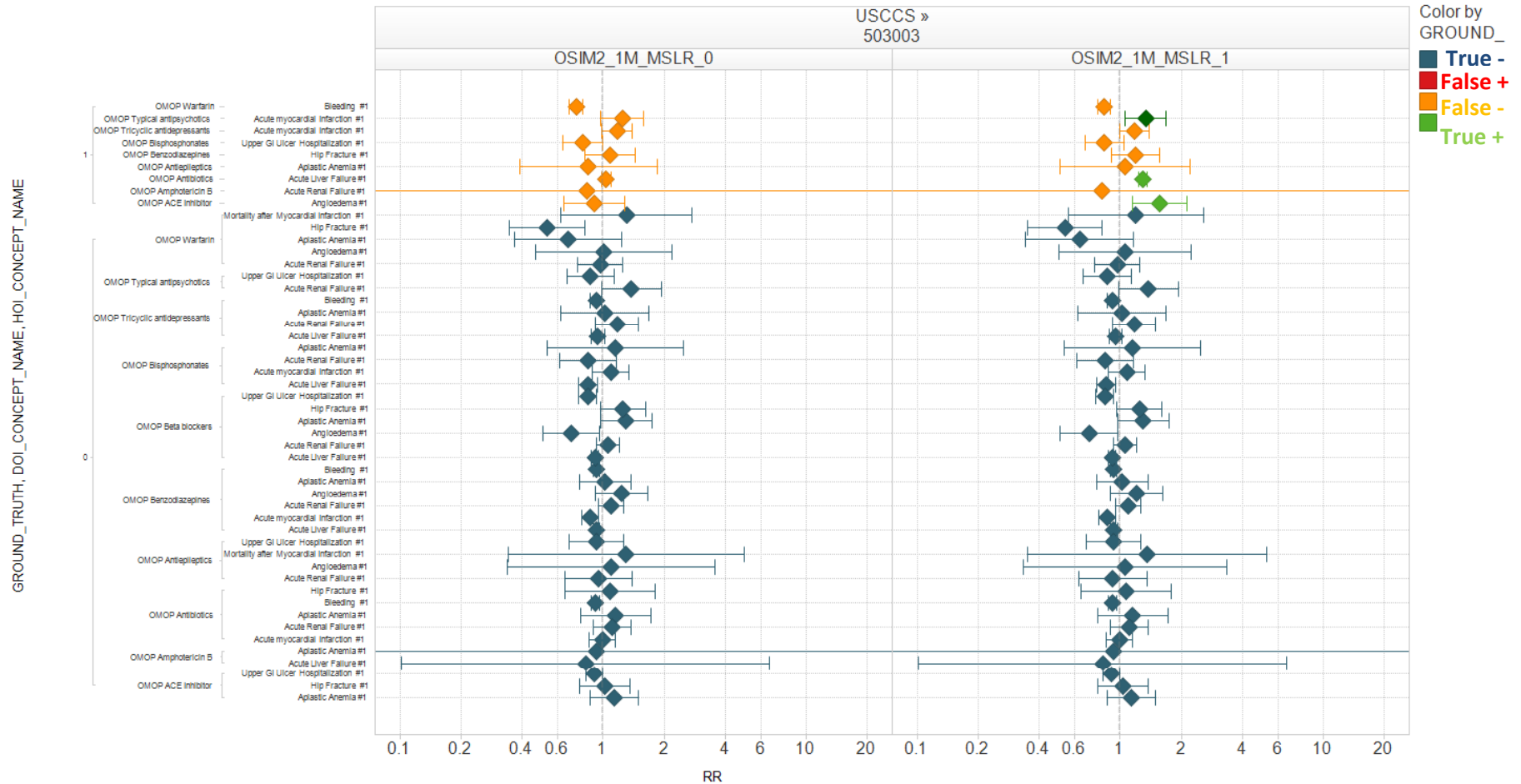


Method reference

ANALYSIS...	METHOD...	OUTPUT_FILE...	RUN_NAME	PARAM_SETTINGS
6004001	HDPS	hdps_NAME_MH_wo180ce30sw30tf100tn200tc100pg5pd30pc30ip0.txt	HDPS_HOI_RUN_4	COVARIATE_ELIGIBILITY_DAYS: 30; ~~~SURVEILLANCE_WINDOW_DAYS: 30; ~~~TOP_CONFOUNDERS: 100; ~~~NUMBER_OF_GROUPS_BY_PROPENSITY_SCORE: 5; ~~~OUTPUT_METRIC: MH; ~~~COMPARATOR_DRUG: 3; ~~~

Method performance pre/post signal

Drug-outcome pair estimates

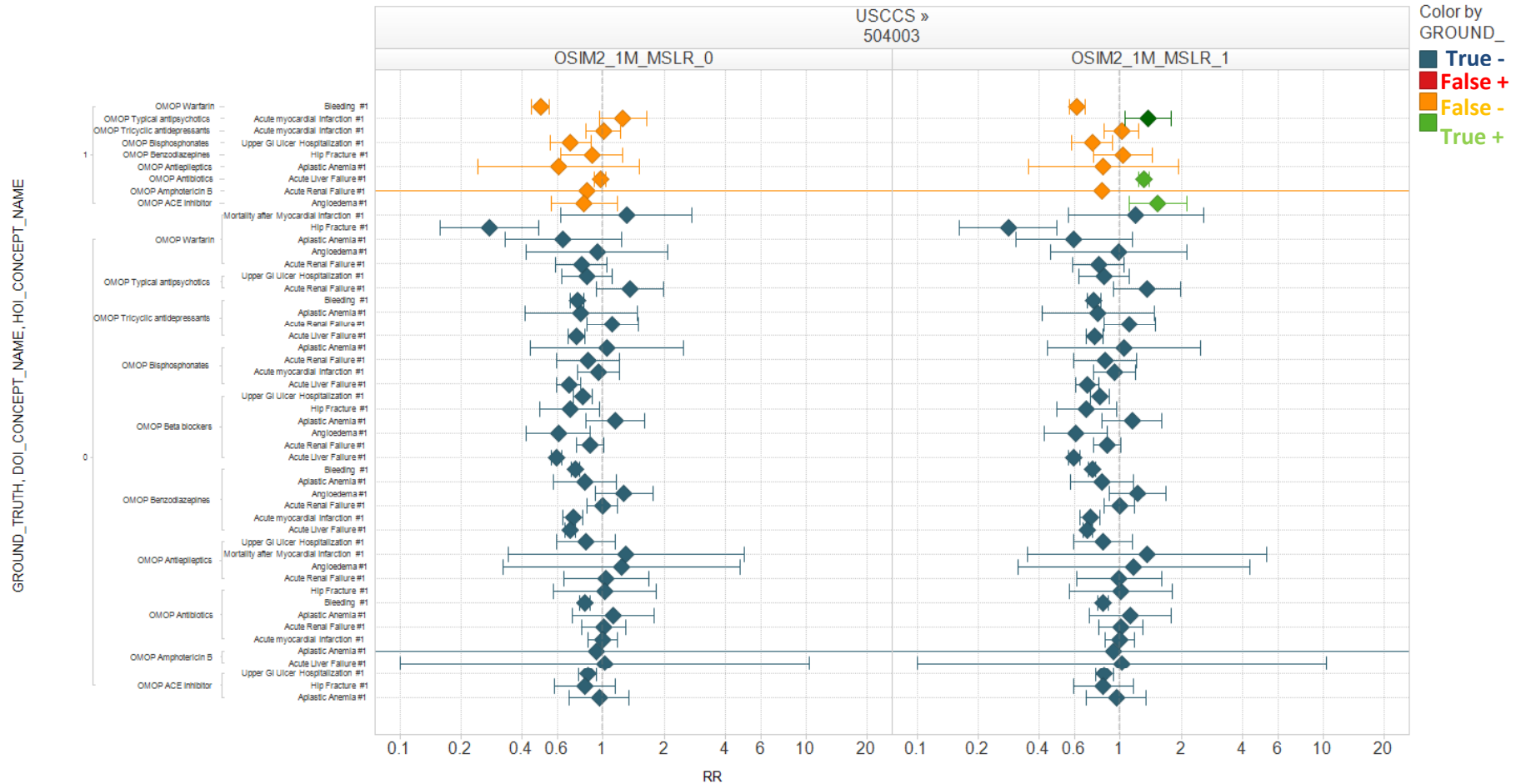


Method reference

ANALYSIS...	METHOD...	OUTPUT_FILE_...	RUN_NAME	PARAM_SETTINGS
503003	USCCS	SCCS30_NAMEct 1b1e0s30d30c30r x0pr0.5.txt	USCCS_HOI_RUN_3	CONDITION_TYPE_1_PREVALENT_OR_2_INCIDENT: 1;~~~DAYS_FROM_THE_DRUG_ERA_START: 1; ~~~PRECISION_OF_THE_PRIOR: 0.5; ~~~SURVEILLANCE_WINDOW_IN_DAYS: 30; ~~~

Method performance pre/post signal

Drug-outcome pair estimates

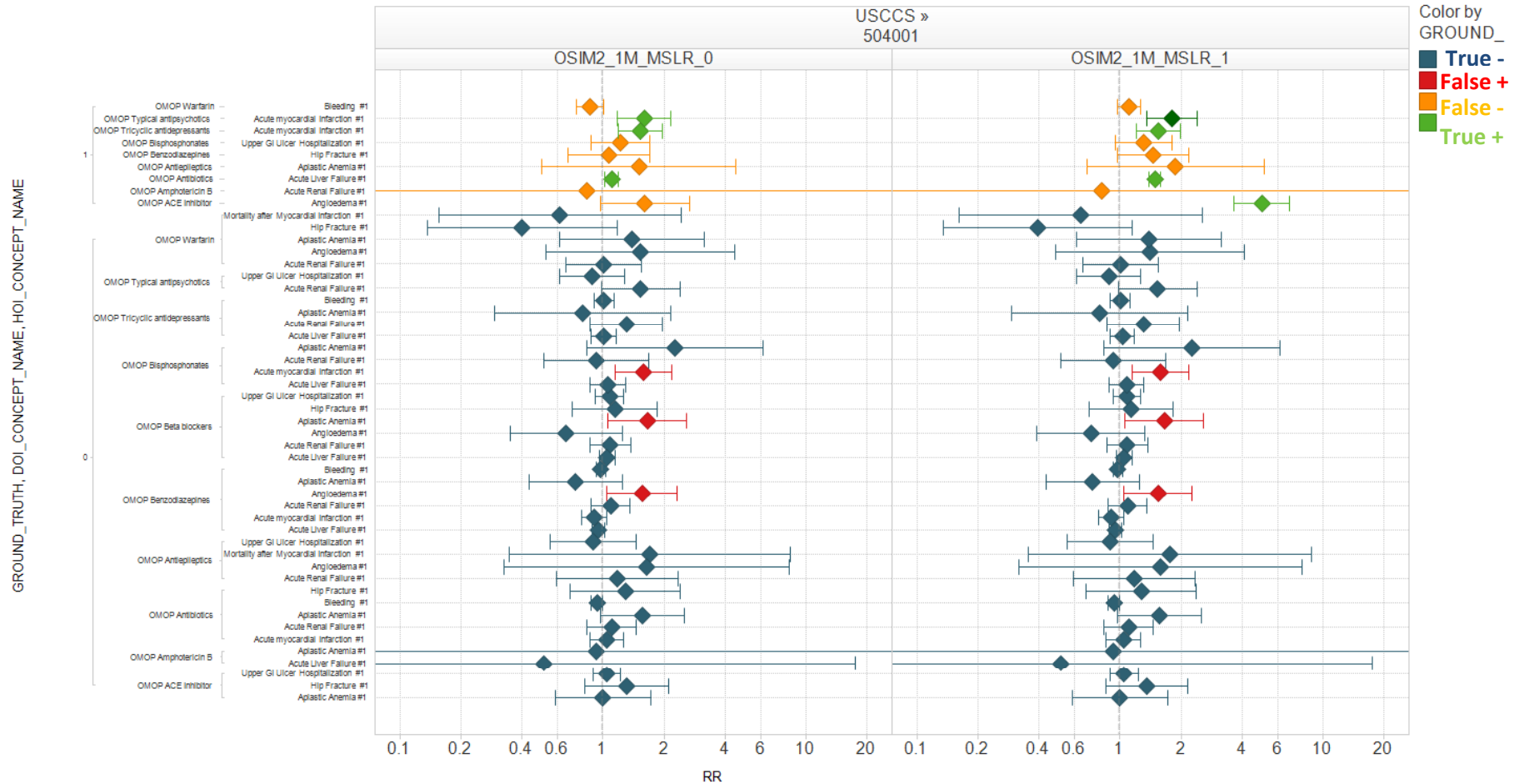


Method reference

ANALYSI...	METHOD...	OUTPUT_FILE_...	RUN_NAME	PARAM_SETTINGS
504003	USCCS	SCCS30_NAMEct 2b1e0s30d30c30r x0pr0.5.txt	USCCS_HOI_RUN_4	CONDITION_TYPE_1_PREVALENT_OR_2_INCIDENT: 2;~~~DAYS_FROM_THE_DRUG_ERA_START: 1; ~~~PRECISION_OF_THE_PRIOR: 0.5; ~~~SURVEILLANCE_WINDOW_IN_DAYS: 30; ~~~

Method performance pre/post signal

Drug-outcome pair estimates



Method reference

ANALYSIS...	METHOD...	OUTPUT_FILE_...	RUN_NAME	PARAM_SETTINGS
504001	USCCS	SCCS30_NAMEct 2b1e0sn30d30c30 rx0pr0.5.txt	USCCS_HOI_RUN_4	CONDITION_TYPE_1_PREVALENT_OR_2_INCIDENT: 2;~~~DAYS_FROM_THE_DRUG_ERA_START: 1; ~~~PRECISION_OF_THE_PRIOR: 0.5; ~~~SURVEILLANCE_WINDOW_IN_DAYS: -30; ~~~

LIMITATIONS

Limitations

- **First-order Markov model doesn't reflect full complexities in data**
- **Drugs aren't tied to indications, no switching/dose tailoring behavior....**
- **Time-stationary, so not modeling evolving clinical practice or new medical product market introductions**
- **Length of exposure does not depend on co-morbidities**
- **'Dose tailoring' and 'switching' between products in drug class not modeled**
- **Non-adherence not reflected**
- **No drug-drug co-pharmacy reflected**
 - **Combination products are under-represented**

Limitations (cont.)

- **Observation Periods**
 - Randomly simulated between database start / end, clustered starts not represented
 - Only 1 observation period per person
- **Visits not modeled, data not clustered around visit dates**
- **Does not simulate procedures or observations**
- **User can't modify database attribute parameters generated from the analysis phase (e.g. change background rates, etc.)**

OSIM2 DELIVERABLES

OSIM2 Types of Deliverables

- **Source Code** for Producing Simulation Results
- Pre-specified **Parameter Files** containing characteristics of OMOP Core databases
- **Simulated Data** files created by executing OSIM2

All deliverables are available for download on the OMOP Website:

omop.fnih.org/OSIM2

OSIM2 **Source Code** Deliverables

- **OSIM2 source code**
- **OSIM2 documentation (and training presentation materials)**
- **OSIM2 execution instructions**
- **Source Code to create Simulation Dashboard from Simulation Results**

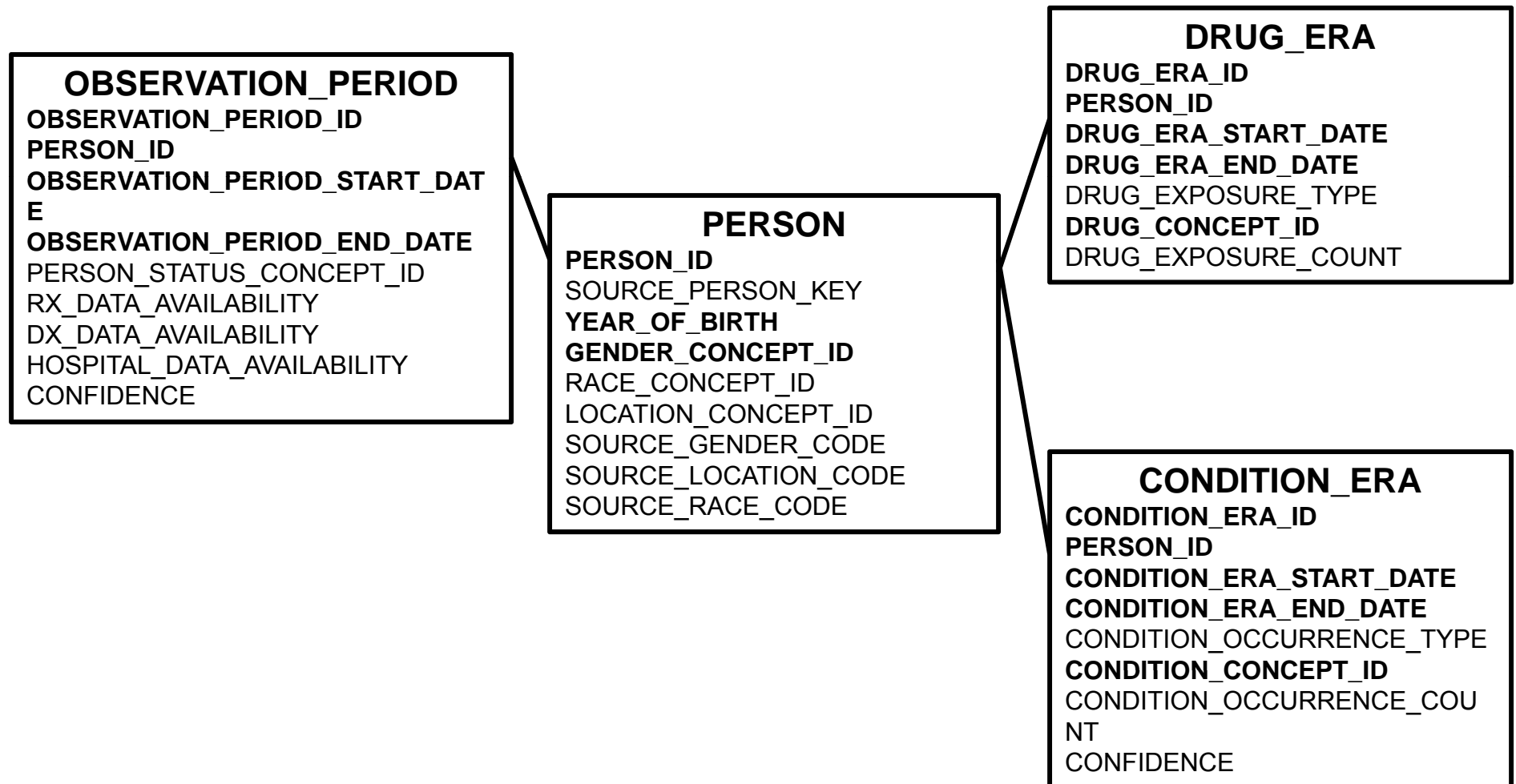
OSIM2 **Parameter File** Deliverables

- **Transition probability matrices for each of 5 central OMOP databases**
- **'Injected signal' file for OMOP HOI experiment**

OSIM2 **Simulated Data** Deliverables

- **1 million person simulated database created from MSLR**
 - With signals for HOI experiment
 - Without signals for HOI experiment
- **Dashboards describing simulation results for each of 5 central databases**

Common data model variables simulated in OSIM2



Uses of OSIM2 Deliverables

- **Create a de-novo simulated replica from an observational database:**
 - Point OSIM2 code at an OMOP CDM database to create transition matrices / probability tables
 - Create simulated dataset using transition matrices as input
- **Create a simulated database using pre-defined transition matrices / probability tables**
 - Load transition matrices (such as those you can download from OMOP website), specify the simulation you want (eg how many people, etc), then run the code.
- **Download simulated databases data directly from OMOP**

SESSION I

SUMMARY AND DISCUSSION

TRANSITION TO SESSION II

Session II Introduction

- Technical session designed for people who need more in-depth understanding of OSIM2 technical operations
 - Overall Module Architecture
 - What the technical pieces are, how they fit together
 - Setup and Execution
 - Execution Modes
 - Required Inputs and parameters
 - Execution Instructions
 - Walkthrough of Program Logic
 - Procedure 1: Source database analysis
 - Procedure 2: Patient Simulation
 - Details / Inventory of Deliverable Package

Conceptual OSIM2 Simulation Process

