

# Synthetic Health Data Challenge Winning Solutions Webinar

Stephanie Garcia, MPH | ONC PCOR Portfolio Manager October 19, 2021







# Office of the National Coordinator for Health Information Technology (ONC)

#### • Mission

• Improve the health and well-being of individuals and communities through the use of technology and health information that is accessible when and where it matters most

#### • Strategic Goals

- Advance Person-Centered and Self-Managed Health
- Transform Health Care Delivery and Community Health
- Foster Research, Scientific Knowledge, and Innovation
- Enhance Nation's Health IT Infrastructure





https://healthit.gov/

3





# Patient-Centered Outcomes Research (PCOR)

- Produce evidence to inform health care decisions made by patients, families, and their health care providers
- Patient-Centered Outcomes Research Trust Fund (PCORTF) managed by the Assistant Secretary for Planning and Evaluation (ASPE)

https://www.healthit.gov/topic/scientific-initiatives/building-data-infrastructure-support-patient-centeredoutcomes-research



# **ONC Synthetic Health Data Project**

#### Accelerate ability to conduct PCOR by:

- Enhancing an open-source synthetic data generator Synthea <sup>™</sup>, developed by The MITRE Corporation, to increase the number and variety of synthetic data
  - Opioid use
  - Pediatric populations
  - Patients with complex care needs
- Engaging broader community to validate the realism and demonstrate the potential uses of newly available synthetic data



https://www.healthit.gov/topic/research-evaluation/synthetic-health-data-generation-to accelerate-patient-centered-outcomes 5



# **Synthetic Health Data Challenge**

**Prize competition** invited a wide array of innovators, researchers, and technology developers to **create and test innovative solutions** that enhance Synthea and the synthetic data it generates

- Advance novel uses of synthetic data for patientcentered outcomes research
- Validate the realism of Synthea-generated synthetic data





# **Challenge Structure**





Phase II: Prototype/

**Solution Development** 



Phase I: Proposals for Innovative Models

- Written proposal describing proposed solution
- Proposals were invited from teams or individuals
- Proposals had to include methodology and intended outcomes

- Approved proposals moved on to Phase II
- Solutions designed and tested
- Final paper describing the solution
- Video demonstration
- Evidence of validation
- Non-proprietary source code

#### Winning Solutions

- Total cash prize pool: \$100,000
- Solutions were judged by a panel based on criteria

Winning Solutions

nd

7

st

FIRST PLACE



### **CodeRx** Medication Diversification Tool

#### SECOND PLACE



#### The Generalistas

Virtual Generalist: Modeling Co-morbidities in Synthea

#### **Team LMI**

On Improving Realism of Disease Modules in Synthea: Social Determinant-Based Enhancements to Conditional Transition Logic

THIRD PLACE	Particle Health	The Necessity of Realistic Synthetic Health Data Development Environments
	Team TeMa	Empirical Inference of Underlying Condition Probabilities Using Synthea-Generated Synthetic Health Data
	<b>UI Health</b>	Spatiotemporal Big Data Analysis of Opioid Epidemic in Illinois

# Medication Diversification Tool (MDT)

Team CodeRx

# **Challenge Category and Use Case**

Challenge Category 1	Enhancement to Synthea
Use Case	Pediatrics (pediatric asthma)



https://www.istockphoto.com/vector/ast hmatic-girl-gm185960170-27680137



Pharmacists who code and developers who (health)care

#### Who we are

CodeRx is a collective of pharmacists and other healthcare professionals who have a skill set in tech and apply it towards building useful things

Website: coderx.io

Founded: early 2020

Membership: 150+ (30-40 active weekly), mostly pharmacists and pharmacy students

#### What we do

- Slack channel engage in discussions about coding / data / tech as it relates to pharmacy and healthcare
- **GitHub organization** collaborate on open source pharm tech / health tech projects
- Newsletter and website share guides, resources, and pertinent topics

# Team CodeRx

For this challenge, Team CodeRx consists of six PharmDs from across the U.S.

Joseph LeGrand, <b>PharmD</b> , MS (team lead)	Lead Application Analyst Vanderbilt University Medical Center
Kent Bridgeman, <b>PharmD</b> , MHI	Informatics Pharmacist Allina Health
Kristen Tokunaga, <b>PharmD</b> , BCGP	Analytics Consulting Manager Komodo Health
Yevgeny Bulochnik, <b>PharmD</b> , ACE, CACP	Formulary Administration Consultant HealthPartners
Robert Hodges, <b>PharmD</b> , MSDS, MBA	Sr. Data Scientist, McKesson RelayHealth (CoverMyMeds)
Dalton Fabian, <b>PharmD</b>	Data Scientist UnityPoint Health

# Objective

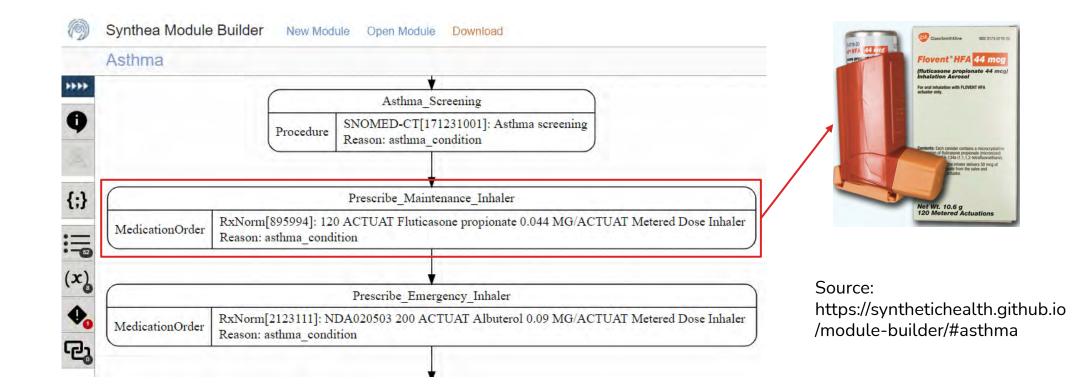
To programmatically generate Synthea medication orders through the use of RxClass and Medical Expenditure Panel Survey (MEPS) data sources



### **Problem Statement**

In the current Synthea asthma module, 100% of Asthma patients are prescribed the same asthma maintenance inhaler (Flovent HFA 44 mcg) regardless of age.

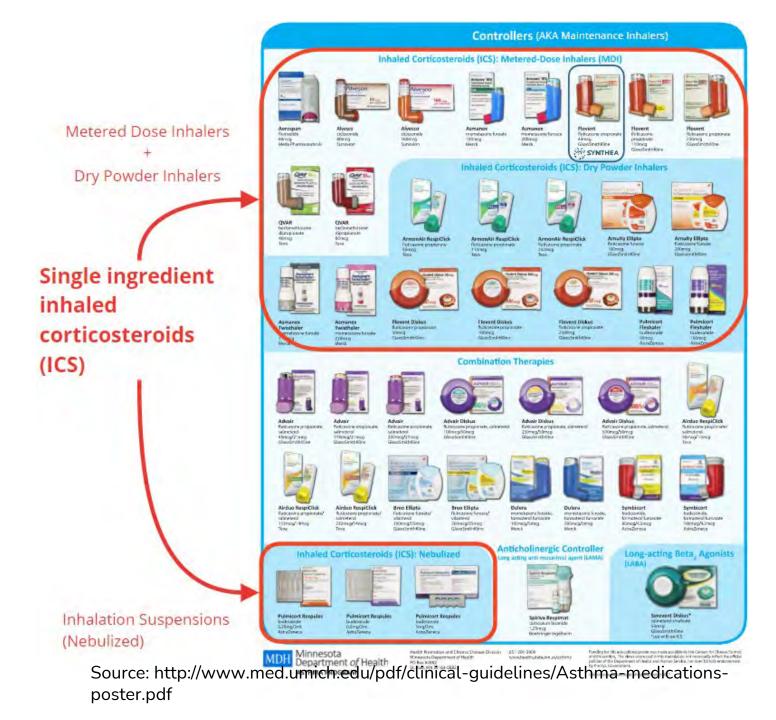
This is not consistent with real-world clinical practice.





# Asthma Maintenance Inhalers on the Market

Pediatric patients are prescribed one of **many** inhaled corticosteroids as a first line therapy.



# Synthea vs MEPS

**Medical Expenditure Panel Survey (MEPS)** is a nationwide set of surveys of households and their medical providers. and the state of the local division in

Prillipi Bachier

Part and the second

The AHRQ conducts this survey annually to collect information on the use and cost of health care.

AHRQ SYNTHEA 1225 **Gold standard Current state** AEPS gold doubland Sendbaugrood Man 3% 0% 26% 0% 14% 0% 7% 0% 100% 34% 16% 0%

Percent of patient population age 0-5 years old with prescribed medication product



# Tools

#### Open-source tools & code

# Packages

- Python Pandas



Publicly-available, government-maintained data sources

# Sources

- **RxNav API**
- RxClass API
- **MEPS**





# **Available Online GUIs**

Already exist - maintained and hosted by National Library of Medicine

al Library of Medicine					About FAQ Tutorial 🔂	NIH) Nati	onal Library of Medicine		About Disclaimer FAQ 1
Conticosterouts (11)     Other nasal     preparations (6)     Sympathomimetics,     combinations excl.     contloseteroids (6)     Sympathomimetics,     piain (11)	Exploring Class	LASS ses for RxNorm Drugs	corficosteroids O by class name/id ● by Ra T Edit Drug Sources	xNorm drug name/id 🛛 🗖 shc	S Q w source data	RxNorm Gra		futicasone     [RXCUI = 41126]  ages Class View Interaction View Status	Q
ITS FOR (3) ATORY TS (11) RATIONS		teroids ±	/ id: R01AD / class type: A	TC1-4 / show contex	Print	Views Classic Simple Table Filters	IN/MIN     (5)       H RK 5     fluticasone       M H RK M     azelastine / fluticasone       M H RK M     fluticasone / salmeterol       M H RK M     fluticasone / umecliginium / vilanterol       M H RK M     fluticasone / vilanterol	PIN (2) H R S fluticasone furoate H R S fluticasone propionate	EN     D1       H Rx M Advair     Au       H Rx M AirDuo     H       H Rx S Aller-Flo     H       H Rx S Armonair     H       H Rx S Armuty     H
74) L	11 RxN	orm generic d	rugs in ATC / similar clas	sses					• HRXS Beser
i6) ses	Type	RXCUI 1347	RxNorm Name     beclomethasone	Relation     DIRECT	All classes     Show	Group Form	H R S fluticasone furoate 0.0275 MG/ACTUAT H R S fluticasone furoate 0.05 MG/ACTUAT H R S fluticasone furoate 0.1 MG/ACTUAT	RNAV	H RX M azelastine hydrochloride 0.137 MG/ACTUAT / fluticasone propionate 0.05 MG/ACTUAT
l	IN	1514	betamethasone	DIRECT	Show	Links	H Resen fluticasone furoate 0.2 MG/ACTUAT H Res S fluticasone propionate 0.00005 MG/MG H Res S fluticasone propionate 0.044 MCCTUAT	Navigating RxNorm Drugs	[Dymista] H RK 5 fluticasone furoate 0.0275 MG/ACTUAT [Flonase Sensimist] 5 fluticasone furoate 0.0275 MG/ACTUAT
	IN	274964	ciclesonide	DIRECT	Show	MIN     Pack     Multi	SCD/GPCK H RX S 120 ACTUAT fluticasone propionate 0.044 H RX M 120 ACTUAT fluticasone propionate 0.045		SED/EPCK [62]
l	IN	3264	dexamethasone	DIRECT	Show	Download	Metered Dose Inhaler	IG/ACTUAT Metered Dose Inhaler	HRX 5 120 ACTUAT Flovent 0.11 MG/ACTUAT Metered Dose Inhaler HRX 5 120 ACTUAT Flovent 0.22 MG/ACTUAT
	IN	25120	flunisolide	DIRECT	Show		Metered Dose Inhaler	IC/ACTUAT Matarad Daga Jabalar	Metered Dose Inhaler
	IN	41126	fluticasone	DIRECT	Show		SCDG	DFC HVRVS Inhalant Product HVRVS Nasal Product	SEDG     BRM Advair Inhalant Product     RKM AirDuo Inhalant Product
om DULE)	IN	8638	prednisolone	DIRECT	Show		H RX M fluticasone / salmeterol inhalant Product H RX M fluticasone / umeclidinium / vilanterol Inhalant Product	w R S Topical Product	H Rx S Aller-Flo Inhalant Product H Rx S Aller-Flo Nasal Product H Rx S Armonair Inhalant Product
-		57057	45	DIRECT			HRVM fluticasone / vilanterol Inhalant Product		HRXS Arnuity Inhalant Product

# **Developer Inputs**

#### **Required**

1. RxClass class ID(s) OR RxNorm ingredient ID(s)

#### <u>Optional</u>

- 1. Dose form filters
- 2. Patient demographic info breakpoints
  - a. Age range(s)
  - b. Gender M/F
  - c. State of residence
- 3. Single vs multi ingredient drugs
- 4. Other Synthea settings



# Methods

**RCLASS** 

Medication class -> ingredient(s) (RxNorm)

Medication ingredient -> product(s) -> NDC(s)

+ dose form filters

+ single vs multi ingredient filters MEPS

NDCs and demographic info and counts of patients who report taking them





•

Use RxClass API to return list of medication ingredients

 "Corticosteroids" = ATC Class R01AD

Medication	ingredients
------------	-------------

beclomethasone	
betamethasone	
budesonide	
ciclesonide	
flunisolide	
fluticasone	
mometasone	
prednisolone	
tixocortol	
triamcinolone	



Filter on RxNorm dose form in:

- Metered Dose Inhaler
- Dry Powder Inhaler
- Inhalation Suspension

Single ingredient products only

• RxNorm term type (TTY) = IN

Medication ingredients

beclomethasone	YES
betamethasone	NO
budesonide	YES
ciclesonide	YES
flunisolide	YES
fluticasone	YES
mometasone	YES
prednisolone	NO
tixocortol	NO
triamcinolone	NO



# Cross-reference population prescription utilization data

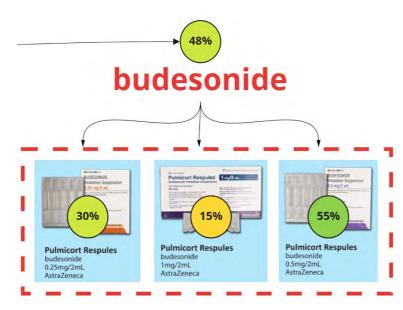
• 0-5 year old age range

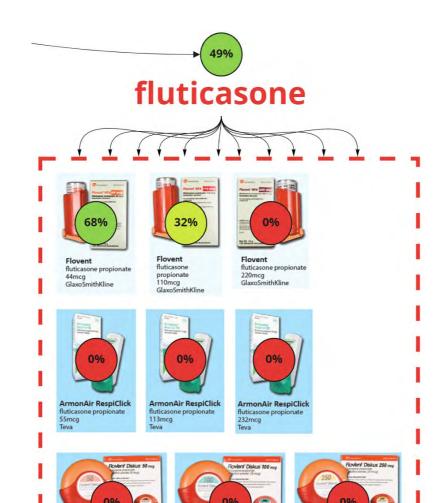
NOTE: for the actual submodule, we would also include the 6-103 year old age range

#### Medication ingredients

beclomethasone	3%	
pelamethasope	968	
budesonide	48%	
ciclesonide	0%	
flunisolide	0%	
fluticasone	49%	
mometasone	0%	
mednisolone	MAA .	
tinoconto i	NVA	
warminoloau	NVA	









ynthea/
- src/
— main/
- resources/
- modules/
medication/
│  │  │  │  │  │  │  │  │  │  │  │  │
l <u>ookup tables/</u>
— maintenance_inhaler_ingredient_distribution.csv
- maintenance_inhaler_fluticasone_product_distribution.csv
— maintenance_inhaler_budesonide_product_distribution.csv
— maintenance_inhaler_beclomethasone_product_distribution.csv
- maintenance_inhaler_mometasone_product_distribution.csv
- asthma.json
$      \vdash \dots$

#### Asthma module JSON:

```
...
"Maintenance_Medication_End": {
    "type": "MedicationEnd",
    "referenced_by_attribute": "maintenance_inhaler",
    "direct_transition": "Emergency_Medication_End"
    },
...
```



- 1. Place MDT module JSON file in the medications folder
- 2. Place MDT lookup table CSV files in the lookup\_tables folder
- Replace existing
   MedicationOrder state in asthma module JSON file with a CallSubmodule state referencing the MDT module

   Ensure asthma module
   MedicationEnd states end medications by attribute, not by name

**MDT Demo** 

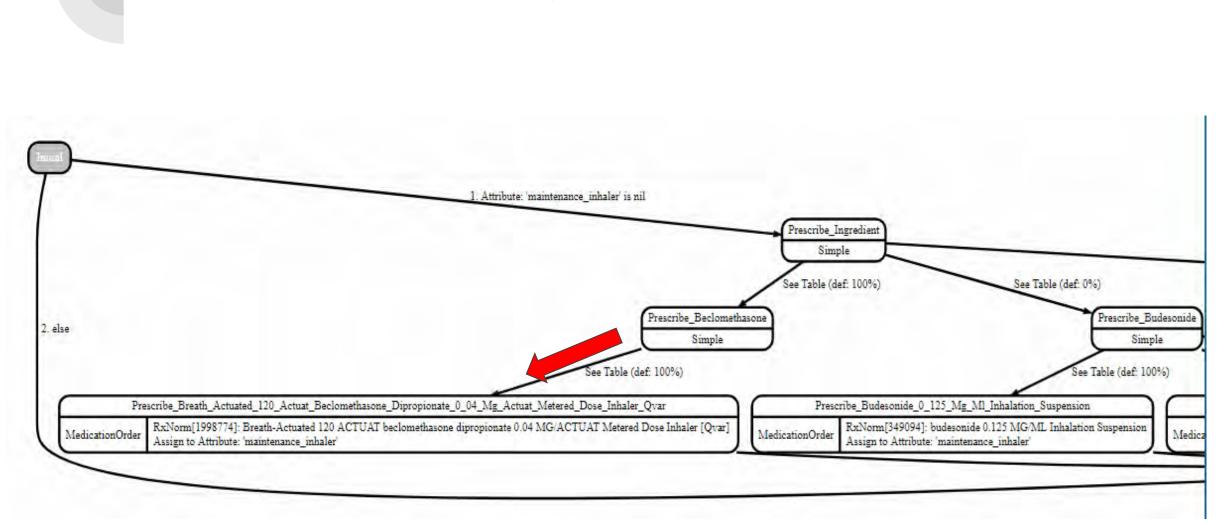
# Results

#### **Asthma Medications using the MDT - Ingredient**

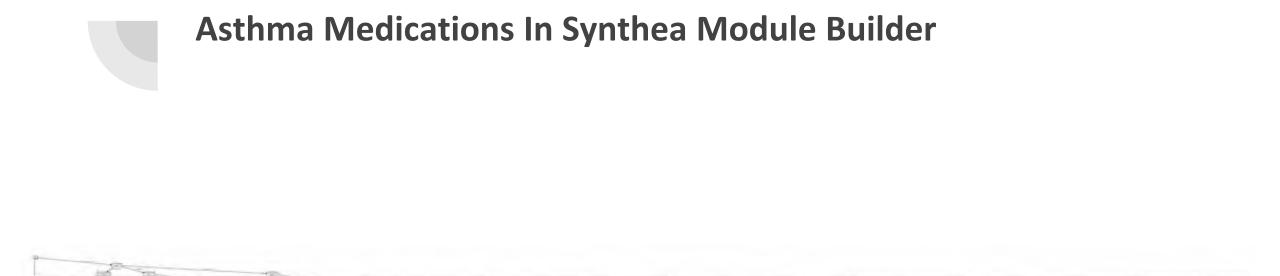
```
"_____"
   " MEDICATION INGREDIENT TABLE TRANSITION
   "_____
   "Ingredients in lookup table:",
      [% pop ] Name",
   "1. [ 3.1% ] Beclomethasone",
   "2. [ 47.7% ] Budesonide",
   "3. [ 49.2% ] Fluticasone"
],
"type": "Simple",
"lookup table transition": [
      "transition": "Prescribe_Beclomethasone",
      "default_probability": "1",
      "lookup_table_name": "maintenance_inhaler_ingredient_distribution.csv"
   },
      "transition": "Prescribe_Budesonide",
```

#### **Asthma Medications using the MDT - Product**

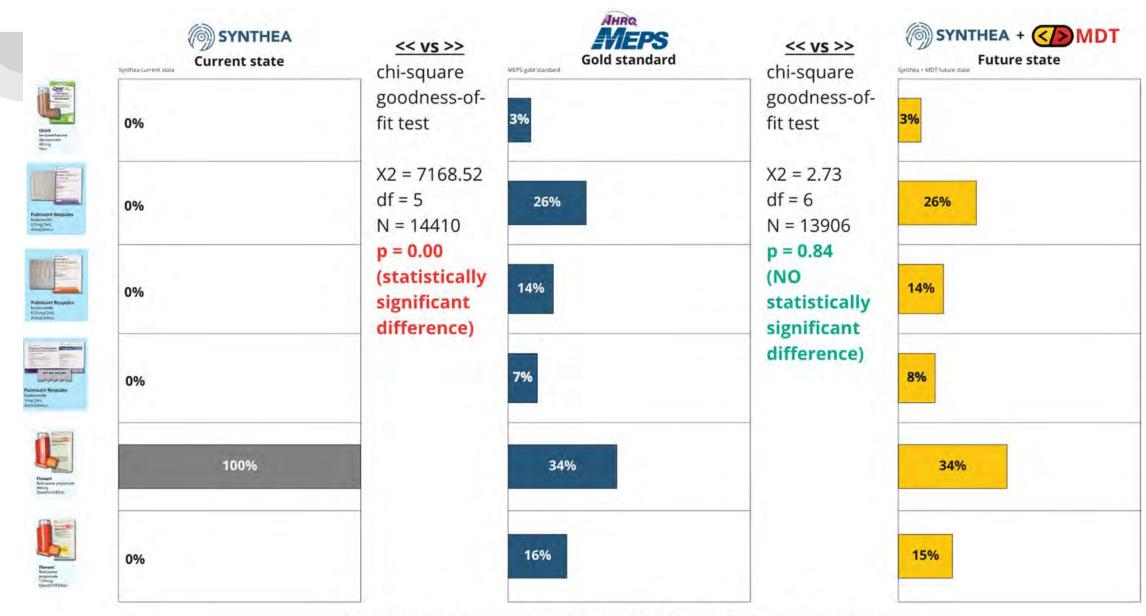
```
" BUDESONIDE MEDICATION PRODUCT TABLE TRANSITION
   "______".
   "Products in lookup table:",
   "# [% pop ] Name",
   "1. [ 29.5% ] Budesonide 0 125 Mg Ml Inhalation Suspension",
   "2. [ 15.1% ] Budesonide_0_125_Mg_Ml_Inhalation Suspension Pulmicort",
   "3. [ 55.3% ] Budesonide 0 25 Mg Ml Inhalation Suspension"
"type": "Simple",
"lookup table transition": [
       "transition": "Prescribe Budesonide 0 125 Mg Ml Inhalation Suspension",
      "default probability": "1",
       "lookup table name": "maintenance inhaler Budesonide product distribution.csv"
   },
      "transition": "Prescribe Budesonide 0 25 Mg Ml Inhalation Suspension",
      "default probability": "0",
       "lookup table name": "maintenance inhaler Budesonide product distribution.csv"
   },
       "transition": "Prescribe Budesonide 0 125 Mg Ml Inhalation Suspension Pulmicort",
      "default probability": "0",
       "lookup table name": "maintenance inhaler Budesonide product distribution.csv"
```



### **Asthma Medications In Synthea Module Builder**



# Validation



Percent of patient population age 0-5 years old with prescribed medication product



- Creates micro-validated medication distributions in Synthea modules
- Loosely test hypothesis prior to obtaining access to PHI
- Identify drug trends to validate on real data



- Encourages incorporation of complex drug treatment options into Synthea modules
- Offers complexity that developers will need to account for in software
- Allows drug related development before having PHI



### **Challenges & Successes**

### Challenges

• Complexity of data

• Difficulty in defining disease-specific drug lists

#### Successes

- Can be used with other Synthea modules & disease states
- Can generate medication distributions by patient age, gender, geographic location, and more
- Can be re-run with updated data
- Has flexibility for user to select drugs
- Designed by 6 Pharmacists who are experts on medication use

# **Future for MDT**

# **Future Enhancements**

The groundbreaking methods used in MDT to integrate public data sources allows for future enhancements:

- 1. Enhance Synthea with other MEPS data elements.
  - a. insurance type, social determinants of health, medical conditions.
- 2. Model prescription fill and medication adherence through meps MEPS data.
- 3. Add allergy or drug-drug interactions logics through NLM<sup>1</sup> data.
- 4. Capture dose ranges (low/medium/high) and progression.
- 5. Improve medication costs modeling through NADAC<sup>2</sup> dataset.

<sup>1</sup>NLM [National Library of Medicine] <sup>2</sup>NADAC [National Average Drug Acquisition Cost]

### Thank You!!!!

### Links

GitHub Repo: <a href="mailto:github.com/coderxio/medication-diversification">github.com/coderxio/medication-diversification</a>

Joseph LeGrand, PharmD, MS <u>linkedin.com/in/jrlegrand/</u>

Kent Bridgeman, PharmD, MHI <u>linkedin.com/in/kentvbridgeman/</u>

Kristen Tokunaga, PharmD, BCGP <u>linkedin.com/in/kristen-tokunaga-pharmd/</u>

Robert Hodges, PharmD, MSDS, MBA <u>linkedin.com/in/robhodgespharmd/</u>

Dalton Fabian, PharmD <u>linkedin.com/in/daltonfabian/</u>

Yevgeny (Eugene) Bulochnik, PharmD ACE CACP <u>linkedin.com/in/yevgeny-eugene-bulochnik-b429a6155/</u>

CodeRx Website: coderx.io/

# Virtual Generalist Modeling co-morbidities in synthea<sup>TM</sup>

Robert Horton, PhD John-Mark Agosta, PhD

Jason Dausman, MD Brandon DeShon Benjamin Dummitt, PhD

github.com/rmhorton/virtual-generalist

Katherine Gundling, MD



www.sustainableharvest.o

## Outline

#### **Bayes nets & CPTs**

• comorbidities matter!

use in Synthea's new lookup\_table\_transition

#### Mapping concepts

•ICD10

• SNOMED

• Synthea attributes

#### Feature engineering

- SQL/Pyspark/R on Databricks
- Now demonstrated with Synthea data!

#### Validation

• co-occurrence matrix

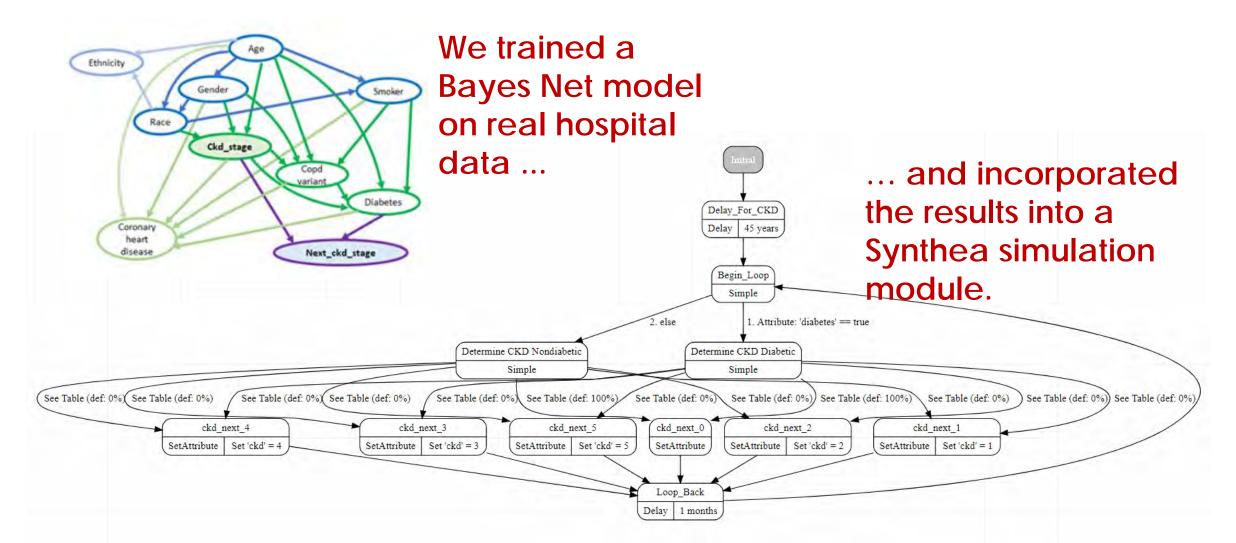
• COPM

#### Suggested design patterns

- No delay: disease is NOT your destiny
- Mechanistic progression: allow interventions
- More modular modules

Separate treatment from disease incidence and progression Use attributes to communicate between modules.

# Bayes Nets decompose joint probabilities into a network of conditional probabilities



```
%r
# patients with diabetes
fit$next_ckd_stage$prob[,'T',] %>% as.matrix %>% t %>% format(digits=3, scientific=FALSE)
```

next\_ckd\_stage

1 %r

z

2

з

# patients without diabetes

3 fit\$next\_ckd\_stage\$prob[,'F',] %>% as.matrix %>% t %>% format(digits=3, scientific=FALSE)

next\_ckd\_stage

ckd_stage	ckd_0	ckd_1	ckd_2	ckd_3	ckd_4	ckd_5
ckd_0	"0.9922398"	"0.0001239"	"0.0007213"	"0.0063517"	"0.0003788"	"0.0001846"
ckd_1	"0.0000000"	"0.9690204"	"0.0053652"	"0.0228453"	"0.0020768"	"0,0006923"
ckd_2	"0.0000000"	"0.0007380"	"0.9623602"	"0.0341439"	"0.0018645"	"0.0008934"
ckd_3	"0.0000000"	"0.0002917"	"0.0025664"	"0.9877009"	"0.0078259"	"0.0016151"
ckd_4	"0.000000"	"0.0001632"	"0.0011015"	"0.0518951"	"0.9211374"	"0.0257027"
ckd_5	"0.0000000"	"0.0000676"	"0,0005068"	"0.0089204"	"0.0116236"	"0,9788816"

Each node in the Bayes Net contains a Conditional Probability Table

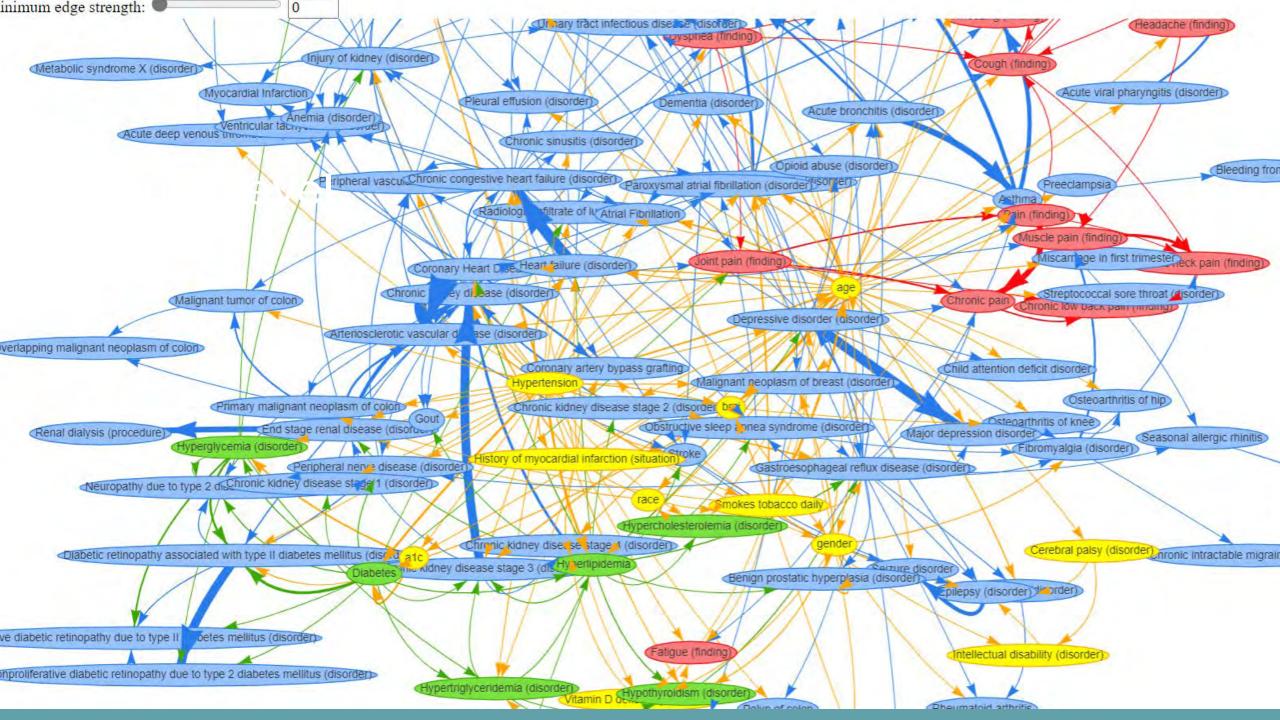
### Mapping concepts

ICD10

**SNOMED** 

### attributes

	attribute 🔺	test 🔺	attribute_type 🔺	icd_pattern 🔺	icd_name 🔺	snomed_concept_name
1	ckd_1	==1	integer	N18.1	Chronic_kidney_disease_stage_1	Chronic kidney disease stage 1 (disorder)
2	ckd_2	==2	integer	N18.2	Chronic_kidney_disease_stage_2	Chronic kidney disease stage 2 (disorder)
3	ckd_3	==3	integer	N18.3	Chronic_kidney_disease_stage_3	Chronic kidney disease stage 3 (disorder)
4	ckd_4	==4	integer	N18.4	Chronic_kidney_disease_stage_4	Chronic kidney disease stage 4 (disorder)
5	ckd_5	==5	integer	N18.[56]	Chronic_kidney_disease_stage_5	End stage renal disease (disorder)
6	smoker	is true	boolean	F17	Nicotine_dependence	Smokes tobacco daily
7	diabetes	is true	boolean	E11	Type_2_diabetes_mellitus	Diabetes
8	coronary_heart_disease	is true	boolean	125	Chronic_ischemic_heart_disease	Coronary Heart Disease
9	copd_variant	is not nil	ConditionOnset	J44	Chronic_obstructive_pulmonary_disease	Chronic obstructive bronchitis (disorder)



### Synthea-Specific ICD10 to SNOMED Mapping

icd_set_id 🔺	snomed_concept_id 🔺	snomed_concept_name	icd_code 🔺	icd_description
43	44054006	Diabetes	E11	Type 2 diabetes mellitus
446	46177005	End stage renal disease (disorder)	N18.5	Chronic kidney disease, stage 5
447	46177005	End stage renal disease (disorder)	N18.6	End stage renal disease
899	75498004	Acute bacterial sinusitis (disorder)	B96.89	Other specified bacterial agents as the cause of diseases classified elsewhere
899	75498004	Acute bacterial sinusitis (disorder)	J01.90	Acute sinusitis, unspecified
1323	301011002	Escherichia coli urinary tract infection	B96.20	Unspecified Escherichia coli [E. coli] as the cause of diseases classified elsewhere
1323	301011002	Escherichia coli urinary tract infection	N39.0	Urinary tract infection, site not specified

#### Patterns

E11 matches E11.0, E11.1, etc

#### Sets

All ICD elements of the set must be present for the SNOMED concept to apply

### Feature engineering

	patient 🔺	month_number 🔺	age_group 🔺	gender 🔺	race 🔺	ethnicity 🔺	ckd_stage 🔺	next		a ta ta S		smoker
726	00037be2-d64b-adb8-c7e7-90dcffa144bf	515	age_45_64	F	white	nonhispanic	_ ckd_3	ckd_3	C	lata	F	
727	00037be2-d64b-adb8-c7e7-90dcffa144bf	516	age_45_64	F	white	nonhispanic	ckd_3	ckd_3			F	F
728	00037be2-d64b-adb8-c7e7-90dcffa144bf	517	age_45_64	F	white	nonhispanic	ckd_3	ckd_3			F	F
729	00037be2-d64b-adb8-c7e7-90dcffa144bf	518	age_45_64	F	white	nonhispanic	ckd_3	ckd_3		F	F	F
730	00037be2-d64b-adb8-c7e7-90dcffa144bf	519	age_45_64	F	white	nonhispanic	ckd_3	ckd_3		F	F	F
731	00037be2-d64b-adb8-c7e7-90dcffa144bf	520	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
732	00037be2-d64b-adb8-c7e7-90dcffa144bf	521	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
733	00037be2-d64b-adb8-c7e7-90dcffa144bf	522	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
734	00037be2-d64b-adb8-c7e7-90dcffa144bf	523	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
735	00037be2-d64b-adb8-c7e7-90dcffa144bf	524	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
736	00037be2-d64b-adb8-c7e7-90dcffa144bf	525	age_45_64	F	white	nonhispanic	ckd_3	ckd_3	F	F	F	F
737	00037be2-d64b-adb8-c7e7-90dcffa144bf	526	age_45_64	F	white	nonhispanic	ckd_3	ckd_4	F	F	F	F
738	00037be2-d64b-adb8-c7e7-90dcffa144bf	527	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
739	00037be2-d64b-adb8-c7e7-90dcffa144bf	528	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
740	00037be2-d64b-adb8-c7e7-90dcffa144bf	529	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
741	00037be2-d64b-adb8-c7e7-90dcffa144bf	530	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
742	00037be2-d64b-adb8-c7e7-90dcffa144bf	531	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
743	00037be2-d64b-adb8-c7e7-90dcffa144bf	532	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
744	00037be2-d64b-adb8-c7e7-90dcffa144bf	533	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
745	00037be2-d64b-adb8-c7e7-90dcffa144bf	534	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
746	00037be2-d64b-adb8-c7e7-90dcffa144bf	535	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
747	00037be2-d64b-adb8-c7e7-90dcffa144bf	536	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
748	00037be2-d64b-adb8-c7e7-90dcffa144bf	537	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
749	00037be2-d64b-adb8-c7e7-90dcffa144bf	538	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
750	00037be2-d64b-adb8-c7e7-90dcffa144bf	539	age_45_64	F	white	nonhispanic	ckd_4	ckd_4	F	F	F	F
751	00037be2-d64b-adb8-c7e7-90dcffa144bf	540	ade 45 64	F	white	nonhispanic	ckd 4	ckd 4	F	F	F	F

Now with

**Synthea** 

### Validation

select description, count(\*) tally from conditions
where description rlike('(Chronic kidney disease|End stage renal)')
group by description order by description

#### missouri\_pre

description	tally
Chronic kidney disease stage 1 (disorder)	3024
Chronic kidney disease stage 2 (disorder)	436
Chronic kidney disease stage 3 (disorder)	25

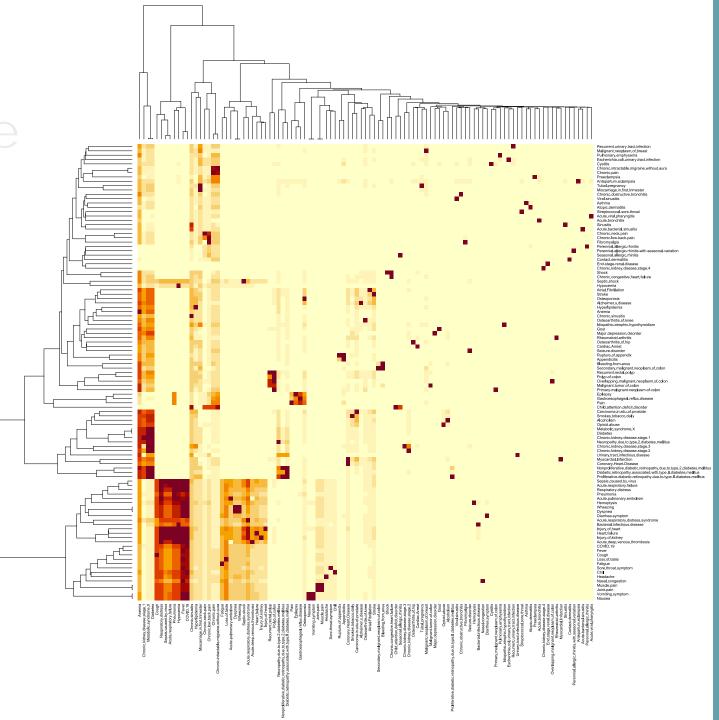
#### missouri\_test

description	tally
Chronic kidney disease stage 1 (disorder)	3837
Chronic kidney disease stage 2 (disorder)	6557
Chronic kidney disease stage 3 (disorder)	18607
Chronic kidney disease stage 4 (disorder)	10585
End stage renal disease (disorder)	17272

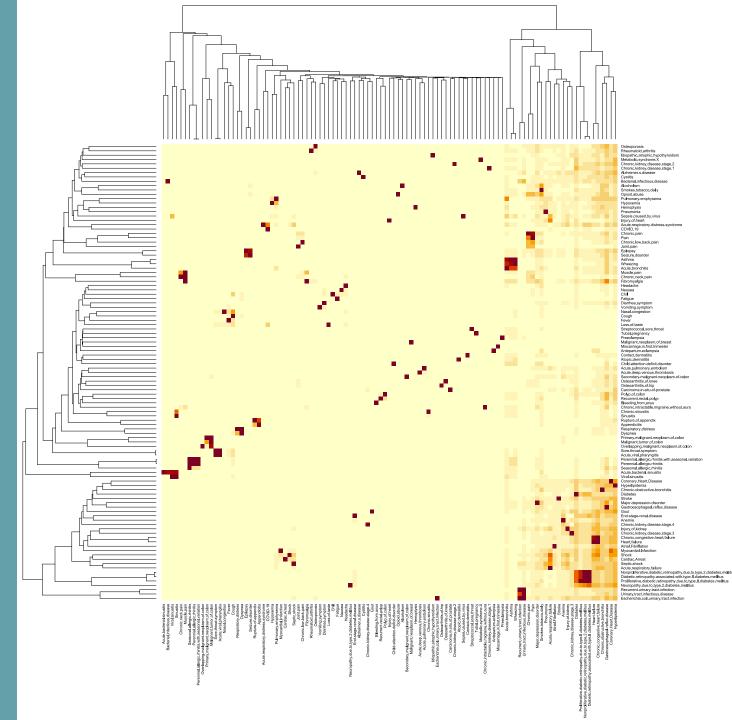
### Individual concepts

	Including Covid	Mercy EHR	Pre-Covid
Rank	Synthea Concept	Mercy EHR Concept	Pre-Covid Synthea Concept
1	Suspected COVID-19	Essential hypertension (disorder)	Viral sinusitis (disorder)
2	COVID-19	Diabetes mellitus type 2 (disorder)	Acute viral pharyngitis (disorder)
3	Fever (finding)	Hyperlipidemia (disorder)	Acute bronchitis (disorder)
4	Cough (finding)	Cough (finding)	Normal pregnancy
5	Loss of taste (finding)	Asthma (disorder)	Streptococcal sore throat (disorder)
6	Viral sinusitis (disorder)	Gastroesophageal reflux disease (disorder)	Otitis media
7	Fatigue (finding)	Coronary arteriosclerosis (disorder)	Unhealthy alcohol drinking behavior (finding)
8	Sputum finding (finding)	Hypertriglyceridemia (disorder)	Severe anxiety (panic) (finding
9	Hypoxemia (disorder)	Joint pain (finding)	Sprain of ankle
10	Respiratory distress (finding)	Body mass index $30+$ - obesity (finding)	Prediabetes
	dominated by Covid-19	common chronic conditions	largely acute conditions

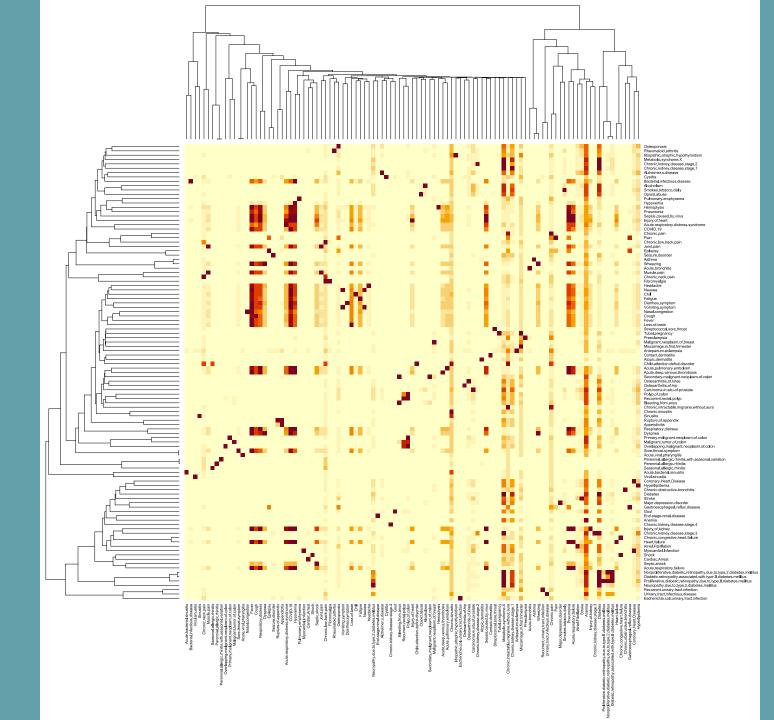
Cooccurrence heatmap for Synthea data



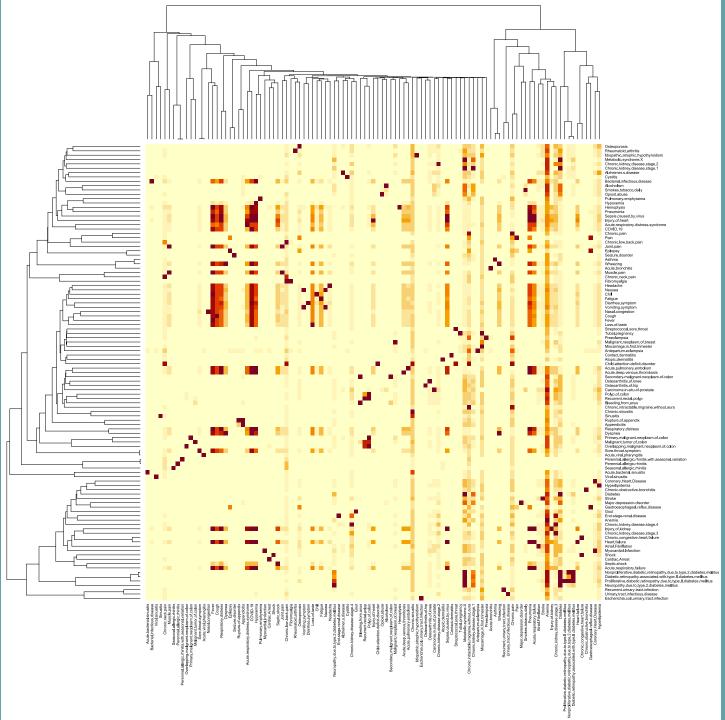
### EMR data



### Synthea data



Synthea data after Virtual Generalist CKD



### **Co-Occurrence Probability Measure (COPM)**

#### a) across all 107 conditions

From To	actual	simulation_pre	simulation_post
actual	0	0.2123	0.2008
simulation_pre		0	0.0110
simulation_post			0

#### b) focused on just 6 CKD-related conditions

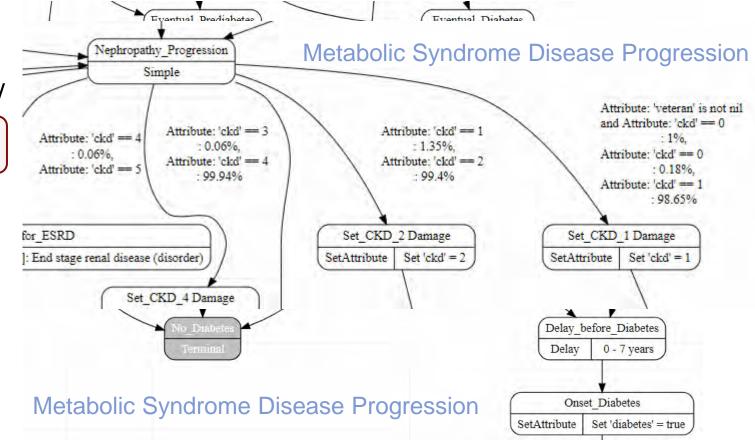
From To	actual	simulation_pre	simulation_post
actual	0	0.8680	0.2430
simulation_pre		0	0.1207
simulation_post			0

### Design pattern recommendations

- No delay
  - disease is not your destiny
- Mechanistic progression
  - allow interventions

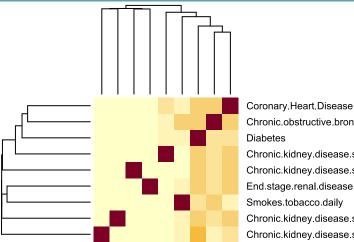
### • More modular modules

- separate treatment from disease incidence and progression
- use attributes to communicate between modules



# **Bonus Slides!** data visualization helps find bugs

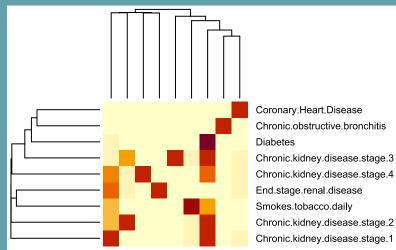
### Debugging Synthea with co-occurrence



Chronic obstructive bronchitis Chronic kidney disease stage 3 Chronic kidney disease stage 4 End.stage.renal.disease Chronic.kidney.disease.stage.2 Chronic kidney disease stage 1

Chronic kidney disease stage 2 End stage renal disease Smokes tobacco daily Diabetes Chronic obstructive bronchitis Chronic kidney disease stage 1 Chronic kidney disease stage Chronic kidney disease stage

Coronary Heart Disease



Smokes tobacco daily Diabetes End stage renal disease Chronic kidney disease stage 3 Chronic obstructive bronchitis Chronic. kidney. disease. stage. Chronic. kidney. disease. stage. Chronic kidney disease stage

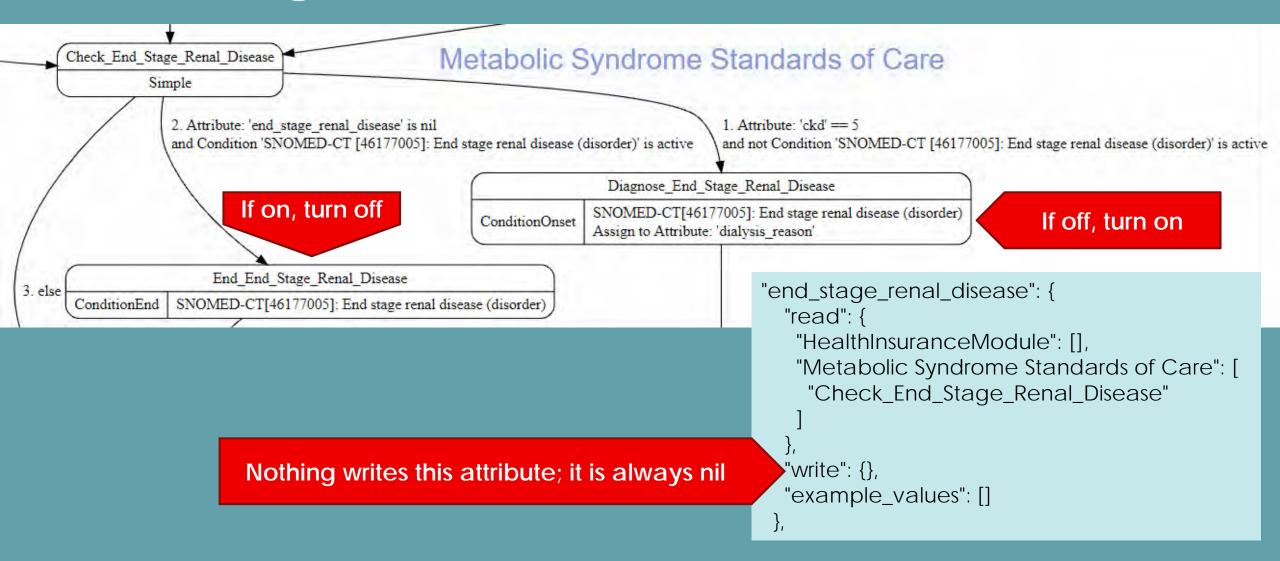
Coronary Heart Disease

# 'End stage renal disease' condition toggles on and off

select patient, description, start, stop, encounter, code from conditions
where description rlike('(Chronic kidney disease|End stage renal)')
order by patient, start

patient	description	start 🔺	stop 🔺	encounter
00118915-7610-1be1-fd03-21811ac23b71	Chronic kidney disease stage 1 (disorder)	2014-09-17	null	cdfd0045-026b-a
00154e43-88d2-f074-2810-23c2ed04235f	Chronic kidney disease stage 3 (disorder)	2010-08-26	null	ac3401ab-e826-
001792aa-daec-beab-969b-1a7a98c0dc67	Chronic kidney disease stage 3 (disorder)	2005-04-17	null	6b2c1374-3280-f
001792aa-daec-beab-969b-1a7a98c0dc67	End stage renal disease (disorder)	2008-07-13	2009-07-19	f6787445-a37a-a
001792aa-daec-beab-969b-1a7a98c0dc67	End stage renal disease (disorder)	2010-07-25	2011-07-31	4f70d0ec-3965-1
001792aa-daec-beab-969b-1a7a98c0dc67	End stage renal disease (disorder)	2012-08-05	2013-08-11	93ce8bb5-5949-

### End Stage Renal Disease



### **ON IMPROVING REALISM OF DISEASE MODULES IN SYNTHEA™**

Social Determinant-Based Enhancements to Conditional Transition Logic

Response to the 2021 HHS Synthetic Health Data Challenge

Category I: Enhancements to Synthea™ Opioids Use Case Team LMI

Brant Horio Greg Pekar Simon Whittle Maureen Merkl Linna Qiao

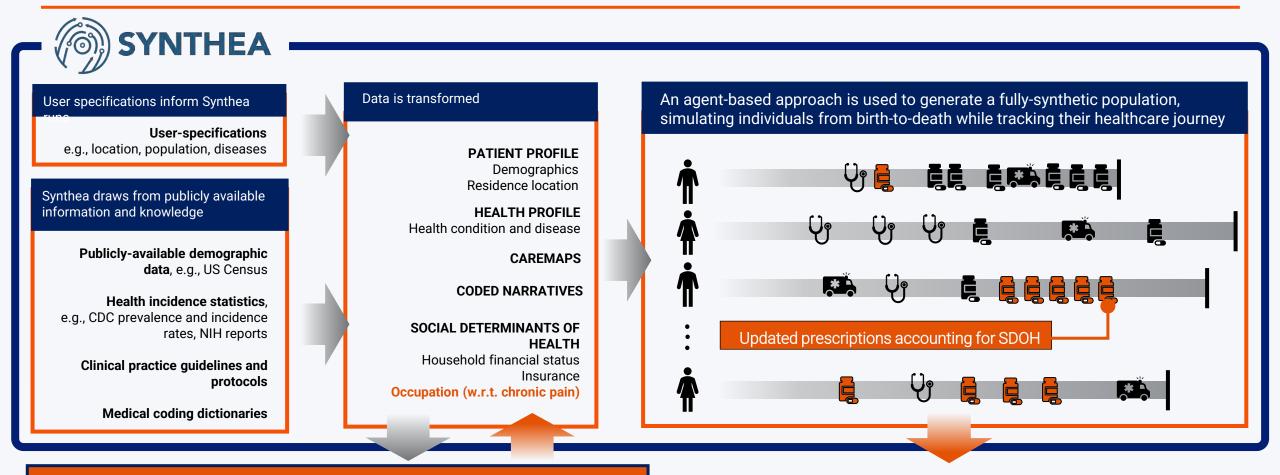
October 19, 2021

LMĨ

LMI Confidential and Proprietary. Not to be copied, distributed, or reproduced without LMI's prior written approval.

- Opioid Use Disorder (OUD) is a crisis
  - **Deadly outcomes:** 69,700+ Americans dying from opioid overdoses in 2020 (36% increase from prior year)
  - Hard to fix: OUD is a highly individual and complex care condition and highly influenced by SDOH
  - Ongoing problem: U.S. CBP confiscated more fentanyl in first half 2021 than last 3 years (Kaminsky 2021)
- Our research focused on one pathway to OUD
  - Prescribed opioids may result in OUD: often due to long term need to help with chronic pain
  - SDOH (occupation) can drive onset of chronic pain: particularly for heavy manual labor in rural areas
- The key technical idea was to demonstrate
  - a software workflow that mines open-source secondary data sources for SDOH (occupation)
  - modifications to the Synthea codebase to operationalize the SDOH (following published findings that could bridge occupation to relevant transition logic in Synthea's OUD-related state machines, and
  - increased realism in Synthea's generated populations with respect to opioid prescriptions

## OUR APPROACH MINED SECONDARY DATA FOR OUD-RELEVANT SDOH TO AUGMENT SIMULATED PERSON JOURNEYS



Repeatable and accessible enhancement to Synthea codebase that introduces SDOH (or other Census tractrelated Person attributes) for more realistic modeling

Our technical approach seeks to automate data mining of publicly available data sources for SDOH that better characterize communities at the local level

Lat/Lon  $\rightarrow$  Census Tract  $\rightarrow$  Localized SDOH (i.e., occupation)

# WE OPERATIONALIZE SDOH DATA AS AGENT ATTRIBUTES TO ENHANCE TRANSITION LOGIC IN SYNTHEA'S MODULE BUILDER

#### Prepare SDOH Data

Mine data and create census tract-indexed file to occupation information for Bangor, ME

#### Assign SDOH Attributes to Person Agents

Assign an occupation to each person based on Census statistics for our targeted occupation classes in their Census tract communities

#### Modify Relevant Disease Modules

Adjust transition probabilities for a chronic low back pain condition, based on occupation and gender

#### Run Synthea and Validate

•

Run ten trials of 32,000 patients with legacy\_Synthea and LMI\_Synthea

Compare simulated outcomes for number of opioid prescriptions per capita



- We scoped research to Bangor, ME due to higher than national average prevalence of OUD and predominant SDOH that strongly influence OUD
- Based on collaboration with University of Maine OUD researchers and published literature, we focused on
  - Maine's prevalence of forestry and fishing occupations
  - Correlation of these occupations to chronic musculoskeletal pain conditions
  - Chronic pain as a pathway to prescribed opioids, potential abuse, and OUD

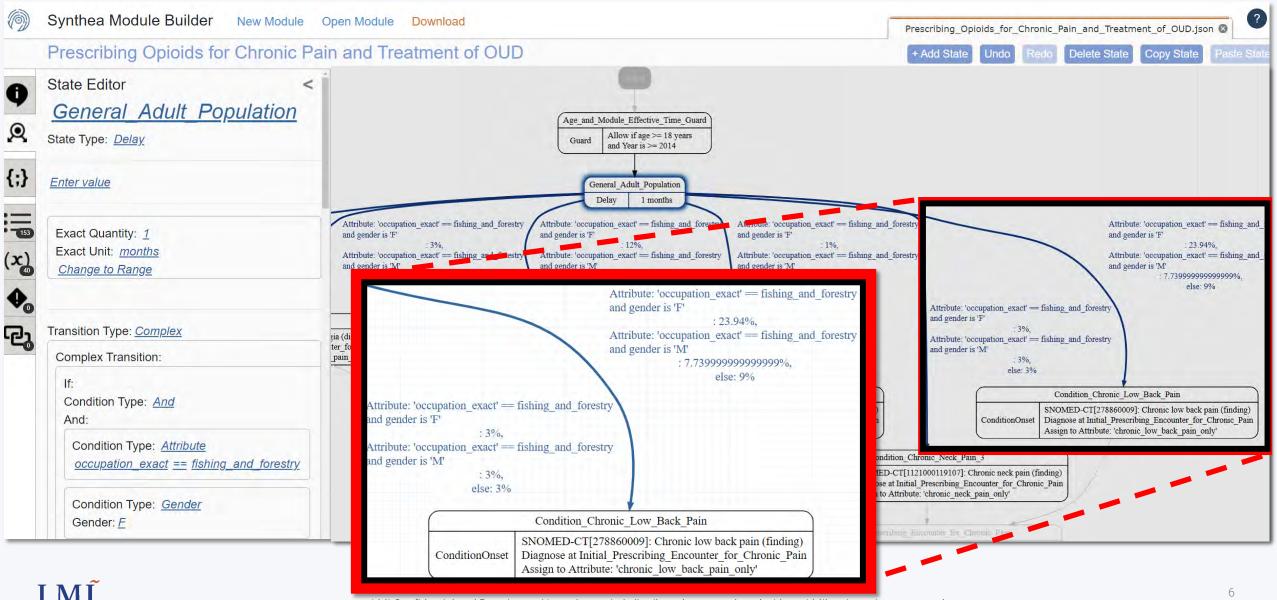


- We processed American Community Survey data to derive likelihood of individuals having forestry and fishing occupations by Census tract in Penobscot County, ME (where Bangor is located) to build a tract-indexed file to assign Person occupations
- Drawing from literature (Yang, Halderman, Lu, and Baker 2016) assessing chronic low back pain risk associated with occupations and gender, to inform state machine transition probabilities
- Validation patterns were collaborated on with University of Maine researchers and focused on opioid prescription counts for State and County



- Built a data ingestion method to access the tract-indexed file we created for occupation data
- Assigned Persons to a Census tract
  - For greater localized level of detail than zip code and to align with our data sources of interest
  - Based on shortest distance between Synthea's provided latitude-longitude residence coordinates to the centroid of the nearest Census block
  - Given Block assignment, then we assigned the Person to the appropriate Census tract
- Assigned occupation to Persons
  - Using assigned tract number, probabilistically assign occupation to Person by referencing occupation file
- Person owns one new attribute for occupation which can now be used for transitional conditional logic in the disease module state machines

### MODIFICATION OF THE DISEASE MODULES

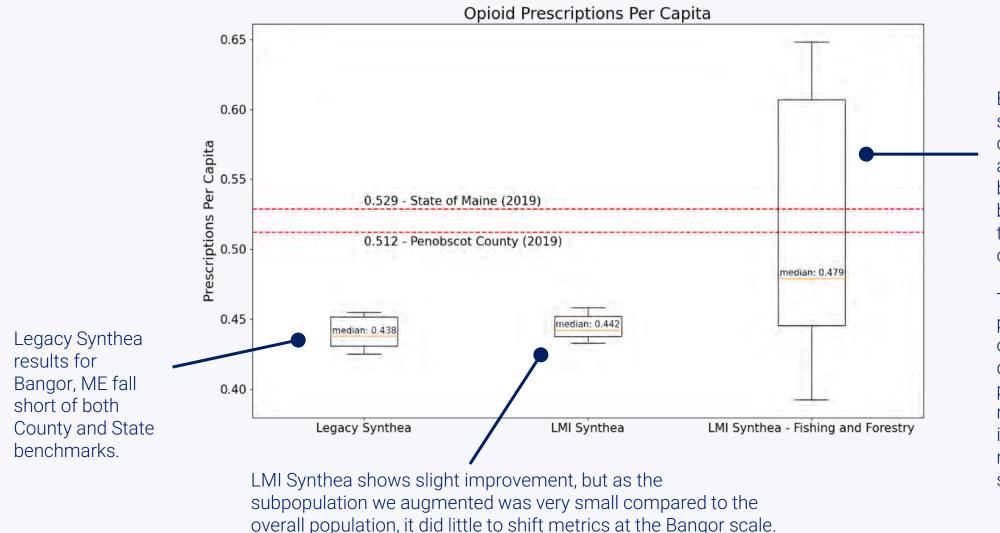


LMI Confidential and Proprietary. Not to be copied, distributed, or reproduced without LMI's prior written approval.



- To validate our modifications to Synthea:
  - We ran 10 trials, each with different random seeds
  - Each run generated 32,000 patients to approximately represent the entire City of Bangor, ME
  - We used the same 10 seeds for legacy\_Synthea and LMI\_Synthea to allow comparison between software versions
- We used the Prescription Monitoring Program Annual Report 2020 (Maine HSS 2021) and data from the CDC (CDC 2020) as our ground truth data for the number of opioid prescriptions in Maine

## VALIDATION RESULTS SHOW BETTER OUTCOMES FOR OUR SUBPOPULATION OF INTEREST



Evaluating only the subpopulation we changed in the fishing and forestry occupation, both State and County benchmarks fall within the interquartile range of our simulated results.

The results are promising in that outcomes are demonstrative of how population level representation might be improved by adjusting many relevant subpopulations.

- Benefits to Synthea
  - Minimal codebase modifications to allow an easy pull request
  - Method of ingesting Census tract level data and assigning to patients can be generalized to other similar data sets at a local scale
  - Focus on enhancing Person attributes to integrate SDOH allows Synthea ecosystem to be fully leveraged (e.g., ModuleBuilder)
- Benefits to researchers
  - Provides additional experiment factors to incorporate into Synthea's disease modules for greater detail for the conditional logic and state transition path possibilities
  - Repeatable and accessible enhancement to Synthea codebase that introduces SDOH (or other Census tract-related Person attributes) for more realistic modeling
- Benefits to health IT developers
  - Provides a working framework to ingest secondary data and assign them as patient attributes
- Broader healthcare community
  - Individualized SDOH drives complex care and critically needs to be better understood, analyzed, and modeled to further advance patient-centered outcomes research

### FUTURE WORK

- Additional SDOH factors based on Census tracts and blocks may be examined (e.g., homelessness, access to care, access to food)
- Work is needed to find better ways to account for relevant correlations between SDOH (e.g., our assignment of occupation neglected potentially relevant relationships to Synthea's assigned socioeconomic status or age)
- The team will be continuing to collaborate with University of Maine researchers with the objective of integrating Synthea for OUD research

- There is a lot of code
  - Big learning curve to understand the codebase and how the modules interact with one another (e.g., geography folder has a fully implemented quad tree we could have used for centroid distance calculations—we implemented a less efficient in a sorted map-based approach to finding the closest centroid)
- Successes in working with existing Synthea code base
  - Minimal modifications to preserve functioning software with least risk of "breaking it"
    - Integration of external analysis (e.g., tract and occupation) into the Synthea process
    - Use of input files and existing data loader methods
    - Primarily modified the pickDemographics() step of the Person generation logic
  - Preserved software practices and workflows to make sure our enhancements looked roughly like the rest
    of the project (would not be a stumbling block to existing Synthea developers and users)
  - Focused on capitalizing on the very polished Module Builder application to operationalize our enhancements in other modules



particle



Category II Entry: Novel Uses of Synthea Generated Synthetic Data

Team: Particle Health, Submitter: Parker Bannister

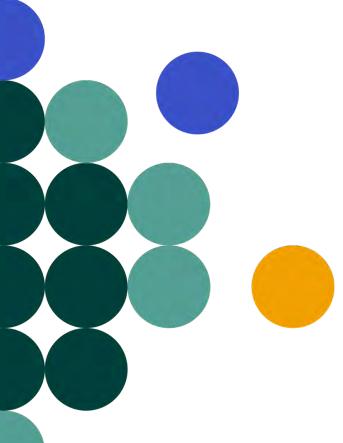
#### particle

# Background and Objectives

- APIs will be the tool driving national access to health data
  - 21st Century Cures Act and TEFCA
- Synthetic health data vs. Real health data
  - o Synthea
    - Single CCDA documents, separately generated free-text notes
  - o Access to Data
    - Download CCDA to Local Machine
    - APIs for FHIR, not CCDA
- Why is a realistic development environment needed?
  - Allows researchers and developers to seamlessly transition to real patient information
    - Time, Cost, and Liability
- The Particle Health Sandbox Objective
  - Point-In-Time documents
  - In-Document Synthetic provider notes
  - Focus on synthetic populations with specific conditions
  - o Validation

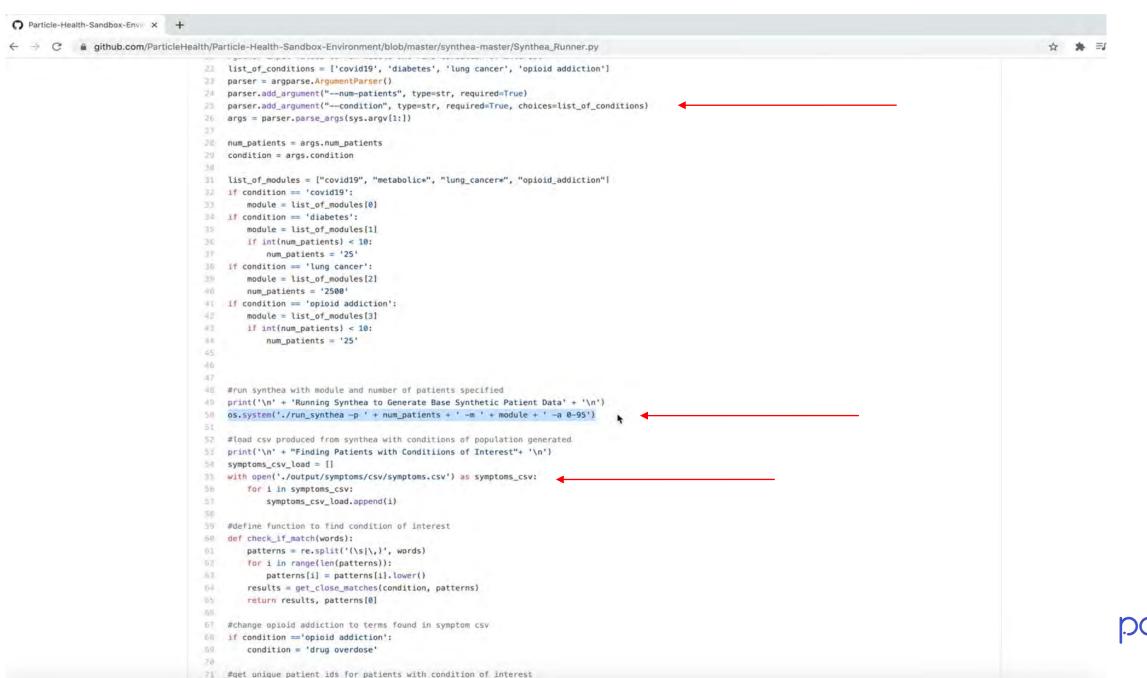
# particle

# Document Generation pt.1



- Synthea\_Runner.py
  - Generates base Synthea documents
  - Finds patients with conditions specified to create population of interest
    - Regex Synthea symptoms.csv
  - Stores files for population of interest and processes them with the point in time document generator
  - Finally Validates Results

#### Synthea\_Runner.py



#### Synthea\_Runner.py

-----121 os.system('python point\_in\_time\_document\_generator.py') 123 #copy output files and directory to output folder: 124 for i in os.listdir('./pitd\_gen\_output'): shutil.copytree('./pitd\_gen\_output/' + i, '../' + condition + '\_output\_' + str(today) + '/generator\_output/' + i) 125 copyfile('./output\_directory.csv', '../' + condition + '\_output\_' + str(today) + '/output\_directory.csv') 128 129 #clear notes, synthea ccds, pitd gen output\_file, directory 130 for i in os.listdir("./Notes"): os.remove('./Notes/' + i) 132 for i in os.listdir("./Synthea\_CCDs"): os.remove('./Synthea\_CCDs/' + i) 134 for i in os.listdir("./output"): if i.startswith('.'): 136 os.remove('./output/' + i) else: 138 shutil.rmtree('./output/' + i, ignore\_errors = True) 139 for i in os.listdir("./pitd\_gen\_output"): 140 shutil.rmtree('./pitd\_gen\_output/' + i, ignore\_errors = True) os.remove('./output\_directory.csv') 143 print('\n' + 'Generation Complete' + '\n') 144 145 #validate point in time ccda documents print('\n' + 'Validating Output Point In Time CCDA Documents' + '\n') 146 148 #loop thru output files to validate patients = [] 149 150 val\_output = [] 151 urllib3.disable\_warnings() 152 for i in os.listdir('../' + condition + '\_output\_' + str(today) + '/generator\_output'): if not i.startswith('.'): 154 print(i) #loop thru folders for patient 156 counter = 0 for j in os.listdir('../' + condition + '\_output\_' + str(today) + '/generator\_output/' + i): 158 if not j.startswith('.'): 159 print('\tFOLDER:' + j) 160 #loop thru files for patient 161 for k in os.listdir('../' + condition + '\_output\_' + str(today) + '/generator\_output/' + i +"/" + j): if not k.startswith('.'): print('\t\tFile: ' + k) 164 patients.append(i) folder\_name = i data\_file = '../' + condition + '\_output\_' + str(today) + '/generator\_output/' + i +"/" + j + '/' + k 167 url = "https://ccda.healthit.gov/scorecard/ccdascorecardservice2" 168 169 myfile = {"ccdaFile": (k, open(data\_file, "rb"))} 170 r = requests.post(url, files = myfile, verify = False).json()

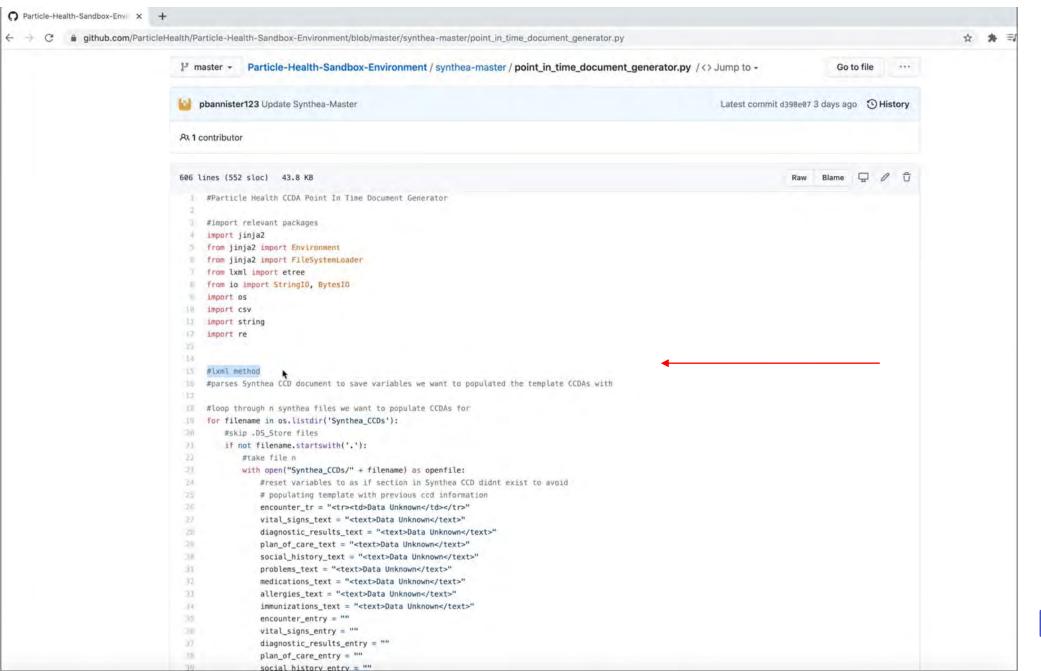
### particle

# Document Generation pt.2



- Parses base Synthea CCDA and stores sections relevant to point in time document types
  - LXML
- Templates sections into new document
  - Jinja2
  - XML Templates for new point in time documents
  - Addition of in-document notes

#### Point\_In\_Time\_Document\_Generator.py



### particle

#### Point\_In\_Time\_Document\_Generator.py

#### O Particle-Health-Sandbox-Env × + igithub.com/ParticleHealth/Particle-Health-Sandbox-Environment/blob/master/synthea-master/point\_in\_time\_document\_generator.py $\leftarrow \rightarrow$ C ☆ **券** immunizations\_entry.append(etree.tounicode(entry, pretty\_print=True)) else: immunizations\_entry = "" immunizations\_entry = "".join(immunizations\_entry) #fix null imaging section error: for child in tree.find("{urn:hl7-org:v3}component/{urn:hl7-org:v3}structuredBody"): for i in child.find("{urn:hl7-org:v3}section"): if i.tag == "{urn:hl7-org:v3}code": if i.attrib['code'] = '18748-4': child.getparent().remove(child) 247 #jinja2 populate template: 248 #fills blank templates with saved data parsed from synthea ccd above #load templates and set up environment for jinja2 template\_file\_loader = FileSystemLoader('templates') env = Environment(loader=template\_file\_loader) encounter\_summary\_template = env.get\_template('Encounter\_Summary\_Template.xml') refill\_summary\_template = env.get\_template('Refill\_Summary\_Template.xml') 254 lab\_summary\_template = env.get\_template('Lab\_Summary\_Template.xml') immunizations\_summary\_template = env.get\_template('Immunizations\_Summary\_Template.xml') #render encounter summary template with saved variables and save to output encounter\_summary\_output = encounter\_summary\_template.render(Effective\_Time = effective\_time, Record Target = record target, 260 Author = author, 201 Custodian = custodian, Documentation\_Of = documentation\_of, Encounter\_TR = encounter\_tr, Encounter\_Entry = encounter\_entry, Vital\_Signs\_Text = vital\_signs\_text, 2861 Vital\_Signs\_Entry = vital\_signs\_entry, Diagnostic\_Results\_Text = diagnostic\_results\_text, Diagnostic\_Results\_Entry = diagnostic\_results\_entry, Plan\_Of\_Care\_Text = plan\_of\_care\_text, 278 Plan\_Of\_Care\_Entry = plan\_of\_care\_entry, Social\_History\_Text = social\_history\_text, Social\_History\_Entry = social\_history\_entry) 274 #render refill summary template with saved variables and save to output refill\_summary\_output = refill\_summary\_template.render(Effective\_Time = effective\_time, Record\_Target = record\_target, Author = author, 278 Custodian = custodian, Documentation\_Of = documentation\_of, 280 Encounter\_TR = encounter\_tr, Encounter\_Entry = encounter\_entry, Plan\_Of\_Care\_Text = plan\_of\_care\_text, 283 Plan\_Of\_Care\_Entry = plan\_of\_care\_entry, 284 Social\_History\_Text = social\_history\_text,

#### Point\_In\_Time\_Document\_Generator.py

→ C a github.com/ParticleH	lealth/Part	icle-Health-Sandbox-Environment/blob/master/synthea-master/templates/Encounter_Summary_Template.xml	\$ * =	
		<realmlode code="US"></realmlode>		
	8	<typeid< td=""><td></td><td></td></typeid<>		
	0	root="2.16.840.1.113883.1.3"		
	16	extension="POCD_HD000040" />		
	11	<templateid root="2.16.840.1.113883.10.20.1"></templateid>		
	12	<templateid< td=""><td></td><td></td></templateid<>		
	13	root="2.16.840.1.113883.10.20.22.1.1"		
	14	extension="2015-08-01" />		
	15	<templateid< td=""><td></td><td></td></templateid<>		
	15	root="2.16.840.1.113883.10.20.22.1.2"		
	17	extension="2015-08-01" />		
	18	<pre><id assigningauthorityname="https://github.com/synthetichealth/synthea" extension="46f6aa9d-c38c-4215-833e-19268dadb4ca" root="2.16.840.1.113883.19.5"></id></pre>		
	19	<code code="11506-3" codesystem="2.16.840.1.113883.6.1" codesystemname="LOINC" displayname="Subsequent evaluation note"></code>		
	20	<pre><tube= <="" <tube="//" codesystem="2.10.040.1.113005.0.1" codesystemmame="cont" displaymame="subsequent" evaluation="" issues="" note="" todesystem="2.10.040.1.113005.0.1" tube="&lt;/td"><td></td><td></td></tube=></pre>		
	20	States for the Encounter Juliand 1997 tatte		
	22	{{Effective_Time}}		
	23	<confidentialitycode< td=""><td></td><td></td></confidentialitycode<>		
	14	code="N"		
	25			
		codeSystem="2.16.840.1.113883.5.25" />		
	26	<languagecode code="en-US"></languagecode>		
	77			
	28	{{Record_Target}}		
	2.0	{{Author}}		
	18	{{Custodian}}		
•	- 11	{{Documentation_0f}}		
	.12	<component></component>		
	10	<structuredbody></structuredbody>		
	14	<component></component>		
	-15	Encounters		
	10	<section nullflavor="NI"></section>		
	3.9	<templateid <="" root="2.16.840.1.113883.10.20.22.2.22" td=""><td></td><td></td></templateid>		
	38	extension="2015-08-01"/>		
	39	<code ="46240-8"<="" td=""><td></td><td></td></code>		
	-40	codeSystem="2.16.840.1.113883.6.1"		
	-41	codeSystemName="LOINC"		
	-12	displayName="History of encounters"/>		
	43	<title>Encounters</title>		
	44	<text></text>		
	-15			
	-46	<thead></thead>		
	-47			
	-11	Start		
	-49	Stop		
	.92	Description		
	11	Code		
	32			
	53			partic
	3.6			
	55			
	56	{{Encounter_TR}}		
				1

## particle

# Validation



- HealthIT.gov's CCDA Scorecard 2.0
  - API Implementation
- CSV of Results for synthetic population generated
  - File score validation per file generated for entire population of synthetic patients

#### Validation Portion of Synthea\_Runner.py and Results

```
147
     #loop thru output files to validate
148
     patients = []
149
     val_output = []
150
     urllib3.disable_warnings()
     for i in os.listdir('../' + condition + '_output_' + str(today) + '/generator_output'):
152
         if not i.startswith('.'):
153
             print(i)
154
             #loop thru folders for patient
155
              counter = 0
             for j in os.listdir('../' + condition + '_output_' + str(today) + '/generator_output/' + i):
                 if not j.startswith('.'):
158
                     print('\tFOLDER:' + j)
159
                     #loop thru files for patient
160
                     for k in os.listdir('.../' + condition + '_output_' + str(today) + '/generator_output/' + i +"/" + j):
161
                         if not k.startswith('.'):
                             print('\t\tFile: ' + k)
                             patients.append(i)
164
                             folder_name = i
                             data_file = '../' + condition + '_output_' + str(today) + '/generator_output/' + i +"/" + j + '/' + k
166
167
                             url = "https://ccda.healthit.gov/scorecard/ccdascorecardservice2"
168
                             myfile = {"ccdaFile": (k, open(data_file, "rb"))}
169
                             r = requests.post(url, files = myfile, verify = False).json()
170
                             val_output.append(list(r.items()))
171
172
     val_table = pd.DataFrame(data = val_output, columns = ['ErrorMessage', 'FileName', 'CCDADocumentType', 'Results', 'ReferenceResults', 'ErrorList', 'SchemaErrors'
173
     val_table.insert(0, "Patient", patients, True)
174
175
     #write validation output to csv
176
     val_table.to_csv('../' + condition + '_output_' + str(today) + '/validation_results.csv')
177
178
     print('\n' + 'Validation Complete' + '\n')
179
```

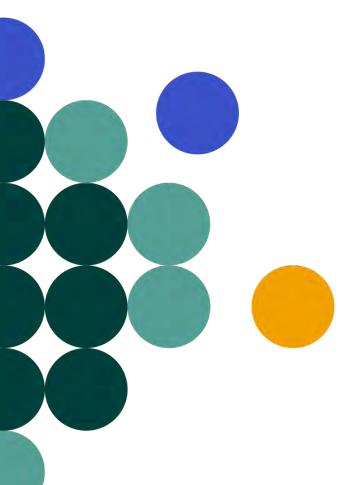


#### Validation Portion of Synthea\_Runner.py and Results

	А В С	D		
1	Patient ErrorMessage	FileName CCDADocumentType	Resu	lts
5	0 Era_Crist ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP877022021-07-08T2( ('ccdaDocumentType'	'CCD') ('resu	ilts', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
3	1 Era_Crist ('errorMessage', None)	('filename', 'Encounter_SummaryPCP877022021-07-08T202520.xml ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
- 4	2 Era_Crist ('errorMestigge', None)	('filename', 'Lab_SummaryPCP877022021-07-08T202520.xml') ('ccdaDocumentType'	'CCD') ('resu	ilts', {'finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
di.	3 Era_Crist ('errorMessage', None)	('filename', 'Immunizations_SummaryPCP877022021-07-08T202520 ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
. 6	4 Lettie_Erdman ('errorMessage', None)	('filename', 'Encounter_SummaryPCP495482021-07-08T071356.xml ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
π.	5 Lettie_Erdman ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP495482021-07-08T07 ('ccdaDocumentType'	'CCD') ('resu	ilts', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
	6 Lettie_Erdman ('errorMessage', None)	('filename', 'Refill_SummaryPCP495482021-07-08T071356.xml') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
10	7 Lettie_Erdman ('errorMessage', None)	('filename', 'Lab_Summary_PCP49548_2021-07-08T071356.xml') ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
10	8 Lettie_Erdman ('errorMessage', None)	('filename', 'Encounter_SummaryPCP495482021-07-08T071356.xml ('ccdaDocumentType'	'CCD') ('resu	ilts', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
71	9 Lettie_Erdman ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP495482021-07-08T07 ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
12	10 Lettie_Erdman ('errorMessage', None)	('filename', 'Immunizations_SummaryPCP495482021-07-08T071356 ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
<u>n</u>	11 Crystle_Price ('errorMessage', None)	('filename', 'Immunizations_SummaryPCP138022021-07-08T105000 ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
7.4	12 Crystle_Price ('errorMessage', None)	('filename', 'Lab_Summary_PCP13802_2021-07-08T105000.xml') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
9.5	13 Crystle_Price ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP138022021-07-08T1( ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList', [{categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
16.	14 Crystle_Price ('errorMessage', None)	('filename', 'Encounter_SummaryPCP138022021-07-08T105000.xml ('ccdaDocumentType'	'CCD') ('resu	ilts', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
12	15 Tammera_MacG ('errorMessage', None)	('filename', 'Immunizations_SummaryPCP1158642021-07-12T15544 ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
10	16 Tammera_MacG ('errorMessage', None)	('filename', 'Lab_SummaryPCP1158642021-07-12T155440.xml') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
19	17 Tammera_MacG ('errorMessage', None)	('filename', 'Encounter_SummaryPCP1158642021-07-12T155440.xn ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-20	18 Tammera_MacG ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP1158642021-07-12T1 ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+'
27	19 Raymon_William ('errorMessage', None)	('filename', 'Lab_Summary_PCP65005_2021-07-10T101916.xmi') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
22	20 Raymon_William ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP650052021-07-10T1( ('ccdaDocumentType'	None) ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-73	21 Raymon_William ('errorMessage', None)	('filename', 'Encounter_SummaryPCP650052021-07-10T101916.xml ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
2 <i>h</i>	22 Raymon_William ('errorMessage', None)	('filename', 'Lab_Summary_PCP65005_2021-07-10T101916.xml') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
25	23 Raymon_William ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP650052021-07-10T1( ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
26	24 Raymon_Willian ('errorMessage', None)	('filename', 'Encounter_SummaryPCP650052021-07-10T101916.xml ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
27	25 Raymon_William ('errorMessage', None)	('filename', 'Refill_SummaryPCP650052021-07-10T101916.xml') ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-73	26 Raymon_William ('errorMessage', None)	('filename', 'Immunizations_SummaryPCP650052021-07-10T101916 ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-27	27 Ara_Prosacco ('errorMessage', None)	('filename', 'Lab_SummaryHALLMARK_HEALTH_MEDICAL_ASSOCIAT ('ccdaDocumentType'	'CCD') ('resu	ilts', {'finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
an a	28 Ara_Prosacco ('errorMessage', None)	('filename', 'Encounter_SummaryHALLMARK_HEALTH_MEDICAL_ASS ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': "C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
31	29 Ara_Prosacco ('errorMessage', None)	('filename', 'Immunizations_SummaryHALLMARK_HEALTH_MEDICAL_, ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList', [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
- 92	30 Ara_Prosacco ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentHALLMARK_HEALTH_MEDI( ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
83	31 Octavio_Hyatt ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentCHICOPEE_EYECARE_PC_ ('ccdaDocumentType'	'CCD') ('resu	ults', {'finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-84	32 Octavio_Hyatt ('errorMessage', None)	('filename', 'Encounter_SummaryCHICOPEE_EYECARE_PC2021-0' ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
15	33 Octavio_Hyatt ('errorMessage', None)	('filename', 'Lab_SummaryCHICOPEE_EYECARE_PC2021-07-09T1 ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
86	34 Octavio_Hyatt ('errorMessage', None)	('filename', 'Immunizations_SummaryCHICOPEE_EYECARE_PC20: ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
-87	35 Tequila_OReilly ('errorMessage', None)	('filename', 'Continuity_of_Care_DocumentPCP1189232021-07-13T1 ('ccdaDocumentType'	'CCD') ('resu	Its', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList'; [{'categoryName': 'Miscellaneous', 'categoryGrade': 'A+',
18	36 Tequila_OReilly ('errorMessage', None)	('filename', 'Encounter_SummaryPCP1189232021-07-13T105356.xn ('ccdaDocumentType'	'CCD') ('resu	ults', ('finalGrade': 'C', 'finalNumericalGrade': 75, 'categoryList': [('categoryName': 'Miscellaneous', 'categoryGrade': 'A+',.

# particle

# Final Output and Usage



- Multiple Point in Time documents generated from Synthea CCDAs
  - Encounter Summary
  - Immunizations Summary
  - Lab Summary
  - Refill Summary
- In-Document Synthetic Provider Notes
- API Interface to Access Information that mirrors the process of National Network APIs

#### Final Output and Usage

```
In [28]: import requests
         url = 'https://sandbox.scratch.particlehealth.com/api/vl/queries'
         headers = {"Content-Type": "application/json",
         'Authorization': jwt}
         data = {
                     "address city": "West Bridgewater",
                     "address lines": [
                       "126 McLaughlin Ferry"
                     1.
                     "address state": "Massachusetts",
                     "date of birth": "1976-03-11".
                     "email": "Arlie@doe.com",
                     "family name": "Rolfson",
                     "gender": "Male",
                     "given name": "Arlie",
                     "npi": "1234",
                     "postal code": "02324", 1
                     "purpose of use": "TREATMENT",
                     "ssn": "123-45-6789",
                     "telephone": "1-234-567-8910"
         r = requests.post(url, headers=headers, json=data)
         print(r.json())
         query id = r.json()['id']
         {'id': 'd5dbf549-ae18-4e51-9a04-765f9113062e', 'demographics': {'given name': 'Arlie', 'family name': 'Rolfson', 'dat
         e_of_birth': '1976-03-11', 'gender': 'MALE', 'ssn': '123-45-6789', 'email': 'Arlie@doe.com', 'address_lines': ['126 M
         cLaughlin Ferry'], 'address state': 'MA', 'address city': 'West Bridgewater', 'postal code': '02324', 'hints': None,
         'telephone': '(234) 567-8910', 'npi': '1234', 'purpose of use': 'TREATMENT'}, 'state': 'PENDING'}
In [29]: url = 'https://sandbox.scratch.particlehealth.com/api/vl/queries/' + query id
         headers = {"Content-Type": "application/json",
         'Authorization': jwt}
         r = requests.get(url, headers=headers)
         print(r.json())
         {'id': 'd5dbf549-ae18-4e51-9a04-765f9113062e', 'demographics': {'given_name': 'Arlie', 'family_name': 'Rolfson', 'dat
         e of birth': '1976-03-11', 'gender': 'MALE', 'ssn': '123-45-6789', 'email': 'Arlie@doe.com', 'address lines': ['126 M
```

cLaughlin Ferry'], 'address\_state': 'MA', 'address\_city': 'West Bridgewater', 'postal\_code': '02324', 'hints': None, 'telephone': '(234) 567-8910', 'npi': '1234', 'purpose\_of\_use': 'TREATMENT'}, 'state': 'COMPLETE', 'files': [4'id': '1462674f-aac9-4eb2-9f7c-lb9aff9771d9', 'title': 'Encounter\_Summary5\_\_PCP10647\_\_2021-07-16T001720.xml', 'type': 'ap plication/xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/1462674f-aac9-4eb2-9f7c-lb9aff9771d9'}, {'id': '24192099-aa08-45e6-8905-2ab4dd65e917', 'title': 'Lab\_Summary\_PCP10647\_\_2021-07-16T001720.xml', 'type': 'ap plication/xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/24192099-aa08-45e6-8905-2ab4dd65e917'}, {'id': '2bf8106a-laba-48d6-afa8-9d3066509edb', 'title': 'Continuity\_of\_Care\_Document6\_\_PCP10647\_\_2021-07-16T001720. xml', 'type': 'application/xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/2bf8106a-laba-48d6-afa8-9 d3066509edb'}, {'id': '34a66d22-3350-4b0a-8447-3e0cdfea2663', 'title': 'Continuity\_of\_Care\_Document\_\_PCP10647\_\_2021 -07-16T001720.xml', 'type': 'application/xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/2bf8106a-laba-48d6-afa8-9 d3066509edb'}, {'id': '34a66d22-3350-4b0a-8447-3e0cdfea2663', 'title': 'Continuity\_of\_Care\_Document\_\_PCP10647\_\_2021 -07-16T001720.xml', 'type': 'application/xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/2bf8113062e/34a66d22-33 50-4b0a-8447-3e0cdfea2663'}, {'id': '6a468531-7fa2-4520-9b4a-f9592686f2a1', 'title': 'Encounter\_Summary7\_\_PCP10647\_ 2021-07-16T001720.xml', 'url': '/api/v1/files/d5dbf549-ael8-4e51-9a04-765f9113062e/2bf8113062e/34a66d22-33

particle

#### Final Output and Usage

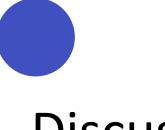
```
Encounter_Summary__RELIANT_MEDICAL_... Continuity_of_Care_Document__RELIANT_M.
          <section nullFlavor="NI">
           <templateId root="2.16.840.1.113883.10.20.22.2.22" extension="2015-08-01"/>
           <code code="46240-8" codeSystem="2.16.840.1.113883.6.1" codeSystemName="LOINC" displayName="History of encounters"/>
           <title>Encounters</title>
             <thead>
                  Start
                  Stop
                  >Description
                  Code
               </thead>
               2019-04-08T04:10:10-04:00
                  2019-04-09T04:10:10-04:00
                  Drug rehabilitation and detoxification
                  http://snomed.info/sct 56876005
              <entry xmlns="urn:hl7-org:v3" xmlns:sdtc="urn:hl7-org:sdtc" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" typeCode="DRIV">
             <encounter classCode="ENC" moodCode="EVN">
              <templateId root="2.16.840.1.113883.10.20.22.4.49"/>
               <id root="a6192761-0527-115c-6aae-00da9b7f9bdb"/>
               <code code="56876005" codeSystem="2.16.840.1.113883.6.96" displayName="Drug rehabilitation and detoxification">
                  <reference value="#encounters-desc-27"/>
                <reference value="#encounters-desc-27"/>
               </text>
                <low value="20190408041010"/>
                <high value="20190409041010"/>
              </effectiveTime>
          <section nullFlavor="NI">
           <templateId root="2.16.840.1.113883.10.20.22.2.6.1" extension="2015-08-01"/>
           <code code="48765-2" codeSystem="2.16.840.1.113883.6.1" codeSystemName="LOINC" displayName="Allergy List"/>
```

### particle

#### Final Output and Usage

```
<item>
                <paragraph><br/>2019-04-08
<br/><br/><br/> # Chief Complaint
<pr/> No complaints.
<br/>
<pr/> # History of Present Illness
<pr/> Austin578 is a 46 year-old non-hispanic white male.
<br/>
<pr/> # Social History
<br/>Patient is married. Patient has a documented history of opioid addiction. Patient is an active smoker and is an alcoholic. Patient identifies as heterosexual.
<br/>
<br/>> Patient comes from a low socioeconomic background. Patient has a high school education. Patient currently has UnitedHealthcare.
<br/>
<br/>
<br/>
# Allergies
<br/>
<br/>
No Known Allergies.
<br/>
<pr/> # Medications
<pr/> No Active Medications.
<br/>
<pr/> # Assessment and Plan
<br/>
<br/>
<br/> ## Plan
<br/>br/>
<br/>
<br/>
<br/>
<br/><br/>
                                                                  </paragraph>
              </item>
```





# Discussion

- Progression from original Synthea (Single CCDA)
  - Why realistic data helps developers innovate
- Validation Component
- Delivering a specific sub-population of patients
  - Impact on innovation and research (Opioid or Complex-Care)
- Synthea solution publically available on our GitHub Repository:
  - <u>https://github.com/ParticleHealth/Particle-Health-Sandbox-Environment</u>
- Leveraged Open-Source tools and libraries
- Visit our website to use our sandbox environment
  - Pre-loaded with Synthea Data modified with our solution
  - <u>https://www.particlehealth.com</u>

# particle

# particle

# Lessons Learned and Future Work

- Lessons Learned
  - Synthea is a powerful tool for generating synthetic CCDA and equivalent FHIR data
  - There are many potential opportunities to develop on top of Synthea to improve upon it and the use cases it can deliver
  - Real Clinical Information is highly variable and comes in different shapes and sizes
  - Quality development environments are important for enabling innovation
  - Policy greatly impacts the future direction of health information technology
- Future Work
  - Expanding Point In Time Document Types
    - ie. Discharge summaries
  - Generating other types of data seen in clinical practice
    - ie. Allergies





# Thank you!

Questions?

go@particlehealth.com





Empirical inference of Underlying Condition Probabilities Using Synthea-Generated Synthetic Health Data Team TeMa

Dr. Michael D. Teter miketeter@yahoo.com Dr. Christopher E. Marks cemarks@alum.mit.edu

Challenge Category: II (Novel Uses of Synthea Generated Data)

# Background

### **Problem Motivation**

- Simulation is often used to investigate complicated phenomena for which analytic determination of outcome probabilities is intractable.
- Synthea is built in a way that makes it well-suited for this purpose.
  - It inputs conditional probabilities that can be validated.
  - Its outputs are the result of tailorable combinations of these input probabilities.

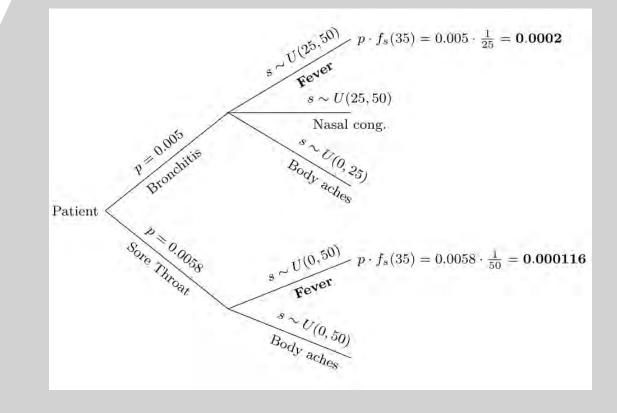
#### Our Task

 Use Synthea-generated data to investigate relationships between a patient's pathology and a given set of symptoms and severities.

# Our Methods (1 of 2)

### **Empirical Bayes**

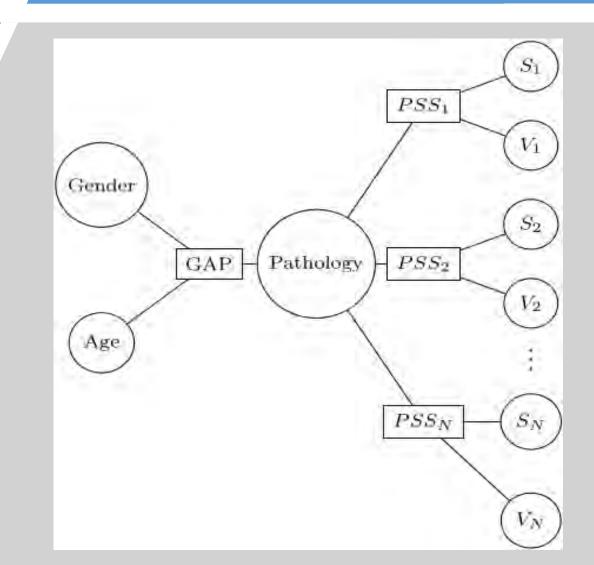
- Canonical Bayesian analysis
- Using empirical distributions in Synthea data, no need to enumerate a complicated tree.



# Our Methods (2 of 2)

### **Bayesian Network**

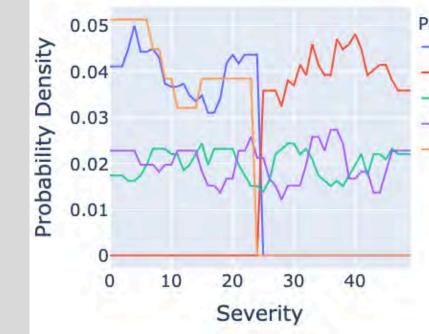
- Graph-based machine learning method.
- We decide which variables are related.
- More versatile than the strictly empirical model.



# Example Outputs

### <u>Patient</u>

- 5 years old
- Female
- Fever



Pathology Viral sinusitis (disorder) Acute bronchitis (disorder) Acute viral pharyngitis (disorder) Streptococcal sore throat (disorder) Sinusitis (disorder)

# Empirical Bayes

- Viral sinusitis (disorder)

Sinusitis (disorder)

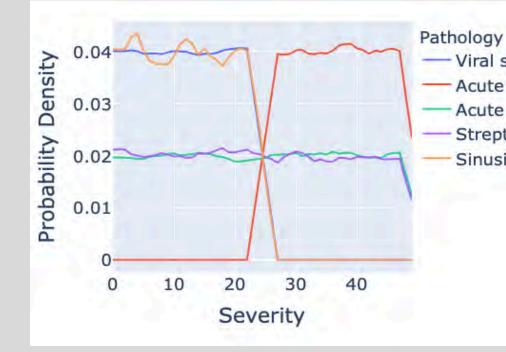
Acute bronchitis (disorder)

Acute viral pharyngitis (disorder)

**Bayesian** 

**Network** 

Streptococcal sore throat (disorder)



# Validation

- Internal Validation through code testing
- External Validation through comparison with existing tools.
- A useful method for validating Synthea!

### External validation: comparison with WebMD

WebMD	Synthea Bayes			
Bacterial Pneumonia	Viral sinusitis (disorder)			
Middle Ear Infection	Acute bronchitis (disorder)			
Viral Pneumonia	Acute viral pharyngitis (disorder)			
Influenza (Flu) Child	Streptococcal sore throat (disorder)			
Strep Throat	Sinusitis (disorder)			

# Summary & Next Steps

- Our approach can be extended to account for demographics, encounter types, patient location, patient history, etc.
- Compare results to known distributions as a way of validating Synthea.
- Identify areas where Synthea can be improved.
  - Standardization!
- Look for real-world applications.
  - Rare pathologies?

# SPATIOTEMPORAL BIG DATA ANALYSIS OF THE OPIOID EPIDEMIC IN ILLINOIS

- Office of the National Coordinator for Health Information Technology (ONC) Synthetic Health Data Challenge
- Category II: Novel Uses of Synthea<sup>™</sup> Generated Synthetic Data
- Arash Jalali, MPH, MSHI
- Sean Huang, MD
- Karl Kochendorfer, MD, FAAFP





Smarter Public Health Prevention Systems

# **UI HEALTH**



- Comprehensive care, education, and research to train health care leaders and foster healthy communities in Illinois and beyond.
- 465 bed tertiary care hospital, 21 outpatient clinics, 11 federally qualified Mile Square Health Center locations
- Campuses in Chicago, Peoria, Quad Cities, Rockford, Springfield, and Urbana
- 7 Health Science colleges: Applied Health Sciences, Dentistry, Medicine, Nursing, Pharmacy, School of Public Health, Jane Addams College of Social Work





Blair Turner, Wilnise Jasmin, Isabel Chung, Ponni Arunkumar, Mark Kiely, Steven Aks, Nikhil Prachand, Allison Arwady. Opioid Overdose Surveillance Report—Chicago 2019. City of Chicago, March 2021.

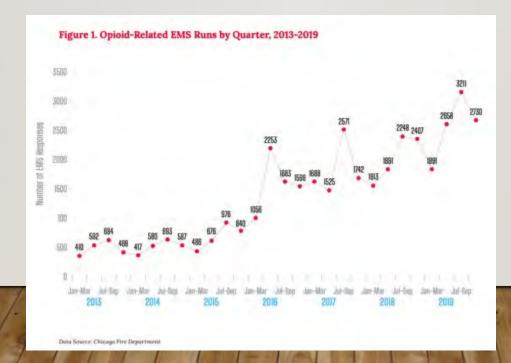
UIC

**Smarter Public Health** 

**Prevention Systems** 

# **OPIOID CRISIS: CHICAGO STATISTICS**

- 2019: 855 people died from opioid overdoses (from 793 previous year)
- 2018 -> 2019: Opioid-related overdose death rate increased by 10.1%
- CFD EMS team responded to average 29 responses per day (increase in 25.4%)



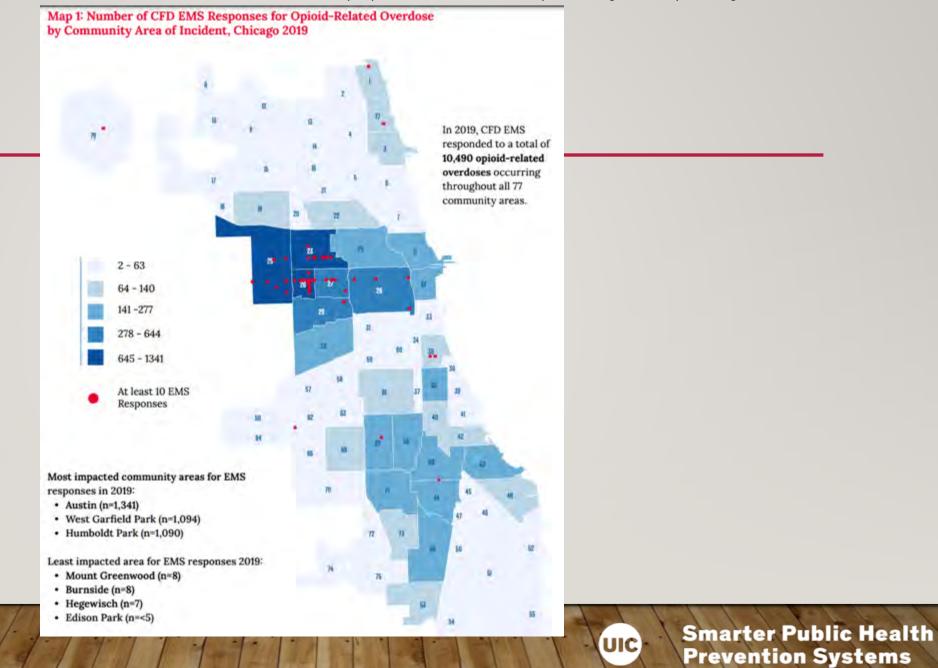
# **OPIOID CRISIS: CHICAGO STATISTICS**

- Men
- Aged 45-64 years old
- Non-Hispanic African-Americans
- Use of combination of other opioids and illicit drugs
  - Cocaine
- High economic hardship
  - Education
  - Income levels, Unemployment
  - Crowded Housing



Smarter Public Health Prevention Systems

Blair Turner, Wilnise Jasmin, Isabel Chung, Ponni Arunkumar, Mark Kiely, Steven Aks, Nikhil Prachand, Allison Arwady. Opioid Overdose Surveillance Report—Chicago 2019. City of Chicago, March 2021.



# WORKPLACE INJURIES

- Especially with prescription pain relievers
- NIOSH, John Howard:



- Potential for addiction may be preceded by injuries that happen in the workplace, with the consequences affecting both an individual's working life as well as their home life
- Exposure to opiate powders -> hazardous environment for healthcare workers





**Smarter Public Health** 

**Prevention Systems** 

# AMA 2021 OVERDOSE EPIDEMIC REPORT

# 2021 OVERDOSE EPIDEMIC REPORT Physicians' actions to help end the nation's drug-related overdose and death epidemic —and what still needs to be done.

"develop and implement systems to collect timely, adequate and standardized data to identify atrisk populations, and implement public health interventions that directly address removing structural and racial inequities."

AMA (2021). 2021 OVERDOSE EPIDEMIC REPORT: Physicians' actions to help end the nation's drug-related overdose and death epidemic—and what still needs to be done. Retrieved from <u>https://end-overdose-epidemic.org/wp-content/uploads/2021/09/AMA-2021-Overdose-Epidemic-Report\_92021.pdf</u>



Smarter Public Health Prevention Systems

#### While data is critical to improving outcomes, current data is:

... incomplete

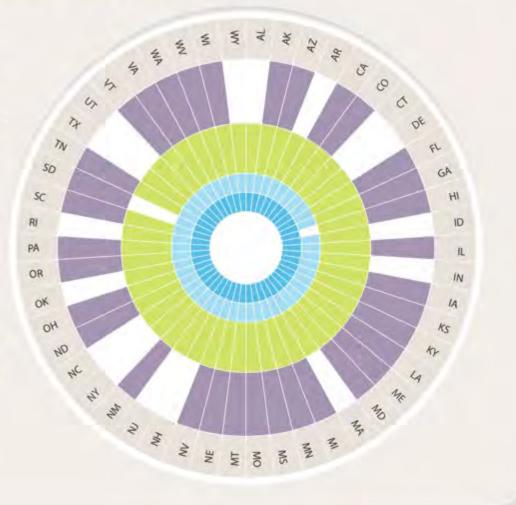
- ... not standardized for comparison
- ... not timely
- ...widely variable from location to location

Difficulties remain in accessing high quality, timely, comprehensive and standardized data. While metrics are generally available for drug-related overdoses, data for non-fatal overdoses and other key indicators are not widely collected or standardized across states and communities. These data gaps greatly hinder understanding of local situations and advancing prevention, treatment and harm reduction efforts.

#### Inadequate data collection prevents effective public health interventions to reduce overdose and death.

Data categories
Prescriptions
PDMP

Fatal overdoses Non-fatal overdoses No data



AMA (2021). 2021 OVERDOSE EPIDEMIC REPORT: Physicians' actions to help end the nation's drugrelated overdose and death epidemic—and what still needs to be done. Retrieved from <u>https://end-</u> overdose-epidemic.org/wp-content/uploads/2021/09/AMA-2021-Overdose-Epidemic-Report 92021.pdf Final Report of the Health Information Technology Advisory Committee's Public Health Data Systems Task Force 2021

### Submitted to the Office of the National Coordinator for Health IT on July 14, 2021

Public Health Data Systems Task Force (2021). Final Report of the Health Information Technology Advisory Committee's Public Health Data Systems Task Force 2021. Retrieved from <u>https://www.healthit.gov/sites/default/files/page/2021-08/2021-07-</u> 14\_PHDS\_TF\_2021\_HITAC%20Recommendations%20Report\_Signed\_508\_0.pdf



Smarter Public Health Prevention Systems

# HITAC RECOMMENDATIONS ON PUBLIC HEALTH DATA SYSTEMS

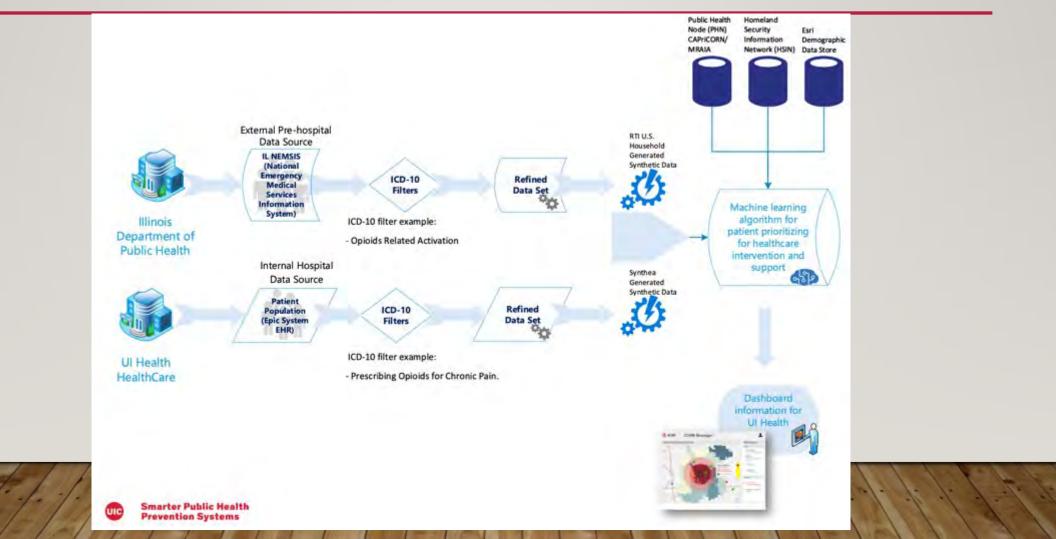
- Improving interoperability
  - NEMSIS
  - Cloud computing
- Synthetic syndromic surveillance to assist "traditionally under-resourced areas to support creation of a public health system able to support health equity and health disparities"
  - Help facilitate interoperability, geolocation
  - Merging with census and other SDOH data
- Explore traditional and non-traditional data sources to assist with early identification of early clusters/outbreaks of disease incidence



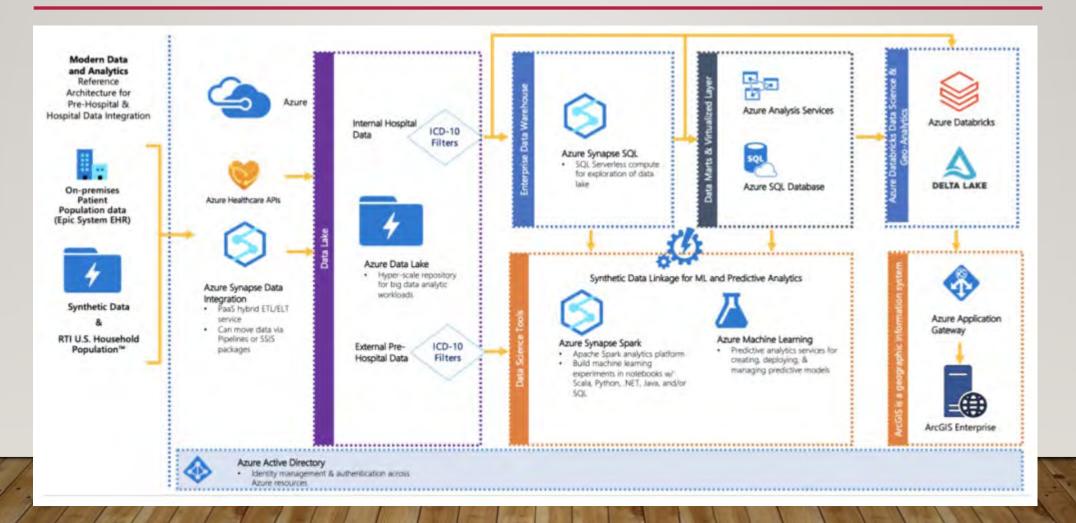
# SPATIOTEMPORAL BIG DATA ANALYSIS OF OPIOID EPIDEMIC IN ILLINOIS

- Spatiotemporal distribution of EMS 911 calls and ambulance dispatches related to drug overdoses
- Obtain Chicago EMS data store in Azure Data Lake. Scripts execute over Azure Cloud
- Opiate cases identified and geospatial information extracted
- Analysis on ArcGIS enterprise
- Enrich opiate cases with Esri demographic and census data of surrounding neighborhoods
- Machine learning to understand features to predict opiate use

### SMARTER PUBLIC HEALTH PREVENTION SYSTEM (SPHPS) SYNTHETIC DATA INTEGRATION OF PRE-HOSPITAL TO HOSPITAL DATA



### AZURE MODERN ANALYTICS ARCHITECTURE FOR SYNTHETIC SYNDROMIC SURVEILLANCE



#### CHICAGO EMS DATA

- National Emergency Medical Services Information System (NEMSIS)
- Identify opiate cases on SQL Server
- Provider's Primary Impression
- Primary Symptom

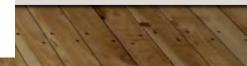
Definition			
		primary problem or most significan , medications, or procedures).	condition which led to
National Element	Yes	Pertinent Negatives (PN)	No
State Element	Yes	NOT Values	Yes
Version 2 Element	E09_15	Is Nilable	Yes
Usage	Required	Recurrence	111
NOT Values (NV) 7701001 - Not Applicable Constraints	7701003 - Not F	Recorded	
Constraints	7701003 - Not F	Recorded	
Pattern (R[0-6][0-9](1,0-9](1,4))?)(R73).9	(((R99)))((A-QSTZ)(0-9)(	0-9A-Z])((10-8A-Z)(1.4))?)	
Data Element Comment			
Code list is represented in ICD-1 https://nemais.org/technical-reso ICD-10-CM Website - http://uts.nim.nih.gov.			



#### eSituation.09 - Primary Sympton Definition The primary sign and symptom present in the patient or observed by EMS personnel. National Element Yes Pertinent Negatives (PN) No State Element Yes NOT Values Yes Version 2 Element E09 13 Is Nillable Yes. Recurrence 1:1 Usage Required Associated Performance Measure Initiatives Airway Cardiac Arrest Pediatric STEMI Stroke Trauma Attributes NOT Values (NV) 7701001 - Not Applicable 7701003 - Not Recorded Constraints Pattern (R)0-6[[0-9](1,[0-9](1,4))7](R731.9))(R99)))/[A-QSTZ][0-9][0-0A-Z])((1,[0-9A-Z](1,4))7) Data Element Comment eSituation 02 (Possible Injury), eSituation 09 (Primary Symptom), eSituation 07 (Chief Complaint Anatomic Location), and eSituation.08 (Chief Complaint Organ System) are grouped together to form the ENS Reason for Encounter Code list is represented in ICD-10-CM Diagnosis Codes. Reference the NEMSIS Suggested Lists at: https://nems/s.org/technical-tesources/version-3/version-3-resources/ ICD-10-CM Wobeite - http://uls.mim.nih.gov

Product - UMLS Metathesaurun

#### https://nemsis.org/



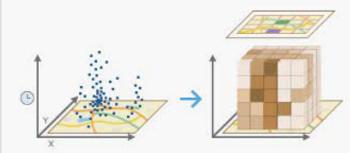
#### CHICAGO EMS DATA

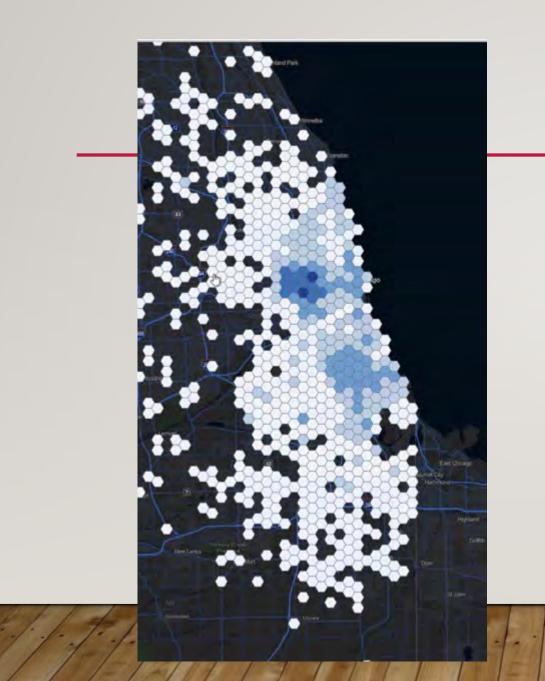
Provider's Primary Impression and/or Primary Symptom = 'Opioid related disorders',
 'Opioid use, unspecified'. Or ICD-10 codes in F11,T40 categories or Z79.891

ProvidersPrimaryimp	PrimarySymptom	WorkRelatedIlnessinj.
Opicid related disord	Gait-Limp/Difficulty	No
Opioid related disord	Vomiting.	No
Opioid related disord	Арлеа	No
Opioid related disord	Abronnal breathing	No
FÚ	Altered mental status	No
Opioid related disord	Analiety or Wormes	No
Opioid use, unspecifi	Abnormal breathing.	No
Opioid use, unspecifi	Slowness/poor respon-	No
Opioid use, unspecifi	Altered mental status	No
Opioid use, unspecifi	Stupor or Semicoma	No
Opicid related disord	Altered mental status:	No
Opicid use, unspecifi	Altered mental status	No
Opioid use, unspecifi	Altered mental status	Na
Opioid use; unspecifi	Altered mental status	No
Opioid related disord	Abnormal breathing	No
Opioid use, unspecifi	Slowness/poor respin	No
FIT	Not Recorded	No
FIT	Coma, unspecified	No
Opioid use, unspecifi	Slowness/poor respo	No
Obioid use unspecifi-	Come unemerified	No

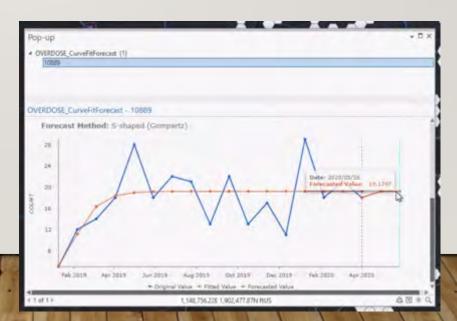
## **ARCGIS ENTERPRISE**

- Geospatial data management, data visualization, analytics, geospatial forecasting of opiates and overdoses
- Space time cubes for all overdoses and opioid cases
- Create predictive models using time series forecasting tools
- Curve fit forecast models
  - Forecast future future values using curve fitting
- Exponential smoothing forecast model predicts values by decomposing time series at each location into seasonal and trend components









lethod	Forecast Equation					
	Xt = a*t+b; a=-0.009804, b=0.137255					
le	Xt = k + a*exp(b*t); k=0.084258, a=-0.000747, b=0.316302					
	Xt = a*t^2+b*t+c; a=0.001548, b=-0.039474, c=0.238390					
	Xt = a*t^2+b*t+c; a=-0.004902, b=0.083333, c=-0.117647					
	Xt = a*t^2+b*t+c; a=-0.002580, b=0.046182, c=-0.083591					
	Xt = k+a*exp(-b*exp(-c*t)); k=0.000000, a=0.224779, b=52.858909, c=0.6076,					
	Xt = a*t^2+b*t+c; a=-0.002580, b=0.046182, c=-0.083591					
	Xt = a*t^2+b*t+c; a=-0.001935, b=0.038313, c=-0.077399					
	Xt = a*t+b; a=-0.007353, b=0.117647					
	Xt = a*t+b; a=0.017157, b=-0.078431					
	Xt = a*t^2+b*t+c; a=0.008256, b=-0.073271, c=0.094943					
	Xt = k+a*exp(-b*exp(-c*t)); k=0.000010, a=0.557301, b=91.371438, c=0.3877.					
	Xt = a*t+b; a=-0.007353, b=0.117647					
	Xt = a*t+b; a=0.014706, b=-0.058824					
	Xt = a*t^2+b*t+c; a=-0.006579, b=0.107714, c=-0.106295					
	Xt = a*t^2+b*t+c; a=-0.005934, b=0.099845, c=-0.158927					
	Xt = k+a*exp(-b*exp(-c*t)); k=0.000000, a=0.194351, b=108.978494, c=0.859.					
	Xt = a*t^2+b*t+c; a=0.004902, b=-0.063725, c=0.254902					
d a	Xt = k + a*exp(b*t); k=0.084258, a=-0.000747, b=0.316302					
	Xt = a*t+b; a=0.009804, b=-0.019608					





#### EXPONENTIAL SMOOTHING FORECAST MODEL

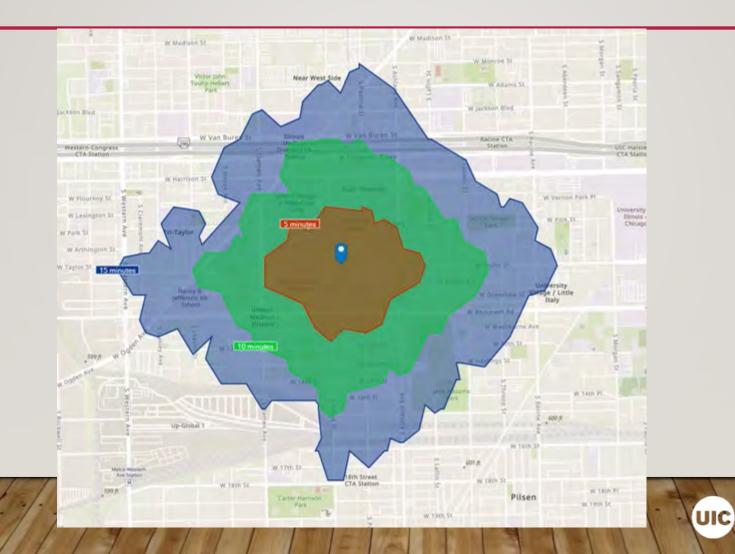




- Geospatial information -> upload into ESRI
- Demographic data store that allows for geocoding and automated enrichment
- USA 2020 demographic data
- USA 2010 Census Demographic Data
- USA 2014/2018 American Community Survey (ACS) Demographic Data,
- USA 2020 Consumer Expenditure data
- USA 2020 Tapestry Segmentation Data.
- Its geography information is updated to 2020/2021.



#### **5-MINUTE WALK TIME**





1740 W Taylor St, Chicago 1740 W Taylor St, Chicago Walk Time: 5 minute radu	o, Illinois, 60612		Prepared by Es
Table (2010) 2 consider only			2000-2010
	2000	2010	Annual Rate
Population	2,564	654	-12.77%
Households	72	60	-1.81%
Nousing Units	85	67	2.35%
Population by Race		Number	Percent
Total		654	100.0%
Population Reporting One Race		622	95.1%
White		251	38.4%
Black		345	22.2%
American Indian		2	0.3%
Asian		195	29.5%
Pacific Islander		1	0.2%
Some Other Race		28	4.3%
Population Reporting Two or More Races		32	4.9%
Total Hispanic Population		79	12.1%
Population by Sex			
Male		302	45.2%
Female		352	53.6%
Population by Age			
Total		655	100,0%
Age 0 - 4		9	1.4%
Age 5 - 9		12	1.8%
Age 10 - 14		11	1.7%
Age 15 - 19		181	27.6%
Age 20 - 24		212	35.4%
Age 25 - 29		94	14.4%
Age 30 - 34		26	4.0%
Age 35 - 39		22	1.4%
Age 40 - 44		13	2.0%
Ade 45 - 49		7	1.1%
Age 50 - 54		8	1.2%
Age 55 - 59		8	1.2%
A00 60 - 64		4	0.6%
Age 65 - 69		7	1.1%
Age 05 - 69 Age 70 - 74		2	0.3%
		7	1.1%
Age 75 - 79		5	0.9%
Age 80 - 64		5	
Age B5+		Þ.	0.9%
Age 16+		613	93.7%
Age 65+		27	6.1%

lesri I	2010 Census Profile		
	1740 W Taylor St, Chicago, Illinois, 60612 S 1740 W Taylor St, Chicago, Illinois, 60612 Walk Time: 5 minute radius		Prepared by Esr
Households by Type			
Total		60	100.0%
Households with 3 Person		20	33.3 <sup>m</sup>
Households with 2+ People		40 27	66.7% 45.0%
Family Households Husband-write Families		9	15.0%
With Own Children			6.7%
		15	30.0%
Other Pamily (No Spouse Pres With Dwn Children	ent)	10	16.7%
Nonfamily Households		13	31.7%
homenny households		12	43.778
All Households with Children		16	26.7%
Multigenerational Households		2	1.3%
Elemented Partner Housebolds		4	6.7%
Male-female		- 4	6.7%
Same-sex		8	0.0%
Average Household State		4.43	
Family Households by Size			
Total		28	100.0%
2 People		11	39.3%
3 People		7	25.0%v
4 People		5	17.9%
5 Phople		3	10.7%
6 People		1	1.6%
7+ People		1	1.6%
Average Family Size		4.25	
Nonfamily Households by Size			
Total		33	100.0%
1 Person		20	60.6%
2 People		6	18.2%
3 People		4	12.1%
# People		2	6.1%
5 Perple		1	3.0%
6 People		8	0.0%
7+ People		0	0.0%
Average Nonfamily Size		4.48	
Population by Relationship and H	desemoid Type		
Totai		654	100.0%
In Households		269	41.1%
In Family Households		420	18.3%
Householder		39	5.8%
Spouse		16	2,4%
Child		49	7.5%
Other relative		13	2.0%
Normalative		5	0.8%
In NonEsmily Husisehblds		145	22.8%
tri Group Quarters		385	58.9%
Institutionalized Population		0	0.0%
Noninstitutionalized Population		385	58.9%



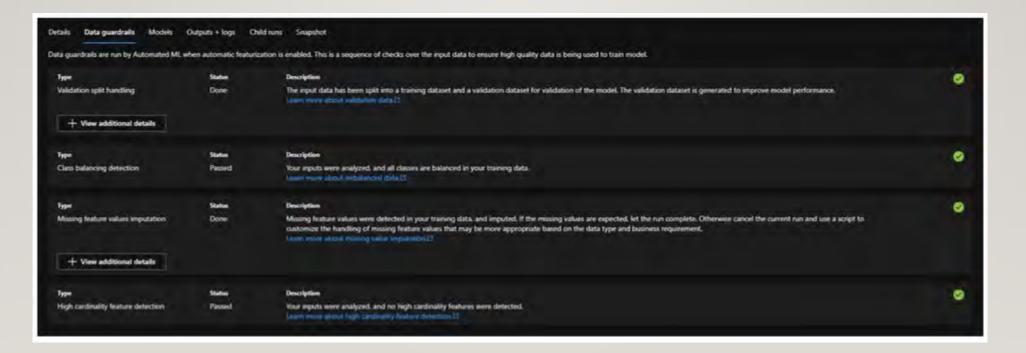


- After data cleaning, variables entered into Azure Machine Learning to run predictions
- Many AutoML experiments created
- Target: opioid activations by EMS. Total overdose case activations by EMS
- Classification machine learning models





• Variables cleaned and filtered. Removed based on overfitting and imbalanced data





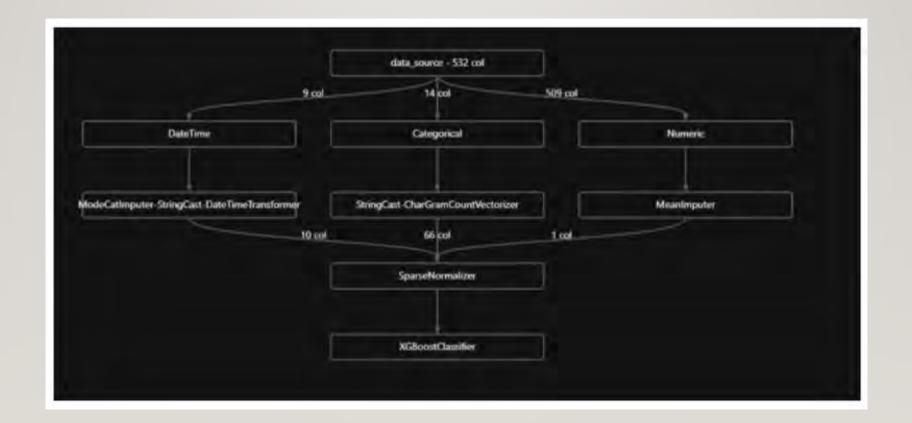
#### RESULTS

• Second to last runs

Algorithm name	Explained	Accuracy ↓
MaxAbsScaler, LogisticRegression		0.82468
MaxAbsScaler, LightGBM		0.82405
MaxAbsScaler, LightGBM		0.82358
SparseNormalizer. XGBoostClassifier		0.82296
StandardScalerWrapper, LightGBM		0.82171
SparseNormalizer. XGBoostClassifier		0.82140
MaxAbsScaler, LightGBM		0.82124
MaxAbsScaler, GradientBoosting		0.82093
MaxAbsScaler, GradientBoosting		0.82093
StandardScalerWrapper, RandomForest		0.81813
SparseNormalizer, LightGBM		0.81563



#### SPARSENORMALIZER, XGBOOST CLASSIFIER



Smarter Public Health Prevention Systems

(UIC)

#### RESULTS

• Final runs

Algorithm name	Explained	Accuracy 1
VotingEnsemble	View explanation	0.84012
StackEnsemble		0.83637
SparseNormalizer, XGBoostClassifier		0.83388
SparseNormalizer, XGBoostClassifier		0.83388
SparseNormalizer, XGBoostClassifier		0.83388
SparseNormalizer, XGBoostClassifier		0.83341
SparseNormalizer, XGBoostClassifier		0.83326
SparseNormalizer, XGBoostClassifier		0.83326
SparseNormalizer, XGBoostClassifier		0.83326
MaxAbsScaler, LightGBM		0.83232
SparseNormalizer, XGBoostClassifier		0.83216



#### **CONSIDERATIONS WITH SYNTHEA**

C:\Synthea\synthea>.\run\_synthea.bat -m "onc\_opioids" -p 255000 Illinois Chicago\_

254984	Elva122 Langworth352 (25 y/o F) Chicago, Illinois
	Drucilla444 Paucek755 (29 y/o F) Chicago, Illinois
	Coleen678 Sauer652 (17 y/o F) Chicago, Illinois
	Tracey100 Gottlieb798 (30 y/o M) Chicago, Illinois
254985	Luigi346 Schmeler639 (39 y/o M) Chicago, Illinois
	Kevin729 Hahn503 (54 y/o M) Chicago, Illinois
254989	Long300 Hammes673 (41 v/o M) Chicago, Illinois DECEASED

		CITY	STATE	COUNTY	ZIP	LAT		LON	_	HE
9	rchard Apt.	Chicago	Illinois	DuPage County	50018	1	41.681		-87.616	
10		Chicago	Illinois	DuPage County	60646		41.774		-87.806	
11	Juite 29	Chicago	Illinois	DuPage County	60616		41.904		-87 779	
12	arade	Chicago	Illinois	DuPage County	50068		41.959		-87.617	
13	Harbor	Chicago	Elinois	DuPage County	60647		41.865		-87.642	
14		Chicago	Illinois	DuPage County	60634		41.944		-87.769	
15	ay	Chicago	minois	DuPage County	60640		41.640		-87.578	
16	ding	Chicago	Illinois	DuPage County	60621		41.734		-87.666	
17	Jnit 29	Chicago	Illinois	DuPage County	50610		41667		-87.629	
18	m	Chicago	Illinois	DuPage County	60661		42.001		-87.689	
19		Chicago	Illinois	DuPage County	60176		41,772		-87.562	
20		Chicago	Illinois	DuPage County	60652		41.986		-87.657	
21	inction	Chicago	Illinois	DuPage County	60610		41.972		-87.785	
22	in .	Chicago	Illinois	DuPage County	60617		41.715		-87.615	
23	Suite 55	Chicago	Illinois	DuPage County	60614		41.809		-87.609	
24	feadow	Chicago	Illinois	DuPage County	60630		41,799		-87.695	
25	ade	Chicago	minois	DuPage County	60604		41.919		-87.672	
26	Gate	Chicago	Illinois	DuPage County	60610		41.815		-87 776	
27	r Unit 36	Chicago	Illinois	DuPage County	60617		41.842		-87.762	
28	hroughwa	Chicago	Illinois	DuPage County	60654		42 029		-87.621	

### PROPOSED METHOD WITH SYNTHEA

- Similar 5 minute walk times
- Enrich synthetic data using USA 2020 demographic data, USA 2010 Census Demographic Data, USA 2014/2018 American Community Survey (ACS) Demographic Data, USA 2020 Consumer Expenditure data, and USA 2020 Tapestry Segmentation Data.
- Azure Machine Learning for similar classification techniques.



## EXPERIENCE WITH SYNTHEA

- Machine learning results not as robust as with real 911 data (NEMSIS).
- Location data not reflective of true demographics of Chicago
- Consider integration of other U.S. Synthetic Household population data (Ex. RTI) into Synthea workflow







### REFERENCES

- AMA (2021). 2021 OVERDOSE EPIDEMIC REPORT: Physicians' actions to help end the nation's drug-related overdose and death epidemic—and what still needs to be done. Retrieved from <a href="https://end-overdose-epidemic.org/wp-content/uploads/2021/09/AMA-2021-Overdose-Epidemic-Report\_92021.pdf">https://end-overdose-epidemic.org/wp-content/uploads/2021/09/AMA-2021-Overdose-Epidemic-Report\_92021.pdf</a>
- Blair Turner, Wilnise Jasmin, Isabel Chung, Ponni Arunkumar, Mark Kiely, Steven Aks, Nikhil Prachand, Allison Arwady. Opioid Overdose Surveillance Report— Chicago 2019. City of Chicago, March 2021.
- DEA Intelligence Report. (2017). The Opioid Threat in the Chicago Field Division (Report No. DEA- CHI-DIR-023-17). DEA United States Drug Enforcement Administration. https://www.dea.gov/documents/2017/2017-06/2017-06-01/opioid-threat-chicago-field-division
- Public Health Data Systems Task Force (2021). Final Report of the Health Information Technology Advisory Committee's Public Health Data Systems Task Force 2021. Retrieved from <a href="https://www.healthit.gov/sites/default/files/page/2021-08/2021-07-14\_PHDS\_TF\_2021\_HITAC%20Recommendations%20Report\_Signed\_508\_0.pdf">https://www.healthit.gov/sites/default/files/page/2021-08/2021-07-14\_PHDS\_TF\_2021\_HITAC%20Recommendations%20Report\_Signed\_508\_0.pdf</a>
- "RTI U.S. Synthetic Household Population TM" *RTI International*. https://www.rti.org/impact/rti-us- synthetic-household-population%E2%84%A2 Accessed July 2021.
- The National Institute for Occupational Safety and Health (NIOSH) (2020, April 13) Opioids in the Workplace. Centers for Disease Control and Prevention. https://www.cdc.gov/niosh/topics/opioids/
- Xiodan Zhou (2020, July 20) Time Series Forecasting 101 Part 4. Forecast and visualize with Exponential Smoothing. ESRI ArcGIS Blog. https://www.esri.com/arcgis-blog/products/arcgis- pro/analytics/time-series-forecasting-101-part-4-forecast-and-visualize-with-exponential-smoothing/





The Office of the National Coordinator for Health Information Technology

# Thank You



- Health IT Feedback Form: https://www.healthit.gov/form/ healthit-feedback-form
- **Twitter:** @onc\_healthIT
- in LinkedIn: Search "Office of the National Coordinator for Health Information Technology"



Subscribe to our weekly eblast at <u>healthit.gov</u> for the latest updates!