

# Machine Learning & Decision Support in Healthcare



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# Financial Disclosures

- None

# Presentation Overview

- What is Machine Learning & how is it integrated into practice
- Coming of age of pharmacogenomics in decision support
- Informatics in clinical care
- The Clinical Informatics Fellowship Training Program

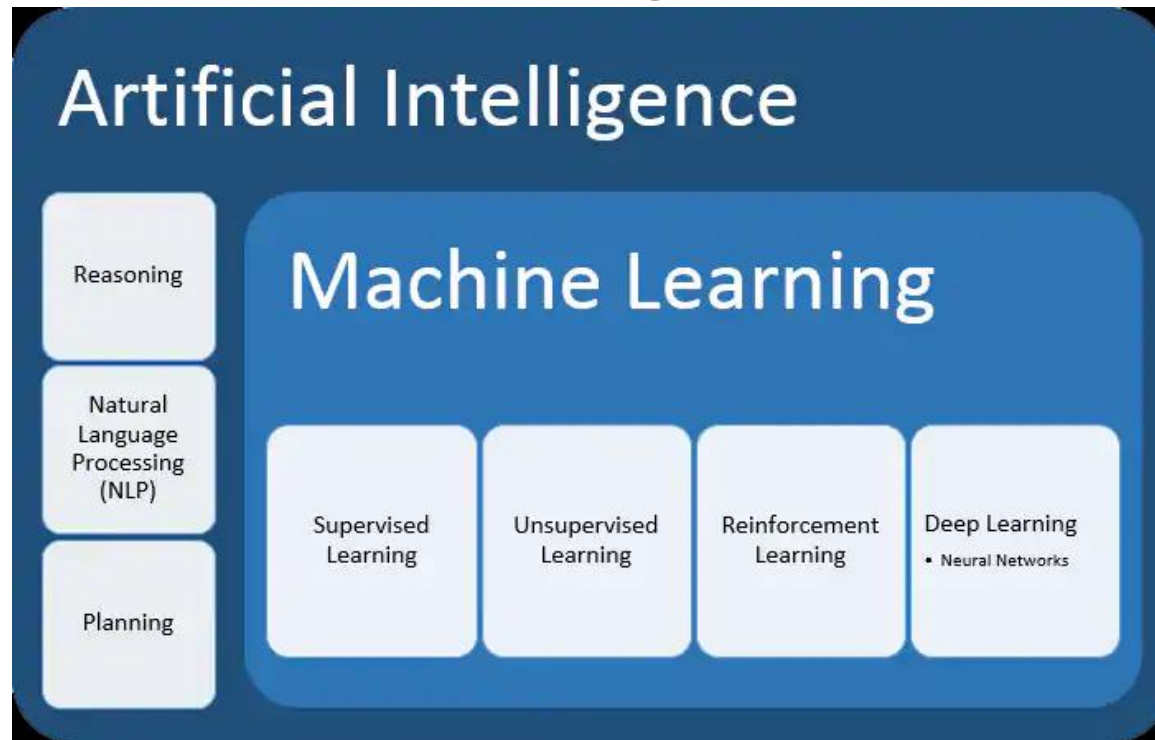
# Learning Objectives

- Describe the role of Machine Learning in healthcare
- Interpret advanced decision support
- Evaluate clinical use cases for Machine Learning algorithms



# Machine Learning

- ...Branch of AI where systems can learn from data, pattern recognition, and decision making.



# Concern



# Reality



# Common Machine Learning Applications

- Amazon recommendations (Market Basket Analysis)
  - Pattern recognition → Ex: If you buy salsa, what else will you buy?

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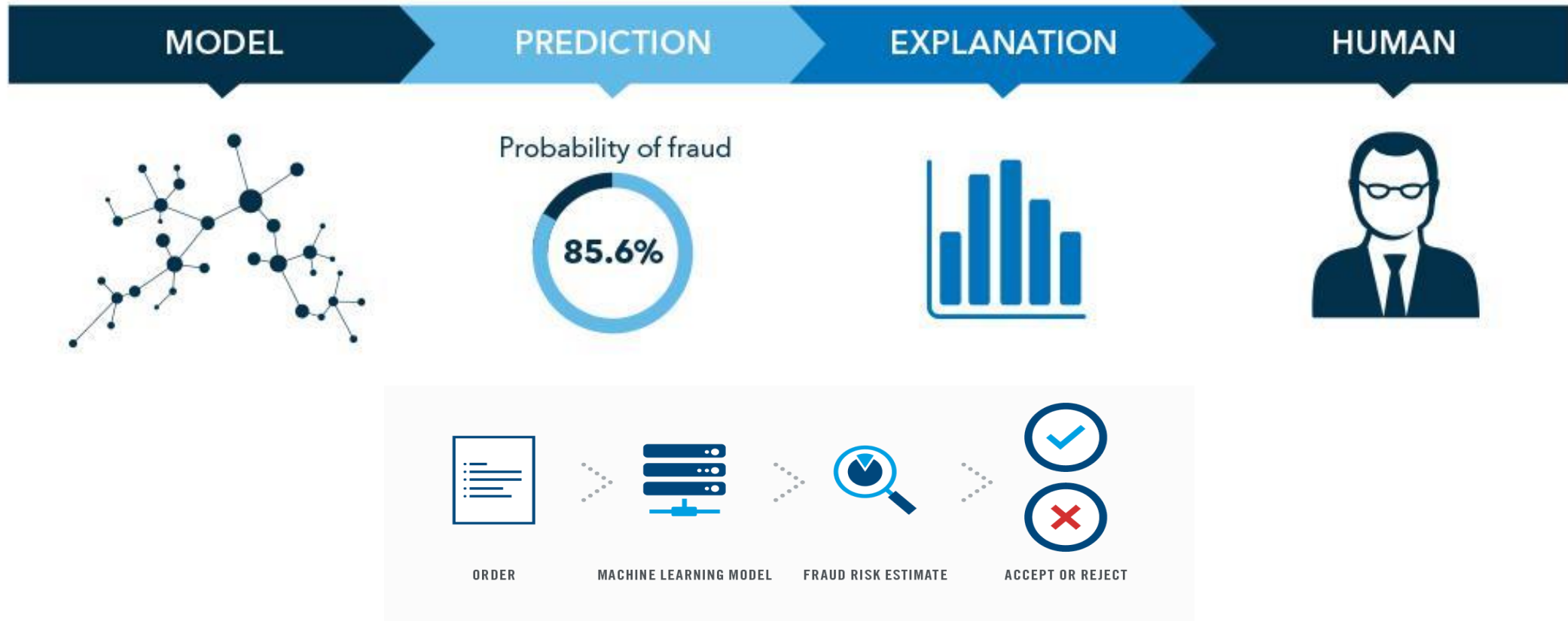
Because you shopped for similar items





# More Machine Learning Applications

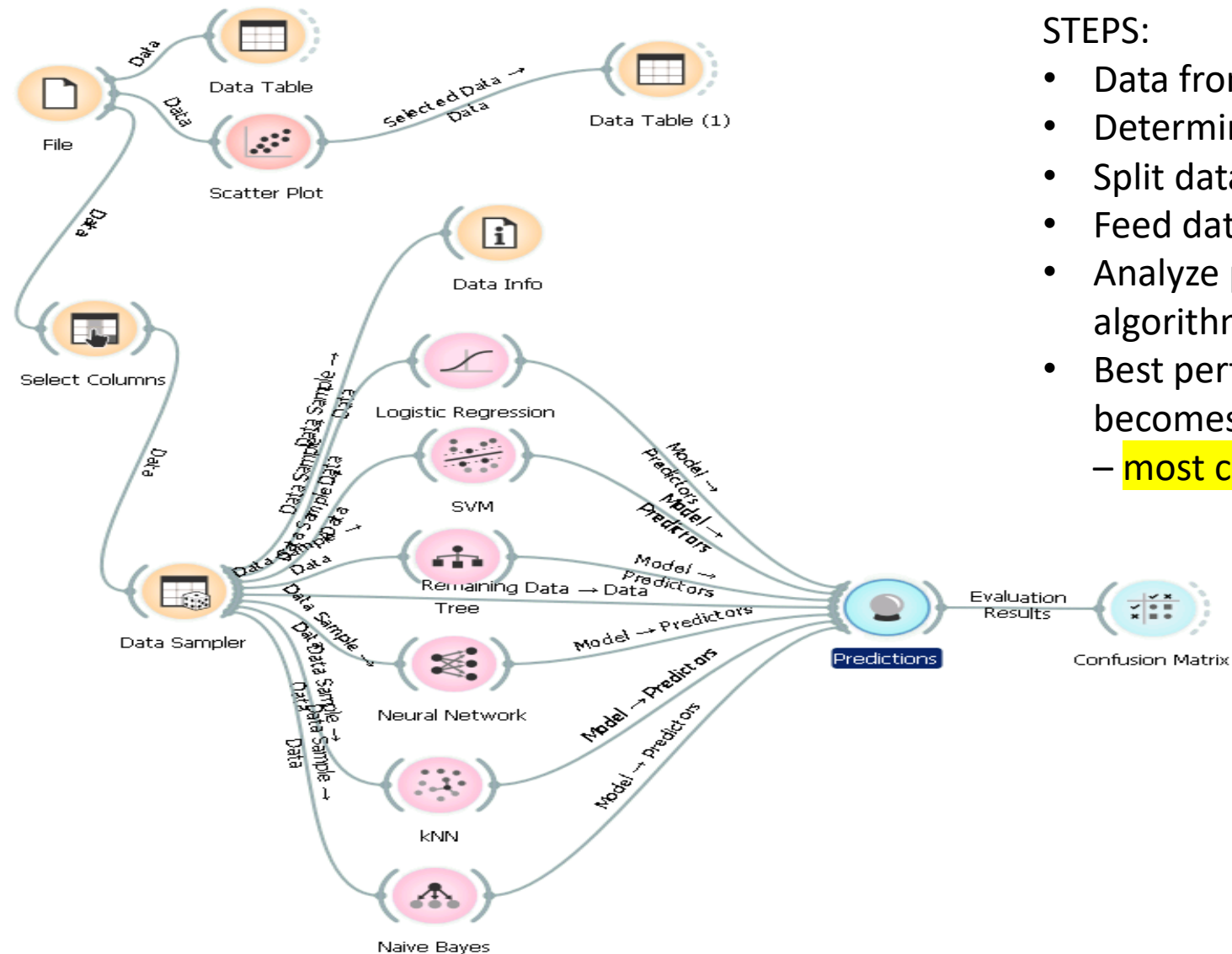
- Fraud Detection



- [https://www.sas.com/en\\_us/insights/articles/risk-fraud/fraud-detection-machine-learning.html](https://www.sas.com/en_us/insights/articles/risk-fraud/fraud-detection-machine-learning.html)
- [http://forms.cybersource.com/LP=1259?dcid=701F0000001lpdo&utm\\_source=The%20Paypers%20Case%20Study&utm\\_medium=Paid%20Advertisement&utm\\_content=EMEA%20Machine%20Learning%20Whitepaper&utm\\_campaign=EMEA\\_Q316\\_Machine%20Learning%20Whitepaper\\_The%20Paypers](http://forms.cybersource.com/LP=1259?dcid=701F0000001lpdo&utm_source=The%20Paypers%20Case%20Study&utm_medium=Paid%20Advertisement&utm_content=EMEA%20Machine%20Learning%20Whitepaper&utm_campaign=EMEA_Q316_Machine%20Learning%20Whitepaper_The%20Paypers)



# Machine Learning Model



## STEPS:

- Data from warehouse
- Determine health factors
- Split data → Training/Test
- Feed data into algorithms
- Analyze performance of algorithms
- Best performing algorithm becomes the model (least error – **most correct classification**)

# Download and Use for Free...



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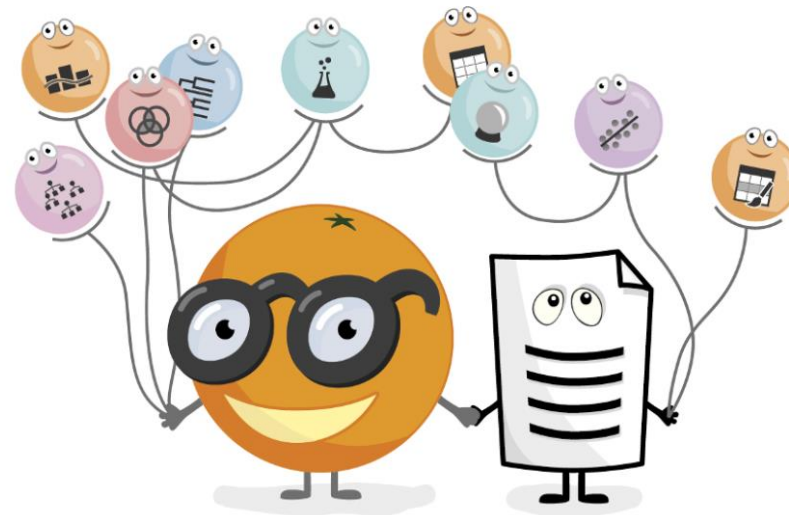
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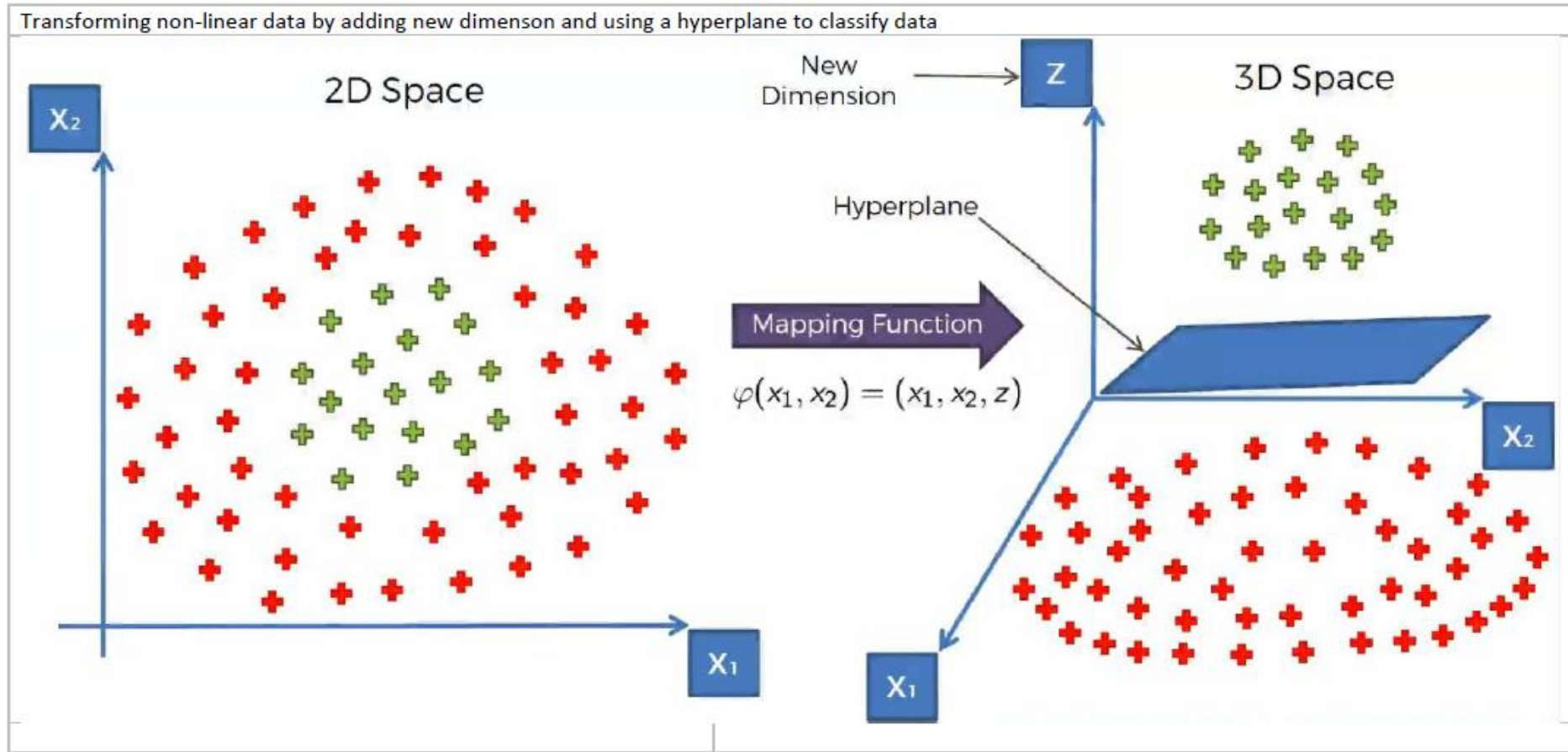
## Data Mining Fruitful and Fun

Open source machine learning and data visualization for novice and expert.  
Interactive data analysis workflows with a large toolbox.

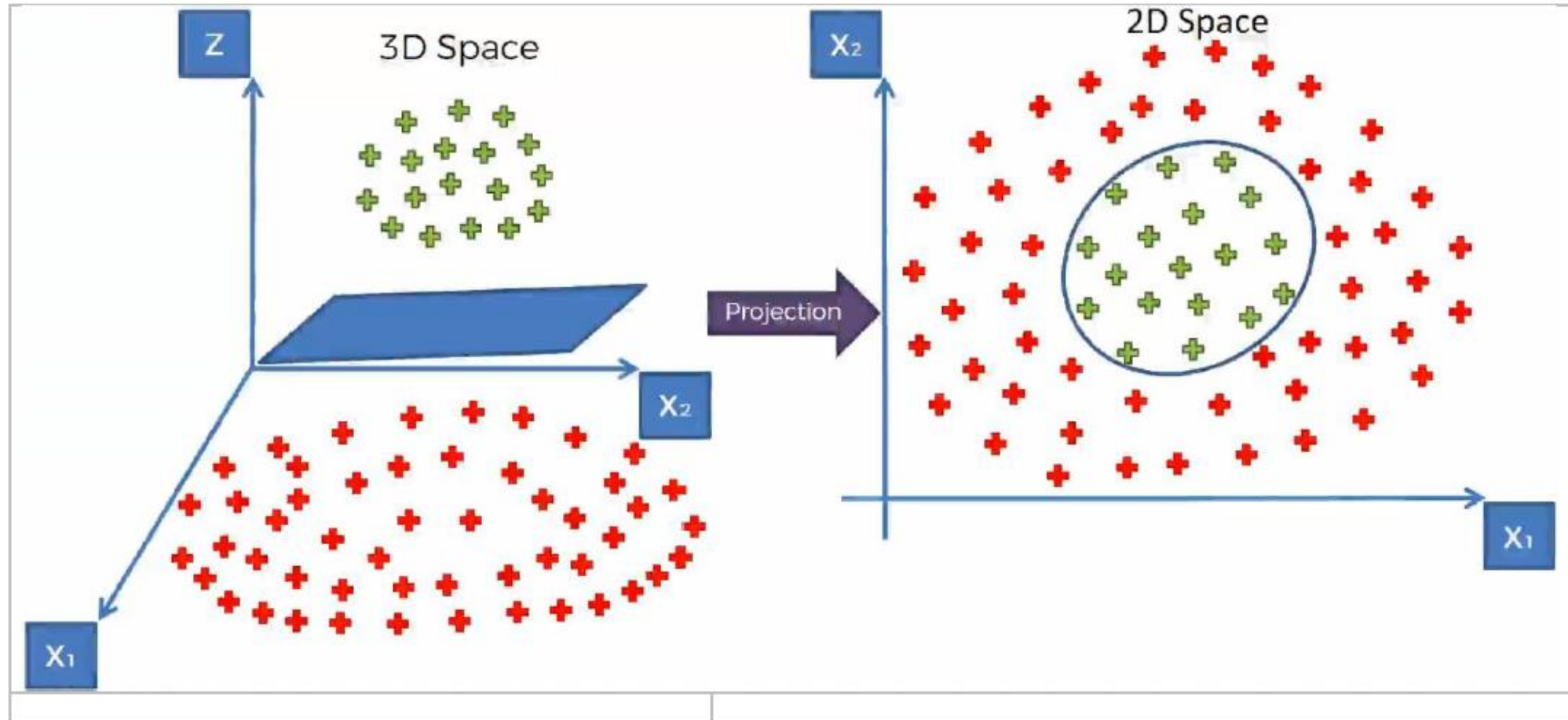
[Download Orange](#)



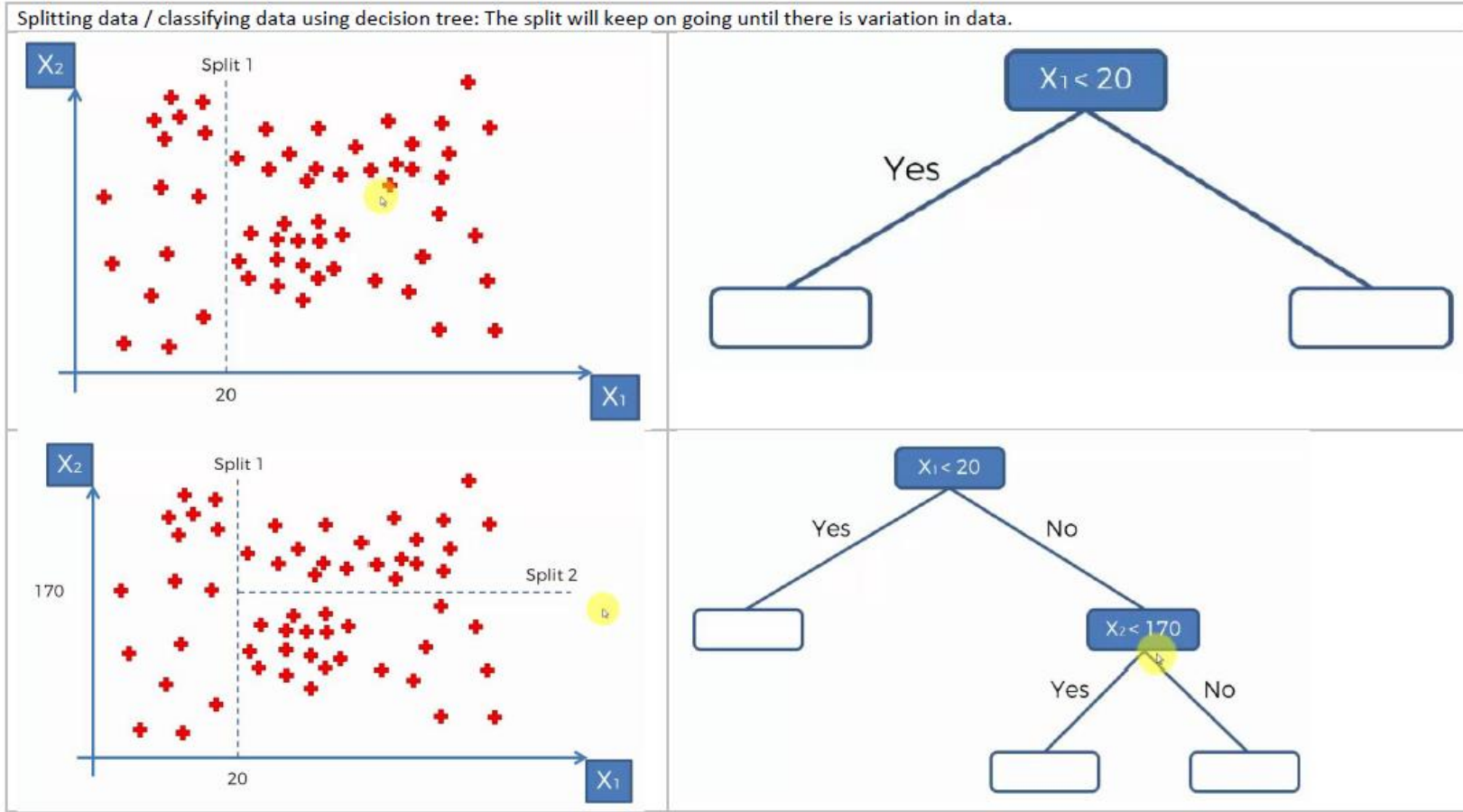
# Classify Your Data



# Projections



# Variation in Data



# Prediction

- Analysis of health data can lead to → Pattern Recognition
  - Labs
  - Vitals
  - Medications
  - Compliance
  - Follow up
  - Diagnoses
  - Genomics
- Pattern Recognition leads to → PREDICTION



# Example of Data Input (Social Determinants)

- Basic item defining factors
- Z-codes: social determinant codes

RowID	Gender	VisitDateTime	Not_Hisp	Ethnicity	Black	White	Asian	American	Native_H	Race_decl	Divorced	Married	Never_M	Separated	Widowed	MaritalSta	Not_Empl	Employed	Employed	Self_Empl	Retired	Unknown	Employm
1	M	11/1/2018 16:04	1	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
2	F	9/11/2018 9:15	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
3	M	8/17/2018 13:40	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
4	M	12/13/2018 12:00	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
5	F	11/8/2017 12:35	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
6	M	4/25/2017 9:00	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
7	F	6/23/2017 15:54	1	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0

Z550	Z551	Z552	Z553	Z554	Z558	Z559	Z560	Z561	Z562	Z563	Z564
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0



# ICD-codes



## SOCIAL DETERMINANTS OF HEALTH ICD-10 CODE LIST EXHIBIT 4-1

Revision Dates: 2/9/2018

### Social Determinants of Health ICD-10 Code List

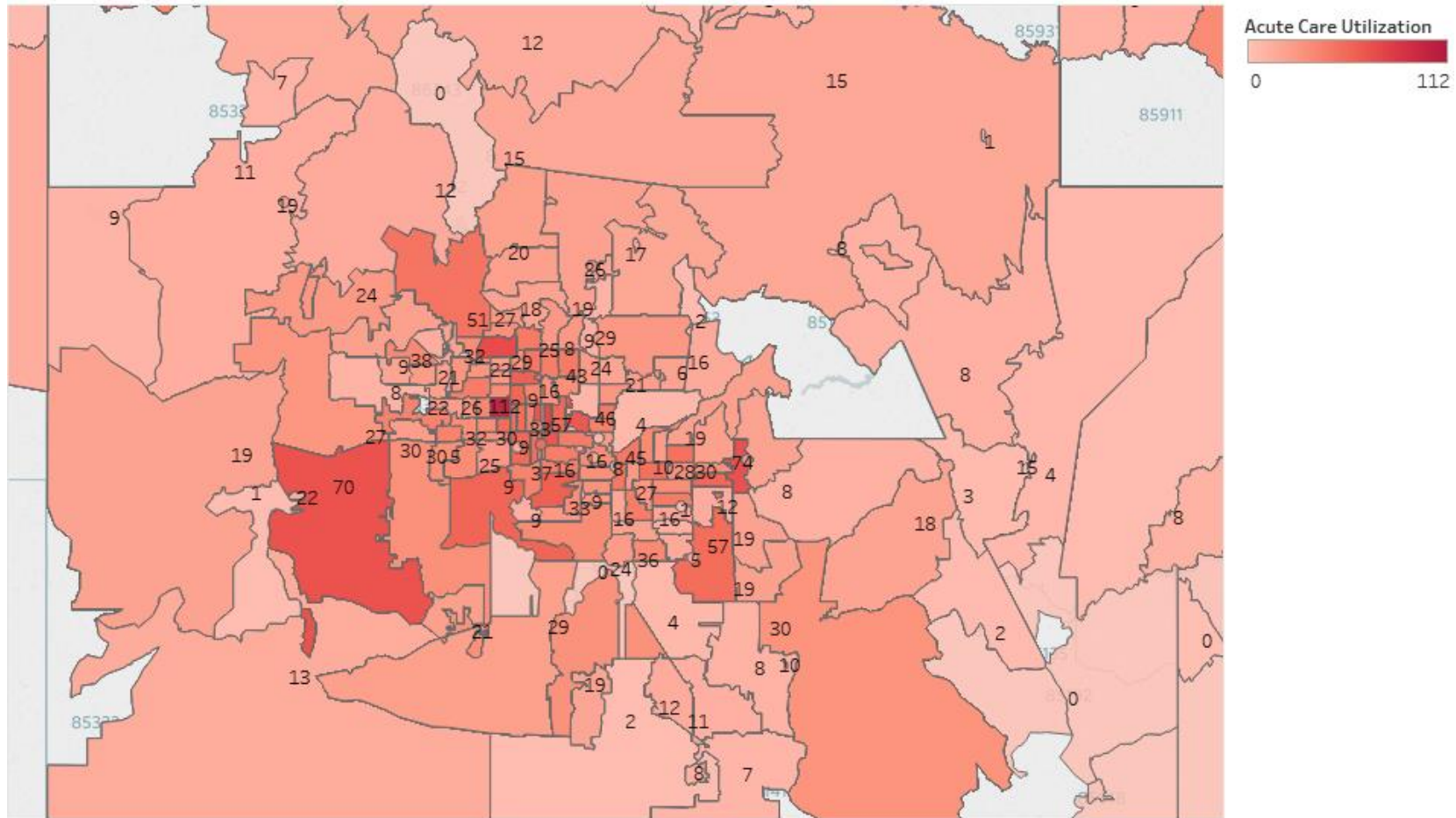
Beginning on March 1<sup>st</sup>, 2018, the following ICD-10 diagnosis codes will be defined as **Social Determinants of Health** codes.

Please note that Social Determinants of Health codes may be added to or updated on a quarterly basis. Providers should remain current in their thorough utilization of these codes.

Z659	Problem related to unspecified psychosocial circumstances
------	---

ICD-Code	Description
Z550	Illiteracy and low-level literacy
Z551	Schooling unavailable and unattainable
Z552	Failed school examinations
Z553	Underachievement in school
Z554	Educational maladjustment and discord with teachers and classmates
Z558	Other problems related to education and literacy
Z559	Problems related to education and literacy, unspecified
Z560	Unemployment, unspecified
Z561	Change of job
Z562	Threat of job loss

# Ability to Localize Care Needs



# End Goal

- Patient outreach:
  - Programs built around advanced analytics
  - How will you do with these patients?



# Next Application: PTSD

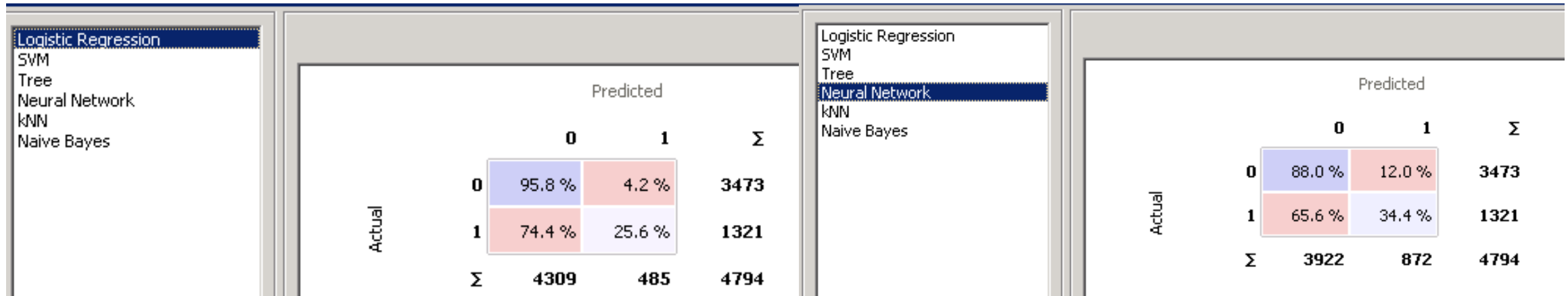
## Social Determinants of Health for PTSD

### ICD-10 Code

<u>ICD-10 Code</u>	<u>Description</u>
Z560	UNEMPLOYMENT, UNSP
Z5681	SEXUAL HARASSMENT ON THE JOB
Z5682	MILITARY DEPLOYMENT STATUS
Z5689	OTHER PROBLEMS RELATED TO EMPLOYMENT
Z569	UNSP PROBLEMS RELATED TO EMPLOYMENT
Z590	HOMELESSNESS
Z591	INADEQUATE HOUSING
Z594	LACK OF ADEQUATE FOOD AND SAFE DRINKING WATER
Z595	EXTREME POVERTY
Z596	LOW INCOME
Z600	PROBLEMS OF ADJUSTMENT TO LIFE-CYCLE TRANSITIONS
Z602	PROBLEMS RELATED TO LIVING ALONE
Z609	PROBLEM RELATED TO SOCIAL ENVIRONMENT, UNSP
Z62810	PERSONAL HISTORY OF PHYSICAL AND SEXUAL ABUSE IN CHILDHOOD
Z62811	PERSONAL HISTORY OF PSYCHOLOGICAL ABUSE IN CHILDHOOD
Z62812	PERSONAL HISTORY OF NEGLECT IN CHILDHOOD
Z62819	PERSONAL HISTORY OF UNSP ABUSE IN CHILDHOOD
Z629	PROBLEMS RELATED TO UPBRINGING
Z630	PROBLEMS IN RELATIONSHIP WITH SPOUSE OR PARTNER
Z634	DISAPPEARANCE AND DEATH OF FAMILY MEMBER
Z635	DISRUPTION OF FAMILY BY SEPARATION AND DIVORCE
Z6371	STRESS IN FAMILY DUE TO RETURN OF FAMILY MEMBER FROM MILITARY DEPLOYMENT
Z6379	OTHER STRESSFUL LIFE EVENTS AFFECTING FAMILY AND HOUSEHOLD
Z650	CONVICTION IN CIVIL AND CRIMINAL PROCEEDINGS WITHOUT IMPRISONMENT
Z651	IMPRISONMENT AND OTHER INCARCERATION
Z652	PROBLEMS RELATED TO RELEASE FROM PRISON
Z653	PROBLEMS RELATED TO OTHER LEGAL CIRCUMSTANCES
Z654	VICTIM OF CRIME AND TERRORISM
Z655	EXPOSURE TO DISASTER, WAR, AND OTHER HOSTILITIES
Z7141	ALCOHOL ABUSE COUNSELING AND SURVEILLANCE OF ALCOHOLIC

# Interpreting Machine Learning Results

- Which algorithmic model predicted most correctly?
  - Training data is classified and can confirm if machine “learned correctly”



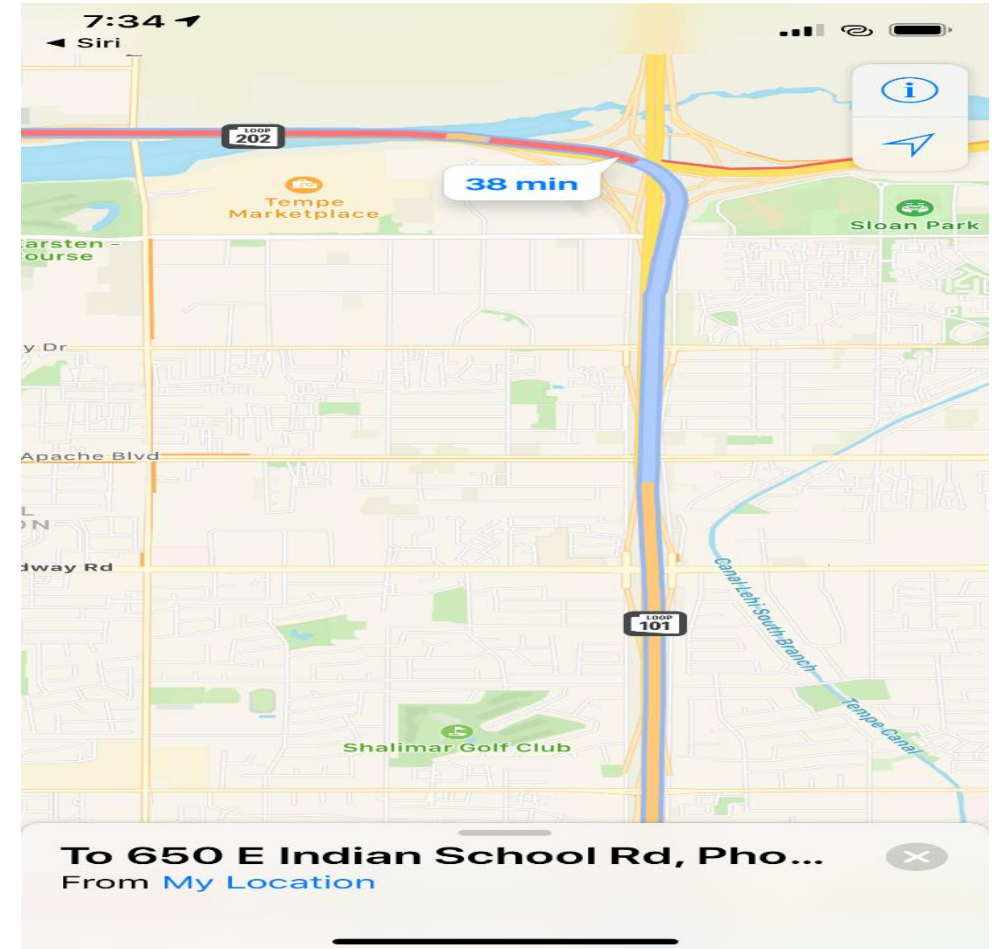
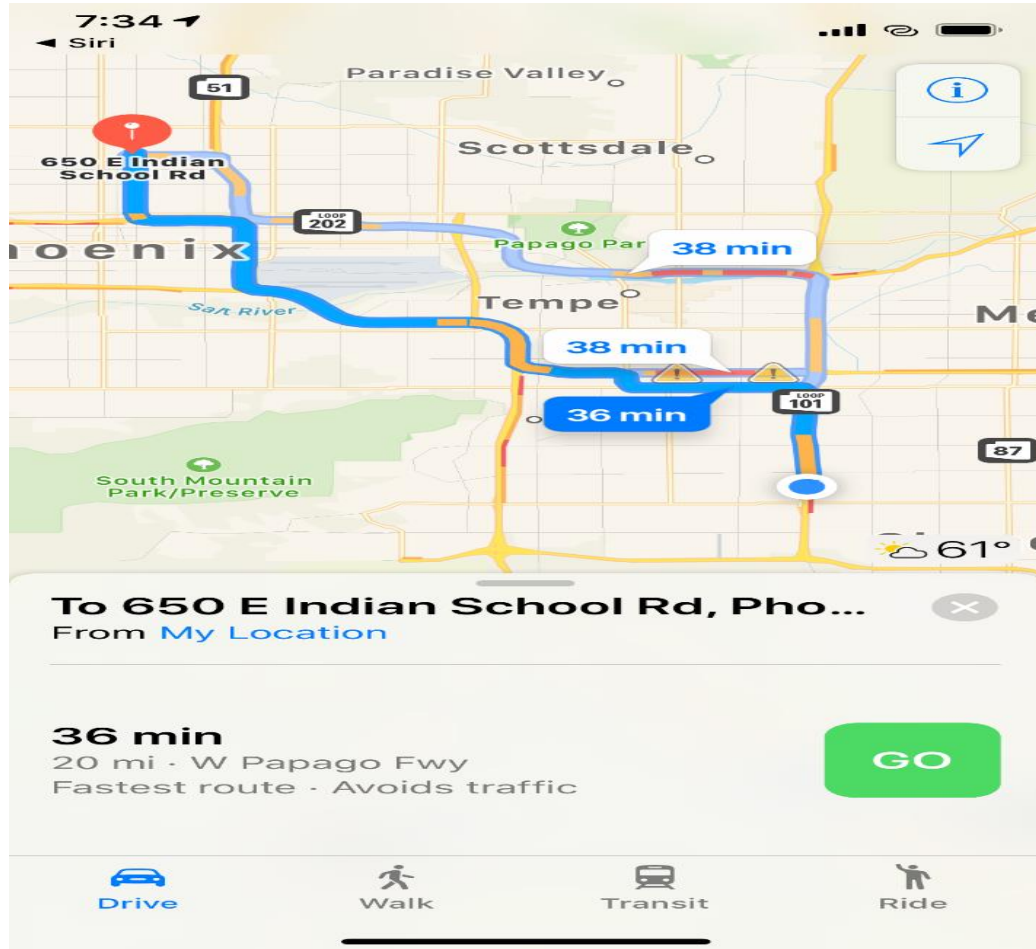
# Moment of Reflection



# Support the Decision



# Decision Support





# Clinical Decision Support



- CDS – clinical knowledge or patient-related information, filtered or presented at appropriate times to enhance patient care.
- Clinical decision support systems (CDSS) are computer systems designed to impact clinician decision making about individual patients at the point in time that these decisions are made.

# 5 Rights of CDS:

- Right **information**,
- Right **person**,
- Right **format**,
- Right **channel**,
- Right time in **workflow**.



# EHR Decision Support

- Examples...

# CDS...

	Risk Level	Risk Factors
<input checked="" type="radio"/>	High Risk	<ul style="list-style-type: none"> <li>• Elective hip or knee arthroplasty</li> <li>• Hip, pelvic, or severe lower extremity fractures</li> <li>• Acute spinal cord injury with paresis</li> <li>• Multiple major trauma</li> <li>• Morbid obesity (&gt; 150 kg)</li> </ul>
<input type="radio"/>	Moderate Risk	<ul style="list-style-type: none"> <li>• Inpatient with an Acute Medical Illness or Surgery</li> </ul> <p><b>Including but not limited to:</b> h/o PE or DVT, acute CHF, malignancy, age &gt; 40, pneumonia, cellulitis, BMI &gt; 30, limited mobility, active tobacco use, CVL or PICC line in place, sepsis, ischemic CVA or previous CVA with paresis, recent major surgery (&lt; 3 months), myocardial infarction (&lt; 3 months), varicose veins, acute or chronic lung disease, severe dehydration, IBD, sickle cell disease, nephrotic syndrome, on estrogen based therapy, post partum &lt; 1 month, collagen vascular disease, etc...</p>
<input type="radio"/>	Low Risk	<p>Less than 5% of inpatients are low risk:</p> <ul style="list-style-type: none"> <li>• Observation patients</li> <li>• Surgery less than 30 minutes</li> <li>• Expected length of stay less than 48 hours</li> <li>• Zero risk factors</li> <li>• <b>Already on therapeutic anticoagulation</b> [i.e. warfarin, dabigatran (Pradaxa), rivoraxaban (Xarelto)]</li> </ul>

## Orders for High Risk Patients

Prophylaxis for High Risk Patient: Choose one pharmacologic option and one mechanical option.

### Pharmacologic:

<input type="radio"/> enoxaparin	30 mg SubQ, Injection, Q12H (int)	(CrCl > 30 mL/min, weight ≤ 150 Kg)
<input type="radio"/> enoxaparin	30 mg SubQ, Injection, Q24H	(CrCl 15 to 30 mL/min)
<input type="radio"/> enoxaparin	40 mg SubQ, Injection, Q12H (int)	(CrCl > 30 mL/min, weight > 150 Kg)
<input type="radio"/> heparin	5,000 unit(s) SubQ, Soln, Q8H (int)	(In hip and knee replacement, spinal cord injury, and trauma patients use heparin ONLY if CrCl < 15 mL/min or on renal replacement therapy)

# Decision Support & Precision Medicine

- **Precision medicine** is a medical **model** that proposes the customization of healthcare, with medical decisions, treatments, **practices**, or **products** being tailored to the **individual** patient.

Lu, Y.-F.; Goldstein, D. B.; Angrist, M.; Cavalleri, G. (24 July 2014). "Personalized Medicine and Human Genetic Diversity". *Cold Spring Harbor Perspectives in Medicine*. 4 (9): a008581–a008581.






# My Pharmacogenomic Profile

Test Details			
Gene	Genotype	Phenotype	Alleles Tested
ANKK1/DRD2	DRD2:Taq1A A/G	Altered DRD2 function	DRD2:Taq1A
Apolipoprotein E	ε3/ε4	Altered APOE function	ε2, ε4
COMT	Val158Met A/G	Intermediate COMT Activity	Val158Met
CYP1A2	*1A/*1W	Normal Metabolizer- Possible Inducibility	*1C, *1D, *1E, *1F, *1J, *1K, *1L, *1V, *1W
CYP2B6	*1/*6	Intermediate Metabolizer	*16, *18, *22, *5, *6, *7, *9
CYP2C19	*1/*2	Intermediate Metabolizer	*10, *17, *2, *3, *4, *4B, *5, *6, *7, *8, *9
CYP2C9	*1/*1	Normal Metabolizer	*11, *2, *3, *4, *5, *6
CYP2D6	*1/*1	Normal Metabolizer	*10, *12, *14A, *14B, *17, *2, *29, *3, *4, *41, *4M, *6, *7, *8, *9, *5 (gene deletion), XN (gene duplication)
CYP3A4	*1/*1	Normal Metabolizer	*1B, *2, *22, *3
CYP3A5	*3/*3	Poor Metabolizer	*2, *3, *3B, *3C, *6, *7, *8, *9
Factor II	rs1799963 GG	Normal Thrombosis Risk	rs1799963
Factor V Leiden	rs6025 CC	Normal Thrombosis Risk	rs6025
MTHFR	c.665C>T GG	Normal MTHFR Activity	c.665C>T
MTHFR	c.1286A>C TT	Normal MTHFR Activity	c.1286A>C
OPRM1	A118G A/G	Altered OPRM1 Function	A118G
SLCO1B1	521T>C T/T	Normal Function	521T>C
VKORC1	-1639G>A G/G	Low Warfarin Sensitivity	-1639G>A

# Meaning of Results

Potentially Impacted Medications			
Category	Standard Precautions	Use With Caution	Consider Alternatives
Anti-HIV Agents	Dolutegravir (Tivicay®, Triumeq®) Raltegravir (Isentress®, Dutrebis®)		
Anti-Hyperuricemics and Anti-Gout Agents	Colchicine (Mitigare®) Febuxostat (Uloric®) Lesinurad (Zurampic®)		
Antimalarials	Proguanil (Malarone®)		
Antiplatelets	Prasugrel (Effient®) Ticagrelor (Brilinta®) Vorapaxar (Zontivity®)		Clopidogrel (Plavix®)
Antipsychotics	Aripiprazole (Abilify®, Aristada®) Asenapine (Saphris®) Brexipiprazole (Rexulti®) Cariprazine (Vraylar®) Chlorpromazine (Thorazine®) Fluphenazine (Prolixin®) Haloperidol (Haldol®) Iloperidone (Fanapt®) Loxapine (Loxitane®, Adasuve®) Lurasidone (Latuda®) Paliperidone (Invega®) Perphenazine (Trilafon®) Pimavanserin (Nuplazid®) Pimozide (Orap®) Quetiapine (Seroquel®) Risperidone (Risperdal®)	Clozapine (Clozaril®) Olanzapine (Zyprexa®)	

# Deeper Interpretation

-  **Bupropion (Wellbutrin®, Zyban®, Aplenzin®, Contrave®)**  
Possibly Decreased Response to Bupropion (CYP2B6 \*1/\*6 Intermediate Metabolizer) Evidence Level: **Informative**  
Bupropion is metabolized to its active metabolite hydroxybupropion by CYP2B6. This metabolite contributes to the therapeutic effects of bupropion when used as a smoking cessation agent or as an antidepressant. Individuals who are CYP2B6 intermediate metabolizers may or may not have lower blood levels of hydroxybupropion which may or may not result in a reduced response to bupropion treatment. Bupropion can be prescribed at standard label-recommended dosage with careful monitoring of the patient's response. Therapeutic monitoring of hydroxybupropion levels may be considered to guide dosing adjustment.
-  **Clobazam (Onfi®)**  
Possible Sensitivity to Clobazam (CYP2C19 \*1/\*2 Intermediate Metabolizer) Evidence Level: **Actionable**  
In CYP2C19 intermediate metabolizers, plasma levels of the active metabolite N-desmethyloclobazam were 2-fold higher than those found in CYP2C19 normal metabolizers. The dose adjustment for intermediate metabolizers is not well established, and therefore the recommendation for poor metabolizers is proposed. The starting dose should be 5 mg/day, and dose titration should proceed slowly according to weight. Patients should be titrated initially to 10 mg /day ( $\leq 30$  kg body weight) or 20 mg/day ( $>30$  kg body weight). If necessary and based upon clinical response, an additional titration to the maximum doses 20 mg/day ( $\leq 30$  kg body weight) or 40 mg/day ( $>30$  kg body weight) may be started on day 21.
-  **Clopidogrel (Plavix®)**  
Reduced Response to Clopidogrel (CYP2C19 \*1/\*2 Intermediate Metabolizer) Evidence Level: **Actionable**  
Consider alternative therapy. Examples of alternative drugs: prasugrel (contraindicated in TIA/Stroke patients), ticagrelor, aspirin, aspirin plus dipyridamole.
-  **Clozapine (Clozaril®)**  
Possible Non-Response to Clozapine (CYP1A2 \*1A/\*1W Normal Metabolizer- Possible Inducibility) Evidence Level: **Informative**  
Smokers may be at risk for non-response at standard doses and may require higher doses. There is an association between high clozapine doses and the risk of seizures, and therefore careful monitoring is recommended during dosing adjustment. Smoking cessation may increase plasma drug levels, leading to adverse events. Therefore, therapeutic drug monitoring accompanied by dose reduction is recommended in patients who have quit smoking.
-  **Dexmethylphenidate (Focalin®)**  
Decreased Response to Dexmethylphenidate (COMT Val158Met A/G Intermediate COMT Activity) Evidence Level: **Informative**

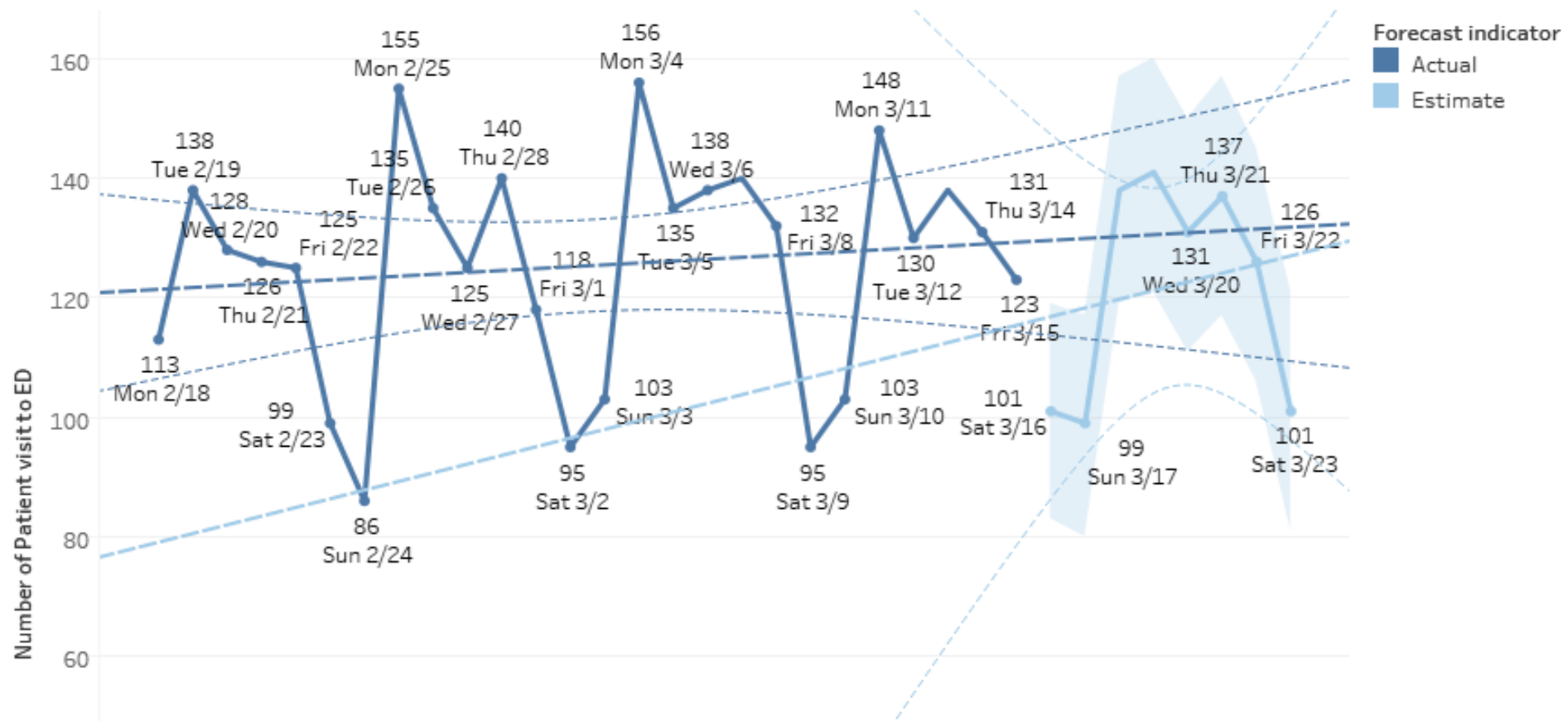


# Integrate the Results!

- Input of results obtained in a structured manner
- Hard wire drug orders to those results
  - Think of Lab orders linked to alerts
  - Allergy profiles linked to medication orders
  - Drug-drug interactions

# Administrative Decision Support

Number of ED visits count by day and disposition



# Rapid Fire

- Other informatics applications
- Tools
- CI Fellowship
- Technology

# Analytics in Action: Lung CA Screening

## ELCAP

**Definition/Cohort:** Early Lung Cancer Action Program (ELCAP)  
 All living tobacco diagnosed Veterans within last 2 years. Shows most recent diagnosis, if CT Scan & type in last year, plus primary care info and if COPD diagnosis  
**How to use this report:** Ensure patients on this list are scheduled for SMI qualifying care including as listed above.  
**Data Source:** VISN Data Warehouse (VDW)  
**Data Frequency:** updated nightly, looks back one year  
**Requestor:** Dr Samuel Aguayo & Providencia Morales, RN  
**Report Created by:** [Pete Fredricks, RN. \(Click to email\)](#)

Tobacco ICD10	Tobacco Diagnosis	Tobacco Diagnosis Date	Primary Secondary	On Problem List	COPD Asthma	CT Name	Reason For Study	Imaging Status	Last Radiology Activity	Patient Name	Patie SSN
Z72.0	Tobacco use	7/5/2017 10:30:00 AM	S	no	No					PatientName, First	
F17.200	Nicotine dependence, unspecified, uncomplicated	7/6/2017 2:00:00 PM	S	Yes	No					PatientName, First	
Z72.0	Tobacco use	7/10/2017 1:30:00 PM	S	no	Yes					PatientName, First	
Z72.0	Tobacco use	7/3/2017 2:00:00 PM	S	no	No					PatientName, First	
Z72.0	Tobacco use	7/11/2017 2:30:00 PM	S	no	No					PatientName, First	
Z72.0	Tobacco use	7/3/2017 8:00:00 AM	S	no	No					PatientName, First	
F17.210	Nicotine dependence, cigarettes, uncomplicated	7/11/2017 1:00:00 PM	S	no	Yes					PatientName, First	
Z72.0	Tobacco use	7/7/2017 1:00:00 PM	P	no	No					PatientName, First	
Z72.0	Tobacco use	7/12/2017 1:00:00 PM	S	no	Yes					PatientName, First	
Z72.0	Tobacco use	7/7/2017 2:30:00 PM	S	no	No					PatientName, First	
Z72.0	Tobacco use	7/11/2017 11:20:21 AM	S	no	No					PatientName, First	

**Parameters**

Station

Select tobacco diagnosis date

COPD Diagnosed?

Select Age



# Analysis Leading to the Right Person



CAN Score
Patient Name
SSN
Age
Probability of Event
Diagnoses Count
ANEMIA
ASTHMA
CHF
COPD
CRF
CVA
DIABETES
DEMENTIA
DEPRSN
HTN
IHD

OBESITY
OSTEO
PTSD
PVD
Home Tele- Health
PALLIATIVE CARE
Last Pal Care Visit
HBPC
Last HBPC Visit
2yr ER/UC Visit Count
2yr Disch Count
Last Disch Date
2yr PC Visit Count
Last PC Visit Location
Last PC Visit Date
Next PCAppt Date
Next PC Visit Location

# Analytics in Action: Fall Risk

## Tempe and Chandler FD Contact List

Description: A list of patients residing in Chandler or Tempe, that have: CAN score >94, or a 5 day Post inpatient visit, or a 5 day post ED visit, or a 90 day post Fall diagnosis, or Medication count > 1, or Diagnosis count > 1, or Fall Risk Diagnosis count > 1

Data Refresh: This data is current from the time the warehouse is updated (approx 0030).

Data sources: EDIS, VISN Data Warehouse (VDW)

Informaticist/designer: Michael Smith RN.Clinical Analytics . Published: 5/2/2016 Rev: 2/22/2017

Weighted Score	Name	Last4	Age	CAN Score	Tele Health Encounter	Inpatient D/C	Fall Date	Joint Replacement Date Time	ED Visit Date	ED Visit Reason	Diagnosis Count	Med Count	Fall Risk Diagnosis Count	last Fall Class Date	Street Address1	Street Address2	City	Zip	Cell	residential	Work
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# Registries

- Paraphrased Definition for Clinical Use:
  - Code based (ICD) data that evaluates outcomes of a particular condition/disease.
    - Combines data from multiple sources so that it can be queried quickly



# Breast Care Registries




Select Station / Healthcare System

End Date

Age Restriction

Mammogram Type

Provider Name

Find | Next   

Page 1 of 2

36 Total Records

\*\* MMG = Mammogram Data Last Refreshed: 1/6/2019 10:48:57 PM

Provider Name	Last Name, First	VAID	Last MMG Date	BI-RADS Code	Next MMG Due	MMG Type	Order Information	Age	Gender
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# CI Fellowship

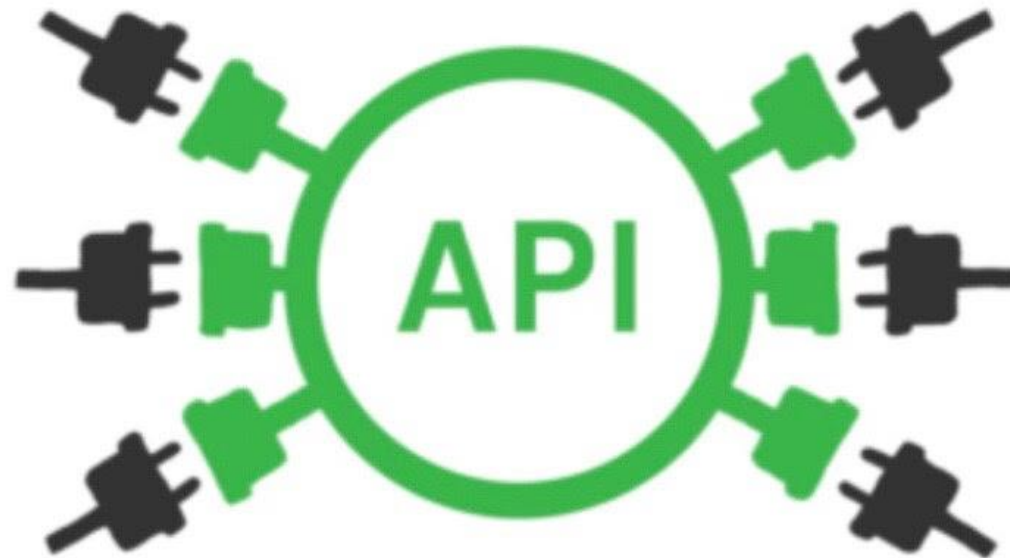
1. Stanford University
2. University of Chicago
3. OHSU
4. Regenstrief Institute
5. **Banner/UA COM-Phoenix**
6. Children's Hospital of Philadelphia
7. Beth Israel Deaconess
8. UCLA
9. Boston Children's Hospital
10. Geisinger Health System
11. Vanderbilt University
12. University of Washington
13. Columbia University



# Natural Language Processing (NLP)



# API's



# Discussion

- Lets collaborate!

[Hamed.Abbaszadegan@va.gov](mailto:Hamed.Abbaszadegan@va.gov)

Or

[habbaszadegan@email.arizona.edu](mailto:habbaszadegan@email.arizona.edu)