Machine Learning for Utilization & Cost

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June 6, 2019

57 Million
Lives

33
Published Papers

7
Countries

2018 Finalist
Microsoft Partner of the Year

2018, 2019 Winner
Microsoft Health Innovation Awards

Agenda

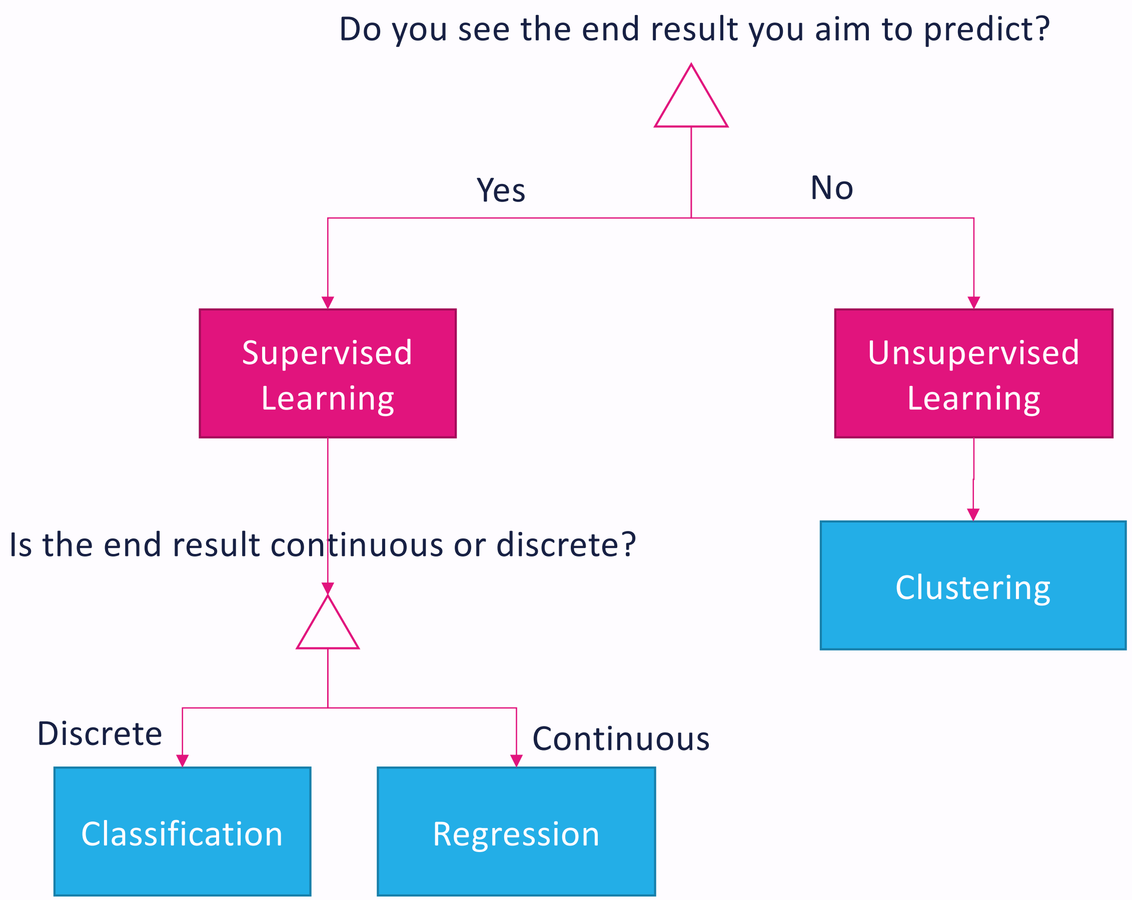
1. Machine Learning Overview
    - Supervised Learning
    - Unsupervised Learning
    - Additional data science techniques
2. Use Cases
    - Utilization & Cost
    - Structuring Employee Health Plans
3. Key Policy Implications
    - Fairness, Accountability, Transparency, and Bias in ML
    - Regulation & Legislation

Supervised Machine Learning

Machine Learning Lifecycle

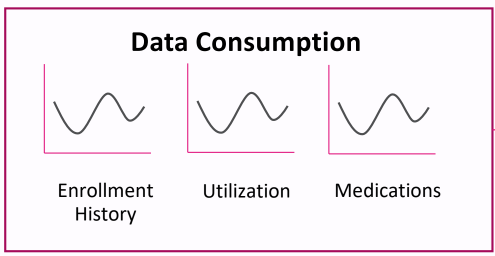
- Define the problem
  - Labeled or non-labeled data?
    - Continuous or discrete?
- Preprocess Data
  - Transformation
  - Filter
- Build Model
  - Labeled -> Classification/Regression
  - Non-labeled -> Clustering
- Evaluate Model
  - Does the model predict accurately?
  - Does the model fit the data?
  - Does the model adapt to different conditions?

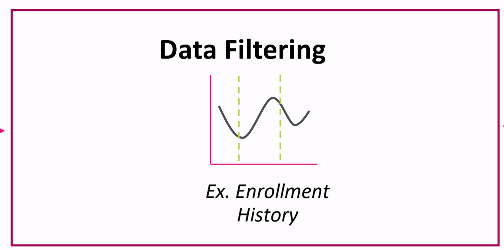
Problem Definition



Data Preprocessing

- Remove what does not matter
- Find what is useful for prediction

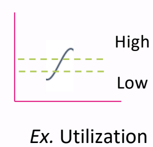




Ex. Exclude those patients who did not have active insurance coverage during the calendar years 2018 and 2019

Feature Engineering

$$f(x)$$



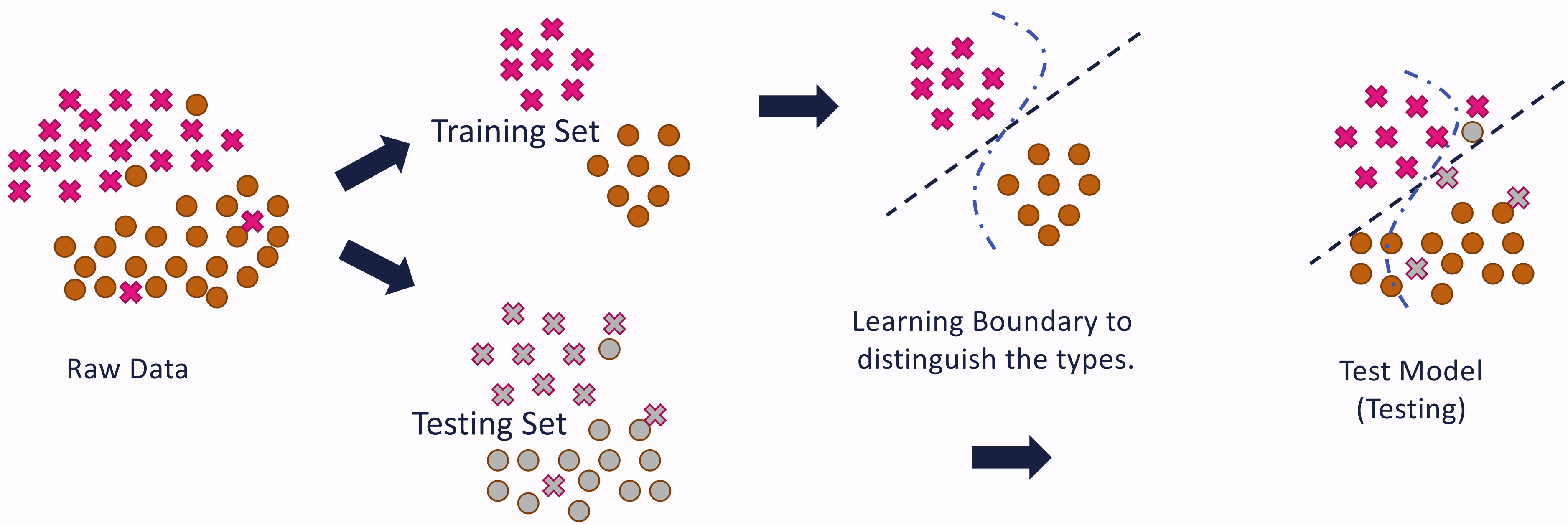
Ex: Patients with >N urgent care visits in last 6 months

Count of Rx Classes	Days Since Last ED Visit	Age Group	Family Size
1	36	3	3
4	372	7	2

Data Readiness for Model

Classification [Labeled Discrete Output]

- ✖ Patient does not have diabetes
- ● Patient has diabetes



Evaluation of Classification Models
Does the model predict accurately?

Example: Correctly Flagging Members with Diabetes

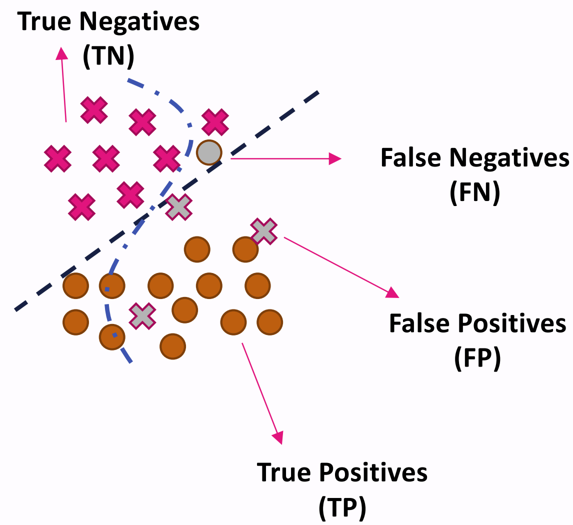
Given the disease…

Sensitivity/Recall is the proportion of members ***with*** *diabetes who test positive for diabetes.*

Specificity is the proportion of members ***without*** *diabetes who test negative for diabetes.*

Given the prediction…

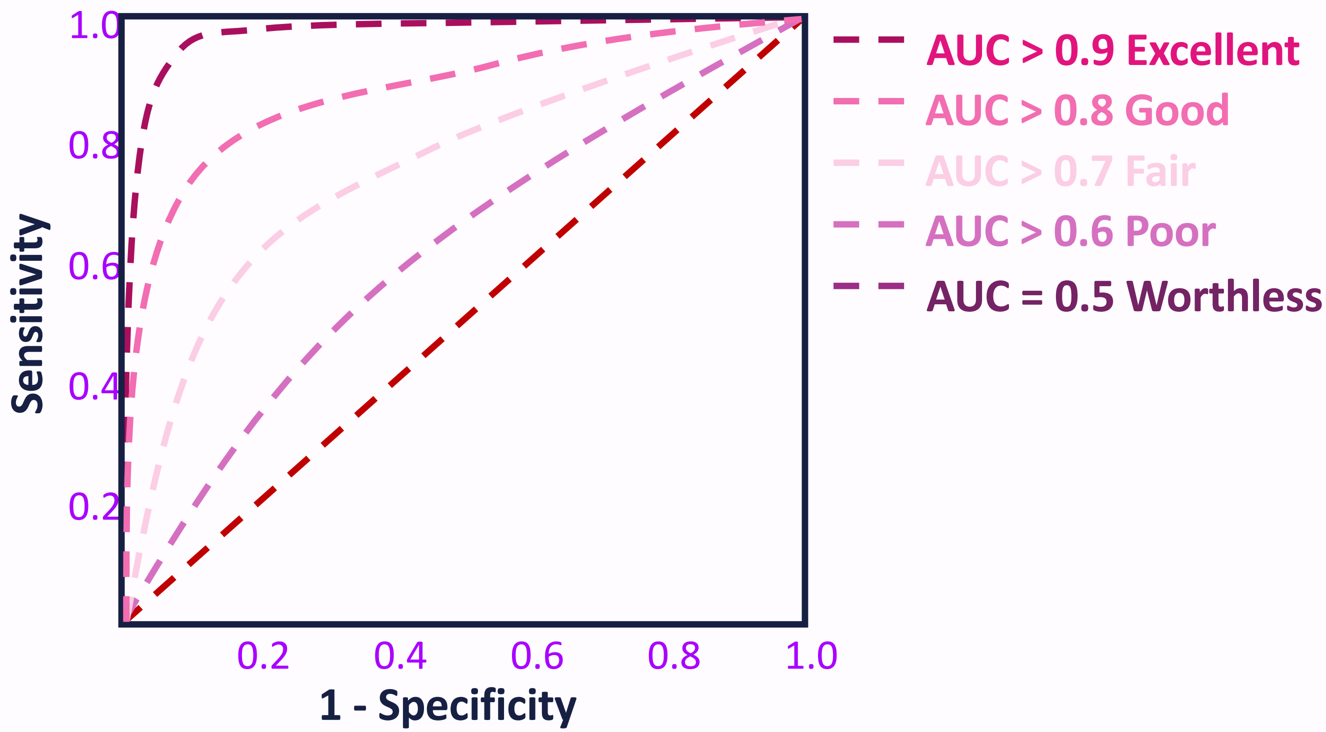
Precision is the proportion of members who test positive and actually have diabetes.



Evaluation of Classification Models

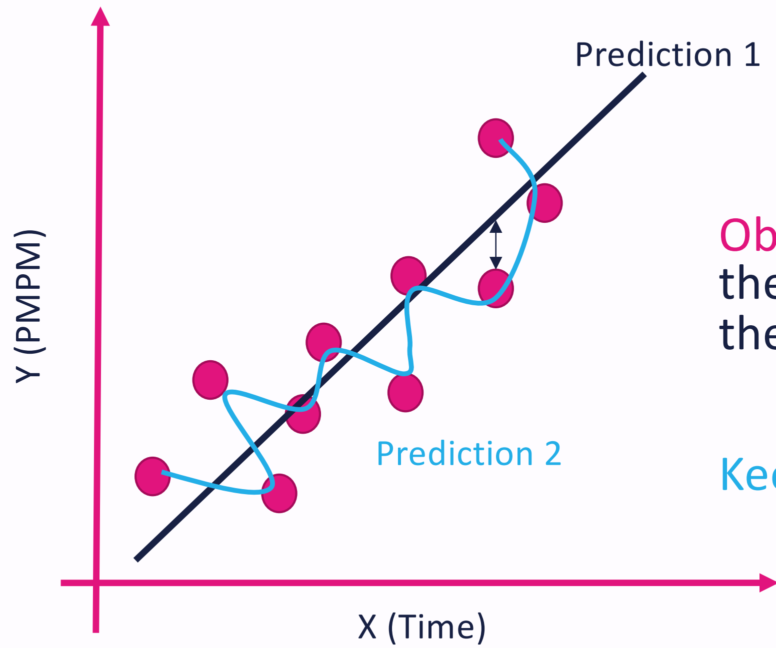
Does the model fit the data?

Area Under the Curve (AUC) measures how well the model fits the data.



Regression [Labeled Continuous Output]

Ex: Monthly medical expenditures



Objective: Fit a line that minimizes the distance between the line and the observation points.

Keep it simple!! (Occam's Razor)

Evaluation of Regression Models

Does the model predict accurately?

- **MAE (Mean Absolute Error):**

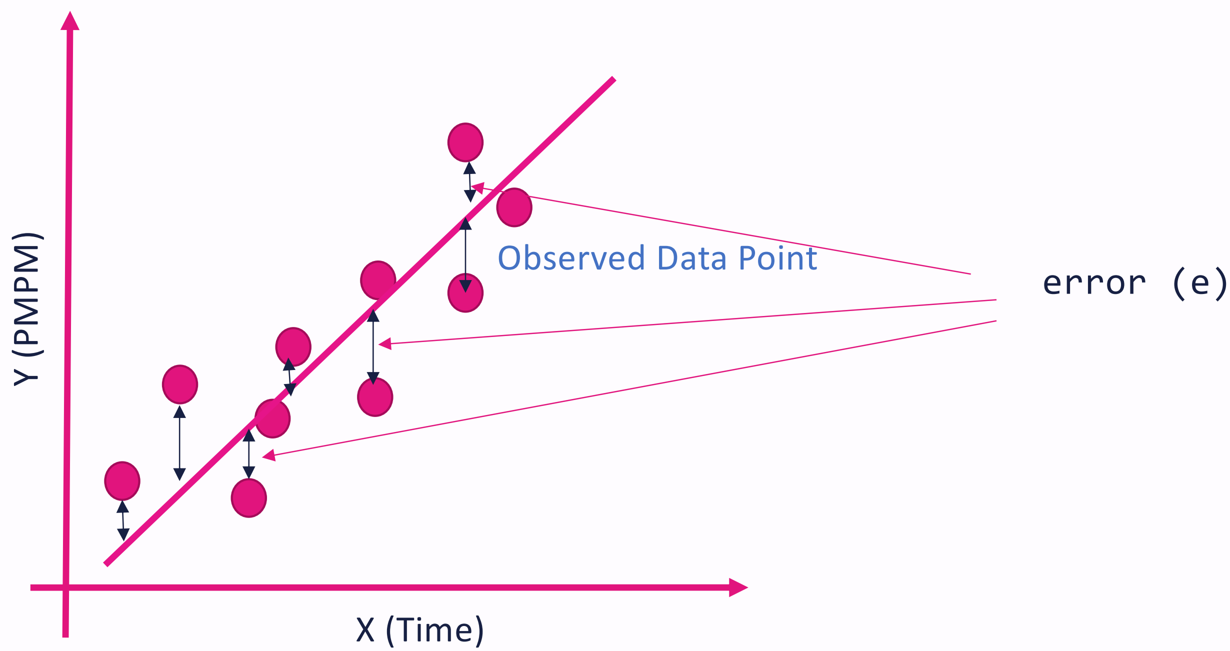
$$\frac{1}{n}\sum |e|$$

- **MSE (Mean Squared Error):**

$$\frac{1}{n}\sum e^2$$

- **RMSE (Root Mean Squared Error)**

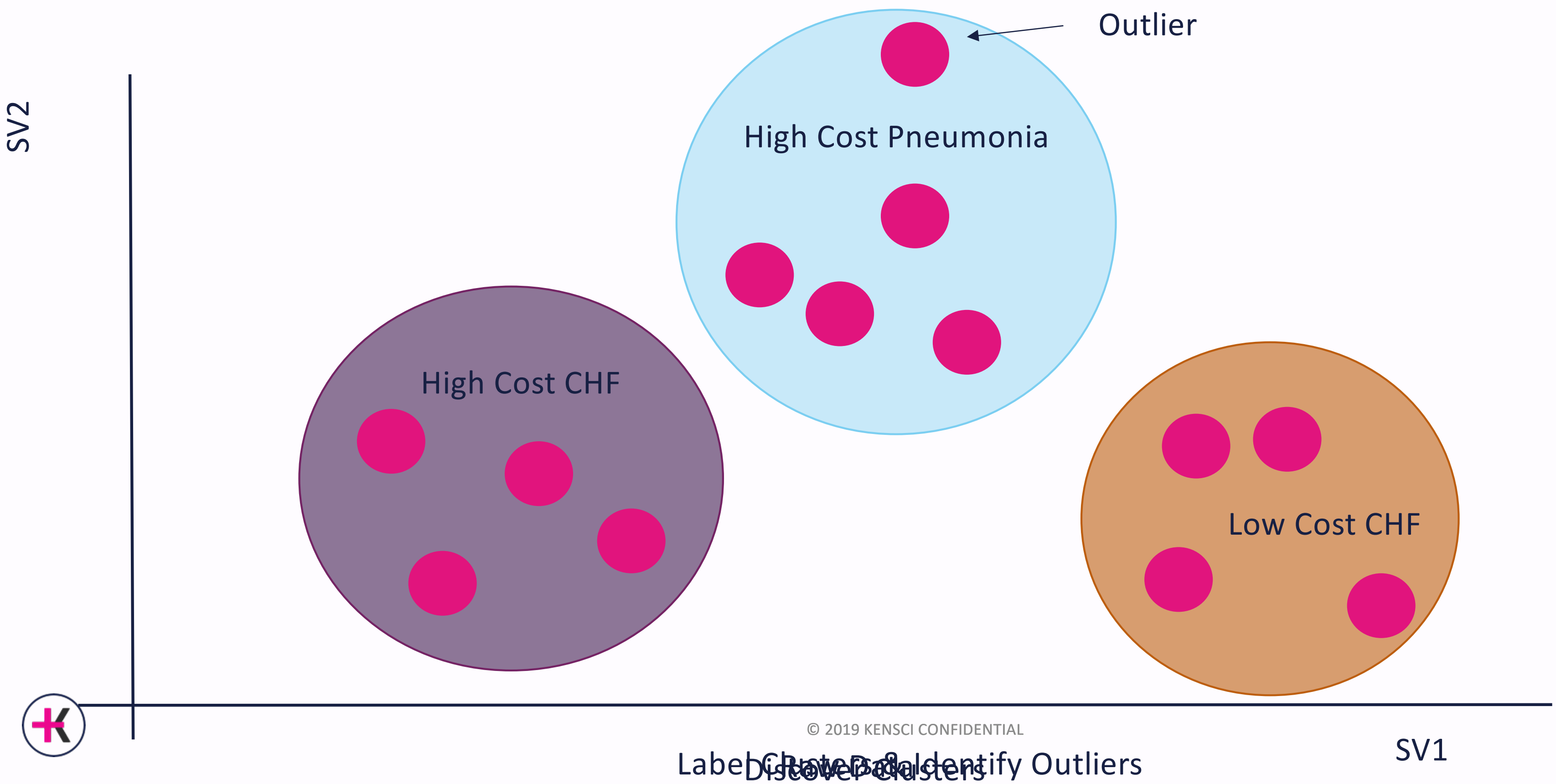
$$\sqrt{MSE}$$



Unsupervised Machine Learning

Clustering [Unlabeled Outputs]

Goal: Find groupings of instances - e.g., patients, claims, events - that are similar to one another; easily spot anomalies



Use Cases

Utilization & Cost Use Cases

Enhance administrative operations alongside member engagement & population health activities.

Reduce **cost of care**

ED Utilization & High Utilizers
Predict members that are likely to use the ED for care more than N times in the next 12 months

Unplanned Acute Utilization
Predict members that are likely to be admitted to the hospital for non-elective reasons

Population Cost Stratification
Identify emerging high cost/receding high cost members and associated drivers of utilization

Improve **care team effectiveness**

Predictive Care Planning
Predict "time to" events that mark transitions in treatment

Transitions of Care
Predict LOS, Discharge Disposition, Readmission Risk, & Rehab Needs

Med Adherence
Predict member adherence to key medication classes

Enhance **administrative operations**

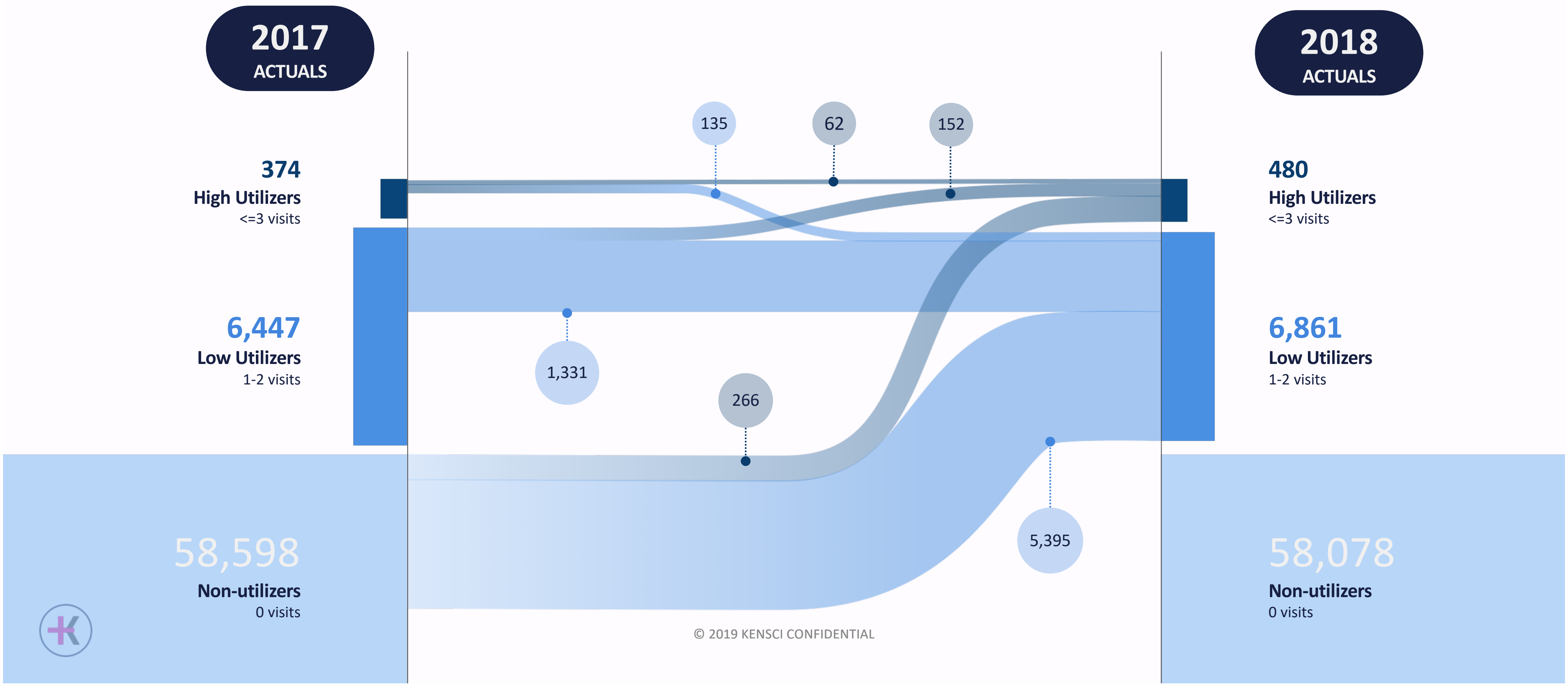
Member Benefit Maximization
Identify variance in network utilization suggest appropriate level/acuity of care for specific procedures

HCC Optimization
Flag members for uncoded or undercoded chronic condition categories

Waste & Abuse
Identify anomalies in billing and coding

Findings Summary

Predicting rising risk is challenging.



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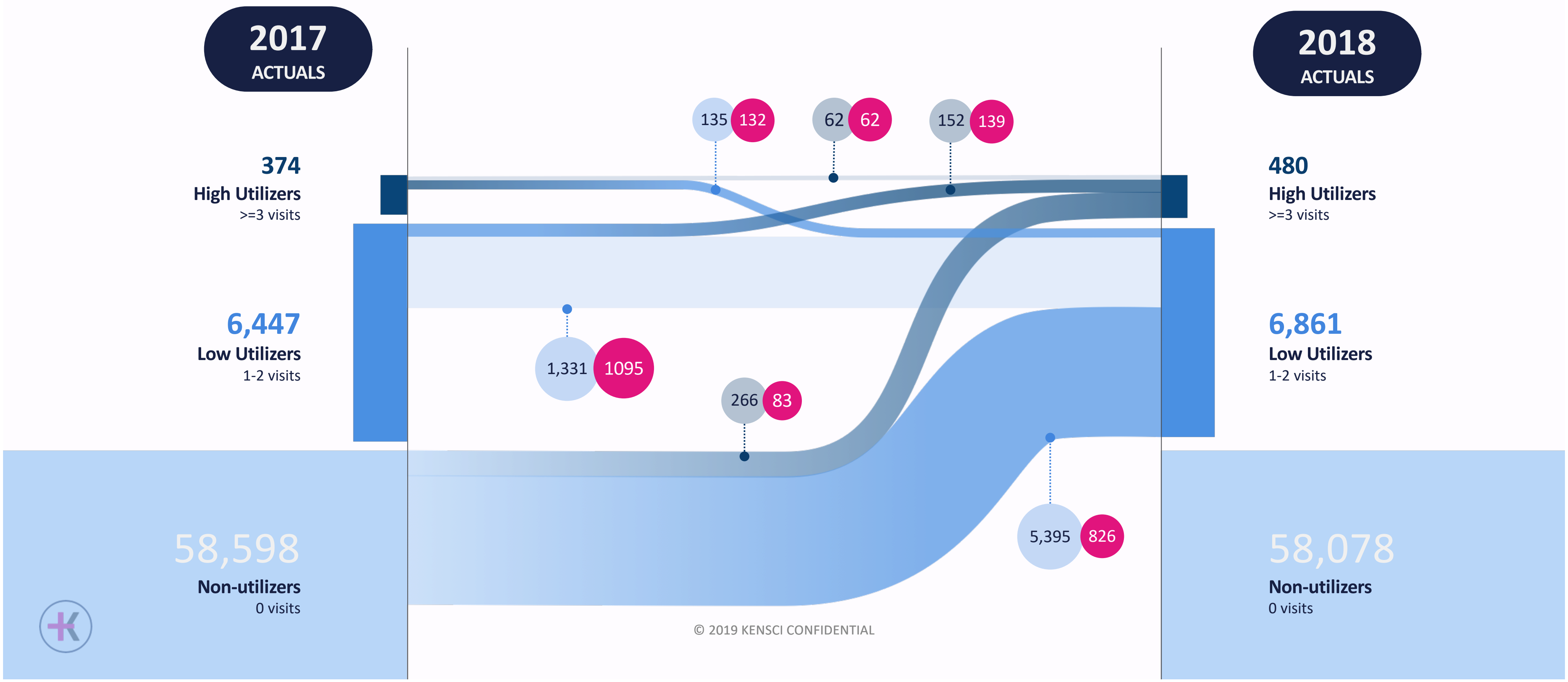


Cohort View

ED Utilization Predictions

powered by KenSci

ED WARNING?

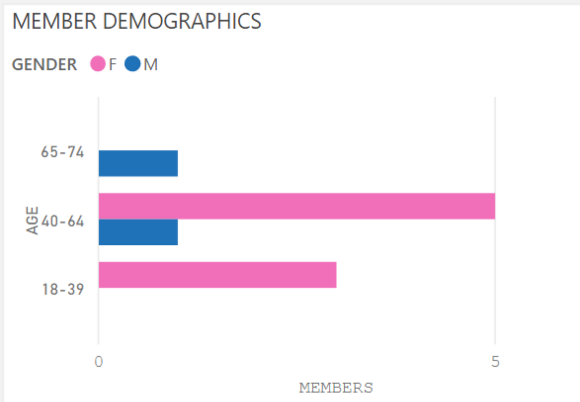
All

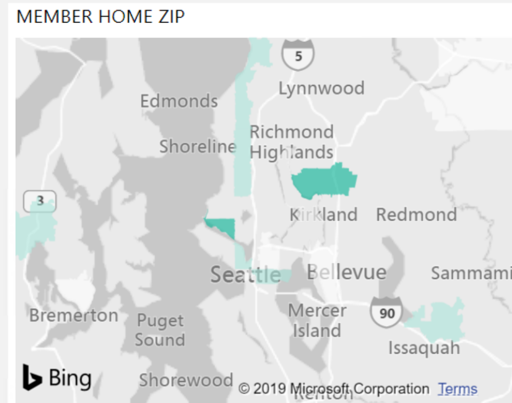
HIGH UTILIZER?

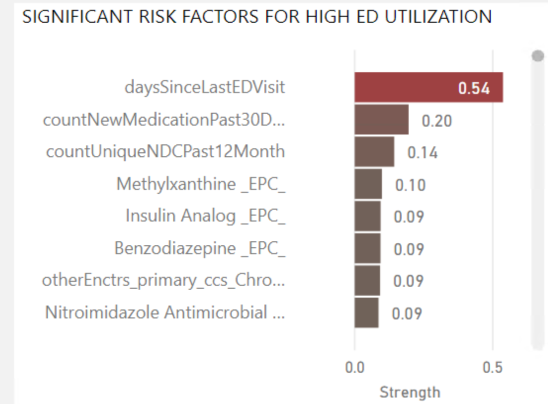
True

LAST YEAR ED VISITS

(Multiple Selections)







Predictions valid from

October 31, 2017

to

October 31, 2018

MemberID	Gender	Age	ED Warning?	ED Score	High Utilizer Risk?	High Utilizer Score	Last Year IP Visits	Last Year ED Visits	Last Year PC-Treatable ED Visits	Last Year Non-Emergent ED Visits
	F	22	True	57	True	6	0	1	1	0
	F	50	True	75	True	6	1	1	1	0
	F	45	True	50	True	10	0	1	1	0
	F	20	True	54	True	33	0	1	0	1
	F	37	True	55	True	7	0	1	0	0
	F	51	True	73	True	11	0	1	0	0
	F	61	True	67	True	7	0	0	0	0
	F	34	True	52	True	12	0	1	0	1
	M	62	True	51	True	16	2	1	0	0

Per-Beneficiary View

Patient Summary as of October 31, 2017

Predictions valid from **October 31, 2017** to **October 31, 2018**

powered by KenSci

MemberID

F
Gender

22
Age

True
Predicted High Utilizer?

33
Risk Score

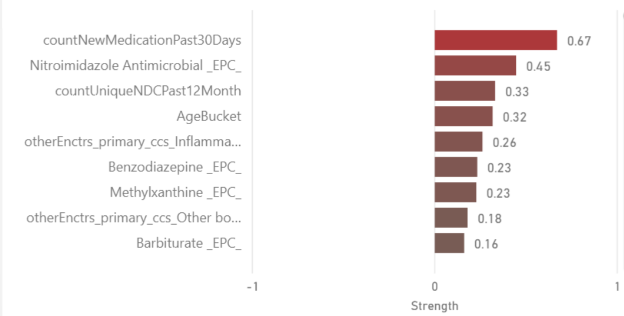
1
ED Past 12 Months

0
Inpatient Past 12 months

AMBULATORY UTILIZATION PRIOR TO PREDICTION

Place of Service	Checked In	Paid	Primary Diagnosis
Outpatient Hospital	01/03/17	$0.00	Anemia, unspecified
Office	02/18/17	$76.64	High risk heterosexual behavior
Office	03/13/17	$10.25	Anorexia
Office	04/15/17	$30.25	Acute pharyngitis, unspecified
Office	05/08/17	$99.49	Other fatigue
Office	05/24/17	$113.34	Diseases of lips
Office	05/31/17	$60.48	Segmental and somatic dysfunction of thoracic region
Office	06/23/17	$113.34	Acne, unspecified
Office	06/26/17	$109.47	Other fatigue
Office	06/30/17	$76.19	Segmental and somatic dysfunction of head region
Office	07/07/17	$119.22	Encounter for oth general cnsl and advice on contracepti
Outpatient Hospital	07/19/17	$137.52	Anxiety disorder, unspecified
Total		**$2,788.06**	

SIGNIFICANT RISK FACTORS FOR HIGH ED UTILIZATION



MEDICATION UTILIZATION PRIOR TO PREDICTION

Date	Status	Medication
January 5, 2017	P	BUTALB-ACETAMIN-CAFF 50-300-40
January 5, 2017	P	BUTALB-ACETAMINOPHEN-CAFF 50-325-40 TAB
January 5, 2017	P	BUTALBITAL-ASA-CAFFEINE CAP
January 5, 2017	X	BUTALB-ACETAMIN-CAFF 50-300-40
January 5, 2017	X	BUTALB-ACETAMINOPHEN-CAFF 50-325-40 TAB
January 5, 2017	X	BUTALBITAL-ASA-CAFFEINE CAP
January 6, 2017	P	BUTALB-ACETAMINOPHEN-CAFF 50-325-40 TAB
January 12, 2017	P	TRETINOIN 0.025% CREAM
January 20, 2017	P	CLINDAMYCIN PHOS 1% PLEDGET
January 23, 2017	P	ALPRAZOLAM 0.25 MG TABLET
January 23, 2017	P	ONDANSETRON HCL 8 MG TABLET
February 2, 2017	P	BUTALB-ACETAMINOPHEN-CAFF 50-325-40 TAB
February 2, 2017	X	BUTALB-ACETAMINOPHEN-CAFF 50-325-40 TAB
February 14, 2017	P	AMOX-CLAV 875-125 MG TABLET

ED AND INPATIENT VISITS PRIOR TO PREDICTION

Visit Type	Checked In	Discharged	Paid	Facility	Primary Diagnosis
ED	02/26/17	02/26/17	$355.26		Viral conjunctivitis, unspecifie
Total			**$355.26**		

Policy Implications

"Health AI research has demonstrated some impressive results, but **its clinical value has not yet been realised, hindered partly by a lack of a clear understanding of how to quantify benefit or ensure patient safety, and increasing concerns about the ethical and medico-legal impact.**"

Challen R, Denny J, Pitt M*, et al*
Artificial intelligence, bias and clinical safety
BMJ Quality & Safety 2019;**28:**231-237.

FAT ML: a Grassroots Movement

- FAT ML
  - Fairness
  - Accountability
  - Transparency
- Why?
  - Compliance
    - GDPR
    - Right to Explanation
  - Impact/Consequences of Results

Risk Prediction with Blackbox Models

Patient ID		*Has Asthma*		*Risk of Death*
84	...	Yes	...	5%
85	...	Yes	...	6%
86	...	No	...	12%
87	...	No	...	15%
...	...	...	...	...

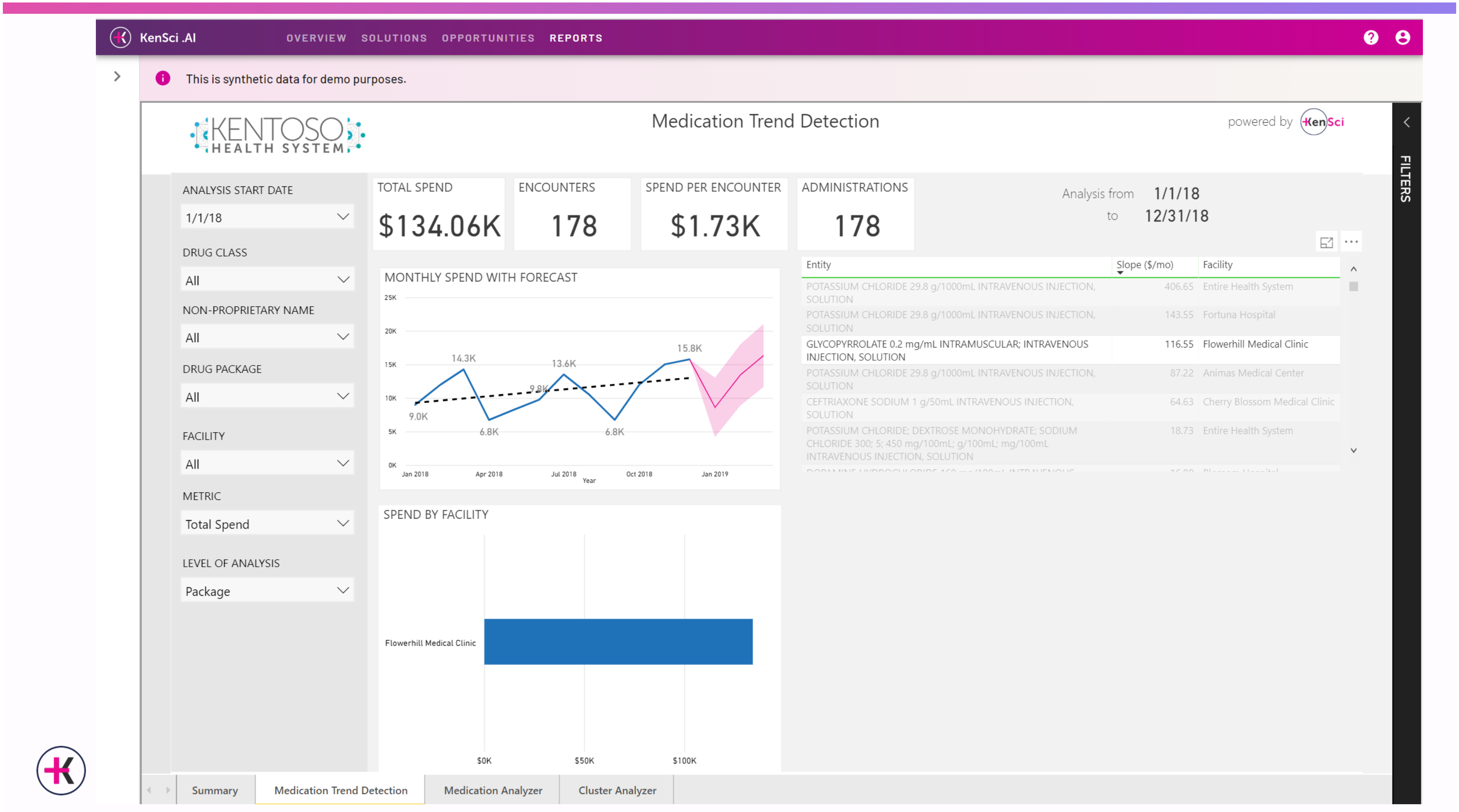
[Caruana 2015, Caruana 2017]

Federal Legislation

- FDA's Pre-Cert Program
  - Provisions in the 21st Century Cures Act (Dec 2016) de-classified certain types of medical software as medical devices (SaMD) – this includes *clinical decision support systems*
  - The FDA has been moving towards a more holistic approach to regulating fast-changing software like machine learning models: certify the *company and its processes regarding safety and quality* vs. incremental product releases
  - Nine companies began to pilot the Pre-Certify activities in 2017; as of May 22, 2019, new companies can apply to test
- Algorithmic Accountability Act
  - Draft legislation that monitors:
    - "automated decision system" such as ML models and output, even if they only *inform* human decisions and are not autonomous
    - "information system" (storage)
  - Strong guiding framework for regular reviews of bias, availability of data to affected consumers, retention policies, and risk of unintentional exposure.

Thank you.

Appendix: Alternate Use Cases


KenSci .AI
OVERVIEW
SOLUTIONS
OPPORTUNITIES
REPORTS
This is synthetic data for demo purposes.
KENTOSO HEALTH SYSTEM
Medication Trend Detection
powered by KenSci
FILTERS
ANALYSIS START DATE
1/1/18
DRUG CLASS
All
NON-PROPRIETARY NAME
All
DRUG PACKAGE
All
FACILITY
All
METRIC
Total Spend
LEVEL OF ANALYSIS
Package
TOTAL SPEND
$134.06K
ENCOUNTERS
178
SPEND PER ENCOUNTER
$1.73K
ADMINISTRATIONS
178
Analysis from 1/1/18
to 12/31/18
MONTHLY SPEND WITH FORECAST
25K
20K
15K
10K
5K
0K
14.3K
13.6K
15.8K
9.8K
9.0K
6.8K
6.8K
Jan 2018
Apr 2018
Jul 2018
Oct 2018
Jan 2019
Year
SPEND BY FACILITY
Flowerhill Medical Clinic
$0K
$50K
$100K
Entity
Slope ($/mo)
Facility
POTASSIUM CHLORIDE 29.8 g/1000mL INTRAVENOUS INJECTION, SOLUTION
406.65
Entire Health System
POTASSIUM CHLORIDE 29.8 g/1000mL INTRAVENOUS INJECTION, SOLUTION
143.55
Fortuna Hospital
GLYCOPYRROLATE 0.2 mg/mL INTRAMUSCULAR; INTRAVENOUS INJECTION, SOLUTION
116.55
Flowerhill Medical Clinic
POTASSIUM CHLORIDE 29.8 g/1000mL INTRAVENOUS INJECTION, SOLUTION
87.22
Animas Medical Center
CEFTRIAXONE SODIUM 1 g/50mL INTRAVENOUS INJECTION, SOLUTION
64.63
Cherry Blossom Medical Clinic
POTASSIUM CHLORIDE; DEXTROSE MONOHYDRATE; SODIUM CHLORIDE 300; 5; 450 mg/100mL; g/100mL; mg/100mL INTRAVENOUS INJECTION, SOLUTION
18.73
Entire Health System
Summary
Medication Trend Detection
Medication Analyzer
Cluster Analyzer

Prediction Encounter Registry

Powered by KenSci

Current Roster	High Readmission Risk (30 D...	Discharges Today
386	61	96

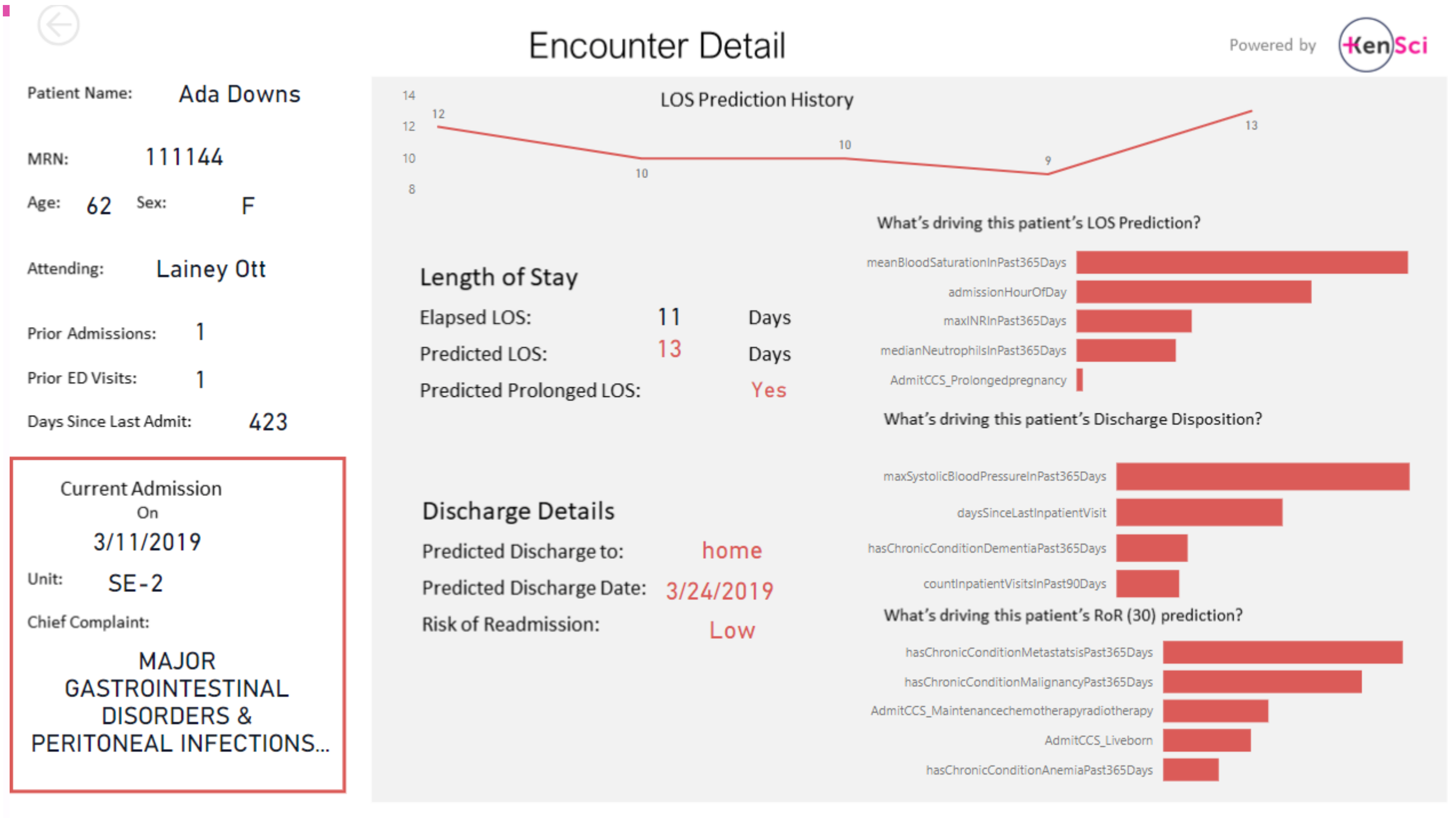
Predicted Discharges				
Tomorrow	+2 Days	+3 Days	+4 Days	>5 Days
74	59	40	44	73

MRN	Full Name	Unit	Age	Sex	Encounter Type	AdmissionDate	Elapsed Length of Stay	Predicted Length of Stay	Chief Complaint	Days to Discharge	Predicted Weekend Discharge	Predicted Readmisison Risk	Predicted Disposition	Prolonged LOS	Admission Type	Service Line	Encounter ID
111112	Aaden Kirk	S-1	71	M	Inpatient	3/2/2019	20	27	DISORDERS OF LIVER EXCEPT MALIG,CIRR,ALC HEPA W CC	7	No	Low	other	Yes	EMERGENCY	Emergency Medicine	15303
111139	Abram Oleary	N-2	56	M	Inpatient	3/2/2019	20	24	NONTRAUMATIC STUPOR & COMA W/O MCC	4	No	High	home	Yes	ROUTINE / ELECTIVE	Obstetrics & Gynecology	15794
111144	Ada Downs	SE-2	62	F	Inpatient	3/11/2019	11	13	MAJOR GASTROINTESTINAL DISORDERS & PERITONEAL INFECTIONS W MCC	2	Yes	Low	home	Yes	URGENT	Vascular Surgery	15990
111147	Ada Leal	N-2	46	F	Inpatient	3/20/2019	2	3	EPISTAXIS W/O MCC	1	Yes	High	home	No	EMERGENCY	Internal Medicine	15861
111153	Adan Carson	E-2	50	M	Inpatient	3/19/2019	3	5	MAJOR SMALL & LARGE BOWEL PROCEDURES W/O CC/MCC	2	Yes	Medium	other	No	EMERGENCY	Emergency Medicine	15652
111161	Addisyn Farmer	S-1	47	F	Observation	3/22/2019	0	0	OTHER KIDNEY & URINARY TRACT PROCEDURES W/O CC/MCC	0	No	Low	home	No	EMERGENCY	Internal Medicine	15954
111165	Adelaide Collins	N-4	58	F	Inpatient	3/11/2019	11	11	MYELOPROLIF DISORD OR POORLY DIFF NEOPL W OTHER O.R. PROC W/O CC/MCC	0	No	Low	home	Yes	EMERGENCY	Hematology/Oncology	15063
111168	Adelina Prescott	S-1	62	F	Inpatient	3/2/2019	20	20	KIDNEY & URINARY TRACT NEOPLASMS W CC	0	No	Medium	home	Yes	EMERGENCY	Internal Medicine	15037

Kentoso Hospital

Units

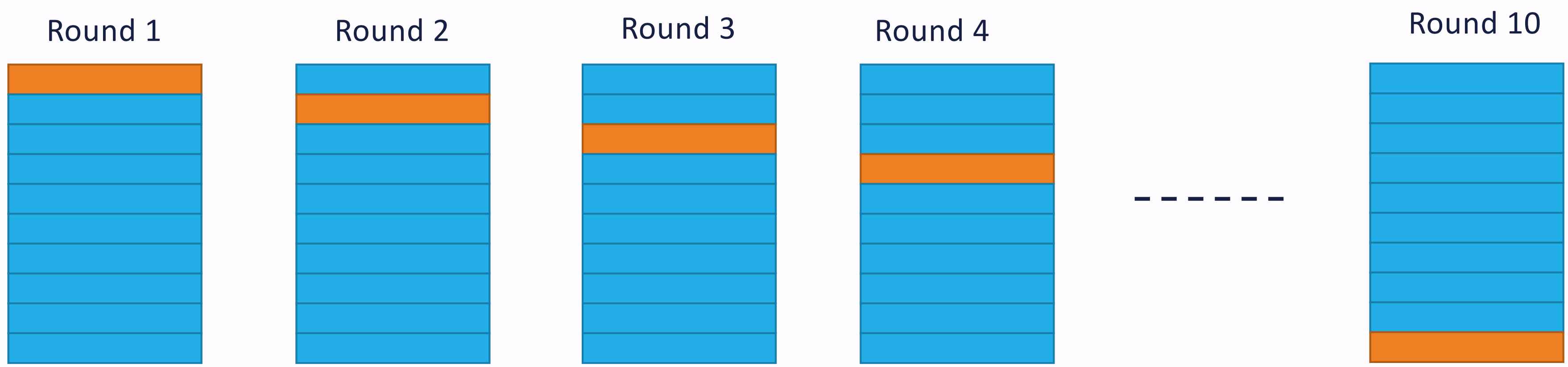
Report Last Updated


Encounter Detail
Powered by KenSci
Patient Name: Ada Downs
MRN: 111144
Age: 62 Sex: F
Attending: Lainey Ott
Prior Admissions: 1
Prior ED Visits: 1
Days Since Last Admit: 423
Current Admission
On
3/11/2019
Unit: SE-2
Chief Complaint:
MAJOR GASTROINTESTINAL DISORDERS & PERITONEAL INFECTIONS...
LOS Prediction History
14
12
10
8
12
10
10
9
13
Length of Stay
Elapsed LOS: 11 Days
Predicted LOS: 13 Days
Predicted Prolonged LOS: Yes
Discharge Details
Predicted Discharge to: home
Predicted Discharge Date: 3/24/2019
Risk of Readmission: Low
What's driving this patient's LOS Prediction?
meanBloodSaturationInPast365Days
admissionHourOfDay
maxINRInPast365Days
medianNeutrophilsInPast365Days
AdmitCCS_Prolongedpregnancy
What's driving this patient's Discharge Disposition?
maxSystolicBloodPressureInPast365Days
daysSinceLastInpatientVisit
hasChronicConditionDementiaPast365Days
countInpatientVisitsInPast90Days
What's driving this patient's RoR (30) prediction?
hasChronicConditionMetastatsisPast365Days
hasChronicConditionMalignancyPast365Days
AdmitCCS_Maintenancechemotherapyradiotherapy
AdmitCCS_Liveborn
hasChronicConditionAnemiaPast365Days

Appendix: Reference Slides

Cross-Validation:
Does the model adapt to different conditions?

- Increase **robustness** to unseen data.
- Remove **bias** from observed data.

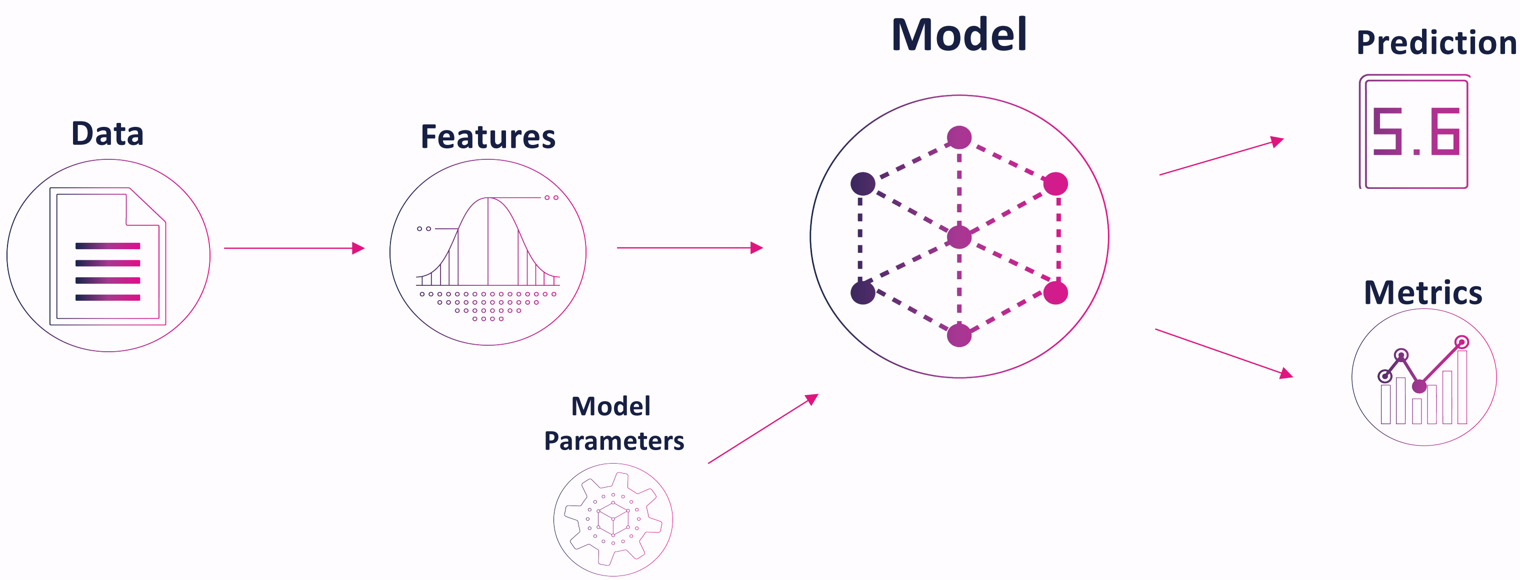


Training Set

Validation Set

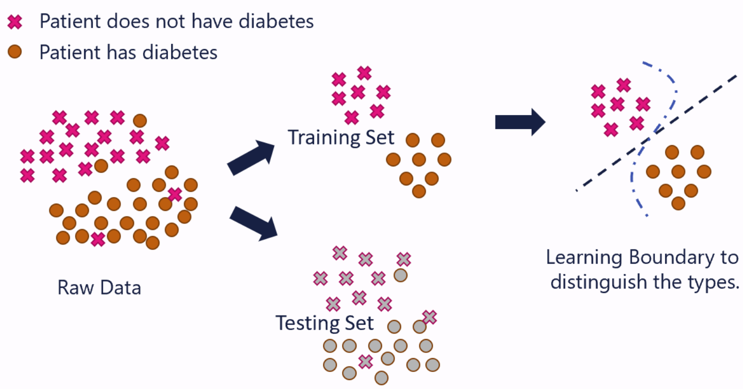
Accuracy = Mean (Accuracy round 1, Accuracy round 2, …. Accuracy round 10)

Supervised Machine Learning



Truncated Slides (if presenting <1 hr)

Classification [Labeled Discrete Output]



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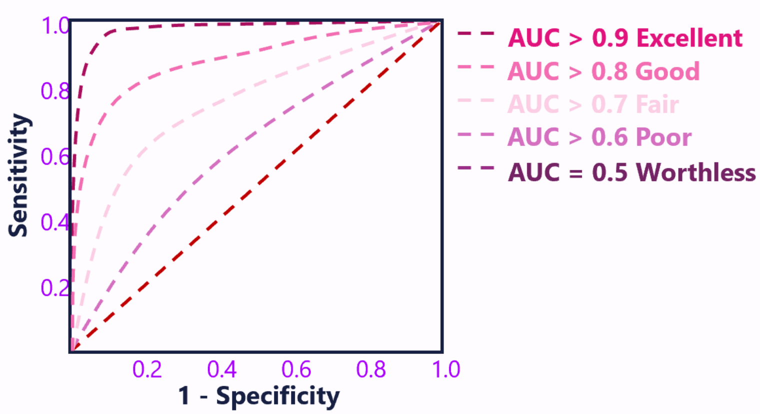
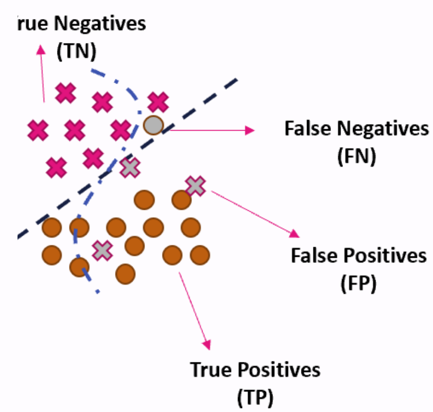
Evaluation: Does the model predict accurately?

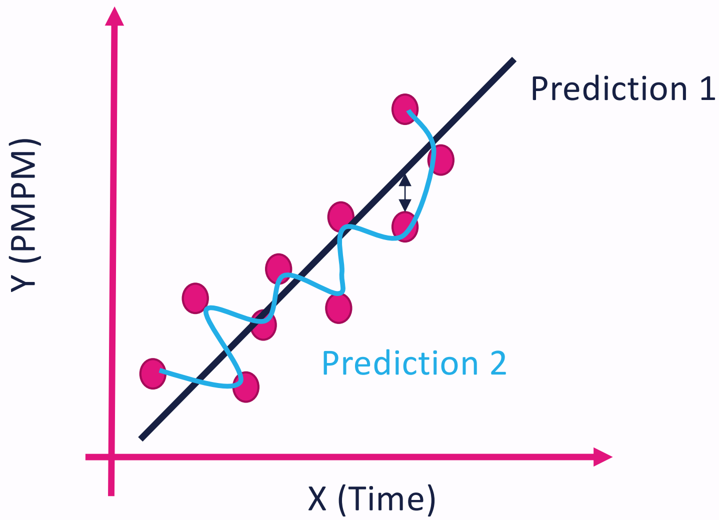
Area Under the Curve (AUC) measures how well the model fits the data.





Regression [Labeled Continuous Output]

Ex: Monthly medical expenditures



Objective: Fit a line that minimizes the distance between the line and the observation points.

Keep it simple!! (Occam's Razor)

Does the model predict accurately?

- **MAE (Mean Absolute Error):**
$$\frac{1}{n}\sum |e|$$
- **MSE (Mean Squared Error):**
$$\frac{1}{n}\sum e^2$$
- **RMSE (Root Mean Squared Error)**
$$\sqrt{MSE}$$