

Data, data, everywhere, Let's all have a drink (*of data*)

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Disclosures

None





Learning Objectives

- 1) Identify applications and challenges of large datasets
- 2) Define and differentiate machine learning, statistical learning, and artificial intelligence
- 3) Identify emerging uses of machine learning in the laboratory
- 4) Explain how laboratorians can participate in algorithm development and implementation

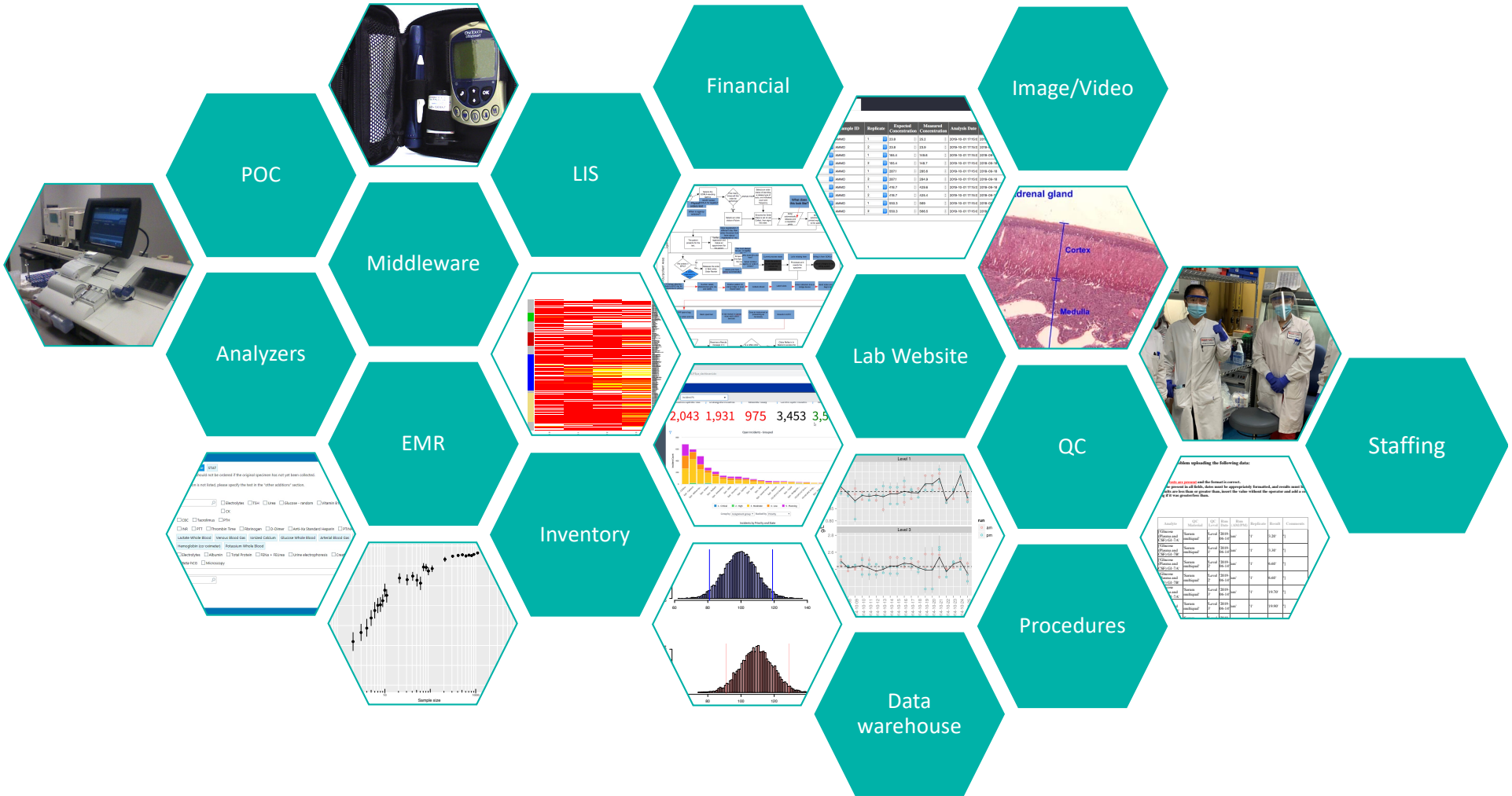




Part I: Lab Data Opportunities



Lab Data Sources



POLL #1

How Many Different Data Sources Do You Use Routinely in the Lab?

- A. 0
- B. 1
- C. 2-3
- D. 4-5
- E. 6+



Lab Data Applications



- Understanding of service
 - Ordering, Test volume, Timing, Results, Trends
- Resource Allocation
- Quality
- Generation of New information

Descriptive

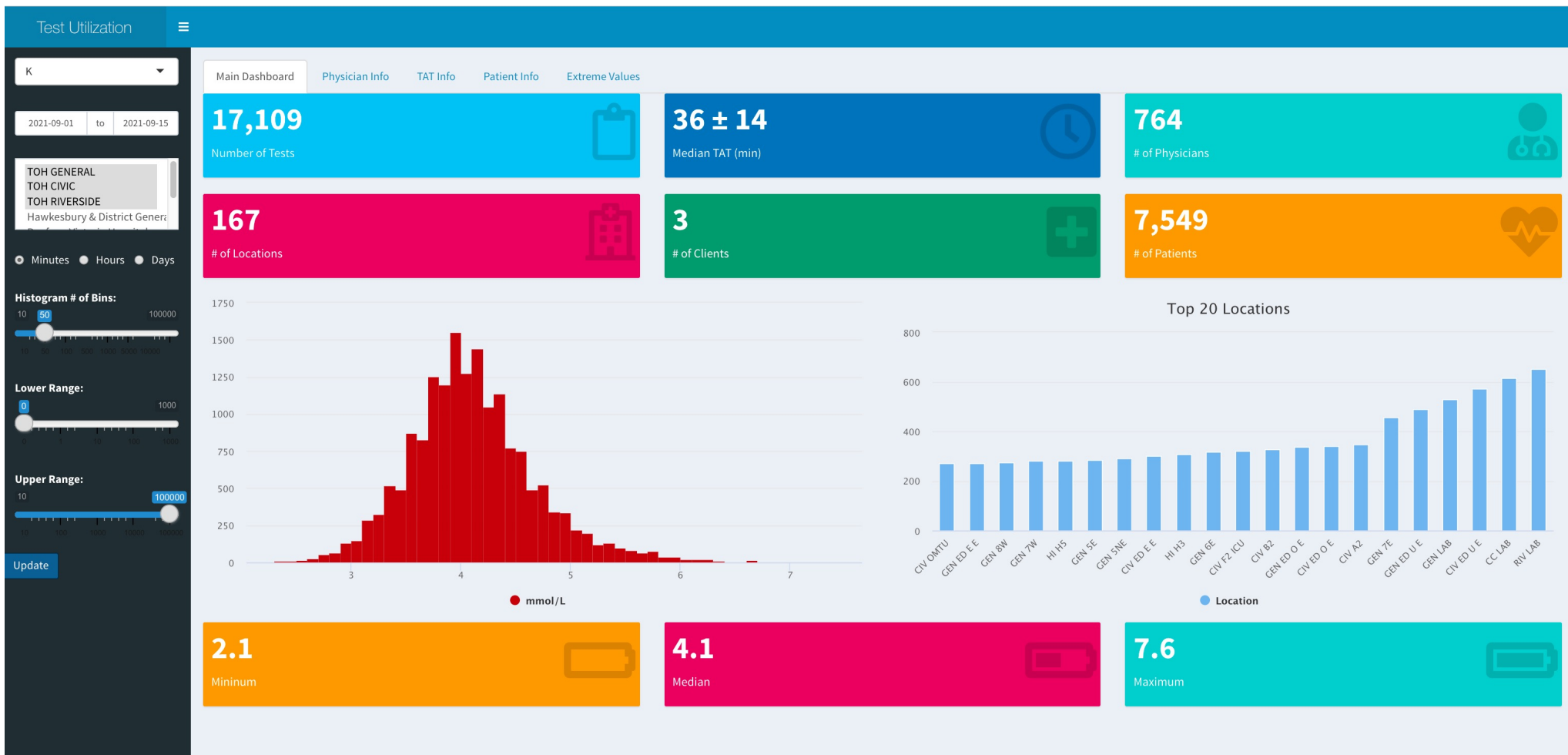
Predictive

Prescriptive



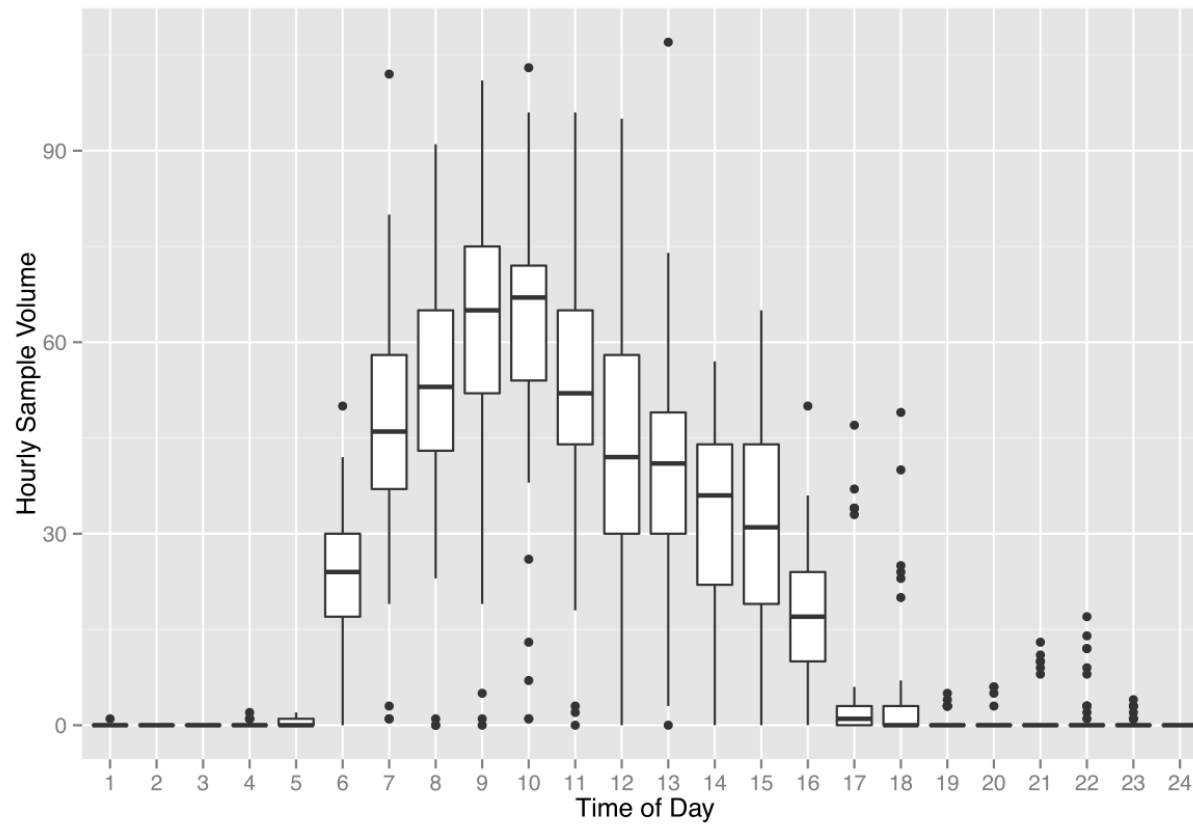


Test Dashboard





Courier Timing

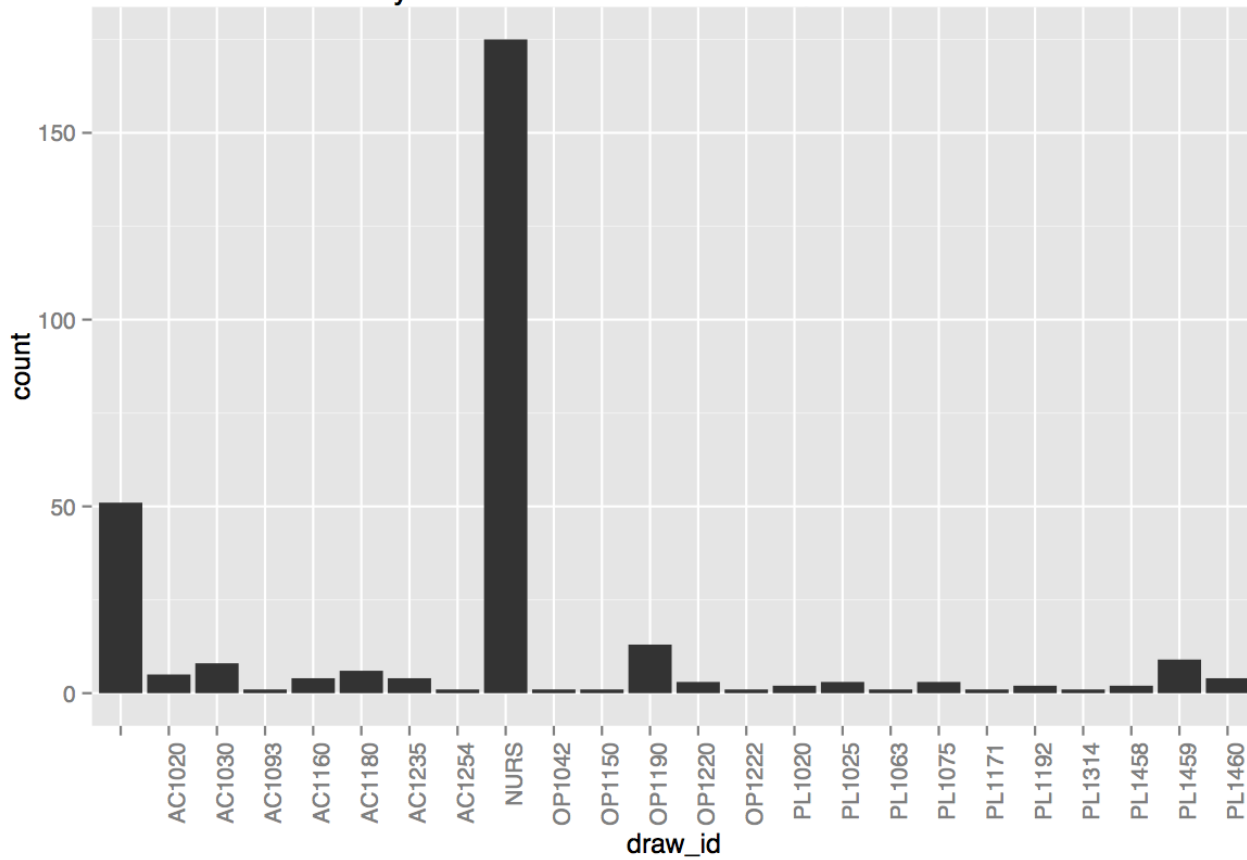




Quality Improvement

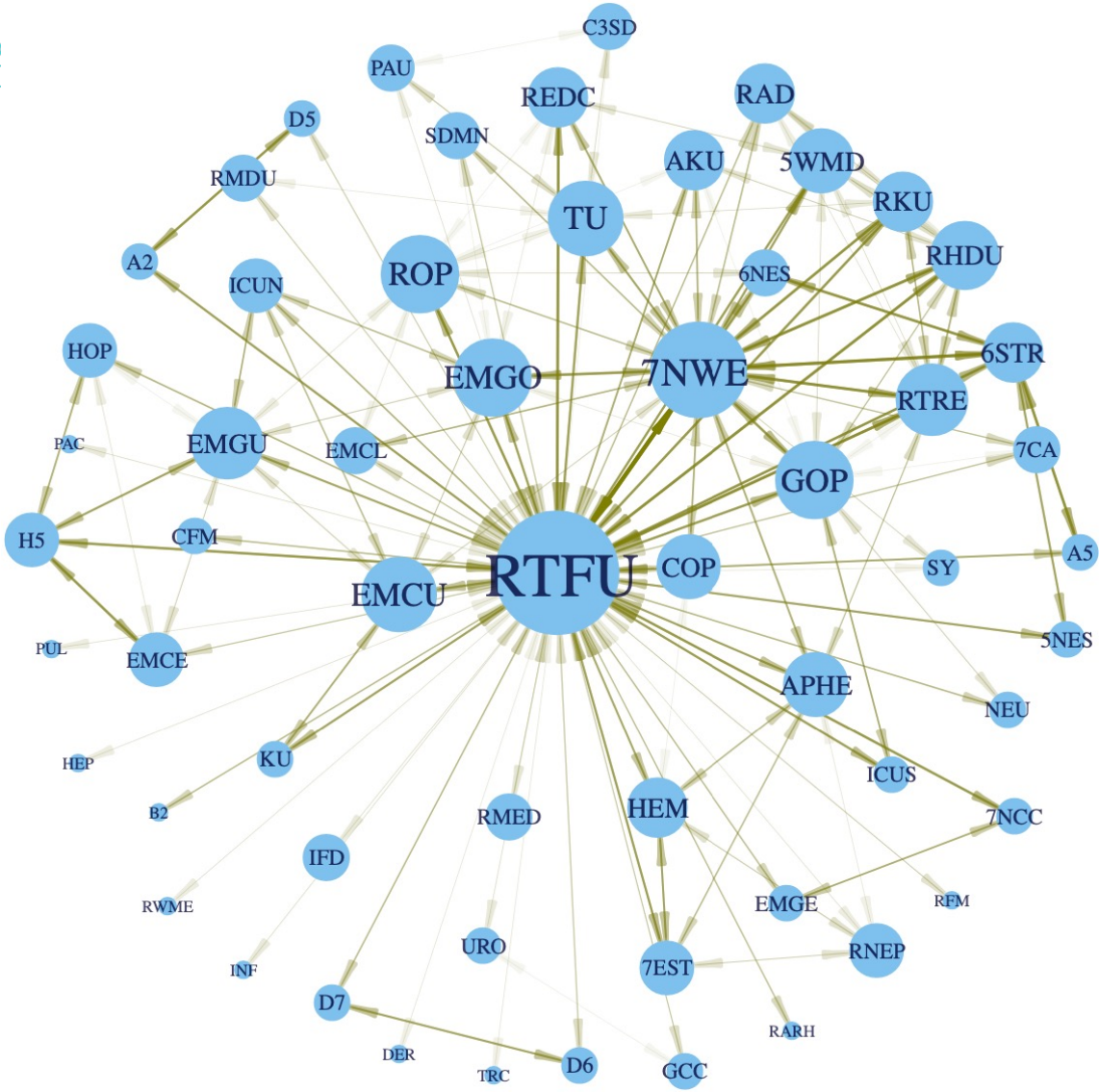


Volume of Hemolyzed Samples at 7EST
by Draw ID

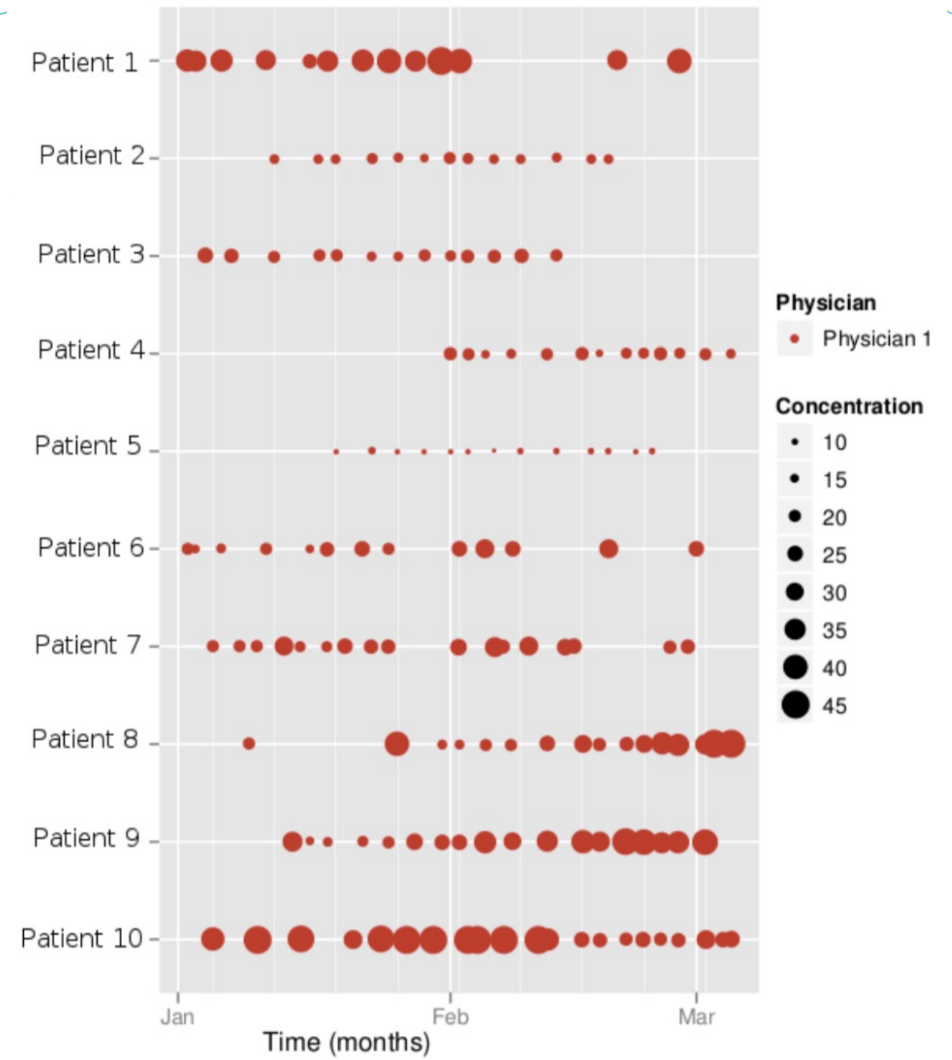




Infection Control

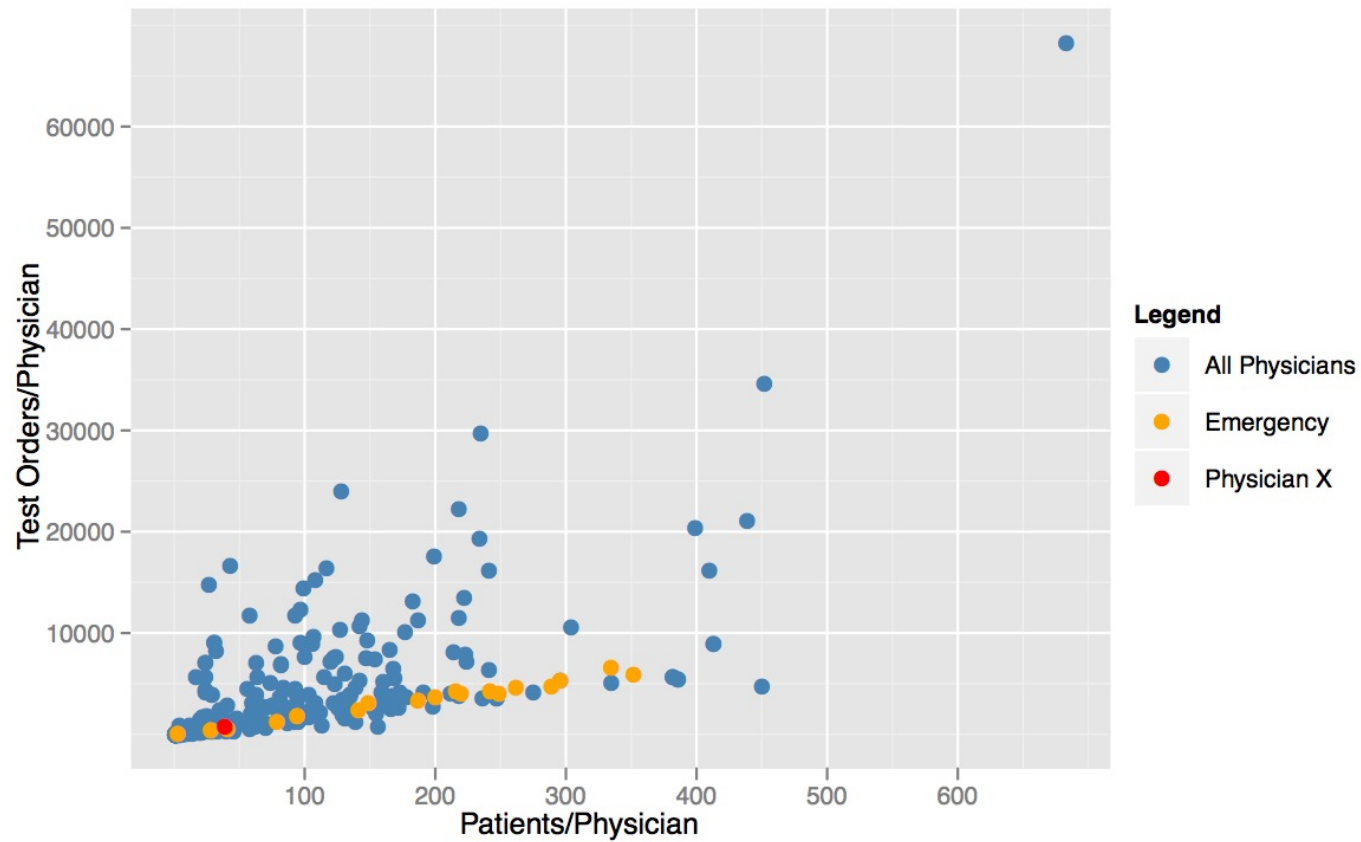


Test utilization

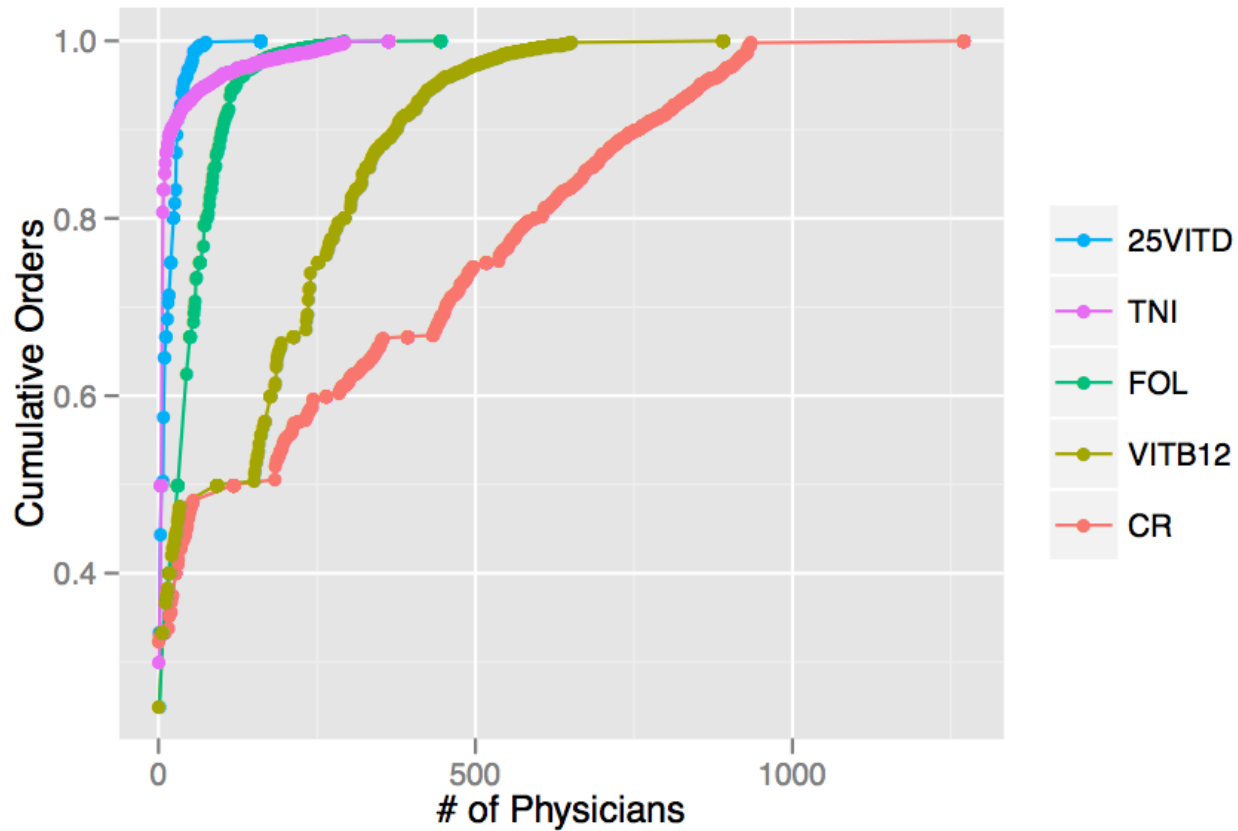




Comparative Test Utilization

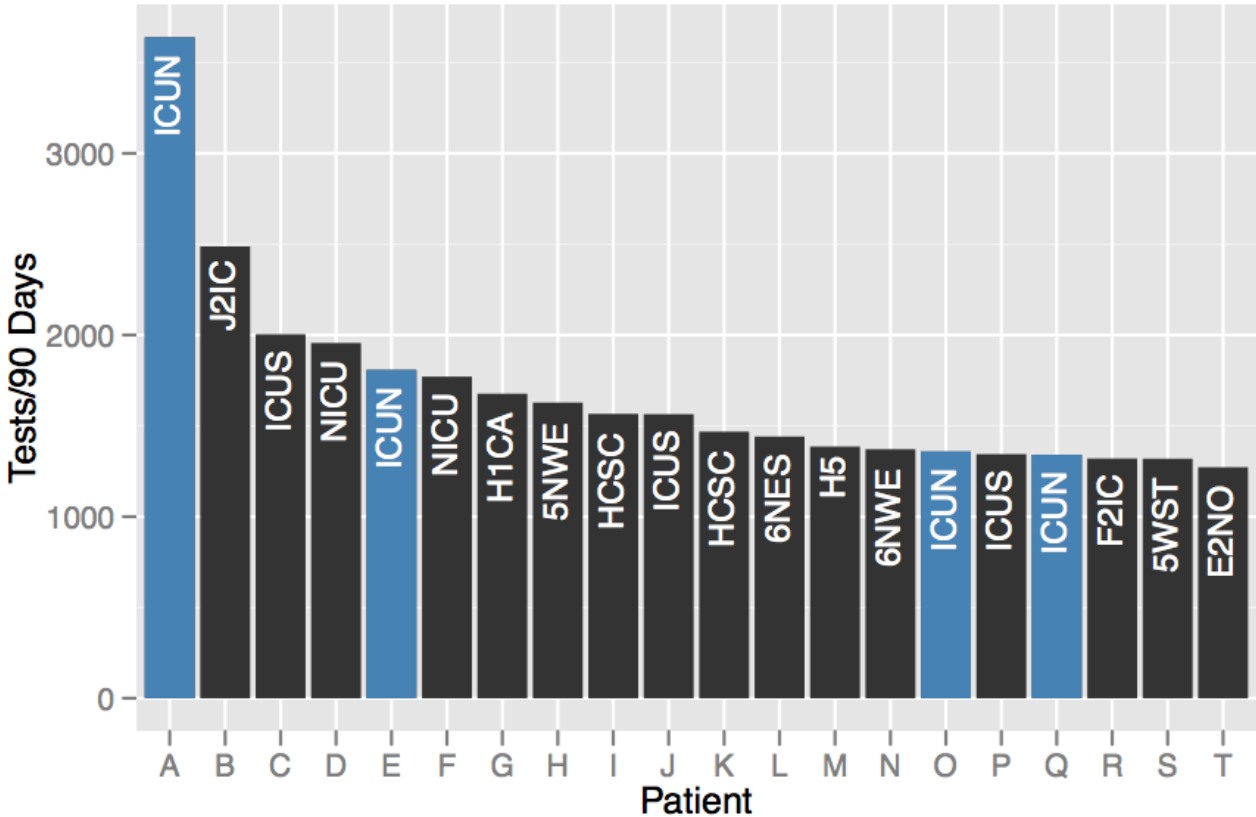


Change Management



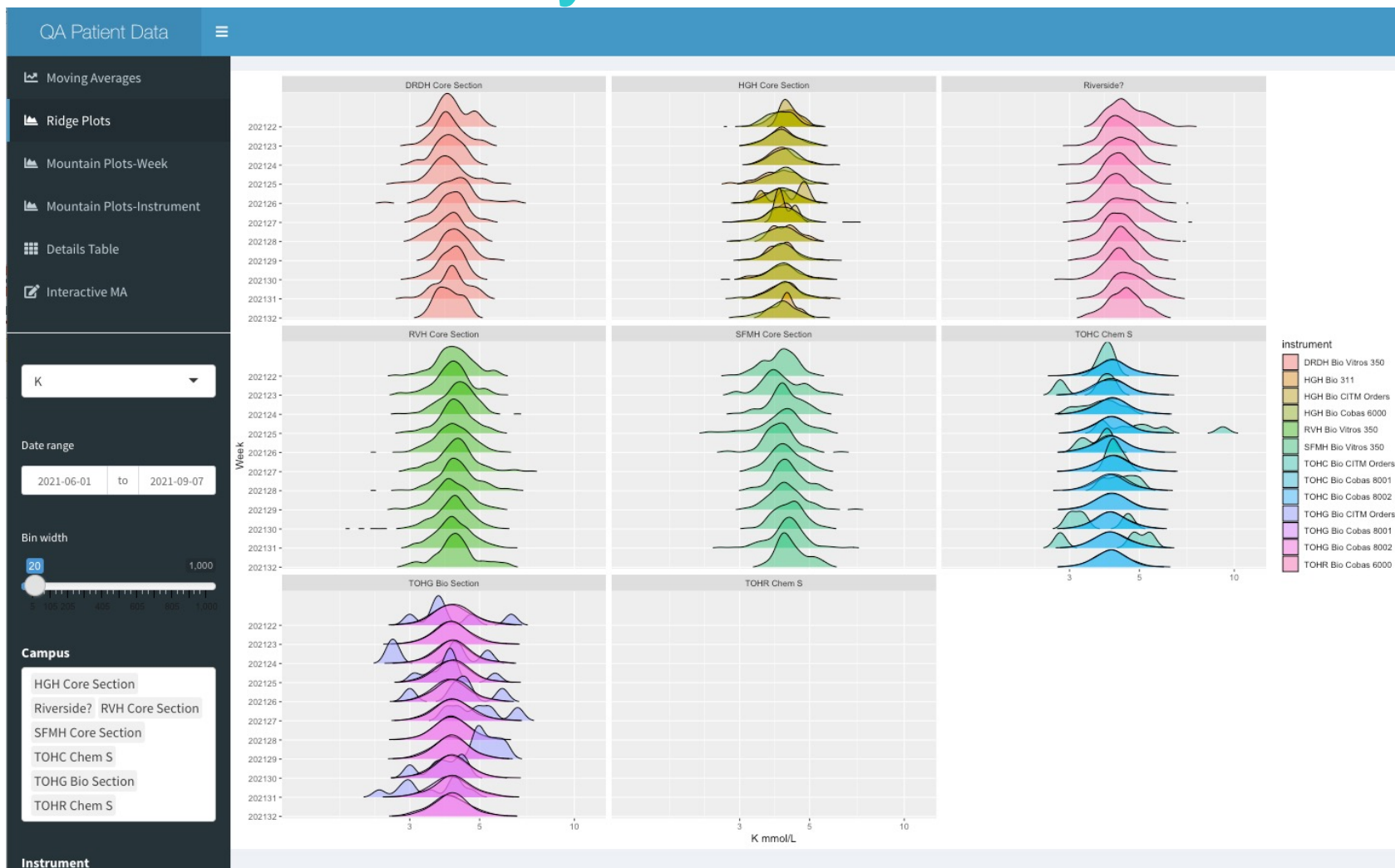


Resource Allocation



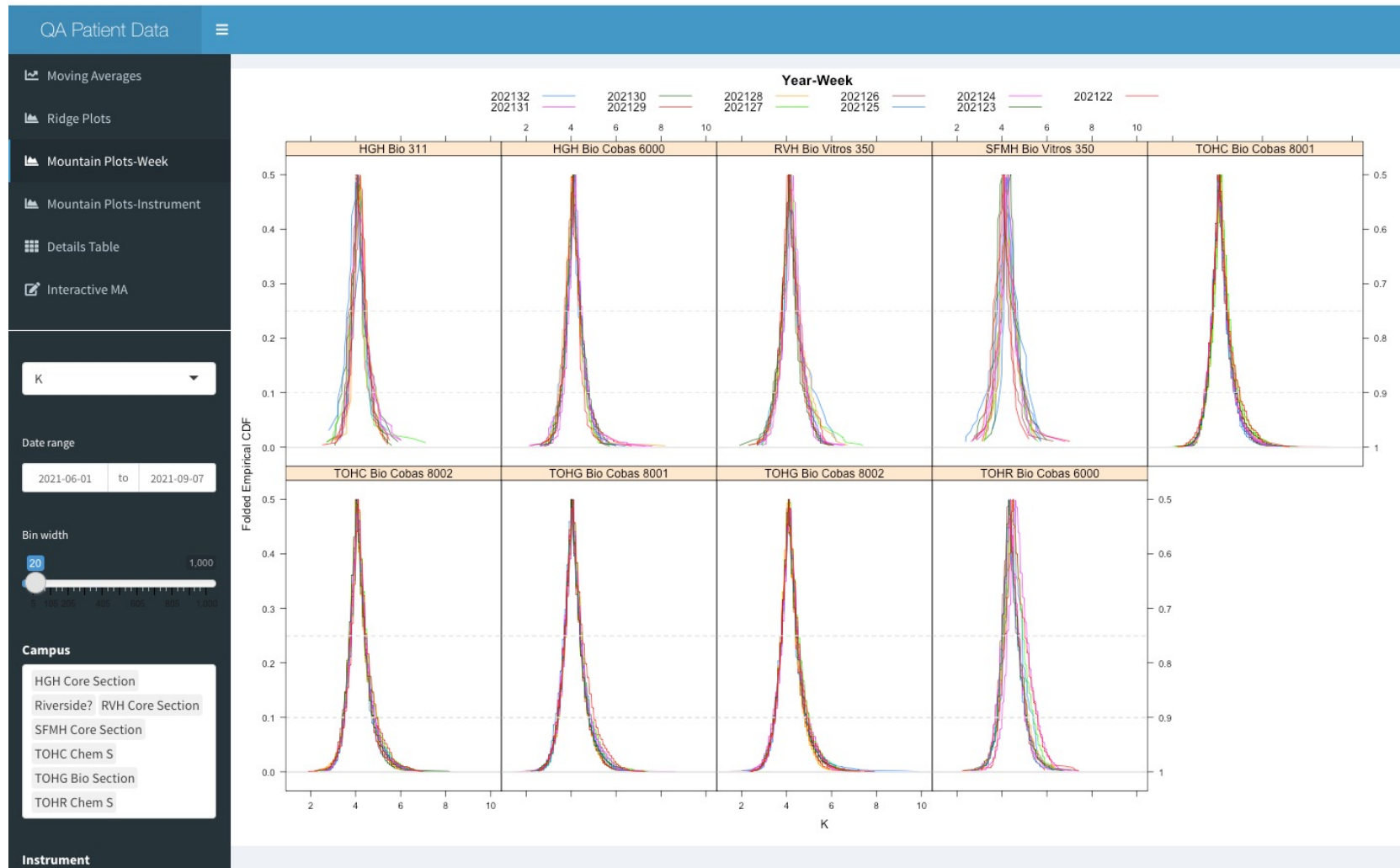


Quality Assurance



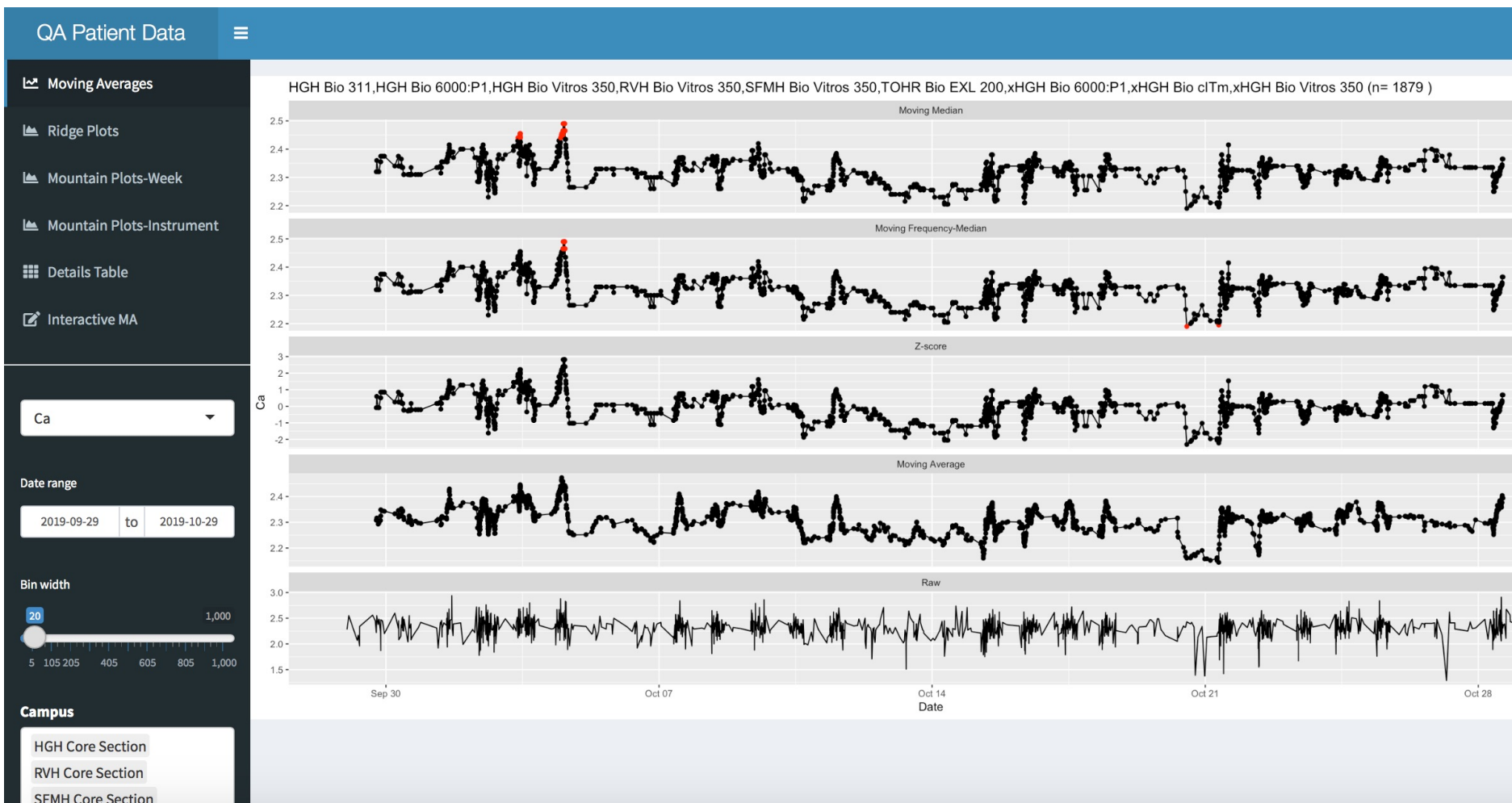


Quality Assurance

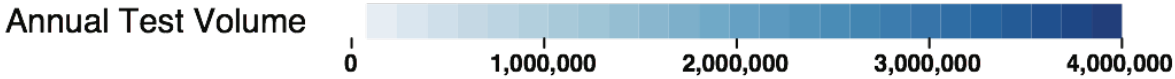
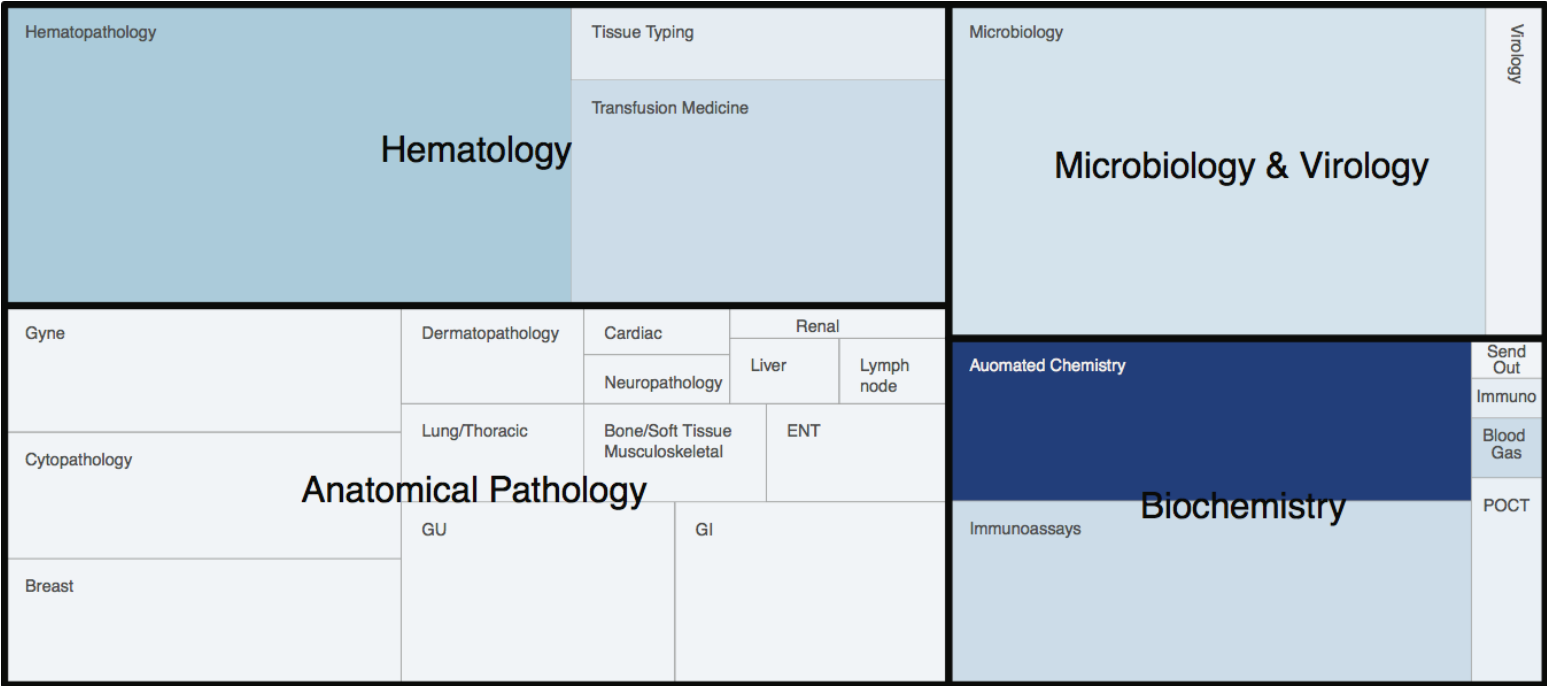




Quality Control



Resource Usage

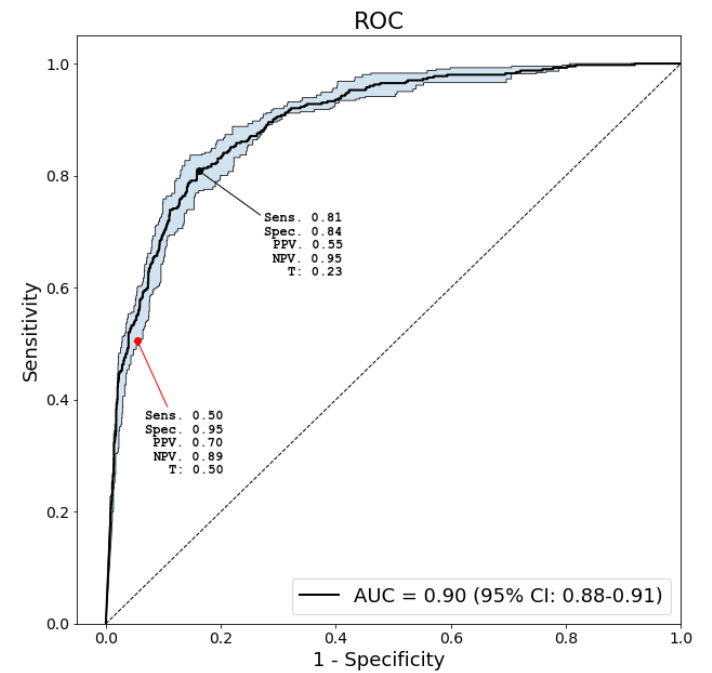
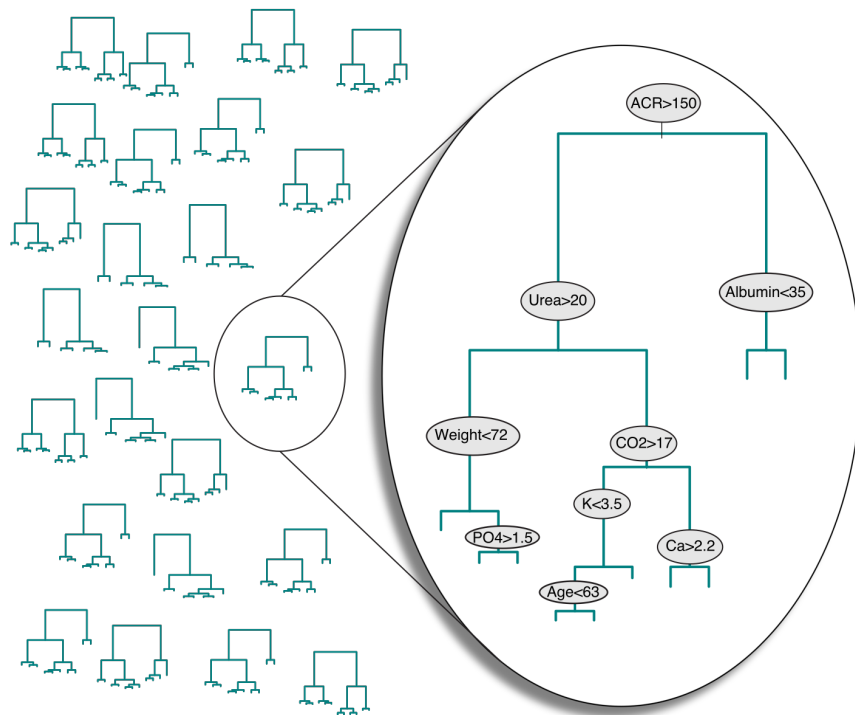


Cost is proportional to Area





Machine Learning





Part II: Lab Data Challenges

POLL #2

What is the hardest part of using lab data to solve a problem?

- A. Accessing the data
- B. Handling the amount of data
- C. Data accuracy
- D. Analysis
- E. Other/Don't know

Lab Data Challenges

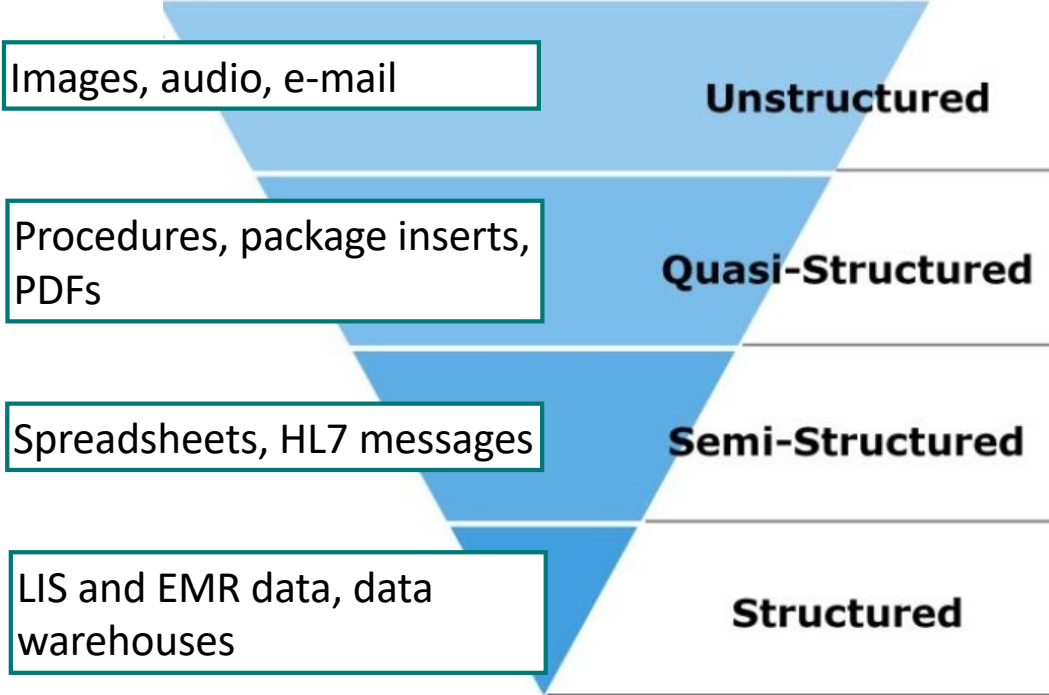
- Access
- Standards
- Human resources/Skills
- Interoperability
- Volume
- Validation
- Accuracy
- Software/Hardware Changes
- Ethics/Privacy/Security

- 4 pm, Thursday, September 16, 2021
- 8:00 UTC 16/09/2021
- 2021-09-16 16:00:01
- 2021-09-16 4:00:01 PM
- 1631642896
- 44456.6666782407
- Thurs, Sept 16
- 09-16-21
- 16/09/21
- 16, Sept
- 21-Sep
- 16/09/2021





Lab Data Types





Data Sizes & Approaches



Size	Storage	Software	Scale	Sample
Tiny	Kilobytes	Excel, R	Human readable	Single test method validation
Small	Megabytes	R, SAS, SPSS, Tableau, Python	Fits in computer memory	One week of LIS data
Medium	Gigabytes	Relational database	Fits on a computer	One year of clinical data
“Big”	Terabytes+	Distributed database	Multiple computers	Enterprise health data





Data Challenges Summary

- No once-size-fits-all approach to data
- Many considerations:
 - size, structure, security, standards
 - access, accuracy, analysis
- Ability to manipulate data is essential
 - Right tools for the job
 - A way of thinking





Part III: AI and the Lab

My Knowledge of Machine Learning Is:

- A. Non-existent
- B. Limited
- C. Moderate
- D. Extensive
- E. My algorithm is answering this for me



AI

Artificial General Intelligence
(Strong AI)

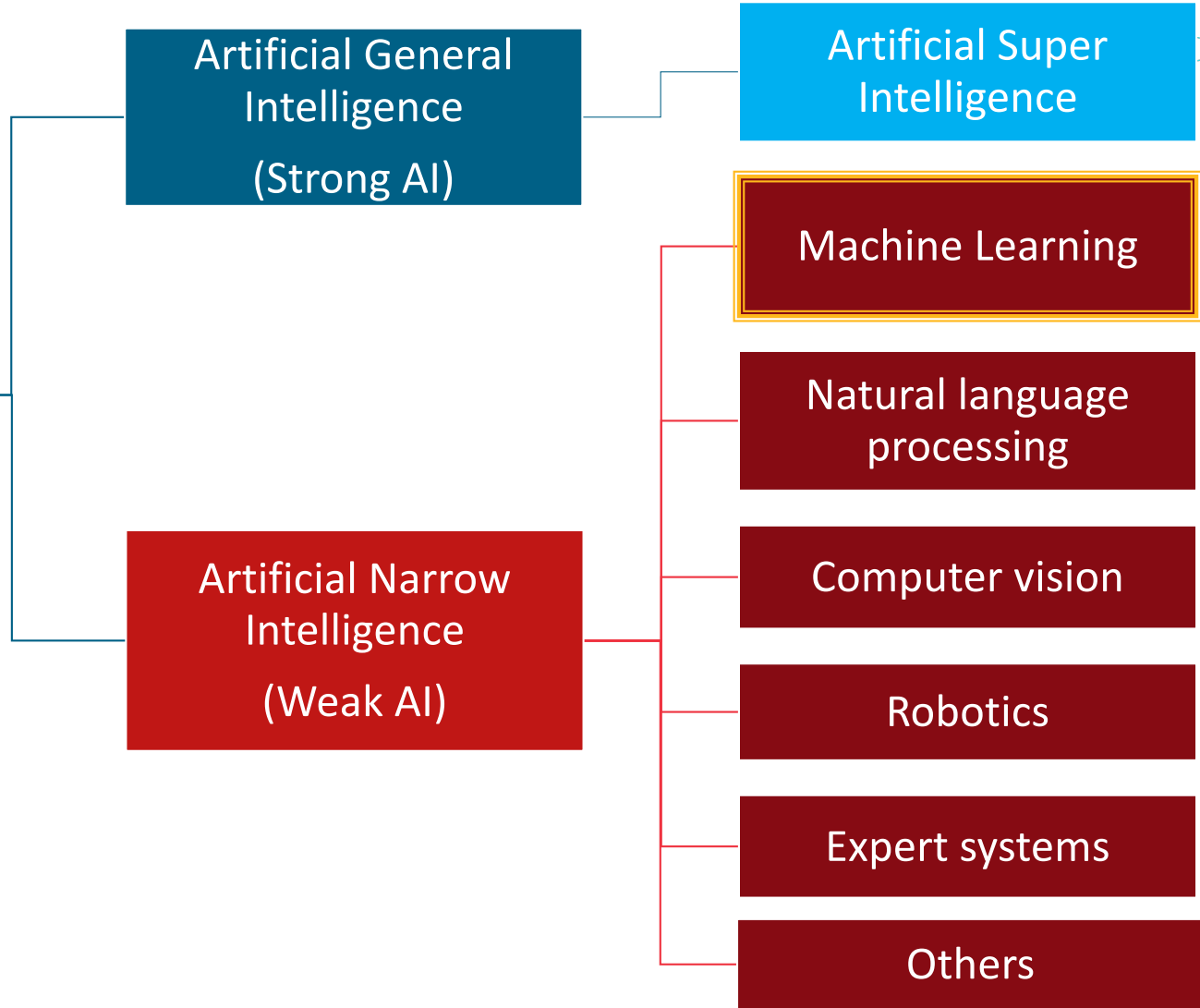


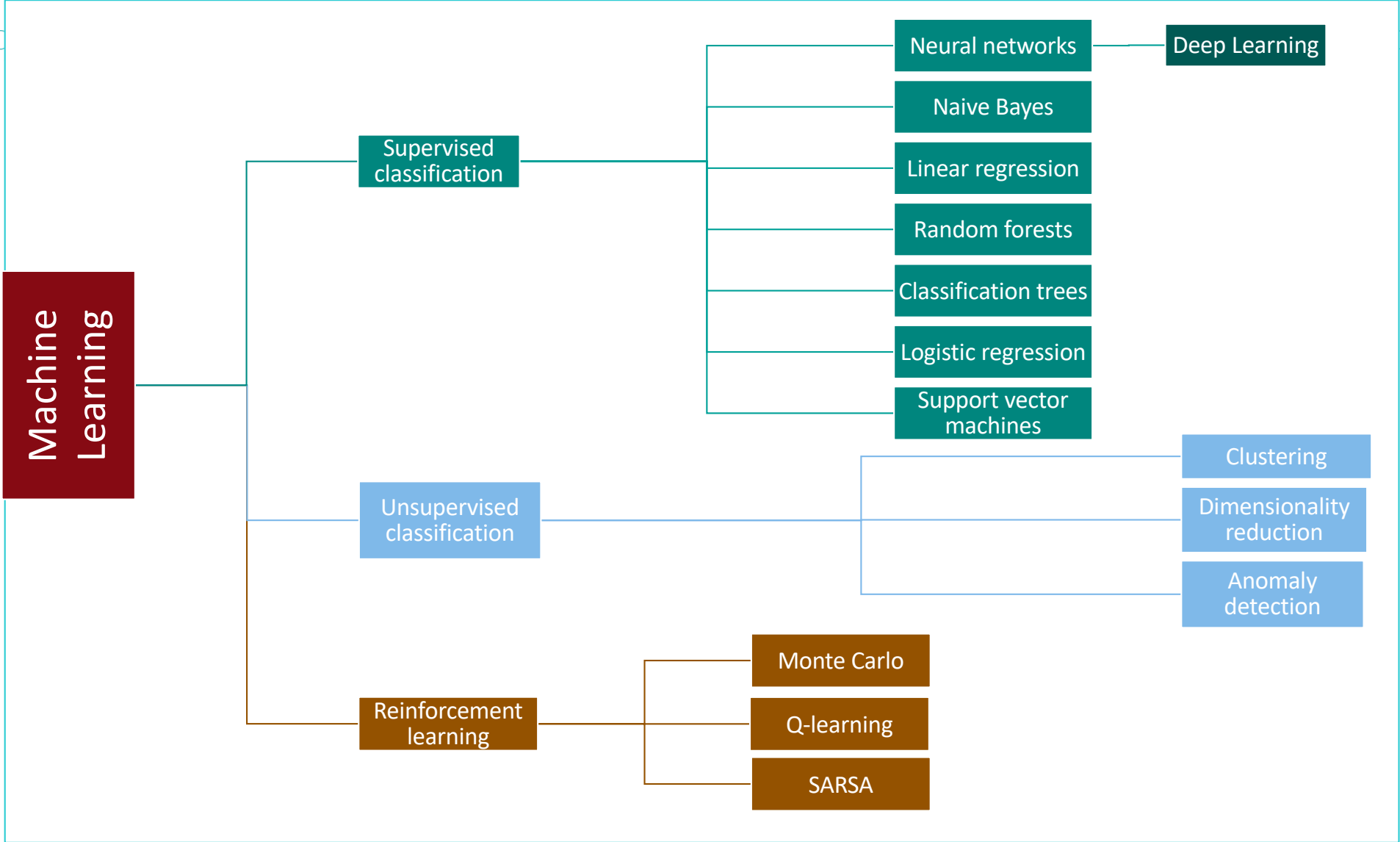
Artificial Narrow Intelligence
(Weak AI)





AI





AI

Machine Learning

- Accuracy
- Less focused on explanation
- e.g. Deep Learning

Statistics

- Understand systems & relationships
- Seeks to explain
- e.g. Hypothesis testing

Regression Methods
Making Predictions

Statistical Learning



POLL #4

I have machine learning in my lab

- A. Yes
- B. No
- C. Don't know
- D. Don't work in a lab
- E. Does a fax machine count?



Machine Learning in the Lab

Growth Areas

- Digital image analysis
 - AP
 - Immunology
 - Hematology
 - UA
- Quality assurance
- Chromatography/MS
- Multi-analyte predictions

Unlikely near term

- Working with people
- Answering complicated (or poorly articulated) questions
- Teaching
- Strategic planning
- Mission, vision, values
- Performance evaluations
- Regulatory



- Digital image analysis
- Integrated interpretations



Analyzer Software

- Stand alone applications
- Chromatography & MS
- Electrophoresis
- Panel interpretations



Quality

- Error detection
- Real time monitoring
- Stewardship
- Reference intervals



Localized Interpretation



Problem Based Predictions

- Disease predictions:
- Chest pain
- COVID
- Sepsis
- AKI
- Acute care

- Patient Wellness
- Early Disease Identification
- Medication recommendations



Complex Predictions



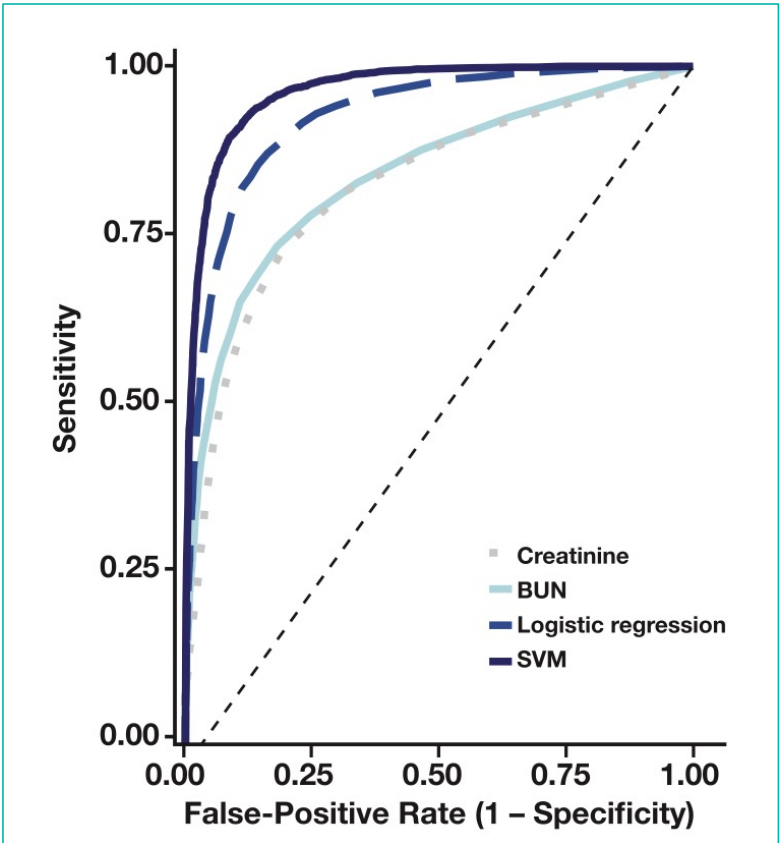


Test Reporting

Neural Network for autoverification

Machine Learning for wrong tube

Quality Review of MS Data





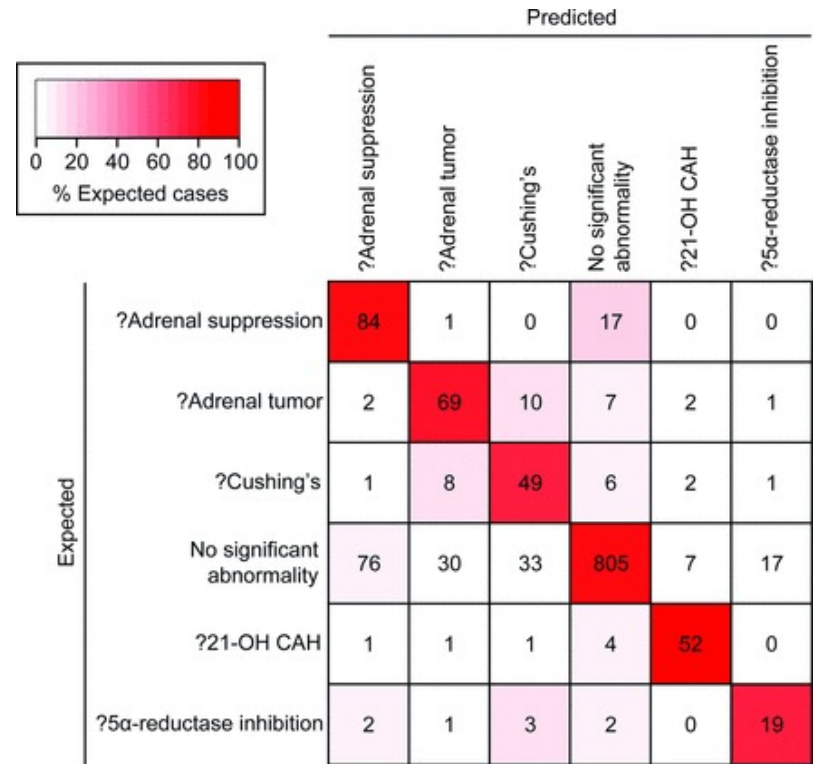
Result Interpretation

Plasma amino acid interpretation

Urine steroid profiles

Acute kidney injury prediction

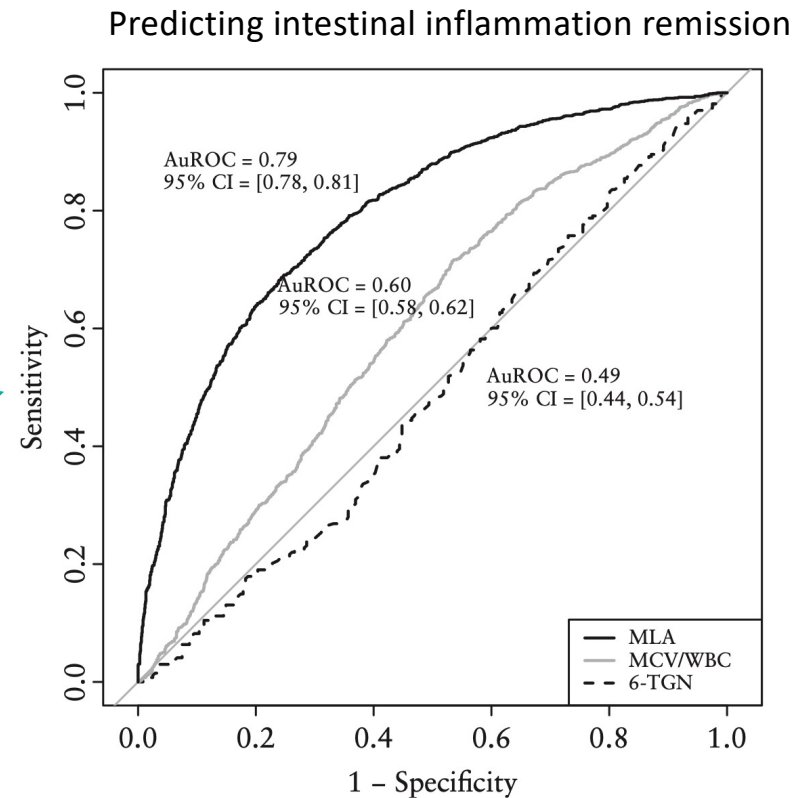
COVID-19 prediction



Machine Learning as a Diagnostic Test

Thiomon:

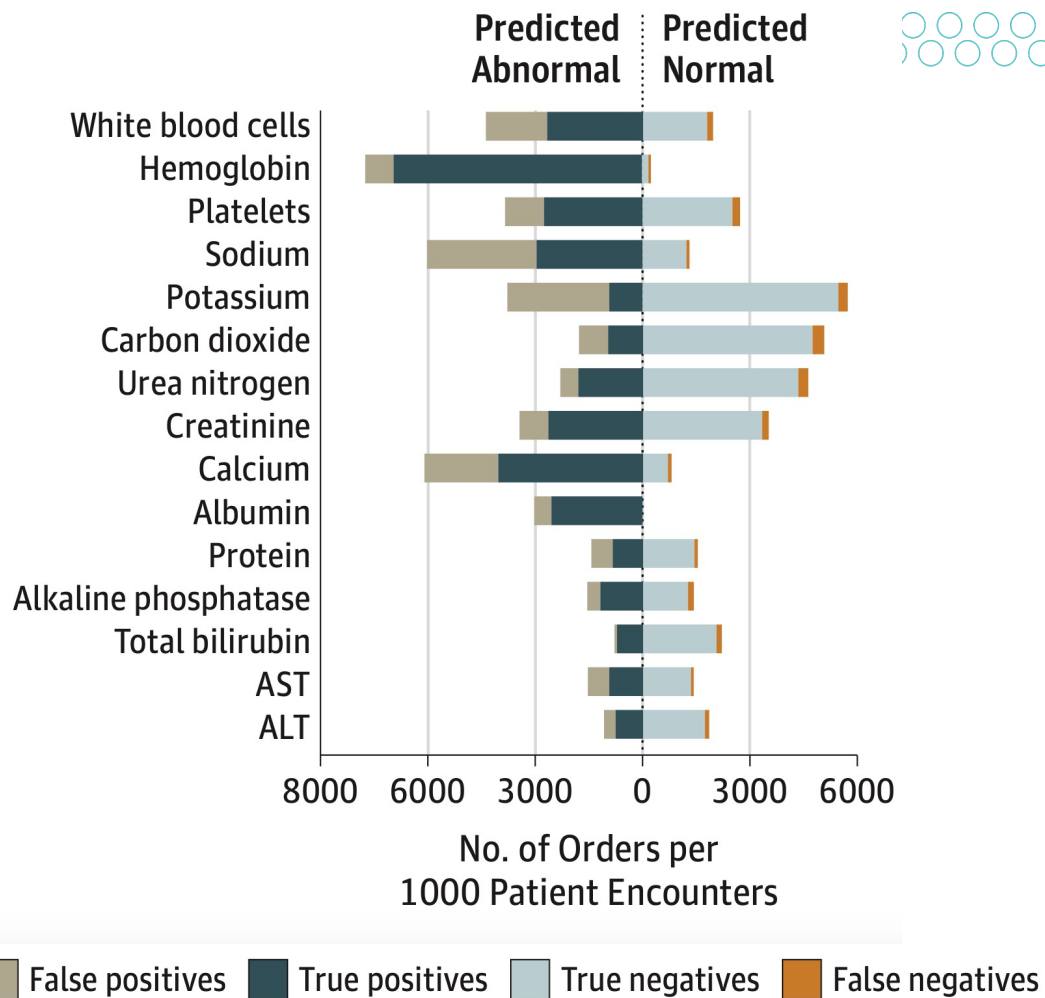
- Prediction of thiopurine treatment success in IBD Patients
- CBC and common chemistry analytes to predict:
 - Response to thiopurines
 - Shunting
 - Compliance





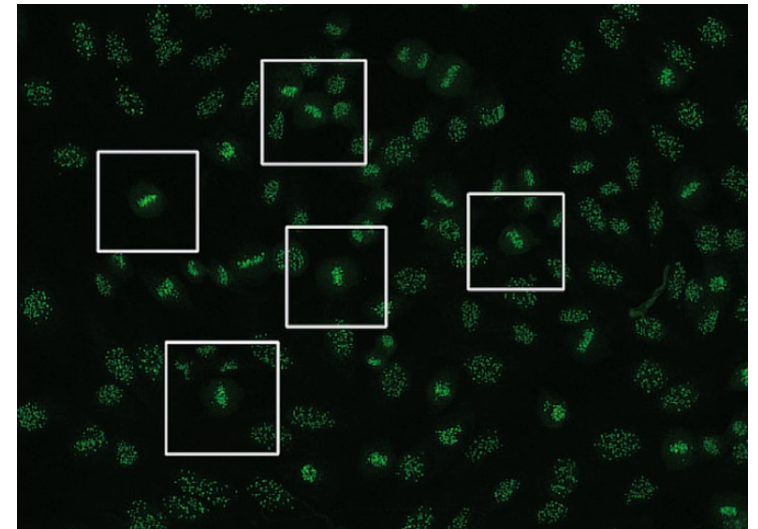
Test Utilization

- Prediction of Low-Yield Tests
 - Inpatients
- LFTs
- Iron deficiency



Automated digital image analysis

- Computer-aided immunofluorescence microscopy
- Automated Urine microscopy
- Peripheral blood smear review



Result of computer
Centromere 1:3200

Visual microscopic result

Official remark

Pattern

Classifier ...

Homogenous	<input type="checkbox"/>
Speckled	<input type="checkbox"/>
Nucleolar	<input type="checkbox"/>
Centromere	1:3.200 <input checked="" type="checkbox"/>
Nuclear dots	<input type="checkbox"/>
Mitosis pattern	<input type="checkbox"/>
Cytoplasmic	<input type="checkbox"/>
Nuclear membrane	<input type="checkbox"/>
Negative	<input type="checkbox"/>

Manual ...

PCNA	<input type="checkbox"/>
Centriole	<input type="checkbox"/>
Spindle fiber	<input type="checkbox"/>
Golgi Apparatus	<input type="checkbox"/>
Midbody	<input type="checkbox"/>
F-Actin	<input type="checkbox"/>
Vimentin	<input type="checkbox"/>





Final Note: Machine Learning in Healthcare Cautions

- Data, Design, & Bias
- Ethics & Legality
- Privacy & Security





Summary

- Lab Data is abundant and rich
- Harvesting and cleaning data can be difficult
- Machine learning is another tool for problem solving
- Treats algorithms as unproven tests



References and Suggested Readings

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