



Practical Applications of Artificial Intelligence in Clinical Microbiology

Daniel D. Rhoads, MD, D(ABMM), FCAP Cleveland Clinic – United States Laboratory Medicine Department



Today's Presenter: Dr. Daniel D. Rhoads, MD, D (ABMM), FCAP

- College of American Pathologists (CAP) Affiliations:
 - Vice Chair of College of American Pathologists
 Microbiology Committee
 - Fellow of College of American Pathologists (CAP)
- Section Head of Microbiology, Robert J. Tomsich
 Pathology & Laboratory Medicine Institute, Cleveland
 Clinic, United States
- Boards Certifications: Clinical Pathology and Medical Microbiology



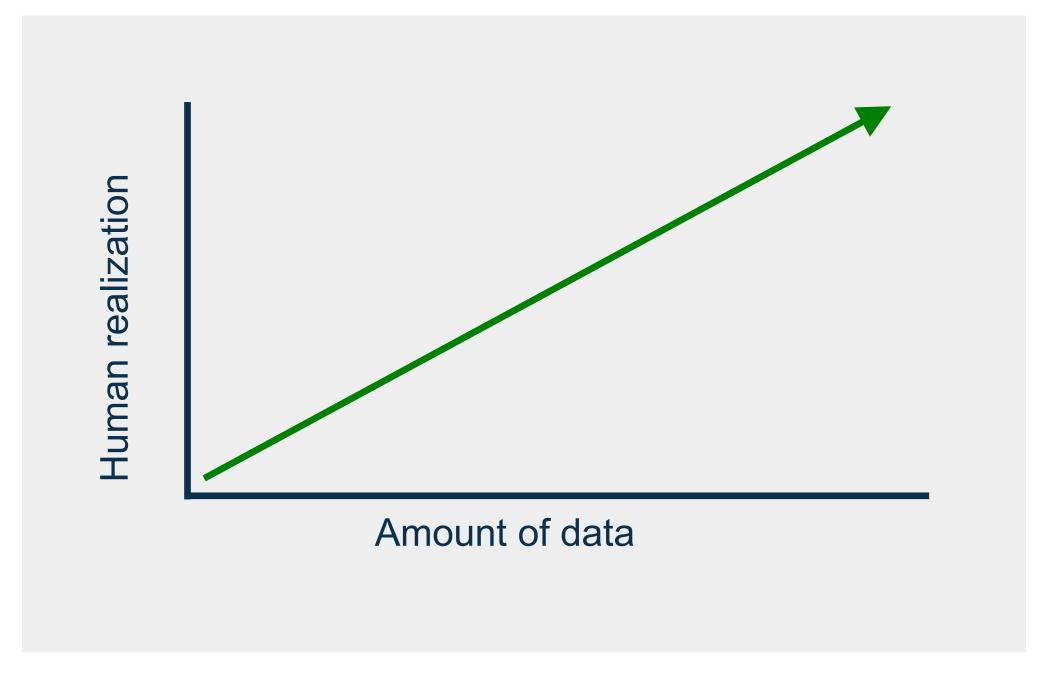
Agenda

- Discuss machine learning
- Review examples using microbiological data
- Q&A

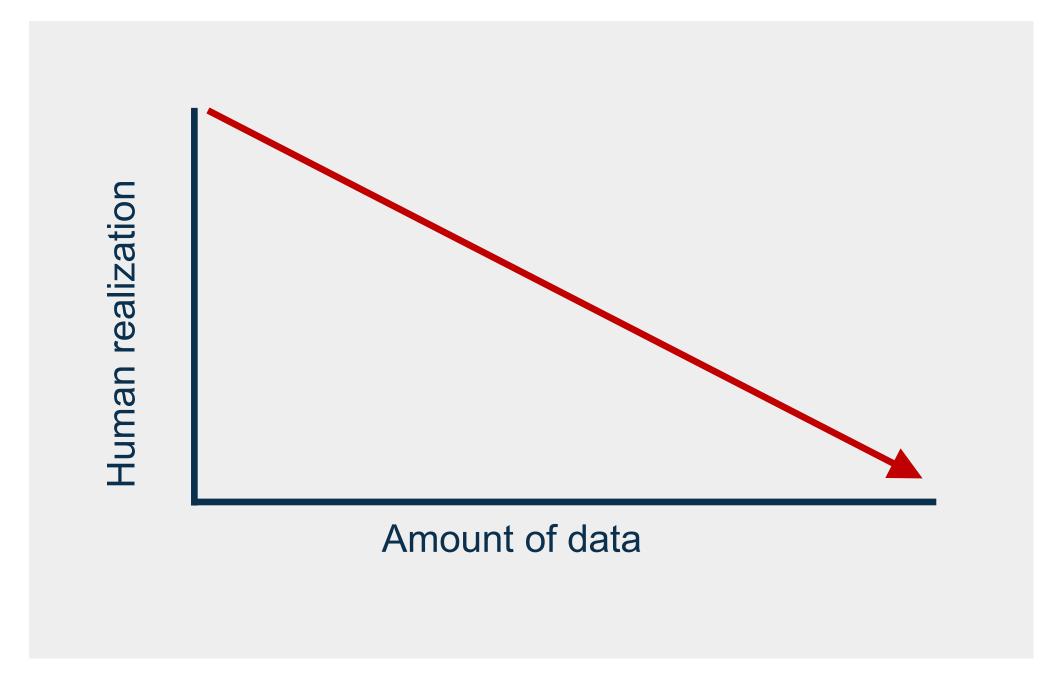
BLUF

The next decade is going to bring **enormous changes** to the practice of clinical microbiology because of the **maturation of sequencing & digital** imaging tools. Both of these applications require **big data solutions**, such as machine learning applications.

20th Century's Data Model:



21st Century's Data Reality:



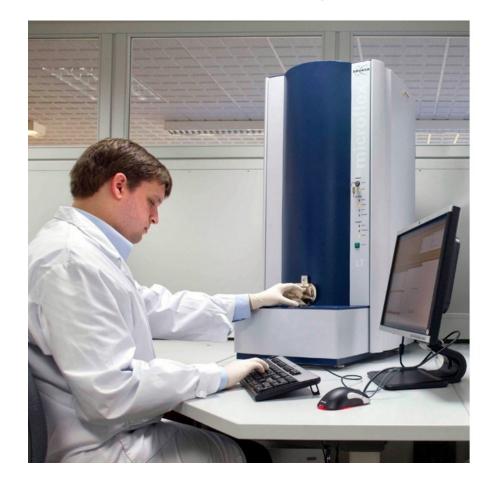
Objectives

- Give one definition of "machine learning."
- Describe how one-way artificial intelligence can be used in clinical microbiology to improve efficiency.
- Describe how one-way artificial intelligence can be used in clinical microbiology to improve quality.



2011-2020

- MALDI for identification of cultured isolates
- Molecular multiplex syndromic panels





2021-2030

- Bigger data
- Better data analysis

Big Data

"Data sets so large and complex that it becomes difficult to process using on-hand data management tools or traditional data processing applications."

Source: https://www.forbes.com/sites/gilpress/2014/09/03/12-big-data-definitions-whats-yours/

Big Data

- Image data (photos)
- MALDI data (mass spectra)
- Sequencing data (DNA reads)

Image Data (Photos)

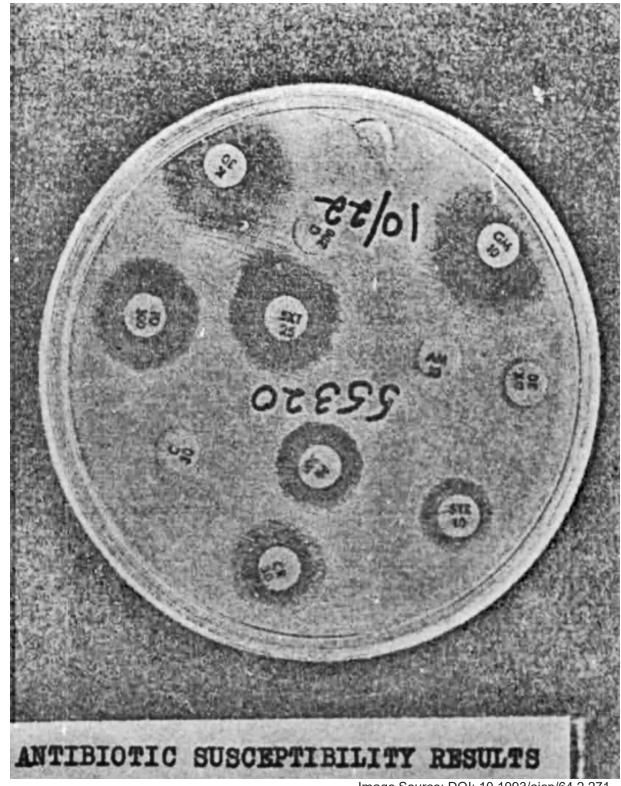
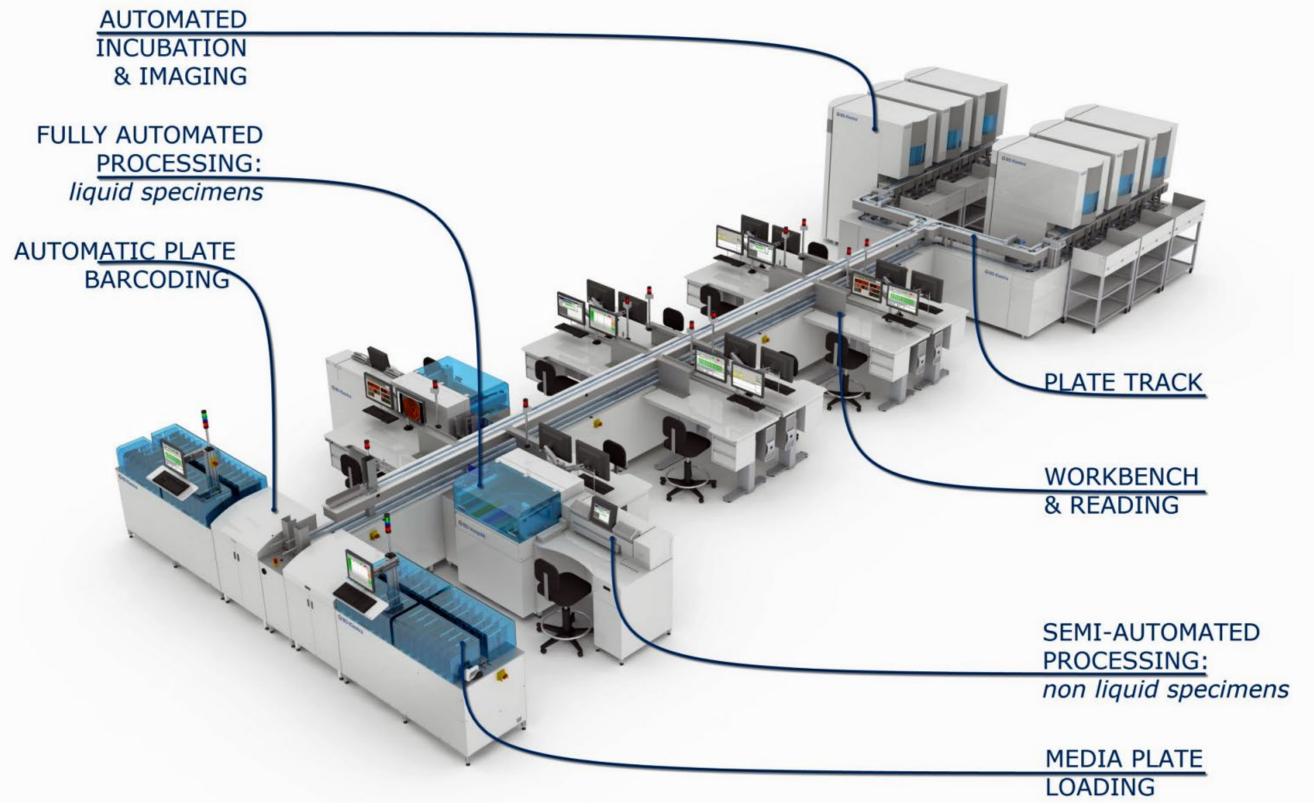


Image Source: DOI: 10.1093/ajcp/64.2.271



Image Source: http://xeroxnostalgia.com/wp-content/uploads/2015/05/Xerox_4000.jpg



Machine Learning

"Machine learning is a current application of artificial intelligence based around the idea that we should really just be able to give machines access to data and let them learn for themselves."

—Bernard Marr



Source: https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial intelligence-and-machine-learning/

Nugent Scored Gram Stains

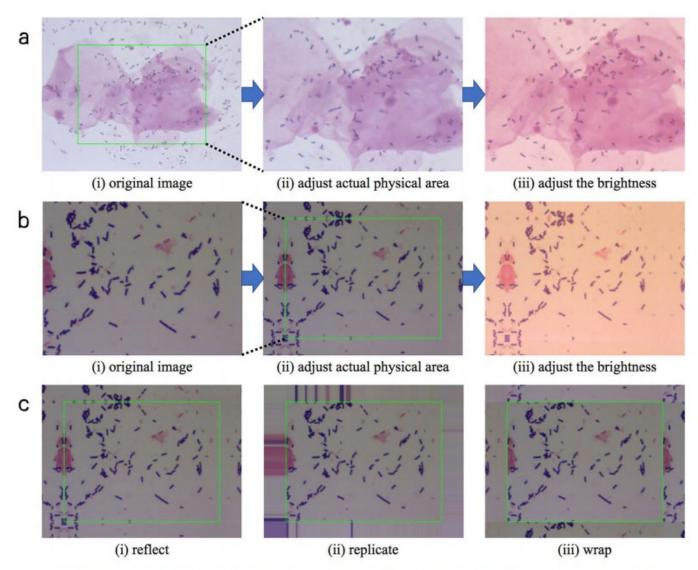


FIG 2 Preprocessing for test sets B (a) and C (b). (c) Three typical edge expansion methods used for panel b, image ii.

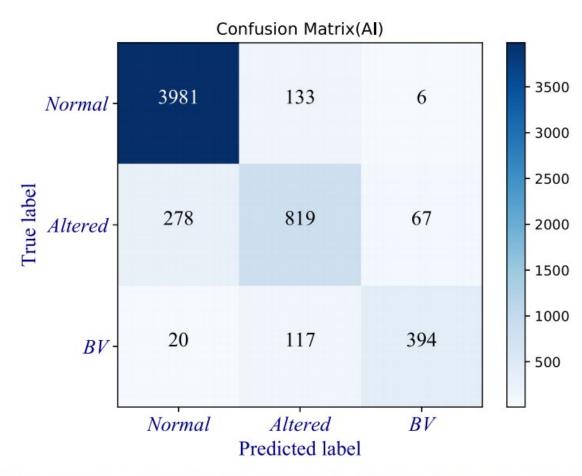


FIG 3 The confusion matrix of the best points of the 1/4 NugentNet on the validation set.

Source: DOI: 10.1128/JCM.02236-20

O&P

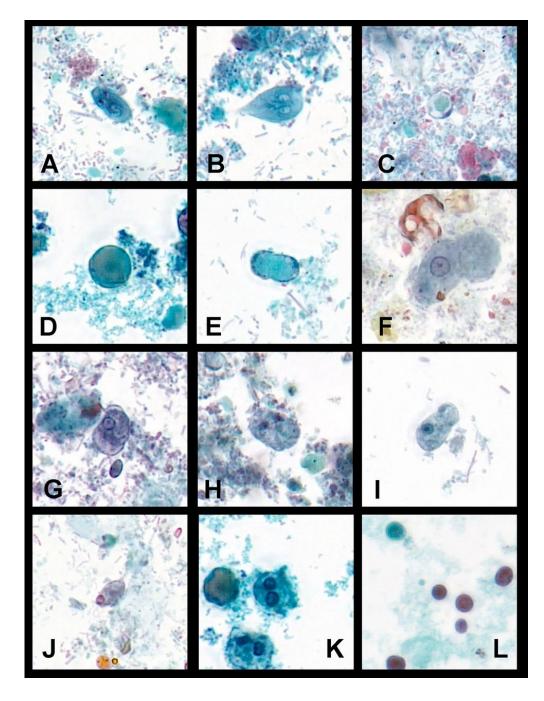


TABLE 3 Limit of detection data for the five runs

	Dilution series 1	
Dilution	Technologist	Model
Neat	Giardia duodenalis,	Giardia duodenalis,
	1+ Blastocystis sp.	1+ Blastocystis sp.
1:1	Giardia duodenalis,	Giardia duodenalis,
	1+ Blastocystis sp.	1+ Blastocystis sp.
1:2	Giardia duodenalis,	Giardia duodenalis,
	1+ Blastocystis sp.	1+ Blastocystis sp.
1:4	Giardia duodenalis,	Giardia duodenalis,
	1+ Blastocystis sp.	1+ Blastocystis sp.
1:8	Giardia duodenalis,	Giardia duodenalis,
	1+ Blastocystis sp.	1+ Blastocystis sp.
1:16	Negative	Giardia duodenalis,
	-	1+ Blastocystis sp.
1:32	Negative	Giardia duodenalis,
		1+ Blastocystis sp.
1:64	Negative	Negative ^a
1:128	Negative	Giardia duodenalis,
		1+ Blastocystis sp.
1:256	Negative	Giardia duodenalis,
		1+ Blastocystis sp.

 $[^]a$ Incomplete scan.

Source: DOI: 10.1128/JCM.02053-19

MALDI Data (Mass Spectra)

MALDI-TOF Mass Spectrometry

Machine Learning

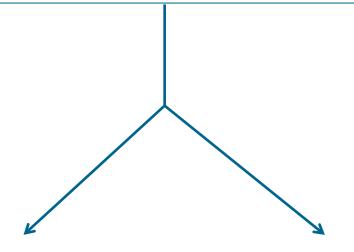
"Machine learning is a current application of artificial intelligence based around the idea that we should really just be able to give machines access to data and let them learn for themselves."

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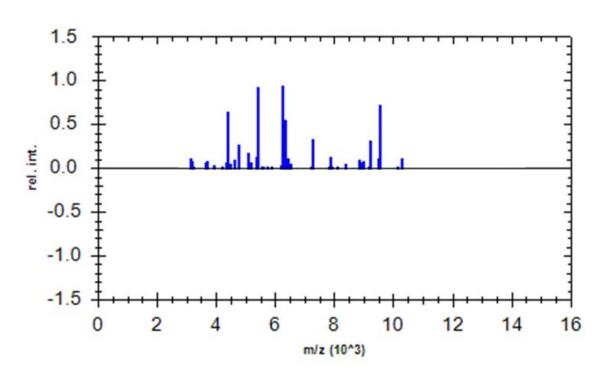
Source: https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial intelligence-and-machine-learning/

194 Acinetobacter baumannii isolates



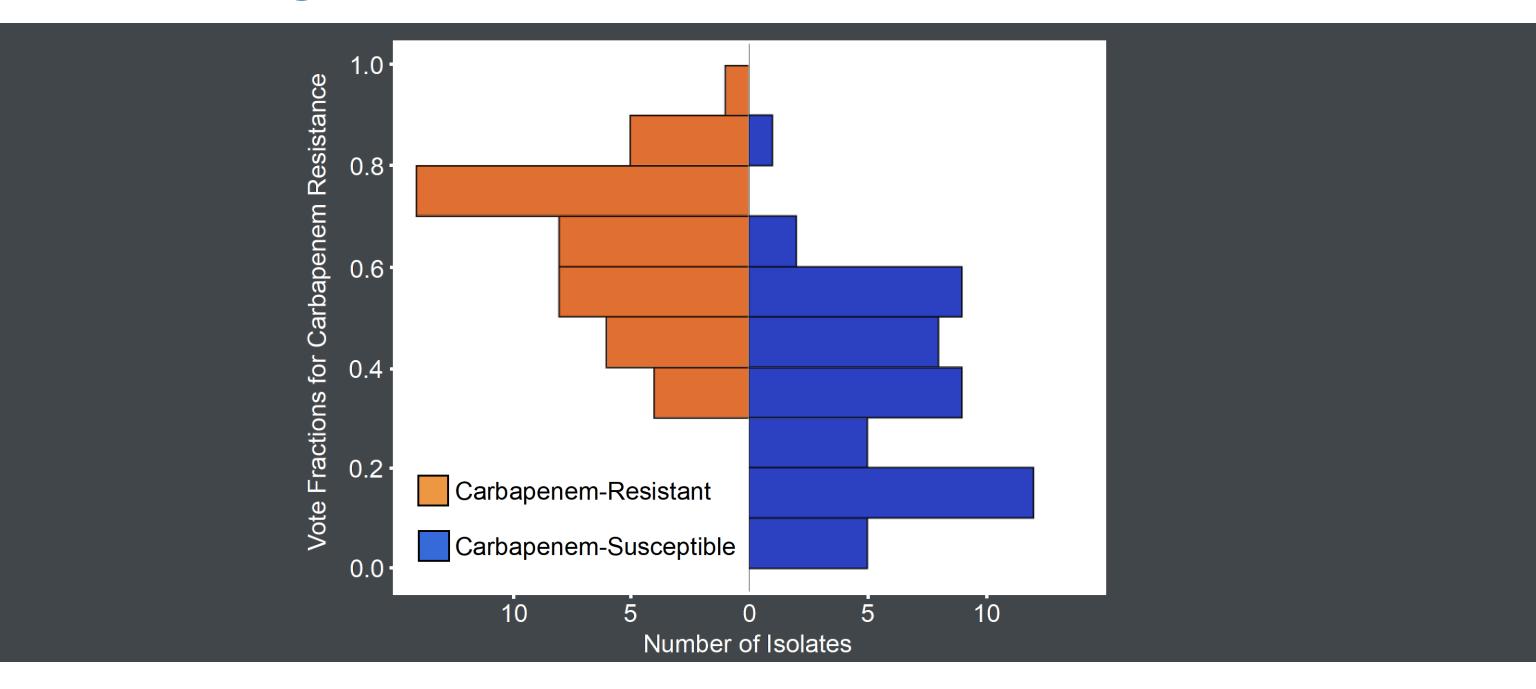
Training Set N = 97

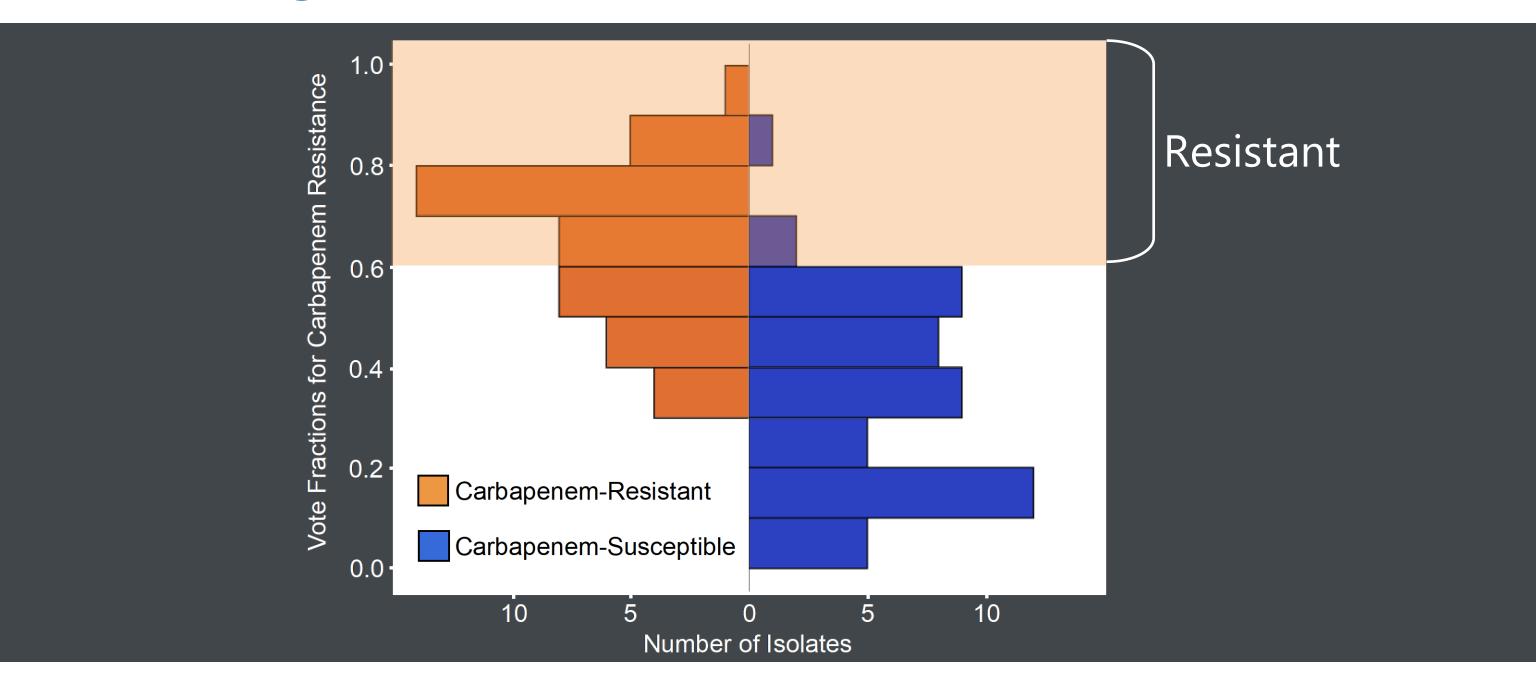
Resistant N = 46Susceptible N = 51 Test Set N = 97

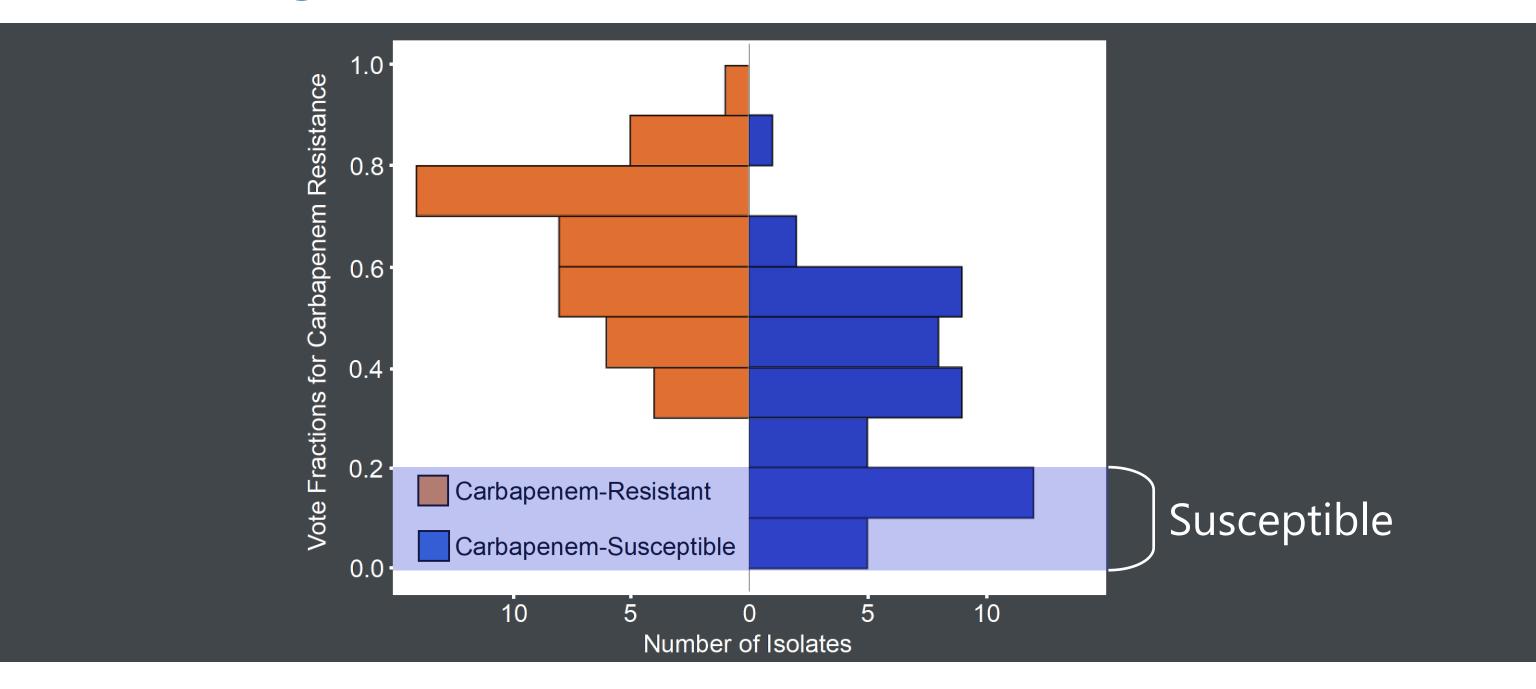


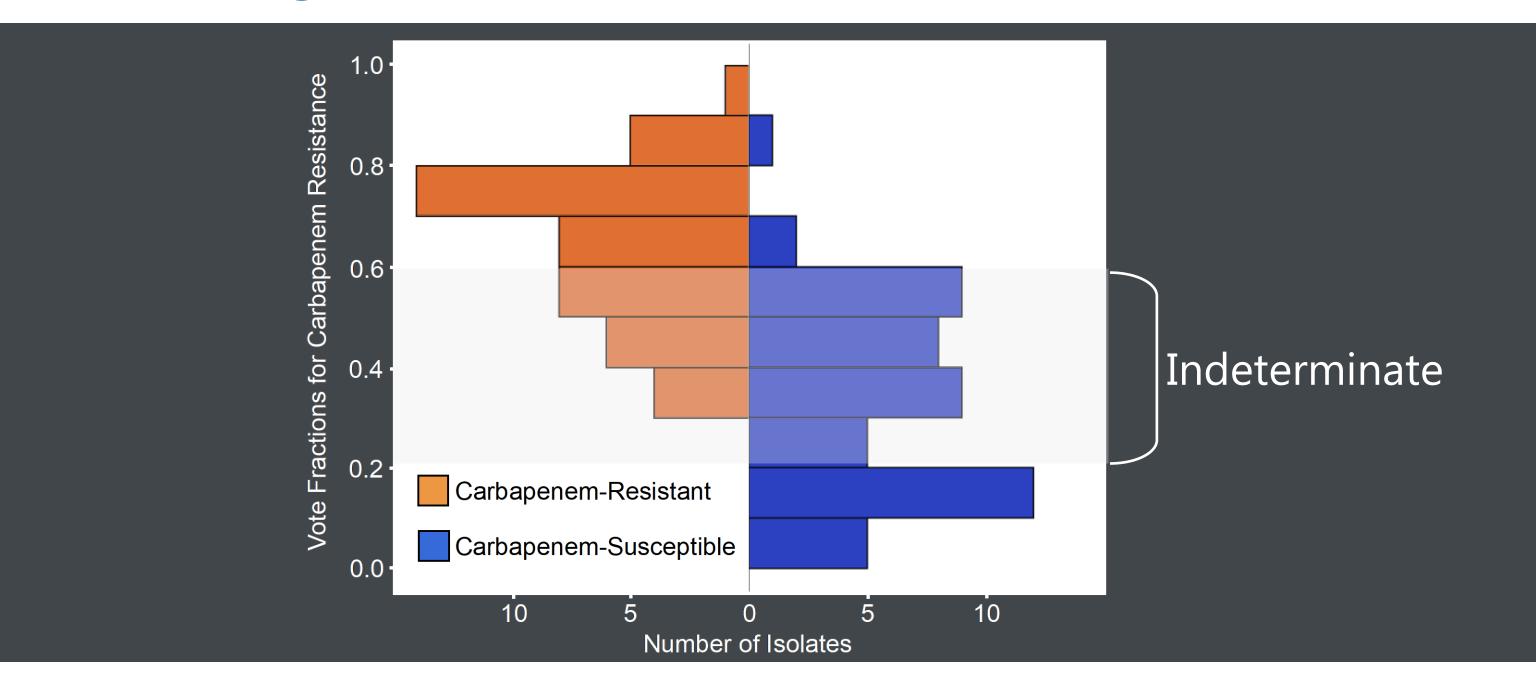
Hannah Wang, MD

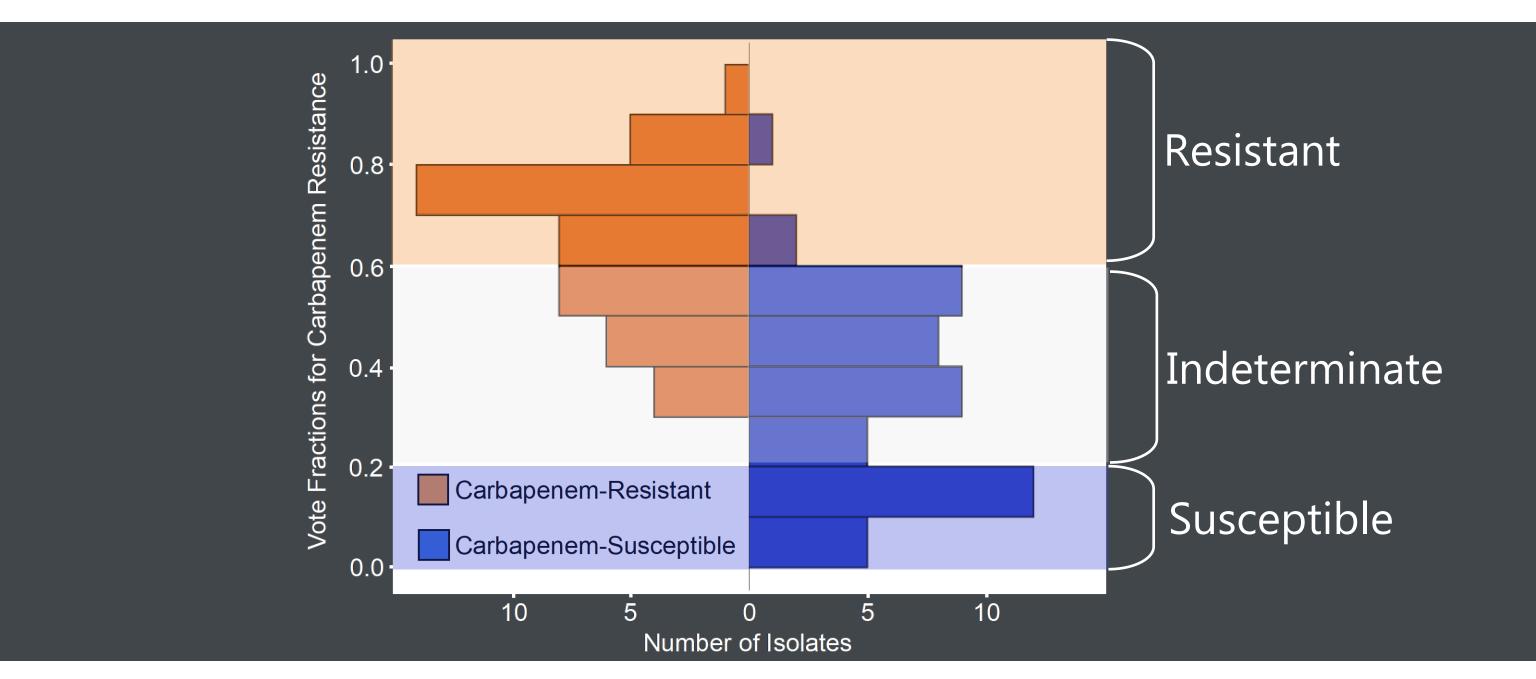




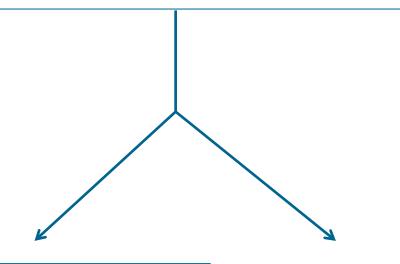






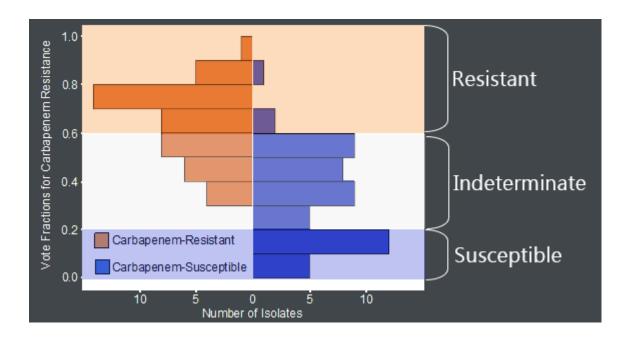


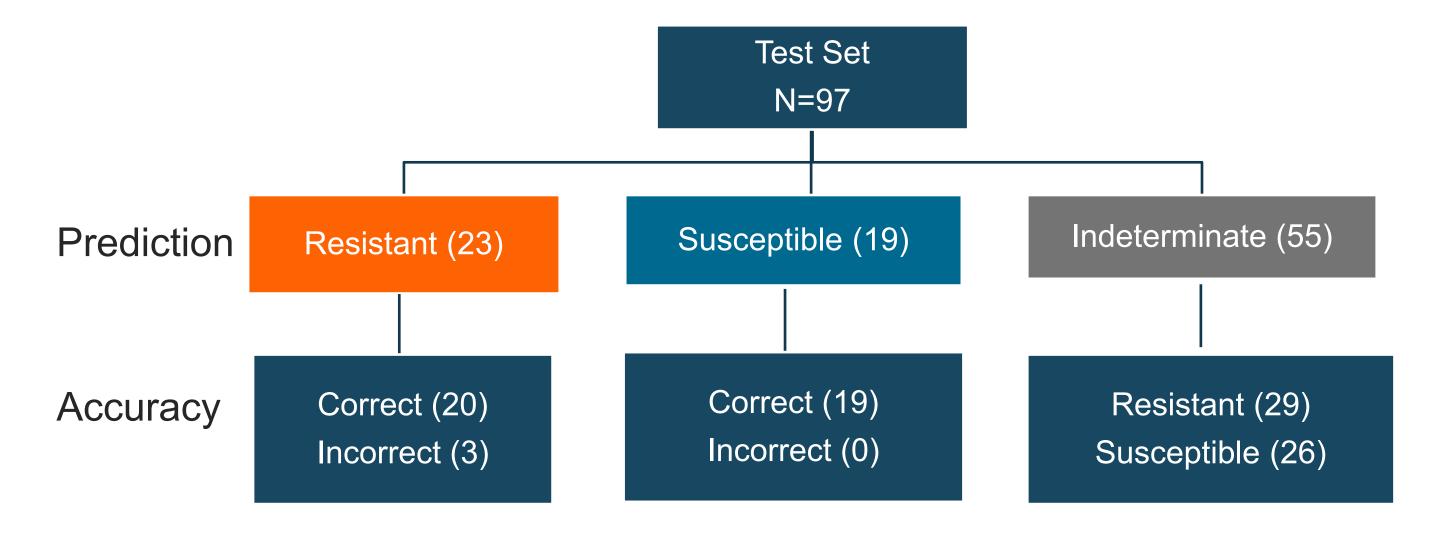
194 Acinetobacter baumannii isolates

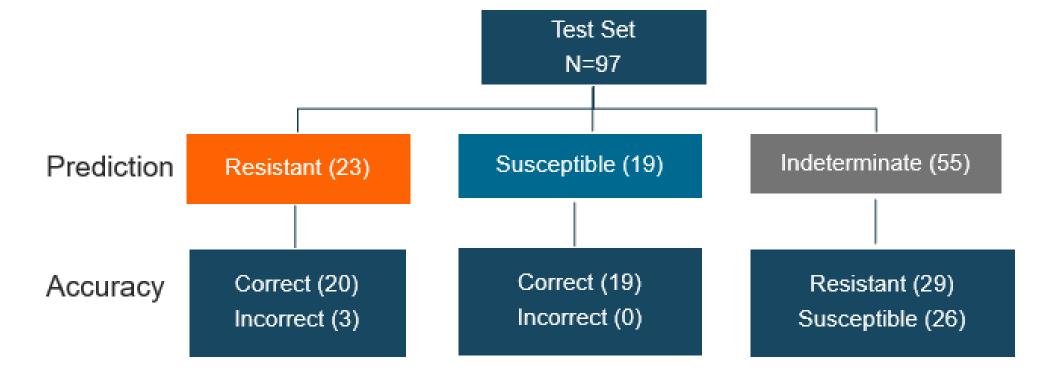


Training Set N = 97

Resistant N = 46 Susceptible N = 51 Test Set N = 97







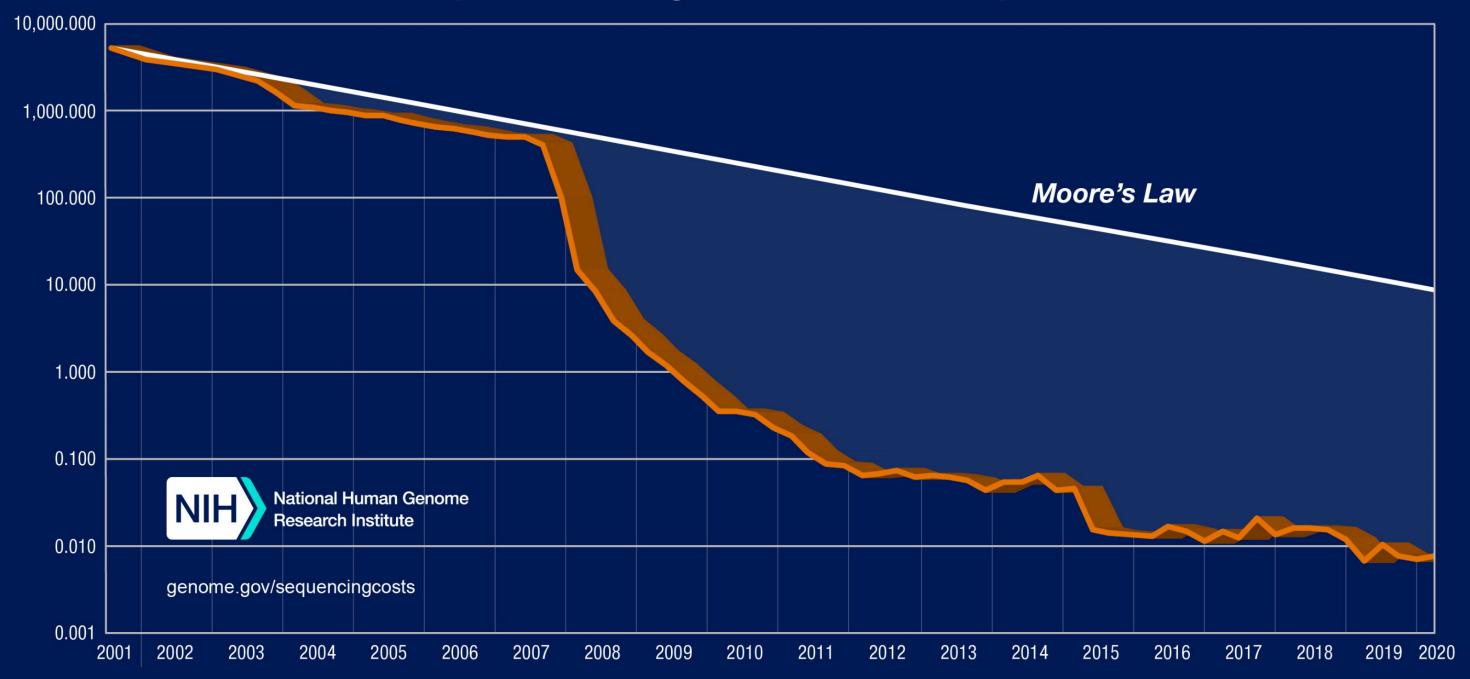
Conclusion: The machine learning model was able to classify almost half of *A. baumannii* isolates as carbapenem susceptible or resistant with 93% accuracy and no very major errors using only mass spectral data.

Hannah Wang, MD



Sequencing Data (DNA Reads)

Cost per Raw Megabase of DNA Sequence



Whole Genome Sequencing

Strain typing (clonality assessment)

https://www.cdc.gov/amd/how-it-works/detecting-outbreaks-wgs.html

Whole Genome Sequencing

- Strain typing (clonality assessment)
- Detection of mutations or acquired genes associated with resistance
- Machine learning to predict resistance...

Machine Learning

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—Bernard Marr



Source: https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial intelligence-and-machine-learning/

Whole Genome Sequencing



BACTERIOLOGY



Using Machine Learning To Predict Antimicrobial MICs and Associated Genomic Features for Nontyphoidal Salmonella

Marcus Nguyen,^{a,b*} [®]S. Wesley Long,^{c,d} Patrick F. McDermott,^e Randall J. Olsen,^{c,d} Robert Olson,^{a,b*} Rick L. Stevens,^{b,f*} Gregory H. Tyson,^e Shaohua Zhao,^e James J. Davis^{a,b*}

^aUniversity of Chicago Consortium for Advanced Science and Engineering, University of Chicago, Chicago, Illinois, USA

^bComputing, Environment and Life Sciences, Argonne National Laboratory, Argonne, Illinois, USA

^cCenter for Molecular and Translational Human Infectious Diseases Research, Department of Pathology and Genomic Medicine, Houston Methodist Research Institute and Houston Methodist Hospital, Houston, Texas, USA

^dDepartment of Pathology and Laboratory Medicine, Weill Cornell Medical College, New York, New York, USA

eU.S. Food and Drug Administration, Center for Veterinary Medicine, Office of Research, Laurel, Maryland, USA

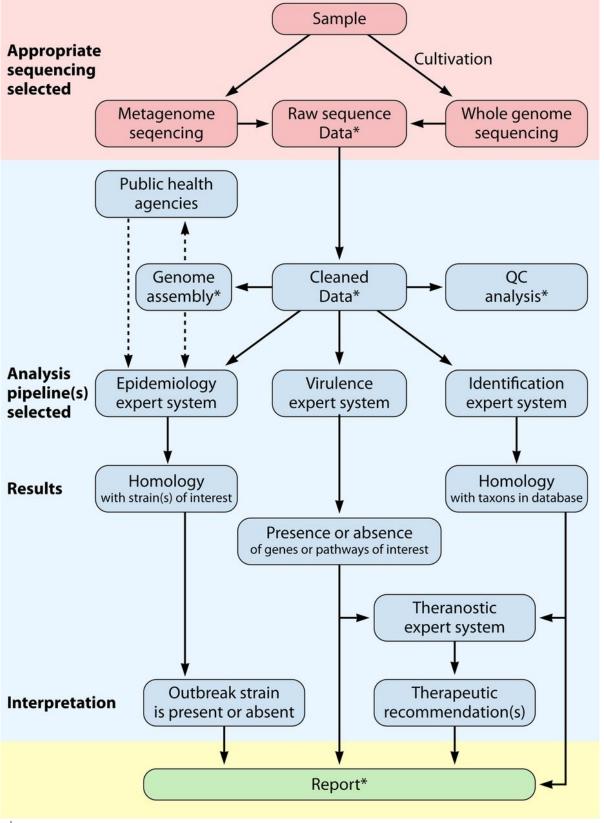
^fDepartment of Computer Science, University of Chicago, Chicago, Illinois, USA

Source: DOI: 10.1128/JCM.01260-18

Whole Genome Sequencing

"5,278 nontyphoidal *Salmonella* genomes, [...] was used to generate [...] machine learning models for predicting MICs for 15 antibiotics. The MIC prediction models had an overall average accuracy of 95% [...] The model predicted MICs with no *a priori* information about the underlying gene content or resistance phenotypes of the strains."

Source: DOI: 10.1128/JCM.01260-18



2021-2030

- Bigger data
- Better data analysis

Today, we already have the data.

Tomorrow, we need to develop better analysis tools.



CAP Pathologist Informatics Education

Informatics Case-Based Education (ICBE/ICBE1)

- New for 2022
- Educates pathologists on common issues encountered in practice, including:
 - Software implementations
 - Test ordering issues
 - Regulatory compliance
 - Data security
- Appropriate for medical directors and/or staff pathologists
- Created by pathologists for pathologists
- 4 cases annually; each case offers 1 CME credit





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- international@cap.org
- (847) 832-7000 Country Code: 001