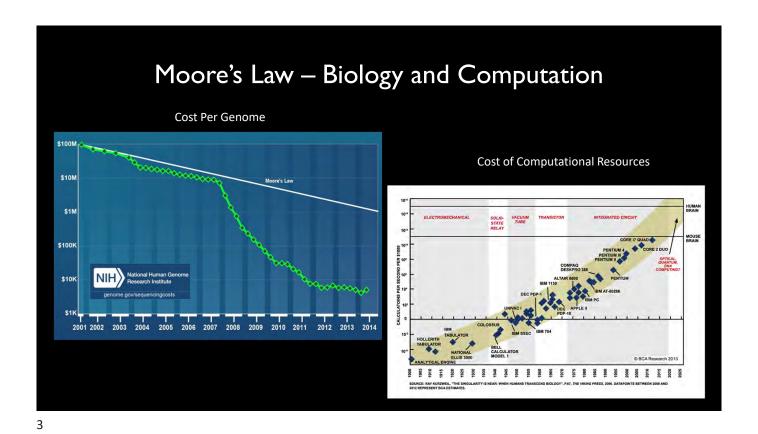


Why Now?

I 1000
GENOMES
GENE EXPRESSION Omnibus

ENCYCLOPEDIA OF DNA ELEMENTS

ENCYCLOPEDIA OF



Integrative Personal "Omics" Profiling

Genome

Transcriptome

Epigenome

Microbiome

# Artificial Intelligence

- A branch of computer science dealing with the simulation of intelligent behavior in computers – making predictions and decisions
- The capability of a machine to imitate intelligent human behavior
- Examples:
  - Visual perception
  - Speech recognition
  - Translation between languages
  - Decision-making



5

# Machine Learning

- Computers are good at following instructions
- Example run a spell checker on a document
- But what if the task is really complicated to describe?

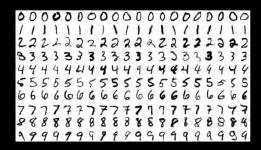


Eugene Davydov, PhD

# Example: Digit Recognition

- Many tasks aren't easy to describe at the level of individual instructions
- We (humans) can recognize handwritten digits because we've seen many examples in our lifetimes

How can we write computer programs that can learn and get better from data?



Eugene Davydov, PhD

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# Machine Learning is Transforming Our Lives

- Machine learning (ML) is a type of artificial intelligence (Al) that provides computers with the ability to learn without being explicitly programmed
- Focuses on the development of computer programs that can change when exposed to new data

Recommender Systems





**Biomedical** 

**Applications** 

Eugene Davydov, PhD

**Image Processing** 

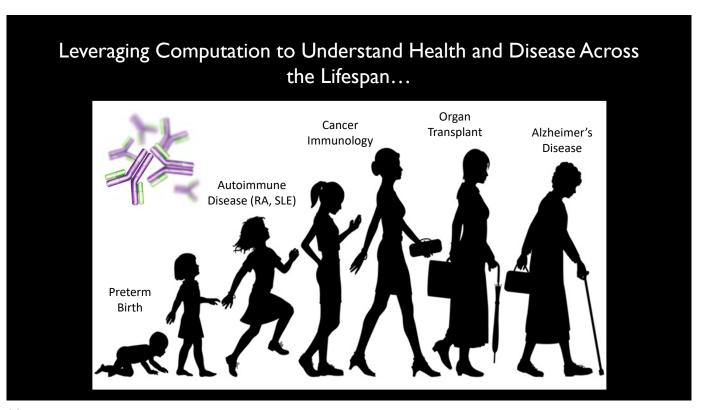






We have been so successful in transforming many everyday industries, but how can these data-driven approaches be applied in biomedicine?





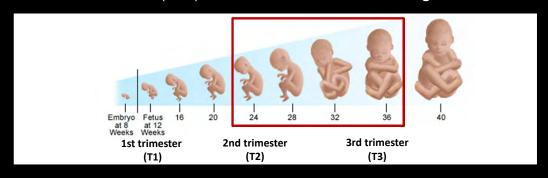
# Pregnancy and Preterm Birth



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# Why Study Preterm Birth?

Preterm birth (PTB) - live birth before week 37 of gestation

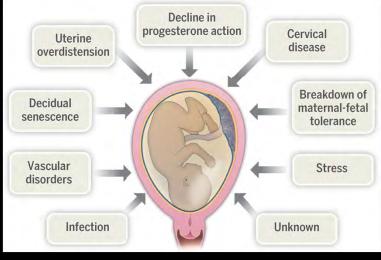


Worldwide, 15 million babies are born premature each year.

One million of these infants die within the first 28 days of life.

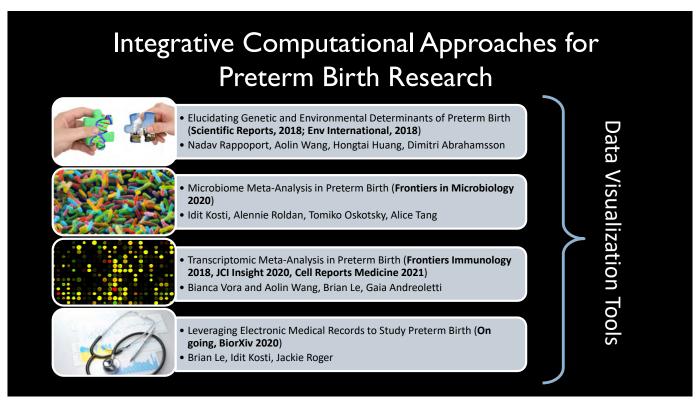
In nearly half of the cases of premature birth, there is no clear cause.

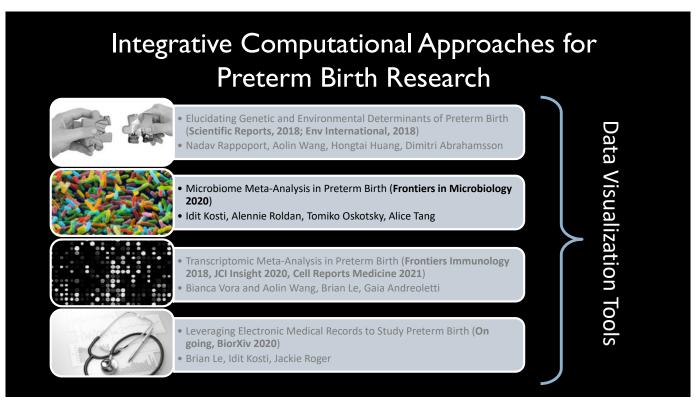
# Many mechanisms have been associated with sPTB



Romero R, et al. Science (2014).

17

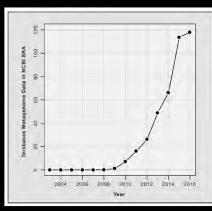




# Microbiome Meta-Analysis: Challenges and Opportunities

• Impossible to combine processed data, need to go back to the raw data

- Sample metadata is hard to get access to
- Lots of potential biases:
  - 16s vs. whole genome
  - Taxa vs. gene analysis
  - Sample prep differences
  - Variable regions of the 16s gene that were sequenced
  - Longitudinal vs. Case-Control



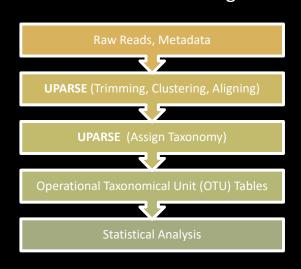
Stephen Nayfach and Katie Pollard, 2016

Public Pregnancy	Microbiome Data
n . f	

	# of samples	Mother/ Baby	# of Subjects	# of body sites	# of Species	# of reads	Reference	Body sites	Type of Data	Time points
НМР	5,298	Controls	242	18	5385	30,336,944	The Human Microbiome Project Consortium	Mouth, Nose, Skin, Gut and Vagina	16s	Controls
Stanford PTB Longitudinal (MOD)	4,399	Mother	51	11	4694	656,308	DiGiulio et al.	Vagina, Gut, Saliva, and Tooth/Gum	16s, WGS	Weekly
Placenta Penn	69	Mother	6	5	2108	207,5881	Lauder et al.	Placenta, Vagina	16s	Delivery
Vaginal PTB	349	Mother	100	1	550	2,213,608	Romero et al.	Vagina	16s	Every 4 weeks until 24, every 2 weeks until the last prenatal visit
Placenta PTB	48	Mother	48	1	TBD	1,348,416	Aagard et al.	Placenta	16s, WGS	Delivery
Gut Microbiome in Pregnancy	972	Mother/ Baby	91	1	2339	112,8572	Koren et al.	Gut	16s	T1,T3,PP
Vaginal Pregnancy	TBD	Mother	42	1	TBD	TBD	MacIntyre et al.	Vagina	16s	T1,T2,T3,PP

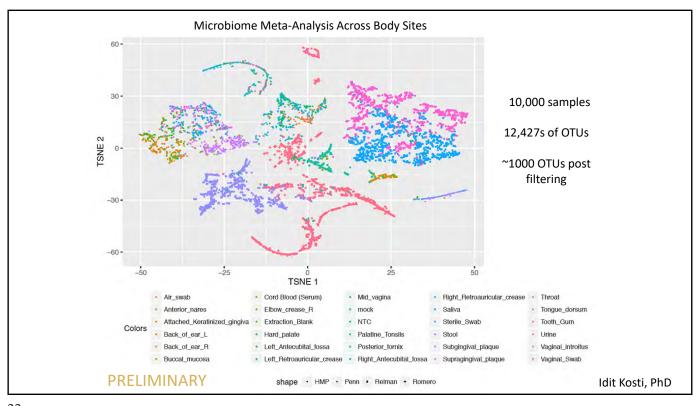
# Microbiome Meta-Analysis Pipeline

Is time consuming and computationally intensive



Study Name	Raw Reads Size
НМР	19.03GB
Stanford PTB Longitudinal (MOD)	8.98GB
Placenta Penn	991.2MB
Vaginal PTB	1.28GB
Placenta PTB	490.9MB
Gut Microbiome in Pregnancy	427.2MB

Idit Kosti, PhD



Can we identify new microbial species associated with PTB in a longitudinal analysis leveraging public data?

## Bacterial Vaginosis is a Known Risk Factor for PTB

- Bacterial vaginosis is a state of an overgrowth of anaerobic bacteria, replacing the normal vaginal Lactobacillus.
- Bacterial vaginosis has been shown to increase the risk for preterm birth.
- Several microbiome studies have been carried out but no meta-analysis to date.

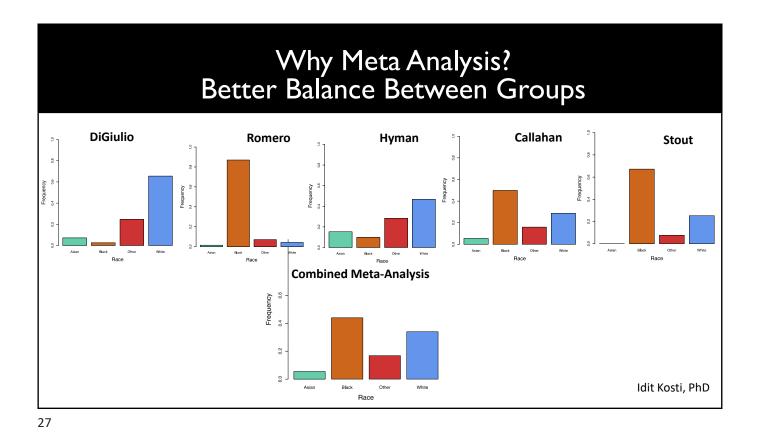
Manns-James L., J Midwifery Womens Health, 2011

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# Meta-Analysis Allows Greater Power

	Callahan et al.	DiGiulio et al.	Hyman et al.	Romero et al.	Stout et al
Total Number of Patients	135	37	82	87	74
PTB Patients	50	5	16	18	23
T1 Samples	42 (10 PTB)	21 (4 PTB)	37 (5 PTB)	6 (2 PTB)	14 (4 PTB)
T2 Samples	135 (50 PTB)	31 (4 PTB)	50 (10 PTB)	76 (17 PTB)	55 (18 PTB)
T3 Samples	123 (39 PTB)	36 (4 PTB)	46 (9 PTB)	60 (5 PTB)	59 (17 PTB)
Overall PTB Ratio	37%	12.5%	21%	17.33%	31.1%
Sampling Time Points	Once per week	Once per week	One per trimester	Once every 4 weeks (< 24 gestation weeks) Once every 2 weeks (> 24 gestation weeks)	Once per trimester

Over 3,000 samples and 350+ women



Raw 16S Sequencing Data OTU - a microbial taxonomic ...ACATCATACAGATACAAATA... ..ACCCATGATAGAGAAACAGA. unit based on sequence divergence. Callahan et al. DiGiulio et al. Hyman et al. Stout et al. HMP Romero et al. 447 samples 631 samples 323 samples 104 samples 131 samples 2012 samples 386 patients 37 patients 87 patients 81 patients 74 patients 135 patients Samples **Data Processing Pipeline UPARSE** Reads preparation, Reads De-replication, Alignment, Taxonomy Prediction, OTU Generation, Tree Generation Data Normalization Batch effect Adjustments Accounting for Study Bias OTU Modeling and Meta-Analysis Weighted Linear Mixed Effects Regression Longitudinal Modeling Accounting for Race, Study, Sampling Frequency Non-Pregnant vs. Term vs. Preterm

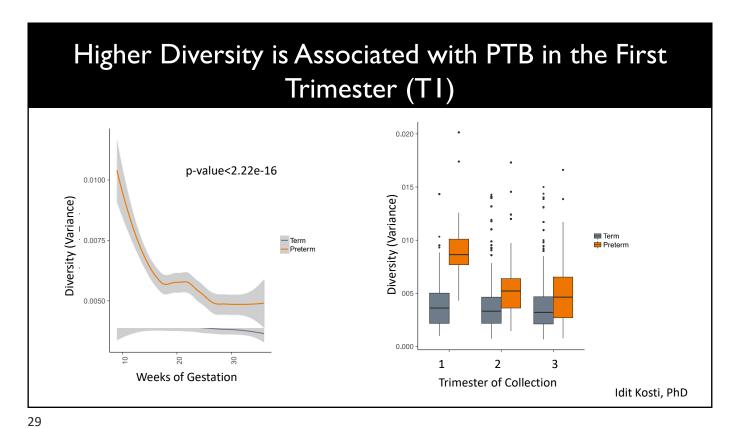
**Association Analysis** 

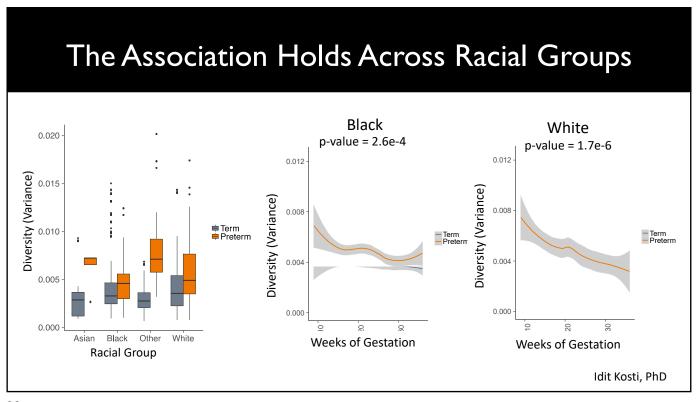
OTU Abundance

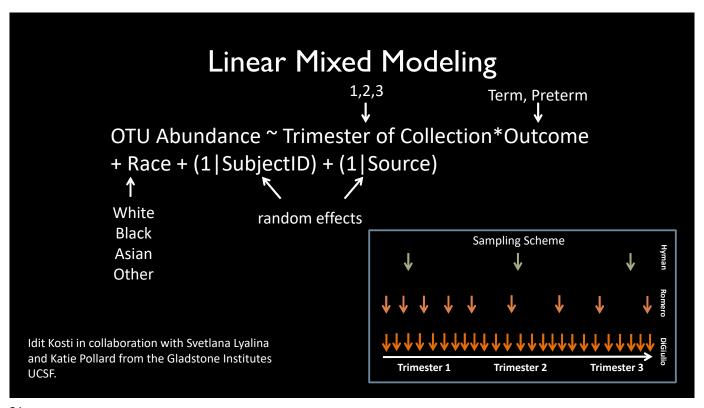
**Diversity Analysis** 

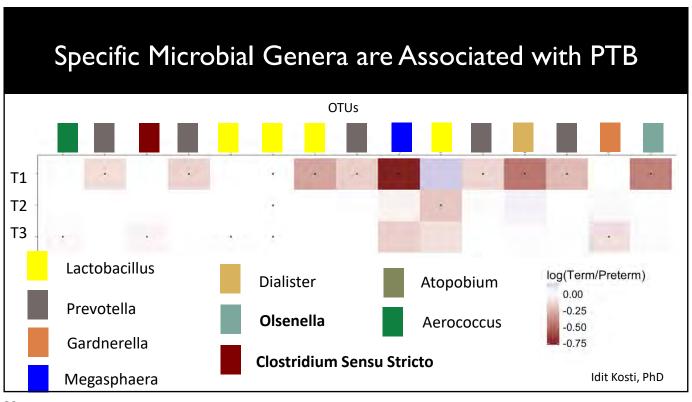
Variance, Shannon Index

Idit Kosti, PhD









# Novel Bacterial Genera Identified by Meta-Analysis

оти	Genera	Trimester	Adj. P- value	Bacterial Vaginosis	Associated with PTB
Otu875	Olsenella	1	<2.2e-16	<b>√</b>	X
Otu1238	Clostridium sensu stricto	3	1.58E-03	X	X

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# Summary

- We observe higher microbial diversity in women who deliver preterm, especially in the first trimester.
- We identify novel bacteria associated with preterm birth using a meta-analysis approach leveraging public data.
- First trimester vaginal sampling may help identify those at risk for preterm birth.

Kosti I, Lyalina S, ... Pollard K, Butte AJ, **Sirota M**. <u>Meta-Analysis of Vaginal Microbiome Data Provides New Insights In Preterm Birth</u>. *Frontiers in Microbiology*, 2020.



ORIGINAL RESEARCH published: 08 April 2020 doi: 10.3389/fmicb.2020.00476



#### Meta-Analysis of Vaginal Microbiome Data Provides New Insights Into Preterm Birth

Idit Kosti<sup>1,2</sup>, Svetlana Lyalina<sup>3</sup>, Katherine S. Pollard<sup>1,4,5,6</sup>, Atul J. Butte<sup>1,2†</sup> and Marina Sirota<sup>1,2\*†</sup>

Bakar Computational Health Sciences Institute, University of California, San Francisco, San Francisco, CA, United States, 
Department of Pediatrics, University of California, San Francisco, San Francisco, CA, United States, 
Integrative Program in Quantitative Biology, Gladstone Institutes, University of California, San Francisco, San Francisco, CA, United States, 
Department of Epidemiology & Biostatistics, Institute for Human Genetics, University of California, San Francisco, San Francisco, CA, United States, Quantitative Biosciences Institute, University of California, San Francisco, San Francisco, CA, United States, Gladstone Institutes, San Francisco, CA, United States, Chan Zuckerberg Biohub, San Francisco, CA, United States

Kosti et al, Frontiers in Microbiology, 2020.

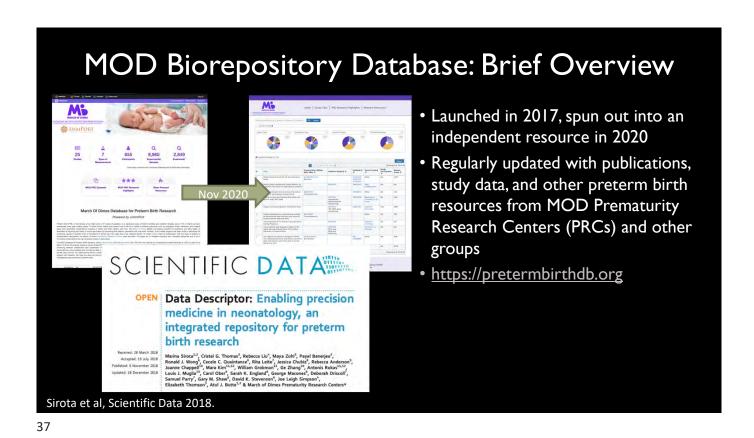
35

# The Goals of Creating a PTB Data Repository

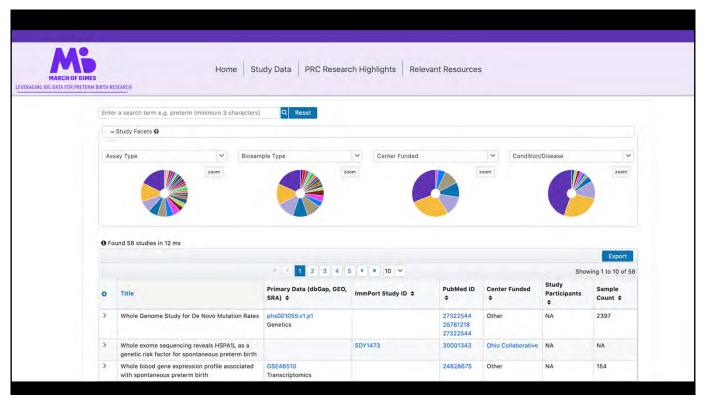
- Serve as a central data repository for omics data across the 6 MOD Transdisciplinary Centers
  - Transcriptomics, genomics, microbiome, proteome, CYTOF, methylation, metabolome, etc.
- Enable new scientific questions
- Enhance collaboration and coordination among centers
- Accelerate the pace of discovery



Tomiko Oskotsky, MD



https://pretermbirthdb.org Home Study Data PRC Research Highlights Relevant Resources March of Dimes O ECHO Child Health Re 4 圓 Q Q 57 27 28093 38970 4054 Types Of Measurements **Participants** Experimental samples Downloads • Statistics reflect data that have been curated and are part of the prematurity research repository.

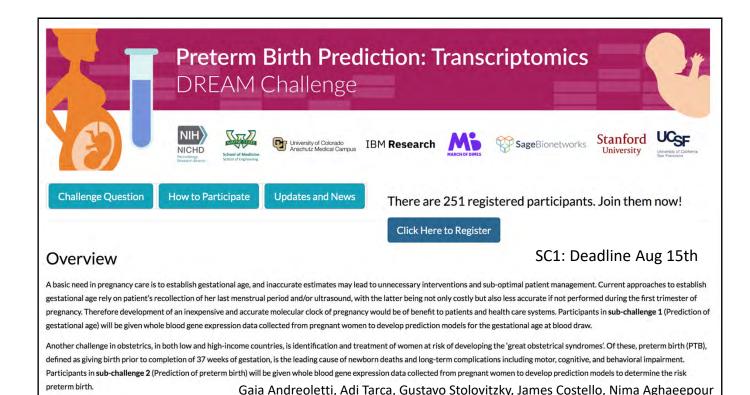


# DREAM Challenges for PTB



- The DREAM Challenges are crowdsourcing challenges examining questions in biology and medicine
- **Goal:** Bring computational community to MOD data resulting in rigorous, reproducible science and innovation
- Question: How can we predict those at higher risk of PTB (term vs. preterm or week of gestation) based on:
  - Transcriptomics Data, Microbiome Data, Multi-omics
  - Can use data in the repository for training, need datasets for testing!

Tomiko Oskotsky, Alennie Roldan, Jonathan Golob, Jake Albrecht, Gaia Andreoletti, Gustavo Stolovitzky, James Costello, Nima Aghaeepour, Adi Tarca, Roberto Romero, David MacIntyre, Phil Bennett, Yooni Li



## DREAM Challenge for PTB: Microbiome

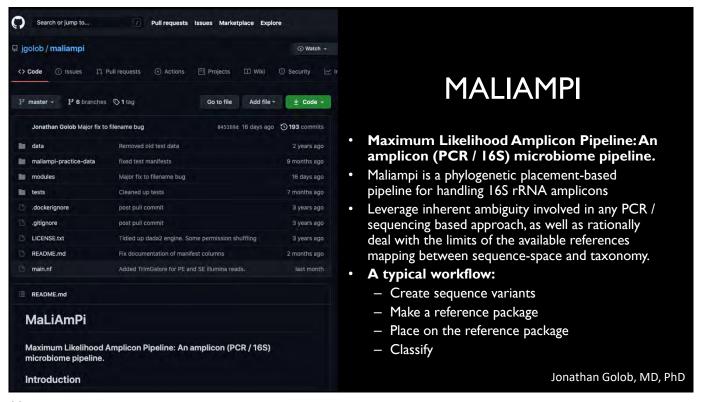
Total # of Studies	Total # of Participants	Total # of Term   Preterm Participants	Total # of Samples	Total # of Term   Preterm Samples
9	1323	911 412	5827	4422 1405

- 9 studies incorporated into metadata analyses
- 1,323 participants ~ 2:1 term:preterm participants (911 term / 412 preterm)
- 5827 samples ~ 3:1 term:preterm samples (4422 term / 1405 preterm)

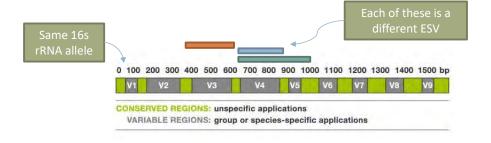
#### Possible Sub-challenges

- 1: Prediction of gestational age
- 2: Prediction of preterm birth

Study Accession ID	Center	Title	# of Participants	# of Term   PTB Participants	# of Samples	# of Term   PTB Samples	V Region Sequences
PRJEB21325	Imperial College London	Vaginal dysbiosis increases risk of preterm fetal membrane rupture, neonatal sepsis and is exacerbated by erythromycin. (Brown 2018)	116	21   95	158	23   135	V1 - V2
PRJEB30642	Imperial College London	Establishment of vaginal microbiota composition in early pregnancy and its association with subsequent preterm prelabor rupture of the fetal membranes.	98	35 63	254	78 176	V1 - V2
PRJNA242473	University of Maryland	The vaginal microbiota of pregnant women who subsequently have spontaneous preterm labor and delivery and those with a normal delivery at term	88	70 18	340	284 56	V1 - V3
PRJNA294119	Washington University	Early pregnancy vaginal microbiome trends and preterm birth	74	51 23	145	99 46	V1 - V3
PRJNA393472	Stanford University	Replication and Refinement of a Vaginal Microbial Signature of Preterm Birth	133	83 50	2134	1586 548	V4
PRJEB11895 & PRJEB12577	Imperial College London	The interaction between vaginal microbiota, cervical length, and vaginal progesterone treatment for preterm birth risk	154	121 33	154	121 33	V1 - V3
SDY465	Stanford University	Temporal and spatial variation of the human microbiota during pregnancy	40	33 7	1005	858   147	V3 - V5
JX871219 & JX871316	UCSF	Diversity of the Vaginal Microbiome Correlates With Preterm Birth	82	65 17	134	110 24	*Nearly* Complete Gene
PRJNA504518 (phs001739.v1.p1.)	University of Pennsylvania	Cervicovaginal microbiota and local immune response modulate the risk of spontaneous preterm delivery	538	432 106	1503	1263   240	V3 - V4



**Problem:** When combining 16S rRNA gene variable region ESVs from *different* studies, using different primers / sequencers / etc, the same organism will be split into different ESVs.



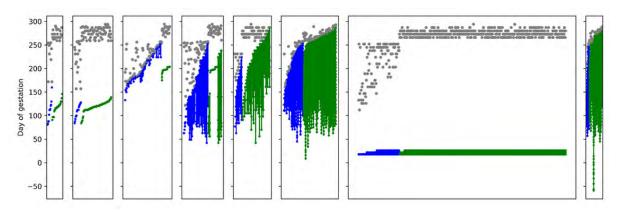
**Solution:** Phylogenetically place the ESVs onto a phylogeny of full-length 16S rRNA alleles possibly in the collection of specimens being analyzed.

Compare the weighted phylogenetic trees across conditions

Jonathan Golob, MD, PhD

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**Most studies have longitudinal collection of specimens from participants.** The time and frequency of collection vary by study. This is both an analytic challenge and opportunity.



Each block is a study.

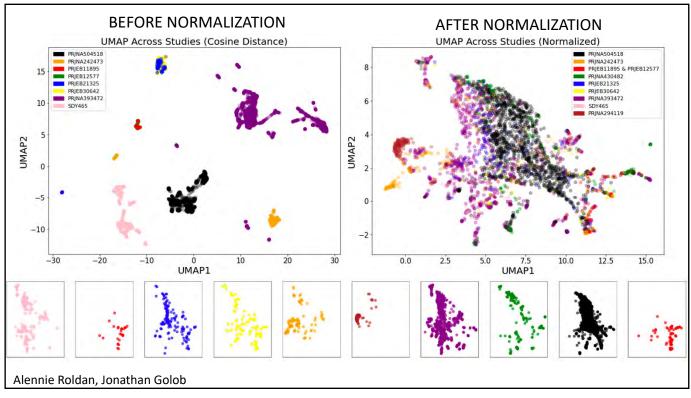
Each column is a participant / pregnancy.

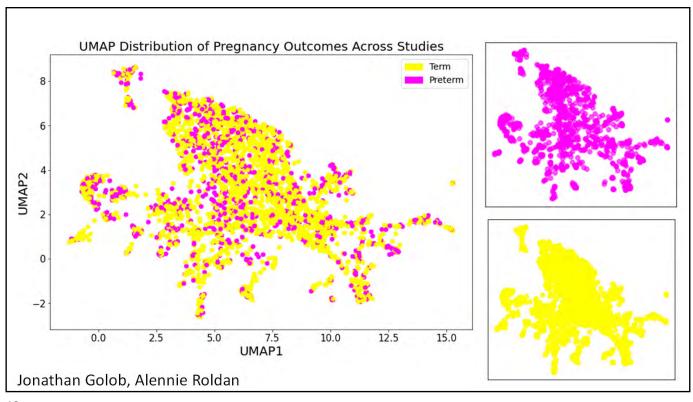
Grey: Gestational day of delivery

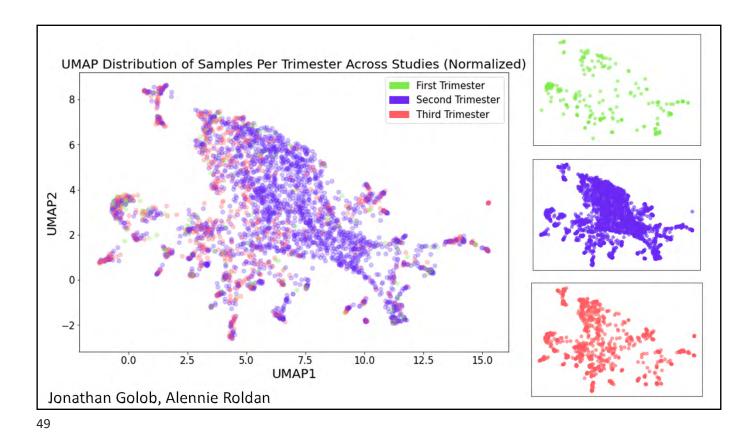
Blue: Specimen collected from pre-term pregnancy

Green: Specimen collected from Term pregnancy

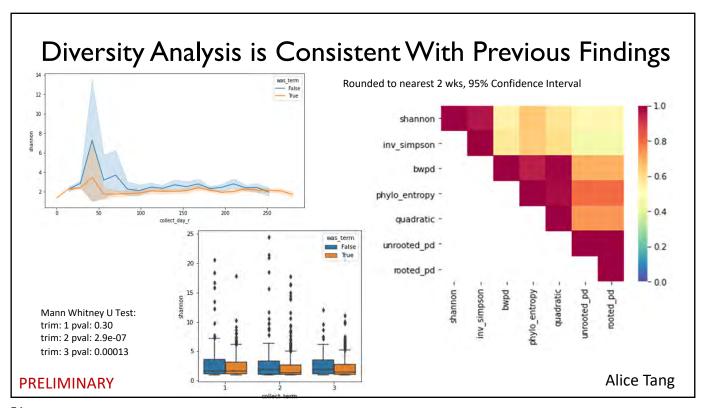
Jonathan Golob, MD, PhD

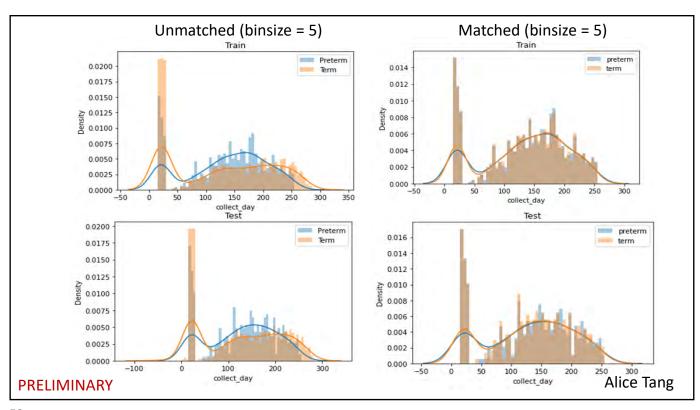




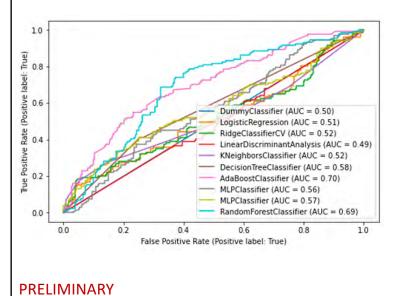


UMAP Racial Distribution of Samples Across Studies (Normalized) Jonathan Golob, Alennie Roldan 8 Black or African American White UMAP2 Unknown Asian American Indian or Alaska Native Native Hawaiian or Other Pacific Islander 7.5 UMAP1 0.0 2.5 10.0 12.5 15.0





# Term/Preterm Prediction. Features: alpha diversity, phylotype, CST, family/genus



#### Random Forest top features

Feature	Importance			
unrooted_pd	0.015155			
Megasphaera	0.014884			
rooted_pd	0.014259			
pt00015	0.012659			
Streptococcaceae	0.012314			
collect_day	0.012055			
bwpd	0.011706			
Lactobacillaceae	0.011488			
Lactobacillus	0.011327			
phylo_entropy	0.011323			
Sneathia	0.010947			
quadratic	0.010646			
pt00001	0.010322			
shannon	0.010175			
Prevotella	0.010130			
Prevotellaceae	0.010126			
inv_simpson	0.010119			
Finegoldia	0.009661			
Veillonellaceae	0.009112			
pt00005	0.008631			

Alice Tang

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# Leveraging Microbiome Data for Education



- Program to empower and teach AI to under-represented and under-resourced high-school students + involvement with research projects. 50 alumni, over 200 applicants this year, 27 students admitted!
- Project: Predicting Reproductive Health Outcomes Using Species Interactions And Microbiome Network

#### **Project TAs:**

Nana Afia Twumasi-Ankrah Alice Tang Eunice Leung Alennie Roldan





#### Goals of project:

- Teach students about bioinformatics, microbiome, and reproductive health
- Utilize ML to predict pregnancy-related complications utilizing microbiome data and investigate how microbial interactions and networks modulate reproductive health
- Interpret and present findings with societal/health impact and equity in



Tomiko Oskotsky, MD

# Al will change the world, Who will change Al?



#### Marina Sirota, PhD

Associate Professor, Bakar Computational Health Sciences Institute, UCSF **Tomiko Oskotsky, MD** 

Research Scientist, Bakar Computational Health Sciences Institute, UCSF

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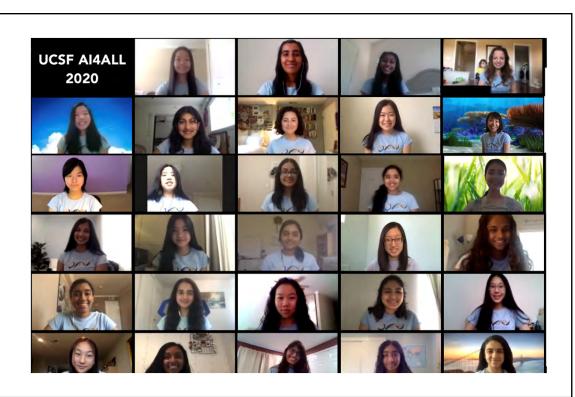


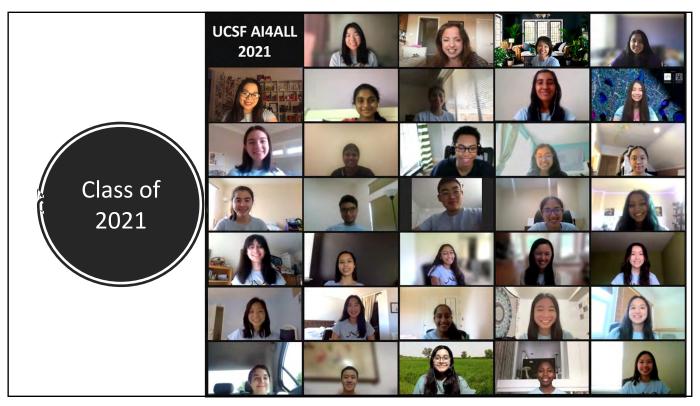
Class of 2019



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Class of 2020





### Over three weeks, our students...

- Learned about AI, Machine Learning, Clustering
- Learned how to code in Python
- Heard a number of faculty guest lecturers talk about their work applying AI in biomedicine
- Various Panels (Alumni, Undergrad, Grad, Industry)
- Attended a personal growth session focused on science communication
- Worked on 5 awesome research project



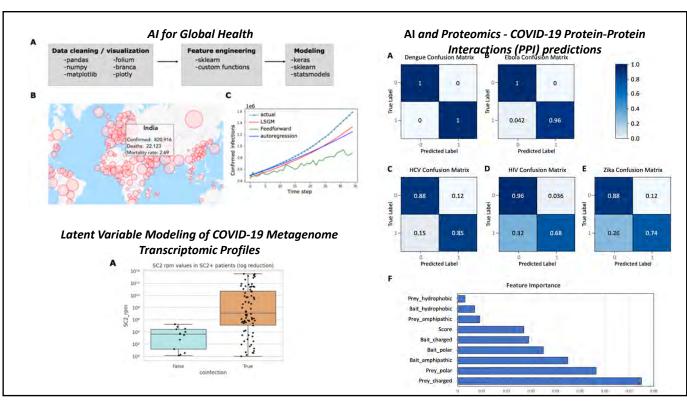
## 2020 Student Research Projects

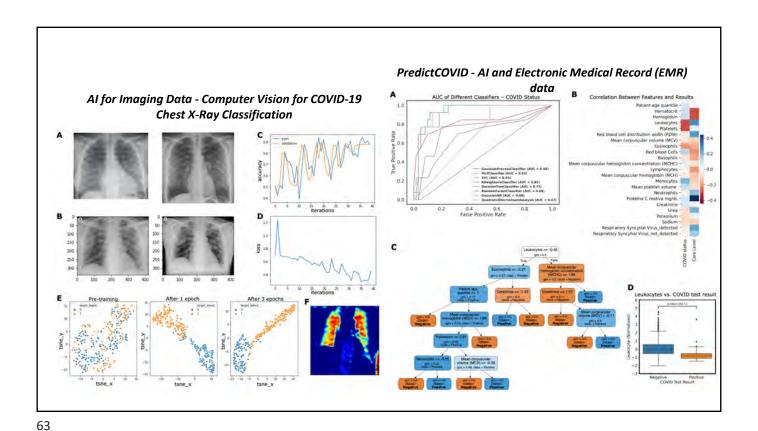
- Project 1:Al for Global Health Al and COVID-19 Time Series Data TAs: Jon Wang, Ishan Kanungo, and Jillian Burchard
- Project 2: COVID-19 Protein-Protein Interactions (PPI) AI and Proteomics
   TAs: Snow Naing and Isha Karim
- Project 3: COVID-19 Chest X-ray Classification Computer Vision TAs: Ina Chen, Tianna Grant, and Janice Yang
- Project 4: Latent Variable Modeling of COVID-19 Host Transcriptomic Response TAs:Will Connell, Ruchika Bajaj, and Claire Swadling
- Project 5: PredictCOVID AI and Electronic Medical Record (EMR) Data TAs: Alice Tang and Bianca Vora



https://www.youtube.com/watch?v=uImjiHI7MDw&feature=youtu.be

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PLOS COMPUTATIONAL BIOLOGY ⑥ OPEN ACCESS № PEER-REVIEWED RESEARCH ARTICLE Nurturing diversity and inclusion in AI in Biomedicine through a virtual summer program for high school students Tomiko Oskotsky 🚳 📵, Ruchika Bajaj 🦁, Jillian Burchard 🚳, Taylor Cavazos 🚳, Ina Chen 🚳, William T. Connell 🚳, Stephanie Eaneff . Tianna Grant . Ishan Kanungo . Karla Lindquist . Douglas Myers-Turnbull . Zun Zar Chi Naing 🚳, Alice Tang 🚳, Bianca Vora 🚳, Jon Wang 🐯, Isha Karim 🐯, Claire Swadling 🐯, Janice Yang 🚳, Al4ALL Student Cohort 2020 💌, Bill Lindstaedt, Marina Sirota 🖾 [ view less ] Version 2 ▼ Published: January 31, 2022 • https://doi.org/10.1371/journal.pcbi.1009719 See the preprint Media Coverage Article Metrics Authors Abstract Abstract Author summary Artificial Intelligence (Al) has the power to improve our lives through a wide variety of 1. Introduction applications, many of which fall into the healthcare space; however, a lack of diversity is contributing to limitations in how broadly AI can help people. The UCSF AI4ALL program was 2. Methods established in 2019 to address this issue by targeting high school students from 3. Results underrepresented backgrounds in AI, giving them a chance to learn about AI with a focus on

# Summary

- Lots of (microbiome) data is available in the public domain data sharing is vital!
- Al can be applied to build predictive models in disease
- Crowdsourcing approaches allow us to bring computational community to the data and interesting questions
- Case study: preterm birth
- Important to train the next generation of AI researchers!

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# Big Data -> Precision Medicine responders The state of t

#### **SIROTA LAB**

Tomiko Oskotsky

<u>Brian Le</u>

Idit Kosti

Gaia Andreoletti

Silvia Pineda

**Dmitry Rychkov** 

Kat Yu

Daniel Bunis

Stella Belonwu

**Dimitri** 

**Abrahamsson** 

Alice Tang

Zachary Cutts

Yaqiao Li

Sarah Woldemariam

<u>Alennie Rodan</u>

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Sota Iwatani

Cele Quaintance

Gary Shaw

Ivana Maric

Dan DiGiulio

David Relman

Ben Callahan

Nima Aghaeepour

Brice Gaudilliere

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Kate Hypes

Ruth Monteiro

Zhiping Gu Bryan Walters

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Gustavo Stolovitzky

James Costello

Adi Tarca

Roberto Romero

Jonathan Golob

Jacques Ravel

**MOD TDC** 

Atul Butte

Sam Parry

Rita Leite Aubrey Bailey

Louis Muglia

Ge Zhang

Joanne Chappell

Rebecca Anderson

Jessica Chubiz

jessica Gilasiz

Sarah England Neal Sondheimer

Antonis Rokas

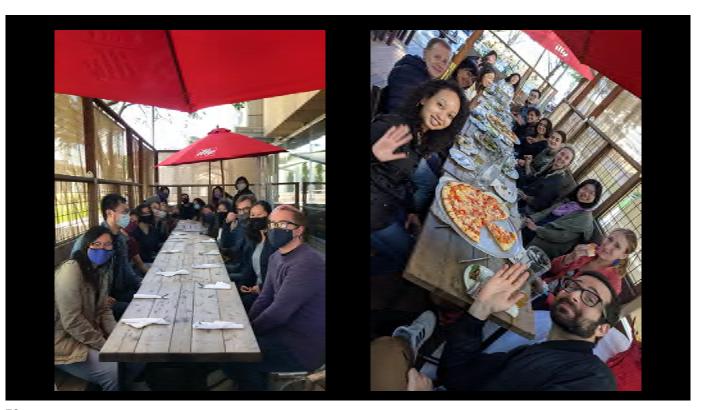
Phil Bennet

Sing Sing Way

Tech and Admin Support: Boris Oskotsky, Edna Rodas







Thanks!

marina.sirota@ucsf.edu

http://sirotalab.ucsf.edu

We are hiring!