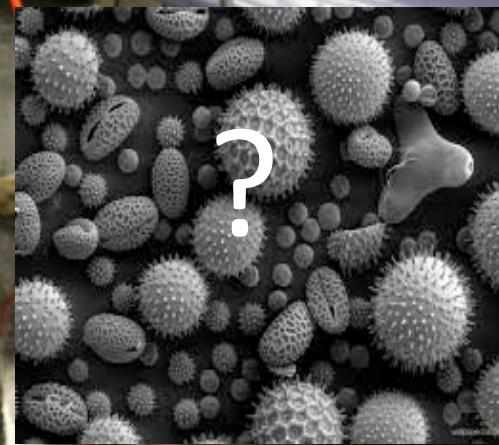


Benchmarking and ensemble approaches for metagenomic classification

Alexa McIntyre
Mason Lab, Weill Cornell Medicine



Tyler Hicks/The New York Times, 2008

PathoMap

New York City Subway



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DATA MAP

BLOG

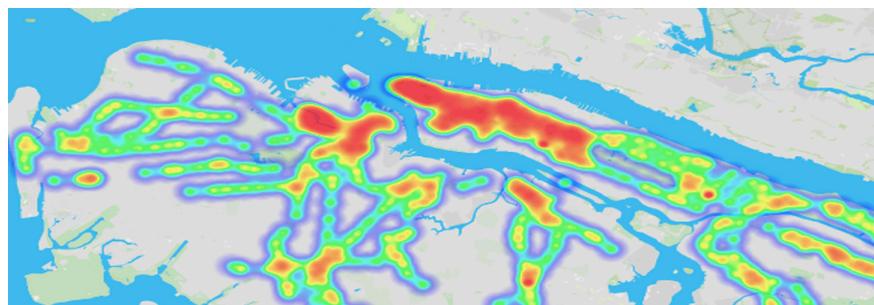
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Creating a Molecular Portrait of New York City

One swab at a time

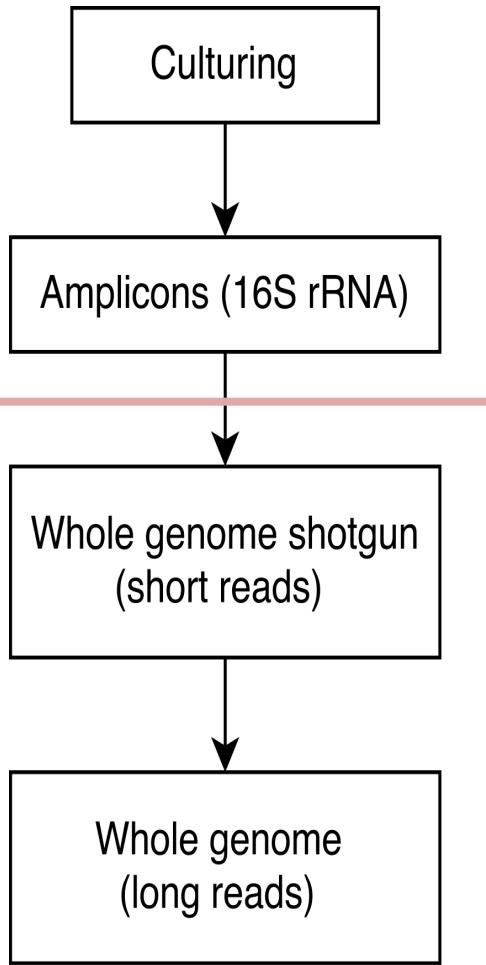


PathoMap is a research project by **Weill Cornell Medical College** to study the microbiome and metagenome of the built environment of NYC.

Check out the full findings [here](#).

Afshinnekoo, et al., 2015

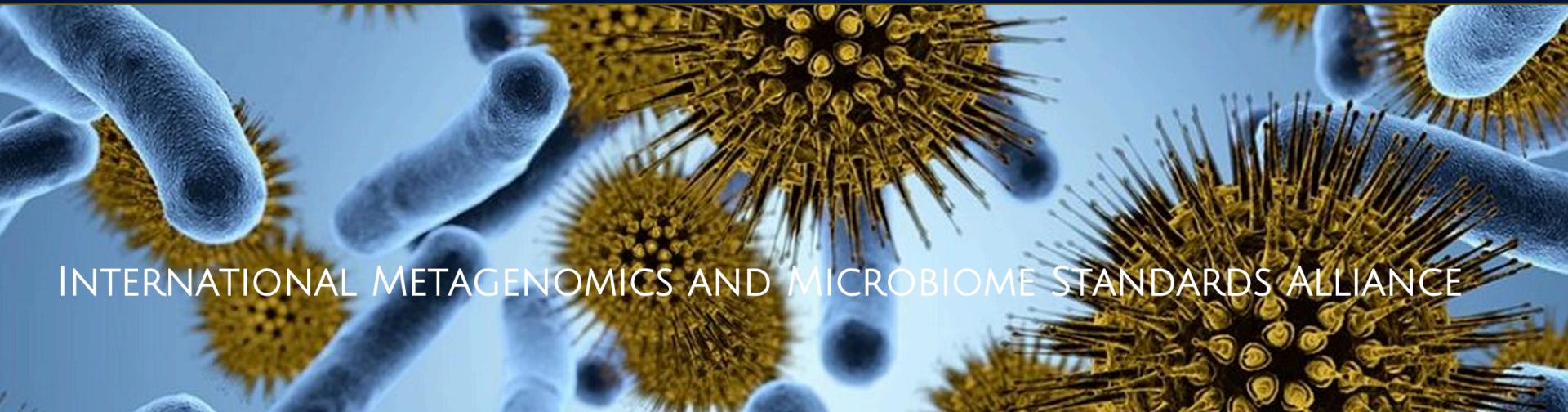
A brief history of microbial genomics



- c. 1960's onwards [1]
 - Est. 1% species culturable [2]
 - c. 1990's onwards [3]
 - Lack of truly universal primers, amplification biases [2]
 - Low species/strain resolution
-
- c. 2000's onwards
 - Species ambiguity
 - Smaller databases
-
- Enables the detection of species at lower abundances [4]

[1] Shine and Dalgarno, 1975, [2] Amann et al., 1995, [3] Weisberg et al., 1991, [4] Kuleshov et al., 2016

Too many tools, too few comparisons



INTERNATIONAL METAGENOMICS AND MICROBIOME STANDARDS ALLIANCE

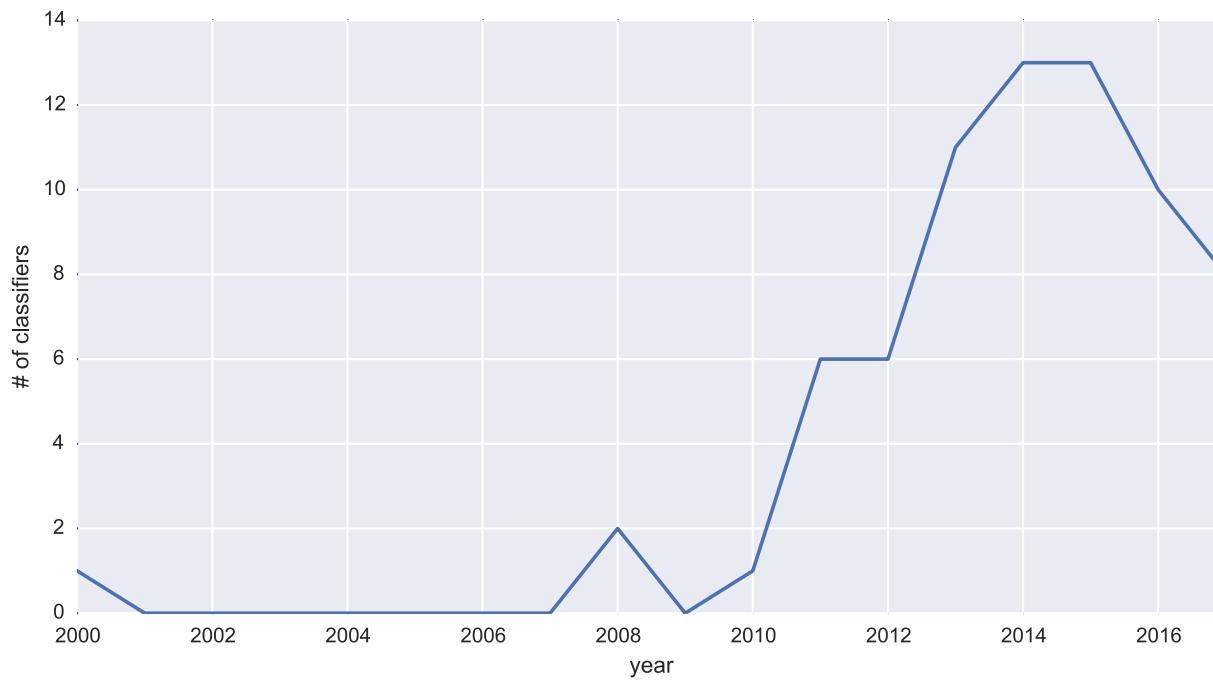
Bioinformatic Resources

[Home](#) > Bioinformatic Resources

IMMSA (2017):

At least 71 tools available for profiling microbial communities using WGS
microbialstandards.org/index.php/bioinformatic-resources

Too many tools, too few comparisons



IMMSA (2017):

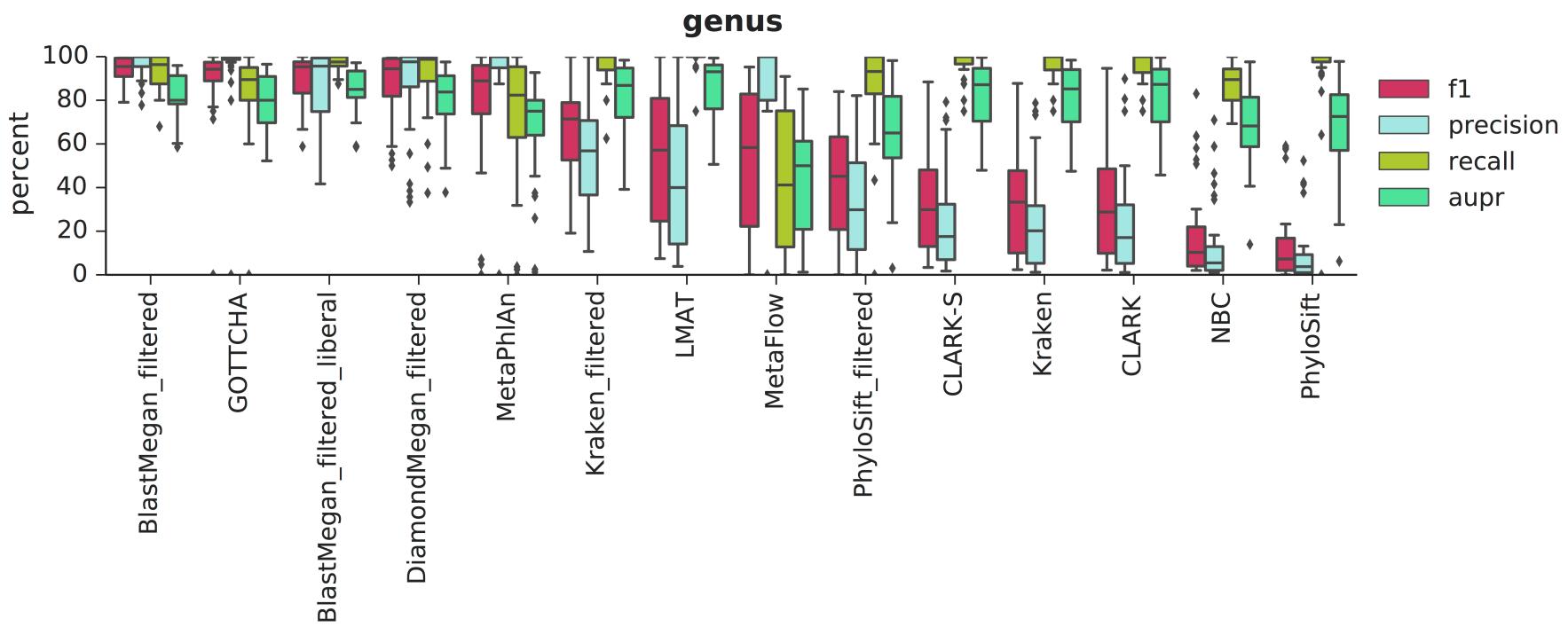
At least 71 tools available for profiling microbial communities using WGS
microbialstandards.org/index.php/bioinformatic-resources

11 selected tools

Table 1: Algorithm Types and Parameters of Usage and Reporting

	Algorithm:	BLAST-MEGAN	CLARK/-S	Diamond-MEGAN	GOTTCHA	Kraken	LMAT	MetaFlow	MetaPhlAn2	NBC	PhyloSift	
Background	Year of release	2015	2015	2014	2015	2014	2015	2016	2014	2010	2014	
	Version number	MEGAN: v5.10.6	v1.2.2-beta	v0.7.9.58, MEGAN: v5.10.6	v1.0b, db v20150825	v0.10.5-beta, "standard db"	v1.2.6	v0.9.2	v2.0.0	Webserver	v1.0.1	
	Classification heuristic	Alignment	Kmer	Alignment	Marker	Kmer	Kmer	Alignment (coverage)	Marker	Kmer	Marker	
Database Size	Bacteria (777 in evaluation)	species	269899	1335	269899	1335	1381	5754	1313	3848	650	2685
		% in db	99.87%	98.58%	99.87%	97.94%	97.30%	97.68%	94.08%	99.10%	59.97%	99.61%
		taxa	280062	2488	280062	2498	2513	20265	1321	12926	960	9776
	Archaea (65 in evaluation)	species	6707	123	6707	140	143	333	143	228	62	134
		% in db	100%	92.31%	100%	100%	100%	100%	96.92%	100%	56.92%	100%
	Viruses (1 in evaluation)	species	6878	144	6878	168	272	401	143	300	72	187
		taxa	10750	4289	10750	4323*	4243	4348	777	3449	*	15
	Fungi (3 in evaluation)	species	106851	4381	106851	4420*	4420	14525	5	3522	2080*	18
		% in db	0	0	0	0	0	337	0	73	49242*	220
		taxa	87132	0	87132	0	0	513	0	74	49242*	2042
Host Range	Other eukaryotes	species	357291	1*	357291	0	1*	1643	0	38	0	1921
		taxa	464911	1*	464911	0	1*	1677	0	38	0	13212
	Includes human	Yes	No (human database available)	Yes	No	No (human database available)	Yes	No	No	No	Yes	
	Facilitates custom databases	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Webserver - No/ Standalone - Yes	Yes	

Performance profiles across 35 datasets



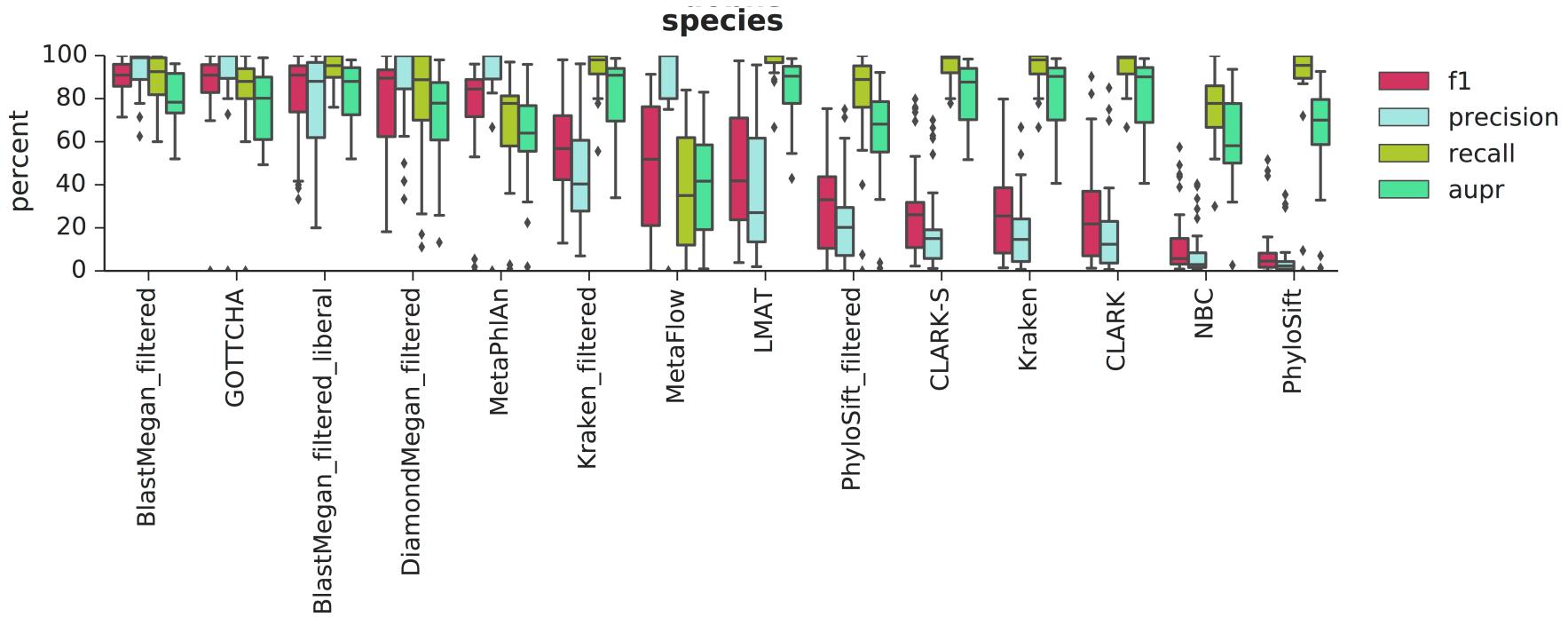
Precision = false positive rate = $TP/(TP+FP)$

Recall = sensitivity = $TP/(TP+FN)$

F1 score = $2(\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$

AUPR = area under the precision recall curve

Performance profiles across 35 datasets



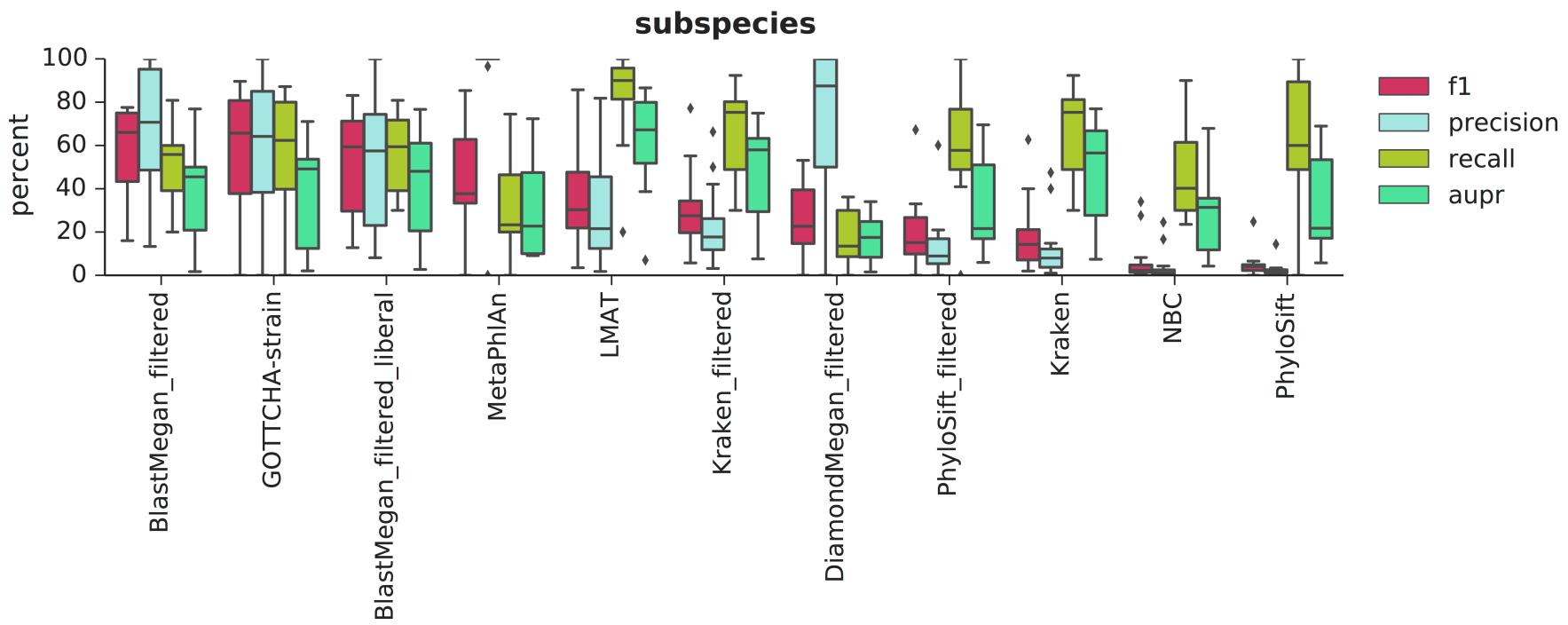
Precision = false positive rate = $TP/(TP+FP)$

Recall = sensitivity = $TP/(TP+FN)$

F1 score = $2(\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$

AUPR = area under the precision recall curve

Performance profiles across 16 datasets



Precision = false positive rate = $TP/(TP+FP)$

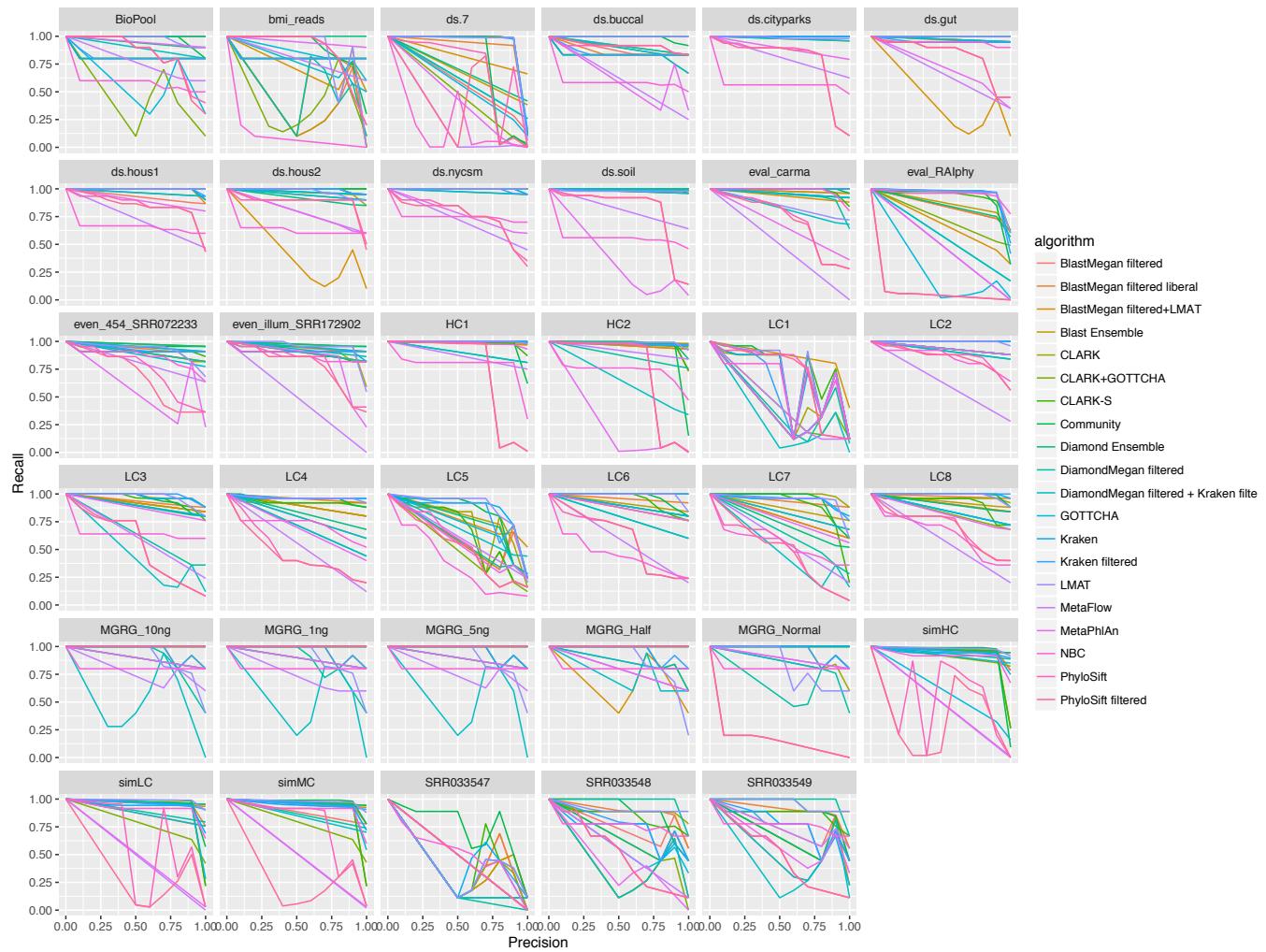
Recall = sensitivity = $TP/(TP+FN)$

F1 score = $2(\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$

AUPR = area under the precision recall curve

Precision-recall curves

Supplementary Figure 3



Precision-recall curves for tools on individual samples.

Read-level classification

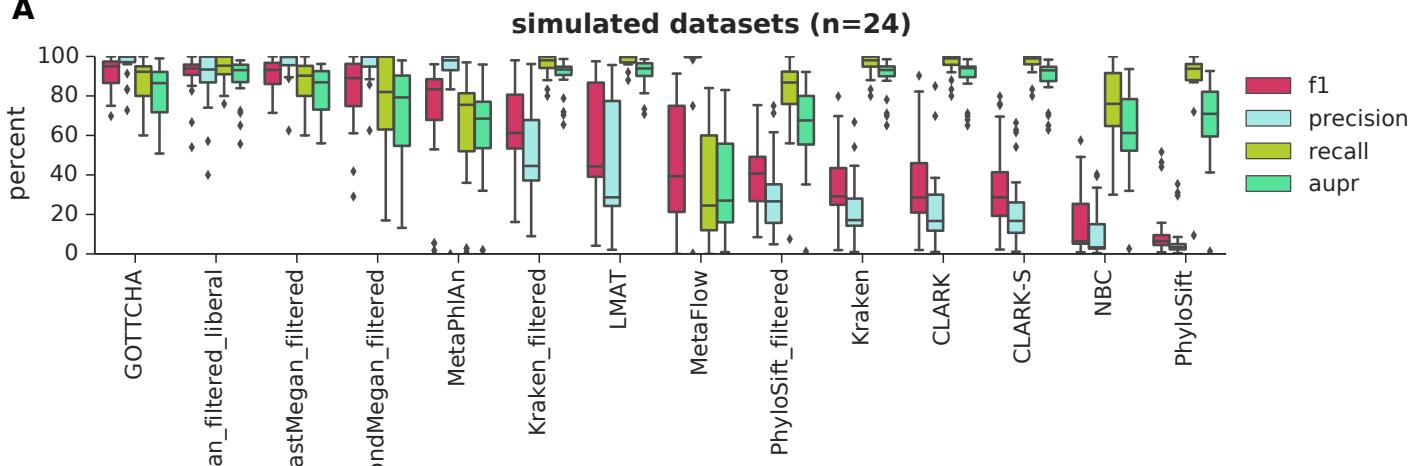
- Classification precision increased for *k*-mer-based tools when calculated at the read-level compared to the organismal level

Dataset	Metric	CLARK	CLARK-S	Kraken	LMAT	<u>BlastMegan</u>	<u>DiamondMegan</u>	NBC
HC1	Precision	99.73	97.79	99.93	99.70	99.98	97.94	94.83
	Recall	85.10	90.30	74.16	74.57	77.38	23.92	62.42
HC2	Precision	99.69	96.57	99.77	99.62	99.97	97.61	93.43
	Recall	83.05	88.07	69.78	72.34	76.49	24.74	59.95
LC1	Precision	95.42	94.23	94.36	95.84	95.39	97.55	94.75
	Recall	85.89	91.05	74.57	79.90	78.25	27.91	69.88
LC2	Precision	99.90	99.76	99.97	99.83	99.99	98.74	99.58
	Recall	92.70	98.16	81.57	90.48	86.50	27.03	69.81

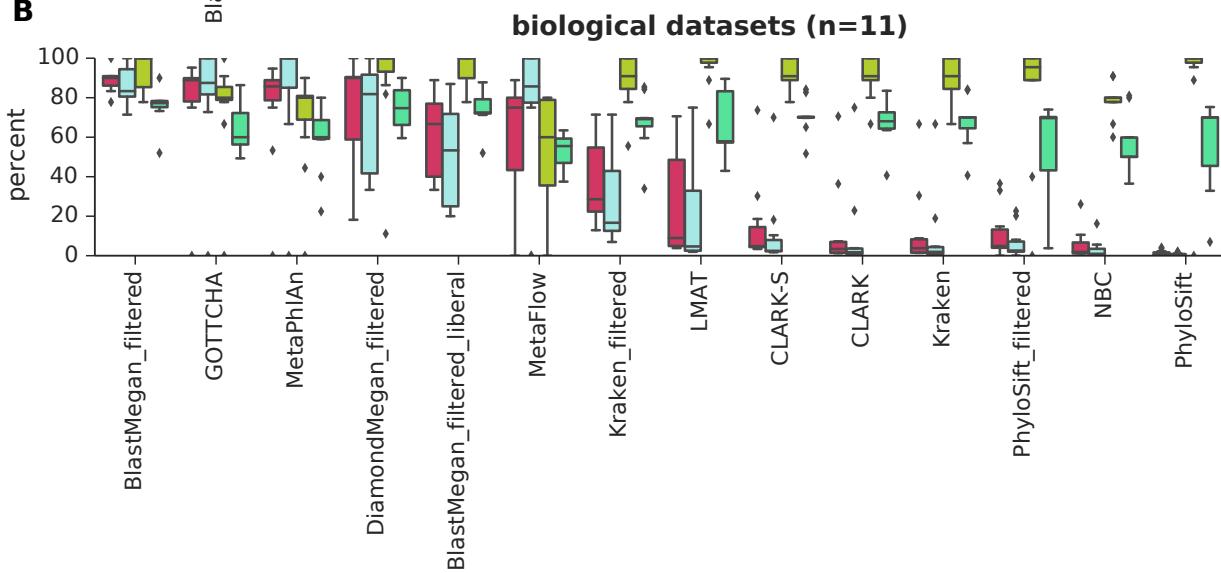
Rachid Ounit

Simulated vs. biological datasets

A

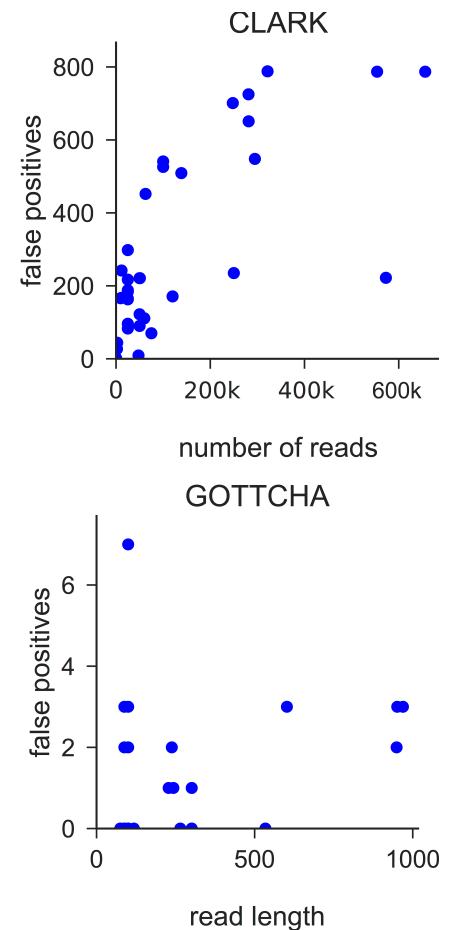
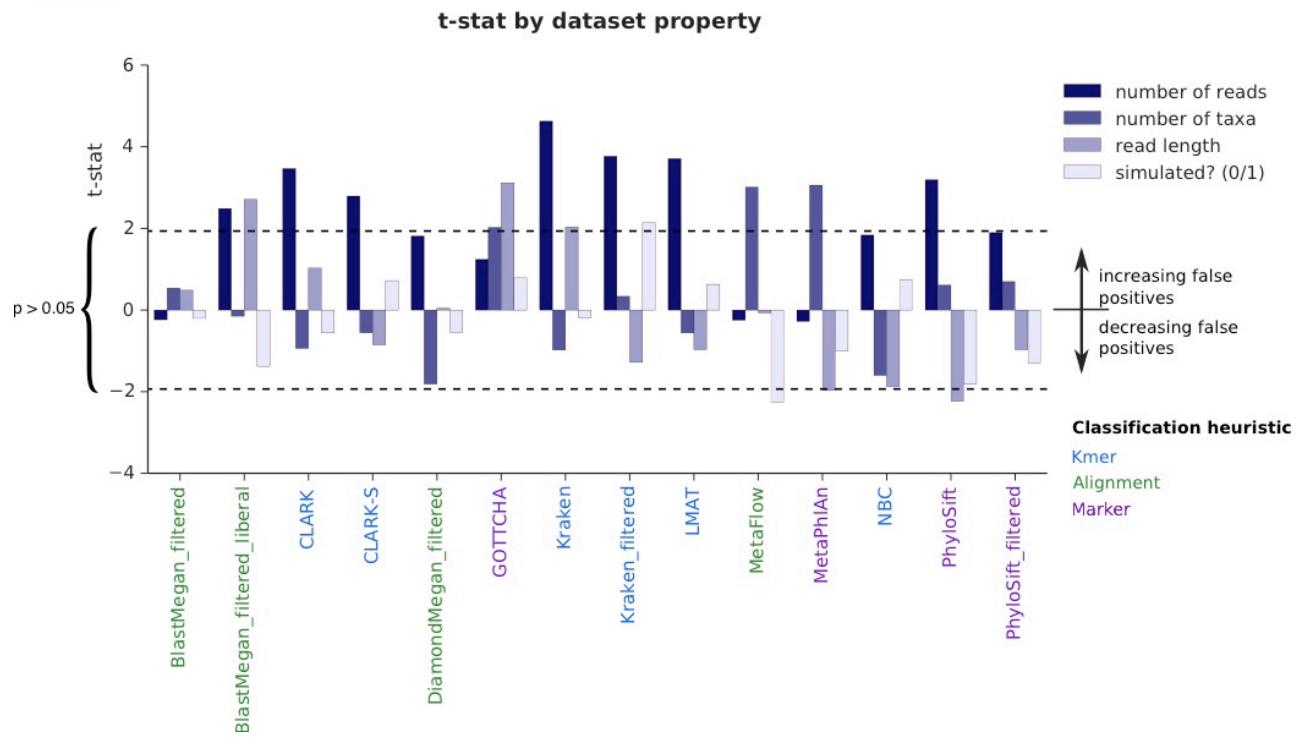


B



False positives by dataset property

Figure 2



$$\# \text{ FP} \sim \text{Nbin}(\beta_0 + \beta_1(\# \text{ reads}) + \beta_2(\# \text{ taxa}) + \beta_3(\text{read length}) + \beta_4(\text{simulated } 0/1))$$

Accuracy by taxa

Common false positives

- Phyla: Proteobacteria, Firmicutes, Actinobacteria
- Genera: *Lactobacillus*, *Staphylococcus*, *Streptococcus*

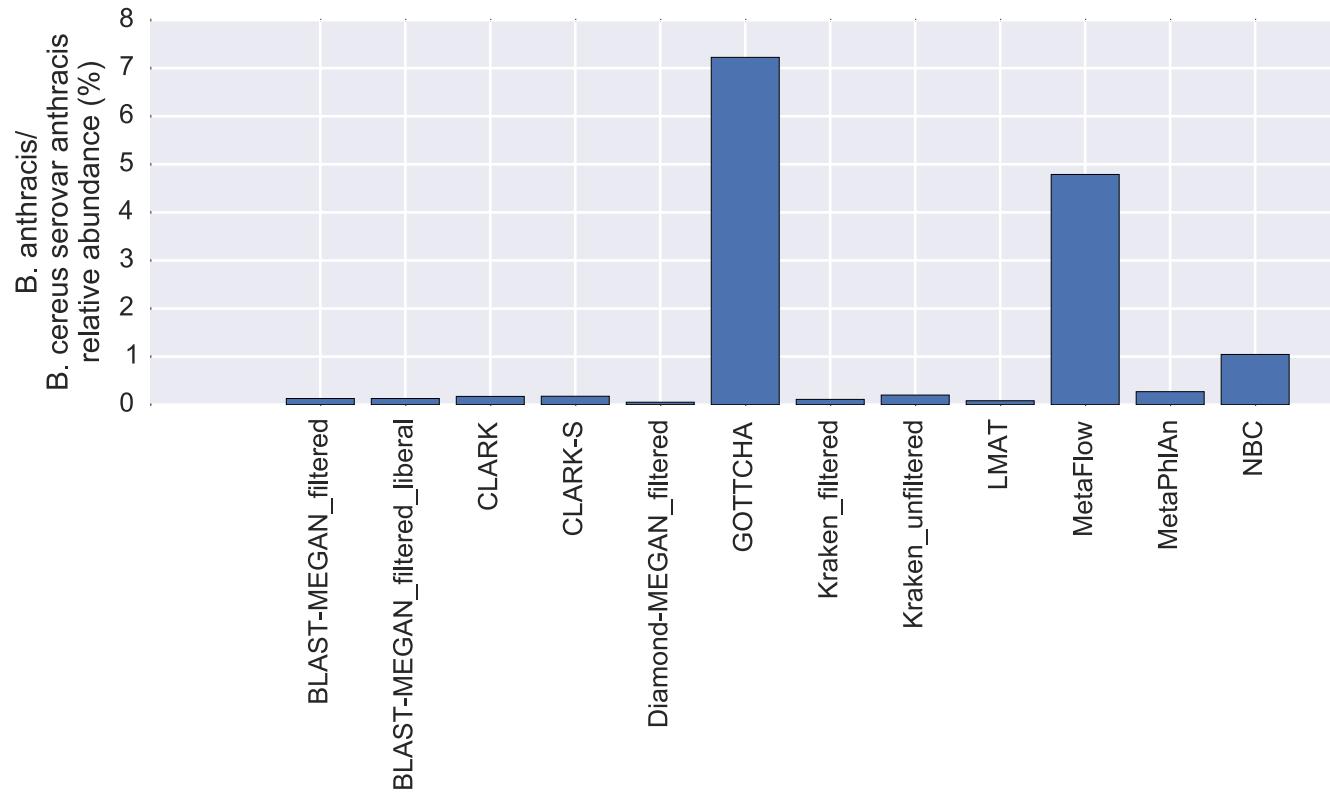
Common false negatives

- Genera: *Bacillus*, *Bifidobacteria*, *Shigella*

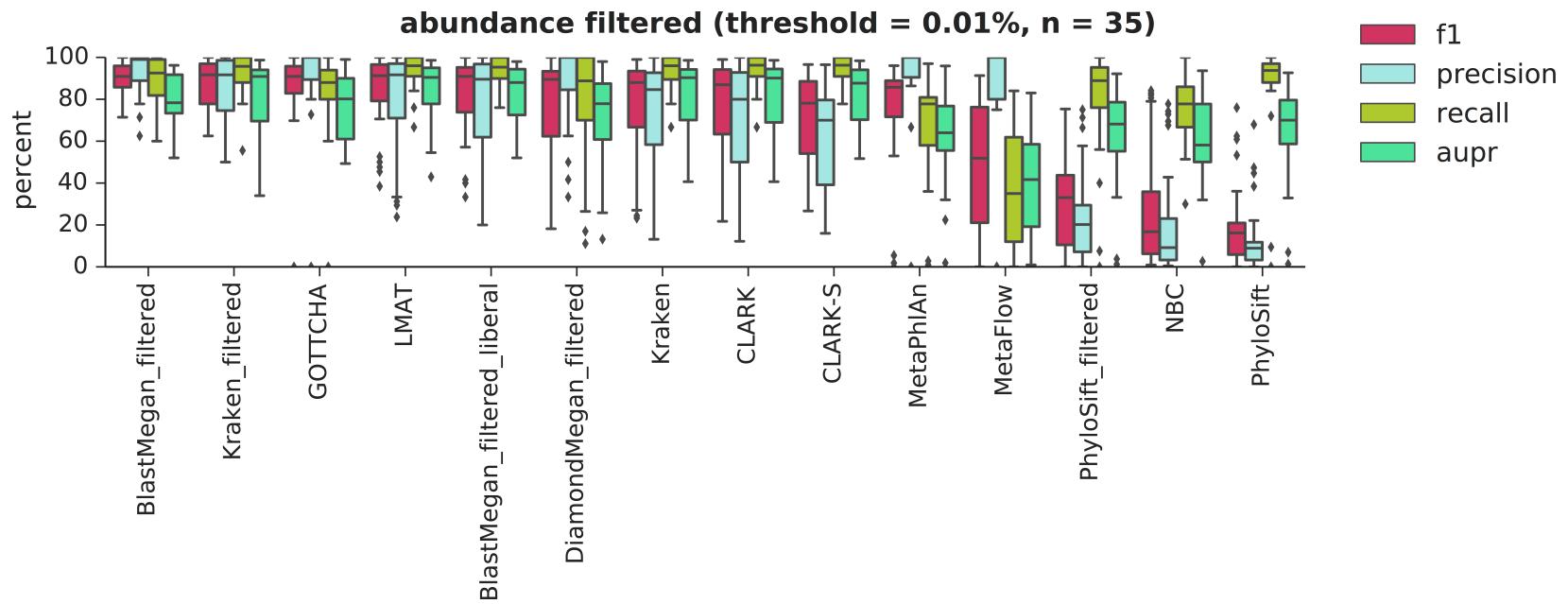
Negative controls

- Human DNA spiked into extraction kit for sequencing contaminants
 - *Escherichia (coli)* and *Acinetobacter*
- Nullomers (combined 17-mers that did not match to any known reference sequence)
 - Size and database biases for NBC (*Sorangium cellulosum*, *Escherichia coli*, *Bacillus cereus*), LMAT (human)

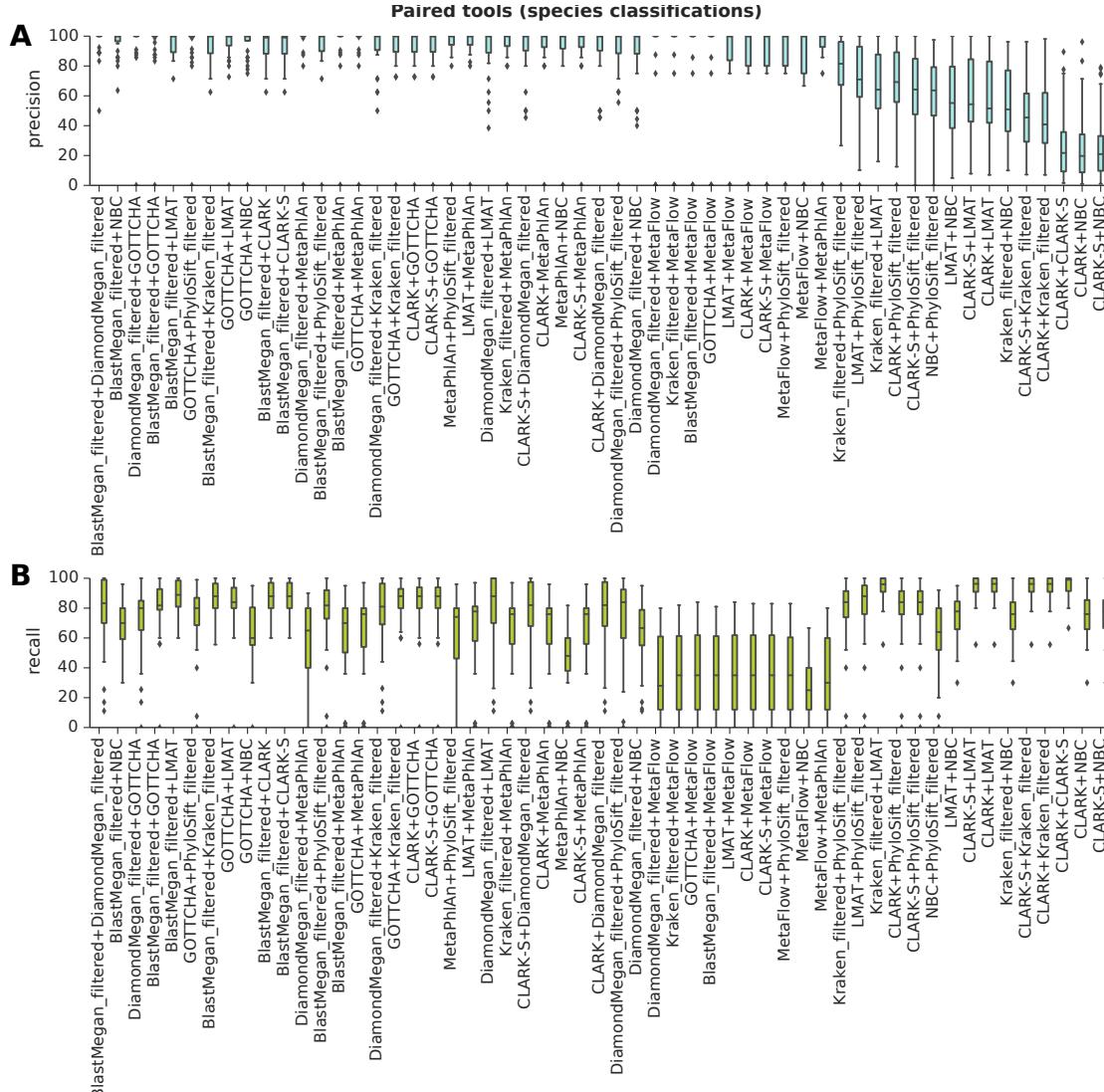
Anthrax on the subway? (No.)



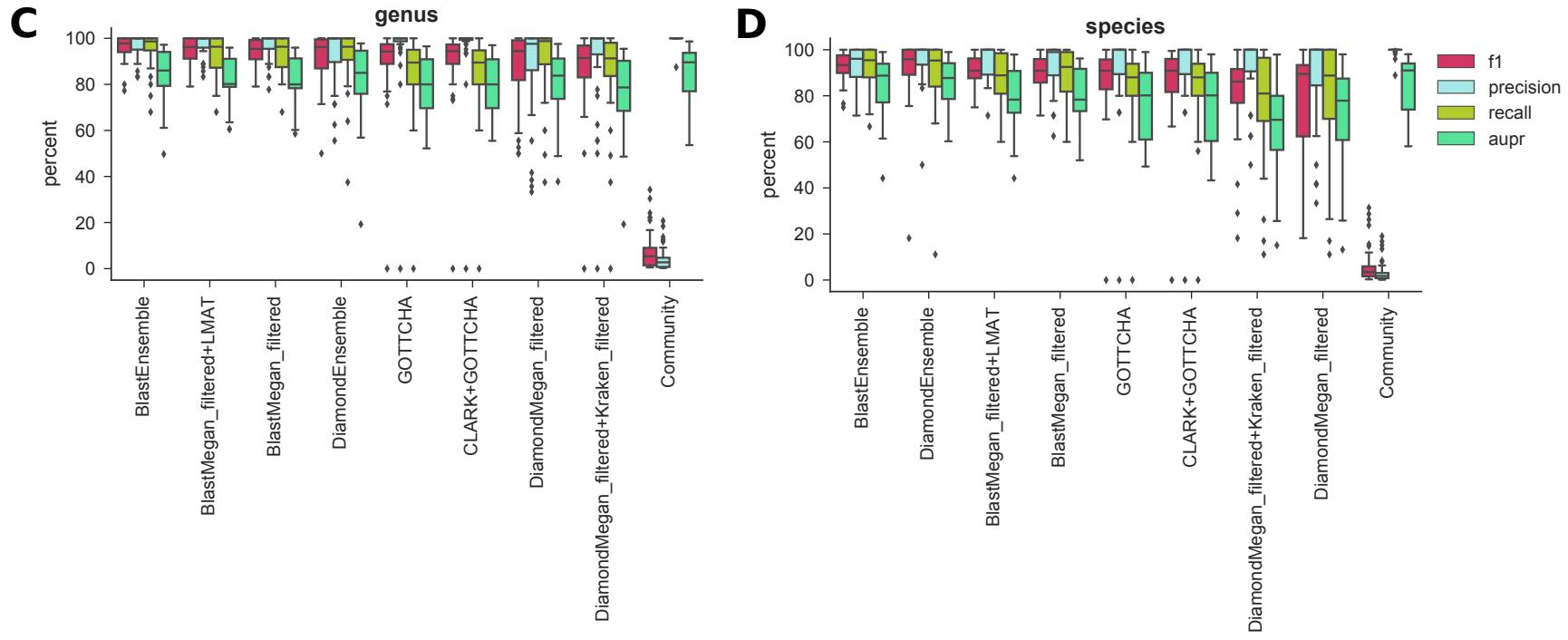
How to solve a problem like *Bacillus*: abundance filtering



How to solve a problem like *Bacillus*: pairing tools

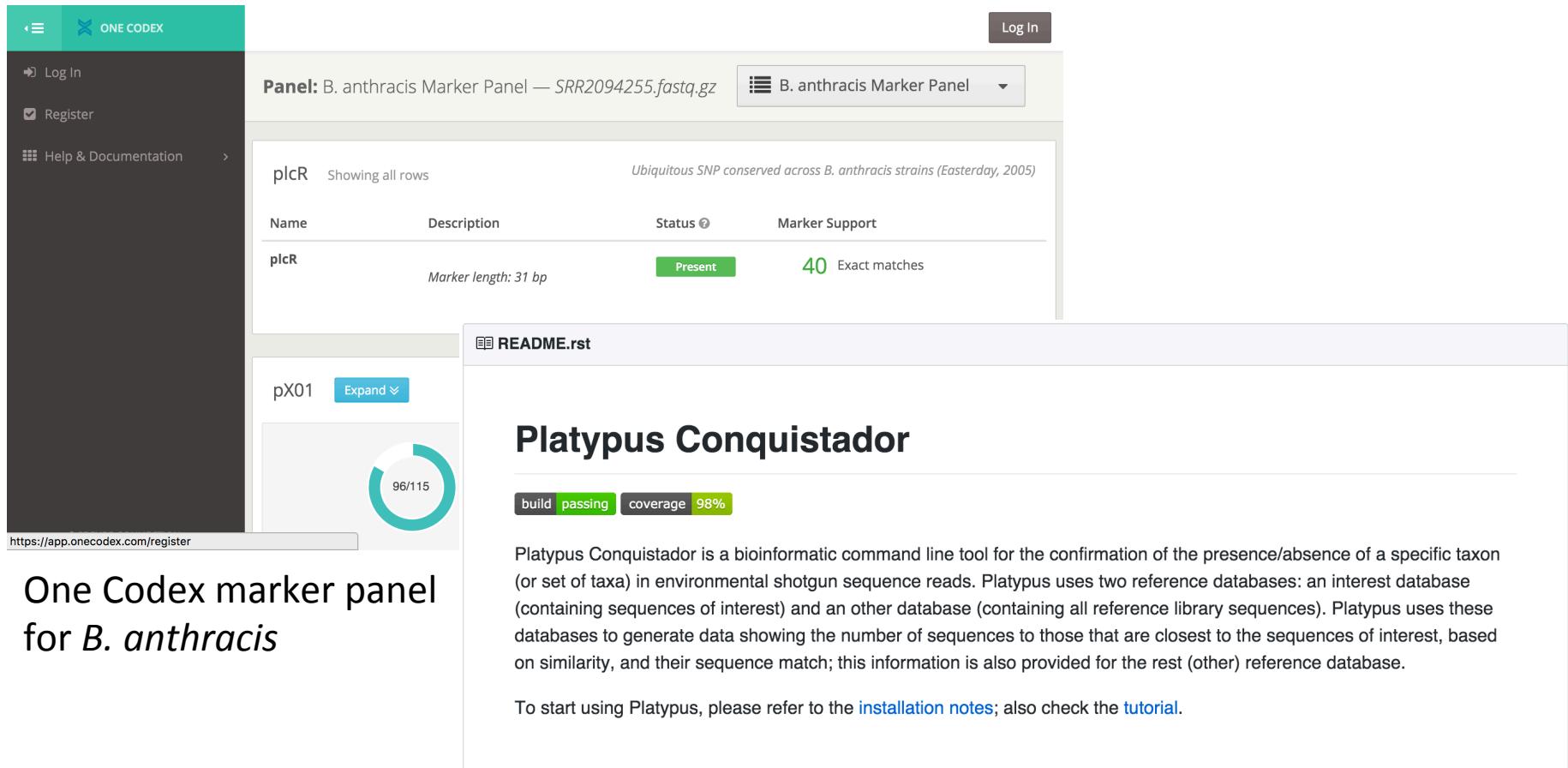


How to solve a problem like *Bacillus*: ensemble methods



Quorum ensembles:
Min 2/4 or 3/5 of set of high-precision tools detect a taxon

Specialized tools for pathogen detection



The screenshot shows the One Codex web interface. On the left, a dark sidebar has a teal header with the "ONE CODEX" logo. It contains links for "Log In" (with a user icon), "Register" (with a checkmark icon), and "Help & Documentation" (with a grid icon). Below the sidebar, the URL <https://app.onecodex.com/register> is visible.

The main content area has a light gray header with the text "Panel: B. anthracis Marker Panel — SRR2094255.fastq.gz" and a "Log In" button. A dropdown menu shows "B. anthracis Marker Panel".

The main panel displays a table for the "plcR" marker. The table has columns: Name, Description, Status, and Marker Support. The data row for "plcR" shows:

Name	Description	Status	Marker Support
plcR	Ubiquitous SNP conserved across <i>B. anthracis</i> strains (Easterday, 2005) Marker length: 31 bp	Present	40 Exact matches

Below the table, there's a section titled "README.rst" with a "pX01" link and an "Expand ▾" button. A circular progress bar indicates "96/115".

The right side of the interface features a large title "Platypus Conquistador" in bold black font. Below it are two green buttons: "build passing" and "coverage 98%".

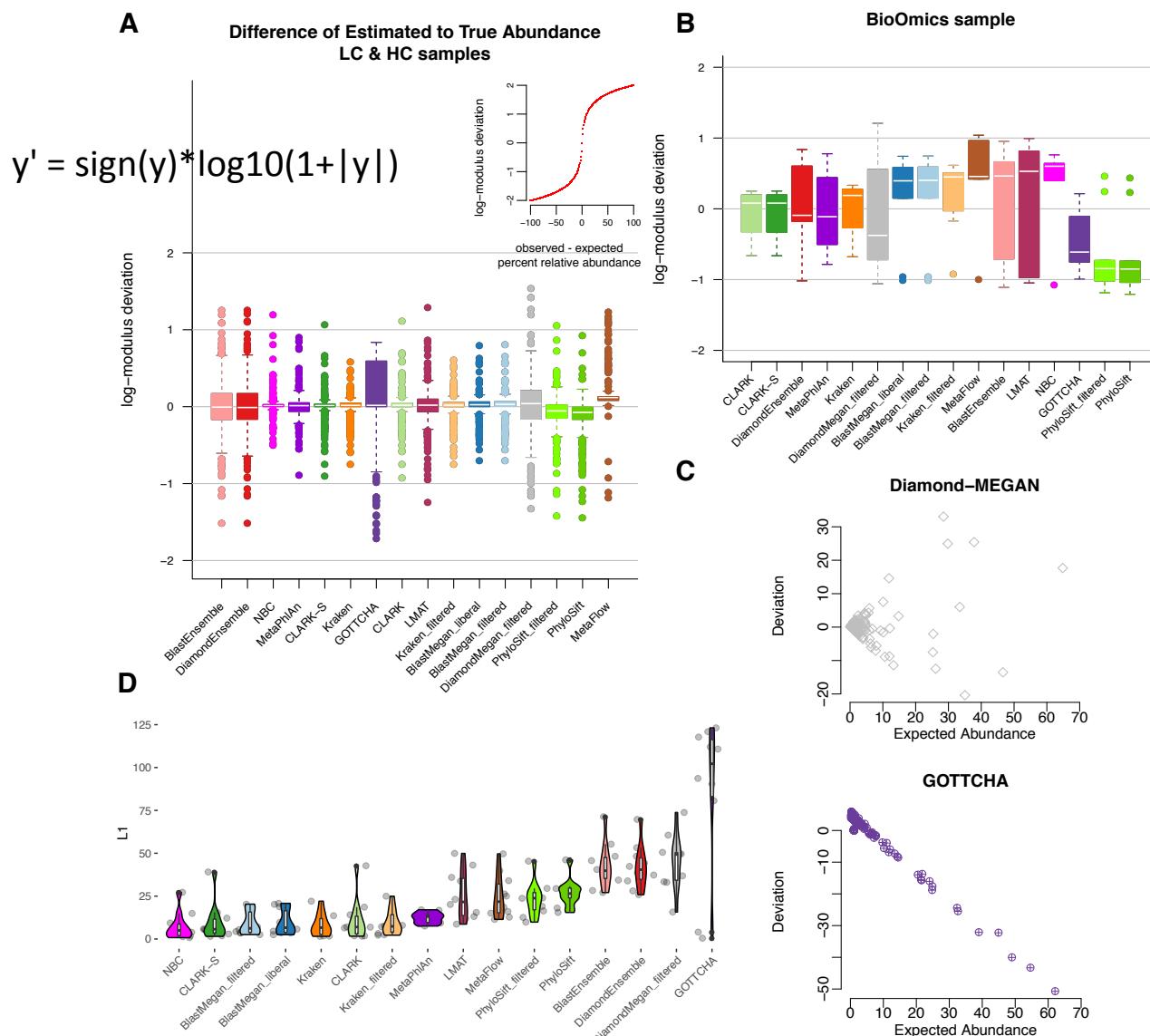
A detailed description follows: "Platypus Conquistador is a bioinformatic command line tool for the confirmation of the presence/absence of a specific taxon (or set of taxa) in environmental shotgun sequence reads. Platypus uses two reference databases: an interest database (containing sequences of interest) and an other database (containing all reference library sequences). Platypus uses these databases to generate data showing the number of sequences to those that are closest to the sequences of interest, based on similarity, and their sequence match; this information is also provided for the rest (other) reference database."

At the bottom, a note says: "To start using Platypus, please refer to the [installation notes](#); also check the [tutorial](#)".

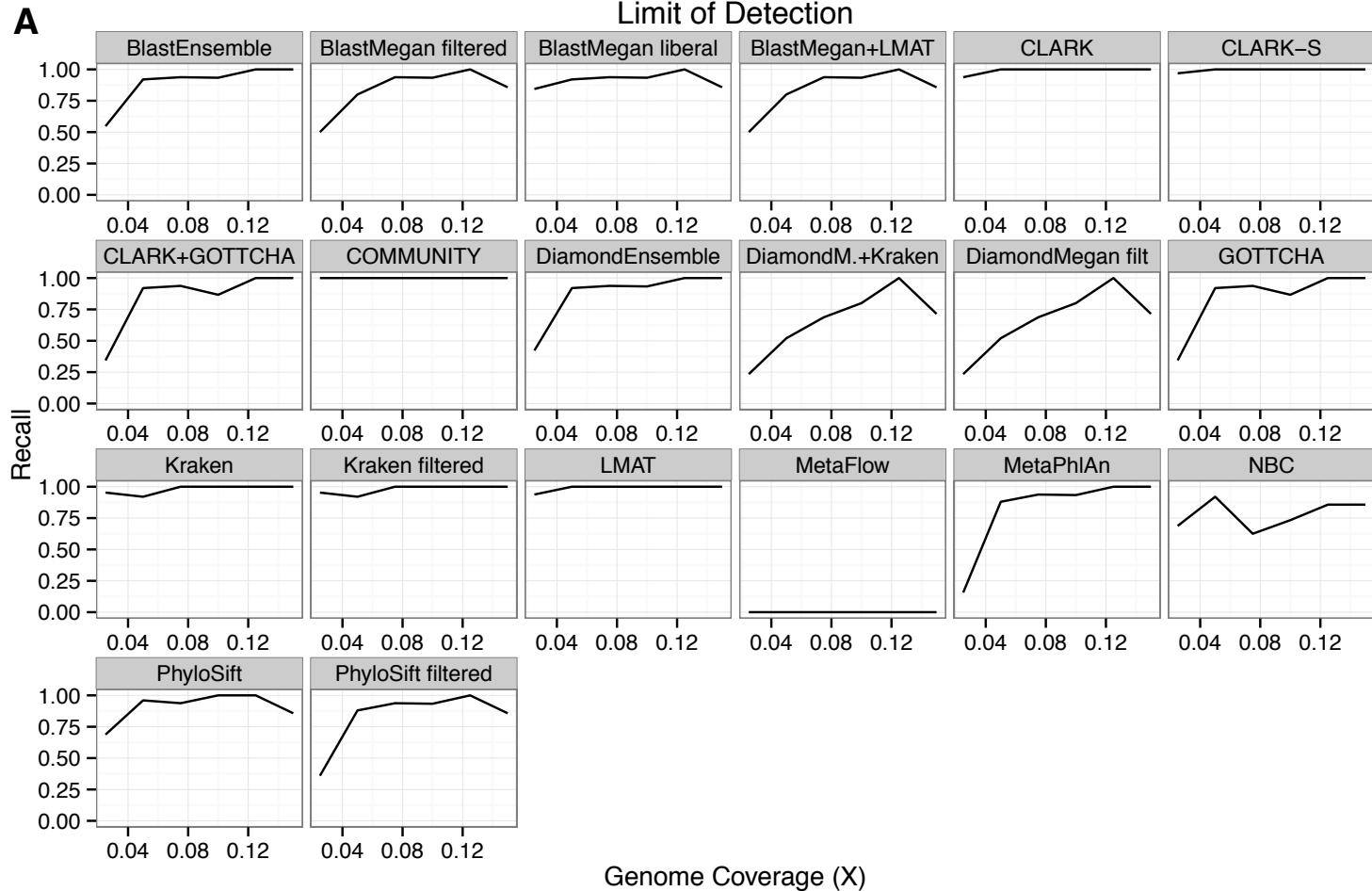
One Codex marker panel
for *B. anthracis*

Knight Lab

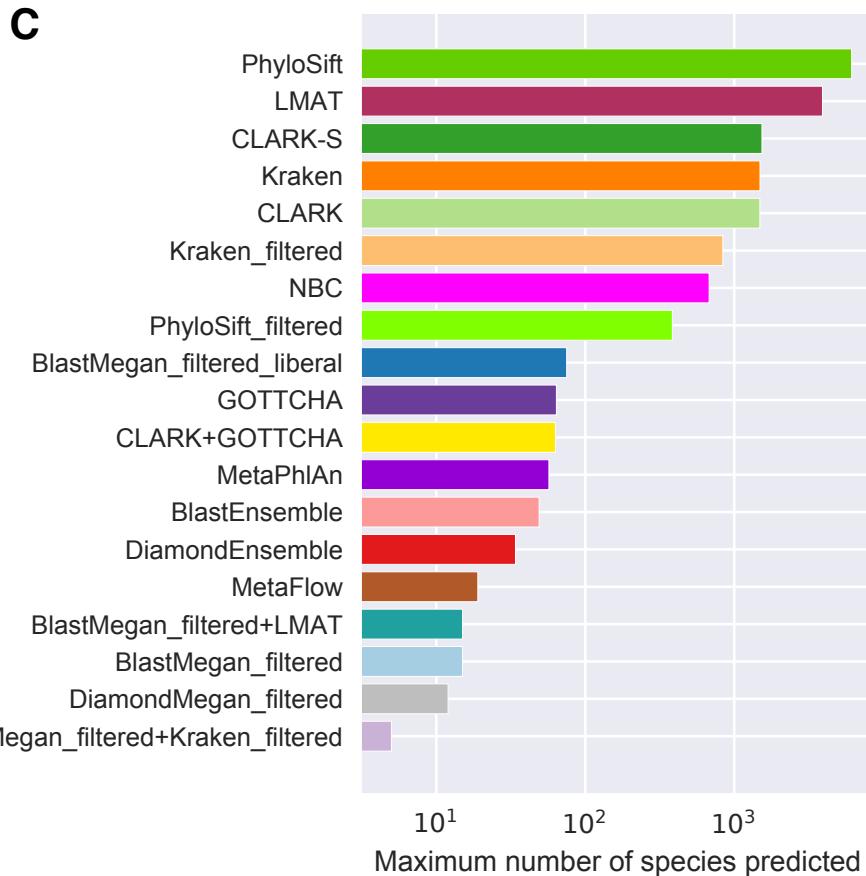
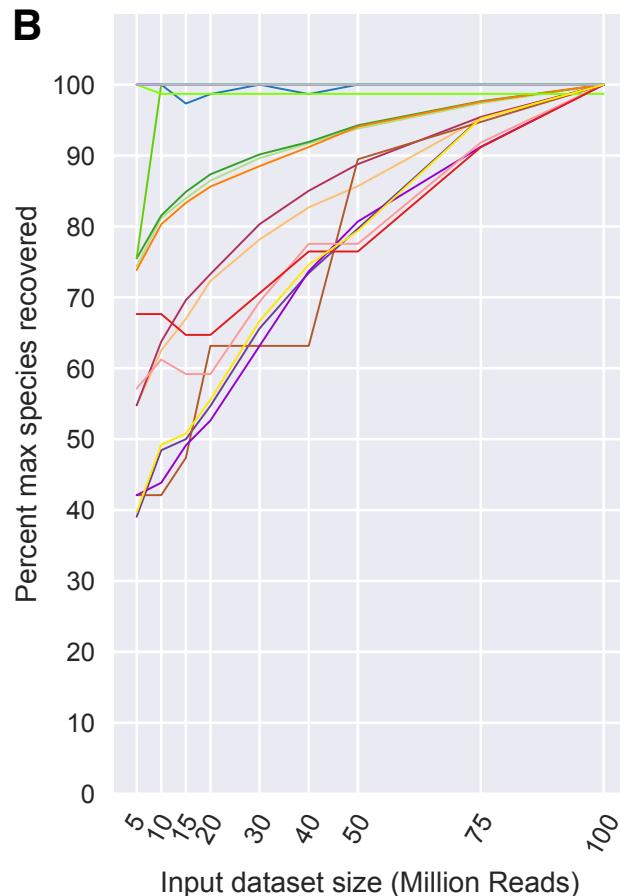
Abundance estimates



Precision/recall trade-offs



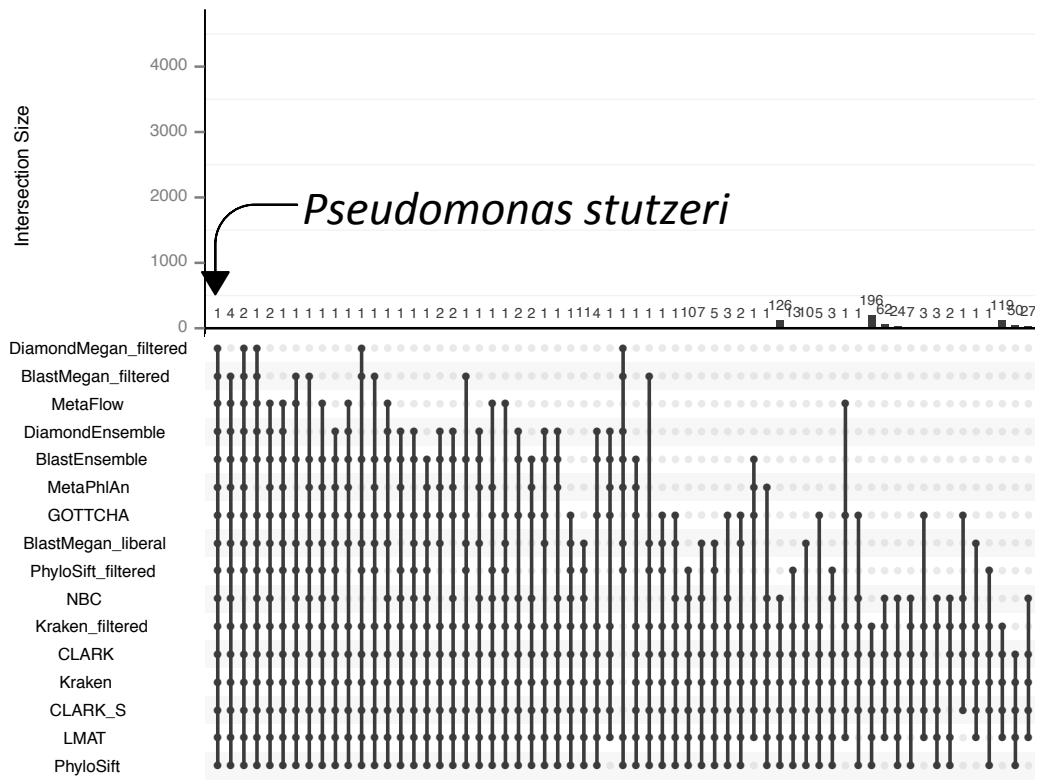
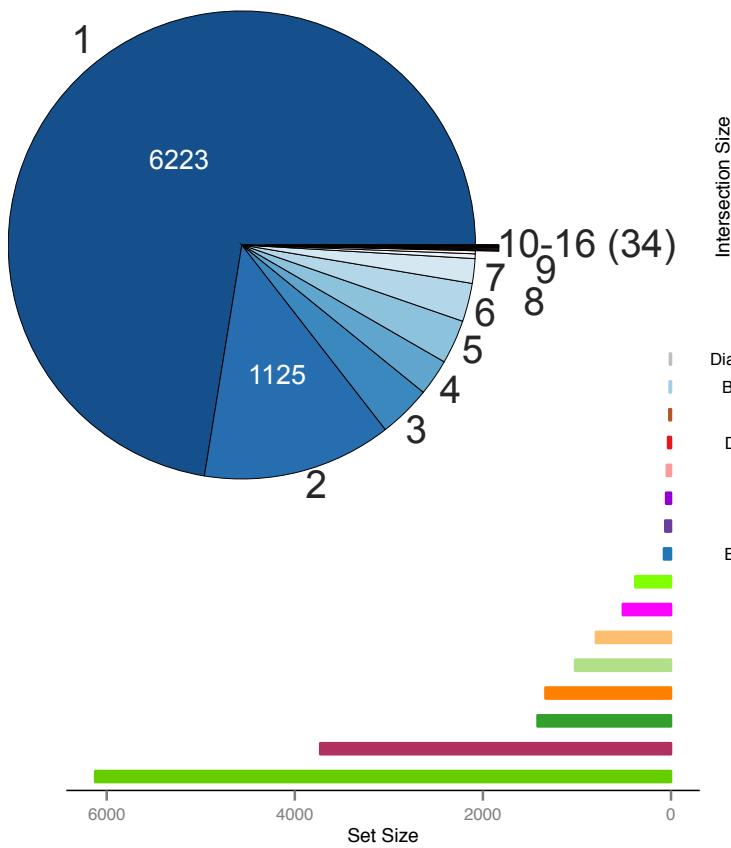
Deep sequenced subway sample



Elizabeth Hénaff

of species detected by all tools = 1

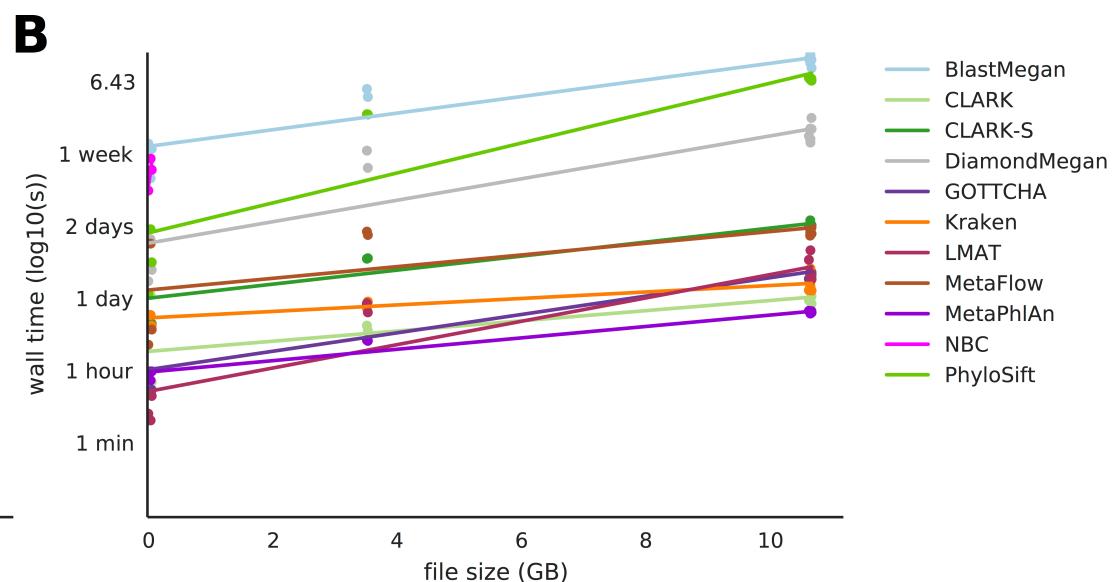
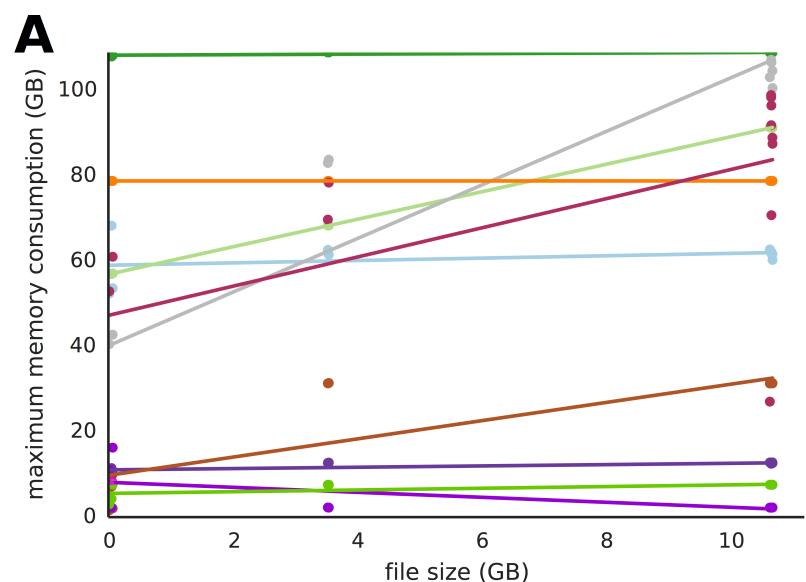
Tool overlap at 100M reads



Some species detected by >= 10 tools

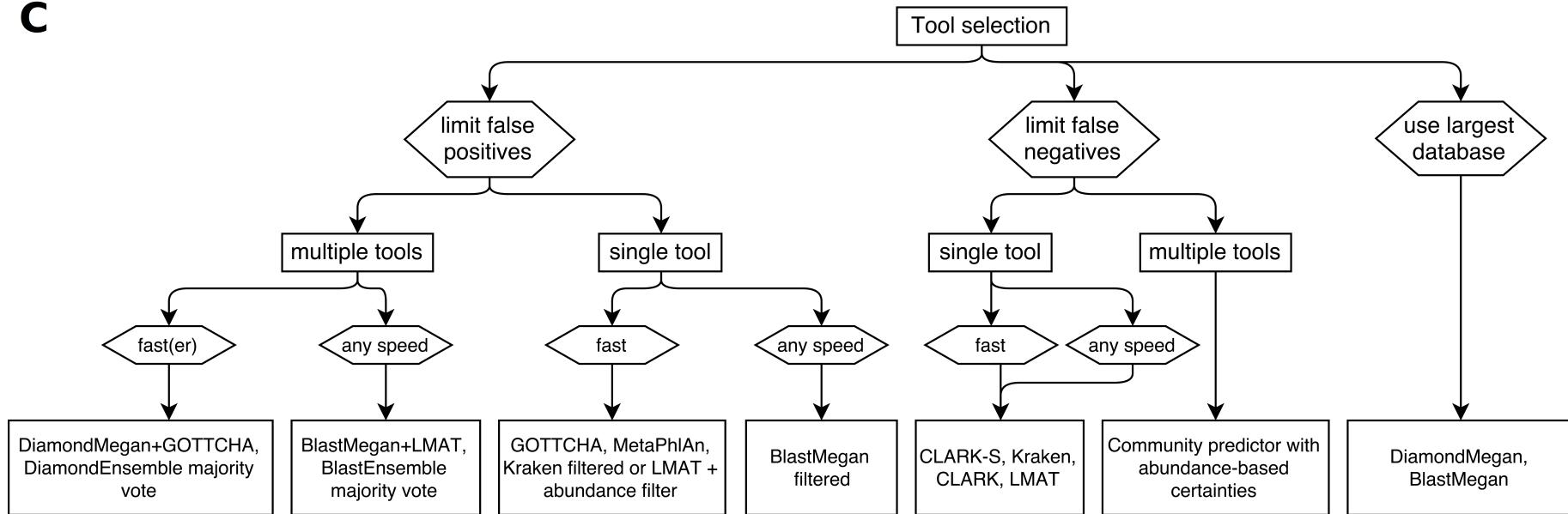
- Widespread: *Pseudomonas stutzeri*, *Micrococcus luteus*, *Escherichia coli*, *Cutibacterium acnes*, ...
- Soil: *Comamonas testosteroni*, *Bacillus pumilus*
- Wastewater: *Rhodococcus hoagii*
- Cheese: *Glutamicibacter arilaitensis*
- Pathogens: *Bacillus anthracis*

Constraints



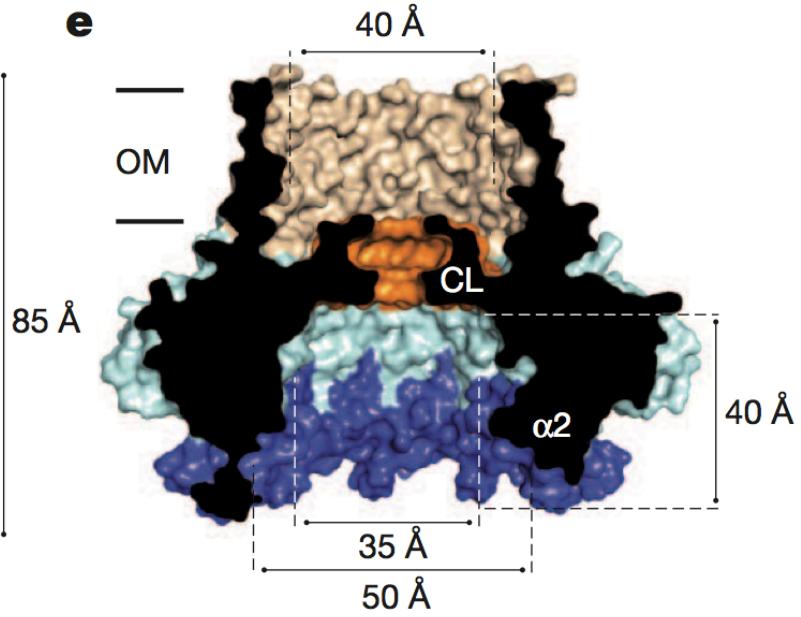
In summary

C

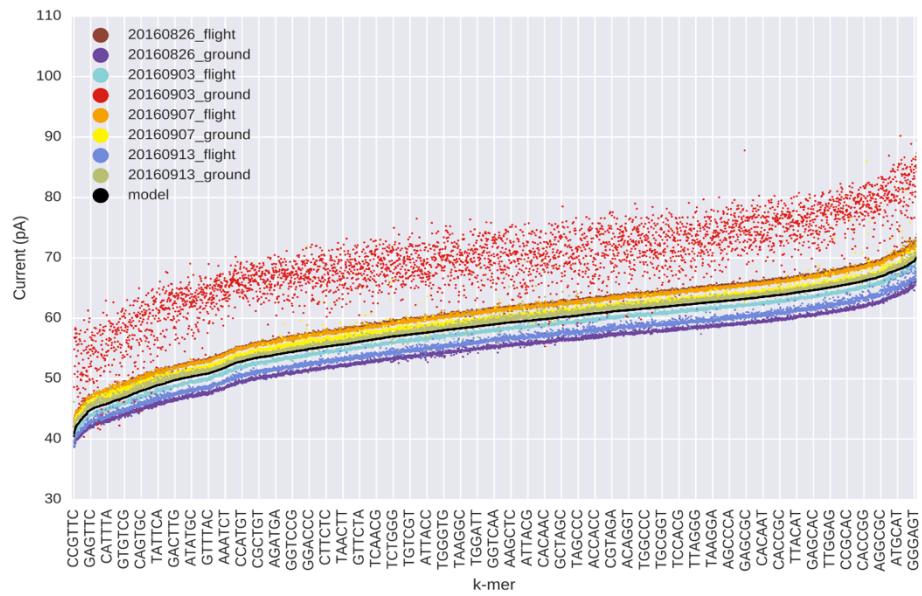


Nanopore sequencing

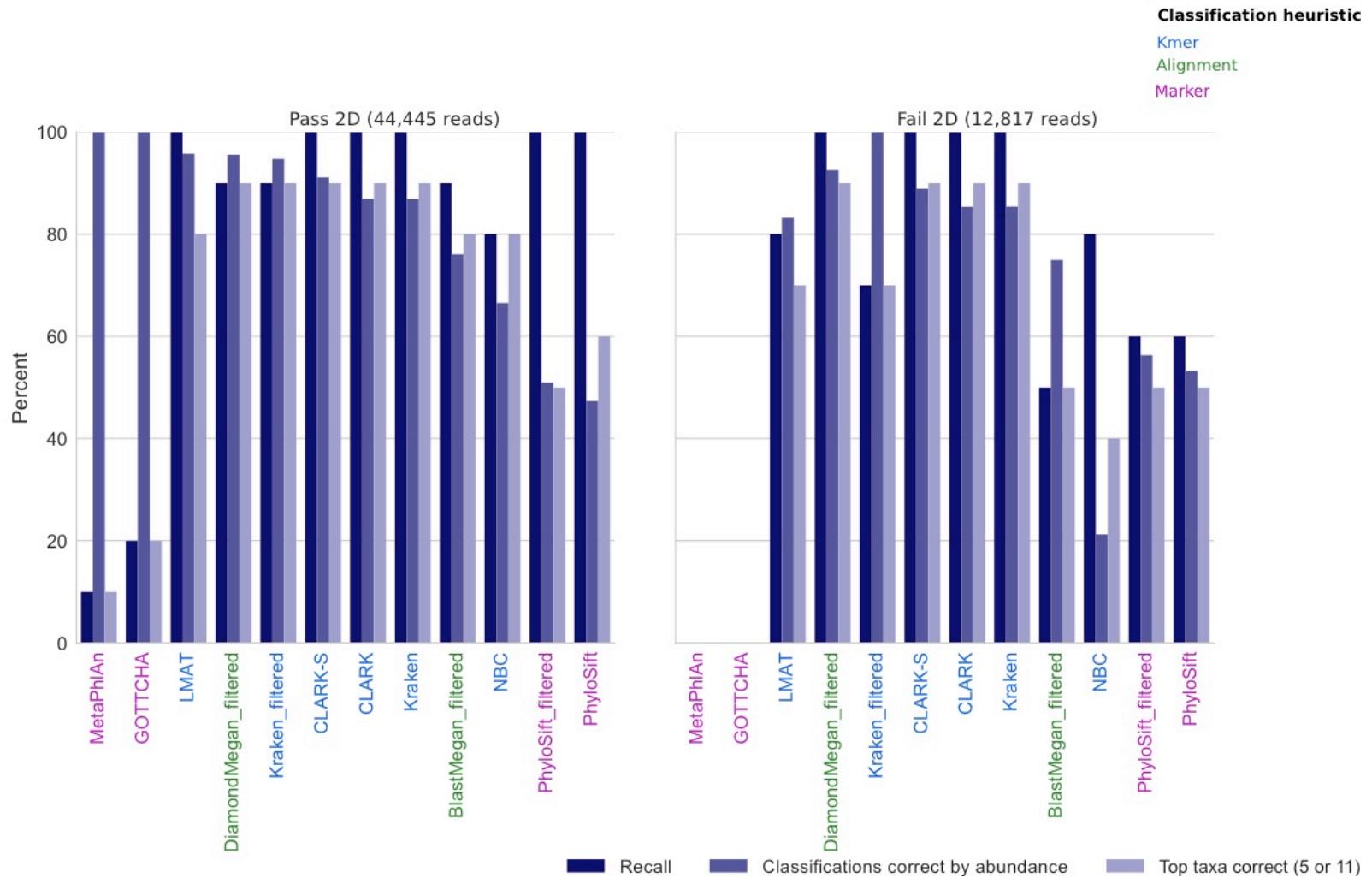
Pores to currents



Currents to k -mers



The long and the short of it



Bacterial epigenomics: N6-methyladenine

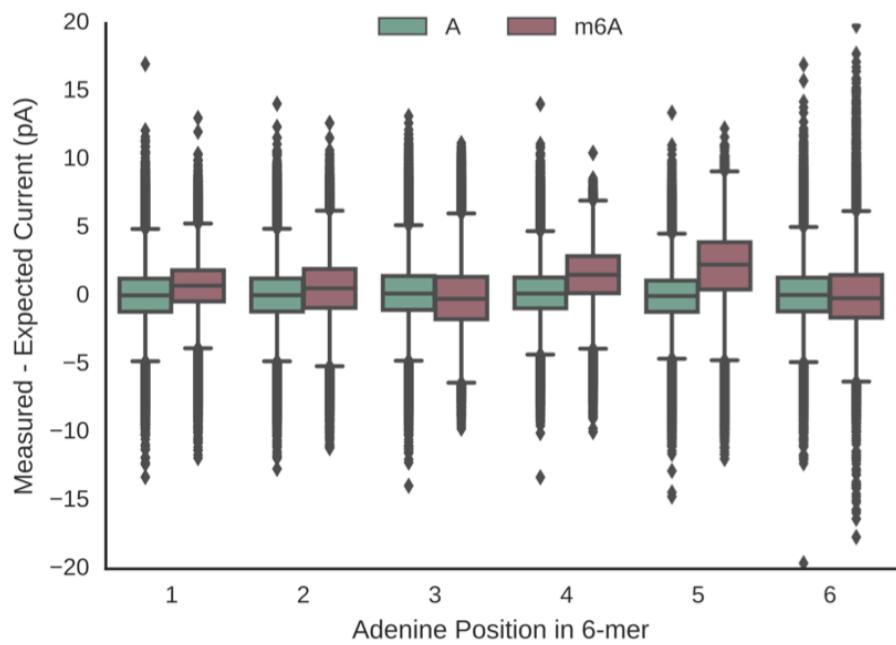
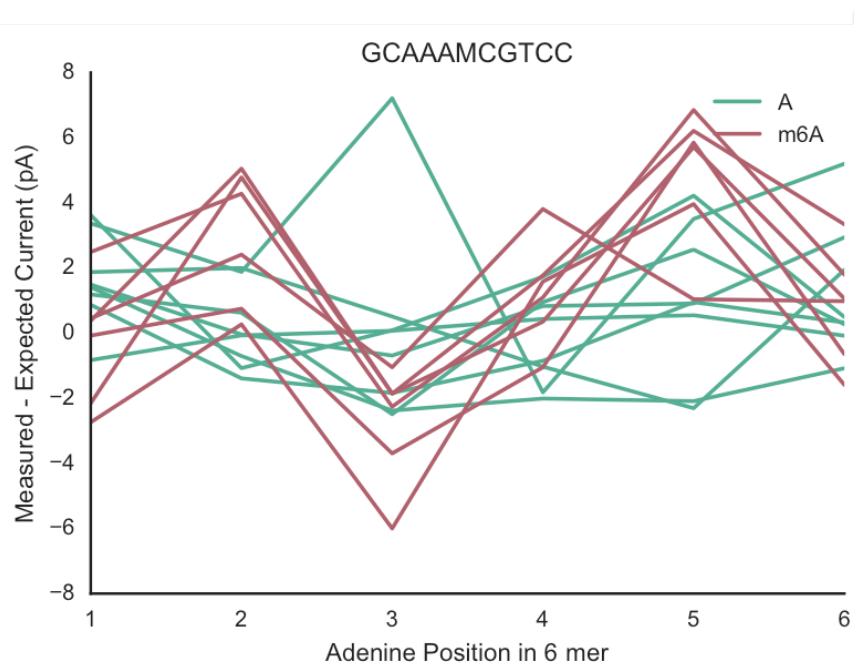


0.00009% m⁶A

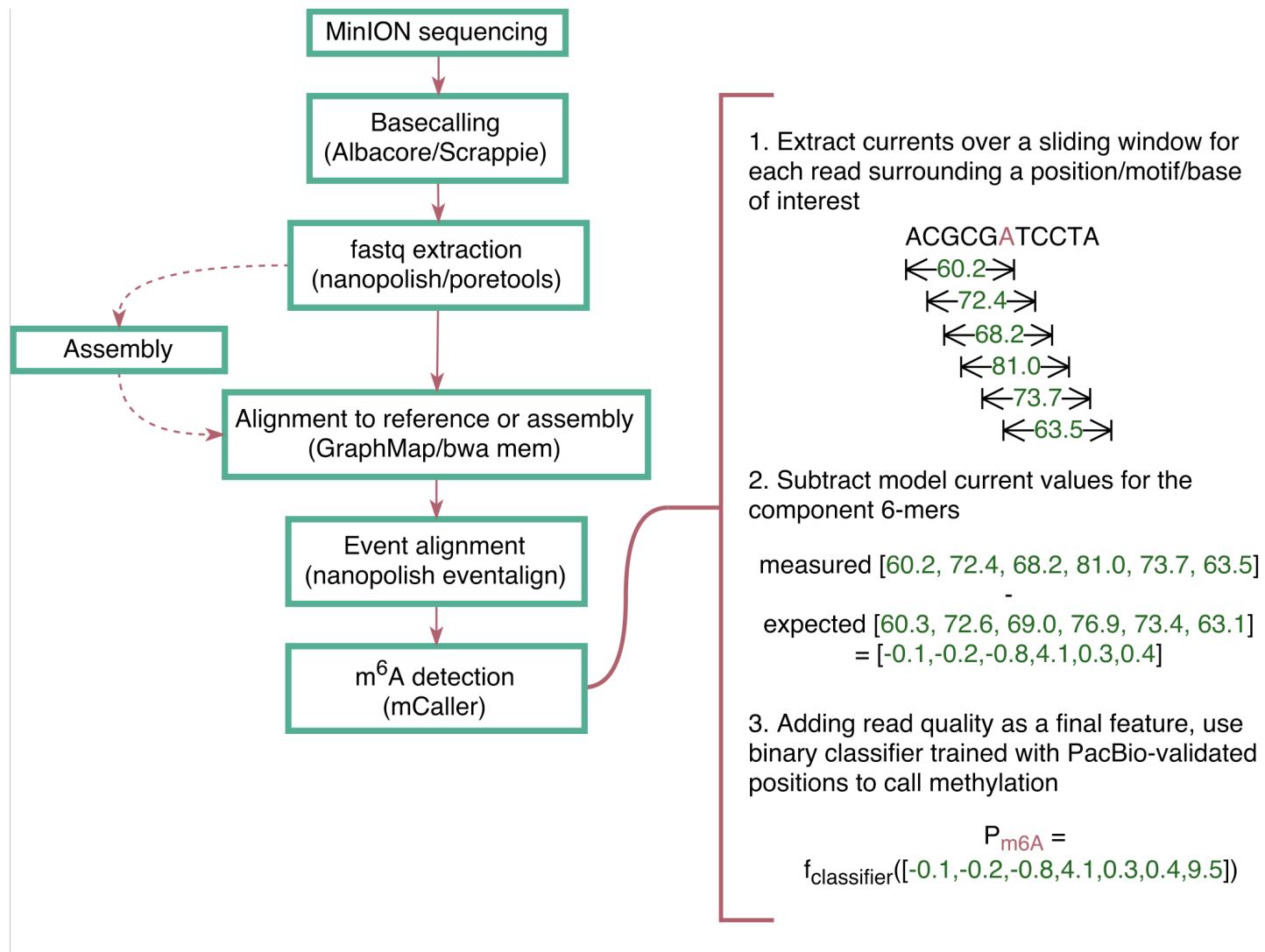
10-20% m⁶A

- Eukaryotes
 - Rare in most
 - Roles:
 - Fertility (*C. elegans*), nucleosome positioning (green algae), unknown (vertebrates)
- Prokaryotes
 - Most common base modification
 - Roles:
 - Defense against foreign DNA, replication repair, pathogenicity

Bacterial epigenomics



Bacterial epigenomics



Benchmarking bioRxiv

- <https://ftp-private.ncbi.nlm.nih.gov/nist-immsa/IMMSA/>

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Comprehensive Benchmarking and Ensemble Approaches for Metagenomic Classifiers

Alexa McIntyre, Rachid Ounit, Ebrahim Afshinnekoo, Robert Prill, Elizabeth Henaff, Noah Alexander, Sam Minot, David Danko, Jonathan Foox, Sofia Ahsanuddin, Scott Tighe, Nur A Hasan, Poorani Subramanian, Kelly Moffat, Shawn Levy, Stefano Lonardi, Nick Greenfield, Rita Colwell, Gail Rosen, Christopher E Mason

doi: <https://doi.org/10.1101/156919>

Abstract

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Metrics

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Abstract

One of the main challenges in metagenomics is the identification of microorganisms in clinical and environmental samples. While an extensive and heterogeneous set of computational tools is available to classify microorganisms using whole genome shotgun sequencing data, comprehensive comparisons of these methods are limited. In this study, we use the largest ($n=35$) to date set of

Posted June 28, 2017.

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Nanopore detection of bacterial DNA base modifications

Alexa B.R. McIntyre, Noah Alexander, Aaron S. Burton, Sarah Castro-Wallace, Charles Y. Chiu, Kristen K. John, Sarah E. Stahl, Sheng Li, Christopher E. Mason
doi: <https://doi.org/10.1101/127100>

This article is a preprint and has not been peer-reviewed [what does this mean?].

Abstract

Info/History

Metrics

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Abstract

The common bacterial base modification N6-methyladenine (m6A) is involved in many pathways related to an organism's ability to survive and interact with its environment. Recent research has shown that nanopore sequencing can detect m5C with per-read accuracy of upwards of 80% but m6A with significantly lower accuracy. Here we use a binary classifier to improve m6A classification by marking adenines as methylated or unmethylated

Posted April 13, 2017.

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- Mason Lab
 - Christopher Mason, Elizabeth Hénaff, Ebrahim Afshinnekoo, David Danko, Jonathan Foox, Noah Alexander, Sofia Ahsanuddin
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- CosmosID
 - Rita Colwell, Nur Hasan, Poorani Subramanian, Kelly Moffat
- One Codex
 - Nick Greenfield, Sam Minot
- Scott Tighe (UVM), Shawn Levy (Hudson Alpha), Stefano Leonardi (UC Riverside), Jonathan Allen (LLNL)
- Biomolecule Sequencer Project (NASA, UCSF)

