

Microbiome analyses of blood and tissues suggest cancer diagnostic approach

2020.11.19

Becca

catalogue

Background (15 mins)

- tissue samples
- blood samples
- microbiome

Paper reading (25 mins)

Discussion

Article | Published: 11 March 2020

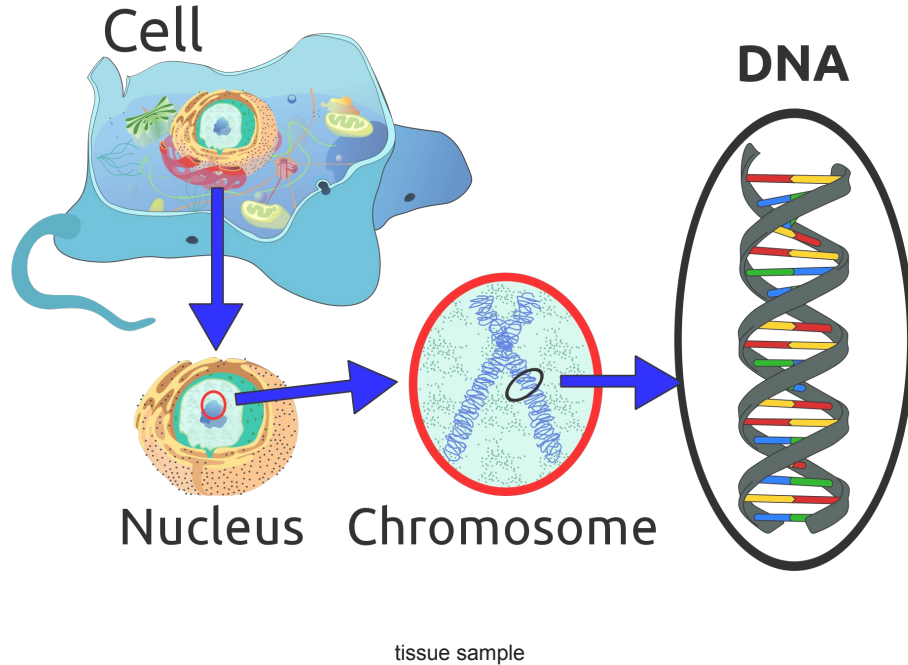
Microbiome analyses of blood and tissues suggest cancer diagnostic approach

Gregory D. Poore, Evguenia Kopylova, Qiyun Zhu, Carolina Carpenter, Serena Fraraccio, Stephen Wandro, Tomasz Kosciolk, Stefan Janssen, Jessica Metcalf, Se Jin Song, Jad Kanbar, Sandrine Miller-Montgomery, Robert Heaton, Rana Mckay, Sandip Pravin Patel, Austin D. Swafford & Rob Knight 

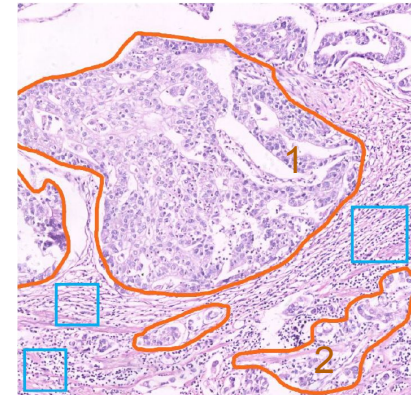
Nature **579**, 567–574(2020) | [Cite this article](#)

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Microbiome analyses of **blood and tissues** suggest cancer diagnostic approach



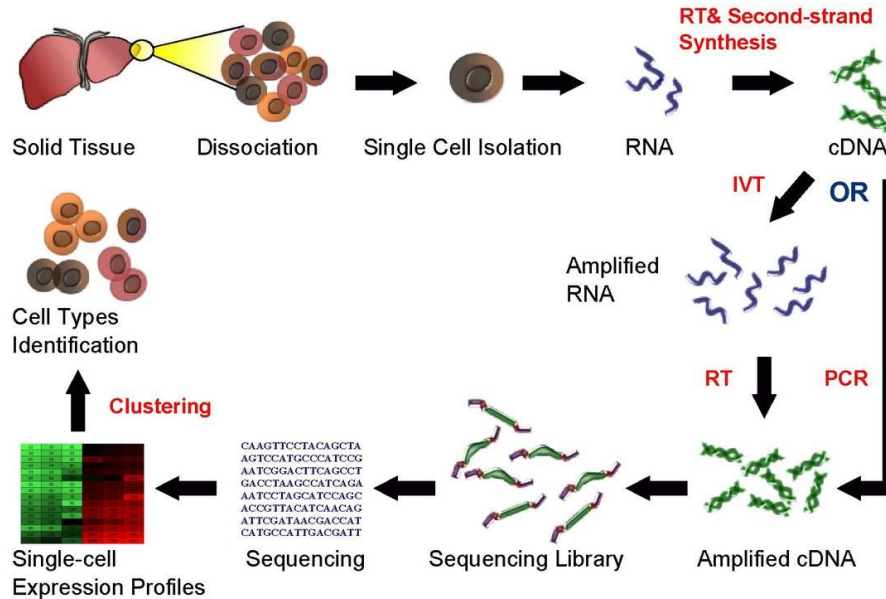
- large populations of mixed cells
- tumour tissue VS solid tissue normal (TCGA)
- heterogeneity



Extend Knowledge

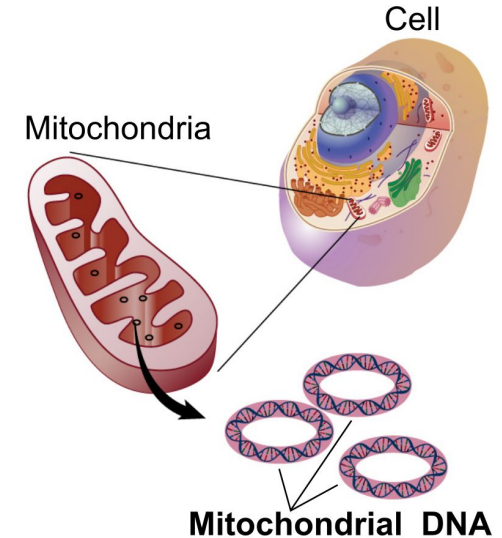
single cell sequencing

Single Cell RNA Sequencing Workflow



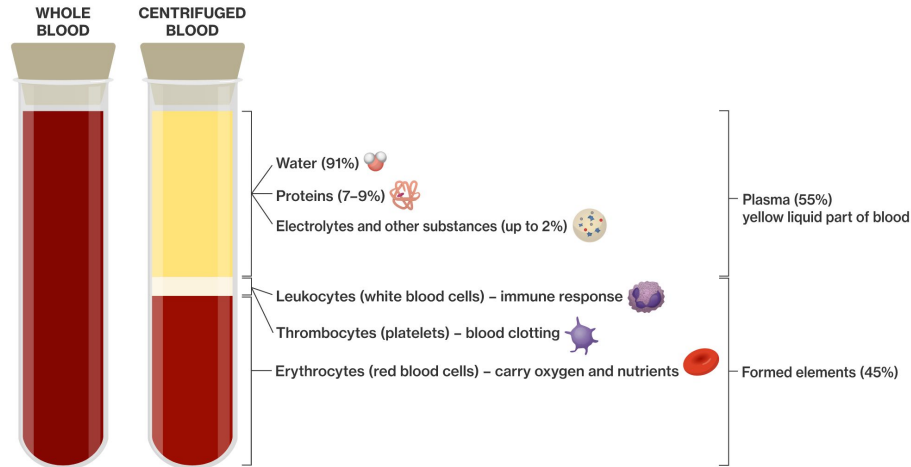
- Fluorescence-activated cell sorting (FACS) & microfluidics isolate cells
- At least 50 single cells to achieve this minimum CV value (3~8K cells)

Mitochondrial DNA

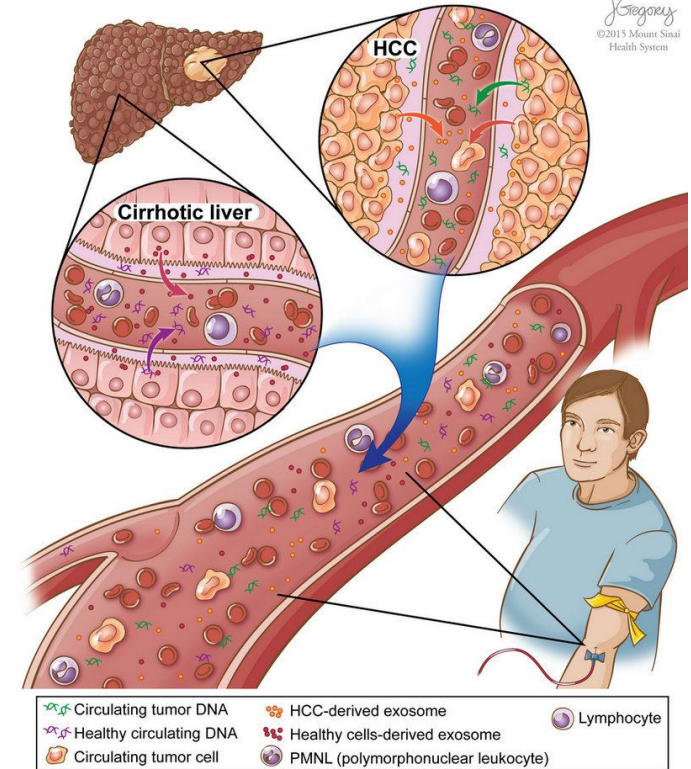


- In sexual reproduction, maternally inherited ,evolutionary analysis.
- human identification, disease diagnosis,relationship with aging and life spans.

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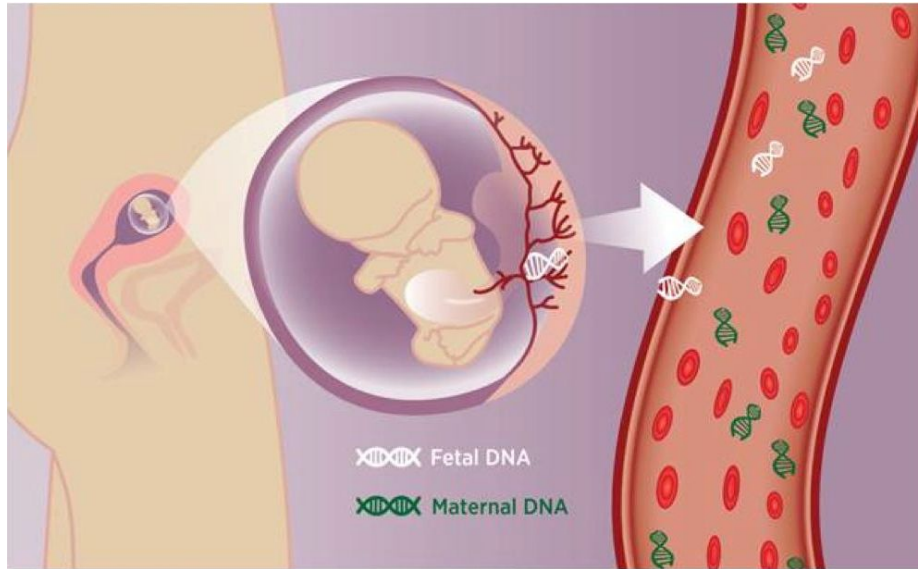
blood sample



- Circulating free DNA (**cfDNA**): degraded DNA fragments released to the blood plasma.
- RNA DE / Somatic variant calling: blood samples VS cancer samples
- Liquid Biopsy: detect **ctDNA** , **CTCs**.
- Non-invasive Prenatal Testing (NIPT) : cffDNA (cell-free fetus DNA)

Extend Knowledge

cffDNA



- originates from placental trophoblasts, fragmented
- size difference (cffDNA ~200bp, shorter than maternal DNA; isolated by centrifuge)
- 11 - 13.4 % of the cfDNA in maternal blood samples
- detectable after 5-7 weeks gestation, till two hours after delivery.

DNA can be detected in blood samples and tissue samples

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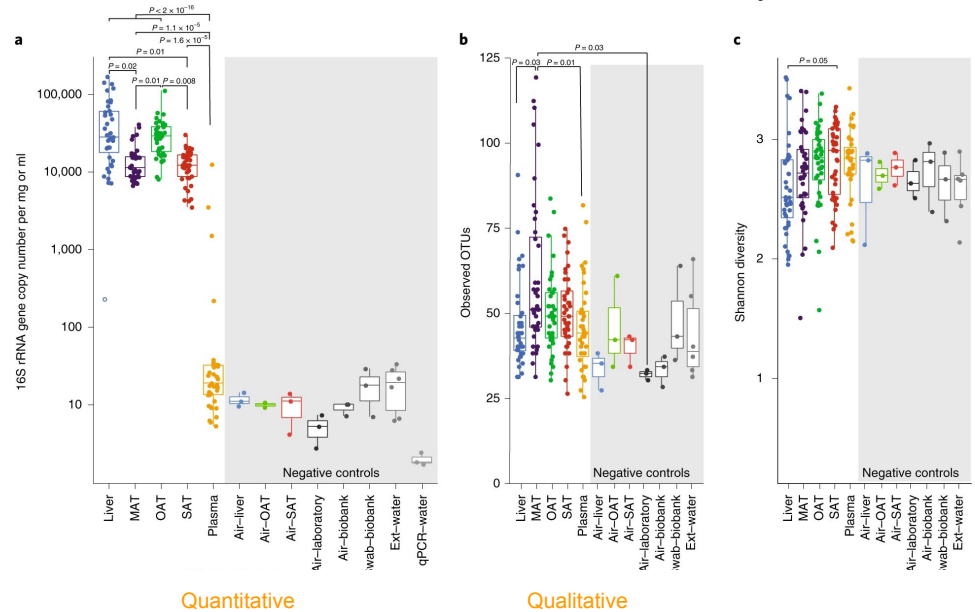
The human microbiome is a complex aggregate of the microbes residing at various sites in the human body and consisting of communities of a variety of microorganisms including Eukaryotes, Archaea, Bacteria, and the virus that reside in the different body habitat including the skin, the oral cavity, respiratory tract, gastrointestinal tract, urinary tract, reproductive tract etc. (Sender et al. 2016; Shreiner et al. 2015)

microbial population differ in early neonatal state, childhood and further changes throughout the lifespan depending upon the life style and diseased condition (Johnson and Versalovic 2012)

microbiome varies enormously at different sites within an organ system (Dethlefsen et al. 2007)

bacterial species population vary significantly among individuals

Bacterial distribution across body sites



cite from Anhê, F.F, 2020

Negative controls were tested to control for environmental sample contamination at major steps in the analysis

Microbiome exist and vary among blood and tissue samples

Abstract

Systematic characterization of the cancer microbiome provides the opportunity to develop techniques that exploit non-human, microorganism-derived molecules in the diagnosis of a major human disease. Following recent demonstrations that some types of cancer show substantial microbial contributions¹⁻¹⁰, we re-examined whole-genome and whole-transcriptome sequencing studies in The Cancer Genome Atlas¹¹ (TCGA) of 33 types of cancer from treatment-naïve patients (a total of 18,116 samples) for microbial reads, and found unique microbial signatures in tissue and blood within and between most major types of cancer. These TCGA blood signatures remained predictive when applied to patients with stage Ia–IIc cancer and cancers lacking any genomic alterations currently measured on two commercial-grade cell-free tumour DNA platforms, despite the use of very stringent decontamination analyses that discarded up to 92.3% of total sequence data. In addition, we could discriminate among samples from healthy, cancer-free individuals ($n = 69$) and those from patients with multiple types of cancer (prostate, lung, and melanoma; 100 samples in total) solely using plasma-derived, cell-free microbial nucleic acids. This potential microbiome-based oncology diagnostic tool warrants further exploration.

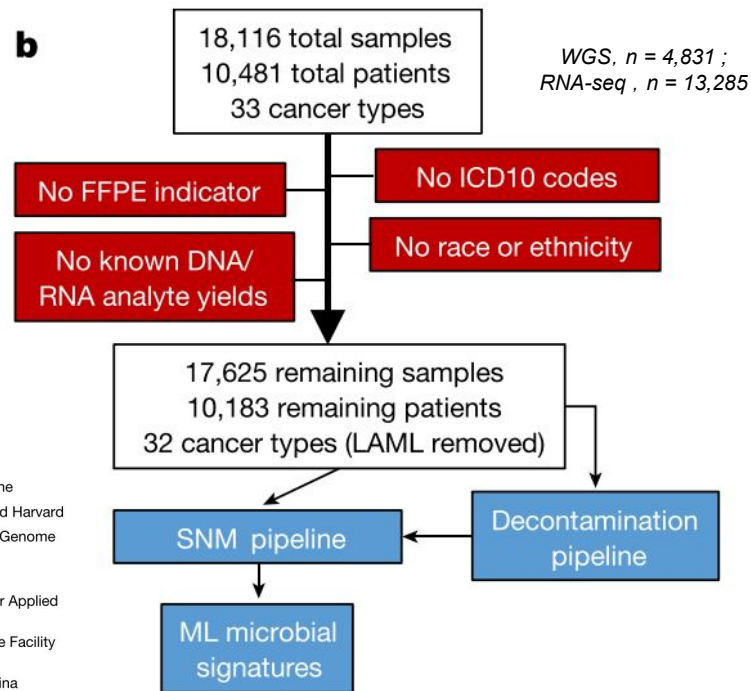
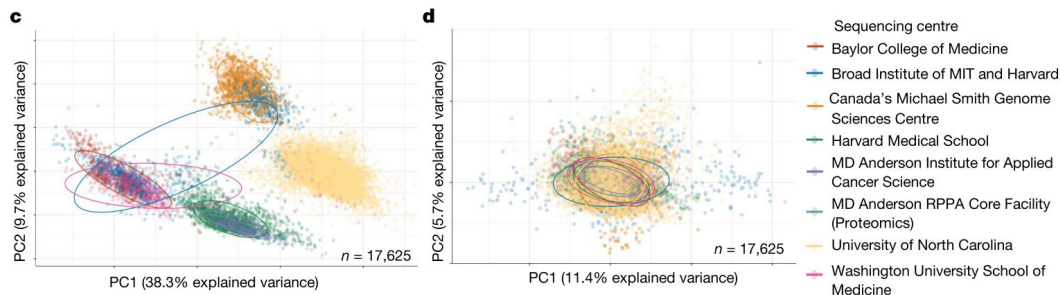
INPUT DATASET

Analysis / Model training

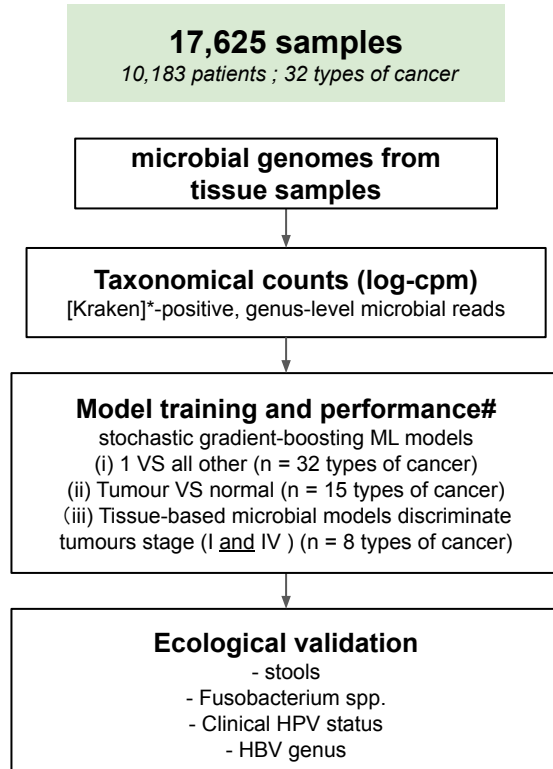
OUTPUT / Contribution

Quality control & normalization

SNM Normalization:
R package limma, edgeR, and snm



Biological relevance of microorganism profiles



Namely, cancers with known microbial ‘drivers’ or ‘commensals’ provided initial evidence that the models were ecologically relevant; for example, **Alphapapillomavirus genus** was the most important feature for identifying **CESC tumours**; for **COAD tumours**, the **Faecalibacterium genus**; for **LIHC tumours**, the **Orthohepadnavirus genus** was the second most important feature.(after the **hepatotoxic Microcystis genus**)

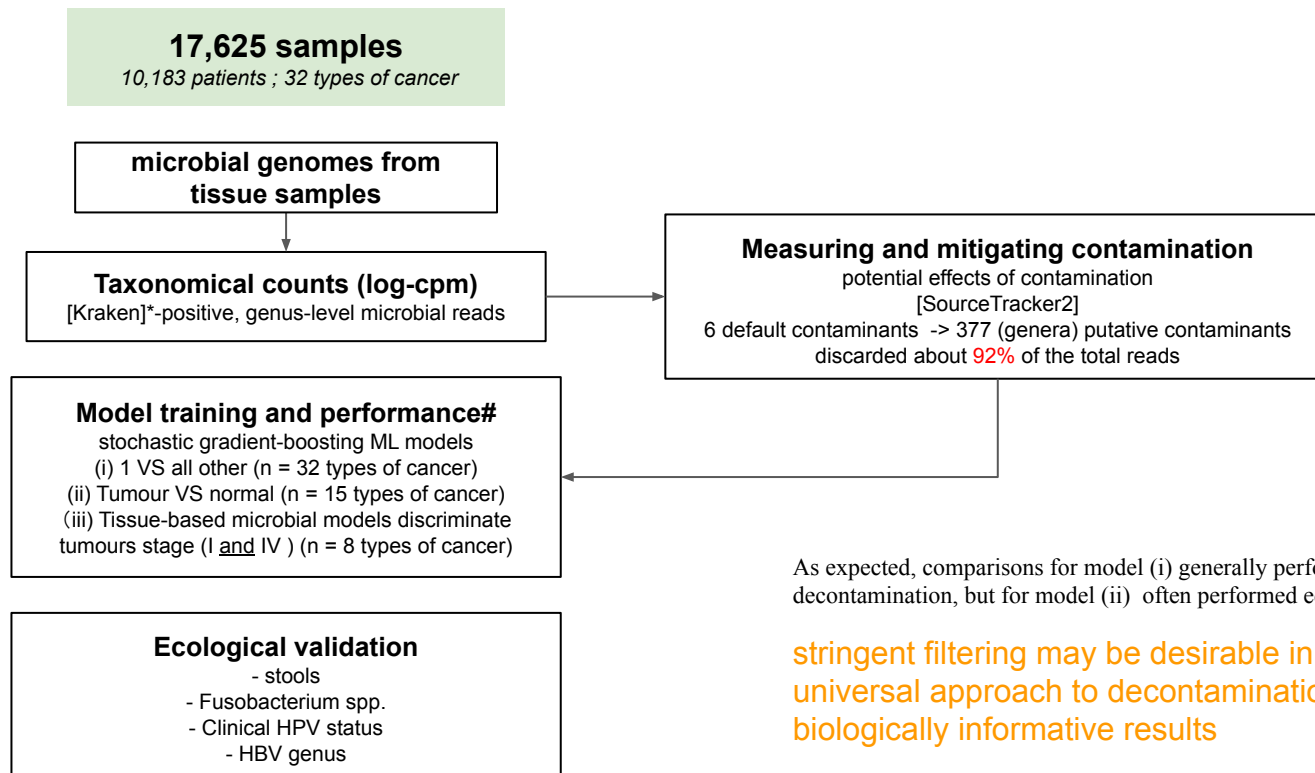
Analysis result consistent with information about feature importance provided by trained models. Prove models reliability

interactive website :

exploration of normalized microbial abundances in TCGA cancers and major sample types

http://cancermicrobiome.ucsd.edu/cancermicrobiome_DataBrowser

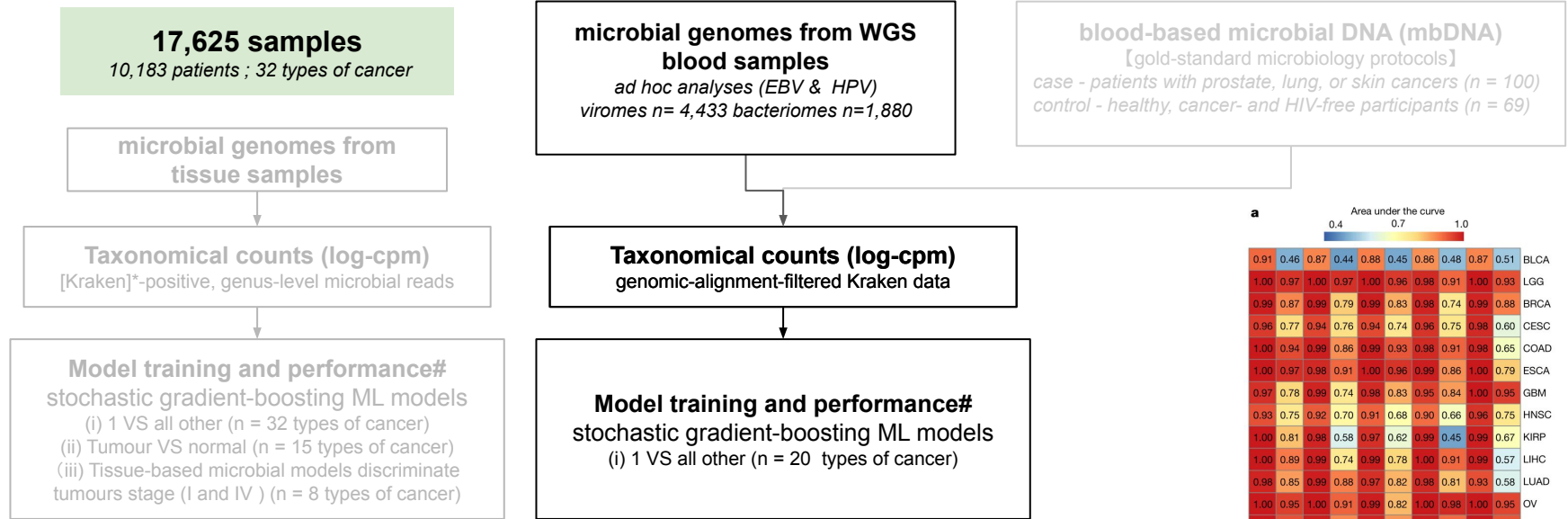
Measuring and mitigating contamination



As expected, comparisons for model (i) generally performed less well with stringent decontamination, but for model (ii) often performed equally well or better.

stringent filtering may be desirable in certain comparisons, but a universal approach to decontamination may preclude biologically informative results

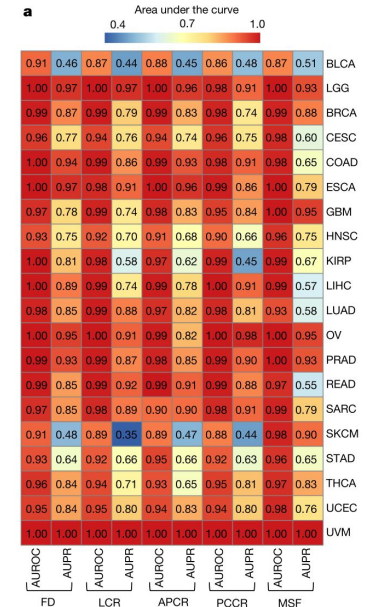
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mbDNA in blood can use for cancer discrimination

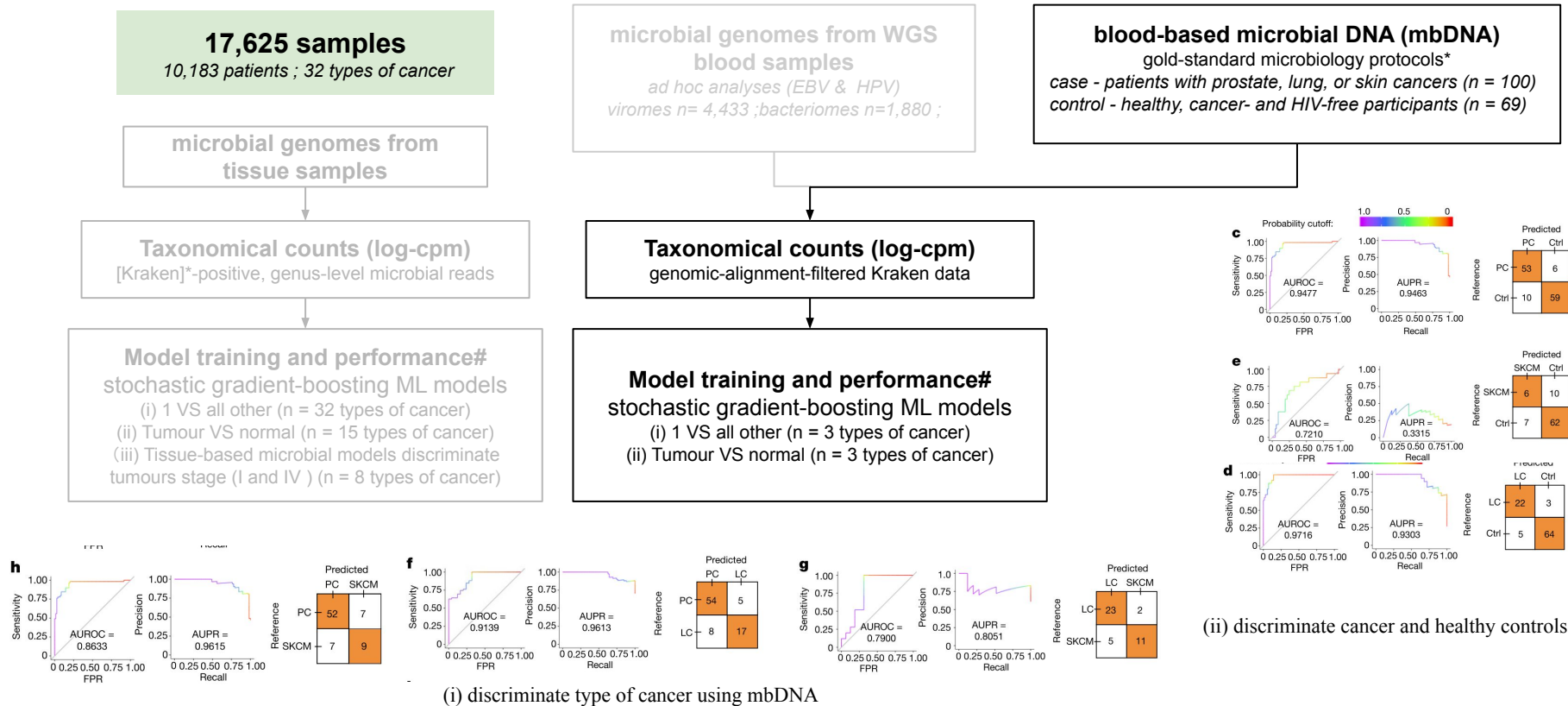
(i) model performances predicting one cancer type versus all others using blood mbDNA

FD, full data; LCR, likely contaminants removed by sequencing centre; APCR, all putative contaminants removed by sequencing centre; PCCR, plate-centre contaminants removed; MSF, most stringent filtering by sequencing centre.

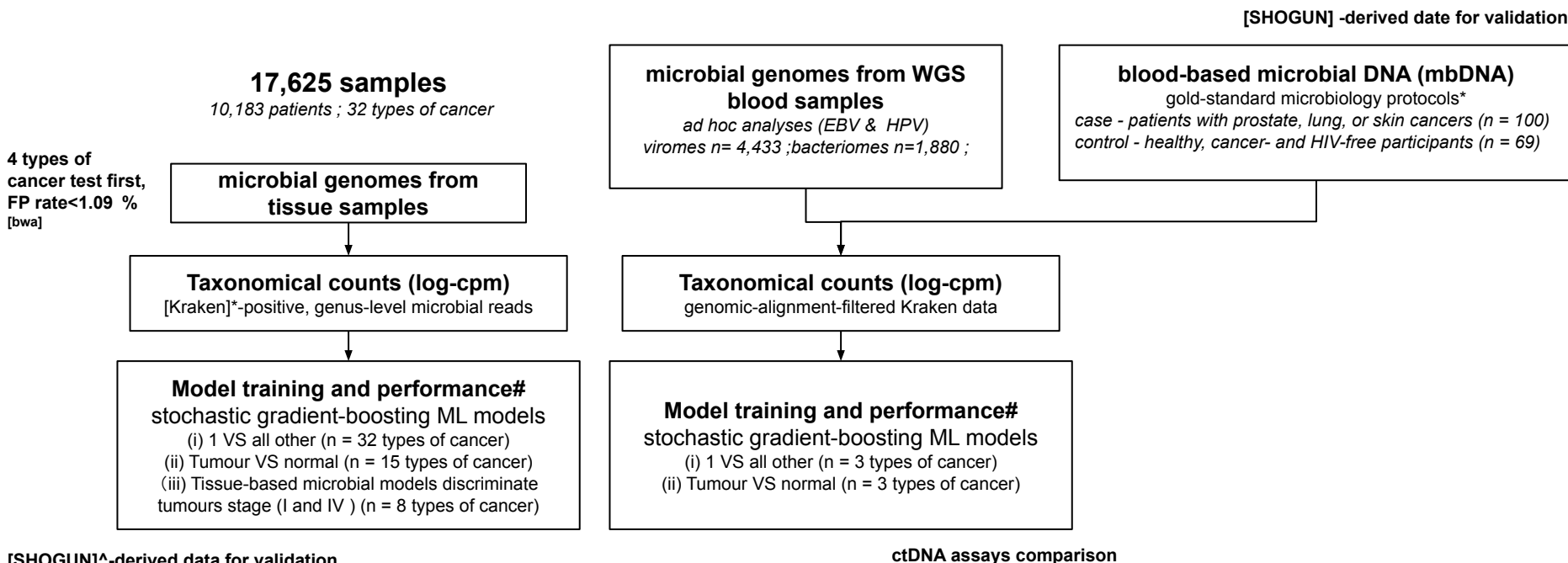


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* Cell-free DNA extracted from plasma samples - whole metagenomic sequencing - Kraken



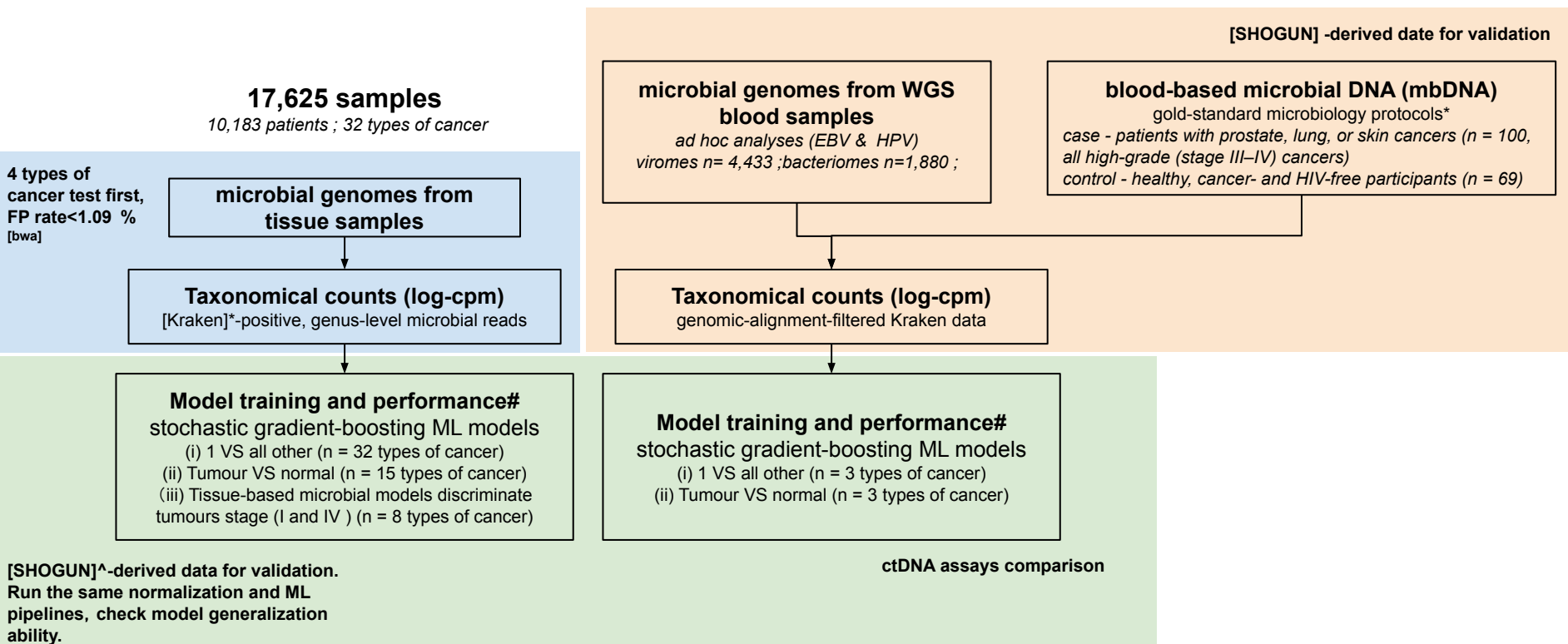
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[SHOGUN]^*-derived data for validation.
Run the same normalization and ML
pipelines, check model generalization
ability.

*kraken: matches short genomic substrings (k-mers) to taxa in a reference database
^SHOGUN:an alignment-based microbial taxonomic pipeline

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Highlight

Verify carefully in most steps

Facing limitation/shortcoming honestly

A lot of meticulous work

Clear figures

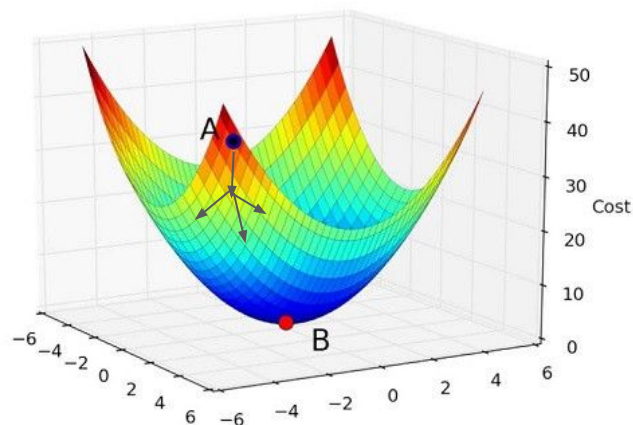
Data availability: [ftp.microbio.me/pub/can](ftp://microbio.me/pub/can).

Code availability: github.com/biocode/tcga

mia)^{8,10}. There is likely to be a continuum of ideal decontamination, as the effect of decontamination on model performance varied across types of cancer, but our filtering was limited by (i) not having access to the primary specimens, (ii) genus-level taxonomic resolution, and (iii) not knowing which non-TCGA samples were concurrently processed.

gregpoore Update All_Tumor_batch_analysisFA.R		c4edac4 on 11 Jan 117 commits
cgc	rm pycache	3 years ago
docker	code updates	3 years ago
jupyter_notebooks	Plasma jupyter notebooks	10 months ago
metadata	updated metadata file and workflow api	4 years ago
python_scripts	rm pycache	3 years ago
r_scripts	Update All_Tumor_batch_analysisFA.R	10 months ago
shell_scripts	SHOGUN example	10 months ago
source_tracker_scripts	greg adding files	2 years ago
sparql_queries	Addition of new SPARQL queries on CGC file size and file counts	4 years ago

gradient boosting machine algorithm (GBM)



Start at point A, how we can arrived at the lowest point (B) ?

following the most **steepest negative** gradient direction

calculate GBM

training set

	x	y
sample1	1	2
sample2	2	4

model

$y = \theta x$, θ is the parameter

using model

when we know $x=3$, $y=3*\theta = 3*2=6$

prediction:

regression: $y=6$

known when $y>3$, group = A

classification: $y=6 > 3$, A

known: $x_1 = 1 \quad y_1 = 2$
 $x_2 = 2 \quad y_2 = 4$
 $y = \theta x$

θ ?

set $J(\theta) = \sum_{i=1}^n (\hat{y}_i - y_i)^2$ real y ; predicted \hat{y}

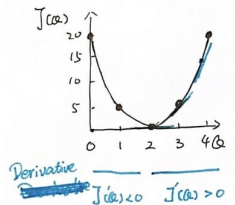
$J(\theta) \rightarrow 0 \quad \hat{y} = y$

$\theta \rightarrow \arg\min J(\theta)$?

$J(\theta) = (\hat{y}_1 - y_1)^2 + (\hat{y}_2 - y_2)^2 = (\theta x_1 - y_1)^2 + (\theta x_2 - y_2)^2 = (\theta - 2)^2 + (2\theta - 4)^2$

$J(\theta=0) = 4 + 16 = 20$; $J(\theta=1) = 1 + 4 = 5$; $J(\theta=2) = 0$

$J(\theta=3) = 1 + 4 = 5$; $J(\theta=4) = 4 + 16 = 20$



update θ

$\theta_{\text{new}} = \theta - \frac{0.1 J'(\theta)}{J'(\theta)}$

~~set~~ learning rate

$\arg\min J(\theta)$? $\rightarrow J'(\theta) \rightarrow 0$

$J'(\theta) = 2(\theta x_1 - y_1)x_1 + 2(\theta x_2 - y_2)x_2$
 $= 2\theta - 2y_1 + 4\theta - 16 = 10\theta - 20$

random start point.

$\theta=3$ ~~$\theta_{\text{new}} = 3 - 0.1 \times (10 \times 3 - 20) = 2$~~

$\theta=2$ $\theta_{\text{new}} = 2 - 0.1 \times (10 \times 2 - 20) = 2$ ✓

random start point

$\theta=1$ $\theta_{\text{new}} = 1 - 0.1 \times (10 \times 1 - 20) = 2$

$\theta=2$ no change ✓

$\therefore \theta=2$, model is $y = 2x$.