# Computational Approaches to Unravel Immune Receptor Sequencing 

Li Zhang<br>Professor of Biostatistics<br>Department of Medicine<br>Department of Epidemiology and Biostatistics<br>HDFCCC Biostatistics Core<br>University of California San Francisco<br>li.zhang@ucsf.edu

## Outline

- Background and Introduction
- T-cell/B-cell Receptor and Repertoire Sequencing
- Proposed Analysis Pipelines with Examples
- Conclusion and Future Work


## T-cell Receptor (TCR) and B-cell Receptor (BCR)

## Receptor Structure

V(D)J Recombination


TCR is a protein complex found on the surface of T cells, or T lymphocytes, that is responsible for recognizing fragments of antigen as peptides bound to MHC molecules.

BCR is composed of immunoglobulin molecules that form a type 1
transmembrane receptor protein usually located on the outer surface of $B$ cells.


## Overview of TCR Repertoire Sequencing


(Adapted from Aaron Logan)

ImmunoSEQ Assay

## NAIR: Proposed Analysis Pipeline



Yang et al 2022 submitted
Neal et al 2022 (ongoing)

## TCR Repertoire Sequences European COVID-19 Patients

## Next-Generation Sequencing of T and B Cell Receptor Repertoires from COVID-19 Patients Showed Signatures Associated with Severity of Disease

recovered without medical intervention

Christoph Schultheiß, ${ }^{1,11}$ Lisa Paschold, ${ }^{1,11}$ Donjete Simnica, ${ }^{1,11}$ Malte Mohme, ${ }^{2}$ Edith Willscher, ${ }^{1}$ Lisa von Wenserski, ${ }^{1}$ Rebekka Scholz, ${ }^{1}$ Imke Wieters, ${ }^{3}$ Christine Dahlke, ${ }^{4,5}$ Eva Tolosa, ${ }^{6}$ Daniel G. Sedding, ${ }^{7}$ Sandra Ciesek, ${ }^{8,9,10}$ Rebekka Scholz,' Imke Wieters, ${ }^{\text {T }}$ Christine
Marylyn Addo, ${ }^{4,5}$ and Mascha Binder ${ }^{1,12,{ }^{\star}}$


+ positive SARS-CoV-2 PCR
* COVID-19 contact
$\Theta$ negative SARS-CoV-2 PCR $\downarrow$ sample collection
$\neq$ death

| cohort | patient ID | age range [y] | sex | diagnosis | severity | respiratory status | duration of sympt.[d] | relevant risk factors ${ }^{\text {s }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 11 | 30-39 | m | PCR | mild | spont. breath. | 25 | none |
|  | 12 | 20-29 | f | PCR | mild | spont. breath. | 19 | none |
|  | 13 | 40-49 | f | serological | mild | spont. breath. | 16 | none |
|  | 14 | 50-59 | m | PCR | mild | spont. breath. | 16 | none |
|  | 16 | 20-29 | m | PCR | mild | spont. breath. | 15 | HTN |
|  | 17 | 30-39 | f | PCR | mild | spont. breath. | 25 | none |
|  | 18 | 30-39 | m | PCR | mild | spont. breath. | 20 | none |
|  | 26 | 40-49 | m | PCR | mild | spont. breath. | 14 | none |
|  | 27 | 20-29 | m | PCR | mild | spont. breath. | 13 | none |
|  | 28 | 30-39 | f | PCR | mild | spont. breath. | 16 | none |
|  | 29 | 30-39 | m | PCR | mild | spont. breath. | 15 | none |
|  | 32 | 20-29 | f | PCR | mild | spont. breath. | 21 | none |
|  | 33 | 30-39 | m | PCR | mild | spont. breath. | 15 | none |
|  | 34 | 40-49 | m | PCR | mild | spont. breath. | 18 | none |
|  | 35 | 60-69 | f | PCR | mild | spont. breath. | 13 | none |
|  | 38 | 20-29 | f | PCR | mild | spont. breath. | 13 | none |
|  | 45 | 30-39 | m | PCR | asymptomatic | spont. breath. | NA | none |
| 1\&2 | 6 | 60-69 | f | PCR | moderate* | spont. breath. | 21 | HTN, age |
|  | 7 | 70-79 | f | PCR | moderate* | spont. breath. | 26 | HTN, DM, age |
| 2 | 19 | 20-29 | m | PCR | moderate* | spont. breath. | 12 | none |
|  | 39 | 30-39 | m | PCR | moderate* | spont. breath. | 4 | none |
|  | 1 | 60-69 | m | PCR | fatal | ECMO | 28 | cancer, age |
|  | 2 | 60-69 | m | PCR | fatal | ECMO | 12 | cancer |
|  | 3 | 70-79 | m | PCR | fatal | mech. vent. | 25 | cancer, age |
|  | 8 | 40-49 | m | PCR | fatal | ECMO | 25d | HTN |
|  | 9 | 60-69 | m | PCR | fatal | есмO | 23 | HTN, CVD, age |
|  | 5 | 60-69 | m | PCR | severe ${ }^{*}$ | ecmo | $42+$ | HTN, DM, age |
|  | 10 | 60-69 | m | PCR | severe ${ }^{\text {\# }}$ | ecmo | $47+$ | CRD, age |
|  | 20 | 50-59 | m | PCR | moderate* | spont. breath. | 29 | HTN, CVD |
|  | 21 | 50-59 | f | PCR | moderate* | spont. breath. | 31 | $\begin{aligned} & \text { DM., HTN, } \\ & \text { CVD } \end{aligned}$ |
|  | 22 | 70-79 | m | PCR | severe ${ }^{\text {\# }}$ | mech. vent. | 54+ | HTN, CVD, DM, age |
|  | 23 | 70-79 | m | PCR | moderate* | spont. breath. | 28 | CVD, age |
|  | 24 | 80-89 | f | PCR | moderate* | spont. breath. | $29+$ | HTN, DM,age |
|  | 25 | 60-69 | m | PCR | severe* ${ }^{\text {\# }}$ | ECMO | 19+ | age |
|  | 40 | 70-79 | f | PCR | severe ${ }^{\text {t }}$ | mech. vent. | 24 | HTN |
|  | 41 | 70-79 | m | PCR | severe ${ }^{\text {\# }}$ | mech. vent. | $22+$ | CVD |
|  | 44 | 70-79 | m | PCR | severe ${ }^{*}$ | ECMO | 18+ | HTN, CVD, CRD, age |

CVD - cardiovascular disease; DM - diabetes; CRD - chronic respiratory disease
million $B C R$ and $>8.3$ million TCR sequences

## Recall Major Pipelines



## Network Analysis

| Node | Account | Nucleotide clone |
| :--- | :--- | :--- |
| Distance | Minimum number of accounts <br> between two accounts | Number of nucleotide differences <br> between two clones |
| Edge | Relationship | Only one nucleotide change between <br> two nodes |
| Distance matrix | Friendship info among a group | Pairwise distances among clones |
| Attributes | Photos or posts | Meta data in nucleotide clone |
| Cluster | Groups in FB | A group of clones having direct or <br> indirect connection |



## Distance Matrix

## Levenshtein distance

- Cat $\rightarrow$ fat (transformation)
distance $=1$
- Health $\rightarrow$ healthy (insertion)
distance $=1$
- Sunny $\rightarrow$ sun (deletion)

Similar as

- ATCG $\rightarrow$ ATGG (transformation) distance $=1$
- ATCG $\rightarrow$ ATTCG (insertion)
- ATCG $\rightarrow$ ACG (deletion) distance $=1$
distance $=1$



## Network Properties

Network property

| Node (vertex) | The fundamental unit of which graphs are formed: $v$ | $\therefore \ddots$ |
| :---: | :---: | :---: |
| Edge (link) | An unordered pair of distinct vertices: $\{v, w\}$ | $\because \square$ |
| Degree | The number of edges incident to a vertex e: $\operatorname{deg}(v)$ | $-!$ |
| Largest component | Largest subgraph in which any two vertices are connected | $\therefore-\Delta$ |
| k-core | A maximal subgraph of a graph in which all vertices have degree of at least $k$ |  |
| Clique | A complete subgraph in a graph |  |
| Diameter | The length of the "longest shortest path" between any two vertices: $\max _{(v, w} d(v, w)$ | 毕 |
| Assortativity coefficient | Pearson correlation coefficient of degree between pairs of linked nodes $r=\{-1,1\}$ | $\forall_{r>0} \leqslant \forall_{r<0}$ |
| Cluster size, number | Connected component of a graph in which any two nodes are connected | $\begin{aligned} & \text { Number }=2 \text { clusters } \\ & \text { Size }=3,6, ~ \\ & 0,0 \end{aligned}$ |
| Clustering coefficient (transitivity) | The probability that the adjacent vertices of a vertex are connected | - |
| Density | The ratio of the number of edges and the number of possible edges | 茄 |
| Centralization | Centrality score based on nodelevel centrality $c$ : $\operatorname{sum}(\max (c(w), w)-c(v), v)$ | 9 |
| Average Degree | The average number of degrees per node: $2 e / v$ | es |
| Neighborhood | Set of all the nodes that are adjacent to a node v : $N(v)$ | $+3 x$ |



## ARTICLE

https://doi.org/10.1038/s41467-019-09278-8 OPEN

## Large-scale network analysis reveals the sequence space architecture of antibody repertoires

Enkelejda Miho ${ }^{1,2,3}$, Rok Roškar ${ }^{4}$, Victor Greiff ${ }^{5}$ \& Sai T. Reddy © ${ }^{1}$

| Network property | Definition* | Illustration |
| :---: | :---: | :---: |
| Eigenvector | Principal eigenvector of $t(A)^{*} A$, where $A$ is the adjacency matrix of the graph: $x_{v}=\frac{1}{\lambda_{t e n t w}} \sum_{t} x_{t}$ |  |
| Authority | Principal eigenvector of $t(A)^{*} A$, where $A$ is the adjacency matrix of the graph |  |
| PageRank | Principal eigenvector of the normalized matrix of the graph |  |
| Closeness | Node centrality in a graph: $C(v)=\frac{1}{\sum_{w} d(v, w)}$ |  |
| Betweenness | Number of shortest paths through $v$ : $B(v)=\sum_{v * v=1} \frac{\delta_{s}(v)}{\delta_{s i}}$ |  |

Supplementary Table 2. Network local properties. *These properties are dimensionless.

[^0]
## Network Properties and Immunological Features



## Finding Public Clusters Workflow

Build the network for each sample

Pick the top K largest clusters or single node with large abundance within each sample

## Within each cluster, identify a representative clone



Generate
public
clusters

Assign global membership to the public clusters

Sample 1
Sample 2

Sample 3



Downstream Analysis

## Downstream Analysis



## Bayes Factor Adjusted Pvalue



## Summary of Public Clusters

| $\begin{aligned} & \text { Public } \\ & \text { Cluster } \\ & \text { ID }^{1} \end{aligned}$ | $\begin{aligned} & \hline \text { No. of } \\ & \text { TCRs } \end{aligned}$ | Motif ${ }^{2}$ | No. of HD Samples ${ }^{3}$ | No. of Active COVID Samples ${ }^{4}$ | No. ofRecoveredCOVIDSamples $^{5}$ | Estimate (95\%CI) Pvalue ${ }^{6}$ |  |  | $\begin{aligned} & \text { Coreness}^{7} \\ & \text { Median } \\ & {[\text { Min,Max] }} \end{aligned}$ | The \% of significant TCRs based on Bayes factor ${ }^{8}$ | Correlation of Atchley factor ${ }^{9}$ Median [IQR] | The \% of TCRs matched with MIRA ${ }^{10}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  | Active COVID vs. HD | Recovered COVID vs. HD | Recovered COVID vs. Active COVID |  |  |  |  |
| 1 | 2092 | CASSEGGGSVEOVF | 12 | 39 | 19 | $\begin{gathered} 0.33(0.02,0.64) \\ p=0.039 \end{gathered}$ | $\begin{gathered} 0.7(0.38,1.02) \\ p<0.001 \end{gathered}$ | $\begin{gathered} 0.37(0.11,0.63) \\ p=0.005 \end{gathered}$ | 1[1,6] | 84.6\% | $\begin{gathered} 0.37 \\ {[0.2,0.53]} \\ \hline \end{gathered}$ | 28.7\% |



## Conclusion \& Discussion

- Used network analysis, other advanced machine learning techniques and statistical approaches, to interrogate and measure immune repertoire architecture in a clinical context.
- Developed customized search algorithms to identify disease associated clones and public shared clones.
- Implemented the proposed methods on different types of datasets that have a wealth of diverse and rich data to demonstrate the flexibility and power of the proposed tools.
- Developed a comprehensive user-friendly bioinformatics tool with visualization to tackle the complexity of the immunosequencing data in a translational fashion.


## Future Work

- Incorporate the abundance into network analysis
- Adapt more features for scRNA-seq data
- A lot more.....


## Acknowledgements



Hai Yang, MS
Senior Statistician Zhang Lab, UCSF


Brian Neal, MS
Student Zhang Lab, UCSF


Jason Cham, MD
Resident Physician Scripps Clinic


Tao He, PhD
Associate Professor SFSU

University of California
San Francisco


[^0]:    Supplementary Table 1. Network global properties.

