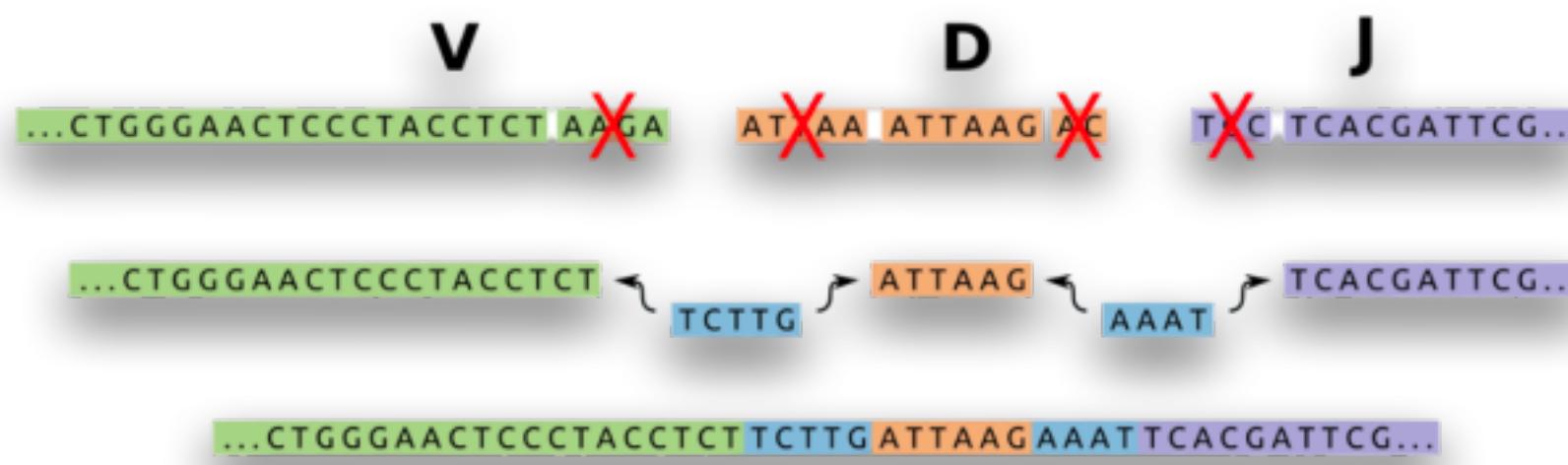


Modelling and predicting the overlap of B- and T-cell receptor repertoires in healthy and SARS-CoV-2 infected individuals

María Ruiz Ortega,
Aleksandra Walczak and Thierry Mora

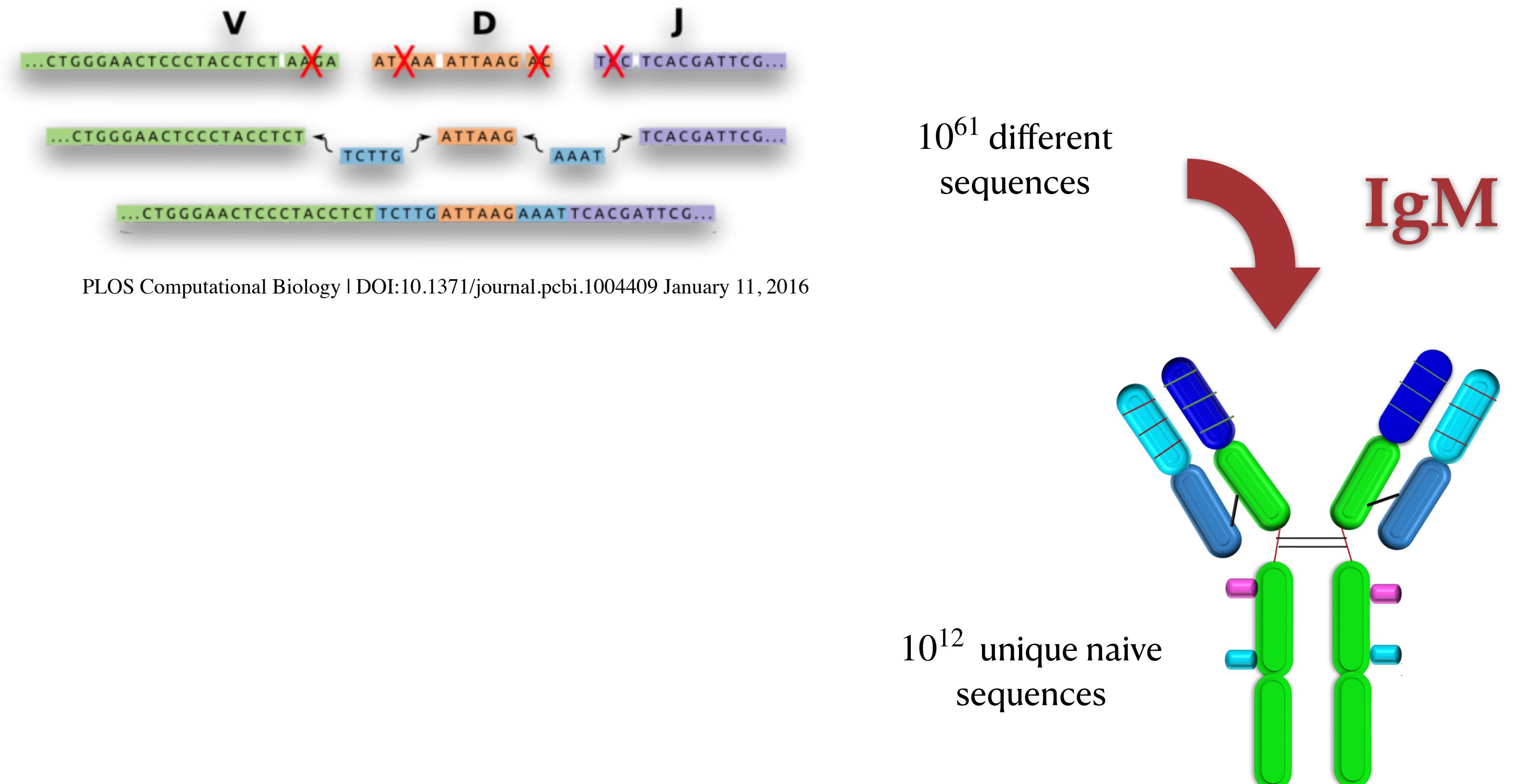
Rencontre des Jeunes Physicien.ne.s 2022

INTRODUCTION

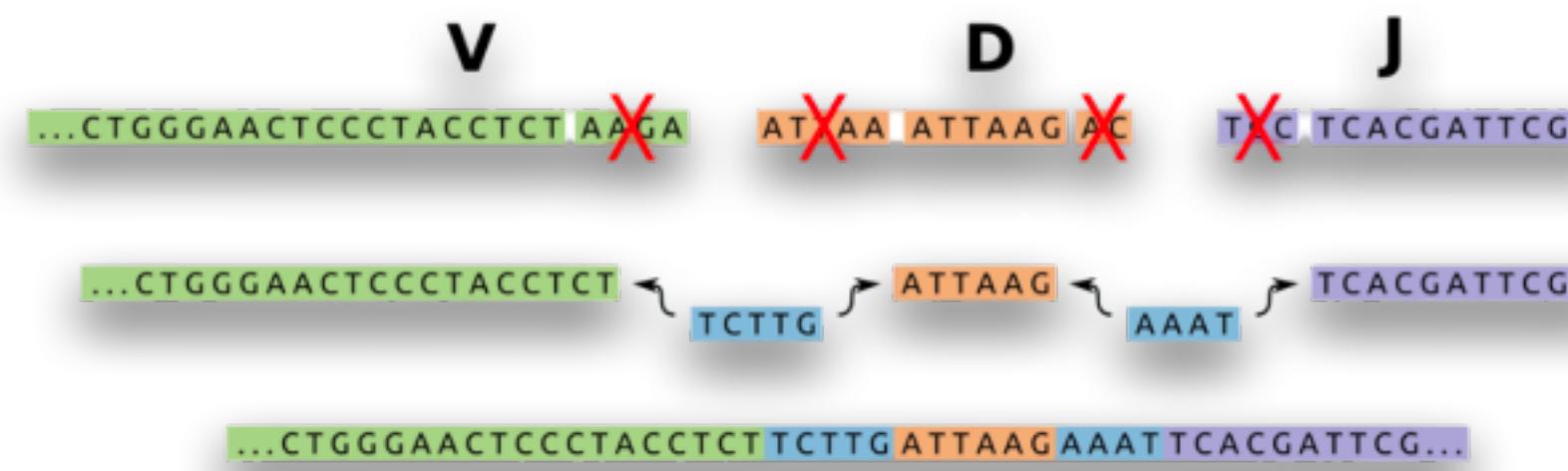


PLOS Computational Biology | DOI:10.1371/journal.pcbi.1004409 January 11, 2016

INTRODUCTION



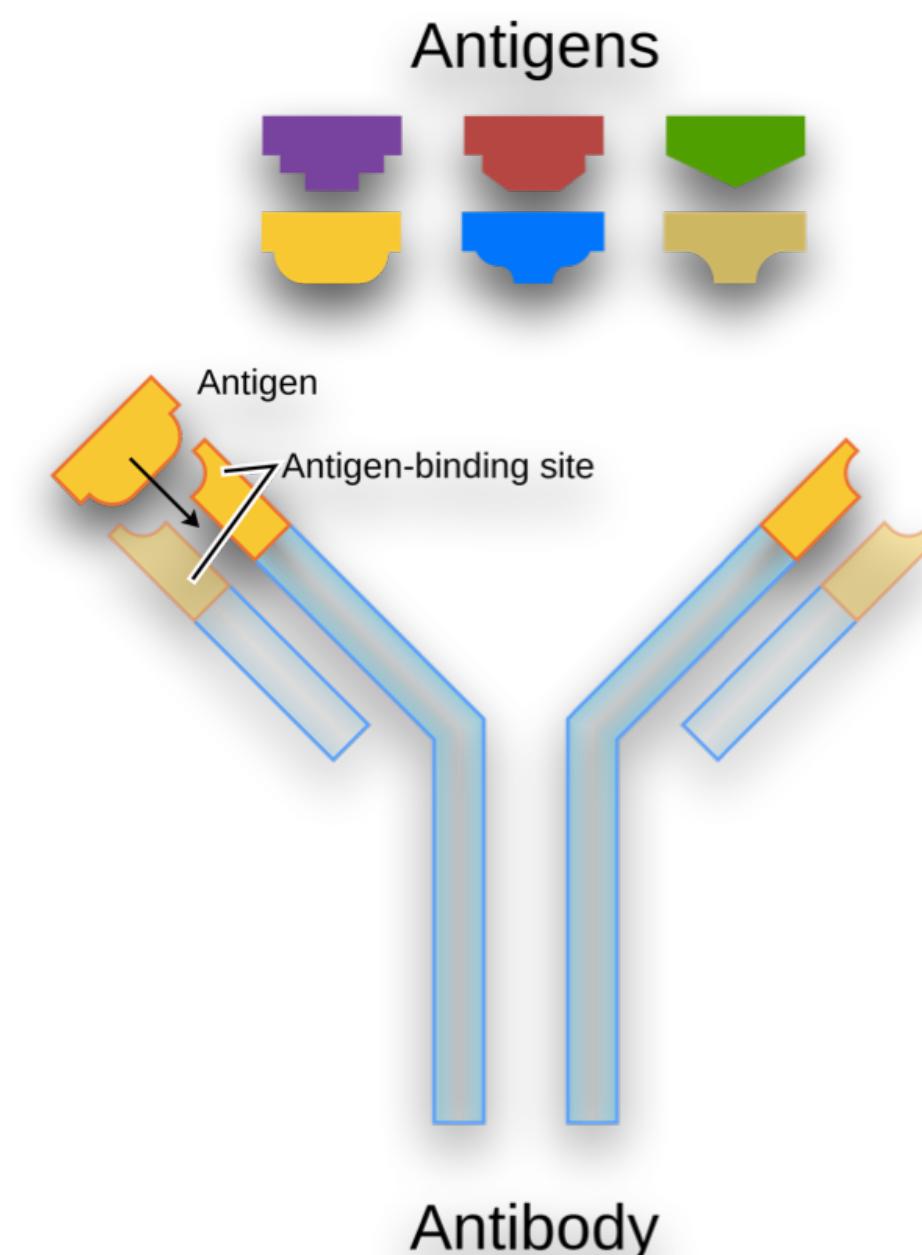
INTRODUCTION



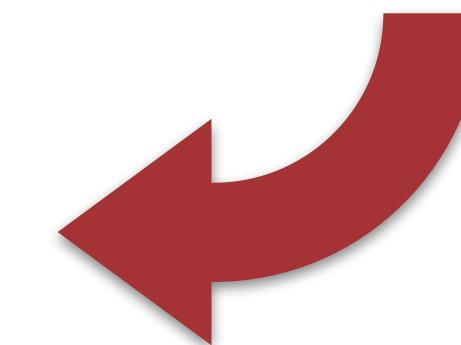
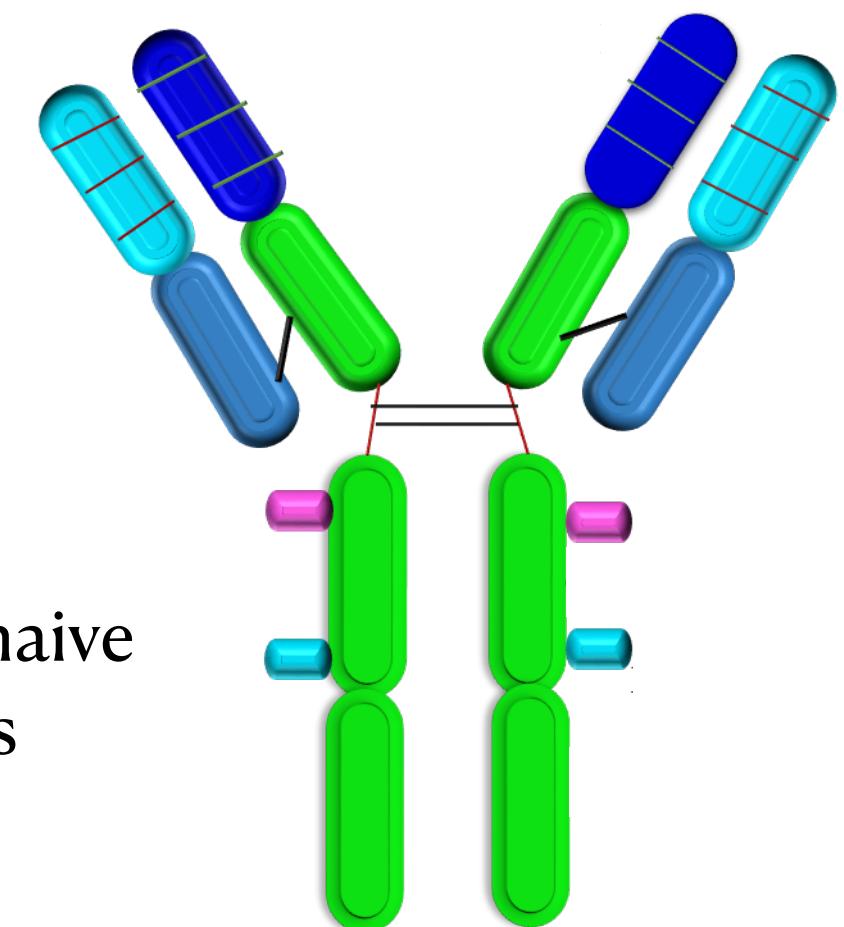
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10^{61} different
sequences

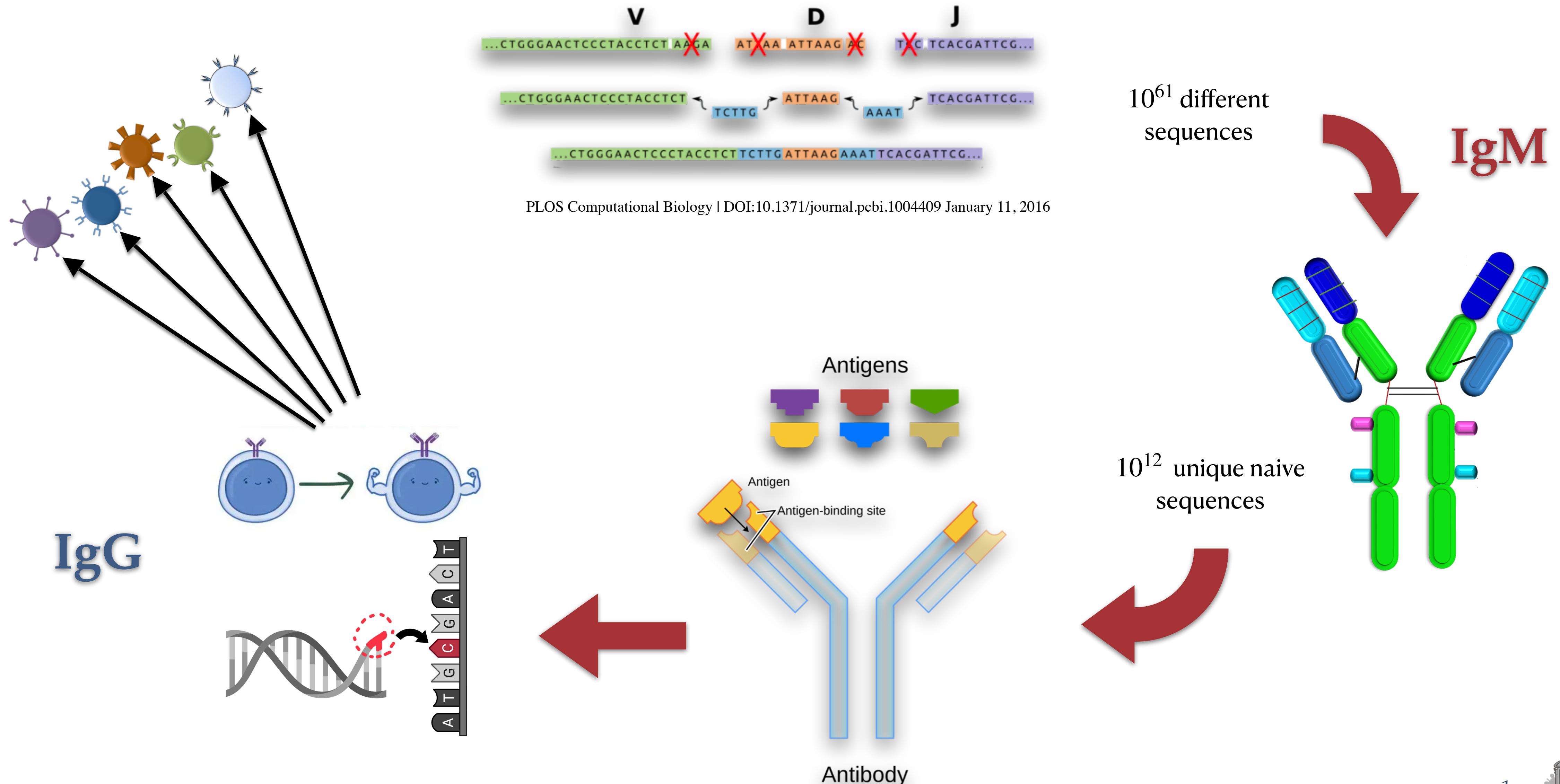
IgM



10^{12} unique naive
sequences



INTRODUCTION

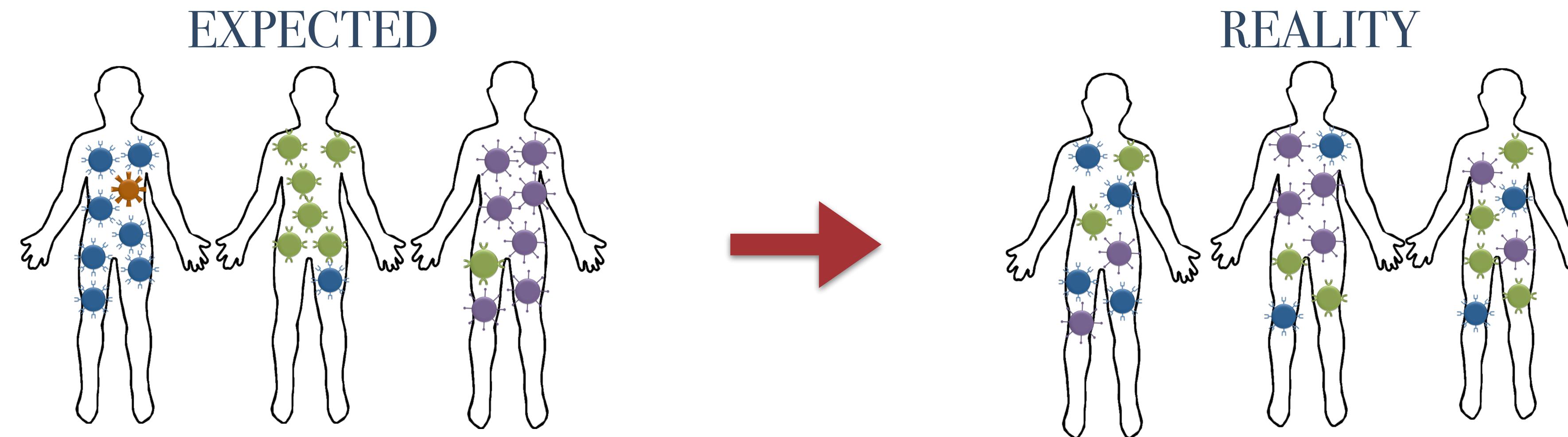


MOTIVATION

- ❖ B cell receptor (BCR) repertoires are highly diverse thanks to V(D)J recombination process + somatic hypermutations.

MOTIVATION

- ❖ B cell receptor (BCR) repertoires are highly diverse thanks to V(D)J recombination process + somatic hypermutations.
- ❖ A higher than expected by chance overlap of receptors is observed when repertoires from different individuals are compared.
- ❖

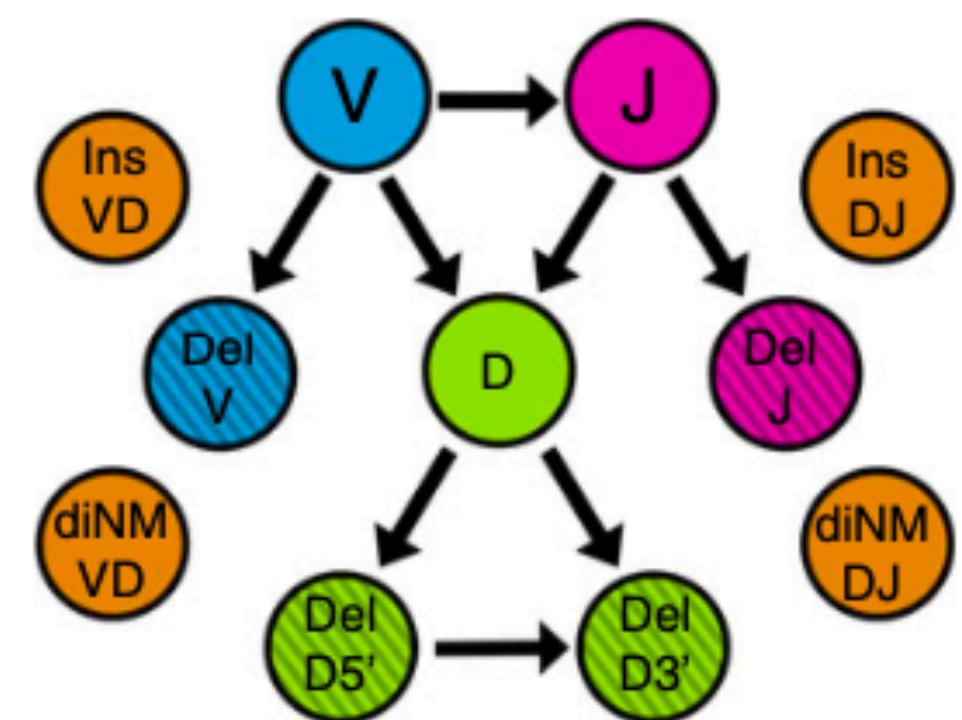


- ❖ **OBJECTIVE:** design a statistical model that is able to predict the number of sequences that will be shared among individuals.

MODELLING THE SHARING MECHANISMS

- ❖ Recombination biases → Not all scenarios all equally likely.

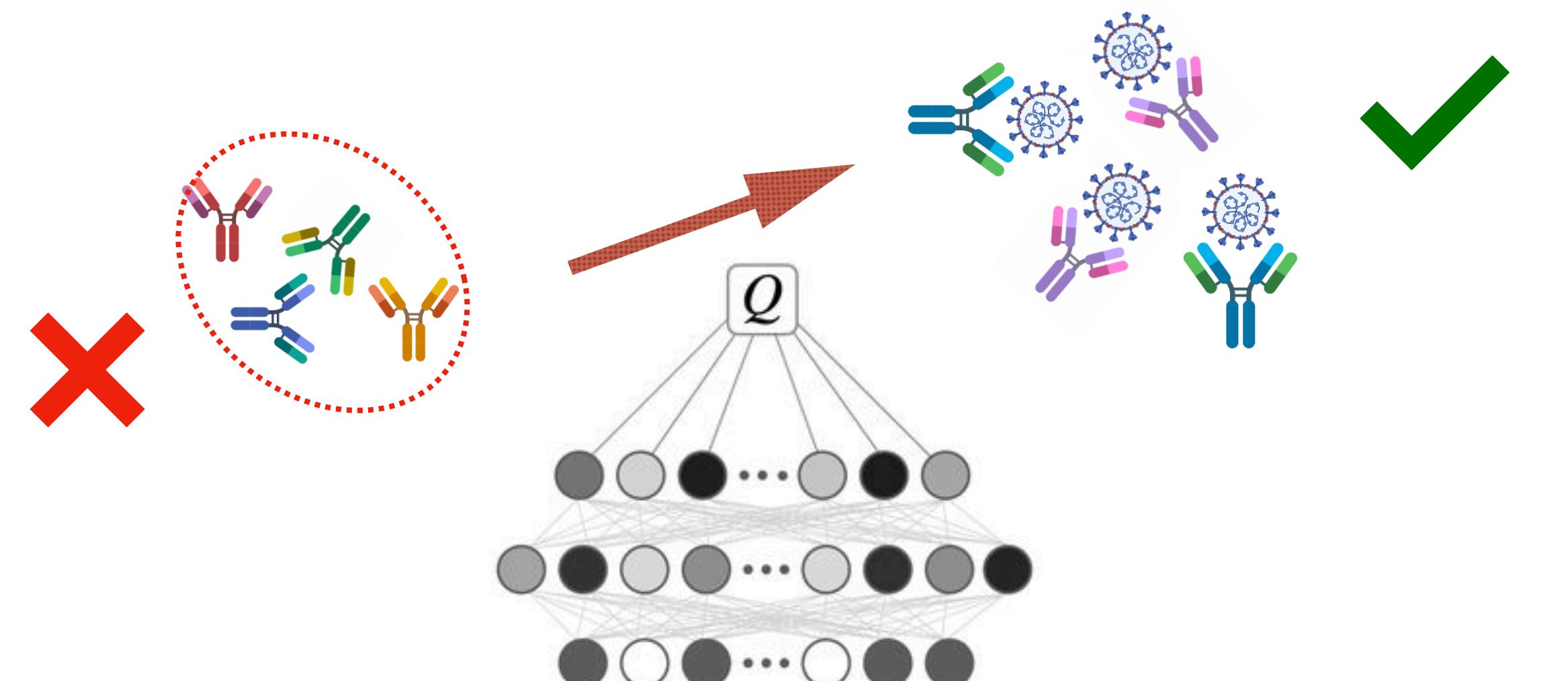
The statistics of V(D)J recombination process are well captured by P_{gen} model.



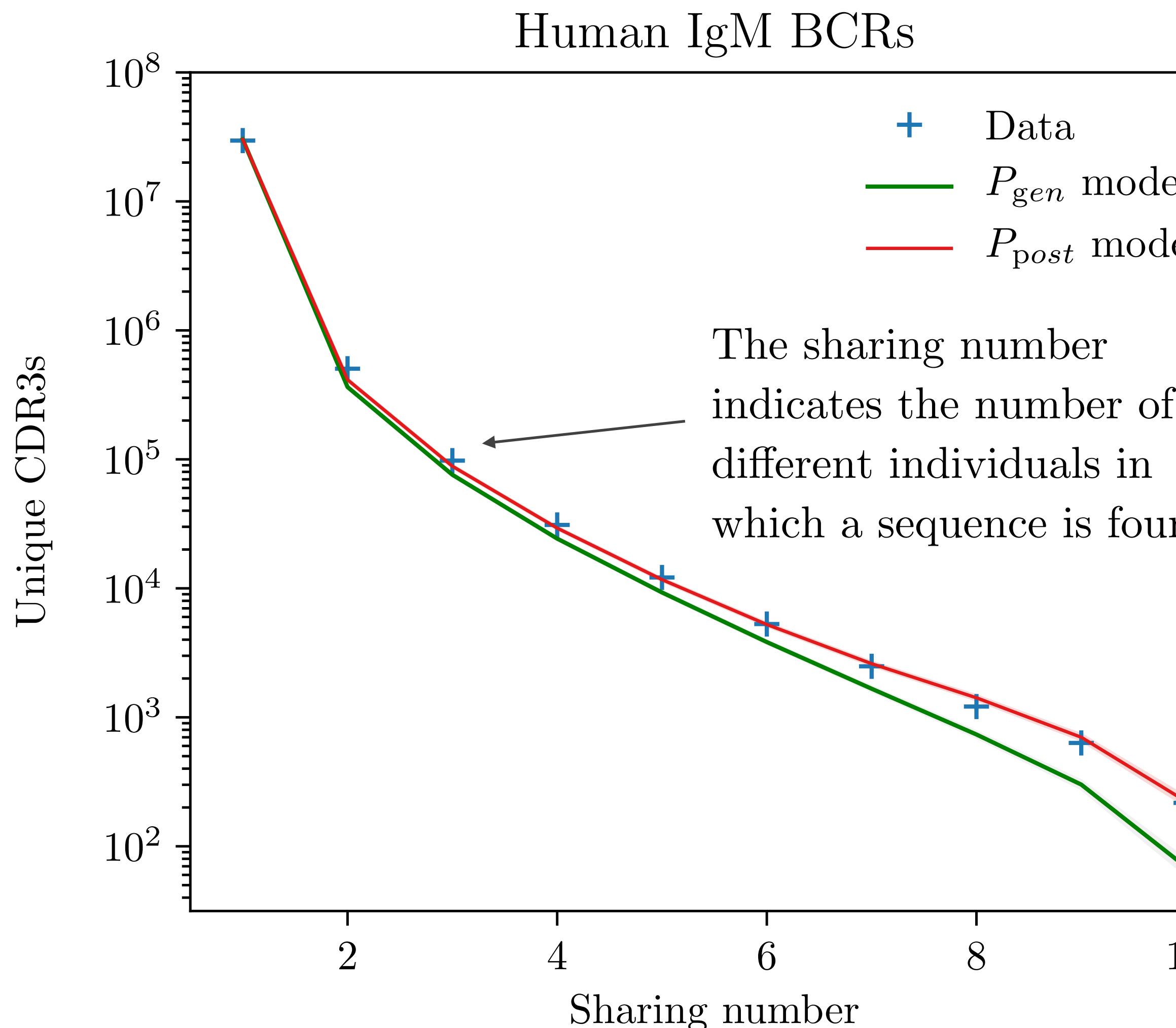
$$\begin{aligned} P(\text{scenario}) = & P(V)P(J|V) P(D|V,J)P(\text{del}V|V) \\ & \times P(\text{del}J|J) P(\text{del}D5'|D) P(\text{del}D3'|\text{de} \\ & \times P(\text{ins}VD) \prod_i^{\text{Ins}VD} P(n_i|n_{i-1}) \\ & \times P(\text{ins}DJ) \prod_i^{\text{Ins}DJ} P(n_i|n_{i-1}) \end{aligned}$$

- ❖ Selection processes → Like central tolerance or clonal selection.

P_{post} is a selection model that identifies sequence features characteristic of functional lymphocyte repertoires



PREDICTING SHARING IN IGM REPERTOIRES



Individual 1	Individual 2	Individual 3
CASSENIQYF	CASSLTEAGEYF	CASSEDNNEQFF
CASSEDNNEQFF		
CASSLVLNTEAFF	CAWTWGGTGGEKLFF	CASNQGSGSTEAFF
CASSELDTQYF	CASSPPAGGVREQFF	CASLLTDTQYF
CASSPPGELFF	CSASVAVSGNQPQHF	CASAAEGLNTEAFF
CASSLGTGARQPQHF	CARCFTGFSLREQYF	CSAKGFGTEAFF
CASSLGQGGSPLHF	CASLLTDTQYF	CASSQGDRHQPQHF
CASTVGVDGYYEQYF	CASSEDNNEQFF	CASSPPGELFF
CASSLTEAGEYF	CASSLTGNNSPLHF	
	CASSLAAREGSSQYF	

SHARING NUMBER = 3

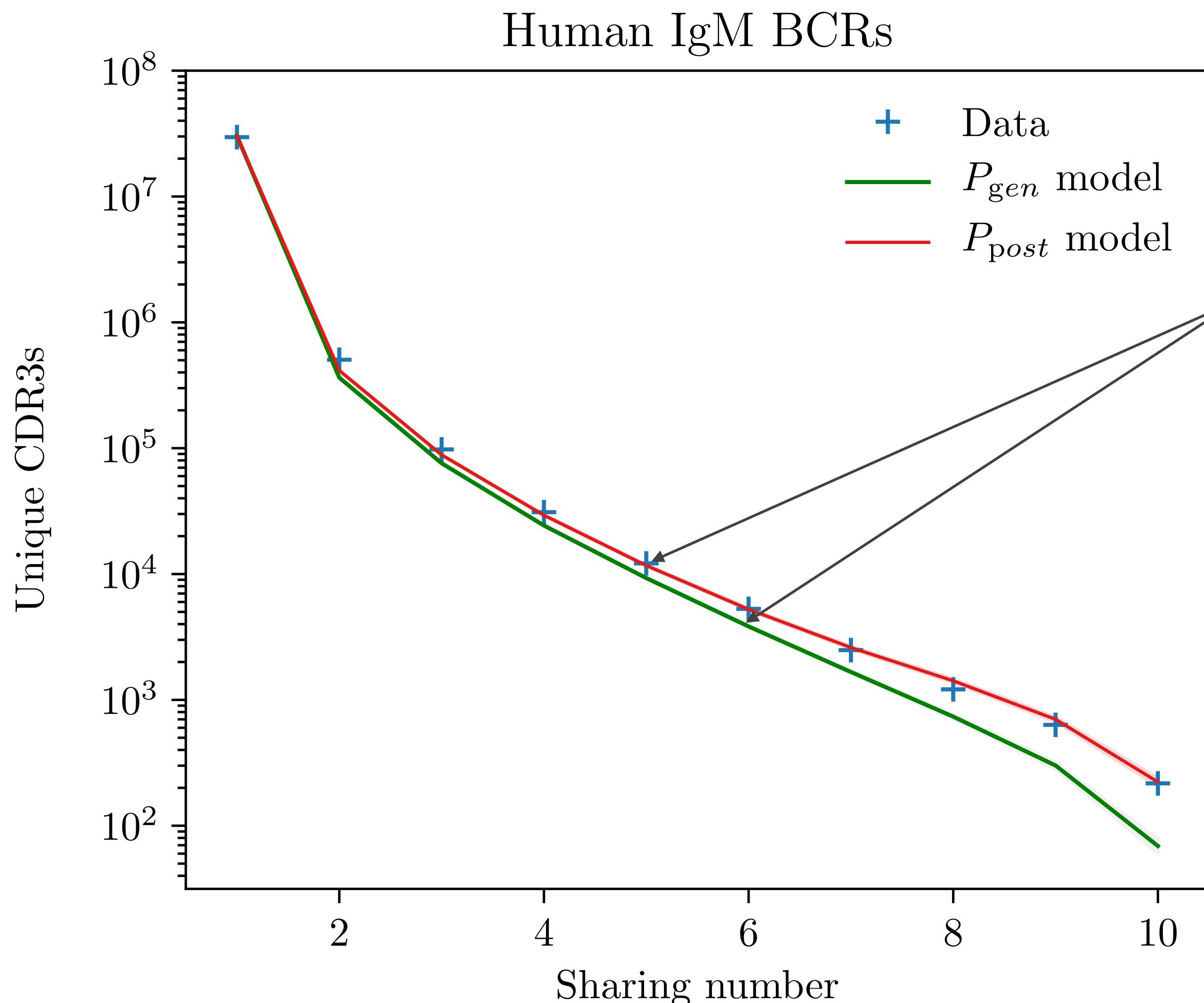
Dataset obtained from:

Briney, B., Inderbitzin, A., Joyce, C. et al. Commonality despite exceptional diversity in the baseline human antibody repertoire.

Nature 566, 393–397 (2019).

<https://doi.org/10.1038/s41586-019-0879->

PREDICTING SHARING IN IGM REPERTOIRES



Theoretical prediction using the generation function:

$$G(x, \{N_i\}) = \sum_{m=0}^n M_m(N_i) x^m = \sum_{s \in S} \prod_{i=1}^n [e^{-p(s)N_i} + (1 - e^{-p(s)N_i})x]$$

Using $p(s) = P_{gen}$ underestimates how many sequences are shared among individuals. But the model of convergent recombination + selection, $p(s) = P_{post}$, accurately predicts this quantity.

Dataset obtained from:

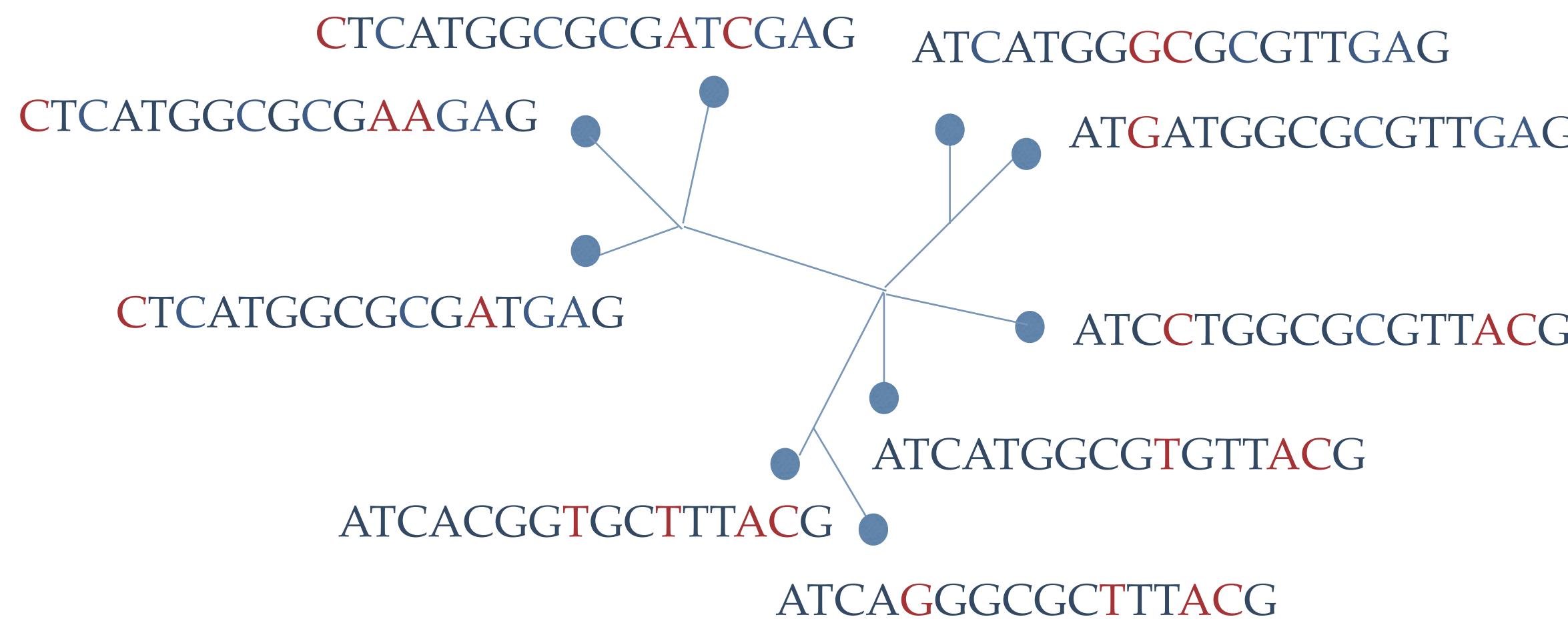
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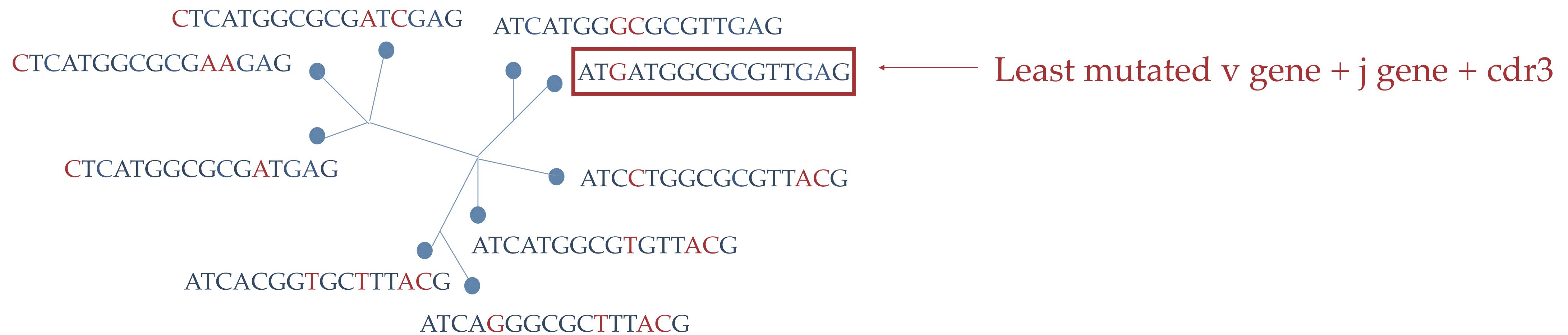
PREDICTING SHARING IN IgG REPERTOIRES

- ❖ The same pipeline can be applied to non mutated IgG repertoires. We need to recover the ancestors of clonal families:



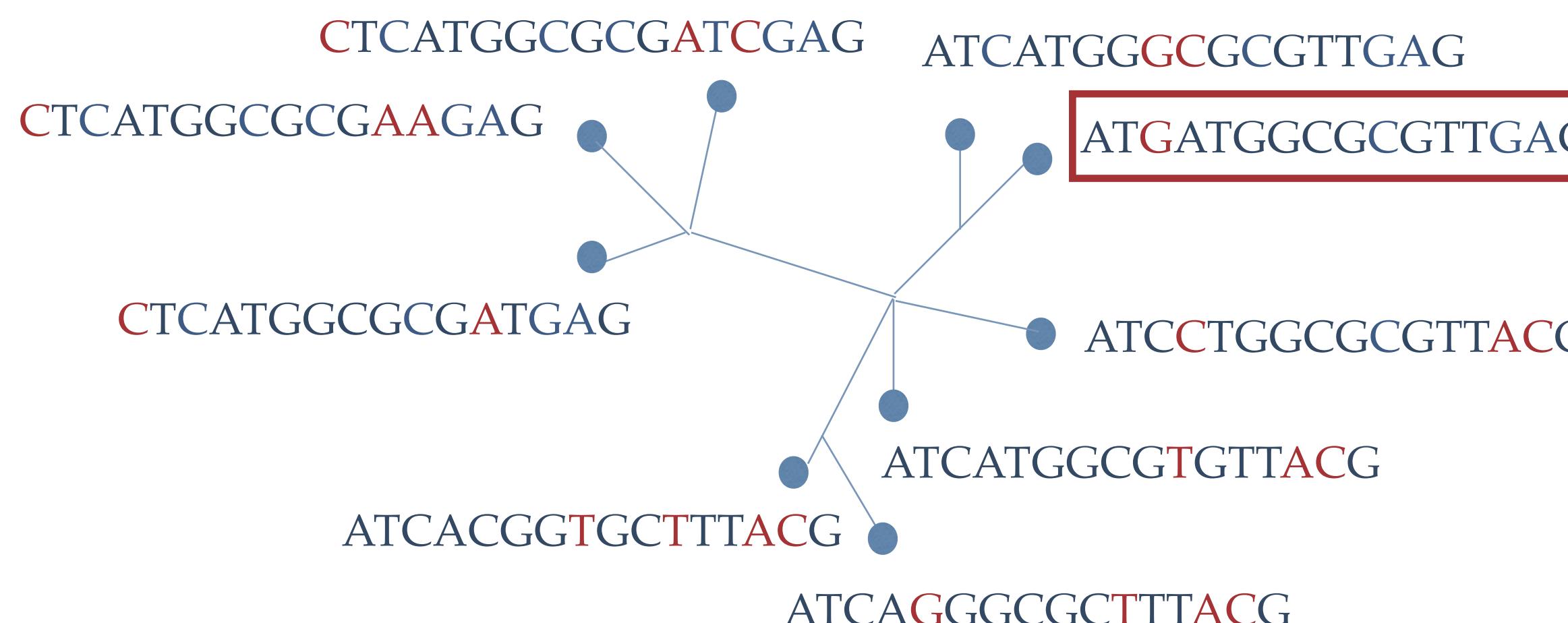
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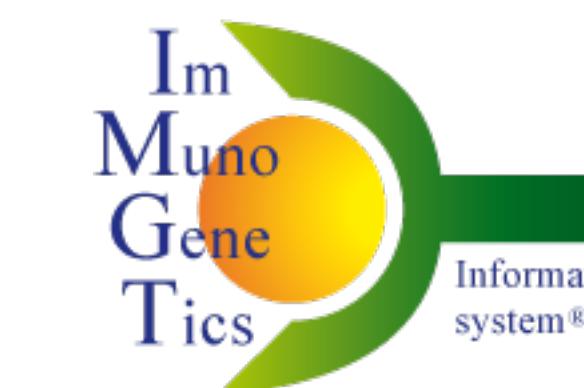
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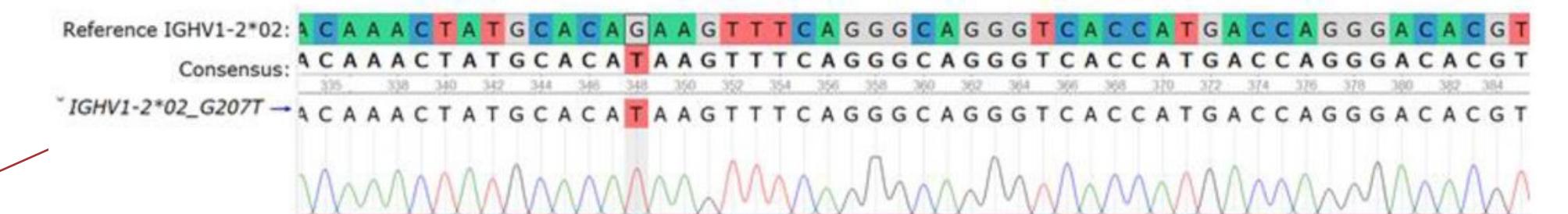


❖ Naive ancestor

ATCATGGCGCGTTGAG



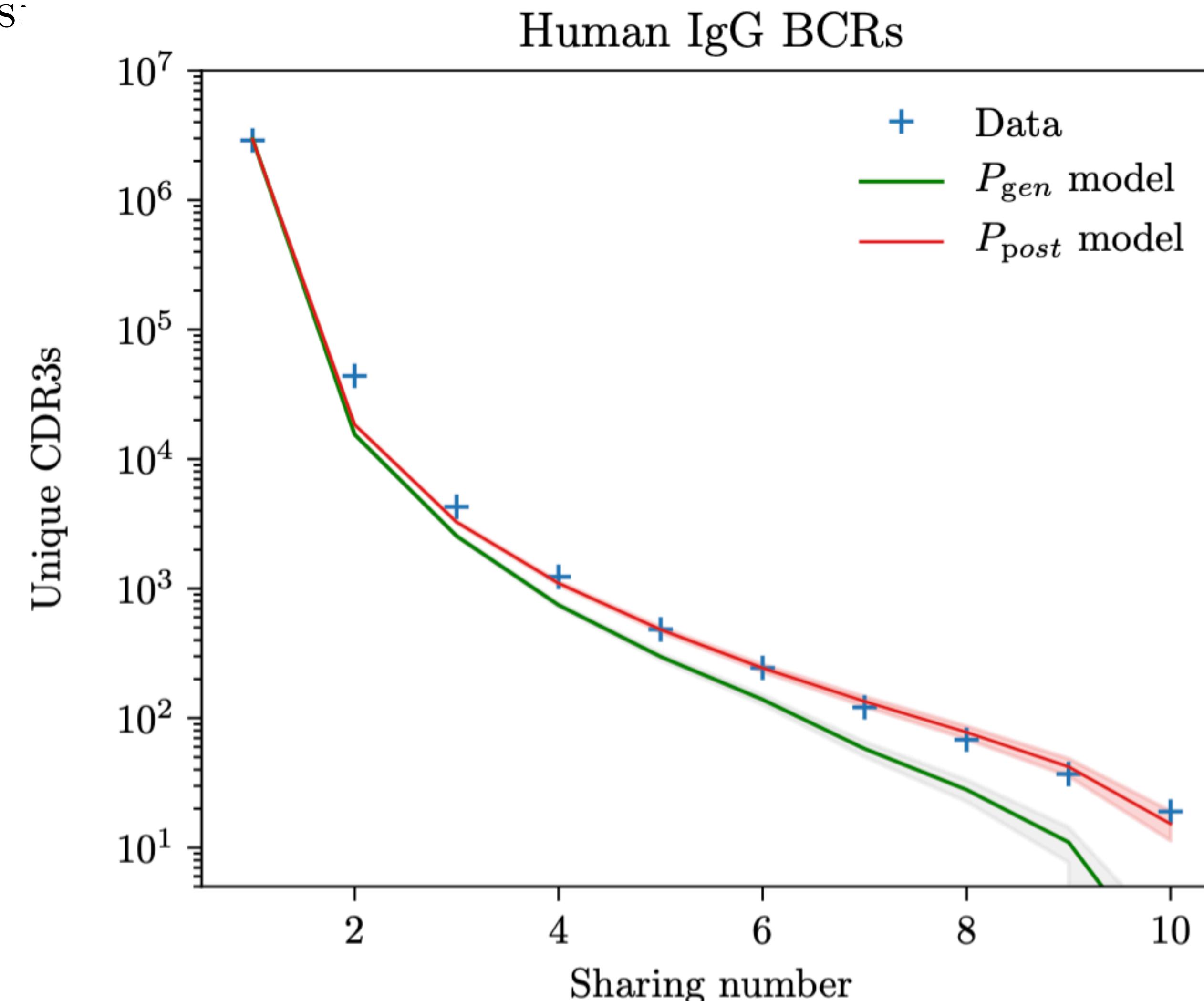
*IGHV1-2*02_G207T*



Remove the mutations comparing with germline templates

PREDICTING SHARING IN IgG REPERTOIRES

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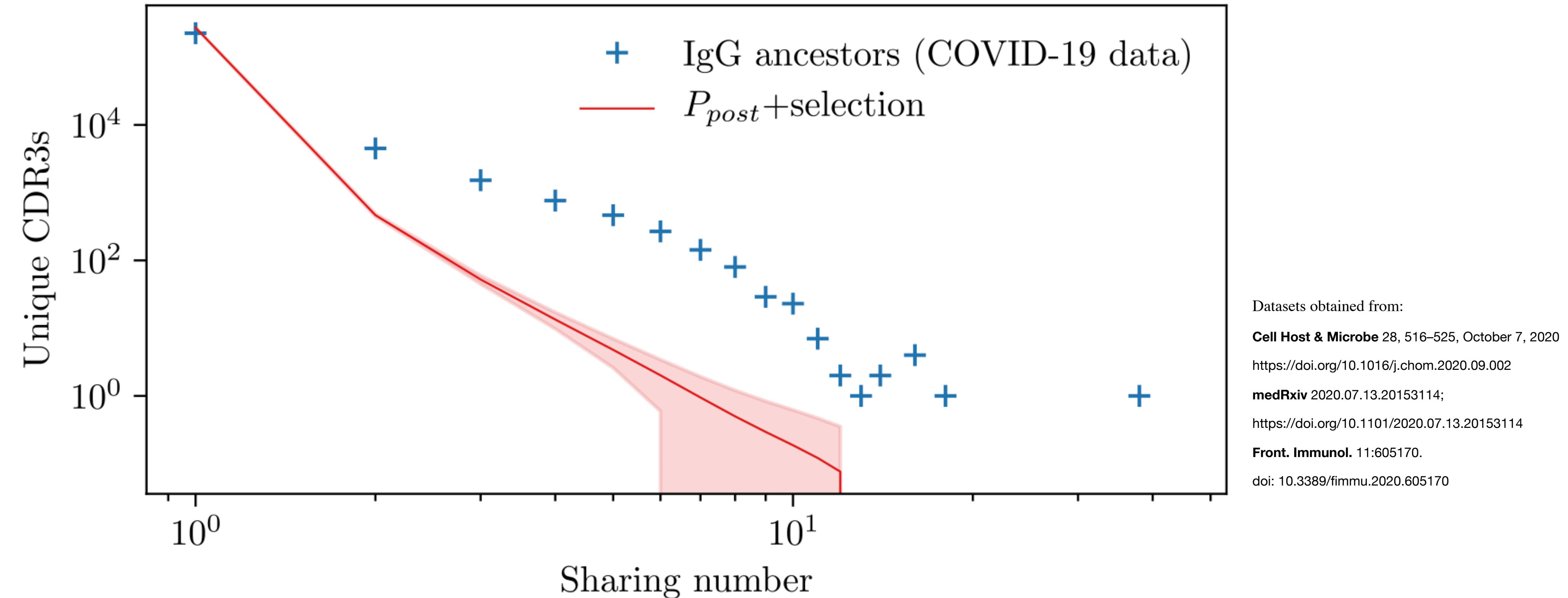
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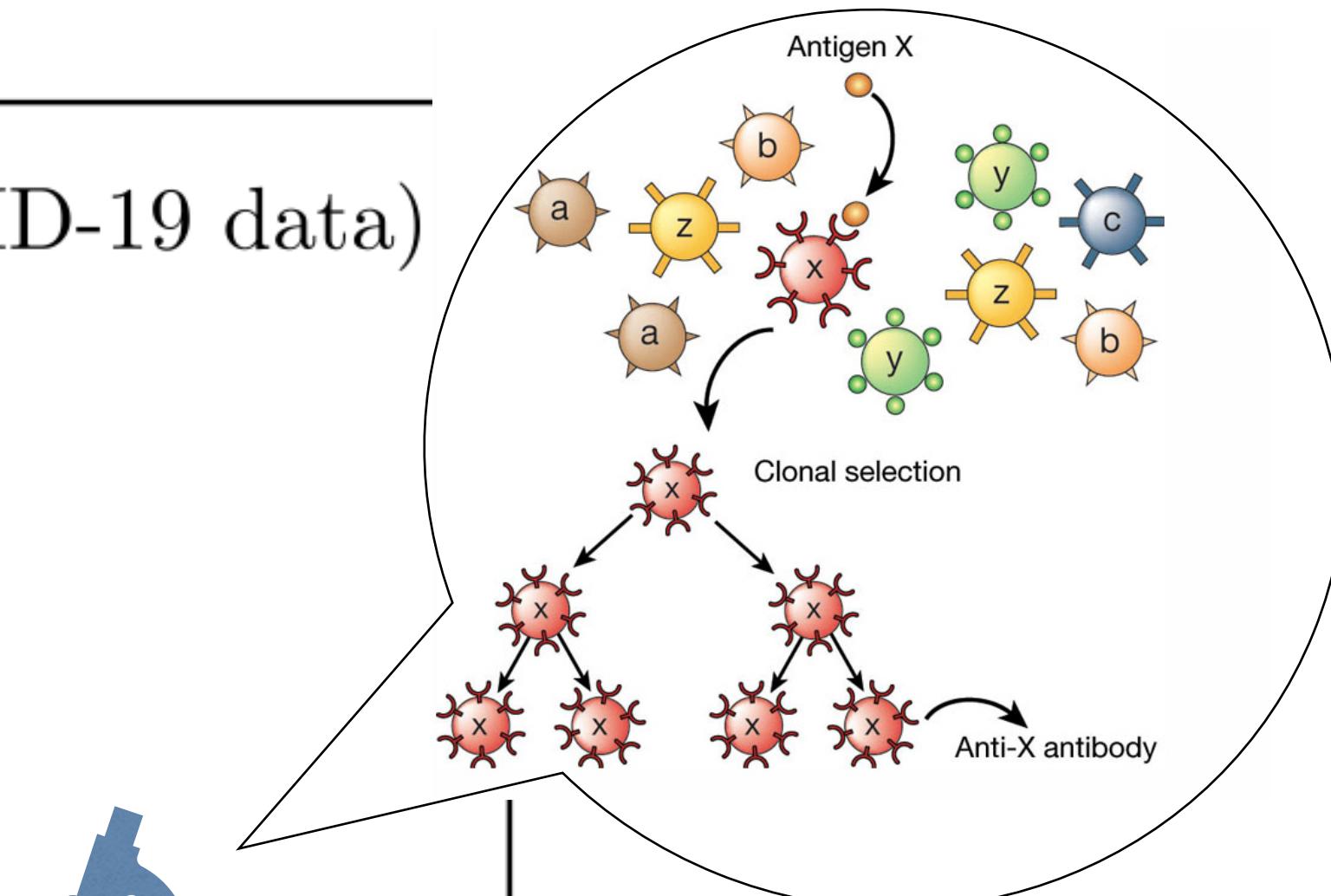
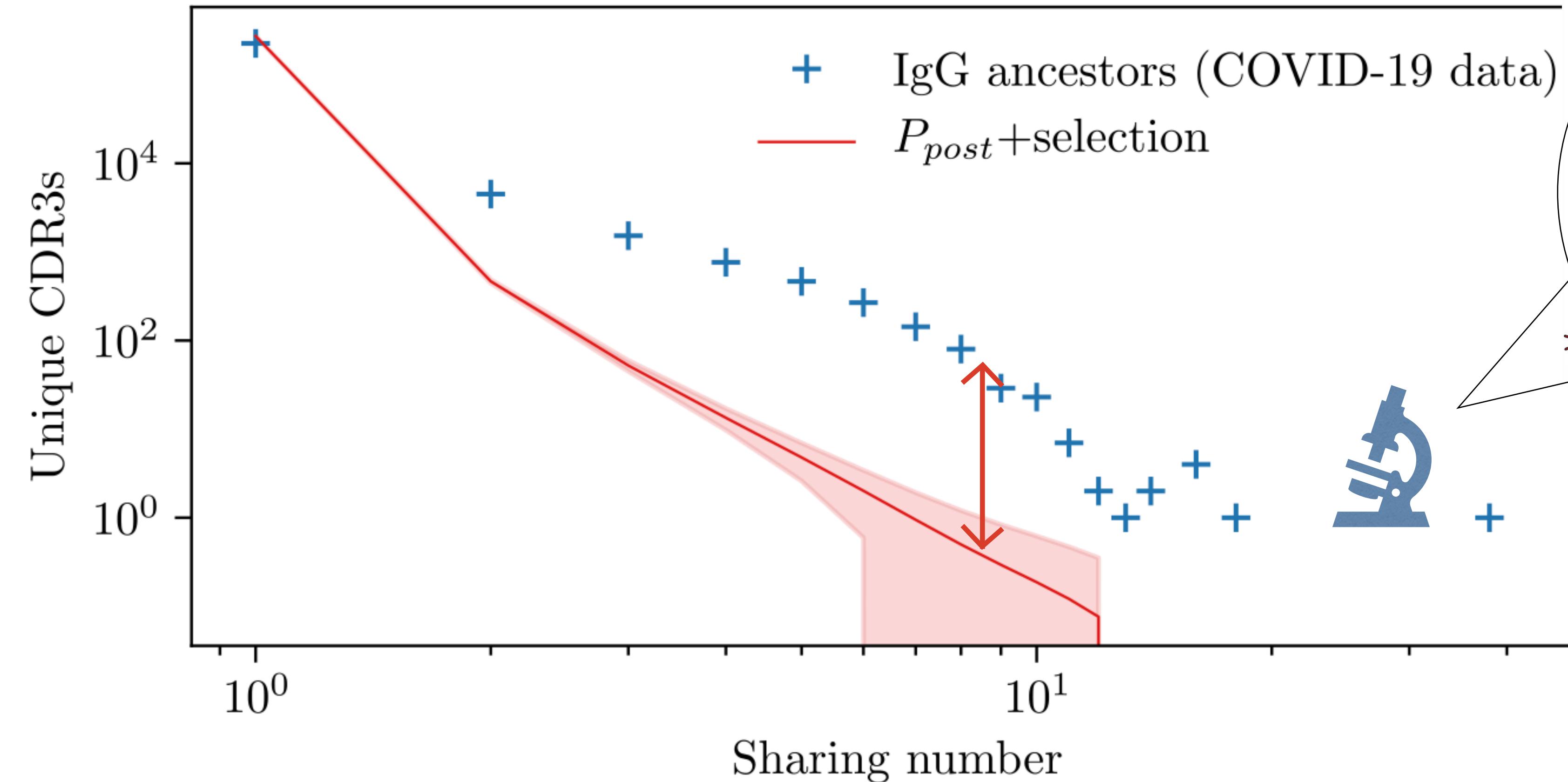
PREDICTING SHARING IN COVID-19 REPERTOIRES

- ❖ Comparison of sharing number distribution in a cohort of 43 individuals **COVID-19 positive** and predictions from P_{post} :



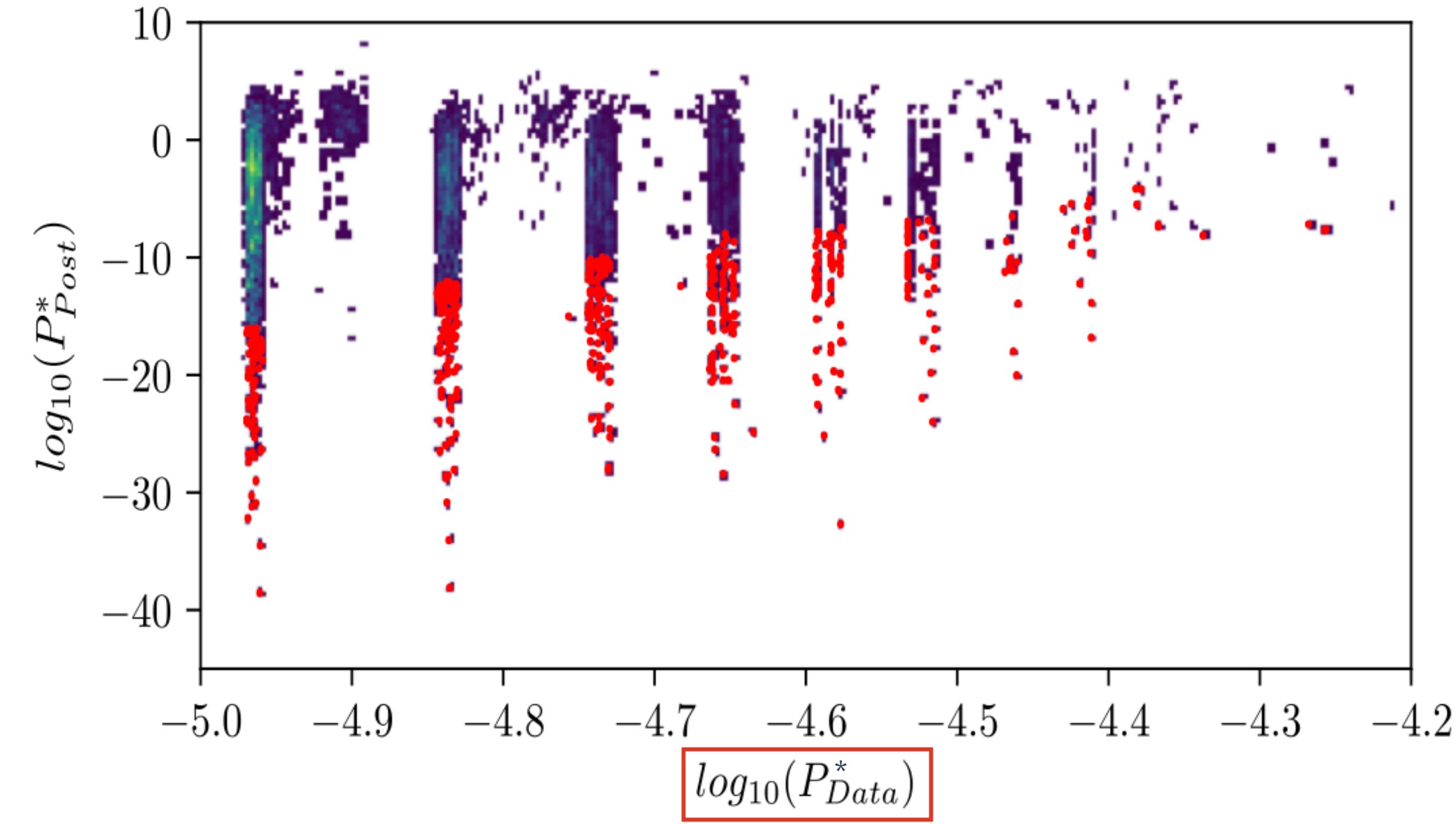
PREDICTING SHARING IN COVID-19 REPERTOIRES

- ❖ Comparison of sharing number distribution in a cohort of 43 individuals **COVID-19 positive** and predictions from P_{post} :



Are these overshared sequences indicative of a specific antibody response to an antigen?

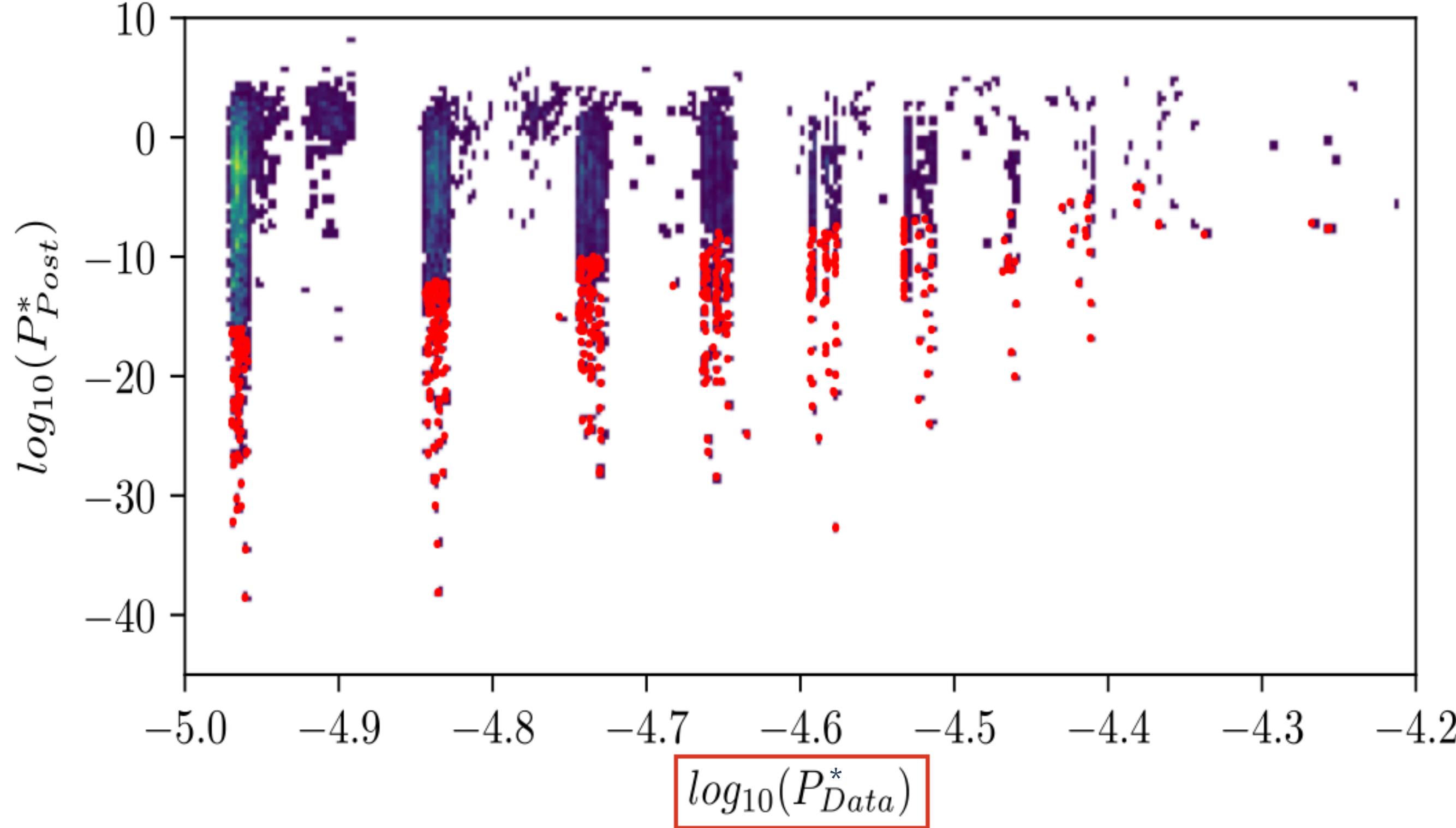
IDENTIFICATION OF ANTIGEN-RESPONDING CLONES



Expected frequency from
the sharing pattern

$$P_{data}^* = \operatorname{argmax}_{P_{data}} \mathbb{P}(x_1, \dots, x_n \mid P_{data})$$

IDENTIFICATION OF ANTIGEN-RESPONDING CLONES



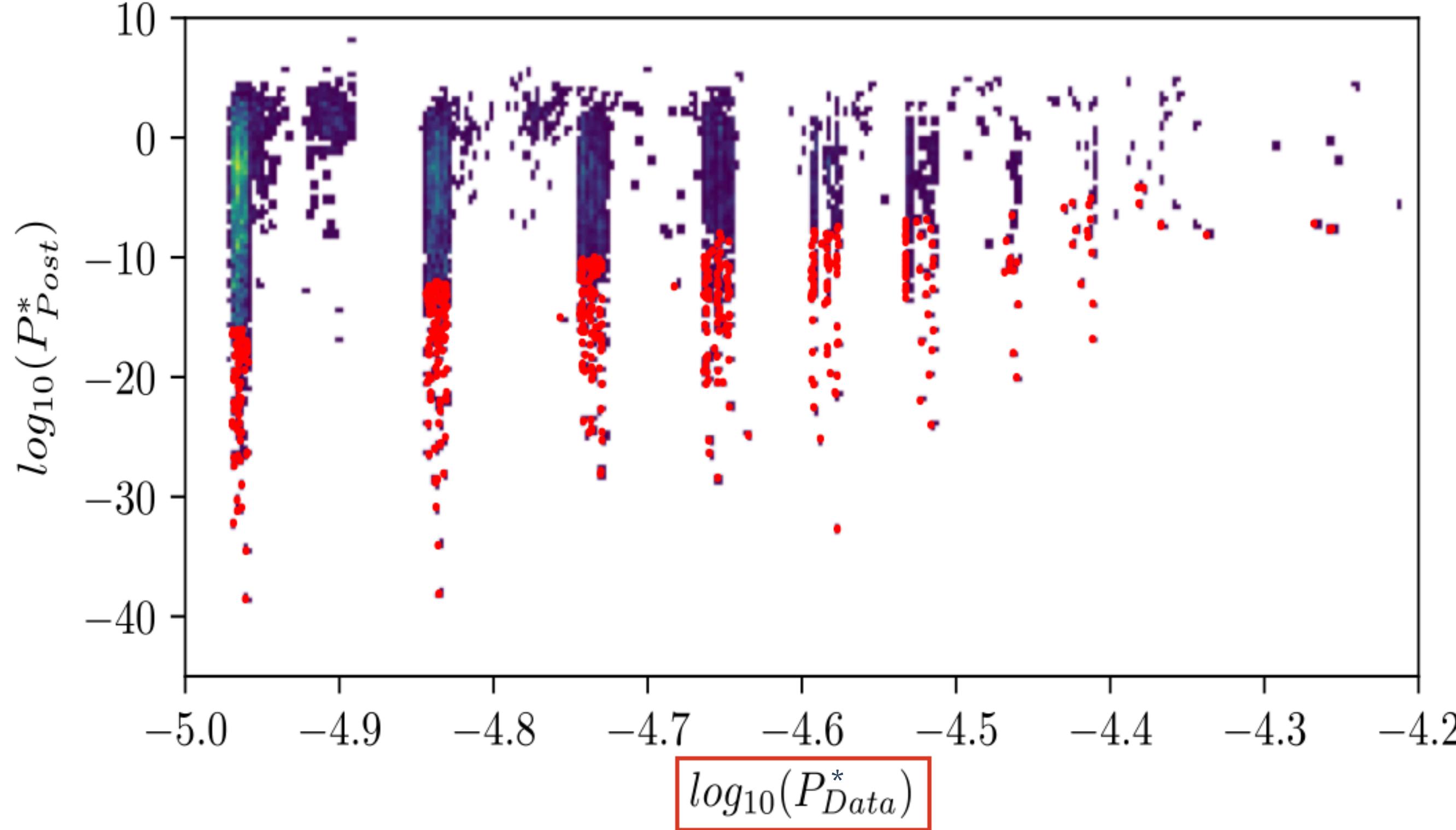
Expected frequency from
the sharing pattern

$$P_{data}^* = \operatorname{argmax}_{P_{data}} \mathbb{P}(x_1, \dots, x_n | P_{data})$$

Level of certitude on P_{data} given the observations $\{x_1, x_2, \dots, x_n\}$:

$$\mathbb{P}(P_{post} > P_{data}) = \int_0^{P_{post}} \frac{\mathbb{P}(x_1, \dots, x_n | P_{data}) \rho_{prior}(P_{data})}{\int_0^1 \mathbb{P}(x_1, \dots, x_n | P_{data}) \rho_{prior}(P_{data}) dP_{data}} dP_{data}$$

IDENTIFICATION OF ANTIGEN-RESPONDING CLONES



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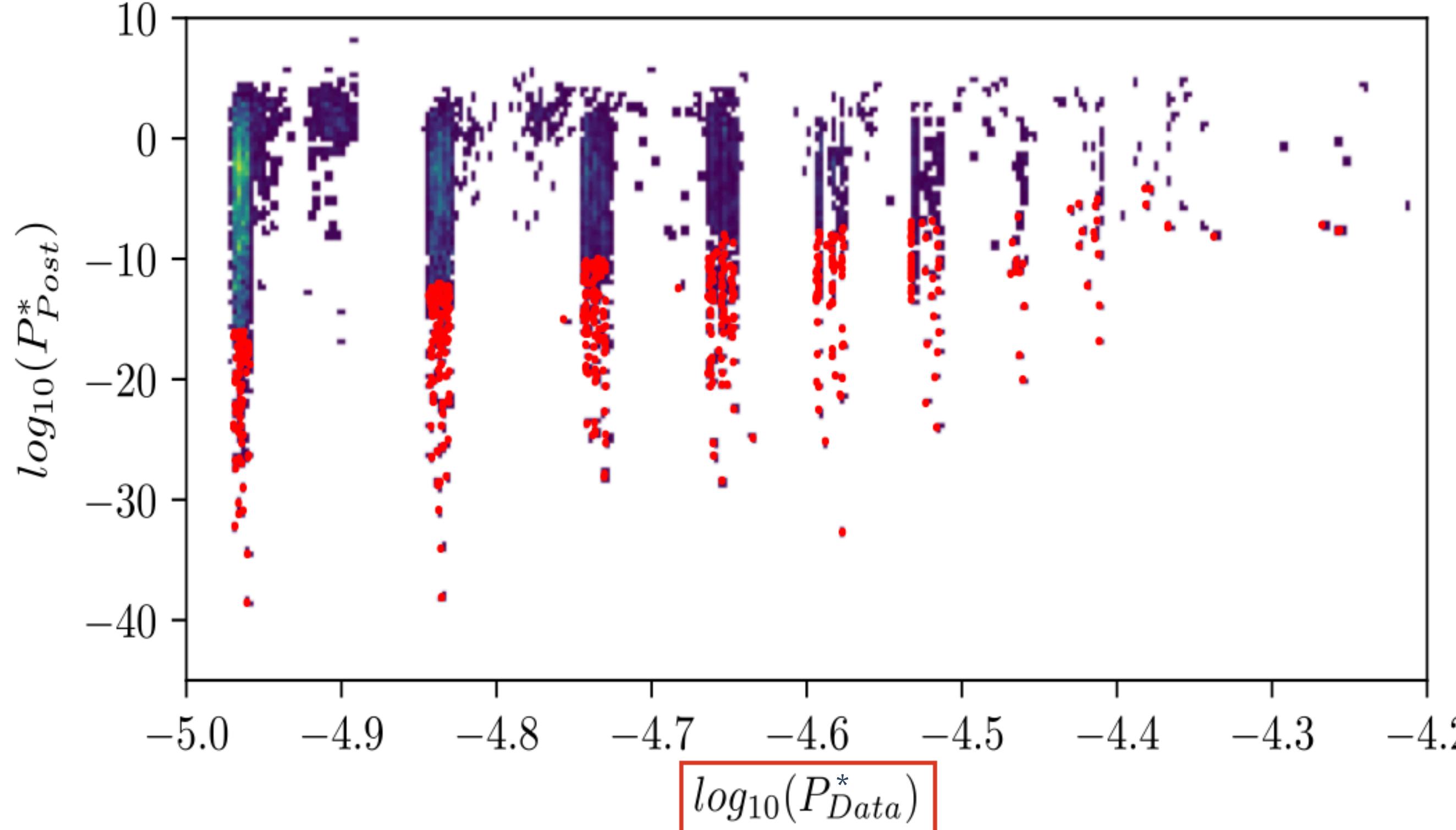
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Bayesian analogous to p-value

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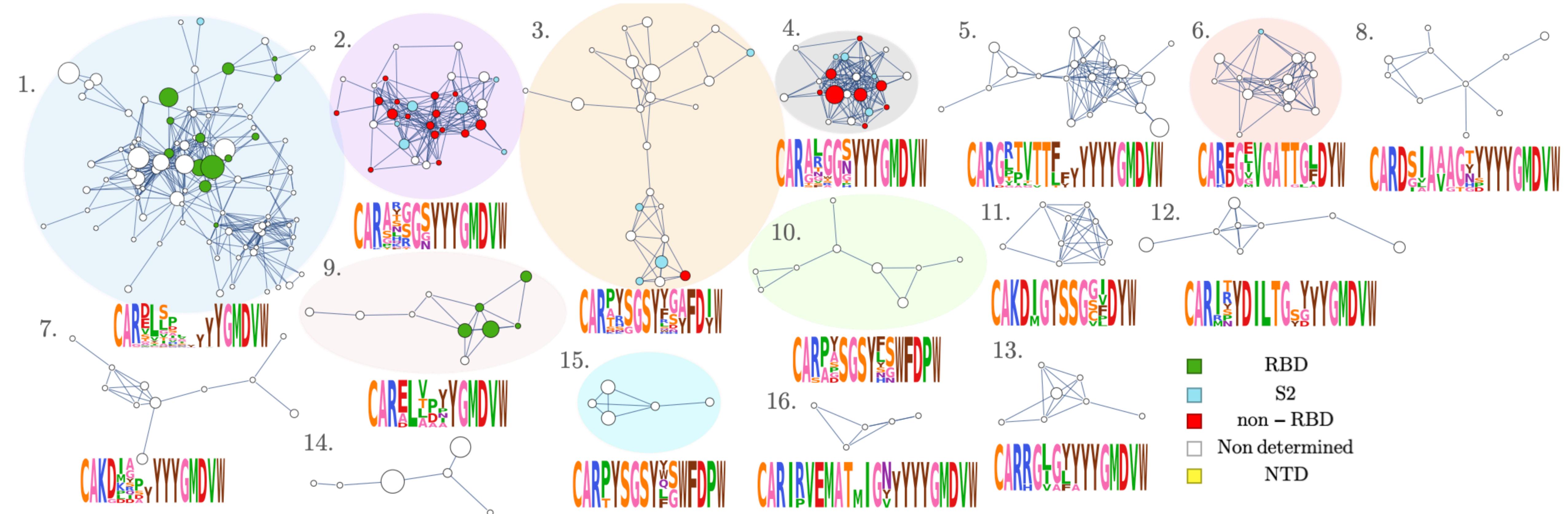
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→ Their frequency can't be explained by a high recombination likelihood.

→ Potential candidates of SARS-CoV-2 antibodies.

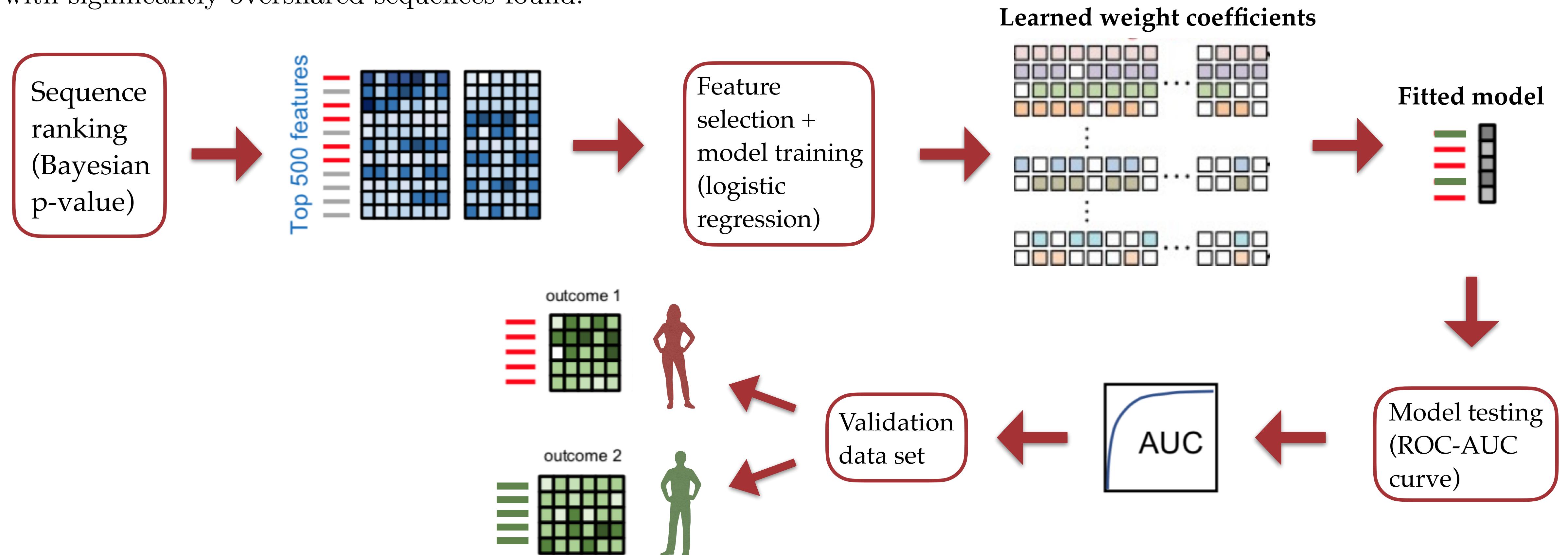
FURTHER ANALYSIS OF OVERSHARED SEQUENCES

(i) Clustering + annotation → Overshared IGH sequences are clustered in networks with Levenshtein distance < 2 and are matched against reported SARS-CoV-2 antibodies.



FURTHER ANALYSIS OF OVERSHARED SEQUENCES

(ii) Learning of regression models for COVID-19 diagnosis → Prediction of COVID-19 status based on the overlap with significantly overshared sequences found.



CONCLUSIONS

- ❖ The statistical model here presented accurately estimates the probability of observing a productive B cell receptor in a repertoire.
- ❖ The model accurately predicts how many sequences will be shared among n healthy individuals but it fails at capturing the selection pressure existing after antigen encounter. The significance of this effect is measured by defining a Bayesian analogous to p-value.
- ❖ The sharing analysis here presented might be particularly useful to help designing a vaccine that elicits a more transverse immune response since the antibodies that have been isolated have been already produced by a large number of individuals.