

Randomly made yet ordered: CD4 T cell receptor and functional repertoires

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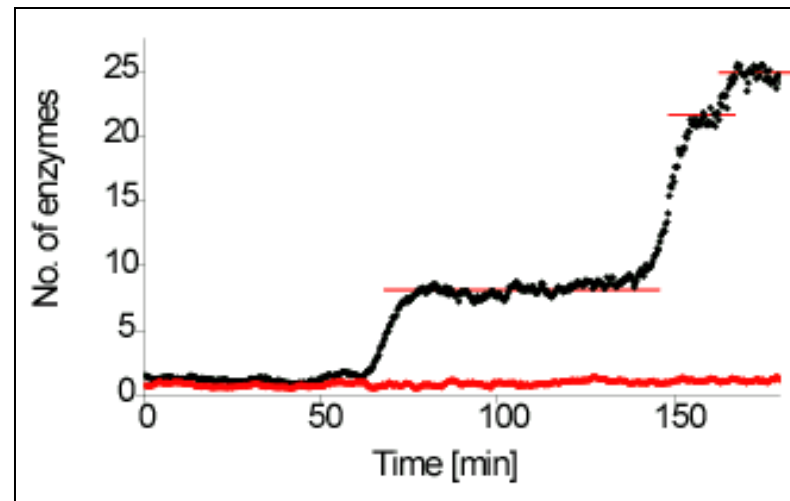
KITP Miniprogram: Quantitative
Immunology - Experiments Meet
Modeling. Dec 11th 2012.



Outline

Randomness in the immune system:

- Random generation of lymphocyte receptors (gene rearrangement)
- Stochasticity in gene expression



Cai, Friedman, Xie, Nature 2006



Outline

Randomness in the immune system:

- Random generation of lymphocyte receptors (gene rearrangement)
- Stochasticity in gene expression

Potential advantages for randomness:

- Recognition of a very large set of antigens (unknown, fast evolving)
- Optimal performance in an unpredictable and changing environment
- Harder to evade?





Mapping TCR repertoires by high-throughput sequencing

**Analysis of the structure of
the TCR β naïve repertoire**



Making of the T cell receptor: V-D-J recombination, a biased random process

- T cell receptors and antibodies are made through random DNA rearrangements
- Crucial for recognition of diverse, unknown antigens

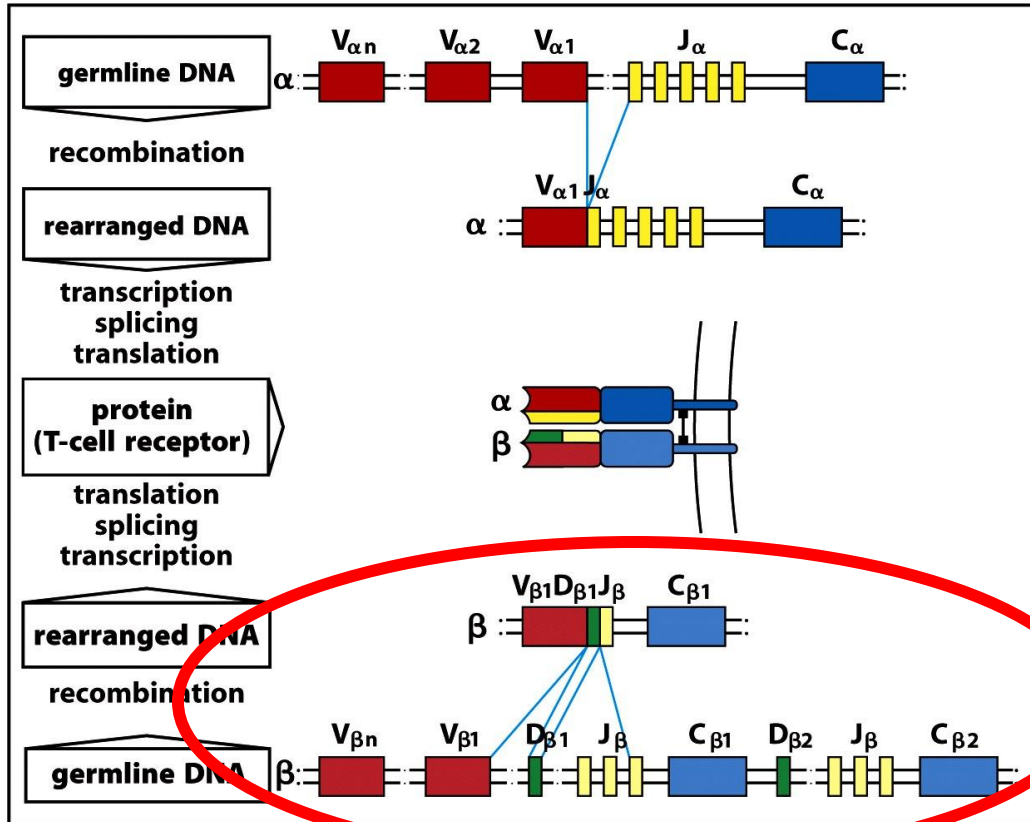


Figure 4-10 Immunobiology, 7ed. (© Garland Science 2008)

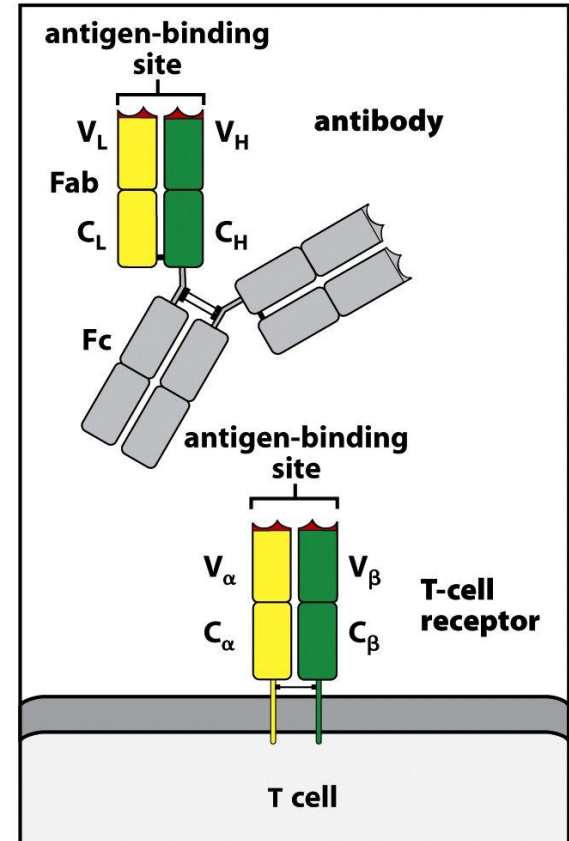


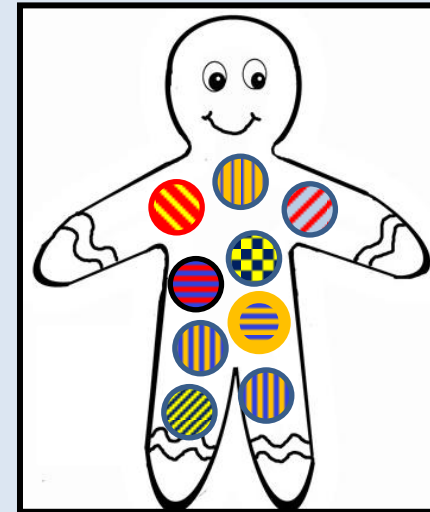
Figure 3-11 Immunobiology, 7ed. (© Garland Science 2008)



The Potential size of the TCR repertoire is huge

Estimated number of possible receptors (TCR $\alpha\beta$, mouse): $\sim 10^{15}$

Number of T cells: mouse: $\sim 10^8$; human: $\sim 10^{11} \ll$ Repertoire size





The TCR repertoire is dynamically changing throughout life

Clonal Selection Theory

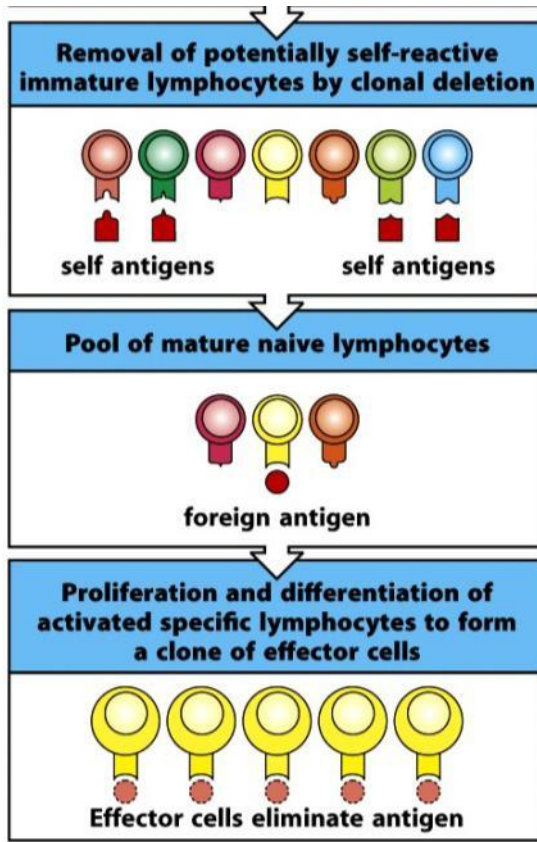


Figure 1-11 Immunobiology, 7ed. (© Garland Science 2008)

The TCR repertoire represents the state of the adaptive immune system and its history

New HTS technologies enable comprehensive repertoire characterization:

- Responses to pathogens
- Vaccinations
- Autoimmunity
- Cancer
- Aging



Mapping TCR repertoires by high-throughput sequencing

Analysis of the structure of the TCR β naïve repertoire

Are there general organizing principles ?



**Hilah
Gal**



**Wilfred
Ndifon**



**Eric
Shifrut**

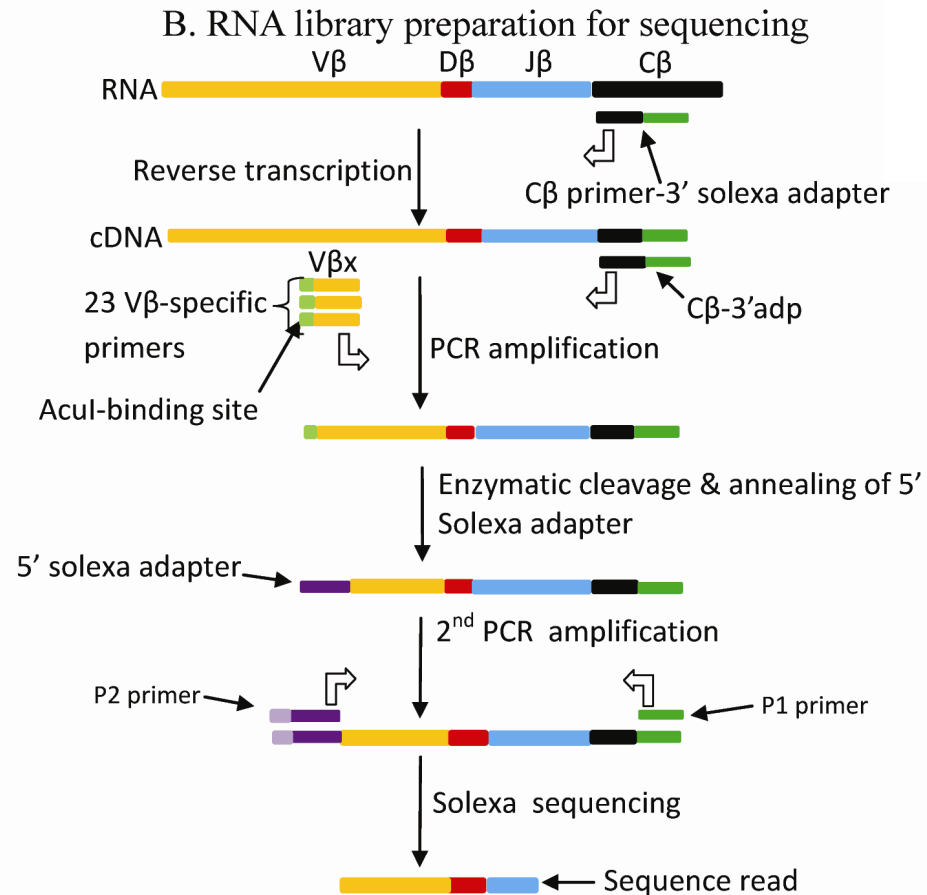


**Asaf
Madi**



A protocol for quantitative multiplexed high throughput sequencing of the TCR β repertoire

- Illumina sequencing
- Compensating PCR biases: Control plasmids library
- Challenges: resolving sequencing errors from real biological variance: Clustering, strict thresholds.

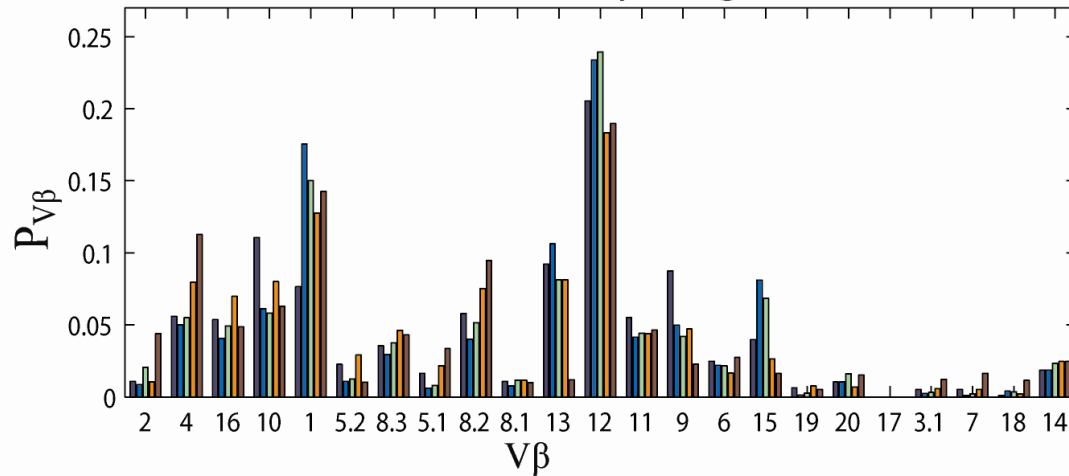




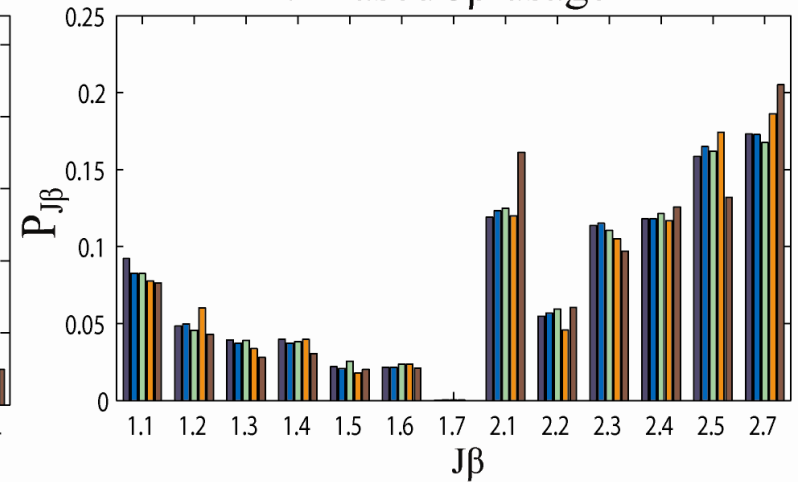
High throughput sequencing (TCR-seq) reveals common biases in the TCR repertoire

The TCR β repertoire has a well defined structure, which is similar among individual mice

E. Biased V β usage



F. Biased J β usage

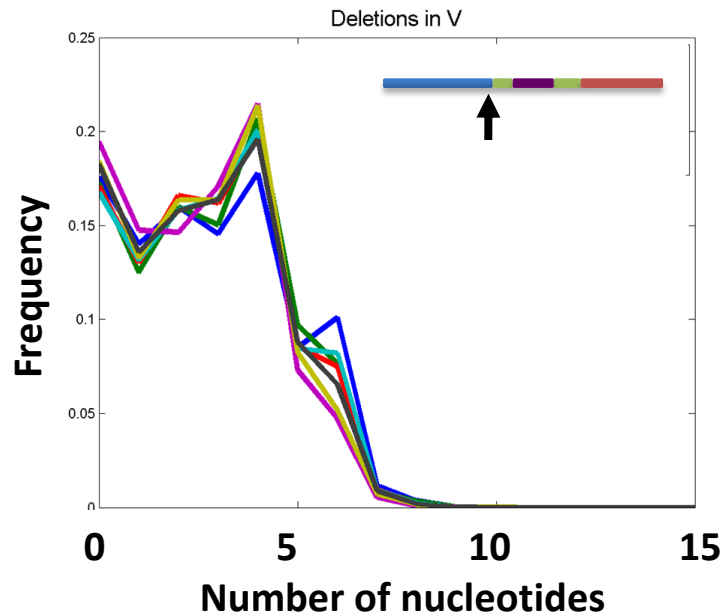




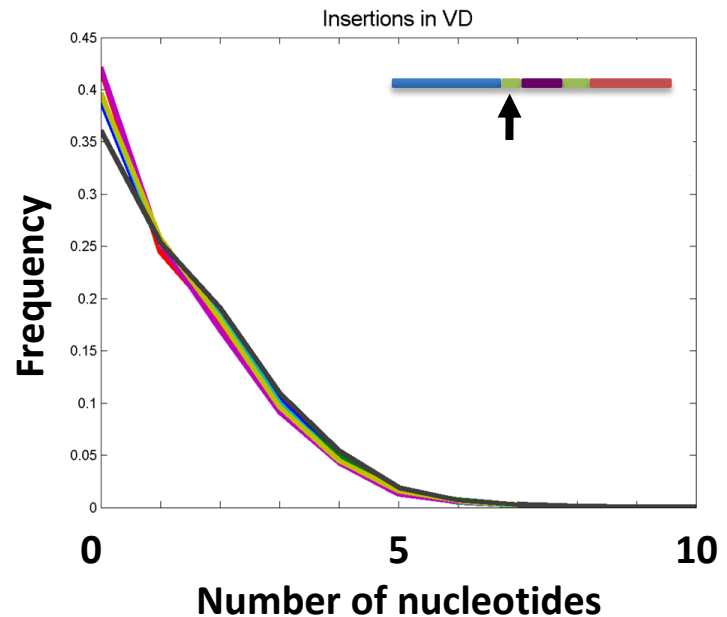
High throughput sequencing (TCR-seq) reveals common biases in the TCR repertoire

The TCR β repertoire has a well defined structure, which is similar among individual mice

Deletions



Insertions





Conclusions I:

The naive TCR β repertoire:

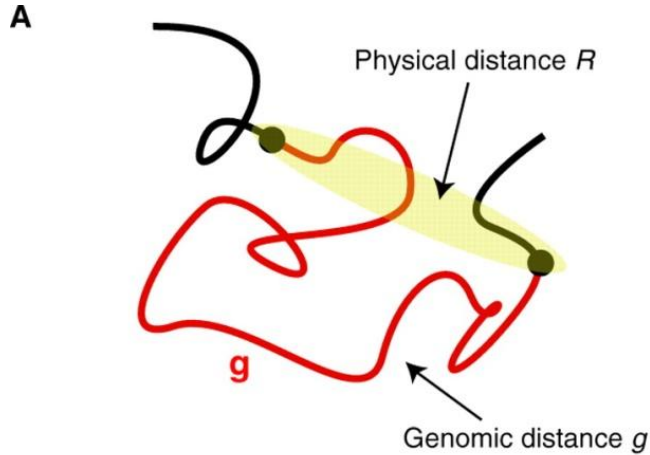
- a. Is highly biased
- b. Has very similar properties among individual mice
genetically identical, including MHC, young, clean environment,...
- c. While randomly made, it has a well defined structure

Similarity suggests common underlying principles

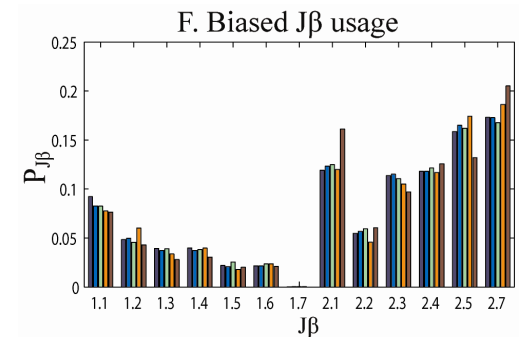
Mechanistic explanations for biases ?



A biophysical model can explain bias in J usage



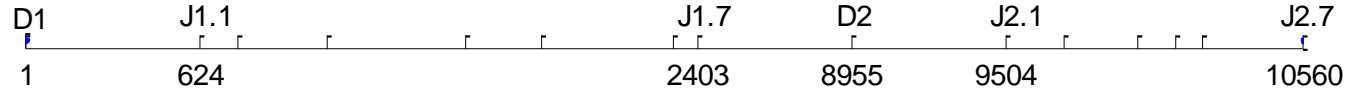
Recombination frequency depends on the **physical distance** between the segments, which in turn depends on their **genomic distance** and **chromatin conformation**



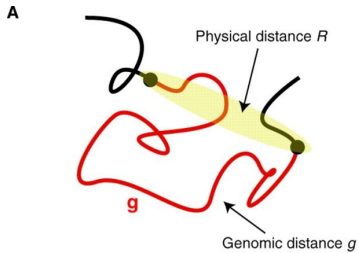


A biophysical model can explain bias in J usage

D. Mouse D β -J β distances



+

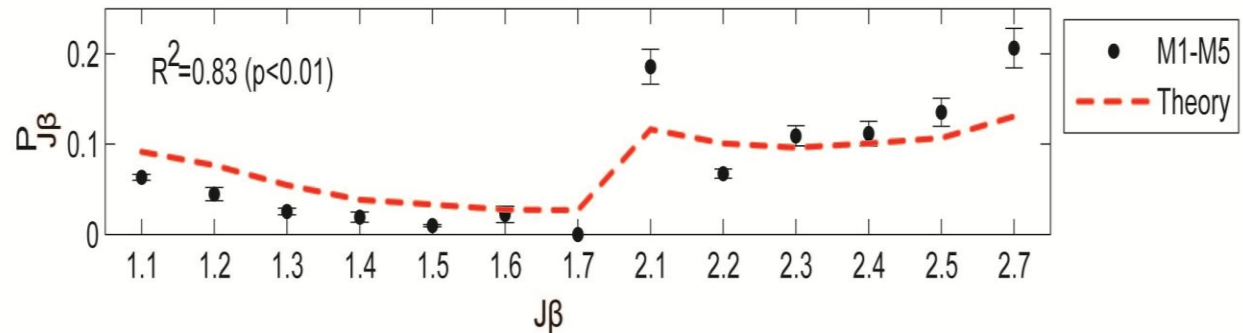


$$P(J\beta_i) = K[\alpha_1^{-3/2} \exp(-2\alpha_1^{-2}) + \alpha_2^{-3/2} \exp(-2\alpha_2^{-2})]$$

Model: Dekker J. et al., Science 2002

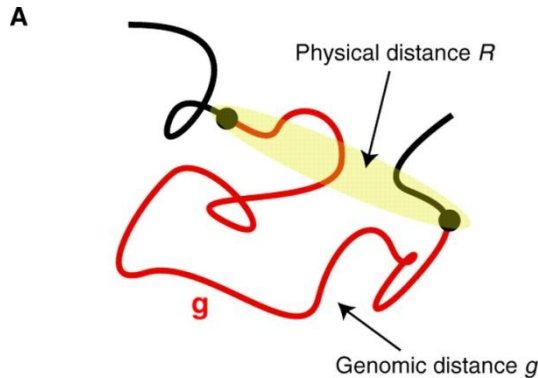
Mouse:

=





A biophysical model can explain bias in J usage



Recombination frequency depends on the **physical distance** between the segments, which in turn depends on their **genomic distance** and **chromatin conformation**

Tark-Dame M et al. J Cell Sci 2011;124:839-845

$$P(J_i) = K \left[\overset{\text{J-D1}}{\alpha_1^{-3/2} \exp(-2\alpha_1^{-2})} + \overset{\text{J-D2}}{\alpha_2^{-3/2} \exp(-2\alpha_2^{-2})} \right]$$

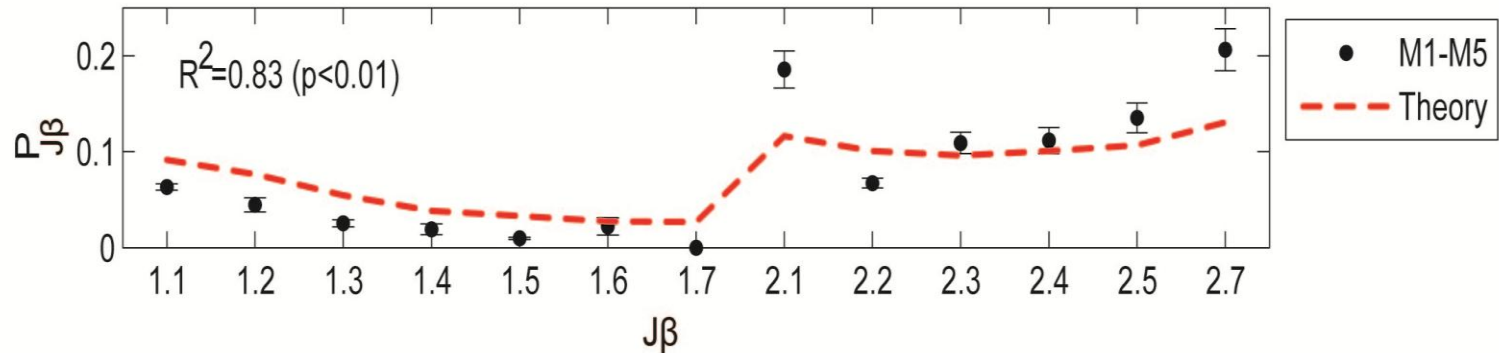
$$\alpha_j = (d_j/b)(1-d_j/c)$$

$d_{i,j}$ is the **genomic distance** between $J\beta_i$ and $D\beta_j$, K is a normalization constant.

b and c are free parameters: **chromatin flexibility** and **curvature**, respectively.



A biophysical model can explain bias in J usage



Model fit predicts a highly flexible chromatin during D-J rearrangement

Persistence length $\sim 20\text{nm}$

(in accordance with existing data on recruitment of chromatin modifiers).



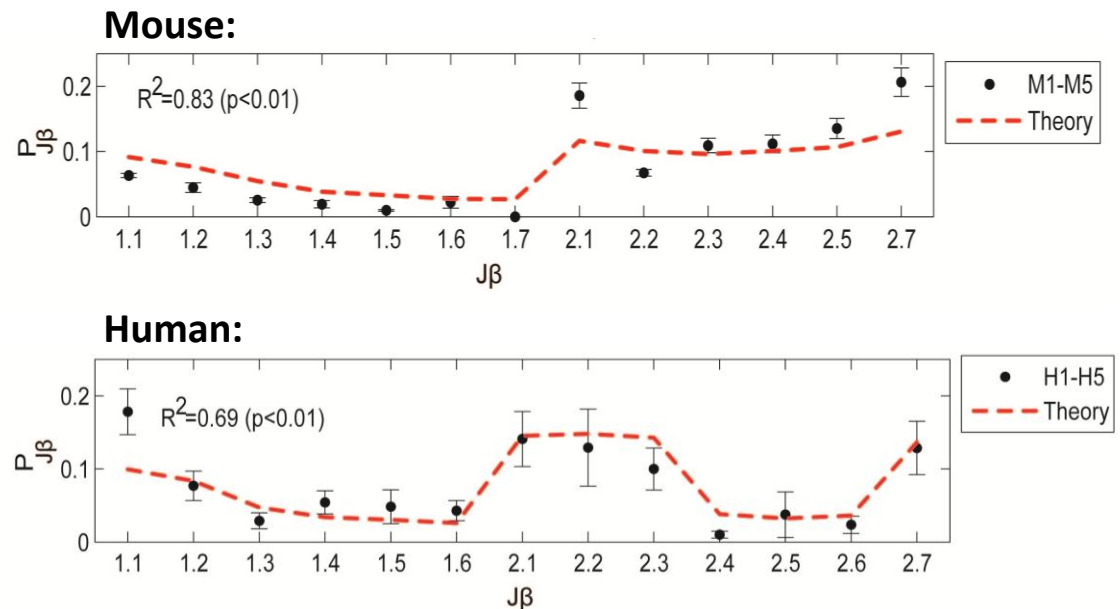
The biophysical model correctly predicts biases in human TCR repertoire

$J\beta$ - $D\beta$ genomic distances are different between species:



We use the model to calculate $J\beta$ frequencies in human

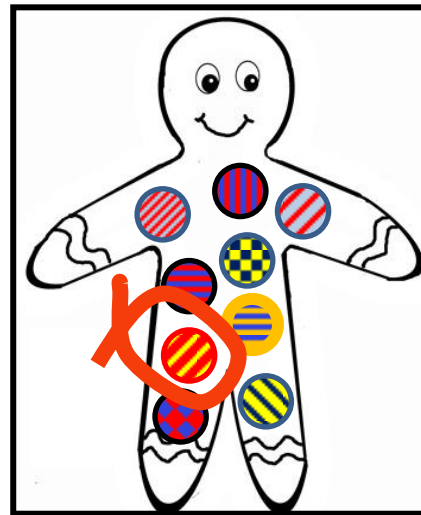
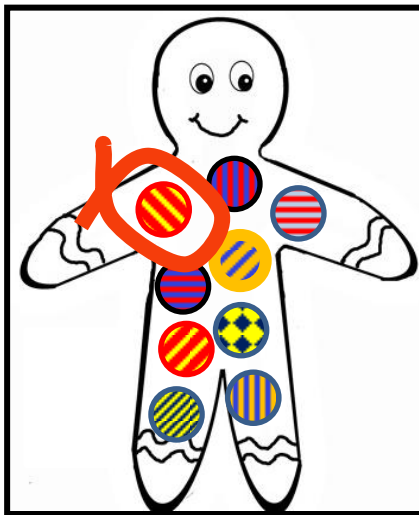
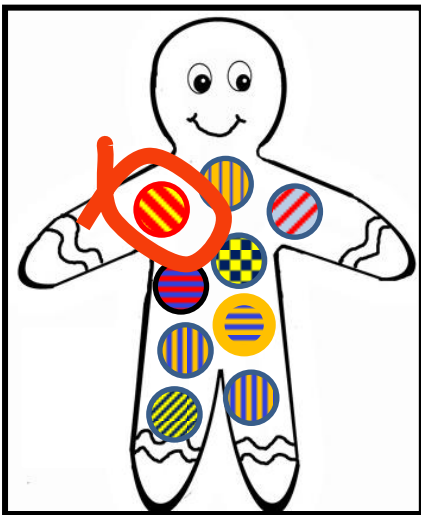
using fitting parameters obtained with mouse data:





Public TCR clones are frequently observed

Shared (“public”) clones were found between individuals that suffer from a similar pathology (viral infection, autoimmune disease, cancer, etc.), and share an HLA allele





Public TCR clones are frequently observed: Viruses, cancer, autoimmunity

<i>Disease/pathogen</i>	<i>Bias class</i>	<i>Target antigen</i>	<i>MHC restriction</i>	<i>TRBV^α</i>	<i>TRBJ^β</i>
<i>Humans</i>					
Influenza A	IV	MP ₅₈₋₆₆	A*0201	19	2-7
Epstein-Barr virus	III	EBNA 3A ₃₃₉₋₃₄₇	B*0801	7-6	2-7
Epstein-Barr virus	III	EBNA 3B ₃₉₉₋₄₀₈	A*1101	29	2-2
Epstein-Barr virus	III and IV	BZLF1 ₅₄₋₆₄	B*3501	10-3	1-5
Epstein-Barr virus	III and IV	EBNA1 ₄₀₇₋₄₁₇	B*3501	9	2-2
Epstein-Barr virus	III and IV	BZLF1 ₅₂₋₆₄	B*3508	6-1	2-7
Epstein-Barr virus	IV	BRLF1 ₁₀₉₋₁₁₇	A*0201	19	Unknown
Epstein-Barr virus	III and IV	BMLF1 ₂₅₉₋₂₆₇	A*0201	20-1	1-2
Cytomegalovirus	III and IV	IE1 ₃₁₆₋₃₂₄	A*0201	5-1	1-3
Cytomegalovirus	III and IV	pp65 ₄₉₅₋₅₀₃	A*0201	12	1-2
Human T-cell leukemia virus type 1	III and IV	Tax ₁₁₋₁₉	A*0201	6-5	2-7
Hepatitis B virus	IV	Unknown	Unknown	5-6	2-1
Hepatitis C virus	IV	Unknown	Unknown	10	2-7
Human immunodeficiency virus	III and IV	Gag ₁₆₂₋₁₇₂	B*5701	19	1-2
<i>Clostridium tetani</i>	III and IV	Tetanus toxin	DRB1*0301	5-4	2-3
Herpes simplex virus	III	Virion protein 22 ₄₉₋₅₇	B*0702	10	2-1
Melanoma	III and IV	Melan-A ₂₆₋₃₅	A*0201	27	2-1

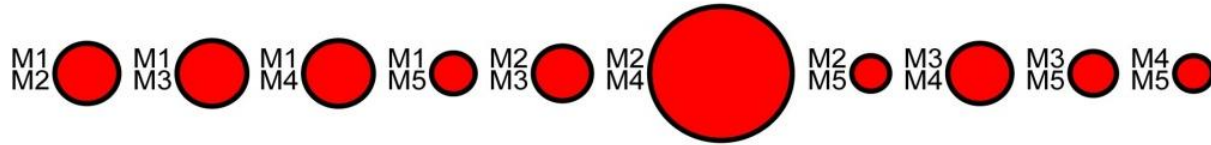
Miles, Douek, Price, Immun. Cell Biol. 2011;

Convergent recombination: Venturi, Price, Douek, Davenport, Nat. Rev. Immun. 2008



Bias affects sequence sharing

C. Sharing of selected AA sequences





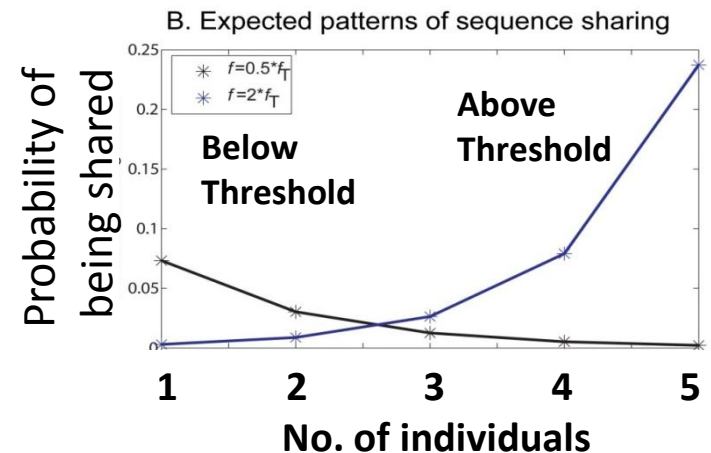
Bias affects sequence sharing: a statistical model

Assumptions:

- Each sequence has an a-priori probability of being made (f).
- Each individual has N sequences (T cell clones),
which are randomly drawn from all possible sequences.

We find that there is a threshold frequency, f_T , above which clones have a higher chance of being public:

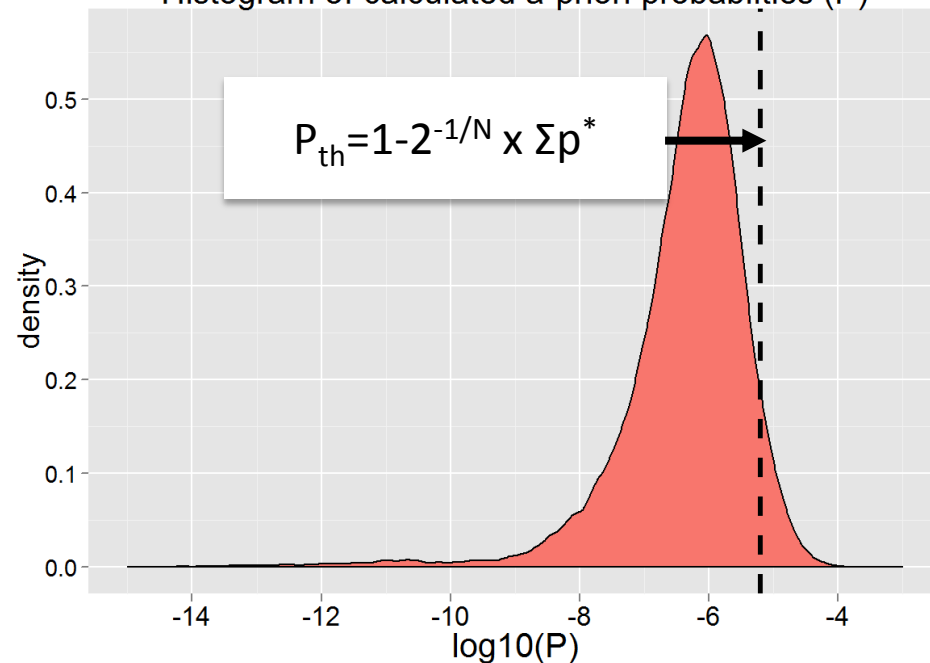
$$f_T = 1 - 2^{-1/N} \approx \ln 2 / N$$



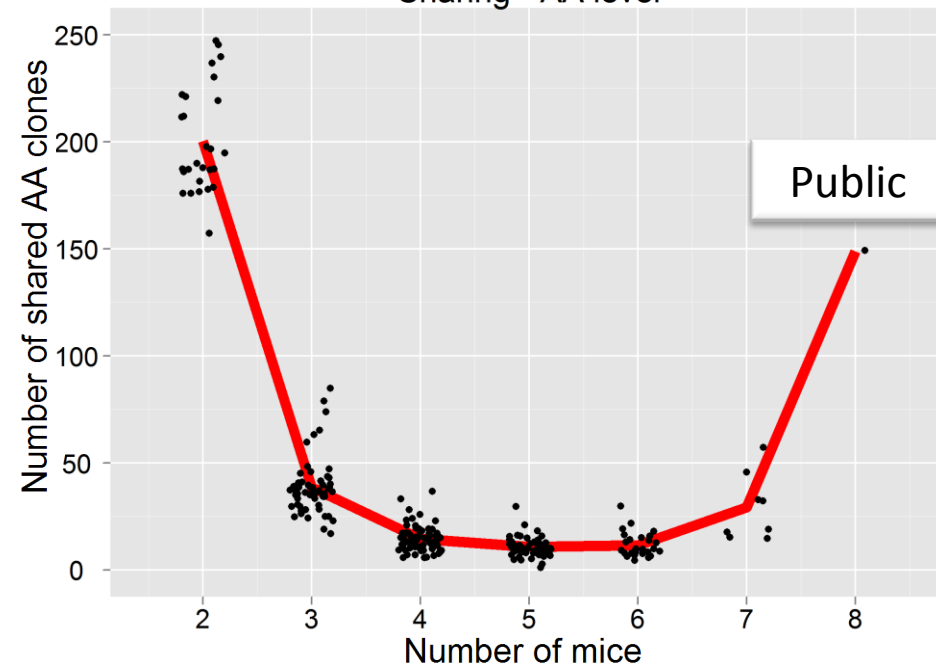
Estimating a-priori probability of clones to be generated

- Randomly sampled 10,000 clones from each mouse – to reduce size bias
- TCR sharing is higher than expected by uniform distribution

Histogram of calculated a-priori probabilities (P)



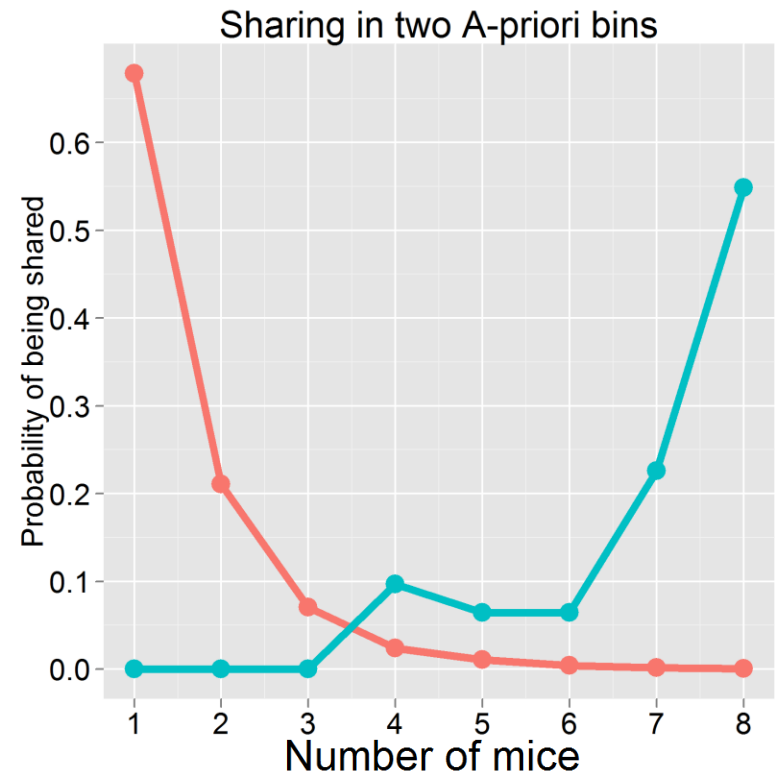
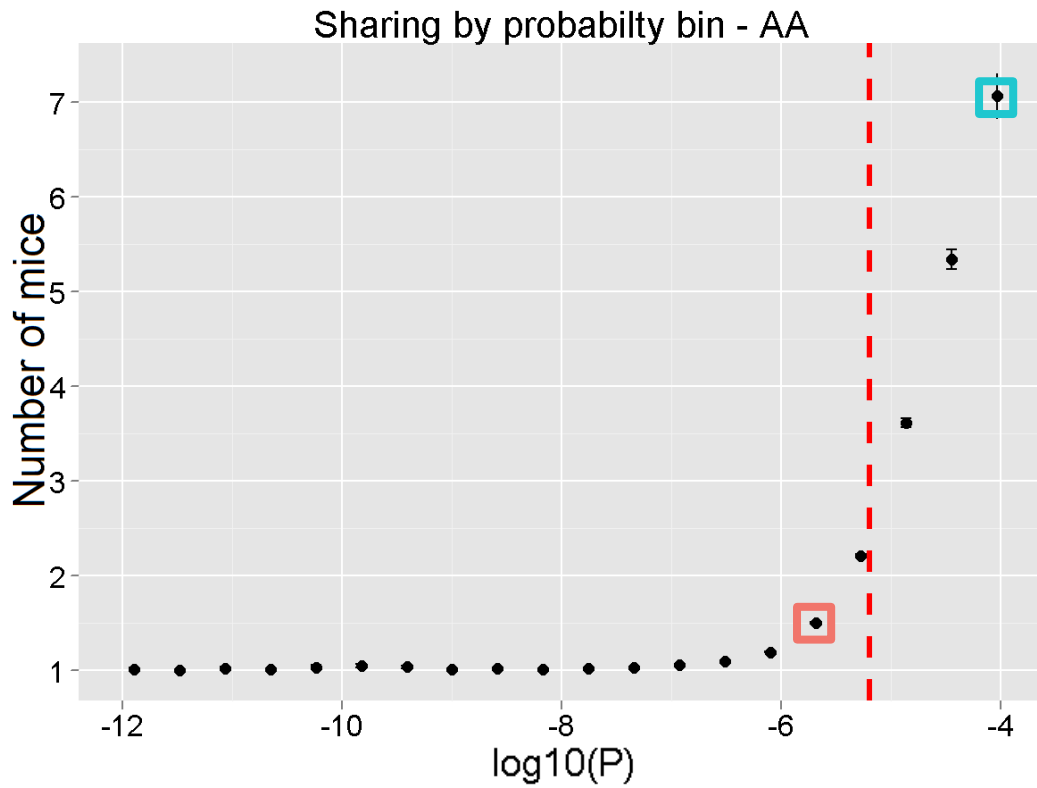
Sharing - AA level



*Ndifon *et al.* PNAS (2012)



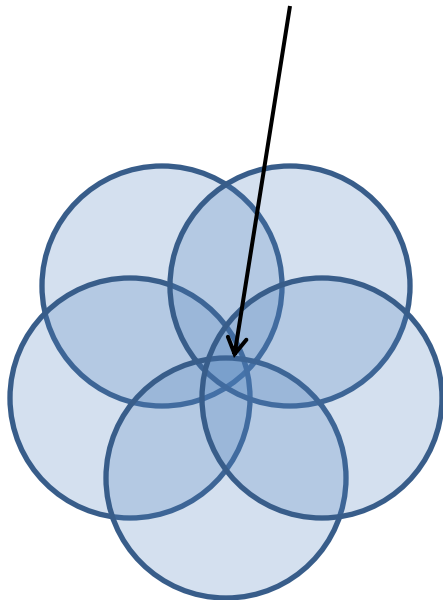
Predicting clone publicity using the a-priori probability





Conclusions II:

- Bias in primary repertoire allows for seemingly contradicting properties:
Huge diversity (against unknown pathogens) together with
a predictable public “core” set of TCRs (against frequent pathogens? Self?)





Thanks:

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Thank You

