

Modeling the Fitness Costs of Neoantigens

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Modeling neoantigen driven evolution

Neoantigen:

- a novel, mutated peptide
- presented by MHC I
- potentially “immunogenic” – recognized by T-cell receptors

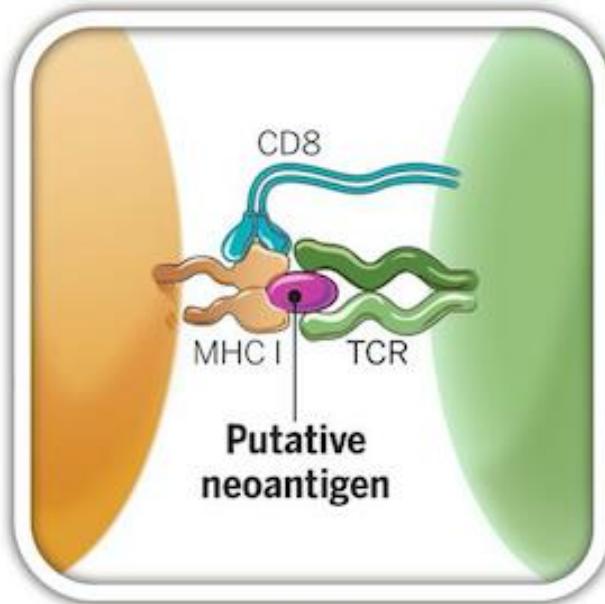


figure adapted from Schumacher & Schreiber, *Science*, 2015

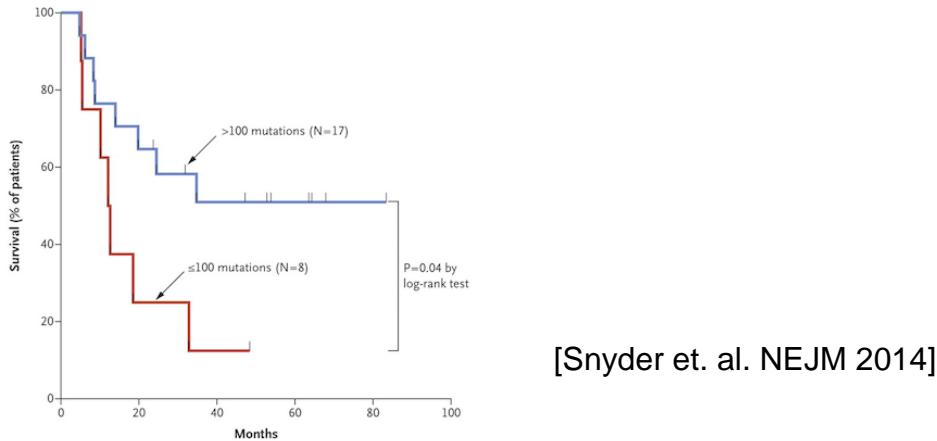
How can we (and others) help?

- These are **physical interactions** that support use of **computationally intensive biophysics**
- Physics “inspired” approaches can help – use of **statistical physics** in machine learning
- Other route (taken here) is to build **minimal (“simple”) models informed by underlying biophysical processes** and experimentally derived features to test hypotheses, make predictions, and design further experiments

Genomic correlates of response

What determines patient's response to therapy?

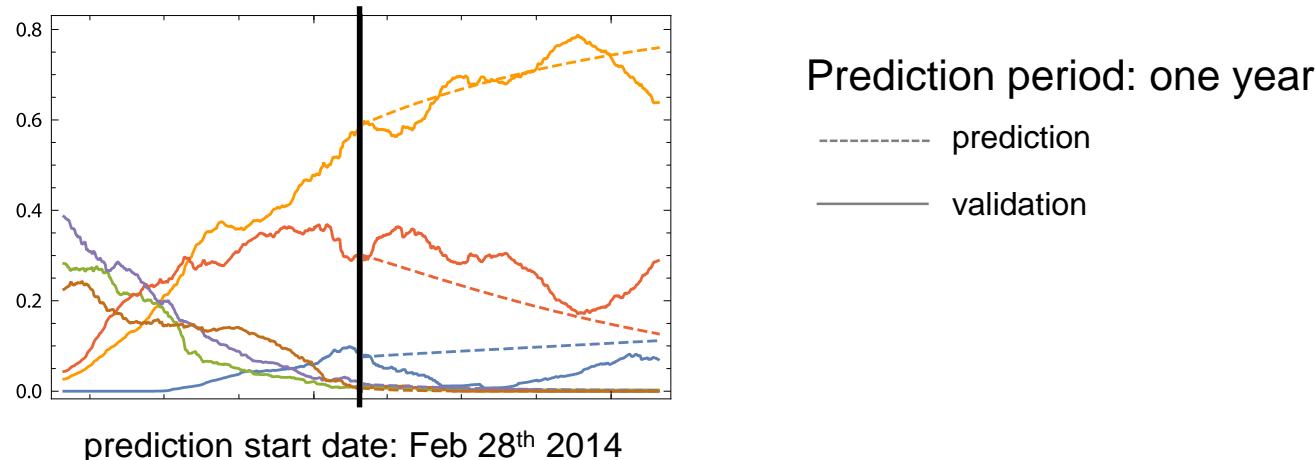
- Highly mutated tumors respond better [Snyder et al. 2014, Rizvi et al. 2015, Van Allen et al. 2015, Riaz et al. 2017]



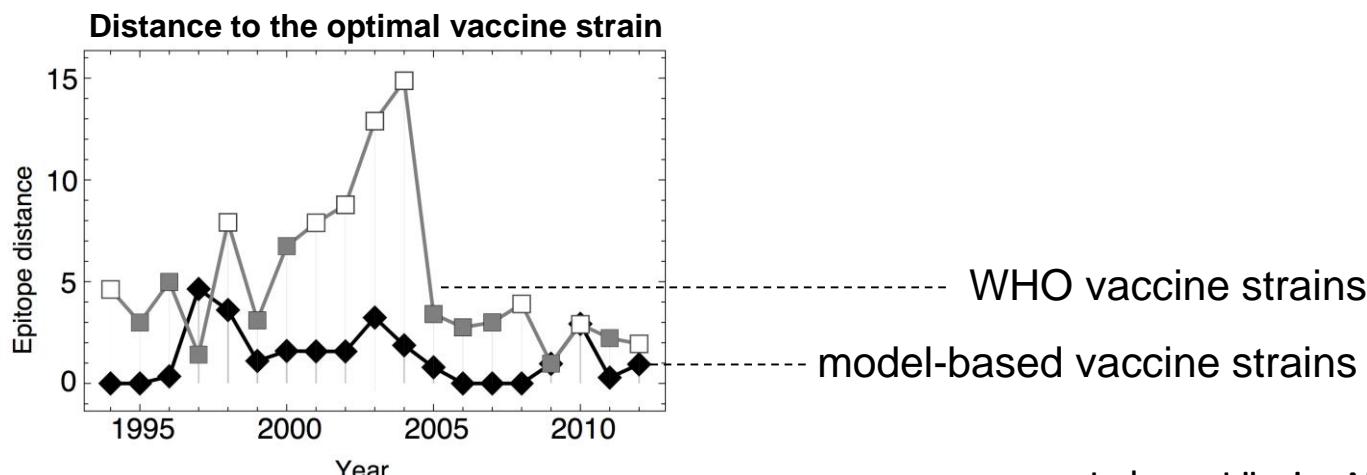
- Tumor heterogeneity may have negative impact on therapy success [McGranahan et al., 2016]
- Other markers such as information from the microenvironment
- **Goal: Integrative mathematical framework reflecting these features**

Fitness model predicts dominant influenza strain

- Clonal frequency predictions for WHO (example of prediction from February 2014)



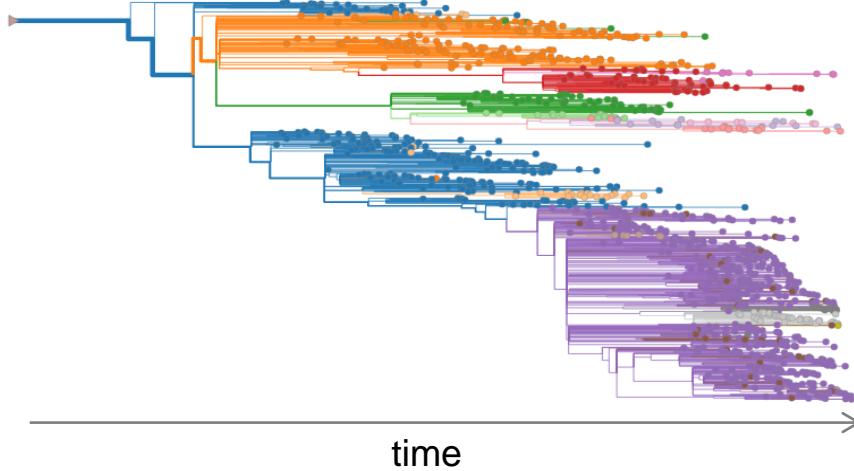
- Vaccine strain selection



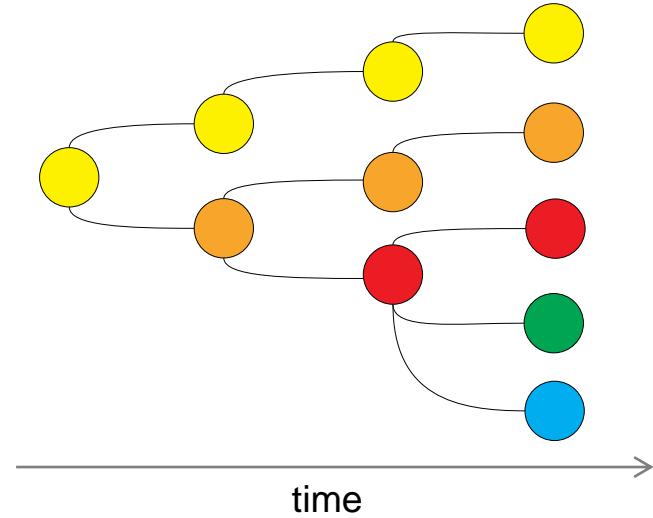
Different principles for checkpoint therapy

(with Marta Łuksza, IAS)

Influenza



Cancer

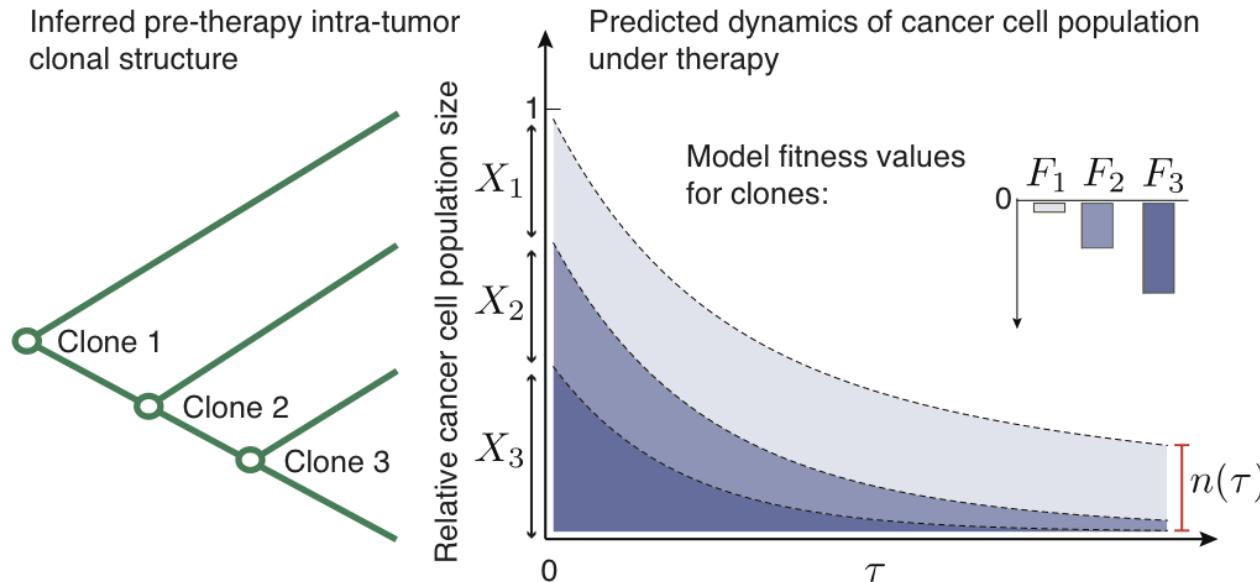


Differences:

Physical fitness interaction: B-cells with known viral epitopes versus T-cells with putative neoantigens

Distribution of fitness effects over tree: Which clone will win competition versus can all clones be suppressed?

Neoantigen driven tumor evolutionary dynamics



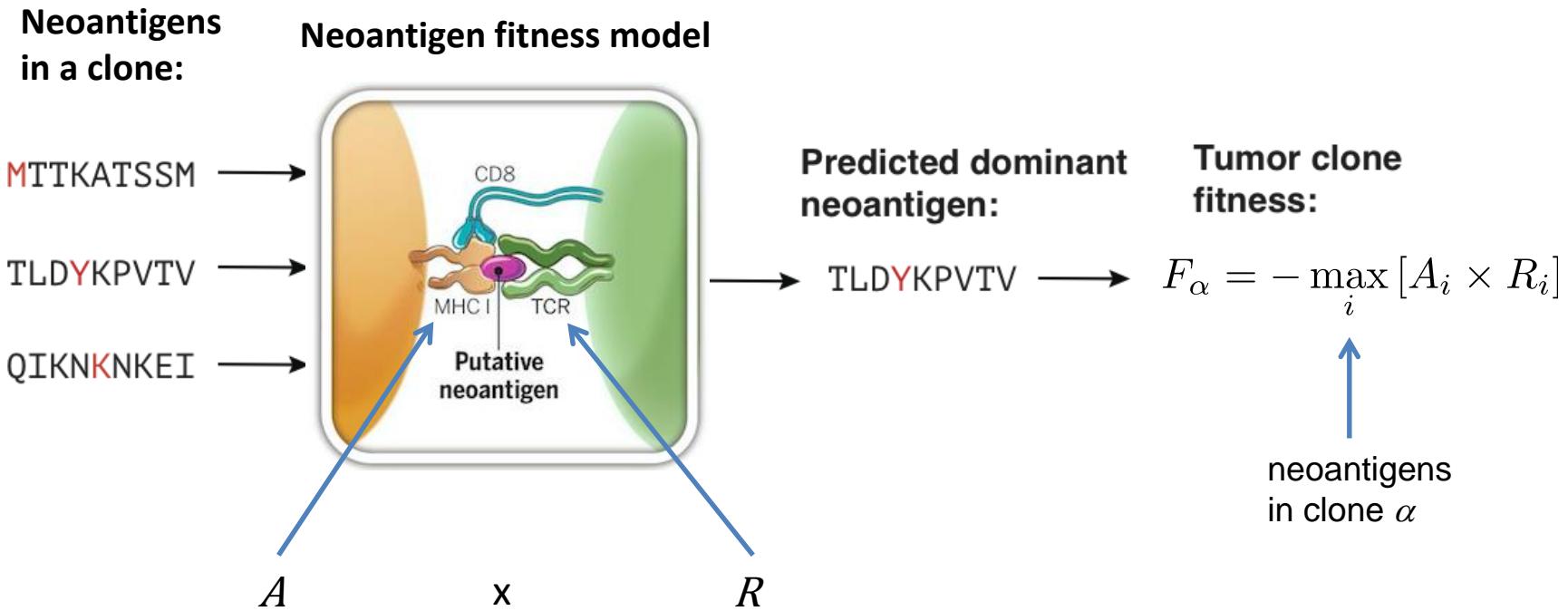
$$n(\tau) = \sum_{\alpha} X_{\alpha} \exp[F_{\alpha}\tau]$$

Relative effective population size after forward evolution

Initial clone frequency (from phylogeny)

Fitness of clone (derived from model)

Model construction: fitness of a clone



Amplitude due to MHC presentation:

- From inferred affinities of wildtype and mutant peptides
- Should relate to discrimination energy by class I HLA molecule
- Measure of peptide “selfness”

TCR recognition probability:

- Use pathogen epitope (IEDB) alignments as proxy for biophysical interactions
- Measure of cross-reactivity with database antigen
- Measure of peptide “non-selfness”

Proof of concept on current data & methods

Three immunotherapy datasets:

Van Allen, et al., *Science*, 2015: Melanoma, anti-CTLA4, 103 samples

Snyder, et al., *NEJM*, 2014: Melanoma, anti-CTLA4, 64 samples

Rizvi, et al., *Science*, 2015: Lung, anti-PD1, 34 samples

Measurements:

- Exome sequencing
- Tumor and normal tissue
- Survival times

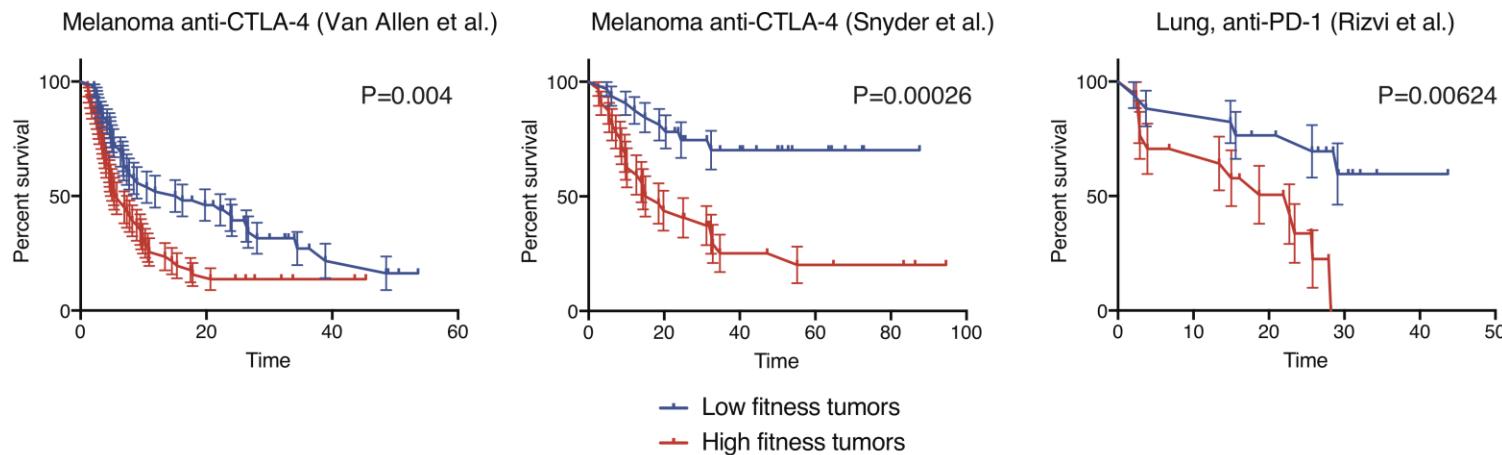
Processing:

- Somatic mutations: 4-caller variant pipeline for mutations (Chan Lab)
- Affinity prediction: NetMHC 3.4
- Nested clonal structure: Deshwar, PhyloWGS, 2015

Benchmarking on public datasets

Survival analysis:

- **Assumption:** predicted effective tumor size $n(\tau)$ anti-correlated with survival
- Split patient cohorts by median $n(\tau)$

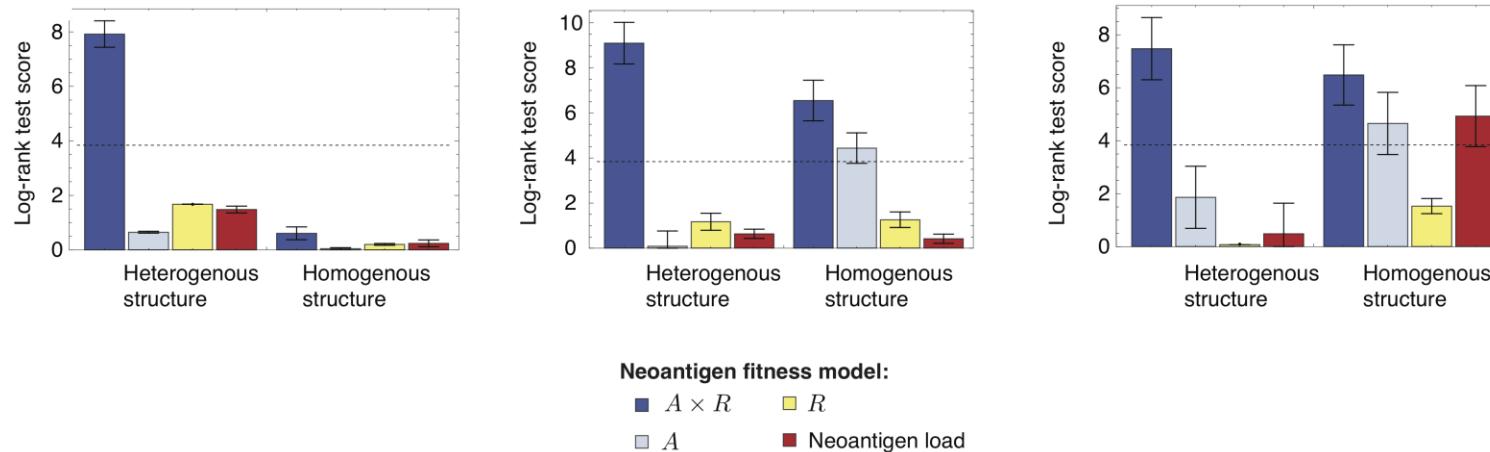


Benchmarking on public datasets

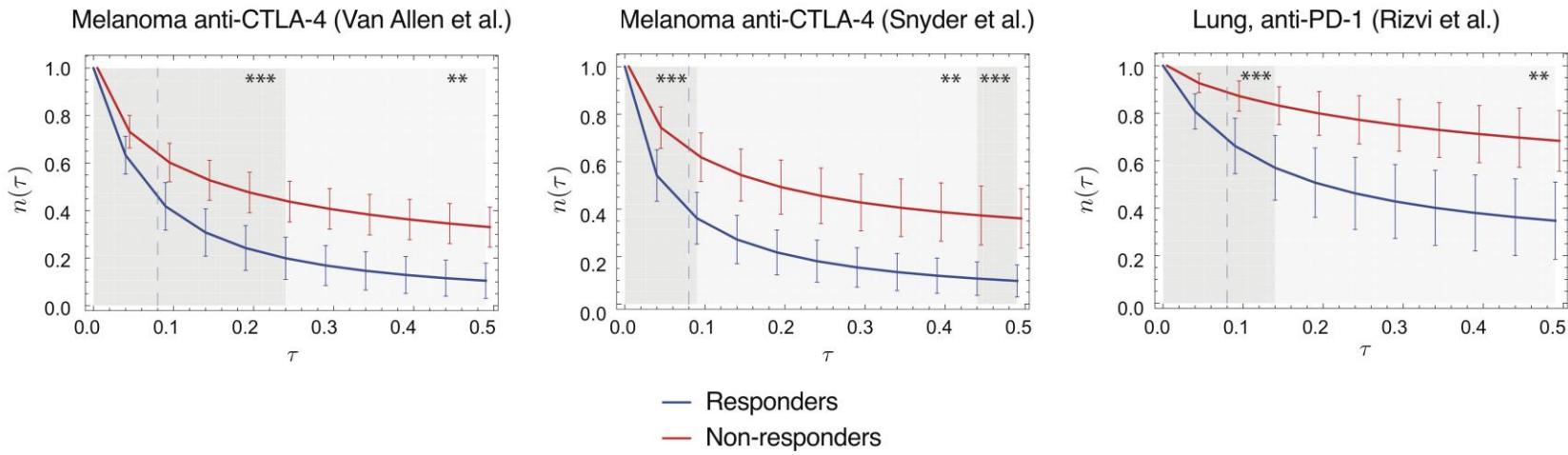
Survival analysis:

- **Assumption:** predicted effective tumor size $n(\tau)$ anti-correlated with survival
- Split patient cohorts by median $n(\tau)$

All model components **are informative and necessary** for predictions:

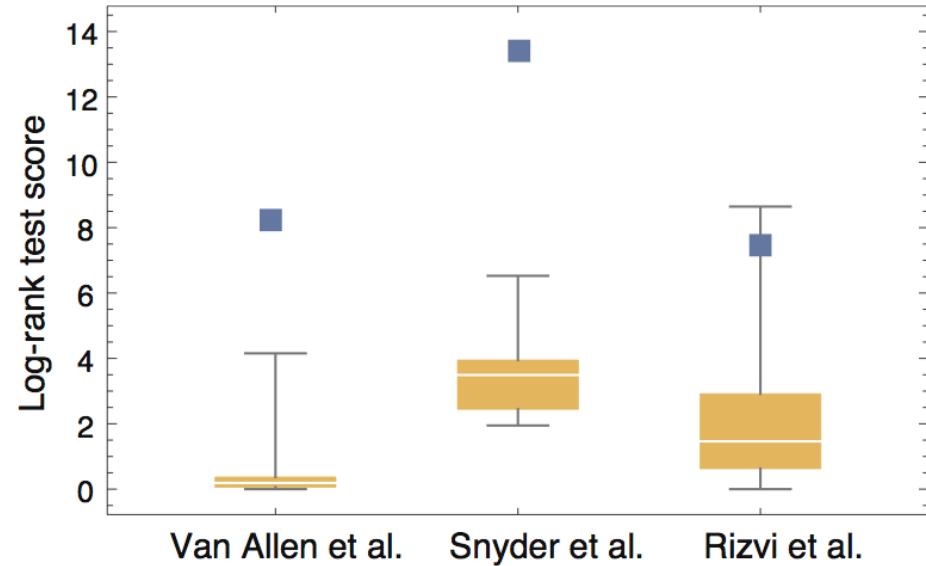


Predictions for responders and non-responders



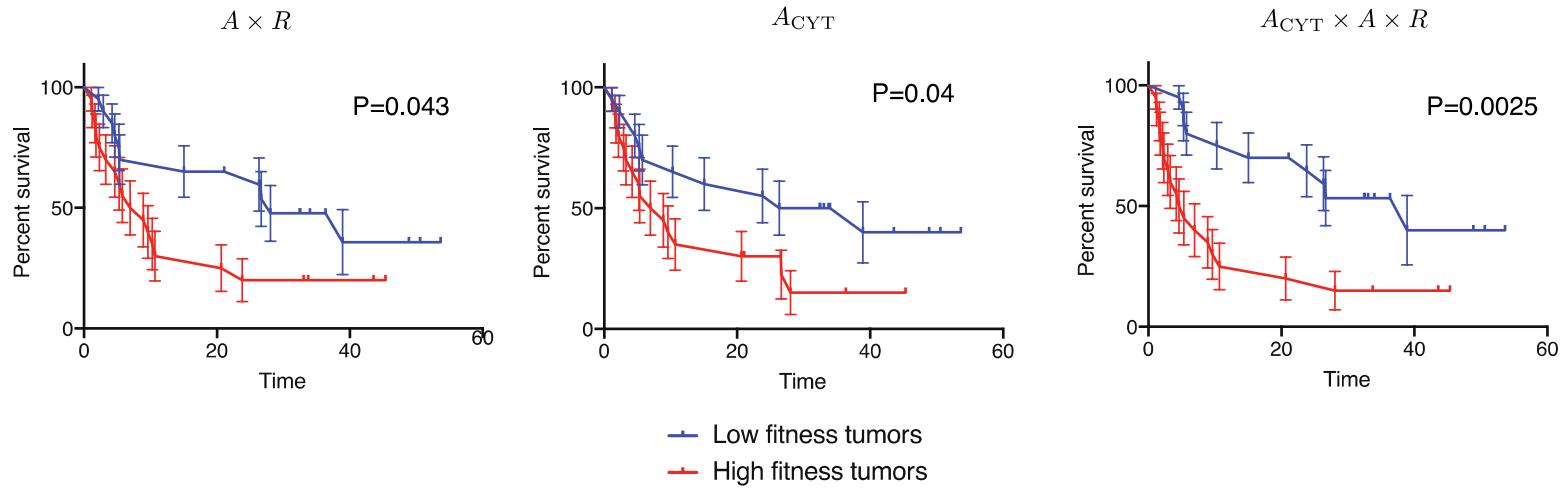
Consistency with underlying processes

Results do not survive shuffling
patient HLA type



Typical discrimination length \sim TCR repertoire discrimination length

Expandable framework can incorporate microenvironment



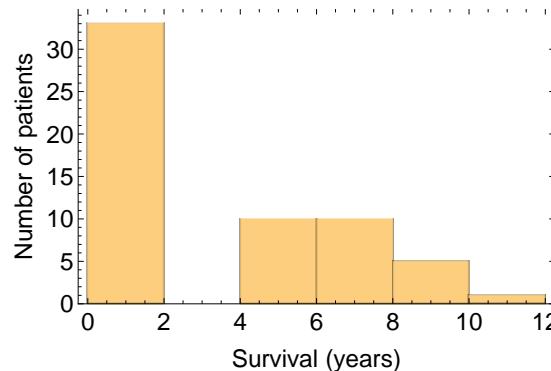
Other variables can be incorporated as well

Can we apply this framework in the
nontherapy setting?

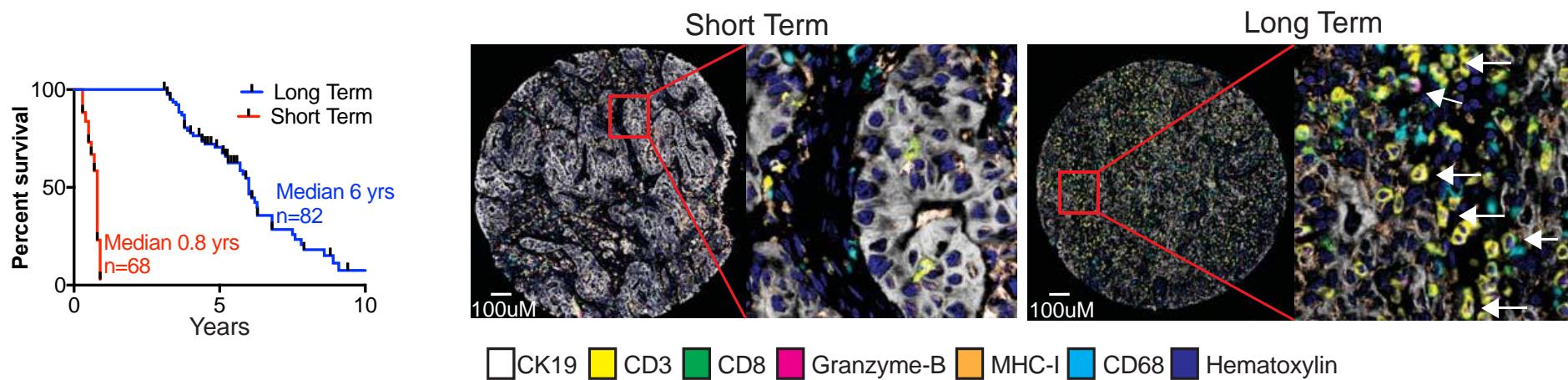
Pancreatic cancer study: beyond immunotherapies

Less than 7% of PDAC patients survive 5 years after diagnosis

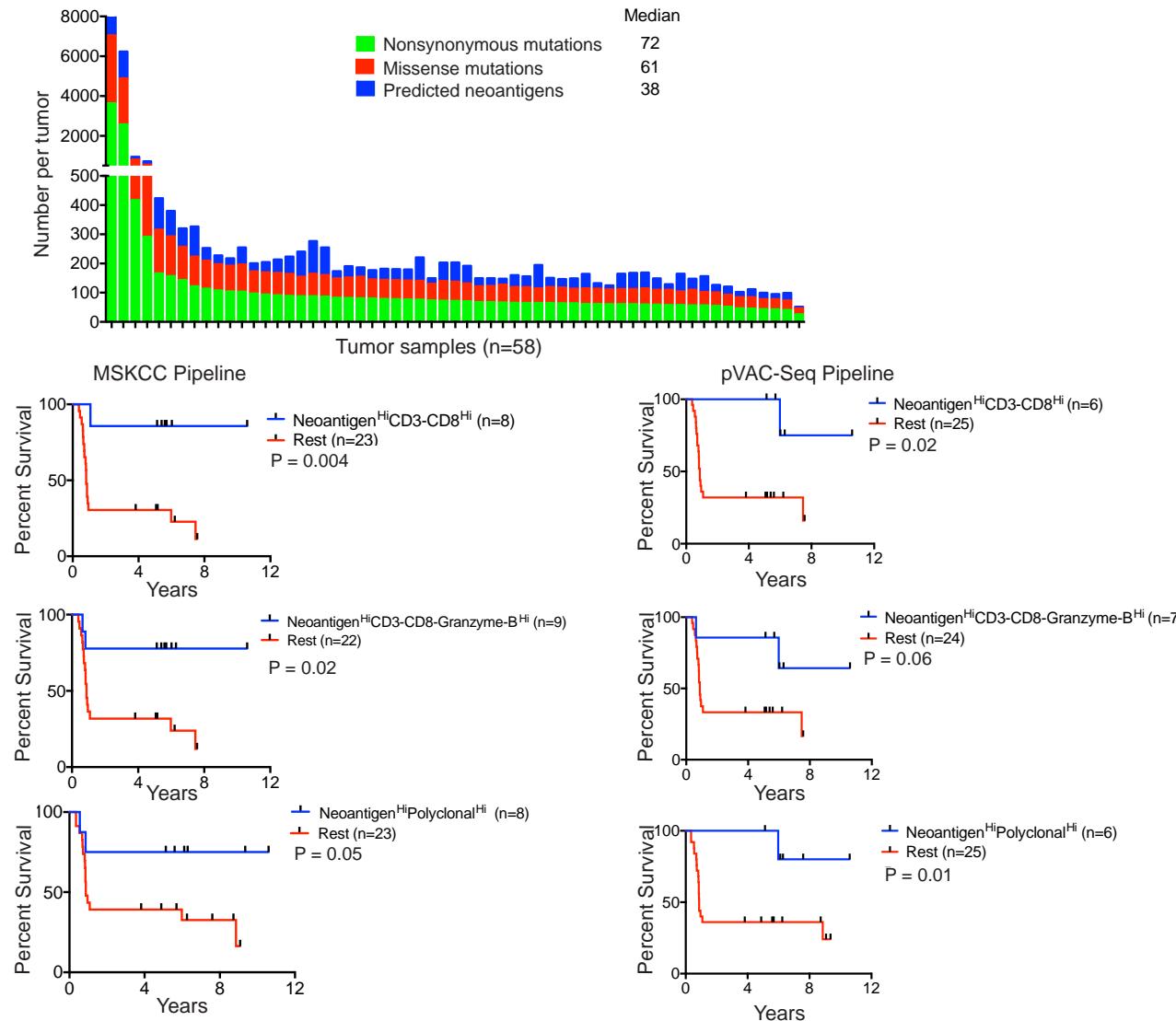
This study: A unique cohort of pancreatic cancer patients with **extreme long-term survivors.**



Immune monitoring indicates T-cell infiltration associates with response



Mutational burden + high T-cell is predictive



Quality model recapitulates survival & monitoring

Quality Score

a) Assess sequence similarity of neoantigen to pathogen

Wild type epitope: PPSARGG₆PL

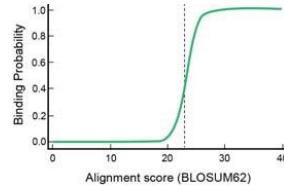
Tumor neoepitope: PPSAR₅R₆PL

Human Herpes Virus (HHV)-8: PPSGQRGP₅VAFRTRV

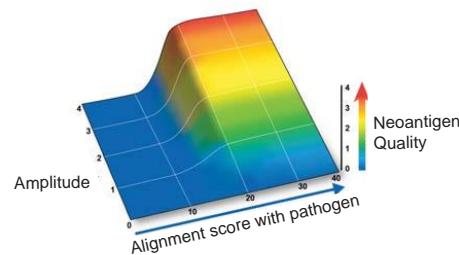
Calculate Alignment score
(BLOSUM62)

b) Scale alignment score to binding probability of a TCR to the cross reacting antigen

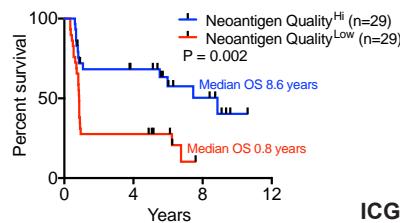
TCR binding probability is
a sigmoid function of
alignment score



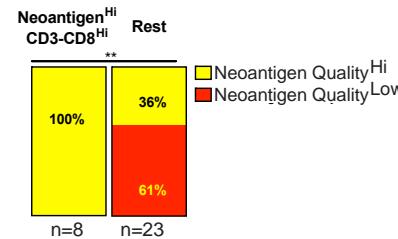
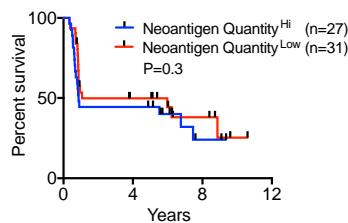
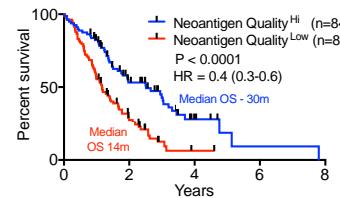
c) Neoantigen cross reactivity for a given neoantigen is a function of alignment score and amplitude (K_d^{WT}/K_d^{Mutant})



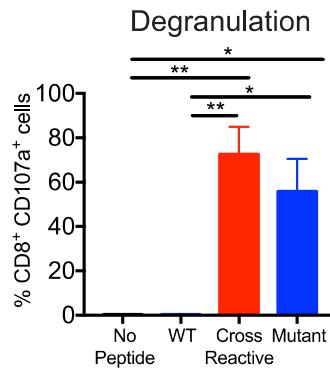
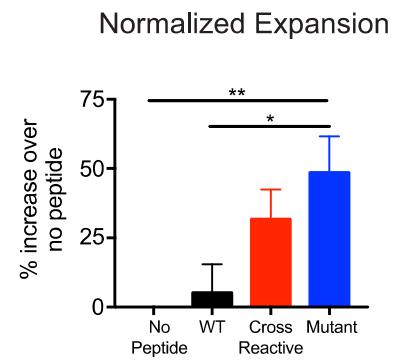
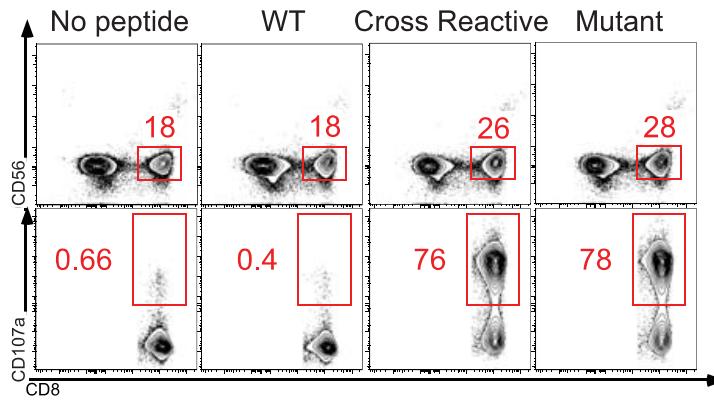
MSKCC



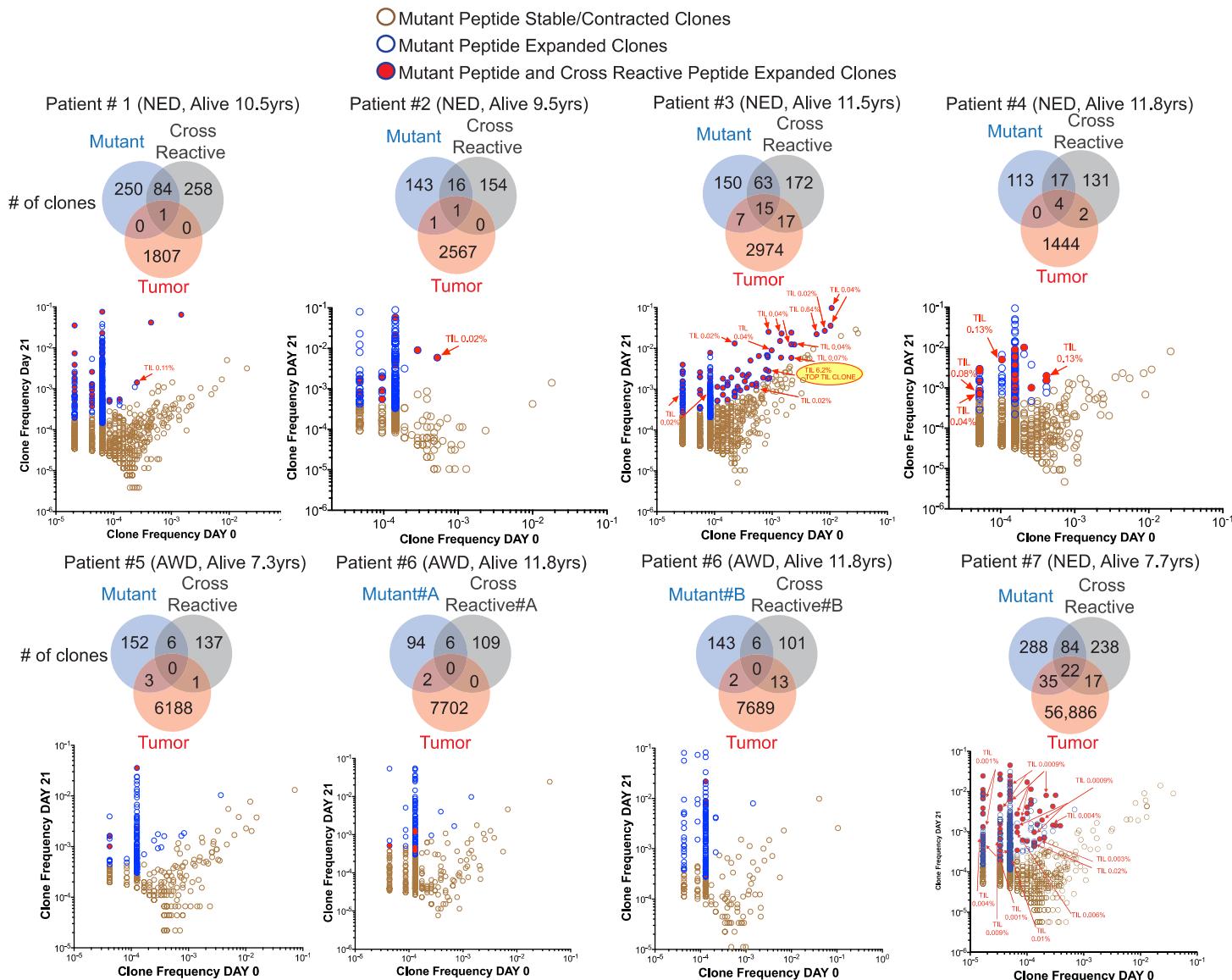
ICGC



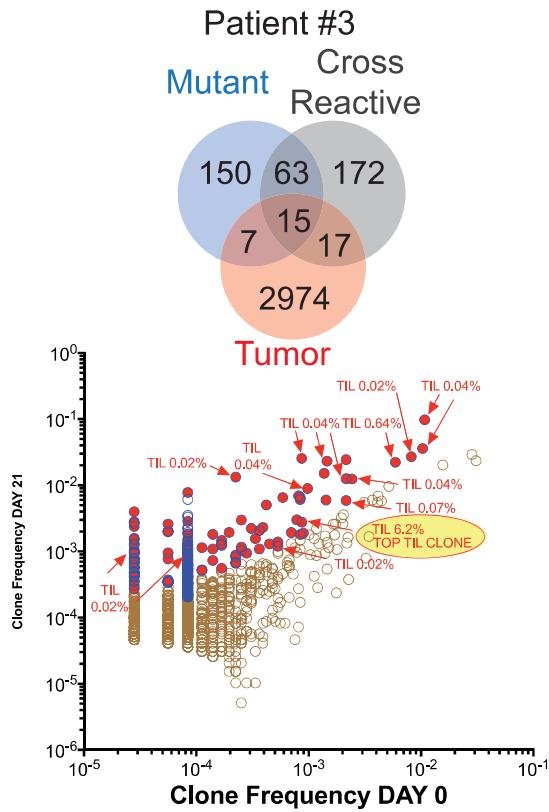
Test in long-term cohort



Can we find TCRs?



Particularly striking case:



Summary

- Approaches from virus vaccine prediction may be relevant in predicting response to checkpoint blockade immunotherapy
- **All neoantigen fitness model components are informative:**
 - Tumor heterogeneity
 - MHC presentation of neoantigens
 - TCR recognition of neoantigens
- The **fitness model can be easily extended** to capture other meaningful effects such as information about the tumor microenvironment

LETTER

doi:10.1038/nature24473

A neoantigen fitness model predicts tumour response to checkpoint blockade immunotherapy

Marta Łuksza¹, Nadeem Riaz^{2,3}, Vladimir Makarov^{3,4}, Vinod P. Balachandran^{5,6,7}, Matthew D. Hellmann^{7,8,9}, Alexander Solovyov^{10,11,12,13}, Naiyer A. Rizvi¹⁴, Taha Merghoub^{7,15,16}, Arnold J. Levine¹, Timothy A. Chan^{2,3,4,7}, Jedd D. Wolchok^{7,8,15,16} & Benjamin D. Greenbaum^{10,11,12,13}

LETTER

doi:10.1038/nature24462

Identification of unique neoantigen qualities in long-term survivors of pancreatic cancer

Vinod P. Balachandran^{1,2,3}, Marta Łuksza⁴, Julia N. Zhao^{1,2,3}, Vladimir Makarov^{5,6}, John Alec Moral^{1,2,3}, Romain Remark⁷, Brian Herbst², Gokce Askan^{2,8}, Umesh Bhanot⁸, Yasin Senbabaoglu⁹, Daniel K. Wells¹⁰, Charles Ian Ormsby Cary¹⁰, Olivera Grbovic-Huezo², Marc Attiyeh^{1,2}, Benjamin Medina¹, Jennifer Zhang¹, Jennifer Loo¹, Joseph Saglimbeni², Mohsen Abu-Akeel⁹, Roberta Zappasodi⁹, Nadeem Riaz^{6,11}, Martin Smoragiewicz¹², Z. Larkin Kelley^{13,14}, Olca Basturk⁸, Australian Pancreatic Cancer Genome Initiative*, Mithat Gönen¹⁵, Arnold J. Levine⁴, Peter J. Allen^{1,2}, Douglas T. Fearon^{13,14}, Miriam Merad⁷, Sacha Gnjatic⁷, Christine A. Iacobuzio-Donahue^{2,5,8}, Jedd D. Wolchok^{3,9,16,17,18}, Ronald P. DeMatteo^{1,2}, Timothy A. Chan^{3,5,6,11}, Benjamin D. Greenbaum¹⁹, Taha Merghoub^{3,9,18}§ & Steven D. Leach^{1,2,5,20}§

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- Nina Bhardwaj, Sacha Gnajic, Miriam Merad, Romain Remark, Vladimir Roudko, Alexander Solovyov, Nicolas Vabret, Tisch Cancer Institute, Icahn School of Medicine at Mount Sinai

Please inquire about positions!

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