Towards personalized cancer treatments using Immunoinformatics

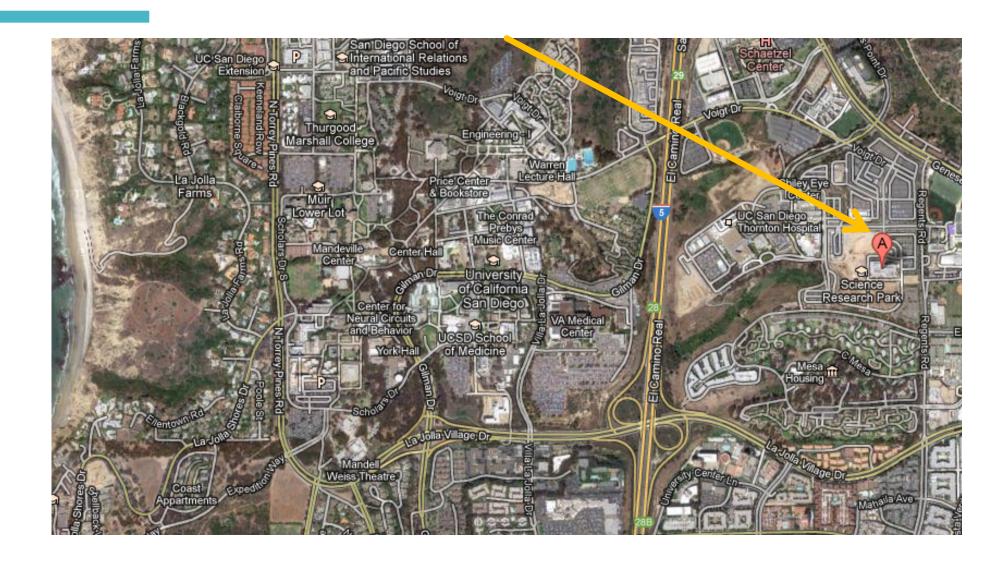
Bjoern Peters

Zeynep Kosaloglu-Yalcin

La Jolla Institute for Immunology



La Jolla Institute for Immunology (LJI)



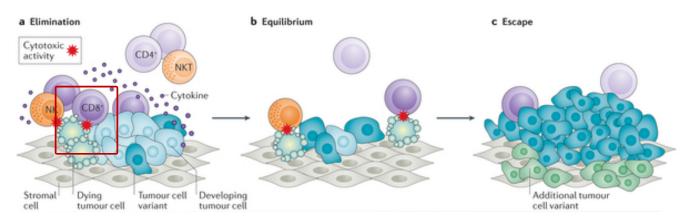
Overview



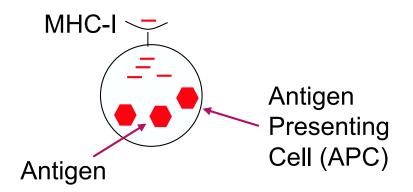
- Background Biology: The immune system can detect and eliminate mutated cancer cells
- Background Immunoinformatics:
 - Mutations can be detected using patient sequencing data
 - Mutations that can be recognized by T cells can be predicted
- Hands on: Design a personalized cancer vaccine

Cancer immune surveillance and escape

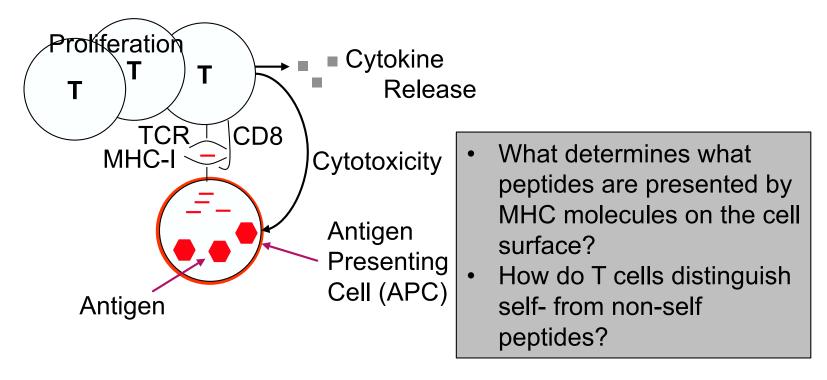
- Mutations in cells occur frequently
- The immune system has the capacity to detect and eliminate such mutated cells, and will do so on a regular basis
- Only when mutated cells find ways to hide from- or suppress an attack by the immune system, they can grow and spread unhindered leading to clinically apparent tumors

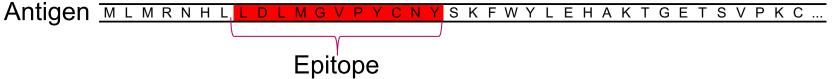


CD8+ T cell epitope recognition

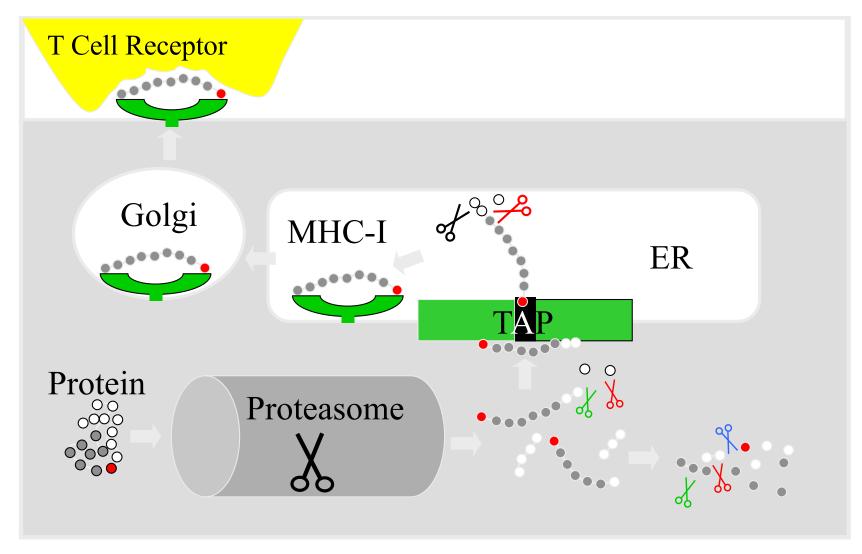


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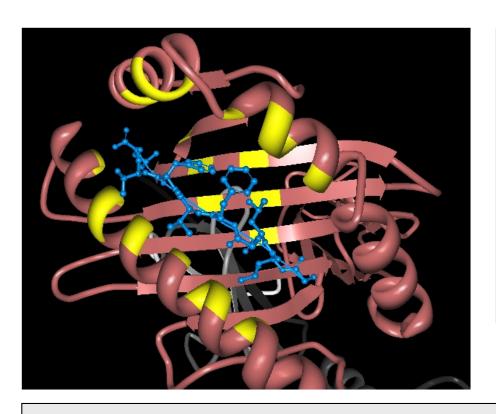


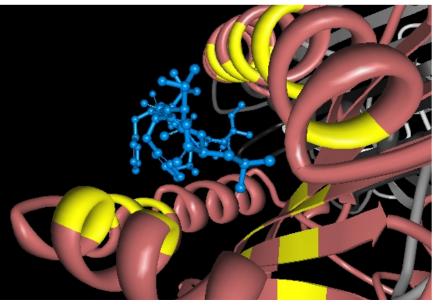
MHC I - Antigen processing and presentation pathway



7 Peters et al, J Mol Biol 2002, Bioinformatics 2003, J Immunol.2003; CMLS 2005; Assarson, J Immunol 2007

MHC:peptide binding mode

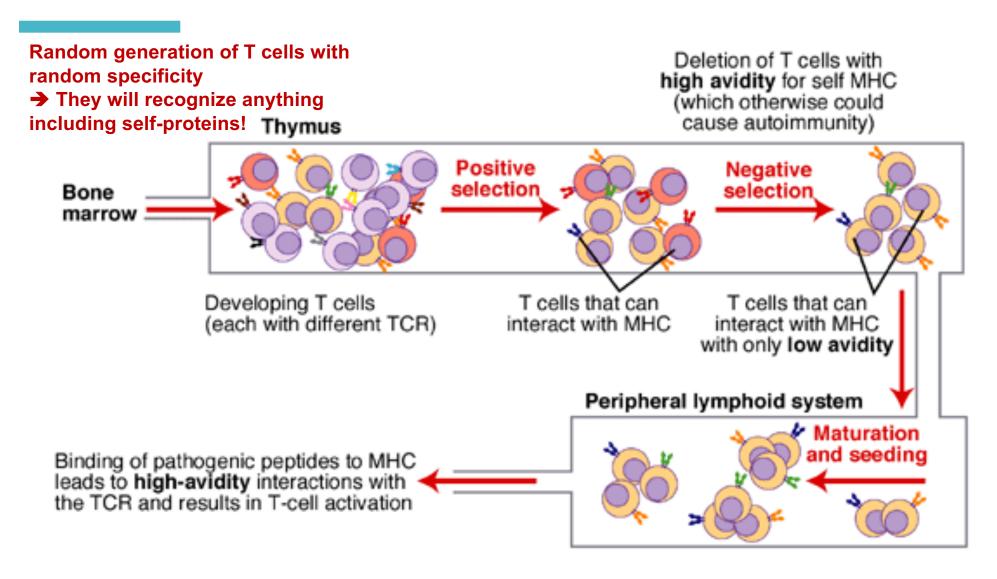




- Each human expresses up to 6 different MHC-I molecules in every cell
- >3000 MHC variants are known
- Distinct binding specificities → individual epitope repertoire

Viewer: Beaver and Ponomarenko, Immunome Research, 2007

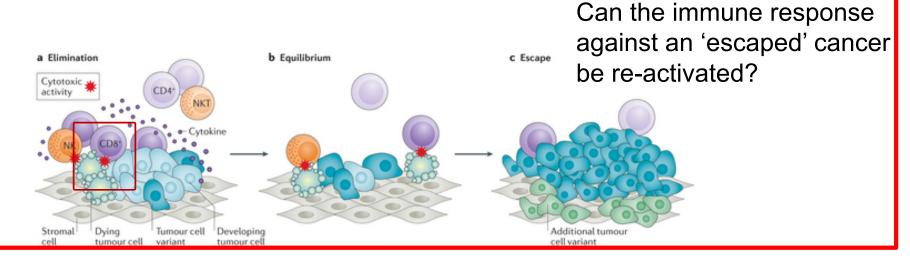
Self –reactive T cells are deleted during maturation



The repertoire of T cells is shaped by both positive and negative selection Expert Reviews in Molecular Medicine © 1999 Cambridge University Press

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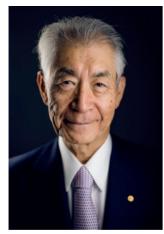
Nobel Prize 2018 in Medicine

- Identification of the molecules PD-1 and CTLA-4 that function as 'T cell brakes' (immune checkpoints)
- Blockade of PD-1 and CTLA-4 results in activation of T cells which has "fundamentally changed the outcome for certain groups of patients with advanced cancer"
- "Similar to other cancer therapies, adverse side effects are seen, which can be serious and even life threatening. They are caused by an overactive immune response leading to autoimmune reactions [...]"



© Nobel Media AB. Photo: A. Mahmoud

James P. Allison



© Nobel Media AB. Photo: A. Mahmoud Tasuku Honjo

"for their discovery of cancer therapy by inhibition of negative immune regulation"

Rationale for Personalized Cancer Immunotherapy

- <u>Vaccination</u>: Introduce or boost an immune response against a specific target (<u>antigen</u>)
- Cancer cells contain non-self antigens that could be recognized by T cells, but presence of cancer means this mechanism has failed, typically by the tumor suppressing immune responses
- Checkpoint blockade treatments: Block immune suppressive mechanisms to boost T cell immune responses against cancer cells.
- Problem: Checkpoint blockade is unspecific, and will also boost unwanted autoimmune responses
- Personalized Cancer Immunotherapy: Boost anti-tumor response with vaccine containing peptides corresponding to cancer mutations that can be recognized by T cells.

UC San Diego Health

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Several trials for personalized cancer vaccines are currently ongoing

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Is the Next Big Step in Cancer Therapy Personalized Vaccines?

UC San Diego Health and La Jolla Institute launch clinical trial harnessing an individual's immune system in a syringe

October 12, 2018 | Yadira Galindo



Ezra Cohen, MD, UC San Diego Health physician scientist, administered the first-of-itskind personalized cancer vaccine to Tamara Strauss, while Aaron Miller, MD, PhD, UC San Diego Health physician scientist, Tamara's mother, Iris Strauss, and Stephen Schoenberger, PhD, La Jolla Institute for Allergy and Immunology professor of immunology, look on.

After sequencing Tamara's tumor and normal tissue, the team identified mutations expressed solely by cancer cells in her body. Schoenberger and LJI's Bjoern Peters, PhD, developed a novel algorithm to select mutations that are recognized by the immune system. This algorithm was deployed to recognize the

neoantigens that generated the strongest T cell response from Tamara's tissue samples.

These neoantigens were then presented to Tamara's own T cells and cultured over a twoweek period using 50 milliliters of her blood to develop a personalized vaccine.

Personalized Cancer Immunotherapy



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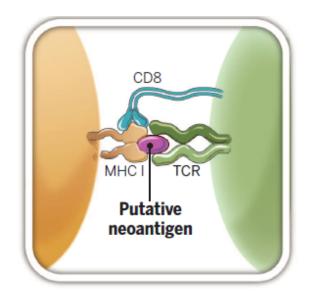
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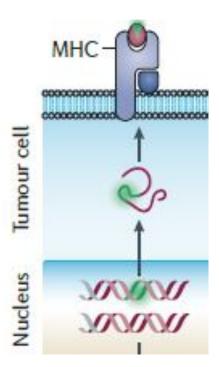
Neoepitopes (Neoantigens)

- Cancers genomes accumulate mutations
- Mutations in coding regions are translated in mutated protein sequences
- Mutated peptides can be presented as epitopes on MHC to T cells

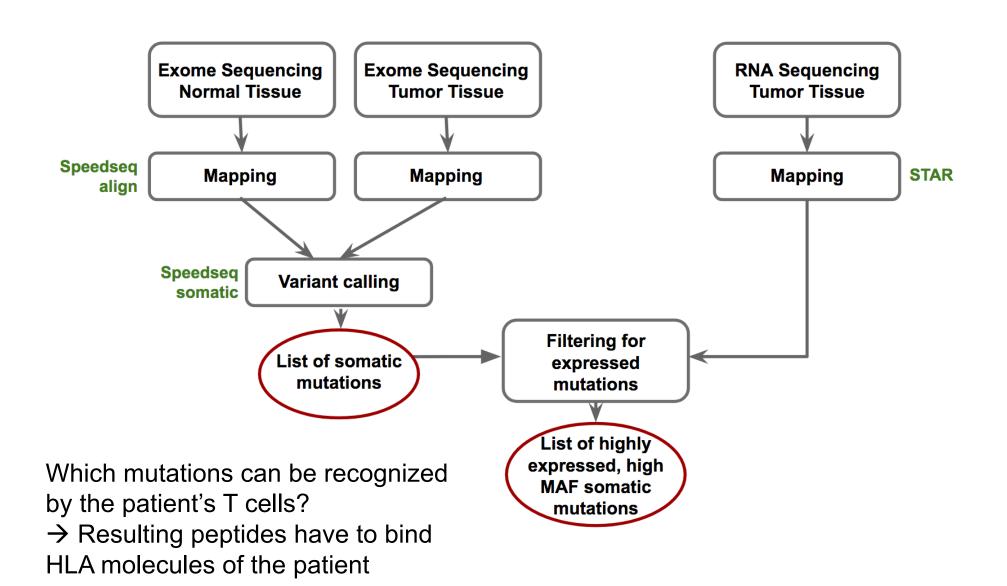
Neoepitopes are presumably recognized by tumor-infiltrating lymphocytes (TILs)

Neoepitopes are highly tumor-specific!





DNA and RNA sequencing identifies tumor specific somatic mutations



Hands On Part 2.1

- Identify mutated sites in the provided p53 protein sequences
- Identify sequence regions that contain all 9-mer peptides that are only found in the tumor (that contain a mutation)

Input data from patient:

>P53 HUMAN Cellular tumor antigen p53 - Healthy Tissue

MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMDDLMLSPDDIEQWFTEDPGP DEAPRMPEAAPPVAPAPAAPTPAAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAK SVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHE RCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFRHSVVVPYEPPEVGSDCTTIHYNYMCNS SCMGGMNRRPILTIITLEDSSGNLLGRNSFEVRVCACPGRDRRTEEENLRKKGEPHHELP PGSTKRALPNNTSSSPQPKKKPLDGEYFTLQIRGRERFEMFRELNEALELKDAQAGKEPG GSRAHSSHLKSKKGQSTSRHKKLMFKTEGPDSD

>P53 HUMAN Cellular tumor antigen p53 - Tumor Tissue

MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMLDLMLSPDDIEQWFTEDPGP DEAPWMPEAAPPVAPAPAAPTPAAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAK SVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHE RCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFVHSVVVPYEPPEVGSDCTTIHYNYMCNS SCMGGMNRRPILTITTEV

Mutated sites

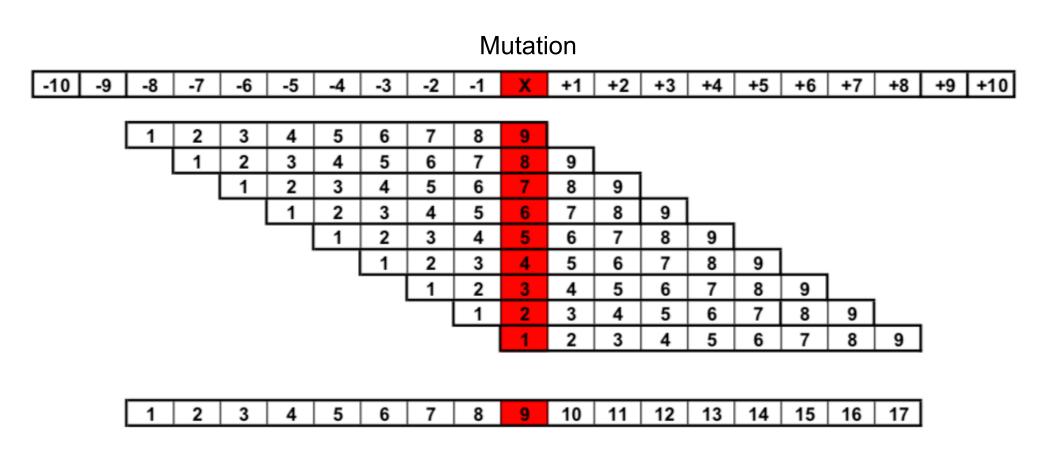
>P53 HUMAN Cellular tumor antigen p53 - Healthy Tissue

MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMDDLMLSPDDIEQWFTEDPGP DEAPRMPEAAPPVAPAPAAPTPAAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAK SVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHE RCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFRHSVVVPYEPPEVGSDCTTIHYNYMCNS SCMGGMNRRPILTIITLEDSSGNLLGRNSFEVRVCACPGRDRRTEEENLRKKGEPHHELP PGSTKRALPNNTSSSPQPKKKPLDGEYFTLQIRGRERFEMFRELNEALELKDAQAGKEPG GSRAHSSHLKSKKGQSTSRHKKLMFKTEGPDSD

>P53 HUMAN Cellular tumor antigen p53 - Tumor Tissue

MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMLDLMLSPDDIEQWFTEDPGP
DEAPWMPEAAPPVAPAPAPAPAPAPAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAK
SVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHE
RCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFVHSVVVPYEPPEVGSDCTTIHYNYMCNS
SCMGGMNRRPILTITTLEV

How long do the sequence regions that contain all 9-mer peptides with the mutation need to be?



→ 17-mer peptide will cover all 9-mers that contain the mutation

Mutated regions

>P53 HUMAN Cellular tumor antigen p53 - Healthy Tissue

MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMDDLMLSPDDIEQWFTEDPGP DEAPRMPEAAPPVAPAPAAPTPAAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAK SVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHE RCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFRHSVVVPYEPPEVGSDCTTIHYNYMCNS SCMGGMNRRPILTIITLEDSSGNLLGRNSFEVRVCACPGRDRRTEEENLRKKGEPHHELP PGSTKRALPNNTSSSPQPKKKPLDGEYFTLQIRGRERFEMFRELNEALELKDAQAGKEPG GSRAHSSHLKSKKGQSTSRHKKLMFKTEGPDSD

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MEEPQSDPSVEPPLSQETFSDLWKLLPENNVLSPLPSQAMLDLMLSPDDIEQWFTEDPGPDEAPWMPEAAPPVAPAPAPAPAPAPAPAPSWPLSSSVPSQKTYQGSYGFRLGFLHSGTAKSVTCTYSPALNKMFCQLAKTCPVQLWVDSTPPPGTRVRAMAIYKQSQHMTEVVRRCPHHERCSDSDGLAPPQHLIRVEGNLRVEYLDDRNTFVHSVVVPYEPPEVGSDCTTIHYNYMCNSSCMGGMNRRPILTIITLEV

>D41L

SPLPSQAMLD**L**MLSPDD

>R65W

DPGPDEAP**W**MPEAAPPV

>R213V

YLDDRNTF**V**HSVVVPYE

>D259V

ILTIITLEV

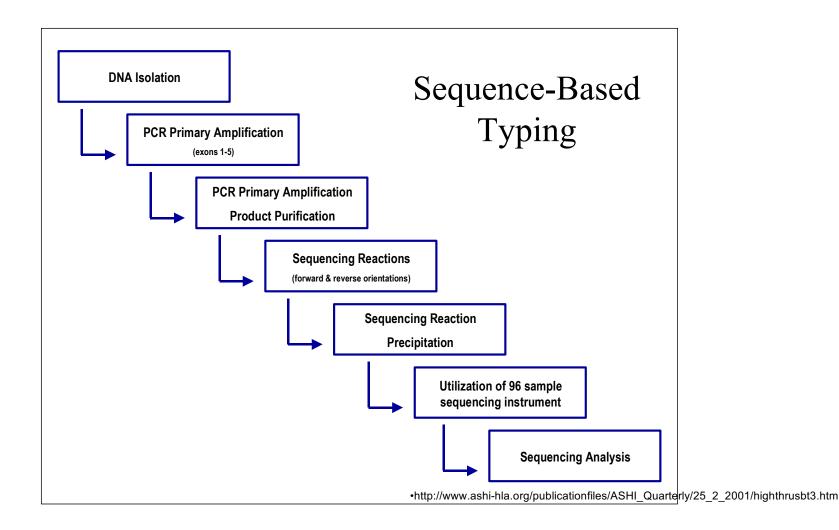
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HLA Typing: Targeted sequencing of HLA locus

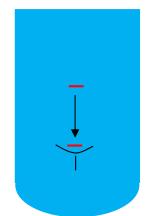


HLA genotype of patient can be determined in the hospital/lab or can also be determined with immunoinformatics tools using the sequencing data

Measuring and predicting MHC:peptide binding

Experimental
Basis: MHC
Binding Assay

List of peptides with allele specific binding affinity



Sequence	IC ₅₀
QIVTMFEAL	3.6
LKGPDIYKG	308
NFCNLTSAF	50,000
AQSQCRTFR	38,000
CTYAGPFGM	143
CFGNTAVAK	50,000

 $log(IC_{50}) \sim Binding free Energy$

low $IC_{50} \rightarrow high affinity$

Impossible to measure all peptides

→ Predict binding peptides using machine learning

Find function F_i in F_1 , F_2 , F_3 , ... F_i (Sequence) \approx Affinity

Many different approaches (ANN, SVM, HMM, LP, ...)

TD 11	ORF 1	MGQIVTMFEALPHI <mark>IDE</mark> V <mark>INIVI</mark> IVLIVITGIKAVYN
T cell	ORF 2	MGLKGPDIYKGVYQFKSVEFDMSHLNLTMPNACSANN
	ORF 3	MHNFCNLTSAFNKKTFDHTLMSIVSSLHLSIDGNSNY
epitope	ORF 4	M S A Q S Q C R T F R G R V L D M F R T A F G G K Y M R S G W G W T G S D
manning	ORF 5	MHCTYAGPFGMSRILLSQEKTKFFTRRLAGTFTWTLS
mapping	ORF 6	MKCFGNTAVAKCNVNHDAEFCDMLRLIDYNKAALSKF
	ORF 7	MLMRNHL <mark>LDLMGVPYCNY</mark> SKFWYLEHAKTGETSVPKC

Calculate scoring matrix from affinities

Machine learning PSSM = Minimize the difference between predicted and measured binding affinities by varying the matrix values

N peptides with
measured binding
affinities

log (IC50)	Peptide				
0.50	FQPQNGSFI				
0.72	ISVANKIYM				
2.37	RVYEALYYV				
3.42	FQPQSGQFI				
3.46	LYEKVKSQL				
4.07	FKSVEFDMS				
4.18	FQPQNGQFH				
4.24	VLMLPVWFL				
4.39	YMTLGQVVF				
4.40	EDVKNAVGV				
4.90	VFYEQMKRF				



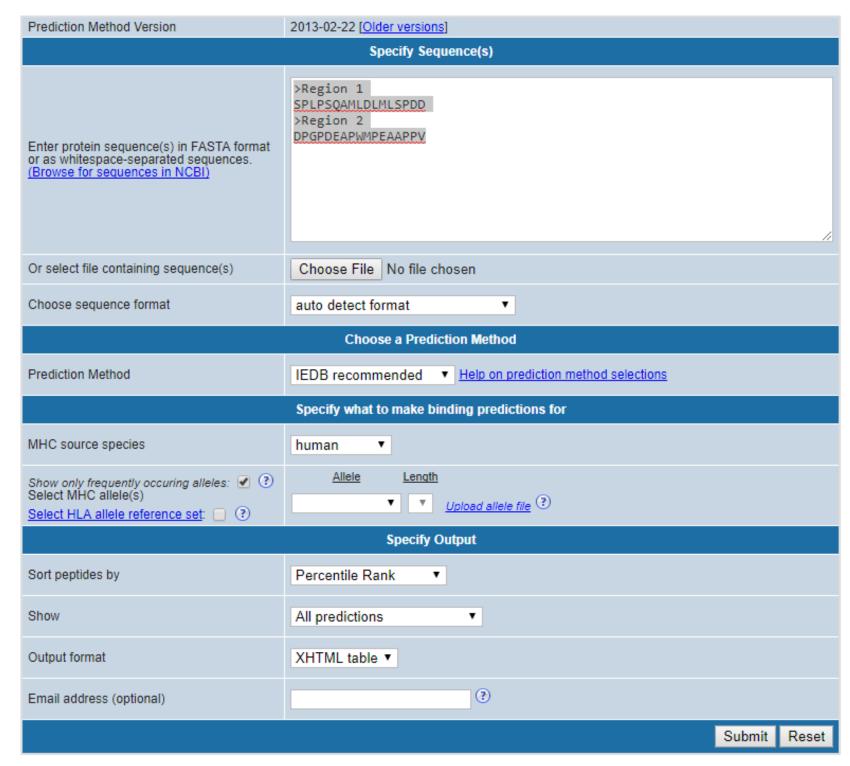
	HLA A*0201								
	1	2	3	4	5	6	7	8	9
Α	-0.3	8.0	-0.3	-0.3	-0.2	-0.3	0.0	0.0	-0.9
С	0.2	0.9	0.0	0.3	-0.5	-0.1	0.1	0.2	0.4
D	8.0	0.9	-0.4	-0.3	0.3	0.2	0.4	0.3	0.6
E,	0.6	-0.4	0.7	-0.2	0.1	-0.4	-0.2	-0.2	-0.5
F	-1.3	0.5	-0.5	0.1	-0.1	0.0	-0.3	-0.4	-0.8
G	-0.2	0.1	0.3	-0.1	0.0	0.4	0.3	-0.1	0.2
Н	1.1	0.9	-0.1	0.4	0.1	0.2	0.0	0.2	0.8
I	-0.4	-0.7	-0.4	0.1	-0.1	-0.4	-0.5	0.5	-1.4
K	-0.3	0.0	1.1	0.1	0.1	0.6	0.9	0.2	0.9
L	0.0	-1.9	-0.4	-0.2	0.0	-0.2	0.0	-0.1	-1.1
M	-0.7	-1.2	-0.7	0.2	-0.6	0.0	0.0	0.0	-0.8
N	-0.1	0.3	0.1	-0.3	-0.1	-0.3	0.0	0.2	0.7
Р	1.2	0.5	0.6	-0.3	0.4	0.0	-0.4	-0.5	0.7
Q	0.4	-1.1	0.0	-0.1	0.4	-0.2	-0.3	0.2	0.7
R	-0.2	0.9	1.0	0.3	0.1	0.4	0.7	0.0	0.9
S	-0.3	0.1	0.1	-0.4	0.1	0.3	-0.2	-0.1	0.2
Т	-0.2	-0.5	0.1	0.4	0.1	-0.5	0.2	0.0	-0.1
V	-0.1	-0.9	-0.1	0.2	0.0	-0.3	0.1	0.1	-1.9
W	0.0	0.7	-0.5	-0.2	-0.1	0.2	-0.3	-0.1	0.4
Υ	-0.3	0 <u>.2</u>	<u>-0.</u> 6	0.2	0.0	0.4	-0.4	-0.3	8.0
O	Offset: 4.3								

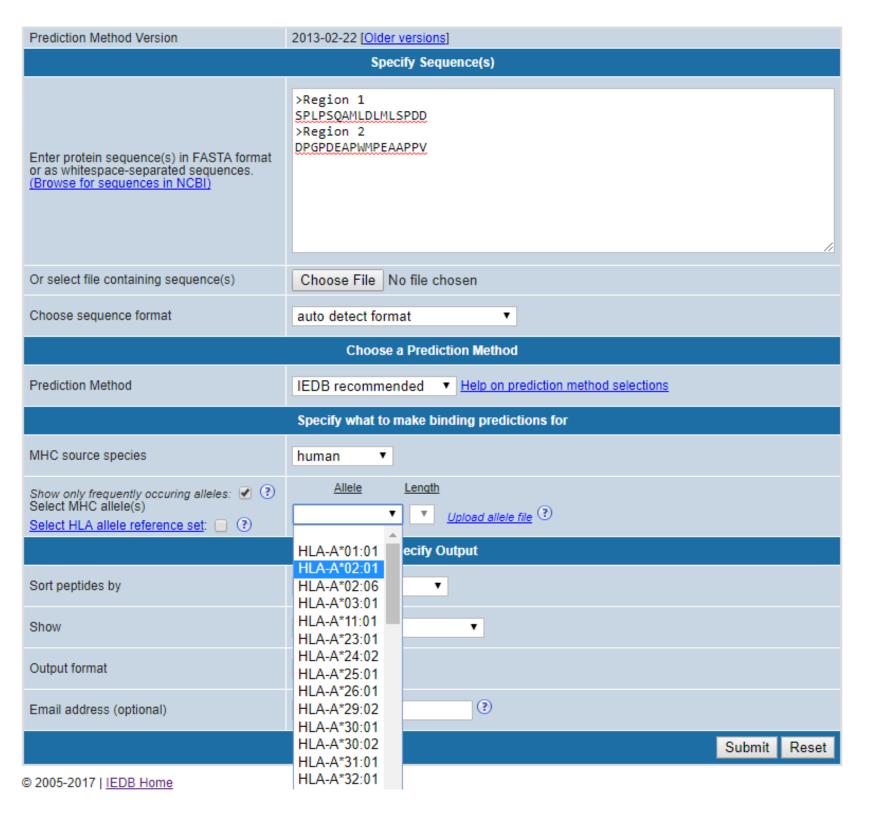
Predictions available as webserver

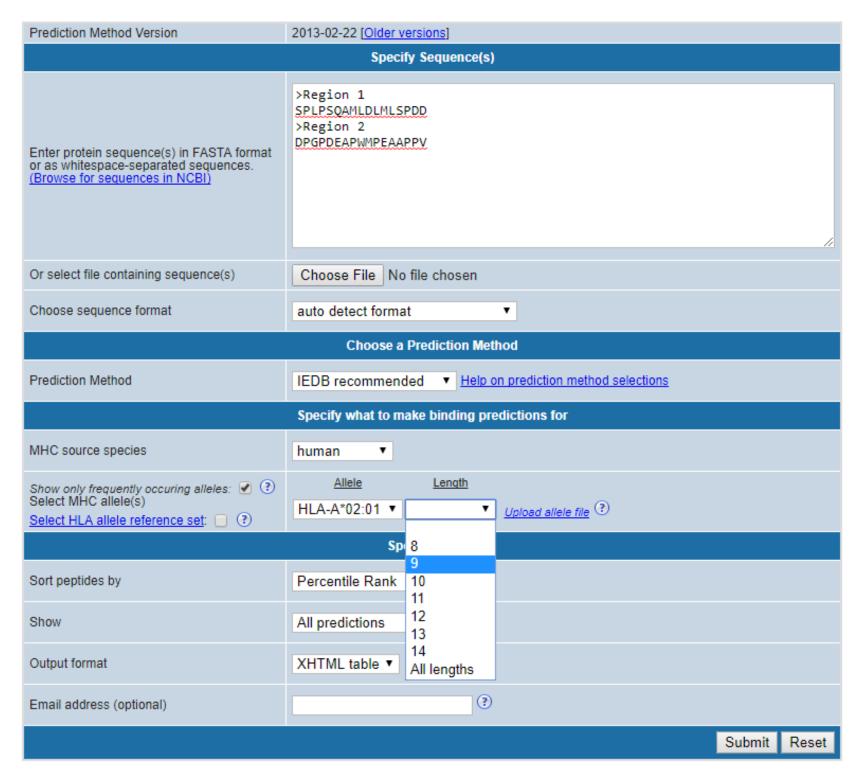
- Immune Epitope Database (IEDB) Analysis resource
- http://tools.iedb.org/mhci/

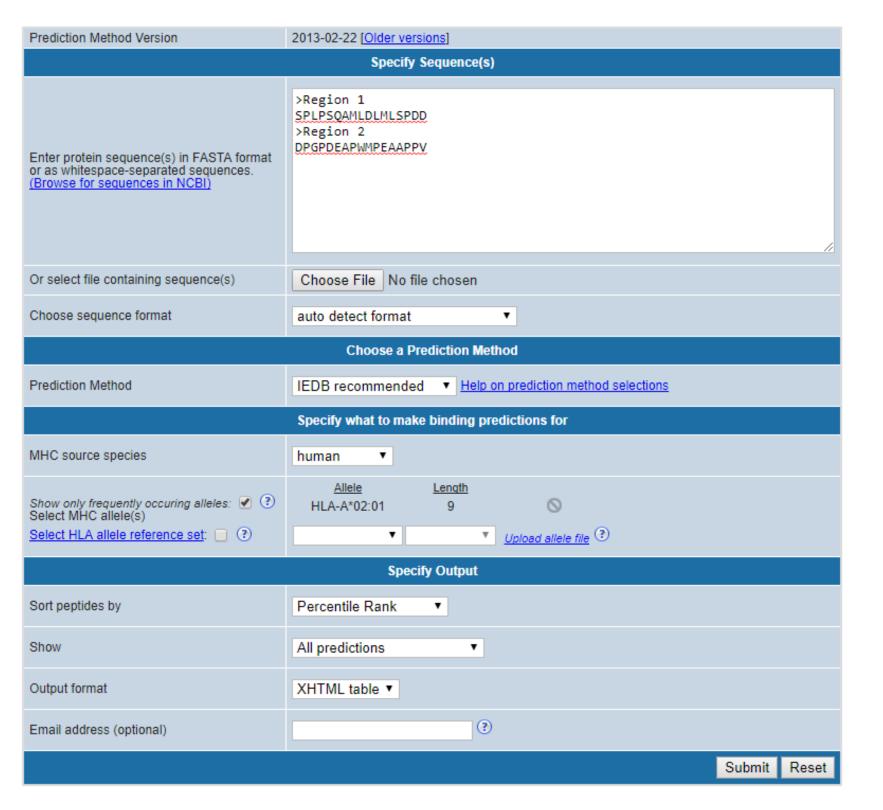
MHC-I Binding Predictions

Prediction Method Version	2013-02-22 [Older versions]
	Specify Sequence(s)
Enter protein sequence(s) in FASTA format or as whitespace-separated sequences. (Browse for sequences in NCBI)	
Or select file containing sequence(s)	Choose File No file chosen
Choose sequence format	auto detect format ▼
	Choose a Prediction Method
Prediction Method	IEDB recommended ▼ Help on prediction method selections
	Specify what to make binding predictions for
MHC source species	human ▼
Show only frequently occuring alleles: Select MHC allele(s) Select HLA allele reference set: ?	Allele Length ▼ Upload allele file ?
	Specify Output
Sort peptides by	Percentile Rank ▼
Show	All predictions ▼
Output format	XHTML table ▼
Email address (optional)	· · · · · · · · · · · · · · · · · · ·
	Submit Reset









Example Reference Contact Home Help Download

MHC-I Binding Predictions



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Supported by a contract from the National Institute of Allergy and Infectious Diseases, a component of the National Institutes of Health in the Department of Health and Human Sen

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MHC-I Binding Prediction Results

Input Sequences

#	Name	Sequence
1	Reg 1	SPLPSQAMLDLMLSPDD
2	Reg 2	DPGPDEAPWMPEAAPPV

Prediction method: IEDB recommended | Low percentile_rank = good binders

Download result

Citations

Check to expand the result: -

#\$	Start \$	End 💠	Length 🔷	Peptide 💠	Method used ♦	Percentile_rank ▼
2	9	17	9	WMPEAAPPV	Consensus (ann/comblib_sidney2008/smm)	0.4
1	8	16	9	MLDLMLSPD	Consensus (ann/comblib_sidney2008/smm)	2.9
1	7	15	9	AMLDLMLSP	Consensus (ann/comblib_sidney2008/smm)	4.0
1	5	13	9	SQAMLDLML	Consensus (ann/comblib_sidney2008/smm)	7.7
1	6	14	9	QAMLDLMLS	Consensus (ann/comblib_sidney2008/smm)	26.0
2	5	13	9	DEAPWMPEA	Consensus (ann/comblib_sidney2008/smm)	32.0
1	1	9	9	SPLPSQAML	Consensus (ann/comblib_sidney2008/smm)	33.0
1	3	11	9	LPSQAMLDL	Consensus (ann/comblib_sidney2008/smm)	39.0
1	4	12	9	PSQAMLDLM	Consensus (ann/comblib_sidney2008/smm)	43.0
	2 1 1 1	2 9 1 8 1 7 1 5 1 6 2 5 1 1 1 3	2 9 17 1 8 16 1 7 15 1 5 13 1 6 14 2 5 13 1 1 9 1 3 11	2 9 17 9 1 8 16 9 1 7 15 9 1 5 13 9 1 6 14 9 2 5 13 9 1 1 9 9 1 3 11 9	2 9 17 9 WMPEAAPPV 1 8 16 9 MLDLMLSPD 1 7 15 9 AMLDLMLSP 1 5 13 9 SQAMLDLML 1 6 14 9 QAMLDLMLS 2 5 13 9 DEAPWMPEA 1 1 9 9 SPLPSQAML 1 3 11 9 LPSQAMLDL	2 9 17 9 WMPEAAPPV Consensus (ann/comblib_sidney2008/smm) 1 8 16 9 MLDLMLSPD Consensus (ann/comblib_sidney2008/smm) 1 7 15 9 AMLDLMLSP Consensus (ann/comblib_sidney2008/smm) 1 5 13 9 SQAMLDLML Consensus (ann/comblib_sidney2008/smm) 1 6 14 9 QAMLDLMLS Consensus (ann/comblib_sidney2008/smm) 2 5 13 9 DEAPWMPEA Consensus (ann/comblib_sidney2008/smm) 1 1 9 9 SPLPSQAML Consensus (ann/comblib_sidney2008/smm) 1 3 11 9 LPSQAMLDL Consensus (ann/comblib_sidney2008/smm)

Evaluating binding predictions

- Percentile rank < 0.5% = high affinity binder
- Percentile rank 0.5%-1% = intermediate binder
- Percentile rank 1% 2% = low affinity binder
- Percentile rank 2% 5% = borderline
- Percentile rank >5% is a non-binder

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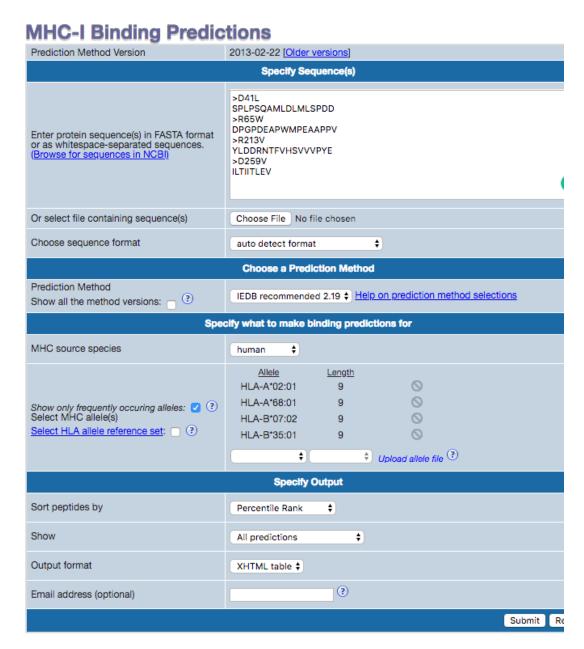
Hands on: Design a personalized cancer vaccine

Hands On Part 2.2

- Step 1: Identify sequence regions that contain all 9mer peptides that are only found in the tumor
- Step 2: Run HLA binding prediction to identify 9-mer peptides in the sequence regions unique to the tumor to select peptides that can be presented to T cells in this patient
 - Step 3: Determine if the identified peptides are specific for the tumor
 - Final question: Which peptide would you choose?

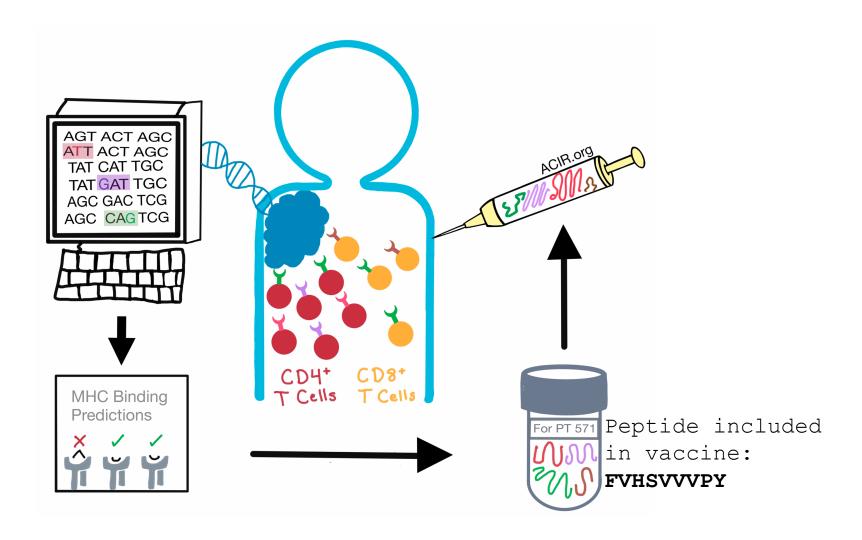
HLA binding Prediction on IEDB

Peptides: >D41L SPLPSQAMLDLMLSPDD HLA-A*68:01 >R65W DPGPDEAPWMPEAAPPV HLA-B*35:01 >R213V YLDDRNTFVHSVVVPYE >D259V HLA-B*35:01



ILTITLEV

Personalized Vaccines for Cancer Immunotherapy



Contact & Feedback

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Feedback link < https://goo.gl/forms/jfrqJHVq0SzCF4JC3 >