

Machine learning in immunology

Prediction of binding affinity of peptide-MHC

Vadim Nazarov

Genomics of Adaptive Immunity Lab, IBCH RAS
National Research University Higher School of Economics

Table of contents

1. Introduction to immunology
2. Introduction to deep learning
3. MHC:peptide binding affinity prediction
4. Conclusion

Introduction to immunology

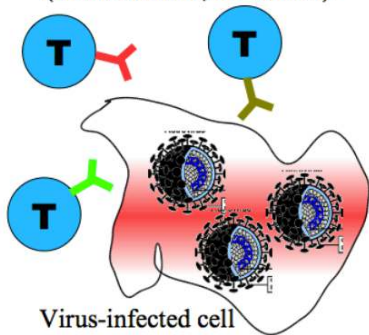
- Recognizes foreign / dangerous substances from the environment (mainly microbes).
- Is involved in elimination of old and damaged cells of the body.
- Attacks tumor and virus-infected cells.

Two branches of immune system

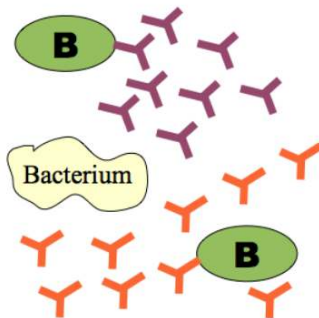
- Innate, nonspecific – very quickly recognizes most foreign substances and eliminates them. No memory or learning.
- Adaptive, specific – high degree of specificity in distinction between self and non-self. The reaction takes several days to be effectively triggered. It learns and memorizes the pathogen landscape.

Adaptive immune system

T cells destroy infected cells
to eradicate intracellular pathogens.
(Some bacteria, all viruses)



B cells secrete antibodies
to attack extracellular pathogens.
(Most bacteria)



The colors of the receptors indicate specificity: each can bind to one specific antigen. Adaptive immunity can only attack targets that it has prepared for.

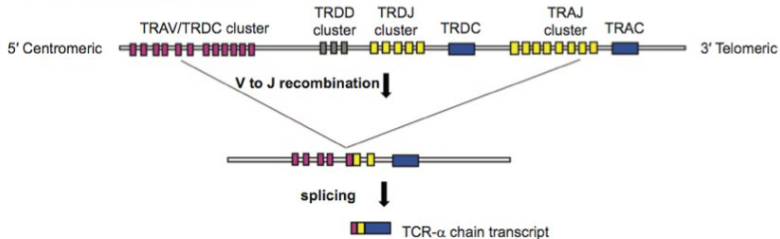
$\alpha\beta$ chain - "classic" adaptive immunity (virus detection)

$\gamma\delta$ chain - terra incognita (phagocytosis, invariant cells)

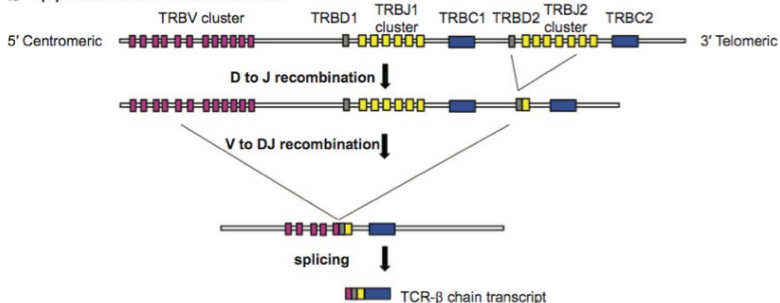
Different generation processes!

V(D)J recombination

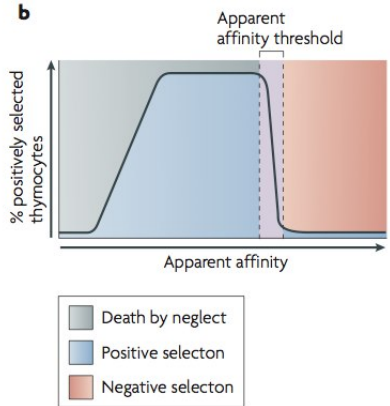
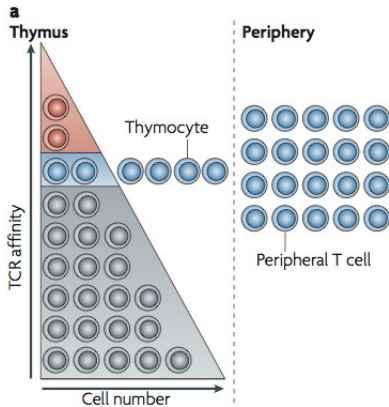
a VJ recombination at the *tra* locus



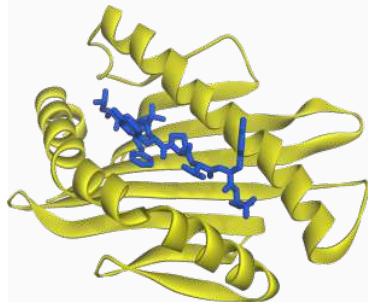
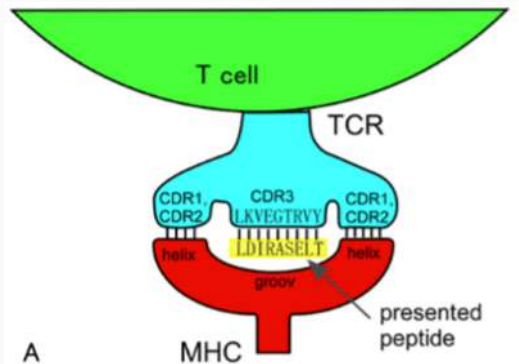
b V(D)J recombination at the *trb* locus



TCR selection



TCR:peptide:MHC interaction



TCR data example

Count	Proportion	CDR3.nucleotide.sequence	CDR3.amino.acid.sequence	V.gene	J.gene
9959.760753	7.416466e-02	TGTGCCAGCAGCCAAGCTCTAGCGGGAGCAGATACGC...	CASSQALAGADTQYF	TRBV4-2	TRBJ2-3
4425.389760	3.295335e-02	TGTGCCAGCAGCTTAGGCCCCAGGAACACCGGGGAGC...	CASSLGRNTGELFF	TRBV13	TRBJ2-2
3890.686845	2.897173e-02	TGTGCCAGCAGTTATGGAGGGGCGGCAGATACGCAGT...	CASSYGGAADTQYF	TRBV12-4, TRBV12-3	TRBJ2-3
221.330500	1.648122e-03	TGCAGTGTGGAGGGATTGAAACCTCTACAATGAGCA...	CSAGGIETSYNEQFF	TRBV20-1	TRBJ2-1
1799.436602	1.339938e-02	TGTGCCAGCTCACCCATCTTAGGGGAGCAGTTCTTC	CASSPILGEQFF	TRBV18	TRBJ2-1
1316.984630	9.806834e-03	TGTGCCAGCAAAAAGACAGGGACTATGGCTACACCTTC	CASKKDRDYGTYF	TRBV6-5	TRBJ1-2
2309.863250	1.720023e-02	TGTGCCAGCAGCCAACAGGGATCTGGAACACCATATA...	CASSQQGSGNTIYF	TRBV7-2	TRBJ1-3
3339.582627	2.486797e-02	TGTGCCAGCAGTTTAGGCTTCACTACGAGCAGTACTTC	CASSLGLHYEQYF	TRBV28	TRBJ2-7

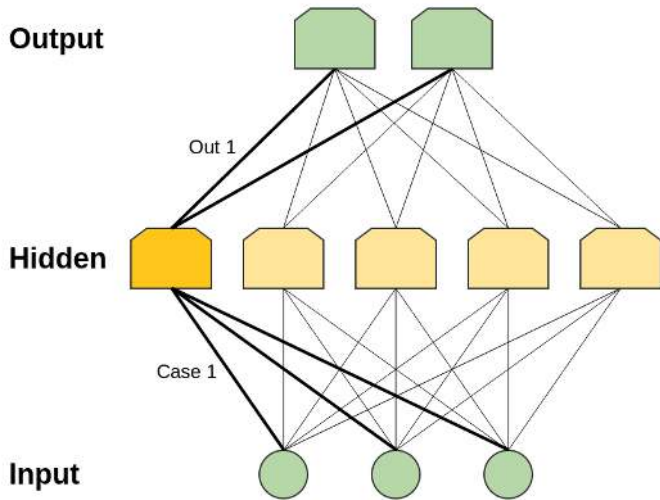
Introduction to deep learning

Fully connected / dense networks (DNN)

Convolutional neural networks (CNN)

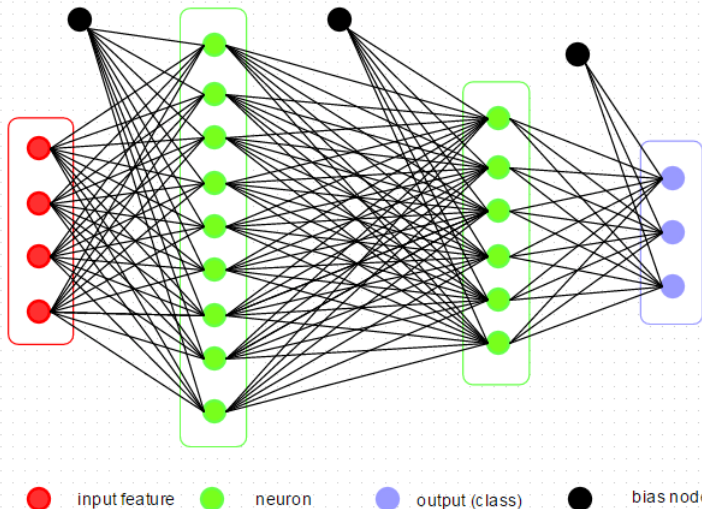
Recurrent neural networks (RNN)

Fully connected networks 1

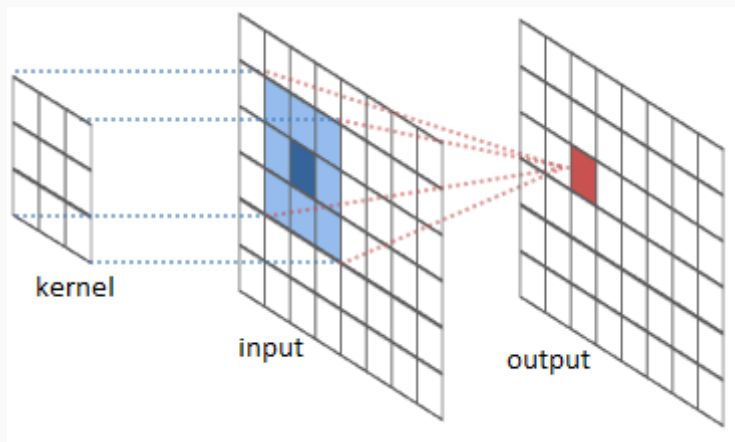


Fully connected networks 2

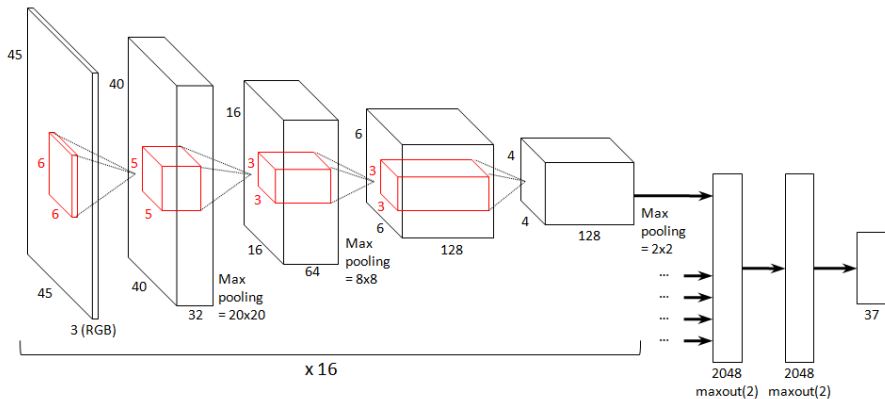
A 3-layers fully connected neural network (DNN)



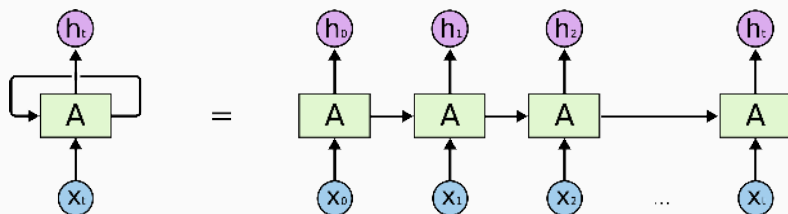
Convolutions



Convolutional neural networks



Recurrent neural networks



MHC:peptide binding affinity prediction

Prediction of strong / weak binders (immunotherapy, etc.)

140,000 pairs of MHC-peptide for training

30,000 pairs of MHC-peptide for testing

species	mhc	peptide_length	cv	sequence	inequality	meas
cow	BoLA-HD6	9	TBD	ALFYKDGKL	=	1.0
cow	BoLA-HD6	9	TBD	ALYEKKLAL	=	1.0
cow	BoLA-HD6	9	TBD	AMKDRFQPL	=	4.52170583277
cow	BoLA-HD6	9	TBD	AQRELFRTL	=	1.0
cow	BoLA-HD6	9	TBD	FMKVKFEAL	=	1.57674703262
cow	BoLA-HD6	9	TBD	FQHERLGQF	=	1.0
cow	BoLA-HD6	9	TBD	FQRAIMNAM	=	1.0
cow	BoLA-HD6	9	TBD	GQFLSFASL	=	1.0
cow	BoLA-HD6	9	TBD	GQFNRYAAM	=	1.0

Paper: just google "netMHCpan paper"

Features:

- Onehot encoding
- Blosum encoding
- Lengths
- Indels

Pseudo-sequences – pan-allele approach

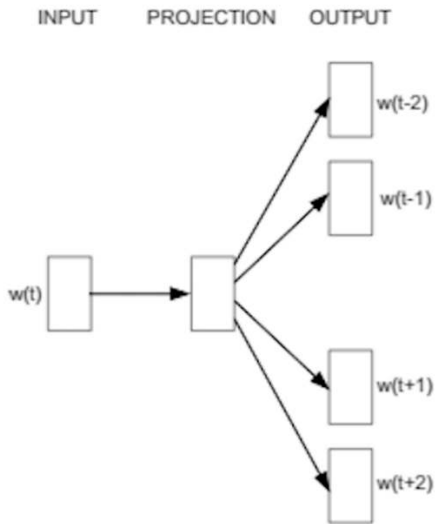
Model: DNN with 60 hidden neurons

F1 score - 0.8

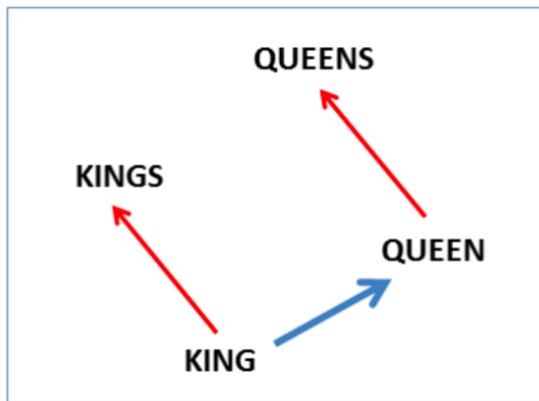
$$F1 = 2 * precision * recall / (precision + recall)$$

$$precision = TP / (TP + FP)$$

$$recall = TP / (TP + FN)$$

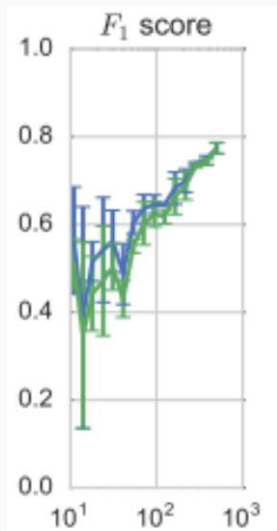


Skip-gram



Imputation

MICE: average multiple imputations generated using Gibbs sampling from the joint distribution of columns.



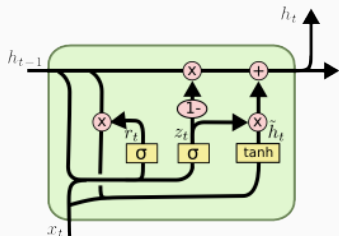
Paper: <http://biorxiv.org/content/biorxiv/early/2016/05/22/054775.full.pdf>

Features:

- Embeddings (per-pseudo-sequence!)

Model: DNN with 60 neurons

F1 score - 0.79



$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Paper:

<http://www.biorxiv.org/content/biorxiv/early/2017/07/27/154757.full.pdf>

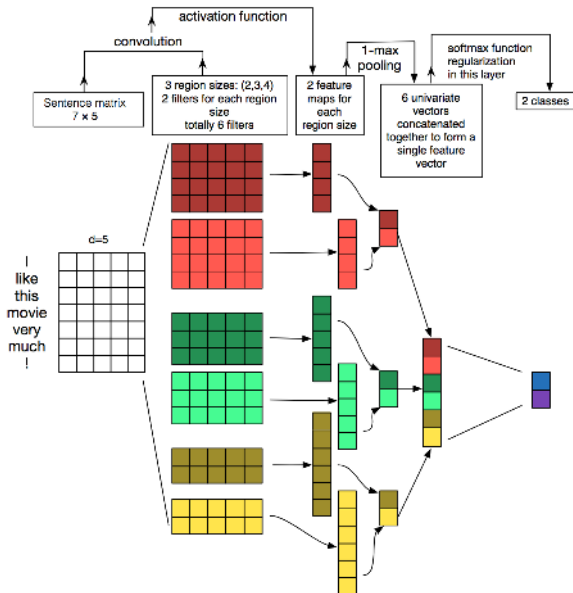
Features:

- One-hot
- Model per-pseudo-sequence (64 units + sigmoid)
- Not even multi-layer or bidirectional!

Model: simple GRU

F1 score - 0.81

CNN for NLP



Paper:

<http://www.biorxiv.org/content/biorxiv/early/2017/07/27/154757.full.pdf>

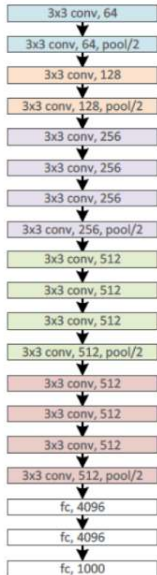
Features:

- Embeddings on the overall data
- Model per-pseudo-sequence (64 units + sigmoid)
- Large convolutions

Model: CNN

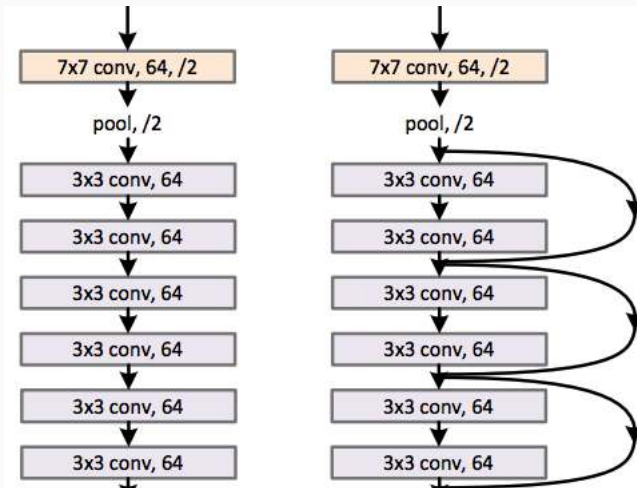
F1 score - 0.75

VGG, 19 layers
(ILSVRC 2014)

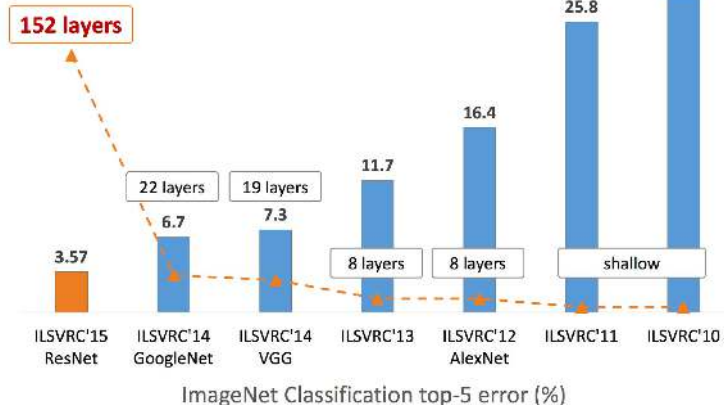


- Gradient vanishing
- Large number of parameters
- Shallowness

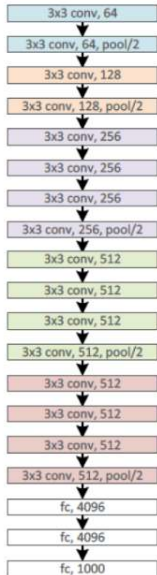
ResNet - proposed model



Revolution of Depth



VGG, 19 layers
(ILSVRC 2014)



ResNet - current deep networks

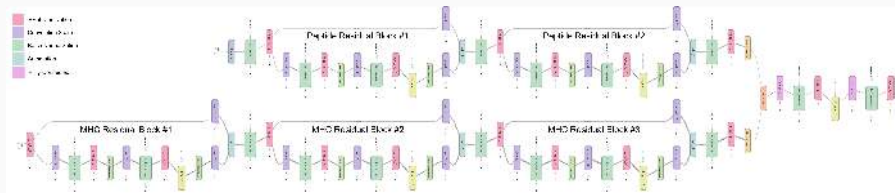
VGG, 19 layers
(ILSVRC 2014)



ResNet, 152 layers
(ILSVRC 2015)



Our approach



Our approach - results

- F1 0.81
- Global models – prediction of binding affinities for unseen MHCs (mean F1 0.72)
- Better models for the per-pseudo-sequence approach.

Conclusion

Vadim I. Nazarov

Genomics of Adaptive Immunity Lab, IBCH RAS
National Research University Higher School of Economics

email: vdm.nazarov@gmail.com

telegram: [@vadimnazarov](https://www.instagram.com/vadimnazarov)