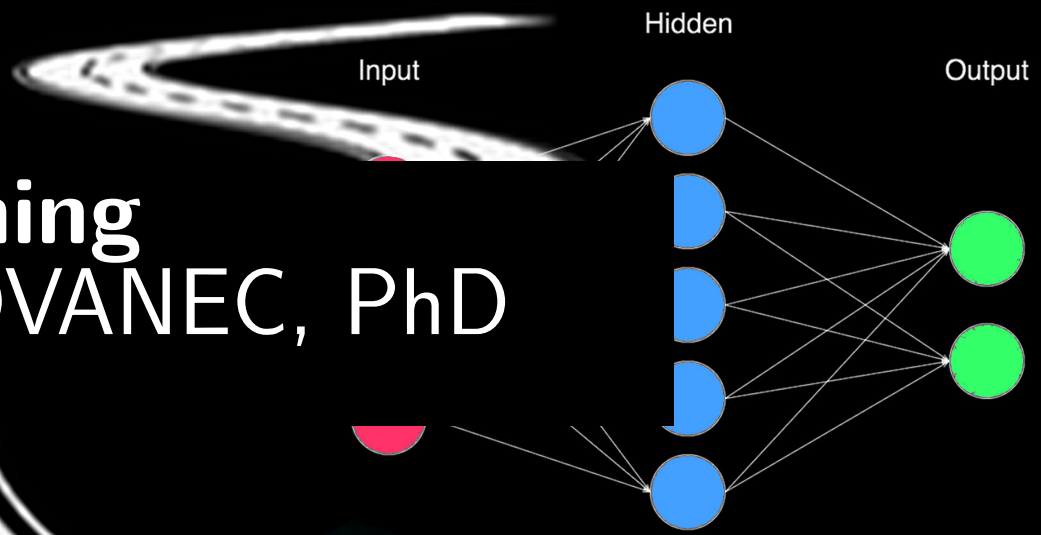
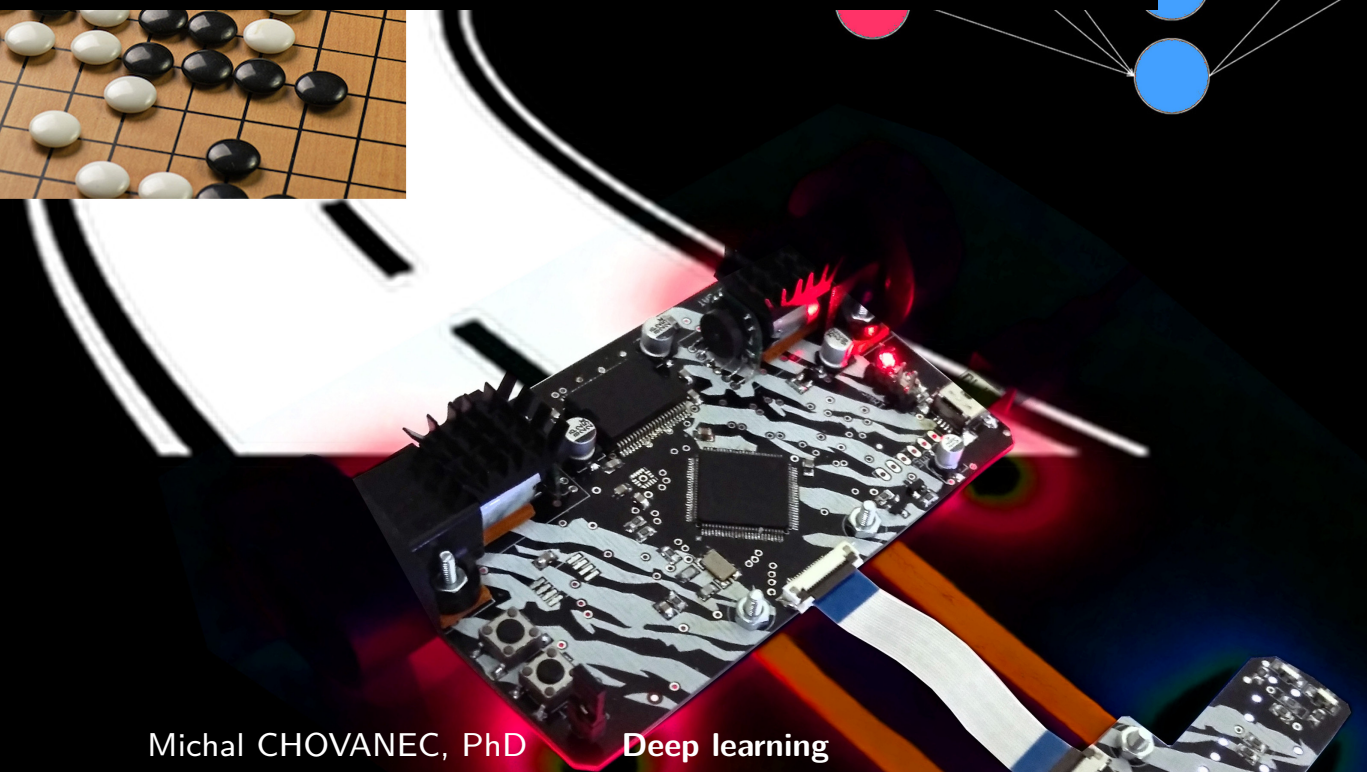
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_{t+1} + \lambda \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right]$$

(The New Action Value = The Old Value) + The Learning Rate × (The New Information − the Old Information)



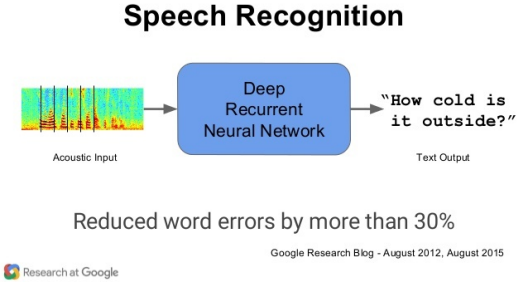
Deep learning

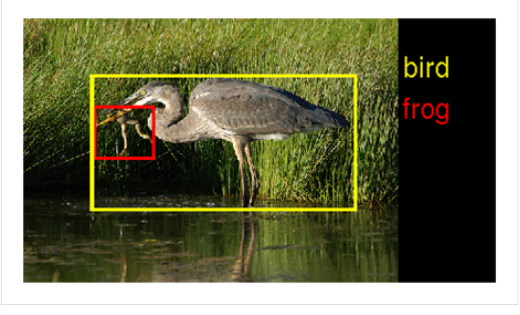
Michal CHOVANEC, PhD

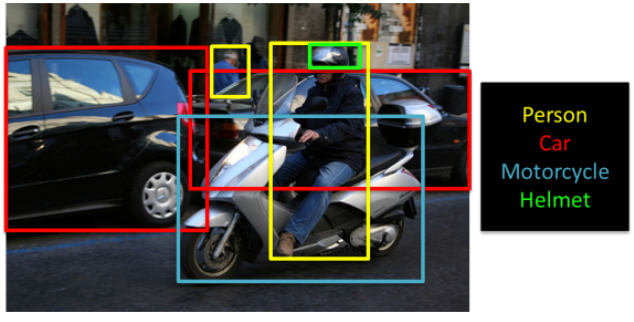


Applications

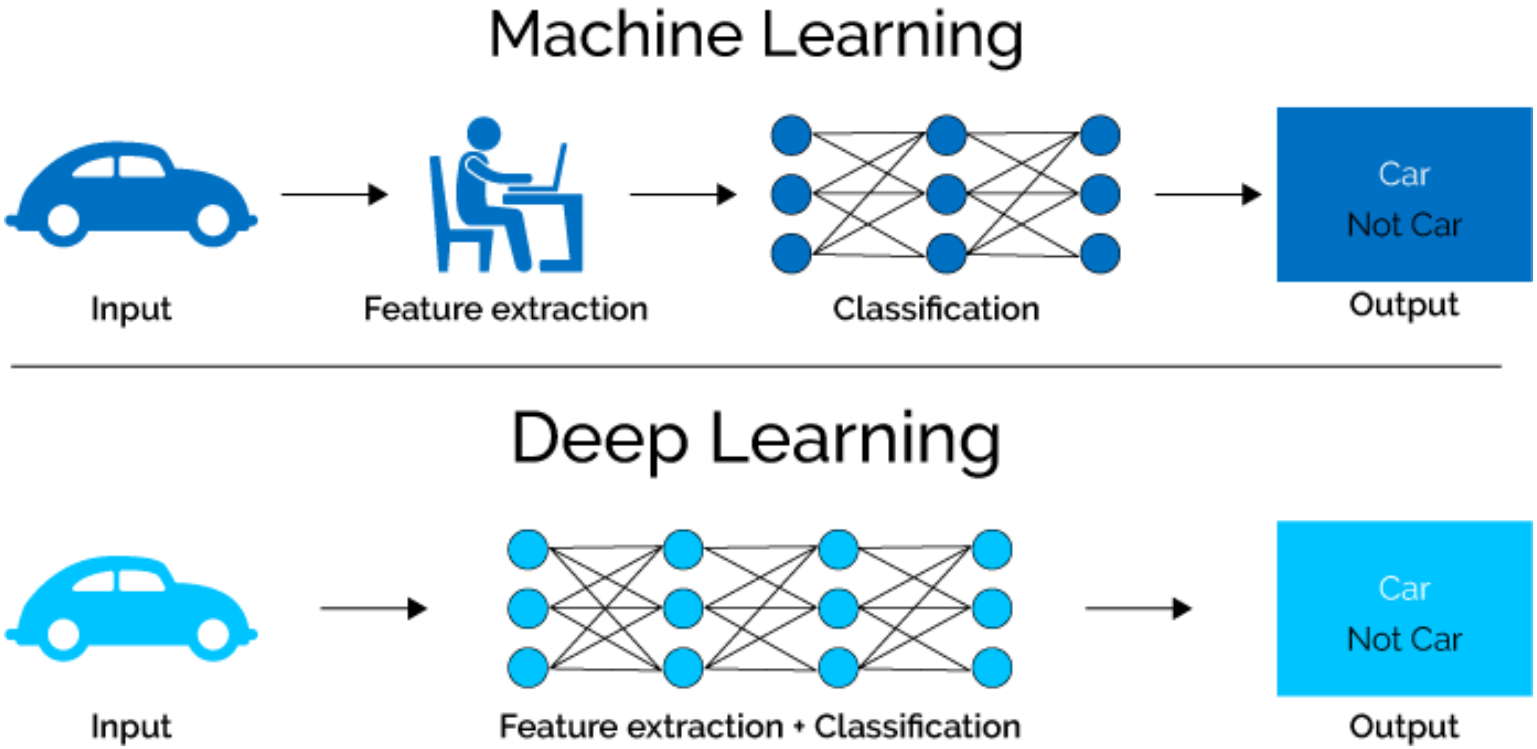
- self driving cars - Tesla model S
- healthcare, biomedical engineering - Cell in fluid
- voice search, control - Google, Amazon Echo
- machine translation - Google translator
- image recognition - Huawei Mate 10
- game bots, robotics - DeepMind, Boston Dynamics







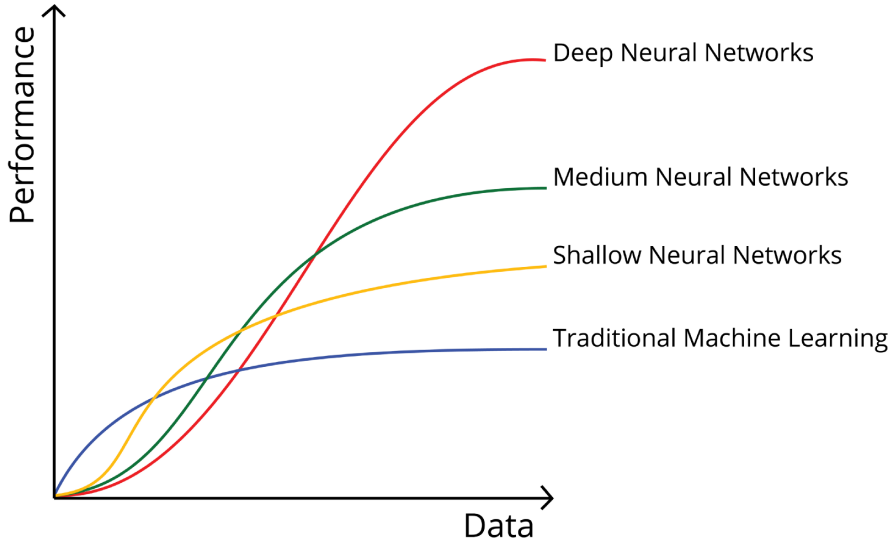
Deep learning [1]



[1] https://medium.com/datamob/clearing-the-buzzwords-in-machine-learning-e395ad73178b

Deep learning

- classification
- object detection
- regression
- unsupervised features extraction
- reinforcement learning



Milestones

- Specters of past
  - vanishing gradient, **solution** : ReLU, Inception, Resnet, DenseNet
  - overfitting, **solution** : L1, L2 regularization, dropout, batch normalisation
  - computation cost, **solution** : NVIDIA Cuda, sharing weights
- ImageNet Classification with Deep ConvolutionalNeural Networks [2]
  - 2012, Alex Krizhevsky, 34887 citations
- Adam
  - 2014, Method for Stochastic Optimization [3]
- AlphaGO, AlphaZero, AlphaStar [4]
  - march 2016, december 2017, januray 2019

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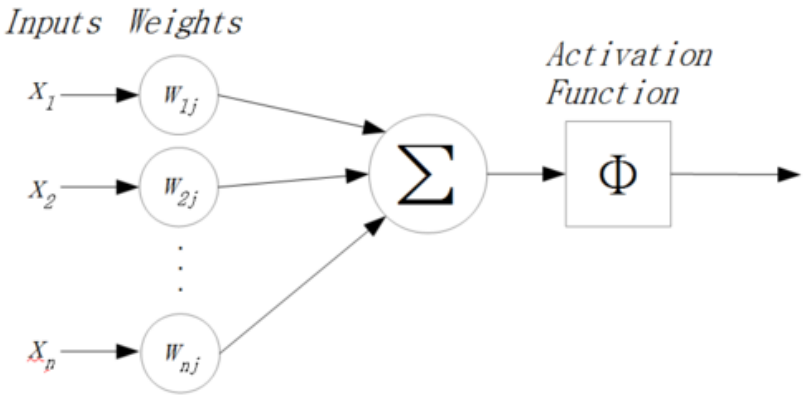
[2] https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

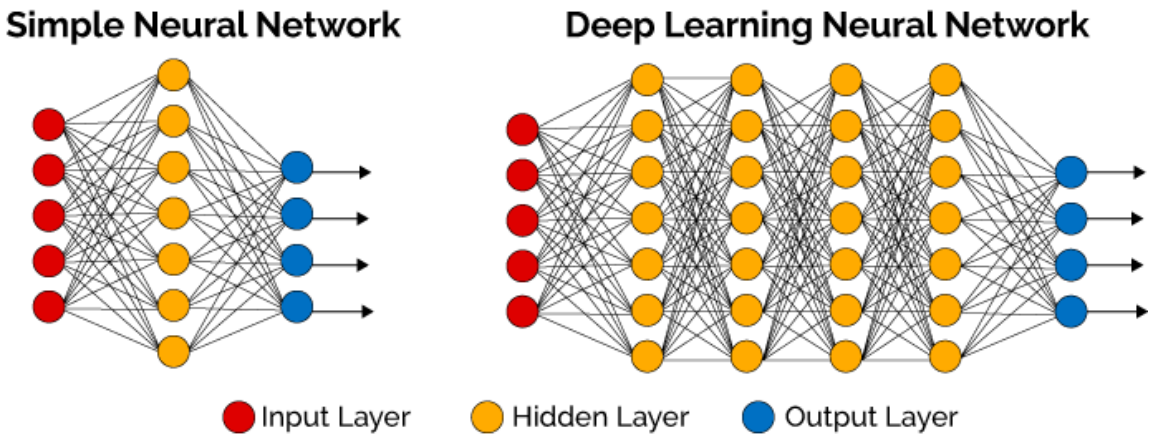
[3] https://arxiv.org/abs/1412.6980

[4] https://deepmind.com/

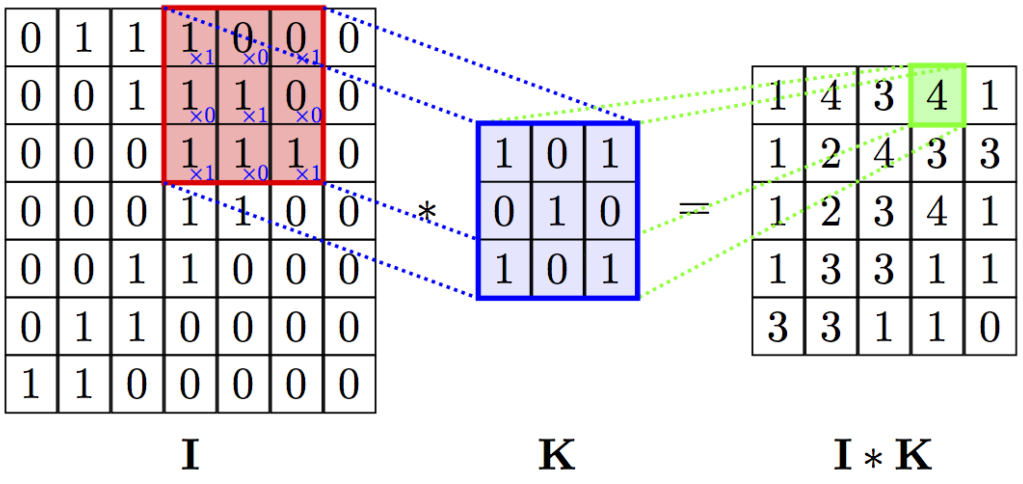
Neural network



$$y(X) = f(\sum_i X_i W_i + b)$$



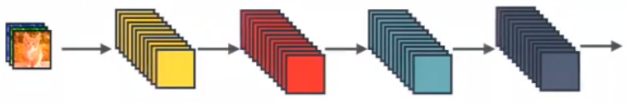
Convolutional layer



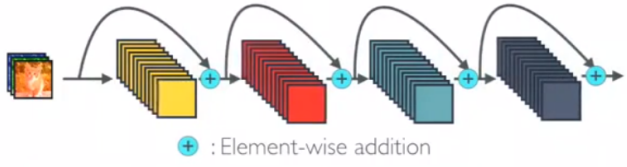
$$Y_{yxl} = \sum_{k}^{in\_depth} \sum_{j}^{kh} \sum_{i}^{kw} X_{k,j+y,i+x} W_{lkji} + b_l$$

Deep neural network

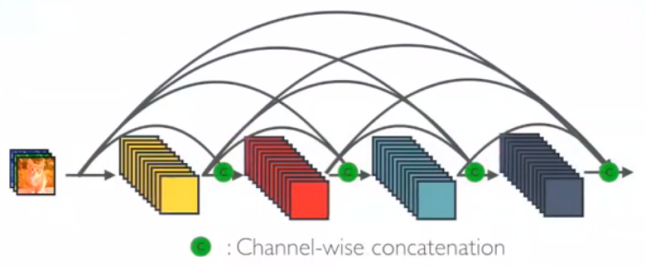
- Old methods (before NN) - 2011, 25.8%
- Convolutional, AlexNet - 2012, 16.4%
- Google inception - 2013, 6.7%
- Microsoft ResNet - 2015, 6.1%
- DenseNet - 2018, 5.17%
- CNN



- ResNET



- DenseNet



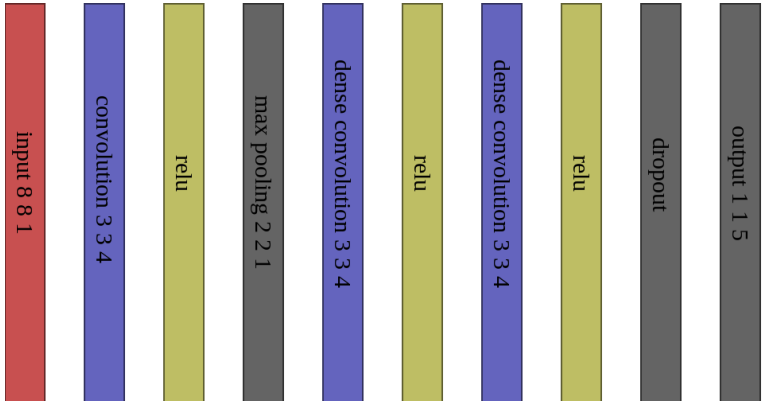
My research

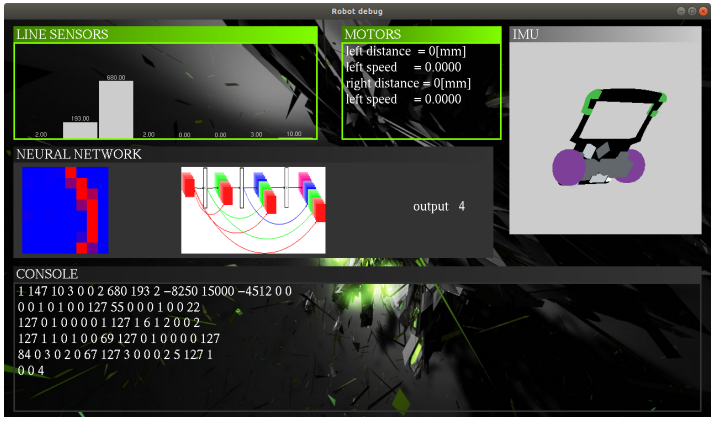
- Robotics - hobby
- Red blood cells trajectory prediction
- Deep reinforcement learning

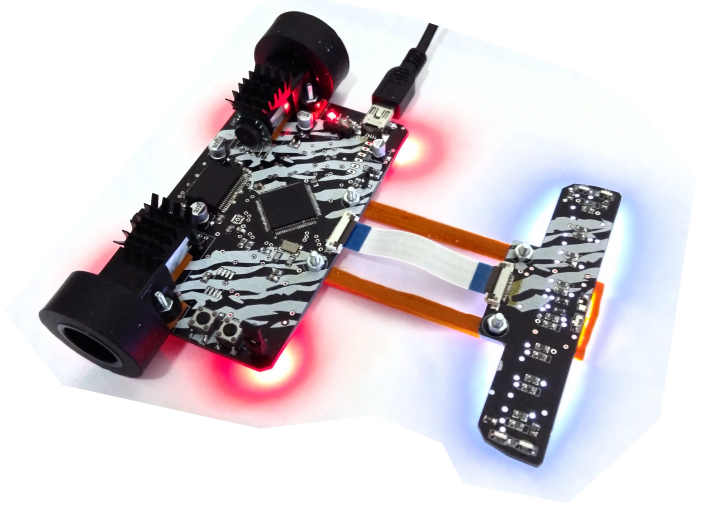
Robotics - line follower

Curve shape classification

- stm32f303 (72MHz), stm32f746 (216MHz)
- 8x 500nm line sensors
- pololu motors, 1:30
- network input : 8 last line sensors results (8x8 matrix)
- response 4..5ms

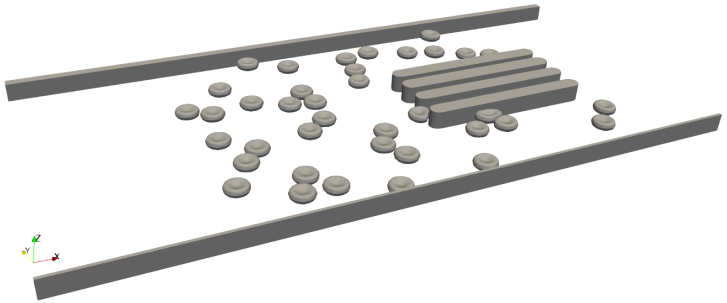


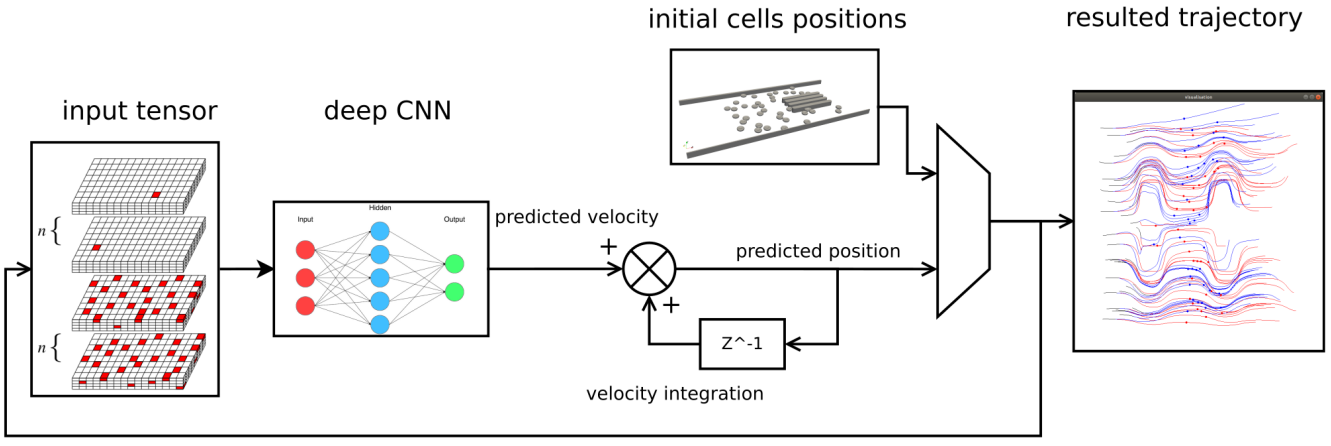




Red blood cells trajectory prediction

- train DNN to predict RBC trajectory from past
- 15 conv layers network (6hours training on GTX1080ti)
- input : RBC position + 7 past frames + other cells position
- output: RBC predicted velocity

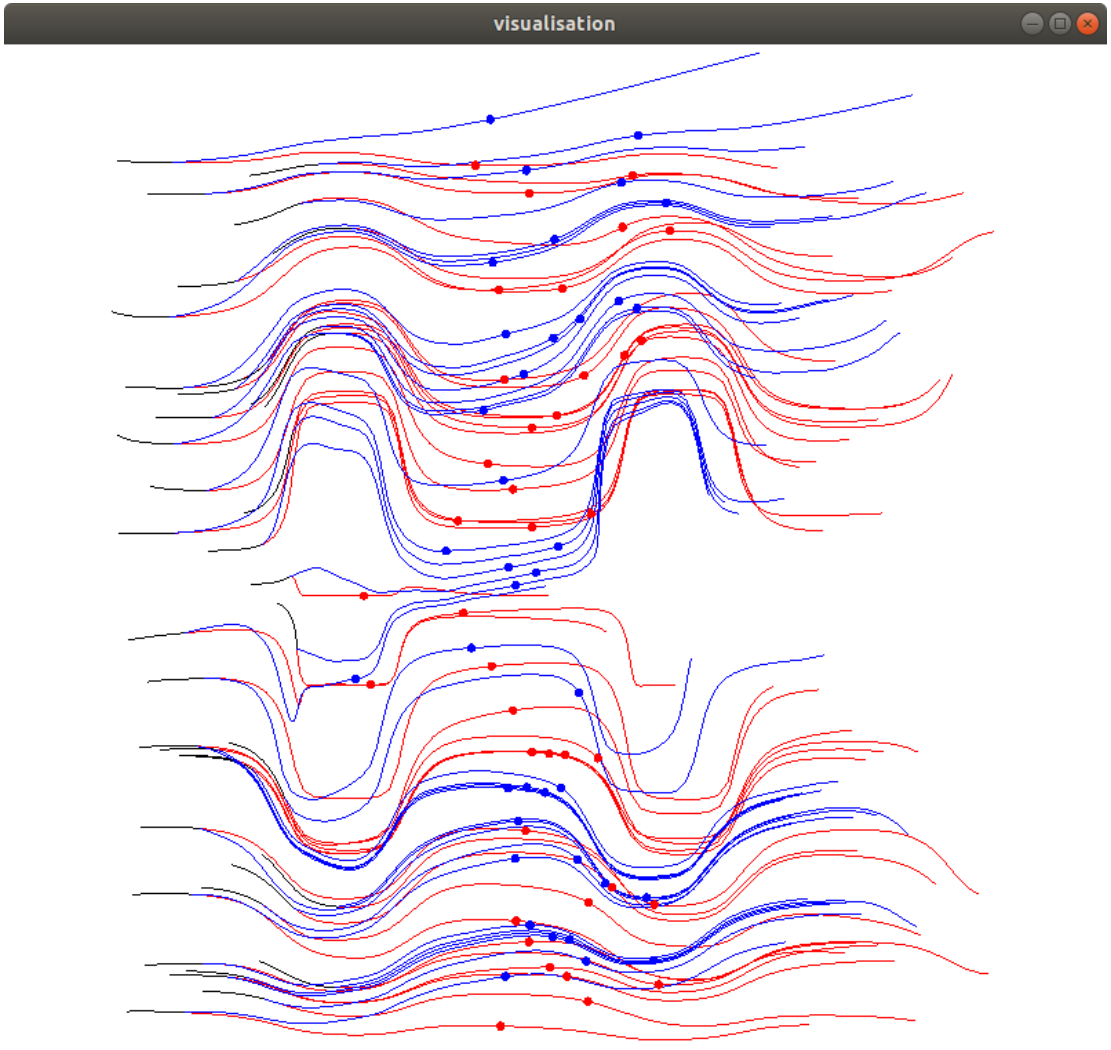




Networks

layer	net 0	net 1	net 2	net 3	net 4	net 5	net 6	net 7
0	fc 256	conv 3x3x32	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
1	fc 64	fc 64	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
2	fc 32	fc 32	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
3	fc 3	fc 3	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
4			conv 1x1x32	conv 1x1x16	conv 1x1x32	conv 1x1x16	conv 1x1x16	conv 1x1x32
5			fc 3	dense conv 3x3x8	fc 3	dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
6				dense conv 3x3x8		dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
7				dense conv 3x3x8		dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
8				dense conv 3x3x8		dense conv 3x3x8	dense conv 3x3x8	dense conv 3x3x8
9				conv 1x1x32		conv 1x1x32	conv 1x1x16	conv 1x1x32
10				fc 3		fc 3	dense conv 3x3x8	dense conv 3x3x8
11							dense conv 3x3x8	dense conv 3x3x8
12							dense conv 3x3x8	dense conv 3x3x8
13							dense conv 3x3x8	dense conv 3x3x8
14							conv 1x1x32	conv 1x1x64
15							fc 3	fc 3

Results



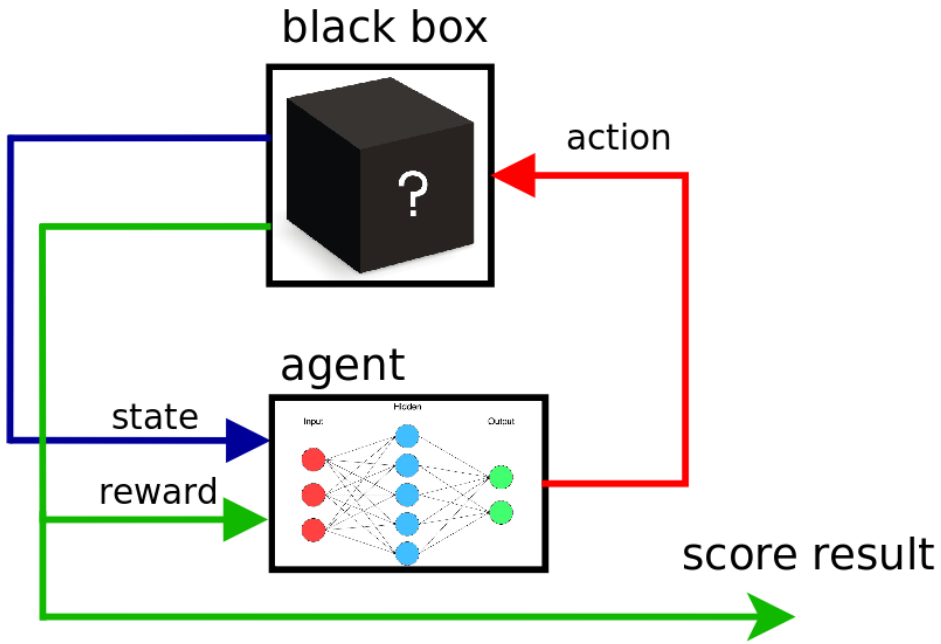
Results

ID	error mean [um]	error sigma [um]	rms [um]	ams [um]	relative_error [%]
0	-8.937	37.229	38.287	14.473	14.681
1	**-33.725**	**205.573**	**208.321**	**41.814**	**42.588**
2	-3.513	22.089	22.367	9.055	12.907
3	-0.292	15.36	15.363	6.942	11.321
4	-1.151	10.928	10.988	3.824	7.701
5	**-0.224**	**10.765**	**10.767**	4.248	7.95
6	-0.777	11.711	11.736	4.156	8.428
7	-1.526	11.373	11.474	**3.735**	**7.556**

Reinforcement learning

- learn from punishment and rewards
- learn to play a game with unknown rules

- obtain **state**
- choose **action**
- **execute** action
- obtain **reward**
- learn from **experiences**

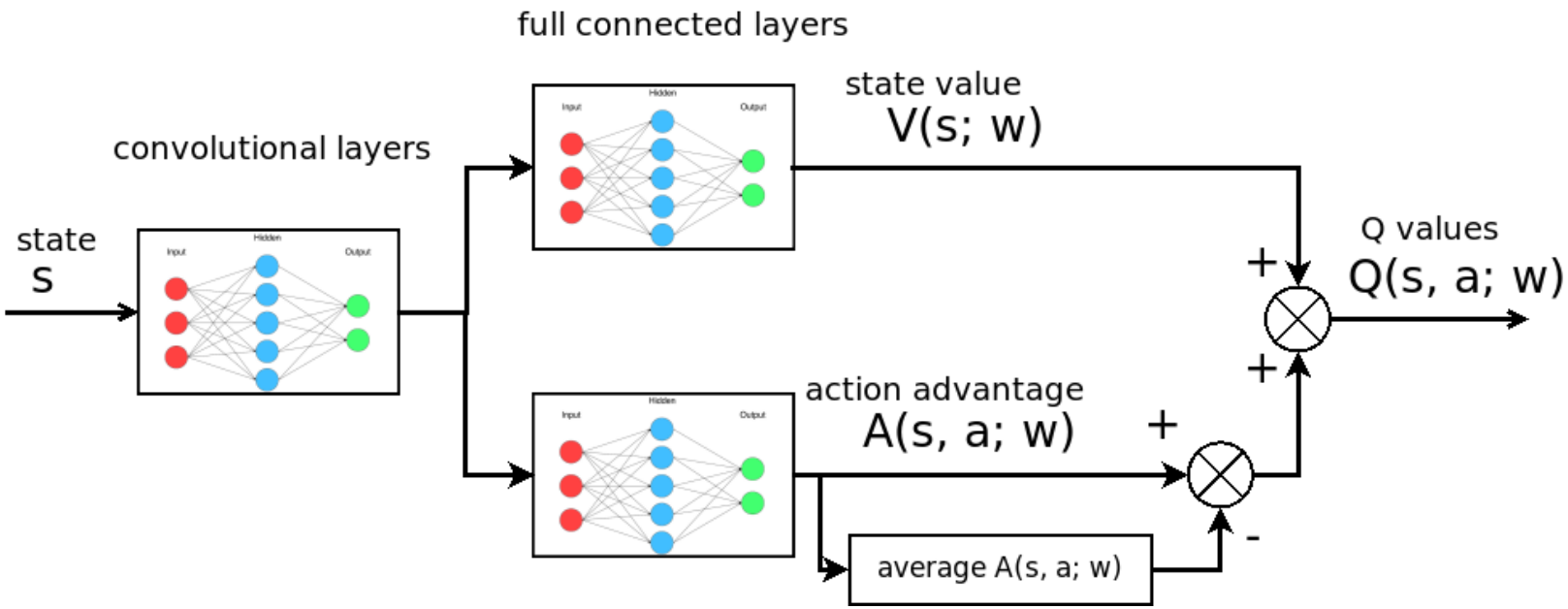


Dueling deep Q network - DDQN (2016)

$$\hat{Q}(s,a;w) = \underbrace{\hat{V}(s;w)}_{\text{value for being in state s}} + \underbrace{\hat{A}(s,a;w)}_{\text{advantage of taking action a at state s}}$$

to avoid identifiability we substract average value of A truth all actions

$$\hat{Q}(s,a;w) = \hat{V}(s;w) + \hat{A}(s,a;w) - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s,\alpha';w)$$



Dueling deep Q network - DDQN

using DQN equation

$$\hat{Q}(s, a; w) = R + \gamma \max_{\alpha'} \hat{Q}(s', \alpha'; w')$$

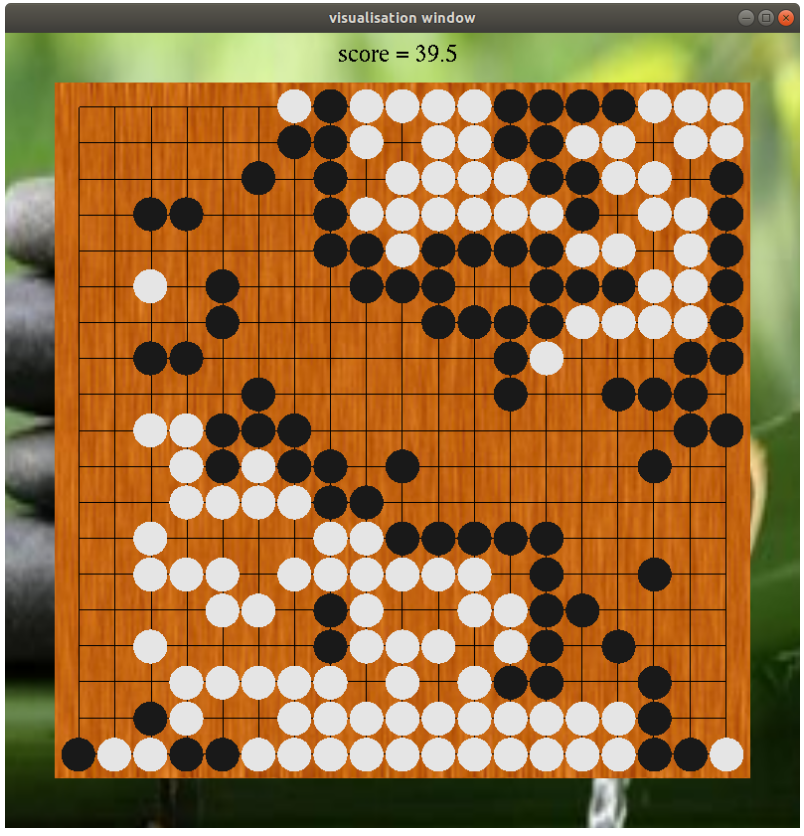
we obtain dueling deep Q network equation

$$\hat{Q}(s, a; w) = R + \gamma \left(\hat{V}(s'; w') + \max_{\alpha'} \hat{A}(s', \alpha'; w') - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s', \alpha'; w') \right)$$

and finally the weights update rule

$$\Delta w = \eta \left(R + \gamma \left(\hat{V}(s'; w') + \max_{\alpha'} \hat{A}(s', \alpha'; w') - \frac{1}{N_{\alpha'}} \sum_{\alpha'} \hat{A}(s', \alpha'; w') \right) - \hat{Q}(s, a; w) \right) \nabla_w \hat{Q}(s, a; w)$$

Playing GO (October 2017)

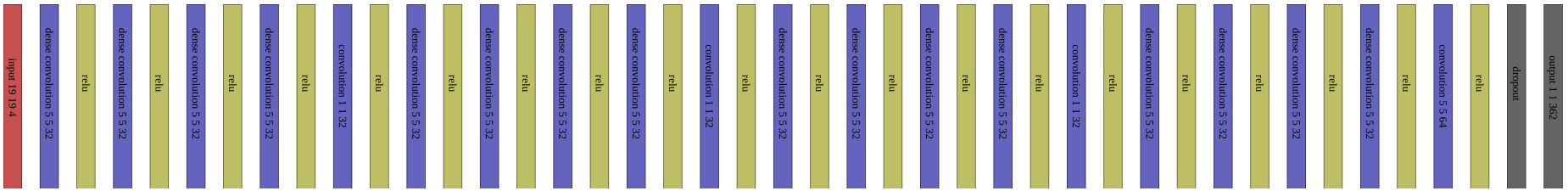


- **supervised training** - train game using Masters games
- **reinforcement learning** - let play two networks against each other

Network architecture

we need to go much deeper for GO

- **28 convolutional layers**
  3 blocks with 8 dense conv + 1 conv layer
- **input**
  4 matrices 19x19: black stones, white stones, empty fields, active player
- **output**
  recommended moves 19x19 + 1 for pass = 362 outputs



Network architecture

layer	net 3	net 5
0	dense conv 5x5x32	dense conv 3x3x32
1	dense conv 5x5x32	dense conv 3x3x32
2	dense conv 5x5x32	dense conv 3x3x32
3	dense conv 5x5x32	dense conv 3x3x32
4	conv 1x1x32	dense conv 3x3x32
5	dense conv 5x5x32	dense conv 3x3x32
6	dense conv 5x5x32	dense conv 3x3x32
7	dense conv 5x5x32	dense conv 3x3x32
8	dense conv 5x5x32	conv 1x1x32
9	conv 1x1x32	dense conv 3x3x32
10	dense conv 5x5x32	dense conv 3x3x32
11	dense conv 5x5x32	dense conv 3x3x32
12	dense conv 5x5x32	dense conv 3x3x32
13	dense conv 5x5x32	dense conv 3x3x32
14	conv 1x1x32	dense conv 3x3x32
15	dense conv 5x5x32	dense conv 3x3x32
16	dense conv 5x5x32	dense conv 3x3x32
17	dense conv 5x5x32	conv 1x1x32
18	dense conv 5x5x32	dense conv 3x3x32
19	conv 5x5x64	dense conv 3x3x32
20	fc 362	dense conv 3x3x32
21		dense conv 3x3x32
22		dense conv 3x3x32
23		dense conv 3x3x32
24		dense conv 3x3x32
25		dense conv 3x3x32
26		conv 1x1x32
27		conv 3x3x64
28		fc 362

Supervised results

74	5	6	6	13	12	26	25	23	19	21	20	19	22	14	12	12	15	82
12	26	43	37	31	35	32	33	35	30	30	35	35	36	31	30	43	26	7
25	39	50	73	42	50	34	35	37	43	34	32	38	50	48	58	48	52	15
15	29	55	82	43	46	41	41	41	31	38	37	38	44	35	55	48	40	16
28	37	62	50	47	43	43	50	51	50	47	46	46	45	44	56	49	48	20
31	34	64	53	44	43	44	48	43	50	46	47	43	44	44	52	54	43	17
35	35	45	43	44	44	48	49	45	45	51	51	44	42	46	49	36	47	21
31	34	46	46	49	45	51	46	50	53	48	48	47	46	50	45	42	49	27
29	33	41	41	48	49	46	50	50	52	47	50	48	46	47	41	46	49	25
27	41	39	34	48	47	48	49	49	54	50	51	48	49	52	35	49	45	29
31	37	42	42	47	49	47	47	49	48	49	50	48	47	47	40	43	45	34
28	39	44	46	45	46	45	49	51	49	51	45	46	43	46	41	44	49	22
29	38	38	45	50	44	48	50	45	43	50	49	51	50	41	49	43	49	20
31	34	73	49	40	41	42	45	42	45	47	47	47	45	48	53	53	49	25
32	30	57	52	44	41	42	44	47	50	51	46	46	43	47	52	49	40	18
24	34	64	77	47	53	41	45	43	30	45	46	41	48	40	61	71	39	8
24	51	56	65	46	58	45	42	41	46	38	35	38	45	63	76	51	52	9
32	26	52	47	44	46	47	39	40	44	43	42	43	37	45	44	46	46	18
77	3	4	3	7	13	13	17	29	34	19	25	20	23	13	9	8	13	66
																		100

Usefull links

CHRISTOPHER J.C.H. WATKINS : Q-learning
http://www.gatsby.ucl.ac.uk/~dayan/papers/cjch.pdf

Richard S. Sutton : Reinforcement Learning: An Introduction
https:
//www.amazon.com/Reinforcement-Learning-Introduction-Adaptive-Computation/dp/0262193981

Google DeepMind : Playing Atari with Deep Reinforcement Learning
https://arxiv.org/pdf/1312.5602.pdf

Google DeepMind : Dueling Network Architectures for Deep Reinforcement Learning
https://arxiv.org/pdf/1511.06581.pdf

Google DeepMind :Mastering the Game of Go without Human Knowledge
https://deepmind.com/documents/119/agz_unformatted_nature.pdf

Andrej Karpathy : Pong from pixels
http://karpathy.github.io/2016/05/31/rl/

Maxim Lapan : Deep reinforcement learning
https://www.amazon.com/Practical-Reinforcement-Learning-Maxim-Lapan/dp/1788834240

Mohit Sewak : Practical Convolutional Neural
Networks
https://www.amazon.com/Practical-Convolutional-Neural-Networks-Implement/dp/1788392302

Densely Connected Convolutional Networks
https://arxiv.org/pdf/1608.06993.pdf

Q&A

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www.youtube.com/channel/UCzVvP2ou8v3afNiVrPAHQGg

github https://github.com/michalnand