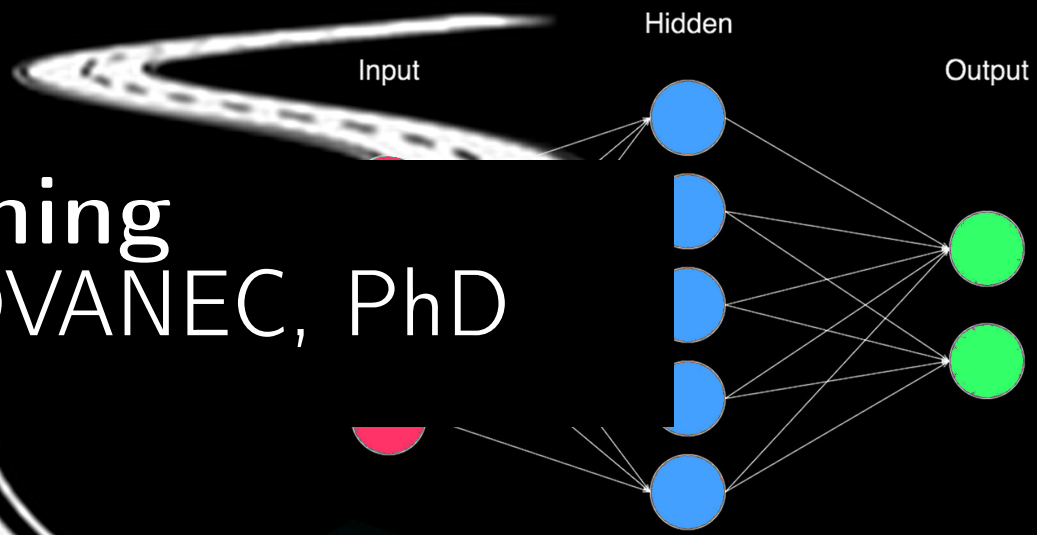
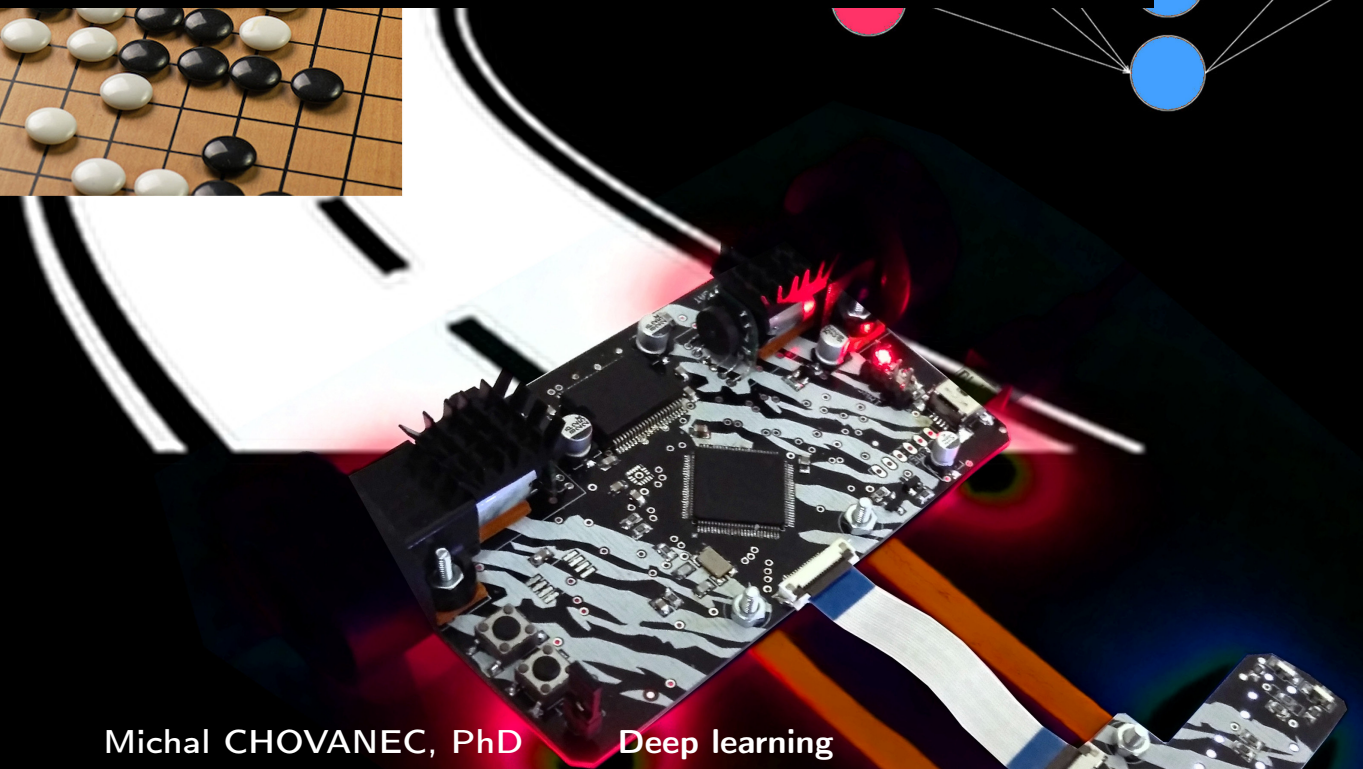
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_{t+1} + \lambda \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right]$$

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



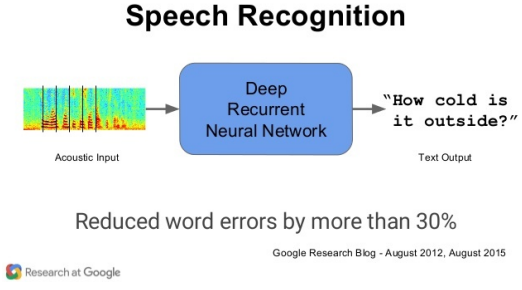
Deep learning

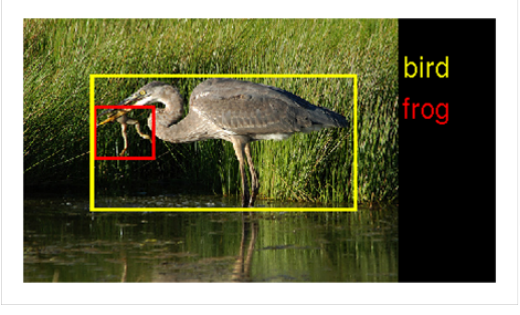
Michal CHOVANEC, PhD

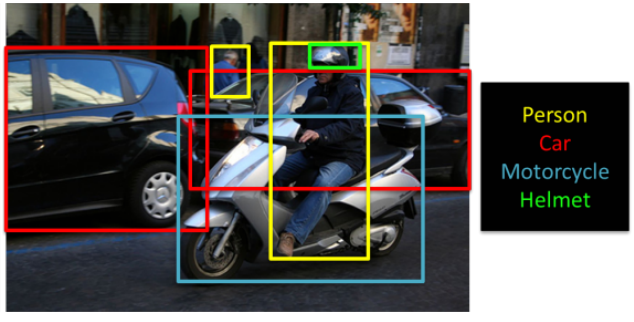


Applications

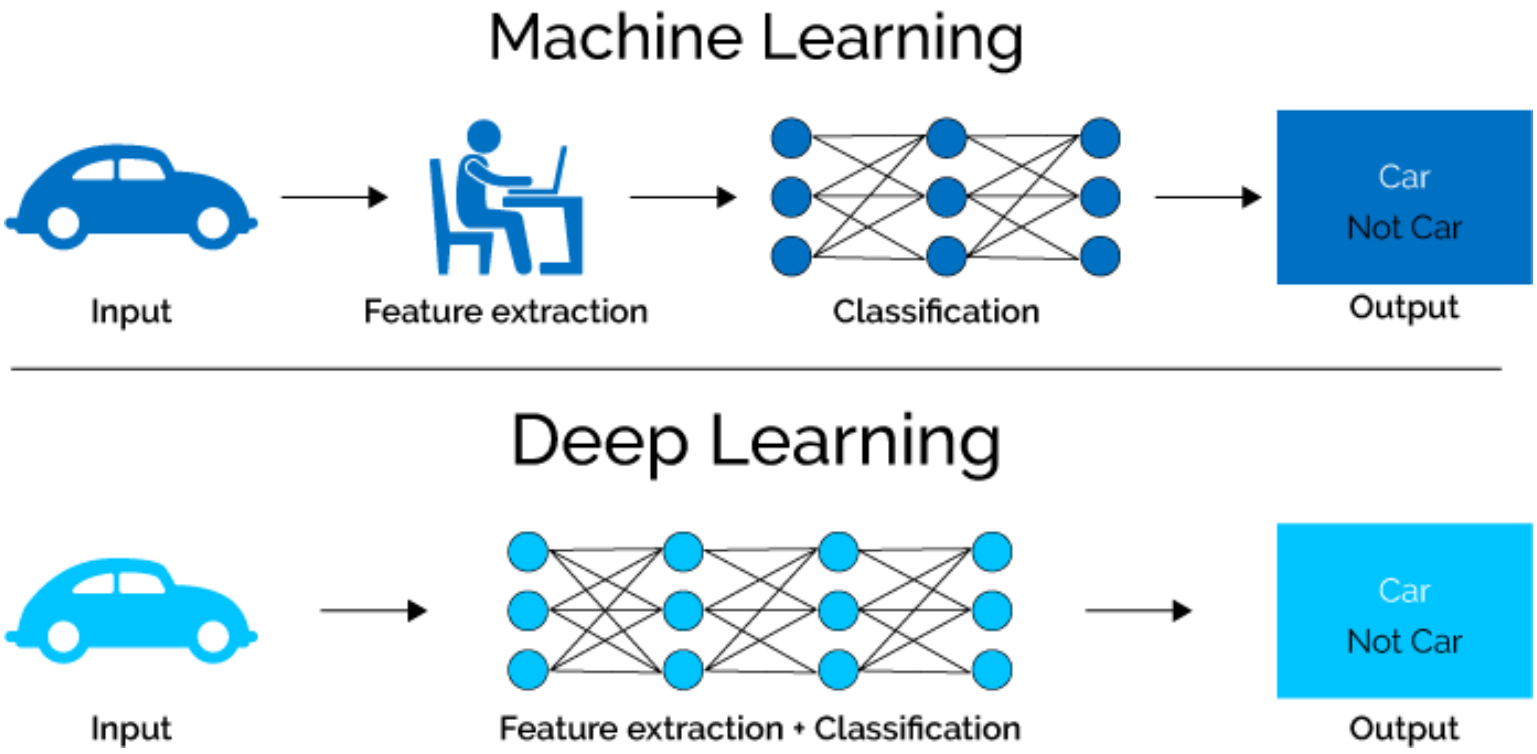
- self driving cars - Tesla model S
- healthcare, biomedical engineering - Cell in fluid
- voice search, control - Google, Amazon Echo
- machine translation - Google translator
- image recognition - Huawei Mate 10
- game bots, robotics - DeepMind, Boston Dynamics



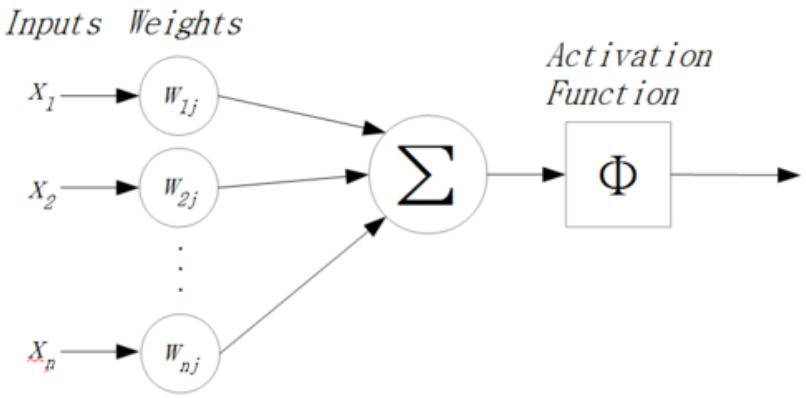




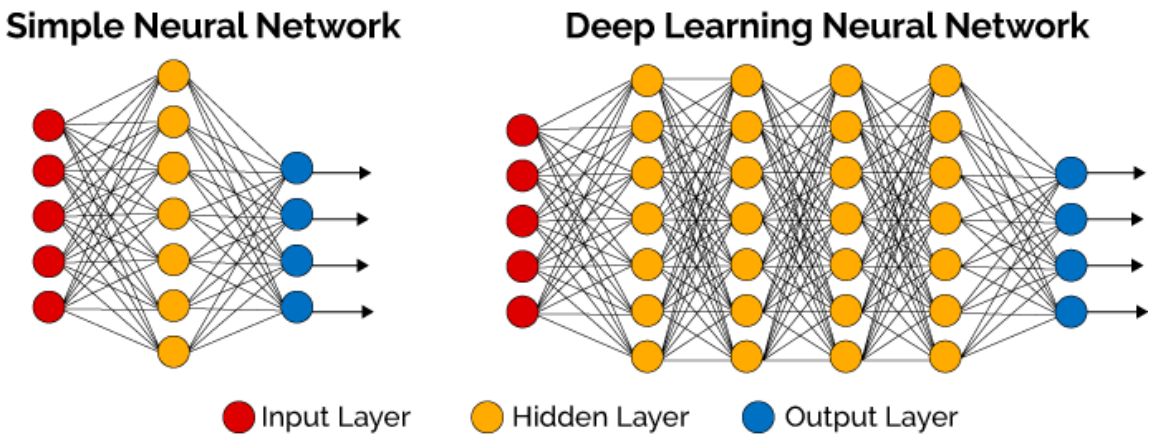
Deep learning



Neural network

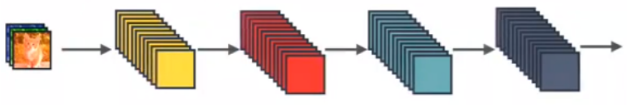


$$y(X) = f(\sum_i X_i W_i + b)$$

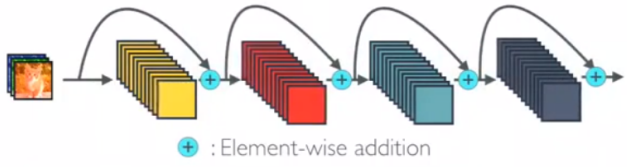


Deep neural network

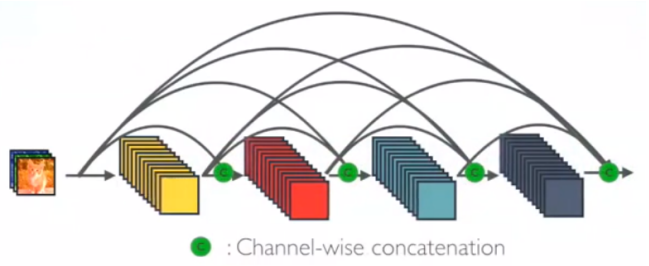
- Old methods (before NN) - 2011, 25.8%
- Convolutional, AlexNet - 2012, 16.4%
- Google inception - 2013, 6.7%
- Microsoft ResNet - 2015, 6.1%
- DenseNet - 2018, 5.17%
- CNN



- ResNET



- DenseNet



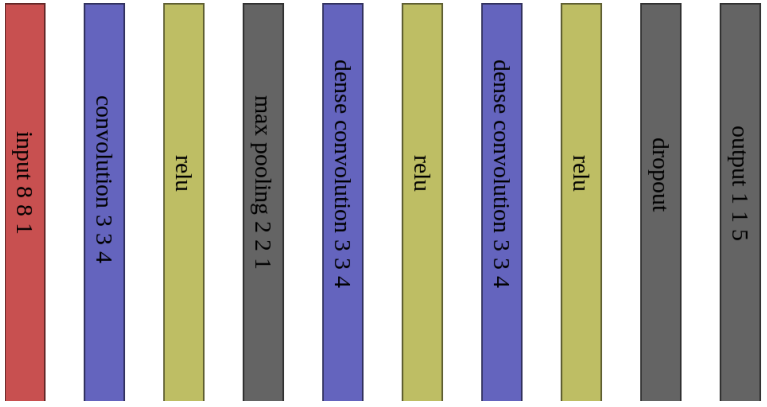
My research

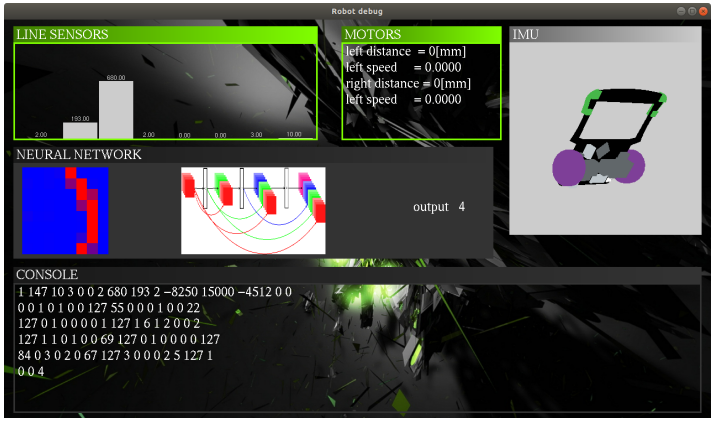
- Robotics - hobby
- Red blood cells trajectory prediction
- Deep reinforcement learning

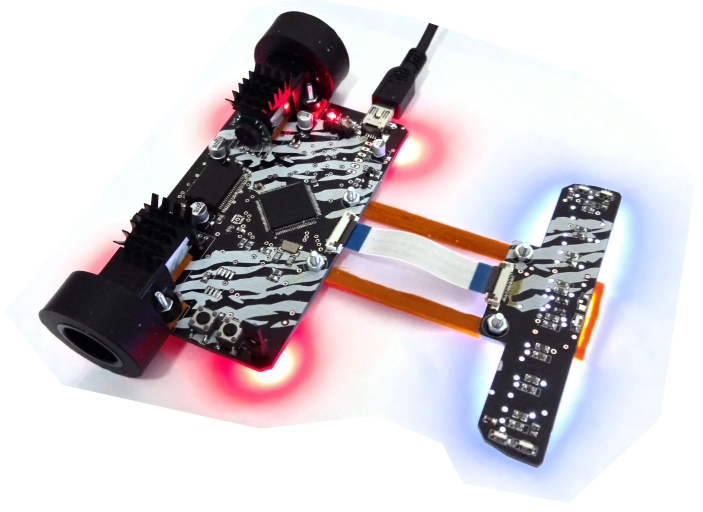
Robotics - line follower

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

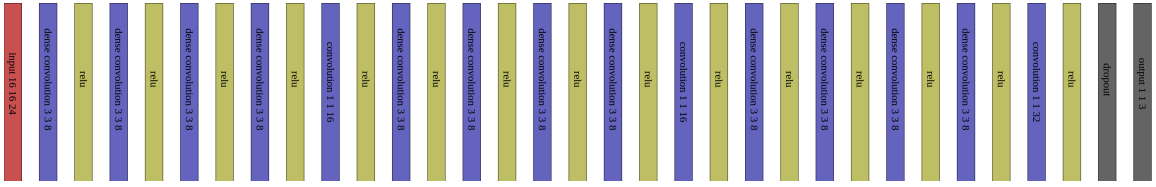


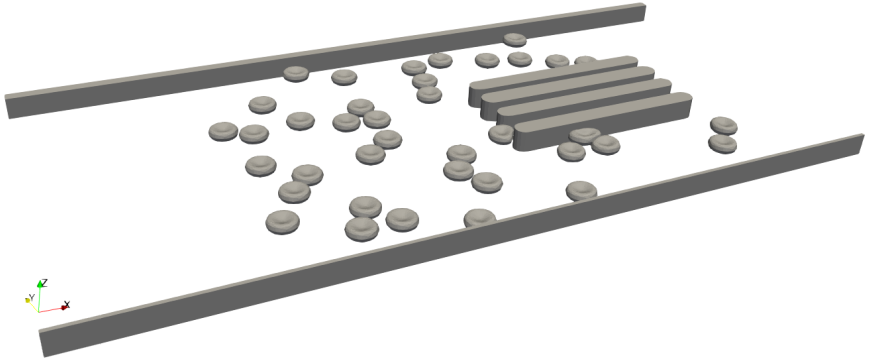


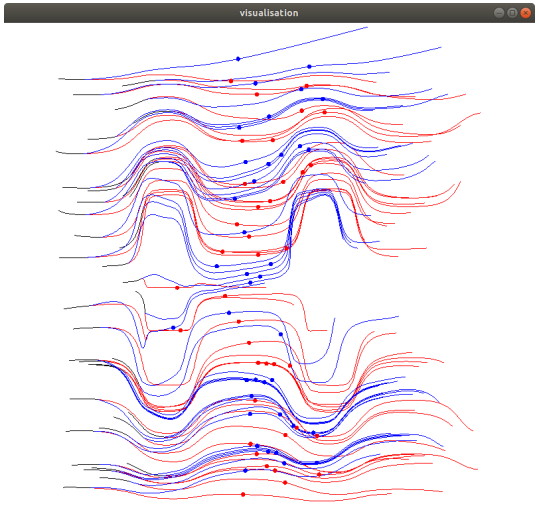


Red blood cells trajectory prediction

- 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



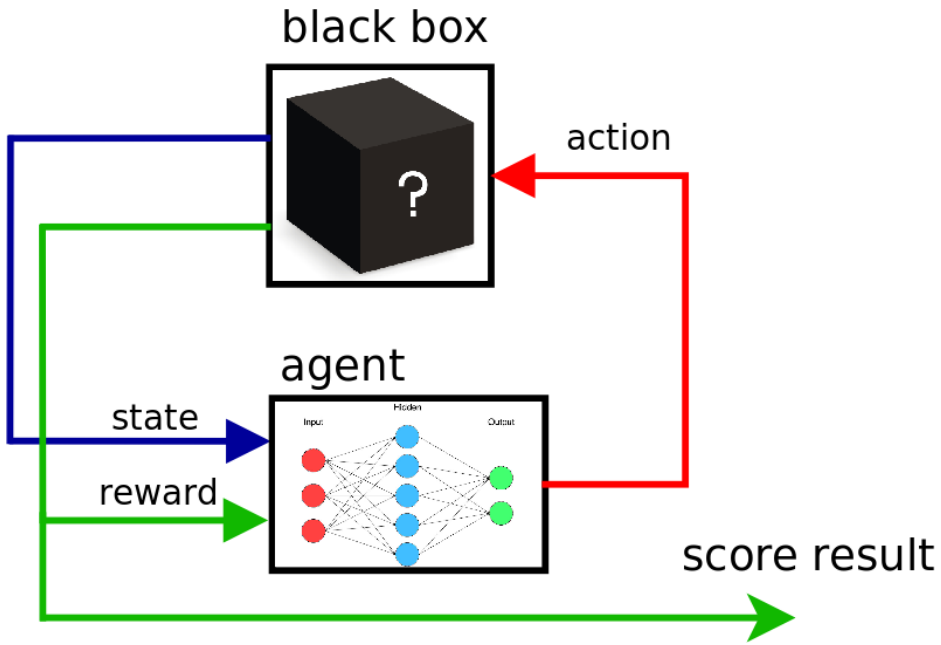




Reinforcement learning

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

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

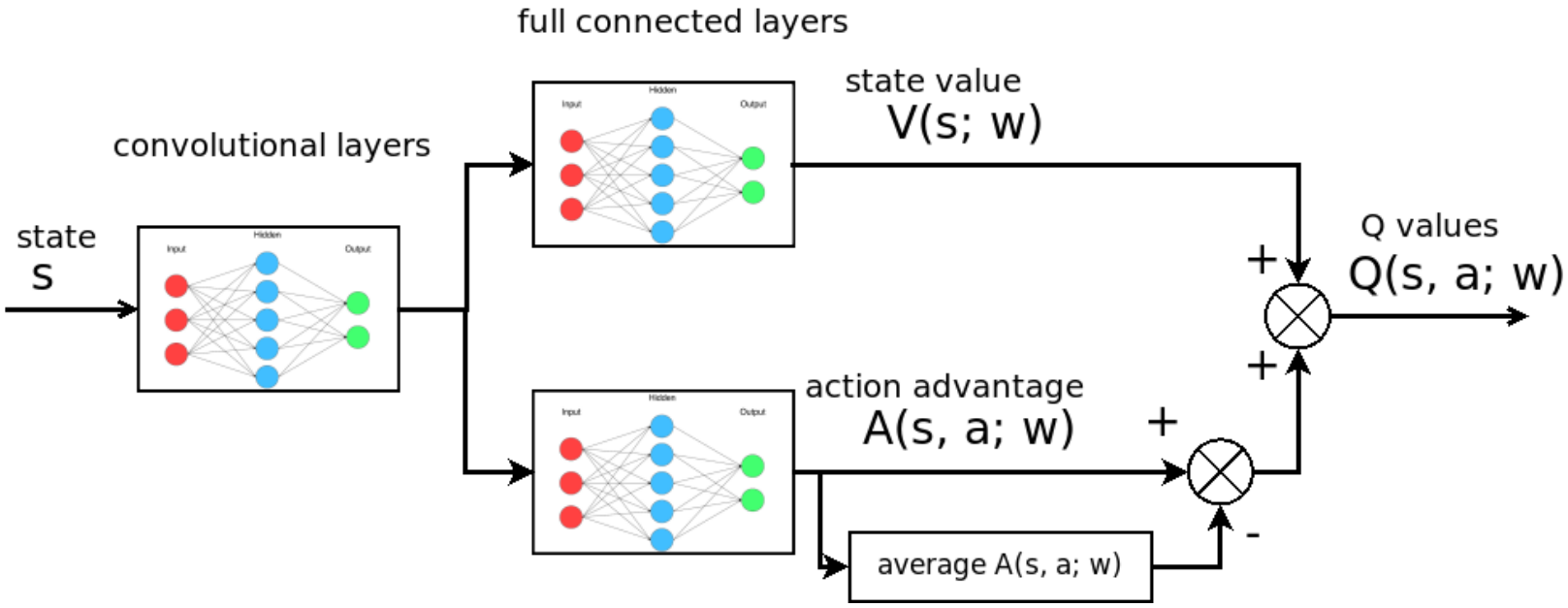


Dueling deep Q network - DDQN (2016)

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

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

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

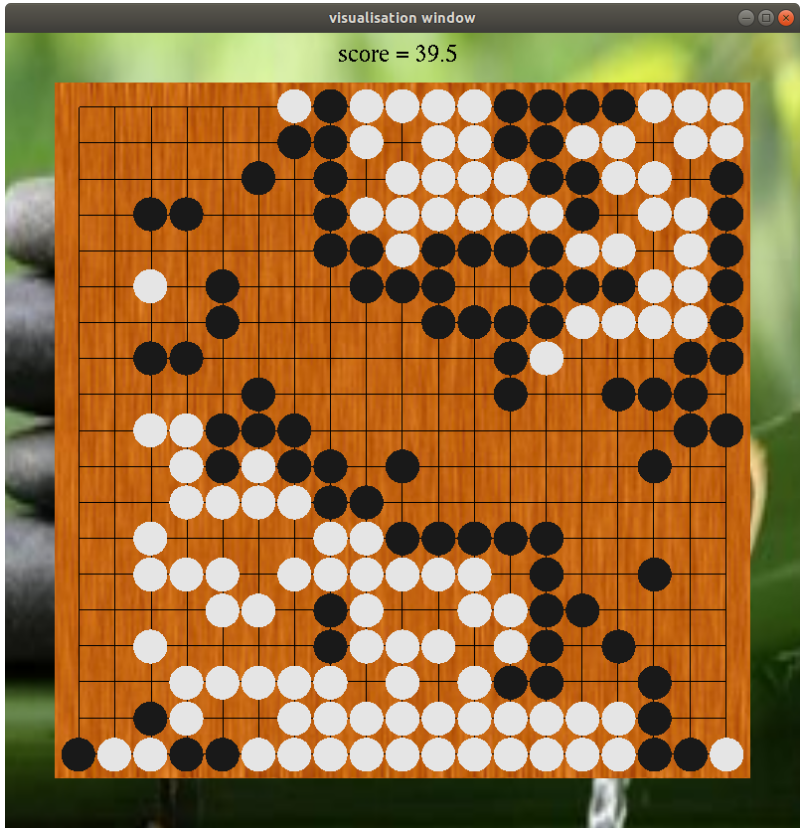
we obtain dueling deep Q network equation

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

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)

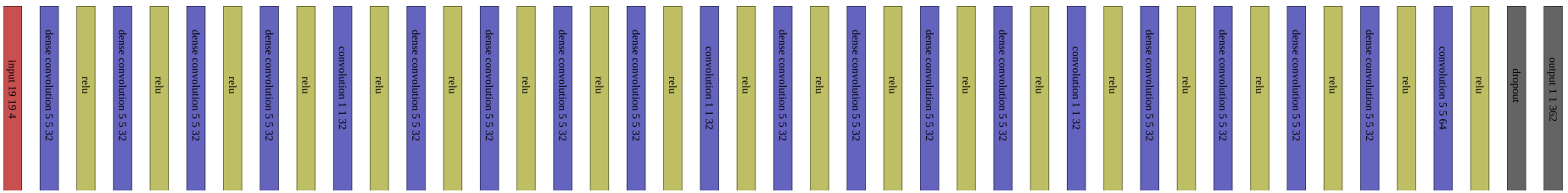


- **supervised training** - train game using Masters games
- **reinforcement learning** - let play two networks against each other

Network architecture

we need to go much deeper for GO

- **20 convolutional layers**
  4 blocks with 4 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 type	input size	kernel size	output size
dense convolution	19x19x4	5x5x32	19x19x36
dense convolution	19x19x36	5x5x32	19x19x68
dense convolution	19x19x68	5x5x32	19x19x100
dense convolution	19x19x100	5x5x32	19x19x132
convolution	19x19x132	1x1x32	19x19x32
dense convolution	19x19x32	5x5x32	19x19x64
dense convolution	19x19x64	5x5x32	19x19x96
dense convolution	19x19x96	5x5x32	19x19x128
dense convolution	19x19x128	5x5x32	19x19x160
convolution	19x19x160	1x1x32	19x19x32
dense convolution	19x19x32	5x5x32	19x19x64
dense convolution	19x19x64	5x5x32	19x19x96
dense convolution	19x19x96	5x5x32	19x19x128
dense convolution	19x19x128	5x5x32	19x19x160
convolution	19x19x160	1x1x32	19x19x32
dense convolution	19x19x32	5x5x32	19x19x64
dense convolution	19x19x64	5x5x32	19x19x96
dense convolution	19x19x96	5x5x32	19x19x128
dense convolution	19x19x128	5x5x32	19x19x160
convolution	19x19x160	5x5x64	19x19x64
full connected	19x19x64	19x19x362	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

michal chovanec (michal.nand@gmail.com)

`www.youtube.com/channel/UCzVvP2ou8v3afNiVrPAHQGg`

github `https://github.com/michalnand`