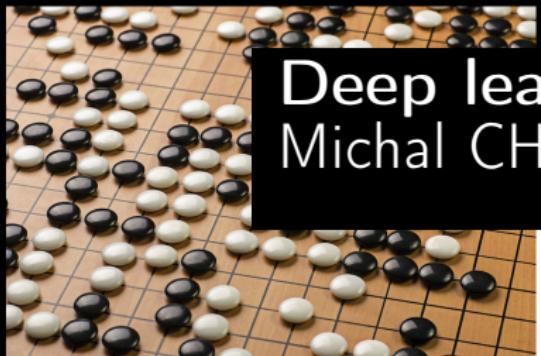


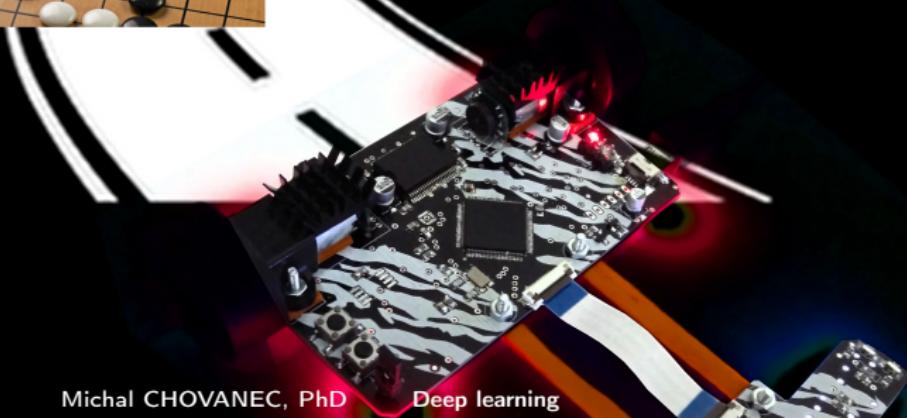
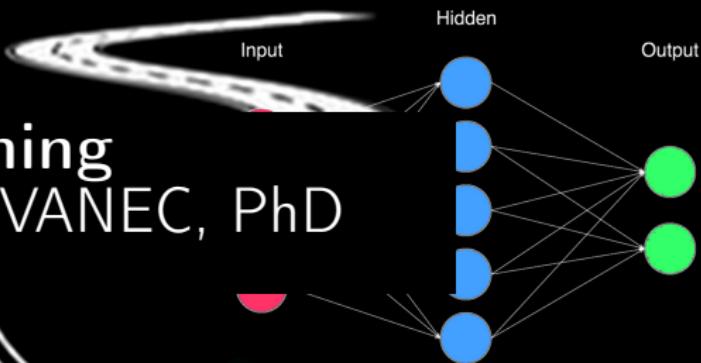
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \lambda \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

(The New Action Value = The Old Value) + The Learning Rate \times (The New Information — the Old Information)



Deep learning

Michal CHOVANEC, PhD

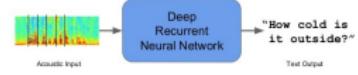


Applications

- 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



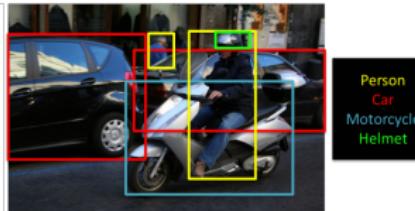
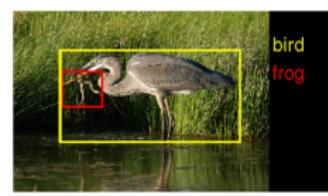
Speech Recognition



Reduced word errors by more than 30%

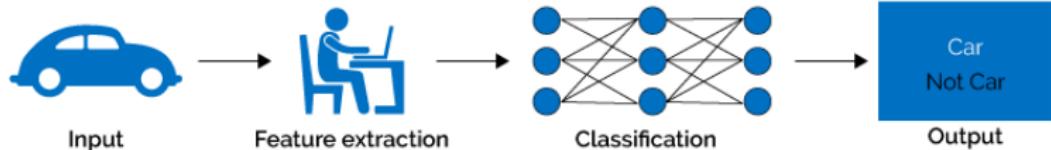
Google Research Blog - August 2012, August 2015

Research at Google

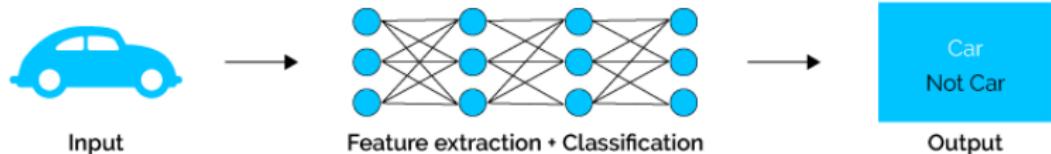


Deep learning

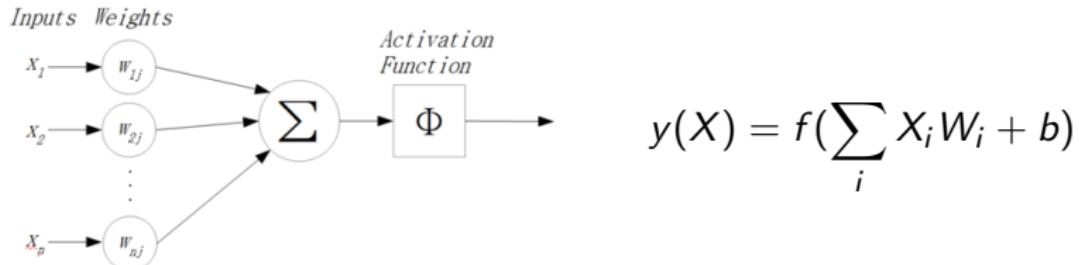
Machine Learning



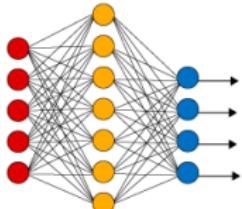
Deep Learning



Neural network



Simple Neural Network

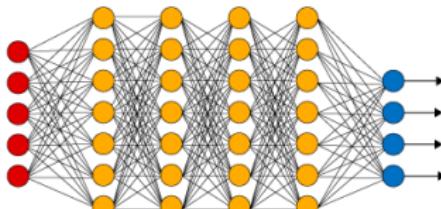


● Input Layer

● Hidden Layer

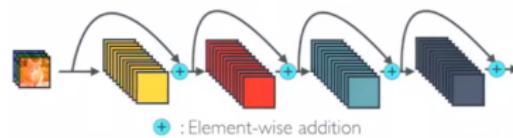
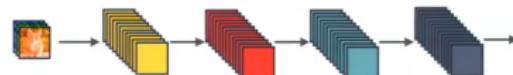
● Output Layer

Deep Learning Neural Network



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%



+ : Element-wise addition



● : Channel-wise concatenation

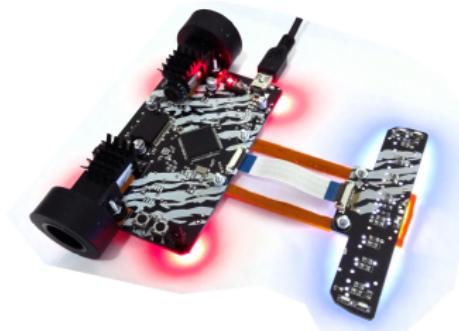
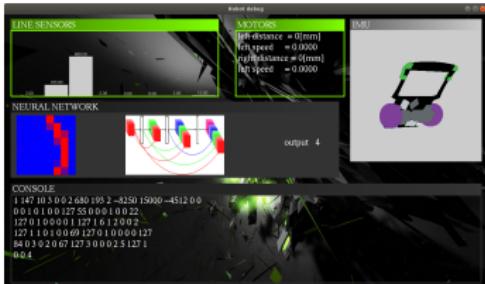
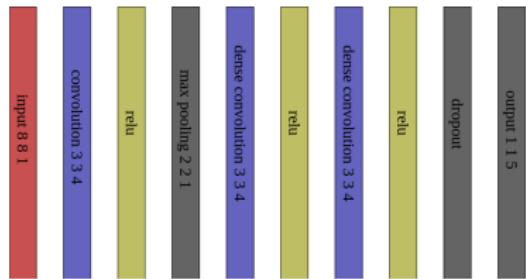
My research

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

Robotics - line follower

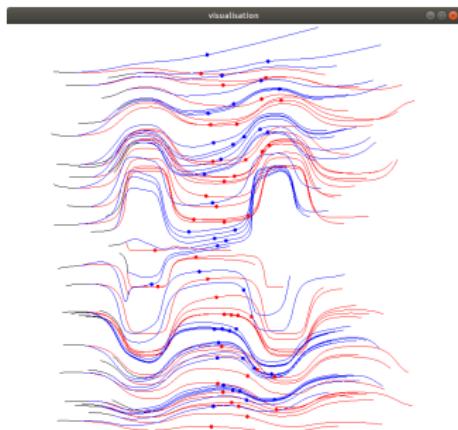
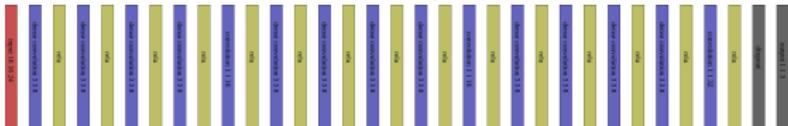
Curve shape classification

- stm32f303, 73MHz
- 8x 500nm line sensors
- pololu motors, 1:30
- network input : 8 last line sensors results (8x8 matrix)
- response 4..5ms



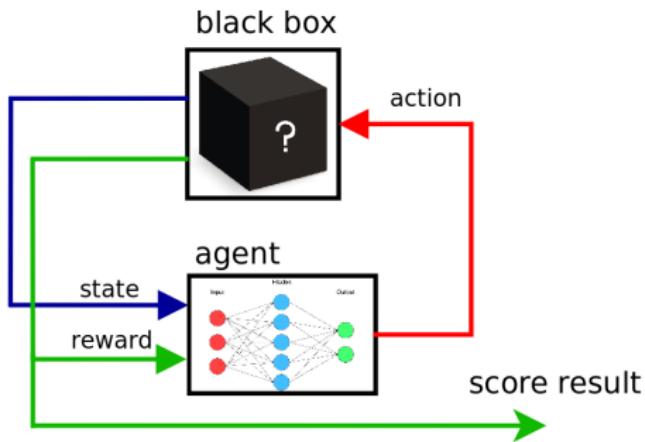
Red blood cells trajectory prediction

- 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**



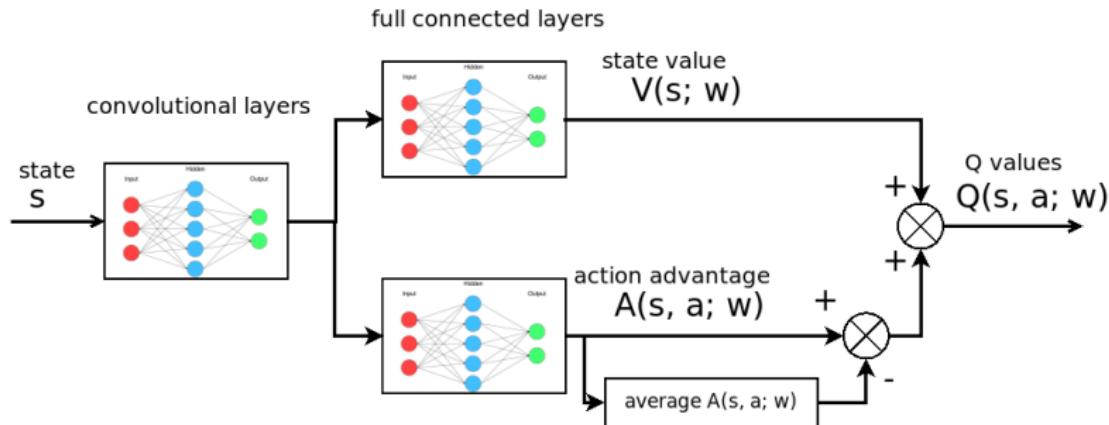
Dueling deep Q network - DDQN (2016)

$$\hat{Q}(s, a, w) = \hat{V}(s, w) + \hat{A}(s, a, w)$$

value for being in state s advantage of taking action a at state s

to avoid identifiability we subtract 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 learning 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)

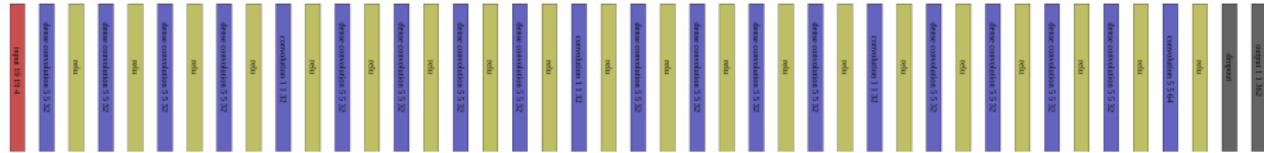


- **supervised training** - train game using Masters games
- **reinforcement learning** - let play two networks against each other

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 19×19 : black stones, white stones, empty fields, active player
 - **output**
recommended moves $19 \times 19 + 1$ 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/r1/>
-  **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>