Making robots learn for the real world

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NAVER LABS

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Superhuman AI – Alpha Go (Zero)

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"Google's AI AlphaGo Is Beating Humanity At Its Own Games"

20 million self-play games

200 000 games per day

Superhuman AI – Dota2

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AI bots trained for 180 years a day to beat humans at Dota-2

Robot Soccer – subhuman AI

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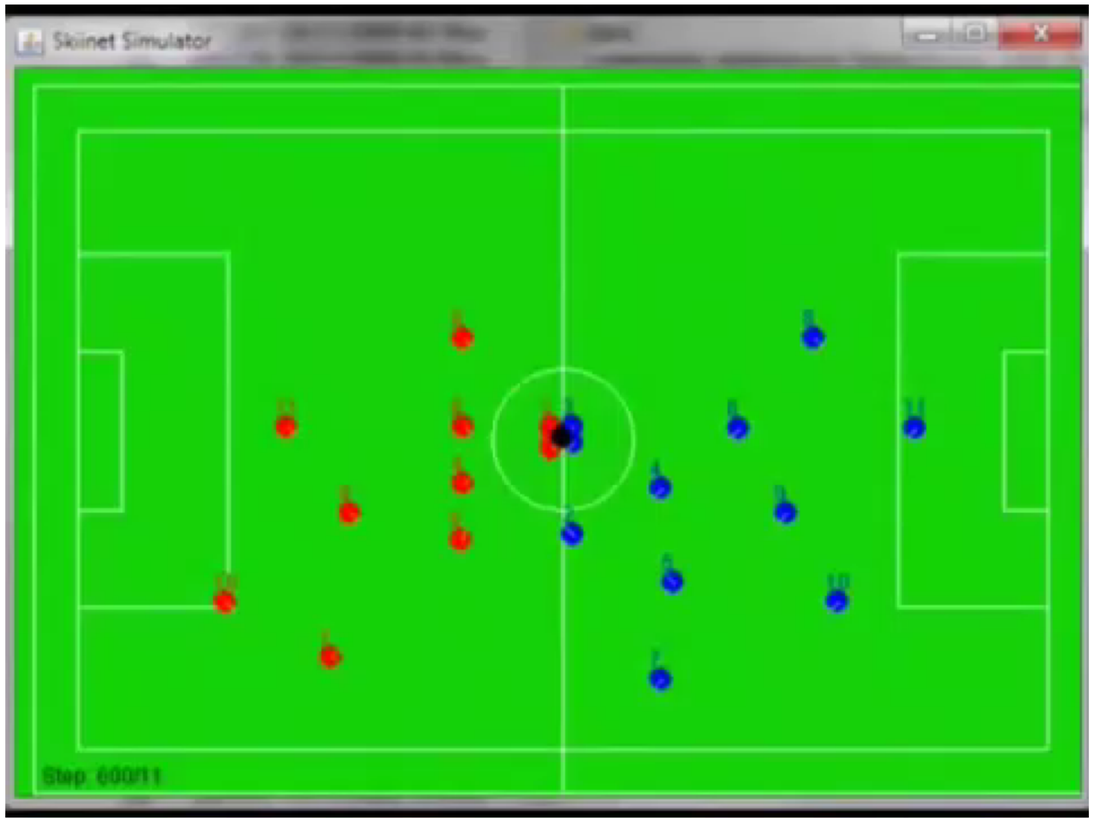
Soccer over chess as a paradigmatic robotic task (Sahota et al. AI-94)



Thus a GAP

and its been widening lately, but why?

Computational power has made it possible to scale RL i.e.,
to make the software agents able to learn end-to-end by trial and error in simulations that can be run fast and in parallel producing huge amounts of training data.

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Should we make robots learn?

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First Conference on Robot Learning 2017, keynote by Rodney Brooks:

1. Well, maybe – just for fun, to see if that is possible
2. To put correct pressure to machine learning methods - my favorite argument
3. To make robots more practical – maybe

So if the Godfather of robotics is not too enthusiastic, we might also want to be skeptical

Learning in robotics is a hot topic

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1. Conference on Robot Learning 2018 (CORL)
2. Robotics: Science and Systems 2018 (RSS)
   - learning to grasp
   - learning to localize
   - transferring from simulations to real life

3. International Conference on Robotics and Automation 2018
   - lot of deep learning

4. International conference on Intelligent Robots and Systems
   - last week in Madrid

Reinforcement learning

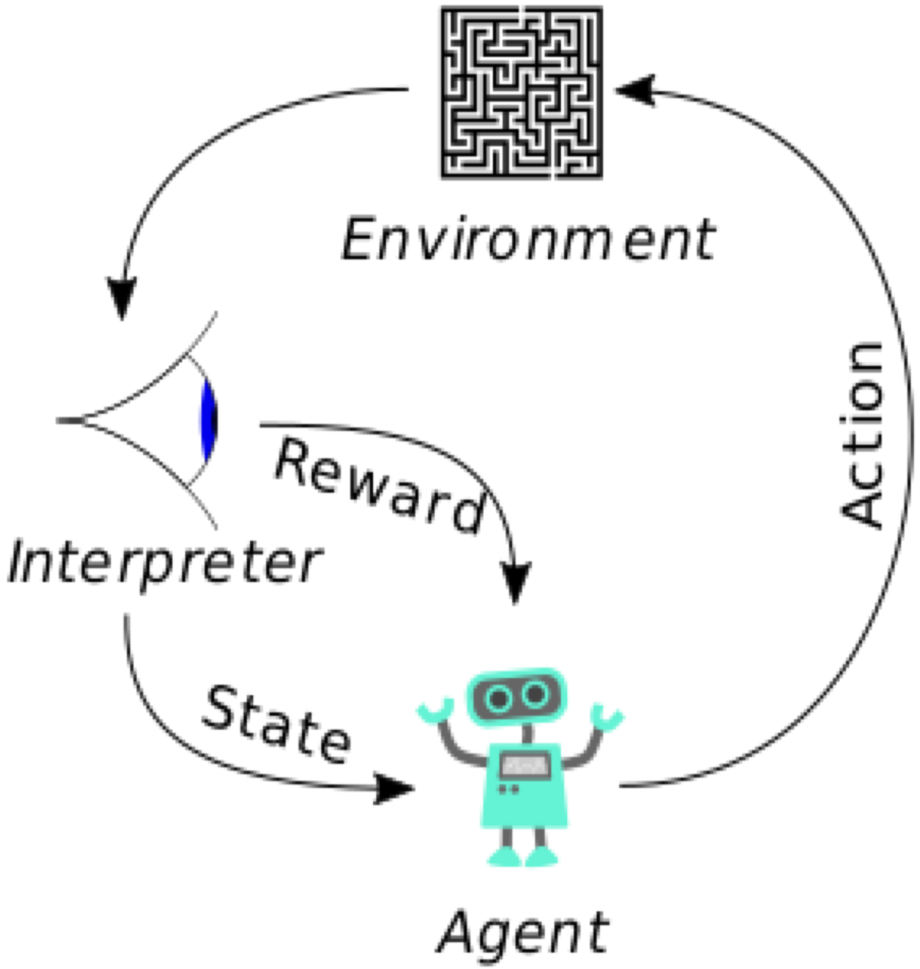
Improving behaviour using evaluative feedback via trial and error.

Target is to learn a behavioural policy:

- "In this situation S it is usually best to do action A in order to accomplish the task"
- accomplishing the task is signaled giving agent a reward for achieving the goal.

The agent learns to optimize it behaviour to get maximal reward

- all this can be formalized using decision processes.



Problems when using RL in real robots

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1. Trying all kind of things is dangerous.
   - it breaks robots and robot lab.
2. Real robot cannot be run in hyper-speed
   - so it will take "forever" before the robot learns.
3. Many tasks are not game–like
   - so robots can not play against each other.
4. Reward signals hard to give.
   - this often requires human interaction.

From Yann LeCun *How Could Machines Learn as Efficeintly as Animals and Humans?*

Before we jump on the RL bandwagon

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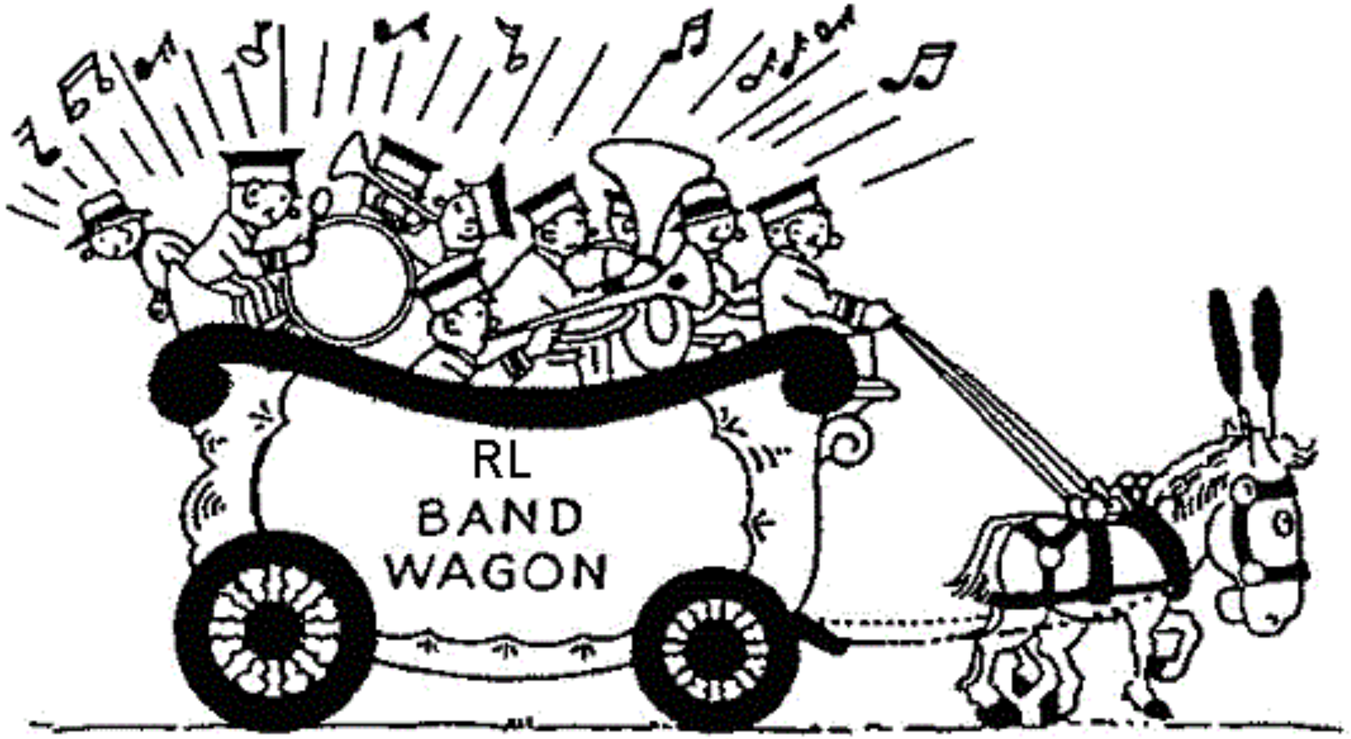

other type of robotic learning
(not by trial and error)

Instruction

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Josh Tenenbaum in his ICML keynote 2018:

"after 18 months, human children mostly learn via language"

Should we make robots understand us so we can just tell them what to do?

- but Tenenbaum talked about instruction from human to human.
- by 18 months old, children have enough "common ground" for instruction by "being told".

Thomas Nagel in The Philosophical Review 1974:

- "What is it like to be a bat?"
- robots "lifeworld" is so different that language communication will be difficult.
- many competencies (e.g., grasping) are also difficult to "explain".

Imitation learning: mimic the expert

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One of the favorite methods in robotics, because of its safety and efficiency!

How:

- supervised learning from state to actions (lot of algorithmic variants)

Why not:

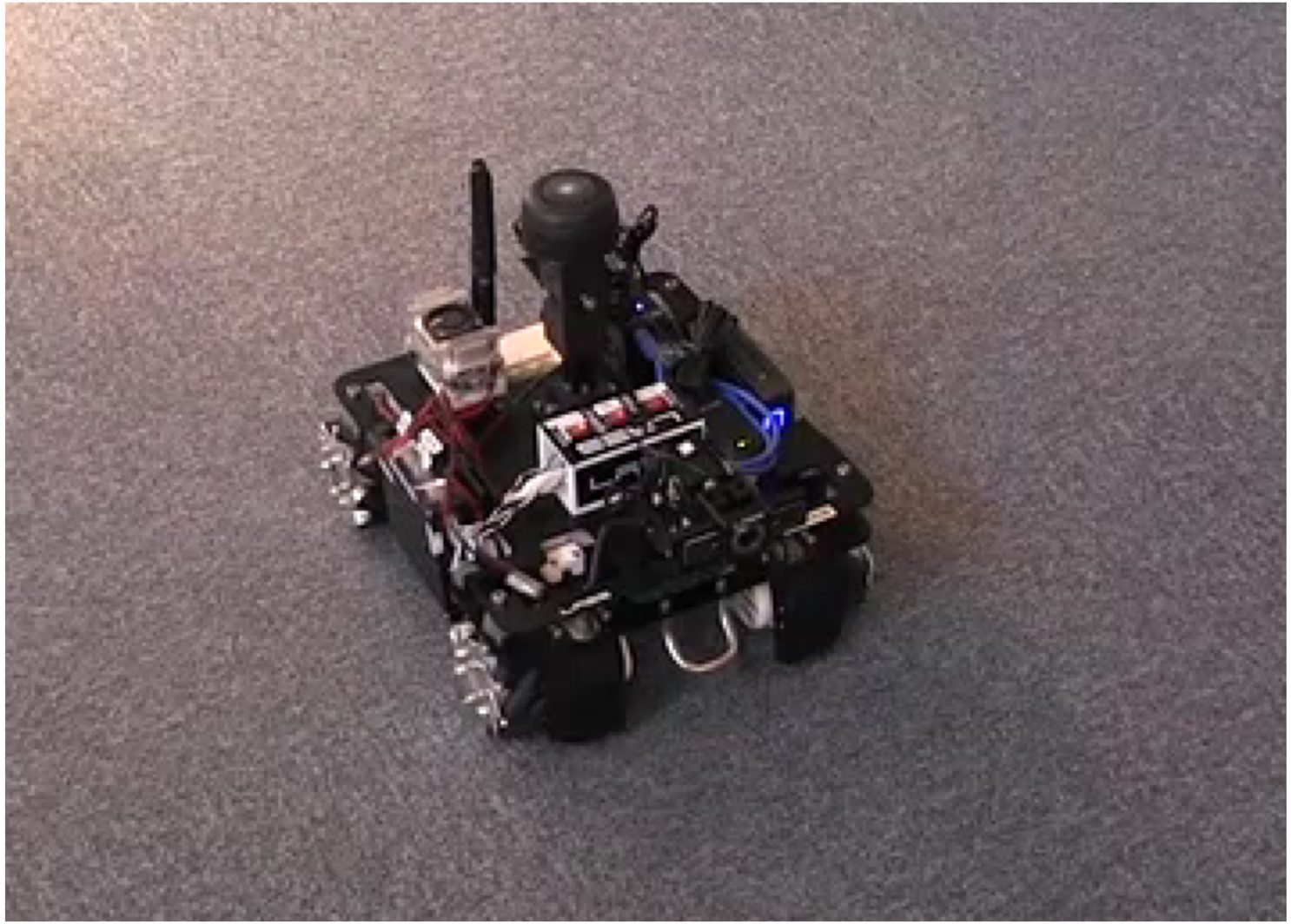
- expert cannot demonstrate behaviour on all possible situations
- so what to do in new situations?

Why traditionally a favorite method:

- robots have been used in controlled environments.

If surprise then HALT!

Playing around: trial, no error



Playing around, recording what happened

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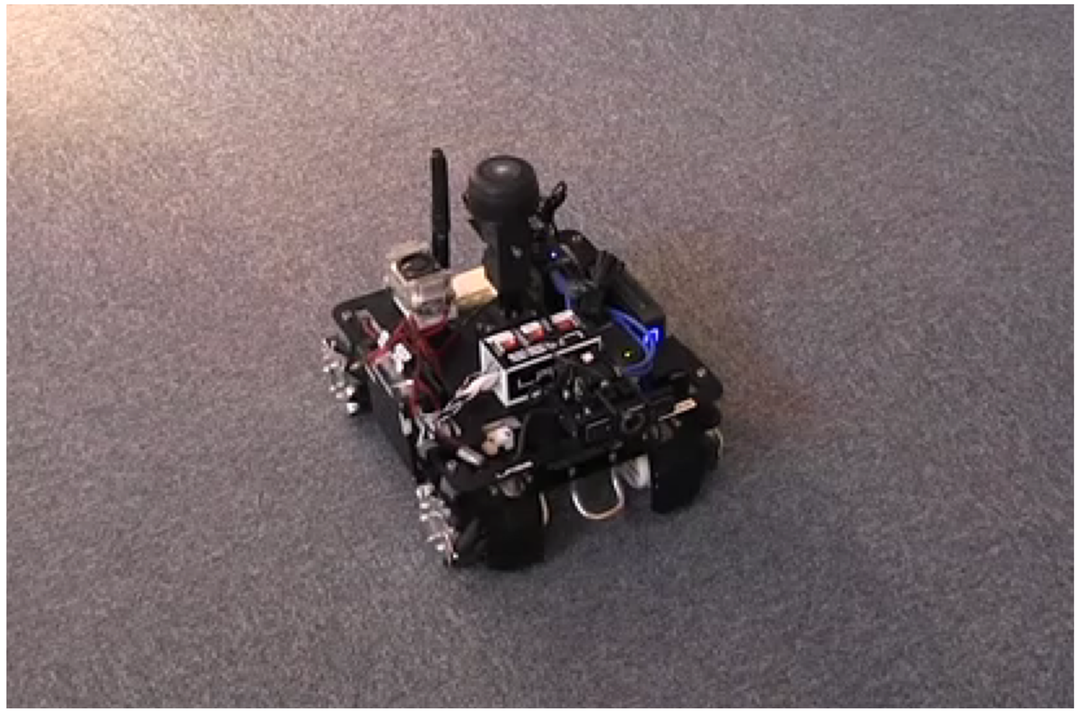

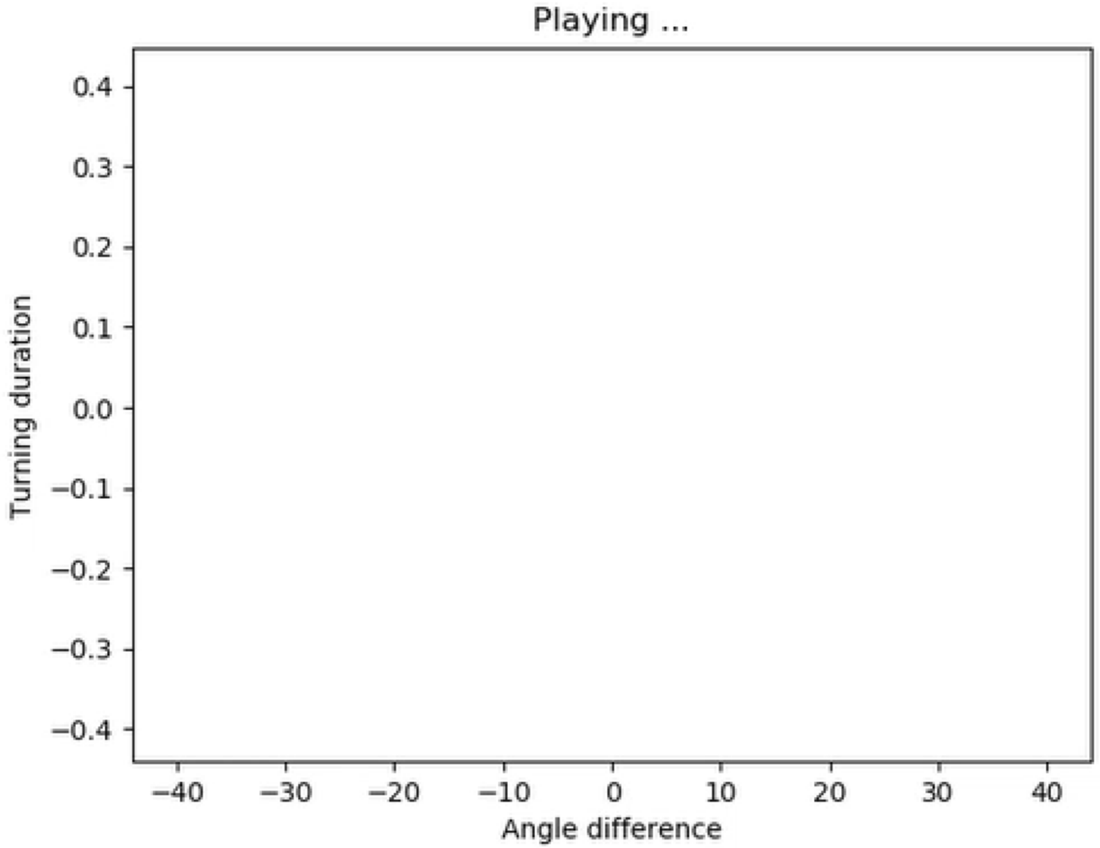

From playing to goal oriented actions

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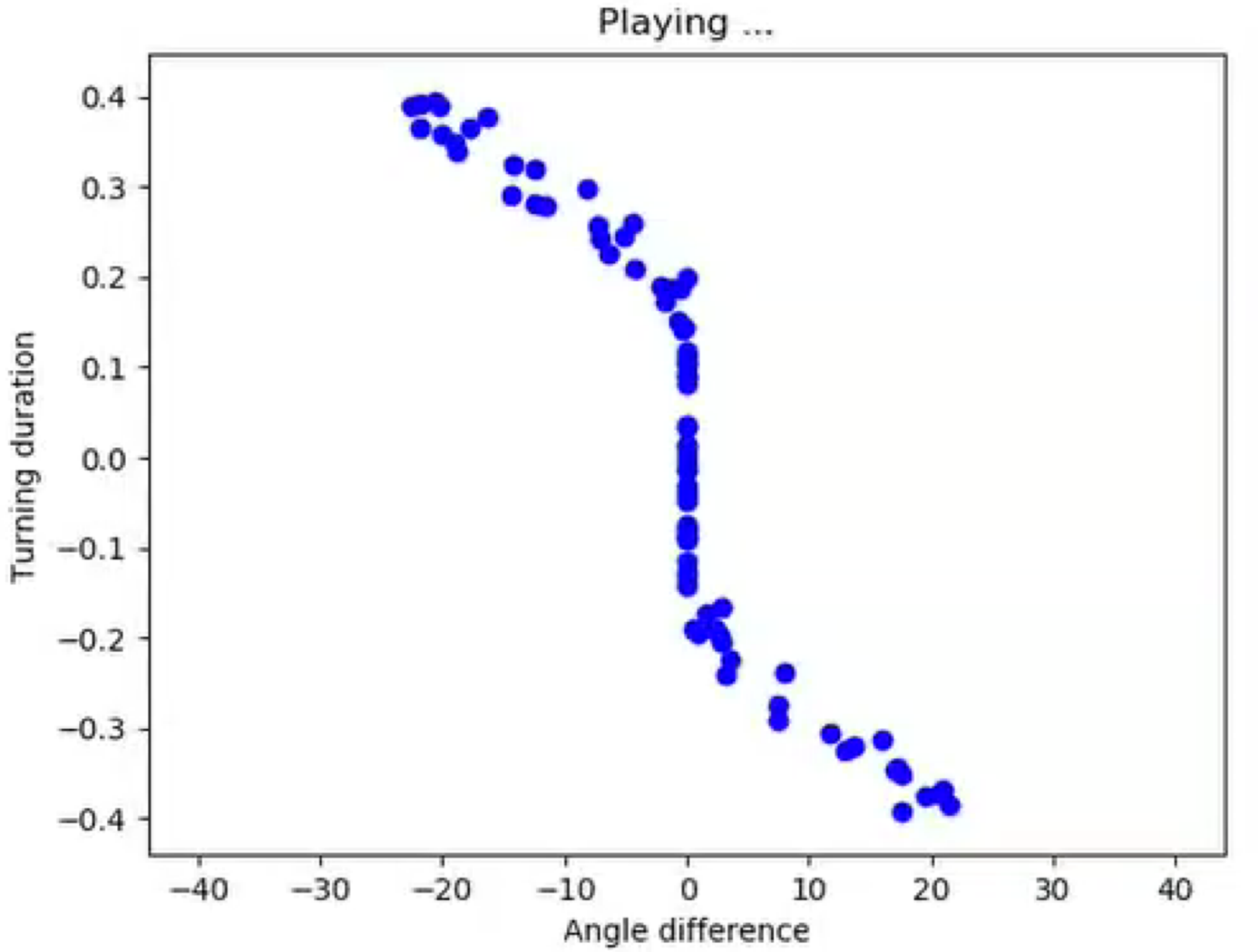

Collecting (s_t, a_t, s_{t+1}) allows us to train the regression/classification model:

$$g(s_t, s_{t+1}) = a_t.$$

If I am in situation s_t, and I want to get to situation s_{t+1}, I should do action a_t.

Self-supervised learning

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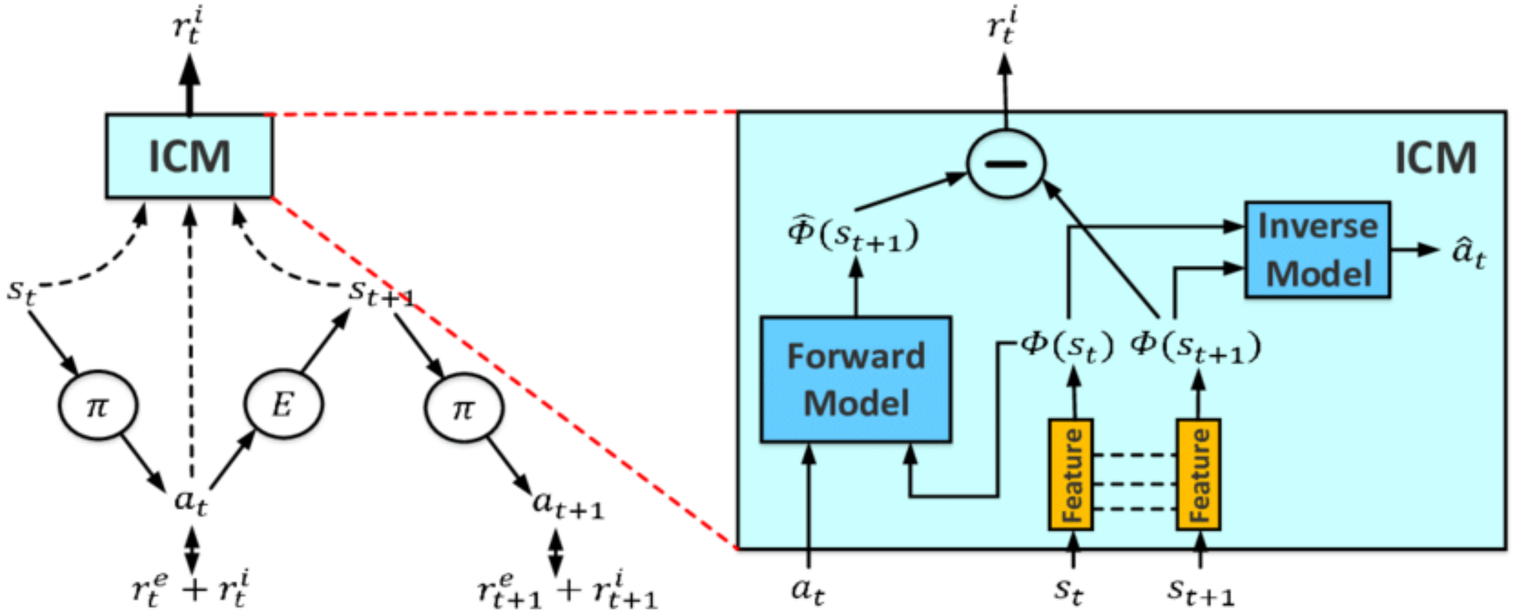
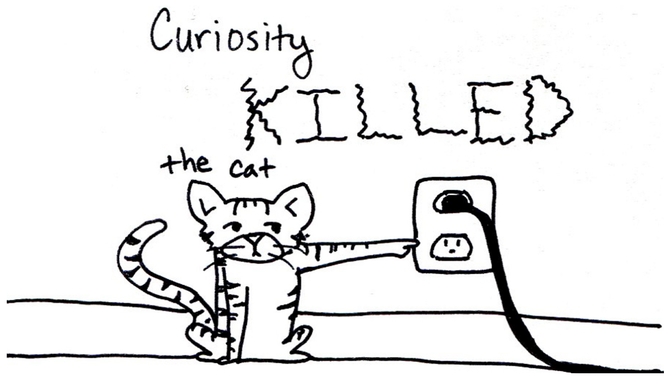
Learning general tasks that are useful for many kind of other tasks:

- grasping, obstacle avoidance, etc.

Curiosity (Pathak et al. ICML 2017):

- trying things consequences of which we cannot yet predict
- learning to explore efficiently





So if we really jump on RL bandwagon

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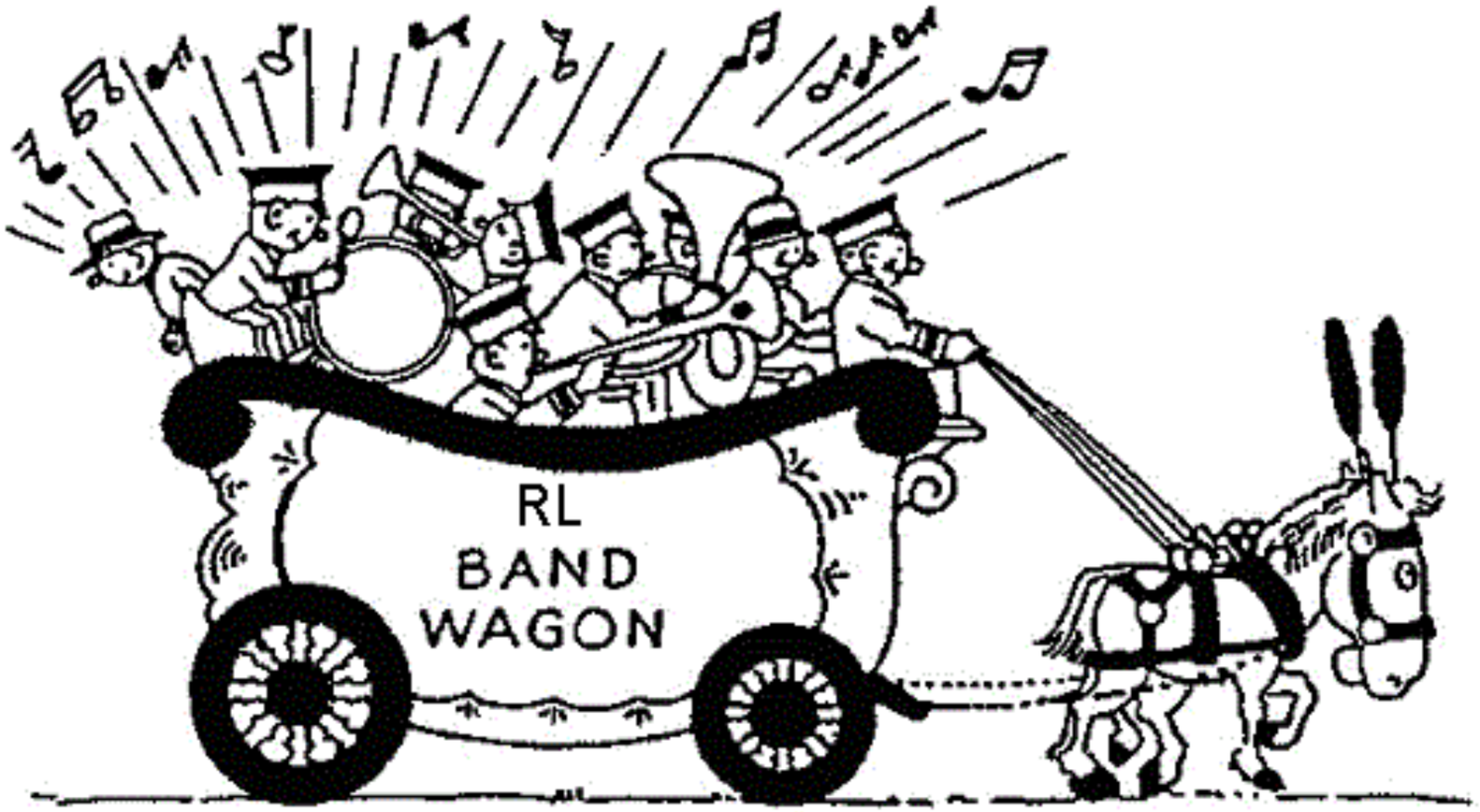
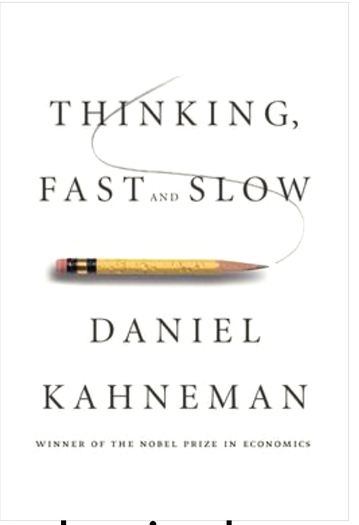


Thinking, Fast and Slow



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System 1:

Fast, automatic, frequent, unconscious

- see if an object is further than another
- localize the source of a sound
- display disgust when seeing a gruesome image
- drive a car on an empty road

System 2:

Slow, infrequent, logical, conscious

- look out for a woman with the gray hear
- dig into your memory to recognize a song
- determine the appropriateness of a behavior in a social context
- count a number of A's in a certain text

Similar dichotomy in RL: System 1 = model-free RL, System 2 = model-based RL

Model-free RL for thinking fast

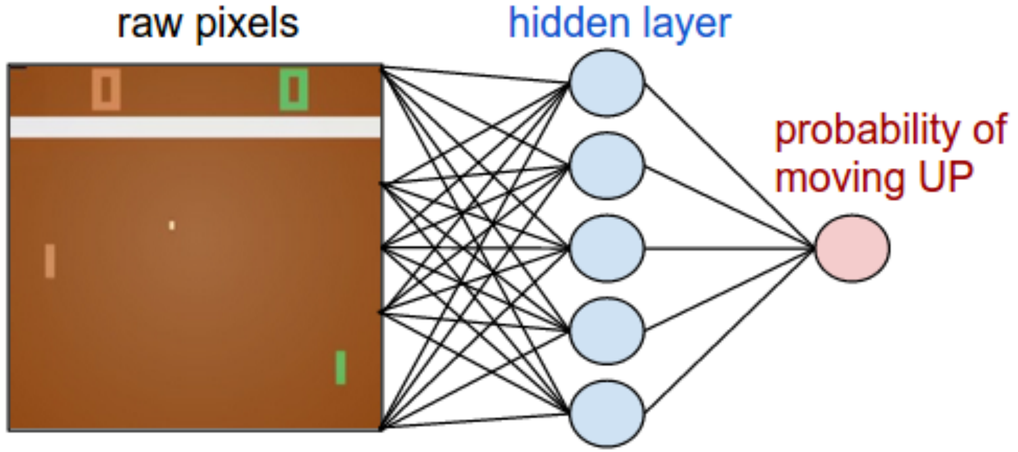
Learn the gut-feeling:

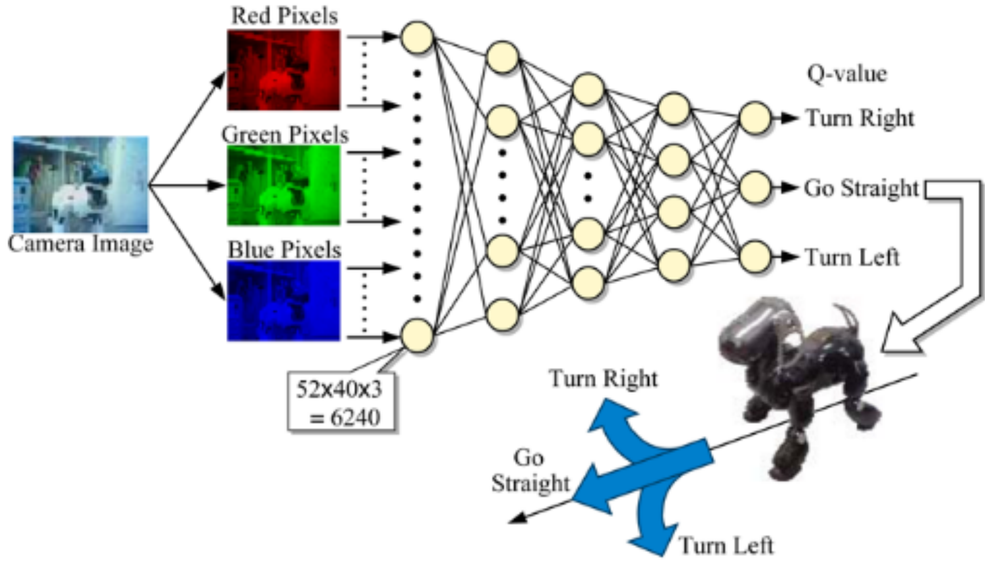
- search in policy space to learn $a(s) = \pi(s;\theta)$.
- after fitting parameters θ^*, just do $\pi(s;\theta^*)$.
- can use expert examples

Suitable when task is "simple"

Deep Q-learning (DQN):

- learn to estimate expected reward of doing action *a* in situation *s*, i.e. $Q(s,a)$.
- in each s just pick $\underset{a}{argmax}\, Q(s,a)$.





Model-based RL for thinking slow

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Learn the model of the world, i.e. consequences of your actions:

- a "forward model" $T(s, a, s')$, i.e.,
- the probability that action *a* changes the situation *s* to *s'*.

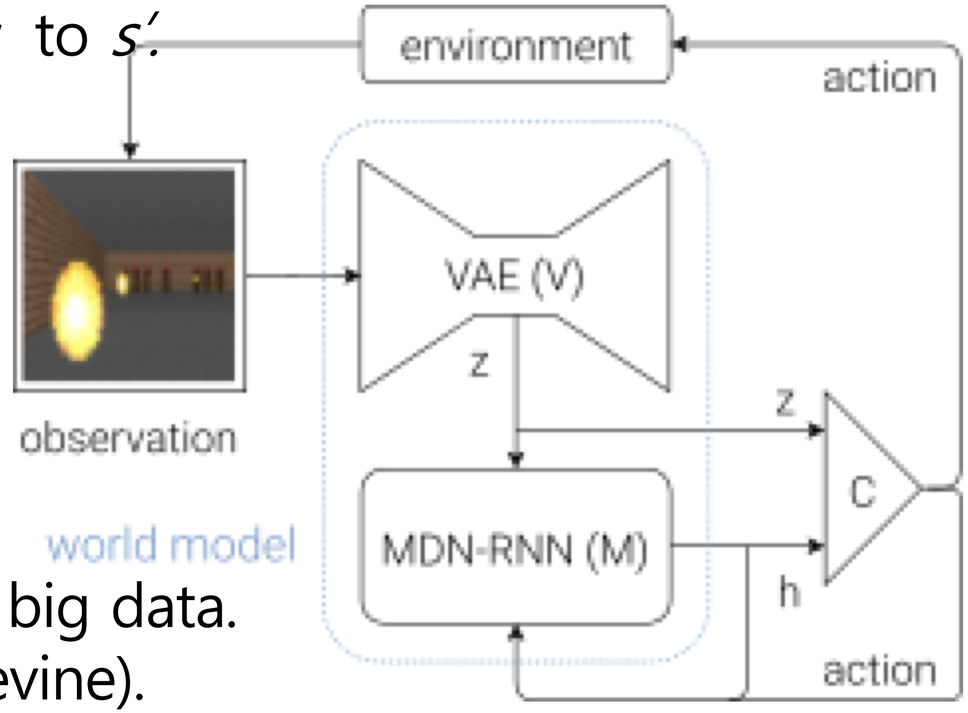
Same model can be used for many tasks.

Schmidhuber (2018):

- "World Models" => policies are simple

Dreaming:

- forward models can be used to simulate the world.
- in hyper-speed, thus allowing methods that require big data.
- not realistic, but it's the versatility that matters (S. Levine).



Our adversarially trained forward model

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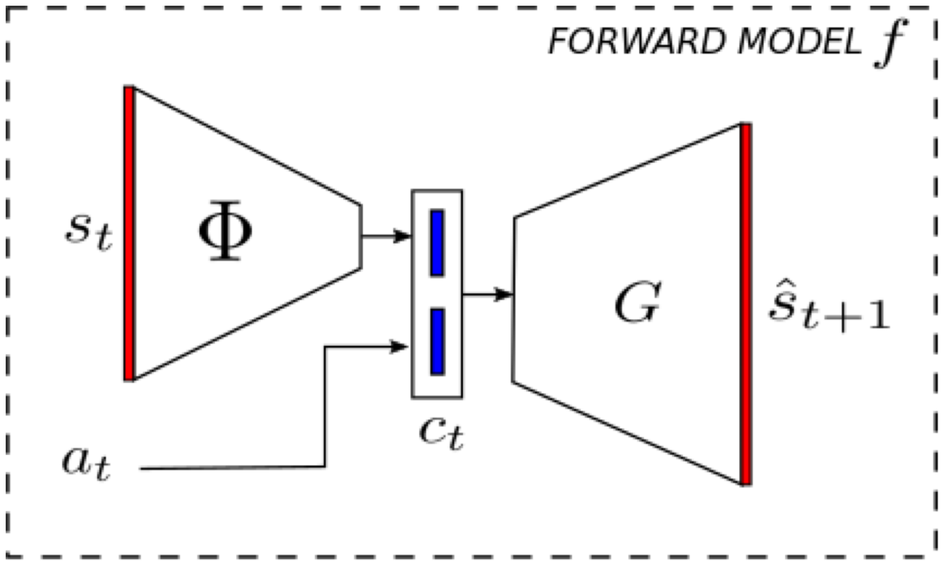
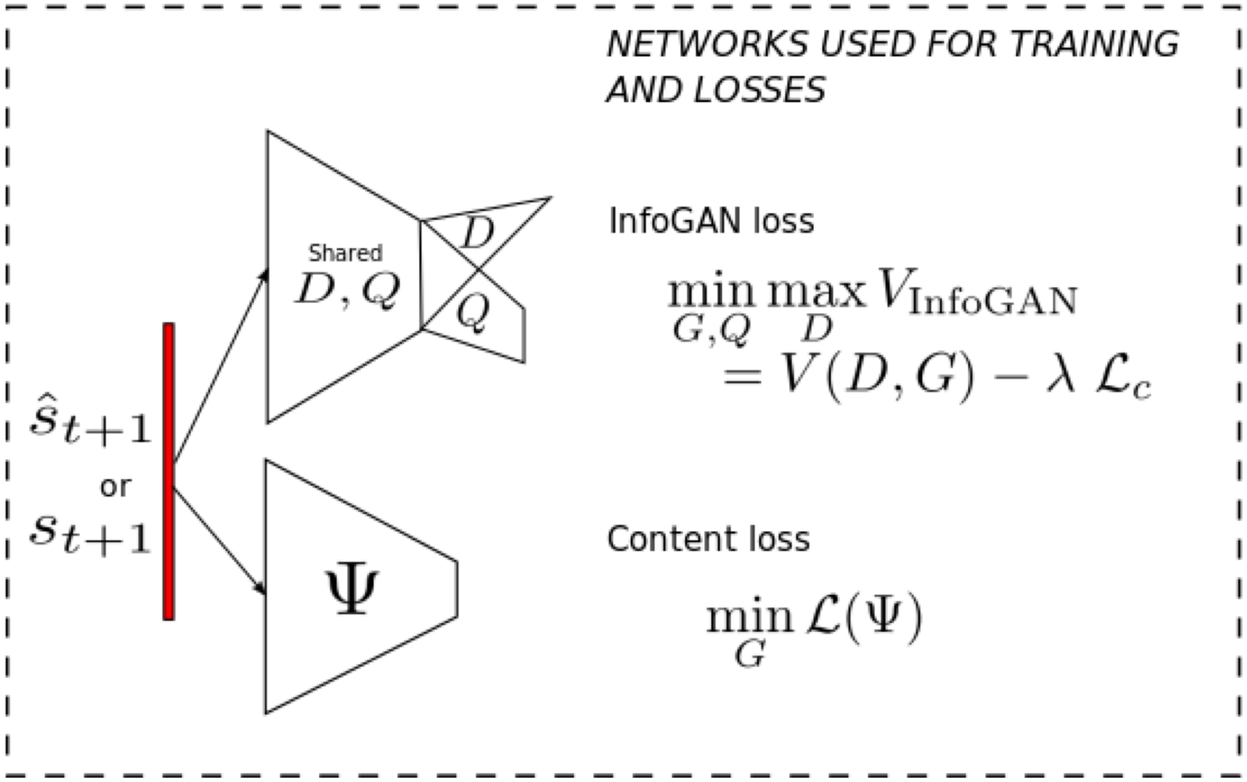
Combines adversarial training and ideas from Info GANs

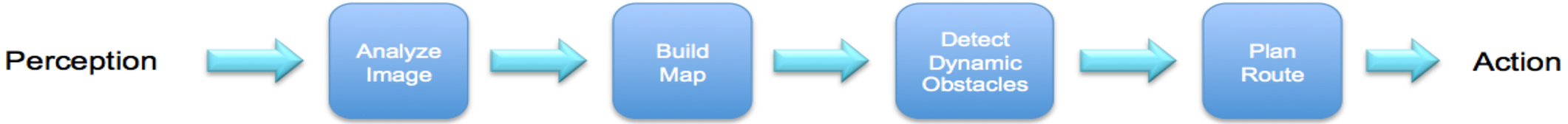




Model based or model-free RL?

NB! People have **both** System 1 and System 2

- rarely done in current RL, but maybe a key to robotics, since



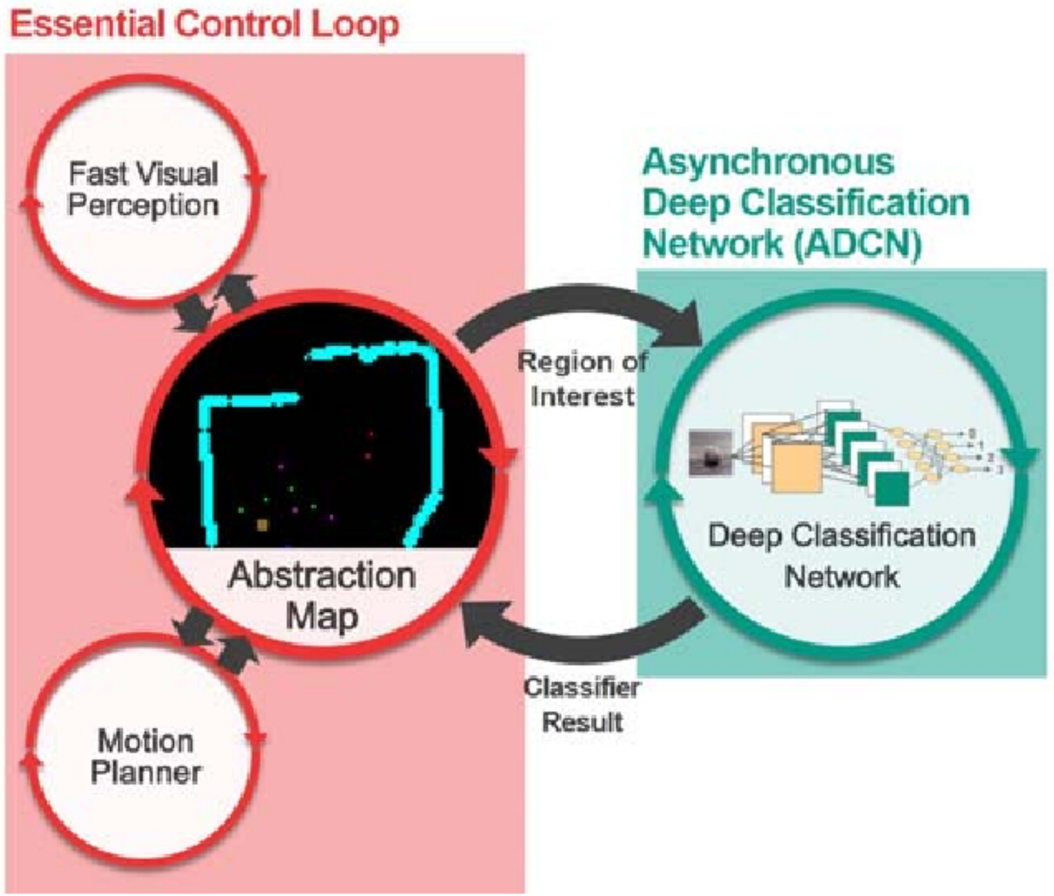
versus

Example of closing the gap

Cognitive architecture for a robot

Processes working asynchronously at different speeds:

- fast for motor control
- slower for object classification
- connected by a central representation that can also be trained via simulation



Gilhyun Ryou, Youngwoo Sim, Seong Ho Yeon and Sangok Seok (ICRA 2018)

Applying Asynchronous Deep Classification Networks and Gaming Reinforcement Learning-Based Motion Planners to Mobile Robots

Thus enter the simulations

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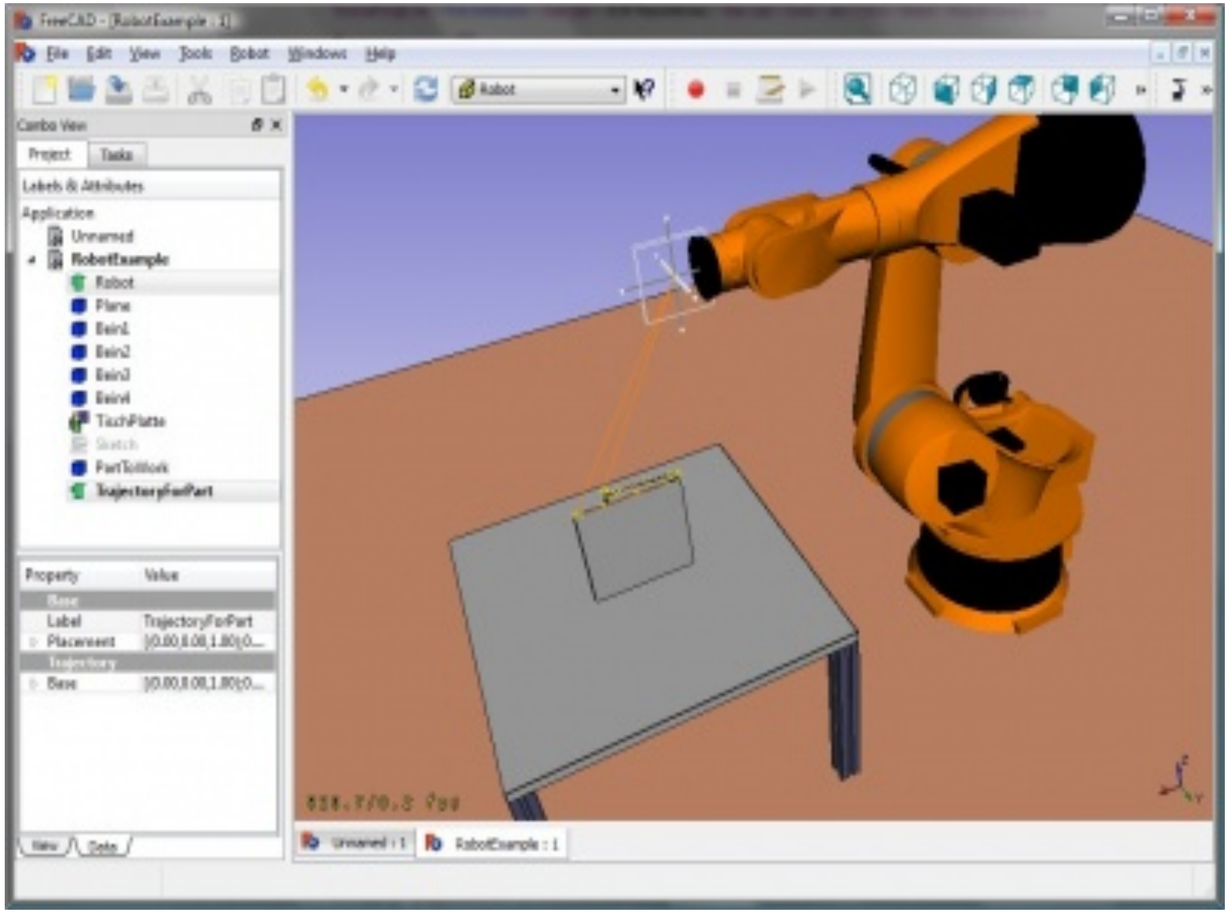
Huge bulk of current “robotic” RL is conducted simulations (it’s faster, safer)

- and then, sometimes(!), tried to transfer to a real robot
- maybe with some *domain adaptation*

Works OK for

- simple spaces and controlled environments where similarity of simulation and reality is easier to establish



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Active Neural Localization

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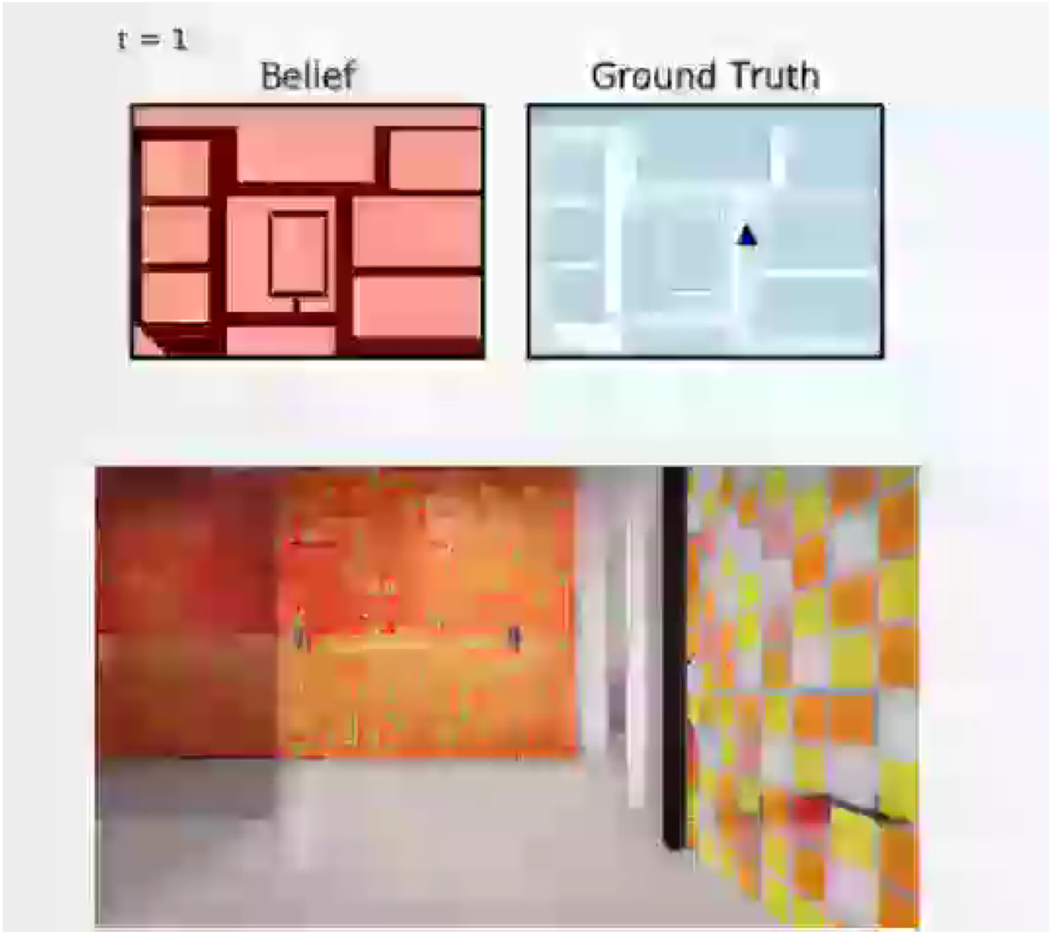
Perception is active, information seeking action (Gibson 1976)

If you are lost, try to look around

D.S. Chaplot et al. (NIPS 2017)

- grid presentations
- discrete angles
- noiseless operations
  - noiseless directions
  - noiseless images



In active localization project we had to

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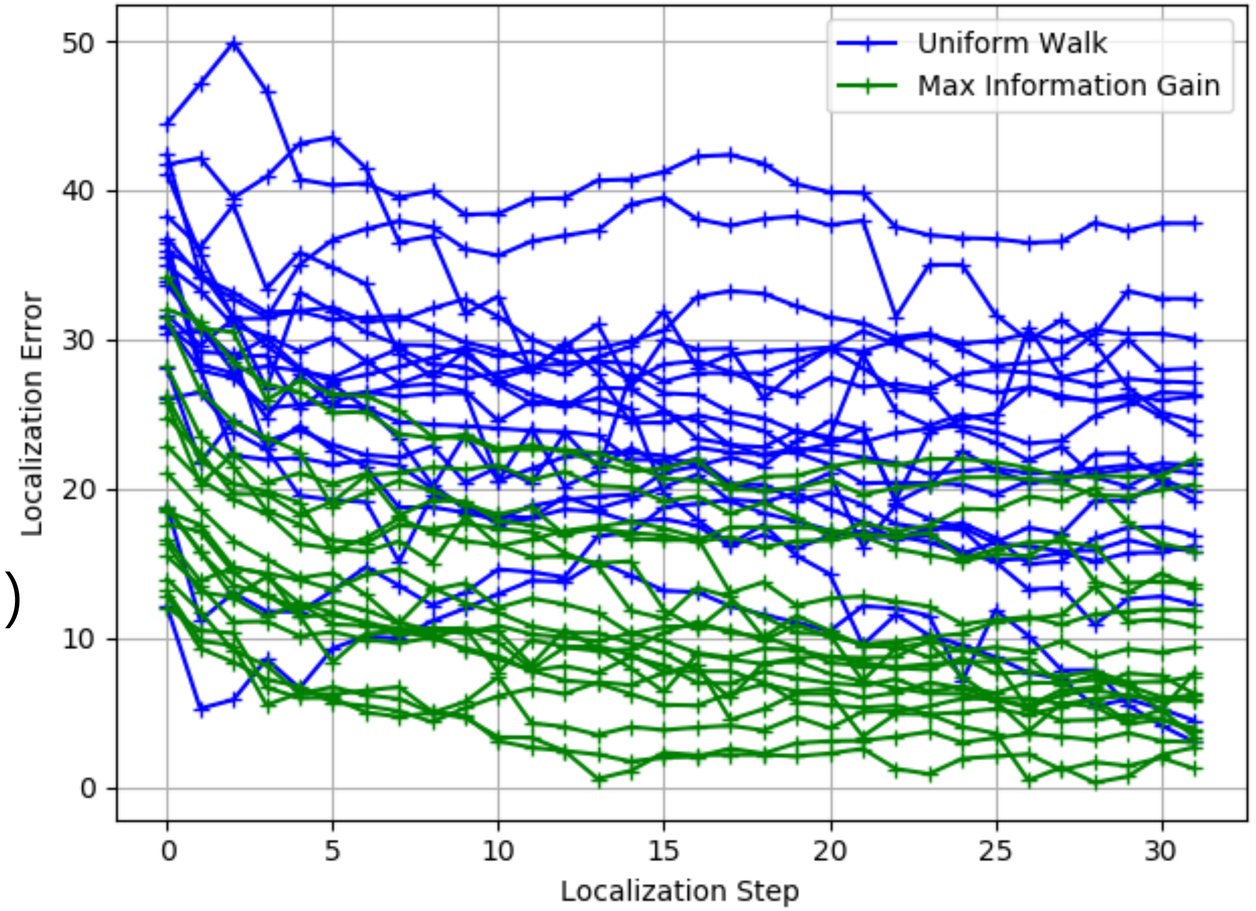
1. Use particle filters instead of grid
2. Continuous, noisy directions
3. Noisy moves
4. Uncertainty in observations

After all that, yes, an active policy (still) performs better than a passive one!



Summary

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There is a big GAP

Community is working hard to close it

- but no evidence yet for the gap diminishing

Some of the promising ways to diminish the gap:

- let the robot play to find out how the world works
- build the simulations to match the reality, not the other way round
- let the robot dream to play in alternative realities.

Q & A

질문은 Slido에 남겨주세요.

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TRACK 4

Thank you