Deep Reinforcement Learning agents playing DOOM

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Reinforcement Learning Final Project

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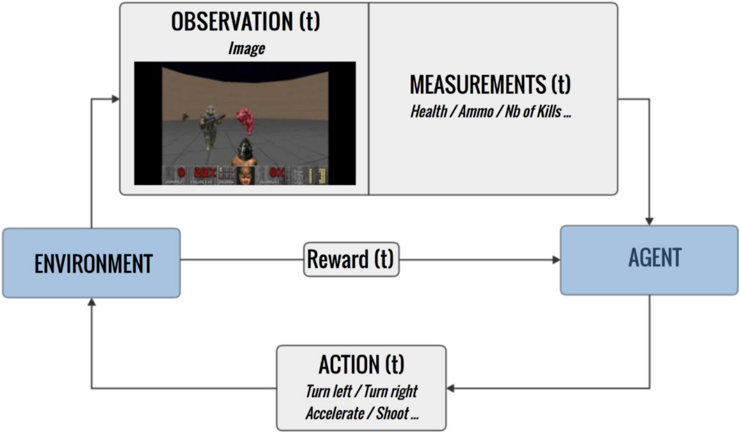
The RL problem to solve

Sensimotor control in a complex and dynamic **3-dimentional** envirionment"



Visual Doom AI Competition

	Limited Deathmatch		Full Deathmatch	
Agent Name	Number of frags	K/D Ratio	Number of frags	K/D Ratio
5vision	142	0.41	12	0.20
AbyssII	118	0.40	-	-
Arnold	413	**2.45**	164	**33.40**
CLYDE	393	0.94	-	-
ColbyMules	131	0.43	18	0.20
F1	**559**	1.45	-	-
IntelAct	-	-	**256**	3.58
Ivomi	-578	0.18	-2	0.09
TUHO	312	0.91	51	0.95
WallDestroyerXxx	-130	0.04	-9	0.01

Figure: Results of the Visual Doom AI Competition 2016. Scores marked with '-' indicate that the agent did not participate in the corresponding track. The best results in each column are marked in bold[1].

[1] Devendra Singh Chaplot and Guillaume Lample. "Arnold: An Autonomous Agent to Play FPS Games". In: *AAAI*. 2017.

Project objectives

- 2 methods :
  - Learning To Act by Prediction the Future (**DFP**)[2]
  - Playing FPS Games with Deep Reinforcement Learning (**Arnold**)[3]
- Replicates each article's main results in Doom
- Optimize the methods
- Evaluation of the methods in an other environment

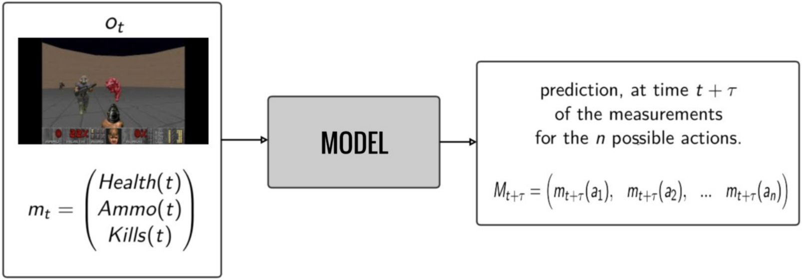
[2] Alexey Dosovitskiy and Vladlen Koltun. "Learning to Act by Predicting the Future". In: *CoRR* abs/1611.01779 (2016). arXiv: 1611.01779. URL: http://arxiv.org/abs/1611.01779.

[3] Guillaume Lample and Devendra Singh Chaplot. "Playing FPS Games with Deep Reinforcement Learning.". In: *Proceedings of AAAI*. 2017.

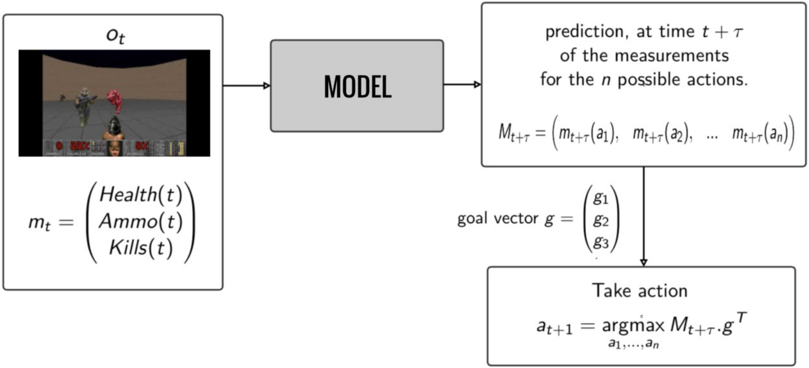
Introduction to the DFP model

Learning To Act by Prediction the Future

At each game time step t : predict future measurements



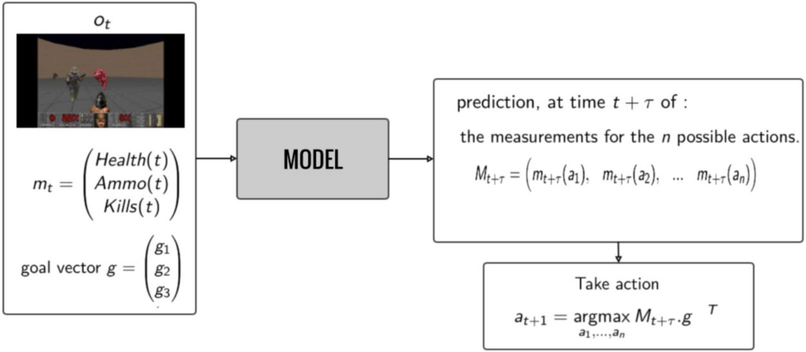
Introduction to the DFP model



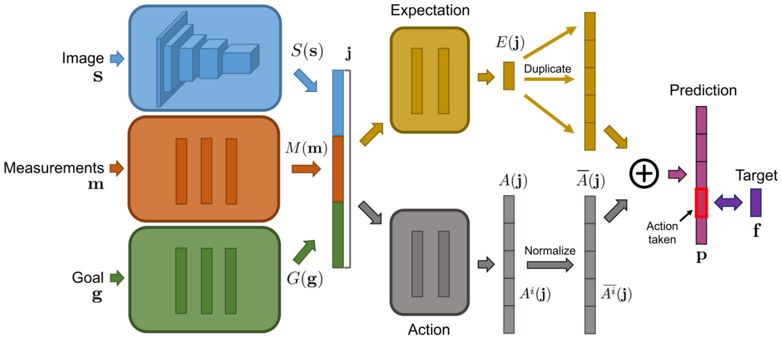
Introduction to the DFP model

We want to specify which measurements we care about at any given time

At each game time step t :



The model



- No scalar reward.
- Trained on experiences previously collected : **Supervised learning**
- Predict future measurement for 3 different future time steps $\tau = (8, 16, 32)$.

Experiments

Two given scenarios :

Name	Health gathering	Battle
Image		
Nb Actions	4	8
Measurements	(Health)	(Ammo,Health,Kills)

Health Gathering scenario

- Basic training from the article : episode limited to 525 steps.

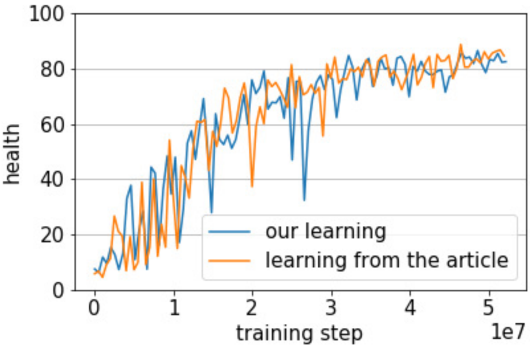
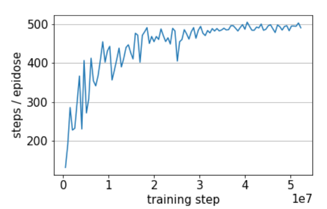
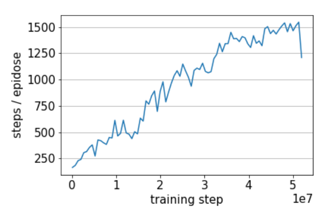


Figure: Health at the end of an episode during training



(a) *episode_timeout* = 525 steps



(b) *episode_timeout* = 2100 steps

Figure: Life time during training for the 2 different *episode_timeout* values.

Training Testing	short episodes	long episodes
short episodes	517	509
long episodes	658	**1166**

Figure: Life time (Number of step of an episode)

Health Gathering scenario

Battle scenario

- Battle original learning. Fixed goal vector input $(0.5, 0.5, 1)$ during training and testing.

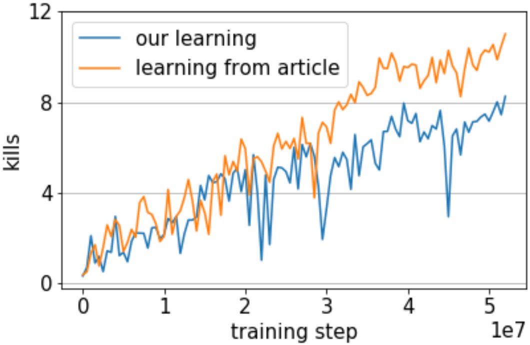


Figure: Average number of kills per episodes during learning.

Battle scenario

- Training with short and long episodes

Testing \ Training	short episodes	long episodes
long episodes	9.8	**15.9**

Figure: Average number of kills

Battle scenario

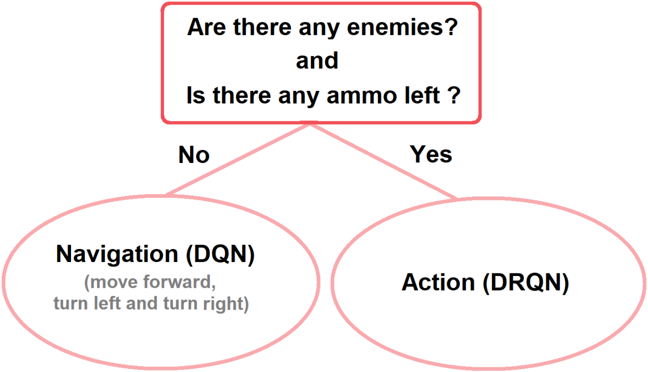
- Choice of the input goal vector at inference time ($Ammo$, $Health$, $Kills$).

Testing \ Training	$(0.5, 0.5, 1)$	Random goal in $[-1, 1]$
$(0.5, 0.5, 1)$	**15.9**	13.5
$(1, 1, 1)$	15.2	**14.7**
$(0, 0, 1)$	1.6	2.4

Figure: Average Kill count for varying input goal vectors.

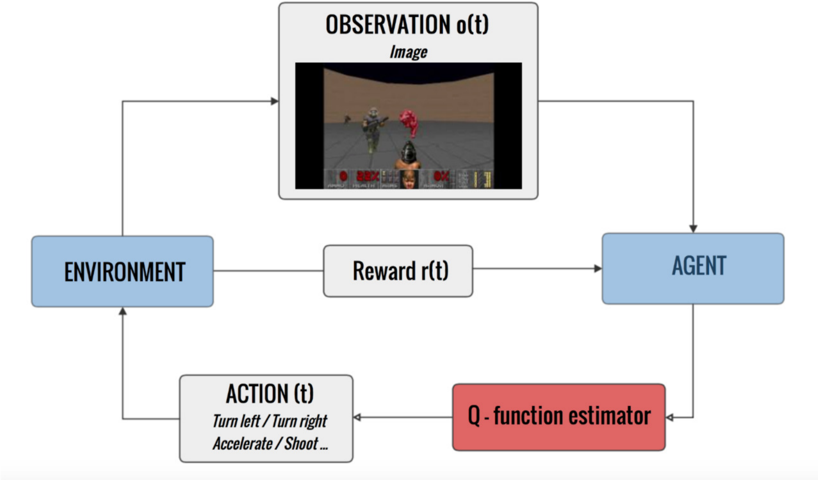
Battle scenario

Arnold's model[4]

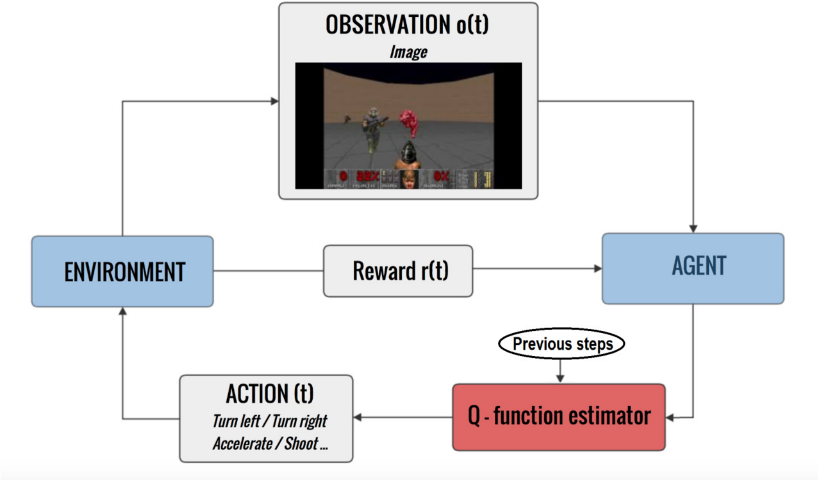


[4] Guillaume Lample and Devendra Singh Chaplot. "Playing FPS Games with Deep Reinforcement Learning.". In: *Proceedings of AAAI*. 2017.

Deep Q-Networks (Navigation)



Deep Recurrent Q-Networks (Action)



Deep Recurrent Q-Networks (Action)

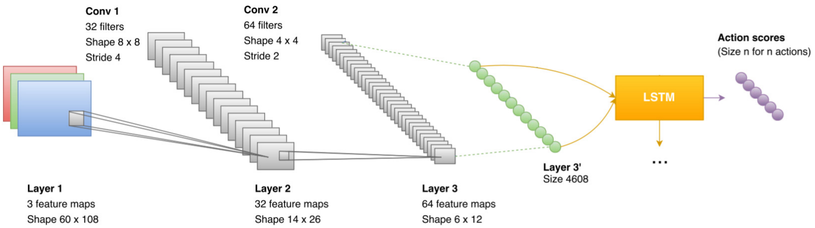


Figure: Initial DRQN model[5].

[5] Matthew J. Hausknecht and Peter Stone. "Deep Recurrent Q-Learning for Partially Observable MDPs". In: *AAAI Fall Symposia*. 2015.

Deep Recurrent Q-Networks (Action)

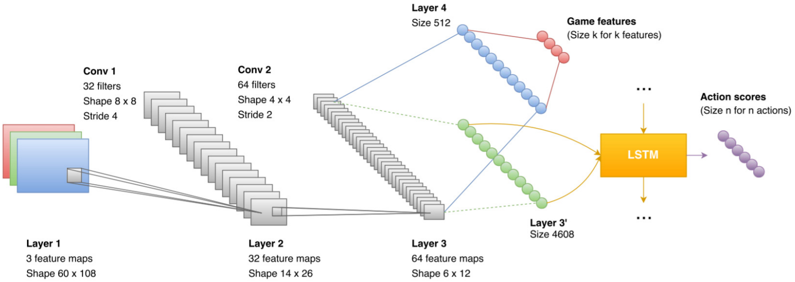


Figure: DRQN model with features[6].

[6] Guillaume Lample and Devendra Singh Chaplot. "Playing FPS Games with Deep Reinforcement Learning.". In: *Proceedings of AAAI*. 2017.

Experiments: Health Gathering

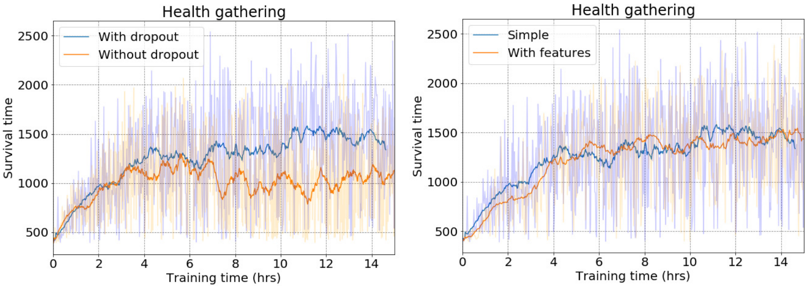


Figure: Performances of the model during the training on Health gathering scenario.

Experiments: Deathmatch

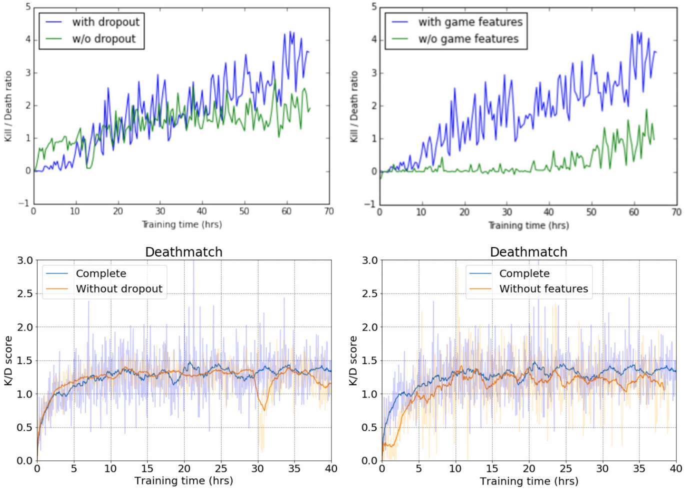


Figure: Performances of the model during the training on Deathmatch scenario.

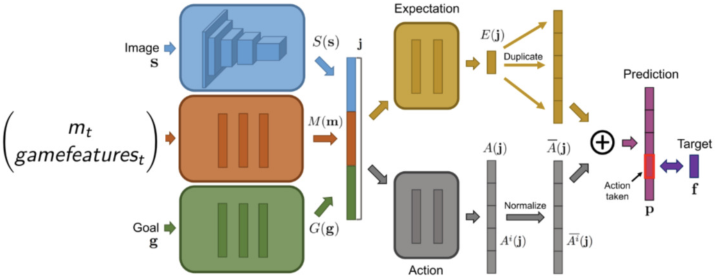
Health Gathering Video

Deathmatch Video

Use game features information on DFP

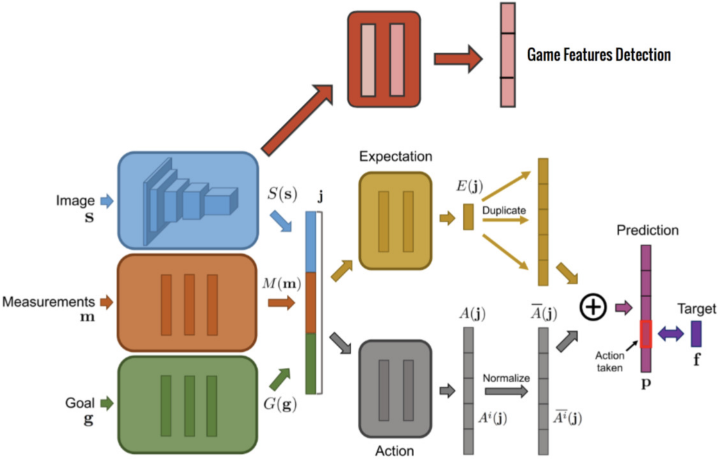
- First strategy :

$$gamefeatures_t = \begin{pmatrix} Medikit \\ Poison \\ Enemy \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \dots \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \dots$$

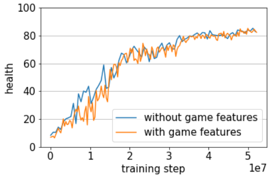
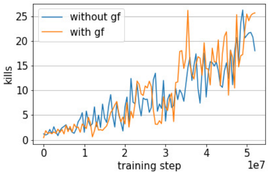
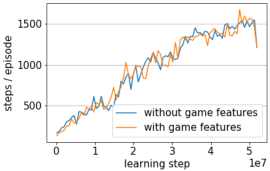
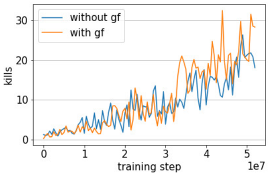


Use game features information on DFP

- Second strategy :



Experiments

	Health Gathering	**Battle**
Features	Health pack / Poison	Enemy
Method 1		
Method 2		

Experiments

Training	**Testing with goal** $(0.5, 0.5, 1)$
Initial network	13.5
Method 1	**15.6**
Method 2	**15.5**

Figure: Average kill count with and without the "enemy" game feature information.

Comparison : Health gathering

Both methods learned on the very same scenario.

	DFP	Arnold
Life time (nb of steps)	**4664**	2058

Comparison : Defend the center

Methods learned on different battle scenarios.

	DFP	Arnold
Kill/Death	**8.9**	8.6

What we have done ...

- Comparison of two different RL formulations : Q-learning (Arnold) vs Supervised Learning (DFP).
- Replicated the main results of both articles.
- Improved the DFP network with ideas from the Q-learning network.

To go further ...

- Optimize the parameters.
- Use Arnold navigation / action network split on the DFP method.
- Adapt to an other 3D environment : CARLA (autonomous driving) and MINOS (Indoor navigation).