Evaluating Reinforcement Learning Agents for Anatomical Landmark Detection

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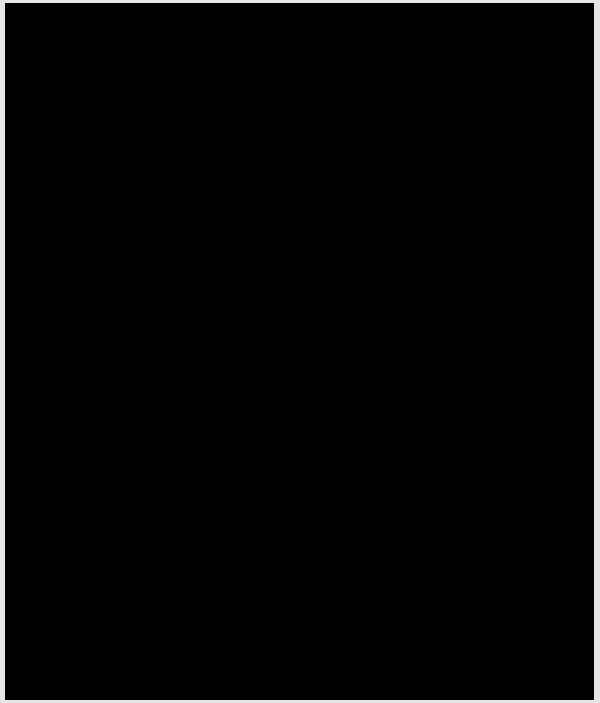
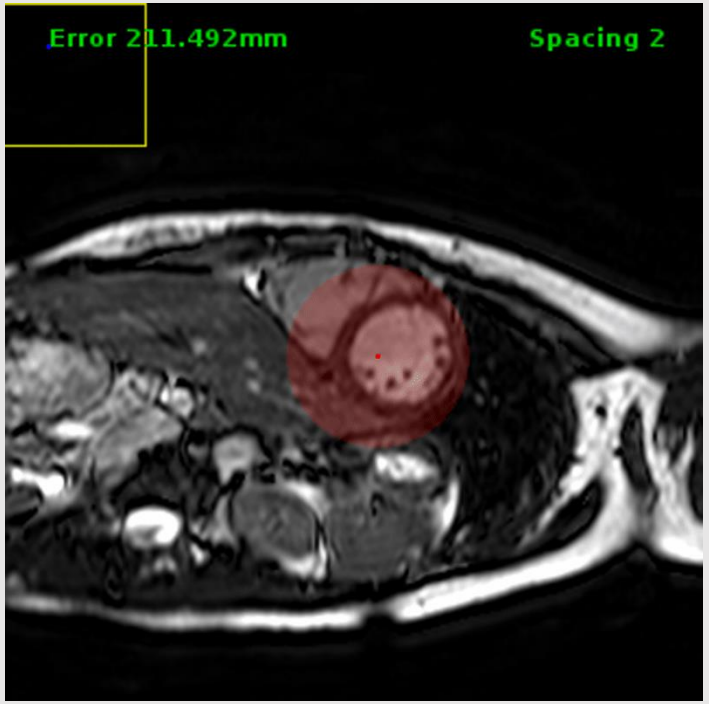
Reinforcement learning - Motivation



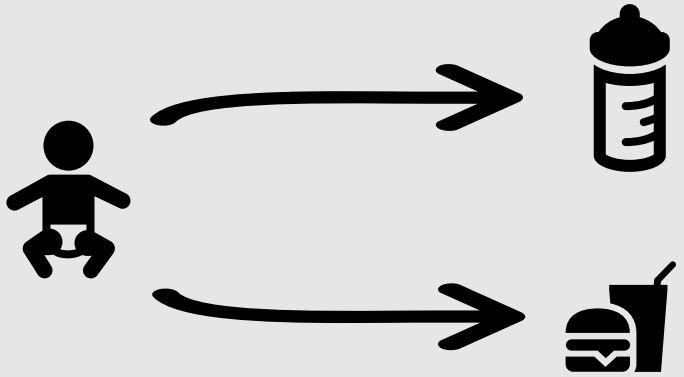
Mnih et al. 2015



Our agent for
landmark detection

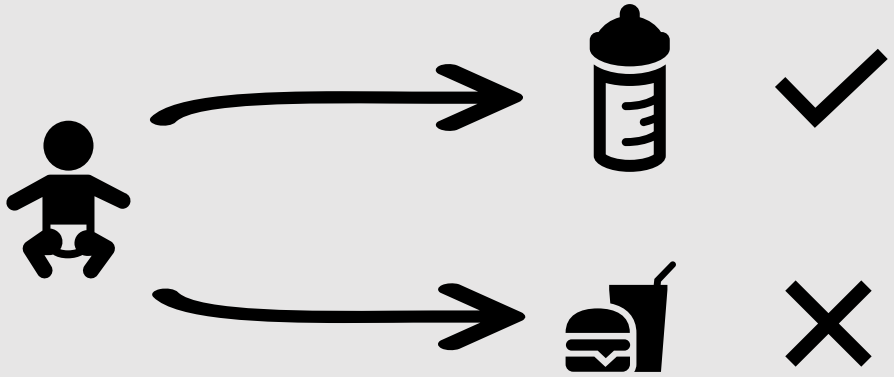
Unsupervised Learning

Explores data and draws inferences from datasets to describe hidden structures from unlabeled data



Supervised Learning

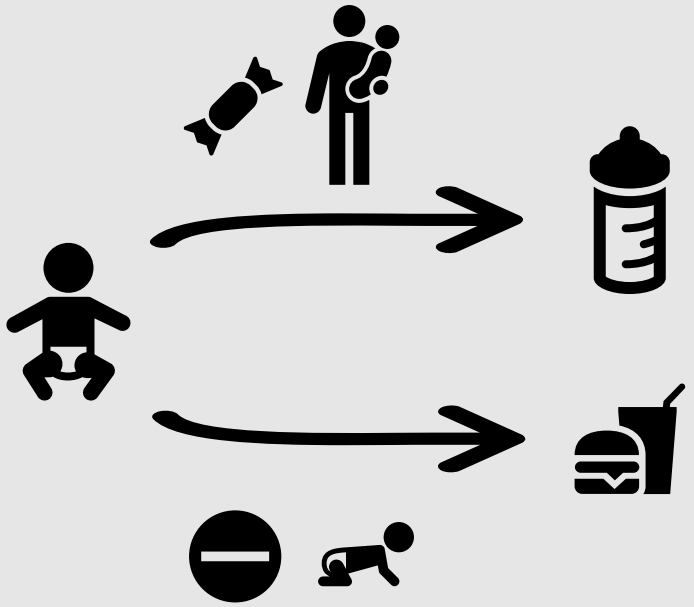
Learning from a training set of labeled examples provided by a knowledgeable external supervisor



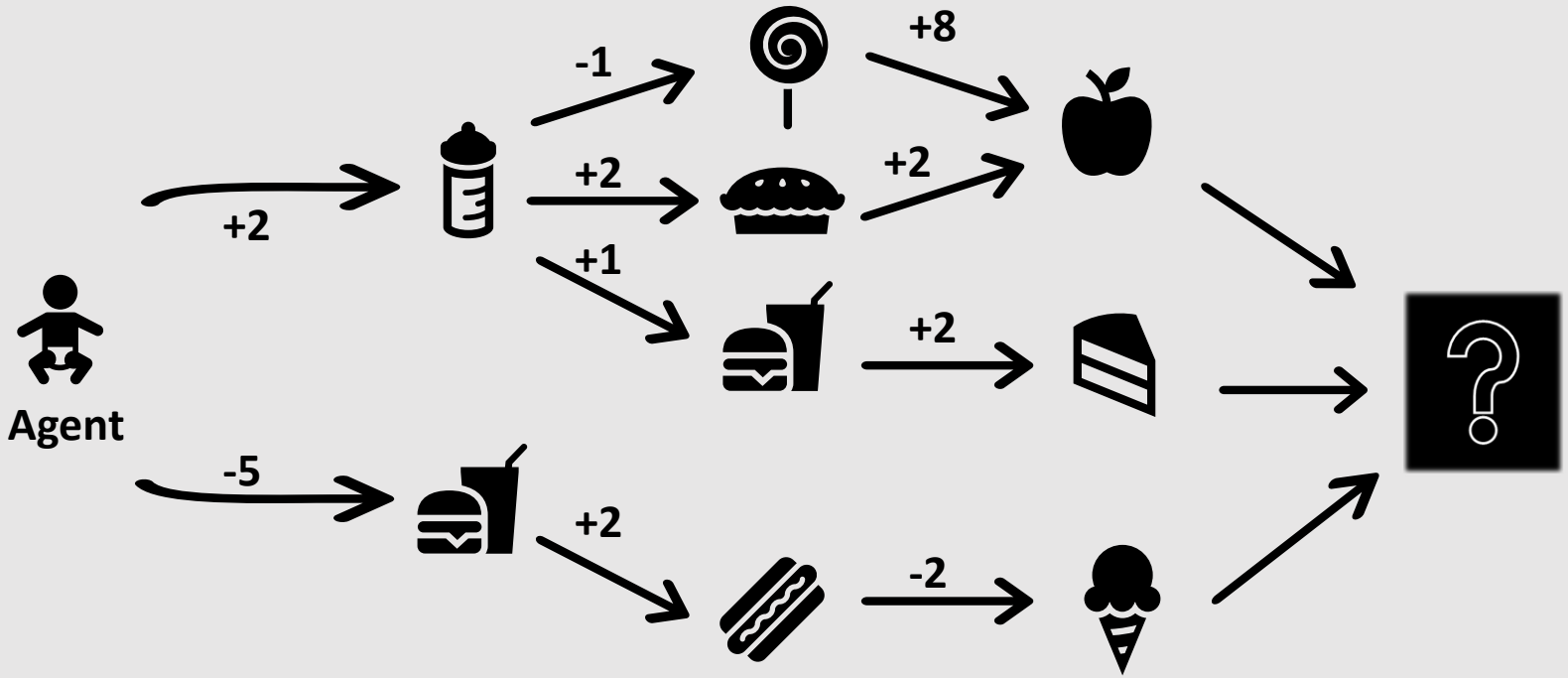
Reinforcement Learning

Computational approach to learn by **<u>interacting</u>** with an environment

- Single decision must be made
  - Multiple actions
  - Each action has a reward associated with it
- Goal is to maximize reward
  - Pick an action with the highest reward



Reinforcement Learning



Sequential decision making

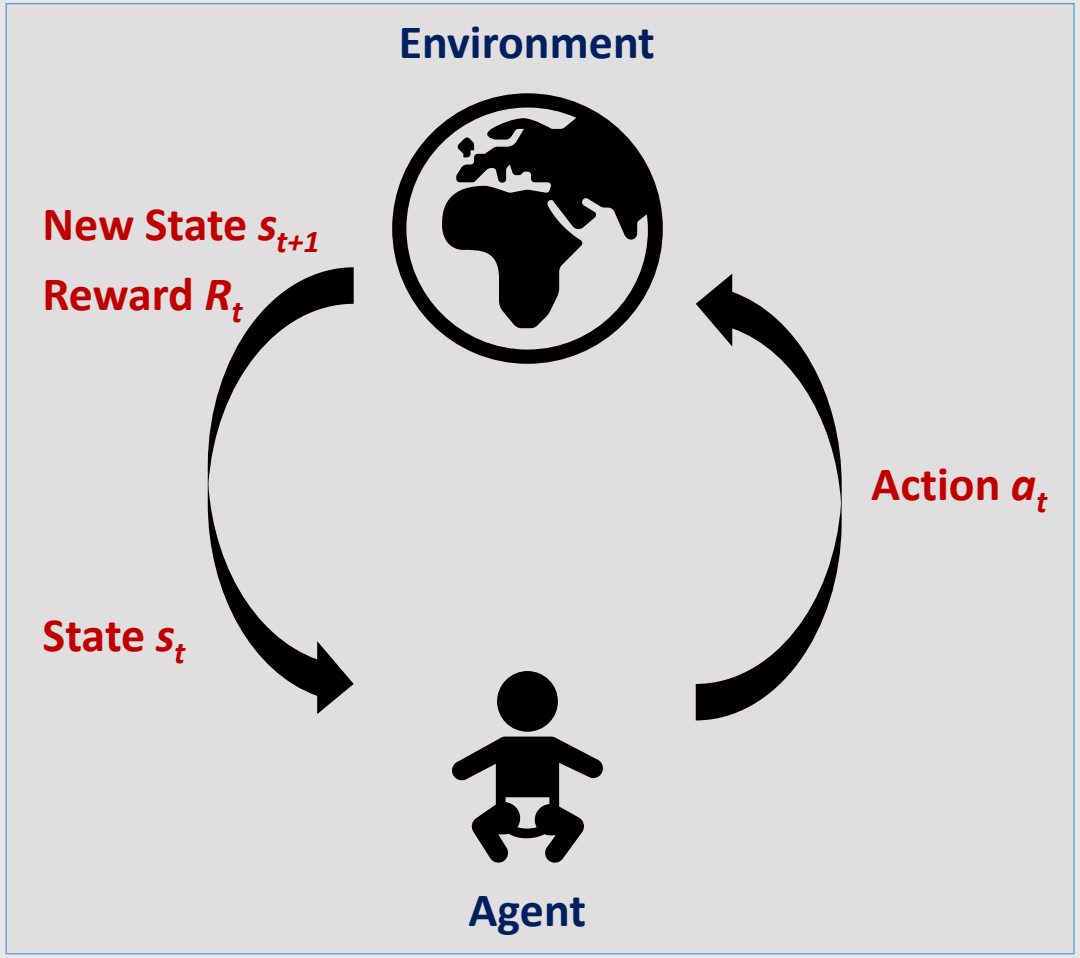
Reinforcement Learning

Markov Decision Process (MDP)

- Set of states **S**
- Set of actions **A**
- Reward signal
  R: s_t x a_t x s_{t+1} ->R
- Transition function
  T: s_t x a_t -> s_{t+1} ≡ P (s_{t+1} | s_t , a_t)

Markov assumption

- s_t and a_t are conditionally independent of all previous states and actions



RL Main Elements

Policy π

- The agent's strategy to choose an action at each state
- **Optimal Policy π*** is the theoretical policy that maximizes the expectation of cumulative rewards

Reward signal

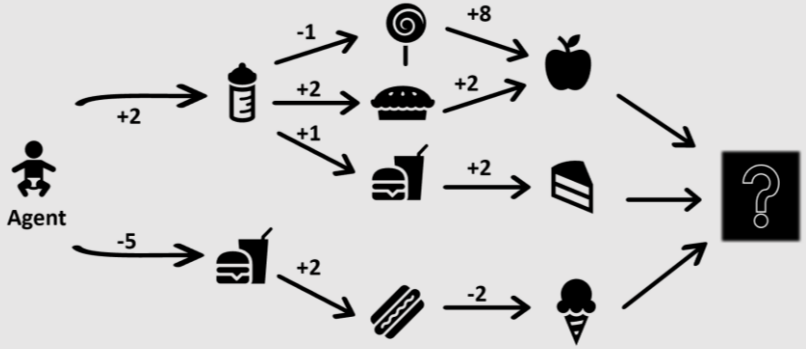
- Specifies what's good and what's bad in an immediate sense

Value function

- The total amount of reward an agent can expect to accumulate over the future

RL Solution

- Approximates iteratively the optimal value function when the whole MDP is unknown by sampling states and actions from the MDP, and learning from experience
  - Certainty equivalence
  - Temporal difference (TD)
  - State-action-reward-state-action (SARSA)
  - Q-learning
  - …



Reinforcement learning

Learning what to do (how to map situations to action) -> so as to maximize sum of numerical rewards seen over the learner's lifetime (**Policy π: S->A)**

Value Functions

- **A value function is defined as a prediction of the expected, accumulated, discounted, future reward in order to measure how good each state or state-action is**

- **State-action value function:** Estimates a value of each action *a* in each state *s* under policy π

$$\boldsymbol{Q^{\pi}(s,a) = E[R|s,a,\pi]}$$

- Optimal policy * achieves the best expected return from *any* initial state

$$\boldsymbol{Q^{*}(s,a) = \max_{\pi} Q^{\pi}(s,a)}$$

Deep Q-Networks (DQN) Mnih 2013

- DQN is an implementation of a standard Q-learning algorithm with function approximation using a ConvNet

$$\boldsymbol{Q^{\pi}(s,a) \approx Q^{\pi}(s,a;\ \theta)}$$

- Objective function: MSE in Q-values

$$\boldsymbol{L(\theta) = E\left[\left(r + \gamma \max_{a'} Q(s`,a`;\theta) - Q(s,a;\theta)\right)^2\right]}$$

- Optimize **end-to-end** by SGD, using $\boldsymbol{\frac{\delta L(\theta)}{\delta \theta}}$

RL in Medical Imaging Analysis

Image Segmentation

- RL for image thresholding and segmentation

Shokri, M. et al. (2003)
Sahba, F. et al. (2006)

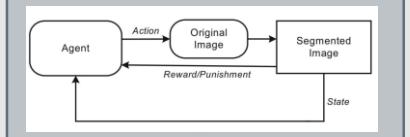
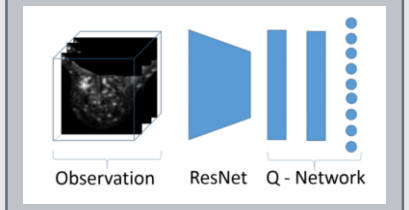


Image Localization

- Deep RL for Active Breast Lesion Detection from DCE-MRI

Maicas, G. et al. (2017)



Landmark Detection

- Artificial agent for anatomical landmark detection in medical images

Ghesu, FC. et al. (2016, 2017)

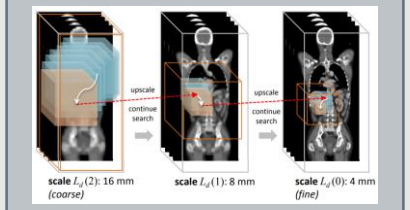
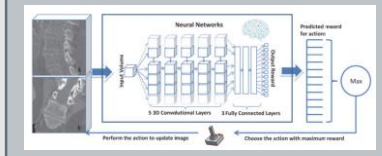


Image Registration

- Artificial Agent for Robust Image Registration (rigid, non-rigid, 2D/3D)

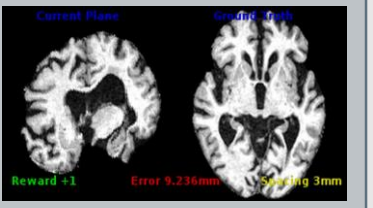
Liao, R. et al. (2017)
Krebs J. et al. (2017)
Miao, S. et al. (2017)



View Planning

- Automatic view planning using deep RL agents

Alansary, A. (2018)



RL in Medical Imaging Analysis

Landmark Detection

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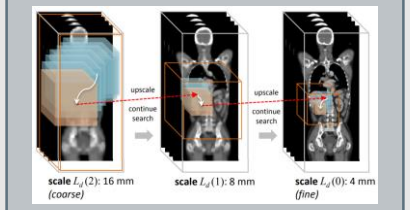


RL Agents for Landmark Detection

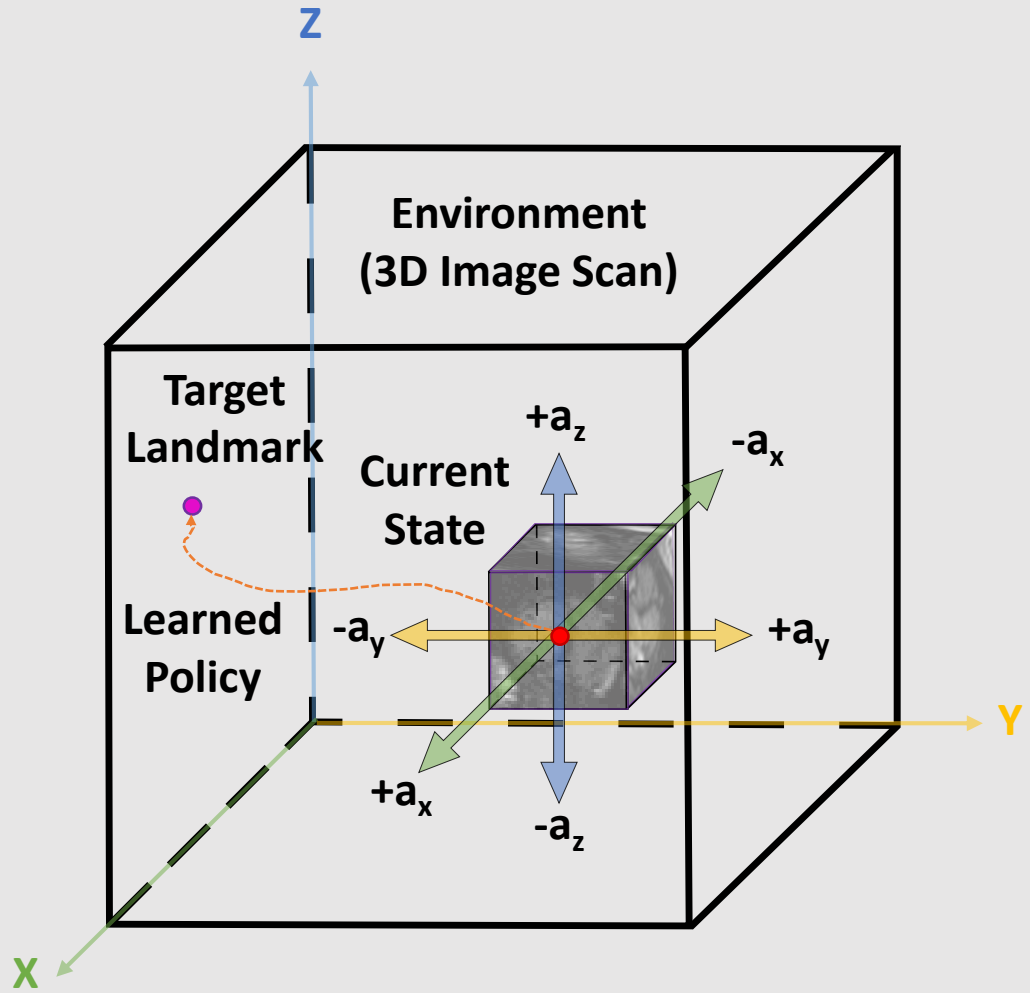
- Sequential decision process , where our RL-agent learns to navigate in an environment towards the target landmark using discrete action-steps

States:

3D region of interest(ROI) centered around the target landmark and current position

Navigation actions:

[left, right, up, down, forward, backward]



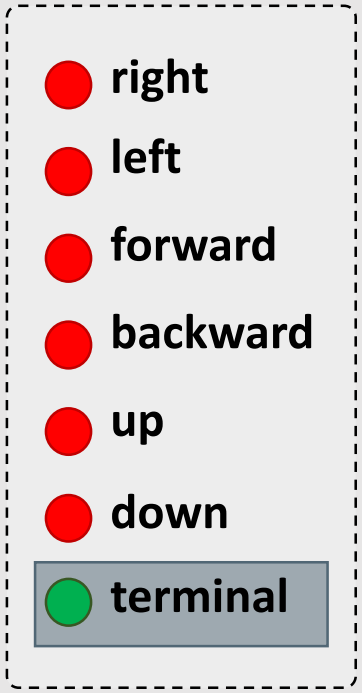
Terminal State

Training:

- Distance to the target landmark is ≤ 1mm

Testing:

1. Extra trigger action that terminates
   + Modifies the environment by marking the region centered around the correct target location
   - Increases the complexity of the task to be learned by increasing the action space size.
2. Oscillation property [1]
   + No added complexity to the action space
   - The correct target location is unmarked in the environment



- Here, we choose the terminating state based on the corresponding lower Q-value, when the agent oscillates
- Q-values are lower when the agent is closer to the target point and higher when it is far
- Intuitively, it encourages awarding higher Q-values to actions for far states from target

[1] Martin Riedmiller “Reinforcement learning without an explicit terminal state.” Neural Networks Proceedings, 1998.

Multi-scale Agent

Motivation

Capture spatial relations within a global neighborhood

Challenge

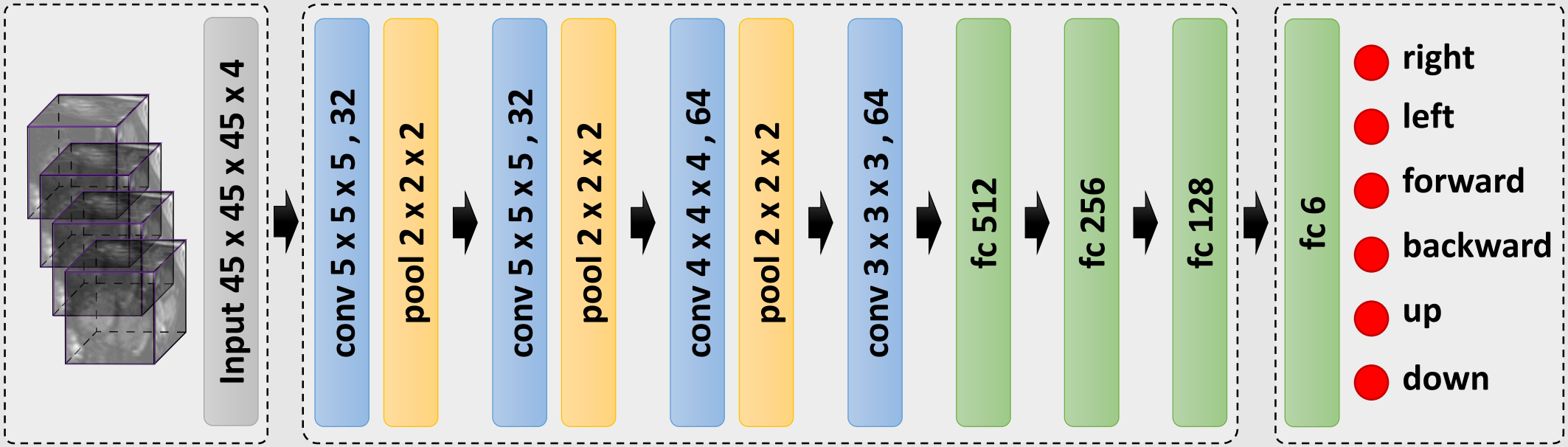
Increasing the network's field of view requires larger memory and higher computational complexity

Solution

+ Multi-scale agent strategy (coarse-to-fine fashion) [Ghesu et al 2017]
  - **Coarser levels** enables the agent to see more structural information
  - **Finer scales** provides more precise adjustments for the final estimation
+ Hierarchical action steps
  - **Larger steps** speed convergence towards the target plane
  - **Smaller steps** fine tune the final estimation of plane parameters

Proposed ConvNet Architecture

- Navigation actions are based on the estimated Q-values from the output of DQN



Reward Function

- Designing good empirical reward functions R is often difficult as RL agents can easily overfit the specified reward and thereby produce undesirable or unexpected results.
- R should be proportional to the improvement that the agent makes to detect a landmark after selecting a particular action.
- We define the reward function,

$$R=D(P_{i-1},P_t)-D(P_i,P_t)$$

  - D: Euclidean distance between two points.
  - P_i : current position at $step_i$
  - P_t: target ground truth landmark's location

Improvements on DQN

We experimentally evaluate two recent state-of-the-art variants of the standard DQN

- **Double DQN (DDQN)** **H. Van Hasselt 2015**

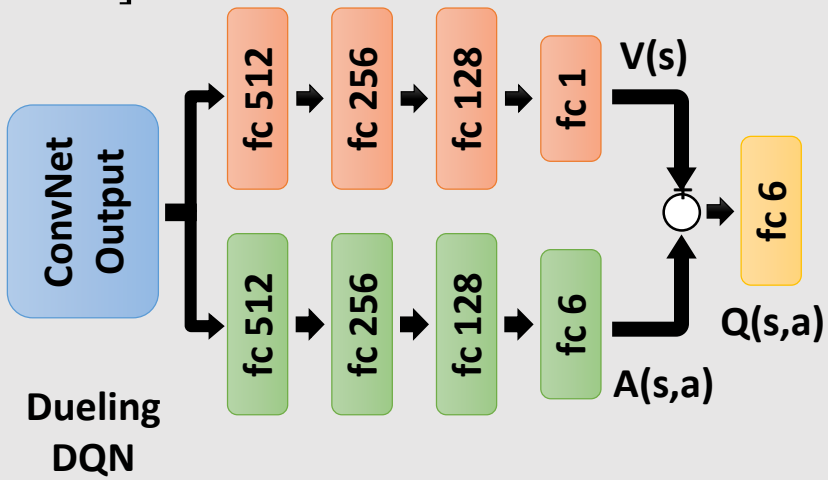
  Removes upward bias caused by maximum approximated action value
  - Current Q-net θ is used to select actions
  - Older target Q-net θ^- is used to evaluate actions

$$L(\theta) = E_{s,r,a,s' \sim D}\left[\left(r + \gamma \max_{a'} Q(s`, Q(s`, a`; \theta), \theta^-) - Q(s, a; \theta)\right)^2\right]$$

- **Dueling DQN** **Z. Wang 2015**

  Split Q-net into two channels:
  - Action-independent value function **V(s)**
  - Action-dependent advantage function **A(s,a)**

$$Q^{\pi}(s, a) = A^{\pi}(s, a) + V^{\pi}(s)$$

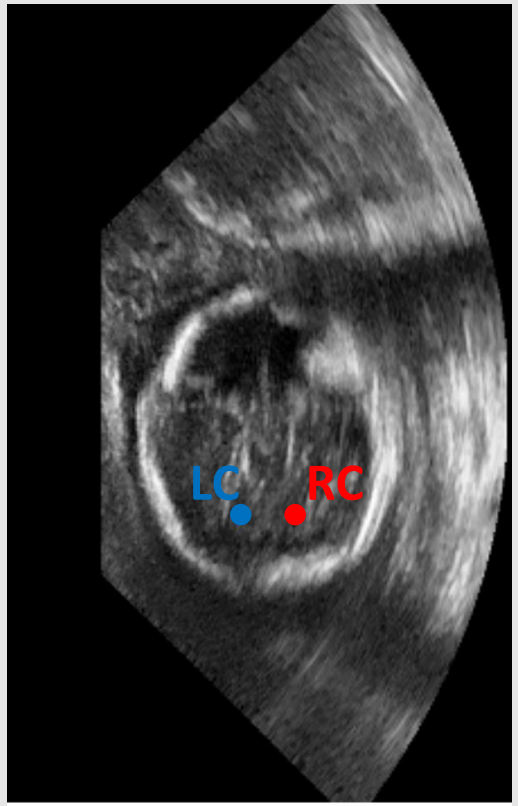


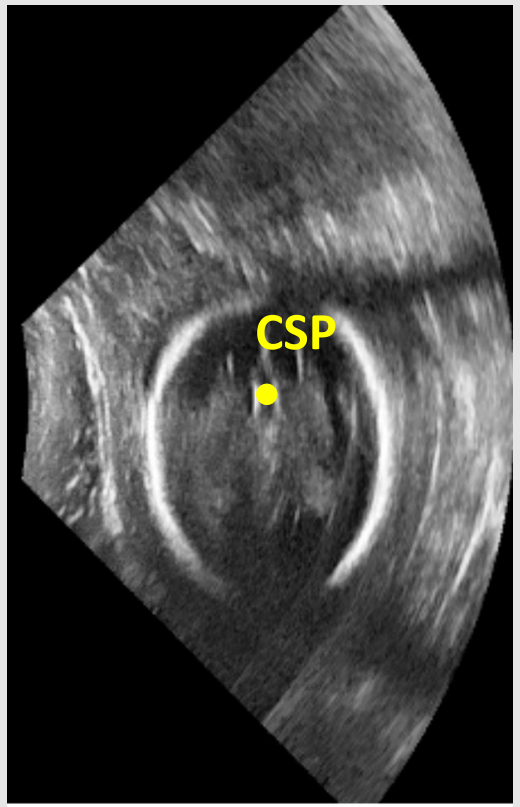
Experiment I - Fetal Head Ultrasound Landmarks

- Finding the target landmarks in fetal ultrasound images is a challenging task because of the shadowing, mirror images, refraction, and fetal motion

Dataset

- 72 fetal head ultrasound scans[1] - 21 testing and 51 training
- Three landmarks:
  1. Right cerebellum (RC)
  2. Left cerebellum (LC)
  3. Cavum septum pellucidum (CSP)





[1] http://www.ifindproject.com/

Comparison with state-of-the-art methods

- Comparison between different DQN –based agents and recent state-of-the-art methods for detecting the Cavum Septum Pellucidum (CSP) point from fetal ultrasound head scans.

Previous Methods	DQN Fixed-scale [Ghesu 2016]	DQN Multi-scale [Ghesu 2017]	Supervised PIN Single Landmark [Li 2018]	Supervised PIN Multiple Landmarks [Li 2018]
Distance Error (mm)	7.37 ± 5.86	6.51 ± 5.41	5.47 ± 4.23	5.50 ± 2.79

Ours Fixed-scale	DQN	DDQN	Duel DQN	Duel DDQN
Distance Error (mm)	4.95 ± 3.09	5.01 ± 2.84	6.29 ± 3.95	5.12 ± 3.15

Ours Multi-scale	DQN	DDQN	Duel DQN	Duel DDQN
Distance Error (mm)	**3.66 ± 2.11**	4.02 ± 2.20	4.17 ± 2.62	4.02 ± 1.55

- Our agents outperforms state-of-the-art methods

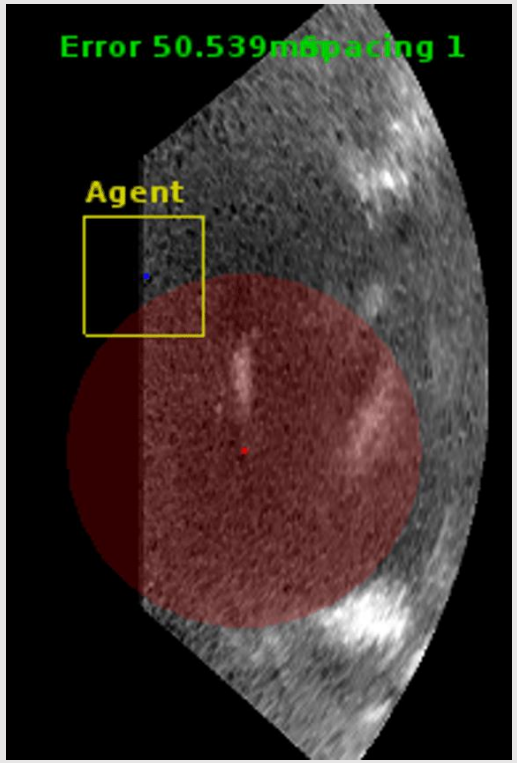
Extended Results

Model	Right Cerebellum		Left Cerebellum		Cavum Septum Pellucidum	
	FS	MS	FS	MS	FS	MS
DQN	4.17 ± 2.32	3.37 ± 1.54	2.78 ± 2.01	3.25 ± 1.59	$\mathbf{4.95 \pm 3.09}$	$\mathbf{3.66 \pm 2.11}$
DDQN	3.44 ± 2.31	3.41 ± 1.54	2.85 ± 1.52	2.95 ± 1.00	5.01 ± 2.84	4.02 ± 2.20
Duel DQN	$\mathbf{2.37 \pm 0.86}$	3.57 ± 2.23	$\mathbf{2.73 \pm 1.38}$	$\mathbf{2.79 \pm 1.24}$	6.29 ± 3.95	4.17 ± 2.62
Duel DDQN	3.85 ± 2.78	$\mathbf{3.05 \pm 1.51}$	3.27 ± 1.89	3.50 ± 1.7	5.12 ± 3.15	4.02 ± 1.55

- The best performing agent varies for each landmark
- Choosing the best DQN architecture is environment-dependent
- Multi-scale agents do not improve significantly the performance upon fixed-scale in images with smaller field of view

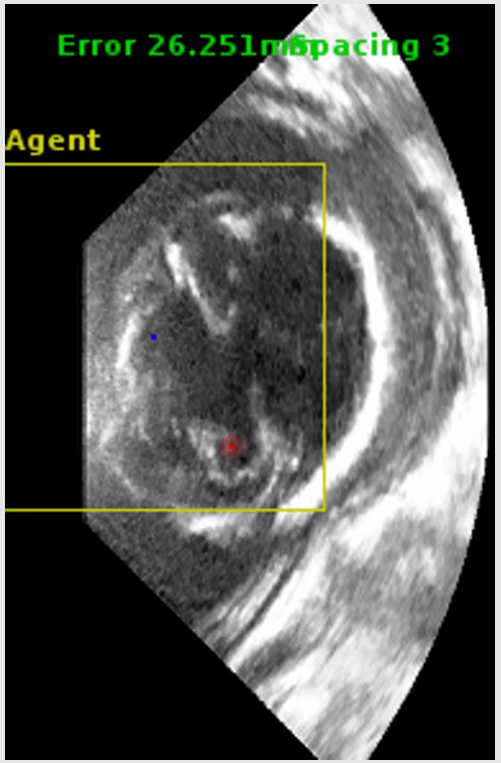
Visualizations

Fixed-Scale



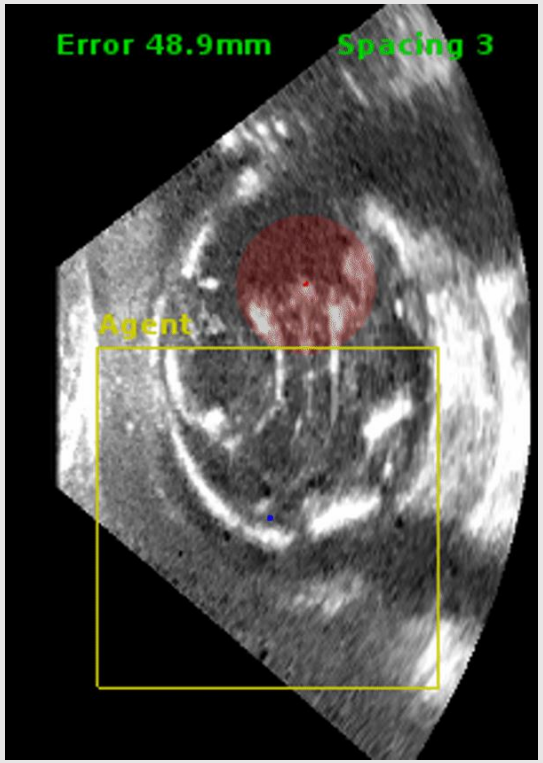
Left Cerebellar Duel DQN

Multi-Scale



Right Cerebellar DuelDoubleDQN

Multi-Scale

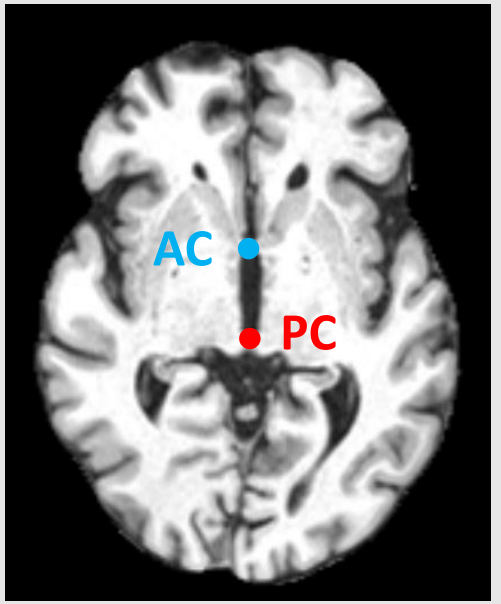


CSP DQN

Experiment II - Brain MRI

- **Anterior** and **posterior commissure** (AC and PC) commonly used by the neuroimaging community to define the axial plane during image acquisition
- **Dataset**
  - 832 isotropic 1mm MR scans from the ADNI database [1]
    - 728 and 104 images for training and testing

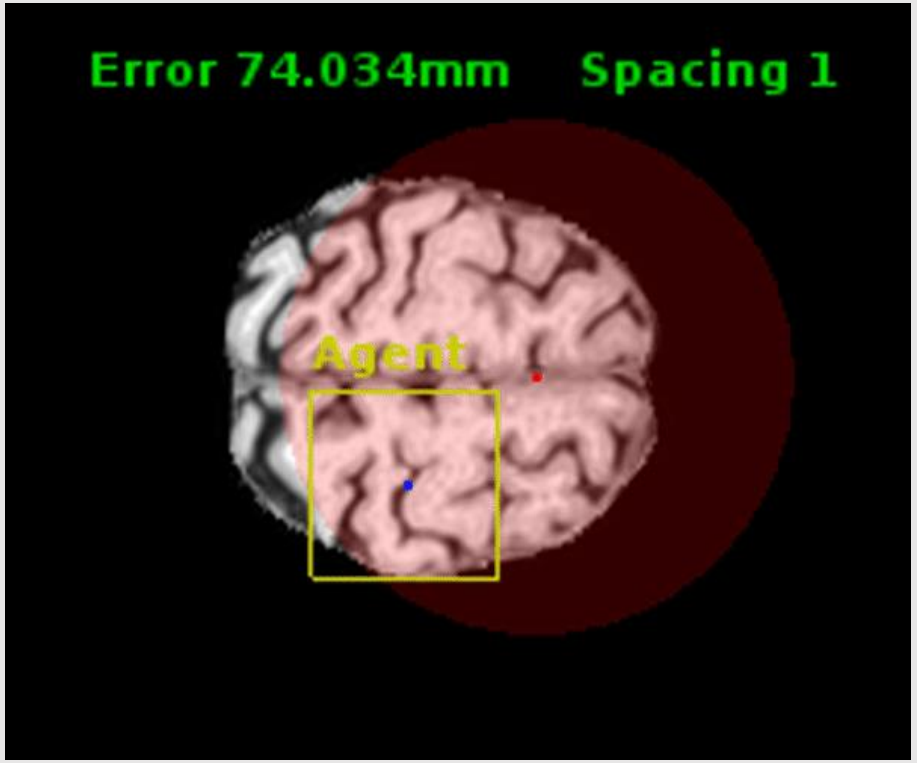
Model	Anterior Commissure		Posterior Commissure	
	FS	MS	FS	MS
DQN	3.04 ± 1.70	2.46 ± 1.44	$\mathbf{2.03 \pm 0.97}$	2.05 ± 1.14
DDQN	$\mathbf{2.62 \pm 1.24}$	2.61 ± 1.64	3.31 ± 1.2	$\mathbf{1.86 \pm 1.07}$
Duel DQN	3.04 ± 1.28	2.4 ± 1.42	3.6 ± 1.46	2.15 ± 1.24
Duel DDQN	2.97 ± 1.23	$\mathbf{2.01 \pm 1.29}$	2.04 ± 1.04	2.27 ± 1.22



[1] Susanne G Mueller, Michael W Weiner, Leon J Thal, Ronald C Petersen, Clifford Jack, William Jagust,John Q Trojanowski, Arthur W Toga, and Laurel Beckett. The Alzheimer's disease neuroimaging initiative.Neuroimaging Clinics, 15(4):869–877, 2005.

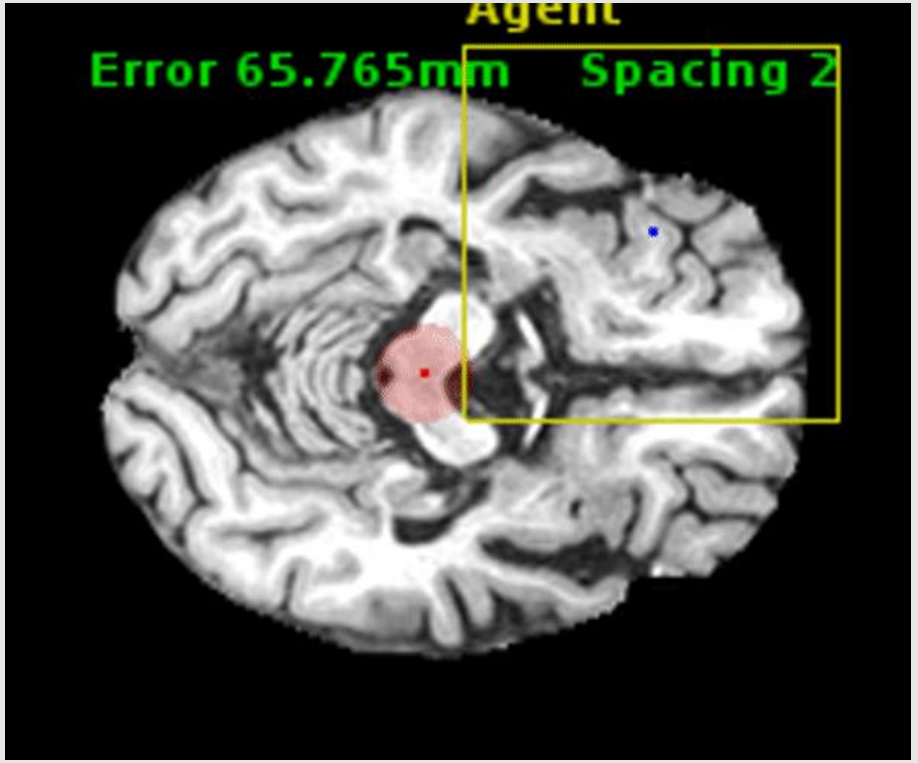
Visualizations

Fixed-Scale



AC - DuelDoubleDQN

Multi-Scale

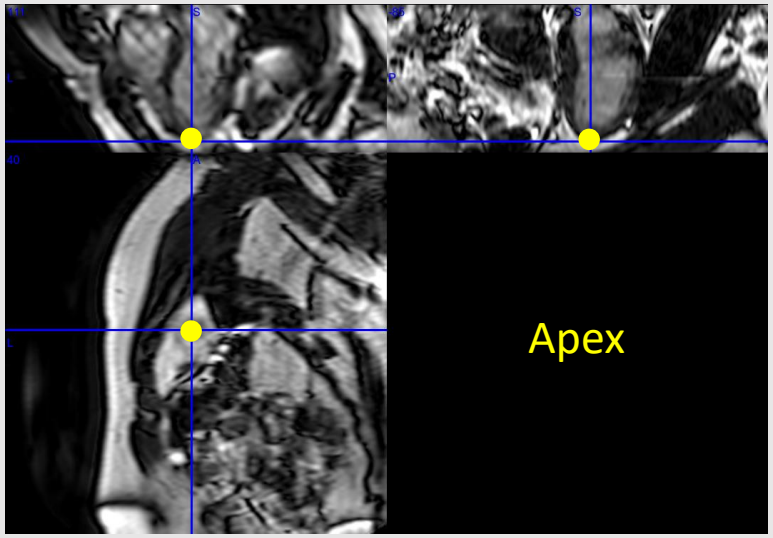


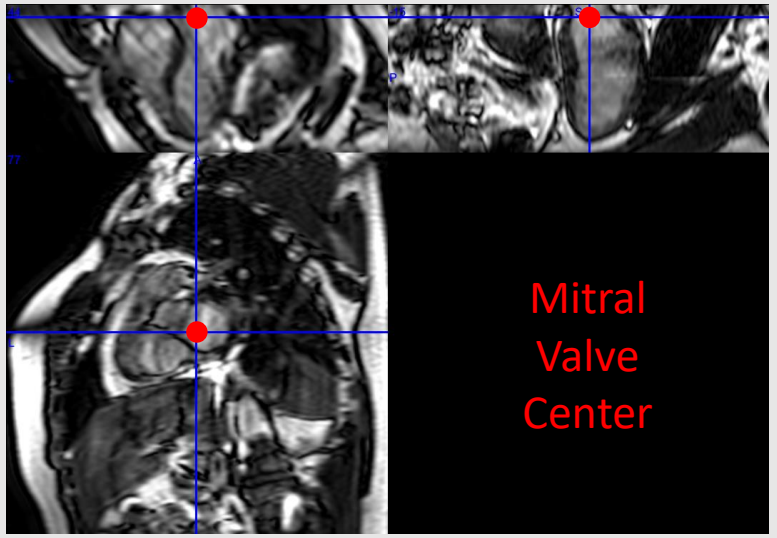
PC – Double DQN

Experiment III – Cardiac MRI

- **Apex** and **center of mitral valve**, commonly used for defining the short axis view during image acquisitions.
- Also used to assist automatic segmentation methods by defining starting and ending slices in the acquired cardiac stack of 2D image sequence.
- **Dataset**
  - 455 short-axis cardiac MR of resolution 1.25x1.25x2mm obtained from the UK Digital Heart Project [1]

  - 364 training and 91 testing





[1] Antonio de Marvao, et al. Population-based studies of myocardial hypertrophy: high resolution cardiovascular magnetic resonance atlases improve statistical power.Journal of Cardiovascular MagneticResonance, 16(1):16, 2014.[42]

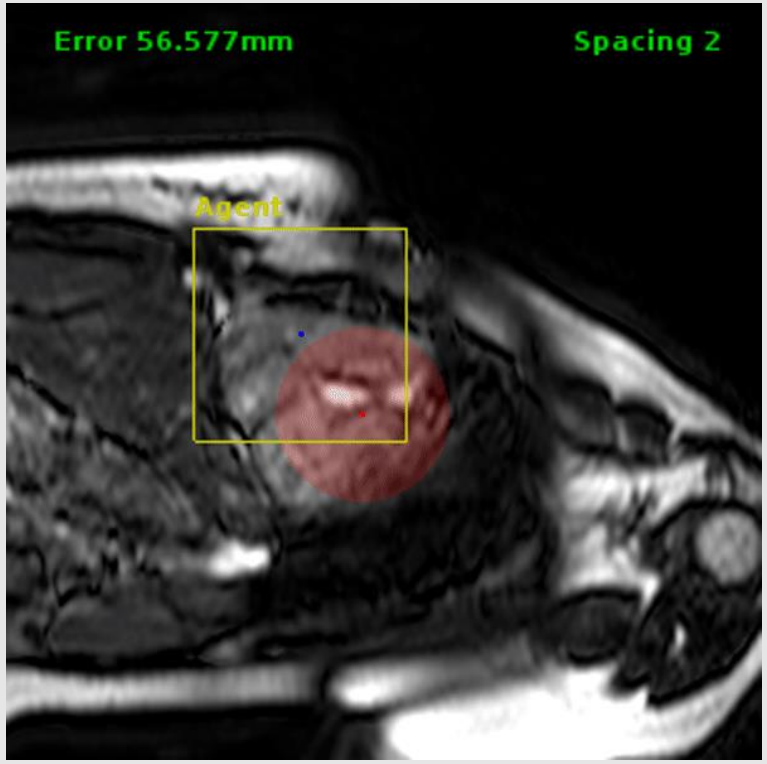
Results

Model	Apex		Mitral valve	
	FS	MS	FS	MS
DQN	7.49 ± 4.05	4.47 ± 2.63	$\mathbf{8.33 \pm 4.70}$	5.73 ± 4.16
DDQN	8.13 ± 5.60	4.53 ± 2.78	8.82 ± 4.80	$\mathbf{5.20 \pm 2.82}$
Duel DQN	$\mathbf{7.17 \pm 4.21}$	$\mathbf{4.42 \pm 2.67}$	8.82 ± 4.80	5.76 ± 3.89
Duel DDQN	7.59 ± 4.17	5.43 ± 3.37	8.63 ± 4.58	5.28 ± 2.61

- Duel DQN performs the best for detecting the apex
- Multi-scale agents significantly improve upon the fixed-scale agents, as the field of the view of cardiac scans is wider
- The performance of the agent improves with larger contextual information

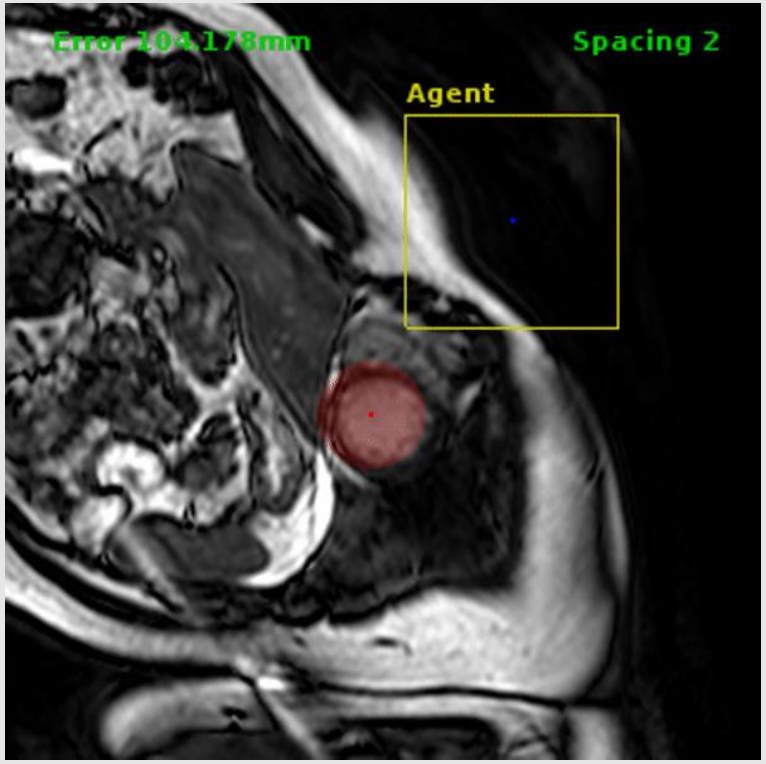
Visualizations

Multi-Scale



Mitral DoubleDQN

Multi-Scale



Apex DuelDQN

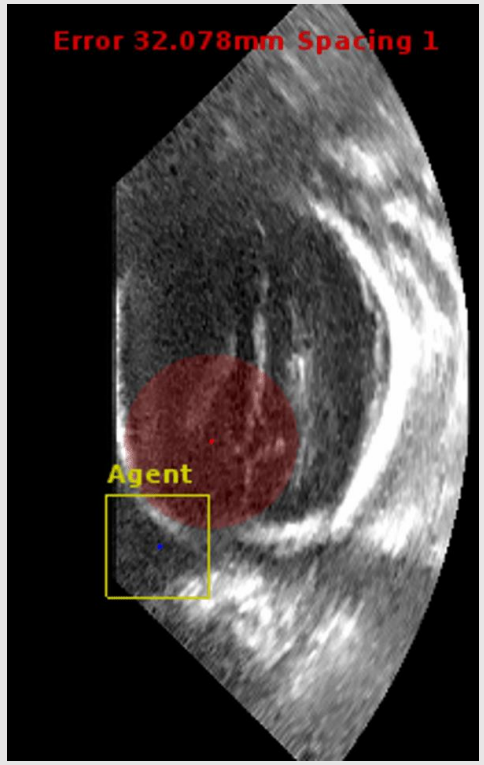
Runtime

- The agent finds the target location using sequential steps
- Total runtime depends on the starting point – the further it is, the longer it will take to find the target landmark
- In our implementation, each step takes around 0.0005-0.001 seconds. For example, if the agent is far 1000 steps from the target, it will take 0.5-1 second to find the target… **Very fast**!

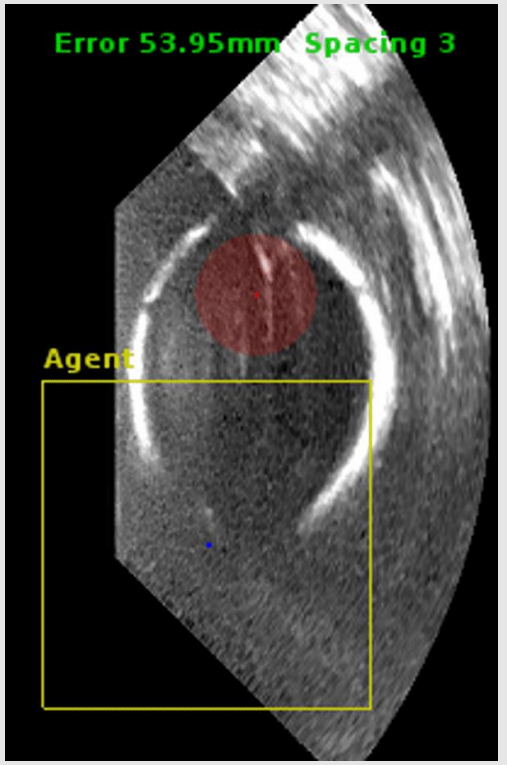
Current Challenges

- Background noise may confuse the agent for finding the accurate location of the target landmark

- No terminal state by following a long circular path around the target. This can be alleviated by using bigger memory to trace agent's recent path and detect oscillations frequencies



Background noise



No terminal

Limitations

- Reinforcement learning is a difficult problem that needs a careful formulation of its elements
- For example, RL tends to overfit to the rewards, which may cause unexpected behaviors
- Our results show that the optimal algorithm for achieving the best performance depends on the target landmark (environment-dependent) – similarly on different Atari games

Conclusion

- Fast automatic RL-agents can achieve the state-of-the-art performance for detecting anatomical landmarks from ultrasound and MRI scans
- Our extensive evaluations using several DQN based strategies show similar performance of all agents. However, multi-scale agents improves the performance in images with larger field of view such as cardiac MRI
- Hierarchical action steps speeds up the performance with larger steps, and yet smaller steps fine tune the fine location precisely

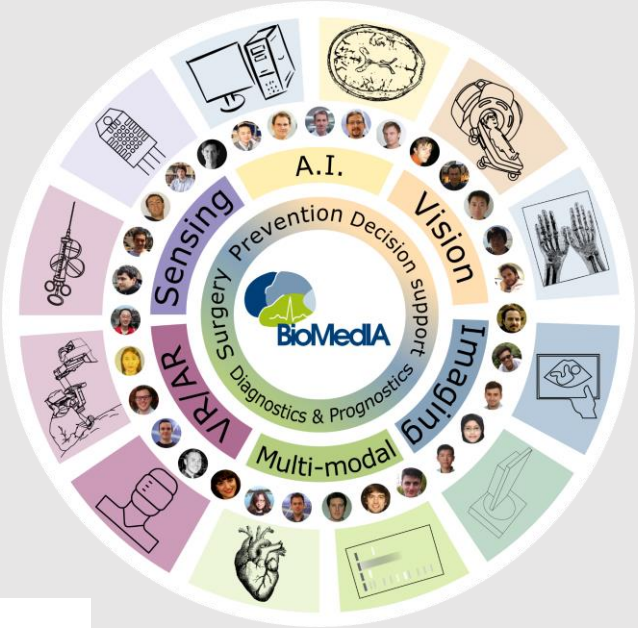
Future Work

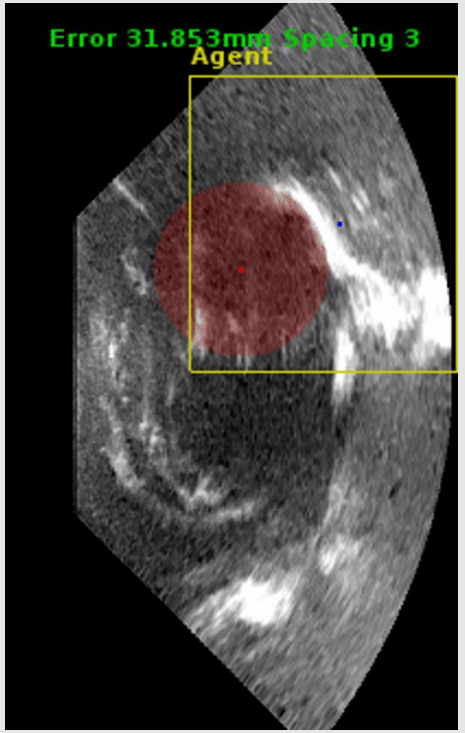
- Investigate using intrinsic geometry instead of intensity patterns for the RL-environment to improve the performance using collaborative or competitive agents
- Explore the use of either competitive or collaborative multi-agents to detect a single or multi-landmarks
- Inspired by AlphaGo RL agents could mimic the moves of a human expert and accumulate this experience, thus learning from experienced operators during real-time observation
- Another future direction, investigate involving human experts for learning the artificial agents actively, inspired by AlphaGo [D. Silver et al. 2016], where the agents can learn from experienced operators by interaction and accumulate this experience.

Code is publicly available

Scan me

https://github.com/amiralansary/tensorpack-medical





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