Multi-Scale Deep Reinforcement Learning for Real-Time 3D-Landmark Detection in CT Scans

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Presented By:
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School of Computing Science
Simon Fraser University
Burnaby, Canada

March 14, 2018

Outline

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Problem Statement

Data and Objects of Interest

- Detection of anatomical structures in CT scans.

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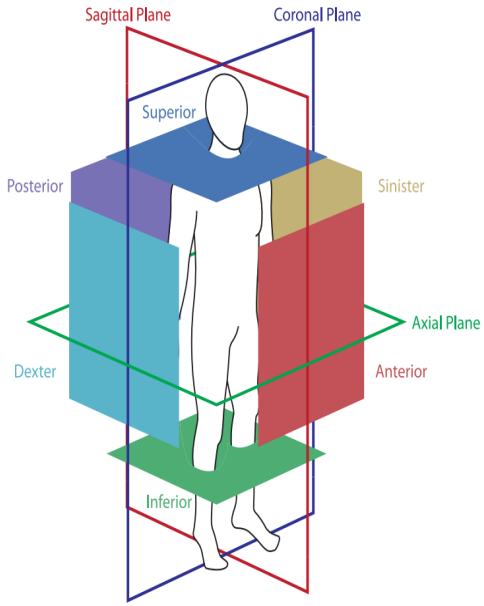

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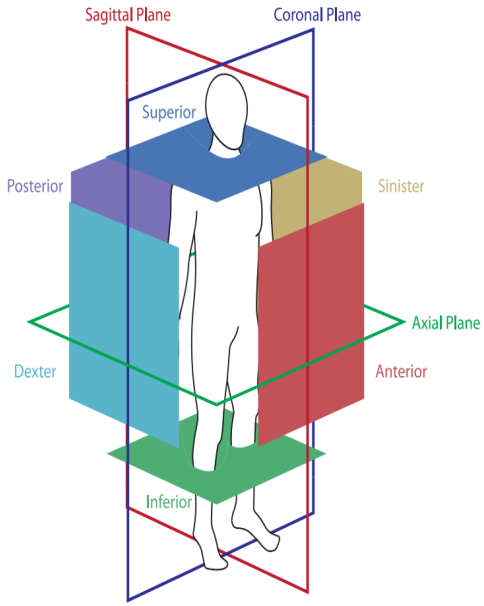

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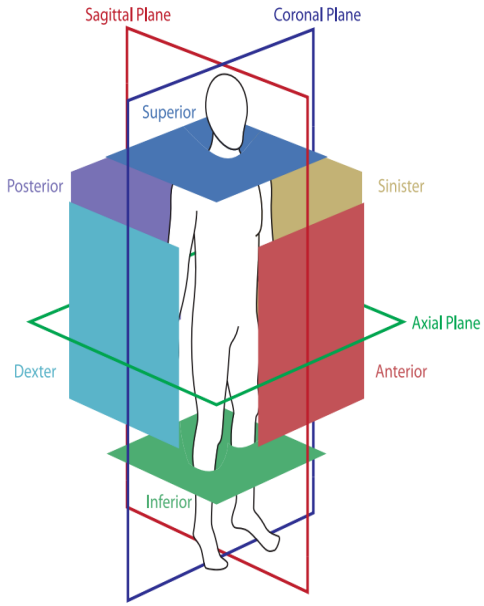

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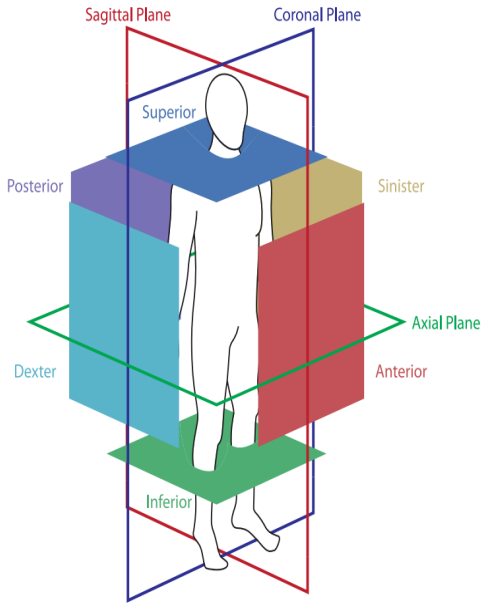

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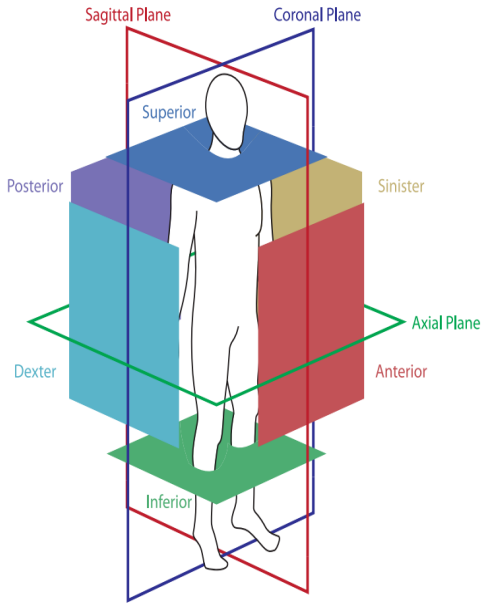

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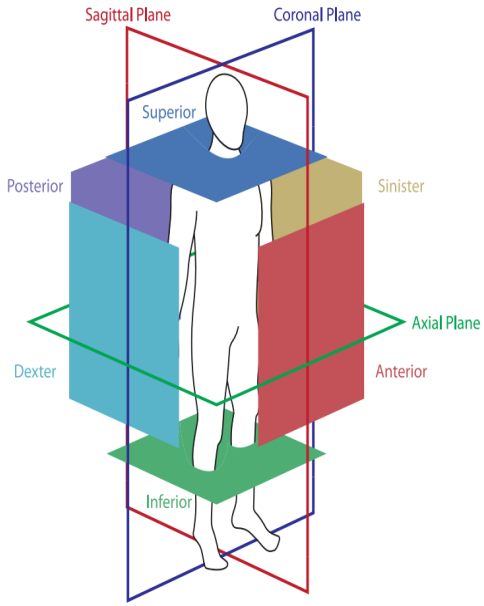
  - And 5 more anatomical structures...



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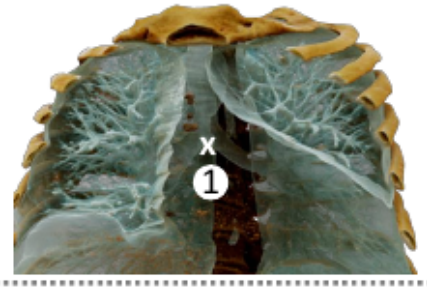
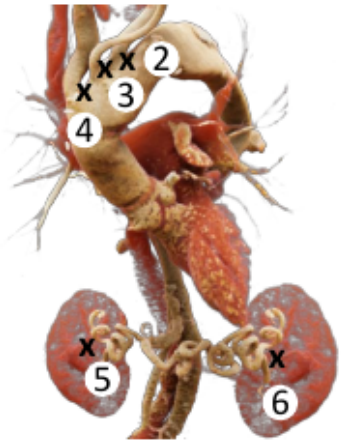


Bronchial Bifurcation



Aortic Arch Bifurcations

Kidneys

Hip Bones

Outline

Previous Work

Scanning Based Systems

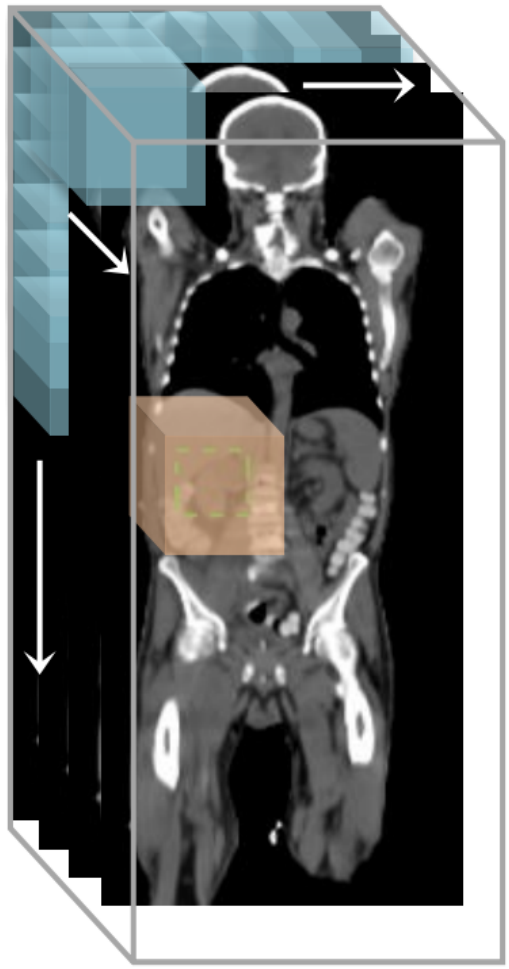


Figure: Systems that scan the image exhaustively or through a smarter region proposal based method.

Previous Work

End-to-End Systems

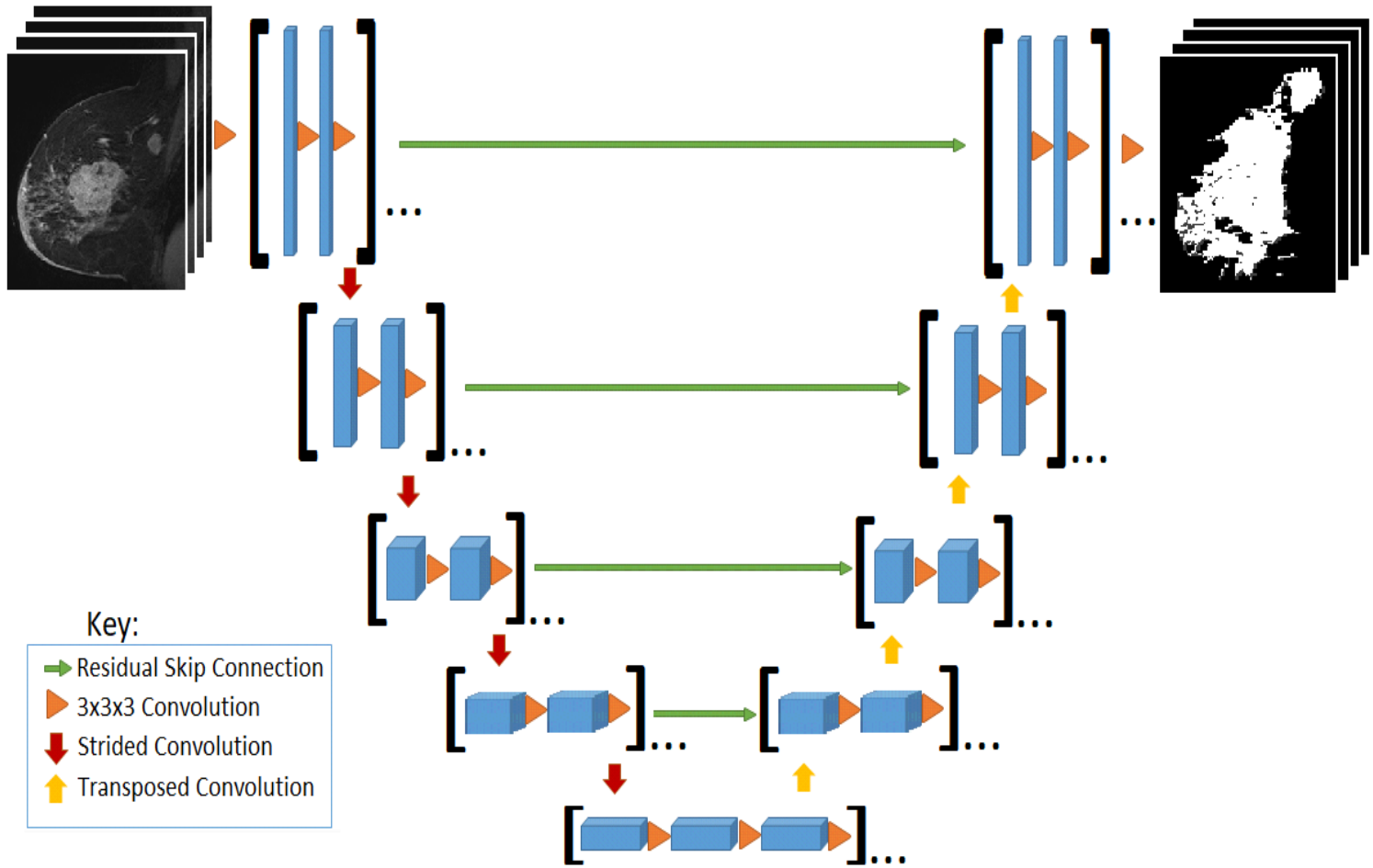


Figure: Systems which output the same sized localization or segmentation maps.

Previous Work

Regression-based Systems

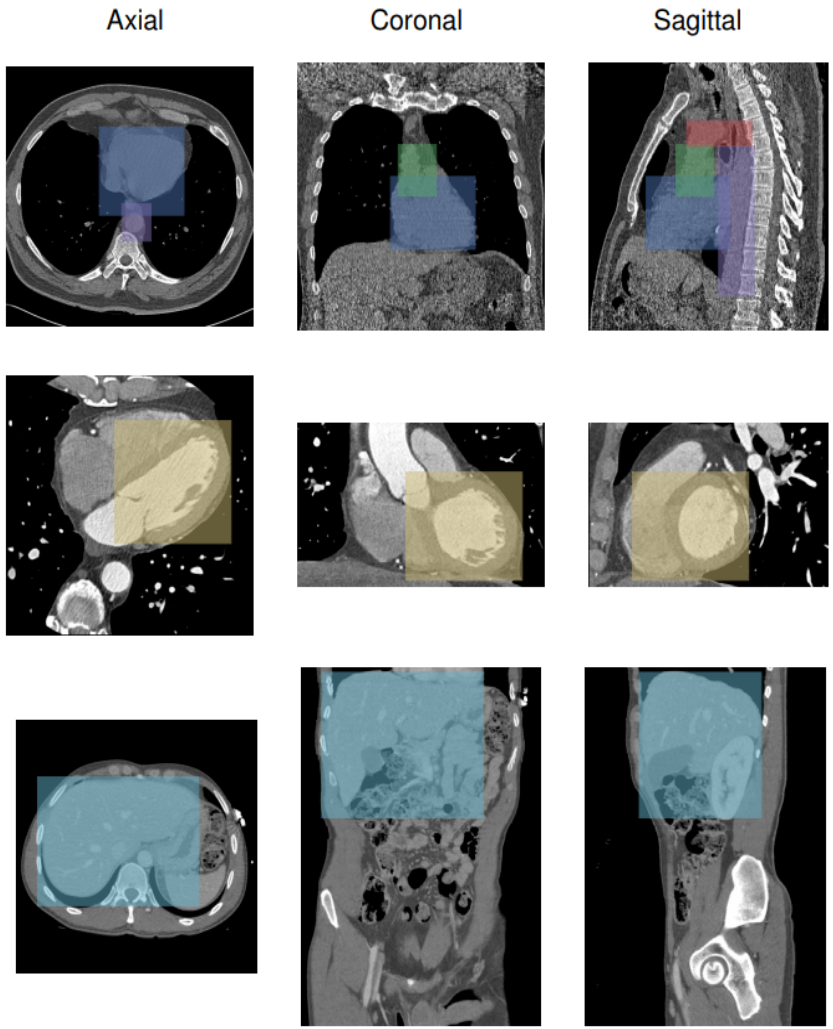


Figure: Systems directly output the position of the structure of interest.

Previous Work

Atlas-based Systems

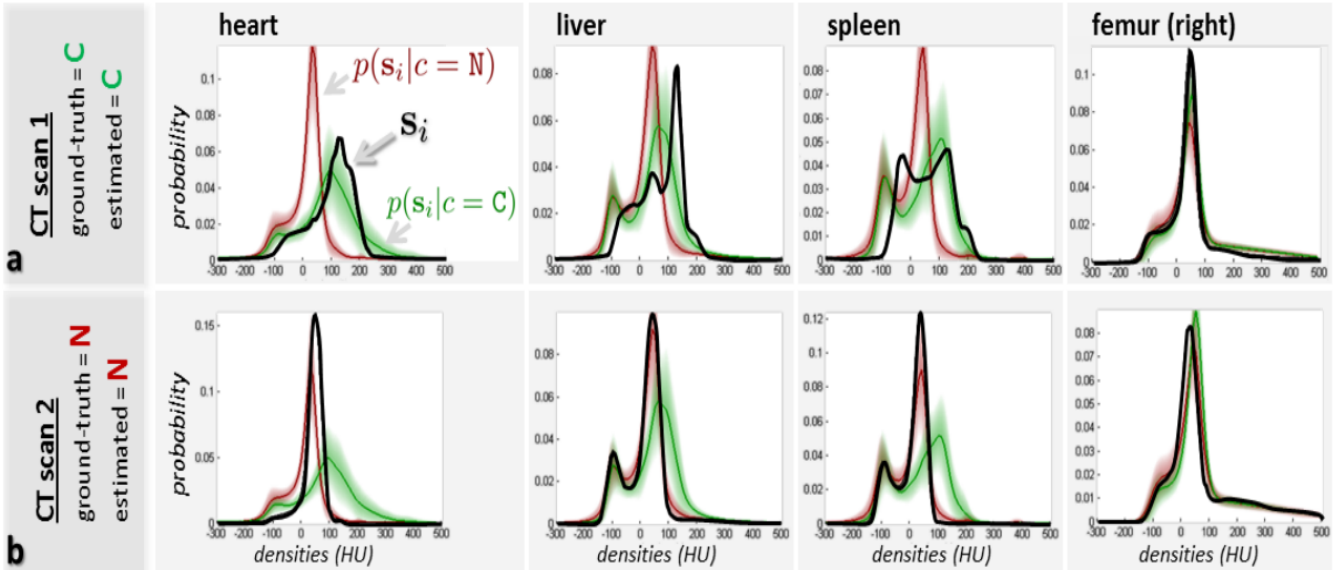


Figure: Systems that search the image using a learnt atlas. Also called Generative Models.

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Proposed Reformulation Overview

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- Model the anatomy of appearance + object search in a unified framework.
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  - and where to find it.
- Model the problem as a Reinforcement Learning Agent.

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In a Nutshell

- Theory and algorithms uniting multiple fields of machine learning, optimal control theory, psychology and neuroscience.

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- Theory and algorithms uniting multiple fields of machine learning, optimal control theory, psychology and neuroscience.
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- Success is measured by a scalar reward signal.
- Goal: select actions to maximize future reward.

Reinforcement Learning

Atari Example

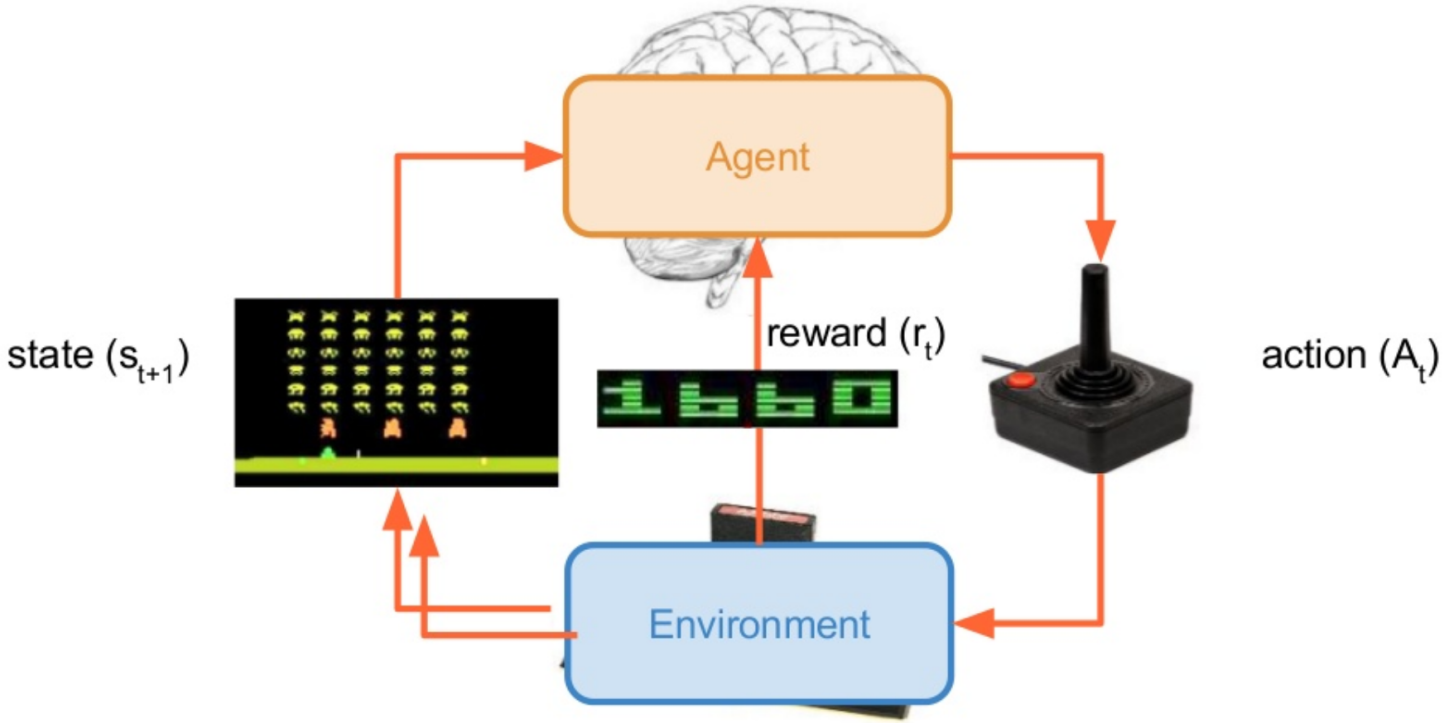

Figure: Agent-Environment interaction

Reinforcement Learning

Game Playing Agent Example

Figure: Mario trying to figure out life (like most grad students)

Reinforcement Learning

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- Think of the agent as a robot playing mario.

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- Should the robot press jump button? (To take the big star?)

Reinforcement Learning

Game Playing Agent Example

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- Think of the agent as a robot playing mario.
- Should the robot press jump button? (To take the big star?)
- Or should it press forward button?

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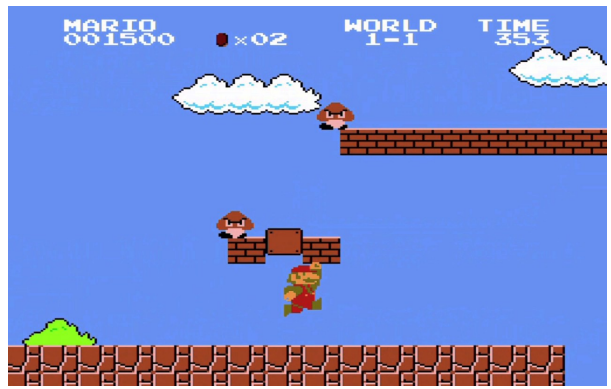
Policy Function

Predict What Action to Take

$$\pi\left(\text{  }\right) = \text{“Jump”}$$

Current State

Policy Function

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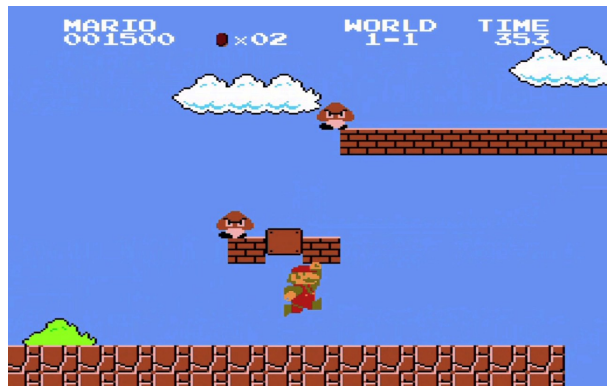
$$\pi\left(\text{  }\right) = \text{“Jump”}$$

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- The state is input to the policy function as an image.

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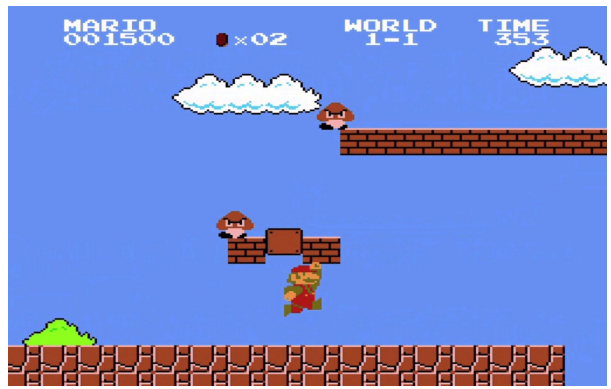
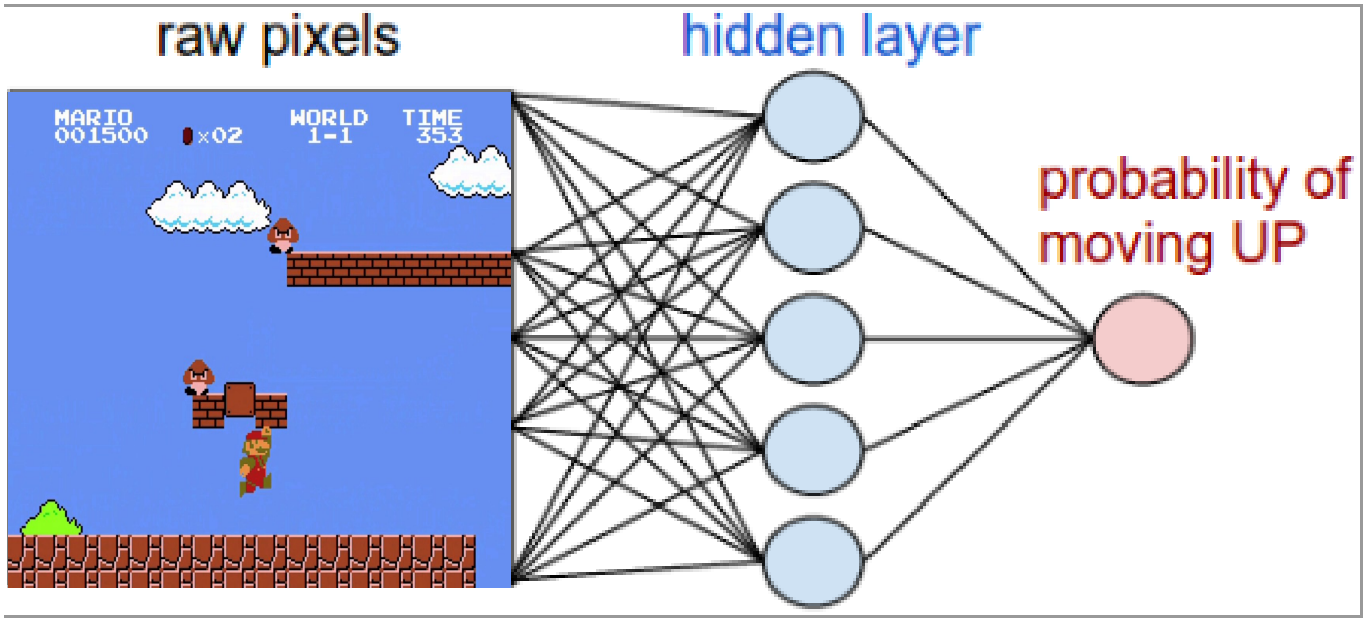
$$\pi\left(\text{  }\right) = \text{“Jump”}$$

Current State

- The state is input to the policy function as an image.
- That is, a “screenshot” of the game at a time stamp t is called the “state” at that time.

Policy Function

Representation



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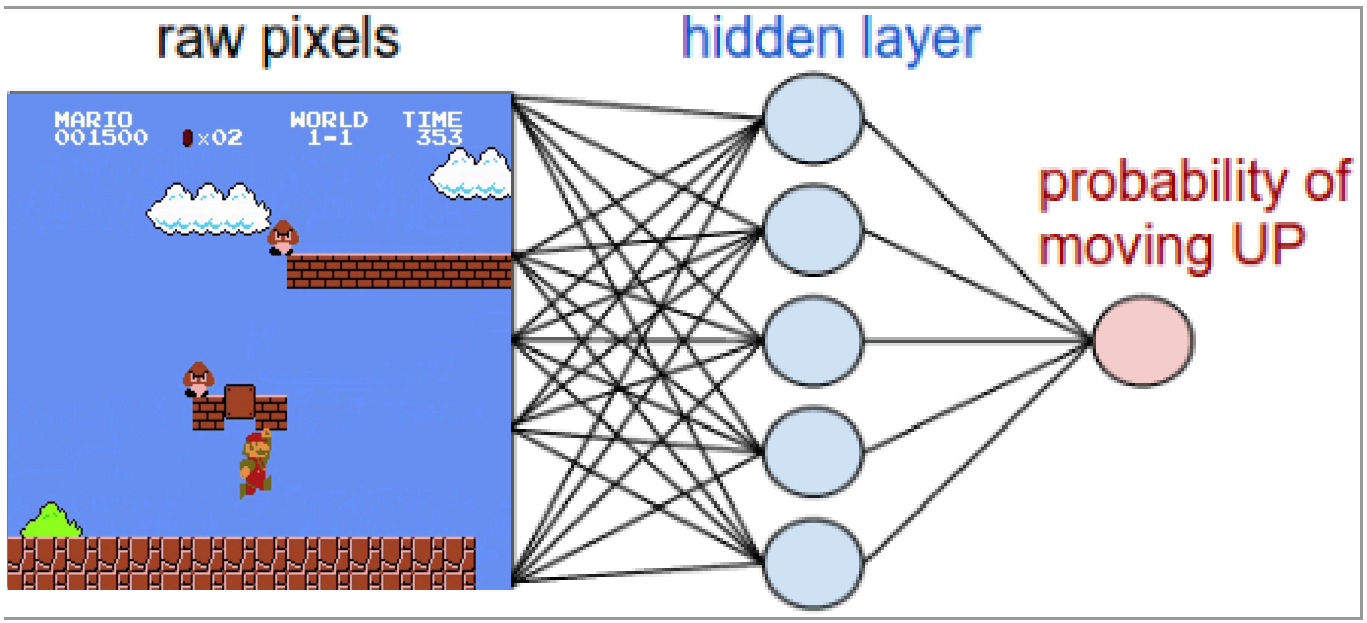
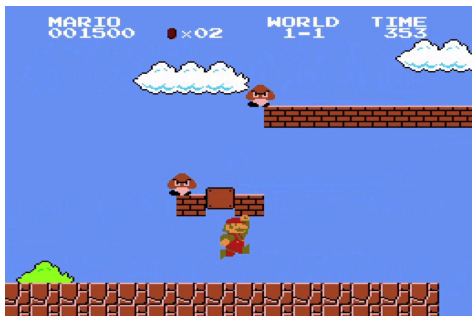


- Policy is represented as a Neural Network which takes the state (in pixels) as input and outputs probability of an action.

Reward Function

Compute Immediate Reward for an Action

$$\mathcal{R}\left(\text{  }, \text{"Jump"}\right) = 100$$

Current State Current Action

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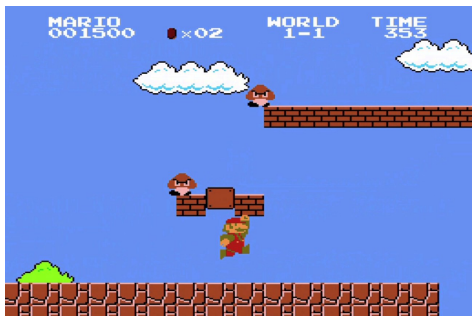
$$\mathcal{R}\left(\underbrace{\text{  }}_{\text{Current State}}, \underbrace{\text{"Jump"}}_{\text{Current Action}}\right) = 100$$

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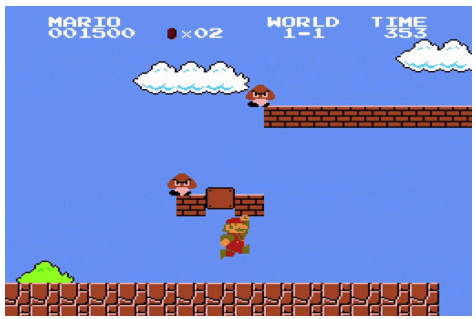
$$\mathcal{R}\left(\text{  }, \text{"Jump"}\right) = 100$$

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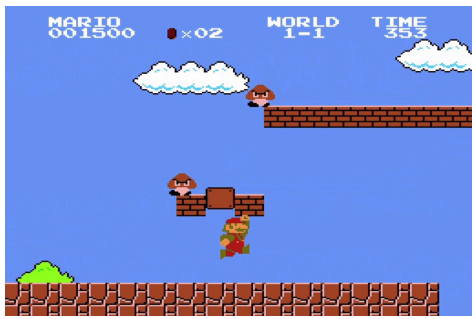
$$\mathcal{R}\left(\text{  }, \text{"Jump"}\right) = 100$$

MARIO 001500 ×02 WORLD 1-1 TIME 353

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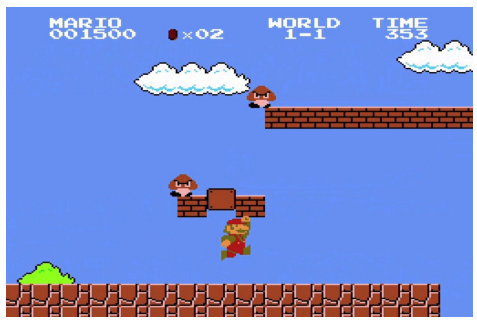
- For real world custom problems, you have to define one yourself.

Value Function

Predict Future Reward for an Action-State

$$\nu\left(\text{  }, \text{"Jump"}\right) \approx 5000$$

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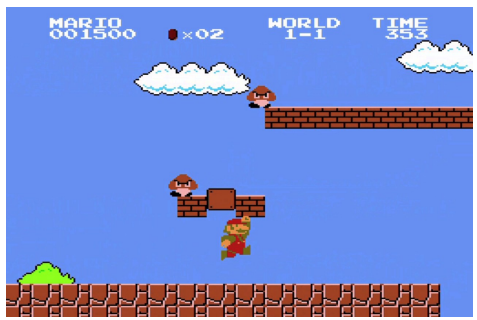
$$\nu\left(\text{  }, \text{"Jump"}\right) \approx 5000$$

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Trajectory

Path Taken by Agent in Environment

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$\tau = ($  "Jump", 10 ,  "Forward", 10 ,  , , , ,  "Jump", 10 $)$

$$\tau = (s_0, a_0, r_0, s_1, a_1, r_1 \ldots\ldots s_n, a_n, r_n)$$

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- Where γ is the "discount factor".
  - Larger the value of γ, greater the influence of later rewards on the return.

Total Reward

Total Reward for a Trajectory

$$\tau = \Big(\text{  } \text{“Jump”, 10} \; , \; \text{  } \text{“Forward”, 10} \; , \; \text{  } \; , \; , \; , \; , \; \text{  } \text{“Jump”, 10} \Big)$$

$$\mathcal{R} = \gamma^0 * 10 \quad + \quad \gamma^1 * 10 \quad + \quad .... \quad \gamma^n * 10$$

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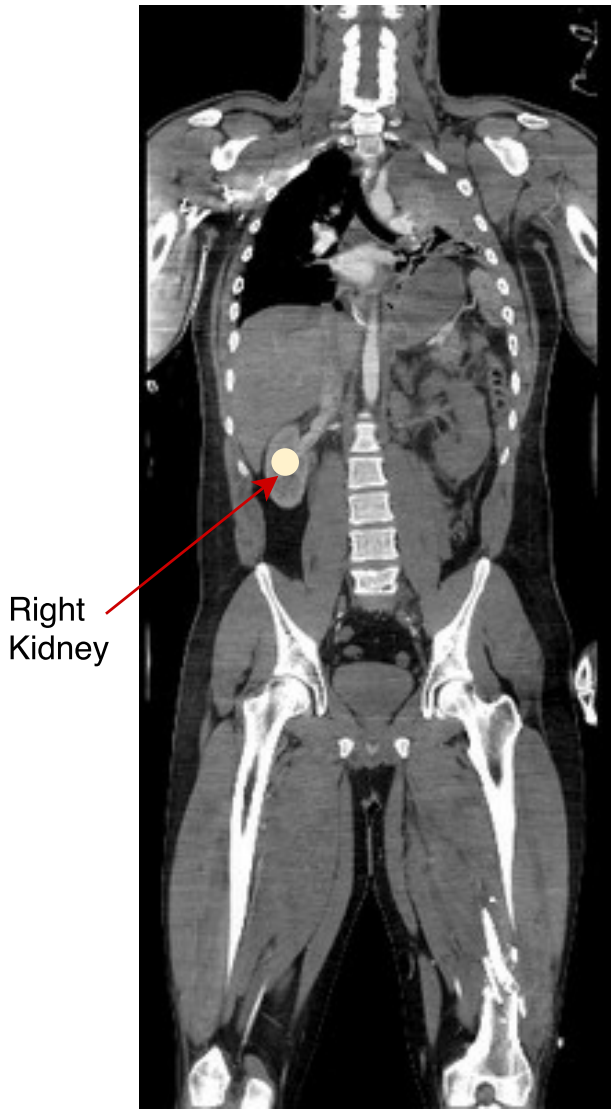

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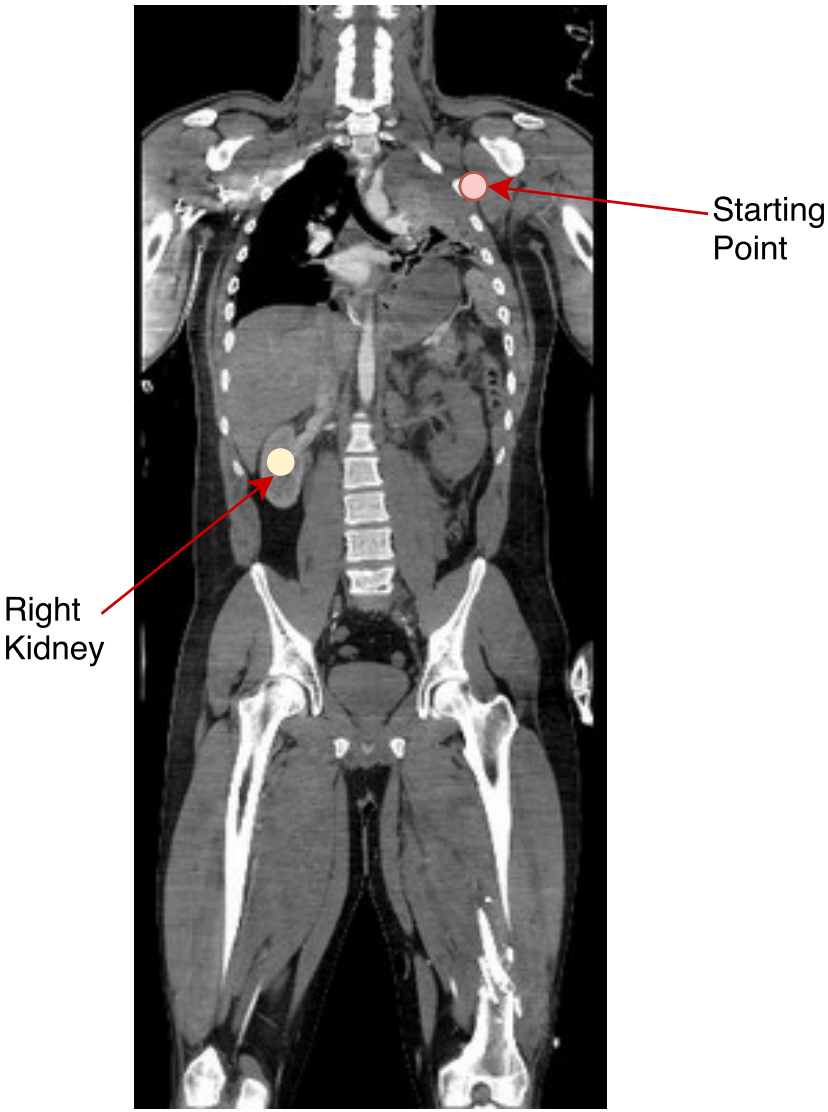

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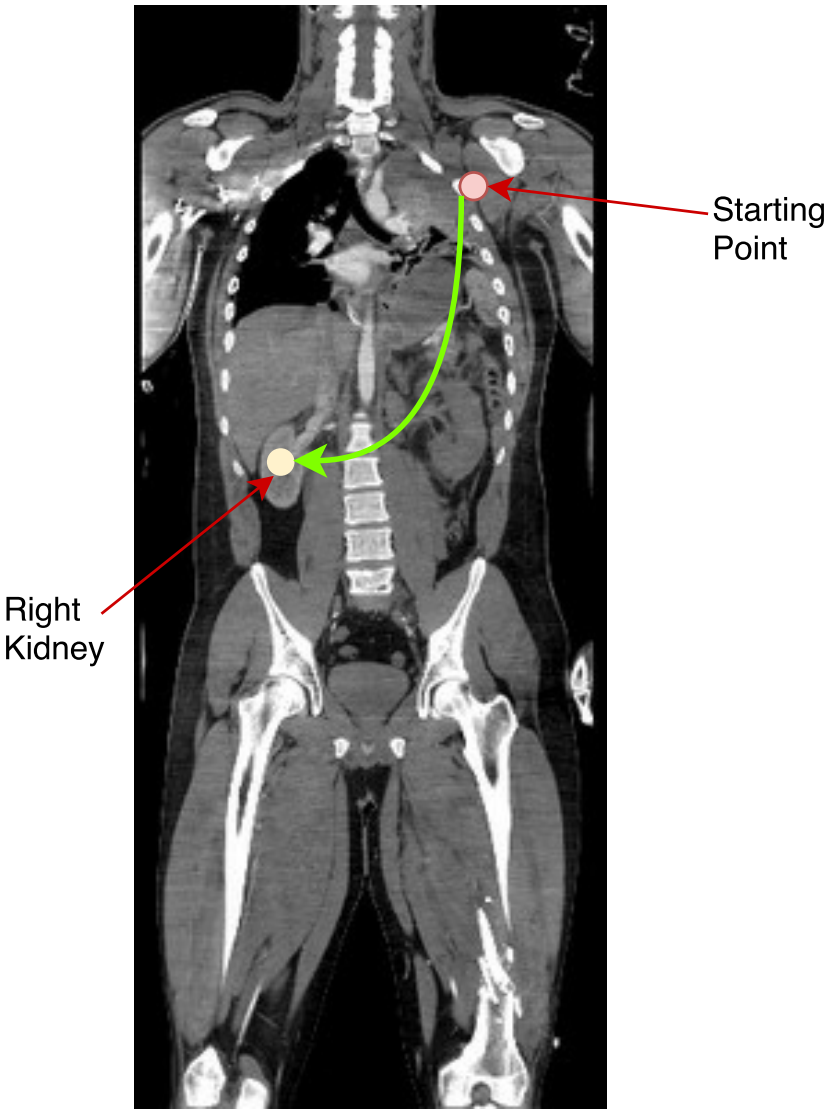

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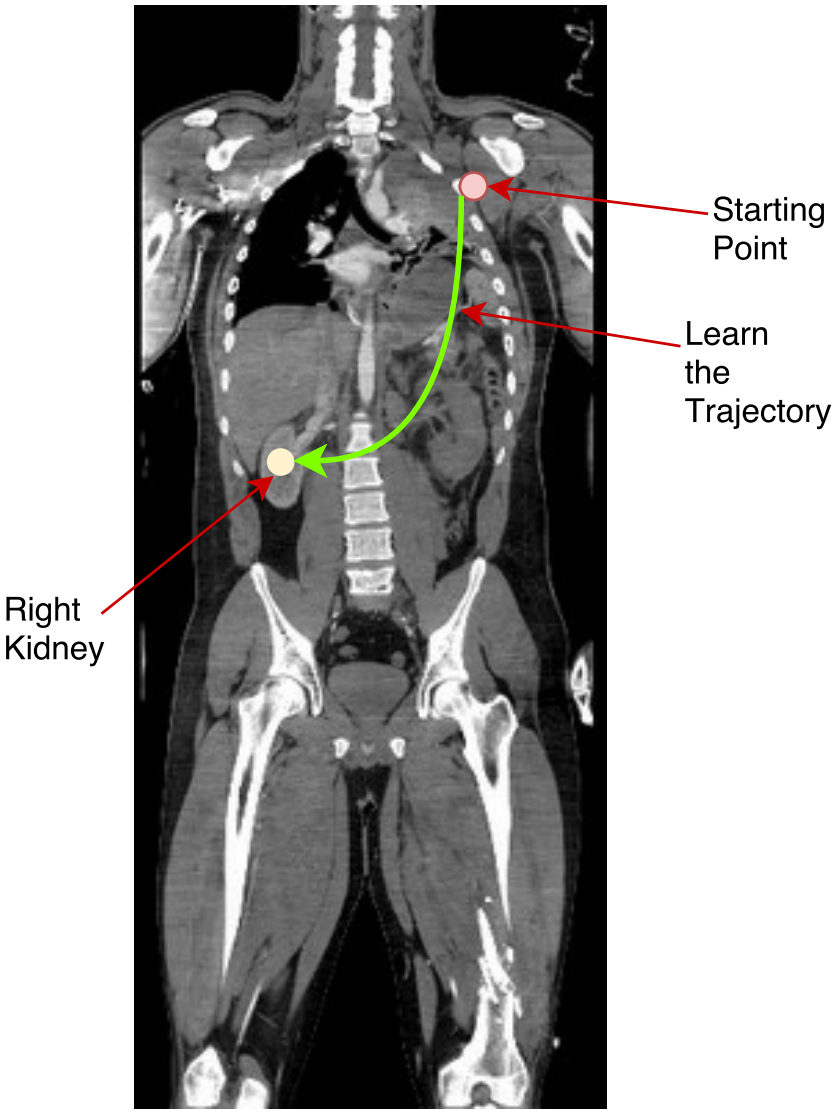

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Modeling the Agent

Agent as a controller of Moving Cube

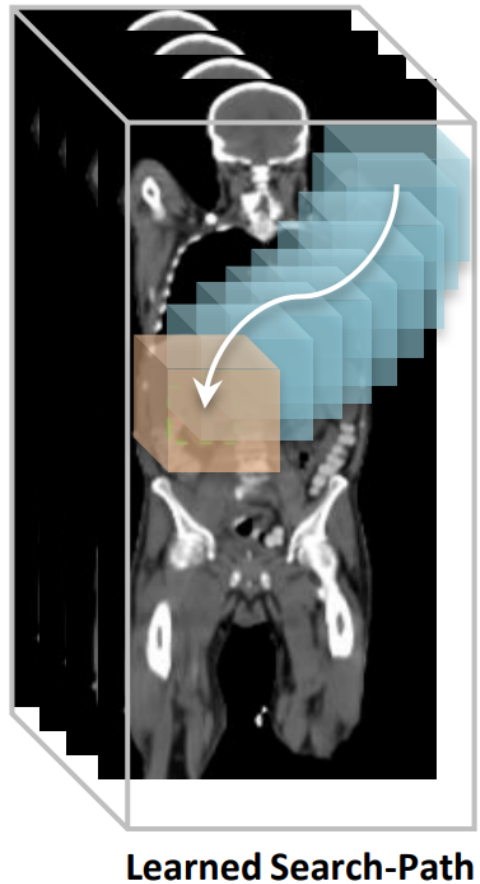

Figure: The search is performed by a moving cube with $\vec{p}_k$ as its centre.

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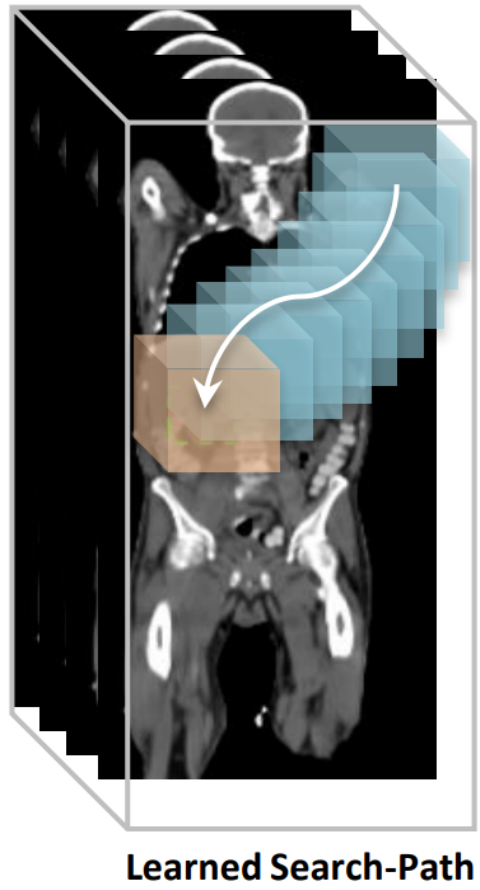

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Mario == Cube

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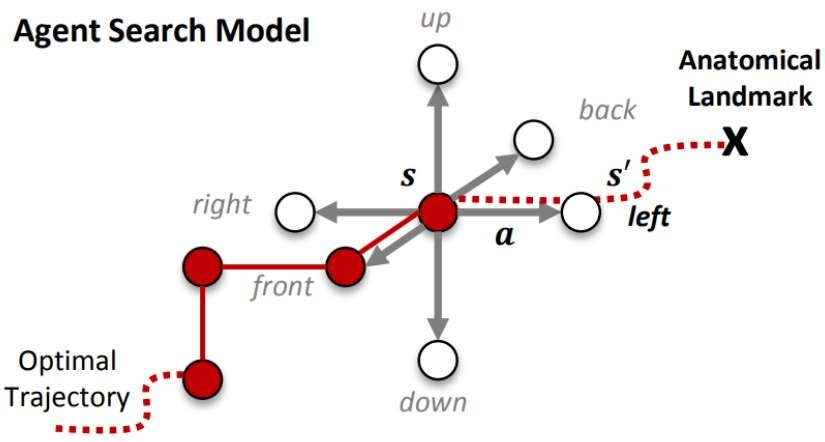

Modeling the Agent

Discrete Action Space

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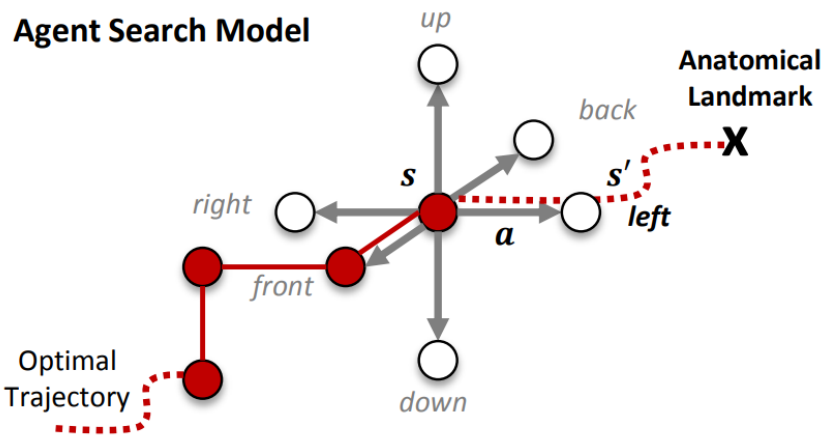
- It can move up, down, left, right, front or back of the 3D volume.



Reward Function

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$$r_k = ||\vec{p}_k - \vec{p}_{GT}||$$

- Euclidean Distance between the current position, and the ground truth position.

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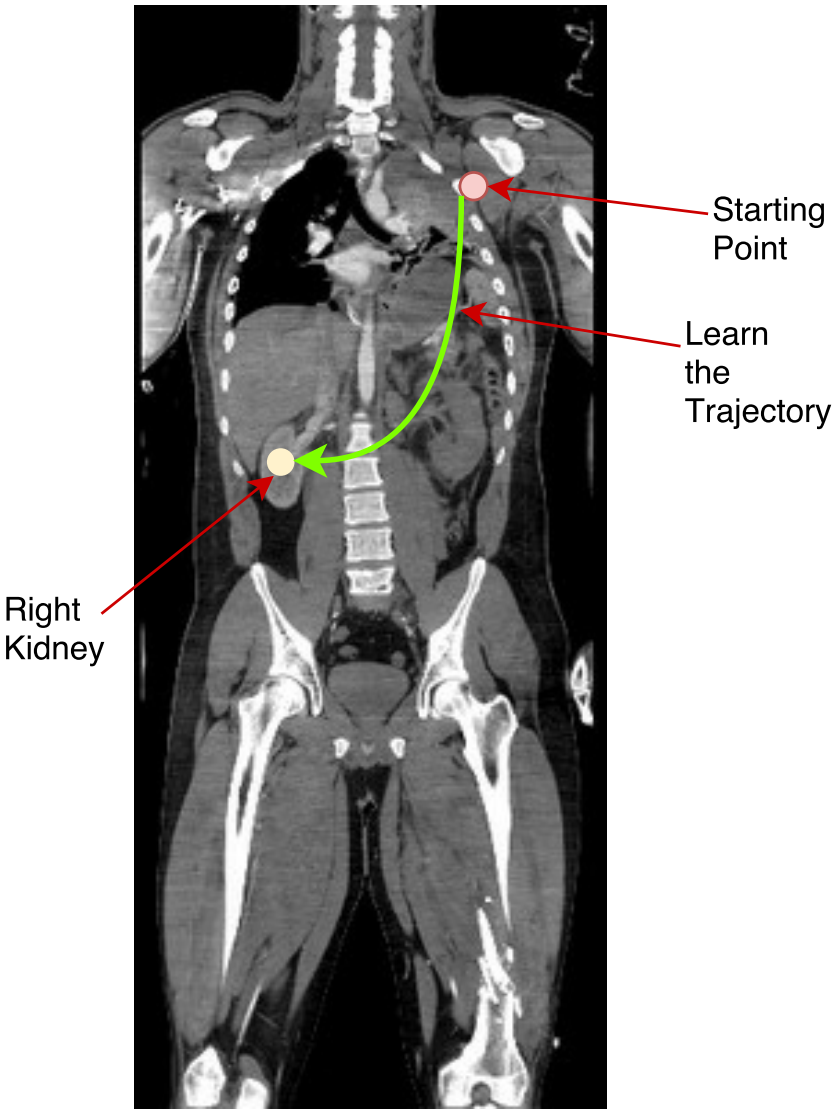

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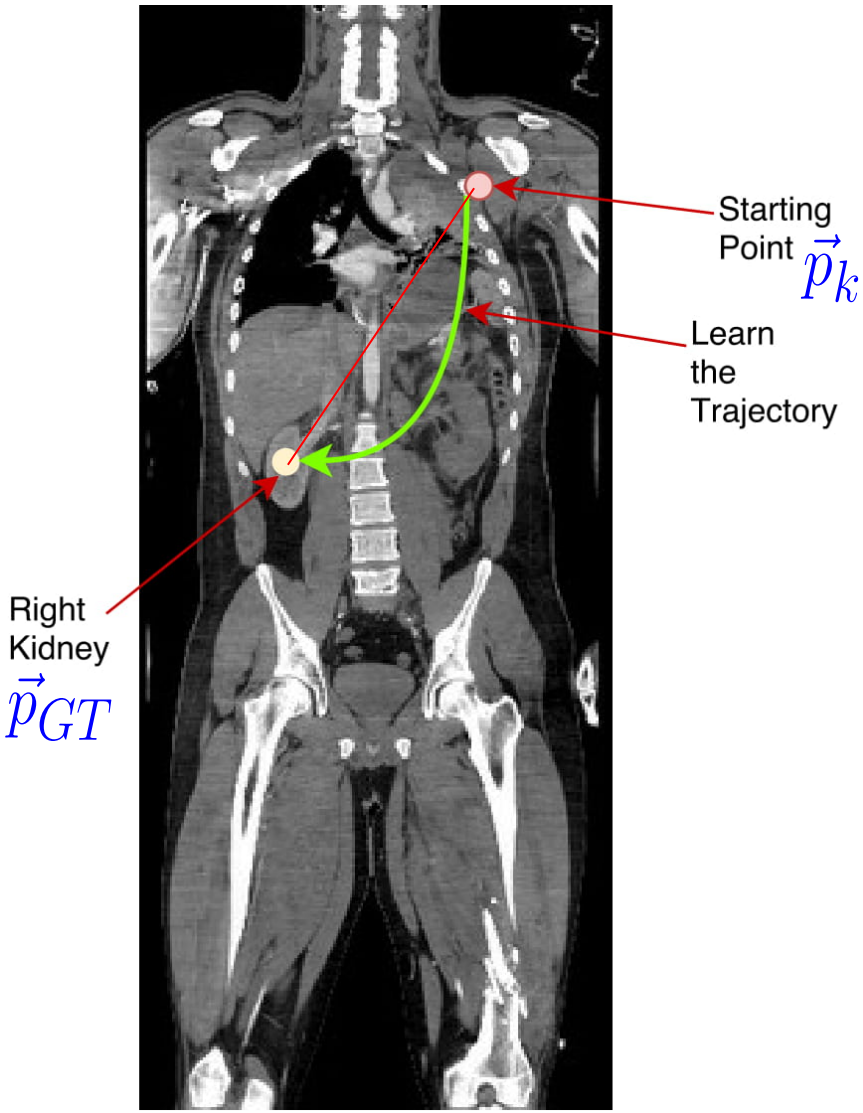

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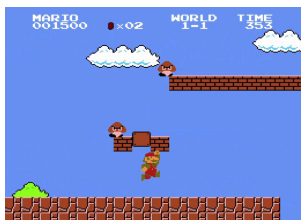
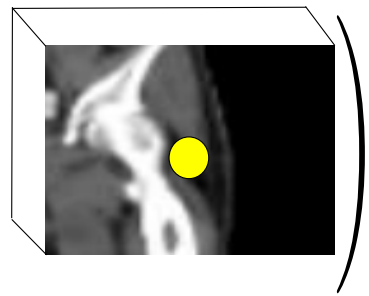
$$\pi\left(\text{  }\right) = \text{“Jump”}$$

Current State

$$\pi\left(\text{  }\right) = \text{“Up”}$$

Current State

In both cases, Policy Function is a Convolutional Neural Network (2D for Atari and 3D for CT).

Drawing Parallels

Game Playing RL vs Object Detection RL: Reward

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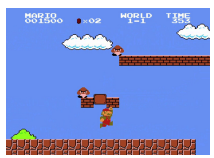
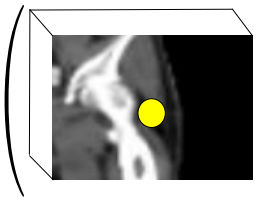
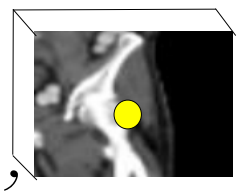
$$\mathcal{R}\left(\text{  }, \text{“Jump”}\right) = 10$$

Current State

Reward function defined by Environment

$$\mathcal{R}\left(\text{  }, \text{  }, \text{“Left”}\right) = ||\vec{p}_{new} - \vec{p}_{GT}||$$

Current State | New State | Action

Reward function defined by User

The reward function in this work was defined as distance between the agent's position and ground truth position.

Drawing Parallels

Game Playing RL vs Object Detection RL: Trajectory

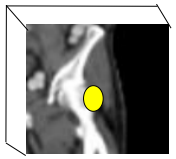
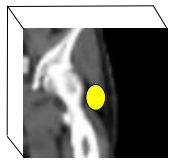
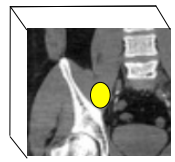
Connect the earlier terminology to this proposed terminology.

Drawing Parallels

Game Playing RL vs Object Detection RL: Trajectory

Connect the earlier terminology to this proposed terminology.

$$\tau = \Big(\text{  } \text{“Jump”, 10} \; , \; \text{  } \text{“Forward”, 10} \; , \; \text{  } \; , \; , \; , \; , \; \text{  } \text{“Jump”, 10} \Big)$$

$$\tau = \Big(\text{  } \text{“Right”, 10} \; , \; \text{  } \text{“Down”, 8} \; , \; \text{  } \text{“Back”, 5} \; , \; , \; , \; , \; \text{  } \text{“Up”, 2.5} \Big)$$

The trajectory vector stores all “states” or 3D patch volumes that it visited, and the corresponding actions that the agent took.

Optimization Function

Traditional vs Deep

- In traditional RL, we use

$$Q^*(s, a) = \mathbb{E}_{s'}\left(r + \gamma max_{a'} Q^*(s', a')\right)$$

- As objective function, also called the Bellman Equation.
- However, due to high dimensional nature of state space (state if defined in terms of position in the 3D image), this function is unsuitable.

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- This is called Deep Q-Network (DQN).

Optimization Function

Bellman Optimality with MSE

- A Deep Q-Network can be trained in a RL setup using iterative approach.

Optimization Function

Bellman Optimality with MSE

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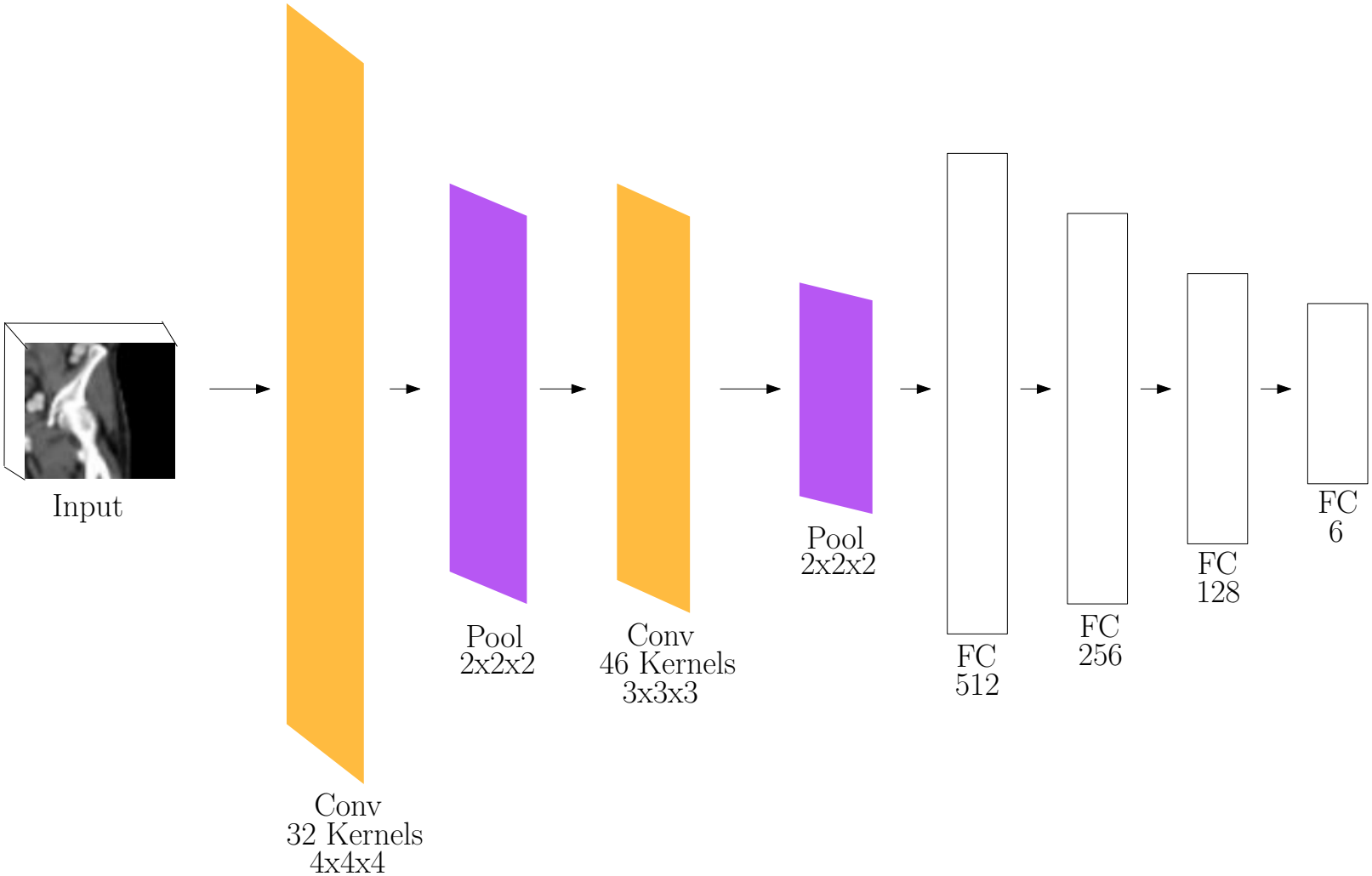
- where $y = r + \gamma max_{a'} Q(s', a'; \theta^{(i)})$

Network Architecture



Network Architecture

Outline

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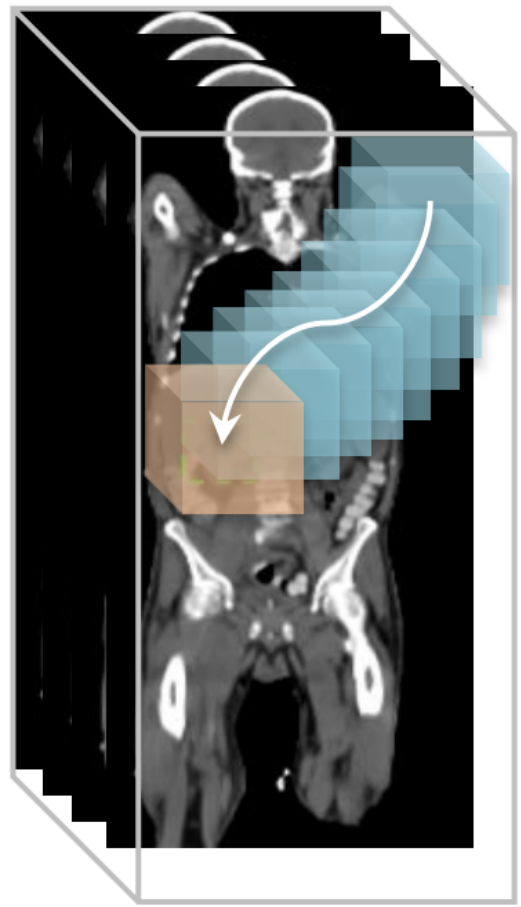

Learned Search-Path

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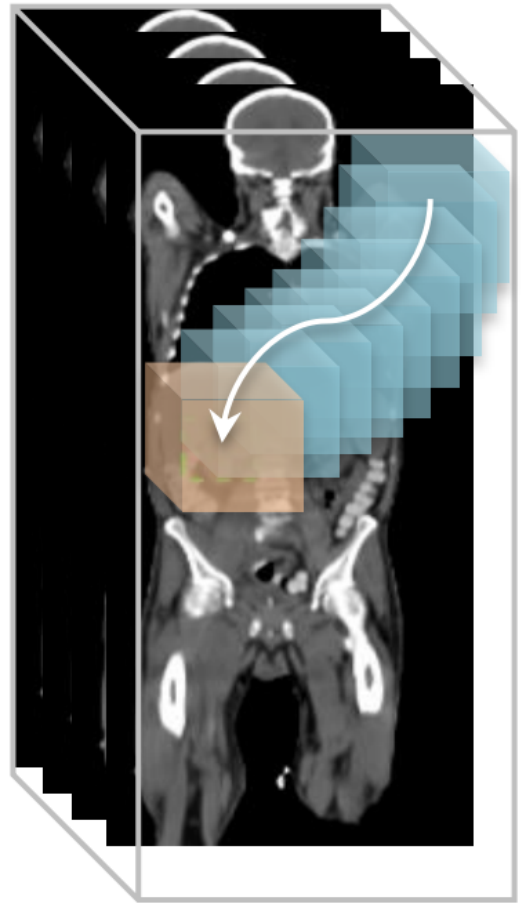

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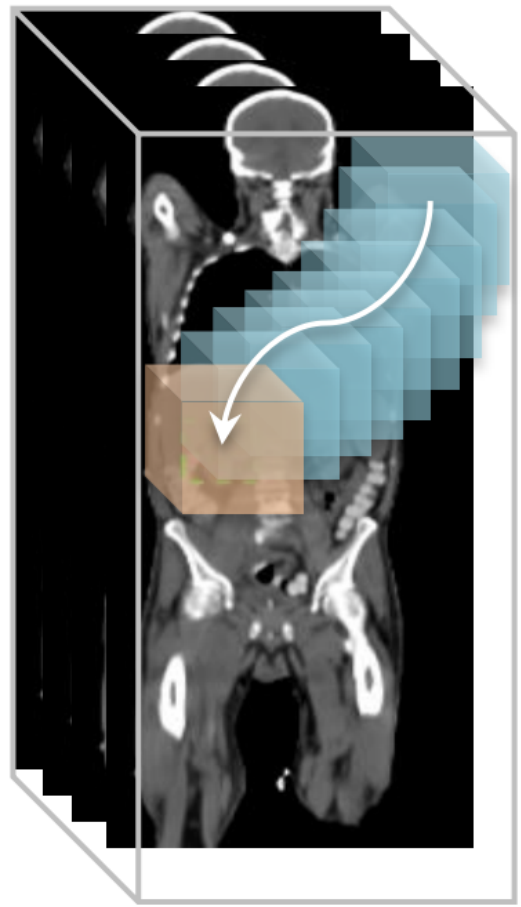

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Major Limitation

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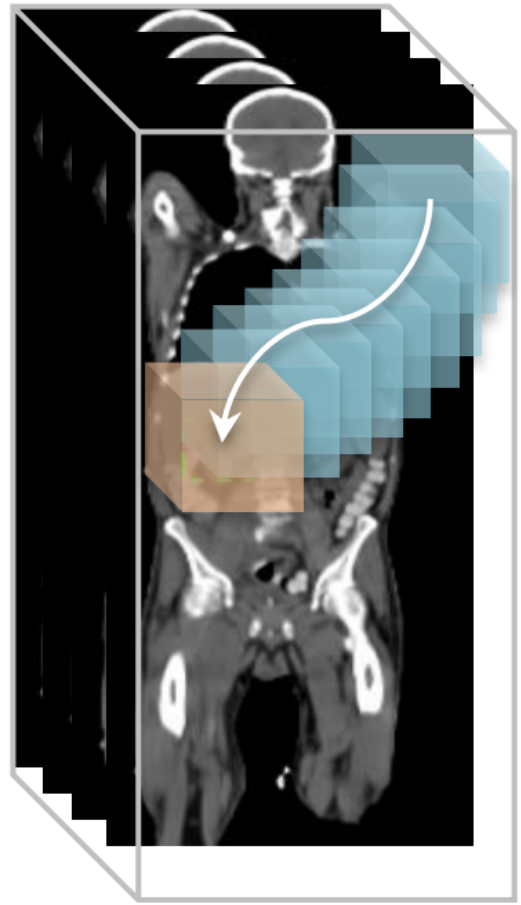
  - Localization is useless if the box is too large.
- Need to make the system scale-invariant.

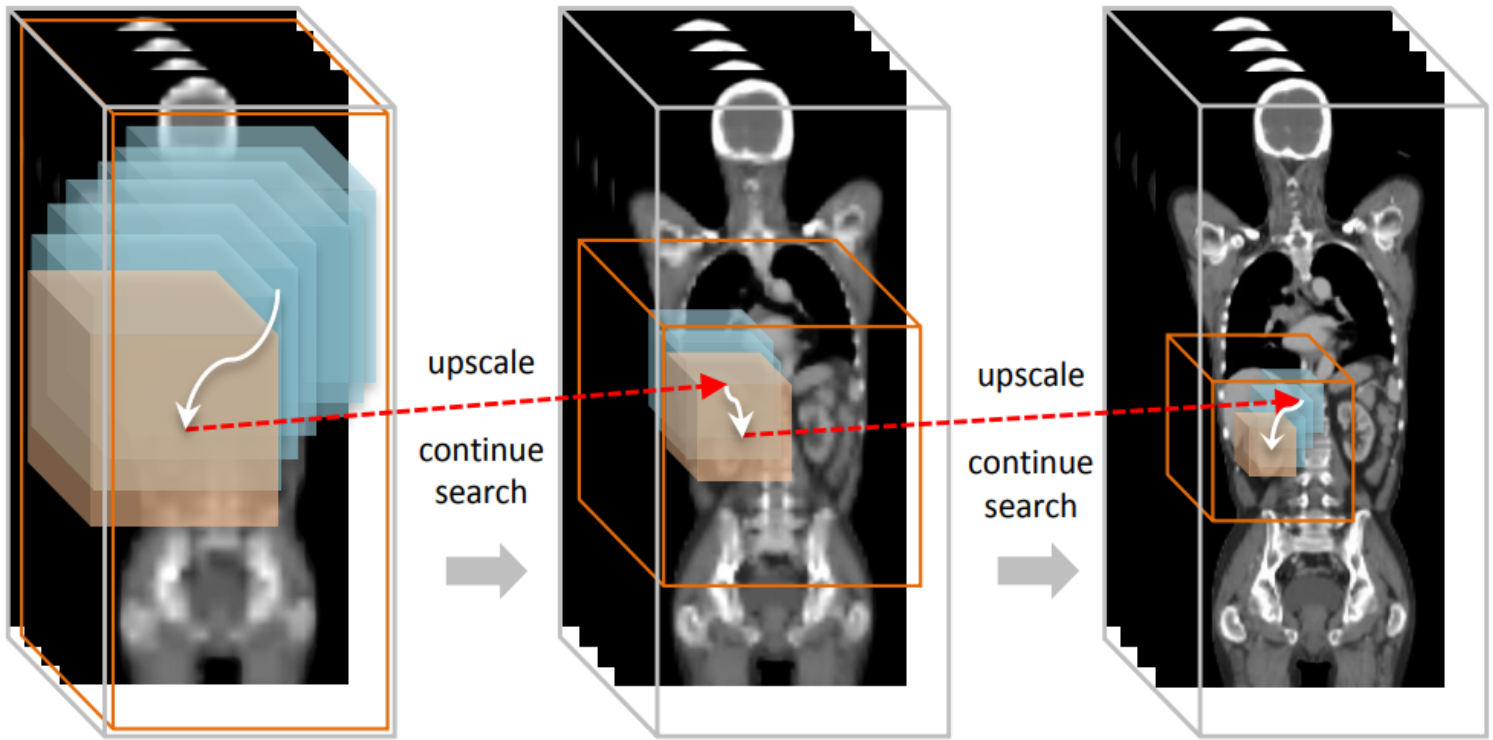


Learned Search-Path

Outline

Multi-Scale Search Strategies

Visualization



Multi-Scale Search Strategies

Solution to Scale-invariance

- Solution: Search on multiple scales of the input 3D volume.
- Obtain a finite number of scaled 3D volumes, starting from coarsest (16mm) to finest (4mm).
- Search algorithm:
  - Start the search from the coarsest scale (lowest resolution).
  - If the agent converges[1], change to finer (higher resolution) scale, and start the search again from the convergence point.
  - Repeat until convergence on finest scale is reached.

[1] discussed in the next slide

Multi-Scale Search Strategies

Convergence Criteria

- The convergence criteria for the agent answers the question: When does the agent know it has found the object of interest?
- Answer: Detect small oscillatory-like cycles in the agent's behaviour.
- If a cycle is detected, save the position, and move to next scale level to continue search.
  - If the scale is finest, return the current position as the position of object of interest.

Multi-Scale Search Strategies

Increased Complexity in Scale Space

- However
- Searching through multiple scale spaces increases the complexity in learning of policy function (CNN).
- The CNN would have to learn
  - how to distinguish an object of interest from background
  - how to navigate the image space by taking actions
  - how to do the above 2 tasks in multiple scales.
- This would make the learning intractable.
- Solution: Authors propose to use multiple CNNs for multiple scales.

Multi-Scale Search Strategies

Increased Complexity in Scale Space

Separate CNNs for separate scale 3D images.

Outline

Comparison

Algorithms compared against

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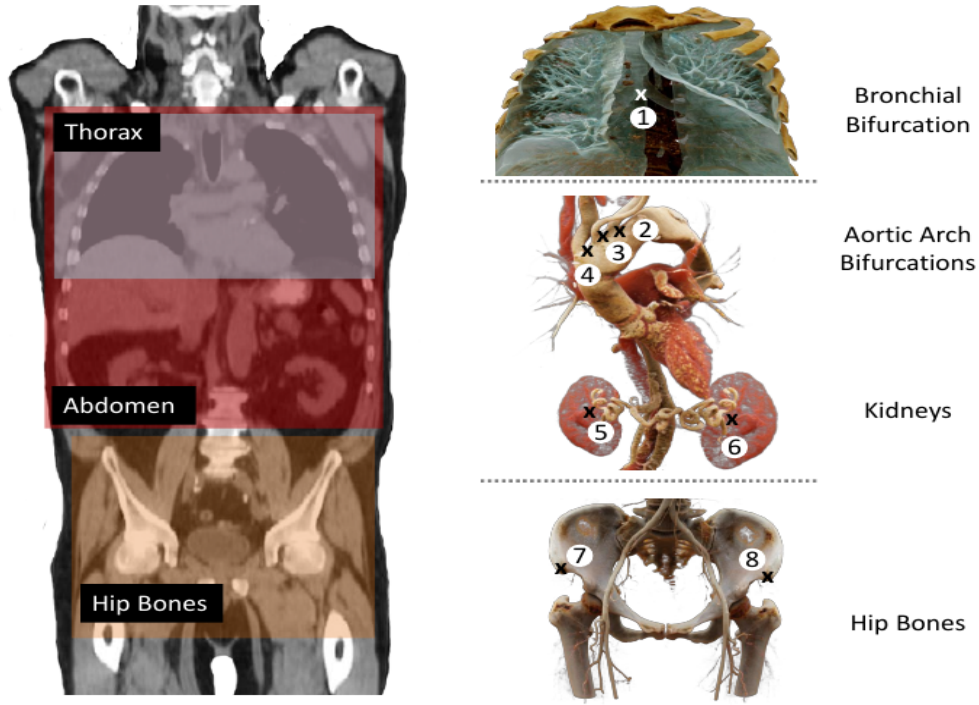
  - Overfeat, adapted to 3D data
  - 3D Deep Learning with Filter Decomposition
  - Scanning with Cascaded Sparse-Adaptive DNN

Dataset

- 1487 3D-CT Volumes from 532 patients.
- Contains different field of views:
  - Cardiac CT Scans
  - CT scans of legs, pelvis, head, neck
  - Scans of thorax



Metrics

- **Failure Percentage Rate**
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- **Speed**
  - Raw speed of detection on their hardware platform

Quantitative Results

Performance Compared to Other Published Works

Solution	Dataset Size (Data/Patients)	Accuracy (mm)	Speed (seconds)
Zhan *et al.* [27]	18/18 CT	4.72	4
Fenchel *et al.* [35]	31/31 MR	22.4	20
Criminisi *et al.* [12]	100/– CT	17.60	1
Pauly *et al.* [32]	33/33 MR	14.95	0.8
Cuingnet *et al.* [11]	233/89 CT	10.5	2.8
Donner *et al.* [10]	20/20 CT	5.25	120
Criminisi *et al.* [31]	400/– CT	13.50	4
Chu *et al.* [30]	10/10 CT	1.90 [1]	30
Potesil *et al.* [37]	83/83 CT	4.70	N/A
de Vos *et al.* [24]	100/– CT	4.80	10
Ours	**1487/532** CT	**4.19** [2]	**0.061**

[1] Evaluated only on vertebrae localization with strong priors.
[2] With no failures of clinical significance. All other solutions did not provide any information in this respect.

Quantitative Results

Speed Compared to Methods Discussed in the Previous Slide

DETECTION TIME per Volume [**seconds**]

Method	Platform	Median	Min	Max
PBT [3]	CPU 8-core	1.051	0.14	16.20
ExtRTrees [10]	CPU 8-core	4.714	0.272	44.535
Overfeat [1] [22]	GPU Titan X	2.175	0.331	14.86
3D-DL [18]	CPU 10-core	57.034	7.161	548.23
SADNN [2] [1]	GPU GTX 1080	0.471	0.064	3.029
Ours	CPU 8-core	0.061	0.035	0.155
Ours	GPU Titan X	**0.033**	**0.018**	**0.085**

[1,2] Evaluated on finest isotropic resolution of 4 mm.

Quantitative Results

Individual Anatomy Detection Comparison with Other Methods

			Failed Cases			Accuracy (excl. failed cases)	
Structure Type	**Landmark**	**Method**	**% Failed**	**Median**	**Max**	**Mean ± STD**	**Median**
Bone	Hip Bone Right Front Corner	PBT [3]	4.35%	38.89	141.88	3.05 ± 1.60	2.77
		ExtRTrees [10]	8.07%	20.27	460.22	5.01 ± 2.40	4.95
		Overfeat [22]	9.31%	35.64	231.29	4.55 ± 1.98	4.31
		3D-DL [18]	0.62%	10.17	10.17	2.84 ± 1.36	2.53
		SADNN [1]	0%	–	–	3.50 ± 1.63	3.37
		Ours	**0%**	–	–	$\mathbf{2.80} \pm 1.46$	**2.53**
	Hip Bone Left Front Corner	PBT [3]	3.75%	14.30	28.57	4.03 ± 1.79	3.86
		ExtRTrees [10]	6.25%	13.43	17.44	5.13 ± 2.78	5.08
		Overfeat [22]	3.75%	127.52	242.05	4.19 ± 1.80	4.15
		3D-DL [18]	2.50%	262.81	513.81	3.14 ± 1.49	2.98
		SADNN [1]	1.25%	12.57	12.57	4.44 ± 1.75	4.43
		Ours	**0%**	–	–	$\mathbf{3.07} \pm 2.14$	**2.85**

Critique

Some Critical Observations

- Authors reimplemented a method without a main subsystem.
- Runtime comparison was performed on heterogeneous systems.
- Self imposed accuracy threshold.
  - If the agent is within 10mm of the body part, it is deemed as successful detection.
  - No analysis of reducing/increasing this threshold to report varying results.
  - Although the authors cite clinical reasons to choose this threshold.
- Starting point of the agent is heuristically chosen to be close to the actual expected location.
  - Makes sense because searching for right kidney does not have to start from the head.
  - However, no results reported about runtime speed and accuracy if the chosen point is randomized.

Critique

Some Critical Observations

Pros

- A brilliantly written paper.
- Highly polished analysis, clear and concise handling of various apparent limitations.

Conclusion

- Authors proposed a new formulation of the object detection problem in 3D CT Scans.
- Posed the problem as Deep Reinforcement Learning based agent learning to navigate the image space and identifying markers.
- Used Deep Q-Learning with 3D Convolutional Neural Network as policy function.
- Reported 0% Failure Percentage Rate for their approach.
- Significant orders of speed-up in detection process, compared to state-of-art methods.

Thank You for listening!

Outline

Starting Point of the Agent

How to set agent's starting point?

- Also, the starting point of the agent is set to a position $\vec{p_0}$ using the expected position of the object of interest.
- This position is sampled from the training data.
- For example, for right kidney, it is known that it is on the right side of the abdomen. Hence set the starting position close to that region.

Object Not in Scan?

How to find out if object is not in scan?

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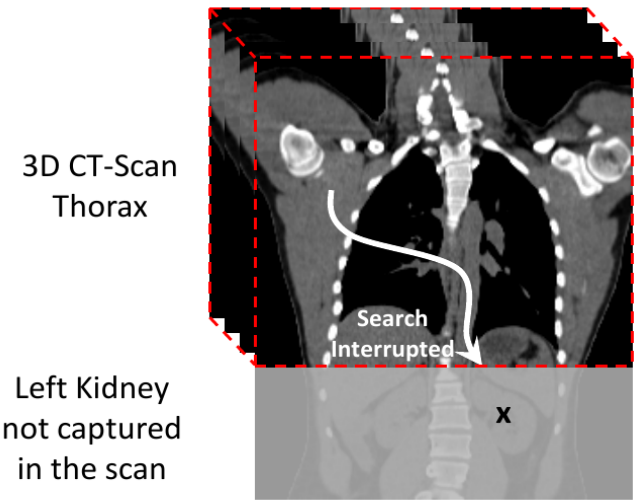

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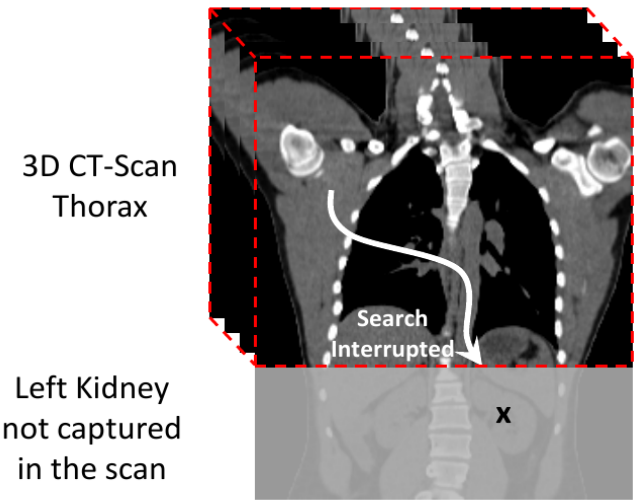
- In this work, a very simple heuristic approach is taken to find out if the object is not present in the scene.
- Approach: Detect if the agent leaves the image space while scanning.
- Although simple, the approach is shown to work atleast for 90%+ negative cases, which show the robustness.



Exploration vs Exploitation

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- Learning the action-value function Q^* enables the agent to effectively search for objects in the image.

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- Learning the action-value function Q^* enables the agent to effectively search for objects in the image.
- However there is a need to balance exploration by the agent against exploitation.
- The authors propose to use three techniques to ensure adequate exploration of the environment.

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- This value is annealed linearly from 1.0 to 0.05 during the training.

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- Use those to train the policy (deep convolutional neural network).

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- As the training progresses, use more experiences of the past rather than making new ones.
- This reduces training time by 30%.