Machine Learning in Robotics

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Outline

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Motivation

Programming robots is a hard work!

- No high-level programming language;
- Sensors and actuators are noisy;
- Robotics is moving towards increasingly unstructured environments.

If only robots could learn how to perform tasks by themselves. . .

Machine Learning

- Machine Learning is:
  - “A **computer program** is said to **learn** from **experience** E with respect to some **class of tasks** T and **performance measure** P, if its performance at tasks in T, as measured by P, **improves with experience** E” *Tom Mitchell. Machine Learning, 1997*
- Key concepts:
  - Experience (data);
  - Task;
  - Performance Measure (metric);
  - Improvement
- Machine Learning can be seen as a search problem of finding a policy that maps states to responses, ($\pi : S \rightarrow R$), to perform a desired task.

Machine Learning

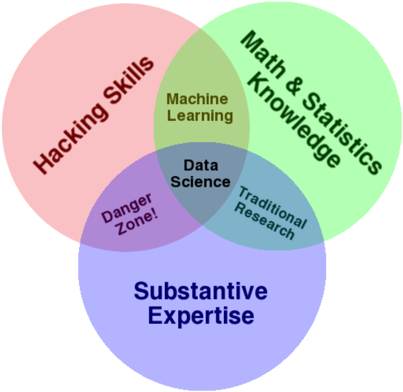


Figure: Data Science Venn Diagram, by Drew Conway

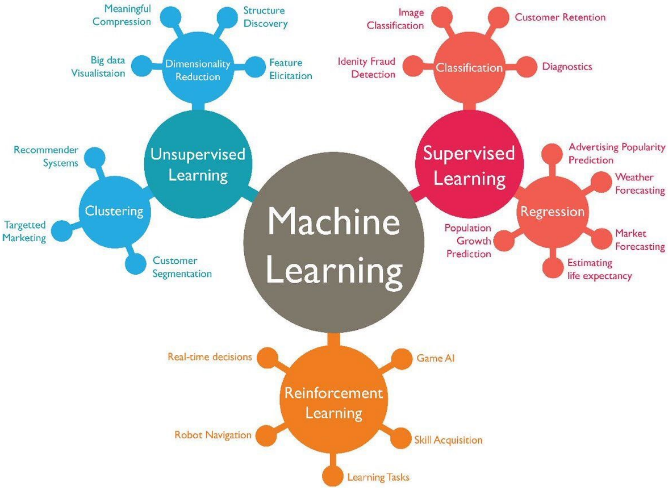
Challenges in Robot Learning

- Limited data;
- Generalization;
- Curse of Dimensionality;
- Which is the best action to take?
- Different Machine Learning paradigms
  - Supervised;
  - Unsupervised;
  - Semi-supervised Learning

Machine Learning Paradigms

- Supervised Learning;
- Unsupervised Learning;
- Reinforcement learning.

Machine Learning Paradigms



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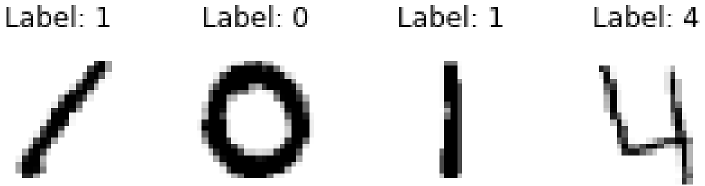
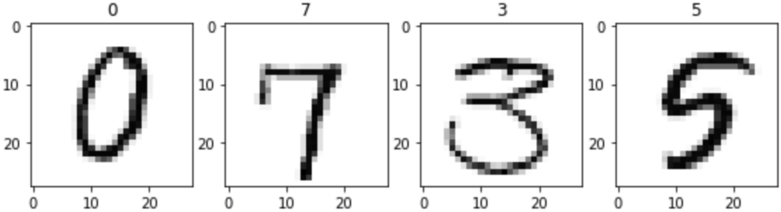
Supervised Learning

- A "teacher" **provides** training data consisting of **states** (S) and the **desired response** (R).
  - The learning process knows the desired output for several inputs.
  - The supervisor indicates what is the best action to take (sometimes).
- The robot must learn to **fit** the training data data and **generalize** a policy to the states not covered by the training data.
- Common methods:
  - k Nearest Neighbor, Neural Networks, Decision Trees, Support Vector Machines, Gaussian Processes, . . .

Supervised Learning





Supervised Learning

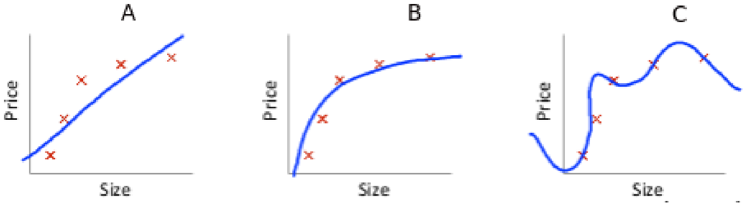


Figure: A regression problem: bias vs. variance

Supervised Learning
Applications

- Very powerful when applied for Perception in Robotics!
  - Pattern Recognition for Robot Vision.
  - Probabilistic Models for Kalman and Particle Filters.
  - Fault detection.
  - Change detection.
- Learning from Demonstration for Control

Supervised Learning
Examples

- Autonomous Car Driving
  - A human drives a car and the driving behaviour is recorded.
  - ALVINN: Autonomous Land Vehicle In a Neural Network (Dean Pomerleau, 1988)
- Robotic Soccer
  - Four Legged League, Sony Aibo Platform.
  - Based on Accelerometer data, the robot was able to determine the surface it was moving on. *(Vail-2004)*
  - Also learned when it was moving freely or stuck or even entangled in other robots. *(Vail-2004)*
- Robotic Arm Control
  - Learn a probabilistic model for control over time.

Supervised Learning
Examples

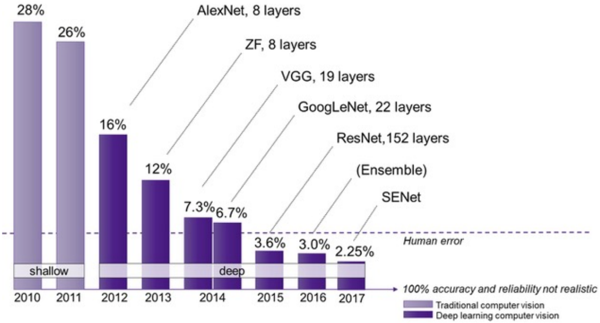


Figure: ImageNet Visual Recognition Challenge Results.

Outline

Unsupervised Learning

- Learns directly from data, without any labeled dataset;
- Finds patterns/structure in data;
- Examples:
  - Clustering;
  - Anomaly detection;
  - Autoencoders, Self-organizing maps.

Clustering

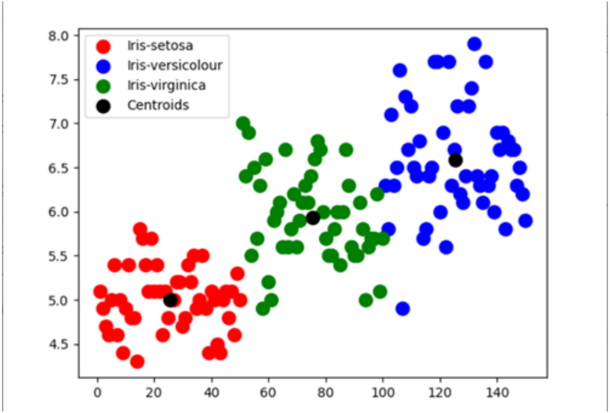


Figure: Clustering flowers.

Outline

Evolutionary Learning

- Unsupervised/Semi-supervised Learning Paradigm.
- A **policy may be encoded** in **strings** (Genetic Algorithms) or in **computer programs** (Genetic Programming).
- The learning process works on a **set of policies** (generation).
- The robot is provided a **fitness function**.
- Each individual on the generation is evaluated given the fitness function.
- **Genetic operators**: selection, crossover, mutation.
- Generations are **regenerated** trying to get better fitness values

Evolutionary Learning
Examples

- Robot Motion
  - Applied in-house to learn biped walking gaits (Picado-2009).
  - Applied in-house to learn kick behavior (Abdolmaleki-2016).
  - Applied to learn the model of the robot (Lipson-2008).
- Robot Hardware
  - Applied to evolve the shape of the robot, to obtain previously unknown robot shapes (Lipson-2006).

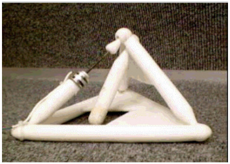


Figure: One of Hod Lipson morphologically evolved robots.

Outline

Reinforcement Learning

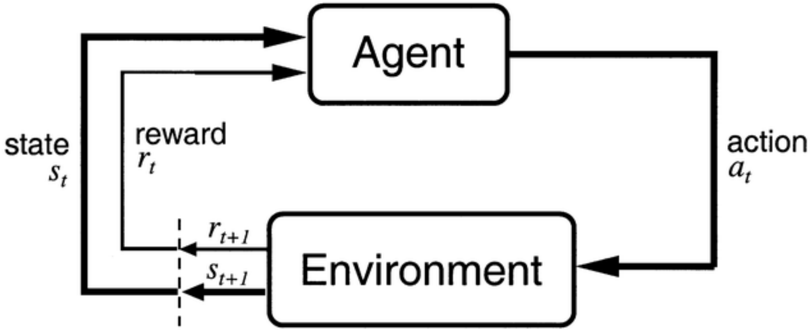


Figure: A Reinforcement Learning System.

Reinforcement Learning

- Unsupervised/Semi-supervised Learning Paradigm.
- Modeled as a Markov Decision Process:
  1. a set of states S;
  2. a set of actions *A(s)*;
  3. a state transition model: $P(s, a, s') \rightarrow [0, 1]$
  4. a reward function : $R(s, a, s') \rightarrow r_t \in \mathbb{R}$
- The goal?
- To determine a policy that maximizes the return, $R_t = \sum_{k=0}^{\infty} \gamma r_{t+k+1}$
- How?
- By calculating a *Value Function*

Reinforcement Learning

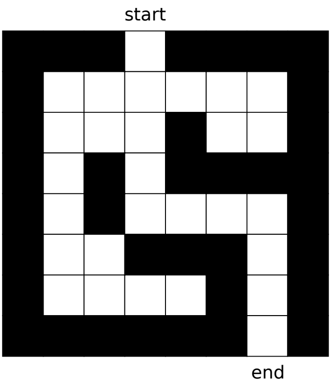


Figure: A maze environment.

Reinforcement Learning

- A Value Function estimates the expected return for *all* states
- $V^{\pi}(s_t) = \mathbb{E}[R_t]$

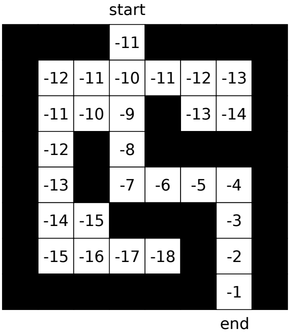


Figure: The optimal value function.

Reinforcement Learning

- A *Value Function* represents "how good" it is to be in a given state, $V^{\pi}(s_t) : s_t \rightarrow \mathbb{E}[R_t]$
- Bellman Equation:

  $$V^{\pi}(s) = r(s, \pi(s), s') + \gamma V(s')), s' = f(s, \pi(s))$$
- How can we learn a Value Function?

Reinforcement Learning

- A *Value Function* represents “how good” it is to be in a given state, $V^{\pi}(s_t) : s_t \rightarrow \mathbb{E}[R_t]$
- Bellman Equation:

  $V(s) = \sum_{s'} P(s, \pi(s), s')[r(s, \pi(s), s') + \gamma V(s')]$
- How can we learn a Value Function?

Reinforcement Learning

Algorithm 1 Policy Iteration (Policy Evaluation)

Require: $V(s)$ arbitrarily initialized, $\forall s \in S$

repeat
    repeat
        $\Delta \leftarrow 0$
        for all $s \in S$ **do**
            $v \leftarrow V(s)$
            $V(s) \leftarrow \sum_{s'} P(s, \pi(s), s')[r(s, \pi(s), s') + \gamma V(s')]$
            $\Delta \leftarrow max(\Delta, |v - V(s)|)$
        end for
    until $\Delta \leq \theta$ ▷ a small positive value
    ...
until StablePolicy == `True`

Reinforcement Learning

Algorithm 2 Policy Iteration (Policy Improvement)

Require: $V(s)$ arbitrarily initialized, $\forall s \in S$

```
repeat
    ...
    StablePolicy ← True
    for all s ∈ S do
        b ← π(s)
        π(s) ← argmax_a Σ_s' P(s,a,s')[r(s,a,s') + γV(s')]
        if b ≠ π(s) then
            StablePolicy ← False
        end if
    end for
until StablePolicy == True
```

$$\pi(s) \leftarrow \arg\max_a \sum_{s'} P(s,a,s')[r(s,a,s') + \gamma V(s')]$$

Reinforcement Learning

Algorithm 3 Value Iteration

Require: $V(s)$ arbitrarily initialized, $\forall s \in S$

1: **repeat**
2: $\Delta \leftarrow 0$
3: **for all** $s \in S$ **do**
4: $v \leftarrow V(s)$
5: $V(s) \leftarrow max_a \sum_{s'} P(s, a, s')[r(s, a, s') + \gamma V(s')]$
6: $\Delta \leftarrow max(\Delta, \|v - V(s)\|)$
7: **end for**
8: **until** $\Delta \leq \theta$ ▷ a small positive value

Reinforcement Learning

- That's nice, but what do we do with a *Value Function*?
- Extract a *policy!*
- A *policy* maps states to actions, $\pi : s \rightarrow a$
- $\pi(s) = \arg\max_a \sum_{s'} P(s, a, s')[r(s, a, s') + \gamma V(s')]$

Reinforcement Learning

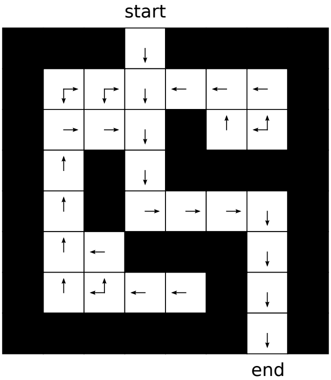


Figure: The optimal policy

Reinforcement Learning

1. Finite State Space
2. Finite Action Space
3. Curse of Dimensionality

Reinforcement Learning

1. Finite State Space
2. Finite Action Space
3. Curse of Dimensionality

Question?

What if we don't know the state transition model?

Example

- Where is the opponent dribbling the ball?
- To where in the goal is the opponent shooting the ball?

Reinforcement Learning

1. Finite State Space
2. Finite Action Space
3. Curse of Dimensionality

Question?

What if we don't know the state transition model?

Example

- Where is the opponent dribbling the ball?
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Reinforcement Learning

- We use an *action* Value Function $Q^{\pi}(s_t, a) = \mathbb{E}[R_t | a_t = a]$
- We let the robot interact with the world and observe the collected rewards
- From that we build a *Value Function*

Reinforcement Learning

Algorithm 4 The Q-Learning algorithm

Require: $Q(s,a)$ initialized arbitrarily $\forall s \in S, \forall a \in A(s)$

```
loop
    Initialize s = s_0
    repeat
        a ← π(s)
        take action a; observe reward, r, and successor state s'
        Q(s,a) ← Q(s,a) + α[r + γ max_b Q(s',b) − Q(s,a)]
        s ← s'
    until s is terminal
end loop
```

$$\begin{array}{l}
\textbf{loop} \\
\quad \text{Initialize } s = s_0 \\
\quad \textbf{repeat} \\
\quad\quad a \leftarrow \pi(s) \\
\quad\quad \text{take action } a\text{; observe reward, } r\text{, and successor state } s' \\
\quad\quad Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_b Q(s',b) - Q(s,a)] \\
\quad\quad s \leftarrow s' \\
\quad \textbf{until } s \text{ is terminal} \\
\textbf{end loop}
\end{array}$$

Reinforcement Learning

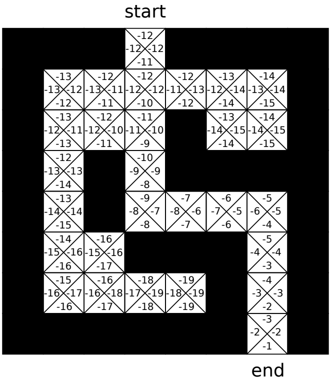

Figure: The optimal Q-function.

- $\pi(s) = \arg\max_a Q(s,a)$

Summary

- Machine Learning is a valid software development tool for programming robotic agents.
- Many paradigms, many challenges, many solutions, even more problems. . .
- The future of Robotics?

References

- Pattern Recognition and Machine Learning, Christopher Bishop, Springer, 2006
- Machine Learning, Tom Mitchell, McGraw Hill, 1997
- Reinforcement Learning: An Introduction, Richard Sutton, Andrew Barto, MIT Press, 2018
- RapidMiner, scikit-learn, clsquare, OpenCV, Shark, TensorFlow, Keras, OpenAI, . . .