Lecture 29: Machine Learning

Marvin Zhang
08/10/2015

(Some images borrowed from CS 188.)
Announcements
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  • Instead, TAs will lead topic-themed discussions Tuesday and Wednesday.
  • Details will be posted on Piazza.
  • Chris and Cale's 9:30-11am labs on Tuesday are NOT canceled.
What is Machine Learning?
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- Natural Language Processing
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- Natural Language Processing
- Computer Vision
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- Computer Vision
- Robotics
- Game Playing
- and much more!
What is Machine Learning?

• Natural Language Processing
• Computer Vision
• Robotics
• Game Playing
• and much more!

• What do these all have in common?
Machine Learning
Machine Learning

What is machine learning?
Machine Learning

What is machine learning?

• A subfield of computer science.
Machine Learning

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• The study of algorithms that *analyze data to make decisions.*
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• Examples of decisions:
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• Examples of decisions:
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Machine Learning

What is machine learning?

• A subfield of computer science.

• The study of algorithms that analyze data to make decisions.

• Examples of decisions:
  
  • Is this email ham or spam?
  
  • How do I translate this sentence?
  
  • Will this user like this restaurant?
Machine Learning Example: Maps
Machine Learning Example: Maps

K-means Clustering
Machine Learning Example: Maps

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K-means Clustering

- The data: restaurant locations
Machine Learning Example: Maps

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- The decision: which cluster does each belong to?
Machine Learning Example: Maps

K-means Clustering

• The data: restaurant locations

• The decision: which cluster does each belong to?

Called *unsupervised learning*, because no one tells it what the correct decision is.
Machine Learning Example: Maps
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Linear Regression
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- The data: user ratings
Machine Learning Example: Maps

Linear Regression

- The data: user ratings
- The decision: what rating would the user give a new restaurant?
Machine Learning Example: Maps

Linear Regression

- The data: user ratings
- The decision: what rating would the user give a new restaurant?

Called *supervised learning*, because some correct decisions are given.
Outline
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• So far, we’ve looked at two specific machine learning algorithms from two different domains.
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• Today, we will focus on a subclass of problems in machine learning, known as reinforcement learning problems, and algorithms for these problems.
Reinforcement Learning
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• Concerned with learning behavior through experience.
Reinforcement Learning

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• Two main components: the agent and the environment.
Reinforcement Learning

What is reinforcement learning?

• Concerned with *learning behavior through experience.*

• Two main components: the *agent* and the *environment.*

• The agent lives in and interacts with the environment, and through this experience learns a good pattern of behavior.
An Analogy
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Suppose you go on a date with someone.
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- In reinforcement learning terms, you are the agent.
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- In reinforcement learning terms, you are the *agent*.
- Everything else (the other person, the setting, etc.) is the *environment*.
An Analogy

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• At the beginning of the date, you might not know how to act, so you try different things to see how the other person responds.
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- As the date goes on, you slowly figure out how you should behave based on what you’ve tried so far, and how it went.
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So… do you like hamsters?
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RL Example: Gridworld
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What is the environment?

What is the agent?
RL Example: Gridworld

The Problem: How do we get to the goal (green) from the start (blue) as quickly as possible while avoiding the obstacles (red)?

What is the environment?

What is the agent?
The RL Setting
The RL Setting

The environment:
The RL Setting

The environment:
- States ($s$):
  Configuration of the agent and environment.
The RL Setting

The environment:
  • States (s):
    Configuration of the agent and environment.
  • Actions (a):
    What can the agent do in a state?
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- Reward function (R):
  What reward does the agent get for each state?
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  Configuration of the agent and environment.
• Actions (a):
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  What reward does the agent get for each state?

The agent:
• Policy ($\pi$):
  Given a state, what action will the agent take?
Gridworld Revisited
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- The environment of Gridworld, in more detail:
Gridworld Revisited

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  • States (s):
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    What square is the agent in?
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Gridworld Revisited

- The environment of Gridworld, in more detail:
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  - Actions (a):
    - Go to an adjacent square, or stay put.
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In RL terminology:
What is the optimal policy \( \pi^* \) that maximizes my expected reward over time?
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-1  -1  -1  -1  -1
-1  -1  -1  -1  -1
-1  -1  -1  -1  0
Value Function
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Value Function

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- How do we determine the value of a state?
  - The value of a state is the reward of the state plus the value of the state we end up in next.
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- The value of a state is the reward of the state plus the value of the state we end up in next.

\[
V^\pi(s) = R(s) + \sum_{s'} P(s, \pi(s), s') V^\pi(s')
\]
Value Function

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Value Function

$$V^\pi(s) = R(s) + \sum_{s'} P(s, \pi(s), s') V^\pi(s')$$

- How do we solve this equation? Use recursion!
Value Function

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- How do we solve this equation? Use recursion!
- What’s our base case?
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- How do we solve this equation? Use recursion!
- What’s our base case?
  - If we’re at our goal, then there is no next state, so the value is just the reward.
Value Function

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- How do we solve this equation? Use recursion!
- What’s our base case?
  - If we’re at our goal, then there is no next state, so the value is just the reward.

```python
def V(s):
    reward = R(s)
    if is_goal(s):
        return reward
    return reward +
    sum([P(s, pi(s), n_s) * V(n_s) for n_s in states])
```
Gridworld Value Function Example
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## Gridworld Value Function Example

<table>
<thead>
<tr>
<th>Gridworld Value Function Example</th>
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<tr>
<td><img src="image" alt="Gridworld Diagram" /></td>
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<tr>
<td>- Arrows denote the policy ( \pi ).</td>
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- Arrows denote the policy $\pi$.
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Policy Evaluation
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• But remember, what we are really interested in is the optimal policy $\pi^*$! How do we find this?
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- Based on the value function, which action of the current policy should we change?
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• Now that we know $V(s)$, we improve our policy $\pi$ to a new policy $\pi'$ as follows:
Policy Iteration

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  • For every state $s$, $\pi'$ picks the action that leads to the next state $s'$ with the highest value.
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• This is called policy iteration.
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• This is called policy iteration.

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    return max(actions,
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Policy Iteration

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