CS 730/730W/830: Intro AI

Scaling RL

Supervised Learning

Regression

1 handout: slides asst 4 milestones were due blog entries were due

Scaling RL

- Summary
- \blacksquare Approx U
- Break
- Class Outline

Supervised Learning

Regression

Scaling Reinforcement Learning

Summary

Scaling RL

Summary

Approx U

Break

Class Outline

Supervised Learning

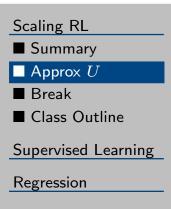
Regression

Model known (solving MDP):

- value iteration
- lacktriangle policy iteration: compute U^π using
 - linear algebra
 - simplified value iteration
 - ◆ a few updates (modified PI)

Model unknown (RL):

- ADP using
 - value iteration
 - ◆ a few updates (eg, prioritized sweeping)
- Q-learning



$$\hat{U}(s) = \theta_0 f_0(s) + \theta_1 f_1(s) + \theta_2 f_2(s) + \dots$$

Scaling RL

Summary

Approx U

Break
Class Outline
Supervised Learning
Regression

$$\hat{U}(s) = \theta_0 f_0(s) + \theta_1 f_1(s) + \theta_2 f_2(s) + \dots$$

 $\hat{U}(x,y) = \theta_0 + \theta_1 x + \theta_2 y$

Scaling RL

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Supervised Learning

Regression

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$$\hat{U}(x,y) = \theta_0 + \theta_1 x + \theta_2 y$$

given sample u at s=x,y, want update to decrease error:

$$E = \frac{(\hat{U}(s) - u)^2}{2}$$

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$$\theta_i \leftarrow \theta_i - \alpha \frac{\delta E}{\delta \theta_i}$$

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$$\theta_i \leftarrow \theta_i - \alpha (\hat{U}(s) - u) \frac{\delta \hat{U}(s)}{\delta \theta_i}$$

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$$\theta_i \leftarrow \theta_i - \alpha (\hat{U}(s) - u) \frac{\delta \hat{U}(s)}{\delta \theta_i}$$

in other words, the updates are:

$$\theta_0 \leftarrow \theta_0 - \alpha(\hat{U}(s) - u)$$

$$\theta_1 \leftarrow \theta_1 - \alpha(\hat{U}(s) - u)x$$

$$\theta_2 \leftarrow \theta_2 - \alpha(\hat{U}(s) - u)y$$

Break

Scaling RL

■ Summary

■ Approx U

■ Break

■ Class Outline

Supervised Learning

- projects: proposals, talks, paper
- asst 4

Class Outline

Scaling RL

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Supervised Learning

Regression

knowledge: specialized, propositional, FOL, STRIPS reasoning: constraints, FOL, induction, planning

- 1. search: heuristics, CSPs, games
- 2. knowledge representation: FOL, resolution
- 3. planning: STRIPS, MDPs
- 4. learning: RL, supervised, unsupervised
- 5. KR with uncertainty: HMMs, Bayes nets

Scaling RL

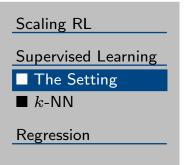
Supervised Learning

- The Setting
- k-NN

Regression

Supervised Learning

The Setting



labeled examples
hypothesis space
free parameters = degrees of freedom
classification vs regression
noise, overfitting

Using the *k*-Nearest Neighbors

Scaling RL

Supervised Learning

■ The Setting



Regression

majority. k=1 gives Voroni cells

$$d(a,b) = \sqrt{\sum_{i} (a_i - b_i)^2}$$

normalize dimensions (divide by $\sqrt{\frac{1}{N}\sum_i(x_i-\bar{x})^2}$) weight by distance?

- +: robust to noise, choose k by easy cross-validation
- -: memory, kd-tree, irrelevant features, sparse data in high d

Scaling RL

Supervised Learning

Regression

- Regression
- On-line Regression
- **■** LMS
- **■** EOLQs

Regression

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$$\hat{y} = \theta_0 f_0(x) + \theta_1 f_1(x) + \theta_2 f_2(x) + \dots$$

Regression

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- **■** LMS
- **■** EOLQs

$$\hat{y} = \theta_0 f_0(x) + \theta_1 f_1(x) + \theta_2 f_2(x) + \dots$$

$$\hat{y} = \theta_0 + \theta_1 x$$

$$\hat{y} = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3$$

$$\hat{y} = \theta_0 + \theta_1 \sin x$$

Scaling RL

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Regression

■ Regression

■ On-line Regression

- **■** LMS
- **■** EOLQs

$$y = \theta f(x)$$

given sample x,y, want update to decrease $E=\frac{(\hat{y}-y)^2}{2}$:

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$$\theta_i \leftarrow \theta_i - \alpha \frac{\delta E}{\delta \theta_i}$$

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given sample x,y, want update to decrease $E=\frac{(\hat{y}-y)^2}{2}$:

$$\theta_{i} \leftarrow \theta_{i} - \alpha \frac{\delta E}{\delta \theta_{i}}$$

$$\frac{\delta E}{\delta \theta_{i}} = \frac{\delta}{\delta \theta_{i}} \frac{(\hat{y} - y)^{2}}{2}$$

$$= (\hat{y} - y) \frac{\delta}{\delta \theta_{i}} (\hat{y} - y)$$

$$= (\hat{y} - y) \frac{\delta}{\delta \theta_{i}} (\theta f(x) - y)$$

$$= (\hat{y} - y) f(x)$$

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given sample x,y, want update to decrease $E=\frac{(\hat{y}-y)^2}{2}$:

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$$= (\hat{y} - y) \frac{\delta}{\delta \theta_{i}} (\hat{y} - y)$$

$$= (\hat{y} - y) \frac{\delta}{\delta \theta_{i}} (\theta f(x) - y)$$

$$= (\hat{y} - y) f(x)$$

$$\theta \leftarrow \theta - \alpha (\hat{y} - y) f(x)$$

The LMS Procedure

Scaling RL

Supervised Learning

- Regression
- On-line Regression
- **LMS**
- **■** EOLQs

$$\begin{array}{rcl} y & = & \theta x \\ \theta & \leftarrow & \theta - \alpha(\hat{y} - y)x \end{array}$$

The LMS Procedure

Scaling RL

Supervised Learning

Regression

- Regression
- On-line Regression
- LMS
- **■** EOLQs

$$\begin{array}{rcl} y & = & \theta x \\ \theta & \leftarrow & \theta - \alpha (\hat{y} - y) x \end{array}$$

for $x = \langle 0, x_1, x_2 \rangle$, the updates are:

$$\theta_0 \leftarrow \theta_0 - \alpha(\hat{y} - y)$$

$$\theta_1 \leftarrow \theta_1 - \alpha(\hat{y} - y)x_1$$

$$\theta_2 \leftarrow \theta_2 - \alpha(\hat{y} - y)x_2$$

 $\alpha \approx 1/N?$ or 100/(100+N)? or 0.1? Δ rule, LMS weight update, Adaline rule, Widrow-Hoff rule, Perceptron rule converges if data are linear perceptron in finite time if linearly separable

EOLQs

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- On-line Regression
- **■** LMS
- EOLQs

- What question didn't you get to ask today?
- What's still confusing?
- What would you like to hear more about?

Please write down your most pressing question about AI and put it in the box on your way out.

Thanks!