

BackProp

Decision Trees

1 handouts: slides
asst 4 is due
730W blog entries were due

BackProp

- Three layers
- Nonlinear
- BackProp
- Break

Decision Trees

BackProp

Supervised Learning: Summary So Far

BackProp

- Three layers
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Decision Trees

k -NN : distance function (any attributes), any labels

Neural network : numeric attributes, numeric or binary labels

Regression: incremental training with LMS

3-Layer ANN: non-linear wrt features

Inductive Logic Programming: logical concepts

The Three-layer Architecture

BackProp

Three layers

Nonlinear

BackProp

Break

Decision Trees

'hidden layer'

non-linear!

training: backwards error propagation

recurrence

Nonlinearity

BackProp

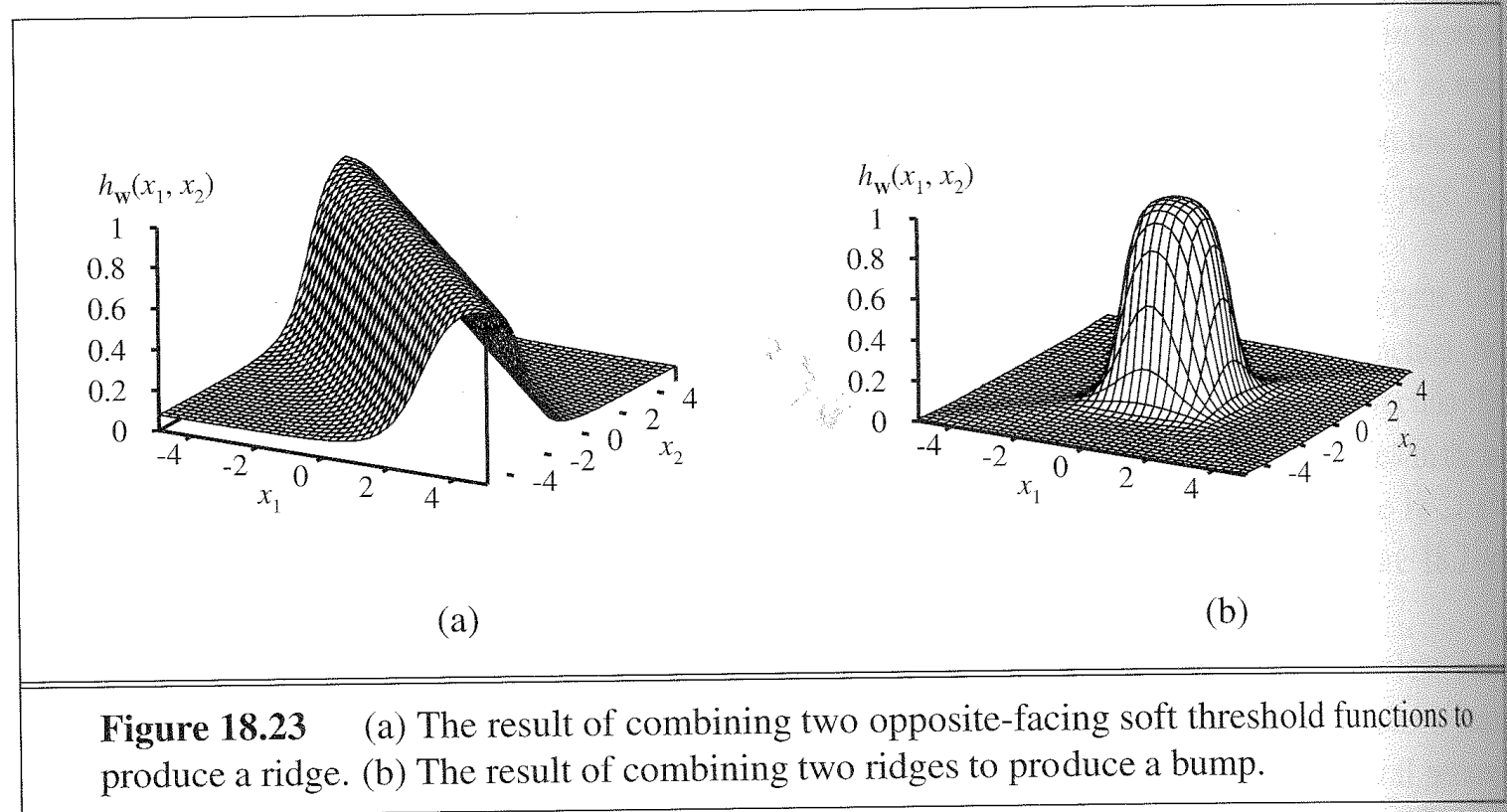
■ Three layers

■ Nonlinear

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Decision Trees



Backwards Error Propagation

BackProp

■ Three layers

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Decision Trees

k inputs, j hidden units, i outputs

$g'(in_i)$ is derivative of activation function wrt input i

$$\begin{aligned}\Delta_i &= g'(in_i)(\hat{y} - y) \\ W_{j,i} &= W_{j,i} - \alpha a_j \Delta_i\end{aligned}$$

Backwards Error Propagation

BackProp

■ Three layers

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Decision Trees

k inputs, j hidden units, i outputs

$g'(in_i)$ is derivative of activation function wrt input i

$$\Delta_i = g'(in_i)(\hat{y} - y)$$

$$W_{j,i} = W_{j,i} - \alpha a_j \Delta_i$$

$$\Delta_j = g'(in_j) \sum_i W_{j,i} \Delta_i$$

$$W_{k,j} = W_{k,j} - \alpha a_k \Delta_j$$

only locally optimal, dependence on structure

Break

BackProp

- Three layers
- Nonlinear
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■ Break

Decision Trees

- asst 4
- asst 5: data, tool, reference
- projects!

BackProp

Decision Trees

- Example
- Construction
- EOLQs

Decision Trees

Example: WillWait

BackProp

Decision Trees

■ Example

■ Construction

■ EOLQs

Example	Attributes										Goal
	<i>Alt</i>	<i>Bar</i>	<i>Fri</i>	<i>Hun</i>	<i>Pat</i>	<i>Price</i>	<i>Rain</i>	<i>Res</i>	<i>Type</i>	<i>Est</i>	<i>WillWait</i>
X_1	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Some</i>	<i>\$\$\$</i>	<i>No</i>	<i>Yes</i>	<i>French</i>	<i>0-10</i>	<i>Yes</i>
X_2	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Full</i>	<i>\$</i>	<i>No</i>	<i>No</i>	<i>Thai</i>	<i>30-60</i>	<i>No</i>
X_3	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>Some</i>	<i>\$</i>	<i>No</i>	<i>No</i>	<i>Burger</i>	<i>0-10</i>	<i>Yes</i>
X_4	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>Yes</i>	<i>Full</i>	<i>\$</i>	<i>Yes</i>	<i>No</i>	<i>Thai</i>	<i>10-30</i>	<i>Yes</i>
X_5	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Full</i>	<i>\$\$\$</i>	<i>No</i>	<i>Yes</i>	<i>French</i>	<i>>60</i>	<i>No</i>
X_6	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>	<i>Some</i>	<i>\$\$</i>	<i>Yes</i>	<i>Yes</i>	<i>Italian</i>	<i>0-10</i>	<i>Yes</i>
X_7	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>No</i>	<i>None</i>	<i>\$</i>	<i>Yes</i>	<i>No</i>	<i>Burger</i>	<i>0-10</i>	<i>No</i>
X_8	<i>No</i>	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>Some</i>	<i>\$\$</i>	<i>Yes</i>	<i>Yes</i>	<i>Thai</i>	<i>0-10</i>	<i>Yes</i>
X_9	<i>No</i>	<i>Yes</i>	<i>Yes</i>	<i>No</i>	<i>Full</i>	<i>\$</i>	<i>Yes</i>	<i>No</i>	<i>Burger</i>	<i>>60</i>	<i>No</i>
X_{10}	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Full</i>	<i>\$\$\$</i>	<i>No</i>	<i>Yes</i>	<i>Italian</i>	<i>10-30</i>	<i>No</i>
X_{11}	<i>No</i>	<i>No</i>	<i>No</i>	<i>No</i>	<i>None</i>	<i>\$</i>	<i>No</i>	<i>No</i>	<i>Thai</i>	<i>0-10</i>	<i>No</i>
X_{12}	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Full</i>	<i>\$</i>	<i>No</i>	<i>No</i>	<i>Burger</i>	<i>30-60</i>	<i>Yes</i>

Figure 18.3 Examples for the restaurant domain.

Building a Decision Tree

BackProp

Decision Trees

■ Example

■ Construction

■ EOLQs

DTLearn(examples, attributes, default)

if no examples, return default

if all same label, return it

$m \leftarrow$ majority label

if no attributes, return m

else

$a \leftarrow$ choose attribute

make node that branches on a

remove a from attributes

for each value v of a

subtree \leftarrow DTLearn(examples with $a = v$, attributes, m)

add branch to subtree for v at node

return node

Branching

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Decision Trees

■ Example

■ **Construction**

■ EOLQs

want attribute that reduces uncertainty

Branching

BackProp

Decision Trees

■ Example

■ Construction

■ EOLQs

want attribute that reduces uncertainty = entropy =

$$H(X) = - \sum_i P(x_i) \log_2 P(x_i)$$

where X is random var that takes value x_i with prob $P(x_i)$

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information gain of attribute A :

$$H(X) - \sum_{a \in A} P(a) H(X_a)$$

where X_a contains only examples with $A = a$

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stop when gain is small (χ^2 test, see p.705) or cross-validate

BackProp

Decision Trees

■ Example

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■ 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!