

# 10-301/601: Introduction to Machine Learning

## Lecture 3 – Decision Trees: Learning

Henry Chai

5/13/25

# Front Matter

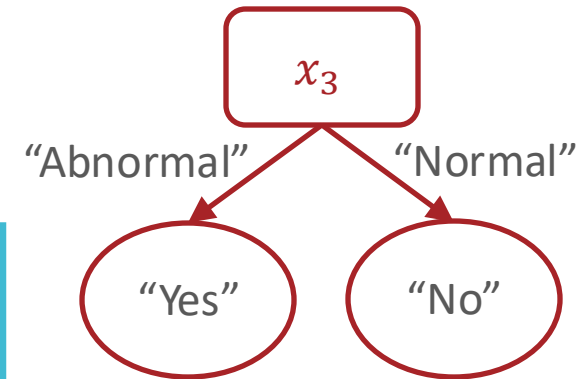
- Announcements:
  - HW1 released on 5/13 (today!), due 5/16 at 11:59 PM
  - You will submit your homework to Gradescope
    1. Submit your code to the “programming” submission slot
    2. Submit a PDF with your answers to the questions “written” submission slot
  - **You must use LaTeX to typeset your responses!**

# Decision Stumps: Questions

1. How can we pick which feature to split on?
2. Why stop at just one feature?
  - a. How can we pick the order of the splits?

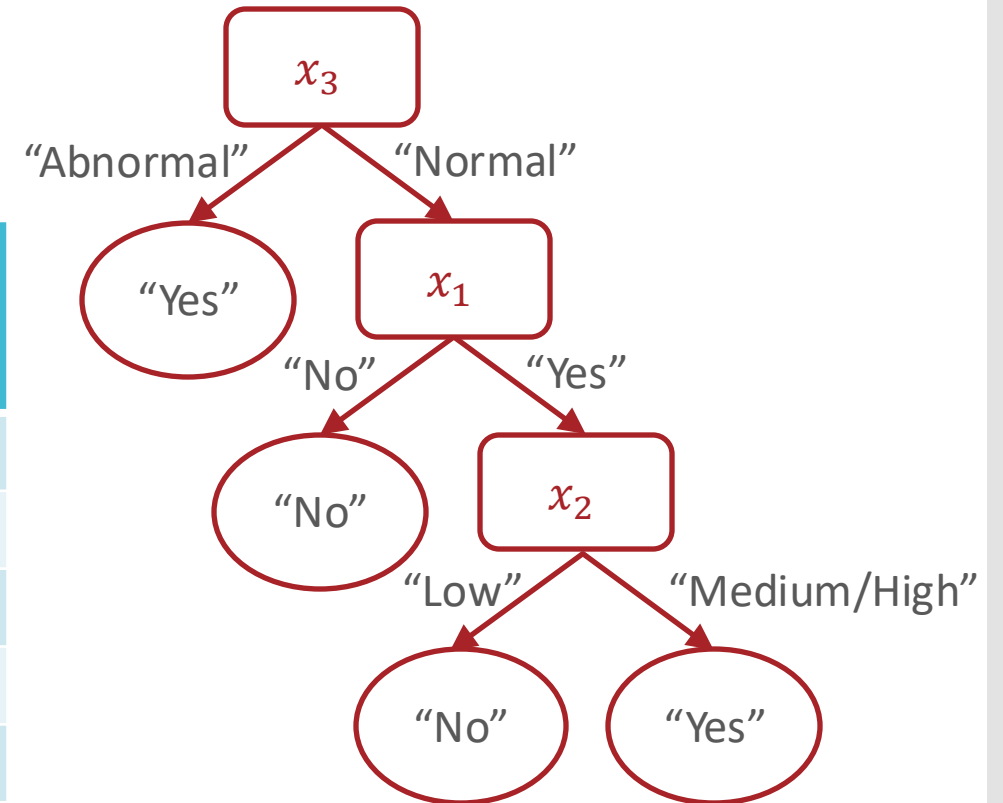
# From Decision Stump ...

$x_1$ Family History	$x_2$ Resting Blood Pressure	$x_3$ Cholesterol	$y$ Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes



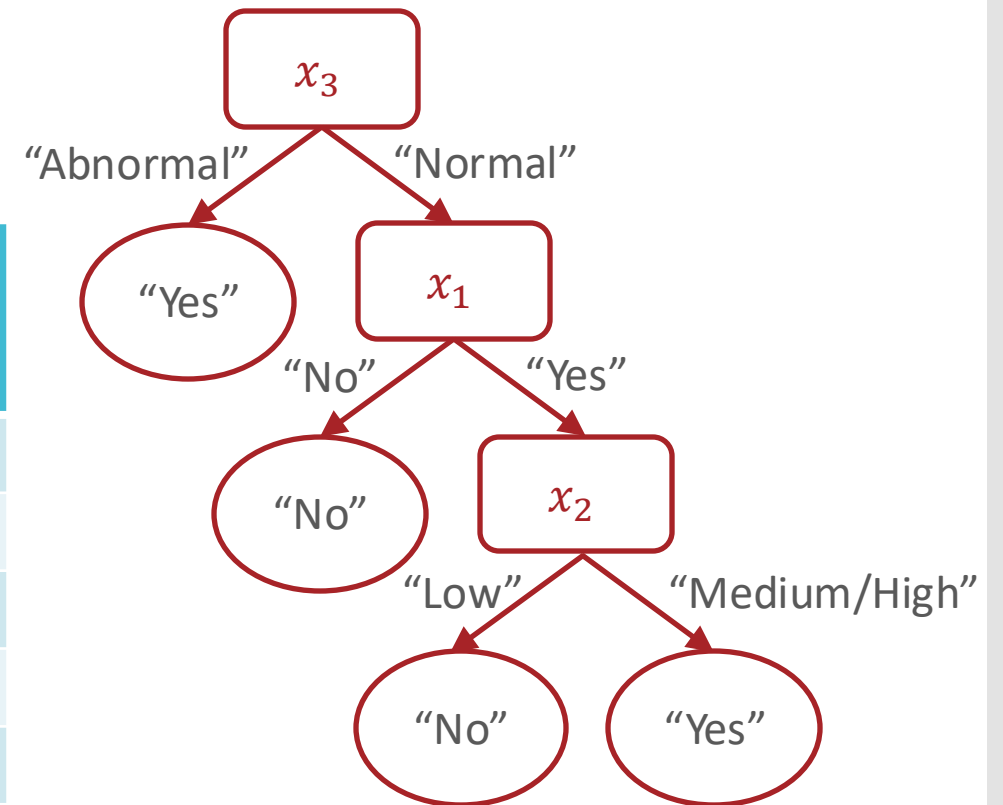
# From Decision Stump to Decision Tree

$x_1$ Family History	$x_2$ Resting Blood Pressure	$x_3$ Cholesterol	$y$ Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes



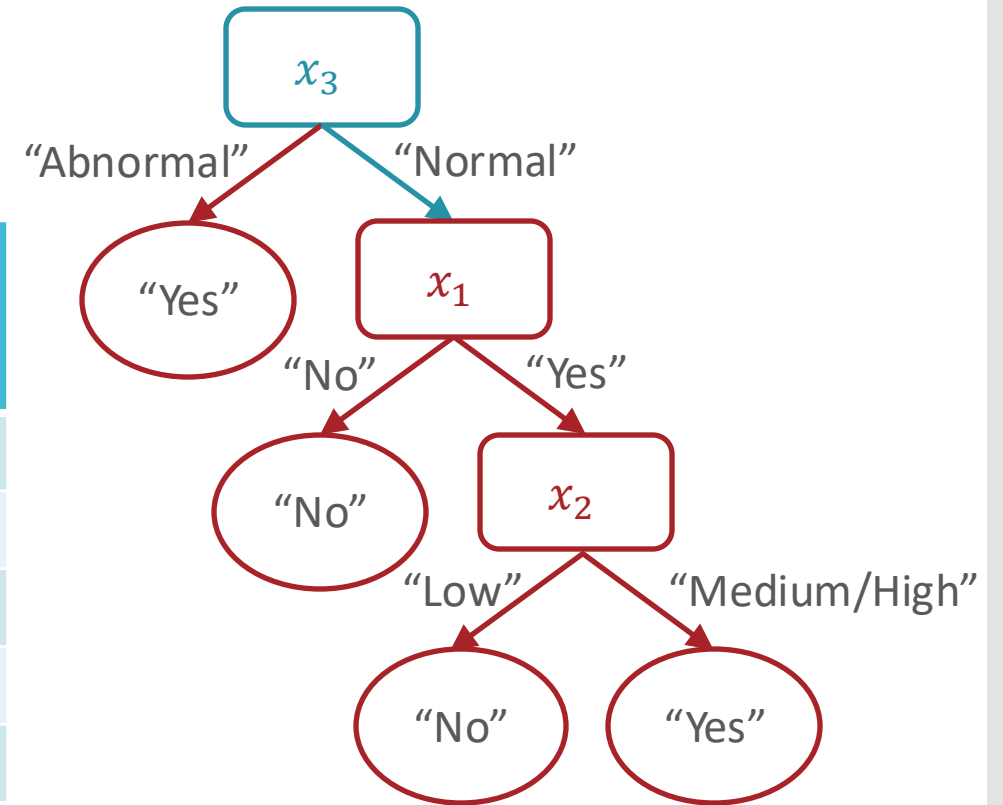
# From Decision Stump to Decision Tree

$x_1$ Family History	$x_2$ Resting Blood Pressure	$x_3$ Cholesterol	$y$ Heart Disease?
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Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes
No	High	Normal	No



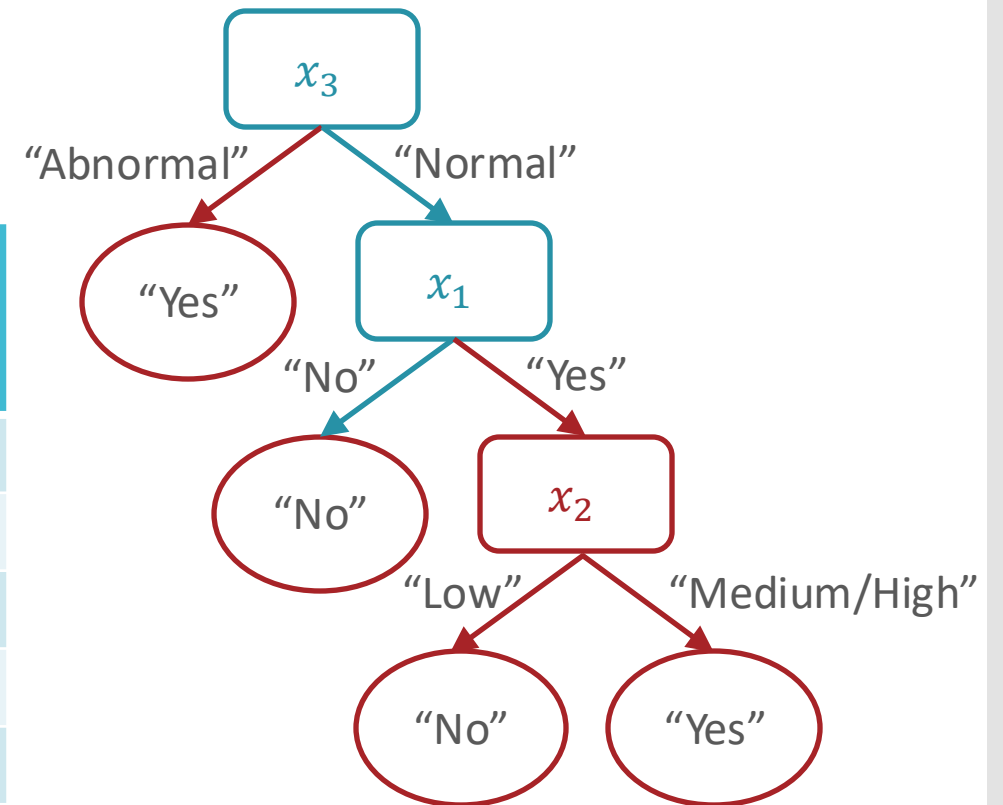
# From Decision Stump to Decision Tree

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# From Decision Stump to Decision Tree

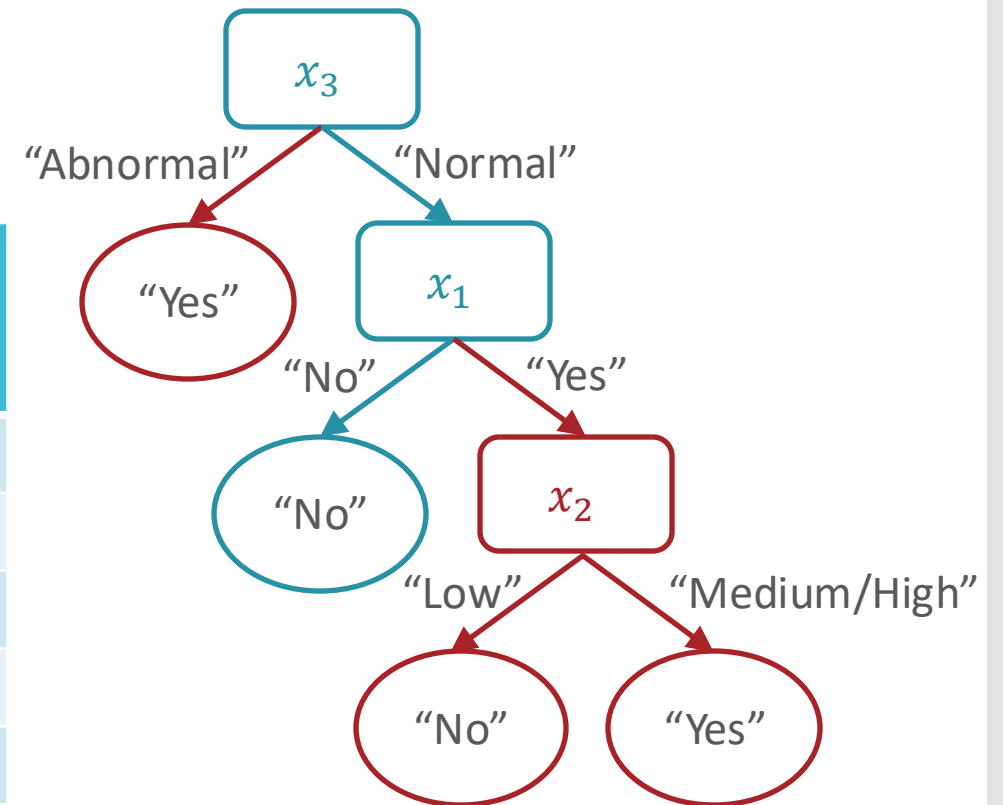
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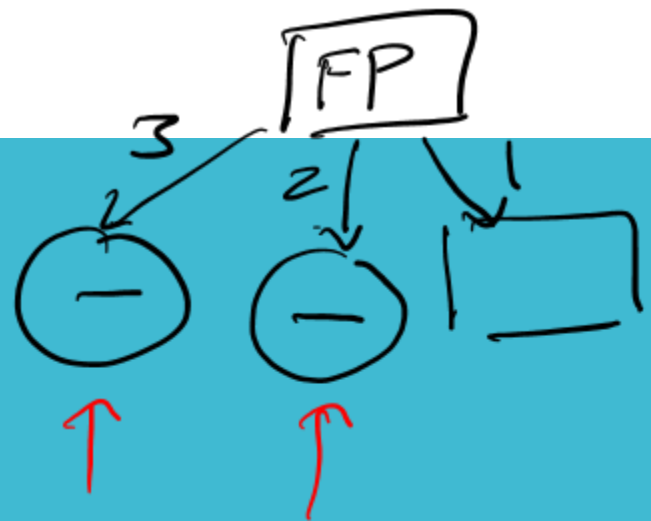




# From Decision Stump to Decision Tree

$x_1$ Family History	$x_2$ Resting Blood Pressure	$x_3$ Cholesterol	$y$ Heart Disease?
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No	Low	Abnormal	Yes
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## Decision Tree: Example



Learned from medical records of 1000 women

Negative examples are C-sections

[833+, 167-] .83+ .17-

→ Fetal\_Presentation = 1: [822+, 116-] .88+ .12-

→ | Previous\_Csection = 0: [767+, 81-] .90+ .10-

→ | | Primiparous = 0: [399+, 13-] .97+ .03-

→ | | Primiparous = 1: [368+, 68-] .84+ .16-

★ | | | Fetal\_Distress = 0: [334+, 47-] .88+ .12-

★ | | | Fetal\_Distress = 1: [34+, 21-] .62+ .38-

→ | Previous\_Csection = 1: [55+, 35-] .61+ .39-

→ Fetal\_Presentation = 2: [3+, 29-] .11+ .89-

→ Fetal\_Presentation = 3: [8+, 22-] .27+ .73-

$$\frac{8}{30} \approx \frac{22}{30}$$

Decision: do we  
train: one of  
the sections?

def predict( $x'$ ):

- walk from the root to a leaf  
while true:

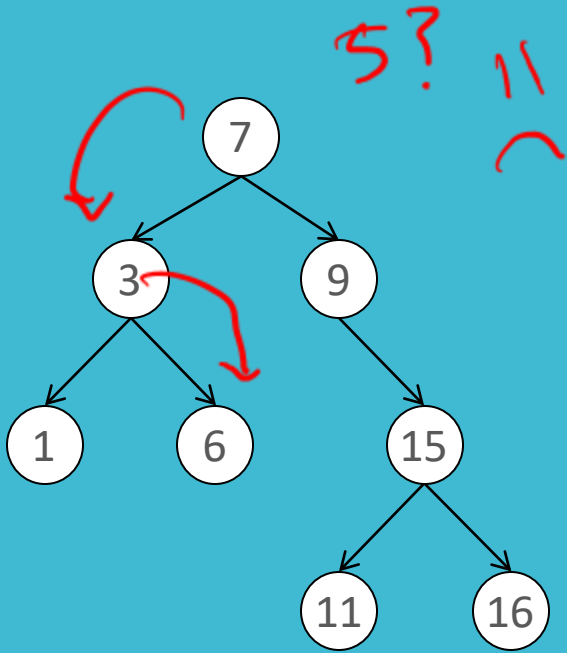
if current\_node is internal:  
check the associated feature  
 $x_d$

go down the branch

according to  $x'_d$   
else if current\_node is leaf:  
return the label stored at  
current\_node

→  $[x'_1, x'_2, \dots, x'_d, \dots, x'_D]$

## Background: Recursion



- A **binary search tree** (BST) consists of nodes, where each node:
  - has a value,  $v$
  - up to 2 children, a left descendant and a right descendant
  - all its left descendants have values less than  $v$  and its right descendants have values greater than  $v$
- We like BSTs because they permit search in  $O(\log(n))$  time, assuming  $n$  nodes in the tree

def contains\_iterative(root, key)  
    curr\_node = root  
    while true:

        if key < curr\_node.value & curr\_node.left exists:

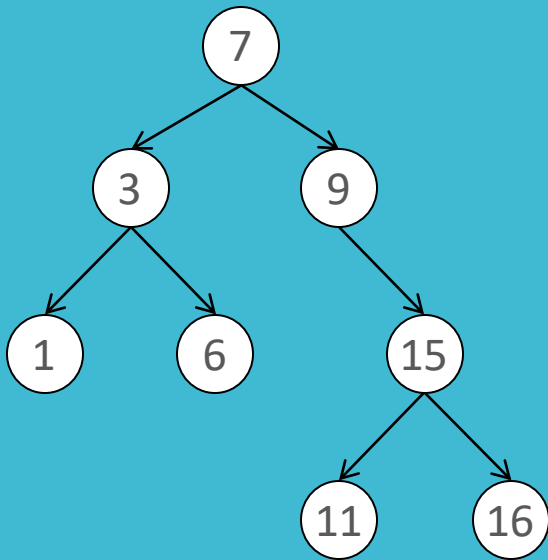
            curr\_node = curr\_node.left

        else if key > curr\_node.value & curr\_node.right exists:

            curr\_node = curr\_node.right

    else:  
        return key == curr\_node.value

## Background: Recursion



- A **binary search tree** (BST) consists of nodes, where each node:
  - has a value,  $v$
  - up to 2 children, a left descendant and a right descendant
  - all its left descendants have values less than  $v$  and its right descendants have values greater than  $v$
- We like BSTs because they permit search in  $O(\log(n))$  time, assuming  $n$  nodes in the tree

```
def contains_recurse(node, key):  
    if key < node.value & node.left exists:  
        contains_recurse(node.left, key)  
    else if key > node.value & node.right exists:  
        contains_recurse(node.right, key)  
    else  
        return key == node.value
```

# Decision Tree: Pseudocode

```
def train( $\mathcal{D}$ ):
```

```
    store root = tree_recurse( $\mathcal{D}$ )
```

```
def tree_recurse( $\mathcal{D}'$ ):
```

```
    q = new node()
```

```
    base case – if (SOME CONDITION):
```

```
    recursion – else:
```

- find the best attribute to split  $\mathcal{D}'$   
on (e.g. using MI),  $X_d$

-  $q.\text{split\_feature} = X_d$

for  $v$  in  $V(X_d) = \{\text{all values } X_d \text{ takes on}\}$

$\mathcal{D}_v = \{(\vec{x}^{(i)}, y^{(i)}) \in \mathcal{D}' \mid x_d^{(i)} = v\}$

$q.\text{children}(v) = \text{tree\_recurse}(\mathcal{D}_v)$

```
    return q
```

0 surveys completed



0 surveys underway

Which of the following are reasonable base cases for training decision trees recursively i.e., when does it make sense to stop splitting a node?

All labels in the node's dataset are the same

All feature vectors in the node's dataset are the same

The node's dataset is empty

The labels in the node's dataset are split 50-50

None of the above



# Decision Tree: Pseudocode

```
def train( $\mathcal{D}$ ):  
    store root = tree_recurse( $\mathcal{D}$ )  
def tree_recurse( $\mathcal{D}'$ ):  
    q = new node()  
    base case – if ( $\mathcal{D}'$  is empty OR  
        all labels in  $\mathcal{D}'$  are the same OR  
        all features in  $\mathcal{D}'$  are identical OR  
        some other stopping criterion):  
        q.label = majority_vote( $\mathcal{D}'$ )  
  
    recursion – else:  
        return q
```

# Decision Tree: Example – How is Henry getting to work?

- Label: mode of transportation
  - $y \in \mathcal{Y} = \{\text{Bike, Drive, Bus}\}$
- Features: 4 categorical features
  - Is it raining?  $x_1 \in \{\text{Rain, No Rain}\}$
  - When am I leaving (relative to rush hour)?  
 $x_2 \in \{\text{Before, During, After}\}$
  - What am I bringing?  
 $x_3 \in \{\text{Backpack, Lunchbox, Both}\}$
  - Am I tired?  $x_4 \in \{\text{Tired, Not Tired}\}$

# Data

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
Rain	After	Backpack	Not Tired	Bus
Rain	After	Backpack	Tired	Bus
Rain	After	Lunchbox	Tired	Drive
No Rain	Before	Backpack	Tired	Bike
No Rain	Before	Lunchbox	Not Tired	Bus
No Rain	Before	Lunchbox	Tired	Drive
No Rain	During	Backpack	Not Tired	Bus
No Rain	During	Both	Tired	Drive
No Rain	After	Backpack	Not Tired	Bike
No Rain	After	Backpack	Tired	Bike
No Rain	After	Both	Not Tired	Bus
No Rain	After	Both	Tired	Drive
No Rain	After	Lunchbox	Not Tired	Bus

Which feature  
would we split on  
first using mutual  
information as  
the splitting  
criterion?

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
Rain	After	Backpack	Not Tired	Bus
Rain	After	Backpack	Tired	Bus
Rain	After	Lunchbox	Tired	Drive
No Rain	Before	Backpack	Tired	Bike
No Rain	Before	Lunchbox	Not Tired	Bus
No Rain	Before	Lunchbox	Tired	Drive
No Rain	During	Backpack	Not Tired	Bus
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No Rain	After	Both	Not Tired	Bus
No Rain	After	Both	Tired	Drive
No Rain	After	Lunchbox	Not Tired	Bus

$$H(S) = - \sum_{v \in V(S)} \frac{|S_v|}{|S|} \log_2 \left( \frac{|S_v|}{|S|} \right)$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
Rain	After	Backpack	Not Tired	Bus
Rain	After	Backpack	Tired	Bus
Rain	After	Lunchbox	Tired	Drive
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$$H(S) = - \sum_{v \in V(S)} \frac{|S_v|}{|S|} \log_2 \left( \frac{|S_v|}{|S|} \right)$$

$$H(Y) = - \left( \frac{3}{16} \log_2 \frac{3}{16} + \frac{7}{16} \log_2 \frac{7}{16} + \frac{6}{16} \log_2 \frac{6}{16} \right)$$

$$H(Y) \approx 1.5052$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
Rain	After	Backpack	Not Tired	Bus
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_1, Y$$

$$IG(x_1, y) = -\frac{7}{16} \log_2 \left( \frac{7}{16} \right)$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_1, Y) \approx 1.5052$$

$$- \frac{6}{16} \left( -\frac{1}{2} \log_2 \left( \frac{1}{2} \right) \right)$$

$$I(x_1, y)$$

$$16 - \frac{1}{16}$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
Rain	During	Both	Not Tired	Bus
Rain	During	Both	Tired	Drive
Rain	After	Backpack	Not Tired	Bus
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_1, Y) \approx 1.5052$$

$$- \frac{6}{16}(1)$$

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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_1, Y) \approx 1.5052$$

$$- \frac{6}{16} (1)$$

$$- \frac{10}{16} \left( -\frac{3}{10} \log_2 \left( \frac{3}{10} \right) \right)$$

$$- \frac{3}{16} \log_2 \left( \frac{3}{16} \right)$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
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$$I(x_d; Y) = H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_1, Y) \approx 1.5052$$

$$- \frac{6}{16}(1)$$

$$- \frac{10}{16}(1.5710)$$

$$\approx 0.1482$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_d, Y)$$

$$x_1 \quad 0.1482$$

$$x_2 \quad 0.1302$$

$$x_3 \quad 0.5358$$

$$x_4 \quad 0.5576$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	Before	Both	Tired	Drive
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Rain	During	Both	Tired	Drive
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Rain	After	Backpack	Tired	Bus
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_d, Y)$$

$$x_1 \quad 0.1482$$

$$x_2 \quad 0.1302$$

$$x_3 \quad 0.5358$$

$$x_4 \quad 0.5576$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_d, Y)$$

$$x_1 \quad 0.1482$$

$$x_2 \quad 0.1302$$

$$x_3 \quad 0.5358$$

$$x_4 \quad 0.5576$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
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$$I(x_d; Y)$$

$$= H(Y) - \sum_{v \in V(x_d)} f_v * H(Y_{x_d=v})$$

$$I(x_d, Y)$$

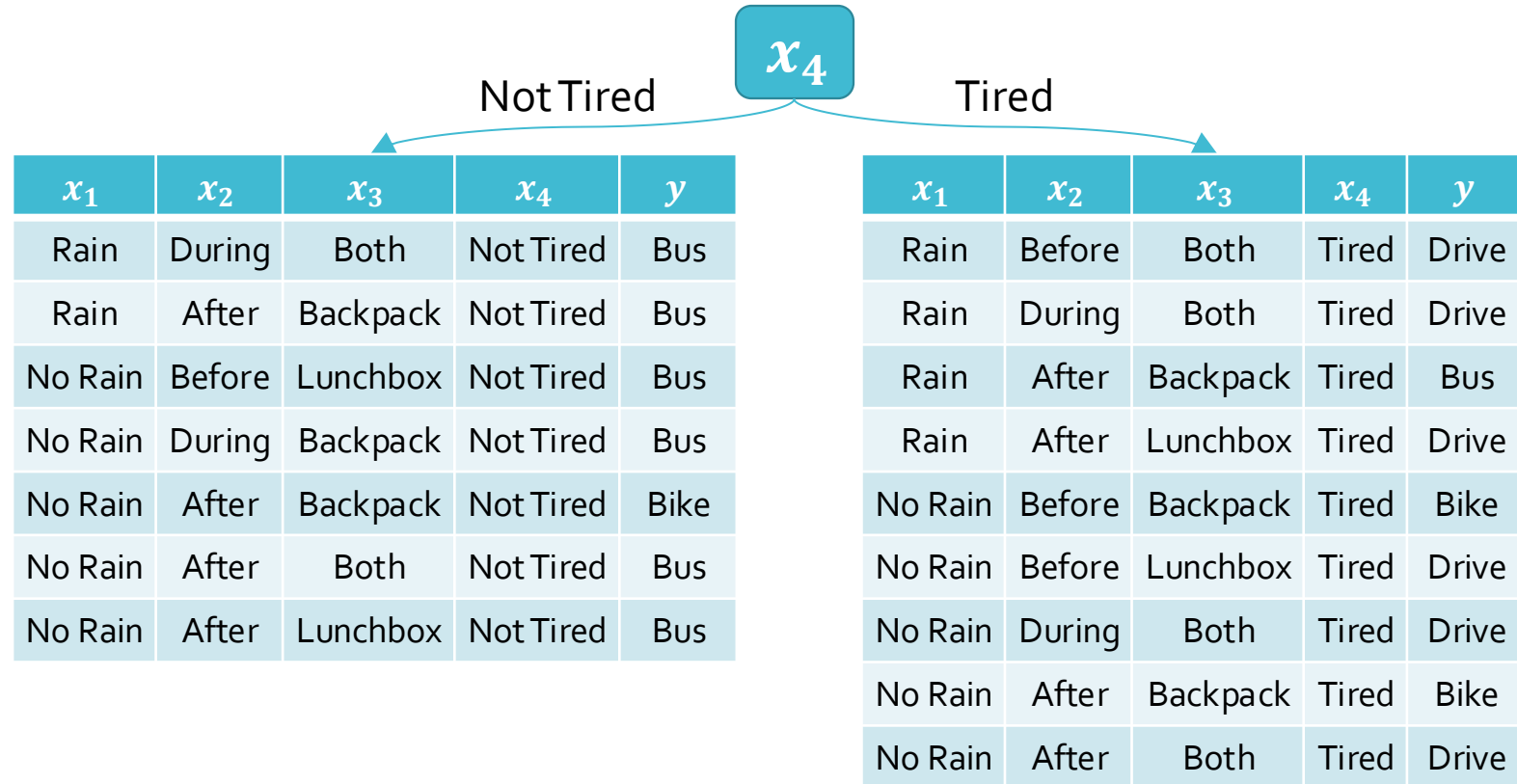
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$$x_2 \quad 0.1302$$

$$x_3 \quad 0.5358$$

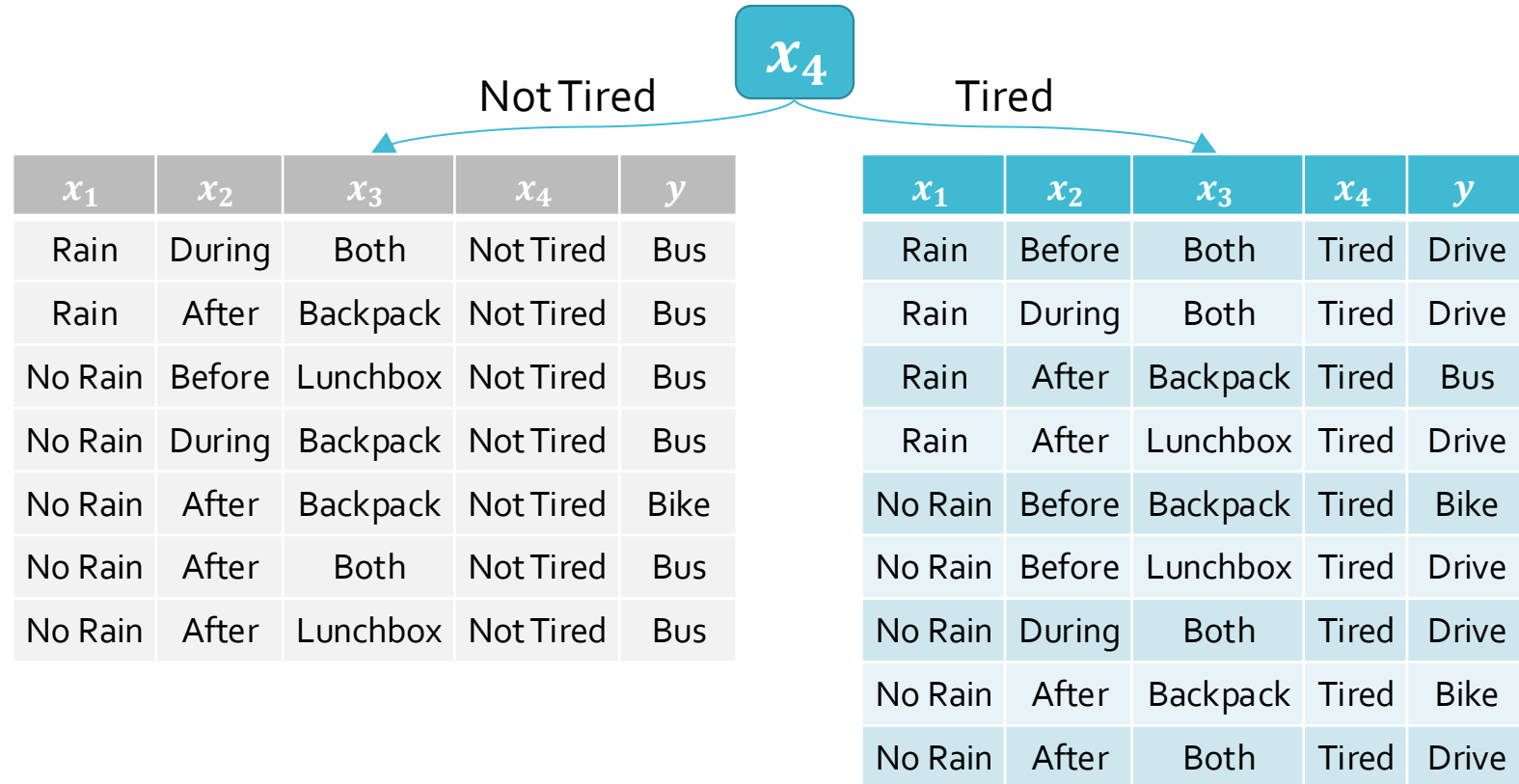
$$x_4 \quad 0.5576$$

$x_1$	$x_2$	$x_3$	$x_4$	$y$
Rain	During	Both	Not Tired	Bus
Rain	After	Backpack	Not Tired	Bus
No Rain	Before	Lunchbox	Not Tired	Bus
No Rain	During	Backpack	Not Tired	Bus
No Rain	After	Backpack	Not Tired	Bike
No Rain	After	Both	Not Tired	Bus
No Rain	After	Lunchbox	Not Tired	Bus
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Rain	During	Both	Tired	Drive
Rain	After	Backpack	Tired	Bus
Rain	After	Lunchbox	Tired	Drive
No Rain	Before	Backpack	Tired	Bike
No Rain	Before	Lunchbox	Tired	Drive
No Rain	During	Both	Tired	Drive
No Rain	After	Backpack	Tired	Bike
No Rain	After	Both	Tired	Drive



# Decision Tree: Example





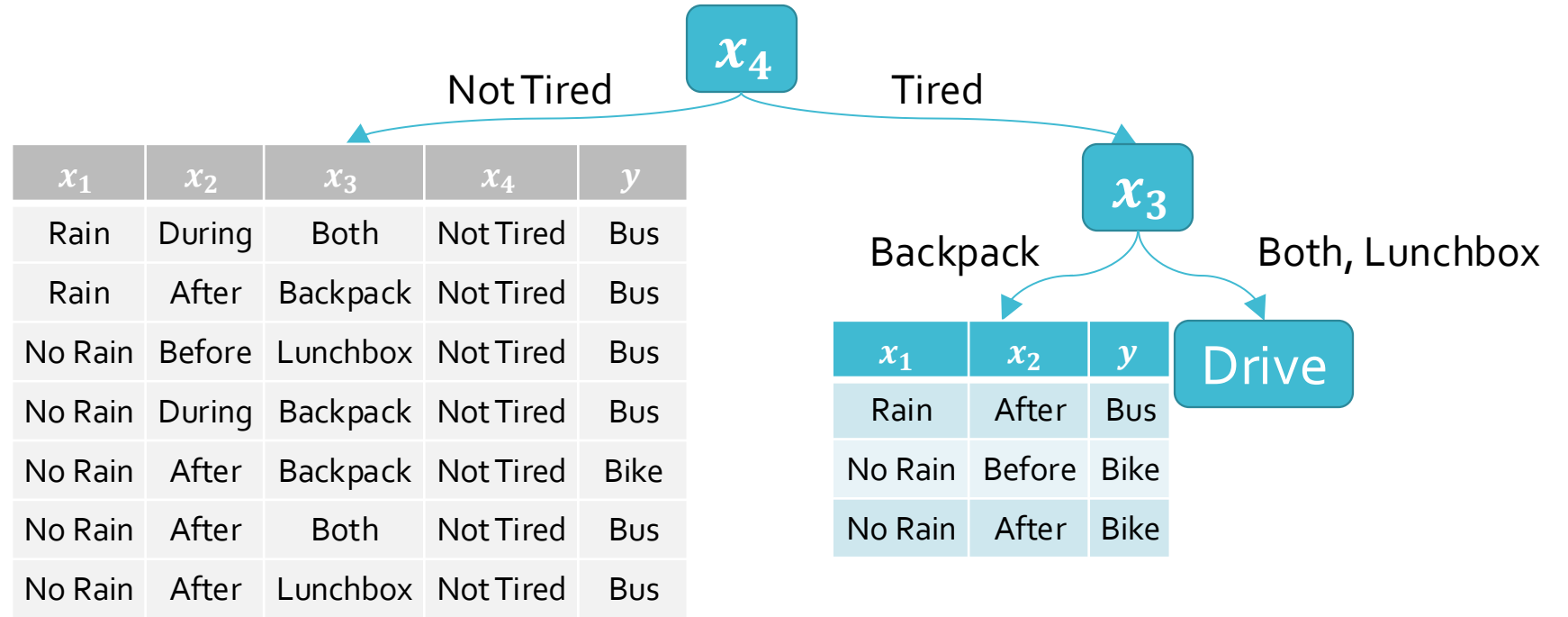








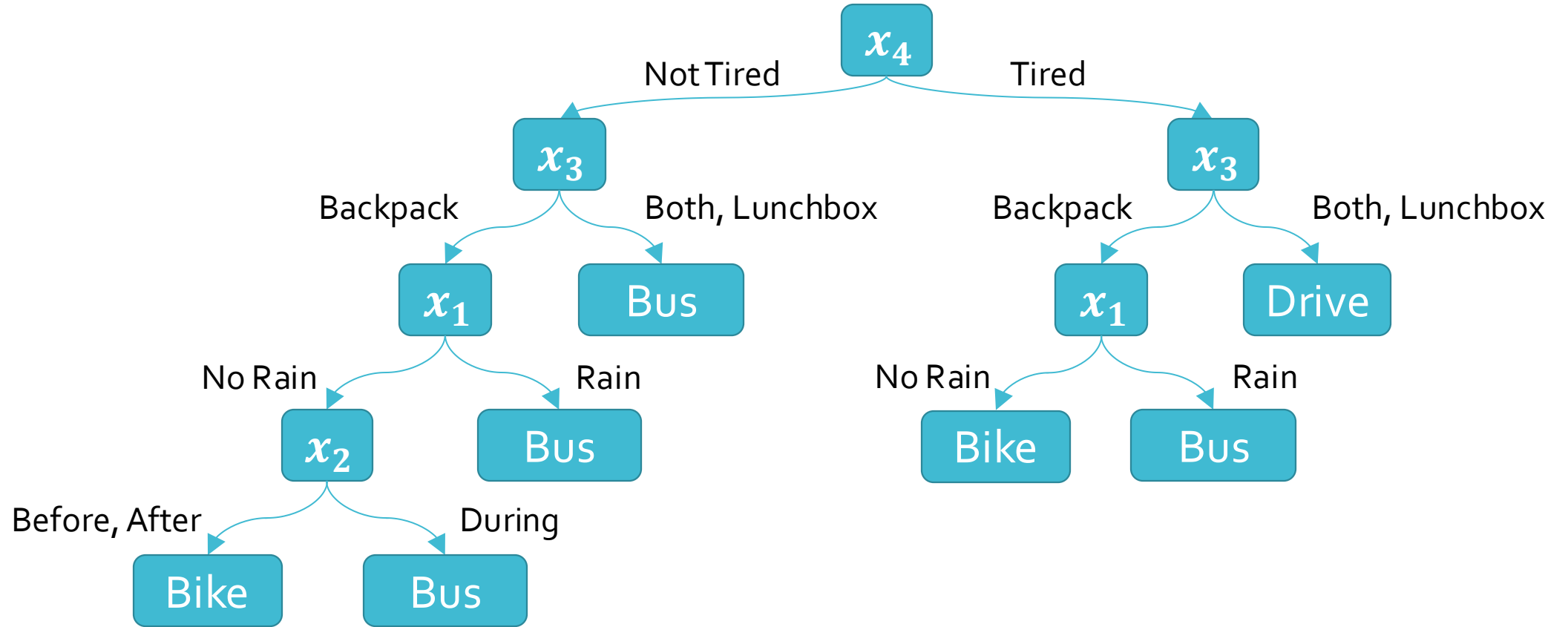




$$I(x_1, Y_{x_4=\text{Tired}}) \approx 0.3244$$

$$I(x_2, Y_{x_4=\text{Tired}}) \approx 0.2516$$

$$I(x_3, Y_{x_4=\text{Tired}}) \approx \mathbf{0.9183}$$





# Decision Stumps: Questions

1. How can we pick which feature to split on?
2. Why stop at just one feature?
  - a. How can we pick the order of the splits?

# Key Takeaways

- Decision tree prediction algorithm
- Decision tree learning algorithm via recursion