CS 383: Machine Learning

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Fall 2024

09/10/2024

Lecture 02

Outline

- Reading Quiz 1
- K-nearest neighbors
- Featurization (intro)
- Entropy & Decision Trees

Outline

1) *Generalization*: ability to answer new questions related to the topic studied

2) No! If we look at the test data (either the *features* or the *labels*), then any measurement of the performance of our algorithm becomes inaccurate

3) *Multiclass classification*

4) *Regression*

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Typical Supervised Learning setup

- X: Input matrix
  - n rows (examples/instances/individuals)
  - m columns (features/attributes)
- y: Label vector
- $\hat{y}$: Prediction vector

Simple Evaluation

How close is $\hat{y}$ to y?

Indicator variable

Accuracy: $\frac{1}{n}\sum_i \mathbb{1}(\hat{y}_i, y_i)$

K-nearest neighbors

Problem: Given a collection of labeled examples, determine the class of a new unlabeled example

Solution: assign the same class as the ***most similar*** examples

Key idea: whats ***most similar***?

K-NN creates implicit decision boundaries

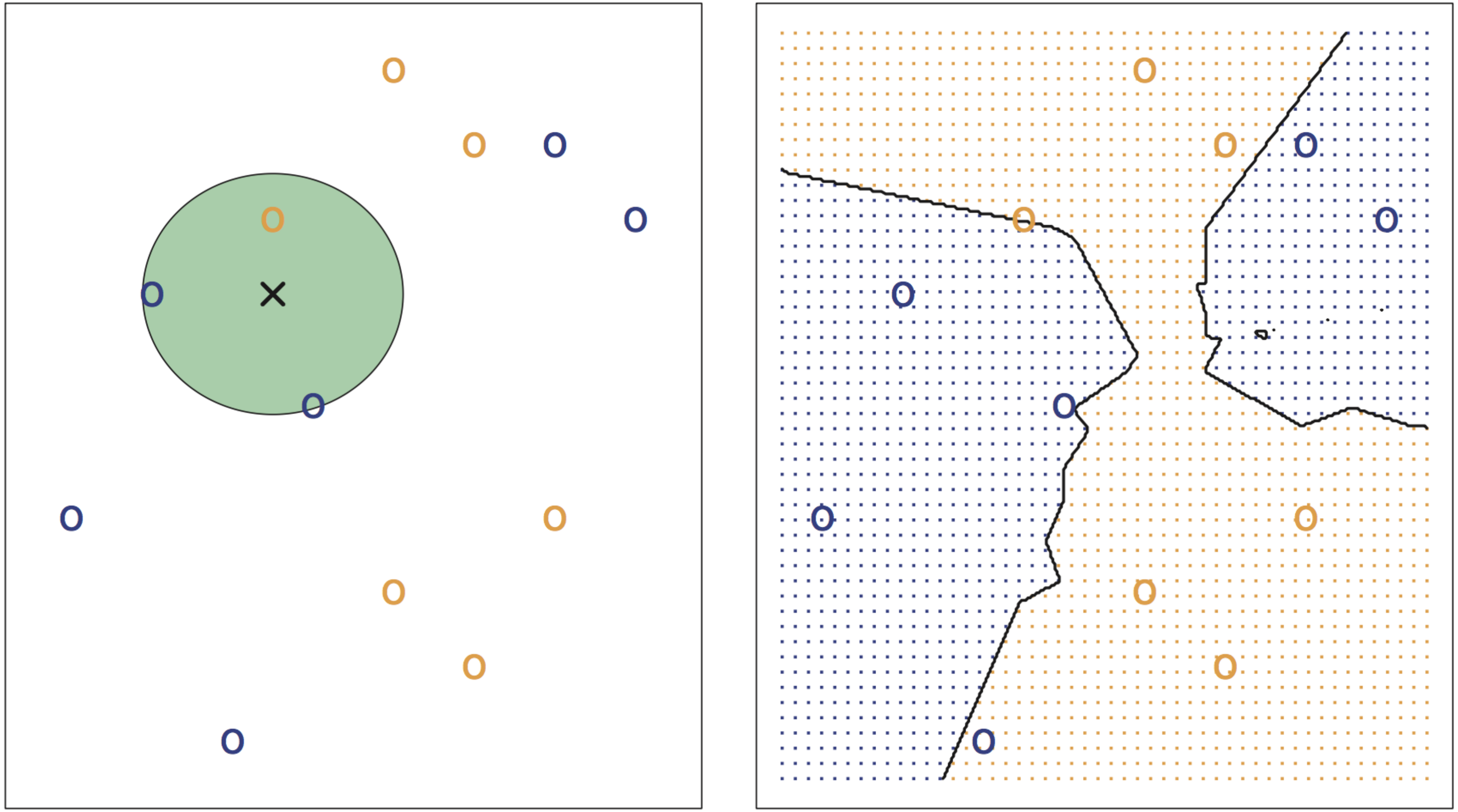

Figure 2.14 from ISL book, KNN with two classes (C=2), and K=3

HW01 – K-Nearest Neighbor

Implement KNN

Given:

- starter code, unit tests
- Train data with labels, dev data with labels, test data w/o labels

Deliverables:

- Implemented code
- Predictions on test data

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Terminology

Features: feature names

- e.g. shape

Feature values: what values are possible

- e.g. {circle, square, triangle}

Feature vector: values for a particular example

- e.g. $\boldsymbol{x} = [x_1, x_2, x_3, \ldots, x_p]$

Terminology

Decision boundary:

separates regions of the feature space that would be classified as positive or negative (or multiclass)

Underfitting:

“had the opportunity to learn something but didn’t” (Duame)

Overfitting:

memorized individual training examples (fit to noise) and can’t generalize

Handout 2
(find and work with a partner)

Comparing Decision Boundaries

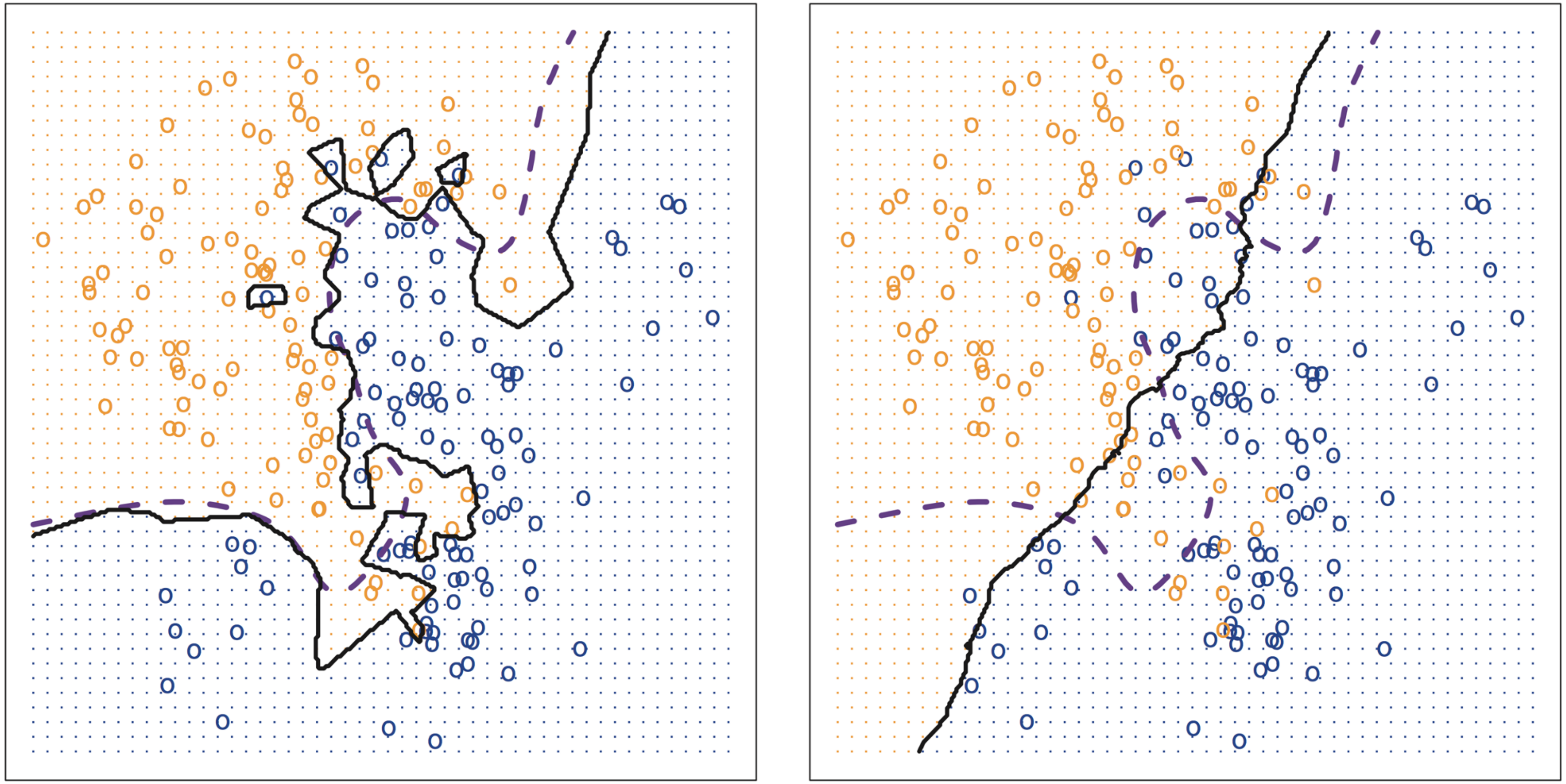
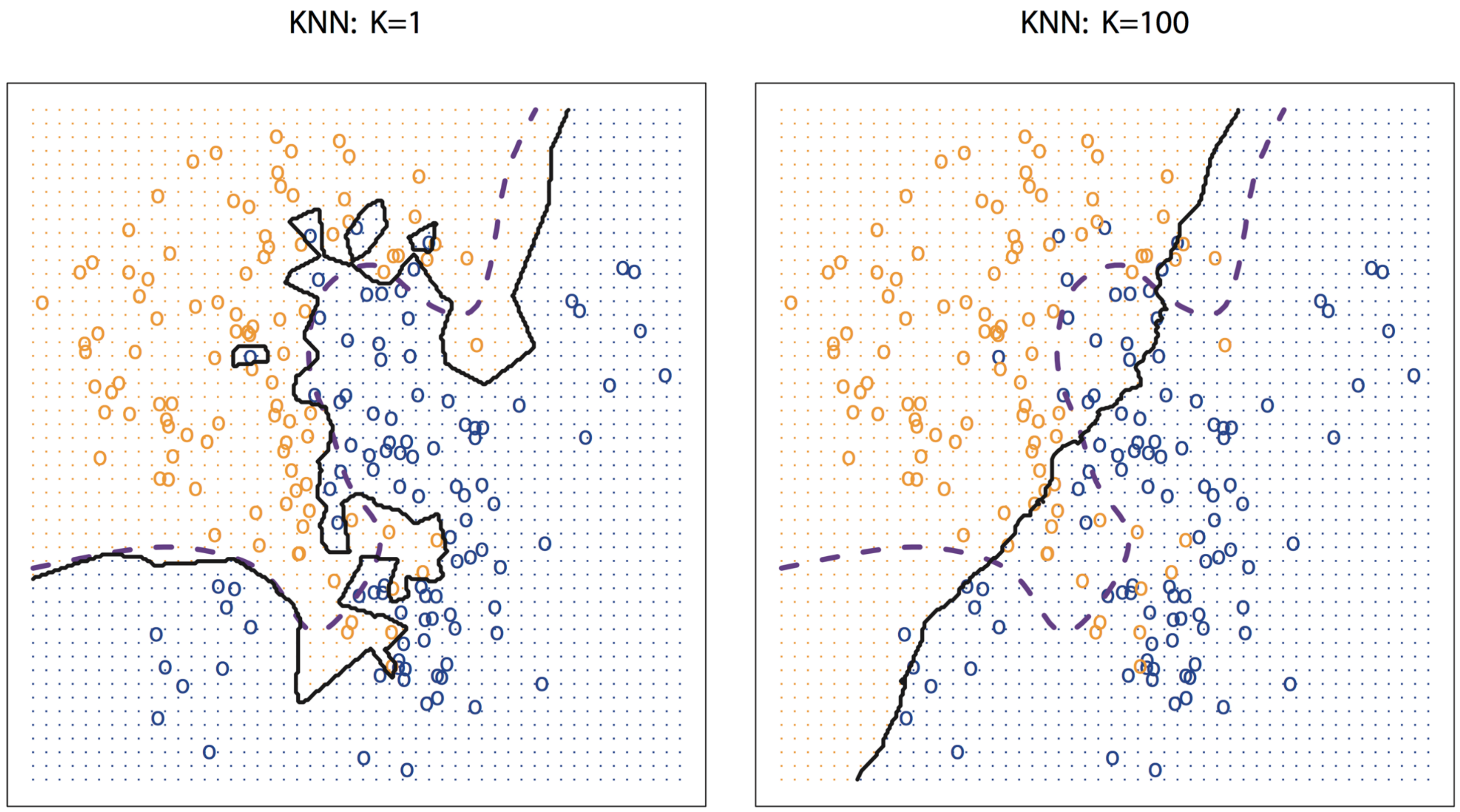


Figure 2.16 from ISL book (dashed line is “ideal” boundary)

Comparing Decision Boundaries



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Comparing Decision Boundaries

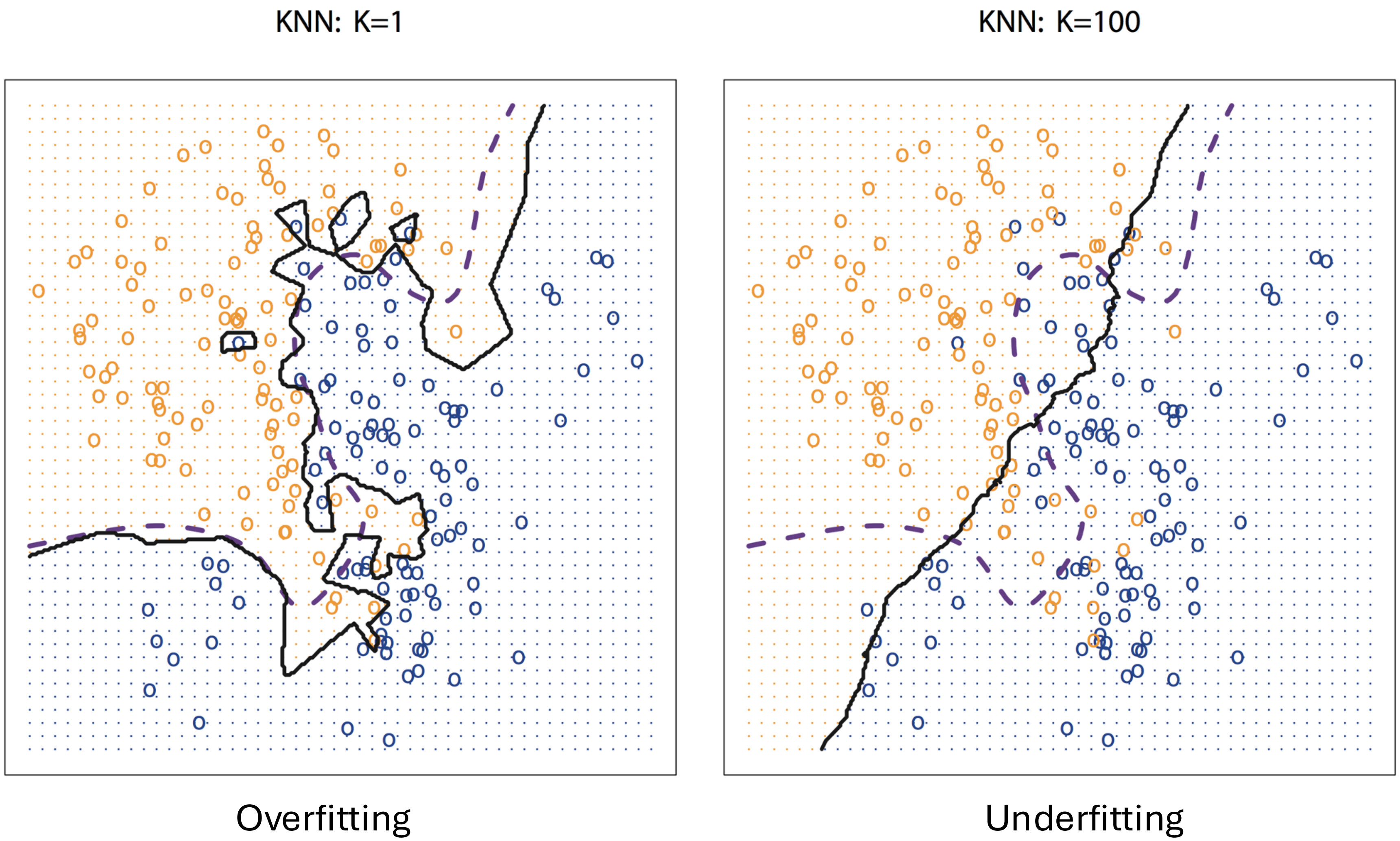

Figure 2.16 from ISL book (dashed line is “ideal” boundary)

Featurization (rule of thumb)

Duame, Chap 3

- Real-valued features get copied directly.
- Binary features become 0 (for false) or 1 (for true).
- Categorical features with V possible values get mapped to V-many binary indicator features.

Haven't discussed:

-normalization

-categorical variables on a spectrum

Handout

4. Using your response from the previous question, what would the *feature vector* become for $\boldsymbol{x}_1$?

Day	Outlook	Temperature	Humidity	Wind	PlayTennis (y)
$\boldsymbol{x}_1$	Sunny	Hot	High	Weak	No
$\boldsymbol{x}_2$	Sunny	Hot	High	Strong	No
$\boldsymbol{x}_3$	Overcast	Hot	High	Weak	Yes
$\boldsymbol{x}_4$	Rain	Mild	High	Weak	Yes
$\boldsymbol{x}_5$	Rain	Cool	Normal	Weak	Yes
$\boldsymbol{x}_6$	Rain	Cool	Normal	Strong	No
$\boldsymbol{x}_7$	Overcast	Cool	Normal	Strong	Yes
$\boldsymbol{x}_8$	Sunny	Mild	High	Weak	No
$\boldsymbol{x}_9$	Sunny	Cool	Normal	Weak	Yes
$\boldsymbol{x}_{10}$	Rain	Mild	Normal	Weak	Yes

Data from Machine Learning by Tom Mitchell (Table 3.2)

Sunny:	{0,1}	
Overcast:	{0,1}	
Rain:	{0,1}	
Temperature:	{0, 1, 2}	(Cool, Mild, Hot)
Humidity:	{0,1}	(Normal, High)
Wind	{0,1}	(Weak, Strong)

	Sunny	Overcast	Rain	Temp	Humidity	Wind
$\boldsymbol{x}_1$	1	0	0	2	1	0

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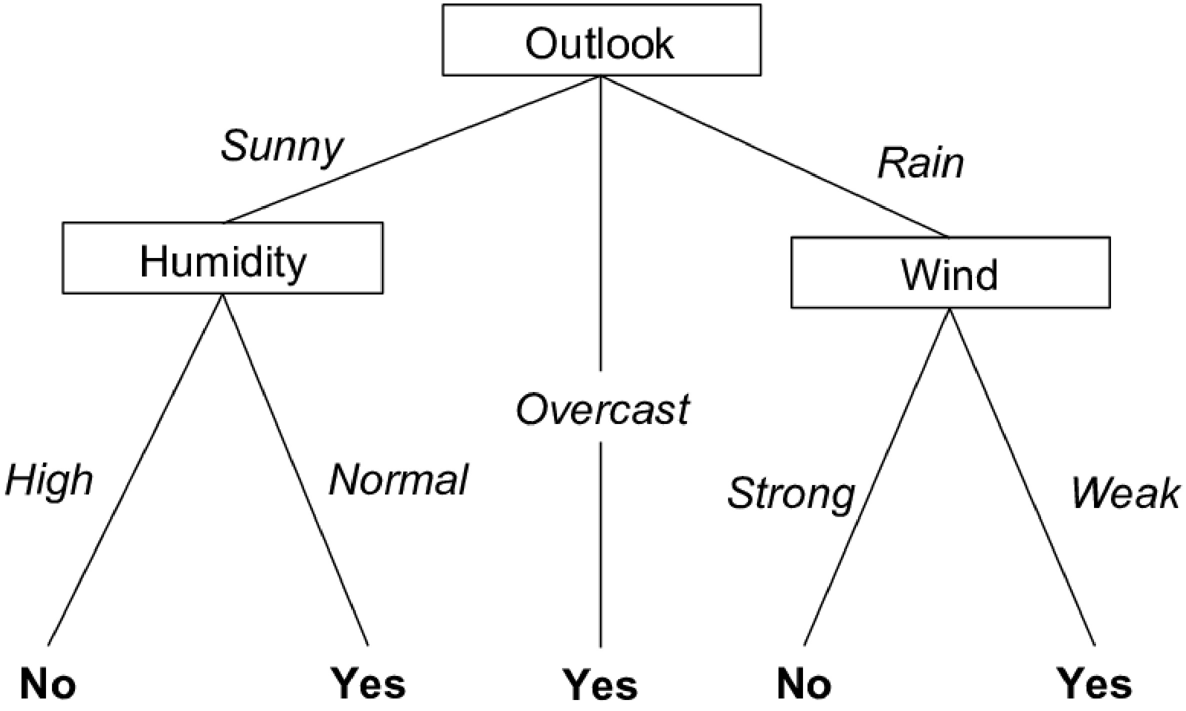
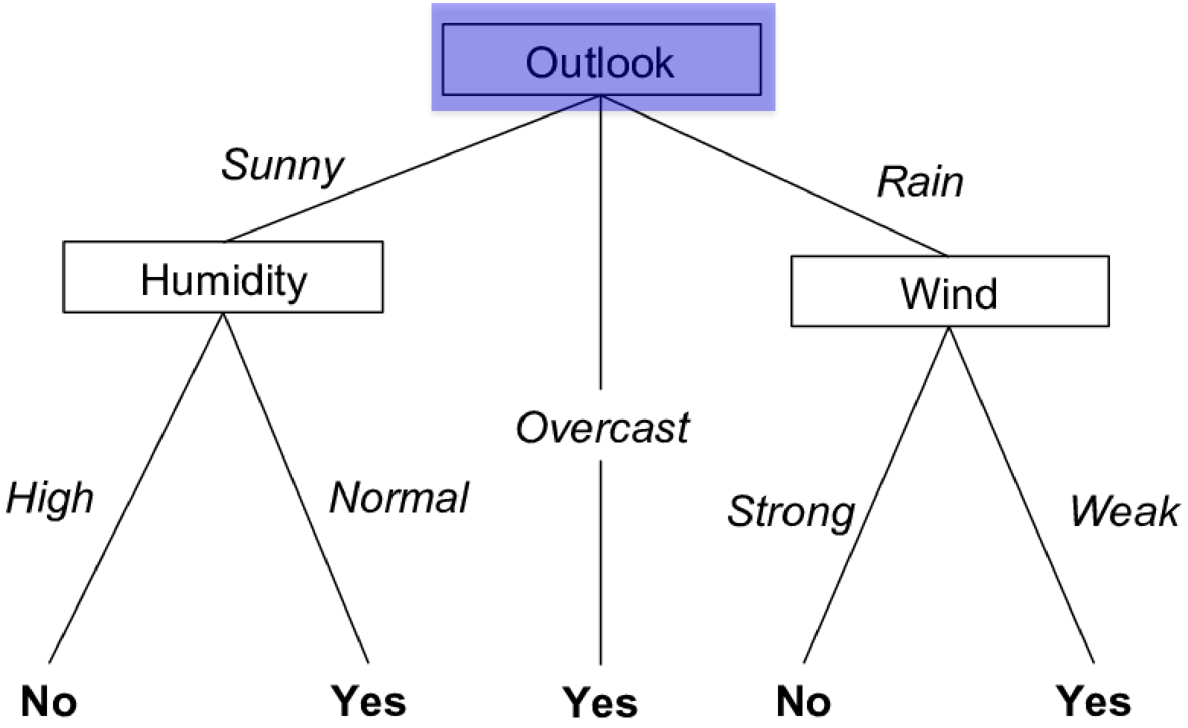
Decision Tree example (tennis)



Each internal node: test one feature
Each branch from node: selects one value of the feature
Each leaf node: predict *y*

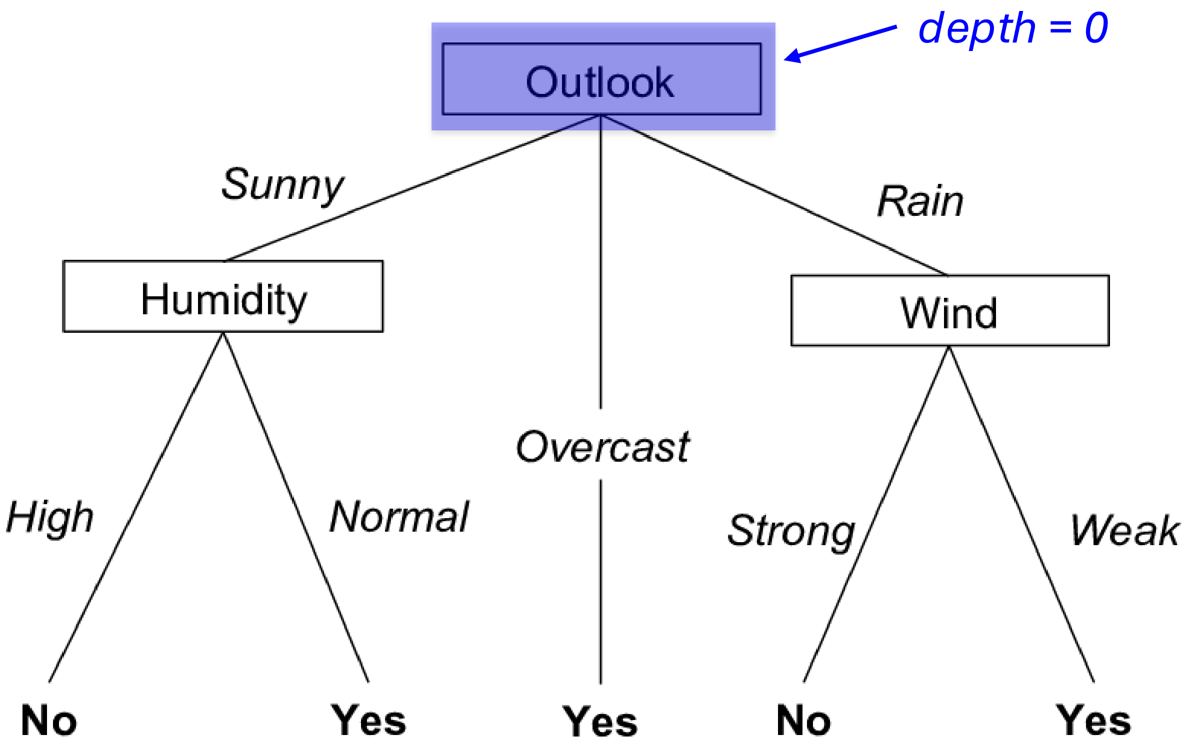
Based on slides by Jessica Wu and Eric Eaton [originally by Tom Mitchell]

Decision Tree example (tennis)



Key term: *depth*

Decision Tree example (tennis)



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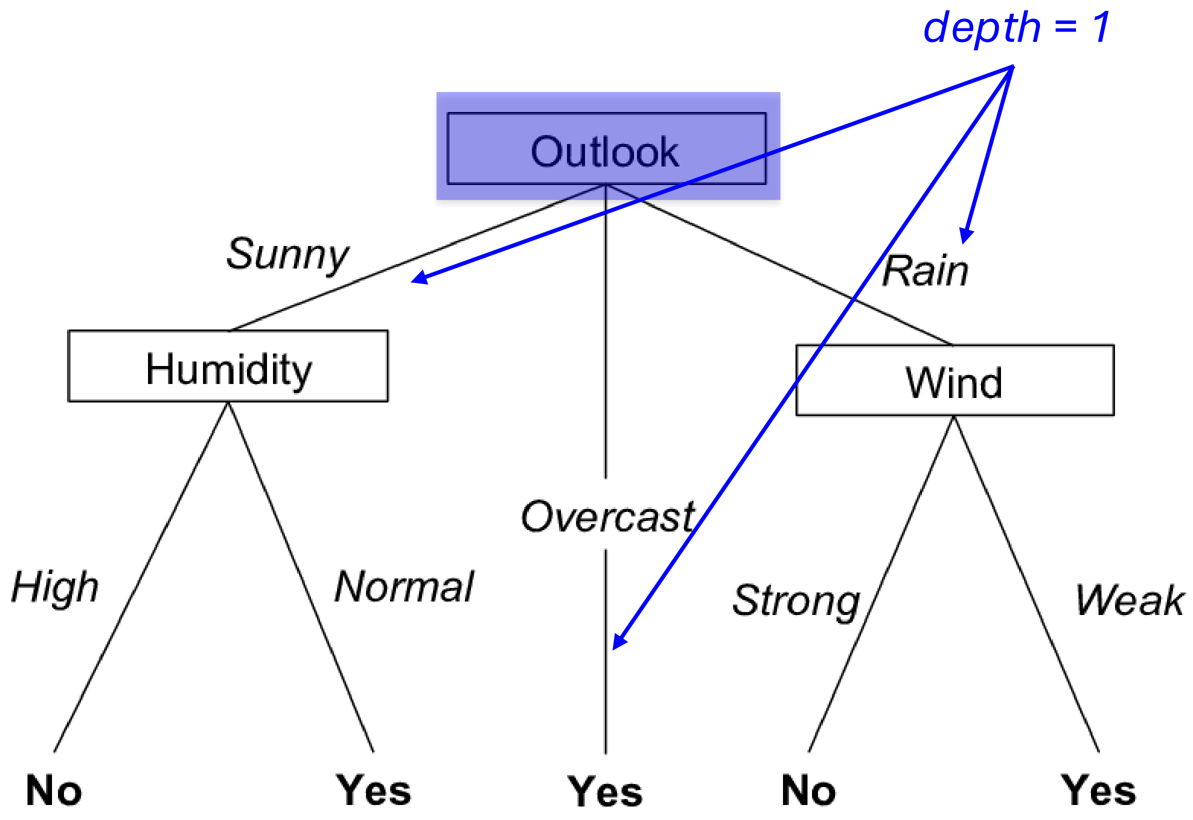
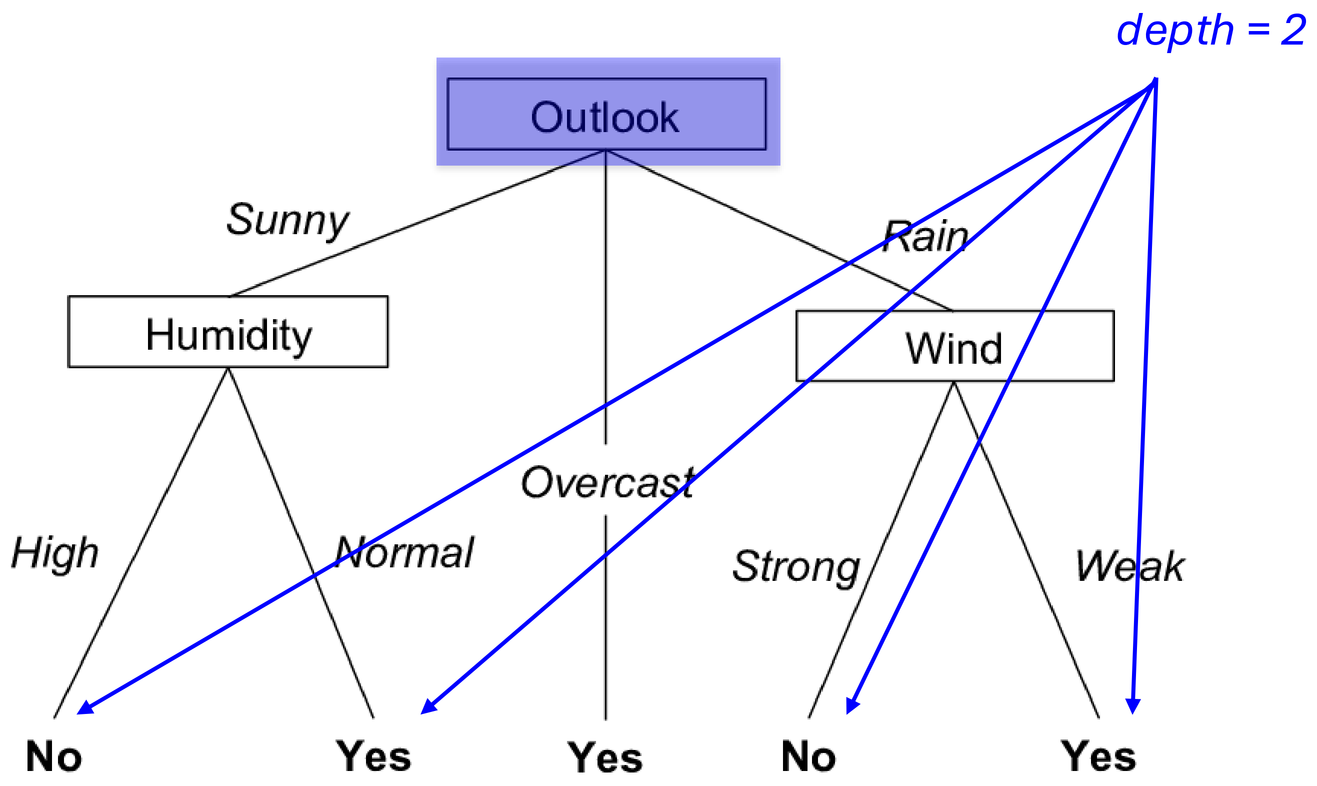
Decision Tree example (tennis)



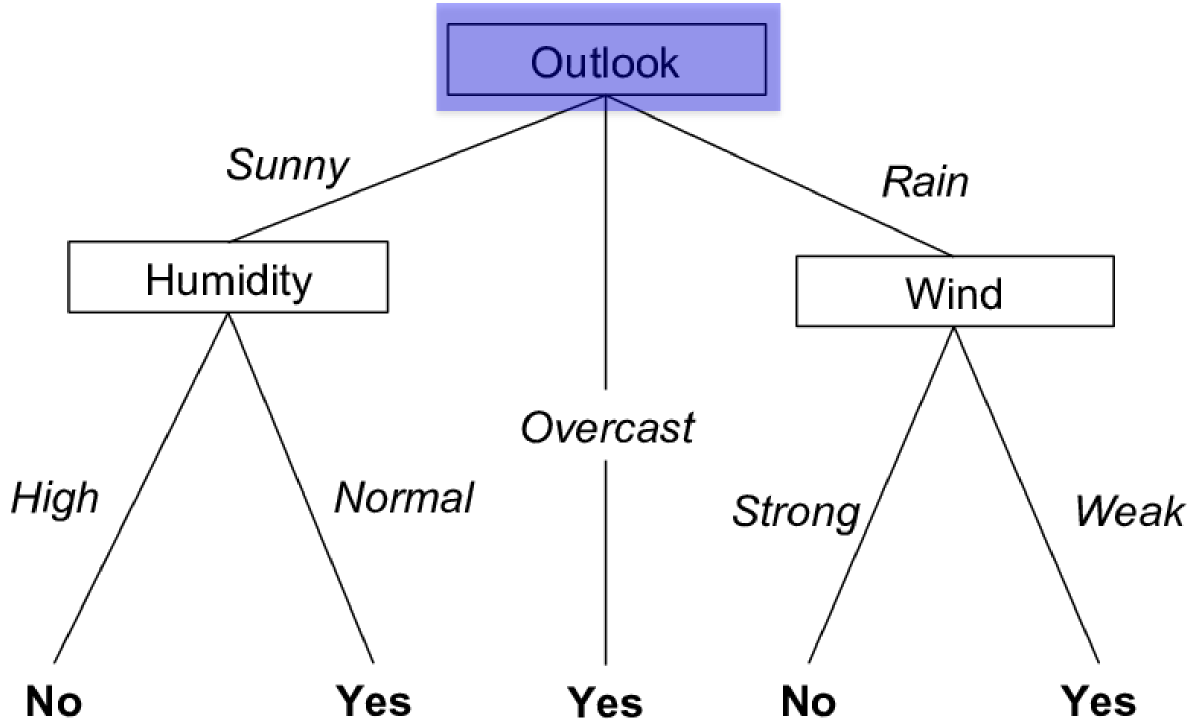
Key term: *depth*

Decision Tree example (tennis)



Key term: *depth*

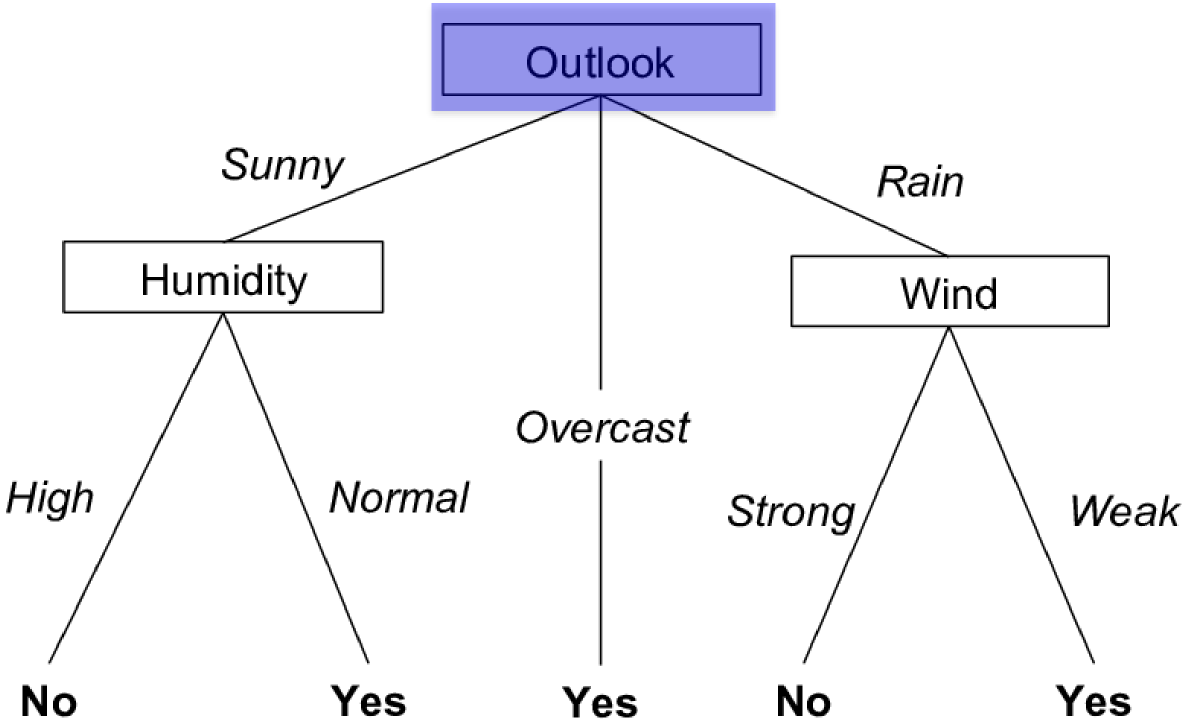
Decision Tree example (tennis)



(test example) $\boldsymbol{x}$ =

Outlook	Temp	Humidity	Wind
Rain	Hot	High	Strong

Decision Tree example (tennis)

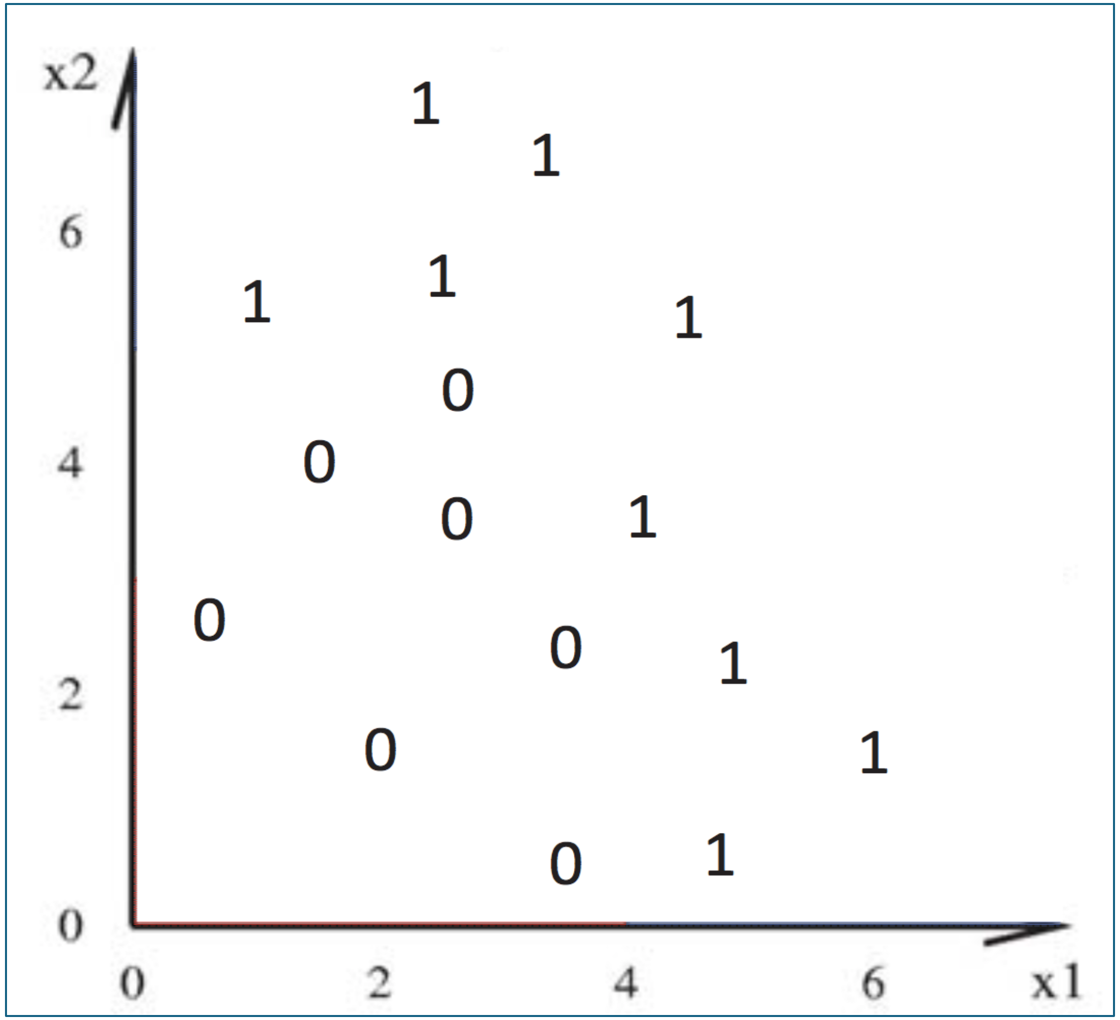


(test example) $\boldsymbol{x}$ =

Outlook	Temp	Humidity	Wind
Rain	Hot	High	Strong

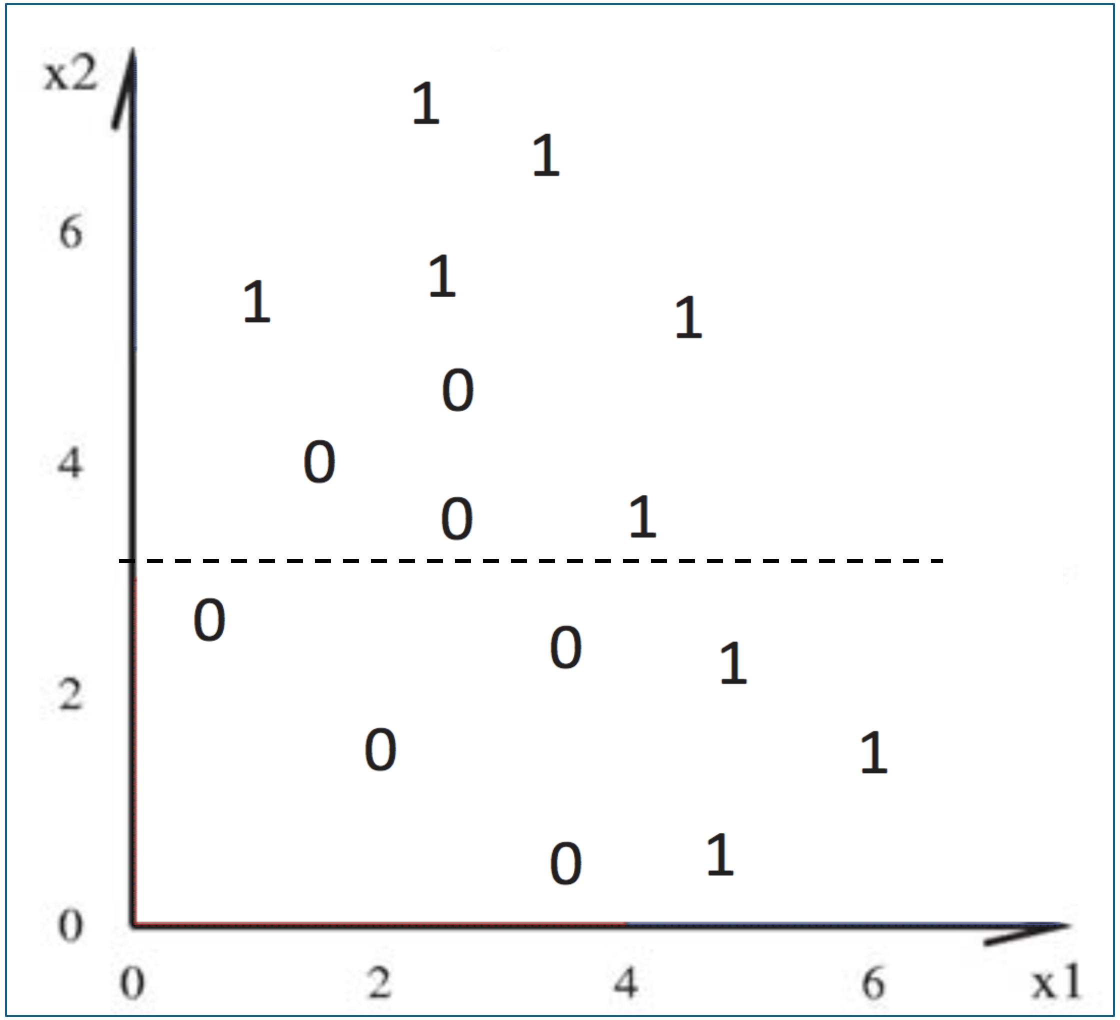
$\hat{y}$ = No

Continuous Features



Example by: Eric Eaton

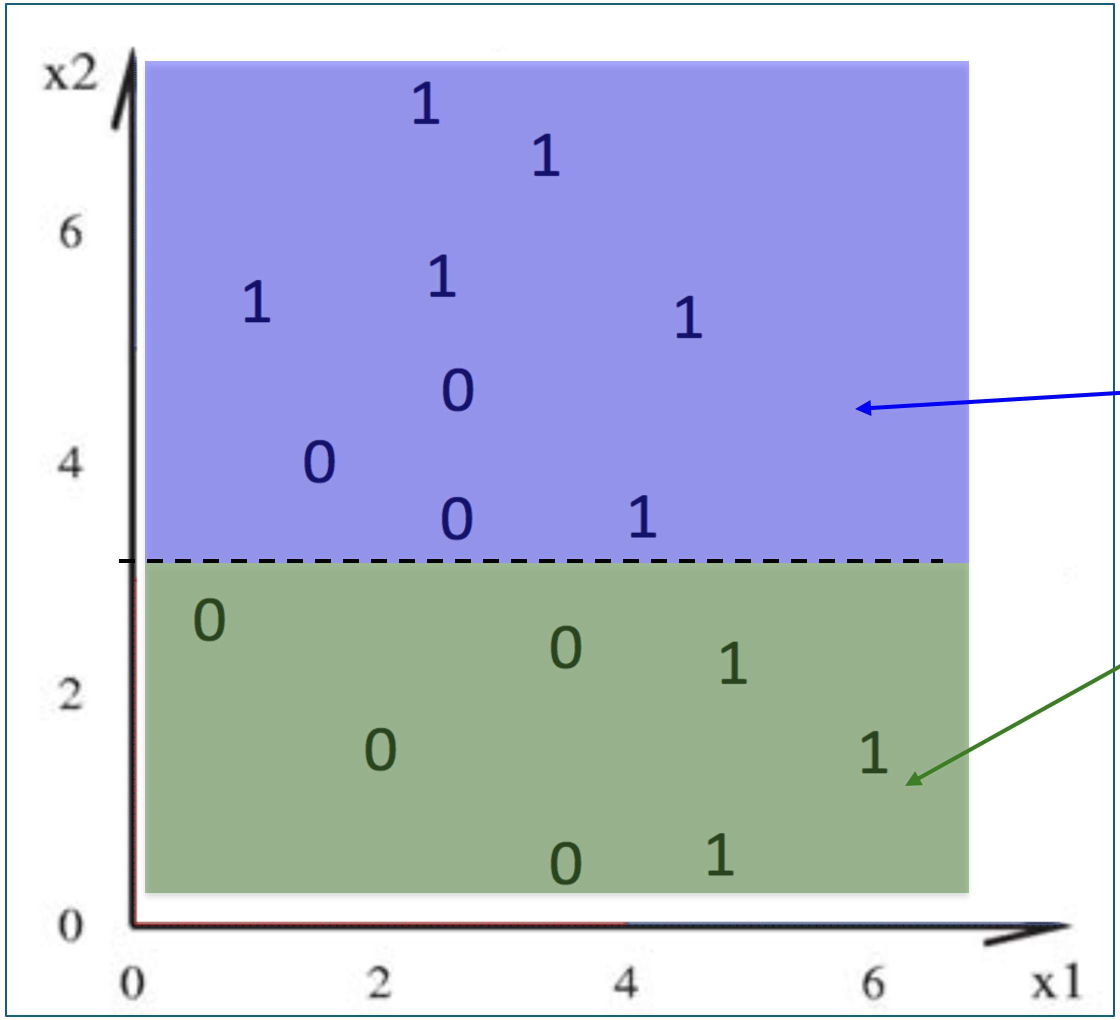
Continuous Features

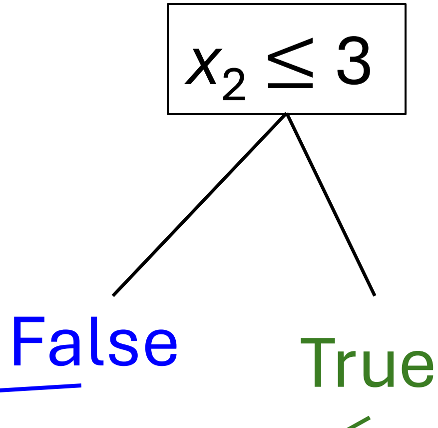


$x_2 \leq 3$

Example by: Eric Eaton

Continuous Features





Correction!

Example by: Eric Eaton

Decision Trees: Pros vs Cons

Discuss with a partner! Think about:

* training and testing
* featurization
* runtime
* human factors

Decision Trees: Pros vs Cons

- Very interpretable! Easy to say *why* we made a classification (can point to which features)

- Compact representation and fast predictions

- Can be brittle (not looking at each example holistically)

- Featurization and implementation difficulties

Next class

- Algorithm to create decision trees
- HW01 due Friday night
- Wednesday’s Lab will be a lecture
- Thursday lecture back on schedule
  - Reading quiz on Thursday