CS 260 – Foundations of Data Science

Lecture 2 – Introduction to modeling: what is a model?

09/03/2026

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Announcements

HW1 due Tuesday night

Complete pre-course survey

Office Hours:

Thursdays 2-4pm, Park 200D

Outline

Data representation and featurization

Introduction to modeling

Why are models useful?

Linear models

Tennis Data

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)

- Input or **features**: outlook, temp, humidity, wind
- Output or "**label**": play tennis (yes or no)

Sea Ice data (Homework 2)

Year	Sea Ice Extent*
1996	7.88
1997	6.74
1998	6.56
1999	6.24
2000	6.32
2001	6.75
2002	5.96
2003	6.15
2004	6.05
2005	5.57
2006	5.92
2007	4.3
2008	4.63

Input or **feature**: year

Output or "**label**": sea ice extent

*Arctic sea ice extent (1,000,000 km^2)

Data Representation Notation

X: Input matrix

- n rows (examples/instances/individuals)
- p columns (features/attributes)

y: Label vector

$\hat{y}$: Prediction vector

Dependent variable y

Ice Extent*

7.88
6.74
6.56
6.24
6.32
6.75
5.96
6.15
6.05
5.57
5.92
4.30
4.63

PlayTennis (y)
No
No
Yes
Yes
Yes
No
Yes
No
Yes
Yes

Ice cream flavor

chocolate
vanilla
Strawberry
Chocolate
Peanut

Feature Terminology

Often called ***covariate*** in statistics & social science

Features: feature names

shape

sea ice extent

Feature values: what values are possible

{circle, square, triangle}

all non-negative values

Feature vector: values for a particular example/data point

$\boldsymbol{x} = [x_1, x_2, x_3, \ldots, x_p]$

Featurization: make numerical

- 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.

Duame, Chap 3

Q: what about features that might already be on a spectrum (e.g. sunny, rain, overcast)?

Handout 2

Handout 2

Q1: n=10, p=4

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
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$\boldsymbol{x}_9$	Sunny	Cool	Normal	Weak	Yes
$\boldsymbol{x}_{10}$	Rain	Mild	Normal	Weak	Yes

Data from Machine Learning by Tom Mitchell (Table 3.2)

Q2

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)

Q3

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

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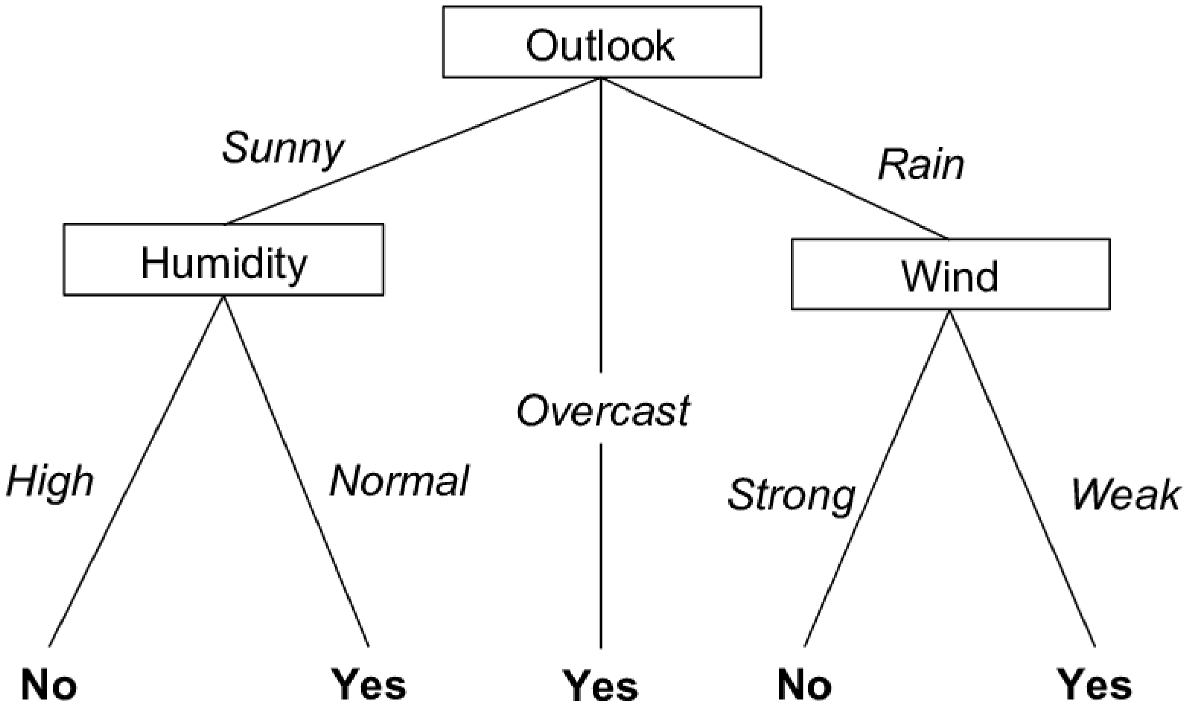
Example of a model

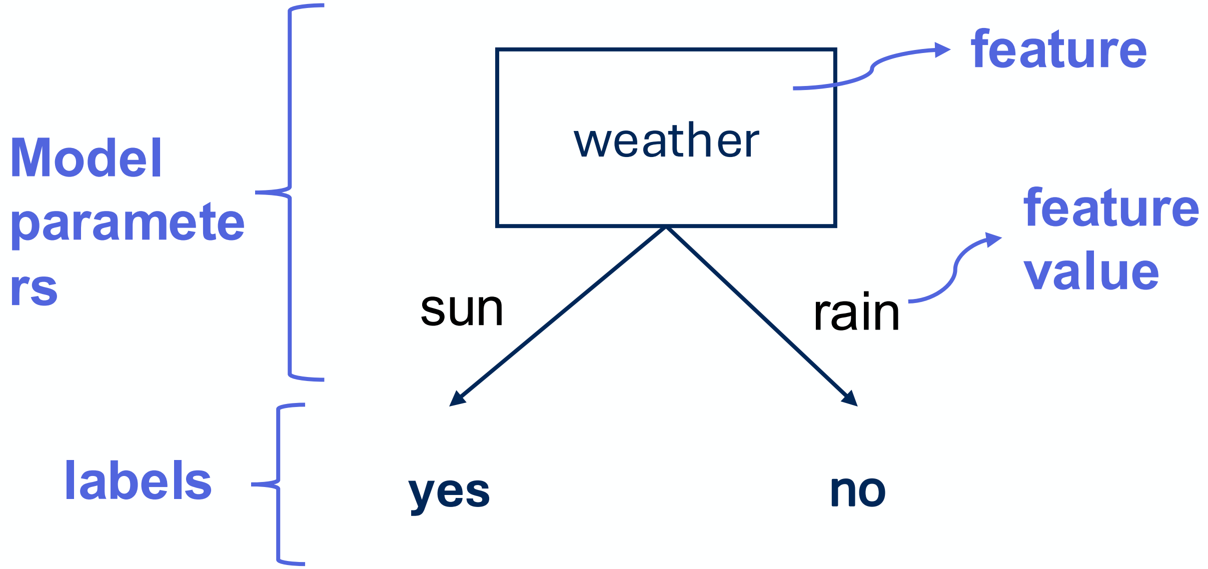


- Each internal node: one feature
- Each branch from node: selects one value of the feature
- Each leaf node: predict y

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

Model Examples

1) Decision Tree



Data

weather	tennis
sun	yes
rain	no
rain	no
sun	yes
sun	no

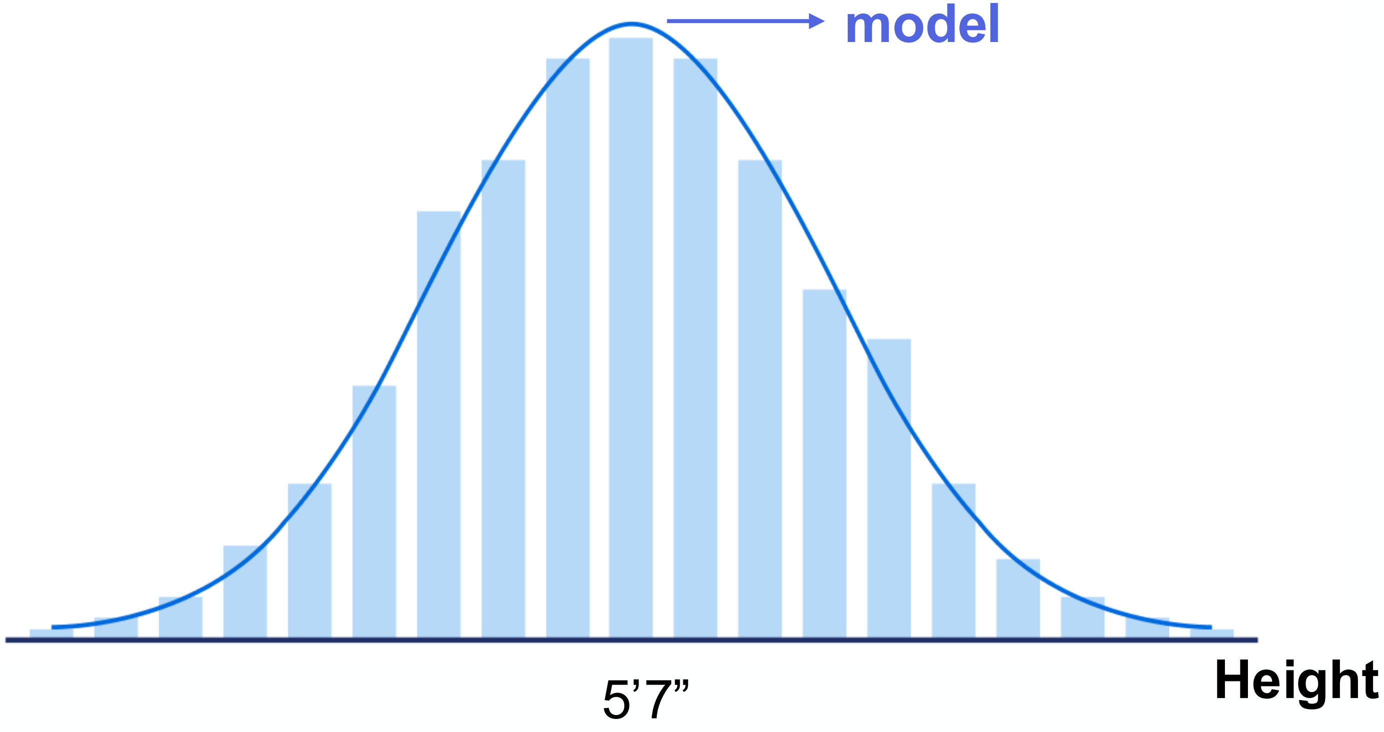
[1, 2] **[2,0]** → **"no" and "yes" label counts**

2/3 correct **2/2 correct**

=> 80% accuracy

Model Examples

2) Normal distribution



mean: 5’7”
variance: 2”

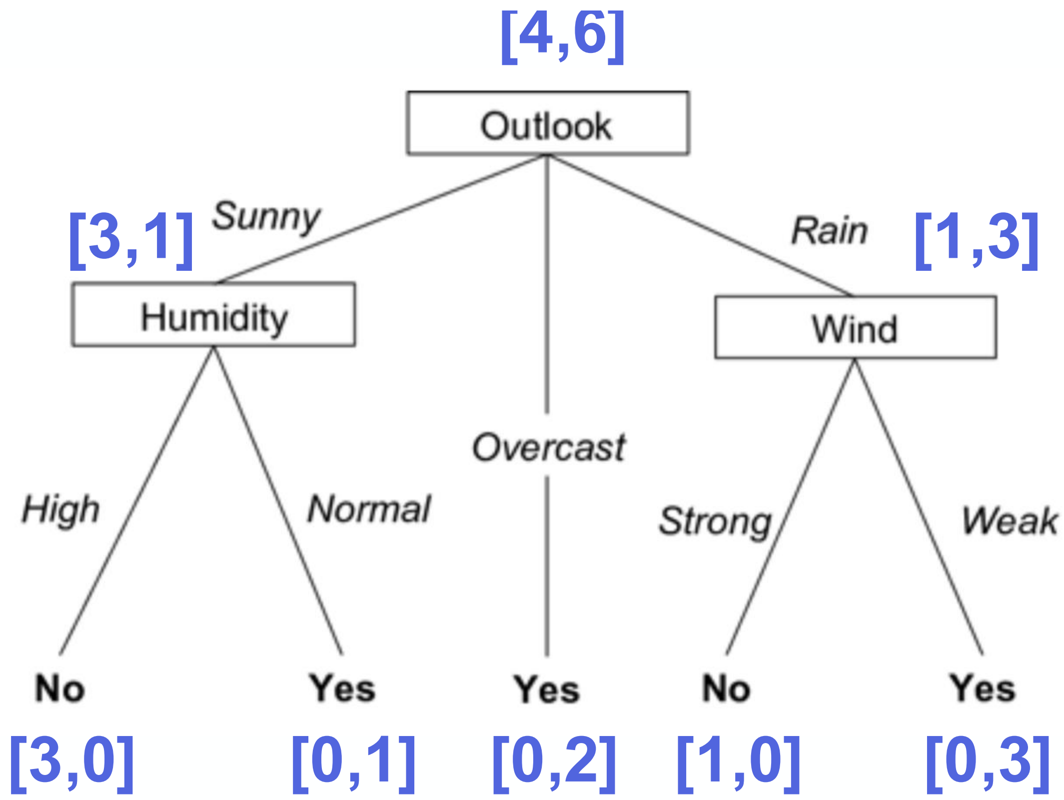
Model parameters

Handout 2

Handout 2

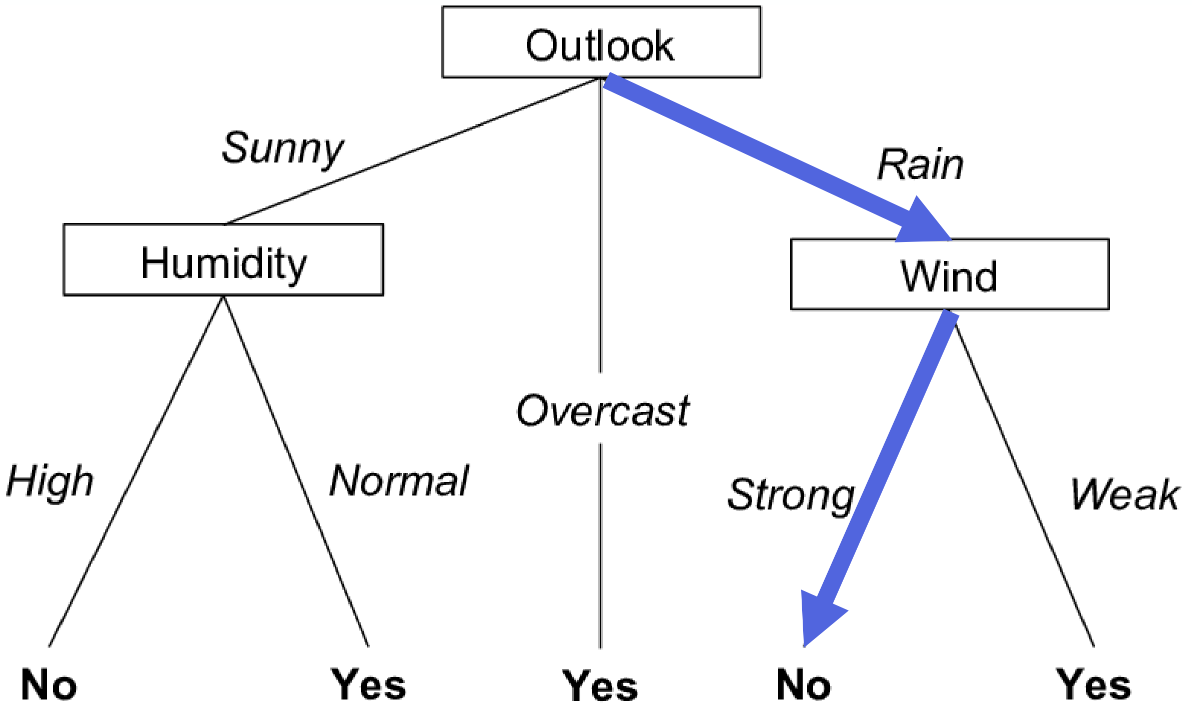
Q4

In the model below, the children of each node divide the data into partitions. Label each node (both internal nodes and leaves) with the counts of “No” and “Yes” labels based on the partition. For example, the counts for the node labeled *Outlook* would be [4,6]. Does this model perfectly classify all examples?



Handout 2

Q5



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

Outloo k	Temp	Humidity	Wind
Rain	Hot	High	Strong

y_{pred} = No

Outline

Data representation and featurization

Introduction to modeling

Why are models useful?

Linear models

Why are models useful?

Understand/explain/interpret the phenomena

Predict outcomes for future examples

What are the most important features?

X				Y
Color	Shape	Size		Likes toy?
red	square	big		+
blue	square	big		+
red	circle	small		-
blue	square	small		-
red	circle	big		+

Example by: Ameet Soni

What are the most important features?

X			Y
Color	**Shape**	**Size**	**Likes toy?**
red	square	big	+
blue	square	big	+
red	circle	**big**	-
blue	square	**big**	-
red	circle	big	+

Example by: Ameet Soni

Outline

Numpy

Data representation and featurization

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Linear Models

Features: $\vec{x}$ (x if p=1)

Output: $y \in \mathbb{R}$

Model: $h_{\vec{w}}(x) = \overset{\overset{b}{\downarrow}}{w_0} + \overset{\overset{m}{\swarrow}}{w_1} x = \hat{y} \longleftarrow$ prediction

Parameters: $\vec{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}$

Goals:

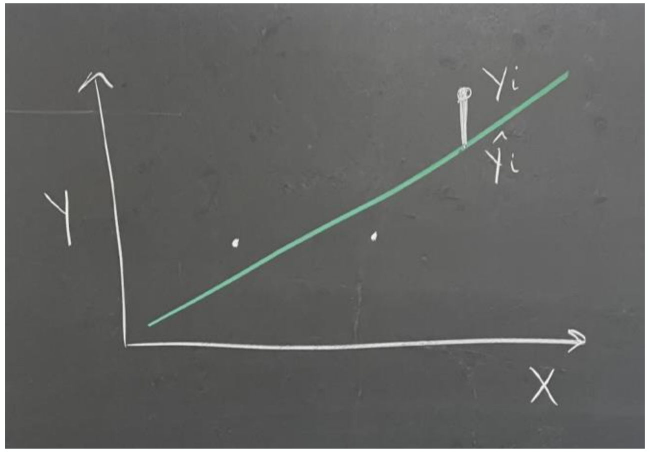
Describe **linear dependence**

Predict output given new data

Linear Models

How good is our model?

Residuals: $\underbrace{y_i}_{\text{truth}} - \underbrace{\hat{y}_i}_{\text{prediction}}$ } one example



$$\underbrace{\textstyle\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RSS: Residual sum of squares
SSE: Sum of squared errors

Goal: Find a model that minimizes SSE

Goals of fitting a linear model

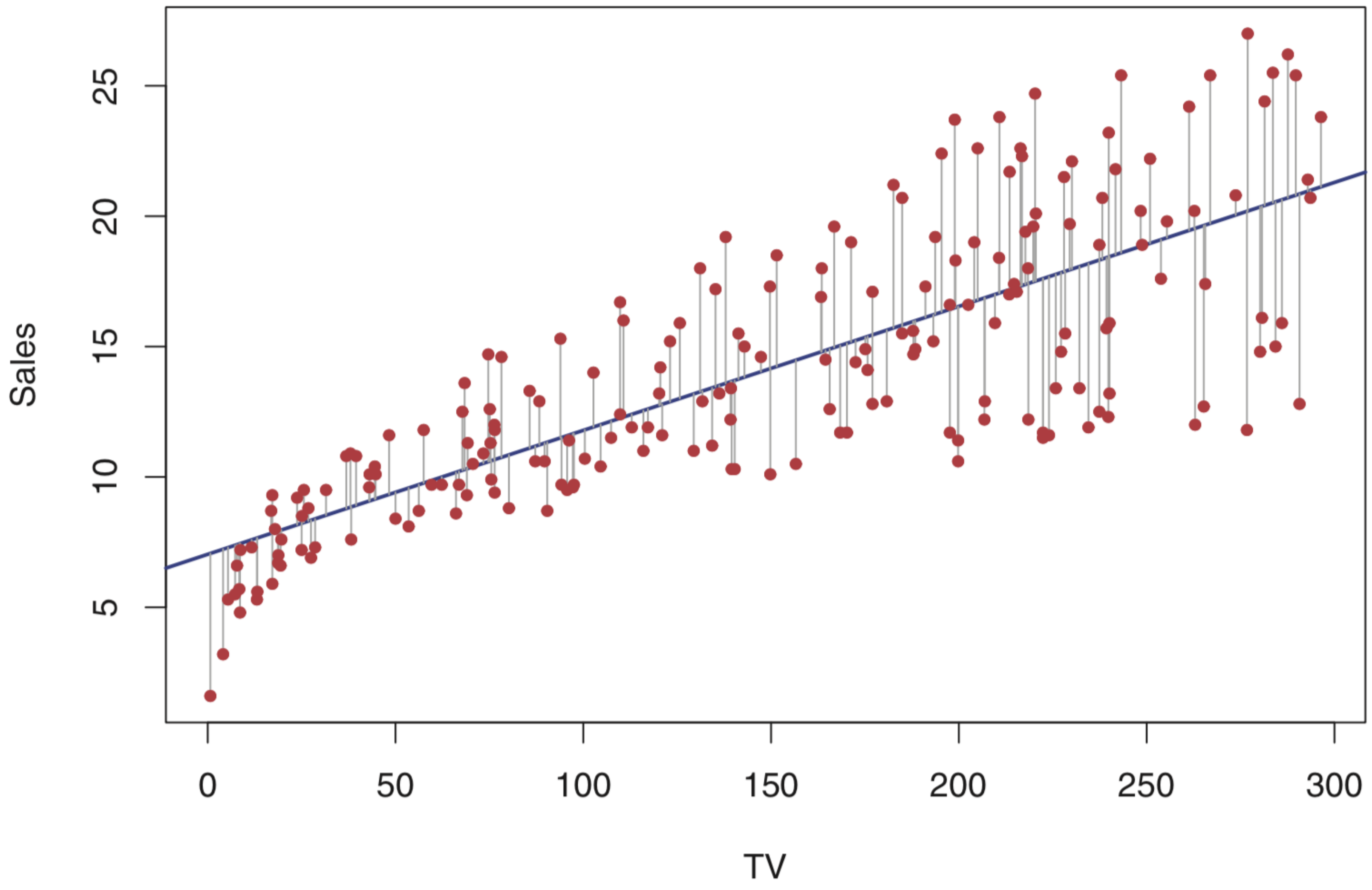
1) Which of the features/explanatory variables/predictors (x) are associated with the response variable (y)?

2) What is the relationship between x and y?

3) Can we (accurately) predict y given a new x?

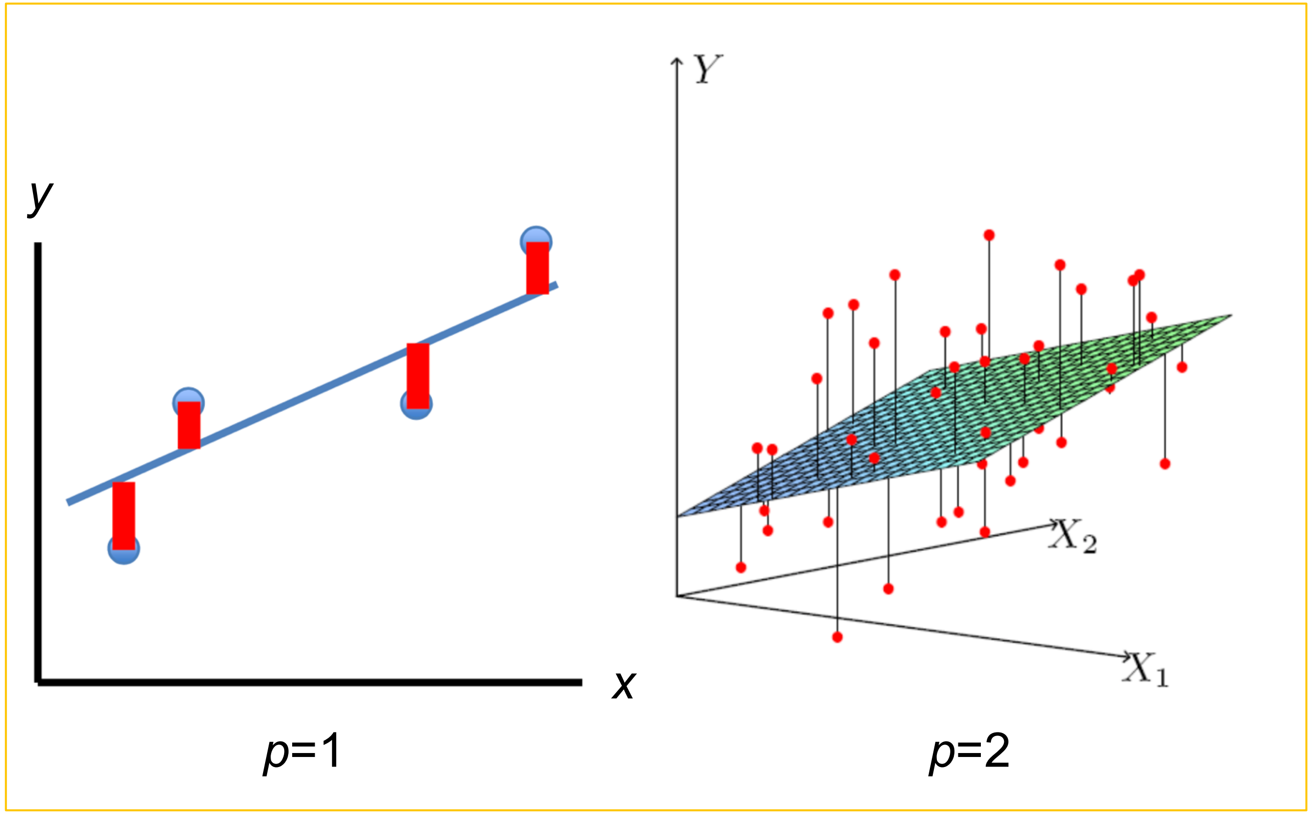
4) Is a linear model enough?

Example: predict sales from TV advertising budget



ISL: Figure 3.1

Linear model with 1 or 2 features



Slide: modified from Jessica Wu
Original: Eric Eaton

Linear Regression

Output (y) is continuous, not a discrete label

Learned model: *linear function* mapping input to output (a *weight* for each feature + *bias*)

Goal: minimize the *RSS* (residual sum of squares) or *SSE* (sum of squared errors)

Maybe a linear model is not enough

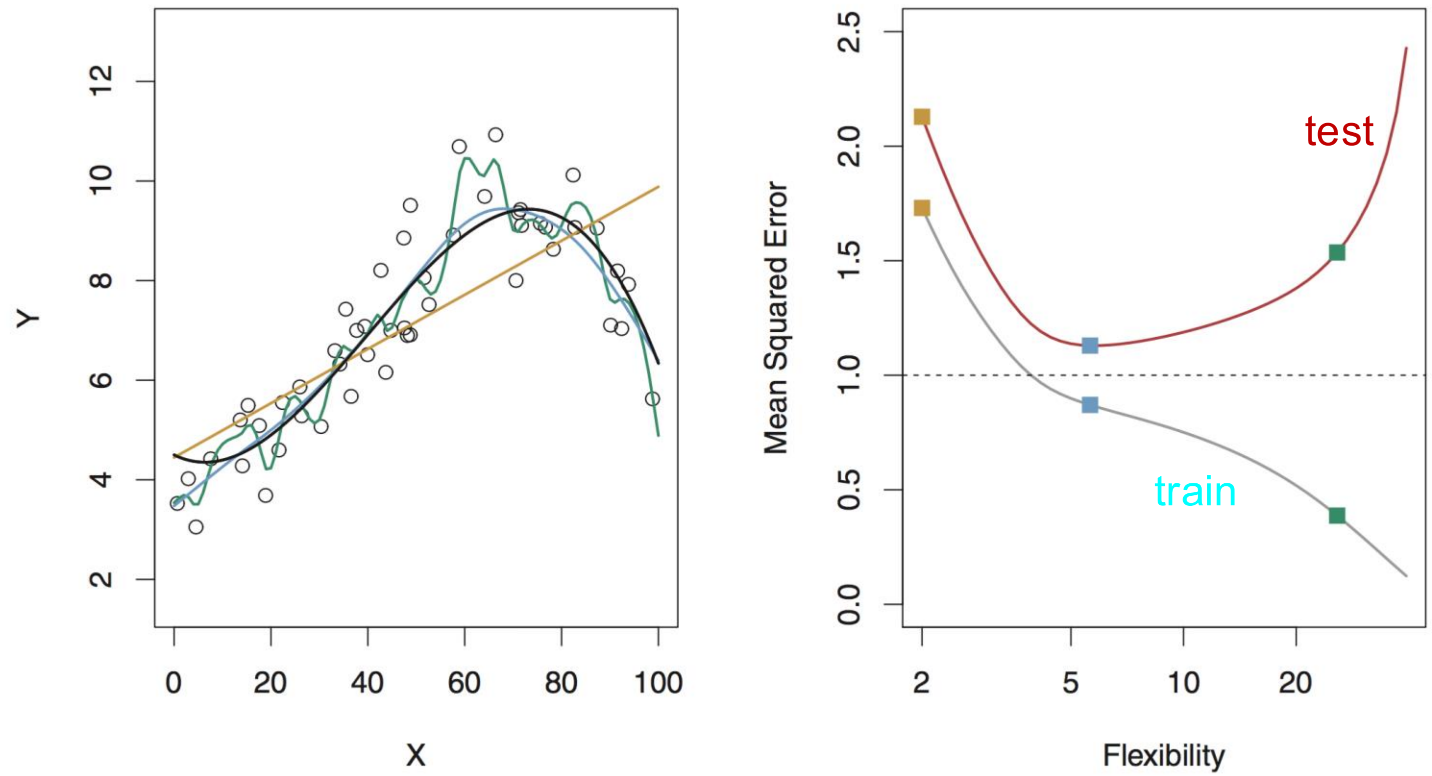


FIGURE 2.9. Left: *Data simulated from f, shown in black. Three estimates of f are shown: the linear regression line (orange curve), and two smoothing spline fits (blue and green curves).* Right: *Training MSE (grey curve), test MSE (red curve), and minimum possible test MSE over all methods (dashed line). Squares represent the training and test MSEs for the three fits shown in the left-hand panel.*

ISL, Fig 2.9