Intro to Linear Regression

Session 4

Slides Link: https://teachla.uclaacm.com/classes/ml

ACM AI + ACM TeachLA





What is your favorite weather?







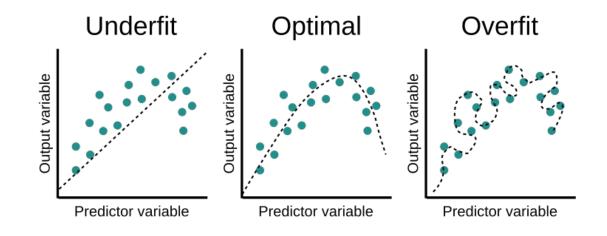
Supervised Machine Learning

- A Machine Learning *model* is a big function
- A Supervised Learning model uses <u>labeled output</u> data, hence the name "supervised"
- Supervised Learning maps the relationship of:

input \rightarrow labeled output

Training

- ML Models "train": finding the <u>relation</u> between input \rightarrow output
- Train on <u>A LOT</u> of diverse data to avoid overfitting/underfitting



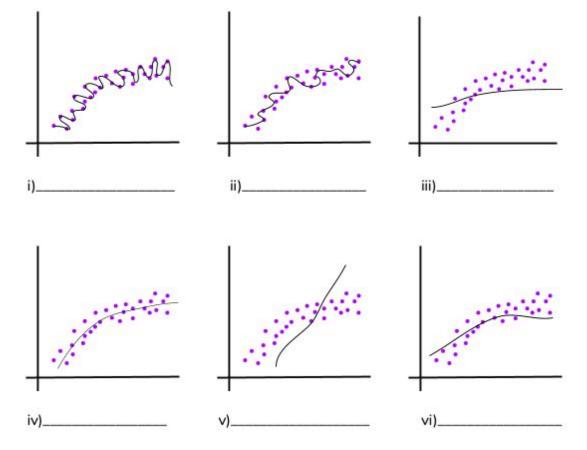




Review

Look at this photoGRAPH!

545



Look at this photoGRAPH (answers)! Fruccuse Overfitting ii) Overfitting iii) Underfitting Optimal Underfitting Optimal iv) vi)

545



and some ~ questions ~

• How can we avoid overfitting?

• How can we avoid underfitting?

• What is the difference between the training dataset and the test dataset?

and some ~ questions ~ (answers)

- How can we avoid overfitting?
 - Use a diverse dataset + more data
- How can we avoid underfitting?
 - Use more data
- What is the difference between the training dataset and the test dataset?
 - We use the training dataset to find a relation between the input and output. We use the testing dataset to evaluate how accurate that relation is after the model has been trained



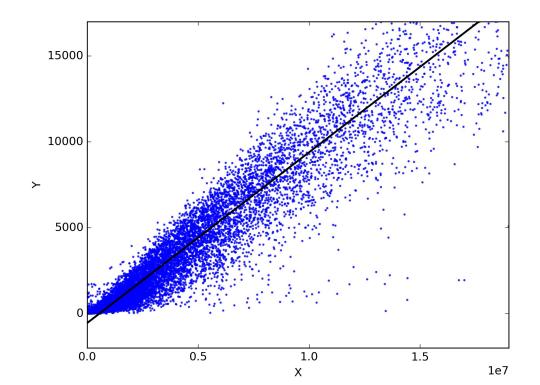
Questions?



Linear Regression









Regression refers to the relationship between two or more variables.

- Data from the real world rarely carries a relationship among its variables that can be modeled perfectly by a function such as a linear function, a quadratic, an exponential, etc.
- Let's look at an example!



Here is some data on the heights and weights of NFL players from 2014. Assume that a taller player usually weighs more than a shorter player.

NFL player	Position	Height (inches)	Weight (pounds)
Jahleel Addae	Defense	71	195
Tim Benford	Offense	71	196
Victor Butler	Defense	74	231
Hebron Fangupo	Offense	73	330
Anthony Fasano	Offense	76	255
Brian Hartline	Offense	74	180
Jason Hatcher	Defense	79	285
Cullen Jenkins	Defense	75	292
Darrin Reaves	Offense	70	210
Scott Simonson	Offense	77	249
Aldon Smith	Defense	77	255
Isaiah Trufant	Defense	68	170

Table 2: Heights and weights of a simple random sample of NFL players from the 2014 season. Data from pro-football-reference.com.

No.

What is linear regression?

Do you think we can use a linear function that relates **all** the heights (x) to weights (y)?

A. Yes

B. No

NFL player	Position	Height (inches)	Weight (pounds)
Jahleel Addae	Defense	71	195
Tim Benford	Offense	71	196
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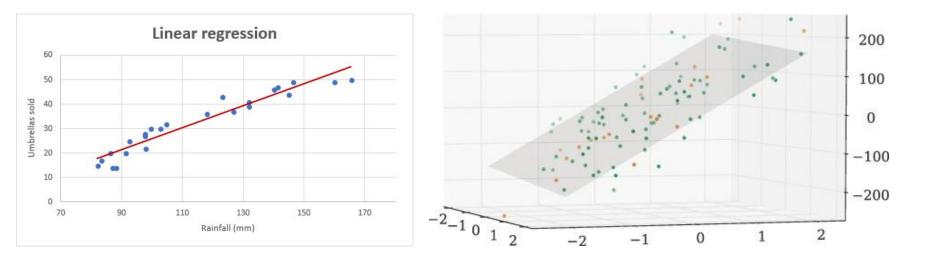
You can tell by looking at the first two players that we can't have a function that contains <u>all</u> these points because Jahleel Addae and Tim Benford are both 71 inches tall but have different weights.

NFL player	Position	Height (inches)	Weight (pounds)
Jahleel Addae	Defense	71	195
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Table 2: Heights and weights of a simple random sample of NFL players from the 2014 season. Data from pro-football-reference.com.



- We want to find a way to take in all our data and create one function that best fits it.
- In case of **linear** regression, that function is a line or a plane!





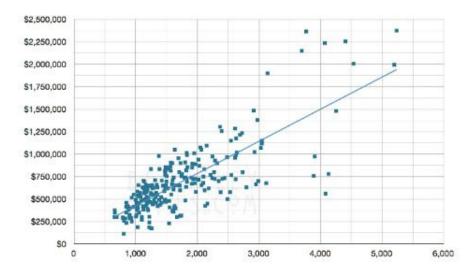
The Goal: Create a line or plane that models the

<u>universal relationship</u> between several inputs and one output.

This is a big idea in DL: **universal approximation!**

• aka Line of Best Fit!





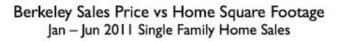
Berkeley Sales Price vs Home Square Footage Jan – Jun 2011 Single Family Home Sales

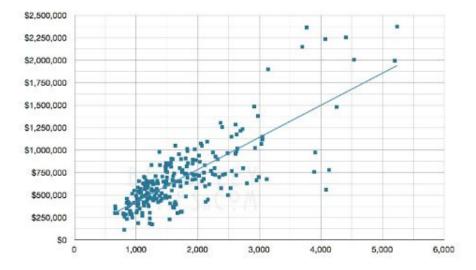
Classic example: Using a line to model the <u>relationship</u> between square footage and property price



Food for thought

- 1. Why use <u>linear regression</u>?
- 2. Why do we want <u>diversity</u> in our training data?







Let's write the training dataset like this:

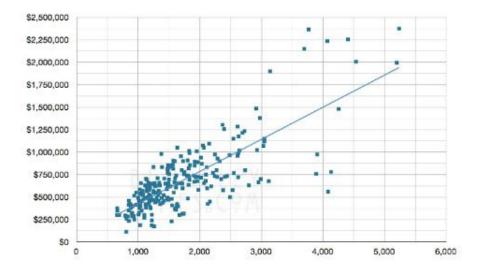
$$[(x_0, y_0),]$$
 Start at 0, not 1
 $(x_1, y_1),]$

..., (x_i, y_i) , $(x_i, y_$

 $(x_{\rm m}, y_{\rm m})$] \longrightarrow *m* total training examples

What do x and y represent in this graph on the right?

Berkeley Sales Price vs Home Square Footage Jan – Jun 2011 Single Family Home Sales



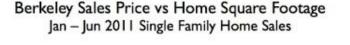


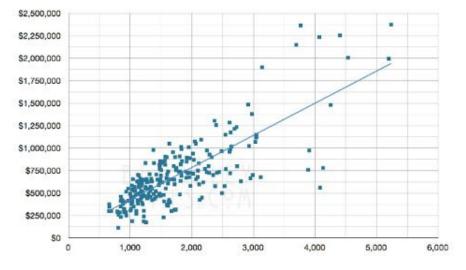
What do x and y represent in this graph on the right?

Answer:

- *x* = home square footage
- *y* = sales price (of the home)

We say that <u>home square footage</u> is an <mark>input feature</mark>. What other features can we use?





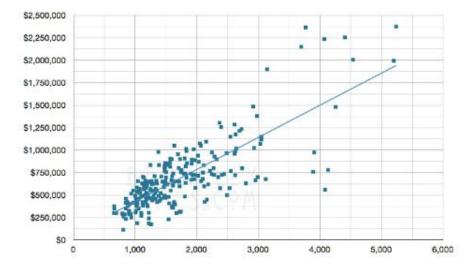


Some possible features:

- Size of the home (ft²)
- Age of the home (yr)
- Distance to nearest shopping center (mi)

$$\left(\begin{array}{c} 2000 \text{ ft}^2 \\ 20 \text{ yr} \\ 2 \text{ mi} \end{array}\right) \leftarrow \text{This is a } \underline{\text{vector!}}$$







Quick Aside: Vectors

- 2000 ft^2 A scalar
- 2000 ft²
 20 yr
 2 mi
 3 features
 3-dimensional

(2000 ft² 20 yr 2 mi **)** • Can also be written like this!

More generally... $(x_0, x_1, ..., x_i, ..., x_n)$

Let's put together what we have so far...

- 1. For some <u>input vector</u> x_i , the corresponding output is the <u>scalar</u> y_i
- 2. *Example*: say we pick (x_2, y_2)

$$x_2 = \begin{pmatrix} 2000\\ 20\\ 2 \end{pmatrix}$$
, $y_2 = 1,500,000$



- How many training examples (*m*)?
 - o 3
- How many features (n)?
 4
 - Input vectors are "4-dimensional"

Say that some training dataset looks like this:

$$x_0 = \left(\begin{array}{ccc} 12 & 3 & 56 & 700 \end{array} \right), \quad y_0 = 5$$

 $x_1 = \left(\begin{array}{ccc} 9 & 6 & 52 & 703 \end{array} \right), \quad y_1 = 7$

$$x_2 = \begin{bmatrix} 11 & 5 & 51 & 698 \end{bmatrix}, \quad y_2 = 4$$



<u>Can we write the training dataset more cleanly?</u> Yes! We can <u>stack</u> the input vectors to form a matrix.



$$X = \begin{bmatrix} 12 & 3 & 56 & 700 \\ x_1 = \begin{bmatrix} 9 & 6 & 52 & 703 \\ y_1 = 7 \\ y_2 = 4 \end{bmatrix}, \quad y_2 = 4 \\ Y = \begin{bmatrix} 5 \\ 7 \\ 4 \end{bmatrix} \end{pmatrix} \quad m = 3$$

$$X = \begin{bmatrix} 12 & 3 & 56 & 700 \\ 9 & 6 & 52 & 703 \\ 11 & 5 & 51 & 698 \end{bmatrix} \quad m = 3$$

$$m = 3$$

$$m = 3$$

$$m = 3$$

$$But why do we write it like this?$$

The Linear Regression problem can be written as $\underline{Y} = WX + B$. We will learn more about how to calculate **Y** in future lessons!

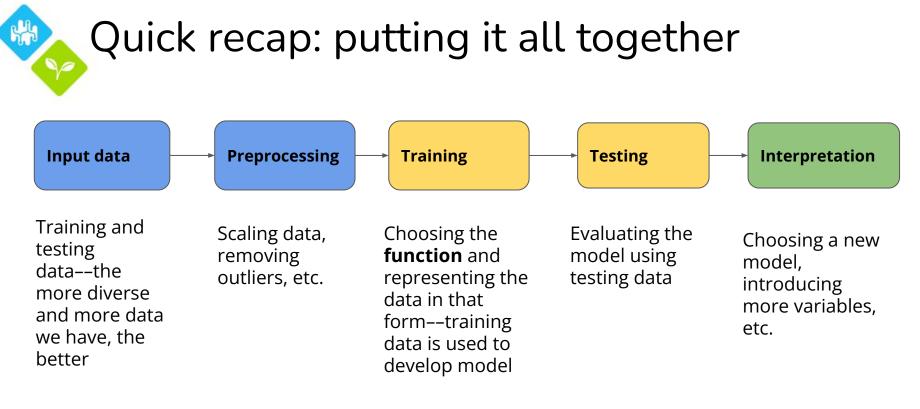
1. What are the dimensions of matrix **X**?

2. What are the dimensions of vector **Y**?



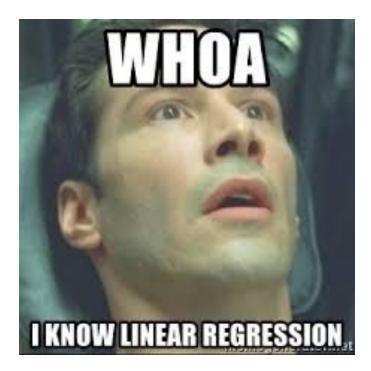
Linear Regression: Y = WX + B

- Find <u>best possible</u> **W** and **B**
- Such that our regression model outputs $Y_{predict}$ very close to $Y_{reality}$



Function/model: maps input data (training examples) to outputs (predictions) Example: y = mx + b

That's it for now, we'll look into the math behind linear regression soon!







Kahoot!





Check out our <u>Github</u> Read our <u>Blog</u> ucla.acm.ai@gmail.com