



Introduction to Machine Learning

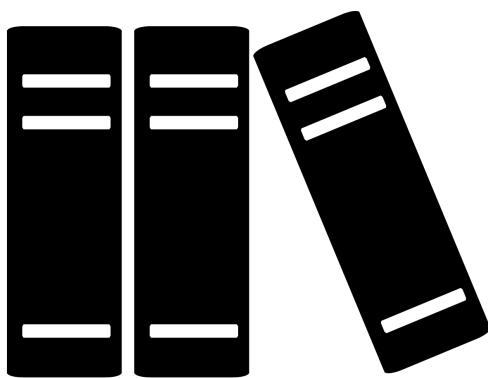
Data Boot Camp
Lesson 21.1



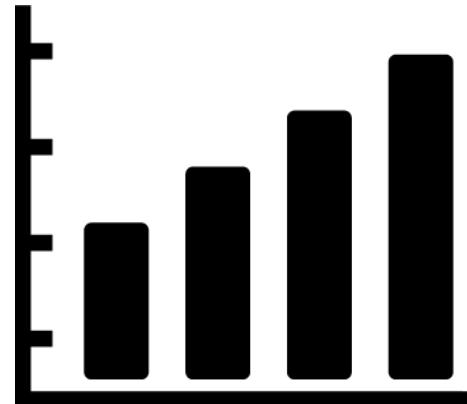


Machine Learning in a Nutshell

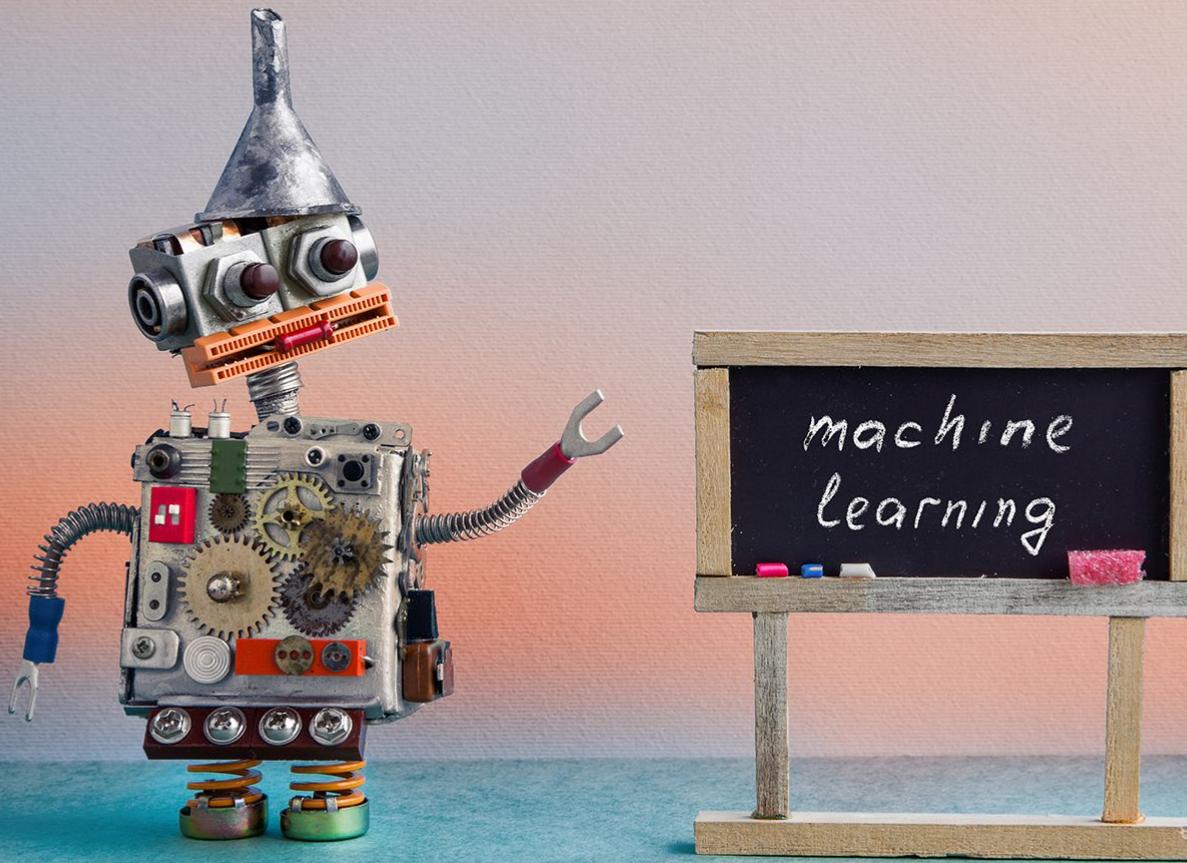
Libraries



Statistics



So It Begins...



Basic Definitions

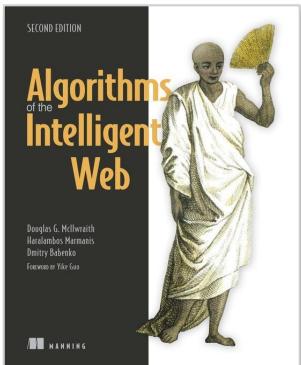
Intelligent Algorithms (Definition)



Intelligent algorithms are ones that use data to modify its behavior. Intelligent algorithms differ in that they can change their behavior as they run, often resulting in a user experience that many would say is intelligent.



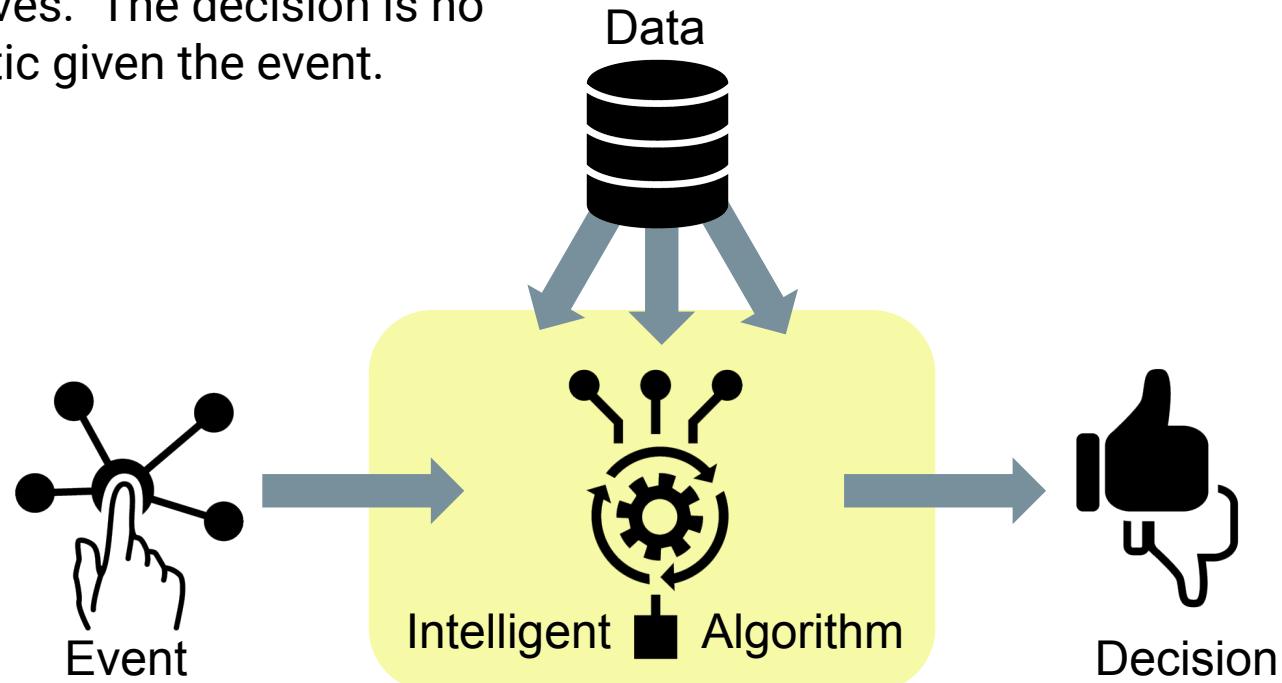
—Algorithms of the Intelligent Web, Second Edition



Algorithms of the Intelligent Web, Second Edition
by Douglas G. McIlwraith Haralambos Marmanis Dmitry Babenko
Publisher: Manning Publications
Release Date: August 2016

Intelligent Algorithms (Diagram)

Intelligent algorithms are ones that respond to data such that the algorithm gets better. It effectively “evolves.” The decision is no longer deterministic given the event.



Intelligent Algorithms (Triad)

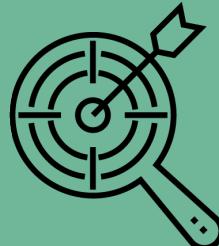
Machine Learning

Capability of software to generalize phenomena (past or future) based on past experience



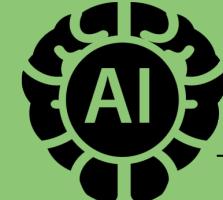
Predictive Analytics

Capability of software to predict future outcomes based on historic data



Artificial Intelligence

Software (and machines) that have a series of options to achieve a particular goal



Artificial Intelligence (Example)



Predictive Analytics (Example)

How retargeting ads work:



Your potential customer



Customer sees your ad



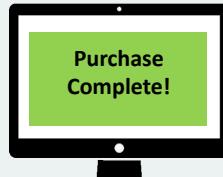
Customer visits your website



Customer leaves your website without any action (purchase)



Your happy customer



Customer completes the purchase

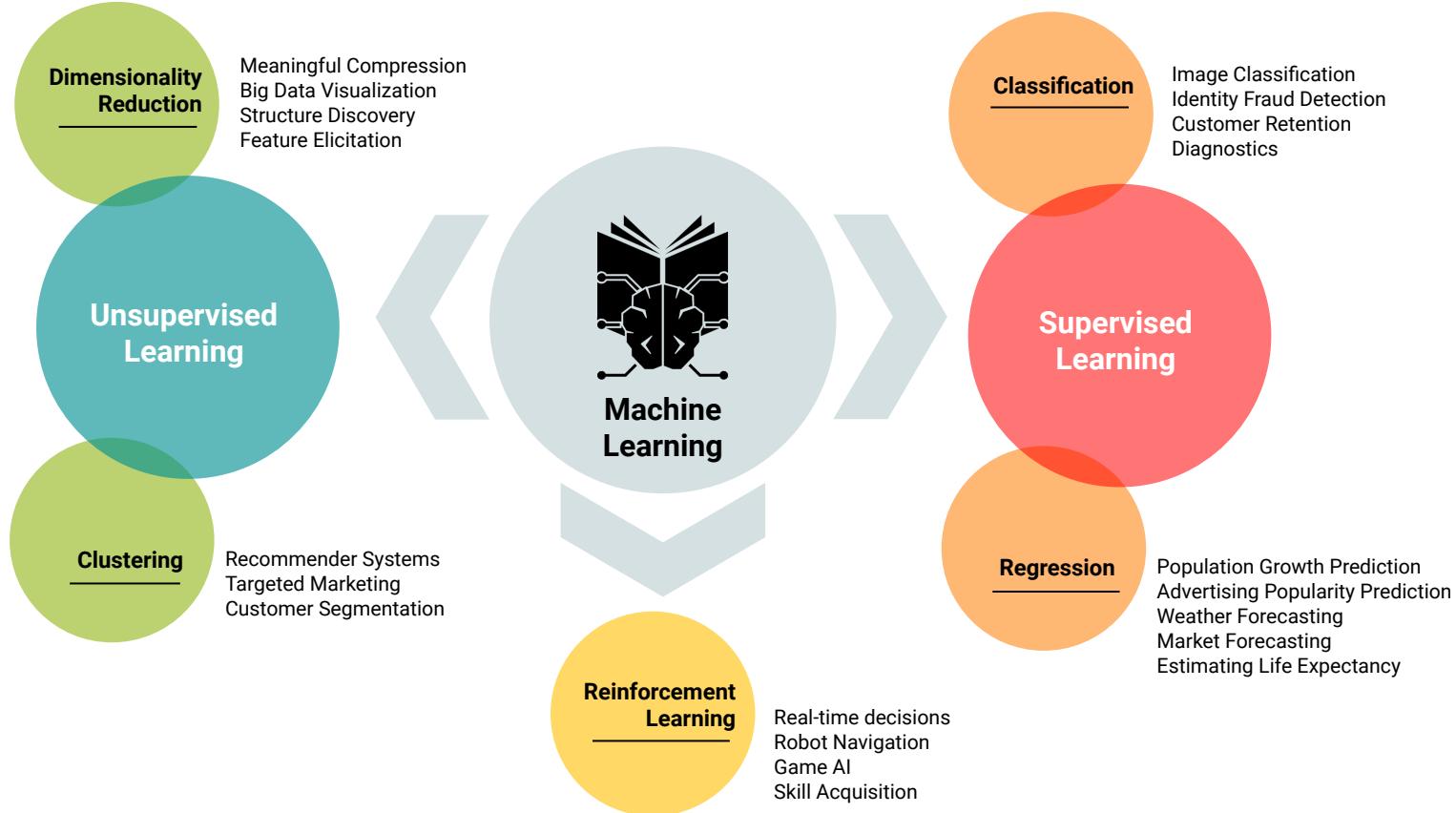


Customer visits your website again

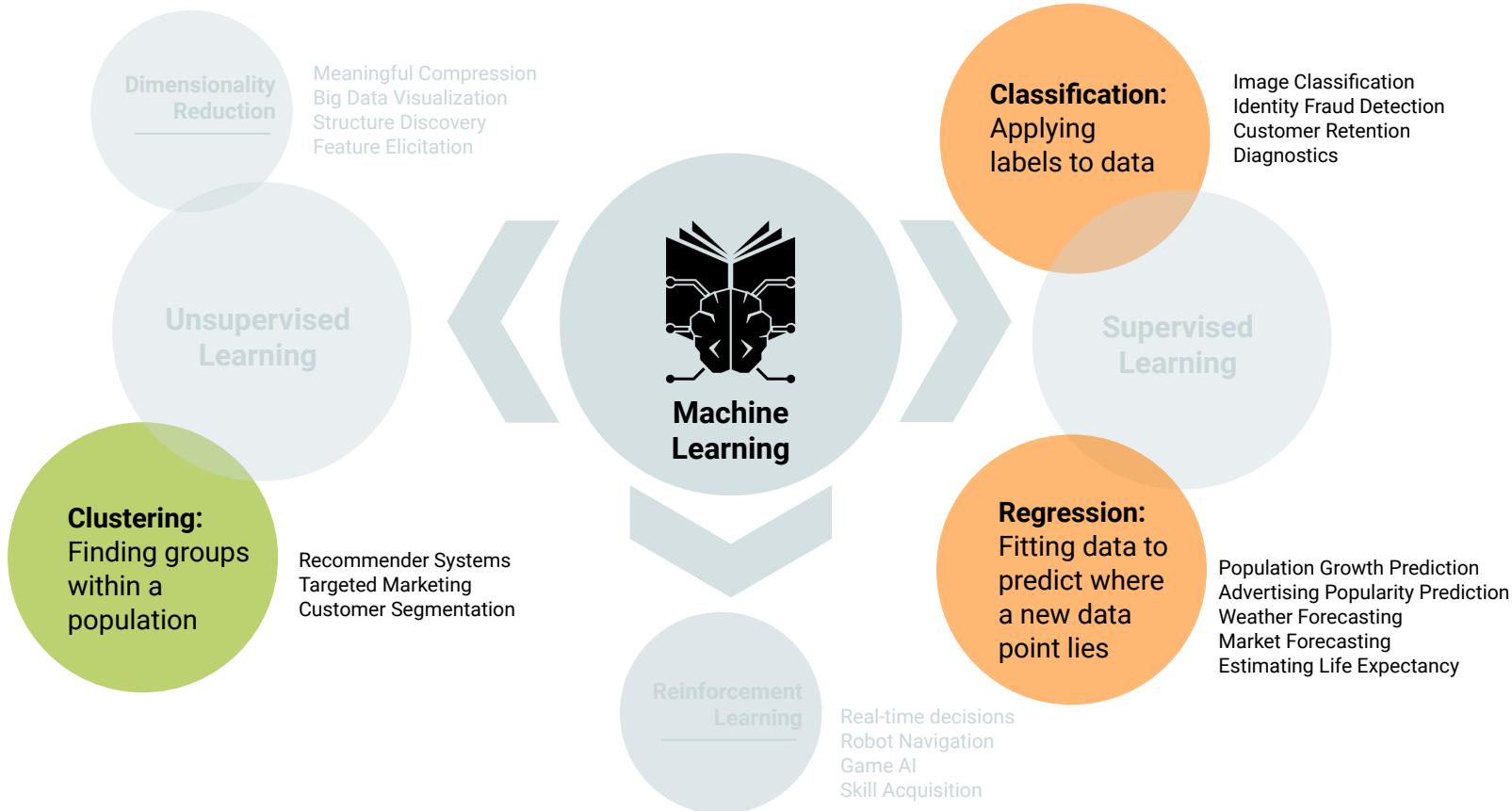


Customer sees your ad on their Facebook feed and partner sites

Machine Learning (Categories)



Machine Learning (Categories)



Machine Learning (Supervised)

Supervised Learning: Algorithms for which the potential outcomes are knowable in advance (i.e., category or numeric range) and can be used to correct the model's predictions.

01

Example

Using data such as credit score, credit history, income, etc., we are trying to predict whether an individual is a credit risk or not.

Known Category:

“Credit Risk” vs. “Not Credit Risk”

02

Example

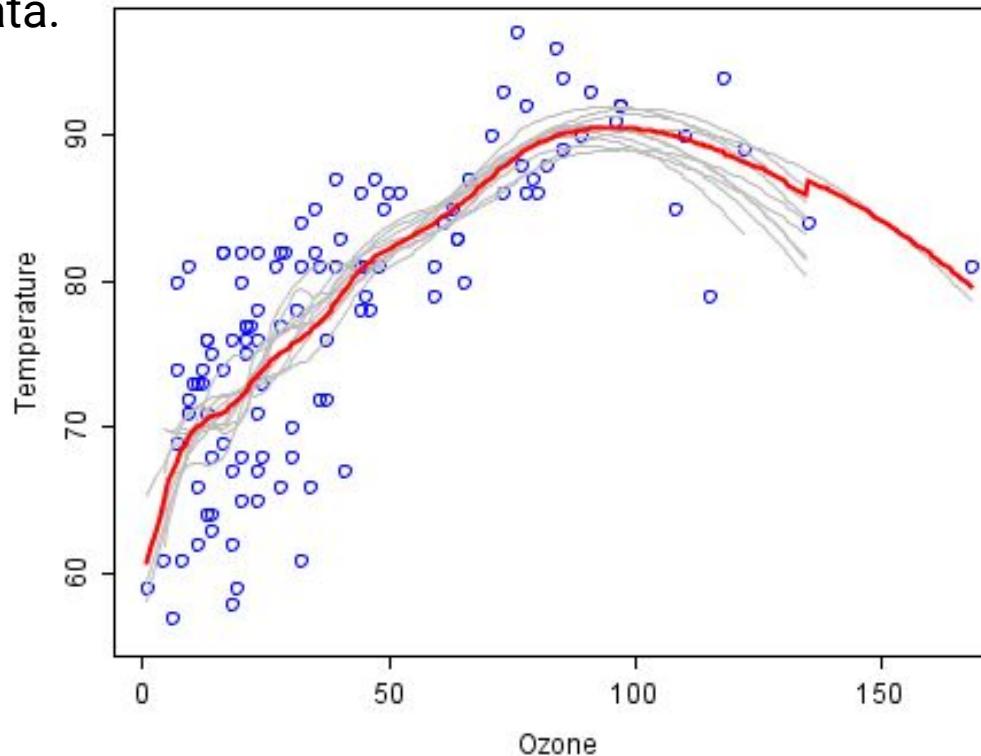
Using features such as number of bedrooms, square feet, etc., we are trying to predict the market value of a house.

Numeric Range:

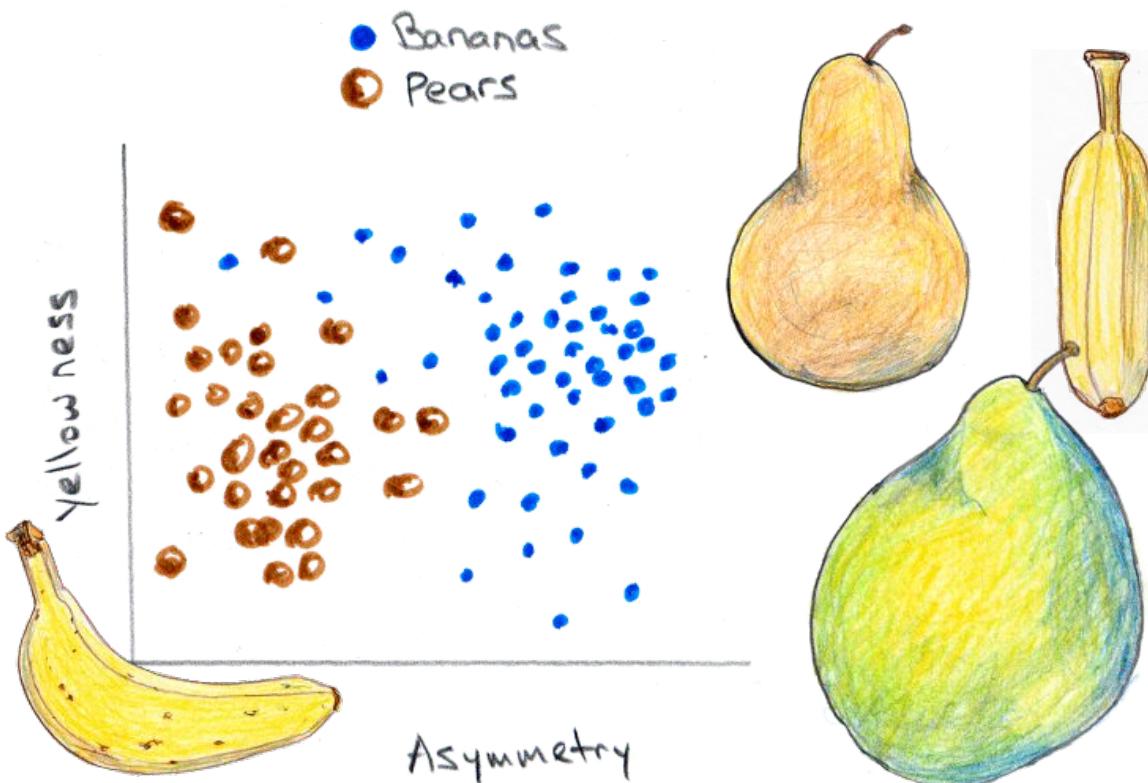
50,000–500,000

Machine Learning (Regression)

We'll be revisiting regression to predict the location of data points based on old data.



Machine Learning (Classification)



Machine Learning (Classification)

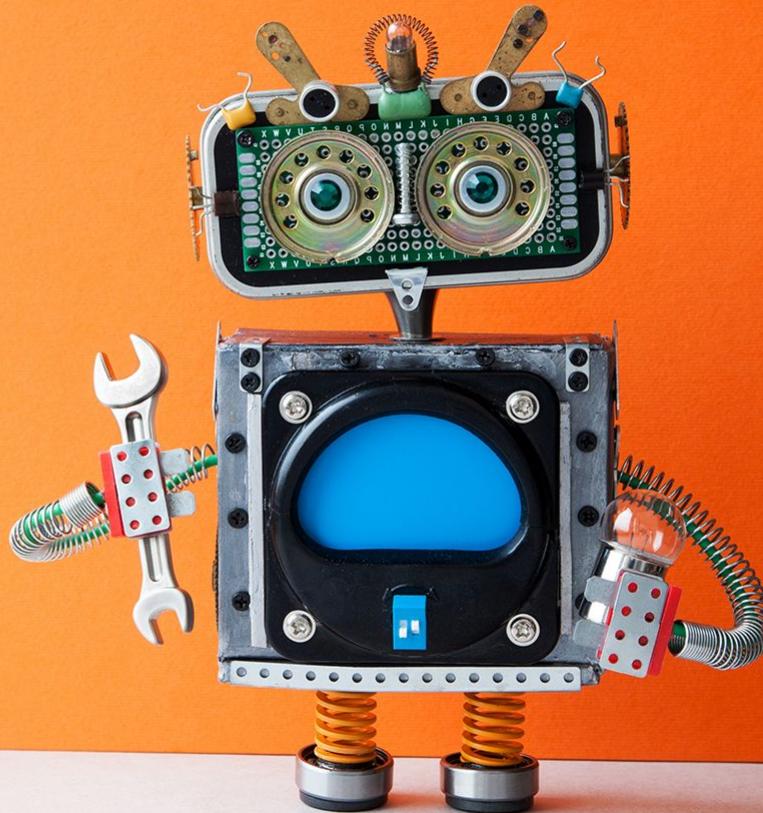
In classification problems, our focus is identifying which predefined label our data falls into, based on the **features** we have.

From: cheapsales@buystufffromme.com To: ang@cs.stanford.edu Subject: Buy now!	From: Alfred Ng To: ang@cs.stanford.edu Subject: Christmas dates?
Deal of the week! Buy now! Rolex w4tchs - \$100 Med1cine (any kind) - \$50 Also low cost M0rgages available.	Hey Andrew, Was talking to Mom about plans for Xmas. When do you get off work? Meet Dec 22? -Alf
Spam	Non-Spam

Machine Learning (Unsupervised)

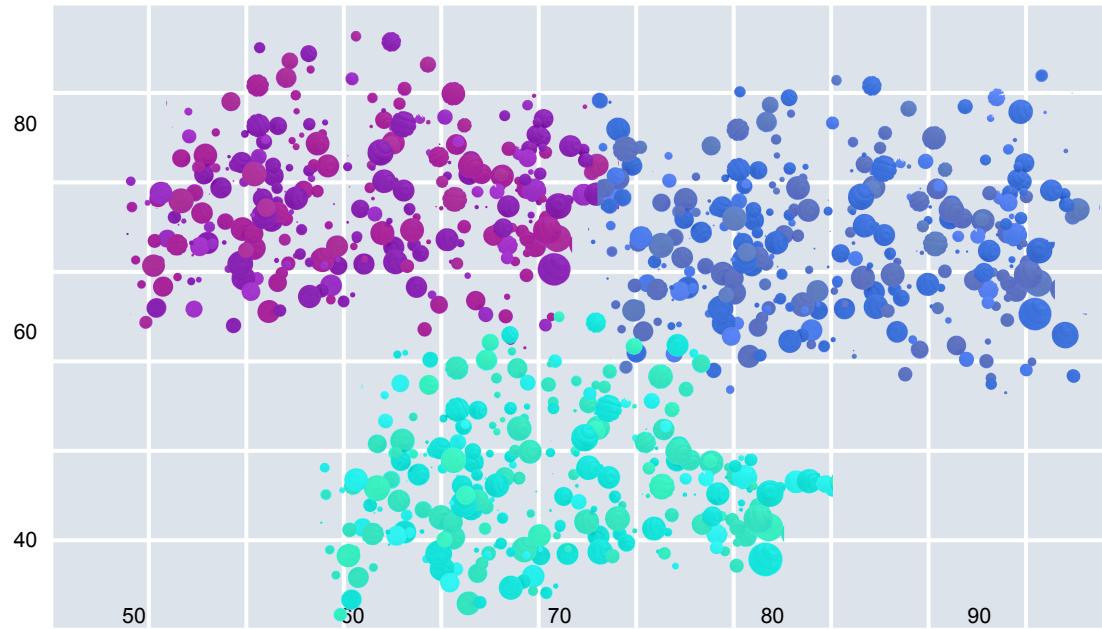
Unsupervised Learning:

Algorithms for which the potential outcomes are unlabeled. Inferences are made directly from the data without feedback from known outcomes or labels.



Machine Learning (Clustering)

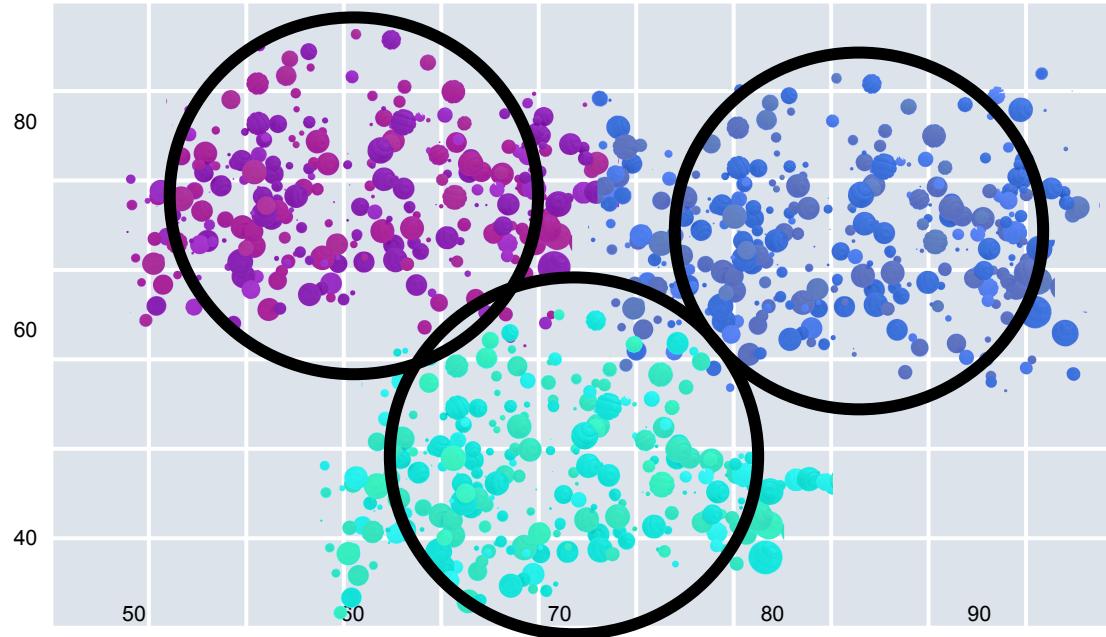
In this clustering problem, we expect our algorithm to find the groupings of data points based on location.



Machine Learning (Clustering)

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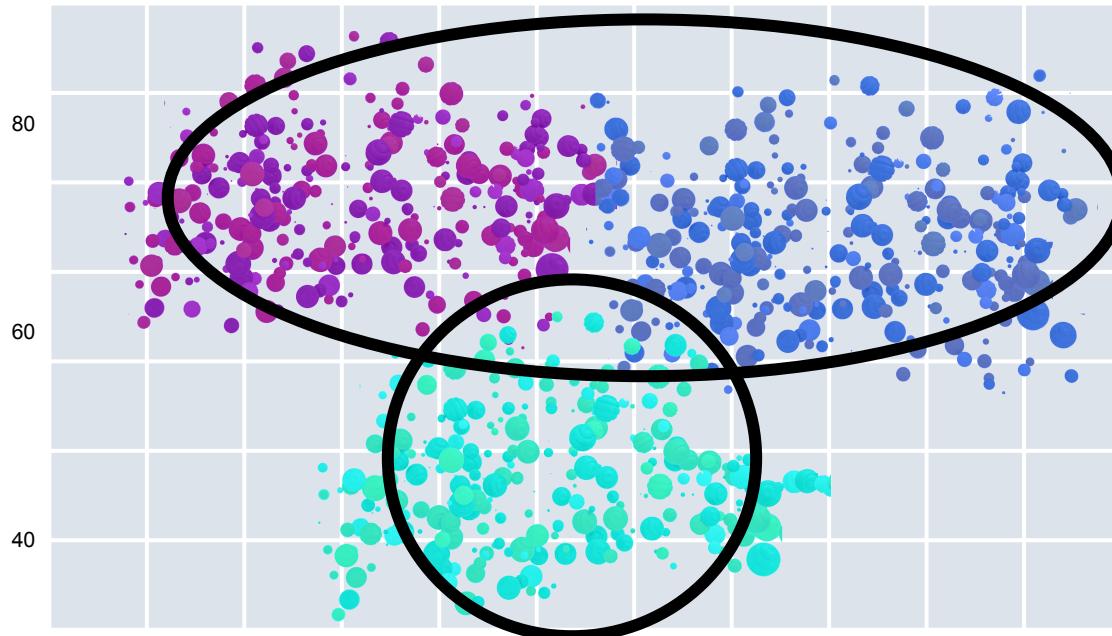
K=3



Machine Learning (Clustering)

But the problem is more complex:

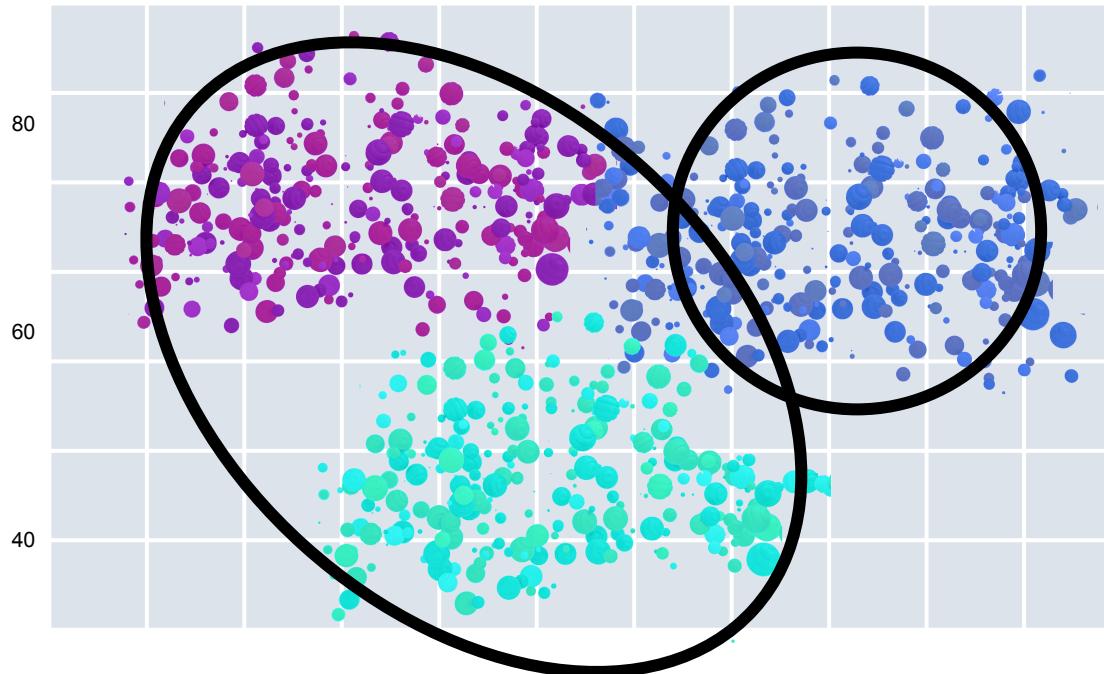
K=2



Machine Learning (Clustering)

Perhaps the clusters are not where we think they are.

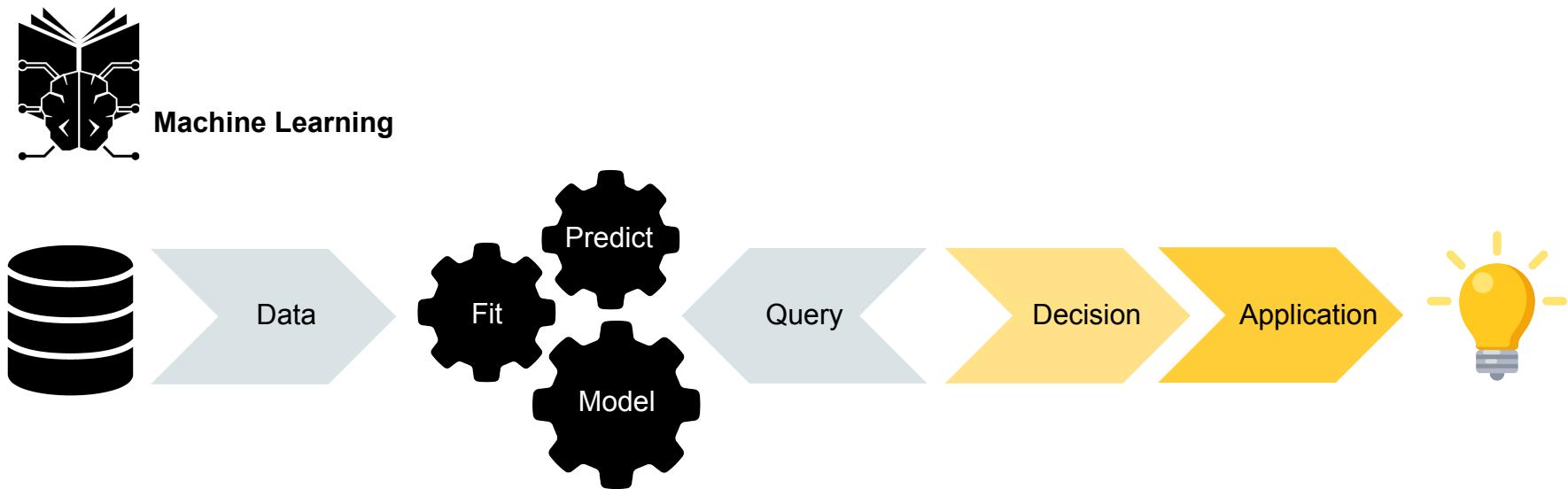
K=2



Training and Predicting

Regardless of the problem type, in Machine Learning we follow a familiar paradigm.

Model → Fit (Train) → Predict



Training and Predicting

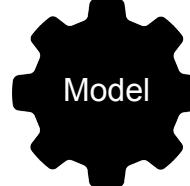
Regardless of the problem type, in Machine Learning we follow a familiar paradigm.

Model → Fit (Train) → Predict

A	B	C	Class
11	16	22	1
10	8	4	2
...

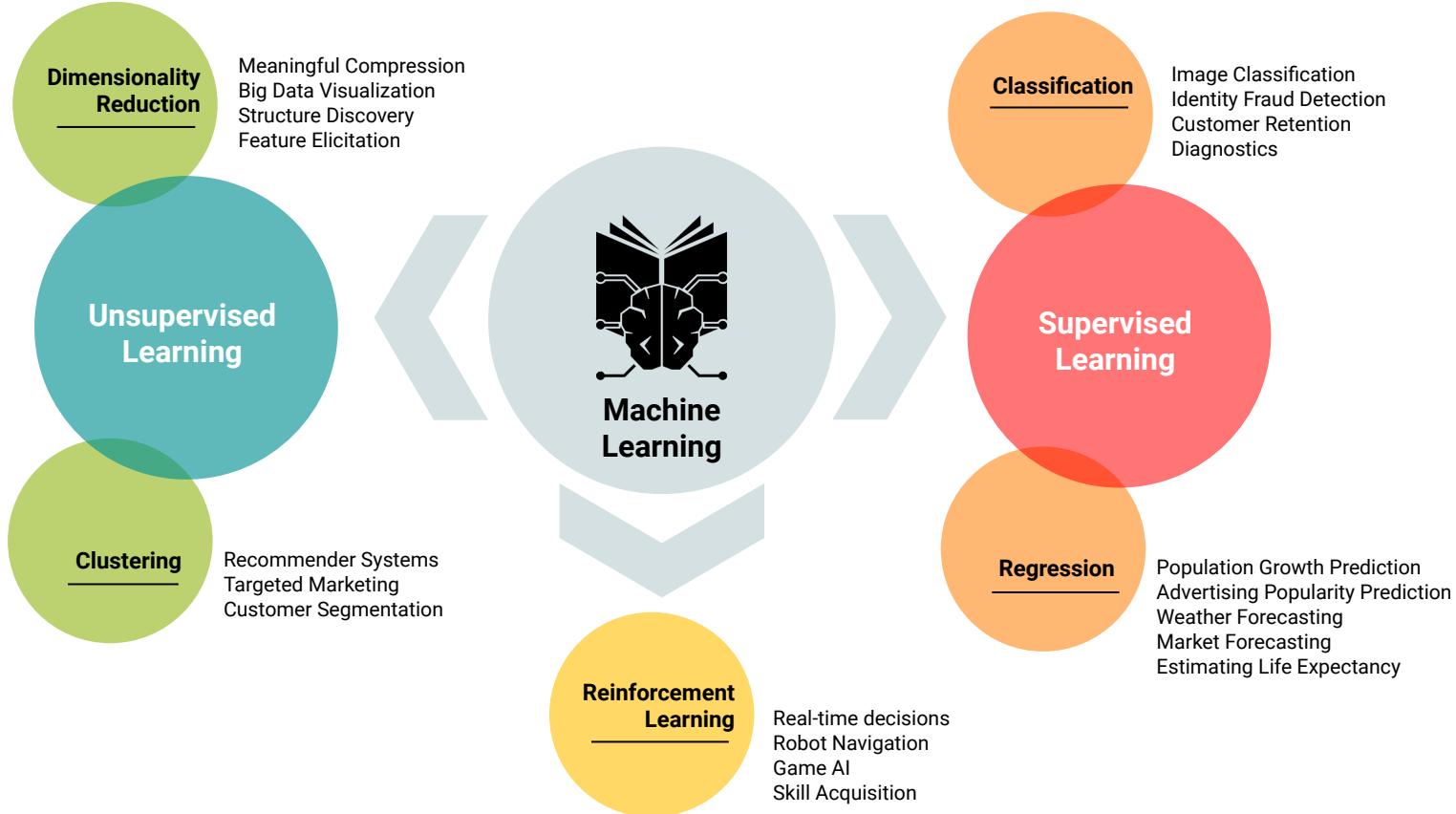


A	B	C	Class
10	15	23	?



Class
1

Many Models: Which Do We Choose?



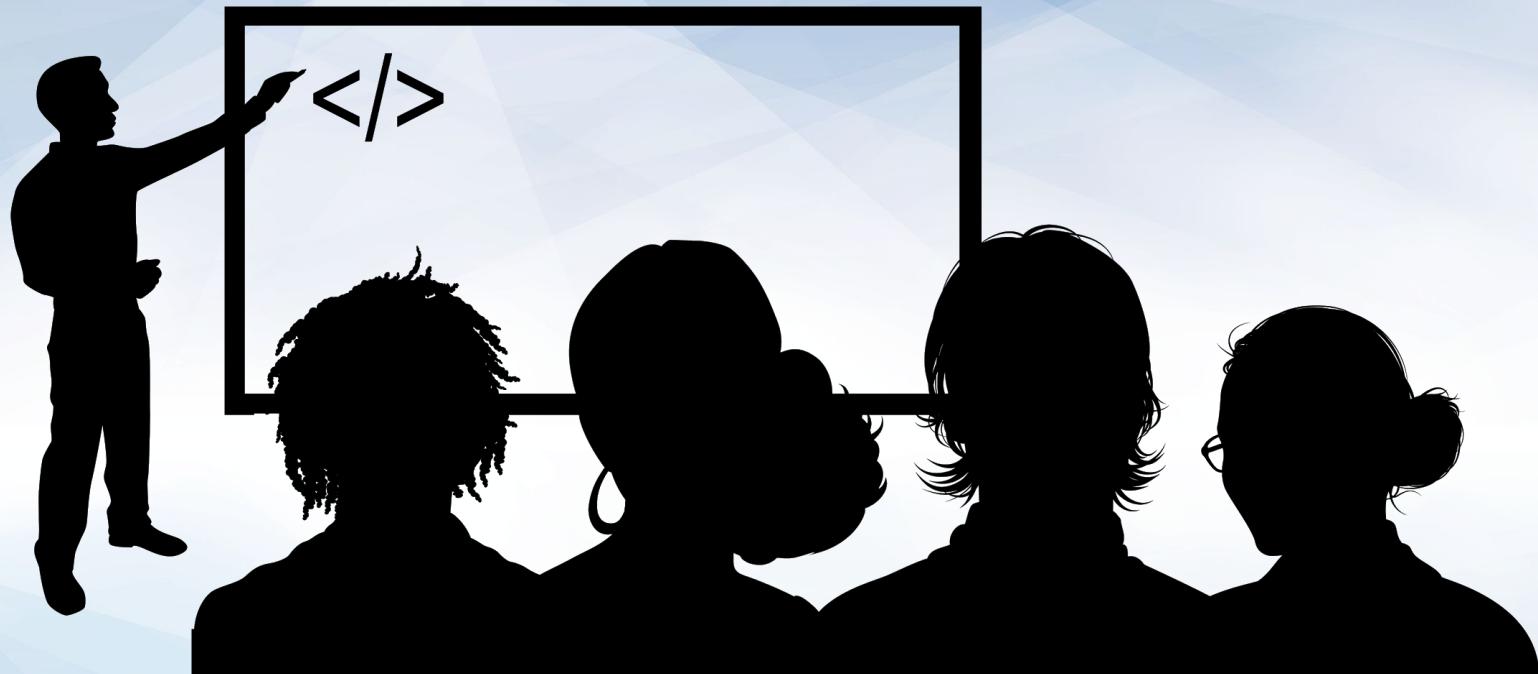
The Future of Machine Learning

Machine Learning will one day likely be relegated to a world of the off-the-shelf formulas readily available by the masses. We're already nearly there.

A screenshot of a Microsoft Excel spreadsheet. The top row shows the formula bar with the cell reference G2 and the formula =ROUND(C2,0). The table has four columns: 'ROUND' (containing values 2.4, 2.4, 3.2, 8.0), 'No formatting' (containing values 2, 2, 3, 8), 'Formatted no decimal places' (containing values 2.0, 2.0, 3.0, 7.0), and 'ROUND Formula' (containing values 2.0, 2.0, 3.0, 7.0). The 'ROUND Formula' column is highlighted with a black border. Row 1 is a header row with bold text. Row 2 is the first data row. Row 3 is the second data row. Row 4 is the third data row. Row 5 is the fourth data row. Row 6 is a blank row.

	G2		=ROUND(C2,0)				
	A	B	C	D	E	F	G
1	ROUND	No formatting		Formatted no decimal places		ROUND	Formula
2			2.4		2	2.0	
3			2.4		2	2.0	
4			3.2		3	3.0	
5			8.0		8	7.0	

Questions?

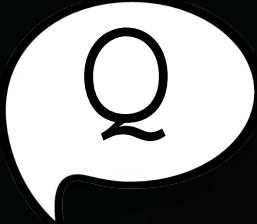


Instructor Demonstration
Univariate Linear Regression

We start with
something
familiar...

...linear regression!





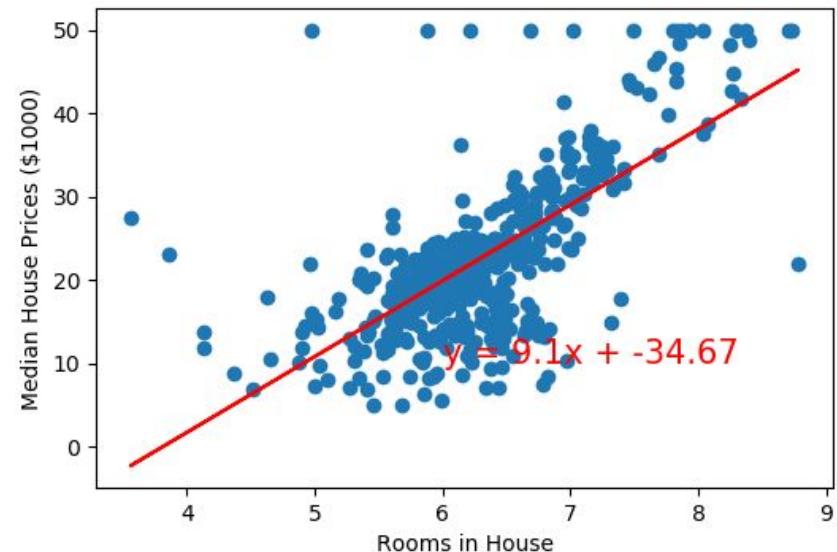
Q

What is **linear regression**?

Linear Regression is Used to Model and Predict A Relationship

Linear regression...

- Predicts a dependent variable, given values from an independent variable.
- There are two basic types
 - Simple linear regression
 - Multiple linear regression
- Both types predict an independent variable using the linear equation



The Equation of a Line

$$y = mx + b$$

A diagram illustrating the components of the linear equation $y = mx + b$. The equation is written in a large, black, serif font. Four red arrows point from labels below the equation to specific terms:

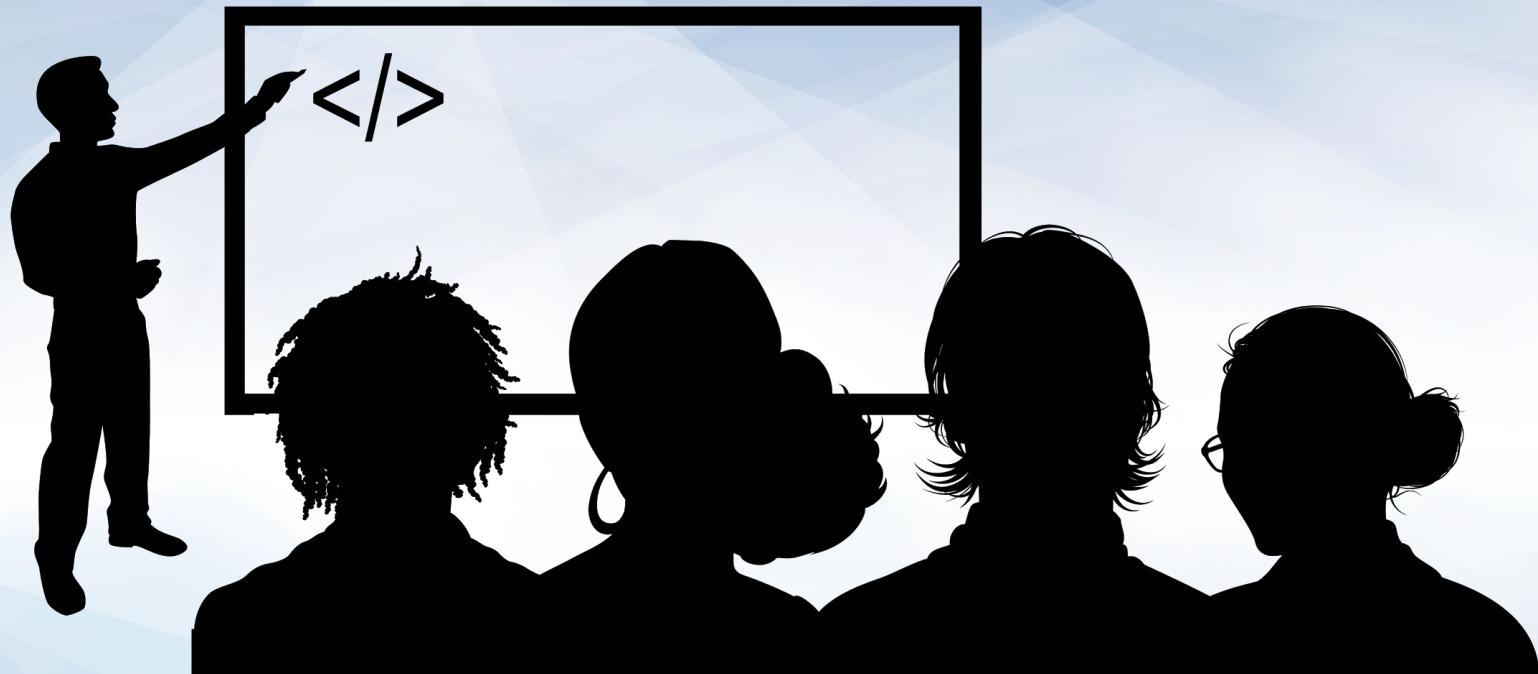
- An arrow points to the variable y with the label "Dependent variable".
- An arrow points to the term mx with the label "Slope".
- An arrow points to the variable x with the label "Independent variable".
- An arrow points to the term b with the label "y-intercept".



Linear regression is *FAST*

<Time to Code>





Instructor Demonstration Quantifying Regression

Common Scoring Metrics

01

R² (R-Squared):

This is the baseline metric that many ML tools report on score. Higher R² values signify that the model is “highly predictive.” An R² value of >0.90 means that our model roughly accounts for 90% of the variability of the data.

02

MSE (Mean Squared Error):

This measures the average of the squares of the errors or deviations.

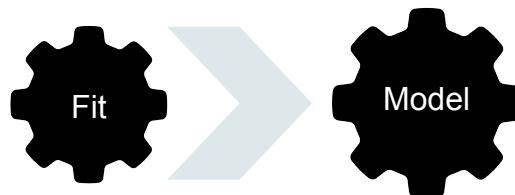
Basic Premise of Validation Using Training/Testing Data

We will cut a slice of this data (80%) to build our model, and then use this slice to predict the values for the remaining 20%.

Full Data Set (Historic)			
N=1000			
# bedrooms	# baths	Sq. feet (k)	Price (k)
2	1	1	200
3	2	1.5	250
...

Training Data Set			
N=800			
# bedrooms	# baths	Sq. feet (k)	Price (k)
4	3.5	3.2	450
2	2	1.5	220
...

Testing Data Set			
N=200			
# bedrooms	# baths	Sq. feet (k)	Price (k)
1	1	.5	60
5	3.5	4.2	780
...



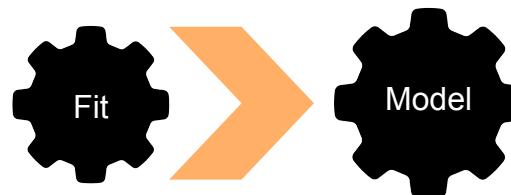
Basic Premise of Validation: Training

We use the training data to fit the model to the data. This is the training step where we build a model that can predict our output (home price) for a given set of features (# bedrooms, # baths, square feet). Once the model is trained, we can use the model to make predictions.

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# bedrooms	# baths	Sq. feet (k)	Price (k)
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3	2	1.5	250
...

Training Data Set			
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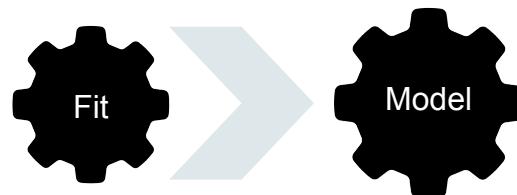
Basic Premise of Validation

We use the test data to make new home price predictions. We can then compare the home price of our prediction vs. the actual price. Based roughly on how often we are “correct,” we get a score for the model as a whole. If the model scores well, we can trust it for future use. We train the model on the training data and score the model based on data that it has never seen before (test data).

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N=1000			
# bedrooms	# baths	Sq. feet (k)	Price (k)
2	1	1	200
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<Time to Code>

