GENERAL ASSEMBLY

DATA SCIENCE

MACHINE LEARNING / KNN

I. WHAT IS MACHINE LEARNING?
II. SUPERVISED LEARNING
III. UNSUPERVISED LEARNING
IV. SUMMARY
V. CLASSIFICATION WITH K-NEAREST NEIGHBORS

I. WHAT IS MACHINE LEARNING?

"A field of study that gives computers the ability to learn without being explicitly programmed." (1959)

Arthur Samuel, AI pioneer
Source: Stanford

Machine Learning is a class of algorithms which are data-driven. Unlike classical algorithms, it is the data that defines a “good” answer and NOT the human

Example:

A **Non-**Machine Learning algorithm might “define” a face as having a roundish structure, two eyes, hair, nose, etc. The algorithm then looks for these “hard-coded” features in test cases.

A Machine Learning algorithm might only be given several pictures of faces and non-faces that are labeled as such. From the examples (called training set) it would “figure out” it’s own definition of a face.

Machine Learning is generally *semi-automatic* meaning that intelligent decisions by humans are still necessary

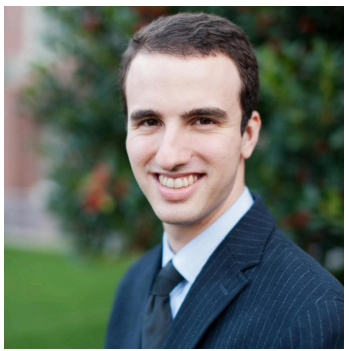
Training set

Face

Not Face

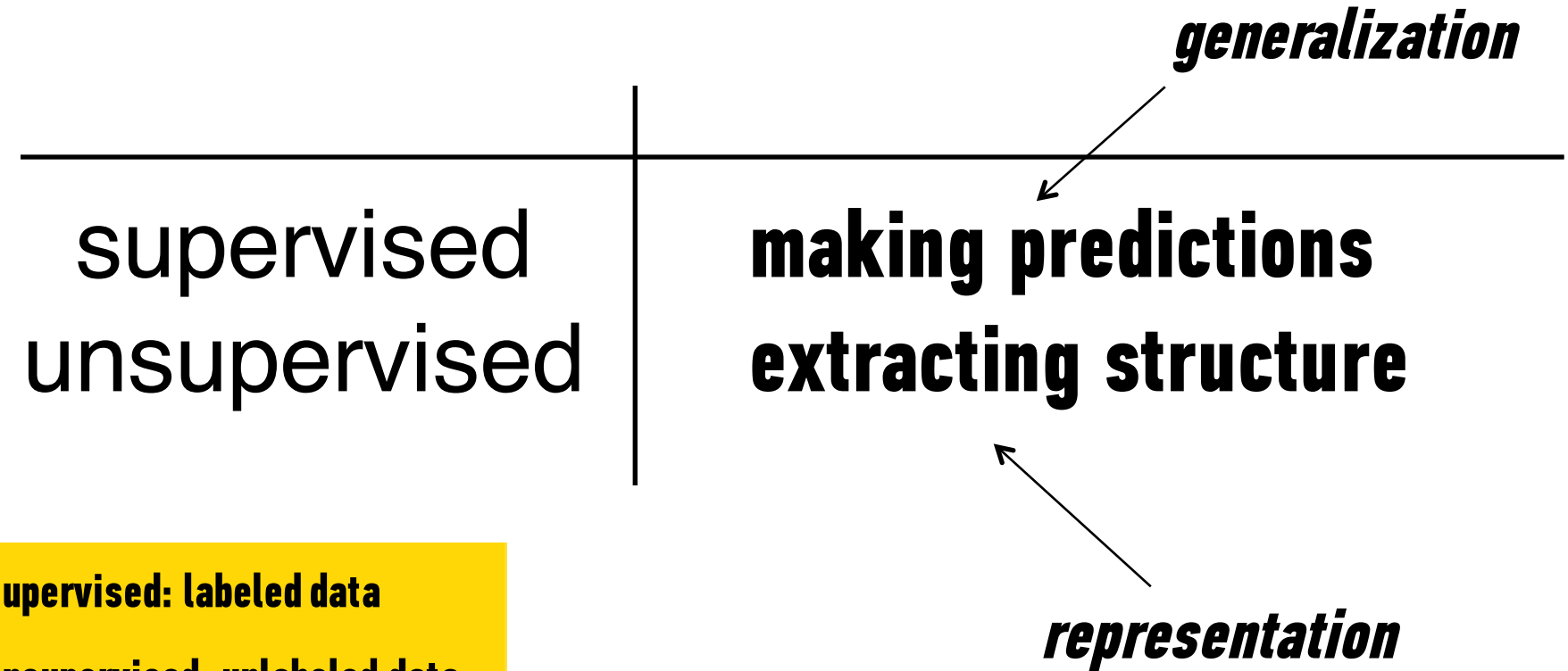
Face

Test



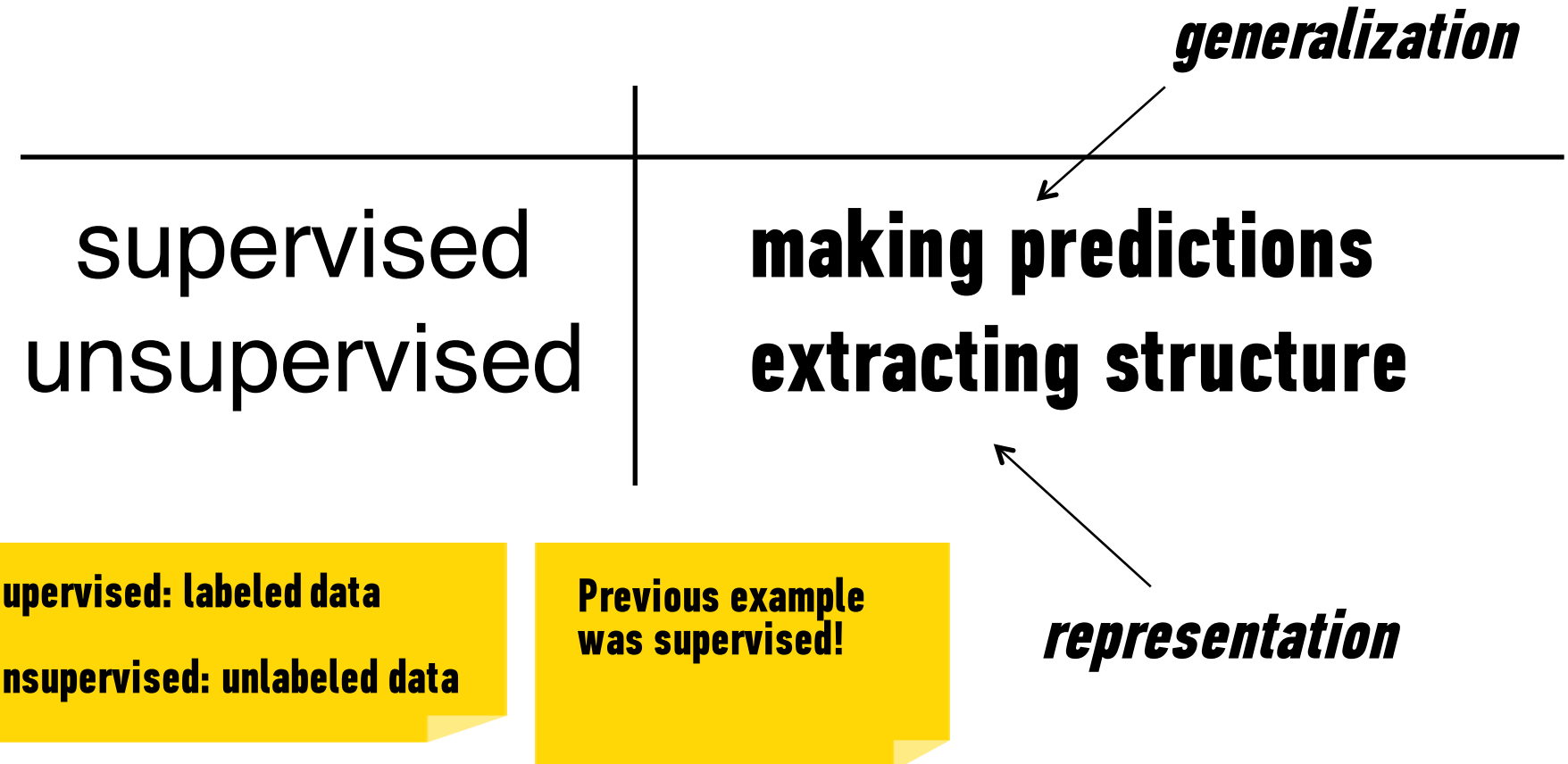
Face?

supervised	**making predictions**
unsupervised	**extracting structure**



Supervised: labeled data

Unsupervised: unlabeled data


generalization
supervised
unsupervised
making predictions
extracting structure
representation
Supervised: labeled data
Unsupervised: unlabeled data
Previous example was supervised!

II. SUPERVISED LEARNING

- All about making *predictions*
- List of "Predictors" X
  - Also known as features, independent variables, inputs, regressors, covariates, attributes
- "Response" y
  - Also known as outcome, label, target, dependent variable
- If y is continuous: **Regression**
  - e.g., price, blood pressure
- If y is categorical (values in a finite, unordered set): **Classification**
  - e.g., spam/ham, digit 0-9, cancer class of tissue sample
- Data are composed of "observations" (predictors and the associated response)
  - Also known as samples, examples, instances, records

Problem: Children born prematurely are at high risk of developing infections, many of which are not detected until after the baby is sick

Goal: Detect subtle patterns in the data that predicts infection before it occurs

Data: 16 vital signs such as heart rate, respiration rate, blood pressure, etc…

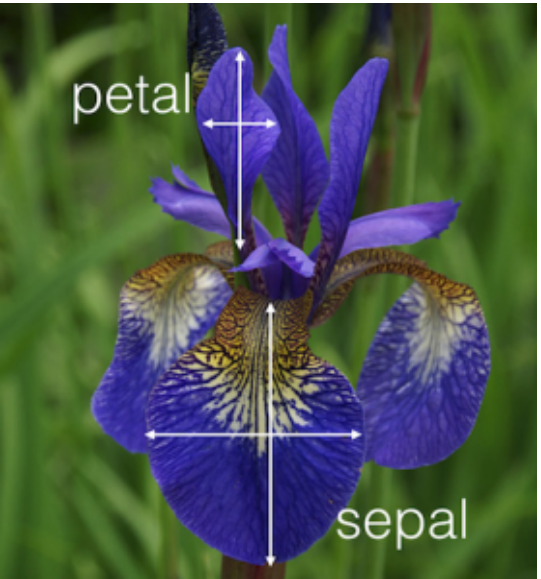
Impact: Model is able to predict the onset of infection 24 hours before the traditional symptoms of infection appear

predictors

Sample response: Did the child develop an infection? True/False

150 observations

(n = 150)



Fisher's *Iris* Data

Sepal length	Sepal width	Petal length	Petal width	Species
5.1	3.5	1.4	0.2	*I. setosa*
4.9	3.0	1.4	0.2	*I. setosa*
4.7	3.2	1.3	0.2	*I. setosa*
4.6	3.1	1.5	0.2	*I. setosa*
5.0	3.6	1.4	0.2	*I. setosa*
5.4	3.9	1.7	0.4	*I. setosa*
4.6	3.4	1.4	0.3	*I. setosa*
5.0	3.4	1.5	0.2	*I. setosa*

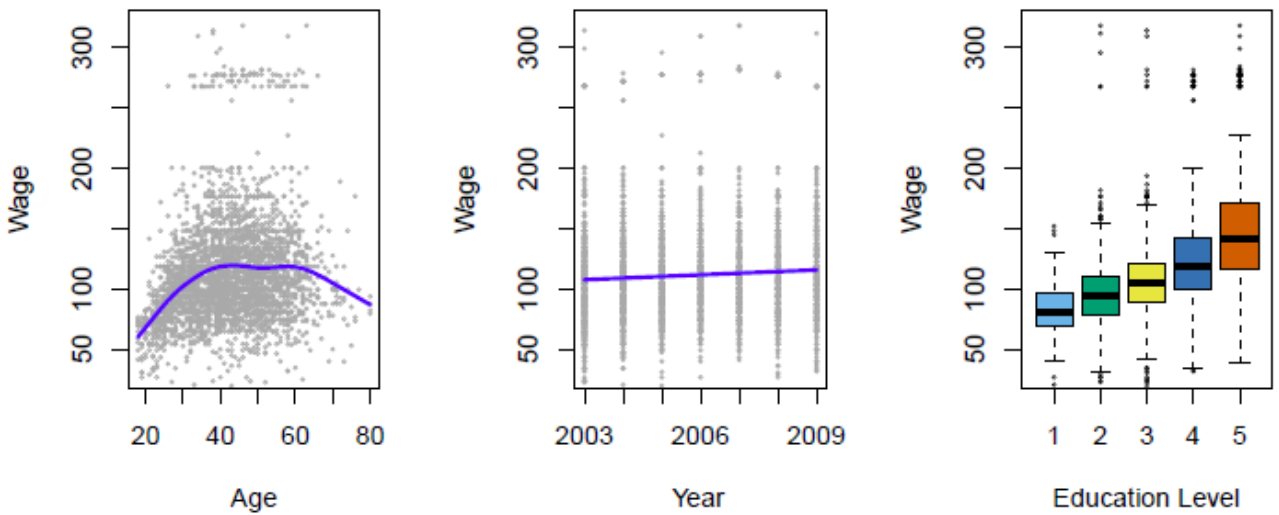
response

4 predictors (p = 4)

- Supervised Learning uses known/labeled "**training** cases" in order to:
  - Accurately predict unseen **test** cases
  - Understand which predictors affect the response, and how
  - *Use the past to predict the future*

REGRESSION EXAMPLE

- Establish the relationship between salary and demographic variables in population survey data

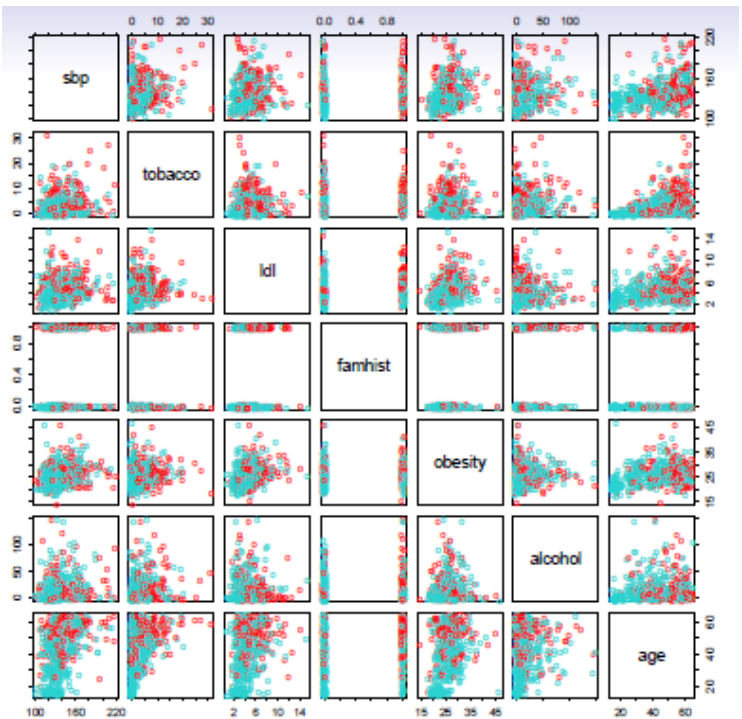


Income survey data for males from the central Atlantic region of the USA in 2009

Source: https://class.stanford.edu/c4x/HumanitiesScience/StatLearning/asset/introduction.pdf

CLASSIFICATION EXAMPLE

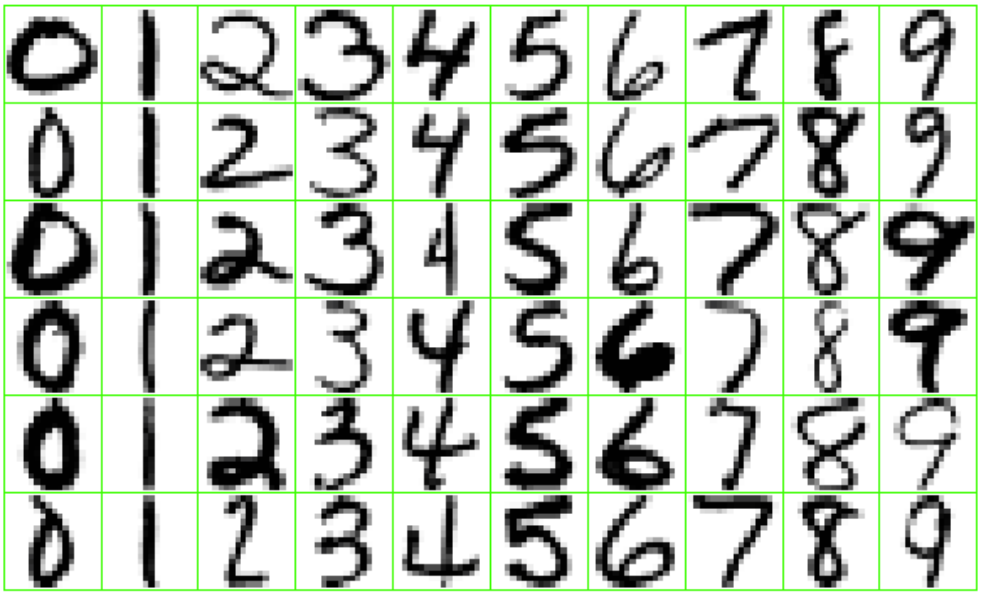
- Predict whether someone will have a heart attack on the basis of demographic, diet and clinical measurements



Case-control sample of men from South Africa
Red = heart disease
Blue = no heart disease

Source: https://class.stanford.edu/c4x/HumanitiesScience/StatLearning/asset/introduction.pdf

- Identify the numbers in a handwritten zip code



Source: https://class.stanford.edu/c4x/HumanitiesScience/StatLearning/asset/introduction.pdf

Knowledge • 219 teams

Shelter Animal Outcomes

Mon 21 Mar 2016 — Sun 31 Jul 2016 (3 months to go)

Dashboard

Home
- Data
- Make a submission

Information
- Description
- Evaluation
- Rules
- Timeline

Forum

Competition Details » Get the Data » Make a submission

Help improve outcomes for shelter animals

Every year, approximately 7.6 million companion animals end up in US shelters. Many animals are given up as unwanted by their owners, while others are picked up after getting lost or taken out of cruelty situations. Many of these animals find forever families to take them home, but just as many are not so lucky. 2.7 million dogs and cats are euthanized in the US every year.

WHAT IS KAGGLE?

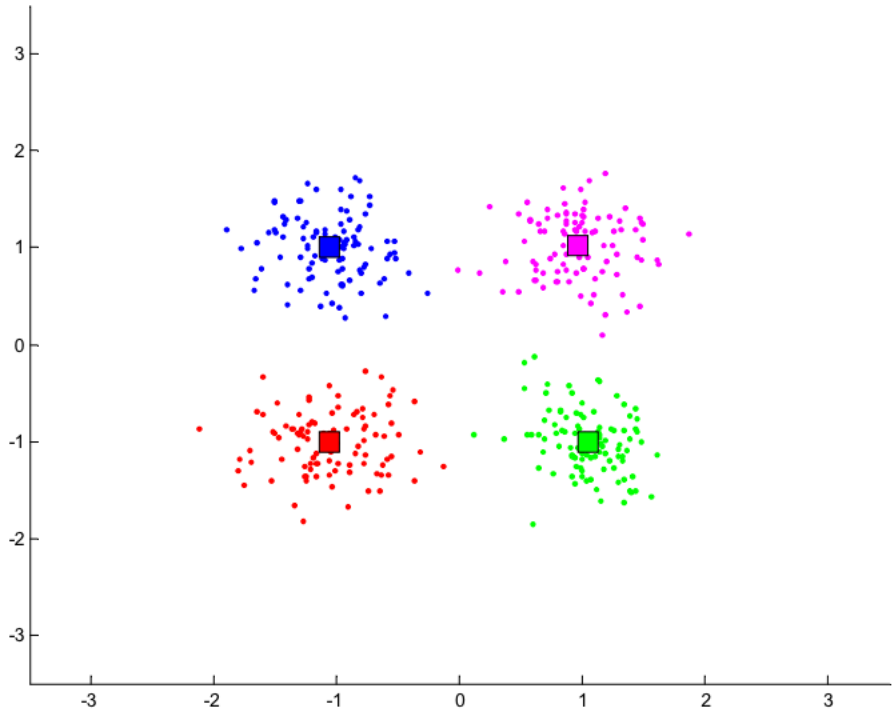
- Data Science challenges
  - Mostly a competition involving machine learning
- Judged by metrics learned in this class
- Some for money, others for knowledge

II. UNSUPERVISED LEARNING

- No response variable y, just a set of predictors X
- Objective is more open:
  - Find groups of observations that behave similarly
  - Find predictors that behave similarly
  - Find combinations of features that explain the variation in the data
- Difficult to evaluate how well you are doing
- Data is easier to obtain for unsupervised learning since it can be "unlabeled" (i.e., it hasn't been labeled with a response)
- Sometimes useful as a preprocessing step for supervised learning
- Common techniques: clustering, principal components analysis

	continuous	categorical
supervised	**regression**	**classification**
unsupervised	**dimension reduction**	**clustering**

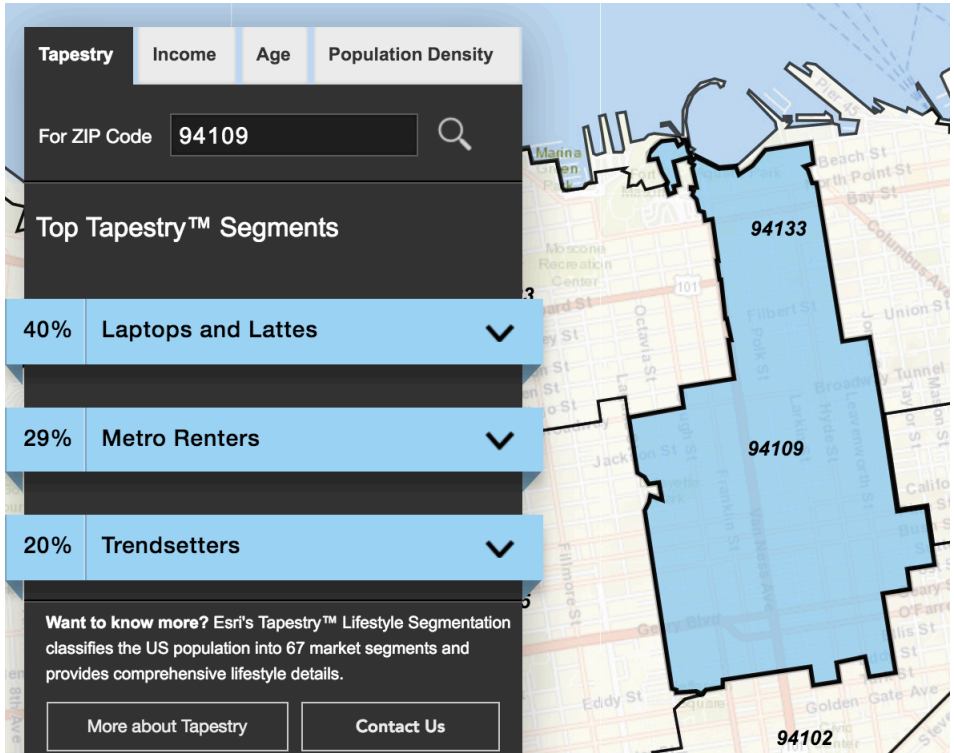
CLUSTERING EXAMPLE



Source: http://people.cs.pitt.edu/~milos/courses/cs2750-Spring03/lectures/class17.pdf

CLUSTERING EXAMPLE

- Classify US residential neighborhoods into 67 unique segments based on demographic and socioeconomic characteristics



Example of cluster: **Laptops and Lattes**

- We're affluent, well-educated singles and partner couples who love life in the big city
- Regular expenses include nice clothes, traveling, and treating ourselves to lattes at Starbucks or treatments at spas. Laptops, cell phones, and iPads are always on so we can stay connected.
- Leisure time is filled with visiting art galleries and museums; attending the theater, opera, and going to bars and clubs.

Source: http://www.esri.com/landing-pages/tapestry/

IV. SUMMARY

	continuous	categorical
supervised	**regression**	**classification**
unsupervised	**dimension reduction**	**clustering**

V. CLASSIFICATION WITH K-NEAREST NEIGHBORS

	continuous	categorical
supervised	**regression**	**classification**
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150 observations
(n = 150)

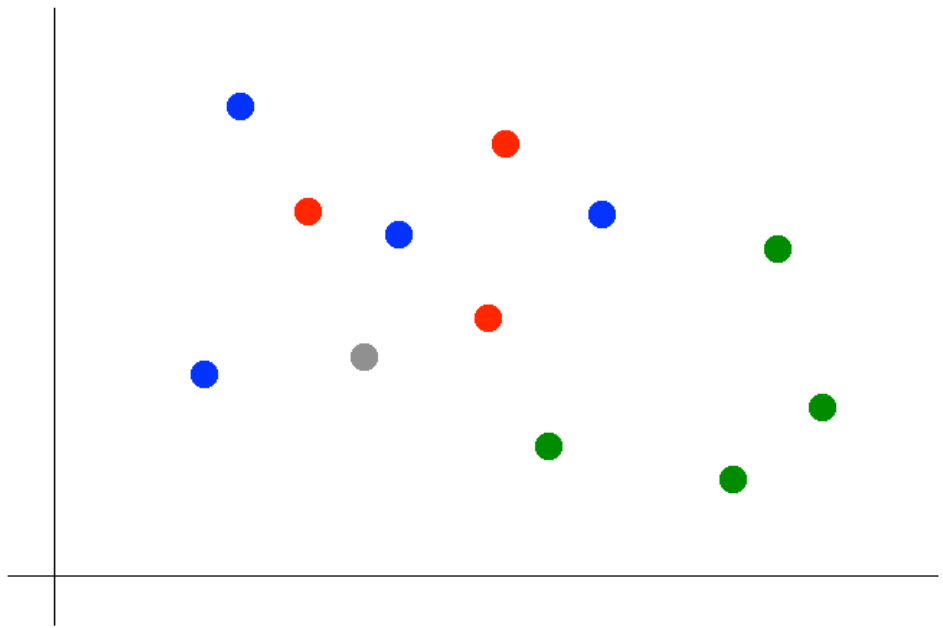
4 predictors (p = 4)

response

Suppose we want to predict the color of the gray dot.

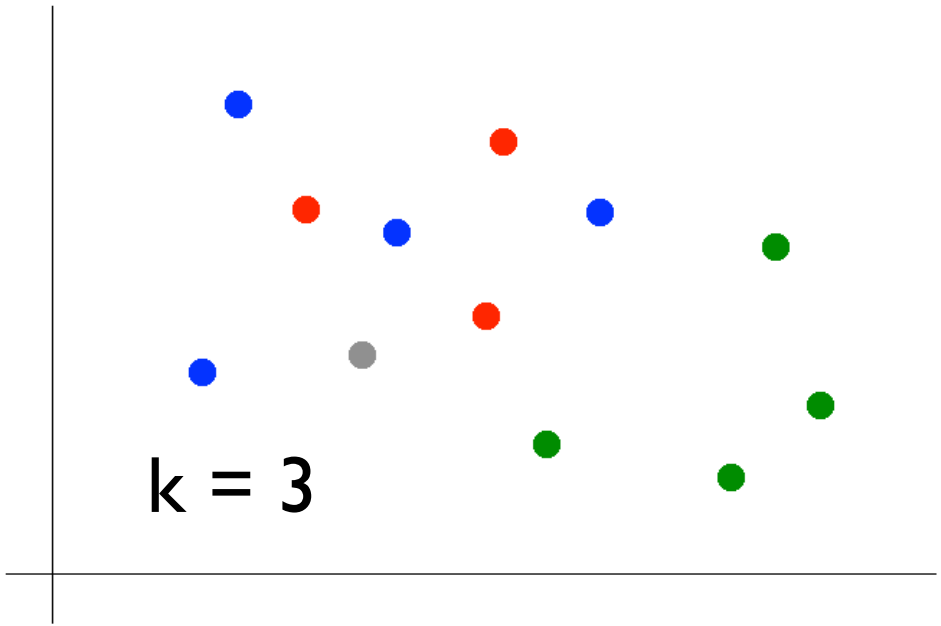
QUESTION:

What are the predictors?
What is the response?



Suppose we want to predict the color of the gray dot.

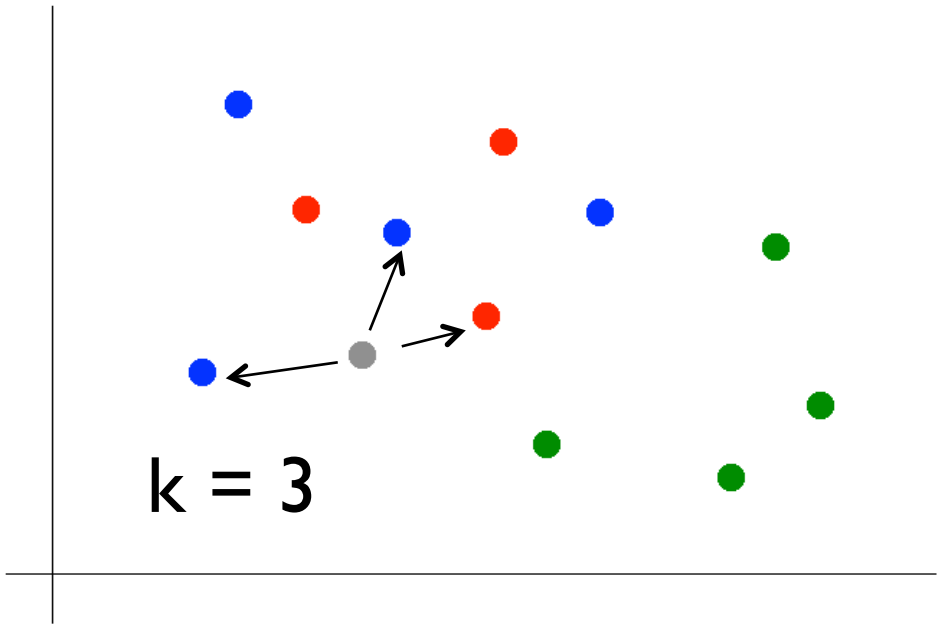
1) Pick a value for k.



Suppose we want to predict the color of the gray dot.

1) Pick a value for k.

2) Find colors of k nearest neighbors.

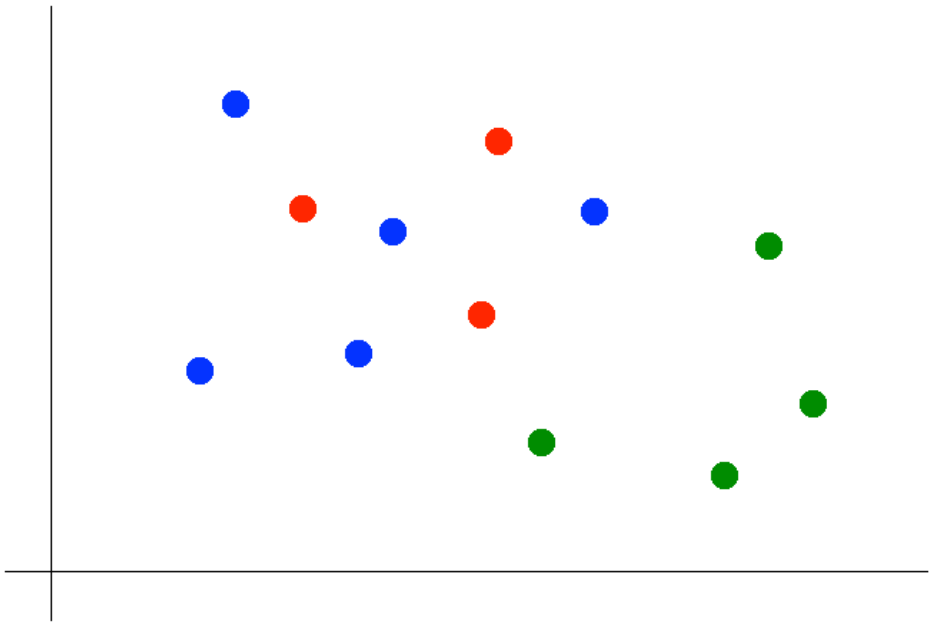


Suppose we want to predict the color of the gray dot.

1) Pick a value for k.

2) Find colors of k nearest neighbors.

3) Assign the most common color to the gray dot.



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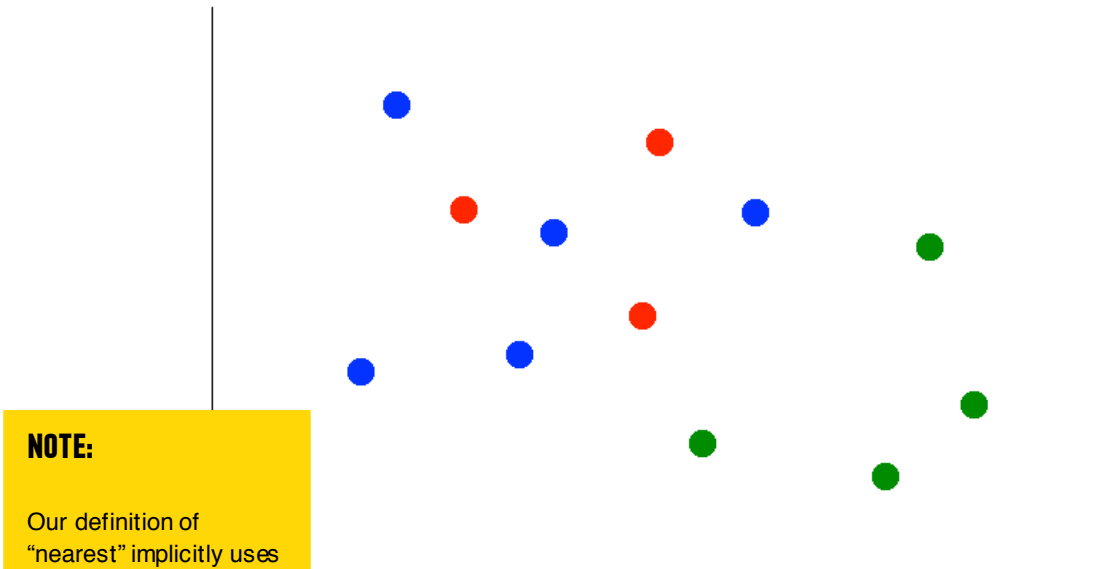

NOTE:

Our definition of "nearest" implicitly uses the *Euclidean distance function.*

Advantages of KNN:

- Simple to understand and explain
- Model training phase is fast
- Non-parametric (does not presume a "form" of the "decision boundary")

Disadvantages of KNN:

- Prediction phase can be slow when n is large
- Sensitive to irrelevant features

DATA SCIENCE