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

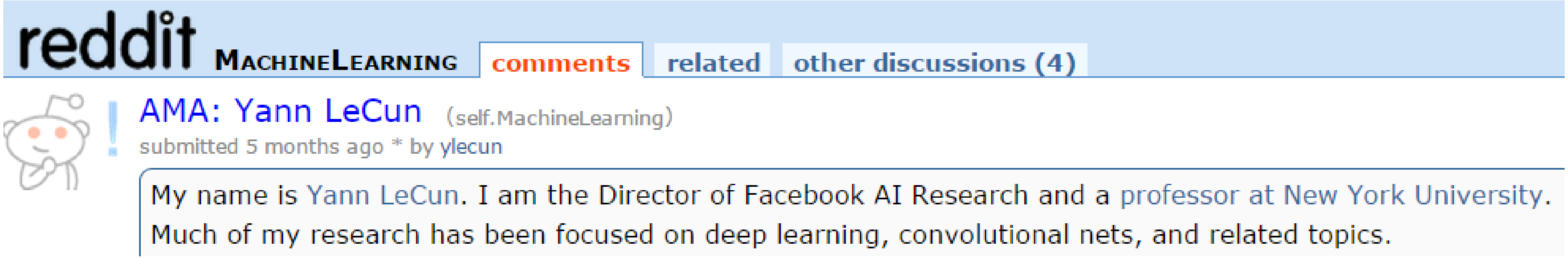
I. WHAT IS MACHINE LEARNING?

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

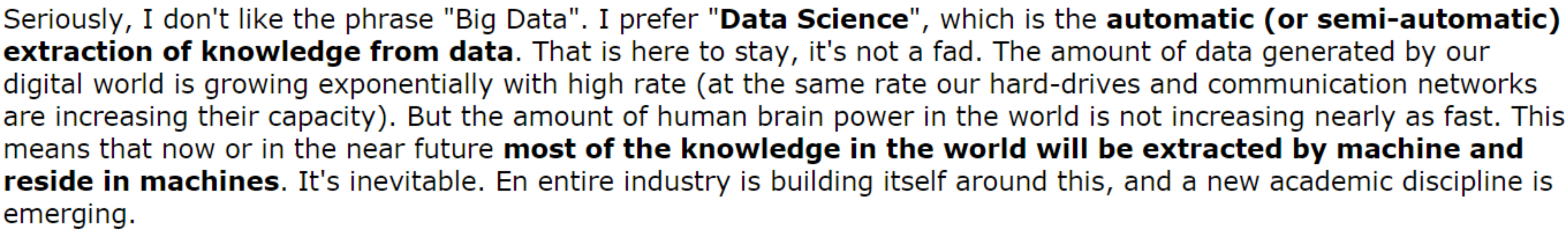
WHAT IS MACHINE LEARNING?



AMA: Yann LeCun (self.MachineLearning)

submitted 5 months ago * by ylecun

My name is Yann LeCun. I am the Director of Facebook AI Research and a professor at New York University. Much of my research has been focused on deep learning, convolutional nets, and related topics.



Seriously, I don't like the phrase "Big Data". I prefer "**Data Science**", which is the **automatic (or semi-automatic) extraction of knowledge from data**. That is here to stay, it's not a fad. The amount of data generated by our digital world is growing exponentially with high rate (at the same rate our hard-drives and communication networks are increasing their capacity). But the amount of human brain power in the world is not increasing nearly as fast. This means that now or in the near future **most of the knowledge in the world will be extracted by machine and reside in machines**. It's inevitable. En entire industry is building itself around this, and a new academic discipline is emerging.

Source: http://www.reddit.com/r/MachineLearning/comments/25lnbt/ama_yann_lecun

WHAT IS MACHINE LEARNING?

From Wikipedia:

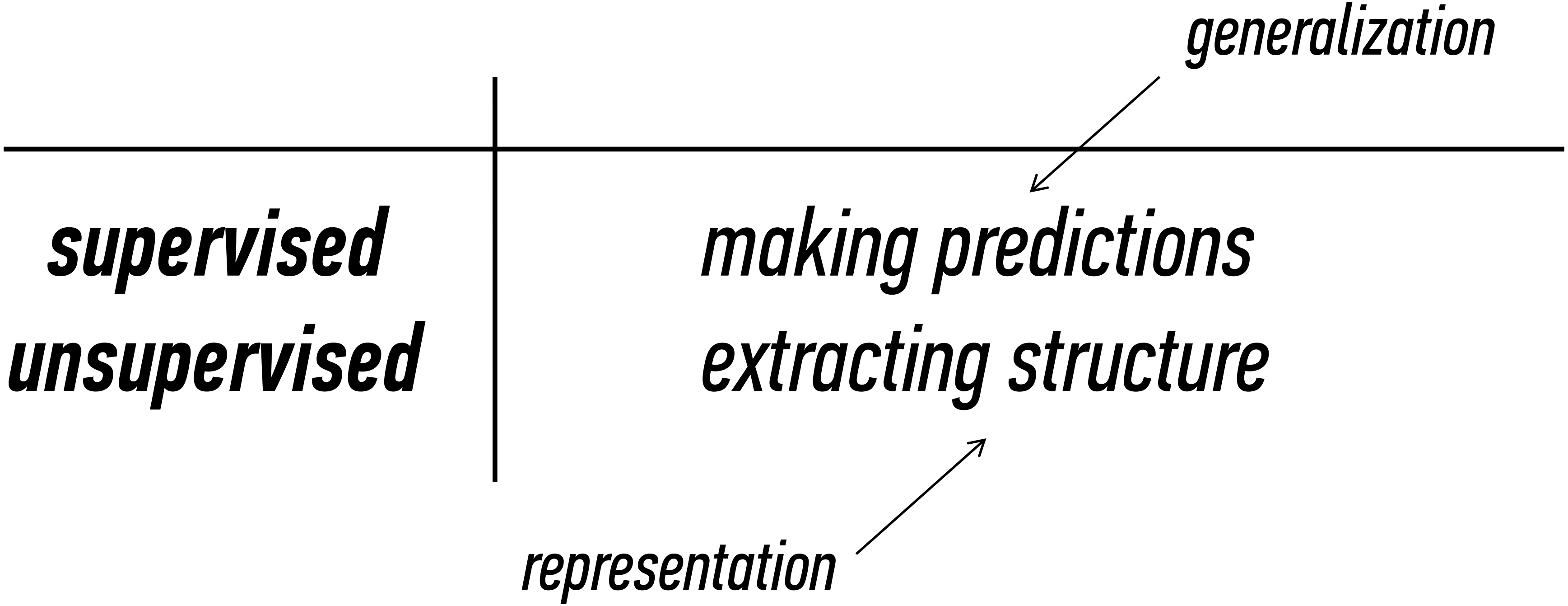
“Machine learning, a branch of artificial intelligence, is about the construction and study of systems that can *learn from data*.”

“The core of machine learning deals with *representation* and *generalization*…”

- *representation* – extracting structure from data
- *generalization* – making predictions from data

Source: http://en.wikipedia.org/wiki/Machine_learning

TYPES OF MACHINE LEARNING PROBLEMS



generalization

supervised — *making predictions*

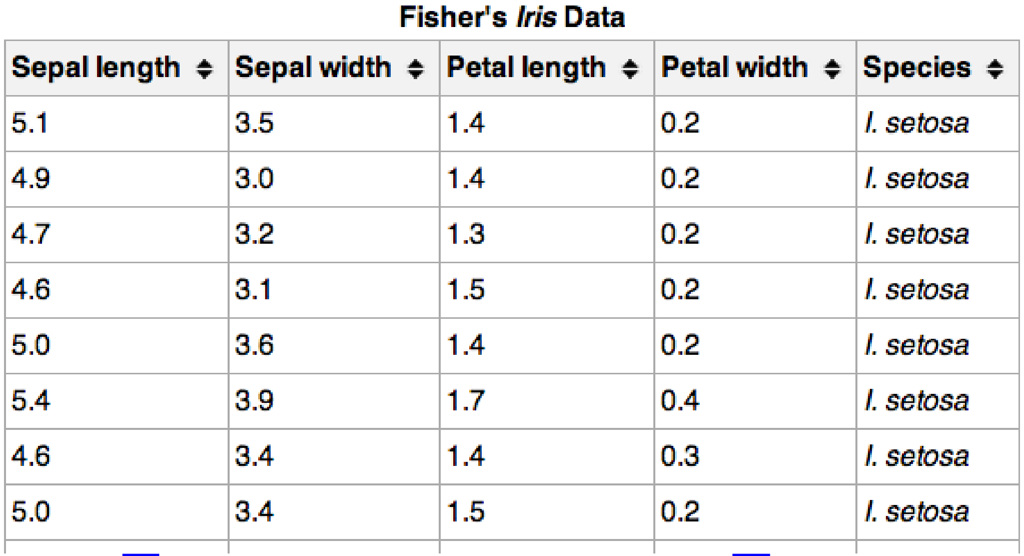
unsupervised — *extracting structure*

representation

II. SUPERVISED LEARNING

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

SUPERVISED LEARNING



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*
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4.6	3.4	1.4	0.3	*I. setosa*
5.0	3.4	1.5	0.2	*I. setosa*

150 observations
(n = 150)

4 predictors (p = 4)

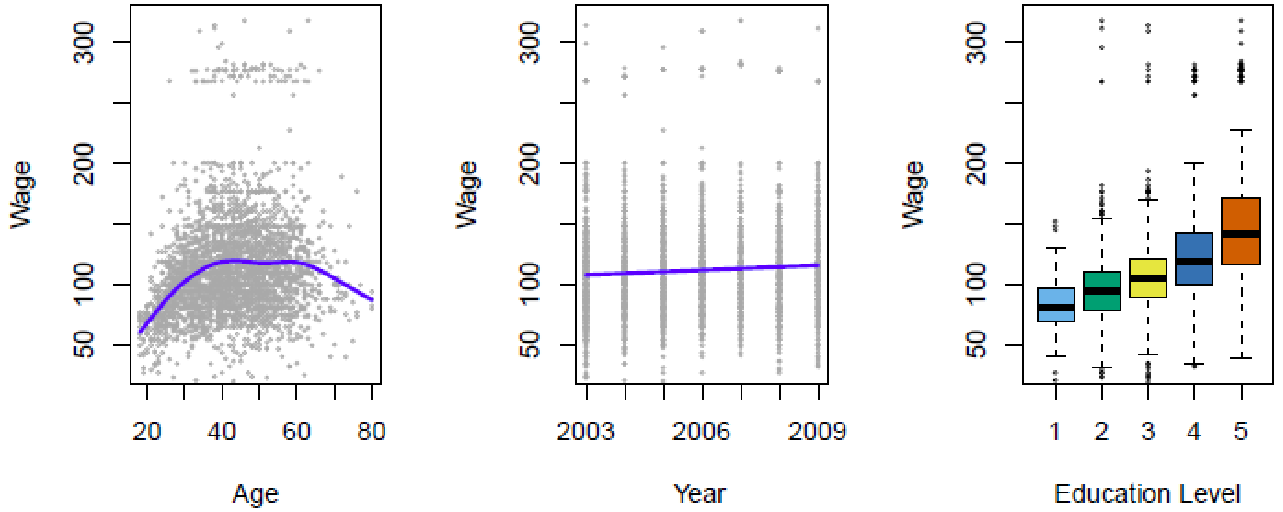
response

SUPERVISED LEARNING

- Objectives of Supervised Learning:
    - Accurately predict unseen test cases
    - Understand which predictors affect the response, and how
    - Assess the quality of our predictions

REGRESSION EXAMPLE

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

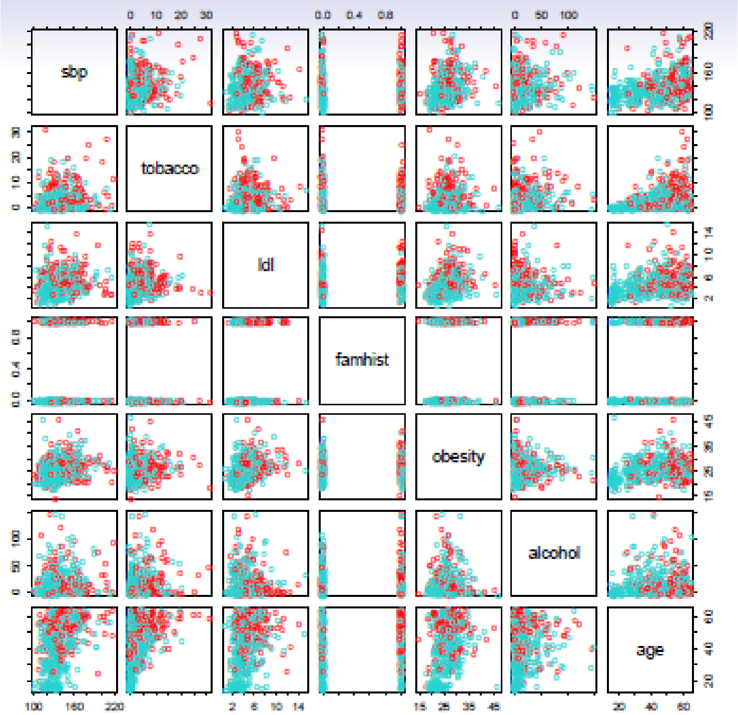


Income survey data for males from the central Atlantic region of the USA in 2009

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

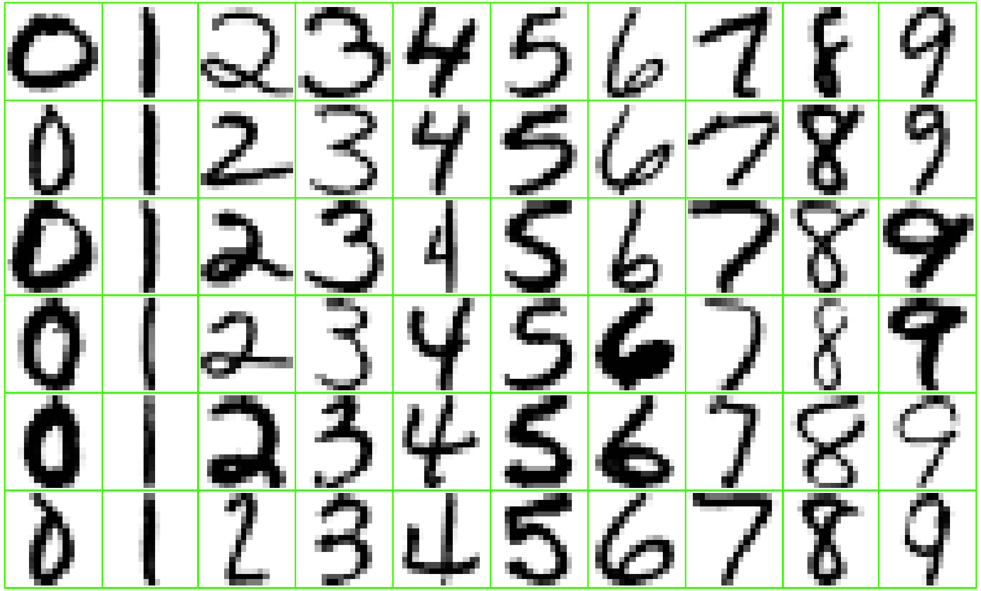


Case-control sample of men from South Africa
Red = heart disease
Blue = no heart disease

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

CLASSIFICATION EXAMPLE

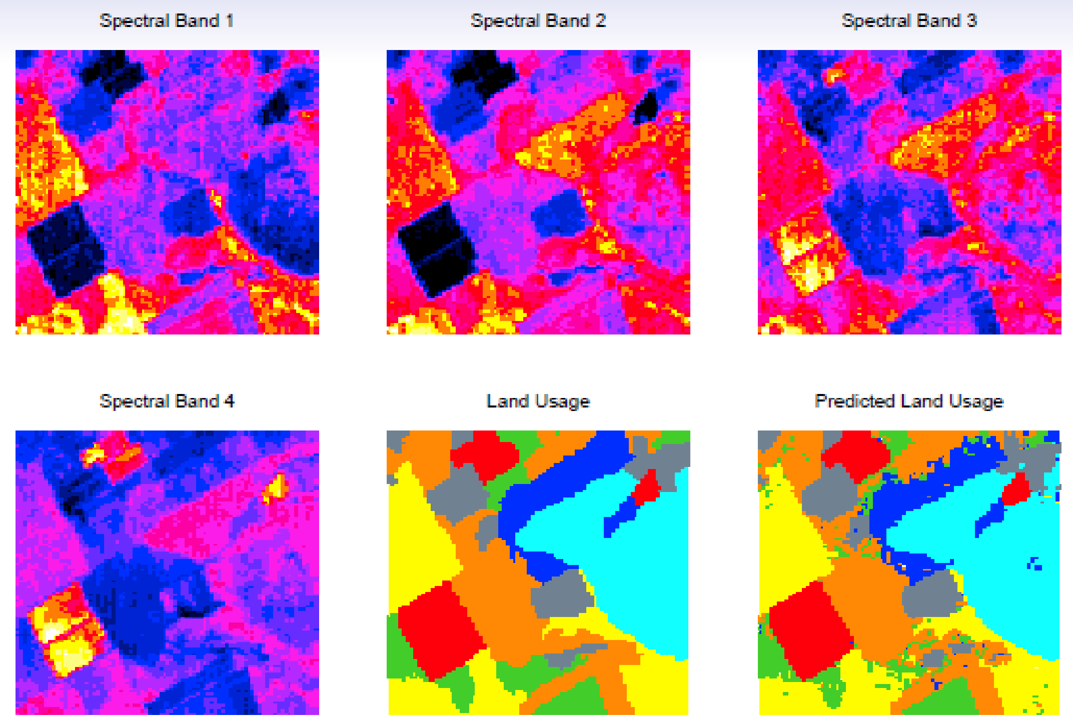
- Identify the numbers in a handwritten zip code



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

CLASSIFICATION EXAMPLE

- Classify the pixels in a LANDSAT image, by land usage



Satellite images of rural Australia

Land usage hand-labeled as one of six categories

Goal: Predict land usage using spectral bands at four frequencies

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

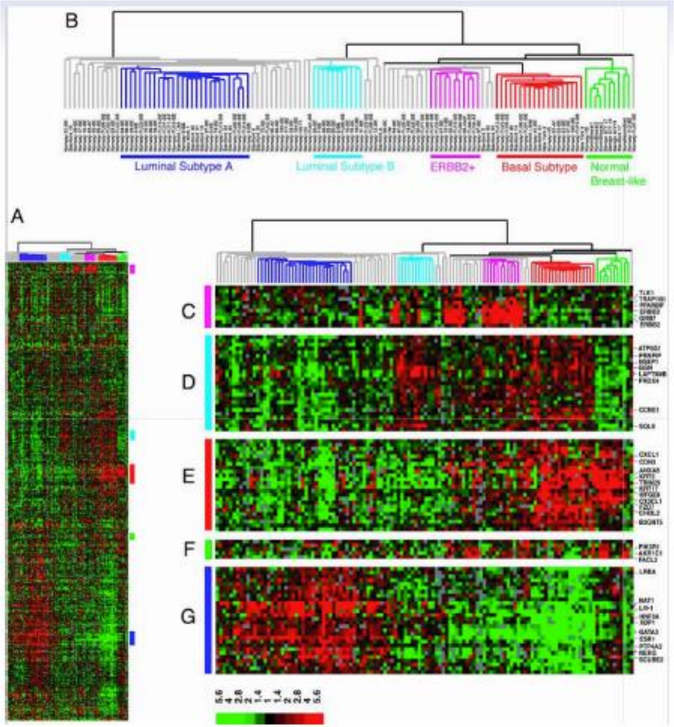
III. UNSUPERVISED LEARNING

UNSUPERVISED LEARNING

- No response variable y, just a set of predictors X
- Objective is more fuzzy:
  - Find groups of observations that behave similarly
  - Find predictors that behave similarly
  - Find linear combinations of features that explain most of 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

CLUSTERING EXAMPLE

- Classify a tissue sample into one of several cancer classes, based on a gene expression



Gene expression data

- Each row is a gene (p=8000)
- Each column is a woman with breast cancer (n=88)

Heatmap represents level of gene expression for each gene and each patient

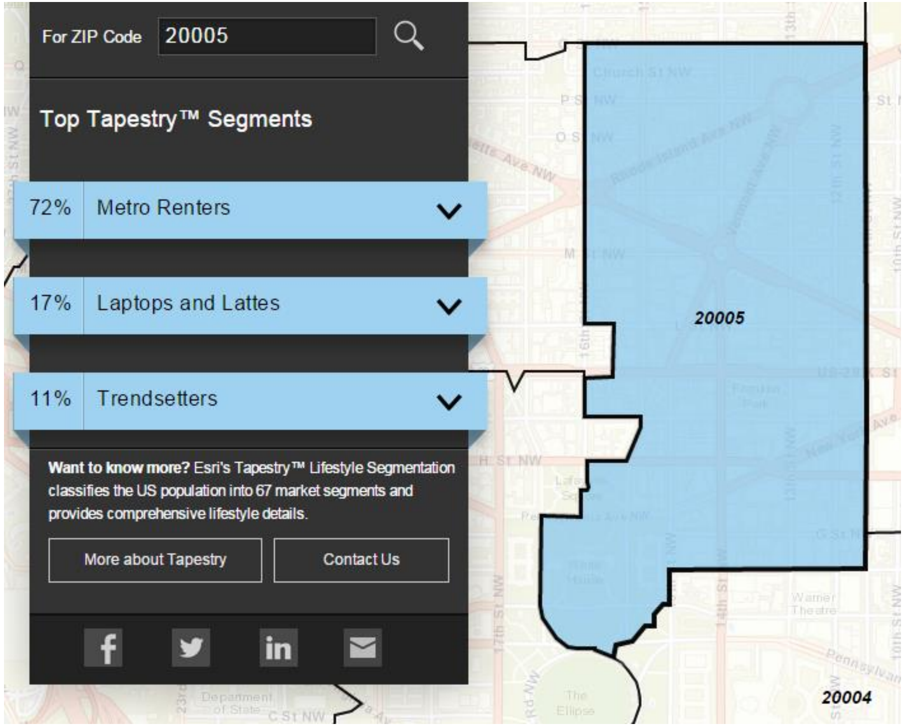
Goal: Locate subcategories of breast cancer showing different gene expressions

Technique: Hierarchical clustering applied to the columns, resulting in six sub-groups of patients

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

CLUSTERING EXAMPLE

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



For ZIP Code 20005

Top Tapestry™ Segments

72% Metro Renters

17% Laptops and Lattes

11% Trendsetters

Want to know more? Esri's Tapestry™ Lifestyle Segmentation classifies the US population into 67 market segments and provides comprehensive lifestyle details.

Metro Renters:

Young, mobile, educated, or still in school, we live alone or with a roommate in rented apartments or condos in the center of the city. Long hours and hard work don’t deter us; we’re willing to take risks to get to the top of our professions… We buy groceries at Whole Foods and Trader Joe’s and shop for clothes at Banana Republic, Nordstrom, and Gap. We practice yoga, go skiing, and attend Pilates sessions.

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

IV. SUMMARY

SUPERVISED VS. UNSUPERVISED LEARNING

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

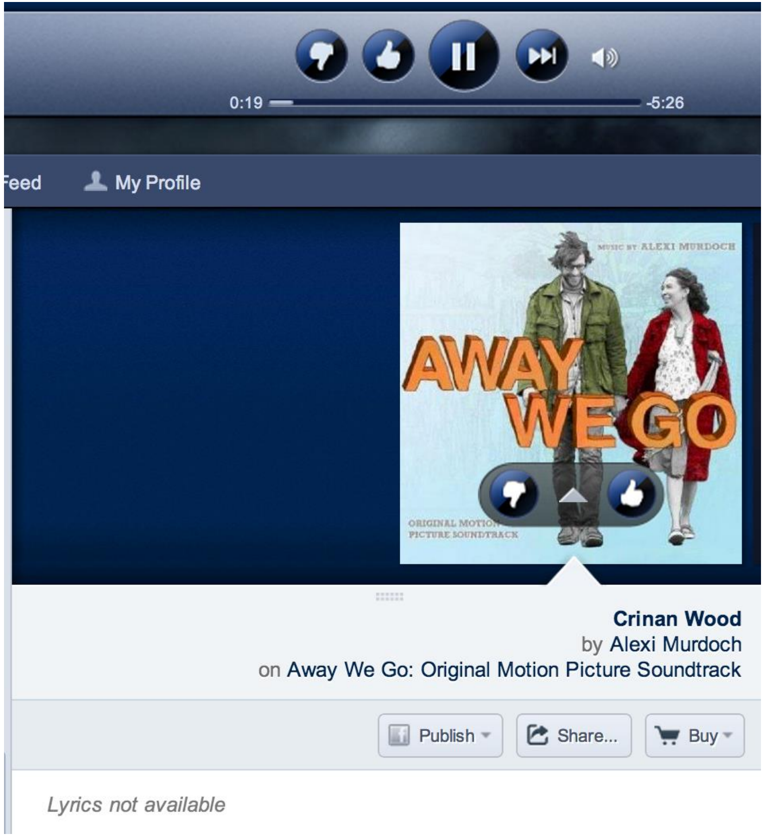
SUPERVISED VS. UNSUPERVISED LEARNING

What type of problem is this?

Music Recommendation
It could be either.

Supervised Learning:
Predict whether a user will
‘thumbs up’ a song

Unsupervised Learning:
Cluster songs based on
attributes and recommend songs
in the same group



Crinan Wood
by Alexi Murdoch
on Away We Go: Original Motion Picture Soundtrack

Lyrics not available

MACHINE LEARNING VS. STATISTICAL LEARNING

- Machine learning arose as a subfield of Artificial Intelligence
- Statistical learning arose as a subfield of Statistics
- There is much overlap:
  - Machine learning has a greater emphasis on large-scale applications and prediction accuracy
  - Statistical learning emphasizes models and their interpretability, and precision and uncertainty
- The distinction has become more and more blurred
- Machine learning has the upper-hand in marketing!

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

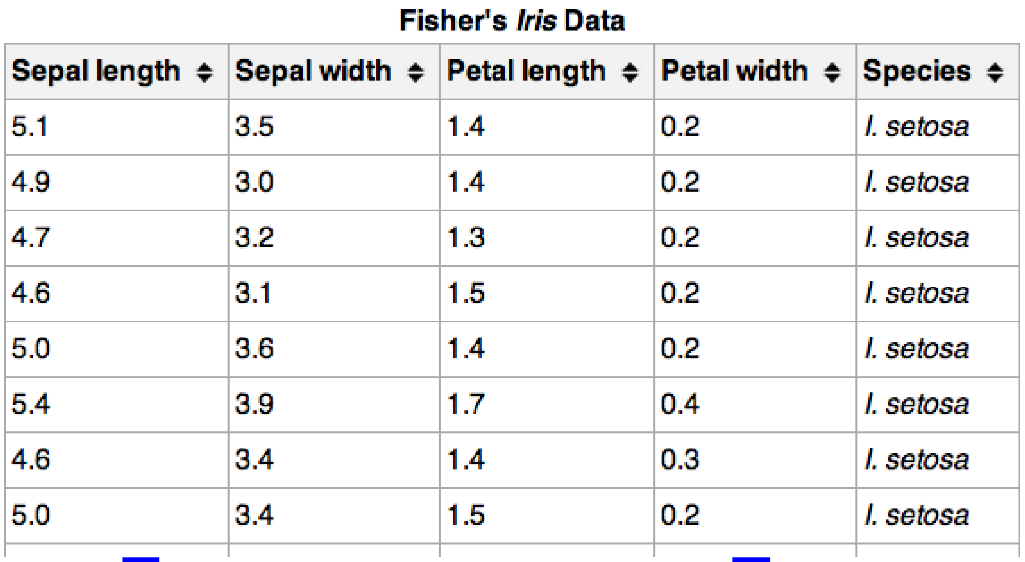
V. CLASSIFICATION WITH K-NEAREST NEIGHBORS

CLASSIFICATION PROBLEMS

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

CLASSIFICATION PROBLEMS

150 observations (n = 150)



Fisher's *Iris* Data

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4 predictors (p = 4)

response

CLASSIFICATION PROBLEMS

Q: How does a classification problem work?

A: Data in, predicted labels out.

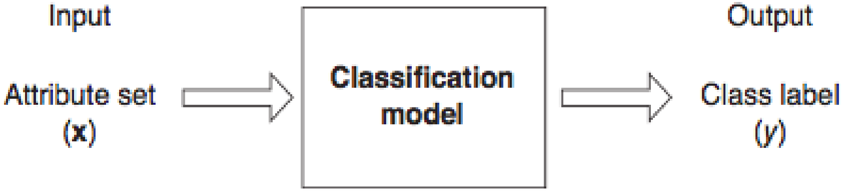


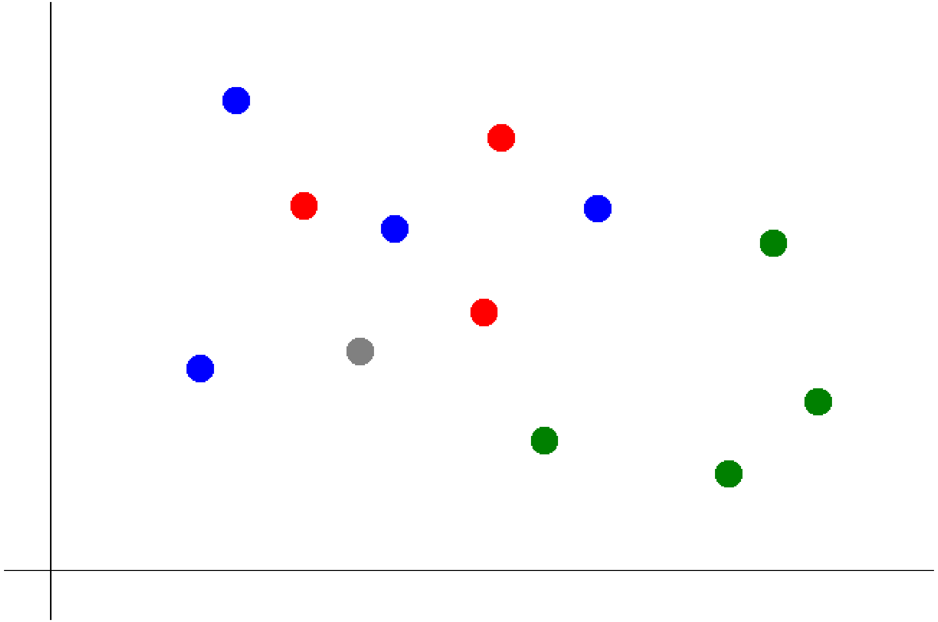
Figure 4.2. Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label y.

Source: http://www-users.cs.umn.edu/~kumar/dmbook/ch4.pdf

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

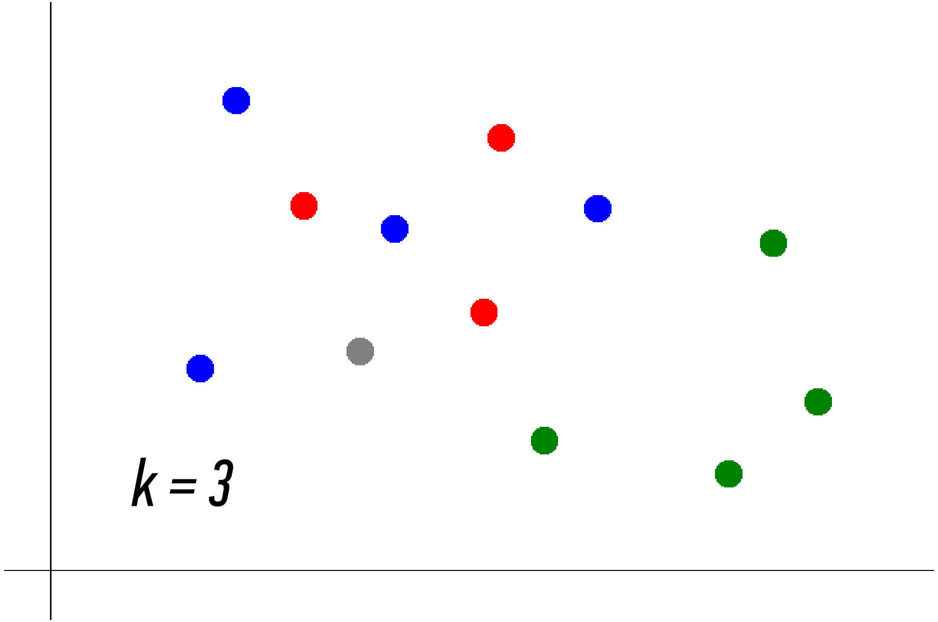
QUESTION:

What are the predictors?
What is the response?



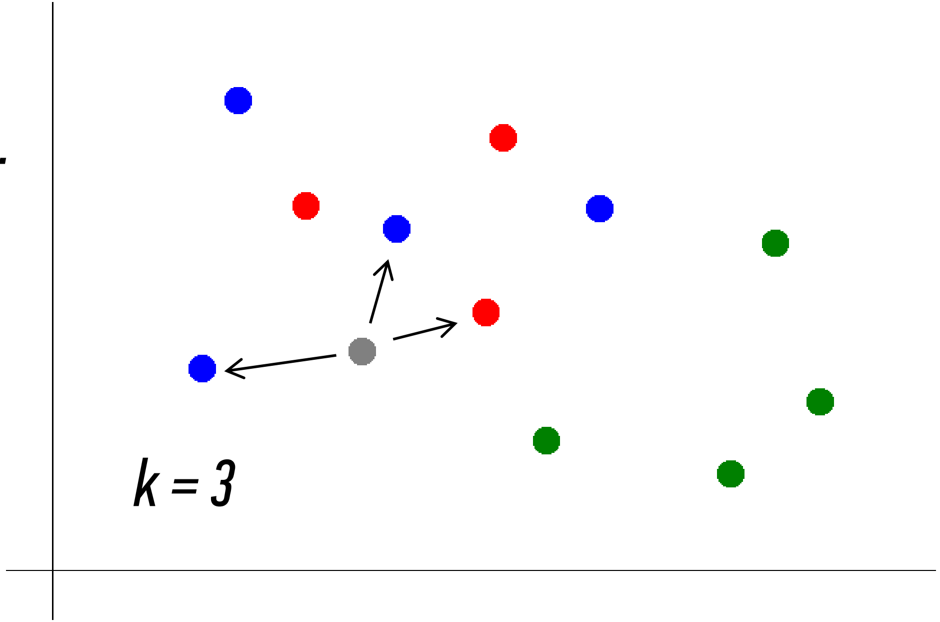
Suppose we want to predict the color of the gray dot.

1) *Pick a value for k.*



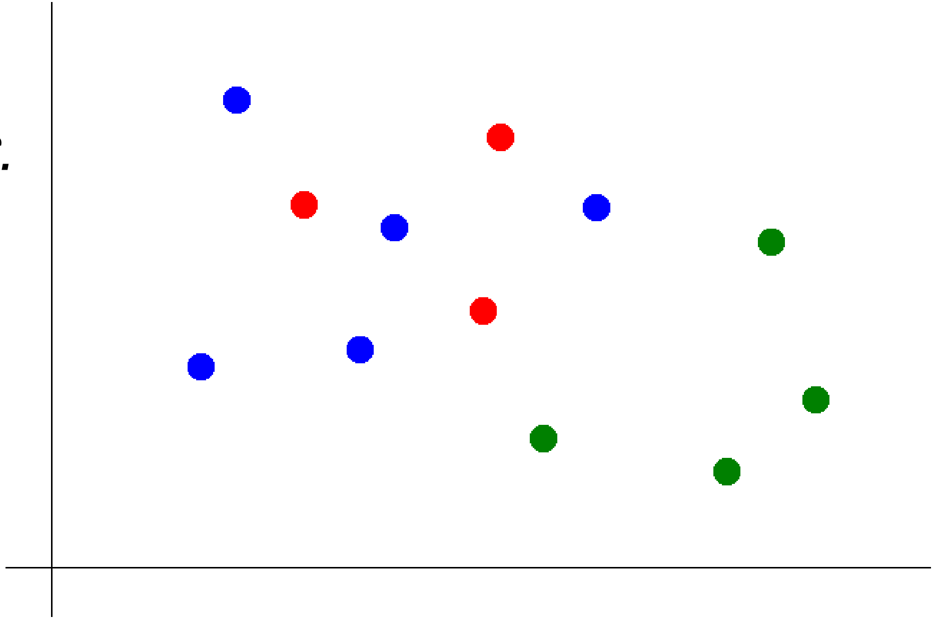
Suppose we want to predict the color of the gray dot.

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.*

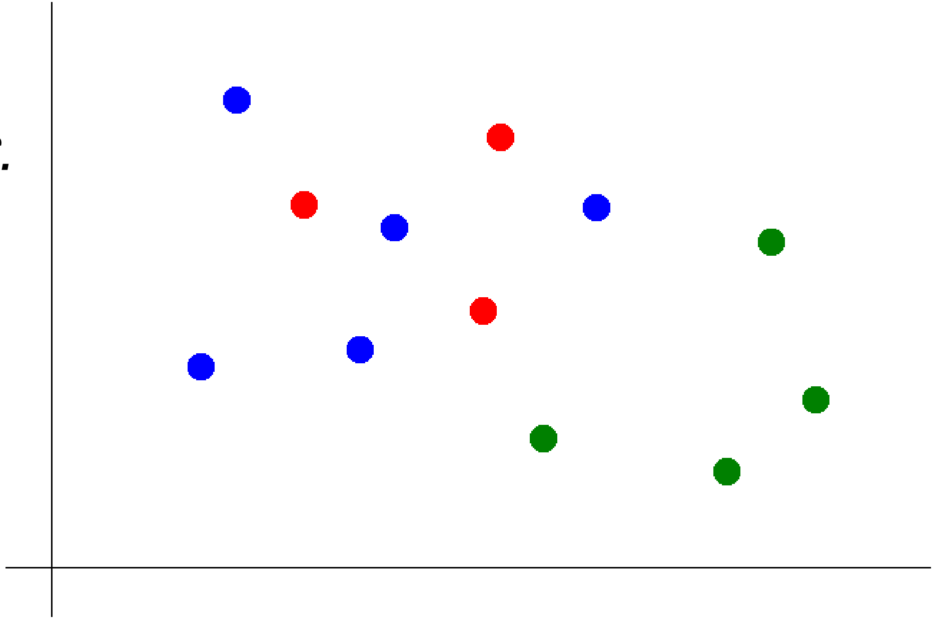


Suppose we want to predict the color of the gray dot.

1) *Pick a value for k.*
2) *Find colors of k nearest neighbors.*
3) *Assign the most common color to the gray dot.*

NOTE:

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



CLASSIFICATION WITH KNN

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
- Parametric methods will be better than KNN if the selected form is close to the “true” form
- Parametric methods tend to be better than KNN for small n and large p
- Does not provide coefficients or p-values
- Sensitive to irrelevant features
- Sensitive to unscaled data

DATA SCIENCE