

Intro to Machine Learning



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MSAN 601 - Linear Regression Analysis



Plan for this Lecture

- What is Machine Learning?
- Notation and the Learning Problem
- Supervised vs. Unsupervised Learning
- Motivation and Applications



What is Machine Learning?

- ① "[A] branch of artificial intelligence [that] concerns the construction and study of systems that can learn from data." - Wikipedia
- ② "A computer program is said to *learn* from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E ." - T. Mitchell
- ③ "Machine learning is a powerful artificial intelligence tool that enables us to crunch petabytes of data and make sense of a complicated world... It's solving previously unsolved problems." - Forbes
- ④ "Statistical learning refers to a vast set of tools for *understanding* data" - ISL book

A Major Component in Modern Data Science

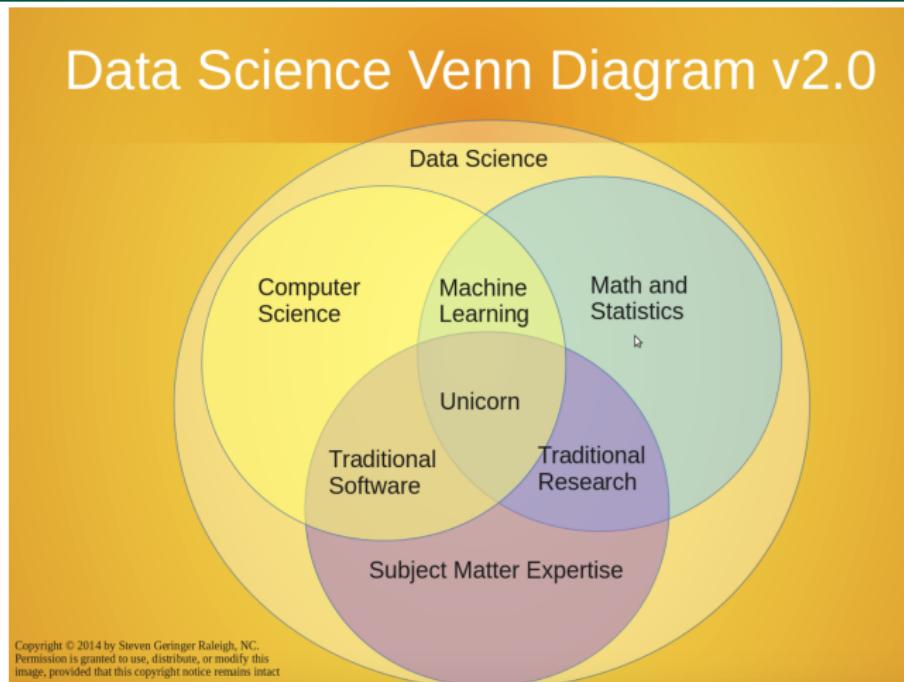


Figure: From www.datasciencecentral.com



Sample / Measurement Data

Experiment: Make p measurements on each of n samples.

Result: **Data matrix** / table X with n rows and p columns

- i th row of X is the vector of measurements on the i th sample
- j th column of X is the vector of values of the j th variable (measurement) across all samples

Different Perspectives on data:

- $n \times p$ matrix X
- n vectors of dimension $p \Leftrightarrow$ **samples**
- p vectors of dimension $n \Leftrightarrow$ **variables**



Notation

Data matrix:
$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix}$$

Rows of X : p variable measurements for each observation.

$$x_i = (x_{i1}, x_{i2}, \dots, x_{ip})^T$$

Columns of X : n observations of each variable.

$$\mathbf{x}_j = (x_{1j}, x_{2j}, \dots, x_{nj})^T$$

Can write X as: $X = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_p) = (x_1^T, x_2^T, \dots, x_n^T)^T$



Data Dimensionality

Old Paradigm: More samples than variables ($n >> p$)

- Number of samples moderate (10s or 100s)
- Number of variables small (1s or 10s)

High Dimensional Paradigm: More variables than samples ($p >> n$)

- Number of samples moderate or large (100s or 1Ks)
- Number of variables *very* large (10Ks or 1Ms)

Big Data Paradigm: Many samples and/or many variables

Source of data: high-throughput measurement technologies for microarray analysis, e-commerce data, click-through rates, etc.



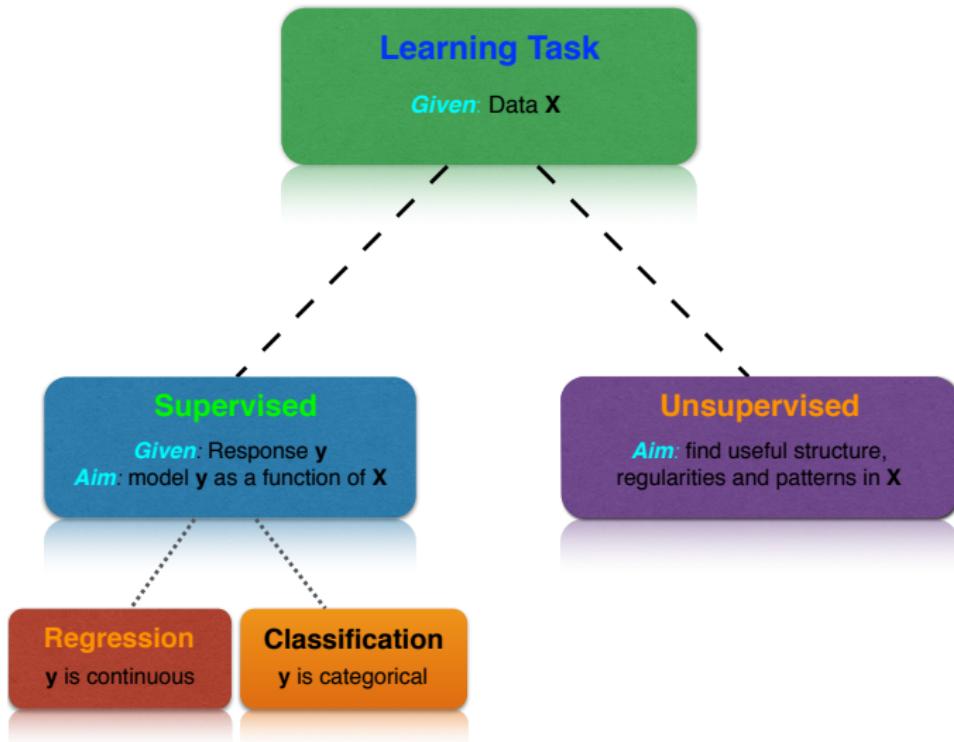
Response / Label

A **response** is an externally defined quantity of interest whose value is measured for each sample.

Notation: y_i denotes the response for the i th sample (or the i th row of the data matrix X). Vector of responses: $y = (y_1, \dots, y_n)^T$

Note: when y_i is categorical, e.g. binary, it is referred to as a **label**.

Machine Learning: High-level Taxonomy





Supervised vs. Unsupervised Learning

Supervised Learning: Data matrix X and response y . In this case, y supervises the model and knowledge that is gained.

Goal: *model the response as a function of the sample.* That is, find the function f that represents the relationship between X and y :

$$y = f(X) + \epsilon$$

Here, ϵ is the error associated with the model.

- **Classification:** y takes discrete values
- **Regression:** y takes continuous values (e.g. linear regression)

Challenges: model selection and model assessment



Supervised vs. Unsupervised Learning

Unsupervised Learning: Data matrix X , but no response to supervise any model!

Goal: identify structure, regularities, and patterns in X

- **Data mining:** finding "special" subsets of a large data set
- **Clustering:** finding patterns in X through partitioning the data

Challenges:

- what structure are we looking for?
- how do we evaluate a method?
- theoretical properties?



- ➊ Ask what kind of data? Supervised or unsupervised problem?
What question are we trying to answer?
- ➋ Prepare / clean data: imputation, outlier removal, etc.
- ➌ Explore data → hypotheses about X and/or model f
- ➍ Apply models and algorithms to answer question
- ➎ Validation of approach



Example: Housing data

Samples: houses *Response:* cost of house

Variables: features of each house

- size (sq. ft.), distance to public transportation
- # bedrooms, # bathrooms
- attached garage? good school district?

Goals:

- *Prediction:* Find function $f(\text{variables})$ to accurately predict the cost of a house that is not in the data set.
- *Variable selection:* Identify a (small) set of important variables that can be used to predict housing cost.



Example: Medical tests

Samples: patients *Response*: disease state (0 or 1)

Variables: results of diagnostic tests

- blood pressure (cystolic, diastolic)
- temperature
- heart rate
- age
- do any relatives have disease?

Goals: predict disease state of new patient (personalized medicine),
identify variables needed for accurate prediction.

Fisher's Iris Data



Figure: Iris setosa. Courtesy of www.wikipedia.org

- Four attributes are measured for $n = 150$ flowers
 - 50 samples each of *Iris Setosa*, *Iris Virginica*, *Iris Versicolor*
 - $p = 4$ measurements: length and width of sepals and petals



Fisher's Iris Data: Scatterplots

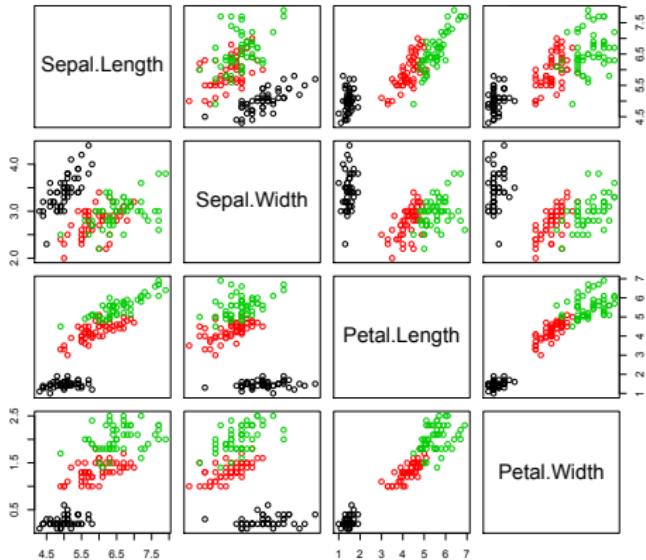


Figure: Pairwise scatterplot of Iris measurements. Colors: *Setosa*, *Virginica*, *Versicolor*.



Fisher's Iris Data: PCA and Clustering

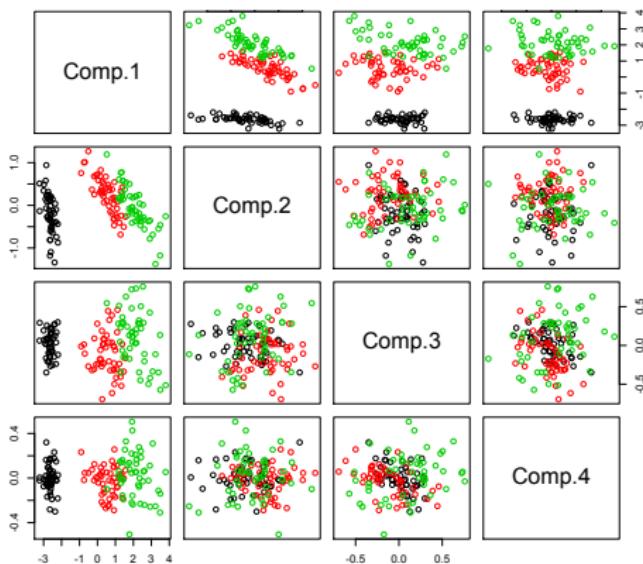


Figure: Pairwise scatterplot of principal components of Iris measurements.

Colors: *Setosa*, *Virginica*, *Versicolor*.



Gene Expression Arrays and Clustering

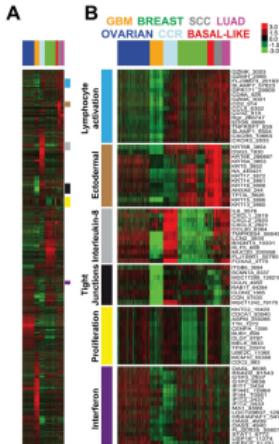


Figure: Gene expression array from *Nature* article

- **Samples:** subjects **Variables:** genes
- **Goal:** cluster subjects according to gene expression to identify relationship among cancer subtypes and genes