Week 4

# Machine Learning and Big Data - DATA622

CUNY School of Professional Studies

# Textbooks

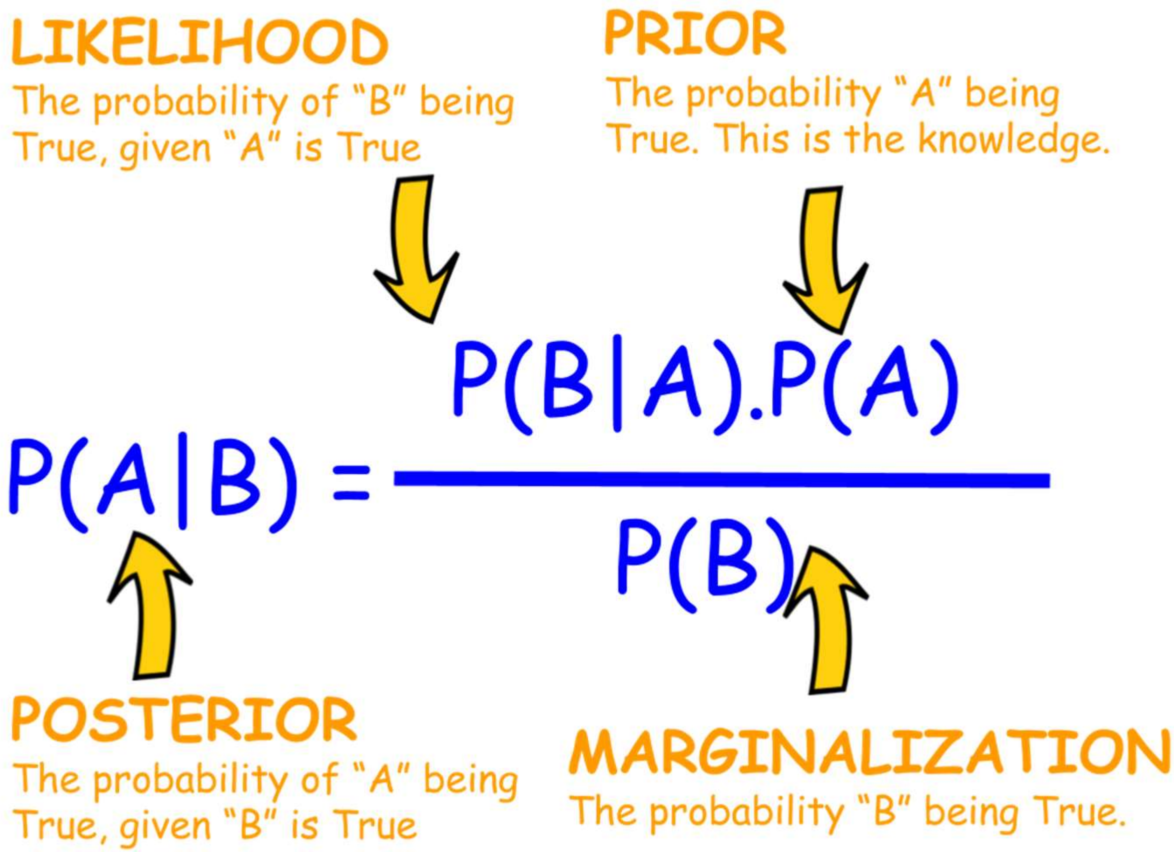
- We are introducing 2 new textbooks to supplement our primary textbook (PMLiR)
- The Elements of Statistical Learning
  - In the notes, "ESL" refers to the book "The Elements of Statistical Learning“
  - You should have from the prerequisite courses.
  - You can buy it here
  - Book is available for free as a PDF here (author's site here)
- An Introduction to Statistical Learning
  - In the notes, "ISLR" refers to the book "An Introduction to Statistical Learning“
  - You should have from the prerequisite courses.
  - You can buy it here
  - Book is available for free as a PDF here (author's site here)

# Naïve Bayes

**Classification using Bayes Theorem.**

School of Professional Studies

# Bayes Theorem




Source: Guide to Intelligent Data Science, Berthold et al

# Naïve Bayes: Example

Predicting whether you should play golf

| Outlook | Temp | Humidity | Windy | Play Golf |
|---|---|---|---|---|
| Rainy | Hot | High | False | No |
| Rainy | Hot | High | True | No |
| Overcast | Hot | High | False | Yes |
| Sunny | Mild | High | False | Yes |
| Sunny | Cool | Normal | False | Yes |
| Sunny | Cool | Normal | True | No |
| Overcast | Cool | Normal | True | Yes |
| Rainy | Mild | High | False | No |
| Rainy | Cool | Normal | False | Yes |
| Sunny | Mild | Normal | False | Yes |
| Rainy | Mild | Normal | True | Yes |
| Overcast | Mild | High | True | Yes |
| Overcast | Hot | Normal | False | Yes |
| Sunny | Mild | High | True | No |

Source: Saed Sayad

# Naïve Bayes: Example

Let's look at the data:

| Frequency Table | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| Outlook | Sunny | 3 | 2 |
| | Overcast | 4 | 0 |
| | Rainy | 2 | 3 |

$$P(x \mid c) = P(Sunny \mid Yes) = 3/9 = 0.33$$

| Likelihood Table | | Play Golf | | |
|---|---|---|---|---|
| | | Yes | No | |
| Outlook | Sunny | 3/9 | 2/5 | 5/14 |
| | Overcast | 4/9 | 0/5 | 4/14 |
| | Rainy | 2/9 | 3/5 | 5/14 |
| | | 9/14 | 5/14 | |

$$P(x) = P(Sunny) = 5/14 = 0.36$$

$$P(c) = P(Yes) = 9/14 = 0.64$$

Posterior Probability: $P(c \mid x) = P(Yes \mid Sunny) = 0.33 \times 0.64 \div 0.36 = 0.60$

Source: Saed Sayad



CUNY School of Professional Studies

# Naïve Bayes: Example

Frequency Table

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Outlook** | Sunny | 3 | 2 |
| | Overcast | 4 | 0 |
| | Rainy | 2 | 3 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Humidity** | High | 3 | 4 |
| | Normal | 6 | 1 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Temp.** | Hot | 2 | 2 |
| | Mild | 4 | 2 |
| | Cool | 3 | 1 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Windy** | False | 6 | 2 |
| | True | 3 | 3 |

Likelihood Table

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Outlook** | Sunny | 3/9 | 2/5 |
| | Overcast | 4/9 | 0/5 |
| | Rainy | 2/9 | 3/5 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Humidity** | High | 3/9 | 4/5 |
| | Normal | 6/9 | 1/5 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Temp.** | Hot | 2/9 | 2/5 |
| | Mild | 4/9 | 2/5 |
| | Cool | 3/9 | 1/5 |

| | | Play Golf | |
|---|---|---|---|
| | | Yes | No |
| **Windy** | False | 6/9 | 2/5 |
| | True | 3/9 | 3/5 |

Source: Saed Sayad

# Naïve Bayes: Example

Will I play golf in the following example?

| Outlook | Temp | Humidity | Windy | Play |
|---|---|---|---|---|
| Rainy | Cool | High | True | ? |

$$P(Yes \mid X) = P(Rainy \mid Yes) \times P(Cool \mid Yes) \times P(High \mid Yes) \times P(True \mid Yes) \times P(Yes)$$

$$P(Yes \mid X) = 2/9 \times 3/9 \times 3/9 \times 3/9 \times 9/14 = 0.00529 \rightarrow 0.2 = \frac{0.00529}{0.02057 + 0.00529}$$

$$P(No \mid X) = P(Rainy \mid No) \times P(Cool \mid No) \times P(High \mid No) \times P(True \mid No) \times P(No)$$

$$P(No \mid X) = 3/5 \times 1/5 \times 4/5 \times 3/5 \times 5/14 = 0.02057 \rightarrow 0.8 = \frac{0.02057}{0.02057 + 0.00529}$$

Source: Saed Sayad

# Naïve Bayes: Strengths and Weaknesses

- Strengths:
  - Simplicity and computational efficiency.
  - It does a great job handling categorical features directly, without any preprocessing.
  - Outperforms more sophisticated classifiers when working with a large number of predictors
  - It handles noisy and missing data pretty well.
- Weaknesses:
  - Needs a sizable amount of data
  - It is naïve: assumption of independence between inputs & classes
  - Doesn’t work well for datasets with a large number of continuous features
  - It assumes that all features within a class are not only independent but are equally important

PC1

Source: Guide to Intelligent Data Science, Berthold et al





9

# Naïve Bayes: Use-cases

- Spam detection
- Sentiment analysis (news articles)
- Document classification
- Many classification problems…

PC1

Source: Guide to Intelligent Data Science, Berthold et al



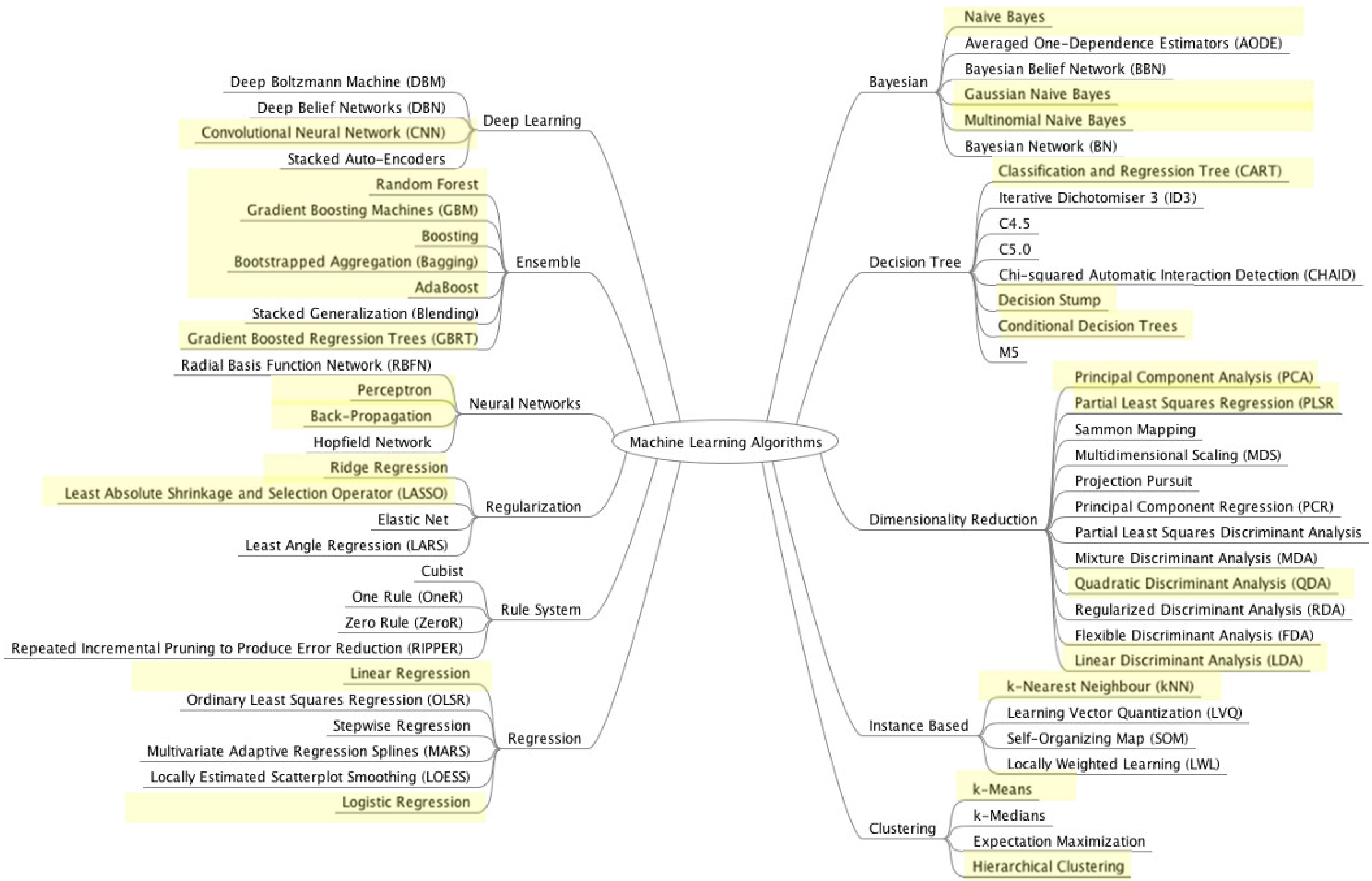


10

# Landscape of algorithms

**We will cover many of the algorithms listed**

CUNY School of Professional Studies



Machine Learning Algorithms
Deep Learning
Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders
Ensemble
Random Forest
Gradient Boosting Machines (GBM)
Boosting
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (Blending)
Gradient Boosted Regression Trees (GBRT)
Neural Networks
Radial Basis Function Network (RBFN)
Perceptron
Back-Propagation
Hopfield Network
Regularization
Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least Angle Regression (LARS)
Rule System
Cubist
One Rule (OneR)
Zero Rule (ZeroR)
Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
Regression
Linear Regression
Ordinary Least Squares Regression (OLSR)
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Logistic Regression
Bayesian
Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Gaussian Naive Bayes
Multinomial Naive Bayes
Bayesian Network (BN)
Decision Tree
Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5
C5.0
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
Conditional Decision Trees
M5
Dimensionality Reduction
Principal Component Analysis (PCA)
Partial Least Squares Regression (PLSR
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Principal Component Regression (PCR)
Partial Least Squares Discriminant Analysis
Mixture Discriminant Analysis (MDA)
Quadratic Discriminant Analysis (QDA)
Regularized Discriminant Analysis (RDA)
Flexible Discriminant Analysis (FDA)
Linear Discriminant Analysis (LDA)
Instance Based
k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)
Clustering
k-Means
k-Medians
Expectation Maximization
Hierarchical Clustering

# No free lunch Theorem

**Bias-free learning is futile**

CUNY School of Professional Studies

# TANSTAAFL

- There ain't no such thing as a free lunch
- No-Free-Lunch Theorem states:
  - No single classifier works the best for all possible problems
  - We need to make assumptions to generalize (we need bias)

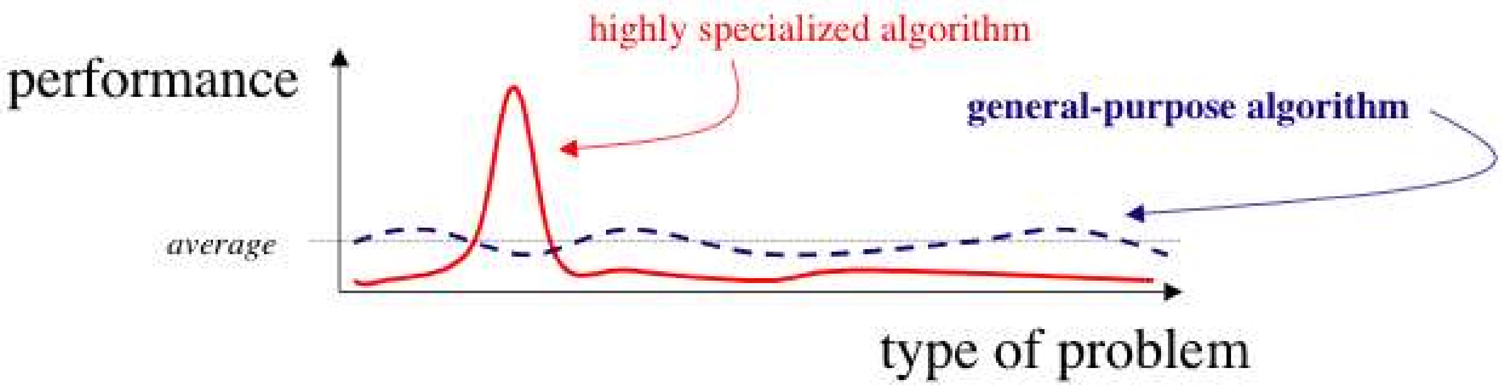

Source: https://medium.com/@LeonFedden/the-no-free-lunch-theorem-62ae2c3ed10c

# TANSTAAFL

Theorem:

*The average performance of any pair of algorithms across all possible problems is identical.*

If an algorithm achieves superior results on some problems, then it must pay with inferiority on the other problems




Source: https://medium.com/@LeonFedden/the-no-free-lunch-theorem-62ae2c3ed10c