



COMP 2211 Exploring Artificial Intelligence
Practice Problems: Naive Bayes, KNN, K-Means, Perceptron, and MLP
Dr. Desmond Tsoi

Department of Computer Science & Engineering
HKUST, Hong Kong SAR, China



Naïve Bayes 1

- Given the following:
 - A doctor knows cold causes fever 50% of the time.
 - The probability of any patient having a cold is $1/50000$.
 - The probability of any patient having a fever is $1/20$.
- If a patient has a fever, what is the probability he/she has a cold?

Naïve Bayes 2

- Given the following dataset:

| Animal | Give Birth | Can Fly | Live in Water | Have Legs | Class |
|---------------|------------|---------|---------------|-----------|-------------|
| Human | Yes | No | No | Yes | Mammals |
| Python | No | No | No | No | Non-mammals |
| Salmon | No | No | Yes | No | Non-mammals |
| Whale | Yes | No | Yes | No | Mammals |
| Frog | No | No | Sometimes | Yes | Non-mammals |
| Komodo | No | No | No | Yes | Non-mammals |
| Bat | Yes | Yes | No | Yes | Mammals |
| Pigeon | No | Yes | No | Yes | Non-mammals |
| Cat | Yes | No | No | Yes | Mammals |
| Leopard Shark | Yes | No | Yes | No | Non-mammals |
| Turtle | No | No | Sometimes | Yes | Non-mammals |
| Penguin | No | No | Sometimes | Yes | Non-mammals |
| Porcupine | Yes | No | No | Yes | Mammals |
| Eel | No | No | Yes | No | Non-mammals |
| Salamander | No | No | Sometimes | Yes | Non-mammals |
| Gila Monster | No | No | No | Yes | Non-mammals |
| Platypus | No | No | No | Yes | Mammals |
| Owl | No | Yes | No | Yes | Non-mammals |
| Dolphin | Yes | No | Yes | No | Mammals |
| Eagle | No | Yes | No | Yes | Non-mammals |

- Is the animal with the attribute values (Give Birth = Yes, Can Fly = No, Live in Water = Yes, Have Legs = No) a mammal?

K-Nearest Neighbors

- Given a dataset of the speed and agility ratings for 20 athletes and whether they were drafted by a professional team.

| ID | Speed | Agility | Draft |
|----|-------|---------|-------|
| 1 | 2.50 | 6.00 | No |
| 2 | 3.75 | 8.00 | No |
| 3 | 2.25 | 5.50 | No |
| 4 | 3.25 | 8.25 | No |
| 5 | 2.75 | 7.50 | No |
| 6 | 4.50 | 5.00 | No |
| 7 | 3.50 | 5.25 | No |
| 8 | 3.00 | 3.25 | No |
| 9 | 4.00 | 4.00 | No |
| 10 | 4.25 | 3.75 | No |

| ID | Speed | Agility | Draft |
|----|-------|---------|-------|
| 11 | 2.00 | 2.00 | No |
| 12 | 5.00 | 2.50 | No |
| 13 | 8.25 | 8.50 | No |
| 14 | 5.75 | 8.75 | Yes |
| 15 | 4.75 | 6.25 | Yes |
| 16 | 5.50 | 6.75 | Yes |
| 17 | 5.25 | 9.50 | Yes |
| 18 | 7.00 | 4.25 | Yes |
| 19 | 7.50 | 8.00 | Yes |
| 20 | 7.25 | 5.75 | Yes |

- Suppose an athlete with speed = 6.75 and agility = 3.00, classify him into one of the two classes (Draft = Yes, Draft = No) using KNN with Euclidean distance metric and $K = 3$.

K-Means Clustering

- Consider 4 data points A, B, C and D as follows:

| | x_1 | x_2 |
|---|-------|-------|
| A | 2 | 3 |
| B | 6 | 1 |
| C | 1 | 2 |
| D | 3 | 0 |

- Form two clusters for the above datapoints by picking two initial centroids, $c_1 = (4, 2)$ and $c_2 = (2, 1)$.
- Assume Euclidean distance is used as the metric. Show all the calculation steps and the final cluster assignments for the 4 data points.

Perceptron

- Suppose we have the following data points:
 - $\mathbf{x} = (1, -2)$, $T = 1$
 - $\mathbf{x} = (0, -1)$, $T = 0$
- Train a perceptron with the initial weights ($w_1 = 0$, $w_2 = -2$), zero bias, learning rate $\eta = 0.5$, and a unit-step activation function:

$$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

until it converges.

- Show all the steps, i.e. the change of weights and bias in each iteration.

Multilayer Perceptron

- Given a multilayer perceptron with two inputs x_1 , x_2 , one hidden unit and one output unit. Both the hidden unit and output use sigmoid activation function. Altogether, the network has 3 weights, w_1 , w_2 , w_3 , and 2 biases, θ_1 , θ_2 .
- All weights are initialized with 0.1, and all the biases are initialized with -0.1.
- Use sigmoid as the activation function for all units, i.e.

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

- Let the training set be as follows:

| x_1 | x_2 | T |
|-------|-------|-----|
| 1 | 0 | 1 |
| 0 | 1 | 0 |

Determine the weights after the first epoch two iterations of the backpropagation algorithm, given a learning rate of $\eta = 0.3$.

Suggested Solutions



Naïve Bayes 1

- Let C be the a patient having a cold, F be a patient having a fever
- According to the question, we have:
 - $P(F|C) = 0.5$
 - $P(C) = 1/50000$
 - $P(F) = 1/20$
- Calculation:

$$\begin{aligned}P(C|F) &= \frac{P(F|C)P(C)}{P(F)} \\&= \frac{0.5 \times (1/50000)}{1/20} \\&= 0.0002\end{aligned}$$

Naïve Bayes 2

- Let GB be “Give Birth”, CF be “Can Fly”, LIW be “Live in Water”, HL be “Have Legs”, M be “Mammals”, NM be “Non-mammals”.
- Apply Naïve Bayes, we have:

$$\begin{aligned} &P(GB = \text{Yes}, CF = \text{No}, LIW = \text{Yes}, HL = \text{No} | M)P(M) \\ &= P(GB = \text{Yes} | M)P(CF = \text{No} | M)P(LIW = \text{Yes} | M)P(HL = \text{No} | M)P(M) \\ &= \frac{6}{7} \times \frac{6}{7} \times \frac{2}{7} \times \frac{2}{7} \times \frac{7}{20} = 0.021 \end{aligned}$$

$$\begin{aligned} &P(GB = \text{Yes}, CF = \text{No}, LIW = \text{Yes}, HL = \text{No} | N)P(N) \\ &= P(GB = \text{Yes} | N)P(CF = \text{No} | N)P(LIW = \text{Yes} | N)P(HL = \text{No} | N)P(N) \\ &= \frac{1}{13} \times \frac{10}{13} \times \frac{3}{13} \times \frac{4}{13} \times \frac{13}{20} = 0.0027 \end{aligned}$$

- As $P(GB = \text{Yes}, CF = \text{No}, LIW = \text{Yes}, HL = \text{No} | M)P(M) > P(GB = \text{Yes}, CF = \text{No}, LIW = \text{Yes}, HL = \text{No} | N)P(N)$, it is mammals.

K-Nearest Neighbors

- Compute the Euclidean distance between each training data point and the test point, and find the 3-nearest neighbors.

| ID | Speed | Agility | Draft | Speed (Test) | Agility (Test) | Distance |
|----|-------|---------|-------|--------------|----------------|----------|
| 1 | 2.5 | 6 | No | 6.75 | 3 | 5.202163 |
| 2 | 3.75 | 8 | No | 6.75 | 3 | 5.830952 |
| 3 | 2.25 | 5.5 | No | 6.75 | 3 | 5.147815 |
| 4 | 3.25 | 8.25 | No | 6.75 | 3 | 6.309715 |
| 5 | 2.75 | 7.5 | No | 6.75 | 3 | 6.020797 |
| 6 | 4.5 | 5 | No | 6.75 | 3 | 3.010399 |
| 7 | 3.5 | 5.25 | No | 6.75 | 3 | 3.952847 |
| 8 | 3 | 3.25 | No | 6.75 | 3 | 3.758324 |
| 9 | 4 | 4 | No | 6.75 | 3 | 2.926175 |
| 10 | 4.25 | 3.75 | No | 6.75 | 3 | 2.610077 |
| 11 | 2 | 2 | No | 6.75 | 3 | 4.854122 |
| 12 | 5 | 2.5 | No | 6.75 | 3 | 1.820027 |
| 13 | 8.25 | 8.5 | No | 6.75 | 3 | 5.700877 |
| 14 | 5.75 | 8.75 | Yes | 6.75 | 3 | 5.836309 |
| 15 | 4.75 | 6.25 | Yes | 6.75 | 3 | 3.816084 |
| 16 | 5.5 | 6.75 | Yes | 6.75 | 3 | 3.952847 |
| 17 | 5.25 | 9.5 | Yes | 6.75 | 3 | 6.670832 |
| 18 | 7 | 4.25 | Yes | 6.75 | 3 | 1.274755 |
| 19 | 7.5 | 8 | Yes | 6.75 | 3 | 5.055937 |
| 20 | 7.25 | 5.75 | Yes | 6.75 | 3 | 2.795085 |

- Among the 3-nearest neighbors, 2 of them with “Draft = No” and 1 with “Draft = Yes”. So, based on majority voting, we classify the test point as “Draft = No”.

K-Means Clustering

- Find the distances between each data point with the 2 centroids $c_1 = (4, 2)$ and $c_2 = (2, 1)$:

| Data Point | A | B | C | D |
|------------|----------|----------|----------|----------|
| x1 | 2 | 6 | 1 | 3 |
| x2 | 3 | 1 | 2 | 0 |
| DC1 | 2.236068 | 2.236068 | 3 | 2.236068 |
| DC2 | 2 | 4 | 1.414214 | 1.414214 |
| Cluster | 2 | 1 | 2 | 2 |

- Re-compute the centroids using the current cluster memberships
 - New 1st centroid:

$$x_1 = 6$$

$$x_2 = 1$$

- New 2nd centroid:

$$x_1 = (2 + 1 + 3)/3 = 2$$

$$x_2 = (3 + 2 + 0)/3 = 1.66667$$

K-Means Clustering

- Find the distances between each data point with the 2 centroids $c_1 = (6, 1)$ and $c_2 = (2, 1.666667)$:

| Data Point | A | B | C | D |
|------------|----------|----------|----------|----------|
| x1 | 2 | 6 | 1 | 3 |
| x2 | 3 | 1 | 2 | 0 |
| DC1 | 4.472136 | 0 | 5.09902 | 3.162278 |
| DC2 | 1.333333 | 4.055175 | 1.054092 | 1.943651 |
| Cluster | 2 | 1 | 2 | 2 |

- As the cluster memberships remain the same, the cluster centers also remain the same.
 - New 1st centroid:

$$x_1 = 6$$

$$x_2 = 1$$

- New 2nd centroid:

$$x_1 = 2$$

$$x_2 = 1.66667$$

- Also, the algorithm converges.

Perceptron

| x_1 | x_2 | T | O | Δw_1 | w_1 | Δw_2 | w_2 | $\Delta \theta$ | θ |
|-------|-------|-----|-----|--------------|-------|--------------|-------|-----------------|----------|
| - | - | - | - | - | 0 | - | -2 | - | 0 |
| 1 | -2 | 1 | 1 | 0 | 0 | 0 | -2 | 0 | 0 |
| 0 | -1 | 0 | 1 | 0 | 0 | 0.5 | -1.5 | -0.5 | -0.5 |
| 1 | -2 | 1 | 1 | 0 | 0 | 0 | -1.5 | 0 | -0.5 |
| 0 | -1 | 0 | 1 | 0 | 0 | 0.5 | -1 | -0.5 | -1 |
| 1 | -2 | 1 | 1 | 0 | 0 | 0 | -1 | 0 | -1 |
| 0 | -1 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | -1 |

Multilayer Perceptron - Round 1 - Step 1, Forward Propagation

- Inputs: $x_1 = 1, x_2 = 0$
- Actual Output: $T = 1$
- Weights: $w_1 = 0.1, w_2 = 0.1, w_3 = 0.1$
- Biases: $\theta_1 = -0.1, \theta_2 = -0.1$.
- Calculations:
 - $\sum_1 = x_1 \cdot w_1 + x_2 \cdot w_2 = 1 \cdot (0.1) + 0 \cdot (0.1) = 0.1$
Output (O_j): $f(\sum_1 + \theta_1) = f(0.1 - 0.1) = 0.5$
 - $\sum_2 = O_j \cdot w_3 = 0.5 \cdot (0.1) = 0.05$
Output (O_k): $f(\sum_2 + \theta_2) = f(0.05 - 0.1) = 0.487503$

Multilayer Perceptron - Round 1 - Step 1, Backward Propagation

- Calculations:

- Output (O_j): $f(\sum_1 + \theta_1) = f(0.1 - 0.1) = 0.5$
- Output (O_k): $f(\sum_2 + \theta_2) = f(0.05 - 0.1) = 0.487503$
- $\delta_k = (O_k - T_k)O_k(1 - O_k) = (0.487503 - 1)(0.487503)(1 - 0.487503) = -0.128044$
- New $w_3 = \text{Old } w_3 - \eta\delta_k O_j = 0.1 - 0.3(-0.128044)(0.5) = 0.119207$
- New $\theta_2 = \text{Old } \theta_2 - \eta\delta_k = -0.1 - (0.3)(-0.128044) = -0.061587$
- $\delta_j = O_j(1 - O_j)\delta_k w_{jk} = 0.5(1 - 0.5)(-0.128044)(0.1) = -0.003201$
- New $w_1 = \text{Old } w_1 - \eta\delta_j x_1 = 0.1 - (0.3)(-0.003201)(1) = 0.100960$
- New $w_2 = \text{Old } w_2 - \eta\delta_j x_2 = 0.1 - (0.3)(-0.003201)(0) = 0.1$
- New $\theta_1 = \text{Old } \theta_1 - \eta\delta_j = -0.1 - (0.3)(-0.003201) = -0.099040$

Multilayer Perceptron - Round 1 - Step 2, Forward Propagation

- Inputs: $x_1 = 0, x_2 = 1$
- Actual Output: $T = 0$
- Weights: $w_1 = 0.100960, w_2 = 0.1, w_3 = 0.119207$
- Biases: $\theta_1 = -0.099040, \theta_2 = -0.061587$.
- Calculations:
 - $\sum_1 = x_1 \cdot w_1 + x_2 \cdot w_2 = 0 \cdot (0.100960) + 1 \cdot (0.1) = 0.1$
Output (O_j): $f(\sum_1 + \theta_1) = f(0.1 - 0.099040) = 0.50024$
 - $\sum_2 = O_j \cdot w_3 = 0.50024 \cdot (0.119207) = 0.059632$
Output (O_k): $f(\sum_2 + \theta_2) = f(0.059632 - 0.061587) = 0.499511$

Multilayer Perceptron - Round 1 - Step 2, Backward Propagation

- Calculations:

- Output (O_j): $f(\sum_1 + \theta_1) = f(0.1 - 0.099040) = 0.50024$
- Output (O_k): $f(\sum_2 + \theta_2) = f(0.059632 - 0.061587) = 0.499511$
- $\delta_k = (O_k - T_k)O_k(1 - O_k) = (0.499511 - 0)(0.499511)(1 - 0.499511) = 0.124878$
- New $w_3 = \text{Old } w_3 - \eta\delta_k O_j = 0.119207 - 0.3(0.124878)(0.50024) = 0.100466$
- New $\theta_2 = \text{Old } \theta_2 - \eta\delta_k = -0.061587 - (0.3)(0.124878) = -0.09905$
- $\delta_j = O_j(1 - O_j)\delta_k w_{jk} = 0.50024(1 - 0.50024)(0.124878)(0.119207) = 0.003722$
- New $w_1 = \text{Old } w_1 - \eta\delta_j x_1 = 0.100960 - (0.3)(0.003722)(0) = 0.100960$
- New $w_2 = \text{Old } w_2 - \eta\delta_j x_2 = 0.1 - (0.3)(0.003722)(1) = 0.098883$
- New $\theta_1 = \text{Old } \theta_1 - \eta\delta_j = -0.099040 - (0.3)(0.003722) = -0.100157$