



Northeastern University, Khoury College of Computer Science

## CS 6220 Data Mining — Assignment 5

Due: November 7, 2023 (100 points)

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<https://github.com/amandaay/CS6220DataMining/tree/main>

# Naïve Bayes, Bayes Rules

The original performance of [acoustic classification for Parkinsons Disease](#) leverages speech recordings from controlled subject responses from variety of questions. The task in the competition was to detect whether or not a person  $X$  had Parkinsons disease from a sampling of data. As of 2018, the state of the art classifiers have achieved 90% correct classification on a held out dataset, both for subjects who had Parkinsons and those who did not (at equal rates). So, when classifier  $Y$  sees person  $X$ , it works correctly 90% of the time.

- Let's say that we run a clinic. This clinic leverages this classifier, which has 90% accuracy. Also, let us say that we know that our current patient load is that 10% of the population have Parkinsons and 90% of the population do not. Let's also say that we're seeing patient  $X$ , and the classification algorithm has detected that they have Parkinson's disease. What's the probability that indeed  $X$  has Parkinson's disease?

Come up with the numerical solution, and show your written work.

①

$$X = \begin{cases} 1 & \text{PK} \\ 0 & \text{No PK} \end{cases}$$

Given:  $P(X=1)=0.1$   
 $P(X=0)=0.9$

correctness  
 $Y = \begin{cases} 1 \\ 0 \end{cases}$

$$P(Y=0 | X=1) = 0.1$$
$$P(Y=1 | X=1) = 0.9$$
$$P(Y=1 | X=0) = 0.1$$
$$P(Y=0 | X=0) = 0.9$$

0.9  
 $Y=1$  correctly detect PK  $(0.9)(0.1)$

0.1  
 $Y=0$  incorrectly detect pt has PK when it doesn't  $(0.1)(0.1)$

0.9  
 $X=1$

0.9  
 $Y=1$  correctly detect pt doesn't have PK  $(0.9)(0.9)$

0.1  
 $Y=0$  incorrectly detects pt doesn't have PK aka pt has PK  $(0.1)(0.1)$

0.1  
 $X=0$

$$P(X=1 | Y=1) = \frac{P(Y=1 | X=1) P(X=1)}{P(Y=1)}$$
$$P(Y=1) = P(Y=1 | X=1) P(X=1) + P(Y=1 | X=0) P(X=0)$$
$$= (0.9)(0.1) + (0.1)(0.9)$$
$$= 0.18$$
$$P(X=1 | Y=1) = \frac{(0.9)(0.1)}{0.18} = 0.5$$

# The Sum of Conditional Probabilities

In class, we reviewed three main rules in Bayesian probability inference:

- Conditional Probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

- Bayes Theorem:

$$P(A|B)P(B) = P(B|A)P(A)$$

- Total Probability:

$$P(A) = \sum_i P(A|B_i)P(B_i)$$

A well-known outcome of the three sets of rules is the fact that the sum of all the conditional probabilities equals one.

2. Prove that:

$$\sum_i P(A_i|B) = 1$$

A handwritten proof on a piece of paper. It starts with a circled '2' in the top left. The proof shows the derivation of the sum of conditional probabilities from the total probability rule. The steps are:  $P(B) = \sum_{\bar{i}} P(B|A_{\bar{i}}) P(A_{\bar{i}})$ , then  $= \sum_{\bar{i}} \frac{P(A_{\bar{i}}|B)P(B)}{P(A_{\bar{i}})} P(A_{\bar{i}})$ , then  $= \sum_{\bar{i}} P(A_{\bar{i}}|B)P(B)$ , then  $= P(B) \sum_{\bar{i}} P(A_{\bar{i}}|B)$ . Finally, it concludes with  $\sum_{\bar{i}} P(A_{\bar{i}}|B) = 1$ .

$$\begin{aligned} \textcircled{2} \quad P(B) &= \sum_{\bar{i}} P(B|A_{\bar{i}}) P(A_{\bar{i}}) \\ &= \sum_{\bar{i}} \frac{P(A_{\bar{i}}|B)P(B)}{P(A_{\bar{i}})} P(A_{\bar{i}}) \\ &= \sum_{\bar{i}} P(A_{\bar{i}}|B)P(B) \\ &= P(B) \sum_{\bar{i}} P(A_{\bar{i}}|B) \\ \sum_{\bar{i}} P(A_{\bar{i}}|B) &= 1 \end{aligned}$$