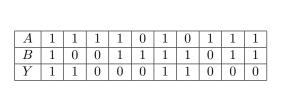
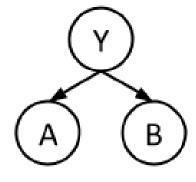
CS188 Fall 2018 Section 9: Machine Learning

1 Naive Bayes

In this question, we will train a Naive Bayes classifier to predict class labels Y as a function of input features A and B. Y, A, and B are all binary variables, with domains 0 and 1. We are given 10 training points from which we will estimate our distribution.





1. What are the maximum likelihood estimates for the tables P(Y), P(A|Y), and P(B|Y)?

Y	P(Y)
0	3/5
1	2/5

A	Y	P(A Y)
0	0	1/6
1	0	5/6
0	1	1/4
1	1	3/4

-	В	Y	P(B Y)
	0	0	1/3
	1	0	2/3
	0	1	1/4
	1	1	3/4

2. Consider a new data point (A = 1, B = 1). What label would this classifier assign to this sample?

$$P(Y = 0, A = 1, B = 1) = P(Y = 0)P(A = 1|Y = 0)P(B = 1|Y = 0)$$
(1)

$$= (3/5)(5/6)(2/3) \tag{2}$$

$$=1/3\tag{3}$$

$$P(Y = 1, A = 1, B = 1) = P(Y = 1)P(A = 1|Y = 1)P(B = 1|Y = 1)$$
(4)

$$= (2/5)(3/4)(3/4) \tag{5}$$

$$=9/40\tag{6}$$

(7)

Our classifier will predict label 0.

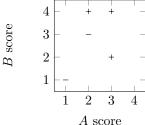
3. Let's use Laplace Smoothing to smooth out our distribution. Compute the new distribution for P(A|Y) given Laplace Smoothing with k=2.

A	Y	P(A Y)
0	0	3/10
1	0	7/10
0	1	3/8
1	1	5/8

2 Perceptron

You want to predict if movies will be profitable based on their screenplays. You hire two critics A and B to read a script you have and rate it on a scale of 1 to 4. The critics are not perfect; here are five data points including the critics' scores and the performance of the movie:

#	Movie Name	A	В	Profit?
1	Pellet Power	1	1	-
2	Ghosts!	3	2	+
3	Pac is Bac	2	4	+
4	Not a Pizza	3	4	+
5	Endless Maze	2	3	_



- 1. First, you would like to examine the linear separability of the data. Plot the data on the 2D plane above; label profitable movies with + and non-profitable movies with and determine if the data are linearly separable. The data are linearly separable.
- 2. Now you decide to use a perceptron to classify your data. Suppose you directly use the scores given above as features, together with a bias feature. That is $f_0 = 1$, $f_1 =$ score given by A and $f_2 =$ score given by B.

Run one pass through the data with the perceptron algorithm, filling out the table below. Go through the data points in order, e.g. using data point #1 at step 1.

step	Weights	Score	Correct?
1	[-1, 0, 0]	$-1 \cdot 1 + 0 \cdot 1 + 0 \cdot 1 = -1$	yes
2	[-1, 0, 0]	$-1 \cdot 1 + 0 \cdot 3 + 0 \cdot 2 = -1$	no
3	[0, 3, 2]	$0 \cdot 1 + 3 \cdot 2 + 2 \cdot 4 = 14$	yes
4	[0, 3, 2]	$0 \cdot 1 + 3 \cdot 3 + 2 \cdot 4 = 17$	yes
5	[0, 3, 2]	$0 \cdot 1 + 3 \cdot 2 + 2 \cdot 3 = 12$	no

Final weights: [-1, 1, -1]

3. Have weights been learned that separate the data? With the current weights, points will be classified as positive if $-1 \cdot 1 + 1 \cdot A + -1 \cdot B \ge 0$, or $A - B \ge 1$. So we will have incorrect predictions for data points 3:

$$-1 \cdot 1 + 1 \cdot 2 + -1 \cdot 4 = -3 < 0$$

and 4:

$$-1 \cdot 1 + 1 \cdot 3 + -1 \cdot 4 = -2 < 0$$

Note that although point 2 has $w \cdot f = 0$, it will be classified as positive (since we classify as positive if $w \cdot f \ge 0$).

- 4. More generally, irrespective of the training data, you want to know if your features are powerful enough to allow you to handle a range of scenarios. Circle the scenarios for which a perceptron using the features above can indeed perfectly classify movies which are profitable according to the given rules:
 - (a) Your reviewers are awesome: if the total of their scores is more than 8, then the movie will definitely be profitable, and otherwise it won't be. Can classify (consider weights [-8, 1, 1])
 - (b) Your reviewers are art critics. Your movie will be profitable if and only if each reviewer gives either a score of 2 or a score of 3. Cannot classify
 - (c) Your reviewers have weird but different tastes. Your movie will be profitable if and only if both reviewers agree. Cannot classify

3 Maximum Likelihood

A Geometric distribution is a probability distribution of the number X of Bernoulli trials needed to get one success. It depends on a parameter p, which is the probability of success for each individual Bernoulli trial. Think of it as the number of times you must flip a coin before flipping heads. The probability is given as follows:

$$P(X = k) = p(1 - p)^{k - 1}$$
(8)

p is the parameter we wish to estimate.

We observe the following samples from a Geometric distribution: $x_1 = 5$, $x_2 = 8$, $x_3 = 3$, $x_4 = 5$, $x_5 = 7$. What is the maximum likelihood estimate for p?

$$L(p) = P(X = x_1)P(X = x_2)P(X = x_3)P(X = x_4)P(X = x_5)$$
(9)

$$= P(X=5)P(X=8)P(X=3)P(X=5)P(X=7)$$
(10)

$$= p^5 (1-p)^{23} \tag{11}$$

$$\log(L(p)) = 5\log(p) + 23\log(1-p) \tag{12}$$

(13)

We must maximize the log-likelihood of p, so we will take the derivative, and set it to 0.

$$0 = \frac{5}{p} - \frac{23}{1-p} \tag{14}$$

$$p = 5/28 \tag{15}$$