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**1: Probabilities**


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$$\boxed{\text{Independent Events} - P(A \cap B) = P(A)P(B)} \quad (1)$$

$$\boxed{\text{Rule of Multiplication} - P(A \cap B) = P(A)P(B|A)} \quad (2)$$

(1) Given  $P(A_1) = P(A_2) = P(A_1|A_2) = \frac{1}{2}$ , we want to prove that  $A_1$  and  $A_2$  are independent events.

Events  $A_1$  and  $A_2$  are independent if and only if Eq. (1) is satisfied.

$$P(A_2 \cap A_1) = P(A_2)P(A_1)$$

We can use Eq. (2) to restate the LHS of Eq. (1) in terms of probabilities we are given.

$$P(A_2)P(A_1|A_2) = P(A_2)P(A_1)$$

$$\frac{1}{2} * \frac{1}{2} = \frac{1}{2} * \frac{1}{2}$$

By showing Eq. (1) is satisfied, we have proven  $A_1$  and  $A_2$  are independent events.

(2) From lecture, we saw the Theorem of Total probability pertaining to mutually exclusive events  $A_1, A_2, \dots, A_n$  where  $\sum_i P(A_i) = 1$ . When this condition is met, we know the following is true:

$$P(B) = \sum_{i=1}^n P(B \cap A_i) = \sum_{i=1}^n P(B|A_i)P(A_i)$$

We have mutually exclusive events  $A_1, A_2$ , and  $A_3$  where the sum of their probabilities is 1. The condition is met, so we can use the Theorem of Total probability. All the needed probabilities to calculate  $P(A_4)$  are provided in the problem.

$$P(A_4) = \sum_{i=1}^3 P(A_4|A_i)P(A_i)$$

$$P(A_4) = \frac{1}{3} * \left( \frac{1}{6} + \frac{1}{3} + \frac{1}{2} \right)$$

$$\boxed{P(A_4) = \frac{1}{3}}$$

$$\boxed{\text{Binomial Distribution} - \binom{n}{k} p^k (1-p)^{n-k}} \quad (3)$$

(3) Let  $X$  be a random variable representing the top of the six-sided die toss. The dice is a fair dice so we know  $P(X=1) = P(X=2) = P(X=3) = P(X=4) = P(X=5) = P(X=6) = \frac{1}{6}$ .

There are six possible events and the total probability of exactly two heads after  $n$  coin tosses is the sum of the probability of each of the six events happening.

$$\sum_{i=1}^6 P(X = i) * B(n = i, k = 2, p = 0.5)$$

Where  $B(n, k, p)$  represents the binomial distribution from Eq. (3). This is the probability that given  $n$  trials, there are exactly  $k$  successes if the probability of success is  $p$  where  $0 \leq p \leq 1$  and  $k \leq n$ . Let  $Y$  be a random variable representing the exact number of heads after  $n$  coin tosses. Note that the probability of getting exactly two heads when only tossing one coin is 0.

$$P(Y = 2) = \sum_{i=1}^6 P(X = i) * B(n = i, k = 2, p = 0.5)$$

$$P(Y = 2) = \frac{1}{6} \sum_{i=1}^6 B(n = i, k = 2, p = 0.5)$$

$$P(Y = 2) = \frac{1}{6} \left( 0 + \frac{1}{4} + \frac{3}{8} + \frac{6}{16} + \frac{10}{32} + \frac{15}{64} \right)$$

$P(Y = 2) = \frac{33}{128} = 0.2578$

Thus this is the probability of getting exactly 2 heads after  $n$  coin flips, where  $n$  is the result of a fair six-sided die toss.

$Rule\ of\ Addition - P(A \cup B) = P(A) + P(B) - P(A)P(B|A)$

(4)

(4) We want to prove that if  $P(A_1) = a_1$  and  $P(A_2) = a_2$  then  $P(A_1|A_2) \geq \frac{a_1 + a_2 - 1}{a_2}$ .

*Proof:* we begin with Eq. (4) which is the rule for union of two events.

$$P(A_2 \cup A_1) = P(A_2) + P(A_1) - P(A_2)P(A_1|A_2)$$

$P(A_2 \cup A_1)$  is a probability so we know it has a upper bound of 1.

$$1 \geq P(A_2 \cup A_1) = P(A_2) + P(A_1) - P(A_2)P(A_1|A_2)$$

$$1 \geq P(A_2) + P(A_1) - P(A_2)P(A_1|A_2)$$

Rearranging terms and multiplying both sides by -1.

$$\frac{1 - P(A_2) - P(A_1)}{P(A_2)} \geq -P(A_1|A_2)$$

$$\frac{P(A_1) + P(A_2) - 1}{P(A_2)} \leq P(A_1|A_2)$$

Replacing  $P(A_1) = a_1$  and  $P(A_2) = a_2$  on the LHS of the inequality.

$$P(A_1|A_2) \geq \frac{a_1 + a_2 - 1}{a_2}$$

Thus arriving at the original inequality and proving it's correctness.

**(5a)** Given two independent random variables  $A_1$  and  $A_2$ , we want to prove that  $E[A_1 + A_2] = E[A_1] + E[A_2]$  is true. We will assume  $A_1$  and  $A_2$  are discrete for this proof. The equality also holds for continuous random variables with a slightly different proof.

Given a discrete random variable  $X$  that can take values  $x_1, x_2, \dots, x_k$ , with respective probabilities  $p_1, p_2, \dots, p_k$ , then the expected value of  $X$  is defined as:

$$\text{Expectation} - E[X] = \sum_{i=1}^k x_i * P(X = x_i) \quad (5)$$

*Proof:* Starting with the LHS of the equality we want to prove, we will use the definition of expectation to arrive at the RHS.

$$E[A_1 + A_2] = \sum_{i=1}^k \sum_{j=1}^k (a_{1i} + a_{2j}) * P(A_1 = a_{1i}, A_2 = a_{2j})$$

Multiply and split RHS into two sets of summations.

$$\begin{aligned} E[A_1 + A_2] &= \sum_{i=1}^k \sum_{j=1}^k a_{1i} * P(A_1 = a_{1i}, A_2 = a_{2j}) + \sum_{i=1}^k \sum_{j=1}^k a_{2j} * P(A_1 = a_{1i}, A_2 = a_{2j}) \\ E[A_1 + A_2] &= \sum_{i=1}^k a_{1i} * P(A_1 = a_{1i}) + \sum_{j=1}^k a_{2j} * P(A_2 = a_{2j}) \end{aligned}$$

The RHS is the definition of expectation for  $A_1$  summed with the expectation of  $A_2$ .

$$E[A_1 + A_2] = E[A_1] + E[A_2]$$

**(5b)** Given two independent random variables  $A_1$  and  $A_2$ , we want to prove that  $var[A_1 + A_2] = var[A_1] + var[A_2]$  is true.

*Proof:* Variance is defined as:

$$\text{Variance} - var[X] = E[(X - E[X])^2] \quad (6)$$

Replacing  $X$  with  $A_1 + A_2$  and using algebra, this can be rewritten as:

$$var[A_1 + A_2] = E[(A_1 + A_2)^2] - E[A_1 + A_2]^2$$

Expanding out the polynomials gives us:

$$\text{var}[A_1 + A_2] = E[A_1^2 + 2A_1A_2 + A_2^2] - E[A_1]^2 - 2E[A_1]E[A_2] - E[A_2]^2$$

Using the proof of linearity of expectation from part a, we can rewrite the first expectation:

$$\text{var}[A_1 + A_2] = E[A_1^2] + 2E[A_1A_2] + E[A_2^2] - E[A_1]^2 - 2E[A_1]E[A_2] - E[A_2]^2$$

When the covariance of two random variables is zero, the expected value operator is multiplicative. That is,  $E[XY] = E[X]E[Y]$ . We know the covariance of  $A_1$  and  $A_2$  is 0 as they are independent of each other.

$$\text{var}[A_1 + A_2] = E[A_1^2] + 2E[A_1]E[A_2] + E[A_2^2] - E[A_1]^2 - 2E[A_1]E[A_2] - E[A_2]^2$$

$$\text{var}[A_1 + A_2] = E[A_1^2] - E[A_1]^2 + E[A_2^2] - E[A_2]^2$$

$$\text{var}[A_1 + A_2] = \text{var}[A_1] + \text{var}[A_2]$$

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## 2: Naïve Bayes

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(1a) Given infinite data drawn from this distribution, the learned probabilities  $\hat{P}$  will be identical to the true probabilities  $P$ . This is a result of the law of large numbers.

$$\hat{P}(y = -1) = 0.1 \text{ and } \hat{P}(y = 1) = 0.9$$

$$\hat{P}(x_1 = -1|y = -1) = 0.8 \text{ and } \hat{P}(x_1 = 1|y = -1) = 0.2$$

$$\hat{P}(x_1 = -1|y = 1) = 0.1 \text{ and } \hat{P}(x_1 = 1|y = 1) = 0.9$$

(1b) Using the conditional independence assumption the naive Bayes model makes, we can calculate the generative distribution of the data using  $\hat{P}(x_1, y) = \hat{P}(y)\hat{P}(x_1|y)$ . A prediction  $y'$  is determined by taking the maximum of the  $\hat{P}(x_1, y)$  for a given value of  $x_1$ .

$x_1$	$\hat{P}(x_1, y = -1)$	$\hat{P}(x_1, y = 1)$	<b>Prediction:</b> $y' = \text{argmax}_y \hat{P}(x_1, y)$
-1	$(0.1)(0.8) = \mathbf{0.08}$	$(0.9)(0.1) = \mathbf{0.09}$	1
1	$(0.1)(0.2) = \mathbf{0.02}$	$(0.9)(0.9) = \mathbf{0.81}$	1

(1c) To determine the error of the classifier, we calculate the probability of  $P(y' \neq y)$  being true. To calculate this we can use the fact that  $P(y' \neq y) = P(y' \neq y, x_1 = -1) + P(y' \neq y, x_1 = 1)$ , using the values from the table in part b.

$$P(y' \neq y) = P(y = -1|x_1 = -1) + P(y = -1|x_1 = 1)$$

$$P(y' \neq y) = (0.1)(0.8) + (0.1)(0.2) = 0.1$$

If we trained a classifier on the given data, it would have an error rate of 0.1.

(2a) The two features  $x_1$  and  $x_2$  are not conditionally independent given  $y$ .

*Proof:* From lecture we saw the definition of conditional independence of three random variables. The random variables are independent if and only if the equality is satisfied.

$$P(X, Y|Z) = P(X|Z)P(Y|Z)$$

$$P(x_1, x_2|y) = P(x_1|y)P(x_2|y)$$

As  $x_1$  and  $x_2$  are identical,  $P(x_1, x_2|y)$  is the same as  $P(x_1|y)$  as  $x_1$  and  $x_2$  always happen or don't happen together. Replacing  $P(x_1, x_2|y)$  with  $P(x_1|y)$  in the conditional independence formula.

$$P(x_1|y) = P(x_1|y)P(x_2|y)$$

We know our given probabilities are non-zero, thus the above equality does not hold. Proving  $x_1$  and  $x_2$  are not conditionally independent.

(2b) As in part 1, using the conditional independence assumption the naive Bayes model makes, we can use  $\hat{P}(x_1|y)$ ,  $\hat{P}(x_2|y)$ , and  $\hat{P}(y)$  to calculate the generative distribution of the data.

$$\hat{P}(x_1, x_2, y) = \hat{P}(y)\hat{P}(x_1|y)\hat{P}(x_2|y)$$

$x_1$	$x_2$	$\hat{P}(x_1, x_2, y = -1)$	$\hat{P}(x_1, x_2, y = 1)$	<b>Prediction:</b> $y' = \operatorname{argmax}_y \hat{P}(x_1, x_2, y)$
-1	-1	$(0.1)(0.8)(0.8) = \mathbf{0.064}$	$(0.9)(0.1)(0.1) = \mathbf{0.009}$	-1
-1	1	$(0.1)(0.8)(0.2) = \mathbf{0.016}$	$(0.9)(0.1)(0.9) = \mathbf{0.081}$	1
1	-1	$(0.1)(0.2)(0.8) = \mathbf{0.016}$	$(0.9)(0.9)(0.1) = \mathbf{0.081}$	1
1	1	$(0.1)(0.2)(0.2) = \mathbf{0.004}$	$(0.9)(0.9)(0.9) = \mathbf{0.729}$	1

(2c) To determine the error of the classifier, we calculate the probability of  $P(y' \neq y)$  being true. To calculate this we can use the fact that  $P(y' \neq y) = P(y' \neq y, x_1 = -1, x_2 = -1) + P(y' \neq y, x_1 = -1, x_2 = 1) + P(y' \neq y, x_1 = 1, x_2 = -1) + P(y' \neq y, x_1 = 1, x_2 = 1)$ , using the values from the table in part b.

$$P(y' \neq y) = 0.009 + 0.016 + 0.016 + 0.004 = 0.045$$

If we trained a classifier on the given data, it would have an error rate of 0.045.

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### 3: Naïve Bayes and Linear Classifiers

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### 4: Experiment

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(1)

$$g(W) = \log(1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i))$$

We want to calculate  $\frac{dg}{dw}$ , or the derivative of the function  $g$  in terms of  $\mathbf{w}$ . We can use the chain rule where  $a = 1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i)$  and  $b = -y_i \mathbf{w}^T \mathbf{x}_i$ .

$$\begin{aligned}\frac{d}{da} \log(a) &= \frac{1}{a} \\ \frac{d}{db} 1 + \exp(b) &= \exp(b) \\ \frac{d}{dw} -y_i \mathbf{w}^T \mathbf{x}_i &= -y_i \mathbf{x}_i\end{aligned}$$

Computing the derivative of the composition of the three functions using the chain rule:

$$\begin{aligned}\frac{dg}{dw} &= \frac{dg}{da} * \frac{da}{db} * \frac{db}{dw} \\ \frac{dg}{dw} &= \frac{1}{a} * e^b * -y_i \mathbf{x}_i \\ \frac{dg}{dw} &= \frac{1}{1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i)} * \exp(-y_i \mathbf{w}^T \mathbf{x}_i) * -y_i \mathbf{x}_i \\ \boxed{\frac{dg}{dw} &= \frac{-y_i \mathbf{x}_i}{1 + \exp(y_i \mathbf{w}^T \mathbf{x}_i)}}\end{aligned}\tag{7}$$

(2) When the entire dataset is composed of a single example, the objective can be express as:

$$\boxed{\text{objective} : J(w) = \log(1 + \exp(-y_i \mathbf{w}^T \mathbf{x}_i)) + \frac{1}{\sigma^2} \mathbf{w}^T \mathbf{w}}\tag{8}$$

This is equivalent to the original optimization problem as finding the min of a summation is redundant when taking only one example.

The gradient of this objective can be found using the derivative found in part 1 plus the derivative of  $\frac{1}{\sigma^2} \mathbf{w}^T \mathbf{w}$ . We use the fact that  $w^T w = w^2$  to make the derivative simple.

$$\boxed{\nabla J(w) = \frac{-y_i \mathbf{x}_i}{1 + \exp(y_i \mathbf{w}^T \mathbf{x}_i)} + \frac{2w}{\sigma^2}}\tag{9}$$

(3)