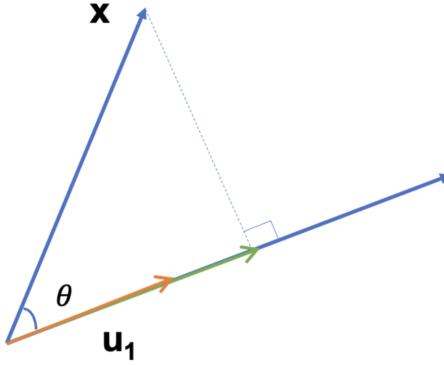


Problem 1

Problem Statement

As the figure shown below, there are two vectors \mathbf{x} and \mathbf{u}_1 (orange color), where \mathbf{u}_1 has unit length. The projection of \mathbf{x} onto \mathbf{u}_1 is represented by the vector in green. Show that the length of the projection of \mathbf{x} onto \mathbf{u}_1 has length $\mathbf{u}_1^T \mathbf{x}$



My solution:

Fact 1: The vector projection is the unit vector $\frac{\mathbf{u}_1}{|\mathbf{u}_1|}$ times the scalar projection of \mathbf{x} onto \mathbf{u}_1 ,

$$\text{Proj}_{\mathbf{u}_1} \mathbf{x} = \frac{\mathbf{x} \cdot \mathbf{u}_1}{|\mathbf{u}_1|^2} \cdot \mathbf{u}_1$$

NOTE: $|\mathbf{u}_1|^2 = 1$ since \mathbf{u}_1 is the unit vector.

Fact 2: We need to establish that $\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \cdot \mathbf{b}$

To see this to be true, note that $\mathbf{a} \cdot \mathbf{b} = a_1 b_1 + a_2 b_2 + \dots + a_n b_n$ for \mathbf{a} is the $n \times 1$ column vector, thus \mathbf{a}^T will be the $1 \times n$ row vector. Then \mathbf{b} is the $n \times 1$ column vector, thus

$$\mathbf{a}^T \cdot \mathbf{b} = [a_1 b_1 + \dots + a_n b_n]$$

is the 1×1 matrix, a scalar. Therefore, $\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$.

Using the facts established above,

$$\text{Proj}_{\mathbf{u}_1} \mathbf{x} = \frac{\mathbf{x} \cdot \mathbf{u}_1}{|\mathbf{u}_1|^2} \cdot \mathbf{u}_1$$

However, $|\mathbf{u}_1|^2 = 1$ thus,

$$\text{Proj}_{\mathbf{u}_1} \mathbf{x} = (\mathbf{x} \cdot \mathbf{u}_1) \cdot \mathbf{u}_1$$

Then using the fact that, $\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^T \mathbf{b}$ and because the dot product is commutative, we have

$$\text{Proj}_{\mathbf{u}_1} \mathbf{x} = (\mathbf{u}_1^T \mathbf{x}) \cdot \mathbf{u}_1$$

The length of this projection vector is the scalar $|\mathbf{u}_1^T \mathbf{x}|$, however, given that \mathbf{u}_1 is the unit vector that is in the same direction as the projection vector, our scalar projection will be positive. We then have that the length of the projection \mathbf{x} onto \mathbf{u}_1 is $\mathbf{u}_1^T \mathbf{x}$, as desired.

Problem 2

Problem Statement

Show that,

$$\frac{1}{N} \sum_{i=1}^N (\mathbf{u}_1^T \mathbf{x}_i - \mathbf{u}_1^T \bar{\mathbf{x}})^2 = \mathbf{u}_1^T \mathbf{S} \mathbf{u}_1$$

Such that \mathbf{S} is the data covariance matrix defined by,

$$\mathbf{S} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T$$

My Solution:

First: Let us expand

$$\Rightarrow \frac{1}{N} \sum_{i=1}^N (\mathbf{u}_1^T \mathbf{x}_i - \mathbf{u}_1^T \bar{\mathbf{x}})(\mathbf{u}_1^T \mathbf{x}_i - \mathbf{u}_1^T \bar{\mathbf{x}})$$

Second: Let us group terms together to get the form of the inner product that is, given a and b are column vectors then $a \cdot b = a^T \cdot b$ this will allow us to rearrange nicely so that we can deal with scalar multiplication (where order doesn't matter),

$$\Rightarrow \frac{1}{N} \sum_{i=1}^N (\mathbf{u}_1^T (\mathbf{x}_i - \bar{\mathbf{x}}))((\mathbf{x}_i - \bar{\mathbf{x}})^T \mathbf{u}_1)$$

Third: Deploy the definition of the covariance matrix and the fact that scalar multiplication is commutative,

$$\Rightarrow \mathbf{u}_1^T \left(\frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \right) \mathbf{u}_1$$

Fourth: Rewrite in matrix notation,

$$\frac{1}{N} \sum_{i=1}^N (\mathbf{u}_1^T \mathbf{x}_i - \mathbf{u}_1^T \bar{\mathbf{x}})^2 = \mathbf{u}_1^T \mathbf{S} \mathbf{u}_1$$

Which is the desired result.

Problem 3

Problem Statement

For a binary classification problem with three binary features, the data is shown below:

a	b	c	K
1	0	1	1
1	1	1	1
0	1	1	0
1	1	0	0
1	0	1	0
0	0	0	1
0	0	0	1
0	0	1	0

- (a) Based on the naive Bayes classifier, what is $P(K = 1|a = 1, b = 1, c = 0)$?
- (b) Based on the naive Bayes classifier, what is $P(K = 0|a = 1, b = 1)$?

My Solution:

PART A

In the case of multiple independent evidences, E_1, E_2, \dots, E_n , the Naive Bayes is:

$$P(H|E_1, E_2, \dots, E_n) = \frac{P(E_1|H)P(E_2|H) \cdots P(E_n|H)P(H)}{\sum_H P(E_1|H)P(E_2|H) \cdots P(E_n|H)P(H)} \quad (2)$$

Usually, we are only interested in calculating the numerator, since the denominator is a normalization constant (once E_1, E_2, \dots, E_n are given, the denominator is fixed).

$$P(a = 1|K = 1) = \frac{2}{4} \Rightarrow P(b = 1|K = 1) = \frac{1}{4} \Rightarrow P(c = 0|K = 1) = \frac{2}{4} \Rightarrow P(K = 1) = \frac{4}{8}$$

$$P(K = 1|a = 1, b = 1, c = 0) \propto \frac{2}{4} \cdot \frac{1}{4} \cdot \frac{2}{4} \cdot \frac{4}{8} = \frac{1}{32} \approx 0.03125$$

Now we find $P(K = 0|a = 1, b = 1, c = 0)$,

$$P(a = 1|K = 0) = \frac{2}{4} \Rightarrow P(b = 1|K = 0) = \frac{2}{4} \Rightarrow P(c = 0|K = 0) = \frac{1}{4} \Rightarrow P(K = 0) = \frac{4}{8}$$

$$P(K = 0|a = 1, b = 1, c = 0) \propto \frac{2}{4} \cdot \frac{2}{4} \cdot \frac{1}{4} \cdot \frac{4}{8} = \frac{1}{32} \approx 0.03125$$

Then,

$$P(K = 1|a = 1, b = 1, c = 0) = \frac{P(a = 1|K = 1)P(b = 1|K = 1)P(c = 0|K = 1)P(K = 1)}{P(K = 1|a = 1, b = 1, c = 0) + P(K = 0|a = 1, b = 1, c = 0)} = \frac{\frac{1}{32}}{\frac{1}{32} + \frac{1}{32}}$$

$$P(K = 1|a = 1, b = 1, c = 0) = \frac{1}{2}$$

PART B

$$P(a = 1|K = 0) = \frac{2}{4} \Rightarrow P(b = 1|k = 0) = \frac{2}{4} \Rightarrow P(K = 0) = \frac{4}{8}$$

$$P(K = 0|a = 1, b = 1) \propto \frac{2}{4} \cdot \frac{2}{4} \cdot \frac{4}{8} = \frac{1}{8} = 0.125$$

Now we find $P(K = 1|a = 1, b = 1)$,

$$P(a = 1|K = 1) = \frac{2}{4} \Rightarrow P(b = 1|k = 1) = \frac{1}{4} \Rightarrow P(K = 1) = \frac{4}{8}$$

$$P(K = 1|a = 1, b = 1) \propto \frac{2}{4} \cdot \frac{1}{4} \cdot \frac{4}{8} = \frac{1}{16} = 0.0625$$

Then,

$$P(K = 0|a = 1, b = 1) = \frac{P(a = 1|k = 0)P(b = 1|K = 0)P(K = 0)}{P(K = 0|a = 1, b = 1) + P(K = 1|a = 1, b = 1)} = \frac{\frac{1}{8}}{\frac{1}{8} + \frac{1}{16}} = \frac{2}{3}$$