

# 1 Probability basics

In statistical signal processing, manipulation of probability expressions is very important. The two tools from probability theory that we will be using frequently to manipulate the expressions are:

- Law of total probability
- Probability chain rule

## 1.1 Law of total probability

If  $A_1, A_2, \dots, A_n$  forms a partition of the sample space  $S$ , then the probability of an event  $B$  is given by

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

Using the definition of conditional probability, we can rewrite the above expression as

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

Thus, the probability of the event  $B$  is the sum of the conditional probabilities  $P(B|A_i)$  weighted by the probability  $P(A_i)$ .

## 1.2 Probability chain rule

For any events  $A$  and  $B$ , we have

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

More generally, for any events  $A_1, A_2, \dots, A_n$  we get

$$P(A_1 \cap A_2 \cap \dots \cap A_n) = \prod_{k=1}^n P(A_k | \cap_{j=1}^{k-1} A_j)$$

You can use induction to show the general version of the probability chain rule.

### 1.3 Practice problems on probability basics

1. A computer manufacturer uses chips from three sources. Chips from sources A, B, and C are defective with probabilities 0.005, 0.001, and 0.010, respectively. If a randomly selected chip is found to be defective, find:

- (a) The probability that the manufacturer was A
- (b) The probability that the manufacturer was C

Assume that the proportions of chips from A, B, and C are 0.5, 0.1, and 0.4, respectively.

2. A box contains three coins. One of the coins is a two-headed coin, the second is a fair coin, and the third is a biased coin with  $P(head) = p$ . One of the coins is picked at random and flipped:

- (a) Find the probability that the coin shows head. What is its maximum value?
- (b) If the coin shows head, find the probability that it is the fair coin. What are its maximum and minimum values?

3. Suppose that the reliability of a chest X-ray test for the detection of tuberculosis is specified as follows: of people with tuberculosis, 90% of the X-ray examinations detect the disease but 10% go undetected. Of people free of tuberculosis, 99% of the X-rays are judged free of the disease, but 1% are diagnosed as showing the tuberculosis. From a large population of which only 0.1% have tuberculosis, one person is selected at random, given a chest X-ray, and the radiologist reports the presence of tuberculosis. What is the probability that the person has tuberculosis?

## 2 Linear Algebra basics

Proficiency in linear algebra is required to have a solid foundation in machine learning. The two linear algebra concepts that we will be using repeatedly in this course are:

- Decomposition of matrices
- Derivatives of vectors and matrices

In this discussion we will focus on the decomposition of matrices, namely:

- Eigendecomposition
- Singular value decomposition

### 2.1 Eigendecomposition

Every real symmetric matrix,  $A \in \mathbf{R}^{n \times n}$ , can be factored as

$$A = Q\Delta Q^T$$

where  $\Delta = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n) \in \mathbf{R}^{n \times n}$ . More specifically we have,

- The set  $\{\lambda_1, \lambda_2, \dots, \lambda_n\}$  are called the eigenvalues of  $A$  and can be found by solving the equation

$$\det(A - \lambda I) = 0$$

- The columns of  $Q$  are an orthonormal set of  $n$  eigenvectors and can be found by solving the equation

$$Av_i = \lambda_i v_i$$

## 2.2 Singular value decomposition

Let  $A \in \mathbf{R}^{m \times n}$  be a matrix with rank  $r$ , then there exists orthogonal matrices  $U \in \mathbf{R}^{m \times m}$  and  $V \in \mathbf{R}^{n \times n}$  such that

$$A = U \Sigma V^T$$

where  $\Sigma = \begin{bmatrix} S & 0 \\ 0 & 0 \end{bmatrix}$ ,  $S = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r) \in \mathbf{R}^{r \times r}$ , and  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$ . More specifically, we have

- The set  $\{\sigma_1, \sigma_2, \dots, \sigma_r\}$  are called the non-zero singular values of  $A$  and can be calculated as

$$\sigma_i(A) = \lambda_i^{\frac{1}{2}}(A^T A) = \lambda_i^{\frac{1}{2}}(A A^T)$$

- The columns of  $U$  are called the left singular vectors of  $A$  (and are the orthonormal eigenvectors of  $A A^T$ ).
- The columns of  $V$  are called the right singular vectors of  $A$  (and are the orthonormal eigenvectors of  $A^T A$ ).

## 2.3 Practice problems on linear algebra basics

1. Show the following properties for matrices

- (a) If  $b^T A b > 0$  for all  $b \in \mathbf{R}^n$ , then all eigenvalues of  $A$  are positive.
- (b) If  $A \in \mathbf{R}^{n \times n}$  is an orthogonal matrix, then all eigenvalues of  $A$  have norm 1.
- (c) If  $A \in \mathbf{R}^{m \times n}$  is a matrix with rank  $r$ , then

$$\sigma_i(A) = \lambda_i^{\frac{1}{2}}(A A^T)$$

2. Determine if the following statements are true or false. If they are true, give a justification. If they are false, give a counterexample.

- (a) If  $\mathbf{A}$  is an orthogonal matrix, then  $\mathbf{A}^T$  is also an orthogonal matrix.
- (b) If  $\mathbf{A}$  and  $\mathbf{B}$  are orthogonal  $n \times n$  matrices, then  $\mathbf{AB}$  is orthogonal.
- (c) If  $\mathbf{A}$  and  $\mathbf{B}$  are orthogonal  $n \times n$  matrices, then  $\mathbf{A} + \mathbf{B}$  is orthogonal.
- (d) If the column vectors of  $\mathbf{A}$  are orthonormal, then the row vectors of  $\mathbf{A}$  must also be orthonormal.