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Examples and Problems in Mathematical Statistics





Examples and Problems in Mathematical Statistics

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Examples and Problems in Mathematical Statistics

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To my wife Hanna, our sons Yuval and David, and their families, with love.

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Preface

I have been teaching probability and mathematical statistics to graduate students for close to 50 years. In my career I realized that the most difficult task for students is solving problems. Bright students can generally grasp the theory easier than apply it. In order to overcome this hurdle, I used to write examples of solutions to problems and hand it to my students. I often wrote examples for the students based on my published research. Over the years I have accumulated a large number of such examples and problems. This book is aimed at sharing these examples and problems with the population of students, researchers, and teachers.

The book consists of nine chapters. Each chapter has four parts. The first part contains a short presentation of the theory. This is required especially for establishing notation and to provide a quick overview of the important results and references. The second part consists of examples. The examples follow the theoretical presentation. The third part consists of problems for solution, arranged by the corresponding sections of the theory part. The fourth part presents solutions to some selected problems. The solutions are generally not as detailed as the examples, but as such these are examples of solutions. I tried to demonstrate how to apply known results in order to solve problems elegantly. All together there are in the book 167 examples and 431 problems.

The emphasis in the book is on statistical inference. The first chapter on probability is especially important for students who have not had a course on advanced probability. Chapter Two is on the theory of distribution functions. This is basic to all developments in the book, and from my experience, it is important for all students to master this calculus of distributions. The chapter covers multivariate distributions, especially the multivariate normal; conditional distributions; techniques of determining variances and covariances of sample moments; the theory of exponential families; Edgeworth expansions and saddle-point approximations; and more. Chapter Three covers the theory of sufficient statistics, completeness of families of distributions, and the information in samples. In particular, it presents the Fisher information, the Kullback–Leibler information, and the Hellinger distance. Chapter Four provides a strong foundation in the theory of testing statistical hypotheses. The Wald SPRT is discussed there too. Chapter Five is focused on optimal point estimation of different kinds. Pitman estimators and equivariant estimators are also discussed. Chapter Six covers problems of efficient confidence intervals, in particular the problem of determining fixed-width confidence intervals by two-stage or sequential sampling. Chapter Seven covers techniques of large sample approximations, useful in estimation and testing. Chapter Eight is devoted to Bayesian analysis, including empirical Bayes theory. It highlights computational approximations by numerical analysis and simulations. Finally, Chapter Nine presents a few more advanced topics, such as minimaxity, admissibility, structural distributions, and the Stein-type estimators.

I would like to acknowledge with gratitude the contributions of my many exstudents, who toiled through these examples and problems and gave me their important feedback. In particular, I am very grateful and indebted to my colleagues, Professors A. Schick, Q. Yu, S. De, and A. Polunchenko, who carefully read parts of this book and provided important comments. Mrs. Marge Pratt skillfully typed several drafts of this book with patience and grace. To her I extend my heartfelt thanks. Finally, I would like to thank my wife Hanna for giving me the conditions and encouragement to do research and engage in scholarly writing.

Shelemyahu Zacks

List of Random Variables

B(n, p)	Binomial, with parameters n and p
$E(\mu)$	Exponential with parameter μ
$EV(\lambda, \alpha)$	Extreme value with parameters λ and α
$F(v_1, v_2)$	Central F with parameters v_1 and v_2
$F(n_1, n_2; \lambda)$	Noncentral F with parameters v_1, v_2, λ
$G(\lambda, p)$	Gamma with parameters λ and p
H(M, N, n)	Hyper-geometric with parameters M, N, n
$N(\mu, V)$	Multinormal with mean vector μ and covariance matrix V
$N(\mu, \sigma)$	Normal with mean μ and σ
$NB(\psi, v)$	Negative-binomial with parameters ψ , and v
$P(\lambda)$	Poisson with parameter λ
R(a, b)	Rectangular (uniform) with parameters a and b
$t[n;\lambda]$	Noncentral Student's t with parameters n and λ
$t[n;\xi,V]$	Multivariate t with parameters n, ξ and V
<i>t</i> [<i>n</i>]	Student's t with n degrees of freedom
$W(\lambda, \alpha)$	Weibul with parameters λ and α
$\beta(p,q)$	Beta with parameters p and q
$\chi^2[n,\lambda]$	Noncentral chi-squared with parameters n and λ
$\chi^2[n]$	Chi-squared with n degrees of freedom

List of Abbreviations

a.s.	Almost surely
ANOVA	Analysis of variance
c.d.f.	Cumulative distribution function
cov(x, y)	Covariance of X and Y
CI	Confidence interval
CLT	Central limit theorem
СР	Coverage probability
CR	Cramer Rao regularity conditions
$E\{X \mid Y\}$	Conditional expected value of X , given Y
$E\{X\}$	Expected value of X
FIM	Fisher information matrix
i.i.d.	Independent identically distributed
LBUE	Linear best unbiased estimate
LCL	Lower confidence limit
m.g.f.	Moment generating function
m.s.s.	Minimal sufficient statistics
MEE	Moments equations estimator
MLE	Maximum likelihood estimator
MLR	Monotone likelihood ratio
MP	Most powerful
MSE	Mean squared error
MVU	Minimum variance unbiased
OC	Operating characteristic
p.d.f.	Probability density function
p.g.f.	Probability generating function
$P\{E \mid A\}$	Conditional probability of E, given A
$P\{E\}$	Probability of <i>E</i>
PTE	Pre-test estimator
r.v.	Random variable
RHS	Right-hand side
S.V.	Stopping variable

SE	Standard error
SLLN	Strong law of large numbers
SPRT	Sequential probability ratio test
$tr{A}$	trace of the matrix A
UCL	Upper control limit
UMP	Uniformly most powerful
UMPI	Uniformly most powerful invariant
UMPU	Uniformly most powerful unbiased
UMVU	Uniformly minimum variance unbiased
$V\{X \mid Y\}$	Conditional variance of X, given Y
$V{X}$	Variance of X
w.r.t.	With respect to
WLLN	Weak law of large numbers

CHAPTER 1

Basic Probability Theory

PART I: THEORY

It is assumed that the reader has had a course in elementary probability. In this chapter we discuss more advanced material, which is required for further developments.

1.1 OPERATIONS ON SETS

Let S denote a **sample space**. Let E_1 , E_2 be subsets of S. We denote the **union** by $E_1 \cup E_2$ and the intersection by $E_1 \cap E_2$. $\overline{E} = S - E$ denotes the **complement** of E. By DeMorgan's laws $\overline{E_1 \cup E_2} = \overline{E_1} \cap \overline{E_2}$ and $\overline{E_1 \cap E_2} = \overline{E_1} \cup \overline{E_2}$.

Given a sequence of sets $\{E_n, n \ge 1\}$ (finite or infinite), we define

$$\sup_{n \ge 1} E_n = \bigcup_{n \ge 1} E_n, \quad \inf_{n \ge 1} E_n = \bigcap_{n \ge 1} E_n.$$
(1.1.1)

Furthermore, $\liminf_{n\to\infty}$ and $\limsup_{n\to\infty}$ are defined as

$$\liminf_{n \to \infty} E_n = \bigcup_{n \ge 1} \bigcap_{k \ge n} E_k, \quad \limsup_{n \to \infty} E_n = \bigcap_{n \ge 1} \bigcup_{k \ge n} E_k.$$
(1.1.2)

If a point of S belongs to $\limsup_{n\to\infty} E_n$, it belongs to infinitely many sets E_n . The sets $\liminf_{n\to\infty} E_n$ and $\limsup_{n\to\infty} E_n$ always exist and

$$\liminf_{n \to \infty} E_n \subset \limsup_{n \to \infty} E_n. \tag{1.1.3}$$

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If $\liminf_{n\to\infty} E_n = \limsup_{n\to\infty} E_n$, we say that a limit of $\{E_n, n \ge 1\}$ exists. In this case,

$$\lim_{n \to \infty} E_n = \liminf_{n \to \infty} E_n = \limsup_{n \to \infty} E_n.$$
(1.1.4)

A sequence $\{E_n, n \ge 1\}$ is called **monotone increasing** if $E_n \subset E_{n+1}$ for all $n \ge 1$. In this case $\lim_{n\to\infty} E_n = \bigcup_{n=1}^{\infty} E_n$. The sequence is **monotone decreasing** if $E_n \supset E_{n+1}$, for all $n \ge 1$. In this case $\lim_{n\to\infty} E_n = \bigcap_{n=1}^{\infty} E_n$. We conclude this section with the definition of a **partition** of the sample space. A collection of sets $\mathcal{D} = \{E_1, \ldots, E_k\}$ is called a finite **partition** of S if all elements of \mathcal{D} are **pairwise disjoint** and their union is S, i.e., $E_i \cap E_j = \emptyset$ for all $i \ne j$; $E_i, E_j \in \mathcal{D}$; and $\bigcup_{i=1}^{k} E_i = S$. If \mathcal{D} contains a countable number of sets that are mutually exclusive and $\bigcup_{i=1}^{\infty} E_i = S$, we say that \mathcal{D} is a countable partition.

1.2 ALGEBRA AND σ -FIELDS

Let S be a sample space. An algebra A is a collection of subsets of S satisfying

We consider $\emptyset = \overline{S}$. Thus, (i) and (ii) imply that $\emptyset \in A$. Also, if $E_1, E_2 \in A$ then $E_1 \cap E_2 \in A$.

The **trivial algebra** is $A_0 = \{\emptyset, S\}$. An algebra A_1 is a subalgebra of A_2 if all sets of A_1 are contained in A_2 . We denote this inclusion by $A_1 \subset A_2$. Thus, the trivial algebra A_0 is a subalgebra of every algebra A. We will denote by A(S), the algebra generated by all subsets of S (see Example 1.1).

If a sample space S has a finite number of points n, say $1 \le n < \infty$, then the collection of all subsets of S is called the **discrete algebra** generated by the elementary events of S. It contains 2^n events.

Let \mathcal{D} be a partition of \mathcal{S} having $k, 2 \leq k$, disjoint sets. Then, the algebra generated by \mathcal{D} , $\mathcal{A}(\mathcal{D})$, is the algebra containing all the $2^k - 1$ unions of the elements of \mathcal{D} and the empty set.

An algebra on S is called a σ -field if, in addition to being an algebra, the following holds.

(iv) If
$$E_n \in \mathcal{A}, n \ge 1$$
, then $\bigcup_{n=1}^{\infty} E_n \in \mathcal{A}$.

We will denote a σ -field by \mathcal{F} . In a σ -field \mathcal{F} the supremum, infinum, limsup, and liminf of any sequence of events belong to \mathcal{F} . If \mathcal{S} is finite, the discrete algebra $\mathcal{A}(\mathcal{S})$ is a σ -field. In Example 1.3 we show an algebra that is not a σ -field.

The minimal σ -field containing the algebra generated by $\{(-\infty, x], -\infty < x < \infty\}$ is called the **Borel** σ -field on the real line \mathbb{R} .

A sample space S, with a σ -field \mathcal{F} , (S, \mathcal{F}) is called a **measurable space**.

The following lemmas establish the existence of smallest σ -field containing a given collection of sets.

Lemma 1.2.1. Let \mathcal{E} be a collection of subsets of a sample space \mathcal{S} . Then, there exists a smallest σ -field $\mathcal{F}(\mathcal{E})$, containing the elements of \mathcal{E} .

Proof. The algebra of all subsets of S, A(S) obviously contains all elements of \mathcal{E} . Similarly, the σ -field \mathcal{F} containing all subsets of S, contains all elements of \mathcal{E} . Define the σ -field $\mathcal{F}(\mathcal{E})$ to be the **intersection** of all σ -fields, which contain all elements of \mathcal{E} . Obviously, $\mathcal{F}(\mathcal{E})$ is an algebra. QED

A collection \mathcal{M} of subsets of \mathcal{S} is called a **monotonic class** if the limit of any monotone sequence in \mathcal{M} belongs to \mathcal{M} .

If \mathcal{E} is a collection of subsets of \mathcal{S} , let $\mathcal{M}^*(\mathcal{E})$ denote the smallest monotonic class containing \mathcal{E} .

Lemma 1.2.2. A necessary and sufficient condition of an algebra A to be a σ -field is that it is a monotonic class.

Proof. (i) Obviously, if A is a σ -field, it is a monotonic class.

(ii) Let \mathcal{A} be a monotonic class.

Let $E_n \in \mathcal{A}, n \ge 1$. Define $B_n = \bigcup_{i=1}^n E_i$. Obviously $B_n \subset B_{n+1}$ for all $n \ge 1$. Hence $\lim_{n \to \infty} B_n = \bigcup_{n=1}^{\infty} B_n \in \mathcal{A}. \text{ But } \bigcup_{n=1}^{\infty} B_n = \bigcup_{n=1}^{\infty} E_n. \text{ Thus, } \sup_{n \ge 1} E_n \in \mathcal{A}. \text{ Similarly, } \bigcap_{n=1}^{\infty} E_n \in \mathcal{A}.$ Thus, \mathcal{A} is a σ -field. QED

Theorem 1.2.1. Let \mathcal{A} be an algebra. Then $\mathcal{M}^*(\mathcal{A}) = \mathcal{F}(\mathcal{A})$, where $\mathcal{F}(\mathcal{A})$ is the smallest σ -field containing \mathcal{A} .

Proof. See Shiryayev (1984, p. 139).

The measurable space (\mathbb{R} , \mathcal{B}), where \mathbb{R} is the real line and $\mathcal{B} = \mathcal{F}(\mathbb{R})$, called the **Borel measurable space**, plays a most important role in the theory of statistics. Another important measurable space is (\mathbb{R}^n , \mathcal{B}^n), $n \ge 2$, where $\mathbb{R}^n = \mathbb{R} \times \mathbb{R} \times \cdots \times \mathbb{R}$ is the Euclidean *n*-space, and $\mathcal{B}^n = \mathcal{B} \times \cdots \times \mathcal{B}$ is the smallest σ -field containing \mathbb{R}^n , \emptyset , and all *n*-dimensional rectangles $I = I_1 \times \cdots \times I_n$, where

$$I_i = (a_i, b_i], \quad i = 1, ..., n, \quad -\infty < a_i < b_i < \infty.$$

The measurable space $(\mathbb{R}^{\infty}, \mathcal{B}^{\infty})$ is used as a basis for probability models of experiments with infinitely many trials. \mathbb{R}^{∞} is the space of ordered sequences $\mathbf{x} = (x_1, x_2, \ldots), -\infty < x_n < \infty, n = 1, 2, \ldots$ Consider the cylinder sets

$$\mathcal{C}(I_1 \times \cdots \times I_n) = \{\mathbf{x} : x_i \in I_i, i = 1, \dots, n\}$$

and

$$\mathcal{C}(B_1 \times \cdots \times B_n) = \{\mathbf{x} : x_i \in B_i, i = 1, \dots, n\}$$

where B_i are Borel sets, i.e., $B_i \in \mathcal{B}$. The smallest σ -field containing all these cylinder sets, $n \ge 1$, is $\mathcal{B}(\mathbb{R}^{\infty})$. Examples of Borel sets in $\mathcal{B}(\mathbb{R}^{\infty})$ are

(a)
$$\{\mathbf{x}:\mathbf{x}\in\mathbb{R}^{\infty}, \sup_{n\geq 1}x_n>a\}$$

or

(b)
$$\{\mathbf{x} : \mathbf{x} \in \mathbb{R}^{\infty}, \limsup_{n \to \infty} x_n \leq a\}.$$

1.3 PROBABILITY SPACES

Given a measurable space (S, \mathcal{F}) , a **probability model** ascribes a countably additive function *P* on \mathcal{F} , which assigns a probability $P\{A\}$ to all sets $A \in \mathcal{F}$. This function should satisfy the following properties.

(A.1) If
$$A \in \mathcal{F}$$
 then $0 \le P\{A\} \le 1$.
(A.2) $P\{S\} = 1$. (1.3.1)

(A.3) If
$$\{E_n, n \ge 1\} \in \mathcal{F}$$
 is a sequence of **disjoint**

sets in
$$\mathcal{F}$$
, then $P\left\{\bigcup_{n=1}^{\infty} E_n\right\} = \sum_{n=1}^{\infty} P\{E_n\}.$ (1.3.2)

Recall that if $A \subset B$ then $P\{A\} \leq P\{B\}$, and $P\{\overline{A}\} = 1 - P\{A\}$. Other properties will be given in the examples and problems. In the sequel we often write AB for $A \cap B$.

Theorem 1.3.1. Let (S, \mathcal{F}, P) be a probability space, where \mathcal{F} is a σ -field of subsets of S and P a probability function. Then

(i) if $B_n \subset B_{n+1}$, $n \ge 1$, $B_n \in \mathcal{F}$, then

$$P\left\{\lim_{n\to\infty}B_n\right\} = \lim_{n\to\infty}P\{B_n\}.$$
 (1.3.3)

(ii) if $B_n \supset B_{n+1}$, $n \ge 1$, $B_n \in \mathcal{F}$, then

$$P\left\{\lim_{n\to\infty}B_n\right\} = \lim_{n\to\infty}P\{B_n\}.$$
(1.3.4)

Proof. (i) Since $B_n \subset B_{n+1}$, $\lim_{n \to \infty} B_n = \bigcup_{n=1}^{\infty} B_n$. Moreover,

$$P\left\{\bigcup_{n=1}^{\infty} B_n\right\} = P\{B_1\} + \sum_{n=2}^{\infty} P\{B_n - B_{n-1}\}.$$
 (1.3.5)

Notice that for $n \ge 2$, since $\bar{B}_n B_{n-1} = \emptyset$,

$$P\{B_n - B_{n-1}\} = P\{B_n \bar{B}_{n-1}\}$$

= $P\{B_n\} - P\{B_n B_{n-1}\} = P\{B_n\} - P\{B_{n-1}\}.$ (1.3.6)

Also, in (1.3.5)

$$P\{B_1\} + \sum_{n=2}^{\infty} P\{B_n - B_{n-1}\} = \lim_{N \to \infty} \left(P\{B_1\} + \sum_{n=2}^{N} (P\{B_n\} - P\{B_{n-1}\}) \right)$$
$$= \lim_{N \to \infty} P\{B_N\}.$$
(1.3.7)

Thus, Equation (1.3.3) is proven.

(ii) Since $B_n \supset B_{n+1}, n \ge 1$, $\overline{B}_n \subset \overline{B}_{n+1}, n \ge 1$. $\lim_{n \to \infty} B_n = \bigcap_{n=1}^{\infty} B_n$. Hence, $P\left(\lim_{n \to \infty} B_n\right) = 1 - P\left\{\overline{\bigcap_{n=1}^{\infty} B_n}\right\}$ $= 1 - P\left\{\bigcup_{n=1}^{\infty} \overline{B}_n\right\}$ $= 1 - \lim_{n \to \infty} P\{\overline{B}_n\} = \lim_{n \to \infty} P\{B_n\}.$ QED

Sets in a probability space are called events.

1.4 CONDITIONAL PROBABILITIES AND INDEPENDENCE

The conditional probability of an event $A \in \mathcal{F}$ given an event $B \in \mathcal{F}$ such that $P\{B\} > 0$, is defined as

$$P\{A \mid B\} = \frac{P\{A \cap B\}}{P\{B\}}.$$
(1.4.1)

We see first that $P\{\cdot | B\}$ is a probability function on \mathcal{F} . Indeed, for every $A \in \mathcal{F}$, $0 \leq P\{A | B\} \leq 1$. Moreover, $P\{S | B\} = 1$ and if A_1 and A_2 are disjoint events in \mathcal{F} , then

$$P\{A_1 \cup A_2 \mid B\} = \frac{P\{(A_1 \cup A_2)B\}}{P\{B\}}$$

$$= \frac{P\{A_1B\} + P\{A_2B\}}{P\{B\}} = P\{A_1 \mid B\} + P\{A_2 \mid B\}.$$
(1.4.2)

If $P{B} > 0$ and $P{A} \neq P{A | B}$, we say that the events A and B are **dependent**. On the other hand, if $P{A} = P{A | B}$ we say that A and B are **independent** events. Notice that two events are independent if and only if

$$P\{AB\} = P\{A\}P\{B\}.$$
 (1.4.3)

Given *n* events in A, namely A_1, \ldots, A_n , we say that they are **pairwise** independent if $P\{A_iA_j\} = P\{A_i\}P\{A_j\}$ for any $i \neq j$. The events are said to be independent in triplets if

$$P\{A_iA_jA_k\} = P\{A_i\}P\{A_j\}P\{A_k\}$$

for any $i \neq j \neq k$. Example 1.4 shows that pairwise independence does not imply independence in triplets.

Given *n* events A_1, \ldots, A_n of \mathcal{F} , we say that they are **independent** if, for any $2 \le k \le n$ and any *k*-tuple $(1 \le i_1 < i_2 < \cdots < i_k \le n)$,

$$P\left\{\bigcap_{j=1}^{k} A_{i_j}\right\} = \prod_{j=1}^{k} P\{A_{i_j}\}.$$
(1.4.4)

Events in an infinite sequence $\{A_1, A_2, \ldots\}$ are said to be **independent** if $\{A_1, \ldots, A_n\}$ are independent, for each $n \ge 2$. Given a sequence of events A_1, A_2, \ldots of a σ -field \mathcal{F} , we have seen that

$$\limsup_{n\to\infty}A_n=\bigcap_{n=1}^{\infty}\bigcup_{k=n}^{\infty}A_k.$$

This event means that points *w* in $\limsup_{n\to\infty} A_n$ belong to infinitely many of the events $\{A_n\}$. Thus, the event $\limsup_{n\to\infty} A_n$ is denoted also as $\{A_n, \text{ i.o.}\}$, where i.o. stands for "infinitely often."

The following important theorem, known as the **Borel–Cantelli Lemma**, gives conditions under which $P\{A_n, i.o.\}$ is either 0 or 1.

Theorem 1.4.1 (Borel–Cantelli). Let $\{A_n\}$ be a sequence of sets in \mathcal{F} .

(*i*) If
$$\sum_{n=1}^{\infty} P\{A_n\} < \infty$$
, then $P\{A_n, i.o.\} = 0$.
(*ii*) If $\sum_{n=1}^{\infty} P\{A_n\} = \infty$ and $\{A_n\}$ are independent, then $P\{A_n, i.o.\} = 1$.

Proof. (i) Notice that $B_n = \bigcup_{k=n}^{\infty} A_k$ is a decreasing sequence. Thus

$$P\{A_n, \text{ i.o.}\} = P\left\{\bigcap_{n=1}^{\infty} B_n\right\} = \lim_{n \to \infty} P\{B_n\}.$$

But

$$P\{B_n\} = P\left\{\bigcup_{k=n}^{\infty} A_k\right\} \le \sum_{k=n}^{\infty} P\{A_k\}.$$

The assumption that $\sum_{n=1}^{\infty} P\{A_n\} < \infty$ implies that $\lim_{n \to \infty} \sum_{k=n}^{\infty} P\{A_k\} = 0.$

(ii) Since A_1, A_2, \ldots are independent, $\bar{A}_1, \bar{A}_2, \ldots$ are independent. This implies that

$$P\left\{\bigcap_{k=1}^{\infty} \bar{A}_{k}\right\} = \prod_{k=1}^{\infty} P\{\bar{A}_{k}\} = \prod_{k=1}^{\infty} (1 - P\{A_{k}\}).$$

If $0 < x \le 1$ then $\log(1 - x) \le -x$. Thus,

$$\log \prod_{k=1}^{\infty} (1 - P\{A_k\}) = \sum_{k=1}^{\infty} \log(1 - P\{A_k\})$$
$$\leq -\sum_{k=1}^{\infty} P\{A_k\} = -\infty$$

since $\sum_{\substack{n=1\\k=1}}^{\infty} P\{A_n\} = \infty$. Thus $P\left\{\bigcap_{k=1}^{\infty} \bar{A}_k\right\} = 0$ for all $n \ge 1$. This implies that $P\{A_n, \text{ i.o.}\} = 1$. QED

We conclude this section with the celebrated **Bayes Theorem**.

Let $\mathcal{D} = \{B_i, i \in J\}$ be a partition of \mathcal{S} , where J is an index set having a finite or countable number of elements. Let $B_j \in \mathcal{F}$ and $P\{B_j\} > 0$ for all $j \in J$. Let $A \in \mathcal{F}$, $P\{A\} > 0$. We are interested in the conditional probabilities $P\{B_j \mid A\}, j \in J$.

Theorem 1.4.2 (Bayes).

$$P\{B_j \mid A\} = \frac{P\{B_j\}P\{A \mid B_j\}}{\sum_{j' \in J} P\{B_{j'}\}P\{A \mid B_{j'}\}}.$$
(1.4.5)

Proof. Left as an exercise.

Bayes Theorem is widely used in scientific inference. Examples of the application of Bayes Theorem are given in many elementary books. Advanced examples of Bayesian inference will be given in later chapters.

1.5 RANDOM VARIABLES AND THEIR DISTRIBUTIONS

Random variables are finite real value functions on the sample space S, such that measurable subsets of F are mapped into Borel sets on the real line and thus can be

QED