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APPENDIX A

MATHEMATICAL BACKGROUND

This appendix contains the mathematical background that is needed to understand Chapter 3, Chapter 4 and Chapter 5. In Section A.1 an overview is given of stochastic calculus. In the last five sections of the appendix the following mathematical concepts or ideas are summarised: Gaussian quadrature, Cholesky factorisation, the method of Lagrangian multipliers and KDE.

A.1 STOCHASTIC CALCULUS

The basic definitions used in Chapter 3 are defined in this section and can also be found in [48, 59, 82].

Definition 1 (A σ -field \mathcal{F}) Let Ω be a non-empty set. A σ -field \mathcal{F} on Ω is a family of subsets of Ω such that

1. the empty set \emptyset belongs to \mathcal{F} ;
2. if A belongs to \mathcal{F} , then so does the complement $\Omega \setminus A$;
3. if A_1, A_2, \dots is a sequence of sets in \mathcal{F} , then their union $A_1 \cup A_2 \cup \dots$ also belongs to \mathcal{F} .

Definition 2 (Family of Borel sets) The family of Borel sets $\mathbb{B} = \mathcal{B}(\mathbb{R})$ is a σ -field on \mathbb{R} . The Borel σ -field in \mathbb{R} is the smallest σ -field containing all intervals in \mathbb{R} .

Definition 3 (Probability measure) Let \mathcal{F} be a σ -field on Ω . A probability measure P is a function

$$P: \mathcal{F} \rightarrow [0, 1]$$

such that

1. $P(\Omega) = 1$;

2. if A_1, A_2, \dots are pairwise disjoint sets (that is, $A_i \cap A_j = \emptyset$ for $i \neq j$) belonging to \mathcal{F} , then

$$P(A_1 \cup A_2 \cup \dots) = P(A_1) + P(A_2) + \dots$$

The triple (Ω, \mathcal{F}, P) is known as a *probability space*. Each set A contained in \mathcal{F} is referred to as an *event*. Whenever the $P(A) = 1$ then event A is said to occur *almost surely*.

Definition 4 (Random variable) If \mathcal{F} is a σ -field on Ω , then a function $\xi : \Omega \rightarrow \mathbb{R}$ is said to be \mathcal{F} -measurable if

$$\{\xi \in B\} \in \mathcal{F}$$

for every Borel set $B \in \mathcal{B}(\mathbb{R})$. If (Ω, \mathcal{F}, P) is a probability space, then such a function ξ is called a *random variable*.

The short-hand notation $\{\xi \in B\}$ in the above definition represents the inverse image $\xi^{-1}(B)$. In expanded form $\{\xi \in B\}$ is written as

$$\{\omega \in \Omega : \xi(\omega) \in B\}.$$

Definition 5 (The σ field generated by a random variable) The σ -field $\sigma(\xi)$ generated by a random variable $\xi : \Omega \rightarrow \mathbb{R}$ consists of all sets of the form $\{\xi \in B\}$, where B is a Borel set in \mathbb{R} .

Definition 6 (The σ field generated by a family of random variables) The σ -field $\sigma\{\xi_i : i \in I\}$ generated by a family $\{\xi_i : i \in I\}$ of random variables is defined to be the smallest σ -field containing all the events of the form $\{\xi_i \in B\}$, where B is a Borel set in \mathbb{R} and $i \in I$ (I is an index set).

Definition 7 (The distribution of a random variable and the cumulative distribution function)

Every random variable $\xi : \Omega \rightarrow \mathbb{R}$ gives rise to a probability measure

$$P_\xi(B) = P\{\xi \in B\}$$

on \mathbb{R} defined on the σ -field of Borel sets $B \in \mathcal{B}(\mathbb{R})$. The probability measure P_ξ is called the *distribution* of ξ . The function $F_\xi : \mathbb{R} \rightarrow [0, 1]$ defined by

$$F_\xi(x) = P\{\xi \leq x\} = P_\xi((-\infty, x]), \quad x \in \mathbb{R}$$

is called the cumulative distribution function of ξ .

Definition 7 implies that the measurability of ξ ensures that ξ generates a probability measure P_ξ on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$, such that $(\mathbb{R}, \mathcal{B}(\mathbb{R}), P_\xi)$ is also a probability space. If P_ξ is known, then the structure of (Ω, \mathcal{F}, P) is no longer needed to describe the behavior of ξ .

Definition 8 (Probability density function) *If there is a Borel function $f_\xi : \mathbb{R} \rightarrow \mathbb{R}$ such that for any Borel set $B \subset \mathbb{R}$*

$$P\{\xi \in B\} = \int_B f_\xi(x)dx,$$

then ξ is said to be a random variable with absolutely continuous distribution and f_ξ is called the density of ξ . If there is a (finite or infinite) sequence of pairwise distinct real number x_1, x_2, \dots such that for any Borel set $B \subset \mathbb{R}$

$$P\{\xi \in B\} = \sum_{x_i \in B} P\{\xi = x_i\},$$

then ξ is said to have discrete distribution with values x_1, x_2, \dots and mass $P\{\xi = x_i\}$ at x_i .

Definition 9 (Essential supremum) *Let $(\xi_i)_{i \in I}$ (where I is an index set) be a family of real-valued random variables on (Ω, \mathcal{F}, P) , bounded by another variable. The essential supremum of $(\xi_i)_{i \in I}$ is Ξ (denoted by $\Xi = \text{ess sup}_I \xi_i$) if*

$$(\forall i \in I) \xi_i \leq \mathcal{X} P\text{-almost surely} \Leftrightarrow \Xi \leq \mathcal{X} P\text{-almost surely}.$$

Definition 10 (Expectation) *A random variable $\xi : \Omega \rightarrow \mathbb{R}$ is said to be integrable if*

$$\int_\Omega |\xi| dP < \infty.$$

Then

$$\mathbb{E}[\xi] = \int_\Omega \xi dP$$

exists and is called the expectation of ξ .

The expectation $\mathbb{E}[\xi]$ can also be expressed as a Riemann integral as follows [48]:

$$\begin{aligned} \mathbb{E}[\xi] &= \int_\Omega \xi dP \\ &= \int_{\mathbb{R}} x dP_\xi \\ &= \int_{-\infty}^{\infty} x dF_\xi(x) \\ &= \int_{-\infty}^{\infty} x f_\xi(x) dx. \end{aligned}$$

It is also important to note that $\frac{d}{dx}F_\xi(x) = f_\xi(x)$.

Definition 11 (Conditioning on an event) For an integrable random variable ξ and any event $B \in \mathcal{F}$ such that $P(B) \neq 0$ the conditional expectation of ξ given B is defined by

$$\mathbb{E}[\xi|B] = \frac{1}{P(B)} \int_B \xi dP.$$

Definition 12 (Conditioning on a discrete random variable) Let ξ be an integrable random variable and let η be a discrete random variable. Then the conditional expectation of ξ given η is defined to be a random variable $\mathbb{E}[\xi|\eta]$ such that

$$\mathbb{E}[\xi|\eta](\omega) = \mathbb{E}[\xi|\{\eta = y_n\}] \text{ if } \eta(\omega) = y_n$$

for any $n = 1, 2, \dots$.

By using Definition 12 the following proposition can be derived (stated here without proof) [82]:

Proposition 1 If ξ is an integrable random variable and η is a discrete random variable, then

1. $\mathbb{E}[\xi|\eta]$ is $\sigma(\eta)$ -measurable;
2. For any $A \in \sigma(\eta)$

$$\int_A \mathbb{E}[\xi|\eta] dP = \int_A \xi dP. \quad (\text{A.1})$$

Definition 13 (Conditioning on an arbitrary random variable) Let ξ be an integrable random variable and let η be an arbitrary random variable. Then the conditional expectation of ξ given η is defined to be a random variable $\mathbb{E}[\xi|\eta]$ such that

1. $\mathbb{E}[\xi|\eta]$ is $\sigma(\eta)$ -measurable;
2. For any $A \in \sigma(\eta)$

$$\int_A \mathbb{E}[\xi|\eta] dP = \int_A \xi dP. \quad (\text{A.2})$$

Definition 14 (Conditioning on a σ -field) Let ξ be an integrable random variable on a probability space (Ω, \mathcal{F}, P) , and let \mathcal{G} be a σ -field contained in \mathcal{F} . Then the conditional expectation of ξ given \mathcal{G} is defined to be a random variable $\mathbb{E}[\xi|\mathcal{G}]$ such that

1. $\mathbb{E}[\xi|\mathcal{G}]$ is \mathcal{G} -measurable

2. For any $A \in \mathcal{G}$

$$\int_A \mathbb{E}[\xi|\mathcal{G}]dP = \int_A \xi dP.$$

Definition 15 (Sample path) The sequence of number $\xi_1(\omega), \xi_2(\omega), \dots$ for any fixed $\omega \in \Omega$ is called a sample path.

Definition 16 (Filtration) A sequence of σ -fields $\mathcal{F}_1, \mathcal{F}_2, \dots$ on Ω such that

$$\mathcal{F}_1 \subset \mathcal{F}_2 \subset \dots \subset \mathcal{F}$$

is called a filtration.

Definition 17 (Adapted to a filtration) A sequence of random variables ξ_1, ξ_2, \dots is adapted to a filtration $\mathcal{F}_1, \mathcal{F}_2, \dots$ if ξ_n is \mathcal{F}_n -measurable for each $n = 1, 2, \dots$.

Definition 18 (Stopping time) A random variable T with values in the set $\{1, 2, \dots\} \cup \{\infty\}$ is called a stopping time (with respect to a filtration \mathcal{F}_n) if for each $n = 1, 2, \dots$

$$\{T = n\} \in \mathcal{F}_n.$$

At this point Wald's identities can be presented (and is stated here without proof) [48]. Wald's identities were used in Chapter 3 to derive the OC and ASN functions.

Theorem 6 (Wald's identities) Suppose $\{s_k; k = 1, 2, \dots\}$ is an i.i.d. sequence adapted to the filtration $\{\mathcal{F}_k\}$, and let S_k denote the sequence of cumulative sums, $S_k = \sum_{i=1}^k s_i$. Then the following statements are true:

1. Suppose $\mathbb{E}[s_1]$ is finite, then for every stopping time T satisfying $\mathbb{E}[T] < \infty$, $\mathbb{E}[S_T] = \mathbb{E}[s_1]\mathbb{E}[T] \implies \mathbb{E}[T] = \frac{\mathbb{E}[S_T]}{\mathbb{E}[s_1]}$ when $\mathbb{E}[s_1] \neq 0$.

2. Suppose $\mathbb{E}[s_1^2]$ is finite, then for ever stopping time T satisfying $\mathbb{E}[T] < \infty$, $\mathbb{E}[S_T - T\mathbb{E}[s_1]]^2 = \mathbb{E}[T]\mathbb{E}[s_1 - \mathbb{E}[s_1]]^2 \implies \mathbb{E}[T] = \frac{\mathbb{E}[S_T^2]}{\mathbb{E}[s_1^2]}$ when $\mathbb{E}[s_1] = 0$.

3. For scalars $a, h > 0$ define the stopping time $T_{-a}^h = \inf\{k | S_k \notin (-b, a)\}$. Suppose $\omega \neq 0$ is such that $\mathbb{E}[e^{-\omega s_1}] < \infty$, then $\mathbb{E}[e^{\omega S_T} (\mathbb{E}[e^{-\omega s_1}])^{-T}] = 1$, holds for any stopping time T such that $P(T \leq T_{-a}^h) = 1$.

Definition 19 (Stochastic process) A stochastic process is a family of random variables $\xi(t)$ parameterised by $t \in \mathcal{T}$, where $\mathcal{T} \subset \mathbb{R}$. When $\mathcal{T} = \{1, 2, \dots\}$ then $\xi(t)$ is a stochastic process in discrete time (a sequence of random variables). When \mathcal{T} is an interval in \mathbb{R} (typically $\mathcal{T} = [0, \infty)$) then $\xi(t)$ is a stochastic process in continuous time. Moreover, for every $\omega \in \Omega$ the function

$$\mathcal{T} \ni t \rightarrow \xi(t, \omega)$$

is called a sample path of $\xi(t)$.

Definition 20 (Brownian motion) The Wiener process (or Brownian motion) is a stochastic process $W(t)$ with values in \mathbb{R} defined for $t \in [0, \infty)$ such that

1. $W(0) = 0$ almost surely;
2. the sample paths $t \rightarrow W(t)$ are almost surely continuous;
3. for any finite sequence of times $0 < t_1 < \dots < t_n$ and Borel sets $A_1, \dots, A_n \subset \mathbb{R}$

$$P\{W(t_1) \in A_1, \dots, W(t_n) \in A_n\} = \int_{A_1} \dots \int_{A_n} p(t_1, 0, x_1) p(t_2 - t_1, x_1, x_2) \dots p(t_n - t_{n-1}, x_{n-1}, x_n) dx_1 \dots dx_n,$$

where

$$p(t, w, y) = \frac{1}{\sqrt{2\pi t}} e^{-\frac{(x-y)^2}{2t}}$$

defined for any $x, y \in \mathbb{R}$ and $t > 0$ is called the transition density.

From Definition 20 the following theorem can be derived (stated here without proof) [82]:

Theorem 7 A stochastic process $W(t)$, $t \geq 0$, is a Wiener process if and only if the following conditions hold:

1. $W(0) = 0$ almost surely;
2. the sample paths $t \rightarrow W(t)$ are almost surely continuous;
3. $W(t)$ has stationary (the distribution of $X(s+t) - X(s)$ does not depend on s for all $s, t > 0$) independent ($\mathbb{E}[(W(u) - W(t))(W(s) - W(r))] = 0$ for any $0 \leq r \leq s \leq t \leq u$) increments;
4. the increment $W(t) - W(s)$ has the normal distribution with mean 0 and variance $t - s$ for any $0 \leq s \leq t$.

Definition 21 (Random step process) A process $f(t), t \geq 0$ is a random step process if there is a finite sequence of numbers $0 = t_0 < t_1 < \dots < t_n$ and square integrable random variables $\eta_0, \eta_1, \dots, \eta_{n-1}$ such that

$$f(t) = \sum_{j=0}^{n-1} \eta_j \mathbf{1}_{[t_j, t_{j+1})}(t),$$

where η_j is \mathcal{F}_{t_j} -measurable for $j = 0, 1, \dots, n-1$. The set of random step processes will be denoted by M_{step}^2 . In Equation A.3, $\mathbf{1}(t)$ represents the indicator function.

Definition 22 (Stochastic integral of a random step process) The stochastic integral of a random step process $f \in M_{step}^2$ is defined by

$$I(f) = \sum_{j=0}^{n-1} \eta_j (W(t_{j+1}) - W(t_j)).$$

Definition 23 M^2 is the class of stochastic processes $f(t), t \geq 0$ that satisfy

$$\mathbb{E} \left[\int_0^\infty |f(t)|^2 dt \right] < \infty$$

and

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[\int_0^\infty |f(t) - f_n(t)|^2 dt \right] = 0. \quad (\text{A.3})$$

In this case the sequence of step processes f_1, f_2, \dots approximates f in M^2 .

Definition 24 (Itô stochastic integral) $I(f) \in L^2$ (L^2 is the space of square integrable random variables) is called the Itô stochastic integral [from 0 to ∞] of $f \in M^2$ if

$$\lim_{n \rightarrow \infty} \mathbb{E}[|I(f) - I(f_n)|^2] = 0$$

for any sequence $f_1, f_2, \dots \in M_{step}^2$ of random step processes that approximates f in M^2 (i.e. such that Equation A.3 is satisfied). $I(f)$ and $\int_0^\infty f(t) dW(t)$ are interchangeable.

A.2 GAUSSIAN QUADRATURE

The Gauss-Legendre quadrature rule is formally expressed as [40]

$$\int_a^b f(x) dx \approx \frac{b-a}{2} \sum_{i=1}^n w_i f \left(\frac{b-a}{2} z_i + \frac{a+b}{2} \right),$$

where z_i is the i -th root of the Legendre polynomial $P_n(z) = \frac{1}{2^n n!} \frac{d^n}{dz^n} [(z^2 - 1)^n]$ and

$$w_i = \frac{2}{(1 - z_i^2) [P_n'(z_i)]^2}.$$

A.3 CHOLESKY FACTORISATION

If \mathbf{A} has real entries and is symmetric ($\mathbf{A} = \mathbf{A}^T$) and positive definite ($\mathbf{z}^T \mathbf{A} \mathbf{z}$ is positive, for any column vector \mathbf{z}), then \mathbf{A} can be written as

$$\mathbf{A} = \mathbf{L} \mathbf{L}^*,$$

where \mathbf{L} has positive diagonal entries and is a lower triangular matrix, and \mathbf{L}^* is equal to the conjugate transpose of \mathbf{L} . Writing \mathbf{A} as the product $\mathbf{L} \mathbf{L}^*$ is known as Cholesky decomposition [40].

The Cholesky algorithm, used to calculate the decomposition matrix \mathbf{L} is described next. The recursive Cholesky algorithm starts by setting $i = 1$ and $\mathbf{A}(1) = \mathbf{A}$. At step i , the matrix $\mathbf{A}(i)$ then has the following form:

$$\mathbf{A}^{(i)} = \begin{pmatrix} \mathbf{I}_{i-1} & 0 & 0 \\ 0 & a_{i,i} & \mathbf{b}_i^* \\ 0 & \mathbf{b}_i & \mathbf{B}^{(i)} \end{pmatrix},$$

where \mathbf{I}_{i-1} is the identity matrix of dimension $i - 1$.

If matrix \mathbf{L}_i is defined as

$$\mathbf{L}_i = \begin{pmatrix} \mathbf{I}_{i-1} & 0 & 0 \\ 0 & \sqrt{a_{i,i}} & 0 \\ 0 & \frac{1}{\sqrt{a_{i,i}}} \mathbf{b}_i & \mathbf{I}_{n-i} \end{pmatrix},$$

then $\mathbf{A}(i)$ can be written as

$$\mathbf{A}^{(i)} = \mathbf{L}_i \mathbf{A}^{(i+1)} \mathbf{L}_i^*$$

where

$$\mathbf{A}^{(i+1)} = \begin{pmatrix} \mathbf{I}_{i-1} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \mathbf{B}^{(i)} - \frac{1}{a_{i,i}} \mathbf{b}_i \mathbf{b}_i^* \end{pmatrix}.$$

Note that $\mathbf{b}_i \mathbf{b}_i^*$ is an outer product. If the above is repeated enough times then at step n (which is also the dimension of the matrix \mathbf{A}), $\mathbf{A}(n+1) = \mathbf{I}$. Hence, the lower triangular matrix \mathbf{L} is equal to

$$\mathbf{L} = \mathbf{L}_1 \mathbf{L}_2 \dots \mathbf{L}_n.$$

A.4 LAGRANGE MULTIPLIERS

The method of Lagrange multipliers is employed to solve the following optimization problem:

$$\begin{aligned} \max_{x,y} f(x,y) \\ \text{s.t. } g(x,y) = c, \end{aligned} \tag{A.4}$$

where f and g are functions that have continuous first order partial derivatives and c is a constant. The Lagrange function is derived from $f(x,y), g(x,y), c$ and a new variable λ (the Lagrange multiplier) and is defined as

$$\mathcal{L}(x,y,\lambda) = f(x,y) + \lambda \cdot (g(x,y) - c).$$

If x_0 and y_0 are solutions of Equation A.4, then there exists an λ_0 such that (x_0, y_0, λ_0) is a stationary point of $\mathcal{L}(x,y,\lambda)$ [40].

A.5 KERNEL DENSITY ESTIMATION

If (x_1, x_2, \dots, x_n) are i.i.d. samples drawn from a distribution with an unknown density f , then the kernel density estimator of f is

$$\hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^n K_h(x - x_i) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right),$$

where $K(x)$ is a symmetric but not necessarily positive function that integrates to one (and is known as the kernel), $h > 0$ is called the bandwidth (functions as a smoothing parameter) and $K_h(x) = 1/hK(x/h)$ (and is known as the scaled kernel). If Gaussian kernels are used to approximate univariate data, and the underlying density being estimated is itself a Gaussian then Silverman's rule of thumb is the optimal choice of h . Silverman's rule of thumb is:

$$h = \left(\frac{4\hat{\sigma}^5}{3n}\right)^{\frac{1}{5}} \approx 1.06\hat{\sigma}n^{-1/5},$$

where $\hat{\sigma}$ is the standard deviation of the samples (x_1, x_2, \dots, x_n) . The multivariate case is approached in a similar way [195].