

Maß- und Wahrscheinlichkeitstheorie Übersicht

Ronert Obst

January 5, 2013

Contents

1	Erstes Kapitel	1
2	Ungelöste Fragen	2
2.1	WS11/12 Februar	2
2.1.1	Aufgabe 1	2
2.2	WS11/12 April alle	2
2.3	One Thousand Exercises in Probability	2
3	Sigma-Fields	2
3.1	Definition	2
3.2	Intersections of Sigma-Algebras	3
3.3	Minimal Sigma-Algebras	3
3.4	Inverse Maps	3
4	Measures	3
4.1	Probability Measures	3
4.1.1	Definition	3
4.2	Measurability	4
4.3	Image Measure	4
5	Integration and Expectation	4
5.1	Expectation	4
5.2	Probability	5
5.3	Distribution Function	5
5.4	Monotone Convergence	5
5.5	Dominated Convergence Theorem	5
5.6	Integrable Random Variables	5
5.7	Properties of Expectation	5
5.8	Fatou's Lemma	5
5.9	Fubini Theorem	5
5.10	Tonelli	5
5.11	Radon-Nikodym	5
5.12	Transformationssatz für Dichten	5
5.13	Convolutions	5
6	Conditional Expectation	7
6.1	Properties of Conditional Expectation	7
6.2	Glättungseigenschaften	7
6.3	Bedingte Dichten	7
6.4	Bedingte Wahrscheinlichkeiten	7

6.5	Examples	7
7	Martingales	8
7.1	Properties	8
7.2	Stopping Times	9
7.3	Martingaldifferenzfolgen	9
7.4	Examples	9
8	Convergence	10
8.1	Almost Sure Convergence	10
8.1.1	Kolmogorov Convergence Criterion	11
8.2	Convergence in Probability	11
8.3	L_p Convergence	11
8.4	Convergence in Distribution (Weak Convergence)	11
8.4.1	Extreme Value Distributions	12
8.5	Implications	12
8.5.1	Converse Implications	12
8.5.2	Slutsky's Theorem	12
9	Appendix	13
9.1	Stammfunktionen	13
9.1.1	Beispiele	13
9.2	Partielle Integration	13
9.3	Sets and Events	13
9.3.1	De Morgan	13
9.3.2	Limits of Sets	13
9.3.3	Borel-Cantelli Lemma	13
9.3.4	Borel Zero-One Law	14
9.4	Inequalities	14
9.4.1	Markov	14
9.4.2	Chebychev	14
9.4.3	Kolmogorov	14
9.4.4	Schwartz	14
9.4.5	Hölder	14
9.4.6	Minkowski	14
9.4.7	Jensen	14
9.5	Stochastics	14
9.5.1	Law of Large Numbers	14
9.5.2	Central Limit Theorem	14
9.6	Extrema and Order Statistics	14
9.6.1	Minima	14
9.6.2	Maxima	15

1 Erstes Kapitel

Duis auctor ligula et lorem fermentum commodo. Quisque
commodo posuere nulla id gravida. Pellentesque pretium
bibendum nisi, nec condimentum ante ullamcorper vitae. Vi-
vamus non sapien mauris, quis tincidunt dui. Nunc cursus luc-
tus felis in sagittis. Proin tincidunt blandit metus, eget conva-
llis risus blandit ut. In hac habitasse platea dictumst. Sed mo-
lestie blandit nibh, vel laoreet nibh pretium accumsan. Proin
id semper erat. Sed elementum congue mi quis dapibus. Nulla
urna nibh, adipiscing sed sodales sit amet, sollicitudin conval-
lis libero. Quisque eros lacus, auctor et egestas vel, gravida sit

amet tortor.

Morbi sed nulla id orci sollicitudin aliquet ac at urna. In eu fringilla risus. Fusce urna ipsum, consequat non tempus nec, suscipit vitae ligula. Morbi volutpat, mauris sed adipiscing venenatis, risus sem porttitor nunc, vel pellentesque est leo vel enim. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Nam a arcu ipsum. Etiam convallis justo eu elit porttitor eget laoreet odio porta. Vivamus at sem enim, id ultrices turpis. Nulla ipsum nibh, convallis vitae lobortis sed, luctus eget augue. Mauris ut velit tortor. Etiam malesuada, nisl quis luctus placerat, dolor augue rutrum magna, id sollicitudin eros est ut neque. Vivamus accumsan, elit eu condimentum facilisis, dui risus commodo ipsum, eget lacinia nunc metus ac tellus. Maecenas felis mi, sollicitudin facilisis ornare quis, elementum bibendum metus. Ut fermentum vestibulum risus consectetur bibendum. Curabitur a diam luctus urna cursus viverra eu eu nisi.

Proin tempus rhoncus arcu sed sagittis. Fusce venenatis nisi eget felis commodo egestas. Ut aliquam, lectus dictum aliquam pulvinar, risus risus condimentum nulla, congue feugiat mauris lacus sit amet ligula. Fusce vel massa dolor. Nullam eleifend augue in enim fermentum elementum. Sed turpis magna, fringilla ut lobortis sit amet, luctus in risus. Vivamus sem nisi, mattis nec mollis vitae, blandit sit amet mauris. In metus magna, tempor at commodo ac, malesuada quis odio. Donec porttitor nunc ac justo dapibus in rutrum purus dictum. Mauris non posuere quam. Sed justo lacus, auctor sit amet placerat nec, auctor quis orci. Pellentesque et sapien vitae dolor malesuada mollis et posuere elit. Cras ut nisi mauris, id lacinia lectus. Curabitur mattis viverra urna vel aliquet. Praesent vitae mi dictum purus sodales auctor in id ante.

Suspendisse mi justo, eleifend vestibulum malesuada vel, luctus vel nulla. Aliquam consectetur nulla a eros suscipit tincidunt. Vestibulum quis adipiscing nunc. Vestibulum vitae diam vitae felis ultricies adipiscing eu non magna. Etiam fringilla arcu id ligula tincidunt semper. Ut quis fermentum erat. Aliquam hendrerit, augue quis malesuada dapibus, diam tellus posuere quam, non semper enim tellus sed velit. Nunc eros elit, placerat eget pretium at, pharetra hendrerit risus. Cras dapibus massa nunc. Proin sed lorem ligula. Donec malesuada odio sed eros malesuada eget commodo tellus cursus. Nam aliquam dictum laoreet. Donec sed lectus ligula.

Duis ultrices scelerisque porttitor. Curabitur rutrum, risus id interdum porta, lorem felis consectetur augue, commodo accumsan enim magna eu tortor. Maecenas varius pellentesque leo, et fermentum dolor dapibus nec. Pellentesque ipsum odio, pellentesque a feugiat nec, ullamcorper quis libero.

2 Ungelöste Fragen

2.1 WS11/12 Februar

2.1.1 Aufgabe 1

Zeigen Sie, dass $P(\mathbb{N})$ die kleinste σ -Algebra auf der Menge \mathbb{N} der natürlichen Zahlen ist, die von allen endlichen Teilmengen von natürlichen Zahlen erzeugt ist.

Sei $A_i \in \mathbb{N}$ die Menge aller endlichen Teilmengen von \mathbb{N} mit $i \in \mathbb{N}$ Elementen, dann ist $\bigcup_{i=0}^{\infty} A_i$ die Menge aller endlichen Teilmengen von \mathbb{N} . Sei $E := A$ und $A_i^C = \mathbb{N} \setminus A_i$.

$$\sigma(E) = \{\Omega, \emptyset, A, A^C\} = P(\mathbb{N})$$

$$(i) \quad \Omega \in P(\mathbb{N})$$

$$(ii) \quad A \in P(\mathbb{N}) \Rightarrow A^C \in P(\mathbb{N})$$

$$(iii) \quad (A_i)_{i \in \mathbb{N}} \subset P(\mathbb{N}) \Rightarrow \bigcup_{i \in \mathbb{N}} A_i \in P(\mathbb{N})$$

$\Rightarrow \sigma(E) = P(\mathbb{N} = \Omega)$ ist σ -Algebra (trivial da $P(\mathbb{N})$ per Definition eine σ -Algebra auf Ω ist).

Ist $\sigma(E)$ aber auch die kleinste σ -Algebra die E enthält?

Satz 2.11 aus Skript: $\sigma(E)$ von E erzeugte σ -Algebra

$\Rightarrow \sigma(E)$ ist kleinste σ -Algebra die E enthält.

$\Rightarrow \sigma(E) = P(\mathbb{N})$ ist kleinste σ -Algebra die von allen endlichen Teilmengen von \mathbb{N} erzeugt wird.

2.2 WS11/12 April alle

2.3 One Thousand Exercises in Probability

- 7.9.5

3 Sigma-Fields

3.1 Definition

1. $\Omega \in A$
2. $A \in A \Rightarrow A^C \in A$
3. $(A_n) \subset A \Rightarrow \bigcup A_n \in A$

The countable/co-countable σ -field. Let $\Omega = \mathbb{R}$
 $\mathbb{Z}_{\mathbb{Z}} : B = \{A \subset \mathbb{R} : A \text{ is countable}\} \cup \{A \subset \mathbb{R} : A^C \text{ is countable}\}$ is a σ -field

$$(M1) \quad \Omega \in B \text{ (since } \Omega^C = \emptyset \text{ is countable)}$$

$$(M2) \quad A \in B \text{ implies } A^C \in B$$

$$(M3) \quad A_i \in B \text{ implies } \bigcap_{i=1}^{\infty} A_i \in B$$

3.2 Intersections of Sigma-Algebras

Man Beweise: Sei Ω eine Menge, sei I eine Indexmenge und für jedes $i \in I$ sei A_i eine σ -Algebra auf Ω . Dann ist auch

$$\cap A_i := \{A \subset \Omega \mid A \in A_i \forall i \in I\}$$

eine σ -Algebra auf Ω .

$$1. \Omega \in A_i \forall i \in I \Rightarrow \Omega \in \cap A_i$$

$$2. A \in \cap A_i \Rightarrow A \in A_i \forall i \in I \Rightarrow A^C \in \cap A_i$$

$$3. A_n \in \cap A_i \forall n \in \mathbb{N} \Rightarrow A_n \in A_i \forall i, n \Rightarrow \cup A_n \in A_i \Rightarrow \cup A_n \in \cap A_i$$

$\Rightarrow \cap A_i$ ist σ -Algebra

3.3 Minimal Sigma-Algebras

Let C be a collection of subsets of Ω . The σ -field generated by C , denoted $\sigma(C)$, is a *minimal* σ -field satisfying

$$(a) \sigma(C) \supset C$$

$$(b) \text{ If } B' \text{ is some other } \sigma\text{-field containing } C, \text{ then } B' \supset \sigma(C)$$

Given a class C of subsets of Ω , there is a unique minimal σ -field containing C .

Proof: Let

$$\mathfrak{N} = \{B : B \text{ is a } \sigma\text{-field, } B \supset C\}$$

be the set of all σ -fields containing C . Then $\mathfrak{N} \neq \emptyset$ since $P(\Omega) \in \mathfrak{N}$. Let

$$B^\supset = \bigcap_{B \in \mathfrak{N}} B.$$

Since each class $B \in \mathfrak{N}$ is a σ -field, so is B^\supset . Since $B \in \mathfrak{N}$ implies $B \supset C$, we have $B^\supset \supset C$. We claim $B^\supset = \sigma(C)$. We checked $B^\supset \supset C$ and, for minimality, note that if B' is a σ -field such that $B' \supset C$, then $B' \in \mathfrak{N}$ and hence $B^\supset \subset B'$.

Let $\Omega = \{1, 2, \dots, 7\}$ and $E = \{\{1, 2\}, \{6\}\}$ then

$$\sigma(E) = \{\emptyset, \{1, 2\}, \{3, 4, 5, 6, 7\}, \{6\}, \{1, 2, 3, 4, 5, 7\}, \{1, 2, 6\}, \{3, 4, 5, 7\}, \Omega\}$$

Let Ω be set and $A \subset \Omega$. If $E = \{A\}$ then

$$\sigma(E) = \{\emptyset, A, A^C, \Omega\}$$

3.4 Inverse Maps

If B' is a σ -field of subsets of Ω' , then $X^{-1}(B')$ is a σ -field of subsets of Ω

Proof:

(M1) Since $\Omega' \in B'$, we have

$$X^{-1}(\Omega') = \Omega \in X^{-1}(B')$$

(M2) If $A' \in B'$, then $(A')^C \in B'$, and so if $X^{-1}(A') \in X^{-1}(B')$ we have

$$X^{-1}((A')^C) = (X^{-1}(A'))^C \in X^{-1}(B')$$

(M3) If $X^{-1}(B'_n) \in X^{-1}(B')$ then since $\bigcup_n B'_n \in B'$

$$\bigcup_n X^{-1}(B'_n) = X^{-1}\left(\bigcup_n B'_n\right) \in X^{-1}(B')$$

If C' is a class of subsets of Ω' then

$$X^{-1}(\sigma(C')) = \sigma(X^{-1}(C'))$$

$\mathbb{Z}_2 : f(A_1) : \{B \subset A_2 : f^{-1}(B) \in A_1\}$ σ -Algebra auf Ω_2

$$(M1) \emptyset \in f(A_1) \Rightarrow \Omega_2 = \emptyset^C \in f(A_1)$$

(M2) Sei $B \in f(A_2)$

$$f^{-1}(B) \in A_1 \Rightarrow (f^{-1}(B))^C \in A_1 \Rightarrow f^{-1}(B^C) \in A_1 \Rightarrow B^C \in f(A_1)$$

(M3) Sei $B_i \in f(A_1)$

$$f^{-1}(B_i) \in A_1 \Rightarrow \bigcup_{i \in \mathbb{N}} f^{-1}(B_i) \in A_1 \Rightarrow f^{-1}\left(\bigcup_{i \in \mathbb{N}} B_i\right) \in A_1 \Rightarrow \bigcup_{i \in \mathbb{N}} B_i \in f(A_1)$$

4 Measures

Let A be a σ -field on Ω . μ is a measure if

$$\mu : A \rightarrow [0, \infty]$$

such that

$$(M1) \mu(\emptyset) = 0$$

(M2) For disjoint A_n

$$\mu\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mu(A_n)$$

4.1 Probability Measures

4.1.1 Definition

$$(M1) \mathbb{P}(A) \geq 0 \forall A \in \mathcal{B}$$

(M2) \mathbb{P} is σ -additive for disjoint Events A_n

$$\mathbb{P}\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mathbb{P}(A_n).$$

(M3) $\mathbb{P}(\Omega) = 1$

4.2 Measurability

- Seien $(\Omega_1, A_1), (\Omega_2, A_2)$ zwei Messräume. X ist $A_1 - A_2$ -mb. falls

$$X^{-1}(A) = \{\omega : X(\omega) \in A\} \in A_1 \forall A \in A_2$$

- Das **Urbild** $X^{-1}(A_2) := \{X^{-1}(A), A \in A_2\}$ ist kleinste σ -Algebra bzgl. derer X mb. ist ($\sigma(X) := X^{-1}(A_2)$)
- Sei E ein **Erzeuger** von A_2 , dann ist X $A_1 - A_2$ -mb. falls $X^{-1}(E) \in A_1 \forall E \in E$

4.3 Image Measure

Sei (Ω, A, μ) ein Maßraum, (Ω', A') ein Messraum und

$$T : (\Omega, A) \rightarrow (\Omega', A')$$

Das durch

$$\mu'(A') = \mu(T^{-1}(A')) \forall A' \in A'$$

definierte Maß μ' auf (Ω', A') heißt **Bildmaß** von μ unter T .

Sei (Ω, A, μ) der Maßraum mit $\Omega := \mathbb{R}$ und der von allen abzählbaren Mengen erzeugten σ -Algebra A , sowie $\mu(A) = 0$ wenn A abzählbar ist und $\mu(A) = 1$ wenn A^C abzählbar ist.

Für $\Omega' := \{0, 1\}$ und $A' := P(\Omega')$ wird die Abbildung $T : \Omega \rightarrow \Omega'$ definiert durch

$$T(\omega) := \begin{cases} 0, & \text{falls } \omega \text{ rational} \\ 1, & \text{falls } \omega \text{ irrational} \end{cases}$$

Man zeige, dass $T : A \rightarrow A'$ -messbar ist, und bestimme das Bildmaß $T(\mu)$.

Antwort: T ist messbar $\Leftrightarrow T^{-1}(A') \in A \forall A' \in A'$
 $\Omega' = \{0, 1\}$ $A' = P(\Omega') = \{\emptyset, \{0, 1\}, \{0\}, \{1\}\}$

$A' \subset A'$	\emptyset	0	1	$\{0, 1\}$
$T^{-1}(A')$	\emptyset	\mathbb{Q}	$\mathbb{R} \setminus \mathbb{Q}$	$\Omega = \mathbb{R}$

$\Rightarrow T : A \rightarrow A'$ -mb

Bildmaß?

$$\begin{aligned} \mu(T^{-1}(\emptyset)) &= \mu(\emptyset) = 0 \\ \mu(T^{-1}(\{0\})) &= \mu(\mathbb{Q}) = 0 \\ \mu(T^{-1}(\{1\})) &= \mu(\mathbb{R} \setminus \mathbb{Q}) = 1 \\ \mu(T^{-1}(\{0, 1\})) &= \mu(\mathbb{R}) = 1 \end{aligned}$$

5 Integration and Expectation

5.1 Expectation

$$\mathbb{E}[X] = \int_{\Omega} X d\mathbb{P} = \int_{\mathbb{R}} xf(x) dx \quad (1)$$

$$\mathbb{E}[h(X)] = \int_{\mathbb{R}} h(x) \mathbb{P}_X dx = \begin{cases} \int_{\mathbb{R}} h(x) f(x) dx & \text{im abs. stetigen Fall} \\ \sum_{k=1}^{\infty} h(x_k) \mathbb{P}[X = x_k] & \text{im diskreten Fall} \end{cases} \quad (2)$$

Erwartungswert von e^x bei Normalverteilung

$X \sim N(0, 1), \mathbb{E}[e^x]?$

$$\begin{aligned} \mathbb{E}[e^x] &= \int_{\Omega} e^x d\mathbb{P} \\ &= \int_{\mathbb{R}} e^t \mathbb{P}_X dt \\ &= \int_{\mathbb{R}} e^t d\lambda(t) \\ &= \int_{\mathbb{R}} e^t \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2} + t} dt \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} * e^{\frac{-t^2 + 2t + 1 - 1}{2}} dt \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{\frac{-(t^2 - 2t + 1)}{2}} dt \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{\frac{-(t-1)^2}{2}} dt \\ &= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{\frac{-(t-1)^2}{2} + \frac{1}{2}} dt \\ &= e^{\frac{1}{2}} \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{\frac{-(t-1)^2}{2}} dt \sim N(1, 1) = \text{Dichte} \\ &= e^{\frac{1}{2}} \end{aligned}$$

Varianz von Exponentialverteilter Zufallsvariable

$X \sim \text{Exp}(\lambda), \mathbb{V}[X]?$

$$\mathbb{E}[X] = \int_0^{\infty} t \lambda e^{-\lambda t} dt \stackrel{PI}{=} -e^{-\lambda t} t \Big|_0^{\infty} - \int_0^{\infty} 1(-e^{-\lambda t}) dt = 0 + \frac{1}{\lambda} = \frac{1}{\lambda}$$

$$\begin{aligned}\mathbb{V}[X] &= \mathbb{E}\left[(X - \mathbb{E}[X])^2\right] = \int_0^\infty \left(t - \frac{1}{\lambda}\right)^2 \lambda e^{-\lambda t} dt \\ &= \int_0^\infty t^2 \lambda e^{-\lambda t} dt - \frac{2}{\lambda} \int_0^\infty t \lambda e^{-\lambda t} dt + \frac{1}{\lambda^2} \int_0^\infty \lambda e^{-\lambda t} dt \\ &\stackrel{PI}{=} -t^2 e^{-\lambda t} \Big|_0^\infty - \int_0^\infty 2te^{-\lambda t} dt - \frac{2}{\lambda^2} + \frac{1}{\lambda^2} \\ &= 0 + \frac{2}{\lambda^2} - \frac{2}{\lambda^2} + \frac{1}{\lambda^2} = \frac{1}{\lambda^2}\end{aligned}$$

5.2 Probability

$$\mathbb{P}[A] = \int_A d\mathbb{P} = \mathbb{E}[\mathbb{1}_A] \quad (3)$$

5.3 Distribution Function

$$F(x) = \mathbb{P}[(-\infty, x]] = \mathbb{P}[X \leq x], \quad x \in \mathbb{R} \quad (4)$$

5.4 Monotone Convergence

If

$$X_n \uparrow X$$

then

$$\mathbb{E}[X_n] \uparrow \mathbb{E}[X]$$

and

$$\mathbb{E}\left[\sum_{i=1}^{\infty} X_i\right] = \sum_{i=1}^{\infty} \mathbb{E}[X_i]$$

5.5 Dominated Convergence Theorem

If

$$X_n \rightarrow X$$

and there exists $Z \in L_1$ such that

$$|X_n| \leq Z$$

then

$$\mathbb{E}[X_n] \rightarrow \mathbb{E}[X] \text{ and } \mathbb{E}[|X_n - X|] \rightarrow 0 \quad (5)$$

5.6 Integrable Random Variables

Define $\mathbb{E}[X] := \mathbb{E}[X^+] - \mathbb{E}[X^-]$. The set of integrable random variables is denoted by L_1 :

$$L_1 = \{\text{random variables } X : \mathbb{E}[|X|] < \infty\} \quad (6)$$

5.7 Properties of Expectation

1. If X is integrable, then

$$\mathbb{P}[X = \pm\infty] = 0$$

2. If $\mathbb{E}[X]$ exists,

$$\mathbb{E}[cX] = c\mathbb{E}[X]$$

3. If $X \geq 0$ then $\mathbb{E}[X] \geq 0$ since $X = X^+$. If $X, Y \in L_1$, and $X \leq Y$ then

$$\mathbb{E}[X] \leq \mathbb{E}[Y]$$

4. Suppose $\{X_n\}$ is a sequence of random variables such that $X_n \in L_1$ for some n . If either

$$X_n \uparrow X$$

or

$$X_n \downarrow X$$

then

$$\mathbb{E}[X_n] \uparrow \mathbb{E}[X]$$

or

$$\mathbb{E}[X_n] \downarrow \mathbb{E}[X]$$

5. If $X \in L_1$,

$$|\mathbb{E}[X]| \leq \mathbb{E}[|X|]$$

6. Variance and Covariance. If $X \in L_2$ then

$$\mathbb{V}[X] := \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \quad (7)$$

$$\text{Cov}(X, Y) := \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] \quad (8)$$

$$\mathbb{V}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{V}[X_i] + \sum_{i=1}^n \text{Cov}(X_i, X_j) \quad (9)$$

5.8 Fatou's Lemma

If there exists $Z \in L_1$ and $X_n \geq Z$ then

$$\mathbb{E}\left[\liminf_{n \rightarrow \infty} X_n\right] \leq \liminf_{n \rightarrow \infty} \mathbb{E}[X_n] \quad (10)$$

and if $X_n \leq Z$ then

$$\limsup_{n \rightarrow \infty} \mathbb{E}[X_n] \leq \mathbb{E}\left[\limsup_{n \rightarrow \infty} X_n\right] \quad (11)$$

5.9 Fubini Theorem

Let $\mathbb{P} = \mathbb{P}_1 \times \mathbb{P}_2$ be a product measure. If X is $B_1 \times B_2$ measurable and integrable with respect to \mathbb{P} then

$$\int_{\Omega_1 \times \Omega_2} X d\mathbb{P} = \int_{\Omega_1} \int_{\Omega_2} X d\mathbb{P}_2 d\mathbb{P}_1 \quad (12)$$

$$= \int_{\Omega_2} \int_{\Omega_1} X d\mathbb{P}_1 d\mathbb{P}_2 \quad (13)$$

5.10 Tonelli

$$\int_{\times_{i=1}^n \Omega_i} f(\omega_1, \dots, \omega_n) d\otimes_{i=1}^n \mu_i(\omega_1, \dots, \omega_n) = \int_{\Omega_1} \int_{\Omega_2} \dots \int_{\Omega_n} f(\omega_1, \dots, \omega_n) \mu_n(d\omega_n) \dots \mu_1(d\omega_1) = \begin{cases} f(t) & \forall t \in \mathbb{R} \setminus \{1, 2, 4\} \\ \alpha_j & \forall t = x_j, j = 1, 2, 3 \end{cases}$$

$$\Rightarrow \hat{\mathbb{P}} \ll \mu$$

5.11 Radon-Nikodym

Sei (Ω, A) ein Messraum, seien μ und ν zwei Maße auf (Ω, A) so dass

$$d\nu = f d\mu$$

für eine A -mb Funktion

$$f : \Omega \rightarrow \mathbb{R} \text{ mit } f(\omega) \geq 0 \forall \omega \in \Omega$$

Dann heisst f **Dichte** oder Dichtefunktion von ν bzgl. μ .

Seien μ und ν Maße auf dem Maßraum (Ω, A) , so dass für jedes $A \in A$ gilt

$$\mu(A) = 0 \Rightarrow \nu(A) = 0$$

Dann sagt man ν ist absolut stetig bzgl. μ . Notation:

$$\nu \ll \mu$$

Radon-Nikodym: Seien μ und ν σ -endliche Maße auf dem Messraum (Ω, A) . Dann sind folgende Aussagen äquivalent:

- (i) ν besitzt eine Dichte bzgl. μ
- (ii) $\nu \ll \mu$

Beispiel Normalverteilung

$$dN(\mu, \sigma^2) = f_{\mu, \sigma^2} d\lambda \quad (14)$$

$$F(t) = \begin{cases} 0 & t < 0 \\ \frac{t}{32} & 0 \leq t < 1 \\ \frac{t^2}{16} & 1 \leq t < 2 \\ \frac{t}{8} + \frac{1}{4} & 2 \leq t < 4 \\ 1 & t \geq 4 \end{cases}$$

$\mathbb{Z}_{\mathbb{Z}}$: Dichte bzgl. $\lambda + \delta_0 + \delta_1 + \delta_2 + \delta_4$

Diskreter Teil: Unstetigkeitsstellen

$$\mathbb{P}[x_i] \geq 0 \quad i = 1, 2, 3 \quad \alpha_i = \mathbb{P}[x_i], \quad x_1 = 1, x_2 = 2, x_3 = 4$$

Absolut stetiger Teil: $F(t)$ abs. stetig auf $\mathbb{R} \setminus \{1, 2, 4\}$

$$\text{d.h. } \mathbb{P}(B) = \int_B d\mathbb{P} = \int_B f(x) d\lambda \quad \forall B \in \mathcal{B}, \{1, 2, 4\} \notin B$$

$$\mathbb{P}(B) = \mathbb{E}(\mathbb{1}_B) = \int \mathbb{1}_B d\mathbb{P} = \int_B d\mathbb{P}$$

$$F(t) = \int_{-\infty}^t f(t) dt \Rightarrow F'(t) = f(t)$$

$$\Rightarrow F'(t) = f(t) = \frac{1}{32} \mathbb{1}(0 < t < 1) + \frac{1}{8} \mathbb{1}(1 < t < 2) + \frac{1}{8} \mathbb{1}(2 < t < 4)$$

5.12 Transformationssatz für Dichten

Sei $f : \mathbb{R}^p \rightarrow \mathbb{R}, (x_1, \dots, x_p) \mapsto f(x_1, \dots, x_p)$ die λ^p -Dichte eines Wahrscheinlichkeitsmaßes \mathbb{P}_X . Seien $G, G' \in \mathcal{B}^{\otimes p}$ offen und die Abbildung

$$T : G \rightarrow G' \quad (15)$$

$$(x_1, \dots, x_p) \mapsto (T_1(x_1, \dots, x_p), \dots, T_p(x_1, \dots, x_p)) \quad (16)$$

bijektiv und samt T^{-1} messbar und differenzierbar.

Dann gilt für die λ^p -Dichte g von $T(\mathbb{P}_X)$:

$$g(y_1, \dots, y_p) = \left| \det J_{T^{-1}}(y_1, \dots, y_p) \right| \cdot f\left(T^{-1}(y_1, \dots, y_p)\right) \\ = \left| \det J_T\left(T^{-1}(y_1, \dots, y_p)\right) \right| \cdot f\left(T^{-1}(y_1, \dots, y_p)\right)$$

(17)

(18)

Im **eindimensionalen** Fall vereinfacht sich die Dichtetransformationsformel zu

$$g(y) = \left| (T^{-1})'(y) \right| \cdot f\left(T^{-1}(y)\right) \quad (19)$$

Sei $X \sim \text{Exp}$ mit der Dichte $f(x) = \lambda e^{-\lambda x} \mathbb{1}_{(0, \infty)}(x)$.

Die Abbildung

$$T : x \mapsto x^2$$

ist bijektiv mit Umkehrfunktion

$$y \mapsto \sqrt{y}$$

Mit Ableitung

$$\frac{dT^{-1}(y)}{dy} = \frac{1}{2} y^{-\frac{1}{2}}$$

Dann ist

$$g(y) = \left| \frac{1}{2} y^{-\frac{1}{2}} \right| \cdot f(\sqrt{y}) = \frac{1}{2} y^{-\frac{1}{2}} \cdot \lambda e^{-\lambda \sqrt{y}}$$

für $y > 0$.

5.13 Convolutions

The Convolution $f = f_1 * f_2$ of two densities f_1 and f_2 is defined by

$$f(z) = \int_{-\infty}^{+\infty} f_1(z-y) f_2(y) dy \quad (20)$$

6 Conditional Expectation

$$\begin{aligned} \mathbb{E}[Y|X] &= \int y \cdot f_{Y|X}(y|x) dy = \int y \cdot \frac{f_{Y,X}(y,x)}{f_X(x)} dy = \int y \cdot \frac{f_{Y,X}(y,x)}{\int f_{Y,X}(y,x) dy} dy \\ \mathbb{E}[X|B] &= \frac{1}{\mathbb{P}[B]} \int_B X d\mathbb{P} = \frac{\mathbb{E}[X \cdot \mathbb{1}_B]}{\mathbb{P}(B)} \\ \mathbb{E}[\psi(Y, X) | X = x] &= \int_{\Omega_2} \int_{\Omega_1} \psi(y, x) \mathbb{P}^{Y|X=x} dy \mathbb{P}^X dx \end{aligned}$$

(21)

(22)

(23)

6.1 Properties of Conditional Expectation

Sei $(\Omega, \mathcal{A}, \mathbb{P})$ ein Wahrscheinlichkeitsraum und Seien

$$f : \Omega \rightarrow \mathbb{R}, \quad f_1 : \Omega \rightarrow \mathbb{R}, \quad f_2 : \Omega \rightarrow \mathbb{R}$$

bzgl. \mathbb{P} integrierbare Funktionen. Sei \mathcal{C} eine Unter- σ -Algebra von \mathcal{A} .

Dann gilt:

1. $\mathbb{E}[f|\mathcal{C}] \in L_1(\Omega, \mathcal{A}, \mathbb{P})$
2. $\mathbb{E}[\mathbb{E}[f|\mathcal{C}]] = \mathbb{E}[f]$
3. f ist \mathcal{C} -messbar $\Rightarrow \mathbb{E}[f|\mathcal{C}] = f$ \mathbb{P} -f.s.
4. $f = g$ \mathbb{P} -f.s. $\Rightarrow \mathbb{E}[f|\mathcal{C}] = \mathbb{E}[g|\mathcal{C}]$ \mathbb{P} -f.s.
5. $f = \text{const} = \alpha \Rightarrow \mathbb{E}[f|\mathcal{C}] = \alpha$ \mathbb{P} -f.s.
6. Wenn X_i iid sind, dann ist

$$\mathbb{E}\left[X \mid \sum_{i=1}^n X_i\right] = \frac{\sum_{i=1}^n X_i}{n}$$

also z.b. $X, Y \sim \text{Exp}(\lambda)$, dann ist

$$\mathbb{E}[X|X+Y] \stackrel{iid}{=} \frac{X+Y}{2}$$

7. Für $\alpha_1, \alpha_2 \in \mathbb{R}$ ist $\mathbb{E}[\alpha_1 f_1 + \alpha_2 f_2 | \mathcal{C}] = \alpha_1 \mathbb{E}[f_1 | \mathcal{C}] + \alpha_2 \mathbb{E}[f_2 | \mathcal{C}]$

8. $f_1 \leq f_2$ \mathbb{P} -f.s. $\Rightarrow \mathbb{E}[f_1 | \mathcal{C}] \leq \mathbb{E}[f_2 | \mathcal{C}]$

9. $|\mathbb{E}[f|\mathcal{C}]| \leq \mathbb{E}[|f| | \mathcal{C}]$

10. **Monotone convergence.** If $X \in L_1$, $0 \leq X_n \uparrow X$, then

$$\mathbb{E}[X_n | \mathcal{C}] \uparrow \mathbb{E}[X | \mathcal{C}]$$

11. Monotone convergence implies the **Fatou Lemma**. If $0 \leq X_n \in L_1$, then

$$\mathbb{E}\left[\liminf_{n \rightarrow \infty} X_n | \mathcal{C}\right] \leq \liminf_{n \rightarrow \infty} \mathbb{E}[X_n | \mathcal{C}]$$

and while if $X_n \leq Z \in L_1$, then

$$\mathbb{E}\left[\limsup_{n \rightarrow \infty} X_n | \mathcal{C}\right] \geq \limsup_{n \rightarrow \infty} \mathbb{E}[X_n | \mathcal{C}]$$

12. Fatou implies **dominated convergence**. If $X_n \in L_1$, $|X_n| \leq Z \in L_1$ and $X_n \rightarrow X_\infty$, then

$$\mathbb{E}\left[\lim_{n \rightarrow \infty} X_n | \mathcal{C}\right] \stackrel{a.s.}{=} \lim_{n \rightarrow \infty} \mathbb{E}[X_n | \mathcal{C}]$$

6.2 Glättungseigenschaften

6.3 Bedingte Dichten

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} \quad (24)$$

6.4 Bedingte Wahrscheinlichkeiten

$$\begin{aligned} \mathbb{P}[A] &= \int_A d\mathbb{P} = \mathbb{E}[\mathbb{1}_A] \\ \mathbb{P}[A|\mathcal{C}] &= \mathbb{E}[\mathbb{1}_A | \mathcal{C}] \\ \mathbb{P}[A|T] &= \mathbb{E}[\mathbb{1}_A | T] \\ \mathbb{P}[A|T=t] &= \mathbb{E}[\mathbb{1}_A | T=t] \\ \mathbb{P}[X \in A | T=t] &= \int_A f_{X|Y}(x|y) dx \end{aligned}$$

6.5 Examples

Let X and Y be jointly continuous random variables with joint density

$$f_{X,Y}(x,y) = \begin{cases} e^{-x-y} & \text{if } y \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Compute $\mathbb{E}[X+Y | X < Y]$:

$$\begin{aligned} \mathbb{P}[X < Y] &= \int_{-\infty}^{\infty} \int_x^{\infty} (f_{X,Y}(x,y)) dy dx \\ &= \int_0^{\infty} \int_x^{\infty} e^{-x-y} dy dx \\ &= \int_0^{\infty} e^{-2x} dx = \frac{1}{2} \end{aligned}$$

Next,

$$\begin{aligned}\mathbb{E}[\mathbb{1}_{(X < Y)}(X + Y)] &= \int_{-\infty}^{\infty} \int_x^{\infty} ((x + y)f_{X,Y}(x, y)) dy dx \\ &= \int_0^{\infty} \int_x^{\infty} (x + y)e^{-x-y} dy dx \\ &= \int_0^{\infty} (2x + 1)e^{-2x} dx = 1\end{aligned}$$

It follows that

$$\mathbb{E}[X + Y | X < Y] = \frac{\mathbb{E}[\mathbb{1}_{(X < Y)}(X + Y)]}{\mathbb{P}[X < Y]} = \frac{1}{1/2} = 2$$

X, Y haben gemeinsame Dichte $f_{X,Y}(x, y) = xe^{-x(y+1)} \cdot \mathbb{1}_{\mathbb{R}^2_+}(x, y)$. Gesucht: $\mathbb{E}[Y | X = x]$

$$\begin{aligned}f_X(x) &= \int f_{X,Y}(x, y) dy \\ &= \int xe^{-x(y+1)} \cdot \mathbb{1}_{\mathbb{R}^2_+}(x, y) dy \\ &= \int_0^{\infty} xe^{-x(y+1)} \cdot \mathbb{1}_{\mathbb{R}_+}(x, y) dy \\ &= e^{-x} \underbrace{\int_0^{\infty} xe^{-xy} \cdot \mathbb{1}_{\mathbb{R}_+}(x, y) dy}_{\text{Dichte einer Exp. Vert.}=1} \\ &= e^{-x} \cdot \mathbb{1}_{\mathbb{R}_+}(x)\end{aligned}$$

$$\begin{aligned}\mathbb{E}[Y | X = x] &= \int y \cdot f_{Y|X}(y | x) dx \\ &= \int y \cdot \frac{f_{X,Y}(x, y)}{f_X(x)} dx\end{aligned}$$

Seien X, Y Zufallsvariablen mit gemeinsamer Dichte $f_{X,Y}(x, y) = x(y - x)e^{-y}$ und $0 \leq x \leq y < \infty$.
Geben Sie $\mathbb{E}[Y | X]$ an.
Tip: (Merhfache) partielle Integration

$$f_{Y|X}(y | x) = \frac{f_{X,Y}(x, y)}{f_X(x)}$$

$$\begin{aligned}\Rightarrow f_X(x) &= \int_x^{\infty} f_{X,Y}(x, y) dy \\ &= \int_x^{\infty} x(y - x)e^{-y} dy \\ &= \int_x^{\infty} xye^{-y} dy - \int_x^{\infty} x^2e^{-y} dy \\ &= x[-e^{-y}(y + 1)]_x^{\infty} - x^2[-e^{-y}]_x^{\infty} \\ &= x[0 + e^{-x}(x + 1)] - x^2[0 + e^{-x}] \\ &= xe^{-x}(x + 1) - x^2e^{-x} \\ &= x^2e^{-x} + xe^{-x} - x^2e^{-x} \\ &= xe^{-x}\end{aligned}$$

$$\begin{aligned}\mathbb{E}[Y | X] &= \int_x^{\infty} yf_{Y|X}(y | x) dy \\ &= \int_x^{\infty} y \frac{x(y - x)e^{-y}}{xe^{-x}} dy \\ &= \int_x^{\infty} y(y - x)e^{x-y} dy \\ &= \int_x^{\infty} y^2e^{x-y} - yxe^{x-y} dy \\ &= e^x \int_x^{\infty} y^2e^{-y} dy - xe^x \int_x^{\infty} ye^{-y} dy \\ &= e^x[-y^2e^{-y}]_x^{\infty} + \int_x^{\infty} 2ye^{-y} dy - xe^x[-e^{-y}(y + 1)]_x^{\infty} \\ &= e^x[x^2e^{-x} + 2[-e^{-y}(y + 1)]_x^{\infty}] - xe^x[e^{-x}(x + 1)] \\ &= e^x x^2e^{-x} + 2e^{-x}(x + 1)e^x - xe^xe^{-x}(x + 1) \\ &= 2 + x\end{aligned}$$

7 Martingales

For integrable random variables $\{X_n, n \geq 0\}$ and σ -fields $\{B_n, n \geq 0\}$ which are sub σ -fields of B , $\{(X_n, B_n), n \geq 0\}$ is a **martingale** if

(M1) Information accumulates, i.e. $A_n \subset A_{n+1}$

(M2) X_n is adapted in the sense that for each n , $X_n \in B_n$; that, X_n is B_n -measurable.

(M3) $\mathbb{E}[|X_n|] < \infty$

(M4) $\mathbb{E}[X_{n+1} | B_n] \stackrel{a.s.}{=} X_n$

Sub-Martingal \leq

Martingal bzgl. $(A_t)_{t \in T} : \iff \forall s \leq t : X_s = \mathbb{E}[X_t | A_s], \mathbb{P} - f.s.$

Super-Martingal \geq

(25)

(26)

(27)

7.1 Properties

1. $(X_t)_{t \in T}$ sei ein Martingal bzgl. $(A_t)_{t \in T}$ mit $X_t \in L_p \forall t \in T$ ($1 \leq p < \infty$). Dann ist $\left(|X_t|^p\right)_{t \in T}$ ein Sub-Martingal bzgl. $(A_t)_{t \in T}$

2. Für jedes $c \in \mathbb{R}$ und Sub-Martingal $(X_t)_{t \in T}$ ist auch $(\max\{c, X_t\})_{t \in T}$ ein Sub-Martingal bzgl. $(A_t)_{t \in T}$. Insbesondere ist mit $c = 0$ dann auch $(X_t^+)_{t \in T}$ ein Sub-Martingal.

3. Ist $(X_t)_{t \in T}$ ein Super-Martingal bzgl. $(A_t)_{t \in T}$, so ist $(X_t^-)_{t \in T}$ ein Sub-Martingal bzgl. $(A_t)_{t \in T}$. Zur Erinnerung: $X_t^- := -\min\{0, X_t\}$.

7.2 Stopping Times

A mapping $\nu : \Omega \mapsto \bar{\mathbb{N}}$ is a stopping time if

$$[\nu = n] \in B_n, \quad \forall n \in \mathbb{N} \quad (28)$$

7.3 Martingaldifferenzfolgen

Sei $\eta_n \in L(\Omega, A, \mathbb{P})$, $n \in \mathbb{N}$, mit $A_n := \sigma(\eta_1, \dots, \eta_n)$ und $a \in \mathbb{R}$ beliebig.

Definiere

$$X_1 := \eta_1 - a \text{ und } X_{n+1} := X_n + \eta_{n+1} - \mathbb{E}[\eta_{n+1} | A_n] \quad (n \geq 1)$$

Dann gilt

$$\begin{aligned} \mathbb{E}[X_{n+1} | A_n] &= \mathbb{E}[X_n | A_n] + \mathbb{E}[\eta_{n+1} | A_n] - \mathbb{E}[\mathbb{E}[\eta_{n+1} | A_n] | A_n] \\ &= X_n + \mathbb{E}[\eta_{n+1} | A_n] - \mathbb{E}[\eta_{n+1} | A_n] \\ &= X_n \end{aligned}$$

Das heißt, die Folge $(X_n)_{n \in \mathbb{N}}$ bildet ein Martingal.

Ist umgekehrt $(X_n)_{n \in \mathbb{N}}$ als Martingal vorausgesetzt und definiert man

$$\eta_1 := X_1 \quad \eta_n := X_n - X_{n-1} \quad (n \geq 2)$$

dann gilt

$$\begin{aligned} \mathbb{E}[\eta_{n+1} | \eta_1, \dots, \eta_n] &= \mathbb{E}[X_{n+1} - X_n | \eta_1, \dots, \eta_n] \\ &= \mathbb{E}[X_{n+1} - X_n | X_1, \dots, X_n] \\ &= \mathbb{E}[X_{n+1} | X_1, \dots, X_n] - X_n \\ &= 0 \end{aligned}$$

Daher ist eine Folge reeller integrierbarer Zufallsvariablen $(\eta_n)_{n \in \mathbb{N}}$ heißt **Martingaldifferenzfolge**, falls

$$\mathbb{E}[\eta_{n+1} | \eta_1, \dots, \eta_n] = 0 \quad \mathbb{P}\text{-f.s., } \forall n \in \mathbb{N} \quad (29)$$

7.4 Examples

Seien Z_1, \dots, Z_n unabhängig und identisch verteilt (iid) mit $Z_i \sim N(0, 1)$ und

$F_n = \sigma(Z_1, \dots, Z_n)$ eine Filtration. Ferner sei $X_n := \exp\left(\sum_{i=1}^n (Z_i - c)\right)$, $n \in \mathbb{N}$, $c \in \mathbb{R}$.

Für welche Werte c ist $(X_n)_{n \in \mathbb{N}}$ ein Martingal, Submartingal bzw. Supermartingal bzgl. (F_n) ?

Bitte begründen Sie Ihre Schritte kurz!

- X_n ist F_n -mb. da Komposition aus Z_i und $F_n = \sigma(Z_1, \dots, Z_n)$

- F_n ist Filtration (Information kommt hinzu) $\Rightarrow F_n \subset F_{n+1} \quad \forall n$

- $\mathbb{E}[|X_n|] < \infty$? (ist Z_n integrierbar?)

$$\begin{aligned} \mathbb{E}[|X_n|] &= \mathbb{E}\left[\exp\left(\sum_{i=1}^n Z_i - c\right)\right] \\ &= \mathbb{E}\left[\prod_{i=1}^n \exp(Z_i - c)\right] \\ &\stackrel{\text{iid}}{=} \left(\mathbb{E}[\exp(Z - c)]\right)^n \\ &= \left(\int_{\mathbb{R}} \exp(z - c) d\mathbb{P}_Z\right)^n \\ &= \left(\int_{\mathbb{R}} \exp(z - c) \frac{1}{\sqrt{2\pi}} \exp\left(-\left(\frac{z^2}{2}\right)\right) dz\right)^n \\ &= \left(\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2} + z - c\right) dz\right)^n \\ &= \left(\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z^2 + 2z - 2c}{2}\right) dz\right)^n \\ &= \left(\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z^2 + 2z - 2c + 1 - 1}{2}\right) dz\right)^n \\ &= \left(\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-((z-1)^2 - 1 + 2c)}{2}\right) dz\right)^n \\ &= \left(e^{\frac{1}{2} - c} \cdot \underbrace{\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-(z-1)^2}{2}\right) dz}_{\sim N(1,1)=1}\right)^n \\ &= (e^{\frac{1}{2} - c})^n \\ &= e^{n(\frac{1}{2} - c)} < \infty \end{aligned}$$

- Martingaleigenschaft: $\mathbb{E}[X_{n+1} | F_n] \stackrel{\text{f.s.}}{=} X_n$?

$$\begin{aligned}\mathbb{E}[X_{n+1} | F_n] &= \mathbb{E}[X_n \cdot \exp(Z_{n+1} - c) | F_n] \\ (X_n \text{ ist } F_n\text{-mb.}) &\Rightarrow = X_n \cdot \mathbb{E}[\exp(Z_{n+1} - c) | F_n] \\ &\stackrel{\text{iid}}{=} X_n \cdot \mathbb{E}[\exp(Z_{n+1} - c)] \\ &= X_n \cdot e^{\frac{1}{2} - c} \\ &= X_n \text{ f\"ur } c = \frac{1}{2}\end{aligned}$$

$$\Rightarrow X_n \text{ Martingal f\"ur } c = \frac{1}{2}$$

$$X_n \text{ Super-Martingal f\"ur } c > \frac{1}{2}$$

$$X_n \text{ Sub-Martingal f\"ur } c < \frac{1}{2}$$

Martingales and smoothing. Suppose $X \in L_1$ and $\{B_n, n \geq 0\}$ is an increasing family of sub σ -fields of B . Define for $n \geq 0$

$$X_n := \mathbb{E}[X | B_n]$$

Then

$$\{(X_n, B_n), n \geq 0\}$$

is a martingale:

$$\begin{aligned}\mathbb{E}[X_{n+1} | B_n] &= \mathbb{E}[\mathbb{E}[X | B_{n+1}] | B_n] \\ &= \mathbb{E}[X | B_n] \quad (\text{smoothing}) \\ &= X_n\end{aligned}$$

Martingales and sums of independent random variables. Suppose that $\{Z_n, n \geq 0\}$ is an independent sequence of integrable random variables satisfying for $n \geq 0$, $\mathbb{E}[Z_n] = 0$. Set $X_0 = 0$, $X_n = \sum_{i=1}^n Z_i$, $n \geq 1$, and $B_n := \sigma(Z_0, \dots, Z_n)$.

Then $\{(X_n, B_n), n \geq 0\}$ is a martingale since $\{(Z_n, B_n), n \geq 0\}$ is a fair sequence.

Es sei $(X_t)_{t \in \mathbb{N}}$ eine Folge von unabhängigen und identisch verteilten Zufallsvariablen mit $\mathbb{E}[X_1] = 1$. Zeigen Sie, dass der stochastische Prozess $(Z_t, t \in \mathbb{N})$ mit

$$Z_t = \prod_{s=1}^t X_s$$

ein Martingal bezüglich der kanonischen Filtration $\sigma(X_1, X_2, \dots)$ ist.

Es gilt für jedes $t \in \mathbb{N}$:

$$\begin{aligned}\mathbb{E}[Z_{t+1} | A_t] &= \mathbb{E}\left[\prod_{i=1}^{t+1} X_i \mid \sigma(X_1, \dots, X_t)\right] \\ &= \mathbb{E}\left[\prod_{i=1}^t X_i \mid \sigma(X_1, \dots, X_t)\right] \cdot \mathbb{E}[X_{t+1} | \sigma(X_1, \dots, X_t)] \\ &= \prod_{i=1}^t X_i \cdot \mathbb{E}[X_{t+1}] = \prod_{i=1}^t X_i = Z_t\end{aligned}$$

Es sei $(X_t)_{t \in \mathbb{N}}$ eine Folge von unabhängigen und identisch verteilten Zufallsvariablen mit $\mathbb{E}[X_1] = 0$ und $\mathbb{E}[X_1^2] = \sigma^2$. Weiter sei $S_t = \sum_{s=1}^t X_s$. Zeigen Sie, dass der stochastische Prozess $(Z_t, t \in \mathbb{N})$ mit

$$Z_t = S_t^2 - t\sigma^2$$

ein Martingal bezüglich der kanonischen Filtration $\sigma(X_1, X_2, \dots)$ ist.

Es gilt für jedes $t \in \mathbb{N}$:

$$\begin{aligned}\mathbb{E}[Z_{t+1} | A_t] &= \mathbb{E}[S_{t+1}^2 - (t+1)\sigma^2 | \sigma(X_1, \dots, X_t)] \\ &= \mathbb{E}[S_t^2 + 2S_t X_{t+1} + X_{t+1}^2 | \sigma(X_1, \dots, X_t)] - (t+1)\sigma^2 \\ &= S_t^2 + \mathbb{E}[X_{t+1}^2] - (t+1)\sigma^2 = S_t^2 - t\sigma^2 = Z_t\end{aligned}$$

8 Convergence

8.1 Almost Sure Convergence

We say that a statement about random elements hold *almost surely* if there exists an event $A \in B$ with $\mathbb{P}[A] = 1$ such that the statement holds if $\omega \in A^C$.

$$\forall \epsilon > 0 : \mathbb{P}\left[\limsup_{n \rightarrow \infty} |X_n - X| > \epsilon\right] = 0 \quad (30)$$

Oder kurz

$$X_n \xrightarrow{n \rightarrow \infty} X \quad \mathbb{P}\text{-f.s.}$$

Let $\{X_r : r \geq 1\}$ be independent Poisson variables with respective parameters $\lambda_r : r \geq 1$. Show that $\sum_{r=1}^{\infty} X_r$ converges or diverges almost surely according as $\sum_{r=1}^{\infty} \lambda_r$

The partial sum $S_n = \sum_{r=1}^n X_r$ is Poisson-distributed with parameters $\sigma_n = \sum_{r=1}^n \lambda_r$. For fixed x , the event $\{S_n \leq x\}$ is decreasing in n , whence by Lemma 1.3.5, if $\sigma_n \rightarrow \sigma < \infty$ and x is non-negative integer.

$$\mathbb{P}\left[\sum_{r=1}^{\infty} X_r \leq x\right] = \lim_{n \rightarrow \infty} \mathbb{P}[S_n \leq x] = \sum_{j=0}^x \frac{e^{-\sigma} \sigma^j}{j!}$$

Hence if $\sigma < \infty$, $\sum_{r=1}^{\infty} X_r$ converges to a Poisson random variable. On the other hand, if $\sigma_n \rightarrow \infty$ then $e^{-\sigma_n} \sum_{j=0}^x \frac{\sigma_n^j}{j!} \rightarrow 0$, giving that $\mathbb{P} \left[\sum_{r=1}^{\infty} X_r > x \right] = 1$ for all x , and therefore the sum diverges with probability 1, as required.

8.1.1 Kolmogorov Convergence Criterion

If

$$\sum_{i=1}^{\infty} \mathbb{V}[X_i] < \infty$$

then

$$\sum_{i=1}^{\infty} (X_i - \mathbb{E}[X_i])$$

converges almost surely.

8.2 Convergence in Probability

$X_n \xrightarrow{P} X$ if for $\forall \epsilon > 0$

$$\lim_{n \rightarrow \infty} \mathbb{P} \left[|X_n - X| \geq \epsilon \right] = 0 \quad (31)$$

Sei $(X_n)_{n \in \mathbb{N}}$ eine Folge unabhängiger Zufallsvariablen, welche $\text{Exp}(1)$ -verteilt sind.
Zeigen Sie, dass $n^\alpha \cdot \min_{k \leq n} X_k$ stochastisch gegen Null konvergiert für alle $\alpha < 1, n \in \mathbb{N}$.

$$\begin{aligned} \forall \epsilon > 0 \quad \lim_{n \rightarrow \infty} \mathbb{P} \left[\left| n^\alpha \min_{k \leq n} X_k \right| \geq \epsilon \right] &= 0 \iff n^\alpha \min_{k \leq n} X_k \xrightarrow{P} 0 \\ &= \lim_{n \rightarrow \infty} \mathbb{P} \left[\min_{k \leq n} X_k \geq \frac{\epsilon}{n^\alpha} \right] \\ &= \lim_{n \rightarrow \infty} \mathbb{P} \left[\bigcap_{1 \leq k \leq n} \{ \omega : X_k(\omega) \geq \frac{\epsilon}{n^\alpha} \} \right] \\ &= \lim_{n \rightarrow \infty} \prod_{k=1}^n \mathbb{P} \left[X_k \geq \frac{\epsilon}{n^\alpha} \right] \\ &\stackrel{\text{iid}}{=} \lim_{n \rightarrow \infty} \left(\mathbb{P} \left[X_1 \geq \frac{\epsilon}{n^\alpha} \right] \right)^n \\ &\stackrel{\text{Exp}(1)}{=} \lim_{n \rightarrow \infty} \left(e^{-\frac{\epsilon}{n^\alpha}} \right)^n = 0 \end{aligned}$$

8.3 L_p Convergence

$X \in L_p$ means $\mathbb{E}[|X|^p] < \infty$. A sequence $\{X_n\}$ of random variables converges in L_p to X , written

$$X_n \xrightarrow{L_p} X$$

if

$$\mathbb{E}[|X_n - X|^p] \rightarrow 0 \quad (32)$$

as $n \rightarrow \infty$.

It follows that if $X_n \xrightarrow{L_p} X$ then $\mathbb{E}[|X_n^p|] \rightarrow \mathbb{E}[|X^p|]$

Suppose $\{X_n\}$ is an iid sequence of random variables with $\mathbb{E}[X_n] = \mu$ and $\mathbb{V}[X_n] = \sigma^2$. Then

$$\bar{X} = \sum_{i=1}^n \frac{X_i}{n} \xrightarrow{L_2} \mu,$$

since

$$\begin{aligned} \left(\mathbb{E} \left[\frac{S_n}{n} - \mu \right] \right)^2 &= \frac{1}{n^2} \left(\mathbb{E}[S_n - n\mu] \right)^2 \\ &= \frac{1}{n^2} \mathbb{V}[S_n] \\ &= \frac{n\sigma^2}{n^2} \rightarrow 0. \end{aligned}$$

Suppose $X_n \xrightarrow{L_1} X$. Show that $\mathbb{E}[X_n] \rightarrow \mathbb{E}[X]$. Is the converse true?

We have that

$$|\mathbb{E}[X_n] - \mathbb{E}[X]| = |\mathbb{E}[X_n - X]| \leq \mathbb{E}[|X_n - X|] \xrightarrow{n \rightarrow \infty} 0$$

The converse is clearly false. If each X_n takes the values ± 1 , each with probability $\frac{1}{2}$, then $\mathbb{E}[X_n] = 0$, but $\mathbb{E}[|X_n - 0|] = 1$.

$$\mathbb{Z} : X_n \xrightarrow{L_2} X \Rightarrow \mathbb{V}[X_n] \rightarrow \mathbb{V}[X]$$

$\mathbb{E}[X_n^2] \rightarrow \mathbb{E}[X^2]$ and $X_n \xrightarrow{L_1} X$. Therefore $\mathbb{E}[X_n] \rightarrow \mathbb{E}[X]$.
Thus $\mathbb{V}[X_n] = \mathbb{E}[X_n^2] - \mathbb{E}[X_n]^2 \rightarrow \mathbb{V}[X]$.

8.4 Convergence in Distribution (Weak Convergence)

$$\begin{aligned} \lim_{n \rightarrow \infty} \mathbb{E}[f \circ X_n] &= \mathbb{E}[f \circ X] \iff \int f \circ X_n d\mathbb{P} \xrightarrow{n \rightarrow \infty} \int f \circ X d\mathbb{P} \\ &\iff \int f d\mathbb{P}_{X_n} \xrightarrow{n \rightarrow \infty} \int f d\mathbb{P}_X \end{aligned}$$

(33)

(34)

Let $\{X_n, n \geq 1\}$ be iid with common unit exponential distribution

$$\mathbb{P}[X_n > x] = e^{-x}, \quad x > 0$$

Set $M_n = \bigvee_{i=1}^n X_i$ for $n \geq 1$. Then

$$M_n - \ln n \Rightarrow Y,$$

where

$$\mathbb{P}[Y \leq x] = \exp(-e^{-x}), \quad x \in \mathbb{R} \quad (35)$$

To prove ??, note that for $x \in \mathbb{R}$,

$$\begin{aligned} \mathbb{P}[M_n - \ln n \leq x] &= \mathbb{P}\left[\bigcap_{i=1}^n (X_i \leq x + \ln n)\right] \\ &= (1 - e^{-(x + \ln n)})^n \\ &= \left(1 - \frac{e^{-x}}{n}\right)^n \rightarrow \exp(-e^{-x}) \end{aligned}$$

Let X_1, X_2, \dots, X_n be i.i.d. Cauchy. Show that $M_n = \max X_i$ is such that $\pi M_n/n$ converges in distribution, the limiting distribution function being given by $F(x) = e^{-1/x}$ if $x \geq 0$.

We have that

$$\mathbb{P}[M_n \leq xn/\pi] = \left\{ \frac{1}{2} + \frac{1}{\pi} \tan^{-1}\left(\frac{xn}{\pi}\right) \right\}^n = \left\{ 1 - \frac{1}{\pi} \tan^{-1}\left(\frac{\pi}{xn}\right) \right\}^n$$

if $x > 0$, by elementary trigonometry. Now $\tan^{-1} y = y + o(y)$ as $y \rightarrow 0$, and therefore

$$\mathbb{P}[M_n \leq xn/\pi] = \left(1 - \frac{1}{xn} + o(n^{-1})\right)^n \rightarrow e^{-1/x} \quad \text{as } n \rightarrow \infty$$

8.4.1 Extreme Value Distributions

$\{X_n, n \geq 1\}$ i.i.d. with common distribution F . The Extreme observation among the first n is

$$M_n := \bigvee_{i=1}^n X_i.$$

Suppose there exist normalizing constants $a_n > 0$ and $b_n \in \mathbb{R}$ such that

$$F^n(a_n x + b_n) = \mathbb{P}\left[\frac{M_n - b_n}{a_n} \leq x\right] \xrightarrow{D} G(x), \quad (36)$$

where the limit distribution G is proper and non-degenerate. Then G is the type of one of the following extreme value distributions:

1. $\Phi_\alpha(x) = \exp(-x^{-\alpha}), \quad x > 0, \quad \alpha > 0,$
2. $\Psi_\alpha(x) = \begin{cases} \exp(-(x)^\alpha), & x < 0, \quad \alpha > 0 \\ 1 & x > 0, \end{cases}$
3. $\Lambda(x) = \exp(-e^{-x}), \quad x \in \mathbb{R}$

The statistical significance is the following. The types of the three extreme value distributions can be united as a one parameter family indexed by shape parameter $\gamma \in \mathbb{R}$:

$$G_\gamma(x) = \exp(-(1 + \gamma x)^{-1/\gamma}), \quad 1 + \gamma x > 0 \quad (37)$$

where we interpret the case of $\gamma = 0$ as

$$G_0 = \exp(-e^{-x}) \quad x \in \mathbb{R} \quad (40)$$

8.5 Implications

$$L_p\text{-Konvergenz} \Rightarrow L_q\text{-Konvergenz} (q \leq p) \Rightarrow \text{stochastische Konvergenz}$$

(38)

sowie

$$\text{fast sichere Konvergenz} \Rightarrow \text{stochastische Konvergenz}$$

(39)

X_i i.i.d., $\mathbb{E}[X_i] = \mu$, $\mathbb{V}[X_i] < \infty$. Show that

$$\binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} X_i X_j \xrightarrow{\mathbb{P}} \mu^2, \quad n \rightarrow \infty$$

$$\binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} X_i X_j = \frac{n}{n-1} \left(\frac{1}{n} \sum_{i=1}^n X_i \right)^2 - \frac{1}{n(n-1)} \sum_{i=1}^n X_i^2$$

Now $n^{-1} \sum_{i=1}^n X_i \xrightarrow{D} \mu$ by law of large numbers $\Rightarrow n^{-1} \sum_{i=1}^n X_i \xrightarrow{\mathbb{P}} \mu$ (see ??). It follows that $(n^{-1} \sum_{i=1}^n X_i)^2 \xrightarrow{\mathbb{P}} \mu^2$. Since if $c_n \rightarrow c$ and $X_n \xrightarrow{\mathbb{P}} X$ then $c_n X_n \xrightarrow{\mathbb{P}} cX$. So

$$\frac{n}{n-1} \left(\frac{1}{n} \sum_{i=1}^n X_i \right)^2 \xrightarrow{\mathbb{P}} \mu^2$$

and

$$\frac{1}{n(n-1)} \sum_{i=1}^n X_i^2 \xrightarrow{\mathbb{P}} 0.$$

The result follows from the fact that If $X_n \xrightarrow{\mathbb{P}} X$ and $Y_n \xrightarrow{\mathbb{P}} Y$ then $X_n + Y_n \xrightarrow{\mathbb{P}} X + Y$.

8.5.1 Converse Implications

- (a) If $X_n \xrightarrow{D} c$, where c is constant, then $X_n \xrightarrow{\mathbb{P}} c$
- (b) If $X_n \xrightarrow{\mathbb{P}} X$ and $\mathbb{P}[|X_n| \leq k] = 1$ for all n and some k , then $X_n \xrightarrow{L_p} X$ for all $p \geq 1$
- (c) If $\mathbb{P}[|X_n - X| > \epsilon]$ satisfies $\sum_n \mathbb{P}[|X_n - X| > \epsilon] < \infty$ for all $\epsilon > 0$, then $X_n \xrightarrow{\text{a.s.}} X$

8.5.2 Slutsky's Theorem

$$X_n \xrightarrow{D} X, \quad A_n \xrightarrow{\mathbb{P}} a \text{ and } B_n \xrightarrow{\mathbb{P}} b \Rightarrow A_n + B_n \cdot X_n \xrightarrow{D} a + b \cdot X$$

(40)

9 Appendix

9.1 Stammfunktionen

$$\begin{aligned}
 \int \frac{1}{x} dx &= \ln|x| + c \\
 \int e^x dx &= e^x + c \\
 \int e^{kx} dx &= \frac{1}{k} e^{kx} + c \\
 \int a^x \ln a dx &= a^x + c \\
 \int \ln x dx &= x \ln x - x \\
 \int \sin(x) dx &= -\cos(x) + c \\
 \int \cos(x) dx &= \sin(x) + c \\
 \int e^{ax} dx &= \frac{1}{a} e^{ax} \\
 \int x e^{ax} dx &= \frac{e^{ax}}{a^2} (ax - 1) \\
 \int x e^{-ax} dx &= \frac{-e^{-ax}}{a^2} (ax + 1) \\
 \int x^2 e^{ax} dx &= \frac{e^{ax}}{a^3} (a^2 x^2 - 2ax + 2) \\
 \int_0^\infty x^2 a e^{-ax} dx &= -x^2 e^{-ax} \Big|_0^\infty + \int_0^\infty 2x e^{-ax} dx = 0 + \frac{2}{a^2} \\
 \int x^n e^{ax} dx &= \frac{1}{a} x^n e^{ax} - \frac{n}{a} \int x^{n-1} e^{ax} dx \\
 \int \frac{1}{1+e^{ax}} dx &= \frac{1}{a} \ln \frac{e^{ax}}{1+e^{ax}} \\
 \int \frac{1}{b+ce^{ax}} dx &= \frac{x}{b} - \frac{1}{ab} \ln|b+ce^{ax}| \\
 \int \frac{e^{ax}}{b+ce^{ax}} dx &= \frac{1}{ac} \ln|b+ce^{ax}|
 \end{aligned}$$

9.1.1 Beispiele

- ??
- ??

9.2 Partielle Integration

$$\int_a^b f'(x) \cdot g(x) dx = [f(x) \cdot g(x)]_a^b - \int_a^b f(x) \cdot g'(x) dx \quad (41)$$

9.3 Sets and Events

9.3.1 De Morgan

$$\begin{aligned}
 \left(\bigcup_i A_i \right)^C &= \bigcap_i A_i^C \\
 \left(\bigcap_i A_i \right)^C &= \bigcup_i A_i^C
 \end{aligned}$$

9.3.2 Limits of Sets

- $\inf_{k \geq n} A_k := \bigcap_{k=n}^\infty A_k$, $\sup_{k \geq n} A_k := \bigcup_{k=n}^\infty A_k$
- $\liminf_{n \rightarrow \infty} A_n = \bigcup_{n=1}^\infty \bigcap_{k=n}^\infty A_k$
- $\limsup_{n \rightarrow \infty} A_n = \bigcap_{n=1}^\infty \bigcup_{k=n}^\infty A_k$
- If $\liminf_{n \rightarrow \infty} B_n = \limsup_{n \rightarrow \infty} B_n = B$ then we say $B_n \rightarrow B$
- $\limsup_{n \rightarrow \infty} A_n = [A_n \text{ i.o.}]$

9.3.3 Borel-Cantelli Lemma

Let $\{A_n\}$ be any events. If

$$\sum_n \mathbb{P}[A_n] < \infty$$

then

$$\mathbb{P}[A_n \text{ i.o.}] = \mathbb{P}\left[\limsup_{n \rightarrow \infty} A_n\right] = 0$$

Let $X_n \sim \text{Exp}(1)$

$$\mathbb{Z}\mathbb{Z}: \quad \mathbb{P}\left[\limsup_{n \rightarrow \infty} \frac{X_n}{\log n} = 1\right] = 1$$

Evidently

$$\mathbb{P}\left[\frac{X_n}{\log n} \geq 1 + \epsilon\right] = \frac{1}{n^{1+\epsilon}}, \quad \text{for } |\epsilon| \leq 1$$

By the Borel-Cantelli lemmas, the events $A_n = \{X_n / \log n \geq 1 + \epsilon\}$ occur a.s. infinitely often for $-1 < \epsilon \leq 0$, and a.s. only finitely often for $\epsilon > 0$.

9.3.4 Borel Zero-One Law

If $\{A_n\}$ is a sequence of independent events, then

$$\mathbb{P}[A_n \text{ i.o.}] = \begin{cases} 0, & \text{iff } \sum_n \mathbb{P}[A_n] < \infty \\ 1, & \text{iff } \sum_n \mathbb{P}[A_n] = \infty \end{cases}$$

9.4 Inequalities

9.4.1 Markov

$$\mathbb{P}[|X| \geq \lambda] \leq \frac{\mathbb{E}[|X|]}{\lambda} \quad (42)$$

9.4.2 Chebychev

$$\mathbb{P}[|X - \mathbb{E}(X)| \geq \lambda] \leq \frac{\mathbb{V}[X]}{\lambda^2}$$

9.4.3 Kolmogorov

$$\mathbb{P}\left[\max_{1 \leq k \leq n} |X_k| \geq \lambda\right] \leq \frac{\mathbb{V}(X_n)}{\lambda^2} = \frac{1}{\lambda^2} \sum_{k=1}^n \mathbb{V}[X_k] \quad (44)$$

9.4.4 Schwartz

$X, Y \in L_2$ then

$$|\mathbb{E}[XY]| \leq \mathbb{E}[|XY|] \leq \sqrt{\mathbb{E}[X^2] \mathbb{E}[Y^2]} \quad (45)$$

9.4.5 Hölder

Suppose p, q satisfy

$$p > 1, q > 1, \frac{1}{p} + \frac{1}{q} = 1$$

and that

$$\mathbb{E}[|X|^p] < \infty, \mathbb{E}[|Y|^q] < \infty$$

then

$$|\mathbb{E}[XY]| \leq \mathbb{E}[|XY|] \leq \left(\mathbb{E}[|X|^p]\right)^{1/p} \left(\mathbb{E}[|Y|^q]\right)^{1/q} \quad (46)$$

9.4.6 Minkowski

For $1 \leq p < \infty$, assume $X, Y \in L_p$. Then $X + Y \in L_p$ and

$$\|X + Y\|_p \leq \|X\|_p + \|Y\|_p \quad (47)$$

9.4.7 Jensen

Suppose $f: \mathbb{R} \mapsto \mathbb{R}$ is convex and $\mathbb{E}[|X|] < \infty$ and $\mathbb{E}[|f(X)|] < \infty$. Then

$$\mathbb{E}[f(X)] \geq f(\mathbb{E}[X]) \quad (48)$$

A special case is

$$\mathbb{E}[X^2] \geq (\mathbb{E}[X])^2 \quad (49)$$

(43) If f is concave, the inequality reverses.

9.5 Stochastics

9.5.1 Law of Large Numbers

$$\frac{1}{n} \sum_{i=1}^n X_i \rightarrow \mu \quad (50)$$

9.5.2 Central Limit Theorem

$$\mathbb{P}\left[\frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}} \leq x\right] \rightarrow N(x) := \int_{-\infty}^x \frac{e^{-u^2/2}}{\sqrt{2\pi}} du \quad (51)$$

9.6 Extrema and Order Statistics

9.6.1 Minima

Seien X_1, X_2, \dots iid auf $[0, 1]$ Gleichverteilt. Gegen welche Verteilung konvergiert $n \cdot \min_{1 \leq k \leq n} X_k$ schwach?

$$\begin{aligned}
\mathbb{P}\left[n \cdot \min_{1 \leq k \leq n} < c\right] &= 1 - \mathbb{P}\left[n \cdot \min_{1 \leq k \leq n} \geq c\right] \\
&= 1 - \mathbb{P}\left[\bigcap_{1 \leq k \leq n} \left\{\omega : X_k(\omega) \geq \frac{c}{n}\right\}\right] \\
&= 1 - \left(\mathbb{P}\left[X \geq \frac{c}{n}\right]\right)^n \\
&= 1 - \left(\int \mathbb{1}_{X \geq \frac{c}{n}}(x) \cdot \frac{1}{1-0} dx\right)^n \\
&= 1 - \left(\int_{\frac{c}{n}}^1 dx\right)^n \\
&= 1 - \left(1 - \frac{c}{n}\right)^n \\
&\xrightarrow{n \rightarrow \infty} 1 - e^{-c}
\end{aligned}$$

Konvergiert gegen ZV die $\text{Exp}(1)$ verteilt ist.

9.6.2 Maxima

$$\begin{aligned}
\mathbb{P}\left[\max_{1 \leq k \leq n} X_k < c\right] &= \mathbb{P}\left[\bigcap_{1 \leq k \leq n} \{\omega : X_k(\omega) < c\}\right] \\
&= \prod_{k=1}^n \mathbb{P}[X_k < c] \\
&= \left(\mathbb{P}[X_1 < c]\right)^n
\end{aligned}$$