Probability and Stochastic Processes Notebook

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1 Mathematics

1.1 Taylor's Series

If $x \to a$,

$$f(x) = \sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!}(x-a)^k$$

Specially,

$$e^x = \sum_{k=0}^{\infty} \frac{e^a}{k!}(x-a)^k = \sum_{k=0}^{\infty} \frac{x^k}{k!} \quad (x \to 0)$$

1.2 Combination

$$C_n^k = \binom{n}{k} = \frac{n!}{(n-k)!\,k!} \quad \text{(Combinations)}$$

$$A_n^k = \frac{n!}{(n-k)!} \quad \text{(Permutations)}$$

1.3 Differentiate

$$\frac{d}{dx}(\sin x) = \cos x$$

$$\frac{d}{dx}(\cos x) = -\sin x$$

$$\frac{d}{dx}(\tan x) = 1 + \tan^2 x$$

1.4 Integral

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\, dx = 1$$

Specially, for $\mu = 0$ and $\sigma^2 = 1$:

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}\, dx = 1$$

1.5 Series

$$\sum_{n=1}^{\infty} \frac{1}{n} \to +\infty$$

$$\sum_{n=1}^{\infty} \frac{1}{n^2} = \frac{\pi^2}{6}$$

1.6 Trigonometric Functions

$$\cos(A+B) = \cos A \cos B - \sin A \sin B$$
$$\sin(A+B) = \sin A \cos B + \cos A \sin B$$
$$\cos(2A) = \cos^2 A - \sin^2 A = 1 - 2\sin^2 A = 2\cos^2 A - 1$$
$$\sin(2A) = 2 \sin A \cos A$$

1.7 Double Integral

Exchange the order of integral,

$$\iint_R f(x,y)\,\mathrm{d}x\,\mathrm{d}y \;=\; \int_{y=0}^{1}\int_{x=y}^{1} f(x,y)\,\mathrm{d}x\,\mathrm{d}y \;=\; \int_{x=0}^{1}\int_{y=0}^{x} f(x,y)\,\mathrm{d}y\,\mathrm{d}x,$$
$$R = \{(x,y) : 0 \le y \le x \le 1\}.$$

1.8 Gamma Integral

$$\int_0^{\infty} u^k e^{-u}\mathrm{d}u = k!$$

2 Lecture 1: Probability & Stochastic Processes

2.1 Normal Distribution

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
$$\mathbb{E}[X] = \mu \qquad \mathrm{Var}(X) = \sigma^2$$

2.2 Poisson Distribution

$$P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}$$
$$\mathbb{E}[X] = \lambda \qquad \mathrm{Var}(X) = \lambda$$

2.3 Function of a Random Variable

Let $y = g(x)$, then:

$$F_Y(y) = \mathbb{P}(Y \le y_0) = \mathbb{P}(g(X) \le y_0) = \int_D f_X(x)\,dx$$
$$f_Y(y) = \frac{dF_Y(y)}{dy}$$

2.4 Mean, Variance, Moments, Characteristic Function

$$\mathbb{E}[X] = \int f_X(x) \cdot x\,dx = \sum_x x \cdot p(x)$$
$$\mathrm{Var}(X) = \mathbb{E}[(X - \bar{X})^2]$$
$$m_n = \mathbb{E}[X^n]$$
$$\varphi_X(\omega) = \mathbb{E}[e^{j\omega X}] = \int e^{j\omega x} f_X(x)\,dx$$

2.5 Other Distributions

Uniform Distribution

$$f_X(x) = \begin{cases} \frac{1}{b-a} & a < x < b \\ 0 & \text{otherwise} \end{cases}$$

Exponential Distribution

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x < 0 \end{cases}$$

Bernoulli Distribution

$$P(X = 0) = p, \quad P(X = 1) = 1 - p$$

Binomial Distribution

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

3 Lecture 2: Joint and Marginal Distributions

3.1 Joint and Marginal

$$F_{XY}(x, y) = \mathbb{P}(X \le x_0, Y \le y_0)$$

$$f_{XY}(x, y) = \frac{\partial^2 F_{XY}(x, y)}{\partial x \, \partial y} \quad \text{(Joint)}$$

Marginal distributions:

$$f_X(x) = \int f_{XY}(x, y) \, dy \qquad f_Y(y) = \int f_{XY}(x, y) \, dx$$

3.2 Function of Two Random Variables

Let $Z = g(X, Y)$, then:

$$F_Z(z) = \mathbb{P}(Z \le z_0) = \mathbb{P}(g(X, Y) \le z_0) = \iint_D f_{XY}(x, y) \, dx \, dy$$

$$f_Z(z) = \frac{dF_Z(z)}{dz}$$

Note: The range of Z needs to be considered. If $1 > X, Y > 0$, then $1 > Z = XY > 0$. The integral area will be affected.

3.3 Two Functions of Two Random Variables

Let:

$$Z = g(X, Y), \quad W = h(X, Y)$$

Then:

$$f_{ZW}(z, w) = \sum_i \frac{1}{|J(x_i, y_i)|} f_{XY}(x_i, y_i) \quad \text{(joint p.d.f.)}$$

Where the Jacobian matrix is:

$$J(x, y) = \det \begin{bmatrix} \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \\ \frac{\partial h}{\partial x} & \frac{\partial h}{\partial y} \end{bmatrix}$$

This concept can be extended to multiple functions of multiple random variables.

3.4 Covariance and Correlation

$$\text{Cov}(X, Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$$

$$\text{Correlation} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)}\sqrt{\text{Var}(Y)}} \quad \in [-1, 1]$$

4 Lecture 3: Inequalities and Limit Theorems

4.1 Inequality

Markov Inequality:

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}[X]}{a}$$

Generalized Inequality:

$$\mathbb{P}(g(X) \geq g(a)) \leq \frac{\mathbb{E}[g(X)]}{g(a)}$$

Chebyshev Inequality: Let $g(x) = (X - \mu)^2$, then:

$$\mathbb{P}(|X - \mu| \geq a) \leq \frac{\mathbb{E}[(X - \mu)^2]}{a^2} = \frac{\sigma^2}{a^2}$$

Chernoff Bound: Let $g(x) = e^{\lambda x}$, then:

$$\mathbb{P}(e^{\lambda x} \geq e^{\lambda a}) \leq \frac{\mathbb{E}[e^{\lambda x}]}{e^{\lambda a}} = \frac{\int e^{\lambda x} f_X(x)\, dx}{e^{\lambda a}}$$

So,

$$\mathbb{P}(X \geq a) \leq \min_{\lambda > 0} e^{-\lambda a} \varphi(\lambda)$$

where $\varphi(\lambda) = \mathbb{E}[e^{\lambda X}]$

4.2 Law of Large Numbers

For N observations of a random variable X, with $\mathbb{E}[X] = \mu$, define:

$$\hat{X} = \frac{X_1 + X_2 + \cdots + X_N}{N}$$

Then:

$$\hat{X} \to \mu \quad \text{as } N \to \infty$$

4.3 Central Limit Theorem

For N i.i.d. random variables with $\mu = 0$, define:

$$Y = \frac{X_1 + X_2 + \cdots + X_N}{N}$$

Then:

$$Y \sim \mathcal{N}(0, \sigma^2)$$

5 Lecture 4: Parameters Estimation

5.1 Maximum Likelihood

$$\hat{\theta} = \arg\max_{\theta} f_X(x_1, x_2, \ldots, x_n; \theta)$$

1. Log-likelihood:
$$\mathcal{L}(x_1, x_2, \ldots, x_n; \theta) = \log f_X(x_1, x_2, \ldots, x_n; \theta)$$

2. Solve:
$$\frac{\partial \mathcal{L}}{\partial \theta} = 0$$

5.2 Cramér-Rao Bound

$$\mathrm{Var}(\hat{\theta}) \geq \frac{1}{I(\theta)}$$

$$I(\theta) = \mathbb{E}\left[\left(\frac{\partial}{\partial \theta} \ln f_X(x_1, x_2, \ldots, x_n; \theta)\right)^2\right]$$

5.3 Unbiased Estimator

The estimator is unbiased if the expected value of estimator equals the desired parameters, i.e.

$$\mathrm{E}(\hat{\theta}) = \theta$$

5.4 MMSE Estimator

$$y(n) = \boldsymbol{w}^T(n)\boldsymbol{x}(n)$$

where:

$$\boldsymbol{w}(n) = \begin{bmatrix} w(n) & w(n-1) & \ldots & w(n-M+1) \end{bmatrix}^T, \quad \boldsymbol{x}(n) = \begin{bmatrix} x(n) & x(n-1) & \ldots & x(n-M+1) \end{bmatrix}^T$$

$$\boldsymbol{w}^*(n) = \mathbf{R}^{-1}\mathbf{P}$$

with:

$$\mathbf{R} = \mathbb{E}[\boldsymbol{x}(n)\boldsymbol{x}^H(n)], \quad \mathbf{P} = \mathbb{E}[d(n)\boldsymbol{x}^*(n)]$$

If $y(n) = x(n+1)$, it becomes an MSE predictor.

MSE Expression:

$$\mathrm{MSE} = \mathbb{E}[(x(n+1) - \hat{x}(n+1))^2] = \mathbb{E}[(x(n+1) - \boldsymbol{w}^T(n)\boldsymbol{x}(n))^2]$$

$$= R(0) - 2\boldsymbol{w}^T\mathbf{P} + \boldsymbol{w}^T\mathbf{R}\boldsymbol{w}$$

$$= R(0) - \boldsymbol{w}^T\mathbf{P}$$

6 Lecture 5: Stochastic Processes

6.1 Stochastic Process

Assume a stochastic process $X(t)$. For fixed t, $X(t)$ is a random variable.

$$F_X(x,t) = \mathbb{P}(X(t) \le x)$$
$$f_X(x,t) = \frac{d}{dx} F_X(x,t)$$

6.2 Mean, Autocorrelation, Covariance

$$\mu(t) \triangleq \int_{-\infty}^{\infty} x_t f_X(x,t)\, dx$$

$$R_{XX}(t_1,t_2) \triangleq \mathbb{E}[X_{t_1} X_{t_2}^*] = \iint X_{t_1} X_{t_2}^* f(x_{t_1}, x_{t_2})\, dx_{t_1} dx_{t_2}$$

$$\mathrm{Cov}(t_1,t_2) \triangleq \mathbb{E}[(X_{t_1} - \mu(t_1))(X_{t_2} - \mu(t_2))^*]$$

Properties:

$$R_{XX}(t_2,t_1) = R_{XX}^*(t_1,t_2)$$

6.3 Stationarity

Strict-Sense Stationary: A process is n-th order strictly stationary if:

$$f(x_1, x_2, \ldots, x_n; t_1, t_2, \ldots, t_n) = f(x_1, x_2, \ldots, x_n; t_1 + c, t_2 + c, \ldots, t_n + c), \quad \forall c$$

i.e., the distribution depends only on the **relative time differences**.
Example:

$$f(x_1, x_2, x_3; t_1, t_2, t_3) = f(x_1, x_2, x_3; t_1 + c, t_2 + c, t_3 + c) = f(x_1, x_2, x_3; 0, t_2 - t_1, t_3 - t_1)$$

Wide-Sense Stationary (WSS): 1st Order:

$$f(x; t_1) = f(x, 0) \quad \text{and} \quad \mathbb{E}[X(t)] = \mu(t) \text{ doesn't depend on } t$$

2nd Order:

$$f(x_1, x_2; t_1, t_2) = f(x_1, x_2; 0, t_2 - t_1)$$
$$\mathbb{E}[X(t_1)X(t_2)] = \mu(t_1, t_2) \text{ depends only on } \tau = t_2 - t_1$$

7 Lecture 6: Power Spectrum

7.1 ARMA Model

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + \sum_{k=0}^{q} b_k y(n-k)$$

Taking the Z-transform:

$$X(z) + \sum_{k=1}^{p} a_k X(z) z^{-k} = \sum_{k=0}^{q} Y(z) b_k z^{-k}$$

$$H(z) = \frac{Y(z)}{X(z)} = \frac{1 + \sum_{k=1}^{p} a_k z^{-k}}{\sum_{k=0}^{q} b_k z^{-k}}$$

7.2 Wiener-Khinchin Theorem

$$R_{XX}(\tau) \xleftrightarrow{\text{FT}} S_{XX}(\omega)$$

$$S_{XX}(\omega) = \int R_{XX}(\tau) e^{-j\omega\tau} d\tau$$

$$R_{XX}(\tau) = \frac{1}{2\pi} \int S_{XX}(\omega) e^{j\omega\tau} d\omega$$

7.3 Matched Filter

Received waveform

$$r(t) = s(t) + w(t), \qquad -\infty < t < \infty,$$

where $s(t)$ is a known deterministic signal and $w(t)$ is zero–mean additive (complex) white Gaussian noise with two–sided *constant* PSD

$$S_W(\omega) = N_0, \qquad -\infty < \omega < \infty.$$

Linear filter output The received signal is passed through an *arbitrary* LTI filter $h(t)$:

$$y(t) = h(t) * r(t) = y_s(t) + n(t),$$

with

$$y_s(t) = h(t) * s(t), \qquad n(t) = h(t) * w(t).$$

The (power) SNR is defined by

$$\text{SNR} = \frac{P_s}{P_n} = \frac{|y_s(t_0)|^2}{\mathbb{E}\big[|n(t_0)|^2\big]} = \frac{|y_s(t_0)|^2}{R_{nn}(0)}.$$

Frequency–domain expressions Let capital letters denote Fourier transforms:

$$S(\omega) = \mathcal{F}\{s(t)\}, \qquad H(\omega) = \mathcal{F}\{h(t)\}.$$

Using the convolution theorem,

$$Y_s(\omega) = S(\omega)H(\omega), \qquad N(\omega) = W(\omega)H(\omega).$$

Hence

$$y_s(t_0) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S(\omega)H(\omega)\, e^{j\omega t_0}\, d\omega.$$

Because the noise is wide–sense stationary,

$$R_{nn}(0) = \mathbb{E}[|n(t_0)|^2] = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_W(\omega)\, |H(\omega)|^2\, d\omega = \frac{N_0}{2\pi} \int_{-\infty}^{\infty} |H(\omega)|^2\, d\omega.$$

SNR in compact form

$$\boxed{\text{SNR}(t_0) = \frac{1}{2\pi} \frac{\left| \displaystyle\int_{-\infty}^{\infty} S(\omega)H(\omega)\, e^{j\omega t_0}\, d\omega \right|^2}{N_0 \displaystyle\int_{-\infty}^{\infty} |H(\omega)|^2\, d\omega}}.$$

Define

$$A(\omega) = S(\omega)\, e^{j\omega t_0}, \qquad B(\omega) = H(\omega).$$

Then

$$\text{SNR}(t_0) = \frac{1}{2\pi\, N_0} \frac{|\langle A, B\rangle|^2}{\langle B, B\rangle}, \qquad \langle X, Y\rangle \equiv \int_{-\infty}^{\infty} X(\omega)Y^*(\omega)\, d\omega.$$

Cauchy–Schwarz inequality

$$|\langle A, B\rangle|^2 \le \langle A, A\rangle\, \langle B, B\rangle,$$

with equality *iff*

$$B(\omega) = k\, A^*(\omega), \qquad k \in \mathbb{C} \setminus \{0\}.$$

Applying this condition gives the **optimum** frequency response

$$\boxed{H_{\text{opt}}(\omega) = K\, S^*(\omega)\, e^{-j\omega t_0}}, \qquad K \in \mathbb{R},$$

which achieves equality in Cauchy–Schwarz and therefore maximises the SNR.

Taking the inverse Fourier transform,

$$h_{\text{opt}}(t) = \mathcal{F}^{-1}\big\{H_{\text{opt}}(\omega)\big\} = K\, s^*(t_0 - t).$$

For real–valued $s(t)$ the conjugate is unnecessary, yielding the familiar *matched filter*

$$\boxed{h_{\text{opt}}(t) = K\, s(t_0 - t)}.$$

With the optimal $H_{\text{opt}}(\omega)$,

$$|\langle A, B\rangle|^2 = \langle A, A\rangle\, \langle B, B\rangle,$$

and the SNR becomes

$$\text{SNR}_{\max} = \frac{1}{2\pi\, N_0}\, \langle A, A\rangle = \frac{1}{2\pi\, N_0} \int_{-\infty}^{\infty} |S(\omega)|^2\, d\omega = \frac{E_s}{N_0},$$

where $E_s = \int_{-\infty}^{\infty} |s(t)|^2\, dt$ is the signal energy (Parseval's theorem).

$$\boxed{H_{\text{opt}}(\omega) = K\, S^*(\omega) e^{-j\omega t_0}, \quad h_{\text{opt}}(t) = K\, s(t_0 - t), \quad \text{SNR}_{\max} = \frac{E_s}{N_0}}$$

8 Lecture 8: Markov Chain

8.1 Markov Chain Definition

Discrete time: $1, 2, \ldots, n, n+1$
Discrete state: $i_0, i_1, \ldots, i_n$

$$\mathbb{P}(X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \ldots, X_0 = i_0) = \mathbb{P}(X_{n+1} = j \mid X_n = i)$$

A **homogeneous** Markov chain satisfies:

$$P_{ij} = \mathbb{P}(X_{n+1} = j \mid X_n = i) \quad \text{(independent of } n\text{)}$$

8.2 Markov Matrix

$$P = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

8.3 Probability Distribution

$\pi^{(0)}$ — probability distribution at $t = 0\pi^{(n)}$ — probability distribution at $t = n$

$$\pi^{(n)} = \pi^{(0)} P^n$$

8.4 Limiting Probability Distribution

$$\pi = \lim_{n\to\infty} \pi^{(n)} = \lim_{n\to\infty} \pi^{(0)} P^n$$

Assume convergence:

$$\pi = \pi P \quad \Rightarrow \quad \pi \cdot \mathbf{1} = \pi P \quad \text{(stationary distribution)}$$

8.5 Stationary Distribution and Eigen Decomposition

Recall eigenvalue relation:

$$\lambda \mathbf{v} = A\mathbf{v}$$

Stationary distribution π is the eigenvector corresponding to $\lambda = 1$.
Example:

$$P = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \quad \Rightarrow \quad \pi = \begin{bmatrix} 0.3047 & 0.3905 & 0.3048 \end{bmatrix}$$

Lecture 8 (Continued): Random Walker / Gambler's Ruin

1. Random Walker

Transition matrix P for a random walk with a left barrier:

$$P = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots \\ q & 0 & p & 0 & \cdots \\ 0 & q & 0 & p & \cdots \\ \vdots & \vdots & \vdots & \ddots & \ddots \end{bmatrix}$$

There is a barrier on the left (at 0) that prevents moving further left.

2. Gambler's Ruin

Transition matrix P for Gambler's Ruin problem:

$$P = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ q & 0 & p & \cdots & 0 & 0 \\ 0 & q & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & p & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1 \end{bmatrix}$$

The gambler stops gambling if they either: - Lose all their money (reach state 0), or - Reach the target amount N.

Ruin Probability: Given initial capital i, the probability of ruin (reaching state 0) is:

$$P_i = \begin{cases} \frac{1-\left(\frac{p}{q}\right)^{N-i}}{1-\left(\frac{p}{q}\right)^{N}} & \text{if } p \neq \frac{1}{2} \\ \frac{N-i}{N} & \text{if } p = \frac{1}{2} \end{cases} = \mathbb{P}(S_T = 0)$$

Notes: - N: Target capital (absorbing boundary at the top) - $\mathbb{P}(S_{n+1} = S_n + 1) = p$ - $\mathbb{P}(S_{n+1} = S_n - 1) = q$ - $p + q = 1$

9 Lecture 9: Continuous-Time Processes

9.1 1. Poisson Processes

Define $X(t) = n(t_1, t_2)$, the number of arrivals in the interval (t_1, t_2). Let $t = t_2 - t_1$. This is a Poisson process if:

$$\mathbb{P}(n(t_1, t_2) = k) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

Expected value:

$$\mathbb{E}[n(t_1, t_2)] = \lambda t$$

Where λ is the expected number of events per unit time. Example: Average one car accident in 5 minutes implies $\lambda = 0.2$ per minute.

9.2 2. Poisson Meets Bernoulli

Suppose: - Number of car accidents follows a Poisson distribution. - Whether a car accident is fatal or not follows a Bernoulli distribution.

Let: - n: total number of accidents - k: number of fatal accidents

Step 1: Poisson distribution for total accidents:

$$\mathbb{P}(n) = \frac{(\lambda t)^n e^{-\lambda t}}{n!}$$

Step 2: Binomial distribution for k fatal out of n:

$$\mathbb{P}(k \mid n) = \binom{n}{k} p^k (1-p)^{n-k}, \quad n \geq k$$

Step 3: Total probability of k fatal accidents:

$$\mathbb{P}(k) = \sum_{n=k}^{\infty} \mathbb{P}(k \mid n)\mathbb{P}(n)$$

$$= \sum_{n=k}^{\infty} \binom{n}{k} p^k (1-p)^{n-k} \cdot \frac{(\lambda t)^n e^{-\lambda t}}{n!}$$

$$= \sum_{n=k}^{\infty} \frac{[(1-p)\lambda t]^{n-k}}{(n-k)!} \cdot \frac{(\lambda t p)^k e^{-\lambda t}}{k!}$$

$$= \frac{(\lambda t p)^k e^{-\lambda t}}{k!} \sum_{n=0}^{\infty} \frac{[(1-p)\lambda t]^n}{n!}$$

$$= \frac{(\lambda t p)^k}{k!} e^{-(1-p)\lambda t} e^{-p\lambda t} = \frac{(\lambda p t)^k e^{-\lambda p t}}{k!}$$

Hence, the number of fatal car accidents also follows a Poisson distribution with parameter $\lambda p t$.

9.3 Inter-arrival Interval

The time interval between any two arrivals τ_n follows exponential distribution, i.e.

$$f_{\tau_n}(t) = \lambda e^{-\lambda t}$$

10 Lecture 10: Martingales

10.1 1. Martingales

A sequence X_n is a martingale if:

$$\mathbb{E}[X_{n+1} \mid X_n, \ldots, X_1] = X_n$$

This represents a form of "stability."

10.2 2. Generalized Martingales

A sequence S_n with finite mean is a martingale with respect to the sequence X_n if:

$$\mathbb{E}[S_{n+1} \mid X_n, \ldots, X_1] = S_n$$

Submartingale:

$$\mathbb{E}[S_{n+1} \mid X_1, X_2, \ldots, X_n] \geq S_n$$

Supermartingale:

$$\mathbb{E}[S_{n+1} \mid X_1, X_2, \ldots, X_n] \leq S_n$$

10.3 3. Stopping Time T

Stopping time is the time at which a stochastic process stops due to some condition or outcome. For example, when a gambler runs out of money, the stochastic process of his money stops.

If X_n is a martingale, then the following property holds:

$$\mathbb{E}[X_T] = \mathbb{E}[X_0]$$