

BIE-PST Cheat Sheet

FIT – CTU in Prague
Winter Semester 2023/2024

Probability	$P(A) = \frac{ A }{ \Omega } = \frac{\text{\# of favorable outcomes}}{\text{\# of all outcomes}}$ or $\frac{\text{size of favorable outcomes}}{\text{size of all outcomes}}$
Conditional probability	$P(A B) = \frac{P(A \cap B)}{P(B)}$
Multiplicative law	$P(A_1 \cap \dots \cap A_n) = P(A_1) P(A_2 A_1) \dots P(A_n A_1 \cap \dots \cap A_{n-1})$
Law of total probability	$P(A) = \sum_j P(A B_j)P(B_j)$
Bayes' theorem	$P(B_i A) = \frac{P(A B_i)P(B_i)}{\sum_j P(A B_j)P(B_j)}$
Independence	$P(A \cap B) = P(A)P(B)$

Distribution function	$F_X(x) = P(X \leq x)$
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Discrete random variable X :

Probabilities of values	$P(X = x)$
Expectation	$E X = \sum_k x_k P(X = x_k)$
Expectation of a function	$E g(X) = \sum_k g(x_k) P(X = x_k)$

Continuous random variable X :

Density	$f_X(x)$
Expectation	$E X = \int_{-\infty}^{+\infty} x f_X(x) dx$
Expectation of a function	$E g(X) = \int_{-\infty}^{+\infty} g(x) f_X(x) dx$
Variance X	$\text{var}(X) = E(X - E X)^2 = E X^2 - (E X)^2$

Distribution	probabilities/density	expectation	variance
Bernoulli	$P(X = 1) = p, P(X = 0) = 1 - p$	p	$p(1 - p)$
Binomial	$P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}, k = 0, \dots, n$	np	$np(1 - p)$
Geometric	$P(X = k) = (1 - p)^{k-1} p, k \in \mathbb{N}$	$\frac{1}{p}$	$\frac{1-p}{p^2}$
Poisson	$P(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}, k \in \mathbb{N}_0$	λ	λ
Uniform	$f(x) = \frac{1}{b-a}, x \in [a, b], \text{ elsewhere } 0$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$
Exponential	$f(x) = \lambda e^{-\lambda x}, x \geq 0, \text{ elsewhere } 0$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
Normal	$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, x \in \mathbb{R}$	μ	σ^2

Joint distribution function	
$F_{X,Y}(x, y) = P(X \leq x \cap Y \leq y)$	
<i>Discrete X and Y</i>	<i>Continuous X and Y</i>
Joint probabilities $P(X = x \cap Y = y)$	Joint density $f_{X,Y}(x, y)$
Marginal distribution X	
$P(X = x) = \sum_y P(X = x \cap Y = y)$	$f_X(x) = \int_{-\infty}^{+\infty} f_{X,Y}(x, y) dy$
Independence of X and Y	
$P(X = x \cap Y = y) = P(X = x)P(Y = y)$	$f_{X,Y}(x, y) = f_X(x)f_Y(y)$
Expectation of E g(X, Y)	
$\sum_{x,y} g(x, y) P(X = x \cap Y = y)$	$\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} g(x, y) f_{X,Y}(x, y) dx dy$
Conditional distribution of X given Y = y:	
$P(X = x Y = y) = \frac{P(X = x \cap Y = y)}{P(Y = y)}$	$f_{X Y}(x y) = \frac{f_{X,Y}(x, y)}{f_Y(y)}$
Conditional expectation of X given Y = y:	
$E(X Y = y) = \sum_x x P(X = x Y = y)$	$E(X Y = y) = \int_{-\infty}^{+\infty} x f_{X Y}(x y) dx$

Central limit theorem $Z_n = \frac{S_n - n\mu}{\sqrt{n\sigma^2}} = \frac{\bar{X}_n - \mu}{\sqrt{\sigma^2/n}} \xrightarrow{\mathcal{D}} \mathbf{N}(0, 1)$
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Sample mean	$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$
Sample variance	$s_n^2 = s_X^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$
Two-sided C.I. for μ with known σ^2	$\left(\bar{X}_n - z_{\alpha/2} \frac{\sigma}{\sqrt{n}}, \bar{X}_n + z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \right)$
Two-sided C.I. for μ with unknown σ^2	$\left(\bar{X}_n - t_{\alpha/2, n-1} \frac{s_n}{\sqrt{n}}, \bar{X}_n + t_{\alpha/2, n-1} \frac{s_n}{\sqrt{n}} \right)$
Two-sided C.I. for σ^2	$\left(\frac{(n-1)s_n^2}{\chi_{\alpha/2, n-1}^2}, \frac{(n-1)s_n^2}{\chi_{1-\alpha/2, n-1}^2} \right)$