Midterm Cheat Sheet

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Monotone Probability Inequality If $A \subset B$ then $\mathbb{P}[A] \leq \mathbb{P}[B]$

Inclusion-Exclusion Principle $\mathbb{P}[A \cup B] = \mathbb{P}[A] + \mathbb{P}[B] - \mathbb{P}[A \cap B]$

Boole's Inequality $\mathbb{P}[A \cup B] \leq \mathbb{P}[A] + \mathbb{P}[B]$

Bonferroni's Inequality $\mathbb{P}[A \cap B] \geq \mathbb{P}[A] + \mathbb{P}[B] - 1$

Disjoint Events $\mathbb{P}[\bigcup\limits_{j=1}^{\infty} A_j] = \sum\limits_{j=1}^{\infty} \mathbb{P}[A_j]$

Conditional Probability $\mathbb{P}[A|B] = \frac{\mathbb{P}[A \cup B]}{\mathbb{P}[B]}$

Statistical Independence $\mathbb{P}[A \cup B] = \mathbb{P}[A]\mathbb{P}[B]$

Law of Total Probability $\mathbb{P}[A] = \sum\limits_{i=1}^{\infty} \mathbb{P}[A|B_j]\mathbb{P}[B_j]$

Bayes Rule $\mathbb{P}[A|B] = \frac{\mathbb{P}[B|A]\mathbb{P}[A]}{\mathbb{P}[B]}$

Permutation $P(N, K) = \frac{N!}{(N_K)!}$

Combination $\binom{N}{K} = \frac{N!}{K!(N-K)!}$

CDF $F(x_i) = \sum\limits_{k=1}^{i} \pi_k$ or a sum of PDF's

PDF $P(a \leq x \leq b) = \int\limits_{a}^{b} f(x)dx$

Exp Cont Rand Var $E(X) = \int\limits_{-\infty}^{\infty} xdF(x)$

Variance $Var(X) = E(X^2) - [E(X)]^2$

Bernoulli $f(x|p) = px + (1-p)(1-x)$

Binomial $\binom{n}{x} p^x (1-p)^{1-x}$

Multinomial $f(x|p_1, ..., p_K) = \sum\limits_{i=1}^{K} p_j = 1$

Poisson $\frac{e^{-\lambda}\lambda^x}{x!}$

Uniform $f(x|a, b) = \frac{1}{b-a},\ a \leq x \leq b$

- $E(X) = \frac{a+b}{2}$, $Var(X) = \frac{(b-a)^2}{12}$

Exponential $f(x|\lambda) = \frac{1}{\lambda} e^{-x/\lambda}, x \geq 0, \lambda > 0$

- $E(X) = \lambda,\ Var(X) = \lambda^2$

Normal $f(x|\mu, \sigma^2) = \frac{1}{\sqrt{w\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

Student t $f(x|r) = \frac{\Gamma(\frac{r+1}{2})}{\sqrt{r\pi}\Gamma(\frac{r}{2})}(1 + \frac{x^2}{r})^{-\frac{r+1}{2}}, x \in R$

Logistic $F(x) = \frac{1}{1+e^{-x}}$, $f(x) = F(x)[1 - F(x)]$

Chi-Square $f(x|r) = \frac{1}{2^{r/2}\Gamma(r/2)} x^{r/2-1} e^{-x/2}$

Independence $E(XY) = E(X)E(Y)$

Covariance and Correlation $cov(X, Y) = E(XY) - E(X)E(Y),\ corr(X, Y) = \frac{cov(X,Y)}{\sqrt{var(X)var(Y)}}$

Sample Mean $\bar{X}_n = \frac{1}{n} \sum\limits_{i=1}^{n} X_i$

Sample Variance $s^2 = \frac{\sum\limits_{i=1}^{n} (x_i - \bar{x})^2}{n-1}$

Estimation Bias $bias(\hat{\theta}) = E(\hat{\theta}) - \theta$

Estimation Variance $var(\sum\limits_{i=1}^{n} X_i) = \sum\limits_{i=1}^{n} Var(X_i)$

Mean Squared Error $MSE(\hat{\theta}) = E[(\hat{\theta} - \theta)^2]$

T-Ratio $T = \frac{\sqrt{n}(\bar{X}_n - \mu)}{s} \sim t_{n-1}$ **WLLN** $\bar{X}_n = \frac{1}{n} \sum\limits_{i=1}^{n} X_i \overset{p}{\to} E(X)$

CLT $\sqrt{n}(\bar{X}_n - \mu) \overset{d}{\to} N(0, \sigma^2)$

Slutsky's Theorem $Z_n + c_n \overset{d}{\to} Z + c,\ Z_n c_n \overset{d}{\to} Zc$ and same with division

Joint Density $F(x, y) = \int\limits_{-\infty}^{x} \int\limits_{-\infty}^{y} f(u, v)dvdu$

Multivariate $\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} X_i$