

Statistical Inference II: Formula Sheet

Standard Distributions:

Exponential For $x \geq 0$ and $\lambda > 0$, $X \sim \text{Exp}(\lambda)$ has pdf

$$f(x) = \lambda e^{-\lambda x},$$

with $\mathbb{E}[X] = \frac{1}{\lambda}$ and $\text{Var}[X] = \frac{1}{\lambda^2}$.

Gamma distribution: For $y > 0$, $\alpha > 0$ and $\beta > 0$, $Y \sim \text{Gamma}(\alpha, \beta)$ has pdf:

$$f(y | \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\beta y},$$

where $\Gamma(\alpha)$ is the Gamma function, and $\mathbb{E}[Y] = \frac{\alpha}{\beta}$ and $\text{Var}[Y] = \frac{\alpha}{\beta^2}$.

Inverse-Gamma distribution: For $y > 0$, $\alpha > 0$ and $\beta > 0$, $Y \sim \text{InvGamma}(\alpha, \beta)$ has pdf:

$$f(y | \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{-(\alpha+1)} e^{-\beta/y},$$

where $\Gamma(\alpha)$ is the Gamma function, and $\mathbb{E}[Y] = \frac{\beta}{\alpha-1}$ for $\alpha > 1$ and $\text{Var}[Y] = \frac{\beta^2}{(\alpha-1)^2(\alpha-2)}$ for $\alpha > 2$.

Gamma function: $\Gamma(x)$ is the Gamma function $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$, with properties:

- $\Gamma(x+1) = x\Gamma(x)$
- $\Gamma(1) = 1$; $\Gamma(\frac{1}{2}) = \sqrt{\pi}$
- For integer z , $\Gamma(z) = (z-1)!$

Beta distribution: For $z \in [0, 1]$, $a > 0$ and $b > 0$, $Z \sim \text{Beta}(a, b)$ has pdf:

$$f(z | a, b) = \frac{1}{B(a, b)} z^{a-1} (1-z)^{b-1},$$

where $B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$, and $\mathbb{E}[Z] = \frac{a}{a+b}$ and $\text{Var}[Z] = \frac{ab}{(a+b)^2(a+b+1)}$.

Normal distribution: For $x \in \mathbb{R}$, $\mu \in \mathbb{R}$ and $\sigma > 0$, $X \sim \mathcal{N}(\mu, \sigma^2)$ has pdf:

$$f(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2} \right\},$$

and $\mathbb{E}[X] = \mu$ and $\text{Var}[X] = \sigma^2$.

Chi-squared For $x > 0$ and $k \in \mathbb{N}$, $X \sim \chi_k^2$ has pdf

$$f(x) = \frac{1}{2^{k/2}\Gamma(k/2)} x^{k/2-1} e^{-x/2},$$

with $\mathbb{E}[X] = k$ and $\text{Var}[X] = 2k$.

Multivariate Normal distribution: For $\mathbf{x} \in \mathbb{R}^p$, $\boldsymbol{\mu} \in \mathbb{R}^p$, and positive definite $p \times p$ variance matrix $\boldsymbol{\Sigma}$, $\mathbf{X} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ has pdf:

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{\frac{p}{2}} (\det(\boldsymbol{\Sigma}))^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right\},$$

with $\mathbb{E}[\mathbf{X}] = \boldsymbol{\mu}$ and $\text{Var}[\mathbf{X}] = \boldsymbol{\Sigma}$.

For $\mathbf{X} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with $\mathbf{Y} = A\mathbf{X} + \mathbf{b}$ where A is a $r \times p$ real matrix and $\mathbf{b} \in \mathbb{R}^r$:

$$\mathbf{Y} \sim \mathcal{N}_r(A\boldsymbol{\mu} + \mathbf{b}, B\boldsymbol{\Sigma}B^T)$$

Distribution Theory

Change of variables: For r.v. $X \in \mathcal{X}$ and $Y = y(X) \in \mathcal{Y}$, under appropriate conditions on $y(\cdot)$:

$$f_Y(y) = f_X(x(y)) \left| \frac{dx(y)}{dy} \right|.$$

Multivariate: For $\mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^p$ and $\mathbf{y}(\mathbf{x}) \in \mathcal{Y} \subseteq \mathbb{R}^p$, then under appropriate conditions on $\mathbf{y}(\cdot)$:

$$f_{\mathbf{Y}}(\mathbf{y}) = f_{\mathbf{X}}(x(\mathbf{y})) |\det(\mathbf{J})|,$$

where \mathbf{J} is the $p \times p$ Jacobian matrix, $[\mathbf{J}]_{ij} = \frac{\partial x_i}{\partial y_j}$.

Normal Sampling

For X_1, \dots, X_n i.i.d $\mathcal{N}(\mu, \sigma^2)$:

1. $\bar{X} \sim \mathcal{N}(\mu, \sigma^2/n)$,
2. $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$,
3. $T = \frac{\bar{X}-\mu}{S/\sqrt{n}} \sim t_{n-1}$.

Likelihood

Information:

Observed information:

$$I(\hat{\theta}) = -\frac{\partial^2}{\partial \theta^2} \log \ell(\theta) \Big|_{\theta=\hat{\theta}} = -\mathcal{L}''(\hat{\theta})$$

Expected (Fisher) information:

$$\mathcal{I}_n(\theta) = \mathbb{E}_{\mathbf{X}}[I(\theta)].$$

:

Cramér-Rao Lower Bound: Unbiased estimator T of parameter θ with regular likelihood from sample of size n has:

$$\text{Var}[T] \geq \frac{1}{\mathcal{I}_n(\theta)}.$$

Large-sample behaviour: For i.i.d sample $\mathbf{X} = (x_1, \dots, x_n)$ from $f(x | \theta)$, then under appropriate conditions MLE $\hat{\theta}$ for scalar θ has a limiting distribution as $n \rightarrow \infty$:

$$\hat{\theta} \rightsquigarrow \mathcal{N}\left(\theta, \frac{1}{\mathcal{I}_n(\theta)}\right).$$

Delta method Under appropriate conditions, a collection of continuously differentiable transformations $\phi = g(\theta)$ of parameter θ , $g : \mathbb{R}^p \rightarrow \mathbb{R}^q$, has pdf for $p = 1$

$$\hat{\phi} = g(\hat{\theta}) \sim \mathcal{N}\left(g(\theta), \frac{1}{\mathcal{I}_n(\theta)} \left(\frac{dg(\hat{\theta})}{d\theta}\right)^2\right),$$

and for $p > 1$

$$\hat{\phi} = g(\hat{\theta}) \sim \mathcal{N}_q\left(g(\theta), \mathbf{J}(\hat{\theta})\mathcal{I}_n(\theta)^{-1}\mathbf{J}(\hat{\theta})^T\right),$$

$$\text{where } \mathbf{J}(\hat{\theta}) = \left[\frac{\partial g_i(\hat{\theta})}{\partial \theta_j} \right]_{ij}.$$

Bayesian statistics

Beta-Binomial: For $X | \pi \sim \text{Bin}(n, \pi)$ and prior $\pi \sim \text{Beta}(a, b)$:

$$\pi | X \sim \text{Beta}(a + x, b + n - x).$$

Gamma-Poisson For c.i.i.d X_1, \dots, X_n , with each $X | \lambda \sim \text{Po}(\lambda)$ and prior $\lambda \sim \text{Gamma}(\alpha, \beta)$:

$$\lambda | \mathbf{X} \sim \text{Gamma}\left(\alpha + \sum_{i=1}^n x_i, \beta + n\right).$$

Normal-Normal For c.i.i.d $\mathbf{X} = (X_1, \dots, X_n)$, with each $X | \mu \sim \mathcal{N}(\mu, \sigma^2 = \frac{1}{\tau})$ with known precision $\tau > 0$ and prior $\mu \sim \mathcal{N}(m_0, \frac{1}{t_0})$ and $t_0 > 0$:

$$\mu | \mathbf{X} \sim \mathcal{N}\left(m_1, \frac{1}{t_1}\right),$$

where

$$t_1 = t_0 + n\tau, \quad \text{and} \quad m_1 = \frac{t_0 m_0 + n\tau \bar{x}}{t_0 + n\tau} = \frac{t_0 m_0 + n\tau \bar{x}}{t_1}.$$

Normal-Gamma For c.i.i.d $\mathbf{X} = (X_1, \dots, X_n)$, where each $X \sim \mathcal{N}(\mu, \frac{1}{\tau})$ and priors

$$\mu | \tau \sim \mathcal{N}\left(m_0, v_0^2 = \frac{1}{k_0 \tau}\right) \quad \text{and} \quad \tau \sim \text{Gamma}(\alpha_0, \beta_0),$$

with constant $k_0 > 0$:

$$\mu | \mathbf{X}, \tau \sim \mathcal{N}\left(m_1, \frac{1}{k_1 \tau}\right) \quad \text{and} \quad \tau | \mathbf{X} \sim \text{Gamma}(\alpha_1, \beta_1),$$

where

$$k_1 = k_0 + n, \quad m_1 = \frac{k_0 m_0 + n \bar{x}}{k_0 + n} = \frac{k_0 m_0 + n \bar{x}}{k_1},$$

$$\alpha_1 = \alpha_0 + \frac{n}{2}, \quad \beta_1 = \beta_0 + \frac{1}{2}(n-1)s^2 + \frac{k_0 n(\bar{x} - m_0)^2}{2k_1}.$$

Jeffreys prior:

Scalar θ : $f(\theta) \propto \sqrt{\mathcal{I}(\theta)}$

Vector θ : $f(\theta) \propto \sqrt{\det(\mathcal{I}(\theta))}$

Bayesian Inference

Large sample posterior: For $X = (X_1, \dots, X_n)$ c.i.i.d with regular likelihood $f(x | \theta)$ and n "large enough", the posterior distribution for $\theta | x$ is approximately

$$f(\theta | \mathbf{x}) \sim \mathcal{N}_p\left(\hat{\theta}, I(\hat{\theta})^{-1}\right),$$

Predictive Distributions **Prior predictive:**

$$f(\mathbf{x}) = \int f(\mathbf{x}, \theta) d\theta = \int f(\mathbf{x} | \theta) f(\theta) d\theta$$

Posterior predictive:

$$f(\mathbf{x}^* | \mathbf{x}) = \int f(\mathbf{x}^*, \theta | \mathbf{x}) d\theta = \int f(\mathbf{x}^* | \theta, \mathbf{x}) f(\theta | \mathbf{x}) d\theta$$

Exponential Family

Probability density function The pdf of \mathbf{X} with vector parameter θ belongs to the q -parameter exponential family of distributions if it can be written in the form

$$f(\mathbf{x} | \theta) = b(\mathbf{x}) \exp \left\{ \phi(\theta)^T \mathbf{t}(\mathbf{x}) - a(\phi) \right\}.$$

Bayes Factors

Bayes factors in favour of null hypothesis Simple vs. simple comparisons:

$$B_{01} = \frac{f(\mathbf{x} \mid \theta = \theta_0)}{f(\mathbf{x} \mid \theta = \theta_1)},$$

Composite vs. composite comparisons:

$$B_{01} = \frac{\int_{\theta \in \Omega_0} f(\mathbf{x} \mid \theta) f_0(\theta) d\theta}{\int_{\theta \in \Omega_1} f(\mathbf{x} \mid \theta) f_1(\theta) d\theta}.$$

Simple vs. composite comparisons:

$$B_{01} = \frac{\int_{\theta \in \Omega} f(\mathbf{x} \mid \theta = \theta_0)}{\int_{\theta \in \Omega} f(\mathbf{x} \mid \theta) f_1(\theta) d\theta}.$$

Posterior probability of null hypothesis

$$p_0 = \left[1 + \frac{1 - \pi_0}{\pi_0} B_{01}^{-1} \right]^{-1}$$

Interpretation of Bayes Factors

$2 \log_e(B_{10})$	B_{10}	Evidence against \mathcal{H}_0
$(-\infty, 0)$	$(0, 1)$	None
$(0, 2)$	$(1, 3)$	Not worth more than a bare mention
$(2, 6)$	$(3, 20)$	Positive
$(6, 10)$	$(20, 150)$	Strong
> 10	> 150	Very strong

Normal approximations to Wilcoxon's test statistics

Rank-sum test statistic For n, m large,

$$W \sim \mathcal{N}(\mu_W, \sigma_W^2),$$

where

$$\mu_W = \frac{1}{2}n(n + m + 1), \quad \sigma_W^2 = \frac{1}{12}nm(n + m + 1).$$

Signed-rank test statistic For large n ,

$$V^+ \sim \mathcal{N}(\mu_V, \sigma_V^2),$$

where

$$\mu_V = \frac{1}{4}n(n + 1), \quad \sigma_V^2 = \frac{1}{24}n(n + 1)(2n + 1),$$

and V^+ is the sum of the ranks of the absolute differences for all pairs with positive difference. The same result applies to V^- (sum of the ranks of the absolute differences for all pairs with negative difference).

Table A: Probabilities for the standard normal distribution

Table entry for z is the probability lying to the left of z for a $N(0, 1)$ distribution.

$$\Phi(z) = P[Z < z]$$

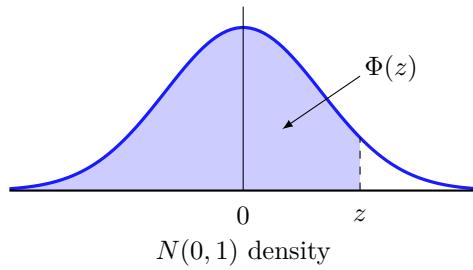


Table B: Probabilities for the t -distribution

Table entry for p and C is the critical value t^* with probability p lying to its right and probability C lying between $-t^*$ and t^* for a t -distribution with k degrees of freedom.

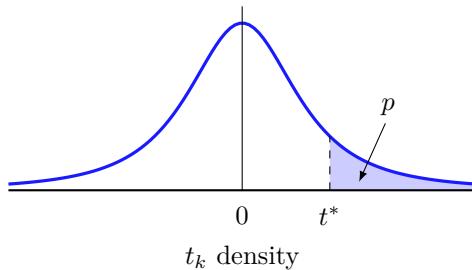


Table C: Probabilities for the χ^2 -distribution

Table entry for p is the point χ^* with probability p lying above it for a χ^2 distribution with k degrees of freedom.

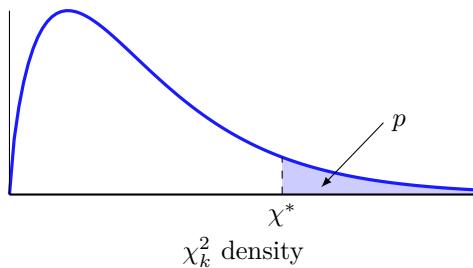


Table D: Critical values for the Rank-sum Test

Reject the hypothesis of identical populations in a two-sided test at level α if the test statistic W from a group of size n is *less than* the value T_L shown in the following table, or greater than the value T_U where

$$T_U = n(n + m + 1) - T_L.$$

		m									
$\alpha = 0.01$		2	3	4	5	6	7	8	9	10	
2	-	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	7	7	
4	-	-	-	-	11	11	12	12	13		
5	-	-	-	16	17	17	18	19	20		
n	6	-	-	22	23	24	25	26	27	28	
	7	-	-	29	30	32	33	35	36	38	
	8	-	-	38	39	41	43	44	46	48	
	9	-	46	47	49	51	53	55	57	59	
	10	-	56	58	60	62	65	67	69	72	

		m									
$\alpha = 0.05$		2	3	4	5	6	7	8	9	10	
2	-	-	-	-	-	-	-	4	4	4	
3	-	-	-	7	8	8	9	9	10		
4	-	-	11	12	13	14	15	15	16		
5	-	16	17	18	19	21	22	23	24		
n	6	-	23	24	25	27	28	30	32	33	
	7	-	30	32	34	35	37	39	41	43	
	8	37	39	41	43	45	47	50	52	54	
	9	46	48	50	53	56	58	61	63	66	
	10	56	59	61	64	67	70	73	76	79	

		m									
$\alpha = 0.10$		2	3	4	5	6	7	8	9	10	
2	-	-	-	4	4	4	5	5	5	5	
3	-	7	7	8	9	9	10	11	11		
4	-	11	12	13	14	15	16	17	18		
5	16	17	18	20	21	22	24	25	27		
n	6	22	24	25	27	29	30	32	34	36	
	7	29	31	33	35	37	40	42	44	46	
	8	38	40	42	45	47	50	52	55	57	
	9	47	50	52	55	58	61	64	67	70	
	10	57	60	63	67	70	73	76	80	83	

Table E: Critical values for the Signed-rank Test

Reject the null hypothesis of identical populations if the test statistic V is *less than* the value T shown in the following table.

Sample size n	Level of significance for a two-sided test					
	20%	10%	5%	2%	1%	0.5%
	10%	5%	2.5%	1%	0.5%	0.25%
Level of significance for a one-sided test						
5	3	1	-	-	-	-
6	4	3	1	-	-	-
7	6	4	3	1	-	-
8	9	6	4	2	1	-
9	11	9	6	4	2	1
10	15	11	9	6	4	2
11	18	14	11	8	6	4
12	22	18	14	10	8	6
13	27	22	18	13	10	8
14	32	26	22	16	13	10
15	37	31	26	20	16	13
16	43	36	30	24	20	16
17	49	42	35	28	24	20
18	56	48	41	33	28	24
19	63	54	47	38	33	28
20	70	61	53	44	38	33
21	78	68	59	50	43	38
22	87	76	66	56	49	43
23	95	84	74	63	55	49
24	105	92	82	70	62	55
25	114	101	90	77	69	61
26	125	111	99	85	76	68
27	135	120	108	93	84	75
28	146	131	117	102	92	83
29	158	141	127	111	101	91
30	170	152	138	121	110	99