

Multivariate Normal Distribution

With a brief introduction to other
probability distributions

Univariate Normal (Gaussian) Distribution

- Bell-shaped distribution with tendency for individuals to clump around the group median/mean
- Used to model many biological phenomena
- Many *estimators* have approximate normal sampling distributions (see Central Limit Theorem)
- Notation: $X \sim N(\mu, \sigma^2)$ where μ is mean and σ^2 is the variance

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}}, -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0$$

Obtaining Probabilities and Quantiles in R:

To obtain: $F(x) = P(X \leq x)$

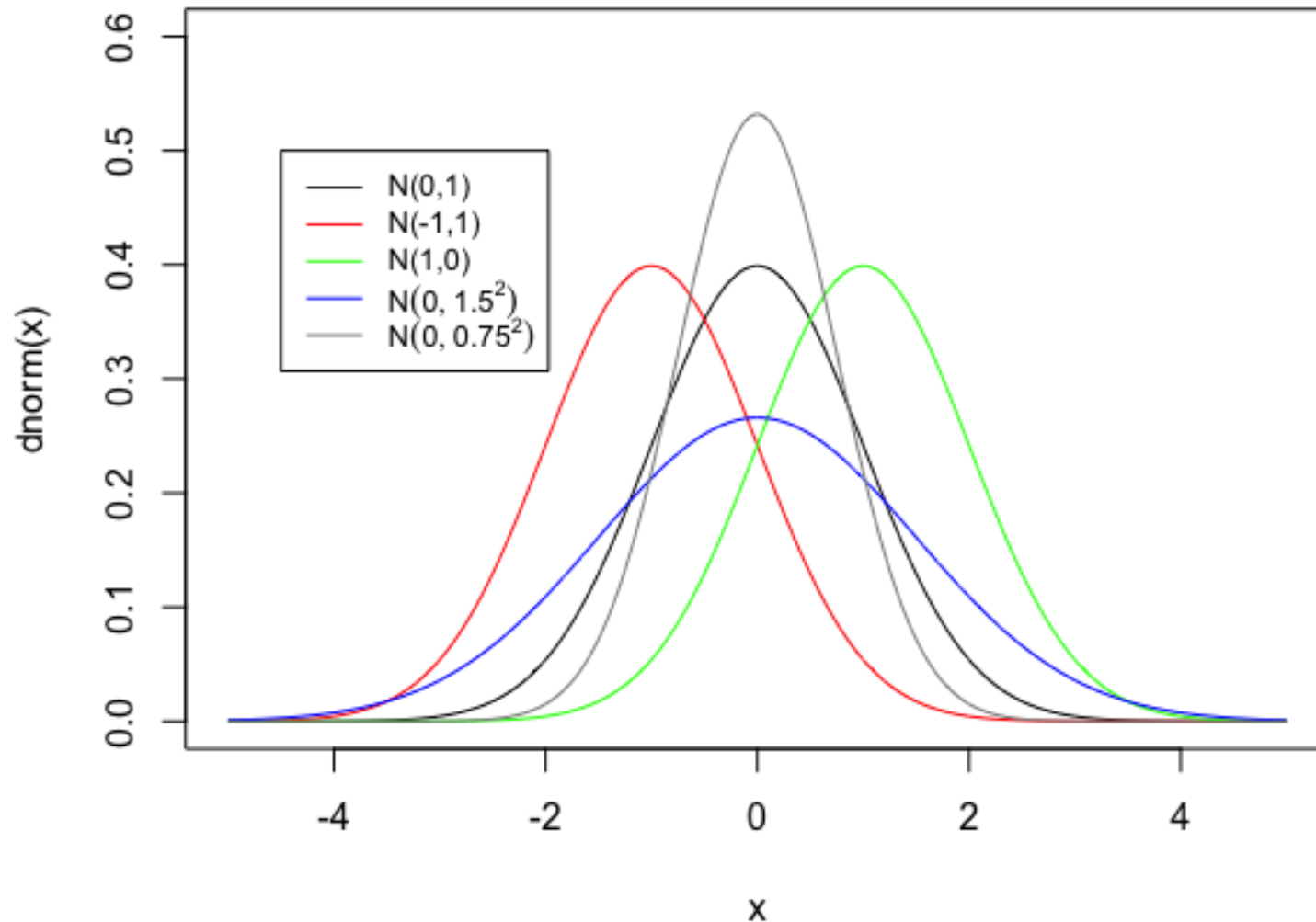
Use Function: `pnorm(x, μ , σ)`

To obtain the p^{th} quantile: $P(X \leq x_p) = p$

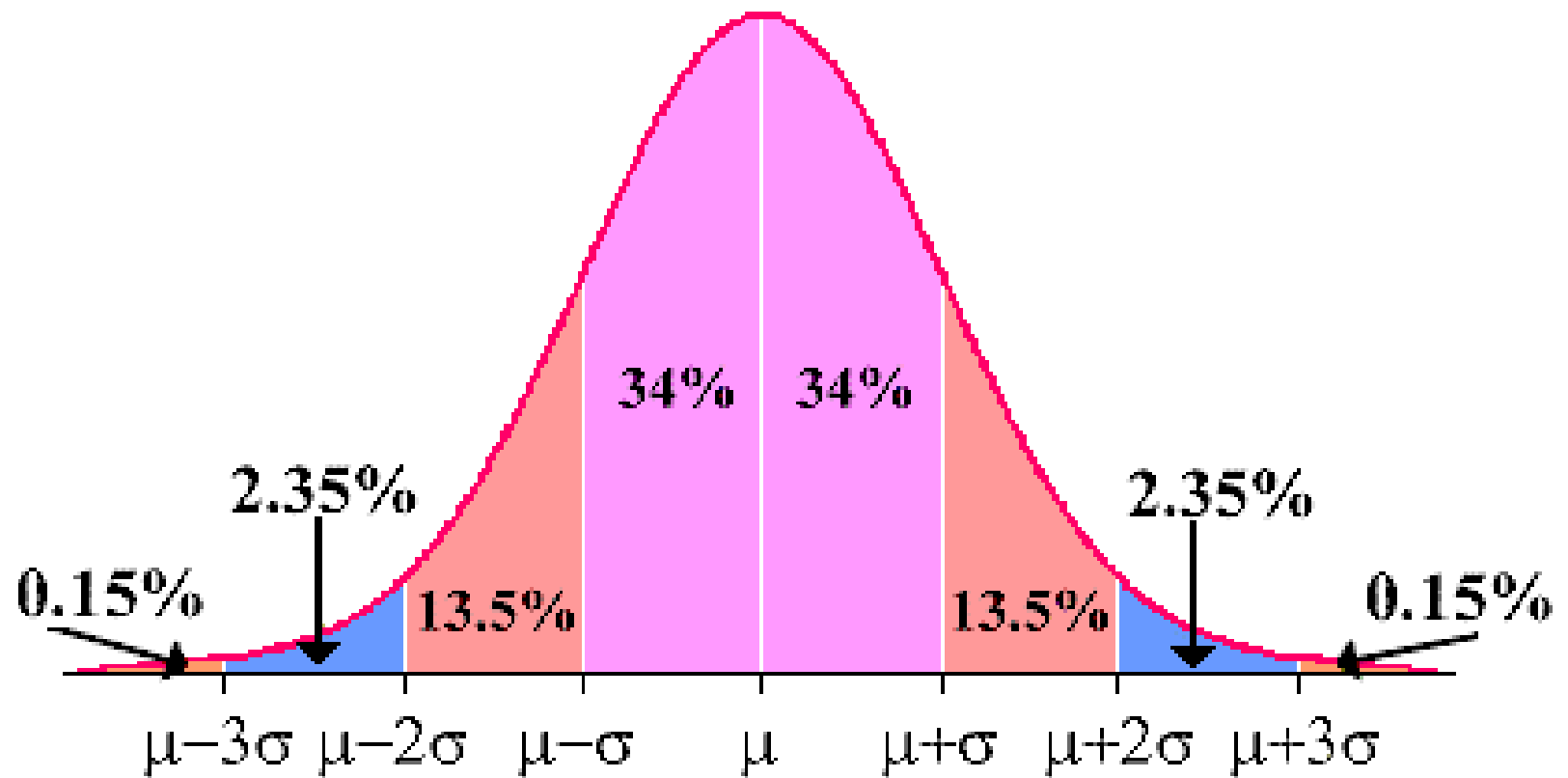
Use Function: `qnorm(p, μ , σ)`

Virtually all statistics textbooks give the cdf (or upper tail probabilities) for standardized normal random variables: $z = (x - \mu) / \sigma \sim N(0, 1)$

Normal Distribution – Density Functions (pdf)



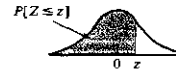
Empirical Rule



Second Decimal Place of z

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TABLE 1 STANDARD NORMAL PROBABILITIES



z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
.7	.7580	.7611	.7642	.7673	.7703	.7734	.7764	.7794	.7823	.7852
.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998
3.5	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998	.9998

Integer part
and first
decimal
place of z

Chi-Square Distribution

- Indexed by “degrees of freedom (ν)” $X \sim \chi_{\nu}^2$
- $Z \sim N(0,1) \Rightarrow Z^2 \sim \chi_1^2$
- Assuming Independence:

$$X_1, \dots, X_n \sim \chi_{\nu_i}^2 \quad i = 1, \dots, n \Rightarrow \sum_{i=1}^n X_i \sim \chi_{\sum \nu_i}^2$$

Density Function:

$$f(x) = \frac{1}{\Gamma\left(\frac{\nu}{2}\right) 2^{\nu/2}} x^{(\nu/2)-1} e^{-x/2} \quad x > 0, \nu > 0 \quad E\{X\} = \nu \quad V\{X\} = 2\nu$$

Obtaining Probabilities in R:

To obtain: $1-F(x) = P(X \geq x)$

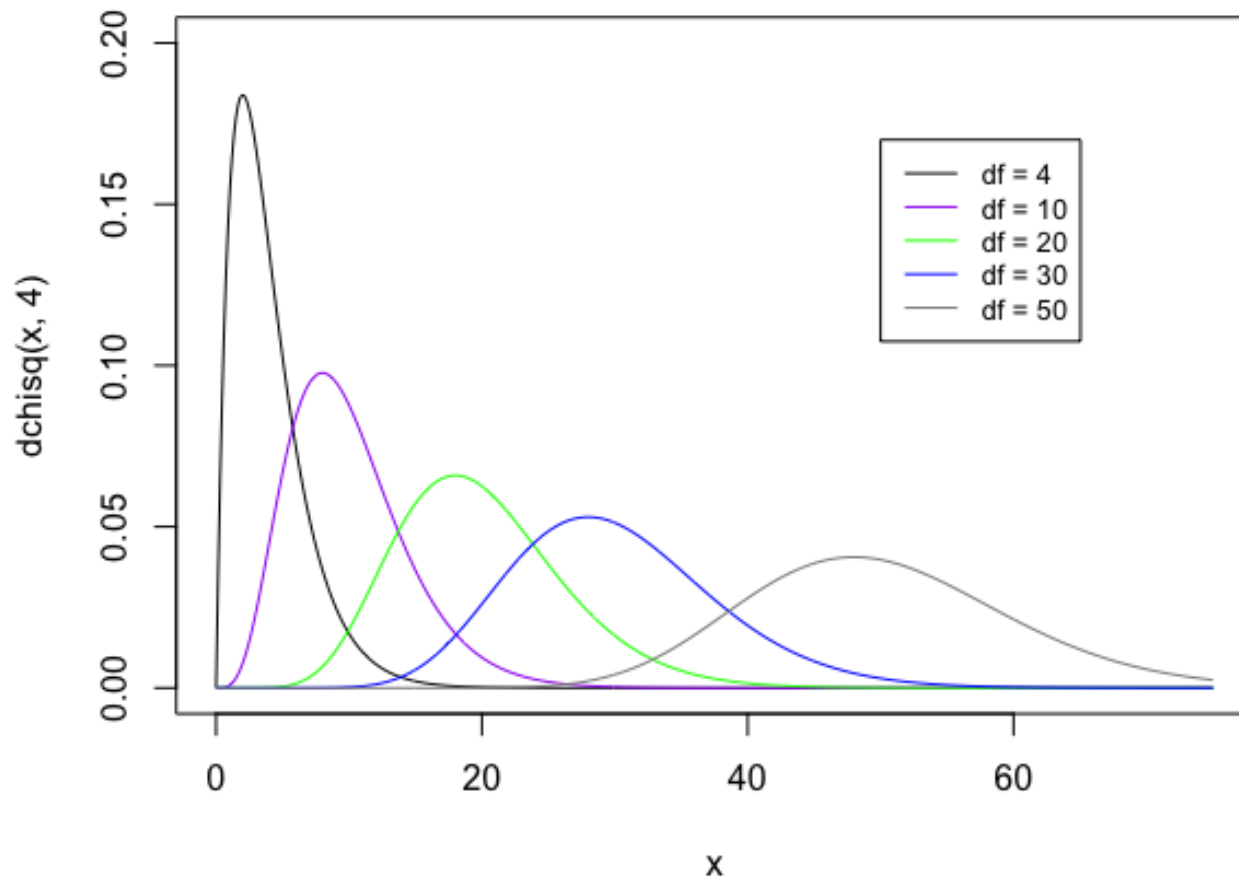
Use Function: `pchisq(x, ν)`

To obtain quantiles: $P(X \leq x_p) = p$

Use Function: `qchisq(x, ν)`

Virtually all statistics textbooks give **upper tail** cut-off values for commonly used upper (and sometimes lower) tail probabilities

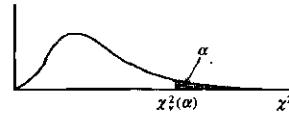
Chi-Square Distributions



Critical Values for Chi-Square Distributions (Mean= ν , Variance= 2ν)

Appendix

TABLE 3 χ^2 DISTRIBUTION PERCENTAGE POINTS



d.f. ν	α								
	.990	.950	.900	.500	.100	.050	.025	.010	.005
1	.0002	.004	.02	.45	2.71	3.84	5.02	6.63	7.88
2	.02	.10	.21	1.39	4.61	5.99	7.38	9.21	10.60
3	.11	.35	.58	2.37	6.25	7.81	9.35	11.34	12.84
4	.30	.71	1.06	3.36	7.78	9.49	11.14	13.28	14.86
5	.55	1.15	1.61	4.35	9.24	11.07	12.83	15.09	16.75
6	.87	1.64	2.20	5.35	10.64	12.59	14.45	16.81	18.55
7	1.24	2.17	2.83	6.35	12.02	14.07	16.01	18.48	20.28
8	1.65	2.73	3.49	7.34	13.36	15.51	17.53	20.09	21.95
9	2.09	3.33	4.17	8.34	14.68	16.92	19.02	21.67	23.59
10	2.56	3.94	4.87	9.34	15.99	18.31	20.48	23.21	25.19
11	3.05	4.57	5.58	10.34	17.28	19.68	21.92	24.72	26.76
12	3.57	5.23	6.30	11.34	18.55	21.03	23.34	26.22	28.30
13	4.11	5.89	7.04	12.34	19.81	22.36	24.74	27.69	29.82
14	4.66	6.57	7.79	13.34	21.06	23.68	26.12	29.14	31.32
15	5.23	7.26	8.55	14.34	22.31	25.00	27.49	30.58	32.80
16	5.81	7.96	9.31	15.34	23.54	26.30	28.85	32.00	34.27
17	6.41	8.67	10.09	16.34	24.77	27.59	30.19	33.41	35.72
18	7.01	9.39	10.86	17.34	25.99	28.87	31.53	34.81	37.16
19	7.63	10.12	11.65	18.34	27.20	30.14	32.85	36.19	38.58
20	8.26	10.85	12.44	19.34	28.41	31.41	34.17	37.57	40.00
21	8.90	11.59	13.24	20.34	29.62	32.67	35.48	38.93	41.40
22	9.54	12.34	14.04	21.34	30.81	33.92	36.78	40.29	42.80
23	10.20	13.09	14.85	22.34	32.01	35.17	38.08	41.64	44.18
24	10.86	13.85	15.66	23.34	33.20	36.42	39.36	42.98	45.56
25	11.52	14.61	16.47	24.34	34.38	37.65	40.65	44.31	46.93
26	12.20	15.38	17.29	25.34	35.56	38.89	41.92	45.64	48.29
27	12.88	16.15	18.11	26.34	36.74	40.11	43.19	46.96	49.64
28	13.56	16.93	18.94	27.34	37.92	41.34	44.46	48.28	50.99
29	14.26	17.71	19.77	28.34	39.09	42.56	45.72	49.59	52.34
30	14.95	18.49	20.60	29.34	40.26	43.77	46.98	50.89	53.67
35	22.16	26.51	29.05	39.34	51.81	55.76	59.34	63.69	66.77
40	29.71	34.76	37.69	49.33	63.17	67.50	71.42	76.15	79.49
45	37.48	43.19	46.46	59.33	74.40	79.08	83.30	88.38	91.95
50	45.44	51.74	55.33	69.33	85.53	90.53	95.02	100.43	104.21
55	53.54	60.39	64.28	79.33	96.58	101.88	106.63	112.33	116.32
60	61.75	69.13	73.29	89.33	107.57	113.15	118.14	124.12	128.30
65	70.06	77.93	82.36	99.33	118.50	124.34	129.56	135.81	140.17

Student's t -Distribution

- Indexed by “degrees of freedom (ν)” $X \sim t_\nu$
- $Z \sim N(0,1)$, $X \sim \chi_\nu^2$
- Assuming Independence of Z and X :

$$T = \frac{Z}{\sqrt{X/\nu}} \sim t_\nu$$

Density Function:

$$f(t) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi\nu}\Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{t^2}{\nu}\right)^{-\frac{\nu+1}{2}} \quad -\infty < t < \infty \quad \nu > 0 \quad E\{T\} = 0 \ (\nu > 1) \quad V\{T\} = \frac{\nu}{\nu-2} \ (\nu > 2)$$

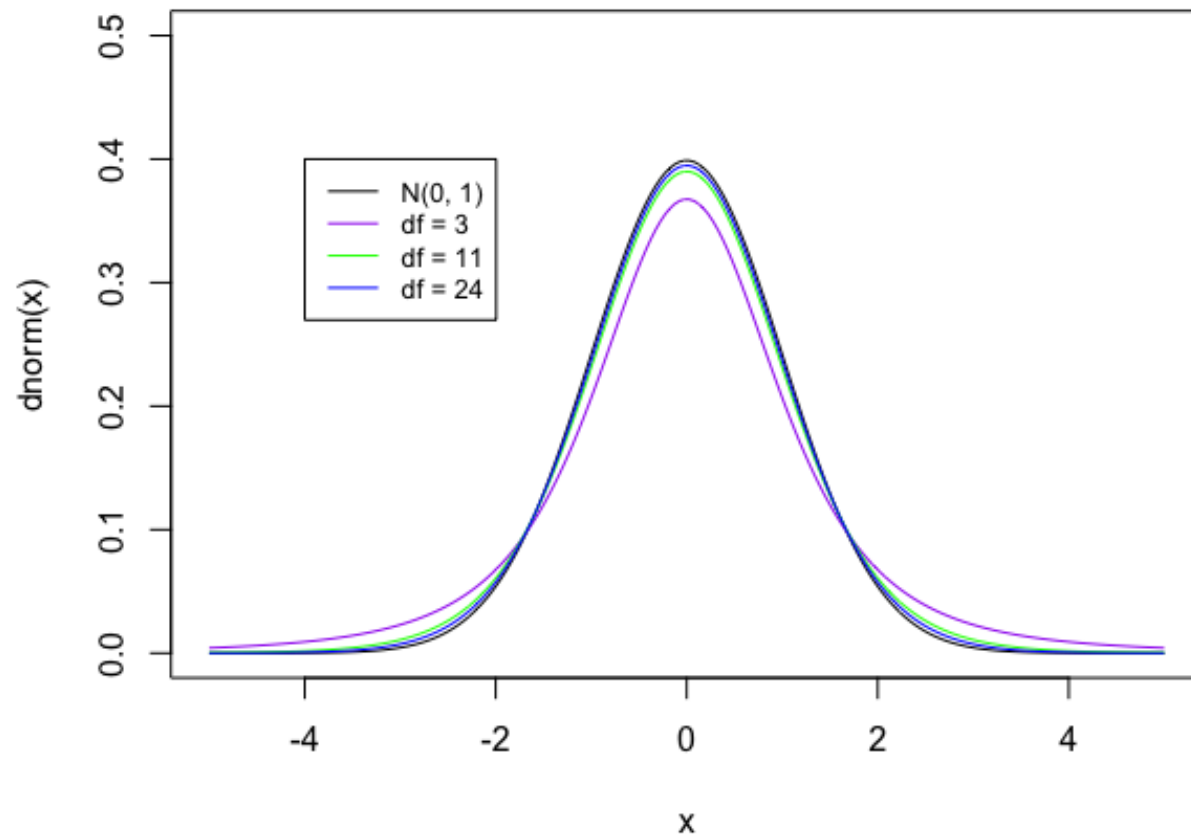
Obtaining Probabilities /Quantiles in R:

To obtain: $F(t) = P(T \leq t)$ `pt(t, ν)`

To obtain: p^{th} quantile `qt(p, ν)`

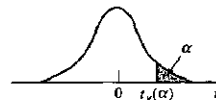
Virtually all statistics textbooks give upper tail cut-off values for commonly used upper tail probabilities

t distributions



Critical Values for Student's t-Distributions

TABLE 2 STUDENT'S t-DISTRIBUTION PERCENTAGE POINTS



d.f. ν	.250	.100	.050	.025	α .010	.00833	.00625	.005	.0025
1	1.000	3.078	6.314	12.706	31.821	38.190	50.923	63.657	127.321
2	.816	1.886	2.920	4.303	6.965	7.649	8.860	9.925	14.089
3	.765	1.638	2.353	3.182	4.541	4.857	5.392	5.841	7.453
4	.741	1.533	2.132	2.776	3.747	3.961	4.315	4.604	5.598
5	.727	1.476	2.015	2.571	3.365	3.534	3.810	4.032	4.773
6	.718	1.440	1.943	2.447	3.143	3.287	3.521	3.707	4.317
7	.711	1.415	1.895	2.365	2.998	3.128	3.335	3.499	4.029
8	.706	1.397	1.860	2.306	2.896	3.016	3.206	3.355	3.833
9	.703	1.383	1.833	2.262	2.821	2.933	3.111	3.250	3.690
10	.700	1.372	1.812	2.228	2.764	2.870	3.038	3.169	3.581
11	.697	1.363	1.796	2.201	2.718	2.820	2.981	3.106	3.497
12	.695	1.356	1.782	2.179	2.681	2.779	2.934	3.055	3.428
13	.694	1.350	1.771	2.160	2.650	2.746	2.896	3.012	3.372
14	.692	1.345	1.761	2.145	2.624	2.718	2.864	2.977	3.326
15	.691	1.341	1.753	2.131	2.602	2.694	2.837	2.947	3.286
16	.690	1.337	1.746	2.120	2.583	2.673	2.813	2.921	3.252
17	.689	1.333	1.740	2.110	2.567	2.655	2.793	2.898	3.222
18	.688	1.330	1.734	2.101	2.552	2.639	2.775	2.878	3.197
19	.688	1.328	1.729	2.093	2.539	2.625	2.759	2.861	3.174
20	.687	1.325	1.725	2.086	2.528	2.613	2.744	2.845	3.153
21	.686	1.323	1.721	2.080	2.518	2.601	2.732	2.831	3.135
22	.686	1.321	1.717	2.074	2.508	2.591	2.720	2.819	3.119
23	.685	1.319	1.714	2.069	2.500	2.582	2.710	2.807	3.104
24	.685	1.318	1.711	2.064	2.492	2.574	2.700	2.797	3.091
25	.684	1.316	1.708	2.060	2.485	2.566	2.692	2.787	3.078
26	.684	1.315	1.706	2.056	2.479	2.559	2.684	2.779	3.067
27	.684	1.314	1.703	2.052	2.473	2.552	2.676	2.771	3.057
28	.683	1.313	1.701	2.048	2.467	2.546	2.669	2.763	3.047
29	.683	1.311	1.699	2.045	2.462	2.541	2.663	2.756	3.038
30	.683	1.310	1.697	2.042	2.457	2.536	2.657	2.750	3.030
40	.681	1.303	1.684	2.021	2.423	2.499	2.616	2.704	2.971
60	.679	1.296	1.671	2.000	2.390	2.463	2.575	2.660	2.915
120	.677	1.289	1.658	1.980	2.358	2.428	2.536	2.617	2.860
∞	.674	1.282	1.645	1.960	2.326	2.394	2.498	2.576	2.813

F-Distribution

- Indexed by 2 “degrees of freedom (ν_1, ν_2)” $W \sim F_{\nu_1, \nu_2}$
- $X_1 \sim \chi_{\nu_1}^2, \quad X_2 \sim \chi_{\nu_2}^2$
- Assuming Independence of X_1 and X_2 :

$$W = \frac{X_1/\nu_1}{X_2/\nu_2} \sim F_{\nu_1, \nu_2}$$

Density Function:

$$f(w) = \frac{\Gamma\left(\frac{\nu_1 + \nu_2}{2}\right)}{\Gamma\left(\frac{\nu_1}{2}\right)\Gamma\left(\frac{\nu_2}{2}\right)} \left(\frac{\nu_1}{\nu_2}\right)^{\frac{\nu_1}{2}} w^{\frac{\nu_1}{2}-1} \left(\frac{1}{2}\right)^{\frac{\nu_1 + \nu_2}{2}} \left[\frac{1}{1 + \frac{w\nu_1}{\nu_2}}\right]^{\frac{\nu_1 + \nu_2}{2}} \quad w > 0 \quad \nu_1, \nu_2 > 0$$

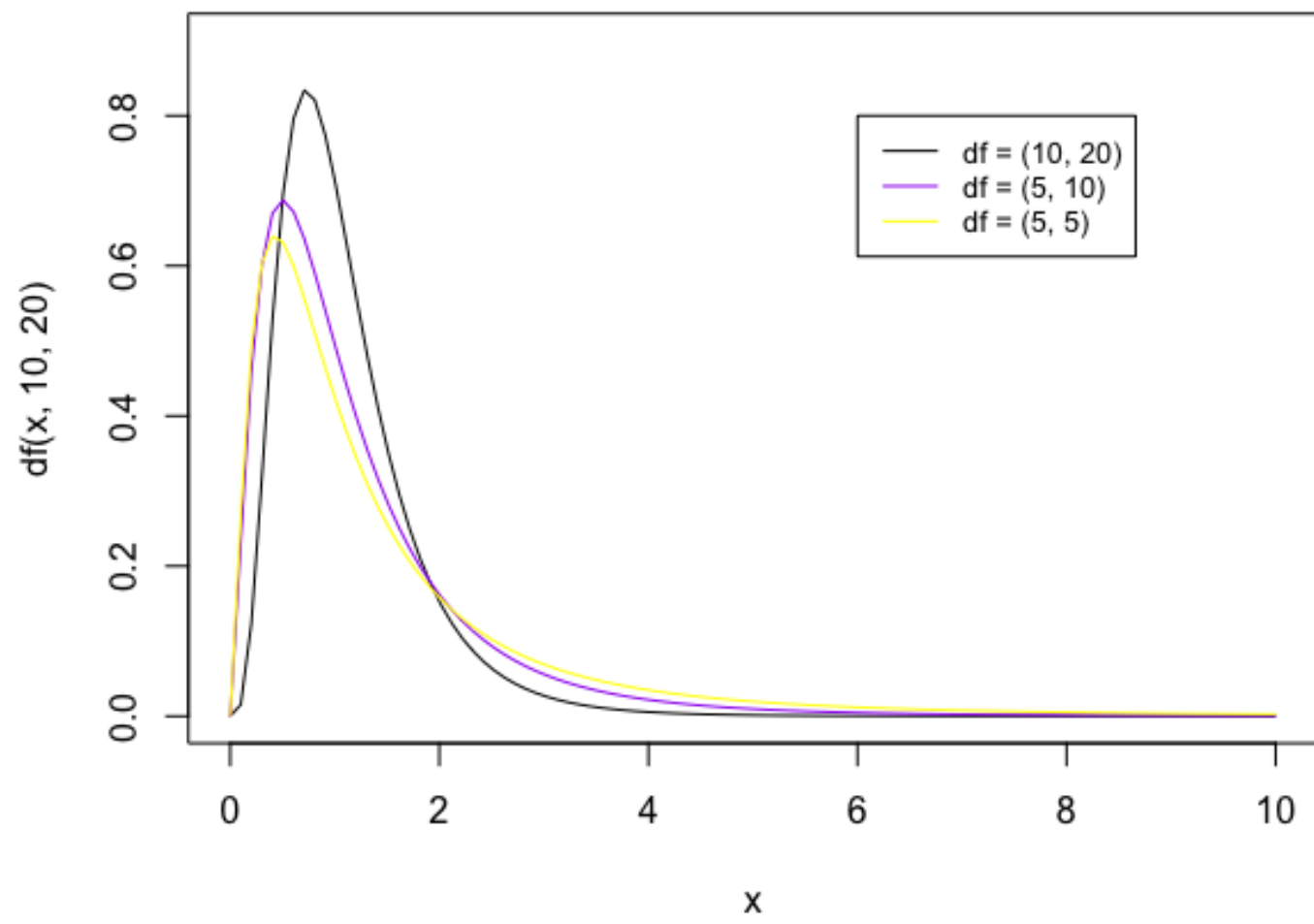
$$E\{W\} = \frac{\nu_2}{\nu_2 - 2} \quad (\nu_2 > 2) \quad V\{W\} = \left(\frac{\nu_2}{\nu_2 - 2}\right)^2 \frac{\nu_1 + \nu_2 - 2}{\nu_1(\nu_2 - 4)} \quad (\nu_2 > 4)$$

Obtaining Probabilities/Quantiles in R:

To obtain: $F(w) = P(W \leq w)$: `pf(w, ν_1 , ν_2)`

p^{th} quantile: `qf(p, ν_1 , ν_2)`

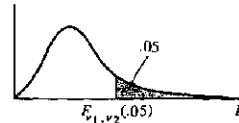
Virtually all statistics textbooks give upper tail cut-off values for some upper probabilities



Critical Values for F-distributions $P(F \leq \text{Table Value}) = 0.95$

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TABLE 5 F-DISTRIBUTION PERCENTAGE POINTS ($\alpha = .05$)



$v_1 \backslash v_2$	1	2	3	4	5	6	7	8	9	10	12	15	20	25	30	40	60
1	161.5	199.5	215.7	224.6	230.2	234.0	236.8	238.9	240.5	241.9	243.9	246.0	248.0	249.3	250.1	251.1	252.2
2	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38	19.40	19.41	19.43	19.45	19.46	19.46	19.47	19.48
3	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.79	8.74	8.70	8.66	8.63	8.62	8.59	8.57
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.96	5.91	5.86	5.80	5.77	5.75	5.72	5.69
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.74	4.68	4.62	4.56	4.52	4.50	4.46	4.43
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	4.06	4.00	3.94	3.87	3.83	3.81	3.77	3.74
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.64	3.57	3.51	3.44	3.40	3.38	3.34	3.30
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	3.35	3.28	3.22	3.15	3.11	3.08	3.04	3.01
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	3.14	3.07	3.01	2.94	2.89	2.86	2.83	2.79
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.98	2.91	2.85	2.77	2.73	2.70	2.66	2.62
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.85	2.79	2.72	2.65	2.60	2.57	2.53	2.49
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.75	2.69	2.62	2.54	2.50	2.47	2.43	2.38
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.67	2.60	2.53	2.46	2.41	2.38	2.34	2.30
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.60	2.53	2.46	2.39	2.34	2.31	2.27	2.22
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.54	2.48	2.40	2.33	2.28	2.25	2.20	2.16
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.49	2.42	2.35	2.28	2.23	2.19	2.15	2.11
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	2.45	2.38	2.31	2.23	2.18	2.15	2.10	2.06
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	2.41	2.34	2.27	2.19	2.14	2.11	2.06	2.02
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	2.38	2.31	2.23	2.16	2.11	2.07	2.03	1.98
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	2.35	2.28	2.20	2.12	2.07	2.04	1.99	1.95
21	4.32	3.47	3.07	2.84	2.68	2.57	2.49	2.42	2.37	2.32	2.25	2.18	2.10	2.05	2.01	1.96	1.92
22	4.30	3.44	3.05	2.82	2.66	2.55	2.46	2.40	2.34	2.30	2.23	2.15	2.07	2.02	1.98	1.94	1.89
23	4.28	3.42	3.03	2.80	2.64	2.53	2.44	2.37	2.32	2.27	2.20	2.13	2.05	2.00	1.96	1.91	1.86
24	4.26	3.40	3.01	2.78	2.62	2.51	2.42	2.36	2.30	2.25	2.18	2.11	2.03	1.97	1.94	1.89	1.84
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	2.24	2.16	2.09	2.01	1.96	1.92	1.87	1.82
26	4.23	3.37	2.98	2.74	2.59	2.47	2.39	2.32	2.27	2.22	2.15	2.07	1.99	1.94	1.90	1.85	1.80
27	4.21	3.35	2.96	2.73	2.57	2.46	2.37	2.31	2.25	2.20	2.13	2.06	1.97	1.92	1.88	1.84	1.79
28	4.20	3.34	2.95	2.71	2.56	2.45	2.36	2.29	2.24	2.19	2.12	2.04	1.96	1.91	1.87	1.82	1.77
29	4.18	3.33	2.93	2.70	2.55	2.43	2.35	2.28	2.22	2.18	2.10	2.03	1.94	1.89	1.85	1.81	1.75
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	2.16	2.09	2.01	1.93	1.88	1.84	1.79	1.74
40	4.08	3.23	2.84	2.61	2.45	2.34	2.25	2.18	2.12	2.08	2.00	1.92	1.84	1.78	1.74	1.69	1.64
60	4.00	3.15	2.76	2.53	2.37	2.25	2.17	2.10	2.04	1.99	1.92	1.84	1.75	1.69	1.65	1.59	1.53
120	3.92	3.07	2.68	2.45	2.29	2.18	2.09	2.02	1.96	1.91	1.83	1.75	1.66	1.60	1.55	1.50	1.43
∞	3.84	3.00	2.61	2.37	2.21	2.10	2.01	1.94	1.88	1.83	1.75	1.67	1.57	1.51	1.46	1.39	1.32

Multivariate Normal Distribution

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}, \mu_x = E(X) = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix}, \Sigma_X = \sigma^2(X) = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1p} & \sigma_{2p} & \cdots & \sigma_{pp} \end{bmatrix}$$

Multivariate normal density function:

$$f(x) = (2\pi)^{-p/2} \left| \Sigma_X^{-1} \right| e^{-\frac{1}{2}(X-\mu_X)' \Sigma_X^{-1} (X-\mu_X)}$$

Notation: $X \sim N_p(\mu_X, \Sigma_X)$

Results:

$$\begin{aligned} X_i &\sim N(\mu_i, \sigma_{ii}), & i &= 1, \dots, p \\ \text{cov}(X_i, X_j) &= \sigma_{ij}, & i &\neq j \end{aligned}$$

Note: If A is a full rank matrix of constants, then:

$$W = AX \sim N(A\mu_x, A\Sigma_x A')$$

Results Involving Multivariate Normal - I

If $\Sigma_{\mathbf{x}}$ is positive definite with eigenvalue/eigenvector pairs $(\lambda_i, \mathbf{e}_i)$ $i = 1, \dots, p$

Then $\Sigma_{\mathbf{x}}^{-1}$ is positive definite with eigenvalue/eigenvector pairs $(1/\lambda_i, \mathbf{e}_i)$ $i = 1, \dots, p$

$$\Rightarrow \Sigma_{\mathbf{x}} = \sum_{i=1}^n \lambda_i \mathbf{e}_i \mathbf{e}_i' = \mathbf{P} \mathbf{\Lambda} \mathbf{P}' \quad \Sigma_{\mathbf{x}}^{-1} = \sum_{i=1}^n \left(\frac{1}{\lambda_i} \right) \mathbf{e}_i \mathbf{e}_i' = \mathbf{P} \mathbf{\Lambda}^{-1} \mathbf{P}'$$

where $\mathbf{P} = [\mathbf{e}_1 \quad \mathbf{e}_2 \quad \dots \quad \mathbf{e}_p]$ $\mathbf{\Lambda} = \text{diag}\{\lambda_i\}$

Contours of constant density for p -dim MVN are ellipsoids wrt \mathbf{x} s.t. $(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}})' \Sigma_{\mathbf{x}}^{-1} (\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}}) = c^2$

Ellipsoids centered at $\boldsymbol{\mu}_{\mathbf{x}}$ with axes $\pm c \sqrt{\lambda_i} \mathbf{e}_i$ $i = 1, \dots, p$

Setting $c^2 = \chi_p^2(\alpha)$ s.t. $P(\chi_p^2 \geq \chi_p^2(\alpha)) = \alpha$

\Rightarrow the solid ellipsoid $(\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}})' \Sigma_{\mathbf{x}}^{-1} (\mathbf{x} - \boldsymbol{\mu}_{\mathbf{x}}) \leq \chi_p^2(\alpha)$ has probability $1 - \alpha$

$\text{COV}\{X_i, X_j\} = 0 \Rightarrow X_i, X_j$ independent

Results Involving Multivariate Normal - II

Conditional Distributions of components are MVN: ($\mathbf{X}_1 \equiv q \times 1$, $\mathbf{X}_2 \equiv (p-q) \times 1$)

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{bmatrix} \sim N_p(\boldsymbol{\mu}_X, \boldsymbol{\Sigma}_X) \quad \boldsymbol{\mu}_X = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix} \quad \boldsymbol{\Sigma}_X = \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{bmatrix} \quad \text{s.t. } |\boldsymbol{\Sigma}_{22}| > 0$$

$\Rightarrow \mathbf{X}_1 | \mathbf{X}_2 = \mathbf{x}_2 \sim N_q$ with

Mean: $\boldsymbol{\mu}_1 + \boldsymbol{\Sigma}_{12} \boldsymbol{\Sigma}_{22}^{-1} (\mathbf{x}_2 - \boldsymbol{\mu}_2) = \boldsymbol{\mu}_{1|x_2}$ and Variance-Covariance Matrix: $\boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12} \boldsymbol{\Sigma}_{22}^{-1} \boldsymbol{\Sigma}_{21} = \boldsymbol{\Sigma}_{11|x_2}$

$$\Rightarrow f(\mathbf{x}_1 | \mathbf{x}_2) = (2\pi)^{-q/2} |\boldsymbol{\Sigma}_{11|x_2}|^{-1/2} \exp \left\{ -\frac{1}{2} (\mathbf{x}_1 - \boldsymbol{\mu}_{1|x_2})' \boldsymbol{\Sigma}_{11|x_2}^{-1} (\mathbf{x}_1 - \boldsymbol{\mu}_{1|x_2}) \right\} \quad -\infty < x_{1i} < \infty \quad i = 1, \dots, q$$

Note that the conditional mean depends on the specific level(s) \mathbf{x}_2 , the conditional variance does not.

Special Case: $p = 2, q = 1$ $X_1 | X_2 = x_2 \sim N(\mu_{1|x_2}, \sigma_{11|x_2})$

$$\mu_{1|x_2} = \mu_1 + \frac{\sigma_{12}}{\sigma_{22}} (x_2 - \mu_2) \quad \sigma_{11|x_2} = \sigma_{11} - \frac{\sigma_{12}^2}{\sigma_{22}} = \sigma_{11} - \left(\frac{\sigma_{11}}{\sigma_{11}} \right) \frac{\sigma_{12}^2}{\sigma_{22}} = \sigma_{11} (1 - \rho_{12}^2)$$

$$\Rightarrow f(x_1, x_2) = \frac{1}{\sqrt{2\pi\sigma_{11}(1-\rho_{12}^2)}} \exp \left\{ -\frac{1}{2\sigma_{11}(1-\rho_{12}^2)} \left(x_1 - \left(\mu_1 + \frac{\sigma_{12}}{\sigma_{22}} (x_2 - \mu_2) \right) \right)^2 \right\} \quad -\infty < x_1 < \infty$$

Example with $\rho = 2$

Joint Distribution:

$$f(x_1, x_2) = \frac{1}{2\pi\sqrt{\sigma_1^2\sigma_2^2(1-\rho^2)}} \exp \left\{ -\left(\frac{1}{2(1-\rho^2)} \right) \left[\frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} \right] \right\} \quad -\infty < x_1, x_2 < \infty$$

Marginal (aka Unconditional) Distributions:

$$f_1(x_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp \left\{ -\frac{(x_1 - \mu_1)^2}{2\sigma_1^2} \right\} \quad -\infty < x_1 < \infty$$

$$f_2(x_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp \left\{ -\frac{(x_2 - \mu_2)^2}{2\sigma_2^2} \right\} \quad -\infty < x_2 < \infty$$

$$X_1 \sim N(\mu_1, \sigma_1^2) \quad X_2 \sim N(\mu_2, \sigma_2^2)$$

Conditional Distributions:

$$f(x_2 | x_1) = \frac{1}{\sqrt{2\pi\sigma_2^2(1-\rho^2)}} \exp \left\{ -\left(\frac{1}{2(1-\rho^2)\sigma_2^2} \right) \left[x_2 - \left(\mu_2 + \frac{(x_1 - \mu_1)\rho\sigma_2}{\sigma_1} \right) \right]^2 \right\} \quad -\infty < x_2 < \infty$$

$$f(x_1 | x_2) = \frac{1}{\sqrt{2\pi\sigma_1^2(1-\rho^2)}} \exp \left\{ -\left(\frac{1}{2(1-\rho^2)\sigma_1^2} \right) \left[x_1 - \left(\mu_1 + \frac{(x_2 - \mu_2)\rho\sigma_1}{\sigma_2} \right) \right]^2 \right\} \quad -\infty < x_1 < \infty$$

$$X_2 | X_1 = x_1 \sim N \left[\mu_2 + \frac{(x_1 - \mu_1)\rho\sigma_2}{\sigma_1}, \sigma_2^2(1-\rho^2) \right] \quad X_1 | X_2 = x_2 \sim N \left[\mu_1 + \frac{(x_2 - \mu_2)\rho\sigma_1}{\sigma_2}, \sigma_1^2(1-\rho^2) \right]$$

Results Involving Multivariate Normal - III

$\mathbf{X}_1, \dots, \mathbf{X}_n$ independent with common variance matrices: $\mathbf{X}_j \sim N_p(\boldsymbol{\mu}_j, \boldsymbol{\Sigma})$

$$\mathbf{W}_1 = a_1 \mathbf{X}_1 + \dots + a_n \mathbf{X}_n \sim N_p \left(\sum_{j=1}^n a_j \boldsymbol{\mu}_j, \left(\sum_{j=1}^n a_j^2 \right) \boldsymbol{\Sigma} \right)$$

$$\mathbf{W}_2 = b_1 \mathbf{X}_1 + \dots + b_n \mathbf{X}_n \sim N_p \left(\sum_{j=1}^n b_j \boldsymbol{\mu}_j, \left(\sum_{j=1}^n b_j^2 \right) \boldsymbol{\Sigma} \right)$$

$\mathbf{W}_1, \mathbf{W}_2$ are jointly distributed normal with

$$\boldsymbol{\mu}_{\mathbf{W}_1 \mathbf{W}_2} = \begin{bmatrix} \sum_{j=1}^n a_j \boldsymbol{\mu}_j \\ \sum_{j=1}^n b_j \boldsymbol{\mu}_j \end{bmatrix} \quad \text{and} \quad \boldsymbol{\Sigma}_{\mathbf{W}_1 \mathbf{W}_2} = \begin{bmatrix} \left(\sum_{j=1}^n a_j^2 \right) \boldsymbol{\Sigma} & \left(\sum_{j=1}^n a_j b_j \right) \boldsymbol{\Sigma} \\ \left(\sum_{j=1}^n a_j b_j \right) \boldsymbol{\Sigma} & \left(\sum_{j=1}^n b_j^2 \right) \boldsymbol{\Sigma} \end{bmatrix}$$

Results Involving Multivariate Normal - IV

Theorem (p. 163): Let $\mathbf{X} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Then:

(a) $(\mathbf{X} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{X} - \boldsymbol{\mu}) \sim \chi^2_p$

(b) The probability that \mathbf{X} is inside the solid ellipsoid

$$\{\mathbf{X}: (\mathbf{X} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{X} - \boldsymbol{\mu}) \leq \chi^2_p(\alpha)\}$$

is $1 - \alpha$, where $\chi^2_p(\alpha)$ denotes the upper α percentile of the χ^2_p distribution.

Exercise

Let $\mathbf{X}_1, \dots, \mathbf{X}_{60}$ be a random sample of size 60 from a four-variate normal distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. Specify the distribution of:

- (a) $\bar{\mathbf{X}}$
- (b) $(\mathbf{X}_1 - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{X}_1 - \boldsymbol{\mu})$
- (c) $n(\bar{\mathbf{X}} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu})$

Multivariate Normal Likelihood Function

$\mathbf{X}_1, \dots, \mathbf{X}_n \equiv$ random sample from $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with joint density:

$$\prod_{j=1}^n \left[(2\pi)^{-p/2} |\boldsymbol{\Sigma}|^{-1/2} \exp \left\{ -\frac{1}{2} (\mathbf{x}_j - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) \right\} \right] = (2\pi)^{-np/2} |\boldsymbol{\Sigma}|^{-n/2} \exp \left\{ -\frac{1}{2} \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) \right\}$$

Exponential term multiplied by $-1/2$:

$$\sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) = \text{tr} \left\{ \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) \right\} = \text{tr} \left\{ \sum_{j=1}^n \boldsymbol{\Sigma}^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) (\mathbf{x}_j - \boldsymbol{\mu})' \right\} = \text{tr} \left\{ \boldsymbol{\Sigma}^{-1} \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu}) (\mathbf{x}_j - \boldsymbol{\mu})' \right\}$$

$$\begin{aligned} \sum_{j=1}^n (\mathbf{x}_j - \boldsymbol{\mu}) (\mathbf{x}_j - \boldsymbol{\mu})' &= \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}} + \bar{\mathbf{x}} - \boldsymbol{\mu}) (\mathbf{x}_j - \bar{\mathbf{x}} + \bar{\mathbf{x}} - \boldsymbol{\mu})' = \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) (\mathbf{x}_j - \bar{\mathbf{x}})' + \sum_{j=1}^n (\bar{\mathbf{x}} - \boldsymbol{\mu}) (\bar{\mathbf{x}} - \boldsymbol{\mu})' + 2 \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) (\bar{\mathbf{x}} - \boldsymbol{\mu})' \\ &= \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) (\mathbf{x}_j - \bar{\mathbf{x}})' + \sum_{j=1}^n (\bar{\mathbf{x}} - \boldsymbol{\mu}) (\bar{\mathbf{x}} - \boldsymbol{\mu})' + 2 \left(\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) \right) (\bar{\mathbf{x}} - \boldsymbol{\mu})' = \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) (\mathbf{x}_j - \bar{\mathbf{x}})' + n (\bar{\mathbf{x}} - \boldsymbol{\mu}) (\bar{\mathbf{x}} - \boldsymbol{\mu})' + 0 \end{aligned}$$

Joint Density / Likelihood Function:

$$(2\pi)^{-np/2} |\boldsymbol{\Sigma}|^{-n/2} \exp \left\{ -\frac{1}{2} \text{tr} \left\{ \boldsymbol{\Sigma}^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}}) (\mathbf{x}_j - \bar{\mathbf{x}})' + n (\bar{\mathbf{x}} - \boldsymbol{\mu}) (\bar{\mathbf{x}} - \boldsymbol{\mu})' \right] \right\} \right\}$$

Maximum Likelihood Estimator of μ

Likelihood Function:

$$\begin{aligned} & (2\pi)^{-np/2} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \text{tr} \left\{ \Sigma^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' + n(\bar{\mathbf{x}} - \mu)(\bar{\mathbf{x}} - \mu)' \right] \right\} \right\} = \\ & (2\pi)^{-np/2} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \left[\text{tr} \left\{ \Sigma^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' \right] \right\} + \text{tr} \left\{ \Sigma^{-1} n(\bar{\mathbf{x}} - \mu)(\bar{\mathbf{x}} - \mu)' \right\} \right] \right\} \\ & (2\pi)^{-np/2} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \left[\text{tr} \left\{ \Sigma^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' \right] \right\} + n(\bar{\mathbf{x}} - \mu)' \Sigma^{-1} (\bar{\mathbf{x}} - \mu) \right] \right\} \end{aligned}$$

Maximum Likelihood Estimator for μ :

$$L(\mu, \Sigma) = (2\pi)^{-np/2} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \left[\text{tr} \left\{ \Sigma^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' \right] \right\} \right] \right\} \exp \left\{ -\frac{1}{2} \left[n(\bar{\mathbf{x}} - \mu)' \Sigma^{-1} (\bar{\mathbf{x}} - \mu) \right] \right\}$$

maximized when $\hat{\mu} = \bar{\mathbf{X}}$ \Rightarrow

$\exp \left\{ -\frac{1}{2} \left[n(\bar{\mathbf{x}} - \mu)' \Sigma^{-1} (\bar{\mathbf{x}} - \mu) \right] \right\} = 1$ is at its maximum since Σ^{-1} is positive definite

Maximum Likelihood Estimator of Σ

Result: $\mathbf{B} \equiv p \times p$ positive definite, scalar $b > 0$, $\Sigma \equiv$ positive definite:

$$\frac{1}{|\Sigma|^b} \exp \left\{ -\frac{1}{2} \text{tr} \left\{ \Sigma^{-1} \mathbf{B} \right\} \right\} \leq \frac{1}{|\mathbf{B}|^b} (2b)^{bp} e^{-bp} \text{ with equality holding at } \Sigma = \left(\frac{1}{2b} \right) \mathbf{B}$$

Maximum Likelihood Estimator for Σ evaluated at $\hat{\boldsymbol{\mu}}$:

$$L(\boldsymbol{\mu}, \Sigma) = (2\pi)^{-np/2} |\Sigma|^{-n/2} \exp \left\{ -\frac{1}{2} \left[\text{tr} \left\{ \Sigma^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' \right] \right\} \right] \right\} \quad \text{setting } b = \frac{n}{2} \quad \mathbf{B} = \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})'$$

$$\Rightarrow \hat{\Sigma} = \left(\frac{1}{2(n/2)} \right) \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' = \frac{1}{n} \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' = \frac{n-1}{n} \mathbf{S}$$

Likelihood Function evaluated at the observed ML estimates:

$$L\left(\hat{\boldsymbol{\mu}}, \hat{\Sigma}\right) = (2\pi)^{-np/2} \left| \hat{\Sigma} \right|^{-n/2} \exp \left\{ -\frac{1}{2} \left[\text{tr} \left\{ \left(\hat{\Sigma} \right)^{-1} \left[\sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})(\mathbf{x}_j - \bar{\mathbf{x}})' \right] \right\} \right] \right\} = (2\pi)^{-np/2} \left| \hat{\Sigma} \right|^{-n/2} e^{-np/2}$$

$$\text{Note: } \left| \hat{\Sigma} \right| = \left| \frac{n-1}{n} \mathbf{S} \right| = \left(\frac{n-1}{n} \right)^p |\mathbf{S}| \Rightarrow$$

$$L\left(\hat{\boldsymbol{\mu}}, \hat{\Sigma}\right) = (2\pi)^{-np/2} e^{-np/2} \left(\frac{n-1}{n} \right)^p |\mathbf{S}| = \text{constant} \times \text{generalized inverse}$$

Results for ML Estimators and Large-Sample Properties

$\boldsymbol{\theta} \equiv$ Parameter vector $h(\boldsymbol{\theta}) \equiv$ function of $\boldsymbol{\theta}$

ML Estimate of $h(\boldsymbol{\theta}) \equiv h\left(\hat{\boldsymbol{\theta}}\right)$

Sufficient Statistics: Joint density of $\mathbf{x}_1, \dots, \mathbf{x}_n$ depends only on the observed data through:

$$\bar{\mathbf{x}} \text{ and } (n-1)\mathbf{S} = \sum_{j=1}^n (\mathbf{x}_j - \bar{\mathbf{x}})'(\mathbf{x}_j - \bar{\mathbf{x}}) \Rightarrow \bar{\mathbf{X}} \text{ and } \mathbf{S} \text{ are Sufficient Statistics}$$

Sampling Distributions of $\bar{\mathbf{X}}$ and \mathbf{S} under Normality and Independence:

$$\bar{\mathbf{X}} \sim N_p\left(\boldsymbol{\mu}, \frac{1}{n}\boldsymbol{\Sigma}\right) \quad (n-1)\mathbf{S} \sim \text{Wishart w/ df} = n-1 \quad \bar{\mathbf{X}} \text{ and } \mathbf{S} \text{ are independent}$$

Wishart distribution with m d.f. : Distribution of $\sum_{j=1}^m \mathbf{Z}_j \mathbf{Z}_j'$ where $\mathbf{Z}_j \sim NID(\mathbf{0}, \boldsymbol{\Sigma})$

$\mathbf{X}_1, \dots, \mathbf{X}_n$ independent with mean $\boldsymbol{\mu}$ and finite variance-covariance $\boldsymbol{\Sigma}$ with Large n and $n-p$:

$\sqrt{n}(\bar{\mathbf{X}} - \boldsymbol{\mu})$ is approximately distributed $N_p(\mathbf{0}, \boldsymbol{\Sigma})$

$n(\bar{\mathbf{X}} - \boldsymbol{\mu})' \mathbf{S}^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu})$ is approximately distributed χ_p^2

Assessing the Assumption of Normality

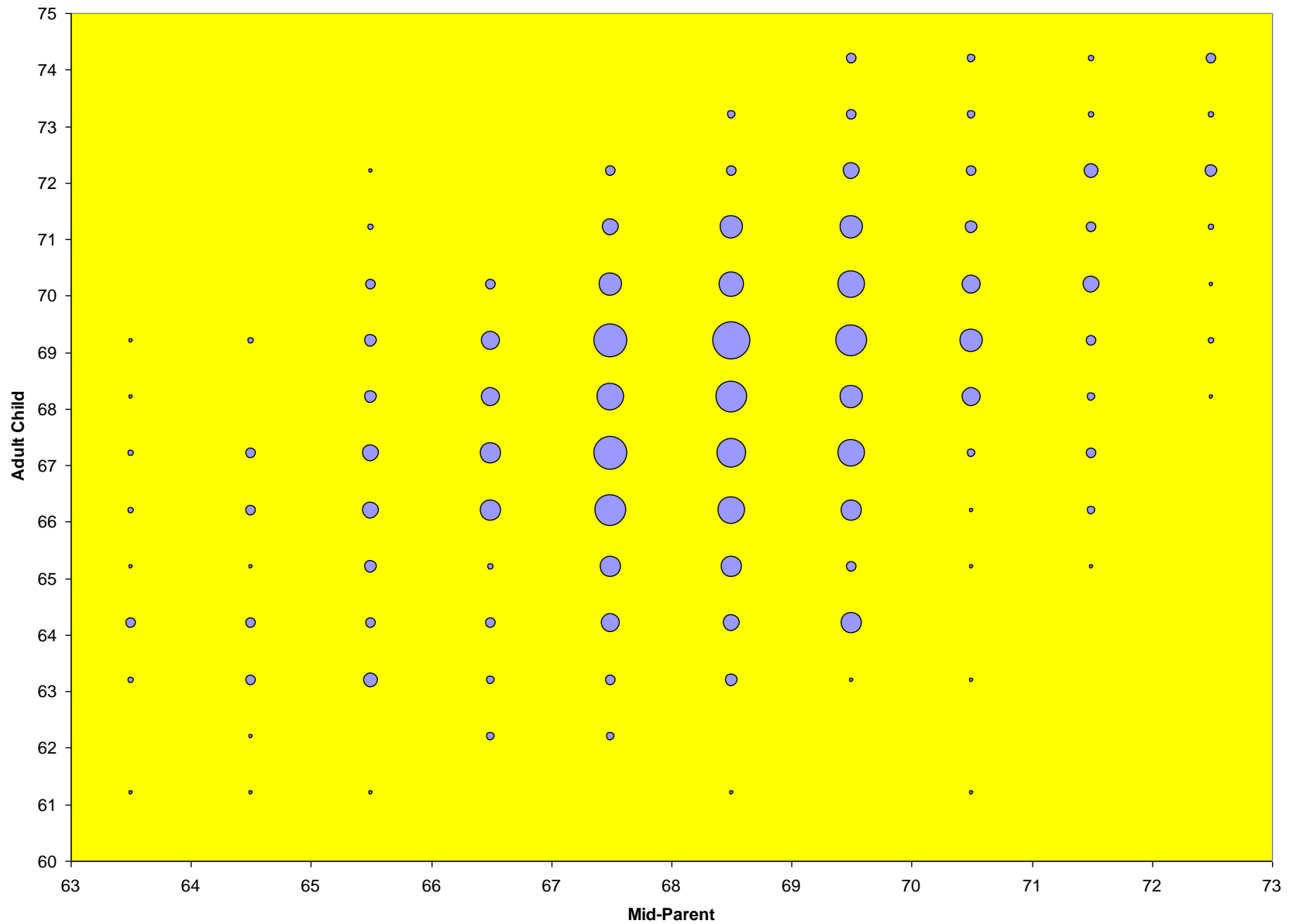
Evaluating normality of the univariate distributions:

- Histogram: compare bin proportions with empirical rule;
- **Q-Q Plot:** plot ordered sample observation $x_{(j)}$ vs. the $(j - 3/8)/(n + 1/4)$ quantile of the normal distribution (should be a 45-degree line);
- Hypotheses tests (**Shapiro-Wilks, Anderson-Darling, Kolmogorov-Smirnov, ...**): note small **p -value rejects normality!**

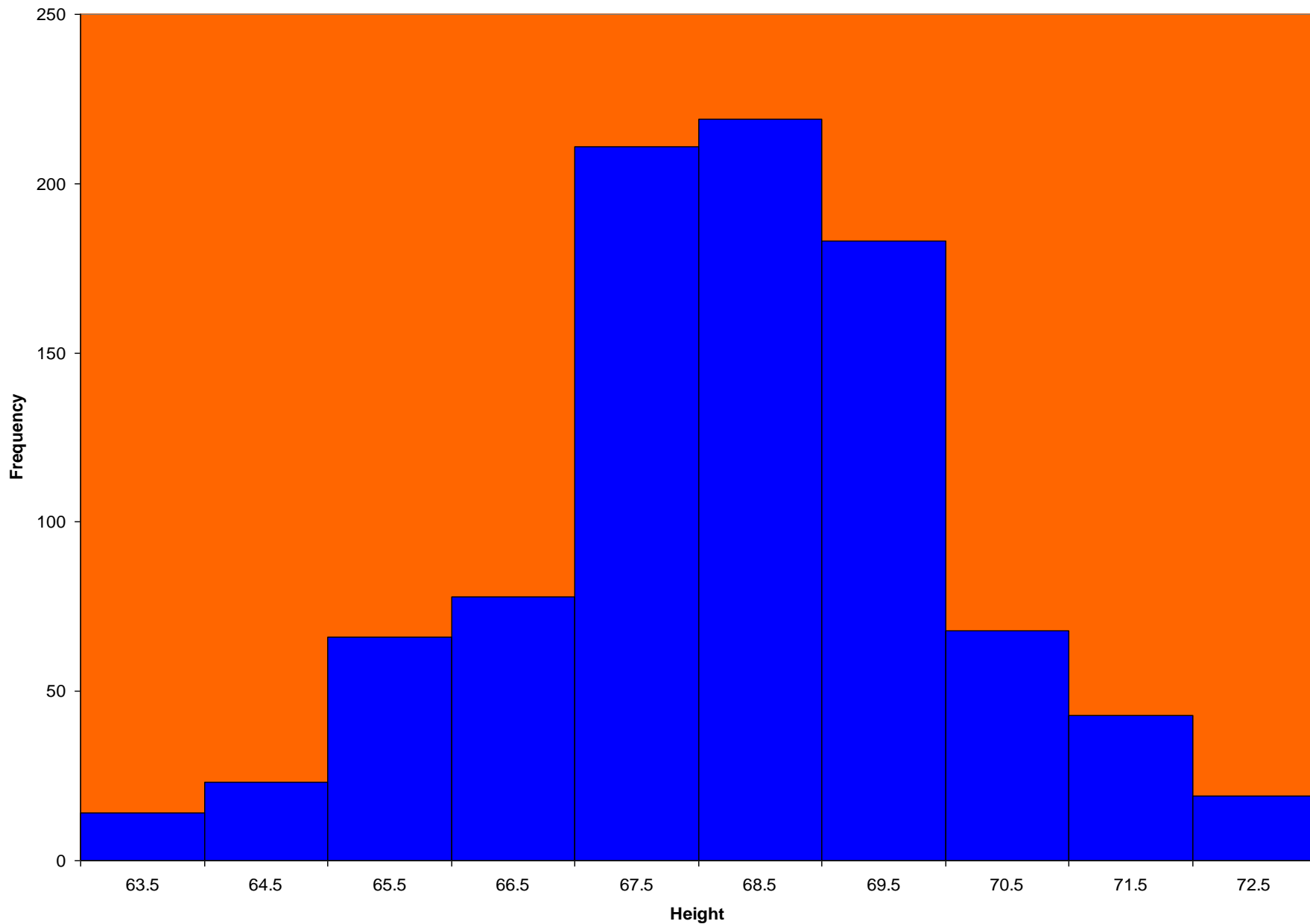
Data – Heights of Adult Children and Parents

- Adult Children Heights are reported by inch, in a manner so that the median of the grouped values is used for each (62.2”,...,73.2” are reported by Galton).
 - He adjusts female heights by a multiple of 1.08
 - We use 61.2” for his “Below”
 - We use 74.2” for his “Above”
- Mid-Parents Heights are the average of the two parents’ heights (after female adjusted). Grouped values at median (64.5”,...,72.5” by Galton)
 - We use 63.5” for “Below”
 - We use 73.5” for “Above”

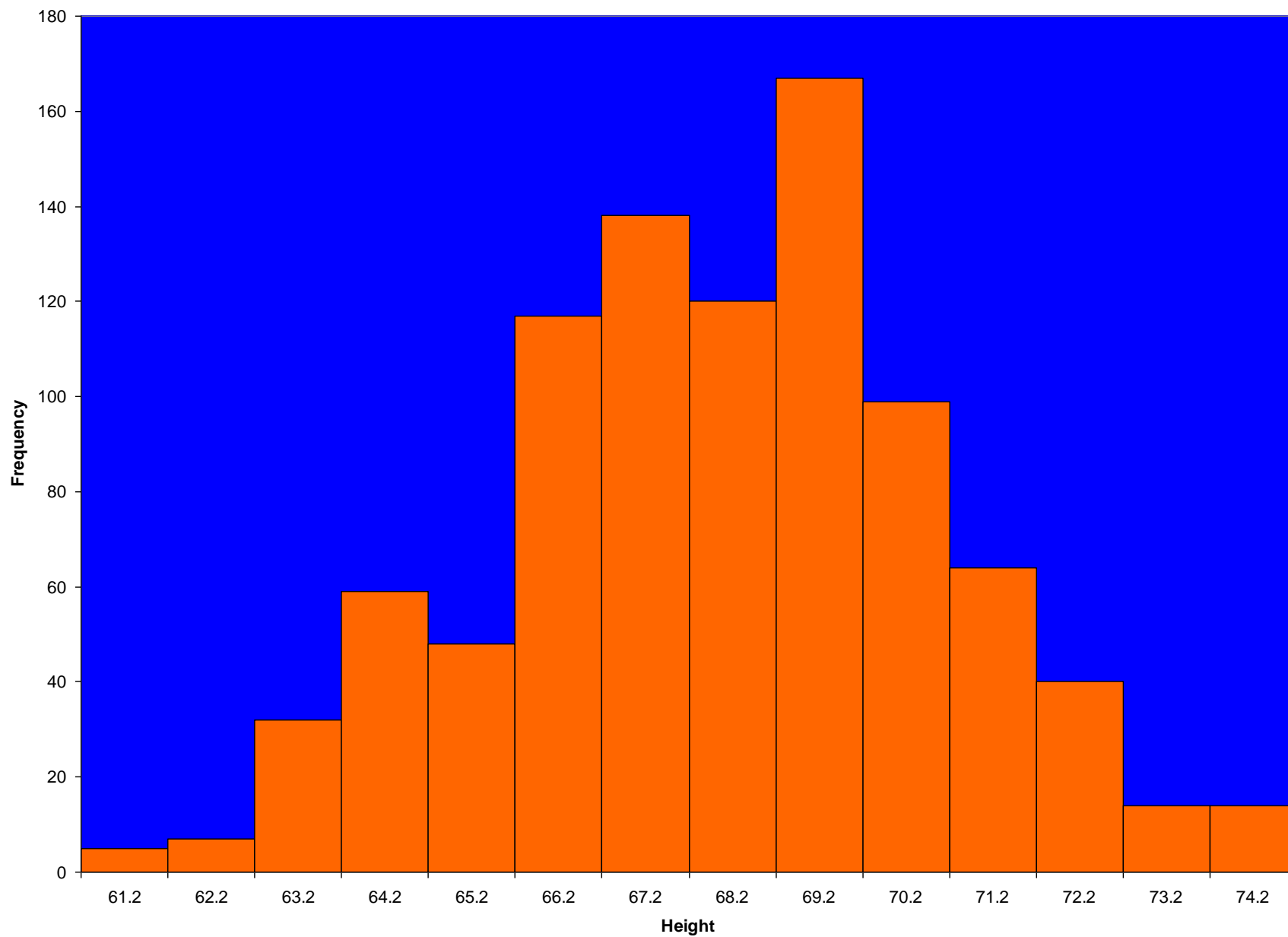
Adult Child vs Mid-Parent Height



Mid-Parent Height



Adult Child Heights



Joint Density Function

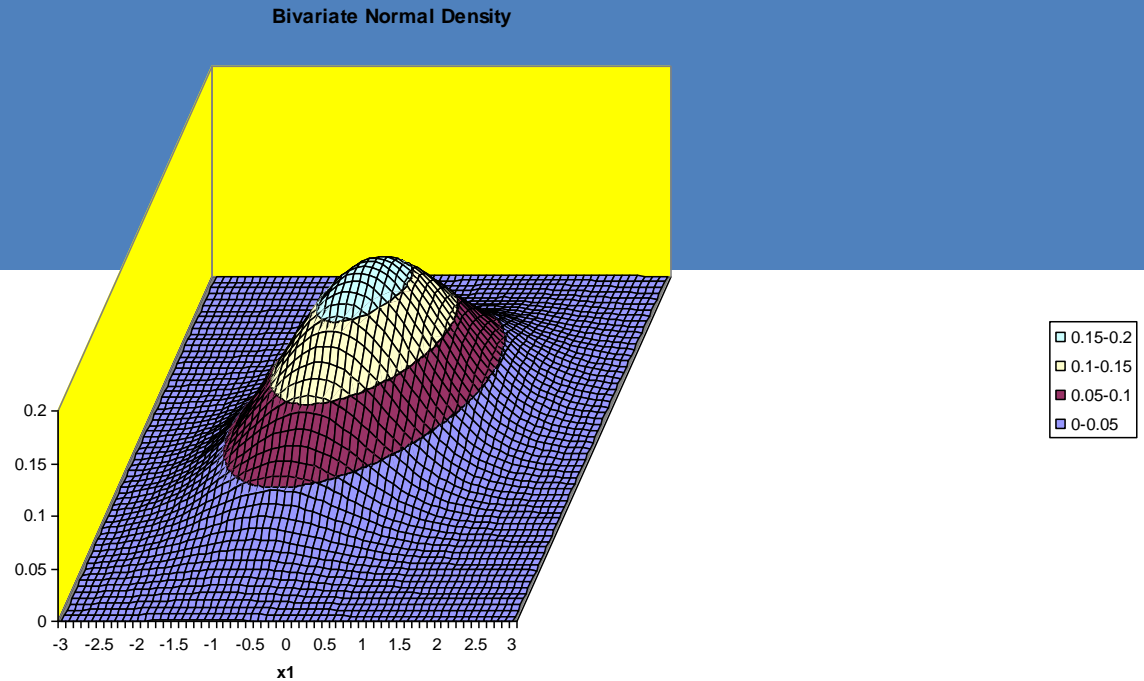
$$f(x_1, x_2) = \frac{1}{2\pi\sqrt{\sigma_1^2\sigma_2^2(1-\rho^2)}} \exp \left\{ - \left(\frac{1}{2(1-\rho^2)} \right) \left[\frac{(x_1 - \mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1 - \mu_1)(x_2 - \mu_2)}{\sigma_1\sigma_2} + \frac{(x_2 - \mu_2)^2}{\sigma_2^2} \right] \right\} \quad -\infty < y_1, y_2 < \infty$$

where:

$$\mu_1 = E\{X_1\} \quad \sigma_1^2 = V\{X_1\}$$

$$\mu_2 = E\{X_2\} \quad \sigma_2^2 = V\{X_2\}$$

$$\rho = \frac{E\{(X_1 - \mu_1)(X_2 - \mu_2)\}}{\sigma_1\sigma_2}$$



$$\mu_1 = \mu_2 = 0 \quad \sigma_1 = \sigma_2 = 1 \quad \rho = 0.4$$