

STA 260 Formulas and Tables

$$\sum_{k=j}^{\infty} a^k = \frac{a^j}{1-a}$$

$$\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x$$

$$(a+b)^n = \sum_{k=0}^n \binom{n}{k} a^k b^{n-k}$$

$$\Gamma(\alpha) = \int_0^{\infty} e^{-t} t^{\alpha-1} dt$$

$$\Gamma(\alpha+1) = \alpha \Gamma(\alpha)$$

$$\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi} \quad \lim_{n \rightarrow \infty} \left(1 + \frac{x}{n}\right)^n = e^x$$

$$I_A(x) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases}$$

$$I(x \in A) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases}$$

$$g(x)I(x \in A) = \begin{cases} g(x) & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases}$$

$$F_X(x) \stackrel{\text{def}}{=} P(X \leq x)$$

$$F_X(x) = \int_{-\infty}^x f_X(t) dt$$

$$F_X(x) = \sum_t I(t \leq x) p_X(t)$$

$$p_X(x) = \sum_y p_{X,Y}(x,y)$$

$$p_{Y|X}(y|x) \stackrel{\text{def}}{=} \frac{p_{X,Y}(x,y)}{p_X(x)}$$

$$p_X(x) = \sum_y p_{X|Y}(x|y) p_Y(y)$$

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$$

$$f_{Y|X}(y|x) \stackrel{\text{def}}{=} \frac{f_{X,Y}(x,y)}{f_X(x)}$$

$$f_X(x) = \int_{-\infty}^{\infty} f_{X|Y}(x|y) f_Y(y) dy$$

$$E(X) \stackrel{\text{def}}{=} \sum_x x p_X(x)$$

$$E(g(X)) = \sum_x g(x) p_X(x)$$

$$E(g(X,Y)) = \sum_x \sum_y g(x,y) p_{X,Y}(x,y)$$

$$E(X) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} x f_X(x) dx$$

$$E(g(X)) = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

$$E(g(X,Y)) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y}(x,y) dx dy$$

$$\text{Var}(X) \stackrel{\text{def}}{=} E((X - \mu)^2)$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$\text{Var}(aX) = a^2 \text{Var}(X)$$

$$\text{Var}(aX + bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y)$$

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

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

$$\text{Cov}(aX, bY) = ab \text{Cov}(X, Y)$$

$$\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j)$$

$$\text{Var}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \text{Var}(X_i) + \sum_{i \neq j} a_i a_j \text{Cov}(X_i, X_j)$$

If X_1, \dots, X_n are independent, $\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i)$

$$M_X(t) \stackrel{\text{def}}{=} E(e^{Xt})$$

$$M_X^{(k)}(0) = E(X^k)$$

$$M_{aX}(t) = M_X(at)$$

$$M_{\sum X_i}(t) = \prod_{i=1}^n M_{X_i}(t) \text{ if the } X_i \text{ are independent.}$$

Convergence in probability:

$T_n \xrightarrow{P} c$ means for all $\epsilon > 0$, $\lim_{n \rightarrow \infty} P\{|T_n - c| \geq \epsilon\} = 0 \Leftrightarrow \lim_{n \rightarrow \infty} P\{|T_n - c| < \epsilon\} = 1$

Variance rule: If $\lim_{n \rightarrow \infty} E(T_n) = c$ and $\lim_{n \rightarrow \infty} Var(T_n) = 0$, then $T_n \xrightarrow{P} c$.

Law of Large Numbers: $\bar{X}_n \xrightarrow{P} \mu = E(X_i)$.

Continuous mapping: If $T_n \xrightarrow{P} c$ and $g(x)$ is continuous at $x = c$, then $g(T_n) \xrightarrow{P} g(c)$

Convergence in Distribution:

$X_n \xrightarrow{d} X$ means $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$ at every point where $F_X(x)$ is continuous.

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i \quad S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$$

Central Limit Theorem: If $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} ?(\mu, \sigma^2)$, then $Z_n = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{d} Z \sim \text{Normal}(0, 1)$.

If $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} ?(\mu, \sigma^2)$ and $\hat{\sigma}_n^2 \xrightarrow{P} \sigma^2$, then $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\hat{\sigma}_n} \xrightarrow{d} Z \sim \text{Normal}(0, 1)$.

$$\bar{X}_n \pm z_{1-\alpha/2} \frac{\hat{\sigma}_n}{\sqrt{n}} \quad T = \frac{Z}{\sqrt{Y/\nu}} \sim t(\nu) \quad \bar{X} \pm t_{1-\alpha/2} \frac{S}{\sqrt{n}}$$

Distribution	$f_X(x \theta)$ or $p_X(x \theta)$	$M_X(t)$	$E(X)$	$Var(X)$
Bernoulli	$\theta^x(1-\theta)^{1-x}I(x=0,1)$	$\theta e^t + 1 - \theta$	θ	$\theta(1-\theta)$
Binomial	$\binom{m}{x}\theta^x(1-\theta)^{m-x}I(x=0, \dots, m)$	$(\theta e^t + 1 - \theta)^m$	$m\theta$	$m\theta(1-\theta)$
Poisson	$\frac{e^{-\lambda}\lambda^x}{x!}I(x=0, 1, \dots)$	$e^{\lambda(e^t-1)}$	λ	λ
Geometric	$(1-\theta)^x\theta I(x=0, 1, \dots)$	$\theta(1 - (1-\theta)e^t)^{-1}$	$\frac{1-\theta}{\theta}$	$\frac{1-\theta}{\theta^2}$
Exponential	$\lambda e^{-\lambda x}I(x > 0)$	$(1 - \frac{t}{\lambda})^{-1}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
Gamma	$\frac{\lambda^\alpha}{\Gamma(\alpha)} e^{-\lambda x} x^{\alpha-1} I(x > 0)$	$(1 - \frac{t}{\lambda})^{-\alpha}$	$\frac{\alpha}{\lambda}$	$\frac{\alpha}{\lambda^2}$
Chi-squared (χ^2)	$\frac{1}{2^{\nu/2}\Gamma(\nu/2)} e^{-x/2} x^{\nu/2-1} I(x > 0)$	$(1 - 2t)^{-\nu/2}$	ν	2ν
Normal	$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$e^{\mu t + \frac{1}{2}\sigma^2 t^2}$	μ	σ^2
Uniform	$\frac{1}{R-L} I(L < x < R)$	$\frac{e^{Rt} - e^{Lt}}{t(R-L)}$	$\frac{L+R}{2}$	$\frac{(R-L)^2}{12}$
Beta	$\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1} I(0 < x < 1)$	Useless	$\frac{\alpha}{\alpha+\beta}$	$\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

If $X \sim \text{Exponential}(\lambda)$, $F_X(x) = 1 - e^{-\lambda x}I(x > 0)$. If $X \sim N(\mu, \sigma^2)$, $\frac{X-\mu}{\sigma} \sim N(0,1)$

A *random sample* is a collection of independent and identically distributed random variables X_1, \dots, X_n . Write $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} P_\theta$, $\theta \in \Omega$. θ is the *parameter*, and Ω is the *parameter space*.

An estimator $T_n = T_n(X_1, \dots, X_n)$ is said to be *unbiased* for θ if $E(T_n) = \theta$ for all $\theta \in \Omega$.

An estimator $T_n = T_n(X_1, \dots, X_n)$ is said to be *consistent* for θ if $T_n \xrightarrow{P} \theta$ for all $\theta \in \Omega$.

Method of Moments: Substitute sample moments for population moments and put hats on.

Least squares: Minimize $Q(\theta) = \sum_{i=1}^n (Y_i - E_\theta(Y_i))^2$

If X_1, \dots, X_n is a random sample from an Exponential(λ) distribution,

- $\bar{X}_n \sim \text{Gamma}(n, n\lambda)$.
- $Y = 2n\lambda\bar{X}_n \sim \chi^2(2n)$.

If $W = W_1 + W_2$ with W_1 and W_2 independent, $W \sim \chi^2(\nu_1 + \nu_2)$, $W_2 \sim \chi^2(\nu_2)$ then $W_1 \sim \chi^2(\nu_1)$.

$$t = \frac{Z}{\sqrt{W/\nu}} \sim t(\nu) \quad F = \frac{W_1/\nu_1}{W_2/\nu_2} \sim F(\nu_1, \nu_2)$$

If X_1, \dots, X_n is a random sample from a Normal(μ, σ^2) distribution, then

- $\hat{\mu} = \bar{X}_n$ and $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2 = \left(\frac{n-1}{n}\right) S^2$.
- \bar{X}_n and S^2 are independent.
- $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$.
- $t = \frac{\sqrt{n}(\bar{X}_n - \mu)}{S} \sim t(n-1)$

If $X_1, \dots, X_{n_1} \stackrel{i.i.d.}{\sim} \text{Normal}(\mu_1, \sigma_1^2)$ and $Y_1, \dots, Y_{n_2} \stackrel{i.i.d.}{\sim} \text{Normal}(\mu_2, \sigma_2^2)$ with X_i independent of Y_i , then

- $F = \frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2} \sim F(n_1 - 1, n_2 - 1)$.
- $T = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(n_1 + n_2 - 2)$ provided $\sigma_1^2 = \sigma_2^2$, where $S_p = \sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2}}$.

For $j = 1, \dots, k$ and $i = 1, \dots, n_j$, $X_{i,j} \stackrel{ind}{\sim} N(\mu_j, \sigma^2)$. Let $\bar{X}_j = \sum_{i=1}^{n_j} \left(\frac{1}{n_j}\right) X_{i,j}$.

$SSTO = SSB + SSW$, where $SSTO = \sum_{j=1}^k \sum_{i=1}^{n_j} (X_{i,j} - \bar{X}_j)^2$, $SSB = \sum_{j=1}^k n_j (\bar{X}_j - \bar{X})^2$ and $SSW = \sum_{j=1}^k \sum_{i=1}^{n_j} (X_{i,j} - \bar{X}_j)^2$. $R^2 = \frac{SSB}{SSTO}$.

Under $H_0 : \mu_1 = \dots = \mu_k$, $F = \frac{SSB/(k-1)}{SSW/(n-k)} = \left(\frac{n-k}{k-1}\right) \left(\frac{R^2}{1-R^2}\right) \sim F(k-1, n-k)$.

$\lambda(\mathbf{x}) = \frac{L(\hat{\theta}_0, \mathbf{x})}{L(\hat{\theta}, \mathbf{x})}$, $C_k = \{\mathbf{x} \in S : \lambda(\mathbf{x}) \leq k\}$, where $0 < k < 1$.

$G_n^2 = -2 \ln \lambda(\mathbf{X}) \xrightarrow{d} Y \sim \chi^2(q)$, where q is the number of = signs in H_0 .

$$\pi(\theta|x) = \frac{f(x|\theta)\pi(\theta)}{\int f(x|t)\pi(t)dt} \propto f(x|\theta)\pi(\theta) \quad E[f(x|\Theta)|\mathbf{x}] = \int f(x|\theta)\pi(\theta|\mathbf{x})d\theta$$

$$L(\theta, \mathbf{x}) = g[\theta, t(\mathbf{x})]h(\mathbf{x}) \quad I(\theta) = E\left(\frac{\partial}{\partial\theta} \ln f(X|\theta)\right)^2 = -E\left(\frac{\partial^2}{\partial\theta^2} \ln f(X|\theta)\right)$$

$$\text{If } E(T) = \theta, \text{Var}(T) \geq \frac{1}{nI(\theta)} \quad \frac{\sqrt{n}(\hat{\Theta}_n - \theta)}{\sqrt{1/I(\theta)}} \xrightarrow{d} Z \sim N(0, 1) \quad \frac{\sqrt{n}(\hat{\Theta}_n - \theta)}{\sqrt{1/I(\hat{\Theta}_n)}} \xrightarrow{d} Z \sim N(0, 1)$$

R Code

Distribution	CDF $F(x \theta)$	Quantile
Exponential(λ)	<code>pexp(2.7, 2)</code>	<code>qexp(0.99, 1)</code>
Gamma(α, λ)	<code>pgamma(1, shape=21, rate=23.35)</code>	<code>qgamma(0.025, 4, 23.25)</code>
Normal(μ, σ)	<code>pnorm(160, mean=100, sd=15)</code>	<code>qnorm(0.975, 0, 1)</code>
Chi-squared(ν)	<code>pchisq(1.7, df=4)</code>	<code>qchisq(0.95, 1)</code>
$t(\nu)$	<code>pt(2.14, df=10)</code>	<code>qt(0.975, df=134)</code>
$F(\nu_1, \nu_2)$	<code>pf(3.17, df1=6, df2=114)</code>	<code>qf(0.95, 6, 114)</code>
Beta(α, β)	<code>pbeta(0.25, 61, 41)</code>	<code>qbeta(0.5, 61, 41)</code>

D.2 | Standard Normal Cdf

If $Z \sim N(0, 1)$, then we can use Table D.2 to compute the cumulative distribution function (cdf) Φ for Z . For example, suppose we want to compute $\Phi(z) = P(Z < 1.03)$. The symmetry of the $N(0, 1)$ distribution about 0 implies that $\Phi(z) = 1 - \Phi(-z)$, so using Table D.2, we have that $P(Z < 1.03) = P(Z < 1.03) = 1 - P(Z < -1.03) = 1 - 0.1515 = 0.8485$.

Table D.2 Standard Normal Cdf										
z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
-3.4	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0002
-3.3	.0005	.0005	.0005	.0004	.0004	.0004	.0004	.0004	.0004	.0003
-3.2	.0007	.0007	.0006	.0006	.0006	.0006	.0006	.0005	.0005	.0005
-3.1	.0010	.0009	.0009	.0009	.0008	.0008	.0008	.0008	.0007	.0007
-3.0	.0013	.0013	.0013	.0012	.0012	.0011	.0011	.0011	.0010	.0010
-2.9	.0019	.0018	.0018	.0017	.0016	.0016	.0015	.0015	.0014	.0014
-2.8	.0026	.0025	.0024	.0023	.0023	.0022	.0021	.0021	.0020	.0019
-2.7	.0035	.0034	.0033	.0032	.0031	.0030	.0029	.0028	.0027	.0026
-2.6	.0047	.0045	.0044	.0043	.0041	.0040	.0039	.0038	.0037	.0036
-2.5	.0062	.0060	.0059	.0057	.0055	.0054	.0052	.0051	.0049	.0048
-2.4	.0082	.0080	.0078	.0075	.0073	.0071	.0069	.0068	.0066	.0064
-2.3	.0107	.0104	.0102	.0099	.0096	.0094	.0091	.0089	.0087	.0084
-2.2	.0139	.0136	.0132	.0129	.0125	.0122	.0119	.0116	.0113	.0110
-2.1	.0179	.0174	.0170	.0166	.0162	.0158	.0154	.0150	.0146	.0143
-2.0	.0228	.0222	.0217	.0212	.0207	.0202	.0197	.0192	.0188	.0183
-1.9	.0287	.0281	.0274	.0268	.0262	.0256	.0250	.0244	.0239	.0233
-1.8	.0359	.0351	.0344	.0336	.0329	.0322	.0314	.0307	.0301	.0294
-1.7	.0446	.0436	.0427	.0418	.0409	.0401	.0392	.0384	.0375	.0367
-1.6	.0548	.0537	.0526	.0516	.0505	.0495	.0485	.0475	.0465	.0455
-1.5	.0668	.0655	.0643	.0630	.0618	.0606	.0594	.0582	.0571	.0559
-1.4	.0808	.0793	.0778	.0764	.0749	.0735	.0721	.0708	.0694	.0681
-1.3	.0968	.0951	.0934	.0918	.0901	.0885	.0869	.0853	.0838	.0823
-1.2	.1151	.1131	.1112	.1093	.1075	.1056	.1038	.1020	.1003	.0985
-1.1	.1357	.1335	.1314	.1292	.1271	.1251	.1230	.1210	.1190	.1170
-1.0	.1587	.1562	.1539	.1515	.1492	.1469	.1446	.1423	.1401	.1379
-0.9	.1841	.1814	.1788	.1762	.1736	.1711	.1685	.1660	.1635	.1611
-0.8	.2119	.2090	.2061	.2033	.2005	.1977	.1949	.1922	.1894	.1867
-0.7	.2420	.2389	.2358	.2327	.2296	.2266	.2236	.2206	.2177	.2148
-0.6	.2743	.2709	.2676	.2643	.2611	.2578	.2546	.2514	.2483	.2451
-0.5	.3085	.3050	.3015	.2981	.2946	.2912	.2877	.2843	.2810	.2776
-0.4	.3446	.3409	.3372	.3336	.3300	.3264	.3228	.3192	.3156	.3121
-0.3	.3821	.3783	.3745	.3707	.3669	.3632	.3594	.3557	.3520	.3483
-0.2	.4207	.4168	.4129	.4090	.4052	.4013	.3974	.3936	.3897	.3859
-0.1	.4602	.4562	.4522	.4483	.4443	.4404	.4364	.4325	.4286	.4247
-0.0	.5000	.4960	.4920	.4880	.4840	.4801	.4761	.4721	.4681	.4641

D.4 t Distribution Quantiles

Table D.4 contains some quantiles for t or Student distributions. For example, if $X \sim t(df)$, with $df = 10$ and $P = 0.98$, then $x_{0.98} = 2.359$ is the 0.98 quantile of the $t(10)$ distribution. Recall that the $t(df)$ distribution is symmetric about 0 so, for example, $x_{0.25} = -x_{0.75}$.

Table D.4 $t(df)$ Quantiles										
P										
df	0.75	0.85	0.90	0.95	0.975	0.98	0.99	0.995	0.9975	0.999
1	1.000	1.963	3.078	6.314	12.71	15.89	31.82	63.66	127.3	318.3
2	0.816	1.386	1.886	2.920	4.303	4.849	6.965	9.925	14.09	22.33
3	0.765	1.250	1.638	2.353	3.182	3.482	4.541	5.841	7.453	10.21
4	0.741	1.190	1.533	2.132	2.776	2.999	3.747	4.604	5.598	7.173
5	0.727	1.156	1.476	2.015	2.571	2.757	3.365	4.032	4.773	5.893
6	0.718	1.134	1.440	1.943	2.447	2.612	3.143	3.707	4.317	5.208
7	0.711	1.119	1.415	1.895	2.365	2.517	2.998	3.499	4.029	4.785
8	0.706	1.108	1.397	1.860	2.306	2.449	2.896	3.355	3.833	4.501
9	0.703	1.100	1.383	1.833	2.262	2.398	2.821	3.250	3.690	4.297
10	0.700	1.093	1.372	1.812	2.228	2.359	2.764	3.169	3.581	4.144
11	0.697	1.088	1.363	1.796	2.201	2.328	2.718	3.106	3.497	4.025
12	0.695	1.083	1.356	1.782	2.179	2.303	2.681	3.055	3.428	3.930
13	0.694	1.079	1.350	1.771	2.160	2.282	2.650	3.012	3.372	3.852
14	0.692	1.076	1.345	1.761	2.145	2.264	2.624	2.977	3.326	3.787
15	0.691	1.074	1.341	1.753	2.131	2.249	2.602	2.947	3.286	3.733
16	0.690	1.071	1.337	1.746	2.120	2.235	2.583	2.921	3.252	3.686
17	0.689	1.069	1.333	1.740	2.110	2.224	2.567	2.898	3.222	3.646
18	0.688	1.067	1.330	1.734	2.101	2.214	2.552	2.878	3.197	3.611
19	0.688	1.066	1.328	1.729	2.093	2.205	2.539	2.861	3.174	3.579
20	0.687	1.064	1.325	1.725	2.086	2.197	2.528	2.845	3.153	3.552
21	0.686	1.063	1.323	1.721	2.080	2.189	2.518	2.831	3.135	3.527
22	0.686	1.061	1.321	1.717	2.074	2.183	2.508	2.819	3.119	3.505
23	0.685	1.060	1.319	1.714	2.069	2.177	2.500	2.807	3.104	3.485
24	0.685	1.059	1.318	1.711	2.064	2.172	2.492	2.797	3.091	3.467
25	0.684	1.058	1.316	1.708	2.060	2.167	2.485	2.787	3.078	3.450
26	0.684	1.058	1.315	1.706	2.056	2.162	2.479	2.779	3.067	3.435
27	0.684	1.057	1.314	1.703	2.052	2.158	2.473	2.771	3.057	3.421
28	0.683	1.056	1.313	1.701	2.048	2.154	2.467	2.763	3.047	3.408
29	0.683	1.055	1.311	1.699	2.045	2.150	2.462	2.756	3.038	3.396
30	0.683	1.055	1.310	1.697	2.042	2.147	2.457	2.750	3.030	3.385
40	0.681	1.050	1.303	1.684	2.021	2.123	2.423	2.704	2.971	3.307
50	0.679	1.047	1.299	1.676	2.009	2.109	2.403	2.678	2.937	3.261
60	0.679	1.045	1.296	1.671	2.000	2.099	2.390	2.660	2.915	3.232
80	0.678	1.043	1.292	1.664	1.990	2.088	2.374	2.639	2.887	3.195
100	0.677	1.042	1.290	1.660	1.984	2.081	2.364	2.626	2.871	3.174
1000	0.675	1.037	1.282	1.646	1.962	2.056	2.330	2.581	2.813	3.098
∞	0.674	1.036	1.282	1.645	1.960	2.054	2.326	2.576	2.807	3.091
	50%	70%	80%	90%	95%	96%	98%	99%	99.5%	99.8%
Confidence level										

Quantiles of the chi-squared Distribution

df	Quantile					
	0.005	0.025	0.05	0.95	0.975	0.995
1	0.00	0.00	0.00	3.84	5.02	7.88
2	0.01	0.05	0.10	5.99	7.38	10.60
3	0.07	0.22	0.35	7.81	9.35	12.84
4	0.21	0.48	0.71	9.49	11.14	14.86
5	0.41	0.83	1.15	11.07	12.83	16.75
6	0.68	1.24	1.64	12.59	14.45	18.55
7	0.99	1.69	2.17	14.07	16.01	20.28
8	1.34	2.18	2.73	15.51	17.53	21.95
9	1.73	2.70	3.33	16.92	19.02	23.59
10	2.16	3.25	3.94	18.31	20.48	25.19
11	2.60	3.82	4.57	19.68	21.92	26.76
12	3.07	4.40	5.23	21.03	23.34	28.30
13	3.57	5.01	5.89	22.36	24.74	29.82
14	4.07	5.63	6.57	23.68	26.12	31.32
15	4.60	6.26	7.26	25.00	27.49	32.80
16	5.14	6.91	7.96	26.30	28.85	34.27
17	5.70	7.56	8.67	27.59	30.19	35.72
18	6.26	8.23	9.39	28.87	31.53	37.16
19	6.84	8.91	10.12	30.14	32.85	38.58
20	7.43	9.59	10.85	31.41	34.17	40.00
21	8.03	10.28	11.59	32.67	35.48	41.40
22	8.64	10.98	12.34	33.92	36.78	42.80
23	9.26	11.69	13.09	35.17	38.08	44.18
24	9.89	12.40	13.85	36.42	39.36	45.56
25	10.52	13.12	14.61	37.65	40.65	46.93
26	11.16	13.84	15.38	38.89	41.92	48.29
27	11.81	14.57	16.15	40.11	43.19	49.64
28	12.46	15.31	16.93	41.34	44.46	50.99
29	13.12	16.05	17.71	42.56	45.72	52.34
30	13.79	16.79	18.49	43.77	46.98	53.67
40	20.71	24.43	26.51	55.76	59.34	66.77
50	27.99	32.36	34.76	67.50	71.42	79.49
60	35.53	40.48	43.19	79.08	83.30	91.95
80	51.17	57.15	60.39	101.88	106.63	116.32
100	67.33	74.22	77.93	124.34	129.56	140.17