

This Week:

Dr. Osonde Osoba

- Continuous Random Variables
 - Review: Random Variables, Continuity
 - Cumulative Distribution Functions
 - BEG CUP Distributions
- Bayesian Inference with Random Variables
 - Conjugacy
 - Examples

H/W 4:

L-6: 3.53, 3.54, 3.57 - 3.59

4.5, 4.25, 4.26, 4.34

4.63, 4.64, 4.67, 4.68

I// Review: Random Variables

(Ω, \mathcal{Q}, P) : probability space

$(\mathbb{R}, \mathcal{B}(\mathbb{R}))$: measurable space

Given a function

$$X: \Omega \rightarrow \mathbb{R}$$

Then X is a random variable

$$\Leftrightarrow X^{-1}(A) \in \mathcal{Q} \quad \forall A \in \mathcal{B}(\mathbb{R})$$

i.e. Pullbacks $(X^{-1}(A))$ are Always Measurable [PAM]

(for any Borel-measurable set A)

OR $\Leftrightarrow X: (\Omega, \mathcal{Q}) \rightarrow (\mathbb{R}, \mathcal{B}(\mathbb{R}))$ is a measurable map

Define the Distribution function $P_X(\cdot)$

as

$$\begin{aligned} P_X(A) &= P(X \in A) = P(X^{-1}(A)) \\ &= P(\{\omega \in \Omega \mid X(\omega) \in A\}) \end{aligned}$$

where A is any Borel set (i.e. $A \in \mathcal{B}(\mathbb{R})$)

Recall that Borel sets include open sets (e.g. (a, b)

$(-\infty, a)$) and any sets that can be written as

countable unions and intersections of open sets e.g.

$\{a\}$ where $a \in \mathbb{R}$ or \mathbb{Z} or \mathbb{N} . The measurability of X

allows the composition $P \circ X^{-1}(A)$ since $P: \mathcal{Q} \rightarrow [0, 1]$ and $X^{-1}(A) \in \mathcal{Q}$.

When X is a discrete random variable
 (i.e. $|X(\Omega)| < |\mathbb{R}|$) [Qu: What does this mean?
Why use this definition?]

then we only need to deal with the
 distribution function over a discrete domain. So

$$A \in \{\{k\} : k \in X(\Omega)\} \subset \mathcal{B}(\mathbb{R})$$

This gives us the probability mass function (PMF)

$$\begin{aligned} p_x(k) &= P(X^{-1}(\{k\})) \\ &= P(X=k) \end{aligned}$$

giving the probability space $(\mathbb{R}, \mathcal{B}(\mathbb{R}), P \circ X^{-1})$
 or more precisely $(\mathbb{Z}, \mathcal{Z} \cap \mathcal{B}(\mathbb{R}), P \circ X^{-1})$

When X is a continuous random variable
 (i.e. $|X(\Omega)| = |\mathbb{R}|$) [Note: this defn is not precise enough
 to define continuous r.v.s. We'll see why]

then we use the half-open intervals

$$A \in \{(-\infty, x] : x \in \mathbb{R}\} \subset \mathcal{B}(\mathbb{R})$$

This gives the cumulative distribution function (CDF)

$$\begin{aligned} F_x(x) &= P(X \in (-\infty, x]) \\ &= P(X \leq x) \end{aligned}$$

if $F_x(\cdot)$ is absolutely continuous then $\exists f_x(x)$:

$$F_x(x) = \int_{-\infty}^x f_x(t) dt.$$

Review of Continuity: (regular, uniform, and absolute)

$$F: \mathbb{R} \rightarrow \mathbb{R}$$

F continuous

$$\Leftrightarrow \forall x \in \mathbb{R}, \forall \epsilon > 0 \exists \delta(x) > 0 : \\ \forall z \in \mathbb{R} \quad |x-z| < \delta(x) \Rightarrow |F(x) - F(z)| < \epsilon$$

F Uniformly Continuous (U.C.)

$$\Leftrightarrow \forall \epsilon > 0, \exists \delta > 0 \quad \forall x, z \in \mathbb{R} : \\ |x-z| < \delta \Rightarrow |F(x) - F(z)| < \epsilon$$

F absolutely continuous (A.C.)

$$\Leftrightarrow \forall \epsilon > 0, \exists \delta > 0 \quad \forall \text{ finite sequences of disjoint intervals } \{(a_i, b_i)\}_{i=1}^k : \\ \sum_{i=1}^k (b_i - a_i) < \delta \Rightarrow \sum_{i=1}^k |F(b_i) - F(a_i)| < \epsilon$$

absolute continuity $\not\Rightarrow$ Uniform continuity $\not\Rightarrow$ continuous

F A.C. (w.r.t. Lebesgue. measure)

- \Rightarrow i/ F is differentiable almost-everywhere
- ii/ \exists a Lebesgue-integrable function, $f(x)$,

$$F(x) = F(a) + \int_a^x f(t) dt \quad [FTC]$$

A EDF F is absolutely continuous

\Leftrightarrow \exists a probability density function (PDF) f :

$$F(x) = \int_{-\infty}^x f(t) dt$$

$$\therefore a, f = dF/dx$$

$$b, \int_{-\infty}^{\infty} f(x) dx = 1$$

CDFs satisfy the following properties in general:

i/ F is non decreasing

$$iv/ \lim_{x \rightarrow \infty} F(x) = 1$$

ii/ F is right-continuous

$$v/ \lim_{x \rightarrow -\infty} F(x) = 0$$

iii/ F has left limits $\forall x \in \mathbb{R}$

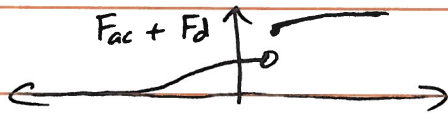
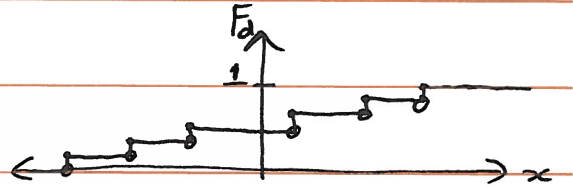
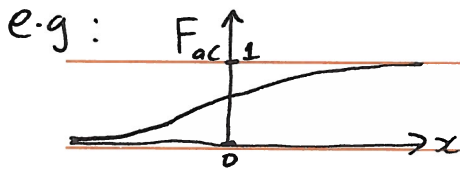
- Absolutely continuous CDFs, F_{ac} , assign non-zero measure only to non-empty open sets (sets with non-zero Lebesgue measure).

- Discrete CDFs, F_d , assign non-zero measure only to singleton sets and countable unions thereof (sets w zero Lebesgue measure)

- Singularly Continuous CDFs, F_{sc} , are continuous-but-not-A/C CDFs. Hence they have no PDFs. F_{sc} assigns non-zero measure to sets w zero-Lebesgue measure also. But these sets are (made up of) not singleton sets and may even be uncountable.

General CDFs are decomposable into these 3 components:

$$F_{\text{gen}} = F_{\text{ac}} + F_{\text{d}} + F_{\text{sc}}$$



F_{sc} : lookup Cantor Function

(Continuous everywhere but
differentiable nowhere.
Difficult to draw)

II // Continuous Random Variables:

B E G C U P
(a) (b) (c) (d)

① Exponential:

The most general distribution in this class is the gamma distribution from which we get the exponential, Chi-squared, and n -Erlang as special cases. This class of pdfs uses the gamma function

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} \cdot \exp(-x) dx \quad \alpha \in \mathbb{R}^+$$

as a foundation.

$X \sim \gamma(\alpha, \theta)$:

$$f(x) = \frac{x^{\alpha-1} \cdot \exp(-x/\theta)}{\Gamma(\alpha) \theta^\alpha}$$

$$x \in \mathbb{R}^+, \alpha \in \mathbb{R}^+, \theta \in \mathbb{R}^+$$

i/ $\alpha=1 \Rightarrow X \sim \exp(\theta)$; $f(x) = \exp(-x/\theta)/\theta$

ii/ $\alpha \in \mathbb{Z}^+ \Rightarrow X \sim \text{Erlang}(\theta)$

iii/ $\alpha = r/2, \theta = 2 \Rightarrow X \sim \chi^2(r)$
 $r \in \mathbb{Z}^+$

② Uniform:

$X \sim U(a, b)$:

$$f(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & x \notin [a, b] \end{cases}$$

U is a special case of Beta(α, β)

$X \sim \text{Beta}(\alpha, \beta)$:

$$f(x) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \cdot x^{\alpha-1} \cdot (1-x)^{\beta-1} & x \in [0, 1] \\ 0 & x \notin [0, 1] \end{cases}$$

$\alpha = \beta = 1 \Rightarrow X \sim U(0, 1)$

© Cauchy:

$$X \sim C(m, d)$$

$$f(x) = \frac{1}{\pi \cdot d \cdot \left(1 + \left(\frac{x-m}{d}\right)^2\right)}$$

m: location $\in \mathbb{R}$

d: dispersion $\in \mathbb{R}^+$

Standard Cauchy: $Z \sim C(0, 1)$

$$f(z) = \frac{1}{\pi(1 + z^2)}$$

① Gaussian:

$$X \sim N(\mu, \sigma^2)$$

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

$\mu \in \mathbb{R}$, $\sigma^2 \in \mathbb{R}^+$

Standard Normal: $Z \sim N(0, 1)$

$$f(z) = \frac{1}{\sqrt{2\pi}} \exp(-z^2/2)$$

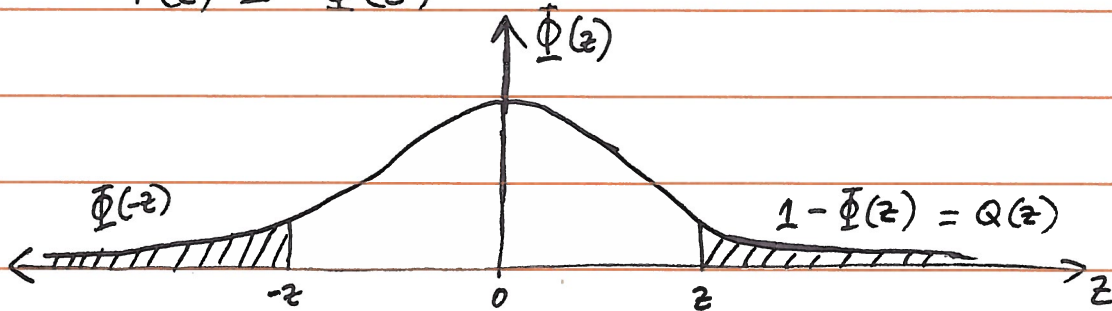
Standardization: $\text{std}(X) = \left(\frac{X-\mu}{\sigma}\right)$

Table of Standard Normal CDF values :

$$Z \sim N(0,1)$$

$$F(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-w^2/2} dw$$

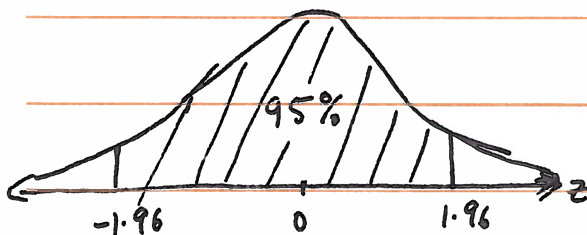
$$F(z) = \Phi(z)$$



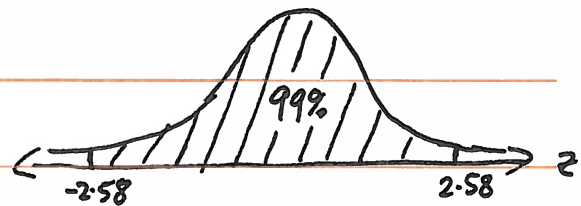
By symmetry $\Rightarrow \Phi(-z) = 1 - \Phi(z)$

$$\Phi(z) = P(Z \leq z) \quad ; \quad Q(z) = P(Z > z)$$

$$\Phi(z) + Q(z) = 1$$



$$P(-1.96 \leq Z \leq 1.96) = 0.95$$



$$P(-2.58 \leq Z \leq 2.58) = 0.99$$

III // Bayesian Inference for Continuous RVs :

Bayes Theorem for Events :

$$P(H_k|E) = \frac{P(H_k) \cdot P(E|H_k)}{\sum_j P(H_j) \cdot P(E|H_j)}$$

Where $P(H_k|E)$ gives the extent to which the event E supports the occurrence of the event H_k .

We can formulate the continuous analogue :

$$f(\theta|x) = \frac{h(\theta) \cdot g(x|\theta)}{\int_{-\infty}^{\infty} h(\theta) g(x|\theta) d\theta} = \frac{h \cdot g}{Q(x)}$$

$h(\theta)$: prior pdf

$g(x|\theta)$: likelihood function

$f(\theta|x)$: posterior pdf.

i.e. How does observing $X=x$ modify our $[h(\theta)]$ prior beliefs about θ ?

Conjugacy:

Bayes theorem maps the pair (h, g) to f .

$$f \propto h \cdot g$$

Conjugacy refers to the cases where h and g belong to the same pdf family.

i) e.g. $\begin{matrix} h & , & g & & f \\ \text{Beta} & , & \text{Binomial} & \longrightarrow & \text{Beta} \end{matrix}$
 "Beta is conjugate to Binomial"

$$\text{i.e. } X \sim b(n, \theta) \Rightarrow g(x|\theta) = \binom{n}{x} \theta^x (1-\theta)^{n-x}$$

$$\theta \sim \text{Beta}(\alpha, \beta) \Rightarrow h(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \theta^{\alpha-1} (1-\theta)^{\beta-1}$$

$$\Rightarrow f(\theta|x) = \frac{\binom{n}{x} \theta^x (1-\theta)^{n-x} \cdot \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \theta^{\alpha-1} (1-\theta)^{\beta-1}}{\int_0^1 \binom{n}{x} \cdot \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \theta^x (1-\theta)^{n-x} \cdot \theta^{\alpha-1} (1-\theta)^{\beta-1} d\theta}$$

$$f(\theta|x) = \frac{\theta^{(\alpha+x)-1} \cdot (1-\theta)^{(\beta+n-x)-1}}{\int_0^1 \theta^{x+\alpha-1} \cdot (1-\theta)^{n-x+\beta-1} d\theta}$$

By definition:

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} = \int_0^1 x^{\alpha-1} (1-x)^{\beta-1} d\theta$$

$$\Rightarrow f(\theta|x) = \frac{\theta^{(\alpha+x)-1} \cdot (1-\theta)^{(\beta+n-x)-1}}{B(\alpha+x, \beta+n-x)}$$

$$\text{i.e. } \theta|X \sim \text{Beta}(\alpha+x, \beta+n-x)$$

ii) (Gamma, Poisson) \longrightarrow Poisson

$$\theta \sim \Gamma(\alpha, \beta) \Rightarrow h(\theta) = \frac{\theta^{\alpha-1} \cdot \exp(-\theta/\beta)}{\Gamma(\alpha) \cdot \beta^\alpha}$$

$$X|\theta \sim \text{Poisson}(\theta) \Rightarrow g(x|\theta) = \frac{e^{-\theta} \cdot \theta^x}{x!}$$

$$\Rightarrow f(\theta|x) = \frac{\theta^{\alpha-1} \cdot \exp(-\theta/\beta) \cdot e^{-\theta} \cdot \theta^x}{x! \cdot \Gamma(\alpha) \cdot \beta^\alpha} \int_0^\infty \frac{\theta^{x+\alpha-1} \cdot \exp(-\theta-\theta/\beta)}{x! \cdot \Gamma(\alpha) \cdot \beta^\alpha} d\theta$$

$$= \frac{\theta^{x+\alpha-1} \cdot \exp(-\theta-\theta/\beta)}{\int_0^\infty \theta^{x+\alpha-1} \cdot \exp(-\theta(1+1/\beta)) d\theta}$$

$$\text{let } s = \theta \left(\frac{\beta+1}{\beta} \right)$$

$$f(\theta|x) = \frac{\theta^{\alpha+x-1} \cdot \exp\left[-\theta / \left(\frac{\beta}{1+\beta}\right)\right]}{\left(\frac{\beta}{1+\beta}\right)^{\alpha+x} \cdot \int_0^\infty s^{x+\alpha-1} \cdot e^{-s} ds}$$

$$f(\theta|x) = \frac{\theta^{\alpha+x-1} \cdot \exp(-\theta / \left(\frac{\beta}{1+\beta}\right))}{\Gamma(\alpha+x) \cdot \left(\frac{\beta}{1+\beta}\right)^{\alpha+x}}$$

$$\text{i.e. } \theta|X \sim \Gamma\left(\alpha+x, \frac{\beta}{1+\beta}\right)$$

Cauchy: $X \sim (m, d)$

$$f(x) = \frac{1}{\pi d \left(1 + \left(\frac{x-m}{d}\right)^2\right)}$$

Continuous Distributions

$$B(\alpha, \beta) = \frac{\Gamma(\alpha) \cdot \Gamma(\beta)}{\Gamma(\alpha + \beta)}$$

Beta
 $0 < \alpha$
 $0 < \beta$

$$f(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}, \quad 0 < x < 1$$

$$\mu = \frac{\alpha}{\alpha + \beta}, \quad \sigma^2 = \frac{\alpha\beta}{(\alpha + \beta + 1)(\alpha + \beta)^2}$$

Chi-square
 $\chi^2(r)$
 $r = 1, 2, \dots$

$$f(x) = \frac{1}{\Gamma(r/2)2^{r/2}} x^{r/2-1} e^{-x/2}, \quad 0 \leq x < \infty$$

$$M(t) = \frac{1}{(1-2t)^{r/2}}, \quad t < \frac{1}{2}$$

$$\mu = r, \quad \sigma^2 = 2r$$

Exponential
 $0 < \theta$

$$f(x) = \frac{1}{\theta} e^{-x/\theta}, \quad 0 \leq x < \infty$$

$$M(t) = \frac{1}{1 - \theta t}, \quad t < \frac{1}{\theta}$$

$$\mu = \theta, \quad \sigma^2 = \theta^2$$

Gamma
 $0 < \alpha$
 $0 < \theta$

$$f(x) = \frac{1}{\Gamma(\alpha)\theta^\alpha} x^{\alpha-1} e^{-x/\theta}, \quad 0 \leq x < \infty$$

$$M(t) = \frac{1}{(1 - \theta t)^\alpha}, \quad t < \frac{1}{\theta}$$

$$\mu = \alpha\theta, \quad \sigma^2 = \alpha\theta^2$$

Normal

$N(\mu, \sigma^2)$

$-\infty < \mu < \infty$

$0 < \sigma$

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

$$M(t) = e^{\mu t + \sigma^2 t^2/2}$$

$$E(X) = \mu, \quad \text{Var}(X) = \sigma^2$$

Uniform

$U(a, b)$

$-\infty < a < b < \infty$

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

$$M(t) = \frac{e^{tb} - e^{ta}}{t(b-a)}, \quad t \neq 0; \quad M(0) = 1$$

$$\mu = \frac{a+b}{2}, \quad \sigma^2 = \frac{(b-a)^2}{12}$$

$$\Gamma(n) \equiv \int_0^\infty x^{n-1} e^{-x} dx$$

$$\therefore \Gamma(1) = 1 \quad \Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$$

$$\Gamma(n) = (n-1)! \quad \text{if } n \in \mathbb{Z}^+$$

Multivariate Hypergeometric

$$f(x) = \frac{\binom{N_1}{x_1} \binom{N_2}{x_2} \dots \binom{N_k}{x_k}}{\binom{N}{n}}$$

$$N_1 + \dots + N_k = N$$

$$x_1 + \dots + x_k = n$$

Discrete Distributions

Bernoulli

$$0 < p < 1$$

$$f(x) = p^x (1-p)^{1-x}, \quad x = 0, 1$$

$$M(t) = 1 - p + pe^t$$

$$\mu = p, \quad \sigma^2 = p(1-p)$$

Binomial

$$b(n, p)$$

$$0 < p < 1$$

$$f(x) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}, \quad x = 0, 1, 2, \dots, n$$

$$M(t) = (1 - p + pe^t)^n$$

$$\mu = np, \quad \sigma^2 = np(1-p)$$

Geometric

$$0 < p < 1$$

$$f(x) = (1-p)^{x-1} p, \quad x = 1, 2, 3, \dots$$

$$M(t) = \frac{pe^t}{1 - (1-p)e^t}, \quad t < -\ln(1-p)$$

$$\mu = \frac{1}{p}, \quad \sigma^2 = \frac{1-p}{p^2} \quad \therefore P(X > k) = q^k$$

Hypergeometric

$$N_1 > 0, N_2 > 0$$

$$N = N_1 + N_2$$

$$f(x) = \frac{\binom{N_1}{x} \binom{N_2}{n-x}}{\binom{N}{n}}, \quad x \leq n, x \leq N_1, n-x \leq N_2$$

$$\mu = n \left(\frac{N_1}{N} \right), \quad \sigma^2 = n \left(\frac{N_1}{N} \right) \left(\frac{N_2}{N} \right) \left(\frac{N-n}{N-1} \right)$$

Negative Binomial

$$0 < p < 1$$

$$r = 1, 2, 3, \dots$$

$$f(x) = \binom{x-1}{r-1} p^r (1-p)^{x-r}, \quad x = r, r+1, r+2, \dots$$

$$M(t) = \frac{(pe^t)^r}{[1 - (1-p)e^t]^r}, \quad t < -\ln(1-p)$$

$$\mu = r \left(\frac{1}{p} \right), \quad \sigma^2 = \frac{r(1-p)}{p^2}$$

Poisson

$$0 < \lambda$$

$$f(x) = \frac{\lambda^x e^{-\lambda}}{x!}, \quad x = 0, 1, 2, \dots$$

$$M(t) = e^{\lambda(e^t - 1)}$$

$$\mu = \lambda, \quad \sigma^2 = \lambda$$

Uniform

$$m > 0$$

$$f(x) = \frac{1}{m}, \quad x = 1, 2, \dots, m$$

$$\mu = \frac{m+1}{2}, \quad \sigma^2 = \frac{m^2-1}{12}$$

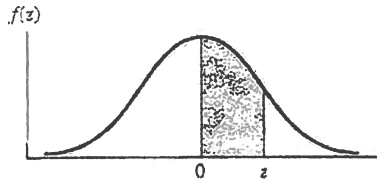
Multinomial

$$f(x) = \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} \dots p_k^{x_k}$$

$$x_1 + \dots + x_k = n$$

$$p_1 + \dots + p_k = 1$$

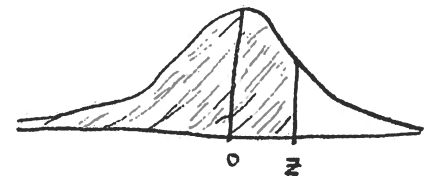
TABLE 4 Normal Curve Areas



z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
.0	.0000	.0040	.0080	.0120	.0160	.0199	.0239	.0279	.0319	.0359
.1	.0398	.0438	.0478	.0517	.0557	.0596	.0636	.0675	.0714	.0753
.2	.0793	.0832	.0871	.0910	.0948	.0987	.1026	.1064	.1103	.1141
.3	.1179	.1217	.1255	.1293	.1331	.1368	.1406	.1443	.1480	.1517
.4	.1554	.1591	.1628	.1664	.1700	.1736	.1772	.1808	.1844	.1879
.5	.1915	.1950	.1985	.2019	.2054	.2088	.2123	.2157	.2190	.2224
.6	.2257	.2291	.2324	.2357	.2389	.2422	.2454	.2486	.2517	.2549
.7	.2580	.2611	.2642	.2673	.2704	.2734	.2764	.2794	.2823	.2852
.8	.2881	.2910	.2939	.2967	.2995	.3023	.3051	.3078	.3106	.3133
.9	.3159	.3186	.3212	.3238	.3264	.3289	.3315	.3340	.3365	.3389
1.0	.3413	.3438	.3461	.3485	.3508	.3531	.3554	.3577	.3599	.3621
1.1	.3643	.3665	.3686	.3708	.3729	.3749	.3770	.3790	.3810	.3830
1.2	.3849	.3869	.3888	.3907	.3925	.3944	.3962	.3980	.3997	.4015
1.3	.4032	.4049	.4066	.4082	.4099	.4115	.4131	.4147	.4162	.4177
1.4	.4192	.4207	.4222	.4236	.4251	.4265	.4279	.4292	.4306	.4319
1.5	.4332	.4345	.4357	.4370	.4382	.4394	.4406	.4418	.4429	.4441
1.6	.4452	.4463	.4474	.4484	.4495	.4505	.4515	.4525	.4535	.4545
1.7	.4554	.4564	.4573	.4582	.4591	.4599	.4608	.4616	.4625	.4633
1.8	.4641	.4649	.4656	.4664	.4671	.4678	.4686	.4693	.4699	.4706
1.9	.4713	.4719	.4726	.4732	.4738	.4744	.4750	.4756	.4761	.4767
2.0	.4772	.4778	.4783	.4788	.4793	.4798	.4803	.4808	.4812	.4817
2.1	.4821	.4826	.4830	.4834	.4838	.4842	.4846	.4850	.4854	.4857
2.2	.4861	.4864	.4868	.4871	.4875	.4878	.4881	.4884	.4887	.4890
2.3	.4893	.4896	.4898	.4901	.4904	.4906	.4909	.4911	.4913	.4916
2.4	.4918	.4920	.4922	.4925	.4927	.4929	.4931	.4932	.4934	.4936
2.5	.4938	.4940	.4941	.4943	.4945	.4946	.4948	.4949	.4951	.4952
2.6	.4953	.4955	.4956	.4957	.4959	.4960	.4961	.4962	.4963	.4964
2.7	.4965	.4966	.4967	.4968	.4969	.4970	.4971	.4972	.4973	.4974
2.8	.4974	.4975	.4976	.4977	.4977	.4978	.4979	.4979	.4980	.4981
2.9	.4981	.4982	.4982	.4983	.4984	.4984	.4985	.4985	.4986	.4986
3.0	.4987	.4987	.4987	.4988	.4988	.4989	.4989	.4989	.4990	.4990

Source: Abridged from Table 1 of A. Hald, *Statistical Tables and Formulas* (New York: Wiley), 1952. Reproduced by permission of A. Hald and the publisher, John Wiley & Sons, Inc.

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-w^2/2} dw \quad \longleftrightarrow$$



Conjugate Priors

Prior $h(\Theta)$	Likelihood $g(\mathbf{x} \Theta)$	Posterior $f(\Theta \mathbf{x})$
$B(\alpha, \beta):$ $\frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1}$	<i>Binomial:</i> $\binom{n}{x} p^x (1-p)^{n-x}$	$B(\alpha + x, \beta + n - x)$
$\Gamma(\alpha, \beta):$ $\frac{\theta^{\alpha-1} e^{-\theta/\beta}}{\Gamma(\alpha)\beta^\alpha}$ if $\theta \geq 0$	<i>Poisson:</i> $\frac{e^{-\theta} \theta^x}{x!}$	$\Gamma\left(\alpha + x, \frac{\beta}{n\beta + 1}\right)$
$N(\mu, \tau^2):$ $\frac{\text{Exp}\left(-\frac{(\theta - \mu)^2}{2\tau^2}\right)}{\tau\sqrt{2\pi}}$	$N(\theta, \sigma^2):$ $\frac{\text{Exp}\left(-\frac{(x - \theta)^2}{2\sigma^2}\right)}{\sigma\sqrt{2\pi}}$	$N\left(\frac{\sigma^2\mu + \tau^2}{\sigma^2 + \tau^2}, \frac{\sigma^2\tau^2}{\sigma^2 + \tau^2}\right)$