Probability Review: Univariate Random Variables

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Univariate Random Variables

Defnition: A random variable (rv) X is a variable that can take on a given set of values, called the sample space S_X, where the likelihood of the values in S_X is determined by the variable's probability distribution function (pdf).

Examples

- $X =$ price of microsoft stock next month. $S_X = \{\mathbb{R} : 0 < X \leq M\}$
- $X =$ simple return on a one month investment. $S_X = \{\mathbb{R} : -1 \leq X < M\}$
- $X = 1$ if stock price goes up; $X = 0$ if stock price goes down. $S_X = \{0, 1\}$

Discrete Random Variables

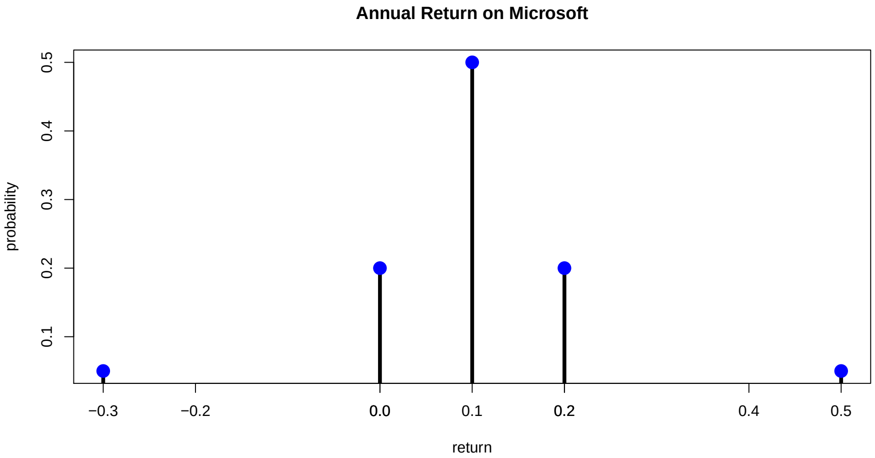
- A discrete rv X is one that can take on a finite number of n different values $x_1, \cdots, x_n$
- The pdf of a discrete rv X, $p(x)$, is a function such that $p(x) = \Pr(X = x)$. The pdf must satisfy
- $p(x) \geqslant 0$ for all $x \in S_X$; $p(x) = 0$ for all $x \notin S_X$
- $\sum_{x \in S_X} p(x) = 1$
- $p(x) \leqslant 1$ for all $x \in S_X$

Example: Probability Distribution for Annual Return on Microsoft

Table 1: Discrete distribution for annual return on Microsoft Stock

state.of.economy	returns	prob
Depression	-0.3	0.05
Recession	0.0	0.20
Normal	0.1	0.50
Mild.boom	0.2	0.20
Major.boom	0.5	0.05

Example: Probability Distribution for Annual Return on Microsoft



Example: Bernouli Distribution

- Consider two mutually exclusive events generically called "success" and "failure".
- $X = 1$ if success occurs and $X = 0$ if failure occurs.
- $\Pr(X = 1) = \pi$, where $0 < \pi < 1$, is the probability of success.
- $\Pr(X = 0) = 1 - \pi$ is the probability of failure.
- A mathematical model describing the distribution of X is

$$p(x) = \Pr(X = x) = \pi^x(1 - \pi)^{1-x},\ x = 0, 1.$$

- When $x = 0$, $p(0) = \pi^0(1 - \pi)^{1-0} = 1 - \pi$ and when $x = 1, p(1) = \pi^1(1 - \pi)^{1-1} = \pi$.

Continuous Random Variables

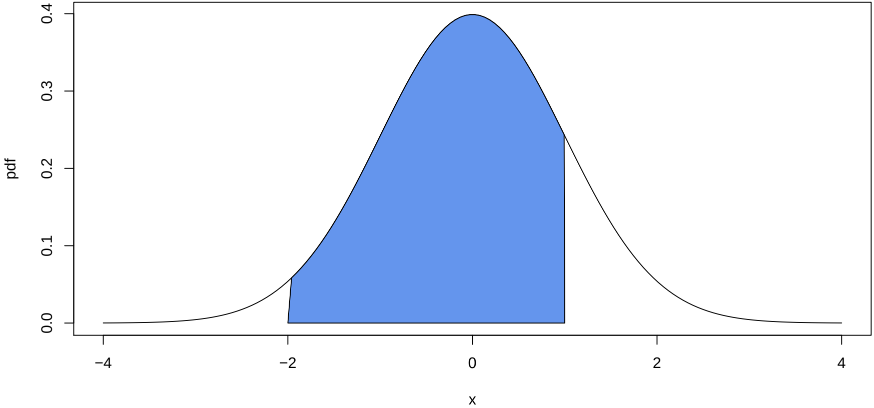
- A continuous rv X is one that can take on any real value
- The pdf of a continuous rv X is a nonnegative function $f(x)$ such that for any interval A on the real line

$$\Pr(X \in A) = \int_A f(x)dx$$

- $\Pr(X \in A) =$ "Area under probability curve over the interval A".
- The pdf $f(x)$ must satisfy $f(x) \geqslant 0$; $\int_{-\infty}^{\infty} f(x)dx = 1$

Probability Curve for Continuous Random Variable

$$Pr(-2 \leq X \leq 1)$$



Example: Uniform Distribution Over $[a, b]$

Let $X \sim U[a, b]$, where "$\sim$" means "is distributed as". Then

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

Properties:

$f(x) \geq 0$, provided $b > a$, and

$$\begin{aligned} \int_{-\infty}^{\infty} f(x)dx &= \int_{a}^{b} \frac{1}{b-a} dx = \frac{1}{b-a} \int_{a}^{b} dx \\ &= \frac{1}{b-a} [x]_{a}^{b} = \frac{b-a}{b-a} = 1 \end{aligned}$$

The Cumulative Distribution Function (CDF)

The CDF, F, of a rv X is $F(x) = \Pr(X \leq x)$.

The Cumulative Distribution Function (CDF)

The CDF has the following properties:

- If $x_1 < x_2$, then $F(x_1) \leq F(x_2)$
- $F(-\infty) = 0$ and $F(\infty) = 1$
- $\Pr(X \geq x) = 1 - F(x)$
- $\Pr(x_1 < X \leq x_2) = F(x_2) - F(x_1)$
- $\frac{d}{dx}F(x) = f(x)$ if X is a continuous rv.

Example: Uniform distribution over $[0,1]$

$$X \backsim U[0,1]$$

$$f(x) = \begin{cases} \frac{1}{1-0} = 1 & \text{for } 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Then

$$F(x) = \Pr(X \leq x) = \int_0^x dz = [z]_0^x = x$$

and, for example,

$$\begin{aligned} \Pr(0 \leq X \leq 0.5) &= F(0.5) - F(0) \\ &= 0.5 - 0 = 0.5 \end{aligned}$$

Example: Uniform distribution over $[0, 1]$

Note:

$$\frac{d}{dx}F(x) = \frac{d}{dx}x = 1 = f(x)$$

Remark:

For a continuous rv

$$\Pr(X \leq x) = \Pr(X < x)$$
$$\Pr(X = x) = 0$$

Quantiles of a Distribution

- X is a rv with continuous CDF $F_X(x) = \Pr(X \leq x)$
- The $\alpha * 100\%$ quantile of F_X for $\alpha \in [0,1]$ is the value q_α such that

$$F_X(q_\alpha) = \Pr(X \leq q_\alpha) = \alpha$$

- The area under the probability curve to the left of q_α is α.
- If the inverse CDF F_X^{-1} exists then

$$q_\alpha = F_X^{-1}(\alpha)$$

is the **quantile** function.

Common Quantiles

$$
\begin{aligned}
1\% \text{ quantile} &= q_{.01} \\
5\% \text{ quantile} &= q_{.05} \\
50\% \text{ quantile} &= q_{.5} = \text{ median} \\
95\% \text{ quantile} &= q_{.95} \\
99\% \text{ quantile} &= q_{.99}
\end{aligned}
$$

Example: Quantile function of uniform distn on [0,1]

$$
\begin{aligned}
F_X(x) = x &\Rightarrow q_\alpha = \alpha \\
q_{.01} &= 0.01 \\
q_{.5} &= 0.5 \\
q_{.99} &= 0.99
\end{aligned}
$$

The Standard Normal Distribution

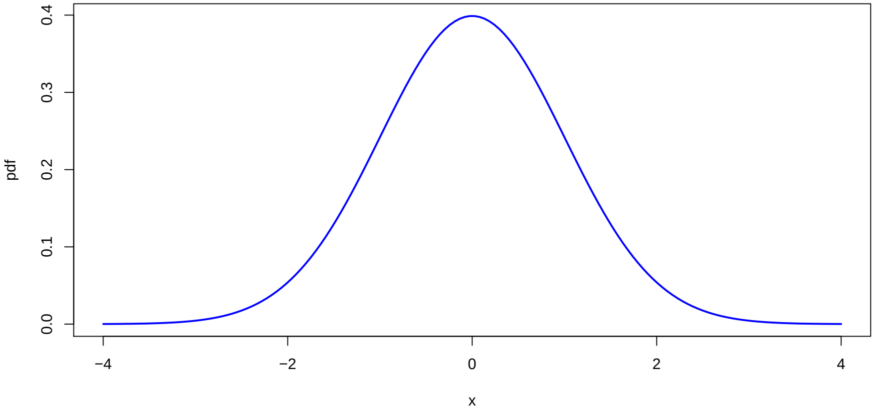
Let X be a rv such that $X \sim N(0,1)$. Then

$$f(x) = \phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x^2\right), \quad -\infty \leq x \leq \infty$$

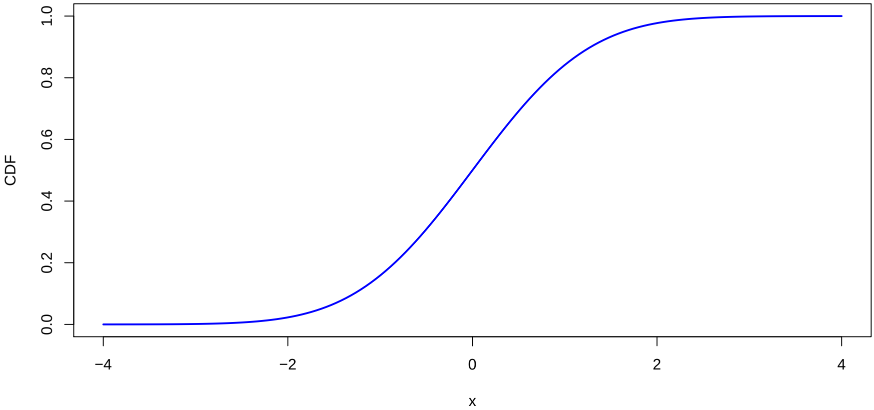
$$\Phi(x) = \Pr(X \leq x) = \int_{-\infty}^{x} \phi(z)dz$$

$$\Phi^{-1}(\alpha) = q_\alpha$$

The Standard Normal Distribution



The Standard Normal Distribution



Finding Areas under the Normal Curve

- $\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = 1$, via change of variables formula in calculus
- $\Pr(a < X < b) = \int_a^b \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = \Phi(b) - \Phi(a)$, cannot be computed analytically!
- Special numerical algorithms are used to calculate $\Phi(z)$ and $\Phi^{-1}(\alpha)$

Shape Characteristics of Standard Normal

- Centered at zero
- Symmetric about zero (same shape to left and right of zero)

$$
\begin{aligned}
\Pr(-1 \leq x \leq 1) &= \Phi(1) - \Phi(-1) \approx 0.67 \\
\Pr(-2 \leq x \leq 2) &= \Phi(2) - \Phi(-2) \approx 0.95 \\
\Pr(-3 \leq x \leq 3) &= \Phi(3) - \Phi(-3) \approx 0.99
\end{aligned}
$$

R functions

- `pnorm` computes $\Pr(X \leq z) = \Phi(z)$
- `qnorm` computes the quantile $z_\alpha = \Phi^{-1}(\alpha)$
- `dnorm` computes the density $\phi(z)$
- `rnorm` computes simulated values of Z

Some Tricks for Computing Area under Normal Curve

- $N(0,1)$ is symmeric about 0
- total area under probability curve $= 1$

$$\Pr(X \leq z) = 1 - \Pr(X \geq z)$$
$$\Pr(X \geq z) = \Pr(X \leq -z)$$
$$\Pr(X \geq 0) = \Pr(X \leq 0) = 0.5$$

Examples

- Compute $\Pr(-1 \leq X \leq 2) = \Pr(X \leq 2) - \Pr(X \leq -1)$ using the R function `pnorm()`:

```
pnorm(2) - pnorm(-1)
```

```
## [1] 0.8185946
```

- Compute 1%, 2.5%, 5% quantiles using the R function `qnorm()`:

```
qnorm(c(0.01, 0.025, 0.05))
```

```
## [1] -2.326348 -1.959964 -1.644854
```

Shape Characteristics of pdfs

- Expected Value or Mean - Center of Mass
- Variance and Standard Deviation - Spread about mean
- Skewness - Symmetry about mean
- Kurtosis - Tail thickness

Expected Value

Discrete rv:

$$E[X] = \mu_X = \sum_{x \in S_X} x \cdot p(x)$$
$$= \sum_{x \in S_X} x \cdot \Pr(X = x)$$

$E[X]$ = probability weighted average of possible values of X

Continuous rv:

$$E[X] = \mu_X = \int_{-\infty}^{\infty} x \cdot f(x) dx$$

Note: In continuous case, $\sum_{x \in S_X}$ becomes $\int_{-\infty}^{\infty}$

Example: Expected Value for Discrete Random Variable

state.of.economy	returns	prob
Depression	-0.3	0.05
Recession	0.0	0.20
Normal	0.1	0.50
Mild.boom	0.2	0.20
Major.boom	0.5	0.05

$$
\begin{aligned}
E[X] &= (-0.3)\cdot(0.05) + (0.0)\cdot(0.20) + (0.1)\cdot(0.5) \\
&\quad + (0.2)\cdot(0.2) + (0.5)\cdot(0.05) \\
&= 0.10.
\end{aligned}
$$

Example: Expected value for Continuous Random Variable

Let $X \sim U[1,2]$. Then

$$E[X] = \int_1^2 x dx = \left[\frac{x^2}{2}\right]_1^2$$
$$= \frac{1}{2}[4-1] = \frac{3}{2}$$

Let $X \sim N(0,1)$. Then

$$\mu_X = E[X] = \int_{-\infty}^{\infty} x \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = 0$$

Expectation of a Function of X

Definition: Let $g(X)$ be some function of the rv X. Then

$$E[g(X)] = \sum_{x \in S_X} g(x) \cdot p(x) \text{ Discrete case}$$
$$E[g(X)] = \int_{-\infty}^{\infty} g(x) \cdot f(x) dx \text{ Continuous case}$$

Variance and Standard Deviation

$$
\begin{aligned}
g(X) &= (X - E[X])^2 = (X - \mu_X)^2 \\
\mathrm{Var}(X) &= \sigma_X^2 = E[(X - \mu_X)^2] = E[X^2] - \mu_X^2 \\
\mathrm{SD}(X) &= \sigma_X = \sqrt{\mathrm{Var}(X)}
\end{aligned}
$$

Note: $\mathrm{Var}(X)$ is in squared units of X, and $\mathrm{SD}(X)$ is in the same units as X. Therefore, $\mathrm{SD}(X)$ is easier to interpret.

Computation of Var and SD

$$\begin{aligned}
\sigma_X^2 &= E[(X-\mu_X)^2] \\
&= \sum_{x \in S_X} (x-\mu_X)^2 \cdot p(x) \text{ if } X \text{ is a discrete rv} \\
&= \int_{-\infty}^{\infty} (x-\mu_X)^2 \cdot f(x)dx \text{ if } X \text{ is a continuous rv} \\
\sigma_X &= \sqrt{\sigma_X^2}
\end{aligned}$$

Remark: For "bell-shaped" data, σ_X measures the size of the typical deviation from the mean value μ_X.

Example: Variance and standard deviation for a discrete random variable

Using the discrete distribution for the return on Microsoft stock in Table 1 and the result that $\mu_X = 0.1$, we have

$$\begin{aligned}
\mathrm{Var}(X) &= (-0.3-0.1)^2 \cdot (0.05) + (0.0-0.1)^2 \cdot (0.20) \\
&\quad + (0.1-0.1)^2 \cdot (0.5) + (0.2-0.1)^2 \cdot (0.2) \\
&\quad + (0.5-0.1)^2 \cdot (0.05) \\
&= 0.020 \\
\mathrm{SD}(X) &= \sigma_X = \sqrt{0.020} = 0.141.
\end{aligned}$$

Given that the distribution is fairly bell-shaped we can say that typical values deviate from the mean value of 0.10 by about 0.141

$$\mu \pm \sigma = 0.10 \pm 0.141 = [-0.041,\ 0.241]$$

Example: Var and SD for Standard Normal

Let $X \sim N(0,1)$. Then

$$
\begin{aligned}
\mu_X &= \int_{-\infty}^{\infty} x \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = 0 \\
\sigma_X^2 &= \int_{-\infty}^{\infty} (x-0)^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = 1 \\
\sigma_X &= \sqrt{1} = 1 \\
&\Rightarrow \text{ size of typical deviation from } \mu_X = 0 \text{ is } \sigma_X = 1
\end{aligned}
$$

The General Normal Distribution

Let $X \sim N(\mu_X,\ \sigma_X^2)$. Then

$$
\begin{aligned}
f(x) &= \frac{1}{\sqrt{2\pi\sigma_X^2}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2\right),\ -\infty \leq x \leq \infty \\
E[X] &= \mu_X = \text{ mean value} \\
\mathrm{Var}(X) &= \sigma_X^2 = \text{ variance} \\
\mathrm{SD}(X) &= \sigma_X = \text{ standard deviation}
\end{aligned}
$$

Shape Characteristics of General Normal Distribution

- Centered at μ_X
- Symmetric about μ_X

$$
\begin{aligned}
\Pr(\mu_X - \sigma_X \leq X \leq \mu_X + \sigma_X) &= 0.67 \\
\Pr(\mu_X - 2 \cdot \sigma_X \leq X \leq \mu_X + 2 \cdot \sigma_X) &= 0.95 \\
\Pr(\mu_X - 3 \cdot \sigma_X \leq X \leq \mu_X + 3 \cdot \sigma_X) &= 0.99
\end{aligned}
$$

- Quantiles of the general normal distribution:

$$
q_\alpha = \mu_X + \sigma_X \cdot \Phi^{-1}(\alpha) = \mu_X + \sigma_X \cdot z_\alpha
$$

Remarks

- $X \sim N(0,1)$: Standard Normal $\Longrightarrow \mu_X = 0$ and $\sigma_X^2 = 1$
- The pdf of the general normal is completely determined by values of μ_X and σ_X^2

R Runctions again

- simulate data: `rnorm(n, mean, sd)`
- compute CDF: `pnorm(q, mean, sd)`
- compute quantiles: `qnorm(p, mean, sd)`
- compute density: `dnorm(x, mean, sd)`
- Default values of `mean` and `sd` are 0 and 1, respectively

Standard Deviation as a Measure of Risk

$$
\begin{aligned}
R_A &= \text{monthly return on asset A} \\
R_B &= \text{monthly return on asset B} \\
R_A &\sim N(\mu_A, \sigma_A^2), R_B \sim N(\mu_B, \sigma_B^2) \\
\mu_A &= E[R_A] = \text{ expected monthly return on asset A} \\
\sigma_A &= \mathrm{SD}(R_A) \\
&= \text{ std. deviation of monthly return on asset A}
\end{aligned}
$$

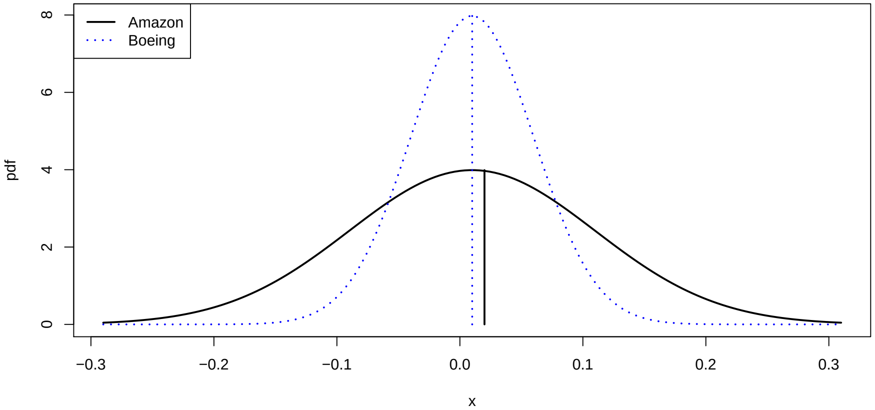
Typically, if

$$\mu_A > \mu_B$$

then

$$\sigma_A > \sigma_B$$

Standard Deviation as a Measure of Risk



Why the normal distribution may not be appropriate for simple returns

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \text{simple return}$$

$$\text{Assume } R_t \sim N(0.05, (0.50)^2)$$

Note: $P_t \geq 0 \implies R_t \geq -1$. However, based on the assumed normal distribution the probability of a return smaller than -1 is:

```
pnorm(-1, 0.05, 0.50)
```

```
## [1] 0.01786442
```

Why the normal distribution may not be appropriate for simple returns

- In this example, because $\sigma = 0.5$ is so large there is a 1.8% probability of a return smaller than -1 (or a price less than 0).
- Assuming a normal distribution can give nonsensical results in certain situations. This is why the normal distribution may not be appropriate for simple returns which cannot take values less than -100%

The normal distribution is more appropriate for cc returns

$$
\begin{aligned}
r_t &= \ln(1 + R_t) = \text{cc return} \\
R_t &= e^{r_t} - 1 = \text{ simple return} \\
\text{Assume } r_t &\sim N(0.05, (0.50)^2)
\end{aligned}
$$

Unlike R_t, r_t can take on values less than -1. For example,

$$
\begin{aligned}
r_t = -2 &\implies R_t = e^{-2} - 1 = -0.865 \\
\Pr(r_t < -2) &= \Pr(R_t < -0.865) = 0.00002
\end{aligned}
$$

The log-normal distribution

$$
\begin{aligned}
X &\sim N(\mu_X, \sigma_X^2), \;\; -\infty < X < \infty \\
Y &= \exp(X) \sim \text{lognormal}(\mu_X, \sigma_X^2), \; 0 < Y < \infty \\
E[Y] &= \mu_Y = \exp(\mu_X + \sigma_X^2/2) \\
\mathrm{Var}(Y) &= \sigma_Y^2 = \exp(2\mu_X + \sigma_X^2)(\exp(\sigma_X^2) - 1)
\end{aligned}
$$

Example: log-normal distribution for simple returns

$$r_t \sim N(0.05, (0.50)^2), \;\; r_t = \ln(1 + R_t)$$

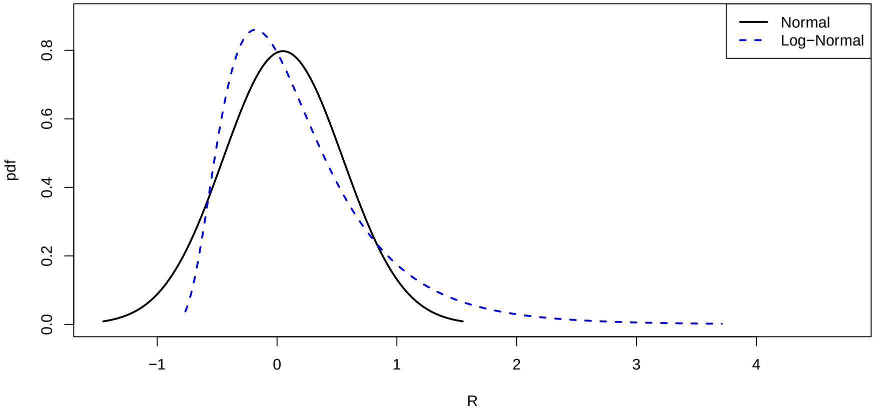
$$\exp(r_t) = 1 + R_t \sim \text{lognormal}(0.05, (0.50)^2)$$

$$\mu_{1+R} = \exp(0.05 + (0.5)^2/2) = 1.191$$

$$\sigma^2_{1+R} = \exp(2(0.05) + (0.5)^2)(\exp(0.5^2) - 1) = 0.563$$

Note: $R_t = \text{lognormal} - 1 = \text{shifted lognormal}, -1 \leq R_t \leq \infty$

Example: log-normal distribution for simple returns



R Runctions

- simulate data: `rlnorm(n, mean, sd)`
- compute CDF: `plnorm(q, mean, sd)`
- compute quantiles: `qlnorm(p, mean, sd)`
- compute density: `dlnorm(y, mean, sd)`

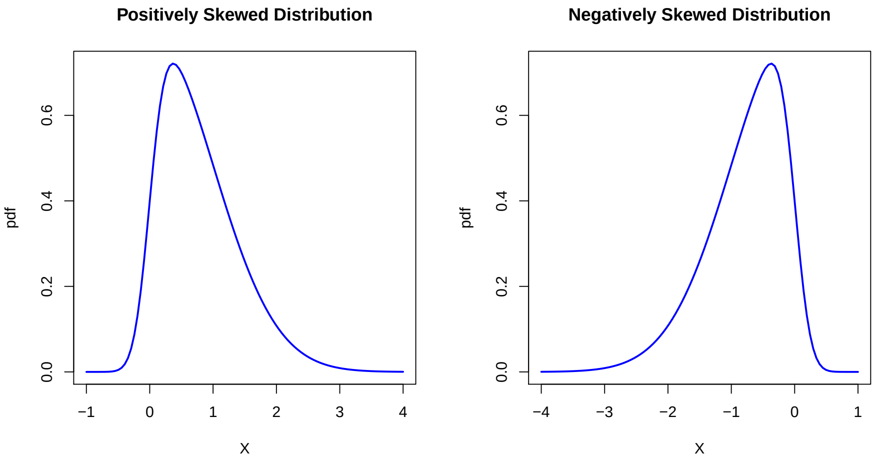
Skewness - Measure of symmetry

$$
\begin{aligned}
g(X) &= ((X - \mu_X)/\sigma_X)^3 \\
\mathrm{Skew}(X) &= E\left[\left(\frac{X - \mu_X}{\sigma_X}\right)^3\right] \\
&= \sum_{x \in S_X} \left(\frac{x - \mu_X}{\sigma_X}\right)^3 p(x) \text{ if } X \text{ is discrete} \\
&= \int_{-\infty}^{\infty} \left(\frac{x - \mu_X}{\sigma_X}\right)^3 f(x)dx \text{ if } X \text{ is continuous}
\end{aligned}
$$

Intuition

- If X has a symmetric distribution about μ_X then $\mathrm{Skew}(X) = 0$
- $\mathrm{Skew}(X) > 0 \Longrightarrow$ pdf has long right tail, and median $<$ mean
- $\mathrm{Skew}(X) < 0 \Longrightarrow$ pdf has long left tail, and median $>$ mean

Illustration of Skewed Distributions



Example: Skewness for Discrete Distribution

Using the discrete distribution for the return on Microsoft stock in Table 1, and the results that $\mu_X = 0.1$ and $\sigma_X = 0.141$, we have

$$\begin{aligned}\mathrm{skew}(X) &= [(-0.3 - 0.1)^3 \cdot (0.05) + (0.0 - 0.1)^3 \cdot (0.20) \\ &+ (0.1 - 0.1)^3 \cdot (0.5) + (0.2 - 0.1)^3 \cdot (0.2) \\ &+ (0.5 - 0.1)^3 \cdot (0.05)]/(0.141)^3 \\ &= 0.0\end{aligned}$$

Example: Skewness for a Normal Distribution

Let $X \sim N(\mu_X, \sigma_X^2)$. Then

$$\mathrm{Skew}(X) = \int_{-\infty}^{\infty} \left(\frac{x - \mu_X}{\sigma_X} \right)^3 \frac{1}{\sqrt{2\pi\sigma_X^2}} \exp\left(^{-\frac{1}{2}(\frac{x-\mu_X}{\sigma_X})^2} \right) dx = 0$$

Example: Skewness for a LogNormal Distribution

$Y \backsim \text{lognormal}(\mu_X, \sigma_X^2)$. Then

$$\text{Skew}(Y) = \left(\exp(\sigma_X^2) + 2\right)\sqrt{\exp(\sigma_X^2) - 1} > 0$$

Kurtosis - Measure of tail thickness

$$
\begin{aligned}
g(X) &= ((X-\mu_X)/\sigma_X)^4 \\
\mathrm{Kurt}(X) &= E\left[\left(\frac{X-\mu_X}{\sigma_X}\right)^4\right] \\
&= \sum_{x\in S_X}\left(\frac{x-\mu_X}{\sigma_X}\right)^4 p(x) \text{ if } X \text{ is discrete} \\
&= \int_{-\infty}^{\infty}\left(\frac{x-\mu_X}{\sigma_X}\right)^4 f(x)dx \text{ if } X \text{ is continuous}
\end{aligned}
$$

Intuition

- Values of x far from μ_X get blown up resulting in large values of kurtosis
- Two extreme cases: fat tails (large kurtosis); thin tails (small kurtosis)

Example: Kurtosis for a Discrete Random Variable

Using the discrete distribution for the return on Microsoft stock in Table 1, and the results that $\mu_X = 0.1$ and $\sigma_X = 0.141$, we have

$$
\begin{aligned}
\mathrm{Kurt}(X) &= [(-0.3 - 0.1)^4 \cdot (0.05) + (0.0 - 0.1)^4 \cdot (0.20) \\
&+ (0.1 - 0.1)^4 \cdot (0.5) + (0.2 - 0.1)^4 \cdot (0.2) \\
&+ (0.5 - 0.1)^4 \cdot (0.05)]/(0.141)^4 \\
&= 6.5
\end{aligned}
$$

Example: Kurtosis for a Normal Random Variable

Let $X \sim N(\mu_X, \sigma_X^2)$. Then

$$\mathrm{Kurt}(X) = \int_{-\infty}^{\infty} \left(\frac{x - \mu_X}{\sigma_X} \right)^4 \frac{1}{\sqrt{2\pi\sigma_X^2}} e^{-\frac{1}{2}\left(\frac{x-\mu_X}{\sigma_X}\right)^2} dx = 3$$

Excess Kurtosis

Definition: Excess kurtosis $= \mathrm{Kurt}(X) - 3 =$ kurtosis value in excess of kurtosis of normal distribution.

- Excess kurtosis $(X) > 0 \Rightarrow X$ has fatter tails than normal distribution
- Excess kurtosis $(X) < 0 \Rightarrow X$ has thinner tails than normal distribution

The Student's-t Distribution

A distribution similar to the standard normal distribution but with fatter tails, and hence larger kurtosis, is the Student's t distribution. If X has a Student's t distribution with degrees of freedom parameter v, denoted $X \sim t_v$, then its pdf has the form

$$f(x) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)}\left(1+\frac{x^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, \quad -\infty < x < \infty, \ v > 0.$$

where $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$ denotes the gamma function.

The Student's-t Distribution

It can be shown that

$$
\begin{aligned}
E[X] &= 0, \;\; v > 1 \\
\mathrm{var}(X) &= \frac{v}{v-2}, \;\; v > 2, \\
\mathrm{skew}(X) &= 0, \;\; v > 3, \\
\mathrm{kurt}(X) &= \frac{6}{v-4} + 3, \;\; v > 4.
\end{aligned}
$$

- The parameter v controls the scale and tail thickness of distribution.
- If v is close to four, then the kurtosis is large and the tails are thick.
- If $v < 4$, then $\mathrm{kurt}(X) = \infty$.
- As $v \to \infty$ the Student's t pdf approaches that of a standard normal random variable and $\mathrm{kurt}(X)$ approaches 3.

R Runctions

- simulate data: `rt(n, df)`
- compute CDF: `pt(q, df)`
- compute quantiles: `qt(p, df)`
- compute density: `dt(x, df)`

Here `df` is the degrees of freedom parameter v

Linear Functions of a Random Variable

Let X be a discrete or continuous rv with $\mu_X = E[X]$, and $\sigma_X^2 = \mathrm{Var}(X)$. Define a new rv Y to be a linear function of X :

$$Y = g(X) = a \cdot X + b$$
$$a \text{ and } b \text{ are known constants}$$

Then

$$\begin{aligned}
\mu_Y &= E[Y] = E[a \cdot X + b] \\
&= a \cdot E[X] + b = a \cdot \mu_X + b \\
\sigma_Y^2 &= \mathrm{Var}(Y) = \mathrm{Var}(a \cdot X + b) \\
&= a^2 \cdot \mathrm{Var}(X) \\
&= a^2 \cdot \sigma_X^2
\end{aligned}$$

Linear Function of a Normal rv

Let $X \sim N(\mu_X, \sigma_X^2)$ and define $Y = a \cdot X + b$. Then

$$Y \sim N(\mu_Y, \sigma_Y^2)$$

with

$$\begin{aligned} \mu_Y &= a \cdot \mu_X + b \\ \sigma_Y^2 &= a^2 \cdot \sigma_X^2 \end{aligned}$$

Remarks

- Proof of result relies on change-of-variables formula for determining pdf of a function of a rv
- Result may or may not hold for random variables whose distributions are not normal

Example - Standardizing a Normal rv

Let $X \sim N(\mu_X, \sigma_X^2)$. The standardized rv Z is created using

$$
\begin{aligned}
Z &= \frac{X - \mu_X}{\sigma_X} = \frac{1}{\sigma_X} \cdot X - \frac{\mu_X}{\sigma_X} \\
&= a \cdot X + b \\
a &= \frac{1}{\sigma_X}, \;\; b = -\frac{\mu_X}{\sigma_X}
\end{aligned}
$$

Example - Standardizing a Normal rv

Properties of Z

$$
\begin{aligned}
E[Z] &= \frac{1}{\sigma_X} E[X] - \frac{\mu_X}{\sigma_X} \\
&= \frac{1}{\sigma_X} \cdot \mu_X - \frac{\mu_X}{\sigma_X} = 0 \\
\mathrm{Var}(Z) &= \left(\frac{1}{\sigma_X}\right)^2 \cdot \mathrm{Var}(X) \\
&= \left(\frac{1}{\sigma_X}\right)^2 \cdot \sigma_X^2 = 1 \\
Z &\sim N(0,1)
\end{aligned}
$$

Example: Linear Function of a Random Variable

Consider a $W_0 = \$10,000$ investment in Microsoft for 1 month. Assume

$$R = \text{simple monthly return on Microsoft}$$
$$R \sim N(0.05, (0.10)^2), \;\; \mu_R = 0.05, \;\; \sigma_R = 0.10$$

Q: What is the probability distribution of end of month wealth, $W_1 = \$10,000 \cdot (1 + R)$?

Example: Linear Function of a Random Variable

$W_1 = \$10,000 \cdot (1 + R)$ is a linear function of R, and R is a normally distributed rv. Therefore, W_1 is normally distributed with

$$
\begin{aligned}
E[W_1] &= \$10,000 \cdot (1 + E[R]) \\
&= \$10,000 \cdot (1 + 0.05) = \$10,500, \\
\mathrm{Var}(W_1) &= (\$10,000)^2 \mathrm{Var}(R) \\
&= (\$10,000)^2 (0.1)^2 = 1,000,000 \\
W_1 &\sim N(\$10,500, (\$1,000)^2)
\end{aligned}
$$

Value-at-Risk: Introduction

Consider a $W_0 = \$10,000$ investment in Microsoft for 1 month. Assume

$$R = \text{simple monthly return on Microsoft}$$
$$R \sim N(0.05, (0.10)^2),\ \mu_R = 0.05,\ \sigma_R = 0.10$$

Q: How much we can lose with 5% probability?

Value-at-Risk: Introduction

Use $R \sim N(0.05, (0.10)^2)$ and solve for the 5% quantile:

$$\Pr(R < q^R_{.05}) = 0.05 \Rightarrow q^R_{.05} = \Phi^{-1}(0.05)$$
$$q^R_{.05} = \text{qnorm}(0.05,\ 0.05,\ 0.10) = -0.114.$$

If $R = -11.4\%$ the loss in investment value is at least

$$\begin{aligned} \$10,000 \cdot (-0.114) &= -\$1,144 \\ &= 5\% \text{ VaR} \end{aligned}$$

Hence, the 5% Value-at-Risk (VaR) is \$1,144

Value-at-Risk: Introduction

In general, the $\alpha \times 100\%$ Value-at-Risk (VaR_α) for an initial investment of $\$W_0$ is computed as

$$\mathrm{VaR}_\alpha = \$W_0 \times q_\alpha^R$$
$$q_\alpha^R = \alpha \times 100\% \text{ quantile of simple return distn}$$

If $R \sim N(\mu_R, \sigma_R^2)$ then $q_\alpha^R = \mu_R + \sigma_R q_\alpha^Z$, $q_\alpha^Z = \alpha \times 100\%$ quantile of $Z \sim N(0,1)$

and

$$\mathrm{VaR}_\alpha = \$W_0 \times \left(\mu_R + \sigma_R q_\alpha^Z \right)$$

Value-at-Risk: Introduction

For example, let $W_0 = \$10,000$, $\mu_R = 0.05$, and $\sigma_R = 0.10$. Then for $\alpha = 0.05, q^Z_{0.05} = -1.645$ and

$$\mathrm{VaR}_\alpha = \$10,000 \times (0.05 + 0.10 \times (-1.645)) = -1,144$$

Note: Because VaR represents a loss, it is often reported as a positive number. For example, $-\$1,144$ represents a loss of $\$1,144$. So the VaR is reported as $\$1,144$.

VaR for Continuously Compounded Returns

$$r = \ln(1 + R), \text{ cc monthly return}$$
$$R = e^r - 1, \text{ simple monthly return}$$

Assume

$$r \sim N(\mu_r, \sigma_r^2)$$
$$W_0 = \text{initial investment}$$

VaR for Continuously Compounded Returns

The distribution of R is log-normal so the $\alpha-$quantile of the distribution of R is not $\mu_r + \sigma_r q_\alpha^Z$. That is,

$$q_\alpha^R \neq \mu_r + \sigma_r q_\alpha^Z$$

Q: What is q_α^R?

VaR for Continuously Compounded Returns

Result: Let X be a rv with CDF $F(X)$ with $\alpha-$ quantile q_{α}^{X}. If $Y = g(X)$ is a monotonic function of X then the $\alpha-$ quantile of Y is

$$q_{\alpha}^{Y} = g(q_{\alpha}^{X})$$

That is, quantiles are preserved under monotonic transformations of a rv.

VaR for Continuously Compounded Returns

- Compute α quantile of Normal Distribution for r:

$$q_{\alpha}^{r} = \mu_{r} + \sigma_{r} z_{\alpha}$$

- Convert α quantile for r into α quantile for R (quantiles are preserved under monotonic transformations):

$$q_{\alpha}^{R} = e^{q_{\alpha}^{r}} - 1$$

- Compute $100 \cdot \alpha\%$ VaR using q_{α}^{R}:

$$\mathrm{VaR}_{\alpha} = \$W_0 \cdot q_{\alpha}^{R}$$

Example: Compute 5% VaR assuming

$$r_t \sim N(0.05, (0.10)^2), W_0 = \$10,000$$

The 5% cc return quantile is

$$\begin{aligned} q^r_{.05} &= \mu_r + \sigma_r z_{.05} \\ &= 0.05 + (0.10)(-1.645) = -0.114 \end{aligned}$$

The 5% simple return quantile is

$$q^R_{.05} = e^{q^r_{.05}} - 1 = e^{-.114} - 1 = -0.108$$

The 5% VaR based on a $10,000 initial investment is

$$\mathrm{VaR}_{.05} = \$10,000 \cdot (-0.108) = -\$1,080$$