

Basics

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$
$$\mu = E(W) = E(a + bX) = a + bE(X)$$
$$\sigma^2 = Var(X) = E[X^2] - \mu_x^2$$
$$\sigma^2 = \sum_{all\ i} \frac{(x_i - \bar{x})^2}{n - 1}$$
$$\sigma = StdDev(X) = \sqrt{\sigma^2}$$
$$Var(X + c) = Var(X)$$
$$Var(cX) = c^2 Var(X)$$
$$Var(X + Y) \neq Var(X) + Var(Y)$$

Chebyshev's Rule:

$$1 - \left(\frac{1}{k^2}\right)$$

yields the % of data that falls with *k* std deviations.

Covariance and Correlation

Covariance gives direction.  
Correlation gives direction and strength.  
Both are *linear*.

$$Cor = \frac{Cov}{\sigma_x \cdot \sigma_y}$$

Return on Portfolio

$$Avgreturn = w_1 \bar{r}_1 + (1 - w_1) \bar{r}_2$$
$$r_{12} = \frac{\sigma_{12}}{\sigma_1 \sigma_2}$$
$$\sigma^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1 w_2 \sigma_1 \sigma_2 \cdot Correlation$$
$$Stockreturn = \alpha + \beta \cdot Indexreturn$$

Probabilities

0 ≤ All probabilities ≤ 1  
*Mutually exclusive and Exhaustive*

$$P(\bar{A}) = 1 - P(A)$$
$$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$
$$P(A|B) = \frac{P(A \text{ and } B)}{P(B)}$$

Joint vs. Marginal probabilities

Independent if  $P(A|B) = P(A)$   
For Independent only:  $P(E \text{ and } F) = P(E) \cdot P(F)$

	B	$\bar{B}$
A	$P(A \text{ and } B) = P(B)P(A B)$	$P(A \text{ and } \bar{B}) = P(\bar{B})P(A \bar{B})$
$\bar{A}$	$P(\bar{A} \text{ and } B) = P(\bar{A})P(B \bar{A})$	$P(\bar{A} \text{ and } \bar{B}) = P(\bar{A})P(\bar{B} \bar{A})$

Random Variables

$$P(X \leq x) \rightarrow CDF$$
$$E(cX) = c \cdot E(X)$$
$$E(X + c) = E(X) + c$$
$$E(X + Y) = E(X) + E(Y)$$

Discrete Probability Distributions

$$\mu_x = E(X) = \sum_{all\ x_i} x_i P(X = x_i)$$
$$\sigma_x^2 = Var(X) = \sum_{all\ x_i} (x_i - \mu_x)^2 P(X = x_i)$$
$$= E[X^2] - (\mu_x)^2$$

	Chebyshev Any Prob	Empirical Normal
$P(\mu - \sigma < x < \mu + \sigma)$	≥ 0	68%
$P(\mu - 2\sigma < x < \mu + 2\sigma)$	≥ 75%	95%
$P(\mu - 3\sigma < x < \mu + 3\sigma)$	≥ 89%	100%

$$W = a + bX$$
$$\mu_W = E(W) = E(a + bX)$$
$$= a + bE(X)$$
$$= a + b\mu_x$$
$$Var(W) = Var(a + bX)$$
$$= b^2 \sigma_x^2$$

Binomial Distribution

- *n* independent trials
- binary result
- same probability of success
- total number of successes

$$X \sim B(n, p)$$
$$\binom{n}{x} = \frac{n!}{x!(n-x)!}$$
$$P(X = x) = \frac{n!}{x!(n-x)!} p^x q^{(n-x)}$$
$$\mu_x = E(X) = n \cdot p$$
$$\sigma^2 = Var(X) = n \cdot p \cdot q = n \cdot p \cdot (1 - p)$$

Shape of distribution depends on *p, n*.  
Small *p*, left skewed. Large *p*, right skewed

all success	$p^n$
all failure	$(1 - p)^n$
at least one failure	$1 - p^n$
at least one success	$1 - (1 - p)^n$

Joint Distribution

$$P_{x,y} = P(X = x \text{ and } Y = y)$$

Independent if **for all values**:  
 $P_{x,y}(X = x \text{ and } Y = y) = P_X(x)P_Y(y)$   
Conditional Distribution:  
 $P_{X|Y}(X = x|Y = y) = \frac{P_{X,Y}(x,y)}{P_Y(y)}$   
Conditional Expectation:  
 $E(X|Y = y) = \sum_{all\ x} x \cdot P(X = x|Y = y)$   
Covariance:

$$\sigma_{XY} = \sum_{i=1}^N [x_i - E(X)][y_i - E(Y)]P(x_i, y_i)$$
$$Cov(X, Y) = E(XY) - E(X)E(Y)$$

Correlation:

$$\rho = \frac{\sigma_{X,Y}}{\sigma_X \sigma_Y}$$

If X and Y are **independent**:

$$E(X + Y) = E(X) + E(Y)$$
$$Var(X + Y) = Var(X) + Var(Y)$$
$$Cov(X, Y) = 0 \text{ because } E(XY) = E(X)E(Y)$$

If X and Y are **not independent**:

$$E(X + Y) = E(X) + E(Y)$$
$$Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y)$$

Most general combination of random variables:

$$E((a + bX) + (c + dY)) = a + bE(X) + c + dE(Y)$$
$$Var((a + bX) + (c + dY)) = b^2 Var(X) + d^2 Var(Y) + 2bdCov(X, Y)$$

## Continuous Probability Distribution

$P(X = x) = 0$  because it is always possible to be more precise.  
Probability of an interval:  $P(a \leq X \leq b) = F_x(b) - F_x(a)$

## Uniform Distribution

$$E(X) = \frac{(a+b)}{2}$$
$$Var(X) = \frac{(b-a)^2}{12}$$

$y$  axis should be a fraction to make area = 1

## Normal Distribution

$$X \sim \mathcal{N}(\mu, \sigma^2)$$
$$Z = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$$
$$P(a \leq X \leq b) = P[(a - \mu) \leq (X - \mu) \leq (b - \mu)]$$
$$= P\left[\frac{(a - \mu)}{\sigma} \leq \frac{(X - \mu)}{\sigma} \leq \frac{(b - \mu)}{\sigma}\right]$$
$$= P\left[\frac{(a - \mu)}{\sigma} \leq Z \leq \frac{(b - \mu)}{\sigma}\right]$$

Checking Normality:

- mean and median close
- $IQR \sim 1.33\sigma$
- $range \sim 6\sigma$
- skewness = 0
- expected distributions (see table)