

3 Random Walks

Random Walks are used to model stock price movements.

S_0 = initial value

$S_1, S_2, \dots, S_t, \dots$

Random values,

Basic Random Walk :

$$S_t = Z_1 + Z_2 + \dots + Z_t$$

where Z_i 's are i.i.d.s,

in particular, $E[Z_i] = E[Z_j]$

$$\text{Var}(z_i) = \text{Var}(z_j)$$

$$\text{Corr}(z_i, z_j) = 0, \quad \text{in particular,}$$

$$E[z_i z_j] = E[z_i] E[z_j] \text{ if}$$

$i \neq j$.

Toy Example:

$$z_i = \begin{cases} 1 & p = \frac{1}{2} \\ -1 & p = \frac{1}{2} \end{cases}$$



$$\text{IF } S_t = z_1 + \dots + z_t$$

$$\begin{aligned} E[S_t] &= E[z_1] + \dots + E[z_t] \\ &= t E[z_i]. \end{aligned}$$

$$\text{Var}(S_t)$$

$$= E[(z_1 + \dots + z_t - t E[z_i])^2]$$

$$= E[((z_1 - E[z_i]) + \dots + (z_t - E[z_i]))^2]$$

$$= \sum_{i=1}^t E[(z_i - E[z_i])^2] + \sum_{i \neq j} E[(z_i - E[z_i])(z_j - E[z_j])]$$

$$= \sum_{i=1}^t \text{Var}(z_i)$$

$$= t \text{Var}(z_i).$$

$$z_i - E[z_i] + z_j - E[z_j]$$

if $i \neq j$ these uncorrelated

if y_1, y_2 uncorrelated

$$E[y_1 y_2] = E[y_1] E[y_2]$$

$$E[(z_i - E[z_i])(z_j - E[z_j])]$$

$\stackrel{?}{=}$

$$= E[(z_i - E[z_i])] E[(z_j - E[z_j])]$$

$$= 0 \times 0 = 0.$$

Normal Generalized Random Walks

$$S_t = \gamma_1 + \gamma_2 + \dots + \gamma_t$$

$$\gamma_i = \mu + \sigma \varepsilon_i .$$

where μ, σ constants

$\varepsilon_i \sim N(0, 1)$ standard normal distribution.

γ_i = Normal distribution
with mean μ and
std. deviation σ .

$$E[S_t] = t\mu$$

$$\text{Var}(S_t) = t\sigma^2$$

Autoregressive and Moving Averages Random Walks

- Autoregressive \sim Reversion to Mean property.



$$S_t = \gamma_1 + \gamma_2 + \dots + \gamma_t$$

$$\gamma_i = C_0 + C_1 \gamma_{i-1} + \dots + \overset{C_p \gamma_{i-p}}{\cancel{\gamma_p}} + \sigma \varepsilon_i$$

- $p = \#$ of lags.

- If $p=0$, we are back to a normal random walk.

- $P = \# \text{ of lags.}$

- Typically want $|c_1| + \dots + |c_p| < 1$

- Assume a stationary condition:

$$E[\gamma_i] = E[\gamma_j] \quad \forall i, j$$

$$\text{Var}(\gamma_i) = \text{Var}(\gamma_j).$$

- $Z_i = \text{standard normal distribution}$

Closer look at AR(1) Random walk:

$$S_t = \gamma_1 + \dots + \gamma_t$$

$$\gamma_i = c_0 + c_1 \gamma_{i-1} + \sigma Z_i$$

Find $E[\gamma_i]$:

$$E[\gamma_i] = c_0 + c_1 E[\gamma_{i-1}] + \sigma \cancel{E[Z_i]}$$

$$\cancel{E[Z_i]} = 0$$

$$E[r_i](1-c_1) = c_0$$

OR

$$E[r_i] = \frac{c_0}{1-c_1} = \overset{\circ}{\mu}$$

Rewrite $r_i = \mu + (\text{Extra stuff})$

$$r_i - \mu = \underline{c_0} + c_1 r_{i-1} + \sigma z_i - \frac{c_0}{1-c_1}$$

$$= \frac{c_0(1-c_1) - c_0}{1-c_1} + c_1 r_{i-1} + \sigma z_i$$

$$= \frac{-c_0 c_1}{1-c_1} + \underline{c_1 r_{i-1}} + \sigma z_i$$

$$= c_1(r_{i-1} - \mu) + \sigma z_i$$

$$\underline{r_i} = \underline{\mu} + \underline{c_1(r_{i-1} - \mu)} + \underline{\sigma z_i}.$$

Use.

$$\underline{\text{Var}(r_i)}$$

$$= E[(r_i - \mu)^2]$$

$$= E[(c_1(r_{i-1} - \mu) + \sigma z_i)^2]$$

↑ ↗

Uncorrelated

$$= E[(c_1(r_{i-1} - \mu))^2] + E[(\sigma z_i)^2]$$

$$= c_1^2 E[(r_{i-1} - \mu)^2] + \sigma^2 E[z_i^2]$$

$$= c_1^2 \text{Var}(r_{i-1}) + \sigma^2$$

$$= c_1^2 \text{Var}(r_i) + \sigma^2$$

$$\text{Var}(r_i)(1-c_i^2) = \sigma^2$$

$$\boxed{\text{Var}(r_i) = \frac{\sigma^2}{1-c_i^2}}.$$

$$E[S_t] = E[r_1 + \dots + r_t]$$

$$= t\mu.$$

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

$$= E[(r_1 + \dots + r_t - t\mu)^2]$$

$$= E[((r_1-\mu) + (r_2-\mu) + \dots + (r_t-\mu))^2]$$

Algebra Magic

$$= \frac{\sigma^2}{1-c^2} \left[t + 2 \sum_{i=1}^{t-1} (t-i)c_i^2 \right]$$

$$r_i = \frac{1}{2} - \frac{1}{2}(r_{i-1} - \frac{1}{2}) + \sigma z_i.$$

Moving Average:



Moving average w/ q lags:

MA(q):

$$S_t = r_1 + r_2 + \dots + r_t.$$

Normal Random Walk: $r_i = \mu + \sigma z_i$

$$r_i = \mu + (\phi_1 z_{i-1} + \dots + \phi_q z_{i-q}) + \sigma z_i$$

Allowing the past

g volatilities to
influence r_i .

$$E[r_i] = \mu + \phi_1 E[r_{t-1}] + \dots + \phi_g E[r_{t-g}] + \sigma E[z_t]$$
$$= \mu.$$

For MA(1):

$$r_t = \mu + \phi_1 z_{t-1} + \sigma z_t.$$

$$\text{Var}(r_t) = E[(r_t - \mu)^2]$$
$$= E[(\phi_1 z_{t-1} + \sigma z_t)^2]$$

uncorrelated

$$= E[(\phi_1 z_{t-1})^2 + (\sigma z_t)^2]$$

$$= \phi_1^2 + \sigma^2.$$

$$E[\sum r_t] = t\mu.$$

$$\text{Var}(S_t) = E[(S_t - t\mu)^2]$$

$$= E[((r_1 - \mu) + (r_2 - \mu) + \dots + (r_t - \mu))^2]$$

$$= \sum_{i=1}^t E[(r_i - \mu)^2] + \sum_{i \neq j} E[(r_i - \mu)(r_j - \mu)]$$

★ $r_i = \mu + \phi_1 z_{i-1} + \sigma z_i$

$r_i - \mu$ and $r_j - \mu$ are uncorrelated if $|i-j| \geq 2$

$$\downarrow$$

$$= t(\phi^2 + \cancel{\mu^2}) + 2 \sum_{1 \leq i \leq t-1} E[(r_i - \mu)(r_{i+1} - \mu)]$$

$$E[(r_i - \mu)(r_{i+1} - \mu)]$$

$$= E[(\phi_1 z_{i-1} + \sigma \varepsilon_i)(\phi_1 z_i + \sigma \varepsilon_{i+1})]$$

$$= E[\sigma \phi_1 z_i^2] = \sigma \phi_1^2.$$

$$\downarrow$$

$$= t(\phi_1^2 + \mu^2) + 2(t-1)\sigma \phi_1$$

$$= (t-1)(\phi_1 + \sigma)^2 + \phi_1^2 + \sigma^2.$$

$ARMA(p,q) = \text{Combine } AR(p) + AR(q)$

$$s_t = \gamma_0 + \dots + \gamma_t$$

AR piece

$$\begin{aligned} \gamma_i &= (\gamma_0 + \gamma_1 \hat{s}_{i-1} + \dots + \gamma_p \hat{s}_{i-p}) \underbrace{\text{AR piece}}_{\text{no}} \\ &\quad + (\phi_1 z_{i-1} + \dots + \phi_q z_{i-q}) \\ &\quad + \underbrace{\sigma z_i}_{\text{Stated noise.}} \end{aligned}$$