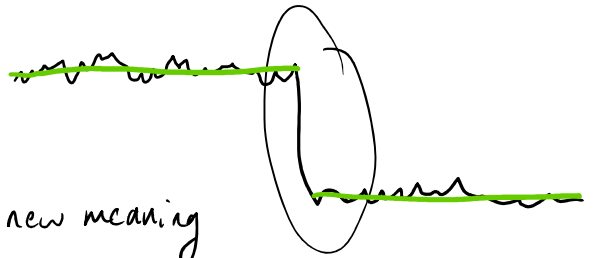


model nonstationary processes

- unit roots / random walks
- structural breaks →

random walks & unit roots

→ trend & intercept take on new meaning



$$p_t = \log(P_t) \quad a_t \sim \text{white noise}$$

$$p_t = p_{t-1} + a_t$$

$$(1 - \phi_1 L) p_t = a_t \quad \phi_1 = 1$$

repeated substitution

$$p_t = p_{t-2} + a_{t-1} + a_t$$

$$p_t = p_{t-3} + a_{t-2} + a_{t-1} + a_t$$

↖ ↗ ↘
permanent past shocks

$$= a_t + a_{t-1} + a_{t-2} + a_{t-3} + \dots$$

$$\text{Var}(p_t) = \text{Var}(a_t + a_{t-1} + a_{t-2} + \dots)$$

$$= \sigma_a^2 + \sigma_a^2 + \sigma_a^2 + \dots \rightarrow \infty$$

Forecast → random walk not mean revert

$$\begin{aligned} \hat{p}_h(1) &= E(p_{h+1} | p_h, p_{h-1}, p_{h-2}, \dots) = E(p_h | p_h) + E(a_{h+1} | p_h) \\ &= p_h + 0 \end{aligned}$$

$$\text{b/c } p_{h+1} = p_h + a_{h+1}$$

$$\hat{p}_h(z) = p_h$$

$$\text{recall } p_{h+2} = p_h + a_{h+1} + a_{h+2}$$

$$e_h(l) = a_{h+1} + a_{h+2} + \dots + a_{h+l}$$

$$\text{Var}(e_h(l)) = \text{Var}(a_{h+1} + a_{h+2} + \dots + a_{h+l}) = l\sigma_a^2$$

forecast error variance is growing with ~~time~~
forecast horizon

Random walk with drift (not trend)

$$p_t = \mu + p_{t-1} + a_t$$

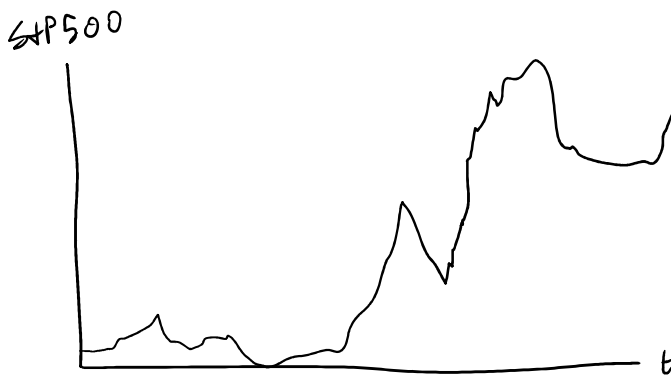
↑
average growth/decline rate of log price

$$p_t - p_{t-1} = r_t = \mu + a_t$$

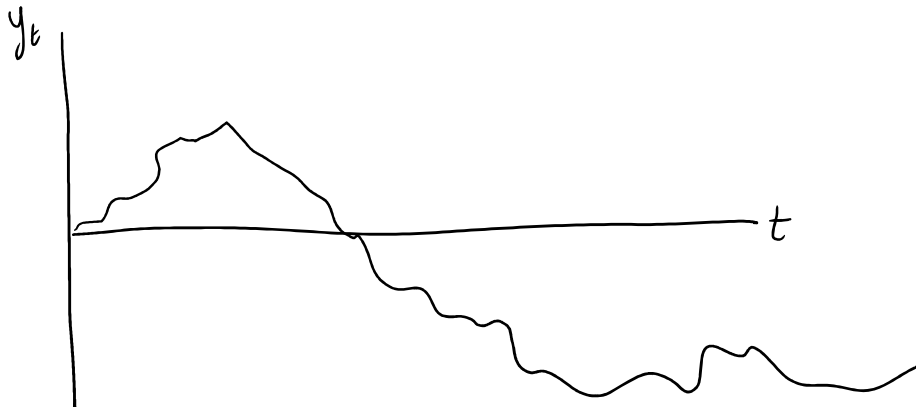
repeated substitution

$$p_t = \mu + (\mu + p_{t-2} + a_{t-1}) + a_t$$

$$\begin{aligned} p_t &= \mu + \mu + (\mu + p_{t-3} + a_{t-2}) + a_{t-1} + a_t \\ &= \underbrace{t\mu}_{\text{drift}} + p_0 + (a_1 + a_2 + \dots + a_t) \end{aligned}$$



sometimes hard to tell w/ eyeball test



Recap: MA(q) stationary: intercept = mean

AR(p) stationary
or ARMA(p,q): intercept proportional to mean

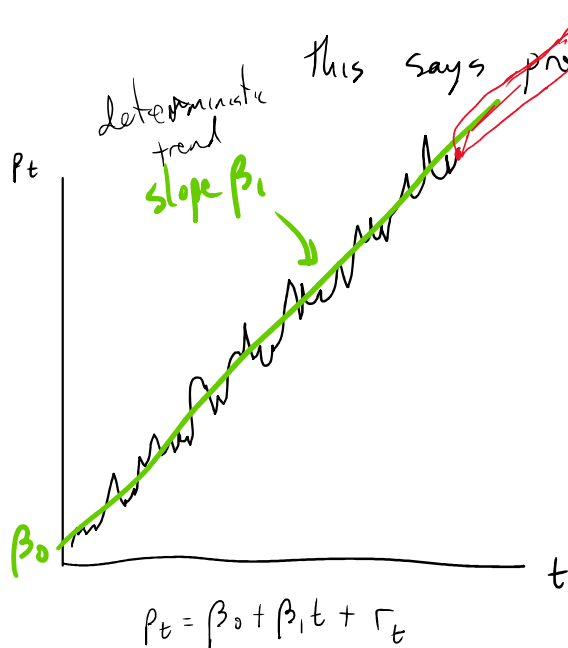
Random walk: intercept is average drift rate (growth or decline)

Alternative model for growth/shrinking over time:

$$p_t = \beta_0 + \beta_1 t + r_t \quad \text{where } r_t \text{ is stationary}$$

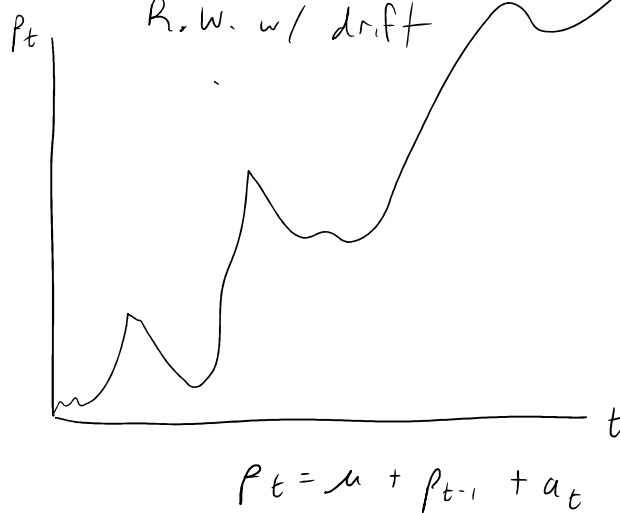
How to distinguish R.W. w/ drift from stationary around a deterministic trend

$$\begin{aligned} \text{Var}(p_t) &= \text{Var}(\underbrace{\beta_0 + \beta_1 t}_{\text{not random}} + r_t) \\ &= \text{Var}(r_t) = \text{constant} \quad (r_t \text{ stationary}) \end{aligned}$$



this says progress is deterministic \rightarrow stationary around $\beta_0 + \beta_1 t$

R.W. w/ drift



Unit root testing

- want a reasonable description of the data under the null hypothesis and the alternative hypothesis

Consider: a possible R.W. without drift

Case 1 (in R: type="none")

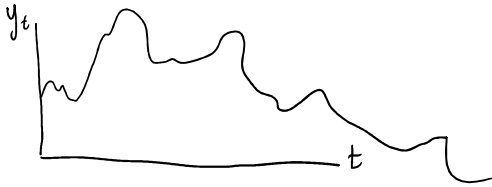
Case 2: (in R: type="drift")

$$y_t = \rho y_{t-1} + \varepsilon_t$$

$$H_0: |\rho| = 1$$

$$H_a: |\rho| < 1$$

Null:



Alternative:



$$y_t = \phi_0 + \rho y_{t-1} + \varepsilon_t$$

$$H_0: \phi_0 = 0, |\rho| = 1 \quad \text{unit root with no drift}$$

$$H_a: \phi_0 \neq 0, |\rho| < 1 \quad \text{stationary process w/ potentially non zero mean}$$

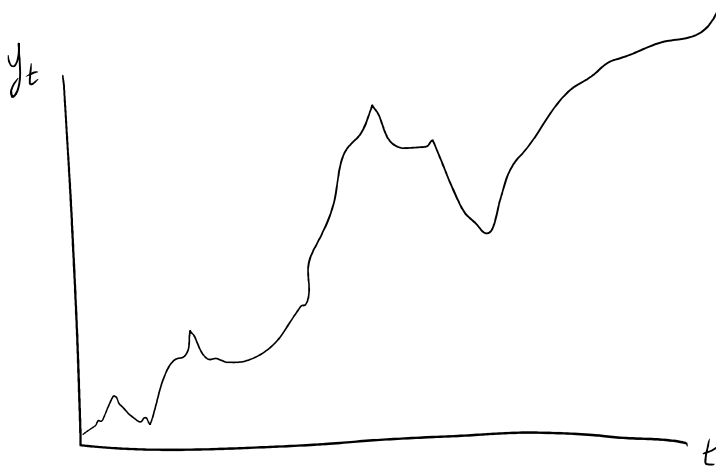
Default in stats packages:

Case 1

Don't use that!

Use Case 2 if the data appears not to trend or drift!!!

- Possible Random Walk with drift



Case 3

$$y_t = \phi_0 + \rho y_{t-1} + \varepsilon_t$$

$$H_0: |\rho| = 1$$

$$H_a: |\rho| < 1$$

$$\text{Impose: } \phi_0 \neq 0$$

Case 4

$$y_t = \phi_0 + \rho y_{t-1} + \beta t + \varepsilon_t$$

$$H_0: \phi_0 > 0, |\rho| = 1, \beta = 0$$

$$H_a: \phi_0 \neq 0, |\rho| < 1, \beta > 0$$

R: type="trend"

Use Case 4 if your eyes
correct drift/trend

Use Case 4 it your eyes
suspect drift/trend

Case 2: we think no drift

$$y_t = \phi_0 + \rho y_{t-1} + \varepsilon_t$$

Rewrite

$$y_t - y_{t-1} = \Delta y_t = \phi_0 + \underbrace{(\rho - 1)}_{\substack{\text{test whether} \\ \text{this is zero}}} y_{t-1} + \varepsilon_t$$

In R:

$$\Delta y_t = \phi_0 + \underbrace{\rho}_{\substack{\text{redefine}}} y_{t-1} + \varepsilon_t$$

Case 4: we suspect drift or trend:

$$y_t = \phi_0 + \rho y_{t-1} + \beta t + \varepsilon_t$$

Rewrite

$$\Delta y_t = \phi_0 + \underbrace{(\rho - 1)}_{\substack{\text{testing} \\ \text{whether} \\ \text{this is zero}}} y_{t-1} + \beta t + \varepsilon_t$$

"Dickey Fuller test"

Augmented Dickey Fuller (ADF)

→ add lags to capture $AR(p)$

→ find AR lag order that minimizes AIC/BIC and eliminates residual autocorrelations

$$\Delta y_t = \phi_0 + \rho y_{t-1} + \beta t + \underbrace{\phi_1 \Delta y_{t-1} + \phi_2 \Delta y_{t-2} + \dots + \phi_p \Delta y_{t-p}}_{\substack{\text{stationary regressors under} \\ \text{the null hypothesis}}} + \varepsilon_t$$

↑
nonstationary
under the null
↑
if Case 4

Covariate - Augmented Dickey Fuller (CADF)

$$\Delta y_t = \phi_0 + \rho y_{t-1} + \beta t + \phi_1 \Delta y_{t-1} + \phi_2 \Delta y_{t-2} + \alpha_1 x_{1t} + \alpha_2 x_{2t} + \varepsilon_t$$

Distribution of ρ across samples

"Nonstandard distribution"

