

homework 1

question 1

$$X_t = \text{trend}_t + \text{seasonal}_t + \text{noise}_t$$

$$\text{trend}_t = 0.8t - 0.02t^2$$

$$\text{seasonal}_t = 15\sin\left(\frac{2\pi t}{12}\right) + 8\cos\left(\frac{2\pi t}{6}\right)$$

$$\text{noise}_t \sim N(0, 5^2)$$

```
In [30]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose

np.random.seed(42)
n = 120 # 10*12=120
t = np.arange(n)

trend = 0.8 * t + 0.02 * t ** 2
seasonal = 15 * np.sin(2 * np.pi * t / 12) + 8 * np.cos(2 * np.pi * t / 6)
noise = np.random.normal(0, 5, n)

time_series = trend + seasonal + noise
dates = pd.date_range(start="2014-01-01", periods=n, freq="ME")
df = pd.DataFrame({"date": dates, "value": time_series})
df.set_index("date", inplace=True)

In [31]: from statsmodels.tsa.seasonal import seasonal_decompose

# decompose the time series
decomposition = seasonal_decompose(df["value"], model="additive", period=12)

# extract the components
decomposed_trend = decomposition.trend
decomposed_seasonal = decomposition.seasonal
decomposed_resid = decomposition.resid

In [32]: fig, axes = plt.subplots(4, 1, figsize=(12, 10), sharex=True)

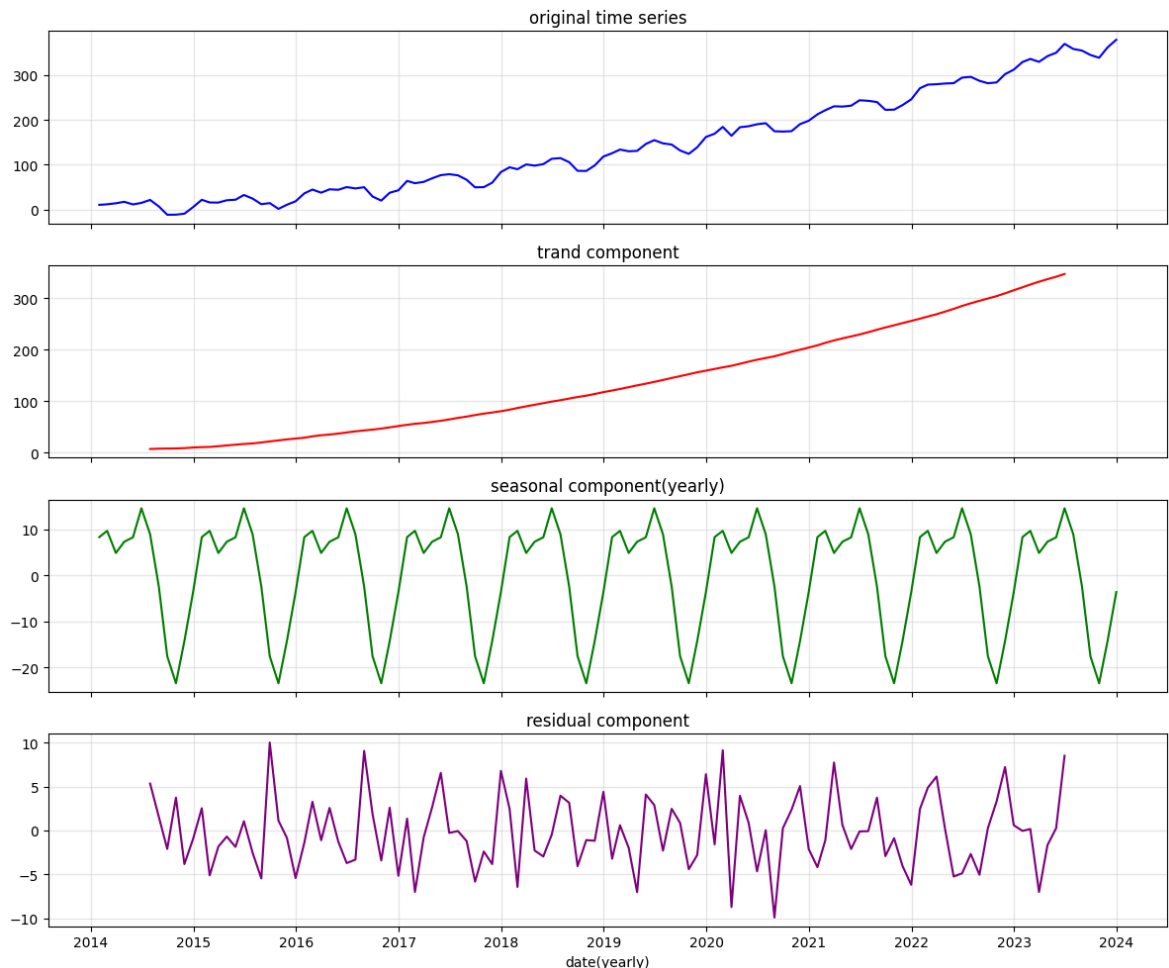
# 1. original time series
axes[0].plot(df.index, df["value"], color="blue")
axes[0].set_title("original time series")
axes[0].grid(alpha=0.3)

# 2. trend component
axes[1].plot(decomposed_trend.index, decomposed_trend, color="red")
axes[1].set_title("trend component")
axes[1].grid(alpha=0.3)

# 3. seasonal component
axes[2].plot(decomposed_seasonal.index, decomposed_seasonal, color="green")
axes[2].set_title("seasonal component(yearly)")
axes[2].grid(alpha=0.3)
```

```
# 4. residual component
axes[3].plot(decomposed_resid.index, decomposed_resid, color="purple")
axes[3].set_title("residual component")
axes[3].set_xlabel("date(yearly)")
axes[3].grid(alpha=0.3)

plt.tight_layout()
plt.show()
```



question 2

consider the time series

$$x_t = \beta_1 + \beta_2 t + \omega_t$$

β_1 and β_2 are known constants and ω_t is a white noise process with variance σ_ω^2 .

(a) determine whether x_t is stationary.

(b) show that the first-order difference of x_t ($y_t = x_t - x_{t-1}$) is stationary.

(c) show the moving average

$v_t = \frac{1}{2q+1} \sum_{j=-q}^q x_{t-j}$ is $\beta_1 + \beta_2 t$, and give a simplified expression for the autocorrelation function.

(a) No, x_t is nonstationary

$E[x_t] = E[\beta_1 + \beta_2 t + \omega_t] = E[\beta_1 + \beta_2 t] \text{ (because } E[\omega_t] = 0) = \beta_1 + \beta_2 t$
which is time-dependent, so x_t is nonstationary.

(b) $y_t = x_t - x_{t-1}$ is stationary

$$y_t = x_t - x_{t-1} = \beta_1 + \beta_2 t + \omega_t - \beta_1 - \beta_2(t-1) - \omega_{t-1} = \beta_2 + \omega_t - \omega_{t-1}$$

$$E[y_t] = E[x_t - x_{t-1}] = E[\beta_1 + \beta_2 t + \omega_t - \beta_1 - \beta_2(t-1) - \omega_{t-1}] = E[\beta_2 + \omega_t - \omega_{t-1}]$$

$$Cov(y_t, y_{t+h}) = E[(y_t - E[y_t])(y_{t+h} - E[y_{t+h}])] = E[(\omega_t - \omega_{t-1})(\omega_{t+h} - \omega_{t+h-1})]$$

when $h = 0$ the $Cov(y_t, y_{t+h}) = E[\omega_t^2] + E[\omega_{t-1}^2] = 2\sigma_\omega^2$, which is constant, so y_t is stationary.

when $h = \pm 1$, $Cov(y_t, y_{t+h}) = -E[\omega_t^2] = -\sigma_\omega^2$, which is also constant, so y_t is stationary.

when $|h| > 1$, $Cov(y_t, y_{t+h}) = 0$, which means y_t is independent of y_{t+h} , so y_t is stationary. so y_t is stationary.

$$(c) v_t = \frac{1}{2q+1} \sum_{j=-q}^q x_{t-j}$$

$$E[v_t] = E\left[\frac{1}{2q+1} \sum_{j=-q}^q x_{t-j}\right] = \frac{1}{2q+1} \sum_{j=-q}^q E[x_{t-j}] = \frac{1}{2q+1} \sum_{j=-q}^q (\beta_1 + \beta_2(t-j))$$

$$Cov(v_t, v_{t+h}) = E[(v_t - E[v_t])(v_{t+h} - E[v_{t+h}])] = E\left[\frac{1}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q (x_{t-j} - E[x_{t-j}]) (x_{t+h-k} - E[x_{t+h-k}])\right]$$

$$= E\left[\frac{1}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q \omega_{t-j} \omega_{t+h-k}\right]$$

$$= \frac{1}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q E[\omega_{t-j} \omega_{t+h-k}]$$

$$\text{when } k = j + h, Cov(v_t, v_{t+h}) = \frac{1}{(2q+1)^2} \sum_{j=-q}^q \sigma_\omega^2 = \frac{2q+1-|h|}{(2q+1)^2} \sigma_\omega^2$$

$$\text{when } k \neq j + h, Cov(v_t, v_{t+h}) = 0$$

consider that j and $k \in [-q, q]$

$$\text{when } |h| \leq q, Cov(v_t, v_{t+h}) = \frac{2q+1-|h|}{(2q+1)^2} \sigma_\omega^2$$

$$\text{when } |h| > q, Cov(v_t, v_{t+h}) = 0$$

question 3

let ω_t for $t = 0, \pm 1, \pm 2, \pm 3, \dots$ be a noise process, and consider the series

$$x_t = \omega_t \omega_{t-1}$$

determine the mean and autocovariance function of x_t for $t = 0, \pm 1, \pm 2, \pm 3, \dots$, and state whether it is stationary or not.

$$E[x_t] = E[\omega_t \omega_{t-1}] = E[\omega_t] E[\omega_{t-1}] = 0 \quad (t \neq t-1)$$

$$\gamma_x(h) = E[(x_t - E[x_t])(x_{t+h} - E[x_{t+h}])] = E[x_t x_{t+h}]$$

$$= E[\omega_t \omega_{t-1} \omega_{t+h} \omega_{t+h-1}]$$

$$\text{when } h = 0, \gamma_x(h) = E[\omega_t^2] E[\omega_{t-1}^2] = \sigma_\omega^4$$

$$\text{when } h = \pm 1, \gamma_x(h) = E[\omega_t \omega_{t-1}^2 \omega_{t-2}] = E[\omega_t] E[\omega_{t-1}^2] E[\omega_{t-2}] = 0$$

$$\text{when } |h| > 1,$$

$$\gamma_x(h) = E[\omega_t \omega_{t-1} \omega_{t+h} \omega_{t+h-1}] = E[\omega_t] E[\omega_{t-1}] E[\omega_{t+h}] E[\omega_{t+h-1}] = 0$$

as $E[x]$ is constant, $\gamma_x(h) = \sigma_\omega^4$ for $h = 0$ and $h = \pm 1$ and $\gamma_x(h) = 0$ for $|h| \geq 1$.

so x_t is a stationary process.

question 3

for the AR(2) model given by: $x_t = 0.9x_{t-2} + \omega_t$, find the roots of the autoregressive polynomial and sketch the ACF, and $\rho(h)$ for the AR(2) model.

$$x_t = 0.9x_{t-2} + \omega_t$$

$$\Phi(z) = 1 - \phi_1 z - \phi_2 z^2 - \phi_3 z^3 - \dots - \phi_n z^n$$

$$\Phi(z) = 1 - 0z - 0.9z^2 = 0$$

$$Z^2 = -\frac{10}{9}$$

$$Z = \sqrt{-\frac{10}{9}}$$

$$Z = \frac{\sqrt{10}}{3}i$$

$|z| \geq 1$ so it is causal

for $\text{ACF}(\rho(h))$ $\rho(h) = \phi_1 \rho(h-1) + \phi_2 \rho(h-2) (h \geq 1)$

as $\phi_1 = 0, \phi_2 = 0.9, \rho(0) = 1, \rho(-h) = \rho(h)$ when $h = 1$,

$$\rho(1) = 0 * \rho(0) + 0.9 * \rho(0) = 0$$

$$\text{when } h = 2, \rho(2) = 0 * \rho(1) + 0.9 * \rho(0) = -0.9$$

$$\text{when } h = 3, \rho(3) = 0 * \rho(2) + 0.9 * \rho(1) = 0$$

$$\text{when } h = 4, \rho(4) = 0 * \rho(3) + 0.9 * \rho(2) = 0.81$$

$$\text{when } h = 5, \rho(5) = 0 * \rho(4) + 0.9 * \rho(3) = 0$$

$$\text{when } h \text{ is odd, } \rho(h) = 0$$

when h is even, $\rho(h) = (-0.9)^{h/2}$ so Even-only non-zero lag, alternating oscillation attenuation factor $\rho(h) = (-0.9)^{h/2}$

question 4

identify the following models as ARMA(p, q) models (watch out for parameter redundancy),

and determine whether they are causal and/ or invertible.

$$(a) x_t = 0.8x_{t-1} - 0.15x_{t-2} + \omega_t - 0.3\omega_{t-1}$$

$$(b) x_t = x_{t-1} - 0.5x_{t-2} + \omega_t - \omega_{t-1}$$

for(a)

$$x_t - 0.8x_{t-1} + 0.15x_{t-2} = \omega_t - 0.3\omega_{t-1}$$

$$\Phi(z) = 1 - 0.8z + 0.15z^2 = (1 - 0.3z)(1 - 0.5z)$$

$$z = \frac{10}{3} \text{ or } z = 2$$

$$\Theta(z) = 1 - 0.3z$$

$$z = \frac{10}{3}$$

so it is ARMA(2, 1)

norm length of z root for $\Phi(z) = 0$ is larger than 1 so it is causal

norm length of z root for $\Theta(z) = 0$ is larger than 1 so it is invertible

for(b)

$$x_t - x_{t-1} + 0.5x_{t-2} = \omega_t - \omega_{t-1} \quad \Phi(z) = 1 - z + 0.15z^2$$

$$z = 1 \pm i$$

$$\Theta(z) = 1 - z$$

$$z = 1$$

so it is ARMA(2, 1)

norm length of z root for $\Phi(z) = 0$ is larger than 1 so it is causal

norm length of z root for $\Theta(z) = 0$ is 1 so it is invertible