# **Time Series Note**

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python python python plotly d3.js plotly

# 1

```
import plotly.graph_objects as go
import numpy as np
```

## 1.1 Time Series v.s. Cross Sectional

(time series) (cross sectional)

Table 1.1: Time Series v.s. Cross Sectional

Time Series	Cross Sectional		
2000/01/01 2020/01/01	2000/01/01 50		

## 1.2

2000/01/01 2020/01/01

# 1.3

- $\quad \quad \boldsymbol{U}_t, t \in \{1, \cdots, T\}$   $\quad \quad \quad \boldsymbol{U}_t$
- $U \rightarrow$
- $t \rightarrow$

 $U_t$ 

```
U_t = T_t + S_t + C_t + R_t \label{eq:ut}
```

```
 \begin{array}{ll} \bullet & T_t: & \text{(Trend component)} \\ \bullet & S_t: & \text{(Seasonal component)} \\ \bullet & C_t: & \text{(Cyclical component)} \\ \bullet & R_t: & \text{(Random component)} \\ \end{array}
```

#### 1.3.1

• Downward Trend: Television Newspaper

• No Trend: Radio

• Upward Trand: Internet

```
title = 'Main Source for News'
labels = ['Television', 'Newspaper', 'Internet', 'Radio']
colors = ['rgb(67,67,67)', 'rgb(115,115,115)', 'rgb(49,130,189)', 'rgb(189,189,189)']
mode_size = [8, 8, 12, 8]
line size = [2, 2, 4, 2]
x_data = np.vstack((np.arange(2001, 2014),)*4)
y_data = np.array([
    [74, 82, 80, 74, 73, 72, 74, 70, 70, 66, 66, 69],
    [45, 42, 50, 46, 36, 36, 34, 35, 32, 31, 31, 28],
    [13, 14, 20, 24, 20, 24, 24, 40, 35, 41, 43, 50],
    [18, 21, 18, 21, 16, 14, 13, 18, 17, 16, 19, 23],
])
fig = go.Figure()
for i in range (0, 4):
    fig.add_trace(go.Scatter(x=x_data[i], y=y_data[i], mode='lines',
        name=labels[i],
```

```
line=dict(color=colors[i], width=line_size[i]),
        connectgaps=True,
    ))
    # endpoints
    fig.add_trace(go.Scatter(
        x=[x_data[i][0], x_data[i][-1]],
        y=[y_data[i][0], y_data[i][-1]],
        mode='markers',
        marker=dict(color=colors[i], size=mode_size[i])
    ))
fig.update_layout(
    xaxis=dict(
        showline=True,
        showgrid=False,
        showticklabels=True,
        linecolor='rgb(204, 204, 204)',
        linewidth=2,
        ticks='outside',
        tickfont=dict(
            family='Arial',
            size=12,
            color='rgb(82, 82, 82)',
        ),
    ),
    yaxis=dict(
        showgrid=False,
        zeroline=False,
        showline=False,
        showticklabels=False,
    ),
    autosize=False,
    margin=dict(
        autoexpand=False,
        1=100,
        r=20,
        t=110,
    ),
    showlegend=False,
    plot_bgcolor='white'
```

```
)
annotations = []
# Adding labels
for y_trace, label, color in zip(y_data, labels, colors):
    # labeling the left side of the plot
    annotations.append(dict(xref='paper', x=0.05, y=y_trace[0],
                                  xanchor='right', yanchor='middle',
                                  text=label + ' {}%'.format(y_trace[0]),
                                  font=dict(family='Arial',
                                             size=16),
                                  showarrow=False))
    # labeling the right_side of the plot
    annotations.append(dict(xref='paper', x=0.95, y=y_trace[11],
                                  xanchor='left', yanchor='middle',
                                  text='{}%'.format(y_trace[11]),
                                  font=dict(family='Arial',
                                             size=16),
                                  showarrow=False))
# Title
annotations.append(dict(xref='paper', yref='paper', x=0.0, y=1.05,
                              xanchor='left', yanchor='bottom',
                              text='Main Source for News',
                              font=dict(family='Arial',
                                        size=30,
                                        color='rgb(37,37,37)'),
                              showarrow=False))
# Source
annotations.append(dict(xref='paper', yref='paper', x=0.5, y=-0.1,
                              xanchor='center', yanchor='top',
                              text='Source: PewResearch Center & ' +
                                    'Storytelling with data',
                              font=dict(family='Arial',
                                         size=12,
                                         color='rgb(150,150,150)'),
                              showarrow=False))
fig.update_layout(annotations=annotations)
fig.show()
```

```
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```

#### 1.3.2

```
title = 'Seasonal Effect'

x_data = np.linspace(-10, 10, 100)

y_data = np.array(
    np.sin(x_data) + np.random.normal(size=x_data.shape) * 0.25
)

fig = go.Figure()

fig.add_trace(go.Scatter(x=x_data, y=y_data, mode='lines+markers', name="sin",
    line=dict(color="blue", width=1),
    connectgaps=True,
))
fig.update_layout(title=title)
fig.show()
```

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```
title = 'Cyclical Effect'

x_data = np.linspace(-10, 10, 100)

y_data = np.array(
    np.sin(x_data)*np.exp(x_data/10) + np.random.normal(size=x_data.shape) * 0.25
)

fig = go.Figure()
```

#### 1.3.3

```
sin

title = 'Seasonal Effect'

x_data = np.linspace(-10, 10, 100)

y_data = np.array(
    np.sin(x_data) + np.random.normal(size=x_data.shape) * 1
)

fig = go.Figure()

fig.add_trace(go.Scatter(x=x_data, y=y_data, mode='lines+markers', name="sin",
    line=dict(color="blue", width=1),
    connectgaps=True,
))
fig.update_layout(title=title)
fig.show()
```

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### 1.4

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## 1.5 Stationary

### 1.5.1 Weak stationary

```
\{Z_t\}
          (second-order or covariance stationary)
  • \mu(t) = C : \mu
  \bullet \quad \gamma(t,t-k) = \gamma(0,k):
                                      (lag)
                                        \sim \mathcal{N}(0, \sigma^2 I)
                                            X_t = X_{t-1} + \epsilon
   \begin{array}{ll} \bullet & \mathbb{E}(X_t) = \mathbb{E}(X_{t-1}) \\ \bullet & \mathrm{Var}(X_t) = t\sigma^2 \end{array} 
 title = 'Seasonal Effect'
 T = 1000
 walks = []
 loc = 0
 for i in range(T):
       loc += + np.random.normal(0,1)
       walks.append(loc)
 walks = np.array(walks)
 fig = go.Figure()
 fig.add_trace(go.Scatter(x=list(range(T)), y=walks, mode='lines',
       name="sin",
       line=dict(color="blue", width=1),
       connectgaps=True,
  fig.update_layout(title=title)
 fig.show()
```

$$D_t = X_t - X_{t-1}$$

- $\mathbb{E}(D_t) = 0$
- $Var(X_t) = \sigma^2$

```
title = 'Seasonal Effect'

D = walks[1:] - walks[:-1]

fig = go.Figure()

fig.add_trace(go.Scatter(x=list(range(T-1)), y=D, mode='lines', name="sin", line=dict(color="blue", width=1), connectgaps=True,
))
fig.update_layout(title=title)
fig.show()
```

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### 1.5.2 Strict stationary

$$\begin{aligned} \{Z_t\} \\ Z_{t_1}, Z_{t_2}, \cdots, Z_{t_n} & Z_{t_1-k}, Z_{t_2-k}, \cdots, Z_{t_n-k} \end{aligned}$$

Note:

•

•

## 1.5.3 Sample AutoCorrelation Function (ACF)

\*\*\*\* \*\* ACF

$$\rho_{\ell} = \frac{\mathrm{cov}(r_t, r_{t-\ell})}{\mathrm{var}(r_t)}$$

?

- $\begin{array}{l} \bullet \quad \gamma_k = \mathrm{Cov}(r_t, r_{t-k}) = E[(r_t \mu)(r_{t-k} \mu)]: \qquad k \\ \bullet \quad \rho_0 = 1: \qquad 1 \end{array}$
- $\rho_k = \rho_{-k}$ :

 $\mu$  ( )  $\text{Lag-}\ell$ 

$$\hat{\rho}_{\ell} = \frac{\Sigma_{t=1}^{T-\ell} (r_t - \bar{r}) (r_{t+\ell} - \bar{r})}{\Sigma_{t=1}^T (r_t - \bar{r})^2}$$

- ullet  $\bar{r}:$
- T:

### 1.5.3.1

( ) T TACF

# 1.5.3.2 Python

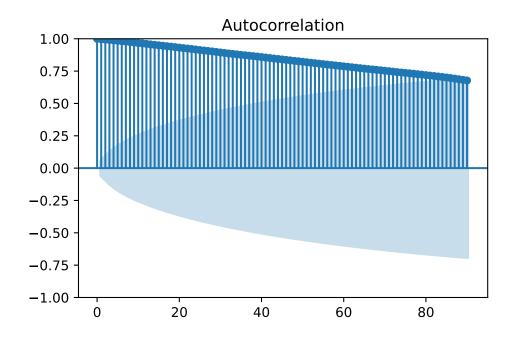
numpy.correlate numpy.correlate(a, v, mode) v filter v a ( ) numpy.correlate

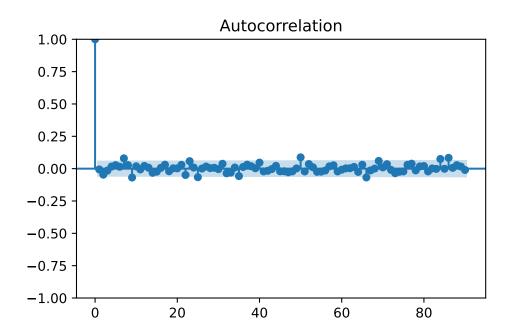
$$c_k = \sum_n a_{n+k} * \bar{v}_n$$

- $\bar{v}_n$  complex conjugation
- mode:

```
- valid: v a
                       \mathbf{a}
    - same: v
                         \mathbf{a}
    - full: v
                        a
def acf(series, lag=None):
    Calculate the autocorrelation function (ACF) for a given time series.
    Parameters:
        series (array-like): The time series data.
        lag (int, optional): The maximum lag for which to calculate the ACF.
            If None (default), the ACF is calculated for all possible lags.
    Returns:
        acf_values (array): Autocorrelation values for the given time series.
            If `lag` is provided, returns a single value representing
            autocorrelation at that lag. Otherwise, returns an array of
            autocorrelation values for all lags.
    11 11 11
    series = np.asarray(series)
    n = len(series)
    mean = np.mean(series)
    centered_data = series - mean
    # Calculate autocovariance function
    acov = np.correlate(centered_data, centered_data, mode='full')
    acf_values = acov / sum(centered_data ** 2)
    if lag is not None:
        return acf_values[(n-1):(n-1+lag)]
    else:
        return acf_values[(n-1):]
       ACF
rw_acf = acf(walks, lag=90)
title = 'ACF Random Walks'
fig = go.Figure()
fig.add_trace(go.Scatter(x=list(range(T)), y=rw_acf, mode='markers',
```

```
name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
  d_acf = acf(D, lag=90)
  title = 'ACF D'
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T-1)), y=d_acf, mode='markers',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
      python statsmodels.graphics.tsaplots.plot_acf
  from statsmodels.graphics.tsaplots import plot_acf
  import matplotlib.pyplot as plt
  import numpy as np
  import pandas as pd
  plot_acf(walks, lags=90)
  plt.show()
  plot_acf(D, lags=90)
  plt.show()
```





$$r_t = \mu + \sum_{i=0}^{\infty} \psi_i a_{t-i}$$

$$\bullet$$
  $u:r$ .

$$\bullet \quad a(t): \quad 0$$

t innovation shock

• 
$$\psi$$
:  $\psi_0 = 1$ 

$$\mathbb{E}(r_t) = \mu, \mathrm{Var}(r_t) = \sigma_a^2 \sum_{i=0}^\infty \psi_i^2$$

$$\mathrm{Var}(a_t) = \sigma_a^2 \qquad \qquad \{\psi^2\} \qquad \qquad i \to \infty \qquad \psi_i^2 \to 0$$

$$\bullet$$
  $t$   $a_{t-i}$ 

$$\rho_{\ell} = \frac{\operatorname{Cov}(r_t, r_{t-\ell})}{\operatorname{Var}(r_t)} = \frac{\gamma_{\ell}}{\gamma_0} = \frac{\sum_{i=0}^{\infty} \psi_i \, \psi_{i+\ell}}{1 + \sum_{i=1}^{\infty} \psi_i^2}, \quad \ell \ge 0$$

$$\begin{array}{ccc} r_t & \mu + \sum_{i=0}^{\infty} \psi_i a_{t-i} & i \to \infty & \psi_i \to 0 \end{array}$$

# 2.1 Auto Regressive (AR)

AR AR

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t$$

- $\bullet \ \phi_0:$
- $\phi_1$ :

$$\mathbb{E}(r_t|r_{t-1}) = \phi_0 + \phi_1 r_{t-1}, \qquad \operatorname{Var}(r_t|r_{t-1}) = \operatorname{Var}(a_t) = \sigma_a^2$$

Note:

• Markov :

## 2.1.1 AR(p)

$$AR(1)$$
  $AR(p)$ 

$$r_t = \phi_0 + \phi_1 r_{t-1} + \dots + \phi_p r_{t-p} + a_t$$

p

## 2.1.2 AR

AR ACF AR(p) ACF ?

import numpy as np
import plotly.graph\_objects as go

def acf(series, lag=None):

1 11 11

Calculate the autocorrelation function (ACF) for a given time series.

Parameters:

```
series (array-like): The time series data.
        lag (int, optional): The maximum lag for which to calculate the ACF.
            If None (default), the ACF is calculated for all possible lags.
    Returns:
        acf_values (array): Autocorrelation values for the given time series.
            If `lag` is provided, returns a single value representing
            autocorrelation at that lag. Otherwise, returns an array of
            autocorrelation values for all lags.
    11 11 11
    series = np.asarray(series)
    n = len(series)
    mean = np.mean(series)
    centered_data = series - mean
    # Calculate autocovariance function
    acov = np.correlate(centered_data, centered_data, mode='full')
    acf_values = acov / sum(centered_data ** 2)
    if lag is not None:
        return acf_values[(n-1):(n-1+lag)]
    else:
        return acf_values[(n-1):]
    ACF
                AR(1)
title = 'Random Walks'
T = 1000
walks = []
loc = 0
for i in range(T):
    loc = loc + np.random.normal(0,1)
    walks.append(loc)
walks = np.array(walks)
fig = go.Figure()
fig.add_trace(go.Scatter(x=list(range(T)), y=walks, mode='lines',
```

```
name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
Unable to display output for mime type(s): text/html
    ACF
  rw_acf = acf(walks, lag=90)
  title = 'ACF Random Walks'
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=rw_acf, mode='markers',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
             ?
                    0.3
                                r_t = 0.3 * r_{t-1} + a_t
  title = 'Random Walks (coef=0.3)'
  T = 1000
  walks = []
```

```
loc = 0
  for i in range(T):
      loc = .7 * loc + np.random.normal(0,1)
      walks.append(loc)
  walks = np.array(walks)
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=walks, mode='lines',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
  rw_acf = acf(walks, lag=90)
  title = 'ACF Random Walks (coef=0.3)'
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=rw_acf, mode='markers',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
  ACF
                                   ACF
2.1.3 AR(1)
         AR \gamma_i j
```

$$\begin{split} r_t &= \phi_0 + \phi_1 r_{t-1} + a_t \\ \mathbb{E}(r_t) &= \phi_0 + \phi_1 \mathbb{E}(r_{t-1}) \\ \mu &= \phi_0 + \phi_1 \mu \\ \mu &= \frac{\phi_0}{1 - \phi_1} \end{split}$$

$$\begin{aligned} \bullet & & \mathbb{E}(r_t) = \mathbb{E}(r_{t-1}) = \mu \\ \bullet & & \phi_0 = 0 \rightarrow E(r_t) = 0 \end{aligned}$$

• 
$$\phi_0 = 0 \rightarrow E(r_t) = 0$$

$$AR(1)$$
  $\phi_0$ 

$$\begin{split} r_t - \mu &= \phi_1 (r_{t-1} - \mu) + a_t \\ r_t - \mu &= a_t + \phi_1 a_{t-1} + \phi_1^2 a_{t-2} + \cdots \end{split}$$

$$=\sum_{i=0}^\infty \phi_1^i a_{t-i}$$

AR

## 2.1.4 AR(1)

$$\begin{split} r_t &= \phi_0 + \phi_1 r_{t-1} + a_t \\ \mathrm{Var}(r_t) &= \phi_1^2 \mathrm{Var}(r_{t-1}) + \sigma_a^2 \\ \mathrm{Var}(r_t) &= \frac{\sigma_a^2}{1 - \phi_1^2} \end{split}$$

$$\bullet \ \operatorname{Cov}(r_{t-1},a_t) = 0: \quad a$$

• 
$$\operatorname{Cov}(r_{t-1},a_t)=0: \quad a_t \qquad \qquad r_{t-1} \quad \phi_0+\phi_1 r_{t-2}+a_{t-1}$$
 •  $\phi_1^2<1:$ 

• 
$$AR(1)$$
  $|\phi_1| < 1$ 

## 2.1.5 AR(1)

$$\begin{split} \phi_\ell &= \gamma_\ell/\gamma_0 & \gamma_0 \ ( \ ) & \gamma_\ell = \mathbb{E}[(r_t-\mu)(r_{t-\ell}-\mu)] \\ \\ \gamma_\ell &= \begin{cases} \phi_1\gamma_1 + \sigma_a^2 & \text{if } \ell = 0, \\ \phi_1\gamma_{\ell-1} & \text{if } \ell > 0. \end{cases} \end{split}$$

$$\begin{array}{ll} \bullet & \gamma_0 = \mathrm{Var}(r_t) = \frac{\sigma_a^2}{1 - \phi_1^2} \\ \bullet & \gamma_\ell = \phi_1 \gamma_{\ell-1} \; (\ell > 0) \end{array}$$

$$\rho_{\ell} = \phi_1 \rho_{\ell-1} = \dots = \phi_1^{\ell} \rho_0, \quad \text{for} \quad \ell \ge 0$$

• AR(1) ACF AR(2)

#### 2.1.6 AR Order

- AIC:
- BIC: BIC

AIC BIC Partial Autocorrelation Function (PACF) PACF Κ lag-K K K 1 ? PACF

$$\begin{split} r_t &= \phi_{0,1} + \phi_{1,1} r_{t-1} + e_{1t}, \\ r_t &= \phi_{0,2} + \phi_{1,2} r_{t-1} + \phi_{2,2} r_{t-2} + e_{2t}, \\ r_t &= \phi_{0,3} + \phi_{1,3} r_{t-1} + \phi_{2,3} r_{t-2} + \phi_{3,3} r_{t-3} + e_{3t}, \\ \vdots &\vdots \end{split}$$

- $\begin{array}{ll} \bullet & \phi_{i,j} & \ \mathrm{AR}(j) & \ r_{t-i} \\ \bullet & e \end{array}$

```
• \phi_0
     \hat{\phi}_{i,j} (lag-i PACF) \hat{\phi}_{2,2}
                                                    PACF OLS, Yule-Walker, Burg"s
                            r_{t-2} AR(1)
method, Levinson-Durbin
                            python
  # source https://www.jianshu.com/p/811f9ea0b52d
  import numpy as np
  from scipy.linalg import toeplitz
  def yule_walker(ts, order):
      Solve yule walker equation
      1.1.1
      x = np.array(ts) - np.mean(ts)
      n = x.shape[0]
      r = np.zeros(order+1, np.float64) # to store acf
       r[0] = x.dot(x) / n # r(0)
      for k in range(1, order+1):
           r[k] = x[:-k].dot(x[k:]) / (n - k) # r(k)
      R = toeplitz(r[:-1])
      return np.linalg.solve(R, r[1:]) # solve `Rb = r` to get `b`
  def pacf(ts, k):
       Compute partial autocorrelation coefficients for given time series unbiased
       1.1.1
      res = [1.]
       for i in range(1, k+1):
           res.append(yule_walker(ts, i)[-1])
       return np.array(res)
             lag-1
                        0
  rw_acf = pacf(walks, k=90)
```

title = 'PACF Random Walks (coef=0.3)'

fig = go.Figure()

```
fig.add_trace(go.Scatter(x=list(range(T)), y=rw_acf, mode='markers',
    name="sin",
    line=dict(color="blue", width=1),
    connectgaps=True,
))
fig.update_layout(title=title)
fig.show()
```

PACF

- $\begin{array}{lll} \bullet & \hat{\phi}_{j,j} \rightarrow \phi_p & \text{as} & T \rightarrow \infty \\ \bullet & \hat{\phi}_{\ell,\ell} \rightarrow 0 & \forall \ell > j \\ \bullet & \hat{\phi}_{\ell,\ell} & 1/T & \ell > j \end{array}$

AR(p) PACF lag-p

### 2.1.7 AR

$$AR(p) \quad AR(p)$$

$$r_t = \phi_0 + \phi_1 r_{t-1} + \dots + \phi_p r_{t-p} + a_t, \quad t = p+1, \dots, T$$

$$T-p$$
 OLS

$$\hat{r}_t = \hat{\phi}_0 + \hat{\phi}_1 r_{t-1} + \dots + \hat{\phi}_p r_{t-p}$$

$$(\quad) \hat{a}_t = r_t - \hat{r}_t$$

AR(p)Note:

#### 2.1.8 AR

forecasting

$$E\{[r_{h+\ell} - \hat{r}_h(\ell)]^2 | F_h\} \leq \min_{q} E[(r_{h+\ell} - g)^2 | F_h]$$

•  $F_h$  h h l MSE g  $AR(p) \quad l$   $r_{h+\ell} = \phi_0 + \phi_1 r_{h+\ell-1} + \cdots + \phi_p r_{h+\ell-p} + a_{h+\ell}$   $1, 2, \cdots, l-1$  AR(p) l

#### 2.1.9 AR

1. AR(3)

$$r_t = 0.01 + 0.1 * r_{t-1} - 0.1 * r_{t-3} + a_t$$

```
np.random.seed(42)

def generate_ar_data(n, mu=0, sigma=1):
    """
    Generate AR data with the specified equation.

Parameters:
    n (int): Number of data points to generate.
    mu (float): Mean of the random noise.
    sigma (float): Standard deviation of the random noise.

Returns:
    np.array: Array of AR data points.

"""

# Initialize arrays
ar_data = np.zeros(n)
epsilon = np.random.normal(mu, sigma, n)
```

```
# Generate AR data
      for t in range(3, n):
          ar_{data}[t] = 0.01 + 0.1 * ar_{data}[t-1] - 0.1 * ar_{data}[t-3] + epsilon[t]
      return ar_data
  data = generate_ar_data(500)
  title = "Simulated AR(3) data"
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=data, mode='lines',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
      ACF plot
  data_acf = acf(data, lag=10)
  title = 'ACF AR(3)'
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=data_acf, mode='markers',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
   lag-3
    PCAF plot
```

```
data_pacf = pacf(data, k=10)
  title = 'PACF AR(3)'
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=list(range(T)), y=data_pacf, mode='markers',
      name="sin",
      line=dict(color="blue", width=1),
      connectgaps=True,
  ))
  fig.update_layout(title=title)
  fig.show()
Unable to display output for mime type(s): text/html
 ACF
         lag-3
  4. AIC AR order
  from statsmodels.tsa.ar_model import AutoReg
  best = float("inf")
  best order = -1
  for order in range(1, 10):
      ar_model = AutoReg(data, lags=order).fit()
      print(f"AR({order}) AIC: ", ar_model.aic)
      if ar_model.aic < best:</pre>
          best = ar_model.aic
          best_order = order
  print("Selected best order: ", best_order)
AR(1) AIC: 1407.3539983067183
AR(2) AIC: 1407.2913499349963
AR(3) AIC: 1402.828223161296
AR(4) AIC: 1398.1094017600367
AR(5) AIC: 1397.0403557874909
AR(6) AIC: 1396.8567941625547
AR(7) AIC: 1393.7280505207527
AR(8) AIC: 1389.2987596911696
AR(9) AIC: 1389.2034251860591
Selected best order: 9
```

## 5. AIC order fit data

ar\_model = AutoReg(data, lags=best\_order).fit()
print(ar\_model.summary())

#### AutoReg Model Results

AUTOREG MODEL RESULTS											
	onditional 1, 04 Mar 2 13:05	(9) Log MLE S.D. 024 AIC :59 BIC 9 HQIC	Likelihood of innovati		500 -683.602 0.974 1389.203 1435.364 1407.331						
coef	std err	z	P> z	[0.025	0.975]						
0.0117 0.0928 0.0003 -0.0903 -0.0882 0.0406 0.0287 -0.0319 -0.0871 -0.0058	0.044 0.045 0.045 0.045 0.045 0.045 0.045 0.045 0.045	0.267 2.053 0.007 -2.003 -1.947 0.894 0.635 -0.708 -1.929 -0.127 Roots	0.790 0.040 0.994 0.045 0.052 0.372 0.526 0.479 0.054 0.899	-0.075 0.004 -0.088 -0.179 -0.177 -0.048 -0.060 -0.120 -0.176 -0.094	0.098 0.181 0.089 -0.002 0.001 0.130 0.117 0.057 0.001 0.083						
======== Real	 Im	aginary	 Modu	======= lus	Frequency						
1.2163 1.2163 0.5383 0.5383 -1.3244 -1.3244 -0.6288 -0.6288	+ - + - + -	0.5437j 1.1338j 1.1338j 0.5728j 0.5728j 1.2763j 1.2763j	1.3 1.2 1.2 1.4 1.4 1.4	323 551 551 430 430 228 228	-0.0669 0.0669 -0.1794 0.1794 -0.4350 0.4350 -0.3229 0.3229 -0.5000						
	Coef  Coef  0.0117 0.0928 0.0003 -0.0903 -0.0882 0.0406 0.0287 -0.0319 -0.0871 -0.0058  Real  1.2163 1.2163 0.5383 0.5383 -1.3244 -1.3244 -0.6288	e:  AutoReg Conditional Mon, 04 Mar 2 13:05  coef std err  0.0117 0.044 0.0928 0.045 0.0003 0.045 -0.0903 0.045 -0.0882 0.045 0.0406 0.045 0.0287 0.045 -0.0319 0.045 -0.0871 0.045 -0.0871 0.045 -0.0871 0.045 -0.0058 0.045  Real Im  1.2163 - Real Im  1.2163 + 1.216	e: y No. AutoReg(9) Log Conditional MLE S.D. Mon, 04 Mar 2024 AIC 13:05:59 BIC 9 HQIC 500  coef std err z  0.0117 0.044 0.267 0.0928 0.045 2.053 0.0003 0.045 0.007 -0.0903 0.045 -2.003 -0.0882 0.045 -1.947 0.0406 0.045 0.894 0.0287 0.045 0.635 -0.0319 0.045 -0.708 -0.0871 0.045 -1.929 -0.0058 0.045 -0.127 Roots  Real Imaginary  1.2163 -0.5437j 1.2163 +0.5437j 0.5383 -1.1338j 0.5383 -1.1338j 0.5383 -1.1338j -1.3244 -0.5728j -1.3244 -0.5728j -1.3244 +0.5728j -0.6288 -1.2763j -0.6288 -1.2763j	e: y No. Observations	e: y No. Observations: AutoReg(9) Log Likelihood Conditional MLE S.D. of innovations Mon, 04 Mar 2024 AIC 13:05:59 BIC 9 HQIC 500  coef std err z P> z  [0.025  0.0117 0.044 0.267 0.790 -0.075 0.0928 0.045 2.053 0.040 0.004 0.0003 0.045 0.007 0.994 -0.088 -0.0903 0.045 -2.003 0.045 -0.179 -0.0882 0.045 -1.947 0.052 -0.177 0.0406 0.045 0.894 0.372 -0.048 0.0287 0.045 0.635 0.526 -0.060 -0.0319 0.045 -0.708 0.479 -0.120 -0.0871 0.045 -1.929 0.054 -0.176 -0.0058 0.045 -0.127 0.899 -0.094 Roots  Real Imaginary Modulus  1.2163 -0.5437j 1.3323 1.2163 +0.5437j 1.3323 0.5383 -1.1338j 1.2551 -1.3244 -0.5728j 1.4430 -1.3244 +0.5728j 1.4430 -1.3244 +0.5728j 1.4430 -0.6288 -1.2763j 1.4228 -0.6288 -1.2763j 1.4228						

6.

fit AR ACF 0

## 2.2 Moving Average (MA)

AR order p order

$$r_t = \phi_0 + a_t + \sum_{i=1}^{\infty} \phi_i r_{t-i}$$

$$\phi_i = -\theta_1^i$$

$$r_t = \phi_0 + a_t + \sum_{i=1}^\infty -\theta_1^i r_{t-i}$$

$$|\theta_i| < 1 \qquad \qquad r_t - \theta_1 r_{t-1}$$

$$r_t = \phi_0(1-\theta_1) + a_t - \theta_1 a_{t-1}$$

MA(1) shock  $a_t$  shock MA

$$r_t = c_0 + a_t + \sum_{i=1}^{q} \theta_i a_{t-i}$$

• 
$$c_0$$
•  $a_i$  shock ( )

MA shocks MA shocks  $r_t$  shocks

Note:

 $a_t$ 

## 2.2.1 MA(q)

shocks  $0 \quad MA(q)$ 

$$\mathbb{E}(r_t) = c_0$$

## 2.2.2 MA(q)

$$a_i \quad a_j \qquad (i \neq j)$$

$$\mathrm{Var}(r_t) = (1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2)\sigma_a^2$$

MA MA

# 2.2.3 MA(q)

$$\mathrm{MA}(1)\;\mathrm{ACF}\qquad \mathrm{MA}(\mathbf{q}) \qquad \qquad c_0=0$$

$$r_{t-\ell}r_t = r_{t-\ell}a_t + \theta_1 r_{t-\ell}a_{t-1}$$

$$\mathrm{Var}(r_t) = (1+\theta_1^2)\sigma_a^2$$

$$\rho_0 = 1, \quad \rho_1 = \frac{\theta_1}{1 + \theta_1^2}, \quad \rho_\ell = 0, \quad \text{for} \quad \ell > 1$$

0 MA(1) Lag-1 0 MA(q) ACF 
$$\rho_e l l = 0$$
  $\ell > q$ 

ACF lag-q

MA(q)

Note:

# References