HAD301201A : Applied Time Series and Forecasting

Session 1

Suyash Thite

August 8, 2022

Unit 1 : Introduction and Basics

- What are time series? What is forecasting?
- Economic time series representations.
- The Lag Operator
- Ergodicity and Stationarity.
- The Wold’s Decomposition theorem.
- Deterministic and stochastic components of time series’

Forecasts

Everyone makes forecasts in their daily lives. What are some situations in which you use forecasts ?

- What decisions are impacted by your forecasts?
- How do you evaluate the quality of your forecasts?
- What is the value to you of a good forecast?
- What is the harm or penalty associated with a bad forecast?
- A **forecast** is a prediction of some future event or events.
- Making good predictions is not always easy.
- “Computers are multiplying at a rapid rate. By the turn of the century there will be 220,000 in the U.S.” Wall Street Journal, 1966
- “1930 will be a splendid employment year.” U.S. Department of Labor

Forecasting Applications

- **Operations Management** : Business organizations routinely use forecasts of product sales or demand for services in order to schedule production, control inventories, manage the supply chain, determine staffing requirements, and plan capacity. Forecasts may also be used to determine the mix of products or services to be offered and the locations at which products are to be produced.

- **Marketing** : Forecasting is important in many marketing decisions. Forecasts of sales response to advertising expenditures, new promotions, or changes in pricing polices enable businesses to evaluate their effectiveness, determine whether goals are being met, and adjust.

- **Finance and Risk Management :** Investors in financial assets are interested in forecasting the returns from their investments. These assets include but are not limited to stocks, bonds, and commodities; other investment decisions can be made relative to forecasts of interest rates, options, and currency exchange rates. Financial risk management requires forecasts of the volatility of asset returns so that the risks associated with investment portfolios can be evaluated and insured, and so that financial derivatives can be properly priced.

Forecasting Applications : Continued

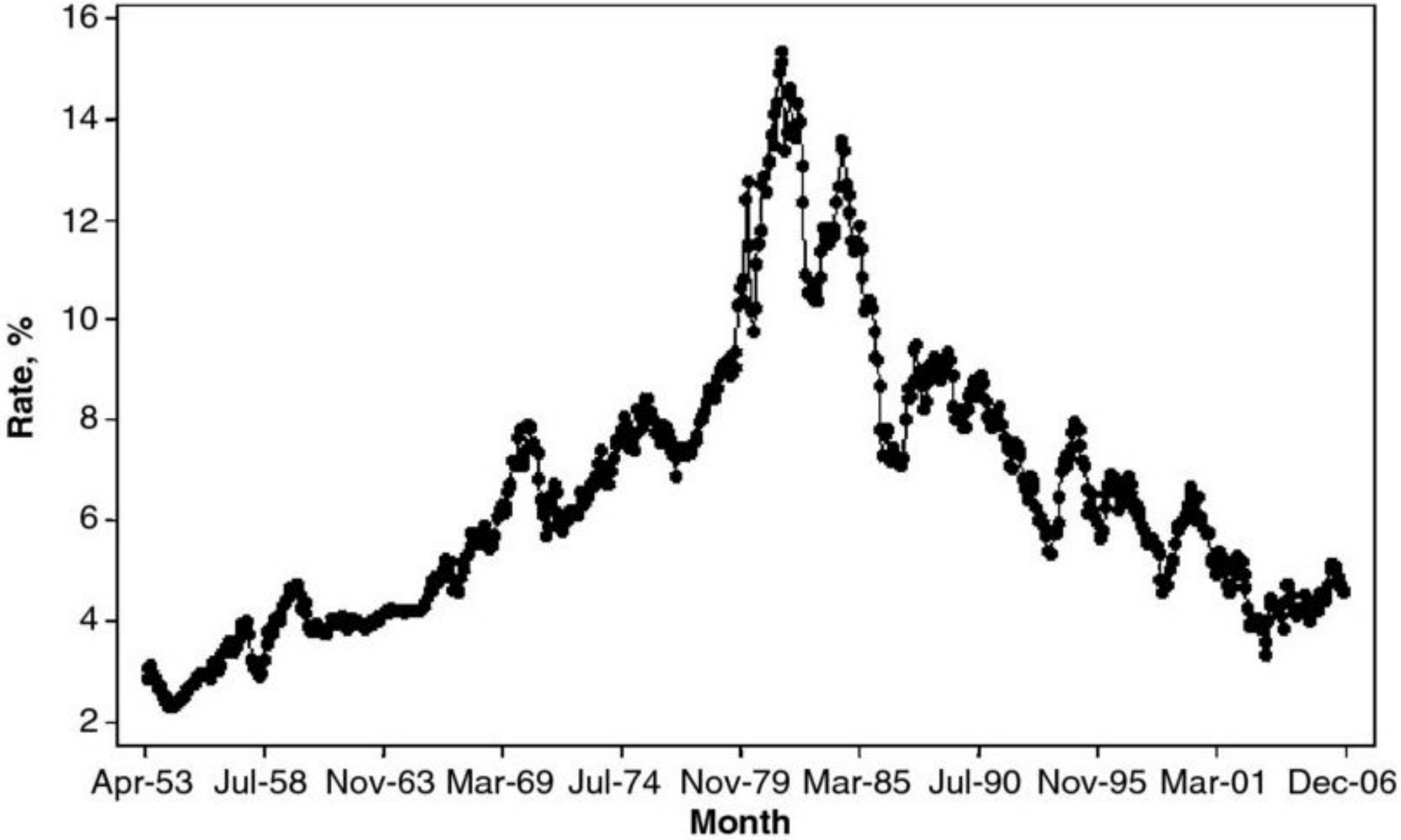
- **Economics** : Governments, financial institutions, and policy organizations require forecasts of major economic variables, such as gross domestic product, population growth, unemployment, interest rates, inflation, job growth, production, and consumption. These forecasts are an integral part of the guidance behind monetary and fiscal policy, and budgeting plans and decisions made by governments. They are also instrumental in the strategic planning decisions made by business organizations and financial institutions.

- **Industrial Process Control :** Forecasts of the future values of critical quality characteristics of a production process can help determine when important controllable variables in the process should be changed, or if the process should be shut down and overhauled. Feedback and feedforward control schemes are widely used in monitoring and adjustment of industrial processes, and predictions of the process output are an integral part of these schemes.

- **Demography** : Forecasts of population by country and regions are made routinely, often stratified by variables such as gender, age, and race. Demographers also forecast births, deaths, and migration patterns of populations. Governments use these forecasts for planning policy and social service actions, such as spending on health care, retirement programs, and antipoverty programs. Many businesses use forecasts of populations by age groups to make strategic plans regarding developing new product lines or the types of services that will be offered.

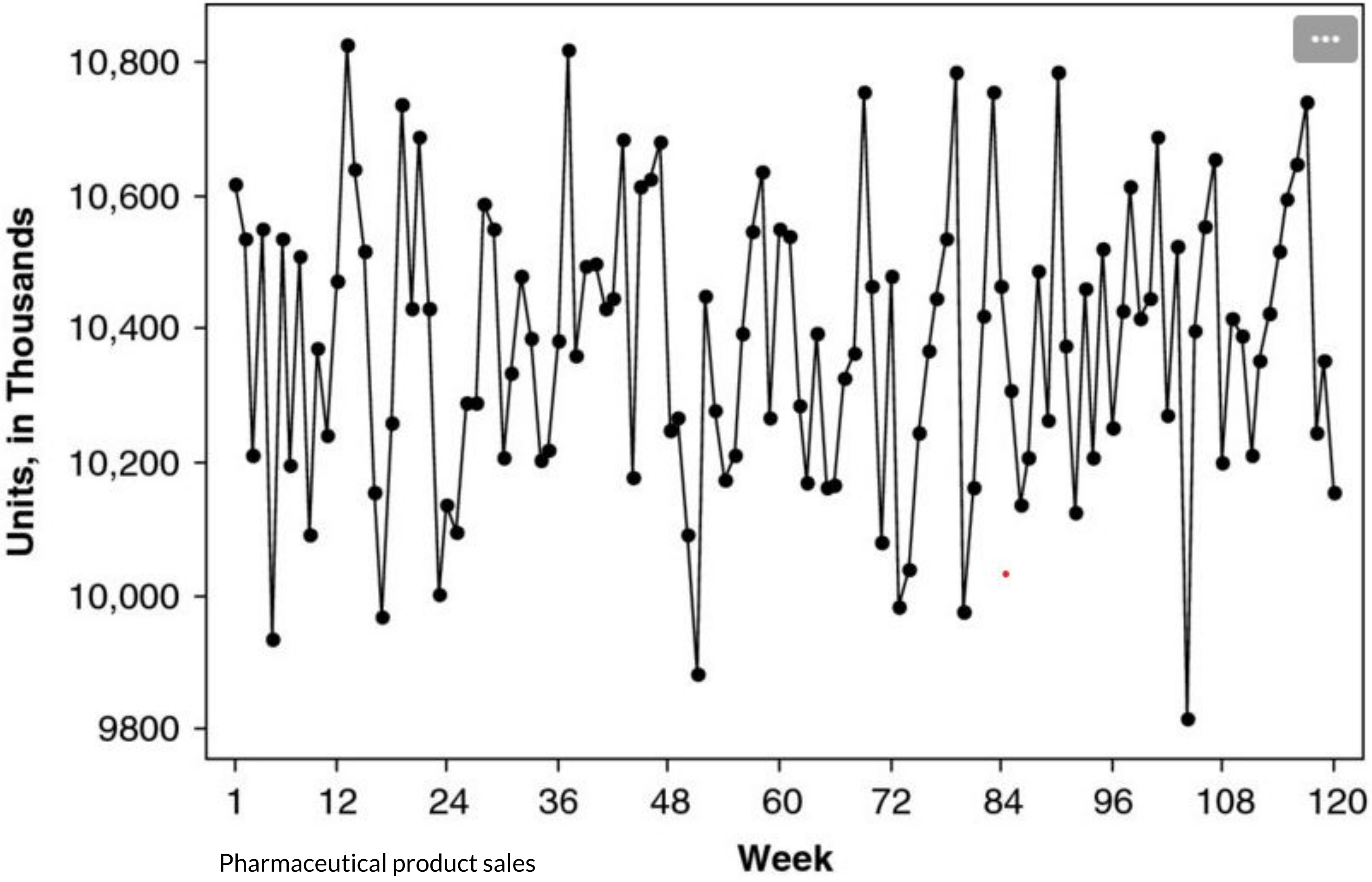
Time Series

A time series is a time-oriented or chronological sequence of observations on a variable of interest.



Time series plot of the market yield on US Treasury Securities at 10-year constant maturity. Source: US Treasury

Time Series : More Examples

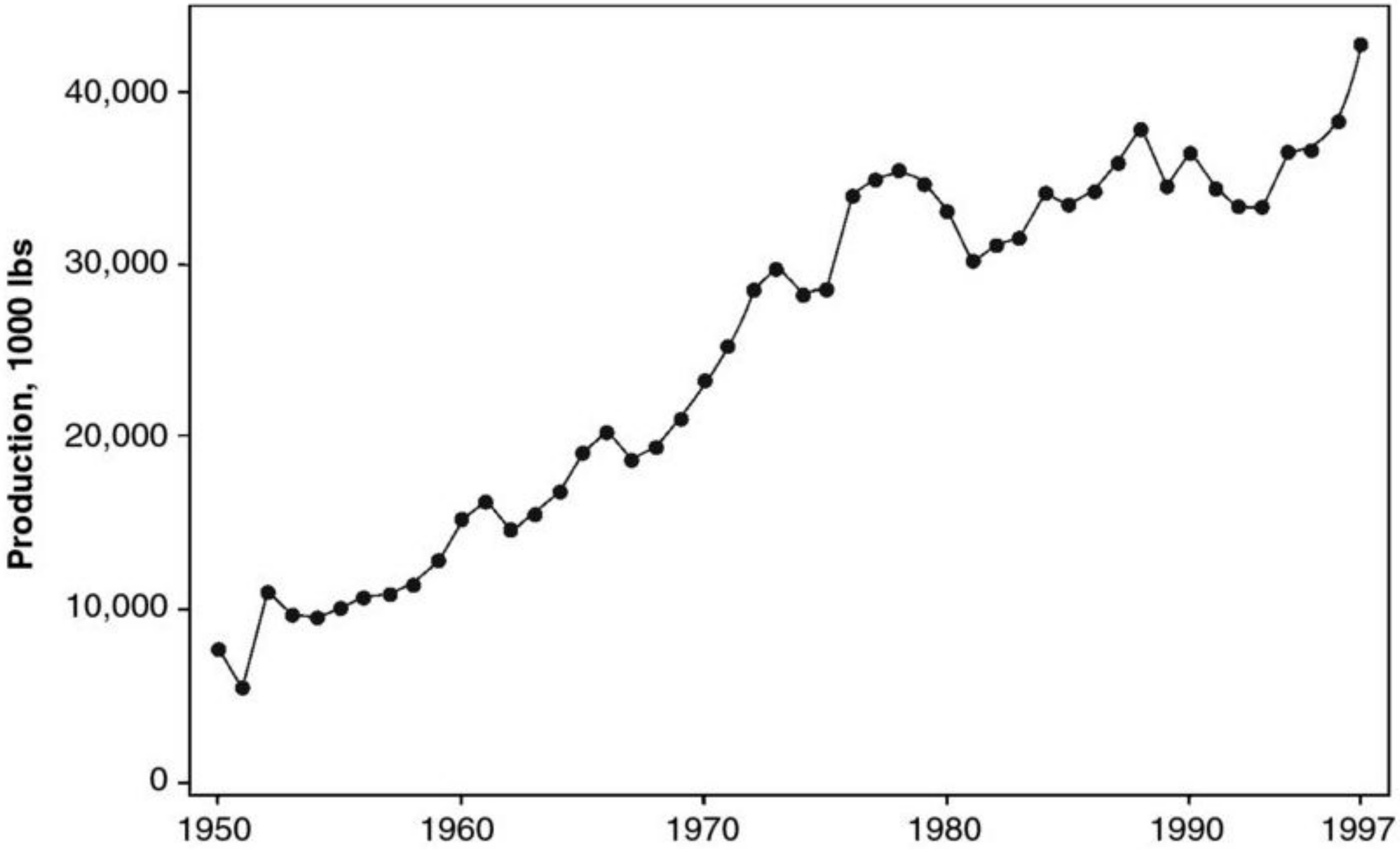


Pharmaceutical product sales

- Time series plots can reveal patterns such as random trends, level shifts, periods or cycles, unusual observations, or a combination of patterns.

- Can you spot any observations in the attached time series?

Time Series : More Examples



US Production of Cheese

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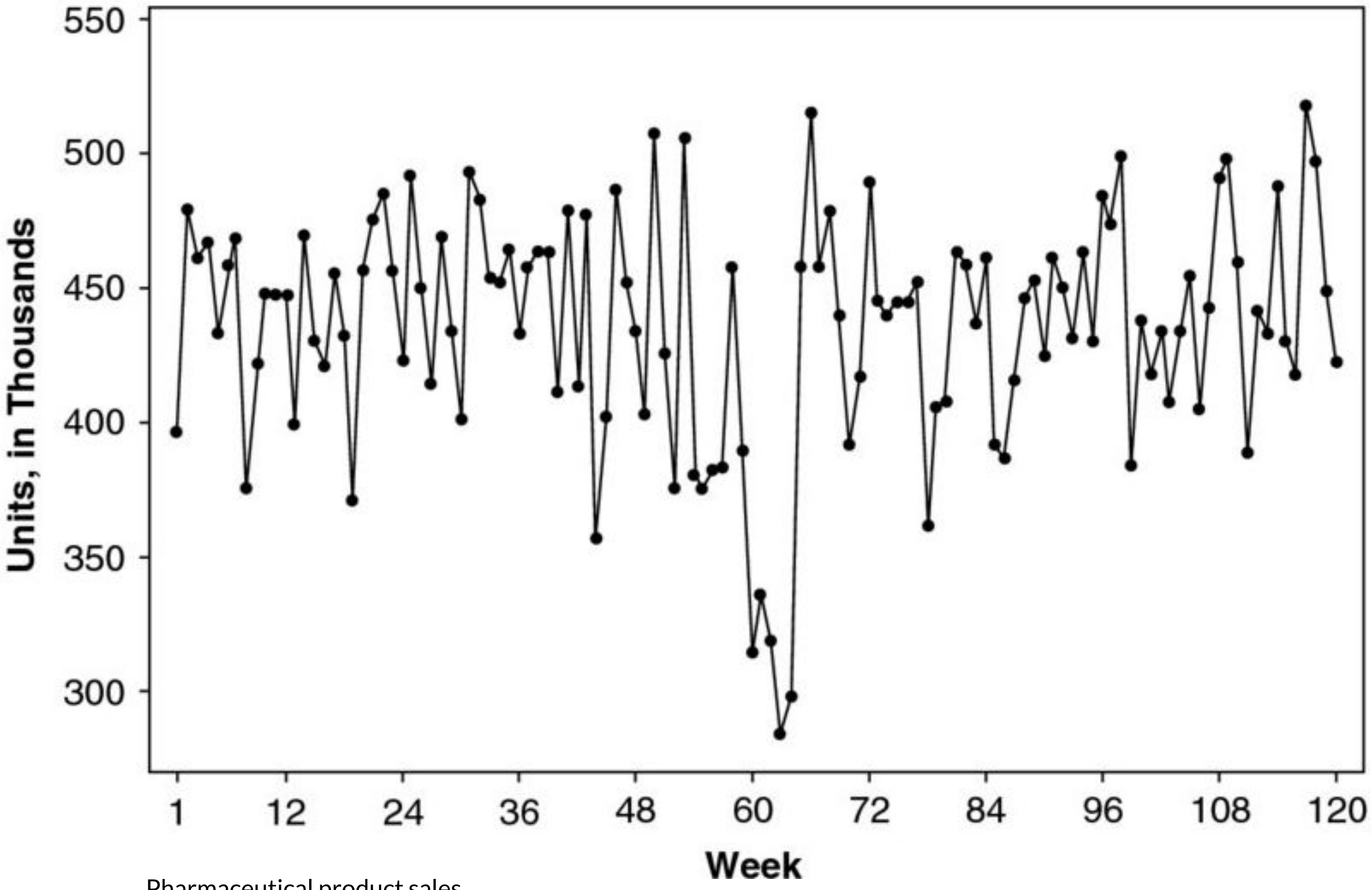
Time Series : More Examples



Pharmaceutical product sales

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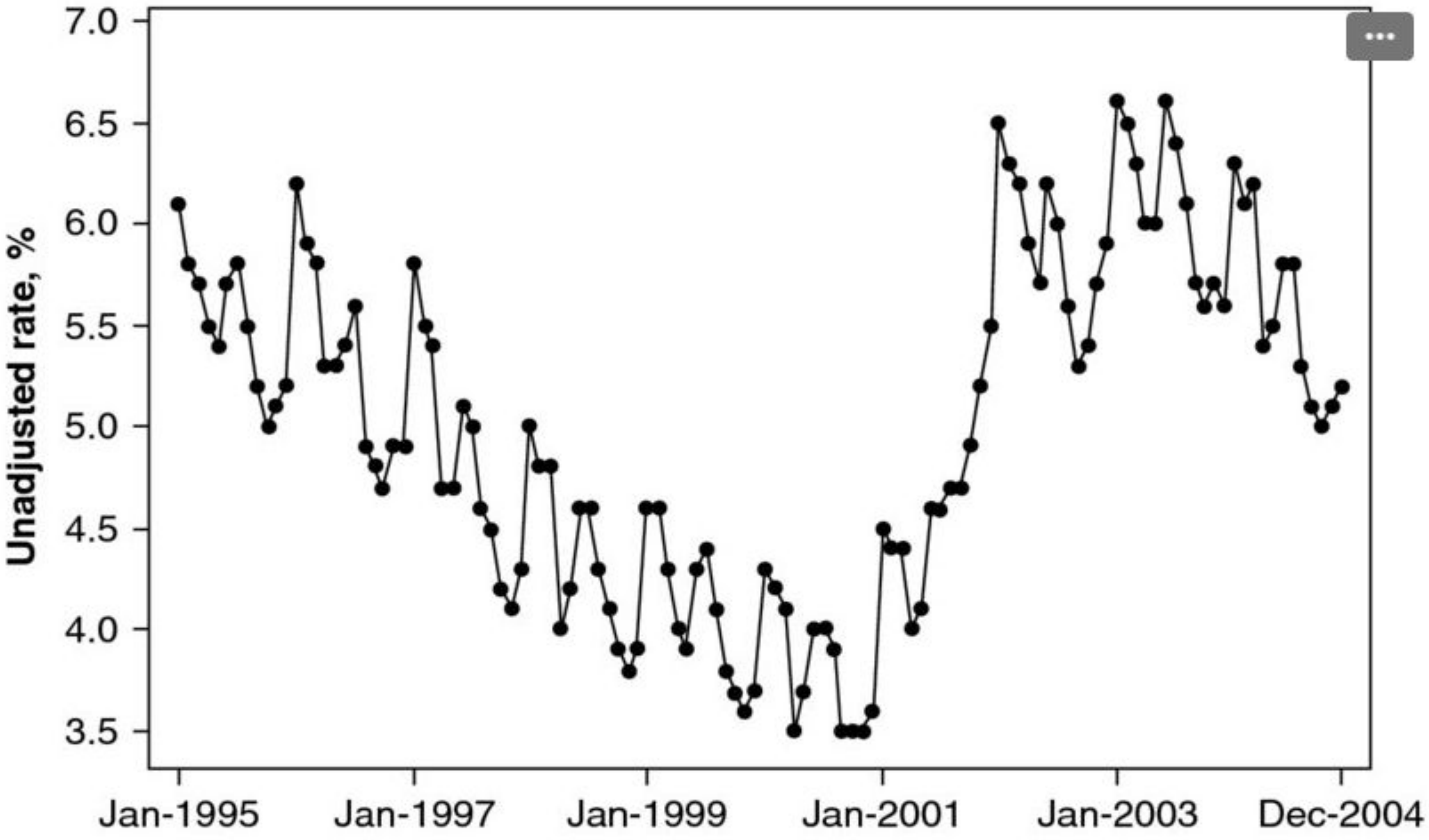
Time Series : More Examples



Unemployment Rent By Month : US Department of Labor

- Time series plots can reveal patterns such as random trends, level shifts, periods or cycles, unusual observations, or a combination of patterns.

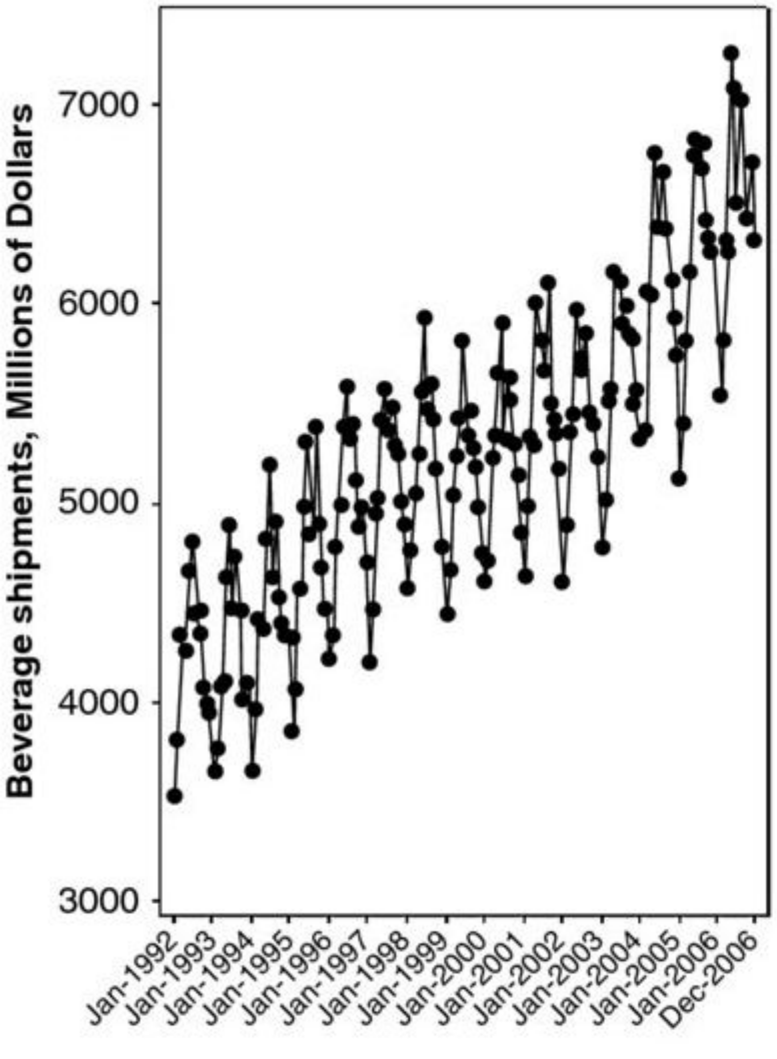
- Can you spot any observations in the attached time series?

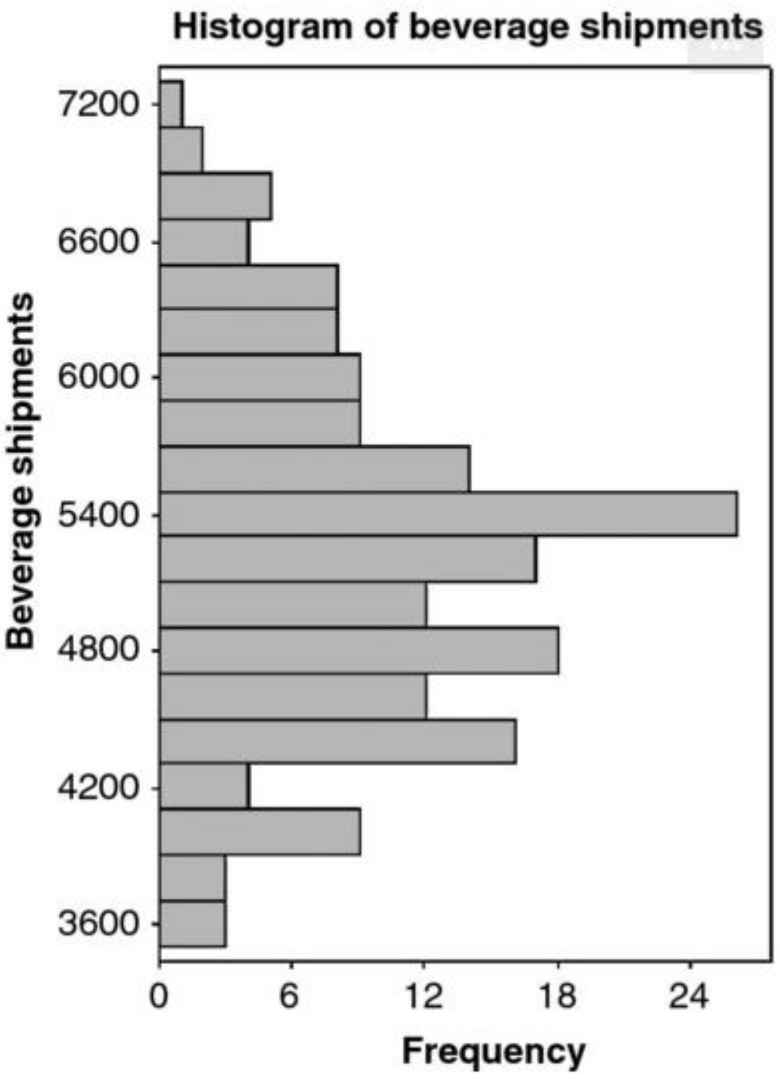
Time Series Components

Based on the previous examples we can now note 4 components/ features of Time Series

- Trend : Gradual growth or decline in time series data.
- Seasonality : Short patterns that correspond to seasonal variations.
- Cyclical: Long term variations.
- Noise/ Irregular : Uncontrolled Circumstance occurrences.

Time Series Plots : Benefits



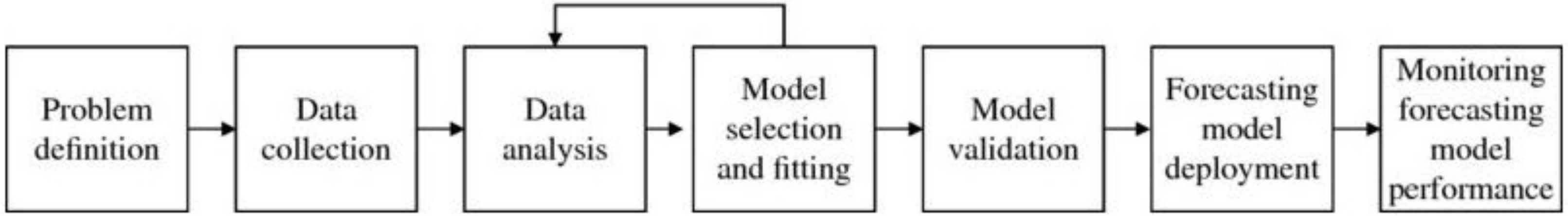


Features such as trend and seasonality are usually easy to see from the time series plot.

Classical tools of descriptive statistics, such as the histogram, are not particularly useful for time series data because they do not take time order into account.

Forecasting Process

Problem definition involves developing understanding of how the forecast will be used along with the expectations of the "customer" (the user of the forecast). Questions that must be addressed during this phase include the desired form of the forecast (e.g., are monthly forecasts required), the forecast horizon or lead time, how often the forecasts need to be revised (the forecast interval), and what level of forecast accuracy is required in order to make good business decisions. This is also an opportunity to introduce the decision makers to the use of prediction intervals as a measure of the risk associated with forecasts, if they are unfamiliar with this approach. Often it is necessary to go deeply into many aspects of the business system that requires the forecast to properly define the forecasting component of the entire problem.


Problem definition
Data collection
Data analysis
Model selection and fitting
Model validation
Forecasting model deployment
Monitoring forecasting model performance

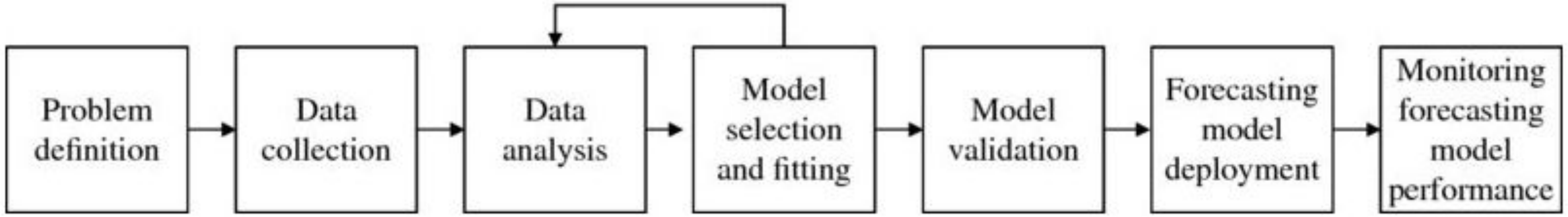
Forecasting Process

Data collection consists of obtaining the relevant history for the variable(s) that are to be forecast, including historical information on potential predictor variables

Data analysis is an important preliminary step to the selection of the forecasting model to be used.

Model selection and fitting consists of choosing one or more forecasting models and fitting the model to the data. By fitting, we mean estimating the unknown model parameters, usually by the method of least squares.

Model validation consists of an evaluation of the forecasting model to determine how it is likely to perform in the intended application
Forecasting model deployment involves getting the model and the resulting forecasts in use by the customer
Monitoring forecasting model performance should be an ongoing activity after the model has been deployed to ensure that it is still performing satisfactorily.


Problem definition
Data collection
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Monitoring forecasting model performance

Statistical Definitions for Time Series Analyses

Analysis vs Forecasting

Analysis : Analyzing time series as is. No predictions involved. Descriptive modeling techniques used to smoothen/ fit time series.

Basic Definitions of some terminology associated with time series.

- Suppose that there are T periods of data available, with period T being the most recent. We will let the observation on this variable at time period t be denoted by Yt, t = 1, 2, … , T.

Forecast Error and residual

- Difference between observed value and forecasted value is known as Forecast Error.

$$e_t(\tau) = y_t - \hat{y}_t(t - \tau).$$

- The Forecast Error at lead time 1 is given by

$$e_t(1) = y_t - \hat{y}_t(t - 1).$$

- Difference between observed value and fitted value is called residual.

$$e_t = y_t - \hat{y}_t.$$

Data Imputation

- **Data imputation** is the process of correcting missing data or replacing outliers with an estimation process. Imputation replaces missing or erroneous values with a “likely” value based on other available information. This enables the analysis to work with statistical techniques which are designed to handle the complete data sets.

- Example : **Mean Value Imputation** -Replace missing values with average. This is advantageous because it is easy to implement but induces errors if there are seasonal components to time series.

- Stochastic Mean Value Imputation : A random variable is added to the mean value to capture some of the noise or variability in the data. The random variable could be assumed to follow a normal distribution with mean zero and standard deviation equal to the standard deviation of the actual observed data.

- For example, consider the time series y1, y2, …, yT and suppose that one observation yj is missing. We can impute the missing value as

$$y_j^* = \frac{1}{2k}\left(\sum_{t=j-k}^{j-1} y_t + \sum_{t-j+1}^{j+k} y_t\right),$$

Plotting smoothed data

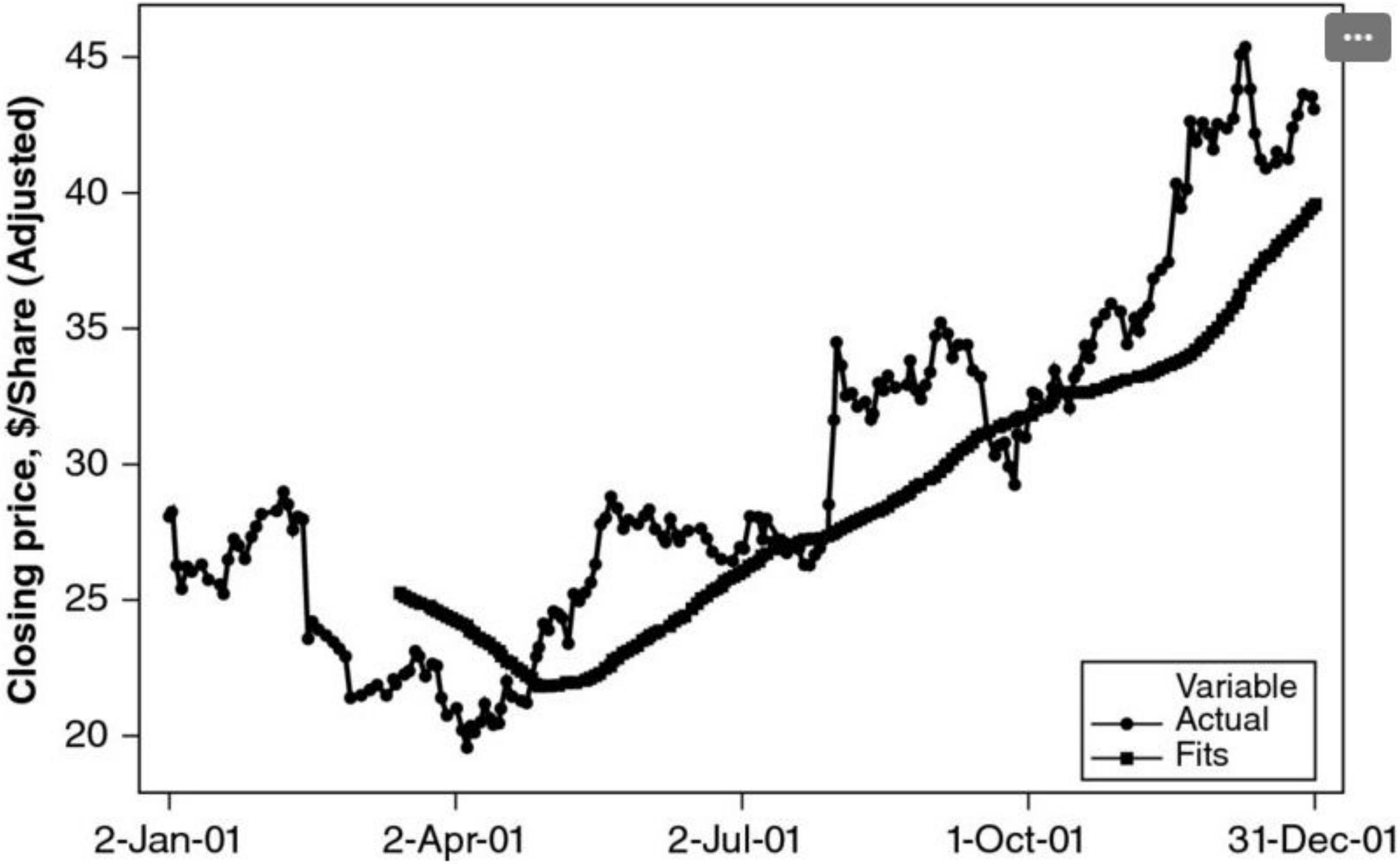
- Sometimes it is useful to overlay a smoothed version of the original data on the original time series plot to help reveal patterns in the original data.
- There are several types of data smoothers that can be employed. One of the simplest and most widely used is the ordinary or simple moving average.

Example

- A simple moving average of span N assigns weights 1/N to the most recent N observations yT, yT − 1, … , yT − N + 1, and weight zero to all other observations. If we let MT be the moving average, then the N-span moving average at time period T is

$$M_T = \frac{y_T + y_{T-1} + \cdots + y_{T-N+1}}{N} = \frac{1}{N} \sum_{t=T-N+1}^{T} y_t$$

Plotting smoothed data : Example



Plotting smoothed data : continued

- An obvious disadvantage of a linear filter such as a moving average is that an unusual or erroneous data point or an outlier will dominate the moving averages that contain that observation, contaminating the moving averages for a length of time equal to the span of the filter.
  Example

- Odd-span moving medians (also called running medians) are an alternative to moving averages that are effective data smoothers when the time series may be contaminated with unusual values or outliers. The moving median of span N is defined as

$$m_t^{[N]} = med(y_{t-u}, \dots, y_t, \dots, y_{t+u}),$$

$$m_t^{[3]} = med(y_{t-1}, y_t, y_{t+1}).$$

Introduction to the Lag Operator

- The Lag operator operates on an element in the time series to produce the previous element. It is also called the backshift operator

- **Example**

HAD301201A : Applied Time Series and Forecasting

Session 2

Suyash Thite
August 16, 2022

Unit 1 : Introduction and Basics

- What are time series? What is forecasting?
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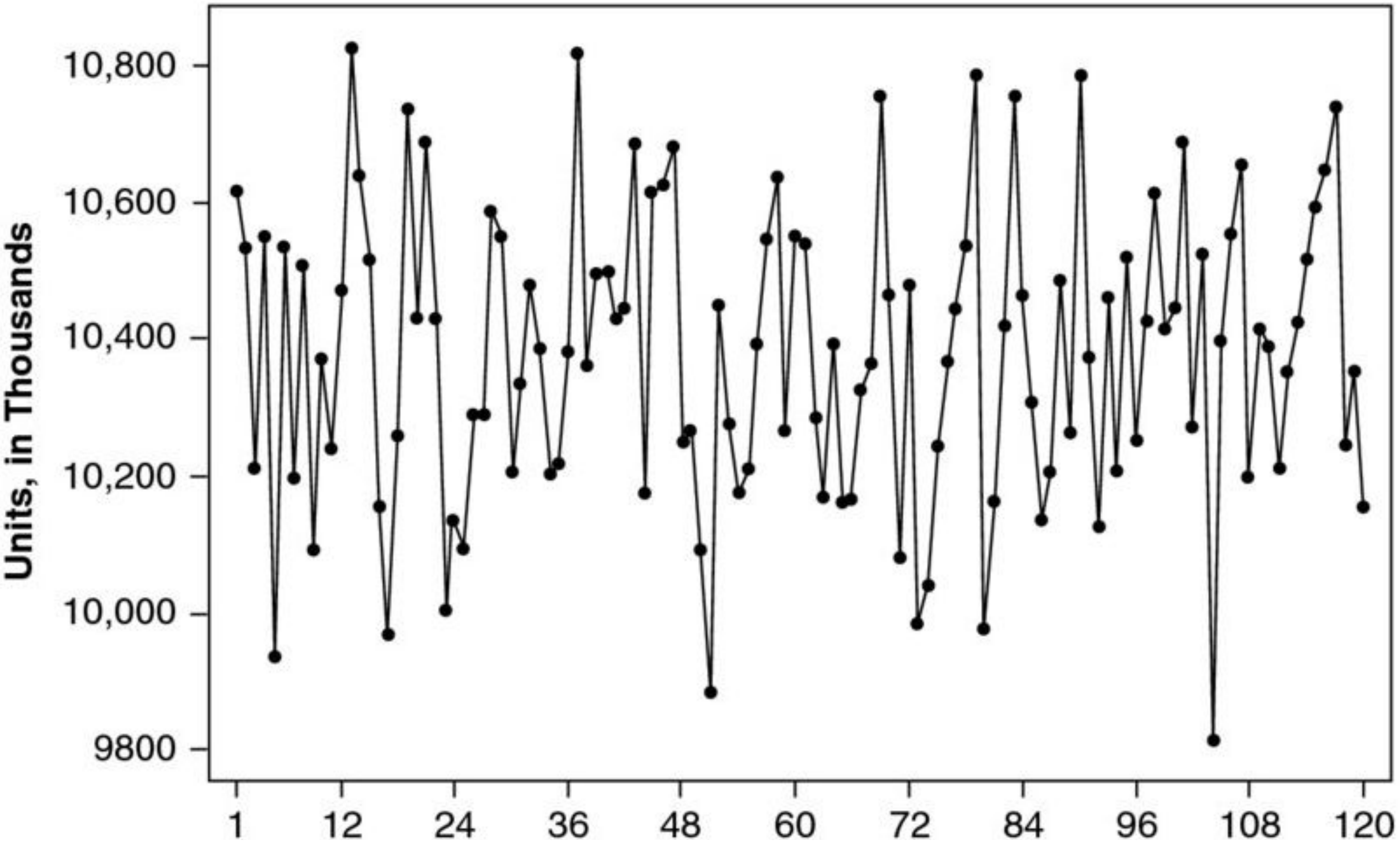
- The Wold’s Decomposition theorem.
- Deterministic and stochastic components of time series’

Session 1 Review

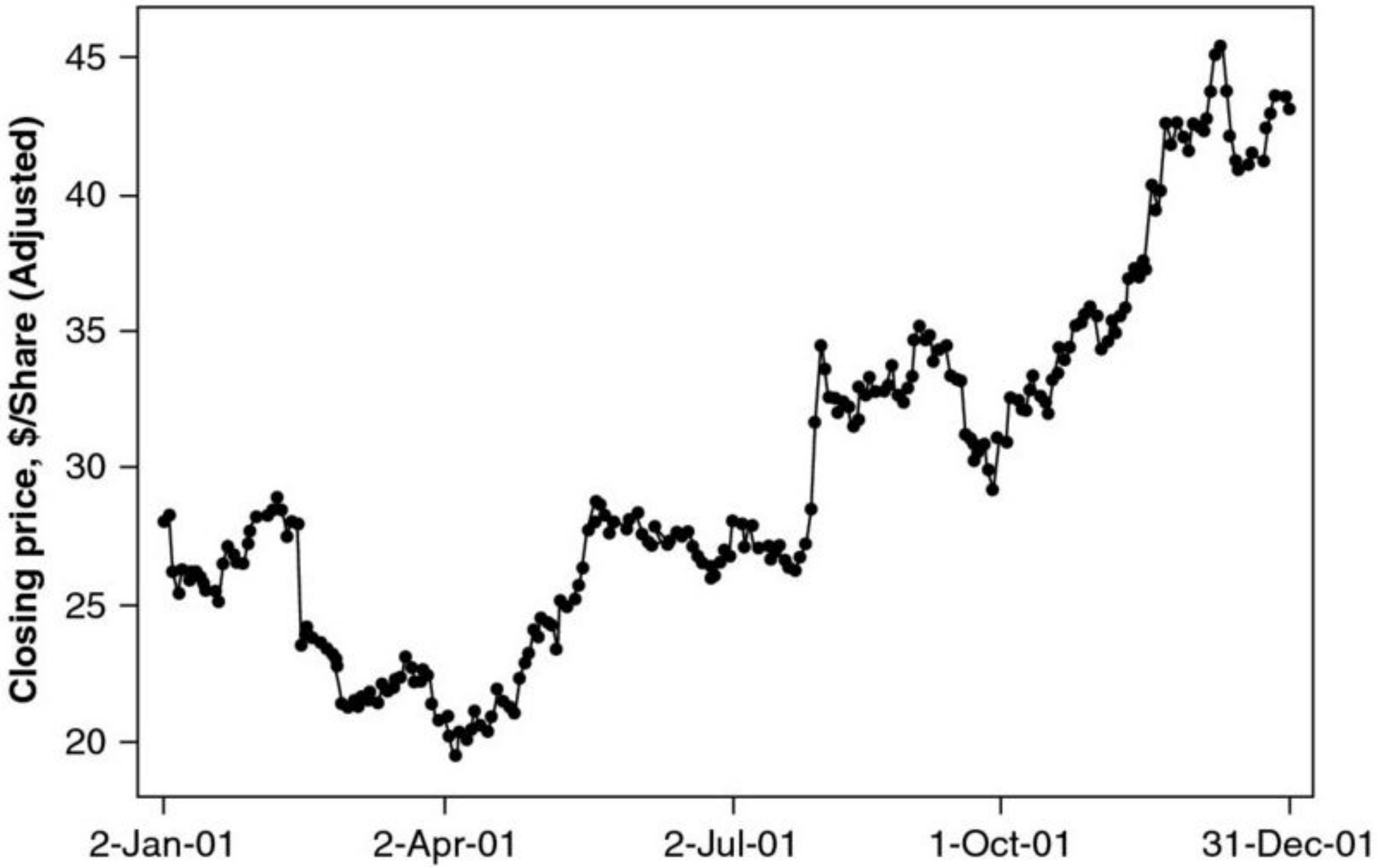
- What is a time series?
- What is a difference between a normal histogram representation of continuous data vs a time series?
- What are the four components of time series?
- What are some applications of a time series?
- What is data imputation? **Example**
- What are forecast errors?

Stationarity in Time Series

- A time series is said to be strictly/strong stationary if its properties are not affected by a change in the time origin.
- Distributions are consistent across windows of time. If we look at two similar subsets of time, distributions are consistent.
- Two types of stationarity : Strong and Weak.
- Mean, Variance, and autocorrelation is consistent over subsets of time.
- Usually, weak stationarity is sufficient for efficient time series analysis.


Units, in Thousands
10,800
10,600
10,400
10,200
10,000
9800
1
12
24
36
48
60
72
84
96
108
120

Non-Stationery time series



Autocovariance Functions

- What is Covariance? How does it differ from Variance? **Example .** Covariance vs Correlation
- **Example** of lagged data

- The covariance between yt and its value at another time period, say, $y_{t + k}$ is called the autocovariance at lag k. **Example**

$$\gamma_k = \mathrm{Cov}(y_t, y_{t+k}) = E[(y_t - \mu)(y_{t+k} - \mu)].$$

- The collection of the values of γ_k, k = 0, 1, 2, ... is called the autocovariance function.
- The autocorrelation coefficient at lag k for a stationary time series is

$$\rho_k = \frac{E[(y_t - \mu)(y_{t+k} - \mu)]}{\sqrt{E[(y_t - \mu)^2]E[(y_{t+k} - \mu)^2]}} = \frac{\mathrm{Cov}(y_t, y_{t+k})}{\mathrm{Var}(y_t)} = \frac{\gamma_k}{\gamma_0}.$$

Sample Autocorrelation Functions (ACF)

- What is sample vs population?
- It is necessary to estimate the autocovariance and ACFs from a time series of finite length, say, y1, y2, …, yT. The usual estimate of the autocovariance function is

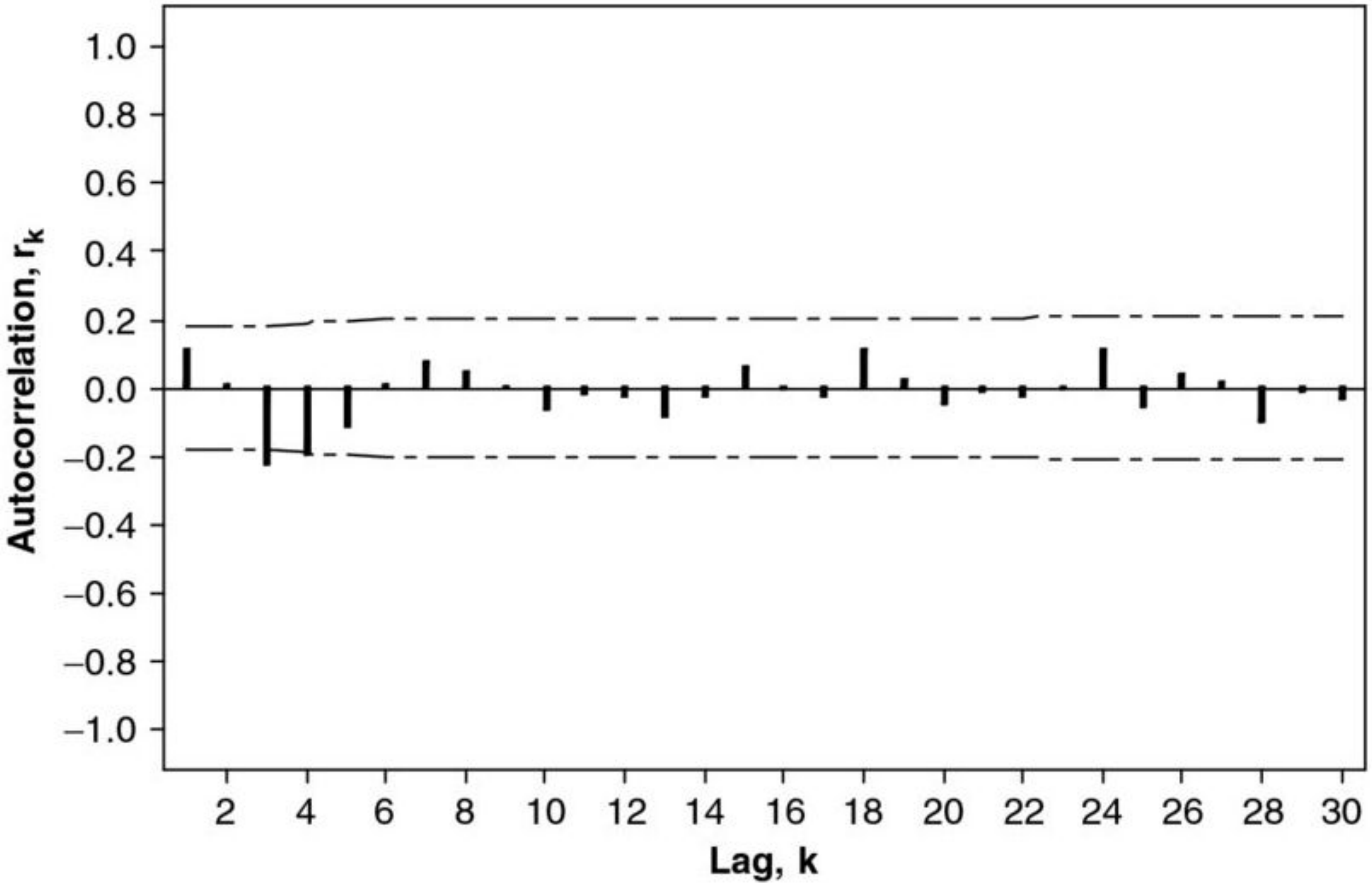
$$c_k = \hat{\gamma}_k = \frac{1}{T}\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y}), \quad k = 0, 1, 2, \ldots, K$$

- ACF is estimated by the sample autocorrelation function (or sample ACF)

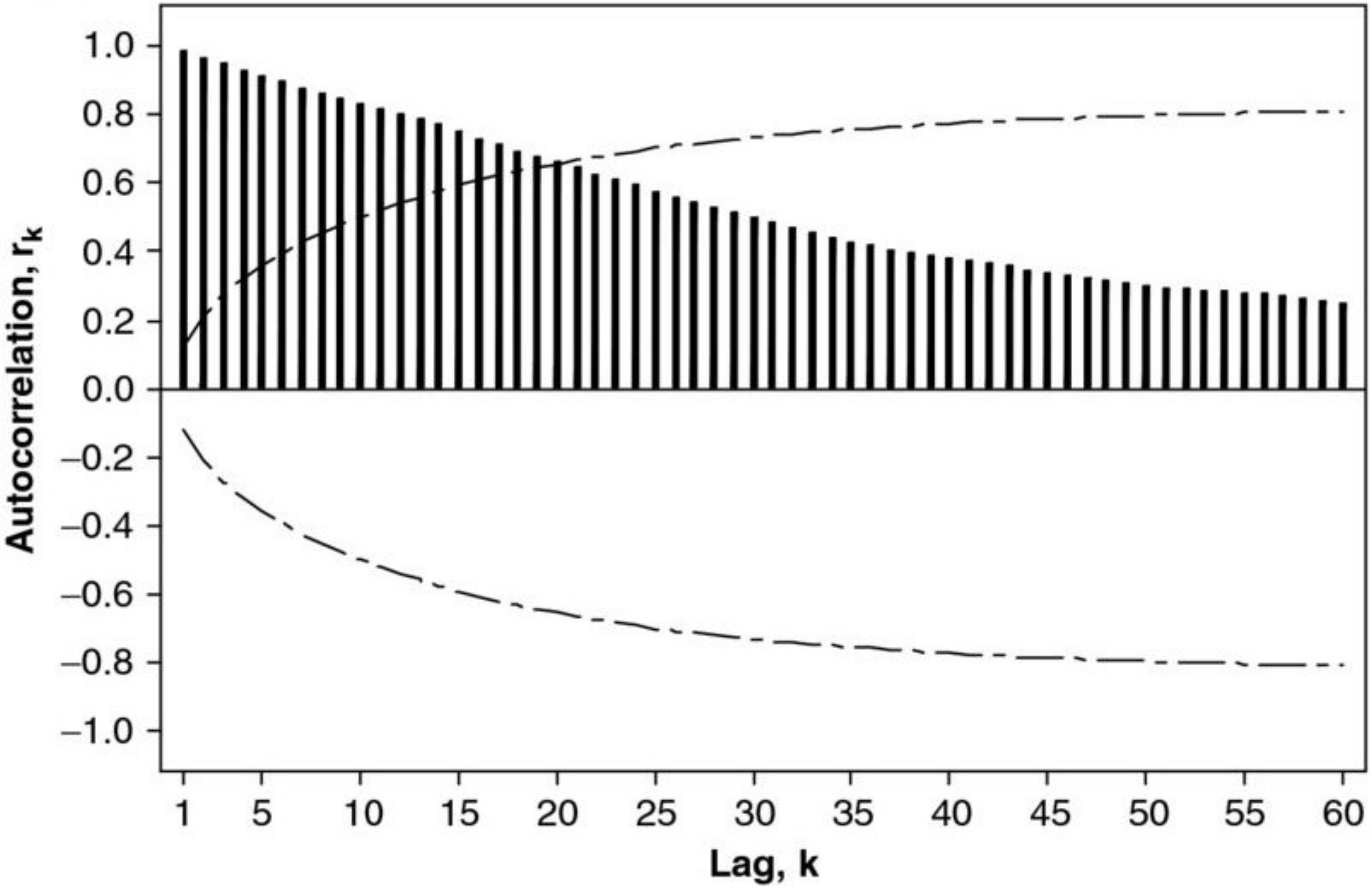
$$r_k = \hat{\rho}_k = \frac{c_k}{c_0}, \quad k = 0, 1, \ldots, K$$

- More information in Unit 3

Autocorrelation in a Stationary time series



Autocorrelation in a Non - Stationary time series



Time series analysis in R

- https://www.forecastingbook.com/resources/data-and-code
- The ts function in R is used to create time series objects.
- ts(data = NA, start = 1, end = numeric(), frequency = 1,   deltat = 1, ts.eps = getOption("ts.eps"), class = , names =)
- Tslm function

Time series analysis in R

- Lag Operator in R and correlation. **Example**

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Session 3

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September 8, 2022

Evaluation (CIE)

- To be conducted in next session.
- 10 Questions, Google Forms.
- Materials Covered in first 2 sessions.

Unit 1 & 2

- What are time series? What is forecasting?
- Economic time series representations.
- The Lag Operator
- Ergodicity and Stationarity.
- The Wold’s Decomposition theorem.
- Deterministic and stochastic components of time series’
- Exploratory Data Analysis on Time Series
- **White Noise**, Random Walk
- Basic Time Series Models : First Order Autoregressive Models
- Moving Average, Linear Drift, Complete Stochastic Processes

General Approach to Time Series Modeling and Forecasting

- The basic steps in modeling and forecasting a time series are as follows:

1)Plot the time series and determine its basic features, such as whether trends or seasonal behavior or both are present.

2)Look for possible outliers or any indication that the time series has changed with respect to its basic features (such as trends or seasonality) over the time period history.

3)Eliminate any trend or seasonal components, either by differencing or by fitting an appropriate model to the data. Also consider using data transformations, particularly if the variability in the time series seems to be proportional to the average level of the series. The objective of these operations is to produce a set of stationary residuals.

4) Develop a forecasting model for the residuals. It is not unusual to find that there are several plausible models, and additional analysis will have to be performed to determine the best one to deploy. Sometimes potential models can be eliminated on the basis of their fit to the historical data. It is unlikely that a model that fits poorly will produce good forecasts.

General Approach to Time Series Modeling and Forecasting

5) Validate the performance of the model (or models) from the previous step. The objective of this step is to select a model to use in forecasting.

6) Also of interest are the differences between the original time series yt and the values that would be forecast by the model on the original scale. To forecast values on the scale of the original time series yt, reverse the transformations and any differencing adjustments made to remove trends or seasonal effects.

7) Develop and implement a procedure for monitoring the forecast to ensure that deterioration in performance will be detected reasonably quickly.

Performance Evaluation of Time Series

- At first glance, we might think it best to choose a model that generates the best forecasts on the data series at hand.

- However, when we use the same data both to develop the forecasting model and to assess its performance, we introduce bias.

- This is because when we choose a model among a set of models that works best with the data, this model's superior performance comes from two sources:

1. a superior model

2. chance aspects of the data that happen to match the chosen model better than they match other models (Overfitting!)

Performance Evaluation of Time Series - Continued

- How to deal with Overfitting?

Normal Cross-sectional Data

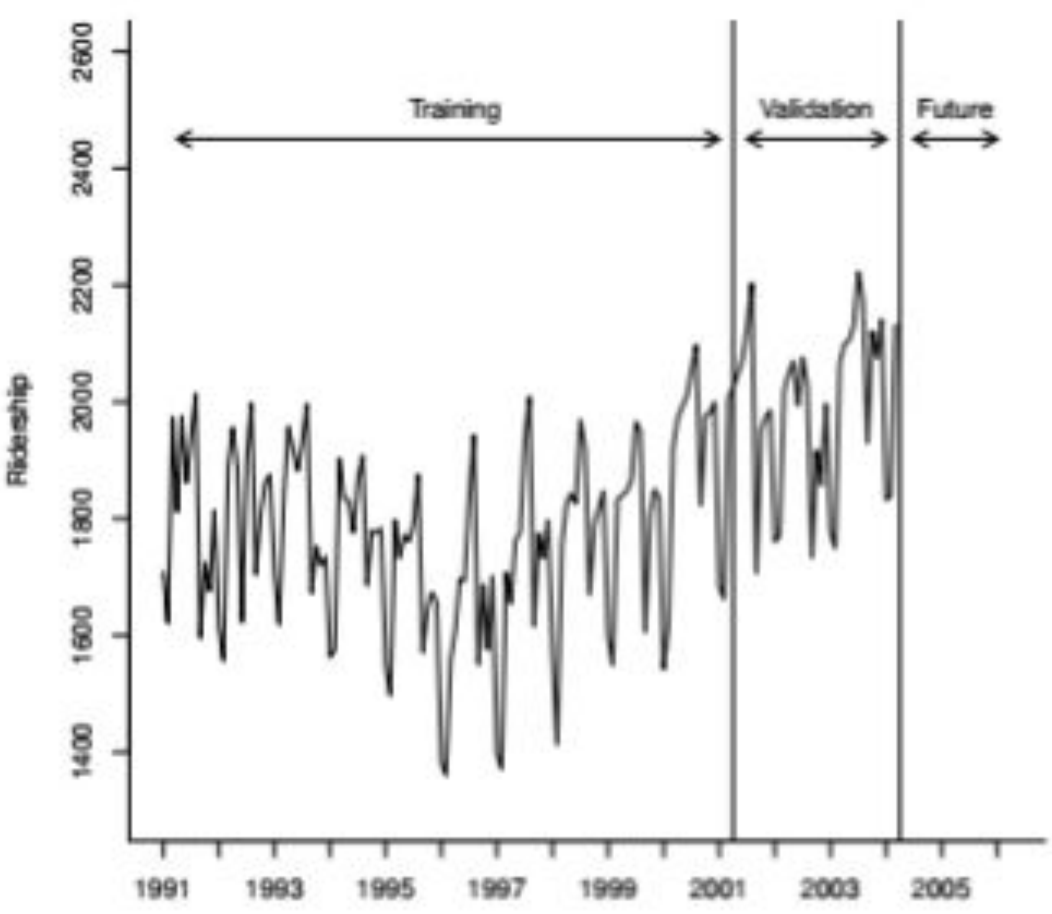
- Partitioning the data into training, validation, and test sets is usually done randomly.
- The training partition, typically the largest partition, contains the data used to build the various models we are examining. The same training partition is generally used to develop multiple models.
- The validation partition is used to assess the performance of each model so that we can compare models and pick the best one.
- The test partition (sometimes called the holdout or evaluation partition) is used to assess the performance of the chosen model with new data.

Performance Evaluation of Time Series - Continued

Time Series Data

- Normal partitions do not work : Models are not able to handle missing data points in time series.
- Temporal Partitioning – Split time series in multiple periods.
- Methods are trained on the earlier training period.
- Performance assessed on the later validation period.
- Test period usually does not exist.

Temporal Partitioning



Temporal Partitioning- Continued

- Unlike cross sectional partitioning, when a model is selected to run, data is recombined in one long series and selected model is re-run.
- Reasons for recombining :
  - Validation period contains most recent data, valuable information closest to current time period.
  - More data available – models work better!
  - If only training period is used, then it will have to skip the validation period forecasts, adding additional forecasts to be performed

Temporal Partitioning- Continued

- Choosing the validation period:
- Length of validation period depends on forecasting goals.
- If you are forecasting yearly data, select a year as validation period. Longer validation period (2 years) means less recent data.
- Shorter validation periods means predictive performance of long-term data is inaccurate.

Measuring Predictive Accuracy

- **Forecast Error?**

- Performed on validation periods.

- Popular metrics for accuracy:
    - Mean Absolute Error
    - Average Error
    - Mean Absolute Percentage Error
    - Root Mean Squared Error

Measuring Predictive Accuracy

- Popular metrics for accuracy:
  - Mean Absolute Error: Magnitude of the average absolute error.

$$\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

  - Average Error: Same as Mean absolute error but retains positive or negative error.
  - Mean Absolute Percentage Error

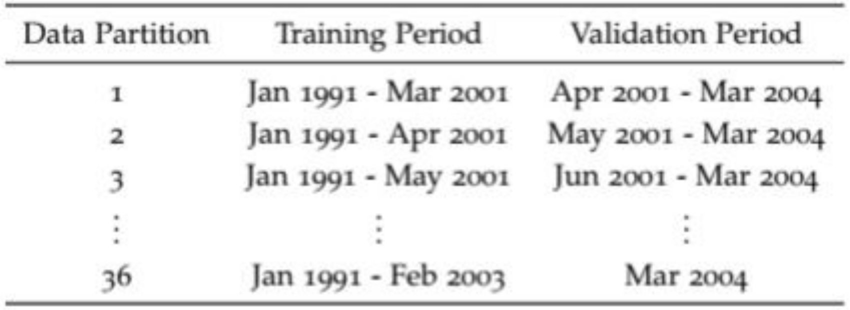
$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

  - Root Mean Squared Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\|y(i) - \hat{y}(i)\|^2}{N}},$$

Advanced Data Partitioning Methods

- Roll Forward Partitioning – Creating Multiple Training- Validation Partitions



Data Partition	Training Period	Validation Period
1	Jan 1991 - Mar 2001	Apr 2001 - Mar 2004
2	Jan 1991 - Apr 2001	May 2001 - Mar 2004
3	Jan 1991 - May 2001	Jun 2001 - Mar 2004
⋮	⋮	⋮
36	Jan 1991 - Feb 2003	Mar 2004

- Refreshes forecasts period by period.

Autocorrelation

- In Time series contexts, values in neighboring periods tend to be correlated. This correlation is called autocorrelation.

$$\rho_{xy} = \frac{\mathrm{Cov}(r_x, r_y)}{\sigma_x \sigma_y}$$

- Typical Autocorrelation is lag-n : meaning correlation between time series and a lag of n time periods.

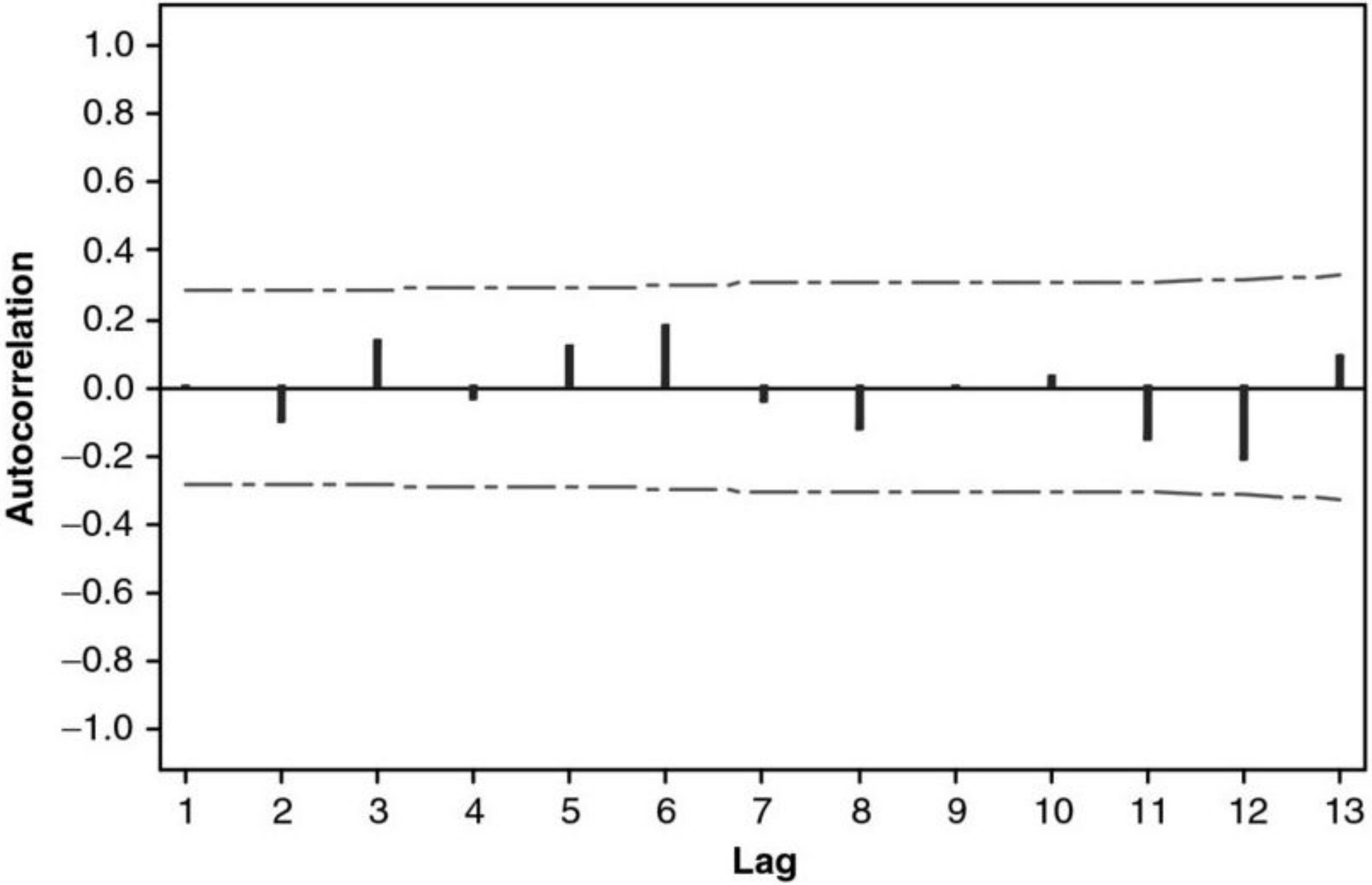
- A Positive lag -1 correlation (Also called stickiness) means that consecutive values move in same direction.
- A negative lag-1 correlation means swings in data set, high values followed by low values and vice-versa

- Autocorrelation analysis leads to trend and seasonality detection : For example, strong autocorrelation at more than lag-1 denotes cyclical patterns

White Noise

- A time series is said to be white noise when
  - Standard Deviation is constant
  - Autocorrelation is not significant
  - Average value is 0

White Noise


Autocorrelation
1.0
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0.6
0.4
0.2
0.0
–0.2
–0.4
–0.6
–0.8
–1.0
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Lag

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September 23, 2022

Unit 1 & 2

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White Noise

- A time series is said to be white noise when

  - Standard Deviation is constant
  - Autocorrelation is not significant
  - Mean value is 0

Demonstration of White Noise in R

Random Walk

- A time series is said to be Random Walk when

    - The Current observation is based on the previous observation
    - A random white noise observation (step up/ step down) is added to the current observation

$$x_t = x_{t-1} + w_t$$

Demonstration of Random Walk in R

Autoregressive Models

- Regression type models that capture Autocorrelation
  - Autoregressive Models (AR)
  - Autoregressive Integrated Moving Average Models (ARIMA)
  - Simple Linear Regression ?

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

  - Autoregressive models use the previous variables to predict future values
  - They are of multiple orders from 1…n
  - A first order autoregressive model AR(1) uses the most recent value in time series to predict following va

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + u_t$$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \epsilon_t$$

  - Mean of Yt is given by

$$\mu = \frac{\beta_0}{1-\beta_1}$$

  - Variance of Yt is given by

Assignment 3

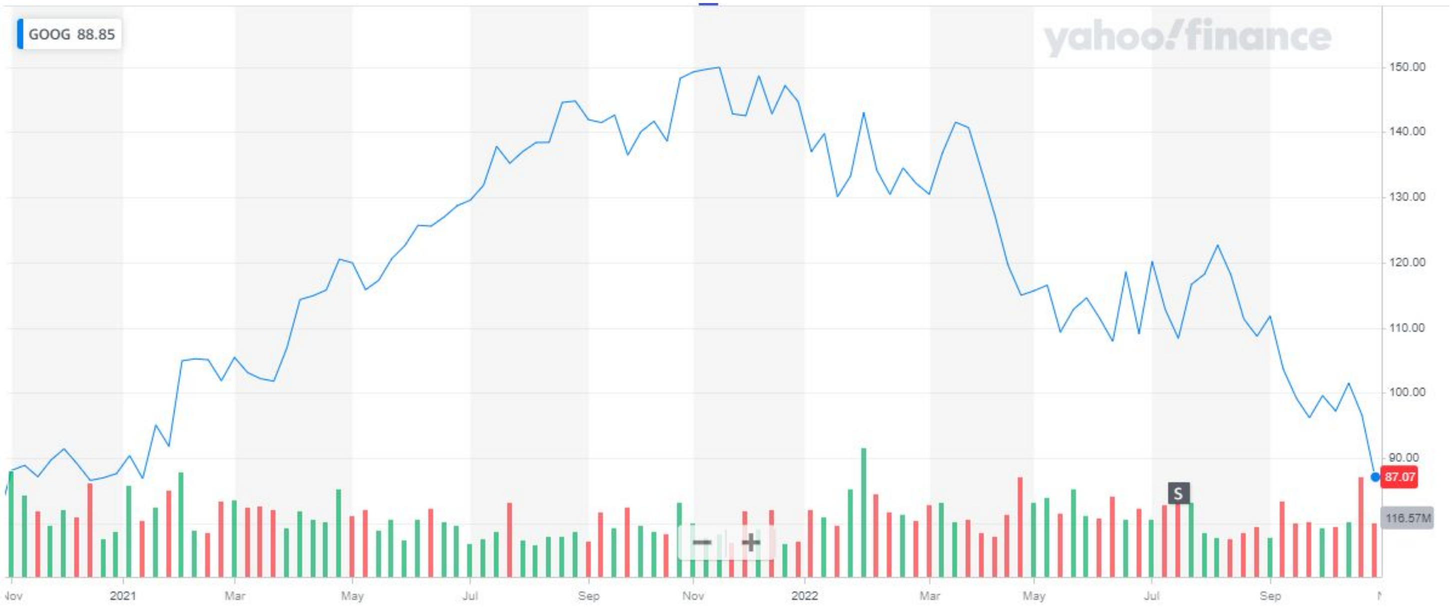
- Exploratory Data Analysis on Time Series data
  - Already available datasets in R.
  - Timeseries Class

HAD301201A : Applied Time Series and Forecasting

Suyash Thite
November 28, 2022

Partial Autocorrelation Function (PACF)

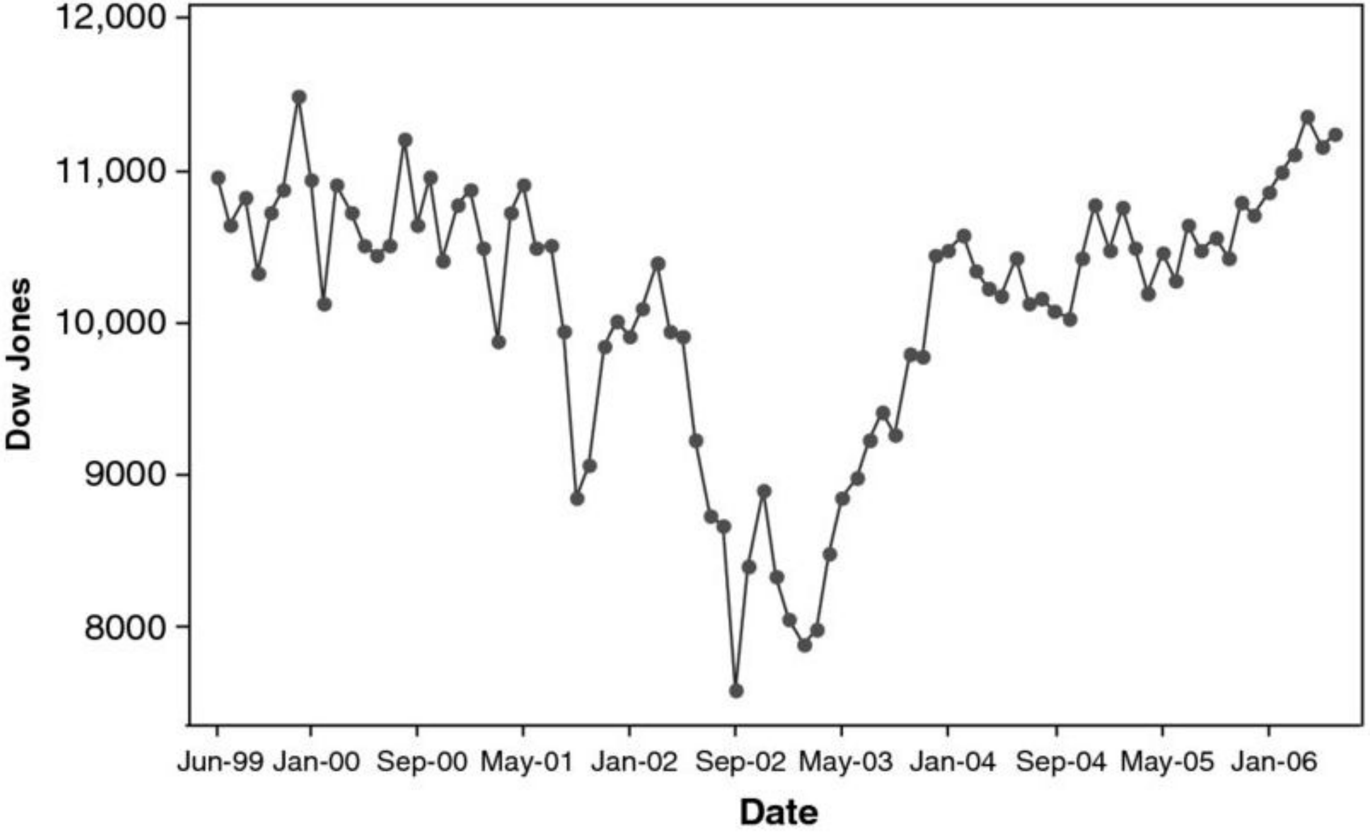
- What is PACF and how does it differ from ACF.



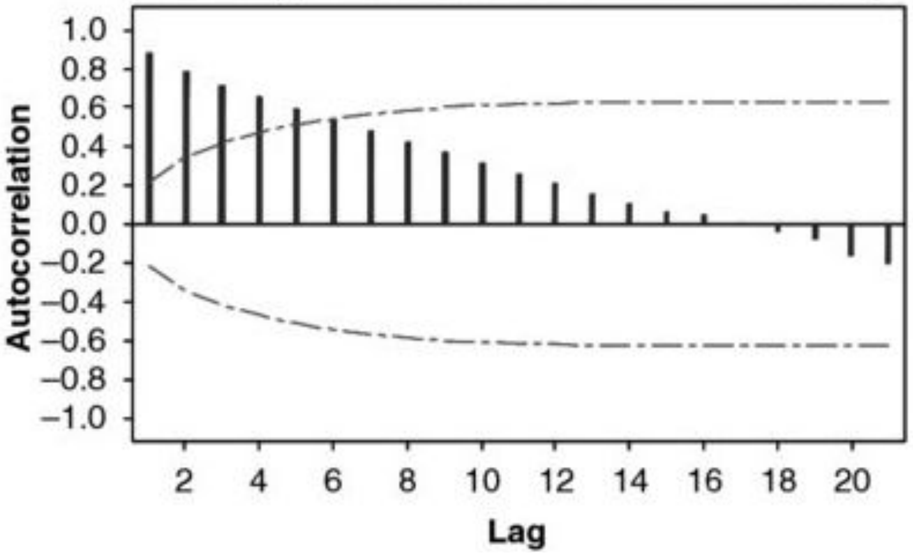
m_t m_{t-1}

m_{t-3} m_{t-2}

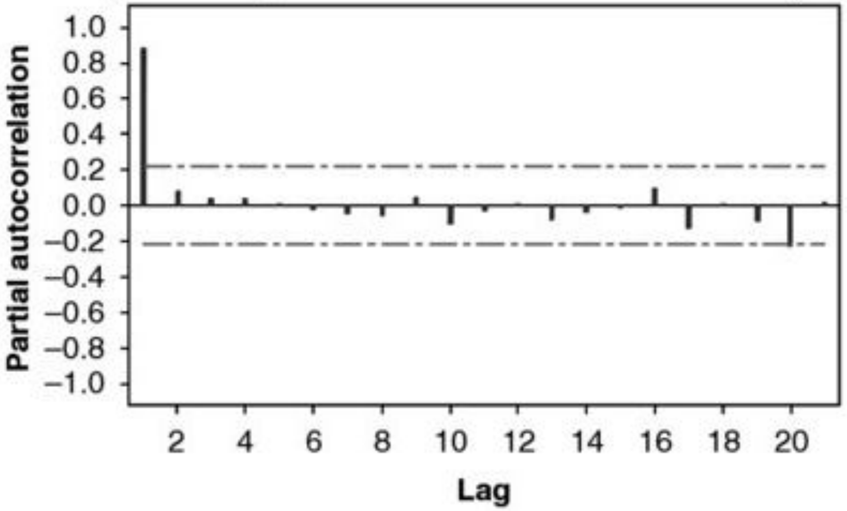
$$m_t = \phi_a m_{t-1} + \phi_b m_{t-2} + \phi_c m_{t-3} + \mathrm{e}$$



Autocorrelation function for Dow Jones index
(with 5% significance limits for the autocorrelations)



Partial autocorrelation function for Dow Jones index
(with 5% significance limits for the autocorrelations)



Autoregressive Model (AM)

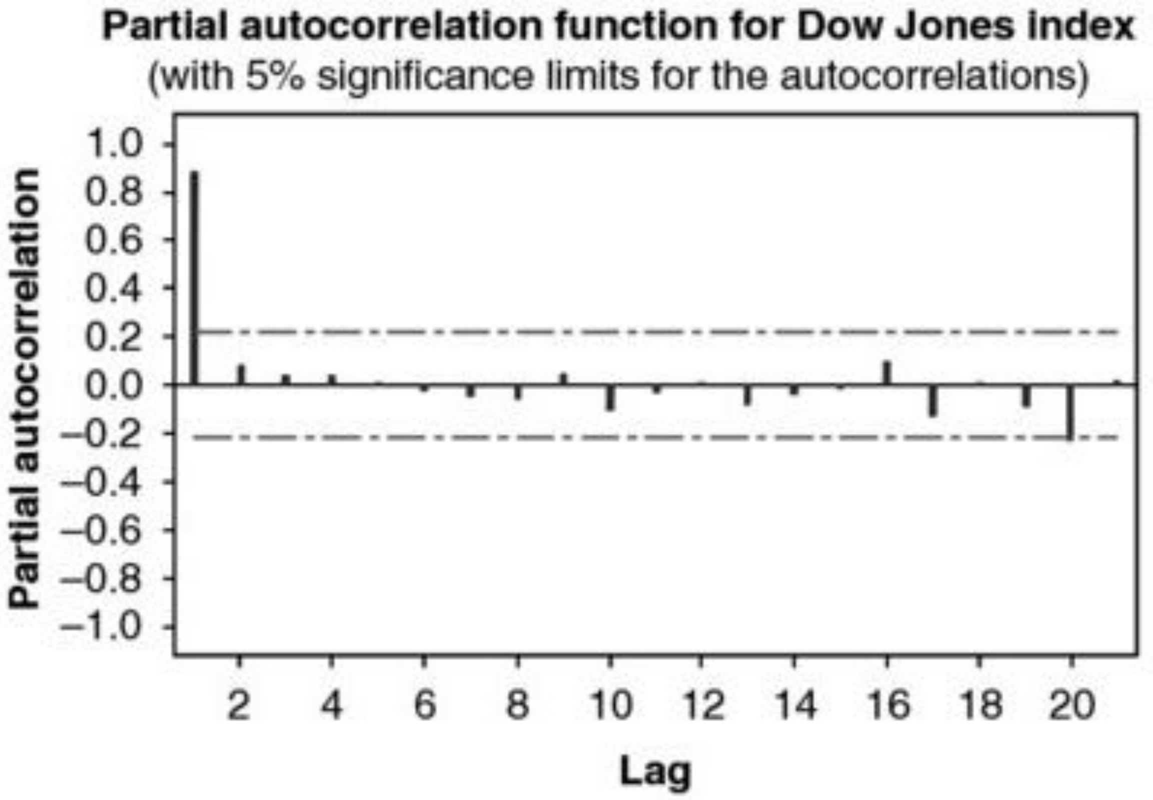
- Time series models are used to forecast future events based on historic data. Examples of time series models are Autoregressive models, Moving average models.

- A model which depends solely on previous outputs / values is called an Autoregressive Model.

- A regression typically predicts dependent variables based on other independent variables.

- Autoregressive models predicts dependent variables based on past values of that variable, hence auto(self) regression.

Autoregressive Model (AM)



$$m_t = \beta_0 + \beta_1 m_{t-1^{+\epsilon_t}}$$

$$m_t = \beta_0 + \beta_1 m_{t-1} + \beta_2 m_{t-4} + \varepsilon_t$$

The notation AR(p) denotes an Autoregressive model of order P. Note that first equation is AR(1) while the second one is AR(2)

Autoregressive Models

- Regression type models that capture Autocorrelation
  - Autoregressive Models (AR)
  - Autoregressive Integrated Moving Average Models (ARIMA)

  - Autoregressive models use the previous variables to predict future values
  - They are of multiple orders from 1…n
  - A first order autoregressive model AR(1) uses the most recent value in time series to predict following values.

  - Mean of Yt is given by $\mu = \frac{\beta_0}{1-\beta_1}$

$$Y = \beta_0 + \beta_1 x + \varepsilon$$

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + u_t$$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \epsilon_t$$

Moving Average Model (MA)

- A moving average model defines that current observations are linearly dependent on current and past ***error*** terms.
- The Errors are assumed to be white noise (Independent and Normally Distributed)
- MA Models can be used for stock trading. Usually, amateur investors use trend to predict stock values. (A stock that is trending upwards will continue to trend upwards and vice versa)
- However, an MA model can help you better understand this trend.

Forecasted Value	Error	Predicted Value
20	-4	16
18	2	20
21	0	21
21	4	25
22	2	

$$y_t = \mu + \epsilon_t + \theta_1\epsilon_{t-1}$$

Error terms have mean =0, sd=1

MA Model of Order 1 – MA(1)

$$y_t = \mu + \epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} + \cdots + \theta_q\epsilon_{t-q}$$

MA Model of Order q – MA(q)

Autoregressive Moving Average Model (ARMA)

- Autoregressive Moving Average(AR) models are a combination of Autoregressive(AR) and Moving Average Models (MA)
- An ARMA model or order (1,1) takes AR(1) and MA(1) into account.

- $m_t = \beta_0 + \beta_1 m_{t-1} + \phi_1 m_{t-1} + \epsilon$

Autoregressive Model of Order 1 in R

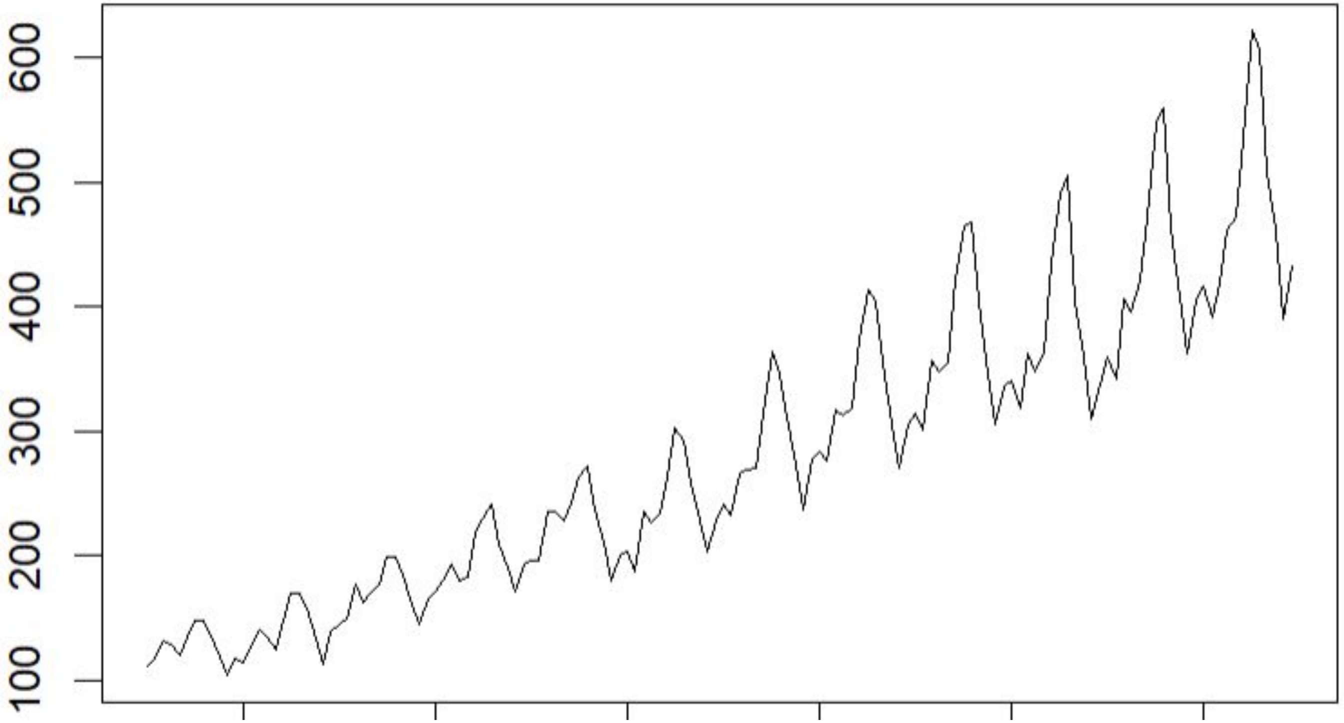
- Example in R

HAD301201A : Applied Time Series and Forecasting

Suyash Thite

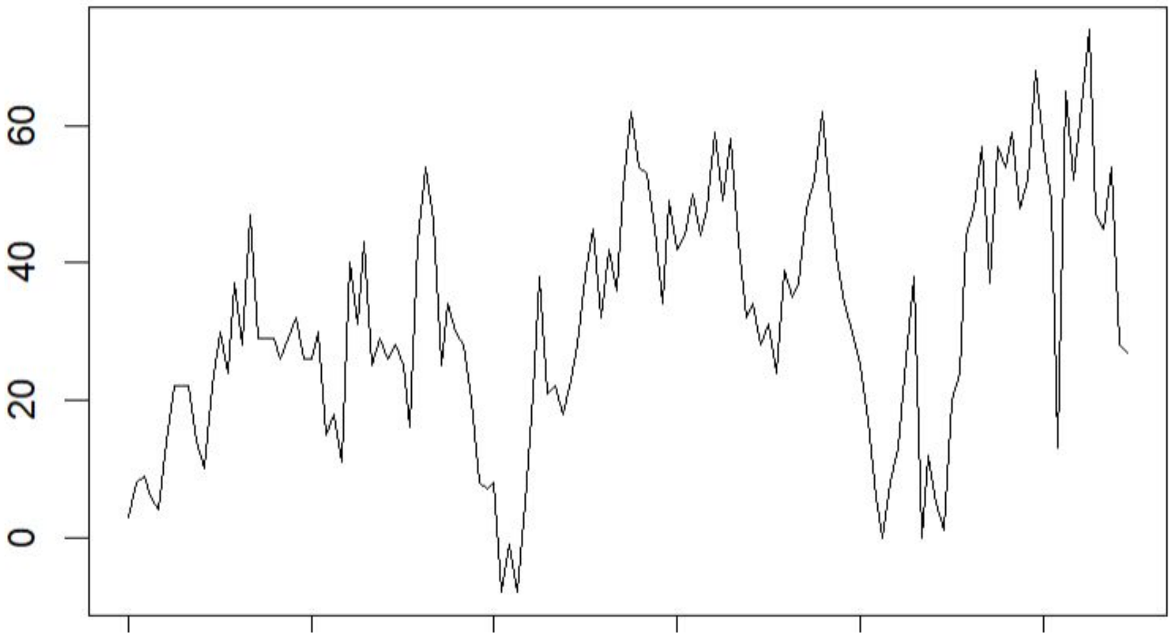
Autoregressive Integrated Moving Average Model (ARIMA)

- ARIMA stands for Autoregressive Integrated Moving Average Model.
- ARIMA models are useful when time series is not stationary, for instance in this time series, the mean is trending upwards.



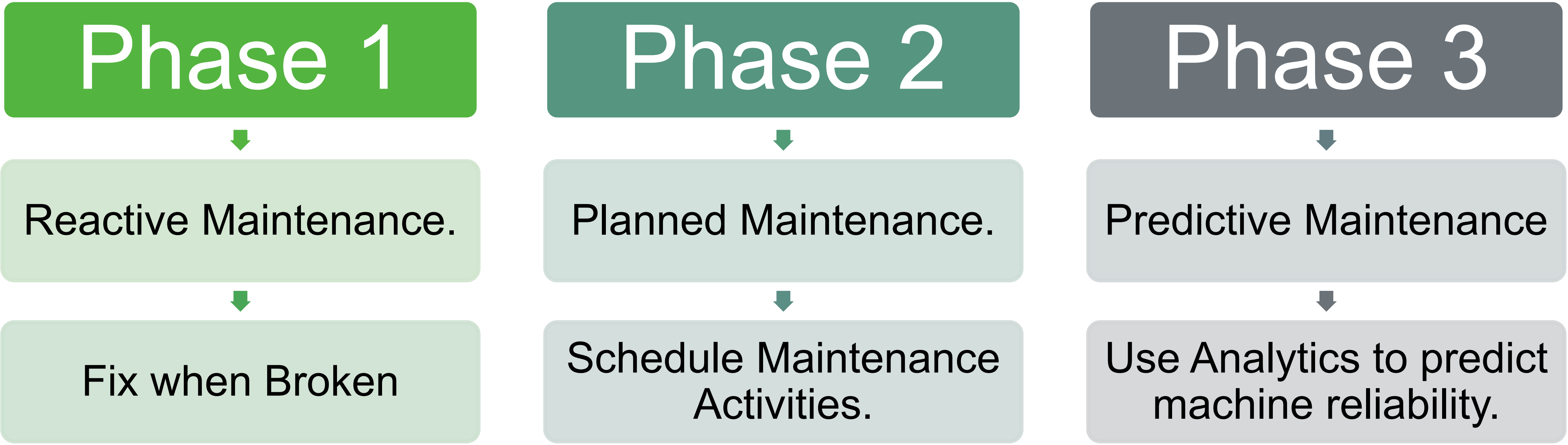
- Consider the number of passengers at any given point to be a_t
- The transformation we are going to define on this time series is given as $z_t = a_{t+1} - a_t$

Autoregressive Integrated Moving Average Model (ARIMA)



- Consider the number of passengers at any given point to be a_t
- The transformation we are going to define on this time series is given as $z_t = a_{t+12} - a_t$
- ARIMA(2,1,2) where p = order of autoregressive model, q = order of moving average model and d is the order of the integrated model.
- $z_t = \phi_1 z_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t$
- $a_0 = \sum_{i=1}^{o-n} z_{0-i} + a_n$

Industrial Maintenance Strategy



Phase 1

Reactive Maintenance.

Fix when Broken

Phase 2

Planned Maintenance.

Schedule Maintenance Activities.

Phase 3

Predictive Maintenance

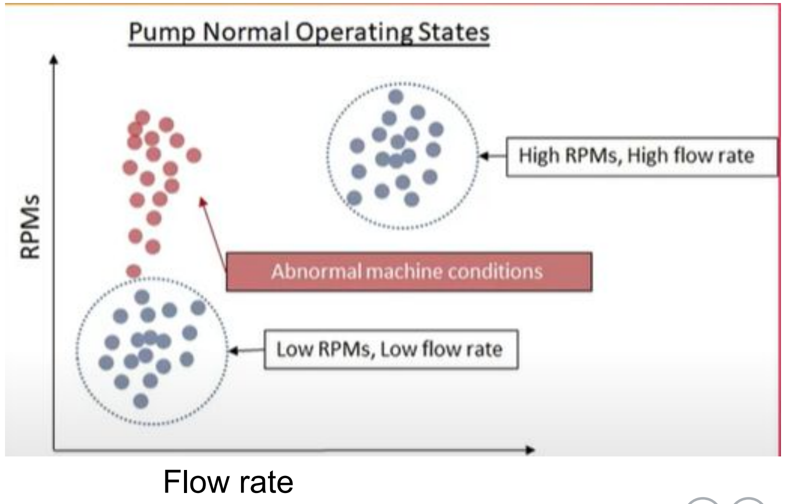
Use Analytics to predict machine reliability.

Predictive Maintenance Datasets

- Predictive Maintenance (PdM) is an ML based strategy that depends on previous data to predict point of failures in machines, example servers, oil pumps, automotive manufacturing machines.
- They make the use of Predictive Maintenance Algorithms to maintain availability by decreasing downtime and increase machine life.
- Various amounts of usage data are collected via smart sensors. These sensors work on various manufacturing equipment and transmit the current status of the equipment.
- The following data points are collected most commonly
    - Usage Data
    - Maintenance Data
    - Condition of Asset
    - History of assets conditions from similar assets used at various companies
    - Environmental data

Predictive Maintenance Datasets : Use Case

- PdM used in Oil and Gas industry.
- Example: Gas Pump Data
- Data points collected : Flow, Vibration, Power via sensors fitted. Data is near – real time.
- Historical data with above information is used to create simulation of potential failure scenarios.
- Other use cases:
- Infrared Imagery (IR cameras): Hot spots of electric wiring
- Acoustic Analysis: Detecting gas and vacuum leaks
- Vibration Analysis: Determining the fluctuations of the vibration of essential components
- Oil Analysis: Checking the condition of a machine’s oil lubrication system


Pump Normal Operating States
RPMs
High RPMs, High flow rate
Abnormal machine conditions
Low RPMs, Low flow rate
Flow rate

- [Source](#)

Predictive Maintenance : Factors to consider

Error history

- An ML model for predictive maintenance requires data both on normal operational patterns and failure patterns before it’s trained. Thus, a training dataset should include enough training examples on normal and error samples.

Maintenance history

- This step refers to the detailed information on the machine repairs in the past, which is a crucial component of the predictive maintenance dataset. Otherwise, one risks getting misleading results from the model.

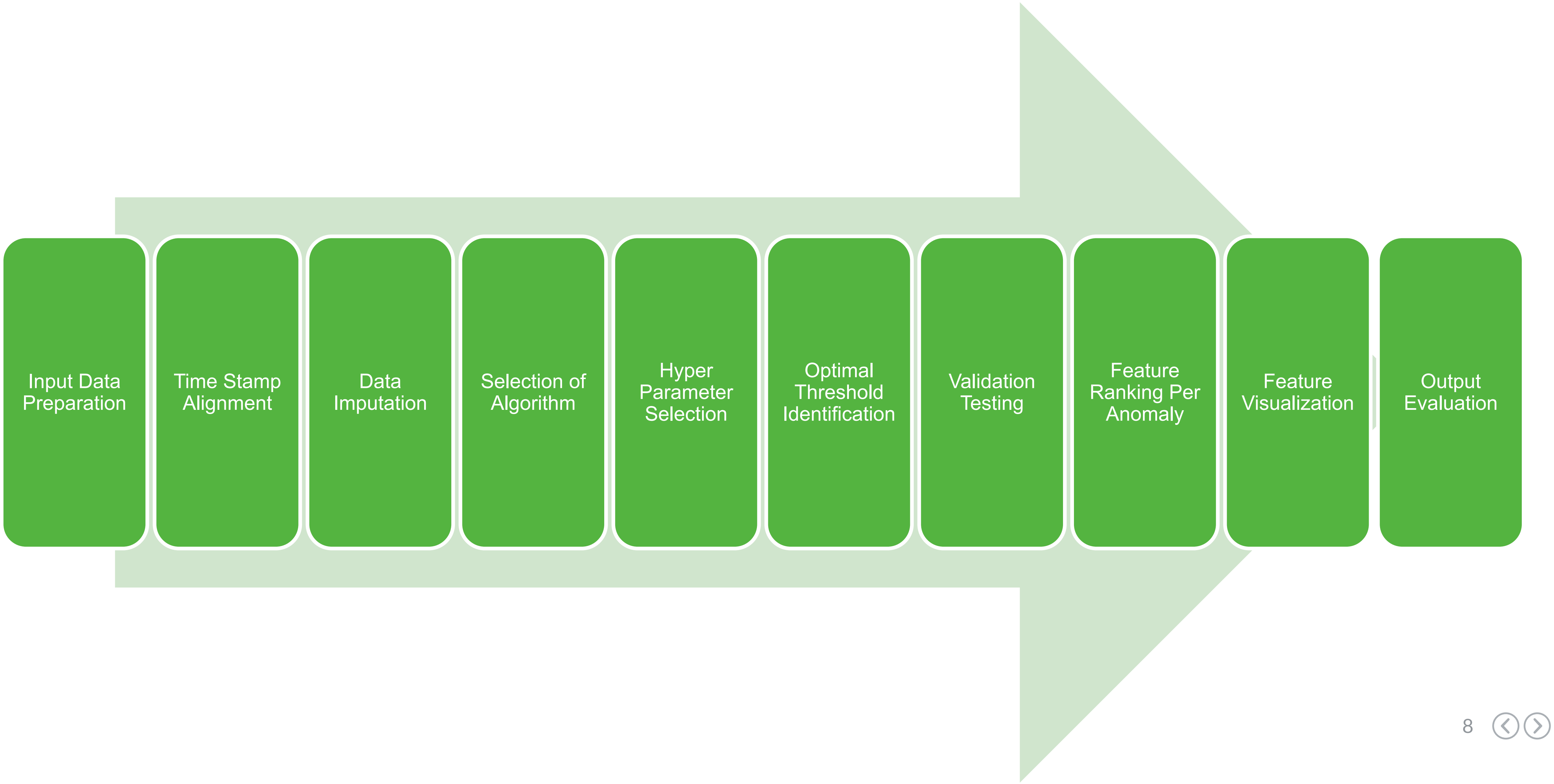
Machine operating conditions

- Another valuable information for the dataset in predictive maintenance is the aging pattern of the asset, given that the condition of machines in production tends to get worse over time as it performs many operations per day. Anomalies should be recorded too to trace the degradation pattern.

Equipment metadata

- Such metadata includes static feature data on the technical information of the equipment in service, like the date of creation, the model, the start date of service, and the system’s location.

How is a predictive maintenance model built?



Input Data Preparation

Time Stamp Alignment

Data Imputation

Selection of Algorithm

Hyper Parameter Selection

Optimal Threshold Identification

Validation Testing

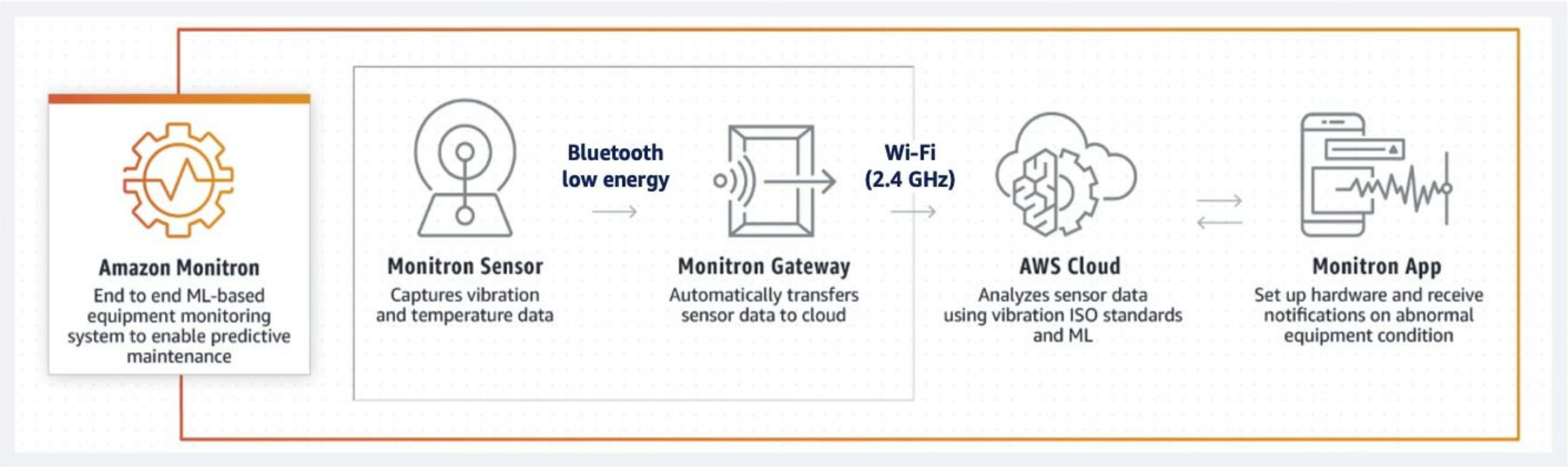
Feature Ranking Per Anomaly

Feature Visualization

Output Evaluation

Source

Predictive Maintenance Datasets : Product - Amazon



Amazon Monitron
End to end ML-based equipment monitoring system to enable predictive maintenance
Monitron Sensor
Captures vibration and temperature data
Bluetooth low energy
Monitron Gateway
Automatically transfers sensor data to cloud
Wi-Fi (2.4 GHz)
AWS Cloud
Analyzes sensor data using vibration ISO standards and ML
Monitron App
Set up hardware and receive notifications on abnormal equipment condition

- Amazon Monitron product is actively being used by manufacturing companies to monitor pumps, compressors, motors.
- Popular low-code/ no-code solution in the market.

Predictive Maintenance : Advantages and Benefits

Uptime Improvement

Cost Reduction

Risk Reduction

Lifetime Extension

New Revenue Streams

Energy Savings

Challenges of Predictive Maintenance

- Finding the right applications of ML technology.
- Diverse assets and quality of data
- Resources : Time, Scale, and talent

BMC Medical Research Methodology

RESEARCH Open Access

Forecasting COVID-19 cases using time series modeling and association rule mining

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Abstracts

Background: The aim of this study was to evaluate the most effective combination of autoregressive integrated moving average (ARIMA), a time series model, and association rule mining (ARM) techniques to identify meaningful prognostic factors and predict the number of cases for efficient COVID-19 crisis management.

Methods: The 3685 COVID-19 patients admitted at Thailand's first university field hospital following the four waves of infections from March 2020 to August 2021 were analyzed using the autoregressive integrated moving average (ARIMA), its derivative to exogenous variables (ARIMAX), and association rule mining (ARM).

Results: The ARIMA (2, 2, 2) model with an optimized parameter set predicted the number of the COVID-19 cases admitted at the hospital with acceptable error scores ($R^2=0.5695$, RMSE = 29.7605, MAE = 27.5102). Key features from ARM (symptoms, age, and underlying diseases) were selected to build an ARIMAX (1, 1, 1) model, which yielded better performance in predicting the number of admitted cases ($R^2=0.5695$, RMSE = 27.7508, MAE = 23.4642). The association analysis revealed that hospital stays of more than 14 days were related to the healthcare worker patients and the patients presented with underlying diseases. The worsening cases that required referral to the hospital ward were associated with the patients admitted with symptoms, pregnancy, metabolic syndrome, and age greater than 65 years old.

Conclusions: This study demonstrated that the ARIMAX model has the potential to predict the number of COVID-19 cases by incorporating the most associated prognostic factors identified by ARM technique to the ARIMA model, which could be used for preparation and optimal management of hospital resources during pandemics.

Keywords: COVID 19, Pandemic, Data mining, Time series analysis, Association rule mining

Background

The crisis outbreak of coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) started in Wuhan, Hubei Province, China in December 2019 [1]. The COVID-19 pandemic has required governments around the world to implement new policies under pressure from vulnerable people and communities [2]. Since the first outbreak, COVID-19 has mutated into many variants including the alpha, beta and delta SARS-COV-2 variants, which have been associated with new waves of infection [3]. The catastrophic effect across the entire world resulted in more than six million deaths worldwide in 2022 [4]. In addition, COVID-19 has caused a rapid deterioration in the condition of the disease, and the number of patients requiring hospitalization has increased significantly, resulting in a high demand for hospital resources [1].

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Data mining is an efficient analytical methodology to recognize and investigate a huge data set to acquire meaningful information [5]. In the medical field, the large numbers of medical records (including demographic information, diagnoses, clinical notes, etc.) in the healthcare information systems are ideal targets for the use of data mining in improving the analysis and prognosis prediction of various diseases [6–8]. Examples include using an Artificial Neural Network (ANN) and Support Vector Machine (SVM) algorithm to predict cardiovascular disease [9], using data mining classification algorithms, Decision Tree and Naive Bayes algorithms to identify liver disease [10] and predict the recovery outcome of Middle East Respiratory Syndrome Coronavirus (MERS-CoV) [11]. With the unprecedented increase in COVID-19 cases worldwide, there is a need for effective prediction models to identify the associated prognostic factors and forecast the number of COVID-19 cases to optimally organize the hospital resources.

Time series analysis and association rule mining (ARM) models have been widely used to predict trends, structural breaks, cycles, and unobserved values, and have proven to be useful in the medical field [12–14]. The auto regressive integrated moving average (ARIMA), a time series analysis model, was shown to have a promising accuracy for forecasting of infectious diseases in medical fields [15, 16]. ARIMA was used to forecast the number of new COVID-19 cases, deaths, and recoveries based on the daily reported data from different countries for assessment of the future outbreak [17–20]. ARM was originally presented by Agrawal et al. as an algorithm for marketing data analysis [21]. ARM has been used to extract medical health information, which is currently being applied for the development of classification and prediction models to identify and forecast the possibility of development and progression of a disease by considering the rules of the disease [22]. ARM was demonstrated to be an effective model for mining the frequent symptom pattern for COVID-19 patients, which could assist clinicians in decision making [23]. Another study used ARM to analyze the patterns of different non-pharmaceutical interventions to manage the infection growth rate in the United States [24]. Even though there are many advanced data-driven time series methods used to predict the future number of COVID-19 patients, a new and more accurate prediction model is important in the pandemic crisis. The associated contributing factors should be considered to improve model performance. Therefore, the combination of ARM and ARIMA models by selecting the most associated prognostic rules and integrating with ARIMA models could increase the accuracy of predicting new cases to better understand the current situation and the progression of COVID-19, which can be easily used by society, organizations, or governments to assess and manage the crisis during the future outbreak.

The aim of this study was to evaluate the most effective combination of ARM techniques and ARIMA models to identify prognostic factors and predict the number of COVID-19 patients. These models are expected to allow for better preparation, organizing hospital resources of further such units and more optimal use of medical personnel and equipment to enhance healthcare decision-making to manage COVID-19 patients in this crisis situation.

Methods

Administration protocol and data collection

The study was conducted at Thailand's first university-based field hospital. The field hospital was transformed from the service apartment style 14-story building of the university dormitory into a 494-bed facility for non-critical COVID-19 patients [25]. The field hospital was managed by the main university hospital and included the patients referred from the project's five university hospitals and hospitals in the central area of Thailand. Sources of funding come mainly from the donations of university alumni, community groups and non-governmental organizations. Upon admission, a nurse records patient data in the COVID-19 screening of the field hospital information system; the patient undergoes a chest x-ray, blood tests for complete blood count (CBC), liver function tests (LFTs), electrolyte, balance urine nitrogen (BUN), and Creatinine (Cr). The doctor interprets the labs and chest x-ray, and records the results in the admission note. The patients are only admitted to the field hospital if they meet all of the following criteria: 1) asymptomatic, mild or moderate symptoms; 2) normal activities of daily living; 3) no important organ dysfunction; 4) no psychiatric history; and 5) resting pulse oxygen saturation (SpO_2) > 95%. To avoid unnecessary contact between patients and medical personnel, the patient reports signs and symptoms, wants and needs via an internal field hospital application. Any consultation with the attending physician is done through a notification form. If the attending physician wishes to speak to the patient, the patient's telephone number is obtained from the respective patient's floor. All prescriptions must be made using a prescription form which will then be processed by the attending nurse and recorded in the progress note in the field hospital information system and in the university hospital electronic medical record system. In this field hospital system, the laboratory and radiographic examination would be performed on symptomatic COVID-19 patients with a history of taking Favipiravir and for severity assessment of symptomatic COVID-19 patients.

For Favipiravir-naive patients: 1) A follow-up chest x-ray may be considered in patients with worsening signs and symptoms (body temperature (BT) > 38.0 °C, cough, fatigue, SpO2 < 96%, or decreased SpO2 > 3% after a stress test); and 2) if the chest x-ray infers pneumonia with respiratory signs and symptoms (as mentioned in 1), refer the patient to the originating hospital for continued treatment with Favipiravir.

For patients previously treated with Favipiravir: 1) Follow-up by chest x-ray, LFTs); 2) if LFTs increase, consider consulting an ID specialist to terminate/adjust medication use; and 3) if the chest x-ray infers a progression of the infiltration accompanied by respiratory signs and symptoms (cough, fatigue, SpO2 < 96% and SpO2 drop > 3% after a stress test), consider referring the patient to the hospital of origin.

Asymptomatic patients who have been hospitalized for at least 14 days after a positive COVID-19 testing will be discharged home. The patients who received Favipiravir should fulfil all the following criteria: 1) The patients signs and symptoms have improved without progression of infiltration on chest x-ray; 2) BT < 37.8 °C continuously for 24–48 hours; 3) respiratory rate (RR) < 20/min; and SpO2 > 96% at rest. In the event of a patient's condition deteriorating, they are quickly transferred to the designated higher-level hospitals.

The criteria for transfer are 1) meeting the criterion of severe or critical, and 2) lung imaging showing a greater than 50% progression of lesions. Patients do not need Real-time Polymerase Chain Reaction (RT-PCR) or Antigen/Antibody detection for COVID-19 prior to discharge. One day before discharge, the attending nurse informs the attending physician of the number of potential discharges, so that the physician can prepare medical certificates and insurance documents according to the patient's needs. Upon discharge, the attending physician updates the patient's progress and discharge summary in the electronic medical record system of the university hospital.

A total number of 3685 patient records were retrieved from the electronic hospital information systems of the referral hospitals and the field hospital information system. In this study, we included all patients confirmed with asymptomatic and mild-to-moderate COVID-19 conditions from March 2020 to August 2021 (four waves of COVID-19 in Thailand). Collected data included patient demographics, comorbidities, body mass index (BMI), job, place of exposure to coronavirus, symptom before field hospital admission, sign of pneumonia in chest x-ray, field hospital length of stay, and the field hospital discharge destination. Table 1 shows the preliminary analysis of the dataset, including attributes, values, and frequency of each attribute-value pair.

Time-series analysis and association analysis

In this work, we present a study to combine time series analysis and association analysis to forecast the COVID-19 admitted cases as well as to analyze their potential factors and characteristics. To estimate the number of new cases and to predict the prognosis for better understanding of the current situation and progression of COVID-19, we exploited the autoregressive integrated moving average (ARIMA) model and its subclasses (i.e., AR, MA, ARMA) [12, 17, 26], and association rule mining (ARM) [21, 24] as tools for investigation (Fig. 1).

The autoregressive (AR) model

In the AR model, the predictive value at the time period t is modeled by the observed values at various time slots $t-1$, $t-2$,. . ., $t-k$. The impact of the value at each previous time period on the value at the current time is determined by the coefficient factor at that particular period of time. With this assumption, the model performs the regression of past time series and then calculates the present or future values in the series, commonly known as an auto regression (AR) model. It can be modeled as follows.

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t$$

Here, y_t is the value at the current time t, and y_{t-1}, y_{t-2}, ..., y_{t-p} are the observed values at the previous p time spots with their corresponding coefficients β_1, β_2, ..., β_p, respectively, β_0 is the intercept, and ε_t is the residual error at the time t. Therefore, $y_t - \varepsilon_t$ is the expected value at the current time t. In this work, the value y_t can be modeled as the number of inpatients, incoming patients, or outgoing patients at the time period t.

The moving-average (MA) model

Since the value of the time period t may be impacted by unexpected external factors, i.e., noises, we can alleviate such impact by means of the moving average method. Analogous to AR, the predicted value at the time period t can be modeled by the previous q lagged forecast errors ϵ_i as follows.

$$y_t = \phi_0 + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} + \varepsilon_t$$

Here, y_t is the value at the current time t and the lagged errors ε_{t-1}, ε_{t-2}, ..., ε_{t-q} are residual errors of the q autoregressive models at time $t-1$ to $t-q$ with ϕ_1, ϕ_2, ..., ϕ_q as their corresponding coefficients, ϕ_0 is the intercept, and y_t is the residual error at the time t.

Table 1 Preliminary analysis of the dataset: attributes, values, and frequency of each attribute-value pair

No	Attribute name	Attribute value	Attribute code	Frequency
1	Gender	Male	sex_male	1711
		Female	sex_female	1974
2	Age (year)	Less than 24	age_24	1148
		25–44	age_45_44	1838
		45–64	age_45_64	625
		More than 65	age_65	74
3	Body Mass Index	Less than 25	bmi_25	2309
		25–29	bmi_25_29	931
		More than 30	bmi_30	445
4	Underlying Diseases	None	ud_none	3392
		Respiratory	ud_repp	82
		Hypertension	ud_ht	39
		Metabolic	ud_meta	53
		Dyslipidemia	ud_dlp	14
		Other	ud_oth	64
		Diabetes mellitus	ud_dm	18
		Pregnant	ud_preg	23
5	Job	General worker	job_gen	3592
		Healthcare worker	job_health	93
6	Source of infection	Community	source_com	3119
		Family	source_fam	475
		Hospital	source_hosp	91
7	Symptom	Asymptomatic	symp_ast	2295
		Mild	sym_mild	1371
		Moderate	sym_mode	19
8	Chest X-ray	No lesion	cxr_no	3213
		Pneumonia	cxr_pneu	472
7	Length of stay (Day)	Less than 14	los_1_14	3625
		More than 14	los_15	60
8	Patient Discharge	Home discharge	dc_home	3600
		Refer to general hospital	dc_hosp	85
9	Current Incidence	Wave 1 (MAR-MAY 2020)	wave_1	55
		Wave 2 (JAN-MAR 2021)	wave_2	311
		Wave 3 (APR-MAY 2021)	wave_3	1779
		Wave 4 (JUN-JUL 2021)	wave_4	1540

The residual error at the time points after $t-1$ can be derived by the auto-regressive (AR) model as follows.

$$\begin{gathered}
\varepsilon_{t-1} = y_{t-1} - (\beta_0 + \beta_1 y_{t-2} + \cdots + \beta_p y_{t-p-1} \\
\varepsilon_{t-2} = y_{t-2} - (\beta_0 + \beta_1 y_{t-3} + \cdots + \beta_p y_{t-p-2} \\
\cdots \ \cdots \\
\varepsilon_{t-q} = y_{t-3} - (\beta_0 + \beta_1 y_{t-q-1} + \cdots + \beta_p y_{t-p-q}
\end{gathered}$$

Although the standard AR and MA may use the autocorrelation function (ACF), which takes into account all of the points, it is possible to apply the partial autocorrelation function (PACF), which accounts for the values of the intervals between.

The autoregressive moving average (ARMA) model

The Auto Regressive Moving Average Model (ARMA) combines the AR and MA models. In ARMA, the impact of previous lags along with the residuals is considered for forecasting the future values of the time series as follows.

$$\begin{aligned}
y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} \\
+ \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} + \varepsilon_t
\end{aligned}$$

Here, β_i represents the coefficients of the AR model, ϕ_i represents the coefficients of the MA model, and ε_t is the residual error at the time t. We assume only one

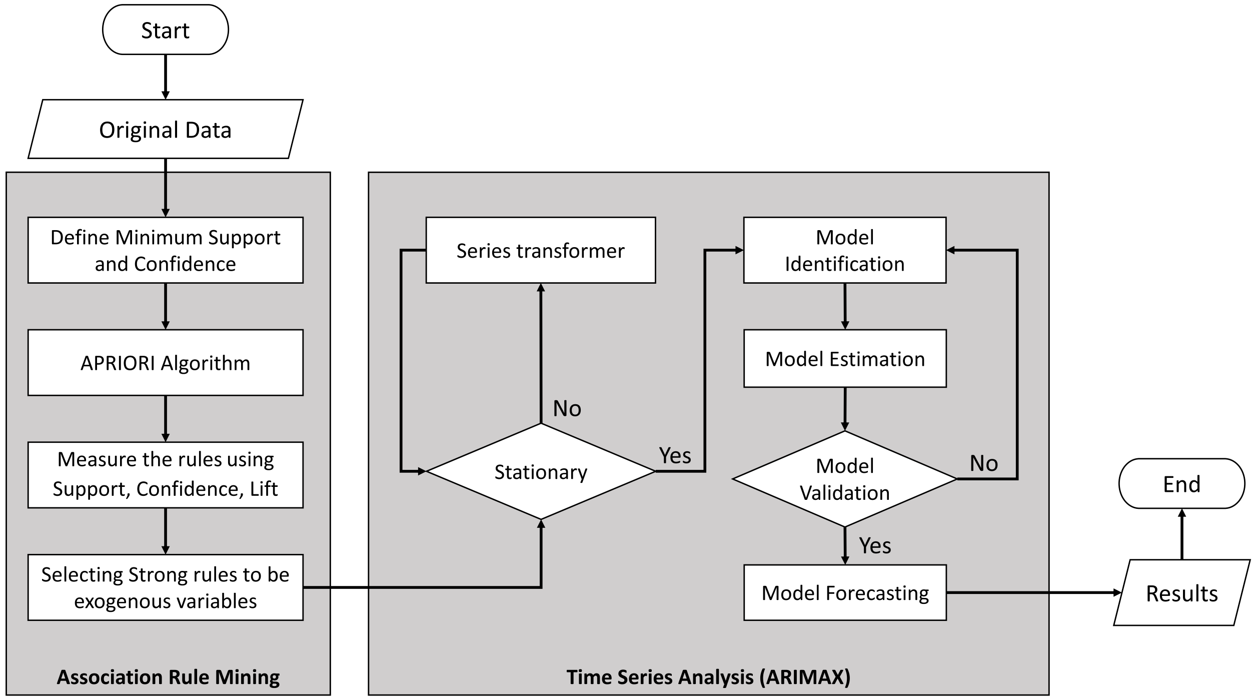

Fig. 1 The summary of the time series and association analysis

significant value from the AR model and one significant value from the MA model, so the ARMA model will be obtained from the combined values of these two models, denoted as the order of ARMA (1,1).

The autoregressive integrated moving average (ARIMA) model

As a generalization of AR, MA, and ARMA, the ARIMA model introduced differencing (integration) into the ARMA model to make the series stationary exploit to forecast future values under the factor of previous lag value and residuals errors. Besides manipulating the time lag and alleviating noise by smoothing, it is also possible to decompose a series into trend, seasonal, and residual components, by assuming an additive model. With this addition, the series can be transformed to a stationary time series. To achieve the transformation, the differencing method is applied. For example, we can subtract the $t-1$ value from t values of time series. After applying the first differentiation, if we are still unable to get the stationary time series, we can again apply the second-order differentiation. The ARIMA model is an extension of the ARMA model by the fact that it includes one more factor known as integrated (i.e., differentiation) which stands for I in the ARIMA model. The ARIMA model, denoted by ARIMA (p,d,q), can be formulated as follows:

$$\begin{aligned} y'_t =& \beta_0 + \beta_1 y'_t + \beta_2 y'_{t-2} + \cdots + \beta_p y'_{t-p} \\ &+ \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} + \varepsilon_t \end{aligned}$$

Here, p is the order of the autoregressive process, d (set to 1 in this case) is the degree of differentiation (the number of times the series was differenced), and q is the order of the moving average component. In this model, the first-order difference ($d=1$) between consecutive observations y'_i was computed and used, instead of the original observed value y_i as shown below.

$$y'_i = y'_i - y'_{i-1}$$

Differencing removes the changes in the level of a time series, eliminating trend and seasonality and, consequently, stabilizing the mean of the time series.

In some situations, we may need to difference the series data a second time (d=2) to obtain a stationary time series, which is referred to as second order differencing as follows:

$$\begin{aligned} &y''_i = y'_i - y_{i-1} \\ &{}'y''_i = \left(\mathrm{y}_t - \mathrm{y}_{t-1}\right) - \left(\mathrm{y}_{t-1} - y_{t-2}\right) \\ &y'_i = y_t - 2y_{t-1} + y_{t-2} \end{aligned}$$

A higher-order differentiation can be pursued analogously in the same manner.

The autoregressive integrated moving average with exogenous covariates (ARIMAX) model

When an ARIMA model includes other time series as input variables, the model is referred to as an Autoregressive Integrated Moving Average with Exogenous Covariates (ARIMAX) model. An ARIMAX model can be viewed as a multiple regression model that takes the impact of covariates on the forecasting into account, improving the comprehensiveness and accuracy of the prediction. The ARIMAX(*p,d,q*) extends the ARIMA(p,d,q) model by including the linear effect that one or more exogenous series has on the stationary response series y_t. This method is suitable for forecasting when data is stationary/non-stationary, and multi-variate with any type of data pattern, i.e., level/trend/seasonality/cyclicity. The ARIMAX(p,d,q) model can be formulated as follows:

$$\begin{aligned} y'_t =& \beta_0 + \beta_1 y'_{t-1} + \beta_2 y'_{t-2} + \cdots + \beta_p y'_{t-p} \\ &+ \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} + \varepsilon_t \\ &+ \theta_1 \left(X_1\right)_t + \theta_2 \left(X_1\right)_t + \cdots + \theta_m \left(X_m\right)_t + \varepsilon_t \end{aligned}$$

Here, d is set to 1, $(X_i)_t$ is the value at the time t of the i - th exogenous covariable (X_1), θ_i is the corresponding coefficient for the covariable X_i, and m is the number of exogenous covariables to be considered, while *p, d*, and *q* indicate the same parameters as in the ARIMA model.

Association rule mining

Besides the time-series analysis, association rule mining (ARM) can be used as a multivariate analysis to help us understand the correlation among factors [24]. Given a dataset containing a collection of records or transactions, each record comprises a set of categorical attributes. An association rule can be denoted by $A \rightarrow B$, where A (the antecedent or LHS) and B (the consequent or RHS) are sets of various attribute-value pairs (also called itemsets), and are disjoint. The rule represents the hypothesis that when variables in A occur in the dataset, the variables in B also occur. Association mining generates a large number of rules from a given dataset. In a dataset with m attributes $n-1$ antecedents and one consequent, each with n values, each can generate a maximum of $nm^{n-1}-1$ rules. However, not all rules are significant. The goal of this approach is to find rules that have high practical significance. To eliminate spurious rules, we use three measures: support, confidence, and lift. In addition, we also use the chi-squared test to measure the statistical significance of the association between the antecedent and the consequent. Given two disjoint sets of attribute-value pairs A and B, and an association rule $A \rightarrow B$; support of the rule refers to the number of records where the attribute-value pairs in either set A or B appear in the dataset relative to the total number of records (transactions or instances). This denotes the prevalence of the rule in the dataset. By definition, the support value is symmetric, that is Support $(A \rightarrow B)$ = Support $(B \rightarrow A)$, and it equals the total numbers of records containing both A and B to the total number of records in the dataset. The confidence of the rule $A \rightarrow B$ measures the conditional probability of B, given A. Thus, the confidence measure for a given rule is asymmetric, that is Confidence $(A \rightarrow B) \neq$ Confidence $(B \rightarrow A)$. The lift measure is the ratio between the observed support and the expected support between the independent variables A and B. Implicitly, lift >1 means a greater degree of dependence, lift <1 specifies negative dependence, and lift = 1 indicates independence between A and B. Lift is also a symmetric measure between the itemsets A and B, that is Lift $(A \rightarrow B)$ = Lift $(B \rightarrow A)$.

$$\begin{aligned} Support(A \rightarrow B) &= \frac{|A \cap B|}{N} \\ Confidence(A \rightarrow B) &= \frac{|A \cap B|}{|A|} \\ Lift(A \rightarrow B) &= \frac{|A \cap B| \times N}{|A||B|} \end{aligned}$$

Here, $|A|$ and $|B|$ are the numbers of records that include A and B, respectively, while $|A \cap B|$ is the number of records that contain both A and B. In this paper, the antecedent A can be either patient demo-graphics (either male or female), age (<24, 25–44, 45–64, and>65), body mass index or BMI (<25, 25–29, and>29), underlying diseases (none, respiratory, hypertension, metabolic, dyslipidemia, diabetes mellitus, pregnant, or others), job (healthcare or non-healthcare patient), inflection source (community inflection, family inflection, or hospital inflection), symptoms before field hospital admission (asymptomatic, mild, or moderate), sign of pneumonia in chest x-ray (no lesion or pneumonia) or length of stay in the field hospital (14 or>14), and patient discharge (home discharge or refer to general hospital), as the contributing factors. On the other hand, for the consequent B we focus on (1) the length of stay (either 1–14 or>14), (2) the patient discharge (either home discharge or hospital discharge), (3) the chest x-ray result, and (4) current incidence (wave 1, 2, 3 or 4). Since one assumption for ARM is that all the values of attributes are discrete, we translate the numerical data used in the study into discrete labels, as well as split the continuous data of infection growth curve into four phases.

Experiment settings

Data collection and parameter settings

The dataset includes 3685 records registered with the electronic hospital information systems of the field hospital during March 2020 to August 2021. It displays characteristics of the dataset, including, attributes, values, and frequency of each attribute-value pair. Each of the nine attributes contains 2–8 possible values. Most attributes have imbalanced numbers in their values, except gender (Table 1). In our time series analysis, the target of prediction is the number of patients in the field hospital for each day during the observation period, that is March 2020 to August 2021. We have explored the value of the three ARIMA parameters as $p \in \{1,2,3\}$, $d \in \{1,2\}12$, $q \in \{1,2,3\}$ due to our preliminary test. In addition, we applied association rule mining to find the most influential factors among the eleven factors, that is patient demographics, age, body mass index, underlying diseases, job, inflection source, symptom before field hospital admission, sign of pneumonia in chest x-ray, length of stay in the field hospital, patient discharge, and current incidence. As an ARIMAX model, we extend the ARIMA(*p,d,q*) model to include the parameters as a series that are the most influential to the prediction of the number of patients in the hospital. The parameters included are known as exogenous series that are expected to trigger the stationary response on the series that we are predicting.

Performance metrics and evaluation

Given a data set has n values, denoted by $y_1, .., y_n$, each associated with a predicted value $f_1, .., f_n$, the following three metrics can be formulated. Coefficient of determination (R^2) is the proportion of the variation in the dependent variable that is predictable from the independent variable(s) as follows:

$$R^2 = 1 - \frac{SS_r}{SS_t} \tag{1}$$

$$SS_r = \sum_i (y_i - f_i)^2 = \sum_i e_i^2 \tag{2}$$

$$SS_t = \sum_i (y_i - \bar{y})^2 \tag{3}$$

$$\bar{y} = \frac{1}{n} \sum_i y_i \tag{4}$$

Here, SS_r is the sum of squares of residuals, SS_t is the total sum of squares, proportional to the variance of the data, and $\bar{y}$ is the mean of the observed data. Ranging from 0 to 1, it provides a measure of how well observed outcomes are replicated by the model. The higher the coefficient value is, the closer the dependent variable and independent variable are.

Root mean square error (RMSE) the standard deviation of the prediction errors [27], which are a measure of the distance of the data from the regression line, indicating the concentration of the data around the line of best fit as follows:

$$RMSE = \sqrt{SS_r} = \sqrt{\frac{1}{2} \sum_i (y_i - f_i)^2} \tag{5}$$

It expresses the dispersion of these errors.

Mean absolute error (MAE) allows measurement of the average magnitude of the errors for a set of predictions, regardless of their direction.

$$MAE = \frac{1}{n} \sum_i |y_i - f_i| \tag{6}$$

It represents the mean of the absolute difference in the sample between the prediction and the actual observation, taking into account that all individual differences are of equal significance. Therefore, compared to RMSE, MAE is less sensitive to outliers.

Results

Time series analysis

This section presents a time series analysis to forecast the number of patients admitted to the field hospital. Figure 2 shows the number of patients from 26 March 2020 to 22 July 2020. Three time series represent the relationships among a number of residing patients that are equal to a cumulative difference between admitted and discharged patients living in the hospital. The graph presents four waves of pandemic following the number of patients in hospital. The four waves are as follows: The first wave (Wave 1), the emergence of SAR-CoV-2, is the smallest period (34 days) from 26 March 2020 to 16 May 2020. The second wave (Wave 2) was from 11 January 2021 to 14 March 2020 (44 days). After that, the third wave (Wave 3) and fourth wave (Wave 4) were the continuous periods from 11 April 2021 to 31 May 2021 (51 days) and 1 June 2021 to 22 July 2021 (52 days), respectively. Finally, the forecasting models are validated by a test dataset from 1 August 2021 to 30 August 2021(30 days).

In this study, the time series models were trained using six training datasets. The first training set (All Wave) covers all datasets Wave 1 to Wave 4 of 228 days; the second training set, Wave 1 of 34 days; the third training set, Wave 2 of 45 days; the fourth training set, Wave 3 of 51 days; the fifth training set, Wave 4 of 52 days; the sixth training set, Wave 3 and Wave 4 of 103 days.

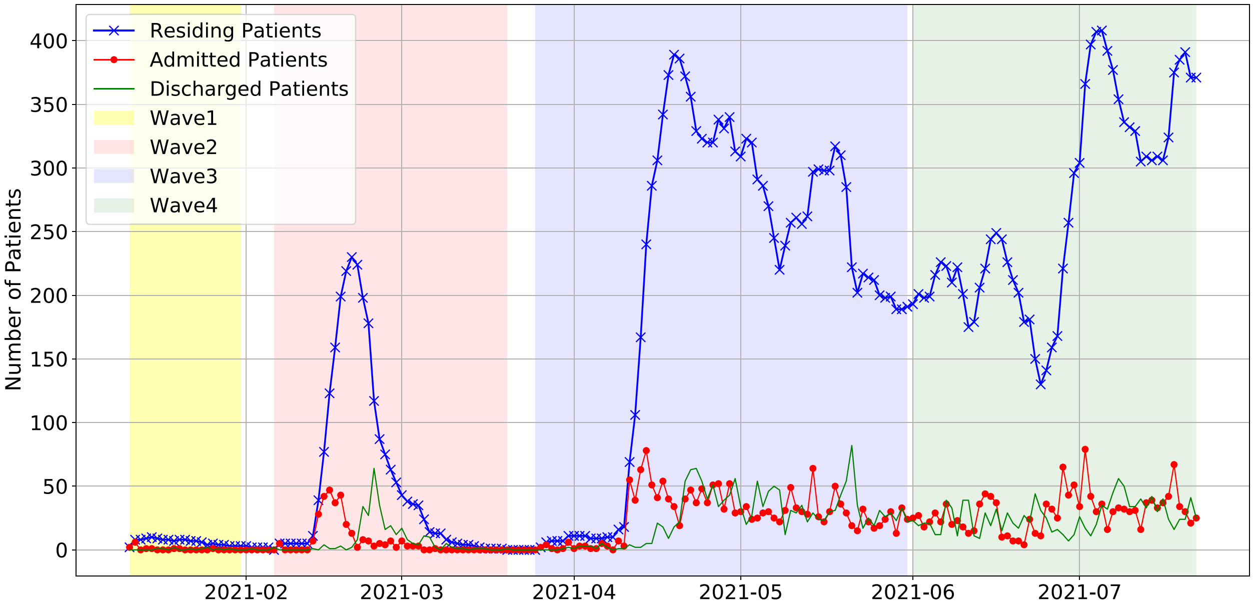

Fig. 2 The number of daily data of patients in the field hospital; New patients; Admitted Patients; Discharged Patients in four waves of COVID-19 pandemics in Thailand

In this work, we tested the estimated model using an autocorrelation function (ACF) and a partial autocorrelation function (PACF) plots to ensure that the model fits the data [17]. Figure 3 presents the steady-state prediction of time-series models. An estimation of the model explored the coefficient (Coef.), the standard error (Std err.) and z. An estimate of the first model was the AR model which gave a coefficiency of 0.3808, standard error of 0.243 and z of 1.565. The second model was an MA model which gave coefficiency of -0.5287, standard error of 6.841 and z of -0.077. The sigma value or constant value was coefficiency of -0.5287, standard error of 6.841 and z of -0.077. Moreover, we further estimated the model with Jarque-Bera of 7.70, heteroskedasticity of 0.57 and skew of 0.68.

For the data set, the time series method was applied using Python (PyFlux library) for time series analysis and prediction to compare the criteria of each setting. The ARIMAX (p,d,q) + X models were parameterized with $X \in \{\phi, x_1, x_2\}$, $p \in \{0,1,2,3\}$, $q \in \{0,1,2,3\}$, $d \in \{0,1,2\}$, where X is additional exogenous variables, with 51 combinations. Moreover, we select key features from association rule mining such as symptoms, age, and underlying diseases, etc. $X = \phi$ specifies no additional exogenous variable used. $X = x_1$ indicates additional exogenous variables. There are 15 variables, composed of three attributes in the symptom feature, four attributes in the age feature, and eight attributes in the underlying diseases feature. $X = x_2$ represents four variables of the selected attributes, that is the 'moderate' symptom, the 'more-than-65' age, and the underlying diseases of 'diabetes mellitus' and 'pregnant.'

The forecasting-accuracy metrics of the 51 models summarized on the six datasets and the evaluation of models with the measures of *RMSE* and *MAE* are shown in Table 2. The forecasts for the admitted patients with prediction confidential intervals (CI) between 5 and 95% are presented in Fig. 4 for ARIMA (2,2,2) and Fig. 5 for ARIMAX (1,1,1)+ x_2. Overall, the most accurate estimation was obtained by improving from ARIMA (2, 2, 2) to ARIMAX (1, 1, 1) + x_2 for the training set in Wave 4, covering from 11 April 2021 to 31 May 2021. For the first setting (All-Wave), the best model is ARIMA (1,2,1) with the *RMSE* of 22.8141 and *MAE* of 19.4133, which was closer to the actual data. For Wave-1, ARIMAX (2,2,2) + x_2 performs the best with the *RMSE* of 277.9974 and *MAE* of 273.4644, which was the highest to the actual data of all models. For Wave-2, AR(1) + $X1$ model is the best with the smallest *RMSE* and *MAE*. Based on *RMSE* and *MAE*, the value of ARIMA (1,1,1) + $X1$ was the closest to the actual data in Wave-3. The *RMSE* and *MAE* of ARIMAX (1,1,1)+ $X2$ appeared to be the best predictive models.

The comparisons among forecasting models are shown in Tables 3, 4 and 5. The models numbered 12–17 in Table 2 are defined to be the baseline models. The models with x_1 are the models numbered 29–34 while the models with x_2 are the models numbered 46–51. The compared

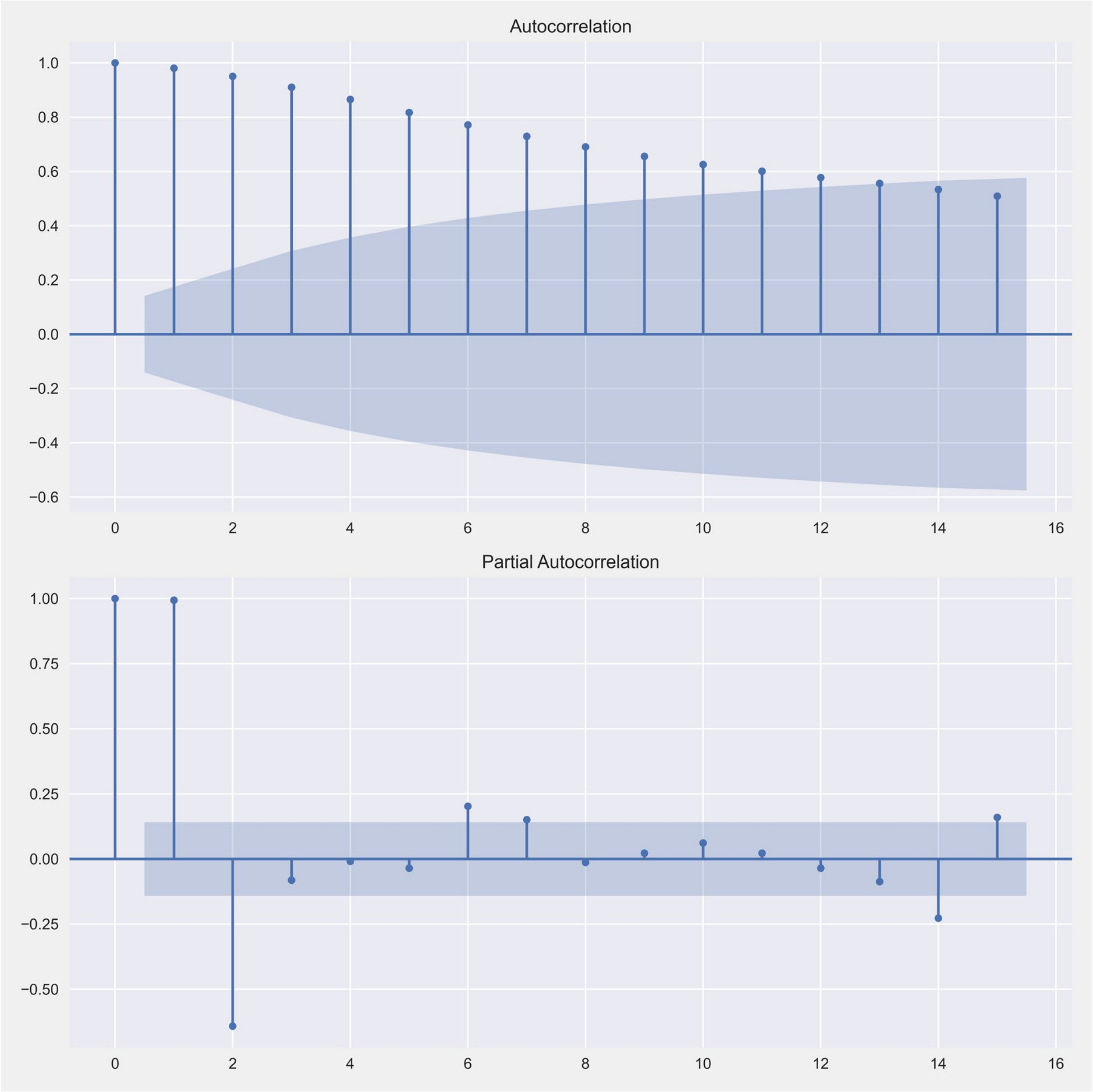

Fig. 3 An autocorrelation function (ACF) and a partial autocorrelation function (PACF) are presented to confirm the steady-state prediction of time-series models

pairs were (baseline vs x_1), (x_1 vs x_2), and (baseline vs x_2). The comparison was done under the same parameter setting. The result of R,^{2} RMSE and MAE (Tables 3, 4 and 5) yielded a good result indicating that time forecasting models could improve correlation of determination when we added exogenous variables.

The predicted values, CI 5% (lower confidence interval) and CI 95% (upper confidence interval), and actual data of the models are shown in Table 6 and Fig. 4. In addition, the improved predictive values of the models by adding exogenous variables are shown in Table 7 and Fig. 5. For example, ARIMA (2, 2, 2) predicted that the number of cumulative confirmed cases for the next 30 days could be 291 to 334 cases. ARIMAX (1, 1, 1) + x_2 predicted that the number of cumulative confirmed cases for the next 30 days could be 293–330 cases.

Table 2 The results of time series analysis model applied to six training sets obtained from statistical tests: Coefficient of determination (R^2), Root mean square error (RMSE), Mean absolute error (MAE)

No	Model	All Wave			Wave 1			Wave 2			Wave 3			Wave 4			Wave 3–4		
		R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE
1	I(1)	0.0899	290.7718	283.8123	0.0331	325.9969	323.9485	0.0904	277.9974	273.4644	0.0328	94.5392	75.6991	0.0145	65.7031	65.7790	0.0522	63.3078	63.8452
2	I(2)	0.2199	188.6716	178.0013	0.2199	325.9572	323.9855	0.2972	285.9000	280.6391	0.0425	77.1222	68.0936	0.0048	83.1201	73.3845	0.0425	80.7247	71.4506
3	AR(1)	0.5835	52.9774	44.8681	0.5172	334.5952	332.3318	0.5186	318.9675	315.8692	0.2275	85.0022	67.6283	0.5543	60.0630	49.5482	0.4259	30.1341	25.6407
4	AR(2)	0.5326	48.9132	45.3217	0.5543	338.2526	336.1396	0.0169	298.2876	295.3547	0.0001	78.0756	66.2715	0.3493	35.2782	26.6954	0.1111	57.0969	46.8206
5	AR(3)	0.5026	71.3773	67.2935	0.5969	337.3307	335.1067	0.1671	292.9912	290.9822	0.0084	82.1250	69.8914	0.1274	53.4205	42.5510	0.1001	61.1195	51.1240
6	MA(1)	0.0004	176.9638	171.7192	0.0004	327.4278	325.3349	0.0004	294.4148	292.0716	0.0004	81.4992	72.4591	0.0004	81.6120	71.7955	0.0004	270.0047	265.8700
7	MA(2)	0.0003	205.0899	199.6313	0.0003	329.3588	327.2778	0.0004	328.9829	326.8977	0.0003	93.4902	85.6784	0.0003	148.8627	141.7412	0.0003	92.1310	83.2050
8	MA(3)	0.0001	307.5673	298.8213	0.0002	328.1374	326.0477	0.0000	333.1808	331.1216	0.0004	149.7222	145.0442	0.0001	125.3216	117.2491	0.0000	79.3442	68.9794
9	ARMA(1,1)	0.5741	40.8981	36.6221	0.5020	334.0945	331.8095	0.4767	315.0413	311.7129	0.1788	85.6014	69.1618	0.5161	42.8637	38.1547	0.3543	33.6863	26.0659
10	ARMA(2,2)	0.5062	67.3449	63.3953	0.6258	339.1666	337.0229	0.0006	299.0722	296.2244	0.5596	203.8326	202.3505	0.1104	56.4891	45.8304	0.0368	72.2012	61.3681
11	ARMA(3,3)	0.5089	68.0282	64.0255	0.6393	334.7573	332.3653	0.0009	306.0231	303.3267	0.1338	147.5160	142.7802	0.1028	56.5914	45.7511	0.3217	62.0183	56.2090
12	ARIMA(1,1,1)	0.4182	121.1567	105.5253	0.0007	327.7731	325.6391	0.3813	275.0749	269.6568	0.2256	61.1524	51.7814	0.5694	43.9619	38.7228	0.7279	35.4740	29.4524
13	ARIMA(2,1,2)	0.4496	188.1384	175.6110	0.1136	331.8481	329.6721	0.0337	274.7054	269.5087	0.5424	241.8948	239.8888	0.0361	60.5829	48.7030	0.8066	37.8168	33.3437
14	ARIMA(3,1,3)	0.5746	100.8429	93.3260	0.0072	327.6217	325.5377	0.1379	291.6125	282.3766	0.0935	145.4436	140.7227	0.0324	60.5233	48.3732	0.2291	99.0573	92.0246
15	ARIMA(1,2,1)	0.6227	22.8141	19.4113	0.0022	327.9731	325.8776	0.5564	307.1235	303.0277	0.1896	85.9017	69.5801	0.5616	43.7555	38.6440	0.3546	33.6537	26.0567
16	ARIMA(2,2,2)	0.5811	108.9374	99.9407	0.0042	330.6365	328.5217	0.0735	280.7723	274.8963	0.5010	221.8999	220.2538	**[a]0.5853**	**[a]29.7605**	**[a]27.6102**	0.0367	78.2477	67.6000
17	ARIMA(3,2,3)	0.5684	105.7827	98.0635	0.0399	328.8342	326.6476	0.0782	269.6121	246.3643	0.7882	147.4570	143.0789	0.1616	85.7303	66.8601	0.3501	81.0317	75.6607
18	I(1) + X1	0.0037	288.6017	283.7774	0.0490	326.2426	324.0655	0.0342	282.0157	279.3011	0.0000	99.6746	75.6989	0.0000	81.8578	72.0013	0.0044	103.9072	83.0929
19	I(2) + X1	0.2592	212.5173	197.9378	0.2592	326.2460	324.1258	0.0005	286.8855	283.5395	0.0019	99.7003	76.0409	0.0048	83.1201	73.3845	0.0068	103.7216	83.5353
20	AR(1) + X1	0.6067	610.2414	519.6976	0.1226	326.8148	324.8728	0.2344	232.7690	219.5232	0.4300	38.4820	32.1837	0.6319	249.6770	198.6695	0.0122	268.9514	263.4326
21	AR(2) + X1	0.5362	67.2016	59.9040	0.1071	327.5698	325.6145	0.0035	263.3728	258.8025	0.6491	36.7028	29.6225	0.3990	88.3833	67.2515	0.8336	100.1792	83.2140
22	AR(3) + X1	0.6796	75.6844	55.5952	0.0890	326.4052	324.4467	0.0017	271.8932	267.0636	0.6816	37.0752	29.5750	0.0373	59.1096	47.5392	0.8428	97.1527	78.2065
23	MA(1) + X1	0.0001	252.3404	248.6892	0.1281	336.3468	334.3429	0.0013	298.9810	296.1156	0.0084	104.0982	76.0860	0.0313	87.0295	76.0244	0.0176	103.1149	81.7565
24	MA(2) + X1	0.0702	221.6587	216.9112	0.2267	335.3732	333.4037	0.1160	336.7430	334.5787	0.0004	75.8666	55.0494	0.0382	134.9549	127.8984	0.0138	88.1465	75.0825
25	MA(3) + X1	0.0005	317.8255	309.4642	0.1913	329.5174	327.5438	0.0001	334.6743	332.6033	0.0060	113.7286	77.5648	0.0139	118.1786	109.4121	0.0008	87.2773	72.8789
26	ARMA(1,1) + X1	0.5916	413.4365	358.2175	0.1774	324.0025	322.1328	0.1541	251.9922	243.5882	0.4516	33.2501	26.5740	0.6405	220.4147	176.9939	0.6106	165.2220	163.3853
27	ARMA(2,2) + X1	0.5949	424.4358	366.5745	0.0723	331.6259	329.4747	0.3369	399.6066	398.4546	0.7118	171.6618	170.5084	0.4607	160.5215	149.9203	0.4951	88.6736	83.4224
28	ARMA(3,3) + X1	0.1833	113.5424	100.8362	0.2160	327.6383	325.7101	0.0107	339.7625	337.6229	0.5940	167.3714	164.8800	0.5863	107.5209	84.9299	0.0044	219.6314	192.1180
29	ARIMAX(1,1,1) + X1	0.4182	183.8188	166.3895	0.1277	322.2422	320.3213	0.2574	267.9366	262.3262	0.5140	45.4581	37.5053	0.5694	43.9619	38.7228	0.7704	83.1827	79.9974
30	ARIMAX(2,1,2) + X1	0.6784	124.4039	99.0967	0.2633	321.7203	319.9461	0.0425	285.4226	281.3559	0.6366	176.3529	174.5772	0.0361	60.5829	48.7030	0.8382	59.1795	47.6580
31	ARIMAX(3,1,3) + X1	0.6510	149.8496	127.6797	0.0302	336.0062	333.9879	0.0007	253.1438	247.7629	0.1191	144.5963	139.6924	0.0324	60.5233	48.3732	0.3812	55.4460	50.4435
32	ARIMAX(1,2,1) + X1	0.2403	143.0063	130.9023	0.1210	322.0322	320.1035	0.2928	278.2316	273.1433	0.4498	49.7481	41.2963	0.5616	43.7555	38.6440	0.7471	79.9917	76.4410

Table 2 (continued)

No	Model	All Wave			Wave 1			Wave 2			Wave 3			Wave 4			Wave 3–4		
		R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE
33	ARIMAX(2,2,2) + X1	0.2168	95.7906	88.9073	0.3083	316.7929	315.1248	0.0490	287.2771	283.2256	0.5580	207.7418	206.2698	0.5853	29.7605	27.6102	0.1473	98.7315	80.6377
34	ARIMAX(3,2,3) + X1	0.4787	63.5331	57.3825	0.1452	337.2546	335.2641	0.0016	257.9516	251.6657	0.0026	144.7672	139.9775	0.1616	85.7303	66.8601	0.4676	74.2653	70.1748
35	I(1) + X2	0.0447	289.1389	281.2524	0.0041	326.0347	323.9383	0.0884	278.0144	273.4693	0.0000	99.6750	75.6992	0.0000	81.8175	71.9843	0.0044	103.9073	83.0939
36	I(2) + X2	0.0105	249.4103	231.4904	0.0421	326.0106	323.9672	0.2082	284.7981	279.4427	0.0019	99.6955	76.0373	0.0048	83.2961	73.5082	0.0068	104.7077	83.9761
37	AR(1) + X2	0.6156	255.7645	212.8672	0.5172	334.5952	332.3319	0.1727	302.2914	298.4389	0.0282	69.9752	58.5275	0.6311	249.1627	198.4651	0.5834	41.9315	35.5895
38	AR(2) + X2	0.5858	64.0891	52.3809	0.5543	338.2531	336.1401	0.0007	293.3307	290.4134	0.0131	70.7792	58.5222	0.3373	82.2578	62.6506	0.4830	42.5877	37.2450
39	AR(3) + X2	0.5264	28.4479	22.4192	0.5969	337.3308	335.1069	0.1030	298.6989	296.3389	0.0111	72.7548	60.1599	0.0092	57.7292	46.8582	0.4188	51.2708	45.6610
40	MA(1) + X2	0.0004	191.3896	187.3443	0.0004	327.4278	325.3349	0.0064	303.3572	300.9790	0.0116	81.3063	71.5271	0.0307	98.0537	87.9097	0.1876	275.7095	268.5105
41	MA(2) + X2	0.0003	208.8616	204.3860	0.0003	329.3588	327.2778	0.0071	329.9775	327.9153	0.0164	94.5079	86.0634	0.0638	143.4629	136.7615	0.0215	93.9181	84.8925
42	MA(3) + X2	0.0000	313.7185	303.9636	0.0002	328.3339	326.2458	0.0050	333.2174	331.1693	0.0168	83.1832	74.0123	0.0624	136.5470	125.2288	0.0435	87.0651	77.3405
43	ARMA(1,1) + X2	0.6070	188.6286	158.6611	0.5020	334.0945	331.8095	0.2345	301.7636	297.9054	0.0152	80.3589	66.8892	0.6260	208.8213	169.3105	0.6516	76.7976	69.1291
44	ARMA(2,2) + X2	0.5069	71.3063	67.2141	0.6257	339.1664	337.0227	0.0149	301.8609	298.7972	0.5278	160.9546	157.4370	0.4919	188.1245	174.4431	0.3916	113.9236	106.8338
45	ARMA(3,3) + X2	0.5675	30.4833	28.1090	0.1795	324.3882	322.5190	0.3004	308.7024	303.8821	0.5828	157.7017	154.2446	0.6386	253.0751	196.3018	0.1300	43.9619	38.7226
46	ARIMAX(1,1,1) + X2	0.3531	168.2529	153.0882	0.0929	318.2668	316.3056	0.2369	268.3102	262.7485	0.4671	50.0191	41.8890	[a]**0.5695**	[a]**27.7508**	[a]**23.4642**	0.7704	83.1909	80.0059
47	ARIMAX(2,1,2) + X2	0.6484	174.1887	148.7599	0.2435	324.9496	322.5022	0.0147	269.1468	263.4866	0.6058	198.4915	197.1301	0.0519	59.5415	47.9796	0.8380	60.6156	48.6302
48	ARIMAX(3,1,3) + X2	0.6375	170.1995	146.9692	0.1756	323.9133	322.0434	0.0324	275.3298	266.7312	0.0229	144.4264	139.5740	0.0474	59.5452	47.7400	0.0752	91.5523	75.5956
49	ARIMAX(1,2,1) + X2	0.0823	124.5007	114.6162	0.1758	324.0920	322.2535	0.2380	277.5598	272.5563	0.4500	49.7456	41.2962	0.5460	43.4074	38.4491	0.7471	80.0006	76.4500
50	ARIMAX(2,2,2) + X2	0.6342	40.4552	34.6242	0.0904	277.9974	273.4644	0.0191	270.5990	264.7709	0.5524	217.1144	215.5897	0.0927	85.8890	67.4658	0.8189	72.6105	57.7871
51	ARIMAX(3,2,3) + X2	0.6638	33.3190	25.3416	0.2972	285.9000	280.6391	0.0443	266.4733	258.2639	0.7216	146.7202	142.1839	0.1618	85.7246	66.8524	0.0204	129.1237	118.5442

[a] the best time series analysis model performance

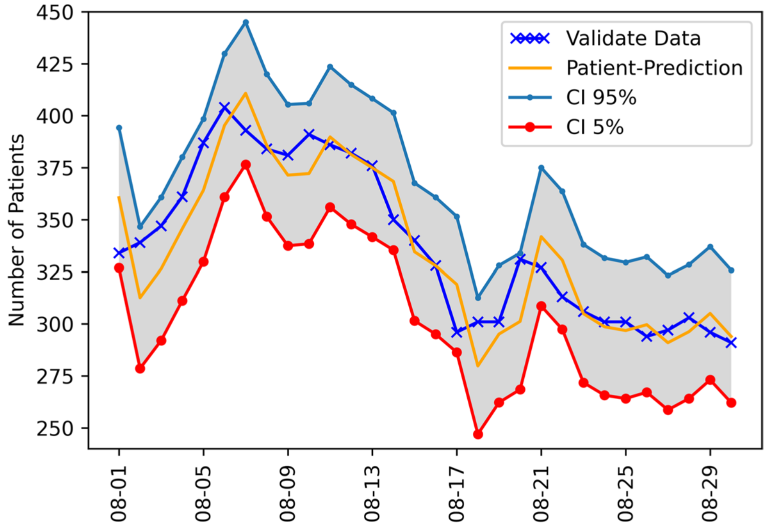

Fig. 4 The ARIMA (2,2,2) forecasting value of the admitted patients with prediction confidential intervals (CI) between 5 and 95%

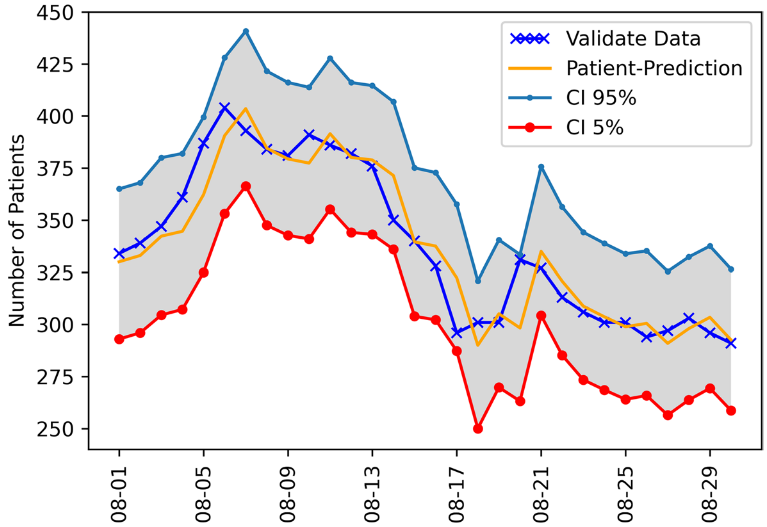

Fig. 5 The ARIMAX (1, 1, 1) + X2 forecasting value of the admitted patients with prediction confidential intervals (CI) between 5 and 95%

Table 3 The comparison of Coefficient of determination (R^2)

No	R^2 Comparison	All Wave		Wave 1		Wave 2		Wave 3		Wave 4		Wave 3–4	
		Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss
1	baseline vs x_1	3	3	6	0	1	5	5	1	0	6	6	0
2	x_1 vs x_2	2	4	3	3	2	4	2	4	4	2	3	3
3	baseline vs x_2	4	2	6	0	0	6	4	2	4	2	4	2
	SUM	9	9	15	3	3	15	11	7	8	10	13	5

Table 4 The comparison of Root mean square error (RMSE)

No	RMSE Comparison	All Wave		Wave 1		Wave 2		Wave 3		Wave 4		Wave 3–4	
		Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss
1	baseline vs x_1	3	3	4	2	4	2	6	0	6	0	2	4
2	x_1 vs x_2	4	2	4	2	3	3	2	4	5	1	1	5
3	baseline vs x_2	3	3	6	0	6	0	6	0	5	1	2	4
	SUM	10	8	14	4	13	5	14	4	16	2	5	13

Table 5 The comparison of Mean Absolute error (MAE)

No	MAE Comparison	All Wave		Wave 1		Wave 2		Wave 3		Wave 4		Wave 3–4	
		Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss	Win	Loss
1	baseline vs x_1	3	3	4	2	3	3	6	0	6	0	2	4
2	x_1 vs x_2	4	2	4	2	3	3	2	4	5	1	1	5
3	baseline vs x_2	3	3	6	0	5	1	6	0	5	1	2	4
	SUM	10	8	14	4	11	7	14	4	16	2	5	13

Association rule mining

This section explores the association analysis when association rule mining is applied. We present significant rules for the data that included four attributes' values in the dataset. Table 1 shows preliminary analysis of dataset that was extracted for a total of 3685 patients. The patient data consist of eleven attributes and 35 attribute values. In addition, an attribute code is defined for item set name and frequency of each attribute code. We extract 595 significant rules for the data.

The association rules grouped by four attributes related to managing hospital resources are shown in Table 8. Length of stay more than 14 days is related to healthcare workers and three underlying diseases other, pregnant, and dyslipidemia that have the same value of 1.017. Length of stay less than 14 give the interesting result on symptom mode (Lift of 6.464), three underlying diseases, and age more than 65 years old.

The interesting rule of discharge had two value attributes. The result showed that referral to hospitals was strongly related to symptom of Mode (Lift of 9.127). In addition, four features in this attribute showed high Lift values; underlying diseases (5.655), metabolic syndrome (4.098), length of stay more than 14 days (3.613), and age more than 65 years old (5.515). Chest x-ray with no lesion presented the same level of Lift. However, two features which showed high numbers of patients were age less than 24 years old (1148) and symptom asymptomatic (2295). Moreover, chest x-ray with pneumonia showed all high interesting value Symptom of Mode (3.287), age more than 65 (3.271), underlying diseases diabetes mellitus (2.169), and underlying diseases Metabolic (2.062). In current incident, Wave 1 showed high interest on Length of stay more than 14-days and source of infection from hospital and healthcare worker patients. Wave 2 was also related to healthcare worker, asymptomatic and source of infection from hospital, as was Wave 3. In Wave 4, underlying diseases, age more than 65 and symptom mode showed strong relationships. Association rules selected key attributes of the data set to be exogenous variables of a time series analysis.

Discussion

The first wave of SARS-CoV-2 occurred in early 2020, and the second, third and fourth waves rapidly spread from early to mid-2021, representing an unprecedented phenomenon in medical services, society and the economy of Thailand. The number of COVID-19 patients shown in this study increased from the first wave of just 55 patients to 311, 1779 and 1540 in the second, third and fourth waves, respectively, which evolved more than 30 times of the total number of patients admitted at the field hospital. Most of patients were at least 44 years old and were predominantly female. Patients included in this study were mostly asymptomatic and had no sign of pneumonia in the chest x-ray due to the field hospital system's focus on patients who did not require advanced treatment. But during the third and fourth waves, the number of mild to moderate symptoms with pneumonia of COVID-19 patients significantly increased because of the greater severity of the delta variant of SARS-COV-2. The huge number of patients was a burden on the limited resources of Thailand's healthcare system. Therefore, this study presented the use of time series modeling and

Table 6 The number of patient prediction for time-series model ARIMA (2, 2, 2) + X2 Training from May 1 to July 22, 2021, Prediction from August 1 to August 30, 2021

Date	Actual data	Prediction	Lower CI	Upper CI
August 1, 2021	334	361	327	394
August 2, 2021	339	313	279	347
August 3, 2021	347	326	292	361
August 4, 2021	361	346	311	380
August 5, 2021	387	364	330	398
August 6, 2021	404	395	361	430
August 7, 2021	393	411	377	445
August 8, 2021	384	386	351	420
August 9, 2021	381	371	337	405
August 10, 2021	391	372	338	406
August 11, 2021	386	390	356	424
August 12, 2021	382	381	348	415
August 13, 2021	376	375	342	408
August 14, 2021	350	368	335	401
August 15, 2021	340	335	302	368
August 16, 2021	328	328	295	361
August 17, 2021	296	319	286	352
August 18, 2021	301	280	247	313
August 19, 2021	301	295	262	328
August 20, 2021	331	301	268	334
August 21, 2021	327	342	309	375
August 22, 2021	313	331	297	364
August 23, 2021	306	305	272	338
August 24, 2021	301	299	266	332
August 25, 2021	301	297	264	330
August 26, 2021	294	300	267	332
August 27, 2021	297	291	259	323
August 28, 2021	303	296	264	328
August 29, 2021	296	305	273	337
August 30, 2021	291	294	262	326

CI confidence interval

Table 7 The number of patient prediction for time-series model ARIMAX (1,1,1) + X2 Training from May 1 to July 22, 2021, Prediction from August 1 to August 30, 2021

Date	Actual data	Prediction	Lower CI	Upper CI
August 1, 2021	334	330	293	365
August 2, 2021	339	333	296	368
August 3, 2021	347	342	305	380
August 4, 2021	361	345	307	382
August 5, 2021	387	362	325	399
August 6, 2021	404	391	353	428
August 7, 2021	393	404	366	441
August 8, 2021	384	385	348	422
August 9, 2021	381	379	343	416
August 10, 2021	391	377	341	414
August 11, 2021	386	392	355	428
August 12, 2021	382	380	344	416
August 13, 2021	376	379	343	415
August 14, 2021	350	371	336	407
August 15, 2021	340	340	304	375
August 16, 2021	328	338	302	373
August 17, 2021	296	322	287	358
August 18, 2021	301	290	250	321
August 19, 2021	301	305	270	341
August 20, 2021	331	298	263	333
August 21, 2021	327	335	304	376
August 22, 2021	313	321	285	356
August 23, 2021	306	309	273	344
August 24, 2021	301	304	269	339
August 25, 2021	301	299	264	334
August 26, 2021	294	301	266	335
August 27, 2021	297	291	256	325
August 28, 2021	303	298	264	332
August 29, 2021	296	303	269	338
August 30, 2021	291	293	259	327

CI confidence interval

association rule mining to forecast the COVID-19 pandemic outbreak as well as to analyze its associated prognostic factors. The method presented a data-oriented approach that applies time-series analysis and association analysis to reveal meaningful hidden patterns for efficient handling of another pandemic crisis.

ARIMA models have been successfully applied for predicting the disease outbreak. Several studies have utilized the ARIMA model to forecast the spread of COVID-19 in many countries including the US, Brazil, India, Russia and Spain [28, 29]. The studies using ARIMA models to predict COVID-19 cases relative to total confirmed cases presented an average RMSE of 144.81 across 6 geographic regions [28], MAE of 787 to 1506 in USA and 82 to 570 in Italy [18], and MAE of 2967 in Indonesia [20]. In this work, ARIMA (2, 2, 2) was selected as the most accurate ARIMA model for predicting the number of admitted COVID-19 cases in the field hospital, which achieved a $R^2 = 0.5695$, RMSE = 29.7605, MAE = 27.5102 (Fig. 4). The forecast results of admitted cases on August 15 and August 30, 2021 were 335 and 294, respectively. In comparison with the actual values reported on the same dates, the forecasted values of our selected ARIMA model were within the upper and lower bounds at 95% confidence intervals. This signified an acceptable accuracy of this model for estimating admitted cases in the field hospital.

ARM is a structured method of discovering frequent patterns in a data set and forming noticeable rules among regular patterns. In the COVID-19 crisis, many nations,

Table 8 Top 5 association rules for different combinations of particular consequence, their Support, Average-confidence, Confidence (LHS ➔ RHS), Confidence (RHS ➔ LHS) and Lift measures

No	LHS	RHS	N(A)	N(B)	N(A,B)	Sup_{LR}	$Conf_{A}$	$Conf_{LR}$	$Conf_{RL}$	$Lift_{LR}$
Length of Stay less than or equal to 14 days										
1	job_health	los_1_14	93	3625	93	2.524	51.283	100.000	2.566	1.017
2	ud_oth	los_1_14	64	3625	64	1.737	50.883	100.000	1.766	1.017
3	ud_preg	los_1_14	23	3625	23	.624	50.317	100.000	.634	1.017
4	ud_dlp	los_1_14	14	3625	14	.380	50.193	100.000	.386	1.017
5	cxr_pneu	los_1_14	472	3625	470	12.754	56.271	99.576	12.966	1.012
Length of Stay more than or equal to 15 days										
1	sym_mode	los_15	19	60	2	.054	6.930	10.526	3.333	6.465
2	ud_meta	los_15	53	60	3	.081	5.330	5.660	5.000	3.476
3	ud_dm	los_15	18	60	1	.027	3.611	5.556	1.667	3.412
4	ud_ht	los_15	39	60	2	.054	4.231	5.128	3.333	3.150
5	age_65	los_15	74	60	2	.054	3.018	2.703	3.333	1.660
Home Discharge										
1	ud_ht	dc_home	39	3600	39	1.058	50.542	100.000	1.083	1.024
2	ud_dm	dc_home	18	3600	18	.488	50.250	100.000	.500	1.024
3	ud_dlp	dc_home	14	3600	14	.380	50.194	100.000	.389	1.024
4	age_24	dc_home	1148	3600	1131	30.692	64.968	98.519	31.417	1.008
5	cxr_pneu	dc_home	472	3600	465	12.619	55.717	98.517	12.917	1.008
Refer to General hospital										
1	sym_mode	dc_hosp	19	85	4	.109	12.879	21.053	4.706	9.127
2	ud_preg	dc_hosp	23	85	3	.081	8.286	13.043	3.529	5.655
3	ud_meta	dc_hosp	53	85	6	.163	9.190	11.321	7.059	4.908
4	los_15	dc_hosp	60	85	5	.136	7.108	8.333	5.882	3.613
5	age_65	dc_hosp	74	85	6	.163	7.583	8.108	7.059	3.515
Chest X-ray is No lesion										
1	job_health	cxr_no	93	3213	91	2.469	50.341	97.849	2.832	1.122
2	source_hosp	cxr_no	91	3213	88	2.388	49.721	96.703	2.739	1.109
3	age_24	cxr_no	1148	3213	1058	28.711	62.545	92.160	32.929	1.057
4	symp_ast	cxr_no	2295	3213	2112	57.313	78.880	92.026	65.733	1.055
5	ud_repp	cxr_no	82	3213	73	1.981	45.648	89.024	2.272	1.021
Chest X-ray is Pneumonia										
1	sym_mode	cxr_pneu	19	472	8	.217	21.900	42.105	1.695	3.287
2	age_65	cxr_pneu	74	472	31	.841	24.230	41.892	6.568	3.271
3	ud_ht	cxr_pneu	39	472	11	.299	15.268	28.205	2.331	2.202
4	ud_dm	cxr_pneu	18	472	5	.136	14.419	27.778	1.059	2.169
5	ud_meta	cxr_pneu	53	472	14	.380	14.691	26.415	2.966	2.062
Current incidence in Wave 1										
1	los_15	wave_1	60	55	13	.353	22.652	21.667	23.636	14.517
2	source_hosp	wave_1	91	55	16	.434	23.337	17.582	29.091	11.780
3	job_health	wave_1	93	55	15	.407	21.701	16.129	27.273	10.806
4	dc_hosp	wave_1	85	55	6	.163	8.984	7.059	10.909	4.729
5	symp_ast	wave_1	2295	55	54	1.465	50.267	2.353	98.182	1.576
Current incidence in Wave 2										
1	job_health	wave_2	93	311	13	.353	9.079	13.978	4.180	1.656
2	symp_ast	wave_2	2295	311	266	7.218	48.560	11.590	85.531	1.373
3	source_hosp	wave_2	91	311	10	.271	7.102	10.989	3.215	1.302
4	bmi_25_29	wave_2	931	311	96	2.605	20.590	10.311	30.868	1.222
5	bmi_30	wave_2	445	311	42	1.140	11.472	9.438	13.505	1.118

Table 8 (continued)

No	LHS	RHS	N(A)	N(B)	N(A,B)	Sup_{LR}	Conf_{A}	Conf_{LR}	Conf_{RL}	Lift_{LR}
Current incidence in Wave 3										
1	symp_ast	wave_3	2295	1779	1285	34.871	64.111	55.991	72.232	1.160
2	age_25_44	wave_3	1838	1779	1009	27.381	55.807	54.897	56.717	1.137
3	cxr_no	wave_3	3213	1779	1635	44.369	71.396	50.887	91.906	1.054
4	ud_none	wave_3	3392	1779	1700	46.133	72.839	50.118	95.559	1.038
5	bmi_25	wave_3	2309	1779	1136	30.828	56.527	49.199	63.856	1.019
Current incidence in Wave 4										
1	ud_preg	wave_4	23	1540	22	.597	48.540	95.652	1.429	2.289
2	ud_dm	wave_4	18	1540	17	.461	47.774	94.444	1.104	2.260
3	age_65	wave_4	74	1540	64	1.737	45.321	86.486	4.156	2.069
4	ud_meta	wave_4	53	1540	43	1.167	41.962	81.132	2.792	1.941
5	sym_mode	wave_4	19	1540	15	.407	39.961	78.947	.974	1.889

including Thailand, have a highest priority to save lives and protect their economies. A previous study using ARM for mining COVID-19 data to analyze factors related to COVID-19 situation management showed that face mask mandates combined with mobility reduction through moderate stay-at-home orders were most effective in reducing the number of COVID-19 cases in United State [24]. In this study, the ARM technique was used to analyze and identify factors related to the length of stay and prognosis of COVID-19 patients and found that the top five factors related to hospital stays longer than 14 days consisted of healthcare workers uncommon underlying diseases such as thalassemia, thyroid diseases, gout and G6PD deficiency, pregnant patients, dyslipidemia and signs of pneumonia in chest x-rays. This study also identified a clinical factor rule related to the worsening condition of the inpatient. Among those who needed more advanced medical treatment, the rules included mild to moderate COVID-19 symptoms, pregnant patients, metabolic syndrome, length of hospital stay more than 14 days, and patients older than 65 years old. These factors are consistent with those in a previous study, which reported similar conditions among patients who had a poor prognosis in COVID-19 infections [1, 30].

In any prediction tasks, more data is needed to achieve better performance from the models. This study developed the combination of the ARM technique and the ARIMA model, as the ARIMAX model. This model worked by selecting the rules related to COVID-19 prognosis from the ARM technique, including mild to moderate COVID-19 symptoms, patients with metabolic syndrome and patients older than 65 years old, and integrating them to the ARIMA model. Experimental results showed that the ARIMAX model (1, 1, 1) improved the accuracy of forecasting the number of admitted COVID-19 cases, which achieved a $R^2 = 0.5695$, RMSE = 27.7508, MAE = 23.4642 (Fig. 5). The forecast value of this model for August 30, 2021 was estimated to be 259 to 327 cases. The actual number of cases on the same date was 291 cases. The actual value also was within the lower and upper prediction bounds for both 95% confidence intervals. To the best of our knowledge, this is the first study to combine the ARM technique with the ARIMA model for forecasting the COVID-19 cases by integrating the optimal exogenous variables from the ARM rules to form a predictive model. This ARIMAX model had the potential to predict the number of COVID-19 patients, which could be one of the reliable forecasting-based models for the future outbreak. These predictive models are intended to help better decision-making to plan an effective management system if the virus outbreak has not subsided.

Limitations

The limitation of this study is that the dataset was based on retrospective data from a single COVID-19 field hospital in Thailand with a limited number of cases and clinical variables of COVID-19 patients.

Future directions

In future work, the collaboration between multi-medical centers for a larger number and different variables of COVID-19 cases, including the medical records of clinical, laboratory and treatment data from various COVID-19 centers, would upgrade the forecasting performance of this AI model to predict the COVID-19 event more accurately. Additionally, geographic data related to the pandemic area could be used as a variable for alternative time series models such as space-time ARIMA models [31], which could be more reliable in predicting future COVID-19 outbreaks.

Conclusion

This study demonstrated that the ARIMAX model has the potential to increase the accuracy for predicting the number of COVID-19 cases by incorporating the most associated prognostic factors identified by ARM technique to the ARIMA model. The result of this study proved to be an effective AI model to predict the number of and to identify prognostic factors of admitted COVID-19 patients. This work is expected to be a novel AI-based decision-making model for preparation, organizing hospital resources and more optimal use of medical personnel and equipment to enhance healthcare decision-making, and to manage the COVID-19 pandemic but as well as other epidemic crises.

Abbreviations

COVID-19: Coronavirus disease 2019; SARS-CoV-2: Severe Acute Respiratory Syndrome-*Coronavirus-2*; MERS-CoV: Middle East Respiratory Syndrome Coronavirus; CBC: Complete blood count; LFTs: Liver function tests; BUN: Balance urine nitrogen; Cr: Creatinine; SpO_2: Pulse oxygen saturation; BT: Body temperature; BMI: Body mass index; G6PD: Glucose-6-Phosphate Dehydrogenase; ANN: Artificial Neural Network; SVM: Support Vector Machine; ARM: Association Rule Mining; ARIMA: Auto Regressive Integrated Moving Average; ARIMAX: Autoregressive Integrated Moving Average with Exogenous Covariates; R^2: Coefficient of determination; RMSE: Root mean square error; MAE: Mean absolute error; CI: Confidence intervals.

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Authors' contributions

Conceptualization: K.W., S.N., S.S.; Methodology: R.S., K.W., T.T., S.S.; Formal analysis and investigation: R.S., K.W., W.A., W.P., T.T., S.S.; Fund acquisition: W.A., T.T; Writing - original draft preparation: K.W., S.S.; Writing - review and editing: K.W., S.S.; Resources: W.A., C.M., K.M., K.S.; Supervision: S.S., S.N. All authors have read and agreed to the published version of the manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable requests.

Declarations

Ethics approval and consent to participate

The study protocol and the exempt from the need to obtain informed consent was approved by the Ethics Committee of the Thammasat University (COE 008/2564) in accordance with the 1964 Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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References

1. Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet. 2020;395(10223):497–506.
2. Wolkewitz M, Puljak L. Methodological challenges of analysing COVID-19 data during the pandemic. BMC Med Res Methodol. 2020;20(1):81.
3. Tao K, Tzou PL, Nouhin J, Gupta RK, de Oliveira T, Kosakovsky Pond SL, et al. The biological and clinical significance of emerging SARS-CoV-2 variants. Nat Rev Genet. 2021;22(12):757–73.
4. World Health Organization: COVID-19 Weekly Epidemiological Update, Edition 95. 2022.
5. Yoo I, Alafaireet P, Marinov M, Pena-Hernandez K, Gopidi R, Chang JF, et al. Data mining in healthcare and biomedicine: a survey of the literature. J Med Syst. 2012;36(4):2431–48.
6. Huang F, Wang S, Chan C. Predicting disease by using data mining based on healthcare information system. In: 2012 IEEE International Conference on Granular Computing: 11–13 Aug. 2012, vol. 2012; 2012. p. 191–4.
7. Koh HC, Tan G. Data mining applications in healthcare. J Healthc Inf Manag. 2005;19(2):64–72.
8. Kriston L. Predictive accuracy of a hierarchical logistic model of cumulative SARS-CoV-2 case growth until May 2020. BMC Med Res Methodol. 2020;20(1):278.
9. Ayatollahi H, Gholamhosseini L, Salehi M. Predicting coronary artery disease: a comparison between two data mining algorithms. BMC Public Health. 2019;19(1):448.
10. Alfisahrin SNN, Mantoro T. Data Mining Techniques for Optimization of Liver Disease Classification. In: 2013 International Conference on Advanced Computer Science Applications and Technologies: 23–24 Dec. 2013, vol. 2013; 2013. p. 379–84.
11. Al-Turaiki I, Alshahrani M, Almutairi T. Building predictive models for MERS-CoV infections using data mining techniques. J Infect Public Health. 2016;9(6):744–8.
12. Abonazel M, Ibrahim A. Forecasting Egyptian GDP using ARIMA models. Rep Econ Finance. 2019;5:35–47.
13. Cryer JD, Chan K-S. Time series analysis with applications in R, 2nd 2008. Edn. New York: Springer New York; 2008.
14. Zaki MJ. Scalable algorithms for association mining. IEEE Trans Knowl Data Eng. 2000;12(3):372–90.
15. Heisterkamp SH, Dekkers AL, Heijne JC. Automated detection of infectious disease outbreaks: hierarchical time series models. Stat Med. 2006;25(24):4179–96.
16. Zhang GP. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing. 2003;50:159–75.
17. Abonazel M, Darwish N. Forecasting confirmed and recovered Covid-19 cases and deaths in Egypt after the genetic mutation of the virus: ARIMA box-Jenkins approach. Commun Math Biol Neurosci. 2022;2022:17.
18. Gecili E, Ziady A, Szczesniak RD. Forecasting COVID-19 confirmed cases, deaths and recoveries: revisiting established time series modeling through novel applications for the USA and Italy. PLoS One. 2021;16(1):e0244173.
19. Singh S, Parmar KS, Makkhan SJS, Kaur J, Peshoria S, Kumar J. Study of ARIMA and least square support vector machine (LS-SVM) models for the

prediction of SARS-CoV-2 confirmed cases in the most affected countries. Chaos, Solitons Fractals. 2020;139:110086.

20. Aditya Satrio CB, Darmawan W, Nadia BU, Hanafiah N. Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET. Proc Comput Sci. 2021;179:524–32.
21. Agrawal R, Imieliński T, Swami A. Mining association rules between sets of items in large databases. In: Proceedings of the 1993 ACM SIGMOD international conference on management of data. Washington, D.C.: Association for Computing Machinery; 1993. p. 207–16.
22. K S L, G DV: Extracting association rules from medical health records using multi-criteria decision analysis. Proc Comput Sci 2017, 115:290–295.
23. Tandan M, Acharya Y, Pokharel S, Timilsina M. Discovering symptom patterns of COVID-19 patients using association rule mining. Comput Biol Med. 2021;131:104249.
24. Katragadda S, Gottumukkala R, Bhupatiraju RT, Kamal AM, Raghavan V, Chu H, et al. Association mining based approach to analyze COVID-19 response and case growth in the United States. Sci Rep. 2021;11(1):18635.
25. Amasiri W, Warin K, Mairiang K, Mingmalairak C, Panichkitkosolkul W, Silanun K, et al. Analysis of characteristics and clinical outcomes for crisis management during the four waves of the COVID-19 pandemic. Int J Environ Res Public Health. 2021;18(23):12633.
26. Time Series Models AR, MA, ARMA, ARIMA; 2020 [cited 2021 7 December] Available from: https://towardsdatascience.com/time-series-models-d9266f8ac7b0.
27. Barnston AG. Correspondence among the correlation, RMSE, and Heidke forecast verification measures; refinement of the Heidke score. Weather Forecast. 1992;7(4):699–709.
28. Hernandez-Matamoros A, Fujita H, Hayashi T, Perez-Meana H. Forecasting of COVID19 per regions using ARIMA models and polynomial functions. Appl Soft Comput. 2020;96:106610.
29. Darapaneni N, Reddy D, Paduri AR, Acharya P, Nithin HS. Forecasting of COVID-19 in India Using ARIMA Model. In: 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON): 28–31 Oct. 2020, vol. 2020; 2020. p. 0894–9.
30. Noor FM, Islam MM. Prevalence and associated risk factors of mortality among COVID-19 patients: a Meta-analysis. J Community Health. 2020;45(6):1270–82.
31. Awwad FA, Mohamoud MA, Abonazel MR. Estimating COVID-19 cases in Makkah region of Saudi Arabia: space-time ARIMA modeling. PLoS One. 2021;16(4):e0250149.

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