Introduction to Business Analytics

Lecture 10: Forecasting in R

Iegor Vyshnevskyi
Woosong University
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Agenda

1. Intro to Forecasting
2. Time Series Data and Forecasting
3. Time Series Forecasting Applications
4. Time Series Components
5. Time Series Forecasting Methods
6. Time Series Forecasting Using the ARIMA Model
7. In-class Assignment

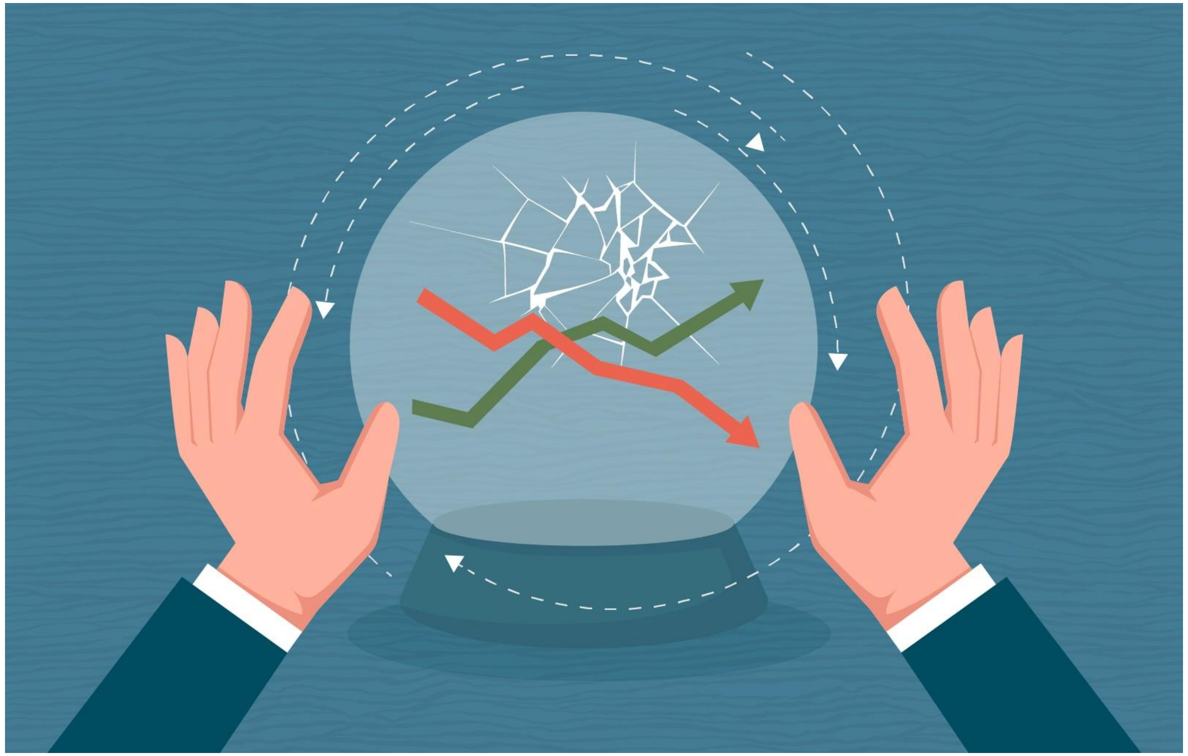
Acknowledgment: Used a number of open sources and materials from the web.

1. Intro to Forecasting

*What is **Forecasting?***

Forecasting is estimating how the sequence of observations will continue into the future.

Forecasting involves making predictions about the future.



Usefulness of Forecasting for Business Analytics

Forecasting is required in many situations:

- deciding whether to build another power generation plant in the next ten years requires forecasts of future demand.
- scheduling staff in a call centre next week requires forecasts of call volumes.
- stocking an inventory requires forecasts of stock requirements.

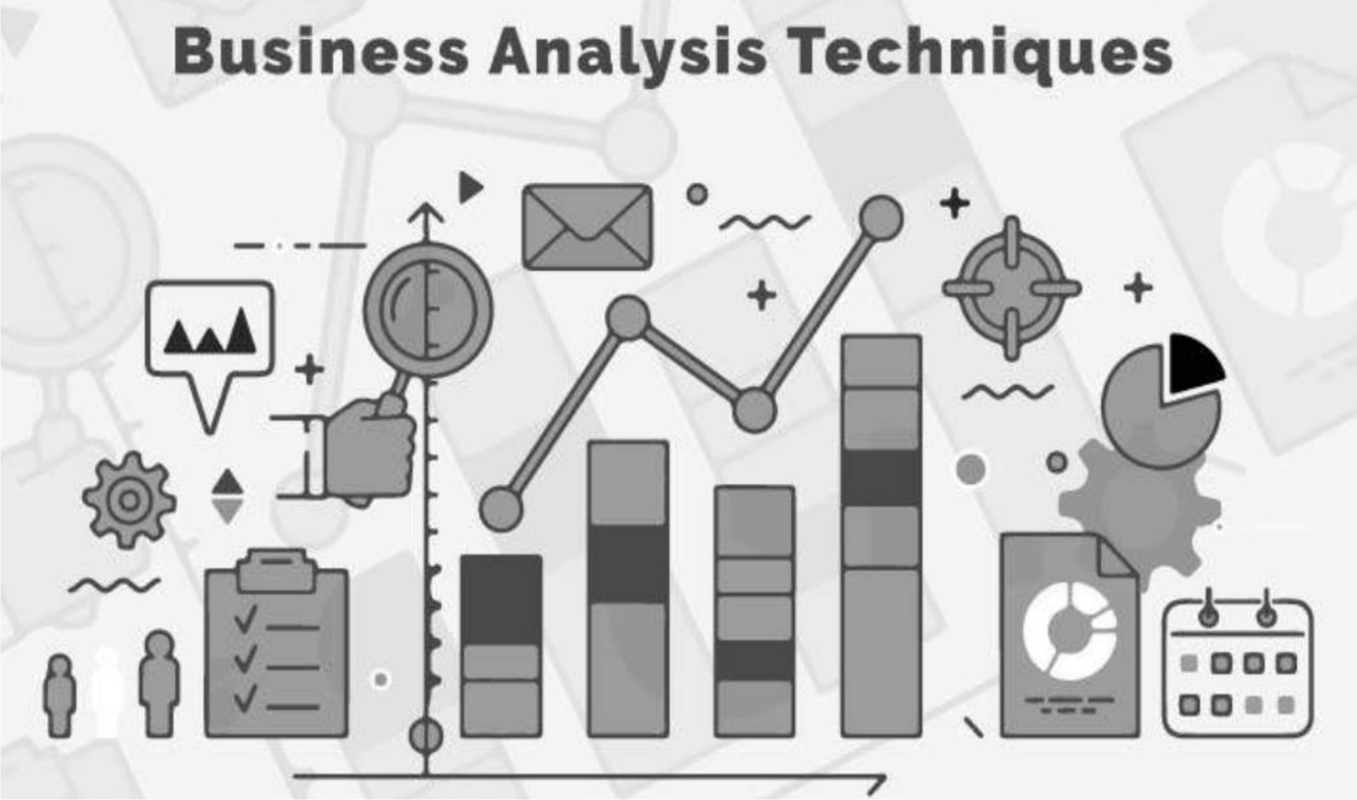
Forecasts can be required several years in advance (for the case of capital investments), or only a few minutes beforehand (for telecommunication routing).

Whatever the circumstances or time horizons involved, forecasting is an important aid to effective and efficient planning.

Usefulness of Forecasting for Business Analytics

Overall, forecasting can be a valuable tool for businesses looking to make data-driven decisions.

However, it should be used in conjunction with other analytical methods to ensure a comprehensive and accurate understanding of business data.



Advantages of using R for Time Series Forecasting

- ***Large community:*** R has a large and active community of users and developers, which means that there are many resources and packages available for time series forecasting, and it also allows for easy collaboration and sharing of knowledge.
- ***Flexibility:*** R provides a wide range of tools and packages for time series forecasting, which allows for flexibility in selecting the appropriate method for a given dataset.
- ***Open-source:*** R is an open-source programming language, which means that it is free to use and can be modified to fit specific needs.
- ***Easy to use:*** R has a simple and intuitive syntax, which makes it easy to learn and use.
- ***High-quality visualization:*** R has powerful data visualization capabilities, which allows for easy interpretation and analysis of time series data.

Disadvantages of using R for Time Series Forecasting

- ***Speed:*** R is an interpreted language, which can make it slower than compiled languages such as C or C++ for large datasets.
- ***Memory usage:*** R can be memory-intensive, which can be a problem for large datasets.
- ***Limited scalability:*** R is not designed for large-scale parallel computing, so it may not be suitable for large-scale time series forecasting tasks.
- ***Steep learning curve:*** R is a powerful programming language, but it has a steep learning curve, which can make it difficult for beginners.
- ***Lack of standardization:*** R provides a wide range of tools and packages for time series forecasting, which can lead to a lack of standardization in the way that time series forecasting tasks are performed, this could make it difficult to compare results across different studies.

2. Time Series Data and Forecasting

Time Series Data

- Series of data observed over time.
  - E.g.: Daily Samsung stock prices, monthly rainfall in Seoul,...
- Not all data that have time values or date values as its features can be considered as a time series data.

Time Series Forecasting

- *Time Series Forecasting* is the method of ***exploring and analyzing time-series data*** recorded or collected over a set period of time.
- This technique is used to ***forecast values and make future predictions***.

Any data fit for time series forecasting should consist of observations over a ***regular, continuous interval***.

3. Time Series Forecasting Applications

Examples of Forecasting Analysis




- Time series forecasting is used in ***stock price prediction*** to predict the closing price of the stock on each given day.
- E-Commerce and retail companies use forecasting to ***predict sales and units sold*** for different products.
- ***Weather prediction*** is another application that can be done using time series forecasting.
- It is used by government departments to predict ***a state's population***, at any particular region, or the nation as a whole.

4. Time Series Components

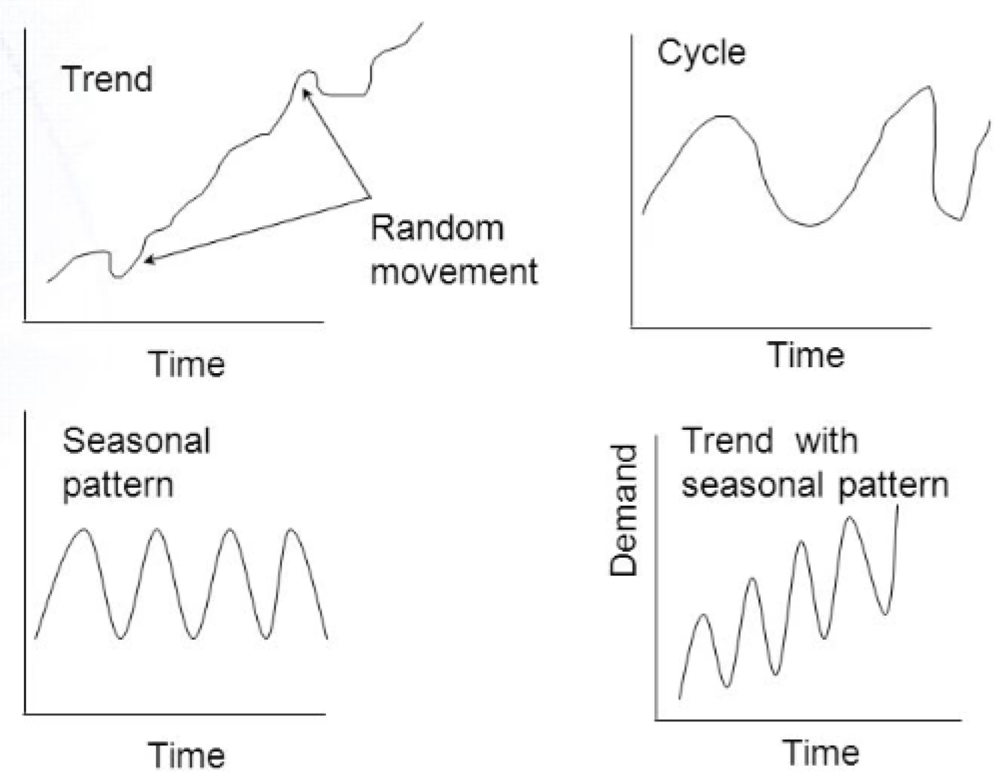
Components

- To use time-series data and develop a model, you *need to understand the patterns in the data over time*.

- These patterns are classified into four components, which are:
  - ***Trend:*** It represents the gradual change in the time series data. The trend pattern depicts long-term growth or decline.
  - ***Level:*** It refers to the baseline values for the series data if it were a straight line.
  - ***Seasonality:*** It represents the short-term patterns that occur within a single unit of time and repeats indefinitely.
  - ***Cyclic:*** A pattern exists where the data exhibits rises and falls that are not of fixed period (duration usually of at least 2 years)
  - ***Noise:*** It represents irregular variations and is purely random. These fluctuations are unforeseen, unpredictable, and cannot be explained by the model.

Seasonal vs cyclic

- Differences between seasonal and cyclic patterns:
  - Seasonal pattern constant length vs. cyclic pattern variable length
  - Average length of cycle longer than length of seasonal pattern
  - Magnitude of cycle more variable than magnitude of seasonal pattern
- The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

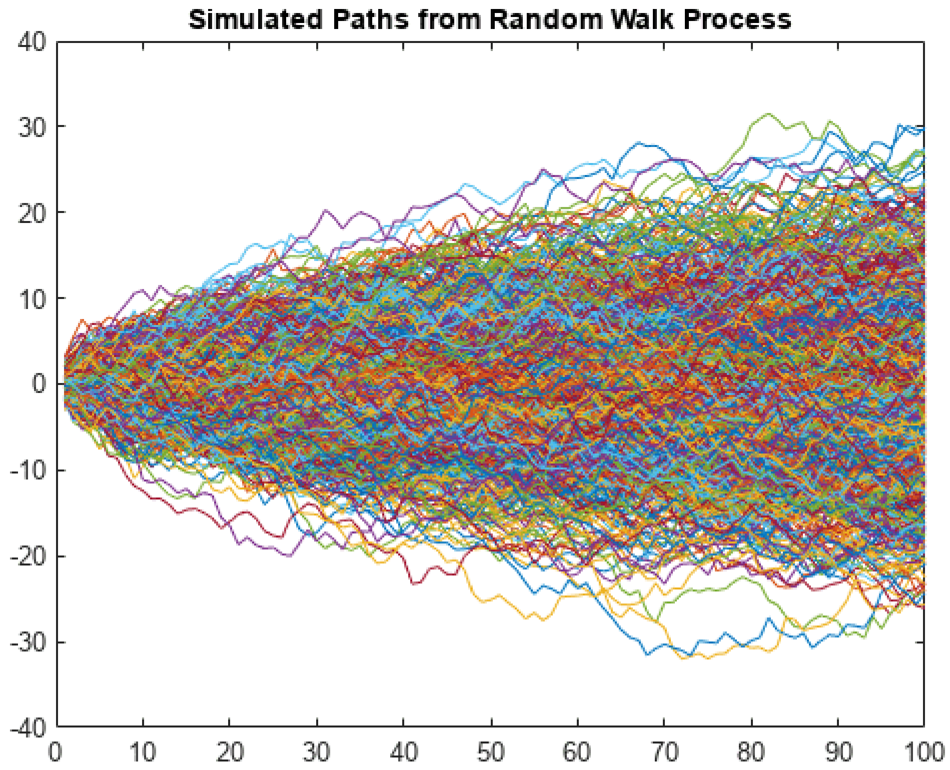


5. Time Series Forecasting Methods

Methods: ARIMA Model

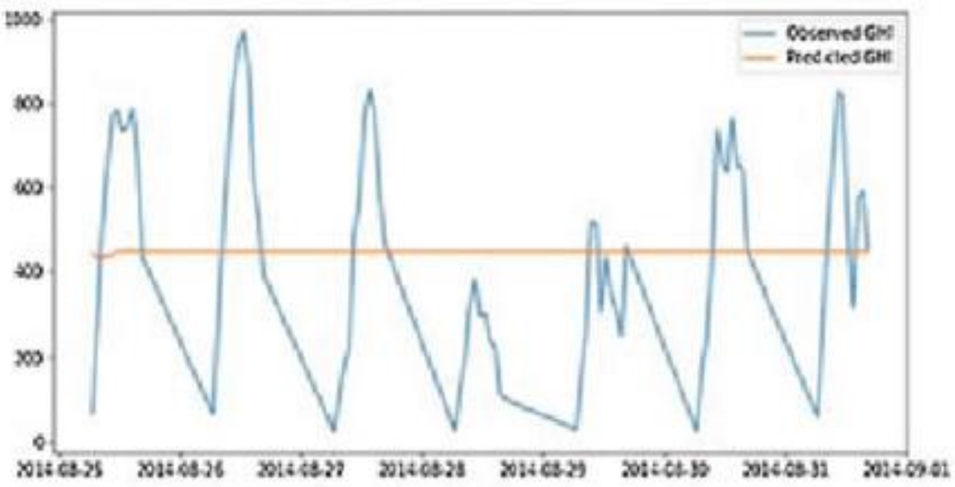
- ARIMA stands for Autoregressive Integrated Moving Average.
- It is a combination of the Autoregressive (AR) and Moving Average (MR) model.

- The AR model forecast corresponds to a linear combination of past values of the variable. The moving average model forecast corresponds to a linear combination of past forecast errors. The "I" represents the data values that are replaced by the difference between their values and the previous values.

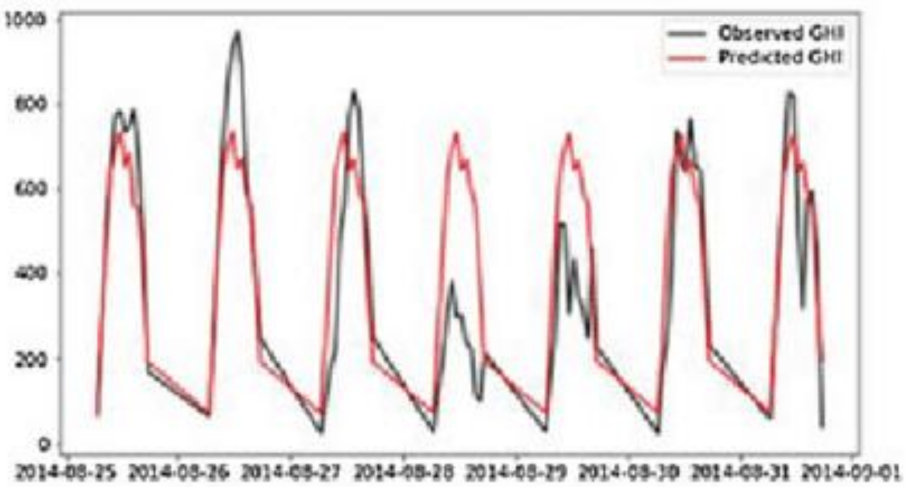


Methods: SARIMA Model

- SARIMA stands for Seasonal Autoregressive Integrated Moving Average.
- It extends the ARIMA model by adding a linear combination of seasonal past values and forecast errors.



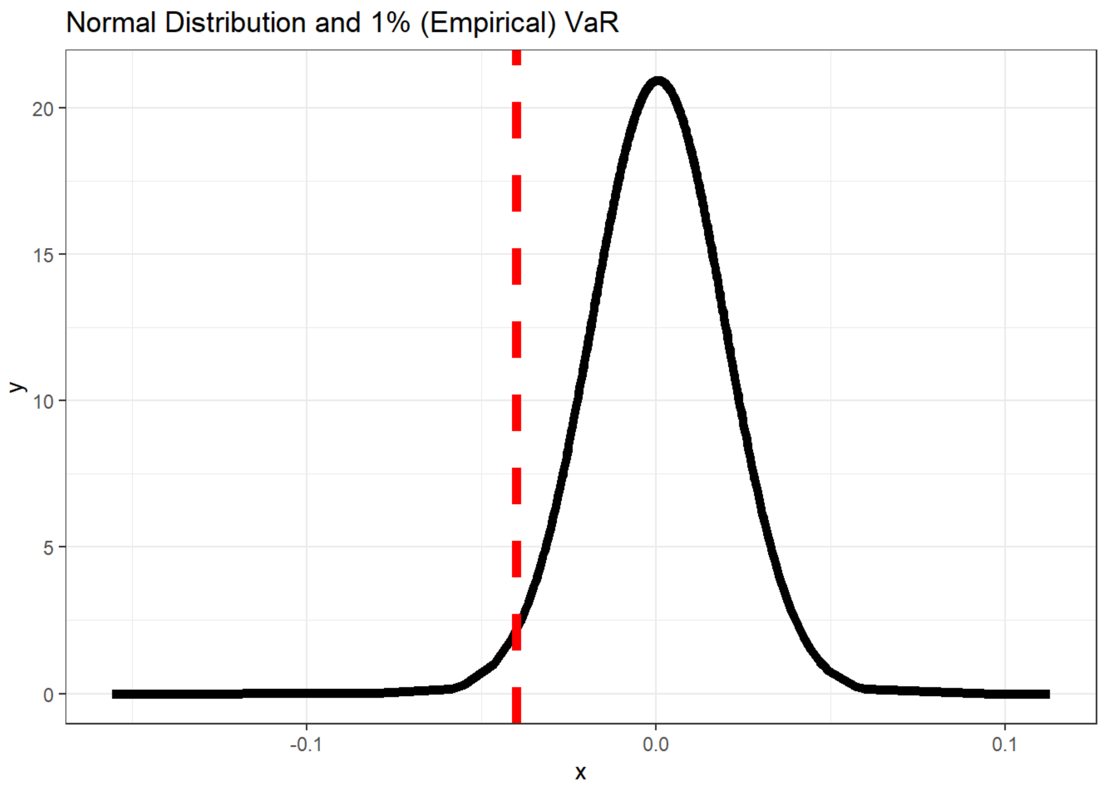
ARIMA 7 Day Ahead Prediction



SARIMA 7 Day Ahead Prediction

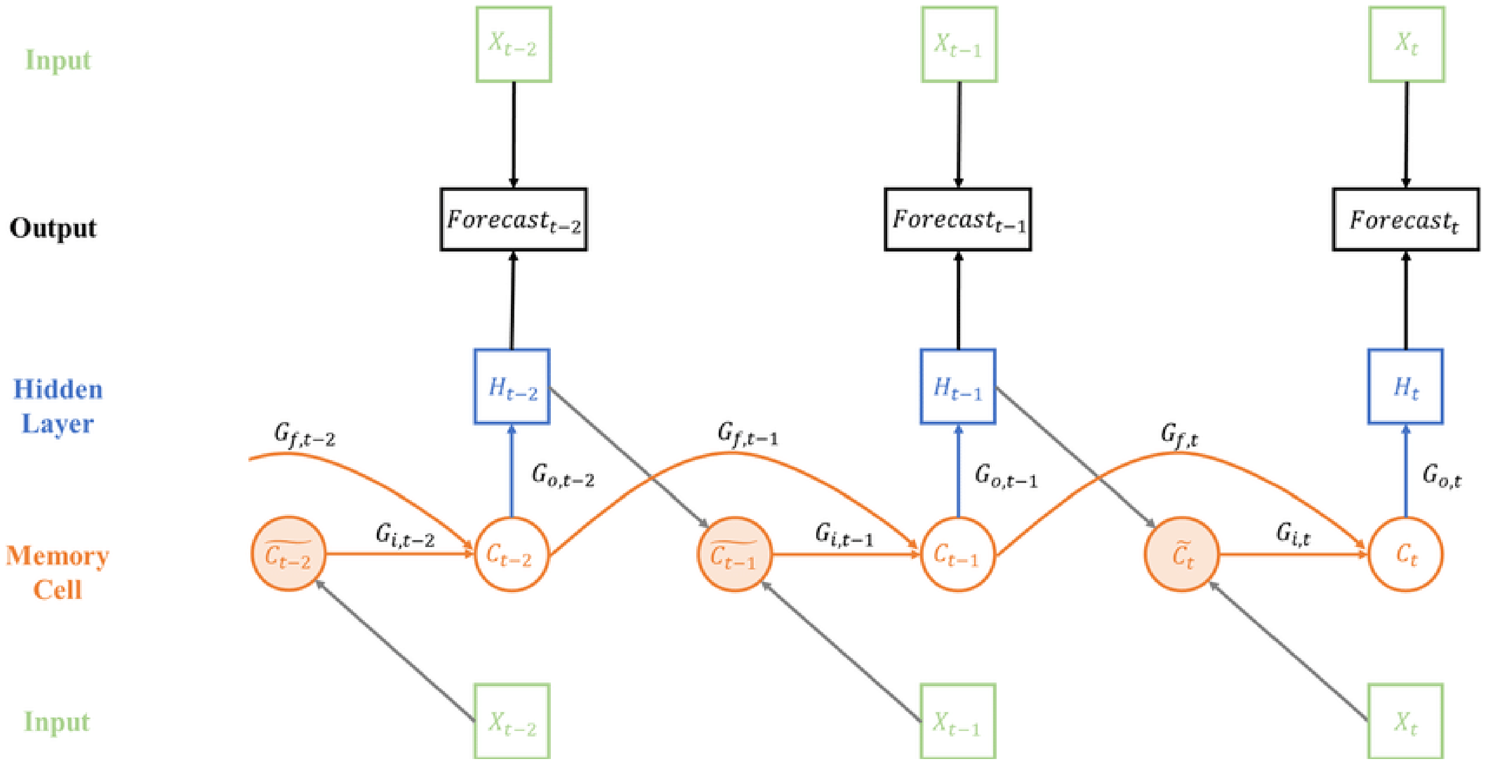
Methods: VAR

- The Vector Autoregression (VAR) method models the next step in each time series using an AR model.
- The VAR model is useful when you are interested in predicting multiple time series variables using a single model.



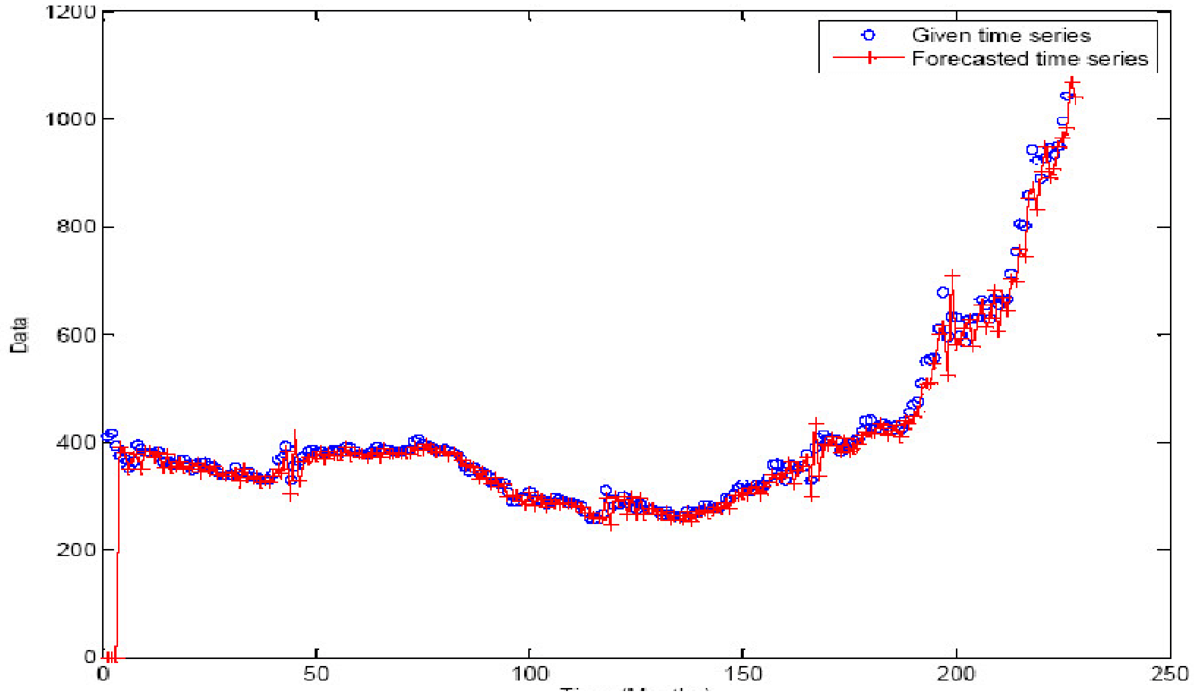
Methods: LSTM

- The Long Short Term Memory network or LSTM is a special kind of recurrent neural network that deals with long-term dependencies.
- It can remember information from past data and is capable of learning order dependence in sequence prediction problems.



Methods: GARCH

- The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models, most popular time series models used for forecasting conditional volatility.
- These models are conditional heteroskedastic as they take into account the conditional variance in a time series.
- GARCH models are one of the most widely used models for forecasting financial risk measures like VaR and Conditional VaR in financial risk modelling and management.



6. Time Series Forecasting Using the ARIMA Model

ARIMA Model: details

- ARIMA models are classified by three factors:
  - p = Number of autoregressive terms (AR).
  - d = How many non-seasonal differences are needed to achieve stationarity (I).
  - q = Number of lagged forecast errors in the prediction equation (MA).

What we do

- We’ll use a dataset with information about air-ticket sales of the airline industry from 1949-1960.
- We’ll predict the Airline tickets’ sales of 1961 using the ARIMA model in R.

- The idea for this analysis is to identify the time series components which are:
  - Trend
  - Seasonality
  - Random behavior of data

Then, we’ll forecast the values based on historical data.

Loading the data

```
# Install forecast library
install.packages('forecast')

# Load forecast library
library(forecast)
```

Install the FORECAST package first.

Load the data and check the class, because we need to have Time Series (i.e., ts) data

```
# Load the Air Passengers' dataset and view its class
data("AirPassengers")

class(AirPassengers)
```

```
> class(AirPassengers)
[1] "ts"
```

Runt AirPassengers to see our data

```
# Display the dataset
AirPassengers
```

```
> AirPassengers
     Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
1949 112 118 132 129 121 135 148 148 136 119 104 118
1950 115 126 141 135 125 149 170 170 158 133 114 140
1951 145 150 178 163 172 178 199 199 184 162 146 166
1952 171 180 193 181 183 218 230 242 209 191 172 194
1953 196 196 236 235 229 243 264 272 237 211 180 201
1954 204 188 235 227 234 264 302 293 259 229 203 229
1955 242 233 267 269 270 315 364 347 312 274 237 278
1956 284 277 317 313 318 374 413 405 355 306 271 306
1957 315 301 356 348 355 422 465 467 404 347 305 336
1958 340 318 362 348 363 435 491 505 404 359 310 337
1959 360 342 406 396 420 472 548 559 463 407 362 405
1960 417 391 419 461 472 535 622 606 508 461 390 432
```

Loading the data: exploration

```
# Let's check on our date values
start(AirPassengers) # start date

end(AirPassengers) # end date
```

```
> start(AirPassengers) # start date
[1] 1949    1
>
> end(AirPassengers) # end date
[1] 1960   12
```

Our start date is January 1949, while the end date is December 1960.

```
> # Find out if there are any missing values
> sum(is.na(AirPassengers))
[1] 0
```

Missing values check. None detected.

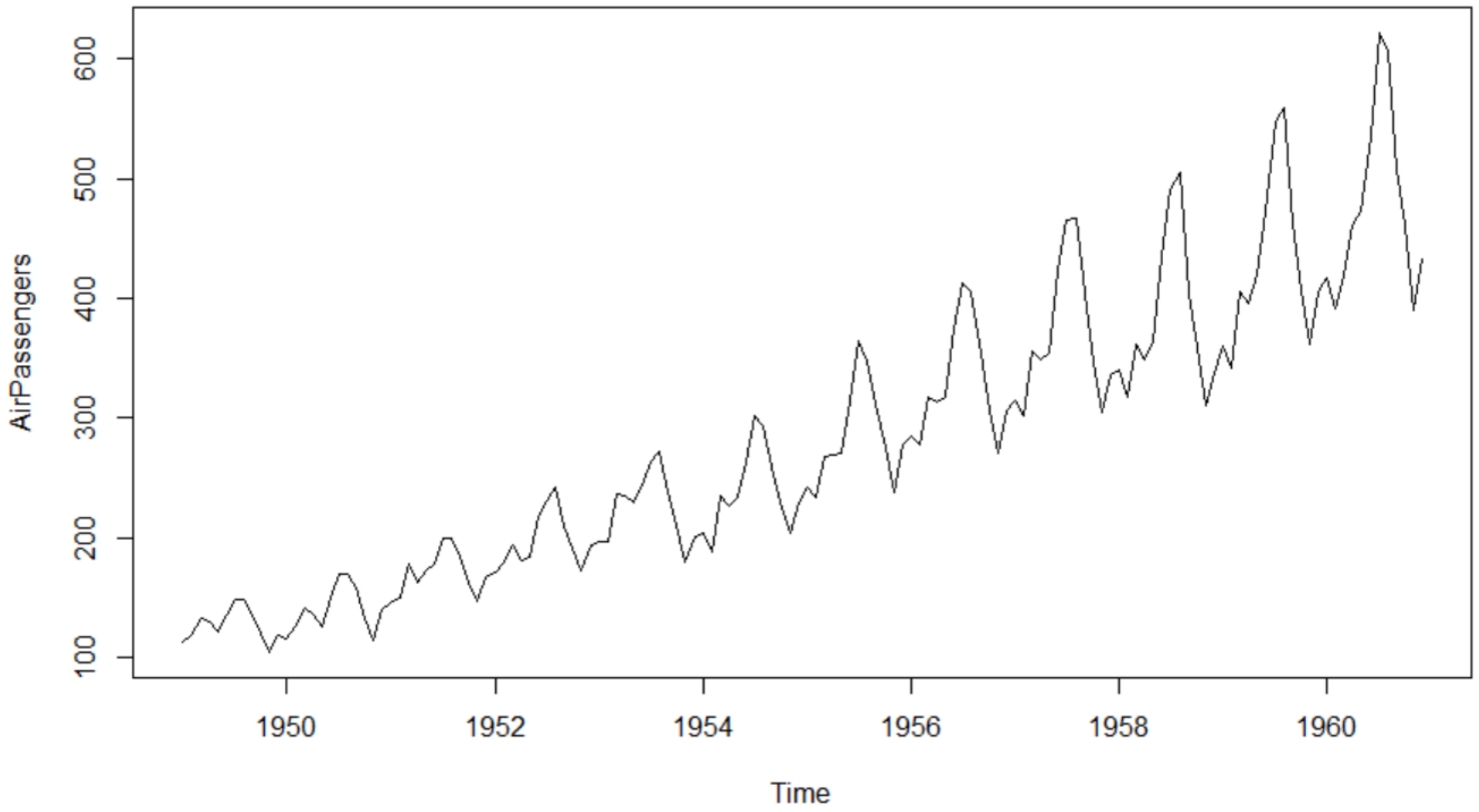
Checking the summary of our data

```
> # Check the summary of the dataset
> summary(AirPassengers)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  104.0   180.0   265.5   280.3   360.5   622.0 
```

Loading the data: exploration

```
# Plot the dataset
plot(AirPassengers)
```

Visualization of our data.



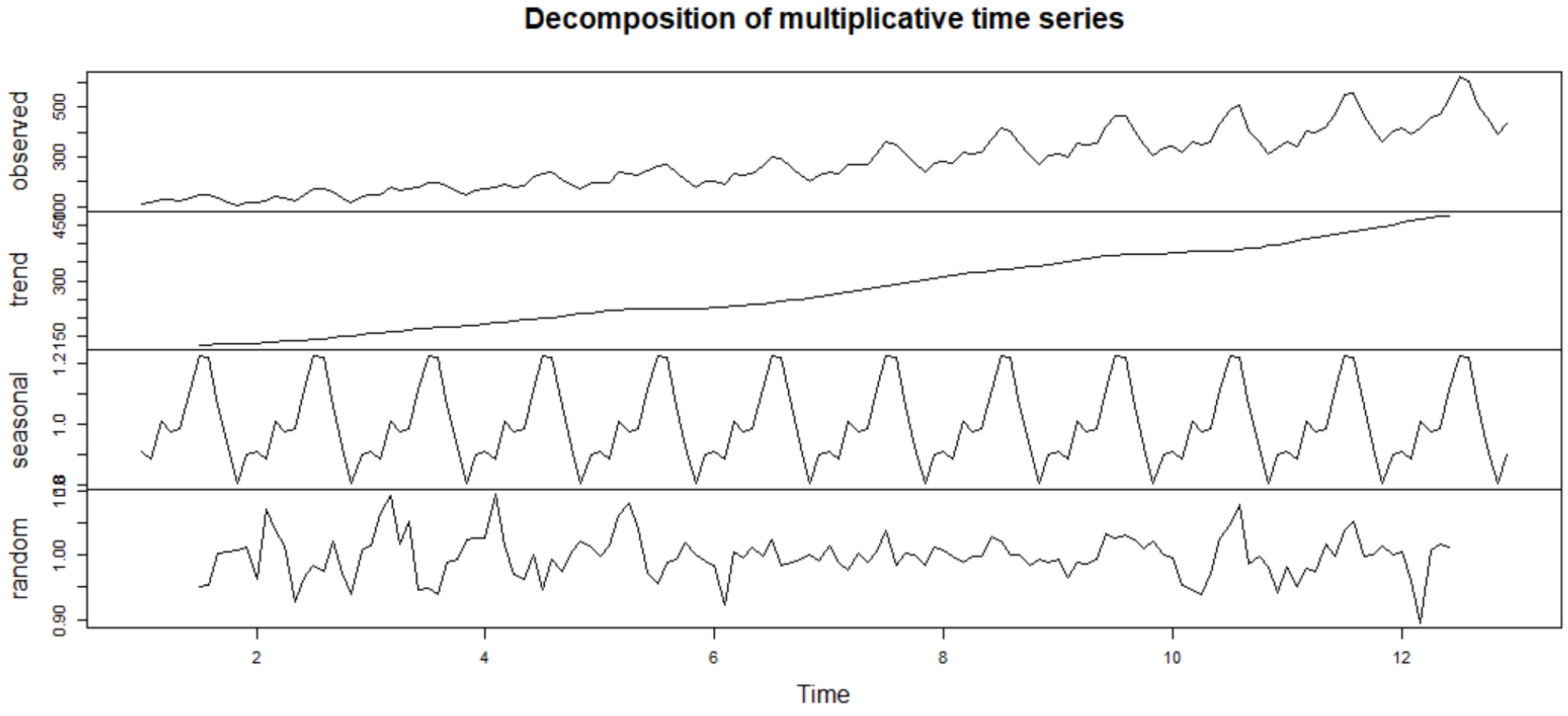
Decompose the data into four components

- Time series data are decomposed into three components :
  - *Seasonal* – Patterns that show how data is being changed over a certain period of time. Example – A clothing e-commerce website will have heavy traffic during festive seasons and less traffic during normal times. Here it is a seasonal pattern as value is being increased only at a certain period of time.
  - *Trend* – It is a pattern that shows how values are being changed. For example how a website is running overall if running successfully trend goes up, if not, the trend comes down.
  - *Random* – The remaining data of the time series after seasonal trends are removed is a random pattern. This is also known as noise.

Decompose the data into four components

```
# Decompose the data into four components and plot
tsdata <- ts(AirPassengers, frequency = 12)
ddata <- decompose(tsdata, "multiplicative")
plot(ddata)
```

The parameter *multiplicative* is added because time series data changes with the trend, if not so, such kinds of data are called "additive".



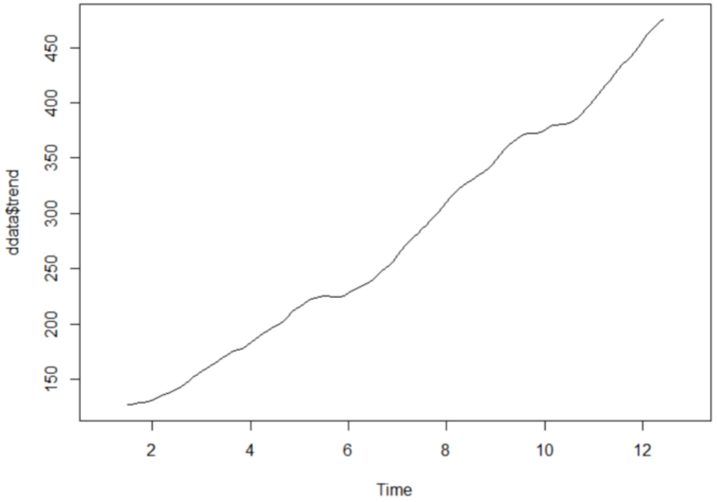
Our original data (in panel 1) is now broken into 3 components.

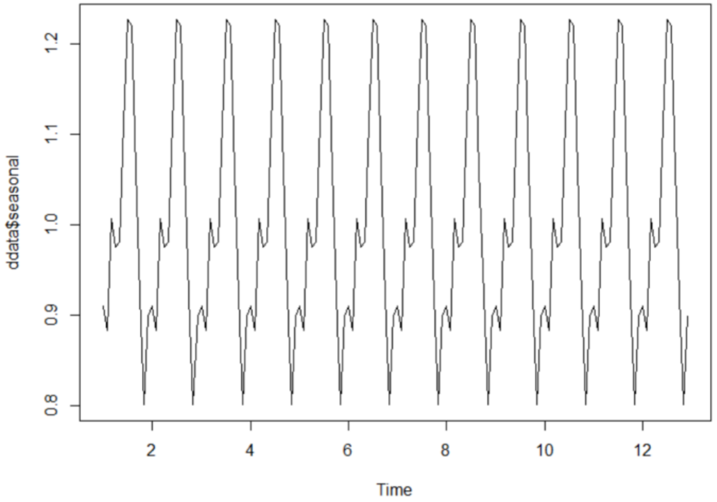
1. a trend component (panel 2)
2. a seasonal component (panel 3)
3. a random/remained (panel 4)

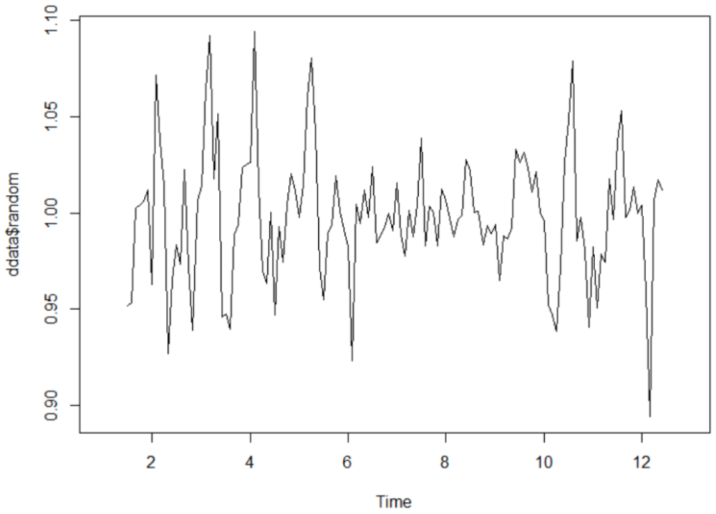
Decompose the data into four components

```
# Plot the different components individually
plot(ddata$trend)

plot(ddata$seasonal)

plot(ddata$random)
```

To check decomposition separately



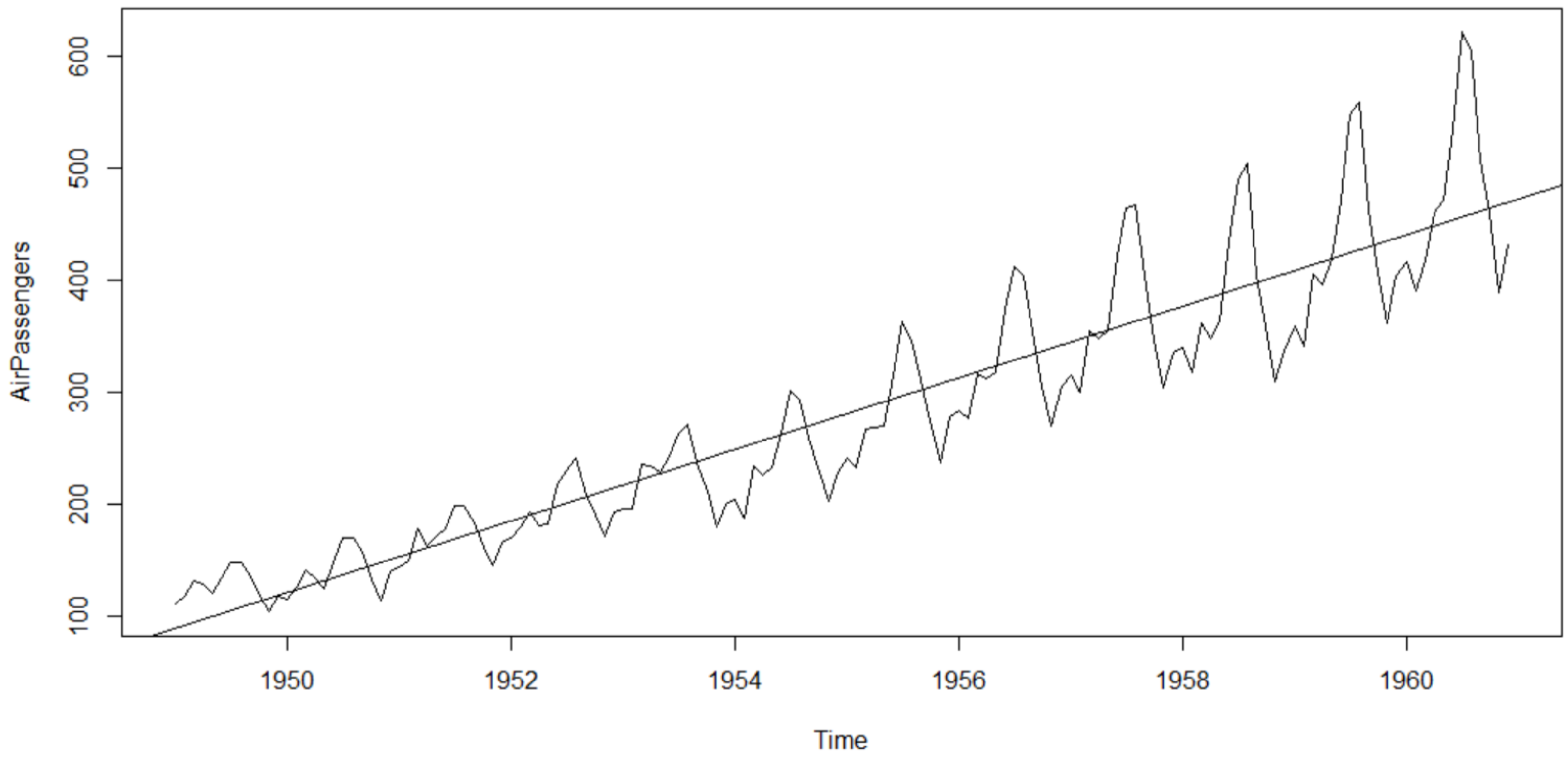




Plot a trendline on the original dataset

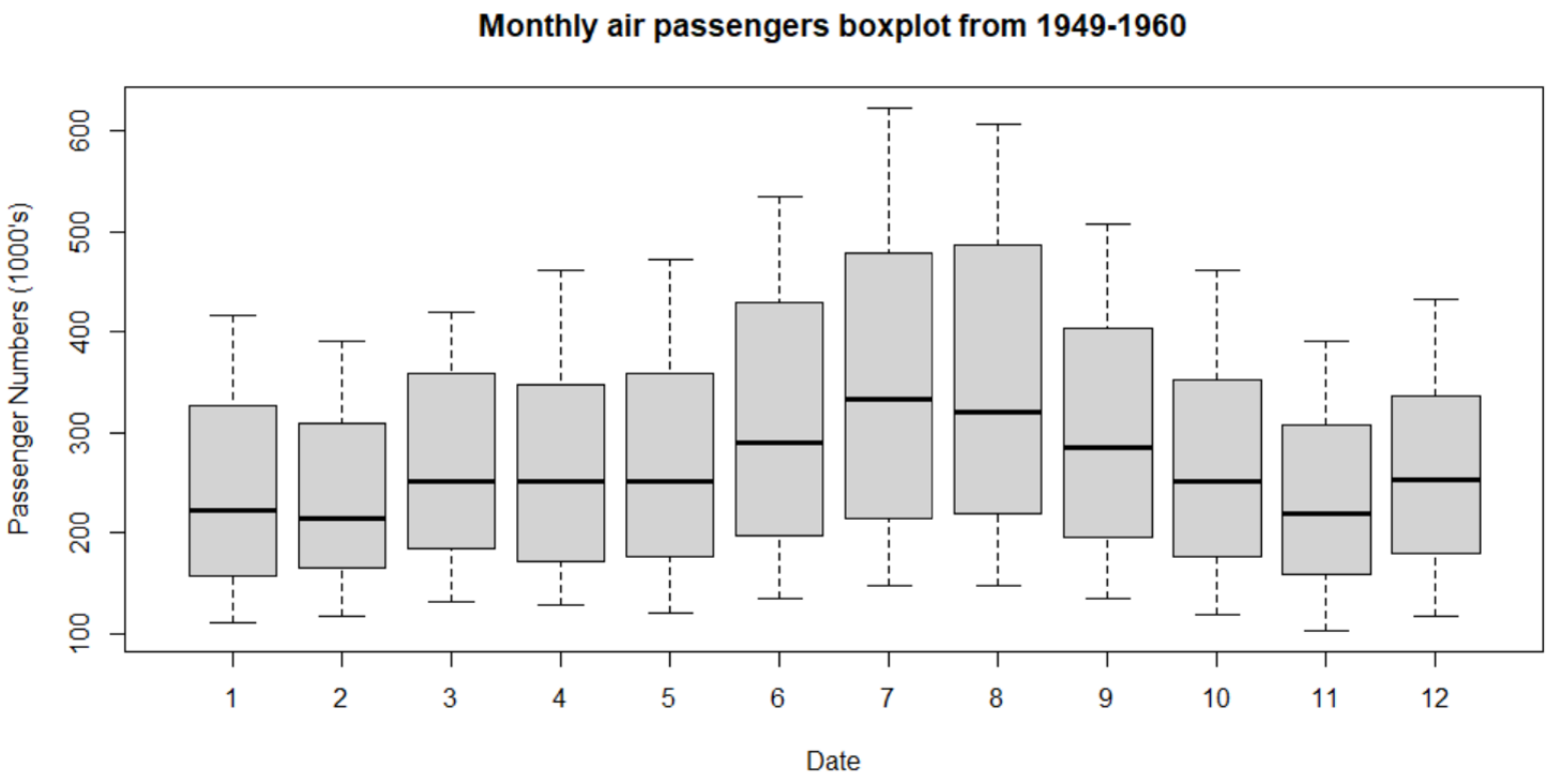
```
# Plot a trend line on the original dataset
plot(AirPassengers)
abline(reg=lm(AirPassengers~time(AirPassengers)))
```

To check the trend



Create a box plot by cycle

```
# Create a box plot by cycle
boxplot(AirPassengers~cycle(AirPassengers),
                            xlab="Date",
                            ylab = "Passenger Numbers (1000's)",
                            main = "Monthly air passengers boxplot from 1949-1960")
```



From the plot, you can see that the number of ticket sales goes higher in **June, July,** and **August** as compared to the other months of the years.

Build the ARIMA Model: combining into ARIMA

- An ARIMA model is simply the sum of the AR (Autoregression), differencing, and MA components (Moving Average).

- We abbreviate an ARIMA model as follows arima(p, d, q)(p, d, q)
  - p indicates the order of the autoregression
  - d indicates the number of times differencing takes place
  - q indicates the number of previous values we use for the moving average
- The first set of parenthesis indicates the non-seasonal (i.e. previous) values in the model.
- The second set of parenthesis indicates the seasonal values used in the model.

- The function Arima(data, order = (p, d, q), seasonal = (p, d, q))

Build the ARIMA Model: using auto.arima() function

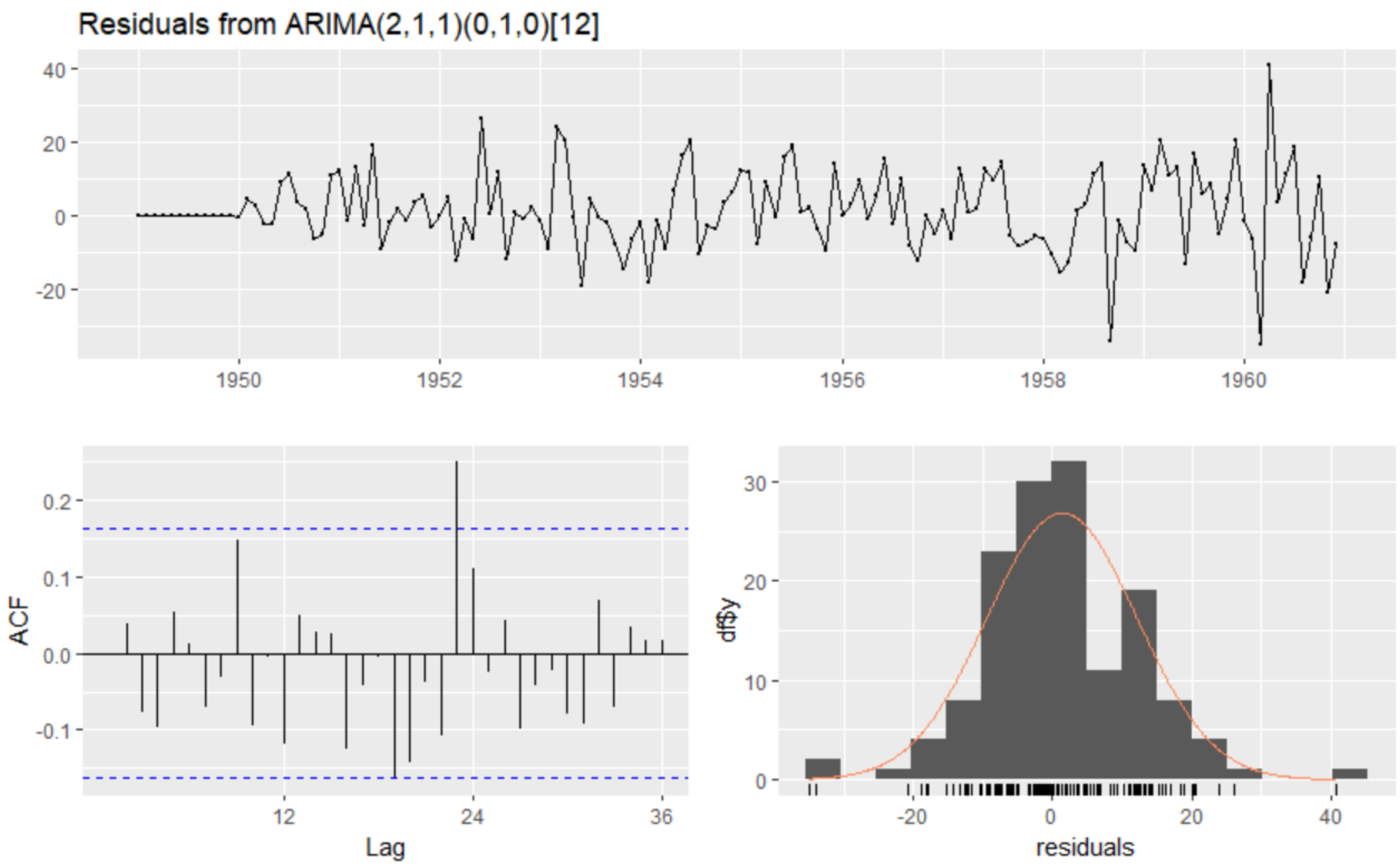
```r
# Build the ARIMA Model: using auto.arima() function
mymodel <- auto.arima(AirPassengers)
mymodel
```

```
> mymodel
Series: AirPassengers
ARIMA(2,1,1)(0,1,0)[12]

Coefficients:
         ar1     ar2      ma1
      0.5960  0.2143  -0.9819
s.e.  0.0888  0.0880   0.0292

sigma^2 = 132.3:  log likelihood = -504.92
AIC=1017.85   AICc=1018.17   BIC=1029.35
```

The auto.arima() function has recommended that we use 2 past values in our regression, the past value for differencing, 1 error in the moving average, and the past value of the same season for seasonal differencing.

Build the ARIMA Model: check the residuals

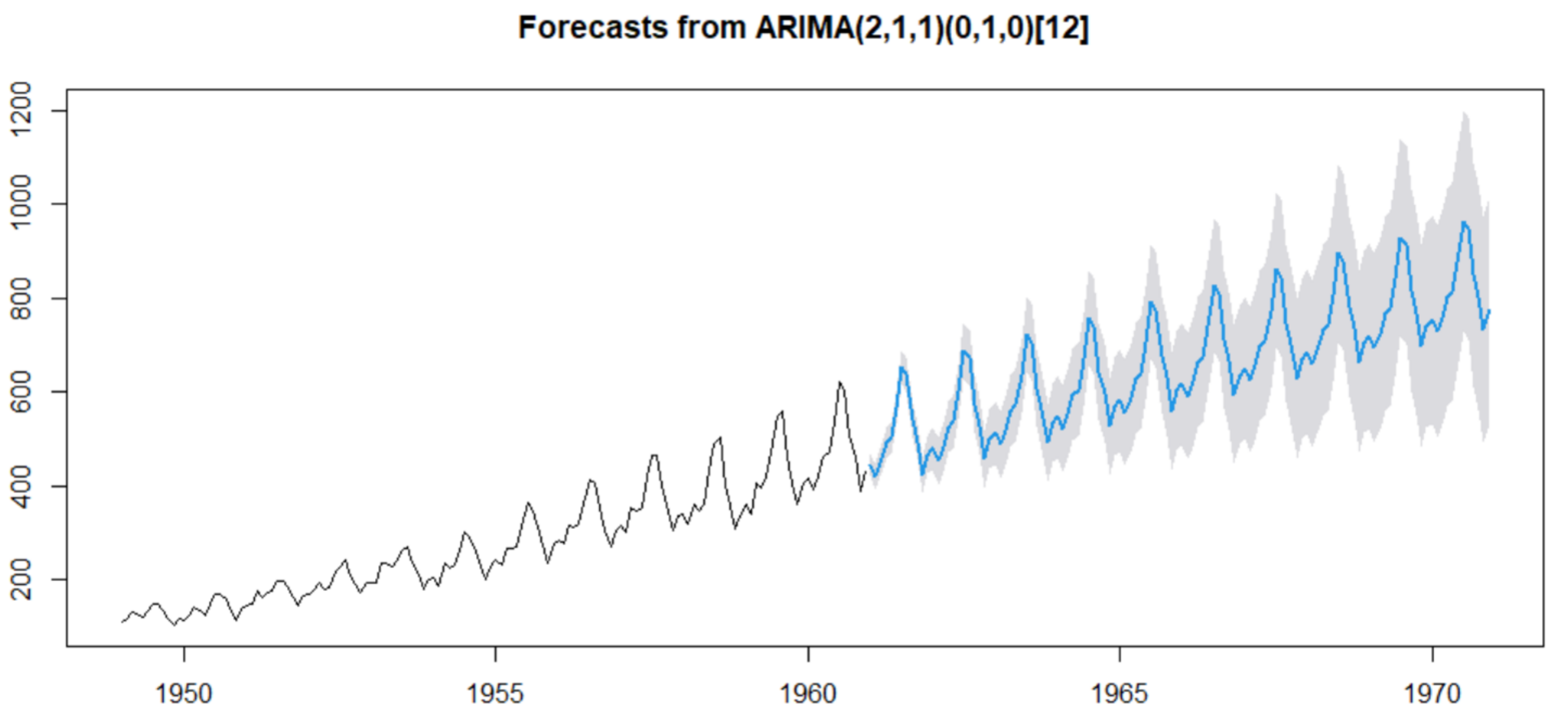
```
# Check that the residuals look like white noise
checkresiduals(mymodel)
```



Residuals are normally distributed.

Build the ARIMA Model: Forecast the values for the next 10 years

```r
# Forecast the values for the next 10 years
myforecast <- forecast(mymodel, level=c(95), h=10*12)
plot(myforecast)
```



The shaded region covers all the values that can possibly occur in the future10 years and the blue color pattern is the average of all values in the shaded part. This is how we can forecast values using any time series dataset.

h: Number of periods for forecasting.

level: Confidence level for prediction intervals.

https://www.rdocumentation.org/packages/forecast/versions/8.4/topics/forecast

Build the ARIMA Model: Validate the model by selecting lag values

```r
# Validate the model by selecting lag values
Box.test(mymodel$resid, lag=5, type="Ljung-Box")
Box.test(mymodel$resid, lag=10, type="Ljung-Box")
Box.test(mymodel$resid, lag=15, type="Ljung-Box")
```

```
> Box.test(mymodel$resid, lag=5, type="Ljung-Box")

        Box-Ljung test

data:  mymodel$resid
X-squared = 2.9244, df = 5, p-value = 0.7116

> Box.test(mymodel$resid, lag=10, type="Ljung-Box")

        Box-Ljung test

data:  mymodel$resid
X-squared = 8.6878, df = 10, p-value = 0.562

> Box.test(mymodel$resid, lag=15, type="Ljung-Box")

        Box-Ljung test

data:  mymodel$resid
X-squared = 11.582, df = 15, p-value = 0.7104
```

Looking at the lower p values, we can say that our model is relatively accurate, and we can conclude that from the ARIMA model, that the parameters (2, 1, 1) adequately fit the data.

5. In-class Assignment

You're going to be working with some retail data from “**Sales.RData**”. The data set contains information retail sales of automotive parts, accessory, and tire stores.

The dataset contains 2 columns:

DATE: monthly data

SALES: sales in Millions of USD,

Seasonally Adjusted

```
> head(sales)
      Jan  Feb  Mar  Apr  May  Jun
1992 3311 3360 3445 3415 3510 3521
```

```
> sales
```

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1992	3311	3360	3445	3415	3510	3521	3470	3461	3521	3576	3592	3579
1993	3600	3636	3525	3672	3739	3721	3811	3815	3861	3837	3810	3761
1994	3984	4037	4040	4100	4017	4066	4138	4179	4127	4185	4189	4223
1995	4233	4153	4199	4274	4276	4340	4312	4397	4405	4404	4520	4476
1996	4484	4557	4539	4569	4596	4626	4645	4573	4617	4732	4704	4766
1997	4787	4807	4860	4856	4785	4890	4909	4952	4979	4915	4996	4818
1998	4943	4959	5013	4946	5040	4958	4994	4981	5015	5073	5015	5073
1999	5117	5144	5087	5185	5165	5165	5195	5150	5358	5344	5434	5350
2000	5373	5284	5406	5220	5289	5293	5210	5236	5490	5191	5166	5317
2001	4956	5020	5036	5130	5117	5144	5151	5167	5072	5103	5088	5111
2002	5180	5189	5110	5226	5204	5250	5284	5280	5272	5234	5213	5159
2003	5219	5199	5265	5250	5307	5341	5369	5381	5500	5476	5499	5422
2004	5439	5507	5577	5481	5541	5476	5530	5526	5514	5610	5603	5743
2005	5935	5824	5728	5853	5754	5828	5784	5833	5769	5799	6022	6024
2006	6210	6031	6013	5989	5901	5962	6014	6030	6103	6074	6001	6118
2007	6105	6047	6248	6131	6268	6194	6229	6261	6295	6411	6283	6219
2008	6228	6230	6237	6287	6374	6422	6463	6298	6349	6346	6442	6395
2009	6411	6366	6247	6277	6262	6204	6143	6102	6051	6098	6016	6089
2010	6097	6218	6314	6491	6419	6452	6475	6648	6641	6657	6720	6771
2011	6609	6664	6806	6757	6828	7029	6947	7120	7134	7025	7057	7022
2012	7193	7067	6980	7004	6959	6935	7044	6905	7047	7051	6965	6978
2013	7001	7104	7005	6983	7088	7037	7084	7162	7132	7282	7332	7374
2014	7227	7319	7314	7309	7200	7108	7119	7189	7176	7184	7595	7156
2015	7292	7389	7450	7559	7593	7685	7725	7627	7581	7597	7727	7652
2016	7771	7748	7665	7554	7624	7726	7599	7696	7635	7705	7609	8175
2017	7773	7678	7760	7814	7767	7721	7805	7705	7891	7753	7884	8120
2018	7783	7823	7800	7814	7938	7923	8006	7925	8046	8008	7961	7922
2019	7721	7994	8113	8090	8108	8110	8089	8189	8066	8096	8132	8054
2020	7971	7866	7128	6743	8391	8950	8671	8713	8589	8251	8240	8183
2021	8446	8358	9467	9487	9299	9283	9349	9460	9413	9642	9669	9974
2022	9975	9943	10066	10212	10417	10353	10423	10487	10662	10543	10608	10655
2023	10648	10837										