Economics 144
Economic Forecasting

Lecture 1
Introduction to Time Series

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Today's Class

- Overview of Time Series Data

- First Order Properties
  - Data inspection
  - Trend
  - Seasonality
  - Cycles

- Second Order Properties
  - Series Decomposition
  - Autocorrelation Functions (ACF & PACF)
  - Stationarity

- Modeling and Forecasting Time Series Data

Overview of Economic Forecasting 1 of 2

- Q1: What is a forecast?

  Ans: A forecast is a statement about the future.
  - Note: Forecasting = the science and the art to predict a future event with some degree of accuracy.

- Q2: How is forecasting done by economists?

  Ans: In economics, methods of forecasting include:
  - Guessing, “rules of thumb”, or “informal models”
  - Expert judgment
  - Extrapolation
  - Leading indicators
  - Surveys
  - Time Series models
  - Econometric systems

Overview of Economic Forecasting 2 of 2

- Q3: What are the main problems?

  Ans: One of the main problems with forecasting in economics is that economies evolve over time and are subject to intermittent, and sometimes large, unanticipated shocks.

- Q4: What are some relevant forecast examples?

  Ans: Some of the relevant areas include:
  - Operations planning and control
  - Marketing
  - Economics
  - Financial asset management
  - Financial risk management
  - Demography
  - Crisis management

Forecasting Problems

- Short-term
  - Predicting only a few periods ahead (hours, days, weeks)
  - Typically based on modeling and extrapolating patterns in the data
- Medium-term
  - One to two years into the future, typically
- Long-term
  - Several years into the future

Standard Notation

Description	Technical name	Notation
Object to analyze:	Time series	$\{y_t\}$
Value at present time t :	Known value of the series	y_t
Future at time $t+h$:	Random variable	Y_{t+h}
Value at future time $t+h$:	Unknown value of the random variable	y_{t+h}
Collection of information :	Univariate information set Multivariate information set	$I_t = \{y_1, y_2, ..., y_t\}$ $I_t = \{y_1, y_2, ..., y_t, x_1, x_2, ..., x_t\}$
Final objective:	Forecast 1-step ahead h-step ahead	 $f_{t,1}$ $f_{t,h}$
Uncertainty:	Forecast error	$e_{t,h} = y_{t+h} - f_{t,h}$

Six Fundamental Considerations in Forecasting
The Forecast Object 1 of 1

Forecast Object
- Event outcome
- Event timing
- Time Series

- Event Outcome Forecasts: Event is certain, outcome is unknown, timing known.

- Event Timing Forecasts: Event is certain, outcome is known, timing unknown.

- Time Series Forecasts: Project the future value of a time series. (most commonly encountered)

Six Fundamental Considerations in Forecasting
The Forecast Statement 1 of 2

- What will the forecast result be?

Most common!

- Point Forecast: Single number (e.g., μ).

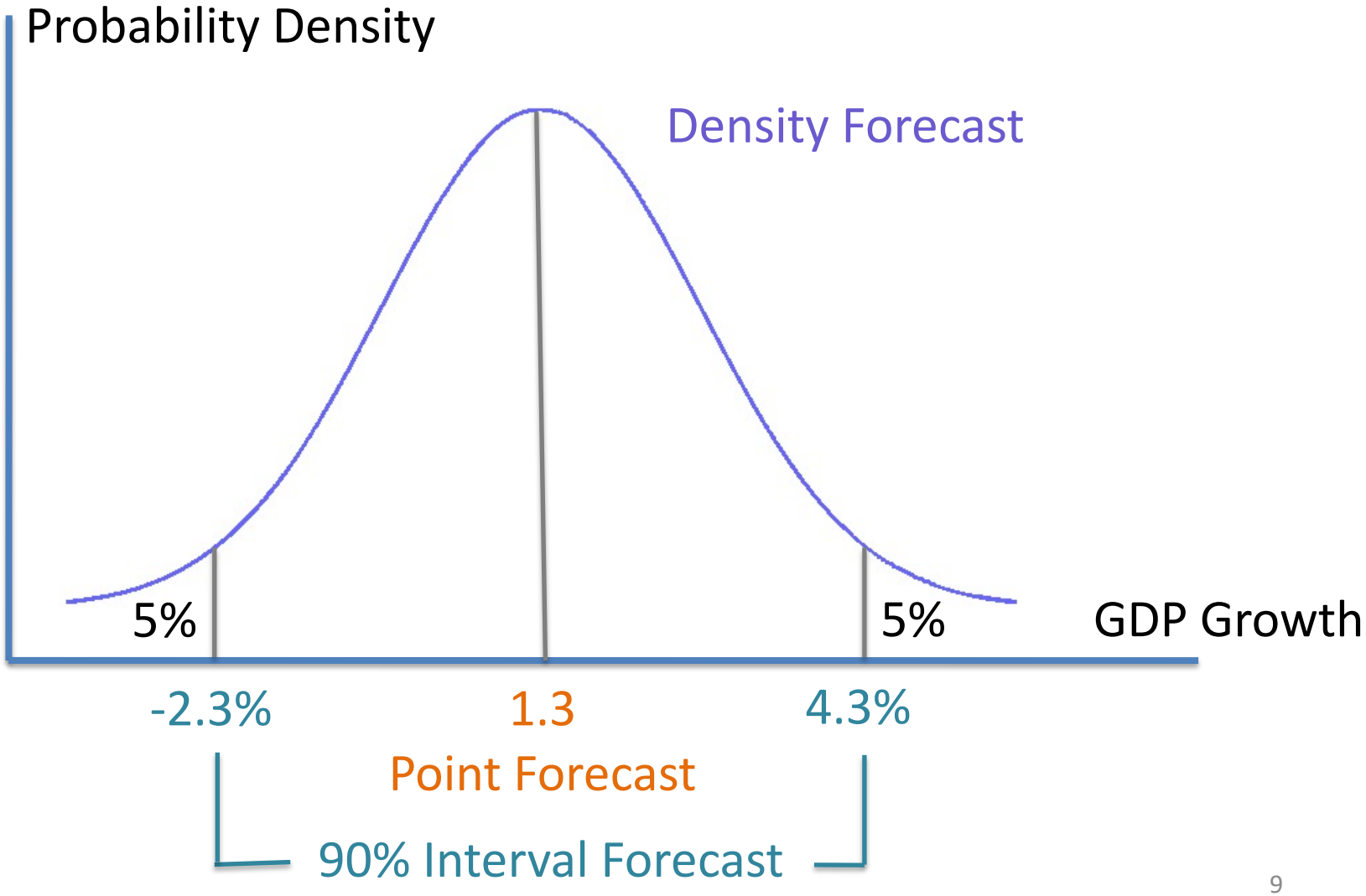
less information

- Interval Forecast: Range of values. (~confidence interval, e.g., $\mu \pm z^{*}\sigma$).

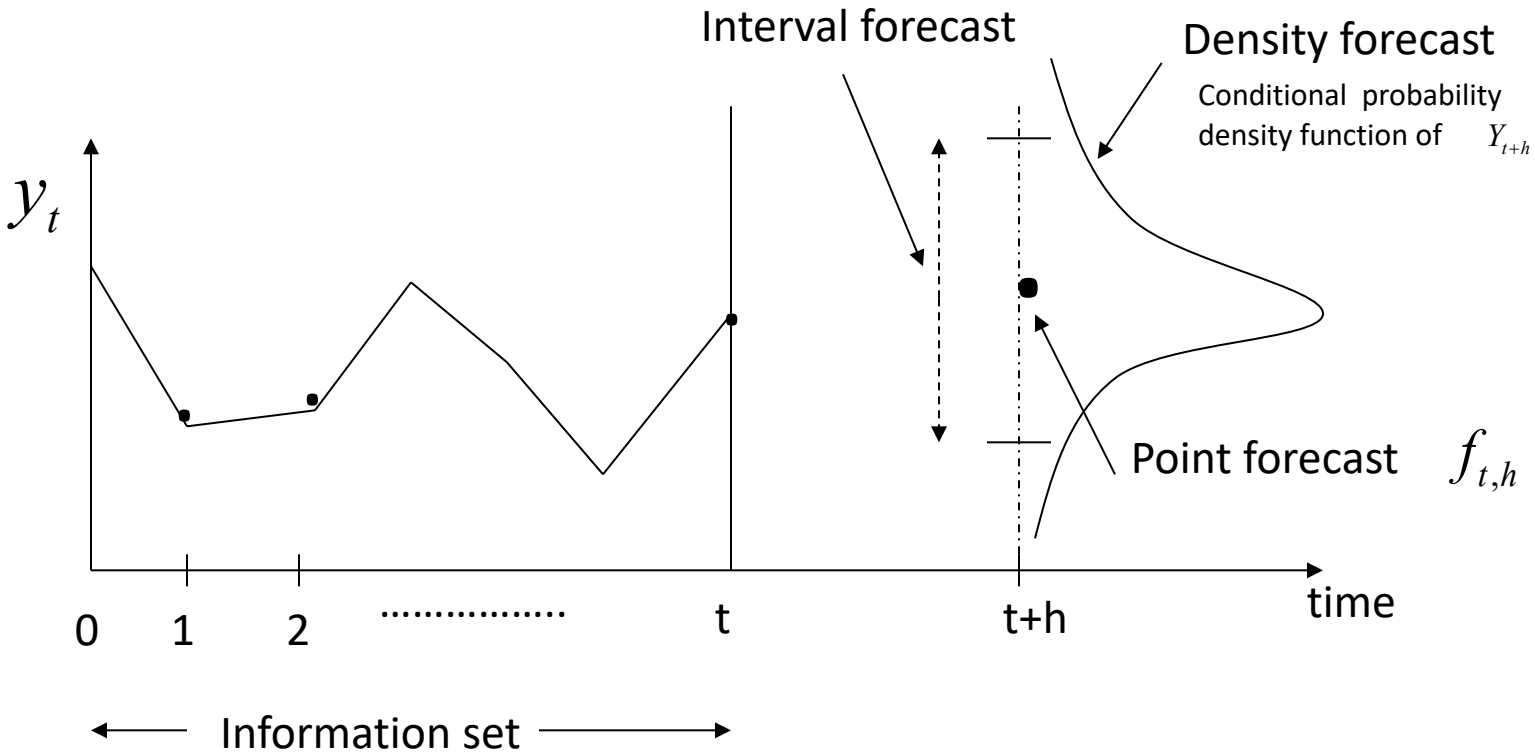
more information

- Density Forecast: Probability Distribution of the of the future value of the series (e.g., $N(\mu, \sigma^2)$).

Six Fundamental Considerations in Forecasting
The Forecast Statement 2 of 2



Six Fundamental Considerations in Forecasting
The Forecast Statement 2 of 2



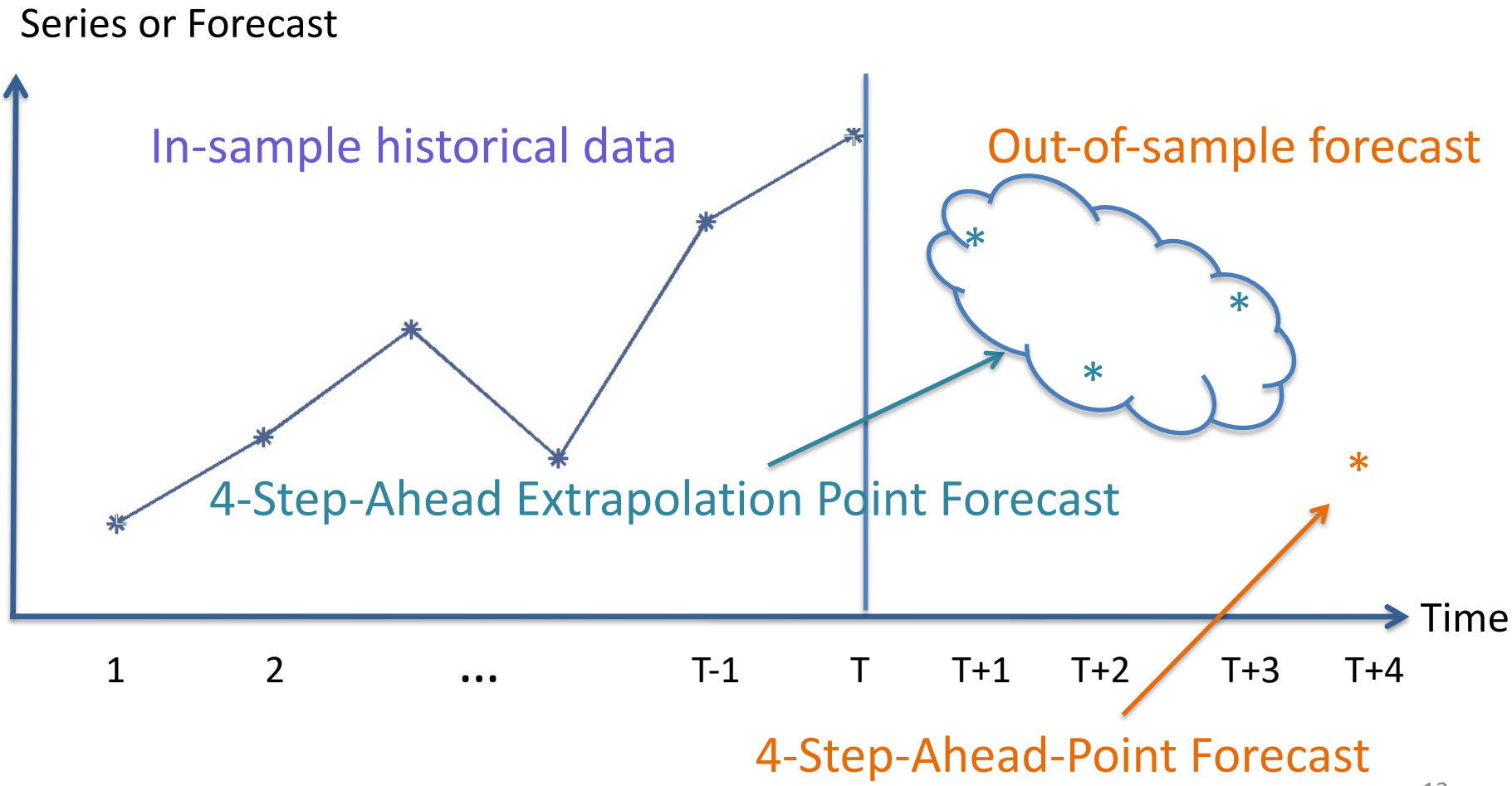
Six Fundamental Considerations in Forecasting
The Forecast Horizon 1 of 2

- Forecast Horizon: Number of periods between today and the end date of the forecast.

  Example: Today: Year =T
  →Forecast GDP for year T+5→Forecast horizon of 5 steps.

- In general: *h-step-ahead forecast* (where h is the step length). The horizon is fixed (h is constant).
- *h-step-ahead extrapolation forecast:* Includes all steps from *1-step-ahead to* : *h-steps-ahead.*

Six Fundamental Considerations in Forecasting
The Forecast Horizon 2 of 2



Six Fundamental Considerations in Forecasting
The Information Set

- Your forecast is conditional on the quality and quantity of your data.
- *Questions:*
  - *What information is available?*
  - *What else could be collected? Or made available?*
  - *Quantitative or Qualitative?*
  - *Can the data be used more efficiently?*
- Univariate Information Set:

$$\Omega_T^{univariate} = \{y_T, y_{T-1}, \ldots, y_1\}$$

- Multivariate Information Set:

$$\Omega_T^{multivariate} = \{x_T, y_T, x_{T-1}, y_{T-1} \ldots, x_1, y_1\}$$

Six Fundamental Considerations in Forecasting Models and Complexity, The Parsimony and Shrinkage Principles 1 of 1

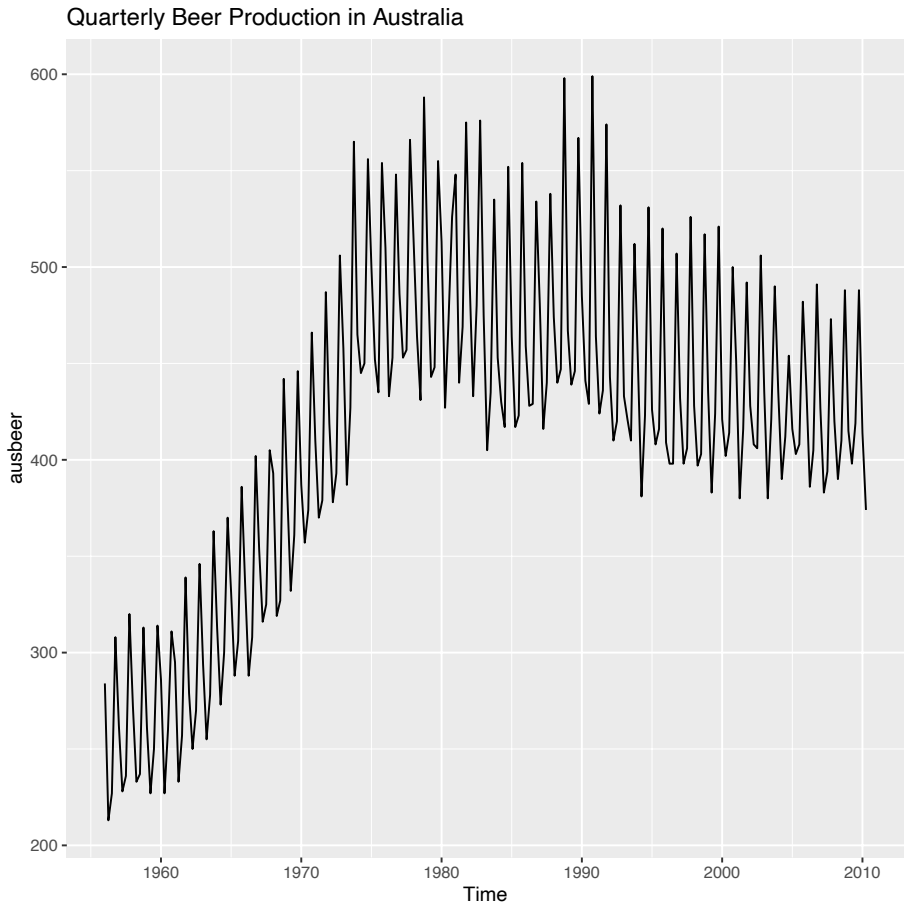
- Your modeling strategy should be based on your forecast task.
- For out-of-sample forecasting in business, finance, and economics, simple (parsimonious) models are better.

- Parsimony Principle: All other things being equal, simpler models are better than complex ones.

- Shrinkage Principle: Imposing restrictions on forecasting models often improves forecast performance.

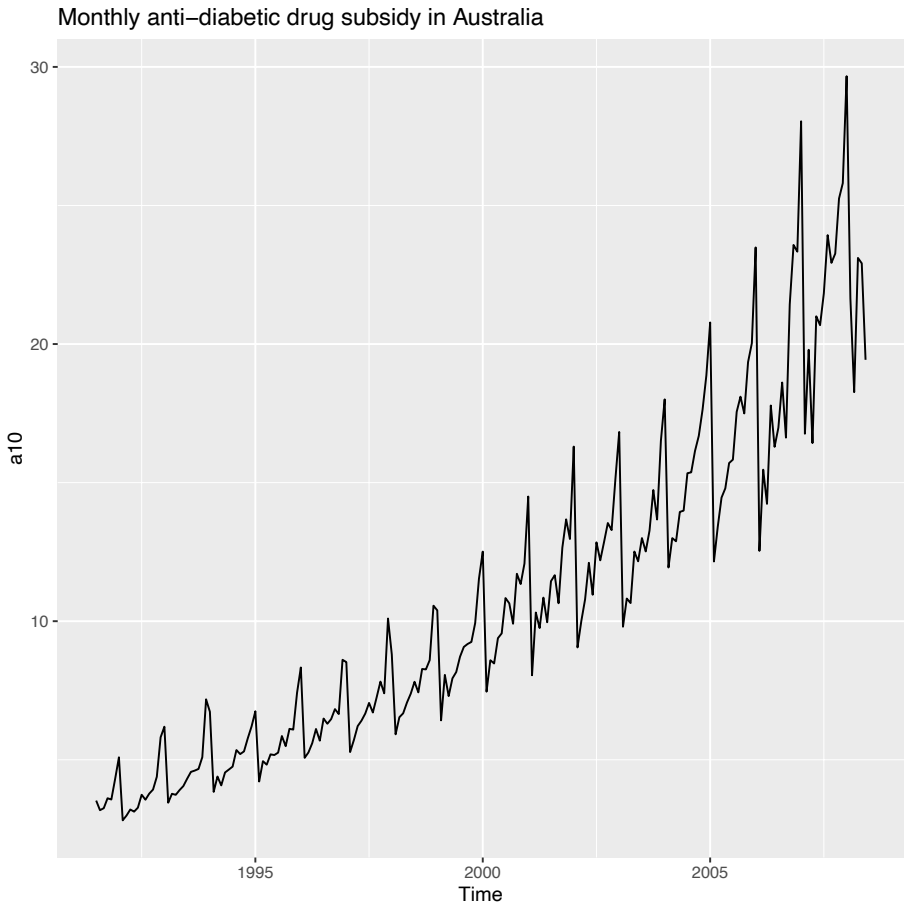
KISS Principle: Keep It Sophisticatedly Simple

Overview of Time Series Data



Trend, Seasonlity, and/or Cycles?

Overview of Time Series Data



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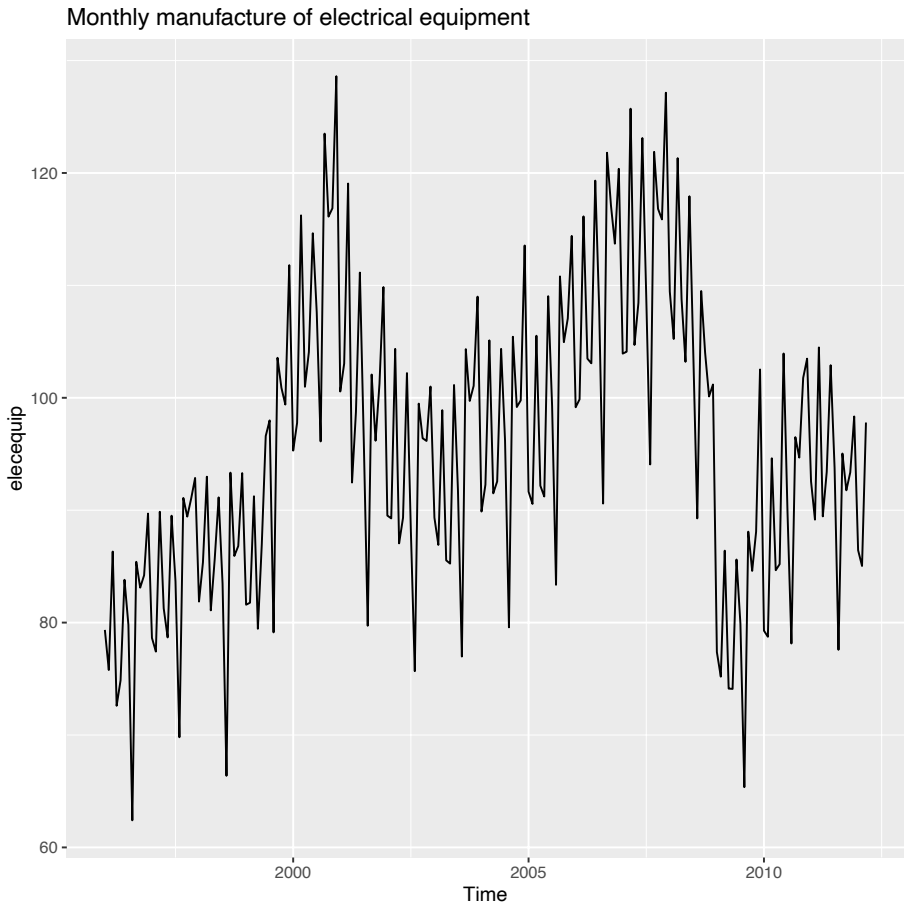

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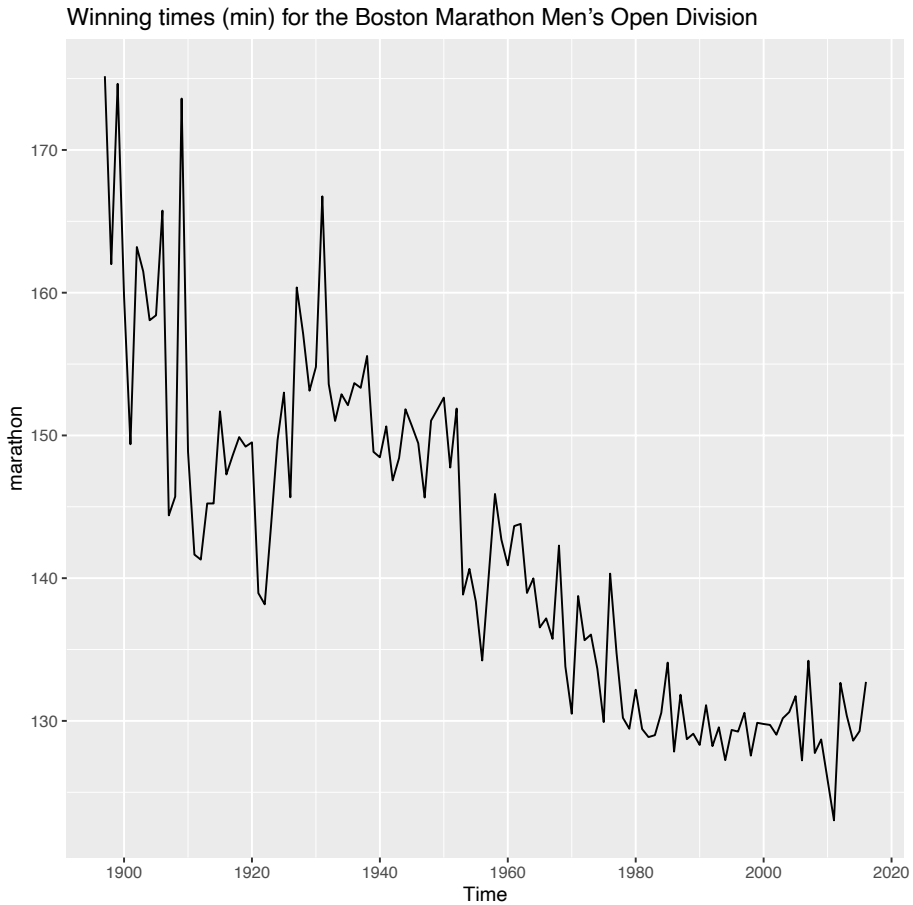
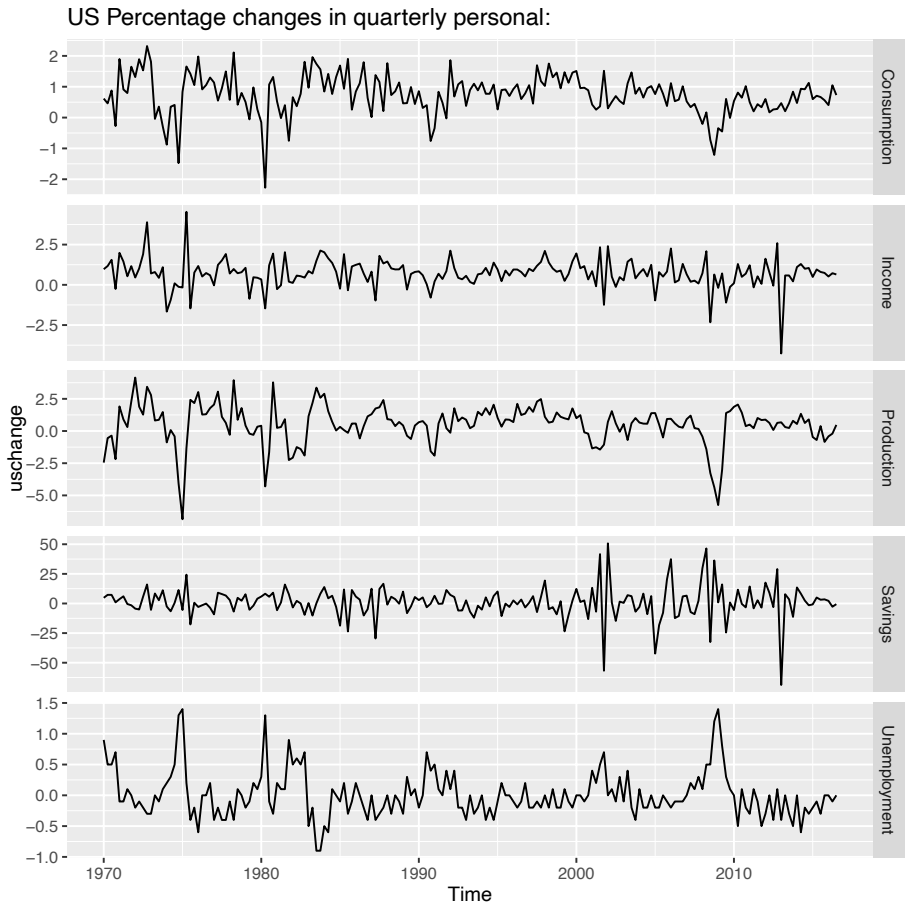


Trend, Seasonlity, and/or Cycles?

Overview of Time Series Data



Trend, Seasonlity, and/or Cycles?

First Order Properties: Data Inspection

```
> ausbeer
     Qtr1 Qtr2 Qtr3 Qtr4
1956  284  213  227  308
1957  262  228  236  320
1958  272  233  237  313
1959  261  227  250  314
1960  286  227  260  311
1961  295  233  257  339
1962  279  250  270  346
1963  294  255  278  363
1964  313  273  300  370
1965  331  288  306  386
1966  335  288  308  402
1967  353  316  325  405
1968  393  319  327  442
1969  383  332  361  446
1970  387  357  374  466
1971  410  370  379  487
1972  419  378  393  506
1973  458  387  427  565
1974  465  445  450  556
1975  500  452  435  554
1976  510  433  453  548
1977  486  453  457  566
1978  515  464  431  588
1979  503  443  448  555
```

First Order Properties: Data Inspection

```
> a10
          Jan       Feb       Mar       Apr       May       Jun       Jul       Aug       Sep       Oct
1991                                                                 3.526591  3.180891  3.252221  3.611003
1992  5.088335  2.814520  2.985811  3.204780  3.127578  3.270523  3.737851  3.558776  3.777202  3.924490
1993  6.192068  3.450857  3.772307  3.734303  3.905399  4.049687  4.315566  4.562185  4.608662  4.667851
1994  6.731473  3.841278  4.394076  4.075341  4.540645  4.645615  4.752607  5.350605  5.204455  5.301651
1995  6.749484  4.216067  4.949349  4.823045  5.194754  5.170787  5.256742  5.855277  5.490729  6.115293
1996  8.329452  5.069796  5.262557  5.597126  6.110296  5.689161  6.486849  6.300569  6.467476  6.828629
1997  8.524471  5.277918  5.714303  6.214529  6.411929  6.667716  7.050831  6.704919  7.250988  7.819733
1998  8.798513  5.918261  6.534493  6.675736  7.064201  7.383381  7.813496  7.431892  8.275117  8.260441
1999 10.391416  6.421535  8.062619  7.297739  7.936916  8.165323  8.717420  9.070964  9.177113  9.251887
2000 12.511462  7.457199  8.591191  8.474000  9.386803  9.560399 10.834295 10.643751  9.908162 11.710041
2001 14.497581  8.049275 10.312891  9.753358 10.850382  9.961719 11.443601 11.659239 10.647060 12.652134
2002 16.300269  9.053485 10.002449 10.788750 12.106705 10.954101 12.844566 12.196500 12.854748 13.542004
2003 16.828350  9.800215 10.816994 10.654223 12.512323 12.161210 12.998046 12.517276 13.268658 14.733622
2004 18.003768 11.938030 12.997900 12.882645 13.943447 13.989472 15.339097 15.370764 16.142005 16.685754
2005 20.778723 12.154552 13.402392 14.459239 14.795102 15.705248 15.829550 17.554701 18.100864 17.496668
2006 23.486694 12.536987 15.467018 14.233539 17.783058 16.291602 16.980282 18.612189 16.623343 21.430241
2007 28.038383 16.763869 19.792754 16.427305 21.000742 20.681002 21.834890 23.930204 22.930357 23.263340
2008 29.665356 21.654285 18.264945 23.107677 22.912510 19.431740
```

First Order Properties: Data Inspection

```
> marathon
Time Series:
Start = 1897
End = 2016
Frequency = 1
  [1] 175.1667 162.0000 174.6333 159.7333 149.3833 163.2000 161.4833 158.0667 158.4167 165.7500 144.4000
 [12] 145.7167 173.6000 148.8667 141.6500 141.3000 145.2333 145.2333 151.6833 147.2667 148.6167 149.8833
 [23] 149.2167 149.5167 138.9500 138.1667 143.7833 149.6667 153.0000 145.6667 160.3667 157.1167 153.1333
 [34] 154.8000 166.7500 153.6000 151.0167 152.8833 152.1167 153.6667 153.3333 155.5667 148.8500 148.4667
 [45] 150.6333 146.8500 148.4167 151.8333 150.6667 149.4500 145.6500 151.0333 151.8333 152.6500 147.7500
 [56] 151.8833 138.8500 140.6500 138.3667 134.2333 140.0833 145.9000 142.7000 140.9000 143.6500 143.8000
 [67] 138.9667 139.9833 136.5500 137.1833 135.7500 142.2833 133.8167 130.5000 138.7500 135.6500 136.0500
 [78] 133.6500 129.9167 140.3167 134.7667 130.2167 129.4500 132.1833 129.4333 128.8667 129.0000 130.5667
 [89] 134.0833 127.8500 131.8333 128.7167 129.1000 128.3167 131.1000 128.2333 129.5500 127.2500 129.3667
[100] 129.2500 130.5667 127.5667 129.8667 129.7833 129.7167 129.0333 130.1833 130.6167 131.7333 127.2333
[111] 134.2167 127.7500 128.7000 125.8667 123.0333 132.6667 130.3667 128.6167 129.2833 132.7333
```

First Order Properties: Data Inspection

```
> sp500.prices
           Adjusted
1991-01-02   326.45
1991-01-03   321.91
1991-01-04   321.00
1991-01-07   315.44
1991-01-08   314.90
1991-01-09   311.49
1991-01-10   314.53
1991-01-11   315.23
1991-01-14   312.49
1991-01-15   313.73
1991-01-16   316.17
1991-01-17   327.97
1991-01-18   332.23
1991-01-21   331.06
1991-01-22   328.31
1991-01-23   330.21
1991-01-24   334.78
1991-01-25   336.07
1991-01-28   336.03
1991-01-29   335.84
1991-01-30   340.91
1991-01-31   343.93
1991-02-01   343.05
1991-02-04   348.34
```

Anything missing?

First Order Properties: Trend

Trend: Is a slow , long-run evolution in the variables that we want to model and forecast.

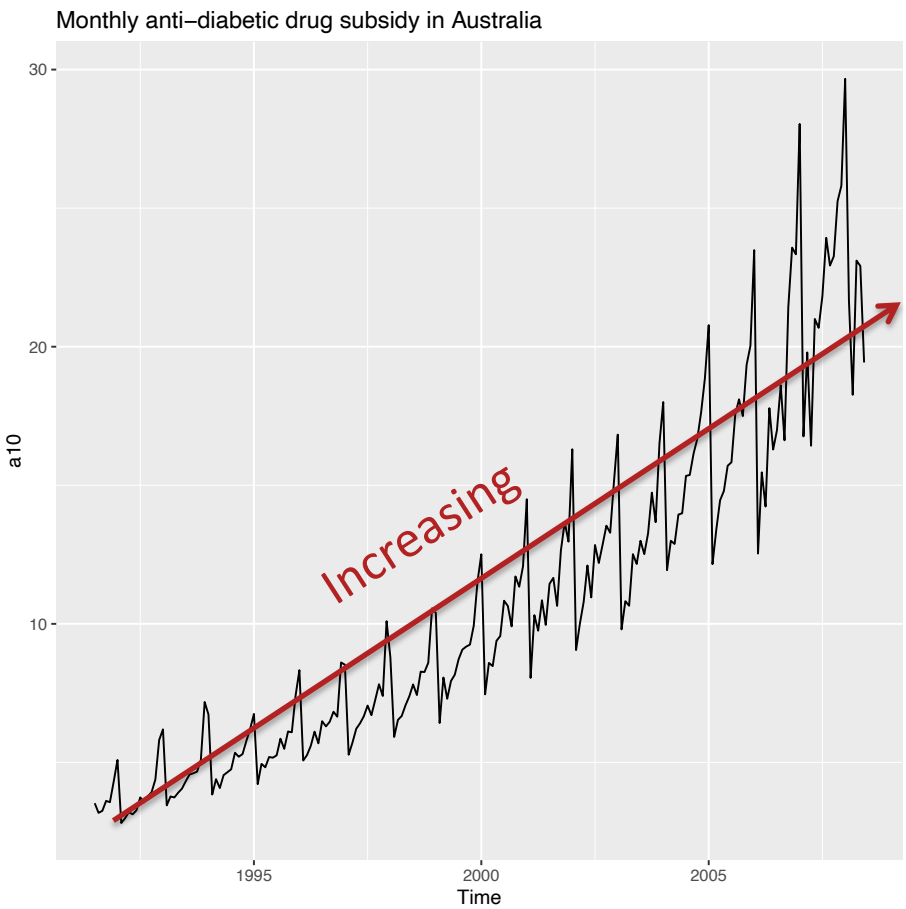
- Deterministic Trend: Trend evolves in a perfectly predictable way.
- Stochastic Trend: Trend evolves in an unpredictable way.

- To characterize a particular trend, we need a model. For example, in the case of linear regression, the model is: $y_t = \beta_0 + \beta_1 x_t$
- Often, given the broad range of time scales encountered in time-series, it is convenient to adopt one common time variable (*time dummy or time trend*) such that: $TIME^* = (1, 2, \ldots, T)$ where TIME=1 is the first period of the sample, and so on.

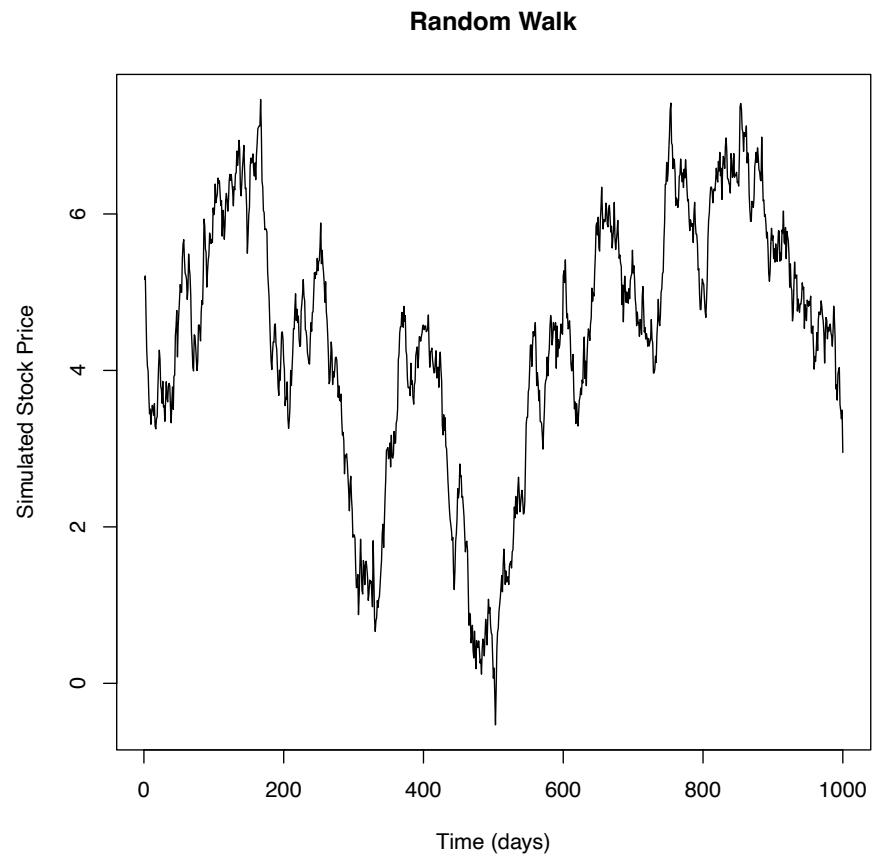
*The notation convention is $TIME_t = t$.

First Order Properties: Trend

Deterministic Trend



Stochastic Trend

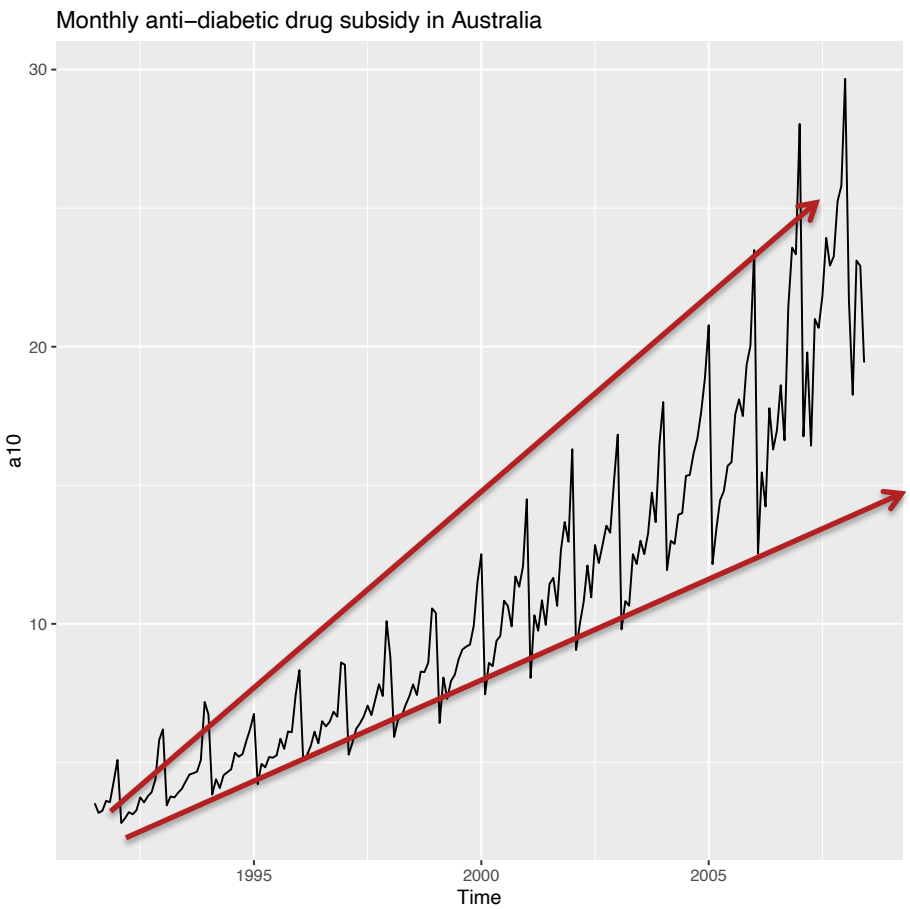


First Order Properties: Seasonality

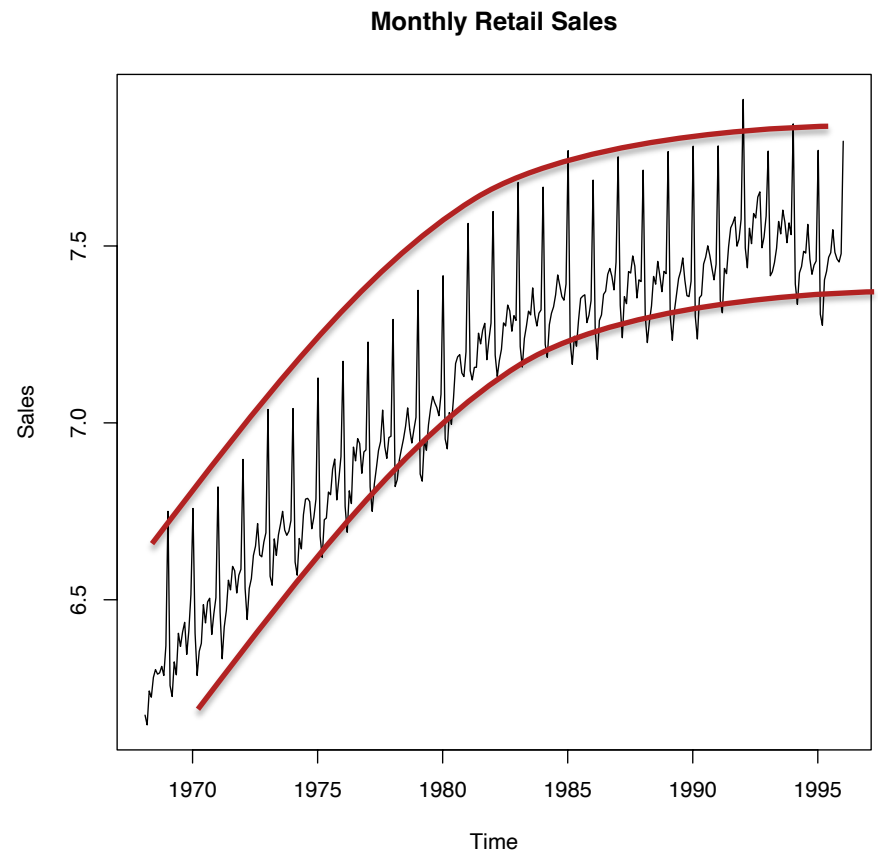
- Additive: $y_t = S_t + T_t + R_t$
  - Good when the seasonal fluctuations do not vary much with time.
  - Seasonally adjusted Series: $y_{adjusted} = y_t - S_t$
- Multiplicative: $y_t = S_t \times T_t \times R_t$
  - Good when the seasonal fluctuations vary with time.
  - Seasonally adjusted Series: $y_{adjusted} = y_t / S_t$

First Order Properties: Seasonality

Multiplicative



Additive

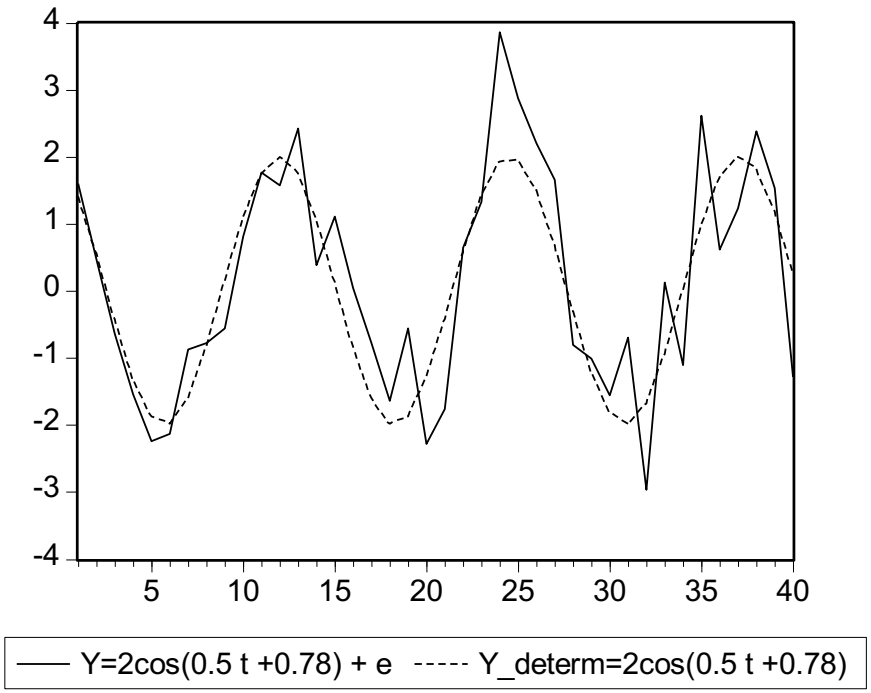


First Order Properties: Cycles

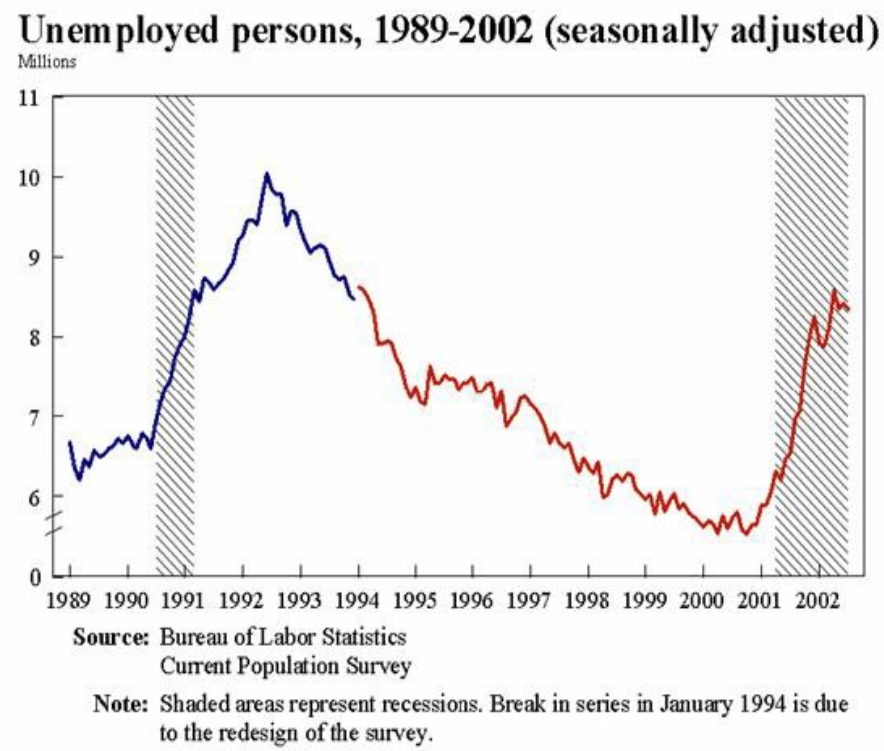
- Def: Cycle = Time series pattern of periodic (~several years) fluctuations.
  - Deterministic: Common in engineering, physical sciences, etc. Example: $Y_t = 2\ cos(0.5t+0.8)+\varepsilon_t$
  - Stochastic: Common in economics, business, etc. Example: $Y_t = 0.5Y_{t-1} + 0.3Y_{t-2} +\varepsilon_t$

First Order Properties: Cycles

Deterministic Cycle

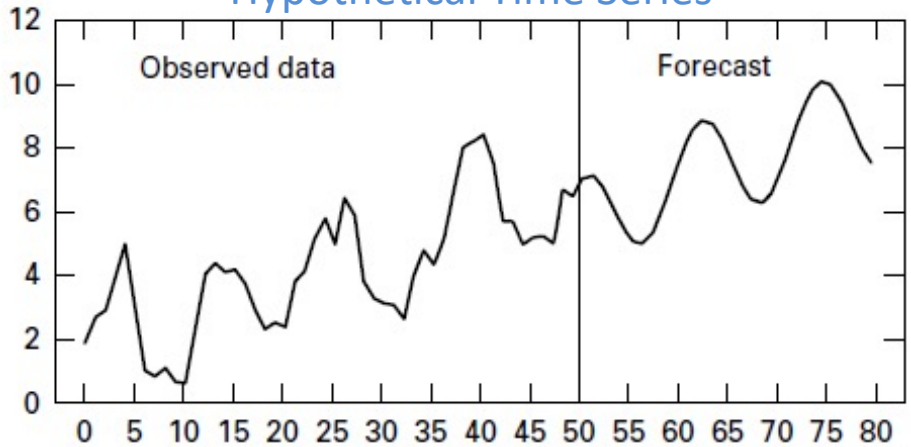


Stochastic Cycle

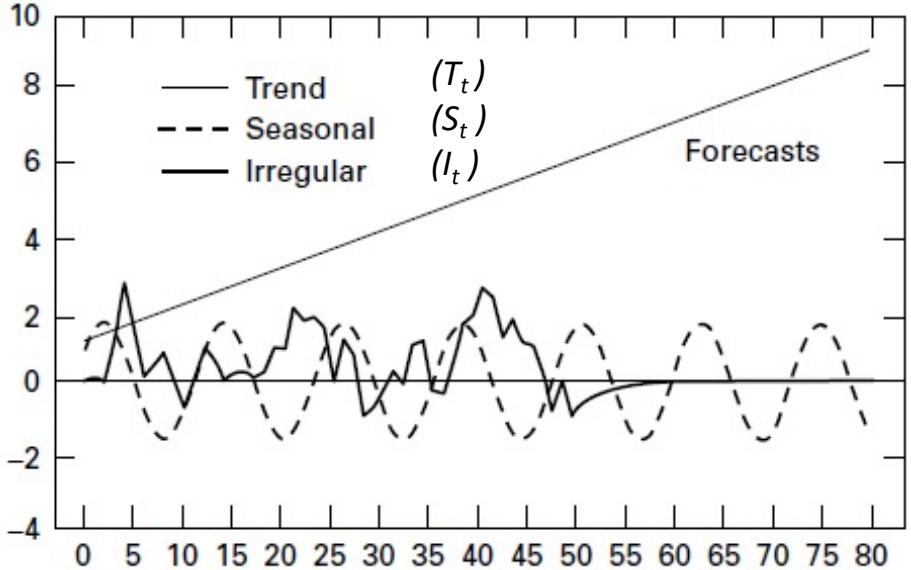


Second Order Properties: Series Decomposition

Hypothetical Time Series

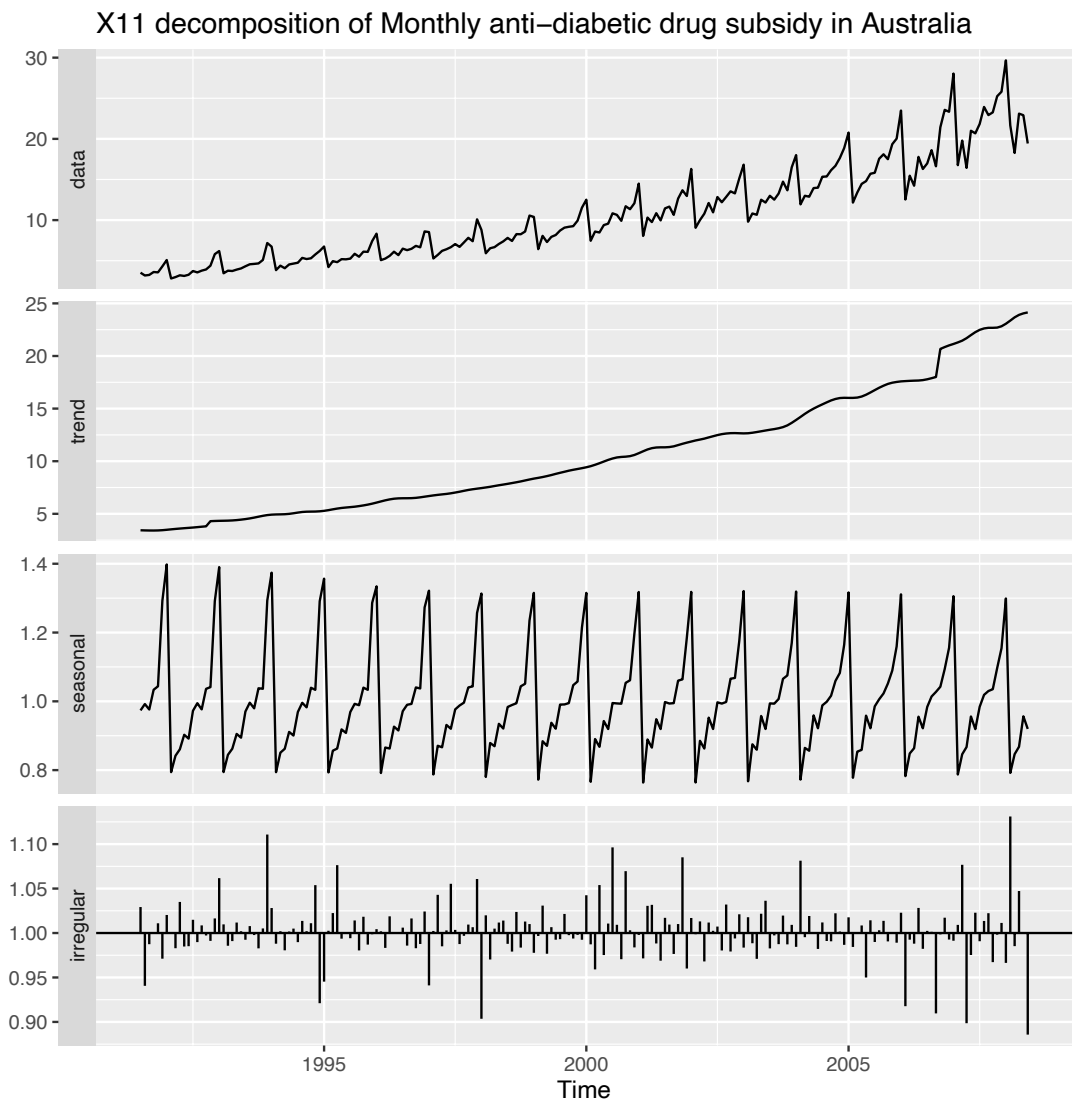


T_t = Value of the trend component in period t
S_t = Value of the seasonal component in period t
I_t = Value of the irregular component in period t
ε_t = a pure random disturbance in period t



$$T_t = 1 + 0.1t$$
$$S_t = 1.6 \sin(\pi t/6)$$
$$I_t = 0.7\, I_{t-1} + \varepsilon_t$$

Second Order Properties: Series Decomposition



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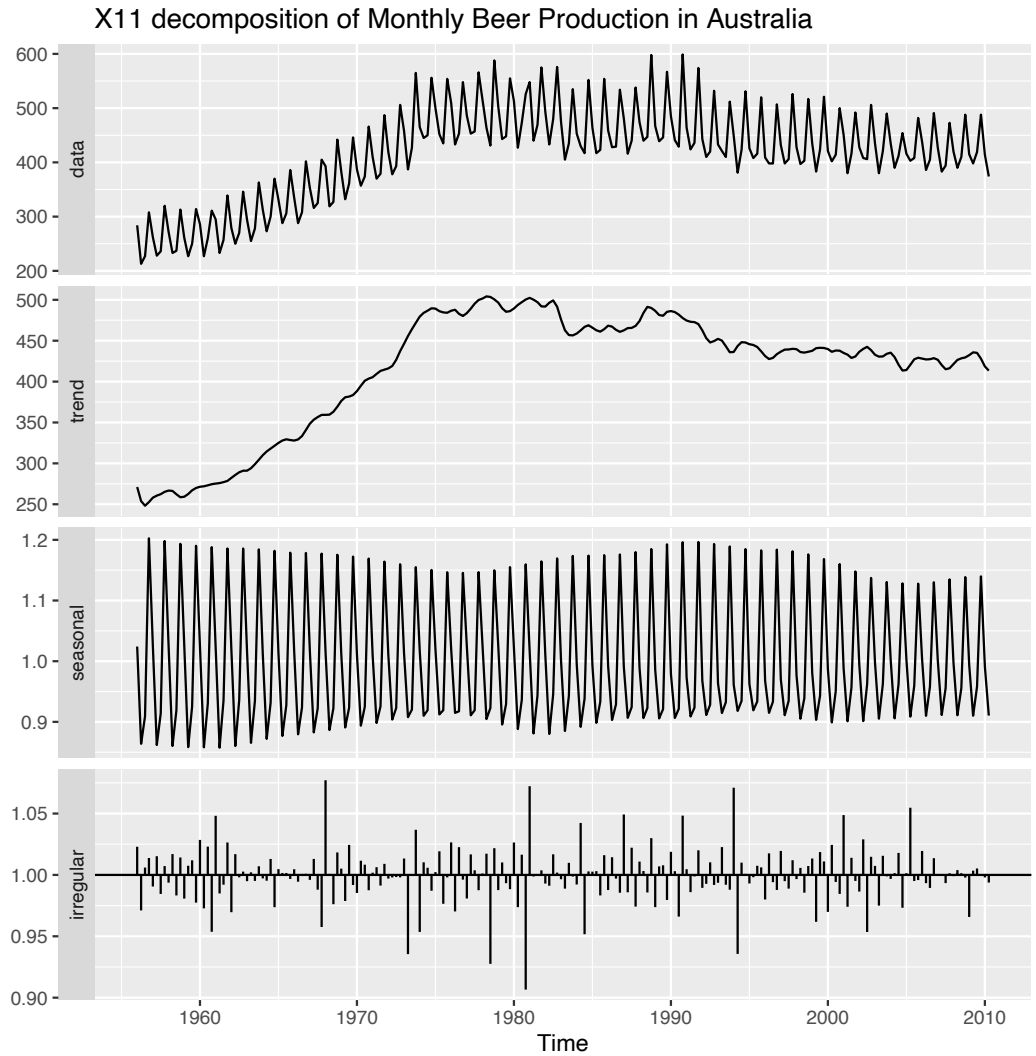


Second Order Properties: The Autocorrelation Functions

- Autocovariance Function ($\gamma(t,k)$): Autocovariance at displacement k is the covariance between y_t and y_{t-k}.

  $$\gamma(t,k) = cov(y_t, y_{t-k}) = E[(y_t - \mu)(y_{t-k} - \mu)]$$

  – Note: $\gamma(t,k) = \gamma(k), \quad t$ (if the covariance of the series is stable over time).

- Properties of the autocovariance function:
  – (i) $\gamma(k) = \gamma(-k), \quad k$ (symmetric: depends only on displacement)
  – (ii) $\gamma(0) = cov(y_t, y_t) = var(y_t)$
  – (iii) max [$|\gamma(k)|$] < $\gamma(0)$ → if $\gamma(0) < \infty \rightarrow \gamma(k) < \infty$

Second Order Properties: The Autocorrelation Functions

- Autocorrelation Function ($\rho_{Yt, Yt-k}$): ACF

Normalized autocovariance. Does not have any units, therefore it is easier to interpret.

$$\underbrace{\rho_{Y_t, Y_{t-k}}}_{\text{Correlation Coefficients}} = \frac{cov(Y_t, Y_{t-k})}{\sqrt{\sigma^2_{Y_t}\sigma^2_{Y_{t-k}}}}$$

$$\boxed{\rho_k = \frac{\gamma_k}{\gamma_0}, \; k = 0, 1, 2, \ldots}$$

ACF of a Covariance Stationary Processes

Second Order Properties: The Autocorrelation Functions

- Partial Autocorrleation Function ($p_t(k)$): PACF

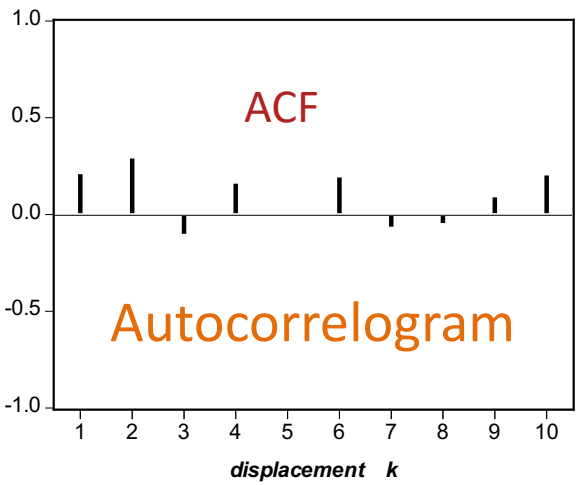
  Provides information about the autocorrelataion between $\mathrm{Y_t}$ and $\mathrm{Y_{t+k}}$ after removing all the observations in between.

- Sample Partial Autocorrelation: Given the fitted regression: $\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 y_{t-1} + \cdots + \hat{\beta}_k y_{t-k}$
  $\rightarrow \hat{p}_t(k) \equiv \hat{\beta}_k$ (sample partial autocorrelation)

	Y_t	Y_{t-1}	Y_{t-3}
1978	-1.0604		
1979	-0.6699	-1.0604	
1980	-1.1018	-0.6699	
1981	-1.2413	-1.1018	-1.0604
1982	-0.6497	-1.2413	-0.6699
1983	-0.7536	-0.6497	-1.1018
1984	-0.6826	-0.7536	-1.2413
1985	-1.3733	-0.6826	-0.6497
1986	-1.1438	-1.3733	-0.7536
1987	-1.3533	-1.1438	-0.6826
1988	-0.3196	-1.3533	-1.3733
1989	-1.4574	-0.3196	-1.1438
1990	-1.4536	-1.4574	-1.3533
1991	-2.0234	-1.4536	-0.3196
1992	-0.5904	-2.0234	-1.4574
1993	-1.4550	-0.5904	-1.4536
1994	0.0264	-1.4550	-2.0234
1995	-0.7087	0.0264	-0.5904
1996	-0.9752	-0.7087	-1.4550
1997	-0.5249	-0.9752	0.0264
1998	-0.2026	-0.5249	-0.7087
1999	-0.7057	-0.2026	-0.9752
2000	-1.2126	-0.7057	-0.5249
2001	-0.8375	-1.2126	-0.2026
2002	-0.7745	-0.8375	-0.7057
2003	-0.4141	-0.7745	-1.2126
2004	0.2950	-0.4141	-0.8375
2005	-0.2879	0.2950	-0.7745
2006	-0.0492	-0.2879	-0.4141
$\hat{\mu}$ Mean:	-0.8026		
Variance:	0.2905		
$\hat{\gamma}_k$ $(k=1,3)$		0.0651	-0.0282
$\hat{\rho}_k$ $(k=1,3)$		0.2240	-0.0970

Second Order Properties: The Autocorrelation Functions

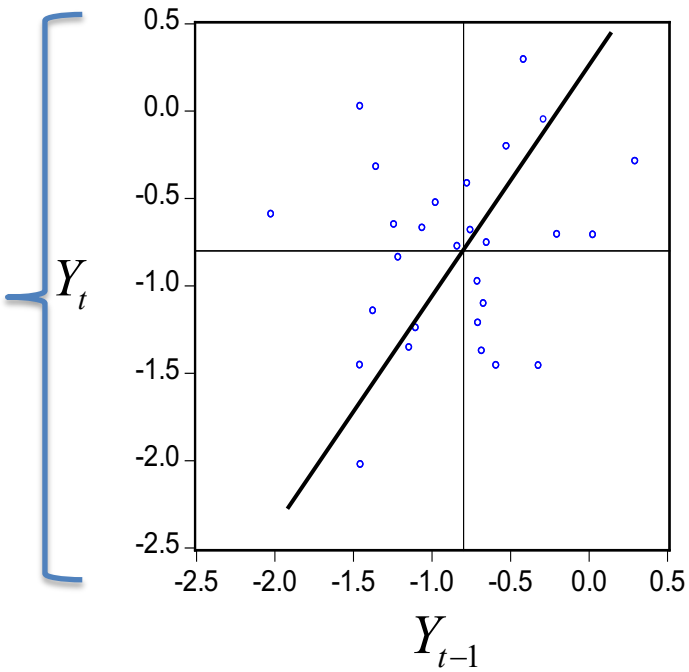
Example: Annual Hours Worked per Person Employed in Germany



Interpretation: Since the autocorrelations are small, there is little dependence on how working hours have changed over time.

Interpretation of $\hat{\rho}_1 = 0.22$:

k=1 → Observations that are 1 year apart, move in the same direction. When Germans increase their working hours, one year later we expect to see an increase.



Second Order Properties: The Autocorrelation Functions

Statistical tests for $\rho_t(k)$ and $p_t(k)$

Assume we would like to test, e.g., the null hypothesis H_0: $\rho_k = 0$ against the alternative H_1: $\rho_k \neq 0$.

If the sample is large enough, then:

$$\hat{\rho}_k \to \mathcal{N}\left(0, \frac{1}{T}\right)$$

Second Order Properties: The Autocorrelation Functions

- Box-Pierce Q-Statistic:

$$Q_{BP} = T \sum_{i=1}^{k} \hat{\rho}_i^2$$

- Ljung-Box Q-Statistic:

$$Q_{LB} = T(T+2) \sum_{i=1}^{k} \left(\frac{1}{T-i} \right) \hat{\rho}_i^2$$

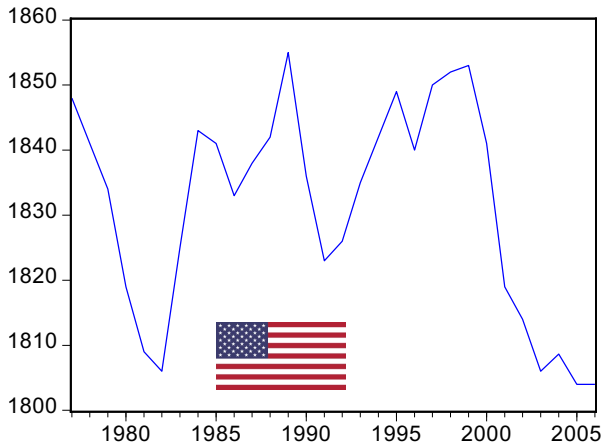
Statistical tests of whether any of a group of autocorrelations of a time series are different from zero.

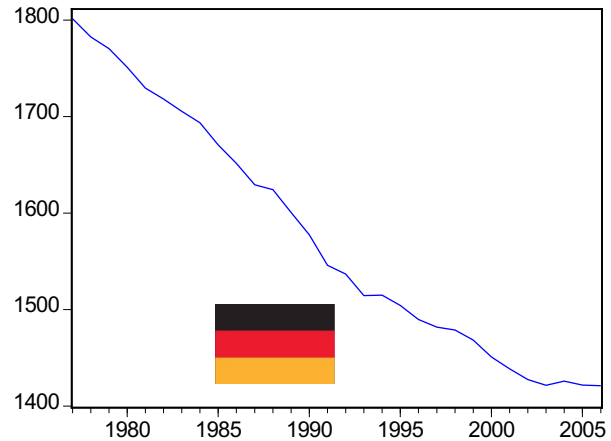
Both test are really testing the joint null hypothesis:

H_0: $\rho_1 = \rho_2 = \cdots = \rho_k = 0$

Second Order Properties: The Autocorrelation Functions

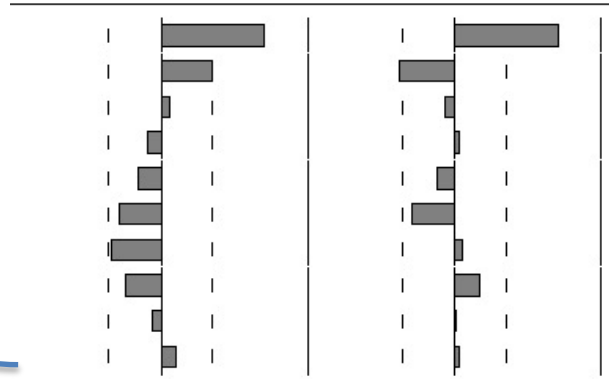
- Example: Annual Working Hours per Employee in the US vs. Germany.





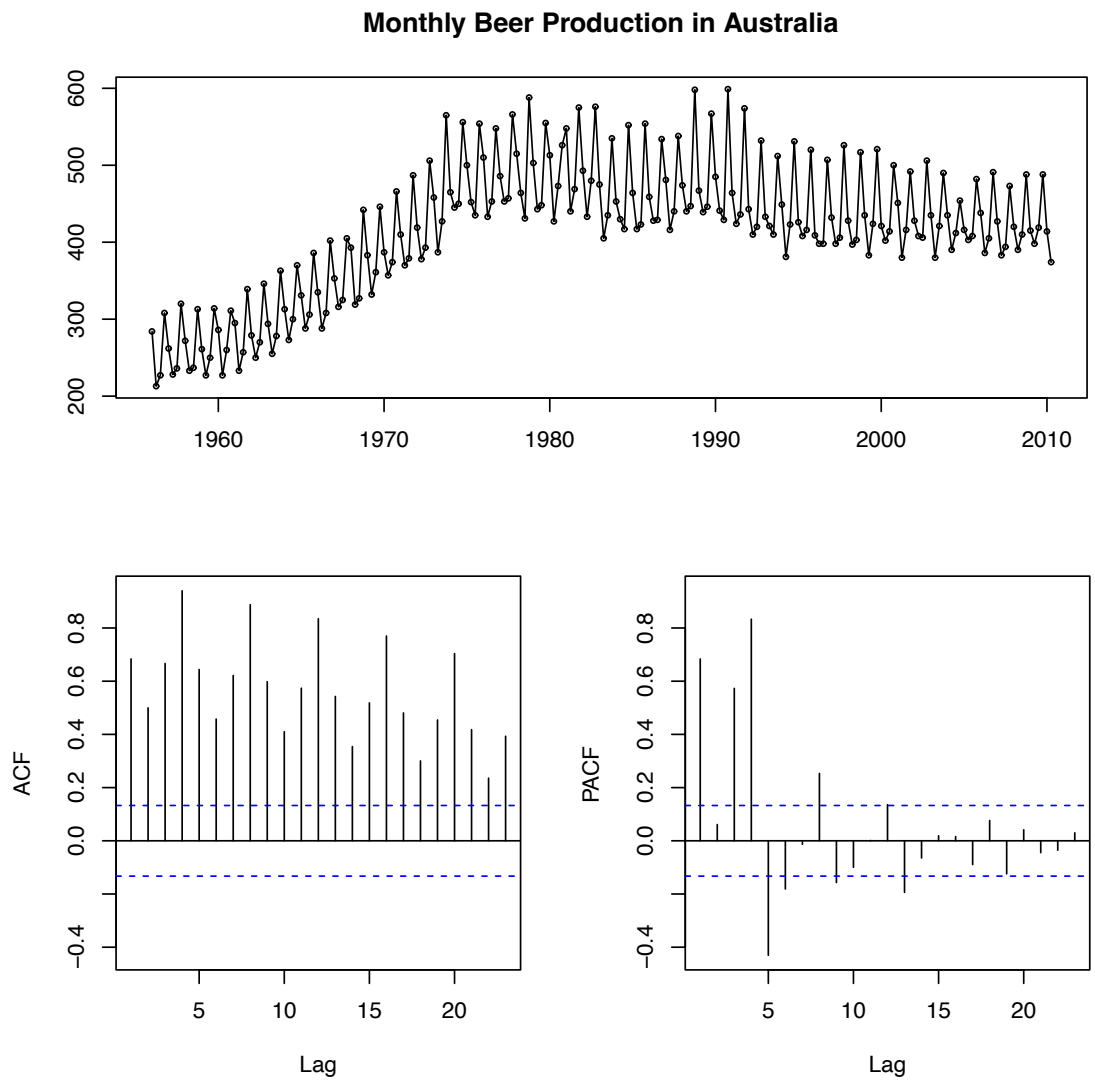
US Data: ACF & PACF

There is a statistically significant time dependence.

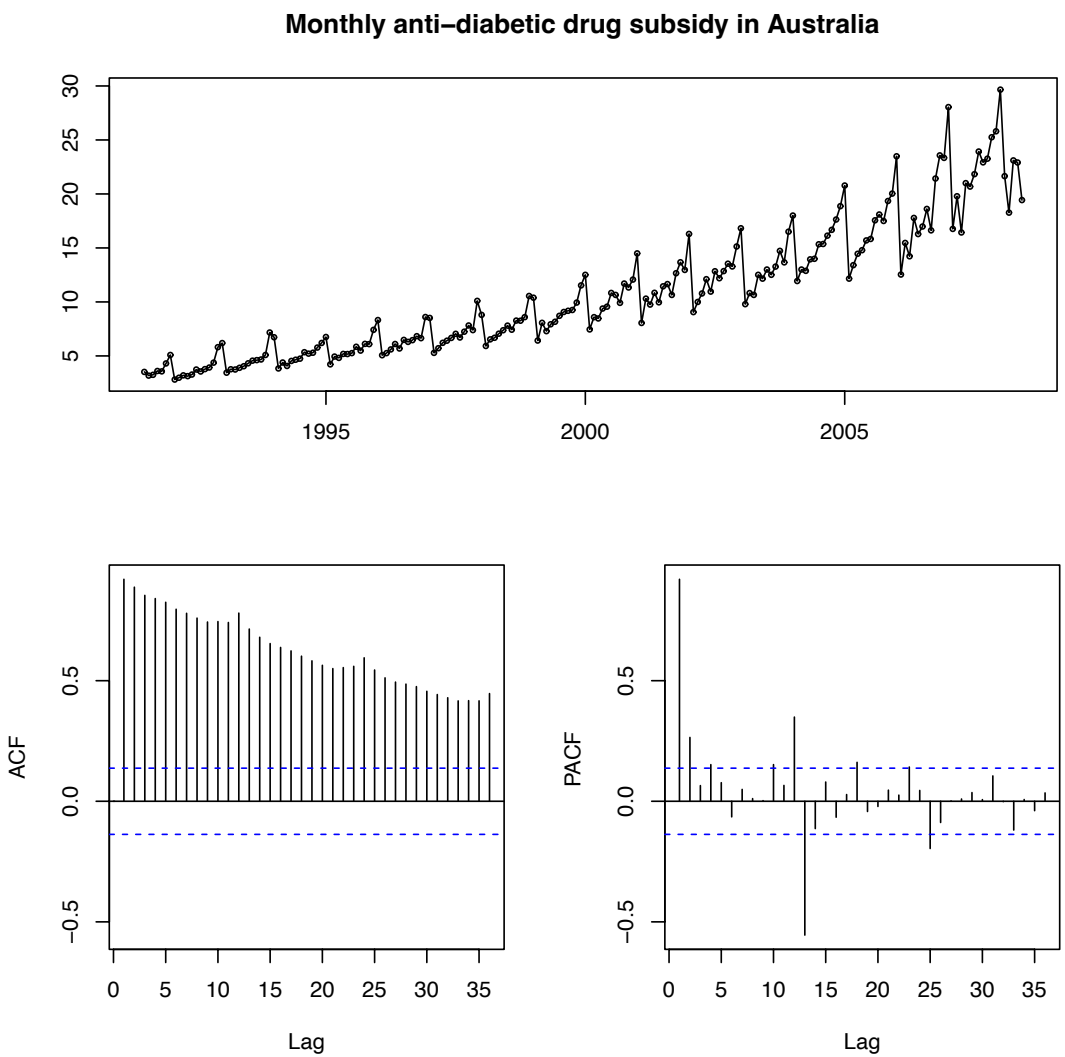


	AC	PAC	Q-Stat	Prob
1	0.737	0.737	17.987	0.000
2	0.364	-0.392	22.537	0.000
3	0.062	-0.058	22.676	0.000
4	-0.086	0.039	22.951	0.000
5	-0.162	-0.126	23.957	0.000
6	-0.288	-0.295	27.270	0.000
7	-0.352	0.052	32.432	0.000
8	-0.253	0.185	35.229	0.000
9	-0.064	0.001	35.416	0.000
10	0.114	0.034	36.035	0.000

Second Order Properties: The Autocorrelation Functions



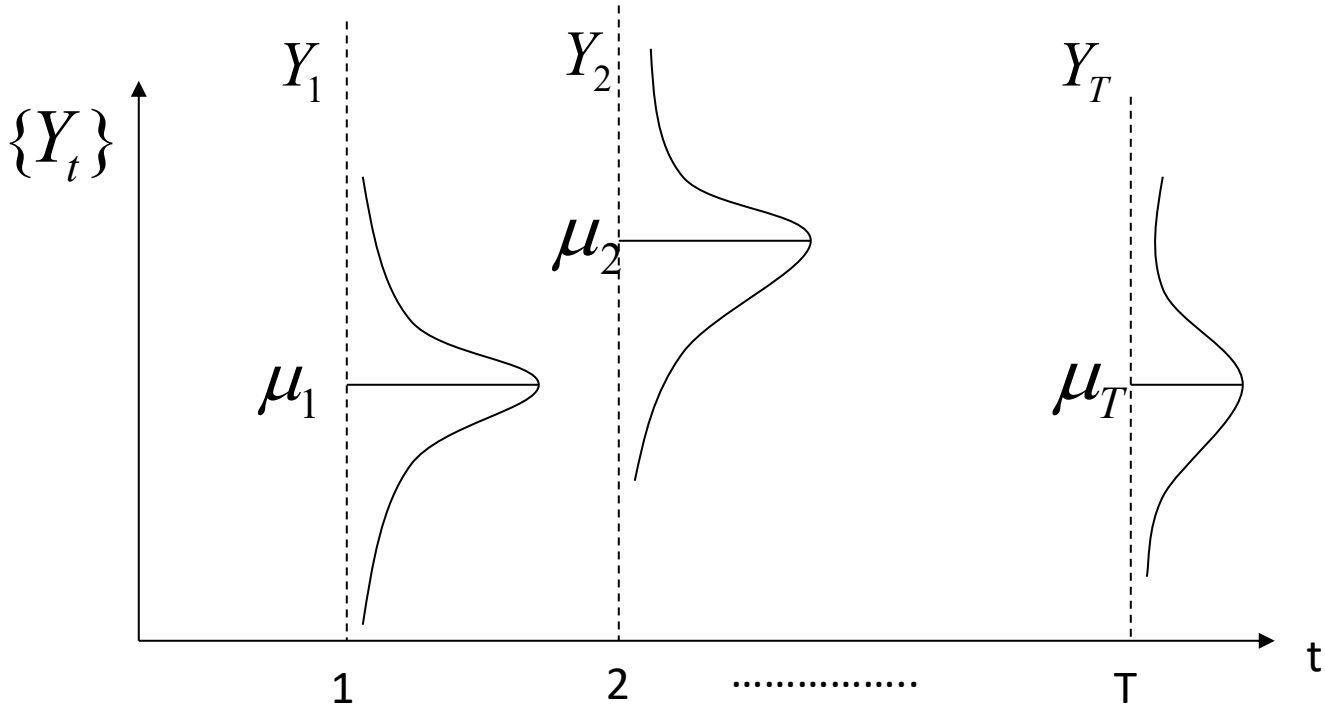
Second Order Properties: The Autocorrelation Functions



Stochastic Process and Time Series

- Def: Stochastic Process

$\{Y_t\} = \{Y_1, Y_2, \ldots Y_T\}$ = Collection of random variables.

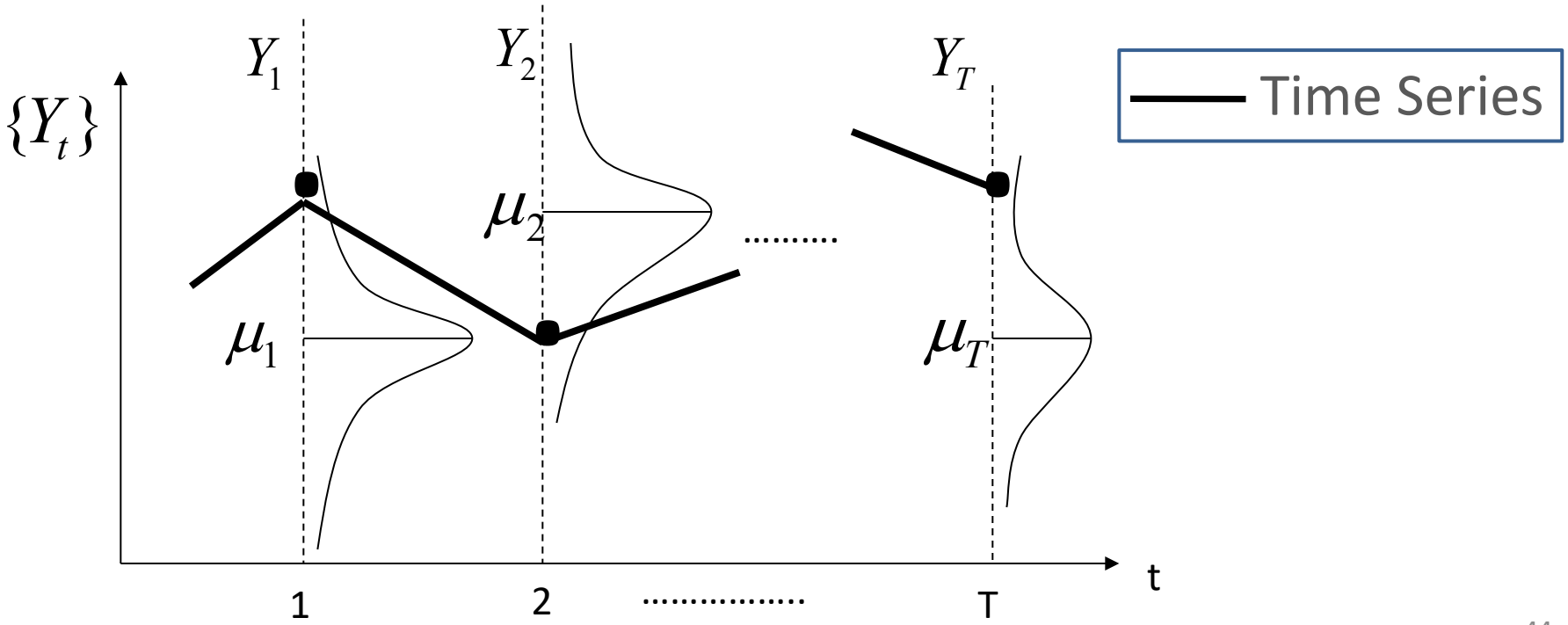


Each R.V can have a different μ, σ, and pdf.

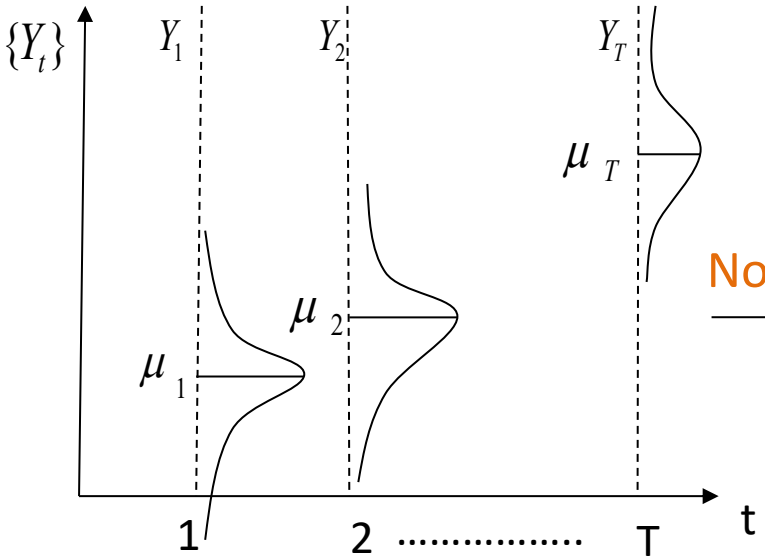
Stochastic Process and Time Series

- Def: Time Series

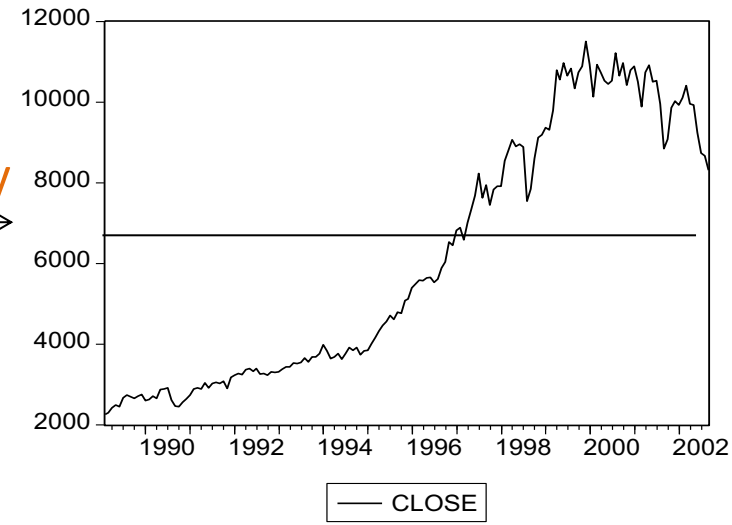
$\{y_t;\ t=1,2,\ldots\} = \{y_1, y_2, \ldots y_T\}$ = Sample realization of a stochastic process.

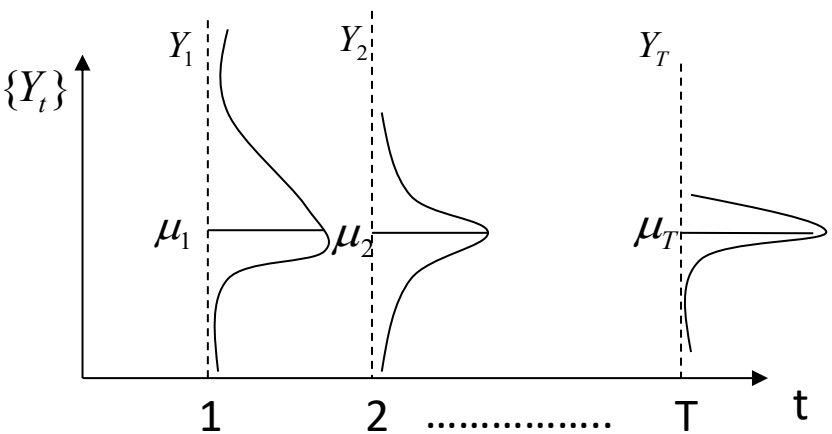


Second Order Properties: Stationarity

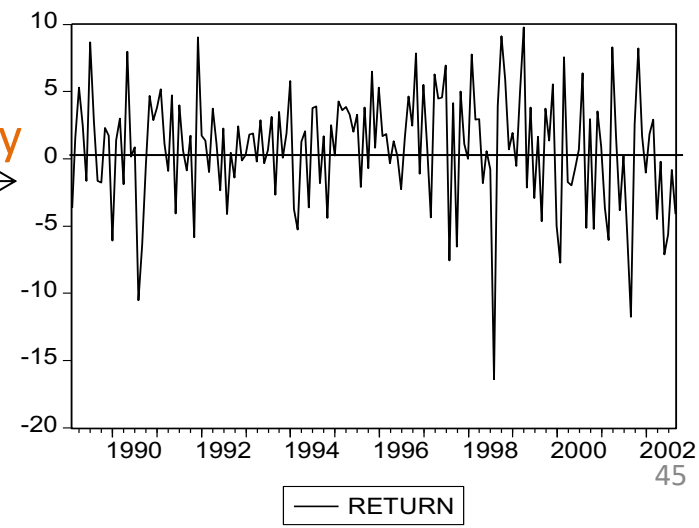


Nonstationary





Stationary

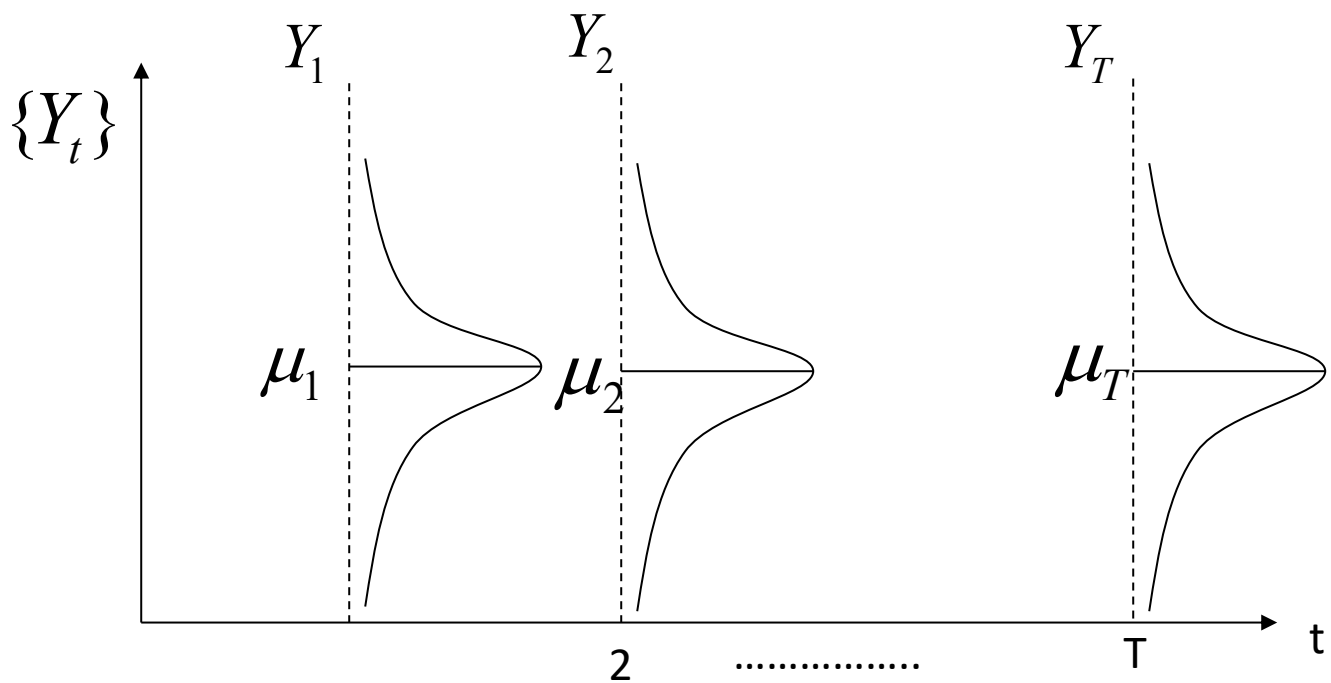


Second Order Properties: Stationarity

- Def: First Order Strongly Stationary

  = All R.Vs have the same pdf's (all moments are the same). $f_{Y_1}(y) = f_{Y_2}(y) = \cdots = f_{Y_T}(y)$

  →

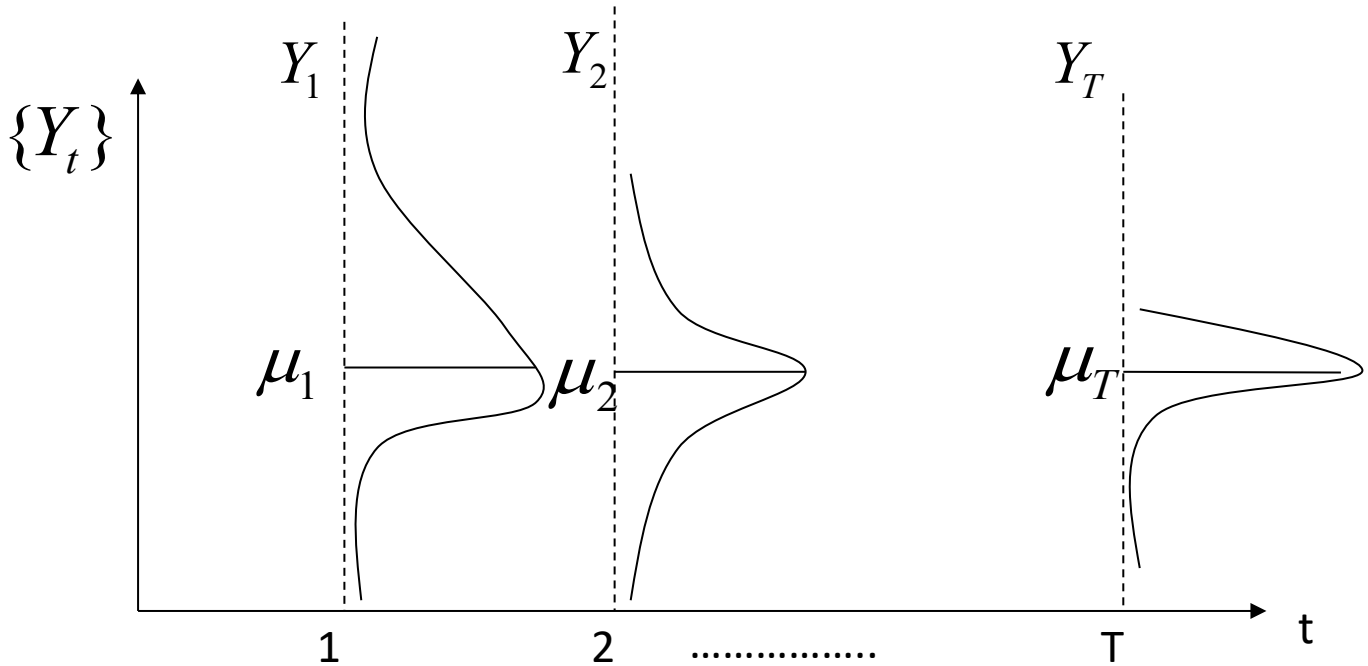


Second Order Properties: Stationarity

- Def: First Order Weakly Stationary

  = All R.Vs have the same means.

  $\rightarrow \mu_{Y_1} = \mu_{Y_2} = \cdots = \mu_{Y_T}$



Second Order Properties: Stationarity

- Def: Second Order Weakly Stationary
  = *Covariance Stationary*

  i. Means: $\mu_{Y_1} = \mu_{Y_2} = \cdots = \mu_{Y_T} = \mu$

  ii. Variances: $\sigma^2_{Y_1} = \sigma^2_{Y_2} = \cdots = \sigma^2_{Y_T} = \sigma^2$

  iii. Time Independent Covariances: $\rho_{Y_t, Y_{t-k}} = \rho_{|k|}$

The strength of the linear association between the two R.Vs only depends on how many periods (k) apart they are.

Second Order Properties: Stationarity

- "The basic idea of stationarity is that the probability laws that govern the behavior of the process do not change over time. In a sense, the process is in statistical equilibrium."
–Kung-Sik Chan

Transformations of Nonstationary Processes

- Q: Can we find a transformation of $\{y_T\}$ such that the resulting process is:
  - (1) first order weakly stationary?
  - Yes: Take the first difference of the data

  - (2) second order weakly stationary?
  - Yes: Take the log of $\{y_T\}$ and then take the first difference of this transformed series.
  - Interpretation: Economic returns or growth rates.

The Lag Operator

- Lag Operator(L): Is a linear operator L such that for any value of y_t : $Ly_t = y_{t-1}$.

- In general, for *m-periods* $L^m y_t = y_{t-m}$.

- Polynomial Lag Operator: $B(L) = b_0 + b_1 L + \ldots + b_m L^m$

- First Difference Operator (Δ): $\Delta y_t = (1-L)\, y_t = y_t - y_{t-1}$

The Lag Operator

- Distributed Lag: Consider a second-order lag operator such as ($1+0.5L + 0.8L^2$):

  $\rightarrow (1+0.5L + 0.8L^2)\, y_t = y_t + 0.5y_{t-1} + 0.8y_{t-2}$

- Infinite-Order Lag Operator:

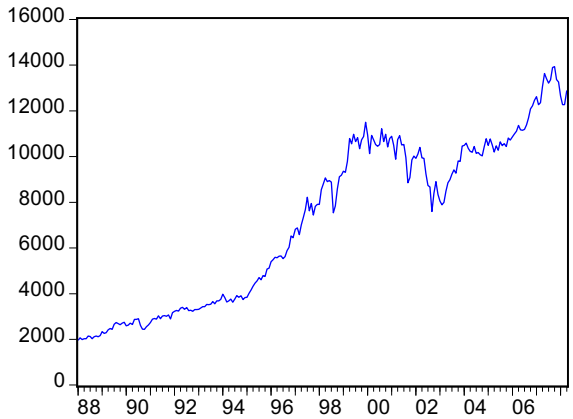
  $$B(L) = b_0 + b_1 L + b_2 L^2 + \cdots = \sum_{i=0}^{\infty} b_i L^i$$

- Example: Infinite distributed lag of current and past shocks:

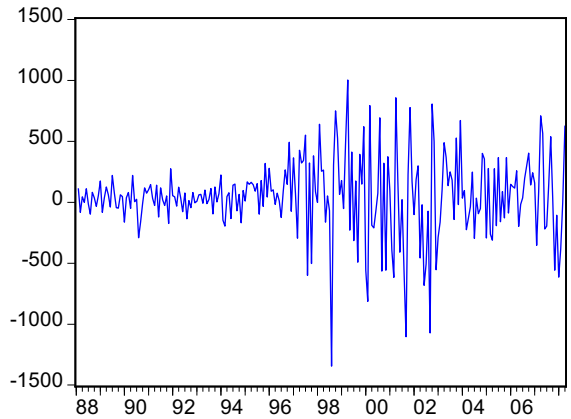
  $$\rightarrow B(L)\varepsilon_t = b_0\varepsilon_t + b_1\varepsilon_{t-1} + b_2\varepsilon_{t-2} + \cdots = \sum_{i=0}^{\infty} b_i \varepsilon_{t-i}$$

The Lag Operator

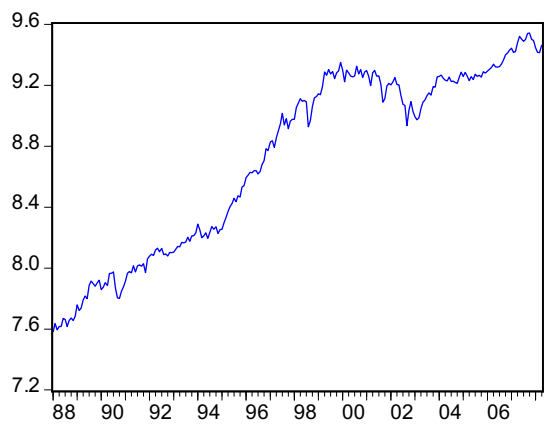
Dow Jones Index



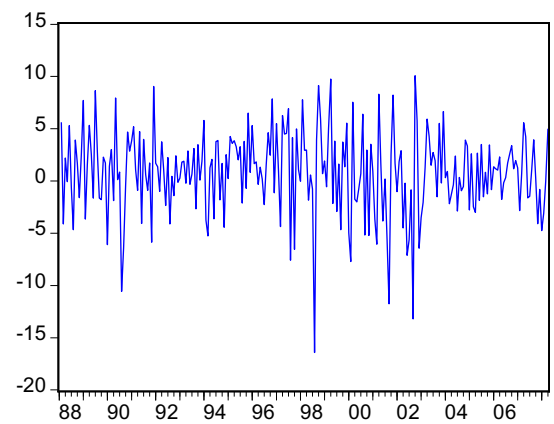
Dow Jones Index level



First difference of Index



Log Index



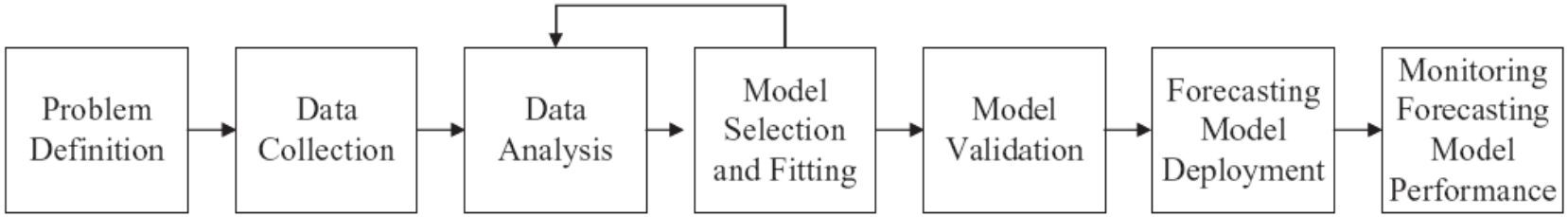
First difference of the log Index (returns)

Covariance Stationary

The Forecasting Process

A process is a series of connected activities that transform one or more inputs into one or more outputs. All work activities are performed in processes, and forecasting is no exception. The activities in the forecasting process are:

1. Problem definition
2. Data collection
3. Data analysis
4. Model selection and fitting
5. Model validation
6. Forecasting model deployment
7. Monitoring forecasting model performance



See D. Montgomery et. al., Intro. To Time Series Analysis and Forecasting, 2015

General Approach to Time Series Modeling and Forecasting (short version)

1. Evaluate the First Order properties
2. Remove the trend component –if it has one
3. Remove the seasonal component –if it has one
4. Check if the residuals are stationary, if not apply a transformation
5. Fit a model to the residuals
6. Forecast the residuals

   → invert the transformations

   → forecast the original series!

General Approach to Time Series Modeling and Forecasting

1. Plot the time series and determine its basic features, such as whether trends or seasonal behavior or both are present. 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.
2. 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.
3. 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.
4. Validate the performance of the model (or models) from the previous step. This will probably involve some type of split-sample or cross-validation procedure. The objective of this step is to select a model to use in forecasting. We will discuss this more in the next section and illustrate these techniques throughout the book.

See D. Montgomery et. al., Intro. To Time Series Analysis and Forecasting, 2015

General Approach to Time Series Modeling and Forecasting

5. Also of interest are the differences between the original time series y_t 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 y_t, reverse the transformations and any differencing adjustments made to remove trends or seasonal effects.
6. For forecasts of future values in period $T + \tau$ on the original scale, if a transformation was used, say, $x_t = \ln y_t$, then the forecast made at the end of period T for $T + \tau$ would be obtained by reversing the transformation. For the natural log this would be

$$\hat{y}_{T+\tau}(T) = \exp[\hat{x}_{T+\tau}(T)]$$

7. If prediction intervals are desired for the forecast (and we recommend doing this), construct prediction intervals for the residuals and then reverse the transformations made to produce the residuals as described earlier. We will discuss methods for finding prediction intervals for most of the forecasting methods presented in this book.
8. Develop and implement a procedure for monitoring the forecast to ensure that deterioration in performance will be detected reasonably quickly. Forecast monitoring is usually done by evaluating the stream of forecast errors that are experienced. We will present methods for monitoring forecast errors with the objective of detecting changes in performance of the forecasting model.