

# Time Series Analysis & Forecasting

## Class 1

Arnab Bose, Ph.D.

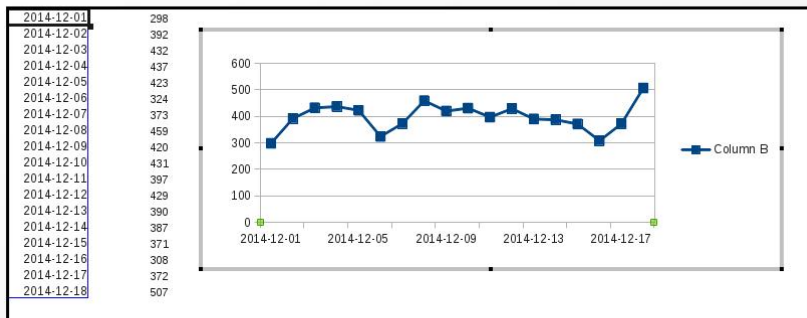
MSc Analytics

University of Chicago

# Time Series (TS)

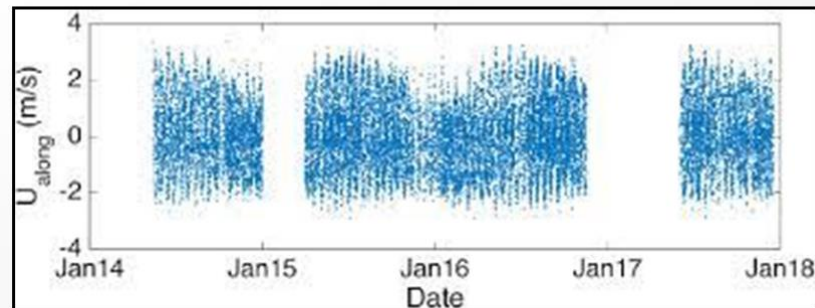
- Data is measured at different time points –

a. Uniform TS – uniform time intervals



<https://stats.stackexchange.com/questions/129339/how-to-calculate-probabilities-based-on-cumulative-of-time-series>

b. Non-uniform TS – non-uniform time intervals (uneven spacing)



[https://www.researchgate.net/figure/Example-of-a-non-uniform-time-series-of-along-channel-velocity-from-ferry-based\\_fig4\\_333984372](https://www.researchgate.net/figure/Example-of-a-non-uniform-time-series-of-along-channel-velocity-from-ferry-based_fig4_333984372)

- Data is represented as  $\{y_t\} = \{y_1, y_2, y_3, \dots, y_t\}$
- Primary objective of TS analysis is to develop mathematical models that provide plausible description of the data
- Data collection -> separate field of study that outlines the challenges in data collection

# Random Variable (RV)

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A variable whose values are defined by a probability distribution. The distribution specifies the probability that the value of the variable is within any given interval.

RV can be

discrete – taking finite or countable list of values

continuous – taking any numerical value

If 2 RVs are independent then they are uncorrelated.

If 2 RVs have joint Gaussian distribution and are uncorrelated, then they are independent.

# Random Variable (RV)

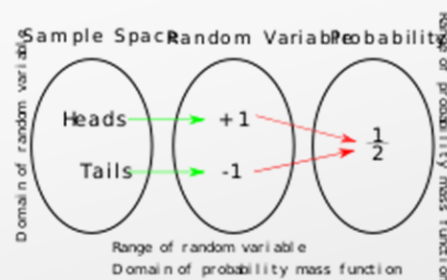
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[https://en.wikipedia.org/wiki/Random\\_variable](https://en.wikipedia.org/wiki/Random_variable)

If 2 RVs

1. are independent then they are uncorrelated
2. have joint Gaussian distribution and are uncorrelated, then they are independent

# White Noise

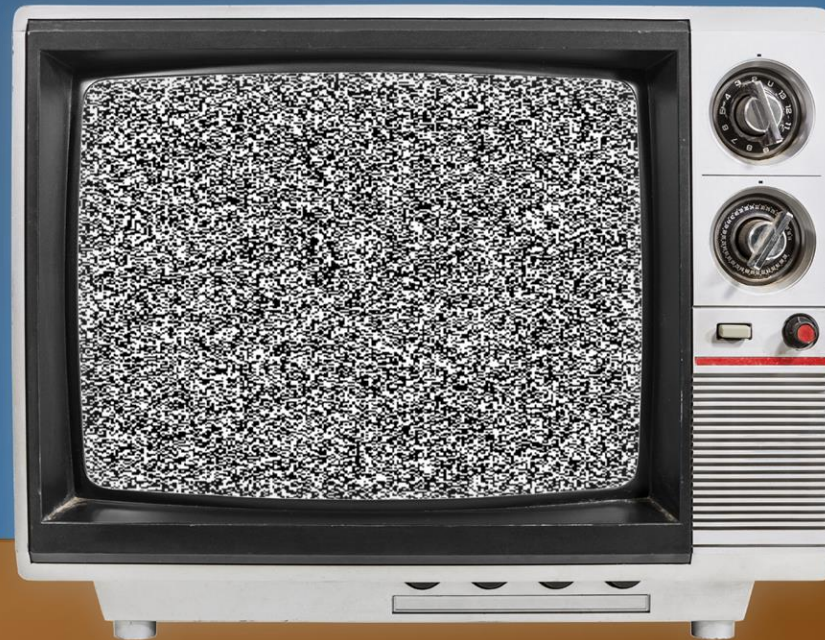
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1. Collection of uncorrelated random variables  $w_t$  that are uncorrelated with mean 0 and variance  $\sigma_w^2$
2. White – analogy with white light where all possible frequencies are present with equal strength
3. Gaussian white noise is independent and identically distributed (iid)

# White Noise – Practical Example

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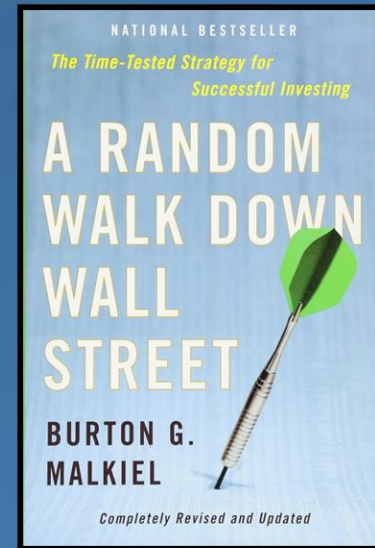
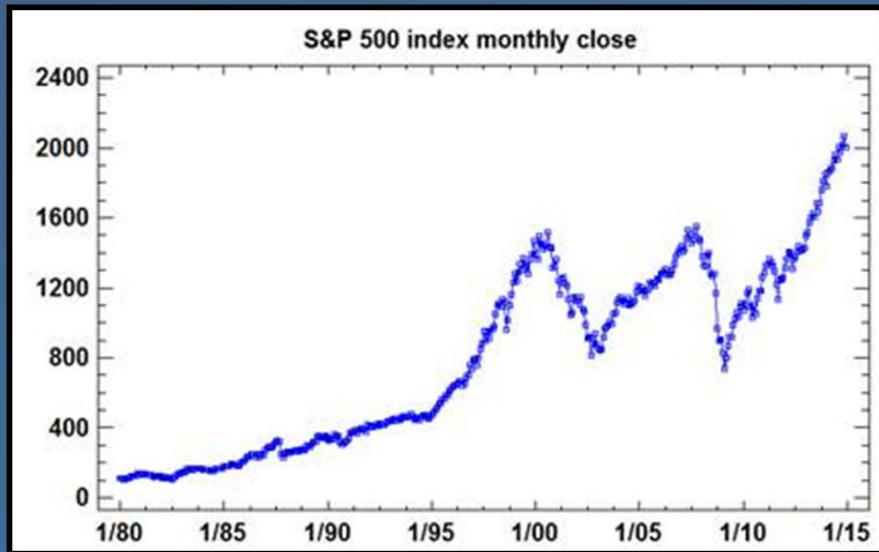


# Random Walk



1. Mathematically represented as  $y_t = y_{t-1} + w_t$
2. Current value  $y_t$  is previous value  $y_{t-1}$  plus completely random white noise  $w_t$

# Random Walk – Practical Example





# TS Characteristics – Autocovariance and Autocorrelation

1. **Autocovariance** – measures the linear dependency between two points in the same TS observed at different times.  
Represented with 2 notations (note that the important concept of time lag or the time difference between the 2 TS)

$$\gamma_{s,t} = Cov(y_s, y_t)$$

$$\gamma_k = Cov(y_s, y_{s-k})$$

2. **Autocorrelation** – normalized autocovariance given by

$$\rho_{s,t} = \frac{Cov(y_s, y_t)}{\sqrt{Cov(y_s, y_s) * Cov(y_t, y_t)}} = \frac{Cov(y_s, y_t)}{\sqrt{Var(y_s) * Var(y_t)}}$$

# Stationarity – Strict

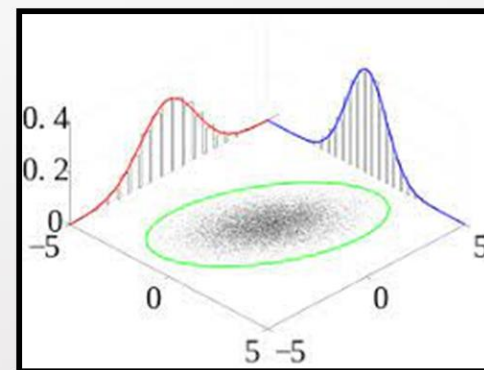
TS is said to be stationary – the process is in statistical equilibrium.

Basic idea is that the laws of probability that govern the process behavior do not change over time.

## STRICT stationarity

1. When the probability behavior of every collection of TS data points  $\{x_{t1}, x_{t2}, x_{t3}, \dots, x_{tk}\}$  is identical to that of time shifted data points  $\{x_{t1+h}, x_{t2+h}, x_{t3+h}, \dots, x_{tk+h}\}$  for all  $h$ .
2. Another definition – the joint probability distribution is constant over time.

[https://en.wikipedia.org/wiki/Joint\\_probability\\_distribution](https://en.wikipedia.org/wiki/Joint_probability_distribution)



# Stationarity – Weak

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WEAK stationarity aka Wide Sense Stationary (WSS) or Covariance Stationary

TS  $\{y_t\}$  has a finite variance process such that

1. Mean is constant and does not depend on time
2. Auto covariance function  $\gamma_{s,t}$  depends on  $s, t$  only through their difference  $|t-s|$

NOTE:

1. IF TS is Gaussian joint distribution (meaning the the RVs are Gaussian) then Weak same as Strict stationary
2. Finite 2<sup>nd</sup> moments are not assumed for strict => strict does not imply weak

# Non-Stationarity

## Trend

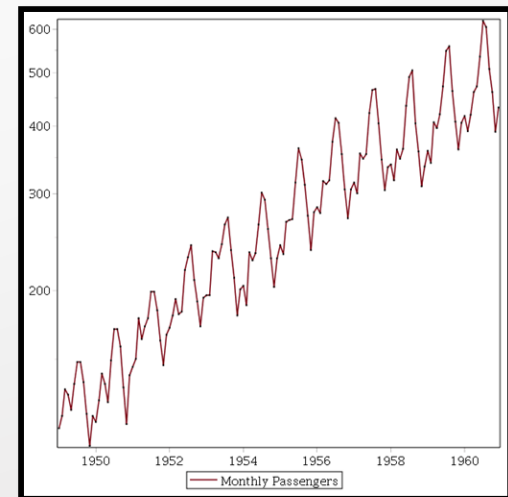
Time Series with trend is non-stationary but can be made stationary by removing the trend → Trend Stationarity

## Seasonality

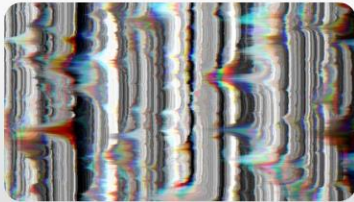
Time Series with seasonality (repeating cycles) is non-stationary.

Examples of seasonality

- = hourly (repeating pattern every 24 hours)
- = weekly
- = monthly
- = quarterly
- = half-yearly
- = yearly



# White Noise Stationarity – first and second order moments



1. Mean =  $\mu = 0$

2. Auto covariance  $\gamma_{s,t} = \begin{cases} \sigma_w^2, & s = t \\ 0, & s \neq t \end{cases}$

3. So white noise is weak stationary since the auto-covariance is dependent on  $s - t$

# Random Walk Stationarity – first order moment



Process

$$\begin{aligned}y_t &= y_{t-1} + w_t \\&= y_{t-2} + w_{t-1} + w_t \\&\vdots \\&= y_0 + w_t + w_{t-1} + w_{t-2} + \cdots + w_1\end{aligned}$$

Assume  $y_0 = 0$

Mean  $\mu = E[y_t] = E[y_0 + \sum_{s=1}^t w_s] = E[y_0] + \sum_{s=1}^t E[w_s] = 0$   
which is time-invariant

# Random Walk Stationarity – second order moment

## Autocovariance

$$\gamma_{t,s} = E[y_t, y_s]$$

$$= E \left[ \sum_{k=1}^t w_k \sum_{m=1}^s w_m \right] = E \left[ \sum_{k=1}^{\min(t,s)} w_k^2 + \sum_{m=1}^t \sum_{n=1, n \neq m}^s w_m w_n \right]$$

$$= E \left[ \sum_{k=1}^{\min(t,s)} w_k^2 \right] = \sum_{\min(t,s)} w^2$$

Assume  $t \leq s$

$$= t\sigma^2$$

NOTE: autocovariance depends on the particular  $t, s$  and not on the distance between two time points  $\Rightarrow$  non-stationary.

## Autocorrelation

$$\rho_{t,s} = \frac{\gamma_{t,s}}{\sqrt{\gamma_{t,t}\gamma_{s,s}}} =$$

$$\frac{t\sigma^2}{\sqrt{t\sigma^2 s\sigma^2}} = \sqrt{\frac{t}{s}}, t \leq s$$

# Stationarity $\leftrightarrow$ Independent and Identically Distributed (iid)

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## **iid $\Rightarrow$ strict stationarity**

Since the joint distribution is the product of common marginal distribution that does not depend on time.

## **Strict stationarity $\nRightarrow$ iid**

Strict stationarity implies RVs are identically distributed but nothing about independence.

Eg. TS  $\{X, X, X, \dots\}$



# Strict Stationarity $\leftrightarrow$ Weak Stationarity

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## **Strict stationarity $\Rightarrow$ weak stationarity**

IFF mean and all the covariance exist and are finite.

Eg, iid Cauchy process is strictly stationary but not weakly since it has not finite 2<sup>nd</sup> order moment.

In other words, a strict stationary process with finite 2<sup>nd</sup> order moment is weak stationary\*.

## **Strict stationarity $\Rightarrow$ weak stationarity**

For example, a white noise is weak stationary and also strict stationary if it is a Gaussian white noise.

NOTE: general white noise only implies uncorrelation while Gaussian white noise also implies independence. Because if a process is Gaussian, uncorrelation implies independence. Therefore, a Gaussian white noise is just iid  $N(0, \sigma^2)$ .

\* <https://stats.stackexchange.com/questions/159899/strictly-stationary-time-series-with-infinite-moments>

# Exploratory Data Analysis

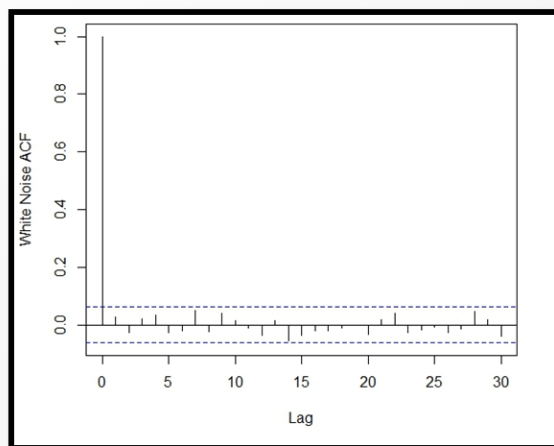
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1. Idea is to understand Time Series datasets, both univariate and multivariate using
  - a. Qualitative – analyze plots
  - b. Quantitative – use tests and numbers
2. Univariate – test for stationarity for example with a unit root test such as Augmented Dickey Fuller (ADF)
3. Augmented in ADF – no assumption about the error term  $u_t$  being uncorrelated
4. To transform a non-stationary TS to stationary TS, iteratively take the difference of the non-stationary TS and verify if the differenced TS is stationary
5. If TS has a unit root, then the first difference is stationary

# Stationarity Tests – Qualitative

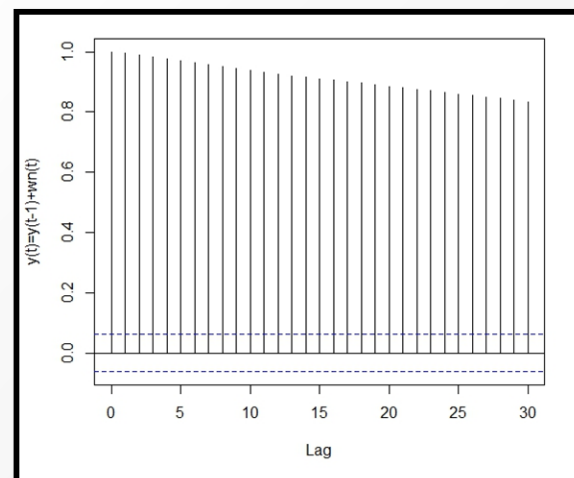
## 1. Stationary

Dying down quickly



## 2. Non-stationary

Dying down extremely slowly



# Stationarity Tests – Quantitative

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## 1. Augmented Dickey-Fuller (ADF) Test

The option alternative in `adf.test()` takes the value 'stationary' or 'explosive'. The value 'explosive' is used to test if the series is stationary about a linear time trend. This means that a constant and trend are to be included in the DF or ADF test regression.

R code

`adf.test()` – check the p-value

## 2. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test will often select fewer differences than the ADF test or a PP test. A KPSS test has a null hypothesis of stationarity, whereas the ADF and PP (Phillips-Perron) tests assume that the data have  $I(1)$  non-stationarity.

R code

`kpss.test()`

$H_0$  – TS is stationary (level – default or trend)

# Statistical Significance of $p$ -Value

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1. P-values indicate how incompatible the data are with a specified statistical model
2. P-values do not measure the probability that the studied hypothesis is true
3. Scientific conclusions and business or policy decisions should not be based on specific threshold
4. Proper inference requires full reporting and transparency
5. P-values do not measure the size or importance of an effect
6. P-value by itself does not provide a good measure of evidence regarding a model or hypothesis

<https://amstat.tandfonline.com/doi/pdf/10.1080/00031305.2016.1154108?needAccess=true>

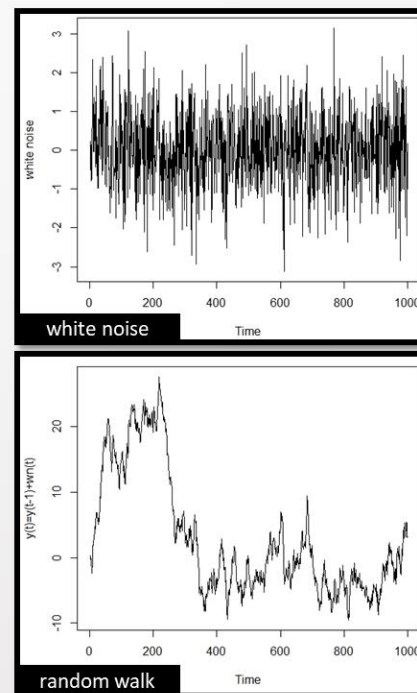
# R code – white noise + random walk

```
wn <- rnorm(500, 0, 1) # White Noise
rw <- cumsum(wn) # Random Walk

plot.ts(wn, main="white noise")
plot.ts(rw, main="random walk")

acf(wn)
acf(rw)

library("tseries")
adf.test(wn)
adf.test(rw)
```



## R code – TS with $\rho = -1$

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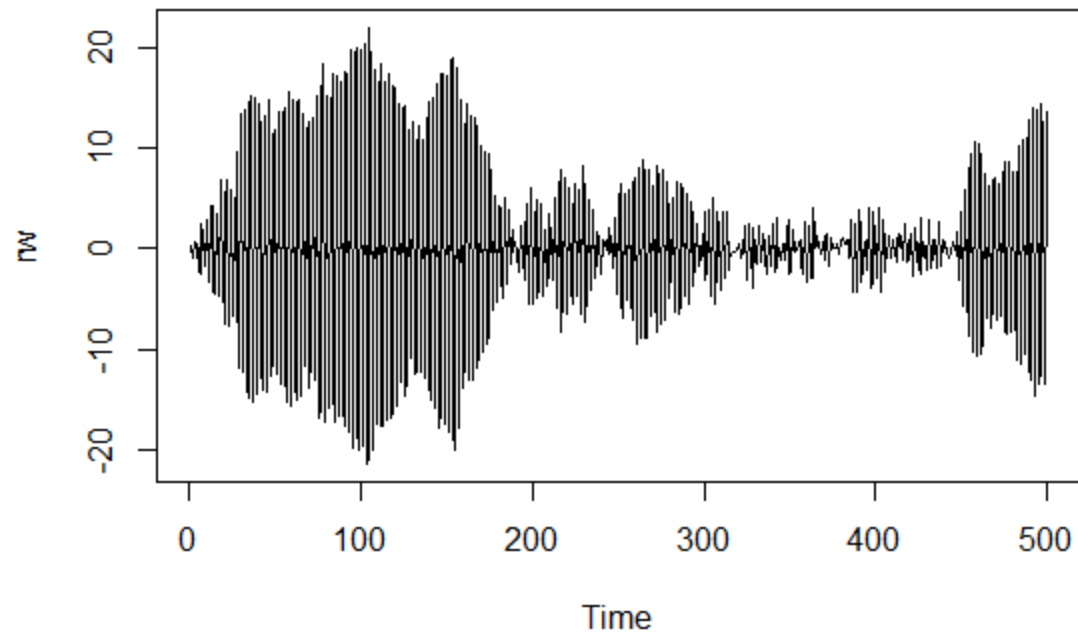
```
rw <- c(0)
wn <- rnorm(500, 0, 1)
rw[1] <- wn[1]

for (i in 2:length(wn))
  rw[i] <- -1 * rw[i-1] + wn[i]

ts.plot(rw)
adf.test(rw)
kpss.test(rw)
```

# Random walk with $\rho = -1$

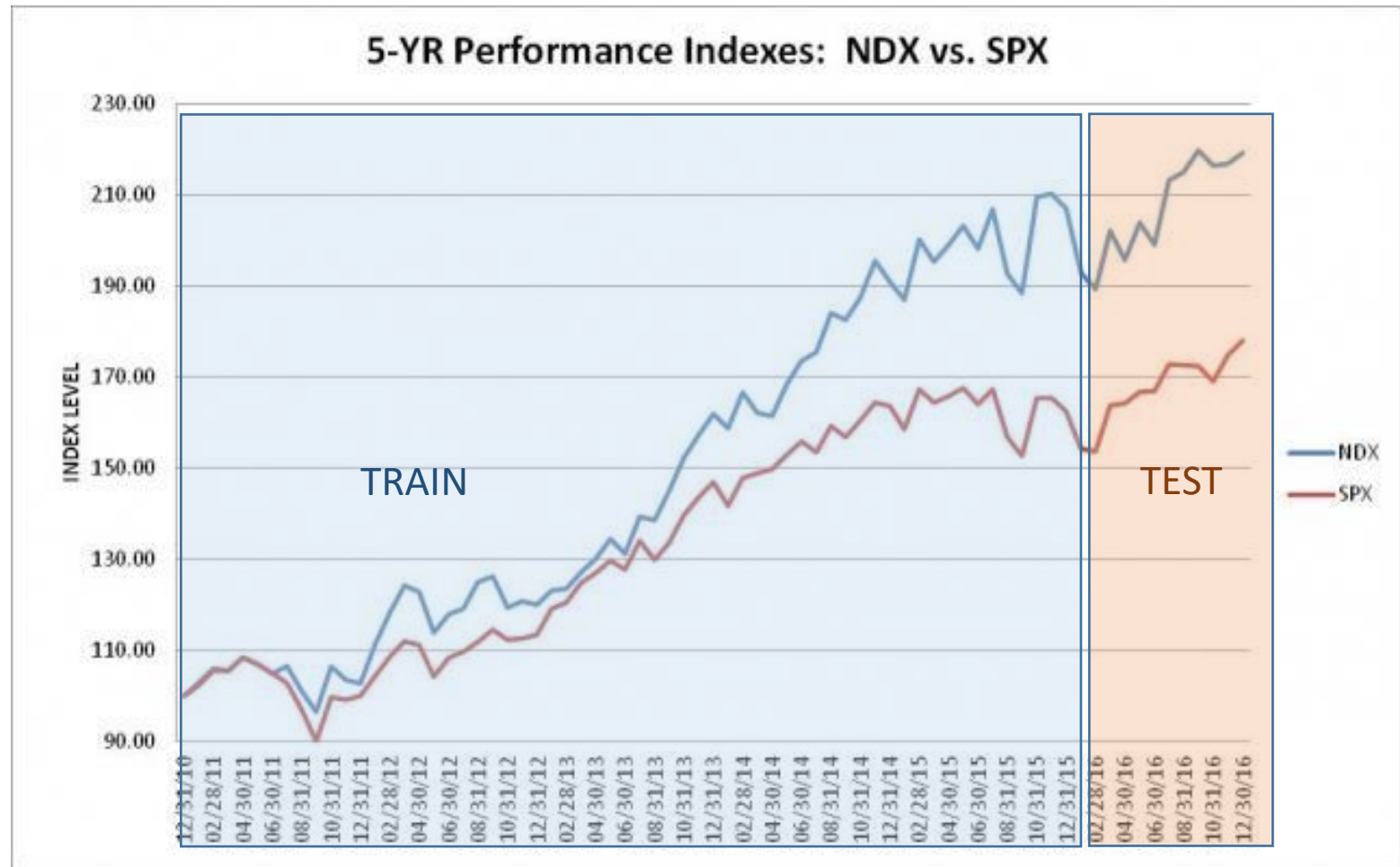
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# Time Travel – What ?!?

Go “back in time” to evaluate a TS Model



# Exponential Smoothing

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- A method to smooth time series using weight  $0 \leq \alpha \leq 1$  where the recent observations are weighted more than the less recent ones.
- Mathematically represent smooth TS as level

$$l_t = \alpha x_t + (1 - \alpha) l_{t-1}$$

- Forecast

$$\hat{y}_{t+\tau}(t) = l_t$$

# Textbook Chapters

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Materials covered available in book chapters:

FPP: 1, 2, 4, 6, 8

PTS: 1 – 5

# Thank You

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