

Time Series Fundamentals

The Logic of Time Series Analysis

Step 1: Nature of Time Series

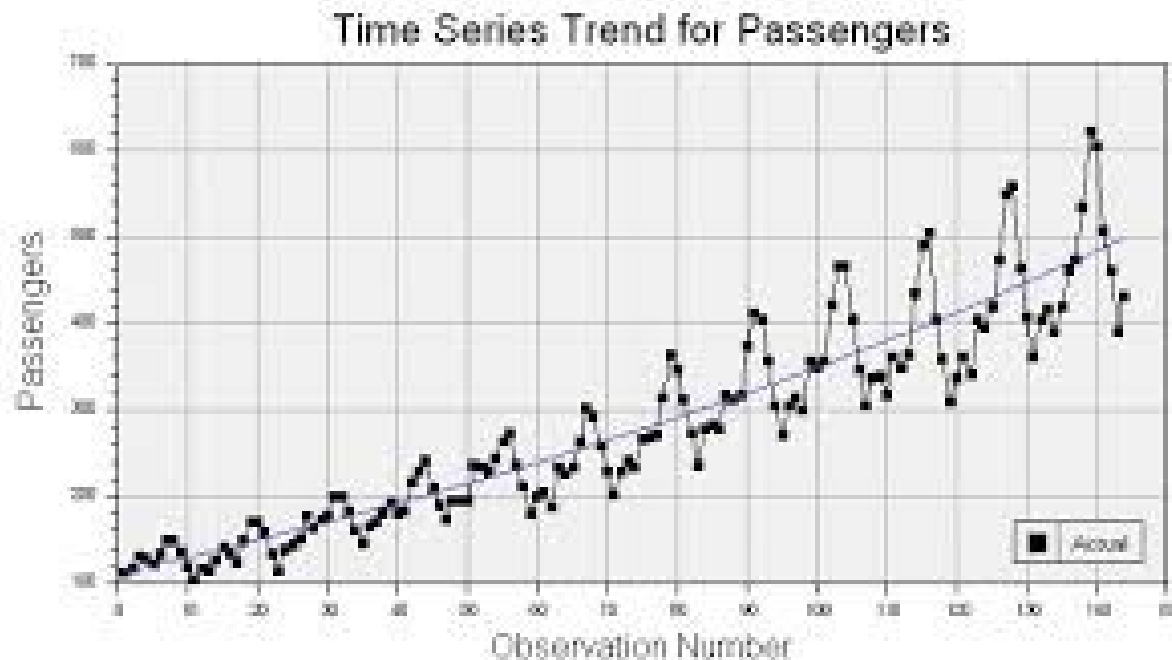
1. We've been working with cross-sectional data – that is data that has been collected all at the same time
2. This data is collected at one point in time and oftentimes comes from a survey and looks at a relationship between variable A and variable B **frozen at one period in time...**
3. But in the “real world” things are changing with time
 1. Some things are one time “shock” things that have effects – **this is where we are going to start**

Step 1: Nature of Time Series

1. But there is a whole world of business data out there that changes in relationship to time
 1. Monthly sales data
 2. Daily stock prices
 3. Exchange rates
 4. Price of commodities, goods and services
 5. Any sort of data that is collected over time and has some sort of time-related

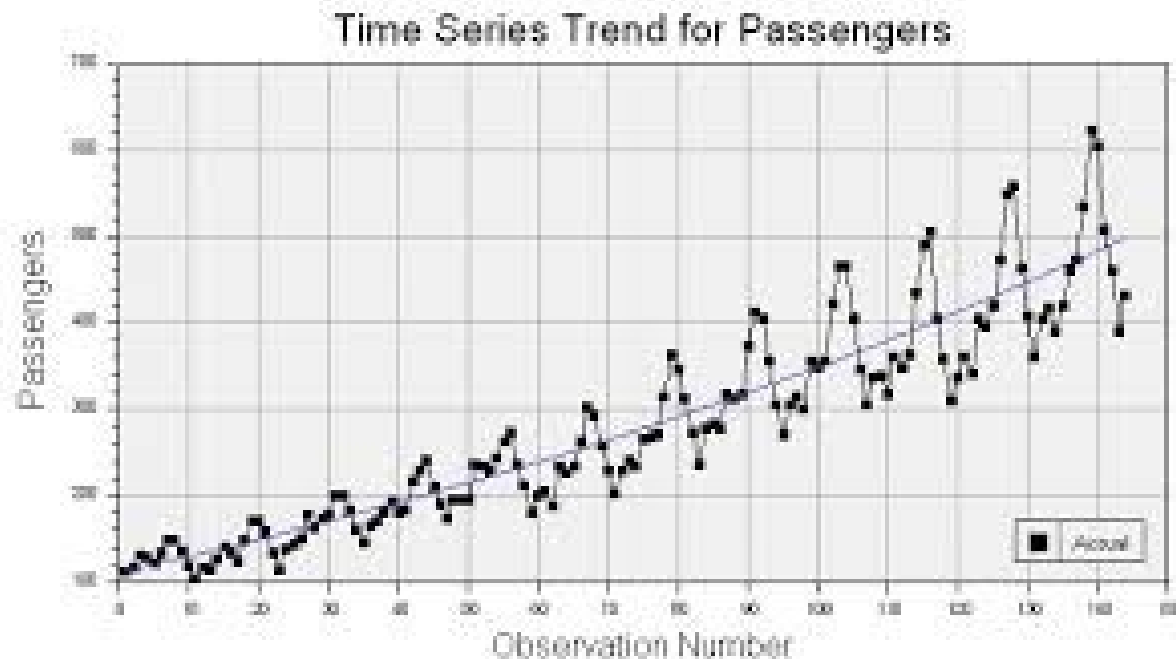
Step 1: Nature of Time Series

1. Why chase time series? Let's see why it might be a good idea...
2. Here is some time series data – we can capture the linear trend component with a regression model



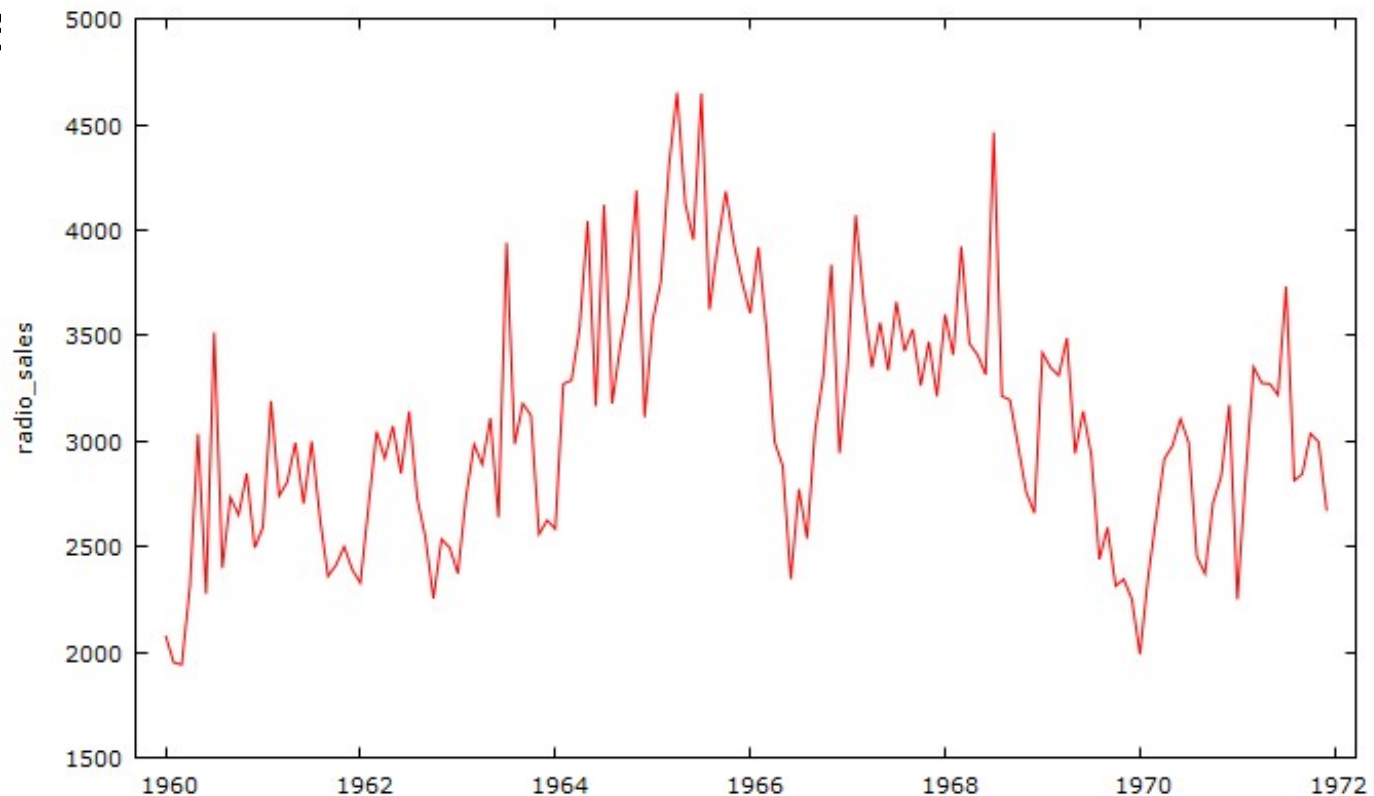
Step 1: Nature of Time Series

1. You can also see seasonality in this data as the data goes up and then down and then up again, then down again, etc.
2. Although we haven't covered it, there are ways to model



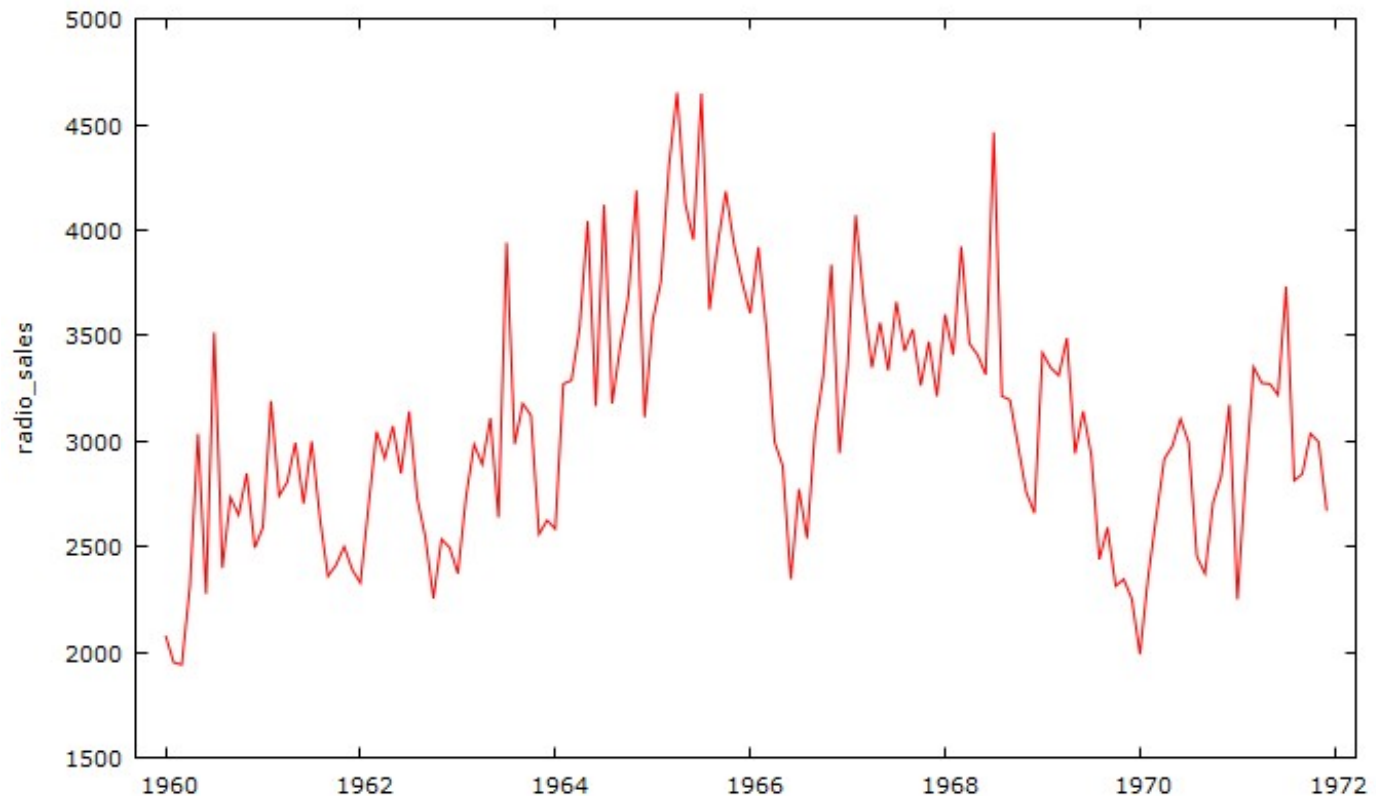
Step 1: Nature of Time Series

1. Look at how the data whipsaws around here – would we want to try to model that? Well, it certainly affects radio sales so we should be interested



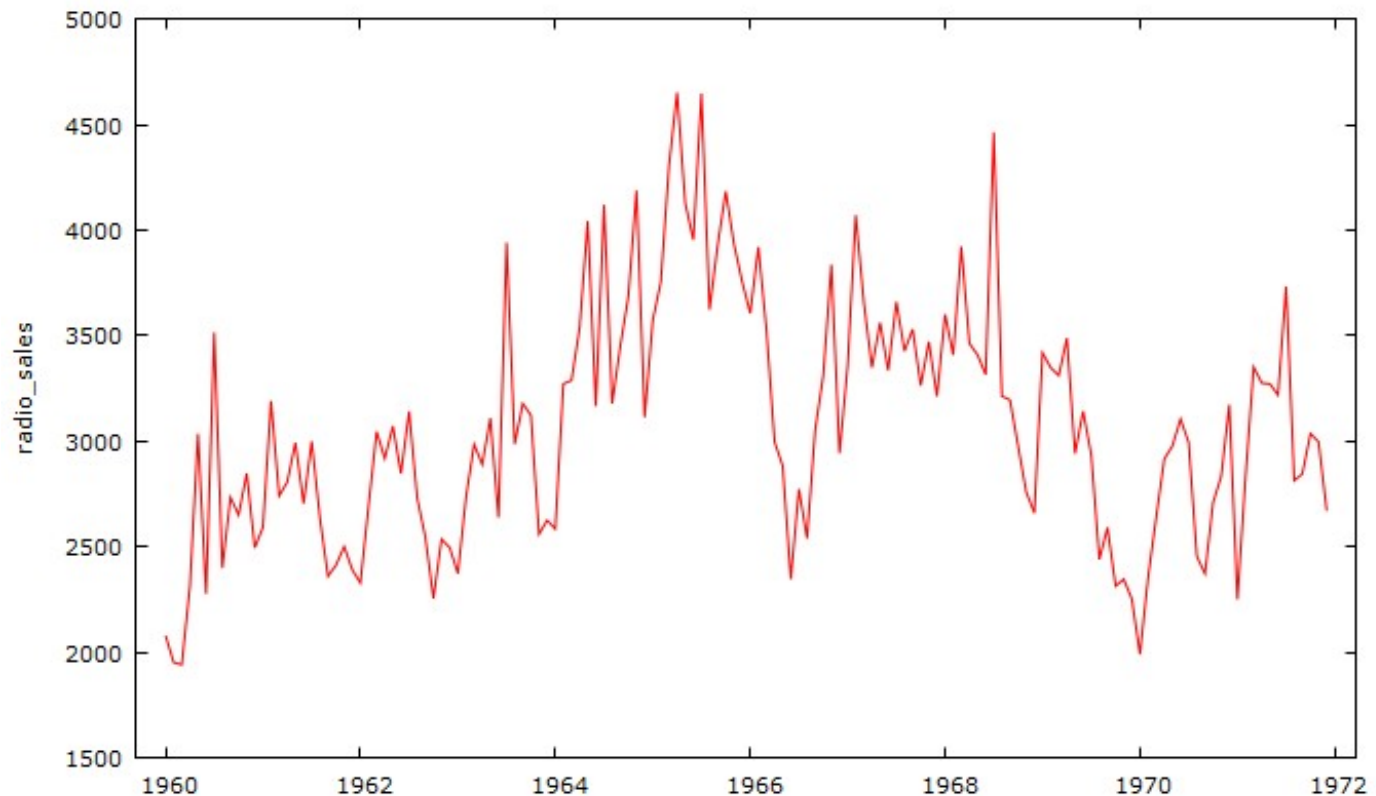
Step 1: Nature of Time Series

1. Maybe not hopeless – if it were truly random we probably would see it bounce up and down randomly



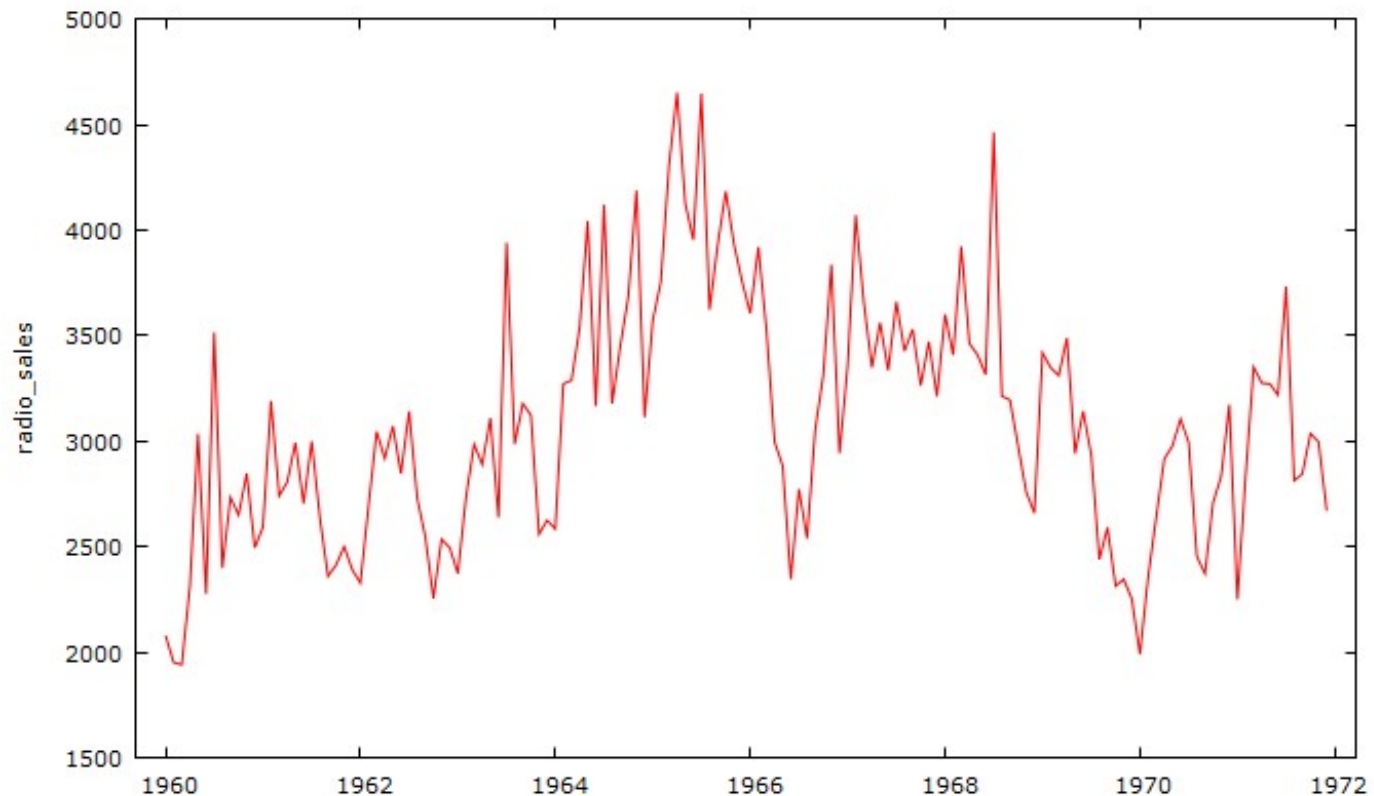
Step 1: Nature of Time Series

1. So there is some pattern to this, but we don't seem to have any independent variables to model it with – we are toast, right?



Step 1: Nature of Time Series

1. Maybe not toast comrade! There are likely a number of variables influencing radio sales and they probably move in correlation to time. So maybe mess



Analytical Tools

Step 1: Time Series Brought to You By...

1. Some of the time series analytics in this lecture deck provided by GRETl - a free time series software package for windows and mac OSX
2. <http://gretl.sourceforge.net/>
3. (and yes...the scripting



Step 1: Time Series Brought to You By...

1. Other time series analytics brought to you by SPSS and SAS



Typical Use, Data Sniff and IDRE

Step 1: Typical Use of the Technique

1. As the head of strategic analytics you have been asked to predict the sales of McFly hoverboards. You have the monthly sales figures for the last 5 years.

Step 1: Typical Use of the Technique

- 1. Our example:** As head of sales for Lenex , want to analyze monthly sales for the last 12 years. So you have 12x12 or 144 months of sales data.

Step 2: Inspect the Data

1. **Our example:** As head of Lenex radio sales, here are the last 12 years sales by month (144 observations)

sales
308
314
321
323
329
337
347
356
350

Step 3: Analysis Run

a. Determine the technique to use from idre chart

1. Sadly, the IDRE chart fails us here. They don't list cluster analysis in the chart. But we can do it here ourselves.

Two or More Dependent Variables with Varying Number and Nature of Independent Variables			
Number of Dependent Variables	Nature of Independent Variables	<u>Nature of Dependent Variable(s)</u>	Test(s)
1			
	0 or more	Typically Interval	Various Time Series Models

Time Series Process and Some Terms

Step 3: Analysis Run

First let's learn about the forecasting process

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

Step 3: Analysis Run

Now some time series terms

Actual data

sales	modeled sales
3083	2910
3149	3230
3218	3149
3239	3260
3295	3321
3374	3420
3475	3390
3569	3578
3597	3622
3725	3705
	3777
	3858
	3913
	4027
	4111

Fitted values

Forecast data

Step 3: Analysis Run

Now some time series terms

Actual data

residuals

Future data arrives

Forecast errors

sale s	modeled sales	error
3083	2910	-173
3149	3230	81
3218	3149	-69
3239	3260	21
3295	3321	26
3374	3420	46
3475	3390	-85
3569	3578	9
3597	3622	25

Moving Averages

Theoretical Stuff

Step 3: Analysis Run

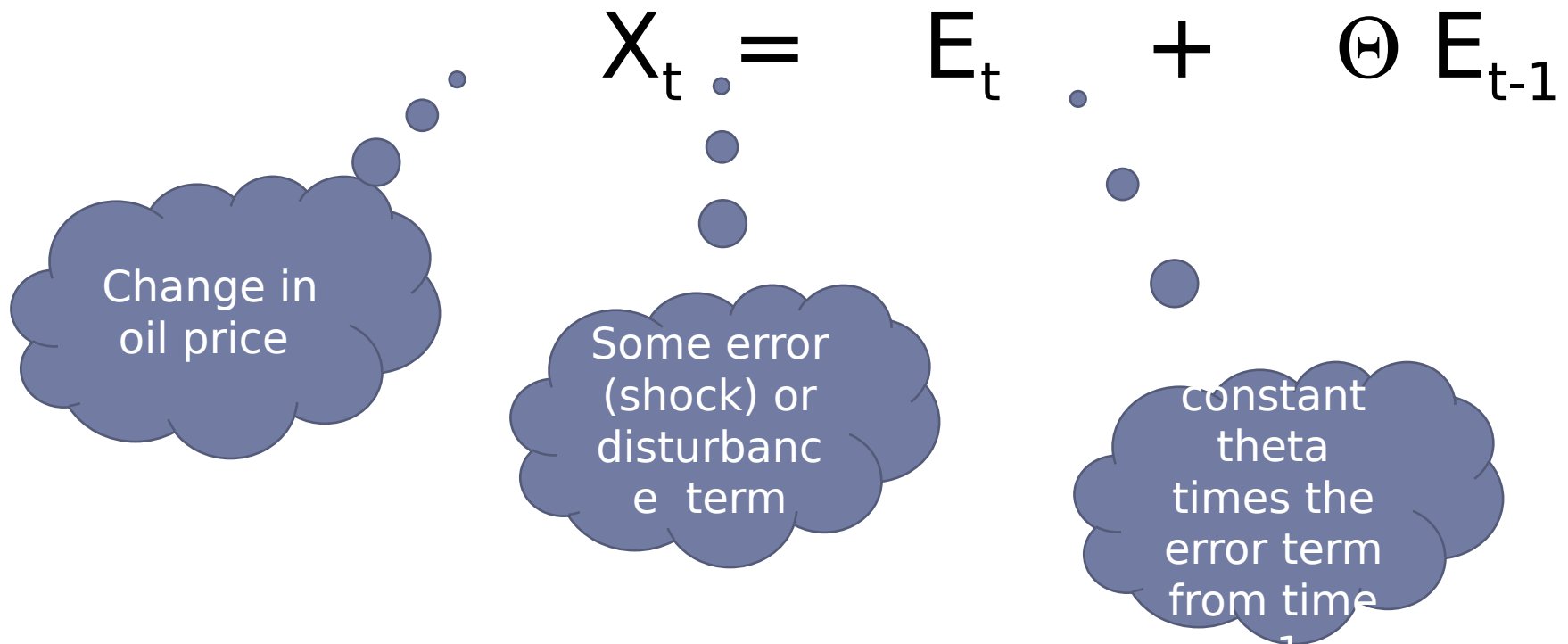
Theoretical Perspective on Moving Averages

1. Let's look first at the theoretical idea of a moving average
2. Let's imagine that we are looking at the change in oil prices over time, we will call that change X_t that might come from a specific type of shock or event
3. So let's imagine that our moving average change in oil price X_t can be described by the equation

$$X = F + \theta F$$

Step 3: Analysis Run

Theoretical Perspective on Moving Averages



1. This is a first order moving average process – it depends upon the value of the previous term

Step 3: Analysis Run

Theoretical Perspective on Moving Averages

$$X_t = E_t + .5 E_{t-1}$$

Change in
oil price

Some error
or disturbanc
e term

estimate
theta
times the
error term
from time
1

1. Let's assume that our theta has the value of .5

Step 3: Analysis Run

Theoretical Perspective on Moving Averages

1. So let's see how this works out across time...

Time						
Oil price	30	30	50	60	60	60
X_t change in oil price	0	0	20	10	0	0
Tanker sinks	0	0	1	0	0	0
E_t	0	0	20	0	0	0
$.5 E_{t-1}$		0	0	10	0	0

Step 3: Analysis Run

Theoretical Perspective on Moving Averages

1. Note that a first ordering moving process has an effect on just two time periods then disappears...

Time						
Oil price	30	30	50	60	60	60
X_t change in oil price	0	0	20	10	0	0
Tanker sinks	0	0	1	0	0	0
E_t	0	0	20	0	0	0
$.5 E_{t-1}$		0	0	10	0	0

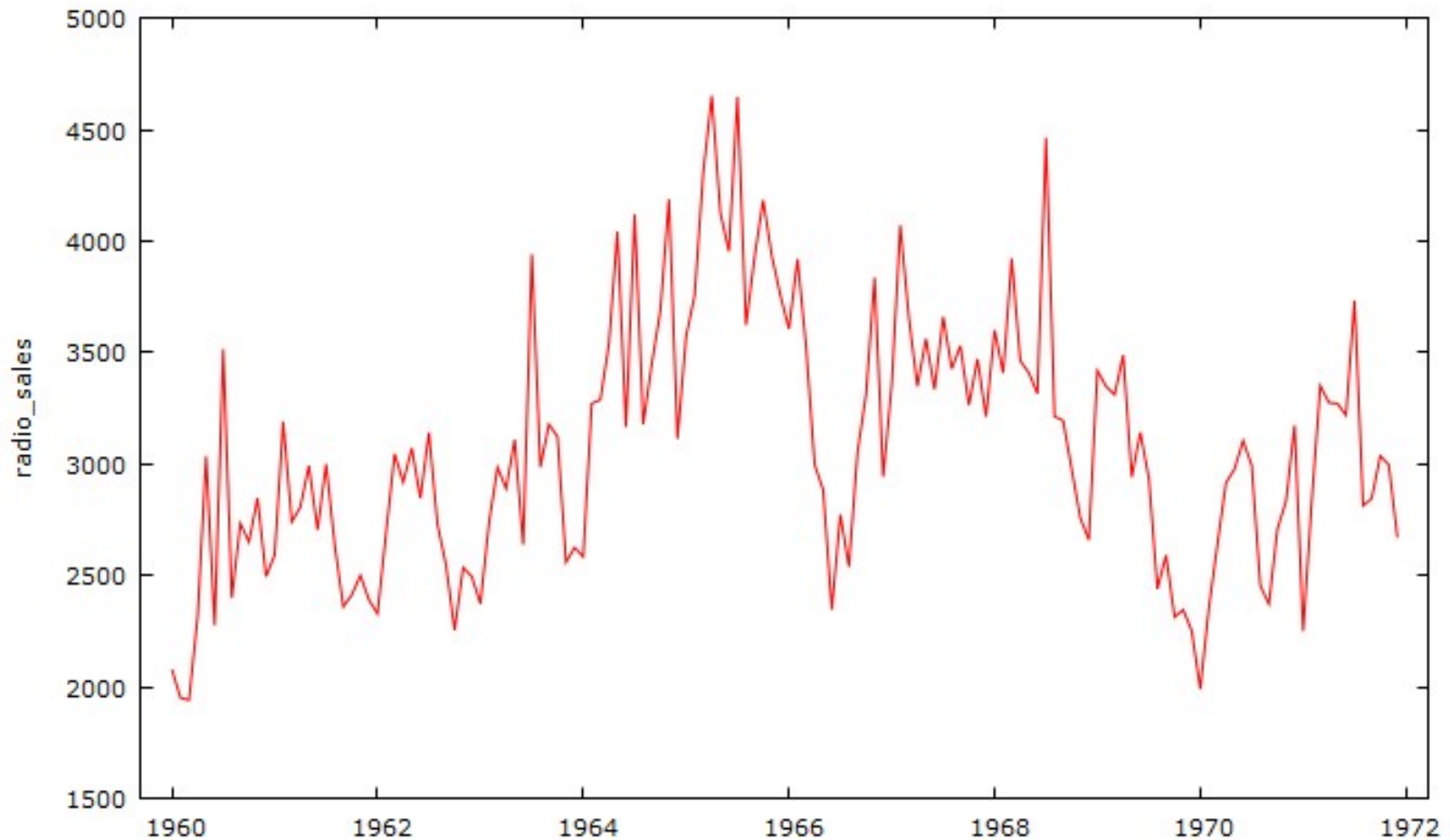
Moving Averages

Actual Effects of Moving
Averages

Step 3: Analysis Run

Typical Time Series Data Set

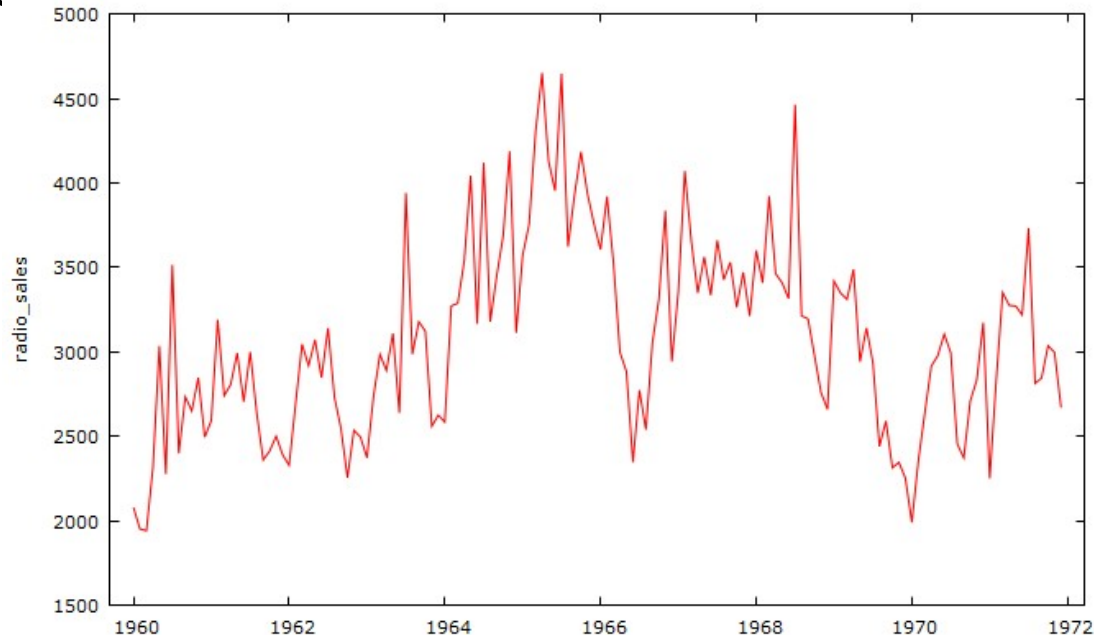
Lenex Radio Sales (in units sold)



Step 3: Analysis Run

Typical Time Series Data Set

1. Notice how “jaggy” the sales line is. It’s a bit hard to interpret, especially if someone asks you how sales trends are going. So in time series analyses there is a way to help smooth out the “jaggys” and it’s called a **moving average**



Step 3: Analysis Run

Moving Averages

1. Here is the formula for a moving average. It works pretty much like you would think an average works...

$$M = \frac{\sum_{t=1}^n v(t)}{n}$$

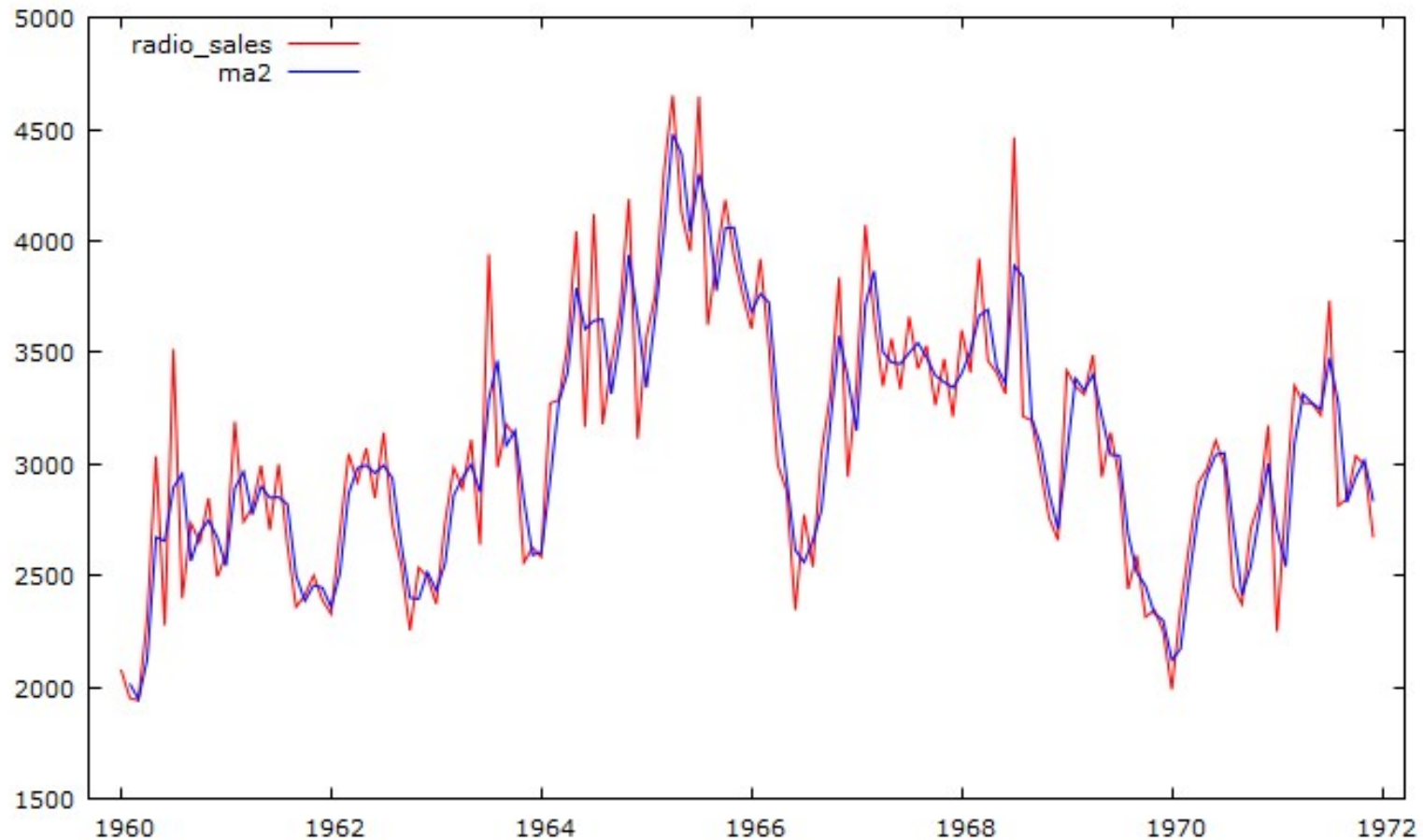
Value for
time
period t

Number of
time
periods
averaged

Step 3: Analysis Run

Moving Averages ma(1)

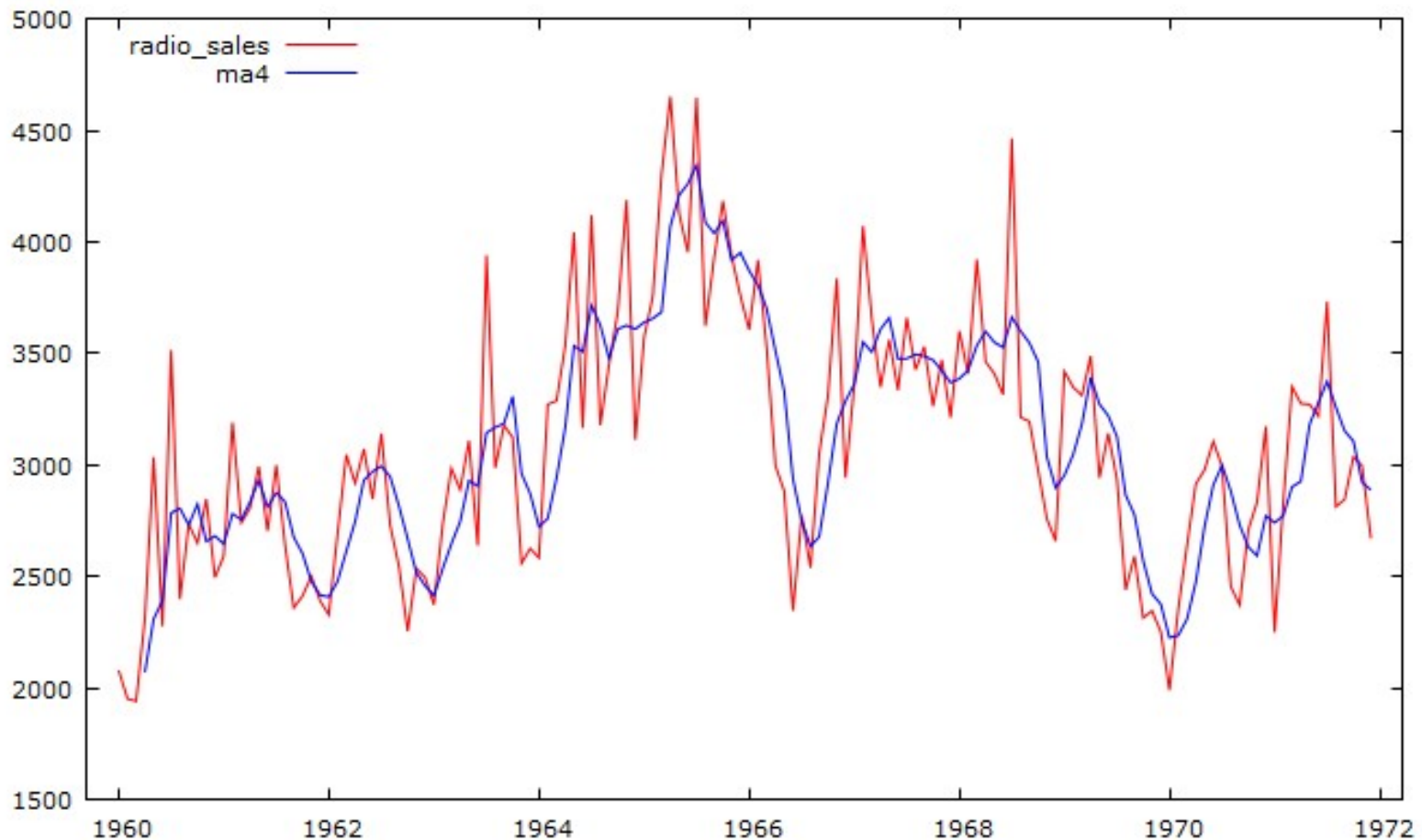
1. Let's start with `ma(1)` - a moving average with two terms `sales` and `sales(-1)`



Step 3: Analysis Run

Moving Averages $ma(3)$

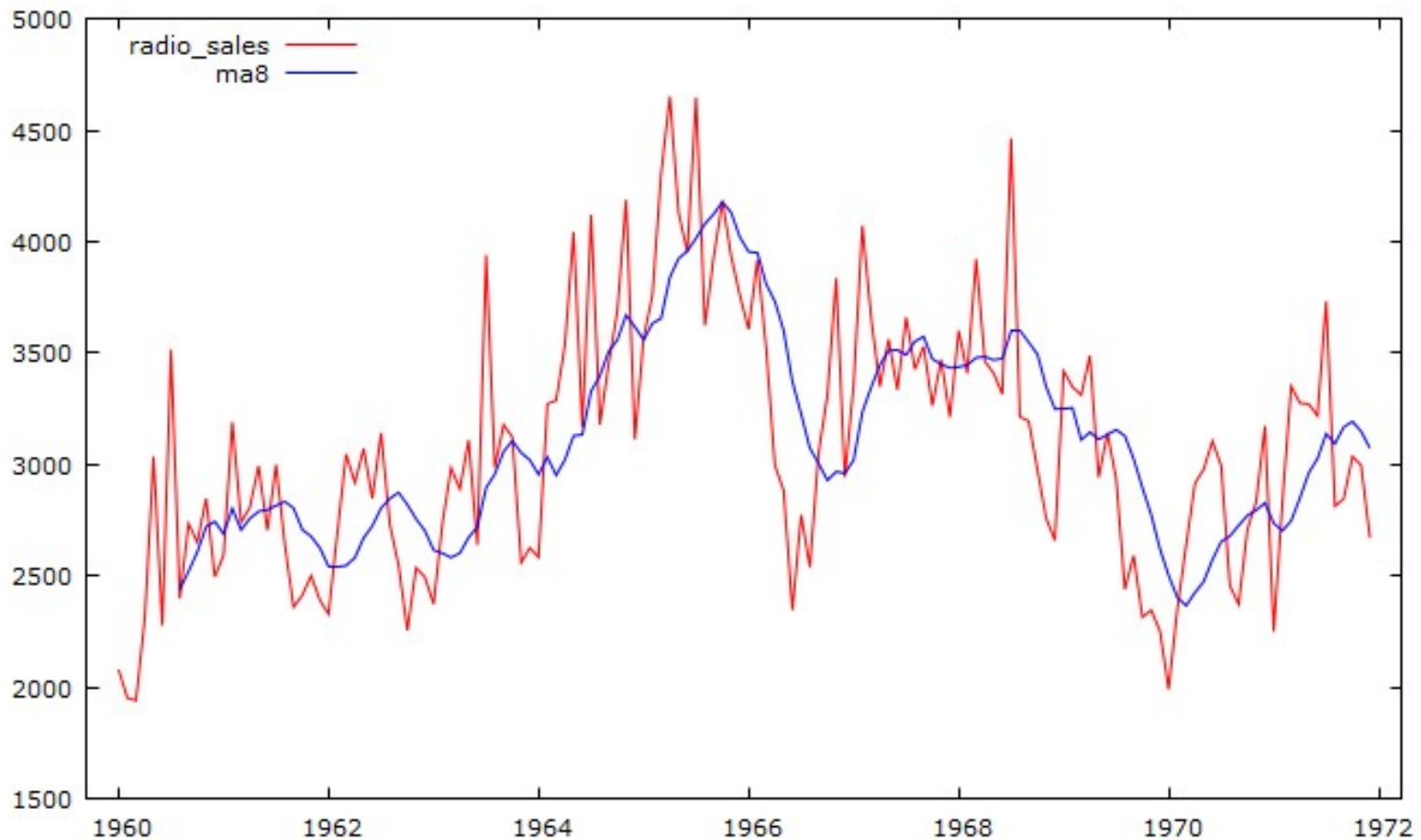
1. Try again with a larger window – $ma(3)$, hmm a bit smoother



Step 3: Analysis Run

Moving Averages ma(7)

1. Let's put our foot down – ma(7), hmm that looks

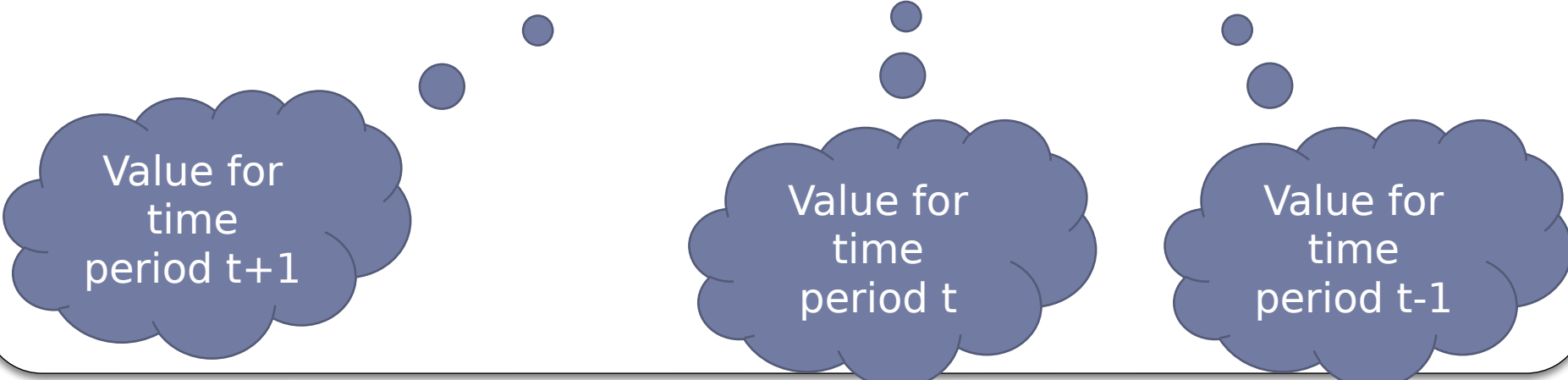


Step 3: Analysis Run

Hanning Filter

1. The previous moving averages were linear – all the points had equal weight. There are other possibilities – one of which is called the Hanning filter. A Hanning filter is a weighted, centered moving average. Let's look at the formula for a three period Hanning filter:

$$M_t^H = 0.25 y_{t+1} + .5 y_t + .25 y_{t-1}$$



Value for
time
period t+1

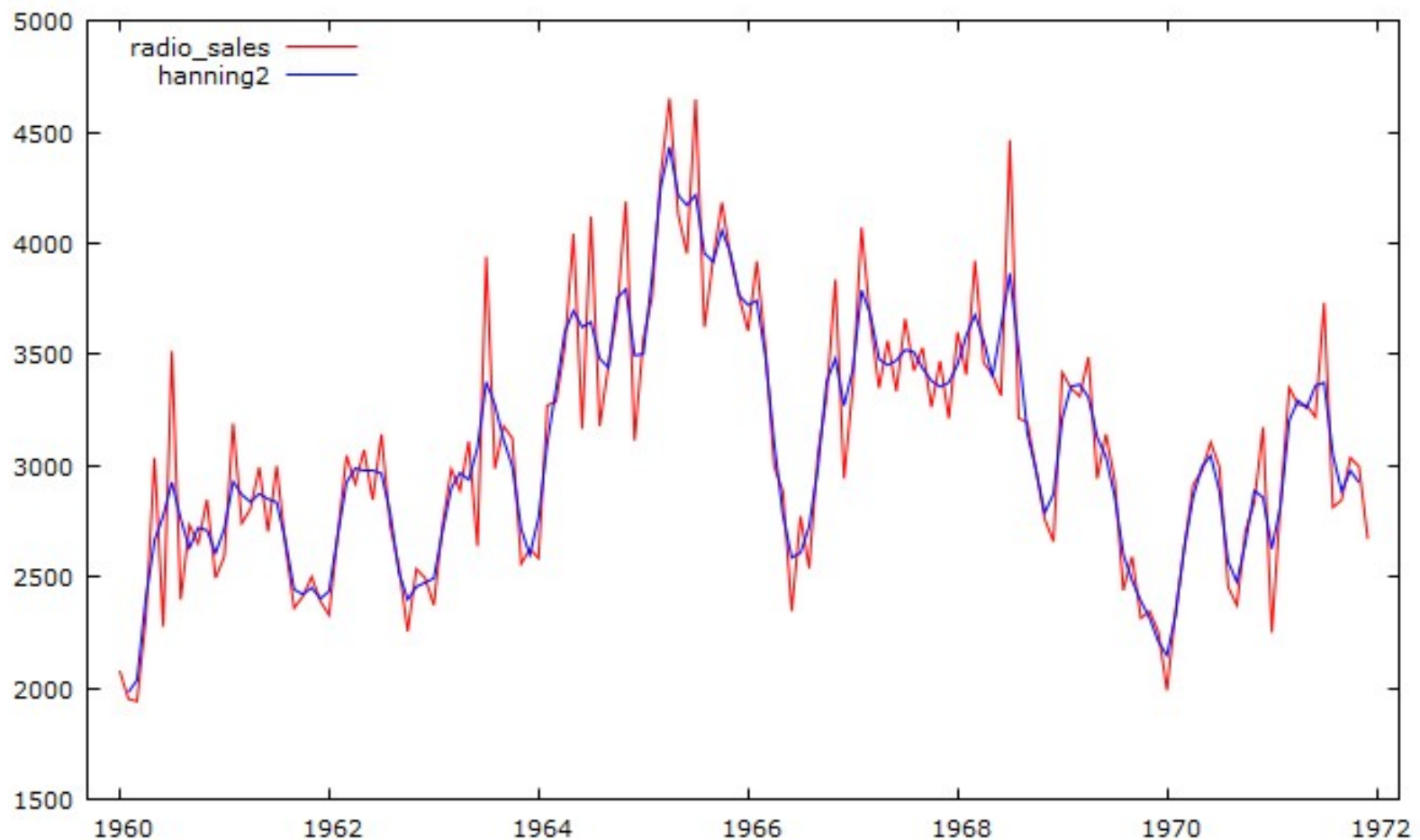
Value for
time
period t

Value for
time
period t-1

Step 3: Analysis Run

Hanning Filter

1. Let's see what the centered Hanning filter in the



Autoregressive Processes

Theoretical Stuff

Step 3: Analysis Run

Theoretical Perspective on Autoregressive Processes

1. Let's look first at the theoretical idea of an autoregressive process
2. Let's imagine that we are looking at the change in oil prices over time, we will call that change X_t that might come from a specific type of shock or event
3. So let's imagine that our autoregressive change in oil price X_t can be described by the equation

$$X_t = \rho X_{t-1} + E_t$$

Step 3: Analysis Run

Theoretical Perspective on Autoregressive Processes

$$X_t = \rho X_{t-1} + E_t$$



Change in oil price

The diagram illustrates the equation $X_t = \rho X_{t-1} + E_t$ with three thought bubbles. The first bubble, labeled 'Change in oil price', is connected to X_t by a series of four small dots. The second bubble, labeled 'Some correlation times the term from time t-1', is connected to ρX_{t-1} by a series of three small dots. The third bubble, labeled 'Error that represents some shock', is connected to E_t by a series of two small dots.

Some correlation times the term from time t-1

Error that represents some shock

1. This is a first order autoregressive process – it depends upon the value of the previous term

Step 3: Analysis Run

Theoretical Perspective on Autoregressive Processes

$$X_t = .4X_{t-1} + E_t$$



Change in oil price

The diagram illustrates the equation $X_t = .4X_{t-1} + E_t$ with three thought bubbles. The first bubble, labeled 'Change in oil price', is connected to X_t by a series of four small circles. The second bubble, labeled 'Some correlation times the term from time t-1', is connected to $.4X_{t-1}$ by a series of three small circles. The third bubble, labeled 'Error that represents some shock', is connected to E_t by a series of two small circles.

Some correlation times the term from time t-1

Error that represents some shock

1. Let's assume that our ρ has a value of .4

Step 3: Analysis Run

Theoretical Perspective on Autoregression

1. So let's see how this works out across time...

Time						
Oil price	30	30	50	58	61.2	62.48
X_t change in oil price	0	0	20	8	3.2	1.28
ME terror attack in oil field	0	0	1	0	0	0
E_t	0	0	20	0	0	0
$.4 X_{t-1}$		0	0	8	3.2	1.28

$$X_t = .4X_{t-1} + E_t$$

Step 3: Analysis Run

Theoretical Perspective on Moving Averages

1. So let's see how this works out across time...

Time						
Oil price	30	30	50	58	61.2	62.48
X_t change in oil price	0	0	20	8	3.2	1.28
ME terror attack in oil field	0	0	1	0	0	0
E_t	0	0	20	0	0	0
$.4 X_{t-1}$		0	0	8	3.2	1.28

keeps having an effect long beyond two time periods