EconS 450

Forecasting – Lecture 1

Forecasting

There are many unknowns involved in decision making. Therefore, virtually all management decisions depend on forecasts.

Forecast:
- to estimate or calculate in advance
- to predict by analysis of data

Forecasting

Forecasts are an important tool when making decisions about sales, scheduling, advertising, planting, contracting, etc.

Forecasting

To be able to forecast prices successfully, you need to understand their movements.

Even if those movements seem random, there is usually value in attempting to *summarize the regularities in the data*

Forecasting

We will address two main issues with respect to forecasting:

- selecting the best forecasting method for a particular situation
- evaluating the accuracy of our forecasts

Forecasting Approaches

There are a number of forecasting methods available.

They can be categorized into three general areas:

- extrapolation
- causal
- judgmental

Extrapolative Forecasts

Extrapolative forecasts:

- use techniques that are also referred to as "time-series" techniques
- make use of past data to predict the future
- are very accurate and popular

Extrapolative Forecasts

The most widely used extrapolative techniques are:

- moving averages
- exponential smoothing
- trend line analysis
- autoregressive models
- Box-Jenkins models

Extrapolative Forecasts

Moving average and exponential smoothing forecasts:

- are closely related extrapolative techniques
- use *averages of the most recent data* to calculate forecasts

Extrapolative Forecasts

Trend line analysis is a regression approach where price is regressed on some function of time.

Examples:

- linear
- exponential
- Logarithmic

The problem here is that time may not contain adequate explanatory power to be a useful predictor

Extrapolative Forecasts

Auto-Regressive Techniques are:

- regression analysis of price on past prices
- generally classified by their "order"
  - an AR(1) says current prices as a function of last periods price

Extrapolative Forecasts

Box-Jenkins models are:

- a popular and quite accurate approach to forecasting
- a sophisticated blend of both auto regressive and moving average techniques
- classified by order of both AR and MA components
- Also known as ARIMA models, some statistical software will estimate these for you (e.g. Stata).

Judgmental Forecasts

There are many situations in which human judgment is the only realistic forecasting method. Example:

- when data are scarce or non-existent
- when structural shifts occur and historical data are no longer representative

Judgmental Forecasts

Potential problems with judgmental forecasts are:

- bias
- conservatism

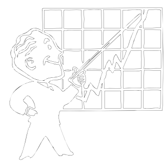
Bias

Examples of bias:

- human judgment is biased
- people believe that the world will somehow compensate them for past injustices

Conservatism

Conservatism occurs when the forecaster refuses to accept evidence of change.



Conservatism

A few days after "Black Thursday" (10/24/29) Herbert Hoover said:

"the fundamental business of the country is on a sound and prosperous basis."

Conservatism

Conservatism causes a forecaster to:

- *underestimate* when prices are *rising*
- *overestimate* when they are *falling*

Avoiding the Pitfalls

Thing to do to avoid pitfalls:

- *keep good records* of the accuracy of your past forecasts
- *critically examine* what has gone wrong, or right in the past
- *separate* forecasting from planning activities

Which Method to Use?

When would you favor extrapolative techniques over judgmental forecasts?

- when data are plentiful
- when many forecasts must be made
- when you want a more objective forecast

Which Method to Use?

Extrapolative methods may reveal *regularities in the data* that would be overlooked by "eye-balling" or using judgmental methods.

Using Both

What if you have both judgmental and extrapolative forecasts available?

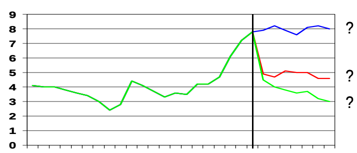
Combine them.

A simple average of two forecasts is *often more accurate* than either one individually.

Forecasting

Successful forecasting techniques exploit regularities in the data.

The goal is to find a pattern that can be extrapolated to the future.



Chinese Food?

I once received the following in a fortune cookie:

The best prophet of the future, is the past.

Time Series Forecasting

Time series techniques look at past prices to predict the future:

- univariate
- multivariate

We will focus on univariate techniques.

Univariate Techniques

Univariate Techniques:

- look only at past values of the price in which we are interested
- summarize regularities in the data
- are among the most accurate techniques

Calculating Forecast Errors

If you have a *forecast* of a price for period t, and the subsequent *realization* of that price, then you can calculate the forecast error.

The forecast error in each period is:

$$e_t = X_t - F_t$$

Accurate Forecasts

Our goal is to develop models which will minimize e_t

How well we do that will be judged by measures based on the magnitude of e_t

Measuring Forecast Accuracy

There are many ways to measure forecast accuracy. We will talk about three of the most common methods.

- ❖ MSE (Mean Squared Error)
- ❖ MAPE (Mean Absolute Percent Error)
- ❖ Theil's U Statistic

Measuring Forecast Accuracy

Different measures of accuracy may rank forecasts differently. It's up to you to determine which measure to use. MSE is probably the most common

Measuring Forecast Accuracy

Given a preferred accuracy measure, how do we know when our forecasts are "good"?

A forecast is good if it:

- provides valuable information
- correctly predicts price or direction of price movement

Measuring Forecast Accuracy

In order to be valuable, a forecast has to be "better than nothing".

We use a *naïve model* as a benchmark for evaluating forecast accuracy. It assumes that the best forecast of tomorrow's price is today's price.

The Naïve Model

The Naïve model forecast is:

$$F_{t+1} = X_t$$

The basic assumption is that any movement from today's price is purely random.

Using the Naïve Model

The first step in analyzing the "value" of a forecast is to *use the naive model to compute a benchmark accuracy*

Any forecasting model that cannot do better than the naive model should be discarded

Constructing Forecasts

When choosing a forecasting model, we use historic data.

We *do not* try to predict the future initially.

This allows us to "try out" our forecasting models in an effort to find the most accurate.

Constructing Forecasts

Your data set will be divided into two parts:

- "warm-up sample"
- "forecasting sample"

The *Warm-Up* Sample

The purpose of the *warm-up* sample is to establish the forecasting model.

For example, use this sample to determine the number of periods for a moving average, or the parameters for an exponential smoothing model.

The *Forecasting* Sample

Once the appropriate model has been chosen, the forecasting sample is used to *measure the accuracy* of the model.

Based on accuracy in the forecasting sample, you may have to go back and choose a new model.

Why Use Two Samples?

We use two separate samples so that the "value" or accuracy of the forecast is measured over data that *was not used* to develop the model.

This gives a fair indication of the model's ability to forecast into the unknown.

Data Issues

How do you divide the data:

- there are no rules
- the two samples do not have to have an equal number of observations
- be sure to have enough observations in the warm-up sample to cover any seasonality.

Simple Forecasting Models

One of the basic forecasting methods is the moving average model.

Two kinds of moving averages can be used, weighted and un-weighted.

Weighted Moving Averages

An example of a weighted moving average is:

$$F_{t+1} = 0.6\, X_t + 0.3\, X_{t-1} + 0.1 X_{t-2}$$

Here the weights *decline over time*, indicating that more emphasis is placed on near-past prices.

Un-Weighted Moving Averages

An example of an un-weighted moving average is:

$$F_{t+1} = \frac{X_t + X_{t-1} + X_{t-2}}{3}$$

In both these examples, a three-year moving average is shown.

A Moving Average Example

If we have the following data:

Period	Price
1	28
2	27
3	33
4	25
5	27

A Moving Average Example

If we are at period 3, our forecast for period 4 would be:

F_4 = (33+27+28)/3 = 29.3

And period 5,

F_5 = (25+33+27)/3 = 28.3

Accuracy of This Forecast

The forecast errors for these two forecasts are as follows:

$F_4 = 29.3$ and $X_4 = 25$,

therefore $e_4 = -4.3$

$F_5 = 28.3$ and $X_5 = 27$,

$e_5 = -1.3$

Accuracy of This Forecast

Mean Squared Error for this forecasting model over this time period would be:

$((-4.3)^2 + (-1.3)^2) / 2$

$= 20.18 / 2 = 10.09$

Mean Squared Error

The general formula for Mean Squared Error is:

$$MSE = \frac{\sum_{i=1}^{n} (X_i - F_i)^2}{n}$$

where *i* indexes the time period, and *n* is the number of time periods

Accuracy of This Forecast

The Mean Absolute Percentage Error can be calculated as follows:

APE_4 = 4.3 / 25 = 17.2%

APE_5 = 1.3 / 27 = 4.81%

MAPE = (17.2 + 4.81) / 2 = 1.005%

Mean Absolute Percentage Error

A general formula for MAPE:

$$\frac{\sum_{i=1}^{n}\left(\left|{(X_i - F_i)}\middle/{X_i}\right|\right)}{n}$$

where i indexes the time period, and n is the number of time periods

Theil's U Statistic

Theil's U statistic is a measure based on root mean squared error (RMSE). RMSE is simply the square root of MSE.

The statistic compares the RMSE from a forecasting model to that of the naïve model.

Theil's U Statistic

Theil's U is calculated as:

$$\frac{RMSE\ of\ the\ forecast}{RMSE\ of\ the\ naive\ forecast}$$

- ❖ The closer Theil's U is to 0, the better the model.
- ❖ Values of 0.55 or less are very good.

Theil's U Statistic

Remember A Theil's U statistic > 1.0 indicates:

- the forecast is NOT better than nothing
- the forecast should be discarded

Simple Exponential Smoothing

Exponential smoothing is slightly another simple and often used technique

Exponential Smoothing models continually adjust according to the *signs of the forecast errors*

Simple Exponential Smoothing

A simple exponential smoothing model adjusts forecasts according to the sign of the forecast error:

- if $(X_t - F_t)$ is positive, the forecast is increased
- if $(X_t - F_t)$ is negative, the forecast is decreased

Exponential Smoothing Formula

An exponential smoothing forecast is calculated as:

$$F_{t+1} = F_t + \alpha e_t$$

where α is the smoothing parameter, and $0 < \alpha < 1$

Exponential Smoothing Formula

In words, with exponential smoothing, the new forecast is equal to the old forecast plus a fraction of the forecast error.

The magnitude of the adjustment is dependent on the value of α

Exponential Smoothing Formula

The question is, how do you choose α?

- in practice, you will *never* have an α less than 0.1
- If α=1, you have the *naive model*
- a smaller α means that the forecast will not change as much

Choosing a Value for α

The more dramatic the changes in the series are, the higher the α should be.