Lecture 1 plus 2. ETS models

ETS = Error, Trend, Seasonality

• How to skip current lecture?

Foreasting principles and practice

ETC3550 Slides on ETS

Stationarity, White-Noise

• def. Stochastic (Random) process — just the sequence of random variables, $(y_t)!$

 y_1 , y_2 , y_3 , y_4 , ...

• def. White noise process, (u_t)

 $E(u_t) = 0$ — zero expected value

 $Var(u_t) = \sigma_u^2$ — constant variance

 $Cov(u_t,u_s)=0$ for t
eq s

• Process (y_t) is weakly statinary if

 $E(y_t) = \mu_y$ — constant expected value

 $Var(y_t) = \sigma_y^2$ — constant variance

 $Cov(y_t,y_s) = \gamma_{t-s}$ — covaraince depends only on difference of t and s

le that means: $Cov(y_1, y_2) = Cov(y_3, y_4)$.

Q. $Cov(y_1, y_{10})$, $Cov(y_{10}, y_{19})$, $Cov(y_3, y_{10})$ which are equal?

A. $Cov(y_1, y_{10}) = Cov(y_{10}, y_{19})$

Theorem. White noise is a stationary process 😃

Proof. Just check the definition.

• def. Random walk, (y_t) :

 y_0 — constant

 $y_t = y_{t-1} + u_t$, where (u_t) — is a white noise process.

Q. Let (y_t) be a random walk

$$\begin{cases} y_0 = 0 \\ y_t = y_{t-1} + u_t \end{cases},$$

 (u_t) is a white noise process with variance σ_u^2 .

Find $E(y_t)$, $Var(y_t)$?

Is (y_t) weakly stationary?

A.
$$y_1 = y_0 + u_1 = u_1$$

$$y_2 = y_1 + u_2 = u_1 + u_2$$

$$y_3 = y_2 + u_3 = u_1 + u_2 + u_3$$

...

$$y_t = u_1 + u_2 + \ldots + u_t = \sum_{i=1}^t u_i$$

$$E(y_t) = E(u_1) + E(u_2) + \ldots + E(u_t) = 0 + 0 + \ldots + 0$$

$$Var(y_1) = Var(u_1) = \sigma_u^2$$

$$Var(y_2) = Var(u_1 + u_2) = \sigma_u^2 + \sigma_u^2 = 2\sigma_u^2$$

$$Var(y_t) = Var(u_1 + u_2 + \ldots + u_t) = Var(u_1) + Var(u_t) + \ldots + Var(u_t) = t \cdot \sigma_u^2.$$

Random walk is not stationary!

ETS(AAA) model without random noise

 (y_t) — quarterly time series

trend + seasonal effects

 y_t — observed time series

 ℓ_t — time series cleared from seasonal effects

 b_t — current growth rate of ℓ_t

 s_t — current seasonal effect

Let's write equations!

Current values depend on past values!

ETS(AAA) without noise:

$$egin{cases} b_t = b_{t-1} \ s_t = s_{t-4} \ \ell_t = \ell_{t-1} + b_{t-1} \ y_t = \ell_{t-1} + b_{t-1} + s_{t-4} \ s_0 + s_{-1} + s_{-2} + s_{-3} = 0 \end{cases}$$

Initial values:

$$b_0 = 2, \ell_0 = 100,$$

$$s_0 = 3$$
, $s_{-1} = 2$, $s_{-2} = -4$, $s_{-3} = -1$.

Initial values are estimated by maximum likelihood on computer.

• notation: $\Delta \ell_t = \ell_t - \ell_{t-1}$

Q. y_{101} ? y_{102} ?

$$b_1 = b_2 = \ldots = 2$$

$$s_{101} = \ldots = s_{-3} = -1$$

$$\ell_{100} = \ell_0 + b_0 + b_1 + \ldots + b_{99} = 100 + 2 \times 100 = 300.$$

$$\ell_1 = \ell_0 + b_0 = 100 + 2 = 102$$

$$\ell_2 = \ell_1 + b_1 = 102 + 2 = 104$$

$$\ell_3 = \ell_2 + b_2 = 104 + 2 = 106 = 100 + 3 \times 2$$

$$y_{101} = \ell_{100} + b_{100} + s_{97} = 300 + 2 + (-1) = 301$$

We need equation $s_0+s_{-1}+s_{-2}+s_{-3}=0$ to interpret ℓ_t as version of y_t cleared from seasonal effects.

Q. ETS(AAA) without noise.

How many parameters do we need to estimate for quarterly data?

A. 5 parameters: b_0 , ℓ_0 , s_0 , s_{-1} and s_{-2} .

Q. ETS(AAA) without noise.

How many parameters do we need to estimate for monthly data?

ETS(AAA) model with random noise

Random noise: (u_t)

ETS(AAA) with noise:

$$\left\{egin{aligned} &u_t \sim N(0;\sigma_u^2), ext{ independent} \ &b_t = b_{t-1} + eta u_t \ &s_t = s_{t-4} + \gamma u_t \ &\ell_t = \ell_{t-1} + b_{t-1} + lpha u_t \ &y_t = \ell_{t-1} + b_{t-1} + s_{t-4} + u_t \ &s_0 + s_{-1} + s_{-2} + s_{-3} = 0 \end{aligned}
ight.$$

Q. ETS(AAA) with noise.

How many parameters do we need to estimate for quarterly data?

A. 5 + alpha + beta + gamma + sigma = 9 parameters

Miracle

Observed values: y_1 , y_2 , ..., y_{100} .

Maximum Likelihood magick 😃

Imagine that 9 parameters are already estimated:

$$\hat{\alpha}$$
, $\hat{\beta}$, $\hat{\gamma}$, $\hat{\ell}_0$, ...

How to make seasonal decomposition using estimated ETS model?

For simplicity I will omit «hat» above estimated parameters. I will think of true values of parameters.

Observed values: $y_1 = 101$, $y_2 = 104$, $y_3 = 106$, ...

True parameters: $b_0=2$, $\ell_0=100$, $s_0=1$, $s_{-1}=2$, $s_{-2}=-2$, $\alpha=0.5$, $\beta=0.5$, $\gamma=0.5$, $\sigma=2$.

Q. Decompose y_1 , y_2 , y_3 into error, trend and seasonal effect.

Find
$$\ell_1,\,\ell_2,\,\ell_3,$$
 $s_1,\,s_2,\,s_3,\,b_1,\,b_2,\,b_3,$ $u_1,\,u_2,\,u_t.$

$$\left\{egin{aligned} &u_t \sim N(0;\sigma_u^2), ext{ independent} \ &b_t = b_{t-1} + eta u_t \ &s_t = s_{t-4} + \gamma u_t \ &\ell_t = \ell_{t-1} + b_{t-1} + lpha u_t \ &y_t = \ell_{t-1} + b_{t-1} + s_{t-4} + u_t \ &s_0 + s_{-1} + s_{-2} + s_{-3} = 0 \end{aligned}
ight.$$

Sequence:

Step 1. Search for u_1 , b_1 , s_1 , ℓ_1

Look at the equation for y_t :

$$y_1 = \ell_0 + b_0 + s_{-3} + u_1$$

From $101 = 100 + 2 + (-1) + u_1$ we have $u_1 = 0$.

Look at the equation for b_1 :

$$b_1 = b_0 + \beta u_1 = 2 + 0.5 \times 0 = 2$$

Look at the equation for s_1 :

$$s_1 = s_{-3} + \gamma u_1 = -1 + 0.5 \times 0 = -1.$$

Look at the equation for ℓ_1 :

$$\ell_1 = \ell_0 + b_0 + \alpha u_1 = \dots = 102.$$

Step 2. Search for u_2 , b_2 , s_2 , ℓ_2

$$u_2=2$$
, $b_2=3$, $s_2=-1$, $\ell_2=105$

Step 3. u_3 , b_3 , s_3 , ℓ_3

How to make predictions using estimated ETS model?

True parameters: $b_0=2$, $\ell_0=100$, $s_0=1$, $s_{-1}=2$, $s_{-2}=-2$, $\alpha=0.5$, $\beta=0.5$, $\gamma=0.5$, $\sigma=2$.

We have done seasonal decomposition up to y_{100} .

The last step gave me:

$$b_{100}=3,\,\ell_{100}=400,\,s_{100}=2,\,s_{99}=1,\,s_{98}=-3,\,s_{97}=-2.$$

Q. Find point forecast for y_{101} . Find 95% predictive interval for y_{101} .

$$y_{101} = \ell_{100} + b_{100} + s_{97} + u_{101} = 400 + 3 + (-2) + u_{101}$$

Given my information:

$$y_{101} = 401 + u_{101}$$
.

 \mathcal{F}_{100} — all available information up to time 100.

Conditional expected value:

$$E(y_{101} \mid \mathcal{F}_{100}) = E_{100}(y_{101}) = 401 + 0$$

Future noise u_{101} is independed of my information \mathcal{F}_{100} .

$$E(u_{101} \mid \mathcal{F}_{100}) = E(u_{101}) = 0$$

Point prediction: $E(u_{101} \mid \mathcal{F}_{100}) = E_{100}(u_{101}) = \hat{y}_{101|100} = 401$.

Let's do **two steps** ahead point prediction:

$$y_{102} = \ell_{101} + b_{101} + s_{98} + u_{102} = (\ell_{100} + b_{100} + \alpha u_{101}) + (b_{100} + \beta u_{101}) + s_{98} + u_{102}$$
 $y_{102} = (400 + 3 + 0.5u_{101}) + (3 + 0.5u_{101}) + (-3) + u_{102} = 403 + u_{101} + u_{102}$

Point forecast:

$$\hat{y}_{102|100} = E(y_{102} \mid \mathcal{F}_{100}) = 403$$

Let's u_{101} is not zero!

We have decomposed y_{101} into two parts: predictable $(\ell_{100}+b_{100}+s_{97})$ and not predictable u_{101} .

My best prediction for u_{101} is zero: $E(u_{101} \mid \mathcal{F}_{100}) = 0$.

Interval forecasts!

Let's calculate conditional variance!

$$Var(y_{101}\mid \mathcal{F}_{100}) = Var(401 + u_{101}\mid \mathcal{F}_{100}) = Var(u_{101}\mid \mathcal{F}_{100}) = Var(u_{101}) = 2^2 = 4$$

Summary:

$$(y_{101} \mid \mathcal{F}_{100}) \sim N(401;4)$$

95% predictive interval (critical value is 1.96)

$$[401 - 1.96\sqrt{4}; 401 + 1.96\sqrt{4}]$$

Normal Elephant is in $[E(Elephant) - 1.96\sqrt{Var(Elephant)}; E(Elephant) + 1.96\sqrt{Var(Elephant)}]$ with probability 0.95;

Let's move on to two steps ahead forecasts:

$$y_{102} = 403 + u_{101} + u_{102}$$

$$E(y_{102} \mid \mathcal{F}_{100}) = 403;$$

$$Var(y_{102} \mid \mathcal{F}_{100}) = Var(403 + u_{101} + u_{102} \mid \mathcal{F}_{100}) = Var(u_{101} + u_{102}) = 4 + 4 = 8$$

Summary:

$$(y_{102} \mid \mathcal{F}_{100}) \sim N(403;8)$$

95% predictive interval (critical value is 1.96)

$$[403 - 1.96\sqrt{8}; 403 + 1.96\sqrt{8}]$$

Write likelihood functions

Versions of ETS model

ETS(AAA)

Additive Error

Additive Trend

Additive Seasonal

We can switch off some components

ETS(ANA)

Additive Error

No Trend: $b_t=0$

Additive Seasonal

ETS(ANN)

Additive Error

No Trend: $b_t=0$

No Seasonal: $s_t=0$

We can consider Multiplicative components:

ETS(AAA)

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-4} + u_t$$

ETS(MMM)

$$y_t = \ell_{t-1} \cdot b_{t-1} \cdot s_{t-4} \cdot (1 + u_t)$$

ETS(MAM)

$$y_t = (\ell_{t-1} + b_{t-1}) \cdot s_{t-4} \cdot (1 + u_t)$$

ETS(NNN): We never use it 😃

 $\ell_t = \ell_{t-1}$

 $y_t = \ell_{t-1}$

Train-test split

 y_1 , y_2 , ..., y_{100}

Training sample: y_1 , ..., y_{80}

Test sample y_{81} , ..., y_{100} .

Estimate my models (ETS(AAA), ETS(MAM)) using training sample.

Do predictions for test sample.

Metrics

You can compare models using:

Mean absolute error

$$MAE = rac{1}{20} \sum_{t=81}^{100} |y_t - \hat{y}_t|$$

Mean squared error:

$$MSE = rac{1}{20} \sum_{t=81}^{100} (y_t - \hat{y}_t)^2$$

Mean absolute percentage error

$$MAPE = rac{1}{20} \sum_{t=81}^{100} |y_t - \hat{y}_t|/|y_t|$$

Symmetric mean absolute percentage error

$$SMAPE = rac{1}{20} \sum_{t=81}^{100} |y_t - \hat{y}_t|/s_t$$

where $s_t = 0.5 |y_t| + 0.5 |\hat{y}_t|$.

Cross-validation