

Exponential Smoothing as State Space

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Exponential Smoothing Models

- Simple Exponential Smoothing

- $\bullet \quad \mathcal{F}_{t+1} = \alpha Y_t + (1 - \alpha) \mathcal{F}_t$

- Holt's Linear

- $\bullet \quad \mathcal{F}_{t+1} = \alpha Y_t + (1 - \alpha)(\mathcal{F}_t + T_t)$

- $\bullet \quad T_{t+1} = \gamma(\mathcal{F}_{t+1} - \mathcal{F}_t) + (1 - \gamma)T_t$

- Holt-Winters (additive)

- $\bullet \quad \mathcal{F}_{t+1} = \alpha(Y_t - S_{t-m}) + (1 - \alpha)(\mathcal{F}_t + T_t)$

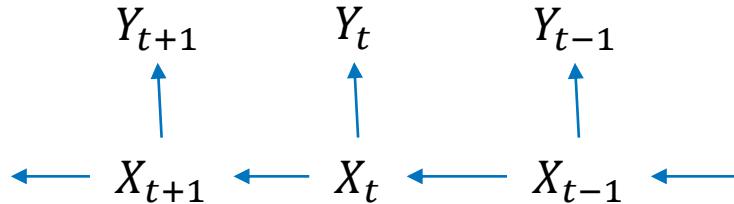
- $\bullet \quad T_{t+1} = \gamma(\mathcal{F}_{t+1} - \mathcal{F}_t) + (1 - \gamma)T_t$

- $\bullet \quad S_{t+1} = \delta(Y_t - \mathcal{F}_{t-1}) + (1 - \delta)S_{t-m}$

- \mathcal{F}_{t+1} : 1-step ahead forecast.
- Y_t : Observation at t .
- T_t : Trend component at t .
- S_t : Seasonal component at t .

State Space Models

- Representation of dynamic systems
 - State Variable(s): X_t
 - Output Variable(s): Y_t
 - State Dynamics: $X_{t+1} \leftarrow X_t$
 - Observation Process: $Y_t \leftarrow X_t$



One Example:

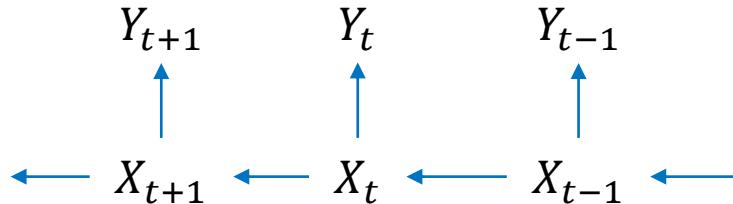
- $Y_t = AX_t + \epsilon_t$
- $X_t = BX_{t-1} + \eta_t$
- ϵ_t and η_t are uncorrelated

Smoothing, State Space, Similarities and Differences

- Holt-Winters (additive)

- $\mathcal{F}_{t+1} = \alpha(Y_t - S_{t-m}) + (1 - \alpha)(\mathcal{F}_t + T_t)$
- $T_{t+1} = \gamma(\mathcal{F}_{t+1} - \mathcal{F}_t) + (1 - \gamma)T_t$
- $S_{t+1} = \delta(Y_t - \mathcal{F}_{t-1}) + (1 - \delta)S_{t-m}$

- Representation of dynamic systems



- T_t, S_t look like state variables, unobservable. Y_t is observation.
- What is \mathcal{F}_t ? What are the state dynamics and observation process?

Exponential Smoothing as State-Space (I)

- Simple Exponential Smoothing (SES)

- $\mathcal{F}_{t+1} = \alpha Y_t + (1 - \alpha) \mathcal{F}_t$ (1)

- State Space Equivalence

- $Y_t = \ell_{t-1} + \epsilon_t$ (2)

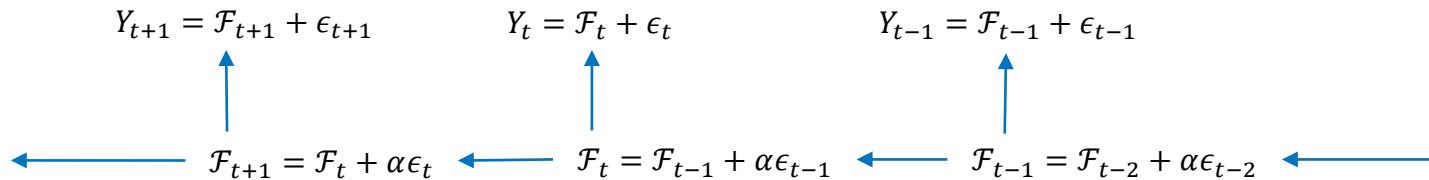
- $\ell_t = \ell_{t-1} + \alpha \epsilon_t$ (3)

- Here define $\ell_t = \mathcal{F}_{t+1}$, define $\ell_{t-1} = \mathcal{F}_t$, and obtain $\epsilon_t = Y_t - \ell_{t-1}$ from (2). Substitute symbols in (3) accordingly, we get (1).

- The smoothing algorithm (1) is to propagate the state dynamics (3).

- The observation process is (2).

- ℓ_t is the state variable. Y_t is the output variable.



Exponential Smoothing as State-Space (II)

- Holt's Linear (HL)

- $\mathcal{F}_{t+1} = \alpha Y_t + (1 - \alpha)(\mathcal{F}_t + T_t)$ (1)

- $T_{t+1} = \gamma(\mathcal{F}_{t+1} - \mathcal{F}_t) + (1 - \gamma)T_t$ (2)

- State Space Equivalence

- $Y_t = \ell_{t-1} + b_{t-1} + \epsilon_t$ (3)

- $\ell_t = \ell_{t-1} + b_{t-1} + \alpha \epsilon_t$ (4)

- $b_t = b_{t-1} + \beta \epsilon_t$ (5)

- Here define $\ell_t = \mathcal{F}_{t+1}$, $\ell_{t-1} = \mathcal{F}_t$, $b_{t-1} = T_t$, and obtain $\epsilon_t = Y_t - \ell_{t-1} - b_{t-1}$ from (3). Substitute symbols in (4) accordingly, we get (1). Similarly, (2) and (5) are equivalent.

- The smoothing algorithm (1,2) is to propagate the state dynamics (4,5).
- The observation process is (3).
- $(\ell_t, b_t)'$ is the state vector. Y_t is the output variable.

Exponential Smoothing as State-Space (III)

- Holt-Winters (additive) (HW)

- $\mathcal{F}_{t+1} = \alpha(Y_t - S_{t-m}) + (1 - \alpha)(\mathcal{F}_t + T_t)$ (1)

- $T_{t+1} = \gamma(\mathcal{F}_{t+1} - \mathcal{F}_t) + (1 - \gamma)T_t$ (2)

- $S_{t+1} = \delta(Y_t - \mathcal{F}_{t-1}) + (1 - \delta)S_{t-m}$ (3)

- State Space Equivalence

- $Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \epsilon_t$ (4)

- $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\epsilon_t$ (5)

- $b_t = b_{t-1} + \beta\epsilon_t$ (6)

- $s_t = s_{t-m} + \theta\epsilon_t$ (7)

- Here define $\ell_t = \mathcal{F}_{t+1}$, $\ell_{t-1} = \mathcal{F}_t$, $b_{t-1} = T_t$, and obtain $\epsilon_t = Y_t - \ell_{t-1} - b_{t-1} - s_{t-m}$ from (3). Substitute symbols in (5) accordingly, we get (1). Similarly, (2) and (6) are equivalent; (3) and (7) are equivalent.

- The smoothing algorithm (1, 2, 3) is to propagate the state dynamics (5, 6, 7).
- The observation process is (4).
- $(\ell_t, b_t, s_t)'$ is the state vector. Y_t is the output variable.

Exponential Smoothing as State-Space (Biopsy)

- Simple Exponential Smoothing (SES)
 - $Y_t = \ell_{t-1} + \epsilon_t$
 - $\ell_t = \ell_{t-1} + \alpha\epsilon_t$
- Holt's Linear (HL)
 - $Y_t = \ell_{t-1} + b_{t-1} + \epsilon_t$
 - $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\epsilon_t$
 - $b_t = b_{t-1} + \beta\epsilon_t$
- Holt-Winters (additive) (HW)
 - $Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \epsilon_t$
 - $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\epsilon_t$
 - $b_t = b_{t-1} + \beta\epsilon_t$
 - $s_t = s_{t-m} + \theta\epsilon_t$

State Variables:

- $X_t: \ell_t, b_t, \text{ and } s_t$

State Dynamics:

- $\ell_t = f_\ell(X_{t-1}, \epsilon_t)$
- $b_t = f_b(X_{t-1}, \epsilon_t)$
- $s_t = f_s(X_{t-1}, \epsilon_t)$

Observation Process:

- $Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \epsilon_t$

Exponential Smoothing as State-Space (Expansion)

	No Seasonal	Additive Seasonal	Multiplicative Seasonal
No Trend	$Y_t = \ell_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}s_{t-m} + \epsilon_t$
+ \mathbf{b}	$Y_t = \ell_{t-1} + b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1})s_{t-m} + \epsilon_t$
+ $\phi\mathbf{b}$	$Y_t = \ell_{t-1} + \phi b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m} + \epsilon_t$
$\times \mathbf{b}$	$Y_t = \ell_{t-1}b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}s_{t-m} + \epsilon_t$
$\times \mathbf{b}^\phi$	$Y_t = \ell_{t-1}b_{t-1}^\phi + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi s_{t-m} + \epsilon_t$

$$\varepsilon_t = 1 + \epsilon_t \quad \text{Multiplicative Error}$$

No Trend	$Y_t = \ell_{t-1}\varepsilon_t$	$Y_t = (\ell_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}s_{t-m}\varepsilon_t$
+ \mathbf{b}	$Y_t = (\ell_{t-1} + b_{t-1})\varepsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1})s_{t-m}\varepsilon_t$
+ $\phi\mathbf{b}$	$Y_t = (\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}\varepsilon_t$
$\times \mathbf{b}$	$Y_t = \ell_{t-1}b_{t-1}\varepsilon_t$	$Y_t = (\ell_{t-1}b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}b_{t-1}s_{t-m}\varepsilon_t$
$\times \mathbf{b}^\phi$	$Y_t = \ell_{t-1}b_{t-1}^\phi\varepsilon_t$	$Y_t = (\ell_{t-1}b_{t-1}^\phi + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi s_{t-m}\varepsilon_t$

Exponential Smoothing as State-Space (Recommended)

$Y_t = \ell_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}s_{t-m} + \epsilon_t$
$Y_t = \ell_{t-1} + b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1})s_{t-m} + \epsilon_t$
$Y_t = \ell_{t-1} + \phi b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m} + \epsilon_t$
$Y_t = \ell_{t-1}b_{t-1} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1} + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}s_{t-m} + \epsilon_t$
$Y_t = \ell_{t-1}b_{t-1}^\phi + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi + s_{t-m} + \epsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi s_{t-m} + \epsilon_t$

$Y_t = \ell_{t-1}\varepsilon_t$	$Y_t = (\ell_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}s_{t-m}\varepsilon_t$
$Y_t = (\ell_{t-1} + b_{t-1})\varepsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = (\ell_{t-1} + b_{t-1})s_{t-m}\varepsilon_t$
$Y_t = (\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}\varepsilon_t$
$Y_t = \ell_{t-1}b_{t-1}\varepsilon_t$	$Y_t = (\ell_{t-1}b_{t-1} + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}b_{t-1}s_{t-m}\varepsilon_t$
$Y_t = \ell_{t-1}b_{t-1}^\phi\varepsilon_t$	$Y_t = (\ell_{t-1}b_{t-1}^\phi + s_{t-m})\varepsilon_t$	$Y_t = \ell_{t-1}b_{t-1}^\phi s_{t-m}\varepsilon_t$

Exponential Smoothing as State-Space (h -ahead Forecast)

$\hat{y}_{t+h} = \ell_t$	$\hat{y}_{t+h} = \ell_t + s_{t-m+h_m}$	
$\hat{y}_{t+h} = \ell_t + hb_t$	$\hat{y}_{t+h} = \ell_t + hb_t + s_{t-m+h_m}$	
$\hat{y}_{t+h} = \ell_t + \phi_h b_t$	$\hat{y}_{t+h} = \ell_t + \phi_h b_t + s_{t-m+h_m}$	

$\hat{y}_{t+h} = \ell_t$	$\hat{y}_{t+h} = \ell_t + s_{t-m+h_m}$	$\hat{y}_{t+h} = \ell_t s_{t-m+h_m}$
$\hat{y}_{t+h} = \ell_t + hb_t$	$\hat{y}_{t+h} = \ell_t + hb_t + s_{t-m+h_m}$	$\hat{y}_{t+h} = (\ell_t + hb_t) s_{t-m+h_m}$
$\hat{y}_{t+h} = \ell_t + \phi_h b_t$	$\hat{y}_{t+h} = \ell_t + \phi_h b_t + s_{t-m+h_m}$	$\hat{y}_{t+h} = (\ell_t + \phi_h b_t) s_{t-m+h_m}$
$\hat{y}_{t+h} = \ell_t b_t^h$		$\hat{y}_{t+h} = \ell_t b_t^h s_{t-m+h_m}$
$\hat{y}_{t+h} = \ell_t b_t^{\phi_h}$		$\hat{y}_{t+h} = \ell_t b_t^{\phi_h} s_{t-m+h_m}$

ϕ_h is a function of ϕ and h . h_m is a function of h and m .

Exponential Smoothing as State-Space (h -ahead Forecast)

ℓ_t : Constant	$\ell_t + s_{t-m+h_m}$: Seasonal Pattern	
$\ell_t + hb_t$: Linear Trend	Linear Trend + Seasonal Pattern	
$\ell_t + \phi_h b_t$: Damped Trend	Damped Trend + Seasonal Pattern	

ℓ_t : Constant	$\ell_t + s_{t-m+h_m}$: Seasonal Pattern	$\ell_t s_{t-m+h_m}$: Seasonal Pattern
$\ell_t + hb_t$: Linear Trend	Linear Trend + Seasonal Pattern	Linear Trend \times Seasonal Pattern
$\ell_t + \phi_h b_t$: Damped Trend	Damped Trend + Seasonal Pattern	Damped Trend \times Seasonal Pattern
$\ell_t b_t^h$: Non-linear Trend		Non-linear Trend \times Seasonal Pattern
$\ell_t b_t^{\phi_h}$: Non-linear Trend		Non-linear Trend \times Seasonal Pattern