

### Adventures in Bayesian Structural Time Series

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- Comprised of 3 components:
  - Structural Time Series model (a.k.a. state space model)
  - ► Spike and Slab regression
  - ► Bayesian model averaging
- Predicting the Present with Bayesian Structural Time Series by Steven L. Scott and Hal Varian (Google)
- ► Implementation
  - R: bsts
    - or Causal Impact
  - ► Python: Causal Impact

## Structural Time Series



- Data from unobserved state space plus noise
- ▶ Model the latent state space instead of the data directly

#### Local Level Model

- ►  $y_t$ : data
- $\blacktriangleright \mu_t$ : latent state

$$y_t = \mu_t + \varepsilon_t$$
  $\varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$   
 $\mu_{t+1} = \mu_t + \xi_t$   $\xi_t \sim N(0, \sigma_{\varepsilon}^2)$ 

Analogous to the inercept in linear regression but allowing for the intercept to vary over time



#### Local Linear Trend Model

- ▶  $y_t, \mu_t$ : same as before
- $\triangleright$   $\nu_t$ : slope (additional state component)

$$y_t = \mu_t + \varepsilon_t \qquad \qquad \varepsilon_t \sim N(0, \sigma_{\varepsilon}^2)$$

$$\mu_{t+1} = \mu_t + \nu_t + \xi_t \qquad \qquad \xi_t \sim N(0, \sigma_{\xi}^2)$$

$$\nu_{t+1} = \nu_t + \zeta_t \qquad \qquad \zeta_t \sim N(0, \sigma_{\zeta}^2)$$

## Structural Time Series



#### General Form

- ▶  $y_t$ : data
- $ightharpoonup \alpha_t$ : state component

$$y_t = Z_t' \alpha_t + \varepsilon_t$$
  $\varepsilon_t \sim N(0, H_t)$  (1)

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \qquad \eta_t \sim N(0, Q_t)$$
 (2)

- ▶ (1): observation equation
- ► (2): transition equation

# Structural Time Series in Bayes SAN DIEGO STATE Unitextsity

- Spike and slab regression
  - Used when regression components are included
  - ► Variable selection technique
  - Prior on regression coefficients
- ► Bayesian Model Averaging
  - Consequence of spike and slab prior
  - ▶ Different  $\beta$ s included in each draw of posterior (i.e. different model on each draw)
- Prior Elicitation and Posterior Sampling
  - ▶ Inclusion probabilities for regression coefficients
  - ightharpoonup Or: expected model size, expected  $R^2$ , weight given to  $R^2$
  - ► Gibbs sampler (stochastic search variable selection) to draw from posterior
  - ► For details see paper by Scott and Varian