ERCOT First Meeting

Jan 13, '17

- J lead, working w/ David Puelz (will be avail Spr + Summer)
- Good SM2 final project.
- David = great resourse for time series modeling.
- Possible grant app due in Feb.
- Begin w/ off-the-shelf basic model, expand from there.
- ERCOT = Electrical Power Grid council for TX.
  "Electric Reliability Council of TX"

Two Goals:

1) <u>Optimization Problem</u>:
   - want to model grid load for several (3-4) days into the future.
   - want to satisfy demand at cheapest cost possible.
   - many sources can be used to power grid (supply load), ea. with different load times, load costs + generation costs.
   - Demand depends on a few covariates - weather (temp), season, time of day.
     Covariates may be highly corr. (Possible non-linear model)
   - Will be vectorized - there are 8 regions to model + predict.
   - Bayesian approach → simulate data from posterior.
   - Worse to project too low than too high; asymmetric loss fctn.
2) <u>Demand Response Model</u>:
   - All sorts of weird contractual stuff where companies can lower their peak day rates by bidding to send electricity back to the grid. Or can commit to limit use in some way.
   - A smoothing problem - want to decrease peaks on high demand days.
   - Want some model for response (chg in bxr) due to this demand response process.

⊛ Bayes DLM (dynamic linear model) or AR (autoregression), vectorized.

⊛ Weather is a complication! See next pg.

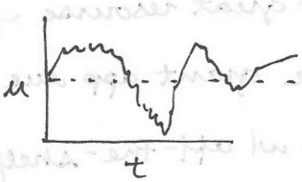
Basic Model

(time of day, season, etc can also be added)

- y_t = demand on day t
- x_t = temp on day t (most obv. predictor - can also add others)

grand mean — stationary (chg in mean over time) AR term

- $y_t = \alpha + \mu_t + \beta_1 x_t + \epsilon_t$
  - weather effect (doesn't chg over time)



- $\mu_t = \phi \mu_{t-1} + \delta_t$

Then what is y_{t+1}?

- $y_{t+1} = \alpha + \mu_{t+1} + \beta_1 x_{t+1} + \epsilon_{t+1}$ where
  - $\mu_{t+1} = \phi \mu_t + \delta_{t+1}$
  - $\epsilon_t \sim N(0, \sigma^2)$
  - $\delta_t \sim N(0, \tau^2)$

⊛ For Bayesian setting, have posteriors.
- So for μ, ϕ, β, α we can predict values by drawing from posterior.

⊛ Catch: we don't know x_{t+1}. Can forecast x_{t+1} using a surrogate model for temp.

Surrogate Model for Temp (x_{t+1})

$$x_{t+1} = \hat{x}_{t+1} + \eta_{t+1}$$

x_{t+1}: tomorrow actual temp; $\hat{x}_{t+1}$: tomorrow forecast temp; η_{t+1}: error in forecast

- Time-varying estimates of temp.
- Need diff btwn forecast + real temp to get error.
- Todd @ARL scraping this data.

- So can simulate x_{t+1} + pop into above model.
- This model can be completely diff type than above model.

Approach

- This type of model is type of FFBS; "Fwd Filter Backward Sampler" Mike West
- Begin w/ Basic, add Surrogate temp model afterwards. (Basic by mid/late Feb?)

Vectorizing

- Model will be vectorised; have 8 regions.
- Will have 2 models:
  1) $\vec{y}|\vec{x}$ (main model; DLM)
  2) $\vec{x}$ (surrogate model)
- Since $P(\bar{y}|\bar{x})P(\bar{x}) = P(\bar{y},\bar{x})$ will have joint model also

DLM Terminology Note

- Technically, a DLM model has covariates which change over time:

$$y_t = \alpha_t + \beta_{1t} x_t + \epsilon_t$$

β_1 varies over time

- Our basic model has β_1 fixed, with a time-varying intercept, so is a special case of DLM.

Next Steps

1) David to send Jenn chapters in West book to review, + Carlos site/time series notes.
2) Jenn to read chapters, articles.
3) Jenn to implement toy ffsb model in R.
4) D/J meet next week to review code.
5) James to send D/J file access.