# To combine forecasts or forecast models (Parameters)

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# Outline



- Forecast combination and model uncertainty
- Research questions
- Experimental Design
- Results
- Conclusion

"Everything should be made as simple as possible, but no simpler." Albert Einstein (Supposedly)

# Model uncertainty



- Model building process
  - Model formulation (or model specification)
  - Model fitting ( or model estimation)
  - … (Chatfield, 1995)

- Sources of uncertainty
  - Model structure
  - Model parameter estimates
  - Unexplained random variations (Draper et al., 1987; Hodges, 1987)

# Forecast combinations



- Given multiple models
  - Select a single (forecast) model
  - Create multiple forecasts
  - Take a simple average of all forecasts
- Does combination work?
  - Generally leads to improved accuracy (Stock and Watson, 2004 ;Fildes, Nikolopoulos et al. 2008) etc…
  - More robust and accurate than individual forecast (Newbold and Granger,74; Palm and Zellner,92) etc…
  - M3-Competition (Makridakis et al. 2000) → simple average (Comb S-H-D) outperforms others
- Nearly 50 years of forecast combination research focused on
  - Combining forecasts
  - Combining model parameters  almost neglected

# Combinations and model uncertainty



- Why combinations work?
  - Usually the model form is unknown to the  forecaster i.e. ‘true model’
  - Data generating process may not be of a simple functional form
  - Things change with time e.g. seasonality and/or trend may disappear, structural breaks
  - Outliers and anomalies may distort structure
  - A finite number of observations, often small samples
  - Large effects are easier to identify than smaller effects

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# Research questions



- Bagged exponential smoothing (Christoph, Hyndman & Benitez, 2014)
  - Perform STL decomposition
  - Bootstrapped residuals of the decomposition
  - Recombine to obtain new series
  - Estimate a model for each bootstrapped series
- Shown to work well – especially for monthly data
  - Combine forecasts from a family of closely related methods
- Consequently the model estimated to be best can vary from data set to data set
- To combine forecasts or forecast models (parameters)?

# Research questions



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  - Combining model parameters – almost neglected
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# Research questions



- [image of bootstrap series]
- [Image of changing models]

# Research questions



- RQ1: Are there benefits to be achieved from combining forecast model parameters rather than model forecasts themselves?
  - RQ 1.1: Given the same forecast model structure?
  - RQ 1.2: When the forecast model structure is allowed to vary?

- RQ2: How can differences in performance be explained?

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# Experimental design - setup



- Combinations
  - Parameter combination
  - Forecast combination
- Combination methods
  - Mean, Median, Mode
- Forecast model generation
  - Bootstrap
  - Simulation
- Conditions
  - Model structure fixed
  - Model structure varies

# Experimental design - setup



- Family of exponential smoothing methods
- Model uncertainty
  - A general class of models where the true model is a special case
  - Models of different structures

| Trend component | Seasonal component | | |
|---|---|---|---|
| | N (none) | A (additive) | M (multiplicative) |
| N (none) | NN | NA | NM |
| A (additive) | AN | AA | AM |
| M (multiplicative) | MN | MA | MM |
| D (damped) | DN | DA | DM |

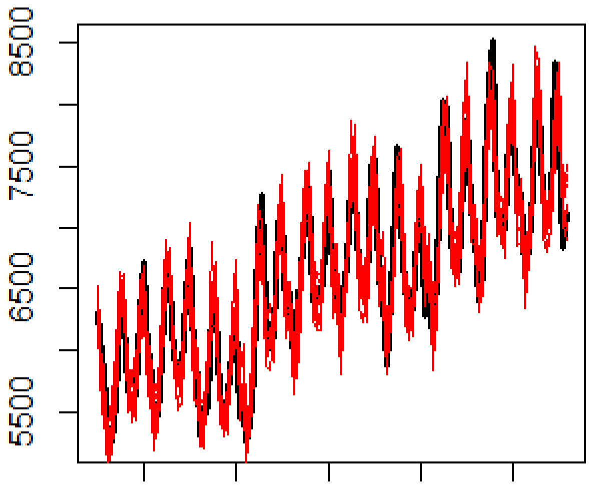
*Source*: Hyndman et al. 2002 based on (Pegels ,1969 ; Gardner 1985)

# Experimental design - benchmarks



- Automatic model selection based on AIC (Hyndman et al. 2002)

- Bagged ETS (Christoph, Hyndman & Benitez, 2014)
  - Perform STL decomposition
  - Bootstrapped residuals of the decomposition
  - Recombine to obtain new series
  - Estimate a model for each bootstrapped series




- Points of comparison:
  - Model selection versus combination
  - Model structure varies across bootstrapped series
  - Forecasts and not parameters are combined

*Source*: Hyndman et al. 2002 based on (Pegels ,1969 ; Gardner 1985)

# Experimental design - evaluation



- Research Question 1:
  - Empirical evaluation
  - M3 Competition data
  - Forecast accuracy using SMAPE and GMRAE

- Research Question 2:
  - Bias-variance decomposition

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# Results

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# Conclusion