MONASH University

MONASH BUSINESS SCHOOL

Probabilistic energy forecasting for smart grids and buildings

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Demand forecasting

Demand forecasting in the smart grid

Figure: `http://solutions.3m.com`

$$\underbrace{\text{Energy sources (fossil fuel, wind, solar, wave, ...)}}_{\text{Supply}} \longrightarrow \underbrace{\text{Energy consumers}}_{\text{Demand}}$$

Demand forecasting in the smart grid

Need demand forecasts for outage planning, energy trading, demand response, system management, ...

Predictors

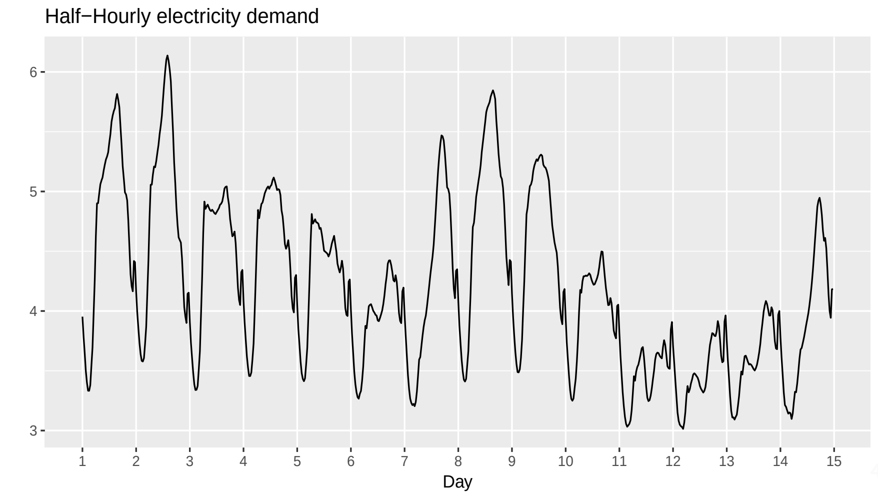
- calendar effects
  - Time of day
  - Day of week
  - Time of year
  - Holidays
- prevailing and recent weather conditions
- demand response incentives
- household characteristics

We build a nonlinear nonparametric stochastic model of demand as a function of these predictors.

Probabilistic forecasting

Probabilistic forecasting

Aim: forecast entire probability distribution of demand, not only the average.



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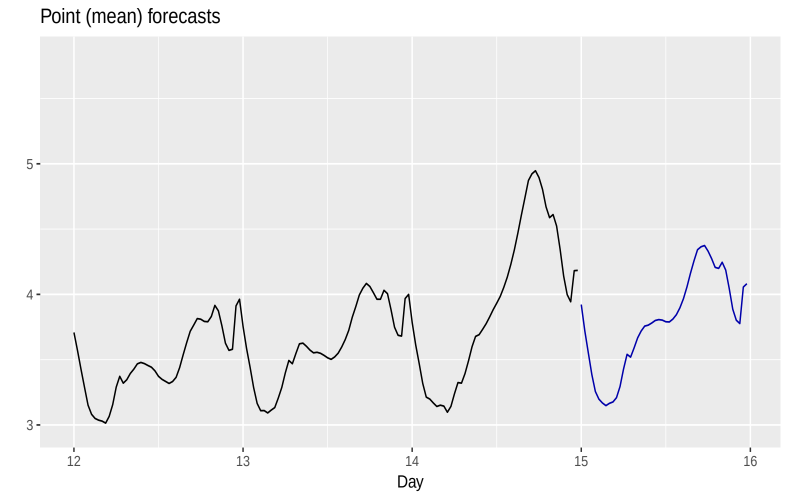

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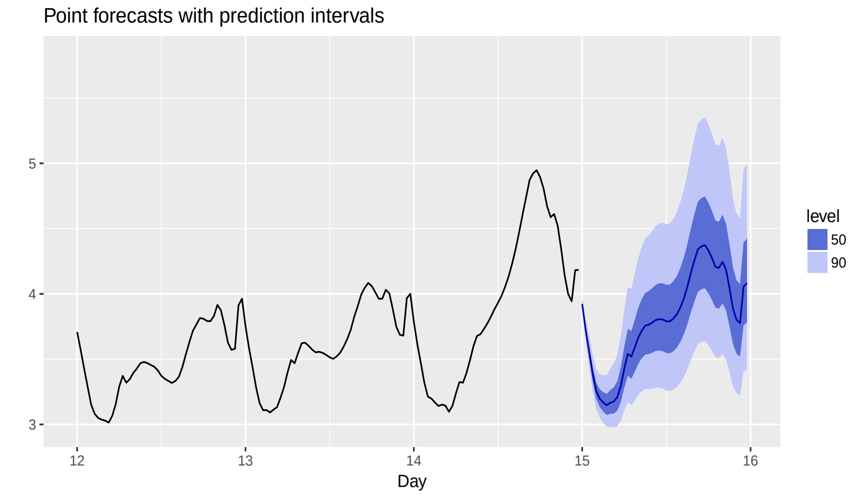

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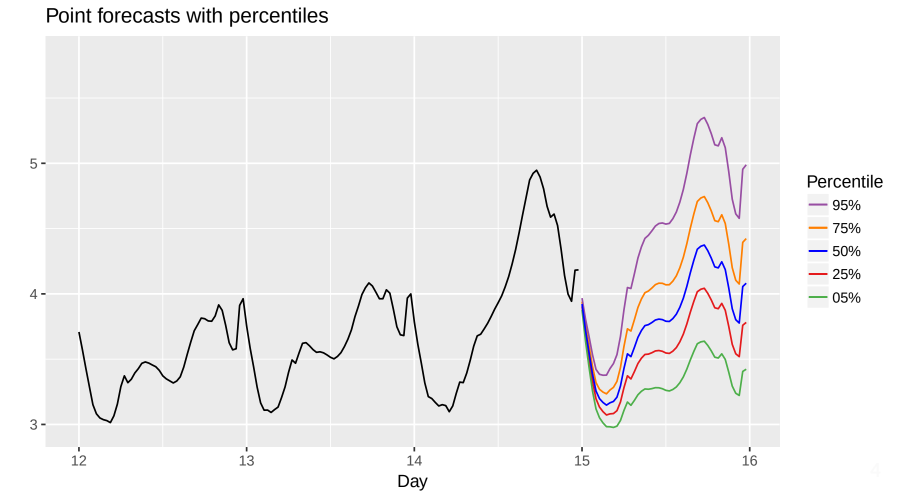

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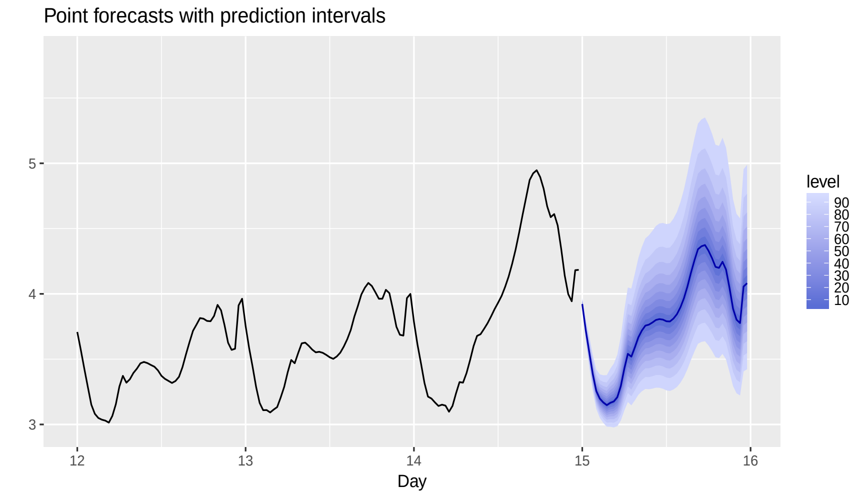

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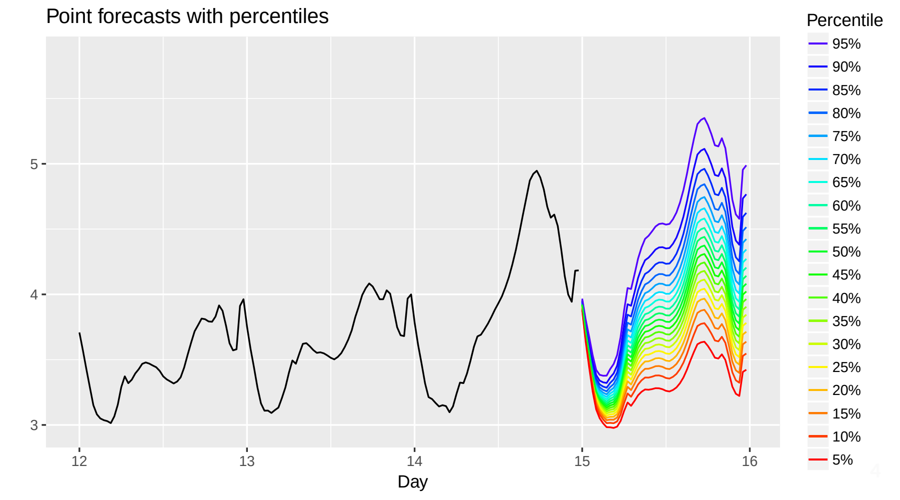

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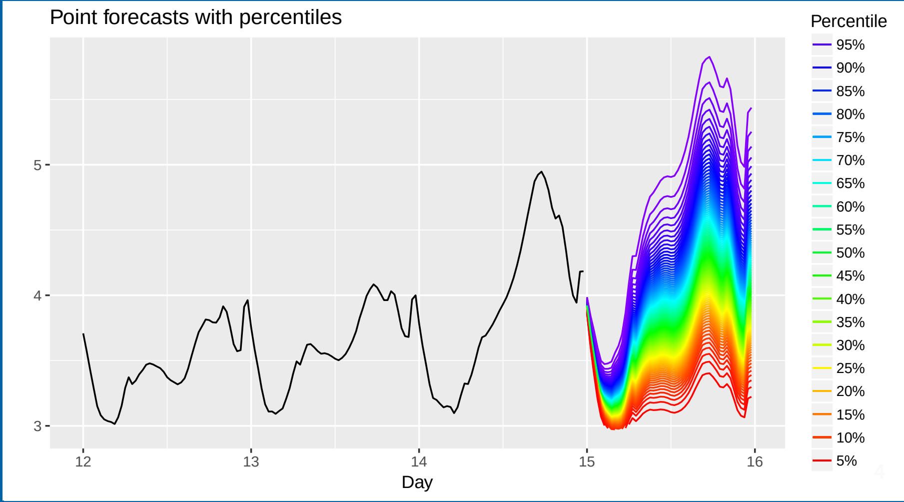
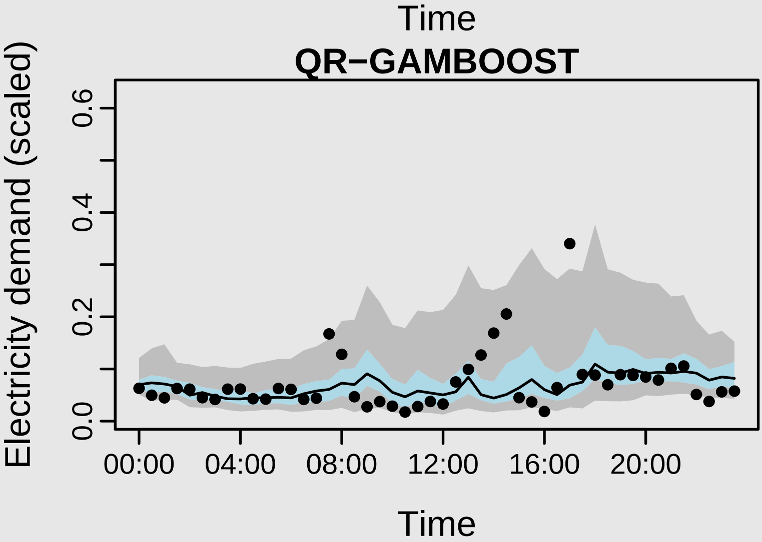


Probabilistic forecasting



Half-hourly data. Blue: 50% region. Grey: 95% region.

Forecast accuracy measures

- MAE: Mean absolute error
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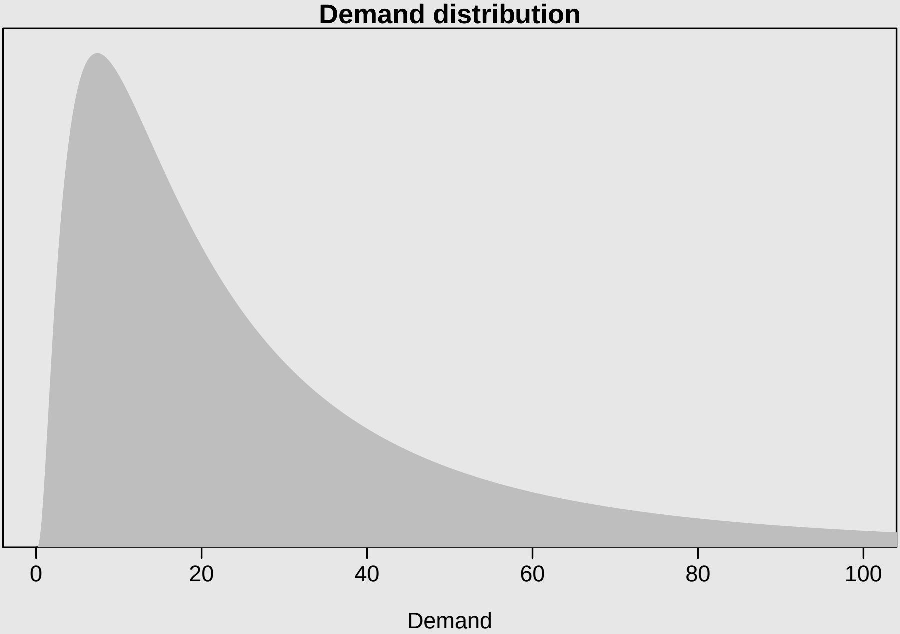
➥ If $q_t(p)$ is accurate, then y_t should be less than $q_t(p)$ about $100p\%$ of the time.

➥ Need to penalize unlikely side more (a “pinball loss” function)

Forecast scoring



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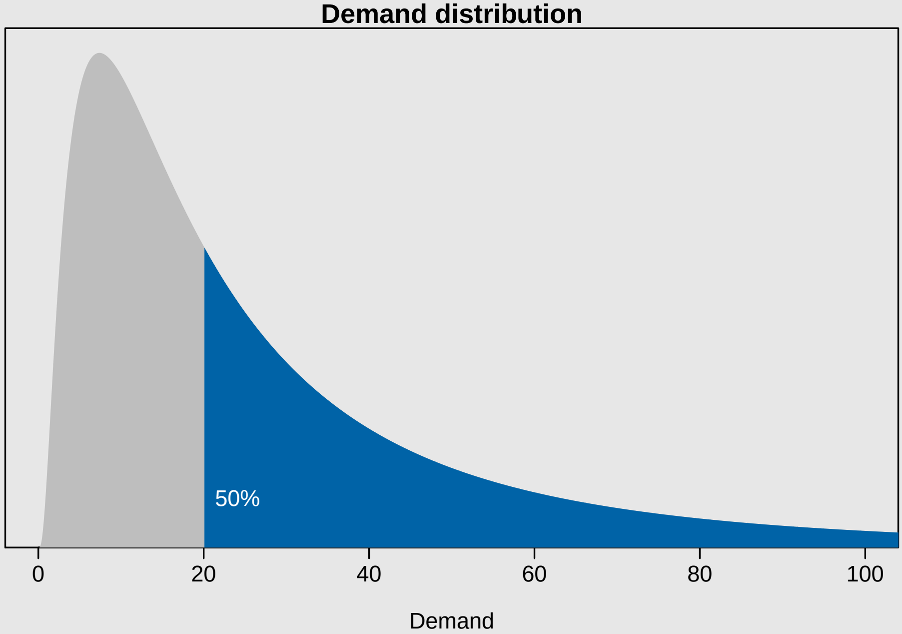

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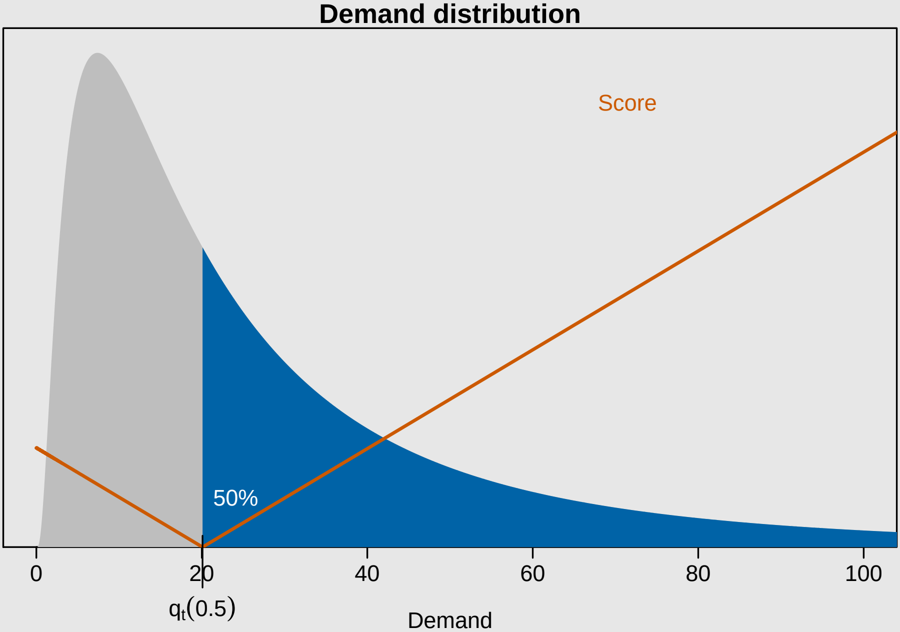

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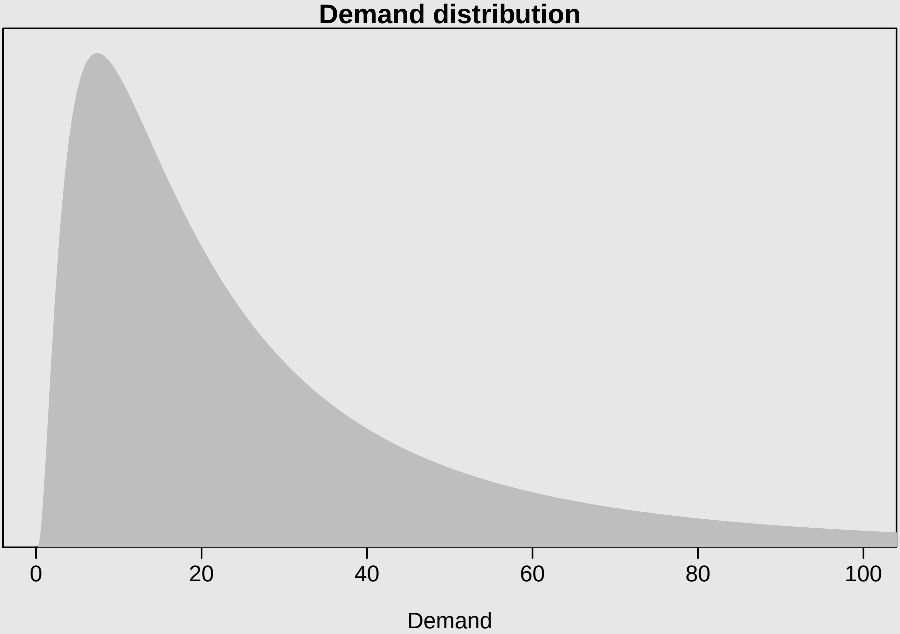

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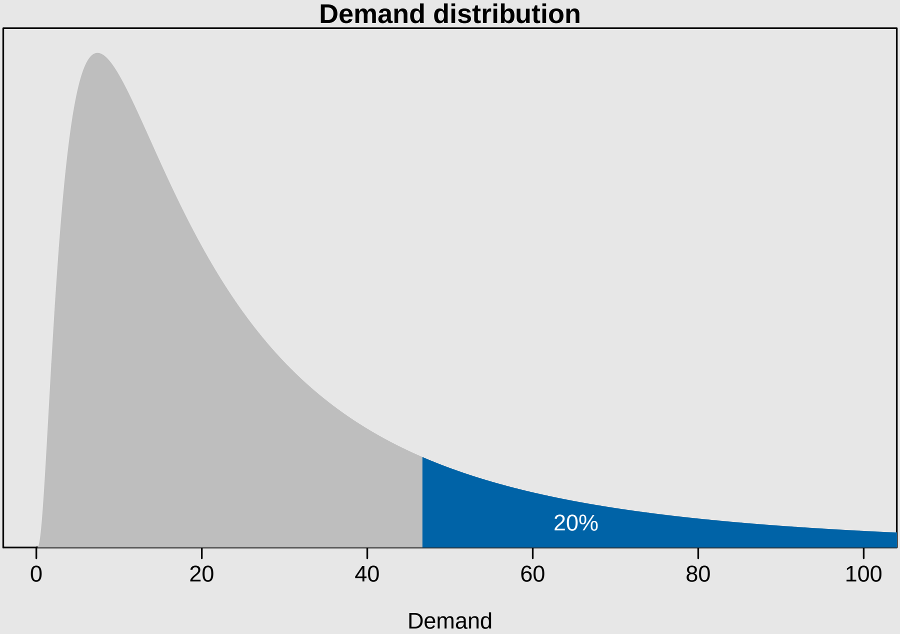

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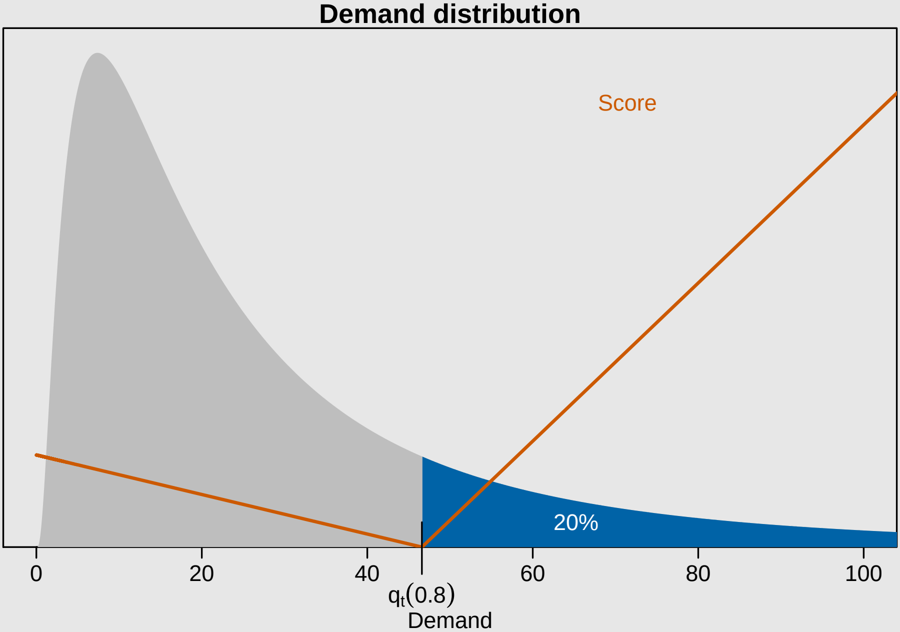

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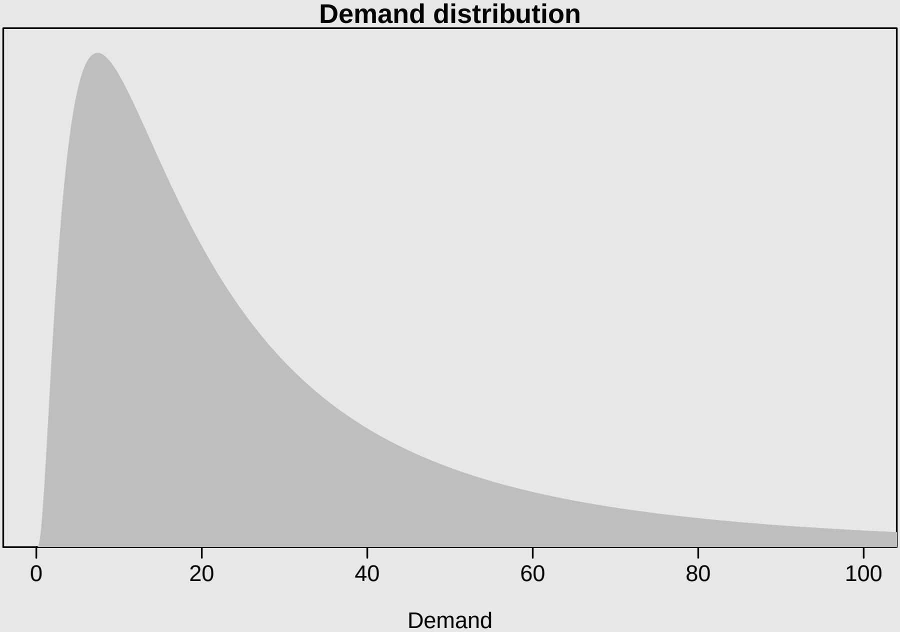

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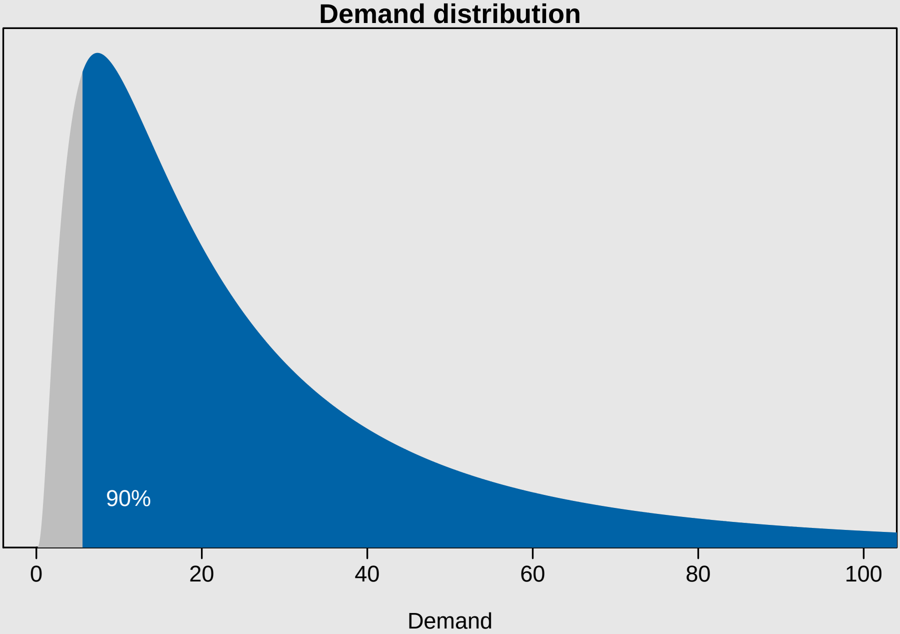

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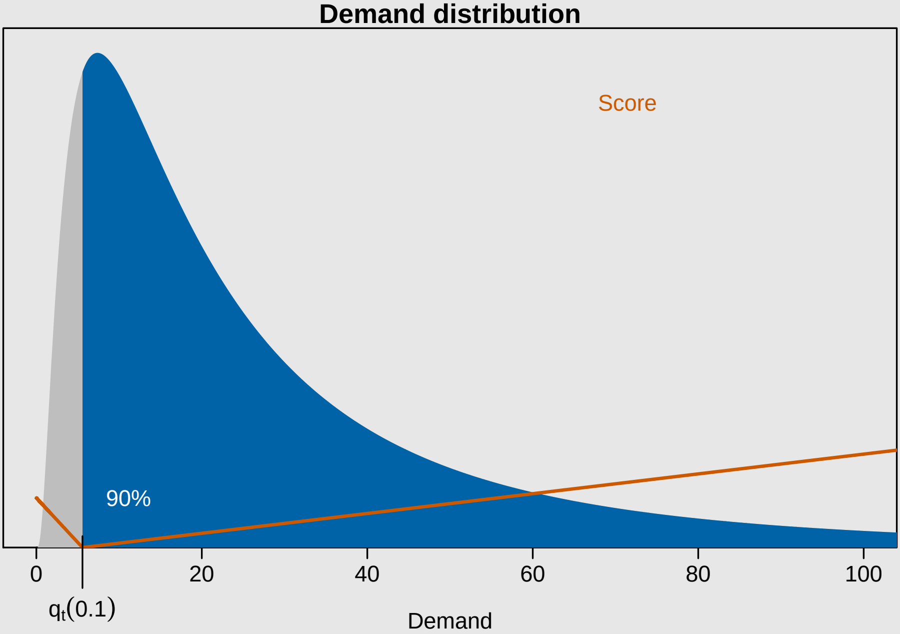


Forecast scoring

Quantile Score for observation y:

For $0 < p < 1$:

$$S(y_t, q_t(p)) = \begin{cases} p(y_t - q_t(p)) & \text{if } y_t \geq q_t(p) \\ (1-p)(q_t(p) - y_t) & \text{if } y_t < q_t(p) \end{cases}$$

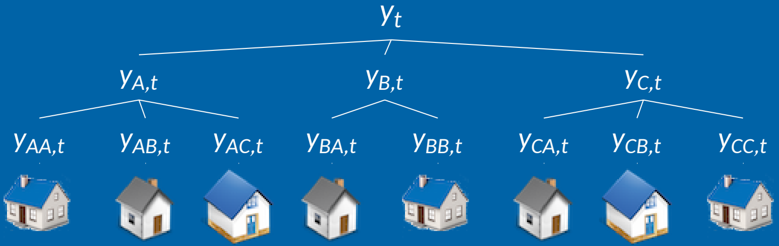
- Scores are averaged over all observed data for each p to measure the accuracy of the forecasts for each percentile.
- Average score over all percentiles gives the best distribution forecast:

$$QS = \frac{1}{99T} \sum_{p=1}^{99} \sum_{t=1}^{T} S(q_t(p), y_t)$$

- Equivalent to CRPS (Continuous Rank Probability Score).
- Reduces to MAE if we are only interested in $p = 0.5$.

Hierarchical forecasting

Hierarchical electricity demand data



$$y_t = y_{A,t} + y_{B,t} + y_{C,t}$$
$$y_{A,t} = y_{AA,t} + y_{AB,t} + y_{AC,t}$$
$$y_{B,t} = y_{BA,t} + y_{BB,t}$$
$$y_{C,t} = y_{CA,t} + y_{CB,t} + y_{CC,t}$$

Aggregations may be based on:

- Geography (suburbs, regions, states)
- Demography (number of people in household, age distributions)
- Appliances (air conditioning, electric heating)

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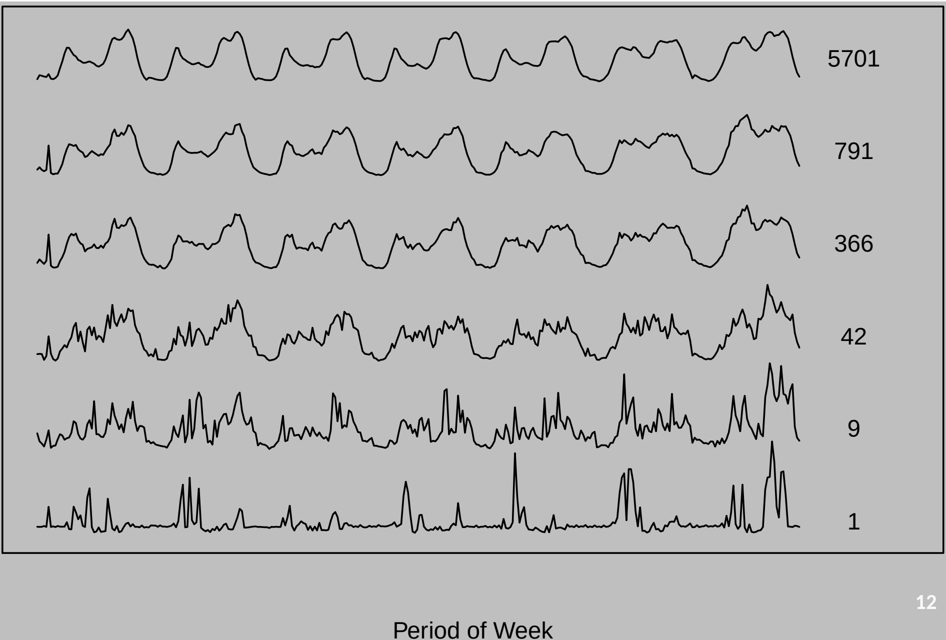

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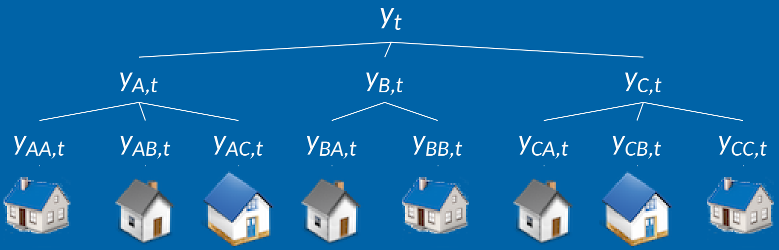


- Easier to forecast at more aggregated levels.
- We forecast at every level and reconcile the forecasts.
- Optimal reconcilation algorithm: Hyndman et al (2011, 2016, 2017)
- Forecast means should add up, but percentiles are more complicated
- **Current research topic:** How to reconcile percentiles at all levels?

Building-level energy forecasting

Managing commercial buildings

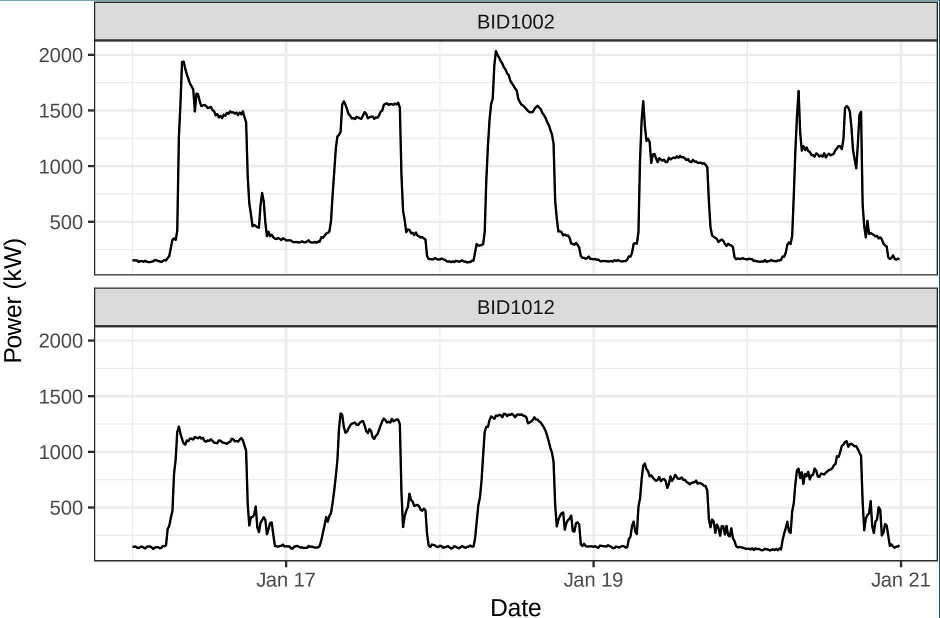
Commercial buildings require energy forecasting to help:

- Manage peak demand.
- Quantify the impacts of building management changes.
- Assess performance and energy efficiency.

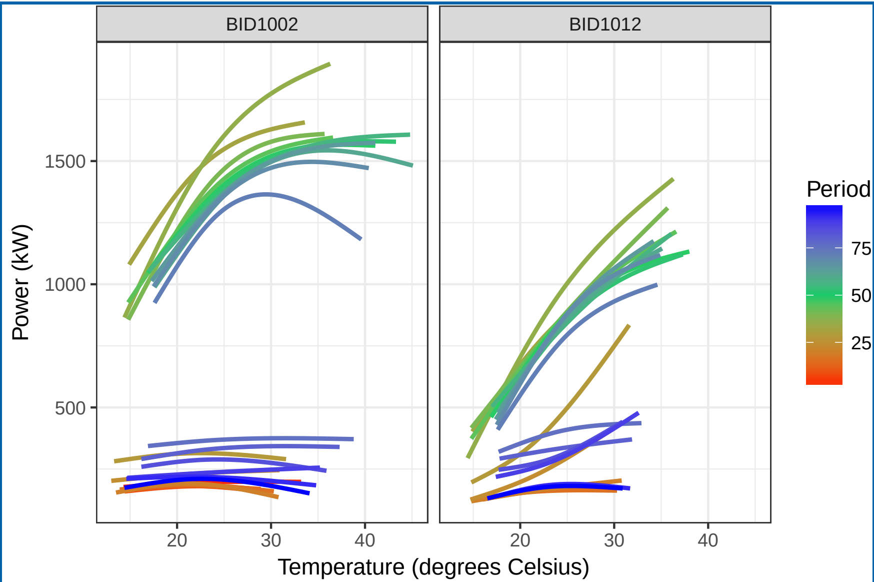
Buildings Alive works with 150+ commercial buildings which include supermarkets, hospitals and office blocks.

Each require daily forecasts to inform facilities managers.

Building Level Data



Building Level Data



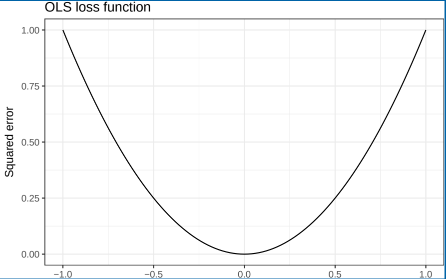
Natural cubic splines for each period of the day (df = 2).

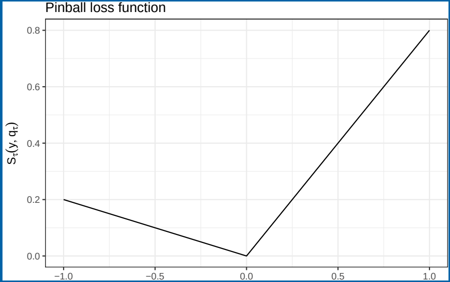
Quantile Regression

Probabilistic forecasts can be produced using quantile regression.

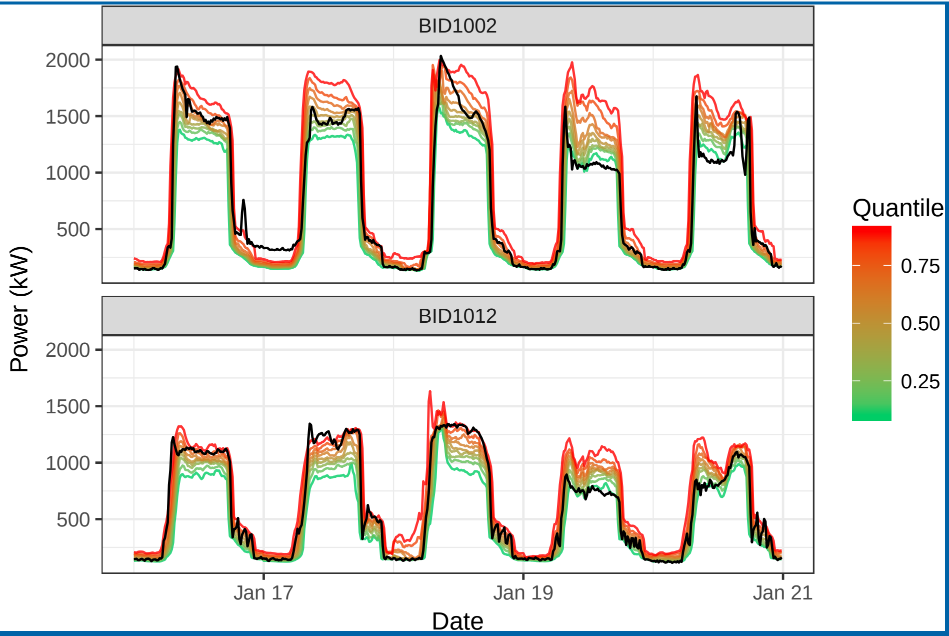
Use the pinball loss function:

$$S_p\left(y, q_p\right) = \begin{cases} p(y - q_p) & \text{for } y \quad q_p, \\ (1-p)(q_p - y) & \text{for } q_p > y. \end{cases}$$





Quantile Regression Forecasting



Assessing performance

- Forecasting a full distribution allows facilities managers to better assess risks and take appropriate actions.
- Allows facilities managers to know the severity **and probability** of demand peaks.
- Can immediately assess if a building's performance was good compared to historical performance under similar conditions.

Competitions, conferences and resources

GEFCom

Global Energy Forecasting Competitions

- Organized by Professor Tao Hong (UNC)
- GEFCom 2012: Load, Wind Forecasting
- GEFCom 2014: Load, Price, Wind, Solar Forecasting
- GEFCom 2017: Hierarchical probabilistic forecasts, real-time, rolling origin.
- **gefcom.org**
- Winning entries published in *International Journal of Forecasting*.
- Huge improvements in forecast accuracy over previously published methods.

International Symposium on Energy Analytics 2017

Predictive Energy Analytics in the Big Data World

Proudly sponsored by International Institute of Forecasters

June 22–23, 2017

Cairns, Australia

Featured speakers

- Yannig Goude, Electricite de France, France
- Rob J Hyndman, Monash University, Australia
- Pierre Pinson, Technical University of Denmark, Denmark
- Richard Povinelli, Marquette University, USA
- Rafal Weron, Wroclaw University of Technology, Poland
- Hamidreza Zareipour, University of Calgary, Canada
- Xun Zhang, Chinese Academy of Sciences, China

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28 February Proposals for invited sessions
28 February Travel grant applications due
17 March Abstract submission deadline
31 March Abstract acceptance/rejection
14 April Early registration deadline

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Some resources

Blogs

- robjhyndman.com/hyndsight/
- blog.drhongtao.com/

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Organizations

- International Institute of Forecasters: forecasters.org
- IEEE Working Group on Energy Forecasting: linkedin.com/groups/ IEEE-Working-Group-on-Energy-4148276

References

References

- Rob J Hyndman and Shu Fan (2010). "Density forecasting for long-term peak electricity demand". *IEEE Transactions on Power Systems* **25**(2), 1142–1153.
- Shu Fan and Rob J Hyndman (2012). "Short-term load forecasting based on a semi-parametric additive model". *IEEE Transactions on Power Systems* **27**(1), 134–141.
- Souhaib Ben Taieb and Rob J Hyndman (2014). "A gradient boosting approach to the Kaggle load forecasting competition". *International Journal of Forecasting* **30**(2), 382–394
- Souhaib Ben Taieb, Raphael Huser, Rob J Hyndman, and Marc G Genton (2015). *Probabilistic time series forecasting with boosted additive models: an application to smart meter data*. Working paper 15/12. Monash University
- Souhaib Ben Taieb, Raphael Huser, Rob J Hyndman, and Marc G Genton (2016). "Forecasting uncertainty in electricity smart meter data by boosting additive quantile regression". *IEEE Transactions on Smart Grid* **7** (5), 2448–2455
- Rob J Hyndman, Alan J Lee, and Earo Wang (2016). "Fast computation of reconciled forecasts for hierarchical and grouped time series". *Computational Statistics & Data Analysis* **97**, 16–32.
- Souhaib Ben Taieb, James W Taylor, and Rob J Hyndman (2017). *Coherent Probabilistic Forecasts for Hierarchical Time Series*. Working paper 17/03. Monash University