Probabilistic Load Forecasting using Ensemble Weather Forecast

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Motivation

- Accurate prediction of building energy load is crucial for control optimization and management of energy resources
- Numerical Weather Predictions can provide probabilistic forecasting of weather variables related to energy demand, but requires some calibration and statistical-postprocessing

Challenges

- Cooling water consumption are usually underpredicted during heat waves (rare and extreme events)
- Limited amount of data are available for days with unusually high temperature

Gaussian Process Regression

Denote \( x \) as our weather forecast variable and \( f(x) \) as our true observation of temperature, then we construct our model using the following covariance matrix:
\[
\text{Cov}(f(x_1), f(x_2)) = C(x_1, x_2)
\]

Then given training data,
\[
y_{\text{train}} = (f(x_1), ..., f(x_n)), x_{\text{train}} = (x_1, ..., x_n),
\]
to predict temperature \( f(x) \) with weather forecast variable, we have
\[
\begin{bmatrix}
    f(x) \\
y_{\text{train}}
\end{bmatrix} \sim N(\mu, \Sigma),
\]
\[
\Sigma = \begin{bmatrix}
    C(x, x) & C(x, x_{\text{train}}) \\
    C(x_{\text{train}}, x) & C(x_{\text{train}}, x_{\text{train}})
\end{bmatrix}
\]
\[
\mu = (\mu_x, \mu_{\text{train}})
\]

Hence,
\[
E(f(x)|y_{\text{train}}) = \mu_x - C(x, x_{\text{train}})C(x_{\text{train}}, x_{\text{train}})^{-1}(y_{\text{train}} - \mu_{\text{train}})
\]
\[
\text{Var}(f(x)|y_{\text{train}}) = C(x, x) - C(x, x_{\text{train}})C(x_{\text{train}}, x_{\text{train}})^{-1}C(x_{\text{train}}, x)
\]

Ensemble Model Output Statistics

We view our true temperature \( T_i \) as realizations from a parametrized normal distribution:
\[
T_i \sim N(\alpha + \beta m_i, \gamma + \delta s_i)
\]
Then we can find optimal values of parameters \( \alpha, \beta, \gamma \) and \( \delta \) by minimizing the negative log-likelihood:
\[
L(\alpha, \beta, \gamma, \delta) = \frac{1}{2} \sum_i \left( \frac{(T_i - \alpha - \beta m_i)^2}{\gamma + \delta s_i} + \sum \log(\gamma + \delta s_i) \right)
\]
We can optimize by using automatic differentiation and custom machine learning optimizers:

Linear Regression with Autoregressive Errors

We can predict the logarithm of cooling load using weather forecast and historical data:
\[
\log(c_t) = \beta t + \omega_t + \epsilon_t, \omega_t = \alpha_1 \omega_{t-1} + \alpha_2 \omega_{t-2}
\]

Calibrated Normal distribution

Probabilistic Prediction of Temperature