Probabilistic Machine Learning
Lecture 11
Gaussian Process Regression:
An Extensive Example

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25 May 2020

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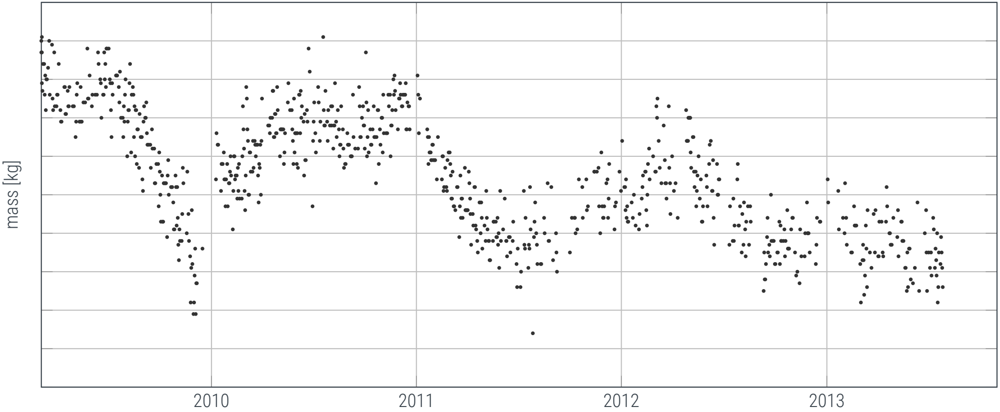
A Dataset

(c) P. Hennig, 2007–2013



A Dataset

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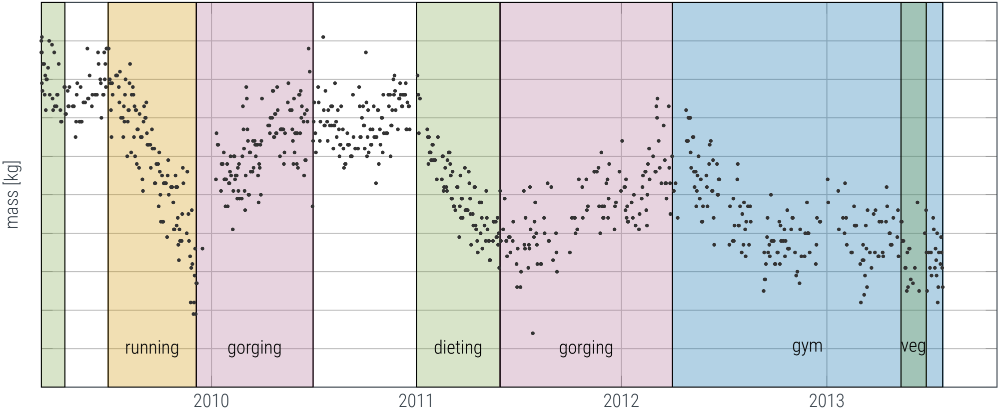

Seeger et al. NeurIPS 2016

Bayesian Intermittent Demand Forecasting for Large Inventories

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Abstract

We present a scalable and robust Bayesian method for demand forecasting in the context of a large e-commerce platform, paying special attention to intermittent and bursty target statistics. Inference is approximated by the Newton-Raphson algorithm, reduced to linear-time Kalman smoothing, which allows us to operate on several orders of magnitude larger problems than previous related work. In a study on large real-world sales datasets, our method outperforms competing approaches on fast and medium moving items.

Matthias Seeger
Principal ML Scientist, Amazon
MPI Tübingen, 2006–2011

Summary:

- An unstructured kernel regression model can only do so much. **Extrapolation** and extracting **structural knowledge** require prior knowledge about the **causal structure**.
- Linear models with elaborate features can be quite expressive, while remaining interpretable (try doing this example with a deep network!)
- Physical processes have **units**
- Complicated processes require complicated (and questionable!) prior assumptions
- analogous process in business environments
  - demand and supply **forecasting**
  - financial engineering
  - ad placement (with minor variations)
  - …

The ability to build structured predictive models is a **key skill**. Everyone can run a TensorFlow script! Masters of structured probabilistic inference are highly sought after.