

# PROBABILISTIC INFERENCE AND LEARNING

## LECTURE 08

### GAUSSIAN PROCESS REGRESSION: AN EXTENSIVE EXAMPLE

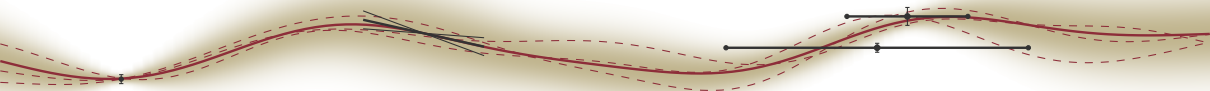
Philipp Hennig

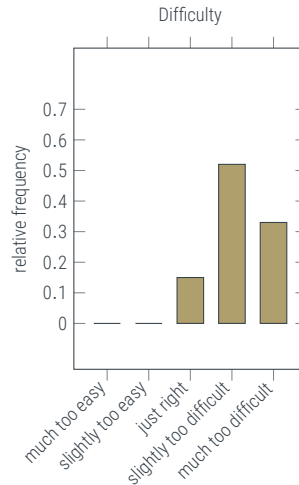
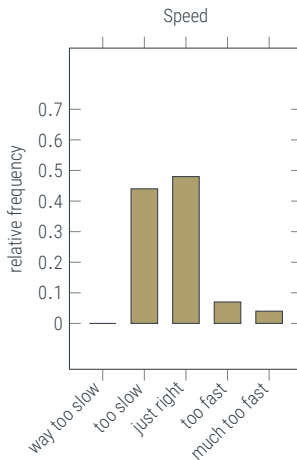
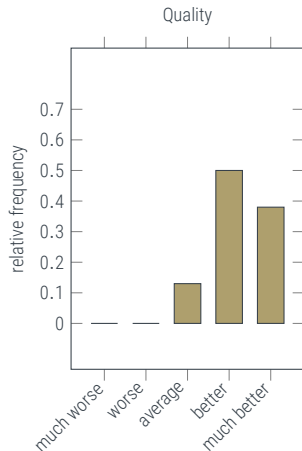
12 November 2018

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CHAIR FOR THE METHODS OF MACHINE LEARNING







## Things you did not like:

- ✦ the math
- ✦ not enough math!
- ✦ "please upload slides before lecture"
- ✦ "too fast toward the end"

## Things you did not understand:

- ✦ the math
- ✦ the RKHS bit
- ✦ the final third

## Things you enjoyed:

- ✦ the math
- ✦ explanations at beginning
- ✦ frequent repetition of "simple" concepts for added clarity
- ✦ that the slides were uploaded before the lecture
- ✦ links to background
- ✦ the RKHS explanations

## Overview of Lectures so far:

0. Introduction to Reasoning under Uncertainty
1. Probabilistic Reasoning
2. Probabilities over Continuous Variables
3. Gaussian Probability Distributions
4. Gaussian Parametric Regression
5. More on Parametric Regression – Connections to Deep Learning
6. Gaussian Processes
7. More on Kernels & GPs

## Today:

- ✦ a concrete example of GP regression

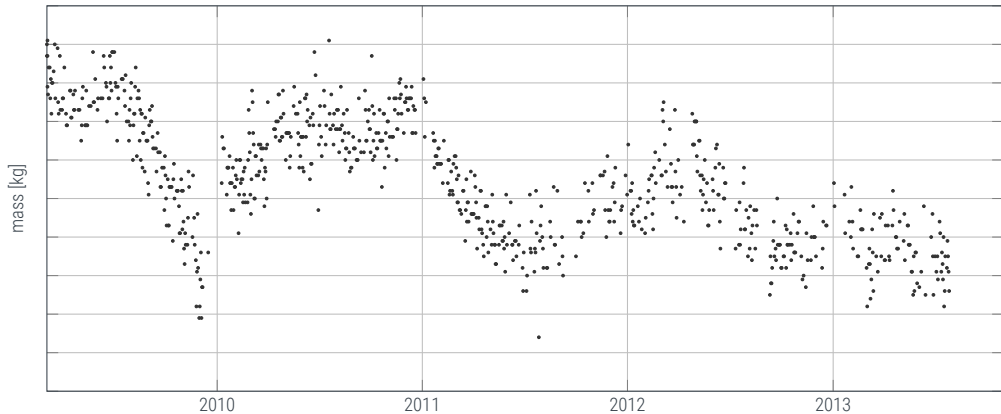


## today's lecture:

- ✦ getting our hands dirty with a simple but realistic problem
- ✦ mostly code
- ✦ a simple (1D) dataset, but with significant structure

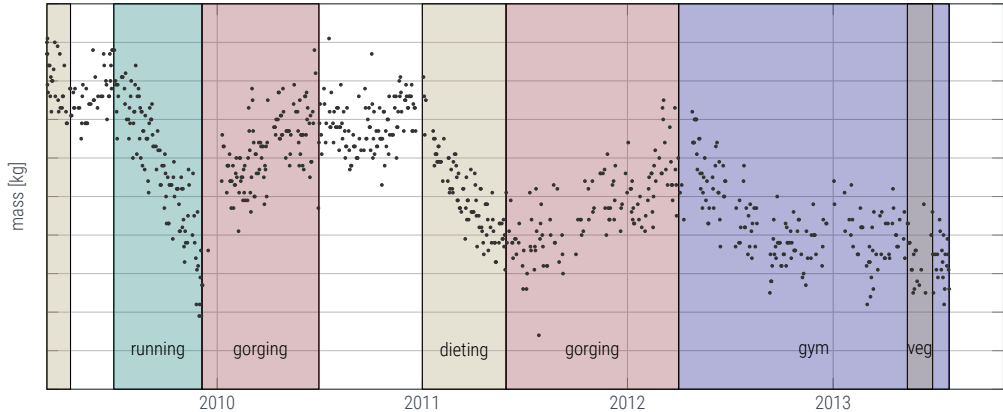
# A Dataset

(c) P. Hennig, 2007–2013



# A Dataset

(c) P. Hennig, 2007–2013





## Bayesian Intermittent Demand Forecasting for Large Inventories

**Matthias Seeger, David Salinas, Valentin Flunkert**

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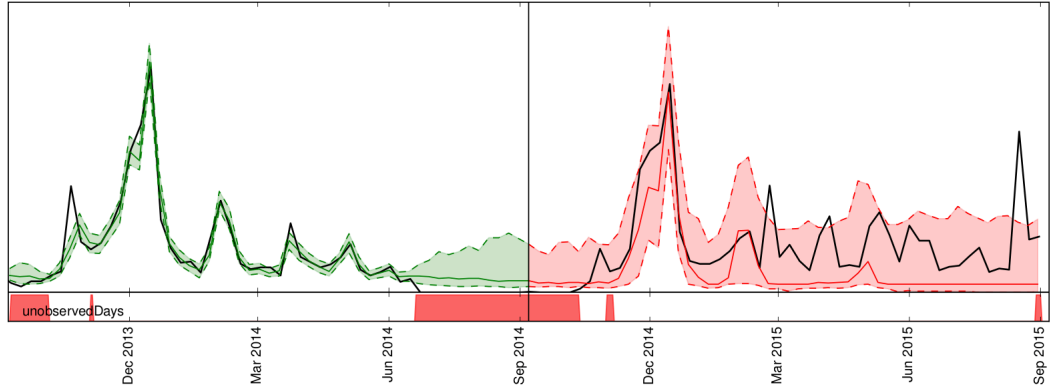
### Abstract

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.

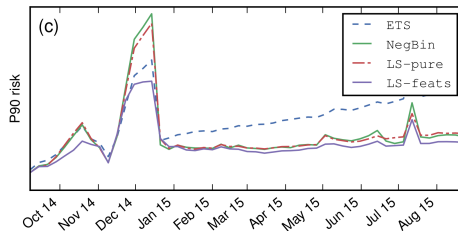
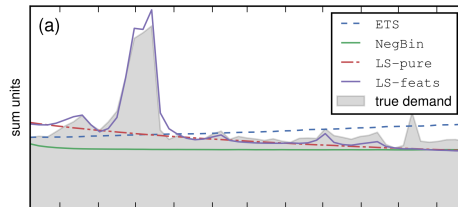
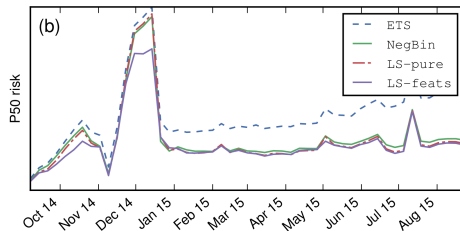


Matthias Seeger  
Principal Applied Scientist, Amazon  
MPI Tübingen, 2006–2011





	Parts	EC-sub	EC-all
# items	19874	39700	534884
Unit $t$	month	day	day
Median $CV^2$	2.4	5.8	9.7
Freq. $z_t = 0$	54%	46%	83%
In-stock ratio	100%	73%	71%
Avg. size series	33	329	293
# item-days	656K	13M	157M



## Summary:

- ✦ An unstructured kernel regression model can only do so much. **Extrapolation** and extracting **structural knowledge** require prior knowledge about **causal process**
- ✦ 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.