

Modern Gaussian Processes: Scalable Inference and Novel Applications

(Part I-a) Introduction

Edwin V. Bonilla and **Maurizio Filippone**

CSIRO's Data61, Sydney, Australia and EURECOM, Sophia Antipolis, France

July 14th, 2019



Gaussian Processes for Machine Learning

Carl E. Rasmussen and Christopher K. I. Williams, 2006

Pattern Recognition and Machine Learning

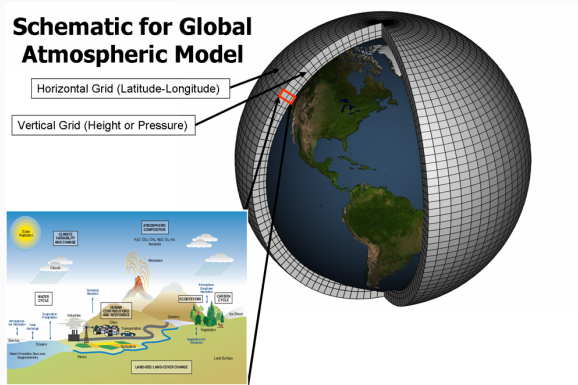
Christopher Bishop, 2006

Tutorial webpage

<https://ebonilla.github.io/gaussianprocesses>

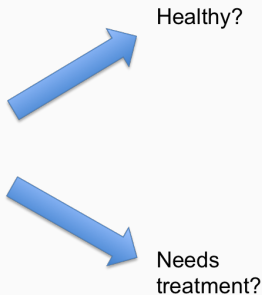
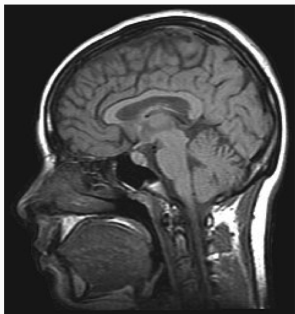
Motivation

- Climate modeling



Motivation

- Classification and progression modeling of neurodegenerative diseases



A Unified Framework

A model might be expensive to simulate/inaccurate

- Emulate model/discrepancy using a surrogate

A Unified Framework

A model might be expensive to simulate/inaccurate

- Emulate model/discrepancy using a surrogate

A model might not even be available

- Make use of a flexible model, e.g., Neural Nets

A Unified Framework

A model might be expensive to simulate/inaccurate

- Emulate model/discrepancy using a surrogate

A model might not even be available

- Make use of a flexible model, e.g., Neural Nets

Quantification of Uncertainty

- Bayesian Neural Nets
- Gaussian Processes

Refresher on Probabilities

Consider two continuous random variables x and y

- Sum rule:

$$p(x) = \int p(x, y) dy$$

- Product rule:

$$p(x, y) = p(x|y)p(y) = p(y|x)p(x)$$

Refresher on Probabilities

Consider two continuous random variables x and y

- Sum rule:

$$p(x) = \int p(x, y) dy$$

- Product rule:

$$p(x, y) = p(x|y)p(y) = p(y|x)p(x)$$

- Bayes' rule:

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)}$$

- NOTE: Bayes' rule is a direct consequence of the product rule

This Tutorial: Outline

- 1 Preamble [MF]
 - ▶ Introduction
 - ▶ Definition of Gaussian Processes
- 2 Approximations
 - ▶ Model Approximations [MF]
 \implies Break \longleftarrow
 - ▶ Inference [EVB]
- 3 Applications, Challenges & Opportunities [EVB]
- 4 Theory and Code [MF]