Bayesian nonparametrics in machine learning

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Outline

Supervised learning with Gaussian Processes

From linear regression to GPs [2, Chapter 2]
Basic theory: Existence and conditioning for GPs [1, Chapter 4]
Modeling with GPs [2, Chapter 4]
Inferring GPs [2, Chapter 5]
Some more applications
References and open issues

Density estimation and clustering with Dirichlet processes

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Commonly-used kernels

covariance function	expression	S	ND
constant	σ_0^2	$\surd$	
linear	$\sum_{d=1}^{D} \sigma_d^2 x_d x'_d$		
polynomial	$(\mathbf{x} \cdot \mathbf{x}' + \sigma_0^2)^p$		
squared exponential	$\exp(-\frac{r^2}{2\ell^2})$	$\surd$	$\surd$
Matérn	$\frac{1}{2^{\nu-1}\Gamma(\nu)} \left(\frac{\sqrt{2\nu}}{\ell} r\right)^{\nu} K_\nu \left(\frac{\sqrt{2\nu}}{\ell} r\right)$	$\surd$	$\surd$
exponential	$\exp(-\frac{r}{\ell})$	$\surd$	$\surd$
γ-exponential	$\exp\left(-(\frac{r}{\ell})^\gamma\right)$	$\surd$	$\surd$
rational quadratic	$(1 + \frac{r^2}{2\alpha\ell^2})^{-\alpha}$	$\surd$	$\surd$
neural network	$\sin^{-1}\left(\frac{2\tilde{\mathbf{x}}^\top \Sigma \tilde{\mathbf{x}}'}{\sqrt{(1+2\tilde{\mathbf{x}}^\top \Sigma \tilde{\mathbf{x}})(1+2\tilde{\mathbf{x}}'^\top \Sigma \tilde{\mathbf{x}}')}}\right)$		$\surd$

Table 4.1: Summary of several commonly-used covariance functions. The covariances are written either as a function of $\mathbf{x}$ and $\mathbf{x}'$, or as a function of $r = |\mathbf{x} - \mathbf{x}'|$. Two columns marked 'S' and 'ND' indicate whether the covariance functions are stationary and nondegenerate respectively. Degenerate covariance functions have finite rank, see section 4.3 for more discussion of this issue.

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Emulators of expensive models

PLOS | ONE

RESEARCH ARTICLE

Bayesian Sensitivity Analysis of a Cardiac Cell Model Using a Gaussian Process Emulator

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Abstract

Models of electrical activity in cardiac cells have become important research tools as they can provide a quantitative description of detailed and integrative physiology. However, cardiac cell models have many parameters, and how uncertainties in these parameters affect the model output is difficult to assess without undertaking large numbers of model runs. In this study we show that a surrogate statistical model of a cardiac cell model (the Luo-Rudy 1991 model) can be built using Gaussian process (GP) emulators. Using this approach we

Nonparametric fits

Gaussian Process Cosmography

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(Dated: July 11, 2012)

Gaussian processes provide a method for extracting cosmological information from observations without assuming a cosmological model. We carry out cosmography – mapping the time evolution of the cosmic expansion – in a model-independent manner using kinematic variables and a geometric probe of cosmology. Using the state of the art supernova distance data from the Union2.1 compilation, we constrain, without any assumptions about dark energy parametrization or matter density, the Hubble parameter and deceleration parameter as a function of redshift. Extraction of these relations is tested successfully against models with features on various coherence scales, subject to certain statistical cautions.

I. INTRODUCTION

Cosmic acceleration is a fundamental mystery of great interest and importance to understanding cosmology, gravitation, and high energy physics. The cosmic expansion rate is slowed down by gravitationally attractive matter and sped up by some other, unknown contribution to the dynamical equations. While great effort is being put into identifying the source of this extra dark energy contribution, the overall expansion behavior also holds important clues to origin, evolution, and present

ing procedures have been suggested, e.g. [6], but tend to induce bias in the function reconstruction due to parametric restriction of the behavior or to have poor error control. Using a general orthonormal basis or principal component analysis is another approach, to describe the distance-redshift relation (e.g. [7]) or the deceleration parameter [8], or using a correlated prior for smoothness on the dark energy equation of state [9], but in practice a finite (and small) number of modes is significant beyond the prior, essentially reducing to a parametric approach. Gaussian processes [10] offer an interesting possibility for

Natural language processing

Using Gaussian Processes for Rumour Stance Classification in Social Media

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Social media tend to be rife with rumours while new reports are released piecemeal during breaking news. Interestingly, one can mine multiple reactions expressed by social media users in those situations, exploring their stance towards rumours, ultimately enabling the flagging of highly disputed rumours as being potentially false. In this work, we set out to develop an automated, supervised classifier that uses multi-task learning to classify the stance expressed in each individual tweet in a rumourous conversation as either supporting, denying or questioning the rumour. Using a classifier based on Gaussian Processes, and exploring its effectiveness on two datasets with very different characteristics and varying distributions of stances, we show that our approach consistently outperforms competitive baseline classifiers. Our classifier is especially effective in estimating the distribution of different types of stance associated with a given rumour, which we set forth as a desired characteristic for a rumour-tracking system that will warn both ordinary users of Twitter and professional news practitioners when a rumour is being rebutted.

1. INTRODUCTION

There is an increasing need to interpret and act upon rumours spreading quickly through social media during breaking news, where new reports are released piecemeal and often have an unverified

Bayesian optimization for hyperparameter tuning

Algorithms for Hyper-Parameter Optimization

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Abstract

Several recent advances to the state of the art in image classification benchmarks have come from better configurations of existing techniques rather than novel approaches to feature learning. Traditionally, hyper-parameter optimization has been the job of humans because they can be very efficient in regimes where only a few

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References

- Textbook by C. Rasmussen and C. Williams [2],
  - great for understanding, methods, pointers to ML and stats.
- Similar videolecture by C. Rasmussen.
- lecture notes by P. Orbanz [1].
  - mathematically clean, without losing the focus on ML.

Some open issues

- Fully Bayesian scalable approaches!
- Natural approaches to constrained GPs.
- Links with other models based on Gaussians and geometry.

References I

[1] P. Orbanz.
Lecture notes on Bayesian nonparametrics, 2014.

[2] C. E. Rasmussen and C. K. I. Williams.
Gaussian Processes for Machine Learning.
MIT Press, 2006.