Parametric Empirical Bayes Methods For Ecological Applications

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Bayesian Hierarchical Models

Bayesian Hierarchical Models

1. Bayes EstimationIntroduction to Bayesian statistics, part 1: The basic concepts ~~Bayesian Data Science: Probabilistic Programming | SciPy 2019 Tutorial | Eric Ma~~ ~~17. Bayesian Statistics~~ Statistics for Genomics: Advanced Differential Expression ~~Empirical Bayesian Credibility Theory Model~~ Effect sizes and Bayes factors Lecture 11: Nonparametric Bayes 3. Bayes Estimation Example ~~\"Bayesian Methods and Probabilistic Models\" with Allen Downey~~ 1. Maximum Likelihood Estimation Basics ~~A visual guide to Bayesian thinking~~ Bayesian vs frequentist statistics

How MLE (Maximum Likelihood Estimation) algorithm works~~StatQuest: Probability vs Likelihood~~ Bayesian Inference: An Easy Example 26 - Prior and posterior predictive distributions - an introduction (ML 7.1) Bayesian inference - A simple example

Maximum Likelihood Estimation and Bayesian Estimation~~Very basic introduction to Bayesian estimation using R~~ BE L21: Empirical Bayes \u0026 Stein Estimation (Chapter 16, Section 1 SFET) (02 May 2016) ~~Bayesian or Frequentist, Which Are You? By Michael I. Jordan (Part 1 of 2)~~ L14.4 The Bayesian Inference Framework ~~Bayesian Deep Learning and Probabilistic Model Construction - ICML 2020 Tutorial~~ Bayesian Analysis (FRM Part 1 Book 2 Chapter 4)

Priors and Hierarchical Bayesian Modeling StatQuest: Maximum Likelihood, clearly explained!!! All About that Bayes: Probability, Statistics, and the Quest to Quantify Uncertainty ~~Parametric Empirical Bayes Methods For~~

Empirical Bayes methods are procedures for statistical inference in which the prior distribution is estimated from the data. This approach stands in contrast to standard Bayesian methods, for which the prior distribution is fixed before any data are observed. Despite this difference in perspective, empirical Bayes may be viewed as an approximation to a fully Bayesian treatment of a hierarchical model wherein the parameters at the highest level of the hierarchy are set to their most likely values

~~Empirical Bayes method - Wikipedia~~

In the broadest sense, the underlying goal of an empirical Bayes method is to use Bayesian methods without fully specifying the prior, either by estimating the prior or its parameters.

~~Parametric Empirical Bayes Methods for Ecological Applications~~

PARAMETRIC EMPIRICAL BAYES METHODS FOR ECOLOGICAL APPLICATIONS1 JAY M. VER HOEF Alaska Department ofFish and Game, 1300 College Road, Fairbanks, Alaska 99701 USA Abstract. This paper reviews ...

~~PARAMETRIC EMPIRICAL BAYES METHODS FOR ECOLOGICAL APPLICATIONS~~

There are several common parametric empirical Bayes models, including the Poissongamma model (below), the Beta-binomial model, the GaussianGaussian model, the Dirichlet-multinomial model, as well specific models for Bayesian linear regression (see below) and Bayesian multivariate linear regression.

~~Empirical Bayes method - WikiMili, The Best Wikipedia Reader~~

Parametric Empirical Bayes Methods for Microarrays Ming Yuan, Deepayan Sarkar, Michael Newton and Christina Kendziorski April 3, 2013 Contents 1 Introduction 1 2 General Model Structure: Two Conditions 2 3 Multiple Conditions 3 4 The Three Models 4

~~Parametric Empirical Bayes Methods for Microarrays~~

Estimate a second level PEB (Parametric Empirical Bayes) model . Having finished the first level analysis, we now create a second level (group) general linear model over the parameters: In the batch editor select SPM -> DCM -> Second level -> Specify / Estimate PEB. Give the analysis a name and select the GCM file created above.

~~SPM/Parametric Empirical Bayes (PEB) - Wikibooks, open ...~~

This chapter outlines parametric empirical Bayes confidence intervals. Empirical Bayes modeling assumes the distributions for the parameters = (1, , k) exist, with taken from a known class of possible parameter distributions. is considered independent N (u, A) distributions on R k. It is called parametric empirical Bayes problem, because   is determined by the parameters (u, A) and so is a parametric family of distributions.

~~Parametric Empirical Bayes Confidence Intervals ...~~

Empirical Bayes The constraints of slow mechanical computation molded classical statistics into a mathe- matically ingenious theory of sharply delimited scope. Emerging after the Second World War, electronic computation loosened the computational stranglehold, allowing a more expansive and useful statistical methodology.

~~Empirical Bayes - Stanford University~~

The idea with empirical Bayesian methods is to use the Bayesian set-up but to estimate the priors from the population of all features. Formally speaking, empirical Bayes are frequentist methods which produce p-values and confidence intervals. However, because we have the empirical priors, we can also use some of the probabilistic ideas from Bayesian analysis. We will be using empirical Bayes methods for differential expression analysis. Moderated Methods

~~2.10 - Bayes, Empirical Bayes and Moderated Methods | STAT 555~~

Assuming first that (51, fli), i = 1, 2, are known, the Bayes estimator of p, with respect to a squared error loss function is given by. ~13 = E(pIX) = (n + 5 1)(~j=IVj " +. (m + 52-1)(~_~in=lUi + ill)'. and the empirical Bayes estimator is defined as. ~ (n + &l)(~7=lVj+ fl2)

~~Empirical Bayes estimation for queueing systems and networks~~

Empirical Bayes methods are a collection of ways to estimate and update the parameters of a prior probability before creating a posterior probability distribution. This technique still follows the general Bayesian statistics model, but turns the process of estimating initial assumptions (prior probability) into a two-step procedure. Empirical Bayes estimation is used instead of the Maximum Entropy Principle when more than one parameter is known, but still not enough is known to create a ...

~~Empirical Bayes Methods Definition | DeepAI~~

empirical Bayesian approach to any hierarchical model that can be expressed in terms of an arbitrary (nonlinear) model at the ﬁrst level and a standard (parametric) empirical Bayesian (PEB) model at higher levels (Efron and Morris, 1973; Kass and Steffey, 1989). In other words, if the parameters of a nonlinear model of subject-speciﬁc data ...

~~Bayesian model reduction and empirical Bayes for group ...~~

Abstract Empirical Bayes methods are often thought of as a bridge between classical and Bayesian inference. In fact, in the literature the term empirical Bayes is used in quite diverse contexts and...

~~(PDF) Empirical Bayes methods in classical and Bayesian ...~~

We show that parametric bootstrapping and empirical Bayes methods for variance shrinkage can improve rhythm detection in genome-wide expression time series. We demonstrate these approaches by building on the empirical JTK_CYCLE method (eJTK) to formulate a method that we term BooteJTK.

~~Bootstrapping and Empirical Bayes Methods Improve Rhythm ...~~

This chapter discusses the Empirical Bayes (EB) method in the context of small area estimation, particularly focusing on parametric empirical Bayes (PEB) approach to small area estimation. The basic area level model with normal random effects is used to introduce the EB methodology. A jackknife method of mean squared error (MSE) estimation is then provided.

~~Empirical Bayes (EB) Method - Small Area Estimation ...~~

alternative method, called the Chinese Restaurant Process or in nite P olya urn (Blackwell 1973). The algorithm is as follows. 1.Draw X 1 F 0. 2.For i= 2;:::;n: draw X ijX 1;:::X i 1 = XF i 1 with probability i 1 i+ 1 XF 0 with probability i+ 1 where F i 1 is the empirical distribution of X 1;:::X i 1. The sample X 1;:::;X n is likely to have ties since F is discrete. Let X

~~Nonparametric Bayesian Methods 1 What is Nonparametric Bayes?~~

deal here only with parametric empirical Bayes methods and will refer to them simply as empirical Bayes methods. Although the idea of a parametric empirical Bayes anal-ysis is not new, the first major work in this area did not appear until the early 1970s in a series of papers by Efron and Morris (1972, 1973, 1975), and one might rightfully

~~An Introduction to Empirical Bayes Data Analysis~~

We compare our method with FAIR and other classiﬁcation meth ods in simulation for sparse and non sparse setups, and in real data examples involving classiﬁcation of normal versus malignant tissues based on microarray data. Keywords: non parametric empirical Bayes, high dimension, classiﬁca tion 1. Introduction

Parametric empirical Bayes methods of point estimation date to the landmark paper of James and Stein (1961). Interval estimation through parametric empirical Bayes techniques has a somewhat shorter history, which is summarized in the recent paper of Laird and Louis (1987). In the exchangeable case, one obtains a naive EB confidence interval by simply taking appropriate percentiles of the estimated posterior distribution of the parameter, where the estimation of the prior parameters (hyperparameters) is accomplished through marginal distribution of the data. Unfortunately, these naive intervals tend to be too short, since they fail to account for the variability in the estimation of the hyperparameters. That is, they don't attain the desired coverage probability in the EB sense defined in Morris (1983a, b). They also provide no statement of conditional calibration (Rubin, 1984). This paper proposes a conditional bias correction method for developing EB intervals which corrects these deficiencies in the naive intervals. As an alternative, several authors have suggested use of the marginal posterior in this regard. We attempt to clarify its role in achieving EB coverage. Results of extensive simulation of coverage probability and interval length for these approaches are presented in the context of several illustrative examples. Keywords: Bias correction, Parametric bootstrap, Conditional calibration. (kr).

Many modern statistical problems require making similar decisions or estimates for many different entities. For example, we may ask whether each of 10,000 genes is associated with some disease, or try to measure the degree to which each is associated with the disease. As in this example, the entities can often be divided into a vast majority of "null" objects and a small minority of interesting ones. Empirical Bayes is a useful technique for such situations, but finding the right empirical Bayes method for each problem can be difficult. Mixture models, however, provide an easy and effective way to apply empirical Bayes. This thesis motivates mixture models by analyzing a simple high-dimensional problem, and shows their practical use by applying them to detecting single nucleotide polymorphisms.

The second edition of Empirical Bayes Methods details are provided of the derivation and the performance of empirical Bayes rules for a variety of special models. Attention is given to the problem of assessing the goodness of an empirical Bayes estimator for a given set of prior data. A chapter is devoted to a discussion of alternatives to the empirical Bayes approach and there is also a chapter giving details of several actual applications of empirical Bayes method.

Bayesian and such approaches to inference have a number of points of close contact, especially from an asymptotic point of view. Both emphasize the construction of interval estimates of unknown parameters. In this volume, researchers present recent work on several aspects of Bayesian, likelihood and empirical Bayes methods, presented at a workshop held in Montreal, Canada. The goal of the workshop was to explore the linkages among the methods, and to suggest new directions for research in the theory of inference.

WILEY-INTERSCIENCE PAPERBACK SERIES The Wiley-Interscience Paperback Series consists of selected books that have been made more accessible to consumers in an effort to increase global appeal and general circulation. With these new unabridged softcover volumes, Wiley hopes to extend the lives of these works by making them available to future generations of statisticians, mathematicians, and scientists. ". . .Variance Components is an excellent book. It is organized and well written, and provides many references to a variety of topics. I recommend it to anyone with interest in linear models." Journal of the American Statistical Association "This book provides a broad coverage of methods for estimating variance components which appeal to students and research workers . . . The authors make an outstanding contribution to teaching and research in the field of variance component estimation." Mathematical Reviews "The authors have done an excellent job in collecting materials on a broad range of topics. Readers will indeed gain from using this book . . . I must say that the authors have done a commendable job in their scholarly presentation." Technometrics This book focuses on summarizing the variability of statistical data known as the analysis of variance table. Penned in a readable style, it provides an up-to-date treatment of research in the area. The book begins with the history of analysis of variance and continues with discussions of balanced data, analysis of variance for unbalanced data, predictions of random variables, hierarchical models and Bayesian estimation, binary and discrete data, and the dispersion mean model.

An accessible introduction to indirect estimation methods, both traditional and model-based. Readers will also find the latest methods for measuring the variability of the estimates as well as the techniques for model validation. Uses a basic area-level linear model to illustrate the methods Presents the various extensions including binary response data through generalized linear models and time series data through linear models that combine cross-sectional and time series features Provides recent applications of SAE including several in U.S. Federal programs Offers a comprehensive discussion of the design issues that impact SAE

"At Statistics Canada, acceptance sampling is used as a method of quality control for survey processing operations. The sampling plans which are used will ensure minimum inspection at a specific incoming error level. This error level is estimated by a quantity known as the process average. It is an unknown parameter which is usually estimated from current inspection results, but frequently the estimation is difficult because of small sample sizes. Greater accuracy in the estimate may be produced by using more data from previous samples to improve upon the current sample result. A non-parametric empirical Bayes estimator of the process average is presented. An approximate confidence interval is also constructed. Examples are provided"--Abstract.

We live in a new age for statistical inference, where modern scientific technology such as microarrays and fMRI machines routinely produce thousands and sometimes millions of parallel data sets, each with its own estimation or testing problem. Doing thousands of problems at once is more than repeated application of classical methods. Taking an empirical Bayes approach, Bradley Efron, inventor of the bootstrap, shows how information accrues across problems in a way that combines Bayesian and frequentist ideas. Estimation, testing and prediction blend in this framework, producing opportunities for new methodologies of increased power. New difficulties also arise, easily leading to flawed inferences. This book takes a careful look at both the promise and pitfalls of large-scale statistical inference, with particular attention to false discovery rates, the most successful of the new statistical techniques. Emphasis is on the inferential ideas underlying technical developments, illustrated using a large number of real examples.