Qualifying Exam Preparation IV
Computational Statistics

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Contents

Preface

Textbook: Computational Statistics by G. H. Givens and J. A. Hoeting (GH)
TBD

Part I

STAT598G Topics

Chapter 1

Basic Computer Knowledge

1.1 Computer Organization, File Systems, Process Management, I/O Devices, Basic Linux Commands

1.2 Programming Languages, Interpreters and Compilers

Chapter 2

C & R Programming Languages

2.1 Basic Variable Types and Scope

2.2 Control Flows: if-else, for/while Loops

2.3 Functions

2.4 I/O Access

2.5 Pointers and Dynamic Memory allocation in C

2.6 Underflow and Overflow

2.7 Vector, Matrix and Distributions in R

2.8 Graphics in R; Calling C from R

Chapter 3

Algorithm and Data Structures

Chapter 4

Statistical applications

4.1 Nonlinear Optimization : Gradient Descent, Coordinate Descent, Newton's Method, Line Search

4.2 Sampling: Generating Uniform Random Numbers, Transformation Method, Importance Sampling, Acceptance Sampling

4.3 Hidden Markov Models: Basic Definitions, Viterby Algorithm and Computing Forward and Backward Probabilities

4.4 Markov Random Fields, the Hammersley-Clifford Theorem, the Elimination Algorithm

4.5 Bootstrap

Part II

STAT598D Topics

Chapter 5

Optimization

5.1 Unconstrained Optimization

5.1.1 Univariate Problems (Bisection, Newton)

Bisection Method

Suppose g' is continuous on $[a_0, b_0]$ and $g'(a_0)g'(b_0) \leq 0$, then the Intermediate Value Theorem implies that there exists at least one x^* for which $g'(x^*) = 0$ and hence x^* is a local optimum of g. To find this local optimum, the Bisection Method systematically halves the interval at each iteration, by checking the product of g'.

The updating equations are

$$[a_{t+1}, b_{t+1}] = \begin{cases} [a_t, x^{(t)}], & \text{if } g'(a_t)g'(x^t) \leq 0 \\ [x^{(t)}, b_t], & \text{if } g'(a_t)g'(x^t) > 0 \end{cases} \tag{5.1}$$

and $x^{t+1} = \frac{a_{t+1}+b_{t+1}}{2}$.

Newton's Method

Suppose g twice differentiable. At iteration t, Newton's method approximates $g'(x^*)$ by the linear Taylor series expansion:

$$g'(x^*) = g'(x^{(t)}) + (x^* - x^{(t)})(g''(x^{(t)})) \tag{5.2}$$

which gives us

$$x^* = x - \frac{g'(x^{(t)})}{g''(x^{(t)})} \tag{5.3}$$

5.2 Quasi-Newton Methods

5.3 Simulated annealing

Chapter 6

The EM-type Algorithms

6.1 The EM algorithm

6.2 The ECM and ECME algorithms

6.3 The PX-EM algorithm

6.4 Computing observed Fisher information matrix

Chapter 7

Integration

7.1 Numerical integration

7.2 Random number generation

7.3 Simulation

7.4 Monte Carlo integration

Chapter 8

Markov chain Monte Carlo (MCMC) methods

8.1 The Data Augmentation algorithm

8.2 The Gibbs sampler

8.3 The Metropolis-Hastings algorithm

8.4 Data Fusion and Particle Filter (Sequential MCMC)

8.5 Reversible jump MCMC

8.6 Convergence Diagnostics