Biostatistics 615/815 Lecture 19: Multidimensional Optimizations

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Recap: Single-dimensional minimization using parabola

Recap: Adaptive Minimization

• Parabolic interpolation often converges faster
  • The preferred algorithm
• Golden search provides worst-case performance guarantee
  • A fall-back for uncooperative functions
• Switch algorithms when convergence is slow
• Avoid testing points that are too close

Announcements

Homework

• Homework #5 due today
• Extension to Thursday is allowed

Today’s lecture

• The Simplex Method Details
• MLE estimation of mixture of normals
The Simplex Method

- Calculate likelihoods at simplex vertices
  - Geometric shape with $k + 1$ corners
  - A triangle in $k = 2$ dimensions
- Simplex crawls
  - Towards minimum
  - Away from maximum
- Probably the most widely used optimization method

Direction for Optimization

Line through worst point and average of other points

Average of all points, excluding worst point

Reflection

This is the default new trial point

Reflection and Expansion

If reflection results in new minimum...

Move further along minimization direction
Contraction (1-dimension)

Try a smaller step

If \( x' \) is still the worst point...

Contraction

"passing through the eye of a needle"

If a simple contraction doesn't improve things, then try moving all points towards the current minimum

Summary: The Simplex Method

class simplex615 { // contains (dim+1) points of size (dim)
    protected:
    std::vector<std::vector<double>> X; // (dim+1)*dim matrix
    std::vector<double> Y; // (dim+1) vector
    std::vector<double> midPoint; // variables for update
    std::vector<double> thruLine; // variables for update
    int dim, idxLo, idxHi, idxNextHi; // dimension, min, max, 2ndmax values
    void evaluateFunction(optFunc & foo); // evaluate function value at each point
    void evaluateExtremes(); // determine the min, max, 2ndmax
    void prepareUpdate(); // calculate midPoint, thruLine
    bool updateSimplex(optFunc & foo, double scale); // for reflection/expansion..
    void contractSimplex(optFunc & foo); // for multiple contraction
    static int check_tol(double fmax, double fmin, double ftol); // check tolerance
}

public:
    simplex615(double * p, int d); // constructor with initial points
    void amoeba(optFunc & foo, double tol); // main function for optimization
    std::vector<double>& xmin(); // optimal x value
    double ymin(); // optimal y value
};
Implementation overview

- Data representation
  - Each $X[i]$ is point of the simplex
  - $Y[i]$ corresponds to $f(X[i])$
  - midPoint is the average of all points (except for the worst point)
  - thruLine is vector from the worse point to the midPoint

- Reflection, Expansion and Contraction
  After calculating midPoint and thruLine
  
  Reflection: Call updateSimplex(foo, -1.0)
  Expansion: Call updateSimplex(foo, -2.0)
  Contraction: Call updateSimplex(foo, 0.5)

Evaluating function values at each simplex point

```cpp
// simple function for evaluating the function value at each simple point
// after calling this function $Y[i] = foo(X[i])$ should hold
void simplex615::evaluateFunction(optFunc& foo) {
    for(int i=0; i < dim+1; ++i) {
        Y[i] = foo(X[i]); // foo is a function object, which will be visited later
    }
}
```

Determine the best, worst, and the second-worst points

```cpp
void simplex615::evaluateExtremes() {
    if ( Y[0] > Y[1] ) {
        idxHi = 0; idxLo = idxNextHi = 1;
    } else {
        idxHi = 1; idxLo = idxNextHi = 0;
    }
    // for each of the next points
    for(int i=2; i < dim+1; ++i) {
        if ( Y[i] <= Y[idxLo] ) { // update the best point if lower
            idxLo = i;
        } else if ( Y[i] > Y[idxHi] ) { // update the worst point if higher
            idxNextHi = idxHi; idxHi = i;
        } else if ( Y[i] > Y[idxNextHi] ) { // update also if it is the 2nd-worst point
            idxNextHi = i;
        }
    }
}
```
Direction for Optimization

Determining the direction for optimization

```cpp
void simplex615::prepareUpdate() {
    for(int j=0; j < dim; ++j) {
        midPoint[j] = 0; // average of all points but the worst point
    }
    for(int i=0; i < dim+1; ++i) {
        if ( i != idxHi ) {
            // exclude the worst point
            for(int j=0; j < dim; ++j) {
                midPoint[j] += X[i][j];
            }
        }
    }
    for(int j=0; j < dim; ++j) {
        midPoint[j] /= dim; // take average
        thruLine[j] = X[idxHi][j] - midPoint[j]; // direction for optimization
    }
}
```

Updating simplex along the line

```cpp
// scale determines which point to evaluate along the line
// scale = 1 : worse point, scale = 0 : midPoint
bool simplex615::updateSimplex(optFunc& foo, double scale) {
    std::vector<double> nextPoint; // next point to evaluate
    nextPoint.resize(dim);
    for(int i=0; i < dim; ++i) {
        nextPoint[i] = midPoint[i] + scale * thruLine[i];
    }
    double fNext = foo(nextPoint);
    if ( fNext < Y[idxHi] ) { // update only maximum values (if possible)
        for(int i=0; i < dim; ++i) {
            // because the order can be changed with
            X[idxHi][i] = nextPoint[i]; // evaluateExtremes() later
        }
        Y[idxHi] = fNext;
        return true;
    } else {
        return false; // never mind if worse than the worst
    }
}
```

Reflection

```
This is the default new trial point
```
Reflection and Expansion

If reflection results in new minimum...

Move further along minimization direction

Contraction (1-dimension)

Try a smaller step

If x' is still the worst point...

Multiple Contraction

"passing through the eye of a needle"

If a simple contraction doesn't improve things, then try moving all points towards the current minimum

// if none of the tried points make things better
// reduce the search space towards the minimum point
void simplex615::contractSimplex(optFunc& foo) {
    for(int i=0; i < dim+1; ++i) {
        if (i != idxLo) {
            // except for the minimum point
            for(int j=0; j < dim; ++j) {
                X[i][j] = 0.5*( X[idxLo][j] + X[i][j] ); // move the point towards minimum
                Y[i] = foo(X[i]); // re-evaluate the function
            }
        }
    }
}
Putting things together

```cpp
void simplex615::amoeba(optFunc& foo, double tol) {
    evaluateFunction(foo); // evaluate the function at the initial points
    while(true) {
        evaluateExtremes(); // determine three important points
        prepareUpdate(); // determine direction for optimization
        if ( check_tol(Y[idxHi], Y[idxLo], tol) ) break; // check convergence
        updateSimplex(foo, -1.0); // reflection
        if ( Y[idxHi] < Y[idxLo] ) {
            updateSimplex(foo, -2.0); // expansion
        } else if ( Y[idxHi] >= Y[idxNextHi] ) {
            if ( !updateSimplex(foo, 0.5) ) { // 1-d contraction
                contractSimplex(foo); // multiple contractions
            }
        }
    }
}
```

Checking convergence

```cpp
// Note that the function is declared as "static" function as //
// static int check_tol(double fmax, double fmin, double ftol);
//
// because it does not use any member variables
int simplex615::check_tol(double fmax, double fmin, double ftol) {
    // calculate the difference
double delta = fabs(fmax - fmin);
    // calculate the relative tolerance
    double accuracy = (fabs(fmax) + fabs(fmin)) * ftol;
    // check if difference is within tolerance
    return (delta < (accuracy + ZEPS));
}
```

Using the Simplex Method Implementation

```cpp
#include <vector>
#include <cmath>
#include <iostream>
#include "simplex615.h"
#define ZEPS 1e-10

int main(int main, char** argv) {
    double point[2] = {-1.2, 1}; // initial point to start
    arbitraryOptFunc foo; // WILL BE DISCUSSED LATER
    simplex615 simplex(point, 2); // create a simplex
    simplex.amoeba(foo, 1e-7); // optimize for a function
    // print outputs
    std::cout << "Minimin = " << simplex.ymin() << ", at (" << simplex.xmin()[0] << "  ", " << simplex.xmin()[1] << ")" << std::endl;
    return 0;
}
```

A general purpose minimization routine
- Works in multiple dimensions
- Uses only function evaluations
- Does not require derivatives
Defining a function using inheritance

```cpp
// this is an abstract base class, which CAN NOT be used as class instance
class optFunc {
public:
    // 'virtual' means inherited method can be used when
    // optFunc class is used via pointer or reference
    virtual double operator() (std::vector<double>& x) = 0; // function disabled
};

// Define a function inherits the function
// when foo() is called at the simplex, this function is actually called
class arbitraryOptFunc : public optFunc {
public:
    virtual double operator() (std::vector<double>& x) {
        // 100*(x1-x0^2)^2 + (1-x0)^2
        return 100*(x[1]-x[0]*x[0])*(x[1]-x[0]*x[0])+(1-x[0])*(1-x[0]);
    }
};
```

A working example

Minimim = 1.35567e-11, at (0.999999, 0.999997)

Recap : Mixture distribution

![Graph of mixture distribution]

Recap : MLE in Gaussian mixture

Parameter estimation in Gaussian mixture

- No analytical solution
- Numerical optimization required
- Multi-dimensional optimization problem
  - \( \mu_1, \mu_2, \cdots, \mu_k \)
  - \( \sigma_1^2, \sigma_2^2, \cdots, \sigma_k^2 \)

Possible approaches

- Simplex Method
- Expectation Maximization
- Markov-Chain Monte Carlo
Gaussian Mixture Function Object

Normal Density

Normal density function

\[ f(x|\mu, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{x - \mu}{\sigma} \right)^2 \right) \]

Implementation

```cpp
class mixLLKFunc : public optFunc {
protected:
    static double dnorm(double x, double mu, double sigma) {
        return 1.0 / (sigma * sqrt(M_PI * 2.0)) * 
               exp (-0.5 * (x - mu) * (x-mu) / sigma / sigma);
    }
    ...
};
```

Likelihood of multiple observations

Calculating in log-space

\[
L = \prod_i p(x_i|\pi, \mu, \sigma) \\
l = \sum_i \log p(x_i|\pi, \mu, \sigma)
\]

Implementation

```cpp
static double mixLLK(...); 
```

Gaussian mixture distribution

Density function

\[ p(x|k, \pi, \mu, \sigma) = \sum_{i=1}^{k} \pi_i f(x|\mu_i, \sigma_i) \]

Implementation

```cpp
static double dmix(double x, std::vector<double>& pis, 
                    std::vector<double>& means, std::vector<double>& sigmas) {
    double density = 0;
    for(int i=0; i < (int)pis.size(); ++i) {
        density += pis[i] * dnorm(x,means[i],sigmas[i]);
    }
    return density;
}
```

Gaussian Mixture Function Object

```cpp
class mixLLKFunc : public optFunc {
protected: // these are internal function
    static double dnorm(double x, double mu, double sigma);
    static double dmix(...);
public: // below are public functions
    mixLLKFunc(int k, std::vector<double>& y) : 
        numComponents(k), data(y), numFunctionCalls(0) {}
    // core function - called when foo() is used
    // x is the combined list of MLE parameters (pis, means, sigmas)
    virtual double operator() (std::vector<double>& x); 
        std::vector<double> data;
        int numComponents;
        int numFunctionCalls;
};
```
Avoiding boundary conditions

Introduction

Overview

Implementation

Mixture

Summary

Problem

- The simplex algorithm do not know that $0 \leq \pi_i \leq 1$, and $\sum_{i=1}^{n} \pi_i = 1$
- During the iteration of simplex algorithm, it is possible that $\pi_i$ goes out of bound

Possible solutions

- Modify simplex algorithm to avoid boundary conditions
- Transform the parameter space to infinite ranges

Implementing likelihood of data

```cpp
virtual double operator()(std::vector<double>& x) { // x has (3*k-1) dims
    std::vector<double> priors;
    std::vector<double> means;
    std::vector<double> sigmas;
    // transform (k-1) real numbers to priors
    double p = 1;
    for(int i=0; i < numComponents-1; ++i) {
        double logit = 1./(1.+exp(0.-x[i]));
        priors.push_back(p*logit);
        p = p*(1.-logit);
    }
    priors.push_back(p);
    for(int i=0; i < numComponents; ++i) {
        means.push_back(x[numComponents-1+i]);
        sigmas.push_back(x[2*numComponents-1+i]);
    }
    return mixLLK(data, priors, means, sigmas);
}
```

Transforming the parameter space

Constraints

- $0 \leq \pi_i \leq 1$
- $\sum_{i=1}^{n} \pi_i = 1$

Mapping between the space

- Given $x \in \mathbb{R}^{n-1}$, for $i = 1, \ldots, n - 1$
  - $\pi_i = \frac{1}{1+e^{-x}}(1 - \sum_{j=1}^{i-1} \pi_j)$
  - $\pi_n = 1 - \sum_{i=1}^{n-1} \pi_i$

Simplex Method for Gaussian Mixture

```cpp
#include <iostream>
#include <fstream>
#include "simplex615.h"
#define ZEPS 1e-10

int main(int main, char** argv) {
    double point[5] = {0, -1, 1, 1, 1}; // 50:50 mixture of N(-1,1) and N(1,1)
    simplex615 simplex(point, 5);
    std::vector<double> data; // input data
    std::ifstream file(argv[1]); // open file
    double tok;
    while(file >> tok) data.push_back(tok); // read data from file
    mixLLKFunc Foo(2, data); // 2-dimensional mixture model
    simplex.amoeba(Foo, 1e-7); // run the Simplex Method
    std::cout << "Minimin = " << simplex.ymin() << ", at pi = "
                << (1./(1.+exp(0.-simplex.xmin()[0]))) << ", " << "between N(" <<
                << simplex.xmin()[1] << "," << simplex.xmin()[3] << ") and N(" <<
                << simplex.xmin()[2] << "," << simplex.xmin()[4] << ")" << std::endl;
    return 0;
}
```
A working example

Simulation of data

> x <- rnorm(1000)
> y <- rnorm(500)+5
> write.table(matrix(c(x,y),1500,1),'mix.dat',row.names=F,col.names=F)

A Running Example

Minimim = 3043.46, at pi = 0.667271,
between N(-0.0304604,1.00326) and N(5.01226,0.956009)
(305 function evaluations in total)

Summary

Today

- Implementation of the Simplex Method
- Application to mixture of normal distributions

Recommended Readings

- Numerical recipes 10.5 - clear description of simplex method
- Subsequent sections contains more sophisticated multivariate normal distribution

Next Lecture

- The Expectation-Maximization Algorithm