Biostatistics 615/815 Lecture 20: Expectation-Maximization (EM) Algorithm

Hyun Min Kang

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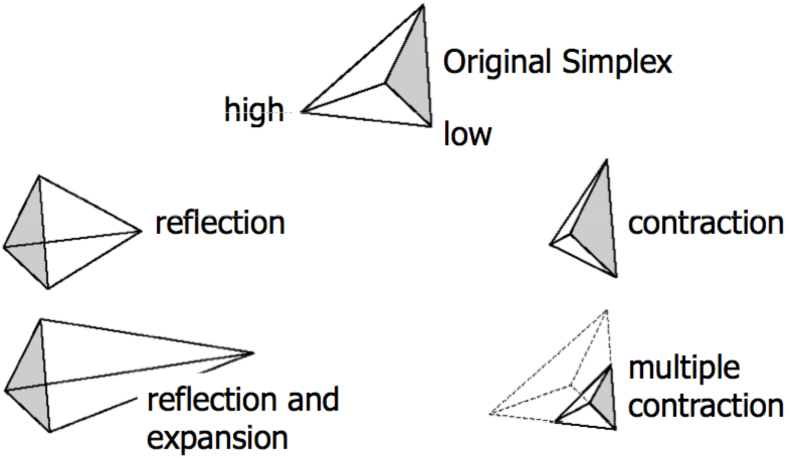
Recap - The Simplex Method

- General method for optimization
    - Makes few assumptions about function
- Crawls towards minimum using simplex
- Some recommendations
    - Multiple starting points
    - Restart maximization at proposed solution

Summary : The Simplex Method



Recap : Mixture of normals - Avoiding boundary conditions

```
// from class mixLLKFunc...
  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 0-mixLLK(data, priors, means, sigmas);
  }
```

Defining a function using inheritance

```
// 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]);
  }
};
```

An appetizer for dynamic polymorphism

```
#include <cmath>
#include <vector>
#include <iostream>

class rectangle {
public:
  double x;
  double y;
  double area() { return x*y; }
};

class circle {
public:
  double r;
  circle(double _r) : r(_r) {}
  double area() { return M_PI*r*r; }
};
```

Using rectangles and circles

```
void printArea(rectangle& r) {
  std::cout << "Area = " << r.area() << std::endl;
}

void printArea(circle& c) {
  std::cout << "Area = " << c.area() << std::endl;
}

int main(int argc, char** argv) {
  rectangle r(3,4);
  circle c(1);
  printArea(r);
  printArea(c);
  return 0;
}
```

Avoiding redundancy

```
// We want to do something like this..
void printArea(shape& s) {
  std::cout << "Area = " << s.area() << std::endl;
}

int main(int argc, char** argv) {
  rectangle r(3,4);
  circle c(1);
  printArea(r);
  printArea(c);
  return 0;
}
```

Using class inheritance

```
class shape {
public:
  double area() { return -1; } // return a dummy value
}

class rectangle : public shape {
public:
  double x;
  double y;
  double area() { return x*y; }
};

class circle : public shape {
public:
  double r;
  circle(double _r) : r(_r) {}
  double area() { return M_PI*r*r; }
};
```

What actually happens is..

```
void printArea(shape& s) {
  std::cout << "Area = " << s.area() << std::endl;
}

int main(int argc, char** argv) {
  rectangle r(3,4);
  circle c(1);
  printArea(r);   // -1 is printed... why?
  printArea(c);   // -1 is printed... why?
  return 0;
}
```

Using 'virtual' to dynamically bind member functions

```
class shape {                 // shape is an abstract class
public:
  virtual double area() = 0;  // shape object will never be created
}

class rectangle : public shape {
public:
  double x;
  double y;
  virtual double area() { return x*y; }
};

class circle : public shape {
public:
  double r;
  circle(double _r) : r(_r) {}
  virtual double area() { return M_PI*r*r; }
};
```

A working example

```
int main(int argc, char** argv) {
  rectangle r(3,4);
  circle c(1);
  printArea(r);      // 12 is printed
  printArea(c);      // 3.14159 is printed

  // must use pointers for referring object using a superclass type
  std::vector<shape*> myShapes;  // myShape can store multiple types
  myShapes.push_back(new rectangle(2,3));
  myShapes.push_back(new circle(2));
  for(int i=0; i < (int)myShapes.size(); ++i) {
    printArea( *(myShapes[i]) ); // 6 and 12.5664 is printed
  }
}
```

Our previous examples

```
class optFunc {
 public:
  virtual double operator() (std::vector<double>& x) = 0;
};
class arbitraryOptFunc : public optFunc {
 public:
  virtual double operator() (std::vector<double>& x) {
    return 100*(x[1]-x[0]*x[0])*(x[1]-x[0]*x[0])+(1-x[0])*(1-x[0]);
  }
};
class mixLLKFunc : public optFunc {
  ... // many auxilrary functions
public:
  std::vector<double> data;
  virtual double operator() (std::vector<double>& x) {
    ...
  }
};
```

Dynamic polymorphism with function objects

```
// Note that optFunc is an abstract class
// We can mas arbitraryFunc or mixLLKFunc as arguments
void simplex615::evaluateFunction(optFunc& foo) {
  for(int i=0; i < dim+1; ++i) {
    // when calling foo(X[i]), the right operator() is called
    // based on the type of the function
    Y[i] = foo(X[i]);
  }
}
```

Summary : Dynamic Polymorphism

- Class inheritance
  - Effective class design strategy to avoid redundancy
  - Typically an child-class object 'is a' super-class object
  - Call-by-reference is strongly encouraged when using inheritance
- Dynamic Polymorphism
  - `virtual` function allows to bind to the function that fits to the actual type of the object
  - Objects have to be passed as reference or pointer type

The E-M algorithm

- General algorithm for missing data problem
- Requires ”specialization” to the problem in hand
- Frequently applied to mixture distributions

Some citation records

- The E-M algorithm
  - Dempster, Laird, and Rubin (1977) J Royal Statistical Society (B) 39:1-38
  - Cited in over 19,624 research articles
- The Simplex Method
  - Nelder and Mead (1965) Computer Journal 7:308-313
  - Cited in over 10,727 research articles

The Basic E-M Strategy

- $X = (Y, Z)$
  - Complete data X - what we would like to have
  - Observed data Y - individual observations
  - Missing data Z - hidden / missing variables
- The algorithm
  - Use estimated parameters to infer Z
  - Update estimated parameters using Y
  - Repeat until convergence

The E-M Strategy in Gaussian Mixtures

When are the E-M algorithms useful?

- Problem is simpler to solve for complete data
  - Maximum likelihood estimates can be calculated using standard methods
- Estimates of mixture parameters would be obtained straightforwardly
  - if the origin of each observation is known

Filling in Missing Data in Gaussian Mixtures

- Missing data is the group assignment of each observation
- Complete data generated by assigning observations to groups 'probabilstically'

E-M formulation of Gaussian Mixture

- Gaussian mixture distribution given $\theta = (\pi, \mu, \sigma)$.

$$p(x_i) = \sum_{k=1}^{K} \pi_K \mathcal{N}(x_i | \mu_k, \sigma_k^2)$$

- Introducing latent variable $\mathbf{z}$
  - $z_i \in \{1, \cdots, K\}$ is class assignment
- The marginal likelihood of observed data

$$L(\theta; \mathbf{x}) = p(\mathbf{x}|\theta) = \sum_{\mathbf{z}} p(\mathbf{x}, \mathbf{z}|\theta)$$

  is often intractable
- Use complete data likelihood to approximate $L(\theta; \mathbf{x})$

The E-M algorithm

Expectation step (E-step)

- Given the current estimates of parameters $\theta^{(t)}$, calculate the conditional distribution of latent variable **z**.
- Then the expected log-likelihood of data given the conditional distribution of **z** can be obtained

$$Q(\theta|\theta^{(t)}) = \mathbf{E}_{\mathbf{z}|\mathbf{x},\theta^{(t)}}\left[\log p(\mathbf{x},\mathbf{z}|\theta)\right]$$

Maximization step (M-step)

- Find the parameter that maximize the expected log-likelihood

$$\theta^{(t+1)} = \arg\max_{\theta} Q(\theta|\theta^{t})$$

Implementing Gaussian Mixture E-M

```
class normMixEM {
public:
  int k;                        // # of components
  int n;                        // # of data
  std::vector<double> data;     // observed data
  std::vector<double> pis;      // pis
  std::vector<double> means;    // means
  std::vector<double> sigmas;   // sds
  std::vector<double> probs;    // (n*k) class probability
  normMixEM(std::vector<double>& input, int _k);
  void initParams();
  void updateProbs();           // E-step
  void updatePis();             // M-step (1)
  void updateMeans();           // M-step (2)
  void updateSigmas();          // M-step (3)
  double runEM(double eps);
};
```

Gaussian mixture : The E-step

Key idea

- Estimate the missing data - 'class assignment'
- By conditioning on current parameter values
- Basically, "classify" each observation to the best of current step.

Gaussian mixture : The E-step

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- Estimate the missing data - 'class assignment'
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Classification Probabilities

$$\Pr(z_i = j | x_i, \pi, \mu, \sigma) = \frac{\pi_j \mathcal{N}(x_i | \mu_j, \sigma_j^2)}{\sum_k \pi_k \mathcal{N}(x_i | \mu_k, \sigma_k^2)}$$

Implementation of E-step

```
void normMixEM::updateProbs() {
  for(int i=0; i < n; ++i) {
    double cum = 0;
    for(int j=0; j < k; ++j) {
      probs[i*k+j] = pis[j]*mixLLKFunc::dnorm(data[i],means[j],sigmas[j]);
      cum += probs[i*k+j];
    }
    for(int j=0; j < k; ++j) {
      probs[i*k+j] /= cum;
    }
  }
}
```

Mixture of Normals : The M-step

- Update mixture parameters to maximize the likelihood of the data
- Becomes simple when we assume that the current class assignment are correct
- Simply use the same proportions, weighted means and variances to update parameters
- This step is guaranteed never to decrease the likelihood

Updating Mixture Proportions

$$\pi_k = \frac{\sum_{i=1}^{n} \Pr(z_i = k | x_i, \mu, \sigma^2)}{n}$$

- Count the observations assigned to each group

Updating Mixture Proportions - Implementations

```
void normMixEM::updatePis() {
  for(int j=0; j < k; ++j) {
    pis[j] = 0;
    for(int i=0; i < n; ++i) {
      pis[j] += probs[i*k+j];
    }
    pis[j] /= n;
  }
}
```

Updating Component Means

$$\begin{aligned}\hat{\mu}_k &= \frac{\sum_i x_i \Pr(z_i = k | x_i, \mu, \sigma^2)}{\sum_i \Pr(z_i = k | x_i, \mu, \sigma^2)} \\ &= \frac{\sum_i x_i \Pr(z_i = k | x_i, \mu, \sigma^2)}{n\pi_k}\end{aligned}$$

- Calculate weighted mean for group
- Weights are probabilities of group membership

Updating Component Means - Implementations

```
void normMixEM::updateMeans() {
  for(int j=0; j < k; ++j) {
    means[j] = 0;
    for(int i=0; i < n; ++i) {
      means[j] += data[i] * probs[i*k+j];
    }
    means[j] /= (n * pis[j] + TINY);
  }
}
```

Updating Component Variances

$$\sigma_k^2 = \frac{\sum_{i=1}(x_i - \mu_k)^2 \Pr(z_i = k | x_i, \mu, \sigma)}{n\pi_k}$$

- Calculate weighted sum of squared differences
- Weights are probabilities of group membership

Updating Component Variances - Implementations

```
void normMixEM::updateSigmas() {
  for(int j=0; j < k; ++j) {
    sigmas[j] = 0;
    for(int i=0; i < n; ++i) {
      sigmas[j] += (data[i]-means[j])*(data[i]-means[j])*probs[i*k+j];
    }
    sigmas[j] = sqrt(sigmas[j] / (n * pis[j] + TINY));
  }
}
```

E-M Algorithm for Mixtures

1. Guesstimate starting parameters
2. Use Bayes' theorem to calculate group assignment probabilities
3. Update parameters using estimated assignments
4. Repeat steps 2 and 3 until likelihood is stable

Implmenetation of E-M algorithm - putting things together

```
double normMixEM::runEM(double eps) {
  double llk = 0, prevLLK = 0;
  initParams();
  while( ( llk == 0 ) || ( check_tol(llk, prevLLK, eps) == 0 ) ) {
    updateProbs();
    updatePis();
    updateMeans();
    updateSigmas();
    prevLLK = llk;
    llk = mixLLKFunc::mixLLK(data, pis, means, sigmas);
  }
  return llk;
}
```

Constructing normMixEM object

```
normMixEM::normMixEM(std::vector<double>& input, int _k) {
  data = input;
  k = _k;
  n = (int)data.size();
  pis.resize(k);
  means.resize(k);
  sigmas.resize(k);
  probs.resize(k * data.size());
}
```

Initializing the parameters

```
void normMixEM::initParams() {
  double sum = 0, sqsum = 0;
  for(int i=0; i < n; ++i) {
    sum += data[i];
    sqsum += (data[i]*data[i]);
  }
  double mean = sum/n;
  double sigma = sqrt(sqsum/n - sum*sum/n/n);
  for(int i=0; i < k; ++i) {
    pis[i] = 1./k;               // uniform priors
    means[i] = data[rand() % n]; // pick random data points
    sigmas[i] = sigma;           // pick uniform variance
  }
}
```

A working example

main() function

```
int main(int main, char** argv) {
  std::vector<double> data;
  std::ifstream file(argv[1]);
  double tok;
  while(file >> tok) data.push_back(tok);
  normMixEM em(data,2);
  double minLLK = em.runEM(1e-6);
  std::cout << "Minimim = " << minLLK << ", at pi = " << em.pis[0] << ","
            << "between N(" << em.means[0] << "," << em.sigmas[0]<< "^2) and N("
            << em.means[1] << "," << em.sigmas[1] << "^2)" << std::endl;
  return 0;
}
```

Running example

```
user@host~/> ./mixEM ./mix.dat
Minimim = -3043.46, at pi = 0.667842,
between N(-0.0299457,1.00791) and N(5.0128,0.913825)
```

Summary : The E-M Algorithm

- Iterative procedure to find maximum likelihood estimate
    - E-step : Calculate the distribution of latent variables and the expected log-likelihood of the parameters given current set of parameters
    - M-step : Update the parameters based on the expected log-likelihood function
- The iteration does not decrese the marginal likelihood function
- But no guarantee that it will converge to the MLE
- Particularly useful when the likelihood is an exponential family
    - The E-step becomes the sum of expectations of sufficient statistics
    - The M-step involves maximizing a linear function, where closed form solution can often be found

Summary

Today

- Dynamic Polymorphisms in C++
- The E-M algorithm

Next lecture

- The Simulated Annealing