SQUAREM

An R package for Accelerating Slowly Convergent Fixed-Point Iterations Including the EM and MM algorithms

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SQUAREM

Speed Is Not All That It's Cranked Up To Be

Evil deeds do not prosper; the slow man catches up with the swift - Homer (Odyssey)



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Fixed-Point Iterations Examples

What is a Fixed-Point Iteration?

$$x_{k+1} = F(x_k), \quad k = 0, 1, \ldots$$

 $F: \Omega \subset \mathbb{R}^{p} \mapsto \Omega$, and differentiable

- Most (if not all) iterations are FPI
- We are interested in contractive FPI
- Guaranteed convergence: $\{x_k\} \rightarrow x^*$

Fixed-Point Iterations Examples

EM Algorithm

Let y, z, x, be observed, missing, and complete data, respectively. The *k*-th step of the iteration:

$$\theta_{k+1} = \operatorname{argmax} Q(\theta|\theta_k); \quad k = 0, 1, \dots,$$

where

$$Q(\theta|\theta_k) = E[L_c(\theta)|y,\theta_k],$$

= $\int L_c(\theta)f(z|y,\theta_k)dz,$

Ascent property: $L_{obs}(\theta_{k+1}) \ge L_{obs}(\theta_k)$

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MM Algorithm

A majorizing function, $g(\theta | \theta^k)$:

 $\begin{array}{rcl} f(\theta_k) & = & g(\theta_k | \, \theta_k), \\ f(\theta_k) & \leq & g(\theta | \, \theta_k), \ \forall \, \theta. \end{array}$

Examples

 To minimize f(θ), construct a majorizing function and minimize it (MM)

$$\theta_{k+1} = \operatorname{argmax} g(\theta|\theta_k); \quad k = 0, 1, \dots$$

- Descent property: $f(\theta_{k+1}) \leq f(\theta_k)$
- Is EM a subclass of MM or are they equivalent? It avoids the E-step.

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Fixed-Point Iterations Examples

Least Squares Multidimensional Scaling

Minimize :
$$\sigma(X) = rac{1}{2}\sum_{j=1}^{n}\sum_{j=1}^{n}w_{ij}(\delta_{ij}-d_{ij}(X))^2$$

over all $m \times p$ matrices X, where: $d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}$

- Jan de Leeuw's SMACOF algorithm: $\xi_{k+1} = F(\xi)$,
- Has descent property: $\sigma(\xi_{k+1}) < \sigma(\xi_k)$
- An instance of MM algorithm

Background

Acceleration of Convergence Results Fixed-Point Iterations Examples

BLP Contraction Mapping

Previous Talk!



Power Method

To find the eigenvector corresponding to the largest (in magnitude) eigenvalue of an $n \times n$ matrix, A.

Not all that academic - Google's PageRank algorithm!

Examples

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$$x_{k+1} = A.x_k / ||A.x_k||$$

- Stop if $||x_{k+1} x_k|| \le \varepsilon$
- Dominant eigenvalue (Rayleigh quotient) = $\frac{\langle A_{x_*, x_*} \rangle}{\langle x_*, x_* \rangle}$
- Geometric convergence with rate $\propto \frac{|\lambda_1|}{|\lambda_2|}$
- Power method does not converge if $|\lambda_1| = |\lambda_2|$, but SQUAREM does!

Why Accelerate Convergence?

- These FPI are globally convergent
- Convergence is linear: Rate = $[\rho(J(x^*))]^{-1}$
- Slow convergence when spectral radius, ρ(J(x*)), is large
- Need to be accelerated for practical application
- Without compromising on global convergence
- Without additional information (e.g. gradient, Hessian, Jacobian)





 An R package implementing a family of algorithms for speeding-up any slowly convergent multivariate sequence

R Package

- Easy to use
- Ideal for high-dimensional problems
- Input: *fixptfn* = fixed-point mapping *F*
- Optional Input: *objfn* = objective function (if any)
- Two main control parameter choices: order of extrapolation and monotonicity
- Available on *R-forge* under optimizer project. install.packages("SQUAREM", repos = "http://R-Forge.R-project.org")



Upshot

SQUAREM works great!

- Significant acceleration (depends on the linear rate of F)
- Globally convergent (especially, first-order locally non-monotonic schemes)
- Finds the same or (sometimes) better fixed-points than FPI (e.g. EM, SMACOF, Power method)



SMACOF Results

Mores code data (de Leeuw 2008). 36 Morse signals compared - 630 dissimilarities & 69 parameters

Scheme	# Fevals	# ObjEvals	CPU (sec)	ObjfnValue
SMACOF	1549	1549	471	0.0593
SQ1	213	141	55	0.0593
SQ2	140	57	32	0.0593
SQ3	113	33	24	0.0457
SQ3*	113	0	19	0.0457

Table: A comparison of the different schemes.



Multidimensional Scaling: SMACOF Power Method for Dominant Eigenvector

Power Method - Part I

Generated a 1000 \times 1000 (arbitrary) matrix with eigenvalues as follows:

```
eigvals <- c(2, 1.99, runif(997, 0, 1.9), -1.8)
```

A cool algorithm using the Soules matrix!

Table: A comparison of the different schemes: Average of 100 simulations

Scheme	# Fevals	CPU (sec)	Converged
Power	1687	8.8	100
SQ1	165	0.88	100
SQ2	121	0.69	100
SQ3	115	0.65	100



Multidimensional Scaling: SMACOF Power Method for Dominant Eigenvector

Power Method - Part II

Generated a 100 \times 100 (arbitrary) matrix with eigenvalues as follows:

```
eigvals <- c(2, 1.99, runif(97, 0, 1.9), -2)
```

Table: A comparison of the different schemes: Average of 100 simulations

Scheme	# Fevals	CPU (sec)	Converged
Power	50000	3.46	0
SQ1	178	0.023	100
SQ2	130	0.031	100
SQ3	122	0.027	100



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For Further Reading I



嗪 R. Varadhan, and C. Roland Scandinavian Journal of Statistics. 2008.

C. Roland, R.Varadhan, and C.E. Frangakis Numerical Mathematics. 2007.

