Package 'fasta'

October 13, 2022

Type Package			
Title Fast Adaptive Shrinkage/Thresholding Algorithm			
Version 0.1.0			
Description A collection of acceleration schemes for proximal gradient methods for estimating penalized regression parameters described in Goldstein, Studer, and Baraniuk (2016) <arxiv:1411.3406>. Schemes such as Fast Iterative Shrinkage and Thresholding Algorithm (FISTA) by Beck and Teboulle (2009) <doi:10.1137 080716542=""> and the adaptive stepsize rule introduced in Wright, Nowak, and Figueiredo (2009) <doi:10.1109 tsp.2009.2016892=""> are included. You provide the objective function and proximal mappings, and it takes care of the issues like stepsize selection, acceleration, and stopping conditions for you.</doi:10.1109></doi:10.1137></arxiv:1411.3406>			
License MIT + file LICENSE			
Encoding UTF-8			
LazyData true			
RoxygenNote 6.0.1			
NeedsCompilation no			
Author Eric C. Chi [aut, cre, trl, cph], Tom Goldstein [aut] (MATLAB original, https://www.cs.umd.edu/~tomg/projects/fasta/), Christoph Studer [aut], Richard G. Baraniuk [aut]			
Maintainer Eric C. Chi <ecchi1105@gmail.com></ecchi1105@gmail.com>			
Repository CRAN			
Date/Publication 2018-04-10 10:01:37 UTC			
R topics documented:			
fasta			
Index			

2 fasta

fasta

Fast Adaptive Shrinkage/Thresholding Algorithm

Description

fasta implements back-tracking with Barzelai-Borwein step size selection

Usage

```
fasta(f, gradf, g, proxg, x0, tau1, max_iters = 100, w = 10,
  backtrack = TRUE, recordIterates = FALSE, stepsizeShrink = 0.5,
  eps_n = 1e-15)
```

Arguments

f	function handle for computing the smooth part of the objective
gradf	function handle for computing the gradient of objective
g	function handle for computing the nonsmooth part of the objective
proxg	function handle for computing proximal mapping
x0	initial guess
tau1	initial stepsize
max_iters	maximum iterations before automatic termination
W	lookback window for non-montone line search
backtrack	boolean to perform backtracking line search
${\tt recordIterates}$	boolean to record iterate sequence
${\it stepsizeShrink}$	multplier to decrease step size
eps_n	epsilon to prevent normalized residual from dividing by zero

Examples

fasta 3

```
g <- function(beta) { 0 }</pre>
proxg <- function(beta, tau) { beta }</pre>
x0 \leftarrow double(p) \# initial starting iterate
tau1 <- 10
sol <- fasta(f,gradf,g,proxg,x0,tau1)</pre>
# Check KKT conditions
gradf(sol$x)
#-----
# LASSO LEAST SQUARES: EXAMPLE 2 (SIMULATED DATA)
set.seed(12345)
n <- 100
p <- 25
X <- matrix(rnorm(n*p),n,p)</pre>
beta <- matrix(rnorm(p),p,1)</pre>
y <- X%*%beta + rnorm(n)</pre>
beta0 <- matrix(0,p,1) # initial starting vector
lambda <- 10
f \leftarrow function(beta){ 0.5*norm(X%*%beta - y, "F")^2 }
gradf <- function(beta){ t(X)%*%(X%*%beta - y) }</pre>
g <- function(beta) { lambda*norm(as.matrix(beta),'1') }
proxg <- function(beta, tau) { sign(beta)*(sapply(abs(beta) - tau*lambda,</pre>
 FUN=function(x) \{max(x,0)\})) \}
x0 <- double(p) # initial starting iterate
tau1 <- 10
sol <- fasta(f,gradf,g,proxg,x0,tau1)</pre>
# Check KKT conditions
cbind(sol$x,t(X)%*%(y-X%*%sol$x)/lambda)
# LOGISTIC REGRESSION: EXAMPLE 3 (SIMLUATED DATA)
set.seed(12345)
n <- 100
p <- 25
X <- matrix(rnorm(n*p),n,p)</pre>
y \leftarrow sample(c(0,1),nrow(X),replace=TRUE)
beta <- matrix(rnorm(p),p,1)</pre>
beta0 <- matrix(0,p,1) # initial starting vector
f \leftarrow function(beta) \{ -t(y) **(X**beta) + sum(log(1+exp(X**beta))) \} # objective function
gradf <- function(beta) { -t(X)%*%(y-plogis(X%*%beta)) } # gradient</pre>
g <- function(beta) { 0 }</pre>
proxg <- function(beta, tau) { beta }</pre>
x0 <- double(p) # initial starting iterate
tau1 <- 10
sol <- fasta(f,gradf,g,proxg,x0,tau1)</pre>
```

4 fasta

```
# Check KKT conditions
gradf(sol$x)
# LASSO LOGISTIC REGRESSION: EXAMPLE 4 (SIMLUATED DATA)
set.seed(12345)
n <- 100
p <- 25
X <- matrix(rnorm(n*p),n,p)</pre>
y <- sample(c(0,1),nrow(X),replace=TRUE)</pre>
beta <- matrix(rnorm(p),p,1)</pre>
beta0 <- matrix(0,p,1) # initial starting vector
lambda <- 5
f <- function(beta) \ \{ \ -t(y) \% * \% (X \% * \% beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% * \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% beta))) \ \} \ \# \ objective \ function(beta) \ + \ sum(log(1+exp(X \% beta))) \ + \ sum(log(1+exp(X \% beta)) \ + \ sum(log(1+exp(X \% beta))) \ + \ sum(log(1+exp(X \% beta))) \ + \ sum(log(1+exp(X \% bet
gradf \leftarrow function(beta) \{ -t(X)\% *\%(y-plogis(X\% *\%beta)) \} # gradient
g <- function(beta) { lambda*norm(as.matrix(beta),'1') }</pre>
proxg <- function(beta, tau) { sign(beta)*(sapply(abs(beta) - tau*lambda,</pre>
       FUN=function(x) \{max(x,0)\})) \}
x0 \leftarrow double(p) \# initial starting iterate
tau1 <- 10
sol <- fasta(f,gradf,g,proxg,x0,tau1)</pre>
# Check KKT conditions
cbind(sol$x,-gradf(sol$x)/lambda)
```

Index

fasta, 2