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1 function [models,logP]=TAmcmc(minit,logPfun,mcCount,varargin)
2 % Cascaded affine invariant ensemble MCMC sampler. "The MCMC hammer"
3 % TAMCMC is a modification of GWMCNC that adds an option for tempering
4 % starting from a unitless temperature of 4000 and cooling to a unitless
5 % temperature of 1 over ~150 steps. Other than that, the usage is the same
6 % as the original GWMCNC script documented below.
7 %
8 % -Matthew Ashner, 2018
9 %
10 % GWMCNC is an implementation of the Goodman and Weare 2010 Affine
11 % invariant ensemble Markov Chain Monte Carlo (MCMC) sampler. MCMC sampling
12 % enables bayesian inference. The problem with many traditional MCMC samplers
13 % is that they can have slow convergence for badly scaled problems, and that
14 % it is difficult to optimize the random walk for high-dimensional problems.
15 % This is where the GW-algorithm really excels as it is affine invariant. It
16 % can achieve much better convergence on badly scaled problems. It is much
17 % simpler to get to work straight out of the box, and for that reason it
18 % truly deserves to be called the MCMC hammer.
19 %
20 % (This code uses a cascaded variant of the Goodman and Weare algorithm).
21 %
22 % USAGE:
23 % [models,logP]=gwmcmc(minit,logPfun,mcCount, Parameter,Value,Parameter,Value);
24 %
25 % INPUTS:
26 %     minit: an MxW matrix of initial values for each of the walkers in the
27 %             ensemble. (M:number of model params. W: number of walkers). W
28 %             should be atleast 2xM. (see e.g. mvnrnd).
29 %     logPfun: a cell of function handles returning the log probability of a
30 %             proposed set of model parameters. Typically this cell will
31 %             contain two function handles: one to the logprior and another
32 %             to the loglikelihood. E.g. {@(m)logprior(m) @(m)loglike(m)}
33 %     mcCount: What is the desired total number of monte carlo proposals.
34 %             This is the total number, -NOT the number per chain.
35 %
36 % Named Parameter-Value pairs:
37 %     'StepSize': unit-less stepsize (default=2.5).
38 %     'ThinChain': Thin all the chains by only storing every N'th step (default=10)
39 %     'ProgressBar': Show a text progress bar (default=true)
40 %     'Parallel': Run in ensemble of walkers in parallel. (default=false)
41 %     'BurnIn': fraction of the chain that should be removed. (default=0)
42 %     'Temper': Temper the chain (default=false)
43 %
44 % OUTPUTS:
45 %     models: A MxWxT matrix with the thinned markov chains (with T samples
46 %             per walker). T=~mcCount/p.ThinChain/W.
47 %     logP: A PxWxT matrix of log probabilities for each model in the
48 %             models. here P is the number of functions in logPfun.
49 %
50 % Note on cascaded evaluation of log probabilities:

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51 % The logPfun-argument can be specified as a cell-array to allow a cascaded
52 % evaluation of the probabilities. The computationally cheapest function should be
53 % placed first in the cell (this will typically be the prior). This allows the
54 % routine to avoid calculating the likelihood, if the proposed model can be
55 % rejected based on the prior alone.
56 % logPfun={logprior loglike} is faster but equivalent to
57 % logPfun={@(m) logprior(m)+loglike(m)}
58 %
59 % TIP: if you aim to analyze the entire set of ensemble members as a single
60 % sample from the distribution then you may collapse output models-matrix
61 % thus: models=models(:, :); This will reshape the MxWxT matrix into a
62 % Mx(W*T)-matrix while preserving the order.
63 %
64 %
65 % EXAMPLE: Here we sample a multivariate normal distribution.
66 %
67 % %define problem:
68 % mu = [5;-3;6];
69 % C = [.5 -.4 0;-.4 .5 0; 0 0 1];
70 % iC=pinv(C);
71 % logPfun={@(m)-0.5*sum((m-mu)'*iC*(m-mu)) }
72 %
73 % %make a set of starting points for the entire ensemble of walkers
74 % minit=randn(length(mu),length(mu)*2);
75 %
76 % %Apply the MCMC hammer
77 % [models,logP]=gwmcmc(minit,logPfun,100000);
78 % models(:,:,1:floor(size(models,3)*.2))=[]; %remove 20% as burn-in
79 % models=models(:,:,1)'; %reshape matrix to collapse the ensemble member dimension
80 % scatter(models(:,1),models(:,2))
81 % prctile(models,[5 50 95])
82 %
83 %
84 % References:
85 % Goodman & Weare (2010), Ensemble Samplers With Affine Invariance, Comm. App. ↵
Math. Comp. Sci., Vol. 5, No. 1, 65-80
86 % Foreman-Mackey, Hogg, Lang, Goodman (2013), emcee: The MCMC Hammer, arXiv: ↵
1202.3665
87 %
88 % WebPage: https://github.com/grinsted/gwmcmc
89 %
90 % -Aslak Grinsted 2015
91 %
92
93
94 persistent isoctave;
95 if isempty(isoctave)
96     isoctave = (exist ('OCTAVE_VERSION', 'builtin') > 0);
97 end
98

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99 if nargin<3
100     error('GWMCMC:toofewinputs', 'GWMCMC requires atleast 3 inputs.')
101 end
102 M=size(minit,1);
103 if size(minit,2)==1
104     minit=bsxfun(@plus,minit,randn(M,M*5));
105 end
106
107
108 p=inputParser;
109 if isoctave
110     p=p.addParamValue('StepSize',2,@isnumeric); %addParamValue is chosen for compatibility with octave. Still Untested.
111     p=p.addParamValue('ThinChain',10,@isnumeric);
112     p=p.addParamValue('ProgressBar',true,@islogical);
113     p=p.addParamValue('Parallel',false,@islogical);
114     p=p.addParamValue('BurnIn',0,@(x) (x>=0)&&(x<1));
115     p=p.addParamValue('Temper',false,@islogical);
116     p=p.parse(varargin{:});
117 else
118     p.addParameter('StepSize',2,@isnumeric); %addParamValue is chose for compatibility with octave. Still Untested.
119     p.addParameter('ThinChain',10,@isnumeric);
120     p.addParameter('ProgressBar',true,@islogical);
121     p.addParameter('Parallel',false,@islogical);
122     p.addParameter('BurnIn',0,@(x) (x>=0)&&(x<1));
123     p.addParameter('Temper',false,@islogical);
124     p.parse(varargin{:});
125 end
126 p=p.Results;
127
128
129 Nwalkers=size(minit,2);
130
131 if size(minit,1)*2>size(minit,2)
132     warning('GWMCMC:minitdimensions','Check minit dimensions.\nIt is recommended that there be atleast twice as many walkers in the ensemble as there are model dimension.')
133 end
134
135 if p.ProgressBar
136     progress=@textprogress;
137 else
138     progress=@noaction;
139 end
140
141
142 Nkeep=ceil(mccount/p.ThinChain/Nwalkers); %number of samples drawn from each walker
143 mccount=(Nkeep-1)*p.ThinChain+1;

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144
145 models=nan(M,Nwalkers,Nkeep); %pre-allocate output matrix
146
147 models(:,:,1)=minit;
148
149 if ~iscell(logPfun)
150     logPfun={logPfun};
151 end
152
153 NPfun=numel(logPfun);
154
155 %calculate logP state initial pos of walkers
156 logP=nan(NPfun,Nwalkers,Nkeep);
157 for wix=1:Nwalkers
158     for fix=1:NPfun
159         v=logPfun{fix}(minit(:,wix));
160         if islogical(v) %reformulate function so that false==inf for logical ↵
constraints.
161             v=-1/v;logPfun{fix}=@(m)-1/logPfun{fix}(m); %experimental ↵
implementation of experimental feature
162         end
163         logP(fix,wix,1)=v;
164     end
165 end
166
167 if ~all(all(isfinite(logP(:,:,:))))
168     error('Starting points for all walkers must have finite logP')
169 end
170
171 %Set up tempering with a power law temperature decay. Temperature profile
172 %can be adjusted by changing the T0 and slope parameters. The default
173 %parameters are well optimized for 200 steps per walker after thinning.
174 %They may need adjusting for different step numbers.
175 if p.Temper
176     T0=4000; %Initial temperature
177     slope=0.97; %Controls rate of temperature decay
178     beta=1./(T0*0.97.^((1:Nkeep)-1)+1);
179 else
180     beta=ones(Nkeep,1); %Keeps temperature of 1 if no tempering.
181 end
182
183 reject=zeros(Nwalkers,1);
184
185
186 curm=models(:,:,1);
187 curlogP=logP(:,:,1);
188 progress(0,0,0)
189 totcount=Nwalkers;
190 for row=1:Nkeep
191     for jj=1:p.ThinChain

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192      %generate proposals for all walkers
193      %(done outside walker loop, in order to be compatible with parfor - some ↵
penalty for memory):
194      %-Note it appears to give a slight performance boost for non-parallel.
195      rix=mod((1:Nwalkers)+floor(rand*(Nwalkers-1)),Nwalkers)+1; %pick a random ↵
partner
196      zz=((p.StepSize - 1)*rand(1,Nwalkers) + 1).^2/p.StepSize;
197      proposedm=curm(:,rix) - bsxfun(@times,(curm(:,rix)-curm),zz);
198      logrand=log(rand(NPfun+1,Nwalkers)); %moved outside because rand is slow ↵
inside parfor
199      if p.Parallel
200          %parallel/non-parallel code is currently mirrored in
201          %order to enable experimentation with separate optimization
202          %techniques for each branch. Parallel is not really great yet.
203          %TODO: use SPMD instead of parfor.
204
205      parfor wix=1:Nwalkers
206          cp=curlogP(:,wix);
207          lr=logrand(:,wix);
208          acceptfullstep=true;
209          proposedlogP=nan(NPfun,1);
210          if lr(1)<(numel(proposedm(:,wix))-1)*log(zz(wix))
211              for fix=1:NPfun
212                  proposedlogP(fix)=logPfun{fix}(proposedm(:,wix)); %haven't ↵
tested workerobjwrapper but that is slower.
213                  if lr(fix+1)>beta(row)*(proposedlogP(fix)-cp(fix)) || ↵
~isreal(proposedlogP(fix)) || isnan(proposedlogP(fix))
214                      %if ~(lr(fix+1)<proposedlogP(fix)-cp(fix))
215                      acceptfullstep=false;
216                      break
217                  end
218              end
219          else
220              acceptfullstep=false;
221          end
222          if acceptfullstep
223              curm(:,wix)=proposedm(:,wix); curlogP(:,wix)=proposedlogP;
224          else
225              reject(wix)=reject(wix)+1;
226          end
227      end
228  else %NON-PARALLEL
229      for wix=1:Nwalkers
230          acceptfullstep=true;
231          proposedlogP=nan(NPfun,1);
232          if logrand(1,wix)<(numel(proposedm(:,wix))-1)*log(zz(wix))
233              for fix=1:NPfun
234                  proposedlogP(fix)=logPfun{fix}(proposedm(:,wix));
235                  if logrand(fix+1,wix)>beta(row)*(proposedlogP(fix)-curlogP( ↵
fix,wix)) || ~isreal(proposedlogP(fix)) || isnan(proposedlogP(fix))

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236             %if ~ (logrand (fix+1,wix) < proposedlogP(fix)-curlogP(fix, wix))
237             %inverted expression to ensure rejection of nan and imaginary logP's.
238             acceptfullstep=false;
239             break
240         end
241     else
242         acceptfullstep=false;
243     end
244     if acceptfullstep
245         curm(:,wix)=proposedm(:,wix); curlogP(:,wix)=proposedlogP;
246     else
247         reject(wix)=reject(wix)+1;
248     end
249 end
250
251 end
252 totcount=totcount+Nwalkers;
253 progress((row-1+jj/p.ThinChain)/Nkeep, curm, sum(reject)/totcount)
254 end
255 models (:,:,row)=curm;
256 logP (:,:,row)=curlogP;
257
258 %progress bar
259
260 end
261 progress(1,0,0);
262 if p.BurnIn>0
263     crop=ceil(Nkeep*p.BurnIn);
264     models (:,:,1:crop)=[];
265     logP (:,:,1:crop)=[];
266 end
267
268
269 % TODO: make standard diagnostics to give warnings...
270 % TODO: make some diagnostic plots if nargout==0;
271
272
273
274 function textprogress(pct,curm,rejectpct)
275 persistent lastNchar lasttime starttime
276 if isempty(lastNchar)||pct==0
277     lasttime=cputime-10;starttime=cputime;lastNchar=0;
278     pct=1e-16;
279 end
280 if pct==1
281     fprintf('%s', repmat(char(8),1,lastNchar));lastNchar=0;
282     return
283 end
284 if (cputime-lasttime>0.1)
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285
286 ETA=datestr((cputime-starttime)*(1-pct)/(pct*60*60*24),13);
287 progressmsg=[183-uint8((1:40)<=(pct*40)).*(183-'*')];
288 %progressmsg=['-'-uint8((1:40)<=(pct*40)).*('-'-'');
289 %progressmsg=[uint8((1:40)<=(pct*40)).*'#' ];
290 curmtxt=sprintf('% 9.3g\n',curm(1:min(end,20),1));
291 %curmtxt=mat2str(curm);
292 progressmsg=sprintf('\nGWMCMC %5.1f%% [%s] %s\n%3.0f%% rejected\n%s\n',↵
pct*100,progressmsg,ETA,rejectpct*100,curmtxt);
293
294 fprintf('%s%s',repmat(char(8),1,lastNchar),progressmsg);
295 drawnow;lasttime=cputime;
296 lastNchar=length(progressmsg);
297 end
298
299 function noaction(varargin)
300
301 % Acknowledgements: I became aware of the GW algorithm via a student report
302 % which was using emcee for python. Great stuff.
303

```