```
% make sure we have a clean environment
clear
rand('state'.0):
randn('state',0);
% Global variables
% H - the recorded head for each time
% TM - the times the head was recorded
% SIGMA - the standard deviation for a time
% D - the distance between the wells
% Q - the volume of the slug
global H;
global TM;
global SIGMA;
global Q;
global D;
global stepsize
% Load the data. Head is measured to the nearest centimeter.
load slugdata.mat
%
% Fixed parameter values.
%
D=60;
Q=50:
% We'll use sigma=1cm.
SIGMA=0.01*ones(size(H));
S sig = 2e-5;
T_{sig} = 4e-2;
stepsize = [S_sig; T_sig];
S0 = 5e-3; T0 = 1;
m0 = [S0;T0];
N = 2e5; BURNIN = 1e4;
skip = 1000;
4.(a) Identify the number of samples that remain after the thinning process. Plot the hisstory of the
thinned posterior samples, and include the true parameters.
logprior = @(m) Logprior(m);
loglikelihood = @(m) Loglikelihood(m);
generate = @(x,stepsize) Generate(x);
logproposal = @(x,y,stepsize) Logproposal(x,y);
[mout,mMAP,pacc]=mcmc(logprior,loglikelihood,generate,logproposal,m0,N)
%downsample results to reduce correlation
k=(BURNIN:skip:N);
mskip=mout(:,k);
disp(['The corresponding number of samples = ',num2str(length(mskip)),' samples']);
```

```
mtrue = [0.00207; 0.585];
%plot parameter sample histories
figure(1)
clf
for i=1:2
 subplot(2,1,i)
 plot([1 length(mskip)],[mtrue(i) mtrue(i)], 'Color',[0.6 0.6 0.6], 'LineWidth',3);
 plot(mskip(i,:),'ko')
 hold off
 if i~=2
  set(gca, 'Xticklabel', []);
 end
 xlim([1 length(mskip)])
xlabel('Sample Number')
subplot(2,1,1)
vlabel('S')
title('Displaying the true parameters and thinned sample histories')
subplot(2,1,2)
ylabel('T')
b) Plot autocorrelations of S and T both before and after thinning. Discuss if there was enough
thinning with skipping every 1000 samples.
figure(2)
clf
laglen=1000;
lags=(-laglen:laglen)';
acorr=zeros(2*laglen+1,2);
acorrn=zeros(2*laglen+1,2);
for i=1:2
    acorrn(:,i)=calc_corr(mout(i,:)',laglen);
end
for i=1:2
 acorr(:,i)=calc_corr(mskip(i,:)',laglen);
 subplot(2,1,i);
 plot([0 laglen],[0 0], 'Color',[0.7 0.7 0.7], 'LineWidth',3); hold on
 plot(lags(laglen+1:10:laglen*2+1),acorr(laglen+1:10:laglen*2+1,i),'bo');
 plot(lags(laglen+1:10:laglen*2+1),acorrn(laglen+1:10:laglen*2+1,i),'ro');
 legend(",'thinned', 'non thinned',Location='best')
 hold off
 if i == 1
   ylabel(['A (S)'])
   title('Autocorrelation of thinned parameter samples ')
   ylabel(['A (T)'])
 end
```

```
if i~=2
  set(gca, 'Xticklabel', []);
 end
end
xlabel('Lag')
(c) Estimate the 95% credible intervals by sorting the ensemble of parameter estimates, as is done in
Exercise 11.4.
% estimate the 95% credible intervals
for i=1:2
 msort=sort(mskip(i,:));
 m2_5(i) = msort(round(2.5/100*length(mskip)));
 m97 	ext{ } 5(i) = msort(round(97.5/100*length(mskip)));}
 disp(['95% confidence interval for m', num2str(i),' is [', num2str(m2_5(i)),',', num2str(m97_5(i)),']'])
end
(d) Estimate the Bayesian confidence intervals as we've done previously, using the standard
deviation of the MCMC samples.
for i=1:2
 msort=sort(mskip(i,:)); Mmap = 1.96*std(msort);
 m97_5b = mMAP(i) + Mmap;
 m2_5b = mMAP(i) - Mmap;
 disp(['95% confidence interval for m', num2str(i),' is [', num2str(m2 5b),',', num2str(m97 5b),']'])
end
(e) As in Figure 11.16, plot the sampled posterior distribution S vs T with the true model as a large
black dot, and the MAP estimate with an open circle. On the same graph plot the thinned samples as
gray dots and 95% credible intervals by a box.
%plot a scatter plot and histogram of the posterior distribution
mlims=[0.0018 0.0023; 0.52 0.64];
figure(3)
clf
for i=1:2
 for i=1:2
  if i==i
     continue
  else
    plot(mskip(j,:),mskip(i,:),'k.','Markersize',6,'Color',[0.6 0.6 0.6]);
   hold on
    % plot the true answer as a large black dot
    plot(mtrue(j), mtrue(i), 'k.', 'Markersize', 24);
    % plot the accepted answers as gray dots
    plot(mMAP(i),mMAP(i),'ko','Markersize',12,'LineWidth',3);
    % plot the 95% ci as a box
    plot([m2_5(j),m97_5(j)],[m2_5(i),m2_5(i)],'k-','LineWidth',1);
    plot([m2_5(j),m97_5(j)],[m97_5(i),m97_5(i)],'k-','LineWidth',1);
    plot([m2_5(j),m2_5(j)],[m2_5(i),m97_5(i)],'k-','LineWidth',1);
    plot([m97_5(j),m97_5(j)],[m2_5(i),m97_5(i)],'k-','LineWidth',1);
    xlim(mlims(j,:));
    ylim(mlims(i,:));
```

```
xlabel('S'); ylabel('T')
   hold off
  end
 end
end
figure(4)
for i = 1:2
  subplot(2,1,i)
  qqplot(sort(mskip(i,:)))
  ylabel('Quantiles of Input Sample');
  xlabel('Standard Normal Quantiles');
  if i == 1
     title('Q-Q plot for S')
  else
     title('Q-Q plot for T')
  end
end
function I = Loglikelihood(m)
  global H;
  global TM;
  global SIGMA;
  global D;
  global Q;
  % Compute the standardized residuals.
  fvec = fun(m);
  % The log likelihood is (-1/2)*sum(fvec(i)^2,i=1..n);
  I = (-1/2)*sum(fvec.^2);
end
function lp = Logprior(m)
  if (m(1)>=0) && (m(1)<=0.01) && (m(2)>=0) && (m(2)<=2)
   lp=0;
  else
   lp=-Inf;
  end
end
function y=Generate(x)
  global stepsize
  y=x+stepsize.*randn(2,1);
end
function Ir=Logproposal(x,y)
  global stepsize
```

 $Ir=(-1/2)*sum((x-y).^2./stepsize.^2);$ end