Problem 15.2

The code in HMC_UTurn.R uses simulates Hamiltonian dynamics for a single particle on the distribution described in the previous question:

In this question we will see how the efficiency of HMC depends on choice of the number of in-termediate steps. In particular we investigate the propensity of a particle undergoing Newtonian dynamics to perform U-Turns.

Get the code provided by author of HMC sampler

```
## Gradient of the potential with respect to x
fGradSimpleX <- function(x,y){</pre>
  aGrad <- -0.5 * exp(1/2 * (-(-20 + x) * (1.38889 * (-20 + x) - x)))
                                              2.22222 * (-5 + y)) - (-2.22222 * (-20 + x) +
                                                                        5.55556 * (-5 + y)) * (-5 + y)) +
                        1/2 * ((-20 + x) * (1.38889 * (-20 + x) -
                                               2.22222 * (-5 + y)) + (-2.22222 * (-20 + x) +
                                                                          5.55556 * (-5 + y)) * (-5 + y))
  return(aGrad)
}
## Gradient of the potential with respect to y
fGradSimpleY <- function(x,y){</pre>
  aGrad < -0.5 * exp(1/2 * (-(-20 + x) * (1.38889 * (-20 + x) -
                                               2.22222 * (-5 + y)) - (-2.22222 * (-20 + x) +
                                                                         5.55556 * (-5 + y)) * (-5 + y)) +
                         1/2 * ((-20 + x) * (1.38889 * (-20 + x) -
                                                2.22222 * (-5 + y)) + (-2.22222 * (-20 + x) +
                                                                           5.55556 * (-5 + y)) * (-5 + y))
  return(aGrad)
## Gradient of U with respect to both coordinates
grad_U <- function(aQ){</pre>
  aGradX <- fGradSimpleX(aQ[[1]],aQ[[2]])
  aGrady <- fGradSimpleY(aQ[[1]],aQ[[2]])
  return(c(aGradX,aGrady))
}
## Potential function given by the -ve log of the posterior
U <- function(aQ){</pre>
  x <- aQ[[1]]
  y \leftarrow aQ[[2]]
  aU \leftarrow -\log(0.265258 * \exp(
    1/2 * (-(-20 + x) * (1.38889 * (-20 + x) -
```

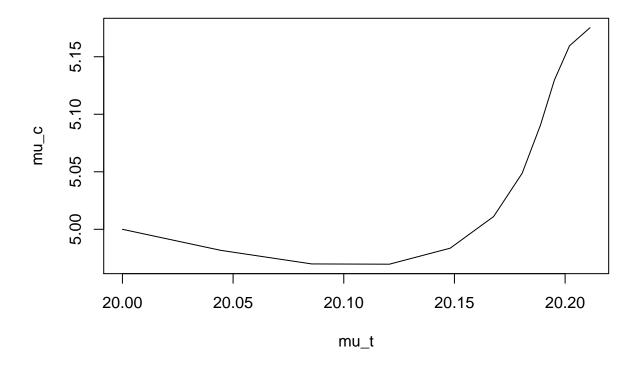
```
2.22222 * (-5 + y)) - (-2.22222 * (-20 + x) +
                                                     5.55556 * (-5 + y)) * (-5 + y)))
 return(aU)
## Keeps all the positions of the particle over time
HMC_keep <- function (current_q, U, grad_U, epsilon, L, aSigma){</pre>
 q = current q
  p = rnorm(length(q),0,aSigma) # independent standard normal variates
 current_p = p
 # Make a half step for momentum at the beginning
 p = p - epsilon * grad_U(q) / 2
 \# Alternate full steps for position and momentum
  lPosition <- matrix(nrow = (L+1),ncol = 2)</pre>
  lPosition[1,] <- q</pre>
  for (i in 1:L)
   # Make a full step for the position
   q = q + epsilon * p
   lPosition[(i+1),] <- q</pre>
   # Make a full step for the momentum, except at end of trajectory
   if (i!=L) p = p - epsilon * grad_U(q)
  # Make a half step for momentum at the end.
 p = p - epsilon * grad_U(q) / 2
  # Negate momentum at end of trajectory to make the proposal symmetric
 p = -p
  # Evaluate potential and kinetic energies at start and end of trajectory
  current_U = U(current_q)
  current_K = sum(current_p^2) / 2
  proposed_U = U(q)
 proposed_K = sum(p^2) / 2
  # print(current_U-proposed_U)
  # print(current_K-proposed_K)
  # Accept or reject the state at end of trajectory, returning either
  # the position at the end of the trajectory or the initial position
```

```
r <- exp(current_U-proposed_U+current_K-proposed_K)
# print(r)
if (runif(1) < r)
{
    return (list(q=q,pos=lPosition)) # accept
}
else
{
    return (list(q=current_q,pos=lPosition)) # reject
}
</pre>
```

15.2.1

Simulate a single particle starting at (20, 5) for L = 10 steps with the following parameters = 0.18 (step size), = 0.18 (momentum proposal distribution width). Plot the path in parameter space.

HMC, L=10



15.2.2

Now try L = 20,50,100 steps, again plotting the results what do you notice about the paths?

```
set.seed(42)
```

```
lSamples_hmc_L10 <- HMC_keep(current_q = c(20,5),U = U, grad_U = grad_U, epsilon = 0.18,</pre>
                                L = 10, aSigma = 0.18)
1Samples_hmc_L20 <- HMC_keep(current_q = c(20,5),U = U, grad_U = grad_U, epsilon = 0.18,</pre>
                                L = 20, aSigma = 0.18)
lSamples_hmc_L50 <- HMC_keep(current_q = c(20,5),U = U, grad_U = grad_U, epsilon = 0.18,</pre>
                                L = 50, aSigma = 0.18)
lSamples_hmc_L100 <- HMC_keep(current_q = c(20,5),U = U, grad_U = grad_U, epsilon = 0.18,</pre>
                                 L = 100, aSigma = 0.18)
par(mfrow=c(1,4))
plot(lSamples_hmc_L10$pos, type = 'l', xlab = "mu_t", ylab = "mu_c", main = "L=10")
plot(lSamples_hmc_L20$pos, type = 'l', xlab = "mu_t", ylab = "mu_c", main = "L=20")
plot(1Samples_hmc_L50$pos, type = '1', xlab = "mu_t", ylab = "mu_c", main = "L=50")
plot(lSamples_hmc_L100$pos, type = 'l', xlab = "mu_t", ylab = "mu_c", main = "L=100")
           L=10
                                    L=20
                                                             L=50
                                                                                      L=100
                                                      5.15
                                                                               5.2
                             5.02
   5.15
                                                     5.10
                            5.00
                                                                               5.1
                                                     5.05
                            4.98
   5.10
                                                 mu_c
                                                                           mu_c
                         mu_c
                            4.96
                                                     5.00
                                                                              5.0
    5.05
                             4.94
                                                      4.95
                                                                               4
9
                            4.92
                                                     4.90
   5.00
                            4.90
```

15.2.3.

20.00

20.15

mu_t

Simulate 100 iterations of the particle starting at (20,5), with each particle running for L=100 steps. Examine the motion of the particle in one of the parameter dimensions, and hence determine an optimal number of steps for this distribution.

19.88

19.96

mu_t

4.85

19.85

20.05

mu_t

20.0

mu_t

19.7

Figure 15.12: The path of 100 particle replicates over in the ..t dimens

