Simple linear Gaussian model

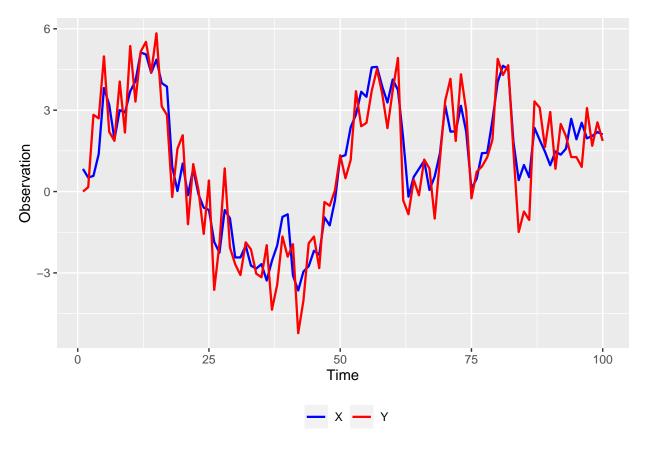
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R. Markdown

```
rm(list=ls())
suppressWarnings({library(MASS)})
suppressWarnings({library(ggplot2)})
suppressWarnings({library(gridExtra)})
suppressWarnings({library(FKF)})
suppressWarnings({library(pmhtutorial)})
                             Q1
set.seed(123456)
simu_func<-function(T,phi,sigma2_V,sigma2_W){</pre>
X<-V<-Y<-W<-numeric(T)
X[1] < -rnorm(1,0,1)
for(t in 2:T){
V[t] <-rnorm(1,0,1)</pre>
X[t] \leftarrow (phi*X[t-1]) + (sqrt(sigma2_V)*V[t])
W[t] \leftarrow rnorm(1,0,1)
Y[t] <-X[t] + (sqrt(sigma2_W) *W[t])
return(list(X=X,Y=Y))
}
observ data<-simu func(100,0.95,1,1)
lable <-c(rep("X",100),rep("Y",100))
observation<-c(observ_data$X,observ_data$Y)</pre>
result_data<-data.frame(observation,lable)</pre>
Dataset <- factor (lable)
plot_data<-ggplot(result_data,aes(x=rep(1:100,2),</pre>
           y=observation,group=factor(lable),colour=Dataset))+
           geom_line(size=0.8)+xlab("Time")+ylab("Observation")+
           scale_color_manual(name="",values=c("X"="blue","Y"="red"),labels=c("X","Y"))+
           theme(legend.position="bottom")
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
observ_data
## $X
   [1] 0.83373317 0.51599874 0.57768623 1.38326204 3.81674435 3.19974155
```

```
##
     [7] 1.92580457 3.00394674 2.91135538 3.69631603 4.07118811 5.12418290
##
    [13] 5.05751359 4.37727485 4.86329021 3.99963410 3.86921072 0.92688180
##
    [19] 0.01885294 1.03299867 -0.13455645 0.83999231 -0.09825759 -0.59529319
    [25] -0.67926267 -1.85694779 -2.25579248 -0.68234204 -0.98779347 -2.42916899
##
##
    [31] -2.42963304 -1.99507564 -2.73216227 -2.84148882 -2.67625761 -3.28035107
##
    [37] -2.55183408 -1.98590347 -0.93377914 -0.83832988 -3.09877976 -3.64857621
    [43] -2.94779585 -2.75335168 -2.18300634 -2.32774211 -0.95125385 -1.24832887
    [49] -0.32182028 1.27786696 1.34268454 2.37410148 2.83725868 3.67844775
##
##
    [55]
        3.49346260 4.57799878 4.59814303 3.87535154
                                                        3.28234373 4.13141487
##
        3.74375734 1.94807498 -0.18993669 0.53728239
    [61]
                                                       0.83743563 1.13700683
    [67] 0.05857812 0.55727368
                               1.41290783 3.17363645
                                                        2.20911398
                                                                   2.21985534
##
    [73] 3.16172882
                     2.20480956
                                0.09956173
                                           0.47544839
                                                        1.41618623
                                                                   1.42701567
##
    [79]
        2.62848196 4.03810942 4.63860344 4.50707331
                                                        1.82590709 0.41963012
    [85] 0.97817041 0.53088265 2.34914177
##
                                                       1.47289070 0.96900246
                                            1.90148403
##
    [91] 1.47992096 1.35895032 1.58023409 2.68309095
                                                        1.92533006 2.53688732
##
    [97] 1.96192621 2.04982657 2.19433724
                                           2.10155338
##
##
  $Y
##
     [1] 0.00000000 0.16099690 2.82994196 2.69567755 4.98497609 2.20361180
##
         1.87007303 4.05716535 2.17631248 5.36452700 3.31721334 5.16267545
##
    [13] 5.52010854 4.39386086 5.83513953 3.14376710 2.82301245 -0.20297781
##
    [19] 1.57892679 2.07699310 -1.20586095 1.01102486 0.06003166 -1.56121580
##
    [25] 0.40668714 -3.62466985 -1.93432660 0.85490058 -2.06524221 -2.68191568
    [31] -3.07861642 -1.87226507 -2.13174054 -3.02615347 -3.16090919 -1.97784355
    [37] -4.35687843 -3.42699243 -1.65676153 -2.40186206 -1.94081619 -5.22239834
##
    [43] -4.01272643 -1.90530425 -1.66020100 -2.82459404 -0.38627365 -0.52351906
##
    [49] 0.04742635 1.33823737 0.49189527 1.16774645 3.70094857
                                                                   2.40718750
    [55] 2.53255245 3.71139189 4.51197481 3.60635262 2.33804622 3.72271080
##
##
    [61] 4.92751319 -0.32436488 -0.83794304 0.43388237 -0.14016170 1.18082922
    [67] 0.85200584 -0.99719668 1.20514003 3.35090083 4.15704645 1.86490621
    [73] 4.32484278 2.98026485 -0.25100046 0.73366217
##
                                                        0.92490808 1.26524495
##
    [79]
        1.90821269 4.89177097 4.29598129
                                            4.65906155
                                                        1.48387811 -1.49042189
##
    [85] -0.73700733 -1.04786566 3.32490132
                                            3.09488498
                                                        1.63925853
                                                                   2.93496106
##
    [91] 0.83841563 2.49309423 2.04263025
                                           1.27336337
                                                        1.26824006 0.90896075
    [97]
         3.08094059 1.68776687 2.55290552
                                            1.86627622
plot_data
```

2

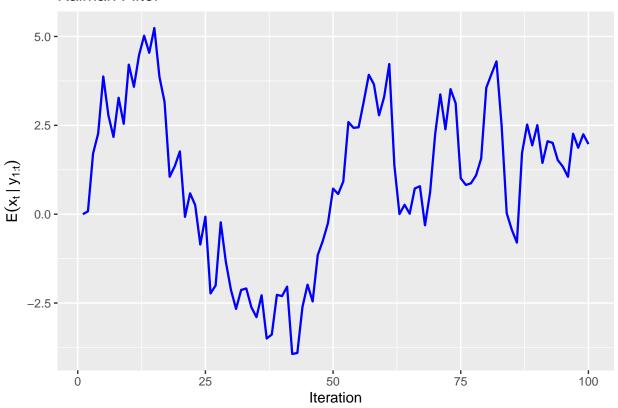


```
Q2
Kalm_filt_func<-function(T,phi,sigma2_V,sigma2_W,y){</pre>
mu<-kalmanFilter(y,theta=c(phi,sqrt(sigma2_V),sqrt(sigma2_W)),initialState=0,</pre>
                 initialStateCovariance=1)$xHatFiltered
return(list(Kalman_Filter=c(mu)))
}
estimates <- Kalm_filt_func(100,0.95,1,1,observ_data$Y)
Kalman_Filter<-estimates$Kalman_Filter</pre>
plot_Kalman_Filter<-ggplot(data.frame(estimates$Kalman_Filter),</pre>
         aes(x=1:100,y=estimates$Kalman_Filter))+
         geom line(size=0.8,colour="blue")+
         xlab("Iteration")+ylab(expression(E(x[t]~"|"~y[1:t])))+
         ggtitle("Kalman Filter")
Kalman_Filter
##
     [1] 0.000000000 0.080498450
                                    1.706650400
                                                  2.271753399
                                                               3.874850883
##
     [6] 2.783459595 2.173887403
                                    3.275492076
                                                  2.543375706
                                                               4.207574002
    [11] 3.584045681
                      4.472882983
                                    5.021405406
                                                  4.541593468
                                                               5.238429411
##
##
    [16] 3.862954593 3.155303813 1.052939742
                                                 1.351864486
                                                              1.765920404
##
    [21] -0.074349861 0.586570768 0.255142509 -0.853463028 -0.071064117
    [26] -2.228801893 -2.006151609 -0.228445710 -1.339981004 -2.129034721
##
    [31] -2.664217381 -2.130762397 -2.089549984 -2.617621940 -2.896358181
##
##
    [36] -2.281450583 -3.497694604 -3.386110061 -2.268939424 -2.305183941
    [41] -2.038569103 -3.933031192 -3.904284934 -2.613121872 -1.982866667
##
```

```
[46] -2.455386113 -1.150039933 -0.746808275 -0.249587193 0.720054735
##
##
    [51] 0.567299666 0.920993856
                                    2.591993624
                                                  2.428851109
                                                               2.444203527
         3.166176752 3.921746860
##
                                    3.653169950
                                                  2.782437925
                                                               3.299144522
    [61] 4.223792554
                      1.377508581
                                    0.004396867
##
                                                  0.265261308
                                                               0.013726136
##
    [66] 0.722575929
                       0.787038800 -0.312485349
                                                  0.615738414
                                                               2.265512150
    [71]
         3.370337180 2.389525886
                                    3.518519525
                                                  3.122446585
                                                               1.011512842
##
##
         0.822847368
                       0.868713627
                                    1.092597100
                                                  1.566718885
                                                               3.556244393
    [76]
    [81]
         3.935925008
                       4.298069889
##
                                    2.503867176
                                                  0.027853459 -0.437414113
##
    [86] -0.799735511
                       1.722040094
                                    2.522378311
                                                  1.936313923
                                                               2.505089497
##
    [91]
         1.443285411
                       2.052819751
                                    2.006351276
                                                  1.521630113
                                                               1.337817867
    [96]
         1.051000243
                       2.263748665
                                    1.869372427
                                                  2.248001571
                                                               1.971962395
```

plot_Kalman_Filter

Kalman Filter

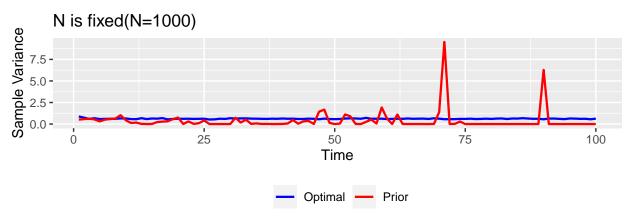


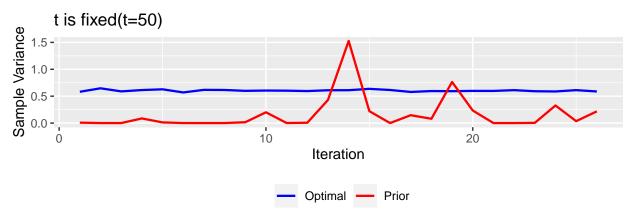
```
Q3-Q4-Q5
                   Sequential Importance Sampler (SIS)
set.seed(123456)
SIS_func<-function(T,phi,sigma2_V,sigma2_W,x,y,N){</pre>
g_Prior<-function(y,x)dnorm(y,mean=x,sd=sqrt(sigma2_W))</pre>
p<-function(y,x)dnorm(y,mean=phi*x,sd=sqrt(sigma2_V+sigma2_W))</pre>
X_hat_prior<-sample_var_prior<-numeric(T)</pre>
```

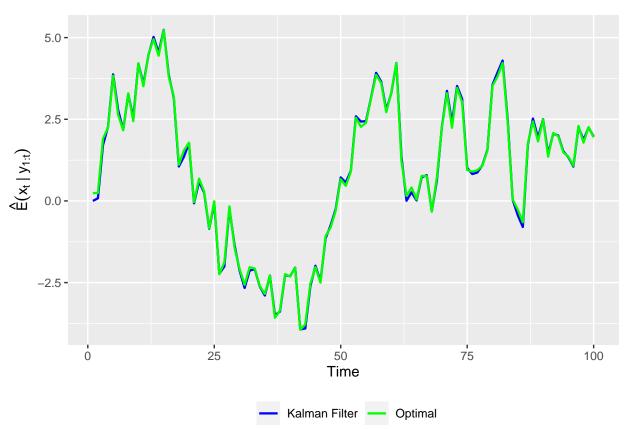
```
X_mat_prior<-wei_prior<-matrix(NA,nrow=T,ncol=N)</pre>
X_mat_prior[1,]<-rnorm(N,0,1)</pre>
wei_prior[1,]<-g_Prior(y[1],X_mat_prior[1,])</pre>
X_hat_prior[1] <-sum(wei_prior[1,]*X_mat_prior[1,])/sum(wei_prior[1,])</pre>
sample_var_prior[1] <-sum(wei_prior[1,]*((X_mat_prior[1,]-X_hat_prior[1])^2))/(sum(wei_prior[1,]))
ESS prior<-numeric(T)</pre>
ESS_prior[1]<-((sum(wei_prior[1,]))^2)/sum(wei_prior[1,]^2)</pre>
X_hat_opt<-sample_var_opt<-numeric(T)</pre>
X_mat_opt<-wei_opt<-matrix(NA,nrow=T,ncol=N)</pre>
sigma_prop_opt<-(sigma2_V*sigma2_W)/(sigma2_V+sigma2_W)</pre>
mean_prop_opt<-sigma_prop_opt*(((phi*x)/sigma2_V)+(y[1]/sigma2_W))</pre>
X mat opt[1,]<-rnorm(N,mean prop opt,sqrt(sigma prop opt))</pre>
wei_opt[1,] \leftarrow p(y[1],x)
X_hat_opt[1] <-sum(wei_opt[1,]*X_mat_opt[1,])/sum(wei_opt[1,])</pre>
sample\_var\_opt[1] < -sum(wei\_opt[1,]*((X_mat\_opt[1,]-X_hat\_opt[1])^2))/(sum(wei\_opt[1,]))
ESS_opt<-numeric(T)</pre>
ESS_opt[1]<-((sum(wei_opt[1,]))^2)/sum(wei_opt[1,]^2)
for(t in 2:T){
X_mat_prior[t,]<-rnorm(N,phi*X_mat_prior[t-1,],sigma2_V)</pre>
wei_prior[t,]<-wei_prior[t-1,]*g_Prior(y[t],X_mat_prior[t,])</pre>
X_hat_prior[t] <-(sum(wei_prior[t,]*X_mat_prior[t,]))/sum(wei_prior[t,])</pre>
sample_var_prior[t] <-sum(wei_prior[t,]*((X_mat_prior[t,]-X_hat_prior[t])^2))/(sum(wei_prior[t,]))</pre>
ESS prior[t] <- ((sum(wei prior[t,]))^2)/sum(wei prior[t,]^2)
mean_prop_opt<-sigma_prop_opt*(((phi*X_mat_opt[t-1,])/sigma2_V)+(y[t]/sigma2_W))</pre>
X_mat_opt[t,]<-rnorm(N,mean_prop_opt,sqrt(sigma_prop_opt))</pre>
wei_opt[t,] \leftarrow p(y[t], X_mat_opt[t-1,])
X_hat_opt[t] <-(sum(wei_opt[t,]*X_mat_opt[t,]))/sum(wei_opt[t,])</pre>
sample_var_opt[t] <-sum(wei_opt[t,]*((X_mat_opt[t,]-X_hat_opt[t])^2))/(sum(wei_opt[t,]))</pre>
ESS_opt[t]<-((sum(wei_opt[t,]))^2)/sum(wei_opt[t,]^2)</pre>
}
return(list(X_mat_prior=X_mat_prior,X_mat_opt=X_mat_opt,
             wei_prior=wei_prior,wei_opt=wei_opt,
             Mu_hat_prior=X_hat_prior,s2_hat_prior=sample_var_prior,
             Mu_hat_opt=X_hat_opt,s2_hat_opt=sample_var_opt,ESS_prior=ESS_prior,ESS_opt=ESS_opt))
}
#
set.seed(123456)
estimates_SIS<-SIS_func(100,0.95,1,1,observ_data$X,observ_data$Y,1000)
lable1<-c(rep("Kalman Filter",100),rep("Optimal",100),rep("Prior",100))</pre>
estimators<-c(estimates_$Kalman_Filter,estimates_$IS$Mu_hat_opt,estimates_$IS$Mu_hat_prior)
result_estim_mu<-data.frame(estimators,lable1)</pre>
Estimators1<-factor(lable1)</pre>
plot_Mu_hat<-ggplot(result_estim_mu,aes(x=rep(1:100,3),</pre>
           y=estimators,group=factor(lable1),colour=Estimators1))+
            geom_line(size=0.8)+
           ylab(expression(hat(E)(x[t]~"|"~y[1:t])))+xlab("Time")+
```



```
Q4
set.seed(123456)
N_{seq} = seq(500, 3000, 100)
var_samp_prior<-var_samp_opt<-matrix(NA,100,length(N_seq))</pre>
for(i in 1:length(N_seq)){
var_initi<-SIS_func(100,0.95,1,1,observ_data$X,observ_data$Y,N_seq[i])</pre>
var_samp_prior[,i]<-var_initi$s2_hat_prior</pre>
var_samp_opt[,i]<-var_initi$s2_hat_opt</pre>
}
lable21<-c(rep("Optimal",100),rep("Prior",100))</pre>
lable22<-c(rep("Optimal",26),rep("Prior",26))</pre>
result_estimators_var1<-data.frame(c(var_samp_opt[,6],var_samp_prior[,6]),lable21)</pre>
result\_estimators\_var2 < -data.frame(c(var\_samp\_opt[50,],var\_samp\_prior[50,]),lable22)
variance1<-factor(lable21)</pre>
variance2<-factor(lable22)</pre>
plot_s2_N_fix<-ggplot(result_estimators_var1,aes(x=rep(1:100,2),</pre>
            y=result_estimators_var1[,1],group=factor(lable21),colour=variance1))+
            geom_line(size=0.8)+
```

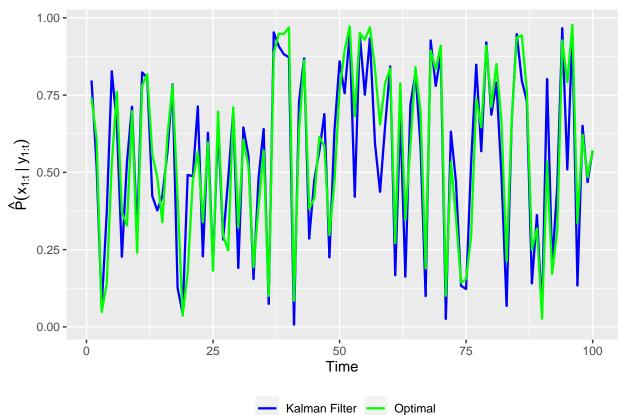






```
for(t in 1:100){
p_hat_value[t] <-p_hat_opt_func(t,estimates_SIS2$X_mat_opt,</pre>
              estimates_SIS2$wei_opt,observ_data$X,1000)$estim_p
sigma < -1/2
b<-0.95*X_init
mean_init<-sigma*(observ_data$Y[t]+b)</pre>
p_exact[t] <-pnorm(observ_data$X[t],mean=mean_init,sd=sqrt(sigma))</pre>
X init<-observ data$X[t]</pre>
}
p_hat_value
##
     [1] 0.74175104 0.60826862 0.04816334 0.13922066 0.52912223 0.76073323
     [7] 0.37020660 0.32783309 0.69815713 0.24030161 0.78086589 0.81752825
##
##
    [13] 0.55794192 0.48329890 0.33850259 0.61833248 0.78256892 0.41814466
   [19] 0.03619375 0.17679272 0.47172435 0.56774468 0.33918296 0.59710977
##
   [25] 0.18190053 0.69678523 0.29531634 0.24782926 0.71047459 0.32207473
##
   [31] 0.60630867 0.51922674 0.19266958 0.39156136 0.57040030 0.09981435
    [37] 0.88586554 0.94894124 0.94782483 0.96890914 0.08422412 0.63735191
##
  [43] 0.86275084 0.38236851 0.41473141 0.61471165 0.58512137 0.29689841
## [49] 0.47339721 0.76613086 0.89430426 0.97261379 0.68171429 0.95121411
   [55] 0.92911771 0.96945547 0.83488065 0.65466230 0.78821327 0.83675190
##
   [61] 0.27105562 0.78858337 0.34541970 0.59045100 0.84044420 0.69589060
  [67] 0.18890638 0.89377751 0.83328547 0.90998372 0.10078725 0.53371504
##
## [73] 0.35329787 0.14344941 0.15443038 0.29540687 0.73993038 0.64571456
   [79] 0.91069425 0.71165969 0.85066054 0.65992063 0.21168953 0.66637885
##
## [85] 0.93646770 0.94355996 0.76451902 0.24935354 0.31822392 0.02673329
## [91] 0.53510133 0.17214635 0.31213340 0.92728611 0.79240807 0.97768086
  [97] 0.33576273 0.62195058 0.48420636 0.57126468
p_exact
     [1] 0.797485386 0.522260966 0.062919014 0.367694597 0.827306040 0.656535279
##
     [7] 0.227147639 0.534151957 0.712426480 0.300967353 0.823529485 0.805463486
##
##
  [13] 0.423448499 0.376791133 0.425134014 0.566092895 0.784932031 0.126143505
   [19] 0.043407628 0.491846321 0.487420461 0.713423659 0.227932771 0.628574134
##
    [25] 0.198134163 0.652915429 0.282649199 0.478407225 0.699081314 0.190675084
##
   [31] 0.645309781 0.553511341 0.154743794 0.482721454 0.640230408 0.074539751
##
  [37] 0.953083922 0.908068789 0.881986868 0.872869961 0.007206084 0.730569767
  [43] 0.868547112 0.285565154 0.474592682 0.568203713 0.688472321 0.224760575
##
   [49] 0.636796359 0.859278474 0.755723222 0.948429677 0.421020993 0.944536404
  [55] 0.751340645 0.933603560 0.593683618 0.437105908 0.650034531 0.842655022
##
  [61] 0.167249995 0.680636809 0.162381302 0.719252079 0.821866579 0.583341584
  [67] 0.099675443 0.927010014 0.779836557 0.878925481 0.025754683 0.631823263
##
    [73] 0.468931167 0.132813461 0.122455669 0.534555873 0.848353623 0.568327027
##
  [79] 0.920630435 0.686537026 0.790930058 0.485450466 0.067500203 0.663041513
  [85] 0.947662273 0.798041747 0.730559723 0.140662184 0.361866764 0.045097413
##
   [91] 0.802100004 0.201809056 0.451272884 0.966564139 0.509444680 0.950694480
    [97] 0.133903042 0.650819677 0.468560348 0.570771829
lable3<-c(rep("Kalman Filter",100),rep("Optimal",100))</pre>
estimators3<-c(p_exact,p_hat_value)</pre>
result_estim_mu2<-data.frame(estimators3,lable3)</pre>
Estimators3<-factor(lable3)
plot_p_hat_opt<-ggplot(result_estim_mu2,aes(x=rep(1:100,2),</pre>
           y=estimators3,group=factor(lable3),colour=Estimators3))+
```

```
geom_line(size=0.8)+
    ylab(expression(hat(P)(x[1:t]~"|"~y[1:t])))+xlab("Time")+
    scale_colour_manual(name="",values=c("Kalman Filter"="blue","Optimal"="green","Prior"="red")
    labels=c("Kalman Filter","Optimal","Prior")) +
    theme(legend.position="bottom")
plot_p_hat_opt
```



```
k<-0
for(i in 1:N){
X star<-rnorm(T,X mat MH init,sqrt(0.01))</pre>
F1<-density func(X star,y)
F2<-density_func(X_mat_MH_init,y)
rho<-F1-F2
if(runif(1) < exp(rho)){</pre>
X_mat_MH[,i]<-X_star</pre>
k<-k+1
}else{
X_mat_MH[,i]<-X_mat_MH_init</pre>
X_mat_MH_init<-X_mat_MH[,i]</pre>
X_hat_MH<-apply(X_mat_MH,1,mean)</pre>
return(list(Mu_hat_MH=X_hat_MH,accept_rate=k/N))
estimates_MH<-MH_sampler(100,0.95,1,1,observ_data$X,observ_data$Y,1000)
estimates_MH$accept_rate
## [1] 0.515
lable3<-c(rep("Kalman Filter",100),rep("MH",100))</pre>
estimators MH<-c(estimates$Kalman Filter, estimates MH$Mu hat MH)
result_estim_mu_MH<-data.frame(estimators_MH,lable3)</pre>
Estimators3<-factor(lable3)</pre>
plot_Mu_hat_MH<-ggplot(result_estim_mu_MH,aes(x=rep(1:100,2),</pre>
           y=estimators_MH,group=factor(lable3),colour=Estimators3))+
           geom_line(size=0.8)+
           ylab(expression(hat(E)(x[t]~"|"~y[1:t])))+xlab("Time")+
           scale_colour_manual(name="",values=c("Kalman Filter"="blue","MH"="red"),
           labels=c("Kalman Filter", "MH"))+ggtitle("Metropolis approach")+
           theme(legend.position="bottom")
#
                 Gibbs Sampler(Gibbs Sampler)
Gibbs_sampler<-function(T,phi,sigma2_V,sigma2_W,x,y,N){</pre>
X_gibbs<-matrix(0,nrow=T,ncol=N)</pre>
mean init<-0
sigma init<-(1/(1+(1/(sigma2 W^2))))
X_init<-rnorm(N,mean_init,sqrt(sigma_init))</pre>
for(t in 1:T){
b<-phi*X_init
sigma<-1/(1/sigma2_W^2+1/sigma2_V^2)
mean_init<-sigma*(y[t]/sigma2_W^2+b/sigma2_V^2)</pre>
X gibbs[t,]<-rnorm(N,mean=mean init,sd=sqrt(sigma))</pre>
X_init<-X_gibbs[t,]</pre>
X_hat_Gibbs<-apply(X_gibbs,1,mean)</pre>
return(list(Mu_hat_Gibbs=X_hat_Gibbs))
}
estimates_Gibbs<-Gibbs_sampler(100,0.95,1,1,observ_data$X,observ_data$Y,1000)
```

Metropolis approach

