ensemble_IC2

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IMPORT DATA

```
data<-read.csv(file="US-Coronavirus-data.csv",header = TRUE) %>%
#data<-data %>%
#mutate(date=as.character(date)) %>%
mutate(date=as.Date(date)) %>%
#mutate(date=paste(month(date),"/",day(date))) %>%
#mutate(date=as.Date(date,"%m-%d")) %>%
#mutate(date=as.Date(date,"%m-%d")) %>%
#mutate(daily.D=D-c(0,D[-length(D)])) %>%
filter(!is.na(C)) %>%
filter(date>=as.Date('2020-02-29'))
D<-data %>%
select(date,I,D,daily.D) %>%
filter(date<=as.Date("2020-07-31"))

trans<-data$I[-1]/data$I[-nrow(data)] #from March to May
#daily<-data$daily.D</pre>
```

MODEL

In this model, we use the same method as in the Imperial College model 1.

However, in model1, we just assume the length of time window is one week, 7 days. In this model, we will use APE to choose the best length of time window. Others are the same as model1.

```
########likelihood

ppd<-function(k){
    #ppd<-c()
    n<-c()
    p<-c()
    ii<-c()
    ii<-c()
    ln_a<-c()</pre>
for (i in 1:(length(D$daily.D)-1)) {
    if (i<=k) {
```

```
next
             }else{
                    daily<-D$daily.D[1:i]</pre>
                    shape=1+sum(tail(daily,k))
                   rate < -1/5
                   for (s in (i-k+1):i) {
                         rate<-rate+mean(daily[1:s-1])</pre>
             }
                    scale<-1/rate
                   n<-append(n,shape)</pre>
                   p<-append(p,mean(daily) *scale / (1+mean(daily) *scale))</pre>
                    \#ppd < -append(ppd, dnbinom(x=D$daily.D[i+1], size=n, prob=p))
                    #ppd[which(ppd==0)]<-10^-320
                    ii<-append(ii,i)</pre>
                    \#\ln_z uhe < -(D\$daily.D[i+1] + shape-1) * (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] * (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) - 1) - (D\$daily.D[i+1] + shape-1) + (\log(D\$daily.D[i+1] + shape-1) + (\log(
                    stirl<-function(n){
                          ##stirling appproximation to get ln(n!)
                          ## return the approximation of ln(n!)
                         return(n*log(n)-n)
                   }
                   ln_zuhe<-stirl(D$daily.D[i+1]+shape-1)-stirl(D$daily.D[i+1])-stirl(shape-1)</pre>
                   ln_a<-append(ln_a,ln_zuhe)</pre>
             }
      }
      return(list(prob=p,i=ii,ln_zuheshu=ln_a,n=n))
}
ape<-function(k){
      sum < -0
      \#sum((-1) * log(ppd(k)\$prob))
      haha<-ppd(k)
      for (i in haha$i) {
             sum<-sum+(-1)*(dnbinom(D$daily.D[i+1],size=haha$n[i-k],prob=haha$prob[i-k],log=TRUE))</pre>
      }
      return(sum)
}
```

```
####optimize APE
## k between 2 and t/2
k.best<-which.min(map_dbl(2:floor(length(D$daily.D)/2),function(k) ape(k)))+1
k.best
## [1] 2</pre>
```

... [-] -

#k.best=2

We can get the best length of time window is 2 days.

Then, we will use the most recent 2 days in training set to estimate the R_t .

```
###estimate Rt
##first set tao=2
##6.30+7.1
###prior of Rt.tao = gamma(1, 1/5)
#set.seed(1)
#shape=1
#rate=1/5
Rt<- tail(trans,1)</pre>
mu<-mean(tail(trans,2))</pre>
v<-var(tail(trans,2))</pre>
rate=mu/v
shape=mu*rate
#daily<-append(daily,rep(0,7))
daily<-D$daily.D
1<-length(daily)</pre>
###posterior of Rt, tao
R<-Rt
A < -c()
#####MCMC
for (i in 1:2000) {
  #1st given Rt
  for (j in 0:(k.best-1)) {
    daily[l-j]<-rpois(1,lambda = Rt * mean(head(daily,l-j-1)) )</pre>
  \#daily[l-0] < -rpois(1, lambda = Rt * mean(head(daily, l-1)))
  shape<-shape+sum(tail(daily,k.best))</pre>
  for (j in 0:(k.best-1)) {
    rate<-rate+mean(head(daily,l-j-1))#+mean(head(daily,l-0-1))
  Rt<-rgamma(1,shape=shape,rate=rate)</pre>
  R<-append(R,Rt)
  A<-rbind(A,tail(daily,k.best))
```

```
R.post<-mean(tail(R,500))
R.post

## [1] 1.013499

w.exam.post.last<-colMeans(A)
```

FORECASTING

In this model, we will first use the estimated $R_t.post$ to do deaths forecasting.

```
####forcast of the following 7 days of daily deaths
t<-7
w<-c()
#set.seed(0)
for (iter in 1:2000) {
  daily<-D$daily.D
  1<-length(daily)</pre>
  for (i in (l+1):(l+t)) {
    d<-rpois(1,R.post* (mean(head(daily,i-1))) )</pre>
    daily[i]<-d
  }
#daily
  total.new<-map_dbl(1:length(daily),function(x) sum(head(daily,x)))</pre>
  w.fore<-tail(total.new,t)</pre>
  w<-rbind(w,w.fore)</pre>
}
answer=colMeans(tail(w,500))
temp<-seq(from=as.Date('2020-08-01'),by='day',length.out = t)</pre>
pred=tibble(date=temp,prediction=answer)
#(pred[1:7,]); (pred[8:14,]); (pred[15:21,]); (pred[22:28,])
pred
```

```
##
     <date>
                     <dbl>
## 1 2020-08-01
                   154826.
## 2 2020-08-02
                   155839.
## 3 2020-08-03
                   156851.
## 4 2020-08-04
                   157863.
## 5 2020-08-05
                   158876.
## 6 2020-08-06
                   159886.
## 7 2020-08-07
                   160896.
#a<-data %>% filter(month(date)==6) %>%select(D)
\#mean((a$D-answer)^2)
```

MSE & RMSE

Since we have the best length of time window is 2 days, so we can just estimate the daily death of the recent 2 days. And then we will remove these 2 days from our training set, and use the new training set with the we finish estimating all the deaths in the previous week.

```
same method to get the best length and estimate other days in the last week. We just repeat the steps till
daily<-D$daily.D
1<-length(daily)</pre>
daily[(l-(k.best-1)):l] < -w.exam.post.last
total<-map_dbl(1:length(daily),function(x) sum(head(daily,x)))</pre>
tail(total,k.best)
## [1] 152369.8 153379.4
mse.last<-mean((tail(total,k.best)-tail(D$D,k.best))^2)</pre>
mse.last
## [1] 115086
D < -head(D, (nrow(D)-2))
trans<-head(trans,(length(trans)-2))</pre>
k.best.middle<-which.min(map_dbl(2:floor(length(D$daily.D)/2),function(k) ape(k)))+1
k.best.middle
## [1] 2
Rt<-tail(trans,1)
mu<-mean(tail(trans,2))</pre>
v<-var(tail(trans,2))</pre>
rate=mu/v
shape=mu*rate
\#daily \leftarrow append(daily, rep(0,7))
daily<-D$daily.D
1<-length(daily)</pre>
```

```
###posterior of Rt, tao
R<-Rt
A < -c()
#####MCMC
for (i in 1:2000) {
  #1st given Rt
  for (j in 0:(k.best.middle-1)) {
    daily[l-j]<-rpois(1,lambda = Rt * mean(head(daily,l-j-1)) )</pre>
  \#daily[l-0] < -rpois(1, lambda = Rt * mean(head(daily, l-1)))
  shape<-shape+sum(tail(daily,k.best.middle))</pre>
  for (j in 0:(k.best.middle-1)) {
    rate<-rate+mean(head(daily,l-j-1))#+mean(head(daily,l-0-1))
  }
  Rt<-rgamma(1,shape=shape,rate=rate)</pre>
  R<-append(R,Rt)
  A<-rbind(A,tail(daily,k.best.middle))
}
R.post<-mean(tail(R,500))
w.exam.post.middle<-colMeans(A)
daily[(l-(k.best.middle-1)):1]<-w.exam.post.middle</pre>
library(purrr)
total<-map_dbl(1:length(daily),function(x) sum(head(daily,x)))</pre>
tail(total,k.best.middle)
## [1] 149555.3 150544.6
mse.middle<-mean((tail(total,k.best.middle)-tail(D$D,k.best.middle))^2)</pre>
mse.middle
## [1] 401526.1
D < -head(D, (nrow(D) - 2))
trans<-head(trans,length(trans)-2)</pre>
k.best.first<-which.min(map_dbl(2:floor(length(D$daily.D)/2),function(k) ape(k)))+1
k.best.first
```

[1] 2

```
Rt<-tail(trans,1)</pre>
mu<-mean(tail(trans,2))</pre>
v<-var(tail(trans,2))</pre>
rate=mu/v
shape=mu*rate
#daily<-append(daily,rep(0,7))
daily<-D$daily.D
1<-length(daily)</pre>
###posterior of Rt, tao
R<-Rt
A < -c()
#####MCMC
for (i in 1:2000) {
  #1st given Rt
  for (j in 0:(k.best.first-1)) {
    daily[l-j] <-rpois(1,lambda = Rt * mean(head(daily,l-j-1)) )</pre>
  \#daily[l-0] < -rpois(1, lambda = Rt * mean(head(daily, l-1)))
  shape<-shape+sum(tail(daily,k.best.first))</pre>
  for (j in 0:(k.best.first-1)) {
    rate < -rate + mean(head(daily, l-j-1)) # + mean(head(daily, l-0-1))
  }
  Rt<-rgamma(1,shape=shape,rate=rate)</pre>
  R<-append(R,Rt)
  A<-rbind(A,tail(daily,k.best.first))
}
R.post<-mean(tail(R,500))
w.exam.post.first<-colMeans(A)</pre>
daily[(l-(k.best.first-1)):1]<-w.exam.post.first</pre>
library(purrr)
total<-map_dbl(1:length(daily),function(x) sum(head(daily,x)))</pre>
tail(total,k.best.first)
```

[1] 147969.8 148975.3

```
mse.first<-mean((tail(total,k.best.first)-tail(D$D,k.best.first))^2)</pre>
mse.first
## [1] 222669.1
D<-head(D,(nrow(D)-2))
trans<-head(trans,length(trans)-2)</pre>
k.best.1<-which.min(map_dbl(2:floor(length(D$daily.D)/2),function(k) ape(k)))+1
k.best.1
## [1] 2
Rt<-tail(trans,1)
mu<-mean(tail(trans,2))</pre>
v<-var(tail(trans,2))</pre>
rate=mu/v
shape=mu*rate
#daily<-append(daily,rep(0,7))
daily<-D$daily.D
1<-length(daily)</pre>
###posterior of Rt, tao
R<-Rt
A < -c()
#####MCMC
for (i in 1:2000) {
  #1st given Rt
  for (j in 0:(k.best.1-1)) {
    daily[l-j]<-rpois(1,lambda = Rt * mean(head(daily,l-j-1)) )</pre>
  \#daily[l-0] < -rpois(1, lambda = Rt * mean(head(daily, l-1)))
  shape<-shape+sum(tail(daily,k.best.1))</pre>
  for (j in 0:(k.best.1-1)) {
    rate<-rate+mean(head(daily,l-j-1))#+mean(head(daily,l-0-1))
  }
  Rt<-rgamma(1,shape=shape,rate=rate)</pre>
  R<-append(R,Rt)</pre>
  A<-rbind(A,tail(daily,k.best.1))
}
```

```
R.post<-mean(tail(R,500))
w.exam.post.i<-colMeans(A)

daily[(1-(k.best.middle-1)):1]<-w.exam.post.1

library(purrr)
total<-map_dbl(1:length(daily),function(x) sum(head(daily,x)))
tail(total,k.best.1)

## [1] 145958.4 146963.7

mse.1<-mean((tail(total,1)-tail(D$D,1))^2)
mse.1

## [1] 1.647372

mse<-mse.last+mse.middle+mse.first+mse.1
mse

## [1] 739282.9

(rmse<-sqrt(mse))

## [1] 859.8156</pre>
```