Advanced Machine Learning (732A96) Lab3

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Questions

The purpose of the lab is to put in practice some of the concepts covered in the lectures. To do so, you are asked to implement the particle filter for robot localization. For the particle filter algorithm, please check Section 13.3.4 of Bishop's book and/or the slides for the last lecture on state space models (SSMs). The robot moves along the horizontal axis according to the following SSM:

Trasition model:

$$p(z_t|z_{t-1})=(N(z_t|z_{t-1},1)+N(z_t|z_{t-1}+1,1)+N(z_t|z_{t-1}+2,1))/3$$
 Emission model:
$$p(x_t|z_t)=(N(x_t|z_t,1)+N(x_t|z_t-1),1)++N(x_t|z_t+1),1))/3$$
 Initial model:
$$p(z_1)=Uniform(0,100)$$

Questions 1

1) Implement the SSM above. Simulate it for T = 100 time steps to obtain $z_{1:100}$ (i.e., states) and $x_{1:100}$ (i.e., observations). Use the observations (i.e., sensor readings) to identify the state (i.e., robot location) via particle filtering. Use 100 particles. Show the particles, the expected location and the true location for the first and last time steps, as well as for two intermediate time steps of your choice.

```
set.seed(12345)
gen_data <- function(N){</pre>
# states
z_t <- vector(length = N)</pre>
# observations
x_t <- vector(length = N)</pre>
# initial conditions
z_t[1] \leftarrow runif(n = 1, min = 0, max = N)
comp \leftarrow sample(1:3, prob = c(1 / 3, 1 / 3, 1 / 3), size = 1)
mu \leftarrow c(z_t[1], z_t[1] - 1, z_t[1] + 1)
x_t[1] \leftarrow rnorm(1, mean = mu[comp], 1)
for (i in 2:N) {
    comp \leftarrow sample(1:3, prob = c(1 / 3, 1 / 3, 1 / 3), size = 1)
    muz \leftarrow c(z_t[i-1], z_t[i-1] + 1, z_t[i-1] + 2)
    z_t[i] \leftarrow rnorm(1, mean = muz[comp], 1)
    mu \leftarrow c(z_t[i], z_t[i] - 1, z_t[i] + 1)
    x_t[i] \leftarrow rnorm(1, mean = mu[comp], 1)
  }
sample_data <- data.frame(observation = x_t, states = z_t,</pre>
                             index=1:N)
# plot of samples
p1 <- ggplot(data=sample_data, aes(x=index)) +
  geom line(aes(y=observation, color="Observations")) +
  geom_line(aes(y=states, color="True location")) +
```

```
scale_colour_manual("", breaks = c("Observations", "True location"),
                        values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
  xlab("Index") +
  vlab("Location") +
  ggtitle("Observed and True location")
print(p1)
# density plots
p2 <- ggplot(data=sample_data) +</pre>
  geom_density(aes(x=observation, color="Observations")) +
  geom_density(aes(x=states, color="True location")) +
        scale_colour_manual("", breaks = c("Observations", "True location"),
                        values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
   xlab("Index") +
  ylab("Density") +
  ggtitle("Desnity of Observed and True location")
print(p2)
return(list(z_t=z_t, x_t=x_t))
```

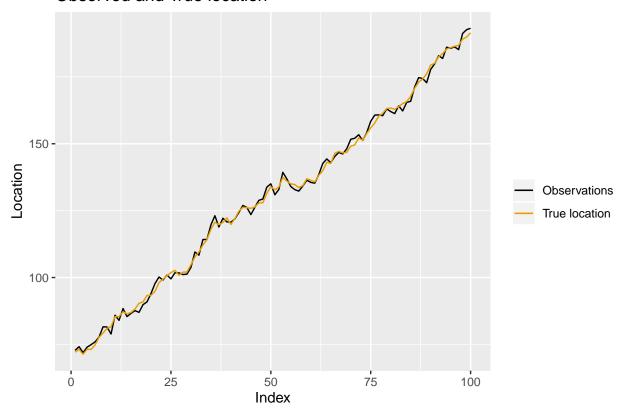
At time step 1, we know $p(z_1)$ and therefore sample L = 100 particles from it. And we also know the emission model $p(x_1|z_1^{(l)})$, which we use to compute the weights:

$$w_n^{(l)} = \frac{p(x_n|z_n^{(l)})}{\sum_{m=1}^{L} p(x_n|z_n^{(l)})}$$

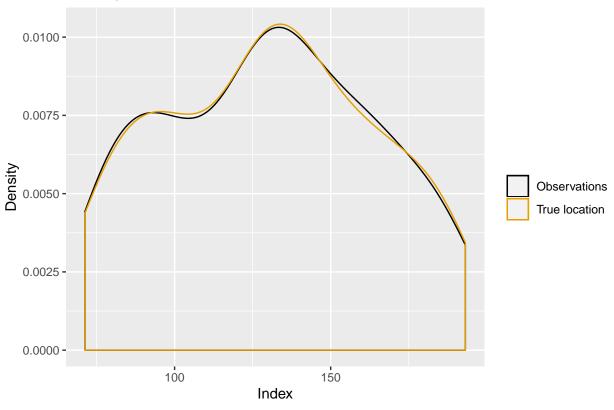
Note that the weights satisfy $0 \le w_n^{(l)}$ and $\sum_l w_n^{(l)} = 1$

```
set.seed(12345)
# generate data
sample_data <- gen_data(N=100)</pre>
```

Observed and True location



Desnity of Observed and True location



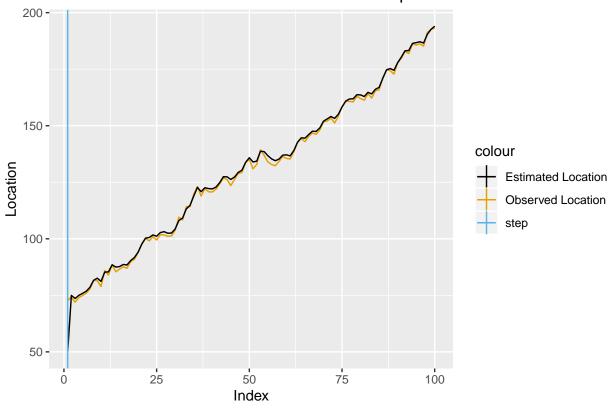
```
# particle filter
particles <- my_particle_filter(M=100, Times = 100, obs=sample_data$x_t,
                                 sd_tra=1, sd_emi=1, ignore_weight = FALSE)
location <- data.frame(true_location=sample_data$z_t,</pre>
                 observed location=sample data$x t,
                 estimated_location = rowMeans(particles, na.rm = TRUE),
                 index = 1:NROW(particles)) %>% as.data.frame()
# plot function
plot_location <- function(step, df){</pre>
plot1 <- ggplot(data=df, aes(x=index)) +</pre>
geom_line(aes(y=observed_location, color="Observed Location")) +
geom_line(aes(y=estimated_location, color="Estimated Location")) +
geom_vline(aes(xintercept=step, color="step")) +
  xlab("Index") +
  ylab("Location") +
      scale_colour_manual(values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
ggtitle(paste0("Observed and Estimated Location for its ", step, " step"))
df <- df[step,]</pre>
result <- data.frame(step = step,</pre>
  true_location = df$true_location,
 observed_location = df$observed_location,
```

```
estimated_location = df$estimated_location)

print(plot1)
kable(result, "latex", booktabs = T) %>% kable_styling(latex_options = "striped")
}

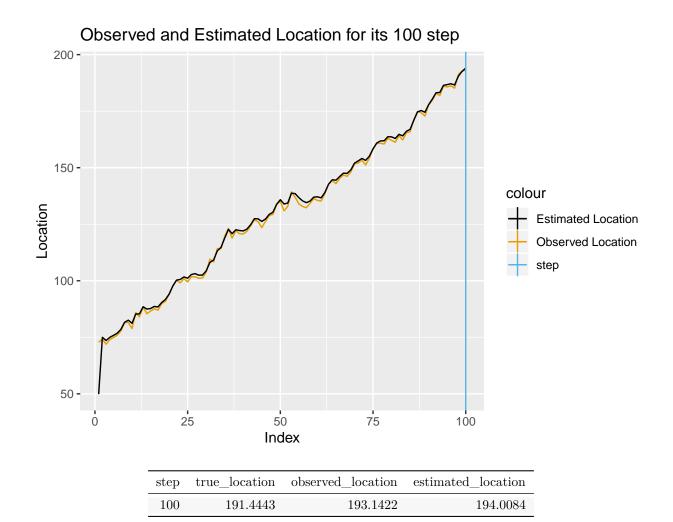
plot_location(step=1, df=location)
```

Observed and Estimated Location for its 1 step

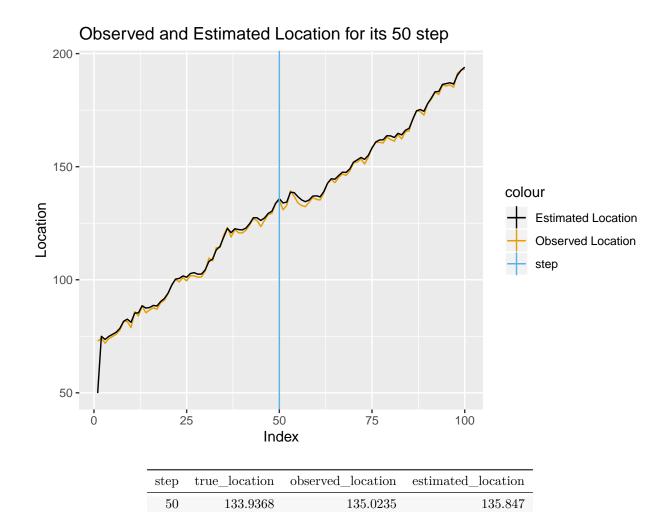


step	$true_location$	$observed_location$	$estimated_location$
1	72.09039	72.79986	49.85403

plot_location(step=100, df=location)

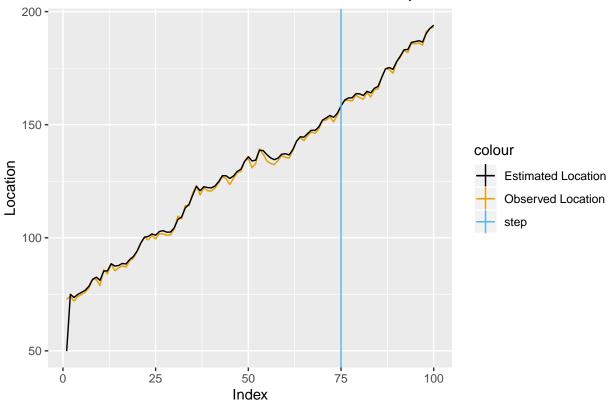


plot_location(step=50, df=location)



plot_location(step=75, df=location)

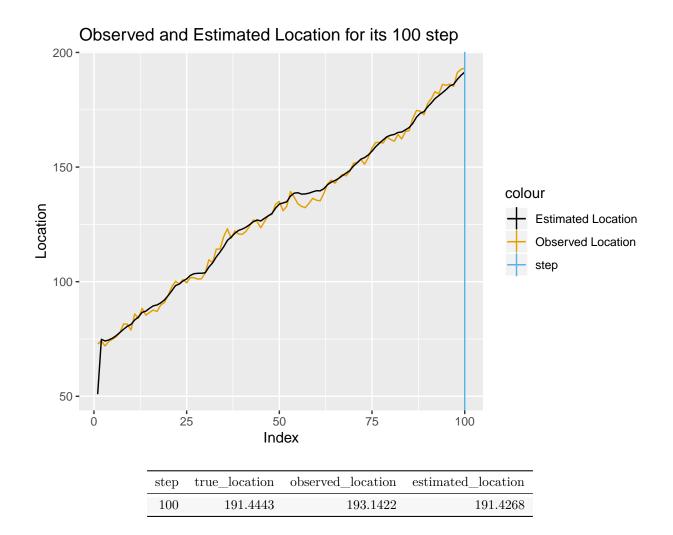




step	$true_location$	$observed_location$	$estimated_location$
75	155.9155	158.3693	158.2851

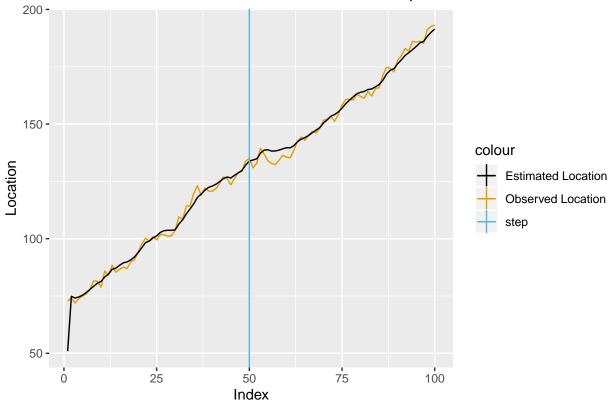
Questions 2

2) Repeat the exercise above replacing the standard deviation of the emission model with 5 and then with 50. Comment on how this affects the results.

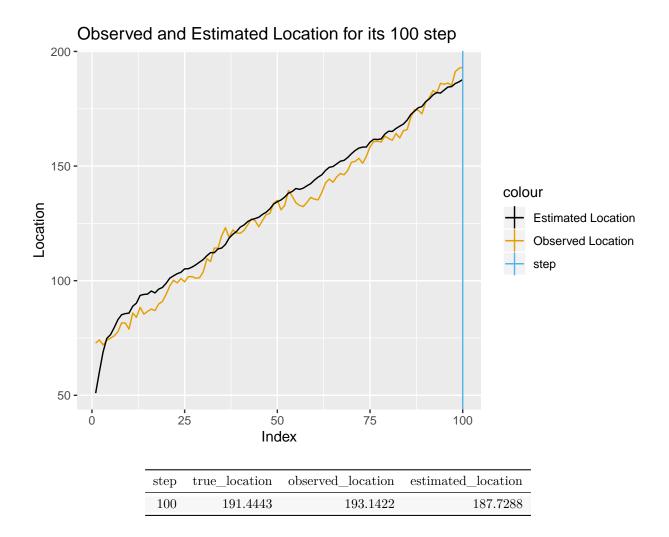


plot_location(step=50, df=location_sd_5)

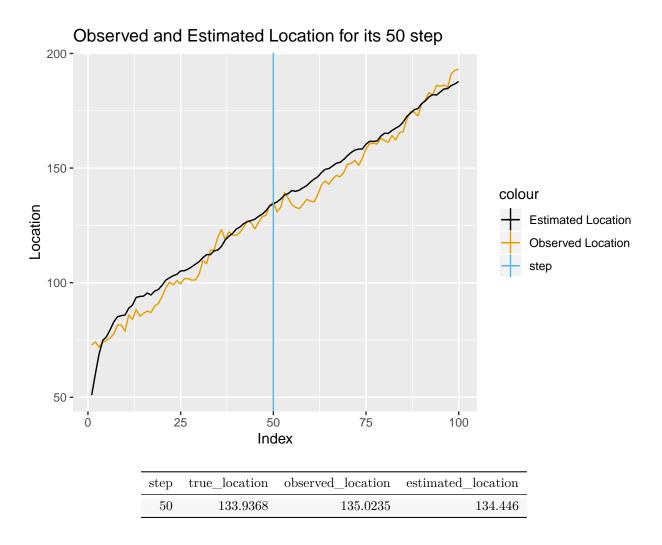




step	${\bf true_location}$	$observed_location$	$estimated_location$
50	133.9368	135.0235	133.8438



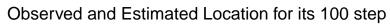
plot_location(step=50, df=location_sd_50)

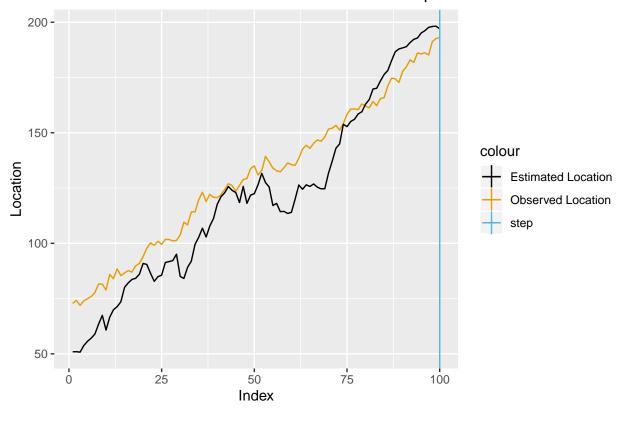


Analysis: With higher standard deviation in emission model, there is greater spread of the particles thus higher uncertainty in for the detection of the robots location.

Questions 3

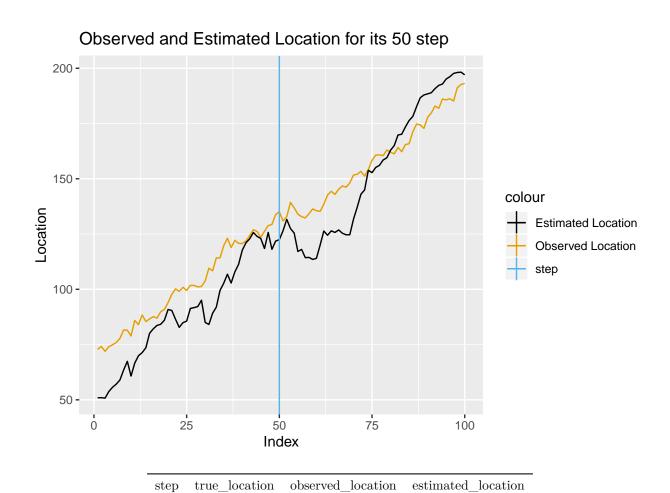
3) Finally, show and explain what happens when the weights in the particle filter are always equal to 1, i.e. there is no correction.





step	$true_location$	$observed_location$	$estimated_location$
100	191.4443	193.1422	197.0318

plot_location(step=50, df=df_no_weight)



Analysis: With no weights for the probability the whole resampling stage of the particle filter is defeated, thus there is no way for us to weed out the unlikely location and we are left with the as much as uncertainty with robots location as before.

135.0235

122.4591

Appendix

50

133.9368

```
gen_data <- function(N){</pre>
# states
z_t <- vector(length = N)</pre>
# observations
x_t <- vector(length = N)</pre>
# initial conditions
z_t[1] \leftarrow runif(n = 1, min = 0, max = N)
comp \leftarrow sample(1:3, prob = c(1 / 3, 1 / 3, 1 / 3), size = 1)
mu \leftarrow c(z_t[1], z_t[1] - 1, z_t[1] + 1)
x_t[1] \leftarrow rnorm(1, mean = mu[comp], 1)
for (i in 2:N) {
    comp \leftarrow sample(1:3, prob = c(1 / 3, 1 / 3, 1 / 3), size = 1)
    muz \leftarrow c(z_t[i-1], z_t[i-1] + 1, z_t[i-1] + 2)
    z_t[i] \leftarrow rnorm(1, mean = muz[comp], 1)
    mu \leftarrow c(z_t[i], z_t[i] - 1, z_t[i] + 1)
    x_t[i] \leftarrow rnorm(1, mean = mu[comp], 1)
  }
sample_data <- data.frame(observation = x_t, states = z_t,</pre>
                            index=1:N)
# plot of samples
p1 <- ggplot(data=sample_data, aes(x=index)) +
  geom_line(aes(y=observation, color="Observations")) +
  geom_line(aes(y=states, color="True location")) +
        scale_colour_manual("", breaks = c("Observations", "True location"),
                         values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
  xlab("Index") +
  vlab("Location") +
  ggtitle("Observed and True location")
print(p1)
# density plots
p2 <- ggplot(data=sample data) +
  geom_density(aes(x=observation, color="Observations")) +
  geom_density(aes(x=states, color="True location")) +
        scale_colour_manual("", breaks = c("Observations", "True location"),
                         values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
    xlab("Index") +
  vlab("Density") +
  ggtitle("Desnity of Observed and True location")
print(p2)
return(list(z_t=z_t, x_t=x_t))
}
my_particle_filter <- function(M, Times, obs, sd_tra, sd_emi, ignore_weight) {
```

```
temp_particles <- NULL</pre>
  weights <- NULL
  # Create matrix that will contain all particles for each time step
  particles <- matrix(NA, nrow = Times, ncol = M)</pre>
  # Generate initial M particles, Uniform(0, 100)
  particles[1, ] \leftarrow runif(n = M, min = 0, max = 100)
  for (t in 2:Times) {
    for (m in 1:M) {
  # transiton matrix
    selection \leftarrow sample(1:3, prob = c(1 / 3, 1 / 3, 1 / 3), size = 1)
    mean\_tra \leftarrow c(particles[t - 1, m], particles[t - 1, m] + 1,
                   particles [t - 1, m] + 2)
    temp_particles[m] <- rnorm(n=1, mean = mean_tra[selection], sd = sd_tra)</pre>
  # emission matrix
    weights[m] <- mean(dnorm(x=obs[t], mean = temp_particles[m]-1, sd = sd_emi),</pre>
                        dnorm(x=obs[t], mean = temp_particles[m], sd = sd_emi),
                        dnorm(x=obs[t], mean = temp_particles[m]+1, sd = sd_emi))
    weights = weights/sum(weights)
    if(ignore_weight == TRUE){
            particles[t, ] <- sample(x = temp_particles, size = M,</pre>
                                       replace = TRUE)
    }else{
      particles[t, ] <- sample(x = temp_particles, size = M, replace = TRUE,</pre>
                            prob = weights)}
 }
 return(particles)
set.seed(12345)
# generate data
sample_data <- gen_data(N=100)</pre>
# particle filter
particles <- my_particle_filter(M=100, Times = 100, obs=sample_data$x_t,
                                  sd_tra=1, sd_emi=1, ignore_weight = FALSE)
location <- data.frame(true_location=sample_data$z_t,</pre>
                  observed_location=sample_data$x_t,
                  estimated_location = rowMeans(particles, na.rm = TRUE),
                  index = 1:NROW(particles)) %>% as.data.frame()
```

```
# plot function
plot_location <- function(step, df){</pre>
plot1 <- ggplot(data=df, aes(x=index)) +</pre>
geom_line(aes(y=observed_location, color="Observed Location")) +
geom line(aes(y=estimated location, color="Estimated Location")) +
geom_vline(aes(xintercept=step, color="step")) +
  xlab("Index") +
  ylab("Location") +
      scale colour manual(values = c("#000000", "#E69F00", "#56B4E9", "#009E73")) +
ggtitle(paste0("Observed and Estimated Location for its ", step, " step"))
df <- df[step,]</pre>
result <- data.frame(step = step,</pre>
  true_location = df$true_location,
  observed_location = df$observed_location,
  estimated_location = df$estimated_location)
print(plot1)
kable(result, "latex", booktabs = T) %>% kable_styling(latex_options = "striped")
plot_location(step=1, df=location)
plot_location(step=100, df=location)
plot_location(step=50, df=location)
plot_location(step=75, df=location)
set.seed(12345)
# with standard deviation of the emission model of 5
particles_sd_emis_5 <- my_particle_filter(M=100, Times = 100, obs=sample_data$x_t,
                                 sd_tra=1, sd_emi=5, ignore_weight = FALSE)
location_sd_5 <- data.frame(true_location=sample_data$z_t,</pre>
                 observed_location=sample_data$x_t,
                 estimated location = rowMeans(particles sd emis 5, na.rm = TRUE),
                 index = 1:NROW(particles_sd_emis_5)) %>% as.data.frame()
plot location(step=100, df=location sd 5)
plot_location(step=50, df=location_sd_5)
set.seed(12345)
# with standard deviation of the emission model of 50
particles_sd_emis_50 <- my_particle_filter(M=100, Times = 100, obs=sample_data$x_t,
                                 sd_tra=1, sd_emi=50, ignore_weight = FALSE)
location_sd_50 <- data.frame(true_location=sample_data$z_t,</pre>
                 observed_location=sample_data$x_t,
                 estimated_location = rowMeans(particles_sd_emis_50, na.rm = TRUE),
                 index = 1:NROW(particles_sd_emis_50)) %>% as.data.frame()
plot location(step=100, df=location sd 50)
plot_location(step=50, df=location_sd_50)
```