Advanced Machine Learning

Lab 4

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Assignment 1

```
sample_transition_component <- function() {</pre>
    sample(1:3, size=1, prob=rep(1, 3) / 3)
}
sample_emission_component <- function() {</pre>
    sample(1:3, size=1, prob=rep(1, 3) / 3)
}
sample_initial_state <- function() {</pre>
    runif(1, 0, 100)
}
sample_transition <- function(z, sigma=1) {</pre>
    component <- sample_transition_component()</pre>
    mu \leftarrow ifelse(component == 1, z, ifelse(component == 2, z + 1, z + 2))
    rnorm(1, mean=mu, sd=sigma)
}
sample_emission <- function(z, sigma=1) {</pre>
    component <- sample_emission_component()</pre>
    mu \leftarrow ifelse(component == 1, z, ifelse(component == 2, z - 1, z + 1))
    rnorm(1, mean=mu, sd=sigma)
}
generate_states_and_emissions <- function(n, sigma) {</pre>
    states \leftarrow rep(0, n)
    emissions <- rep(0, n)
    initial_state <- sample_initial_state()</pre>
    current_state <- initial_state</pre>
    for (i in 1:n) {
         current_emission <- sample_emission(current_state, sigma)</pre>
        states[i] <- current_state</pre>
         emissions[i] <- current_emission</pre>
        current_state <- sample_transition(current_state, sigma)</pre>
    }
    list(states=states, emissions=emissions)
}
```

```
get_emission_density_given_state <- function(emission, state, sigma=1) {</pre>
    (dnorm(emission, mean=state, sd=sigma) +
     dnorm(emission, mean=state - 1, sd=sigma) +
     dnorm(emission, mean=state + 1, sd=sigma)) / 3
}
get_sampling_weights <- function(emission, particles, sigma=1) {</pre>
    unnormalized weights <- sapply(particles, function(state) {
        get_emission_density_given_state(emission, state, sigma)
    unnormalized_weights / sum(unnormalized_weights)
}
particle_filtering <- function(x, nparticles, sigma) {</pre>
    steps <- length(x)
    particles <- matrix(NA, nrow=steps, ncol=nparticles)</pre>
    weights <- matrix(NA, nrow=steps, ncol=nparticles)</pre>
    particles[1, ] <- runif(nparticles, 0, 100)</pre>
    weights[1, ] <- get_sampling_weights(x[1], particles[1, ], sigma=sigma)</pre>
    for (i in 2:steps) {
        predictions <- sample(particles[i - 1, ], size=nparticles,</pre>
                                replace=TRUE, prob=weights[i - 1, ])
        particles[i, ] <- sapply(predictions, sample_transition, sigma=sigma)</pre>
        weights[i, ] <- get_sampling_weights(x[i], particles[i, ], sigma=sigma)</pre>
    list(particles=particles, weights=weights)
}
get_expected_states <- function(particles, weights) {</pre>
    rowSums(weights * particles)
}
plot_everything <- function(states, emissions, particles, expected) {</pre>
    nparticles <- ncol(particles)</pre>
    old <- par(mfrow=c(2, 1))
    plot(states, type="1",
         main="Black=State, Red=Emission",
         ylim=c(min(c(states, emissions)), max(c(states, emissions))))
    lines(emissions, col="red")
    plot(1:nparticles, states, type="l",
         main="Black=State, Orange=Expected",
         ylim=c(min(c(states, expected)), max(c(states, expected))))
    lines(1:nparticles, expected, col="orange")
    par(old)
    plot_helper <- function(idx) {</pre>
        p <- particles[idx,]</pre>
        ex <- expected[idx]</pre>
        s <- states[idx]
```

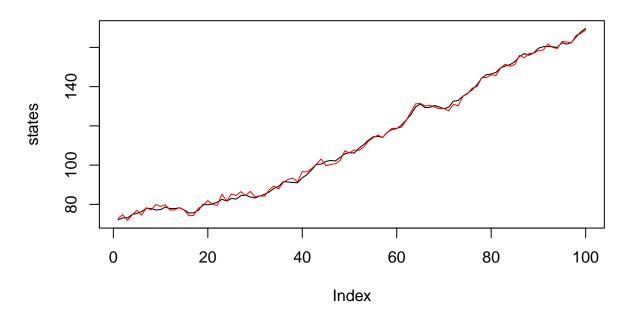
```
em <- emissions[idx]</pre>
        hist(p, breaks=20,
             main=paste("Step", idx, sep=" "),
             xlab="val", xlim=c(min(c(p, ex, s, em)), max(c(p, ex, s, em))))
        abline(v=s, col="blue", lwd=2)
        abline(v=em, col="red", lwd=2)
        abline(v=ex, col="orange", lwd=2)
    }
    old <- par(mfrow=c(2, 2), oma=c(0, 0, 2, 0))
    plot_helper(1)
   plot_helper(33)
   plot_helper(66)
    plot_helper(100)
    title(main="Red=State, Blue=Emission, Orange=Expected",outer=T)
    par(old)
}
```

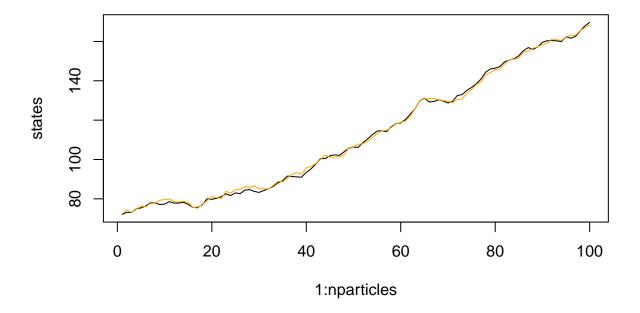
Sigma 1

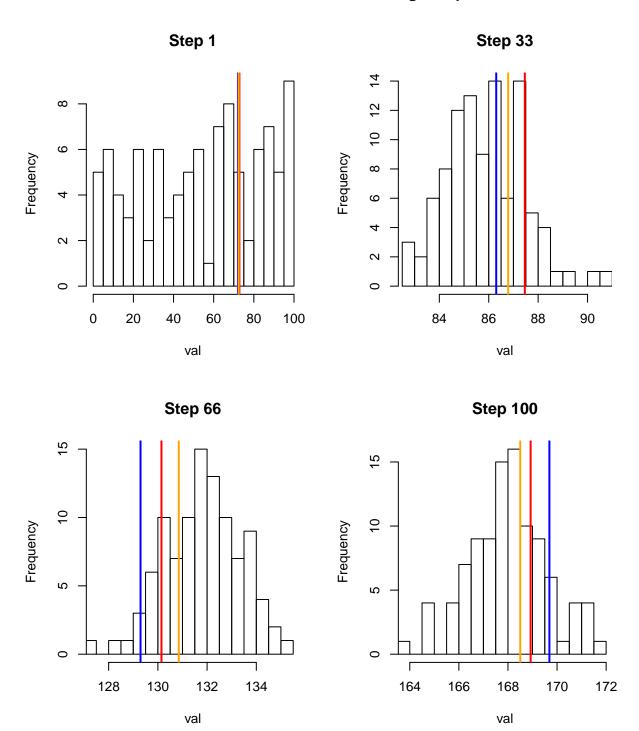
```
sigma <- 1
set.seed(12345)
samples <- generate_states_and_emissions(100, sigma)

nparticles <- 100
particles <- particle_filtering(samples$emissions, nparticles, sigma)

expected <- get_expected_states(particles$particles, particles$weights)</pre>
```





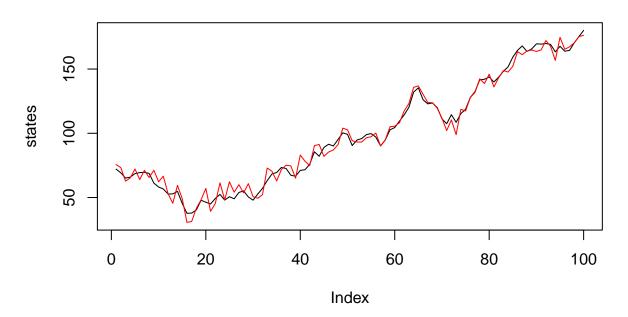


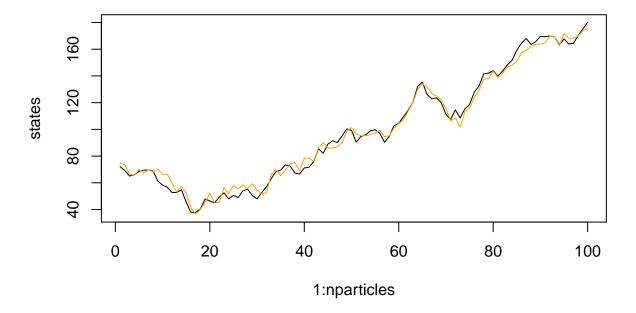
Sigma 5

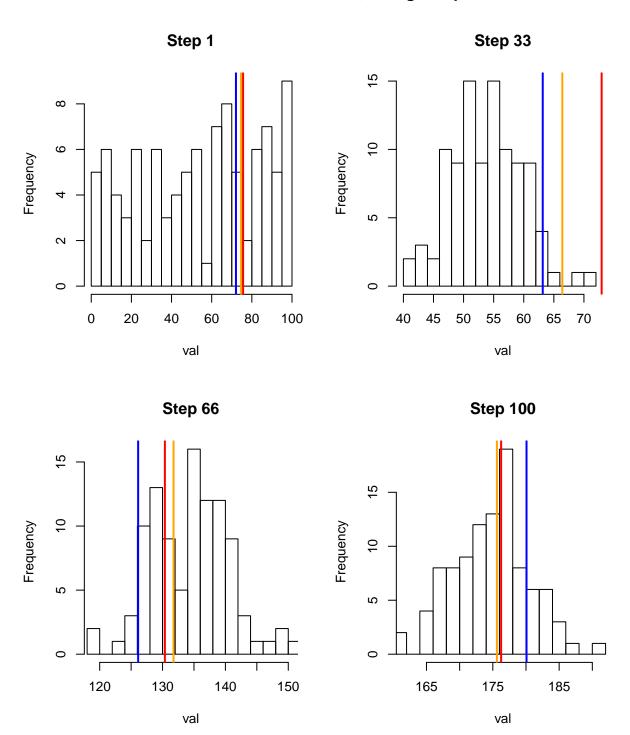
```
sigma <- 5
set.seed(12345)
samples <- generate_states_and_emissions(100, sigma)

nparticles <- 100
particles <- particle_filtering(samples$emissions, nparticles, sigma)

expected <- get_expected_states(particles$particles, particles$weights)</pre>
```







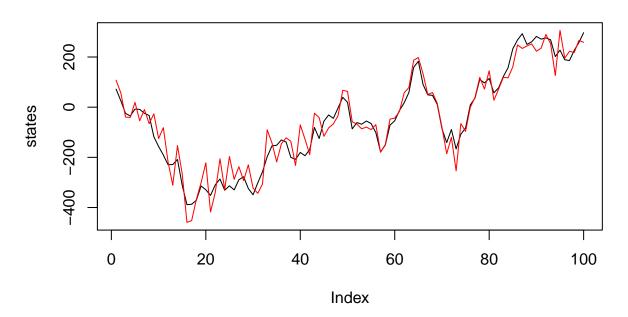
Sigma 50

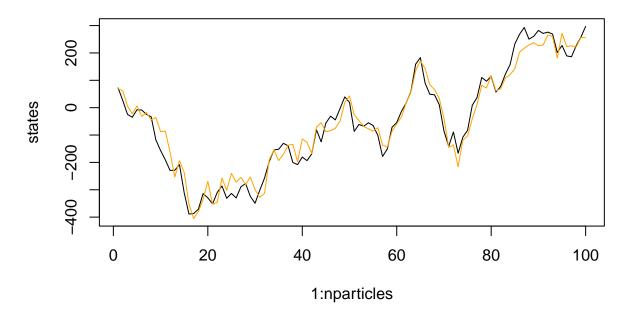
```
sigma <- 50

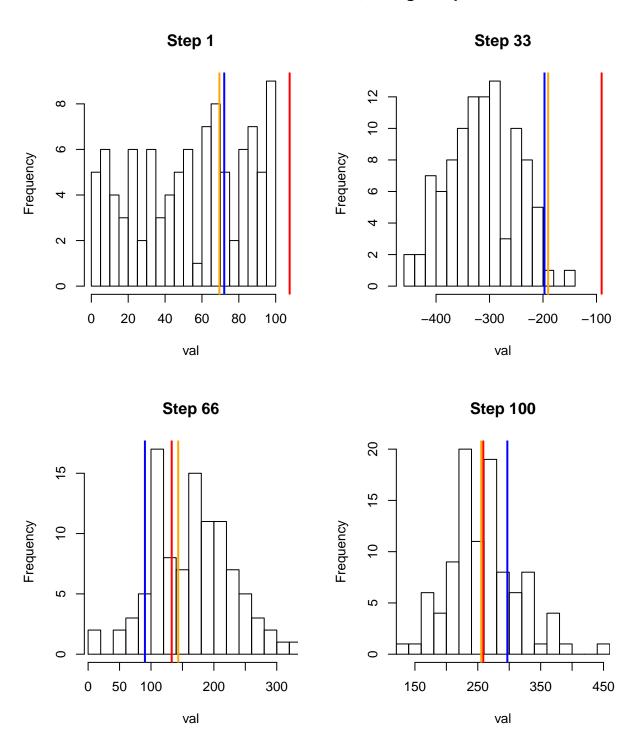
set.seed(12345)
samples <- generate_states_and_emissions(100, sigma)

nparticles <- 100
particles <- particle_filtering(samples$emissions, nparticles, sigma)

expected <- get_expected_states(particles$particles, particles$weights)</pre>
```

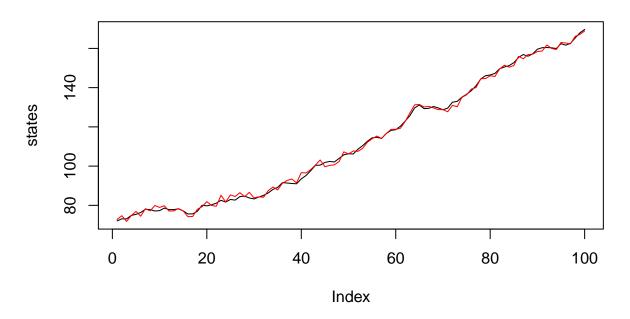


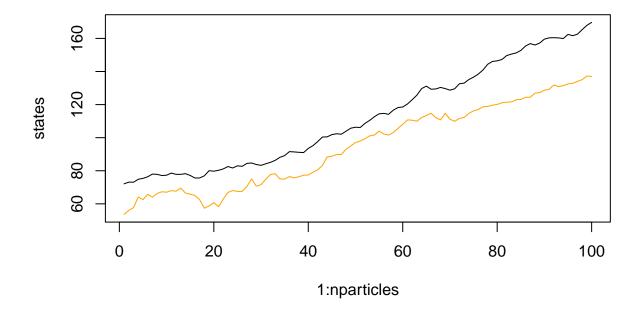


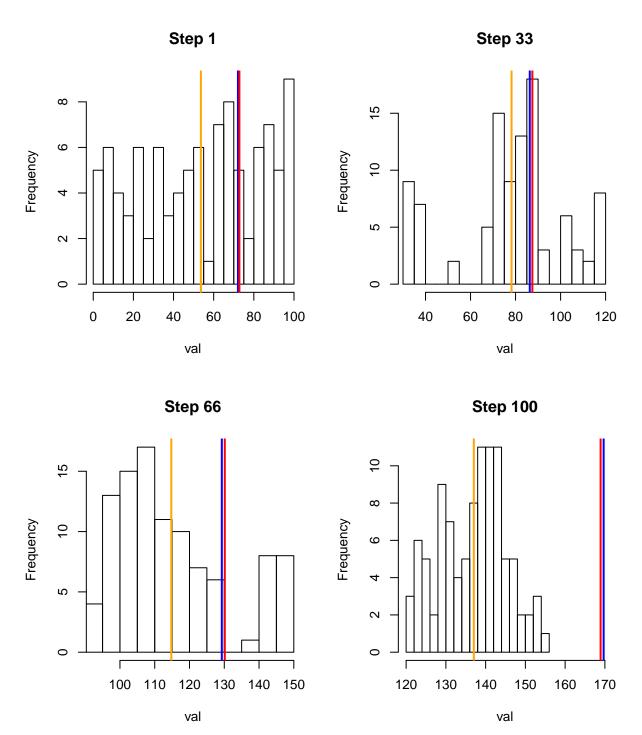


Sigma 1 without weight correction

```
get_uniform_sampling_weights <- function(emission, particles) {</pre>
    rep(1, length(particles)) / length(particles)
particle_filtering_without_correction <- function(x, nparticles, sigma) {</pre>
    steps <- length(x)</pre>
    particles <- matrix(NA, nrow=steps, ncol=nparticles)</pre>
    weights <- matrix(NA, nrow=steps, ncol=nparticles)</pre>
    particles[1, ] <- runif(nparticles, 0, 100)</pre>
    weights[1, ] <- get_uniform_sampling_weights(x[1], particles[1, ])</pre>
    for (i in 2:steps) {
        predictions <- sample(particles[i - 1, ], size=nparticles,</pre>
                                replace=TRUE, prob=weights[i - 1, ])
        particles[i, ] <- sapply(predictions, sample_transition, sigma=sigma)</pre>
        weights[i, ] <- get_uniform_sampling_weights(x[i], particles[i, ])</pre>
    }
    list(particles=particles, weights=weights)
sigma <- 1
set.seed(12345)
samples <- generate_states_and_emissions(100, sigma)</pre>
nparticles <- 100
particles <- particle_filtering_without_correction(samples$emissions, nparticles, sigma)</pre>
expected <- get_expected_states(particles$particles, particles$weights)</pre>
```







Without using weight correction we do not use our emission data to learn better estimations of the true states. All particles becomes equally good no matter how likely or unlikely they correspond to the sensor readings.