Advanced Machine Learning

Lab 4

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Assignment 1

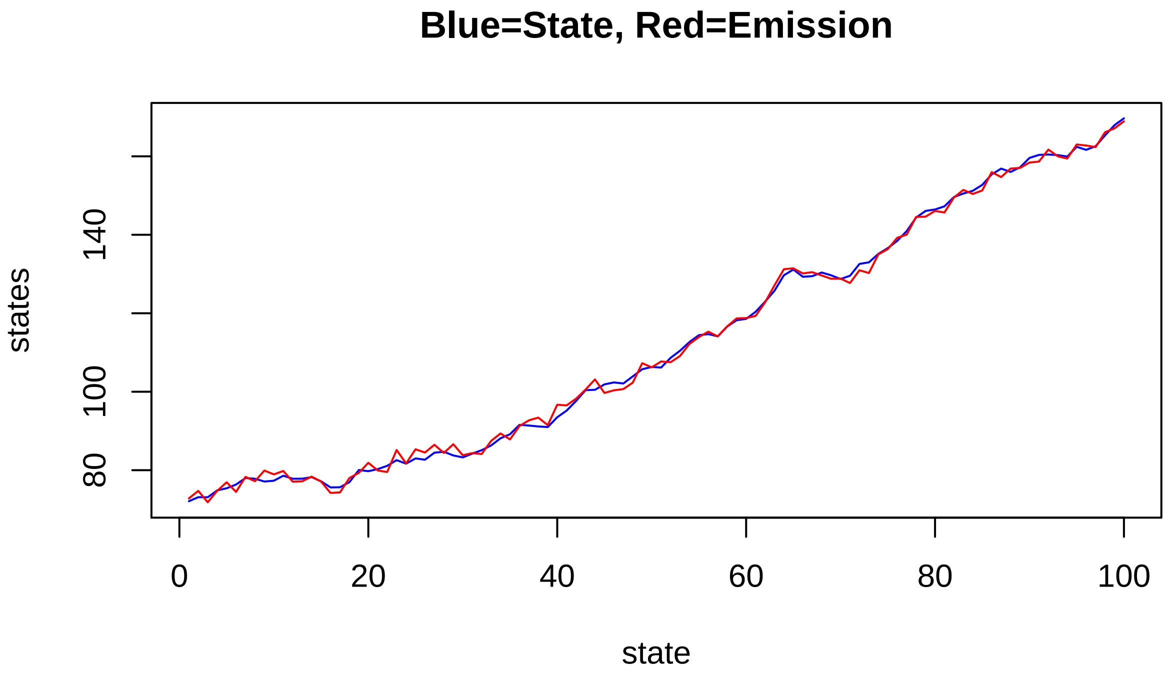
```
sample_transition_component <- function() {
    sample(1:3, size=1, prob=rep(1, 3) / 3)
}

sample_emission_component <- function() {
    sample(1:3, size=1, prob=rep(1, 3) / 3)
}

sample_initial_state <- function() {
    runif(1, 0, 100)
}

sample_transition <- function(z) {
    component <- sample_transition_component()
    mu <- ifelse(component == 1, z, ifelse(component == 2, z + 1, z + 2))
    rnorm(1, mean=mu, sd=1)
}

sample_emission <- function(z, sigma=1) {
    component <- sample_emission_component()
    mu <- ifelse(component == 1, z, ifelse(component == 2, z - 1, z + 1))
    rnorm(1, mean=mu, sd=sigma)
}

generate_states_and_emissions <- function(n, sigma) {
    states <- rep(0, n)
    emissions <- rep(0, n)

    initial_state <- sample_initial_state()
    current_state <- initial_state

    for (i in 1:n) {
        current_emission <- sample_emission(current_state, sigma)

        states[i] <- current_state
        emissions[i] <- current_emission

        current_state <- sample_transition(current_state)
    }

    list(states=states, emissions=emissions)
}
```

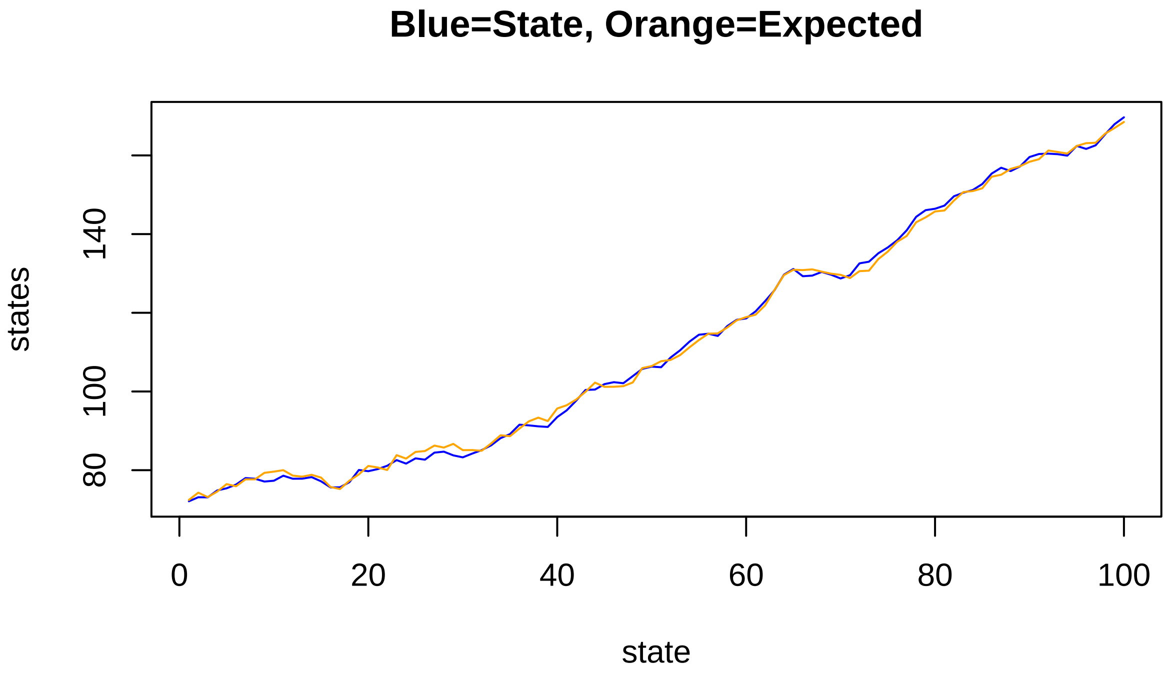
```
get_emission_density_given_state <- function(emission, state, sigma=1) {
    (dnorm(emission, mean=state, sd=sigma) +
     dnorm(emission, mean=state - 1, sd=sigma) +
     dnorm(emission, mean=state + 1, sd=sigma)) / 3
}

get_sampling_weights <- function(emission, particles, sigma=1) {
    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) {
    steps <- length(x)
    particles <- matrix(NA, nrow=steps, ncol=nparticles)
    weights <- matrix(NA, nrow=steps, ncol=nparticles)

    particles[1, ] <- runif(nparticles, 0, 100)
    weights[1, ] <- get_sampling_weights(x[1], particles[1, ], sigma=sigma)

    for (i in 2:steps) {
        predictions <- sample(particles[i - 1, ], size=nparticles,
                              replace=TRUE, prob=weights[i - 1, ])
        particles[i, ] <- sapply(predictions, sample_transition)
        weights[i, ] <- get_sampling_weights(x[i], particles[i, ], sigma=sigma)
    }

    list(particles=particles, weights=weights)
}

get_expected_states <- function(particles, weights) {
    rowSums(weights * particles)
}

plot_everything <- function(states, emissions, particles, expected) {
    nparticles <- ncol(particles)

    old <- par(mfrow=c(2, 1))
    plot(states, type="l", col="blue",
         main="Blue=State, Red=Emission",
         xlab="state",
         ylim=c(min(c(states, emissions)), max(c(states, emissions))))
    lines(emissions, col="red")
    plot(1:nparticles, states, type="l", col="blue",
         main="Blue=State, Orange=Expected",
         xlab="state",
         ylim=c(min(c(states, expected)), max(c(states, expected))))
    lines(1:nparticles, expected, col="orange")
    par(old)

    plot_helper <- function(idx) {
        p <- particles[idx,]
```

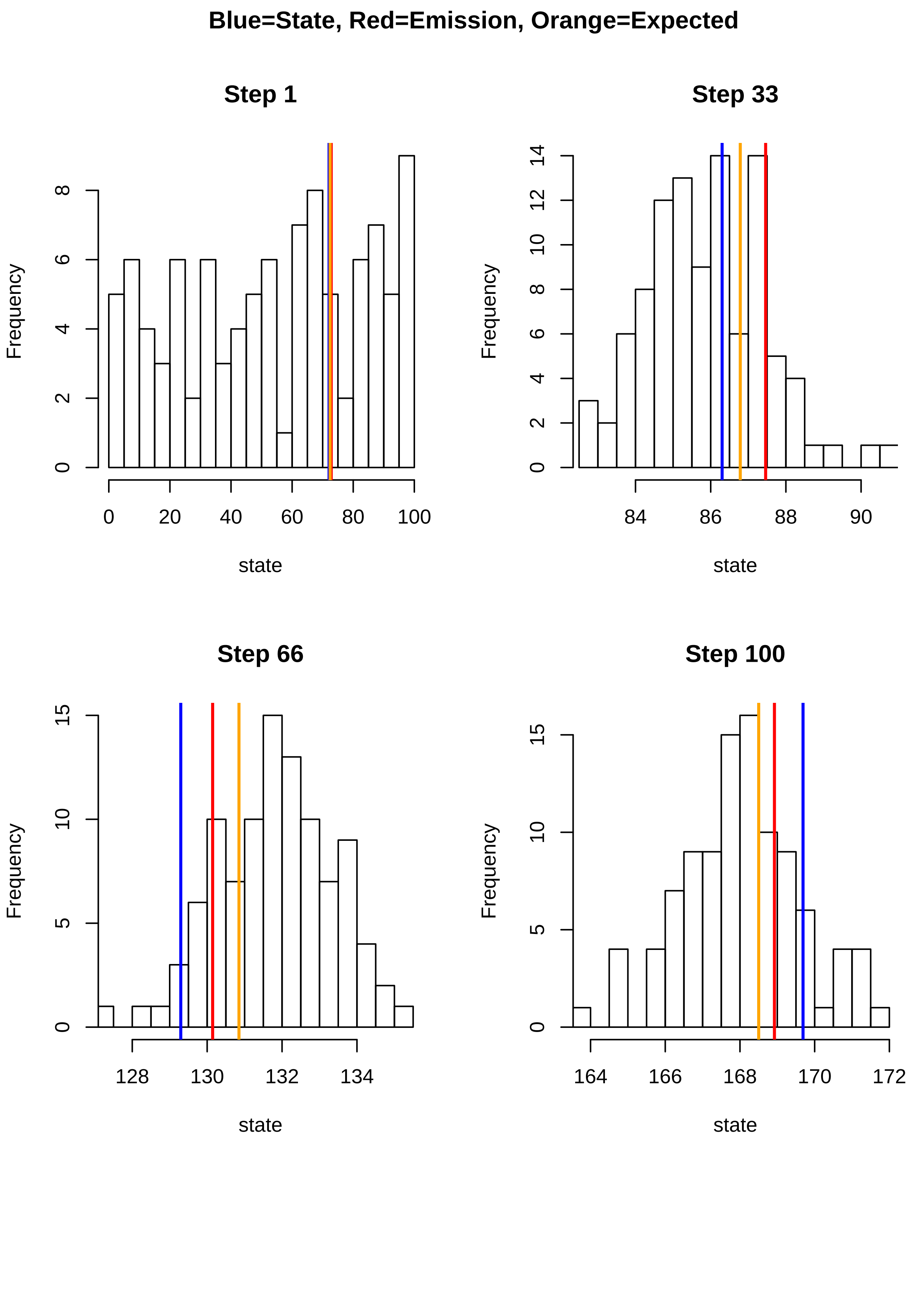
```r
        ex <- expected[idx]
        s <- states[idx]
        em <- emissions[idx]

        hist(p, breaks=20,
             main=paste("Step", idx, sep=" "),
             xlab="state", 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="Blue=State, Red=Emission, Orange=Expected",outer=T)
    par(old)
}
```

Sigma 1

```r
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)
```

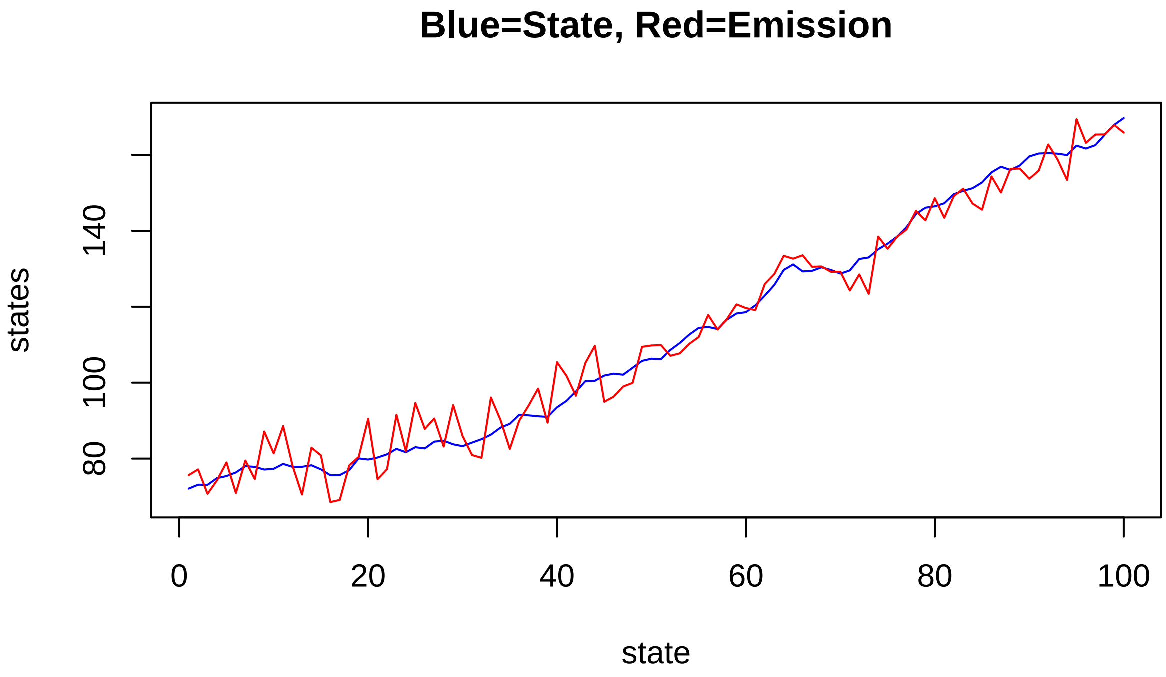

Blue=State, Red=Emission
states
80
100
140
0
20
40
60
80
100
state

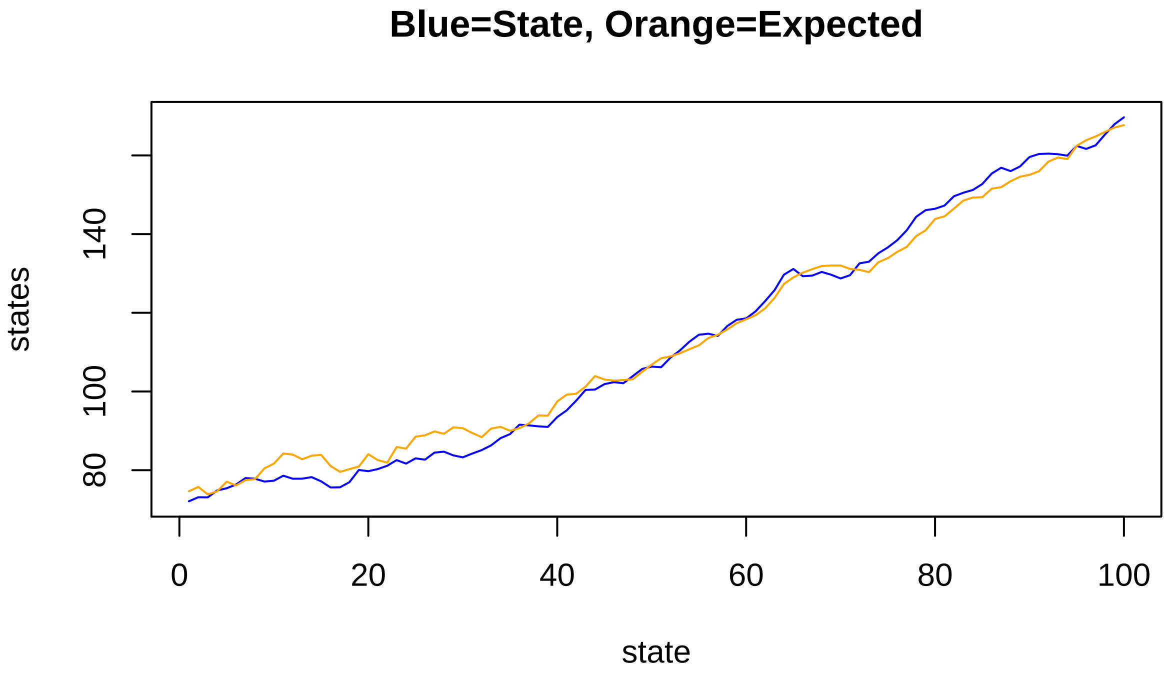

Blue=State, Orange=Expected
states
80
100
140
0
20
40
60
80
100
state

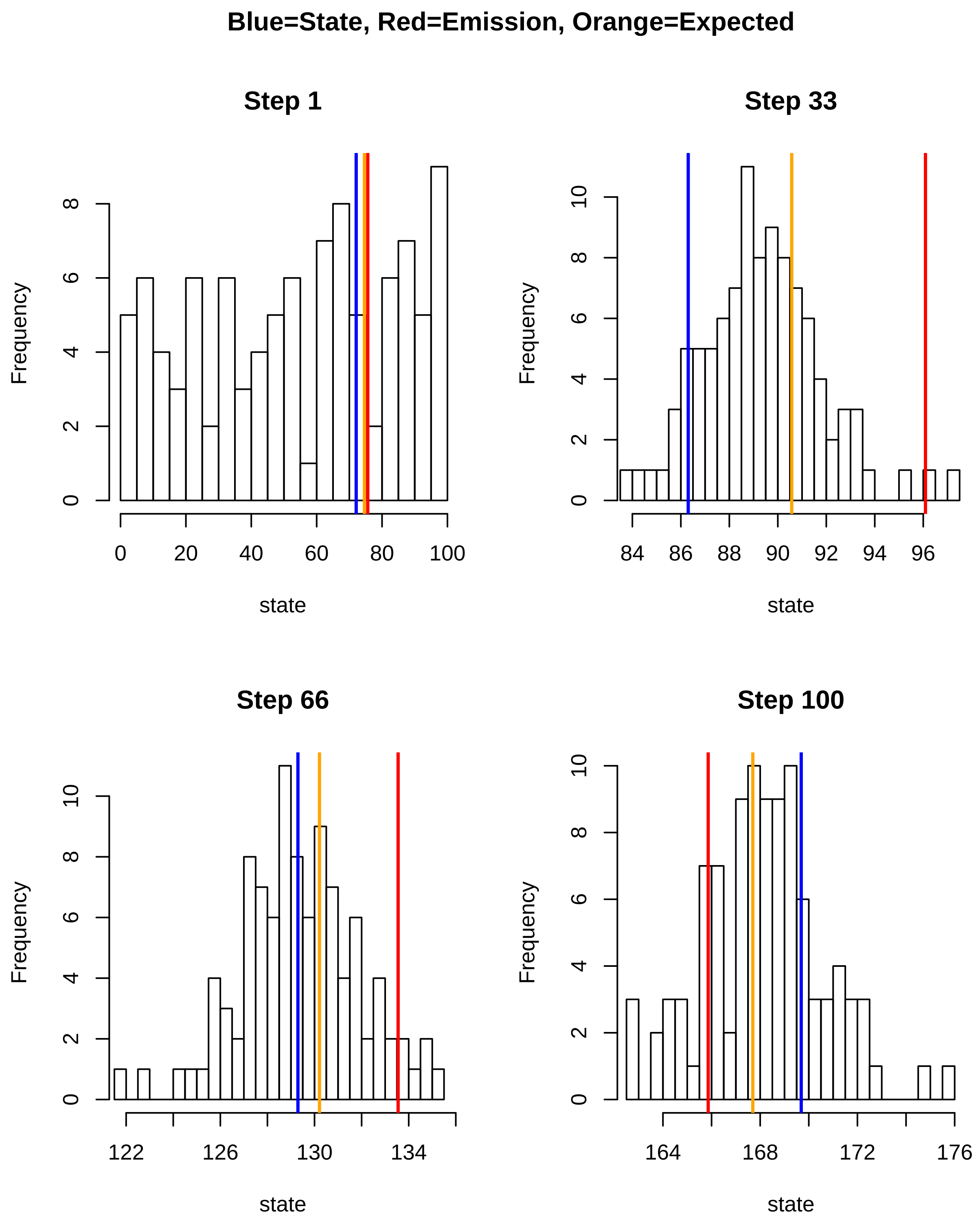

Blue=State, Red=Emission, Orange=Expected
Step 1
Frequency
0
2
4
6
8
0
20
40
60
80
100
state
Step 33
Frequency
0
2
4
6
8
10
12
14
84
86
88
90
state
Step 66
Frequency
0
5
10
15
128
130
132
134
state
Step 100
Frequency
0
5
10
15
164
166
168
170
172
state

Sigma 5

```r
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)
```

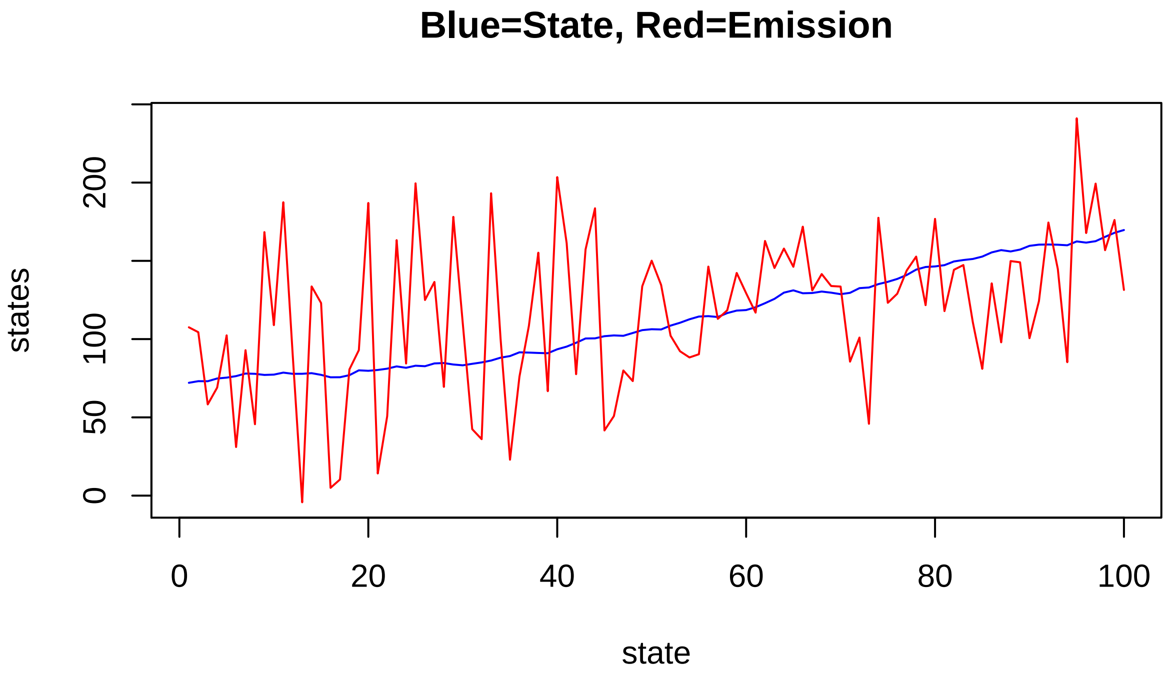

Blue=State, Red=Emission
states
80
100
140
0
20
40
60
80
100
state

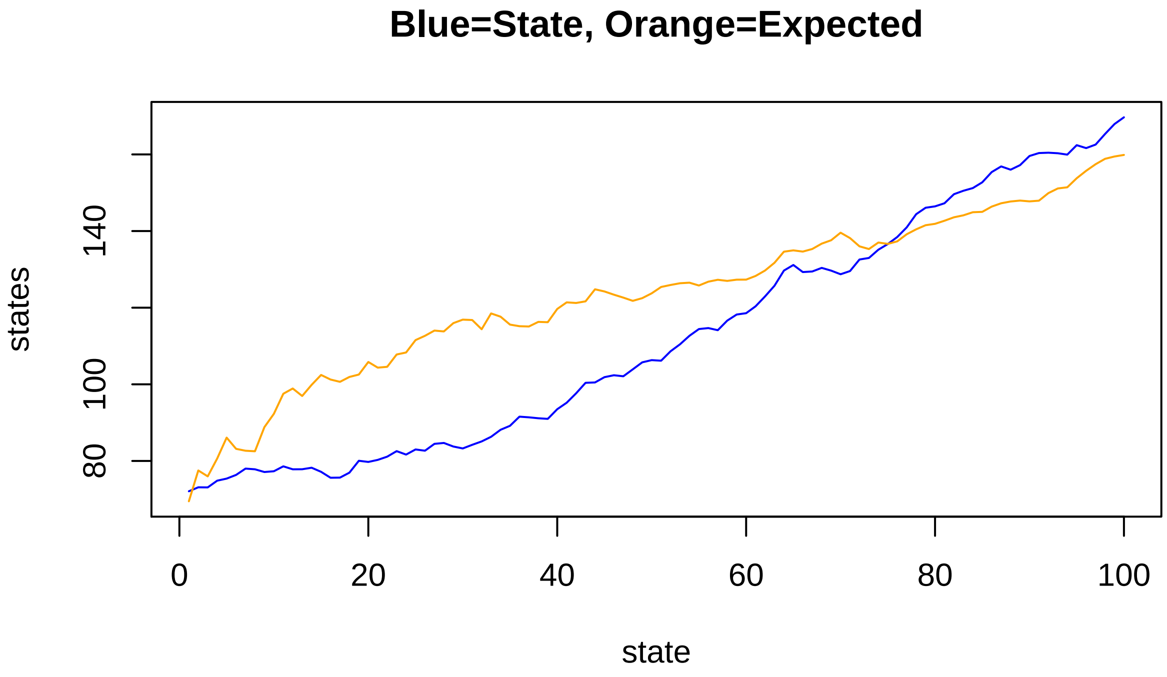

Blue=State, Orange=Expected
states
80
100
140
0
20
40
60
80
100
state

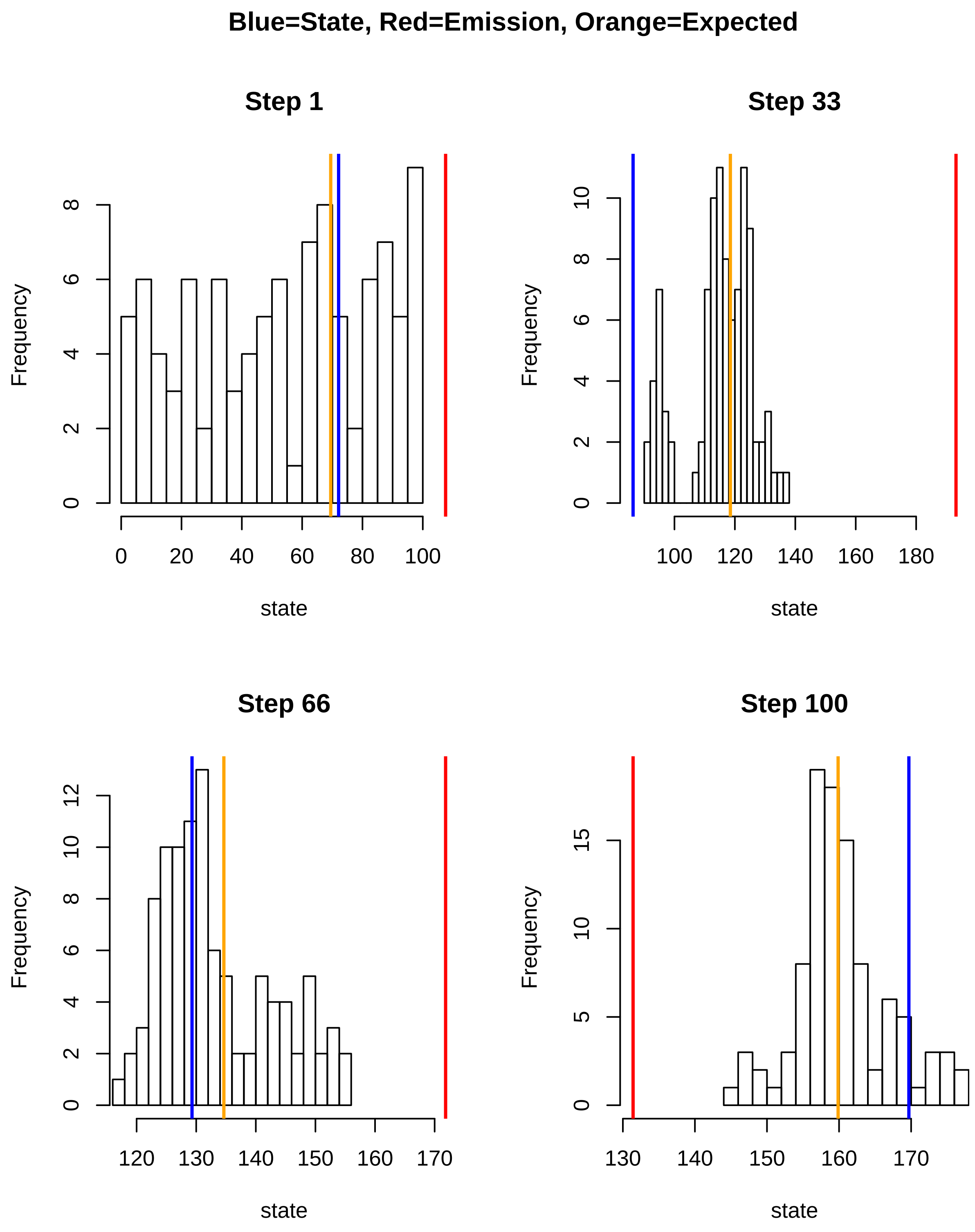

Blue=State, Red=Emission, Orange=Expected
Step 1
Frequency
0
2
4
6
8
0
20
40
60
80
100
state
Step 33
Frequency
0
2
4
6
8
10
84
86
88
90
92
94
96
state
Step 66
Frequency
0
2
4
6
8
10
122
126
130
134
state
Step 100
Frequency
0
2
4
6
8
10
164
168
172
176
state

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)
```


Blue=State, Red=Emission
states
0
50
100
200
0
20
40
60
80
100
state


Blue=State, Orange=Expected
states
80
100
140
0
20
40
60
80
100
state


Blue=State, Red=Emission, Orange=Expected
Step 1
Frequency
0
2
4
6
8
0
20
40
60
80
100
state
Step 33
Frequency
0
2
4
6
8
10
100
120
140
160
180
state
Step 66
Frequency
0
2
4
6
8
10
12
120
130
140
150
160
170
state
Step 100
Frequency
0
5
10
15
130
140
150
160
170
state

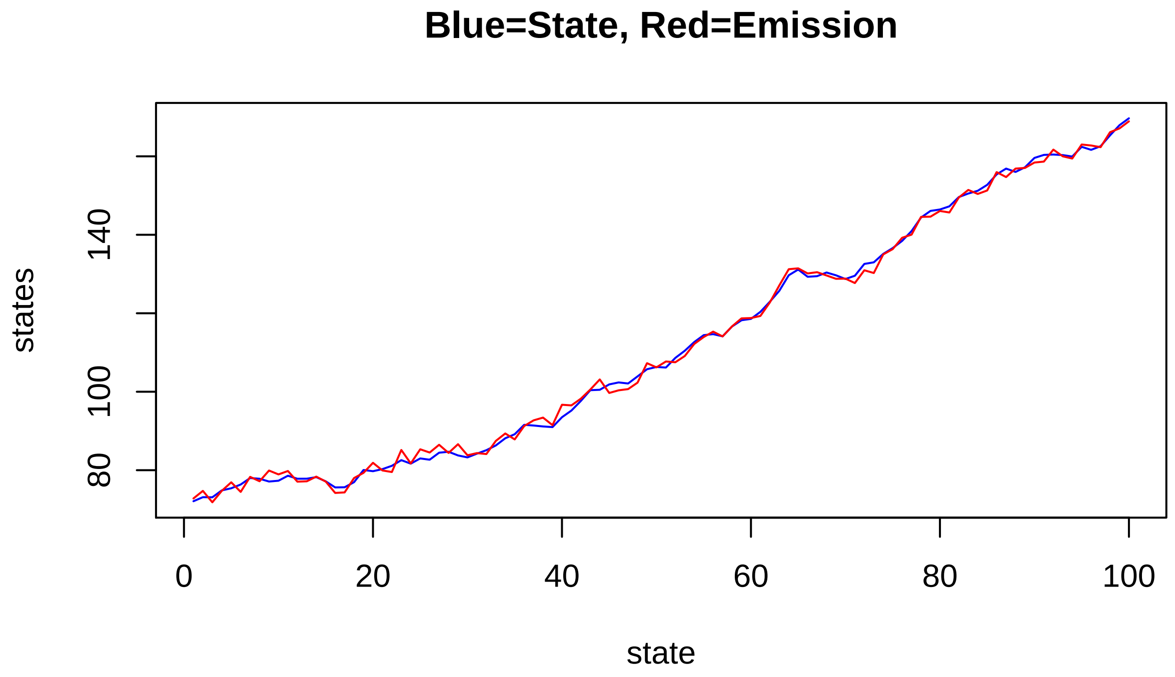
Analysis

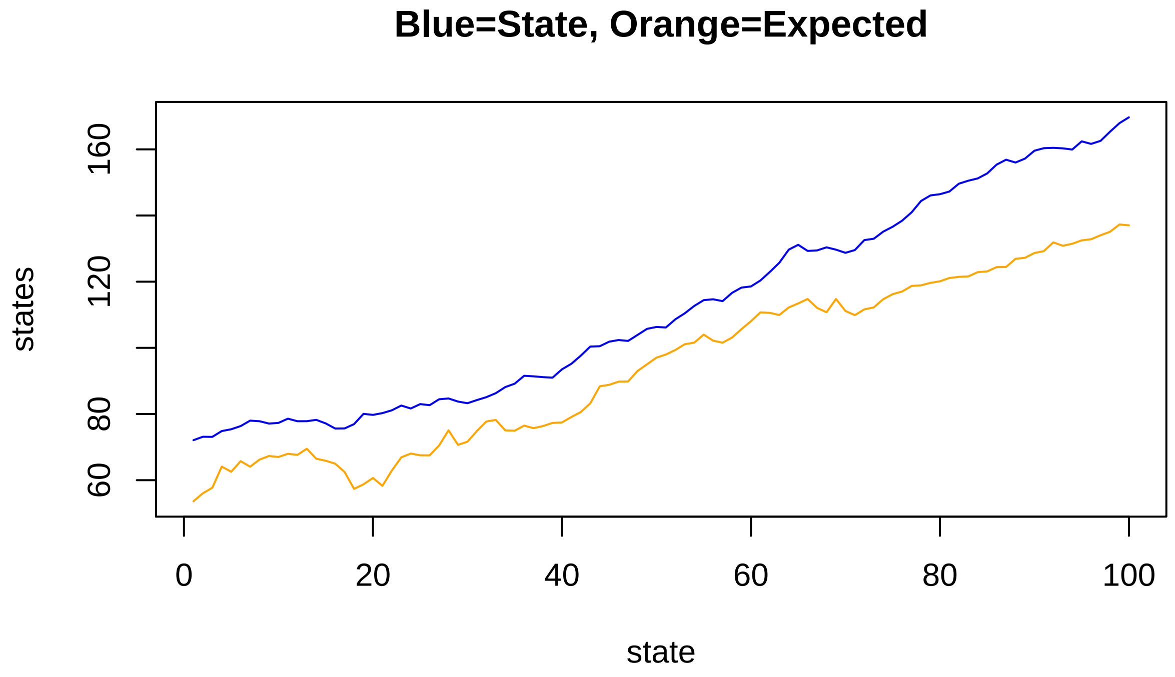
Increasing the variance in the emission model will obviously make the readings less reliable. Since the particles are based on the readings they will also become less accurate. However, the particle estimations are still pretty good which indicate that particle filter can handle high uncertainty in the sensor readings and still be useful.

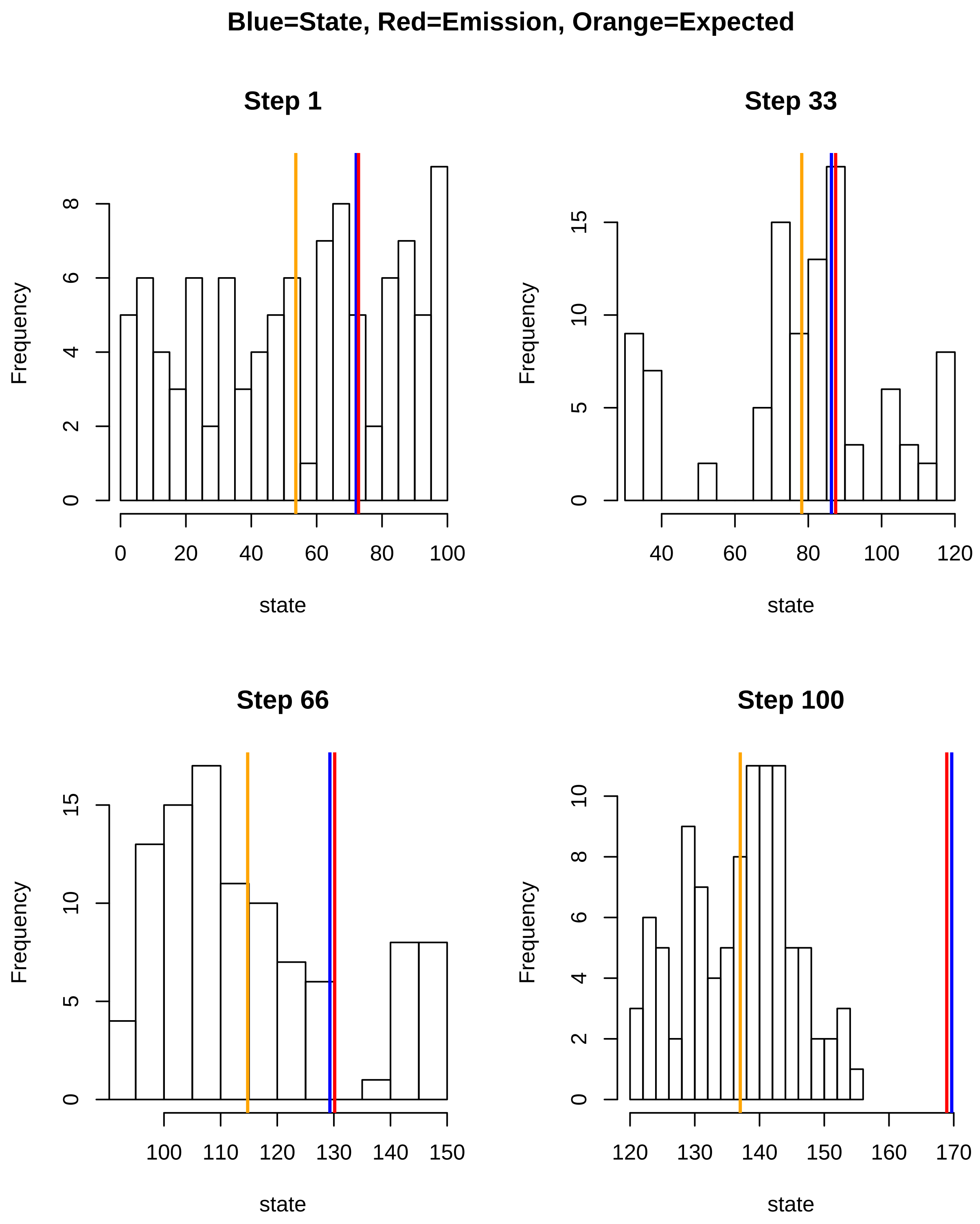
Sigma 1 without weight correction

```
get_uniform_sampling_weights <- function(emission, particles) {
    rep(1, length(particles)) / length(particles)
}

particle_filtering_without_correction <- function(x, nparticles, sigma) {
    steps <- length(x)
    particles <- matrix(NA, nrow=steps, ncol=nparticles)
    weights <- matrix(NA, nrow=steps, ncol=nparticles)

    particles[1, ] <- runif(nparticles, 0, 100)
    weights[1, ] <- get_uniform_sampling_weights(x[1], particles[1, ])

    for (i in 2:steps) {
        predictions <- sample(particles[i - 1, ], size=nparticles,
                              replace=TRUE, prob=weights[i - 1, ])
        particles[i, ] <- sapply(predictions, sample_transition)
        weights[i, ] <- get_uniform_sampling_weights(x[i], particles[i, ])
    }

    list(particles=particles, weights=weights)
}
```

```
sigma <- 1

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

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

expected <- get_expected_states(particles$particles, particles$weights)
```


Blue=State, Red=Emission
states
80
100
140
0
20
40
60
80
100
state


Blue=State, Orange=Expected
states
60
80
120
160
0
20
40
60
80
100
state



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.