

3nd Assignment: Continuous Time Stochastic Modelling (SDEs)

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Part 1: Simulation and discretization of diffusion processes

In the following exercise, the Euler-Maruyama approximation to the Bonhoeffer-Van der Pol equations is simulated, e.g.:

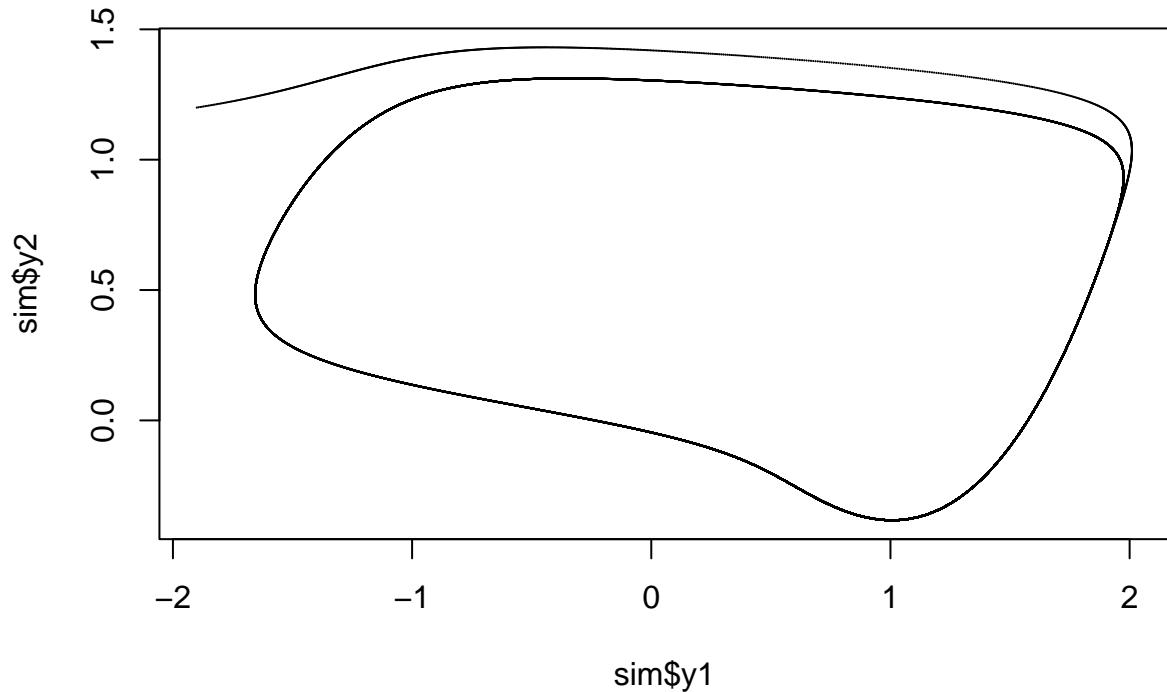
$$\begin{aligned} Y_{n+1}^1 &= Y_n^1 + \theta_3 \left(Y_n^1 + Y_n^2 - \frac{1}{3} (Y_n^1)^3 + \theta_4 \right) \Delta + \sigma \Delta W_{n+1}^1 \\ Y_{n+1}^2 &= Y_n^2 - \frac{1}{\theta_3} (Y_n^1 + \theta_2 Y_n^2 - \theta_1) \Delta \end{aligned}$$

1a - Without stochasticity

Initially, I will simulate the deterministic, ODE version of the above system, e.g. where $\sigma = 0$. I decided to increase the length of the simulation to $0 \leq t \leq T = 1000$ with a discretization step of $\Delta = 2^{-9}$. I will use the parameter values as stated in the problem description.

```
# Let's define a function to simulate the system
SDEsim = function(y1_init = -1.9, y2_init=1.2, delta = 2^(-9),
                  theta1=0.7, theta2=0.8, theta3=3.0, theta4=-0.34,
                  sigma=0, T=200/delta){
  # Init
  D = list()
  y1 = rep(NaN, T); y1[1] = y1_init;
  y2 = rep(NaN, T); y2[1] = y2_init;

  # Run the system
  for (i in 1:(T-1)){
    y1[i+1] = y1[i] + theta3*(y1[i] + y2[i] - 1/3*y1[i]^3 + theta4)*delta + sigma * rnorm(1,0,sqrt(delta))
    y2[i+1] = y2[i] - 1/theta3 * (y1[i] + theta2*y2[i] - theta1) * delta
  }
  # Save and return list
  D$y1 = y1
  D$y2 = y2
  return(D)
}
sim = SDEsim(sigma=0)
plot(sim$y1, sim$y2, cex=0.01)
```

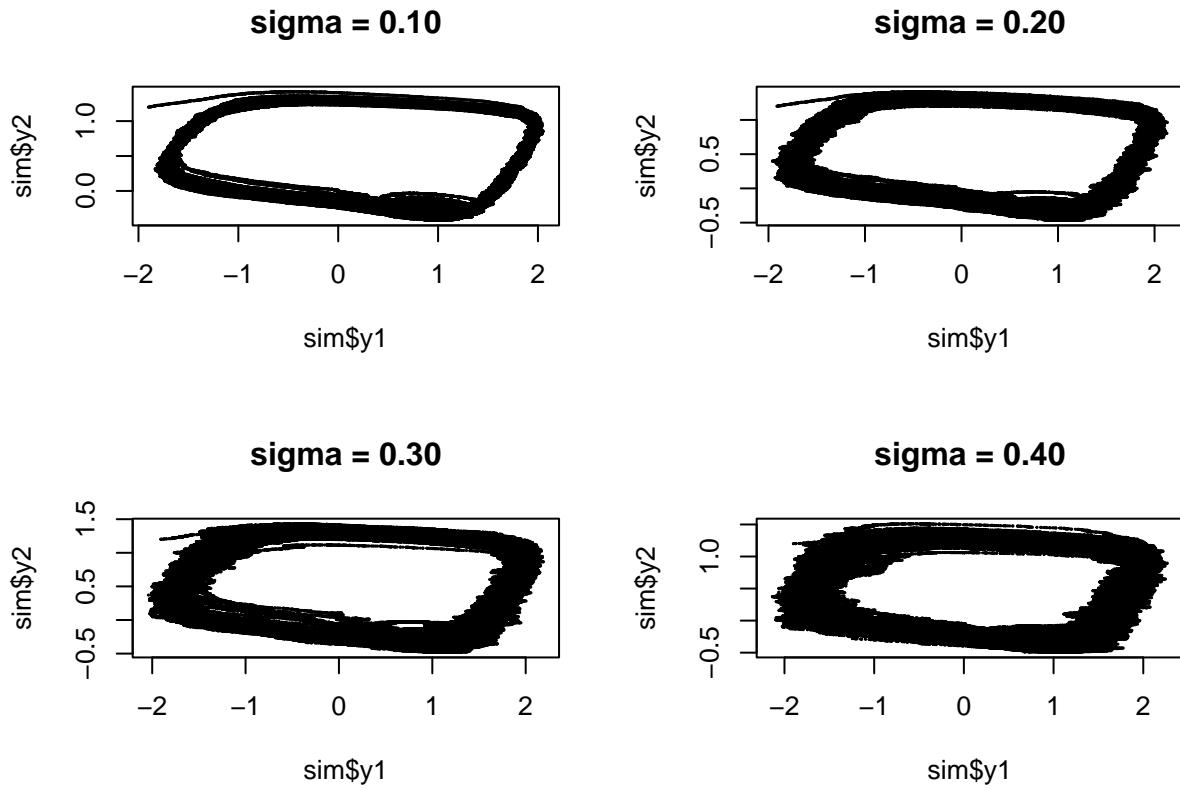


The system clearly enters a *limit cycle* after a bit of time.

Introducing stochasticity

Let's simulate the system with the following diffusion sizes: $\sigma \in \{0.1, 0.2, 0.3, 0.4\}$.

```
par(mfrow=c(2,2))
for (sd in c(0.1, 0.2, 0.3, 0.4)){
  sim = SDEsim(sigma=sd)
  plot(sim$y1, sim$y2, cex=0.1, main=sprintf("sigma = %.2f", sd))
}
```



Interestingly, there seems to occur a bifurcation of another limit cycles with small perturbations in the system at $\sigma = 0.1$. However, with increasing diffusion size the system seems to generally circle around the ODE limit cycle. It's quite hard to see, so instead let's visualize the density of the trajectories using a heatmap.

1b

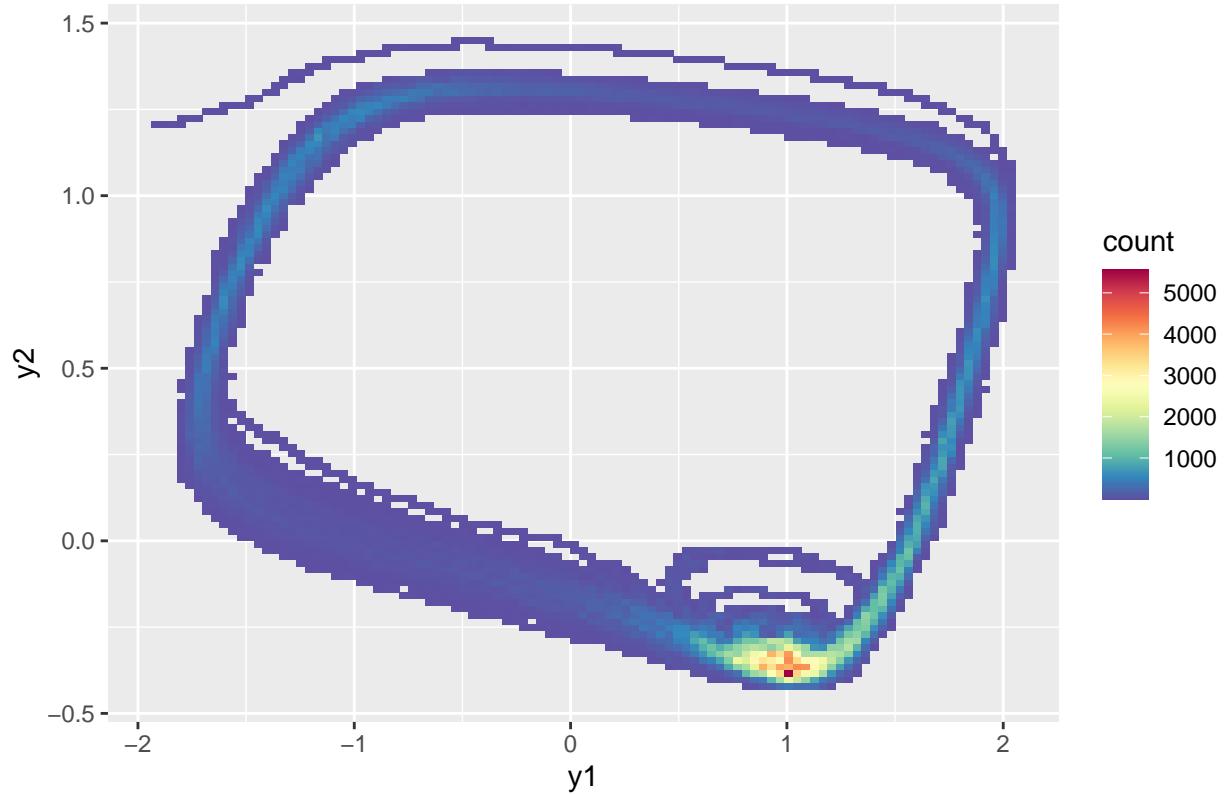
```
sim = data.frame(SDEsim(sigma=0.1))

# Ref: https://www.r-bloggers.com/2014/09/5-ways-to-do-2d-histograms-in-r/
#install.packages("ggplot2")
library(ggplot2)

# Default call (as object)
p <- ggplot(sim, aes(y1,y2))

# Add colouring and change bins
library(RColorBrewer)
rf <- colorRampPalette(rev(brewer.pal(11, 'Spectral')))
r <- rf(32)
h3 <- p + stat_bin2d(bins=100) + scale_fill_gradientn(colours=r) + ggtitle(sprintf("Simulations with sig"))
h3
```

Simulations with sigma = 0.10



Here it is clearly seen that perturbations in the lower right corner results in new cycles and completely different trajectories, whereas perturbations in the other areas doesn't result in much different trajectories.

Similarly for $\sigma = \{0.2, 0.3, 0.4\}$

```

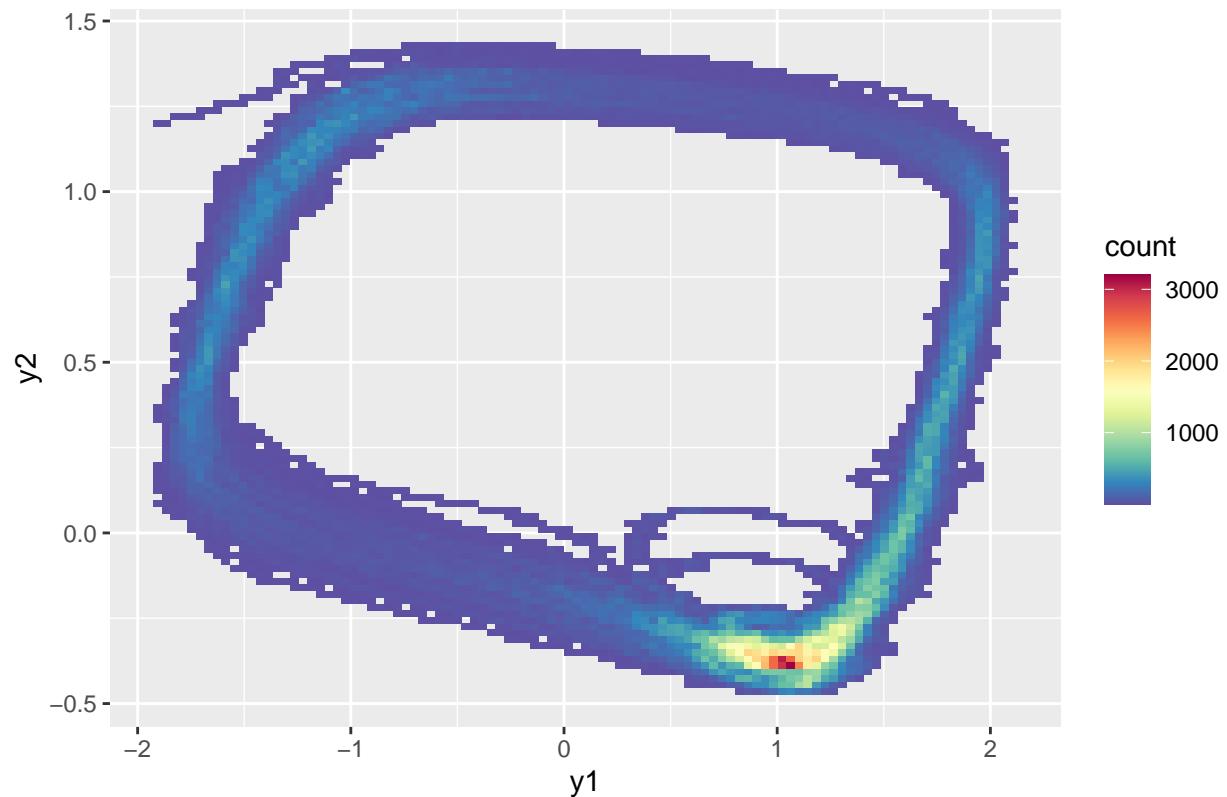
sim2 = data.frame(SDEsim(sigma=0.20))
sim3 = data.frame(SDEsim(sigma=0.30))
sim4 = data.frame(SDEsim(sigma=0.40))

# Default call (as object)
p2 <- ggplot(sim2, aes(y1,y2))
p3 <- ggplot(sim3, aes(y1,y2))
p4 <- ggplot(sim4, aes(y1,y2))

# Add colouring and change bins
library(RColorBrewer)
rf <- colorRampPalette(rev(brewer.pal(11, 'Spectral')))
r <- rf(32)
(h2 <- p2 + stat_bin2d(bins=100) + scale_fill_gradientn(colours=r) + ggtitle(sprintf("Simulations with ")))

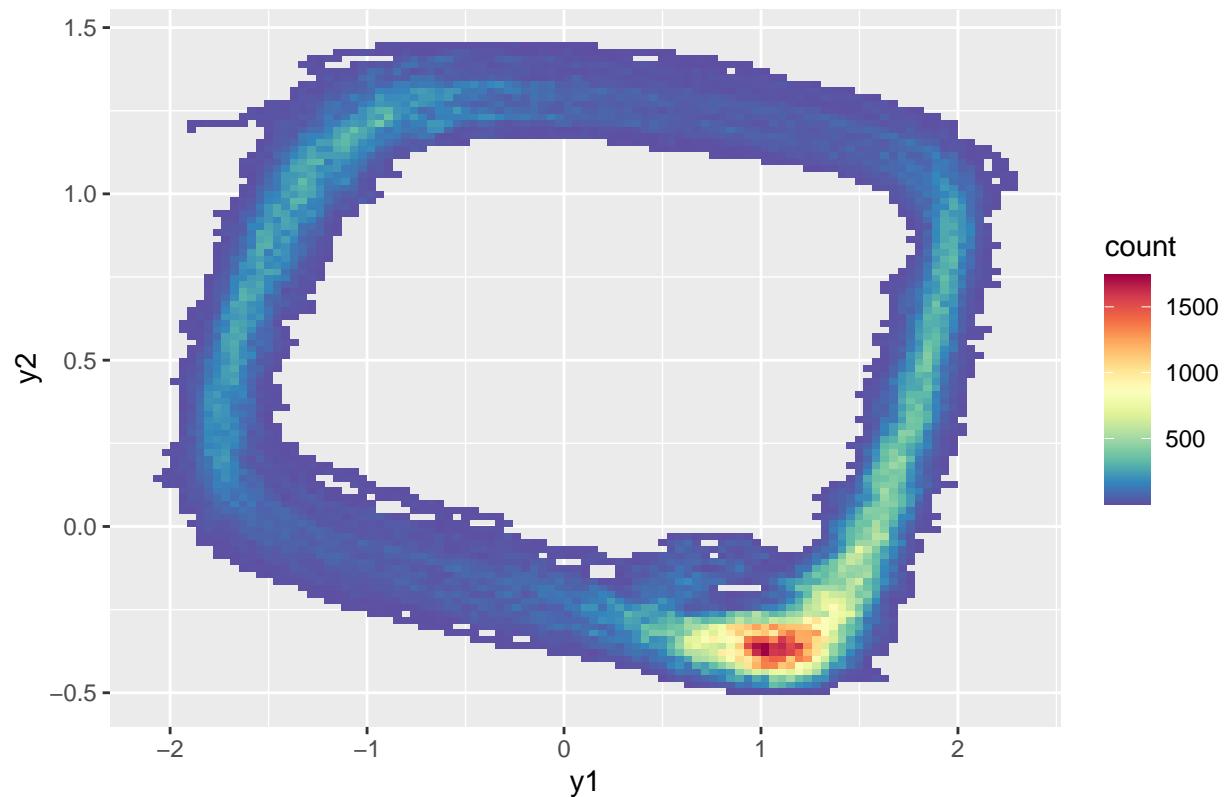
```

Simulations with sigma = 0.20



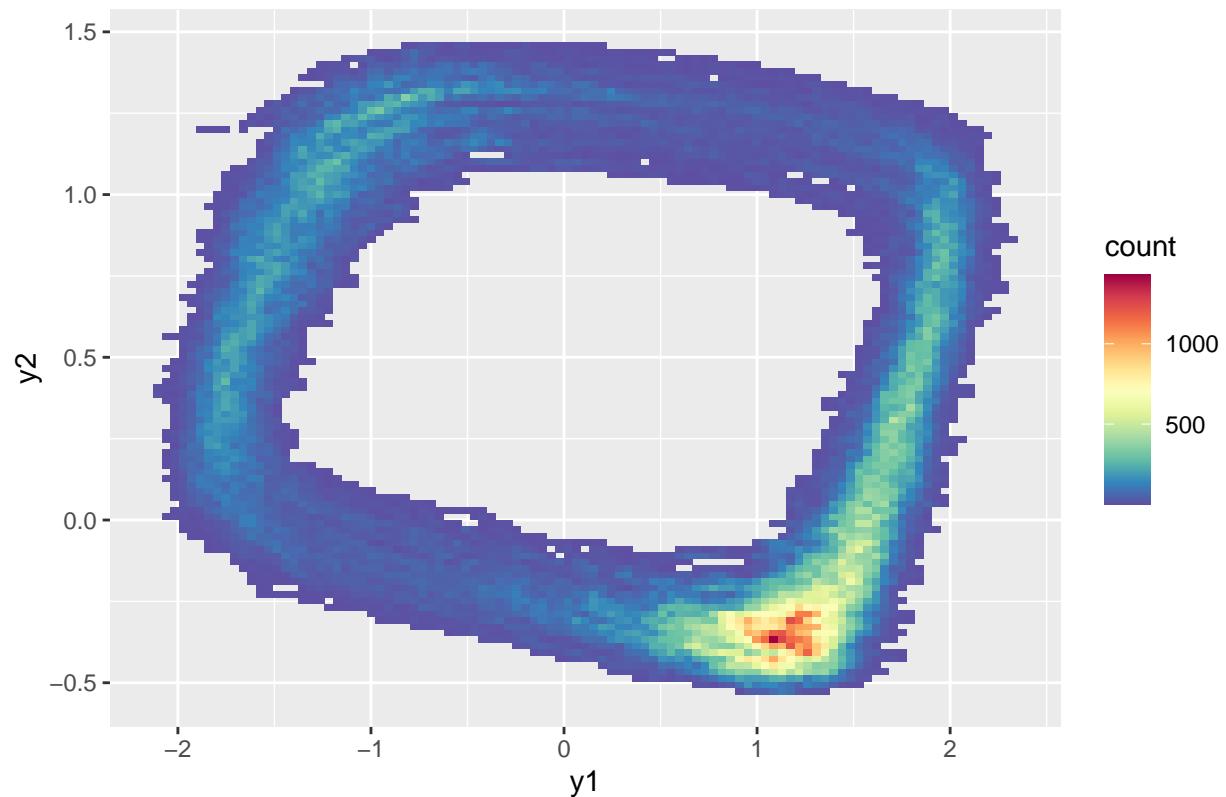
```
(h3 <- p3 + stat_bin2d(bins=100) + scale_fill_gradientn(colours=r) + ggtitle(sprintf("Simulations with s
```

Simulations with sigma = 0.30



```
(h4 <- p4 + stat_bin2d(bins=100) + scale_fill_gradientn(colours=r) + ggtitle(sprintf("Simulations with s"))
```

Simulations with sigma = 0.40



Clearly, with the increasing σ , the trajectories more often takes “the full round” as defined by the deterministic ODE.

END OF 3A