

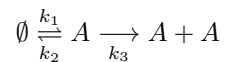
Positive feedback measures

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Positive feedback model

The purpose of this document is to present and explore different measures of positive feedback. For this, we consider a model governed by the following three reactions:



where k_1 is the birth rate, k_2 is the decay rate and k_3 is the positive feedback strength. We want to study stochastic realisations of this model using the stochastic simulation algorithm which is implemented in the function “simple_positive_feedback.r”, so first we must source the function.

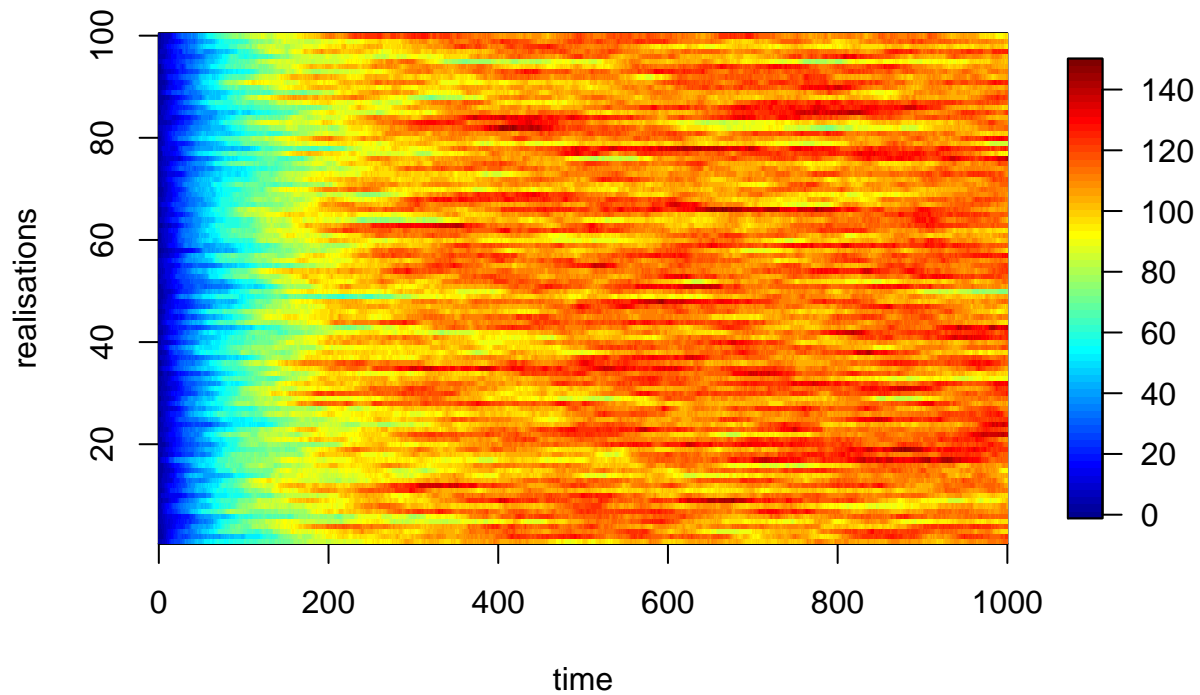
```
source('simple_positive_feedback.r')
```

Let's define parameters, run 100 trajectories of the model and obtain the output:

```
k_1 = 1
k_2 = 0.01;
k_3 = 0.001;
maxtime = 1000;
timestep = 0.1;
numberofrealisations = 100;
output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations);
```

We can also make a heatmap plot (you may have to install the “fields” package for this – install.packages(“fields”)):

```
time = seq(0,maxtime,by=timestep);
realisations = 1:numberofrealisations;
image.plot(time,realisations,output);
```

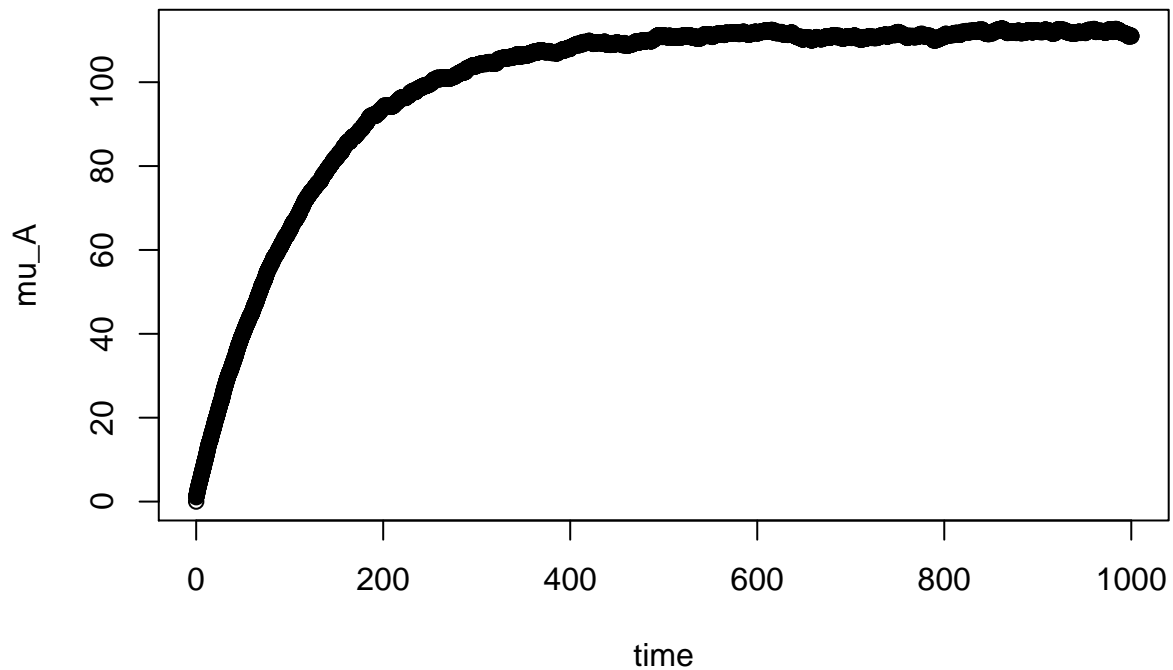


Now that we have a stochastic model with positive feedback strength as a parameter, we can try to find measures that are suitable for identifying positive feedbacks.

Mean

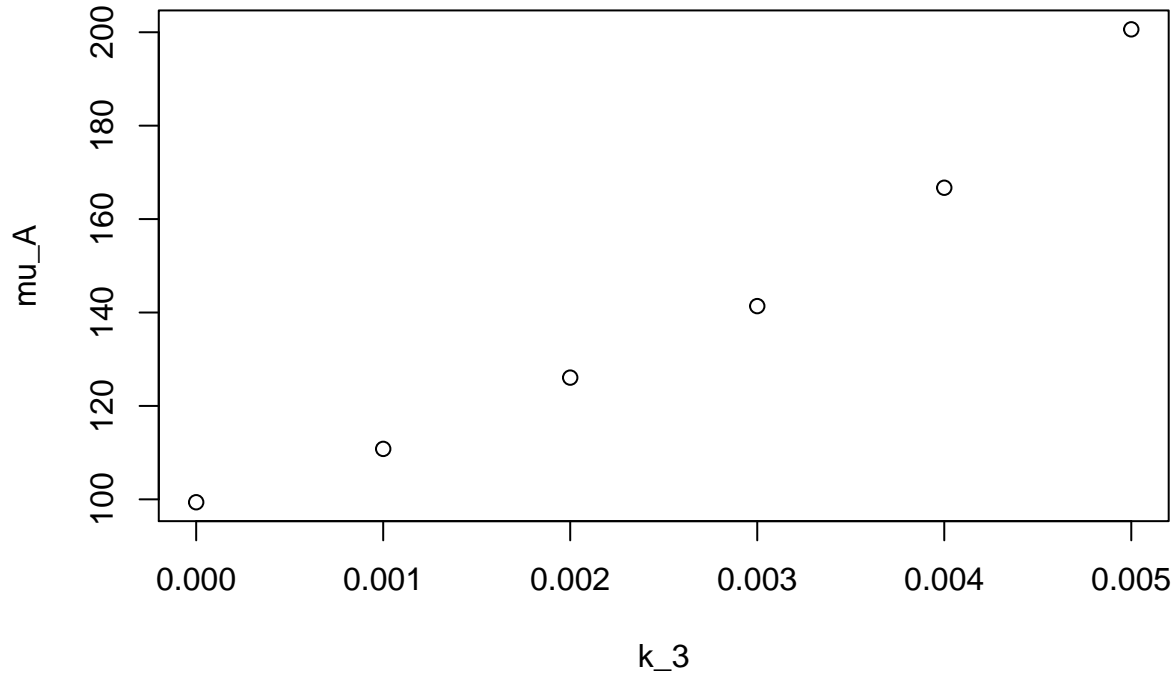
The first and most obvious measure is the mean. The mean value of A should increase with the positive feedback strength, k_3 . To study this, first we can plot the mean time series for a single value of k_3 :

```
time = seq(0,maxtime,by=timestep);
mu_A = rowMeans(output);
plot(time,mu_A);
```



Since the value of k_3 is small, the mean value (μ) of A takes a value just above the steady state with no positive feedback ($\frac{k_1}{k_2}$). We can now look at how the final value of this time series varies with k_3 .

```
count = 0;
mu_A <- rep(0, 6);
for (k_3 in seq(0,0.005,by=0.001)){
  count = count + 1;
  output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations);
  temp_mean_A = rowMeans(output);
  mu_A[count] = temp_mean_A[length(temp_mean_A)];
}
k_3 = seq(0,0.005,by=0.001);
plot(k_3,mu_A);
```



We can see that the mean value increases with positive feedback strength. The next measure we will inspect is the noise of A , specifically the Fano Factor.

Fano Factor

The Fano Factor (F) of A is defined as

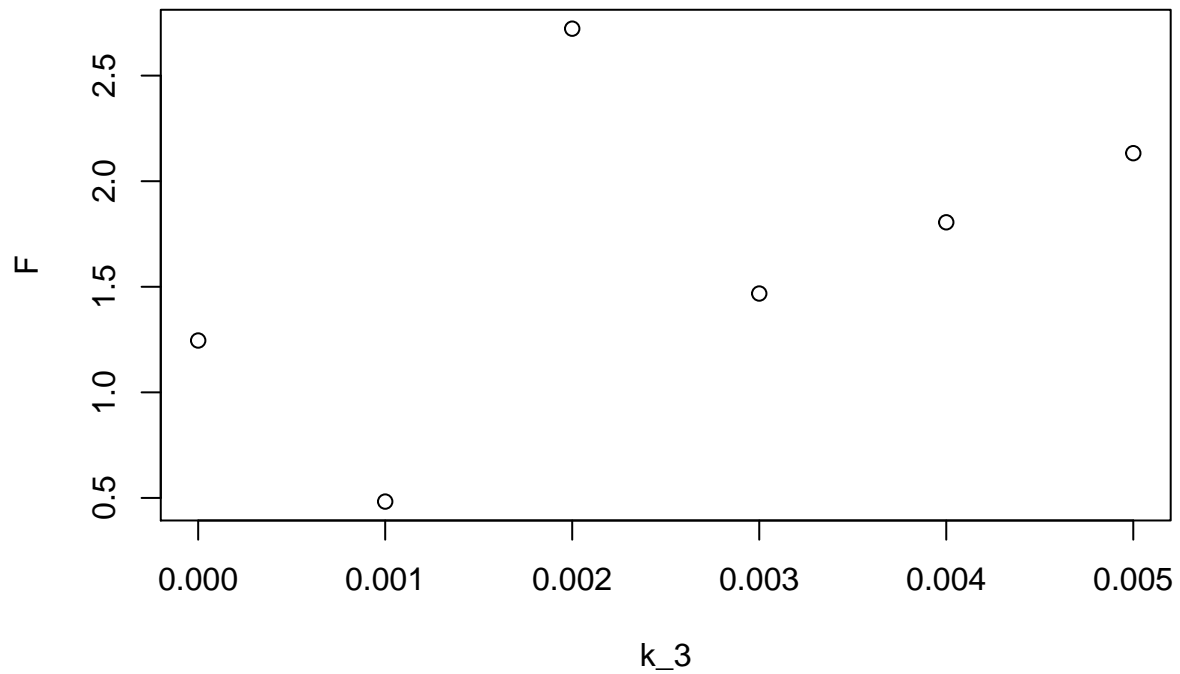
$$F = \frac{\sigma^2}{\mu}$$

where σ^2 is the variance of A . To compute this, we need to define the variance, which can be done using the following function:

```
RowVar <- function(x) {
  rowSums((x - rowMeans(x))^2)/(dim(x)[2] - 1)
}
```

We can now examine the relationship between the positive feedback strength and Fano Factor. Probably need more realisations to get a decent estimate of the Fano Factor.

```
numberofrealisations = 20;
count = 0;
F <- rep(0, 6);
for (k_3 in seq(0,0.005,by=0.001)){
  count = count + 1;
  output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations);
  temp_mean_A = rowMeans(output);
  temp_var_A = RowVar(output);
  F[count] = temp_var_A[length(temp_var_A)]/temp_mean_A[length(temp_mean_A)];
}
k_3 = seq(0,0.005,by=0.001);
plot(k_3,F);
```



Autocorrelation

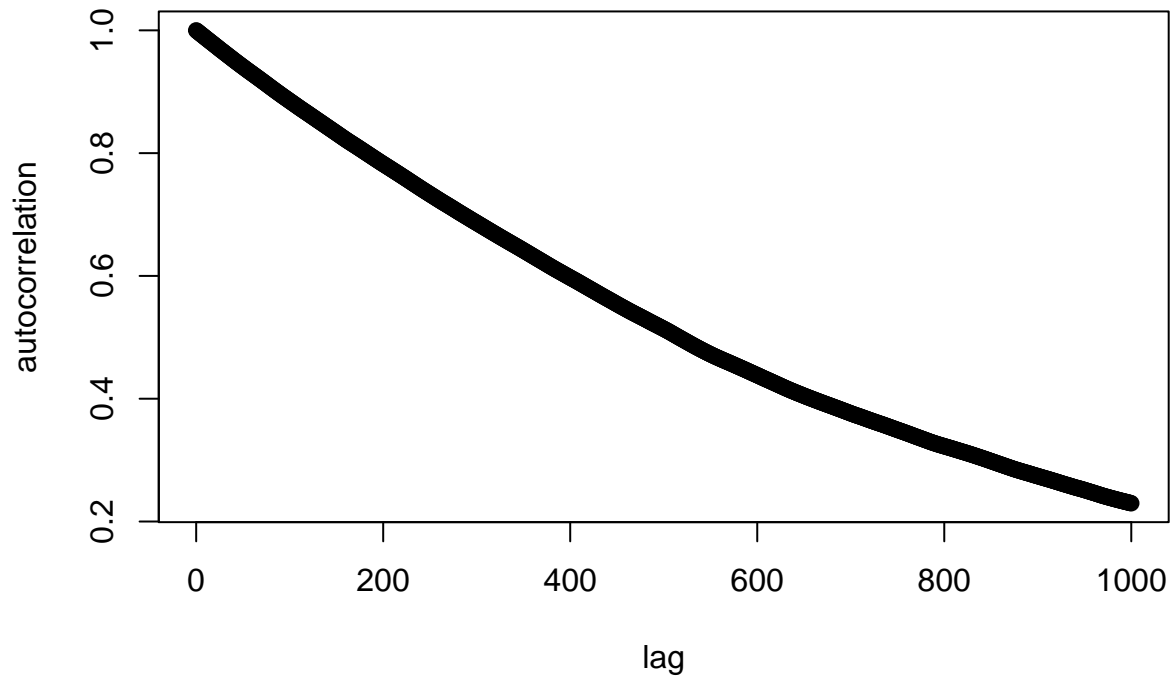
For a discrete process with known mean and variance for which we observe n observations $\{X_1, X_2, \dots, X_n\}$, an estimate of the autocorrelation may be obtained as

$$\hat{R}(k) = \frac{1}{(n-k)\sigma^2} \sum_{t=1}^{n-k} (X_t - \mu)(X_{t+k} - \mu)$$

We can plot an example autocorrelation for a single trajectory of the model and plot it.

```
output = simple_positive_feedback(1,0.01,0.001,1000,0.1,1);
autocorr = acf(output,lag.max = 1000,plot = FALSE)
test <- min(abs(autocorr$acf-0.5))
half_autocorr = which(abs(autocorr$acf-0.5) == test)
lag = autocorr$lag;
autocorrelation = autocorr$acf;
plot(lag,autocorrelation,main=paste("Half autocorrelation = ", half_autocorr))
```

Half autocorrelation = 517



Now we can examine how the half autocorrelation (which is displayed in the title of the previous plot) varies with k_3 .

```
numberofrealisations = 10;
maxlag=5000;
count1 = 0;
half_autocorr <- matrix(0,nrow=6,ncol=numberofrealisations);

for (k_3 in seq(0,0.005,by=0.001)){
  count1 = count1 + 1;
  autocorr <- matrix(0,1,ncol=maxlag);
  for (count2 in seq(1,numberofrealisations,by=1)){
    output = simple_positive_feedback(1,0.01,k_3,1000,0.1,1);
    autocorr1 = acf(output,lag.max = maxlag,plot = FALSE);
    test <- min(abs(autocorr1$acf-0.5))
    autocorr=rbind(autocorr,as.vector(autocorr1$acf))
    half_autocorr[count1,count2] = which(abs(autocorr1$acf-0.5) == test);
  }
  if (count1==1){
    plot(seq(1,maxlag,by=1),colMeans(autocorr),type="l",col=count1)
  }
  else{
    lines(seq(1,maxlag,by=1),colMeans(autocorr),type="l",col=count1)
  }
  #lines(lag,autocorrelation,col="green")
}
```

```
## Warning in rbind(autocorr, as.vector(autocorr1$acf)): number of columns of
```



```
## result is not a multiple of vector length (arg 2)

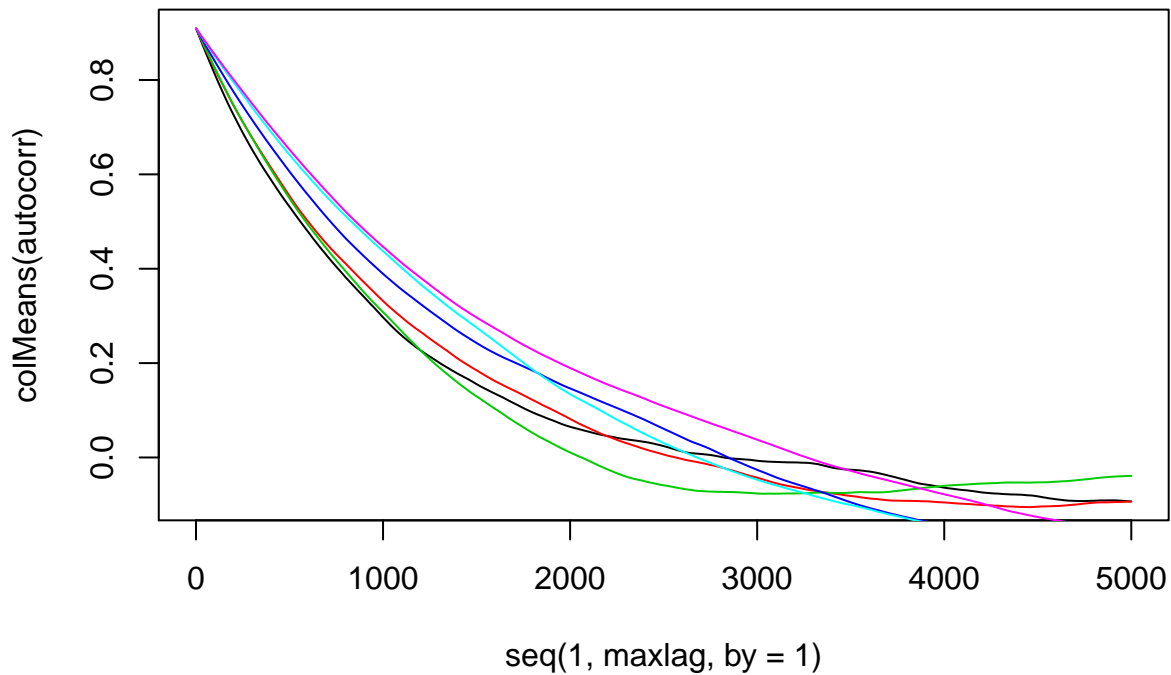
## Warning in rbind(autocorr, as.vector(autocorr1$acf)): number of columns of
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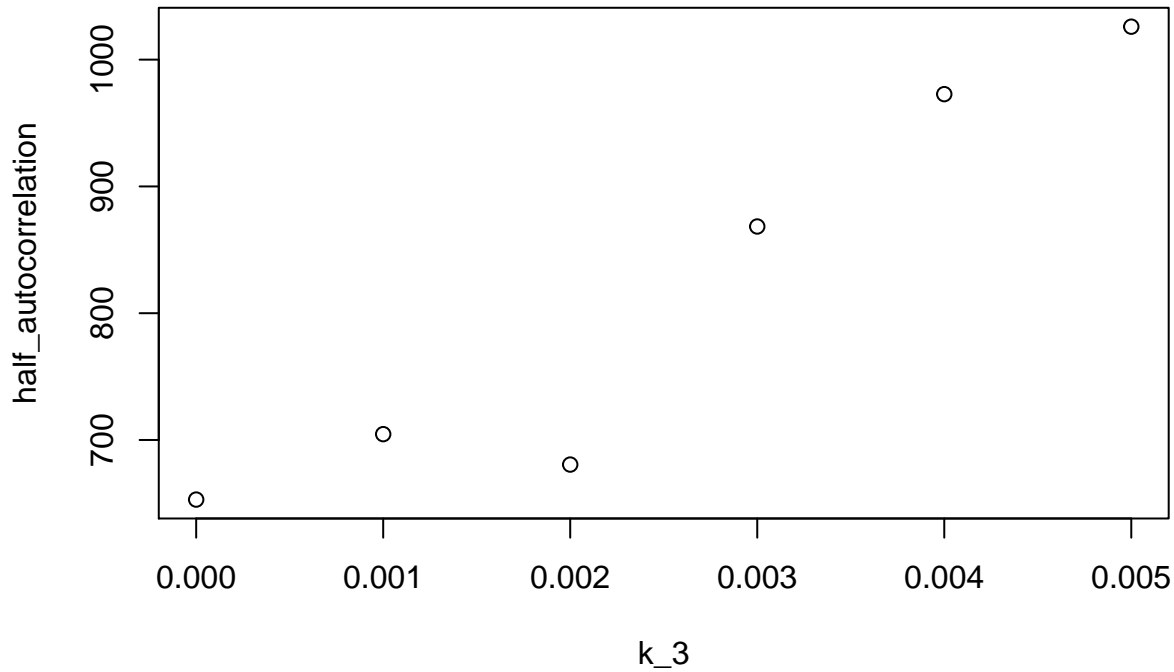
## Warning in rbind(autocorr, as.vector(autocorr1$acf)): number of columns of
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## result is not a multiple of vector length (arg 2)
```



```
k_3 = seq(0,0.005,by=0.001);
half_autocorrelation = rowMeans(half_autocorr)
plot(k_3,half_autocorrelation);
```



Entropy

Named after Boltzmann's H -theorem, Shannon defined the entropy H (Greek letter H) of a discrete random variable X with possible values x_1, \dots, x_n and probability mass function $P(X)$ as:

$$H(X) = E[I(X)] = E[-\ln(P(X))]$$

.

Here E is the expected value operator, and I is the information content of X . $I(X)$ is itself a random variable.

The entropy can explicitly be written as

$$H(X) = \sum_{i=1}^n P(x_i) I(x_i) = - \sum_{i=1}^n P(x_i) \log_b P(x_i),$$

where b is the base of the logarithm used. Common values of b are 2, Euler's number e , and 10, and the unit of entropy is shannon for $b = 2$, nat for $b = e$, and hartley for $b = 10$. When $b = 2$, the units of entropy are also commonly referred to as bits.

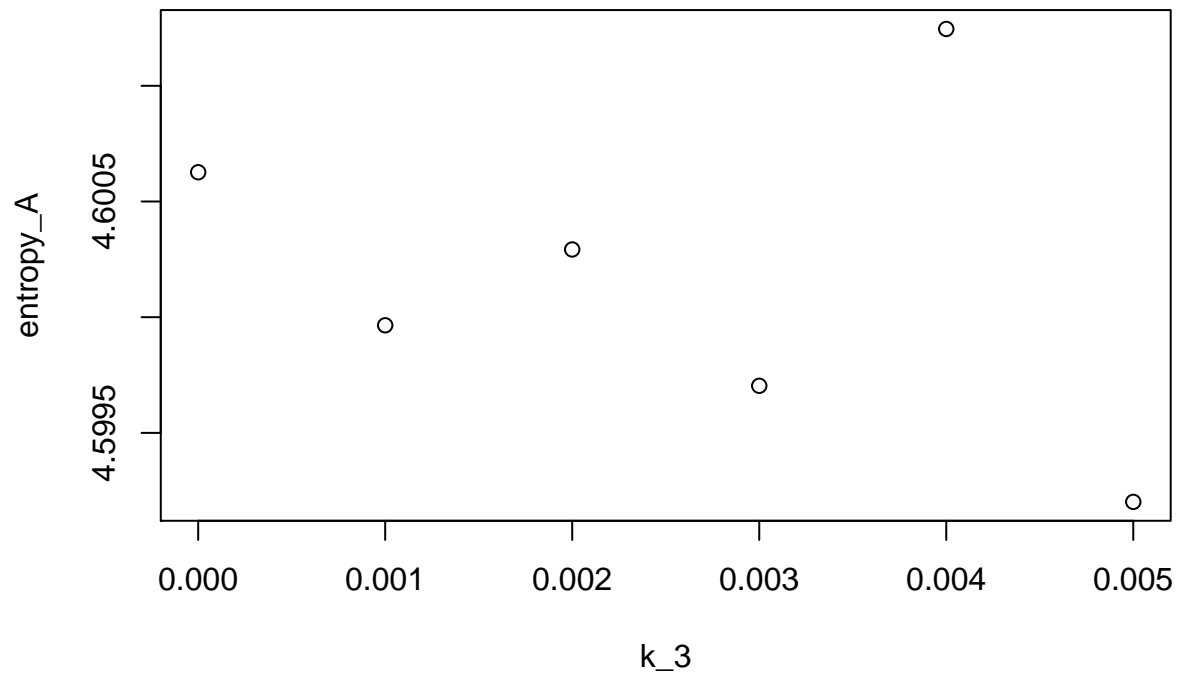
We can see how the entropy varies with k_3 by doing the following:

```
numberofrealisations = 100;
entropy_A <- rep(0,6);
count1 = 0;
for (k_3 in seq(0,0.005,by=0.001)){
  count1 = count1 + 1;
  A_end <- rep(0, numberofrealisations);
  for (count2 in seq(1,numberofrealisations,by=1)){
    output = simple_positive_feedback(1,0.01,k_3,1000,0.1,1);
    temp_A = output[length(output)]; #use final time series value
    A_end[count2] = temp_A;
  }
}
```

```

    }
    entropy_A[count1] = entropy(A_end);
  }
  k_3 = seq(0,0.005,by=0.001);
  plot(k_3,entropy_A);

```



non entropy appears to remain constant, making it useless for positive feedback detection.

Shan-