

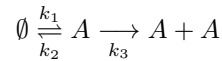
# Positive feedback measures

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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:



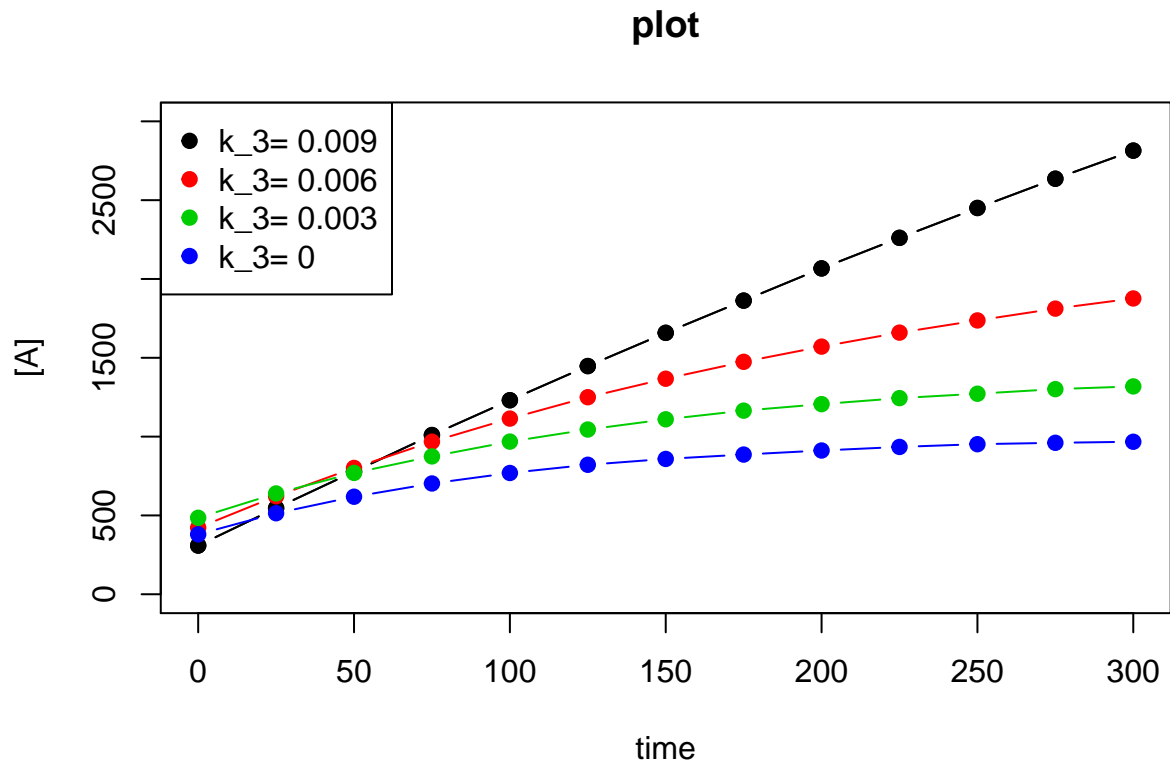
where  $k_1$  is the birth rate,  $k_2$  is the decay rate and  $k_3$  is the positive feedback strength. We want to study stochastic realisations of this model using the stochastic simulation algorithm which is implemented in the function “simple\_positive\_feedback.r”, so first we must source the function.

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

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

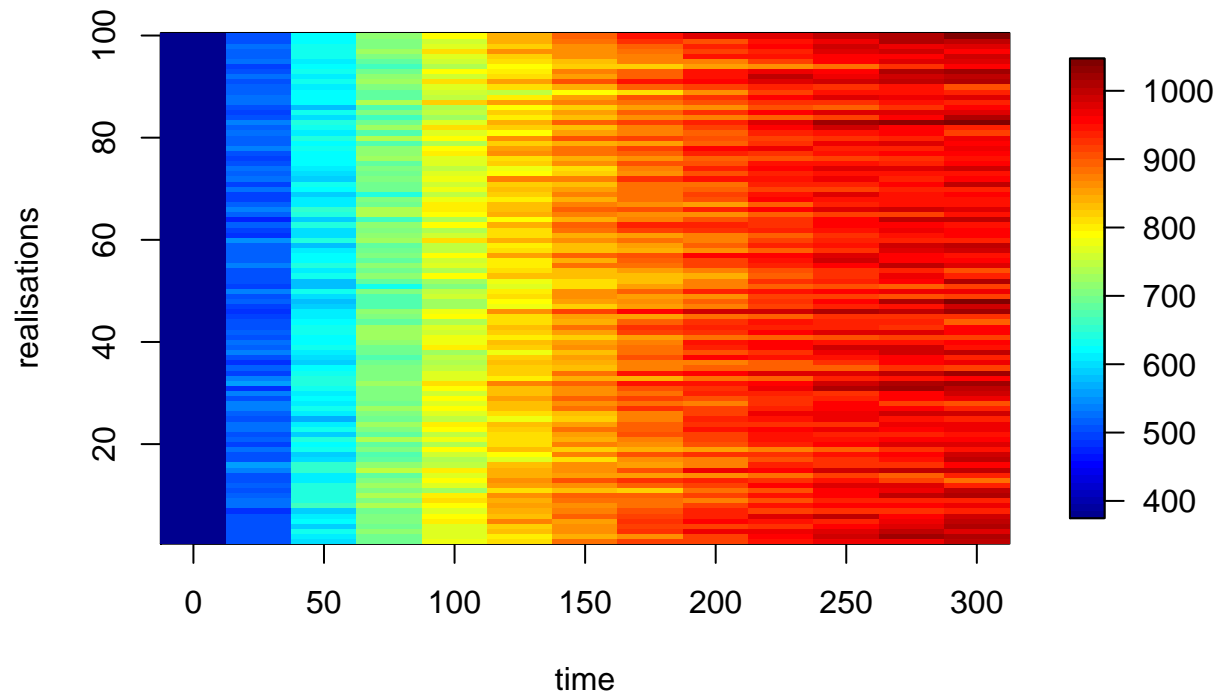
```
k_1 = 10;
k_2 = 0.01;
k_3 = 0.001;
k_steady = k_1/(k_2-k_3);
maxtime = 300;
timestep = 25;
numberofrealisations = 100;
#output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations,round(runif(1,min=
#plot(seq(0,maxtime,timestep),t(rowMeans(output)))));
count = 0;
mu_A <- rep(0, 6);
leg <- matrix(0,1,ncol=length(seq(0.006,0,by=-0.002)))
for (k_3 in seq(0.009,0,by=-0.003)){
  count = count + 1;
  output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations,round(runif(1,min=
  temp_mean_A = rowMeans(output);
  mu_A[count] = temp_mean_A[length(temp_mean_A)];

  if (count==1){plot(seq(0,maxtime,timestep),t(rowMeans(output)),type='b',pch=19,col=count,ylim=c(0,300))
  }
  {lines(seq(0,maxtime,timestep),t(rowMeans(output)),type='b',pch=19,col=count)
  }
  leg[count]<-k_3
}
legend("topleft",c(paste('k_3=',leg[1]),paste('k_3=',leg[2]),paste('k_3=',leg[3]),paste('k_3=',leg[4]))
```



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);
```



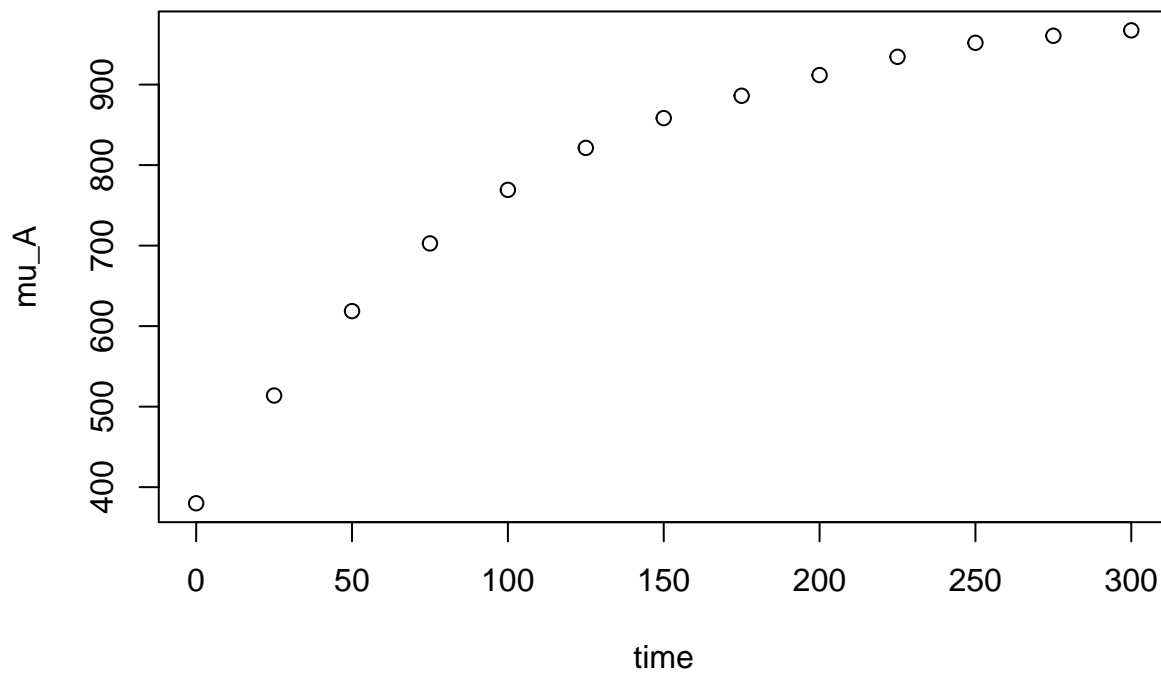
Now that we have a stochastic model with positive feedback strength as a parameter, we can try to find

measures that are suitable for identifying positive feedbacks.

## Mean

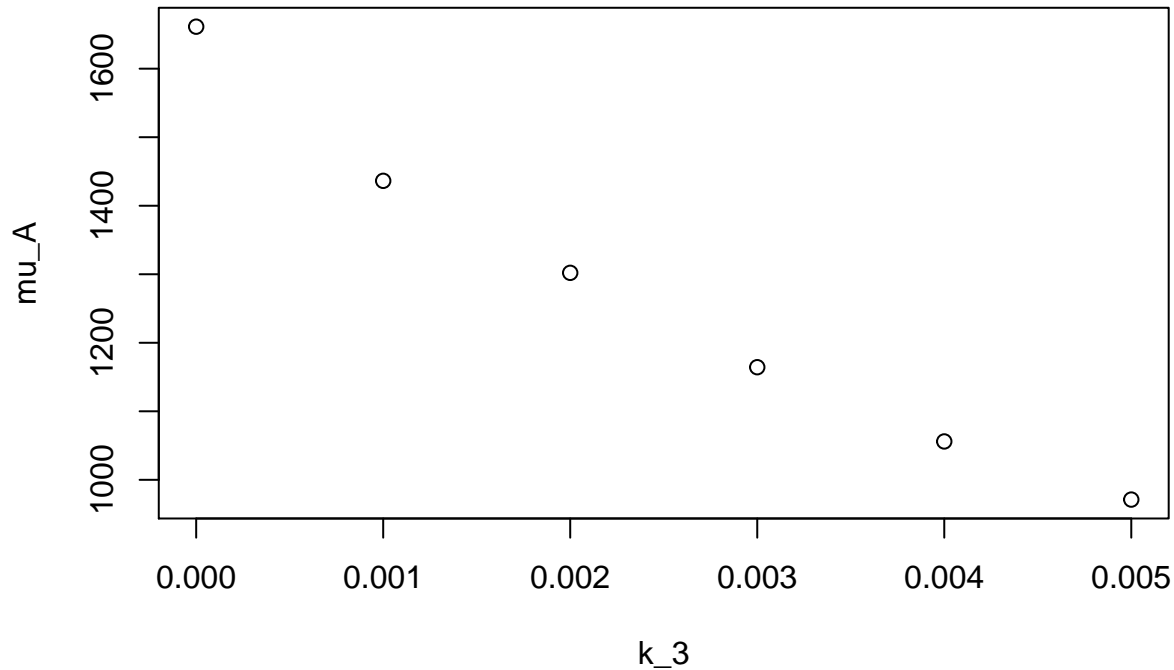
The first and most obvious measure is the mean. The mean value of  $A$  should increase with the positive feedback strength,  $k_3$ . To study this, first we can plot the mean time series for a single value of  $k_3$ :

```
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 ( $\mu$ ) 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(0.005,0,by=-0.001)){  
  count = count + 1;  
  output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,numberofrealisations,round(runif(1,min  
  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

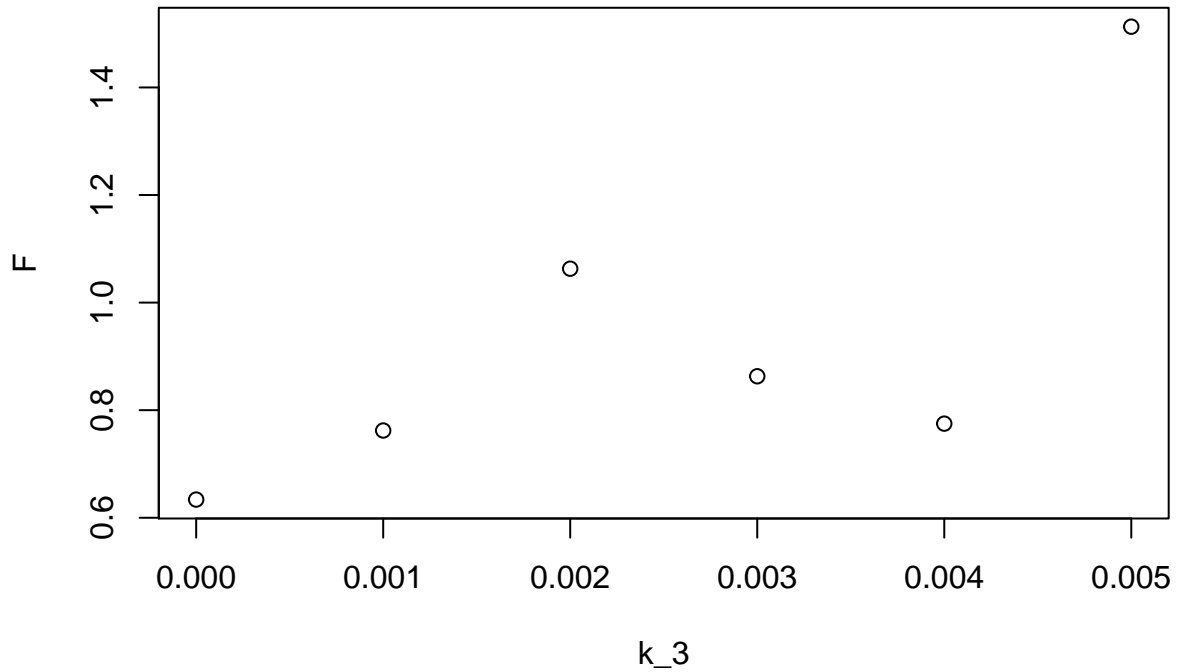
$$F = \frac{\sigma^2}{\mu}$$

where  $\sigma^2$  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

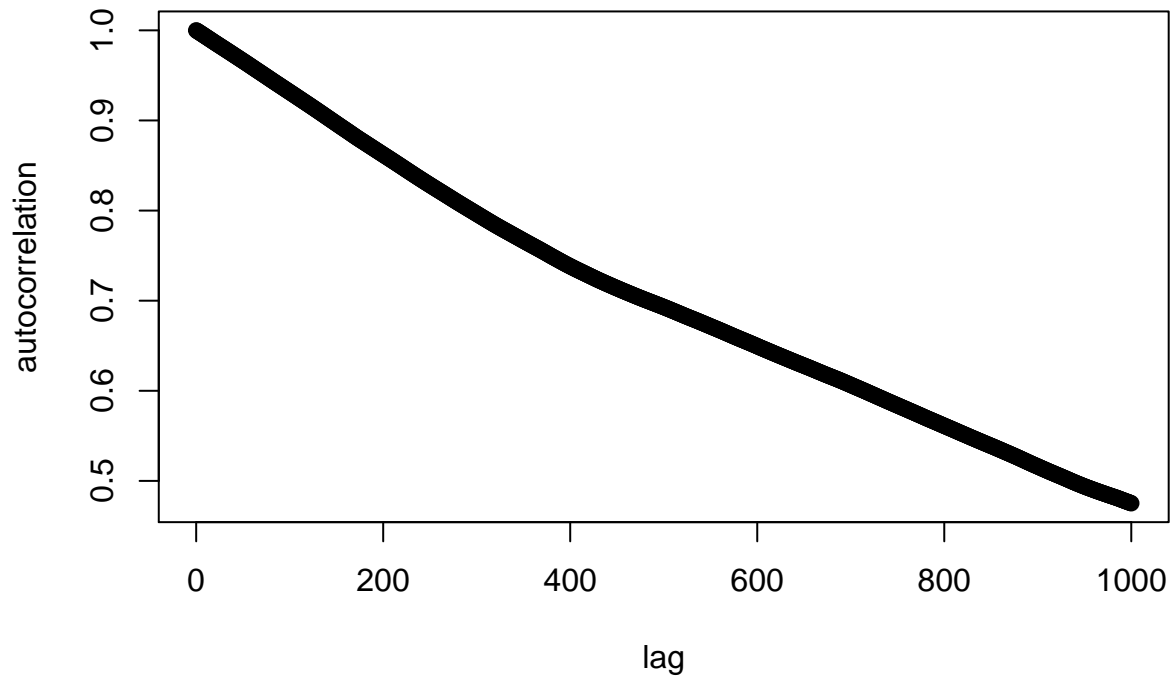
For a discrete process with known mean and variance for which we observe  $n$  observations  $\{X_1, X_2, \dots, X_n\}$ , an estimate of the autocorrelation may be obtained as

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

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 = 937



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

```
warningnumberofrealisations = 10;
maxlag=20;
k_1 = 10;
k_2 = 0.01;
k_3 = 0.001;
k_steady = k_1/(k_2-k_3);
maxtime = 300;
timestep = 25;
numberofrealisations = 100;
count1 = 0;
half_autocorr <- matrix(0,nrow=6,ncol=numberofrealisations);

for (k_3 in seq(0.009,0,by=-0.003)){
  count1 = count1 + 1;
  autocorr <- matrix(0,1,ncol=maxlag+1);
  for (count2 in seq(1,numberofrealisations,by=1)){
    output = simple_positive_feedback(k_1,k_2,k_3,maxtime,timestep,1,round(runif(1,min=.3,max=.5)*1000));
    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(0,maxlag,by=1),colMeans(autocorr),type="b",pch=19,col=count1)
  }
  else{
```

```

lines(seq(0,maxlag,by=1),colMeans(autocorr),type="b",pch=19,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)

```

```

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```

[illegible]















































```
## 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)
```

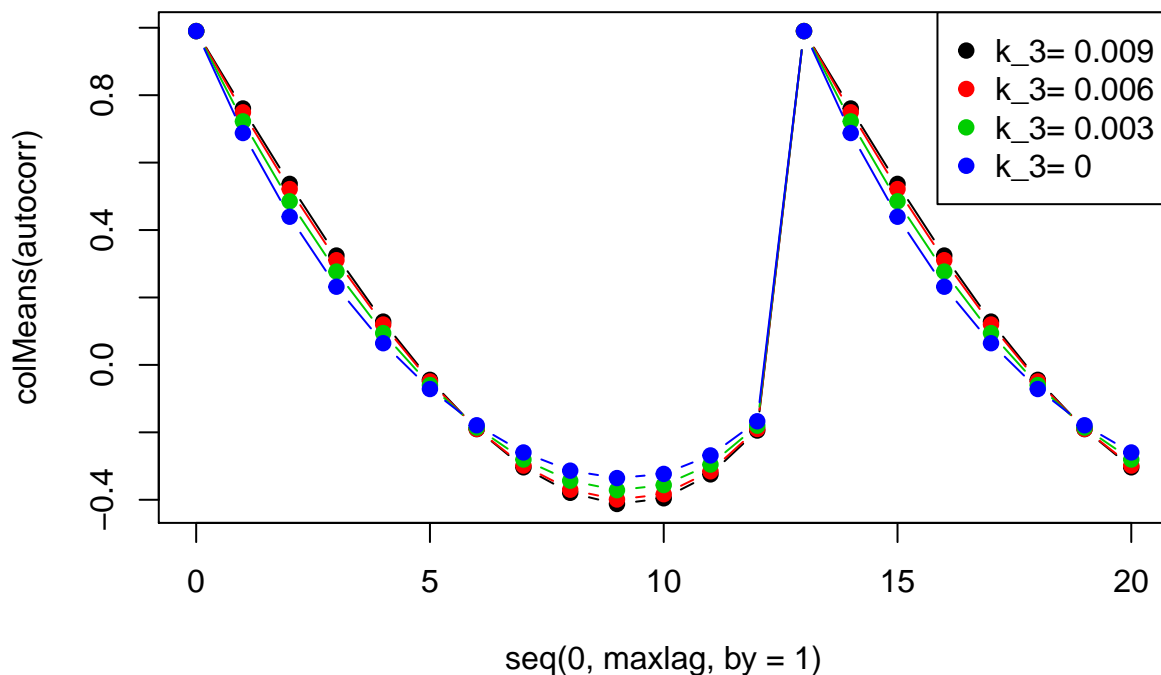
```
## Warning in rbind(autocorr, as.vector(autocorr1$acf)): number of columns of
## result is not a multiple of vector length (arg 2)
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```
## Warning in rbind(autocorr, as.vector(autocorr1$acf)): number of columns of
## result is not a multiple of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

```
legend("topright",c(paste('k_3=',leg[1]),paste('k_3=',leg[2]),paste('k_3=',leg[3]),paste('k_3=',leg[4]))
```



```
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:

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

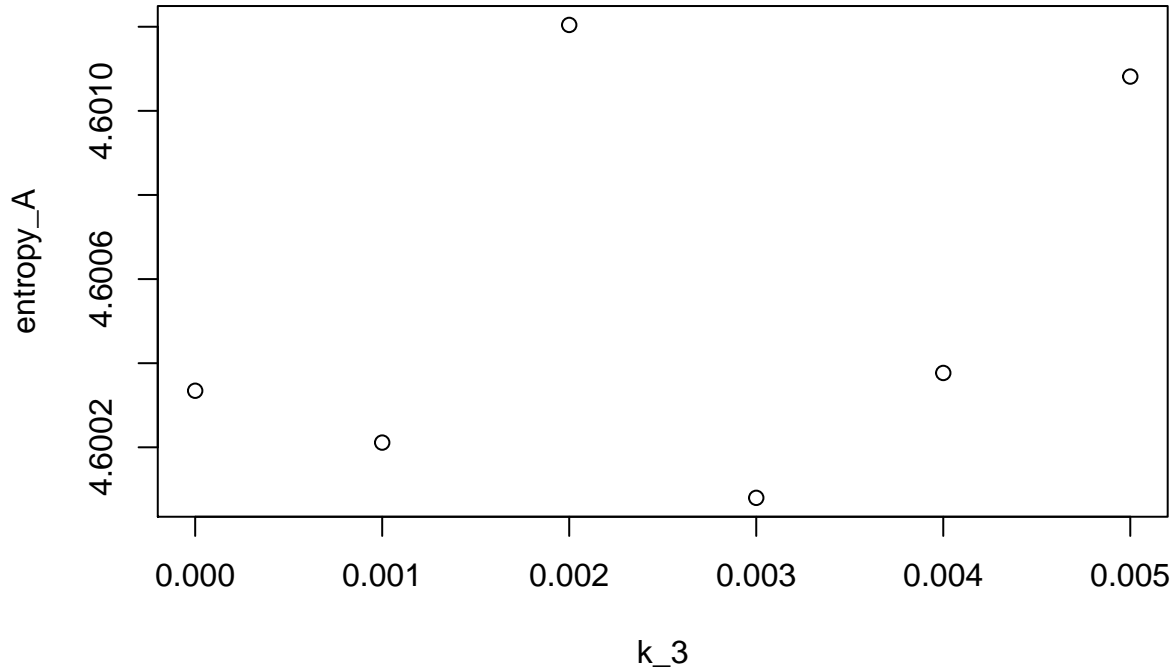
Here  $E$  is the expected value operator, and  $I$  is the information content of  $X$ .  $I(X)$  is itself a random variable. The entropy can explicitly be written as

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

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-