Università di Pisa

A COMPUTATIONAL MODEL OF THE DOPAMINERGIC SYSTEM FOR THE STUDY OF THE ADDICTION PHENOMENA

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INTRODUCTION

- **Aim:** to study the problem of Internet addiction and its spread through interaction on social network
- **Our proposal:** a Hybrid Automata model of the Dopaminergic System, used to simulate the activity of a user type on a virtual social network

TABLE OF CONTENTS

WHAT IS ADDICTION?

Addiction is a complex phenomenon influenced by **environmental**, **social** and **biological** factors.

Environmental factors:

- Education and family background
- Availability
- Economic Resources

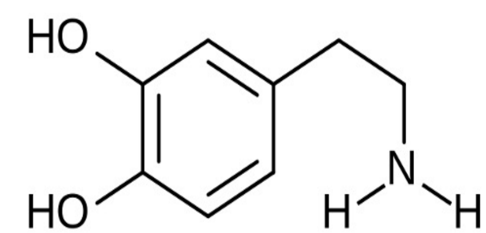
Social factors:

- Consensus
- Consistency
- Distinctiveness

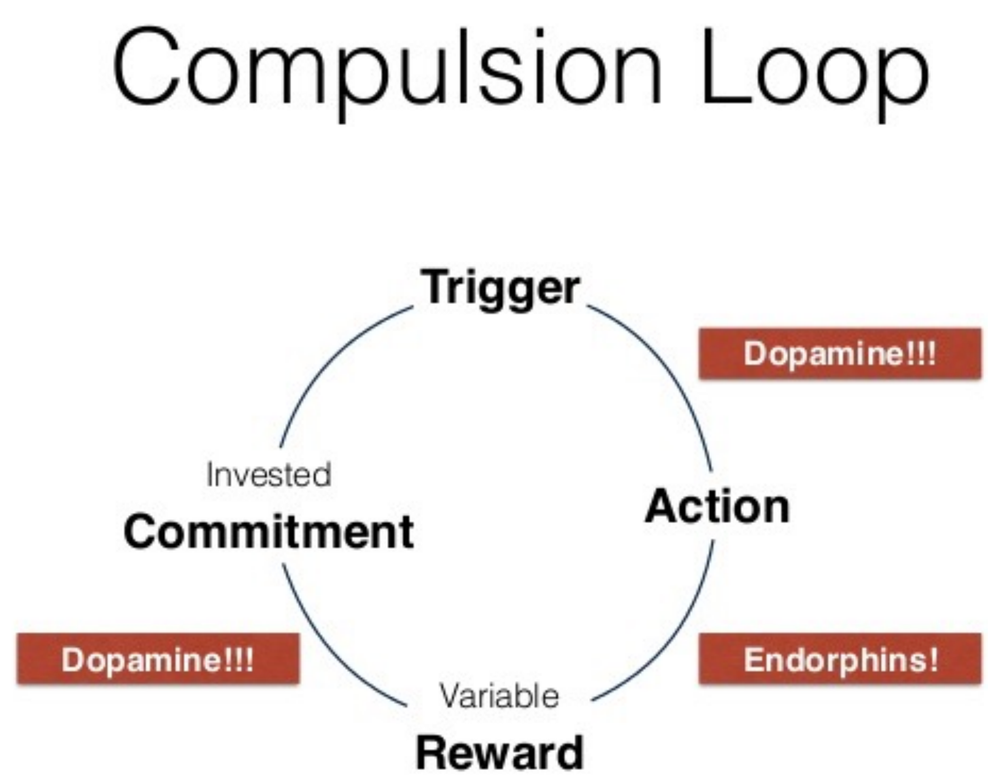
THE ROLE OF BRAIN

- Dopamine System:

Dopamine is a neurotransmitter. In addiction context, at the beginning its level increases; later, after loop, it doesn't reach anymore the same level.



Dopamine



GUTKIN'S MODEL

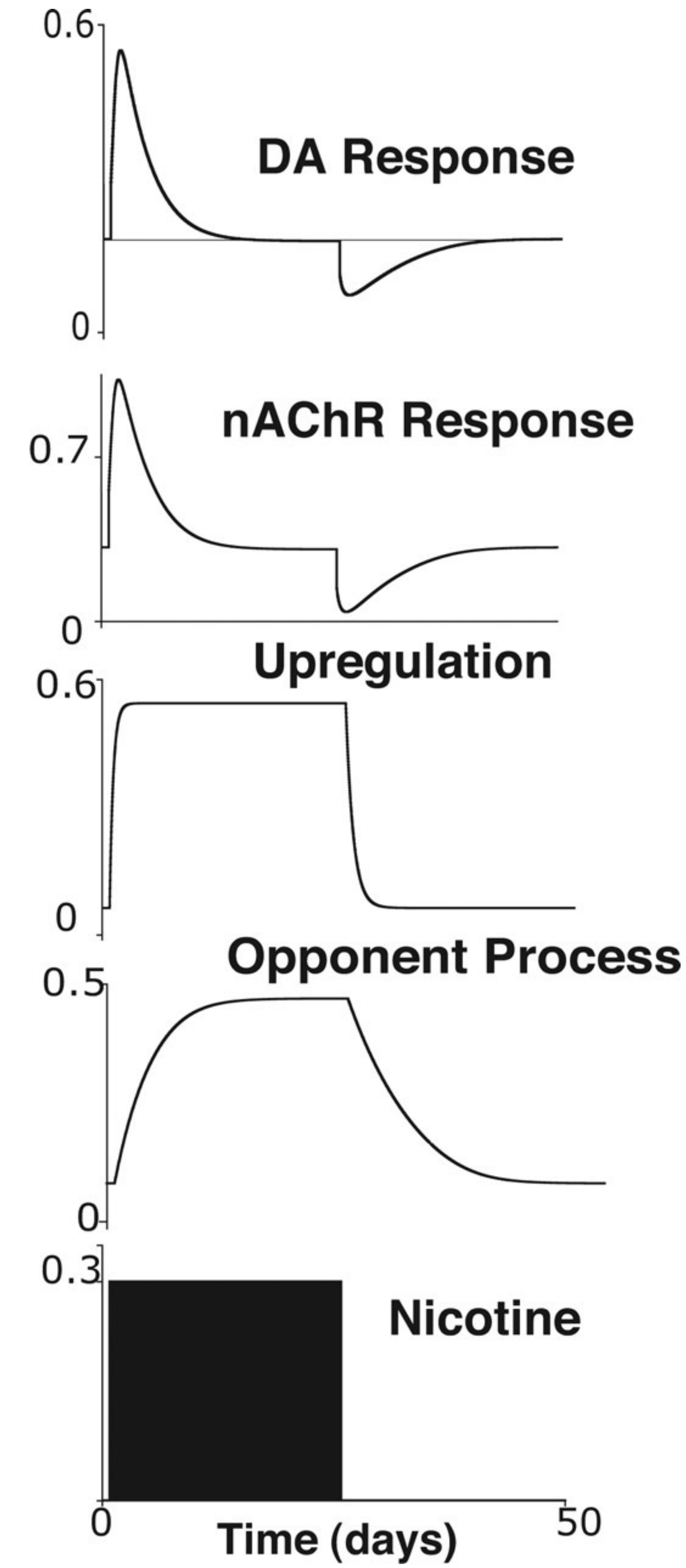
The Gutkin's model(1) specifically analyses nicotine addiction. It shows how a constant stimulus causes a consequent decrease in neurons activity.

$$\frac{dU_{DA}}{dt} = -U_{DA} + S_{DA}\left\{\sum_i r_i;\, N(t)\right\}$$

$$S_{DA} = \frac{1}{2}\left(1 + \tanh\left(N(t)\sum_i r_i(t) - \theta_{DA}\right)\right).$$

$$\tau_A \frac{dU_1^A}{dx} = -U_1^A + S_A\{w_{11}^e U_1^A - w_{12}^i U_2^A - \theta_A\} + \sigma\xi \text{ and}$$

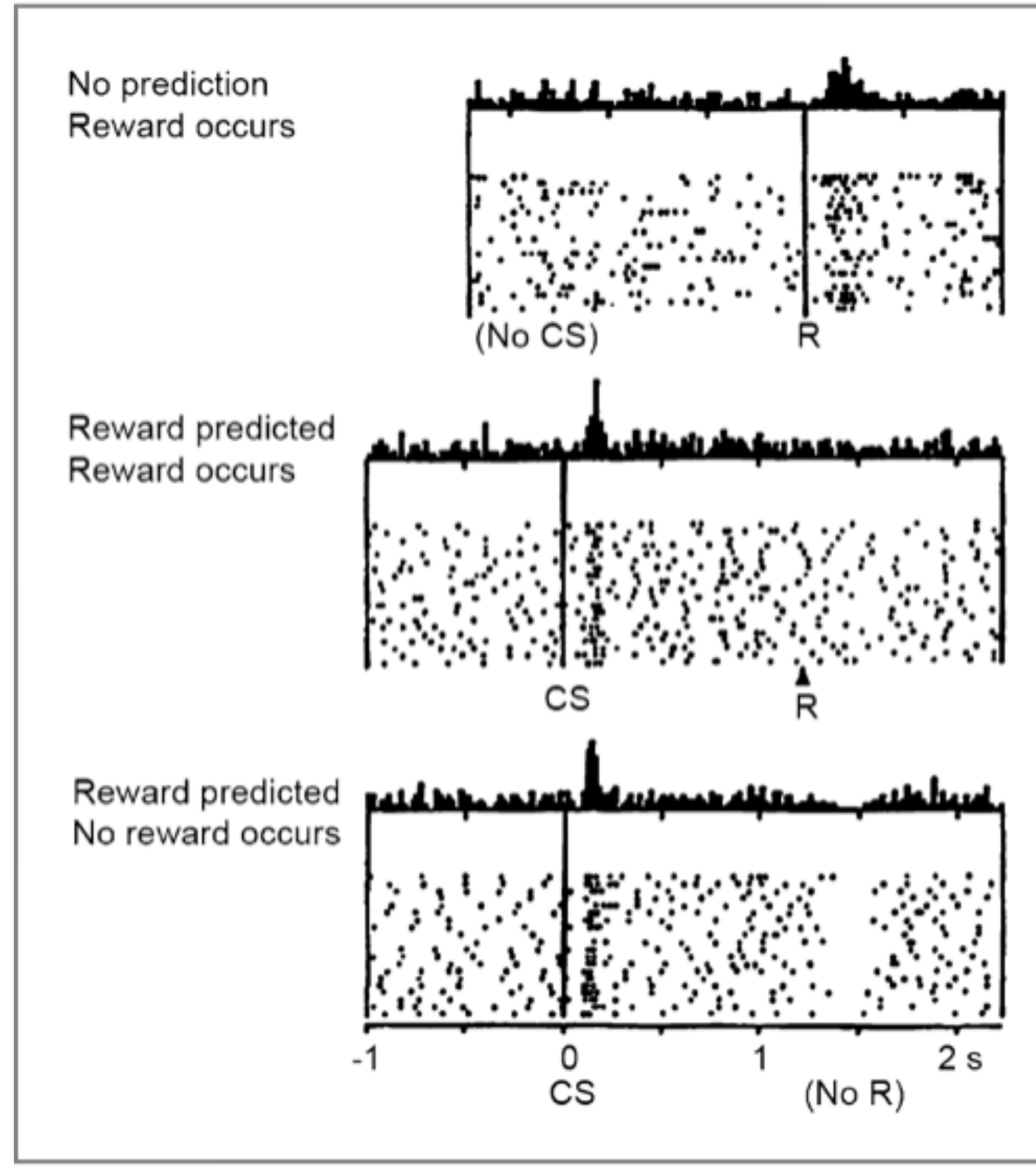
$$\tau_A \frac{dU_2^A}{dx} = -U_2^A + S_A\{w_{22}^e U_2^A - w_{21}^i U_1^A - \theta_A\} + \sigma\xi.$$



(1) Boris S Gutkin, Stanislas Dehaene, and Jean-Pierre Changeux. A neurocomputational hypothesis for nicotine addiction. Proceedings of the National Academy of Sciences of the United States of America, 103(4):1106{1111, 2006.

SAMSON'S MODEL

The Samson's model[2] focuses on the role of dopamine as reward signal.



Neurons are activated in two cases:

- when there is an *imminent* reward
- when there is a *predicted* reward

[2]RD Samson, MJ Frank, and Jean-Marc Fellous. Computational models of reinforcement learning: the role of dopamine as a reward signal. Cognitive neurodynamics, 4(2):91{105, 2010.

THE MODEL OF DOPAMINERGIC SYSTEM

- **Dopamine concentration.** The equation describes the dynamics of variable *D* representing the dopamine concentration in the prefrontal cortex:

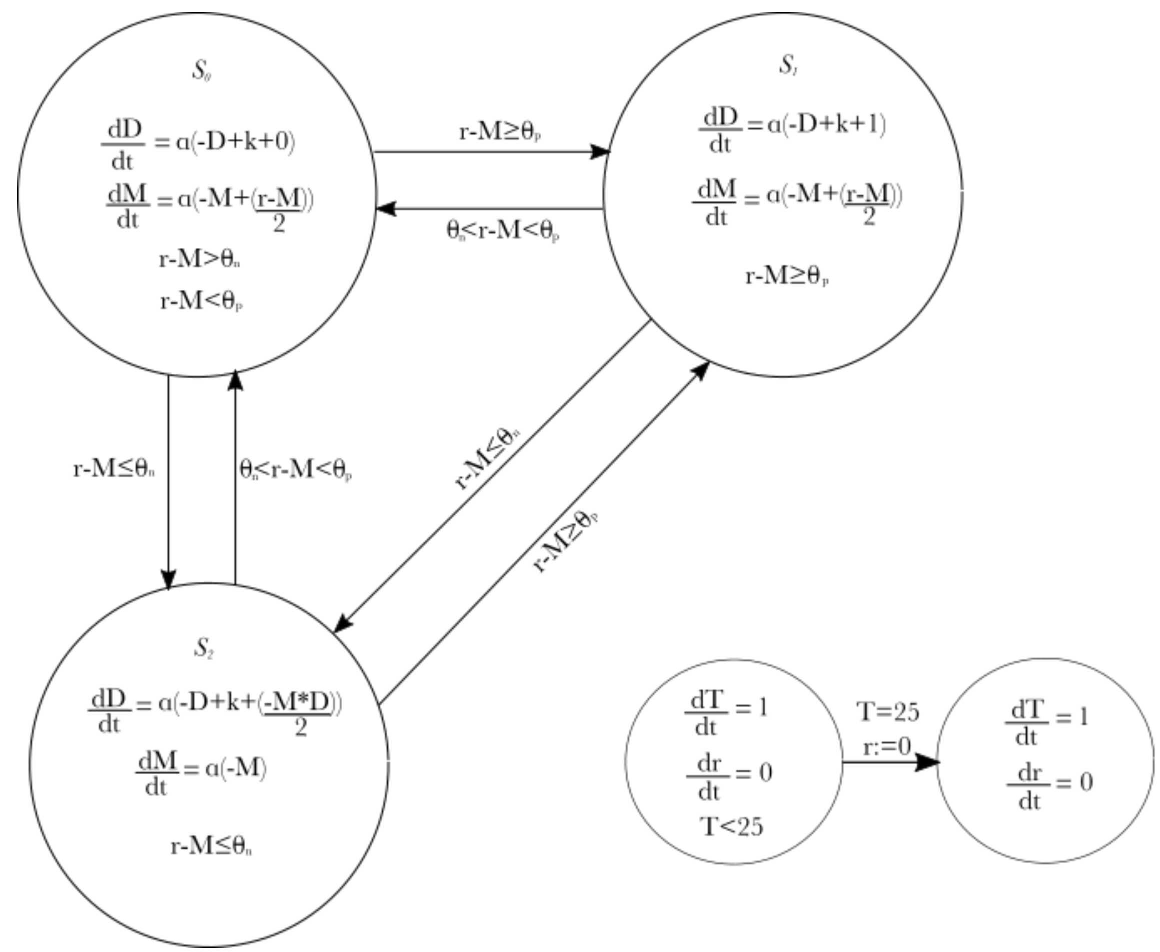
$$\frac{dD}{dt} = \alpha \left(-D + k + \begin{cases} 1, & if\ r - M \geq \theta_p \\ 0, & if\ \theta_n \leq r - M \leq \theta_p \\ -\frac{D*M}{2}, & if\ r - M \leq \theta_n \end{cases} \right)$$

- **Memory.** The equation describes the opponent process (a contrary emotional reaction to a previous stimulus) that is modelled as a memorisation process of previous stimuli.

$$\frac{dM}{dt} = \alpha \left(-M + \begin{cases} \frac{r-M}{2}, & if\ r > M \\ 0, & otherwise \end{cases} \right)$$

HYBRID AUTOMATA MODEL

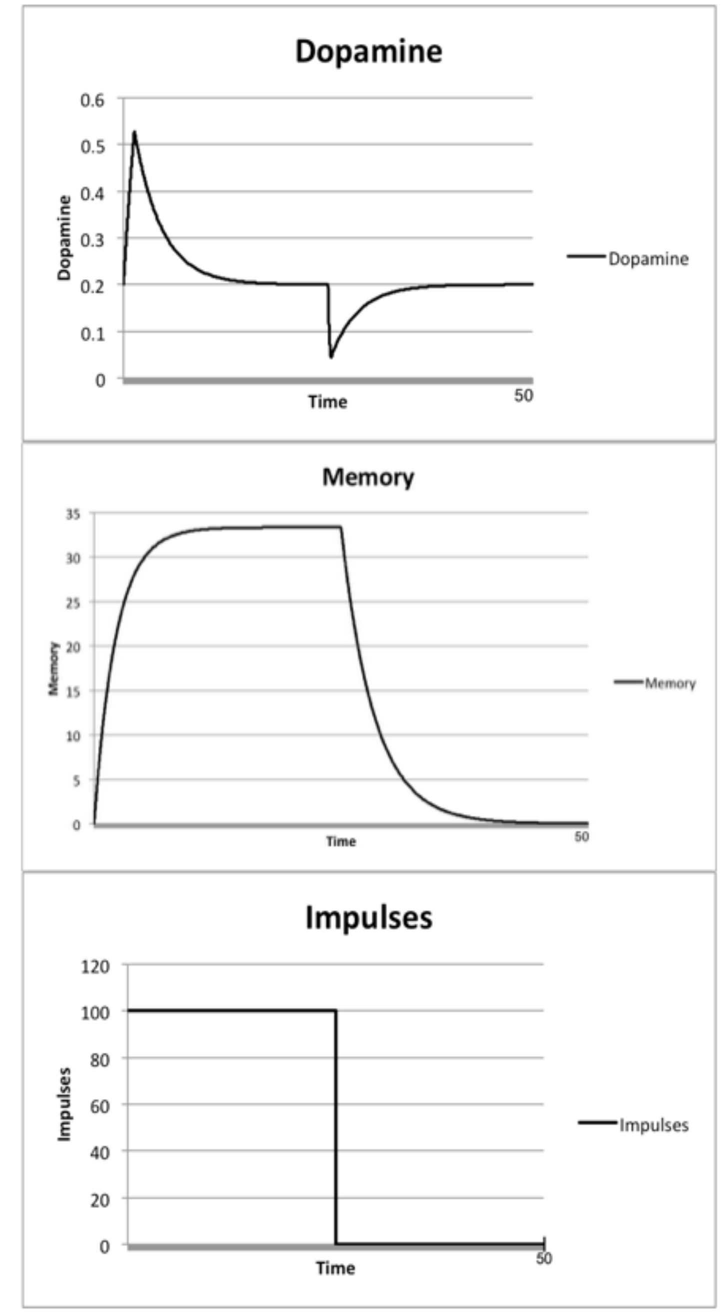
Hybrid Automata are finite state automata in which states are associated to differential equations that describe the dynamics of a set of continuous variables.



- Compositionality of Hybrid Automata
- Better description of transition

SIMULATION AT CONSTANT PULSE

The **trend of dopamine**, similar to the graph obtained by Gutkin, shows an initial peak which results in a withdrawal symptom, previous to the interruption of the stimulus itself.

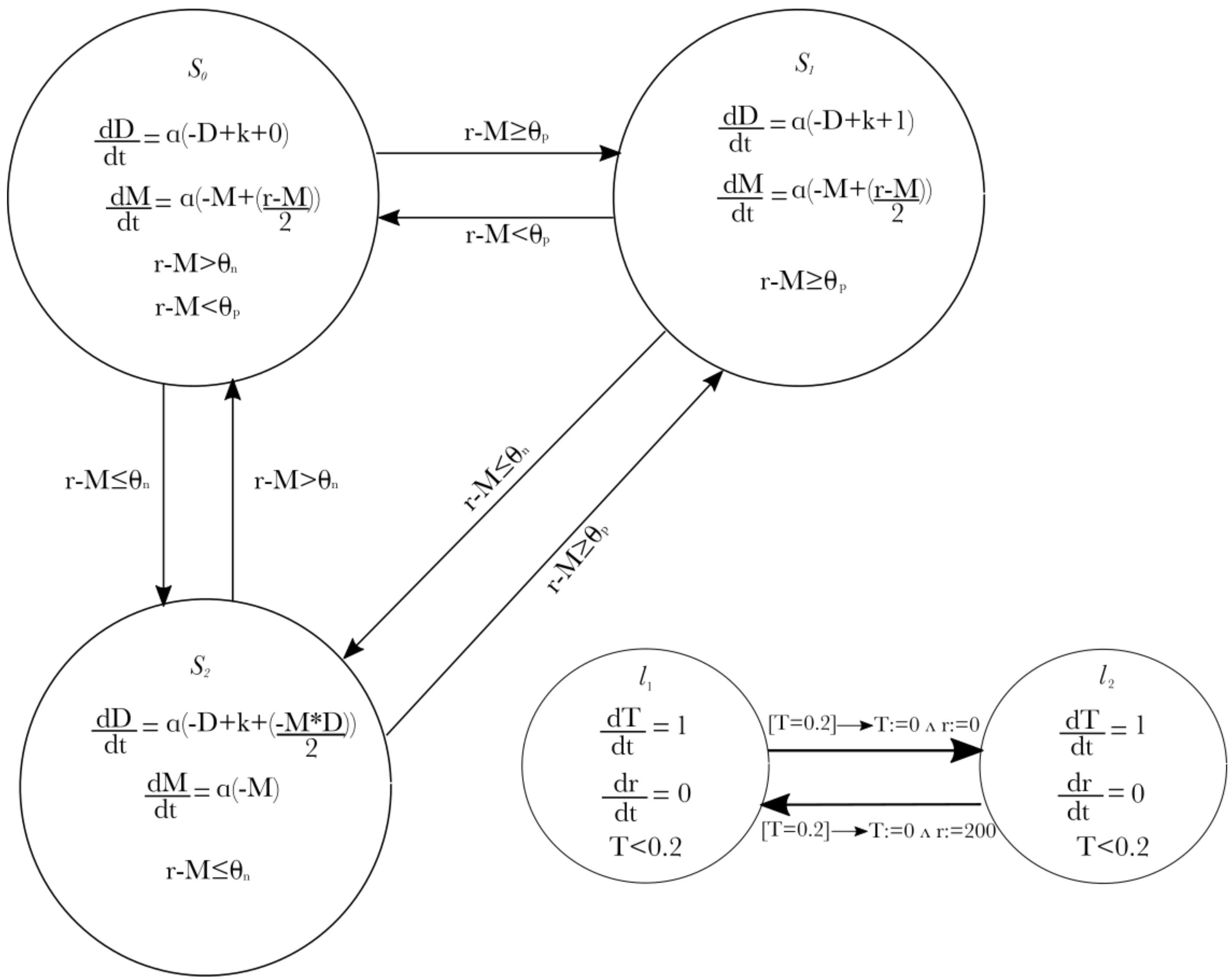


The performance of the memory, however, corresponds to the **opponent process**.

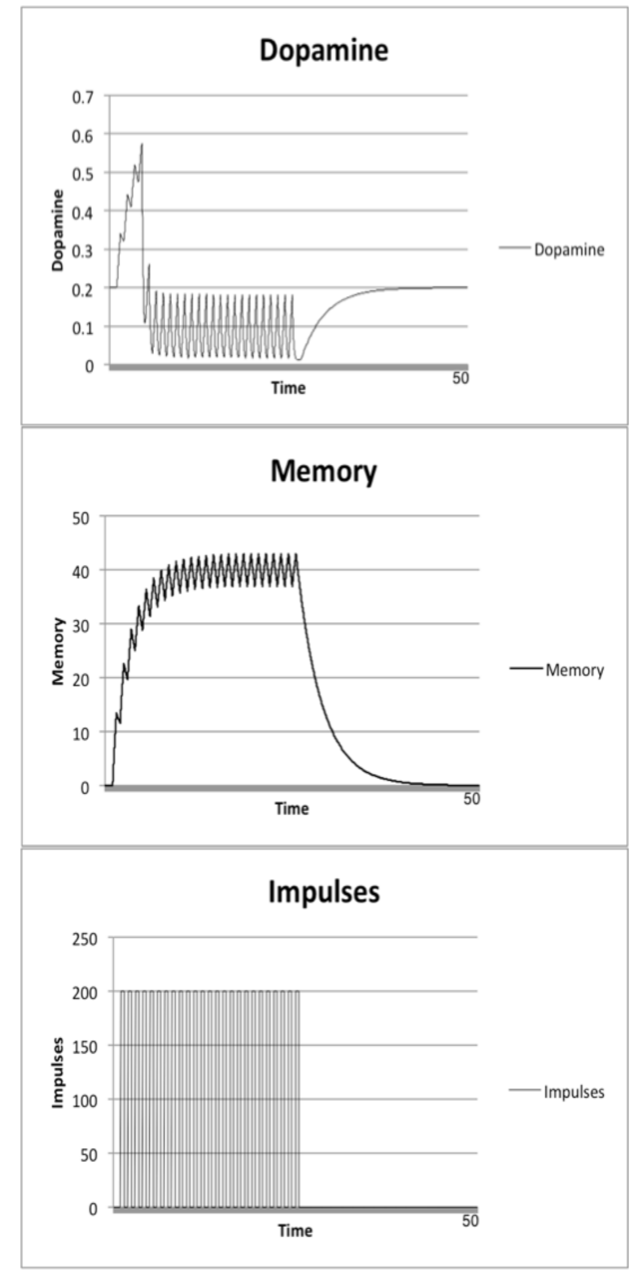
To establish if a user became addicted, we consider the memory threshold: $M>=15$

HYBRID AUTOMATA AT CLOSE FREQUENCY PULSES

Hybrid Automata

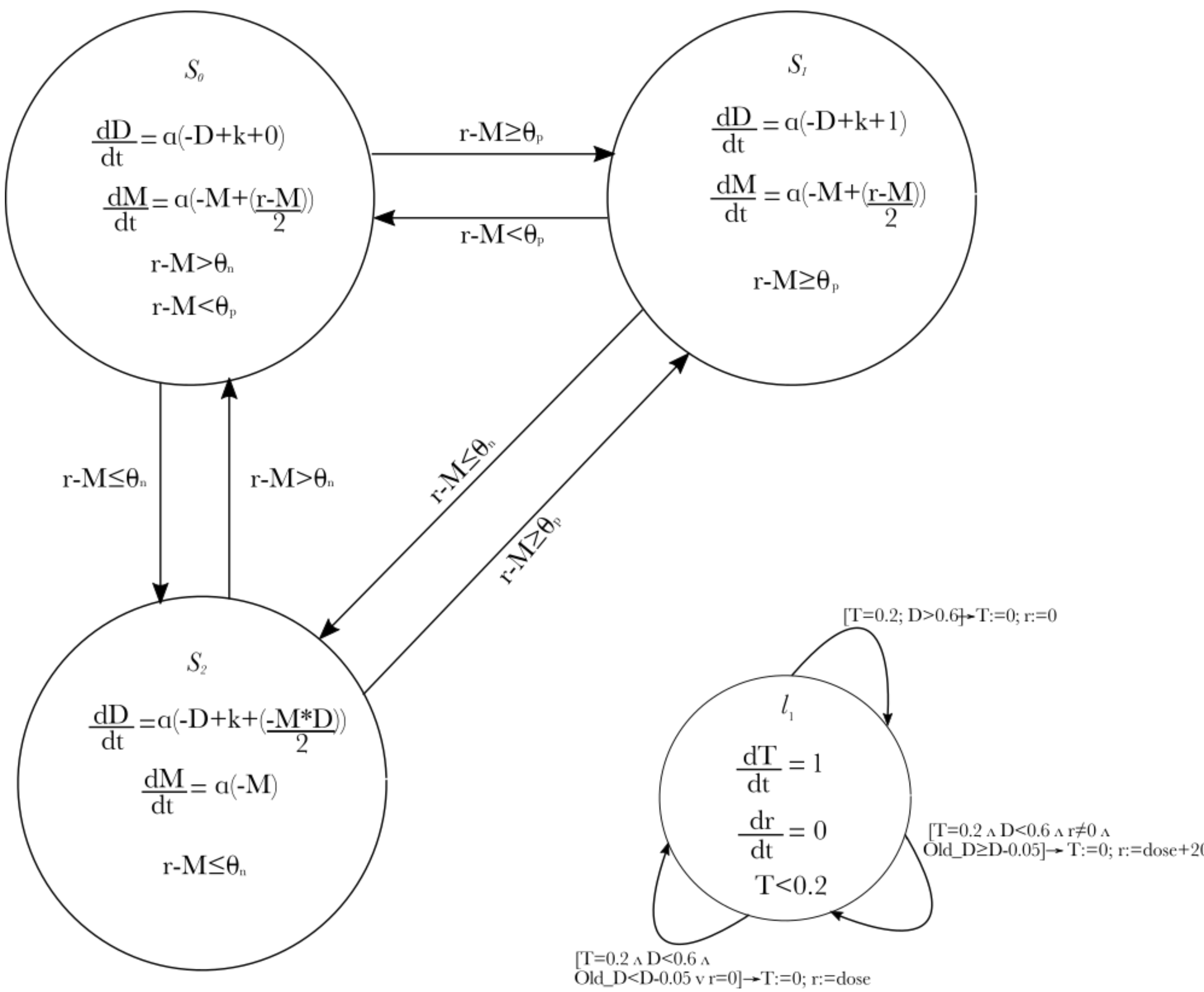


Simulation results

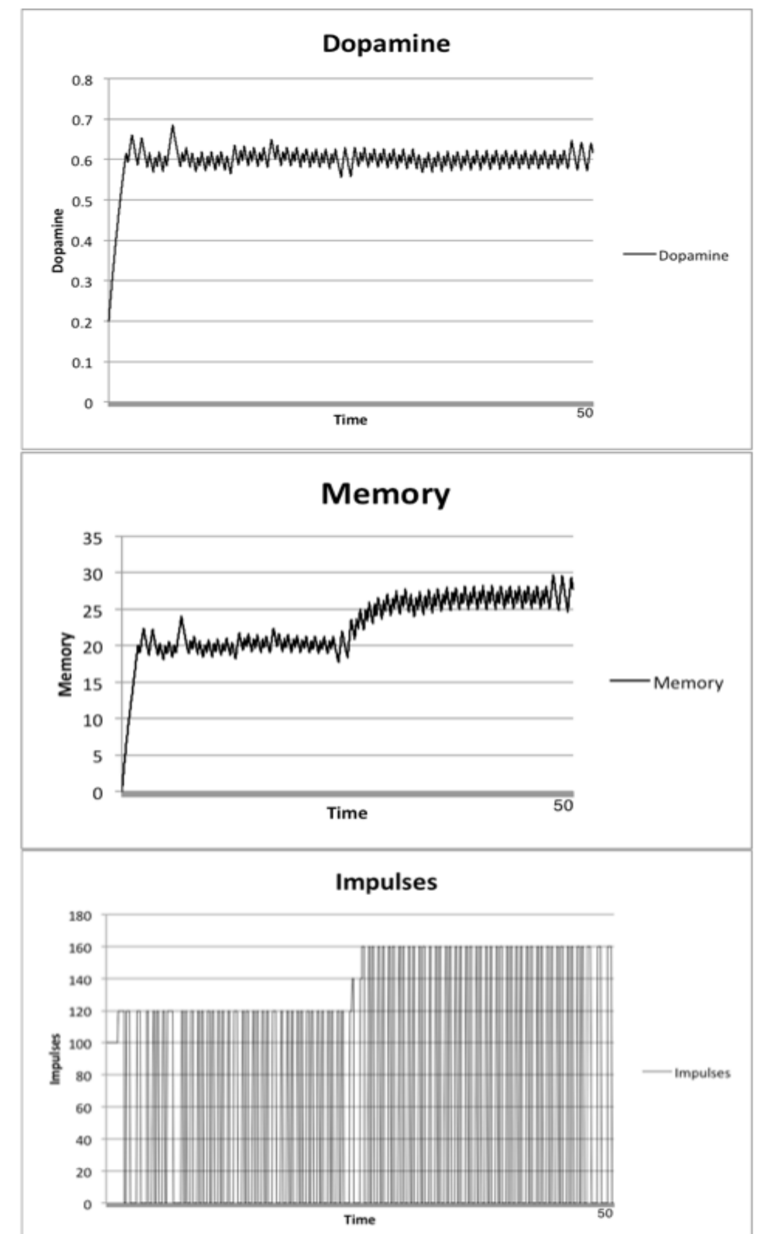


HYBRID AUTOMATA AT INCREASING INTENSITY AND FREQUENCY PULSES

Hybrid Automata



Simulation results



THE INTERNET ADDICTION

Excessive use of Internet as a mechanism to **escape** from the daily dissatisfaction.

Main expressions:

- Gaming
- Social network
- Surfing

We represent the social network as a **graph**:

- Each node of graph is a **user**
- Each user is characterised by the Dopaminergic System and the **propensity factor**

THE PROPENSITY FACTOR

- It is a parameter, which spans the range [0,1], to model the user's predisposition to communicate

- It influences the probability to send (or reply) messages through the social network

THE NETWORK COMMUNICATION MODEL

- Each user can send at most **one message each day**
- The probability to send a message is proportional to his/her propensity factor. If he/she sends a message, this is received by his/her neighbours
- On the same day, all users that have received one or more messages choose whether to reply or not, again with a probability proportional to their propensity factors.

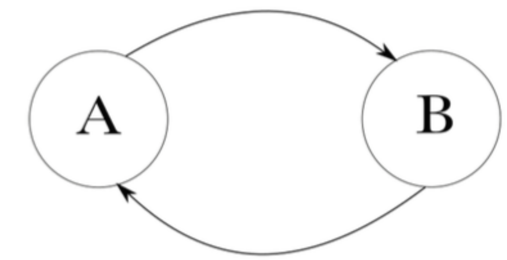
Stimuli:

- **medium-high:** when user receives a message
- **high:** when an addicted* user sends a message (*prediction error phenomenon*)

*Memory$\geq$15

GRAPH WITH ONLY TWO NODES

This graph is used to **examine the role of the propensity factor**. All the possible combinations of users have been tested to study the behaviour of the Dopaminergic System in different situations



User B

User A	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0
0.1	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=66	A=0; B=97	A=0; B=99
0.2	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=83	A=0; B=100	A=0; B=100	A=0; B=100	A=0; B=100	A=0; B=100	A=0; B=100
0.3	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=0	A=0; B=95	A=1; B=100	A=2; B=100	A=6; B=100	A=6; B=100	A=5; B=100	A=8; B=100
0.4	A=0; B=0	A=0; B=0	A=90; B=0	A=96; B=3	A=95; B=96	A=93; B=100	A=91; B=100	A=96; B=100	A=91; B=100	A=94; B=100	A=93; B=100
0.5	A=0; B=0	A=0; B=0	A=100; B=0	A=100; B=5	A=100; B=94	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100
0.6	A=0; B=0	A=0; B=0	A=100; B=0	A=100; B=6	A=100; B=96	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100
0.7	A=0; B=0	A=0; B=0	A=100; B=0	A=100; B=2	A=100; B=95	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100
0.8	A=0; B=0	A=51; B=0	A=100; B=0	A=100; B=2	A=100; B=99	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100
0.9	A=0; B=0	A=88; B=0	A=100; B=0	A=100; B=5	A=100; B=96	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100
1	A=0; B=0	A=99; B=0	A=100; B=0	A=100; B=2	A=100; B=96	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100	A=100; B=100

None One Both

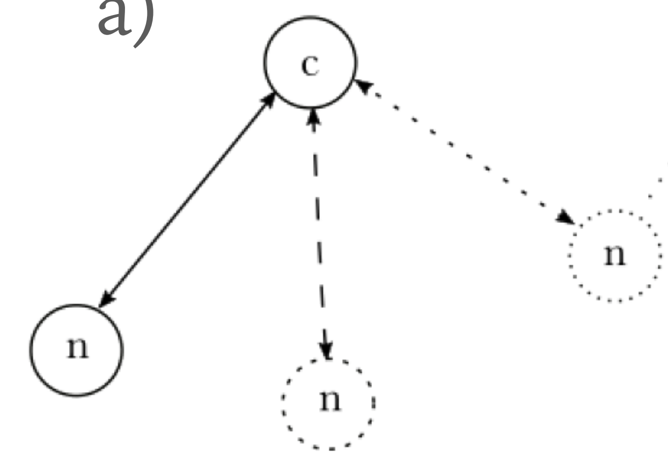
We find three values:

- low propensity: 0.2
- medium propensity: 0.35
- high propensity: 0.9

EXPERIMENTS WITH STAR GRAPH

a) **To study the propagation of addiction** in a graph, we start by considering how many peripheral nodes ***n*** are necessary to cause addiction of the central node ***c***, according to different propensity factor.

a)

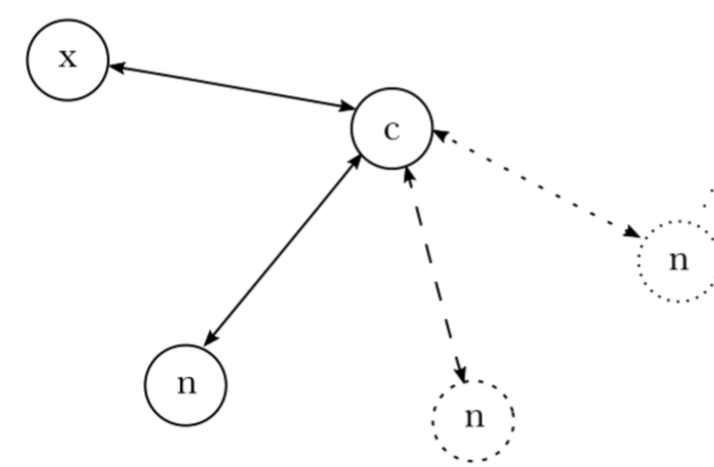


Node C \ Nodes N	0.2	0.35	0.9
0.2	9	7	4
0.35	3	1	1
0.9	1	1	1

Few Nodes ◻ More Nodes ◼

b) After, we study how one of the peripheral nodes ***x*** whose propensity factor is 0.2 (fixed) can be influenced by the others (both ***c*** and ***n***).

b)



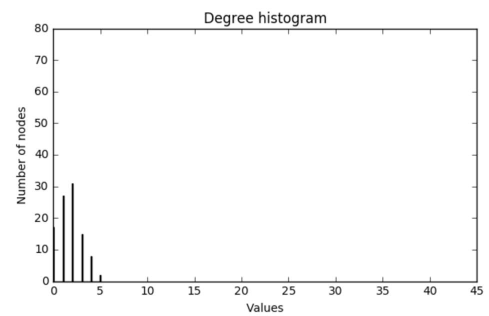
Node C \ Nodes N	0.2	0.35	0.9
0.2	44	36	17
0.35	17	13	5
0.9	15	7	4

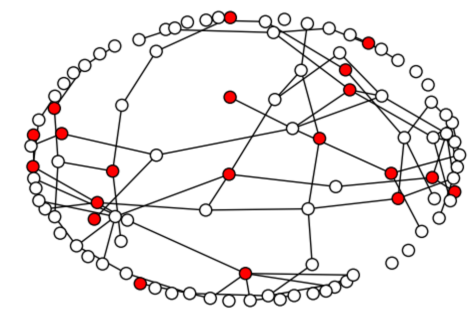
Few Nodes ◻ More Nodes ◼

EXPERIMENTS WITH RANDOM AND SCALE-FREE NETWORKS

For our experiments, we used three kinds of networks of 100 nodes, generated in different ways:

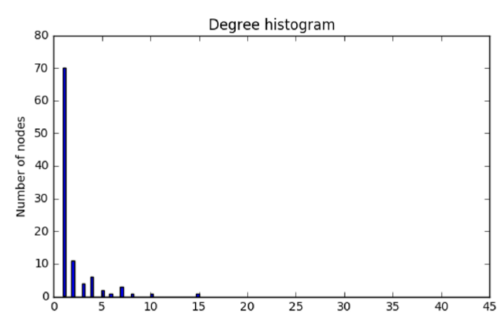
a) with the Erdős-Rényi graph (ER), approach:

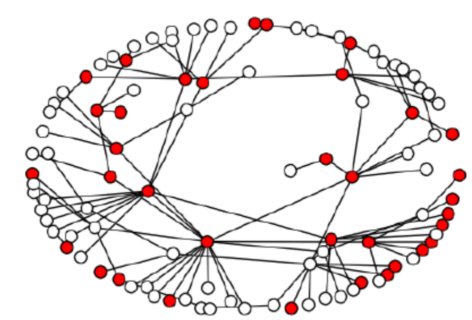




20 nodes addicted in ER

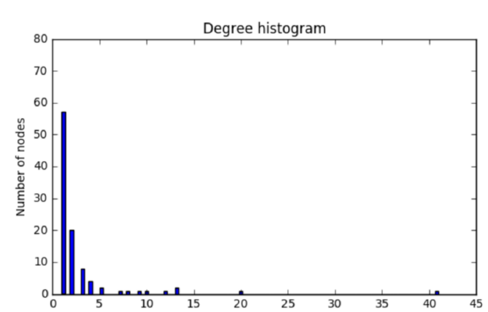
b) with the Barabási-Albert (BA) approach:

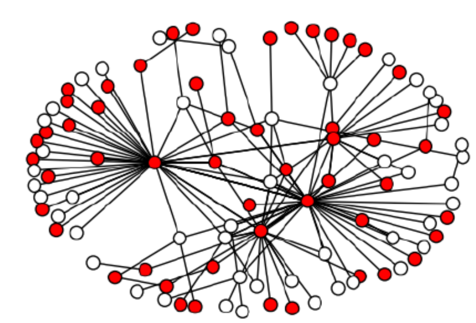




35 nodes addicted in BA

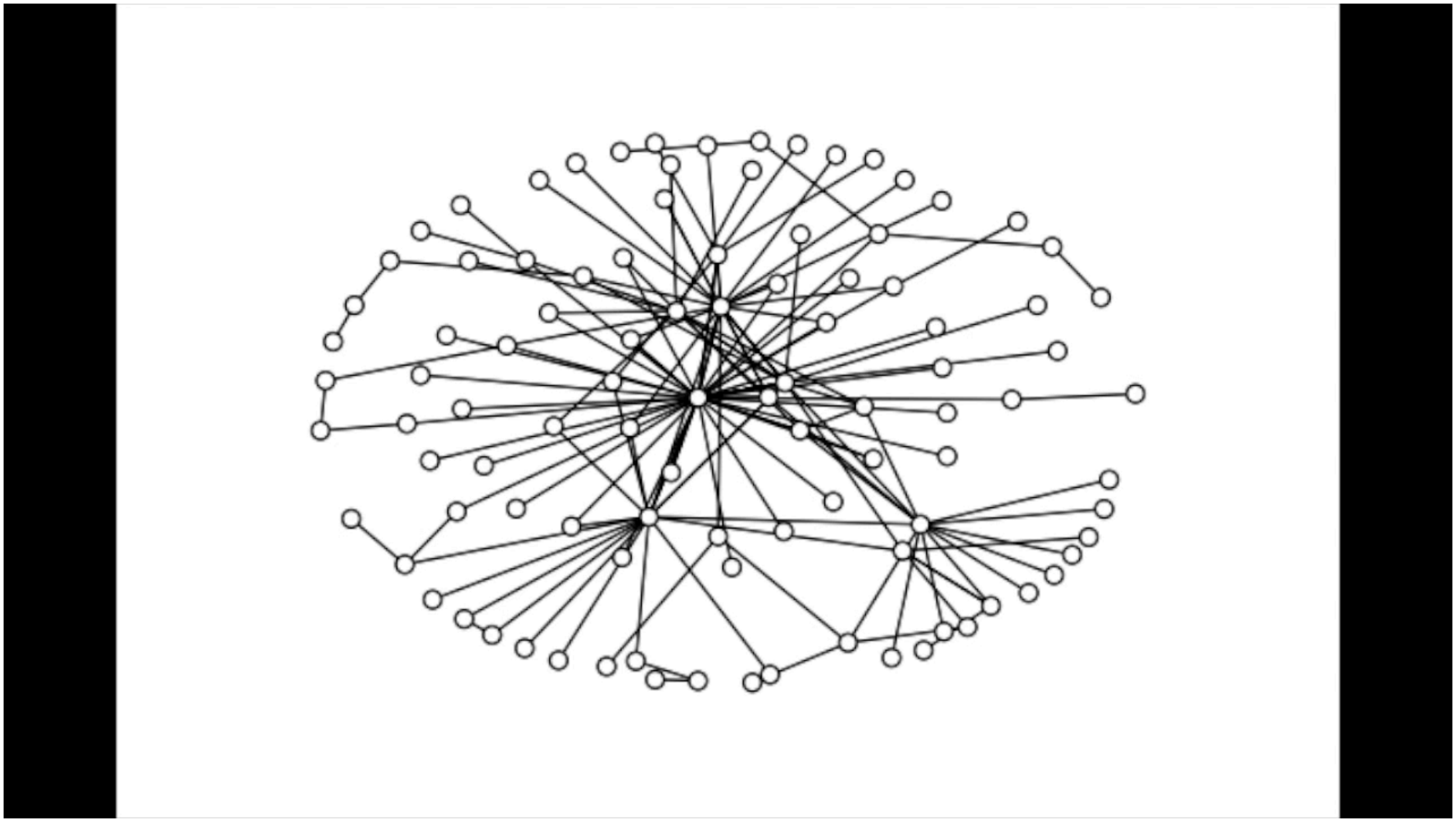
c) with the Bollobás-Riordan (BR) approach:





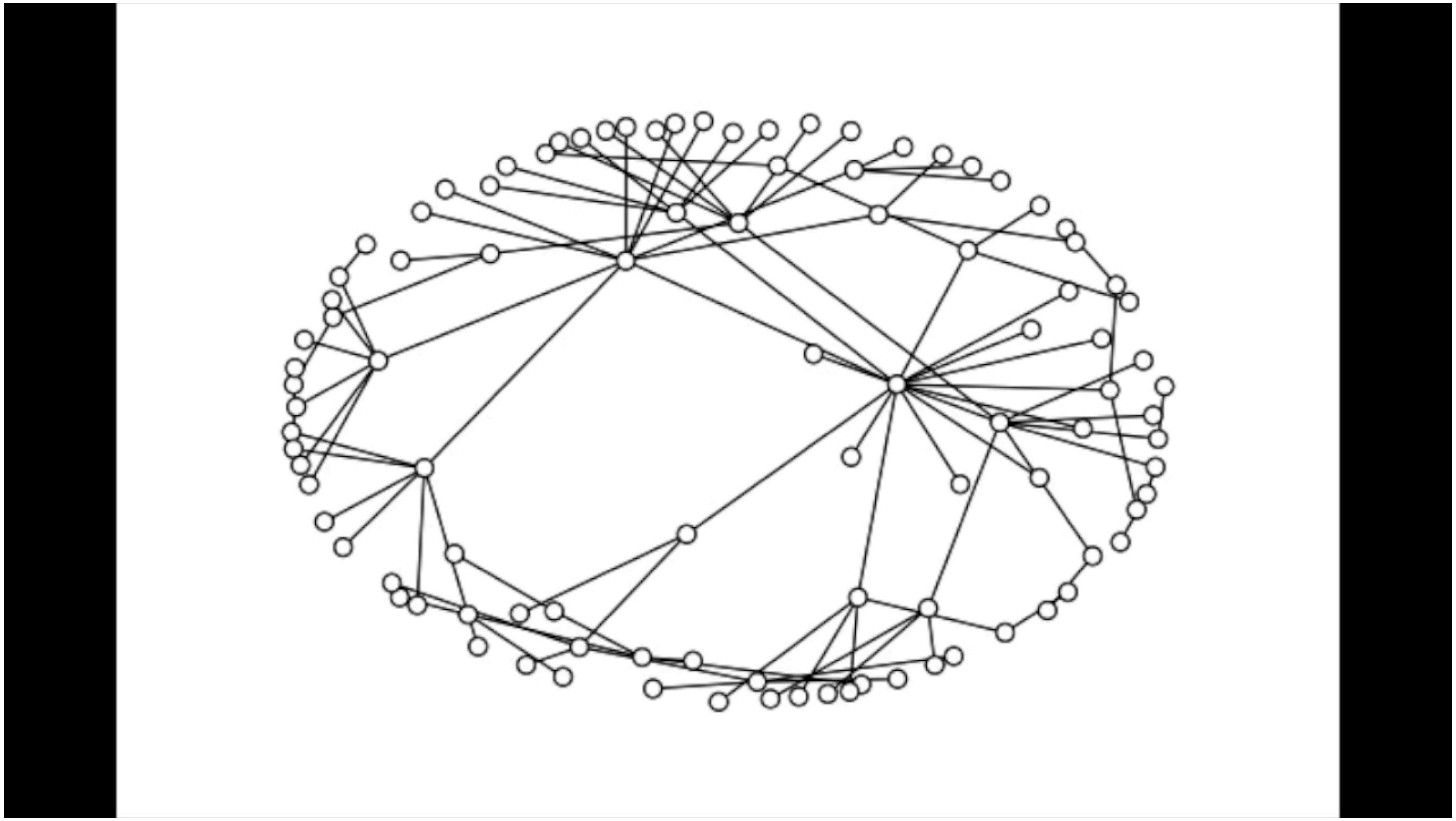
52 nodes addicted in BR

SIMULATION EXAMPLE: BOLLOBÁS-RIORDAN MODEL



A BR network, characterised by 100 nodes with the same propensity (0.2)

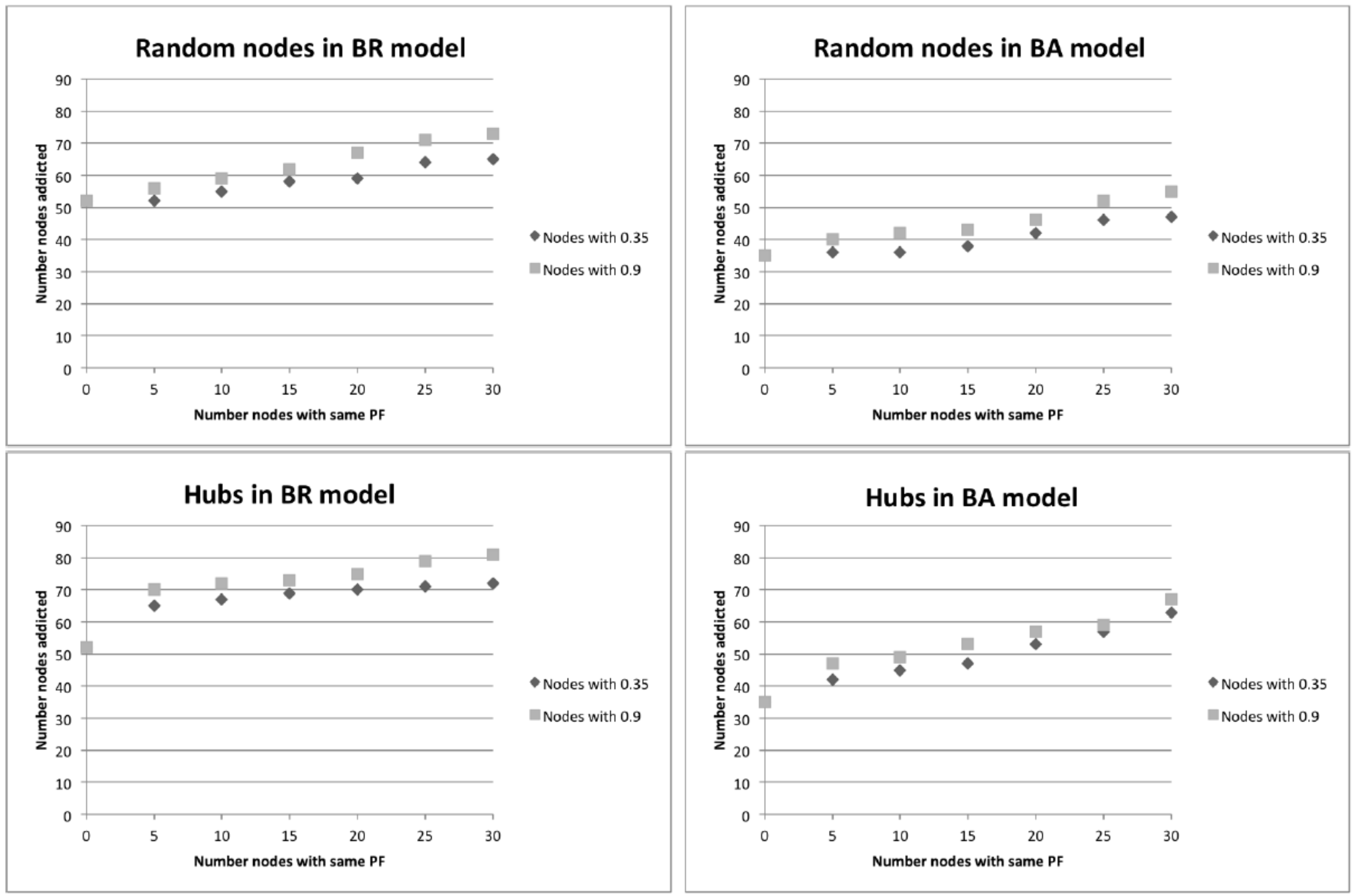
SIMULATION EXAMPLE: BARABÁSI-ALBERT MODEL



A BA network, characterised by 100 nodes with the same propensity (0.2)

EXPERIMENTS WITH RANDOM NODES AND HUBS

Greater number of addicted nodes

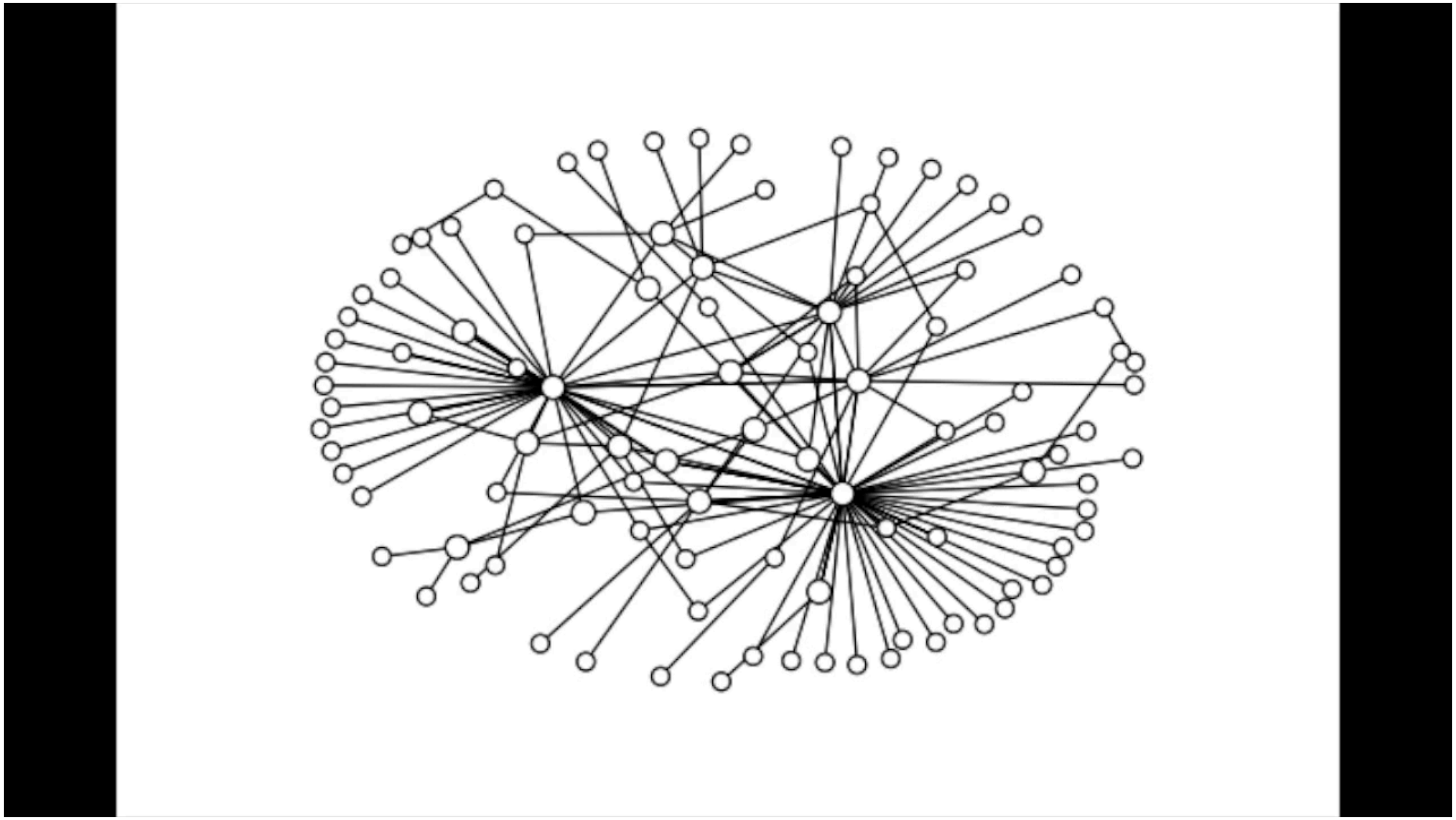


To explore the difference between networks, we associated medium and high propensity factors (0.35, 0.9), to particular nodes:

1) Random nodes

2) Hubs

SIMULATION EXAMPLE: HUBS WITH DIFFERENT PROPENSITY FACTOR



A BR network, characterised by 100 nodes with 20 hubs with 0.35 as PF

CONCLUSIONS

- To propose a computational framework for the study of addiction
- To use the theory of Hybrid Automata to develop a modular model of the Dopaminergic System
- To study how addiction is correlated to network topologies

Future work:

- To explore other kinds of communication
- To investigate different stimuli
- To consider non-constant propensity factors.

Thank you!