

ASSIGNMENT-1

Computational Cognitive Science (CS786)

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1) Implementation of neural network

We have take five boolean funtions in form of truth table as given:

x1	x2	x3	y1	y2	y3	y4	y5
0	0	0	0	0	1	0	0
0	0	1	0	1	1	1	1
0	1	0	0	0	0	1	0
0	1	1	0	1	0	0	1
1	0	0	1	1	1	1	0
1	0	1	1	0	0	0	1
1	1	0	1	1	1	0	0
1	1	0	1	1	1	1	1

We have implemented a neural network with one hidden layer which consisting of ten nodes. For activation we have used sigmoid function.

Results of prediction and loss over epochs are in python file for all five functions

2) Q-learning

We have used epsilon greedy strategy for Q-learning instead of taking constant value of epsilon.

Initially epsilon is set to 1 and then we decay epsilon as episodes increases

Therefore initially agent will explore the grid and then as no of episodes increases it start to exploit.

$$\epsilon = \min_epsilon + (\max_epsilon - \min_epsilon) * \exp -x \quad (1)$$

1)

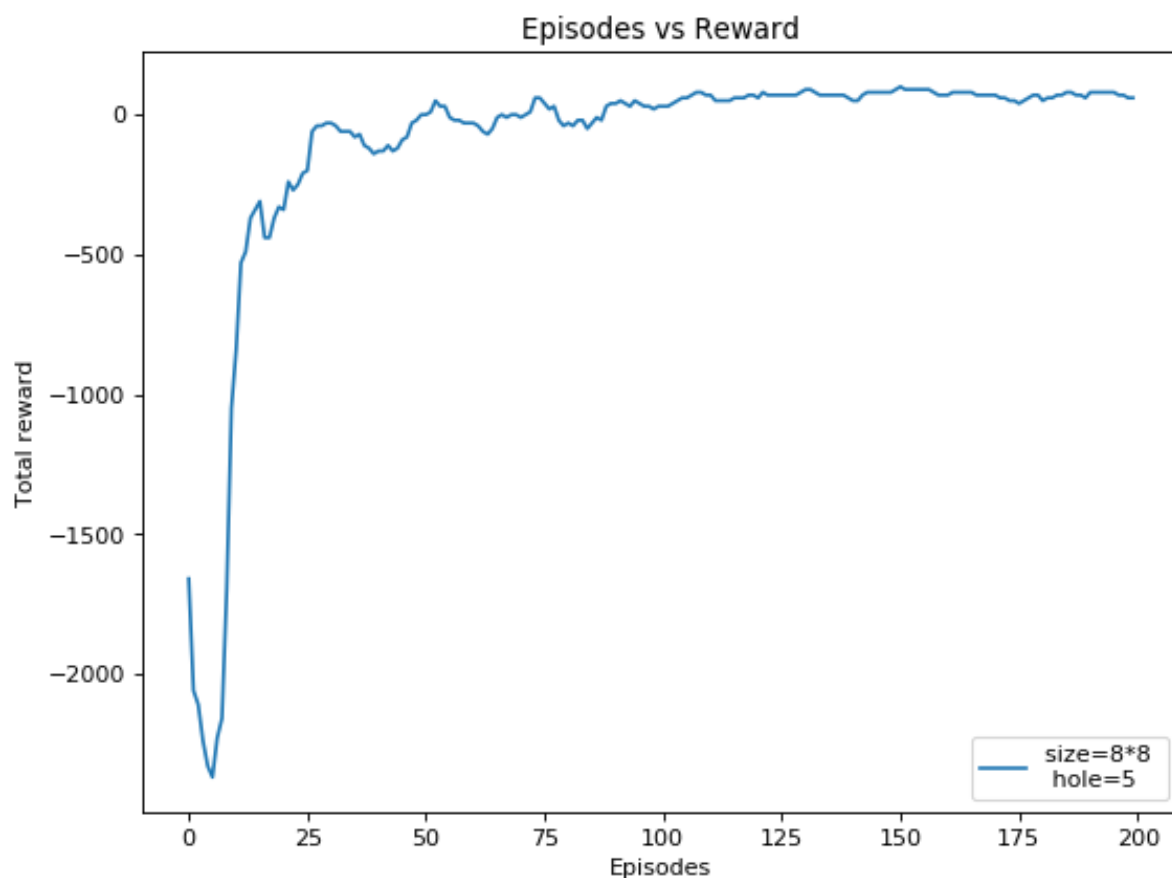


Figure 1: Episode vs total

As no of episodes increases, total received reward per episodes seem to stabilize. Curve increases quickly and approach saturation afterwards.

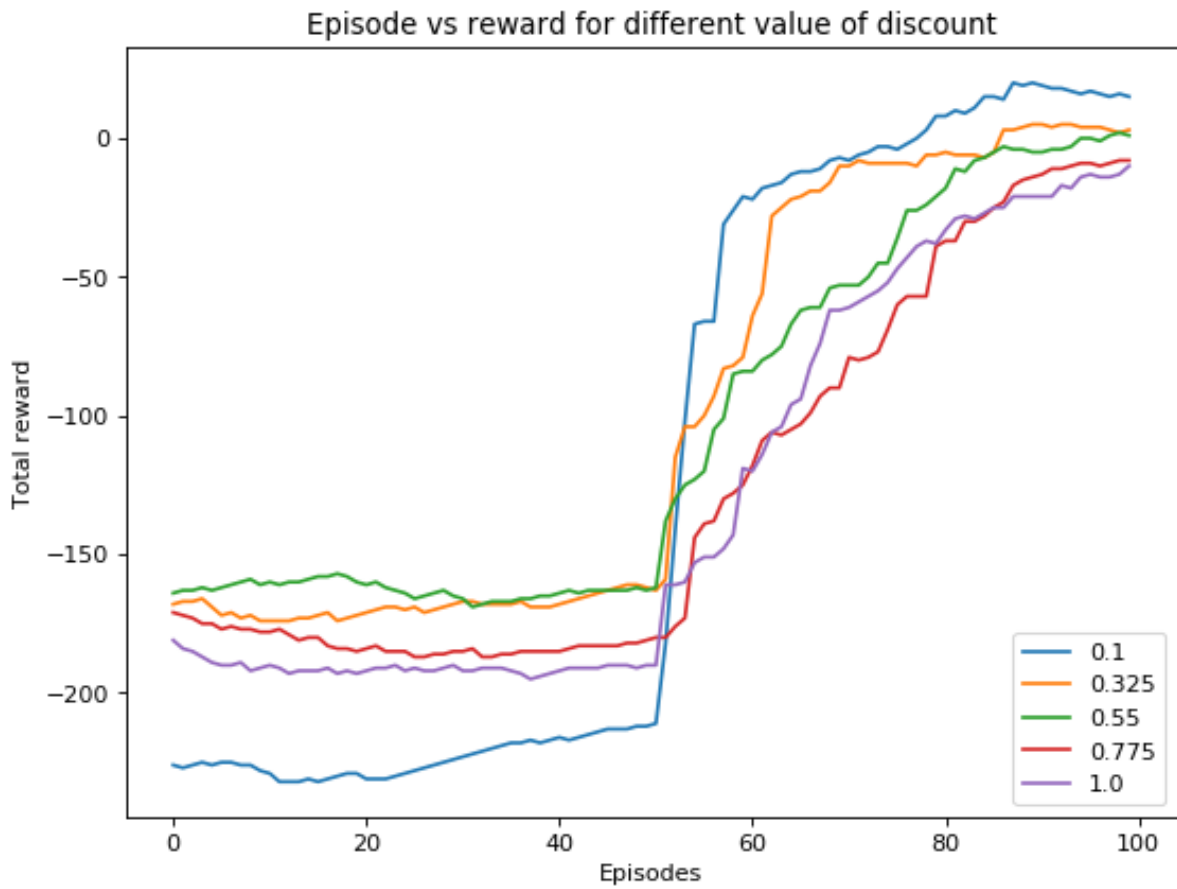


Figure 2: influence of value of discount

As value of discount increases graph of episodes vs total reward move toward saturation much quickly. Increases in value of discount means we are considering large fraction of future state value, thus overall performance improve.

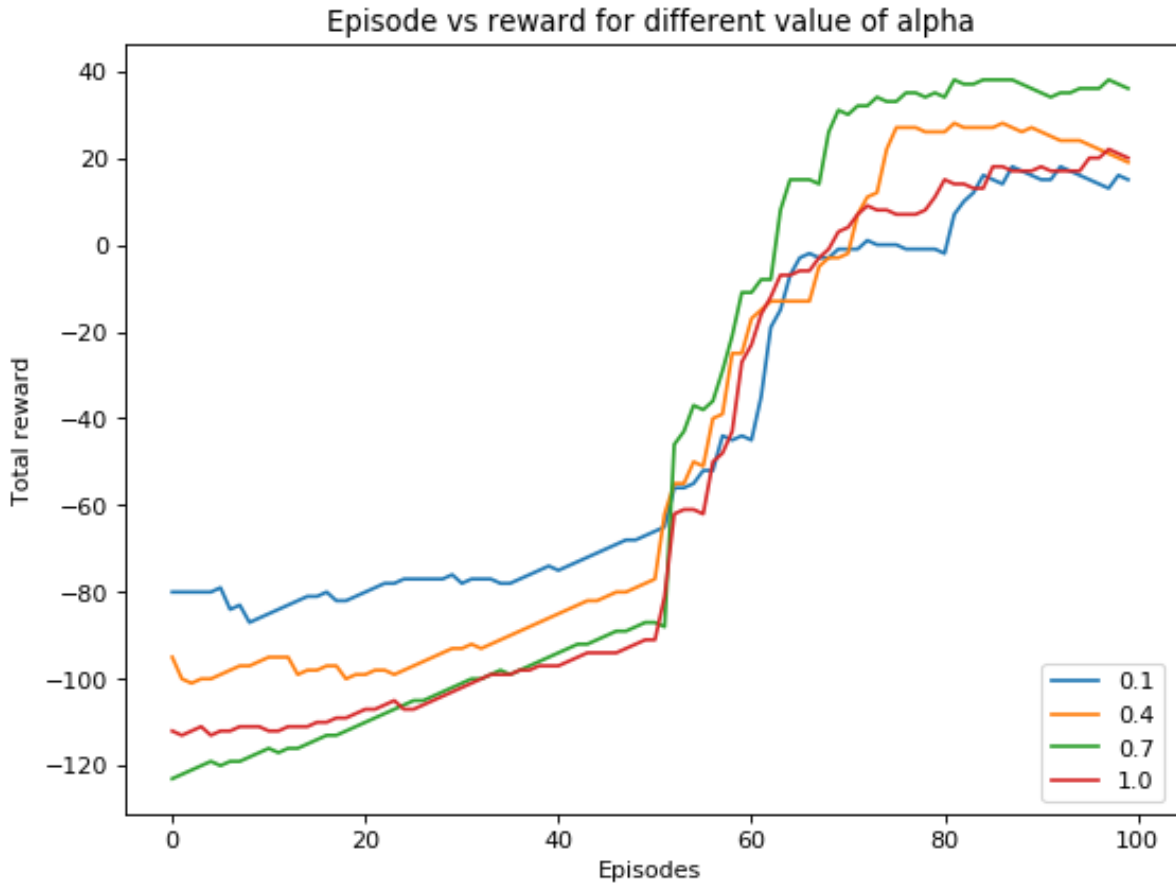


Figure 3: influence of value of alpha

As value of alpha, learning performance improves, saturation is earlier, but as alpha approaches to maximum value or around (0.8 to 1) learning performance decreases this is because small fraction of future reward is considered with increase in alpha.

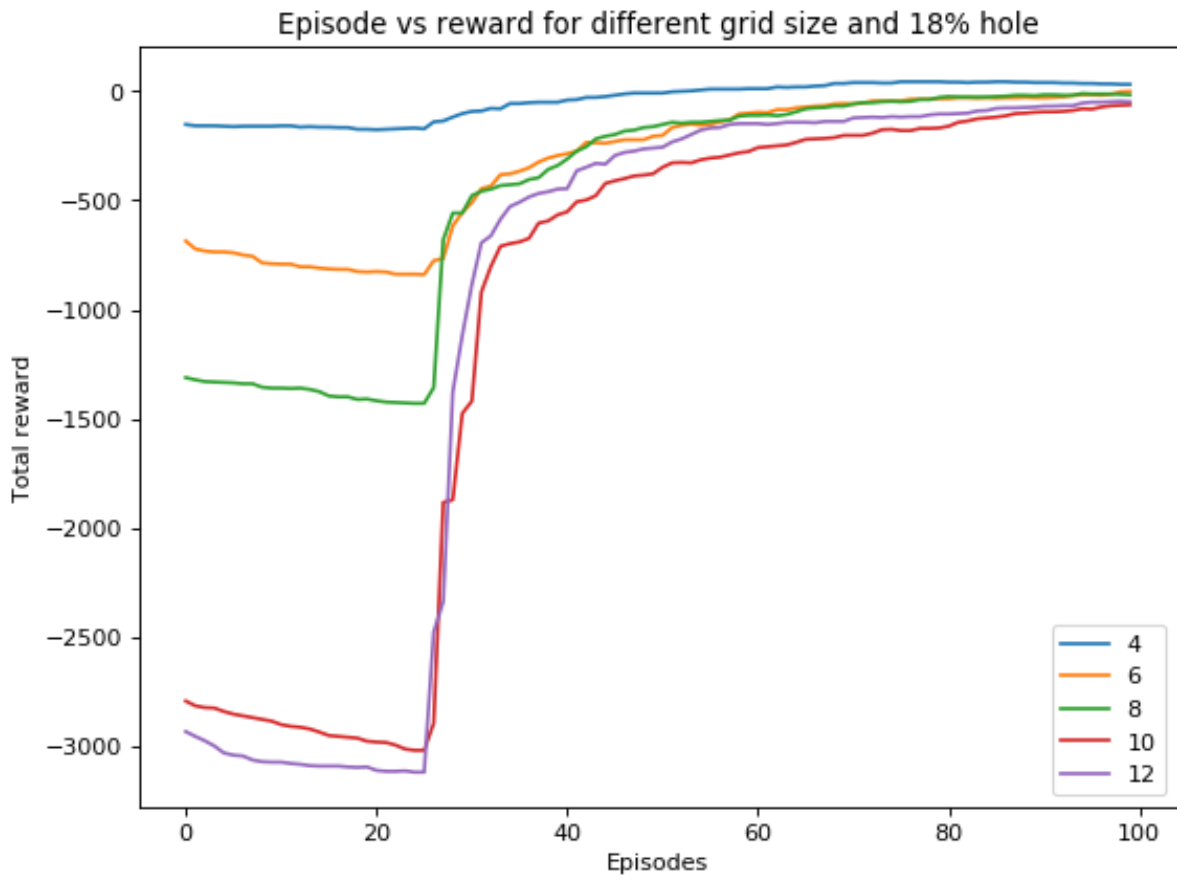


Figure 4: Influence of grid size

for small grid size curve is smooth i.e variation in total reward per episodes is less, as grid size increases it require more and more time for agent to reach optimal policy. With increase in size, variation of total reward is much larger between episodes.

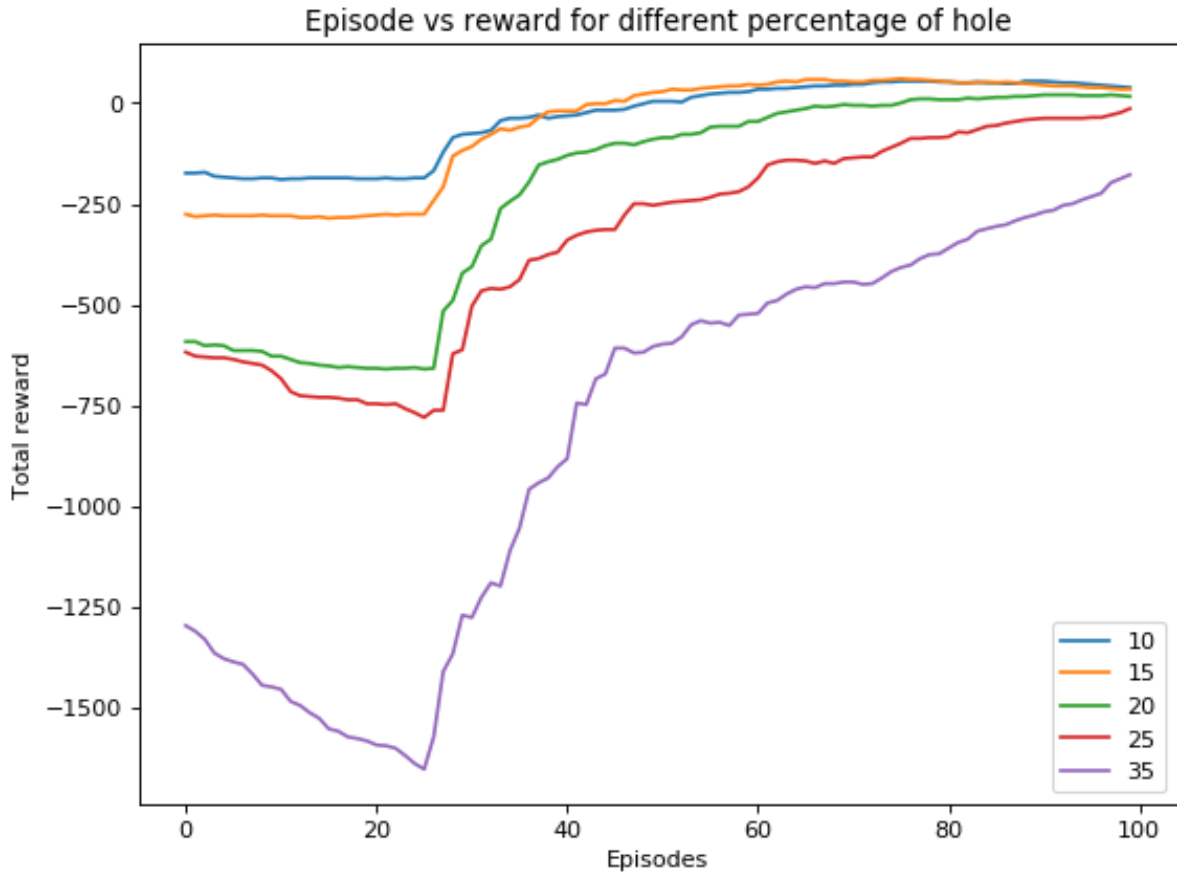


Figure 5: Influence of hole percentage

Increases in percentage of hole highly affect learning performance. As we can see with 35% hole we haven't reached saturation even in 100 episodes, while for only 10% hole, graph approach saturation in just 40 episodes.

3) Rulkov map

1) The shape of the nonlinear function $f(x,y)$, plotted for $\alpha=6.0$ and $y=3.93$

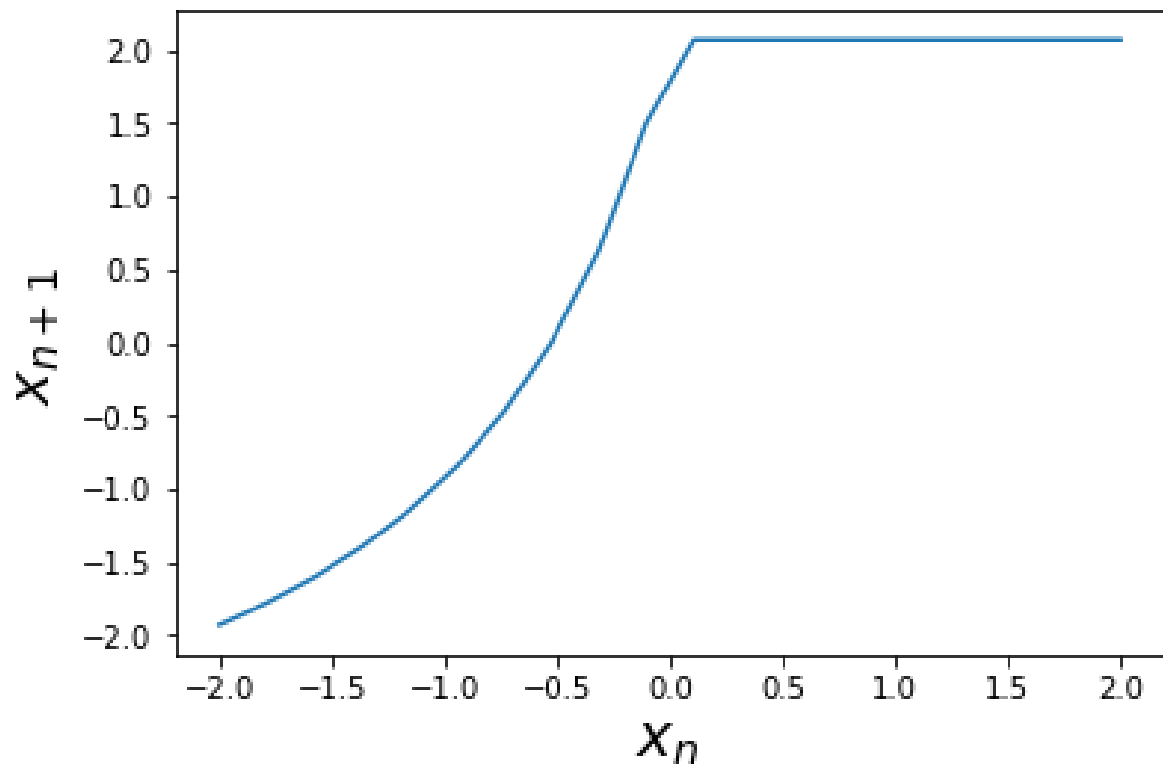


Figure 6: $f(x,y)$

2) Wave forms of neuronal action potential

a) Transition to the **regime of silence** with $\text{alp}=4$ and $\text{sig}=-0.1$

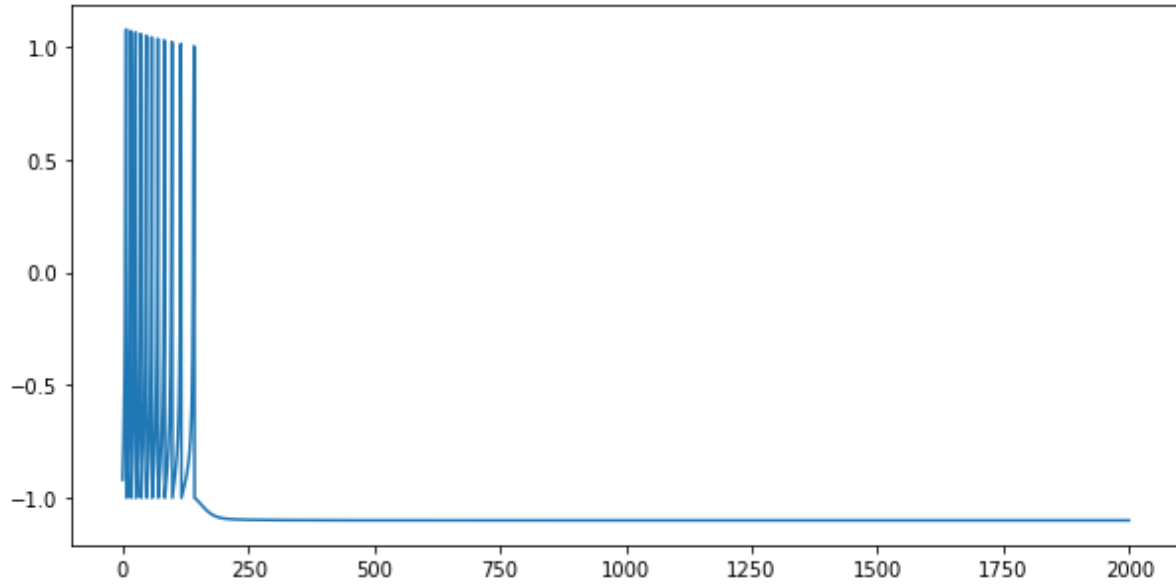


Figure 7: regime of silence

b) The regimes of **continuous tonic spiking** mapped for $\text{alp}=4$ and $\text{sig}=0.01$

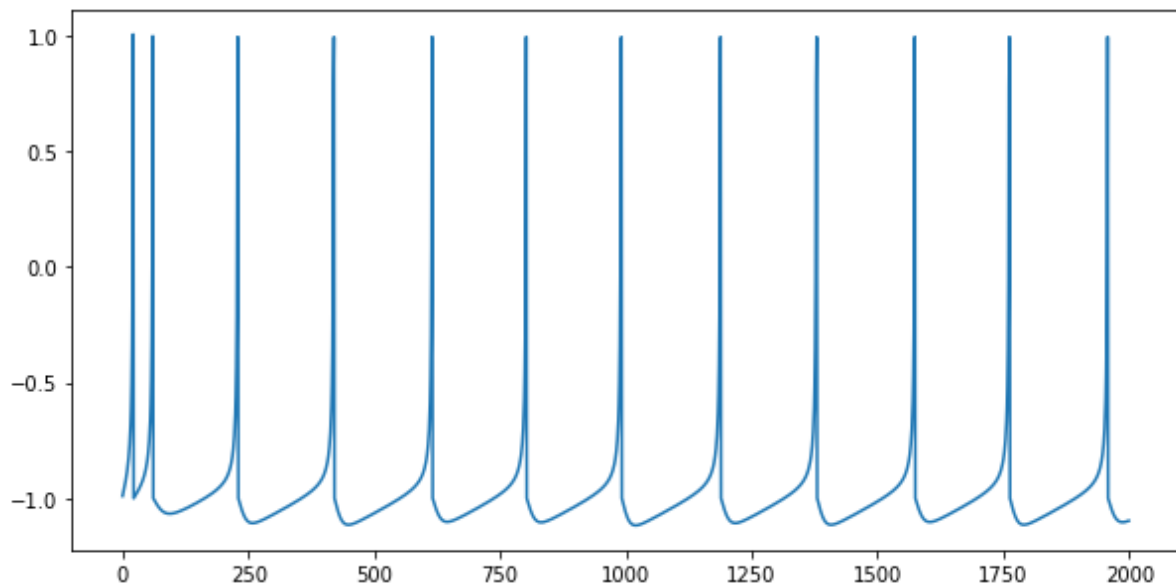


Figure 8: regime of continuous tonic spiking with $\text{sig}=0.1$

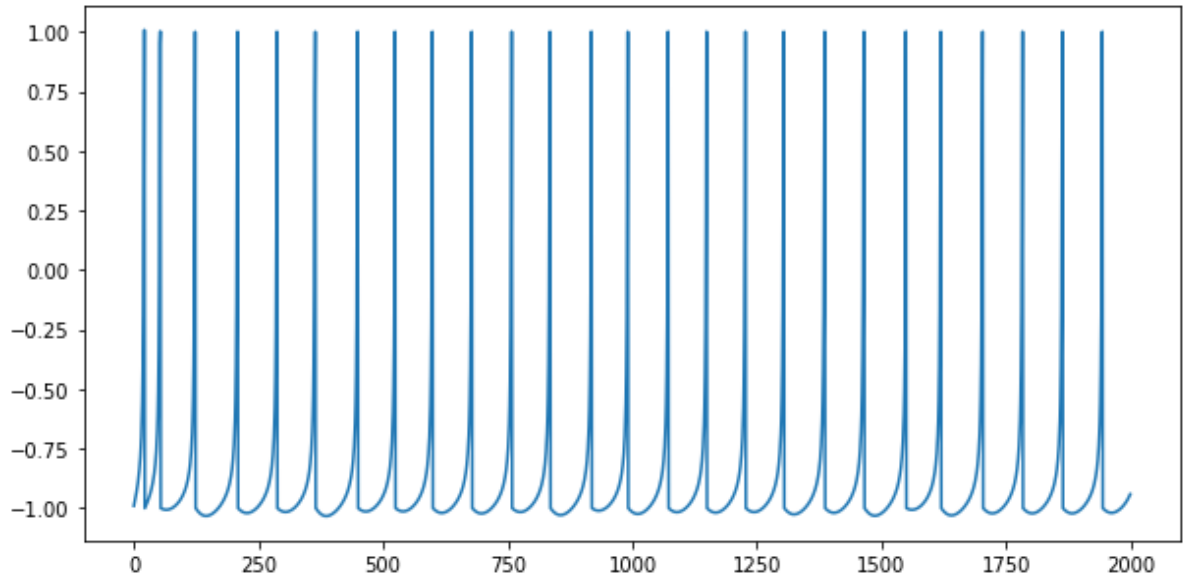


Figure 9: regime of continuous tonic spiking with $\text{sig}=0.01$

c) Spiking-bursting behavior

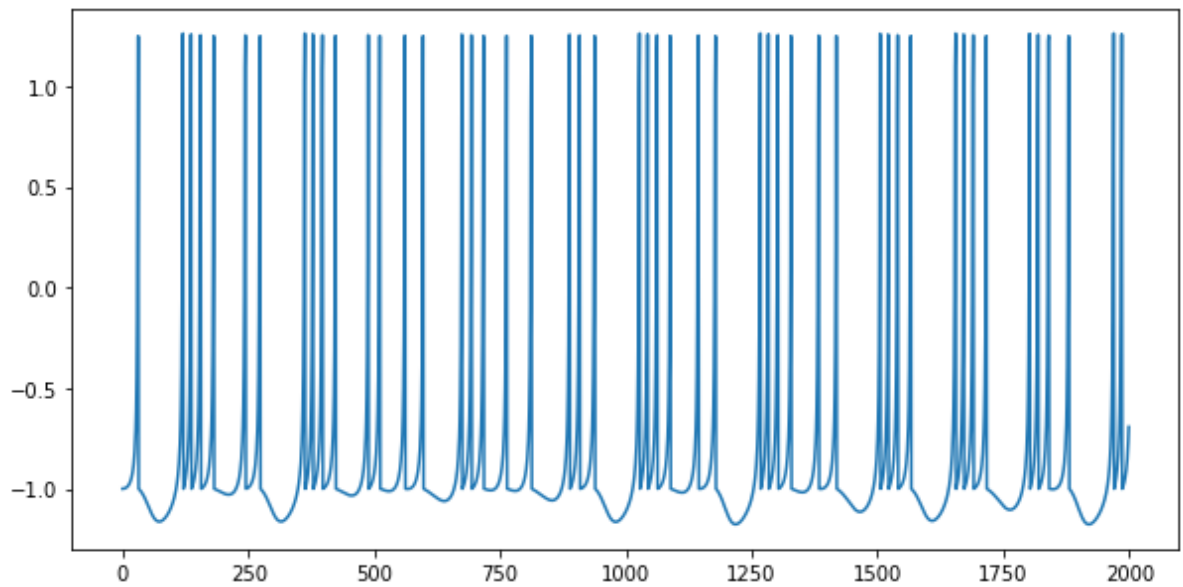


Figure 10: mapped for $\text{alp}=4.5$ and $\text{sig}=0.14$

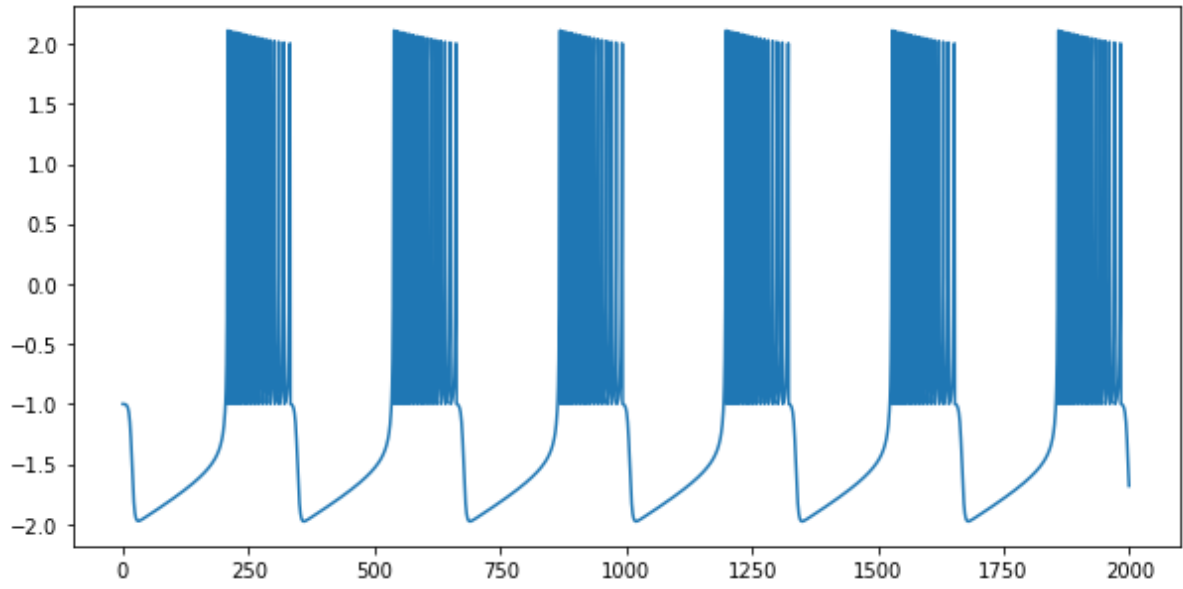


Figure 11: mapped for $\text{alp}=6$ and $\text{sig}=-0.1$

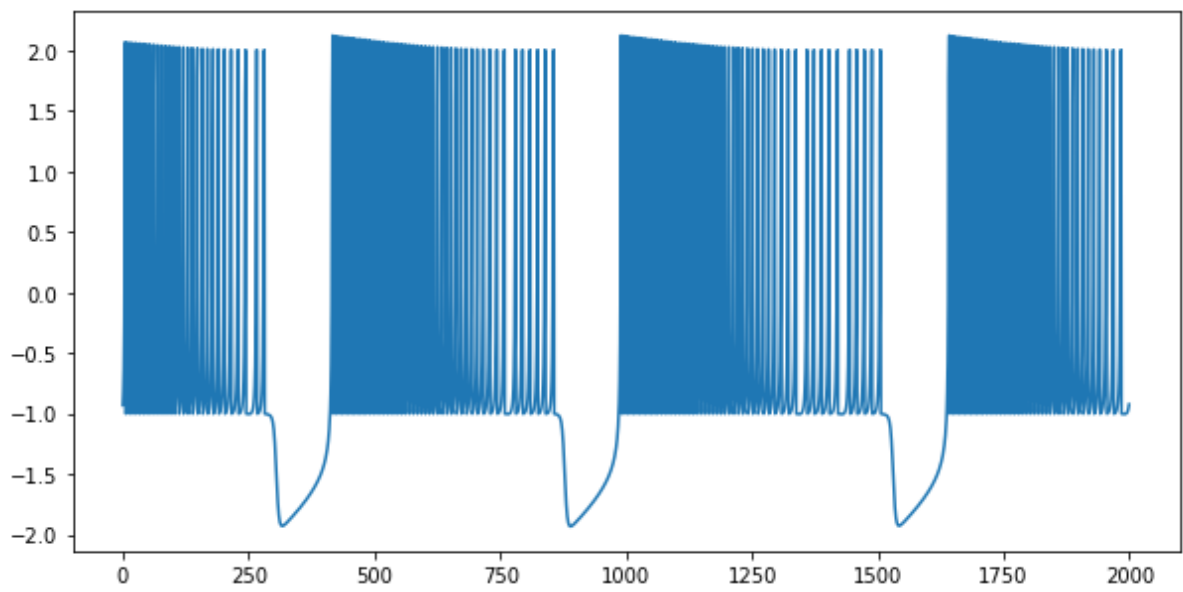


Figure 12: mapped for $\text{alp}=6$ and $\text{sig}=0.386$