

# Goldman Lab Work

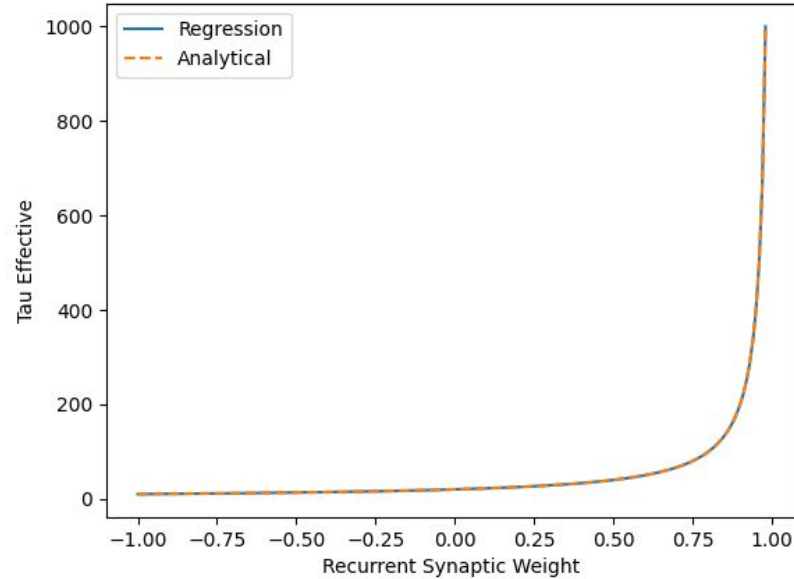
Alexandru Tapus

# Week: 3/14/24-3/21/24

- Simulated a nonlinear autapse neuron
  - Graphed equation  $r^p/(a+r^p)$  for varying values of  $a$  and  $p$
  - Found the fixed points of a neuron with this nonlinear firing rate
  - Graphed the firing rate over time for a rate model using a form of the graphed nonlinearity
- Predicted the effective time constant given the firing rate over time
  - Fed a linear rate model simulation into a linear regression model
    - X:  $\Delta t$  from a time  $t_0$
    - Y:  $\ln(r)$  at time  $t_0 + \Delta T$
  - Repeated the aforementioned procedure for synaptic weights from -1 to .99

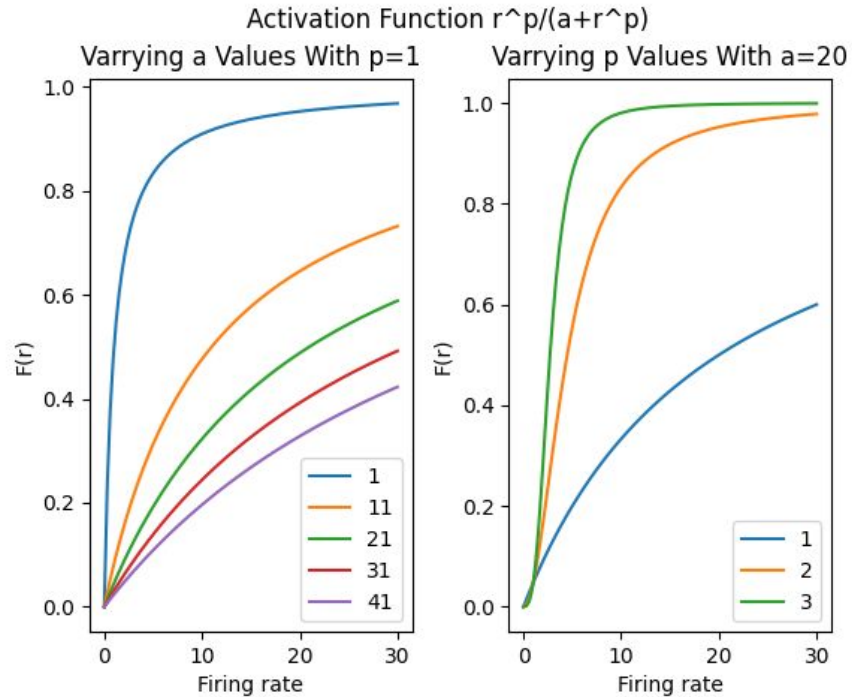
# Effective Time Constant Over Synaptic Weights (Linear)

Relationship Between Tau Effective and Synaptic Weights



$$\tau_{\text{eff}} \cong \tau / (1 - w)$$

# Graphs of Nonlinear Functions

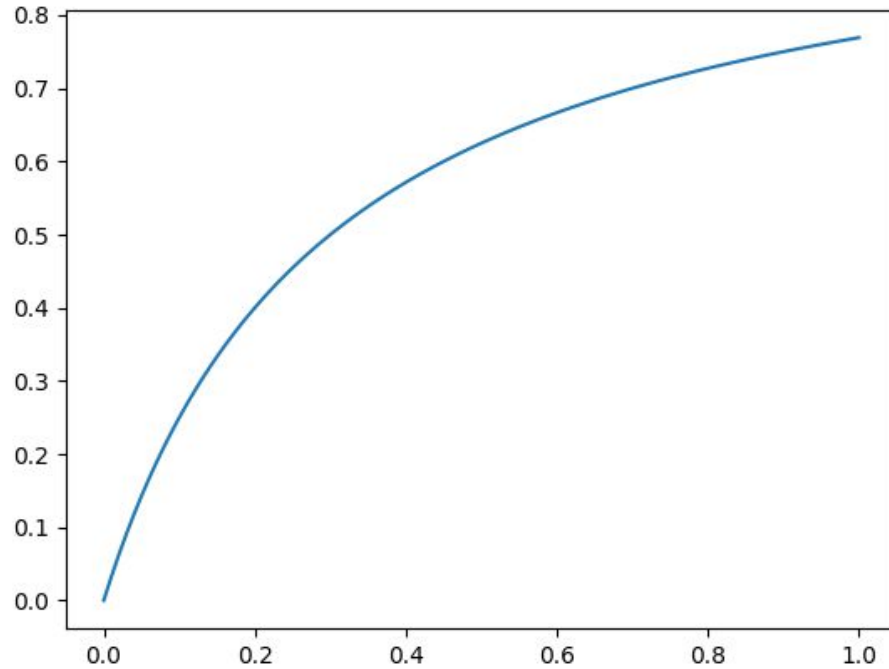


## Trends in the functions

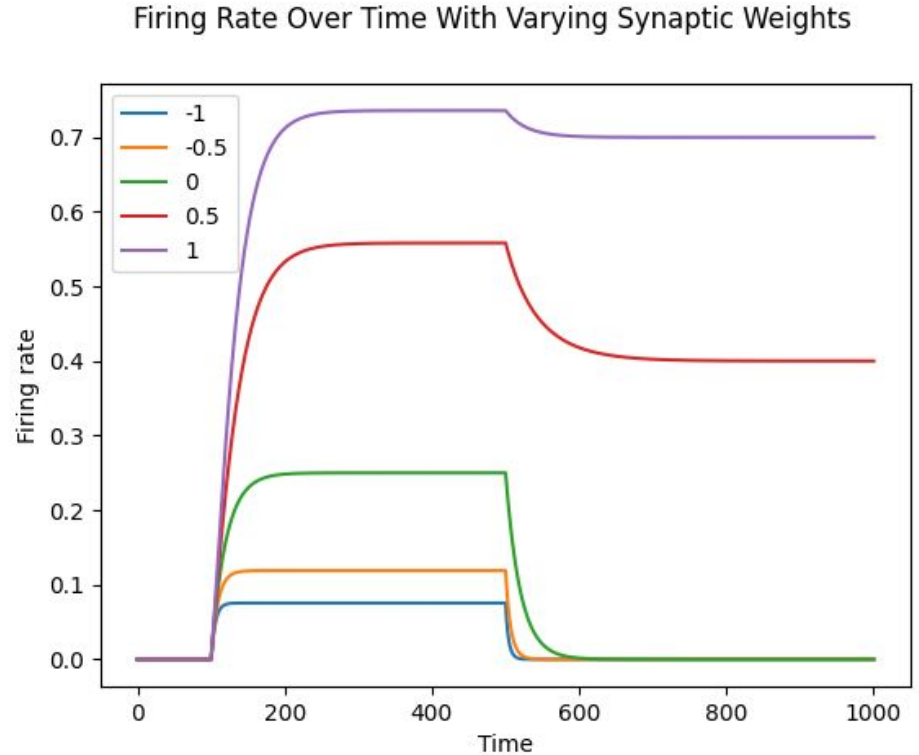
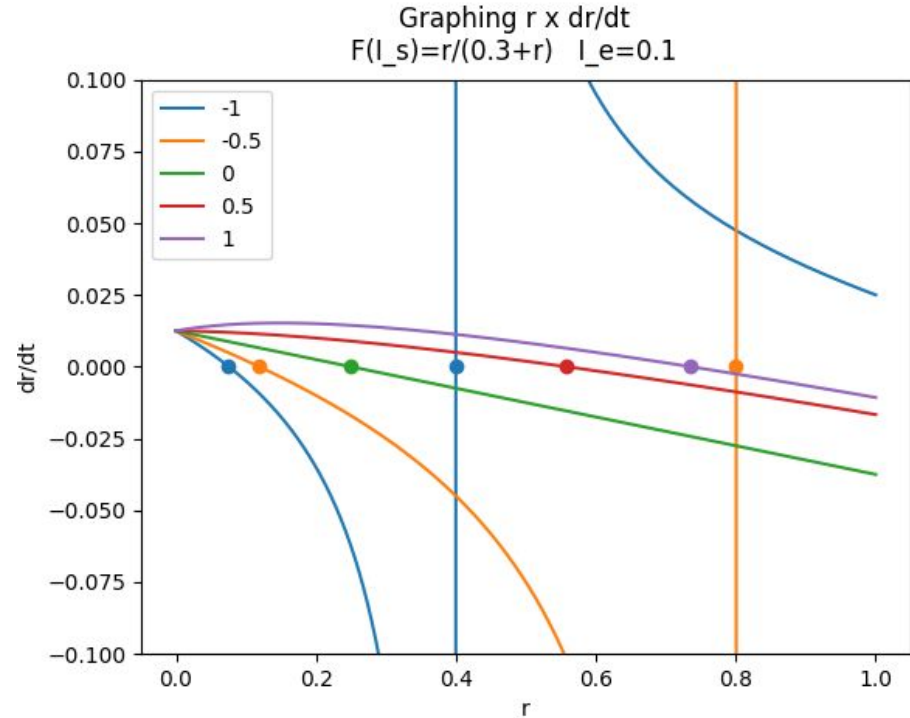
- Increasing  $a$  decreases slope
- Increasing  $p$  increases slope

# Nonlinear Function Used

Sigmoid Function  $a=0.3$   $p=1$



# Fixed Points and Firing Rate Over Time (Incorrect)



# Notes

## Notes

- Used external input of arbitrary value of .1 spikes/sec
- Any large  $r$  will quickly overrun  $a=.3$  and reach one
  - However, a larger  $a$  value would not change that  $\lim_{r \rightarrow \infty} (r/(a+r))$  always = 1, it would just approach 1 way slower

# Week of 3/21/24-3/28/24

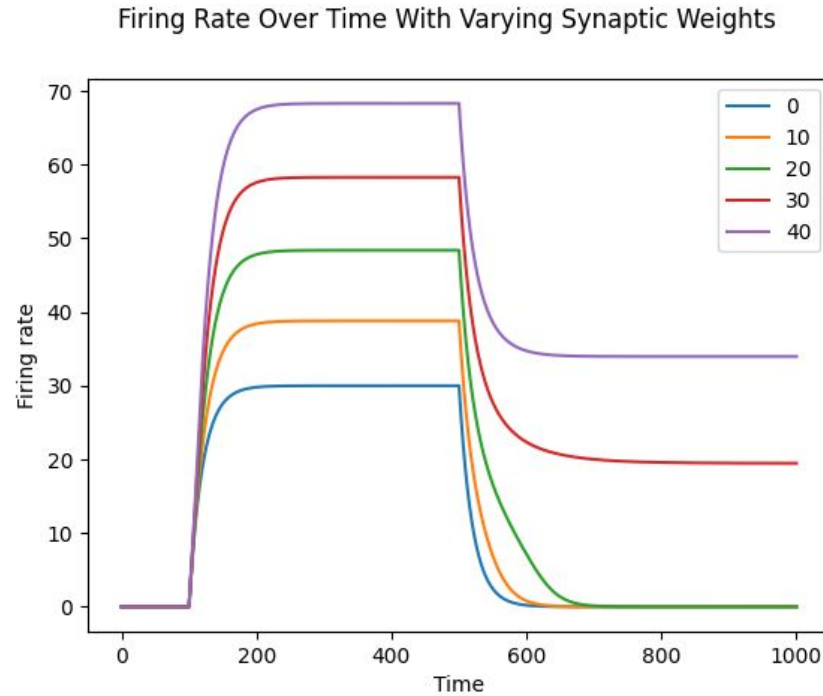
## Finding Fixed Points of Nonlinear Autapse Neurons

- Found the fixed points of the nonlinear autapse neurons
- Categorized them as stable or unstable
- Drew two representations for representing where the fixed points occur
  - Graph of  $dr/dt$  vs  $r$
  - Graph of decay and input vs  $r$  (looking at where they intersect)

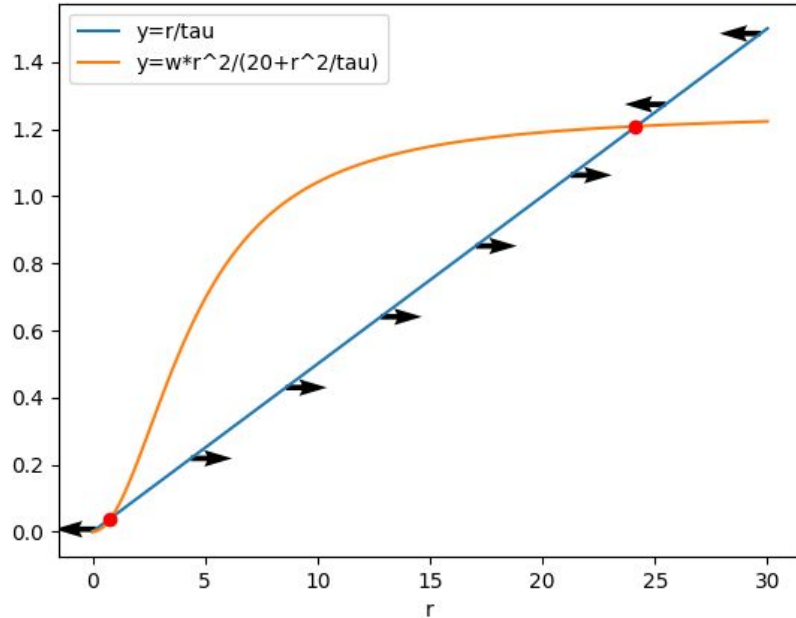
Redrew the correct firing rate curves for a nonlinear autapse neuron



# Correct Nonlinear Autapse Neuron Firing Rate

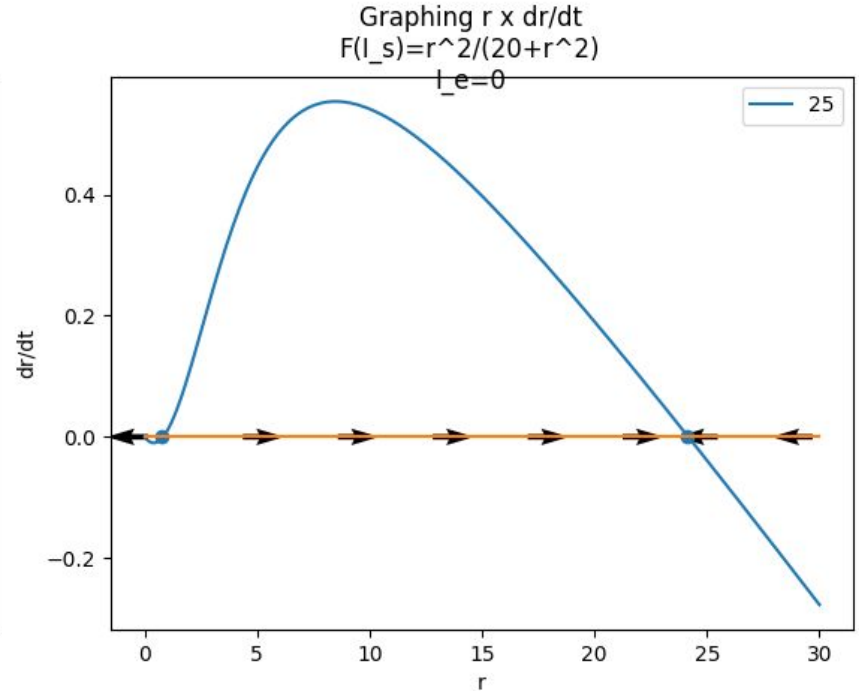


# Fixed Points With $w=25$ and $F(r) = r^2/(20 + r^2)$



Unstable Point: .800801

Stable Point: 24.1241



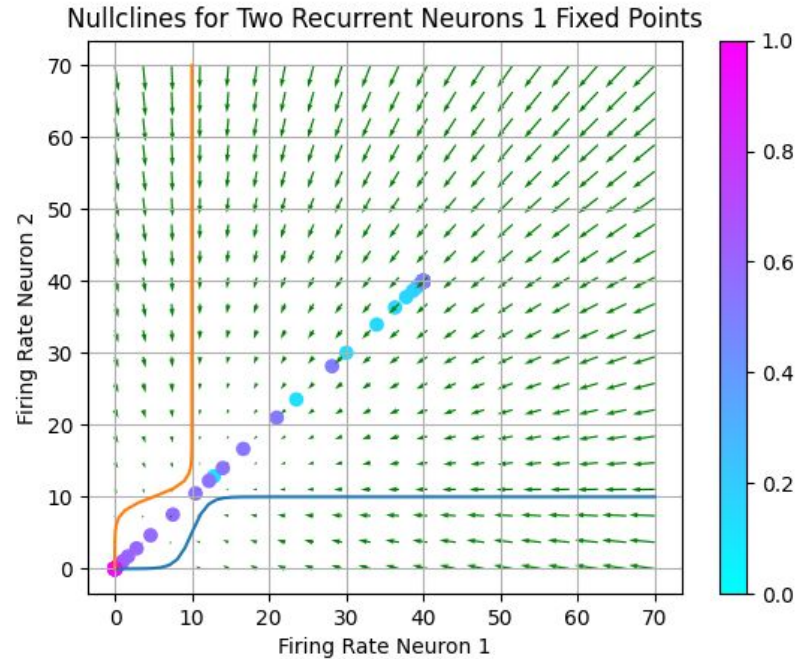
# Week 4/8/24

## Two Recurrently Connected Nonlinear Neurons

- Graphed the firing rates of the two neurons as a function of each other over time. (As well as on the actual  $r_1$   $r_2$  graph to see the relationship between the nullclines and the change in firing rate)
- Drew the nullclines for several activation functions.
  - Attempted to have 1, 2, and 3 fixed points.
- Drew the vector field formed by the nullclines showing how the fixed points are approached.

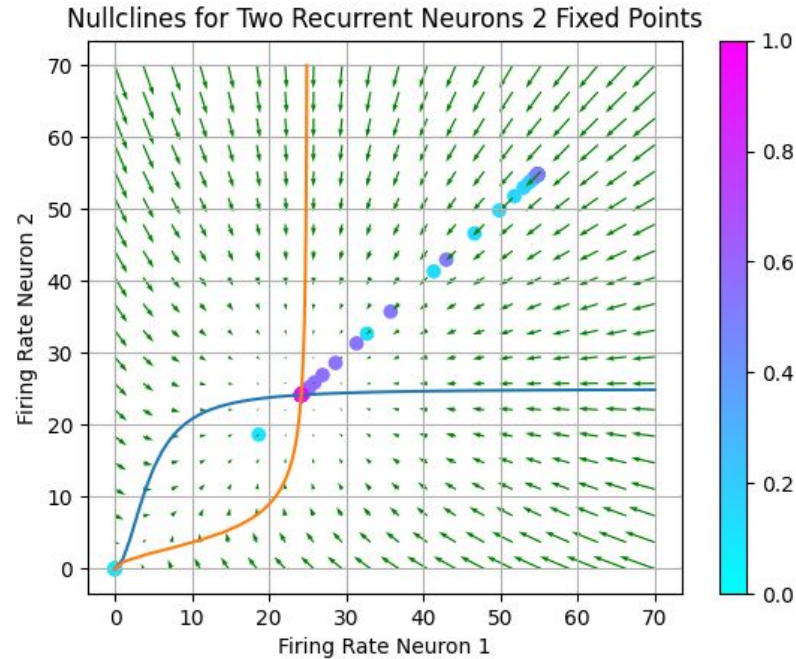
# Two Recurrently Connected Neurons (Nonlinear)

## 1 Fixed Point



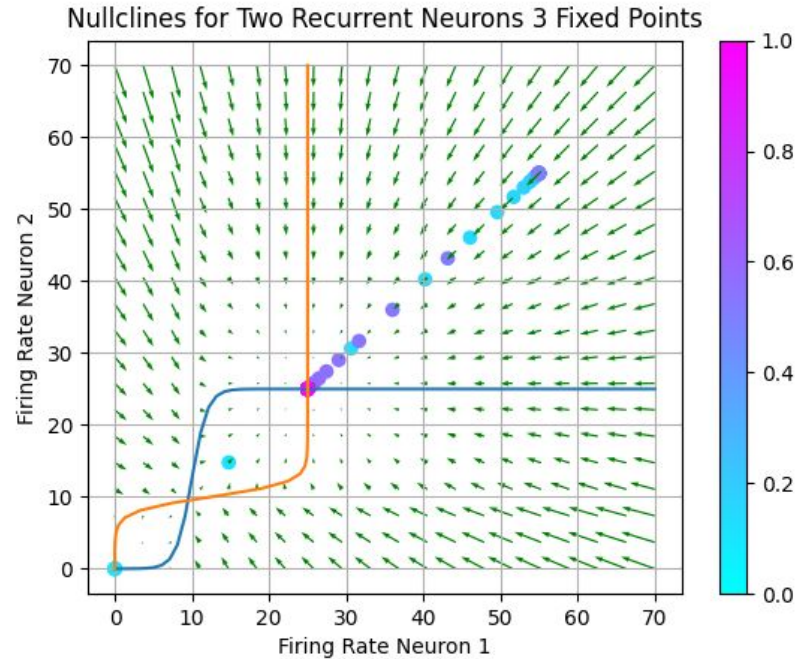
# Two Recurrently Connected Neurons (Nonlinear)

## 2 Fixed Points



# Two Recurrently Connected Neurons (Nonlinear)

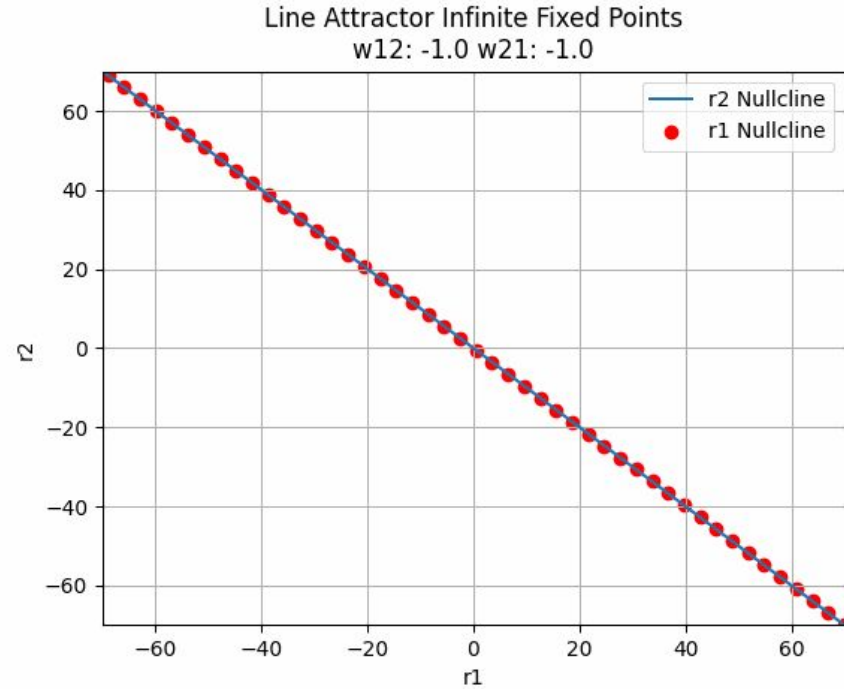
## 3 Fixed Points



# Line Attractor Conditions

For two recurrently connected neurons.

- The two weight values have to be reciprocals of each other
- More line attractors can be made by allowing shifting with positive and negative external inputs.



# To Do Next Week

Used the e sigmoid function on an autapse neuron.

Created an animation showing how the nullclines shift with the application of external inputs. (Next Week)

- Quick pulse current (on off)
- Box current
- Trapezoid shift for more gradual change

(Each nullcline is showing the conditions of no change for a given input) (Change the input and don't always make it symmetrical)



# Week 4/22 (Woods Hole Problem Set)

Calculating and proving the eigenvectors for a simple two neuron network

Calculating the amplification constant, effective time constant, and steady state values of the network

Running a simulation to validate the mathematical approach

Discover the weight values for which the neural system integrates the difference between the two neurons

Creating a winner-takes-all network

(If time, creating a model of perceptual rivalry by setting an  $r_{\max}$  and slowly decreasing it until the other neuron takes over.  $R_{\max}$  is reset when it gets close to 0 again)

# Mathematical Analysis of the Network

Weight Matrix	Eigenvectors	Eigenvalues
$\begin{bmatrix} w_{self} & w_{other} \\ w_{other} & w_{self} \end{bmatrix}$	$\begin{bmatrix} 1, 1 \\ 1, -1 \end{bmatrix}$	$w_{self} + w_{other}$ $w_{self} - w_{other}$

$I_{common}$ :attenuated

$I_{different}$ :amplified

For  $w_{self}=.2$   $w_{other}=-.7$

- $1/(1-.5) = 2/3$        $1/(1-.9) = 10$

$\tau_{eff} = \tau/(1-\lambda)$

- $18/(2/3)= 27$        $18/10 = 1.8$

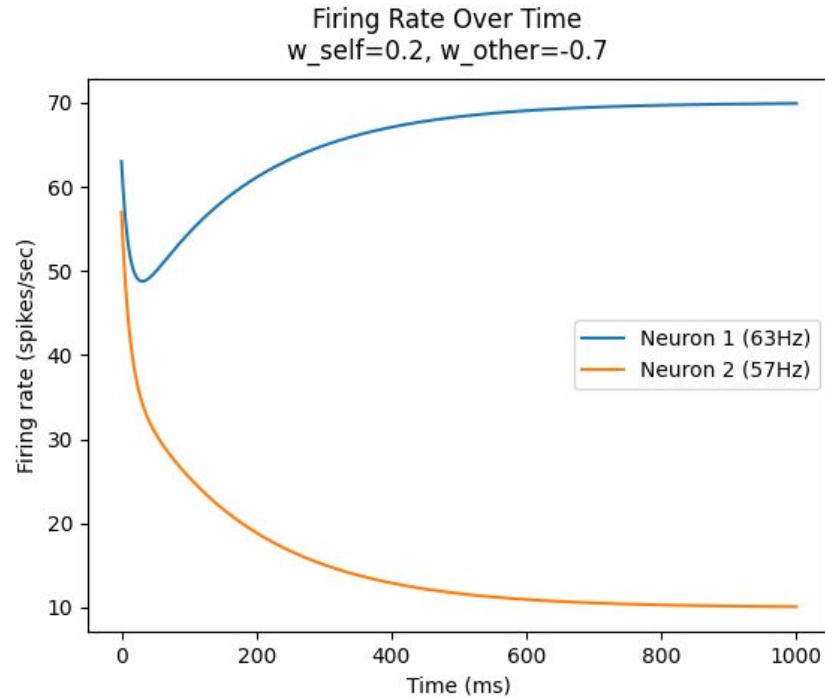
For current of (63Hz, 53Hz):

- $[b_1-b_2, b_1+b_2]=[63,57] \Rightarrow b_1=60, b_2=-3$

Calculating Steady State Firing Rate

- $60*2/3*[1,1] + -3*10*[1,-1] \Rightarrow [10,70]$

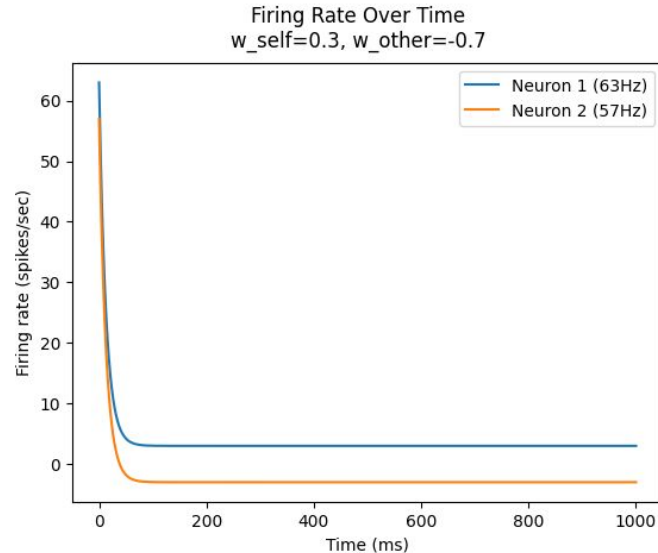
# Simulation for Provided Weight Values



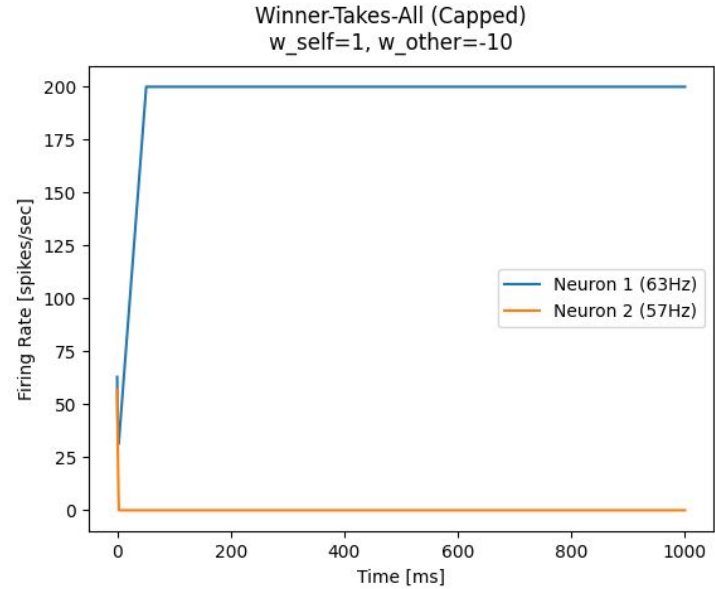
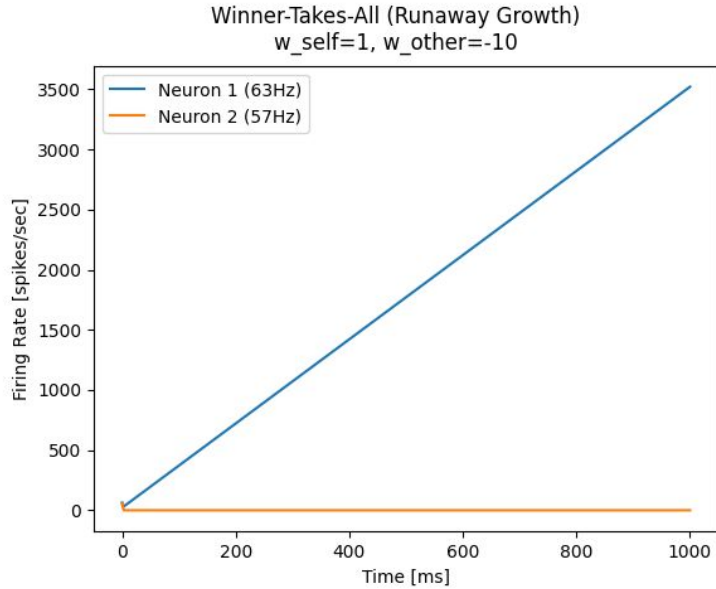
# Integrating the Difference Between the Neurons

If the sum of the absolute values is 0, the difference is integrated

- (e.g.  $w_{\text{self}} = .3$ ,  $w_{\text{other}} = -.7$ )
- No current added



# Creating a Winner-Takes-All Algorithm



# To Do Next Week

What is the condition that makes the winner neuron go to infinity? (Prove mathematically)

Make a 100 neuron network

Make an eigenvalue spectrum (Real and imaginary components of the network)

- Choose the weight matrix to be from a normal distribution  $N(M=?, SD=?)$

Be able to look at any two neurons relative to each other

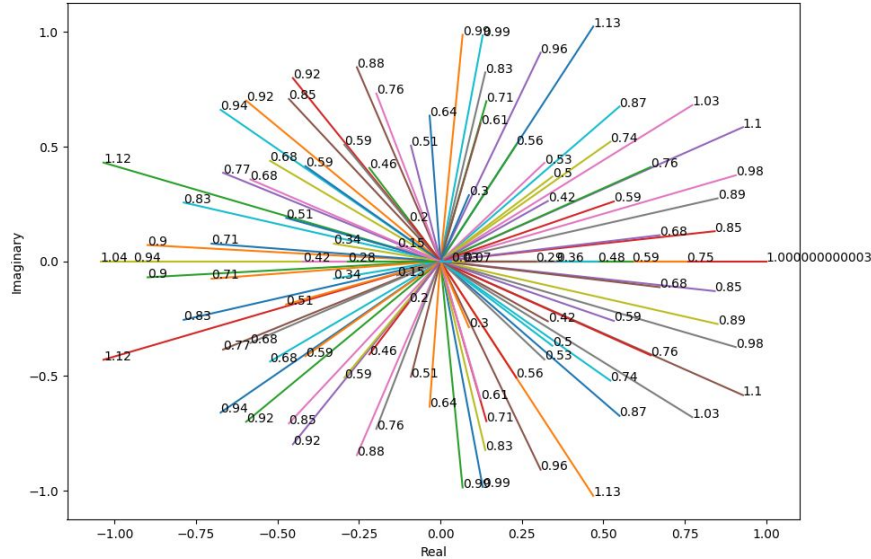
# Proof of Condition For Going To Infinity

The difference between the two neurons in a winner takes all network is accentuated by an eigenvalue of  $w_{\text{self}} - w_{\text{other}}$ .

- When  $w_{\text{self}}$  is small a small positive number and  $w_{\text{other}}$  is a large negative:
  - $w_{\text{self}} - w_{\text{other}} > 1$  and the model experiences exponential growth on that eigenvector.

# 100 Neuron Network Eigenvalue Plot

### Eigenvalue Plot for 100 Neuron Network

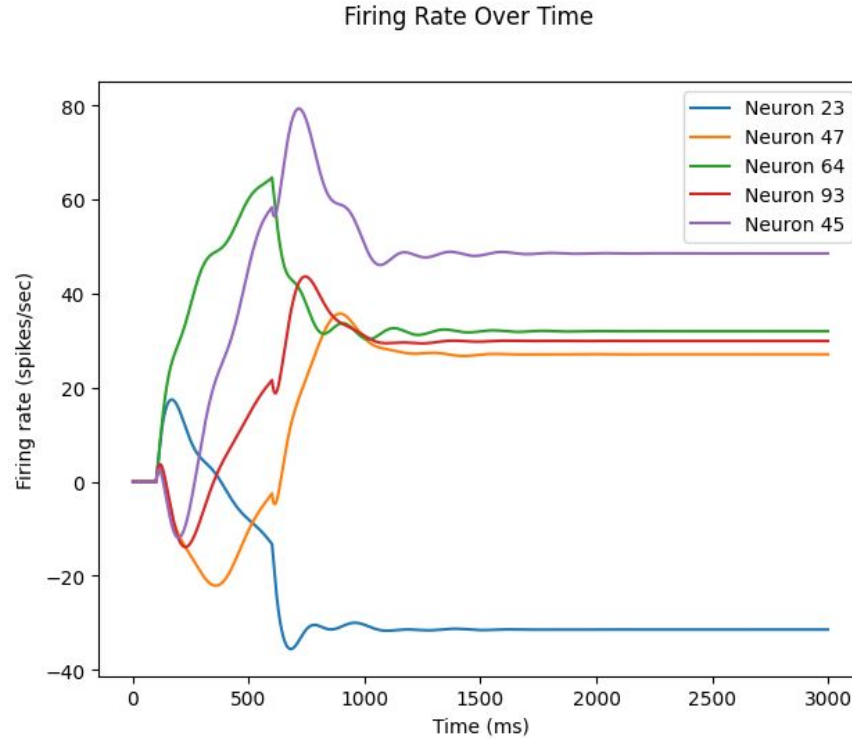


## Findings:

- Addition had no predictable effect on eigenvectors but increased the value of the real eigenvalues.
- Division by a constant divided all the eigenvalues by that same constant.
- Eigenvalue of 1 means that the network is an integrator.



# Plot of Several Neurons in the Network Over Time



# To Do

Look at the leading eigenvalue of the eigenvector.

Add a pulse of input that corresponds to the eigenvector.

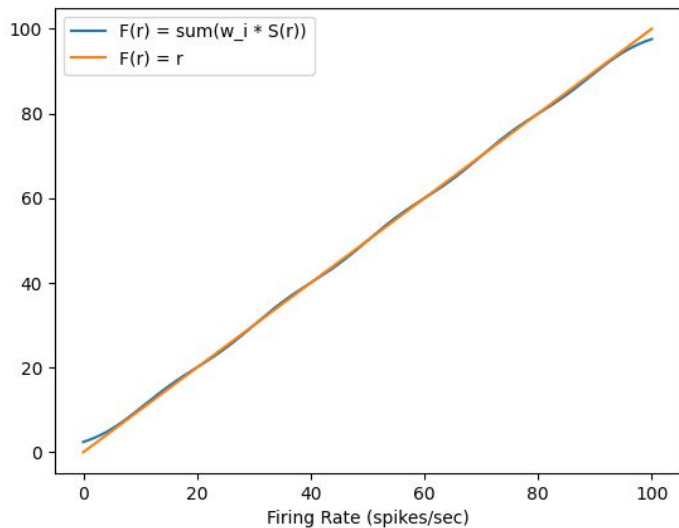
What does the leading eigenvalue represent (dict of eigenvalues and eigenvectors)

Create a matrix with eigenvalue  $1+xi$ ,  $0+i$

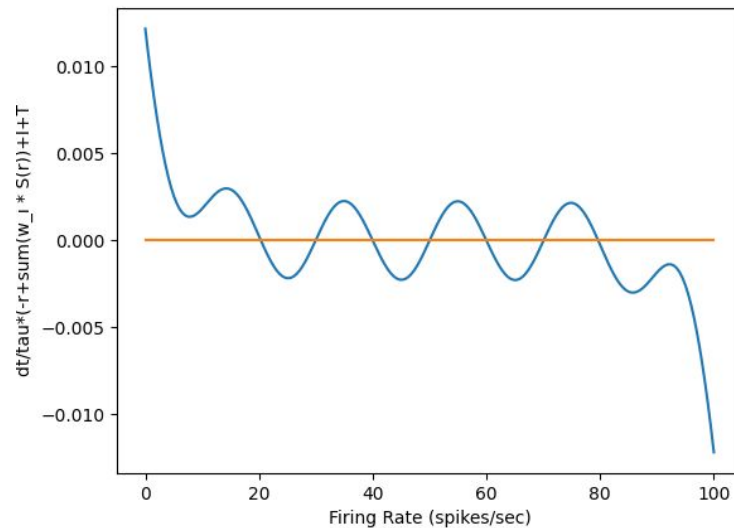
Creating a line attractor using a single synaptically connected neuron

# Finding the Fixed Points of a Recurrent Synaptic Autapse

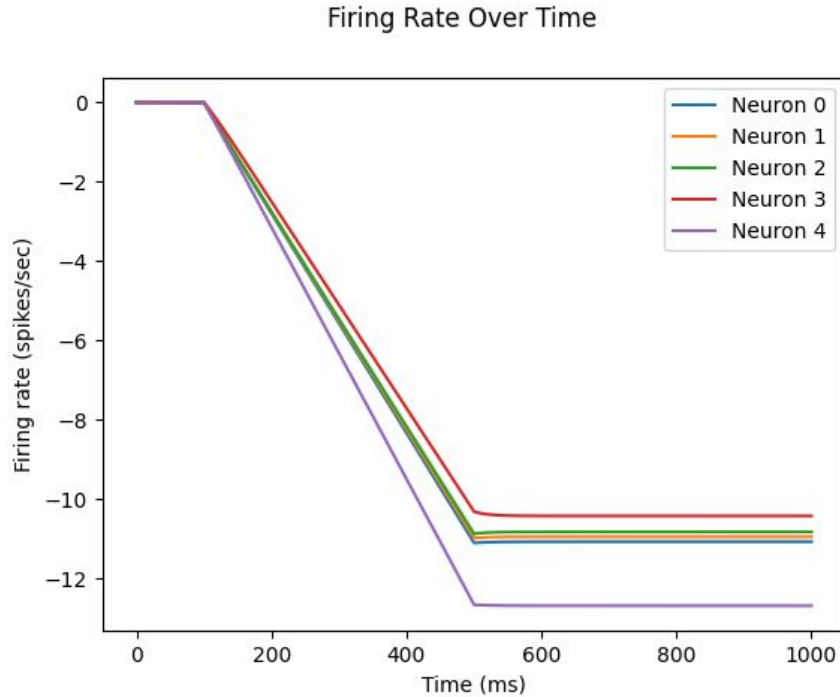
Finding Fixed Points for a Nonlinear Synaptic Autapse



Finding Fixed Points for a Nonlinear Synaptic Autapse



# Applying Current Along a Real Eigenvector

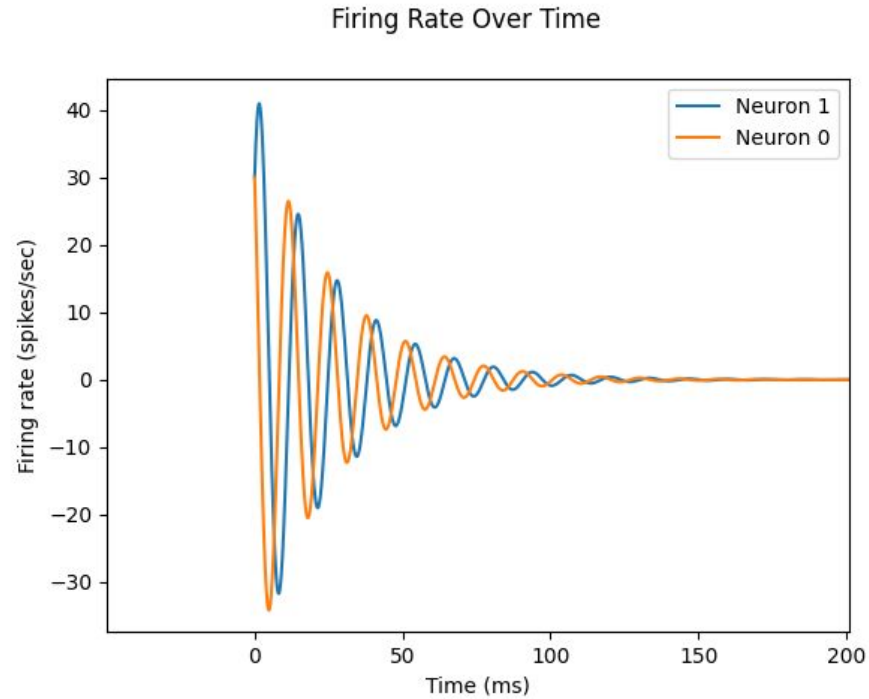


# Week 5/13

Proved Euler's Formula Using Taylor Series

Observed complex eigenvector oscillations in a linear recurrent model (2 neurons)

# Oscillations



Weight matrix =  $\begin{bmatrix} 0 & 10 \\ -9 & 0 \end{bmatrix}$

# Taylor Series and Imaginary Numbers

$$e^{\lambda_I t \cdot i} = \cos(\lambda_I t) + i \sin(\lambda_I t)$$

$$1 + \frac{\lambda_I i}{1!} x + \frac{(\lambda_I i)^2}{2!} x^2 + \frac{(\lambda_I i)^3}{3!} x^3 =$$

$$\boxed{1} + \boxed{\lambda_I i x} + \boxed{-\frac{\lambda_I^2}{2!} x^2} + \boxed{-\frac{\lambda_I^3 i}{3!} x^3} + \boxed{\frac{\lambda_I^4}{4!} x^4} =$$

$$= \left(1 - \frac{\lambda_I^2}{2!} x^2 + \frac{\lambda_I^4}{4!} x^4 - \frac{\lambda_I^6}{6!} x^6 + \dots\right) + i \left(\lambda_I x - \frac{\lambda_I^3}{3!} x^3 + \frac{\lambda_I^5}{5!} x^5 - \dots\right)$$

$e^{\lambda_I t \cdot i} f(x)$   
 $\lambda_I i e^{\lambda_I t \cdot i} f'(x)$   
 $(\lambda_I i)^2 e^{\lambda_I t \cdot i}$   
 $\cos(\lambda_I t)$   
 $-\sin(\lambda_I t) \cdot \lambda_I$   
 $-\cos(\lambda_I t) \cdot \lambda_I^2$   
 $+\sin(\lambda_I t) \cdot \lambda_I^3$

# To Do

Nonlinear Recruitment Network



# Github Project Files

<https://github.com/AlexHackathon/GoldmanTapusWork>