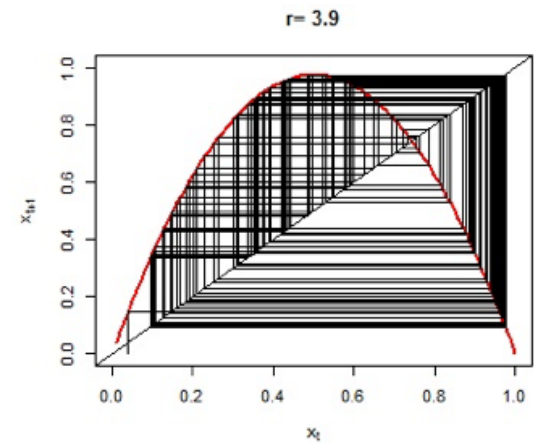
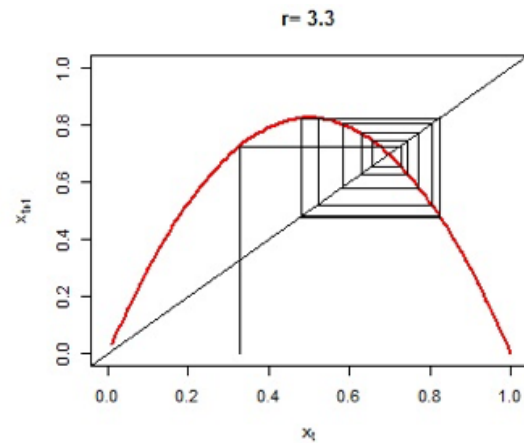
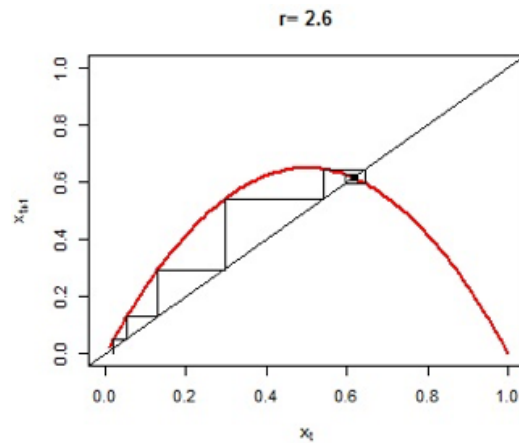


# Discrete-Time Models



Dr. Dylan McNamara  
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mcnamarad](http://people.uncw.edu/mcnamarad)

# Dynamical systems theory

- Considers how systems change along time
  - Ranges from Newtonian mechanics to modern nonlinear dynamics theories
  - Probes underlying dynamical mechanisms, not just static properties of observations
  - Provides a suite of useful tools

# What is a dynamical system?

- A system whose state is uniquely specified by a finite set of variables and whose behavior is uniquely determined by predetermined "rules"
  - Simple population growth
  - Simple pendulum swinging
  - Motion of celestial bodies

# Mathematical formulations of dynamical systems

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- **Discrete-time model:** (difference/recurrence equations; iterative maps)

$$x_t = F(x_{t-1}, t)$$

- **Continuous-time model:** (differential equations)

$$dx/dt = F(x, t)$$

$x_t$ : State variable(s) of the system at time  $t$

$F$ : Some function that determines the rule that the system's behavior will obey

# **Discrete-Time Models**

# Discrete-time model

---

- Easy to understand, develop and simulate
  - Doesn't require an expression for the rate of change (derivative)
  - Can model abrupt changes and/or chaotic dynamics using fewer variables
  - Directly translatable to simulation in a computer
  - Experimentally, we often have samples of system states at specific points of time

# Difference equation and time series

- Difference equation

$$x_t = F(x_{t-1}, t)$$

produces series of values of variable  $x$  starting with initial condition  $x_0$ :

$\{ x_0, x_1, x_2, x_3, \dots \}$  “time series”

- A prediction made by the above model  
(to be compared to experimental data)

# Types of Discrete-Time Models

- Linear:

- Right hand side is just a first-order polynomial of variables

$$x_t = \underline{a x_{t-1} + b x_{t-2} + c x_{t-3} \dots}$$

- Nonlinear:

- Anything else

$$x_t = a x_{t-1} + b \underline{x_{t-2}^2} + c \underline{\sqrt{x_{t-1} x_{t-3}}} \dots$$



# Types of Discrete-Time Models

---

- 1st-order:

- Right hand side refers only to the immediate past

$$x_t = a \underline{x_{t-1}} (1 - \underline{x_{t-1}})$$

- Higher-order:

- Anything else

$$x_t = a \underline{x_{t-1}} + b \underline{x_{t-2}} + c \underline{x_{t-3}} \dots$$

(Note: this is different from the order of terms in polynomials)

# Types of Discrete-Time Models

---

- **Autonomous:**

- Right hand side includes only state variables ( $x$ ) and not  $t$  itself

$$x_t = a x_{t-1} x_{t-2} + b x_{t-3}^2$$

- **Non-autonomous:**

- Right hand side includes terms that explicitly depend on the *value* of  $t$

$$x_t = a x_{t-1} x_{t-2} + b x_{t-3}^2 + \underline{\sin(t)}$$

# Things that you should know

- Non-autonomous, higher-order equations can always be converted into autonomous, 1st-order equations

# Things that you should know

- **Linear equations**

- are analytically solvable
- show either equilibrium, exponential growth/decay, periodic oscillation (with  $>1$  variables), or their combination

- **Nonlinear equations**

- may show more complex behaviors
- do not have analytical solutions in general

# **Simulating Discrete-Time Models**

# Simulating discrete-time models

- Simulation of a discrete-time model can be implemented by iterating updating of the system's states
  - Every iteration represents one discrete time step - use a loop!

**Try in class Exercise**

# **Building Your Own Model Equation**

# Mathematical modeling tips

- Grab an existing model and tweak it
- Implement each assumption one by one
- Find where to change, replace it by a function, and design the function
- Adopt the simplest form
- Check the model with extreme values



# Example: Saturation of growth

- Simple exponential growth model:

$$x_t = a x_{t-1}$$

- Problem: How can one implement the **saturation** of growth in this model?
- Think about a new nonlinear model:

$$x_t = f(x_{t-1}) x_{t-1}$$

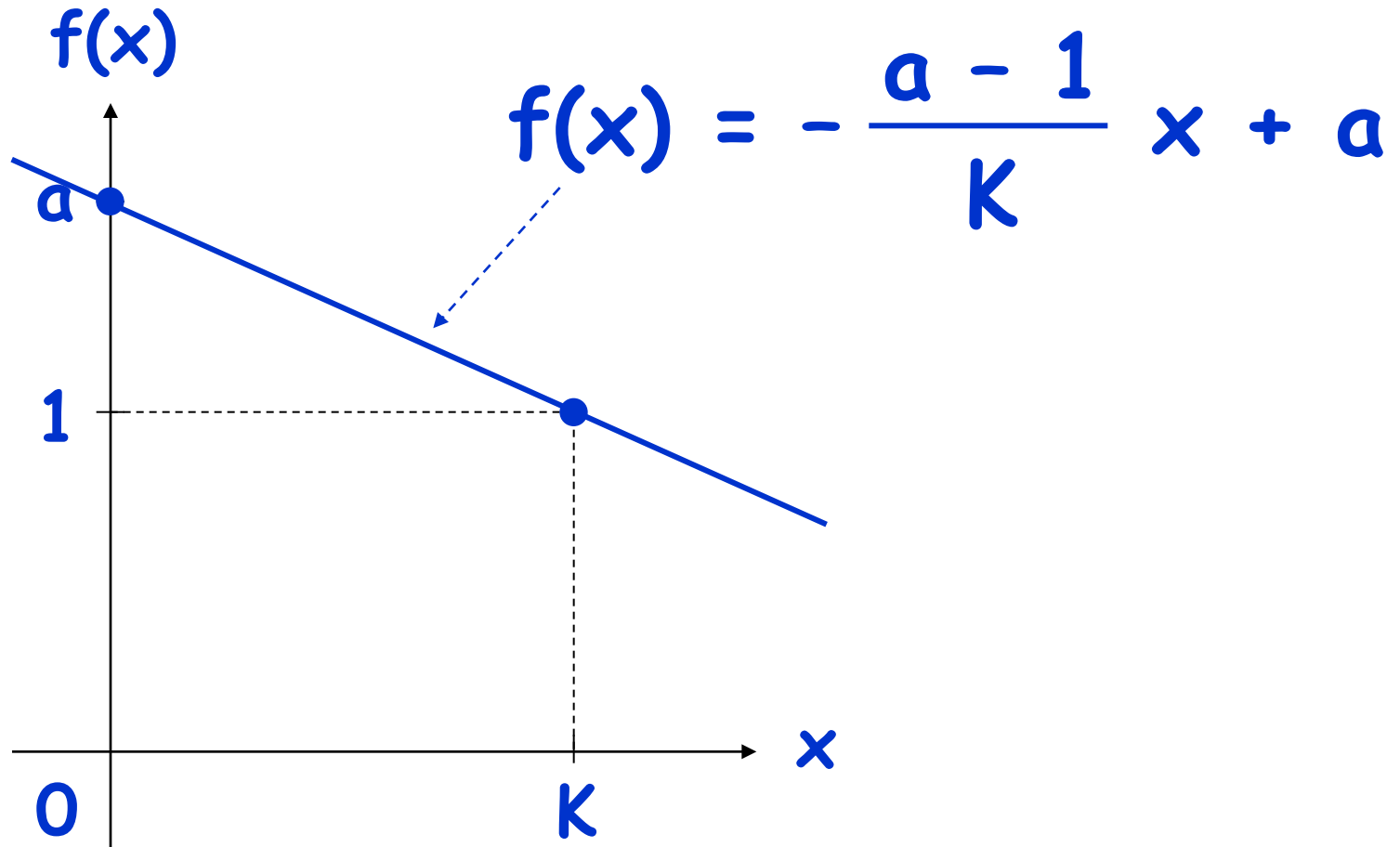
- Coefficient replaced by a function of  $x$

# Modeling saturation of growth

$$x_t = f(x_{t-1}) x_{t-1}$$

- $f(x)$  should approach 1 (no net growth) when  $x$  goes to a carrying capacity of the environment, say  $K$
- $f(x)$  should approach the original growth rate  $a$  when  $x$  is very small (i.e., with no saturation effect)

# What should $f(x)$ be?



# A new model of growth

$$\begin{aligned}x_t &= f(x_{t-1}) x_{t-1} \\&= ( - (a - 1) x_{t-1} / K + a ) x_{t-1}\end{aligned}$$

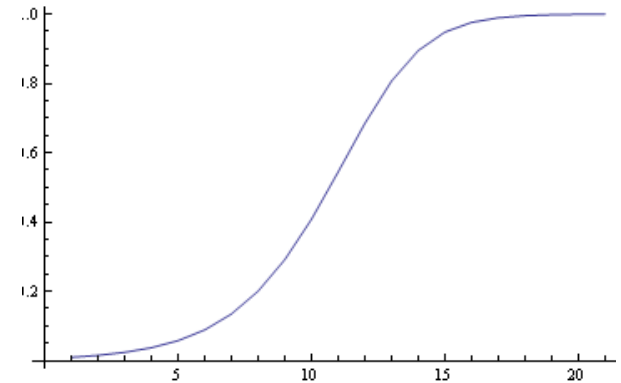
- Using  $r = a - 1$ :

$$\begin{aligned}x_t &= ( - r x_{t-1} / K + r + 1 ) x_{t-1} \\&= x_{t-1} + \underbrace{r x_{t-1} ( 1 - x_{t-1} / K )}_{\text{Net growth}}\end{aligned}$$

Net growth

# Example: Logistic growth model

- **N**: Population
- **r**: Population growth rate
- **K**: Carrying capacity



- Discrete-time version:

$$N_t = N_{t-1} + r N_{t-1} \left( 1 - N_{t-1}/K \right)$$

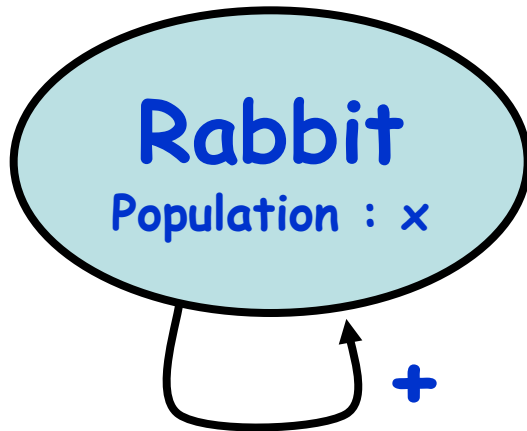
Nonlinear  
terms

# Modeling with multiple variables

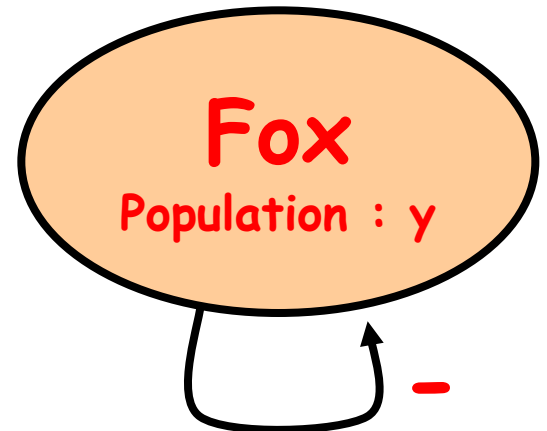
- Problem: Develop a nonlinear model of a simple ecosystem made of predator and prey populations



# Think about how variables behave in isolation

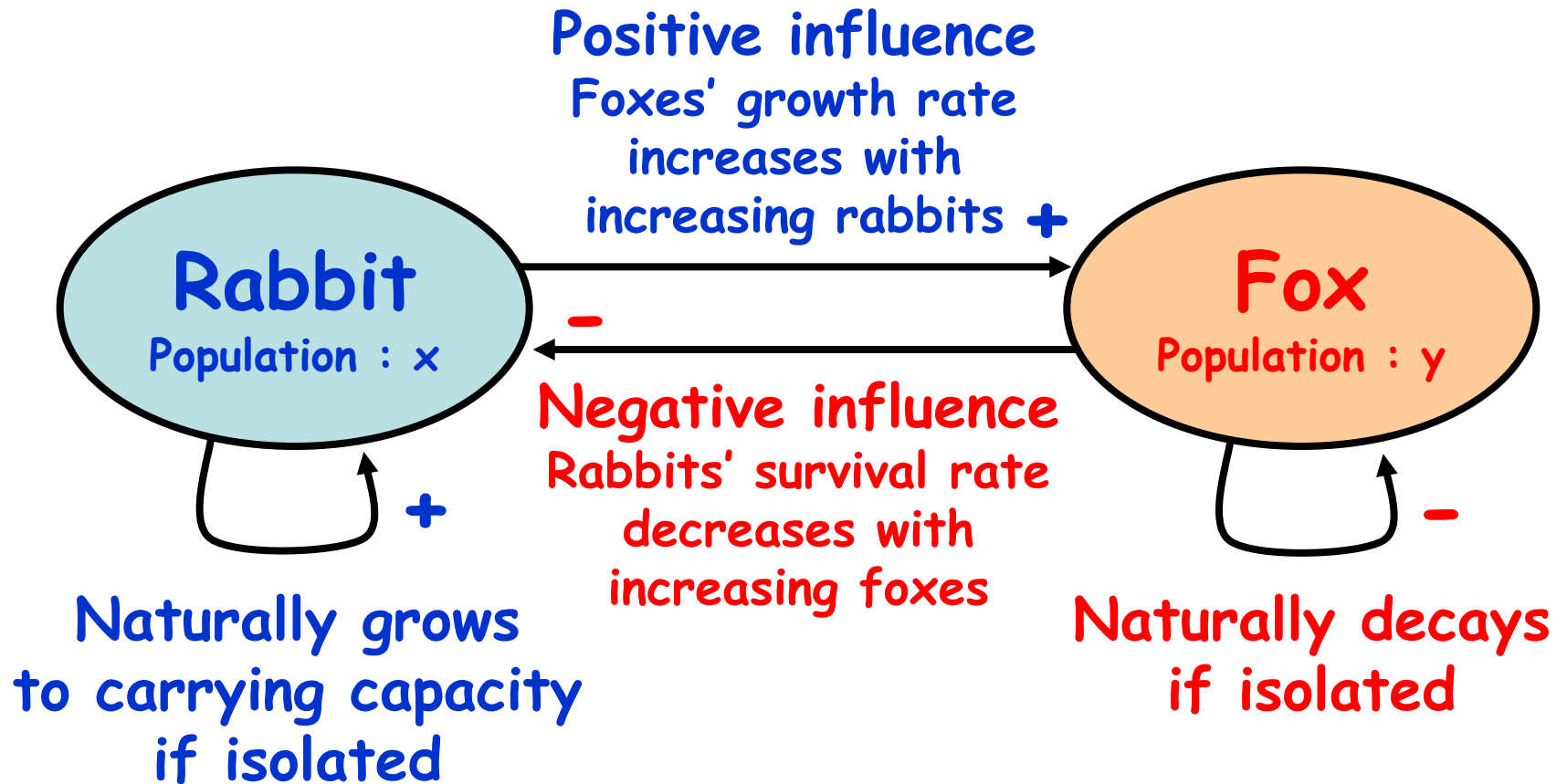


Naturally grows  
to carrying capacity  
if isolated



Naturally decays  
if isolated

# Think about how variables interact with each other





# Lotka-Volterra model

---

- The model derived in class can be rewritten

$$x_t - x_{t-1} = \alpha x_{t-1} (1 - x_{t-1}) - \beta x_{t-1} y_{t-1}$$

$$y_t - y_{t-1} = -\gamma y_{t-1} + \delta x_{t-1} y_{t-1}$$

- Known as the “Lotka-Volterra” equations (of discrete-time version with carrying capacity)
- Models predator-prey dynamics in a general form
- One of the most famous nonlinear systems with multiple variables

# **Analysis of Discrete-Time Models**

# Equilibrium/Fixed point

- A state of the system at which state will not change over time
  - A.k.a. steady state
- Can be calculated by solving

$$x_t = x_{t-1}$$

# Exercise

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- Calculate equilibrium points in the following model

$$N_t = N_{t-1} + r N_{t-1} ( 1 - N_{t-1}/K )$$

# **Phase Space Visualization**

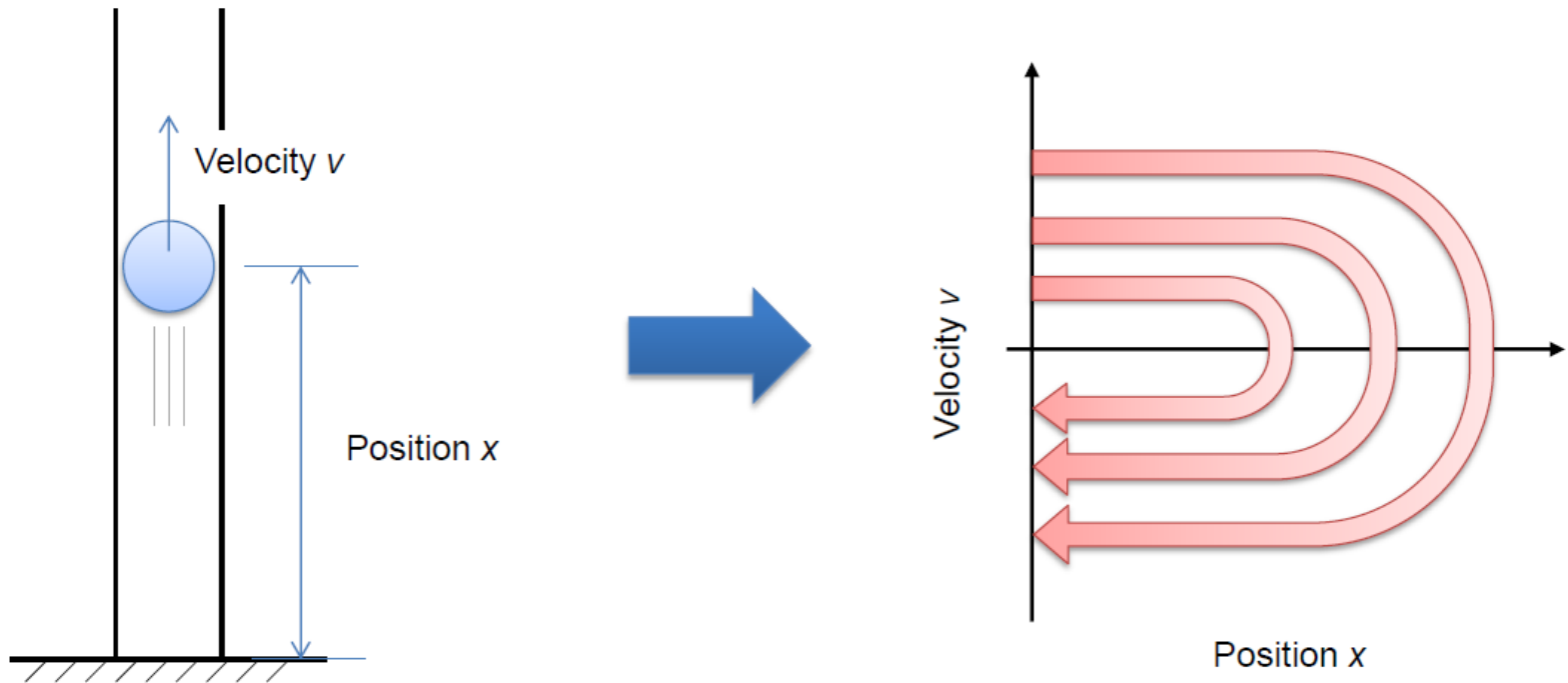
# Geometrical approach

- Developed in the late 19C by J. Henri Poincare
- Visualizes the behavior of dynamical systems as **trajectories in a phase space**
- Produces a lot of intuitive insights on **geometrical structure** of dynamics that would be hard to infer using purely algebraic methods



# Phase space (state space)

- A theoretical space in which every state of a dynamical system is mapped to a spatial location



# Phase space (state space)

- Created by “orthogonalizing” state variables of the system
- Its dimensionality equals # of variables needed to specify the system state (a.k.a. degrees of freedom)
- Temporal change of the system states can be drawn in it as a trajectory



# Attractor and basin of attraction

- **Attractor:**

A state (or a set of states) from which no outgoing edges or flows running in phase space

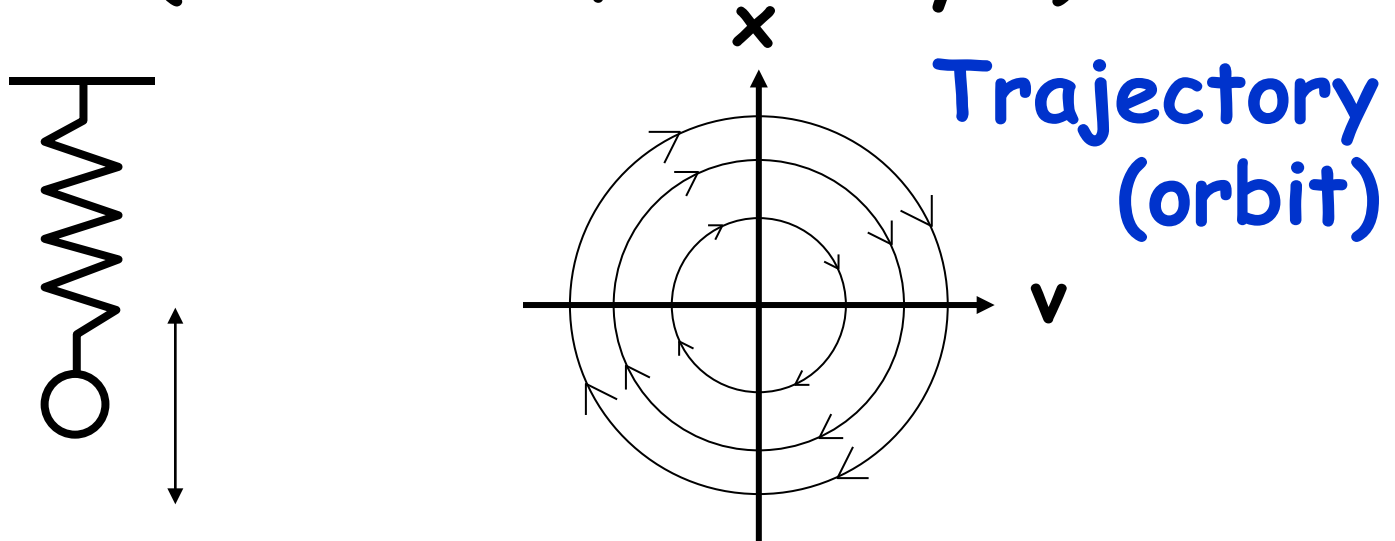
- Static attractors (equilibrium points)
- Dynamic attractors (e.g. limit cycles)

- **Basin of attraction:**

A set of states which will eventually end up in a given attractor

# Phase space of continuous-state models

- E.g. a simple vertical spring oscillator
- State can be specified by two real variables (location  $x$ , velocity  $v$ )



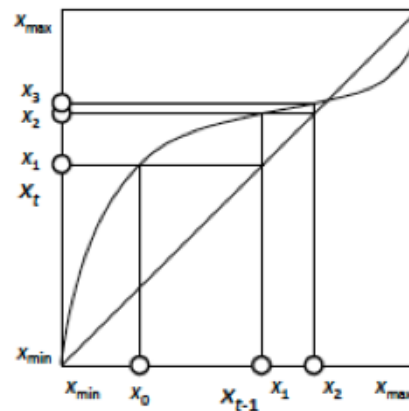
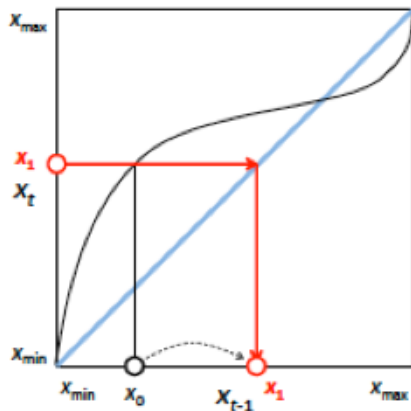
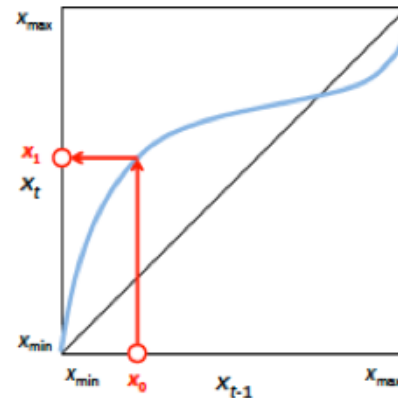
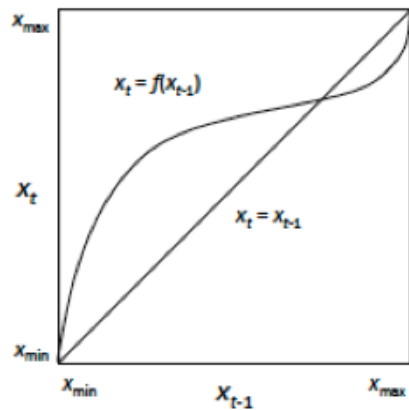
Dynamics of continuous models can be depicted as "flow" in a continuous phase space

# Cobweb plot

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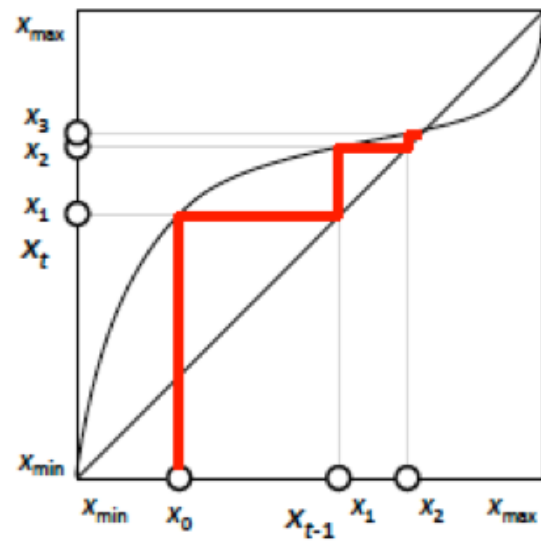
- A visual tool to study the behavior of 1-D iterative maps
- Take  $x_{t-1}$  and  $x_t$  for two axes
- Draw the map of interest ( $x_t = F(x_{t-1})$ ) and the " $x_t = x_{t-1}$ " reference line
  - They will intersect at "equilibrium points"
- Trace how time series develop from an initial value by jumping between these two curves

# Cobweb Plot



# Cobweb Plot

---



# Rescaling Variables

# Rescaling variables

- Dynamics of a system won't change qualitatively by linear rescaling of variables (e.g.,  $x \rightarrow \alpha x'$ )
- You can set arbitrary rescaling factors for variables to simplify the model equations
- If you have  $k$  variables, you may eliminate  $k$  parameters

# Exercise

---

- Simplify the logistic growth model by rescaling  $x \rightarrow \alpha x'$

$$x_t = x_{t-1} + r x_{t-1} (1 - x_{t-1}/K)$$



# Linear Systems

# Linear systems

- Some systems can be modeled as linear systems
  - Their dynamics is described by a product of matrix and state vector
  - Either in continuous or discrete time
- Dynamics of such linear systems can be studied analytically

# Linear systems

---

- Linear systems are the simplest cases where states of nodes are continuous-valued and their dynamics are described by a time-invariant matrix
- Discrete-time:  $x_t = A x_{t-1}$ 
  - $A$  is called a “coefficient” matrix
  - We don't consider constants (as they can be easily converted to the above forms)

# **Asymptotic Behavior of Linear Systems**

Where will the system go eventually?

$$\mathbf{x}_t = \mathbf{A} \mathbf{x}_{t-1}$$

This equation gives the following exact solution:

$$\mathbf{x}_t = \mathbf{A}^t \mathbf{x}_0$$

# Where will the system go eventually?

$$\mathbf{x}_t = \mathbf{A} \mathbf{x}_{t-1}$$

- What happens if the system starts from non-equilibrium initial states and goes on for a long period of time?
- Let's think about their asymptotic behavior  $\lim_{t \rightarrow \infty} \mathbf{x}_t$

# Considering asymptotic behavior

- Let  $\{ v_i \}$  be  $n$  linearly independent eigenvectors of the coefficient matrix  
(They might be fewer than  $n$ , but here we ignore such cases for simplicity)
- Write the initial condition using eigenvectors, i.e.  
$$x_0 = b_1 v_1 + b_2 v_2 + \dots + b_n v_n$$

# Considering asymptotic behavior

- Then:

$$\begin{aligned} \mathbf{x}_t &= \mathbf{A}^t \mathbf{x}_0 \\ &= \lambda_1^t \mathbf{b}_1 \mathbf{v}_1 + \lambda_2^t \mathbf{b}_2 \mathbf{v}_2 + \dots + \lambda_n^t \mathbf{b}_n \mathbf{v}_n \end{aligned}$$



# Dominant eigenvector

---

- If  $|\lambda_1| > |\lambda_2|, |\lambda_3|, \dots$ ,

$$\mathbf{x}_t = \lambda_1^t \{ \mathbf{b}_1 \mathbf{v}_1 + \cancel{(\lambda_2/\lambda_1)^t \mathbf{b}_2 \mathbf{v}_2} + \dots + \cancel{(\lambda_n/\lambda_1)^t \mathbf{b}_n \mathbf{v}_n} \}$$

$$\lim_{t \rightarrow \infty} \mathbf{x}_t \sim \lambda_1^t \mathbf{b}_1 \mathbf{v}_1$$

If the system has just one such **dominant eigenvector**  $\mathbf{v}_1$ , its state will be eventually along that vector **regardless of where it starts**

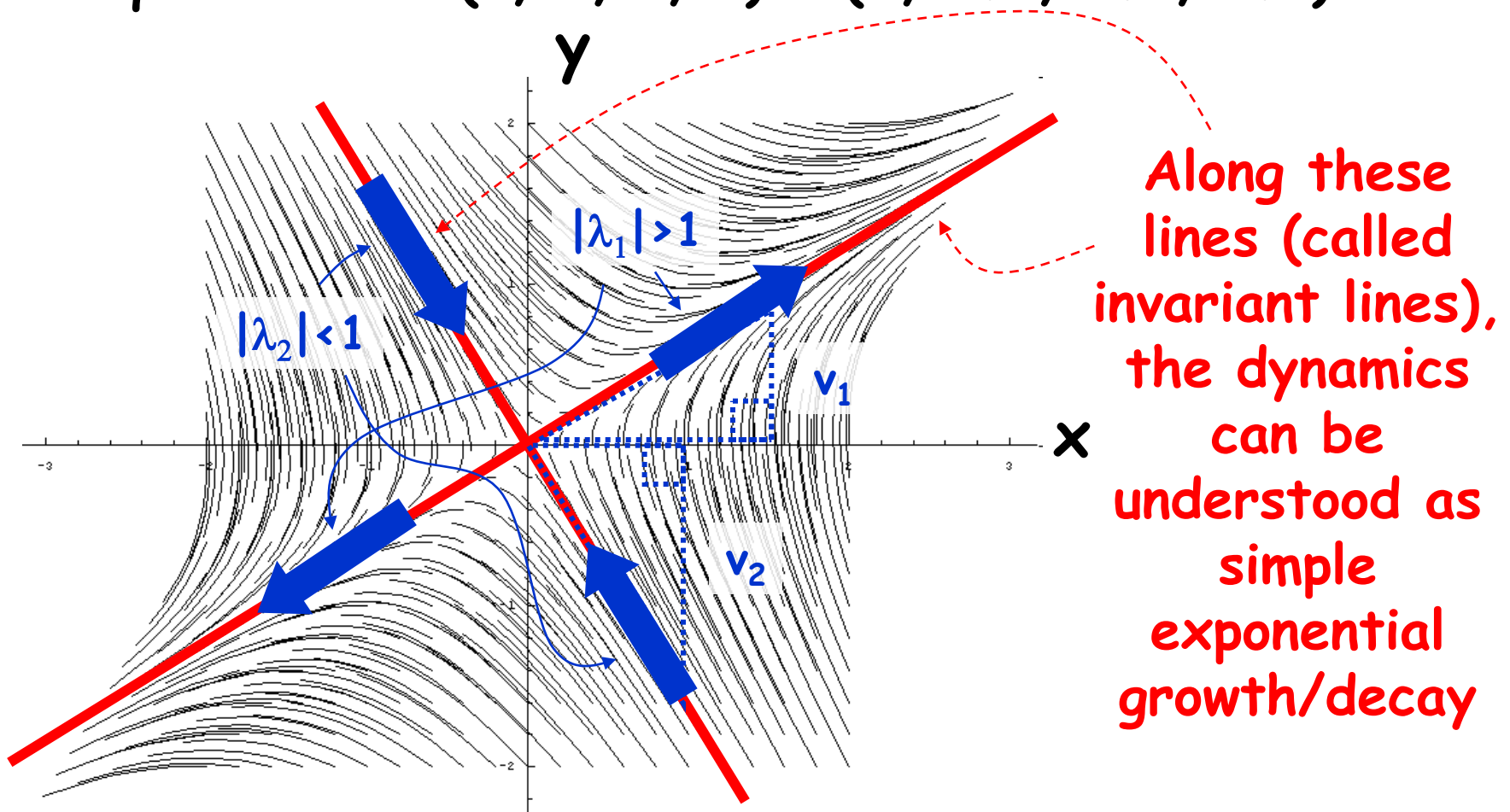
# What eigenvalues and eigenvectors can tell us

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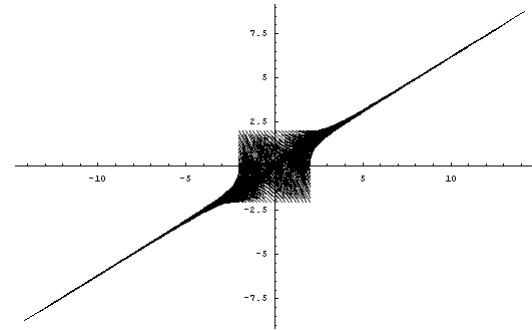
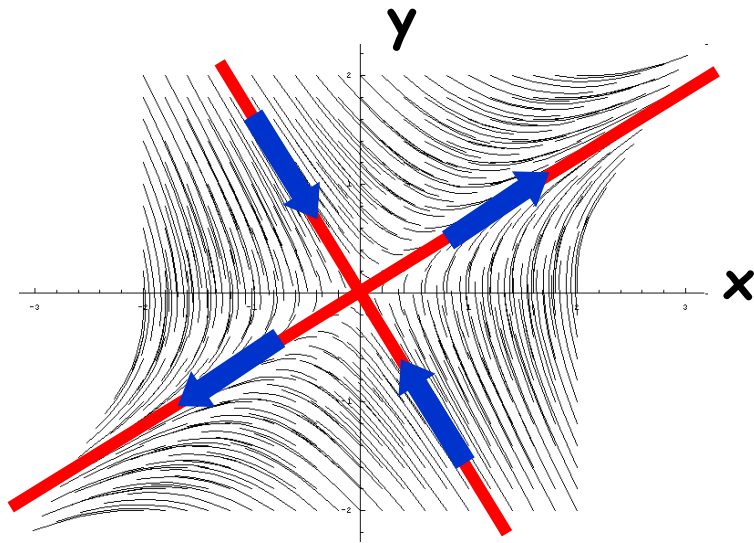
- An eigenvalue tells whether a particular “state” of the system (specified by its corresponding eigenvectors) grows or shrinks by interactions between parts
  - $|\lambda| > 1 \rightarrow$  growing
  - $|\lambda| < 1 \rightarrow$  shrinking

# Example

- Phase space of a two-variable linear difference equation with  $(a, b, c, d) = (1, 0.1, 0.1, 0.9)$

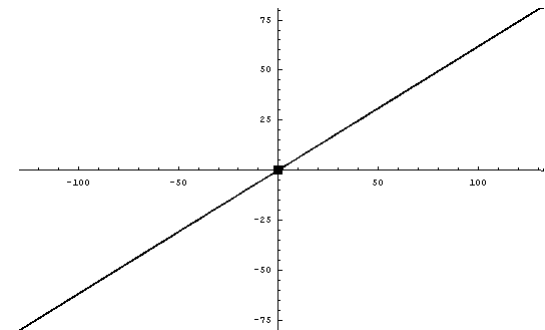


# Example



This could be regarded as a very simple form of **self-organization** (though completely predictable);

Order spontaneously emerges in the system as time goes on



# **Linear Stability Analysis of Nonlinear Systems**

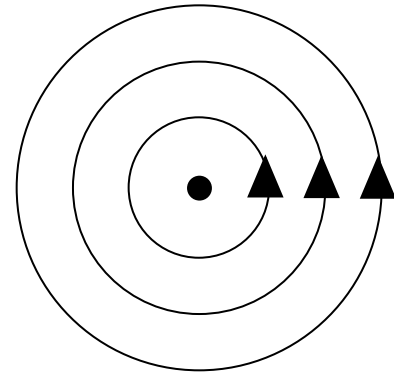
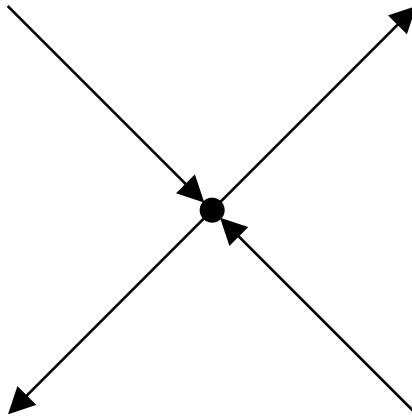
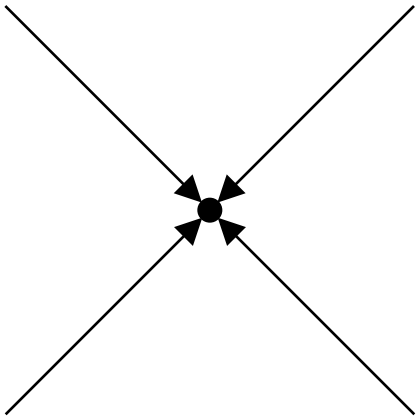
# Stability of equilibrium points

- If a system at its equilibrium point is slightly perturbed, what happens?
- The equilibrium point is called:
  - **Stable (or asymptotically stable)** if the system eventually falls back to the equilibrium point
  - **Lyapunov stable** if the system doesn't go far away from the equilibrium point
  - **Unstable** otherwise

# Question

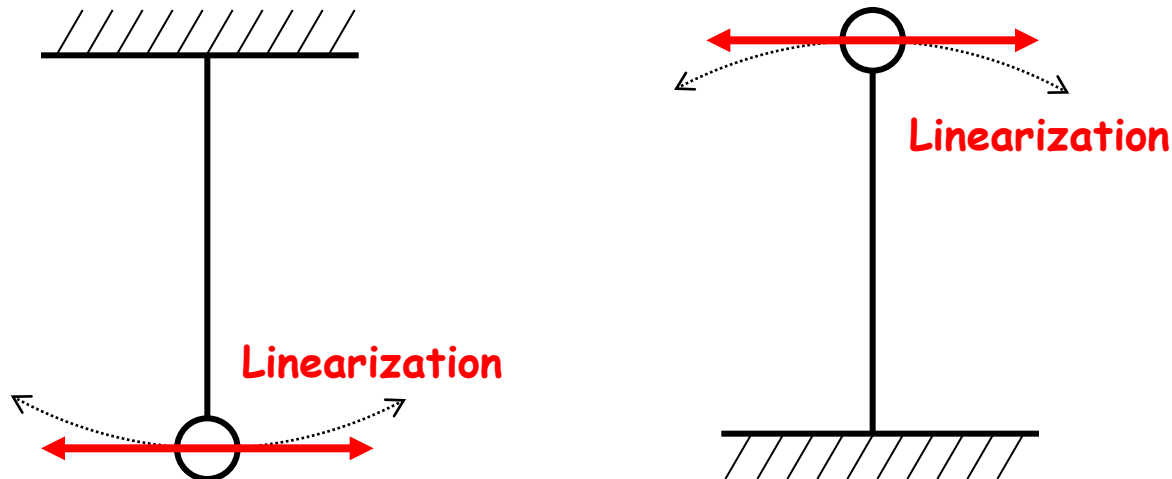
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- What is the stability of each of the following equilibrium points?



# Linear stability analysis

- Studies whether a nonlinear system is stable or not at its equilibrium point by locally linearizing its dynamics around that point





# Local linearization

---

- Let  $\Delta x$  be a small difference between the system's current state  $x$  and its equilibrium point  $x_e$ , i.e.  $x = x_e + \Delta x$
- Plug  $x = x_e + \Delta x$  into differential equations and ignore quadratic or higher-order terms of  $\Delta x$  (hence the name "linearization")

# Local linearization

---

- This operation does the trick to convert the dynamics of  $\Delta x$  into a product of a matrix and  $\Delta x$
- By analyzing eigenvalues of the matrix, one can predict whether  $x_e$  is stable or not
  - I.e. whether a small perturbation ( $\Delta x$ ) grows or shrinks over time

# Mathematically speaking...

- This operation is similar to “linear approximation” in calculus

Taylor series expansion:

$$F(x) = \sum_{n=0 \sim \infty} F^{(n)}(a)/n! (x-a)^n$$

Let  $x \rightarrow x_e + \Delta x$  and  $a \rightarrow x_e$ , then

$$F(x_e + \Delta x) = F(x_e) + F'(x_e) \Delta x$$

Ignore  ~~$+ O(\Delta x^2)$~~

# Linearizing discrete-time models

- For discrete-time models:

$$x_t = F(x_{t-1})$$

$$\text{Left} = x_e + \Delta x_t$$

$$\begin{aligned}\text{Right} &= F(x_e + \Delta x_{t-1}) \\ &\sim F(x_e) + F'(x_e) \Delta x_{t-1} \\ &= x_e + F'(x_e) \Delta x_{t-1}\end{aligned}$$

Therefore,

$$\Delta x_t = F'(x_e) \Delta x_{t-1}$$

# First-order derivative of vector functions

---

- Discrete-time:  $\Delta \mathbf{x}_t = \mathbf{F}'(\mathbf{x}_e) \Delta \mathbf{x}_{t-1}$

This can hold even if  $\mathbf{x}$  is a vector

What corresponds to the first-order derivative in such a case:

$$\mathbf{F}'(\mathbf{x}_e) = d\mathbf{F}/d\mathbf{x}_{(\mathbf{x}=\mathbf{x}_e)} = \begin{pmatrix} \frac{\partial F_1}{\partial x_1} & \frac{\partial F_1}{\partial x_2} & \dots & \frac{\partial F_1}{\partial x_n} \\ \frac{\partial F_2}{\partial x_1} & \frac{\partial F_2}{\partial x_2} & \dots & \frac{\partial F_2}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial F_n}{\partial x_1} & \frac{\partial F_n}{\partial x_2} & \dots & \frac{\partial F_n}{\partial x_n} \end{pmatrix}_{(\mathbf{x}=\mathbf{x}_e)}$$

Jacobian matrix at  $\mathbf{x}=\mathbf{x}_e$

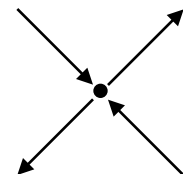
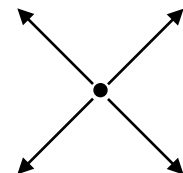
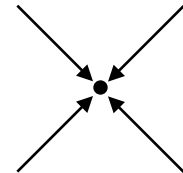
# Eigenvalues of Jacobian matrix

- A Jacobian matrix is a linear approximation around the equilibrium point, telling you the local dynamics: “how a small perturbation will grow, shrink or rotate around that point”
  - The equilibrium point serves as a local origin
  - The  $\Delta x$  serves as a local coordinate
  - Eigenvalue analysis applies

# With real eigenvalues

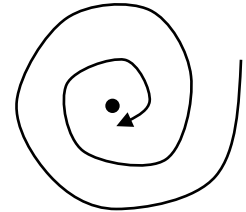
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- If all the eigenvalues indicate that  $\Delta x$  will shrink over time  
-> **stable point**
- If all the eigenvalues indicate that  $\Delta x$  will grow over time  
-> **unstable point**
- If some eigenvalues indicate shrink and others indicate grow of  $\Delta x$  over time  
-> **saddle point** (this is also unstable)

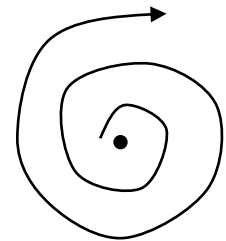


# With two complex conjugate eigenvalues (for 2-D systems)

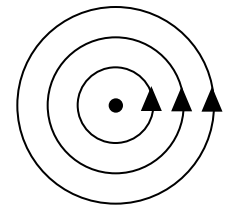
- If both eigenvalues indicate that  $\Delta x$  will shrink over time  
-> **stable spiral focus**



- If both eigenvalues indicate that  $\Delta x$  will grow over time  
-> **unstable spiral focus**



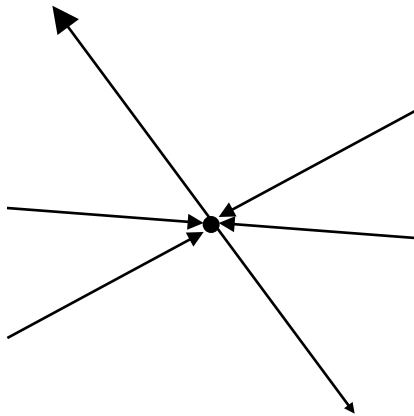
- If both eigenvalues indicate neither shrink nor growth of  $\Delta x$   
-> **neutral center** (but this may or may not be true for nonlinear models; further analysis is needed to check if nearby trajectories are truly cycles or not)



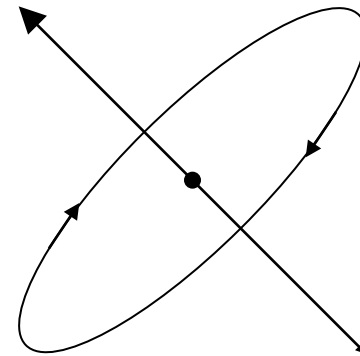


# With real and complex eigenvalues mixed (for higher-dimm. systems)

- Each eigenvalue (or a pair of complex conjugate eigenvalues) tell you distinct dynamics simultaneously seen at the equilibrium point:



All real eigenvalues (1 indicates growth; other 2 indicates shrink)



1 real eigenvalue indicates growth;  
other 2 indicates rotation (complex  
conjugates with no growth or shrink)