

# Nonlinear Dynamics

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# Lecture 1: Strogatz Section 2.1

## Flows on a Line

→ Follow book until 3<sup>rd</sup> dimension is introduced

Definition: Dynamical Systems → Deterministic  
(i.e., not stochastic (noisy) or quantum mechanical)

Measurable spaces:

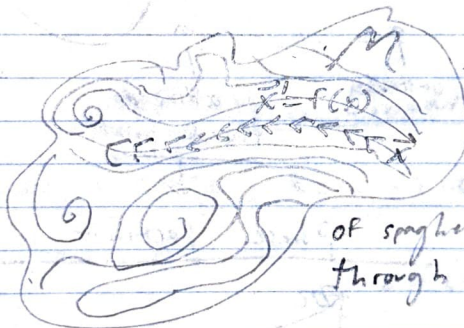
$(M, f)$

describe the system

$M$ : what are I describing?

$f$ : how does it change

1. State Space  $M$ , a set of numbers/coordinates  $\vec{x} = (x_1, \dots, x_n)$  that represent properties of the system, defining a unique state. Can be thought of as a manifold
2. Governing law:  $\dot{x} = f(x)$



- Manifold representing state space with the constraint of  $f(x)$   
- If law is not time dependent, this space represents a "ball of spaghetti" with all possible points connected through orbits.

This is largely effectively a course in differential equations  
⇒ time is continuous

→  $\dot{x} = f(x)$ : represents a vector derivative, i.e., a velocity in state space. The tangents of each orbit are described by this eqn.

→ Consider a linear law  $f$ : (like Hooke's law)

$$f(x) = \sum_{i=1}^n a_i x_i = a_1 x_1 + \dots + a_n x_n$$

→ solve linear system w/  
Laplace, Jordan Normal forms

→ or a nonlinear one:

$$f(x) = \sum_{i,j=1}^n b_{ij} x_i x_j = b_{12} x_1 x_2 + b_{23} x_2 x_3 + \dots$$

$$f(x) = ax^2 \rightarrow (\text{since 1910, has led to Fields medals, Abel prizes, math today})$$

"Our mind is not quantum mind"

→ An example of flow on a line

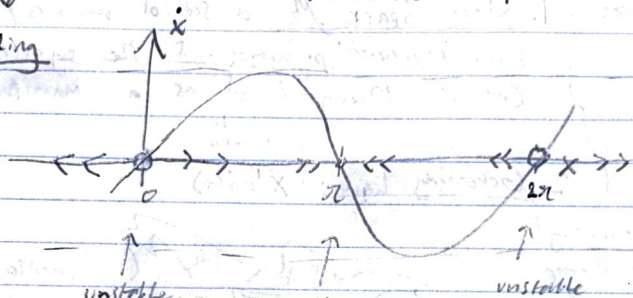
$$f: \dot{x} = \sin x$$

$$M = \mathbb{R}^1$$

$$\frac{dx}{dt} = \sin x \rightarrow dt = \frac{dx}{\sin x} = \csc x dx$$

$$\Rightarrow \int_0^t dt = \int_{x_0}^x dx \csc x \Rightarrow t = \ln \left| \frac{\csc x_0 + \cot x_0}{\csc x + \cot x} \right| \rightarrow \text{but what does this tell us?}$$

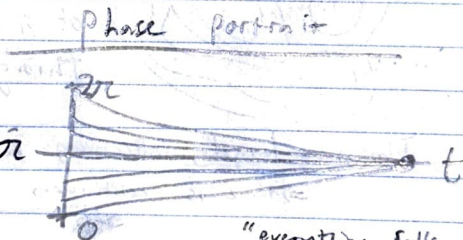
→ Seek qualitative understanding



zeros:

$$Z = \{k\pi : k \in \mathbb{N}\}$$

Set of measure zero:  $\mu(Z) = 0$



"everything falls into the hole"

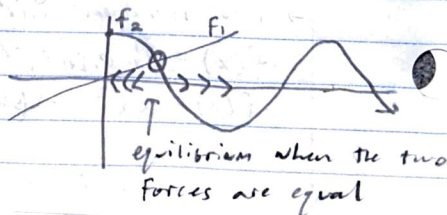
→ Equilibria: stable points of the system, i.e., fixed points  
 ↳ values of state space for which "nothing" happens

Stability: fixed points are stable, unstable, or "marginal" (saddle)

$$\dot{x} = x - \cos x$$

linear, easy ( $e^x$ )      subtract a "spring"

$f_1$        $f_2$





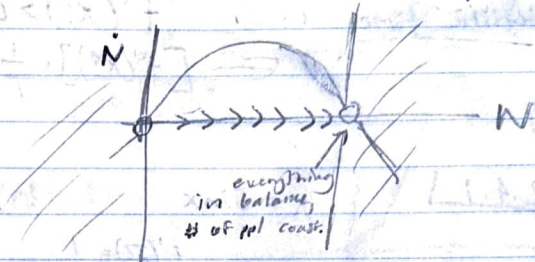
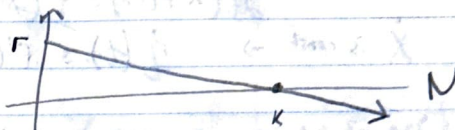
# Lecture 2: 08/21/25

## 2.3 Population (British movement early 1700s)

Malthus:  $\dot{N} = rN$   $r > 0$ : grows,  $r < 0$ : shrinks

Verhulst:  $r = r(N)$ :

$$\dot{N} = rN \left(1 - \frac{N}{K}\right)$$



in reality, this model breaks down when considering the coupling b/w 2 populations

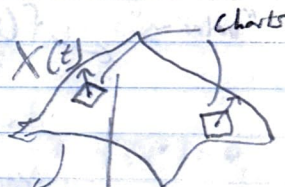
## 2.4 Stability, Linearization

consider a state  $X(x_0, t)$  @ time  $t_0$  & point  $x_0$

$t=0$ :  $x_0$   $x_0 + \eta$

now consider a small perturbation  $\eta$  in the initial condition of the state

$X(x_0, t)$   
 $\eta(t)$   
 $X(x_0 + \eta, t)$



This process is called linearization.   
  $\rightarrow$  sometimes it fails, when the 1<sup>st</sup> derivative is zero.   
 Differentiable, smooth Manifold.   
 Hence you can place a tangent plane (i.e., a chart) on any local neighborhood

Linearize via Taylor expansion in higher dim, this becomes Jacobian

$$f(x_0 + \eta, t) = f(x_0, t) + f'(x_0, t) \eta(t)$$

$$\eta(t) = f'(x_0, t) \eta(0)$$

$$\dot{X}(t) = f(X(t))$$

consider equilibrium  $X^*$

what happens close to  $q$ ?  $\dot{X}(X^*) = 0$   
 $\dot{X}(X^* + \eta)$

Q: is there a case where  $f(x)$  is linear / locally linear / linear approximation  
breaks down? i.e., when  $\dot{x}$

$$\dot{x}(t) = f(x(t))$$

$$= f(x^* + \eta(t))$$

$$\frac{d}{dt}(\dot{x} + \eta(t)) = f(x^*) + f'(x^*)\eta(t)$$

$\dot{x}$  is const  $\rightarrow$

$$\dot{\eta}(t) = f'(x^*)\eta(t)$$

$\Rightarrow$  if:

$$f'(x^*) < 0$$

$\rightarrow$  stable

exponentially towards  $x^*$  and other

$$f'(x^*) = 0$$

linear, not sufficient

$$f'(x^*) > 0$$

points exponentially

separate (unstable)

characteristic time

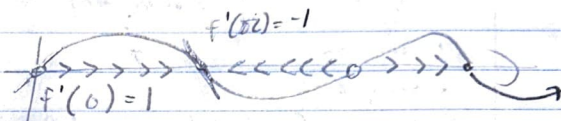
$$\frac{1}{f'(x^*)}$$

$$\left[ f'(x^*) \right] = \frac{1}{T}$$

example 2.4.1

$$\dot{x} = \sin x$$

$$\dot{\eta} = f'(x^*)\eta$$

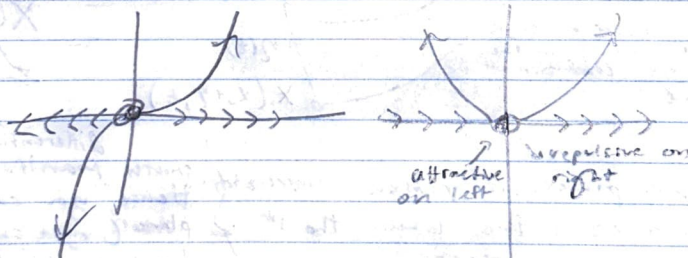


Non-linear Stability: example 2.4.3

"velocity"

$$f(x) = x^3$$

$$f(x) = x^3$$



Section 2.5

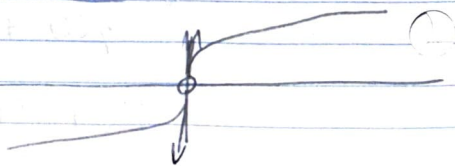
example 2.5.1

Non-uniqueness

$$f(x) = x^{1/3}$$

$$f'(0) = \infty$$

$$\frac{dx}{dt} = x^{1/3} \rightarrow \int \frac{dx}{x^{1/3}} = \int dt$$





→ plug in this eq.

→ previous believes 3D smooth solutions to NS are not possible (Millennium prize)

The equation  $\int \frac{dx}{x^{1/3}} = \int dt$  has many solutions:

$$\frac{3}{2} x^{2/3} = t + C$$

$$x = 0 \quad \forall t$$

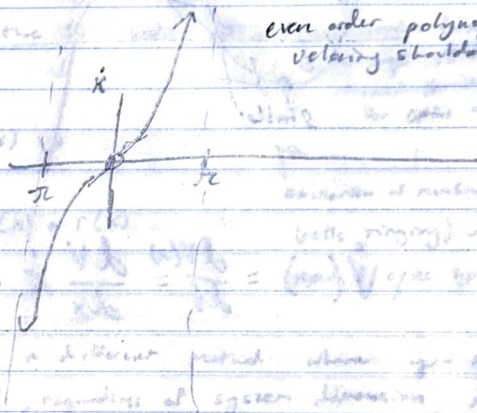
$$x(t) = \left(\frac{2}{3}t\right)^{3/2}$$

example 2.5.2 Blow-up (Millennium prize for NS)

$$\dot{x} = 1 + x^2$$

$$x(t) = \tan x$$

→ linear (sinx) near origin, but it blows up moving away from origin

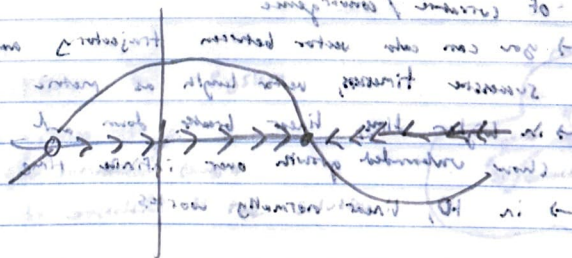


even order polynomial since velocity should be symmetric

## Section 2.6 / No Oscillatory Systems

system can oscillate if it has a limit cycle or a periodic orbit

→ because an oscillation passes through  $f(x^*) = 0$ , must (intersects) at rest (equilibrium point), the oscillation cannot persist unless the equilibrium point is reached.



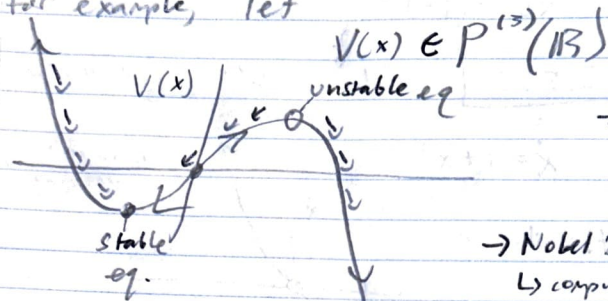
$$f(x) \equiv \dot{x}$$

## Section 2.7: Potential functions

$$f(x) = -\frac{dV(x)}{dx}$$

define  $V(x)$  as a potential function.

For example, let



→ extremely useful in high dimensional problems

→ Nobel 2024: Hopfield

↳ computational neuroscience,  
describe memory in neurons  
as potential function

$$\dot{V}(x) = \frac{dV(x)}{dt} = \frac{dV}{dx} \dot{x} = -\left(\frac{dV}{dx}\right)^2$$

↳ potential function has to be positive, so  $\dot{V} \leq 0$

Answer to Q: What happens when trajectories are large

- Compare linear approximation to 2nd order term
- when / before two are comparable, you determine "radius" of curvature / convergence
- you can calc vector between trajectory and  $\text{traj} + E$  at successive times, vector length as metric
- in higher dims, linear breaks down and hyperbolic exponents show unbounded growth over infinite time
- in 1D, linear normally works



# Lecture 3: 08/26/25

## Connection to Numerics

- ODEs

(x is time)

$$\frac{d^2 y}{dx^2} = r(x)$$

acceleration      forcing

$$\rightarrow \frac{d^2 y}{dx^2} + q(x) \frac{dy}{dx} = r(y(x))$$

acc.      friction      forcing, driven

$r(y(x), x)$   
or autonomous

→ dynamical systems can be recast as ODEs

→ consider systemizing the 2nd order ODE: (Hamiltonian formulation)

let

$$\frac{dy}{dx} = z(x)$$

$$\frac{dz}{dx} = -q(x)z(x) + r(x)$$

at age 16 → learned Hamiltonian dynamics for optics only, then extended  
oscillation of membranes (i.e., chiral bells ringing) vs. 4th derivative, need 4 eqns system + 4 initial data

in late 18th century, a different method where you specify a single function (energy), regardless of system dimension, and from this equation (with variational techniques) an intelligent guess is a solution to the EOM: Variational principle to solve ODE systems

Newtonian → Lagrangian

Quantum mech → QFT

linear regressions → machine learning

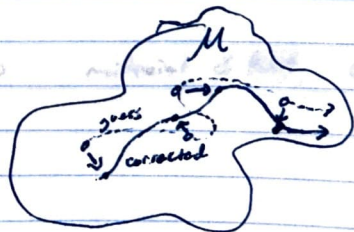
This technique does not integrate the system, but writes a general law.

Consider a system

with guesses  $0$

+ slight variation  $0 \rightarrow \delta$

can be corrected to the solution



next thing is a fact of life...



we consider everything to be a continuous:

## Discretization

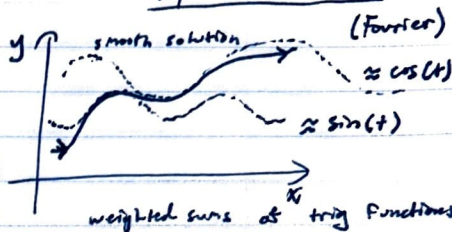
### Lattice methods

simple approach:  
3D grid mesh  
or a  
hypercube lattice



versus

### spectral methods



FFT: take small  
subset of series truncation,  
using symmetries natural to  
sinusoids, that allows  
you to have a great representation  
rapidly

→ very powerful; invented ~1980

$$y(x) \approx \sum_{n=-\infty}^{\infty} c_n b_n(x) \leftarrow \text{can integrate spectral basis}$$

$$\approx \sum_{n=-N/2}^{N/2} c_n b_n(x)$$

### example bases

Fourier,  
Chebyshev,  
Hermite, etc.

"selecting the right set of coordinates/observables  
is a dark art, but it is critical" (spectral representation ↔ Latent representation)

### Euler's Method

$x(0)$

$$t \rightarrow t_0 + k \Delta t$$

$$x(t) \approx x(k \Delta t) = x_k$$

$$\frac{dy}{dt} = \frac{y_{n+1} - y_n}{h} = f(x_n, y_n)$$

$f$  is velocity  
field,

$$y_{n+1} = y_n + h f(x_n, y_n) + \mathcal{O}(h^2)$$

Euler's estimate                      error

→ higher order discretizations, such as midpoint & RK4, exist