

Agenda: Complex Processes in Nature and Laboratory

Systems and dynamics, qualifiers

Examples (climate, planetary motion),

Order and Chaos, determinism and stochastic unpredictability

1D dynamics: phase space curves/orbits

Non-linear dynamics in nature and their modeling

Mathematical model (logistic map, climate,.....)

Stability criteria, stationary states

Self replicating structures out of simplicity

Cellular automata and fractal structures,

Self-organization in coupled chemical reactions

Thermodynamic states and their transformations

Collective and chaotic multi-dimensional systems

Energy types equilibration,

flow of heat and radiation

Reading Assignments

Weeks 1&2

LN I: Complex processes

Kondepudi Ch.19

Additional Material

J.L. Schiff:

Cellular Automata,
Ch.1, Ch. 3.1-3.6

McQuarrie & Simon

Math Chapters

MC B, C, D,

Intermediate Summary

Linear force laws are deterministic → lead to predictable time evolution and are not sensitive to initial conditions: Small changes in initial conditions → small changes in final positions and momenta. 1D appr. $f(x + \Delta x) \approx f(x) + \Delta x \cdot f'(x) := g(x)$

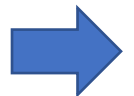
$$\text{Stepwise iteration } f_{i+1} = g_i \text{ with In. Cond.: } i = 0, g_0 = g(x_0)$$

Trajectory $x(t) \rightarrow x_i := x(t_i); \dot{x}(t) \rightarrow \dot{x}_i := \dot{x}(t_i)$ **Phase curve** $\{x(t_i), \dot{x}(t_i)\}; i = 0, \dots$

- Complex, unpredictable (Chaotic) dynamics can be caused by non-linear force laws for certain complex systems, which have specific sets of properties (→ model parameters).
- Complex, unpredictable (Chaotic) dynamics can be caused by correlated motion along different degrees of freedom. Rate equations for different d.o.f. become substantially entangled.
- Unpredictable (“chaotic”) dynamics has high sensitivity to initial conditions.
- Chaotic dynamics can produce couplings (transitions) between different classes of periodic or (quasi-) random asymptotic states (vibrations/oscillations ↔ rotations).

Important examples: global climate, 3-body dynamics, forced mechanical or molecular oscillators, biological population dynamics, organ functionality, catalytic chemical reactions.

Analyze a simple (1D) chaotic system (climate rad balance, electric circuits)



Non-Linear Predator-Prey Dynamics



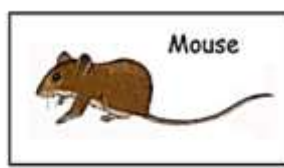
Owl



Snowshoe Hare



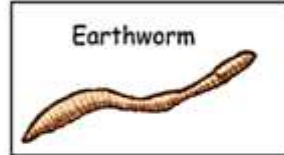
Bat



Mouse



Garter Snake



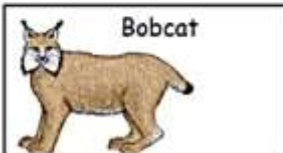
Earthworm



Bald Eagle



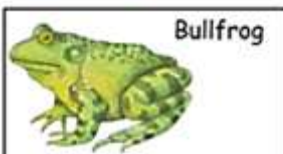
Mosquito



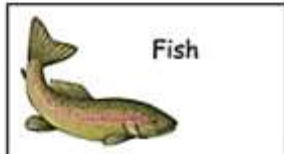
Bobcat



Grasshopper



Bullfrog



Fish

Predator-Prey competition for survival
Populations:

Species A $\rightarrow x(t) \leq 1$; reproduction rate a

Species B $\rightarrow y(t) \leq 1$; reproduction rate b

$$\dot{x} = \frac{dx}{dt} = (a - b)x \cdot [1 - x]$$

$$\dot{y} = \frac{dy}{dt} = (b - a)y \cdot [1 - y]$$

For small populations

$$x \ll x_{max} := 1 \rightarrow x(t) \propto \exp\{-(a - b) \cdot t\}$$

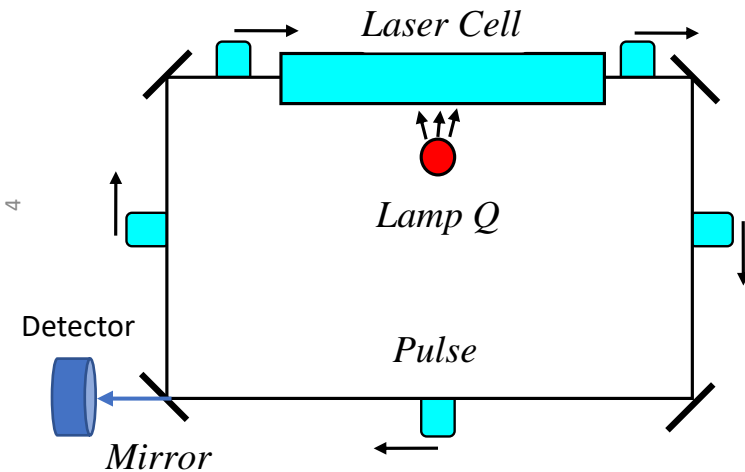
$$y \ll y_{max} := 1 \rightarrow y(t) \propto \exp\{-(b - a) \cdot t\}$$

$$\dot{x} = a \cdot x^2 - \phi(x, y) \cdot x$$

$$\dot{y} = b \cdot y^2 - \phi(x, y) \cdot y$$

Laboratory Experiments On Complex (Chaotic) Dynamics

Nonlinear Laser Amplifier



To investigate expected behavior of physical system \rightarrow study mathematical properties of profile function and associated maps.

\rightarrow Test with laboratory experiments.

Initial maximum laser cavity intensity $I = 1$

Once around the track $\rightarrow I_0 < 1 \rightarrow$ cavity

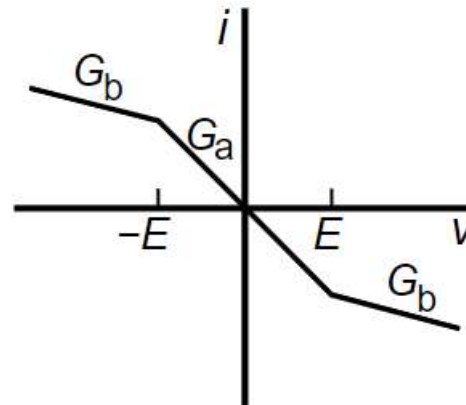
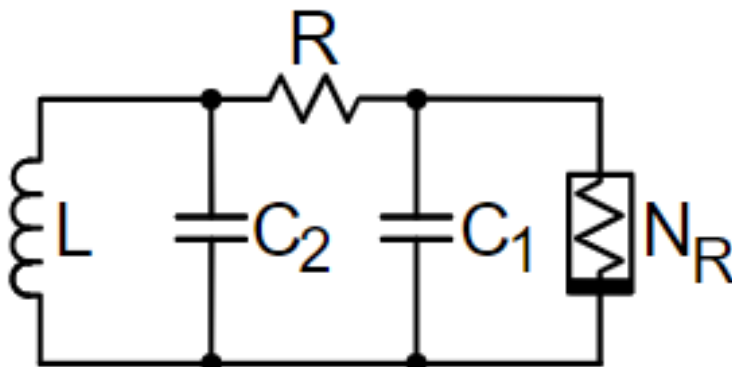
Stimulated emission \propto product of trigger intensity \times available inversion

$$\Rightarrow I_1 = \mu \cdot I_0 \cdot (1 - I_0) \text{ etc } n > 0$$

Logistic Map

$n =$ number of circuits completed

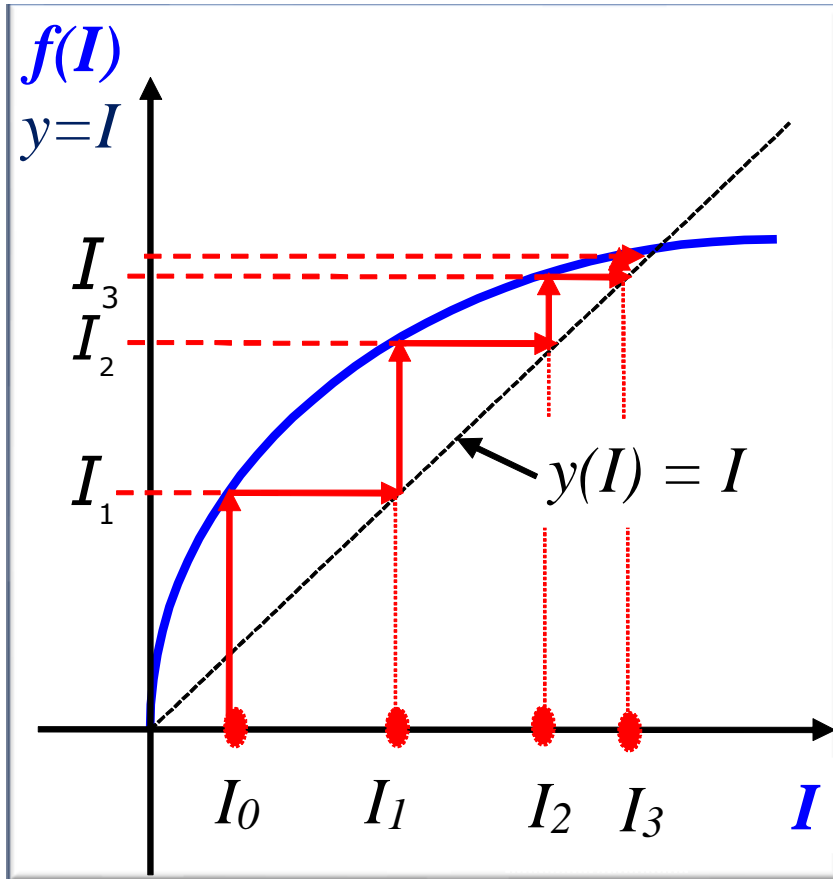
Chua's Nonperiodic Oscillator



Chua Diode N_R :
nonlinear negative
resistance =
amplifier with
positive feedback.

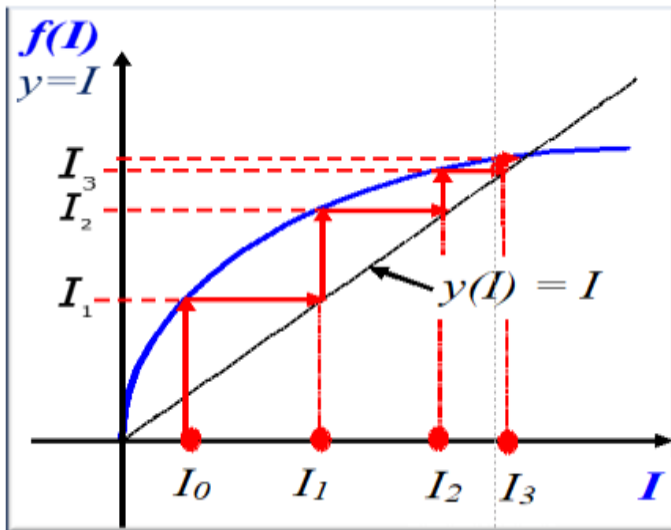
Graphing An Iteration (“Cobweb Plot”)

Sequence $I, f(I), f^2(I), \dots, f^n(I) \dots$
Plotted in 2D : $f(I_n)$ vs. I_n



1. Draw horizontal (I) and vertical (f) axes of a 2D Cartesian coordinate system, with equal divisions.
2. Plot the map profile function $f(I)$ vs. I .
3. Plot the diagonal line $y(I) = I$.
4. Start drawing the trajectory I_n , ($n = 0, 1, \dots$) by marking the initial point $I_{n=0}$ on the horizontal axis.
5. Draw a vertical arrow, from point I_n , to its functional value $I_{n+1} = f(I_n)$ on the profile curve.
6. Draw a horizontal arrow from point $f(I_n)$ to the point $f(I_n) = I_n$ on the $y = I$ line. This identifies the abscissa coordinate I_n for the next iteration.
7. Go to 5) and repeat 5) and 6) until done.

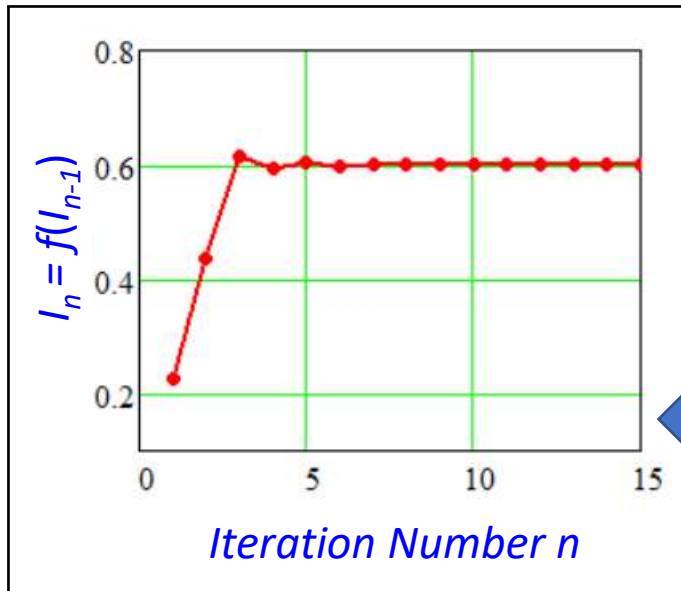
Graphing An Iteration II



Sequence $I, f(I), f^2(I), \dots, f^n(I) \dots$
Plotted in 2D

$$f(I_n) \text{ vs. } I_n$$

Different I_n : Laser intensity flickers

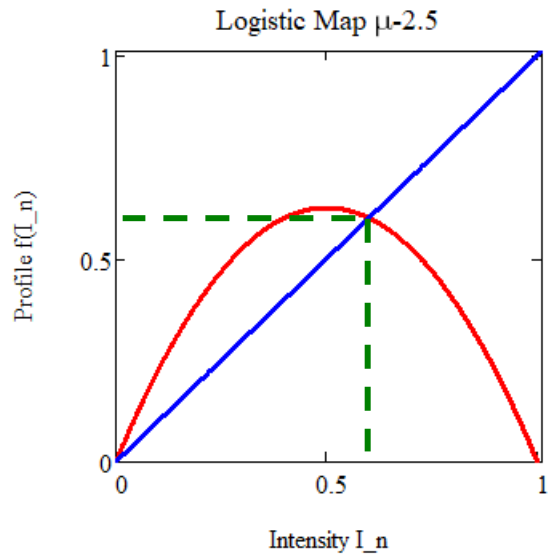


Sequence $I, f(I), f^2(I), \dots, f^n(I) \dots$
Plotted in 1D vs. I

Intensity I_n vs. Iteration number n

Intensity increases at first, then oscillates slightly. Finally, gets to steady-state operation after a few initial circuits (periods).

Logistic Map Features



Features of an iteration on a map depend on the profile function f , specifically on the amplification factor μ and the initial conditions, InCon for 1D: just the starting point I_0 .

Periodic point I_{pm} , period m : $f^m(I_{pm}) = I_{pm}$

*Fixpoints I_f : $f(I_f) = I_f$ *Trivial $I_f = 0$**

Non-trivial FP exist if $f(I)$ and $y(I) = I$ intersect

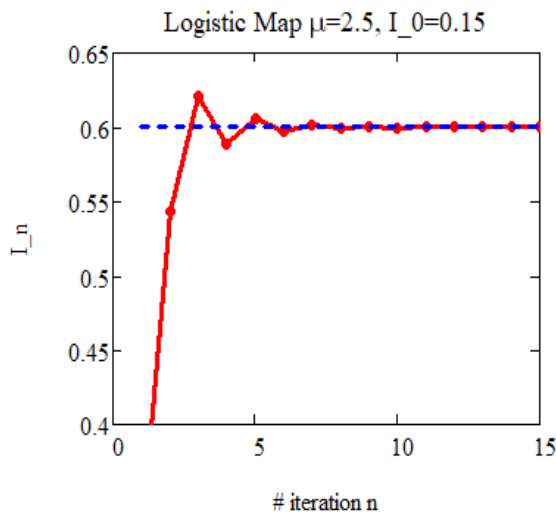
$$\text{Condition } I_f = \frac{\mu - 1}{\mu} \geq 0$$

Trajectory ensembles with $I_0 \approx I_f$

fixpoints "attract" or "repel" (scatter)

$$\left| \left(\frac{df}{dI} \right)_{I_f} \right| < 1 \quad (I_f = \text{Attractor}) \qquad \left| \left(\frac{df}{dI} \right)_{I_f} \right| > 1 \quad (I_f = \text{Repellor})$$

$$\left| \left(\frac{df}{dI} \right)_{I_f} \right| = 0 \quad (I_f = ???)$$

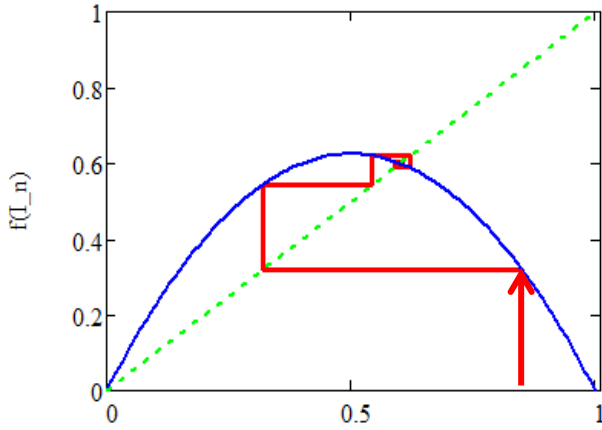


Chaotic behavior if sensitivity to initial condition.

Order and Chaos Parameter Dependence

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Logistic Map $\mu=2.5$, $I_0=0.85$



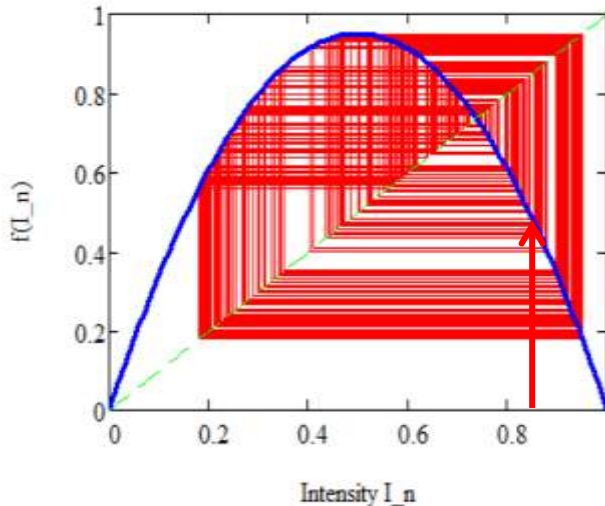
$\mu = 2.5$: Fixpoint = attractor. All trajectories end up in this point: Laser operation stable after startup.

$\mu = 3.8$ Fixpoint = strange attractor.

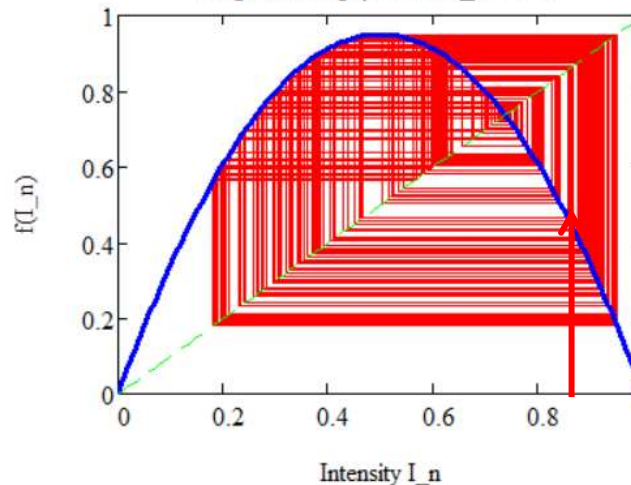
Trajectories spiral initially around fixpoint: intensity blinks slightly. After a few cycles, oscillations between 3 and 4 different brightness levels, highly unstable, essentially right after start.

Sensitivity to initial conditions \rightarrow chaotic operation

Logistic Map $\mu=3.8$, $I_0=0.85$

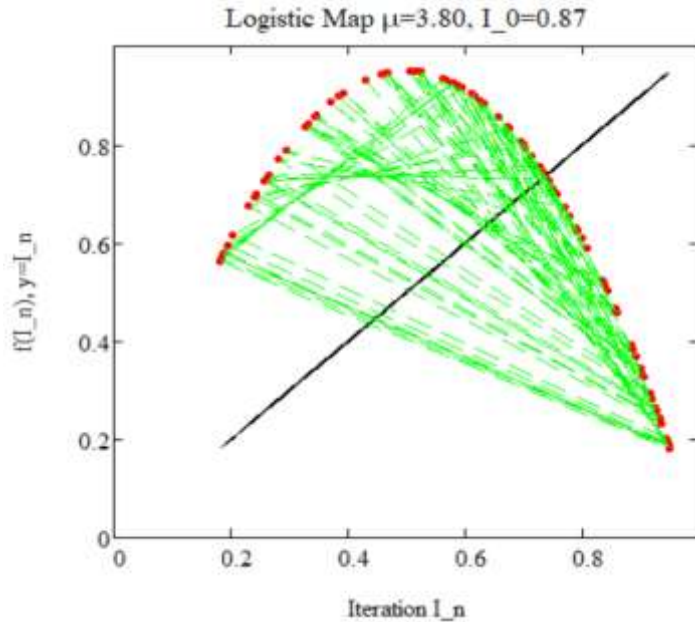


Logistic Map $\mu=3.8$, $I_0=0.87$



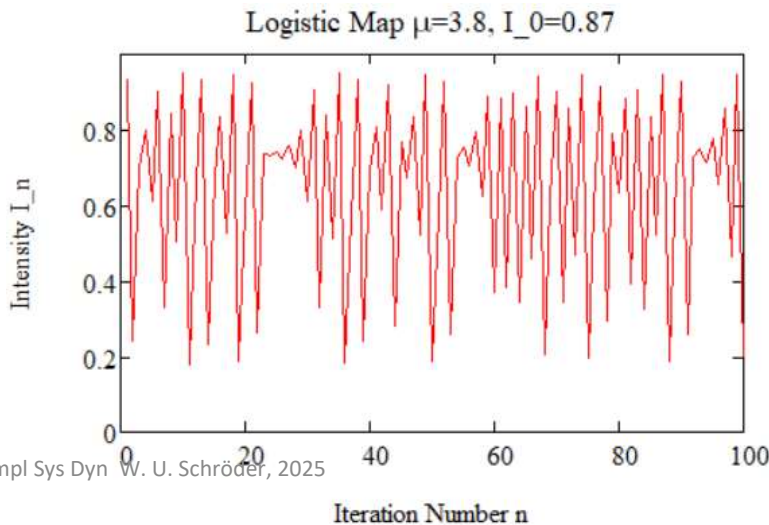
Slightly different I_0 lead to very different time behavior.
N=500 iterations

Chaotic Map Trajectories



Same example as above, plot showing only the iterative intensities I_n on the curve representing the map profile function $f(I)$.

A large part of the brightness spectrum is covered by the trajectory already after 500 iteration. No apparent intensity pattern. Intensity flashes between bright and dim.



Same example as above, plot shows iterative intensities I_n vs n . Some, but not exact similarities, intermittency domains, strongly dependent on initial condition I_0 .

Sensitivity to Initial Conditions

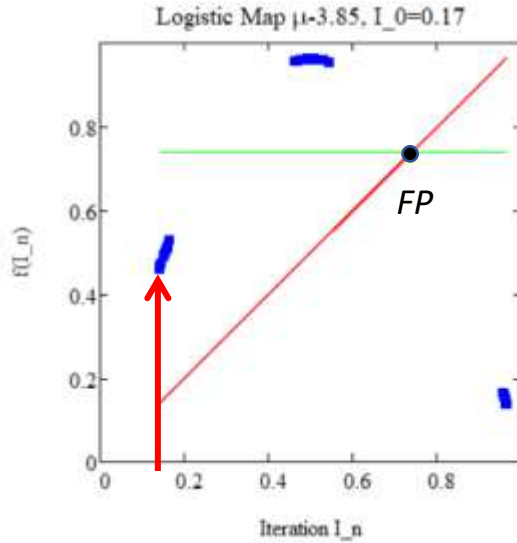


Illustration of sensitivity to initial conditions for $\mu = 3.85$, fixpoint at $I = 0.74$, *strange attractor*
IC: $I_0 = 0.170$, $N = 100$ iterations
 Blinking alternatively with 3 different intensities

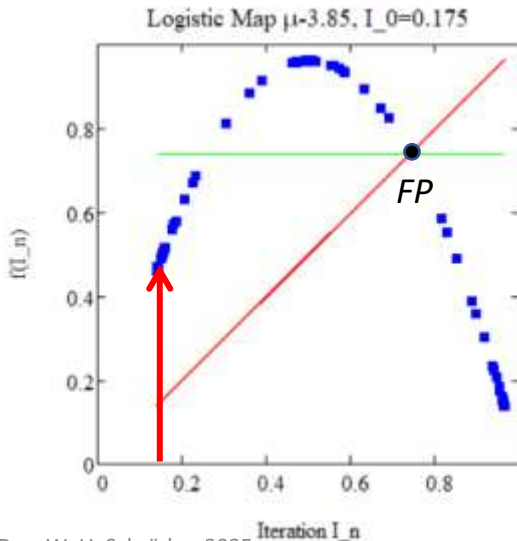


Illustration of sensitivity to initial conditions for $\mu = 3.85$, fixpoint at $I = 0.74$, *strange attractor*
IC: $I_0 = 0.175$, $N = 100$ iterations
 Blinking alternatively with a continuum of intensities filling most of the accessible intensity range

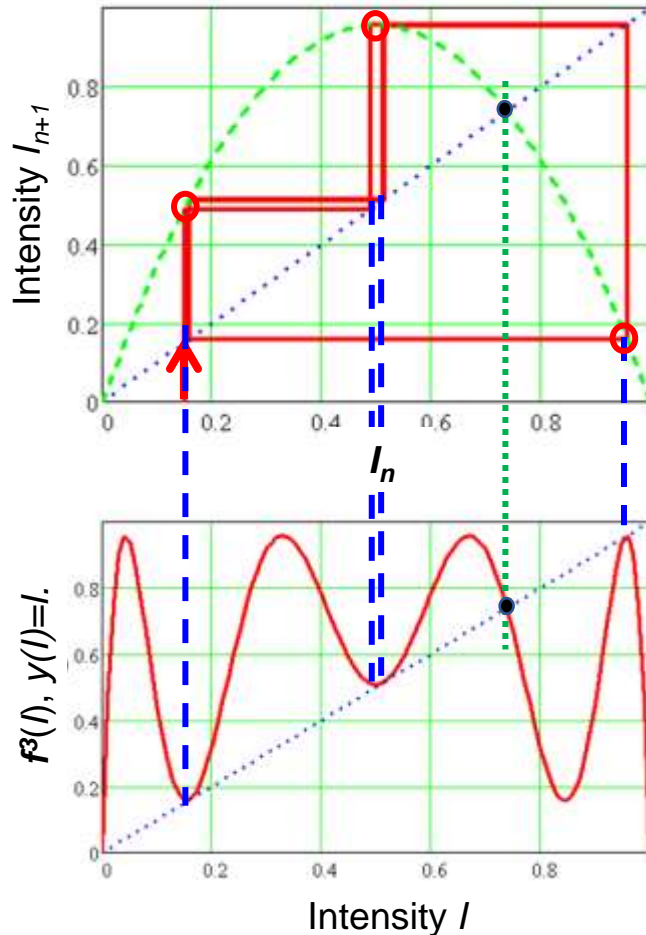
Question: What would the probability distribution look like for the entire chain of N_{total} iterations?

$$I \in \left[I - \frac{\Delta I}{2}, I + \frac{\Delta I}{2} \right) \rightarrow \frac{\Delta P(I)}{\Delta I} := \frac{N(I_n = I)}{N_{total}}; 0 \leq I(t) \leq 1$$

$$\text{Normalization} : P = \sum_{n=1}^{N_{total}} \left(\frac{\Delta P(I_n)}{\Delta I} \right) \cdot \Delta I = 1 \quad (= 100\%)$$

Periodic Flashes

Metastable/intermittent processes, strange but predictable trajectories: search for “periodic points.” Points of period $n =$ stable (attractor) fixpoints of $f^n(x)$.

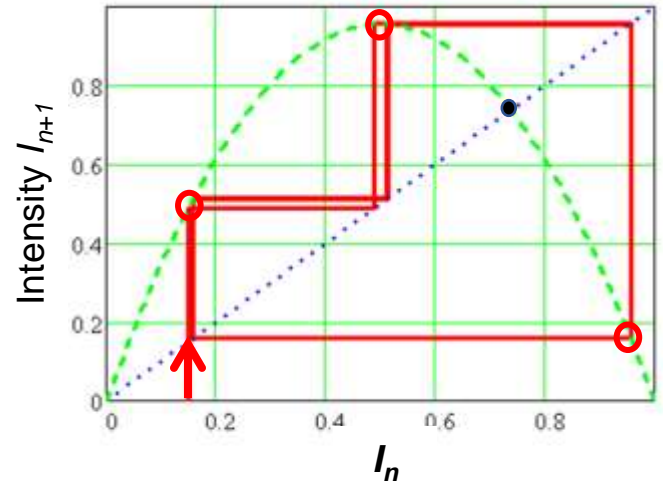


Fixpoint at $I_f = 0.653$ (black dot)
 = “strange” attractor:
 Trajectory cycles around I_f in 3 periods.

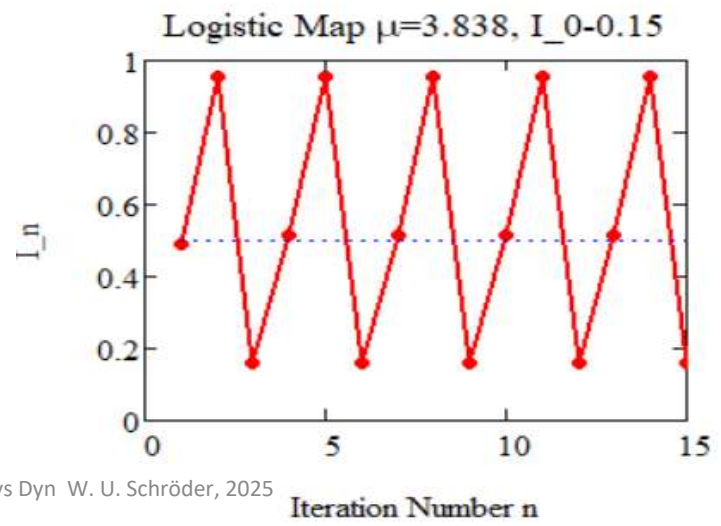
Finding members of strange cycle: look
 for tangential touching of curve
 $f^3(\mu, I)$ at $y(I)=I$.

Periodic Flashes

Metastable/intermittent processes, strange but predictable trajectories: search for “periodic points.” Points of period $n =$ stable (attractor) fixpoints of $f^n(x)$.



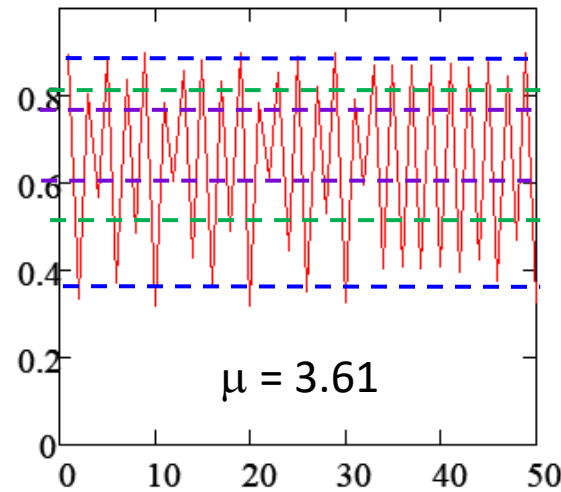
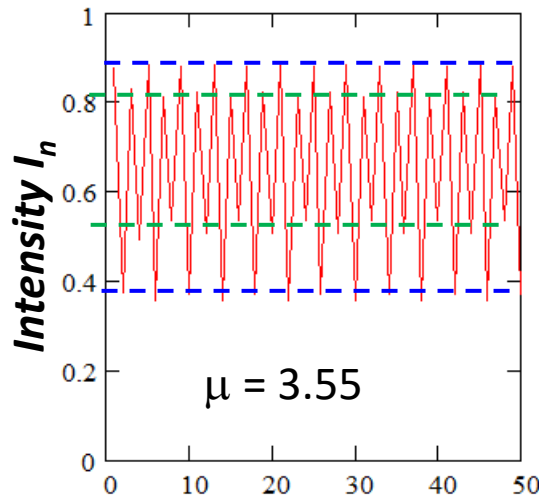
Fixpoint at $I_f = 0.653$ (black dot)
 = “strange” attractor:
 Trajectory cycles around I_f in 3 periods.



Pattern $f(\mu, I)$ exhibiting periodic triplet
 blinking patterns : medium, high, low
 intensity.
 Deterministic

Linear and Non-Linear Dynamical Regimes

- $0.0 \leq \mu \leq 1.0$: No non-trivial fixpoints $\rightarrow I_n \xrightarrow{n \rightarrow \infty} 0$
 $1.0 < \mu \leq 3.0$: 1 non-trivial attractor fixpoint, "deterministic chaos"
 Trajectory deterministic for precise initial condition
 $3.0 < \mu \leq 3.6$: 1 non-trivial repellor fixpoint, "deterministic chaos"
bi-stable flickering with alternating intensities, several n -frequency doublings (bifurcations)
 $3.6 < \mu < 3.8$: 1 non-trivial repellor fixpoint, *intermittent flicker*
 $3.8 \leq \mu < 4.0$: 1 non-trivial repellor fixpoint, *chaotic dynamics*

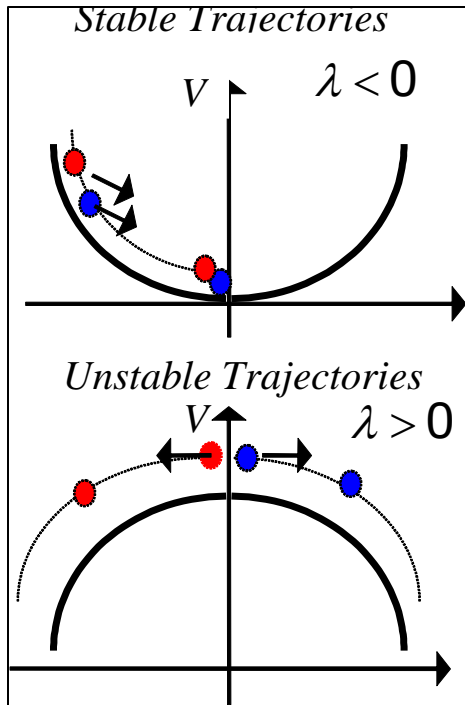


Left: Frequency doubling

Right: Two frequency doublings with intermittency.

Iteration Number n

Lyapunov Stability Criterion



2 trajectories initially separated by $\Delta x = \varepsilon$
 Separation at iteration n (time t_n)

$$\delta(\varepsilon, n) := |f^n(x) - f^n(x + \varepsilon)| = |\varepsilon| \cdot e^{\lambda \cdot n}$$

Stability $\lambda < 0$

$$\text{Ln} \left\{ \frac{|f^n(x) - f^n(x + \varepsilon)|}{\varepsilon} \right\} = \lambda \cdot n \rightarrow \lambda = \frac{1}{n} \cdot \text{Ln} \left| \frac{df^n(x)}{dx} \right|$$

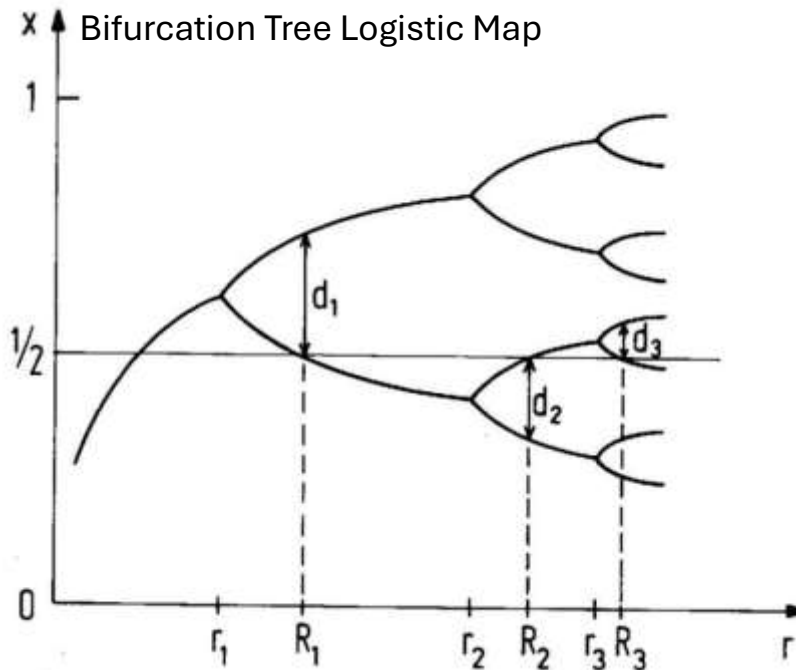
$$f^n(x) = f(x_{n-1}) = f(f(x_{n-2})) = \dots = f(\dots(x_0)\dots)$$

$$\frac{df^n}{dx} = \frac{df(x_{n-1})}{dx_{n-1}} \cdot \frac{dx_{n-1}}{dx} = \frac{df(x_{n-1})}{dx_{n-1}} \cdot \frac{dx_{n-1}}{dx_{n-2}} \cdot \frac{dx_{n-2}}{dx} = \dots =$$

$$df^n/dx = f'(x_{n-1}) \cdot f'(x_{n-2}) \cdot f'(x_{n-3}) \cdot f'(x_{n-4}) \cdot \dots \cdot f'(x_0)$$

$\lambda = \frac{1}{n} \cdot \sum_{i=0}^{n-1} \text{Ln} f'(x_i) $
--

Tree of Successive Bifurcations



On ordinate $x_{i \rightarrow \infty}$ asymptotic iterates (fix or periodic points x_n , for large n) plotted vs. amplification/scaling factor r , for the logistic map. Similar behavior for related maps of the kind

$$f(x) := \mu \cdot x^k \cdot (1 - x^k)^{1/k};$$

Logistic map $k = 1$

Feigenbaum Scaling : Bifurcation points

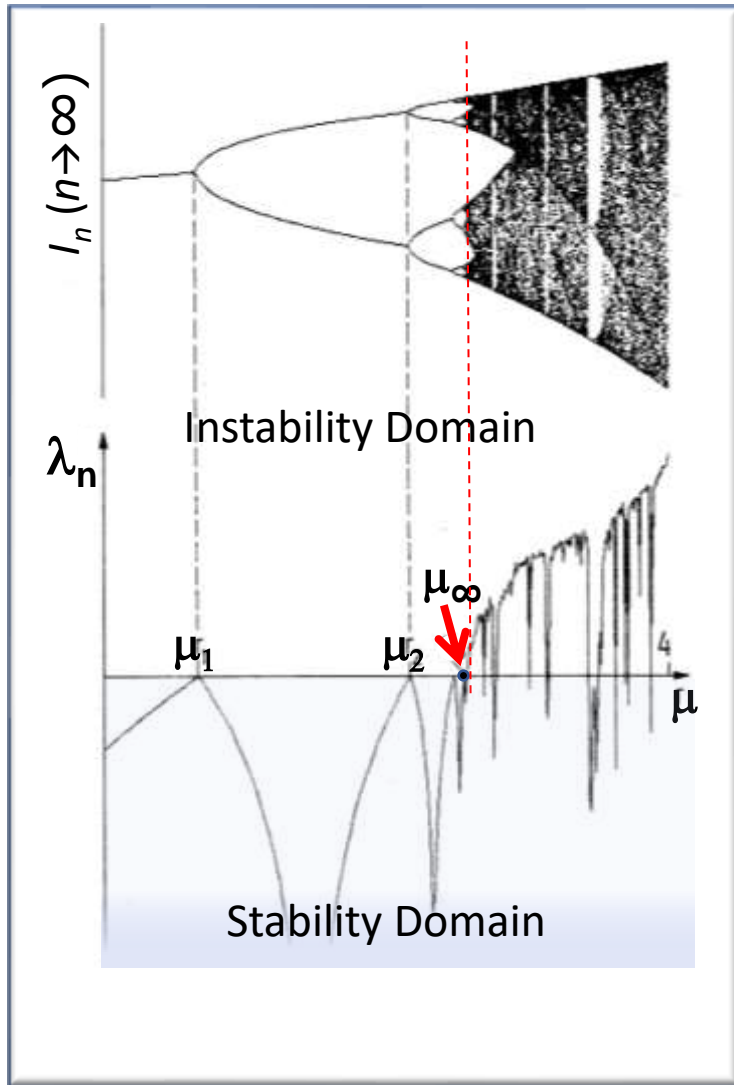
$$r_n = r_\infty - \text{const} \cdot \delta^{-n}, n \gg 1$$

$$r_\infty = 3.5699456$$

$$\delta = 4.66920160$$

$$\frac{d_n}{d_{n+1}} = -\alpha, \quad n \gg 1; \quad \alpha = 2.502907875$$

Lyapunov Exponent = $f(\mu)$



Asymptotic iterates and Lyapunov exponent for the logistic map:

Gain factors μ determine dynamics

$\mu \geq \mu_1$: at least 1 bifurcation

$\mu \geq \mu_2$: at least 2 bifurcations

$\mu \geq \mu_\infty$: λ generally > 0 , \rightarrow Chaotic system behavior, small special domains for (relatively) orderly behavior.

Similar :

$$f(x) := \mu \cdot x^k (1 - x^k)^{1/k} \text{ and}$$

$$f(x) := \mu(x) \cdot x^k (1 - x^k)^{1/k}$$

Outlook and Conclusions (for our environment)

- ❑ Non-linear dynamics of complex systems can lead to orderly or chaotic behavior, depending on non-linearity → amplification μ for log. map. strength of **positive feed back** loops.
- ❑ Chaotic dynamics include sudden wild oscillations in system properties at “Tipping Points,”
- ❑ Given an observed non-linear behavior for a specific system (example: Earth albedo), it is possible to estimate a Logistic-Map model amplification parameter μ .
- ❑ Extensions of simple 1D Logistic-Map model include multiple dimensions $\{x,y\}$ provide understanding of **population dynamics** (predator-prey)
$$dx/dt = \mu(x,y) \cdot x \cdot [1 - x] \quad dy/dt = \mu(x,y) \cdot y \cdot [1 - y]$$
- ❑ Earth albedo can change rapidly, leading to tipping points in climate.




Lyapunov Exponent

$$\lambda = \frac{1}{n} \operatorname{Ln} \left| \frac{df^n(x)}{dx} \right|$$

Implicit function

$$f^n(x) = f(x_{n-1}) = \dots = f(f(f(x_{n-4}))) \dots$$

 = x_0

Chain Rule for differentiation:

$$\frac{df^n(x)}{dx} = \frac{df(x_{n-1})}{dx_{n-1}} \cdot \frac{dx_{n-1}}{dx} = \frac{df(x_{n-1})}{dx_{n-1}} \cdot \frac{dx_{n-1}}{dx_{n-2}} \cdot \frac{dx_{n-2}}{dx_{n-3}} \dots \frac{dx_1}{dx_0}$$

$$= \frac{df(x_{n-1})}{dx_{n-1}} \cdot \frac{df(x_{n-2})}{dx_{n-2}} \cdot \frac{df(x_{n-3})}{dx_{n-3}} \dots \frac{df(x)}{dx}$$

$$\operatorname{Ln} \left| \frac{df^n}{dx} \right| = \operatorname{Ln} \prod_{i=0}^{n-1} |f'(x_i)|_{x_i} = \sum_{i=0}^{n-1} \operatorname{Ln} |f'(x_i)|_{x_i}$$



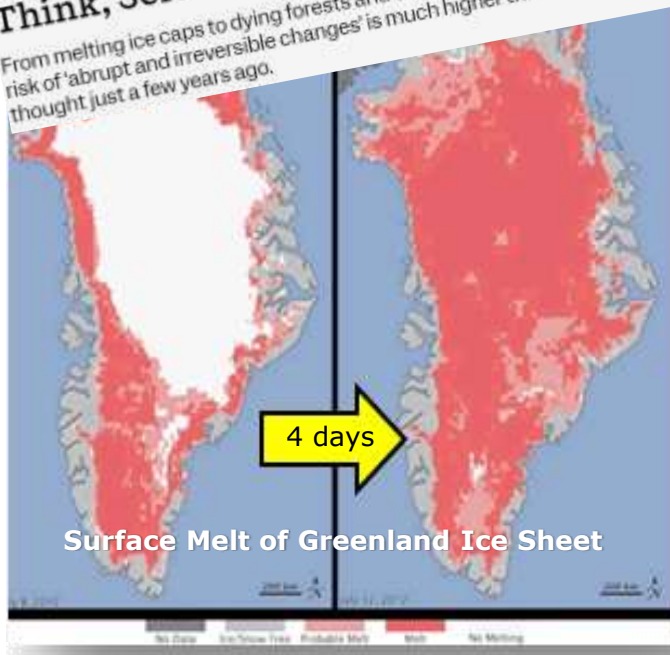
explicit, direct

$$\lambda_n = \frac{1}{n} \cdot \sum_{i=0}^{n-1} \operatorname{Ln} |f'(x_i)|_{x_i}$$

Large $n \rightarrow \infty$, test the shape of f at many positions x_i

Tipping Points in Earth Climate ?

Science
Climate Tipping Points Are Closer Than We Think, Scientists Warn
From melting ice caps to dying forests and thawing permafrost, the risk of 'abrupt and irreversible changes' is much higher than thought just a few years ago.



Non-linear and coupled effects in Earth current climate evolution → global warming, melting of sea ice , ice cap, desertification, ocean acidification, sea level rise,.....

Historic climate facts:

Earth climate has alternated between **Ice ages** (little and major) and **greenhouse** periods. Transition speed?

Do we have time to adapt or change pace?

Mind the fate of planet Venus (NYT 012921)

Earth albedo or surface reflectivity ϵ = important in maintaining radiation balance

Glaciation: increasing ice cover $\Delta\epsilon > 0 \rightarrow$ surface temperature change $\Delta T < 0$

Warming: decreasing ice cover $\Delta\epsilon < 0 \rightarrow$ surface temperature change $\Delta T > 0$

Albedo is non-monotonic function of important driving parameters, has extrema!

Earth Albedo Model

Albedo is **non-monotonic function** of important driving parameters.

Combine ε parameter dependence to model **non-linear** dependence on history:

$$\varepsilon(t + \Delta t) = \alpha \cdot \varepsilon(t) - \beta \cdot \varepsilon^2(t) + \dots; \quad \text{parameters } \alpha, \beta = f(\text{CO}_2, \dots)?$$

Since $\varepsilon(t)$ is non – monotonic and must have an extremum

*→ **sign**(α) = **sign**(β), choose $\alpha, \beta > 0$*

Adopt discrete time steps t_n (days, months, years, ..., centuries) →

$$\varepsilon_{n+1} = \varepsilon_n(t + n \cdot \Delta t) \approx \alpha \cdot \varepsilon_n - \beta \cdot \varepsilon_n^2 \quad \text{"Iteration"}$$

Variable transformation →

Profile function $f(\varepsilon) = \mu \cdot \varepsilon \cdot (1 - \varepsilon)$ "Logistic Map"

$$\varepsilon_{n+1} = f(\varepsilon_n) = f(f(\varepsilon_{n-1})) = f(f(f(\varepsilon_{n-2}))) = f^3(\varepsilon_{n-2}) \quad \text{Iterative Logistic Map}$$

Intermediate Summary

Linear force laws are deterministic → lead to predictable time evolution and are not sensitive to initial conditions: Small changes in initial conditions → small changes in final positions and momenta

$$f(x + \Delta x) \approx f(x) + \Delta x \cdot f'(x)$$

- Complex, unpredictable (Chaotic) dynamics can be caused by non-linear force laws for certain complex systems, which have specific sets of properties (→ model parameters).
- Complex, unpredictable (Chaotic) dynamics can be caused by correlated motion along different degrees of freedom. Rate equations for different d.o.f. become substantially entangled.
- Predictable (“orderly”) dynamics is characterized by insensitivity to initial conditions.
- Unpredictable (“chaotic”) dynamics is associated with high sensitivity to initial conditions.
- Both, orderly and chaotic dynamics can lead to asymptotically ($t \rightarrow \infty$) predictable states (deterministic chaos).
- Chaotic dynamics can lead to different classes of periodic or (quasi-) random asymptotic states.

Important examples: global climate, biological population dynamics (intra/inter-species competition), organ functionality, catalytic chemical reactions.

Analyze a simple (1D) chaotic system (climate rad balance, electric circuits)

