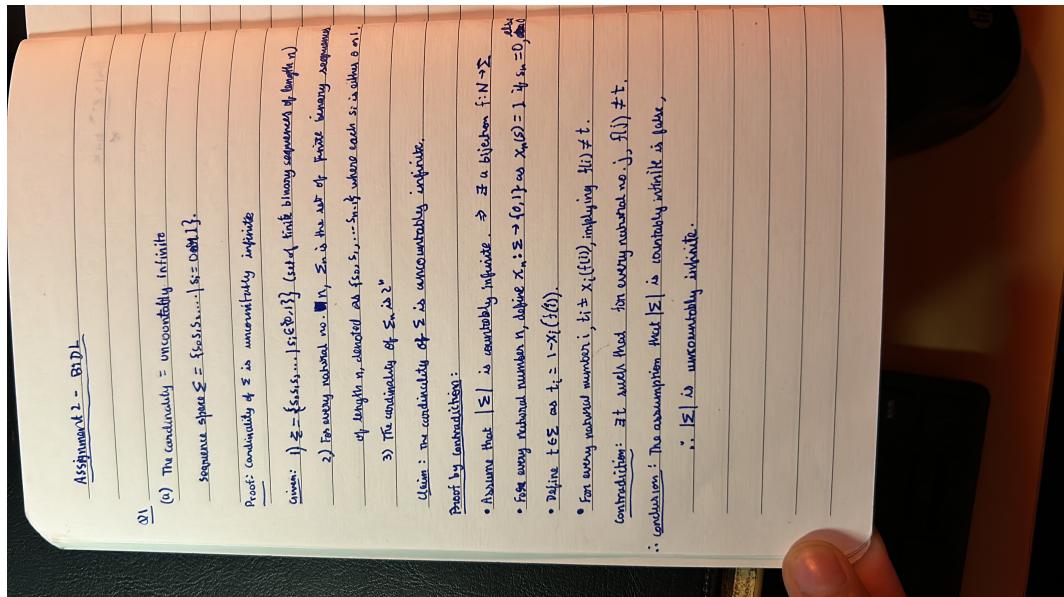


Assignment2

February 21, 2024

Q1.



a)

91

(c) Prove: Shift Map $\sigma(\cdot)$ and some properties of σ -chaos.

3) separatrix s

- A dynamical system $\sigma : \Sigma \rightarrow \Sigma$ is the set of infinite binary sequences, denoted $s = s_0 s_1 s_2 \dots$ where each s_i is either 0 or 1.
- The shift map $\sigma(s)$ is defined as $\sigma(s_0 s_1 s_2 \dots) = s_1 s_2 s_3 \dots$
- $d(s, t)$ is the metric on Σ , defined as $\sum_{i=0}^{\infty} \frac{|s_i - t_i|}{2^i}$ (metric on Σ)

Claim: The shift map $\sigma(\cdot)$ satisfies all three properties of chaos

- Then $d(s, t)$
- Given n
- Construct sequences
- From this
- Then $d(s, t) < \epsilon/2^n$ if $d(s_i, t_i) < \epsilon/2^n$ for all $0 \leq i \leq n-1$

Proof:

1) Define Periodic Points

- A periodic point x of σ has period k , i.e. $\sigma^k(x) = x$ for some k . Conclusion: The
- Every rational number p/q (where $q \neq 0$) can be represented as a periodic point with period $k = q$.

QED

2) Transitivity

- Define x with $x_i = 1$ if $i \equiv 0 \pmod{q}$ and $x_i = 0$ otherwise
- $\sigma(x)_i = x_{(i+1) \pmod{q}}$ and 0 otherwise
- After q steps $\sigma^q(x) = x$, making x periodic with period q .
- The set of rational nos. with odd denominators is dense, so the periodic points under σ are also dense in Σ .
- Conclusion: The shift map satisfies the density of periodic points property.

2) Density

3) A dynamical system is transitive if for any open sets $U, V \subseteq \Sigma$, there exists $n \in \mathbb{N}$ such that $\sigma^n(U) \cap V \neq \emptyset$

Let U and V be non-empty open sets in Σ . Construct a sequence $s \in U$ and $t \in V$ with the first n digits matching U and last m digits 1's. Then $\sigma^n(s)$ will have the first n digits equal to U , achieving $\sigma^n(s) \cap V \neq \emptyset$

Conclusion: The shift map satisfies the transitivity property.

b)

(b) Proof: continuity of the shift map

Given: 1) $\Sigma = \{s_0 s_1 s_2 \dots\}$ ($s_i = 0, 1$) (set of infinite binary sequences)

2) $\sigma : \Sigma \rightarrow \Sigma$ is defined as $\sigma(s_0 s_1 s_2 \dots) = s_1 s_2 s_3 \dots$

3) $d(s, t) := \sum_{i=0}^{\infty} |s_i - t_i|/2^i$ (metric on Σ)

* Claim: The shift map $\sigma(\cdot)$ is continuous

Proof

- For $s, t \in \Sigma$ and $\epsilon > 0$, find $\delta > 0$ such that if $d(s', t') < \delta$ for every
- any $s' \in \Sigma$, then $d(\sigma(s'), \sigma(t')) < \epsilon$
- choose $N \in \mathbb{N}$ such that $2^{-N} < \epsilon/2$.
- Set $\delta = \epsilon/2^N$. If $d(s', t') < \delta$, then $|s'_i - t'_i| < \epsilon/2^N$ for all $0 \leq i \leq N-1$
- Analyze $d(\sigma(s'), \sigma(t'))$

$$\begin{aligned} d(\sigma(s'), \sigma(t')) &= \sum_{i=0}^{\infty} |\sigma(s')_i - \sigma(t')_i| = \sum_{i=0}^{\infty} |s'_{i+N} - t'_{i+N}| + \sum_{i=N}^{\infty} |s'_{i+N} - t'_{i+N}| \\ &\stackrel{\text{Bound the terms for } i < N}{\Rightarrow} \sum_{i=0}^{N-1} |s'_{i+N} - t'_{i+N}| \leq \sum_{i=0}^{N-1} \frac{|s'_i - t'_i|}{2^i} = \frac{\epsilon}{2^N} \\ &\stackrel{\text{Bound the terms for } i \geq N}{\Rightarrow} \sum_{i=N}^{\infty} |s'_{i+N} - t'_{i+N}| \leq \sum_{i=N}^{\infty} \frac{2}{2^i} = \frac{2}{2^N} = \frac{\epsilon}{2} \\ &\Rightarrow \text{Combine the bounded terms} \end{aligned}$$

$d(\sigma(s'), \sigma(t')) \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$

Conclusion: For any $\epsilon > 0$, there exists $\delta > 0$ such that if $d(s', t') < \delta$ for any $s' \in \Sigma$, then $d(\sigma(s'), \sigma(t')) < \epsilon$.

Therefore the shift map $\sigma(\cdot)$ is continuous

2) sensitive dependence on initial conditions:

- A dynamical system is sensitively dependent on initial conditions if for any $x \in \mathbb{Z}$ and any $\varepsilon > 0$, there exists $y \in \mathbb{Z}$ with $d(x, y) < \varepsilon$ and $n \in \mathbb{N}$ such that $|\sigma^n(x) - \sigma^n(y)| > \varepsilon$
- Let $x \in \mathbb{Z}$ and $\varepsilon > 0$, choose n large enough that $2^{-n} < \varepsilon/2$
- Construct y by changing only the n th digit of x (from 0 to 1 or vice versa)
- Then $d(x, y) = 2^{-n} < \varepsilon/2$
- After n iterations, the difference between $\sigma^n(x)$ and $\sigma^n(y)$ will be necessarily the n th digit difference, making $|\sigma^n(x) - \sigma^n(y)| = 1 > \varepsilon$

Remark. Condition 2) The shift map satisfies the sensitive dependence on initial conditions

because

$$QFD \text{ (shift map)} \quad d(\sigma^n(x), \sigma^n(y)) \geq 2^{-n} \text{ for all } n \in \mathbb{N}.$$

Therefore, the shift map $\sigma(\cdot)$ exhibits all three properties of chaos, solidifying its chaotic behavior within the dynamical system (\mathbb{Z}, d, σ) .

$$\sigma^n([x, y]) = [x, y] + [0, 2^{-n}]$$

or similarly

$$d(\sigma^n(x), \sigma^n(y)) = 2^{-n} \text{ for all } n \in \mathbb{N}.$$

Q.E.D.

$$3 < \lambda < 4 \quad |\lambda - 3| < 1 \quad : \quad \exists n \in \mathbb{N} \text{ such that }$$

\Rightarrow chaos: $\lambda > 3$ is a necessary condition for chaos

thus

when

as λ

boundary

Q2.

Q2

Based: Repelling Fixed point ($|f'(p)| > 1$)

Conclusion: f is continuously differentiable f^n with fixed point $x = p$,
 $|f'(x)| \geq |f'(p)| > 1$ with $\exists \delta > 0$ for all $x \in \mathbb{R}$ from some $\delta > 0$.

Claim: The fixed point $x = p$ is repelling

Proof:

(1) Mean value theorem: take backwards of f^n around p :

- since f is differentiable, there exist $\delta > 0$: for all $x \in \mathbb{R}$,

$$|x - p| < \delta \text{ implies there exist } c \in (x, p) \text{ such that}$$

$$|f(x) - f(p)| = |f(c)| |x - p|.$$

2) lower bound:

- choose δ so that $|f'(c)| > 1/2$ for $c \in (x, p)$ and $|x - p| < \delta$

$$\bullet \text{Then: } |f(x) - f(p)| \geq |x - p| / 2$$

3) N-fold iteration:

- apply the inequality n times (where n is chosen later)

$$|f^n(x) - f^n(p)| \geq |x - p| / 2^n$$

4) choosing n

- select n such that $2^{-n} < \varepsilon/4$. For any $x \neq p$ with $|x - p| < \varepsilon$: $|f^n(x) - p| \geq \varepsilon/4 > \varepsilon$

Conclusion: For every $\varepsilon > 0$, there exists $n \in \mathbb{N}$: for all $x \in \mathbb{R}$,

$$|f^n(x) - p| > \varepsilon$$

$\therefore p$ is repelling

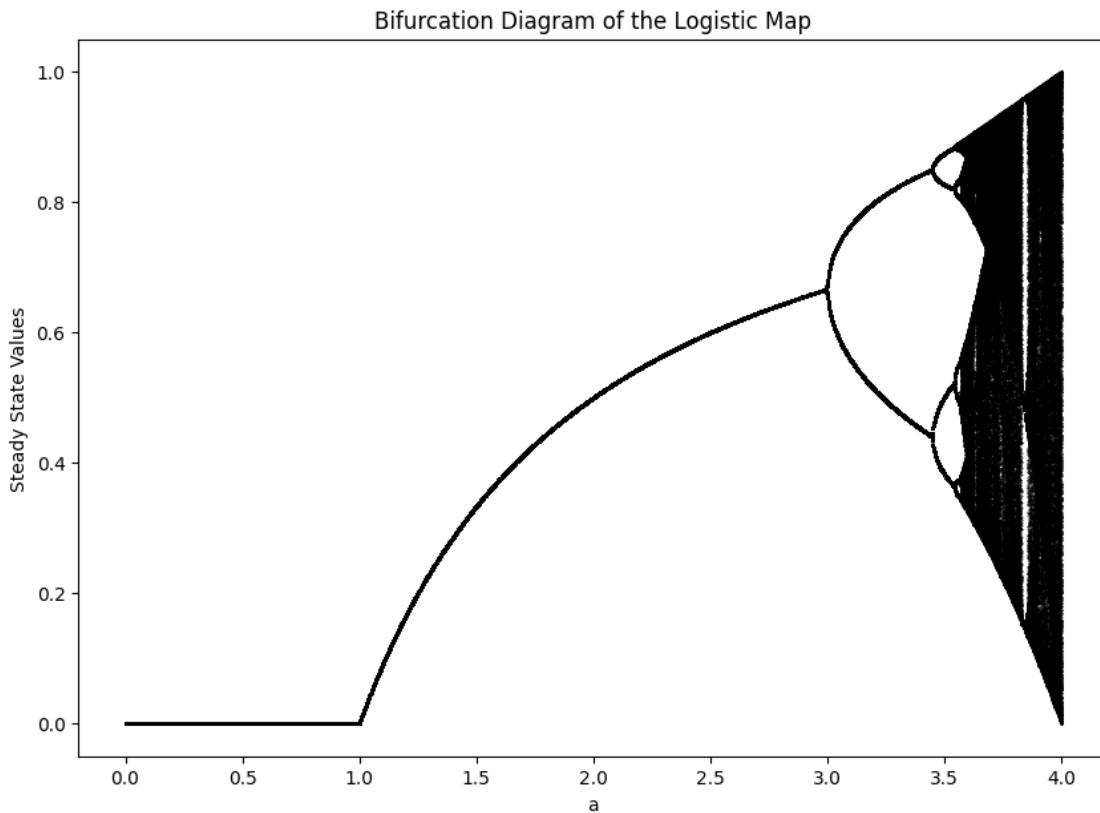
```

# After the first 500 transient values, store the steady state values
if i >= 500:
    steady_states.append((a, x))

# Convert the list of steady state values into a numpy array
steady_states = np.array(steady_states)

# Plot the bifurcation diagram
plt.figure(figsize=(10, 7))
plt.scatter(steady_states[:, 0], steady_states[:, 1], s=0.1, color='black')
plt.title('Bifurcation Diagram of the Logistic Map')
plt.xlabel('a')
plt.ylabel('Steady State Values')
plt.show()

```



```
[15]: # Generate different values of a between 0 and 1
a_values = np.linspace(0, 1, 2000)

# Initialize an empty list to store the steady state values
steady_states = []
```

```

# Iterate over the a values
for a in a_values:
    # Start from a random initial value
    x = np.random.rand()

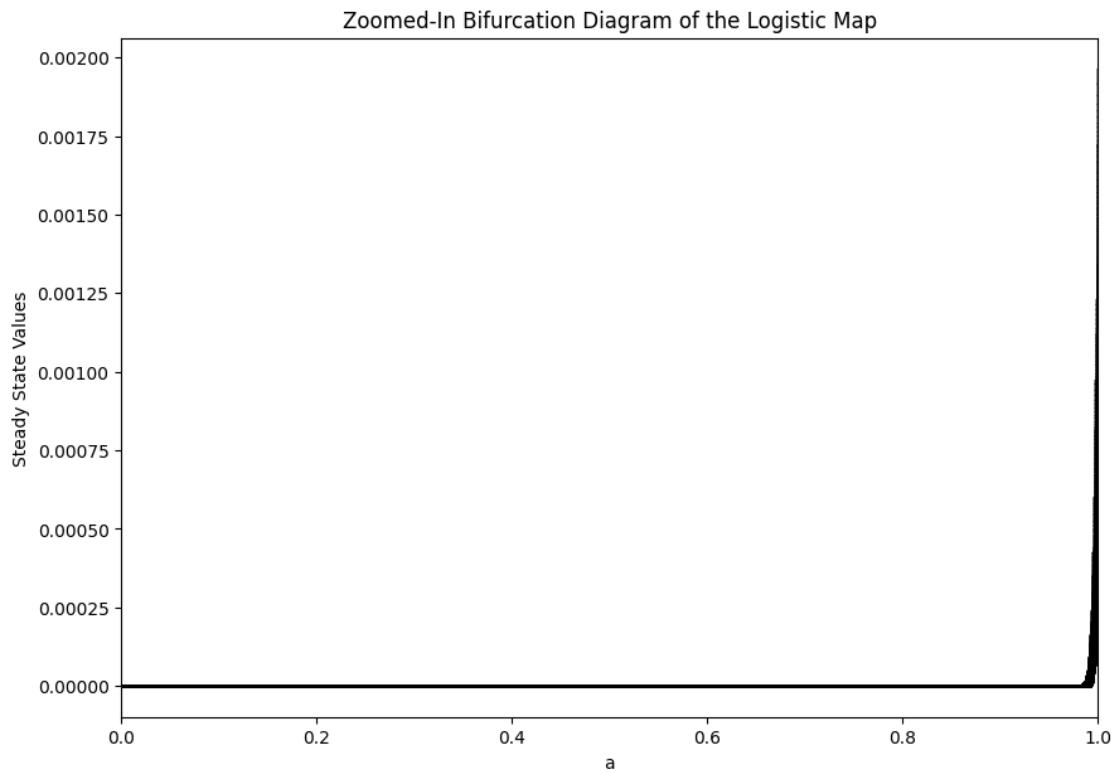
    # Perform 1000 iterations
    for i in range(1000):
        x = logistic_map(x, a)

    # After the first 500 transient values, store the steady state values
    if i >= 500:
        steady_states.append((a, x))

# Convert the list of steady state values into a numpy array
steady_states = np.array(steady_states)

# Plot the zoomed-in bifurcation diagram
plt.figure(figsize=(10, 7))
plt.scatter(steady_states[:, 0], steady_states[:, 1], s=0.1, color='black')
plt.title('Zoomed-In Bifurcation Diagram of the Logistic Map')
plt.xlabel('a')
plt.ylabel('Steady State Values')
plt.xlim([0, 1])
plt.show()

```



As for the mathematical explanation, the logistic map equation is defined as $x_n = ax_n - 1(1 - xn - 1)$

When a is between 0 and 1, the logistic map will always converge to 0 regardless of the initial value of x . This is because for $0 < a < 1$, the term $ax(1 - x)$ will always be less than x for any x in the interval $[0, 1]$. Therefore, the sequence $\{x_n\}$ generated by the logistic map will be a decreasing sequence that converges to 0. This is why you see a concentration of values at zero in the bifurcation diagram for $0 < a < 1$.

```
[16]: # Generate different values of a between 1 and 3
a_values = np.linspace(1, 3, 2000)

# Initialize an empty list to store the steady state values
steady_states = []

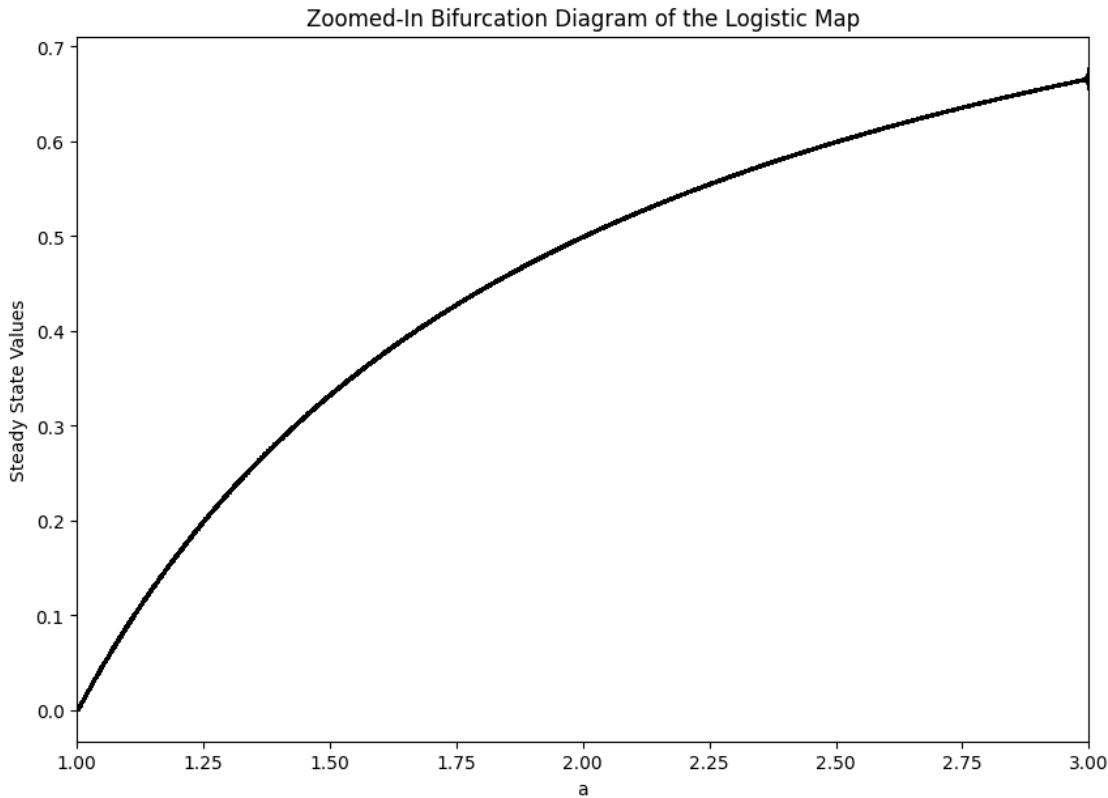
# Iterate over the a values
for a in a_values:
    # Start from a random initial value
    x = np.random.rand()

    # Perform 1000 iterations
    for i in range(1000):
        x = logistic_map(x, a)

    # After the first 500 transient values, store the steady state values
    if i >= 500:
        steady_states.append((a, x))

# Convert the list of steady state values into a numpy array
steady_states = np.array(steady_states)

# Plot the zoomed-in bifurcation diagram
plt.figure(figsize=(10, 7))
plt.scatter(steady_states[:, 0], steady_states[:, 1], s=0.1, color='black')
plt.title('Zoomed-In Bifurcation Diagram of the Logistic Map!')
plt.xlabel('a')
plt.ylabel('Steady State Values')
plt.xlim([1, 3])
plt.show()
```



mathematical explanation, when a is between 1 and 3, the logistic map will converge to a single value that is not zero. This is because for $1 < a < 3$, the term $ax(1 - x)$ will be less than x for $x > 1/a$, and greater than x for $x < 1/a$. Therefore, the sequence $\{x_n\}$ generated by the logistic map will oscillate around $1/a$ and eventually converge to this value. This is why there is a spread of values in the bifurcation diagram for $1 < a < 3$, and not a concentration at zero.

```
[23]: # Generate different values of a between 3 and 3.4
a_values = np.linspace(3, 3.4, 2000)

# Initialize an empty list to store the steady state values
steady_states = []

# Iterate over the a values
for a in a_values:
    # Start from a random initial value
    x = np.random.rand()

    # Perform 1000 iterations
    for i in range(1000):
        x = logistic_map(x, a)

    # After the first 500 transient values, store the steady state values
    if i >= 500:
        steady_states.append(x)
```

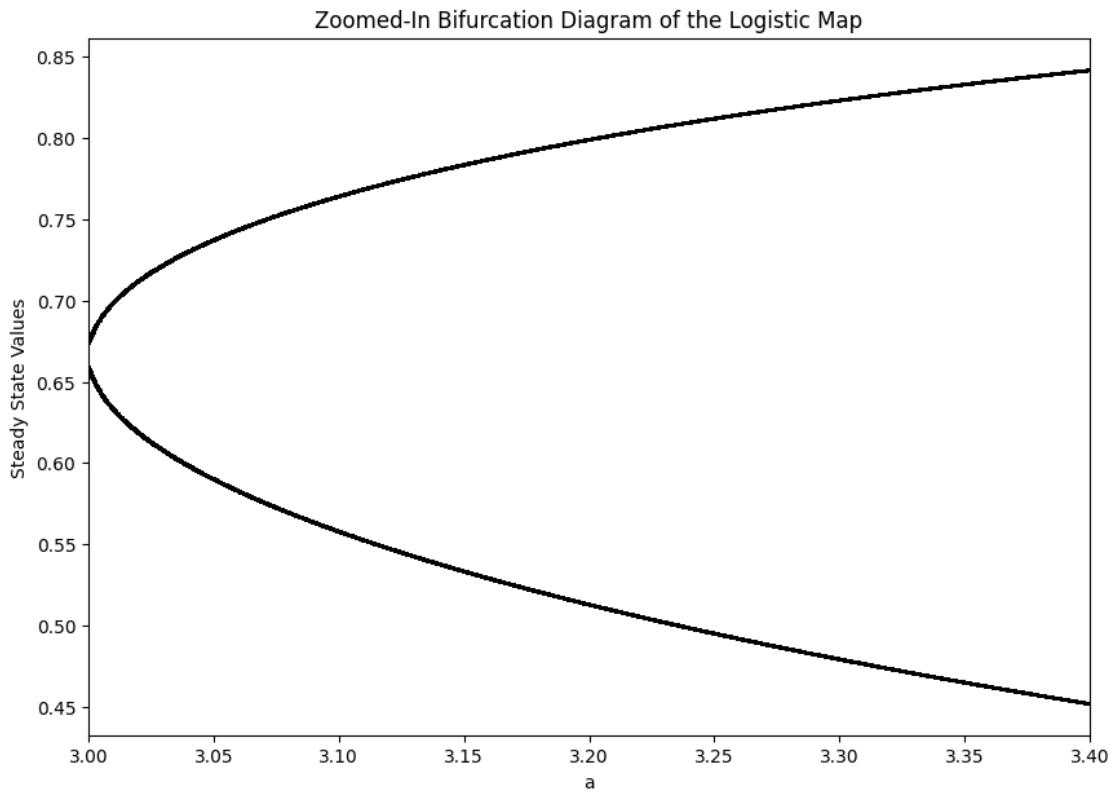
```

if i >= 500:
    steady_states.append((a, x))

# Convert the list of steady state values into a numpy array
steady_states = np.array(steady_states)

# Plot the zoomed-in bifurcation diagram
plt.figure(figsize=(10, 7))
plt.scatter(steady_states[:, 0], steady_states[:, 1], s=0.1, color='black')
plt.title('Zoomed-In Bifurcation Diagram of the Logistic Map')
plt.xlabel('a')
plt.ylabel('Steady State Values')
plt.xlim([3, 3.4])
plt.show()

```



mathematical explanation, when a is between 3 and 3.4, the logistic map will exhibit period-doubling bifurcation. This means that the system will oscillate between two values instead of converging to a single value. The two values are called period-two fixed points.

The period-two fixed points are stable if the absolute value of the derivative of the logistic map at these points is less than 1. The derivative of the logistic map is $a(1 - 2x)$. So, the stability condition for the period-two fixed points x_1 and x_2 is $|a(1 - 2x_1)| < 1$ and $|a(1 - 2x_2)| < 1$.

The initial conditions leading to period-two orbits can be any value in the interval $[0, 1]$. This is because the logistic map is a chaotic system, which means that its behavior is highly sensitive to initial conditions. Even a small change in the initial value can lead to drastically different trajectories.

```
[18]: # Generate different values of a between 3.44949 and 3.54409
a_values = np.linspace(3.44949, 3.54409, 2000)

# Initialize an empty list to store the steady state values
steady_states = []

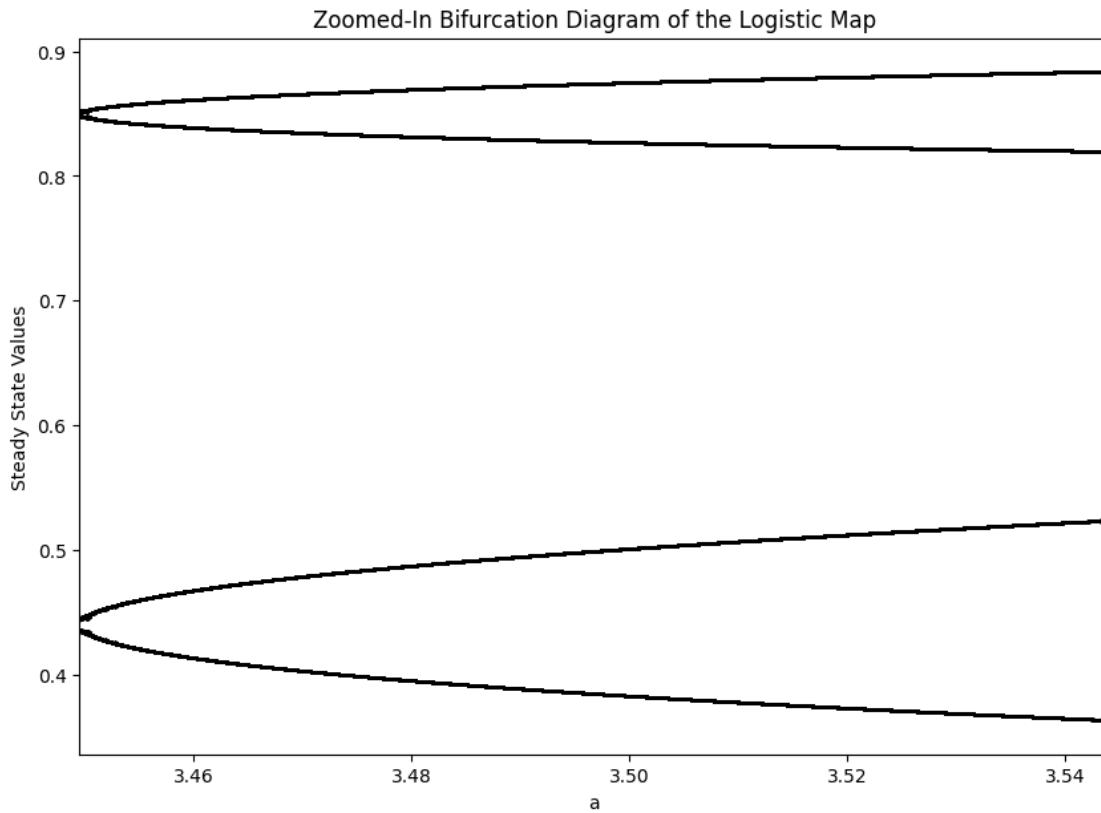
# Iterate over the a values
for a in a_values:
    # Start from a random initial value
    x = np.random.rand()

    # Perform 1000 iterations
    for i in range(1000):
        x = logistic_map(x, a)

    # After the first 500 transient values, store the steady state values
    if i >= 500:
        steady_states.append((a, x))

# Convert the list of steady state values into a numpy array
steady_states = np.array(steady_states)

# Plot the zoomed-in bifurcation diagram
plt.figure(figsize=(10, 7))
plt.scatter(steady_states[:, 0], steady_states[:, 1], s=0.1, color='black')
plt.title('Zoomed-In Bifurcation Diagram of the Logistic Map')
plt.xlabel('a')
plt.ylabel('Steady State Values')
plt.xlim([3.44949, 3.54409])
plt.show()
```



observations, when a is between 3.44949 and 3.54409, the logistic map exhibits period-doubling bifurcation. This means that the system will oscillate between four values instead of converging to a single value or oscillating between two values. The four values are called period-four fixed points. This is a characteristic behavior of chaotic systems, where a small change in the parameter a can lead to drastically different behaviors.

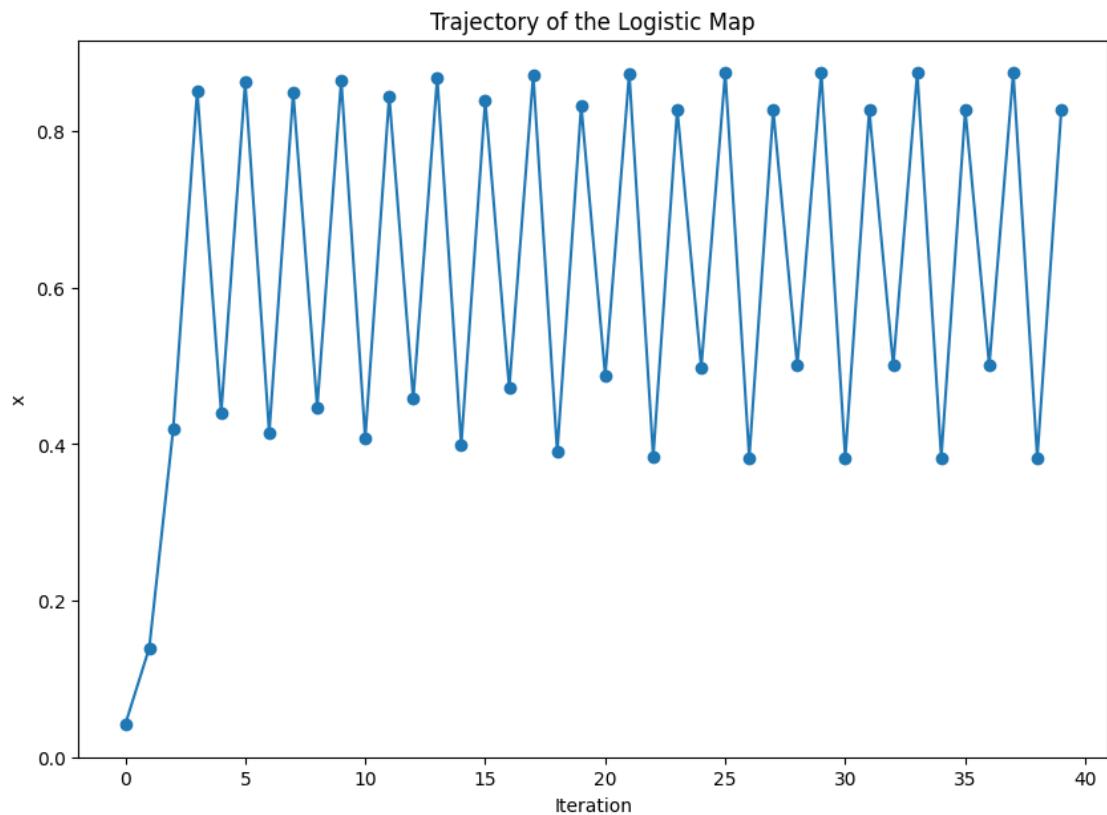
```
[20]: # Define the logistic map function
def logistic_map(x, a):
    return a * x * (1 - x)

# Initialize the parameter a and the initial value x0
a = 3.5
x0 = 0.012

# Initialize an empty list to store the trajectory
trajectory = []

# Perform 40 iterations
for i in range(40):
    x0 = logistic_map(x0, a)
    trajectory.append(x0)
```

```
# Plot the trajectory
plt.figure(figsize=(10, 7))
plt.plot(range(40), trajectory, 'o-')
plt.title('Trajectory of the Logistic Map')
plt.xlabel('Iteration')
plt.ylabel('x')
plt.show()
```



observations, the trajectory does not settle down to a fixed point. Instead, it appears to oscillate between four different values. This is a characteristic behavior of the logistic map when a is in the regime of $3 < a < 3.57$, where it exhibits period-doubling bifurcations leading to chaos.

The value $a = 3.5$ is in this regime, and the logistic map exhibits complex behavior, despite being a simple deterministic system. The trajectory's behavior is highly sensitive to the initial condition x_0 , and even a tiny change in x_0 can lead to drastically different trajectories. This sensitivity to initial conditions is one of the hallmarks of chaos.

```
[21]: # Define the logistic map function
def logistic_map(x, a):
    return a * x * (1 - x)
```

```

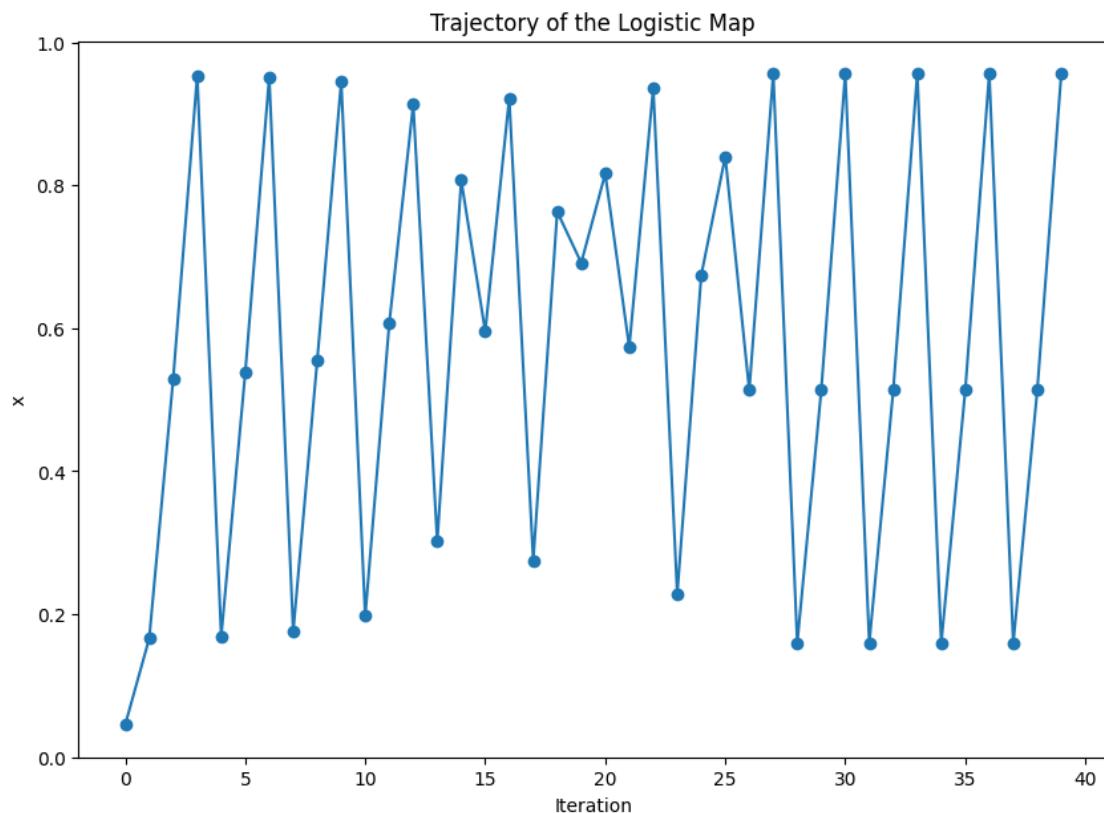
# Initialize the parameter a and the initial value x0
a = 1 + 2*np.sqrt(2)
x0 = 0.012

# Initialize an empty list to store the trajectory
trajectory = []

# Perform 40 iterations
for i in range(40):
    x0 = logistic_map(x0, a)
    trajectory.append(x0)

# Plot the trajectory
plt.figure(figsize=(10, 7))
plt.plot(range(40), trajectory, 'o-')
plt.title('Trajectory of the Logistic Map')
plt.xlabel('Iteration')
plt.ylabel('x')
plt.show()

```



Observations, the trajectory does not settle down to a fixed point or a small cycle. Instead, it

appears to jump around chaotically among many different values. This is a characteristic behavior of the logistic map when a is in the chaotic regime.

The value $a = 1 + 2\sqrt{2}$ is approximately 3.8284, which is in the chaotic regime ($3.57 < a < 4$). In this regime, the logistic map exhibits complex and unpredictable behavior, despite being a simple deterministic system. The trajectory's behavior is highly sensitive to the initial condition x_0 , and even a tiny change in x_0 can lead to drastically different trajectories. This sensitivity to initial conditions is one of the hallmarks of chaos.

Why are we not choosing $a > 4$ for logistic map? .

The logistic map is defined as $x_{n+1} = ax_n(1-x_n)$ where x is a number between 0 and 1, and a is the bifurcation parameter.

When $a > 4$, the logistic map no longer behaves as expected because the values of x can exceed the interval $[0, 1]$. This is contrary to the original biological motivation for the logistic map, which was to model population growth with a carrying capacity (the maximum population size that the environment can sustain indefinitely). In this model, x represents the population size as a proportion of the carrying capacity, so it should always be between 0 and 1.

Moreover, for $a > 4$, the logistic map becomes unstable and the values of x can become very large or negative, which doesn't make sense in the context of population dynamics. Therefore, we usually restrict a to the interval $[0, 4]$ when studying the logistic map.

[]: