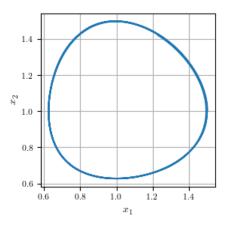
# Exercise 3-1

```
In []: import pysindy as ps
import numpy as np
from numpy.typing import ArrayLike, NDArray
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

In [2]: plt.rcParams.update({
    "text.usetex": True,
    "font.family": "serif",
    "font.serif": "Computer Modern Roman",
    "font.size": 10,
    "xtick.labelsize": 8,
    "ytick.labelsize": 8,
})
```

#### 3.1.1 Numerical Simulation

```
In [ ]: def lv dynamics(
            t: float,
            x: ArrayLike,
            alpha: float=2,
            beta: float=2,
            delta: float=2,
            gamma: float=2,
        ) -> NDArray:
            """Dynamics of the Lotka-Volterra predator-prey system
                x (ArrayLike): N x 2 array of [prey, predator] population
                alpha (float, optional): prey growth rate. Defaults to 2.
                beta (float, optional): prey death rate due to predators. Defaults to 2.
                delta (float, optional): predator growth rate due to prey. Defaults to 2.
                gamma (float, optional): predator death rate. Defaults to 2.
            Returns:
            NDArray: N x 2 array of time derivatives of x1 and x2 ^{"""}
            return np.array([alpha * x[0] - beta * x[0] * x[1], delta * x[0] * x[1] - gamma * x[1]])
In [4]: # Compute trajectory
        x0 = np.array([1.5, 1])
        dt = 0.01
        t = np.arange(0, 10+dt, dt)
        solution = solve_ivp(lv_dynamics, (t[0], t[-1]), x0, t_eval=t)
        x = solution.y.T
In [5]: # Compute time derivative
        dxdt_true = np.array([lv_dynamics(0, _x) for _x in x])
        dxdt estimate = np.array([np.gradient( x, t) for x in x.T])
In [ ]: # Plot phase portrait
        plt.figure(figsize=(3, 3))
        plt.plot(x[:, 0], x[:, 1])
        plt.xlabel("$x 1$")
        plt.ylabel("$x_2$")
        # plt.title("Lotka-Volterra System Phase Portrait")
        plt.grid(True)
        plt.savefig("plfigl.pdf", bbox inches="tight")
        plt.show()
```



### 3.1.2 SINDy with 2nd-Order Polynomials

```
In [7]: thresholds = np.array([0.2, 0.19, 0.18, 0.17, 0.16, 0.15])
         feature_library = ps.feature_library.PolynomialLibrary(degree=2)
         for threshold in thresholds:
              model = ps.SINDy(optimizer=ps.STLSQ(threshold=threshold), feature_names=["x1", "x2"])
              model.fit(x, t=t)
              print(f"threshold: {threshold}")
              model.print()
              print("")
        threshold: 0.2
        (x1)' = 2.001 x1 + -2.001 x1 x2
        (x2)' = -2.002 x2 + 2.002 x1 x2
        threshold: 0.19
        (x1)' = 2.001 \times 1 + -2.001 \times 1 \times 2
        (x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
        threshold: 0.18
        (x1)' = 2.001 \times 1 + -2.001 \times 1 \times 2
        (x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
        threshold: 0.17
        (x1)' = 2.001 \times 1 + -2.001 \times 1 \times 2
        (x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
        threshold: 0.16
        (x1)' = 2.001 x1 + -2.001 x1 x2
        (x2)' = 0.408 \ 1 + -0.408 \ x1 + -2.450 \ x2 + 0.197 \ x1^2 + 1.998 \ x1 \ x2 + 0.216 \ x2^2
        threshold: 0.15
        (x1)' = -0.381 \ 1 + 2.374 \ x1 + 0.427 \ x2 + -0.182 \ x1^2 + -1.996 \ x1 \ x2 + -0.206 \ x2^2
        (x2)' = 0.408 \ 1 + -0.408 \ x1 + -2.450 \ x2 + 0.197 \ x1^2 + 1.998 \ x1 \ x2 + 0.216 \ x2^2
```

### 3.1.4 SINDy with 3rd-Order Polynomials

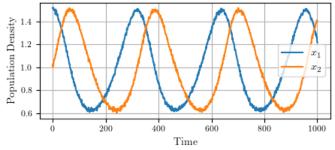
```
In [8]: thresholds = np.array([0.2, 0.19, 0.18, 0.17, 0.16, 0.15])
    feature_library = ps.feature_library.PolynomialLibrary(degree=3)
    for threshold in thresholds:
        model = ps.SINDy(optimizer=ps.STLSQ(threshold=threshold), feature_names=["x1", "x2"])
        model.fit(x, t=t)
        print(f"threshold: {threshold}")
        model.print()
        print("")
```

```
threshold: 0.2
(x1)' = 2.001 \times 1 + -2.001 \times 1 \times 2
(x2)' = -2.002 x2 + 2.002 x1 x2
threshold: 0.19
(x1)' = 2.001 x1 + -2.001 x1 x2
(x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
threshold: 0.18
(x1)' = 2.001 x1 + -2.001 x1 x2
(x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
threshold: 0.17
(x1)' = 2.001 x1 + -2.001 x1 x2
(x2)' = -2.002 \times 2 + 2.002 \times 1 \times 2
threshold: 0.16
(x1)' = 2.001 \times 1 + -2.001 \times 1 \times 2
(x2)' = 0.408\ 1 + -0.408\ x1 + -2.450\ x2 + 0.197\ x1^2 + 1.998\ x1\ x2 + 0.216\ x2^2
(x1)' = -0.381\ 1 + 2.374\ x1 + 0.427\ x2 + -0.182\ x1^2 + -1.996\ x1\ x2 + -0.206\ x2^2
(x2)' = 0.408 \ 1 + -0.408 \ x1 + -2.450 \ x2 + 0.197 \ x1^2 + 1.998 \ x1 \ x2 + 0.216 \ x2^2
```

## 3.1.5 SINDy with Noise

```
In [9]: np.random.seed(0)
    x_noisy = x + 0.01 * np.random.randn(*x.shape)
    dxdt_noisy_estimate = np.array([np.gradient(_x, t) for _x in x_noisy.T]).T

In []: plt.figure(figsize=(5, 2))
    plt.plot(x_noisy)
    plt.xlabel("Time")
    plt.ylabel("Population Density")
    # plt.title("Lotka-Volterra Noisy Trajectory")
    plt.legend(("$x_1$", "$x_2$"), loc="right")
    plt.grid(True)
    plt.savefig("plfig2.pdf", bbox_inches="tight")
    plt.show()
```



```
In [11]: for threshold in thresholds:
    model = ps.SINDy(optimizer=ps.STLSQ(threshold=threshold), feature_names=["x1", "x2"])
    model.fit(x_noisy, t=t)
    print(f"threshold: {threshold}")
    model.print()
    print("")
```

```
threshold: 0.2
(x1)' = 1.996 x1 + -2.003 x1 x2
(x2)' = -2.013 x2 + 2.015 x1 x2
threshold: 0.19
(x1)' = 1.996 x1 + -2.003 x1 x2
(x2)' = -2.013 \times 2 + 2.015 \times 1 \times 2
threshold: 0.18
(x1)' = 0.106\ 1 + 1.939\ x1 + -0.136\ x2 + -0.001\ x1^2 + -1.959\ x1\ x2 + 0.044\ x2^2
(x2)' = -2.013 \times 2 + 2.015 \times 1 \times 2
threshold: 0.17
(x1)' = 0.106\ 1 + 1.939\ x1 + -0.136\ x2 + -0.001\ x1^2 + -1.959\ x1\ x2 + 0.044\ x2^2
(x2)' = -2.013 x2 + 2.015 x1 x2
threshold: 0.16
(x1)' = 0.106 \ 1 + 1.939 \ x1 + -0.136 \ x2 + -0.001 \ x1^2 + -1.959 \ x1 \ x2 + 0.044 \ x2^2
(x2)' = -2.013 x2 + 2.015 x1 x2
threshold: 0.15
```

 $(x1)' = 0.106\ 1 + 1.939\ x1 + -0.136\ x2 + -0.001\ x1^2 + -1.959\ x1\ x2 + 0.044\ x2^2$ 

 $(x2)' = -2.013 \times 2 + 2.015 \times 1 \times 2$