

1. Numerical methods of Lyapunov coefficient calculation

$$d(t) = d_0 e^{\lambda_1 t}$$

$$\ln d(t) = \ln d_0 + \lambda_1 t$$

Consider a dynamical system:

$$\begin{cases} \dot{x} = f_1(x, y), \\ \dot{y} = f_2(x, y) \end{cases}$$

A trajectory consisting of points that are stable by Lyapunov is called an attractor.

A time series can be split into $z_i = [x_i, \dots, x_{i+m-1}]$. This is a transition from time series to a dynamical system. It can be transitioned forward by Δt and then be taking the last z -vector one can have a new time series.

1. 1. Rosenstein algorithm

Let x_1, \dots, x_n be a dataset,

$$\begin{aligned} Y_i &= [x_i, x_{i+1}, \dots, x_{i+m-1}] \\ Y_i &= [x_i, x_{i+\tau}, \dots, x_{i+\tau(m-1)}]. \end{aligned}$$

Step-by-step:

1. $\{x_i\} \rightarrow \{Y_i\}$.
2. Finding nearest neighbours.

$$\forall Y_i : \tilde{N}_i = \{Y_j \mid \varepsilon_{\min} < \|Y_i - Y_j\| < \varepsilon_{\max} \text{ and } |i - j| > \varepsilon_t\},$$

3. Take k nearest neighbours:

$$N_i = \{Y_{j_1}, \dots, Y_{j_k}\}.$$

4. Calculate the distances after k steps: $d_{ij}(k) = \|Y_{i+k} - Y_{j+k}\|$ for each $k = 0, \dots, T$.
5. Average those distances:

$$S(k) = \frac{1}{M'} \sum_{i=1}^{M'} \frac{1}{|N_i|} \sum_{Y_j \in N_i} d_{ij}(k),$$

Where M' is the number of Y -vectors used in computations (not all of them can be used).

6. Calculate Lyapunov exponent using linear regression:

$$S(k) \approx \alpha + \lambda_i(k \cdot \Delta t).$$

Hyperparameters: $m, \tau, \varepsilon_{\min}, \varepsilon_{\max}, \varepsilon_t, k, T$. It is important to know that this algorithm is extremely sensitive to hyperparameter values.

1. 2. Kantz algorithm

This algorithm differs only in the way that data is averaged.

Step-by-step:

5. Average dataset:

$$S(k) = \frac{1}{M'} \sum_{i=1}^{M'} \frac{1}{|N_i|} \sum_{Y_j \in N_i} d_{ij}(k).$$

6.

$$\begin{aligned} S(k) &\approx S(0)e^{\lambda_1(k \cdot \Delta t)} \\ \ln S(k) &\approx \ln S(0) + \lambda_1(k \cdot \Delta t). \end{aligned}$$

2. Lyapunov spectre estimation

2. 1. Local linear maps method

Assume that locally $Y_{i+1} \approx A_i B_i + b_i$.

Let

$$\begin{pmatrix} Y_{j_1+1}^T \\ Y_{j_2+1}^T \\ \vdots \\ Y_{j_k+1}^T \end{pmatrix} = \begin{pmatrix} Y_{j_1}^T & 1 \\ Y_{j_2}^T & 1 \\ \vdots & \vdots \\ Y_{j_k}^T & 1 \end{pmatrix} \times \begin{pmatrix} A_i^T \\ b_i^T \end{pmatrix}.$$

Step-by-step:

1. Reconstruction: $\{x_i\} \rightarrow \{Y_i\}$.
2. Search for the k nearest neighbours.

$$N_i = \{Y_{j_1}, \dots, Y_{j_k}\}, \quad Y_{j_k} \in \{Y_j \mid \|Y_i - Y_j\| < \varepsilon \text{ and } |i - j| > \varepsilon_t\}.$$

3. $\forall Y_j \in N_i : Y_{j+1} \approx A_i Y_j + b_i$. Then, minimize MSE:

$$\sum_{Y_j \in N_i} \|Y_{j+1} - A_i Y_j - b_i\| \rightarrow \min_{A_i, b_i}$$

4. Form an orthonormal basis.

- 4.1. Y_{i_0}
- 4.2. $Q_0 = [q_1^0, q_2^0, \dots, q_m^0]$, $Q_0^T Q_0 = I$.
- 4.3. $L_j = 0$, $j = 1, \dots, m$.

5. Find A_{i_n} for each Y_{i_n} (see step 3)

$$V_{n+1} = A_{i_n} Q_n.$$

Then, use QR decomposition of A_{i_n} : $V_{n+1} = Q_{n+1} R_{n+1}$, where Q_{n+1} is an orthonormal basis, R_{n+1} is an upper triangular matrix. Then, $L_j = L_j + \ln(R_{n+1})_{ji}$, $i_{n+1} = i_n + 1$.

6. Calculate the Lyapunov exponents:

$$\lambda_j = \frac{L_j}{N_{\text{iter}} \Delta t}.$$

Note that A_i is a jacobian matrix of our dynamical system.

2. 2. Wolf method

Step-by-step:

1. Reconstruction $\{x_i\} \rightarrow \{Y_i\}$.
2. Initialization. Let $Y_0 = Y_i$, define an orthonormal basis for it: $q_1^0 = [1, 0, \dots, 0]^T, q_2^0 = [0, 1, 0, \dots, 0]^T, \dots$
3. Take Y_k and evolve it in time by $\{q_1^k, q_2^k, \dots, q_m^k\}$, $Y_{k+1} = Y_{i+1}$, then $\forall q_i$:

$$\|Y_j - Y_k\| < \varepsilon_{\max}$$

$$|j - k| > \varepsilon_t$$

$$\delta = Y_j - Y_k : \alpha = \arccos \left(\frac{\delta \cdot q_i^k}{\|\delta\| \|q_i^k\|} \right) < \varepsilon_{\min}$$

4. $v_j = Y_{j+\Delta} - Y_{k+\Delta} \Rightarrow \{v_1, v_2, \dots, v_m\}$.

5. For $j = \overline{1, \dots, m}$:

for $j = 1$: $u_1 = \frac{v_1}{\|v_1\|}, L_1^k = \ln \|v_1\|$

for $j = 2$: $w_2 = v_2 - (v_2 \cdot u_1)u_1, u_2 = \frac{w_2}{\|w_2\|}, L_2^k = \ln \|w_2\|$ and so on.

6. $q_1^{k+1} = u_1, \dots, q_m^{k+1} = u_m$.

for j :

$$\begin{aligned} w_j &= v_j - \sum_{i=1}^{j-1} (v_j \cdot u_i) u_i \\ u_j &= \frac{w_j}{\|w_j\|} \\ L_j^k &= \ln \|w_j\|. \end{aligned}$$

Them,

$$\lambda_j = \sum_{k=1}^{\text{max_iter}} \frac{L_{jk}^k}{\text{max_iter} \cdot \Delta \cdot \Delta t}.$$

3. Entropy-complexity plane

Blah-blah-blah.

4. How to choose the size of reconstruction

False nearest neighbours approach. For $m = m_{\min}, \dots, m_{\max}$.

1. Sample z^m vectors of size m .
2. # of NN = $|\{(z_i^m, z_j^m) \mid \|z_i^m - z_j^m\| < \varepsilon\}| \forall z_i^m, z_j^m$.
3. Sample z^{m+1} – vectors of size $m + 1$.
- 4.

$$\begin{aligned} \text{\# of false NN} = & |\{(z_i^{m+1}, z_j^{m+1}) \mid \|z_i^m - z_j^m\| < \varepsilon, \\ & \|z_i^{m+1} - z_j^{m+1}\| > \varepsilon, |i - j| > \tau\}|, \forall z_i^{m+1}, z_j^{m+1}. \end{aligned}$$

FNN has a dip at the best m .