

数据驱动的降阶模型

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本堂课大纲

- 谱分解
- Koopman算子理论
 - Koopman算子的谱分解
 - Koopman模态
- Koopman算子近似算法
 - 动力学模态分解
 - 扩展动力学模态分解



谱分解

➤ 线性常微分方程

$$\frac{d}{dt} \mathbf{u}(t) = A\mathbf{u}(t)$$

➤ 基底选择

$$A\mathbf{v}_k = \lambda_k \mathbf{v}_k, \quad k = 1, 2, \dots, N$$

➤ 快速求解

$$\mathbf{u}(t) = \sum_k a_k(t) \mathbf{v}_k$$

$$\frac{d}{dt} a_k(t) = \lambda_k a_k(t) \quad a_k(t) = a_k(0) e^{\lambda_k t}$$



谱分解

- 线性常微分方程(离散时间)

$$\mathbf{u}(m+1) = A\mathbf{u}(m)$$

- 基底选择

$$Av_k = \lambda_k v_k, \quad k = 1, 2, \dots, N$$

- 快速求解

$$\mathbf{u}(m) = \sum_k a_k(m) v_k$$

$$a_k(m+1) = \lambda_k a_k(m)$$

$$a_k(m) = a_k(0) \lambda_k^m$$



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Koopman 算子

➤ 连续时间非线性模型

$$\frac{d}{dt}\mathbf{u} = f(\mathbf{u}) \quad \mathbf{u} \in \mathcal{M} \in \mathbb{R}^N \quad \mathcal{M} \text{ 是 } N \text{ 维空间中流形}$$

半群：

$$F_t: \mathbf{u}(t_0) \rightarrow \mathbf{u}(t_0 + t) = \mathbf{u}(t_0) + \int_{t_0}^{t_0+t} f(\mathbf{u}(\tau)) d\tau$$

$$F_{t+s} = F_t \circ F_s$$

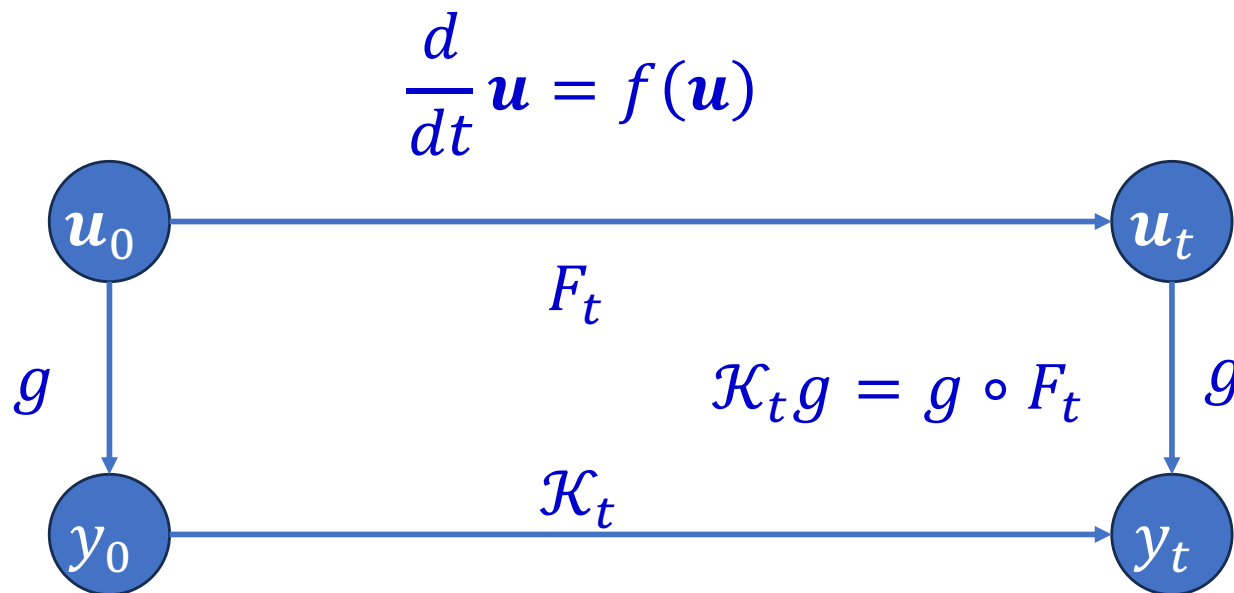


Koopman 算子

➤ Koopman算子(连续时间系统)

考虑由观测函数 g 构成的空间 \mathfrak{G} ，Koopman算子 $\mathcal{K}_t: \mathfrak{G} \rightarrow \mathfrak{G}$ ，满足

$$\mathcal{K}_t g = g \circ F_t$$





Koopman 算子

➤ Koopman算子(连续时间系统)

线性算子

$$\begin{aligned}\mathcal{K}_t(g + g') &= (g + g') \circ F_t \\ &= g \circ F_t + g' \circ F_t = \mathcal{K}_t g + \mathcal{K}_t g'\end{aligned}$$

半群

$$\begin{aligned}\mathcal{K}_{t+s}g &= g \circ F_{t+s} = g \circ (F_t \circ F_s) \\ &= (g \circ F_t) \circ F_s = \mathcal{K}_t(g \circ F_s) = \mathcal{K}_t \mathcal{K}_s g\end{aligned}$$



Koopman 算子

➤ 离散时间非线性模型

$$\mathbf{u}(m+1) = F(\mathbf{u}(m)) \in \mathcal{M} \in \mathbb{R}^N \quad \mathcal{M} \text{ 是 } N \text{ 维空间中流形}$$

$$\mathbf{u}(m) = F^m(\mathbf{u}(0))$$

➤ Koopman算子(离散时间系统)

考虑由观测函数 g 构成的空间 \mathfrak{G} ，Koopman算子 \mathcal{K} ：
 $\mathfrak{G} \rightarrow \mathfrak{G}$ ，满足

$$\begin{aligned}\mathcal{K}g &= g \circ F \\ \mathcal{K}^m g &= g \circ F^m\end{aligned}$$



Koopman 算子

Koopman 算子是(无限维)线性算子

连续时间系统： $\mathcal{K}_t g = g \circ F_t$

离散时间系统： $\mathcal{K} g = g \circ F$



Koopman 算子的谱分解

➤ Koopman 特征函数(连续时间系统)

无穷小生成元满足：

$$\mathcal{K}\varphi = \left. \frac{d\mathcal{K}_t\varphi}{dt} \right|_{t=0} = \lim_{t \rightarrow 0} \frac{\mathcal{K}_t\varphi - \varphi}{t} = \lambda\varphi$$

对于观测函数 φ

$$\mathcal{K}_t\varphi = \varphi \circ F_t = e^{\lambda t}\varphi$$

对于特征函数对 (λ_1, φ_1) 和 (λ_2, φ_2)

$$\mathcal{K}[\varphi_1\varphi_2](u) = (\lambda_1 + \lambda_2)\varphi_1(u)\varphi_2(u)$$

⇒ 特征函数对 $(\lambda_1 + \lambda_2, \varphi_1\varphi_2)$



Koopman 算子的谱分解

➤ Koopman 特征函数(连续时间系统)

例子：考虑非线性模型

$$\frac{du}{dt} = -u - u^3, u \in R$$

特征函数满足

$$\mathcal{K}\varphi(u) = \left. \frac{d\mathcal{K}_t\varphi}{dt} \right|_{t=0} (u) = \nabla\varphi \cdot (-u - u^3) = \lambda\varphi$$

特征函数：

$$\varphi(u) = \frac{u}{\sqrt{1+u^2}} \quad \lambda = -1$$

$$\varphi_k(u) = \left(\frac{u}{\sqrt{1+u^2}} \right)^k \quad \lambda_k = -k$$



Koopman 算子的谱分解

➤ Koopman 特征函数(离散时间系统)

对于观测函数 φ

$$\mathcal{K}\varphi = \varphi \circ F = \lambda\varphi$$

对于特征函数对 (λ_1, φ_1) 和 (λ_2, φ_2)

$$\begin{aligned}\mathcal{K}[\varphi_1\varphi_2](u) &= \varphi_1(Fu)\varphi_2(Fu) \\ &= \lambda_1\lambda_2\varphi_1(u)\varphi_2(u)\end{aligned}$$

\Rightarrow 特征函数对 $(\lambda_1\lambda_2, \varphi_1\varphi_2)$



Koopman 算子的谱分解

➤ Koopman 特征函数(离散时间系统)

例子：考虑线性模型

$$F(u) = Fu, u \in R^N$$

F 的左特征值和特征向量满足

$$w_j^T F = \lambda_j w_j^T$$

Koopman 算子的特征值和特征函数包含

$$\lambda_j, \varphi_j(u) = w_j^T u$$

$$\mathcal{K} \varphi_j(u) = \varphi_j(Fu) = w_j^T Fu = \lambda_j \varphi_j(u)$$



Koopman 模态 (Modes)

➤ Koopman模态展开

给定Koopman算子的特征函数 $\{\varphi_j\}_{j=1}^{\infty}$ ，对于观测函数

$$g = \sum_{j=1}^{\infty} v_j(g) \varphi_j$$

这些系数 v_j 称为与可观测函数 g 相关的Koopman模态。

连续时间系统： $\mathcal{K}_t g = \sum_{j=1}^{\infty} e^{\lambda_j t} \varphi_j v_j(g)$

离散时间系统： $\mathcal{K}^m g = \sum_{j=1}^{\infty} \lambda_j^m \varphi_j v_j(g)$



Koopman 模态 (Modes)

➤ Koopman模态展开

考虑恒等观测量($id(\mathbf{u}) = \mathbf{u}$)

$$id = \sum_{j=1}^{\infty} v_j(id) \varphi_j$$

连续时间系统：

$$\mathbf{u}(t) = \mathcal{K}_t id(\mathbf{u}(0)) = \sum_{j=1}^{\infty} e^{\lambda_j t} \varphi_j(\mathbf{u}(0)) v_j(id)$$

离散时间系统：

$$\mathbf{u}(m) = \mathcal{K}^m id(\mathbf{u}(0)) = \sum_{j=1}^{\infty} \lambda_j^m \varphi_j(\mathbf{u}(0)) v_j(id)$$



Koopman 模态 (Modes)

➤ 例子

考虑非线性系统

$$\begin{aligned}\dot{u}_1 &= \mu u_1 \\ \dot{u}_2 &= \lambda(u_2 - u_1^2)\end{aligned}$$

Koopman 算子

$$\mathcal{K} = \mu u_1 \frac{\partial}{\partial u_1} + \lambda(u_2 - u_1^2) \frac{\partial}{\partial u_2}$$

Koopman 算子的特征值和特征函数包含

$$\begin{aligned}\lambda_1 &= \mu, & \varphi_1(u) &= u_1 \\ \lambda_2 &= \lambda, & \varphi_2(u) &= u_2 + \frac{\lambda}{2\mu - \lambda} u_1^2 \\ \lambda_3 &= 2\mu, & \varphi_3(u) &= u_1^2\end{aligned}$$

我们有恒等算子

$$id(u) = \varphi_1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \varphi_2 \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \varphi_3 \begin{bmatrix} 0 \\ \lambda \\ -\frac{\lambda}{2\mu - \lambda} \end{bmatrix}$$



Koopman 模态 (Modes)

➤ 例子

考虑线性模型 $\mathbf{u}_{k+1} = F\mathbf{u}_k \in \mathbb{R}^N$

F 的左右特征值和特征向量满足 (假设 $w_i^T v_j = \delta_{ij}$)

$$w_j^T F = \lambda_j w_j^T \quad F v_j = \lambda_j v_j$$

Koopman 算子的特征值和特征函数包含 $\{\lambda_j, \varphi_j(u) = w_j^T u\}$, $\{v_j\}$ 为恒等观测函数 id 相关的 Koopman 模式

$$id(\mathbf{u}(0)) = \sum_{j=1}^N v_j \varphi_j(\mathbf{u}(0))$$

我们有

$$\mathbf{u}(m) = \mathcal{K}^m id(\mathbf{u}(0)) = \sum_{j=1}^{\infty} \lambda_j^m v_j w_j^T \mathbf{u}(0)$$



Koopman 算子

Koopman算子是(无限维)线性算子

连续时间系统： $\mathcal{K}_t g = g \circ F_t$

离散时间系统： $\mathcal{K} g = g \circ F$

近似Koopman算子的谱和模态，能得到观测的演化

连续时间系统： $\mathbf{u}(t) = \sum_{j=1}^{\infty} e^{\lambda_j t} \varphi_j(\mathbf{u}(0)) v_j(id)$

离散时间系统： $\mathbf{u}(m) = \sum_{j=1}^{\infty} \lambda_j^m \varphi_j(\mathbf{u}(0)) v_j(id)$



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Koopman 算子的近似

➤ 有限维近似

考虑观测函数 g 构成的空间 \mathfrak{G} 的 N 维子空间

$$\mathfrak{G}_N \subset \mathfrak{G}$$

以及相应的投影映射 $\Pi: \mathfrak{G} \rightarrow \mathfrak{G}_N$

对于 Koopman 算子 \mathcal{K} ，我们可以限制在 \mathfrak{G}_N 上，定义

$$\mathcal{K}_N = \Pi \mathcal{K} \Big|_{\mathfrak{G}_N} : \mathfrak{G}_N \rightarrow \mathfrak{G}_N$$

用 \mathcal{K}_N 来近似 \mathcal{K} 。



动力学模态分解

➤ 投影映射 $\Pi: \mathcal{G} \rightarrow \mathcal{G}_N$

\mathcal{G}_N 的基底: $\Psi = [\psi_1 \ \psi_2 \ \cdots \ \psi_N]$

系数函数: $\Gamma: \mathcal{G} \rightarrow \mathcal{C}^N$

$\Pi = \Psi\Gamma: g \rightarrow \Psi c \ (c = \Gamma g \in \mathcal{C}^N)$

$\Gamma\Psi = I$

➤ Koopman算子

$$\mathcal{K}_N g = \Pi\mathcal{K}\Pi g = \Psi\Gamma\mathcal{K}\Psi\Gamma g = \Psi K\Gamma g$$

其中

$$K: \mathcal{C}^N \rightarrow \mathcal{C}^N, \quad Ka = \Gamma\mathcal{K}\Psi a$$

是 \mathcal{K}_N 的矩阵表示形式。它被称为系统的 Koopman 矩阵，并对应于 Koopman 运算符在坐标系 Ψ 下对观测函数 g 的作用。



动力学模态分解

➤ 数据收集

$$X = [\mathbf{u}(t_0) \quad \mathbf{u}(t_1) \quad \cdots \quad \mathbf{u}(t_{n-1})]$$

$$Y = [\mathbf{u}(t_1) \quad \mathbf{u}(t_2) \quad \cdots \quad \mathbf{u}(t_n)]$$

$$t_m = k\Delta t$$

$$\mathbf{u}(m) = \mathbf{u}(m\Delta t)$$

➤ Koopman算子

$$\mathcal{K}g(\mathbf{u}(m)) = g(\mathbf{u}(m+1))$$

➤ 动力学模态分解(Dynamic model decomposition)

- \mathfrak{G}_N 是 \mathbf{u} 在网格点的值，在 x_i 上的取值： $\psi_i(\mathbf{u})$

- 找到最合适的 K 使得 $Y \approx KX$



动力学模态分解

➤ 动力学模态分解

目标：找到最合适的 K 使得 $Y \approx KX$

奇异值分解： $X = U\Sigma V^T$ $\Sigma \in R^{n \times n}$

Koopman矩阵： $K = YV\Sigma^{-1}U^T$

特征值、特征向量计算：

计算 $\tilde{K} := U^T Y V \Sigma^{-1}$

\tilde{K} 的特征值 $\{\tilde{\lambda}_j\}$ 和左右特征向量 $\{\tilde{w}_j\}\{\tilde{v}_j\}$ ，对应Koopman矩阵的特征值和左右特征向量

$$\lambda_j = \tilde{\lambda}_j$$

$$w_j = U\tilde{w}_j$$

$$v_j = YV\Sigma^{-1}\tilde{v}_j$$

复杂度： $\mathcal{O}(Nn^2)$



动力学模态分解

➤ 流体分析

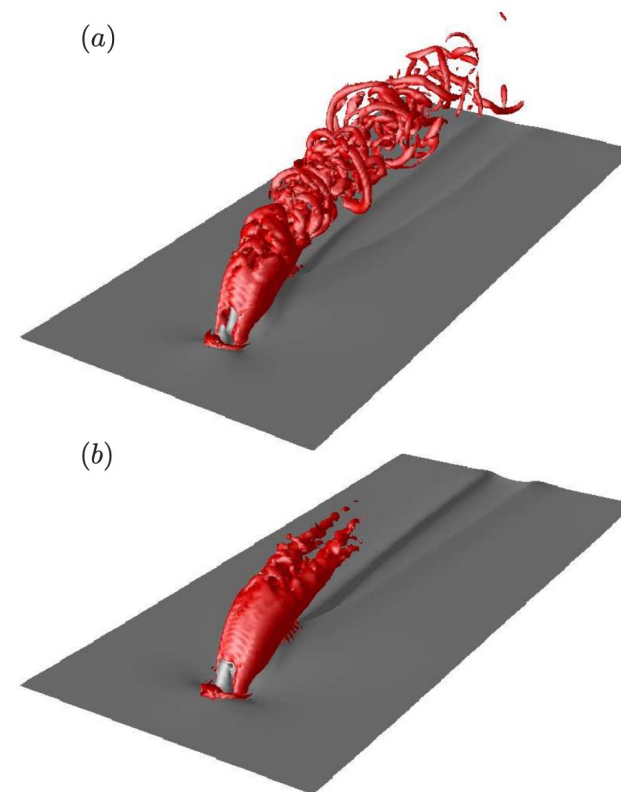
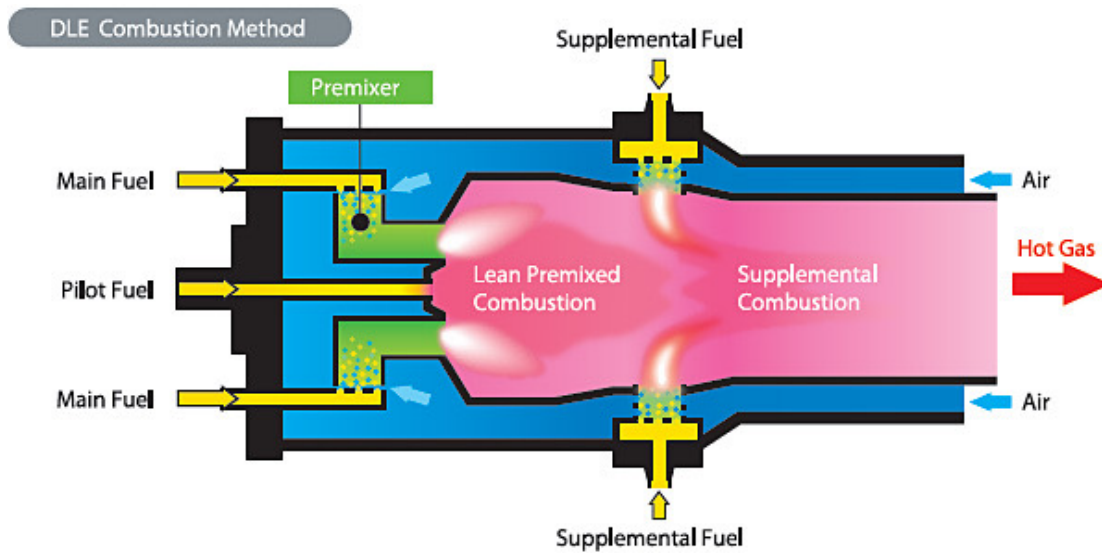
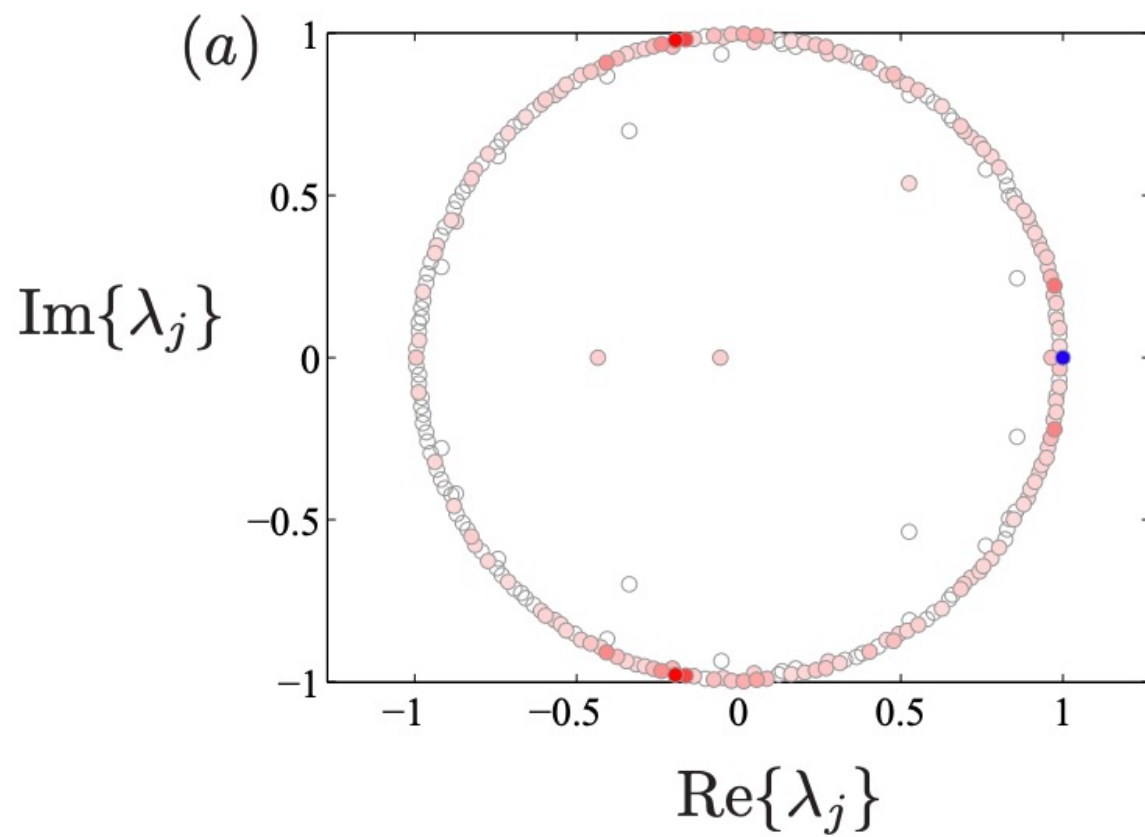


FIGURE 1. (a) Snapshot of the flow field at $t = 400$. Red and gray isocontours represent $\lambda_2 = -0.1$ and $u = 0.2$ (near the wall) respectively. (b) The same quantities for the time-averaged flow which is also the first Koopman mode.



动力学模态分解

➤ 流体分析





动力学模态分解

➤ 流体分析

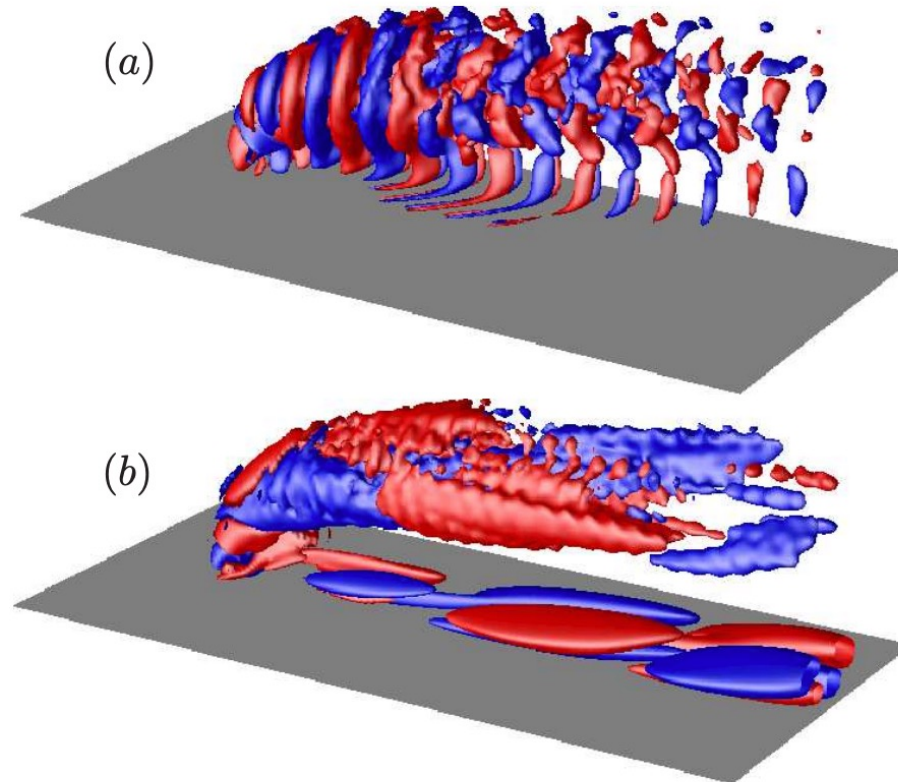


FIGURE 4. Positive (red) and negative (blue) contour levels of the streamwise velocity components of two Koopman modes. The wall is shown in gray. (a) Mode 2, with $\|\mathbf{v}_2\| = 400$ and $St_2 = 0.141$. (b) Mode 6, with $\|\mathbf{v}_6\| = 218$ and $St_6 = 0.0175$.



动力学模态分解

➤ 动力学模态分解

基于数据的模型： $\mathbf{u}(t_{m+1}) = K\mathbf{u}(t_m)$

快速求解：

$$\mathbf{u}(t_m) = \sum_{j=1} \lambda_j^m \mathbf{v}_j \mathbf{w}_j^T \mathbf{u}(t_0)$$

相比本征正交分解求得的基底，动力学模态分解求得的基底包含**时序或是动力学信息**。



扩展动力学模态分解

➤ 升维

用更多特征来近似Koopman算子

在 \mathcal{M} 上的函数空间中选择有限个的函数作为基函数：

$$\Psi = [\psi_1; \psi_2; \dots; \psi_D]$$

Koopman 算子近似：

$$\mathcal{K}_l g = \Pi \mathcal{K} \Pi g = \Psi \Gamma \mathcal{K} \Psi \Gamma g = \Psi K \Gamma g$$

其中

$$K: C^D \rightarrow C^D, \quad K a = \Gamma \mathcal{K} \Psi a$$

$$\mathcal{K} \psi_i(\mathbf{u}) = \sum_{j=1}^D K_{i,j} \psi_j(\mathbf{u}) \quad K \in R^{D \times D}$$



扩展动力学模态分解

➤ 基函数选取

傅里叶函数： $\psi(\mathbf{u}) = \langle \mathbf{u}, \sin 2\pi kx \rangle$

多项式函数： $\psi(\mathbf{u}) = \langle \mathbf{u}, ax^2 + bx + c \rangle$

高维函数： $\psi(\mathbf{u}) = \prod_i f_i(\mathbf{u}_i)$

基底函数：

$$\Psi = [\psi_1 \ \psi_2 \ \cdots \cdots \ \psi_l]$$



扩展动力学模态分解

➤ 扩展动力学模态分解

$$X = [\Psi(\mathbf{u}_0) \Psi(\mathbf{u}_1) \cdots \Psi(\mathbf{u}_{n-1})] \in R^{D \times n}$$

$$Y = [\Psi(\mathbf{u}_1) \Psi(\mathbf{u}_2) \cdots \Psi(\mathbf{u}_n)] \in R^{D \times n}$$

$$Y \approx KX$$

➤ 谱分解

K 的特征值 $\{\lambda_j\}$ 和左特征向量 $\{w_j\}$ ，对应Koopman算子的特征值 $\{\lambda_j\}$ 和特征向量 $\{w_j^T \Psi\}$

$$\mathcal{K}(w_j^T \Psi) \approx w_j^T K \Psi = \lambda_j w_j^T \Psi$$

➤ Koopman模态

$$\text{id}(\mathbf{u}) = \sum_{j=1}^D w_j^T \Psi(\mathbf{u}) v_j \quad F^{(m)}(\mathbf{u}) = \sum_{j=1}^D \lambda_j^m w_j^T \Psi(\mathbf{u}) v_j$$



扩展动力学模态分解

➤ 计算特征值、特征向量

Koopman矩阵： $K = Y(X^T X)^{-1} X^T$

计算特征值和左特征向量

$$w_j^T K = \lambda_j w_j^T$$

➤ 计算Koopman模态

$$id(\mathbf{u}) = \sum_{j=1}^D w_j^T \Psi(\mathbf{u}) v_j$$

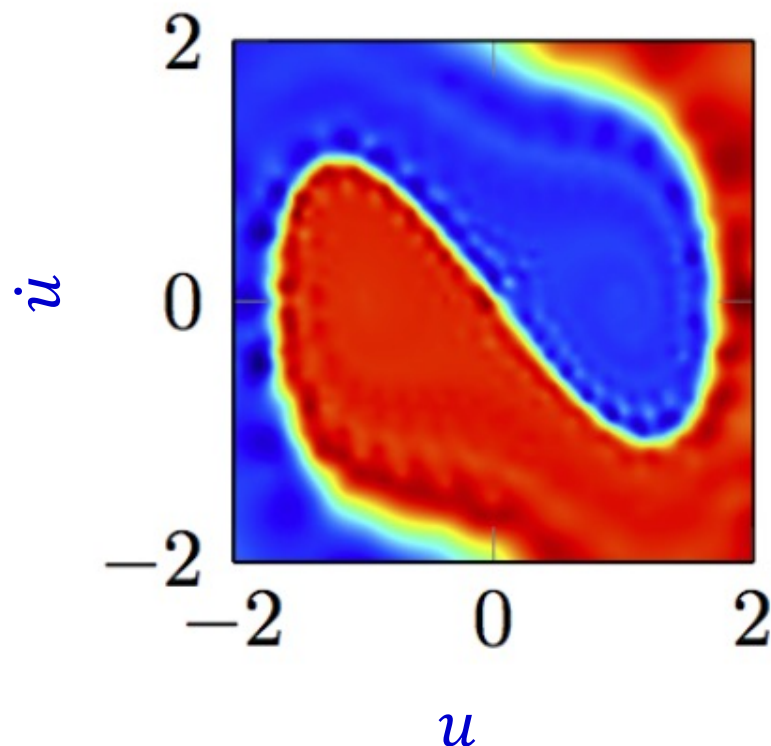
$$\begin{aligned} & [\mathbf{u}_0 \ \mathbf{u}_1, \dots, \mathbf{u}_{n-1}] \\ &= [v_1, v_2, \dots, v_D] \begin{bmatrix} w_1^T \\ w_2^T \\ \vdots \\ w_D^T \end{bmatrix} [\Psi(\mathbf{u}_0) \Psi(\mathbf{u}_1) \dots \Psi(\mathbf{u}_{n-1})] \end{aligned}$$



扩展动力学模态分解

➤ 无强迫Duffing振荡器

$$\ddot{u} = -\delta\dot{u} - u(\beta + \alpha u^2) \quad (\delta = 0.5, \alpha = 1, \beta = -1)$$



薄板样条: $\psi_i = r_i^2 \log(r_i^2)$, $r_i^2 = (u - x_i)^2 + (\dot{u} - y_i)^2$



扩展动力学模态分解

➤ 核函数

$$\Psi = [\psi_1 \ \psi_2 \ \cdots \ \psi_D] \quad \Psi(x)^T \Psi(y) = \kappa(x, y)$$

$$X = [\Psi(\mathbf{u}_0) \ \Psi(\mathbf{u}_1) \ \cdots \ \Psi(\mathbf{u}_{n-1})] \in R^{D \times n}$$

$$Y = [\Psi(\mathbf{u}_1) \ \Psi(\mathbf{u}_2) \ \cdots \ \Psi(\mathbf{u}_n)] \in R^{D \times n} \quad Y \approx KX$$

$$X^T Y = \begin{bmatrix} \kappa(\mathbf{u}_0, \mathbf{u}_1) & \kappa(\mathbf{u}_0, \mathbf{u}_2) & \cdots & \kappa(\mathbf{u}_0, \mathbf{u}_n) \\ \kappa(\mathbf{u}_1, \mathbf{u}_1) & \kappa(\mathbf{u}_1, \mathbf{u}_2) & \cdots & \kappa(\mathbf{u}_1, \mathbf{u}_n) \\ \vdots & \vdots & \ddots & \vdots \\ \kappa(\mathbf{u}_{n-1}, \mathbf{u}_1) & \kappa(\mathbf{u}_{n-1}, \mathbf{u}_2) & \cdots & \kappa(\mathbf{u}_{n-1}, \mathbf{u}_n) \end{bmatrix}$$

$$X^T X = \begin{bmatrix} \kappa(\mathbf{u}_0, \mathbf{u}_0) & \kappa(\mathbf{u}_0, \mathbf{u}_1) & \cdots & \kappa(\mathbf{u}_0, \mathbf{u}_{n-1}) \\ \kappa(\mathbf{u}_1, \mathbf{u}_0) & \kappa(\mathbf{u}_1, \mathbf{u}_1) & \cdots & \kappa(\mathbf{u}_1, \mathbf{u}_{n-1}) \\ \vdots & \vdots & \ddots & \vdots \\ \kappa(\mathbf{u}_{n-1}, \mathbf{u}_0) & \kappa(\mathbf{u}_{n-1}, \mathbf{u}_1) & \cdots & \kappa(\mathbf{u}_{n-1}, \mathbf{u}_{n-1}) \end{bmatrix}$$



扩展动力学模态分解

► 计算特征值、特征向量

Koopman矩阵： $X^T X = V \Sigma^2 V^T$ ($X = U \Sigma V^T$)

$$K = Y V \Sigma^{-1} U^T$$

$$\tilde{K} = U^T K U = \Sigma^{-1} V^T X^T Y V \Sigma^{-1}$$

\tilde{K} 的特征值和左特征向量满足

$$\tilde{w}_j^T \tilde{K} = \tilde{\lambda}_j \tilde{w}_j^T$$

那么 K 的特征值和左特征向量满足

$$w_j^T K = \lambda_j w_j^T$$

其中 $\lambda_j = \tilde{\lambda}_j$ $w_j^T = \tilde{w}_j^T U^T$



扩展动力学模态分解

➤ 计算Koopman模态

$$id(\mathbf{u}) = \sum_{j=1}^D w_j^T \Psi(\mathbf{u}) v_j$$

$$\begin{aligned} [\mathbf{u}_0 \ \mathbf{u}_1, \dots, \mathbf{u}_{m-1}] &= [v_1, v_2, \dots, v_D] \begin{bmatrix} w_1^T \\ w_2^T \\ \vdots \\ w_D^T \end{bmatrix} X \\ &= [v_1, v_2, \dots, v_D] \begin{bmatrix} \tilde{w}_1^T \\ \tilde{w}_2^T \\ \vdots \\ \tilde{w}_D^T \end{bmatrix} \Sigma V^T \end{aligned}$$



扩展阅读

➤ 文献

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