

An invariant for the comparison of composition operators for reproducing kernel Hilbert spaces

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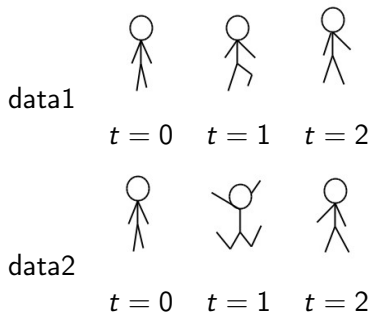
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- 1 Introduction
- 2 Review of reproducing kernel Hilbert space (RKHS)
- 3 Koopman operators for feature maps
- 4 Definition of the invariant (“angle”)
- 5 Examples
- 6 Empirical results

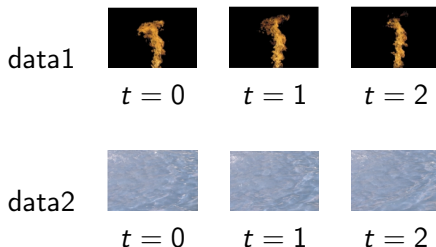
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Classifying or clustering time-series data is important

Human activities



Nature



Problem

How to compare time series datas ??

Given time series data in a Hilbert space \mathcal{H}'' : $y_0, y_1, y_2, \dots, y_t, \dots \in \mathcal{H}''$

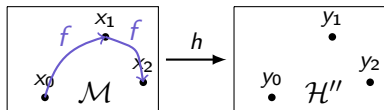
Assume $\{y_t\}_{t \geq 0}$ is generated by a **dynamical system**

$$f: \mathcal{M} \rightarrow \mathcal{M}, \{x_t\} \subset \mathcal{M}$$

$$h: \mathcal{M} \rightarrow \mathcal{H}''$$

$$x_{t+1} = f(x_t)$$

$$y_t = h(x_t)$$



\rightsquigarrow

\mathcal{H} : RKHS

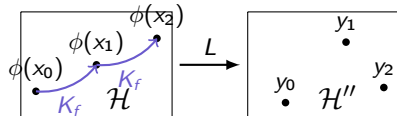
$\phi: \mathcal{M} \rightarrow \mathcal{H}$: feature map

$K_f: \mathcal{H} \rightarrow \mathcal{H}$: Koopman operator

$L_h: \mathcal{H} \rightarrow \mathcal{H}''$: bounded linear

$$\phi(x_{t+1}) = K_f \phi(x_t)$$

$$y_t = L_h \phi(x_t)$$



In terms linear algebra (\mathcal{H} , K_f , L_h e.t.c), we can define a “good” invariant !

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\mathcal{M} : set

Definition

$k: \mathcal{M} \times \mathcal{M} \rightarrow \mathbb{C}$: **positive definite kernel** if

for any $n > 0$ and $x_1, \dots, x_n \in \mathcal{M}$,

$$(k(x_i, x_j))_{i,j=1,\dots,n}$$

is a **positive semi-definite Hermitian matrix**.

$k_a: \mathcal{M} \rightarrow \mathbb{C}$: $k_a(x) := k(x, a)$ ($a \in \mathcal{M}$).

$\phi: \mathcal{M} \rightarrow \mathbb{C}^{\mathcal{M}}$; $x \mapsto k_x$: **feature map**

Theorem (Moore-Aronszajn)

k : positive definite kernel on \mathcal{M}

$\exists! \mathcal{H} \subset \mathbb{C}^{\mathcal{M}}$: **reproducing kernel Hilbert space (RKHS)**

characterized by

$$\left\{ \begin{array}{l} \bullet \mathcal{H} = \overline{\sum_{a \in \mathcal{M}} \mathbb{C}k_a} = \overline{\text{span}(\phi(\mathcal{M}))} \\ \bullet \langle k_a, k_b \rangle_{\mathcal{H}} = k(a, b) \end{array} \right.$$

Example

① $\mathcal{M} = \mathbb{R}^d$

$$k(x, y) := x \cdot y$$

$$\mathcal{H} := \text{Hom}_{\mathbb{R}}(\mathbb{R}^d, \mathbb{C}) \cong \mathbb{C}^N$$

② (Gaussian kernel) $\mathcal{M} = \mathbb{R}^d$

$$k(x, y) := e^{-|x-y|^2/\sigma^2}$$

$$\mathcal{H} := \left\{ f \in L^2(\mathbb{R}^d) \mid \int_{\mathbb{R}^d} |\widehat{f}(x)|^2 e^{\pi^2 \sigma^2 |x|^2} dx < \infty \right\}$$

③ (Szegő kernel) $\mathcal{M} = \mathbb{D} := \{z \in \mathbb{C} \mid |z| < 1\}$,

$$k(z, w) := (1 - z\bar{w})^{-1}$$

$$\mathcal{H} := \left\{ f: \text{regular on } \mathbb{D} \mid \sup_{0 < r < 1} \int_{|z|=r} |f(z)|^2 dz < \infty \right\}$$

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k : positive definite kernel on \mathcal{M}

\mathcal{H} : RKHS

$\mathcal{N} \subset \mathcal{M}$: subset

$$\mathcal{H}_{\mathcal{N}} := \overline{\text{span}(\phi(\mathcal{N}))}$$

Definition (Kawahara)

$f : \mathcal{N} \rightarrow \mathcal{N}$: map

The **Koopman operator for the feature map** is a linear operator

$$K_f : \mathcal{H}_{\mathcal{N}} \longrightarrow \mathcal{H}_{\mathcal{N}}$$

satisfying

- 1 K_f : **bounded**
- 2 For any $y \in \mathcal{N}$, $K_f(\phi(y)) = \phi(f(y))$

If K_f exists, K_f is uniquely determined.

Example

- ① $\mathcal{M} = \mathbb{R}^d$, $\mathcal{N} \subset \mathbb{R}^d$: open, $k(x, y) = e^{-|x-y|^2/\sigma^2}$

For $f : \mathcal{N} \rightarrow \mathcal{N}$: **linear map**,

- ② $\mathcal{M} = \mathcal{N} = \mathbb{D}$, K_f exists $\iff f: \mathbb{D} \rightarrow \mathbb{D}$ invertible & $\|f\| \leq 1$

For $f : \mathbb{D} \rightarrow \mathbb{D}$: **holomorphic map**, by Littlewood,

$\rightsquigarrow K_f$ exists

- ③ (Fock space) $\mathcal{M} = \mathcal{N} = \mathbb{C}^d$, $k(z, w) = e^{z \cdot w/2}$

For $f : \mathbb{C}^d \rightarrow \mathbb{C}^d$: **holomorphic map**, by Carswell-MacCluer-Schuster,

K_f exists

$$\iff f(z) = Az + b: \text{ affine map} \quad \text{s.t.} \quad \begin{cases} \|A\| \leq 1 \\ A\zeta \cdot b = 0 \text{ for } |A\zeta| = |\zeta| \end{cases}$$

Problem

Whether K_f exists or not is difficult !!

Remark

When $\mathcal{N} = \mathcal{M}$,

K_f exists \iff composition operator for f is bounded

With example 1, there are no example of a non-linear dynamical system such that its Koopman operator exists ! (in progress)

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\mathcal{H} : RKHS with feature map $\phi : \mathcal{M} \rightarrow \mathcal{H}$

$\mathcal{N} \subset \mathcal{M}$: subset

Definition

\mathcal{H}'' : Hilbert space

$h : \mathcal{N} \rightarrow \mathcal{H}''$: **generalized observable** on $\mathcal{H}_{\mathcal{N}}$ if

$\exists L_h : \mathcal{H}_{\mathcal{N}} \rightarrow \mathcal{H}''$: bounded linear s.t.

$$h = L_h \circ \phi|_{\mathcal{N}}$$

Examples of generalized observable

① $h = \phi|_{\mathcal{N}} : \mathcal{N} \rightarrow \mathcal{H}$

$L_h : \mathcal{H}_{\mathcal{N}} \hookrightarrow \mathcal{H}$: inclusion

② $h(x) = (g_i(x))_{i=1}^N : \mathcal{N} \rightarrow \mathbb{C}^N$ ($g_i \in \mathcal{H}$)

$$L_h(v) = (\langle g_i, v \rangle_{\mathcal{H}})_{i=1}^N$$

$\mathcal{M}_1, \mathcal{M}_2 \subset \mathcal{M}$: subsets

$\mathcal{H}', \mathcal{H}''$: Hilbert spaces

For $i = 1, 2$,

$f_i: \mathcal{M}_i \longrightarrow \mathcal{M}_i$: map (**dynamical system**)

$h_i: \mathcal{M}_i \longrightarrow \mathcal{H}''$: generalized observable

$X_i: \mathcal{H}' \longrightarrow \mathcal{H}_{\mathcal{M}_i}$: Hilbert-Schmidt operator (**initial value**)

Assume for $i = 1, 2$,

$$\exists K_{f_i}: \mathcal{H}_{\mathcal{M}_i} \longrightarrow \mathcal{H}_{\mathcal{M}_i}$$

$$\exists L_{h_i}: \mathcal{H}_{\mathcal{M}_i} \longrightarrow \mathcal{H}''$$

For $T, m > 0$,

$$d_m^T((L_{h_1}, K_{f_1}, X_1), (L_{h_2}, K_{f_2}, X_2)) := \text{tr} \left(\bigwedge_{r=1}^m \sum_{r=1}^T (L_{h_2} K_{f_2}^r X_2)^* L_{h_1} K_{f_1}^r X_1 \right)$$

$$A_m^T((h_1, f_1, X_1), (h_2, f_2, X_2)) := \frac{|d_m^T((L_{h_1}, K_{f_1}, X_1), (L_{h_2}, K_{f_2}, X_2))|^2}{2 \prod_{i=1}^T d_m^T((L_{h_i}, K_{f_i}, X_i), (L_{h_i}, K_{f_i}, X_i))}$$

$$\tilde{A}_m^T := \frac{1}{T} \sum_{t=1}^T A_m^t$$

Definition (The angle of dynamical systems)

If $\lim_T \tilde{A}_m^T((h_1, f_1, X_1), (h_2, f_2, X_2))$ exists, we define

$$A_m((h_1, f_1, X_1), (h_2, f_2, X_2)) := \lim_{T \rightarrow \infty} \tilde{A}_m^T((h_1, f_1, X_1), (h_2, f_2, X_2))$$

Remark

We prove some sufficient conditions for the convergence of \tilde{A}_m^T in the case of $\mathcal{H}' = \mathbb{C}^N$.

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$$\mathcal{M} = \mathcal{M}_1 = \mathcal{M}_2 = \mathbb{R}^N, k(x, y) = x \cdot y, \mathcal{H}' = \mathcal{H}, \mathcal{H}'' = \mathbb{C}^M$$

For $i = 1, 2$, consider a **state space model** (without noise):

$$\mathbf{x}_{t+1} = \mathbf{A}_i \mathbf{x}_t$$

$$\mathbf{y}_t = \mathbf{C}_i \mathbf{x}_t$$

where $\mathbf{A}_i \in \mathbb{R}^{N \times N}$, $\mathbf{C}_i \in \mathbb{R}^{M \times N}$

Theorem

For any $m > 0$,

$$\lim_{T \rightarrow \infty} \tilde{A}_m^T((\mathbf{C}_1, \mathbf{A}_1, \mathbf{I}_N), (\mathbf{C}_2, \mathbf{A}_2, \mathbf{I}_N)) \text{ exists}$$

Remark

*In the case $m = N$ and state space models are **stable** (i.e. the eigenvalues of \mathbf{A}_i are smaller than 1), DeCock-DeMoor define an angle between the state space models, which is the same as $A_N((\mathbf{C}_1, \mathbf{A}_1, \mathbf{I}_N), (\mathbf{C}_2, \mathbf{A}_2, \mathbf{I}_N))$.*

$$\mathcal{M} = \mathcal{M}_1 = \mathcal{M}_2 = \mathbb{R}^N, k(x, y) = x \cdot y, \mathcal{H}' = \mathcal{H}, \mathcal{H}'' = \mathbb{C}$$

Two AR models of order N ($i = 1, 2$):

$$(M_i) \quad x_t = a_{i,1}x_{t-1} + \cdots + a_{i,N}x_{t-N}$$



Two state space models:

$$\mathbf{x}_t = \mathbf{A}_i \mathbf{x}_{t-1},$$

$$y_t = \mathbf{C}_i \mathbf{x}_t$$

$$\mathbf{A}_i = \begin{pmatrix} a_{i,1} & \cdots & a_{i,N} \\ \mathbf{I}_{N-1} & & \mathbf{0} \end{pmatrix}, \quad \mathbf{C}_i = (1, 0, \dots, 0)$$

Let's compute $A_N((\mathbf{C}_1, \mathbf{A}_1, \mathbf{I}_N), (\mathbf{C}_2, \mathbf{A}_2, \mathbf{I}_N))$!

$\gamma_{i,1}, \dots, \gamma_{i,N}$: roots of $X^N - a_{i,1}X^{N-1} - \dots - a_{i,N} = 0$

$$P_i := \left\{ \gamma_{i,n} \mid |\gamma_{i,n}| > 1 \right\}, \quad Q_i := \left\{ \gamma_{i,n} \mid |\gamma_{i,n}| = 1 \right\}$$

$$R_i := \left\{ \gamma_{i,n} \mid |\gamma_{i,n}| < 1 \right\}.$$

Theorem

If $|P_1| = |P_2|$, $|R_1| = |R_2|$, and $Q_1 = Q_2$, we have

$$\begin{aligned} & A_N((\mathbf{C}_1, \mathbf{A}_1, \mathbf{I}_N), (\mathbf{C}_2, \mathbf{A}_2, \mathbf{I}_N)) \\ &= \frac{\prod_{\alpha, \beta \in P_1} (1 - \alpha\bar{\beta}) \cdot \prod_{\alpha, \beta \in P_2} (1 - \alpha\bar{\beta}) \cdot \prod_{\alpha, \beta \in R_1} (1 - \alpha\bar{\beta}) \cdot \prod_{\alpha, \beta \in R_2} (1 - \alpha\bar{\beta})}{\prod_{\alpha \in P_1, \beta \in P_2} |1 - \alpha\beta|^2 \cdot \prod_{\alpha \in R_1, \beta \in R_2} |1 - \alpha\beta|^2}, \end{aligned}$$

otherwise, $A_N((\mathbf{C}_1, \mathbf{A}_1, \mathbf{I}_N), (\mathbf{C}_2, \mathbf{A}_2, \mathbf{I}_N)) = 0$

Remark

If M_i 's are *stable* (i.e. $P_i = Q_i = \emptyset$), it is the same as the metric between M_i 's defined by Martin via cepstrum coefficients.

A formula for computations

$$\mathcal{H}' = \mathbb{C}^N, \mathcal{H}'' = \mathcal{H}$$

$$h_i = \phi|_{\mathcal{M}_i}$$

For $i = 1, 2, \dots, N$ time series sequences are given:

$$\{x_{i,0}^1, x_{i,1}^1, x_{i,2}^1, \dots\} \subset \mathcal{M}_i$$

$$\{x_{i,0}^2, x_{i,1}^2, x_{i,2}^2, \dots\} \subset \mathcal{M}_i$$

$$\vdots$$

$$\{x_{i,0}^N, x_{i,1}^N, x_{i,2}^N, \dots\} \subset \mathcal{M}_i$$

Assume

$$f_i(x_{i,t}^r) = x_{i,t+1}^r.$$

$$X_i : \mathbb{C}^N \rightarrow \mathcal{H}$$

$$X_i((0, \dots, 0, \overset{r}{1}, 0, \dots, 0)) := \phi(x_{i,0}^r).$$

For $m = 1, \dots, N$,

Theorem

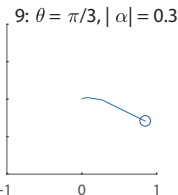
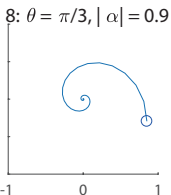
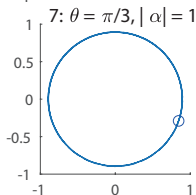
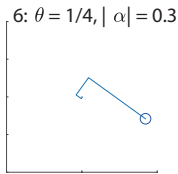
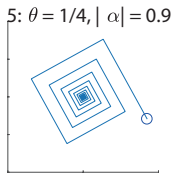
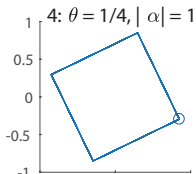
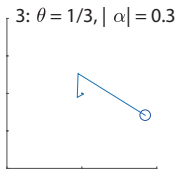
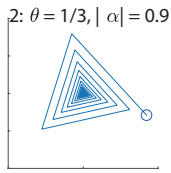
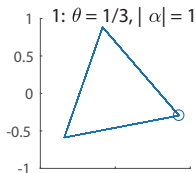
$$d_m^T((L_{h_1}, K_{f_1}, X_1), (L_{h_2}, K_{f_2}, X_2)) \\ = \sum_{t_1, \dots, t_m=0}^T \sum_{0 < s_1 < \dots < s_m \leq N} \det \begin{pmatrix} k(x_{i,t_1}^{s_1}, x_{j,t_1}^{s_1}) & \dots & k(x_{i,t_1}^{s_1}, x_{j,t_m}^{s_m}) \\ \vdots & \ddots & \vdots \\ k(x_{i,t_m}^{s_m}, x_{j,t_1}^{s_1}) & \dots & k(x_{i,t_m}^{s_m}, x_{j,t_m}^{s_m}) \end{pmatrix}$$

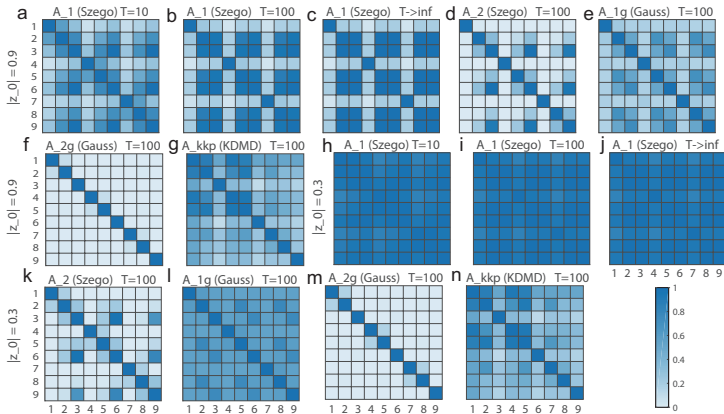
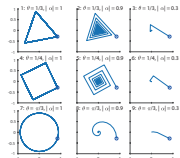
Point

We can compute A_m from only the value of k (**kernel trick**).

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Consider 9 dynamical systems (the multiplication of $\alpha = |\alpha|e^{i\theta}$ on \mathbb{D}):





m	data
1	$z_0, \alpha z_0, \dots$
2	$z_0, \alpha z_0, \dots$ $\alpha z_0, \alpha^2 z_0, \dots$

A_m (Szego) T=? = $A_m^?$ w.r.t Szegö
 A_1 (Szego) T->inf = $\lim_T A_1^T$ w.r.t Szegö
 A_{mg} (Gauss) T=? = $A_m^?$ w.r.t Gaussian
 A_{kkp} (KDMD) = other method

Thank you for listening !

For detail, check [arXiv 1805.12324](https://arxiv.org/abs/1805.12324) !