

# Dimension reduction using Poincaré inequalities

Alexandre PASCO

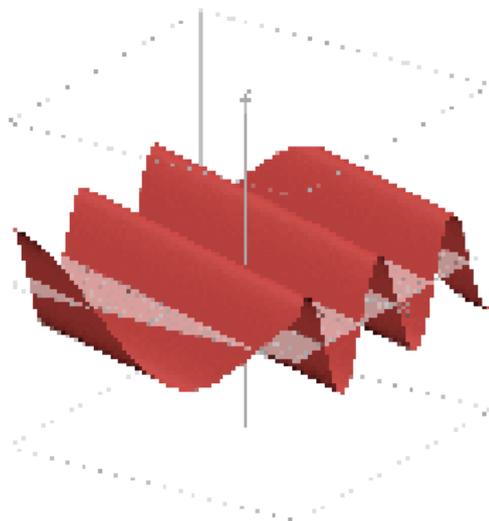
Centrale Nantes, Nantes Université, France  
In collaboration with Anthony NOUY.



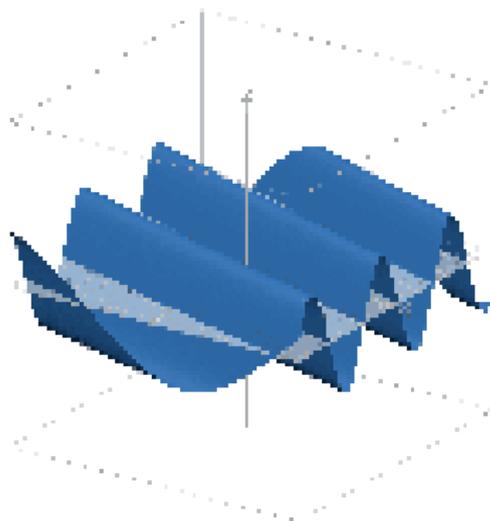
# Introduction

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$$u(x) = e^{x_1+3x_2}$$

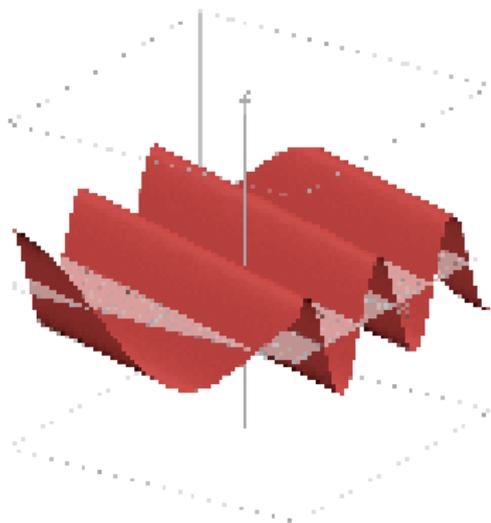


$$v(x) = e^{x_1+3x_2+0.05x_1x_2}$$

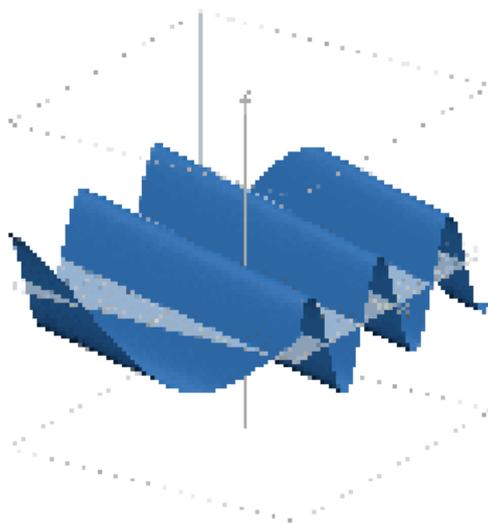


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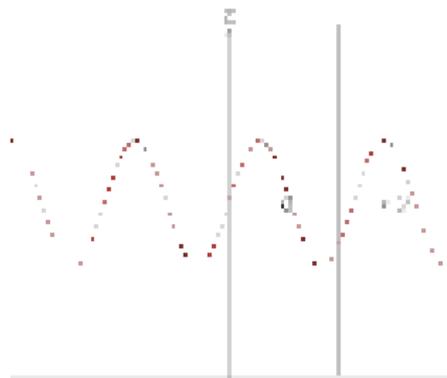


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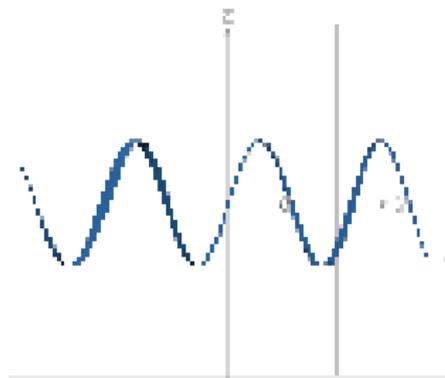


# Introduction

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- Goal: Approximate  $u : \mathbb{R}^d \rightarrow \mathbb{R} \in \mathcal{C}^1$  with  $d \gg 1$ , i.e. minimize

$$\mathcal{E}(\tilde{u}) := \mathbb{E} [(u(\mathbf{X}) - \tilde{u}(\mathbf{X}))^2]$$

where  $\mathbf{X}$  has probability density  $\mu_{\mathbf{X}}$ .

- Model class: ridge functions

$$\tilde{u}(x) = f(G^T x)$$

with  $G \in \mathbb{R}^{d \times m}$  and  $f : \mathbb{R}^m \rightarrow \mathbb{R}$

- Minimizing  $\mathcal{E}(\tilde{u})$  means solving

$$\inf_{G \in \mathbb{R}^{d \times m}} \inf_{f: \mathbb{R}^m \rightarrow \mathbb{R}} \mathbb{E} [(u(\mathbf{X}) - f(G^T \mathbf{X}))^2]$$

- For  $G \in \mathbb{R}^{d \times m}$  of rank  $k$ , we can decompose  $G = QR$  with  $Q \in \mathbb{R}^{d \times k}$  such that  $Q^T Q = I_k$  and  $R \in \mathbb{R}^{k \times m}$ .
- For some  $f: \mathbb{R}^m \rightarrow \mathbb{R}$  we can write

$$f(G^T x) = \tilde{f}(Q^T x) \quad \text{where} \quad \tilde{f} = f \circ R^T.$$

→ **Only range( $G$ ) matters !** Now assume  $m < d$  and  $G^T G = I_m$ .

On the function  $f$

## On the function $f$

- For a given  $G \in \mathbb{R}^{d \times m}$  let  $\mathbf{Z} = G^T \mathbf{X}$ , then the solution of

$$\inf_{f: \mathbb{R}^m \rightarrow \mathbb{R}} \mathbb{E} [(u(\mathbf{X}) - f(\mathbf{Z}))^2]$$

is given by  $f_G : z \mapsto \mathbb{E} [u(\mathbf{X}) | \mathbf{Z} = z]$

- We have an explicit expression for  $f_G$ , for any  $z \in \mathbb{R}^m$ ,

$$f_G(z) = \mathbb{E} [u(Gz + (I_d - GG^T)\mathbf{X})],$$

where  $I_d - GG^T$  is the orthogonal projector onto  $\text{range}(G)^\perp$ .

- For a given  $G \in \mathbb{R}^{d \times m}$  we can re-write the initial problem as

$$\inf_{\tilde{u}=f \circ G^T} \mathcal{E}(\tilde{u}) = \inf_{\substack{G \in \mathbb{R}^{d \times m} \\ G^T G = I_m}} \mathbb{E} [(u(\mathbf{X}) - \mathbb{E}[u(\mathbf{X})|G^T \mathbf{X}])^2]$$

- In practice we compute some  $\tilde{f}_G \neq f_G$  by regression.

# Poincaré Inequality

# Poincaré Inequality: the classic

- Let  $U \subset \mathbb{R}^n$  open and bounded with  $\mathcal{C}^1$  boundary.
- There exists  $C(U) < \infty$  such that

$$C(U) := \left( \inf_{h \in H_0^1(U)} \frac{\int_U \|\nabla h\|^2}{\int_U h^2} \right)^{-1}$$

- For any  $h \in H_0^1(U)$ , the following Poincaré Inequality holds

$$\int_U h^2 \leq C(U) \int_U \|\nabla h\|^2.$$

## Poincaré Inequality: the probabilistic

- Let  $\mathbf{Y} \in \mathbb{R}^n$  with probability density  $\gamma$ .
- Let  $C(\gamma) \in \mathbb{R} \cup \{+\infty\}$  the smallest constant such that

$$\mathbb{E} [h(\mathbf{Y})^2] \leq C(\gamma) \mathbb{E} [\|\nabla h(\mathbf{Y})\|^2]$$

for any  $h : \mathbb{R}^d \rightarrow \mathbb{R}$  such that  $h \in \mathcal{C}^1(\mathbb{R}^d)$  and  $\mathbb{E} [h(\mathbf{Y})] = 0$ ,

- We can bound  $C(\gamma)$  for some classical  $\gamma$ .

# Poincaré Inequality: bounds for the constant

- If  $\gamma = \mathcal{N}(0, 1)$  then  $C(\gamma) = 1$ .
- If  $\gamma = \mathcal{N}(m, \Sigma)$  then  $C(\gamma) = \lambda_{\min}(\Sigma)^{-1}$ .
- If  $\gamma$  is  $\alpha$ -uniformly log-concave then  $C(\gamma) = \alpha^{-1}$ , where

$$\gamma(dy) = \exp(-V(y))dx \quad \text{with} \quad \alpha = \inf_{y \in \mathbb{R}^n} \lambda_{\min}(V''(y)).$$

- If  $\gamma \propto \mathcal{U}(\mathcal{Y})$  with  $\mathcal{Y}$  bounded convex then  $C(\gamma) \leq \frac{\text{diam}(\mathcal{Y})^2}{\pi^2} \frac{\sup \gamma}{\inf \gamma}$ .
- For those examples  $C(\gamma)$  is independent on the dimension  $n$ . In general this is not the case !

# Poincaré Inequality and $G$

# Poincaré Inequality and G

- Recall that  $\mathbf{Z} = G^T \mathbf{X}$  and  $f_G(\mathbf{Z}) = \mathbb{E} [u(\mathbf{X}) | \mathbf{Z}]$

$$\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2] = \mathbb{E} [\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2 | \mathbf{Z}]]$$

- Decompose  $\mathbf{X} = G\mathbf{Z} + (I_d - GG^T)\mathbf{X}$ , thus we can write

$$\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2 | \mathbf{Z}] = \mathbb{E} [h_{\mathbf{Z}}(\mathbf{X})^2 | \mathbf{Z}]$$

where  $h_{\mathbf{Z}}(\mathbf{X}) := u(G\mathbf{Z} + (I_d - GG^T)\mathbf{X}) - f_G(\mathbf{Z})$ .

- We have  $\mathbb{E} [h_{\mathbf{Z}}(\mathbf{X}) | \mathbf{Z}] = 0$  and

$$\nabla h_{\mathbf{Z}}(\mathbf{X}) = (I_d - GG^T) \nabla u(\mathbf{X}).$$

- Applying the Poincaré Inequality gives

$$\mathbb{E} [h_{\mathbf{Z}}(\mathbf{X})^2 | \mathbf{Z}] \leq C(\mu_{\mathbf{X}|\mathbf{Z}}) \mathbb{E} [\|(I_d - GG^T)\nabla u(\mathbf{X})\|^2 | \mathbf{Z}]$$

- Assuming that  $C(G, \mu_{\mathbf{X}}) := \sup_{\mathbf{Z}} C(\mu_{\mathbf{X}|\mathbf{Z}}) < +\infty$  we obtain

$$\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2] \leq C(G, \mu_{\mathbf{X}}) \mathbb{E} [\|(I_d - GG^T)\nabla u(\mathbf{X})\|^2]$$

- Let  $G_{\perp} \in \mathbb{R}^{d \times (d-m)}$  s.t.  $G_{\perp}^T G_{\perp} = I_{d-m}$  and  $G_{\perp}^T G = 0$  then

$$\|(I_d - GG^T)\nabla u(\mathbf{X})\|^2 = \|G_{\perp}^T \nabla u(\mathbf{X})\|^2$$

$$\|(I_d - GG^T)\nabla u(\mathbf{X})\|^2 = \text{Trace}(G_{\perp}^T \nabla u(\mathbf{X}) \nabla u(\mathbf{X})^T G_{\perp})$$

$$\mathbb{E} [\|(I_d - GG^T)\nabla u(\mathbf{X})\|^2] = \text{Trace}(G_{\perp}^T H G_{\perp})$$

where

$$H := \mathbb{E} [\nabla u(\mathbf{X}) \nabla u(\mathbf{X})] \in \mathbb{R}^{d \times d}$$

- We are now with

$$\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2] \leq C(G, \mu_{\mathbf{X}}) \text{Trace}(G_{\perp}^T H G_{\perp})$$

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- Trace term minimized by taking  $G_{\perp}$  as the  $d - m$  last eigen vectors of  $H$ , i.e. taking  $G$  as the first  $m$  ones, which gives

$$\text{Trace}(G_{\perp}^T H G_{\perp}) = \lambda_{m+1} + \cdots + \lambda_d$$

- Ok, but what about  $C(G, \mu_{\mathbf{X}})$  ? Just take the previous examples and everything goes well ?

## Poincaré Inequality and $G$ : bounding conditional constant

- Recall that  $C(G, \mu_{\mathbf{X}}) := \sup_{\mathbf{z}} C(\mu_{\mathbf{X}|\mathbf{z}})$ .
- What property do we preserve when taking a "slice" of  $\mu_{\mathbf{X}}$  ?
- If  $\mu_{\mathbf{X}}$  is gaussian,  $\alpha$ -uniformly log-concave, or proportional to  $\mathcal{U}(\mathcal{X})$  with  $\mathcal{X}$  bounded convex, then so is  $\mu_{\mathbf{X}|G^T\mathbf{X}}$  and

$$C(\mu_{\mathbf{X}|G^T\mathbf{X}}) \leq C(\mu_{\mathbf{X}})$$

for any orthonormal  $G$ .

## Poincaré Inequality and $G$ : final bound

- Assuming that  $\sup_G \sup_{\mathbf{X}} C(\mu_{\mathbf{X}|G^T \mathbf{X}}) = C < +\infty$ , then

$$\mathbb{E} [(u(\mathbf{X}) - f_G(\mathbf{Z}))^2] \leq C \text{Trace}(G_{\perp}^T H G_{\perp})$$

- Choosing the  $m$  first eigen vectors for  $G$  leads to

$$\min_{f: \mathbb{R}^d \rightarrow \mathbb{R}} \mathbb{E} [(u(\mathbf{X}) - f(G^T \mathbf{X}))^2] \leq C \sum_{k=m+1}^d \lambda_k.$$

with  $\lambda_1 \geq \dots \geq \lambda_d \geq 0$  the eigen values of  $H = \mathbb{E} [\nabla u \nabla u^T]$ .

- Remark: this bound is in general not sharp.

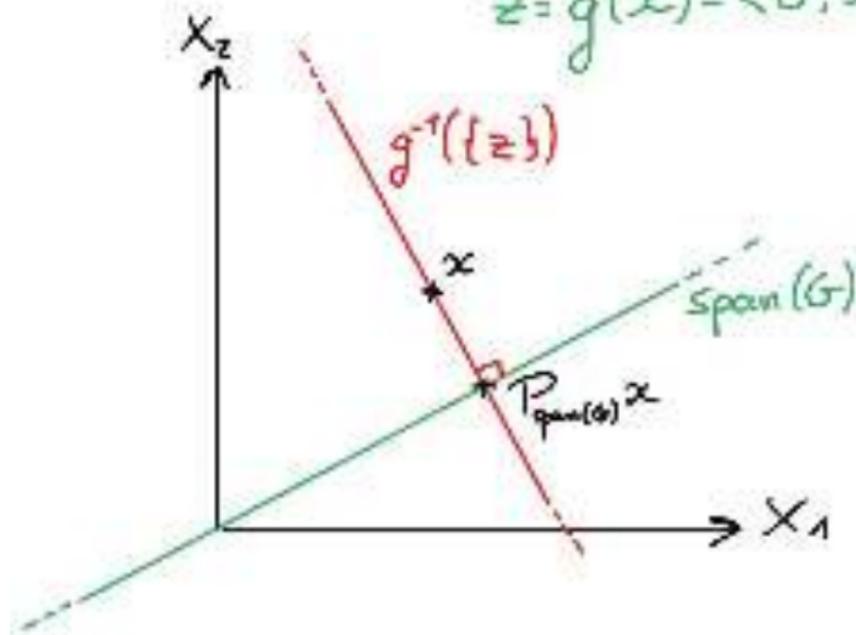
# Towards nonlinear dimension reduction

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- Approximate  $u(\mathbf{X})$  by  $f(\mathbf{Z})$  with  $\mathbf{Z} = g(\mathbf{X})$  where  $g \in \mathcal{G}_m \subset \mathcal{C}^1(\mathbb{R}^d, \mathbb{R}^m)$  may be nonlinear.
  - If  $J_g(\mathbf{X})$  has full rank then  $\mu_{\mathbf{X}|\mathbf{Z}}$  where  $\mathbf{Z} = g(\mathbf{X})$  is supported on the  $m$ -dimensional submanifold  $g^{-1}(\mathbf{Z}) \subset \mathbb{R}^d$ .
- + Allows for lower  $m$ , i.e. better dimension reduction.
- The support of  $\mu_{\mathbf{X}|\mathbf{Z}}$  not affine anymore, but a Riemannian submanifold of  $\mathbb{R}^d$ .
  - Cannot say much on the Poincaré Constant  $C(\mu_{\mathbf{X}|\mathbf{Z}})$ .
  - The Poincaré Inequality involves  $\mathbb{E} [\|\nabla u|_{g^{-1}(\mathbf{z})}(\mathbf{X})\|^2]$ , which is not minimized by an eigen-value problem anymore...

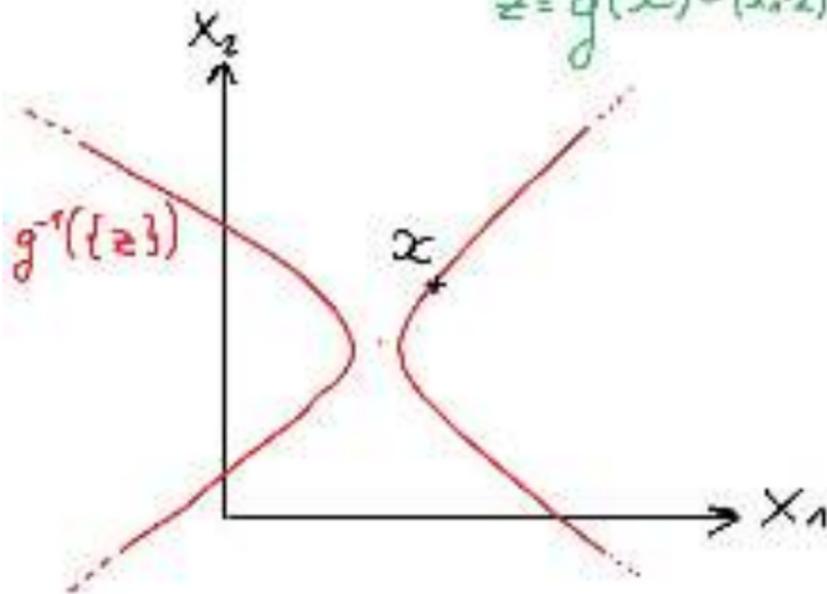
## Linear level sets

$$z = g(x) = \langle G, x \rangle$$



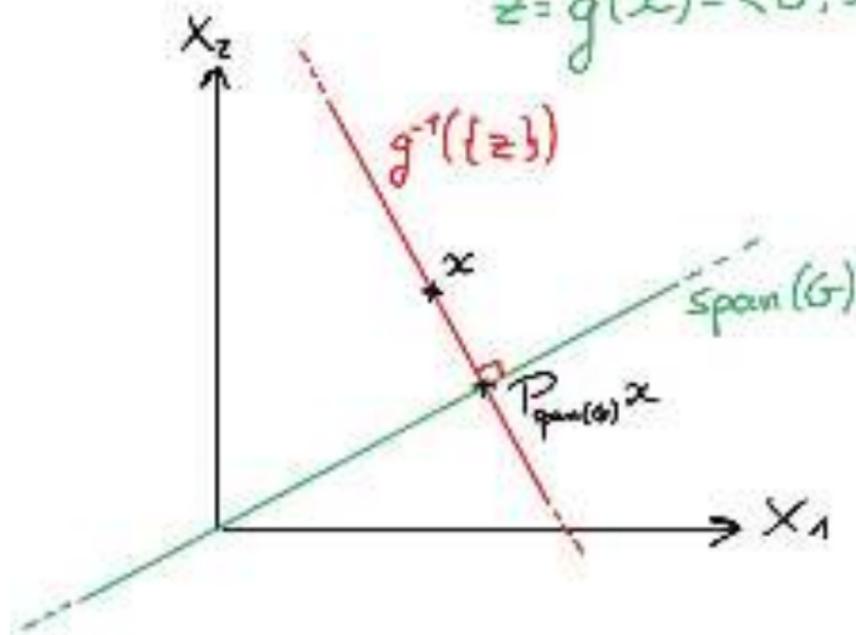
## Nonlinear level sets

$$z = g(x) = (x_1 - 2)^2 - (x_2 - 2)^2$$



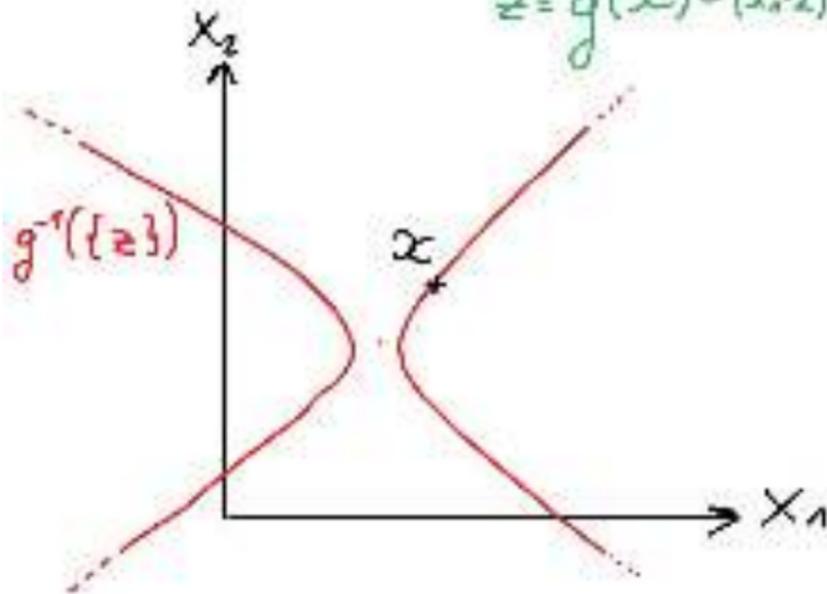
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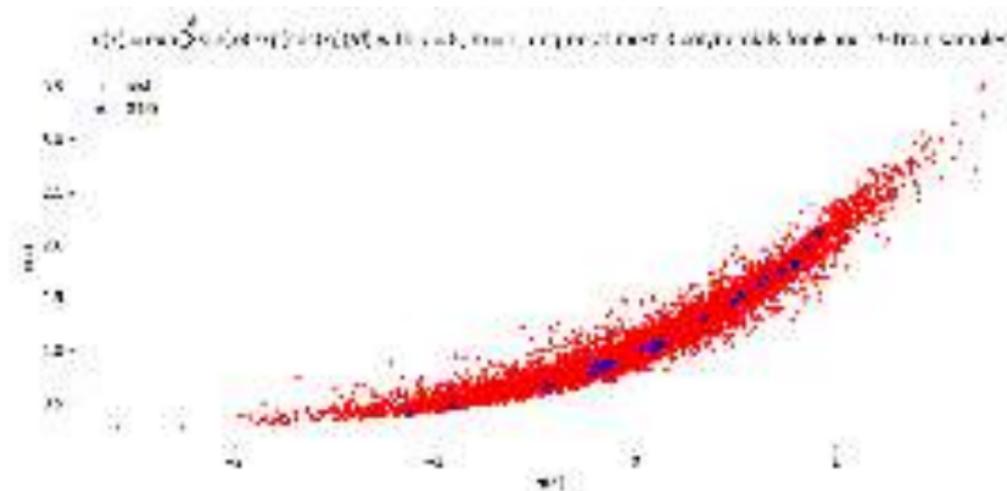


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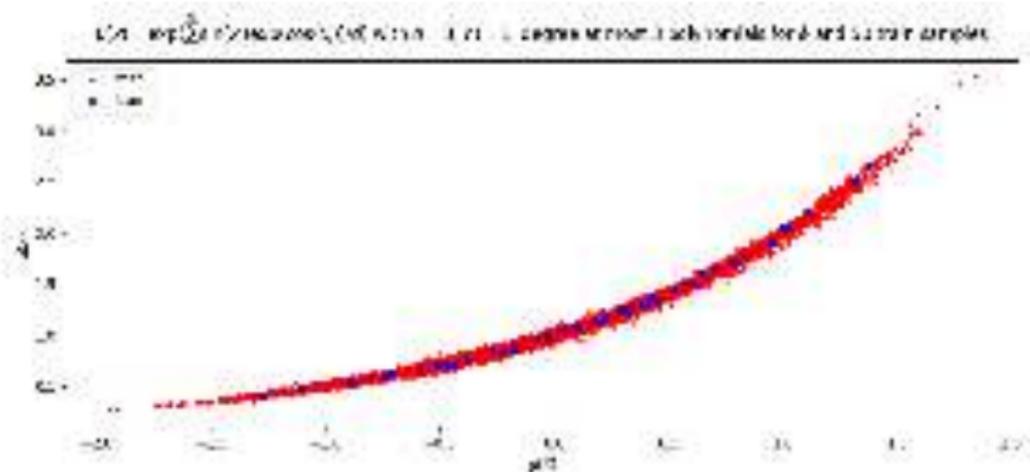
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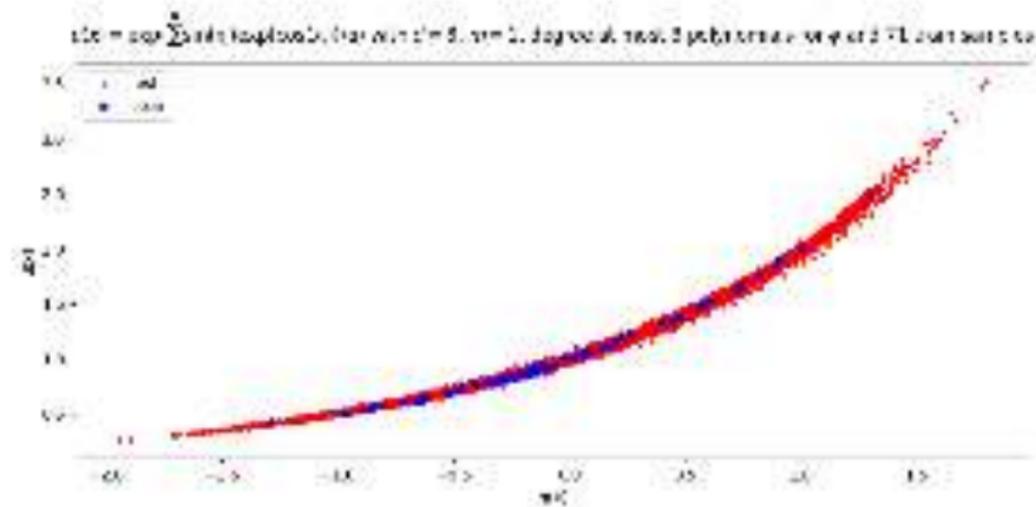
# Towards nonlinear dimension reduction: numerics



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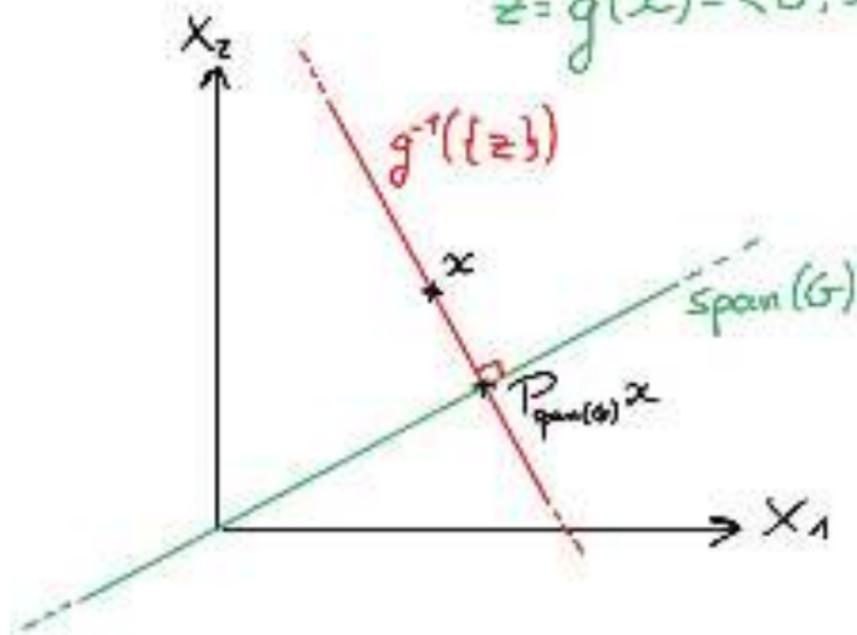


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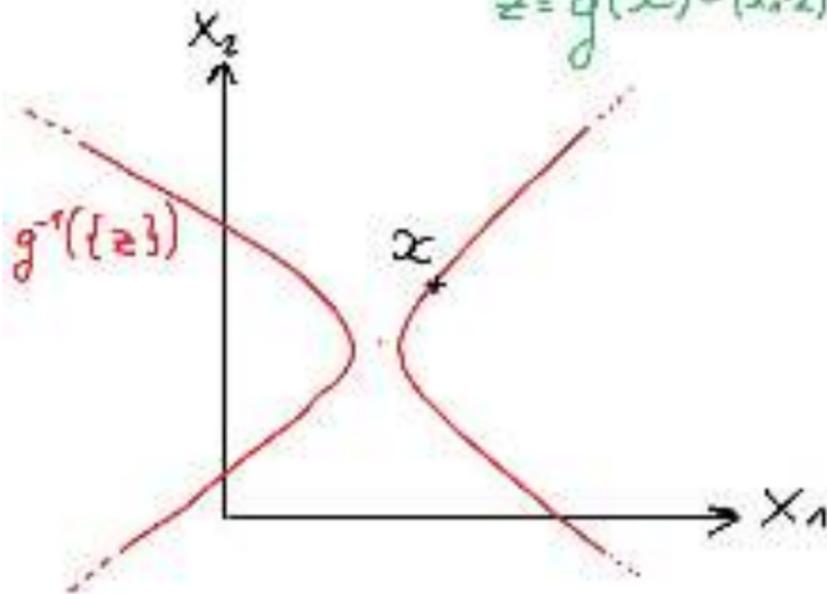
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Thank you for your attention !

# References

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- Bounds for the Poincaré constant: [Teixeira Parente et al., 2020]
- PI for dimension reduction:  
[Constantine et al., 2014, Zahm et al., 2020]
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Thank you !

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