

# **A reproducible comparative study of categorical kernels for Gaussian process regression, with new clustering-based nested kernels**

Raphaël Carpintero Perez

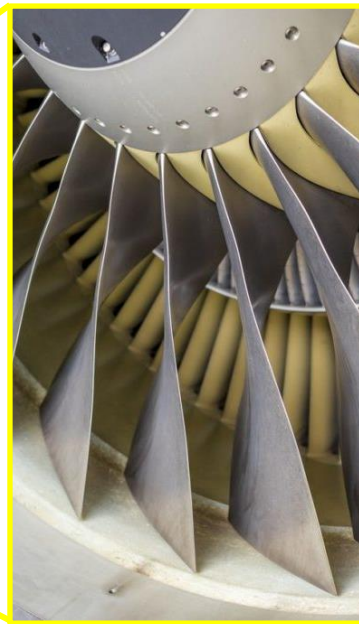
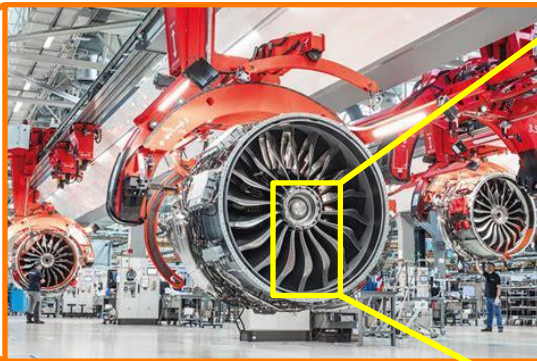
Sébastien Da Veiga  
Josselin Garnier

10/10/2025

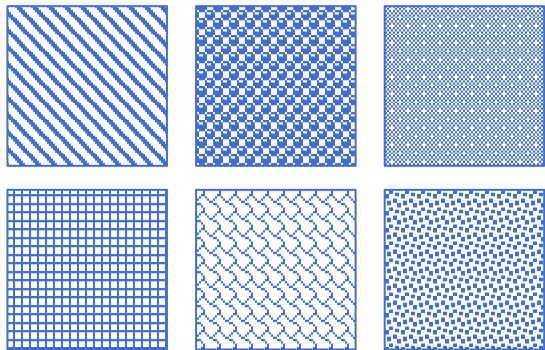
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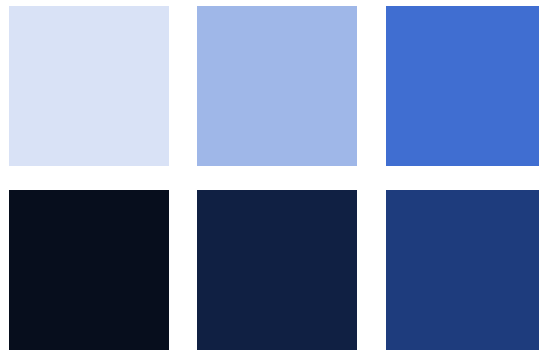
# Objectives



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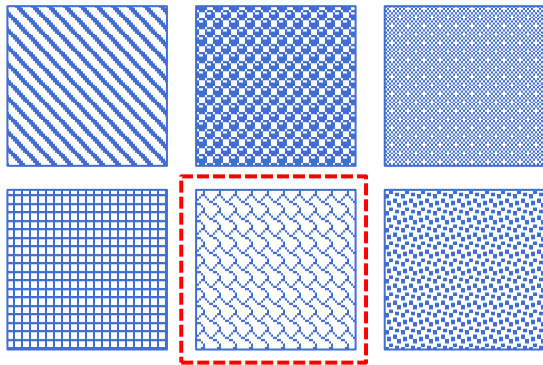


Input 1: weaving

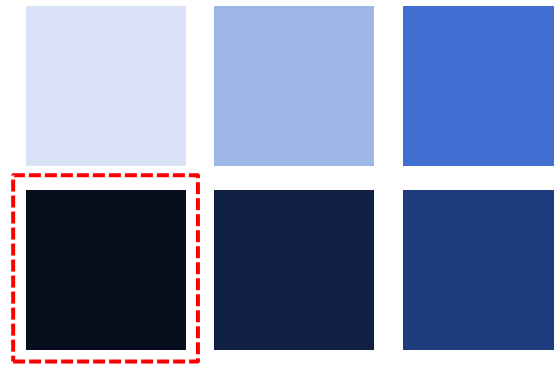


Input 2: type of material

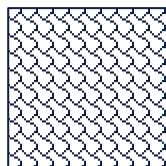
# Objectives



Input 1: weaving



Input 2: type of material



Gaussian  
Process  
regression

Quantity of  
Interest

# GP in mixed spaces

$$f : \boxed{\mathbb{R}^n} \times \boxed{\mathcal{Z}} \rightarrow \mathbb{R}$$

Continuous inputs      Categorical inputs

$$\mathcal{Z} = \prod_{i=1}^m \boxed{Z_i}$$

Unordered set, finite number of levels  
e.g.  $Z_i = \{A, B, \dots, E\}$

# GP in mixed spaces

$$f : \boxed{\mathbb{R}^n} \times \boxed{\mathcal{Z}} \rightarrow \mathbb{R}$$

Continuous inputs      Categorical inputs

$$\mathcal{Z} = \prod_{i=1}^m \boxed{\mathcal{Z}_i}$$

Unordered set, finite number of levels  
e.g.  $\mathcal{Z}_i = \{A, B, \dots, E\}$

$$k_{mixed}((x, z), (x', z')) = k_{cont}(x, x') \times \prod_{i=1}^m k(z_i, z'_i) \quad \text{for } (x, z), (x', z') \in \mathbb{R}^n \times \mathcal{Z}$$

How to choose the categorical kernel  $k$ ?  $\longrightarrow$  In the following,  $\mathcal{Z} = \{1, \dots, C\}$



# 1- Review of existing approaches

a) Encoding

b) Covariance matrix parametrization

2- Experiments for datasets with known group structure

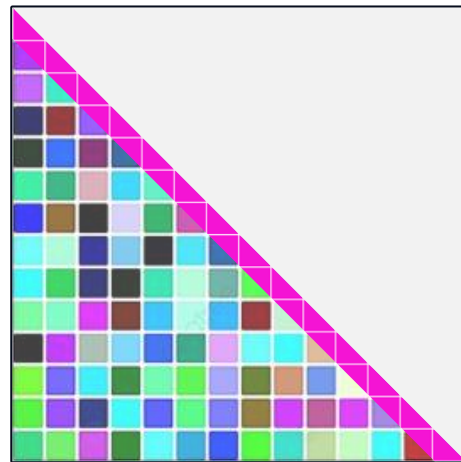
3- Automatic selection of groups

4- Experiments for datasets with no known group structure

# One-hot encoding

$C$  parameters

Level	Encoding
1	$E(1) = (1, 0, 0 \dots, 0)$
2	$E(2) = (0, 1, 0 \dots, 0)$
$\vdots$	
$C$	$E(C) = (0, 0, 0 \dots, 1)$



$$k(z, z') = \prod_{i=1}^C e^{-\frac{(E(z)_i - E(z')_i)^2}{2\theta_i^2}} = \delta_{z,z'} + e^{-\frac{1}{2}(\theta_z^{-2} + \theta_{z'}^{-2})}(1 - \delta_{z,z'})$$

ARD RBF kernel  
between encodings



# Latent Variables (LVGP)

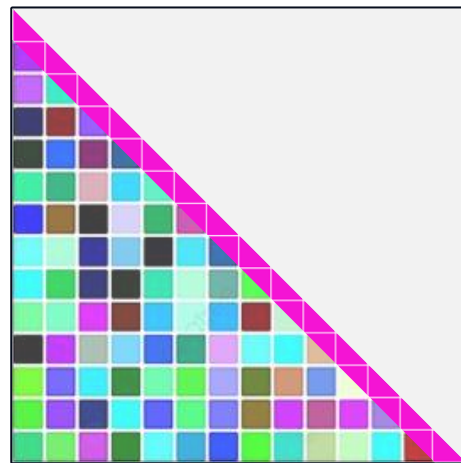
[Zhang et al., 2020]

$2C - 3$  parameters

$\phi: \{1, \dots, C\} \rightarrow \mathbb{R}^2$  : learned function



$$k(z, z') = e^{-\|\phi(z) - \phi(z')\|_2^2}$$



ARD RBF kernel between learned representations in dimension 2



# 1- Review of existing approaches

a) Encoding

b) Covariance matrix parametrization

2- Experiments for datasets with known group structure

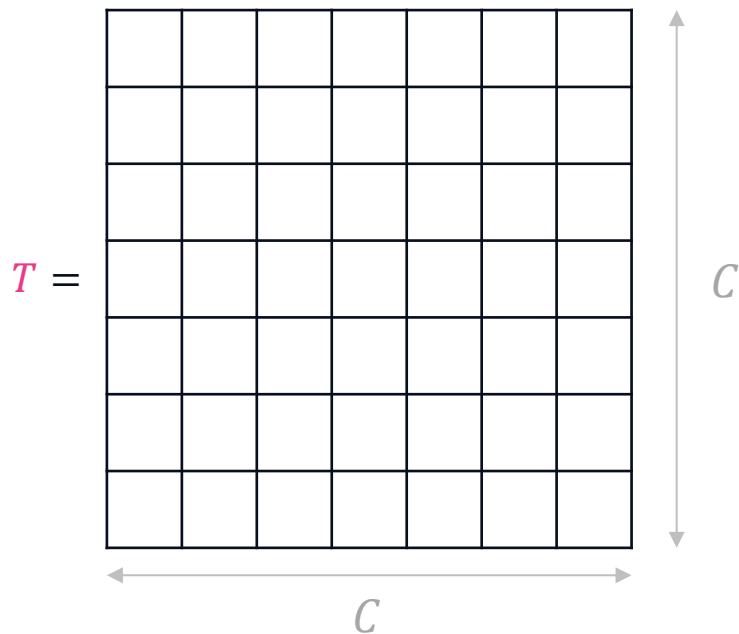
3- Automatic selection of groups

4- Experiments for datasets with no known group structure

# Matrix parametrization

$$k : \mathcal{Z} \times \mathcal{Z} \rightarrow \mathbb{R}$$

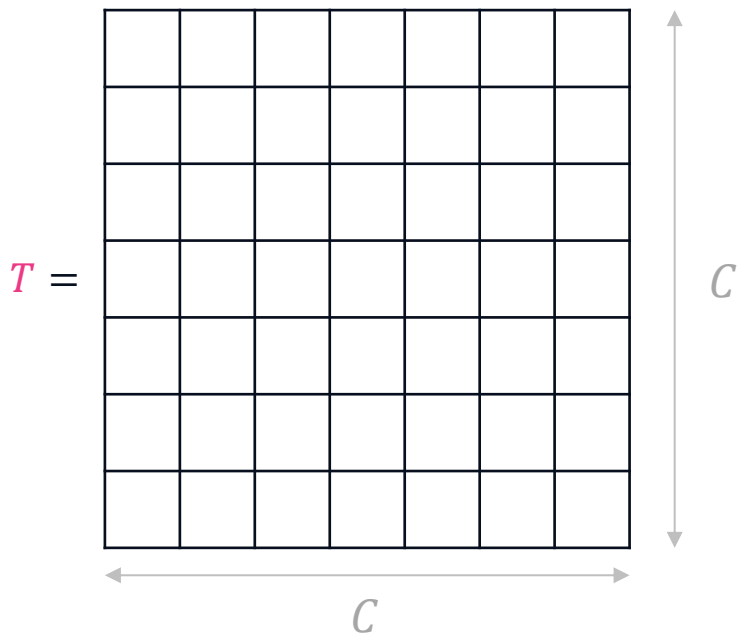
$\sim$



# Matrix parametrization

$$k : \mathcal{Z} \times \mathcal{Z} \rightarrow \mathbb{R}$$

~



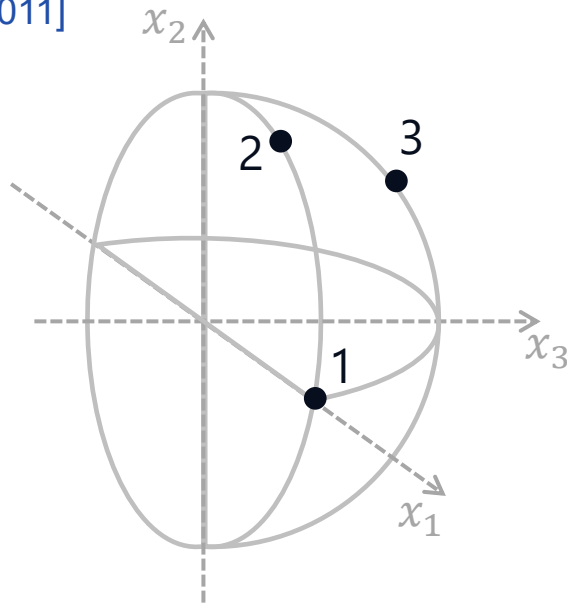
$T$  symmetric positive definite matrix

Cholesky decomposition

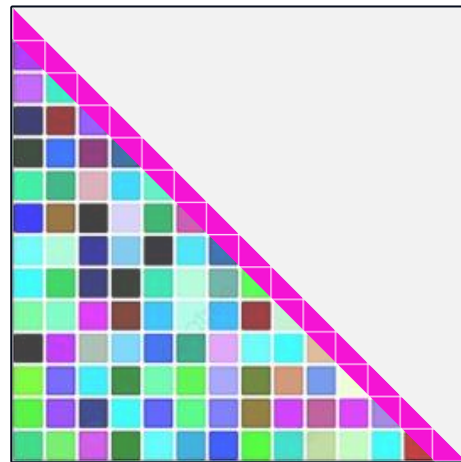
$$T = LL^T \quad L = \underline{L(\theta)}$$

# Homoscedastic Hypersphere (Ho)

[Zhou et al., 2011]



$\frac{1}{2}C(C-1)$  parameters



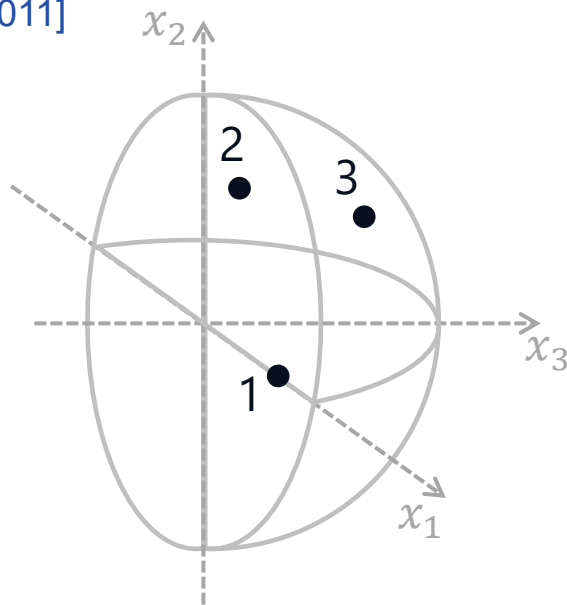
$$L = \begin{bmatrix} 1 & 0 & 0 \\ \cos(\theta_{21}) & \sin(\theta_{21}) & 0 \\ \cos(\theta_{31}) & \sin(\theta_{31}) \cos(\theta_{32}) & \sin(\theta_{31}) \sin(\theta_{32}) \end{bmatrix}$$

$\theta_{ij} \in (0, \frac{\pi}{2}) \rightarrow$  Positive correlations

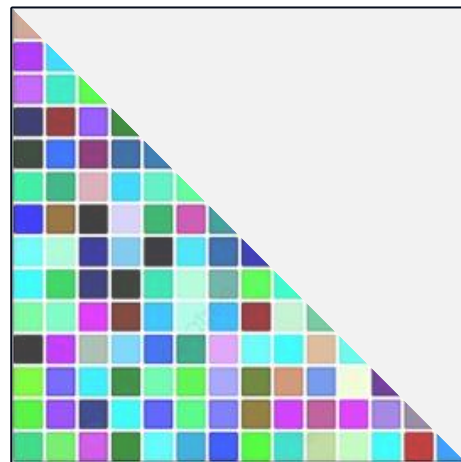
$\theta_{ij} \in (0, \pi) \rightarrow$  Negative correlations

# Heteroscedastic Hypersphere (He)

[Zhou et al., 2011]



$\frac{1}{2}C(C + 1)$  parameters



$$L = \begin{bmatrix} \theta_{10} & 0 & 0 \\ \theta_{20}\cos(\theta_{21}) & \theta_{20}\sin(\theta_{21}) & 0 \\ \theta_{30}\cos(\theta_{31}) & \theta_{30}\sin(\theta_{31})\cos(\theta_{32}) & \theta_{30}\sin(\theta_{31})\sin(\theta_{32}) \end{bmatrix}$$

# Exp Homoscedastic Hypersphere(EHH)

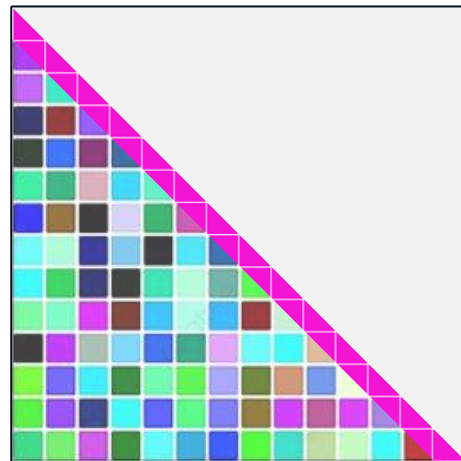
[Saves et al., 2023]

$\frac{1}{2}C(C+1)$  parameters

$L$  : homoscedastic hypersphere

$$\tau_{z,z'} = \log( (LL^T)_{z,z'} - 1 )$$

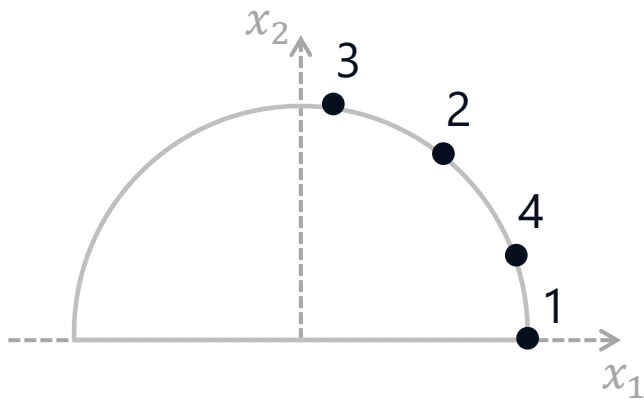
$$k(z, z') = \delta_{z,z'} + e^{-2\tau_{z,z'}}(1 - \delta_{z,z'})$$



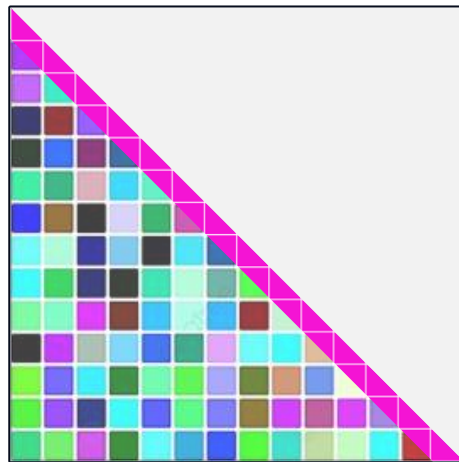
# Low rank Hypersphere (Ho\_2)

[Kirchhoff et al., 2020]

$C - 1$  parameters



$$L = \begin{bmatrix} \overbrace{\begin{matrix} 1 & 0 \end{matrix}}^{\text{Rank 2}} & 0 & 0 \\ \sin(\theta_{21}) & \cos(\theta_{21}) & 0 \\ \sin(\theta_{31}) & \cos(\theta_{31}) & 0 \\ \sin(\theta_{41}) & \cos(\theta_{41}) & 0 \end{bmatrix}$$





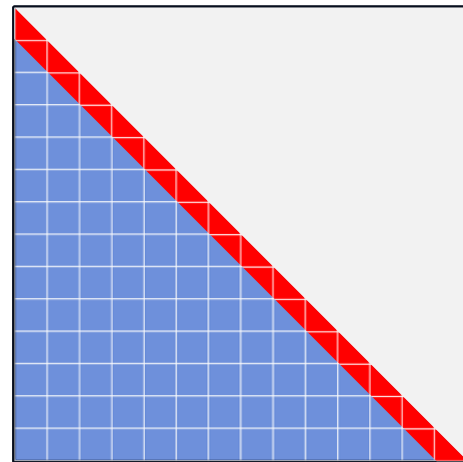
# Compound symmetry (CS)

[Katz., 2011]

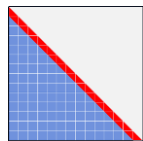
2 parameters

$$k(z, z') = v\delta_{z,z'} + c(1 - \delta_{z,z'})$$

$$v > 0, \quad \frac{c}{v} \in \left(\frac{-1}{c-1}, 1\right)$$



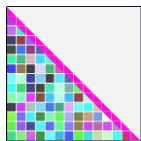
# Summary of the methods



$\mathcal{O}(1)$



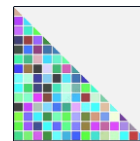
CS



$\mathcal{O}(C)$



One hot  
LVGP  
Ho\_2 , Ho\_3



$\mathcal{O}(C^2)$  # params



Ho, He  
EHH

# Nested Kernels

[Roustant et al., 2020]

Requires  $\gamma$  groups of levels:

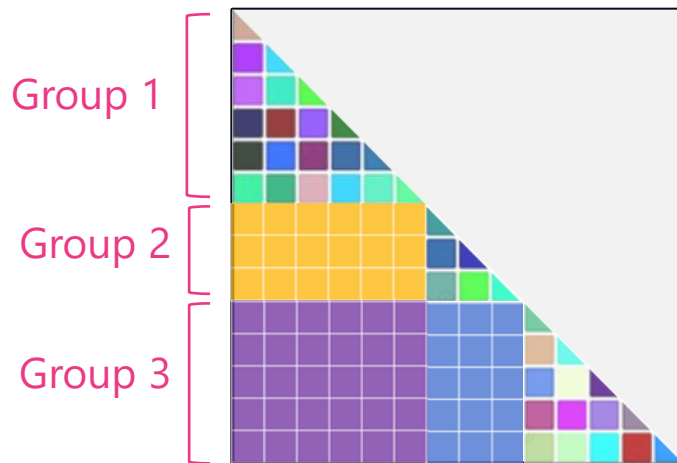
$$\{1, \dots, C\} = \bigcup_{1 \leq l \leq \gamma} G_l \quad (G_l \text{ of size } n_l)$$

$$T = \begin{bmatrix} W_1 & B_{12} & B_{13} \\ B_{21} & W_2 & B_{23} \\ B_{31} & B_{32} & W_3 \end{bmatrix}$$

Block covariance matrix

- Cov « Within group »
- Cov « Between groups »

$$\sum_{l=1}^{\gamma} \frac{n_l(n_l + 1)}{2} + \frac{\gamma(\gamma + 1)}{2} \text{ parameters}$$



Nested\_He\_He

Between

Within

# Nested Kernels

[Roustant et al., 2020]

Requires  $\gamma$  groups of levels:

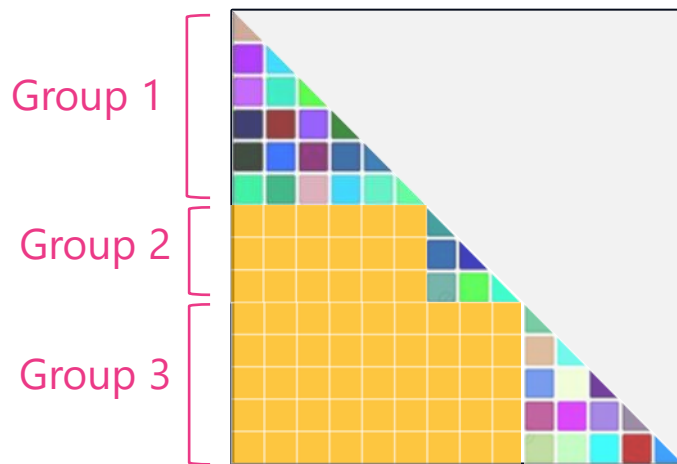
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Block covariance matrix

- Cov « Within group »
- Cov « Between groups »

$$\sum_{l=1}^{\gamma} \frac{n_l(n_l + 1)}{2} + 2 \quad \text{parameters}$$



Nested\_CS\_He

Between

Within

# Nested Kernels

[Roustant et al., 2020]

Requires  $\gamma$  groups of levels:

$$\{1, \dots, C\} = \bigcup_{1 \leq l \leq \gamma} G_l \quad (G_l \text{ of size } n_l)$$

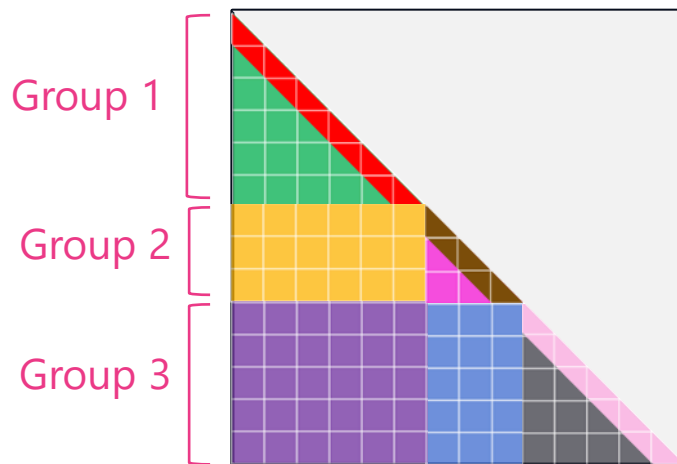
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Block covariance matrix

- Cov « Within group »
- Cov « Between groups »

$$\gamma + \frac{\gamma(\gamma + 1)}{2}$$

parameters



Nested\_Ho\_CS

Between

Within

# Nested Kernels

[Roustant et al., 2020]

Requires  $\gamma$  groups of levels:

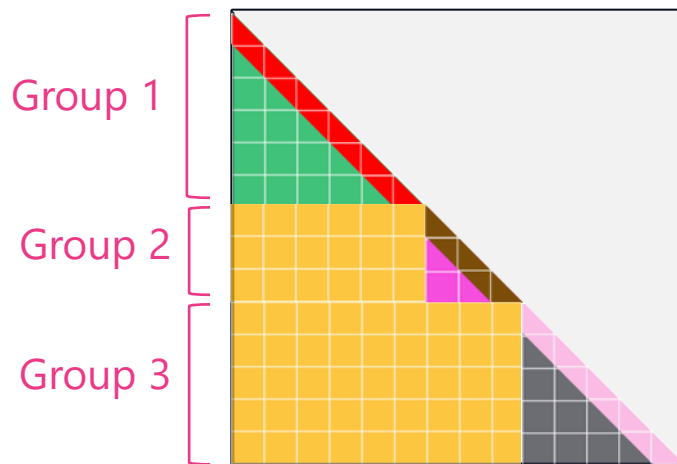
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Block covariance matrix

- Cov « Within group »
- Cov « Between groups »

$\gamma + 2$  parameters

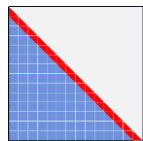


Nested\_CS\_CS

Between

Within

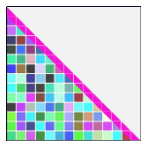
# Summary of the methods



$\mathcal{O}(1)$



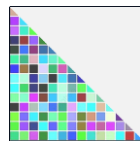
CS



$\mathcal{O}(C)$



One hot  
LVGP  
Ho\_2 , Ho\_3

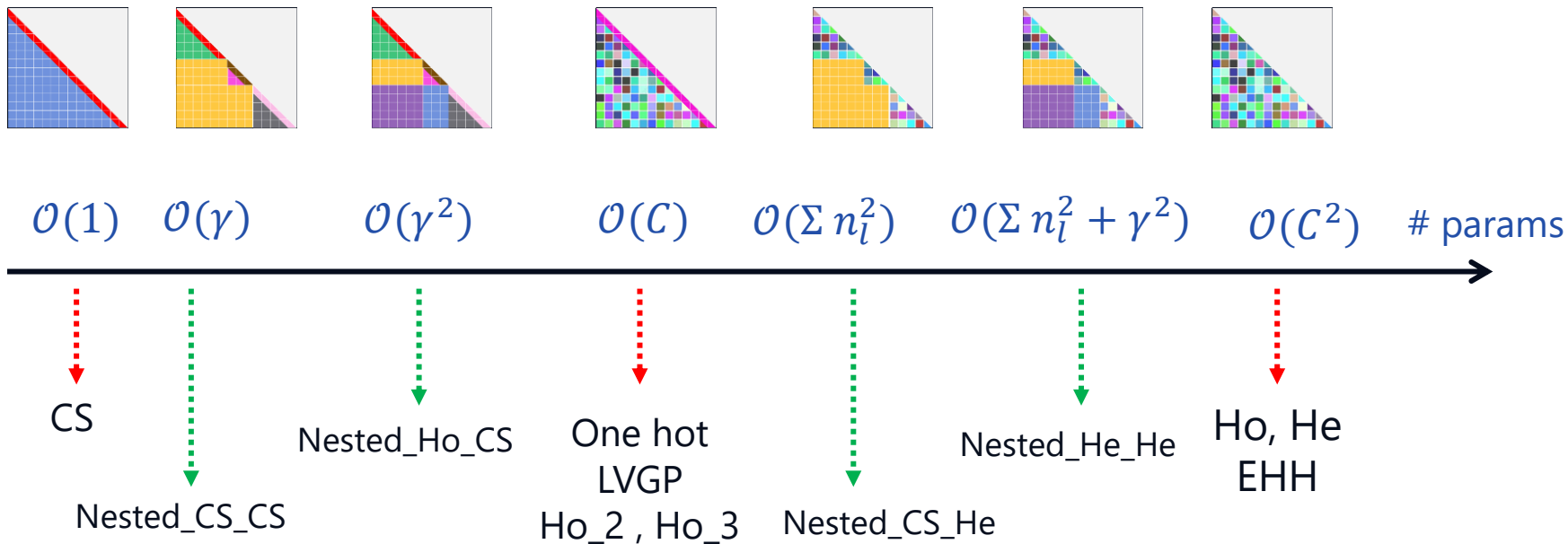


$\mathcal{O}(C^2)$  # params



Ho, He  
EHH

# Summary of the methods







## 1- Review of existing approaches

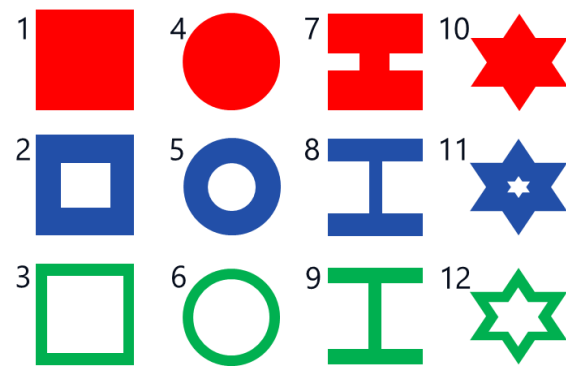
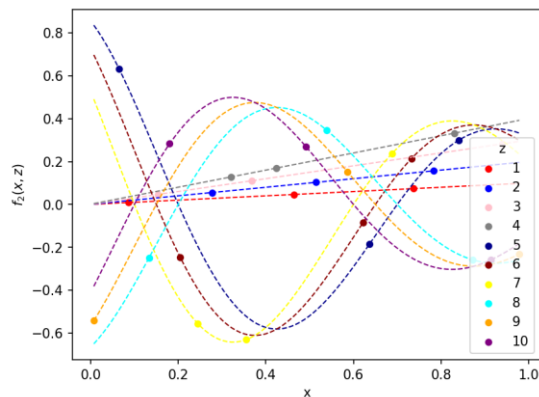
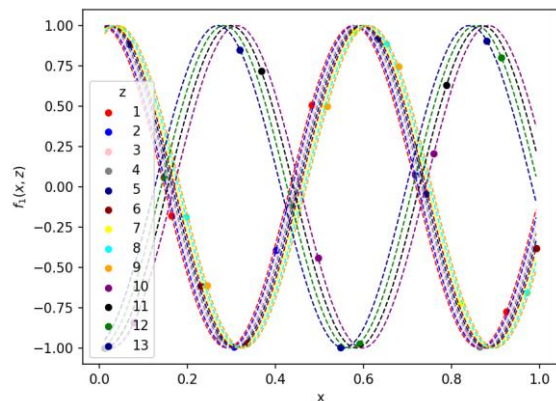
- a) Encoding
- b) Covariance matrix parametrization
- c) Kernels from the BO litterature

## 2- Experiments for datasets with known group structure

## 3- Automatic selection of groups

## 4- Experiments for datasets with no known group structure

# Datasets with known group structure



Name	Cont	Cat	Train	Test	Groups	Source
$f_1$	1	1 (13)	39/78/117/156/195	1001	True	<a href="#">Roustant et al. (2020)</a>
$f_2$	1	1 (10)	30/60/90/120/150	1000	True	<a href="#">Roustant et al. (2020)</a>
Beam bending	2	1 (12)	36/72/108/144/180	1000	True	<a href="#">Roustant et al. (2020)</a>

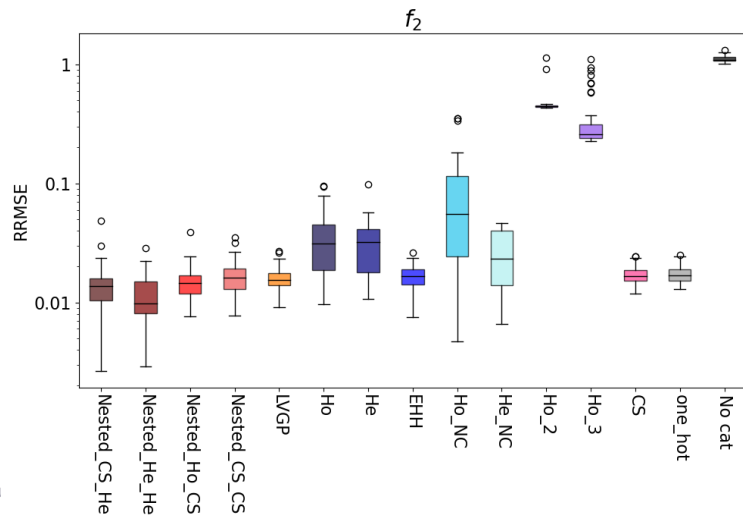
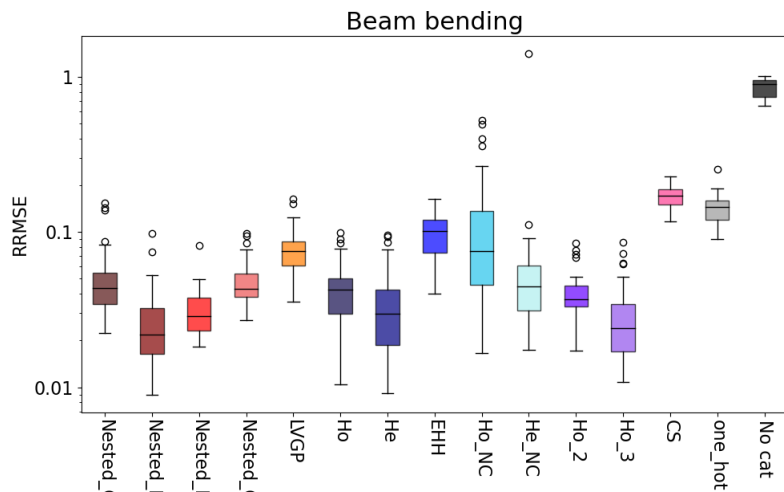
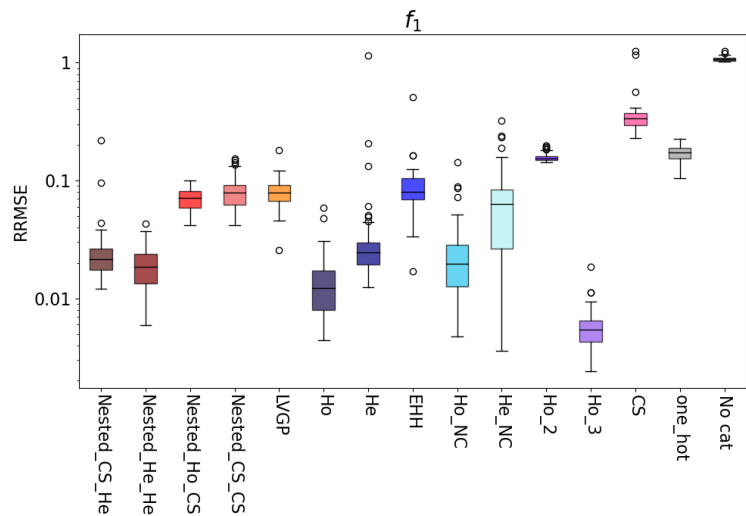
# Presentation of the methods/kernels

Category	Name	Description
Hypersphere	Ho	Homoscedastic, only positive correlations
	Ho_NC	Homoscedastic, allowing negative correlations
	He	Heteroscedastic, only positive correlations
	He_NC	Heteroscedastic, allowing negative correlations
	Ho_2	Homoscedastic, only positive correlations (rank 2)
	Ho_3	Homoscedastic, only positive correlations (rank 3)
	EGH	Exponential Homoscedastic Hypersphere
LVGP	LVGP	Latent dimension 2
CS	CS	Compound symmetry
One-hot	One_hot	One hot encoding
No cat	No cat	Only continuous variables

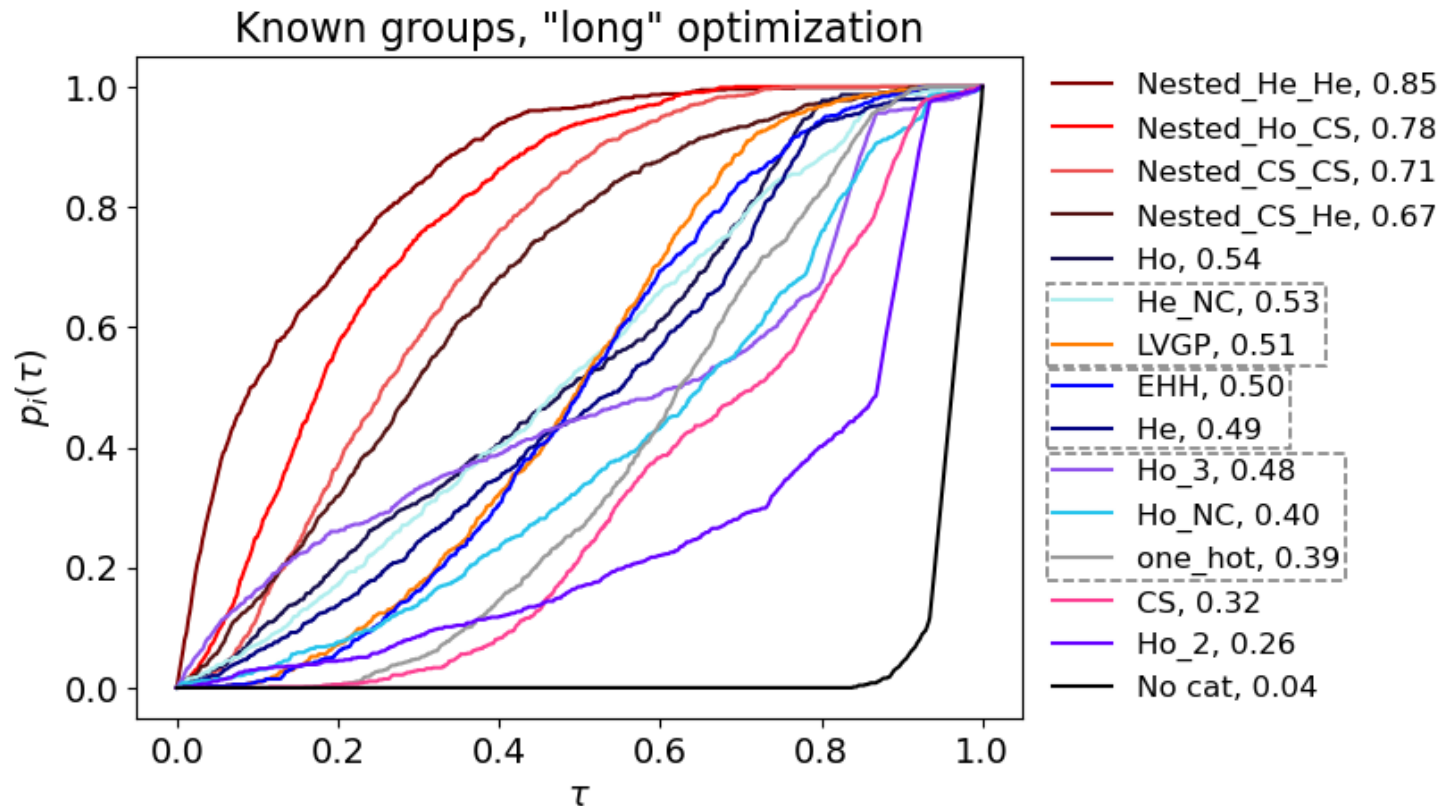
# Presentation of the methods/kernels

Category	Name	Description
Nested	Nested_CS_He	Between = CS, Within = He
	Nested_He_He	Between = He, Within = He
	Nested_Ho_CS	Between = Ho, Within = CS
	Nested_CS_CS	Between = CS, Within = CS

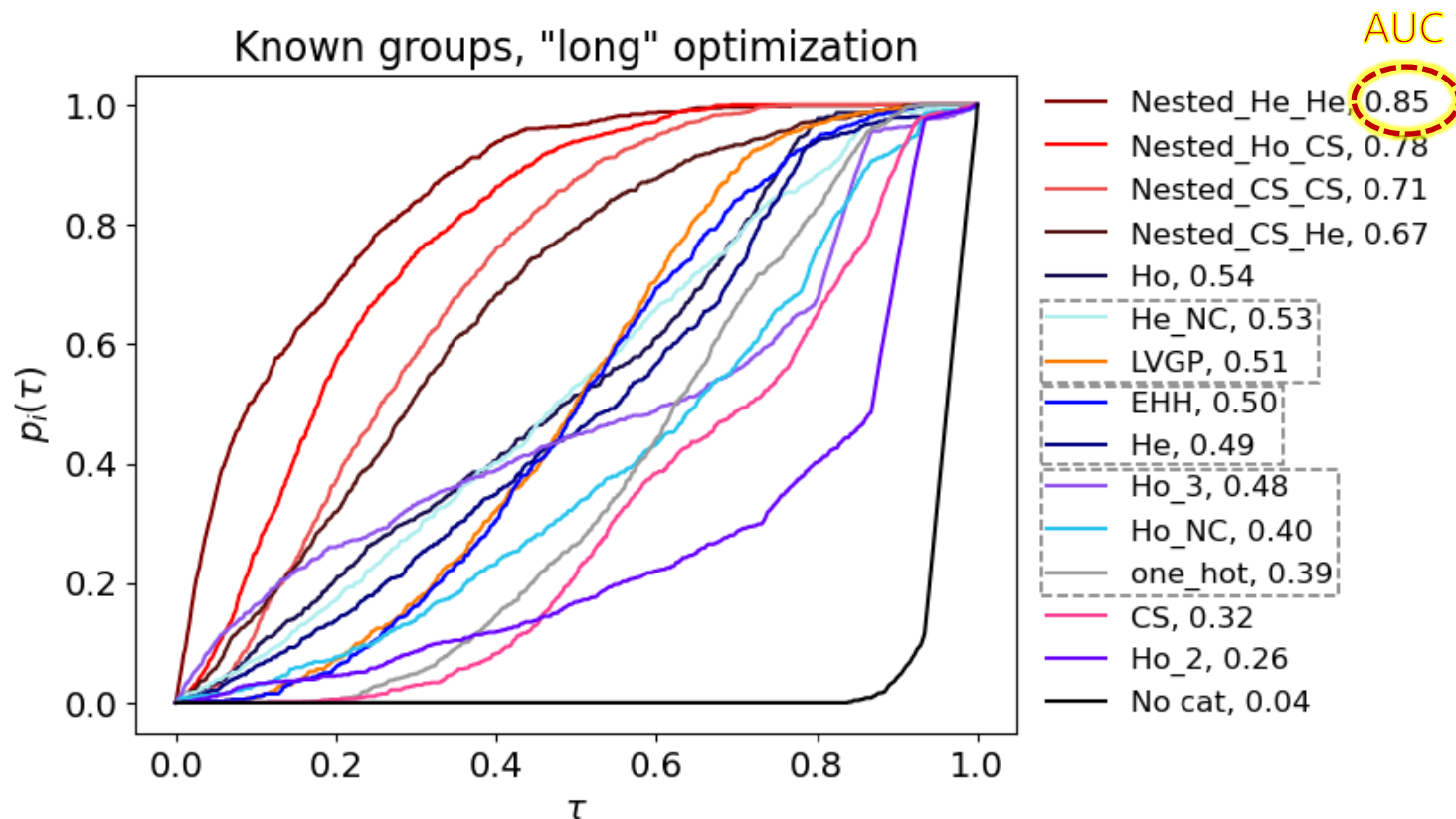
# Individual results



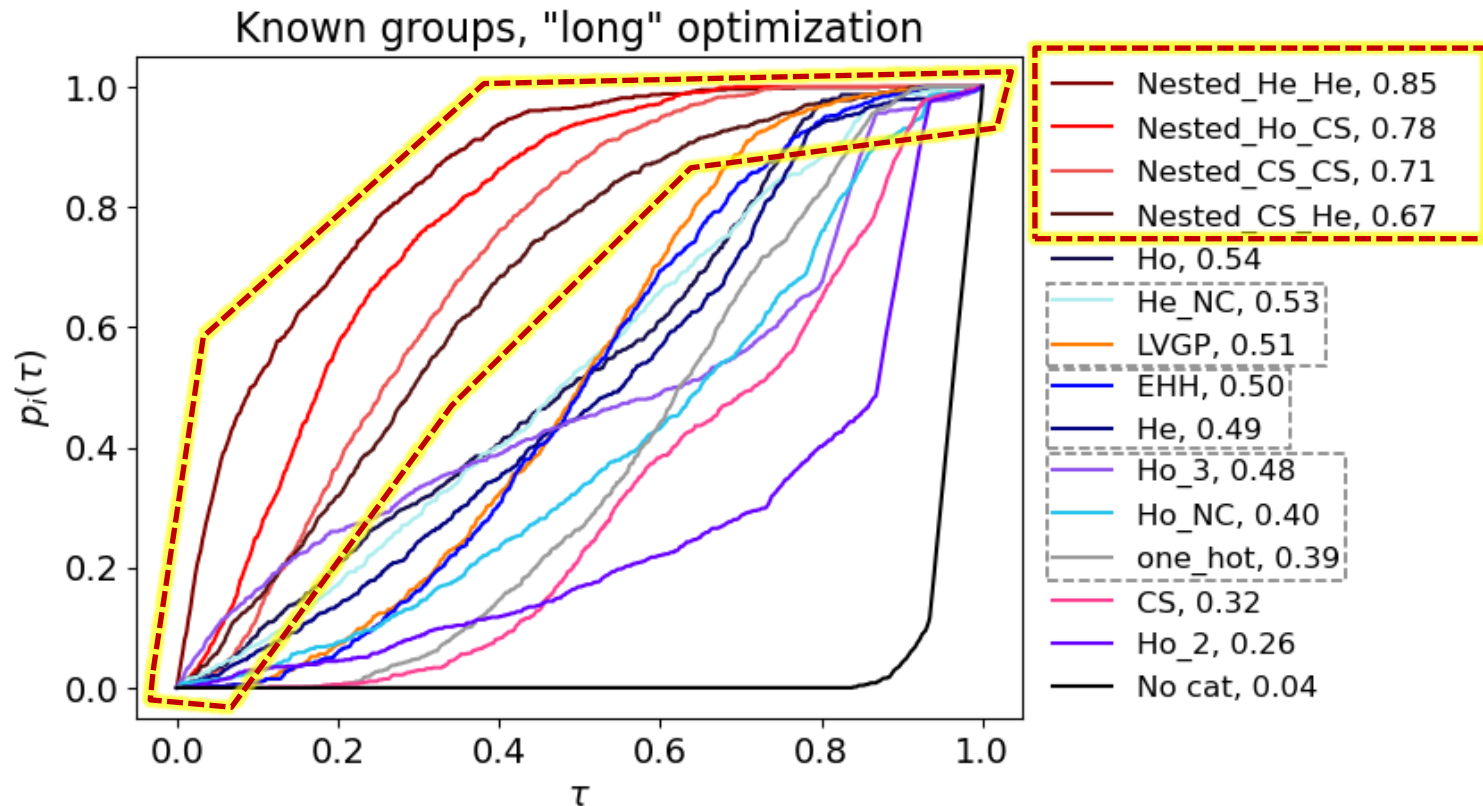
# Performance profiles (known groups)



# Performance profiles (known groups)

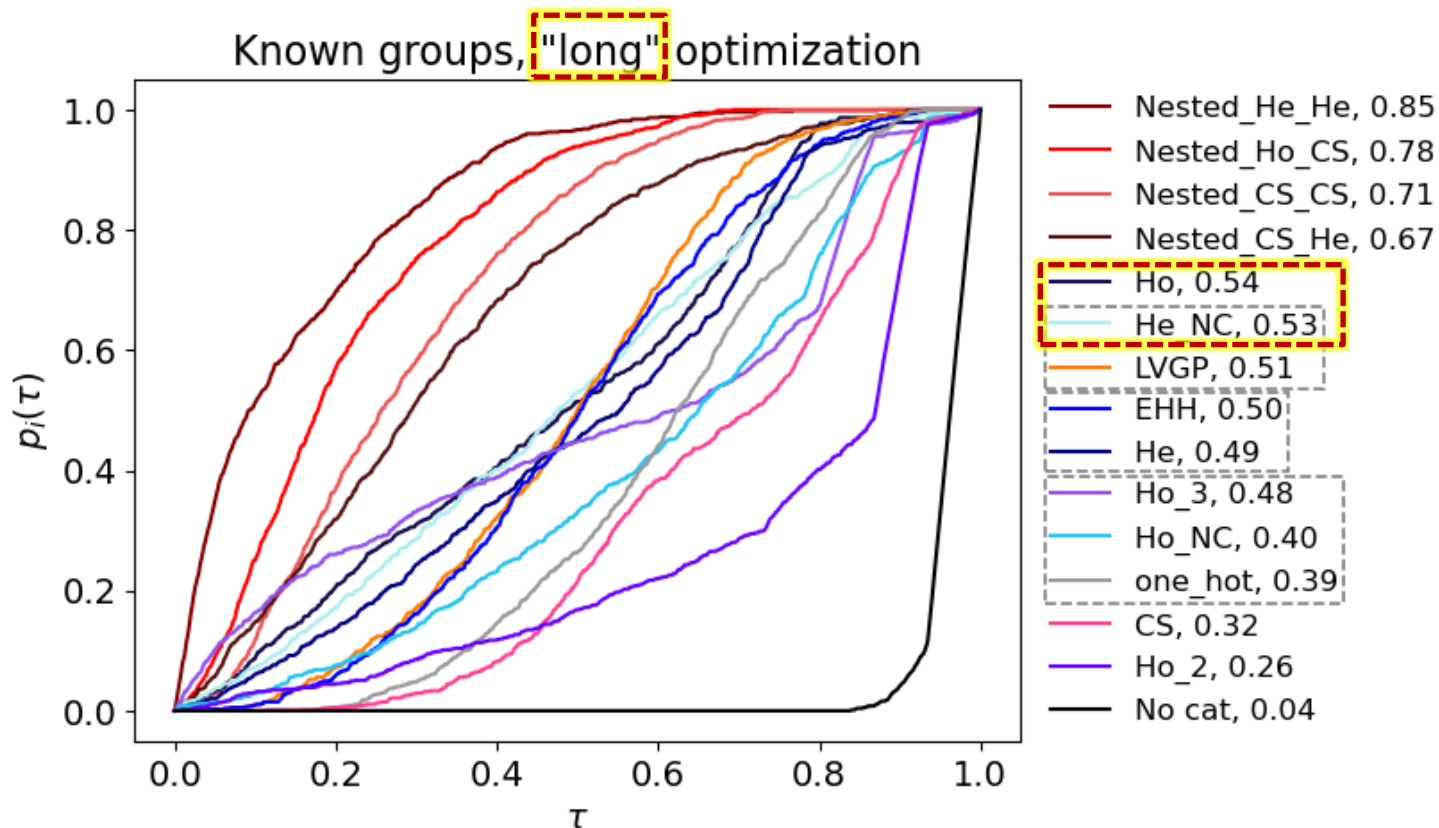


# Performance profiles (known groups)





# Performance profiles (known groups)





## 1- Review of existing approaches

- a) Encoding
- b) Covariance matrix parametrization
- c) Kernels from the BO litterature

## 2- Experiments for datasets with known group structure

## 3- Automatic selection of groups

## 4- Experiments for datasets with no known group structure

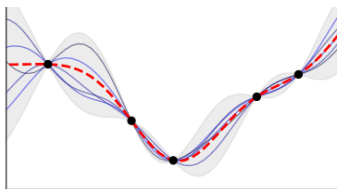
# Selection of groups when they are not known

Objective: Use Nested kernels.

Issue: no known groups [Roustant et al., 2020]

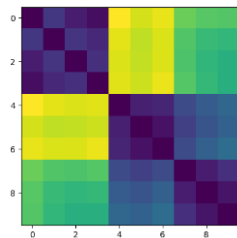
## 1- Train a GP#1

Kernel = LVGP



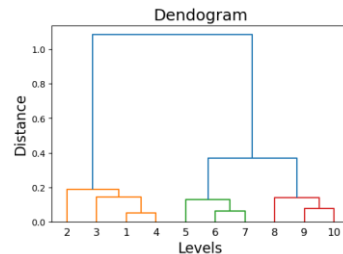
## 2- Get $T^{prox}$ from GP#1

$$d(z, z') = \left( T_{z,z}^{prox} + T_{z',z'}^{prox} - 2T_{z,z'}^{prox} \right)^{1/2}$$



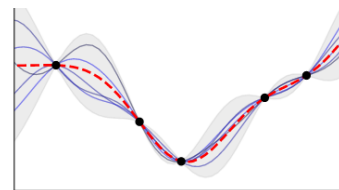
## 3- Clustering

Hierarchical, from  $d$



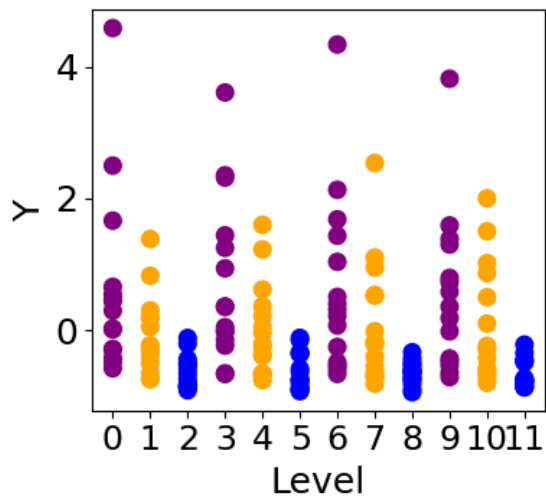
## 4- Train a GP#2

Kernel = Nested



✗ Requires to train another GP model before to get the groups

# Target encodings



Train inputs  $(x^{(i)}, z^{(i)})$  and outputs  $y^{(i)}$

$$v_c = \frac{1}{|i: z^{(i)} = c|} \sum_{i: z^{(i)} = c} \delta_{y^{(i)}}$$

Target encoding of the level  $c$

Choose  $d(z, z') = \mathcal{D}(v_z, v_{z'})$

Divergence between  
empirical measures

# Target encodings

In practice, since  $v_c$  is of small size ( $<10$ ), we can use:

$\mu_c$  mean and  $\sigma_c$  SD of  $v_c$

Train inputs  $(x^{(i)}, z^{(i)})$  and outputs  $y^{(i)}$

$$v_c = \frac{1}{|i: z^{(i)} = c|} \sum_{i: z^{(i)} = c} \delta_{y^{(i)}}$$



Target encoding of the level  $c$

$$\mathcal{D}(z, z') = \|(\mu_z, \sigma_z) - (\mu_{z'}, \sigma_{z'})\|_2$$

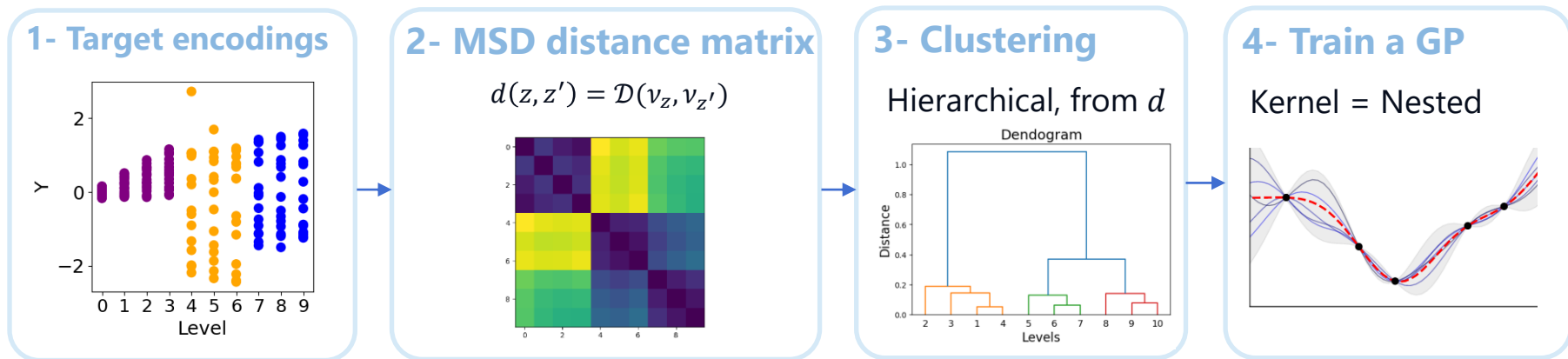
Choose  $d(z, z') = \mathcal{D}(v_z, v_{z'})$

Divergence between  
empirical measures

# New selection of groups when they are not known

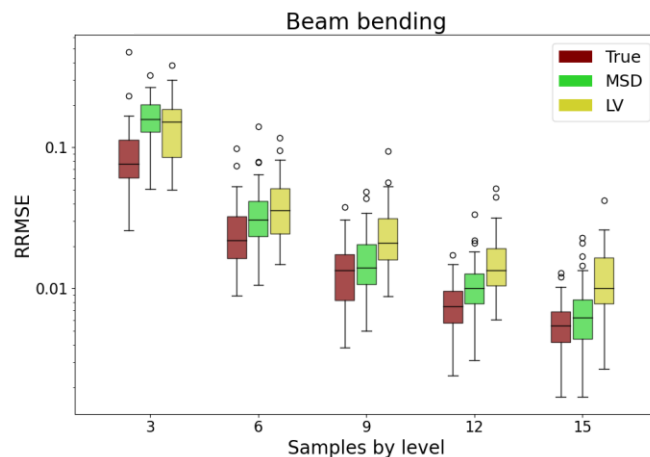
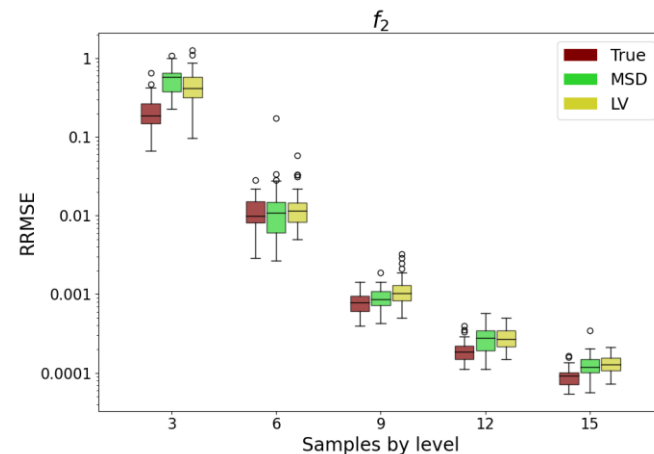
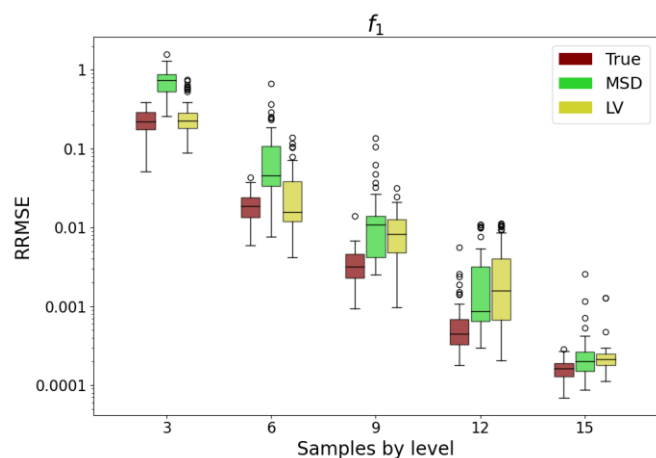
Objective: Use Nested kernels.

Issue: no known groups



✓ Only one GP training is required

# Impact of the group selection strategy: scores





## 1- Review of existing approaches

- a) Encoding
- b) Covariance matrix parametrization
- c) Kernels from the BO litterature

## 2- Experiments for datasets with known group structure

## 3- Automatic selection of groups

## 4- Experiments for datasets with no known group structure



# Datasets with no known group structure

Name	Cont	Cat	Train	Test	Groups	Source
Borehole	6	2 (3-4)	36/72/108/144/180	1008	False	<a href="#">Zhang et al. (2020)</a>
Borehole2	6	1 (12)	36/72/108/144/180	1008	False	<a href="#">Zhang et al. (2020)</a>
OTL	4	2 (4-6)	72/144/216	1008	False	<a href="#">Zhang et al. (2020)</a>
OTL2	4	1 (24)	72/144/216	1008	False	<a href="#">Zhang et al. (2020)</a>
Piston	5	2 (5-3)	45/90/135	1005	False	<a href="#">Zhang et al. (2020)</a>
Piston2	5	1 (15)	45/90/135	1005	False	<a href="#">Zhang et al. (2020)</a>
Goldstein	2	1 (9)	27/54/81/108/135	999	False	<a href="#">Pelamatti et al. (2021)</a>

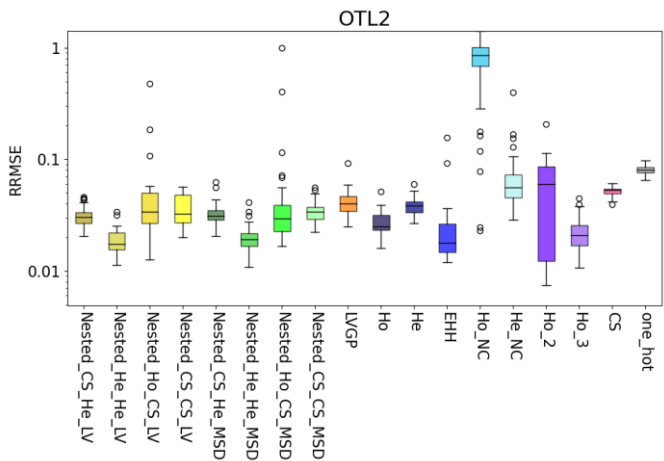
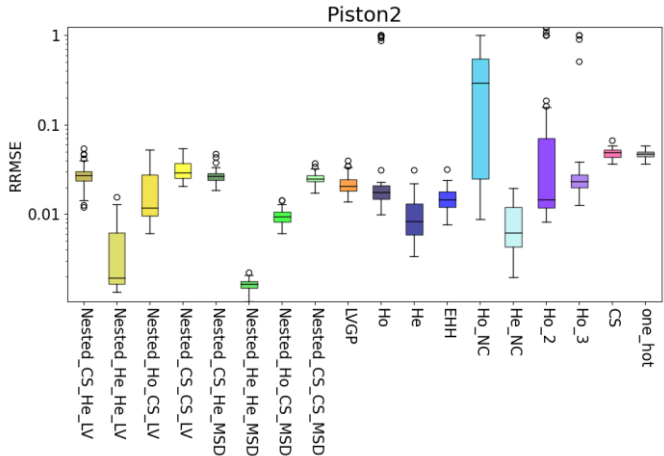
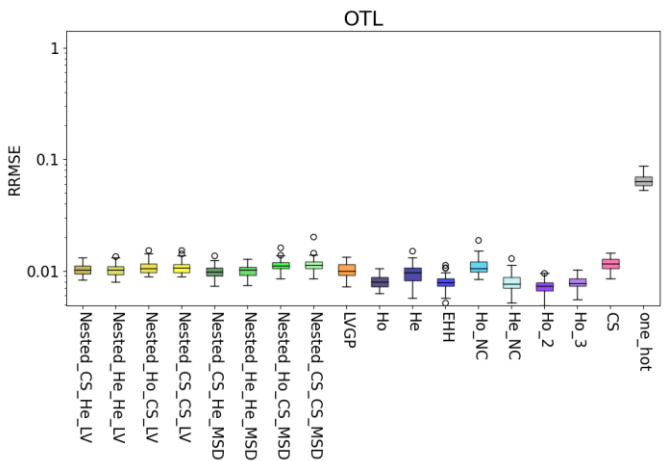
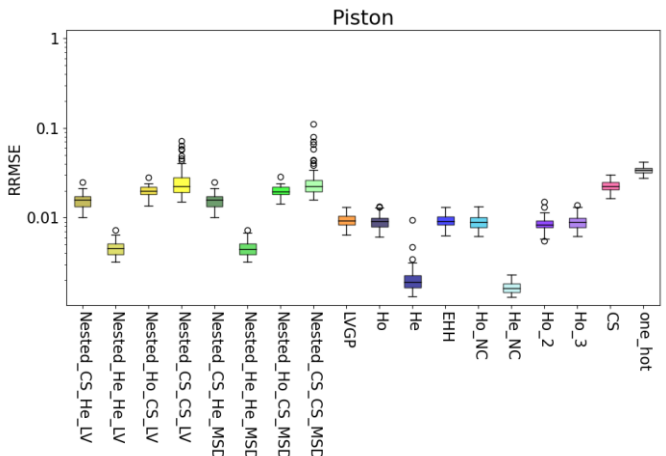
# Presentation of the methods/kernels

Category	Name	Description
Hypersphere	Ho	Homoscedastic, only positive correlations
	Ho_NC	Homoscedastic, allowing negative correlations
	He	Heteroscedastic, only positive correlations
	He_NC	Heteroscedastic, allowing negative correlations
	Ho_2	Homoscedastic, only positive correlations (rank 2)
	Ho_3	Homoscedastic, only positive correlations (rank 3)
	EHH	Exponential Homoscedastic Hypersphere
LVGP	LVGP	Latent dimension 2
CS	CS	Compound symmetry
One-hot	One_hot	One hot encoding
No cat	No cat	Only continuous variables

# Presentation of the methods/kernels

Category	Name	Description
Nested (auto LV)	Nested_CS_He_LV	Between = CS, Within = He
	Nested_He_He_LV	Between = He, Within = He
	Nested_Ho_CS_LV	Between = Ho, Within = CS
	Nested_CS_CS_LV	Between = CS, Within = CS
Nested (auto MSD)	Nested_CS_He_MSD	Between = CS, Within = He
	Nested_He_He_MSD	Between = He, Within = He
	Nested_Ho_CS_MSD	Between = Ho, Within = CS
	Nested_CS_CS_MSD	Between = CS, Within = CS

# Individual results



# Performance profiles (no known groups)

« long »

Max iter	3000
Max func. evaluations	$3000 \times$ (#params + cst)
Tolerance	$10^{-10}$

# Performance profiles (no known groups)

« long »

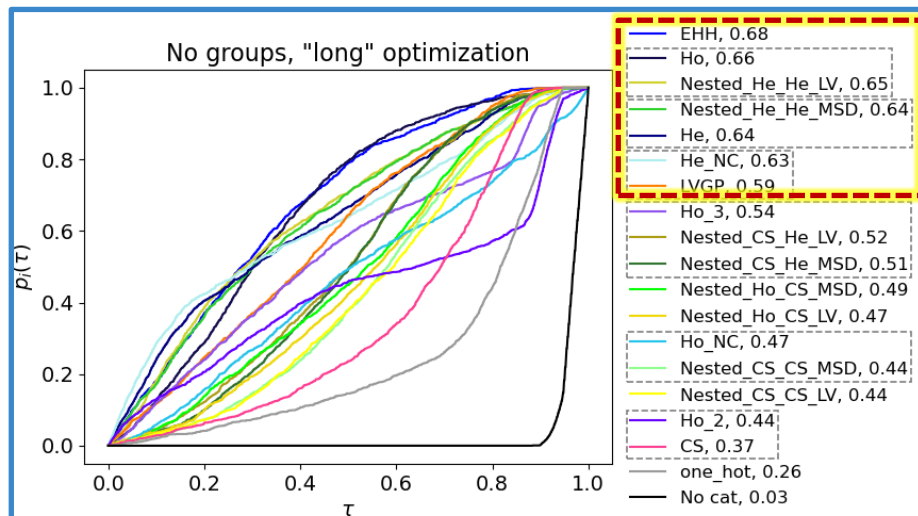
Max iter	3000
Max func. evaluations	$3000 \times$ (#params + cst)
Tolerance	$10^{-10}$

« short »

Default in  
scipy

Max iter	Ø
Max func. evaluations	15000
Tolerance	$10^{-9}$

# Performance profiles (no known groups)



« long »

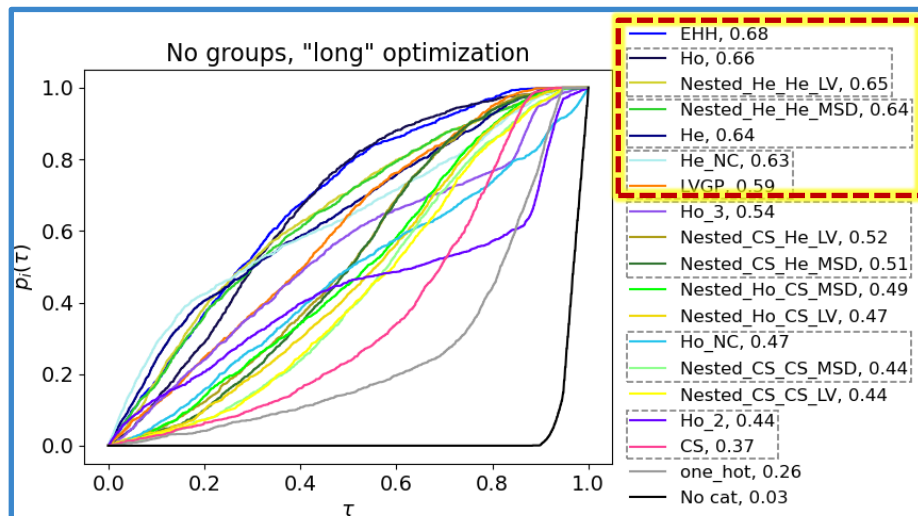
Max iter	3000
Max func. evaluations	3000 × (#params + cst)
Tolerance	$10^{-10}$

« short »

Default in  
scipy

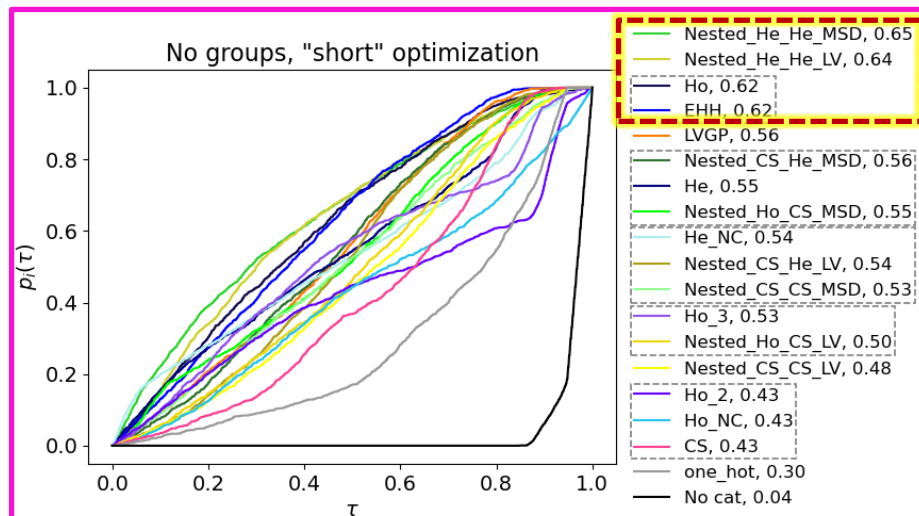
Max iter	0
Max func. evaluations	15000
Tolerance	$10^{-9}$

# Performance profiles (no known groups)



« long »

Max iter	3000
Max func. evaluations	$3000 \times (\#params + cst)$
Tolerance	$10^{-10}$



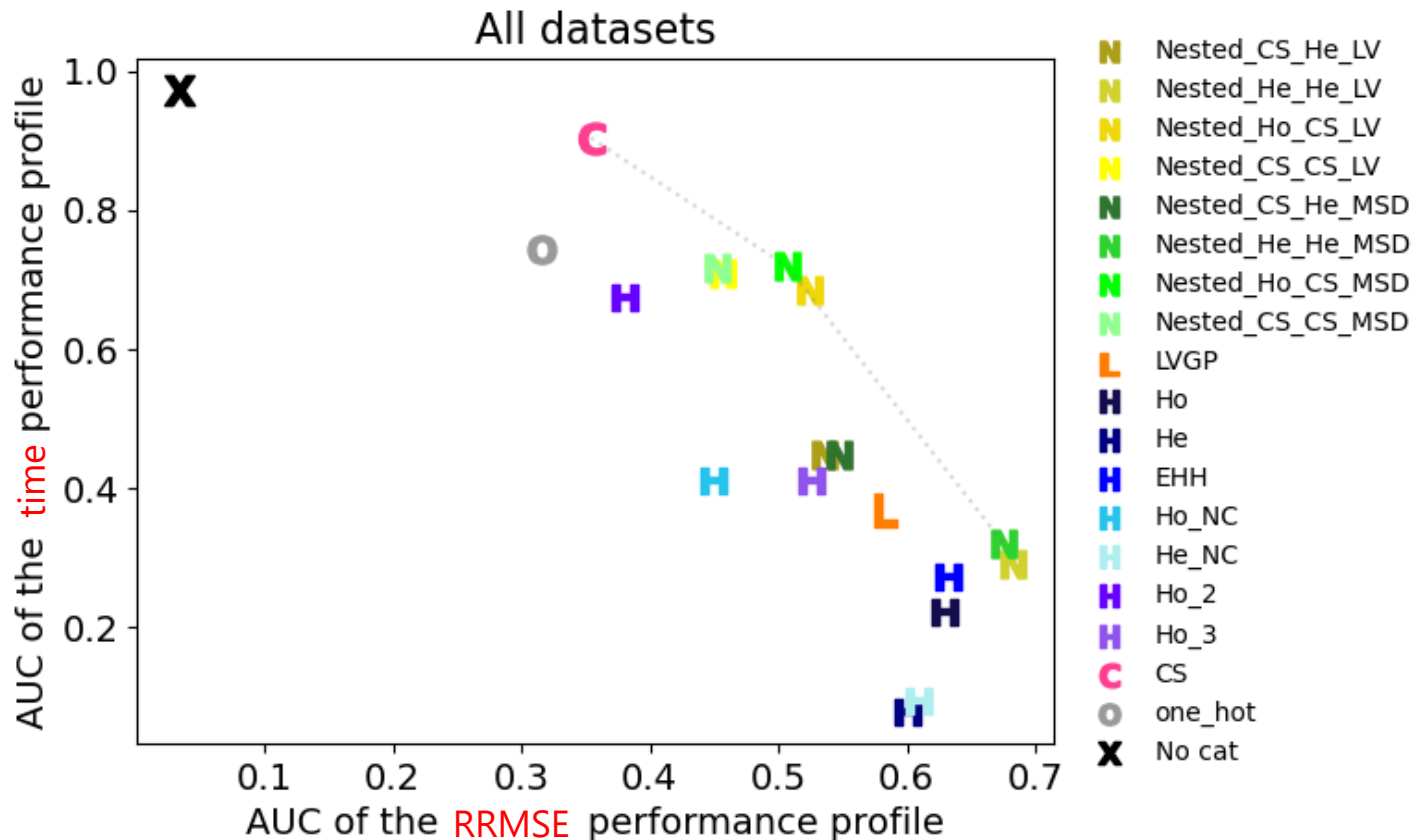
« short »

Default in  
scipy

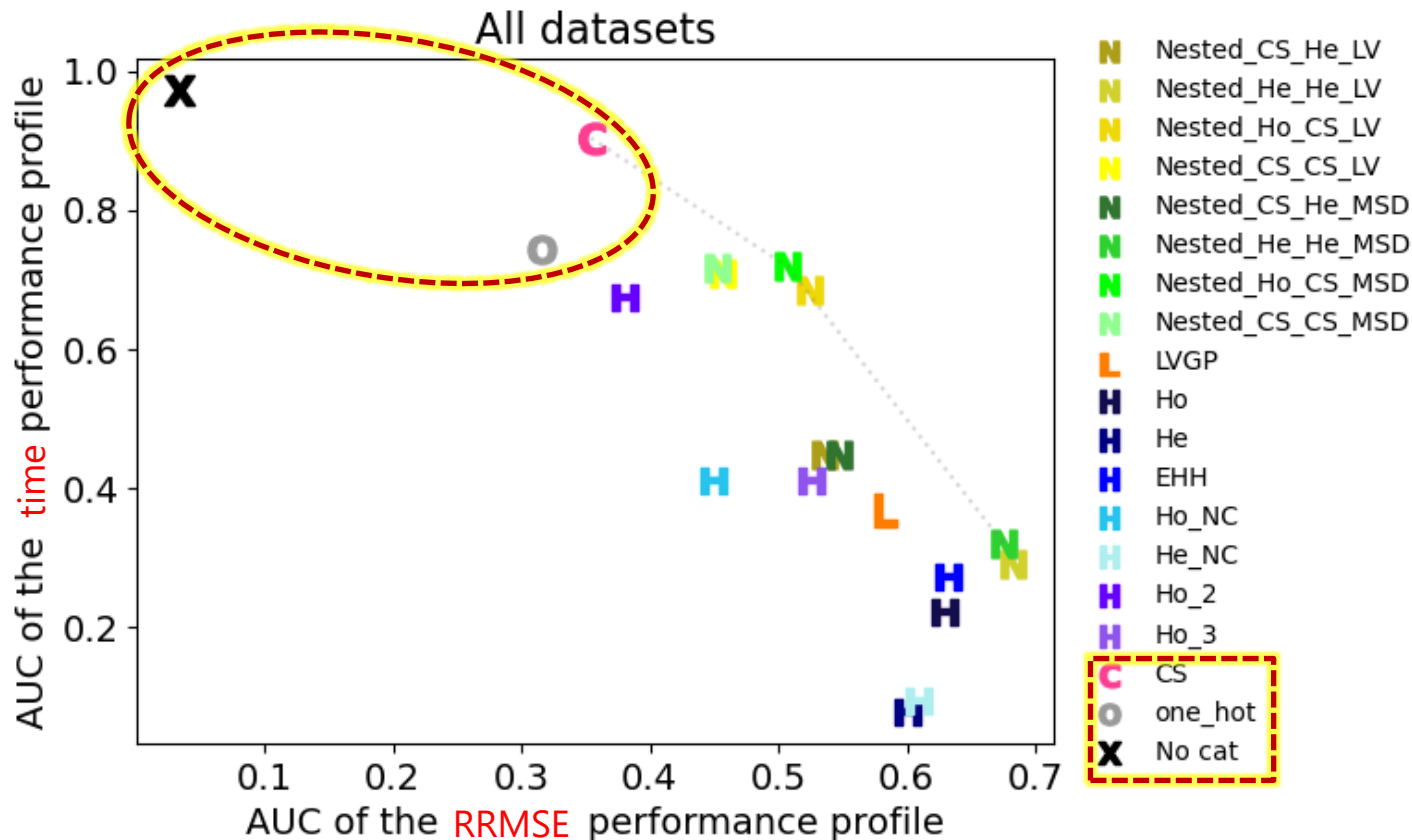
Max iter	$\infty$
Max func. evaluations	15000
Tolerance	$10^{-9}$



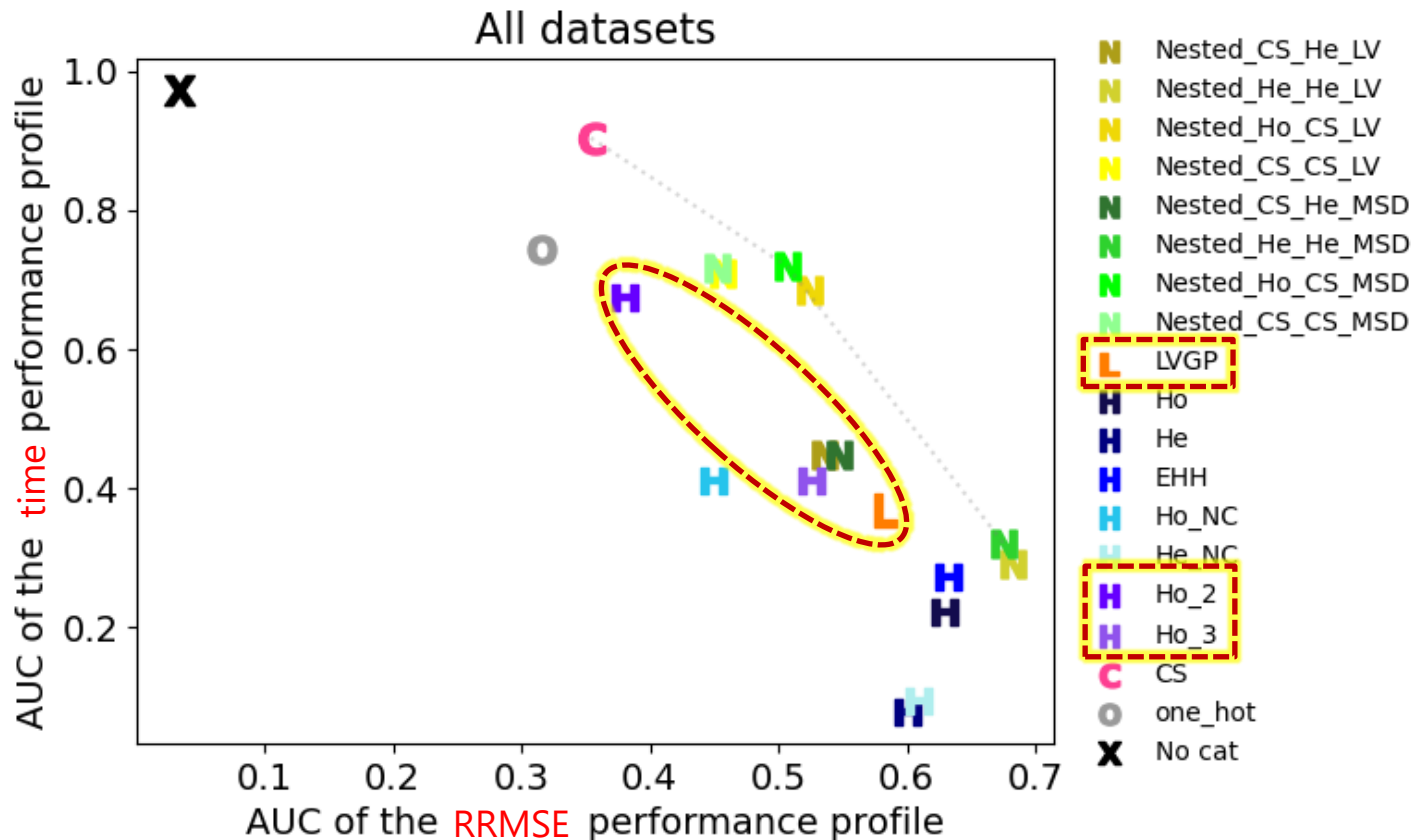
# AUCS of perf. profiles: time vs RRMSE (all datasets)



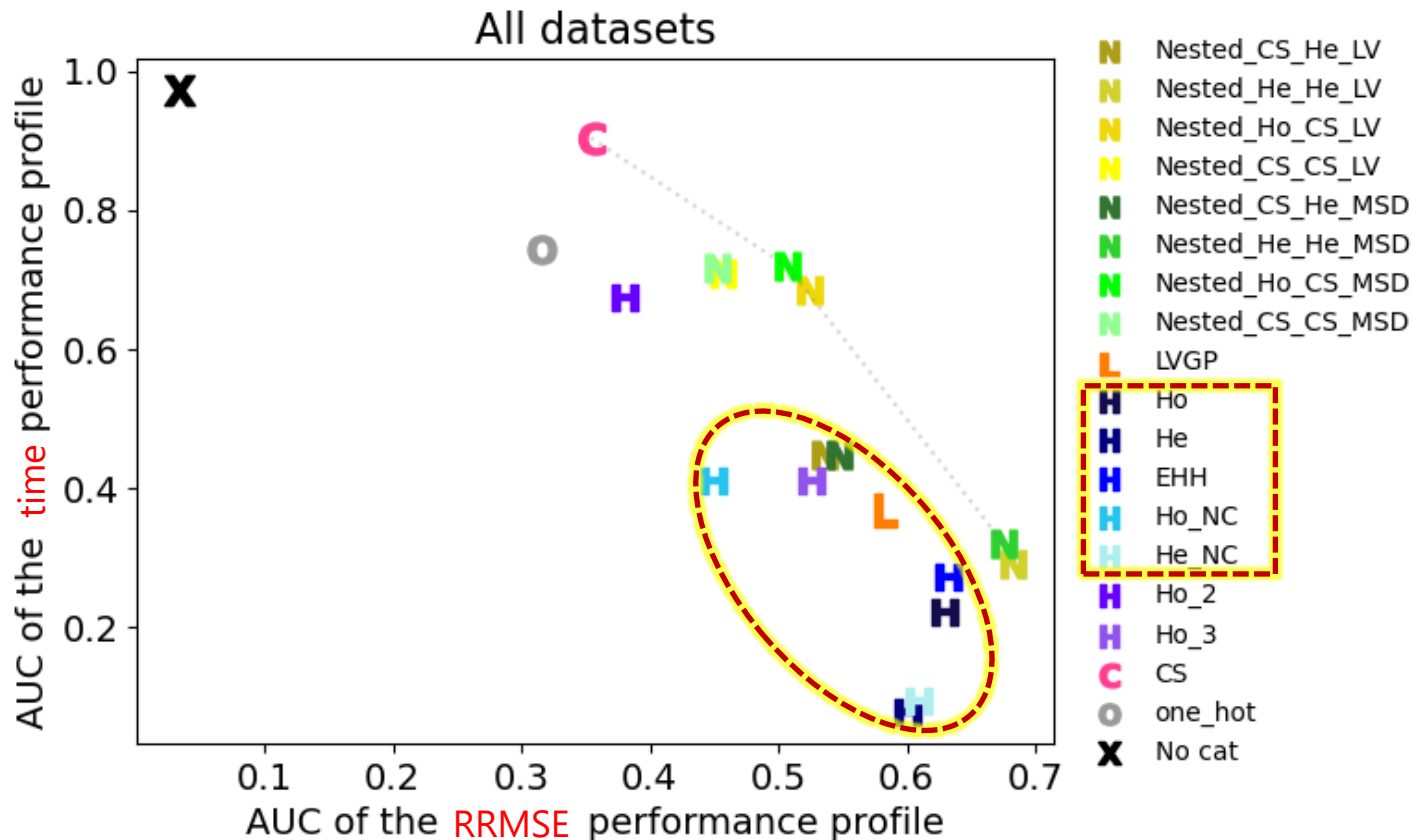
# AUCS of perf. profiles: time vs RRMSE (all datasets)



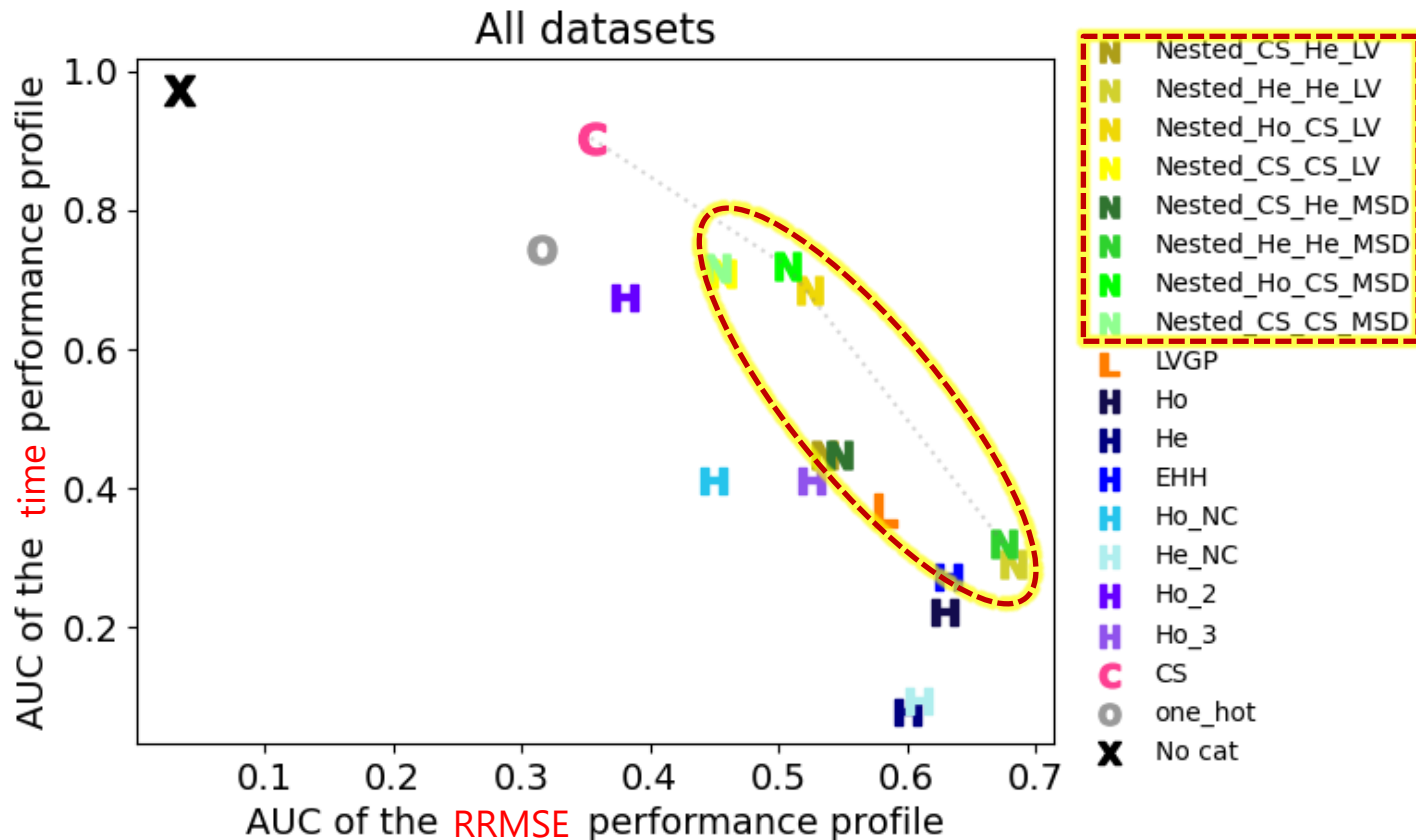
# AUCS of perf. profiles: time vs RRMSE (all datasets)



# AUCS of perf. profiles: time vs RRMSE (all datasets)



# AUCS of perf. profiles: time vs RRMSE (all datasets)



# Conclusion

## Contributions

- Reproducible comparative study available at : [https://gitlab.com/drti/cat\\_gp/](https://gitlab.com/drti/cat_gp/)
  - 23 kernels including: Hypersphere, Nested, LVGP, CS models
  - 42 datasets with varying sizes, continuous and categorical variables with different numbers of levels
  - Datasets with/without known groups
- New global evaluation metrics: **performance profiles**
- New **clustering-based nested kernels** using target encodings

## Take home messages

- **Optimization** has an important impact, especially on **hypersphere** models
- **Nested kernels** outperform other kernels when groups are known
- Even when groups are unknown, they are among the best methods with the **automatic group selection** strategies

# Acknowledgments

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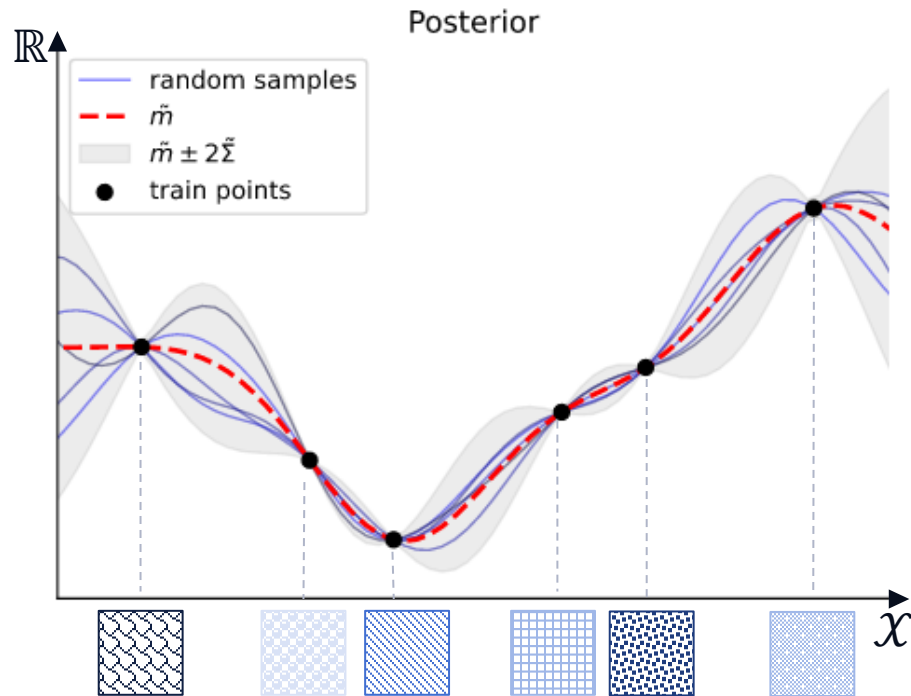
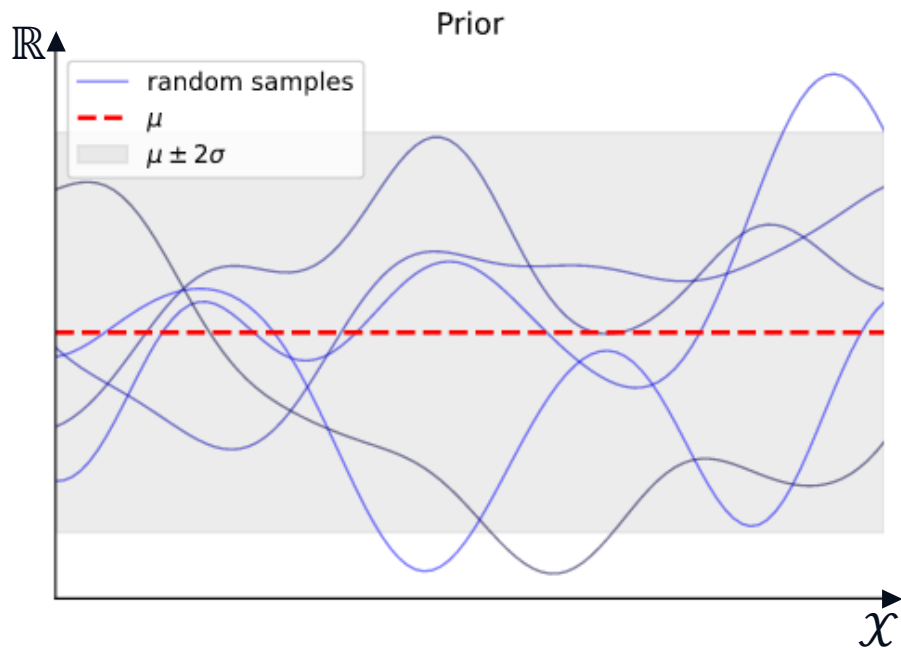


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# Gaussian process regression



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