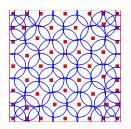
# OLSE and BLUE for the location scale model and energy minimization

Anatoly Zhigljavsky, Cardiff (joint work with Luc Pronzato)



Workshop on kernel approximations and space-filling, Cardiff, July 1, 2022

### Energy

Let  $\mathcal{X}$  be a (compact) set and K(x,x') be a continuous kernel. For any signed measure  $\mu$  on  $\mathcal{X}$ , its energy is

$$\mathcal{E}(\mu) = \int_{\mathcal{X}} \int_{\mathcal{X}} K(x, x') \mu(dx) \mu(dx').$$

If the kernel K is IPD (integrally positive definite), then  $\mathcal{E}(\mu) \geq 0$  for any  $\mu$  and  $\mathcal{E}(\mu)$  is a convex functional of  $\mu$  (conditions on K can be relaxed).

Minimum-energy signed measure of mass 1:  $\mu^* = \arg\min_{\mu \in \mathcal{M}} \mathcal{E}(\mu)$ , where  $\mathcal{M}$  is the set of signed measures  $\mu$  with  $\mu(\mathcal{X}) = 1$ .

Minimum-energy probability measure:  $\mu^+ = \arg \min_{\mu \in \mathcal{M}^+} \mathcal{E}(\mu)$ .

 $\mu^+$  always exists but  $\mu^*$  exists very rarely.

Maximum mean discrepancy:  $\mathrm{MMD}(\mu,\nu) = \sqrt{\mathcal{E}(\mu-\nu)}$ 

# Minimum-energy measures: optimality conditions

#### Theorem

- (i)  $\mu$  is a minimum-energy probability measure iff  $P_{\mu}(x) \geq \mathcal{E}(\mu)$  for all  $x \in \mathcal{X}$  and  $P_{\mu}(x) = \mathcal{E}(\mu)$  on the support of  $\mu$ . (ii)  $\mu$  is a minimum-energy signed measure of total mass one iff
- $P_{\mu}(x) = \mathcal{E}(\mu)$  for all  $x \in \mathcal{X}$ .

# Here $P_{\mu}(x) = \int K(x, x') \mu(dx')$ is the potential (kernel imbedding) of $\mu$ .

### Corollary

- 1 is a potential of some positive measure iff  $\mu^+ = \mu^*$ .
- 1 is a potential of a finite signed measure iff  $\mu^*$  exists.

### **Questions:**

When does 1 belong to the space of potentials? If it does, when the corresponding measure is positive?

# When minimum-energy measure is a probability measure?

### Corollary

Let  $\mu^+$  be a minimum-energy probability measure (always exists!). If  $\mu^+$  is supported on the whole set  $\mathcal{X}$ , then  $\mu^+$  is also a minimum-energy signed measure of total mass one.

### Theorem (PZ, 2020)

Let K be ISPD and translation invariant, with  $K(x,x')=\psi(x-x')$  and  $\psi$  continuous, twice differentiable except at the origin, with Laplacian  $\Delta\psi(x)=\sum_{i=1}^d\partial^2\psi(x)/\partial x_i^2\geq 0,\ \forall x\neq 0$ . Then there exists a unique mass 1 minimum-energy signed measure, which is a probability measure.

Idea of proof: potential  $P_{\mu^*}$  is subharmonic outside the support of  $\mu^*$ . Particular case:  $d=1, \ \psi(x)$  is convex for x>0 (Hàjek, 1956).

It is easy to construct translation invariant kernels for d=1 such that  $\psi(x)$  is not convex for x>0 but mass 1 minimum-energy signed measure  $\mu^*$  is a probability measure (help of T. Karvonen is appreciated).

### OLSE, n-point design

Design:  $X_n = \{x_1, \dots, x_n\} \in \mathcal{X}$ 

Model: 
$$y(x_j) = \theta + \varepsilon(x_j)$$
,  $\mathbb{E}\varepsilon(x) = 0$ ,  $\mathbb{E}\varepsilon(x)\varepsilon(x') = K(x, x')$ ,

K is a (conditionally) positive definite kernel

OLSE of  $\theta$ :

$$\hat{\theta}_{OLSE,n} = \int y(x) \mu_n(dx) = \bar{y} = \frac{1}{n} \mathbf{1}_n^\top Y,$$

where  $Y = (y(x_1), \dots, y(x_n))^{\top}$ ,  $1_n = (1, \dots, 1)^{\top}$  and  $\mu_n$  is the empirical probability measure assigning weights 1/n to points  $x_j \in X_n$ .

# Variance of OLSE, n-point design

$$\operatorname{var}(\hat{\theta}_{OLSE,n}) = \frac{1}{n^2} \mathbf{1}_n^{\top} K_n \mathbf{1}_n = \frac{1}{n^2} \sum_{i,j=1}^n K(x_i, x_j)$$
$$= \int \int K(x, x') \mu_n(dx) \mu_n(dx'),$$

where  $K_n = (K(x_i, x_j))_{i,j=1}^n$  is the kernel matrix

That is,

$$\operatorname{var}(\hat{\theta}_{OLSE,n}) = \int \int K(x,x')\mu_n(dx)\mu_n(dx') = \mathcal{E}(\mu_n),$$

which is a discrete energy.

# OLSE: approximate design; optimal designs

Approximate design: any probability measure  $\mu$  on  $\mathcal X$ 

$$\hat{\theta}_{OLSE} = \int y(x)\mu(dx)$$

$$\operatorname{var}(\hat{\theta}_{OLSE}) = \int \int K(x, x') \mu(dx) \mu(dx') = \mathcal{E}(\mu)$$

Minimum-energy probability measure  $\mu^+ = \arg\min_{\mu \in \mathcal{M}^+} \mathcal{E}(\mu)$  is the optimal approximate design for OLSE (easy to construct numerically).

Optimal n-point design for OLSE is the minimum-energy n-point probability measure (hard to construct numerically).

### BLUE of $\theta$ , *n*-point design

Design:  $X_n = \{x_1, \dots, x_n\} \in \mathcal{X}$ ,  $x_j$  are pair-wise different points.

$$\hat{\theta}_{BLUE,n} = w_n^* Y; \quad w_n^* = 1_n^\top K_n^{-1} / 1_n^\top K_n^{-1} 1_n; \quad \text{var}(\hat{\theta}_{BLUE,n}) = 1 / 1_n^\top K_n^{-1} 1_n$$

 $\textit{w}^*_\textit{n}$  gives the weights of  $\mu^*_\textit{n}$ , the optimal signed measure minimizing the discrete energy

$$\mathcal{E}(\nu_n) = \int \int K(x, x') \nu_n(dx) \nu_n(dx'),$$

where  $\nu_n$  are discrete signed measures supported on  $X_n$  with  $\nu_n(X_n)=1$ .

$$\hat{\theta}_{BLUE,n} = \int y(x)\mu_n^*(dx), \ \operatorname{var}(\hat{\theta}_{BLUE,n}) = \mathcal{E}(\mu_n^*)$$

Construction of optimal n-point designs for BLUE is a difficult computational problem (Sacks, Ylvisaker (1965), etc.)

# Comparison of $var(\hat{\theta}_{OLSE,n})$ versus $var(\hat{\theta}_{BLUE,n})$

Of course,

$$\operatorname{var}(\hat{\theta}_{BLUE,n}) = 1/(1_n^{\top} K_n^{-1} 1_n) = \mathcal{E}(\mu_n^*) \le$$

$$\operatorname{var}(\hat{\theta}_{OLSE,n}) = \frac{1}{n^2} (1_n^{\top} K_n 1_n) = \mathcal{E}(\mu_n)$$

Matrix analysis approach:

$$\frac{\operatorname{var}(\hat{\theta}_{OLSE,n})}{\operatorname{var}(\hat{\theta}_{BLUE,n})} = \frac{1}{n^2} (1_n^\top K_n 1_n) (1_n^\top K_n^{-1} 1_n) \ge 1$$

by the Cauchy-Schwarz inequality (as  $1_n^{\top}1=n^2$ ), where we have equality if and only if  $1_n$  is an eigenvector of  $K_n$ ; that is,  $K_n 1_n = \lambda 1_n$  for some  $\lambda > 0$  ( = row sums of  $K_n$  are the same).

 $\operatorname{var}(\hat{\theta}_{OLSE,n}) - \operatorname{var}(\hat{\theta}_{BLUE,n})$ 

$$u^{\top}u \leq (u^{\top}K_nu)(u^{\top}K_n^{-1}u) \leq \frac{1}{4}\left(\sqrt{\frac{\lambda_1}{\lambda_n}} + \sqrt{\frac{\lambda_n}{\lambda_1}}\right)^2$$

Left inequality: Cauchy-Schwarz. Right inequality: Kantorovich (poor).

Better upper bound: using the optimality theorems, for a design  $\mu(=\mu_n)$  and OLSE=  $\int y(x)\mu(dx)$ :

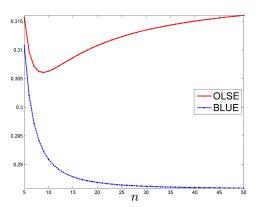
$$1 \ge \frac{\operatorname{var}(\hat{\theta}_{BLUE})}{\operatorname{var}(\hat{\theta}_{OLSE})} \ge 2\frac{\inf_{x \in \mathcal{X}} P_{\mu}(x)}{\mathcal{E}(\mu)} - 1$$

Useful relation:

$$\mathrm{MMD}^{2}(\mu_{n}, \mu_{n}^{*}) = \mathrm{var}(\hat{\theta}_{OLSE,n}) - \mathrm{var}(\hat{\theta}_{BLUE,n}).$$

### Smit's paradox; behaviour of the variances as n increases

Smit's paradox (1961): for particular stationary kernels in one dimension and equidistant points,  $var(\hat{\theta}_{OLSE,n})$  increases for  $n \ge n_0$ .



Red curve converges to the energy of the limiting design (e.g. uniform). Where does the blue curve converge? How fast is the convergence? How different could be the two limits?

### Q: What is the limit of the BLUE curve?

Let  $x_1, x_2, \ldots$  be a dense sequence of distinct points in compact  $\mathcal{X}$ .

Designs:  $X_n = \{x_1, \dots, x_n\};$ 

Model:  $y(x_j) = \theta f(x_j) + \varepsilon(x_j)$  (we have  $f(x) = 1_{\mathcal{X}}(x)$ ).

### Theorem (Parzen, 1971)

 $f \in H(K)$  if and only if

$$\operatorname{var}(\widehat{\theta}_{BLUE,n}) \to 1/\|f\|_{H(K)} = \operatorname{var}(\widehat{\theta}_{BLUE,\infty}) \text{ as } n \to \infty.$$

Here  $\hat{\theta}_{BLUE,\infty}$  is the continuous BLUE of  $\theta$  but we may not be able to write it in the form  $\hat{\theta}_{BLUE,\infty}=\int y(x)\mu(dx)$ 

(recall 
$$\hat{\theta}_{BLUE,n} = \int y(x) \mu_n^*(dx)$$
)

So, the limit of the BLUE curve is  $1/\|1\|_{H(K)}$  but there may be no limit of the signed measures  $\mu_n^*$  defining the discrete BLUEs.

Rate of convergence=MMD( $\mu_n^*, \mu^*$ ) if  $\mu^*$  exists; optimal design for BLUE.

### Q: When the limits of the two curves coincide?

**Answer:** When the minimum-energy probability measure is the minimum-energy signed measure  $\mu^*$  (see above) and the limit of  $\mu_n$  defining the OLSEs converges to this measure.

From any C(I)PD kernel K we can construct a kernel (reduced kernel) such that given  $\mu$  is the minimum-energy measure:

$$K_{\mu}(x,x') = K(x,x') - P_{\mu}(x) - P_{\mu}(x') + \mathcal{E}(\mu)$$

A useful relation:  $\mathsf{MMD}^2(\mu,\nu) = \mathcal{E}(\mu-\nu) = \mathcal{E}_{\mathcal{K}_{\mu}}(\nu)$ .

### Theorem (LP & AZ)

- (i)  $[K_{\mu}]_{\nu} = K_{\nu}$
- (ii)  $\mu$  discrete: K CPD iff  $K_{\mu}$  is PD
- (iii) K is CIPD iff  $K_{\mu}$  is IPD
- (iv)  $\mu$  has infinite support; K is bounded and CISPD  $\Rightarrow$   $K_{\mu}$  is ISPD

(ii) is a generalization of Schoenberg's result in which  $\mu$  is a delta measure. This property is very important, e.g., for the energy distance.

# Special role of the constant function $1 = 1_{\mathcal{X}}(x)$

#### **Questions:**

- (i) Does 1 belong to the RKHS H(K)?
- (ii) Does 1 belong to the space of potentials P(K)?

 $P(K) = \{P_{\mu}(x) = \int K(x, x')\mu(dx') \text{ for a finite signed measure } \mu\}$ 

(iii) In case of (ii), is  $\mu$  a positive measure?

#### Importance:

- (i) ⇔ continuous BLUE exists
- (ii)  $\Leftrightarrow$  continuous BLUE exists and has the form  $\hat{\theta}_{BLUE,\infty} = \int y(x)\mu(dx)$
- (iii)  $\Leftrightarrow$  continuous BLUE exists, has the form above and coincides with continuous OLSE for the optimal design.

More results: K is PD,  $K(x, x') = \psi(x - x')$ 

- Spectral measure of  $\psi$  is moment-determinant (e.g.,  $\psi$  is an analytic function) and has no mass at  $0 \Rightarrow 1 \notin H(K)$  (H.Dette & AZ, 2021)
- If  $\mathcal{X} = [0,1]$ ,  $\psi(t)$  is non-negative, non-constant, bounded and decreasing for t>0, then the uniform measure  $\mu_0$  cannot be minimum-energy measure (simply  $P_{\mu_0}(0.5) > P_{\mu_0}(0)$ ).

### Conclusions

# Conjectures; PD kernels $K(x, x') = \psi(x - x')$

- **1**  $\notin$  H(K)  $\Rightarrow$  the spectral measure of  $\psi$  is moment-determinant or it has a positive mass at 0.
- ②  $\psi$  is differentiable at  $0 \Rightarrow 1 \notin P(K)$  (so that  $\hat{\theta}_{BLUE,\infty} \neq \int y(x)\mu(dx)$  even if it exists)
- ① Uniform measure on  ${\mathcal X}$  cannot be minimum-energy (not true if  $\psi(0)=\infty$ )
- Let  $\psi(0) < \infty$ ,  $\mu^*$  (if it exists) and  $\mu^+$  be minimum-energy measures  $(\mu^*(\mathcal{X}) = \mu^+(\mathcal{X}) = 1)$ . Then  $\mu^*(\partial \mathcal{X}) > 0$  and  $\mu^+(\partial \mathcal{X}) > 0$ .

# Conjectures; PD kernels $K(x, x') = \psi(x - x')$

- $1 \notin H(K) \Rightarrow$  the spectral measure of  $\psi$  is moment-determinant or it has a positive mass at 0.
- ②  $\psi$  is differentiable at  $0 \Rightarrow 1 \notin P(K)$  (so that  $\hat{\theta}_{BLUE,\infty} \neq \int y(x)\mu(dx)$  even if it exists)
- ① Uniform measure on  ${\mathcal X}$  cannot be minimum-energy (not true if  $\psi({\mathbf 0})=\infty$ )
- Let  $\psi(0) < \infty$ ,  $\mu^*$  (if it exists) and  $\mu^+$  be minimum-energy measures  $(\mu^*(\mathcal{X}) = \mu^+(\mathcal{X}) = 1)$ . Then  $\mu^*(\partial \mathcal{X}) > 0$  and  $\mu^+(\partial \mathcal{X}) > 0$ .

### Other directions of possible research ( $K(x,x') = \psi(x-x')$ , d > 1):

- **①** Extension of Smit's paradox to d>1 and relaxation of conditions on  $\psi$
- Structure of minimum-energy measures
- 8
- 4