

# Lecture 19

①

## 1. Kernels and determinantal point processes

$\Lambda = [\alpha, \beta]$ . Recall  $K(x, y) \in L^2(\Lambda \times \Lambda)$  defines bounded linear op.  $\mathbb{K} : L^2(\Lambda) \rightarrow L^2(\Lambda)$  by

$$(\mathbb{K}f)(x) = \int_{\Lambda} K(x, y) f(y) dy.$$

Def: If  $\mathbb{K}$  is

- Hermitian ( $K(x, y) = \overline{K(y, x)}$ )
- Non-negative definite ( $\det_{k \times k} (K(x_i, x_j)) \geq 0$   
 $\forall x_1, \dots, x_k \in \Lambda$ )
- Of finite rank ( $\text{Im } \mathbb{K} \subset L^2(\Lambda)$  is finite dim.)

then we say  $\mathbb{K}$  (or  $K$ ) is a finite admissible kernel. (FA for short)

Fact from linear algebra I: If  $\mathbb{K}$  is FA (2)

(of rank  $N$ ), then  
$$K(x, y) = \sum_{\ell=1}^N \lambda_{\ell} \varphi_{\ell}(x) \overline{\varphi_{\ell}(y)}$$
 for  $\{\varphi_{\ell}\}$  orthonormal in  $L^2(\Lambda)$  and  $\lambda_{\ell} \geq 0 \forall \ell$

(spectral thm applied to  $\mathbb{K}$ )

Fact from linear algebra II: If  $\mathbb{K}$  is FA

and  $D \subset \Lambda$  and  $\mathbb{K}_D$  is the restriction of  $\mathbb{K}$  to  $D$  (i.e. the operator  $\mathbb{K}_D: L^2(D) \rightarrow L^2(D)$  defined by

$$(K_D f)(x) = \int_D K(x, y) f(y) dy$$

← if  $\pi_D$  is the projection onto functions supported on  $D$ ,

$$\mathbb{K}_D = \pi_D \mathbb{K} \pi_D$$

then  $\mathbb{K}_D$  is also FA.

(Finite rank is only nontrivial part: note  $\text{rank}(\pi_D \mathbb{K} \pi_D) \leq \text{rank}(\mathbb{K}).$ )

Def: A point process  $\xi$  is simple if for any single point  $a \in \mathbb{R}$ , the event  $\#\{a\}(\xi) \geq 2$  does not occur.

Def: A point process  $\xi$  is said to be determinantal with FA kernel  $K$

if its  $k$ -th joint intensities are

$$\mathbb{E} \sum_{\substack{j_1, \dots, j_k \\ \text{distinct}}} \eta(\xi_{j_1}, \dots, \xi_{j_k}) = \int_{\Lambda^k} \eta(x) \cdot \det_{k \times k} (K(x_i, x_j)) dx$$

for FA kernel  $K$ . (Det. point process = DPP)

## 2. Some facts about DPP with FA kernels (4)

Prop: If  $\xi$  is a DPP with FA kernel, of rank  $N$ , then  $\#_{\Lambda}(\xi) \leq N$  almost surely.

Proof: For an interval  $D$ ,

$$\#_D(\#_D - 1) \cdots (\#_D - (k-1)) = \sum_{\substack{j_1, \dots, j_k \\ \text{distinct}}} \mathbb{1}_D(\xi_{j_1}) \cdot \mathbb{1}_D(\xi_{j_2}) \cdots \mathbb{1}_D(\xi_{j_k})$$

(for general point processes)

so

$$\mathbb{E} \#_{\Lambda}(\#_{\Lambda} - 1) \cdots (\#_{\Lambda} - (k-1)) = \int_{\Lambda^k} \det_{k \times k} (K(x_i, x_j)) d^k x \quad (*)$$

But

$$\left( K(x_i, x_j) \right)_{i,j=1}^k = \underbrace{\begin{pmatrix} \lambda_1 \varphi_1(x_1) & \lambda_2 \varphi_2(x_1) & \dots & \lambda_N \varphi_N(x_1) \\ \lambda_1 \varphi_1(x_2) & \lambda_2 \varphi_2(x_2) & \dots & \dots \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_1 \varphi_1(x_n) & \dots & \dots & \lambda_N \varphi_N(x_n) \end{pmatrix}}_{A_\lambda(x)} \underbrace{\begin{pmatrix} \varphi_1(x_1) & \dots & \varphi_1(x_n) \\ \vdots & & \vdots \\ \varphi_N(x_1) & \dots & \varphi_N(x_n) \end{pmatrix}}_{B(x)}$$

$A_\lambda(x) \xleftarrow{\leq \text{rank}(N)} \xrightarrow{\nearrow} B(x)$

so

$$\det_{k \times k} \left( K(x_i, x_j) \right) = 0 \quad \text{for } k > N,$$

and

$$(*) = 0 \quad \text{for } k = N+1$$

$$\Rightarrow \#_\lambda = 0, 1, \dots, \text{ or } N \quad \text{a.s.} \quad \square$$

(5)

Cor: If  $\xi$  and  $\xi'$  are DPP with FA (6)

Kernel with joint intensities that coincide,

then  $\xi$  and  $\xi'$  have the same distribution

(i.e.  $\mathbb{P}(C_{n_1}^{B_1} \cap C_{n_2}^{B_2} \cap \dots \cap C_{n_k}^{B_k})$  is the same

for both  $\xi$  and  $\xi'$ ).

Proof: Discussed joint intensities  
 $\Rightarrow$  distribution

if  $\#_D$  has exponential tails,

But  $\#_D$  is bounded.

"B"

### 3. Projection processors are building blocks ⑦

Thm: Let  $\xi$  be a DPP with FA kernel

$$K(x, y) = \sum_{\ell=1}^N \lambda_{\ell} \varphi_{\ell}(x) \overline{\varphi_{\ell}(y)} \quad \text{with } \lambda_{\ell} \in [0, 1] \quad \forall \ell$$

Let  $I_1, \dots, I_N$  be Bernoulli rv with  $P(I_{\ell} = 1) = \lambda_{\ell}$ . Form a point process  $\xi'$  by first sampling  $I_1, \dots, I_N$ , and then sampling from the projection process with kernel

$$K_{\mathbf{I}}(x, y) = \sum_{\ell=1}^N I_{\ell} \varphi_{\ell}(x) \overline{\varphi_{\ell}(y)}.$$

$\xi$  and  $\xi'$  have the same dist.

(proof next time)