# Approximation of Bandlimited Functions from Finitely Many Samples

Karlheinz Gröchenig

Faculty of Mathematics University of Vienna

http://homepage.univie.ac.at/karlheinz.groechenig/

Chicheley Hall

### **Bandlimited functions**

$$\mathcal{B} = \{f \in L^2(\mathbb{R}^d) : \mathsf{supp}\, \hat{f} \subseteq [-1/2, 1/2]^d\}$$

Mathematical problem: Recover  $f \in \mathcal{B}$  from samples  $f(x_j), \in J$ .

History: Whittaker-Shannon-Kotelnikov, Paley-Wiener, Duffin-Schaeffer, Beurling, Malliavin, Landau, Pavlov, ...

### Facts of life:

- amount of data is finite
- sampling points are non-uniform
- relevant sampling



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# **Problem**

Given samples  $f(x_j)$  of  $f \in \mathcal{B}$  in region  $x_j \in [-M-1, M+1]^d$ 

Find approximation of f from samples  $f(x_j)$ .

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# **Discrete Model for Numerical Analysis**

Discrete sampling problem, use trigonometric polynomials  $\mathcal{P}_{M}$  instead of  $\mathcal{B}$ 

$$\mathcal{P}_{M} = \{ p : p(x) = (2M+1)^{-d/2} \sum_{|k|_{\infty} \le M} a_{k} e^{2\pi i k \cdot t/(2M+1)} \}$$

Period 2M + 1, degree M, dimension of  $\mathcal{P}_M$  is  $(2M + 1)^d$ .

Observe: If  $p \in \mathcal{P}_M$ , then

$$\hat{p} = (2M+1)^{-d/2} \sum_{|k|_{\infty} \leq M} a_k \delta_{\frac{k}{2M+1}}$$

$$\hat{a} \in [-1/2, 1/2]^d$$

supp 
$$\hat{p} \subseteq [-1/2, 1/2]^d$$



# **Solution for Finitely Many Samples**

Given samples  $f(x_j)$  of  $f \in \mathcal{B}$  on region  $x_j \in [-M-1, M+1]^d$ . Solve the least square problem

$$p_M = \operatorname{argmin}_{p \in \mathcal{P}_M} \sum_{|x_j|_{\infty} \le M+1} |f(x_j) - p(x_j)|^2 w_j$$

Connection to Generalized Sampling of Adcock, Hansen, etc.:

Sampling space 
$$S = \text{span} \{ T_{x_j} \text{sinc} : x_j \in [-M-1, M+1]^d \}$$

Reconstruction space  $\mathcal{R} = \mathcal{P}_M$  or rather  $\mathcal{P}_M \cdot \chi_{[-M-1/2,M+1/2]^d}$ 



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# From Sampling to Linear Algebra

$$y_j = f(x_j) = (2M+1)^{-d/2} \sum_{|k|_{\infty} \le M} a_k e^{2\pi i k \cdot x_j/(2M+1)}$$

# Structure:

1. Sampling matrix  $V_M$  with entries

$$(V_M)_{ik} = (2M+1)^{-d/2} e^{2\pi i k \cdot x_j/(2M+1)}$$

- is *Vandermonde matrix*, and measurements are  $\mathbf{y} = V_M \mathbf{a}$ .
- 2. Then  $T_M = V_M^* V_M$  is (block) *Toeplitz matrix* with entries

$$(T_M)_{kl} = (2M+1)^{-d} \sum_{x_i \in [-M-1,M+1]^d} e^{2\pi i(k-l) \cdot x_j}$$

3. So

$${f a} = (V_M^* V_M)^{-1} V_M^* {f y} = T_M^{-1} V_M^* {f y} = V_M^\dagger {f y}$$

# From Sampling to Linear Algebra

$$\sqrt{w_j}y_j = \sqrt{w_j}f(x_j) = (2M+1)^{-d/2}\sqrt{w_j}\sum_{|k|_{\infty} \leq M} a_k e^{2\pi i k \cdot x_j/(2M+1)}$$

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2. Then  $T_M = V_M^* V_M$  is (block) *Toeplitz matrix* with entries

$$(T_M)_{kl} = (2M+1)^{-d} \sum_{x_j \in [-M-1,M+1]^d} e^{2\pi i(k-l) \cdot x_j} w_j$$

3. So

$$\mathbf{a} = (V_M^* V_M)^{-1} V_M^* \mathbf{y} = T_M^{-1} V_M^* \mathbf{y} = V_M^{\dagger} \mathbf{y}$$

# **Algorithm**

Step 1: Compute  $b_M = V_M^* \mathbf{y} \in \mathbb{C}^{(2M+1)^d}$ 

Step 2: Compute 
$$a_M = T_M^{-1}b_M = V_M^{\dagger} \mathbf{y} \in \mathbb{C}^{(2M+1)^d}$$

Step 3: Compute the trigonometric polynomial  $p_M \in \mathcal{P}_M$ 

$$p_M(x) = \sum_{|k|_{\infty} < M} a_M(k) (2M+1)^{-d/2} e^{2\pi i k \cdot x/(2M+1)}$$

Then

$$p_M = \operatorname{argmin}_{p \in \mathcal{P}_M} \sum_{x_i \in [-M-1, M+1]^d} |p(x_j) - y_j|^2 \frac{w_j}{w_j}$$



### Remarks

Adaptive weights with Conjugate gradient acceleration and Toeplitz structure (Feichtinger, G., Strohmer)

- Weights are used to improve condition number of  $T_M$  ("density compensation factors")
- NUFFT (nonuniform FFT)
- Operation count:  $\mathcal{O}(M^d \log M)$  operations

Fast Toeplitz inversion

### From Finite to Infinite Dimension

Q: What does  $p_M$  (= output of numerical algorithm) say about f (solution of infinite dimensional problem)?

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# **Theorem**

lf

$$\sigma(T_M) \subseteq [\alpha, \beta]$$
 for all  $M$ ,

then

$$\lim_{M \to \infty} \int_{[-M,M]^d} |f(x) - p_M(x)|^2 dx = 0$$

and  $\lim_{M\to\infty} p_M(x) = f(x)$  uniformly on compact sets for all  $f\in\mathcal{B}$ 

# From Finite to Infinite Dimension

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# Corollary

Sampling inequality for all  $f \in \mathcal{B}$ 

$$\alpha \|f\|_2^2 \le \sum_{j \in J} |f(x_j)|^2 \le \beta \|f\|_2^2$$

# **Accomplishments**

- validation of numerical algorithm
- new method for derivation of sampling theorems
- explicit rates of convergence

For  $0 < L \le M$  we have (in dimension 1)

$$\begin{aligned} & \text{err} = \int_{|x| \le M + 1/2} |f(x) - p_M(x)|^2 \, dx \\ & \le C (1 - \delta)^{-2} \Big( \frac{L^2}{M^3} ||f||_2^2 + ||f||_2 \Big( \int_{|x| \ge L} (|f(x)|^2 + |f'(x)|^2) \, dx \Big)^{1/2} \\ & + \sup_{|x - M - 1/2| \le 1/2} (|f(\pm x)|^2 + |f'(\pm x)|^2) \Big) \end{aligned}$$

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+ \sup_{|x - M - 1/2| \le 1/2} (|f(\pm x)|^2 + |f'(\pm x)|^2) \Big)$$

# **Uniform Condition Numbers**

### Recall that

$$(T_M)_{kl} = (2M+1)^{-d} \sum_{x_j \in [-M-1,M+1]^d} e^{2\pi i (k-l) \cdot x_j} w_j \qquad |k|_{\infty} \leq M$$

# Theorem (Dimension d = 1)

Assume that  $\sup_{j \in J} (x_{j+1} - x_j) = \delta < 1$  and choose  $w_j = \frac{1}{2} (x_{j+1} - x_{j-1})$  as the weights in  $T_M$ . Then

$$\sigma(T_M) \subseteq [(1-\delta)^2, 6] \tag{1}$$

*REMARK:* Similar theorem in higher dimensions with  $w_j \approx$  size of Voronoi region at  $x_j$  (but: density depends on dimension)

REMARK: Compare to finite section method



# Ingredients of the Proof

Let  $Q_M$  be orthogonal projection onto sampling space generated by the (orthonormal) basis  $\Phi_{k,M}(t) = (2M+1)^{-d/2}e^{2\pi ik \cdot t/(2M+1)}$ , thus

$$Q_{M}f = \sum_{\|k\|_{\infty} \leq M} \langle f, \phi_{k,M} \rangle \phi_{k,M}$$

**Step 1.** Show that for all  $f \in \mathcal{B}$ 

$$\lim_{M\to\infty}\|f-Q_Mf\|_2=0.$$

Step 2. Show that

$$\lim_{M\to\infty} \sum_{|x_i|_\infty \le M} |f(x_j) - Q_M f(x_j)|^2 w_j = 0.$$

**Step 3.** Show that there exist  $\alpha, \beta > 0$  such that

$$\sigma(T_M) \subseteq [\alpha, \beta]$$

# **Trends - New Aspects**

- Impose additional conditions on  $\hat{f}$  and reconstruct with respect to other bases, e.g., wavelet bases (Adcock, Gataric, Hansen; Kutyniok etc.)
- Random sampling (Bass-KG)
- Possible Extensions: model sparsity either by assuming supp  $\hat{f} \subseteq E \subseteq [-1/2, 1/2]^d$  with meas (E) small or supp  $\hat{f} \subseteq \{\xi \in [-1/2, 1/2]^d : \prod_{k=1}^d |\xi_k| \le \delta << 1\}$

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