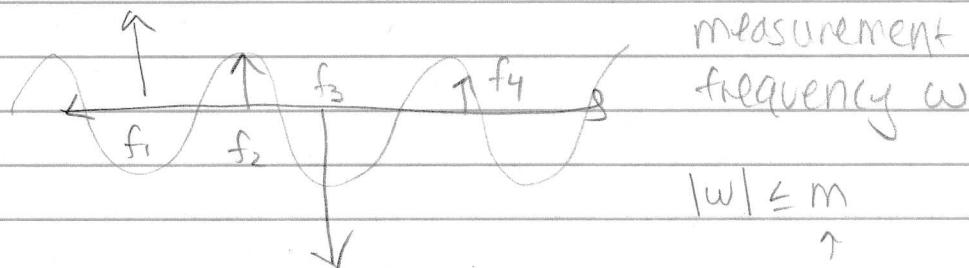


(Super resolution

Many optical devices are inherently lowpass

Main Question: Can we recover fine-grained structure from coarse measurements?

[Donoho] introduced the setup



$$x(t) = \sum_{j=1}^k u_j \delta_{f_j}(t)$$

delta function at f_j

$$P_w = \int_0^1 e^{i2\pi wt} x(t) dt$$

$$= \sum_{j=1}^k u_j e^{i2\pi f_j w}$$

Can we recover the parameters (coefficients u_j and frequencies f_j) from low frequency measurements?

Proposition [Phony] when there is no noise, \exists polynomial time algorithm for exact recovering from any $2k+1$ distinct measurements

This theorem seems forgotten in the literature, e.g.

Compressed Sensing: can recover a k -sparse vector $x \in \mathbb{R}^n$ from $O(k \log \frac{n}{k})$ noisy linear measurements

"We can beat Shannon-Nyquist by assuming sparsity"

Applications in MRI, etc

But notice Prony's method:

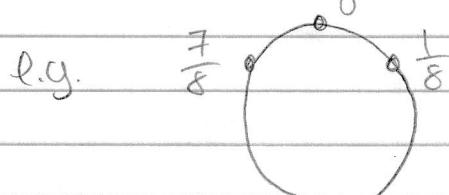
(1) gets $O(k)$ measurements

(2) doesn't require points on a grid

But is it stable? More on this later

definition: The wrap around distance d_w is

$$d_w(x, y) = \min(|x-y|, |1+x-y|)$$



$$d_w(1/8, 7/8) = 1/4$$

History, minus Prony

Let $\Delta = \min_{i \neq j} d_w(f_i, f_j')$

[Donoho] Asymptotic bounds for $m = \frac{1}{\Delta}$ on grid
stability

[Candes, Fernandez-Granda] Convex program for
 $m \geq \frac{2}{\Delta}$, no noise

[Fernandez-Granda] Same, but with noise

[Liao, Fannjiang] (independent) Algorithm
for $m = \frac{1 + C(\Delta)}{\Delta}$, with noise

Theorem. There is a polynomial time algorithm
that works with noise, for $m \geq \frac{1}{\Delta} + 1$ and
for any $m \leq \frac{(1-\varepsilon)}{\Delta}$ it is impossible (i.e. noise
must be exponentially small)

Matrix Pencil Method (No noise)

definition: Let $\alpha_j = e^{i \cdot 2\pi j / k}$ and let

$$(V =) V_m^k = \begin{bmatrix} 1 & 1 & 1 \\ \alpha_1 & \alpha_2 & \alpha_k \\ \vdots & \vdots & \vdots \\ \alpha_1^{m-1} & \alpha_2^{m-1} & \alpha_k^{m-1} \end{bmatrix}$$

Now consider the matrix

$$A = V D_u V^H$$

↑
diagonal matrix of u_j 's

and B

Claim: The entries of A_j correspond to measurements at integer frequencies $-m+1 \leq w \leq m-1$

Proof: By direct computation

$$A_{jj} = [\alpha_1^{j-1}, \alpha_2^{j-1}, \dots, \alpha_k^{j-1}] \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} = P_{j-j'} B$$

Similarly define

$$B = V D_u D_\alpha V^H$$

↑
diagonal matrix of α_j 's

Fact: If α_j 's are distinct and $m \geq k$, then V has full column rank

Lemma: Under same conditions, and u_j 's are nonzero then $\lambda = \frac{1}{\alpha_j}$ are unique solns to

$$Ax = \lambda Bx$$

Proof: By the fact V^H has a right inverse R s.t.

$$V^H R = I_k$$

then $r_j = j^{\text{th}}$ column of R satisfies

$$A r_j = V D_u V^H r_j = V D_u e_j$$

$$= u_j V e_j = u_j v_j$$

jth column of V

$$B r_j = V D_u D_\alpha V^H r_j = u_j \alpha_j v_j$$

This is a generalized eigenvalue problem,
similar uniqueness. \exists

Thus our algorithm is

Construct A and B

For $Ax = \lambda Bx$, find all values of $\lambda = \frac{1}{\alpha_j}$

Solve $V \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}$ to find coefficients

Noise stability

When is the MPA robust to noise?

generalized eigenvalue problem

i.e. can we get accuracy guarantees that are polynomial in magnitude of noise?

We'll show a sharp phase transition in the condition number of the complex Vandermonde

Theorem $\|V_m^k u\|^2 = (m-1 \pm \frac{1}{\Delta}) \|u\|^2$

Theorem: If $m = \frac{(1-\varepsilon)}{\Delta}$, $\exists \alpha_j$'s and u_j 's s.t.

$$\|V_m^k u\|^2 \leq e^{-\varepsilon k} \|u\|^2$$

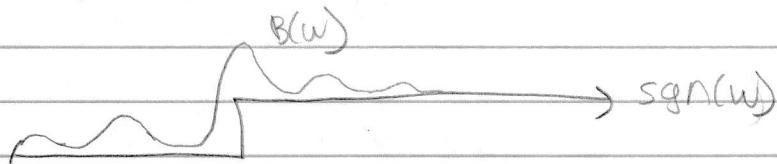
Thus the noise needs to be exponentially small
to superresolve

Extremal Functions

Theorem: There is a function $B(w)$ satisfying

$$(1) \operatorname{sgn}(w) \leq B(w)$$

i.e. it majorizes



$$(2) \hat{B}(x) = \text{Fourier transform of } B(w)$$

is supported on $[-1, 1]$

i.e. it is smooth

$$(3) \int_{-\infty}^{\infty} B(w) - \operatorname{sgn}(w) dw = 1$$

Explicitly we have

$$B(w) = \left(\frac{\sin(\pi w)}{\pi} \right)^2 \left(\sum_{j=0}^w (w-j)^{-2} - \sum_{j=1}^w (w+j)^{-2} + \frac{2}{w} \right)$$

This comes from reconstruction formula for functions whose Fourier transform is supported on $[-1, 1]$

Similarly there is a minorant $b(w)$

$$(1) b(w) \leq \text{sgn}(w)$$

$$(2) \hat{b}(w) \text{ supported in } [-1, 1]$$

$$(3) \int_{-\infty}^{\infty} |\text{sgn}(w) - b(w)| dw = 1$$

and these are sharp

Relatedly we can sandwich the indicator of an interval $E \subseteq \mathbb{R}$

Corollary There are functions $C_E^u(w)$ and $C_E^l(w)$ with $E = [0, m-1]$ that satisfy

$$(1) C_E^l(w) \leq \mathbb{1}_{E^c}(w) \leq C_E^u(w)$$

(2) $\hat{C}_E^l(x)$ and $\hat{C}_E^u(x)$ are supported on $[-\Delta, \Delta]$

$$(3) \int_{-\infty}^{\infty} |C_E^u(w) - \mathbb{1}_{E^c}(w)| dw = \int_{-\infty}^{\infty} |\mathbb{1}_{E^c}(w) - C_E^l(w)| dw$$

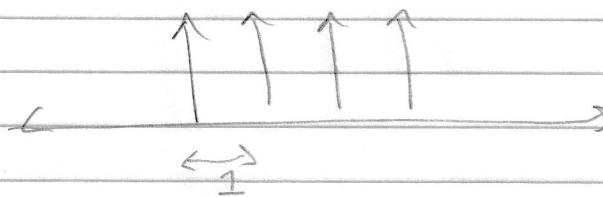
$$= \frac{1}{\Delta},$$

Now let's prove the condition number bound

Proof: We have

$$\|V_m^k u\|^2 = \sum_{w=0}^{m-1} |P_w|^2 = (*)$$

Now let $h(w) = \text{Dirac comb function}$, i.e.



i.e. $h(w) = \sum_{t=-\infty}^{\infty} \delta_t(w)$

$$\text{then } (*) = \int_{-\infty}^{\infty} h(w) I_E(w) |P_w|^2 dw$$

$$\stackrel{(1)}{=} \int_{-\infty}^{\infty} h(w) C_E(w) |P_w|^2 dw$$

Now the Fourier transform of a comb is a comb so

$$h(w) = \sum_{t=-\infty}^{\infty} e^{i 2\pi t w}$$

②

we get that

Now since $|Pw|^2 = Pw^* Pw$ and

$$Pw = \sum_{j=1}^k u_j e^{i2\pi f_j w}$$

we get that the RHS is

$$\sum_{j=1}^k \sum_{j'=1}^k u_j u_j^* \int_{-\infty}^{\infty} h(w) C_E^u(w) e^{i2\pi(f_j - f_{j'})w} dw$$

$$= \sum_{t=-\infty}^{\infty} \sum_{j=1}^k \sum_{j'=1}^k u_j u_j^* \int_{-\infty}^{\infty} e^{i2\pi tw} C_E^u(w) e^{i2\pi(f_j - f_{j'})w} dw$$

$\overbrace{}^{\hat{C}_E^u(f_j - f_{j'} + t)}$

But the f_j 's are Δ separated and C_E^u is supported on $[-\Delta, \Delta]$ thus the cross terms are zero!

$$= \sum_{j=1}^k |u_j|^2 \hat{c}(0)$$

$$\ell_1 \text{ norm of } C_E^u = |E| + \frac{1}{\Delta}$$

$$= \sum_{j=1}^k |u_j|^2 (|E| + \frac{1}{\Delta})$$

The same proof works for minorant. \square

Thus we have

extremal functions \Rightarrow sharp bounds \Rightarrow stability of MPM

\Rightarrow sharp bounds for super-resolution