

# Compressive System Identification

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Joint work with R. Heckel

# Some applications of system identification

- Channel sounding

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- Channel sounding
  - in wireless communications

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  - in underwater acoustic communications

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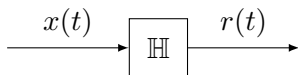
# Some applications of system identification

- Channel sounding
  - in wireless communications
  - in underwater acoustic communications
- Control engineering
- Radar imaging
  - in astronomy
  - in air and on water



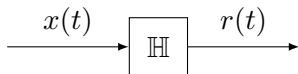
# Formal problem statement

$\mathbb{H}$  is an unknown linear operator (e.g., system or channel)



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Determine  $\mathbb{H}$  from response  $r(t)$  to known probing signal  $x(t)$

# Is this always possible?

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{bmatrix} = \begin{bmatrix} h_{1,1} & h_{1,2} & \dots & h_{1,N} \\ h_{2,1} & h_{2,2} & \dots & h_{2,N} \\ \vdots & \vdots & & \vdots \\ h_{N,1} & h_{N,2} & \dots & h_{N,N} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

Cannot extract  $N^2$  coefficients from  $N$  observations

# The aim of this talk

- Review the **fundamental limits** of system identification

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- Review the **fundamental limits** of system identification
- Show how we can **“break” these limits** when  $\mathbb{H}$  is “sparse”

# Identification of linear operators

All “reasonable” bounded, linear operators can be represented as [*Gröchenig, 2001*]:

$$\begin{aligned}r(t) &= (\mathbb{H}x)(t) = \iint S_{\mathbb{H}}(\tau, \nu)x(t - \tau)e^{j2\pi\nu t} d\nu d\tau \\ &= \int h(t, \tau)x(t - \tau)d\tau\end{aligned}$$

$$\underbrace{h(t, \tau)}_{\text{kernel}} = \int \underbrace{S_{\mathbb{H}}(\tau, \nu)}_{\text{spreading function}} e^{j2\pi\nu t} d\nu$$

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$$\underbrace{h(t, \tau)}_{\text{kernel}} = \int \underbrace{S_{\mathbb{H}}(\tau, \nu)e^{j2\pi\nu t}}_{\text{spreading function}} d\nu$$

Determine  $h(t, \tau)$  (or  $S_{\mathbb{H}}(\tau, \nu)$ ) from  $r(t)$  and knowledge of  $x(t)$

# Identification of LTI systems

- For LTI systems:

$$r(t) = \int g(\tau)x(t - \tau)d\tau$$



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LTI systems are always identifiable

## Why it always works in the LTI-case

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_{N-1} \\ r_N \end{bmatrix} = \begin{bmatrix} g_1 & g_2 & \dots & g_{N-1} & g_N \\ g_2 & \dots & \dots & g_N & g_1 \\ \vdots & & \ddots & \ddots & \\ g_{N-1} & g_N & g_1 & & \\ g_N & g_1 & g_2 & \dots & g_{N-1} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

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The  $N \times N$  Toeplitz (or circulant) system matrix  $\mathbb{H}$  is fully specified by  $N$  parameters

# The general case

Identification in the linear time-varying (LTV) case:

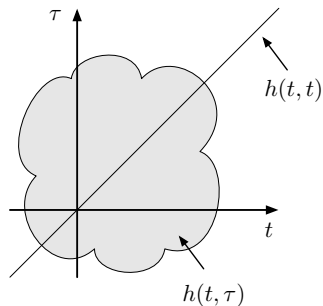
$$x(t) = \delta(t) \Rightarrow r(t) = \int h(t, \tau) \delta(t - \tau) d\tau = h(t, t)$$

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**Not sufficient** to identify the system



# Identification by using a Dirac train

Track evolution of LTV system by transmitting a Dirac train

$$x(t) = \sum_{\ell=-\infty}^{\infty} \delta(t - \ell t_0)$$

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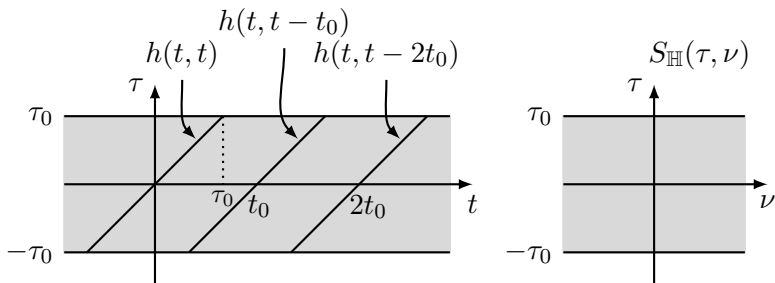
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Corresponding output signal is

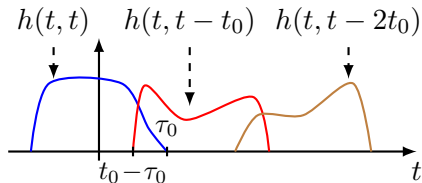
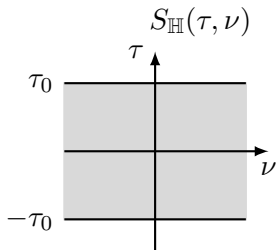
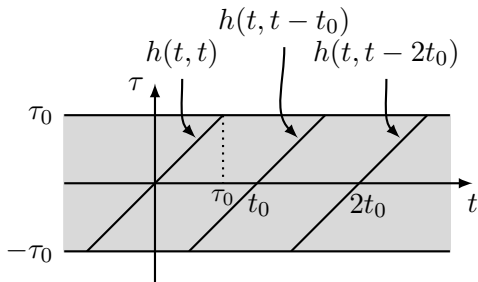
$$r(t) = \sum_{\ell=-\infty}^{\infty} h(t, t - \ell t_0)$$



# Identification by using a Dirac train cont'd

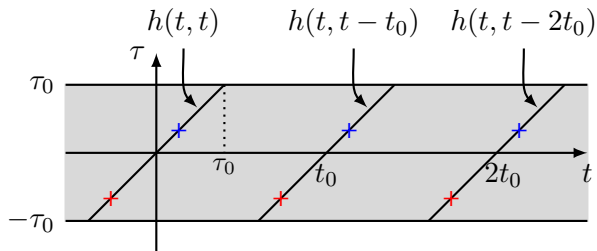


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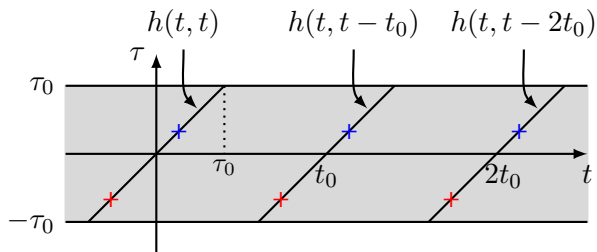


no overlap if  
 $t_0 \geq 2\tau_0$

# Identification by using a Dirac train cont'd

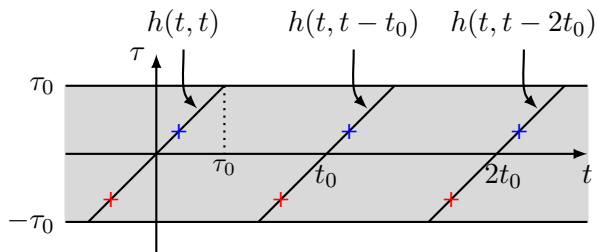


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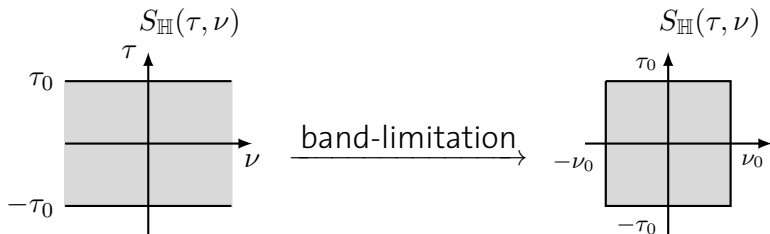


Assume that  $h(t, \tau)$  is band-limited to  $[-\nu_0, \nu_0]$  with respect to  $t$

# Identification by using a Dirac train cont'd



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# Sufficient condition for identifiability

- To recover  $h(t, \tau)$  from  $r(t)$  it is sufficient to have

sampling theorem

$$\underbrace{2\tau_0 \leq t_0}_{\text{no overlap}} \leq \frac{1}{2\nu_0}$$

no overlap

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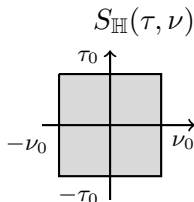
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between  $h(t, t-lt_0)$

- $\mathbb{H}$  is identifiable if

$$\underbrace{4\tau_0\nu_0 \leq 1}_{\mathcal{A}(\text{supp}(S_{\mathbb{H}}))}$$



Theorem [*Kailath, 1963*]

The set  $\mathcal{H} \triangleq \{\mathbb{H} : \text{supp}(S_{\mathbb{H}}) \subseteq [-\tau_0, \tau_0] \times [-\nu_0, \nu_0]\}$  is identifiable if and only if

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## Theorem [*Kailath, 1963*]

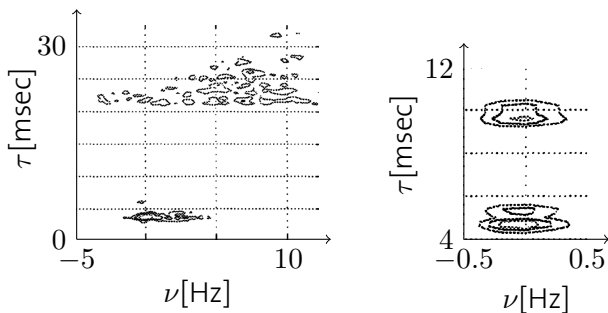
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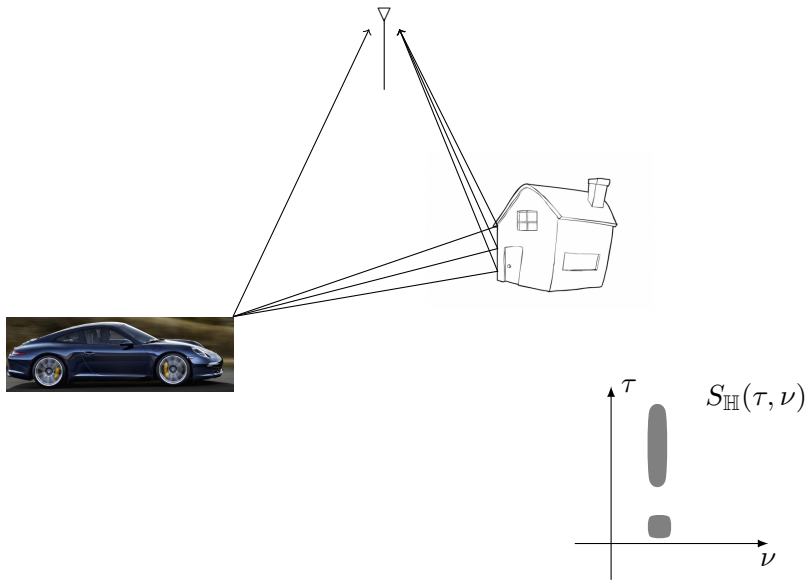
- **Underspread** channels  $\Rightarrow \mathcal{A}(\text{supp}(S_{\mathbb{H}})) \leq 1$
- **Overspread** channels  $\Rightarrow \mathcal{A}(\text{supp}(S_{\mathbb{H}})) > 1$

# Practical systems are often “sparse”

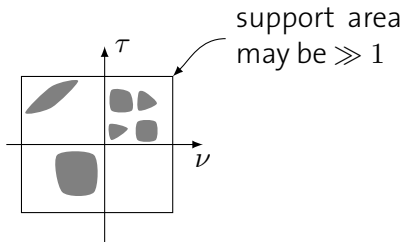
Underwater acoustic communication channels [Eggen, 1997]



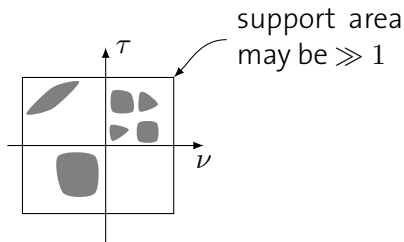
# Sparse spreading function in mobile communications



# General support area for $S_{\text{III}}$



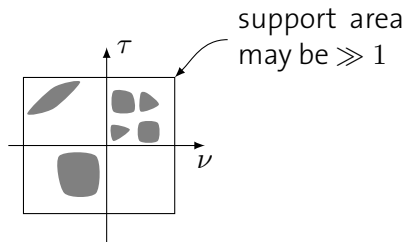
# General support area for $S_{\mathbb{H}}$



General support area [*Bello 1969; Pfander & Walnut 2006*]

$\mathcal{H}_M \triangleq \{\mathbb{H} : \text{supp}(S_{\mathbb{H}}) \subseteq M\}$  is identifiable if and only if  $\mathcal{A}(M) \leq 1$ .

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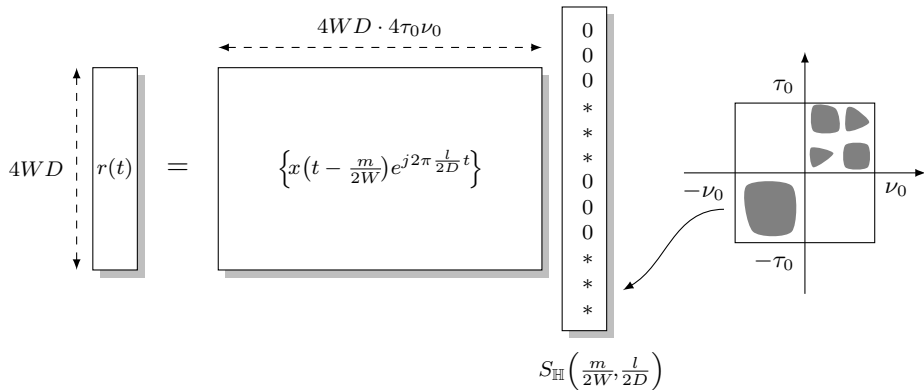
**But** support area needs to be known!

# Counting signal space dimensions [*Kailath, 1963*]

- Input signal has bandwidth  $2W$
- Output signal observed over an **interval** of length  $2D$
- Use the  $2WT$ -Theorem [*Landau, Pollak, Slepian, 1961-62*]

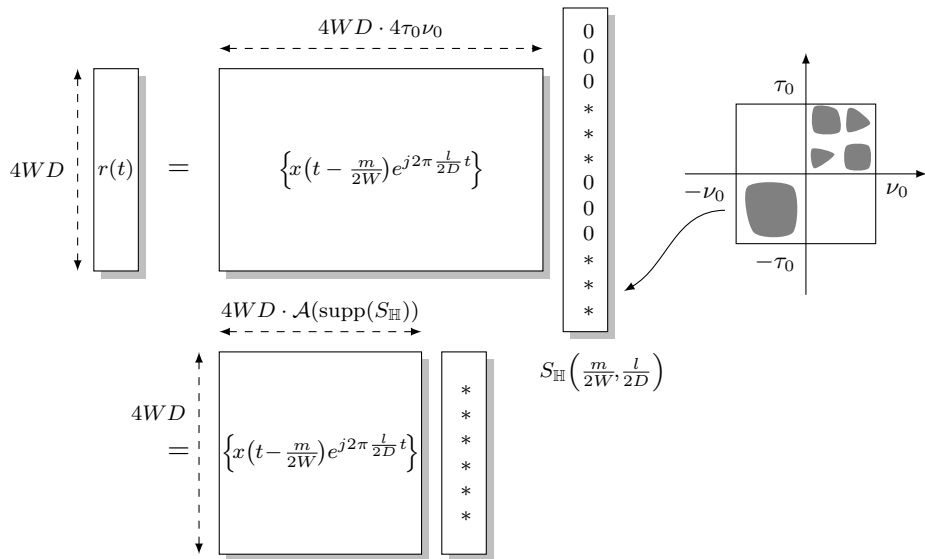


# Counting signal space dimensions cont'd

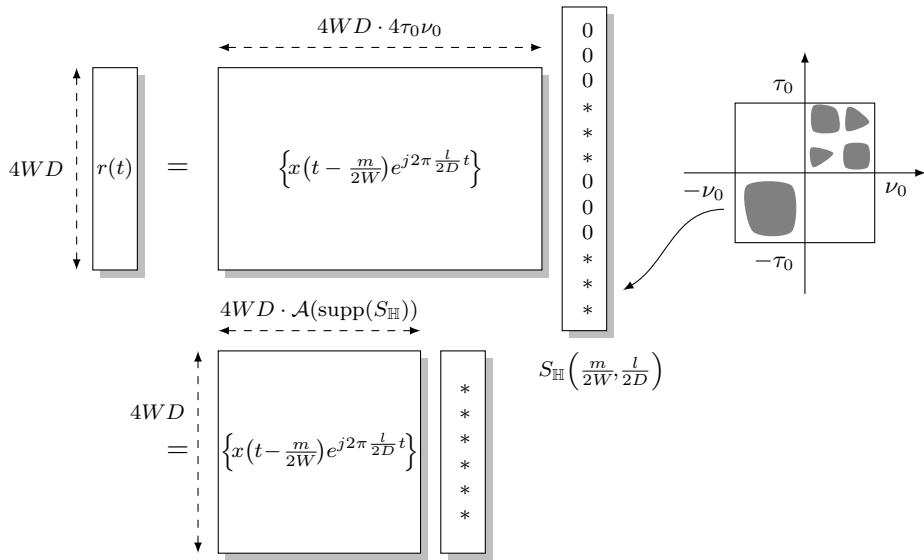




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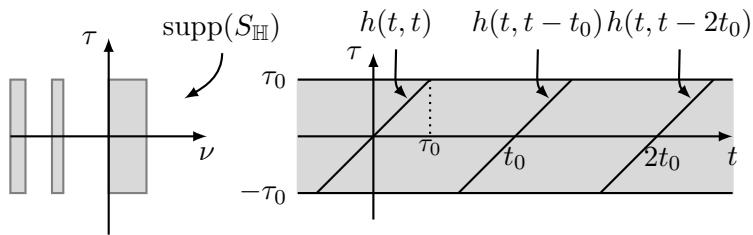


# Counting signal space dimensions cont'd



**Identification:**  $4WD \geq 4WD \cdot \mathcal{A}(\text{supp}(S_{\mathbb{H}})) \Rightarrow \mathcal{A}(\text{supp}(S_{\mathbb{H}})) \leq 1$

# Unknown support in $\nu$ direction only

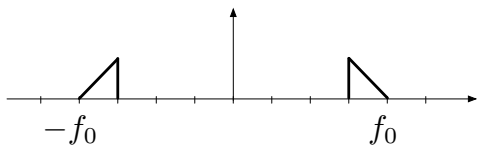


$S_{\mathbb{H}}(\tau, \nu)$  is a “sparse” multi-band signal as a function of  $\nu$

An excursion into sampling of  
(sparse) multi-band signals

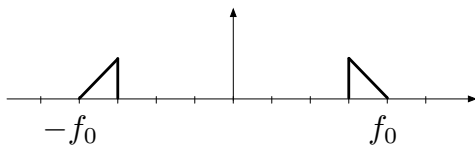
# Sampling of multi-band signals

Spectrum has sparse support in  $[-f_0, f_0]$

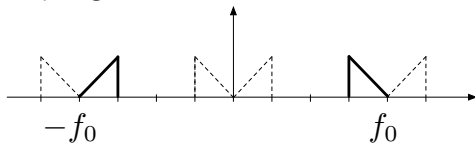


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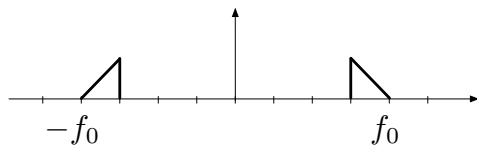


2-fold undersampling:  $f_s = f_0$

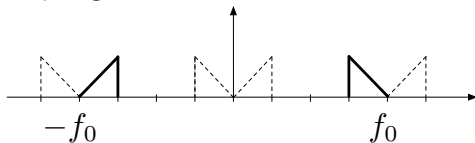


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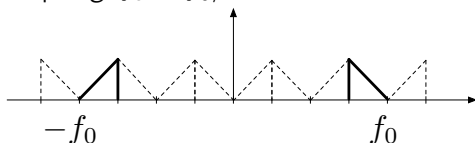
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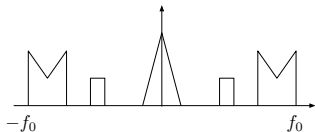


4-fold undersampling:  $f_s = f_0/2$



# Landau's multi-band sampling theorem

- Spectral occupancy  $\mathcal{T} \in [-f_0, f_0]$
- Sampling set  
 $\mathcal{P} = \{t_n\} \rightarrow \{x(t_n)\}$



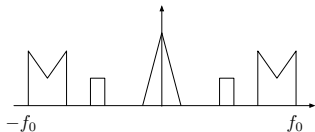


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[Landau, 1967]: To reconstruct *stably* need

$$D^-(\mathcal{P}) = \liminf_{r \rightarrow \infty} \inf_{t \in \mathbb{R}} \frac{|\mathcal{P} \cap [t, t+r]|}{r} \geq |\mathcal{T}|$$

$D^-(\mathcal{P})$ : lower Beurling density

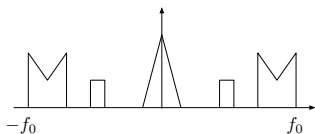


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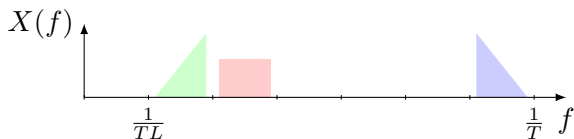


$D^-(\mathcal{P})$ : lower Beurling density

- There exists a stable universal sampling set  $\mathcal{P}$  with  $D^-(\mathcal{P}) = |\mathcal{T}|$  [[Venkataramani & Bresler, 2001](#)]

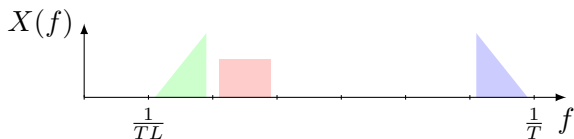
# Unknown spectral support set

- Consider the set of all signals with  $|\text{spectral support}| \leq C$

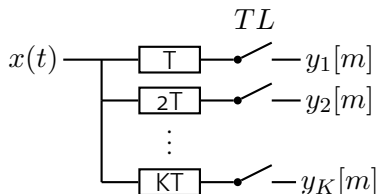


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- Multicoset sampling [*Bresler, Feng, 1996,...*]

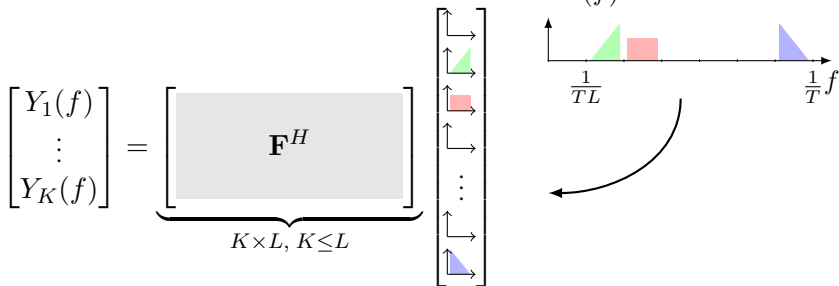


Overall sampling rate:

$$D^-(\mathcal{P}) = \frac{K}{TL}$$

# A stable universal sampling set

$$Y_k(f) = \mathcal{F}\{y_k[m]\} = \sum_{m \in \mathbb{Z}} X\left(f + \frac{m}{TL}\right) e^{j2\pi \frac{mk}{L}}, \quad f \in [0, 1/(TL))$$



# A stable universal sampling set $\mathcal{P}$ with $D^-(\mathcal{P}) = 2C$

$$\underbrace{\begin{bmatrix} Y_1(f) \\ \vdots \\ Y_K(f) \end{bmatrix}}_{\mathbf{y}(f)} = \underbrace{\begin{bmatrix} \text{---} \\ \mathbf{F}^H \\ \text{---} \end{bmatrix}}_{K \times L, K \leq L} \underbrace{\begin{bmatrix} \uparrow \rightarrow \\ \uparrow \rightarrow \\ \uparrow \rightarrow \\ \vdots \\ \uparrow \rightarrow \\ \uparrow \rightarrow \end{bmatrix}}_{\mathbf{x}(f)}$$

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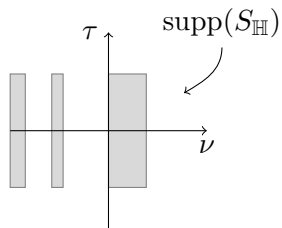
Spectrum-blind sampling entails a factor-of-two penalty in the sampling rate



Back to operator identification

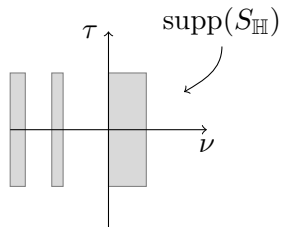
# Unknown support in $\tau$ or $\nu$ direction only

Unknown support in  
 $\nu$ -direction only

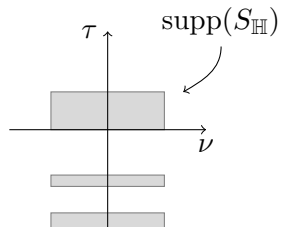


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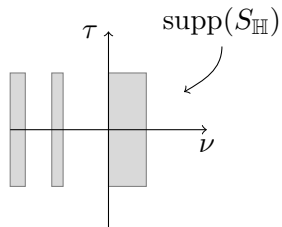


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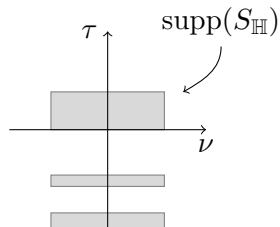


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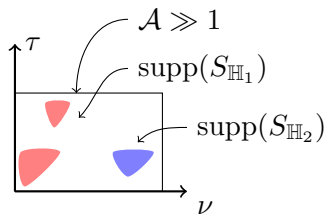


How do we account for unknown support in  $\tau$  and  $\nu$  concurrently?

# Main results [*Heckel and HB, 2011*]

$$\mathcal{X}(\Delta) = \{\mathbb{H} : \mathcal{A}(\text{supp}(S_{\mathbb{H}})) \leq \Delta\}$$

Example:  $\mathbb{H}_1, \mathbb{H}_2 \in \mathcal{X}(\Delta)$

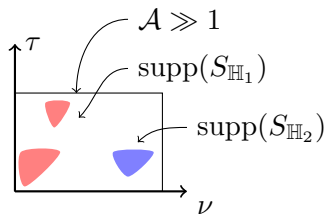


The set  $\mathcal{X}(\Delta)$  is identifiable if and only if  $\Delta \leq 1/2$ .

# Main results [*Heckel and HB, 2011*]

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Example:  $\mathbb{H}_1, \mathbb{H}_2 \in \mathcal{X}(\Delta)$



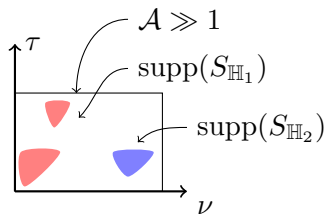
The set  $\mathcal{X}(\Delta)$  is identifiable if and only if  $\Delta \leq 1/2$ .

**Almost all**  $\mathbb{H} \in \mathcal{X}(\Delta)$  can be identified if  $\Delta < 1$ .

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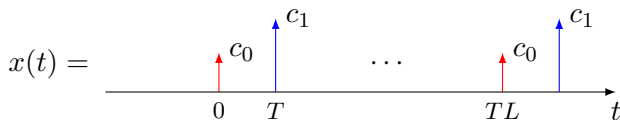
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**Almost all**  $\mathbb{H} \in \mathcal{X}(\Delta)$  can be identified if  $\Delta < 1$ .

$\Rightarrow$  There is no penalty for not knowing  $\text{supp}(S_{\mathbb{H}})$  upfront!

# Sufficiency of $\Delta \leq 1/2$

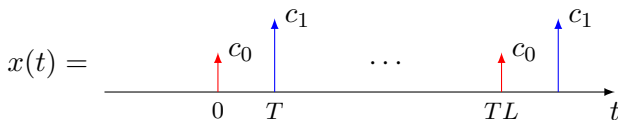
- Probing signal: **Periodic weighted Dirac train**





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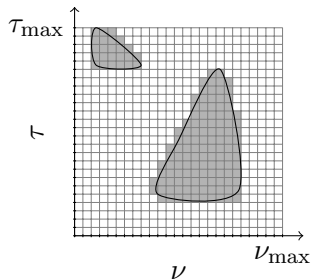
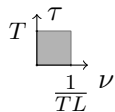
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- Reduce problem to **solution of (continuum of) linear system of equations** where  $S_{\mathbb{H}}$  is the unknown

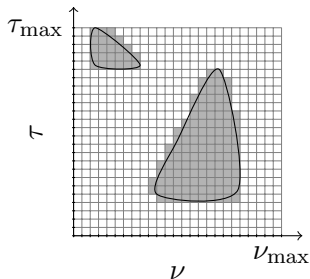
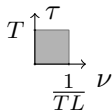
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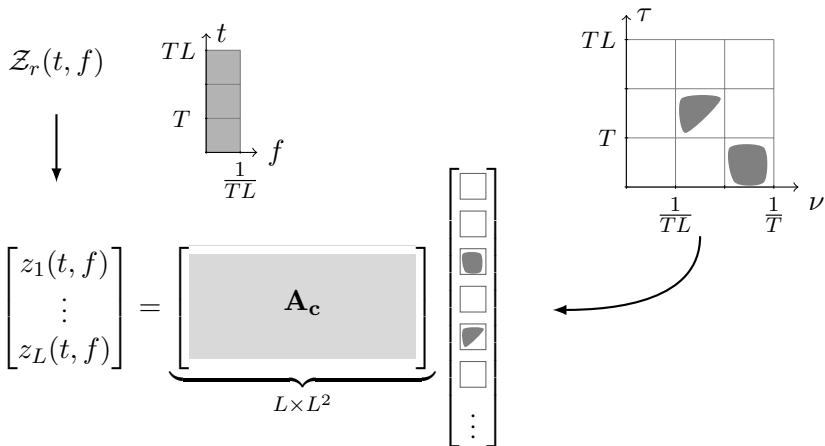
- Approximate  $\text{supp}(S_{\mathbb{H}})$  by rectangles of area  $1/L$ :



- Zak transform [[Janssen, 1988](#)] of  $r(t) = (\mathbb{H}x)(t)$ :

$$\mathcal{Z}_r(t, f) \triangleq \sum_{m \in \mathbb{Z}} r(t - mTL) e^{j2\pi mTLf}$$

# Sufficiency of $\Delta \leq 1/2$ cont'd

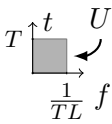


$\mathbf{A}_c$ : Time-frequency translates of weighting sequence  $\mathbf{c}$

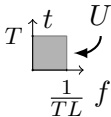
# A continuum of compressed sensing problems

$$\underbrace{\begin{bmatrix} z_1(t, f) \\ \vdots \\ z_L(t, f) \end{bmatrix}}_{\mathbf{z}(t, f)} = \underbrace{\begin{bmatrix} \phantom{z_1(t, f)} \\ \phantom{z_1(t, f)} \\ \mathbf{A}_c \\ \phantom{z_1(t, f)} \\ \phantom{z_1(t, f)} \end{bmatrix}}_{L \times L^2}, (t, f) \in U$$

$\underbrace{\begin{bmatrix} \square \\ \square \\ \blacksquare \\ \square \\ \blacksquare \\ \square \\ \vdots \end{bmatrix}}_{\mathbf{s}(t, f)}$

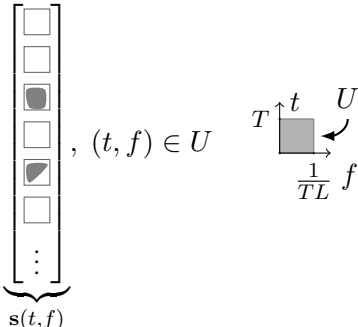


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- By [Lawrence *et al.* 2005], there exists  $\{c_0, \dots, c_{L-1}\}$  such that **every**  $L \times L$  submatrix of  $\mathbf{A}_c$  has full rank

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The diagram illustrates the compressed sensing problem. On the left, a vector  $\mathbf{z}(t, f)$  of size  $L$  is shown. This is equal to a matrix  $\mathbf{A}_c$  of size  $L \times L^2$  multiplied by a vector  $\mathbf{s}(t, f)$  of size  $L^2$ . The matrix  $\mathbf{A}_c$  is represented as a grid of squares, with some squares shaded to indicate non-zero entries. The vector  $\mathbf{s}(t, f)$  is represented as a column of squares, with some squares shaded to indicate non-zero entries. The domain  $U$  is shown as a square in the  $(t, f)$  plane, with axes  $t$  and  $f$ , and a shaded region  $U$ .

- By [Lawrence et al. 2005], there exists  $\{c_0, \dots, c_{L-1}\}$  such that **every**  $L \times L$  submatrix of  $\mathbf{A}_c$  has full rank
- No two different  $\mathbf{s}(t, f)$  can map to the same  $\mathbf{z}(t, f)$   
 $\|\mathbf{s}(t, f)\|_0 \leq \frac{L}{2}$ , i.e., if  $\Delta \leq \frac{L}{2} \frac{1}{L} = \frac{1}{2}$

# Eliminating the factor of two penalty

There is no penalty for not knowing  $\text{supp}(S_{\text{H}})$  upfront

$$\begin{bmatrix} z_1(t, f) \\ \vdots \\ z_L(t, f) \end{bmatrix} = \begin{bmatrix} \text{---} \\ \mathbf{A}_{\mathbf{c}} \\ \text{---} \end{bmatrix} \begin{bmatrix} \square \\ \square \\ \blacksquare \\ \square \\ \square \\ \square \\ \vdots \end{bmatrix}$$

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- Can identify  $\text{supp}(S_{\mathbb{H}})$  if dimension of subspace spanned by  $\mathbf{s}(t_1, f_1), \mathbf{s}(t_2, f_2), \dots$  is sufficiently large

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- MUSIC [[Schmidt, 1986](#)] or ESPRIT [[Paulraj et al., 1985](#)] provably recover  $S_{\mathbb{H}}$  when  $\mathcal{A}(\text{supp}(S_{\mathbb{H}})) < 1$

Thank you