

# Bounds on Subframes

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This set of lines forms a frame in a natural way; Jasper, Mixon, and Fickus use frames to give applications of this problem to coding theory in [3].

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In this context the study of frames has powerful applications to signal processing, wavelets, and data compression (see [1]).

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- $L^2[0, 1]$ , the functions  $f : [0, 1] \rightarrow \mathbb{F}$  such that  $\int_0^1 |f(x)|^2 dx$  converges, with  $\langle f, g \rangle = \int_0^1 f(x) \overline{g(x)} dx$ .

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Both of the examples of inner product spaces from last slide are also Hilbert spaces.

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$$A\|x\|^2 \leq \sum_{i \in I} |\langle x, \varphi_i \rangle|^2 \leq B\|x\|^2$$

for all  $x \in \mathcal{H}$ .

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For example, if  $\{\varphi_i\}$  happen to form an orthonormal basis, then  $\sum_{i \in I} |\langle x, \varphi_i \rangle|^2 = \|x\|^2$  so this is a frame with  $A = B = 1$ .

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In the infinite case, things are a bit more complicated since we need to ensure positivity (since  $A > 0$ ) and finiteness (since  $B < \infty$ ). Fortunately, we will be dealing mostly with the finite case.

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A tight frame is **Parseval** if  $A_F = B_F = 1$ .

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$$\begin{aligned} t_F(x) &= \frac{1}{\|x\|^2} \sum_{i \in I} |\langle x, \varphi_i \rangle|^2 \\ &= \frac{(x_2)^2 + ((\sqrt{3}/2)x_1 - (1/2)x_2)^2 + (-\sqrt{3}/2)x_1 - (1/2)x_2)^2}{x_1^2 + x_2^2} \end{aligned}$$

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## A **good** frame: the Mercedes-Benz frame

The **Mercedes-Benz frame** consists of the following three vectors in  $\mathbb{R}^2$ :

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So  $A_F = B_F = 3/2$ , meaning the Mercedes-Benz frame is tight ( $\Omega(F) = 1$ ). It's not Parseval; we could make it Parseval by scaling the  $\varphi_i$  by a factor of  $\sqrt{2/3}$ .



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In short, the obscurity measures **how far from symmetry** our frame is (in a certain sense).

### Question

Given a large frame, under what conditions does there exist a smaller frame of specified size with small obscurity?

# Our strategy

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The last step relies on the following lemma.

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## Lemma

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$$\Omega(F \cup G) \leq \max(\Omega(F), \Omega(G))$$

In other words, if we glue two frames together, the resultant frame is no worse than the frames we started with.

# Proof of lemma

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This completes the proof of the lemma; using this we can build frames out of smaller ones.

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Using this lemma, we can prove the following result:

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Suppose we have a frame  $F$  consisting of  $n$  nonzero vectors in  $\mathbb{R}^d$ , with  $a$  the ratio between the largest and smallest norm, and  $d|k \leq n$ . Then if we can find  $d$  disjoint subsets  $E_1, E_2, \dots, E_d \subset F$  each containing  $\geq k/d$  vectors such that the angle between vectors in different subsets is  $\geq \beta$ , there is a subframe  $E \subset F$  such that  $|E| = k$  and:



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- $A_E \geq (1/2)(1 - \cos \beta)$  so long as  $d = 2$

If  $d > 2$  we need a stronger condition on  $F$  to get a good bound on  $A_E$ .

## A word on angles

Incidentally, the **angle** between two vectors  $x, y$  is defined as the unique  $\theta \in [0, \pi/2]$  such that

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The reason for this nonstandard definition is that replacing a vector  $\varphi_i$  in a frame by  $-\varphi_i$  does not affect obscurity since  $|\langle x, \varphi_i \rangle|^2 = |\langle x, -\varphi_i \rangle|^2$ .

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## $A_E$ in higher dimensions

In higher dimensions we need the following (stronger) assumptions to get the following (stronger) result:

### Theorem

Suppose we have a frame  $F$  consisting of  $n$  nonzero unit vectors in  $\mathbb{R}^d$ , and  $d|k \leq n$ . Suppose further that there exists an orthonormal basis  $\{f_i\}$  and an angle  $\gamma < \pi/4$  such that for each  $f_i$  there exist at least  $k/d$  vectors of  $F$  with angle  $\leq \gamma$  from  $f_i$ . Then there exists a subframe  $E$  of  $F$  with



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This means  $\Omega(E) \leq \frac{1+\gamma}{1-\gamma}$ .

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## Theorem

Suppose we pick  $N$  points uniformly at random on the unit circle, and  $2 \ll r \ll N$  with  $2|r$ . Then for any  $k > 2$ ,  $2|k$ , there is a  $\geq q$  probability of finding a subframe  $F$  with  $|F| = k$  and

$$\Omega(F) \leq \cot^2(\pi/4 - \pi/r) = \tan^2(\pi/4 + \pi/r)$$

so long as

$$\Phi^*(2k) \leq \sqrt{\frac{2(1-q)}{r}}$$

where  $\Phi^*$  is the cdf of a normal distribution with mean  $N$  and standard deviation  $\sqrt{N(r-1)}$ .

# Unpacking this theorem

Equivalently:

$$\frac{1}{\sqrt{2\pi N(r-1)}} \int_{-\infty}^{\infty} e^{-\frac{(t-N)^2}{2N(r-1)}} dt \leq \sqrt{\frac{2(1-q)}{r}}.$$

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This looks ghastly; but it's quite useful. Suppose we let  $N = 1000$  and  $r = 100$ . Then we get that for 1000 points, distributed randomly on a circle, the probability of having a subframe of size  $k$  with obscurity at most  $\tan^2(\pi/4 + \pi/100) \approx 1.134$  is at least:

$$.999958 \quad (k = 10) \quad .998486 \quad (k = 100) \quad .486196 \quad (k = 300)$$

# Unpacking this theorem

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Results in higher dimensions, though, would require bounds on sphere packings which are still open problems!

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