

Medical Image Analysis and Processing

Image Noise Filtering

Sparse Denoising

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Norm Definition

› Consider $x \in \mathbb{R}^n$

› p -norm:

$$\|x\|_p = \sqrt[p]{|x_1|^p + |x_2|^p + \cdots + |x_n|^p}, \quad p > 0$$

› Euclidean Norm, 2-Norm, ℓ_2 Norm:

$$\|x\|_2 = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$$

› Manhattan Norm, 1-Norm, ℓ_1 Norm

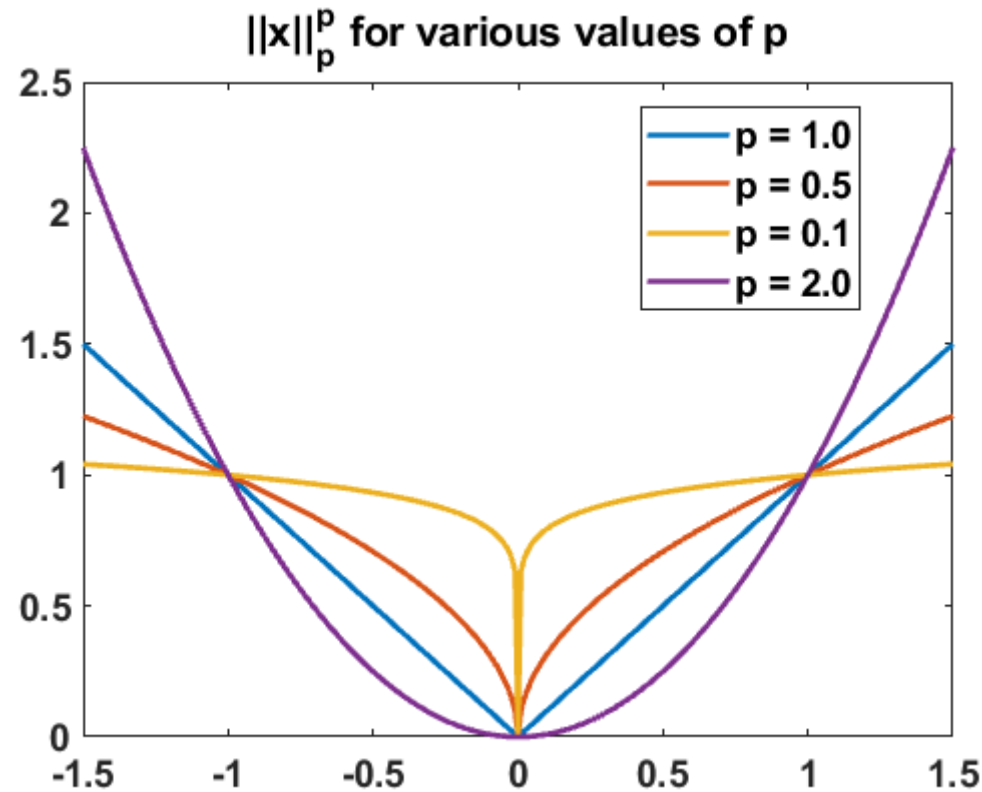
$$\|x\|_1 = |x_1| + |x_2| + \cdots + |x_n|$$

› zero-Norm, ℓ_0 Norm (number of non-zero entries of the vector x):

$$\|x\|_0 = |x_1|^0 + |x_2|^0 + \cdots + |x_n|^0, \quad 0^0 \stackrel{\text{def}}{=} 0$$

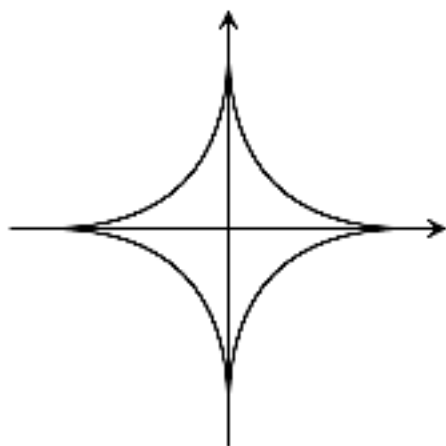
Norm Definition

› The behavior of $\|x\|_p^p$ for various values of p

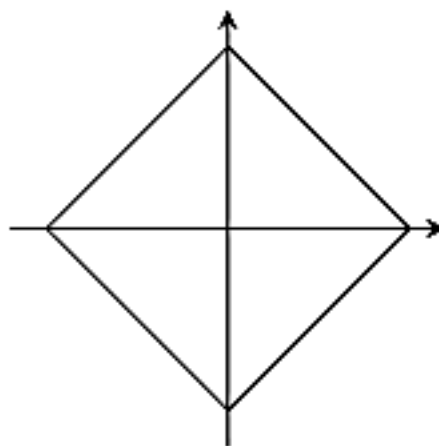


Norm Definition

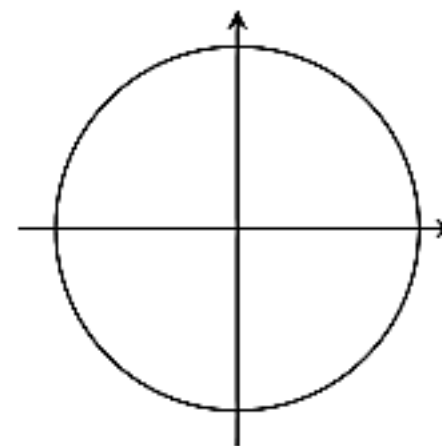
› Unit Circles ($\|x\|_p=1$) in different norms:



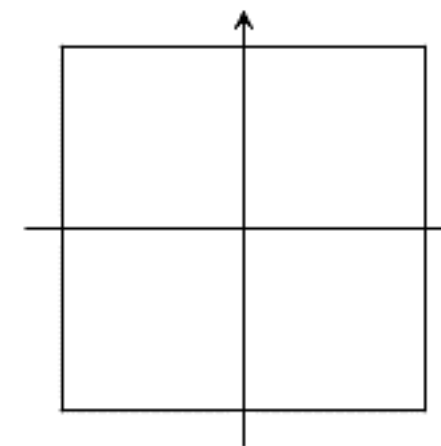
$$p = \frac{1}{2}$$



$$p = 1$$



$$p = 2$$



$$p = \infty$$

Sparse Approximation

› Start with an under-determined set of equations:

$$D_{n \times k} x_{k \times 1} = y_{n \times 1}, \quad k > n$$

› n -equations and k -unknown \rightarrow infinitely many solutions

› Example:

$$\begin{cases} x_1 + 3x_2 - x_3 = y_1 \\ x_1 - 8x_2 + 2x_3 = y_2 \end{cases}, n = 2, k = 3$$

$$\begin{bmatrix} 1 & 3 & -1 \\ 1 & -8 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

Sparse Approximation

- › Signal processing perspective of set-of- equations

$$D_{n \times k} x_{k \times 1} = y_{n \times 1}, \quad k > n$$

- › $y_{n \times 1}$: signal
- › $x_{k \times 1}$: representation of signal
- › $D_{n \times k}$: Dictionary
- › An old fashion example (but determined, $k = n$):

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-jk \frac{2\pi}{N}} \Leftrightarrow x(n) = \sum_{k=0}^{N-1} X(k) e^{jk \frac{2\pi}{N}}$$

Sparse Approximation

› An old fashion example (but determined):

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-jk \frac{2\pi}{N}} \Leftrightarrow x(n) = \sum_{k=0}^{N-1} X(k) e^{jk \frac{2\pi}{N}}$$

› In matrix formulation:

$$\mathbf{X} = \mathbf{W}^H \mathbf{x} \Leftrightarrow \mathbf{x} = \mathbf{W} \mathbf{X}$$

› Where:

$$- \mathbf{X} = [X(0) \quad X(1) \quad \dots \quad X(N-1)]^T$$

$$- \mathbf{x} = [x(0) \quad x(1) \quad \dots \quad x(N-1)]^T$$

$$- \mathbf{W} = [e^{jk \frac{2\pi}{N} n}]_{k,n=0}^{N-1}$$

Sparse Approximation

- › What is dictionary role?

$$D_{n \times k} x_{k \times 1} = y_{n \times 1}$$

- › Let show D with its columns (atoms):

$$D = [\mathbf{d}_1 | \mathbf{d}_2 | \dots | \mathbf{d}_k]$$

$$y = Dx = [\mathbf{d}_1 | \mathbf{d}_2 | \dots | \mathbf{d}_k] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix} = \sum_{i=1}^k x_i \mathbf{d}_i$$

- › Signal (y) represented by an expansion using dictionary atoms (\mathbf{d}_i 's) as basis and (x_i 's) as coefficients

Sparse Approximation

› Example

$$\begin{bmatrix} \textcolor{blue}{1} & \textcolor{green}{3} & \textcolor{red}{-1} \\ \textcolor{blue}{1} & \textcolor{green}{-8} & \textcolor{red}{2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_1 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \textcolor{blue}{1} \\ \textcolor{blue}{1} \end{bmatrix} x_1 + \begin{bmatrix} \textcolor{green}{3} \\ \textcolor{green}{-8} \end{bmatrix} x_2 + \begin{bmatrix} \textcolor{red}{1} \\ \textcolor{red}{2} \end{bmatrix} x_3$$

› Thus we may use $(x_i$'s) instead of $(y_i$'s)

Sparse Approximation

- › Let find solution(s) for:

$$D_{n \times k} x_{k \times 1} = y_{n \times 1}, \quad k > n$$

- › Obviously there is infinitely many solutions.
- › We solve the following constrained optimization problems:

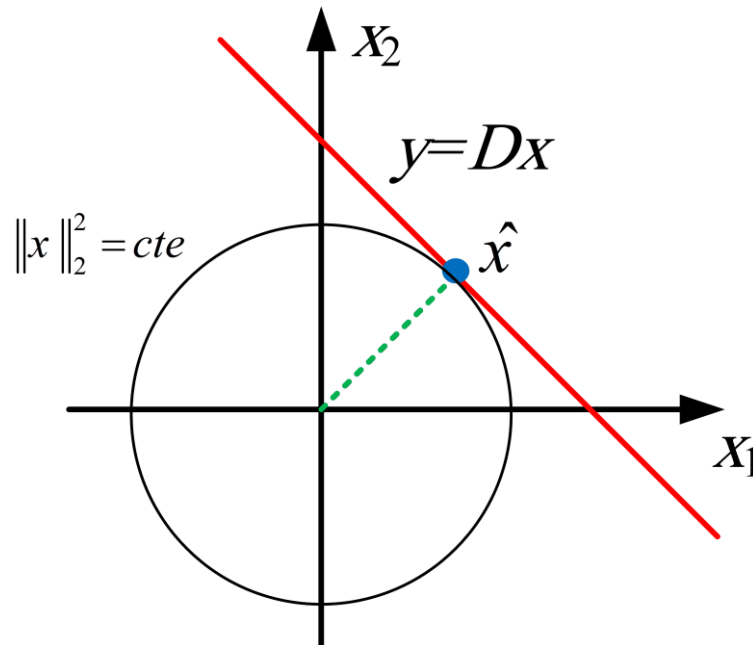
$$\hat{x} = \underset{x}{\operatorname{argmin}} J(x), \quad s.t. Dx = y$$

- › Cost function, J , depends on problems

Sparse Approximation

› Example:

$$\hat{x} = \underset{x}{\operatorname{argmin}} \|x\|_2^2, \quad \text{s.t. } Dx = y \Rightarrow \hat{x} = D^+ y = D^T (DD^T)^{-1} y$$

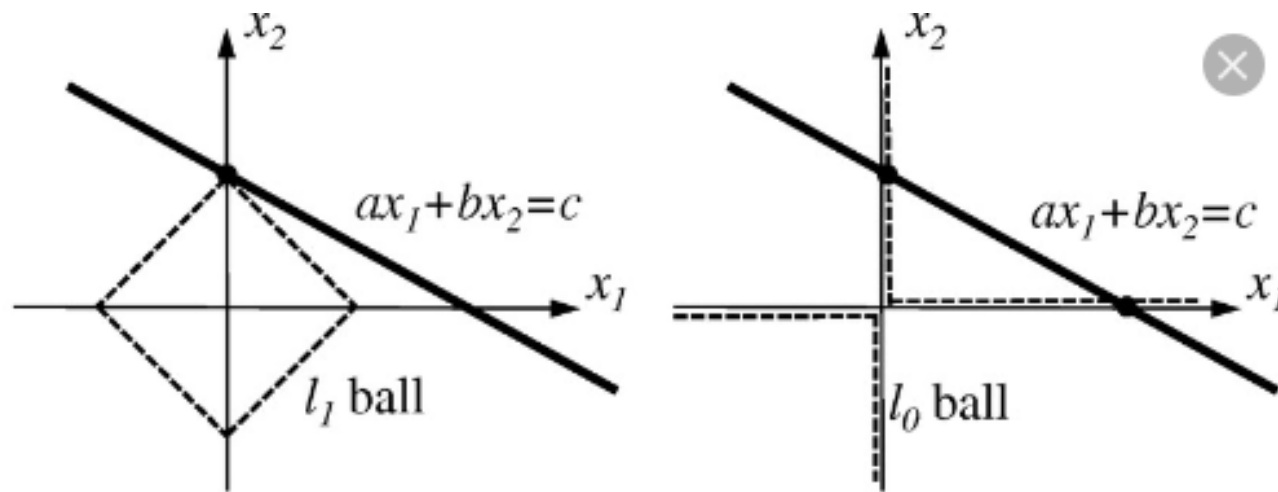


Sparse Approximation

› Other solution(s):

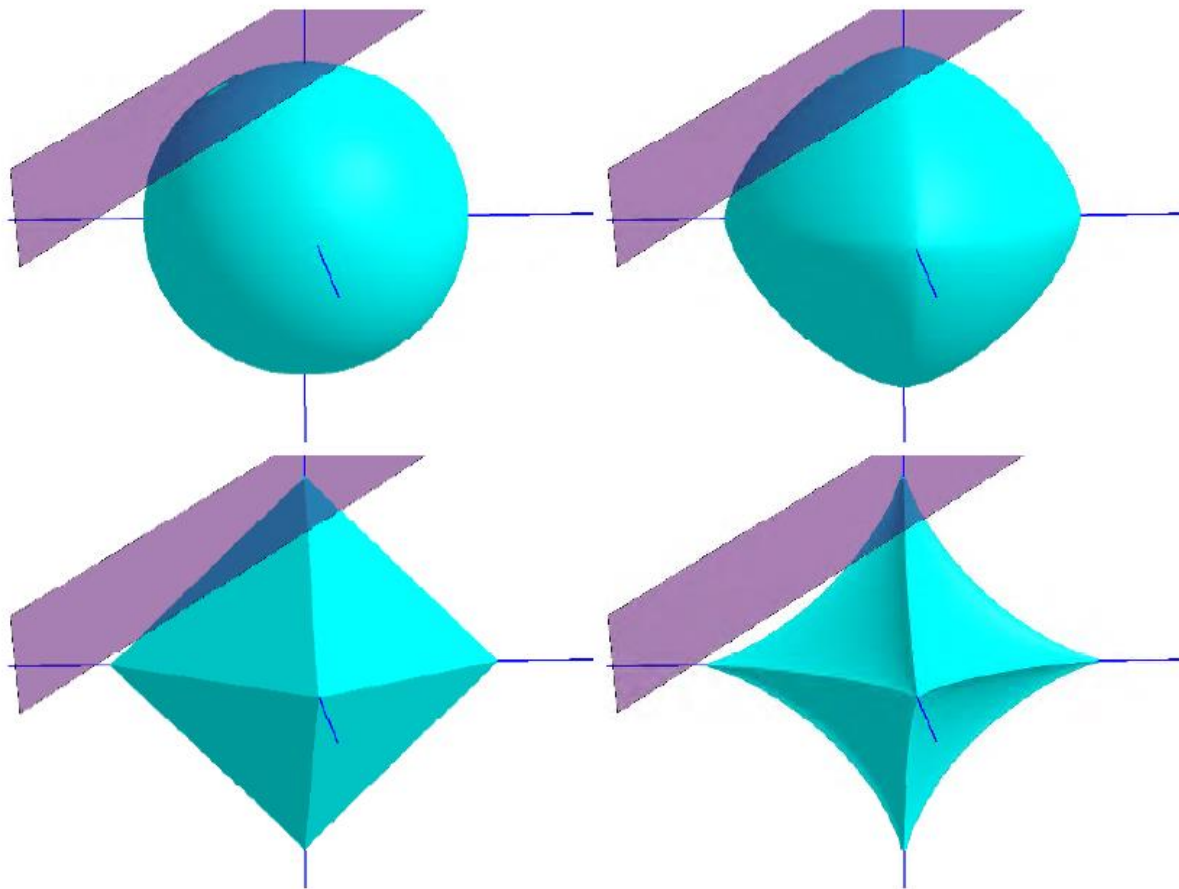
$$\hat{x} = \underset{x}{\operatorname{argmin}} \|x\|_1, \quad s.t. \ Dx = y$$

$$\hat{x} = \underset{x}{\operatorname{argmin}} \|x\|_0, \quad s.t. \ Dx = y$$



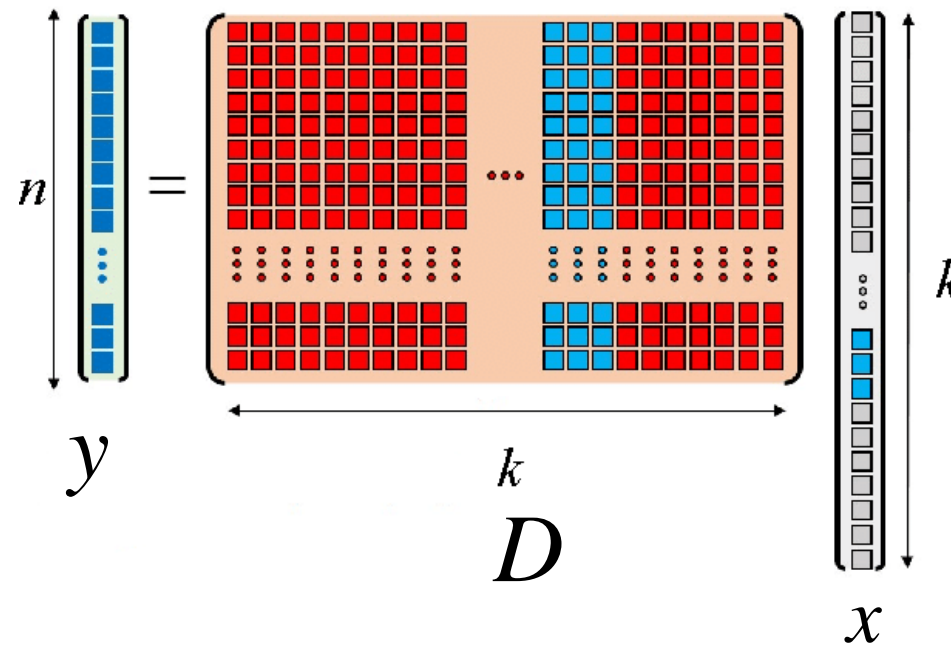
Sparse Approximation

› 3D illustration:



Sparse Approximation

- › We focus on ℓ_0 -norm minimization, why? Sparsity!



- › High dimension representation (x) may be sparse for a well-chosen dictionary, D

Sparse Approximation

› How to solve:

$$\hat{x} = \underset{x}{\operatorname{argmin}}\{\|x\|_0\}, \quad s.t. Dx = y$$

› $\|x\|_0$ is too sensitive to noise, perfect solution is impossible, we solve an alternative:

$$\hat{x} = \underset{x}{\operatorname{argmin}}\{\|x\|_0\}, \quad s.t. \|Dx - y\|_2^2 \leq \varepsilon$$

› where ε is closely related to the properties of the noise.

› Or alternatively:

$$\hat{x} = \underset{x}{\operatorname{argmin}}\{\|Dx - y\|_2^2\}, \quad s.t. \|x\|_0 \leq T_0$$

Sparse Approximation

- › Several approach for solving ℓ_0 -norm has been proposed:
- › Relaxation approach are well-known (that smooth the ℓ_0 -norm and solve the alternative problem):
- › Method #1) convexise” the ℓ_0 -norm and replace it with ℓ_1 -norm

$$\hat{x} = \underset{x}{\operatorname{argmin}} \{ \|x\|_1 \}, \quad s.t. \|Dx - y\|_2^2 \leq \varepsilon$$

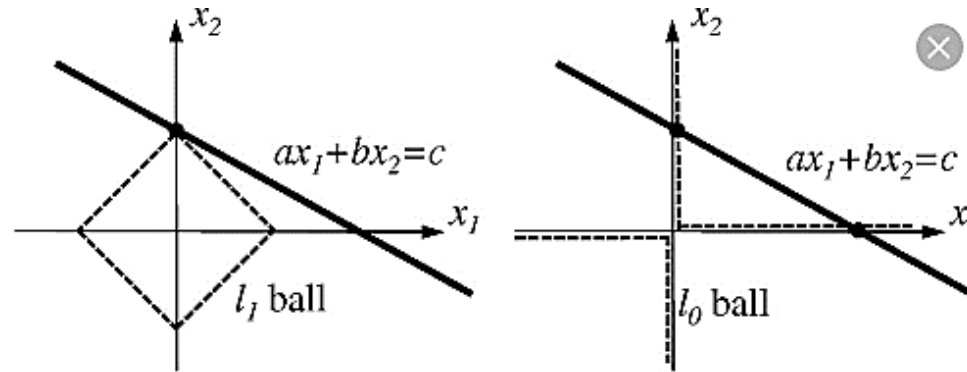
- › For an appropriate Lagrange multiplier λ , we may solve this equivalent problem:

$$\hat{x} = \underset{x}{\operatorname{argmin}} \left\{ \frac{1}{2} \|Dx - y\|_2^2 + \lambda \|x\|_1 \right\}$$

- › Where λ is function of D , y , and ε

Sparse Approximation

› Why this may works:



› Method #2) replace $\|x\|_0$ with:

$$\sum_{i=1}^k \left(1 - \exp(-\beta x_i^2)\right), \beta \rightarrow \infty$$

Dictionary

- › Dictionary is too important to generate sparse representation
- › Example:

- › Sparse representation of a signal with just one non-zero value:

$$y = \delta[n - n_0], y \in \mathbb{R}^N \Rightarrow y = I_{N \times N} x, \quad x \in \mathbb{R}^N$$

- › where $I_{N \times N}$ is identity matrix (Dirac dictionary) of size N

- › Sparse representation of a signal with just two non-zero values:

$$y = \sin[\omega_0 n], y \in \mathbb{R}^N \Rightarrow y = W_{N \times N} x, \quad x \in \mathbb{R}^N$$

- › where $W_{N \times N}$ is inverse Fourier matrix of size N

Dictionary

- › What about combination of two signals:

$$y = \sin[\omega_0 n] + \delta[n - n_0]?$$

- › Solution is an overcomplete dictionary and under-determined representation:

$$y = \underbrace{[I_{N \times N} | W_{N \times N}]}_D x, x \in \mathbb{R}^{2N}, D \in \mathbb{R}^{N \times 2N}$$

- › How to determine dictionary:
 - Building
 - Learning

π

Dictionary

› Example:

$$\begin{bmatrix} 0.6533 \\ 0.2706 \\ -0.2706 \\ -0.6533 \end{bmatrix} = \begin{bmatrix} 0.5000 & 0.6533 & 0.5000 & 0.2706 \\ 0.5000 & 0.2706 & -0.5000 & -0.6533 \\ 0.5000 & -0.2706 & -0.5000 & 0.6533 \\ 0.5000 & -0.6533 & 0.5000 & -0.2706 \end{bmatrix} \begin{bmatrix} 0 \\ \mathbf{1} \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \mathbf{1} \\ 0 \end{bmatrix}$$

Dictionary

› Example, Now consider:

$$\begin{bmatrix} 0.6533 \\ 0.2706 \\ -0.2706 \\ -0.6533 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5000 & 0.6533 & 0.5000 & 0.2706 \\ 0.5000 & 0.2706 & -0.5000 & -0.6533 \\ 0.5000 & -0.2706 & -0.5000 & 0.6533 \\ 0.5000 & -0.6533 & 0.5000 & -0.2706 \end{bmatrix} \underbrace{\begin{bmatrix} 0.5000 \\ 0.7294 \\ -0.5000 \\ 0.6533 \end{bmatrix}}_{\|x\|_0=4}$$

$$\begin{bmatrix} 0.6533 \\ 0.2706 \\ -0.2706 \\ -0.6533 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \underbrace{\begin{bmatrix} 0.6533 \\ 0.2706 \\ 0.7294 \\ -0.6533 \end{bmatrix}}_{\|x\|_0=4}$$

π

Dictionary

› Example, But:

$$\begin{bmatrix} 0.6533 \\ 0.2706 \\ -0.2706 \\ -0.6533 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5000 & 0.6533 & 0.5000 & 0.2706 & 1 & 0 & 0 & 0 \\ 0.5000 & 0.2706 & -0.5000 & -0.6533 & 0 & 1 & 0 & 0 \\ 0.5000 & -0.2706 & -0.5000 & 0.6533 & 0 & 0 & 1 & 0 \\ 0.5000 & -0.6533 & 0.5000 & -0.2706 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ \mathbf{1} \\ 0 \\ 0 \\ 0 \\ \mathbf{1} \\ 0 \\ 0 \end{bmatrix}$$

$\underbrace{\quad}_{\|x\|_0=2}$

The End

› AnY QuEsTiOn?

