EE123
Digital Signal Processing

Lecture 24
Compressed Sensing III

M. Lustig, EECS UC Berkeley

RADIOS

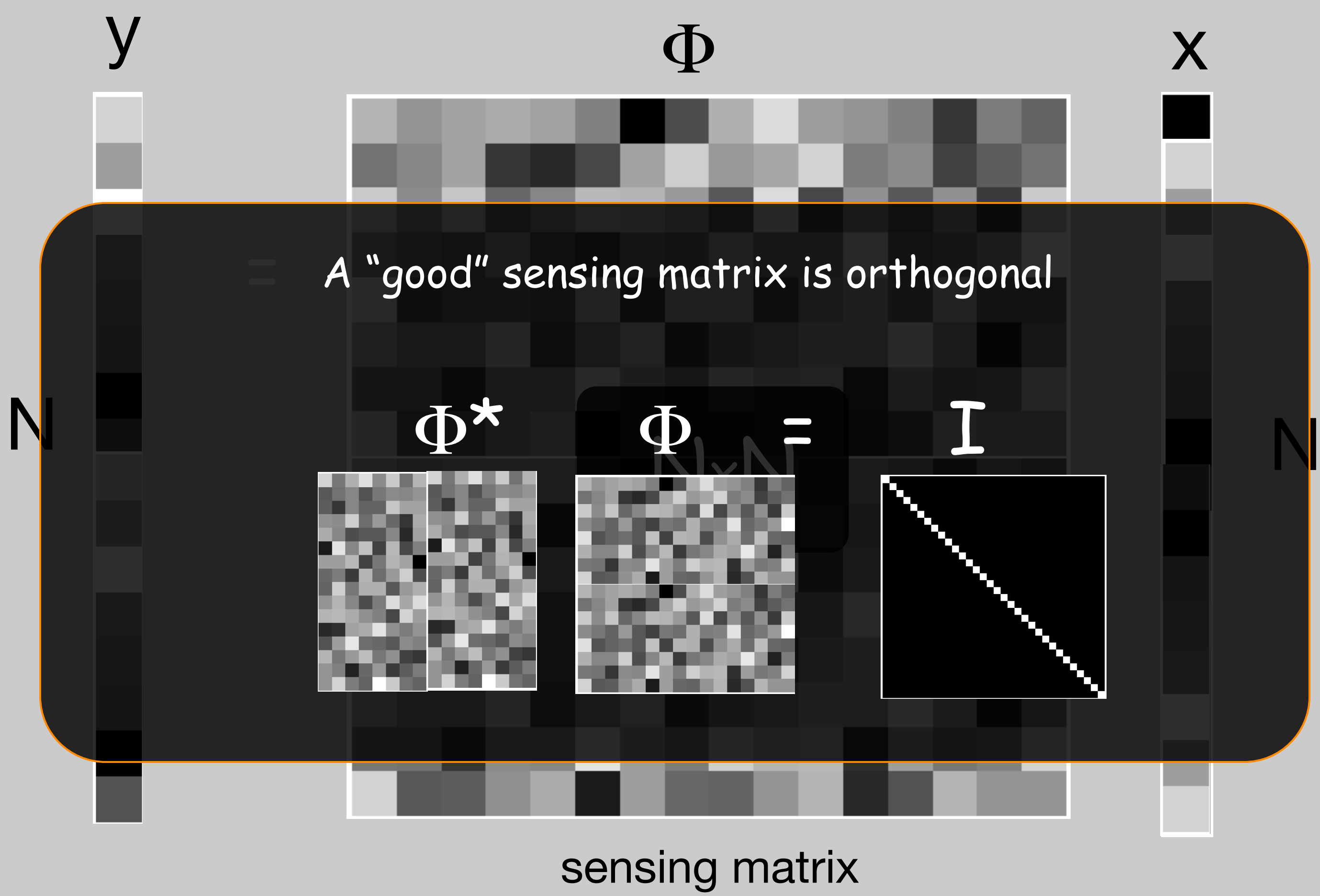
- https://inst.eecs.berkeley.edu/~ee123/sp15/radio.html
- Interfaces and radios on Wednesday -- please come to pick up

- Midterm II this Friday -- same deal - open everything covers everything including 2D

Traditional Sensing

- $x \in \Re^N$ is a signal
- Make N linear measurements

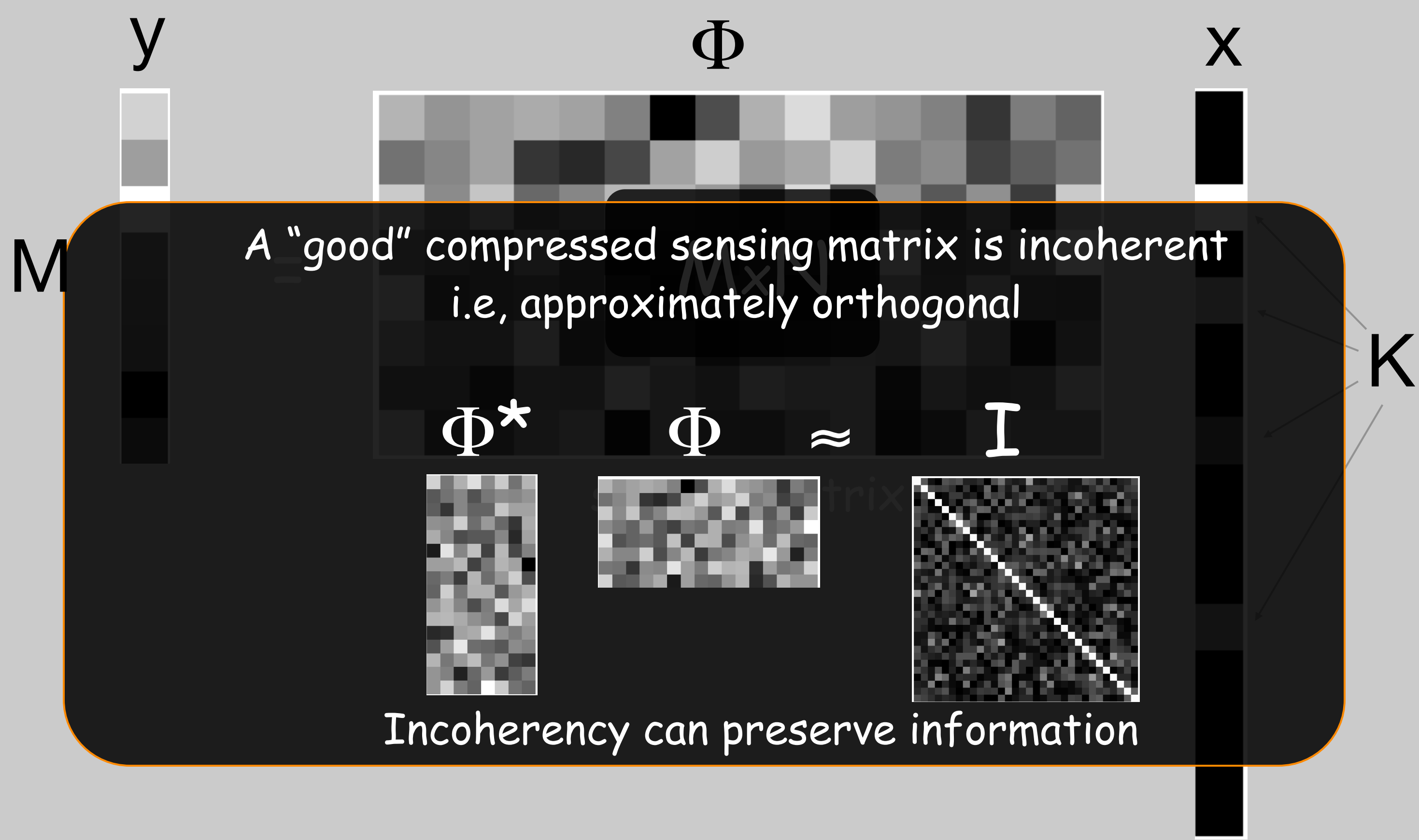
Arbitrary sensing



Compressed Sensing

(Candes, Romber, Tao 2006; Donoho 2006)

- $x \in \Re^N$ is a K-sparse signal (K<<N)
- Make M (K<M<<N) incoherent linear projections

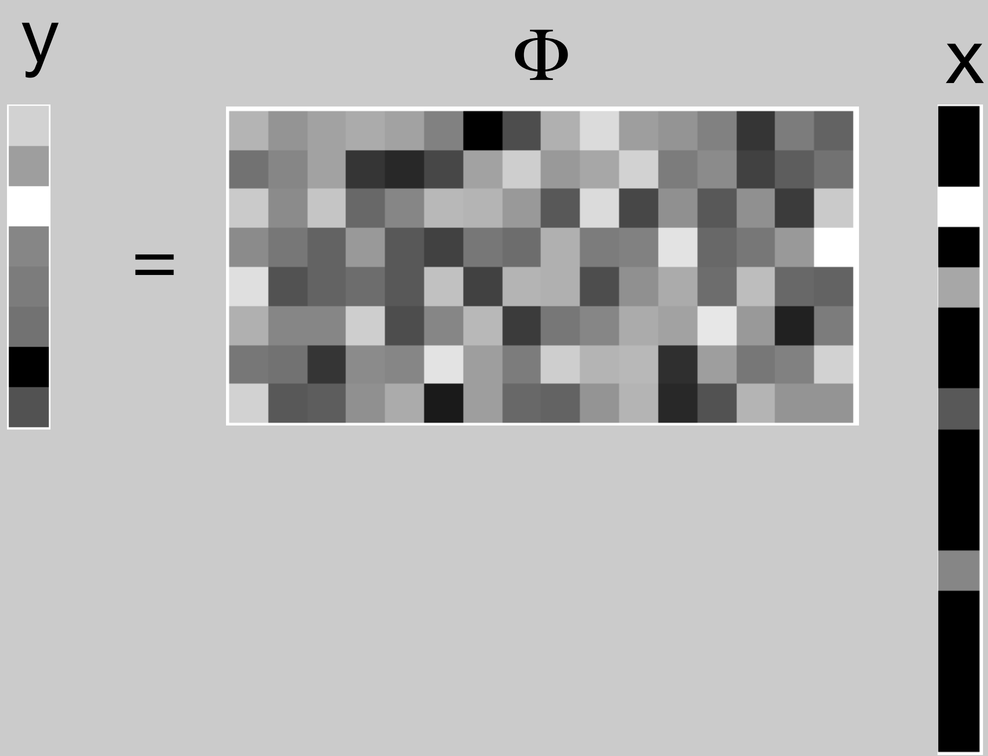


CS recovery

- Given $y = \Phi x$
  find x

Under-determined

- But there's hope, x is sparse!



CS recovery

- Given $y = \Phi x$
  find x } Under-determined
- But there's hope, x is sparse!

CS recovery

- Given $y = \Phi x$
  find x

  } Under-determined

- But there's hope, x is sparse!

minimize $||x||_2$

s.t. $y = \Phi x$

WRONG!

CS recovery

- Given $y = \Phi x$
  find x
  } Under-determined
- But there's hope, x is sparse!

minimize $||x||_0$

s.t. $y = \Phi x$

HARD!

CS recovery

- Given $y = \Phi x$
  find x

  } Under-determined

- But there's hope, x is sparse!

$$\text{minimize } \|x\|_1$$

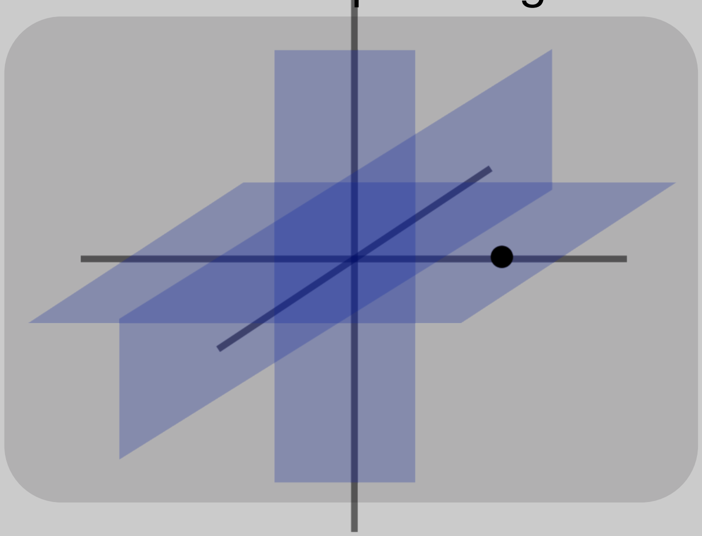
$$\text{s.t. } y = \Phi x$$

need $M \approx K \log(N) << N$

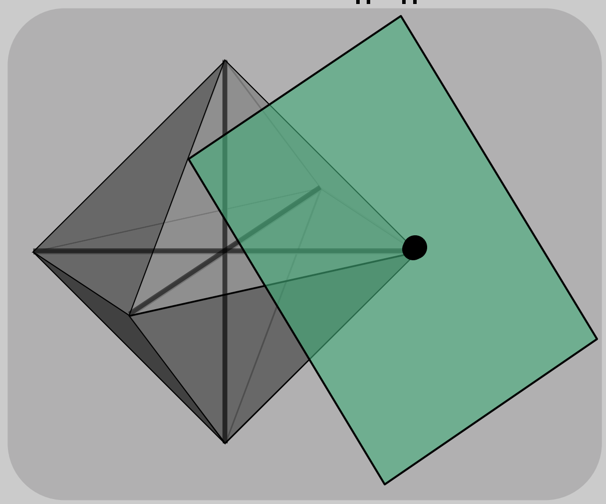
Solved by linear-programming

Geometric Interpretation

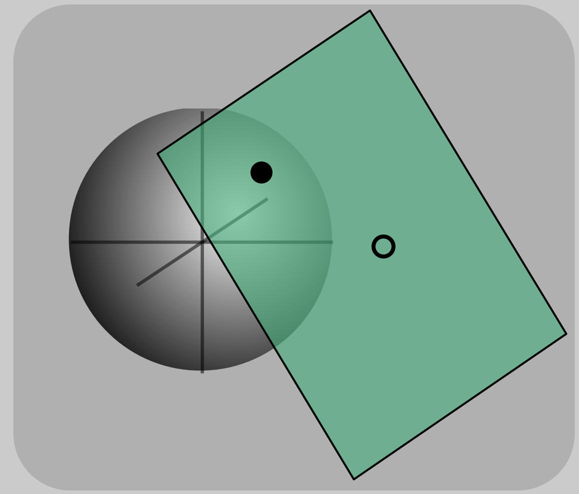
domain of sparse signals



minimum $||x||_1$



minimum $||x||_2$



$$\begin{bmatrix} 0 \\ 3 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} y_1 \end{bmatrix}$$

A non-linear sampling theorem

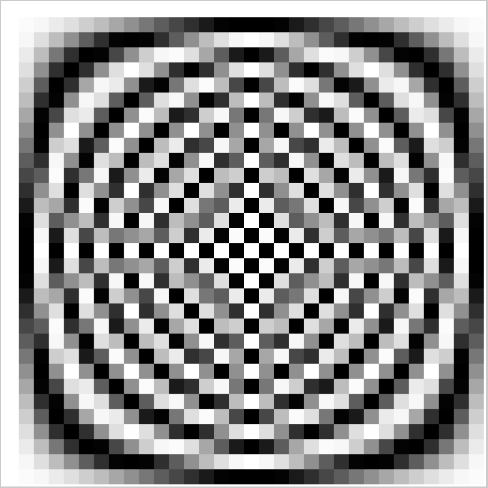
- $f \in C^N$ supported on a set Ω in Fourier
- Shannon:
  - Ω is known connected set, size B
  - Exact recovery from B equispaced time samples
  - Linear reconstruction by sinc interpolation

- Non-linear sampling theorem
  - Ω is an arbitrary, unknown set of size B
  - Exact recovery from ~ B logN (almost) arbitrary placed samples
  - Nonlinear reconstruction by convex programming

Practicality of CS

- Can such sensing system exist in practice?

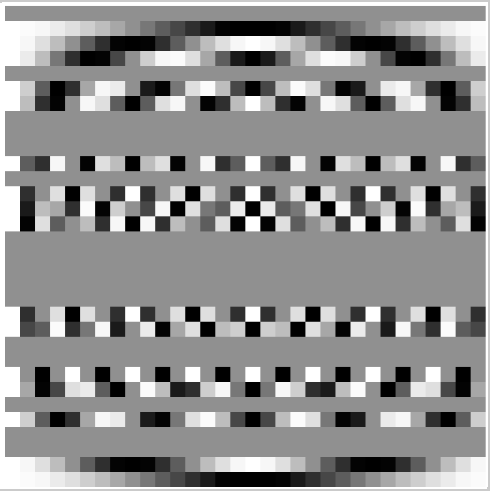
Fourier matrix



Practicality of CS

- Can such sensing system exist in practice?

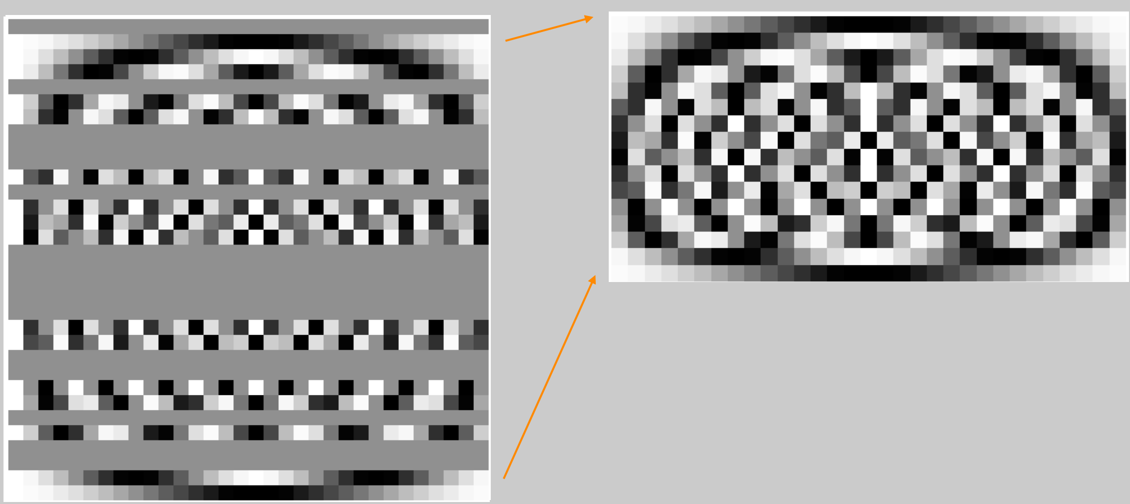
Fourier matrix



Practicality of CS

- Can such sensing system exist in practice?

Fourier matrix



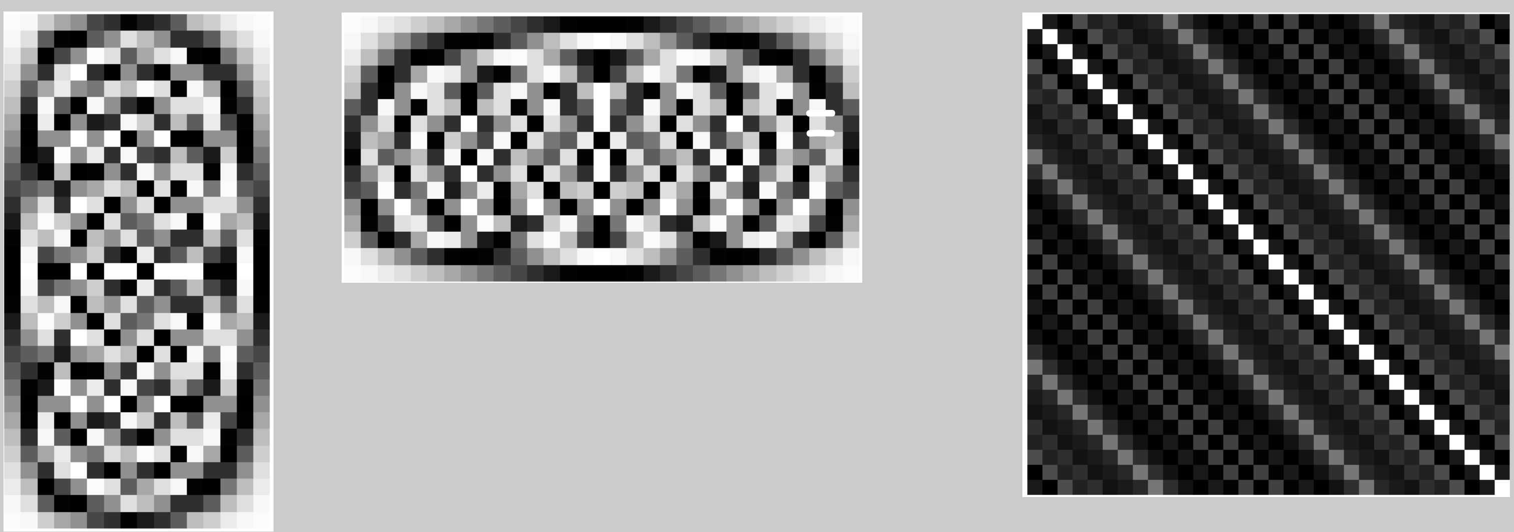
Practicality of CS

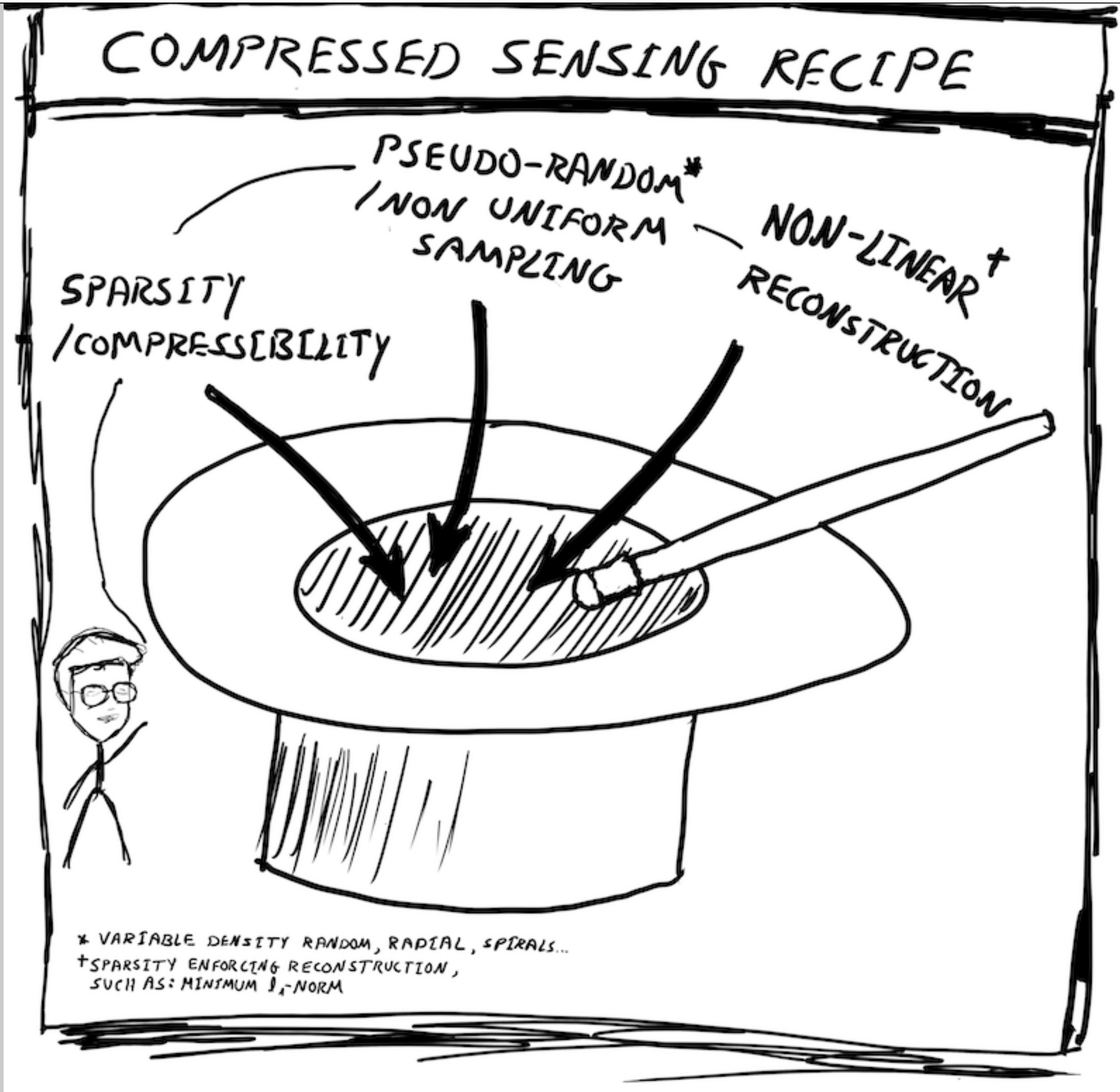
- Can such sensing system exist in practice?

- Randomly undersampled Fourier is incoherent

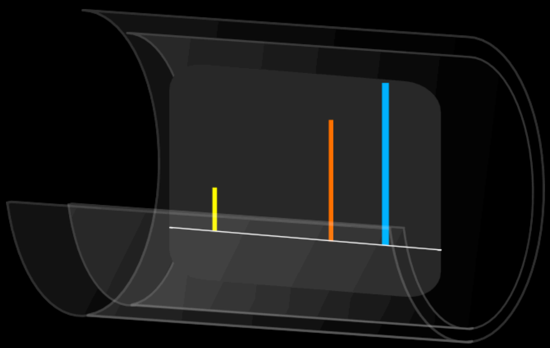
- MRI samples in the Fourier domain!

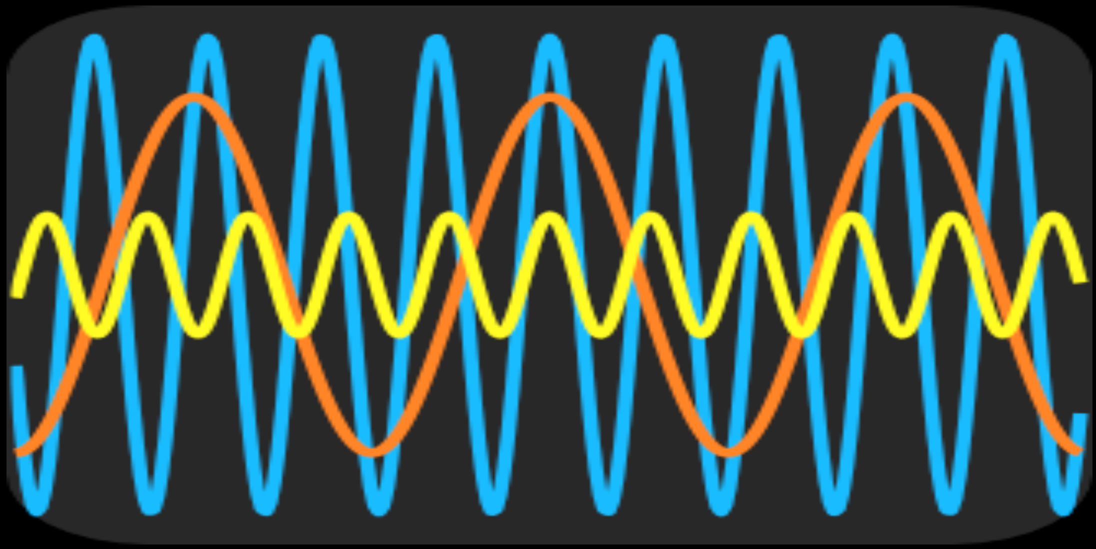
$$\Phi^* \quad \Phi \approx I$$



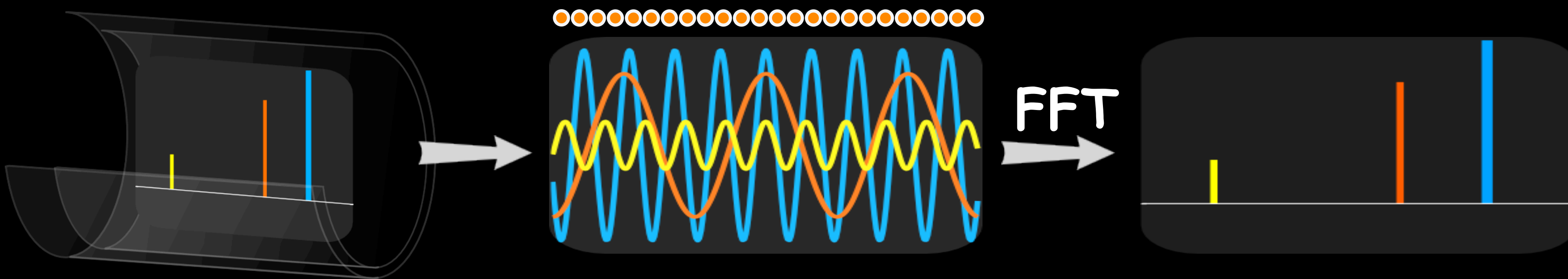

COMPRESSED SENSING RECIPE
SPARSITY /COMPRESSIBILITY
PSEUDO-RANDOM* /NON UNIFORM SAMPLING
NON-LINEAR+ RECONSTRUCTION
* VARIABLE DENSITY RANDOM, RADIAL, SPIRALS...
+SPARSITY ENFORCING RECONSTRUCTION, SUCH AS: MINIMUM ℓ_1-NORM

Intuitive example of CS

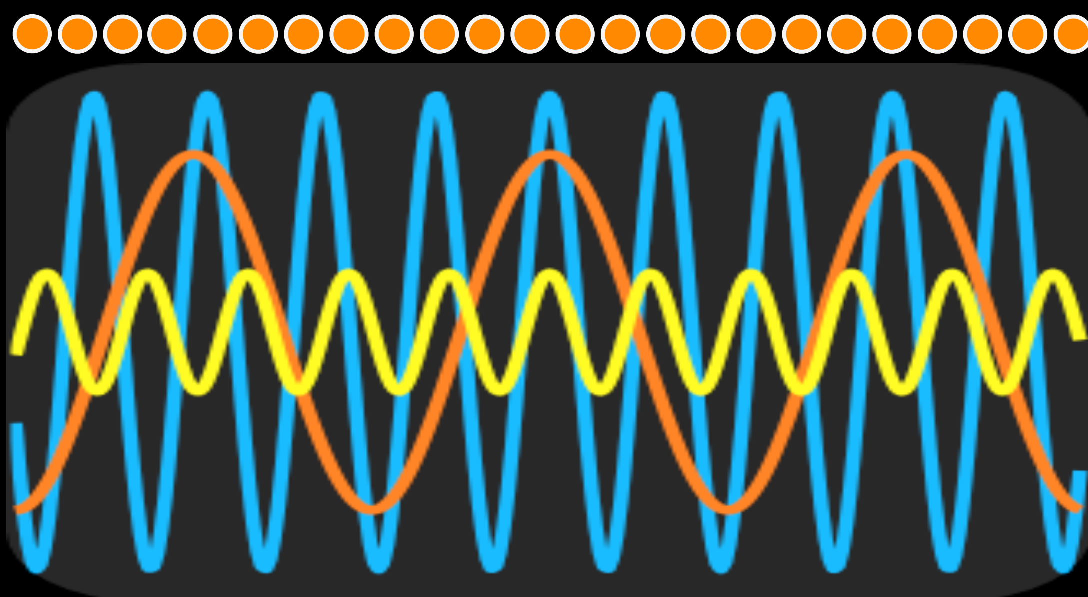




Intuitive example of CS

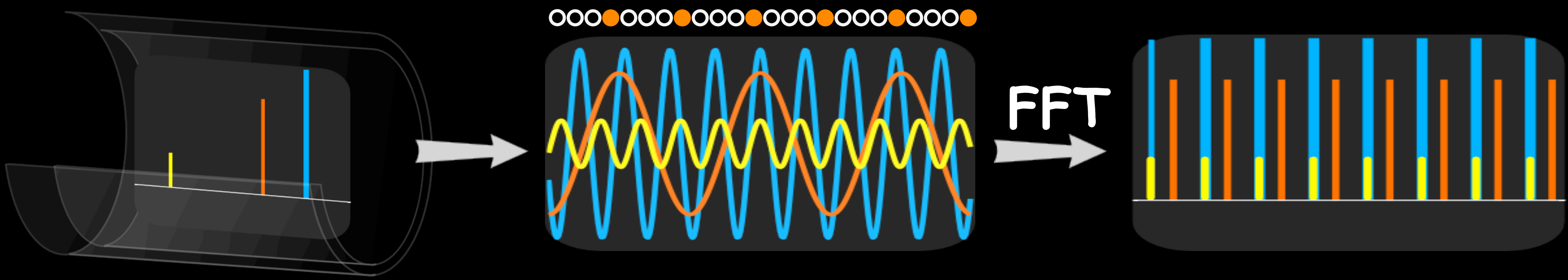


sampling

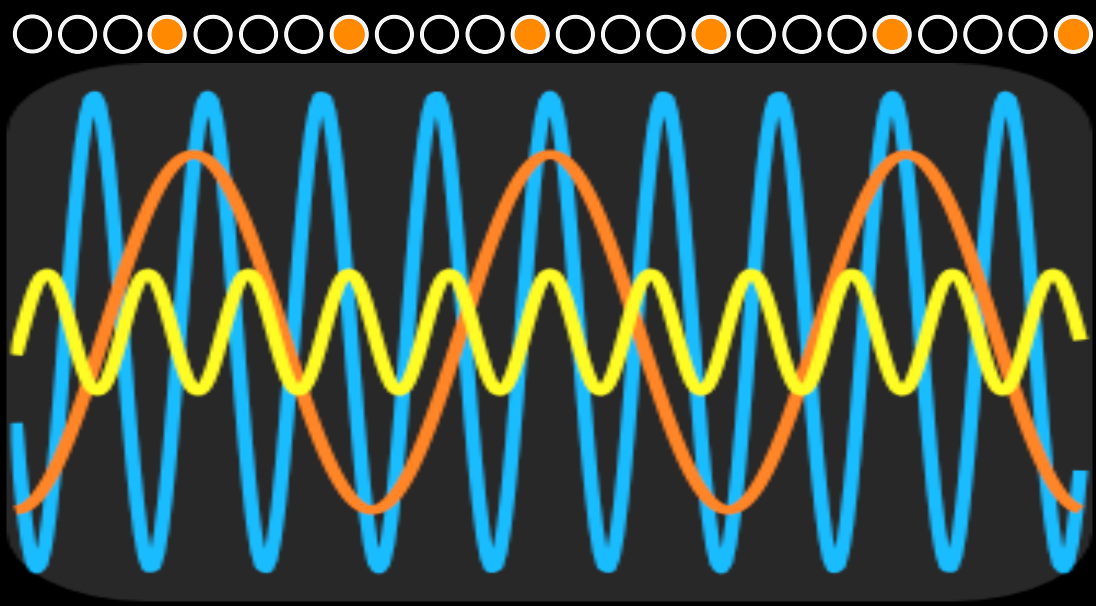


Nyquist

Intuitive example of CS

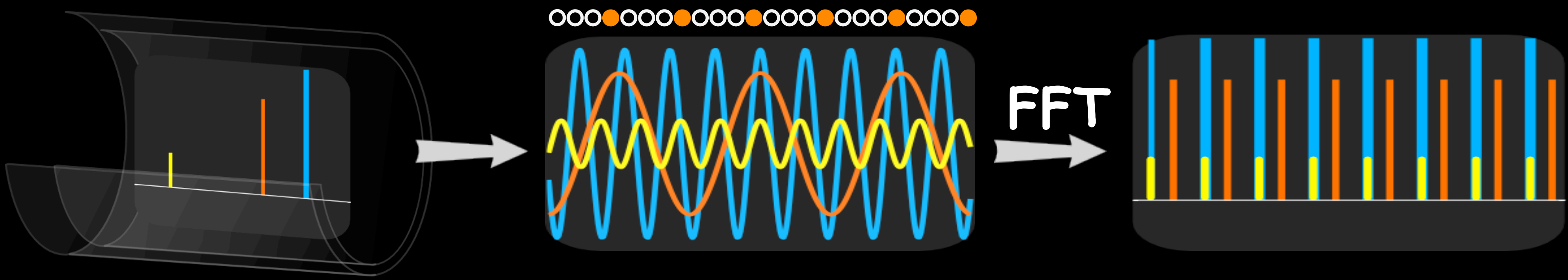


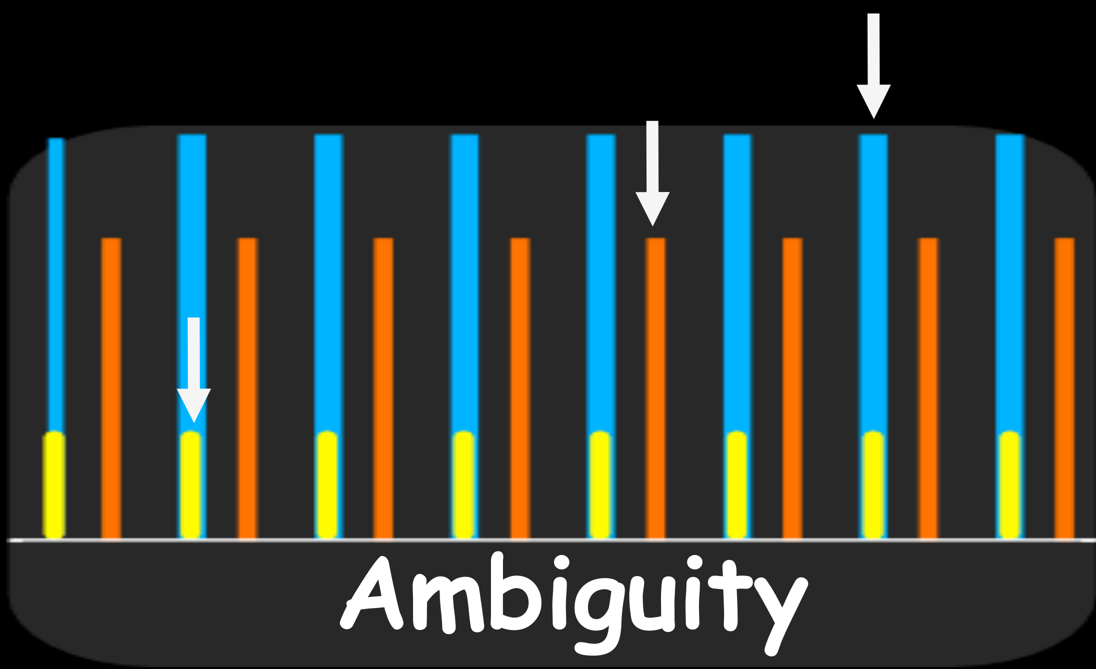
equisped →



sub-Nyquist

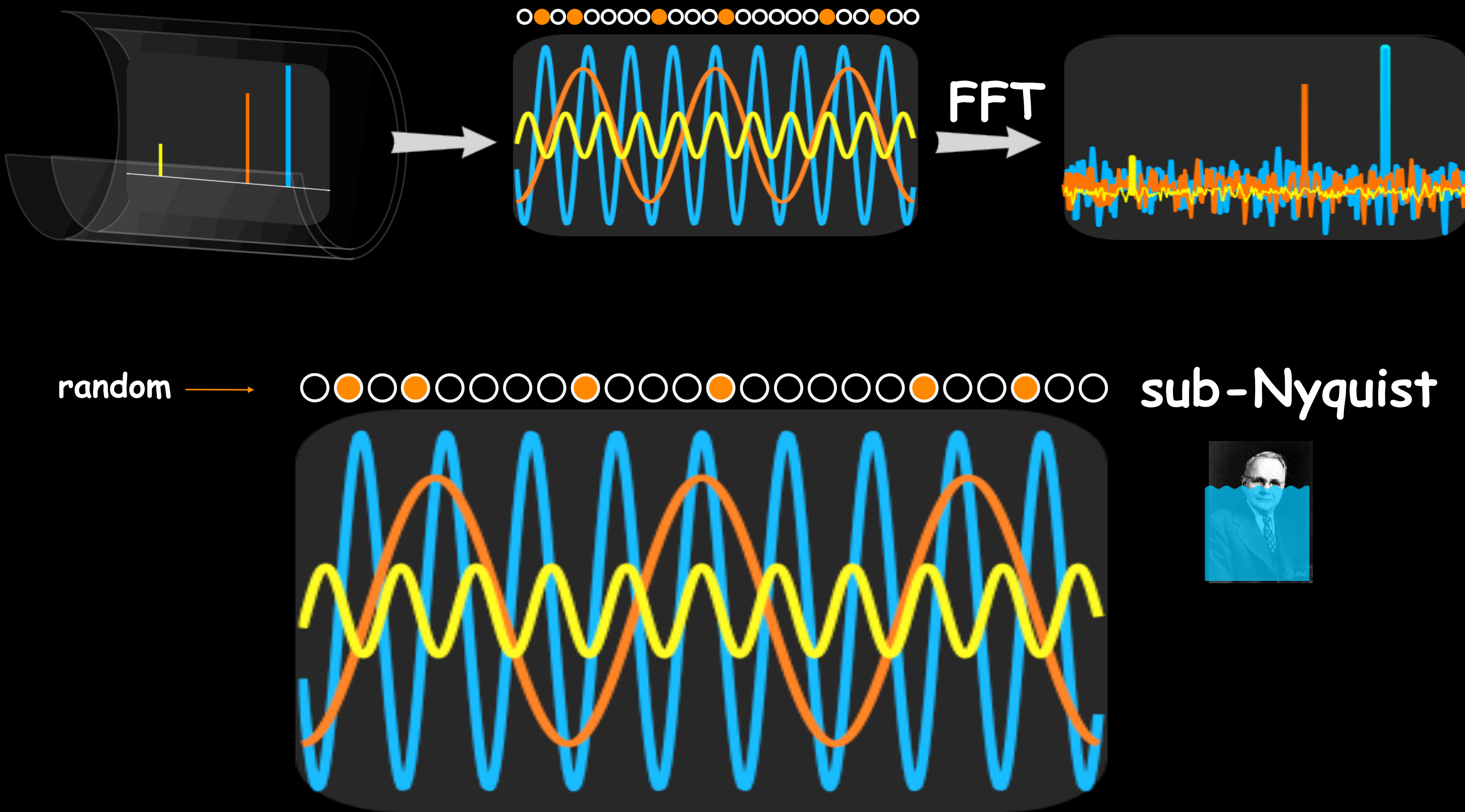
Intuitive example of CS

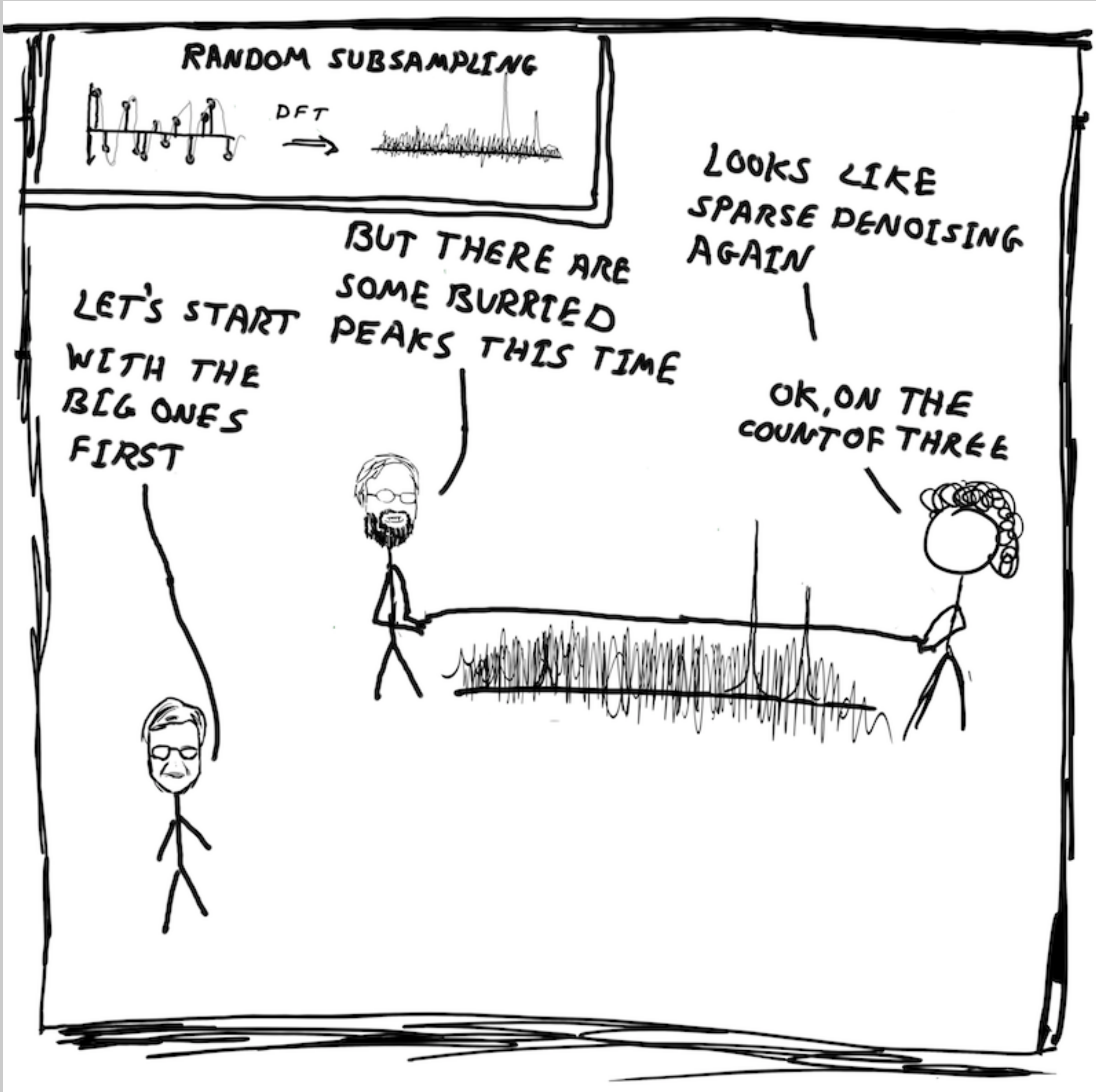




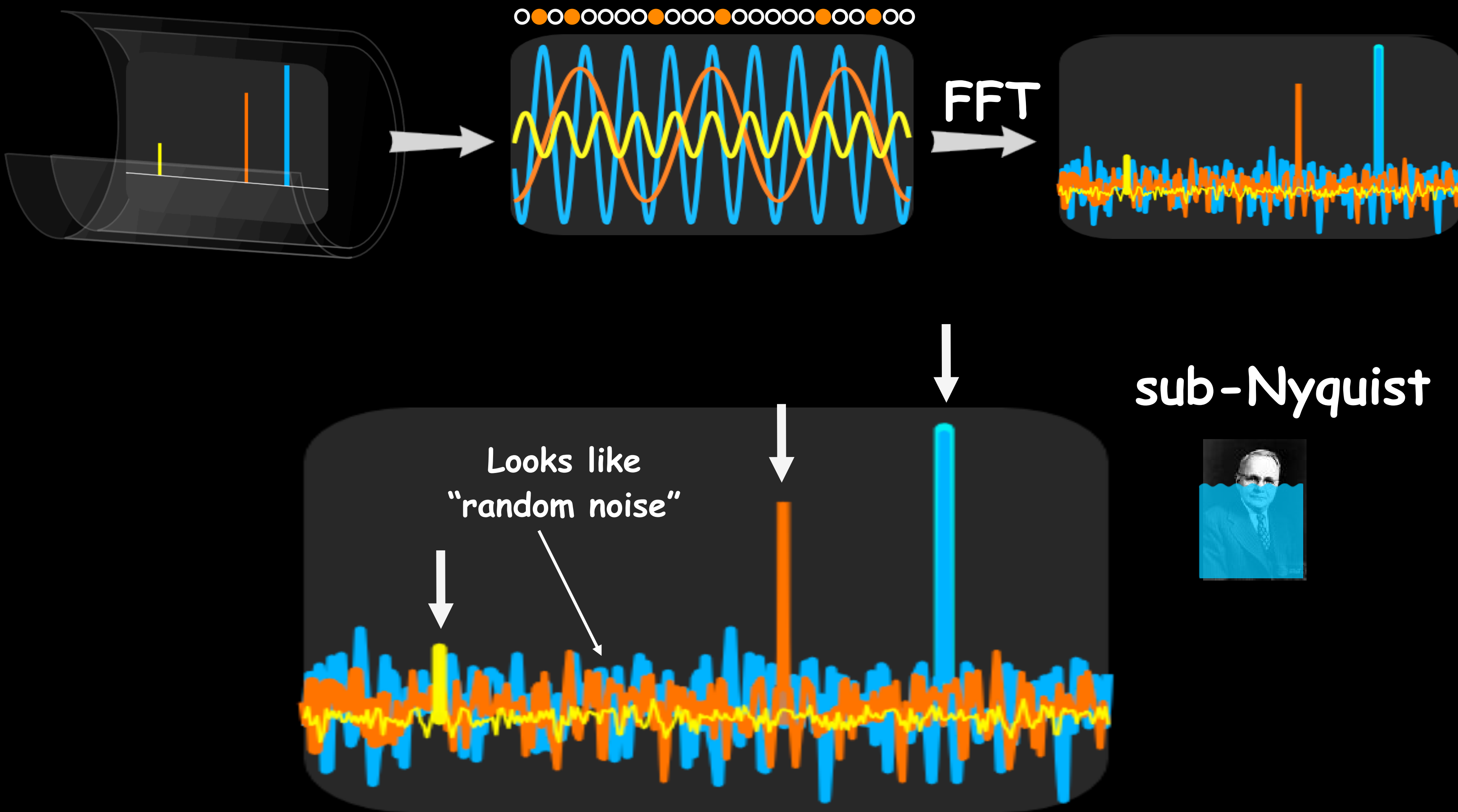
sub-Nyquist

Intuitive example of CS

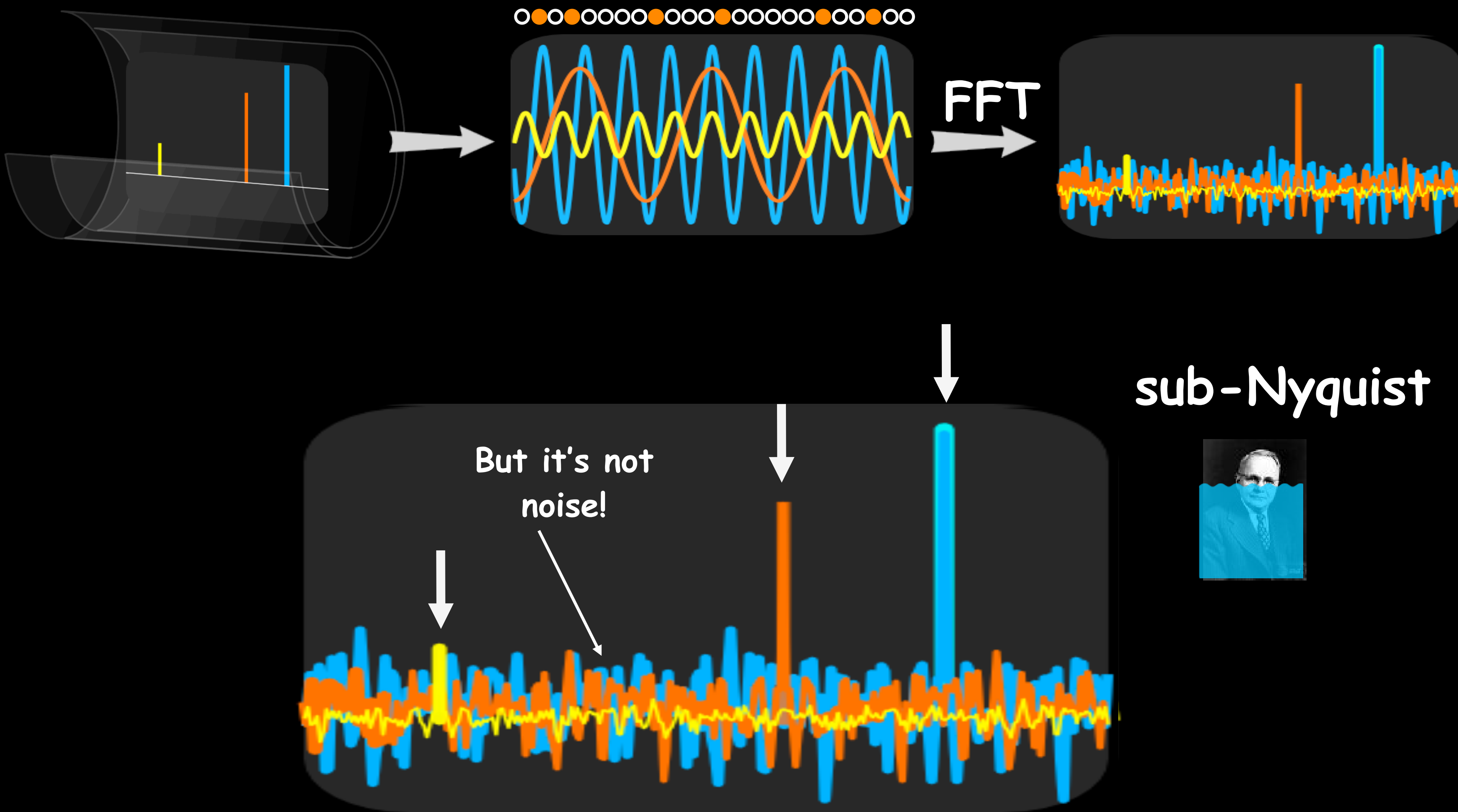



RANDOM SUBSAMPLING
DFT
LET'S START WITH THE BIG ONES FIRST
BUT THERE ARE SOME BURRIED PEAKS THIS TIME
LOOKS LIKE SPARSE DENOISING AGAIN
OK, ON THE COUNT OF THREE

Intuitive example of CS

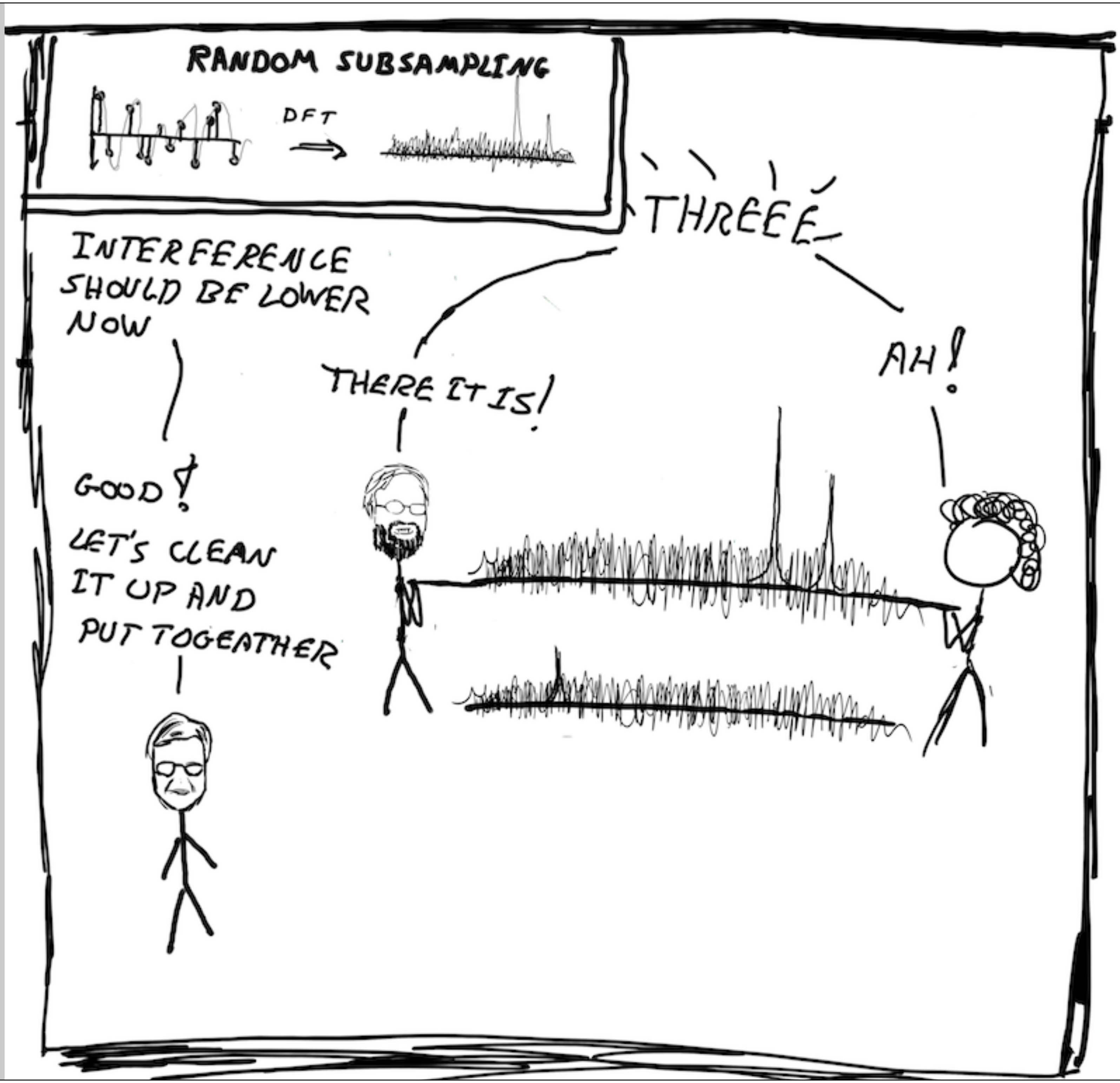


Intuitive example of CS



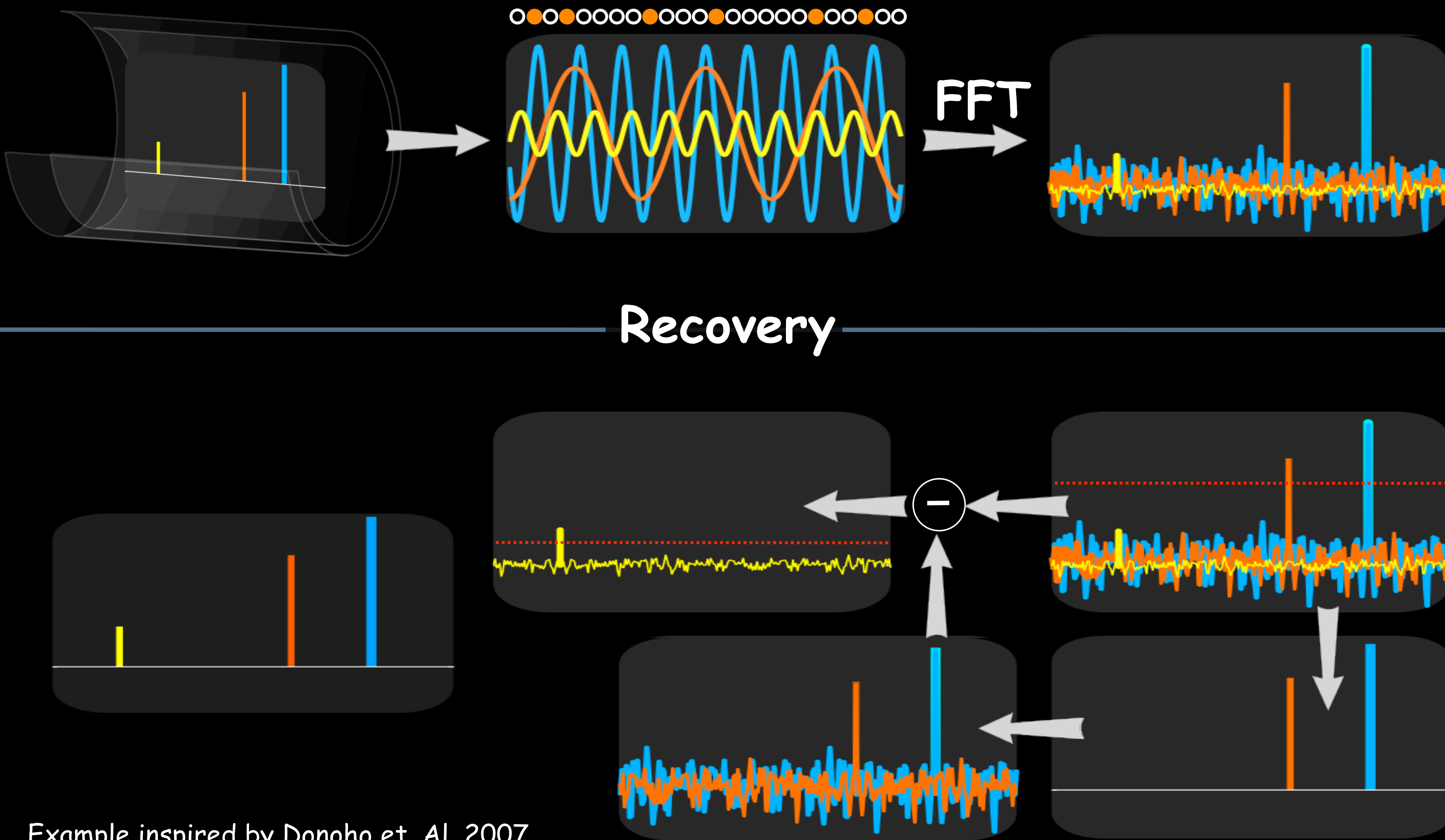

RANDOM SUBSAMPLING
DFT
ONE
TWO
WE CAN CALCULATE THE INTERFERENCE THEY CREATE AND REMOVE IT

C Berkeley

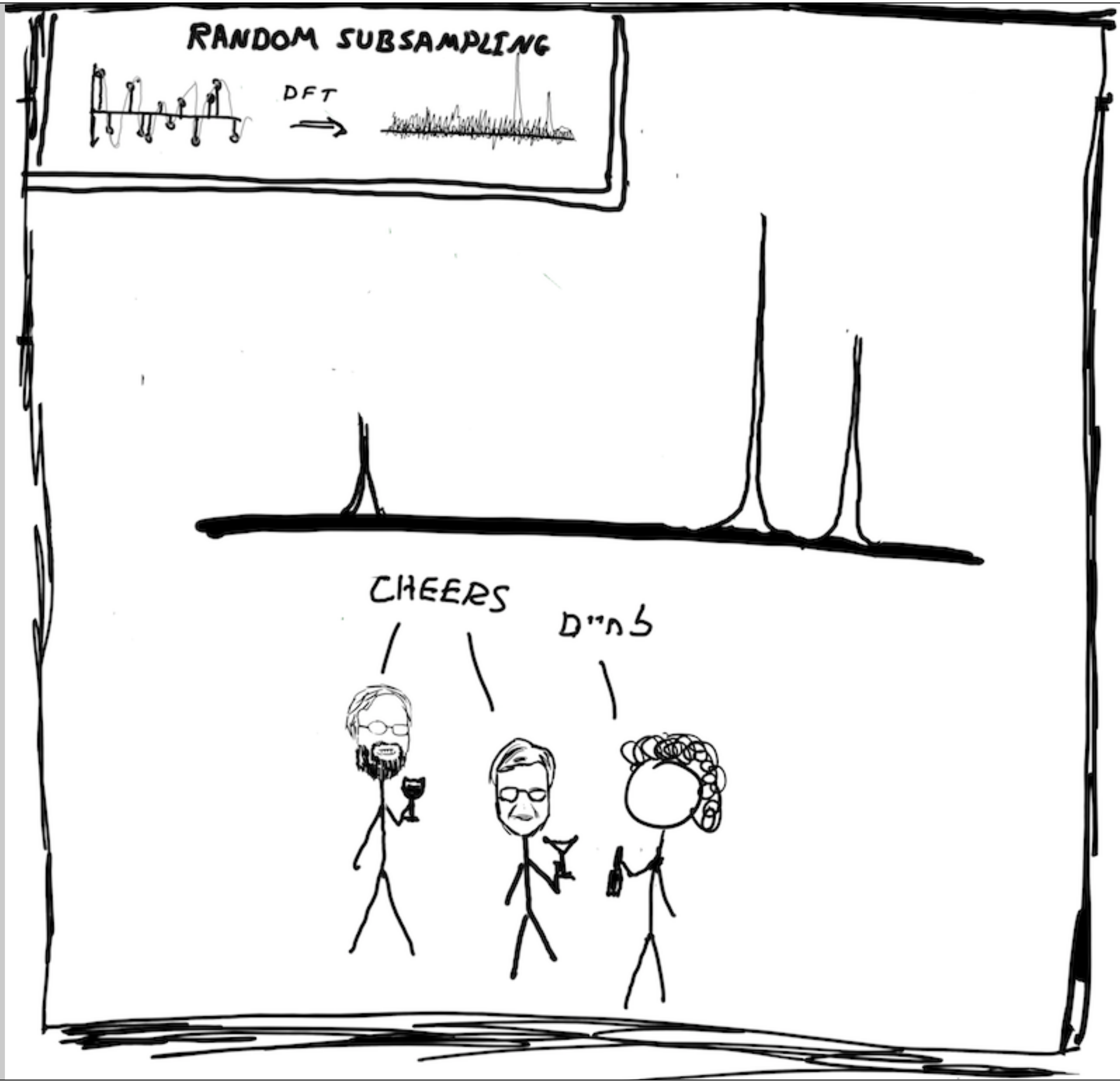

RANDOM SUBSAMPLING
DFT
INTERFERENCE SHOULD BE LOWER NOW
GOOD!
LET'S CLEAN IT UP AND PUT TOGEATHER
THERE IT IS!
THREEE
AH!

C Berkeley

Intuitive example of CS



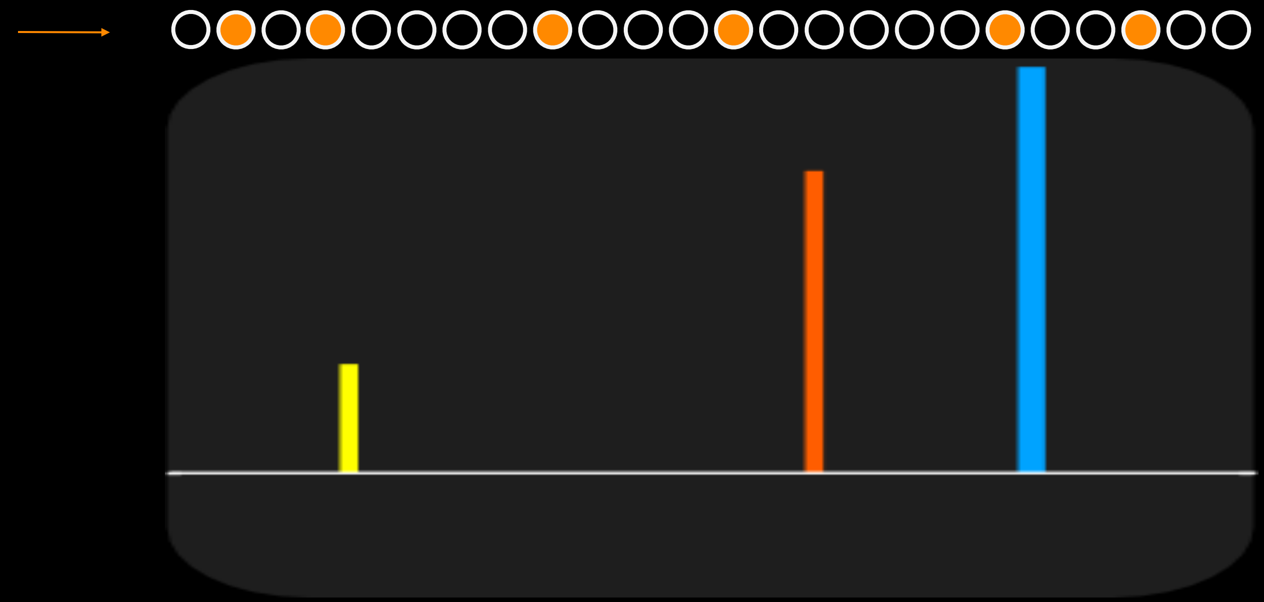
Example inspired by Donoho et. Al, 2007


RANDOM SUBSAMPLING
DFT
CHEERS
לח"ם

Question!

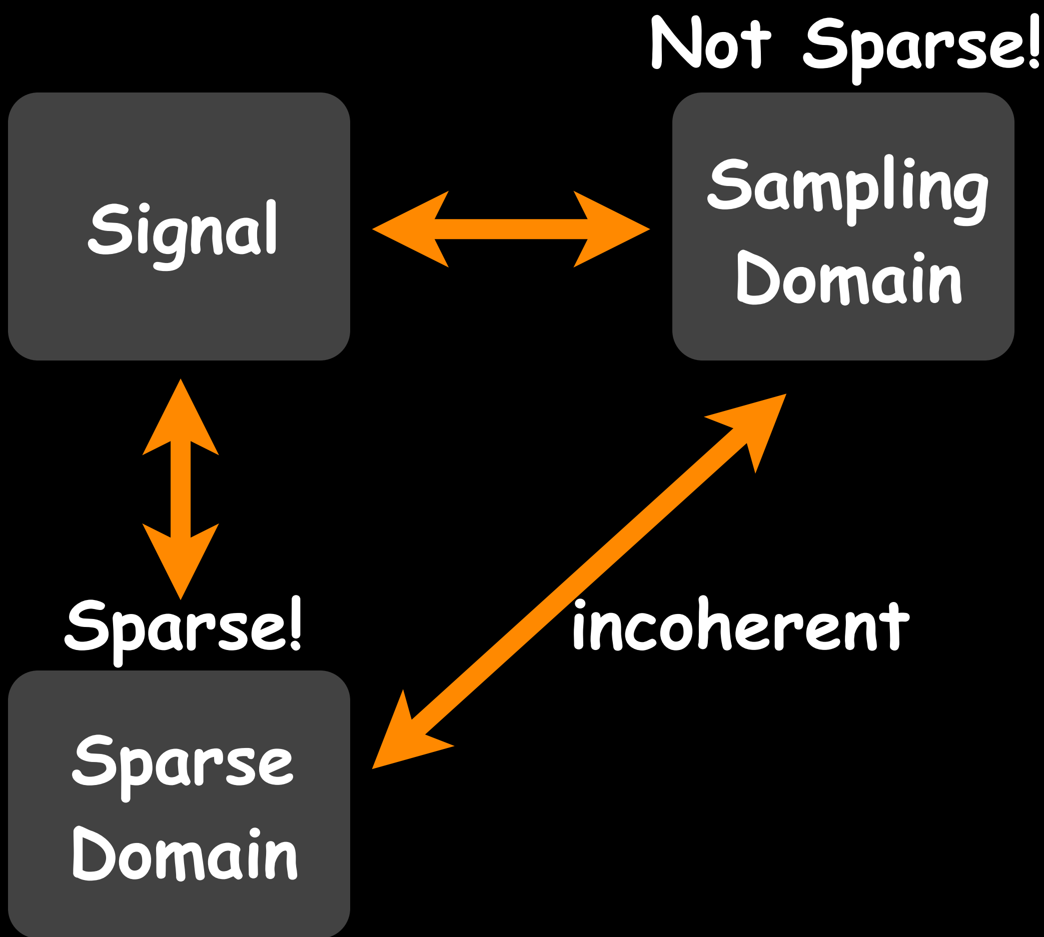
- What if this was the signal?
- Would CS still work?

random

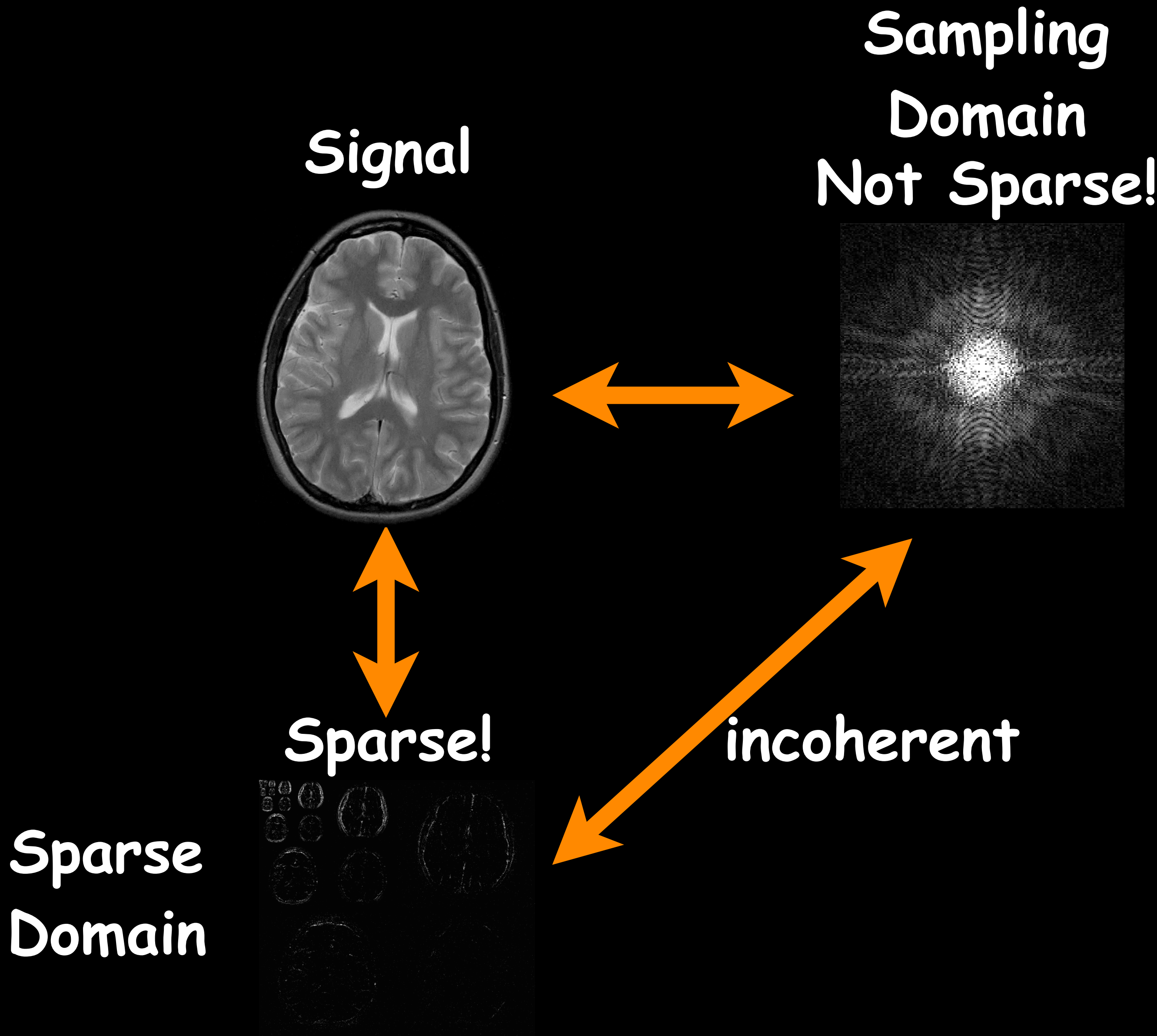


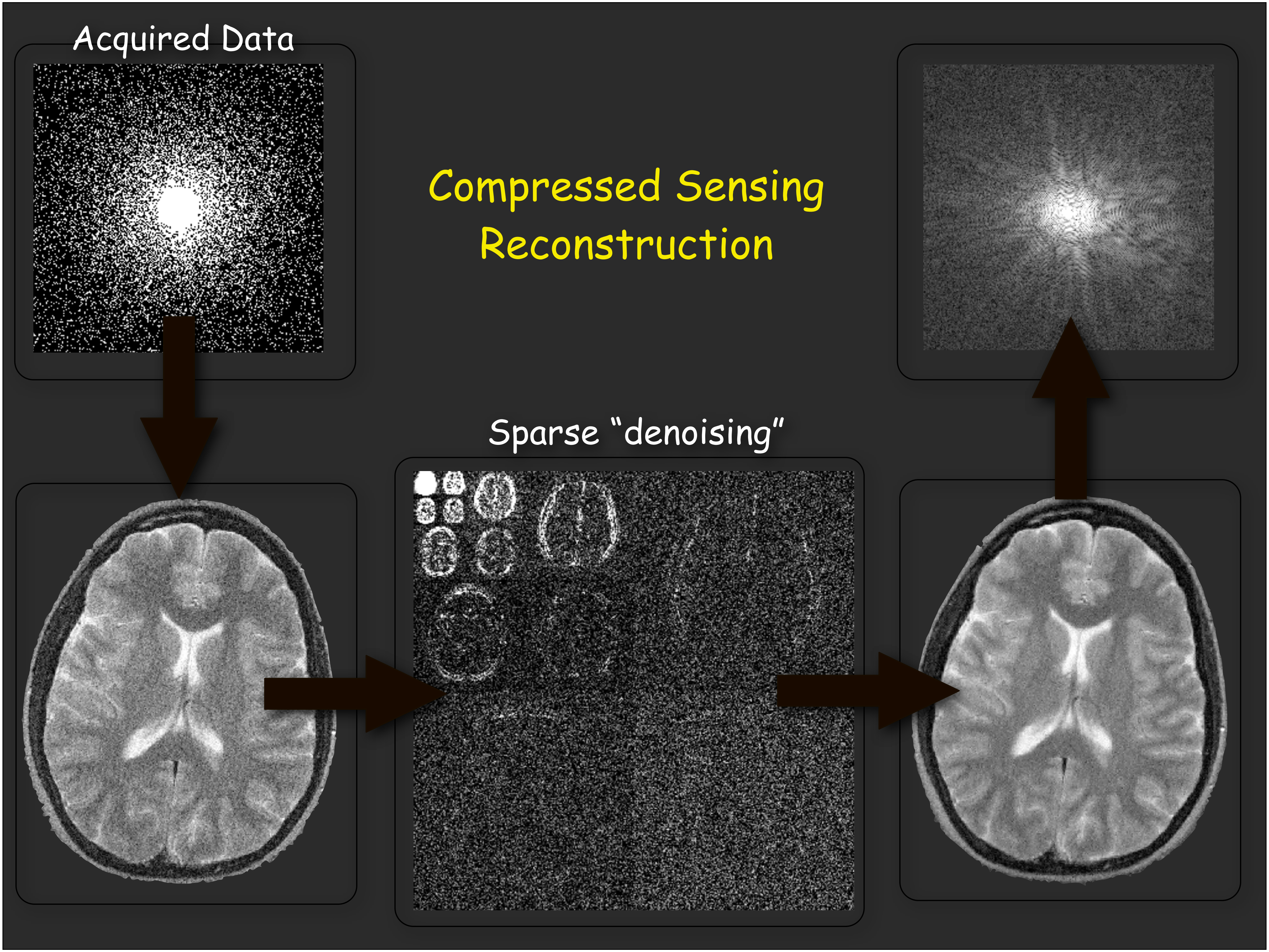
sub-Nyquist

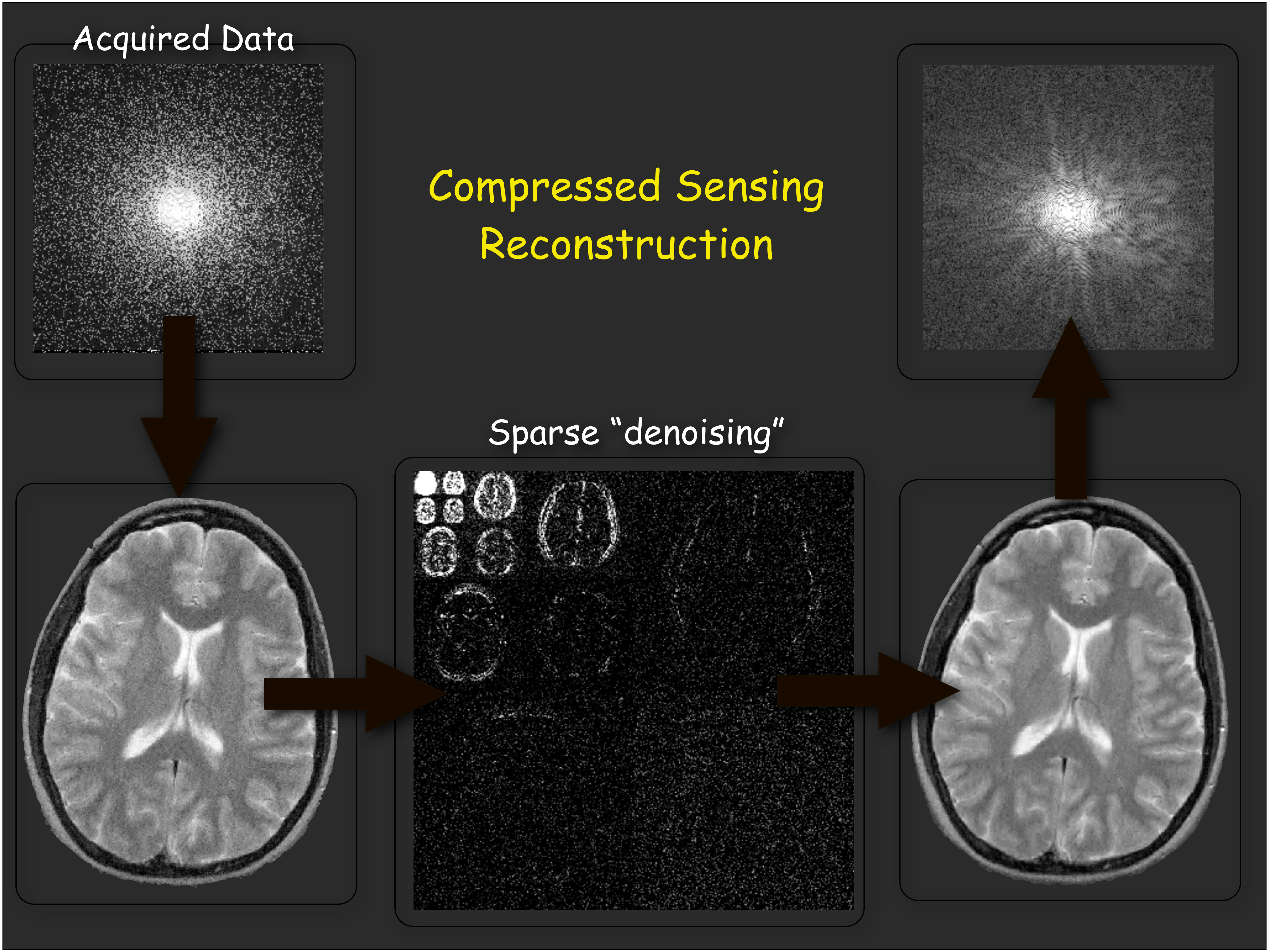
Domains in Compressed Sensing

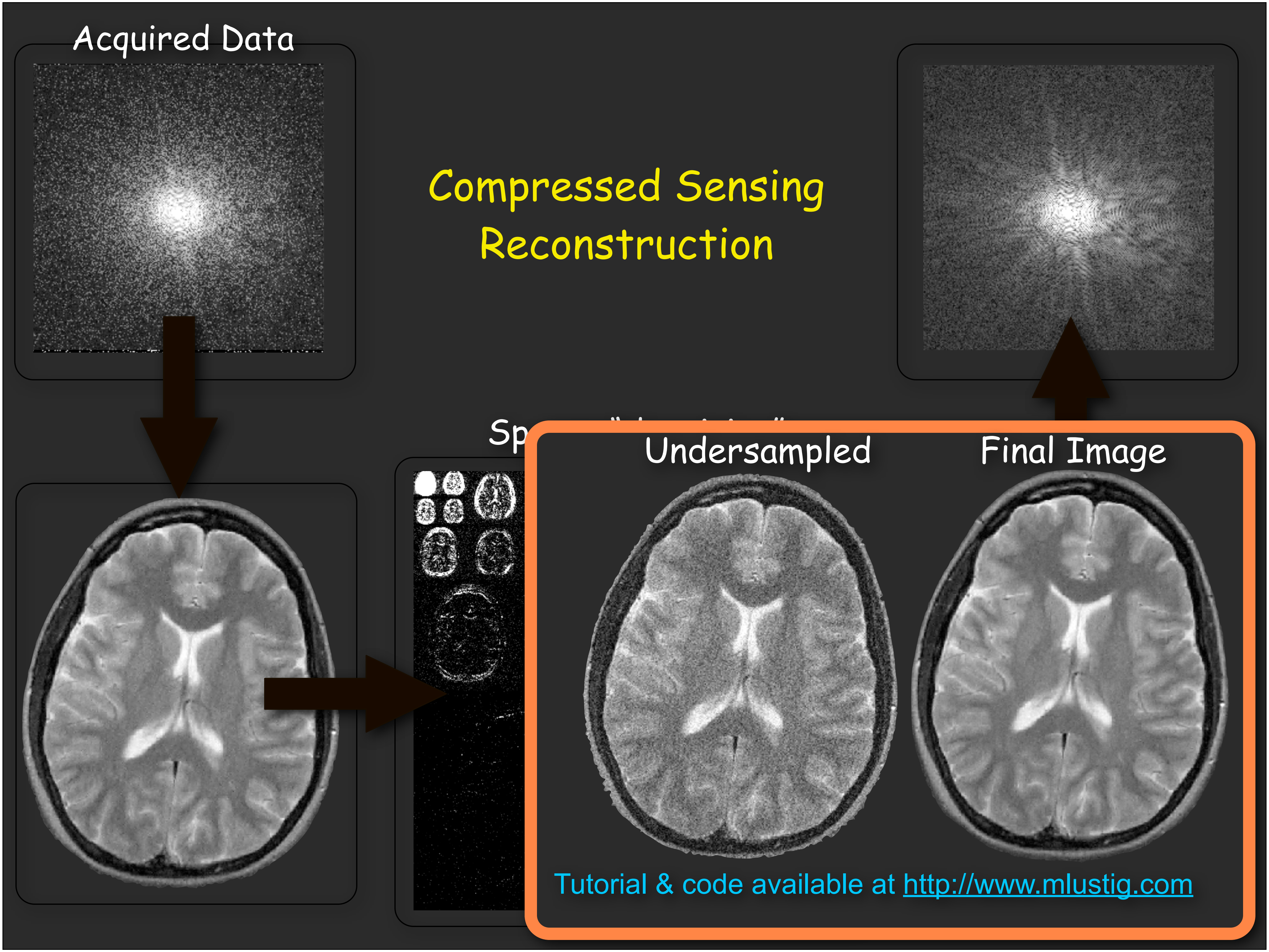


MRI


Sampling
Domain
Not Sparse!
Signal
Sparse!
incoherent
Sparse
Domain

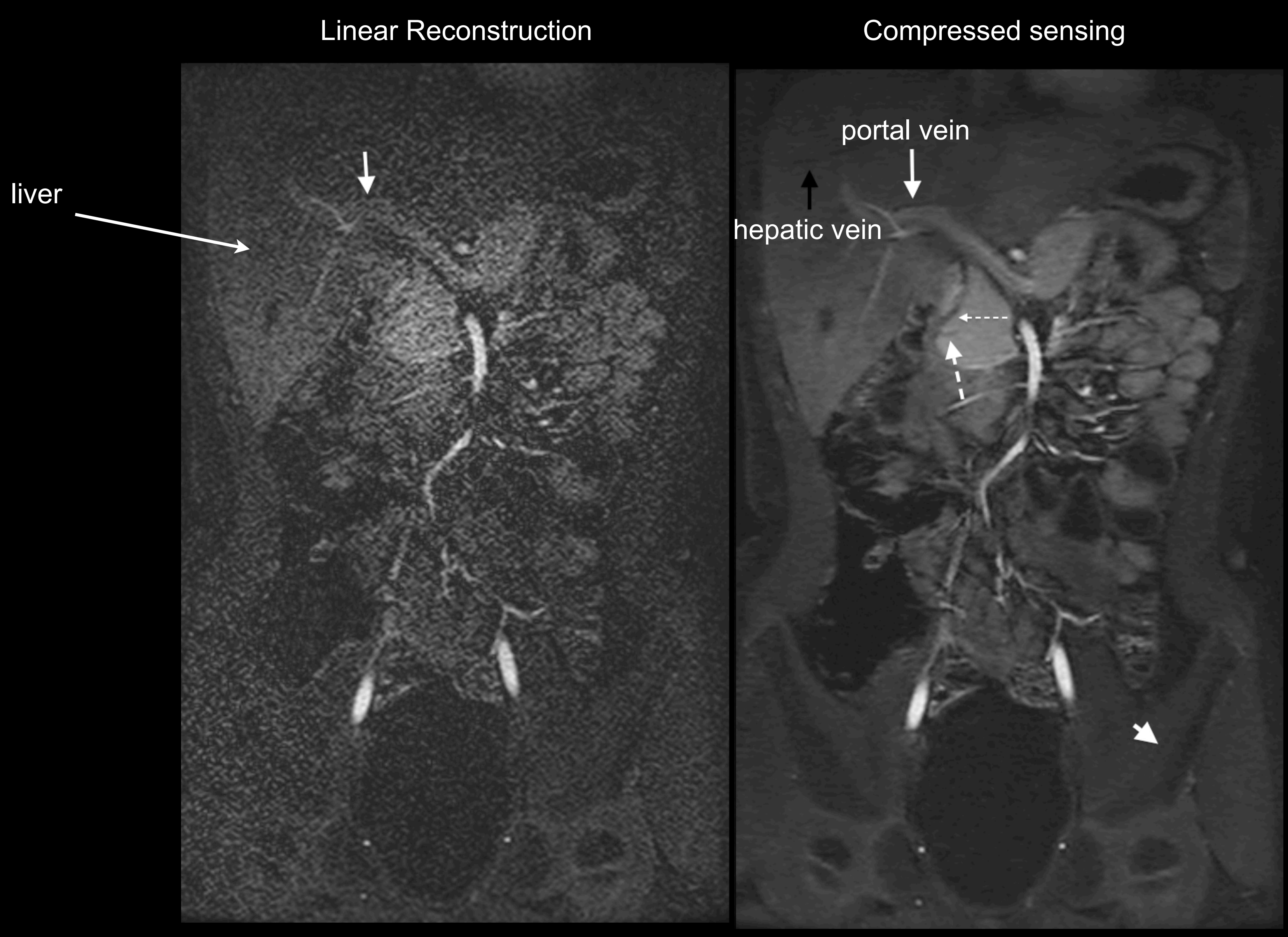

Acquired Data
Compressed Sensing Reconstruction
Sparse "denoising"


Acquired Data
Compressed Sensing
Reconstruction
Sparse “denoising”

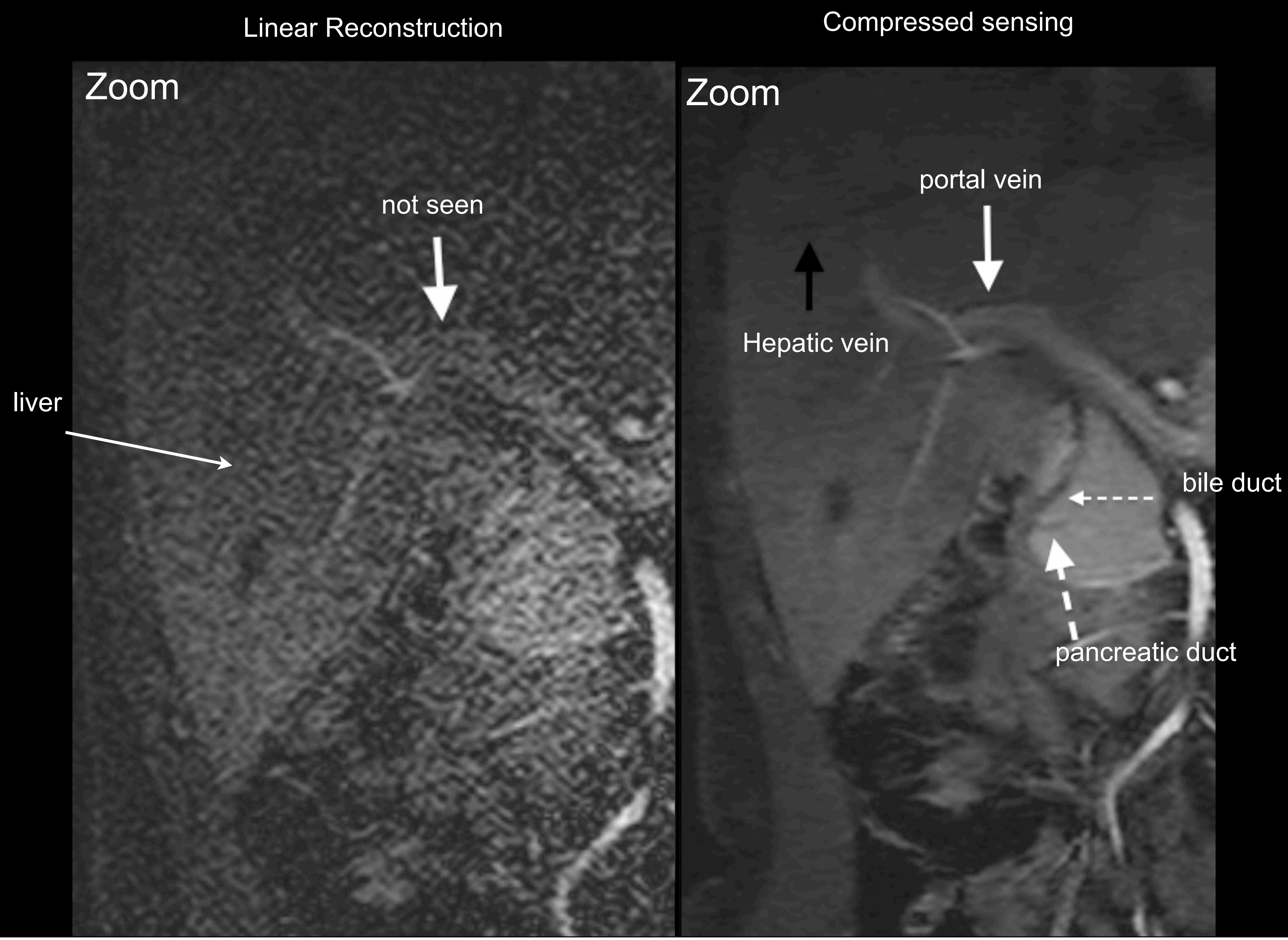


Acquired Data
Compressed Sensing
Reconstruction
Undersampled
Final Image
Tutorial & code available at http://www.mlustig.com

6 year old male abdomen. Fine structures (arrows) are buried in noise (artifactual + noise amplification) and are recovered by CS with L1-wavelets. x8 acceleration

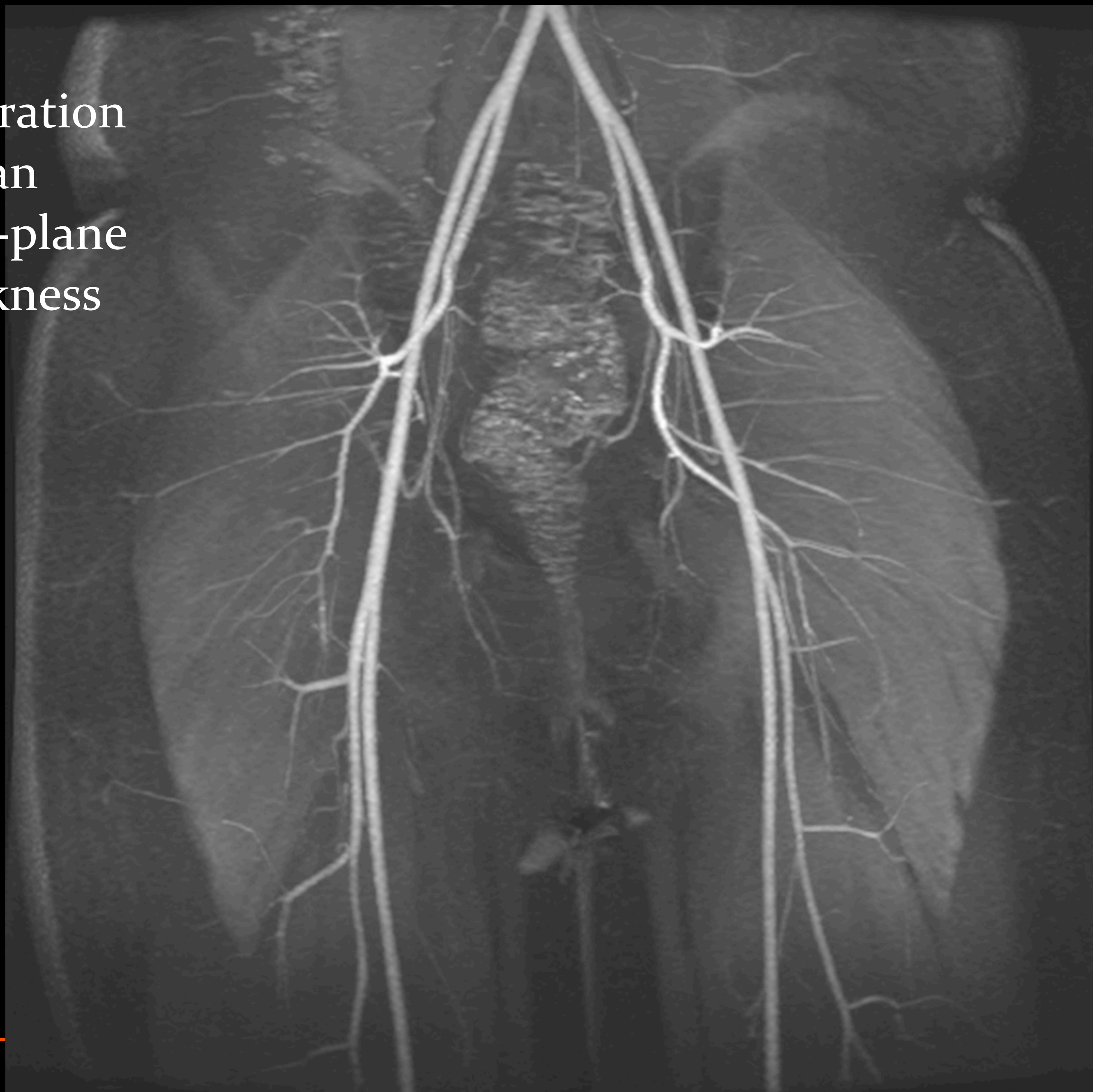


6 year old male abdomen. Fine structures (arrows) are buried in noise (artifactual + noise amplification) and are recovered by CS with L1-wavelets.

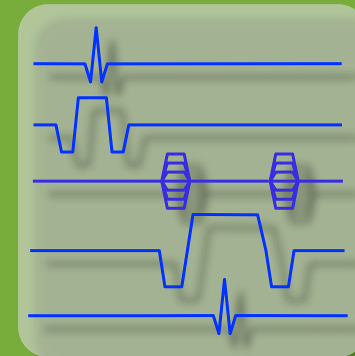


Back to Results

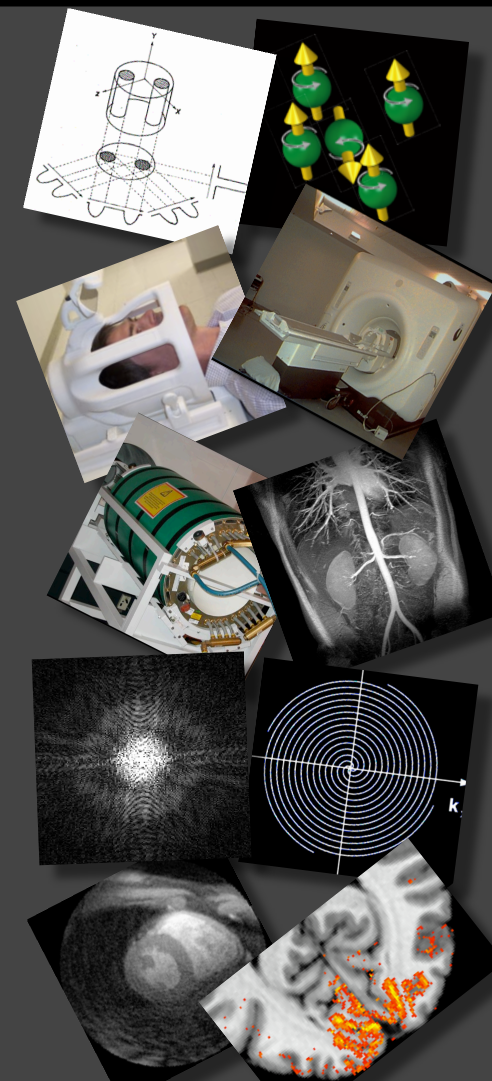
6 year old
8-fold acceleration
16 second scan
0.875 mm in-plane
1.6 slice thickness



Principles of Magnetic Resonance Imaging
EE c225E / BIOE c265



Spring 2016



Shameless Promotion

Other Applications

- Compressive Imaging
- Medical Imaging
- Analog to information conversion
- Biosensing
- Geophysical Data Analysis
- Compressive Radar
- Astronomy
- Communications
- More ......

Resources

- CS + parallel imaging matlab code, examples

  http://www.eecs.berkeley.edu/~mlustig/software/

- Rice University CS page: papers, tutorials, codes, ….
  http://www.dsp.ece.rice.edu/cs/

- IEEE Signal Processing Magazine, special issue on compressive sampling 2008;25(2)

- March 2010 Issue Wired Magazine: “Filling the Blanks”

- Igor Caron Blog: http://nuit-blanche.blogspot.com/

Thank you!
תודה רבה