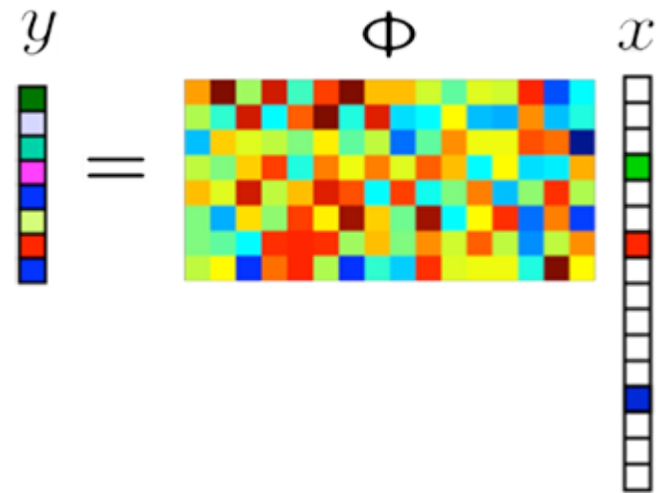




SciPy India 2016

# Compressive Sensing: A glimpse into the Magic Reconstruction

*Saurabh Kumar*



# Signals

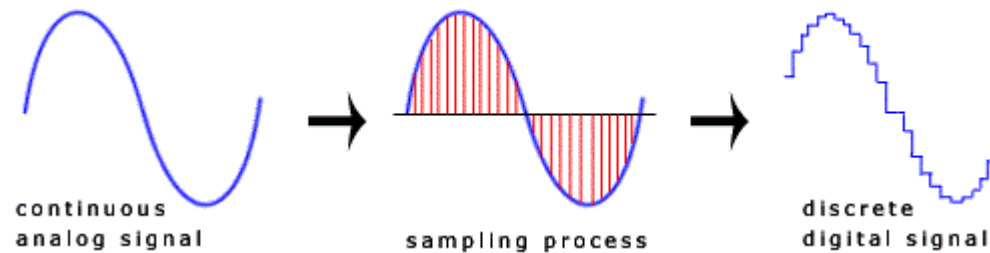


Provide information about the behavior or attributes of some phenomenon.

Eg. Audio, Video, Speech, Image, Communications, Geophysical, Sonar, Radar, medical and Musical Signals

# Sampling

Converting a continuous-time signal to discrete time signal



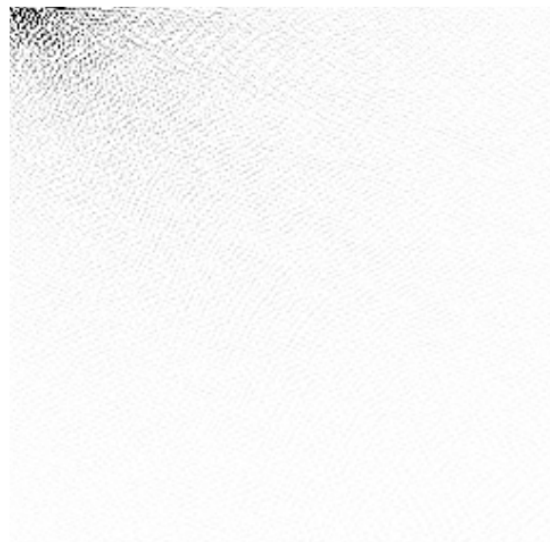
# What are we going to talk about today?

- Data Compression
- Nyquist-Shannon Sampling Theorem
- Matrix Representation of Sampling
- Compressive Sensing
- $l_1$  minimization
- Applications

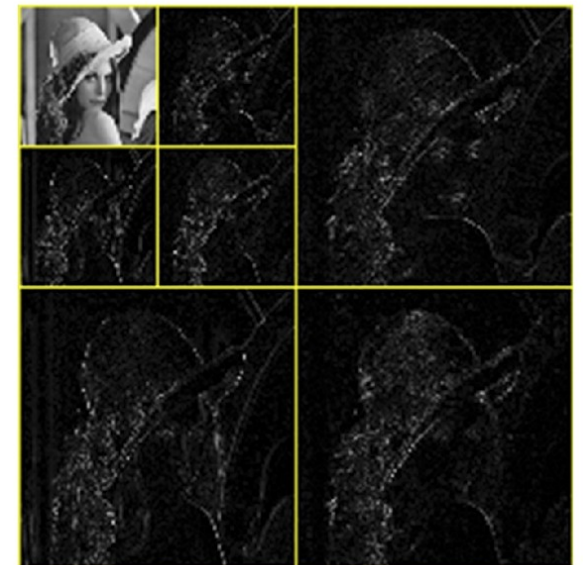
# Data Compression



Original Lena Image



DCT of Lena Image

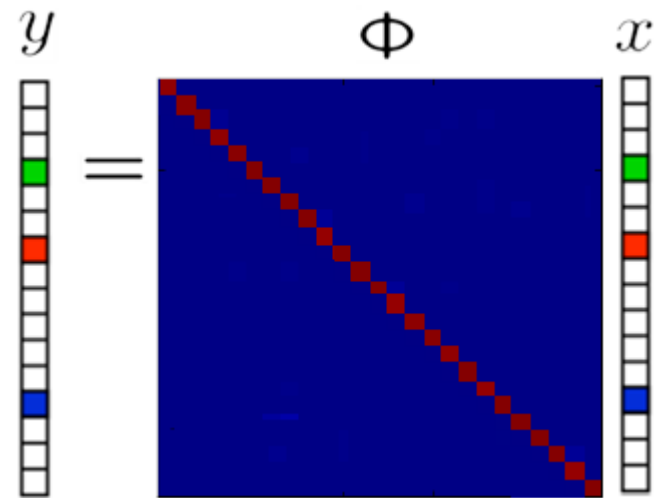


DWT of Lena Image

## Nyquist-Shannon Sampling Theorem

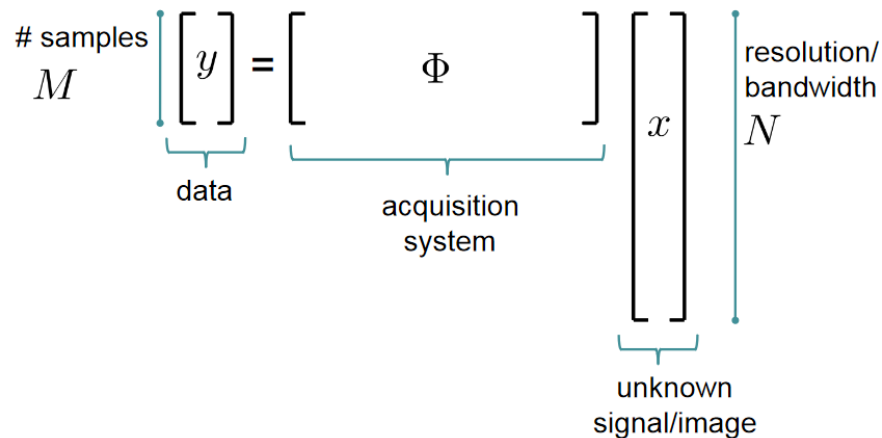
A sample rate of at least twice the maximum frequency present in a signal permits its sampled discrete sequence to capture all the information of the continuous time signal.

## Matrix Representation of Sampling



Ideal Sampling

# Compressive Sensing



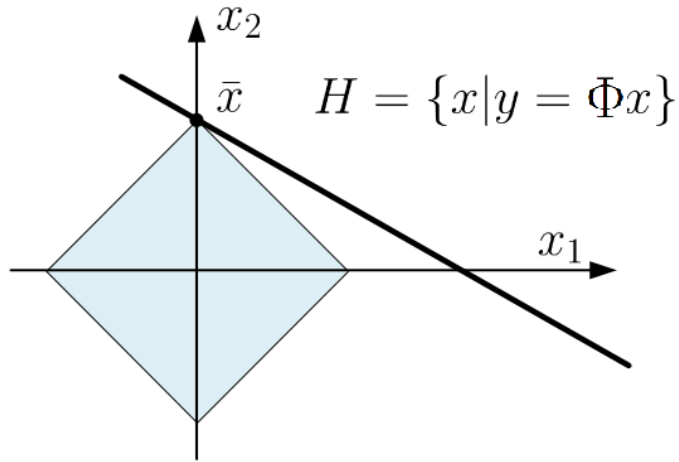
Measured signal is smaller in size than the original and hence the name compressive sensing.

If the given signal is sparse or is sparse in one of the transform domains, we can get back the signal by solving a l1 minimization problem.

l1 is a type of metric like l2(euclidean distance) but it induces sparsity.

And in doing so, we can get back a signal from its discrete signals samples which are the signal sampled at much lower than the Nyquist rate.

# **l1 minimization**



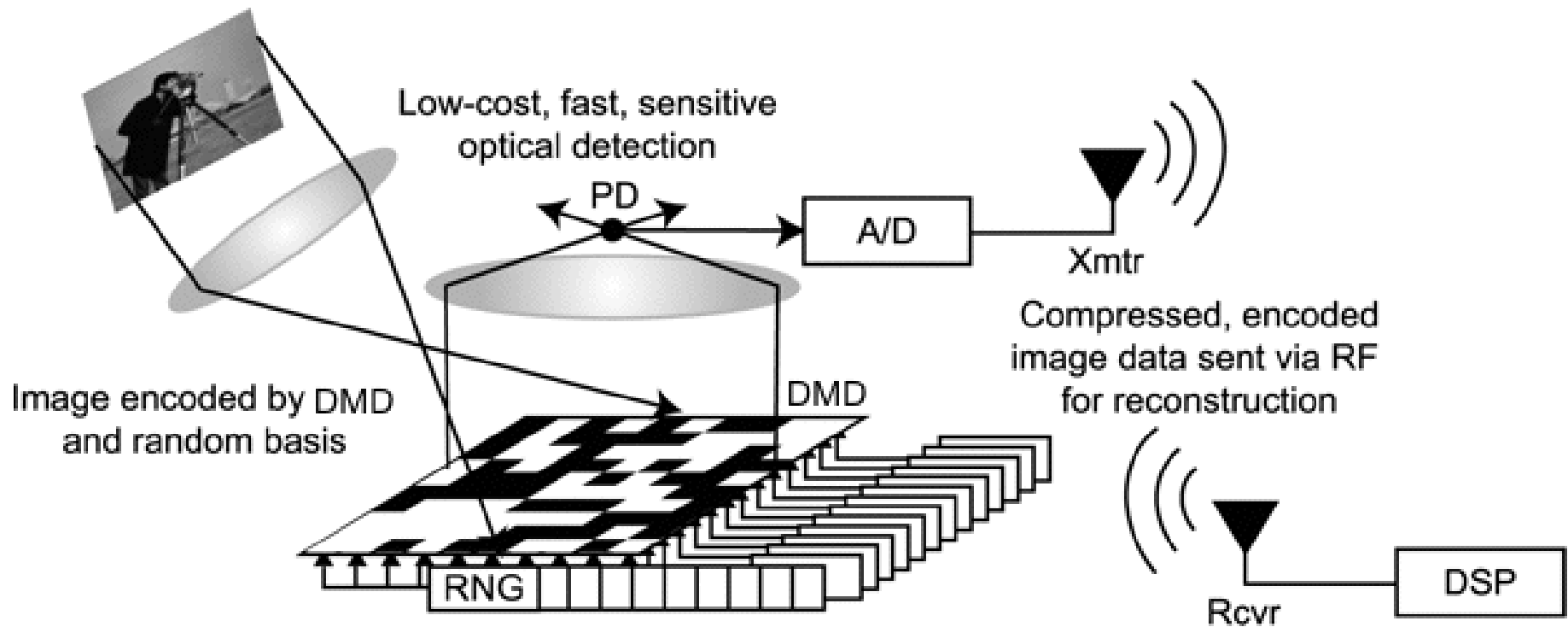
- We wish to get back  $x$  from  $y$ .
- More unknown than number of equations.
- $M \ll N$ , implies this is an ill posed problem.
- We solve it using:

$$\min_x \|x\|_1 \quad \text{subject to} \quad \Phi x = y.$$



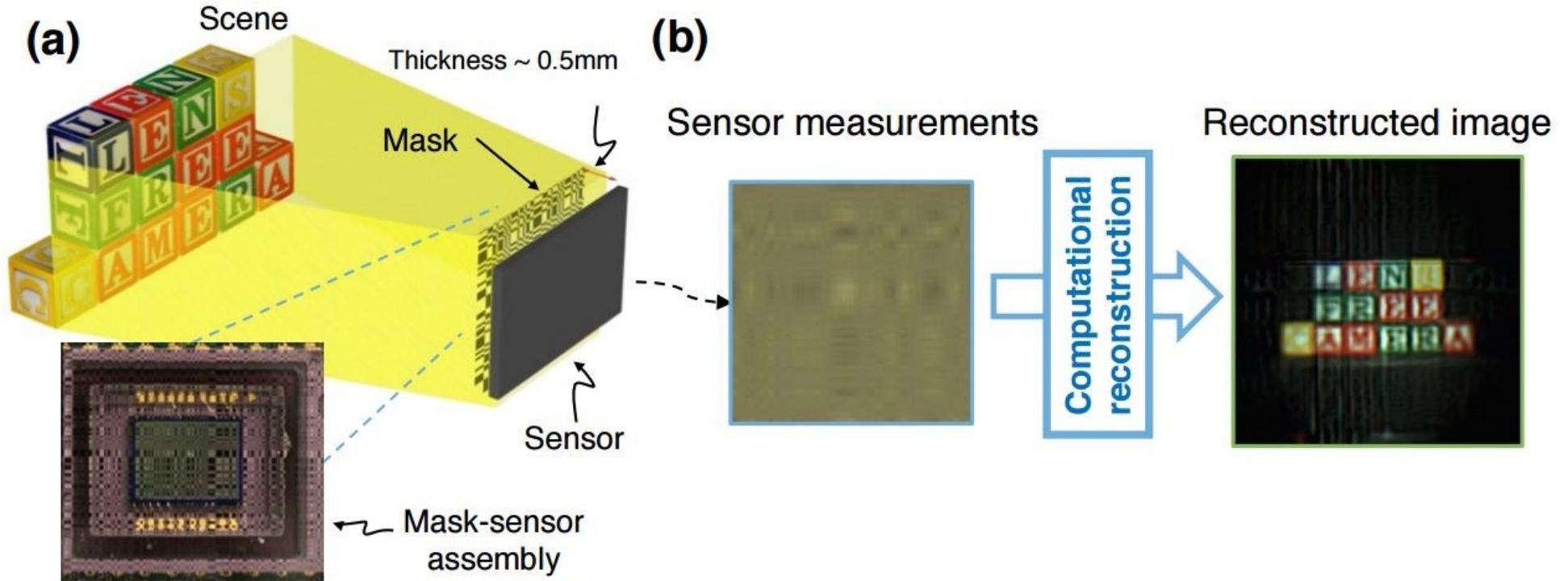
# Applications

## Single Pixel Camera



# Applications

## Lens-less camera



Faster MRI, Better CT scans and many more.

# Thank You!

Slides: [speakerdeck.com/saurabhkm](https://speakerdeck.com/saurabhkm)