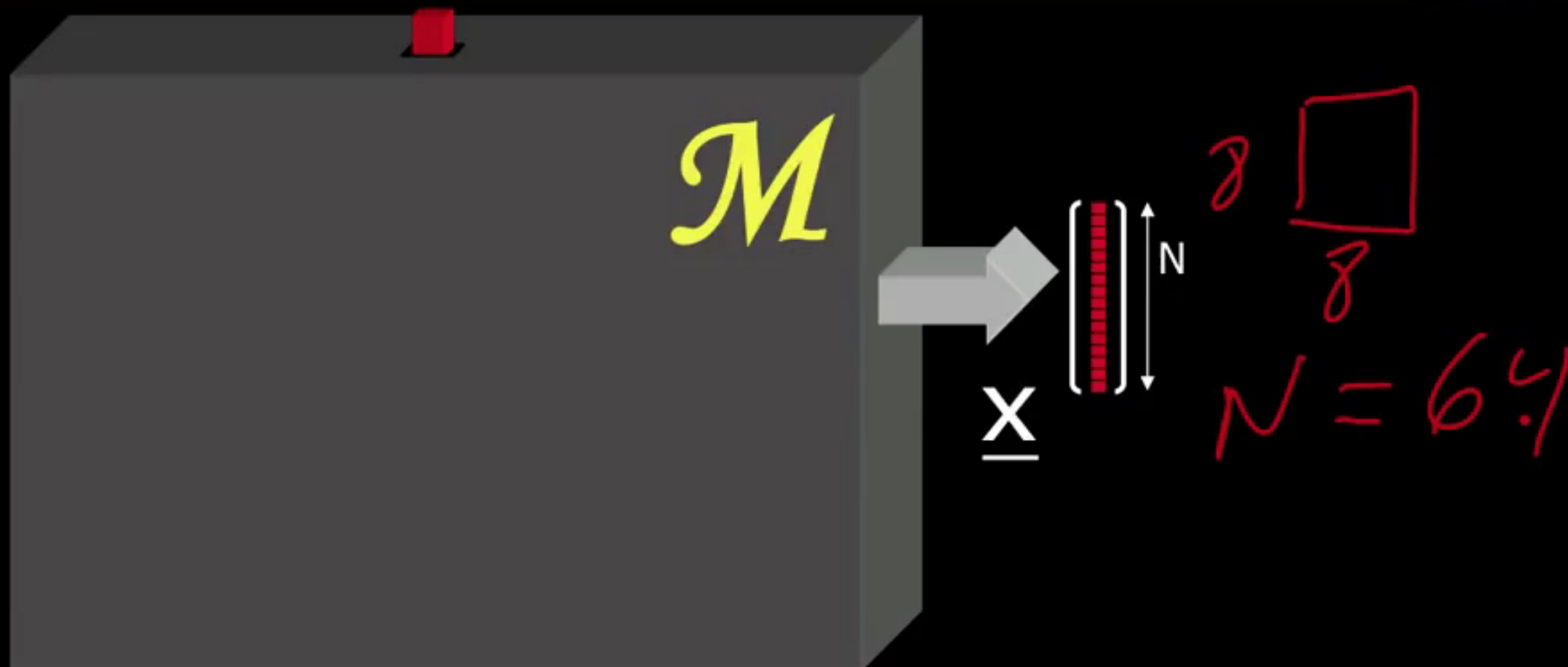
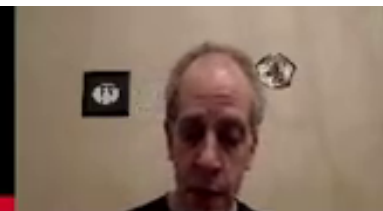
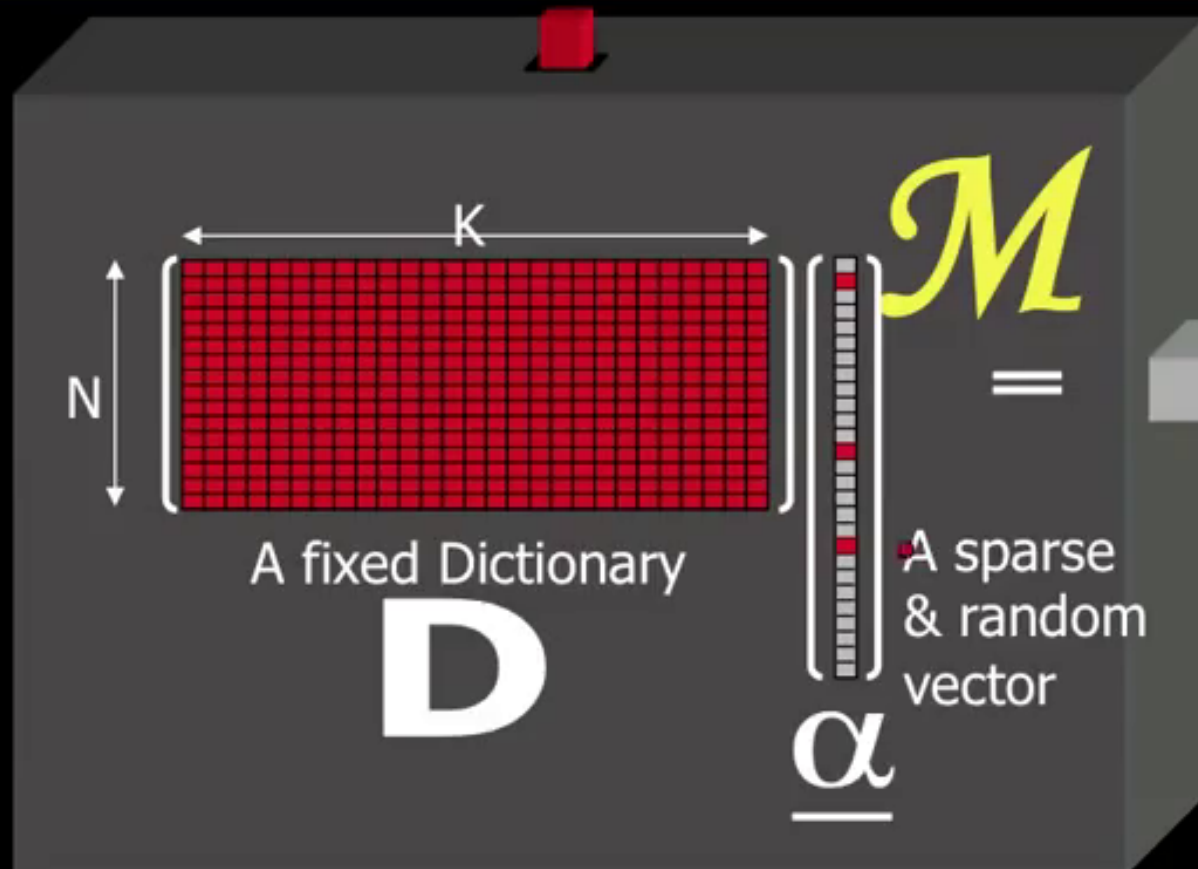


Sparse Modeling of Signals

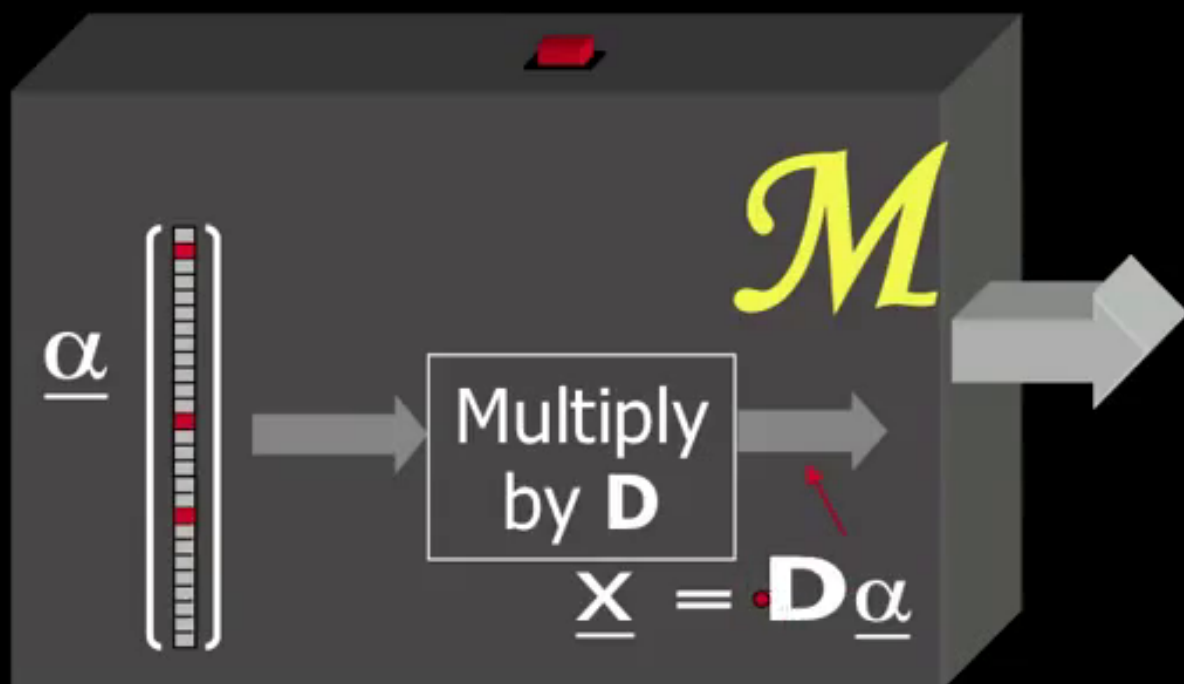
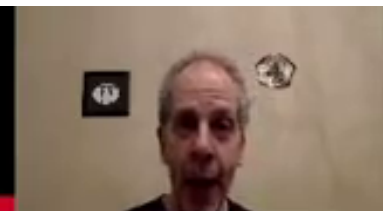


Sparse Modeling of Signals



- D (dictionary) is a set of prototype signals (atom).
- The vector α is generated with few (L) non-zeros.

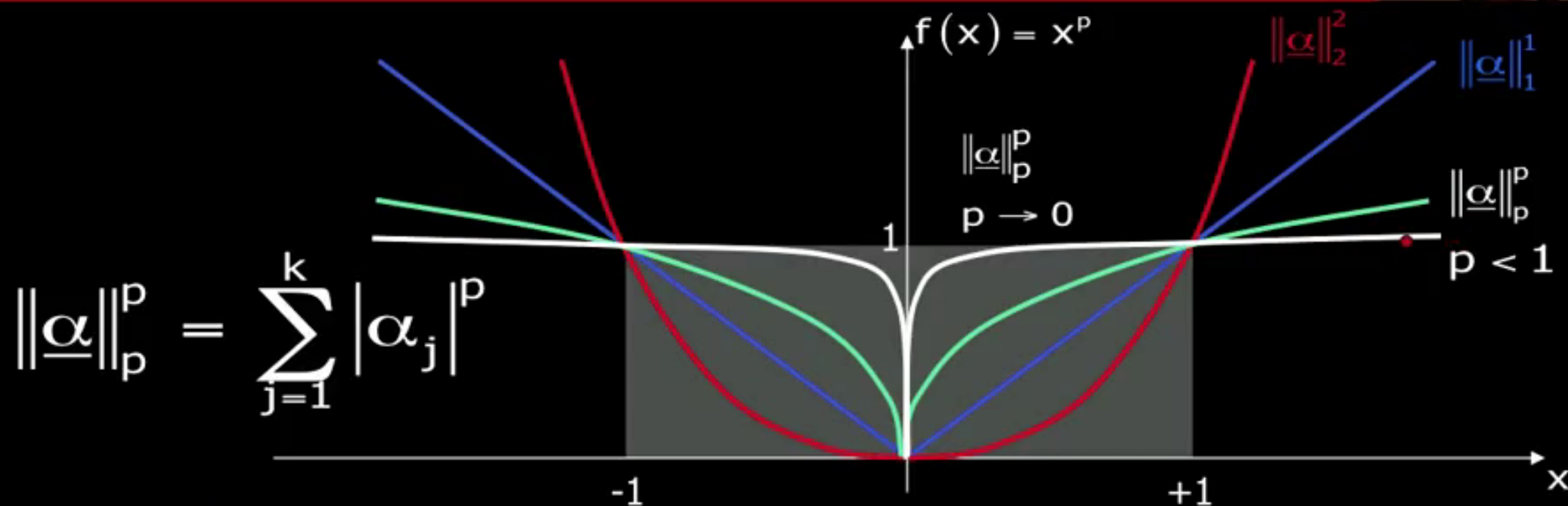
Sparseland Signals are Special



- **Simple:** Every generated signal is built as a linear combination of **few atoms** from our **dictionary \mathbf{D}**
- **Rich:** A general model: the obtained signals are a **union of many low-dimensional spaces**.
- **Familiar:** We have been using this model in other context for a while now

JPEG

Sparse & Redundant Rep. Modeling



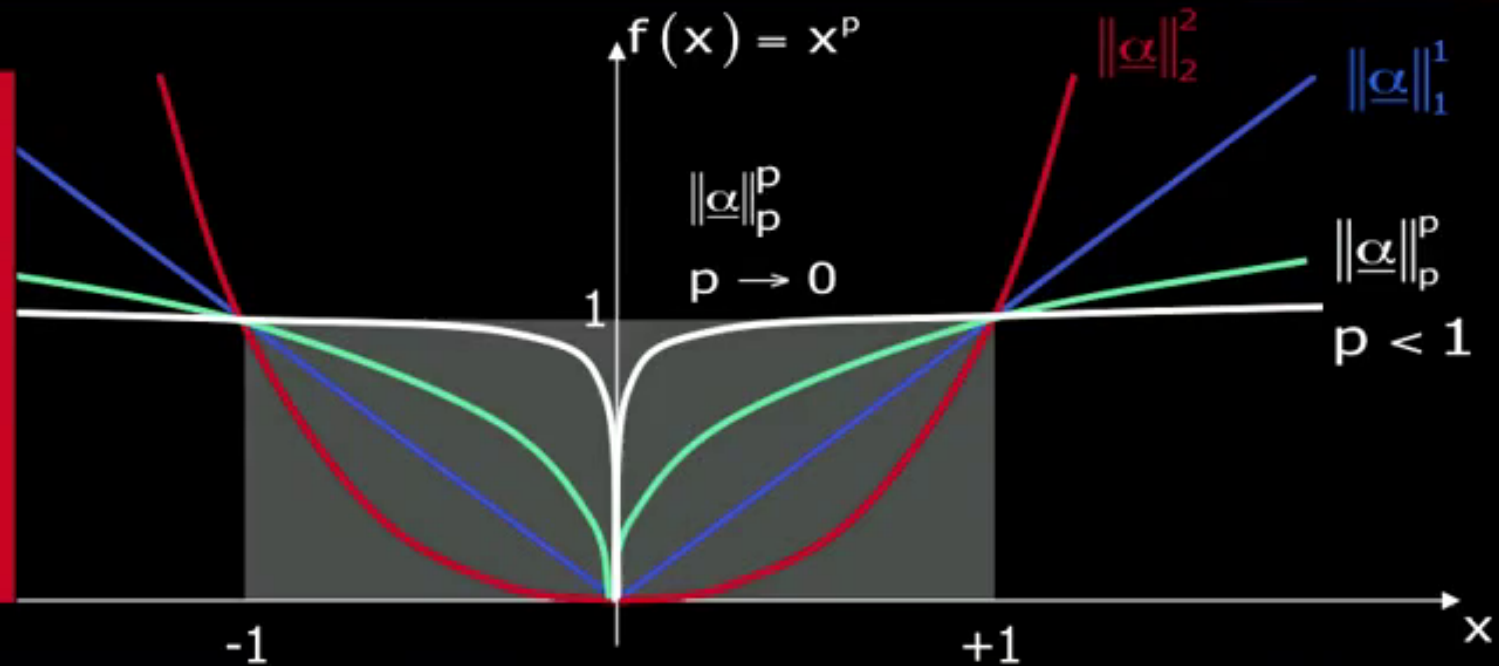
Our signal model $\underline{x} = \mathbf{D}\underline{\alpha}$ where $\underline{\alpha}$ is sparse

Sparse & Redundant Rep. Modeling



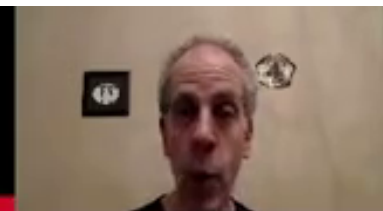
As $p \rightarrow 0$ we
get a count
of the non-zeros
in the vector

→ $\|\underline{\alpha}\|_0^0$



Our signal model $\underline{x} = \mathbf{D}\underline{\alpha}$ where $\|\underline{\alpha}\|_0^0 \leq L$

Back to Our MAP Energy Function



$$\frac{1}{2} \| \underline{x} - \underline{y} \|_2^2$$

Back to Our MAP Energy Function



$$\frac{1}{2} \|\mathbf{D}_{\underline{\alpha}} - \underline{y}\|_2^2$$

Back to Our MAP Energy Function



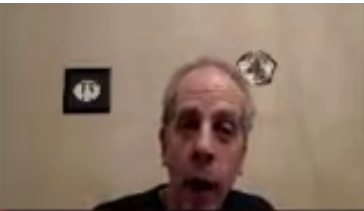
- L_0 "norm" is effectively counting the number of non-zeros in $\underline{\alpha}$.

$$\hat{\underline{\alpha}} = \arg \min_{\underline{\alpha}} \frac{1}{2} \|\mathbf{D}\underline{\alpha} - \underline{y}\|_2^2 \text{ s.t. } \|\underline{\alpha}\|_0 \leq L$$

$$\hat{\underline{x}} = \mathbf{D}\hat{\underline{\alpha}}$$

$$\mathbf{D}\underline{\alpha} - \underline{y} =$$

Back to Our MAP Energy Function



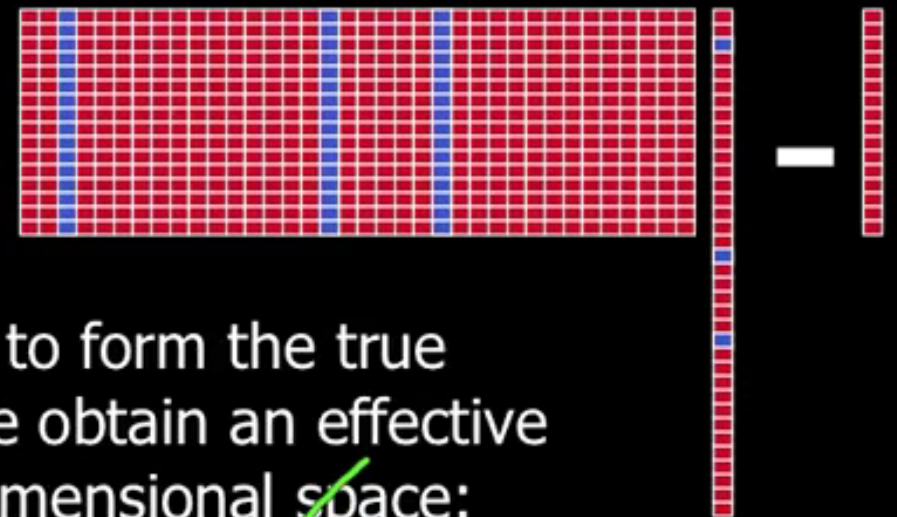
- L_0 "norm" is effectively counting the number of non-zeros in $\underline{\alpha}$.

$$\hat{\underline{\alpha}} = \arg \min_{\underline{\alpha}} \frac{1}{2} \|\mathbf{D}\underline{\alpha} - \underline{y}\|_2^2 \text{ s.t. } \|\underline{\alpha}\|_0 \leq L$$

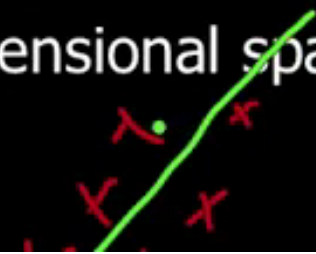
$$\hat{\underline{x}} = \mathbf{D}\hat{\underline{\alpha}}$$

- The vector $\underline{\alpha}$ is the representation signal x .

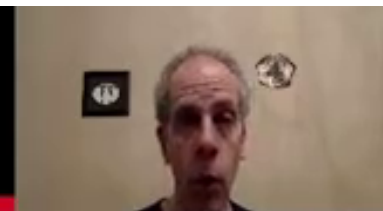
$$\mathbf{D}\underline{\alpha} - \underline{y} =$$



- Few (L out of K) atoms can be combined to form the true signal, the noise cannot be fitted well. We obtain an effective projection of the noise onto a very low-dimensional space:
Denoising



Wait! There are Some Issues



- **Numerical Problems:** How should we solve or approximate the solution of the problem

$$\min_{\underline{\alpha}} \|\mathbf{D}\underline{\alpha} - \underline{y}\|_2^2 \quad \text{s.t.} \quad \|\underline{\alpha}\|_0^0 \leq L$$

$$\min_{\underline{\alpha}} \|\underline{\alpha}\|_0^0 \quad \text{s.t.} \quad \|\mathbf{D}\underline{\alpha} - \underline{y}\|_2^2 \leq \varepsilon^2$$

$$\min_{\underline{\alpha}} \lambda \|\underline{\alpha}\|_0^0 + \|\mathbf{D}\underline{\alpha} - \underline{y}\|_2^2$$

- **Theoretical Problems:** Is there a unique sparse representation? If we are to approximate the solution somehow, how close will we get?
- **Practical Problems:** What dictionary \mathbf{D} should we use, such that all this leads to effective denoising? Will all this work in applications?

To Summarize So Far ...

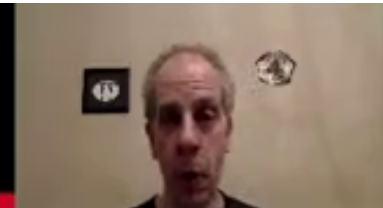


Image denoising
(and many other
problems in image
processing) requires
a model for the
desired image

What do
we do?

We proposed a
model for signals/
images based on
sparse and
redundant
representation

Great!
No?

There are some issues:

1. Theoretical
2. How to approximate?
3. What about **D**?