

Sparse and Overcomplete Data Representation

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Agenda

1. A Visit to *Sparseland*

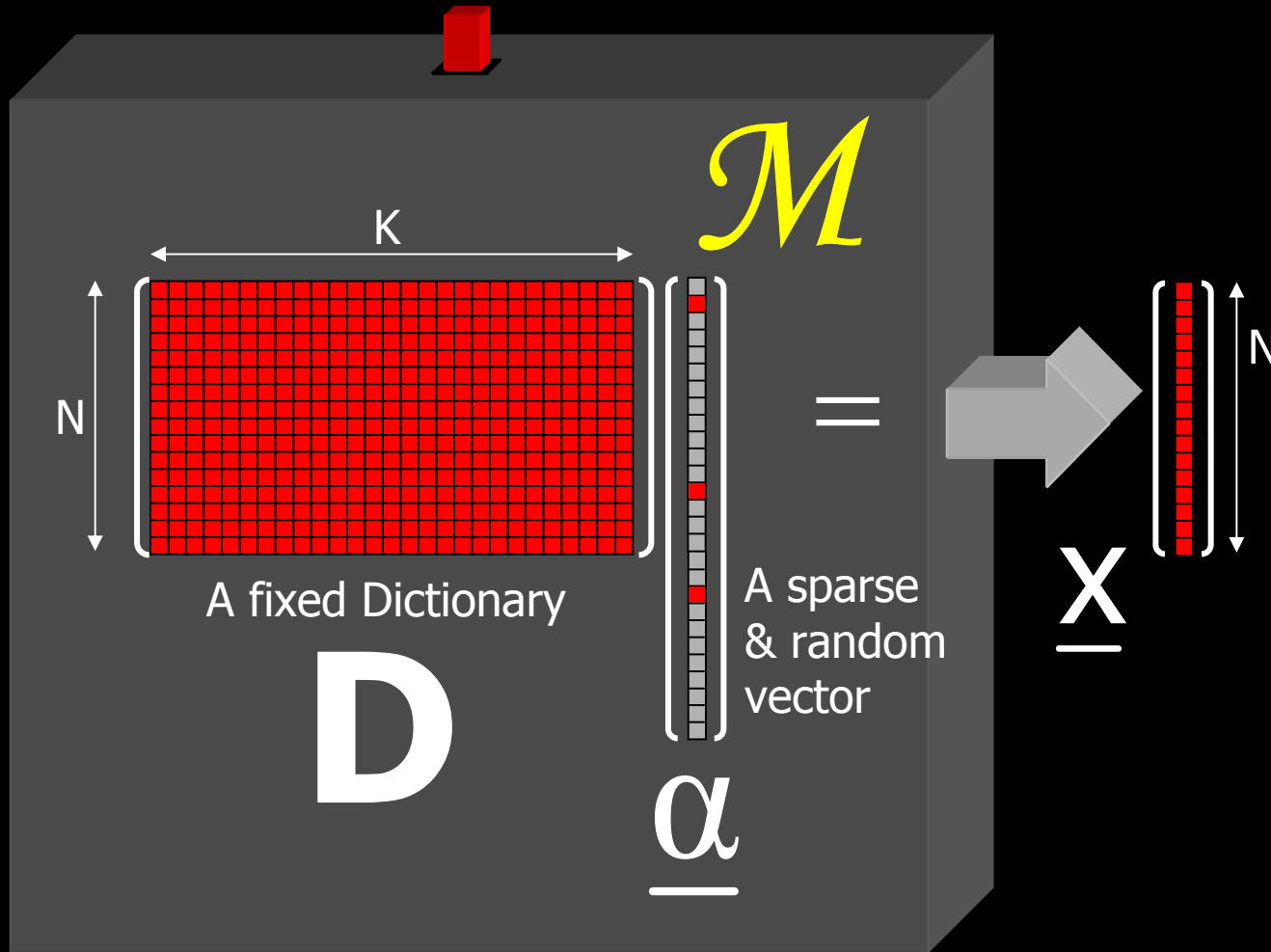
Motivating Sparsity & Overcompleteness

2. Answering the 4 Questions

How & why should this work?

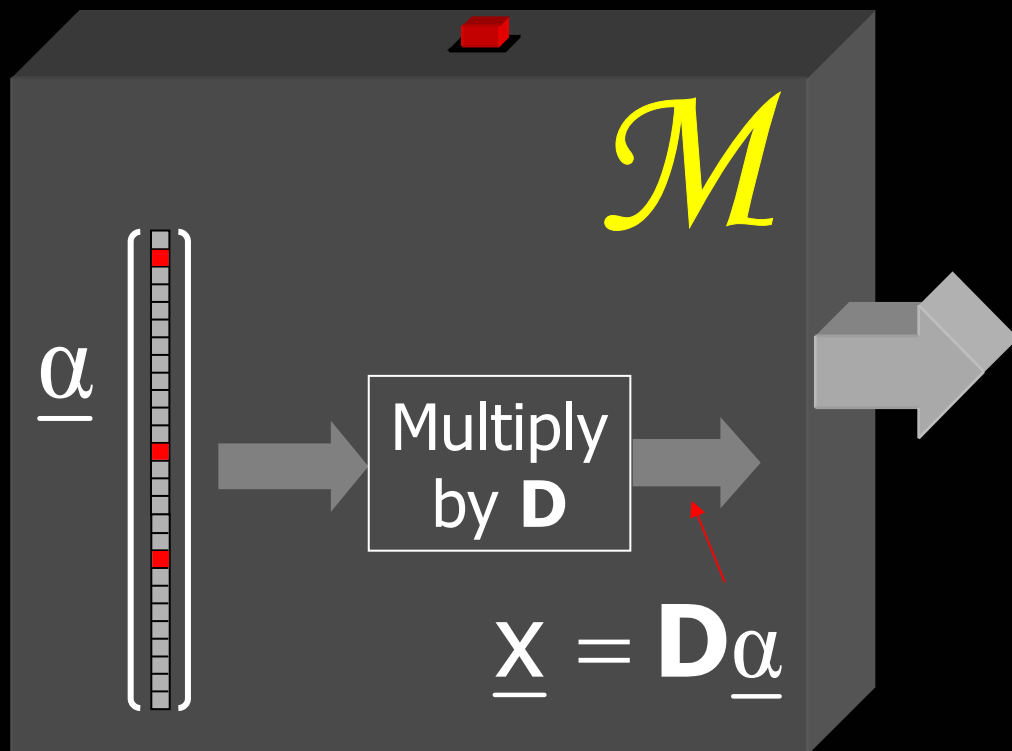


Data Synthesis in *Sparseland*



- Every column in D (**dictionary**) is a prototype data vector (**Atom**).
- The vector $\underline{\alpha}$ is generated randomly with few non-zeros in random locations and random values.

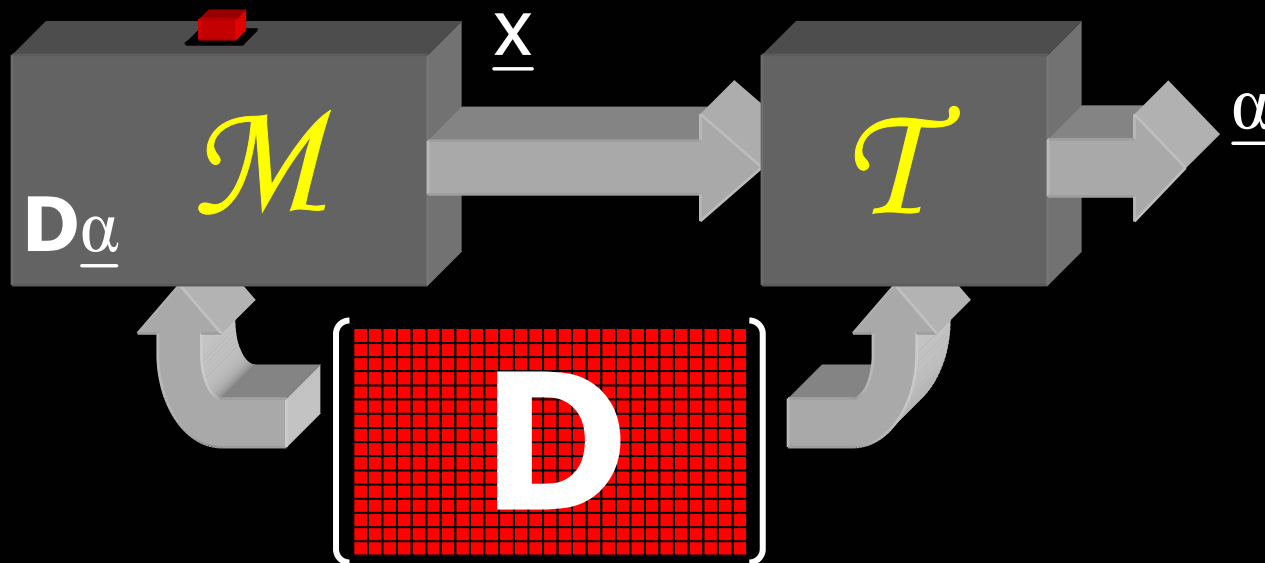
Sparse Data is Special



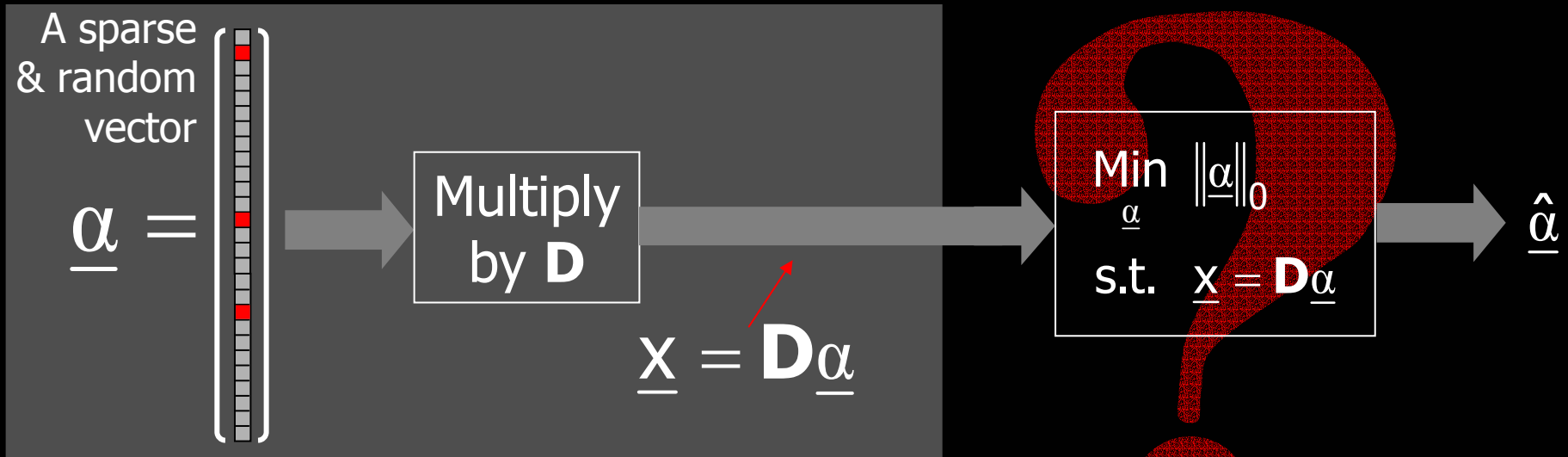
- **Simple:** Every generated vector is built as a linear combination of few atoms from our dictionary \mathbf{D}
- **Rich:** A general model: the obtained vectors are a special type mixture-of-Gaussians (or Laplacians).

Transforms in *Sparseland* ?

- Assume that \underline{x} is known to emerge from \mathcal{M} .
- We desire simplicity, independence, and expressiveness.
- How about “Given \underline{x} , find the $\underline{\alpha}$ that generated it in \mathcal{M} ” ?



Difficulties with the Transform



4 Major Questions

- Is $\hat{\underline{\alpha}} = \underline{\alpha}$? Under which conditions?
- Are there practical ways to get $\hat{\underline{\alpha}}$?
- How effective are those ways?
- How would we get \mathbf{D} ?

Why Is It Interesting?

Several recent trends from signal/image processing worth looking at:

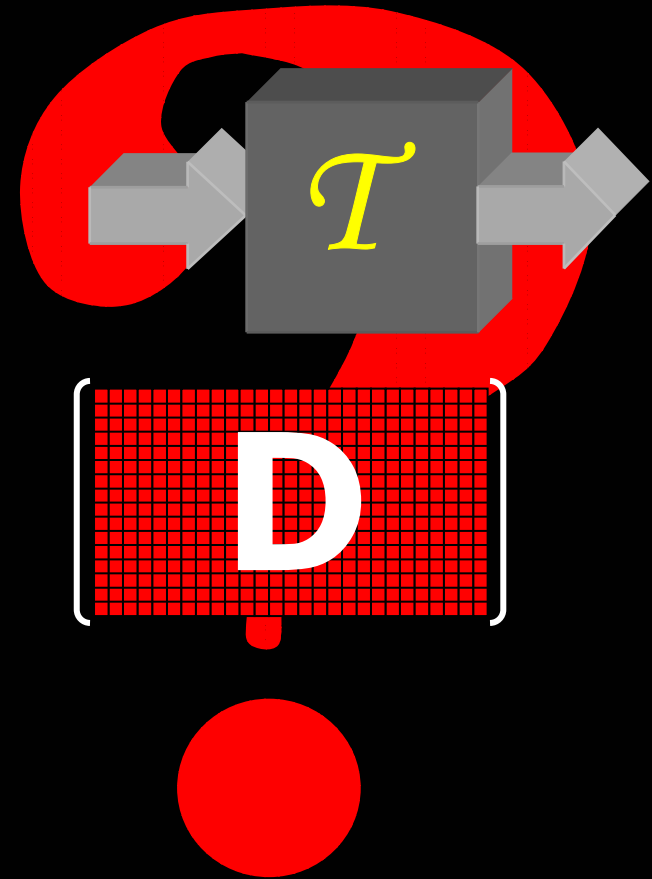
- JPEG to JPEG2000 - From (Linear) to (Wavelet and non-linear approximation)
- From L_2 to L_1 . (Fourier) **Sparsity.**
- From unitary to shift-invariant. **Overcompleteness.**
- Approximating non-linear approximation **Sparsity & Overcompleteness.**
- ICA and related models **Independence and Sparsity.**

Sparseland
IS HERE !

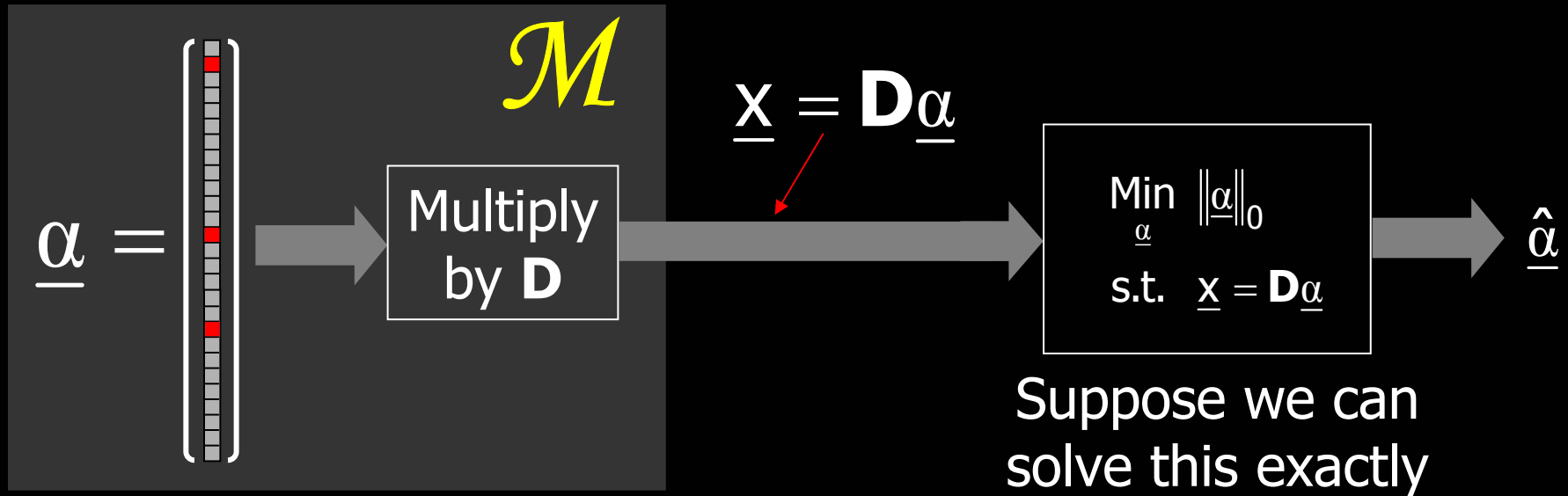


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How & why should this work?



Question 1 – Uniqueness?



Why should we necessarily get $\hat{\underline{\alpha}} = \underline{\alpha}$?

It might happen that eventually $\|\hat{\underline{\alpha}}\|_0 < \|\underline{\alpha}\|_0$.

Matrix "Spark"

Definition: Given a matrix \mathbf{D} , $\sigma = \text{Spark}\{\mathbf{D}\}$ is the smallest number of columns that are linearly dependent.

Donoho & Elad ('02)

Example:

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

Rank = 4

Spark = 3



Uniqueness Rule

Suppose this problem has been solved somehow

$$\text{Min}_{\underline{\alpha}} \|\underline{\alpha}\|_0 \quad \text{s.t.} \quad \underline{x} = \mathbf{D}\underline{\alpha}$$

Uniqueness

Donoho & Elad ('02)

If we found a representation that satisfy

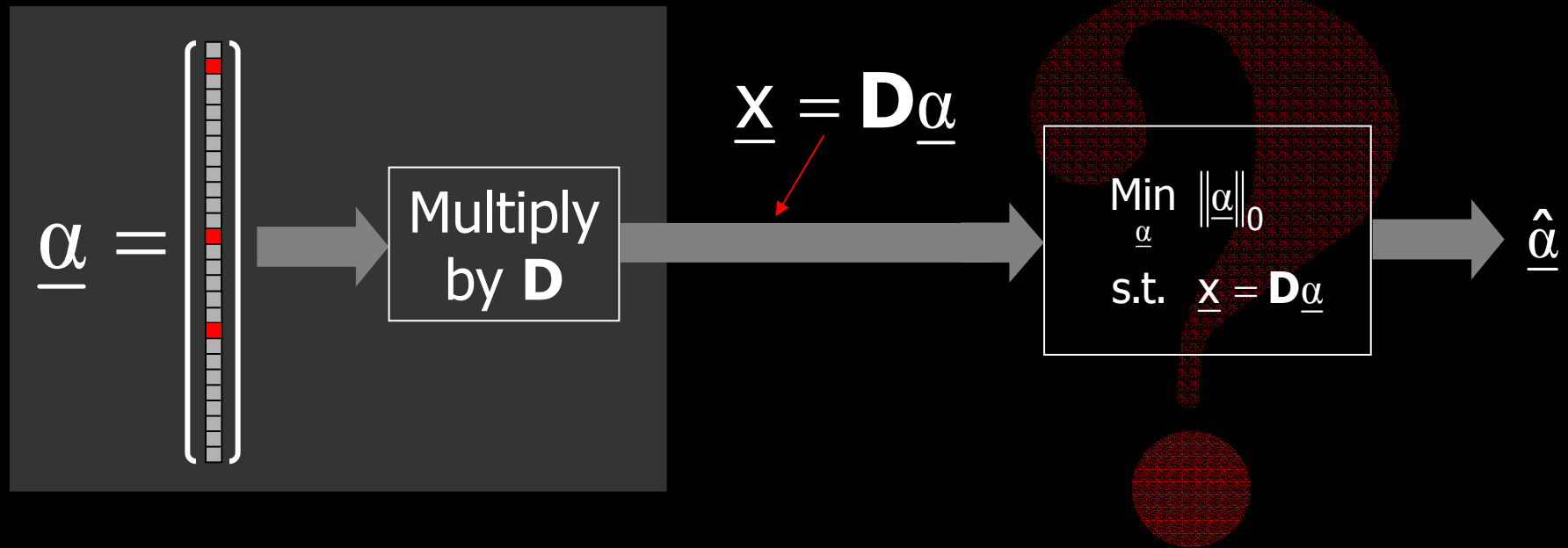
$$\frac{\sigma}{2} > \|\underline{\alpha}\|_0$$

then necessarily it is unique (the sparsest).

This result implies that if \mathcal{M} generates vectors using “sparse enough” $\underline{\alpha}$, the solution of the above will find it exactly.



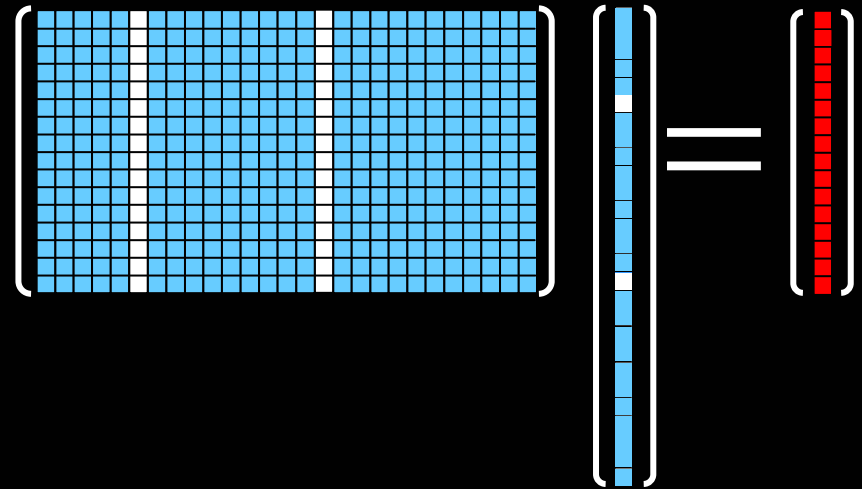
Question 2 – Practical P_0 Solver?



Are there reasonable ways to find $\hat{\underline{\alpha}}$?

Matching Pursuit (MP) Mallat & Zhang (1993)

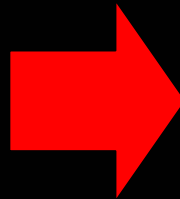
- The MP is a greedy algorithm that finds one atom at a time.
- Step 1: find the one atom that **best matches** the signal.
- Next steps: given the previously found atoms, find the next **one** to **best fit** ...
- The Orthogonal MP (OMP) is an improved version that re-evaluates the coefficients after each round.



Basis Pursuit (BP) Chen, Donoho, & Saunders (1995)

Instead of solving

$$\text{Min}_{\underline{\alpha}} \|\underline{\alpha}\|_0 \quad \text{s.t.} \quad \underline{x} = \mathbf{D}\underline{\alpha}$$



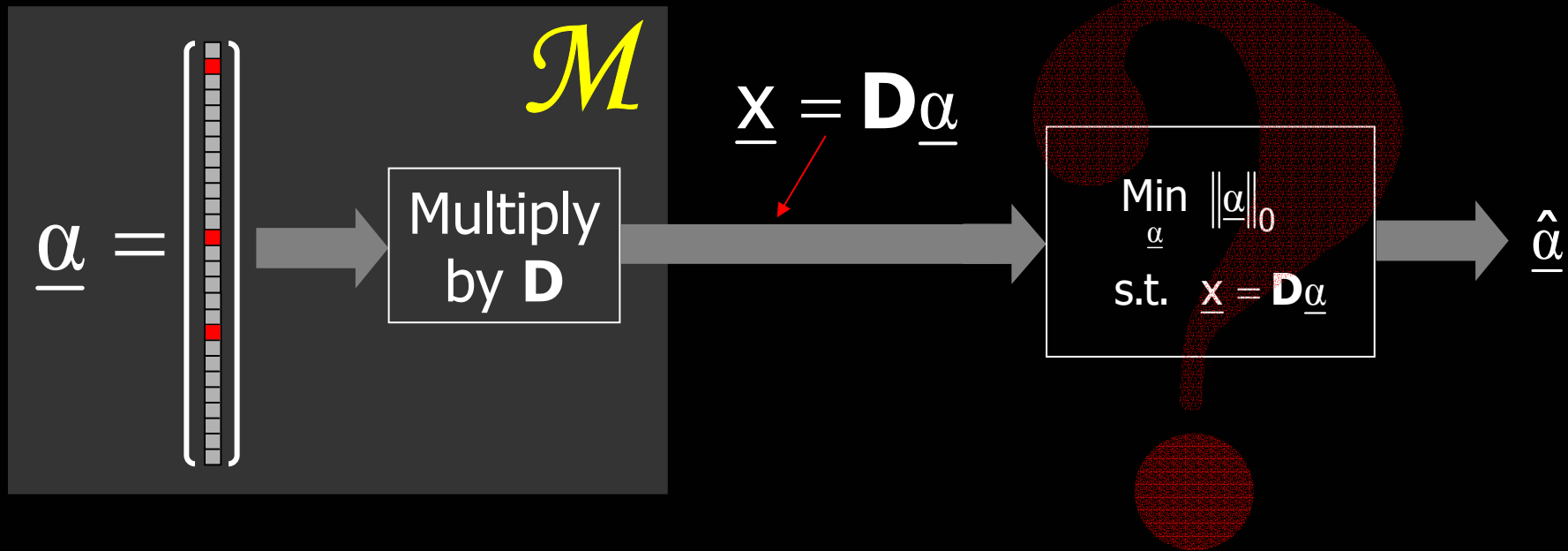
Solve Instead

$$\text{Min}_{\underline{\alpha}} \|\underline{\alpha}\|_1 \quad \text{s.t.} \quad \underline{x} = \mathbf{D}\underline{\alpha}$$

- The newly defined problem is convex.
- It has a Linear Programming structure.
- Very efficient solvers can be deployed:
 - Interior point methods [Chen, Donoho, & Saunders ('95)] ,
 - Sequential shrinkage for union of ortho-bases [Bruce et.al. ('98)],
 - If computing $\mathbf{D}\underline{x}$ and $\mathbf{D}^T\underline{\alpha}$ are fast, based on shrinkage [Elad ('05)].



Question 3 – Approx. Quality?



**How effective are the MP/BP
in finding $\hat{\alpha}$?**

Mutual Coherence

- Compute $\begin{bmatrix} \mathbf{D}^T \\ \mathbf{D} \end{bmatrix} = \begin{bmatrix} \mathbf{D}^T \mathbf{D} \end{bmatrix}$ Assume normalized columns

- The **Mutual Coherence** μ is the largest entry in absolute value outside the main diagonal of $\mathbf{D}^T \mathbf{D}$.
- The Mutual Coherence is a property of the dictionary (just like the “Spark”). The smaller it is, the better the dictionary.

BP and MP Equivalence

Equivalence

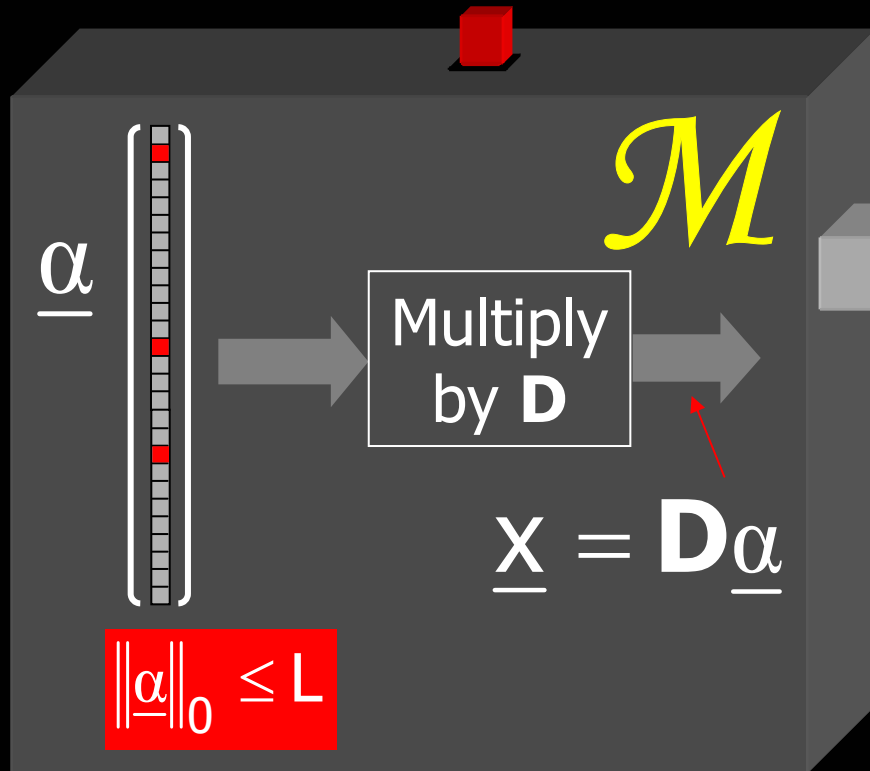
Donoho & Elad ('02)
Gribonval & Nielsen ('03)
Tropp ('03)
Temlyakov ('03)

Given a vector \underline{x} with a representation $\underline{x} = \mathbf{D}\underline{\alpha}$,
Assuming that $\|\underline{\alpha}\|_0 < 0.5(1 + 1/\mu)$, BP and MP are
Guaranteed to find the sparsest solution.

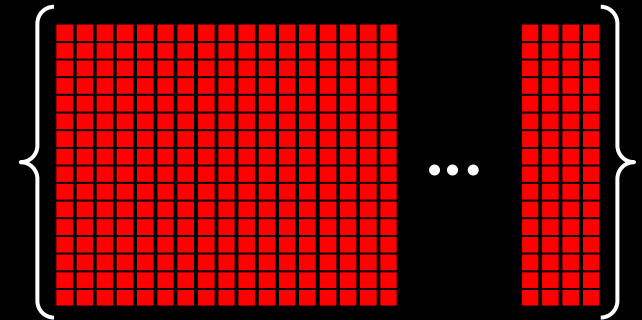
- MP is typically inferior to BP!
- The above result corresponds to the worst-case.
- Average performance results are available too, showing much better bounds [Donoho ('04), Candes et.al. ('04), Elad and Zibulevsky ('04)].



Question 4 – Finding D?



$$\left\{ \underline{X}_j \right\}_{j=1}^P$$



Given these P examples and a fixed size $[N \times K]$ dictionary \mathbf{D} :

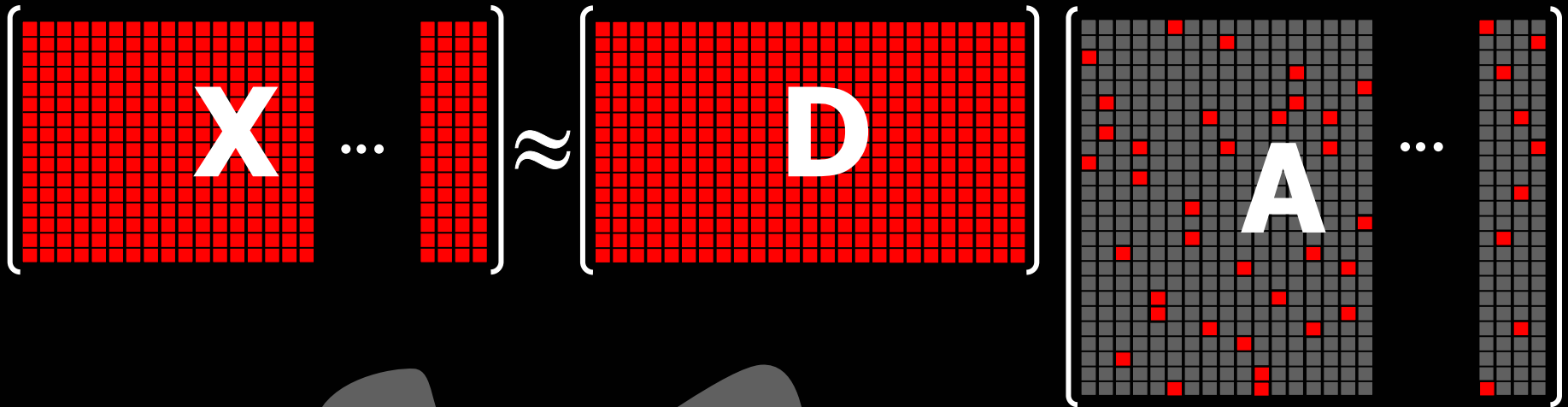
1. Is \mathbf{D} unique? (**Yes**)
2. How to find \mathbf{D} ?



Train!! The **K-SVD** algorithm



Training: The Objective



Min
 \mathbf{D}, \mathbf{A}

$$\sum_{j=1}^P \left\| \mathbf{D} \underline{\alpha}_j - \underline{x}_j \right\|_2^2$$

Each example is a linear combination of atoms from \mathbf{D}

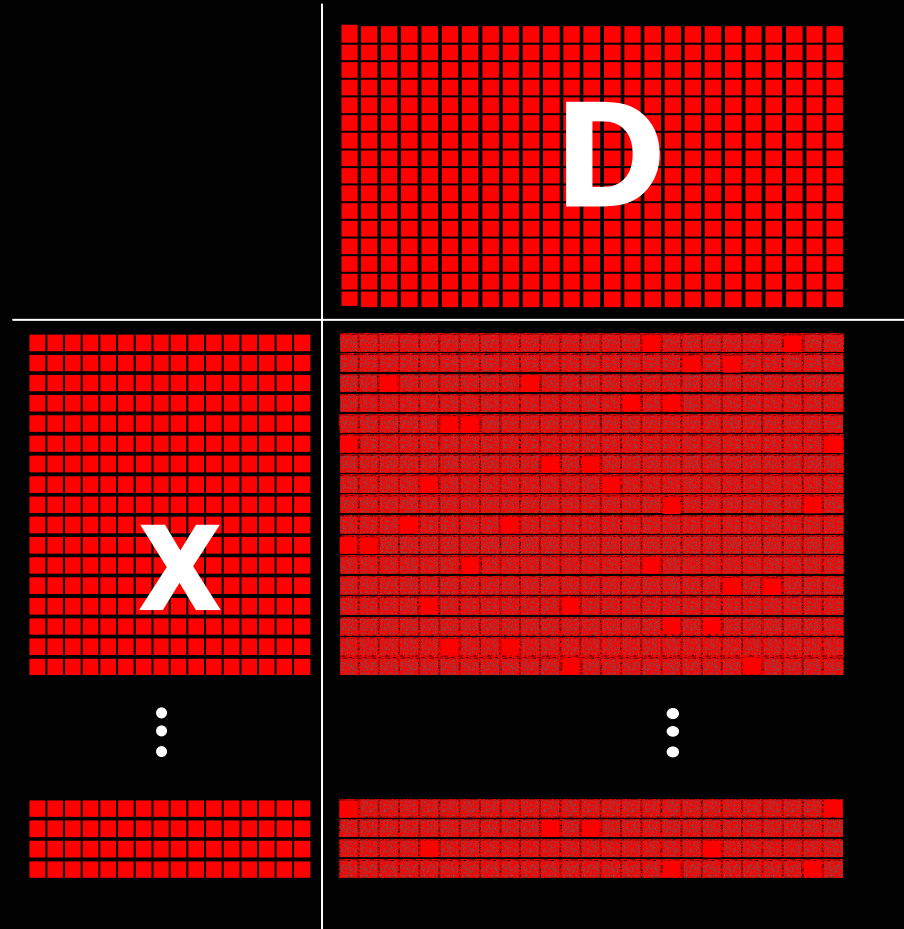
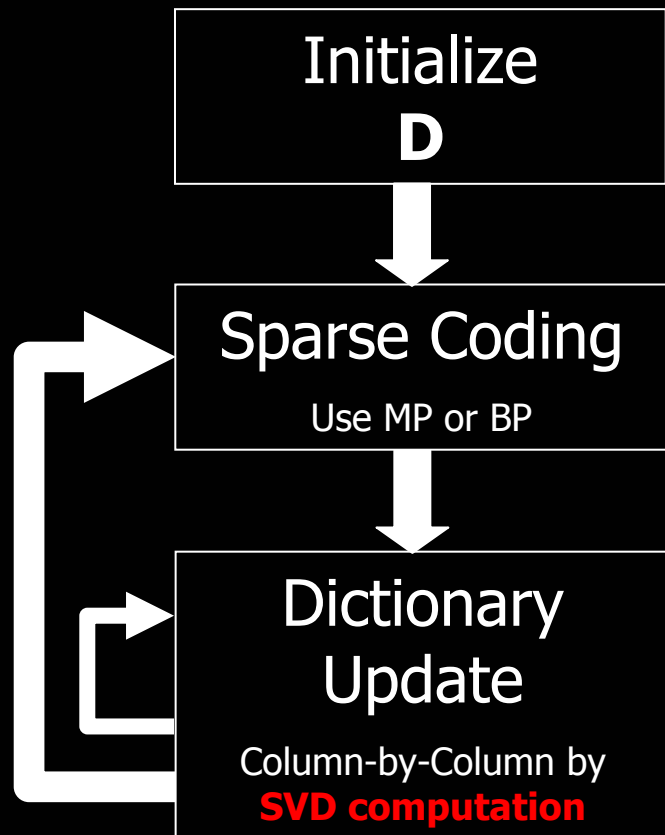
s.t.

$$\forall j, \left\| \underline{\alpha}_j \right\|_0 \leq L$$

Each example has a sparse representation with no more than L atoms

The K-SVD Algorithm

Aharon, Elad, & Bruckstein ('04)



Today We Discussed

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Summary

Sparsity and **Over-completeness** are important ideas that can be used in designing better tools in data/signal/image processing

There are difficulties in using them!

We are working on resolving those difficulties:

- Performance of pursuit alg.
- Speedup of those methods,
- Training the dictionary,
- Demonstrating applications,
- ...

Future transforms and regularizations will be **data-driven, non-linear, overcomplete**, and promoting **sparsity**.

The dream?

