# Sparse Representation and Dictionary Learning

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# Part I

# Sparse Representation and Dictionary Learning

# Sparse representation problem

**Terms:** Sparse Representation (稀疏表現)/Sparse Coding (稀疏編碼)

**SR problem:** *Given a signal vector* $\boldsymbol{x} \in \mathbb{R}^m$ *and a dictionary matrix* $\boldsymbol{D} \in \mathbb{R}^{m \times n}$*, we seek a sparse coefficient vector* $\boldsymbol{z}^* \in \mathbb{R}^n$ *such that*

$$\boldsymbol{z}^* = \arg\min_{\boldsymbol{z}} \left( \frac{1}{2} \|\boldsymbol{x} - \boldsymbol{D}\boldsymbol{z}\|_2^2 + \lambda \|\boldsymbol{z}\|_0 \right),$$

*where* $\lambda > 0$ *is a penalty parameter and* $\|\boldsymbol{z}\|_0$ *counts the number of nonzero components of* $\boldsymbol{z}$*.*

**Remarks:**

- In the matrix-vector multiplication $\boldsymbol{D}\boldsymbol{z}$, the components of $\boldsymbol{z}$ are the coefficients with respect to columns (also called *atoms*) of $\boldsymbol{D}$.
- We call $\|\boldsymbol{z}\|_0$ the $\ell^0$ norm of $\boldsymbol{z}$, even though $\ell^0$ is *not* really a norm, since the *homogeneity property* fails, $\|\alpha \boldsymbol{z}\|_0 \neq |\alpha| \|\boldsymbol{z}\|_0$.
- It is inefficient to compute $\|\boldsymbol{z}\|_0$ directly when $n$ is large. In practice, we will use the $\ell^1$ norm instead of the $\ell^0$ norm.

## Two dual $\ell^0$ minimization problems

In [Sharon-Wright-Ma 2007], they studied the following two *dual* $\ell^0$ minimization problems:

- **Sparse error correction (SEC):** *Given* $\mathbf{0} \neq \boldsymbol{y} \in \mathbb{R}^n$ *and* $\boldsymbol{A} \in \mathbb{R}^{n \times p}$ *with* $n > p$ *and* $\operatorname{rank}(\boldsymbol{A}) = p$, *we seek* $\boldsymbol{w}^* \in \mathbb{R}^p$ *such that*

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_0. \tag{1}$$

- **Sparse signal reconstruction (SSR):** *Given* $\boldsymbol{D} \in \mathbb{R}^{m \times n}$ *with* $m < n$ *and* $\mathbf{0} \neq \boldsymbol{x} \in C(\boldsymbol{D})$ *the column space of* $\boldsymbol{D}$, *we seek* $\boldsymbol{z}^* \in \mathbb{R}^n$ *such that*

$$\boldsymbol{z}^* = \arg\min_{\boldsymbol{z}} \|\boldsymbol{z}\|_0 \quad \text{subject to} \quad \boldsymbol{x} = \boldsymbol{D}\boldsymbol{z}. \tag{2}$$

Note that (1) is a *decoding problem*, while (2) is a *sparse representation problem*. These two problems are *dual* in the sense that we can convert one problem to the other, see page 8 below.

# Existence and uniqueness of solution

1. **Existence:**
   - Existence of $\boldsymbol{w}^*$: If $\exists\, \boldsymbol{w} \in \mathbb{R}^p$ s.t. $\|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_0 = 0$, then $\boldsymbol{w}^* = \boldsymbol{w}$. Otherwise, define

     $$\mathcal{S} := \{k \in \mathbb{N} : \exists\, \boldsymbol{w} \in \mathbb{R}^p \text{ s.t. } \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_0 = k\}.$$

     Then $\varnothing \neq \mathcal{S} \subseteq \mathbb{N}$. *By the well-ordering principle,* $\exists\, k_0 \in \mathcal{S}$ *the minimum of* $\mathcal{S}$. i.e., $\exists\, \boldsymbol{w}^*$ such that $\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_0$.
   - Existence of $\boldsymbol{z}^*$: It can be shown in a similar way!
2. **Uniqueness:** *It will generally be true* that these two dual problems have a unique solution if
   - *$\exists\, \boldsymbol{w}_0$ such that the error $\boldsymbol{e} := \boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}_0$ is sparse enough, or*
   - *$\exists\, \boldsymbol{z}_0$ sparse enough such that $\boldsymbol{x} = \boldsymbol{D}\boldsymbol{z}_0$.*

     e.g., if any set of $2T$ columns of $\boldsymbol{D}$ are linearly independent, then any $\boldsymbol{z}_0 \in \mathbb{R}^n$ with $\|\boldsymbol{z}_0\|_0 \leq T$ such that $\boldsymbol{D}\boldsymbol{z}_0 = \boldsymbol{x}$ is the unique solution to SSR problem (2).

# Why we require matrix $A$ full rank $p$ in the SEC problem?

Note that $\boldsymbol{A}$ is of size $n \times p$ and $n > p$.

Suppose that $\boldsymbol{A}$ is not full rank $p$. Then $\text{rank}(\boldsymbol{A}) < p$.

Since $\dim N(\boldsymbol{A}) + \text{rank}(\boldsymbol{A}) = p$, we have $\dim N(\boldsymbol{A}) > 0$.

Thus, nullspace $N(\boldsymbol{A}) \neq \{\mathbf{0}\}$ and $\exists\, \widetilde{\boldsymbol{w}} \neq \mathbf{0}$ such that $\boldsymbol{A}\widetilde{\boldsymbol{w}} = \mathbf{0}$.

If $\boldsymbol{w}^*$ is a solution of the SEC problem, then

$$\|\boldsymbol{y} - \boldsymbol{A}(\boldsymbol{w}^* + \widetilde{\boldsymbol{w}})\|_0 = \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}^*\|_0.$$

Hence, $\boldsymbol{w}^* + \widetilde{\boldsymbol{w}}$ is also a solution of the SEC problem.

*Therefore, in order to ensure the uniqueness, we require $\boldsymbol{A}$ full rank $p$.*

# How to convert problem (2) to problem (1)?

- *The decoding problem (1) can be converted to the sparse representation problem (2).* [Candès *et al.* 2005, IEEE Symposium on FOCS]
- **Converting (2) to (1):** *Let $p = n - \text{rank}(\boldsymbol{D}) > 0$ and $\boldsymbol{A}$ be a full-rank $n \times p$ matrix whose columns span the nullspace of $\boldsymbol{D}$, i.e., $\boldsymbol{DA} = \boldsymbol{0}$. Find any $\boldsymbol{y} \in \mathbb{R}^n$ so that $\boldsymbol{Dy} = \boldsymbol{x}$ and define $f(\boldsymbol{w}) = \boldsymbol{y} - \boldsymbol{Aw}$. Then*

$$\underbrace{\arg\min_{\boldsymbol{z}\ \&\ \boldsymbol{Dz}=\boldsymbol{x}} \|\boldsymbol{z}\|_0}_{\boldsymbol{z}^*} = \underbrace{f\left(\arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{Aw}\|_0\right)}_{f(\boldsymbol{w}^*)}. \qquad (3)$$

*Proof:* First, note that for all $\boldsymbol{w} \in \mathbb{R}^p$, we have

$$\boldsymbol{D}f(\boldsymbol{w}) = \boldsymbol{D}(\boldsymbol{y} - \boldsymbol{Aw}) = \boldsymbol{Dy} - \boldsymbol{DAw} = \boldsymbol{Dy} = \boldsymbol{x}.$$

Claim: $\exists\ \widetilde{\boldsymbol{w}} \in \mathbb{R}^p$ such that $f(\widetilde{\boldsymbol{w}}) = \boldsymbol{y} - \boldsymbol{A}\widetilde{\boldsymbol{w}} = \boldsymbol{z}^*$.

$\because\ \boldsymbol{Dz}^* = \boldsymbol{x}$ and $\boldsymbol{D}(\boldsymbol{y} - \boldsymbol{Aw}) = \boldsymbol{x},\ \forall \boldsymbol{w} \implies \boldsymbol{D}(-\boldsymbol{z}^* + \boldsymbol{y} - \boldsymbol{Aw}) = \boldsymbol{0}$

$\therefore\ \exists\ \bar{\boldsymbol{w}}$ such that $\boldsymbol{A}\bar{\boldsymbol{w}} = -\boldsymbol{z}^* + \boldsymbol{y} - \boldsymbol{Aw} \implies \boldsymbol{z}^* = \boldsymbol{y} - \boldsymbol{A}(\boldsymbol{w} + \bar{\boldsymbol{w}}) := f(\widetilde{\boldsymbol{w}})$

Claim: $\widetilde{\boldsymbol{w}} = \boldsymbol{w}^* := \arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{Aw}\|_0$, and then $f(\boldsymbol{w}^*) = \boldsymbol{z}^*$.

$\because\ \|f(\boldsymbol{w}^*)\|_0 \leq \|f(\widetilde{\boldsymbol{w}})\|_0 = \|\boldsymbol{z}^*\|_0 \leq \|f(\boldsymbol{w}^*)\|_0 \implies \|f(\boldsymbol{w}^*)\|_0 = \|f(\widetilde{\boldsymbol{w}})\|_0$

By the uniqueness of $\boldsymbol{w}^*$, we obtain $\widetilde{\boldsymbol{w}} = \boldsymbol{w}^*$ and then $f(\boldsymbol{w}^*) = \boldsymbol{z}^*$.

# The $\ell^1$-$\ell^0$ equivalence problem

- In general, the $\ell^0$ minimizations (1) and (2) are *NP-hard problems:*

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_0 , \tag{1}$$

$$\boldsymbol{z}^* = \arg\min_{\boldsymbol{z}} \|\boldsymbol{z}\|_0 \quad \text{subject to} \quad \boldsymbol{x} = \boldsymbol{D}\boldsymbol{z}. \tag{2}$$

- The equivalence between $\ell^0$ and $\ell^1$ minimizations is conditional.

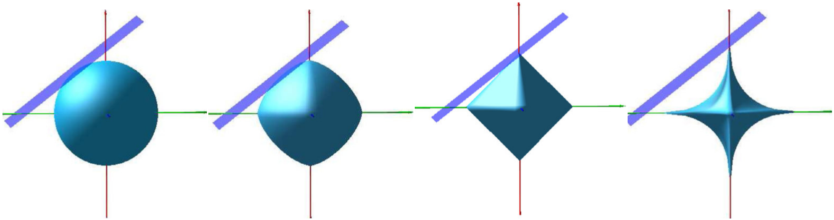
  David L. Donoho, *For most large underdetermined systems of linear equations the minimal $\ell_1$-norm solution is also the sparsest solution,* CPAM, 59 (2006), pp. 797-829.

  *If the error $\boldsymbol{e} := \boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}^*$ or the solution $\boldsymbol{z}^*$ is sufficiently sparse, then the solutions to (1) and (2) are the same as (4) and (5), respectively.*

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{w}\|_1 , \tag{4}$$

$$\boldsymbol{z}^* = \arg\min_{\boldsymbol{z}} \|\boldsymbol{z}\|_1 \quad \text{subject to} \quad \boldsymbol{x} = \boldsymbol{D}\boldsymbol{z}. \tag{5}$$

# 3-D ball in different $\ell^r$ norms and the constraint $Dz = x$




*3-D ball in the different $\ell^r$ norms for $r = 2,\ 1.5,\ 1,\ 0.5$*

$$z^* = \arg\min_{z} \|z\|_1 \quad \text{subject to} \quad \underbrace{x}_{\text{given}} = D \underbrace{z}_{\text{many}} \tag{5}$$

## The sparse representation problem

- We have introduced some ideas about the $\ell^1$-$\ell^0$ equivalence. In what follows, we don't consider the original SR problem. We consider the following $\ell^1$ minimization problem instead:

  **SR problem:** *Given a signal vector $\boldsymbol{x} \in \mathbb{R}^m$ and a dictionary matrix $\boldsymbol{D} \in \mathbb{R}^{m\times n}$, we seek a coefficient vector $\boldsymbol{z}^* \in \mathbb{R}^n$ such that*

  $$\boldsymbol{z}^* = \arg\min_{\boldsymbol{z}} \left( \frac{1}{2} \|\boldsymbol{x} - \boldsymbol{D}\boldsymbol{z}\|_2^2 + \lambda \|\boldsymbol{z}\|_1 \right), \qquad \lambda > 0. \qquad (\star)$$

  The existence (and uniqueness) of solution of the SR problem $(\star)$ can be ensured because matrix $\boldsymbol{D}^\top \boldsymbol{D}$ is symmetric (+ *positive definite*) and the second term $\lambda\|\cdot\|_1$ is a *convex function*.

- Problem $(\star)$ is also a regression analysis method in statistics and machine learning. It is the so-called *least absolute shrinkage and selection operator (LASSO).*

  R. J. Tibshirani, The lasso problem and uniqueness, *Electronic Journal of Statistics*, 7 (2013), pp. 1456-1490 $\oplus$ A. Ali, 13 (2019), pp. 2307-2347.

## Alternating direction method of multipliers (ADMM)

We will use the *"Alternating Direction Method of Multipliers"* to solve the above $\ell^1$-norm SR problem.

- ADMM is an iterative scheme for solving the following equality constrained convex optimization problems:

$$\min_{\boldsymbol{z}} f(\boldsymbol{z}) \quad \text{subject to} \quad \boldsymbol{A}\boldsymbol{z} = \boldsymbol{b}.$$

- ADMM consists of three steps:
  1. *adding an auxiliary variable* $\boldsymbol{y}$ *and a dual variable (multipliers)* $\boldsymbol{v}$ *and then scaled as* $\boldsymbol{u}$
  2. *separating the new cost function into a sum of* $f(\boldsymbol{z})$ *and* $g(\boldsymbol{y})$
  3. *using an iterative method to solve the problem*

- Then the optimization problem can be re-posed as

$$\min_{\boldsymbol{z},\boldsymbol{y}} \left(f(\boldsymbol{z}) + g(\boldsymbol{y})\right) \quad \text{subject to} \quad \boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} = \boldsymbol{c}.$$

# Derivation of the ADMM: augmented Lagrangian

First, we formulate the *augmented Lagrangian*

$$L_\rho(\boldsymbol{z},\boldsymbol{y},\boldsymbol{v}) := f(\boldsymbol{z}) + g(\boldsymbol{y}) + \underbrace{\boldsymbol{v}^\top}_{\text{multipliers}} (\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c}) + \underbrace{\frac{\rho}{2}\|\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c}\|_2^2}_{\text{penalty term}},$$

where $\rho > 0$ is the penalty parameter. Then the iterative scheme of the *augmented Lagrangian method (ALM)* is given by

$$\begin{aligned}
(\boldsymbol{z}^{(i+1)}, \boldsymbol{y}^{(i+1)}) &= \arg\min_{\boldsymbol{z}} L_\rho(\boldsymbol{z},\boldsymbol{y},\boldsymbol{v}^{(i)}),\\
\boldsymbol{v}^{(i+1)} &= \boldsymbol{v}^{(i)} + \rho\left(\boldsymbol{A}\boldsymbol{z}^{(i+1)} + \boldsymbol{B}\boldsymbol{y}^{(i+1)} - \boldsymbol{c}\right).
\end{aligned}$$

In ADMM, $\boldsymbol{z}$ and $\boldsymbol{y}$ are updated in an alternating or sequential fashion, which accounts for the term *alternating direction*.

$$\begin{aligned}
\boldsymbol{z}^{(i+1)} &= \arg\min_{\boldsymbol{z}} L_\rho(\boldsymbol{z},\boldsymbol{y}^{(i)},\boldsymbol{v}^{(i)}),\\
\boldsymbol{y}^{(i+1)} &= \arg\min_{\boldsymbol{y}} L_\rho(\boldsymbol{z}^{(i+1)},\boldsymbol{y},\boldsymbol{v}^{(i)}),\\
\boldsymbol{v}^{(i+1)} &= \boldsymbol{v}^{(i)} + \rho(\boldsymbol{A}\boldsymbol{z}^{(i+1)} + \boldsymbol{B}\boldsymbol{y}^{(i+1)} - \boldsymbol{c}).
\end{aligned}$$

## Scaled form of the augmented Lagrangian

The ADMM can be written in a slightly different form, which is often more convenient, by combining the linear and quadratic terms in the augmented Lagrangian and scaling the dual variable (multipliers) $\boldsymbol{v}$.

Define the residual $\boldsymbol{r} := \boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c}$. Then

$$\begin{aligned}
&\boldsymbol{v}^\top(\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c}) + \frac{\rho}{2}\|\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c}\|_2^2 \\
&\qquad = \boldsymbol{v}^\top\boldsymbol{r} + \frac{\rho}{2}\|\boldsymbol{r}\|_2^2 = \frac{\rho}{2}\|\boldsymbol{r} + \frac{1}{\rho}\boldsymbol{v}\|_2^2 - \frac{1}{2\rho}\|\boldsymbol{v}\|_2^2.
\end{aligned}$$

Set $\boldsymbol{u} = \frac{1}{\rho}\boldsymbol{v}$. Then $L_\rho(\boldsymbol{z},\boldsymbol{y},\boldsymbol{v}) = L_\rho(\boldsymbol{z},\boldsymbol{y},\boldsymbol{u})$, and

$$L_\rho(\boldsymbol{z},\boldsymbol{y},\boldsymbol{u}) = f(\boldsymbol{z}) + g(\boldsymbol{y}) + \frac{\rho}{2}\|\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c} + \boldsymbol{u}\|_2^2 - \frac{\rho}{2}\|\boldsymbol{u}\|_2^2.$$

# ADMM: scaled form

The ADMM in the scaled form is given by

$$\begin{aligned}
\boldsymbol{z}^{(i+1)} &= \arg\min_{\boldsymbol{z}} \left( f(\boldsymbol{z}) + g(\boldsymbol{y}^{(i)}) + \frac{\rho}{2}\|\boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y}^{(i)} - \boldsymbol{c} + \boldsymbol{u}^{(i)}\|_2^2 - \frac{\rho}{2}\|\boldsymbol{u}^{(i)}\|_2^2 \right), \\
\boldsymbol{y}^{(i+1)} &= \arg\min_{\boldsymbol{y}} \left( f(\boldsymbol{z}^{(i+1)}) + g(\boldsymbol{y}) + \frac{\rho}{2}\|\boldsymbol{A}\boldsymbol{z}^{(i+1)} + \boldsymbol{B}\boldsymbol{y} - \boldsymbol{c} + \boldsymbol{u}^{(i)}\|_2^2 - \frac{\rho}{2}\|\boldsymbol{u}^{(i)}\|_2^2 \right) \\
\boldsymbol{u}^{(i+1)} &= \boldsymbol{u}^{(i)} + \boldsymbol{A}\boldsymbol{z}^{(i+1)} + \boldsymbol{B}\boldsymbol{y}^{(i+1)} - \boldsymbol{c},
\end{aligned}$$

where $\rho > 0$ is the *penalty parameter* which is related to the convergent rate of the iterations.

*Note that the terms in blue can be omitted in practical computations!*

**References:**


- S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the ADMM, *Foundations and Trends in Machine Learning,* 3 (2010), pp. 1-122.
- ADMM算法原理詳解：https://zhuanlan.zhihu.com/p/448289351

# ADMM for the $\ell^1$-norm SR problem

- For the $\ell^1$-norm SR problem,

$$z^* = \arg\min_{z} \left( \frac{1}{2} \|x - Dz\|_2^2 + \lambda \|z\|_1 \right), \qquad \lambda > 0, \qquad (\star)$$

we set

$$f(z) := \frac{1}{2}\|x - Dz\|_2^2,\ g(y) := \lambda\|y\|_1,\ Az + By = c \Leftrightarrow z - y = 0.$$

- The ADMM for the $\ell^1$-norm SR problem is given by

$$z^{(i+1)} = \arg\min_{z} \left( \frac{1}{2}\|x - Dz\|_2^2 + \frac{\rho}{2}\|z - y^{(i)} + u^{(i)}\|_2^2 \right), \qquad (6_1)$$

$$y^{(i+1)} = \arg\min_{y} \left( \lambda\|y\|_1 + \frac{\rho}{2}\|z^{(i+1)} - y + u^{(i)}\|_2^2 \right), \qquad (6_2)$$

$$u^{(i+1)} = u^{(i)} + z^{(i+1)} - y^{(i+1)}, \qquad (6_3)$$

where $\rho > 0$ is *penalty parameter* related to the convergent rate of the iterations.

# Solving minimization problem $(6_1)$

Define

$$F_1(\boldsymbol{z}) := \frac{1}{2}\|\boldsymbol{x} - \boldsymbol{D}\boldsymbol{z}\|_2^2 + \frac{\rho}{2}\|\boldsymbol{z} - \boldsymbol{y}^{(i)} + \boldsymbol{u}^{(i)}\|_2^2.$$

Then $F_1$ is a quadratic function in variables $z_1, z_2, \cdots, z_n$ and $F_1(\boldsymbol{z}) \geq 0 \ \forall\, \boldsymbol{z} \in \mathbb{R}^n$. To solve "$\min\limits_{\boldsymbol{z}} F_1(\boldsymbol{z})$", first we compute

$$\begin{aligned}
\nabla F_1(\boldsymbol{z}) &= -\boldsymbol{D}^\top(\boldsymbol{x} - \boldsymbol{D}\boldsymbol{z}) + \rho\boldsymbol{I}(\boldsymbol{z} - \boldsymbol{y}^{(i)} + \boldsymbol{u}^{(i)}) \\
&= (\boldsymbol{D}^\top\boldsymbol{D} + \rho\boldsymbol{I})\boldsymbol{z} - \left(\boldsymbol{D}^\top\boldsymbol{x} + \rho(\boldsymbol{y}^{(i)} - \boldsymbol{u}^{(i)})\right).
\end{aligned}$$

Letting $\nabla F_1(\boldsymbol{z}) = \boldsymbol{0}$, we have

$$(\boldsymbol{D}^\top\boldsymbol{D} + \rho\boldsymbol{I})\boldsymbol{z} = \left(\boldsymbol{D}^\top\boldsymbol{x} + \rho(\boldsymbol{y}^{(i)} - \boldsymbol{u}^{(i)})\right).$$

Therefore, we obtain the solution

$$\boldsymbol{z}^{(i+1)} = (\boldsymbol{D}^\top\boldsymbol{D} + \rho\boldsymbol{I})^{-1}\left(\boldsymbol{D}^\top\boldsymbol{x} + \rho(\boldsymbol{y}^{(i)} - \boldsymbol{u}^{(i)})\right).$$

## Solving minimization problem $(6_2)$

Using the *soft-thresholding function* $\mathcal{S}_{\lambda/\rho}$, the solution of problem $(6_2)$ has the closed form (see next few pages):

$$\boldsymbol{y}^{(i+1)} = \mathcal{S}_{\lambda/\rho}(\boldsymbol{z}^{(i+1)} + \boldsymbol{u}^{(i)}),$$

where

$$\mathcal{S}_{\lambda/\rho}(\boldsymbol{v}) = \operatorname{sign}(\boldsymbol{v}) \odot \max(\boldsymbol{0}, |\boldsymbol{v}| - \lambda/\rho),$$

and $\operatorname{sign}(\cdot)$, $\max(\cdot,\cdot)$, and $|\cdot|$ are all applied to the input vector $\boldsymbol{v}$ component-wisely, and $\odot$ is the Hadamard product.

Finally, the iterative scheme can be posed as follows:

$$\begin{aligned} \boldsymbol{z}^{(i+1)} &= (\boldsymbol{D}^\top \boldsymbol{D} + \rho \boldsymbol{I})^{-1}(\boldsymbol{D}^\top \boldsymbol{x} + \rho(\boldsymbol{y}^{(i)} - \boldsymbol{u}^{(i)})), & (7_1) \\ \boldsymbol{y}^{(i+1)} &= \mathcal{S}_{\lambda/\rho}(\boldsymbol{z}^{(i+1)} + \boldsymbol{u}^{(i)}), & (7_2) \\ \boldsymbol{u}^{(i+1)} &= \boldsymbol{u}^{(i)} + \boldsymbol{z}^{(i+1)} - \boldsymbol{y}^{(i+1)}. & (7_3) \end{aligned}$$

## Details of the solution of problem $(6_2)$

Recall the problem $(6_2)$,

$$\boldsymbol{y}^{(i+1)} = \arg\min_{\boldsymbol{y}} \left( \lambda \|\boldsymbol{y}\|_1 + \frac{\rho}{2} \|\boldsymbol{z}^{(i+1)} - \boldsymbol{y} + \boldsymbol{u}^{(i)}\|_2^2 \right). \qquad (6_2)$$

Let $\boldsymbol{v} := \boldsymbol{z}^{(i+1)} + \boldsymbol{u}^{(i)} \in \mathbb{R}^n$. Then we have

$$\boldsymbol{y}^{(i+1)} = \arg\min_{\boldsymbol{y}} \left( \lambda \|\boldsymbol{y}\|_1 + \frac{\rho}{2} \|\boldsymbol{v} - \boldsymbol{y}\|_2^2 \right).$$

Define a real-valued function $F_2(\boldsymbol{y})$ as follows:

$$\begin{aligned} F_2(\boldsymbol{y}) &= \lambda \|\boldsymbol{y}\|_1 + \frac{\rho}{2} \|\boldsymbol{v} - \boldsymbol{y}\|_2^2 \\ &= \left( \lambda |y_1| + \frac{\rho}{2} (v_1 - y_1)^2 \right) + \cdots + \left( \lambda |y_n| + \frac{\rho}{2} (v_n - y_n)^2 \right) \\ &:= f_1(y_1) + \cdots + f_n(y_n), \end{aligned}$$

where we define

$$f_j(y) := \lambda |y| + \frac{\rho}{2} (v_j - y)^2 \quad \forall\, j = 1, 2, \cdots, n.$$

## Analysis of functions $f_j$

For simplicity of the presentation, we consider the function

$$f(y) = \lambda|y| + \frac{\rho}{2}(v-y)^2.$$

Computing the derivative of $f(y)$ for $y \neq 0$, we have

$$f'(y) = \begin{cases} \lambda - \rho(v-y) & \forall\, y > 0, \\ -\lambda - \rho(v-y) & \forall\, y < 0. \end{cases}$$

Let $f'(y) = 0$. Then we have

$$y = v - \frac{\lambda}{\rho} \text{ for } y > 0 \quad \text{and} \quad y = v + \frac{\lambda}{\rho} \text{ for } y < 0.$$

Therefore, the all critical numbers of $f$ are given by

$$c = v - \frac{\lambda}{\rho} \text{ if } c > 0, \quad c = v + \frac{\lambda}{\rho} \text{ if } c < 0, \quad c = 0.$$

*In order to find the minimum of $f$, we consider the following three cases:*

$$v > \frac{\lambda}{\rho}, \quad v < -\frac{\lambda}{\rho}, \quad -\frac{\lambda}{\rho} \leq v \leq \frac{\lambda}{\rho}.$$

## **Case 1:** $v > \frac{\lambda}{\rho}$

In this case, $c = v - \frac{\lambda}{\rho} > 0$ is the only critical number and

$$\begin{aligned} f(c) = f(v - \frac{\lambda}{\rho}) &= \lambda(v - \frac{\lambda}{\rho}) + \frac{\rho}{2}(v - (v - \frac{\lambda}{\rho}))^2 \\ &= \frac{\rho}{2}\left(v^2 - (v - \frac{\lambda}{\rho})^2\right) < \frac{\rho}{2}v^2 = f(0). \end{aligned}$$

For $y \geq 0$, since $f$ is a quadratic polynomial in $y$ with positive leading coefficient, we can conclude that $f(c) \leq f(y)$ for all $y \geq 0$.

For $y < 0$, $f(y)$ is monotone decreasing since

$$\begin{aligned} f'(y) &= \lambda \text{sign}(y) - \rho(v - y) = -\lambda - \rho v + \rho y \\ &< -\lambda - \lambda + \rho y = -2\lambda + \rho y < 0, \end{aligned}$$

which implies $f(y) > f(0)$ for all $y < 0$.

*Therefore, $f$ has a minimum at $c = v - \frac{\lambda}{\rho} > 0$.*

## Case 2: $v < -\frac{\lambda}{\rho}$

In this case, $c = v + \frac{\lambda}{\rho} < 0$ is the only critical number and

$$\begin{aligned} f(c) = f(v + \frac{\lambda}{\rho}) &= -\lambda(v + \frac{\lambda}{\rho}) + \frac{\rho}{2}\left(v - (v + \frac{\lambda}{\rho})\right)^2 \\ &= \frac{\rho}{2}\left(v^2 - (v + \frac{\lambda}{\rho})^2\right) < \frac{\rho}{2}v^2 = f(0). \end{aligned}$$

For $y \le 0$, since $f$ is a quadratic polynomial in $y$ with positive leading coefficient, we can conclude that $f(c) \le f(y)$ for all $y \le 0$.

For $y > 0$, $f(y)$ is monotone increasing since

$$\begin{aligned} f'(y) &= \lambda \text{sign}(y) - \rho(v - y) = \lambda - \rho v + \rho y \\ &> \lambda + \lambda + \rho y = 2\lambda + \rho y > 0, \end{aligned}$$

which implies $f(y) > f(0)$ for all $y > 0$.

*Therefore, $f$ has a minimum at $c = v + \frac{\lambda}{\rho} > 0$.*

## Case 3: $-\frac{\lambda}{\rho} \leq v \leq \frac{\lambda}{\rho}$

In this case, we have no critical number except the non-differentiable point $y = 0$.

For $y > 0$, we have

$$\begin{aligned} f'(y) &= \lambda - \rho(v - y) = \lambda - \rho v + \rho y \\ &\geq \lambda - \lambda + \rho y = \rho y > 0. \end{aligned}$$

Thus, $f(y)$ is monotone increasing and then $f(y) > f(0)$ for all $y > 0$.

For $y < 0$, we have

$$\begin{aligned} f'(y) &= -\lambda - \rho(v - y) = -\lambda - \rho v + \rho y \\ &\leq -\lambda + \lambda + \rho y = \rho y < 0. \end{aligned}$$

Thus, $f(y)$ is monotone decreasing and then $f(y) > f(0)$ for all $y < 0$.

*Therefore, $f$ has a minimum at 0.*

## Solution of problem $(6_2)$

By the above discussions, we have

$$\arg\min_y f(y) = \begin{cases} v + \frac{\lambda}{\rho}, & \text{if } v < -\frac{\lambda}{\rho}, \qquad \text{(case 2)} \\ 0, & \text{if } |v| \le \frac{\lambda}{\rho}, \qquad \text{(case 3)} \\ v - \frac{\lambda}{\rho}, & \text{if } v > \frac{\lambda}{\rho}. \qquad \text{(case 1)} \end{cases}$$

In other words, we have

$$\arg\min_y f(y) = \mathcal{S}_{\lambda/\rho}(v) = \operatorname{sign}(v) \max(0, |v| - \lambda/\rho).$$

Therefore,

$$\boldsymbol{y}^{(i+1)} = \arg\min_{\boldsymbol{y}} F_2(\boldsymbol{y}) = \mathcal{S}_{\lambda/\rho}(\boldsymbol{v}) = \mathcal{S}_{\lambda/\rho}(\boldsymbol{z}^{(i+1)} + \boldsymbol{u}^{(i)}).$$

where the soft-thresholding,

$$\mathcal{S}_{\lambda/\rho}(\boldsymbol{v}) := \operatorname{sign}(\boldsymbol{v}) \odot \max(\boldsymbol{0}, \ |\boldsymbol{v}| - \lambda/\rho),$$

and $\operatorname{sign}(\cdot)$, $\max(\cdot,\cdot)$, and $|\cdot|$ are all applied to the input vector $\boldsymbol{v}$ component-wisely, and $\odot$ is the Hadamard product.

## Application to signal denoising

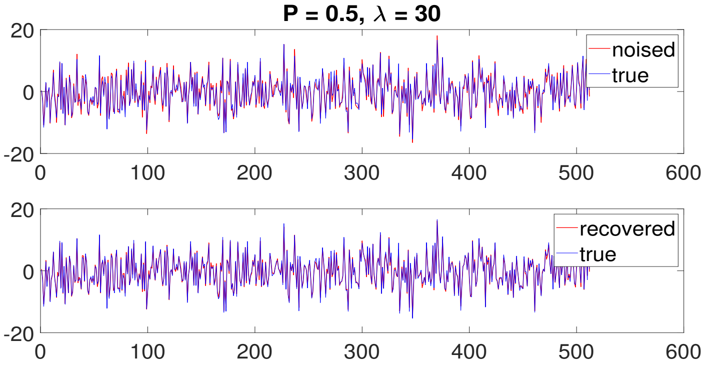
- First, we construct a random dictionary matrix $\boldsymbol{D} \in \mathbb{R}^{512\times 2048}$ and a random sparse vector $\boldsymbol{z} \in \mathbb{R}^{2048}$ with $\|\boldsymbol{z}\|_0 = 32$. We then have the true signal $\boldsymbol{x} := \boldsymbol{D}\boldsymbol{z}$.
- Define the noise signal $\boldsymbol{x}_n := \boldsymbol{x} + \boldsymbol{n}$, where $\boldsymbol{n} \in \mathbb{R}^{512}$ is a random white Gaussian noise with noised powers $P = 0.5, 1, 5$ (噪聲功率). We consider $\lambda = 5, 10, 20, 30$ for the minimization problem.
- *Peak signal-to-noise ratio (PSNR，峰值訊噪比)*: We define the mean squared error (MSE) and then the PSNR as follows:

$$MSE := \frac{1}{512}\sum_{i=1}^{512}\left(\text{true}(i) - \text{approx}(i)\right)^2,$$

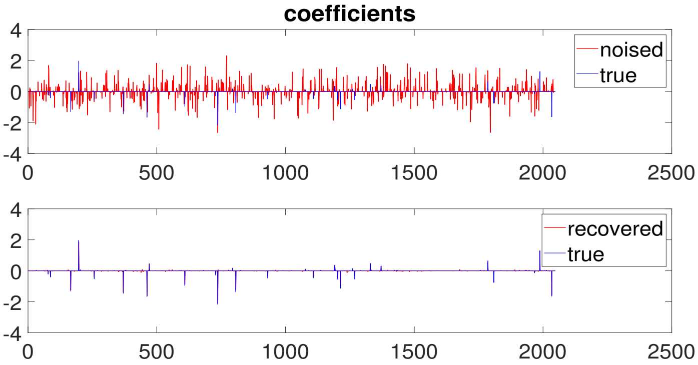
$$PSNR := 10 \times \log_{10}\left(\frac{\max^2}{MSE}\right),$$

  where "max" is the maximum amplitude of the true signal $\boldsymbol{x}$.
- Source of matlab code: `http://brendt.wohlberg.net/software/SPORCO/`

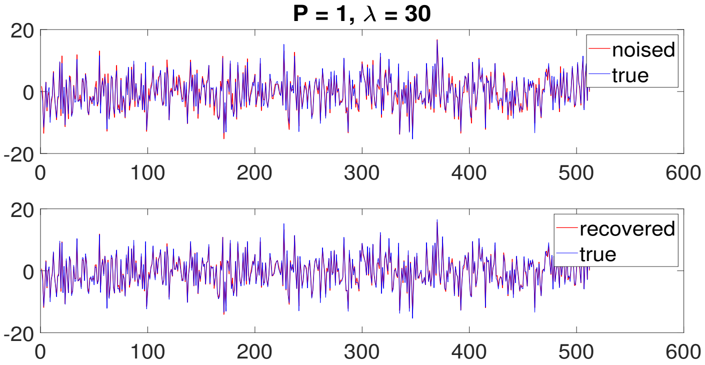
# Numerical results for $P = 0.5$ and $\lambda = 30$



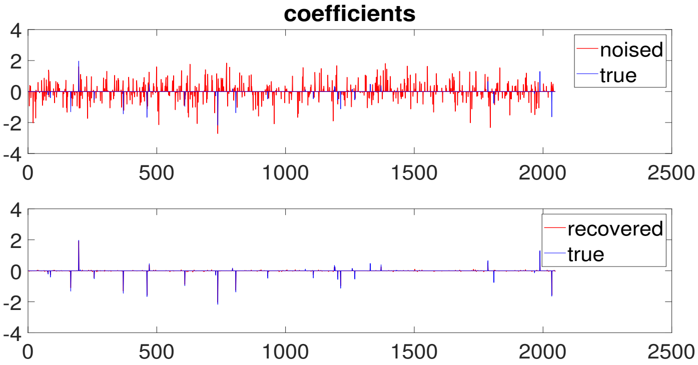
# Coefficients for $P = 0.5$ and $\lambda = 30$



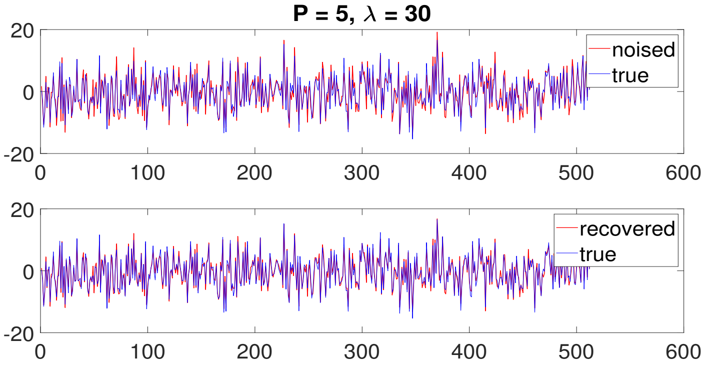
# Numerical results for $P = 1$ and $\lambda = 30$



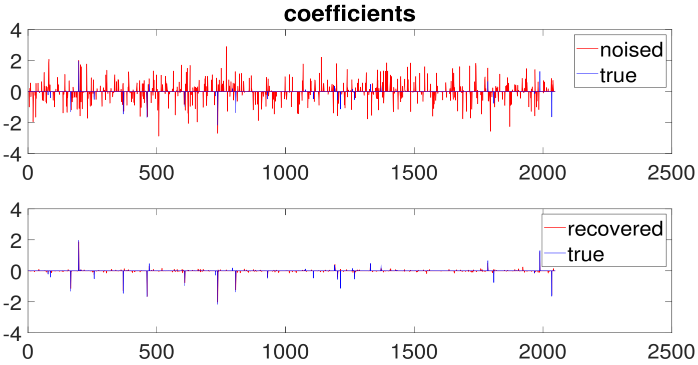
# Coefficients for $P = 1$ and $\lambda = 30$



# Numerical result for $P = 5$ and $\lambda = 30$



# Coefficients for $P = 5$ and $\lambda = 30$



# PSNR values and iteration numbers

*In general, the higher the value of PSNR the better the quality of the recovered signals.*

PSNR values

| $P$ | 0.5 | 0.5 | 1 | 1 | 5 | 5 |
|---|---|---|---|---|---|---|
| $\lambda$ | noised | rcvered | noised | rcvered | noised | rcvered |
| 5 | 29.51 | 30.36 | 29.71 | 30.41 | 25.57 | 26.11 |
| 10 | 29.51 | 31.16 | 29.71 | 31.10 | 25.57 | 26.63 |
| 20 | 29.51 | 32.55 | 29.71 | 32.23 | 25.57 | 27.62 |
| 30 | 29.51 | **33.45** | 29.71 | **32.77** | 25.57 | **28.50** |

Iteration numbers of ADMM

| $\lambda \backslash P$ | 0.5 | 1 | 5 |
|---|---|---|---|
| 5 | 550 | 664 | 569 |
| 10 | 301 | 303 | 320 |
| 20 | 172 | 169 | 186 |
| 30 | **129** | **130** | **154** |

## Sparse dictionary learning problem

*In the SR problem, the solution of interest $\mathbf{z}^*$ is the coefficient vector of a linear combination of over-complete basis elements (columns) from a given dictionary $\mathbf{D}$ under some sparsity constraint. Therefore, it is typically accompanied by a dictionary learning mechanism.*

We are going to study a more general problem. The dictionary $\boldsymbol{D}$ is unknown and needed to be sought together with the sparse solution.

**SDL problem:** *Let $\{\boldsymbol{x}_i\}_{i=1}^N \subset \mathbb{R}^m$ be a given dataset of signals. We seek a dictionary matrix $\boldsymbol{D} = [\boldsymbol{d}_1, \boldsymbol{d}_2, \cdots, \boldsymbol{d}_n] \in \mathbb{R}^{m\times n}$ together with the sparse coefficient vectors $\{\boldsymbol{z}_i\}_{i=1}^N \subset \mathbb{R}^n$ that solve the minimization problem:*

$$\min_{\boldsymbol{D},\{\boldsymbol{z}_i\}} \left( \frac{1}{2} \sum_{i=1}^N \|\boldsymbol{x}_i - \boldsymbol{D}\boldsymbol{z}_i\|_2^2 + \lambda \sum_{i=1}^N \|\boldsymbol{z}_i\|_1 \right)$$
$$\text{subject to } \|\boldsymbol{d}_k\|_2 \le 1,\ \forall\, 1 \le k \le n,$$

*where $\lambda > 0$ is a penalty parameter.*

## Problem formulation in a more compact form

To simplify the formulation of the SDL problem, we define

$$\begin{aligned} \boldsymbol{X} &= [\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_N] \in \mathbb{R}^{m\times N}, \\ \boldsymbol{Z} &= [\boldsymbol{z}_1, \boldsymbol{z}_2, \cdots, \boldsymbol{z}_N] \in \mathbb{R}^{n\times N}. \end{aligned}$$

Then the SDL problem can be posed as follows: *Given a training data matrix* $\boldsymbol{X}$*, find a dictionary matrix* $\boldsymbol{D}$ *and a coefficient matrix* $\boldsymbol{Z}$ *such that*

$$\min_{\boldsymbol{D},\,\boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{X} - \boldsymbol{D}\boldsymbol{Z}\|_F^2 + \lambda \|\boldsymbol{Z}\|_{1,1} \right) \qquad (\star\star)$$

$$\text{subject to } \|\boldsymbol{d}_k\|_2 \le 1, \ \forall\, 1 \le k \le n,$$

*where* $\|\cdot\|_F$ *denotes the Frobenius norm and* $\|\boldsymbol{Z}\|_{1,1}$ *is the* $L_{1,1}$*-norm which is defined as*

$$\|\boldsymbol{Z}\|_{1,1} := \sum_{i=1}^{N} \|\boldsymbol{z}_i\|_1.$$

## An iterative approach for solving the SDL problem

In the SDL problem $(\star\star)$, we have two unknown matrices $\boldsymbol{D}$ and $\boldsymbol{Z}$. We will use a simple iterative approach together with the ADMM to solve $(\star\star)$, though it is more complicated.

Given an initial guess $\boldsymbol{D}_{(0)}$, for $j = 0, 1, \cdots$, we solve the following two sub-problems alternatingly:

$$\boldsymbol{Z}_{(j)} = \arg\min_{\boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{X} - \boldsymbol{D}_{(j)}\boldsymbol{Z}\|_F^2 + \lambda \|\boldsymbol{Z}\|_{1,1} \right), \tag{8}$$

$$\boldsymbol{D}_{(j+1)} = \arg\min_{\boldsymbol{D}} \left( \frac{1}{2} \|\boldsymbol{X} - \boldsymbol{D}\boldsymbol{Z}_{(j)}\|_F^2 + \lambda \|\boldsymbol{Z}_{(j)}\|_{1,1} \right) \quad \text{subject to } \|\boldsymbol{d}_k\|_2 \le 1, \ \forall\, 1 \le k \le n. \tag{9}$$

We iterate (8) and (9) until convergence is achieved. As we have introduced previously, problems (8) and (9) will be solved by ADMM.

# ADMM for solving problem (8)

- Adding an *auxiliary variable* $\boldsymbol{Y}$ and a *dual variable* $\boldsymbol{U}$, we define

$$f(\boldsymbol{Z}) := \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{D}_{(j)}\boldsymbol{Z}\|_F^2, \quad g(\boldsymbol{Y}) := \lambda\|\boldsymbol{Y}\|_{1,1}, \quad \boldsymbol{Z} = \boldsymbol{Y}.$$

- Then the ADMM for solving (8) is given by

$$\begin{aligned}
\boldsymbol{Z}^{(i+1)} &= \arg\min_{\boldsymbol{Z}} \left( \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{D}_{(j)}\boldsymbol{Z}\|_F^2 + \frac{\rho}{2}\|\boldsymbol{Z} - \boldsymbol{Y}^{(i)} + \boldsymbol{U}^{(i)}\|_F^2 \right), \quad (8_1) \\
\boldsymbol{Y}^{(i+1)} &= \arg\min_{\boldsymbol{Y}} \left( \lambda\|\boldsymbol{Y}\|_{1,1} + \frac{\rho}{2}\|\boldsymbol{Z}^{(i+1)} - \boldsymbol{Y} + \boldsymbol{U}^{(i)}\|_F^2 \right), \quad (8_2) \\
\boldsymbol{U}^{(i+1)} &= \boldsymbol{U}^{(i)} + \boldsymbol{Z}^{(i+1)} - \boldsymbol{Y}^{(i+1)}. \quad (8_3).
\end{aligned}$$

- Similar to the SR problem, we will use the same methods to solve the sub-problems $(8_1)$ and $(8_2)$.

# Solving minimization problem $(8_1)$

Define

$$F_1(\boldsymbol{Z}) := \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{D}_{(j)}\boldsymbol{Z}\|_F^2 + \frac{\rho}{2}\|\boldsymbol{Z} - \boldsymbol{Y}^{(i)} + \boldsymbol{U}^{(i)}\|_F^2.$$

To solve "$\min_{\boldsymbol{Z}} F_1(\boldsymbol{Z})$", first we compute

$$\begin{aligned}\nabla F_1(\boldsymbol{Z}) &= -\boldsymbol{D}_{(j)}^\top(\boldsymbol{X} - \boldsymbol{D}_{(j)}\boldsymbol{Z}) + \rho\boldsymbol{I}(\boldsymbol{Z} - \boldsymbol{Y}^{(i)} + \boldsymbol{U}^{(i)}) \\ &= (\boldsymbol{D}_{(j)}^\top\boldsymbol{D}_{(j)} + \rho\boldsymbol{I})\boldsymbol{Z} - \left(\boldsymbol{D}_{(j)}^\top\boldsymbol{X} + \rho(\boldsymbol{Y}^{(i)} - \boldsymbol{U}^{(i)})\right).\end{aligned}$$

Letting $\nabla F_1(\boldsymbol{Z}) = 0$, we have

$$(\boldsymbol{D}_{(j)}^\top\boldsymbol{D}_{(j)} + \rho\boldsymbol{I})\boldsymbol{Z} = \left(\boldsymbol{D}_{(j)}^\top\boldsymbol{X} + \rho(\boldsymbol{Y}^{(i)} - \boldsymbol{U}^{(i)})\right).$$

Therefore, we obtain the solution

$$\boldsymbol{Z}^{(i+1)} = (\boldsymbol{D}_{(j)}^\top\boldsymbol{D}_{(j)} + \rho\boldsymbol{I})^{-1}\left(\boldsymbol{D}_{(j)}^\top\boldsymbol{X} + \rho(\boldsymbol{Y}^{(i)} - \boldsymbol{U}^{(i)})\right).$$

# Solving minimization problem $(8_2)$

Using the component-wise soft-thresholding function, the solution of problem $(8_2)$ has the closed form:

$$\boldsymbol{Y}^{(i+1)} = \mathcal{S}_{\lambda/\rho}(\boldsymbol{Z}^{(i+1)} + \boldsymbol{U}^{(i)}),$$

where

$$\mathcal{S}_{\lambda/\rho}(\boldsymbol{V}) = \text{sign}(\boldsymbol{V}) \odot \max(\boldsymbol{0}, |\boldsymbol{V}| - \lambda/\rho),$$

with $\text{sign}(\boldsymbol{V})$ and $|\boldsymbol{V}|$ are element-wisely applied to the matrix $\boldsymbol{V}$ and $\odot$ is the Hadamard product.

Therefore, the iterative scheme can be posed as follows:

$$\boldsymbol{Z}^{(i+1)} = (\boldsymbol{D}_{(j)}^\top \boldsymbol{D}_{(j)} + \rho \boldsymbol{I})^{-1}(\boldsymbol{D}_{(j)}^\top \boldsymbol{X} + \rho(\boldsymbol{Y}^{(i)} - \boldsymbol{U}^{(i)})), \qquad (10_1)$$

$$\boldsymbol{Y}^{(i+1)} = \mathcal{S}_{\lambda/\rho}(\boldsymbol{Z}^{(i+1)} + \boldsymbol{U}^{(i)}), \qquad (10_2)$$

$$\boldsymbol{U}^{(i+1)} = \boldsymbol{U}^{(i)} + \boldsymbol{Z}^{(i+1)} - \boldsymbol{Y}^{(i+1)}. \qquad (10_3)$$

# Solving minimization problem (9)

Recall that

$$D_{(j+1)} = \arg\min_{D} \left( \frac{1}{2} \|X - DZ_{(j)}\|_F^2 + \lambda \|Z_{(j)}\|_{1,1} \right)$$
$$\text{subject to } \|d_k\|_2 \leq 1, \ \forall\, 1 \leq k \leq n. \qquad (9)$$

*Since the term $\lambda \|Z_{(j)}\|_{1,1}$ is a fixed number when $Z_{(j)}$ is given, problem (9) can be replaced by*

$$D_{(j+1)} = \arg\min_{D} \frac{1}{2} \|X - DZ_{(j)}\|_F^2$$
$$\text{subject to } \|d_k\|_2 \leq 1, \ \forall\, 1 \leq k \leq n. \qquad (9')$$

Next, we introduce an *auxiliary variable* $G$ and a *dual variable* $H$ in ADMM for solving (9′).

# ADMM for solving problem (9′)

Define

$$\begin{aligned} g(G) &:= \{[d_1, d_2, \cdots, d_n] : \|d_k\|_2 \le 1, \ \forall\, 1 \le k \le n\}, \\ G &:= D. \end{aligned}$$

The ADMM for solving problem (9′) is given by

$$\begin{aligned} D^{(i+1)} &= \arg\min_{D} \left( \frac{1}{2}\|X - DZ_{(j)}\|_F^2 + \frac{\rho}{2}\|D - G^{(i)} + H^{(i)}\|_F^2 \right), \quad (9_1) \\ G^{(i+1)} &= \mathrm{proj}_{g(G)}\{D^{(i+1)}\}, \quad (9_2) \\ H^{(i+1)} &= H^{(i)} + D^{(i+1)} - G^{(i+1)}. \quad (9_3) \end{aligned}$$

For solving problem $(9_1)$, we define

$$F_2(D) := \frac{1}{2}\|X - DZ_{(j)}\|_F^2 + \frac{\rho}{2}\|D - G^{(i)} + H^{(i)}\|_F^2.$$

## Solving minimization problem $(9_1)$

Computing $\nabla F_2(\boldsymbol{D})$, we have

$$\begin{aligned}\nabla F_2(\boldsymbol{D}) &= (\boldsymbol{X} - \boldsymbol{D}\boldsymbol{Z}_{(j)})(-\boldsymbol{Z}_{(j)}^\top) + \rho \boldsymbol{I}_m(\boldsymbol{D} - \boldsymbol{G}^{(i)} + \boldsymbol{H}^{(i)}) \\ &= \boldsymbol{D}(\rho \boldsymbol{I}_n + \boldsymbol{Z}_{(j)}\boldsymbol{Z}_{(j)}^\top) + \boldsymbol{X}\boldsymbol{Z}_{(j)}^\top - \rho(\boldsymbol{G}^{(i)} - \boldsymbol{H}^{(i)}).\end{aligned}$$

Letting $\nabla F_2(\boldsymbol{D}) = \boldsymbol{0}$, we have

$$\boldsymbol{D}(\boldsymbol{Z}_{(j)}\boldsymbol{Z}_{(j)}^\top + \rho \boldsymbol{I}_n) = \boldsymbol{X}\boldsymbol{Z}_{(j)}^\top - \rho(\boldsymbol{G}^{(i)} - \boldsymbol{H}^{(i)}).$$

Therefore, we obtain the solution

$$\boldsymbol{D}^{(i+1)} = \left(\boldsymbol{X}\boldsymbol{Z}_{(j)}{}^\top - \rho(\boldsymbol{G}^{(i)} - \boldsymbol{H}^{(i)})\right)\left(\boldsymbol{Z}_{(j)}\boldsymbol{Z}_{(j)}{}^\top + \rho \boldsymbol{I}_n\right)^{-1}.$$

Finally, the ADMM for problem (9') is given by

$$\begin{aligned}\boldsymbol{D}^{(i+1)} &= \left(\boldsymbol{X}\boldsymbol{Z}_{(j)}{}^\top - \rho(\boldsymbol{G}^{(i)} - \boldsymbol{H}^{(i)})\right)\left(\boldsymbol{Z}_{(j)}\boldsymbol{Z}_{(j)}{}^\top + \rho \boldsymbol{I}_n\right)^{-1}, \quad (11_1) \\ \boldsymbol{G}^{(i+1)} &= \operatorname{proj}_{\boldsymbol{g}(\boldsymbol{G})}\{\boldsymbol{D}^{(i+1)}\}, \quad (11_2) \\ \boldsymbol{H}^{(i+1)} &= \boldsymbol{H}^{(i)} + \boldsymbol{D}^{(i+1)} - \boldsymbol{G}^{(i+1)}. \quad (11_3)\end{aligned}$$

## Convergence and stopping criterion

- In [Boyd *et al.* 2010], there are more details about convergence results of the ADMM.
- In the iterative scheme $(10_1), (10_2), (10_3)$, we define

$$\boldsymbol{R}_z = \boldsymbol{Y}^{(i+1)} - \boldsymbol{Y}^{(i)}, \quad \boldsymbol{S}_z = \boldsymbol{U}^{(i+1)} - \boldsymbol{U}^{(i)}.$$

If $\boldsymbol{R}_z$ and $\boldsymbol{S}_z$ less than the tolerances $\varepsilon_{R_z}$ and $\varepsilon_{S_z}$, then we say that the iteration of coefficients $\boldsymbol{Z}^{(i+1)}$ converges.

In the iterative scheme $(11_1), (11_2), (11_3)$, we define

$$\boldsymbol{R}_d = \boldsymbol{G}^{(i+1)} - \boldsymbol{G}^{(i)}, \quad \boldsymbol{S}_d = \boldsymbol{H}^{(i+1)} - \boldsymbol{H}^{(i)}.$$

If $\boldsymbol{R}_d$ and $\boldsymbol{S}_d$ less than the tolerances $\varepsilon_{R_d}$ and $\varepsilon_{S_d}$, then we say that the iteration of dictionary $\boldsymbol{D}^{(i+1)}$ converges.

# References and source codes

**$\ell^1$-$\ell^0$ equivalence problem:**

[1] D. L. Donoho, For most large underdetermined systems of linear equations the minimal $\ell_1$-norm solution is also the sparsest solution, *Communications on Pure and Applied Mathematics, 59 (2006), pp. 797-829.*

[2] Y. Sharon, J. Wright, and Y. Ma, Computation and relaxation of conditions for equivalence between $\ell^1$ and $\ell^0$ minimization, *UIUC Technical Report UILU-ENG-07-2008, 2007.*

**ADMM:**

[1] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the ADMM, *Foundations and Trends in Machine Learning, 3 (2010), pp. 1-122.*

**Sparse dictionary learning:**

https://en.wikipedia.org/wiki/Sparse_dictionary_learning

**Matlab codes:** http://brendt.wohlberg.net/software/SPORCO/

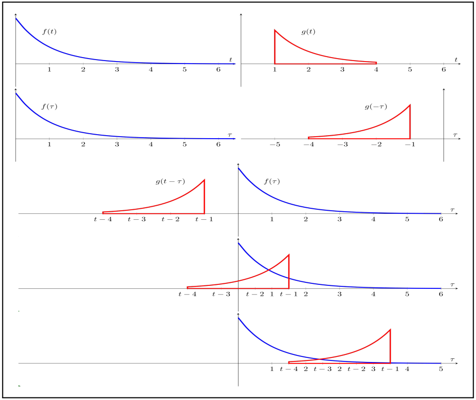
# Part II

# Convolutional Sparse Representation and Dictionary Learning

# Convolution of two functions

Let $f$ and $g$ be two integrable functions with compact supports in $\mathbb{R}$. Then the convolution of $f$ and $g$ is defined as a function in variable $t$,

$$(f * g)(t) := \int_{-\infty}^{\infty} f(\tau)g(t-\tau)\,d\tau, \quad t \in \mathbb{R}.$$



## Convolution of two vectors

**Definition:** *Let* $\boldsymbol{u} = [u_1, \cdots, u_n]^\top \in \mathbb{R}^n$ *and* $\boldsymbol{v} = [v_1, \cdots, v_m]^\top \in \mathbb{R}^m$. *The convolution of* $\boldsymbol{u}$ *and* $\boldsymbol{v}$*, denoted by* $\boldsymbol{u} * \boldsymbol{v}$*, is defined as follows:*

$$\boldsymbol{u} * \boldsymbol{v} := \begin{bmatrix} u_1 v_1 \\ u_1 v_2 + u_2 v_1 \\ u_1 v_3 + u_2 v_2 + u_3 v_1 \\ \vdots \\ u_{n-2} v_m + u_{n-1} v_{m-1} + u_n v_{m-2} \\ u_{n-1} v_m + u_n v_{m-1} \\ u_n v_m \end{bmatrix} \in \mathbb{R}^{m+n-1}.$$

*More specifically, for* $i = 1, 2, \cdots, (m+n-1)$*, the* $i$*-th component of* $\boldsymbol{u} * \boldsymbol{v}$ *is given by*

$$(\boldsymbol{u} * \boldsymbol{v})_i = \sum_{j=\max(1, i-m+1)}^{\min(i,n)} u_j v_{i-j+1}.$$

**Remark:** Convolutional operator $*$ is commutative, i.e., $\boldsymbol{u} * \boldsymbol{v} = \boldsymbol{v} * \boldsymbol{u}$.

# Convolutional sparse representation (CSR) problem

**CSR problem:** *Given a signal* $\boldsymbol{x} \in \mathbb{R}^m$ *and a dictionary* $\boldsymbol{D} = [\boldsymbol{d}_1, \cdots, \boldsymbol{d}_n] \in \mathbb{R}^{\ell \times n}$, *we seek a sparse matrix* $\boldsymbol{Z} = [\boldsymbol{z}_1, \cdots, \boldsymbol{z}_n] \in \mathbb{R}^{k \times n}$, $m = \ell + k - 1$, *which solves the following minimization problem:*

$$\min_{\boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{x} - \sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j\|_2^2 + \lambda \sum_{j=1}^{n} \|\boldsymbol{z}_j\|_1 \right),$$

*where* $\lambda > 0$ *is a penalty parameter.*

**Remarks:**

- In SR, we use $\boldsymbol{D}\boldsymbol{z}$ to recover the signal $\boldsymbol{x}$,

$$\boldsymbol{x} \approx \boldsymbol{D}\boldsymbol{z} = \boldsymbol{d}_1 z_1 + \boldsymbol{d}_2 z_2 + \cdots + \boldsymbol{d}_n z_n = \sum_{j=1}^{n} \boldsymbol{d}_j z_j.$$

  In CSR, we use $\sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j$ instead,

$$\boldsymbol{x} \approx \boldsymbol{d}_1 * \boldsymbol{z}_1 + \boldsymbol{d}_2 * \boldsymbol{z}_2 + \cdots + \boldsymbol{d}_n * \boldsymbol{z}_n = \sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j.$$

- Convolution is a way to regulate $\boldsymbol{d}_j * \boldsymbol{z}_j$ such that $\boldsymbol{x} \approx \sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j$. It is more flexible than $\boldsymbol{x} \approx \sum_{j=1}^{n} \boldsymbol{d}_j z_j$, but indeed more expensive!

## Toeplitz matrix

We define an $(m+n-1) \times m$ matrix $\boldsymbol{U}$ in terms of $u_i$, which is called a *Toeplitz matrix*, as follows:

$$
\boldsymbol{U} := \begin{bmatrix}
u_1 & 0 & \cdots & 0 & 0 \\
u_2 & u_1 & \ddots & 0 & 0 \\
\vdots & u_2 & \ddots & 0 & 0 \\
\vdots & \vdots & \ddots & u_1 & 0 \\
u_{n-1} & \vdots & \vdots & u_2 & u_1 \\
u_n & u_{n-1} & \vdots & \vdots & u_2 \\
0 & u_n & \ddots & \vdots & \vdots \\
0 & 0 & \ddots & u_{n-1} & \vdots \\
\vdots & \vdots & \ddots & u_n & u_{n-1} \\
0 & 0 & \cdots & 0 & u_n
\end{bmatrix}_{(m+n-1)\times m}
$$

Then one can check that $\boldsymbol{u} * \boldsymbol{v} = \boldsymbol{U}\boldsymbol{v}$, where $\boldsymbol{u} = [u_1, \cdots, u_n]^\top \in \mathbb{R}^n$ and $\boldsymbol{v} = [v_1, \cdots, v_m]^\top \in \mathbb{R}^m$.

## CSR problem using Toeplitz matrices

With the help of Toeplitz matrix, we can rewrite the CSR problem as

$$\min_{\widetilde{z}} \left( \frac{1}{2} \left\| x - \widetilde{D}\widetilde{z} \right\|_2^2 + \lambda \|\widetilde{z}\|_1 \right), \qquad (12)$$

*with*

$$\widetilde{z} = [z_1^\top, z_2^\top, \cdots, z_n^\top]^\top_{nk \times 1} \quad \text{and} \quad \widetilde{D} = [D_1, D_2, \cdots, D_n]_{(\ell+k-1)\times nk},$$

*where* $D_j$ *is a Toeplitz* $(\ell + k - 1) \times k$ *matrix associated with the column vector* $d_j \in \mathbb{R}^\ell$, *and* $\ell + k - 1 = m$.

**Remarks:**

- We can use the same way for SR problem to solve the CSR problem (12). We can employ the ADMM, but it is too expensive since the matrix size of $\widetilde{D}$ is too large.
- *The discrete Fourier transform* $\mathcal{F} : \mathbb{C}^N \to \mathbb{C}^N$ *can help us to address this computational issue.*

# Discrete Fourier transform (DFT) and its inverse (IDFT)

- $\widehat{\boldsymbol{x}} = \mathcal{F}(\boldsymbol{x})$ : The DFT $\mathcal{F} : \mathbb{C}^N \to \mathbb{C}^N$ transforms a finite vector $\boldsymbol{x} = [x_1, x_2, \cdots, x_N]^\top$ into another vector $\widehat{\boldsymbol{x}} = [\widehat{x}_1, \widehat{x}_2, \cdots, \widehat{x}_N]^\top$, which is defined by

$$\widehat{x}_k = \sum_{n=1}^{N} x_n e^{-\frac{i2\pi}{N}(k-1)(n-1)}.$$

*Then DFT is an invertible linear transformation.*

- $\boldsymbol{x} = \mathcal{F}^{-1}(\widehat{\boldsymbol{x}})$ : The inverse discrete Fourier transform (IDFT) $\mathcal{F}^{-1} : \mathbb{C}^N \to \mathbb{C}^N, \widehat{\boldsymbol{x}} \mapsto \boldsymbol{x}$, is given by

$$x_n = \frac{1}{N} \sum_{k=1}^{N} \widehat{x}_k e^{\frac{i2\pi}{N}(k-1)(n-1)}.$$

- Euler's formula: $e^{i\theta} = \cos\theta + i\sin\theta, \forall\, \theta \in \mathbb{R}$.

https://en.wikipedia.org/wiki/Discrete_Fourier_transform

# Hadamard product

- Let $\boldsymbol{u} \in \mathbb{R}^n$ and $\boldsymbol{v} \in \mathbb{R}^m$. Then $\boldsymbol{u} * \boldsymbol{v} \in \mathbb{R}^{m+n-1}$ and
$$\mathcal{F}(\boldsymbol{u} * \boldsymbol{v}) = \mathcal{F}(\boldsymbol{u}') \odot \mathcal{F}(\boldsymbol{v}'),$$
where $\mathcal{F}$ denotes the DFT, $\boldsymbol{u}'$ and $\boldsymbol{v}'$ are respectively *the zero padding of* $\boldsymbol{u}$ *and* $\boldsymbol{v}$ with the same size of $\boldsymbol{u} * \boldsymbol{v}$, i.e.,
$$\boldsymbol{u}' = [\boldsymbol{u}^\top, 0, \cdots, 0]^\top, \quad \boldsymbol{v}' = [\boldsymbol{v}^\top, 0, \cdots, 0]^\top \in \mathbb{R}^{m+n-1},$$
and $\odot$ is the Hadamard product.
- The Hadamard product $\odot$ of two vectors is a component-wise product. Let $\boldsymbol{u} = [u_1, u_2, \cdots, u_n]^\top$, $\boldsymbol{v} = [v_1, v_2, \cdots, v_n]^\top \in \mathbb{R}^n$,
$$\boldsymbol{u} \odot \boldsymbol{v} := [u_1 v_1, u_2 v_2, \cdots, u_n v_n]^\top.$$
We can define a diagonal matrix $\boldsymbol{U}$ such that $\boldsymbol{u} \odot \boldsymbol{v} = \boldsymbol{U}\boldsymbol{v}$, where
$$\boldsymbol{U} := \begin{bmatrix} u_1 & 0 & \cdots & 0 \\ 0 & u_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & u_n \end{bmatrix}.$$

## Recalling the CSR problem

**CSR problem:** *Given $\boldsymbol{x} \in \mathbb{R}^m$ and $\boldsymbol{D} = [\boldsymbol{d}_1, \cdots, \boldsymbol{d}_n] \in \mathbb{R}^{\ell \times n}$, we seek $\boldsymbol{Z} = [\boldsymbol{z}_1, \cdots, \boldsymbol{z}_n] \in \mathbb{R}^{k \times n}$ with $m = \ell + k - 1$ solving*

$$\min_{\boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{x} - \sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j\|_2^2 + \lambda \sum_{j=1}^{n} \|\boldsymbol{z}_j\|_1 \right).$$

To solve the above minimization problem, we first use the ADMM algorithm to split it into three subproblems:

$$\begin{aligned}
\boldsymbol{Z}^{(i+1)} &= \arg\min_{\boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{x} - \sum_{j=1}^{n} \boldsymbol{d}_j * \boldsymbol{z}_j\|_2^2 + \frac{\rho}{2} \sum_{j=1}^{n} \|\boldsymbol{z}_j - \boldsymbol{y}_j^{(i)} + \boldsymbol{u}_j^{(i)}\|_2^2 \right), \\
\boldsymbol{Y}^{(i+1)} &= \arg\min_{\boldsymbol{Y}} \left( \lambda \sum_{j=1}^{n} \|\boldsymbol{y}_j\|_1 + \frac{\rho}{2} \sum_{j=1}^{n} \|\boldsymbol{z}_j^{(i+1)} - \boldsymbol{y}_j + \boldsymbol{u}_j^{(i)}\|_2^2, \right) \\
\boldsymbol{U}^{(i+1)} &= \boldsymbol{U}^{(i)} + \boldsymbol{Z}^{(i+1)} - \boldsymbol{Y}^{(i+1)}.
\end{aligned}$$

## Using discrete Fourier transform for $Z$

We will use the discrete Fourier transform and Hadamard product to solve the subproblem of $\boldsymbol{Z}$. We can rewrite these subproblems as

$$
\begin{aligned}
\widehat{\boldsymbol{Z}}^{(i+1)} &= \arg\min_{\widehat{\boldsymbol{Z}}} \left( \frac{1}{2} \|\widehat{\boldsymbol{x}} - \sum_{j=1}^{n} \widehat{\boldsymbol{d}}_j' \odot \widehat{\boldsymbol{z}}_j' \|_2^2 + \frac{\rho}{2} \sum_{j=1}^{n} \|\widehat{\boldsymbol{z}}_j' - \widehat{\boldsymbol{y}}_j'^{(i)} + \widehat{\boldsymbol{u}}_j'^{(i)} \|_2^2 \right), \\
\boldsymbol{Y}^{(i+1)} &= \arg\min_{\boldsymbol{Y}} \left( \lambda \sum_{j=1}^{n} \|\boldsymbol{y}_j\|_1 + \frac{\rho}{2} \sum_{j=1}^{n} \|\mathcal{F}^{-1}(\widehat{\boldsymbol{z}}_j'^{(i+1)}) - \boldsymbol{y}_j + \boldsymbol{u}_j^{(i)} \|_2^2 \right), \\
\boldsymbol{U}^{(i+1)} &= \boldsymbol{U}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}^{(i+1)}) - \boldsymbol{Y}^{(i+1)},
\end{aligned}
$$

where

$$
\mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}) = [\mathcal{F}^{-1}(\widehat{\boldsymbol{z}}_1'), \mathcal{F}^{-1}(\widehat{\boldsymbol{z}}_2'), \cdots, \mathcal{F}^{-1}(\widehat{\boldsymbol{z}}_n')].
$$

## Why can we use the discrete Fourier transform?

Note that the discrete Fourier transform $\mathcal{F}$ is linear. Thus, we have

$$\begin{aligned}
\frac{1}{2}\|\boldsymbol{x}-\sum_{j=1}^{n}\boldsymbol{d}_j*\boldsymbol{z}_j\|_2^2 &= \frac{1}{2m}\|\mathcal{F}(\boldsymbol{x}-\sum_{j=1}^{n}\boldsymbol{d}_j*\boldsymbol{z}_j)\|_2^2 \quad \text{(Plancherel theorem)}\\
&= \frac{1}{2m}\|\mathcal{F}(\boldsymbol{x})-\mathcal{F}(\sum_{j=1}^{n}\boldsymbol{d}_j*\boldsymbol{z}_j)\|_2^2\\
&= \frac{1}{2m}\|\widehat{\boldsymbol{x}}-\sum_{j=1}^{n}\mathcal{F}(\boldsymbol{d}_j*\boldsymbol{z}_j)\|_2^2 = \frac{1}{2m}\|\widehat{\boldsymbol{x}}-\sum_{j=1}^{n}\widehat{\boldsymbol{d}_j'}\odot\widehat{\boldsymbol{z}_j'}\|_2^2.
\end{aligned}$$

Similarly, the second term of subproblem $\boldsymbol{Z}$ can be rewritten as

$$\begin{aligned}
\frac{\rho}{2}\sum_{j=1}^{n}\|\boldsymbol{z}_j-\boldsymbol{y}_j^{(i)}+\boldsymbol{u}_j^{(i)}\|_2^2 &= \frac{\rho}{2}\sum_{j=1}^{n}\|\boldsymbol{z}_j'-\boldsymbol{y}_j'^{(i)}+\boldsymbol{u}_j'^{(i)}\|_2^2\\
&= \frac{\rho}{2m}\sum_{j=1}^{n}\|\widehat{\boldsymbol{z}_j'}-\widehat{\boldsymbol{y}_j'}^{(i)}+\widehat{\boldsymbol{u}_j'}^{(i)}\|_2^2.
\end{aligned}$$

**Note:** $\boldsymbol{x}\in\mathbb{R}^m$, $\boldsymbol{d}_j\in\mathbb{R}^\ell$, $\boldsymbol{z}_j\in\mathbb{R}^k$, $\boldsymbol{d}_j*\boldsymbol{z}_j\in\mathbb{R}^{\ell+k-1}=\mathbb{R}^m$, $\boldsymbol{d}_j', \boldsymbol{z}_j'\in\mathbb{R}^m$.

## The subproblem of $\widehat{Z}$

We first define

$$\widehat{\boldsymbol{D}_j} = \operatorname{diag}(\widehat{\boldsymbol{d}'_j}). \quad (m \times m \textit{ disgonal matrix})$$

Then the subproblem in the Fourier domain can be posed as:

$$\widehat{\boldsymbol{z}}^{(i+1)} = \arg\min_{\widehat{\boldsymbol{z}}} \Big( \frac{1}{2} \|\widehat{\boldsymbol{x}} - \widehat{\boldsymbol{D}}\widehat{\boldsymbol{z}}\|_2^2 + \frac{\rho}{2} \|\widehat{\boldsymbol{z}} - \widehat{\boldsymbol{y}}^{(i)} + \widehat{\boldsymbol{u}}^{(i)}\|_2^2 \Big),$$

where

$$\widehat{\boldsymbol{D}} = [\widehat{\boldsymbol{D}}_1, \widehat{\boldsymbol{D}}_2, \cdots, \widehat{\boldsymbol{D}}_n]_{m \times mn}, \quad \widehat{\boldsymbol{z}} = [\widehat{\boldsymbol{z}'_1}^\top, \widehat{\boldsymbol{z}'_2}^\top, \cdots, \widehat{\boldsymbol{z}'_n}^\top]^\top_{mn \times 1},$$

and

$$\widehat{\boldsymbol{y}} = [\widehat{\boldsymbol{y}'_1}^\top, \widehat{\boldsymbol{y}'_2}^\top, \cdots, \widehat{\boldsymbol{y}'_n}^\top]^\top_{mn \times 1}, \quad \widehat{\boldsymbol{u}} = [\widehat{\boldsymbol{u}'_1}^\top, \widehat{\boldsymbol{u}'_2}^\top, \cdots, \widehat{\boldsymbol{u}'_n}^\top]^\top_{mn \times 1}.$$

*Note that we drop the scalar factor $1/m$ in the subproblem.*

## Rewriting the subproblems of ADMM

Using the above definitions, we can rewrite the subproblems of ADMM as:

$$\widehat{\boldsymbol{z}}^{(i+1)} = \min_{\widehat{\boldsymbol{z}}} \left( \frac{1}{2} \| \widehat{\boldsymbol{x}} - \widehat{\boldsymbol{D}} \widehat{\boldsymbol{z}} \|_2^2 + \frac{\rho}{2} \| \widehat{\boldsymbol{z}} - \widehat{\boldsymbol{y}}^{(i)} + \widehat{\boldsymbol{u}}^{(i)} \|_2^2 \right), \quad (13_1)$$

$$\boldsymbol{y}^{(i+1)} = \min_{\boldsymbol{y}} \left( \lambda \| \boldsymbol{y} \|_1 + \frac{\rho}{2} \sum_{j=1}^{n} \| \mathcal{F}^{-1}(\widehat{\boldsymbol{z}}^{(i+1)}) - \boldsymbol{y} + \boldsymbol{u}^{(i)} \|_2^2 \right), \quad (13_2)$$

$$\boldsymbol{u}^{(i+1)} = \boldsymbol{u}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{z}}^{(i+1)}) - \boldsymbol{y}^{(i+1)}, \quad (13_3)$$

where

$$\boldsymbol{y} = [\boldsymbol{y}_1'^{\top}, \boldsymbol{y}_2'^{\top}, \cdots, \boldsymbol{y}_n'^{\top}]_{mn\times 1}^{\top}, \quad \boldsymbol{u} = [\boldsymbol{u}_1'^{\top}, \boldsymbol{u}_2'^{\top}, \cdots, \boldsymbol{u}_n'^{\top}]_{mn\times 1}^{\top}.$$

## Solving minimization problem $(13_1)$

First we define

$$F(\widehat{\boldsymbol{z}}) = \frac{1}{2}\|\widehat{\boldsymbol{x}} - \widehat{\boldsymbol{D}}\widehat{\boldsymbol{z}}\|_2^2 + \frac{\rho}{2}\|\widehat{\boldsymbol{z}} - \widehat{\boldsymbol{y}}^{(i)} + \widehat{\boldsymbol{u}}^{(i)}\|_2^2.$$

To solve $\min_{\widehat{\boldsymbol{z}}} F(\widehat{\boldsymbol{z}})$, we compute

$$\begin{aligned} \nabla F(\widehat{\boldsymbol{z}}) &= -\widehat{\boldsymbol{D}}^\top(\widehat{\boldsymbol{x}} - \widehat{\boldsymbol{D}}\widehat{\boldsymbol{z}}) + \rho \boldsymbol{I}(\widehat{\boldsymbol{z}} - \widehat{\boldsymbol{y}}^{(i)} + \widehat{\boldsymbol{u}}^{(i)}) \\ &= (\widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{D}} + \rho\boldsymbol{I})\widehat{\boldsymbol{z}} - \left(\widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{x}} + \rho(\widehat{\boldsymbol{y}}^{(i)} - \widehat{\boldsymbol{u}}^{(i)})\right). \end{aligned}$$

Letting $\nabla F(\widehat{\boldsymbol{z}}) = \boldsymbol{0}$, we have

$$(\widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{D}} + \rho\boldsymbol{I})_{mn\times mn}\widehat{\boldsymbol{z}} = \widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{x}} + \rho(\widehat{\boldsymbol{y}}^{(i)} - \widehat{\boldsymbol{u}}^{(i)}).$$

Therefore, we obtain the solution

$$\widehat{\boldsymbol{z}}^{(i+1)} = (\widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{D}} + \rho\boldsymbol{I})^{-1}\left(\widehat{\boldsymbol{D}}^\top\widehat{\boldsymbol{x}} + \rho(\widehat{\boldsymbol{y}}^{(i)} - \widehat{\boldsymbol{u}}^{(i)})\right).$$

## Solving minimization problem $(13_2)$

The way to solve minimization problem $(13_2)$ is similar to that for solving problem $(6_2)$.

Finally, we obtain the ADMM iterative scheme as follows:

$$\widehat{\boldsymbol{z}}^{(i+1)} = (\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{D}} + \rho \boldsymbol{I})^{-1} (\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{x}} + \rho(\widehat{\boldsymbol{y}}^{(i)} - \widehat{\boldsymbol{u}}^{(i)})), \quad (14_1)$$

$$\boldsymbol{y}^{(i+1)} = \mathcal{S}_{\lambda/\rho}(\mathcal{F}^{-1}(\widehat{\boldsymbol{z}}^{(i+1)}) + \boldsymbol{u}^{(i)}), \quad (14_2)$$

$$\boldsymbol{u}^{(i+1)} = \boldsymbol{u}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{z}}^{(i+1)}) - \boldsymbol{y}^{(i+1)}. \quad (14_3)$$

Next, we will introduce the *Sherman-Morrison formula* which can be applied to solve $\widehat{\boldsymbol{z}}^{(i+1)}$ in a more efficient way.

## The Sherman-Morrison formula: a special case

Let $\boldsymbol{A}$ and $\boldsymbol{B}$ be two $n \times n$ matrices. In general, $(\boldsymbol{A}+\boldsymbol{B})$ is not invertible, even though $\boldsymbol{A}$ is invertible. However, if $\boldsymbol{A}$ is invertible and $\boldsymbol{B}$ has some certain structure, then $(\boldsymbol{A}+\boldsymbol{B})^{-1}$ exists.

**A special case of the Sherman-Morrison formula:** *Let $\boldsymbol{I}$ be the $n \times n$ identity matrix and $\boldsymbol{u}$, $\boldsymbol{v}$ be two given vectors in $\mathbb{C}^n$. If $1+\boldsymbol{v}^\top \boldsymbol{u} \neq 0$, then $\boldsymbol{I}+\boldsymbol{u}\boldsymbol{v}^\top$ is invertible and*

$$(\boldsymbol{I}+\boldsymbol{u}\boldsymbol{v}^\top)^{-1} = \boldsymbol{I} - \frac{\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}}.$$

*Proof:* We check that

$$\begin{aligned}
(\boldsymbol{I}+\boldsymbol{u}\boldsymbol{v}^\top)\left(\boldsymbol{I} - \frac{\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}}\right) &= \boldsymbol{I} - \frac{\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} + \boldsymbol{u}\boldsymbol{v}^\top - \frac{\boldsymbol{u}\boldsymbol{v}^\top\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} \\
&= \boldsymbol{I} + \frac{-\boldsymbol{u}\boldsymbol{v}^\top + \boldsymbol{u}\boldsymbol{v}^\top + \boldsymbol{v}^\top\boldsymbol{u}\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} - \frac{\boldsymbol{u}\boldsymbol{v}^\top\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} \\
&= \boldsymbol{I} + \frac{\boldsymbol{v}^\top\boldsymbol{u}\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} - \frac{\boldsymbol{u}\boldsymbol{v}^\top\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}} = \boldsymbol{I}. \quad (\boldsymbol{v}^\top\boldsymbol{u} : \textit{scalar}) \quad \square
\end{aligned}$$

## How to derive the inverse?

Given $\boldsymbol{b} \in \mathbb{C}^n$, we consider the linear system $(\boldsymbol{I} + \boldsymbol{u}\boldsymbol{v}^\top)\boldsymbol{x} = \boldsymbol{b}$. Assume that $\boldsymbol{I} + \boldsymbol{u}\boldsymbol{v}^\top$ is invertible. Then the unique solution $\boldsymbol{x}$ exists.
Let $k = \boldsymbol{v}^\top\boldsymbol{x} \in \mathbb{C}$. Then $\boldsymbol{x} + k\boldsymbol{u} = \boldsymbol{b} \;\Rightarrow\; \boldsymbol{v}^\top\boldsymbol{x} + k\boldsymbol{v}^\top\boldsymbol{u} = \boldsymbol{v}^\top\boldsymbol{b}$
$\Rightarrow\; k + k(\boldsymbol{v}^\top\boldsymbol{u}) = \boldsymbol{v}^\top\boldsymbol{b}$, which implies

$$k = \frac{\boldsymbol{v}^\top\boldsymbol{b}}{1+\boldsymbol{v}^\top\boldsymbol{u}}, \quad \text{if } 1+\boldsymbol{v}^\top\boldsymbol{u} \neq 0.$$

Therefore, we know that

$$\boldsymbol{x} = \boldsymbol{b} - k\boldsymbol{u} = \boldsymbol{b} - \frac{\boldsymbol{v}^\top\boldsymbol{b}}{1+\boldsymbol{v}^\top\boldsymbol{u}}\boldsymbol{u} = \boldsymbol{b} - \frac{\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}}\boldsymbol{b} = \overbrace{\left(\boldsymbol{I} - \frac{\boldsymbol{u}\boldsymbol{v}^\top}{1+\boldsymbol{v}^\top\boldsymbol{u}}\right)}^{\text{inverse of } \boldsymbol{I}+\boldsymbol{u}\boldsymbol{v}^\top}\boldsymbol{b}.$$

**The Sherman-Morrison formula:** *Suppose that $\boldsymbol{A} \in \mathbb{C}^{n\times n}$ is an invertible matrix and $\boldsymbol{u}, \boldsymbol{v} \in \mathbb{C}^n$. Then $\boldsymbol{A} + \boldsymbol{u}\boldsymbol{v}^\top$ is invertible if and only if $1 + \boldsymbol{v}^\top\boldsymbol{A}^{-1}\boldsymbol{u} \neq 0$. In this case, we have*

$$(\boldsymbol{A} + \boldsymbol{u}\boldsymbol{v}^\top)^{-1} = \boldsymbol{A}^{-1} - \frac{\boldsymbol{A}^{-1}\boldsymbol{u}\boldsymbol{v}^\top\boldsymbol{A}^{-1}}{1+\boldsymbol{v}^\top\boldsymbol{A}^{-1}\boldsymbol{u}}.$$

## How to compute $(14_1)$?

Recall that

$$\left(\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{D}} + \rho \boldsymbol{I}\right) \widehat{\boldsymbol{z}}^{(i+1)} = \left(\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{x}} + \rho(\widehat{\boldsymbol{y}}^{(i)} - \widehat{\boldsymbol{u}}^{(i)})\right), \quad (14_1)$$

where matrix $\widehat{\boldsymbol{D}}$ has the following structure:

$$\begin{aligned}
\widehat{\boldsymbol{D}} &= [\widehat{\boldsymbol{D}}_1, \widehat{\boldsymbol{D}}_2, \cdots, \widehat{\boldsymbol{D}}_n]_{m\times mn} \\
&= \begin{bmatrix}
\widehat{d'_{1,1}} & 0 & \cdots & 0 & \widehat{d'_{2,1}} & 0 & \cdots & 0 & \cdots \\
0 & \widehat{d'_{1,2}} & \ddots & \vdots & 0 & \widehat{d'_{2,2}} & \ddots & \vdots & \cdots \\
\vdots & \ddots & \ddots & 0 & \vdots & \ddots & \ddots & 0 & \cdots \\
0 & \cdots & 0 & \widehat{d'_{1,m}} & 0 & \cdots & 0 & \widehat{d'_{2,m}} & \cdots
\end{bmatrix},
\end{aligned}$$

where

$$\widehat{\boldsymbol{D}_j} = \operatorname{diag}(\widehat{\boldsymbol{d}'_j}) \quad (m \times m \text{ } \textit{diagonal matrix}).$$

## The structure of matrix $\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{D}} + \rho \boldsymbol{I}$

Note that

$$\begin{aligned}
\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{D}} + \rho \boldsymbol{I} &= \begin{bmatrix} \widehat{\boldsymbol{D}}_1^\top \\ \widehat{\boldsymbol{D}}_2^\top \\ \vdots \\ \widehat{\boldsymbol{D}}_n^\top \end{bmatrix} [\widehat{\boldsymbol{D}}_1, \widehat{\boldsymbol{D}}_2, \cdots, \widehat{\boldsymbol{D}}_n] + \rho \boldsymbol{I} \\
&= \begin{bmatrix} \widehat{\boldsymbol{D}}_1^\top \widehat{\boldsymbol{D}}_1 + \rho \boldsymbol{I}_m & \widehat{\boldsymbol{D}}_1^\top \widehat{\boldsymbol{D}}_2 & \cdots & \widehat{\boldsymbol{D}}_1^\top \widehat{\boldsymbol{D}}_n \\ \widehat{\boldsymbol{D}}_2^\top \widehat{\boldsymbol{D}}_1 & \widehat{\boldsymbol{D}}_2^\top \widehat{\boldsymbol{D}}_2 + \rho \boldsymbol{I}_m & \cdots & \widehat{\boldsymbol{D}}_2^\top \widehat{\boldsymbol{D}}_n \\ \vdots & \vdots & \ddots & \vdots \\ \widehat{\boldsymbol{D}}_n^\top \widehat{\boldsymbol{D}}_1 & \widehat{\boldsymbol{D}}_n^\top \widehat{\boldsymbol{D}}_2 & \cdots & \widehat{\boldsymbol{D}}_n^\top \widehat{\boldsymbol{D}}_n + \rho \boldsymbol{I}_m \end{bmatrix}_{mn \times mn}.
\end{aligned}$$

*By re-ordering the equations, the $mn \times mn$ system $\left(\widehat{\boldsymbol{D}}^\top \widehat{\boldsymbol{D}} + \rho \boldsymbol{I}\right) \widehat{\boldsymbol{z}}^{(i+1)} = \boldsymbol{R}$ can be replaced by $m$ independent linear systems of size $n \times n$, each of which consists of a rank one component plus a diagonal component, then solved by the Sherman-Morrison formula, see [Wohlberg 2016, Appendix A].*

## Convolutional sparse dictionary learning problem

We now consider the convolutional sparse dictionary learning problem, where the dictionary $\boldsymbol{D}$ is unknown and needed to be sought together with the convolutional sparse solution.

**Convolutional SDL problem:** *Let* $\{\boldsymbol{x}_i\}_{i=1}^N \subset \mathbb{R}^m$ *be a given dataset of signals. We seek a dictionary matrix* $\boldsymbol{D} = [\boldsymbol{d}_1, \boldsymbol{d}_2, \cdots, \boldsymbol{d}_M] \in \mathbb{R}^{\ell \times M}$ *and the coefficient matrices* $\{\boldsymbol{Z}_i\}_{i=1}^N \subset \mathbb{R}^{k \times M}$ *with* $\boldsymbol{Z}_i = [\boldsymbol{z}_{1,i}, \boldsymbol{z}_{2,i}, \cdots, \boldsymbol{z}_{M,i}]$ *and* $m = \ell + k - 1$ *such that* $\boldsymbol{D}$ *and* $\{\boldsymbol{Z}_i\}_{i=1}^N$ *solve the following minimization problem:*

$$\min_{\{\boldsymbol{d}_j\}_{j=1}^M, \{\boldsymbol{z}_{j,i}\}_{j=1,i=1}^{M,N}} \left( \frac{1}{2} \sum_{i=1}^N \|\boldsymbol{x}_i - \sum_{j=1}^M \boldsymbol{d}_j * \boldsymbol{z}_{j,i}\|_2^2 + \lambda \sum_{i=1}^N \sum_{j=1}^M \|\boldsymbol{z}_{j,i}\|_1 \right)$$

$$\text{subject to } \|\boldsymbol{d}_j\|_2 \le 1 \quad \forall\, j = 1, 2, \cdots, M,$$

*where* $\lambda > 0$ *is a given penalty parameter.*

## Toeplitz matrix

- Define $\widetilde{\boldsymbol{D}} = \begin{bmatrix} \boldsymbol{D}_1 & \boldsymbol{D}_2 & \cdots & \boldsymbol{D}_M \end{bmatrix}$ with each $\boldsymbol{D}_j$ is the *Toeplitz matrix* defined with respect to $\boldsymbol{d}_j$ as before.

  Define $\boldsymbol{z}_i = \begin{bmatrix} \boldsymbol{z}_{1,i}^\top & \boldsymbol{z}_{2,i}^\top & \cdots & \boldsymbol{z}_{M,i}^\top \end{bmatrix}^\top$ for $i = 1, 2, \cdots, N$, where each $\boldsymbol{z}_i$ is the coefficient vector with respect to the data $\boldsymbol{x}_i$.

  Define $\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{z}_1 & \boldsymbol{z}_2 & \cdots & \boldsymbol{z}_N \end{bmatrix}$ and $\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}_1 & \boldsymbol{x}_2 & \cdots & \boldsymbol{x}_N \end{bmatrix}$.

- The convolutional SDL problem can be simplified as

$$\min_{\widetilde{\boldsymbol{D}},\, \boldsymbol{Z}} \left( \frac{1}{2} \|\boldsymbol{X} - \widetilde{\boldsymbol{D}}\boldsymbol{Z}\|_F^2 + \lambda \|\boldsymbol{Z}\|_{1,1} \right)$$
$$\text{subject to } \|\boldsymbol{d}_j\|_2 \leq 1 \quad \forall\, j = 1, 2, \cdots, M,$$

  where $\|\boldsymbol{Z}\|_{1,1}$ is defined as before.

## How to solve the convolutional SDL problem?

Though we can still use the ADMM iterative scheme to solve

$$\min_{\widetilde{D},\, Z} \left( \frac{1}{2} \| X - \widetilde{D} Z \|_F^2 + \lambda \| Z \|_{1,1} \right)$$
$$\text{subject to } \| d_j \|_2 \le 1 \quad \forall\, j = 1, 2, \cdots, M,$$

the sizes of the involved matrices are too large. Thus, we will use the DFT and the Sherman-Morrison formula to deal with this problem. The steps are similar to the CSR problem, but more complicated.

Recall the convolutional SDL problem:

$$\min_{\{d_j\}_{j=1}^M, \{z_{j,i}\}_{j=1,i=1}^{M,N}} \left( \frac{1}{2} \sum_{i=1}^N \| x_i - \sum_{j=1}^M d_j * z_{j,i} \|_2^2 + \lambda \sum_{i=1}^N \sum_{j=1}^M \| z_{j,i} \|_1 \right)$$
$$\text{subject to } \| d_j \|_2 \le 1 \quad \forall\, j = 1, 2, \cdots, M.$$

For solving this problem, we split it into two parts.

## Step 1: Solving the coefficient $Z$

For solving the convolutional SDL problem, we first give an initial dictionary $\boldsymbol{D} = [\boldsymbol{d}_1, \boldsymbol{d}_2, \cdots, \boldsymbol{d}_M]$ to solve coefficient $\boldsymbol{Z}$ and then further use ADMM algorithm to split this problem into three subproblems:

$$\widehat{\boldsymbol{Z}}^{(i+1)} = \arg\min_{\widehat{\boldsymbol{Z}}} \Big( \frac{1}{2} \sum_{i=1}^{N} \|\widehat{\boldsymbol{x}}_i - \sum_{j=1}^{M} \widehat{\boldsymbol{d}'_j} \odot \widehat{\boldsymbol{z}'_{j,i}} \|_2^2 + \frac{\rho}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} \| \widehat{\boldsymbol{z}'_{j,i}} - \widehat{\boldsymbol{y}'_{j,i}}^{(i)} + \widehat{\boldsymbol{u}'_{j,i}}^{(i)} \|_2^2 \Big)$$

$$\boldsymbol{Y}^{(i+1)} = \arg\min_{\boldsymbol{Y}} \Big( \lambda \sum_{i=1}^{N} \sum_{j=1}^{M} \|\boldsymbol{y}_{j,i}\|_1 + \frac{\rho}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} \| \mathcal{F}^{-1}(\widehat{\boldsymbol{z}'_{j,i}}) - \boldsymbol{y}_{j,i} + \boldsymbol{u}'_{j,i} \|_2^2 \Big),$$

$$\boldsymbol{U}^{(i+1)} = \boldsymbol{U}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}^{(i+1)}) - \boldsymbol{Y}^{(i+1)},$$

with

$$\mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}) = \begin{bmatrix} \mathcal{F}^{-1}(\widehat{\boldsymbol{z}'_{1,1}}) & \cdots & \mathcal{F}^{-1}(\widehat{\boldsymbol{z}'_{1,M}}) \\ \vdots & \ddots & \vdots \\ \mathcal{F}^{-1}(\widehat{\boldsymbol{z}'_{N,1}}) & \cdots & \mathcal{F}^{-1}(\widehat{\boldsymbol{z}'_{N,M}}) \end{bmatrix}.$$

## Rewritten in a compact form

For convenience, we can rewrite these subproblems as follows:

$$
\begin{aligned}
\widehat{\boldsymbol{Z}}^{(i+1)} &= \arg\min_{\widehat{\boldsymbol{Z}}} \left( \frac{1}{2} \|\widehat{\boldsymbol{X}} - \widehat{\boldsymbol{D}}\widehat{\boldsymbol{Z}}\|_F^2 + \frac{\rho}{2} \|\widehat{\boldsymbol{Z}} - \widehat{\boldsymbol{Y}}^{(i)} + \widehat{\boldsymbol{U}}^{(i)}\|_F^2 \right), \\
\boldsymbol{Y}^{(i+1)} &= \arg\min_{\boldsymbol{Y}} \left( \lambda \|\boldsymbol{Y}\|_{1,1} + \frac{\rho}{2} \|\mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}^{(i+1)}) - \widehat{\boldsymbol{Y}} + \widehat{\boldsymbol{U}}^{(i)}\|_F^2 \right), \\
\boldsymbol{U}^{(i+1)} &= \boldsymbol{U}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{Z}}^{(i+1)}) - \boldsymbol{Y}^{(i+1)},
\end{aligned}
$$

with

$$
\widehat{\boldsymbol{X}} = [\widehat{\boldsymbol{x}_1}, \widehat{\boldsymbol{x}_2}, \cdots, \widehat{\boldsymbol{x}_N}], \quad \widehat{\boldsymbol{D}} = [\widehat{\boldsymbol{D}_1}, \widehat{\boldsymbol{D}_2}, \cdots, \widehat{\boldsymbol{D}_M}],
$$

and

$$
\boldsymbol{Y} = \begin{bmatrix} \boldsymbol{y}'_{1,1} & \cdots & \boldsymbol{y}'_{1,M} \\ \vdots & \ddots & \vdots \\ \boldsymbol{y}'_{N,1} & \cdots & \boldsymbol{y}'_{N,M} \end{bmatrix}, \quad \boldsymbol{U} = \begin{bmatrix} \boldsymbol{u}'_{1,1} & \cdots & \boldsymbol{u}'_{1,M} \\ \vdots & \ddots & \vdots \\ \boldsymbol{u}'_{N,1} & \cdots & \boldsymbol{u}'_{N,M} \end{bmatrix}.
$$

Using the similar ways as that for solving CSR problem, we can solve the above subproblems.

## Step 2: Solving the dictionary $D$

Recall the convolutional SDL problem:

$$\min_{\{d_j\}_{j=1}^M,\ \{z_{j,i}\}_{j=1,i=1}^{M,N}} \left( \frac{1}{2} \sum_{i=1}^N \|x_i - \sum_{j=1}^M d_j * z_{j,i}\|_2^2 + \lambda \sum_{i=1}^N \sum_{j=1}^M \|z_{j,i}\|_1 \right)$$
$$\text{subject to } \|d_j\|_2 \le 1 \quad \forall\, j = 1, 2, \cdots, M.$$

When the coefficient $Z$ is obtained, the blue term is a given number. Solving the dictionary $D$ is equivalent to solve

$$\min_{\{d_j\}_{j=1}^M} \frac{1}{2} \sum_{i=1}^N \|x_i - \sum_{j=1}^M d_j * z_{j,i}\|_2^2 \text{ subject to } \|d_j\|_2 \le 1, \quad \forall\, j = 1, 2, \cdots, M.$$

# Using ADMM algorithm to solve Step 2

We use the ADMM algorithm to solve the above problem:

$$
\begin{aligned}
\boldsymbol{D}^{(i+1)} &= \arg\min_{\boldsymbol{D}} \Big( \frac{1}{2} \sum_{i=1}^{N} \| \boldsymbol{x}_i - \sum_{j=1}^{M} \boldsymbol{d}_j * \boldsymbol{z}_j \|_2^2 + \frac{\rho}{2} \sum_{j=1}^{M} \| \boldsymbol{d}_j - \boldsymbol{g}_j^{(i)} + \boldsymbol{h}_j^{(i)} \|_2^2 \Big), \\
\boldsymbol{G}^{(i+1)} &= \mathrm{proj}_{g_{(G)}} \{ \boldsymbol{D}^{(i+1)} \}, \\
\boldsymbol{H}^{(i+1)} &= \boldsymbol{H}^{(i)} + \boldsymbol{D}^{(i+1)} - \boldsymbol{G}^{(i+1)},
\end{aligned}
$$

and then use the Fourier transform and similar ways as before,

$$
\begin{aligned}
\widehat{\boldsymbol{D}}^{(i+1)} &= \arg\min_{\widehat{\boldsymbol{D}}} \Big( \frac{1}{2} \sum_{i=1}^{N} \| \widehat{\boldsymbol{x}}_i - \sum_{j=1}^{M} \widehat{\boldsymbol{d}}_j' \odot \widehat{\boldsymbol{z}}_j' \|_2^2 + \frac{\rho}{2} \sum_{j=1}^{M} \| \widehat{\boldsymbol{d}}_j' - \widehat{\boldsymbol{g}}_j'^{(i)} + \widehat{\boldsymbol{h}}_j'^{(i)} \|_2^2 \Big), \\
\boldsymbol{G}^{(i+1)} &= \mathrm{proj}_{g_{(G)}} \{ \mathcal{F}^{-1}(\widehat{\boldsymbol{D}}^{(i+1)}) \}, \\
\boldsymbol{H}^{(i+1)} &= \boldsymbol{H}^{(i)} + \mathcal{F}^{-1}(\widehat{\boldsymbol{D}}^{(i+1)}) - \boldsymbol{G}^{(i+1)},
\end{aligned}
$$

where

$$
\mathcal{F}^{-1}(\widehat{\boldsymbol{D}}) = [\mathcal{F}^{-1}(\widehat{\boldsymbol{d}_1'}), \mathcal{F}^{-1}(\widehat{\boldsymbol{d}_2'}), \cdots, \mathcal{F}^{-1}(\widehat{\boldsymbol{d}_M'})].
$$

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