



DOWNSAMPLING FOR SPARSE SUBSPACE CLUSTERING

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Background & Motivation

- **Sparse Subspace clustering (SSC)**
 - Cluster samples lying on a union of subspaces
- **Problem:**
 - Recovering subspaces from huge amount of samples without labels is time-consuming
 - Sample amounts are often unbalanced in different subspaces
- **Our solution: SSC with downsampling (SSCD)**

Basic Idea

- **Notations:** x_i , the i^{th} sample; l_i , the label of the subspace which x_i belongs to; N_l , amount of samples in the l^{th} subspace; p_i , downsampling probability of x_i .
- p_i should be in **reverse ratio** to N_{l_i} .
- **Mutual linear representation**

$$\hat{c}_i = \operatorname{argmin} \|c\|_1, \quad s.t. \quad X_i c = x_i, \quad \forall i \in \{1, \dots, N\} \quad (1)$$

- $\|\hat{c}_i\|_1$ is closely related to N_{l_i} :

- **Lemma [3].** Assuming that $B^{(d)}$ is the Euclidean ball in \mathcal{R}^d , and A_N is a random inscribed polytope with all of its N vertices independently uniformly chosen on the boundary of $B^{(d)}$, i.e., S^{d-1} , one has

$$\mathbb{E}\{Vol_d(A_N)\} = Vol_d(B^{(d)}) - (c_{B^{(d)}} + o(1))N^{-\frac{2}{d-1}},$$

where $Vol_d(\cdot)$ denotes the d -dimensional volume and $c_{B^{(d)}}$ is a constant depending on d .

Theoretical Analysis: Balancing Guarantee

- **Atomic norm and volume of polytope**

- **Proposition1.** For a deterministic polytope $\operatorname{conv}(\mathcal{A})$ with all vertices fixed on S^{d-1} and a random variable $x \in \mathcal{R}^d$ satisfies a uniform distribution on S^{d-1} , one has

$$\mathbb{E}\left\{\frac{1}{\|x\|_d^d}\right\} = \frac{Vol_d(\operatorname{conv}(\mathcal{A}))}{Vol_d(B^{(d)})},$$

where $B^{(d)} = \{x \in \mathcal{R}^d \mid \|x\|_2 \leq 1\}$.

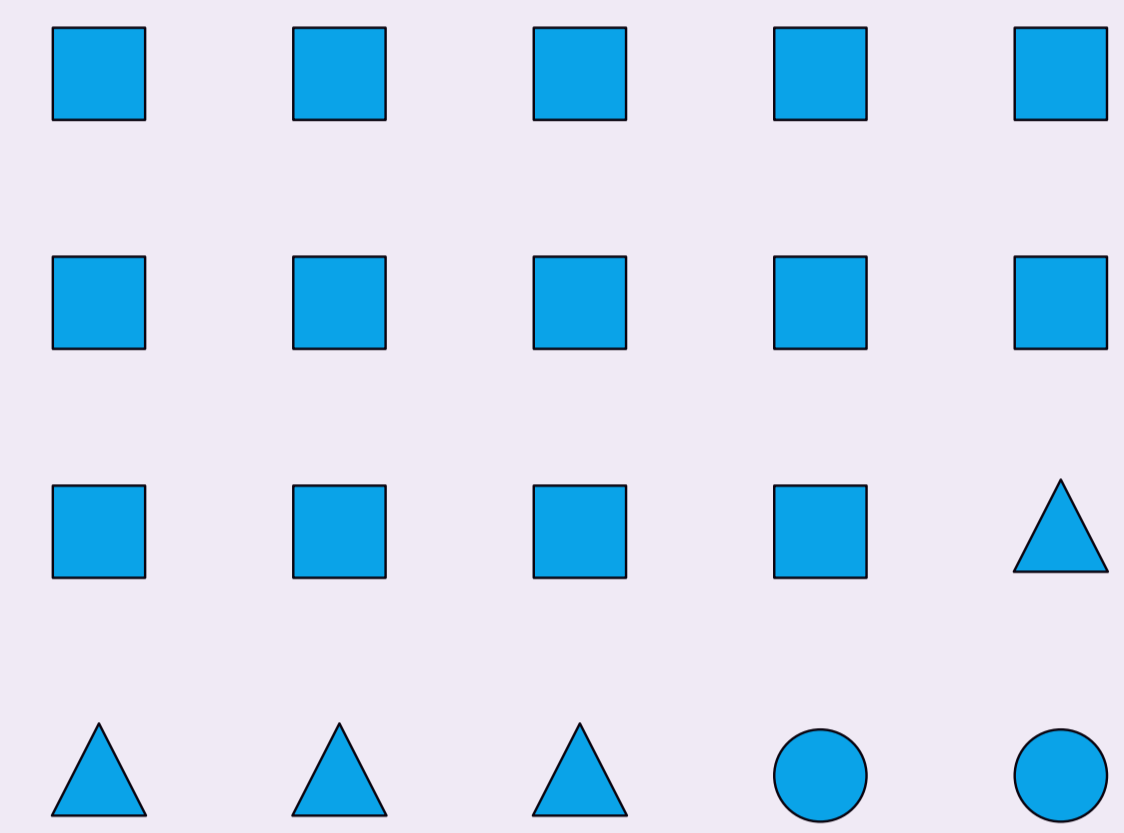
- **Estimation of the amount of samples in the l^{th} subspace**

- **Proposition2.** N_l can be approximated by
- $$\hat{N}_l = C_d \left(1 - \mathbb{E}\left\{\frac{1}{\|\hat{c}_i\|_1^d} \mid x_i \in U_l\right\}\right)^{\frac{d-1}{2}},$$

where C_d is a constant only depending on d .

SSC versus SSCD

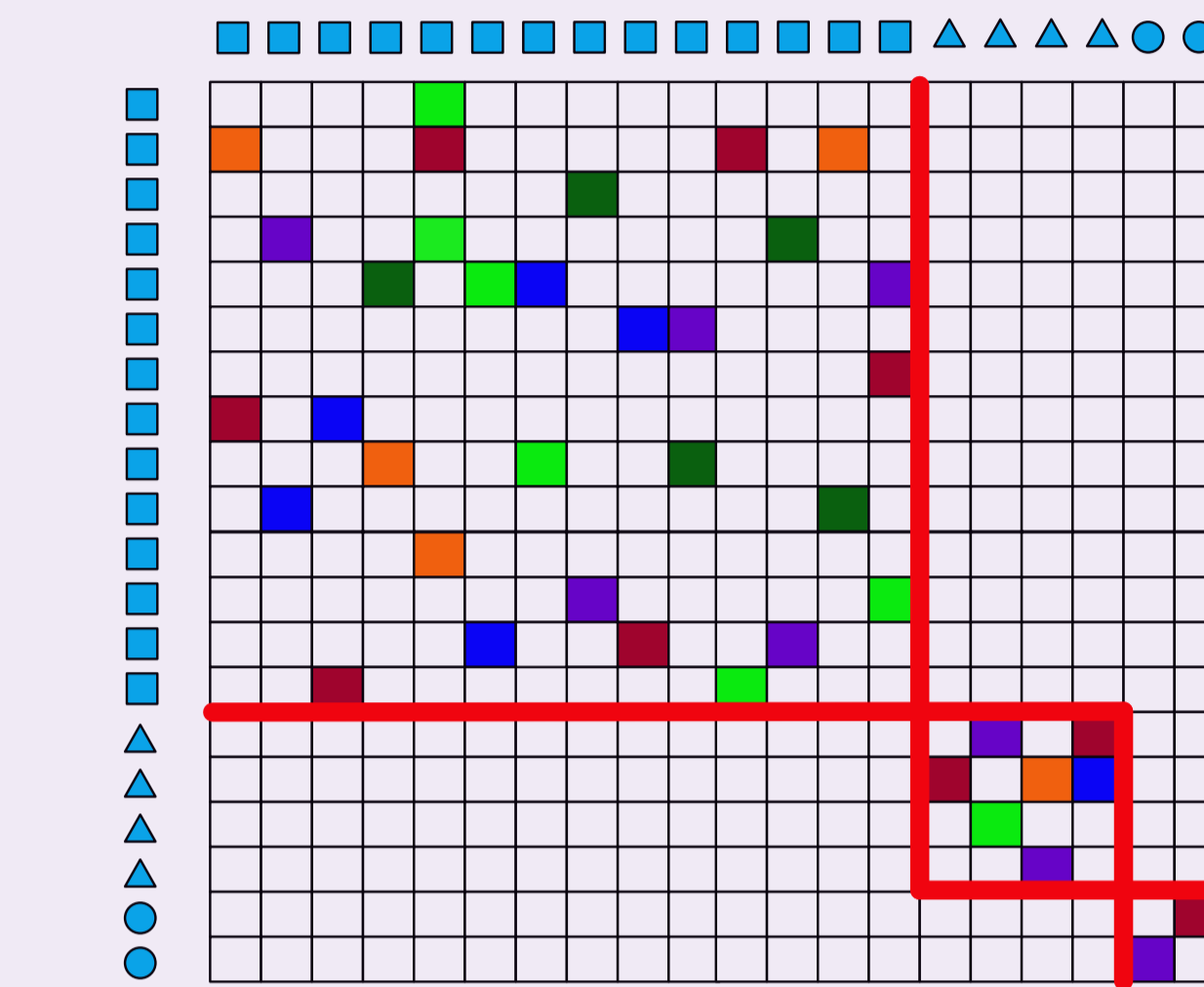
Input: N samples



Mutual linear representation

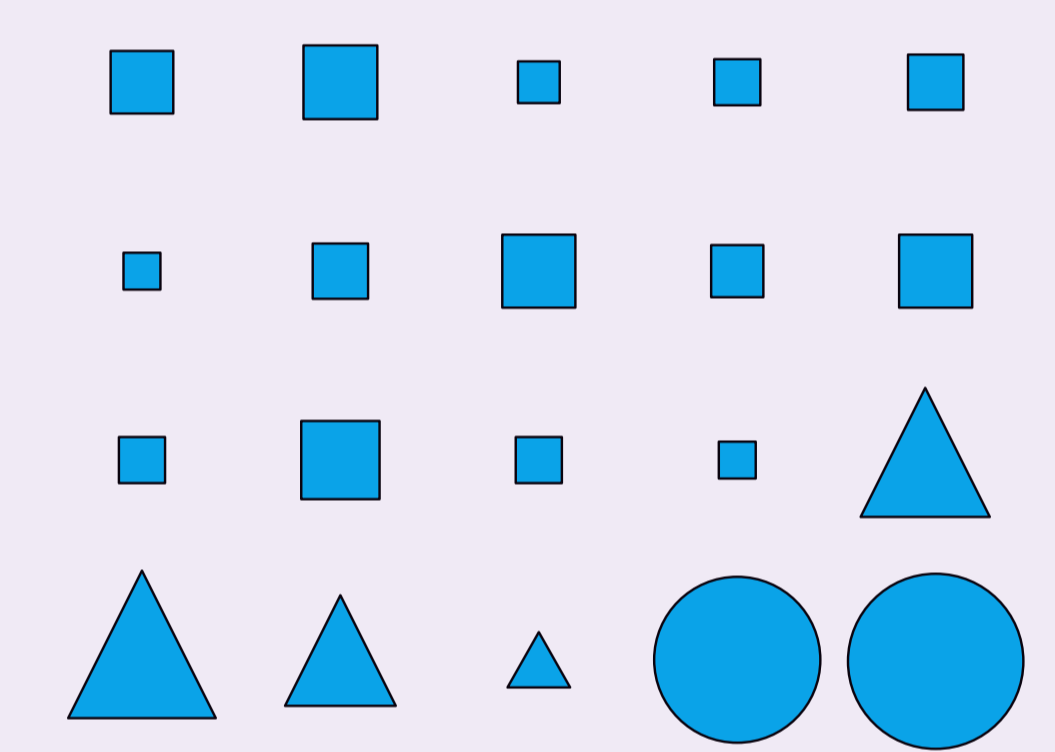
Mutual linear representation

Similarity matrix (S.M.) in SSC



D1

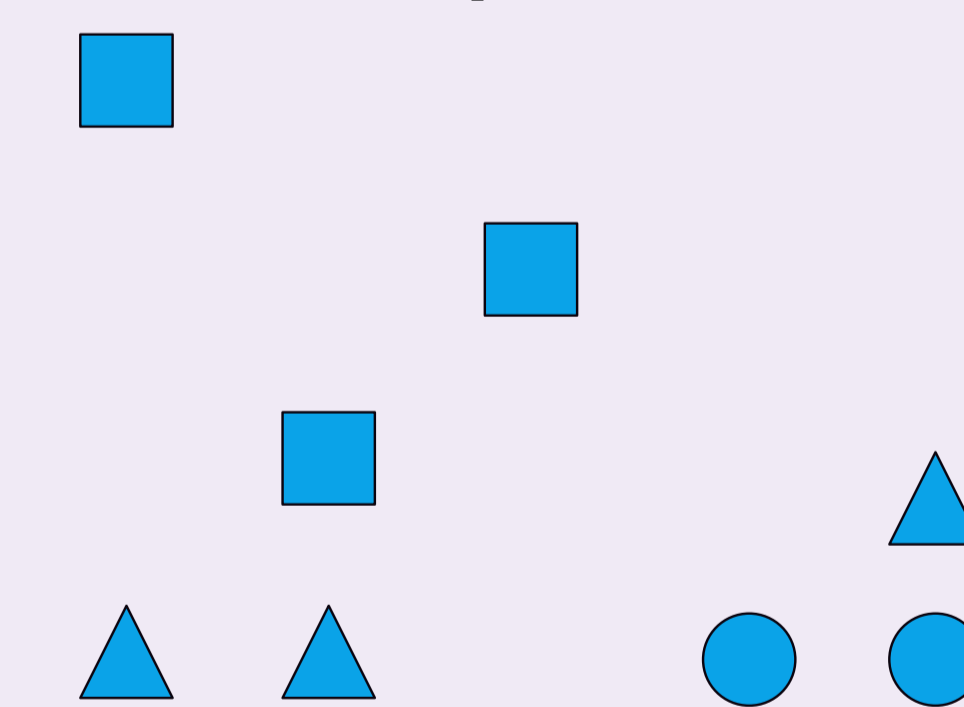
Downsampling probabilities



Size of each sample denotes the corresponding downsampling probability

D2

Downsampled dataset

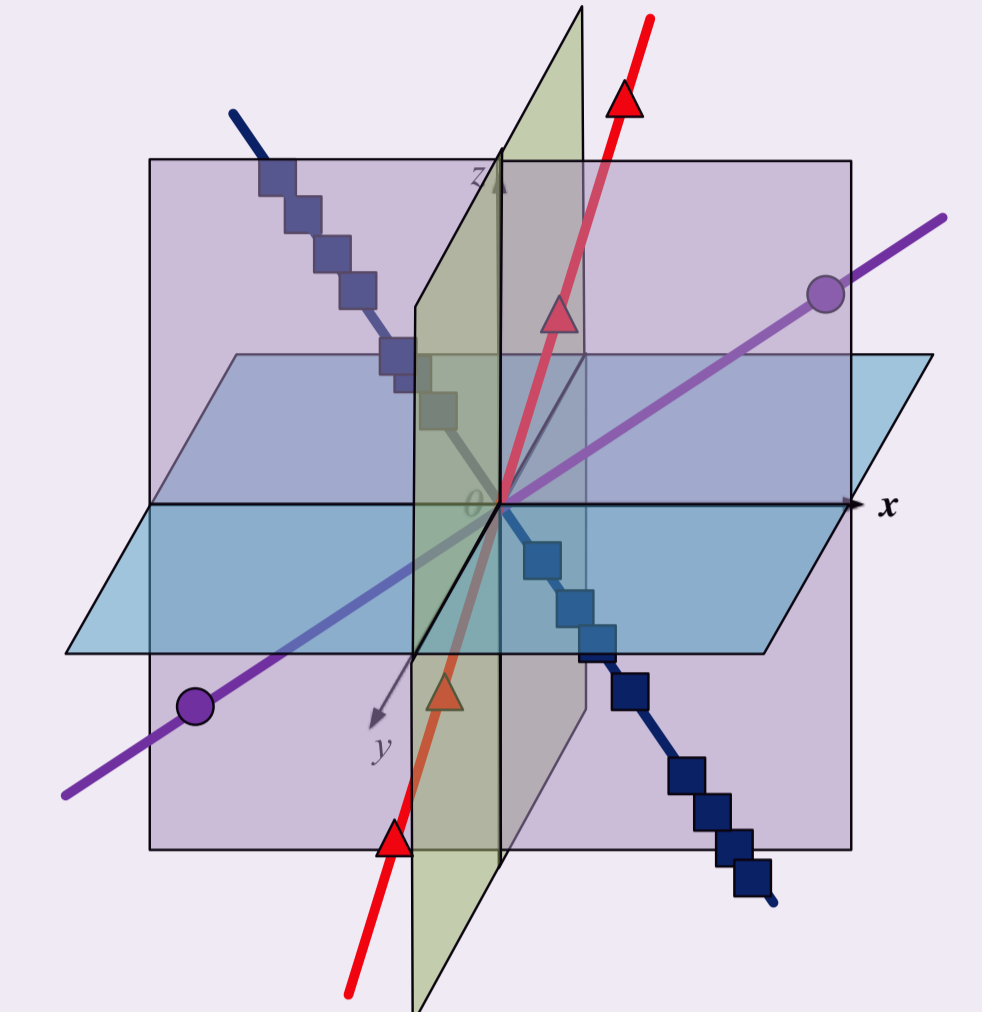


Mutual linear representation

Recovered union of subspaces

Computational complexity: $\mathcal{O}(N^3)$

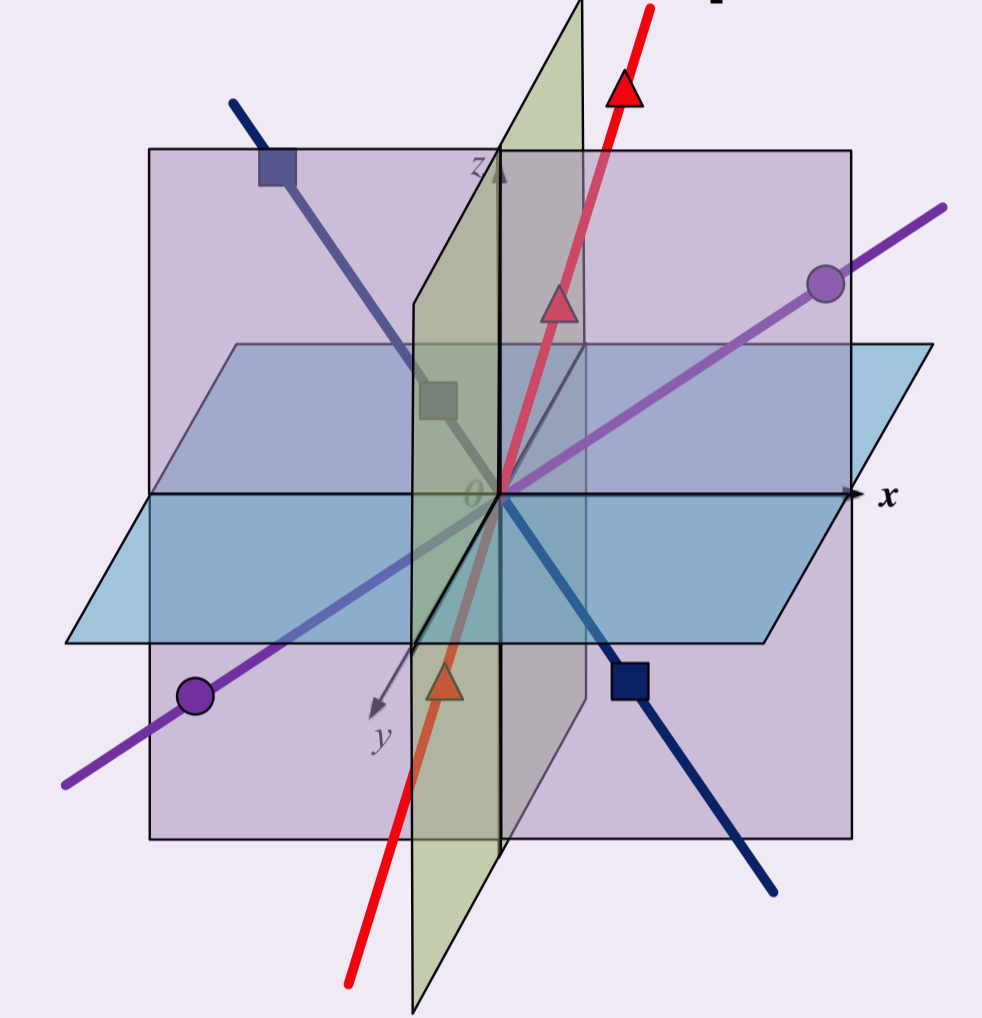
Spectral clustering & subspace recovery (S.C. & S.R.)



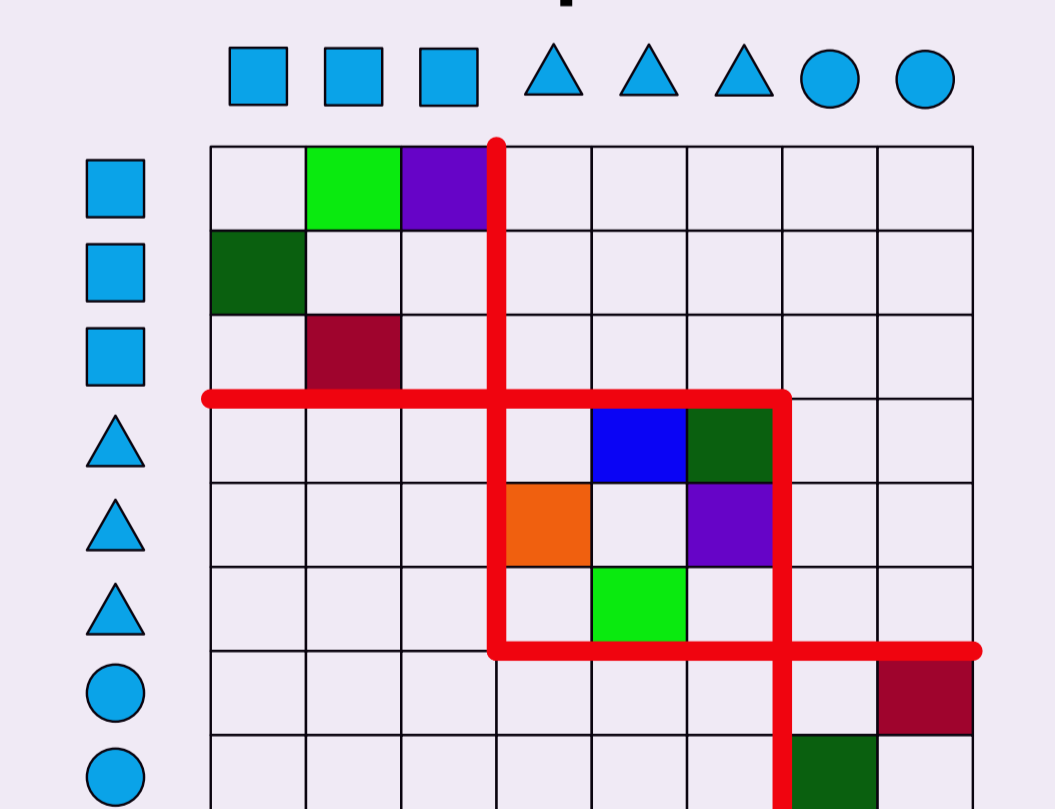
Recovered union of subspaces

Computational complexity: $\mathcal{O}(N^3/D^3)$

S.C. & S.R.



S.M. of downsampled dataset



Purpose of Downsampling:

- To **Balance** the amounts of samples in different subspaces
- To **Reduce** the computational complexity

Downsampling strategy:

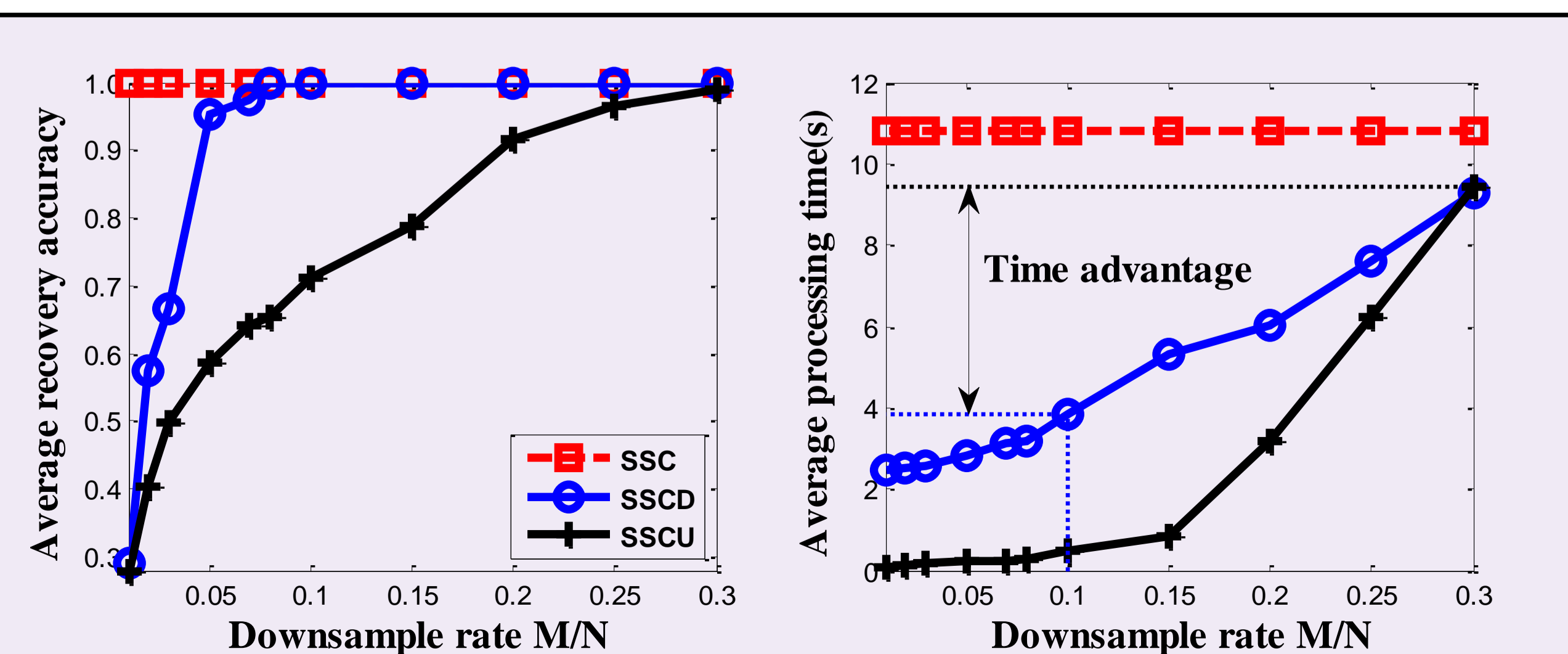
- D1:** Assigning downsampling probabilities according to the optimal value of (1). The downsampling probability of the i^{th} sample

$$p_i = w_i / \sum_{j=1}^N w_j,$$

where $w_i = (1 - 1/\|\hat{c}_i\|_1^d)^{\frac{d-1}{2}}$.

- D2:** With downsampling ratio D , randomly choose N/D different samples from the original sample set according to the p_i s as assigned in step D1.

Simulation Results



References

- [1] E. Elhamifar and R. Vidal, "Sparse subspace clustering," in IEEE Conference on Computer Vision and Pattern Recognition, pp. 2790–2797, 2009.
- [2] B. Cheng, J.C. Yang, S.C. Yan, Y. Fu, and T.S. Huang, "Learning with ℓ_1 -Graph for Image Analysis," IEEE Trans. Image Processing vol. 19, no. 4, pp. 858–866, Apr. 2010.
- [3] E. W. Carsten Schütt, Polytopes with Vertices Chosen Randomly from the Boundary of a Convex Body. Geometric Aspects of Functional Analysis, 2003.
- [4] V. Chandrasekaran, B. Recht, P. A. Parrilo, and A. S. Willsky, "The convex geometry of linear inverse problems," Foundations of Computational Mathematics, vol. 12, no. 6, pp. 805–849, 2012.