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Organization

- Noisy Subspace Clustering via Matching Pursuits
- Weighted Matrix Completion and Recovery With Prior Subspace Information
- Generalized Line Spectral Estimation via Convex Optimization

Noisy Subspace Clustering via Matching Pursuits

(M.Tschannen and H. Bolcskei)

- sparse subspace clustering(SSC), Thresholding-SC (TSC), nearest subspace neighbor (NSN)
- SSC-OMP, SSC-MP - proposed, Analytic performance characterization for noisy data. Better clustering performance and running time.
- $Y = Y_1 \cup \dots \cup Y_L$, $Y_\ell \in S_\ell \subset \mathbb{R}^m$, $\dim(S_\ell) = d_\ell$, randomly distributed on $S_\ell \cap \mathbb{S}^{m-1}$, perturbed by additive random noise
- $y_i^\ell = x_i^\ell + z_i^\ell = U^{(\ell)} a_i^\ell + z_i^\ell$, $i \in [n_\ell]$, $U^{(\ell)} \in \mathbb{R}^{m \times d_\ell}$ – orthonormal basis for S_ℓ , a_i^ℓ 's independently and uniformly distributed on \mathbb{S}^{d_ℓ} , $z_i^\ell \sim iid\mathcal{N}(0, \frac{\sigma^2}{m})$

Continue ...

- $\text{aff}(S_k, S_\ell) =: \frac{1}{\sqrt{\min\{d_k, d_\ell\}}} \|U^{(k)^T} U^{(\ell)}\|_F = \sqrt{\frac{\cos^2(\theta_1) + \dots + \cos^2(\theta_{\min\{d_k, d_\ell\}})}{\min\{d_k, d_\ell\}}}, \theta_1 \leq \dots \leq \theta_{\min\{d_k, d_\ell\}}$ principle angles between S_k and S_ℓ .
- No false connections (NFC) property: The graph G satisfies NFC property if, for all $\ell \in [L]$, the nodes corresponding to ℓ are connected to the other nodes corresponding to Y_ℓ only.
- Sampling density $\rho_\ell := \frac{(n_\ell - 1)}{d_\ell}$, $d_{\max} := \max_{\ell \in [L]} d_\ell$, $\rho_{\min} = \min_{\ell \in [L]} \rho_\ell$
- Assume $m \geq 2d_{\max}$, $\rho_{\min} \geq c_\rho$, $\sigma \leq \frac{1}{2}$,
 $s_{\max} \leq \min_{\ell \in [L]} \{c_s d_\ell / \log(n_\ell - 1)e / s_{\max}\}$,
 $c_\rho > 1$, $0 < c_s \leq 1/10$

Performance guarantee:

- (SSC-OMP with DI-Stopping): The clustering condition

$$\max_{k,\ell: k \neq \ell} \text{aff}(S_k, S_\ell) + \frac{10\sigma}{\sqrt{\log(N^3 s_{\max})}}$$

$$\left(\frac{\sqrt{d_{\max}}}{\sqrt{m}} c_\rho + \frac{\sqrt{2}}{\sqrt{\rho_{\min}}} \left(1 + \frac{3}{2}\rho\right) \right) \leq \frac{1}{8 \log(N^3 s_{\max})}$$

with $c_\rho = 10 + 13\sigma$ guarantees the graph generated by SSC-OMP satisfies NFC property w.p. at least

$$P^* := 1 - 6/N - 5N e^{-c_m m} - 6 \sum_{\ell \in [L]} n_\ell e^{c_d d_\ell}$$

for $0 < c_d \leq 1/18$ and $0 < c_m \leq 1/8$.

Weighted Matrix Completion and Recovery With Prior Subspace Information (A. Eftekhari, D. Yang, M. Wakin)

- Goal: Use of prior knowledge on matrix recovery and completion problem
- $M_{n \times n} = U \sum V^*$, for $r \leq n$ define
 $U_r, V_r, \sum_r, M_r = U_r \sum_r V_r^*, M_{r+} = M - M_r$
- Matrix recovery: $y = R_m(M + E)$, $\|R_m(E)\|_2 \leq e$, R_m linear operator collects m measurements of M . Recover M from y .
- Matrix completion: $R_p(M) = \sum_{i,j=1}^n \frac{\epsilon_{ij}}{p} M[i,j] C_{ij}$, $\{\epsilon_{ij}\}_{i,j}$ is a sequence of independent Bernoulli random variables taking one with probability p and zero elsewhere, $R(\cdot) : M \rightarrow R_M$ observe each entry of M with probability $p = m/n^2$, $R_p(M)$ contains m entries of M . $Y = R_p(M + E)$, $\|R_p(E)\|_F \leq e$, recover M from Y

Existing results:

- (r, δ_r) -RIP: $(1 - \delta_r)\|X\|_F \leq \|R_m(X)\|_2 \leq (1 + \delta_r)\|X\|_F$,
 $\text{rank}(X) \leq r$
- $\min_X \|X\|_*$, subject to $\|R_m(X) - y\|_2 \leq e$ (1)
- $\delta_{5r} \leq 0.1$, then

$$\|\tilde{M} - M\|_F \leq \frac{\|M_{r^+}\|_*}{\sqrt{r}} + e,$$

\tilde{M} solution of (1)

- $\eta(M_r) = \frac{n}{r} \max\{\|U_r\|_{2 \rightarrow \infty}^2, \|V_r\|_{2 \rightarrow \infty}^2\}$, $\|X\|_{2 \rightarrow \infty}^2$ largest ℓ_2 norm of the rows of X
- $\min_X \|X\|_*$, subject to $\|R_p(X) - Y\|_F \leq e$ (2)

$$\|\tilde{M} - M\|_F \leq \frac{\|M_{r^+}\|_*}{\sqrt{r}} + e\sqrt{pn}, 1 \geq p \geq \frac{\eta(M_r)r \log^2 n}{n},$$

\tilde{M} solution of (2)

Prior information: Matrix recovery

- \tilde{U}_r, \tilde{V}_r prior knowledge on column and row spaces of M_r , define $Q_{\tilde{U}_r, \lambda} := \lambda P_{\tilde{U}_r} + P_{\tilde{U}_r^\perp}$ and $Q_{\tilde{V}_r, \rho}$
- $\min_X \|Q_{\tilde{U}_r, \lambda} X Q_{\tilde{V}_r, \rho}\|$, sub to $\|R_m(X) - y\|_2 \leq e$ (3)
- $U_r = \text{span}(M_r), V_r = \text{span}(M_r^*), u = \angle[U_r, \tilde{U}_r], v = \angle[V_r, \tilde{V}_r]$
 $R_m(\cdot)$ is (r, δ_{32r}) – RIP with

$$\delta_{32r} \leq \frac{0.9 - \max[\alpha_3, \alpha_4]/\sqrt{30}}{0.9 + \max[\alpha_3, \alpha_4]/\sqrt{30}}$$

then

$$\|\tilde{M} - M\|_F \leq \frac{\|M_{r^+}\|_*}{\sqrt{r}} + e,$$

\tilde{M} solution of (3), $\alpha_i = \text{function}(u, v, \lambda, \rho)$

Prior information: Matrix completion

- $\min_X \|Q_{\tilde{U}_r, \lambda} X Q_{\tilde{V}_r, \rho}\|$, sub to $\|R_p(X) - Y\|_F \leq \epsilon$ (4)
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$$\|\tilde{M} - M\|_F \leq \frac{\|M_{r^+}\|_*}{\sqrt{r}} + \epsilon \sqrt{pn}, \quad 1 \geq p \geq \frac{\eta(M_r)r \log^2 n}{n},$$

except with probability $o(n^{-19})$ and provided

$$1 \geq p \geq \max[\log(\alpha_5 n), 1] \cdot \frac{\eta(M_r)r \log n}{n} \cdot \max[\alpha(1 + \sqrt{\frac{\eta_{\tilde{U}\tilde{V}^*}}{\eta_{U_r} V_r^*}})]$$

\tilde{M} solution of (4)

Generalized Line Spectral Estimation via Convex Optimization (R. Heckel and M. Soltanolkotabi)

- $z \in \mathbb{C}^{2N+1}$ - equispaced samples of a complex sinusoids
$$z = \sum_{k=1}^S b_k f(\nu_k),$$

$$f(\nu_k) := [e^{-i2\pi N\nu}, e^{-i2\pi(N-1)\nu}, \dots, e^{i2\pi N\nu}]^T$$

 $b_k \in \mathbb{C}$ -coefficients, $\{\nu_k \in [0, 1]\}$ -frequency parameter
- Recover b_k, ν_k from $y = Az$, where $A \in \mathbb{C}^{M \times L}$ and $L = 2N + 1$.
- A invertible - line spectral estimation problem (LSEP), $M < L$ - generalized LSEP
- Sparse recovery problem: recovery of $\{(b_k, \nu_k)\}$ corresponding to recovery of a sparse signal in the continuous indexed dictionary $\{Af(\nu) : \nu \in [0, 1]\}$

- Components of the mixtures are sufficiently separated,
 $|v_k - v_{k'}| \geq \frac{2}{N}, \forall k, k' \in [S] \ k \neq k'$
- F corresponds to a distribution that picks a vector $a \in \mathbb{C}^L$ uniformly at random from the rows of A .
- Isotropy property: $a \sim F$ obey $\mathbb{E}_{a \sim F}[aa^H] = \frac{1}{M}\mathbf{I}$.
- Incoherence property: if for all $a \sim F$
 $\sup_{f \in \mathbb{C}^L: \|f\|_\infty \leq 1} |\langle f, a \rangle|^2 = \|a\|_{\ell_1}^2 \leq \frac{L}{M}\mu$, μ incoherence parameter
- Subsampled Orthogonal Matrices: $\mu = \max_k \frac{L}{M} \|u_k\|_{\ell_1}^2$,
 $u_k : k\text{-th row of } U$.

Extensions to Higher Dimensions

- $z = \sum_{k=1}^S b_k f(r_k)$, $r_k \in [0, 1]^d$, $f(r) = [f(r)_p] = e^{i2\pi\langle p, r \rangle}$, p is an integer vector with ℓ -th entry, $\ell = 1, \dots, d$, given by $[p]_\ell = -N, \dots, N$. If $d = 2$ then $f(r) = [e^{i2\pi(-Nr_1-Nr_2)}, e^{i2\pi(-Nr_1-(N-1)r_2)}, \dots, e^{i2\pi(Nr_1+Nr_2)}]$
- $y = Az$, where $A \in \mathbb{C}^{M \times L^d}$ and $L = 2N + 1$.
- minimum separation condition:
$$\max_{\ell=1, \dots, d} |[r_k]_\ell - [r_{k'}]_\ell| \geq \frac{c(d)}{N}$$
- Atomic norm: $\mathcal{A} := \{f(r) : r \in [0, 1]^d\}$

$$\|z\|_{\mathcal{A}} := \inf_{b_k \in \mathbb{C}, r_k \in [0, 1]^d} \left\{ \sum_k |b_k| : z = \sum_k b_k f(r_k) \right\}$$

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$$AN(y) : \min_{\tilde{z}} \|\tilde{z}\|_{\mathcal{A}} \quad \text{sub to} \quad y = A\tilde{z} \quad (1)$$

Results

Theorem

$A \in \mathbb{C}^{M \times L^3}$ with $L \geq 1024$, be a random matrix with rows a_r chosen independently from a distribution obeying the isometry and incoherence property

$\mathbb{E}[a_r a_r^H] = \frac{1}{M} \mathbf{I}$ and $\sup_{f \in \mathbb{C}^{L^3}: \|f\|_\infty \leq 1} |\langle f, a_r \rangle|^2 \leq \frac{L^3}{M} \mu$ for fixed $\mu \geq 1$. $y = Az$ with $z = \sum_{k=1}^S b_k f(r_k)$. $(b_k) \sim iid$ symmetric distributions on the complex unit circle and $r_k = (\beta_k, \tau_k, \nu_k)$ obeys minimum separation condition

$\max(|\beta_k - \beta_{k'}|, |\tau_k - \tau_{k'}|, |\nu_k - \nu_{k'}|) \geq \frac{5}{N}$, $k \neq k'$. Then as long as

$$m \geq c \log^2(L/\delta),$$

with c a fixed numerical constant, z is the unique minimizer of $AN(y)$ in (1) with probability at least $1 - \delta$.

Thank You