

Sparse Subspace Clustering for the Popularity Adjusted Block Model

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Abstract

TODO

1 Introduction

1.1 Notation

P denotes the edge probability matrix for the PABM. $A_{ij} \stackrel{\text{indep}}{\sim} \text{Bernoulli}(P_{ij})$ for $i > j$, and $A_{ji} = A_{ij}, A_{ii} = 0 \forall i, j \leq n$ to make A the edge weight matrix for a hollow, unweighted, and undirected graph. X is an ASE of A while Y is constructed using the popularity vectors $\{\lambda^{(kl)}\}_K$ and the projection matrix Π as an ASE of P . $Z = XQ - Y$ for $Q = \arg \min_{Q \in \mathbb{O}(p,q)} \|XQ - Y\|_F$. Let $x_i^\top, y_i^\top, z_i^\top$ be the rows of X, Y, Z . $X^{(n)}$ represents the full X matrix for a sample of size n . $X^{(n,k)}$ represents the k^{th} block of $X^{(n)}$.

2 Main Results

Theorem 1. The subspace detection property holds for Y with probability at least $1 - \sum_k^K n_k e^{-\sqrt{K(n_k-1)}}$.

This falls out of Theorem 2.8 from Soltanolkotabi and Candés [2]. The subspaces in Y are orthogonal, so $\text{aff}(S_k, S_l) = 0 \forall k, l \leq K$.

Property 2. By Rubin-Delanchy et al. [1], $\max_i \|Q_n x_i^{(n)} - y_i^{(n)}\| = \max_i \|z_i^{(n)}\| = \delta^{(n)} = O_P\left(\frac{(\log n)^c}{n^{1/2}}\right)$. Then $\|Z^{(n)}\|_F \rightarrow 0$, $\delta^{(n)} \rightarrow 0$, and $r(X^{(n,l)} Q^{(n,l)}) \rightarrow r(Y^{(n,l)})$. Here we assume $r(Y^{(n,l)}) > 0 \forall n > K + 1$ and $l \leq K$.

Property 3. $P(\mu(Y^{(n,k)}) = 0) \geq 1 - \frac{1}{K} \sum_{k \neq l} \frac{4e^{-2t}}{(n_k+1)n_l}$ [2].

Theorem 4. *TODO* Find property 3 for X or XQ (?).

Theorem 5. $\exists M \in \mathbb{N}$ such that $\mu(X^{(n,l)}) < r(X^{(n,l)}) \forall n \geq M$.

Corollary. If $n \geq M$, $\exists \lambda > 0$ such that the LASSO subspace detection property holds for $X^{(n)}$ with parameter λ .

This falls out of Theorem 6 of Wang and Xu [3] and Theorem 6 of this paper.

References

- [1] Patrick Rubin-Delanchy, Joshua Cape, Minh Tang, and Carey E. Priebe. A statistical interpretation of spectral embedding: the generalised random dot product graph, 2017.
- [2] Mahdi Soltanolkotabi and Emmanuel J. Candès. A geometric analysis of subspace clustering with outliers. *Ann. Statist.*, 40(4):2195–2238, 08 2012. doi: 10.1214/12-AOS1034. URL <https://doi.org/10.1214/12-AOS1034>.
- [3] Yu-Xiang Wang and Huan Xu. Noisy sparse subspace clustering. In Sanjoy Dasgupta and David McAllester, editors, *Proceedings of the 30th International Conference on Machine Learning*, volume 28 of *Proceedings of Machine Learning Research*, pages 89–97, Atlanta, Georgia, USA, 17–19 Jun 2013. PMLR. URL <http://proceedings.mlr.press/v28/wang13.html>.