

RES-PCA: A Scalable Approach to Recovering Low-rank Matrices

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1. Proof of Theorem 3.1

Proof. The objective function of the optimization problem in (6) is a quadratic function of Q , which can be simplified as follows:

$$\begin{aligned} & \text{Tr}(Q(I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)Q^T) \\ &= \text{Tr}(Q(I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)(I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)^T Q^T) \\ &= \|Q(I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)\|_2^2 \\ &= \sum_{i=1}^n \|\mathbf{q}_i - \bar{\mathbf{q}}\|_2^2, \end{aligned}$$

where $\bar{\mathbf{q}} := \frac{1}{n} \sum_{i=1}^n \mathbf{q}_i$. In the above, the second equality holds because

$$I - \frac{1}{n}\mathbf{I}\mathbf{I}^T = (I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)(I - \frac{1}{n}\mathbf{I}\mathbf{I}^T)^T.$$

Now the original optimization problem can be equivalently written in vector form of \mathbf{q}_i as follows:

$$\min_{\mathbf{q}_i \in \mathcal{R}^p} \sum_{i=1}^n \|\mathbf{q}_i - \bar{\mathbf{q}}\|_2^2,$$

subject to

$$\begin{aligned} & \|\mathbf{q}_i\|_2^2 - s_i \leq 0, i = 1, \dots, n, \\ & \sum_{i=1}^n (\mathbf{q}_i - \bar{\mathbf{q}}) = 0. \end{aligned}$$

We define the Lagrangian function for the optimization function by using the new vector form in \mathbf{q}_i :

$$\mathcal{L} := \sum_{i=1}^n \|\mathbf{q}_i - \bar{\mathbf{q}}\|_2^2 + \sum_{i=1}^n \alpha_i (\mathbf{q}_i^T \mathbf{q}_i - s_i) + \beta^T \sum_{i=1}^n (\mathbf{q}_i - \bar{\mathbf{q}}),$$

where $\alpha_i \geq 0, i = 1, \dots, n$ are dual variables for inequalities in the original constraints (7), and $\beta \in \mathcal{R}^p$ is the dual vector for equality constraint given by the definition of $\bar{\mathbf{q}}$.

Taking partial derivative of \mathcal{L} with respect to \mathbf{q}_i and letting it equal to 0, we have

$$\frac{\partial \mathcal{L}}{\partial \mathbf{q}_i} = 2(\mathbf{q}_i - \bar{\mathbf{q}}) + 2\alpha_i \mathbf{q}_i + \beta = 0, \text{ for } i = 1, \dots, n.$$

Then we can obtain the root of the above equation:

$$\mathbf{q}_i^* = \frac{1}{1 + \alpha_i} (\bar{\mathbf{q}} - \frac{1}{2}\beta), \text{ for } i = 1, \dots, n.$$

As the optimization problem has a quadratic objective function and quadratic constraints, Kuhn-Tucker condition is both necessary and sufficient to achieve the optimality. Therefore, $\mathbf{q}_i^*, i = 1, \dots, n$, is an optimizer of the given optimization problem. Since the minimizer of the optimization problem is linearly dependent, the conclusion follows. \square