On the Recovery Limit of Sparse Signal Using Orthogonal Matching Pursuit

Authors: Jian Wang and Byonghyo Shim

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Short summary: In the paper, the authors give a sufficient condition of the Orthogonal Matching Pursuit (OMP) algorithm. In [2], Wakin and Davenport insisted that OMP can reconstruct any K sparse signal if $\delta_{K+1} < 1/\left(3\sqrt{K}\right)$, where δ_K is the restricted isometry constant. However, in this talk, an improved sufficient condition that guarantees the perfect recovery of OMP is presented

I. Final Summary of the Paper

a. A strategy of the proof of Theorem 1.

1) We aim to find a condition such that the OMP algorithm selects a correct index in the first iteration.

=> We need to show that $\min_{i\in\mathcal{I}}\left|\langle \mathbf{a}_i,\mathbf{y}\rangle\right| > \max_{j\notin\mathcal{I}}\left|\langle \mathbf{a}_j,\mathbf{y}\rangle\right|$. (e.g., see from (7) to (10).)

2) Let us suppose that the initial k iterations of the OMP algorithm are successful, and that $\mathcal{T}^k$ is the estimated support set after the initial k iterations. Now, the OMP algorithm selects a correct index, which belongs to $\mathcal{I}\setminus\mathcal{T}^k$, in the $k+1$ iteration.

=> Clearly, $\mathcal{T}^k \subseteq \mathcal{I}$, therefore $\mathbf{r}^k = \mathbf{y} - \mathbf{A}_{\mathcal{T}^k}\hat{\mathbf{x}}_{\mathcal{T}^k} = \mathbf{P}^{\perp}_{\mathcal{T}^k}\mathbf{y} \in span\left(\mathbf{A}_{\mathcal{I}}\right)$ can be considered as a linear combination of the K columns of $\mathbf{A}_{\mathcal{I}}$. Thus, $\mathbf{r}^k = \mathbf{A}\mathbf{b}$, where $\|\mathbf{b}\|_0 \le K$, and $\mathrm{supp}(\mathbf{b}) \subseteq \mathrm{supp}(\mathbf{x}) = \mathcal{I}$.

=> Again, we find a condition such that the OMP algorithm selects a correct index t^{k+1} which belongs to $\mathrm{supp}(\mathbf{b})$.

=> Furthermore, for any $i \in \mathcal{T}^k$, we have $\left|\langle \mathbf{r}^k, \mathbf{a}_i\rangle\right| = 0$. Thus, $t^{k+1} \in \mathcal{I}\setminus\mathcal{T}^k$.

3) Thus, we conclude that the OMP algorithm can reconstruct K sparse signal provided that the condition of 1) and the condition of 2) are satisfied

b. Comparison between the result by the authors in this paper and the result by Davenport and Wakin.

According to the authors, the improvement is possible due to 1) contradiction based construction of the success condition in the first iteration ($\min_{i\in\mathcal{I}} |\langle \mathbf{a}_i, \mathbf{y}\rangle| > \max_{j\notin\mathcal{I}} |\langle \mathbf{a}_j, \mathbf{y}\rangle|$) , and 2) observation that the residual in the general iteration preserves the sparsity level of the input signal. ($\mathbf{r}^k = \mathbf{A}\mathbf{b}$, where $\|\mathbf{b}\|_0 \le K$, and $\mathrm{supp}(\mathbf{b}) \subseteq \mathrm{supp}(\mathbf{x}) = \mathcal{I}$).

In fact, the authors again improved the result by Davenport and Wakin.

The more detailed explanations are referred to the paper.

c. Future Works

1) Can we apply the techniques, which are used in the proof, to find a sufficient condition of an algorithm based from the OMP algorithm? For example, the SOMP algorithm selects a index i such as $\arg\max_i \left\|\mathbf{a}_i^T \mathbf{R}^{(k)}\right\|_q$, where $\mathbf{R}^{(k)} = \left[\mathbf{r}_1^{(k)} \quad \cdots \quad \mathbf{r}_S^{(k)}\right]$, $\mathbf{r}_i^{(k)} = \mathbf{y}_i - \mathbf{A}_{\mathcal{T}^k} \hat{\mathbf{x}}_{i,\mathcal{T}^k}$, and $q = 1 \text{ or } 2$. Can we find a condition such that the SOMP algorithm selects a correct index?

II. History of Sufficient Conditions of the OMP Algorithm

In the below table 1, sufficient conditions that the OMP algorithm reconstructs a K spars signal from a set of linear measurements $\mathbf{y} = \mathbf{A}\mathbf{x}$, where $\mathbf{A} \in \Re^{M\times N}$ ($N > M$), are given.

Year	A sufficient condition
2007[1]	$\mu < 1/(2K-1)$
2010[2]	$\delta_{K+1} < 1/\left(3\sqrt{K}\right)$

Besides, there are many theoretical papers which analyze algorithms based on the OMP algorithm. In here, it is not scope of this seminar. Therefore, we do not care about them.

III. System Model

Let us consider the below equation:

$$\mathbf{y} = \mathbf{A}\mathbf{x}, \qquad (1)$$

where $\mathbf{A} \in \Re^{M\times N}$ ($N > M$), and $\mathbf{x} \in \Re^N$ is a K sparse signal, and $\mathbf{y} \in \Re^M$ is a set of linear measurements. The smallest constant δ_K called “the restricted isometry constant” satisfies

$$(1-\delta_K)\|\mathbf{x}\|_2^2 \le \|\mathbf{A}\mathbf{x}\|_2^2 \le (1+\delta_K)\|\mathbf{x}\|_2^2 \tag{2}$$

for any K sparse signal $\mathbf{x}$.

IV. Main Results

A. *Improved Recovery Bound of the OMP algorithm*

Theorem 1: For any K sparse signal $\mathbf{x}$, the OMP algorithm perfectly reconstructs $\mathbf{x}$ from $\mathbf{y}$ if the isometry constant δ_{K+1} satisfies

$$\delta_{K+1} < \frac{1}{\sqrt{K}+1}. \tag{3}$$

In this talk, we try to understand a proof of Theorem 1.

Before we study the proof, let us consider whether the OMP algorithm perfectly reconstructs $\mathbf{x}$ or not if $\delta_{K+1} = 1/\sqrt{K}$.

B. *The OMP algorithm can fail under $\delta_{K+1} = 1/\sqrt{K}$.*

Example 1: Let us consider the problem of reconstructing a K sparse signal $\mathbf{x} \in \Re^{K+1}$ such as $x_{K+1} = 0$, and $x_i = 1$ for $i = 1, \cdots, K$ from $\mathbf{y} = \mathbf{A}\mathbf{x}$, where

$$\mathbf{A}^T\mathbf{A} = \begin{bmatrix} 1 & b & \cdots & b \\ b & 1 & & \vdots \\ \vdots & & \ddots & b \\ b & \cdots & b & 1 \end{bmatrix} \in \Re^{(K+1)\times(K+1)}.$$

Obviously, all the Eigen values of $\mathbf{A}^T\mathbf{A}$ are $\lambda_1 = \lambda_2 = \cdots = \lambda_K = 1-b,$ and $\lambda_{K+1} = 1+Kb.$ (See Example 1 on Appendix). When we assume $b = -1/\left(K\sqrt{K}\right)$, $\mathbf{A}^T\mathbf{A}$ becomes

$$\mathbf{A}^T\mathbf{A} = \begin{bmatrix} 1 & -1/\left(K\sqrt{K}\right) & \cdots & -1/\left(K\sqrt{K}\right) \\ -1/\left(K\sqrt{K}\right) & 1 & & \vdots \\ \vdots & & \ddots & -1/\left(K\sqrt{K}\right) \\ -1/\left(K\sqrt{K}\right) & \cdots & -1/\left(K\sqrt{K}\right) & 1 \end{bmatrix} \in \Re^{(K+1)\times(K+1)}, \tag{4}$$

and the smallest and biggest Eigen values are

$$\lambda_{\min} = 1-1/\sqrt{K}, \text{ and } \lambda_{\max} = 1+1/\left(K\sqrt{K}\right).$$

Therefore, we have $\delta_{K+1} = 1/\sqrt{K}$ (In fact, all the Eigen values of $\mathbf{A}_{\mathcal{S}}^T\mathbf{A}_{\mathcal{S}}$ must be contained in the interval $\left[1-\delta_{|\mathcal{S}|}, 1+\delta_{|\mathcal{S}|}\right]$, Thus, $\delta_{K+1} = \max\left\{\lambda_{\max}\left(\mathbf{A}_{\mathcal{S}}^T\mathbf{A}_{\mathcal{S}}\right)-1, 1-\lambda_{\min}\left(\mathbf{A}_{\mathcal{S}}^T\mathbf{A}_{\mathcal{S}}\right)\right\}$). Now, we investigate a quantity $\left|\langle \mathbf{a}_i, \mathbf{y}\rangle\right|$ for $i = 1, \cdots, K+1$. For the OMP algorithm to reconstructs $\mathbf{x}$, $\left|\langle \mathbf{a}_{K+1}, \mathbf{y}\rangle\right|$ must be less than any $\left|\langle \mathbf{a}_i, \mathbf{y}\rangle\right|$ for $i = 1, \cdots, K$. This is reason that we investigate the quantities. First, for $i \in \{1, \cdots, K\}$, we have

$$\begin{aligned} \left|\langle \mathbf{a}_i, \mathbf{y}\rangle\right| &\overset{(a)}{=} \left|\langle \mathbf{a}_i, \mathbf{A}\mathbf{x}\rangle\right| \\ &\overset{(b)}{=} \left|\left\langle \mathbf{A}^T\mathbf{a}_i, \mathbf{x}\right\rangle\right| \\ &\overset{(c)}{=} 1 - \frac{K-1}{K\sqrt{K}}, \end{aligned} \tag{5}$$

where (a) from the fact $\mathbf{y} = \mathbf{A}\mathbf{x}$, (b) from the fact $\langle \mathbf{a}_i, \mathbf{A}\mathbf{x}\rangle = \mathbf{a}_i^T\mathbf{A}\mathbf{x} = \mathbf{x}^T\mathbf{A}^T\mathbf{a}_i = \left\langle \mathbf{x}, \mathbf{A}^T\mathbf{a}_i\right\rangle$, and (c) from the fact that $\mathbf{A}^T\mathbf{a}_i$ is the i^{th} column of $\mathbf{A}^T\mathbf{A}$ presented in (4), and $\mathbf{x}$ such as $x_{K+1} = 0$, and $x_i = 1$ for $i = 1, \cdots, K$. Second, for $i = K+1$, we have

$$\begin{aligned} \left|\langle \mathbf{a}_{K+1}, \mathbf{y}\rangle\right| &= \left|\langle \mathbf{a}_{K+1}, \mathbf{A}\mathbf{x}\rangle\right| \\ &= \left|\left\langle \mathbf{A}^T\mathbf{a}_{K+1}, \mathbf{x}\right\rangle\right| \\ &= \frac{1}{\sqrt{K}}. \end{aligned} \tag{6}$$

Obviously, the OMP algorithm must fail in the first iteration if an inequality $\left|\langle \mathbf{a}_{K+1}, \mathbf{y}\rangle\right| \geq \left|\langle \mathbf{a}_i, \mathbf{y}\rangle\right|$ for all $i \in \{1, \cdots, K\}$. The inequity becomes

$$\frac{1}{\sqrt{K}} \geq 1 - \frac{K-1}{K\sqrt{K}}$$

which is always true if $K = 2$. Thus, the OMP algorithm in the first iteration selects an incorrect index.

V. Proof of Theorem 1

A. Notations

The below notations will be used throughout the rest of this presentation. $\mathcal{T} = \operatorname{supp}(\mathbf{x}) := \{i \mid x_i \neq 0\}$ is the set of indices corresponding to non-zero coefficients of $\mathbf{x}$. $|\mathcal{T}|$ is the cardinality of $\mathcal{T}$, and $\mathcal{T} \setminus \mathcal{I}$ is the set of elements belonging to $\mathcal{T}$ but not to $\mathcal{I}$. $\mathbf{A}_{\mathcal{T}} \in \Re^{M\times|\mathcal{T}|}$ is a sub-matrix of $\mathbf{A}$ which contains columns corresponding to indices of $\mathcal{T}$. $\mathbf{x}_{\mathcal{T}} \in \Re^{|\mathcal{T}|}$ is a restriction of $\mathbf{x}$ to the elements indexed by $\mathcal{T}$. $span(\mathbf{A}_{\mathcal{T}})$ is the span of columns in $\mathbf{A}_{\mathcal{T}}$, $\mathbf{A}_{\mathcal{T}}^T$ is the transpose of $\mathbf{A}_{\mathcal{T}}$, and $\mathbf{A}_{\mathcal{T}}^{\dagger} = \left(\mathbf{A}_{\mathcal{T}}^T \mathbf{A}_{\mathcal{T}}\right)^{-1} \mathbf{A}_{\mathcal{T}}^T$ is the pseudo inverse of $\mathbf{A}_{\mathcal{T}}$. $\mathbf{P}_{\mathcal{T}} = \mathbf{A}_{\mathcal{T}} \mathbf{A}_{\mathcal{T}}^{\dagger}$ is the orthogonal projection onto $span(\mathbf{A}_{\mathcal{T}})$, and $\mathbf{P}_{\mathcal{T}}^{\perp} = \mathbf{I} - \mathbf{P}_{\mathcal{T}}$ is the orthogonal projection onto the orthogonal complement of $span(\mathbf{A}_{\mathcal{T}})$.

B. Lemmas

We need the below lemmas to prove Theorem 1.

Lemma 1: For a set $\mathcal{I}$, if $\delta_{|\mathcal{I}|} < 1$, then

$$\left(1-\delta_{|\mathcal{I}|}\right)\|\mathbf{v}\|_2 \le \left\|\mathbf{A}_{\mathcal{I}}^T \mathbf{A}_{\mathcal{I}} \mathbf{v}_{\mathcal{I}}\right\|_2 \le \left(1+\delta_{|\mathcal{I}|}\right)\|\mathbf{v}\|_2$$

holds for any $\mathbf{v}$ supported on $\mathcal{I}$.

Lemma 2: For disjoint sets $\mathcal{I}, \mathcal{J}$, if $\delta_{|\mathcal{I}|+|\mathcal{J}|} < 1$, then

$$\left\|\mathbf{A}_{\mathcal{I}}^T \mathbf{A} \mathbf{v}\right\|_2 = \left\|\mathbf{A}_{\mathcal{I}}^T \mathbf{A}_{\mathcal{J}} \mathbf{v}_{\mathcal{J}}\right\|_2 \le \delta_{|\mathcal{I}|+|\mathcal{J}|} \|\mathbf{v}\|_2$$

holds for any $\mathbf{v}$ supported on $\mathcal{J}$.

Lemma 3: If the sensing matrix satisfies the RIP of both orders K_1 and K_2, then $\delta_{K_1} \le \delta_{K_2}$ for any $K_1 \le K_2$

All proofs of the above lemmas are given in [3].

C. Proof of Theorem 1

1) We provide a condition under which the OMP algorithm selects a correct index in the first iteration. 2) We show that the residual in the general iteration preservers the sparsity of a K sparse signal. 3) The condition for the first iteration can be extended to the general iteration. 4) Theorem 1 is established from the conditions. The statements are an overall strategy of Proof of Theorem1.

First, we need investigate the condition when the OMP algorithm selects a correct index in the first iteration. Let us denote t^k be the index of the column maximally correlated with the residual $\mathbf{r}^{k-1}$. In the first iteration, we have

$$t^1 = \arg\max_i \left\|\left\langle \mathbf{a}_i, \mathbf{r}^0 \right\rangle\right\| = \arg\max_i \left\|\left\langle \mathbf{a}_i, \mathbf{y} \right\rangle\right\|. \tag{7}$$

Now, let us suppose that t^1 always belong to the support set $\mathcal{I}$ of $\mathbf{x}$. From (7), we have

$$\begin{aligned} \left\|\left\langle \mathbf{a}_{t^1}, \mathbf{y}\right\rangle\right\| &= \left\|\mathbf{A}_{\mathcal{I}}^T \mathbf{y}\right\|_\infty \\ &\overset{(a)}{\geq} \frac{1}{\sqrt{K}} \left\|\mathbf{A}_{\mathcal{I}}^T \mathbf{y}\right\|_2 \\ &\overset{(b)}{\geq} \frac{1}{\sqrt{K}} \left(1-\delta_K\right) \left\|\mathbf{x}_{\mathcal{I}}\right\|_2, \end{aligned} \tag{8}$$

where (a) from the norm inequalities, and (b) from the fact that $y = \mathbf{A}_{\mathcal{I}}\mathbf{x}_{\mathcal{I}}$ and Lemma 1.Suppose that t^1 does not belong to the support set $\mathcal{I}$, then

$$\begin{aligned} \left\|\left\langle \mathbf{a}_{t^1}, \mathbf{y}\right\rangle\right\| &= \left\|\mathbf{a}_{t^1}^T \mathbf{A}_{\mathcal{I}} \mathbf{x}_{\mathcal{I}}\right\| \\ &\overset{(a)}{\leq} \left(1-\delta_{K+1}\right) \left\|\mathbf{x}_{\mathcal{I}}\right\|_2, \end{aligned} \tag{9}$$

where (a) from Lemma 2. Clearly, t^1 must belong to the support set $\mathcal{I}$. Thus, if

$$\frac{1}{\sqrt{K}}\left(1-\delta_K\right)\left\|\mathbf{x}_{\mathcal{I}}\right\|_2 > \left(1-\delta_{K+1}\right)\left\|\mathbf{x}_{\mathcal{I}}\right\|_2 \tag{10}$$

then, the OMP algorithm selects a correct index in the first iteration. The equation (10) becomes $\sqrt{K}\delta_{K+1} + \delta_K < 1$. From Lemma 3, the inequality becomes $\sqrt{K}\delta_{K+1} + \delta_{K+1} < 1$ which leads to

$$\delta_{K+1} < \frac{1}{\sqrt{K}+1} \tag{11}$$

In short, if (11) is true, then the OMP algorithm always selects a correct index in the first iteration.

Now, we investigate a condition such that the OMP algorithm selects a correct index in the $(k+1)^{\text{th}}$ iteration. Let us suppose that initial k iterations of the OMP algorithm are successful. Namely, $\mathcal{T}^k = \left\{t^1, \cdots, t^k\right\} \in \mathcal{I}$. Then, $\mathbf{r}^k = \mathbf{y} - \mathbf{A}_{\mathcal{T}^k}\hat{\mathbf{x}}_{\mathcal{T}^k} \in span\left(\mathbf{A}_{\mathcal{I}}\right)$ because $\mathbf{y} = \mathbf{A}_{\mathcal{I}}\mathbf{x}_{\mathcal{I}}$ and $\mathbf{A}_{\mathcal{T}^k}$ is a sub-matrix of $\mathbf{A}_{\mathcal{I}}$. Thus, $\mathbf{r}^k$ can be expressed as $\mathbf{r}^k = \mathbf{A}\mathbf{x}^k$ (i.e., $\mathbf{r}^k$ is a linear combination of the K columns of $\mathbf{A}_{\mathcal{I}}$), where the support set of $\mathbf{x}^k$ belongs to the support set of $\mathbf{x}$. If the OMP algorithm selects a correct index belonging to the support set of $\mathbf{x}^k$, then the OMP algorithm also selects a correct index belonging to the support set of $\mathbf{x}$. Clearly, if $\sqrt{K}\delta_{K+1} + \delta_{K+1} < 1$ is satisfied, then the OMP algorithm success in the $(k+1)^{\text{th}}$ iteration.

Last, we need to show that the index t^{k+1} selected at the $(k+1)^{\text{th}}$ iteration of the OMP algorithm does not belong to T^k. First, we have $\hat{\mathbf{x}}_{\mathcal{T}^k} = \mathbf{A}_{\mathcal{T}^k}^{\dagger}\mathbf{y}$, and $\mathbf{r}^k = \mathbf{y} - \mathbf{A}_{\mathcal{T}^k}\hat{\mathbf{x}}_{\mathcal{T}^k} = \mathbf{P}_{\mathcal{T}^k}^{\perp}\mathbf{y}$. Second, for all $i \in \mathcal{T}^k$, we have

$$\begin{aligned}\langle \mathbf{a}_i, \mathbf{r}^k \rangle &= \langle \mathbf{a}_i, \mathbf{y} - \mathbf{A}_{\mathcal{T}^k} \hat{\mathbf{x}}_{\mathcal{T}^k} \rangle \\ &= \langle \mathbf{a}_i, \mathbf{y} \rangle - \{ \mathbf{a}_i, \mathbf{A}_{\mathcal{T}^k} \hat{\mathbf{x}}_{\mathcal{T}^k} \} \\ &= \mathbf{a}_i^T A_{\mathcal{I}} x_{\mathcal{I}} - \mathbf{a}_i^T \mathbf{A}_{\mathcal{T}^k} \mathbf{A}_{\mathcal{T}^k}^{\dagger} \mathbf{y} \\ &= 0.\end{aligned}$$

Therefore, we conclude that $\mathbf{r}^k$ is orthogonal to the columns $\mathbf{a}_i$ for all $i \in T^k$. It leads to $t^{k+1} \notin \mathcal{T}^k$. Furthermore, if $\mathbf{r}^k \neq \mathbf{0}$ and $\mathbf{r}^k \in span(\mathbf{A}_{\mathcal{I}})$, then there exists $i \in \mathcal{I}$ such as $\langle \mathbf{a}_i, \mathbf{r}^k \rangle \neq 0$. Therefore, the OMP algorithm selects $i \in \mathcal{I} \setminus \mathcal{T}^k$.

Now, we apply the mathematical induction. First, we proved that the OMP algorithm selects a correct index if $\delta_{K+1} < \frac{1}{\sqrt{K}+1}$. Second, when we assume that the initial k iterations of the OMP algorithm are successful, the OMP algorithm selects a correct index in the $(k+1)^{\text{th}}$ iteration if $\delta_{K+1} < \frac{1}{\sqrt{K}+1}$. Thus, the OMP algorithm will terminate after the K^{th} iteration if $\delta_{K+1} < \frac{1}{\sqrt{K}+1}$.

VI. Discussion on Theorem 1

It is hard for us to determine δ_{K+1} from a sensing matrix because we need to examine all possible *K* sparse signal. However, the below result is known

Result [4]: If an $M \times N$ sensing matrix $\mathbf{A}$ whose entries are i.i.d. $\mathcal{N}(0, 1/M)$, then $\mathbf{A}$ obeys the RIP condition $\delta_K \leq \varepsilon$ with high probability under

$$M \geq \frac{\rho K \log\left(\frac{N}{K}\right)}{\varepsilon^2} \tag{12}$$

where ρ is a positive constant. When we utilize the above inequalities, we indirectly compare the result obtained by [2].

	A sufficient condition	A sufficient condition on M
[1]	$\delta_{K+1} < 1/(3\sqrt{K})$	$M \geq \rho 9K(K+1)\log\left(\frac{N}{K+1}\right)$

The paper	$\delta_{K+1} < 1/\left(\sqrt{K}+1\right)$	$M \ge \rho(K+1)\left(\sqrt{K}+1\right)^2 \log\frac{N}{K+1}$

Appendix

Example 1) computing all the Eigen values of $\begin{bmatrix} 1 & b & \cdots & b \\ b & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & b \\ b & \cdots & b & 1 \end{bmatrix}$.

$$\begin{vmatrix} 1-\lambda & b & b \\ b & 1-\lambda & b \\ b & b & 1-\lambda \end{vmatrix} = \begin{vmatrix} 1-\lambda & b & b \\ 0 & 1-\lambda-b & b-(1-\lambda) \\ b & b & 1-\lambda \end{vmatrix} = \begin{vmatrix} 1-\lambda-b & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) \\ b & b & 1-\lambda \end{vmatrix}$$

$$= \begin{vmatrix} 1-\lambda-b & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) \\ 0 & b & 1-\lambda+b \end{vmatrix} = \begin{vmatrix} 1-\lambda-b & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) \\ 0 & 0 & 1-\lambda+2b \end{vmatrix}$$

$$= (1-\lambda-b)^2(1-\lambda+2b)$$

Therefore, $\lambda_1 = \lambda_2 = 1-b$, and $\lambda_3 = 1+2b$.

$$\begin{vmatrix} 1-\lambda & b & b & b \\ b & 1-\lambda & b & b \\ b & b & 1-\lambda & b \\ b & b & b & 1-\lambda \end{vmatrix} = \begin{vmatrix} 1-\lambda & b & b & b \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ b & b & 1-\lambda & b \\ b & b & b & 1-\lambda \end{vmatrix} = \begin{vmatrix} 1-\lambda & b & b & b \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ 0 & 0 & 1-\lambda-b & b-(1-\lambda) \\ b & b & b & 1-\lambda \end{vmatrix}$$

$$= \begin{vmatrix} 1-\lambda-b & 0 & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ 0 & 0 & 1-\lambda-b & b-(1-\lambda) \\ b & b & b & 1-\lambda \end{vmatrix} = \begin{vmatrix} 1-\lambda-b & 0 & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ 0 & 0 & 1-\lambda-b & b-(1-\lambda) \\ 0 & b & b & 1-\lambda+b \end{vmatrix}$$

$$= \begin{vmatrix} 1-\lambda-b & 0 & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ 0 & 0 & 1-\lambda-b & b-(1-\lambda) \\ 0 & 0 & 2b & 1-\lambda+b \end{vmatrix} = \begin{vmatrix} 1-\lambda-b & 0 & 0 & b-(1-\lambda) \\ 0 & 1-\lambda-b & b-(1-\lambda) & 0 \\ 0 & 0 & 1-\lambda-b & b-(1-\lambda) \\ 0 & 0 & 0 & 1-\lambda+3b \end{vmatrix}$$

$$= (1-\lambda-b)^3(1-\lambda+3b)$$

Therefore, $\lambda_1 = \lambda_2 = \lambda_3 = 1-b$, and $\lambda_4 = 1+3b$

Thus, we concluded all the Eigen values of a $(K+1)\times(K+1)$ $\begin{bmatrix} 1 & b & \cdots & b \\ b & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & b \\ b & \cdots & b & 1 \end{bmatrix}$ are

$\lambda_1 = \cdots = \lambda_K = 1-b,$ and $\lambda_{K+1} = 1+Kb$.

Reference

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