

# Some Theorems and Proofs Regarding Orthogonal Projections\*

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## 1 Theorems

**Theorem 1.** (Theorem 2.3, part 1 in [3]) For any matrix  $A$  and  $B$  the following statement is true.

Let  $P_A$  be orthogonal projector onto the range of  $A$  and let  $P_B$  be orthogonal projector onto the range of  $B$ . If  $\text{rank}(A) = \text{rank}(B)$ :

1. The singular values of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  are the same.
2. The nonzero singular values  $\sigma_i$  of  $P_A P_B^\perp$  correspond to pairs  $\pm\sigma_i$  of eigenvalues of  $P_B - P_A$ , so that

$$\|P_B - P_A\|_2 = \|P_A P_B^\perp\|_2 = \|P_B P_A^\perp\|_2 \quad (1)$$

**Theorem 2.** (Theorem 2.3, part 2 in [3]) For any two matrices  $A_{m \times n}$  and  $B_{m \times l}$  and two orthogonal projectors  $P_A$  and  $P_B$  onto the ranges of  $A$  and  $B$  respectively we have:

$$\|P_B - P_A\|_2 < 1 \Rightarrow \text{rank}(A) = \text{rank}(B) \quad (2)$$

### 1.1 Auxiliary Proofs

**Lemma 1.** Let  $X$  and  $Y$  be subspaces of  $\mathbb{C}^n$  and  $P_X, P_Y$  orthogonal projections onto  $X$  and  $Y$ , respectively.  $\sigma_i$  is a singular value of  $P_X P_Y$  if and only if  $\sigma_i^2$  is an eigenvalue of  $P_X P_Y$ .

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\*This work resulted from me reading [3] and trying to understand all the steps. The theorems stated here are stated but not proven in [3]. Instead, references are cited for the proofs. I went through some of the references and presented the proofs here. Some proofs follow the proofs in the references closely, some rely on the knowledge I gained from the references and adapted into my own proofs.

*Proof.* This proof was taken from [5] and slightly expanded.

We are going to prove the lemma in two parts. First, we will prove that if  $\sigma_i$  is a singular value of  $P_X P_Y$  then  $\lambda_i = \sigma_i^2$  is an eigenvalue of  $P_X P_Y$ . Then we shall prove that for each eigenvalue  $\lambda_i$  of  $P_X P_Y$  there is a singular value  $\sigma_i = \sqrt{\lambda_i}$  of  $P_X P_Y$ .

- **First direction**

We know that singular values of a matrix  $A$  are square roots of eigenvalues of matrix  $A^* A$  or  $AA^*$ . In other words:

$$P_X P_Y (P_X P_Y)^* v = \sigma_i^2 \cdot v \quad (3)$$

for some eigenvector  $v$  of  $P_X P_Y (P_X P_Y)^*$ .

We have:

$$P_X P_Y (P_X P_Y)^* v = P_X P_Y P_Y^* P_X^* v = P_X P_Y P_X v = \sigma_i^2 v \quad (4)$$

From expression above we see that, **if  $\sigma_i > 0$**   $v$  is in the range of  $P_X$  which means:

$$P_X P_Y v = \sigma_i^2 v \quad (5)$$

This shows that for every non-zero singular value  $\sigma_i$  of  $P_X P_Y$  there exists an eigenvalue  $\sigma_i^2$  of  $P_X P_Y$ .

Now to complete this direction of the proof we shall show that for every 0 valued singular value of  $P_X P_Y$  there is a 0 valued eigenvalue of that same matrix. We know that in order for  $P_X P_Y$  to have a 0 valued singular value that there has to exist a vector  $v$  such that  $(P_X P_Y)^* P_X P_Y v = 0$ . If we multiply the equality with  $v^*$  on the left we get:  $v^* (P_X P_Y)^* P_X P_Y v = \|P_X P_X v\|_2 = 0 \rightarrow P_X P_Y v = 0$  which means that  $v$  is an eigenvector of  $P_X P_Y$  with eigenvalue 0. Hence, if 0 is a singular value of  $P_X P_Y$  it is also its eigenvalue.

- **Second direction** We start by showing that for each eigenvalue  $\lambda_i > 0$  of  $P_X P_Y$  there is a singular value  $\sigma_i = \sqrt{\lambda_i}$  of the same matrix:

$$P_X P_Y v = \lambda_i \cdot v \quad (6)$$

$$P_X P_Y v = P_X P_Y P_X v = P_X P_Y P_Y^* P_X^* v = P_X P_Y (P_X P_Y)^* v = \lambda_i \cdot v \quad (7)$$

Hence, every eigenvector-non zero eigenvalue pair of  $P_X P_Y$  is also an eigenvector-eigenvalue pair of  $P_X P_Y (P_X P_Y)^*$ . This means that there is a singular value  $\sigma_i = \sqrt{\lambda_i}$ . In equation (7) we could substitute  $v$  with  $P_X v$  because for  $\lambda_i \neq 0$ ,  $v$  is in range of  $P_X$ .

Next we prove that if 0 is an eigenvalue of  $P_X P_Y$  that it is also an eigenvalue of  $(P_X P_Y)^* P_X P_Y$ . By our assumption we have  $P_X P_Y v = 0$ . This entails  $(P_X P_Y)^* P_X P_Y v = (P_X P_Y)^* \cdot 0 = 0$  which means that if  $P_X P_Y$  has an eigenvalue  $\lambda_i = 0$  then so does  $(P_X P_Y)^* P_X P_Y$ . This ends the proof of the second direction. □

**Corollary 1.1.** *Let  $P_X$  and  $P_Y$  be orthogonal projectors. For each eigenvalue  $\lambda_i$  of  $P_X P_Y$  we have  $0 \leq \lambda_i \leq 1$ . Same is true for each singular value of  $\sigma_i$  of  $P_X P_Y$ ,  $0 \leq \sigma_i \leq 1$ .*

*Proof.* Lemma 1 states that each eigenvalue  $\lambda_i$  of  $P_X P_Y$  corresponds to the square of a singular value of  $P_X P_Y$ :  $\lambda_i = \sigma_i^2 \geq 0$  which proves the lower bound. We can use the fact that for orthogonal projectors  $\|P_X\|_2 = \|P_Y\|_2 = 1$  to prove the upper bound:

$$\lambda_i = |\lambda_i| = \|\lambda_i v\|_2 / \|v\|_2 = \|P_X P_Y v\|_2 / \|v\|_2 \leq \|P_X\|_2 \|P_Y\|_2 \|v\|_2 / \|v\|_2 = 1 \quad (8)$$

Thus we have proven  $0 \leq \lambda_i \leq 1$ . From (8) we get  $\sigma_i = \sqrt{\lambda_i} \leq 1$  and since singular values are positive by definition we have  $0 \leq \sigma_i \leq 1$  □

Next, the concept of reciprocal vectors is introduced and some facts about the reciprocal vectors are stated and proven. This part is taken from [1].

**Definition 1.1.** Reciprocal vectors Let us observe two orthogonal projectors  $P_A$  and  $P_B$ . Let vector  $u$  be in  $range(P_A)$  and vector  $v$  be in  $range(P_B)$ . We say that vectors  $u$  and  $v$  are reciprocal to each other and call them a pair of reciprocal vectors if the following holds:  $\alpha \cdot u = P_A v$  and  $\beta \cdot v = P_B u$  for some scalars  $\alpha \neq 0, \beta \neq 0$ . In other words, vector  $u$  is projected into the ray that spans vector  $v$  and vice versa.

**Lemma 2.** *Any reciprocal vectors  $u, v$  in the range of  $P_A$  and  $P_B$  are eigenvectors of  $P_A P_B$  and  $P_B P_A$  respectively with eigenvalue  $\cos^2 \theta$  where  $\theta$  represents the angle between  $u$  and  $v$  and  $\cos \theta = u^* v / (\|u\|_2 \|v\|_2)$ . Also, if  $u$  is an eigenvector of  $P_A P_B$  for a nonzero eigenvalue  $\cos^2 \theta$  then  $v = P_B u$  is an eigenvector of  $P_B P_A$  for the same eigenvalue and  $u$  and  $v$  are reciprocal vectors in column spaces of  $P_A$  and  $P_B$  respectively with angle  $\theta$  between them.*

*Proof.* Based on the definition of reciprocal vectors we can write:

$$P_A P_B u = P_A \beta v = \beta P_A v = \beta \alpha \cdot u \quad (9)$$

Similarly we have:

$$P_B P_A v = \beta \alpha \cdot v \quad (10)$$

We see that each pair of reciprocal vectors corresponds to the eigenvectors of matrices  $P_A P_B$  and  $P_B P_A$  respectively with corresponding eigenvalue for both eigenvectors being the same:  $\alpha \cdot \beta$ .

We can express the eigenvalue in terms of the angle between the two reciprocal vectors:

$$\alpha \|u\|_2^2 = u^* u \alpha = u^* P_A v = u^* P_A^* v = (P_A u)^* v = u^* v \quad (11)$$

$$\beta \|v\|_2^2 = v^* v \beta = v^* P_B u = v^* P_B^* u = (P_B v)^* u = v^* u \quad (12)$$

$$\alpha \cdot \beta = (u^* v)^2 / (\|u\|_2^2 \|v\|_2^2) = \cos^2 \theta \quad (13)$$

$\theta$  being the angle between the two vectors i.e. the rays they span.

From the equations (9)-(13) we see that each pair of reciprocal vectors corresponds to eigenvectors of  $P_A P_B$  and  $P_B P_A$  with eigenvalue  $\cos^2 \theta$ .

Now we want to prove the second part of the Lemma: that each eigenvector  $u$  of  $P_A P_B$  with nonzero corresponding eigenvalue makes a reciprocal pair of vectors with an eigenvector  $v$  of  $P_B P_A$  with the same nonzero eigenvalue. Let  $u$  be an eigenvector of  $P_A P_B$  with eigenvalue  $\lambda_i$ :  $P_A P_B u = \lambda_i u$ . Let  $v$  be  $v = P_B u$ . Then we have  $P_A v = P_A P_B u = \lambda_i u$  and  $P_B P_A v = P_B \lambda_i u = \lambda_i v$  meaning that  $v$  is an eigenvector of  $P_B P_A$  with same eigenvalue and  $u$  and  $v$  are reciprocal vectors with  $\alpha = \lambda_i$  and  $\beta = 1$ . The angle between the two vectors is by (13)  $\theta = \arccos \sqrt{\alpha \beta} = \arccos \sqrt{\lambda_i}$  and thus the eigenvalue  $\lambda_i = \cos^2 \theta$ .

To sum up, each eigenvalue  $\lambda_i > 0$  of  $P_A P_B$  and  $P_B P_A$  is attached to a pair of reciprocal vectors for  $P_A$  and  $P_B$ .  $\square$

**Lemma 3.** *Let  $P_X$  and  $P_Y$  be orthogonal projectors onto some subspaces  $X$  and  $Y$  of  $\mathbb{C}^n$ .  $0 < \lambda'_i < 1$  is an eigenvalue of  $P_X P_Y$  and  $P_Y P_X$  if and only if  $\lambda_i = 1 - \lambda'_i$  is an eigenvalue of both  $P_X P_Y^\perp$  and  $P_Y P_X^\perp$ . Note: the condition  $0 \leq \lambda'_i \leq 1$  can be restated as  $\lambda'_i \neq 0 \wedge \lambda'_i \neq 1$  because the interval for possible eigenvalues for a product of orthogonal projectors is  $[0, 1]$  (see Corollary 1.1).*

*Proof.* Let us observe the following for some eigenvalue  $0 < \lambda_i < 1$  of  $P_X P_Y^\perp$ :

$$P_X P_Y^\perp \cdot v = \lambda_i \cdot v \quad (14)$$

$$P_X (I - P_Y) v = P_X v - P_X P_Y v = \lambda_i \cdot v \quad (15)$$

Since  $\lambda_i > 0$  we know that  $P_X v = v$  so based on equation (15) we can write:

$$P_X P_Y v = (1 - \lambda_i) v \quad (16)$$

We see that  $v$  is an eigenvector of  $P_X P_Y$  with eigenvalue  $1 - \lambda_i$ . Since  $(P_X P_Y)^* = P_Y P_X$  matrices  $P_X P_Y$  and  $P_Y P_X$  have the same eigenvalues. In other words there is an eigenvector  $u$  for matrix  $P_Y P_X$  such that:

$$P_Y P_X u = (1 - \lambda_i) u \Rightarrow u - P_Y P_X u = \lambda_i u \quad (17)$$

Since we are observing  $0 < \lambda_i < 1$ , we have  $0 < 1 - \lambda_i < 1$  which means  $P_Y u = u$  so we can write:

$$u - P_Y P_X u = P_Y u - P_Y P_X u = P_Y (I - P_X) u = P_Y P_X^\perp u = \lambda_i u \quad (18)$$

We have thus proven that any eigenvalue  $0 < \lambda_i < 1$  of  $P_X P_Y^\perp$  is also an eigenvalue of  $P_Y P_X^\perp$  and there exists an eigenvalue  $\lambda'_i = 1 - \lambda_i$  of both  $P_X P_Y$  and  $P_Y P_X$ . Similarly, we can start with an eigenvalue  $\lambda_i$  of  $P_Y P_X^\perp$  and prove that  $P_X P_Y^\perp$  has the same eigenvalue and that both  $P_X P_Y$  and  $P_Y P_X$  have an eigenvalue  $\lambda'_i = 1 - \lambda_i$ .

Now we need to prove the other direction of our lemma: that for each  $0 < \lambda'_i < 1$  eigenvalue of both  $P_X P_Y$  and  $P_Y P_X$  there is an eigenvalue  $\lambda_i = 1 - \lambda'_i$  of both  $P_X P_Y^\perp$  and  $P_Y P_X^\perp$ :

$$P_X P_Y v = \lambda'_i v \Rightarrow P_X P_Y v - P_X v = \lambda'_i v - v \Rightarrow P_X P_Y^\perp v = (1 - \lambda'_i) v \quad (19)$$

Similarly we can get  $P_Y P_X^\perp u = (1 - \lambda'_i) u$  where  $u$  is an eigenvector of  $P_Y P_X$  associated with the eigenvalue  $\lambda'_i$ . We have thus proven that  $P_X P_Y^\perp$  and  $P_Y P_X^\perp$  have an eigenvalue  $\lambda_i = 1 - \lambda'_i$ ,  $0 < \lambda_i < 1$ , for each eigenvalue  $0 < \lambda'_i < 1$  of  $P_X P_Y$  and  $P_Y P_X$ .  $\square$

## 1.2 Theorem Proofs

*Proof of Theorem 1, Part 1.* Since  $P_A^\perp$  and  $P_B^\perp$  as well as  $P_A$  and  $P_B$  are all orthogonal projectors by Lemma 1 we can compare eigenvalues of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  in lieu of their singular values.

We did a lion's share of work by proving Lemma 3. By Lemma 3, we know that  $P_A P_B^\perp$  and  $P_B P_A^\perp$  share all eigenvalues  $0 < \lambda_i < 1$ . By Lemma 1 we know that applies to the singular values  $0 < \sigma_i < 1$  of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  as well.

Since both  $P_A P_B^\perp$  and  $P_B P_A^\perp$  are products of orthogonal projectors, their singular values are in range  $0 \leq \sigma_i \leq 1$  (see Corollary 1.1). We have proven that  $P_A P_B^\perp$  and  $P_B P_A^\perp$  share all the singular values in the range  $0 < \sigma_i < 1$ . What is left to prove is that both matrices have the same number of singular values with value 1. We can analyze the trace of matrices  $P_A P_B^\perp$  and  $P_B P_A^\perp$  to prove this.

We know that the trace of a matrix is equal to the sum of its eigenvalues.<sup>1</sup> We also know that all the eigenvalues of any orthogonal projector  $P$  are either 0 or 1. We can verify that by observing the singular value decomposition of an orthogonal projector (see [4], proof of Theorem 6.1) which is also its eigenvalue decomposition. These two facts imply  $\text{trace}(P) = \text{rank}(P)$  for any orthogonal projector  $P$ .

<sup>1</sup>This can be derived from the fact that each matrix can be written in the Jordan canonical form (see [2])  $A = SJS^{-1}$  where  $J$  has eigenvalues on its diagonal and the fact that  $\text{trace}(AB) = \text{trace}(BA)$ . The equality  $\text{trace}(AB) = \text{trace}(BA)$  can be proven by simply writing out the sums that correspond to the traces of matrices  $AB$  and  $BA$  and rearranging them to be in the same form. By using the equality  $\text{trace}(AB) = \text{trace}(BA)$  we can write  $\text{trace}(A) = \text{trace}(SJS^{-1}) = \text{trace}(S^{-1}SJ) = \text{trace}(J) = \sum_i \lambda_i$  where  $\lambda_i$  are eigenvalues of  $A$ .

For orthogonal projectors we could use the eigenvalue decomposition to prove the fact that  $\text{trace}(P) = \sum_i \lambda_i$ . By using the Jordan canonical form we get a more general result.

We can write:

$$\begin{aligned} \text{rank}(A) &= \text{trace}(P_A) = \text{trace}(P_A(P_B + P_B^\perp)) \\ &= \text{trace}(P_A P_B) - \text{trace}(P_A P_B^\perp) \end{aligned} \quad (20)$$

$$\begin{aligned} \text{rank}(B) &= \text{trace}(P_B) = \text{trace}(P_B(P_A + P_A^\perp)) \\ &= \text{trace}(P_B P_A) - \text{trace}(P_B P_A^\perp) \end{aligned} \quad (21)$$

We know that  $(P_A P_B)^* = P_B P_A \Rightarrow \text{trace}(P_A P_B) = \text{trace}(P_B P_A)$ . Theorem 1. assumes  $\text{rank}(A) = \text{rank}(B)$ . Based on this and the equations (20) and (21) we get:

$$\text{trace}(P_A P_B^\perp) = \text{trace}(P_B P_A^\perp) \quad (22)$$

Let us delve deeper into equation (22). We denote the number of eigenvalues with value 1 of matrix  $P_A P_B^\perp$  as  $n_{AB^\perp}$  and for matrix  $P_B P_A^\perp$  as  $n_{BA^\perp}$ . We can write:

$$\text{trace}(P_A P_B^\perp) = \sum_{\lambda_i \neq 1} \lambda_i(P_A P_B^\perp) + n_{AB^\perp} \cdot 1 \quad (23)$$

$$\text{trace}(P_B P_A^\perp) = \sum_{\lambda_i \neq 1} \lambda_i(P_B P_A^\perp) + n_{BA^\perp} \cdot 1 \quad (24)$$

We know that  $P_A P_B^\perp$  and  $P_B P_A^\perp$  have the same eigenvalues in range  $0 < \lambda_i < 1$ , hence  $\sum_{\lambda_i \neq 1} \lambda_i(P_A P_B^\perp) = \sum_{\lambda_i \neq 1} \lambda_i(P_B P_A^\perp)$ . From this we get  $n_{AB^\perp} = n_{BA^\perp}$ , i.e.  $P_A P_B^\perp$  and  $P_B P_A^\perp$  have exactly the same number of eigenvalues with value 1 and therefore by Lemma 1 also the same number of singular values with value 1. Hence, all the singular values of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  are the same.  $\square$

*Proof of Theorem 1, Part 2.* The second part of our theorem states that all nonzero eigenvalues of  $P_A - P_B \pm \sigma_i$  correspond to singular values  $\sigma_i$  of  $P_A P_B^T$  and  $P_B P_A^T$  and vice versa.

This proof is split in two parts. The first part is about proving the statement for eigenvalues  $\lambda_i \neq \pm 1$  of  $P_B - P_A$  and the second part focuses on the case when  $\lambda_i = \pm 1$ .

- $|\lambda_i| \neq 1$

We prove this part by showing that a vector  $v$  is an eigenvector of  $P_A - P_B$  with eigenvalues satisfying this condition if and only if  $v$  is a difference of reciprocal vectors of  $P_A$  and  $P_B$ . Then we give an expression for the associated eigenvalue.

Let us try to construct eigenvectors of  $P_A - P_B$  from reciprocal vectors of  $P_A$  and  $P_B$ .

We know from the Definition 1.1 of the reciprocal vectors  $u$  and  $v$  that  $\alpha u = P_A v$  and  $\beta v = P_B u$ . Let us see whether we can tune  $\alpha$  and  $\beta$  so that the difference of two reciprocal vectors  $u - v$  is an eigenvector of  $P_A - P_B$ .

$$(P_A - P_B) \cdot (u - v) = u - \alpha u - \beta v + v = (1 - \alpha)u - (\beta - 1)v \quad (25)$$

In order for  $u - v$  to be an eigenvector of  $P_A - P_B$  we need to find  $\alpha$  and  $\beta$  such that the following holds:

$$1 - \alpha = \beta - 1 = \lambda_i \quad (26)$$

where  $\lambda_i$  would be the eigenvalue associated with the eigenvector  $u - v$ .

From Lemma 2 we know that there is a nonzero eigenvalue  $\lambda'_i$  of  $P_A P_B$  with value  $\lambda'_i = \alpha\beta = \cos^2\theta$ .

In order for  $u - v$  to be an eigenvector of  $P_A - P_B$  we need to have  $\alpha = 2 - \beta$  (see (26)). We get:

$$\alpha\beta = (2 - \beta)\beta = \lambda'_i \quad (27)$$

$$\beta^2 - 2\beta + \lambda'_i = 0 \quad (28)$$

$$\beta = \frac{(2 \pm \sqrt{4 - 4\lambda'_i})}{2} = 1 \pm \sqrt{1 - \lambda'_i} \quad (29)$$

From there we have:

$$\lambda_i = \beta - 1 = \pm\sqrt{1 - \lambda'_i} \quad (30)$$

From Lemma 3 and the fact that  $\lambda'_i = 1 - \lambda_i^2 \neq 0, 1$  because we are looking at  $\lambda_i \neq 0, 1$  we know that there is an eigenvalue  $\lambda_i''$  of both  $P_A P_B^\perp$  and  $P_B P_A^\perp$  such that  $\lambda_i'' = 1 - \lambda'_i$ . Using that and Lemma 1 we can write:

$$\lambda_i = \pm\sqrt{\lambda_i''} = \pm\sigma_i \quad (31)$$

with  $\sigma_i$  being any nonzero singular value of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  such that  $\sigma_i \neq 1$ .

To complete this part of the proof, we need to prove that each nonzero eigenvalue  $\lambda_i$  of  $P_A - P_B$  s.t.  $|\lambda_i| \neq 1$  is associated with an eigenvector that is a difference of two reciprocal vectors of  $P_A$  and  $P_B$ . This is necessary to establish that  $P_A - P_B$  does not have any additional eigenvalues  $\lambda_i \neq \pm 1$  that are not equal to  $\pm\sigma_i$  for some singular value  $\sigma_i$  of  $P_A P_B^\perp$  and  $P_B P_A^\perp$ .

For each eigenvector  $v$  of  $P_A - P_B$  with eigenvalue  $\lambda_i$ , s.t.  $\lambda_i \neq 0$  we can write  $P_A v - P_B v = \lambda_i v$ . From there we can get  $v = P_A v / \lambda_i - P_B v / \lambda_i$ . Hence, if  $P_A v$  and  $P_B v$  are reciprocal vectors,  $v$  is a difference of two

reciprocal vectors of  $P_A$  and  $P_B$ . We now prove that  $P_A v$  and  $P_B v$  are in fact reciprocal vectors when  $|\lambda_i| \neq 1$ .

We need to find  $\alpha, \beta > 0$  such that  $\alpha P_A v = P_A P_B v$  and  $\beta P_B v = P_B P_A v$ . We can find such  $\alpha$  and  $\beta$  by multiplying  $P_A v - P_B v = \lambda_i v$  by  $P_A$  or  $P_B$  respectively. In case of  $P_A$  we get:

$$(1 - \lambda_i) \cdot P_A v = P_A P_B v \quad (32)$$

When multiplying by  $P_B$  we get:

$$(1 + \lambda_i) \cdot P_B v = P_B P_A v \quad (33)$$

We have found  $\alpha = 1 - \lambda_i$  and  $\beta = 1 + \lambda_i$  which are both nonzero when  $|\lambda_i| \neq 1$  which proves that  $P_A v$  and  $P_B v$  are reciprocal vectors for any eigenvector  $v$  of  $P_A - P_B$  that is associated with an eigenvalue  $|\lambda_i| \neq 1$ . Hence, all eigenvectors of  $P_A - P_B$  with nonzero eigenvalues  $|\lambda_i| \neq 1$  are a difference of two reciprocal vectors.

- $\lambda_i = \pm 1$

Next we want to prove that  $P_A - P_B$  has eigenvalues with value  $\pm 1$  if and only if  $P_A P_B^\perp$  and  $P_B P_A^\perp$  have singular values  $\sigma_i = 1$ .

First we prove that if  $P_A P_B^\perp$  and  $P_B P_A^\perp$  have eigenvalues 1 that  $P_A - P_B$  has eigenvalues  $\pm 1$ .

$$P_A P_B^\perp v = v \Rightarrow \|P_A P_B^\perp v\|_2 = \|v\|_2 \quad (34)$$

$$\|v\|_2 = \|P_A P_B^\perp v\|_2 \leq \|P_A\|_2 \|P_B^\perp v\|_2 \leq \|P_B^\perp v\|_2 \quad (35)$$

$$\|P_B^\perp v\|_2 \leq \|P_B^\perp\|_2 \|v\|_2 = \|v\|_2 \quad (36)$$

$$\|v\|_2 \leq \|P_B v^\perp\|_2 \leq \|v\|_2 \Rightarrow \|P_B^\perp v\|_2 = \|v\|_2 \quad (37)$$

Since  $P_B^\perp$  is an orthogonal projector we know that for any vector  $v$  we have  $\|P_B v\|_2^2 + \|P_B^\perp v\|_2^2 = \|v\|_2^2$ . From there and equation (37) we get  $\|P_B v\|_2 = 0 \Rightarrow P_B v = 0 \wedge P_B^\perp v = v$ . This reduces the eigenvector-eigenvalue expression from equation (34) to  $P_A v = v$ . For this eigenvector  $v$  we can write  $P_A v - P_B v = v - 0 = v$  which means that  $v$  is also an eigenvector of  $P_A - P_B$  with eigenvalue 1.

We have proven earlier that when  $P_A$  and  $P_B$  have same rank, then  $P_A P_B^\perp$  and  $P_B P_A^\perp$  they have the same number of eigenvalues with value 1. Using similar reasoning as above, eigenvector  $u$  of  $P_B P_A^\perp$  with associated eigenvalue 1 is in the range of  $P_B$  and is orthogonal to the range of  $P_A$ . This



would lead to  $(P_A - P_B)u = P_A u - P_B u = 0 - u = -u$  which means that for each eigenvalue 1 of  $P_B P_A^\perp$ ,  $P_A - P_B$  has eigenvalue  $-1$  associated with the same eigenvector  $u$ . Therefore, for any singular value 1 of both  $P_A P_B^\perp$  and  $P_B P_A^\perp$  we have  $\pm 1$  eigenvalues of  $P_A - P_B$ .

Now we need to prove that  $P_A - P_B$  has eigenvalues  $\pm 1$  only when  $P_A P_B^\perp$  and  $P_B P_A^\perp$  have eigenvalues 1 to avoid cases where  $P_A - P_B$  would have eigenvalues  $\pm 1$  without corresponding eigenvalues/singular values for  $P_A P_B^\perp$  and  $P_B P_A^\perp$ .

Let us observe vector  $v$  that is an eigenvector of  $P_A - P_B$  with eigenvalue 1. The following holds:  $P_A v - P_B v = v \Rightarrow -P_B v = P_A^\perp v$ . From there we have:

$$P_B^\perp v - v = P_A^\perp v \quad (38)$$

If we multiply both sides of the equation with  $(P_A^\perp v)^*$  on the left side we get:

$$\begin{aligned} (P_A^\perp v)^* P_B^\perp v - (P_A^\perp v)^* v &= (P_A^\perp v)^* P_A^\perp v \\ - (P_B v)^* P_B^\perp v - v^* P_A^\perp P_A^\perp v &= (P_A^\perp v)^* P_A^\perp v \\ - v^* P_B P_B^\perp v - (P_A^\perp v)^* P_A^\perp v &= (P_A^\perp v)^* P_A^\perp v \\ 2 \cdot (P_A^\perp v)^* P_A^\perp v = 0 &\Rightarrow P_A^\perp v = P_B v = 0 \end{aligned} \quad (39)$$

From the result in (39) we see that  $P_A - P_B$  has eigenvalue 1 only for an eigenvector  $v$  that is in range of  $P_A$  and is orthogonal to the range of  $P_B$ . Such a vector is also an eigenvector of  $P_A P_B^\perp$  with eigenvalue 1.

Using a similar approach we can prove that if a vector  $u$  is an eigenvector of  $P_A - P_B$  with eigenvalue  $-1$  then it is also an eigenvector of  $P_B P_A^\perp$  with eigenvalue 1. From that and Lemma 1 we now know that for each eigenvalue pair  $\pm 1$  of  $P_A - P_B$  there is a singular value 1 of both  $P_A P_B^\perp$  and  $P_B P_A^\perp$ .

We have proven that nonzero singular values  $\sigma_i$  of  $P_A P_B^\perp$  and  $P_B P_A^\perp$  correspond to pairs of  $\pm \sigma_i$  of eigenvalues of  $P_B - P_A$ . Since  $P_B - P_A$  is a Hermitian matrix, absolute values of its eigenvalues are equal to its singular values (see [4], Theorem 5.5.) so we have:

$$\|P_A - P_B\|_2 = \|P_A P_B^\perp\|_2 = \|P_B P_A^\perp\|_2 \quad (40)$$

□

*Proof.* Proof of Theorem 2 We will prove this by proving the contrapositive. That is, that  $\text{rank}(A) \neq \text{rank}(B) \Rightarrow \|P_B - P_A\|_2 \geq 1$ .

Let us assume without loss of generality that  $\text{rank}(A) > \text{rank}(B)$ . We know that  $\dim(\text{range}(A)) = \dim(\text{range}(P_A))$  and  $\dim(\text{range}(B)) = \dim(\text{range}(P_B))$ .

Let the dimension of column space of  $B$  be  $p$  and of column space of  $A$  be  $p+k$  for some  $k > 0$ . We know that the dimension of the subspace orthogonal to the range of  $B$  is  $m-p$  where  $m$  is the number of rows of matrices  $A$  and  $B$ . We have  $\dim(\text{range}(A)) + \dim(\text{range}(P_B^\perp)) = p+k+m-p = m+k$  with  $k > 0$ . This means that the intersection of range of  $A$  and the subspace orthogonal to the range of  $B$  is a non-empty set. If we pick a vector  $v$  from that intersection we get:

$$\begin{aligned} \|(P_B - P_A)v\|_2 &= \|P_B v - P_A v\|_2 = \|0 - v\|_2 = \|v\|_2 \Rightarrow \\ \Rightarrow \|P_B - P_A\|_2 &\geq \frac{\|(P_B - P_A)v\|_2}{\|v\|_2} = 1 \end{aligned} \quad (41)$$

We arrive to the same conclusion if we start with  $\text{rank}(B) > \text{rank}(A)$ .  $\square$

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