

## THE PERRON-FROBENIUS THEOREM

We state and prove here a simplified version of the Perron-Frobenius Theorem, that has manifold applications.

**Theorem 0.1.** *Let  $A$  be an  $n \times n$  matrix with strictly positive matrix elements. There exists an eigenvalue  $\lambda_{\max} > 0$  which is not degenerate and whose eigenvector  $x_{\max}$  has strictly positive components. Moreover, any other eigenvector  $x$  of  $A$  with non-negative entries is equal to  $x_{\max}$ . Further, if  $\lambda$  is any other eigenvalue of  $A$  (which may be complex), then  $|\lambda| \leq \lambda_{\max}$ .*

Let  $Q$  be the positive orthant in  $\mathbb{R}^n$ . Let  $x \in Q$ ,  $x \neq 0$  and set

$$E(x) = \min_{i, x_i \neq 0} \frac{(Ax)_i}{x_i} .$$

We first start with a lemma.

**Lemma 0.2.** *The function  $E(x)$  is bounded, in fact*

$$E(x) \leq \max_k \sum_i a_{ki} .$$

*Further, for any  $x \in Q$ ,  $x \neq 0$  we have that*

$$E(Ax) \geq E(x)$$

*with equality only if  $x$  satisfies  $Ax = E(x)x$ , i.e.,  $x$  is an eigenvector.*

*Proof.* The definition of  $E(x)$  is equivalent with the statement that  $E(x)$  is the largest number such that

$$(Ax)_i - E(x)x_i \geq 0, i = 1, \dots, n .$$

To see that

$$E(Ax) \geq E(x) ,$$

simply note that

$$[A(Ax - E(x)x)]_i \geq 0, i = 1, \dots, n$$

since  $(Ax)_i - E(x)x_i \geq 0, i = 1, \dots, n$ . This means that

$$E(Ax) = \min_i \frac{(A^2x)_i}{(Ax)_i} \geq E(x) .$$

Note that since  $A$  has strictly positive elements and  $x \in Q$  is not the zero vector we have that  $Ax$  has strictly positive components. Now, suppose that  $x \in Q$  is not an eigenvector of  $A$ . Then, as noted above,  $(Ax)_i - E(x)x_i \geq 0, i = 1, \dots, n$  and not all of them are equal to zero. Hence

$$[A(Ax - E(x)x)]_i > 0, i = 1, \dots, n$$

with a strict inequality. Thus  $E(Ax) > E(x)$ .

Finally to see that  $E(x)$  is bounded, note that for any given  $x \in Q$ ,  $x \neq 0$  we have that

$$\min_{i, x_i \neq 0} \frac{(Ax)_i}{x_i} \leq \frac{(Ax)_k}{x_k}$$

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where  $x_k = \max_i x_i$ . But then  $(Ax)_k = \sum_i a_{ki}x_i \leq (\sum_i a_{ki})x_k$  so that

$$\frac{(Ax)_k}{x_k} \leq \left( \sum_i a_{ki} \right).$$

□

To gather some more information about  $E(x)$  we have to introduce the set  $\Sigma$  which is the intersection of  $Q$  and the unit sphere in  $\mathbb{R}^n$ . The next step is the analytical part of the proof. The key fact from analysis is that if a function is continuous on a compact set, then it attains its maximum and minimum on that set. The problem is that  $E(x)$  may not be continuous on the set  $\Sigma$ . Since the ratio  $\frac{(Ax)_i}{x_i}$  is only defined for  $i$  with  $x_i$  non-zero. What can happen is that  $\min_i \frac{(Ax)_i}{x_i}$  could jump as one varies the vector  $x \in Q$  and one or more components vanish during that process. Thus  $E$  is not continuous on  $\Sigma$ , but it is on  $A(\Sigma)$  as we shall show next.

**Lemma 0.3.** *Consider the set  $A(\Sigma)$ , i.e., the image of the set  $\Sigma$  under  $A$ . This set is closed and bounded. Moreover, on this set  $A(\Sigma)$  the function  $E(x)$  is continuous.*

*Proof.* The set  $\Sigma$  is closed and bounded and hence compact. Multiplication by a matrix is a continuous operation and hence  $A(\Sigma)$  is also compact. Since  $A$  has strictly positive matrix elements, we have that

$$\min_{x \in \Sigma} (Ax)_i \geq m_i > 0, \quad i = 1, \dots, n.$$

Hence  $E$  is continuous on  $A(\Sigma)$ . □

*Proof of the Theorem.* The function  $E$  being continuous on  $A(\Sigma)$  and  $A(\Sigma)$  being compact, attains its maximum on  $A(\Sigma)$ . Moreover, since  $E(Ax) \geq E(x)$  it also attains its maximum on  $\Sigma$ . Let's denote a vector where the maximum attained by  $z$ . We have that  $E(Az) \geq E(z)$  and since  $E(z)$  is the maximum, we have that  $E(Az) = E(z)$ . By the first lemma the vector  $z$  must be an eigenvector. Moreover  $z$  has strictly positive components because  $Az = E(z)z$  and the components of  $Az$  are strictly positive. We set  $\lambda_{\max} := E(z)$ . Note that  $\lambda_{\max}$  is strictly positive, for otherwise  $A$  would be the zero matrix.

Now let  $y$  be any eigenvector of  $A$  with eigenvalue  $\lambda$  which could be complex. Then taking absolute values in the equation  $\lambda y_i = \sum_j a_{ij}y_j$  we get using the triangle inequality

$$|\lambda||y_i| \leq \sum_j a_{ij}|y_j|.$$

Hence

$$|\lambda| \leq \min_{i, |y_i| \neq 0} \frac{\sum_j a_{ij}|y_j|}{|y_i|} = E(|y|) \leq \lambda_{\max}$$

where we denote by  $|y|$  the vector that has the components  $|y_i|, i = 1, \dots, n$ . This proves that any eigenvalue  $\lambda$  must satisfy  $|\lambda| \leq \lambda_{\max}$ .

We have to show that  $\lambda_{\max}$  has geometric multiplicity one. Suppose that there exists  $x \in Q, x \neq 0$  such that  $Ax = \lambda_{\max}x$ . Then  $x$  must have strictly positive components. If  $x$  and  $z$  are not proportional they span a two dimensional space and hence there are number  $a, b$  so that the vector  $y := az + bx$  has a zero component. Then  $Ay = \lambda_{\max}y$  and as before taking magnitudes

$$\lambda_{\max}|y_i| \leq \sum_j a_{ij}|y_j|$$

and we conclude as before that

$$\lambda_{\max} \leq E(|y|) \leq \lambda_{\max}$$

and hence there must be equality. Because  $\lambda_{\max} \geq E(A|y|) \geq E(|y|) = \lambda_{\max}$  the vector  $|y|$  must be an eigenvector, i.e.,  $A|y| = \lambda_{\max}|y|$ . But, this means that all the components of  $|y|$  must be strictly positive contradicting the fact that  $y$  has a zero component.

What is left is to show that if  $Ax = \lambda x$  and  $x$  has non-negative components, then  $\lambda = \lambda_{\max}$  and  $x$  is a positive multiple of  $z$ . To prove this, we consider the transpose  $A^T$  which also has strictly positive matrix elements. Hence we may apply the same reasoning and find a vector  $w$  with strictly positive entries such that  $A^T w = \mu w, \mu > 0$ . The claim is that  $\mu = \lambda_{\max}$ . To see this we compute

$$\mu w^T z = (A^T w)^T z = w^T A z = \lambda_{\max} w^T z$$

and since  $w^T z > 0$  we have that  $\mu = \lambda_{\max}$ . Let  $x$  be any eigenvector of  $A$  with non-negative entries, i.e.,  $(Ax)_i = \lambda x_i, i = 1, \dots, n$ . Then by the same reasoning, using that  $w$  has strictly positive components, we find that  $w^T x > 0$  and hence

$$\lambda_{\max} = \lambda.$$

Since the eigenvalue  $\lambda_{\max}$  has geometric multiplicity one, the vector  $x$  must be a positive multiple of  $z$ .  $\square$

We assumed that the matrix elements  $a_{ij}$  are strictly positive and we can say a bit more.

**Theorem 0.4.** *Suppose that  $Ay = \lambda y$  and  $|\lambda| = \lambda_{\max}$ . Here  $\lambda$  may be complex and  $y$  a complex vector. Then  $y = cz$  where  $c \neq 0$  is in general a complex number. In other words, if  $Ay = \lambda y$  and  $y$  is not proportional to  $z$  then  $|\lambda| < \lambda_{\max}$ .*

*Proof.* The reasoning is as before. We have

$$\lambda_{\max}|y_i| = |\lambda||y_i| \leq \sum_j a_{ij}|y_j|$$

from which we conclude as before that the vector  $|y|$  having the components  $|y_i|$  is an eigenvector with non-negative entries with eigenvalue  $\lambda_{\max}$  and hence proportional to  $z$ . Hence we must have the equality

$$|\sum_j a_{ij}y_j| = \sum_j a_{ij}|y_j|, i = 1, \dots, n.$$

The rest follows by an inductive application of the simple lemma below.  $\square$

**Lemma 0.5.** *Let  $a, b > 0$ . Then*

$$|a + e^{i\phi}b| = |a + b|$$

*implies that  $e^{i\phi} = 1$ .*

*Proof.* We compute

$$|a + e^{i\phi}b|^2 = a^2 + b^2 + 2ab\Re e^{i\phi} = a^2 + b^2 + 2ab$$

from which we get that  $\Re e^{i\phi} = 1$ . Since  $|e^{i\phi}| = 1$ , we have that  $e^{i\phi} = 1$ .  $\square$