

# Proof of the Perron-Frobenius Theorem

Based on exercise 1.20 of Introduction to Stochastic Processes  
by Gregory F. Lawler

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## Definition

Let  $\vec{u} = (u^1, \dots, u^n)$  and  $\vec{v} = (v^1, \dots, v^n)$  be vectors.

We write  $\vec{u} \geq \vec{v}$  if  $u^i \geq v^i$  for all  $i$ , and  $\vec{u} > \vec{v}$  if  $u^i > v^i$  for all  $i$ .

$|\vec{v}| = (|v^1|, \dots, |v^n|)$ , and  $\vec{0} = (0, \dots, 0)$ .

# Statement of Theorem

## Perron-Frobenius Theorem

Let  $\mathbf{A} = (a_{ij})$  be an  $n \times n$  matrix with  $a_{ij} > 0$  for all  $i, j$ .  $\mathbf{A}$  has a real eigenvalue  $\alpha > 0$  with a unique eigenvector  $\vec{v} > \vec{0}$  of norm 1 such that  $|\lambda| < \alpha$  for any other eigenvalue  $\lambda$  of  $\mathbf{A}$ . Moreover,  $\alpha$  is a simple eigenvalue (i.e., it is a root of the characteristic polynomial of  $\mathbf{A}$  with multiplicity 1).

1.20(c) shows that  $\alpha > 0$  is an eigenvalue of  $\mathbf{A}$ .

1.20(d) shows that there is  $\alpha$  has a unique eigenvector  $\vec{v} \geq \vec{0}$  with norm 1.

1.20(e) shows that, in fact,  $\vec{v} > \vec{0}$ .

1.20(f) shows that all other eigenvalues  $\lambda$  of  $\mathbf{A}$ ,  $|\lambda| < \alpha$ .

1.20(i) shows that  $\alpha$  is a simple eigenvalue of  $\mathbf{A}$ .

## Theorem

*Every stochastic  $n \times n$  matrix  $\mathbf{P}$  with positive entries has a unique invariant probability distribution  $\vec{\pi}$  with all positive components.*

## 1.20(j)

### Theorem

Every stochastic  $n \times n$  matrix  $\mathbf{P}$  with positive entries has a unique invariant probability distribution  $\vec{\pi}$  with all positive components.

### Proof:

$\mathbf{P}^T$  is a square matrix with all positive entries. By the Perron-Frobenius theorem,  $\mathbf{P}^T$  has a real eigenvalue  $\alpha > 0$  with a unique eigenvector  $\vec{v} > \vec{0}$  of norm 1. Let  $\pi^j = \frac{v^j}{\sum_{i=1}^n v_i}$ . Then  $\vec{\pi} = (\pi^1, \dots, \pi^n) > \vec{0}$  is a probability distribution. Since  $\mathbf{P}$  is a stochastic matrix,  $\mathbf{P}^T \vec{\pi} = \alpha \vec{\pi}$  is a probability distribution. Therefore,  $\alpha = \alpha \sum_{i=1}^n \pi^i = \sum_{i=1}^n \alpha \pi^i = 1$ . So  $\mathbf{P}^T \vec{\pi} = \vec{\pi}$ , and  $\vec{\pi} \mathbf{P} = \vec{\pi}$  if we equate  $\vec{\pi}$  with  $\vec{\pi}^T$ . Therefore,  $\vec{\pi}$  is an invariant probability distribution of  $\mathbf{P}$ .

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# Use of the Perron-Frobenius Theorem

## Theorem

If  $\mathbf{P}$  be a stochastic matrix with positive entries and a unique invariant

probability distribution  $\vec{\pi}$ , then  $\lim_{n \rightarrow \infty} \mathbf{P}^n = \begin{pmatrix} \vec{\pi} \\ \vdots \\ \vec{\pi} \end{pmatrix}$

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## Proof:

By the Perron-Frobenius theorem and the proof of 1.20(j),  $\mathbf{P}^T$  has a simple eigenvalue of 1 and all other eigenvalues of  $\mathbf{P}^T$  have absolute value less than 1. The same is true for  $\mathbf{P}$ .

Therefore, the Jordan canonical form of  $\mathbf{P}$  is  $\mathbf{J} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & & & \\ \vdots & & \mathbf{M} & \\ 0 & & & \end{pmatrix}$

where  $\mathbf{M}$  has entries with absolute value less than 1 on the diagonal, 1's or 0's on the superdiagonal, and 0's everywhere else.  $\lim_{n \rightarrow \infty} \mathbf{M}^n = \mathbf{0}$ .

# Use of the Perron-Frobenius Theorem (continued)

## Proof Continued:

$\mathbf{P}$  is similar to its Jordan canonical form. That is,  $\mathbf{P} = \mathbf{Q}\mathbf{J}\mathbf{Q}^{-1}$ .

$$(1, \dots, 1)^T = \mathbf{P}(1, \dots, 1)^T = \mathbf{Q}\mathbf{J}\mathbf{Q}^{-1}(1, \dots, 1)^T = \mathbf{Q}\mathbf{J}(1, 0, \dots, 0)^T = \mathbf{Q}(1, 0, \dots, 0)^T.$$

It follows that the first column of  $\mathbf{Q}$  is all 1's.

$$\vec{\pi} = \mathbf{P}^T \vec{\pi} = (\mathbf{Q}^{-1})^T \mathbf{J}^T \mathbf{Q}^T \vec{\pi} = (\mathbf{Q}^{-1})^T \mathbf{J}^T (1, 0, \dots, 0)^T = (\mathbf{Q}^{-1})^T (1, 0, \dots, 0)^T.$$

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It follows that the first row of  $\mathbf{Q}^{-1}$  is  $\vec{\pi}$ . Therefore,

$$\lim_{n \rightarrow \infty} \mathbf{P}^n = \mathbf{Q}(\lim_{n \rightarrow \infty} \mathbf{J}^n)\mathbf{Q}^{-1} = \mathbf{Q} \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & & & \\ \vdots & & \mathbf{0} & \\ 0 & & & \end{pmatrix} \mathbf{Q}^{-1} = \begin{pmatrix} \vec{\pi} \\ \vdots \\ \vec{\pi} \end{pmatrix}.$$

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QED

## Remark

There is an analytic proof to the previous theorem that uses less machinery.

## Lemma

If  $\vec{v} \geq \vec{0}$  and  $\vec{v} \neq \vec{0}$ , then  $\mathbf{A}\vec{v} > \vec{0}$ .

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## Proof:

If  $\vec{v} \geq \vec{0}$  and  $\vec{v} \neq \vec{0}$ , then the  $v^j$  are all non-negative and not all zero. That is,  $v^j \geq 0$  for all  $j$  and there is a  $j_0$  such that  $v^{j_0} > 0$ . Thus, the  $i$ th coordinate of  $\mathbf{A}\vec{v}$  equals  $\sum_{j=1}^n a_{ij}v^j \geq a_{ij_0}v^{j_0} > 0$ . Therefore,  $\mathbf{A}\vec{v} > \vec{0}$ .

QED

# Another Definition

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For any nonzero  $\vec{v} \geq \vec{0}$ , let  $g(\vec{v})$  be the largest  $\lambda$  such that  $\mathbf{A}\vec{v} \geq \lambda\vec{v}$

Let's verify that there indeed is a largest such  $\lambda$ .

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Let's verify that there indeed is a largest such  $\lambda$ .

Consider a nonzero vector  $\vec{v} \geq \vec{0}$ . Let  $[\mathbf{A}\vec{v}]^i$  denote the  $i$ th coordinate of  $\mathbf{A}\vec{v}$ . If  $v^i \neq 0$ , let  $\lambda_i = \frac{[\mathbf{A}\vec{v}]^i}{v^i}$ . For such  $i$ ,  $[\mathbf{A}\vec{v}]^i = \lambda_i v^i$ . Let  $\lambda = \min\{\lambda_i\}$ . If  $v_i \neq 0$ ,  $[\mathbf{A}\vec{v}]^i = \lambda_i v^i \geq \lambda v^i$ , and if  $v^i = 0$ ,  $[\mathbf{A}\vec{v}]^i > 0 = \lambda v^i$  by 1.20(a). Therefore,  $\mathbf{A}\vec{v} \geq \lambda\vec{v}$ .

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If  $\lambda' > \lambda$ , then  $\lambda' > \lambda_i$  for some  $i$  such that  $v_i \neq 0$ . In that case,  $[\mathbf{A}\vec{v}]^i = \lambda_i v^i < \lambda' v^i$ . So it is not true that  $\mathbf{A}\vec{v} \geq \lambda'\vec{v}$ . Thus,  $\lambda$  is the largest number such that  $\mathbf{A}\vec{v} \geq \lambda\vec{v}$ .

## Lemma

*For any nonzero  $\vec{v} \geq \vec{0}$ ,  $g(\vec{v}) > 0$ , and if  $c > 0$ , then  $g(c\vec{v}) = g(\vec{v})$*

## 1.20(b)

### Lemma

For any nonzero  $\vec{v} \geq \vec{0}$ ,  $g(\vec{v}) > 0$ , and if  $c > 0$ , then  $g(c\vec{v}) = g(\vec{v})$

### Proof:

From the previous slide, we know that  $g(\vec{v}) = \min \left\{ \frac{[\mathbf{A}\vec{v}]^i}{v_i} : v_i \neq 0 \right\}$ . By 1.20(a),  $[\mathbf{A}\vec{v}]^i > 0$  for all  $i$ . Therefore,  $g(\vec{v}) > 0$ .

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For the second part of the statement, let  $c > 0$ .

$\mathbf{A}(c\vec{v}) = c(\mathbf{A}\vec{v}) \geq cg(\vec{v})\vec{v} = g(\vec{v})(c\vec{v})$ . Thus,  $g(c\vec{v}) \geq g(\vec{v})$ .

$\mathbf{A}\vec{v} = \frac{1}{c}(\mathbf{A}(c\vec{v})) \geq \frac{1}{c}g(c\vec{v})(c\vec{v}) = g(c\vec{v})\vec{v}$ . Thus,  $g(\vec{v}) \geq g(c\vec{v})$ .

Therefore,  $g(c\vec{v}) = g(\vec{v})$ . QED

## Defining $\alpha$

Let  $\alpha = \sup\{g(\vec{v}) : \vec{v} \geq \vec{0}, \vec{v} \neq \vec{0}\}$ . I will show that  $\alpha$  is an eigenvalue of  $\mathbf{A}$ .

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For any nonzero vector  $\vec{v} \geq \vec{0}$ , there is a vector  $\vec{w} = \frac{\vec{v}}{\|\vec{v}\|} \geq \vec{0}$  with norm 1 ( $\|\vec{w}\| = \|\frac{\vec{v}}{\|\vec{v}\|}\| = \frac{\|\vec{v}\|}{\|\vec{v}\|} = 1$ ) such that  $g(\vec{w}) = g(\frac{\vec{v}}{\|\vec{v}\|}) = g(\vec{v})$  by 1.20(b).

Therefore,  $\alpha = \sup\{g(\vec{v}) : \vec{v} \geq \vec{0}, \|\vec{v}\| = 1\}$ .

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Therefore,  $\alpha = \sup\{g(\vec{v}) : \vec{v} \geq \vec{0}, \|\vec{v}\| = 1\}$ .

The function  $g(\vec{v})$  can be shown to be a continuous function, and the set  $\{\vec{v} \in \mathbb{R}^n : \vec{v} \geq \vec{0}, \|\vec{v}\| = 1\}$  is a compact subset of  $\mathbb{R}^n$ . Therefore,  $g$  attains a maximum value on  $\{\vec{v} \in \mathbb{R}^n : \vec{v} \geq \vec{0}, \|\vec{v}\| = 1\}$ .

That is to say, there is a vector  $\vec{v} \geq \vec{0}$  with norm 1 such that  $g(\vec{v}) = \alpha$ .

## Theorem (part 1)

For any vector  $\vec{v} \geq \vec{0}$  ( $\vec{v} \neq \vec{0}$ ) with  $g(\vec{v}) = \alpha$ ,  $\mathbf{A}\vec{v} = \alpha\vec{v}$

## Theorem (part 1)

For any vector  $\vec{v} \geq \vec{0}$  ( $\vec{v} \neq \vec{0}$ ) with  $g(\vec{v}) = \alpha$ ,  $\mathbf{A}\vec{v} = \alpha\vec{v}$

## Proof:

Suppose  $\mathbf{A}\vec{v} \neq \alpha\vec{v}$ . Since  $g(\vec{v}) = \alpha$ ,  $\mathbf{A}\vec{v} \geq \alpha\vec{v}$ . Thus,  $\mathbf{A}\vec{v} - \alpha\vec{v} \geq \vec{0}$  and  $\mathbf{A}\vec{v} - \alpha\vec{v} \neq \vec{0}$ . So by part (a),  $\mathbf{A}(\mathbf{A}\vec{v} - \alpha\vec{v}) > \vec{0}$ . Therefore, there is a  $\lambda > 0$  small enough such that  $\mathbf{A}(\mathbf{A}\vec{v} - \alpha\vec{v}) \geq \lambda(\mathbf{A}\vec{v})$ . Then  $\mathbf{A}(\mathbf{A}\vec{v}) \geq (\alpha + \lambda)(\mathbf{A}\vec{v})$ , and  $\mathbf{A}\vec{v} > \vec{0}$  by part (a). Thus,  $g(\mathbf{A}\vec{v}) \geq \alpha + \lambda > \alpha$ . This contradicts the fact that  $\alpha$  is the supremum of  $g(\vec{w})$  over all nonzero  $\vec{w} \geq \vec{0}$ . Therefore,  $\mathbf{A}\vec{v} = \alpha\vec{v}$ . QED

## Theorem (part 2)

*There is a unique  $\vec{v} \geq \vec{0}$  with  $\|\vec{v}\| = 1$  such that  $g(\vec{v}) = \alpha$ .*

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## Proof:

Let  $\vec{v}_1, \vec{v}_2 \geq \vec{0}$  have norm 1 and be such that  $g(\vec{v}_1) = g(\vec{v}_2) = \alpha$ .

Suppose  $\vec{v}_1 \neq \vec{v}_2$ . Then  $|\vec{v}_1 - \vec{v}_2| \geq \vec{0}$  and  $|v_1 - v_2| \neq 0$ .

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| \geq |\mathbf{A}(\vec{v}_1 - \vec{v}_2)| = |\mathbf{A}\vec{v}_1 - \mathbf{A}\vec{v}_2| = |\alpha\vec{v}_1 - \alpha\vec{v}_2| = \alpha|\vec{v}_1 - \vec{v}_2|$ .

Thus,  $g(|\vec{v}_1 - \vec{v}_2|) = \alpha$ . So  $\mathbf{A}|\vec{v}_1 - \vec{v}_2| = \alpha|\vec{v}_1 - \vec{v}_2|$  by 1.20(c). Therefore,

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| \geq |\mathbf{A}(\vec{v}_1 - \vec{v}_2)| = \alpha|\vec{v}_1 - \vec{v}_2| = \mathbf{A}|\vec{v}_1 - \vec{v}_2|$ . So

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| = |\mathbf{A}(\vec{v}_1 - \vec{v}_2)|$ .

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There is a unique  $\vec{v} \geq \vec{0}$  with  $\|\vec{v}\| = 1$  such that  $g(\vec{v}) = \alpha$ .

## Proof:

Let  $\vec{v}_1, \vec{v}_2 \geq \vec{0}$  have norm 1 and be such that  $g(\vec{v}_1) = g(\vec{v}_2) = \alpha$ .

Suppose  $\vec{v}_1 \neq \vec{v}_2$ . Then  $|\vec{v}_1 - \vec{v}_2| \geq \vec{0}$  and  $|v_1 - v_2| \neq 0$ .

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| \geq |\mathbf{A}(\vec{v}_1 - \vec{v}_2)| = |\mathbf{A}\vec{v}_1 - \mathbf{A}\vec{v}_2| = |\alpha\vec{v}_1 - \alpha\vec{v}_2| = \alpha|\vec{v}_1 - \vec{v}_2|$ .

Thus,  $g(|\vec{v}_1 - \vec{v}_2|) = \alpha$ . So  $\mathbf{A}|\vec{v}_1 - \vec{v}_2| = \alpha|\vec{v}_1 - \vec{v}_2|$  by 1.20(c). Therefore,

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| \geq |\mathbf{A}(\vec{v}_1 - \vec{v}_2)| = \alpha|\vec{v}_1 - \vec{v}_2| = \mathbf{A}|\vec{v}_1 - \vec{v}_2|$ . So

$\mathbf{A}|\vec{v}_1 - \vec{v}_2| = |\mathbf{A}(\vec{v}_1 - \vec{v}_2)|$ . Thus, the  $i$ th coordinate of  $\mathbf{A}|\vec{v}_1 - \vec{v}_2|$  and

$|\mathbf{A}(\vec{v}_1 - \vec{v}_2)|$  are equal:  $\sum_{j=1}^n a_{ij}|v_1^j - v_2^j| = |\sum_{j=1}^n a_{ij}(v_1^j - v_2^j)|$ . It then

follows from properties of the absolute values that  $\vec{v}_1 \geq \vec{v}_2$  or  $\vec{v}_2 \geq \vec{v}_1$ . As

$\|\vec{v}_1\| = \|\vec{v}_2\|$ , it must be that  $\vec{v}_1 = \vec{v}_2$  contradicting the supposition.

Therefore,  $\vec{v}_1 = \vec{v}_2$ . QED

## Theorem (part 3)

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## Proof:

By 1.20(a),  $\mathbf{A}\vec{v} > \mathbf{0}$ .  $\mathbf{A}(\mathbf{A}\vec{v}) = \mathbf{A}(\alpha\vec{v}) = \alpha(\mathbf{A}\vec{v})$ . So  $g(\mathbf{A}\vec{v}) = \alpha$ . Let  $\vec{w} = \mathbf{A}\vec{v}/\|\mathbf{A}\vec{v}\|$ . Then  $\vec{w} > \vec{0}$ ,  $\|\vec{w}\| = 1$ , and by 1.20(b),  $g(\vec{w}) = g(\mathbf{A}\vec{v}/\|\mathbf{A}\vec{v}\|) = g(\mathbf{A}\vec{v}) = \alpha$ . But  $\vec{v}$  is the unique vector satisfying these properties, so  $\vec{v} = \vec{w} > \vec{0}$ . QED

## Theorem (part 4)

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## Proof:

Let  $\vec{u}$  be an eigenvector that corresponds to the eigenvalue  $\lambda$ .  $\mathbf{A}\vec{u} = \lambda\vec{u}$ . Then  $|\vec{u}| \geq \vec{0}$  is nonzero. Furthermore,  $\mathbf{A}|\vec{u}| \geq |\mathbf{A}\vec{u}| = |\lambda\vec{u}| = |\lambda||\vec{u}|$ . Therefore,  $|\lambda| \leq g(|\vec{u}|) \leq \alpha$ . Suppose  $|\lambda| = \alpha$ . Then  $\mathbf{A}|\vec{u}| \geq |\mathbf{A}\vec{u}| = \alpha|\vec{u}| = \mathbf{A}|\vec{u}|$ . So  $\mathbf{A}|\vec{u}| = |\mathbf{A}\vec{u}|$ .

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If  $\lambda \neq \alpha$  is an eigenvalue of  $\mathbf{A}$ , then  $|\lambda| < \alpha$ .

## Proof:

Let  $\vec{u}$  be a eigenvector that corresponds to the eigenvalue  $\lambda$ .  $\mathbf{A}\vec{u} = \lambda\vec{u}$ . Then  $|\vec{u}| \geq \vec{0}$  is nonzero. Furthermore,  $\mathbf{A}|\vec{u}| \geq |\mathbf{A}\vec{u}| = |\lambda\vec{u}| = |\lambda||\vec{u}|$ . Therefore,  $|\lambda| \leq g(|\vec{u}|) \leq \alpha$ . Suppose  $|\lambda| = \alpha$ . Then  $\mathbf{A}|\vec{u}| \geq |\mathbf{A}\vec{u}| = \alpha|\vec{u}| = \mathbf{A}|\vec{u}|$ . So  $\mathbf{A}|\vec{u}| = |\mathbf{A}\vec{u}|$ . Thus, the  $i$ th coordinate of  $\mathbf{A}|\vec{u}|$  and  $|\mathbf{A}\vec{u}|$  are equal:  $\sum_{j=1}^n a_{ij}|\vec{u}^j| = |\sum_{j=1}^n a_{ij}\vec{u}^j|$ . It then follows from properties of the absolute values that  $\vec{u} = e^{i\theta}\vec{w}$  for some angle  $\theta$  and vector  $\vec{w} \geq \vec{0}$ . Then  $\mathbf{A}\vec{w} = \lambda\vec{w}$ , so it must be that  $\lambda \geq 0$ . Hence,  $\lambda = \alpha$  contradicting the fact that  $\lambda \neq \alpha$ . Therefore,  $|\lambda| < \alpha$ . QED

## Lemma

Let  $\mathbf{B}^k$  be the submatrix of  $\mathbf{A}$  obtained by deleting the  $k$ th row and the  $k$ th column. All the eigenvalues of  $\mathbf{B}^k$  have absolute value strictly less than  $\alpha$ .

## 1.20(g)

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### Proof:

$\mathbf{B}^k = (b_{ij})$  is a matrix with positive entries. Therefore, we may apply 1.20(a)-(f) to  $\mathbf{B}^k$ . For any nonzero  $\vec{w} \geq \vec{0}$ , let  $h(\vec{w})$  be the largest  $\lambda$  such that  $\mathbf{B}^k \vec{w} \geq \lambda \vec{w}$ , and let  $\beta = \sup\{h(\vec{w}) : \vec{w} \geq \vec{0}, \vec{w} \neq \vec{0}\}$ . Then there is a unique vector  $\vec{w} > \vec{0}$  with norm 1 such that  $\mathbf{B}^k \vec{w} = \beta \vec{w}$ . Thus  $\beta$  is an eigenvalue of  $\mathbf{B}^k$ , and  $|\lambda| < \beta$  for all other eigenvalues  $\lambda$  of  $\mathbf{B}^k$ .

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Let  $\vec{w}_0 = (w^1, \dots, w^{k-1}, 0, w^k, \dots, w^{n-1})$ .  $\vec{w}_0 \geq \vec{0}$  and  $\|\vec{w}_0\| = \|\vec{w}\| = 1$ .

If  $i = k$ ,  $[\mathbf{A}\vec{w}_0]^i = \sum_{j=1}^n a_{ij} w_0^j = \sum_{j \neq k} a_{ij} w_0^j > 0 = \beta w_0^i$ . And if  $i \neq k$ ,

$[\mathbf{A}\vec{w}_0]^i = \sum_{j=1}^n a_{ij} w_0^j = \sum_{j \neq k} a_{ij} w_0^j = \sum_{j=1}^{n-1} b_{ij} w^j = [\mathbf{B}^k \vec{w}]^i = \beta w^i = \beta w_0^i$ .

Therefore,  $\mathbf{A}\vec{w}_0 \geq \beta \vec{w}_0$ , but the two are not equal. So  $\beta \leq g(\vec{w}_0) \leq \alpha$ . If  $\beta = \alpha$ , then  $\mathbf{A}\vec{w}_0$  must equal  $\beta \vec{w}_0$  by 1.20(c), which is not the case. Thus,  $\beta < \alpha$ , and for all eigenvalues  $\lambda$  of  $\mathbf{B}^k$ ,  $|\lambda| < \beta < \alpha$ . QED

## 1.20(h)

### Lemma

Let  $f(\lambda) = \det(\lambda \mathbf{I} - A)$  be the characteristic polynomial of  $\mathbf{A}$ .

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Let  $\lambda \mathbf{I} - \mathbf{A} = (c_{ij})$ , and  $\lambda \mathbf{I} - \mathbf{B}^k = (d_{ij}^k)$ .

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$\det(\lambda \mathbf{I} - \mathbf{B}^k)$  is polynomial in  $\lambda$  of degree  $n - 1$  with leading term  $\lambda^{n-1}$ . Therefore,  $\det(\lambda \mathbf{I} - \mathbf{B}^k) > 0$  for all  $\lambda$  greater than the largest real eigenvalue of  $\mathbf{B}^k$ . By 1.20(g),  $\alpha$  is greater than the largest real eigenvalue of  $\mathbf{B}^k$ . Therefore,  $f'(\alpha) = \sum_{k=1}^n \det(\alpha \mathbf{I} - \mathbf{B}^k) > 0$ .

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$f(\lambda) = (\lambda - \alpha)^m q(\lambda)$  where  $q$  is a nonzero polynomial whose roots have absolute value less than  $\alpha$ .  $m \in \mathbb{N}$  is the multiplicity of  $\alpha$ . If  $m \neq 1$ , then  $f'(\alpha) = m(\alpha - \alpha)^{m-1} q(\alpha) + (\alpha - \alpha)^m q'(\alpha) = 0$ , which contradicts the fact that  $f'(\alpha) > 0$ . Therefore,  $\alpha$  is a root of the characteristic polynomial of  $\mathbf{A}$  with multiplicity 1. That is,  $\alpha$  is a simple eigenvalue for  $\mathbf{A}$ . QED

## Perron-Frobenius Theorem

Let  $\mathbf{A} = (a_{ij})$  be an  $n \times n$  matrix with  $a_{ij} > 0$  for all  $i, j$ .  $\mathbf{A}$  has a real eigenvalue  $\alpha > 0$  with a unique eigenvector  $\vec{v} > \vec{0}$  of norm 1 such that  $|\lambda| < \alpha$  for any other eigenvalue  $\lambda$  of  $\mathbf{A}$ . Moreover,  $\alpha$  is a simple eigenvalue (i.e., it is a root of the characteristic polynomial of  $\mathbf{A}$  with multiplicity 1).

1.20(c) shows that  $\alpha > 0$  is an eigenvalue of  $\mathbf{A}$ .

1.20(d) shows that there is  $\alpha$  has a unique eigenvector  $\vec{v} \geq \vec{0}$  with norm 1.

1.20(e) shows that, in fact,  $\vec{v} > \vec{0}$ .

1.20(f) shows that all other eigenvalues  $\lambda$  of  $\mathbf{A}$ ,  $|\lambda| < \alpha$ .

1.20(i) shows that  $\alpha$  is a simple eigenvalue of  $\mathbf{A}$ .