

Chapter 8: Applications

8.3. Markov Matrices, Population, and Economics

Most of this material is presented clearly enough in the presentation for Unit 11, but here is a bit of supplementary material.

The proof of the Perron-Frobenius Theorem of positive matrices given in the text has some gaps, so here is a complete proof.

Theorem. Perron-Frobenius Theorem for $A > 0$. Suppose A is an $n \times n$ matrix with all (strictly) positive entries. Then the largest eigenvalue λ_{\max} of A in absolute value is (real) positive and has an eigenvector with strictly positive entries.

Proof. Consider the function f on the piece P of the hyperplane $x_1 + x_2 + \cdots + x_n = 1$ in \mathbb{R}^n where all the x_i 's are positive, given by

$$f(\mathbf{x}) = \min_i ((A\mathbf{x})_i)/x_i = \min_i \left(\sum_j a_{ij} \frac{x_j}{x_i} \right).$$

The minimum of a family of continuous functions is continuous, so f is continuous on P . For \mathbf{x} 's approaching an edge of P , where $x_i = 0$, say, the function $\sum_j a_{ij}(x_j/x_i)$ for that i approaches ∞ , so the minimum, i.e., the value of f , is given by one (or more) of the other functions, which are continuous near that edge. So we can extend f continuously to the boundary of P and get a function f from \bar{P} , i.e., P together with its boundary, into \mathbb{R} .

A continuous function on a “compact” set like \bar{P} always takes on its highest value (this is called the Extreme Value Theorem in Math 323), so we can pick \mathbf{x} in \bar{P} for which $f(\mathbf{x}) = t_{\max}$ is highest. We claim this \mathbf{x} is not on the boundary of P : Assume, by way of contradiction, that it is on the edge $x_i = 0$, and take the function $f_k = \sum_j a_{kj} \frac{x_j}{x_k}$ that gives the value of f near that point (so $x_k \neq 0$). Then $\partial f_k / \partial x_i = a_{ki}/x_k > 0$, so f is increasing in the direction of the positive x_i -axis. (In fact, it is increasing in the direction of all axes except x_k .) So $f(\mathbf{x})$ is not the largest f ever gets, and we have the contradiction. So f takes its largest value on P , not on the edge.

Next, we want to show $A\mathbf{x} = t_{\max}\mathbf{x}$; so assume not. Now the strange definition of f was chosen so that $A\mathbf{u} \geq f(\mathbf{u})\mathbf{u}$ (i.e., the “ \geq ” holds in every component) with equality in at least one component, for every \mathbf{u} in P ; so our assumption that we don't have equality means we must have the strict inequality $(A\mathbf{x})_i > t_{\max}x_i$ for some i . Now $A\mathbf{x}$ is probably not on the hyperplane that contains P , but the formula for f takes the same value on the whole ray from the origin through $A\mathbf{x}$, and that ray hits P somewhere, say at \mathbf{y} . Because $A\mathbf{x} - t_{\max}\mathbf{x}$ has one strictly positive entry and all the entries of A are strictly positive, all the entries of $A(A\mathbf{x} - t_{\max}\mathbf{x})$ are strictly positive; so we get that $(A\mathbf{y})_i > t_{\max}y_i$ in every component, i.e., $f(\mathbf{y}) > t_{\max} = f(\mathbf{x})$. But that contradicts our choice of \mathbf{x} . Therefore, $A\mathbf{x} = t_{\max}\mathbf{x}$; i.e., t_{\max} is an eigenvalue of A , with eigenvector \mathbf{x} with all positive entries.

One last detail: Is it possible that some eigenvalue λ of A , maybe negative or complex, has absolute value greater than t_{\max} ?

(Interlude: The absolute value of a complex number $a + bi$ is $\sqrt{a^2 + b^2}$, its distance from the origin in the complex plane. We still have $|p + q| \leq |p| + |q|$ and $|pq| = |p||q|$, even for complex scalars p, q .)

The answer is no, because we can take absolute values and use the Triangle Inequality.: If $A\mathbf{z} = \lambda\mathbf{z}$ where λ and \mathbf{z} may have positive entries, then

$$|\lambda||\mathbf{z}| = |A\mathbf{z}| \leq A|\mathbf{z}|,$$

where $|\mathbf{z}|$, the vector with entries the absolute values of the entries in \mathbf{z} , is in \overline{P} , so $|\lambda| \leq f(|\mathbf{z}|) \leq t_{max}$. \square

For our purposes, the point of this theorem is that, if a Markov matrix M has all nonzero entries, then it has a maximum eigenvalue, with a corresponding vector of positive entries. That maximum eigenvalue must be 1, because if \mathbf{x} is an eigenvector corresponding to the eigenvalue t_{max} , then for every vector we have

$$t_{max} \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix} \mathbf{x} = \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix} M \mathbf{x} = \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix} \mathbf{x}.$$

So repeated left multiplications by M will produce a sequence of vectors approaching a steady state, no matter what vector we start with.

At this point, switch back to the presentation for Unit 11.