Math 525: Lecture 20

March 27, 2018

1 Limiting distribution

We have already seen many situations involving the *limiting distribution*

$$\alpha^\intercal = \lim_{n\to\infty} \mu^\intercal P^n \tag{1}$$

of a Markov chain, where μ is the *initial distribution* (i.e., $\mathbb{P}(X_0 = i) = \mu_i$). To stress that α is a function of μ, we will write $\alpha(\mu)$.

Example 1.1 (Gambler's ruin)**.** We determined the probability of ruin by substituting

$$P = \begin{pmatrix} 1 & 0 & & & & \\ 1/2 & 0 & 1/2 & & & \\ & 1/2 & 0 & 1/2 & & \\ & & \ddots & \ddots & \ddots & \\ & & & 1/2 & 0 & 1/2 \\ & & & & 0 & 1 \end{pmatrix} \qquad \text{and} \qquad \mu = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

into (1). There, we found that

$$\alpha(\mu) = \begin{pmatrix} 1/2 \\ 0 \\ \vdots \\ 0 \\ 1/2 \end{pmatrix}.$$

More generally, it is natural to ask:

1. Is (1) always independent of the initial distribution μ?
2. Is (1) an equilibrium/stationary distribution? (i.e., $\alpha(\mu)^\intercal P = \alpha(\mu)^\intercal$)

The answer to the first question is very easily seen to be no:

Example 1.2. Consider the transition matrix $P = I$. Then, $P^n = I$ and hence

$$\alpha(\mu) = \lim_{n\to\infty} \mu^\intercal P^n = \lim_{n\to\infty} \mu^\intercal = \mu^\intercal.$$

Worse yet, the limit does not even have to exist:

Example 1.3. Consider

$$P = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \qquad \text{and} \qquad \mu = \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

Note that $P^{2n} = I$ and $P^{2n+1} = P$. Therefore,

$$\mu^\intercal P^{2n+1} = \begin{pmatrix} 0 & 1 \end{pmatrix} \qquad \text{and} \qquad \mu^\intercal P^{2n} = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

so that $\alpha(\mu)$ does not exist.

As for the second question, suppose the limit exists. Then, by continuity,

$$\alpha(\mu)^\intercal P = \left(\lim_{n \to \infty} \mu^\intercal P^n \right) P = \lim_{n \to \infty} \mu^\intercal P^{n+1} = \alpha(\mu)^\intercal.$$

For the remainder, we will try to understand when the limit is independent of the initial distribution. As in the gambler's ruin, the limiting distribution tells us a lot about the problem, and can even be considered as an approximation for $\mu^\intercal P^n$ with n large. Moreover, we will see that in many of these cases, the limit can be computed efficiently.

2 Primitive matrices

Definition 2.1. Let A be a square matrix that is nonnegative (i.e., $A_{ij} \geq 0$). We say A is *primitive* if there exists a positive integer m such that A^m is positive (i.e., $(A^m)_{ij} > 0$).

Lemma 2.2. *If A is primitive, then A is irreducible.*

Proof. We prove this by contrapositive. Suppose A is reducible. By definition, we can find a permutation matrix K such that

$$KAK^\intercal = \begin{pmatrix} B & C \\ 0 & D \end{pmatrix}.$$

Let m be a positive integer. Then,

$$(KAK^\intercal)^m = KA^m K^\intercal = K \begin{pmatrix} B^m & X \\ 0 & D^m \end{pmatrix} K^\intercal$$

where X is some matrix (depending on B, C, D, and m). The above implies that A is not primitive since A^m has some entries equal to zero. $\square$

Proposition 2.3. *Let A be a nonnegative square matrix. Then, A is irreducible and aperiodic (i.e., has period equal to one) if and only if it is primitive.*

Before we give a proof, let's discuss some consequences. Given a matrix A, recall that

$$i \to j$$

means that we can find a walk

$$i = i_1 \dashrightarrow i_2 \dashrightarrow \cdots \dashrightarrow i_k = j$$

from i to j. We refer to the number of edges in a walk as its *length* (in the above example, the length is $k-1$). Recall also that the period of i is defined as

$$d(i) = \gcd(\{n \geq 1 \colon (A^n)_{ii} > 0\}).$$

Moreover,

$$(A^n)_{ii} > 0 \iff \text{there exists a walk of length } n \text{ from } i \text{ to itself.}$$

Therefore, we can equivalently define the period as

$$d(i) = \gcd(\{\text{length}(w) \colon w \text{ is a walk from } i \text{ to itself}\}).$$

This observation gives us a quick way to check if a matrix is primitive by checking the gcd of walks from a node to itself. One particularly useful consequence is given below.

Corollary 2.4. *Let $A = (A_{ij})$ be a nonnegative and irreducible square matrix. If $A_{ii} > 0$ for some i, then A is primitive.*

Proof. By the assumptions, $d(i) = 1$ and hence A is aperiodic. Therefore, by Proposition 2.3, A is primitive. □

Example 2.5. The matrix

$$P = \begin{pmatrix} 1/2 & 1/2 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix}.$$

satisfies Corollary 2.4. Indeed, matrix multiplication reveals

$$P^4 = \begin{pmatrix} 0.5625 & 0.3125 & 0.1250 \\ 0.2500 & 0.2500 & 0.5000 \\ 0.6250 & 0.1250 & 0.2500 \end{pmatrix}.$$

Let's now return to our goal of proving Proposition 2.3. First, we need an intermediate result from number theory/algebra, which we state without proof.

Lemma 2.6 (Semigroup lemma)**.** *Any set of non-negative integers which is closed under addition and which has greatest common divisor 1 must contain all but finitely many of the non-negative integers.*

We will just prove the forward direction of Proposition 2.3:

Proof of Proposition 2.3 (⇒). Let A be an irreducible and aperiodic matrix. For each row i of A let

$$J_i = \{n \geq 1 \colon (A^n)_{ii} > 0\}.$$

Now, let n_1 and n_2 be elements of J_i. Then,

$$(A^{n_1+n_2})_{ii} = (A^{n_1}A^{n_2})_{ii} = \sum_k (A^{n_1})_{ik}(A^{n_2})_{ki} \geq (A^{n_1})_{ii}(A^{n_2})_{ii} > 0$$

and hence $n_1 + n_2$ is also in J_i. That is, J_i is closed under addition. Moreover, $\gcd(J_i) = 1$ by the presumed aperiodicity.

Applying lemma 2.6 to J_i, we can find $M(i)$ such that for all $n \geq M(i)$, we have $(A^n)_{ii} > 0$. Since A is irreducible, we can find $m(i,j)$ such that $(A^{m(i,j)})_{ij} > 0$. Therefore, for $n \geq M(i)$,

$$(A^{n+m(i,j)})_{ij} = \sum_k (A^n)_{ik}(A^{m(i,j)})_{kj} \geq (A^n)_{ii}(A^{m(i,j)})_{ij} > 0.$$

Let $M = \max_i\{M(i)\} + \max_{i,j}\{m(i,j)\}$. Then, $(A^M)_{ij} > 0$ for all i, j as desired. □

Definition 2.7. A Markov chain whose transition matrix is primitive is called *regular.*

Proposition 2.8. *Let P be the transition matrix of a regular Markov chain. Then, there exists a vector α such that for any vector μ,*

$$\alpha^\intercal = \lim_{n\to\infty} \mu^\intercal P^n. \tag{2}$$

Moreover,

$$\alpha^\intercal P = \alpha^\intercal. \tag{3}$$

In fact, $\alpha = c_1 v_1$ where v_1 is a positive eigenvector corresponding to the eigenvalue $\lambda = 1$ of $P^\intercal$ and c_1 is a normalizing constant which ensures that α is a probability vector.

You are asked to prove this when $P^\intercal$ admits a full set of linearly independent eigenvectors in assignment 8. The general case can also be proved using the Jordan decomposition of $P^\intercal$. Some observations:

- (2) states that the limiting distribution is independent of μ.
- (3) states that the limiting distribution is an equilibrium of the Markov chain.
- α can be obtained by computing an eigenvector of $P^\intercal$ associated with the eigenvalue $\lambda = 1$. For small matrices, you can do this by hand. In practice, there are various computational methods to do this, the simplest of which is the *power method.*

Of course, there are "irregular" Markov chains which still have limiting distributions:

Example 2.9. Note that

$$\mu^\intercal \begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} \mu_1 + \mu_2 \\ 0 \end{pmatrix}^\intercal$$

for any vector μ.

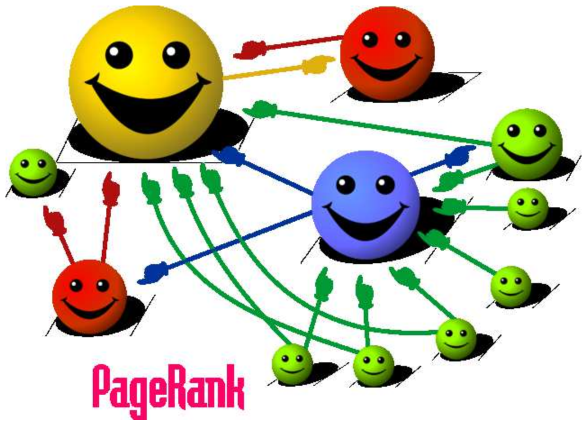

Figure 1: The "goodness" of each page is proportional to the number of links to that page.

3 Page Rank

We close by discussing an application of regular Markov chains: Page Rank. This is an algorithm used by Google to determine the "goodness" of a page so as to determine the order of a search query.

Consider a web with N pages. Links between pages are recorded in a binary matrix $G = (G_{ij})$. That is,

$$G_{ij} = \begin{cases} 1 & \text{if there is a link from page } i \text{ to page } j \\ 0 & \text{otherwise.} \end{cases}$$

Letting e denote the column vector of ones in $\mathbb{R}^N$, note that

$$(Ge)_i = \text{number of outgoing links from } i.$$

We wish to model a *web surfer*. Suppose first that each page has at least one outgoing link. If the surfer is at page i at time n, then they choose a page from the set

$$\{j : G_{ij} = 1\}$$

to visit at time $n+1$ with uniform probability. Our assumption guarantees that the above is nonempty. The transition matrix corresponding to this Markov chain is

$$\tilde{P} = \operatorname{diag}(Ge)^{-1} G$$

where

$$\operatorname{diag}(x) = \begin{pmatrix} x_1 & & & \\ & x_2 & & \\ & & \ddots & \\ & & & x_N \end{pmatrix}$$

is the diagonal matrix obtained by placing the entries of the vector x on the diagonal. There are two problems with this preliminary model: (1) it's not realistic and (2) it's not a regular Markov chain.

We would like to incorporate the notion that the web surfer is *restless* and can, at any point in time, pick any page (not necessarily via an outgoing link) at random. Let

$$E = ee^\intercal = \begin{pmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & 1 & 1 & \cdots & 1 \\ 1 & 1 & \vdots & & \vdots \\ 1 & 1 & 1 & \cdots & 1 \end{pmatrix}$$

where e is the vector of ones. Then, incorporating the restlessness, we arrive at the new transition matrix

$$P = (1-\alpha)\operatorname{diag}(Ge)^{-1}G + \alpha\frac{1}{m}E$$

where $0 < \alpha \leq 1$. The closer α is to one, the "more restless" our web surfer. Since $\frac{1}{m}E$ is a positive transition matrix, P' is trivially a regular Markov chain.

Remark 3.1. The assumption that each page has at least one outgoing link is not particularly restrictive. Indeed, we can replace G by G', which is defined by

$$G'_{ij} = \begin{cases} G_{ij} & \text{if } (Ge)_i > 0 \\ 1 & \text{otherwise.} \end{cases}$$

This corresponds to a surfer that, having encountered a page with no outgoing links, becomes restless and picks a page at random.

Since P is regular, the limiting distribution

$$\nu^\intercal = \lim_{n\to\infty} \mu^\intercal P^n$$

gives us an idea of the random surfers distribution after n steps, assuming n is large. Since P is regular, this does not depend on the initial distribution μ. Now, let

$$\hat{\nu} = \begin{pmatrix} 1 & \nu_1 \\ 2 & \nu_2 \\ \vdots & \vdots \\ N & \nu_N \end{pmatrix}$$

and sort the rows of $\hat{\nu}$ according to the second column:

Example 3.2. Suppose

$$\nu = \begin{pmatrix} 0.2 \\ 0.1 \\ 0.3 \\ 0.4 \\ 0.1 \end{pmatrix} \implies \hat{\nu} = \begin{pmatrix} 1 & 0.2 \\ 2 & 0.1 \\ 3 & 0.3 \\ 4 & 0.4 \\ 5 & 0.1 \end{pmatrix}.$$

After sorting,

$$\hat{\nu}_{\text{sorted}} = \begin{pmatrix} 4 & 0.4 \\ 3 & 0.3 \\ 1 & 0.2 \\ 2 & 0.1 \\ 5 & 0.1 \end{pmatrix}$$

and hence we can conclude that page 4 has the highest rank, page 3 the second highest, etc.