

Lecture 09: Perron-Frobenius Theory

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Our goal in this lecture is to prove Perron-Frobenius Theorem, which we stated in the last lecture for the adjacency matrix \mathbf{M} of a graph G , but which in fact has a more general statement for symmetric, non-negative matrices. We will provide the more general statement shortly.

First, let \mathbf{A} be an $n \times n$ symmetric matrix with non-negative entries. Define $\text{diag}(\mathbf{A})$ as the $n \times n$ matrix with the diagonal of \mathbf{A} on its diagonal, and zeroes elsewhere. Note that we can decompose \mathbf{A} as:

$$\mathbf{A} = \text{diag}(\mathbf{A}) + \mathbf{M},$$

where \mathbf{M} is an $n \times n$, symmetric matrix with zeros down its diagonal. We use the notation \mathbf{M} because, indeed, \mathbf{M} defines an adjacency matrix of a weighted graph $G(\mathbf{A}) = (V, E, w)$ with vertices $V = \{1, \dots, n\}$, edges

$$E = \{(a, b) \in V \times V : \mathbf{M}(a, b) > 0\},$$

and weights $w(a, b) = \mathbf{M}(a, b)$. We refer to $G(\mathbf{A})$ as the *graph induced by \mathbf{A}* . We are now ready to state the more general version of the Perron-Frobenius Theorem.

Theorem 26 (Perron-Frobenius Theorem, more general version). *Let \mathbf{A} be an $n \times n$ symmetric matrix with non-negative entries, with eigenvalues $\mu_1 \geq \mu_2 \geq \dots \geq \mu_n$, and with corresponding orthonormal eigenvectors $\phi_1, \phi_2, \dots, \phi_n$. If the graph $G(\mathbf{A})$ induced by \mathbf{A} is connected, then*

1. *One can take $\phi_1(a) > 0$ for all $a \in V$*
2. *$\mu_1 \geq |\mu_n|$*
3. *$\mu_1 > \mu_2$*

As mentioned last time, we will need two results to prove Theorem 24. The first of these was the following theorem.

Theorem 25. *Let \mathbf{A} be a real-valued, symmetric matrix and let μ_1 be the largest eigenvalue of \mathbf{A} . If*

$$\mu_1 = \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{x}},$$

for some $\mathbf{x} \in \mathbb{R}^n$, then $\mathbf{A} \mathbf{x} = \mu_1 \mathbf{x}$. The same result holds for μ_n , the minimum eigenvalue of \mathbf{A} .

We proved Theorem 25 in the last lecture. The second result we will need is the following lemma.

Lemma 27. *Let \mathbf{A} be an $n \times n$ symmetric matrix with non-negative entries such that the graph $G(\mathbf{A})$ induced by \mathbf{A} is connected. Let ϕ be an eigenvector of \mathbf{A} such that $\phi(a) \geq 0$ for all $a \in V$. Then $\phi(a) > 0$ for all $a \in V$.*

Proof. Suppose ϕ is not strictly positive. Then there exists some vertex $a \in V$ for which $\phi(a) = 0$. Since $G = G(\mathbf{A}) = (V, E, w)$ is connected, there must also be a vertex $b \in V$ (possibly with $b = a$) such that $\phi(b) = 0$ and for some $c \in N(b)$, $\phi(c) > 0$. Let μ be the eigenvalue of ϕ . Then:

$$0 = \mu\phi(b) = \mathbf{A}\phi(b) = \mathbf{A}(b, b)\phi(b) + \sum_{v \in N(b)} \mathbf{A}(b, v)\phi(v) \geq \mathbf{A}(b, c)\phi(c) > 0,$$

since $(b, c) \in E$ implies that $\mathbf{A}(b, c) > 0$. However, this is a contradiction. \square

Now we can prove the Perron-Frobenius Theorem.

Proof of Theorem 24. Let $G = G(\mathbf{A}) = (V, E, w)$ be the graph induced by \mathbf{A} .

First part: Let ϕ_1 be an eigenvector of \mathbf{A} with eigenvalue μ_1 and with unit norm, $\|\phi_1\| = 1$. Set

$$\mathbf{y}(a) := |\phi_1(a)|, \quad a \in V.$$

Notice that $\|\mathbf{y}\| = \|\phi_1\| = 1$ as well, so for both vectors their Rayleigh quotient has denominator equal to one. We have:

$$\begin{aligned} \mu_1 &= \phi_1^T \mathbf{A} \phi_1 = \sum_{a \in V} \mathbf{A}(a, a) \phi_1(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \phi_1(a) \phi_1(b) \\ &\leq \sum_{a \in V} \mathbf{A}(a, a) |\phi_1(a)|^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) |\phi_1(a)| |\phi_1(b)| \\ &= \sum_{a \in V} \mathbf{A}(a, a) \mathbf{y}(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \mathbf{y}(a) \mathbf{y}(b) \\ &= \mathbf{y}^T \mathbf{A} \mathbf{y}. \end{aligned}$$

But by the Courant-Fischer Theorem (Theorem 3),

$$\mu_1 = \max_{\substack{\mathbf{x} \in \mathbb{R}^n \\ \mathbf{x} \neq \mathbf{0}}} \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{x}},$$

which means that we must have $\mu_1 = \mathbf{y}^T \mathbf{A} \mathbf{y}$. But then, by Theorem 25, \mathbf{y} must be an eigenvector of \mathbf{A} . Finally, applying Lemma 27, we see that \mathbf{y} must be strictly positive.

Second part: Let ϕ_n be an eigenvector of \mathbf{A} with eigenvalue μ_n and with unit norm, $\|\phi_n\| = 1$. Similarly to the first part, set

$$\mathbf{y}(a) := |\phi_n(a)|, \quad a \in V.$$

We have:

$$\begin{aligned}
|\mu_n| &= |\phi_n^T \mathbf{A} \phi_n| = \left| \sum_{a \in V} \mathbf{A}(a, a) \phi_n(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \phi_n(a) \phi_n(b) \right| \\
&\leq \sum_{a \in V} \mathbf{A}(a, a) |\phi_n(a)|^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) |\phi_n(a)| |\phi_n(b)| \\
&= \sum_{a \in V} \mathbf{A}(a, a) \mathbf{y}(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \mathbf{y}(a) \mathbf{y}(b) \\
&= \mathbf{y}^T \mathbf{A} \mathbf{y} \\
&\leq \mu_1.
\end{aligned}$$

Third part: Take ϕ_1 to be the normalized eigenvector of \mathbf{A} with eigenvalue μ_1 that is strictly positive (using part 1). Let ϕ_2 be an eigenvector of \mathbf{A} with eigenvalue μ_2 , unit norm, $\|\phi_2\| = 1$, and that is orthogonal to ϕ_1 . Following the same method as the previous two parts, set

$$\mathbf{y}(a) := |\phi_2(a)|, \quad a \in V.$$

We have that

$$\begin{aligned}
\mu_2 &= \phi_2^T \mathbf{A} \phi_2 = \sum_{a \in V} \mathbf{A}(a, a) \phi_2(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \phi_2(a) \phi_2(b) \\
&\leq \sum_{a \in V} \mathbf{A}(a, a) |\phi_2(a)|^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) |\phi_2(a)| |\phi_2(b)| \\
&= \sum_{a \in V} \mathbf{A}(a, a) \mathbf{y}(a)^2 + 2 \sum_{(a, b) \in E} \mathbf{A}(a, b) \mathbf{y}(a) \mathbf{y}(b) \\
&= \mathbf{y}^T \mathbf{A} \mathbf{y} \\
&\leq \mu_1.
\end{aligned}$$

Of course we already knew $\mu_1 \geq \mu_2$, but the important parts of the above calculation are the steps in between. Now suppose that $\mu_1 = \mu_2$. Then, by the above calculation, $\mathbf{y}^T \mathbf{A} \mathbf{y} = \mu_1$. Thus, by Theorem 25, \mathbf{y} must be an eigenvector of \mathbf{A} with eigenvalue μ_1 . Since \mathbf{y} is a non-negative eigenvector of \mathbf{A} , we can apply Lemma 27 to conclude that \mathbf{y} is strictly positive, which in turn implies that $\phi_2(a) \neq 0$ for all $a \in V$.

Now, since $\langle \phi_1, \phi_2 \rangle = 0$ and $\phi_1(a) > 0$ for all $a \in V$, it must be that ϕ_2 has some positive entries and some negative entries. Since G is connected and since $\phi_2(a) \neq 0$ for all $a \in V$, it must be that there exists an $(u, v) \in E$ such that

$$\phi_2(u) < 0 < \phi_2(v).$$

But if that is the case, then

$$\begin{aligned}\mu_2 &= \sum_{a \in V} \mathbf{A}(a, a) \phi_2(a)^2 + 2 \sum_{\substack{(a,b) \in E \\ (a,b) \neq (u,v)}} \mathbf{A}(a, b) \phi_2(a) \phi_2(b) + \underbrace{2\mathbf{A}(u, v) \phi_2(u) \phi_2(v)}_{<0} \\ &< \sum_{a \in V} \mathbf{A}(a, a) |\phi_2(a)|^2 + 2 \sum_{(a,b) \in E} \mathbf{A}(a, b) |\phi_2(a)| |\phi_2(b)| = \mu_1.\end{aligned}$$

Thus $\mu_2 < \mu_1$, which contradicts the assumption that $\mu_2 = \mu_1$; we thus conclude that indeed $\mu_2 < \mu_1$. \square

Remark 16. Let $\mu_1 \geq \mu_2 \geq \dots \geq \mu_n$ be the eigenvalues of the adjacency matrix, \mathbf{M} , of a graph $G = (V, E)$. One can show if G is connected, then $\mu_1 = -\mu_n$ if and only if G is bipartite. The details can be found in [1, Chapter 4]

We can extend the Perron-Frobenius Theorem to the graph Laplacian (this was already clear) and graph Laplacian like matrices. Here is the result.

Corollary 28. Let $\tilde{\mathbf{L}}$ be a symmetric, $n \times n$ matrix with non-positive off-diagonal entries, so that

$$\tilde{\mathbf{L}} = \text{diag}(\tilde{\mathbf{L}}) - \mathbf{M},$$

where \mathbf{M} is a symmetric, real-valued matrix with non-negative entries and zeroes down its diagonal. Suppose the graph G induced by \mathbf{M} is connected. Let $\tilde{\lambda}_1$ be the smallest eigenvalue of $\tilde{\mathbf{L}}$ with eigenvector $\tilde{\psi}_1$. Then $\tilde{\psi}_1$ may be taken to be strictly positive, and $\tilde{\lambda}_1$ has multiplicity one.

Proof. Set

$$\mathbf{A} = \sigma \mathbf{I} - \tilde{\mathbf{L}} = (\sigma \mathbf{I} - \text{diag}(\tilde{\mathbf{L}})) + \mathbf{M}.$$

If we set σ such that

$$\sigma \geq \max_{a \in V} \tilde{\mathbf{L}}(a, a),$$

then the matrix \mathbf{A} will be a symmetric matrix with non-negative entries such that the graph $G(\mathbf{A})$ is connected. We may therefore apply the Perron-Frobenius Theorem (the general version, Theorem 26) to the matrix \mathbf{A} , and conclude that its largest eigenvalue, μ_1 , has multiplicity one, and the eigenvector associated to μ_1 , ϕ_1 , may be taken to be strictly positive. But any eigenvector ϕ of \mathbf{A} is an eigenvector of $\tilde{\mathbf{L}}$, and if $\mathbf{A}\phi = \mu\phi$ then $\tilde{\mathbf{L}}\phi = (\sigma - \mu)\phi$, i.e., $\tilde{\lambda} = \sigma - \mu$ is the corresponding eigenvalue of $\tilde{\mathbf{L}}$. Thus $\tilde{\lambda}_1 = \sigma - \mu_1$ has multiplicity one. \square

References

- [1] Daniel A. Spielman. Spectral and algebraic graph theory. Book draft, available at: <http://cs-www.cs.yale.edu/homes/spielman/sagt/>, 2019.

- [2] Michael Perlmutter, Feng Gao, Guy Wolf, and Matthew Hirn. Geometric scattering networks on compact Riemannian manifolds. In *Proceedings of The First Mathematical and Scientific Machine Learning Conference, Proceedings of Machine Learning Research*, volume 107, pages 570–604, 2020.