# Calculating numerically eigenvalues by cascading power method iterations

#### Frank Nielsen

(I reinvented a method that is called deflation. See Izaac, Joshua, et al. "The eigenvalue problem." Computational Quantum Mechanics (2018): 265-307.

Let  $M(d, \mathbb{F})$  be the space of  $d \times d$  matrices with coefficients in number field  $\mathbb{F}$ . A pair  $(\lambda, v)$  of eigenvalue  $\lambda$  and eigenvector v satisfies

$$Mv = \lambda v$$

One can find the eigenvalues by solving the characteristic polynomial:

$$|M - \lambda I| = 0.$$

The fundamental theorem of algebra yields the following polynomial factorization:

$$|M - \lambda I| = \prod_{i=1}^{d} (\lambda - \lambda_i).$$

Let  $\lambda_1^{\downarrow}, \ldots, \lambda_d^{\downarrow}$  denote the d eigenvalues sorted in decreasing order. The algebraic multiplicity of an eigenvalue  $m_a(\lambda_i)$  is the multiplicity as a root of the characteristic polynomial:

$$|M - \lambda I| = \prod_{i=1}^{l} (\lambda - \lambda_i)^{m_a(\lambda_i)},$$

where  $l \leq d$  is the number of distinct eigenvalues.

Eigenvalues of symmetric real matrices are always real, but some eigenvalues of real non-symmetric matrices may be complex.

A matrix  $M \in M(d, \mathbb{C})$  is Hermitian iff  $\overline{M}^{\top} = M$  where  $\overline{z}$  is the complex conjugation and  $M^{\top}$  the transpose matrix operation. Eigenvalues of positive definite Hermitian matrices are always real (includes the real symmetric positive definite matrices).

The spectral decomposition theorem of a symmetric positive definite matrix P states that

$$P = \sum_{i=1}^{d} \lambda_i e_i e_i^{\top} = E \operatorname{diag}(\lambda_1, \dots, \lambda_d) E^{\top},$$

where  $E[=e_1,\ldots,e_d]$ . Let  $\lambda_i$  denote the *i*-th dominant eigenvalue so that

$$|\lambda_1| \geq \ldots \geq |\lambda_d|$$
.

## 1 Cascading power method iterations to numerically calculate the matrix spectrum

The power method [5] (1929) is a simple method to calculate the maximum absolute eigenvalue of a real symmetric invertible matrix: the spectral radius  $\rho(M) = \max_i |\lambda_i(M)|$ . Start with a random vector  $v_0$  and

iteratively repeat:

$$v_{t+1} = \frac{Mv_t}{\|Mv_t\|}$$

After T iterations, we have

$$\rho(M) \approx \frac{v_T^\top M v_T}{v_T^\top v_T}.$$

We normalize  $v_T$  such that  $||v_T|| = 1$  is an approximation of the eigenvector.

The convergence is geometric with ratio  $\left|\frac{\lambda_2}{\lambda_1}\right|$ , where  $\lambda_2$  is the second dominant eigenvalue.

Eigenspace, rank and geometric multiplicity.

## 2 A simple algorithm for calculating numerically the matrix spectrum

Power method [4], p. 259-261.

Algorithm PowerSpectrum $(M, n_1, \ldots, n_d)$ :

- 1. Initialization: Let  $t \leftarrow 1$  and  $M_t = M$ .
- 2. Compute  $\lambda_t = \text{PowerMethod}(M_t, n_t)$  using the power method with  $n_t$  iterations
- 3. Let  $M_{t+1} = M_t \lambda_t e_t e_t^{\top}$ . If  $t \leq d$  goto Step 2.

The PM converges to the spectral radius of the matrix but the eigenvector may jump at iterations [4]. shifted inverse PM, deflation

When  $E[=e_1,\ldots,e_d]$  is not an orthonormal basis (up to prescribed  $\epsilon$ ), we adjust  $n_t$  according to the current estimate  $\left|\frac{\lambda_t}{\lambda_{t+1}}\right|$ , and restart until we get an orthonormal basis.

If  $e_i$  is orthonormal to  $e_j$  for j < i, Then  $\lambda_i$  is, the *i*th dominant eigenvalue, is the dominant eigenvalue of  $M_i$ .

For example,

$$\lambda_2 = \lambda_1 (M - \lambda_1 e_1 e_1^\top)$$

$$(M - \lambda_1 e_1 e_1^\top) e_2 = \lambda_2 e_2$$

vields

$$Me_2 = \lambda_2 e_2$$

since

$$-\lambda_1 e_1 e_1^{\top} e_2 = 0$$

because  $e_1^{\top} e_2 = 0$  (orthonormal bases).

Thus at stage t, we can test that  $|e_j^{\top}e_t| \leq \epsilon$  for all j < t in order to determine  $n_t$ . Books [6, 2]

### References

- [1] Inderjit S Dhillon and Beresford N Parlett. Orthogonal eigenvectors and relative gaps. SIAM Journal on Matrix Analysis and Applications, 25(3):858–899, 2003.
- [2] James E Gentle. Matrix algebra. Springer texts in statistics, Springer, New York, NY, doi, 10:978-0, 2007.

- [3] Nicholas J Higham and Françoise Tisseur. Bounds for eigenvalues of matrix polynomials. *Linear algebra and its applications*, 358(1-3):5–22, 2003.
- [4] Nicholas Loehr. Advanced linear algebra. CRC Press, 2014.
- [5] RV Mises and Hilda Pollaczek-Geiringer. Praktische verfahren der gleichungsauflösung. ZAMM-Journal of Applied Mathematics and Mechanics/Zeitschrift für Angewandte Mathematik und Mechanik, 9(2):152–164, 1929.
- [6] James Hardy Wilkinson. The algebraic eigenvalue problem, volume 662. Oxford Clarendon, 1965.