

# Challenge 1 APC 2024

October 2024

## 1 Introduction

In the Linear Algebra course you learned how to calculate eigenvalues of square matrices of size  $n \times n$  by solving the characteristic equation:

*CHAR equation.*  $\left( \lambda^n + c_{n-1}\lambda^{n-1} + c_{n-2}\lambda^{n-2} + \dots + c_0 = 0. \right) \quad (1)$

For large values of  $n$ , polynomial equations like (1) are difficult and time-consuming to solve. Moreover, numerical techniques for approximating roots of polynomial equations of high degree are sensitive to rounding errors.

The *Power Iteration* method is an iterative algorithm used to find the dominant eigenvalue (the eigenvalue with the largest absolute value) and its corresponding eigenvector of a matrix. Although this restriction may seem severe, dominant eigenvalues are of primary interest in many real-world applications, such as when dealing with dynamic processes.

## 2 The Power Iteration method

Let  $\mathbf{A} \in \mathbb{R}^{n \times n}$  be a square, diagonalizable matrix, and let

- $\{\lambda_1, \lambda_2, \dots, \lambda_n\}$  be the eigenvalues of  $\mathbf{A}$  and assume that the following holds:

$$|\lambda_1| > |\lambda_2| \geq \dots \geq |\lambda_n|.$$

- $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$  be the corresponding eigenvectors of  $\mathbf{A}$  such that

$$\|\mathbf{x}_i\| = 1 \quad \forall i \in \{1, 2, \dots, n\}.$$

- $\mathbf{x}^{(0)} \in \mathbb{R}^n$ , such that  $\|\mathbf{x}^{(0)}\| = 1$ .

The *Power Iteration* method finds the *dominant eigenvalue* building the following successions:

$$\boxed{\mathbf{z}^{(k+1)} = \mathbf{A}\mathbf{x}^{(k)}} \quad ! \quad (2)$$

1

$$\begin{aligned} \mathbf{z}^{(k+1)} &= \mathbf{A} \mathbf{x}^{(k)} \\ \mathbf{x}^{(k+1)} &= \frac{\mathbf{z}^{(k+1)}}{\|\mathbf{z}^{(k+1)}\|} \end{aligned} \quad \text{aggiorno } \mathbf{x}$$

$$\nu^{(k+1)} = \langle \mathbf{x}^{(k+1)}, \mathbf{A} \mathbf{x}^{(k+1)} \rangle$$

$$\{\nu^{(k)}\} \xrightarrow[k \rightarrow \infty]{} \lambda_1$$

$$\mathbf{x}^{(k+1)} = \frac{\mathbf{z}^{(k+1)}}{\|\mathbf{z}^{(k+1)}\|} \quad \text{where } \mathbf{z}^{(k+1)} = \mathbf{A} \mathbf{x}^{(k)} \quad (3)$$

$$\nu^{(k+1)} = \langle \mathbf{x}^{(k+1)}, \mathbf{A} \mathbf{x}^{(k+1)} \rangle \quad (4)$$

The notation  $\langle \cdot, \cdot \rangle$  denotes the scalar product between two quantities.

It can be proven that:

$$\bullet \{\mathbf{x}^{(k)}\}_{k \geq 0} \xrightarrow[k \rightarrow \infty]{} e^{i\theta} \mathbf{x}_1.$$

$$\bullet \{\nu^{(k)}\}_{k \geq 0} \xrightarrow[k \rightarrow \infty]{} \lambda_1.$$

$$\bullet \text{ The error at the } k^{th} \text{ iteration is bounded by } \left| \frac{\lambda_2}{\lambda_1} \right|^k.$$

$$e_k \leq \left| \frac{\lambda_2}{\lambda_1} \right|^k$$

To define convergence criteria, we introduce the following quantities:

$$\text{residual}^{(k)} = \|\mathbf{A} \mathbf{x}^{(k)} - \nu^{(k)} \mathbf{x}^{(k)}\|, \quad \text{RESIDUAL}_k: \|\mathbf{A} \mathbf{x}^{(k)} - \nu^{(k)} \mathbf{x}^{(k)}\|$$

$$\text{increment}^{(k)} = \frac{|\nu^{(k)} - \nu^{(k-1)}|}{|\nu^{(k)}|}, \quad \text{INCREMENT}_k: \frac{|\nu^{(k)} - \nu^{(k-1)}|}{|\nu^{(k)}|}$$

The convergence criterion of the algorithm is: Stop at the  $k^{th}$  iteration if both the following conditions are met

$$\text{STOP} \iff \begin{cases} \text{residual}^{(k)} < \text{tolerance} \\ \text{increment}^{(k)} < \text{tolerance} \end{cases} \quad (5)$$

Algorithm 1 presents the complete algorithm for the Power Iteration method. Note that in Algorithm 1 the value of *tolerance* is set to  $10^{-6}$  and that of  $T_{max}$  is set to 10000. The algorithm takes as input a matrix  $\mathbf{A}$  and a vector  $\mathbf{x}^{(0)}$ , where the latter must satisfy the condition  $\|\mathbf{x}^{(0)}\| = 1$ .

---

**Algorithm 1** Power Iteration method.

---

```

1: Input:  $\mathbf{A} \in \mathbb{R}^{n \times n}$ ,  $\mathbf{x}^{(0)} \in \mathbb{R}^n$  such that  $\|\mathbf{x}^{(0)}\| = 1$ 
2: Initialize:  $\text{tolerance} \leftarrow 10^{-6}$ ,
3:            $T_{max} \leftarrow 10000$ ,
4:            $\text{residual} \leftarrow \text{increment} \leftarrow \text{tolerance} + 1$ ,
5:            $t \leftarrow 0$ ,
6:            $\text{converged} \leftarrow \text{False}$ 
7: while not converged and  $t < T_{max}$  do
8:   Compute  $\mathbf{x}^{(k+1)}$  and  $\nu^{(k+1)}$  as in (2)-(4)
9:    $\text{converged} \leftarrow$  Check convergence as defined in (5)
10:   $t \leftarrow t + 1$ 
11: end while

```

---

## 3 Variants of the Power Iteration method

### 3.1 Inverse Power Iteration method

The *Inverse Power Iteration* method allows us to approximate the eigenvalue of minimum modulus (i.e.,  $|\lambda_n|$ ) of  $\mathbf{A}$ . The key idea is that the eigenvalues of  $\mathbf{A}^{-1}$  are the reciprocals of the eigenvalues of  $\mathbf{A}$ . Therefore, the minimum modulus eigenvalue of  $\mathbf{A}$  can be computed through the following process:

- Compute the *dominant eigenvalue*  $\tilde{\lambda}_1$  of  $\mathbf{A}^{-1}$  using the *Power Iteration* method.
- Compute the minimum modulus eigenvalue as  $\lambda_n = \tilde{\lambda}_1^{-1}$ .

Note that, for this method, the error at the  $k^{th}$  iteration is bounded by  $\left| \frac{\lambda_n}{\lambda_{n-1}} \right|^k$ .

### 3.2 Inverse Power Iteration method with shift

Let  $\mu \in \mathbb{R}$ . The *Inverse Power Iteration method with shift* allows us to approximate the eigenvalue of  $\mathbf{A}$  that is closest to  $\mu$ . The core idea is the following: if  $\lambda$  is an eigenvalue of  $\mathbf{A}$ , then  $\tilde{\lambda} = \lambda - \mu$  is an eigenvalue of  $\mathbf{A} - \mu\mathbf{I}$ . Therefore, the eigenvalue of  $\mathbf{A}$  closest to  $\mu$  can be computed as follows:

- Compute the minimum modulus eigenvalue  $\tilde{\lambda}_\mu$  of  $\mathbf{A} - \mu\mathbf{I}$  using the *Inverse Power Iteration* method.
- Compute the eigenvalue of  $\mathbf{A}$  closest to  $\mu$  as  $\lambda_\mu = \mu + \tilde{\lambda}_\mu$ .

Note that if  $\mu$  is an eigenvalue of  $\mathbf{A}$ , the method fails (in our case, we defined the test matrices in such a way that the algorithm never fails).

## 4 Code implementation

The provided code, zipped in `Assignment1.initial.zip`, contains:

- the `vectorhelpers` header and source files;
- the `squarematrix` header and source files;
- the `matrixhelpers` header and source files;
- the `power_iteration` class implementation;
- the `inverse_power_iteration` class implementation;
- the `shift_inverse_power_iteration` class implementation;
- the `eig_finder_helpers.h` file;
- the `inputs` folder;

- the `main.cpp` file.

After carefully reading the code, you have to implement the following functions:

```
double power_iteration::solve(
    const linear_algebra::square_matrix& A,
    const std::vector<double>& x0) const;

double inverse_power_iteration::solve(
    const linear_algebra::square_matrix& A,
    const std::vector<double>& x0) const;

double shift_inverse_power_iteration::solve(
    const linear_algebra::square_matrix& A,
    const double& mu,
    const std::vector<double>& x0) const;
```

These functions implement, respectively, the *Power Iteration* method, the *Inverse Power Iteration* method, and the *Inverse Power Iteration method with shift*. Each function takes the square matrix  $\mathbf{A}$  and the initial vector  $\mathbf{x}^{(0)}$  as inputs and returns an approximation of the desired eigenvalue. The last function also takes  $\mu$  as input, as defined in the previous section.

**Remark:** for the *Inverse Power Iteration* method(s), you do not need to explicitly invert  $\mathbf{A}$ . Instead, you should rely on the *LU* factorization, solving the following linear system:

$$\mathbf{Ax} = \mathbf{b}.$$

By factorizing  $\mathbf{A}$  as  $\mathbf{A} = \mathbf{LU}$ —where  $\mathbf{L}$  and  $\mathbf{U}$  are lower and upper triangular matrices, respectively—the linear system becomes:

$$\mathbf{LUx} = \mathbf{b}.$$

This system can be solved by breaking it into the following two triangular systems:

$$\mathbf{Ly} = \mathbf{b}$$

$$\mathbf{Ux} = \mathbf{y}.$$

The first step is a *forward substitution*, and the second step is a *backward solution*.

You can rely on the following functions implemented in the `matrixhelpers` files:

```
void lu(const square_matrix& A, square_matrix& L, square_matrix& U);

std::vector<double> backsolve(const square_matrix& U,
    const std::vector<double>& b);
```

```
std::vector<double> forwardsolve(const square_matrix& L,
                                const std::vector<double>& b);
```

Note that these three functions are defined in the `linear_algebra` namespace.

**Important:** the only files to be modified are

- `power_iteration.cpp`,
- `inverse_power_iteration.cpp` and
- `shift_inverse_power_iteration.cpp`.

The implementations must be consistent with the declarations.

You can rely on the already implemented functions for your own implementation.

The following is an extract of the `main` function in the `main.cpp` file.

```
int main() {

    std::string filename = "../inputs/input_10.txt";

    linear_algebra::square_matrix A(filename);
    std::vector<double> x0(A.size());
    x0[0] = 1.;    //starting point

    eigenvalue::power_iteration pi(10000, 1e-6, BOTH);

    double max_expected;

    if (filename == "../inputs/input_10.txt"){
        max_expected = 5.10274;
    }

    double max_obtained = pi.solve(A, x0);
    std::string result;
    if (std::abs(max_obtained - max_expected) < 1e-3)
        result = "CONVERGED";
    else
        result = "NOT CONVERGED";

    return 0;
}
```

Note that you can retrieve the input files from the `inputs` folder, and you need to modify the string value of the `filename` variable to match the desired file in order to test different matrices. Additionally, in the `if` block(s), you will

find the expected outputs of the three algorithms for the three different input matrices we provide. From these results, we will consider all solutions with a predetermined tolerance to be acceptable. In order to compare the results with those in the `main.cpp` file, it is important that you do not change the algorithm parameters, otherwise the algorithm may work but not show the same results.

**Important:** During the evaluation, we will test your code not only on the provided tests, but also on some matrices that are not available to you.

## 5 Delivery Instructions

The assignment is not mandatory. If the solution is implemented correctly, it can lead to a +1 point in the final grade.

Please, follow these instructions for the delivery:

- Download the zipped folder `Assignment1_initial.zip` from WeBeep.
- Unzip the `Assignment1_initial.zip` folder.
- Change the name of the **unzipped** folder in “YourCodicePersona” (e.g., “10699999”). **It is important to do this before re-zipping the project with your solution.**
- Implement your code within the provided files.
- Test the code on the provided three test cases (changing the input file in `main.cpp`).
- Zip the folder containing the entire project, making sure that the resulting file name is “YourCodicePersona.zip” (e.g., “10699999.zip”).
- Upload on WeBeep → Assignments → Assignment1.

**Attention:** The assignment is personal; no group nor team work is allowed. In case of plagiarism, you will be assessed 2 penalty points (i.e., a -2 on the total score), and you will not be able to participate in the next assignments.

If you have questions, post them on the WeBeep Assignments forum. **Note that we will not provide feedback in the last 24 hours before the deadline.**

**Code submission opens on 21/10/2024 at 08:00 and closes on 25/10/2024 at 18:00 (Rome time).**

If something changes in the source code we provided, an announcement will notify you. So, keep an eye on WeBeep these days.