

Numerical Analysis

Mathematics of Scientific Computing

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目录

1 Matrix Eigenvalue Problem by Power Methods

- Power Method
- Inverse Power Method
- Summary

2 QR-Factorization

内容提要

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下一节内容

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To compute the dominant eigenvalue of A ,
 A has the following two properties:

- There is a single eigenvalue of maximum modulus.
- There is a linearly independent set of n eigenvectors.

Two assuming:

- The eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ can be labeled $|\lambda_1| > |\lambda_2| \geq \dots \geq |\lambda_n|$.
- There is a basic $u^{(1)}, u^{(2)}, \dots, u^{(n)}$, for that $Au^{(j)} = \lambda_j u^{(j)}$

$$\begin{aligned}
 x^{(0)} &= a_1 u^{(1)} + a_2 u^{(2)} + \dots + a_n u^{(n)} & (a_1 \neq 0) \\
 x^{(1)} &= Ax^{(0)} & x^{(2)} = Ax^{(1)} \dots & x^{(k)} = Ax^{(k-1)} \\
 x^{(k)} &= A^k x^{(0)}
 \end{aligned}$$

$$\begin{aligned}
 x^{(0)} &= u^{(1)} + u^{(2)} + \dots + u^{(n)} \\
 x^{(k)} &= A^k u^{(1)} + A^k u^{(2)} + \dots + A^k u^{(n)} \\
 x^{(k)} &= \lambda_1^k u^{(1)} + \lambda_2^k u^{(2)} + \dots + \lambda_n^k u^{(n)} \\
 x^{(k)} &= \lambda_1^k [u^{(1)} + (\lambda_2/\lambda_1)^k u^{(2)} + \dots + (\lambda_n/\lambda_1)^k u^{(n)}]
 \end{aligned}$$

Since $|\lambda_1| > |\lambda_j|$, so $k \rightarrow \infty$, $(\lambda_j/\lambda_1)^k \rightarrow 0$

$$\begin{aligned}
 x^{(k)} &= \lambda_1^k [u^{(1)} + \varepsilon^{(k)}] \\
 \varphi(x^{(k)}) &= \lambda_1^k [\varphi(u^{(1)}) + \varphi(\varepsilon^{(k)})]
 \end{aligned}$$

$$\text{When } k \rightarrow \infty, r_k = \frac{\varphi(x^{(k+1)})}{\varphi(x^{(k)})} = \lambda_1 \frac{[\varphi(u^{(1)}) + \varphi(\varepsilon^{(k+1)})]}{[\varphi(u^{(1)}) + \varphi(\varepsilon^{(k)})]} \rightarrow \lambda_1$$

Algorithm of Power Method

input A, x, M

for $k = 1$ to M do

$y \leftarrow Ax$

$r \leftarrow \varphi(y)/\varphi(x)$

$x \leftarrow y$

output k, x, r

end do


```
1 function [x,r]=powerMethod(A,x,M)
2 for k=1:M
3     y=A*x
4     r=linearFun(y)/linearFun(x)
5     x=y/max(abs(y))
6 end
```

```
1 function f=linearFun(x)
2 f=x(2);
```

下一节内容

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The inverse power method computes the smallest eigenvalue of A .

Eigenvalues of A can be arranged as follows:

$$|\lambda_1| > |\lambda_2| \geq \dots \geq |\lambda_n| > 0.$$

Eigenvalues of A^{-1} can be arranged as follows:

$$|\lambda_n^{-1}| > |\lambda_{n-1}^{-1}| \geq \dots \geq |\lambda_1^{-1}| > 0.$$

$$x^{(k+1)} = A^{-1}x^{(k)}$$

```
1 function [x,r]=inversepower(A,x,M)
2 for k=1:M
3     y=A\x
4     r=linearFun(y)/linearFun(x)
5     x=y/max(abs(y))
6 end
```

```
1 function f=linearFun(x)
2 f=x(2);
```

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Summary

Method	Equation	Computes
power	$x^{(k+1)} = Ax^{(k)}$	largest eigenvalue
inverse power	$Ax^{(k+1)} = x^{(k)}$	smallest eigenvalue
shifted power	$x^{(k+1)} = (A - uI)x^{(k)}$	eigenvalue farthest from u
shifted inverse power	$(A - uI)x^{(k+1)} = x^{(k)}$	eigenvalue closest to u

The code of shifted power

```
1 function [x,r]=shiftpower(A,x,M,u, I)
2 for k=1:M
3     y=(A-u*I)*x
4     r=linearFun(y)/linearFun(x)
5     x=y/max(abs(y))
6 end
```

```
1 function f=linearFun(x)
2 f=x(2);
```

The code of shifted inverse power

```
1 function [x,r]=invshiftpower(A,x,M,u, I)
2 for k=1:M
3     y=(A-u*I)\x
4     r=linearFun(y)/linearFun(x)
5     x=y/max(abs(y))
6 end
```

```
1 function f=linearFun(x)
2 f=x(2);
```


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QR-Factorization

$$A = QR$$

A is an $m \times n$ matrix, Q is an $m \times m$ unitary matrix and R is an $m \times n$ upper triangular matrix.

$$A_1 = A$$

$$A_1 = Q_1 R_1$$

$$A_2 = R_1 Q_1, A_2 \sim A_1 = A$$

$$A_2 = Q_2 R_2$$

$$A_3 = R_2 Q_2, A_3 \sim A_2 \sim A_1 = A$$

we have iterative process as follows:

$$A_k = Q_k R_k \quad (A_1 = A)$$

$$A_{k+1} = R_k Q_k, \quad (k = 1, 2, \dots)$$

$$A_{k+1} \sim A$$

A_k converges to the upper triangular matrix whose diagonal elements are $\lambda_1, \lambda_2, \dots, \lambda_n$.