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Suppose we want to define the smallest Eigenvalue:

Input: $A, v_0, \text{tol}, \text{matIter}$

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\label{eq:while_error} \begin{split} & while(error < tol~\&\&~iter < matIter) \\ & \{~v1 = 1~/~magnitude(y)~*~y \\ & w = A~*~v1 \\ & \lambda_1 = \nu_1^t * w \\ & error = abs(\lambda_0 - \lambda_1) \\ & iter + +; \\ & \lambda_0 = \lambda_1 \\ & \} \end{split}
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Finding the smallest Eigenvalue: If λ_1 is the largest eigenvector of A, then $\frac{1}{\lambda_1}$ is the smallest eigenvalue of A^{-1} . If λ_n is the smallest eigenvalue of A. the $\frac{1}{n}$ is the largest eigenvalue of A^{-1}

We have the means to compute approximations of λ_1 and λ_n

- λ_1 : Use the power method
- λ_n : Use the inverse power method

properties of eigenvalues:

return λ_1 , error;

if (λ,ν) an eigen pair, $\nu\neq 0$. this means $A\nu=\lambda\nu$. Then for $\mu\in\mathbb{R},$ $(A\nu-\mu I\nu)=(A-\mu I)\nu=\lambda\nu-\mu I\nu=(\lambda-\mu)\nu$ $\to (\lambda-\mu)$ is an eigenvalue of $(A-\mu I)$. So, $(A-\mu I)\nu=(\lambda-\mu)\nu$

The idea is choose μ close our eigenvalue. We can use inverse iteration to derive an approximation of $\lambda - \mu$ and then add μ back to get λ .

Iteratively finding eigenvalues:

$$v_0 = a_1 v_1 + a_2 v_2 + ... + a_n v_n$$

$$Av_0 = a_1(\lambda_1 v_1) + a_2(\lambda_2 v_2) + ... + a_n(\lambda_n v_n)$$

where $\lambda_1/>\lambda_2\geq ...\geq \lambda_{n-1}/>0$

Properties

- 1. $\frac{A\nu_k}{\|\nu_k\|} \rightarrow \nu_1$
- $2. \ \frac{v_k^t A_{v_k}}{v_k^t v_k}$
- 3. If λ is an eigenvalue of A, the $\frac{1}{\lambda}$ is an eigenvalue of A^{-1}
- 4. $A\vec{\nu} = \lambda\vec{\nu} \rightarrow A\vec{\nu} \mu\nu = (\lambda \mu)\nu \rightarrow (A \mu I)\nu$. If λ is an eigenvalue of A, then $\lambda \mu$ is an eigenvalue of $A\mu I$

Using this approach allows us to utilize parallelism. This means we can use a tool like openMP to easily parallelize code written in C, C++, fortran, etc

Lamczos Algorithm

$$\begin{array}{l} Ax \to b \\ \left[\sum_{j=i}^{n} \alpha_{i,j} x_{j} \\ \sum_{j=i}^{n} \alpha_{i,j} x_{j} \\ \dots \end{array} \right] = \begin{bmatrix} b_{1} \\ b_{2} \\ \dots \\ b_{n} \end{bmatrix} \\ x_{1} \begin{bmatrix} \alpha_{1,1} \\ \alpha_{1,2} \\ \dots \\ \alpha_{1,n} \end{bmatrix} + x_{2} \begin{bmatrix} \alpha_{2,1} \\ \alpha_{2,2} \\ \dots \\ \alpha_{2,n} \end{bmatrix} + \dots + x_{n} \begin{bmatrix} \alpha_{n,1} \\ \alpha_{n,2} \\ \dots \alpha_{n,n} \end{bmatrix} \\ for(int \ i = 0; \ i \ ; \ n; \ i++)\{ \\ double \ sum = 0.0; \\ for(int \ j = 0; \ j \ ; \ n; \ j++)\{ \\ sum \ += \ a[i][j] \ * \ x[j]; \\ \} \\ b[i] = \ sum; \\ \}$$