

Matrix Theory
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Interlacing theorem (Continued)

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E2 212 Matrix Theory
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HAPPY NEW YEAR!

Thm. Let n be a +ve integer, and let $\{\lambda_i\}_{i=1}^n$ & $\{\hat{\lambda}_i\}_{i=1}^{n+1}$ be two given sequences of real # s.t.
 $\hat{\lambda}_1 \leq \lambda_1 \leq \hat{\lambda}_2 \leq \lambda_2 \leq \dots \leq \lambda_{n-1} \leq \hat{\lambda}_n \leq \lambda_n \leq \hat{\lambda}_{n+1}.$
 let $\Lambda = \text{diag}(\lambda_1 \dots \lambda_n)$. Then, $\exists a \in \mathbb{R}$ and $y \in \mathbb{R}^n$ s.t.
 $\{\hat{\lambda}_1, \dots, \hat{\lambda}_{n+1}\}$ are the EVals of the real symmetric matrix

$$\hat{A} = \begin{bmatrix} \Lambda & y \\ y^T & a \end{bmatrix} \in \mathbb{R}^{(n+1) \times (n+1)}.$$

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Proof: $\{\lambda_1, \dots, \lambda_n\}$ are the EVals of Λ ; $a = \sum_{i=1}^{n+1} \hat{\lambda}_i - \sum_{i=1}^n \lambda_i \geq 0$.

$$p_{\hat{A}}(t) = \det(tI - \hat{A}) = \left[(t-a) - \sum_{i=1}^n \frac{y_i^2}{t - \lambda_i} \right] \prod_{i=1}^{n+1} (t - \hat{\lambda}_i). \quad (*)$$

 (Want $p_{\hat{A}}(t) = \prod_{i=1}^{n+1} (t - \hat{\lambda}_i)$, i.e., $p_{\hat{A}}(\hat{\lambda}_k) = 0, k=1, 2, \dots, n+1$.)
 Consider $f(t) = \prod_{i=1}^{n+1} (t - \hat{\lambda}_i)$; $g(t) = \prod_{i=1}^n (t - \lambda_i)$.
 Euclidean algo: $f(t) = g(t)(t-c) + r(t)$.
 Comparing coeffs. of t^n , we get $c=a$.
 Also, $f(\lambda_k) = r(\lambda_k), k=1, \dots, n$, so $r(t)$ known at n points. Assume λ_k distinct.

So, we begin. The last time we were looking at this theorem, which said that if n is a positive integer and λ_i going from 1 to n and $\hat{\lambda}_i$, i going from 1 to $n+1$. Two sequences of real numbers, such that they (interlace), these two sequences interlaced with each other, meaning that $\hat{\lambda}_1$ is the smallest of these numbers followed by λ_1 followed by $\hat{\lambda}_2$, followed by λ_2 , etcetera, up to at the very end, you will have λ_{n-1} is less than or equal to $\hat{\lambda}_n$, λ_n is less than or equal to $\hat{\lambda}_{n+1}$.

So, λ_{n+1} is the biggest, λ_1 is the smallest and all the other numbers are in between. And if we denote the diagonal matrix containing λ_1 to λ_n as its diagonal entries as this capital Λ , then there exists a real scalar, real value scalar, and an n length real-valued vector y such that these other numbers λ_1, λ_2 , up to λ_{n+1} are the eigenvalues of the real symmetric matrix A , which is $\Lambda y, y^T A$, which is an $(n+1) \times (n+1)$ matrix.

So, we were going over the proof of this, we had gone most of the way, but there is some part that needed to be completed. So, we will begin by filling in the rest of this proof. So, first of all, λ_1 through, just to recall where we were λ_1 through λ_n , of course, the eigenvalues of Λ .

And further, by noting that the trace of A must be the summation of λ_i , while the trace of Λ must be equal to λ_1 plus etcetera λ_n , we know that this value A here, in order for λ_1 through λ_n to be the eigenvalues of this matrix, A must be such that A is equal to summation i equal to 1 to $n+1$ λ_i minus the summation i equal to 1 to n λ_i .

This is always going to be greater than or equal to 0. Now, if we look at the characteristic polynomial of A by definition, it is the determinant of $tI - A$. And if we substitute that and expand it out, we were able to show that it can be written in the following form where it has a factor with $t - y_i$ squared over this $t - \lambda_i$ is showing up in the denominator here, times the product of these terms, i equal to 1 to n $t - \lambda_i$.

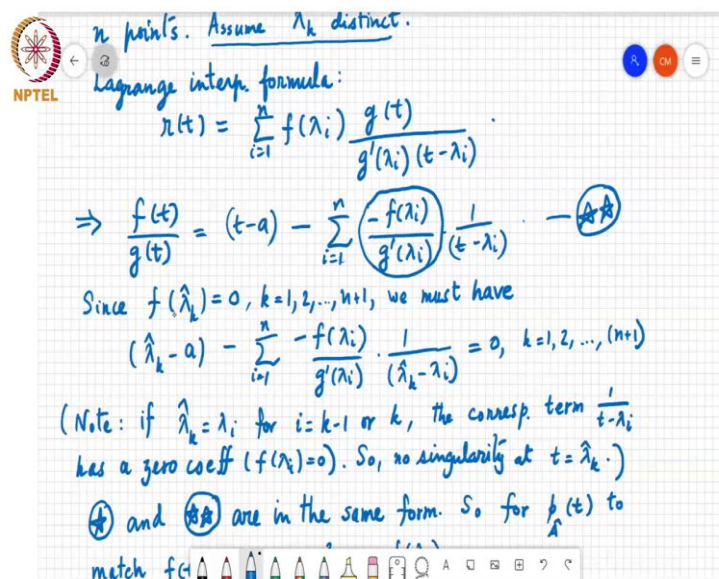
And note that this is exactly the characteristic polynomial of this matrix Λ . Now, what we want is that this p_A of t must end up being equal to the product i equal to 1 plus 1 to n plus 1 $t - \lambda_i$, that will ensure that λ_i going from 1 to $n+1$ are the 0s of p_A of t . And so that this matrix we can then be assured that this matrix has λ_1 through λ_{n+1} as its eigenvalues. Now, to do that, we consider two functions.

The first is f of t , which is the product this is our desired characteristic function, which is the product i equal to 1 plus 1 to n plus 1 $t - \lambda_i$ and g of t is the characteristic function of capital Λ . And that is just the product i equal to 1 to n $t - \lambda_i$. Now, this is an $(n+1)$ degree polynomial, this is an n degree polynomial. So, we can always write f of t to be some g of t times t minus some constant c .

That is because the t power $n + 1$ term has a coefficient of 1 and the t power n has a coefficient of 1 here. And so, it can be written as G of t times t minus c plus some r of t this is a remainder polynomial and this has a degree at most $n - 1$. Now, if so, obviously, the t power $n + 1$ th coefficients here match already by construction, but if we compare the coefficients at t to the n , we did this the last time we ended up with saying that c must be equal to a .

Now, further, because g of λ_k is equal to 0 for k going from 1 to n because there is a t minus λ_i factor here, what we have is f of λ_k must be equal to r of λ_k . So, what this means is this r of t is known to us at n points because we know what f of t is, it is just this polynomial, so we can substitute λ_k , k going from 1 to n . And we can calculate the value of f of λ_k , that tells us what the value of r of λ_k is, and it is a degree at most $n - 1$ polynomial, and it is known now at n different points.

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n points. Assume λ_k distinct.

Lagrange interp. formula:

$$n(t) = \sum_{i=1}^n f(\lambda_i) \frac{g(t)}{g'(\lambda_i)(t-\lambda_i)}$$

$$\Rightarrow \frac{f(t)}{g(t)} = (t-a) - \sum_{i=1}^n \left(\frac{-f(\lambda_i)}{g'(\lambda_i)} \right) \frac{1}{(t-\lambda_i)} \quad \text{--- (A)}$$

Since $f(\hat{\lambda}_k) = 0$, $k=1, 2, \dots, n+1$, we must have

$$(\hat{\lambda}_k - a) - \sum_{i=1}^n \frac{-f(\lambda_i)}{g'(\lambda_i)} \cdot \frac{1}{(\hat{\lambda}_k - \lambda_i)} = 0, \quad k=1, 2, \dots, (n+1)$$

(Note: if $\hat{\lambda}_k = \lambda_i$ for $i=k-1$ or k , the corresp. term $\frac{1}{t-\lambda_i}$ has a zero coeff ($f(\lambda_i)=0$). So, no singularity at $t=\hat{\lambda}_k$.)

(A) and (B) are in the same form. So for $p_A(t)$ to match $f(t)$

$f(\hat{\lambda}_k) = 0, k=1, 2, \dots, n+1$, we must have

$$(\hat{\lambda}_k - a) - \sum_{i=1}^n \frac{-f(\lambda_i)}{g'(\lambda_i)} \cdot \frac{1}{(\hat{\lambda}_k - \lambda_i)} = 0, k=1, 2, \dots, (n+1)$$
 (Note: if $\hat{\lambda}_k = \lambda_i$ for $i=k-1$ or k , the corresp. term $\frac{1}{t-\lambda_i}$ has a zero coeff ($f(\lambda_i)=0$). So, no singularity at $t=\hat{\lambda}_k$.)
 (*) and (**) are in the same form. So for $p_k(t)$ to match $f(t)$, set $y_i = \frac{-f(\lambda_i)}{g'(\lambda_i)}, i=1, 2, \dots, n$.
 \Rightarrow Need to show that $\frac{-f(\lambda_i)}{g'(\lambda_i)} \geq 0, i=1, \dots, n$.
 Use the interlacing assump.: $\hat{\lambda}_1 < \lambda_1 < \hat{\lambda}_2 < \dots < \lambda_{n-1} < \hat{\lambda}_n < \lambda_n < \lambda_{n+1}$
 $\Rightarrow f(\lambda_i) = (-1)^{n-i+1} \prod_{j=1}^{n+1} |\lambda_i - \lambda_j|$

Now, if we assume that lambda ks are distinct, and I, as I mentioned will, at the end, talk about what happens when there are repeated lambda ks. But if they are distinct, we can write the following Lagrange interpolation formula. So, knowing the value r of lambda k at k equal to 1 to n, we can directly write out what r of t is, r of t is this polynomial here. And notice that it is, it has a g of t divided by t minus lambda i, and g of t itself is this product of all such factors.

So, each factor will cancel one of these factors here. And so, each of these ratios is a degree n minus 1 polynomial. And that is getting weighted by f of lambda i divided by g dash of lambda i, and then added together. So overall, this has a degree at most n minus 1. But this is the expression for r of t. So, if you find r of lambda k, k going from 1 to n, you will find that it is equal to f of lambda k.

So, it meets this constraint that we have set on these on r of t. Now, if we use this formula here, f of t equals g of t into t minus c plus r of t, and we divide throughout by g of t, then we get that f of t divided by g of t is equal to t minus a, c is equal to a minus this whole thing divided by g of t and the g of t, g of t will cancel and so you are left with, so here it was plus r of t, so I write it as minus of minus, minus i equal to 1 to n, f minus f of lambda i divided by g dash of lambda i times 1 over t minus lambda i.

Now this, this thing is, so if I write it this way, f of t is equal to this whole coefficient times g of t, and g of t is this product here. And so now, if you look back at pA hat of t, that also has the same form, it is t minus a minus something times the product, this thing, which is exactly equal to my g of t. So, f of t is now equal to the same is, f of t is now in the same form as this pA hat of t.

And so, for these two polynomials to completely match, we just need to choose y_i squared to be equal to this coefficient here, minus f of λ_i over g dash of λ_i . So, yeah, so since f of λ_k equals 0, for i equal to 1 to n plus 1, we must have that if I substitute λ_k here, this must be equal to 0 for i equal to 1 to n plus 1. This is another condition that this polynomial ratio here will satisfy.

And as I said this two are the same forms. So, if you want these two to match, all we need is to set y_i squared to be equal to this coefficient minus f of λ_i over g dash of λ_i . So, for you to be able to find a real-valued vector y , such that y_i squared equal to the negative of this, we need that these numbers should be positive numbers, then I can find a real-valued y_i such that y_i squared equals this thing. So, we just need to show that these are all greater than or equal to 0 for i equal to 1 to n .

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Need to show that $-\frac{f(\lambda_i)}{g'(\lambda_i)} \geq 0, i=1, \dots, n$.

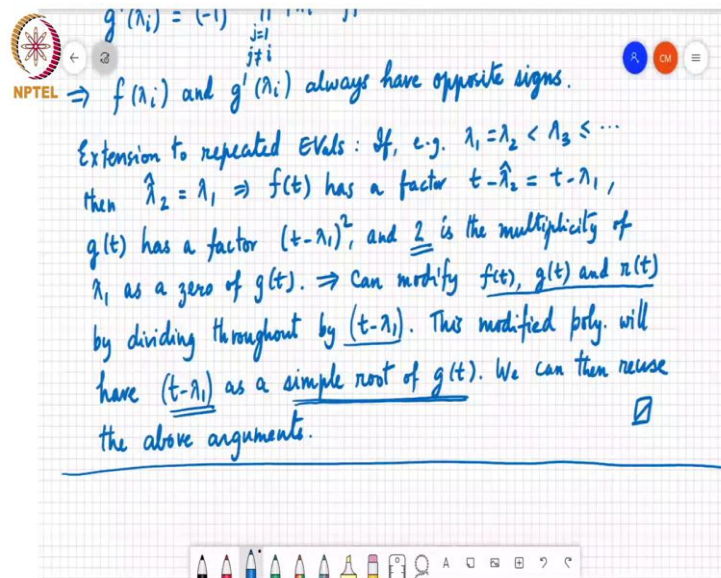
Use the interlacing assump. : $\hat{\lambda}_1 \leq \lambda_1 \leq \hat{\lambda}_2 \leq \dots \leq \lambda_{n-1} \leq \hat{\lambda}_n$

$\Rightarrow f(\lambda_i) = (-1)^{n-i+1} \prod_{j=1}^{n+1} |\lambda_i - \hat{\lambda}_j|$

$g'(\lambda_i) = (-1)^{n-i} \prod_{\substack{j=1 \\ j \neq i}}^n |\lambda_i - \lambda_j|$

$\Rightarrow f(\lambda_i)$ and $g'(\lambda_i)$ always have opposite signs.

Extension to repeated EVs : If, e.g. $\lambda_1 = \lambda_2 < \lambda_3 \leq \dots$
 then $\hat{\lambda}_2 = \lambda_1 \Rightarrow f(t)$ has a factor $t - \hat{\lambda}_2 = t - \lambda_1$,
 $g(t)$ has a factor $(t - \lambda_1)^2$, and 2 is the multiplicity of
 λ_1 as a zero of $g(t)$. \Rightarrow Can modify $f(t)$, $g(t)$ and $\pi(t)$
 by dividin



So, we now finally use the interlacing assumption. Notice that in the proof, so far, we are not using this fact that this λ s and $\hat{\lambda}$ s are an interlacing set of numbers. So, we will use this interlacing assumption. And now, if I take the, so you can see here that λ_1 is between $\hat{\lambda}_1$ and $\hat{\lambda}_2$ and so on. So, more generally, λ_i is lower bounded by $\hat{\lambda}_i$ and upper bounded by $\hat{\lambda}_{i+1}$.

So, what this means is that if I take any $\hat{\lambda}_j$, where j is less than i , then $\lambda_i - \hat{\lambda}_j$ will be a positive number. This is minus something which is on this side. And similarly, if I take any j which is greater than i , then $\lambda_i - \hat{\lambda}_j$ is going to be negative. These are all the $\hat{\lambda}$ s on this side that are bigger numbers.

And so, based on that, if I look at what $f'(\lambda_i)$ is, $f'(\lambda_i)$ is the product of $\lambda_i - \hat{\lambda}_j$ for j going from 1 to $n+1$, but out of these all these numbers are positive and all these numbers are negative. So, there are $n - i + 1$ negative numbers over here. And so, if I pull that out, I can write this as $(-1)^{n-i+1}$ product j going from 1 to $n+1$ the modulus of $\lambda_i - \hat{\lambda}_j$.

And similarly, $g'(\lambda_i)$ is just the same product. So, g' is this $t - \lambda_i$ but not including the i th term because you are taking the derivative and evaluating it at λ_i . And so, this product and again all these terms will be positive and all these terms will be negative. So, there are $n - i$ such negative terms. So, I can write it as $(-1)^{n-i}$ times the product of all positive numbers, modulus of $\lambda_i - \hat{\lambda}_j$.

And so, you will see that this is multiplied by minus 1 to the $n - i + 1$ this is multiplied by minus 1 to the $n - i$ times a positive number. And so, what that means is that f of λ_i and g dash of λ_i will always have opposite signs because there is a plus 1 extra here. And so, their ratio will be negative, or negative of that ratio will be positive.

So, that establishes that we can choose y_i squared to be minus f of λ_i over g dash of λ_i . So, the only thing left is to handle the case where there are repeated eigenvalues. So, this is a very simple argument. Suppose, for example, that λ_1 equals λ_2 which is strictly less than λ_3 , and so on. For all other cases, the argument is very similar.

So, the you can consider an example like this and see what happens. Now, if that is the case, because it has this interlacing property if λ_1 equals λ_2 then λ_2 hat must be equal to λ_1 and which is in turn equal to λ_2 . So, that means that f of t which is the product of $t - \lambda_i$, it has a factor $t - \lambda_2$ hat, which is the same as $t - \lambda_1$.

Similarly, g of t has two factors which are equal to $t - \lambda_1$. So, it has the factor $t - \lambda_1$ square because the first term and the second term are both $t - \lambda_1$ and (t) , so the first term and second term at $t - \lambda_1$ into $t - \lambda_2$, but since λ_1 equals λ_2 you have a factor like $t - \lambda_1$ squared. And so, the multiplicity of λ_1 as a 0 of g of t is exactly equal to 2.

And so, what we can do is to modify our f of t , g of t , and r of t by dividing throughout by $t - \lambda_1$ and this modified polynomial will be exactly like before, it will have $t - \lambda_1$ as a simple root of g of t . And that was the reason why we assumed that the eigenvalues are distinct, so, that the eigenvalues turned out to be simple roots, and then we can reuse all of the above arguments.

So, that is the is the proof. So, the proof directly extends to the case where there are repeated eigenvalues. So, this argument the main point of this argument here is that g of t always has one greater degree for repeated root compared to f of t and that means that we can remove these common factors, and then we will be left with distinct eigenvalues and we can reuse the same arguments as we used to establish this.

Any questions about this proof? So, what did this result tell us, it told us that if you are given a set of interlacing numbers, we can construct matrices such that the first set of numbers is

are the eigenvalues of a matrix. And the second set of numbers are the eigenvalues of a matrix that is obtained by taking the first matrix and bordering it on the right and below by y and y transpose respectively and on the bottom right by some number a .

So, and the result prior to that said that if you take a matrix A and then you border it by a vector y and on the right and y Hermitian below and small a on the bottom right, you will get an n plus 1 cross n plus 1 matrix and the eigenvalues of the n cross n matrix and the n plus 1 cross n plus 1 matrix interlaced with each other.

Well, there is no nothing very special about adding a row and column to a matrix, the same result applies to deleting a row or a column or in fact, the last row or column of a matrix. When you delete the last row or column, the eigenvalues of the reduced matrix will interlace with the eigenvalues of the original matrix. And of course, if you think about it, there is not no sanctity in deleting the last row or column nothing special about the last row or column, the results apply equally well if you delete any row or column.

So, when you delete any row or column you, so, if you take an n cross n matrix and delete a particular row and column you get what is called an n minus 1 cross n minus 1 principle sub matrix of that matrix and the eigenvalues of the principles of matrix interlaced with the eigenvalues of the original matrix and you can apply this repeatedly and then you will get interlacing results for that (happens), you will get results related to the interlacing of eigenvalues when you delete say r rows or say k rows and columns of a matrix. And so, this kind of results are called inclusion principles. And here is one such example result.

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the above argument

Thm. $A \in \mathbb{C}^{n \times n}$ Herm. Let integer $r: 1 \leq r \leq n$.

Let A_r denote any $r \times r$ principal submatrix of A
(obtained by $(n-r)$ rows and corresp. cols from A .)

For each integer k s.t. $1 \leq k \leq r$,

$$\lambda_k(A) \leq \lambda_k(A_r) \leq \lambda_{k+n-r}(A).$$

Proof: Suppose A_r is formed by deleting rows i_1, \dots, i_{n-r} and corresp. cols of A . Let $1 \leq k \leq r$.

$$\lambda_{k+n-r}(A) = \min_{\omega_1, \dots, \omega_{n-k} \in \mathbb{C}^n} \max_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{n-k}}} \frac{x^H A x}{x^H x}.$$

$$\begin{aligned}
& \geq \min_{\omega_1, \dots, \omega_{n-k} \in \mathbb{C}^n} \max_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{n-k} \\ x \perp e_{i_1}, \dots, e_{i_{n-k}}} \frac{x^H A x}{x^H x} \\
& = \min_{v_1, \dots, v_{n-k} \in \mathbb{C}^n} \max_{\substack{y \neq 0, y \in \mathbb{C}^n \\ y \perp v_1, \dots, v_{n-k}}} \frac{y^H A_r y}{y^H y} = \lambda_k(A_r)
\end{aligned}$$

Similarly,

$$\begin{aligned}
\lambda_k(A) & = \max_{\omega_1, \dots, \omega_{k-1} \in \mathbb{C}^n} \min_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{k-1} \\ x \perp e_{i_1}, \dots, e_{i_{n-k}}} \frac{x^H A x}{x^H x} \\
& \leq \max_{\omega_1, \dots, \omega_{k-1} \in \mathbb{C}^n} \min_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{k-1} \\ x \perp e_{i_1}, \dots, e_{i_{n-k}}} \frac{x^H A x}{x^H x}
\end{aligned}$$

$$\begin{aligned}
& = \min_{v_1, \dots, v_{k-1} \in \mathbb{C}^n} \max_{\substack{y \neq 0, y \in \mathbb{C}^n \\ y \perp v_1, \dots, v_{k-1}}} \frac{y^H A_r y}{y^H y} = \lambda_k(A_r)
\end{aligned}$$

Similarly,

$$\begin{aligned}
\lambda_k(A) & = \max_{\omega_1, \dots, \omega_{k-1} \in \mathbb{C}^n} \min_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{k-1} \\ x \perp e_{i_1}, \dots, e_{i_{n-k}}} \frac{x^H A x}{x^H x} \\
& \leq \max_{\omega_1, \dots, \omega_{k-1} \in \mathbb{C}^n} \min_{\substack{x \neq 0, x \in \mathbb{C}^n \\ x \perp \omega_1, \dots, \omega_{k-1} \\ x \perp e_{i_1}, \dots, e_{i_{n-k}}} \frac{x^H A x}{x^H x} \\
& = \max_{v_1, \dots, v_{k-1} \in \mathbb{C}^n} \min_{\substack{y \neq 0, y \in \mathbb{C}^n \\ y \perp v_1, \dots, v_{k-1}}} \frac{y^H A_r y}{y^H y} = \lambda_k(A_r). \quad \square
\end{aligned}$$

So, this is theorem. You can prove this theorem by using this result on adding a row and column and converting it to deleting a row and column and applying it repeatedly. But then it is equally easy to prove this result directly which is what we will do. So, the theorem says that A is an n cross n Hermitian matrix and let r be an integer such that 1 is less than or equal to r is less than or equal to n .

Let A_r denote any r cross r principal submatrix of A . So, then you obtained the principles of submatrix by deleting n minus r rows and the corresponding columns. So, you have to delete the same row and column index, so then for each integer k 1 less than or equal to k less than or equal to r λ_k of A less than or equal to λ_k of A_r is less than or equal to λ_k plus n minus r of A . Again, we are arranging these eigenvalues in increasing order.

So, I did not write that explicitly, but λ_1 of A is the smallest eigenvalue of A and λ_n of A is the largest eigenvalue of A , and λ_k of A_r is the k th largest eigenvalue of the principal submatrix A_r . So, proof. So, the essential ideas of this proof we have already seen, so, we can quickly run through the proof. So, suppose A_r is formed by deleting rows, it will delete n minus r rows.

So, $i = 1$ up to $i = n$ minus r and the corresponding columns of A and let $1 \leq k \leq R$. Now, just using the Courant-Fischer theorem, we have that. So, first of all, we want to show a lower bound like this. So, lower bound, as you remember, as you might remember, we will use the min-max formulation of the result. So, λ_k plus n minus r of A is equal to the min over w_1 through $w_{n - r}$ of this index, and n minus this index is $n - k - n + r$, which is $r - k$.

These are in C^n , the maximum over $x \neq 0$, $x \in C^n$, and x perpendicular to all these vectors of $x^H A x$ divided by $x^H x$. Now, this trick is something we saw earlier, this is greater than or equal to the minimum over the same vectors w_1 through $w_{r - k}$ in C^n , the maximum over $x \neq 0$, $x \in C^n$, x perpendicular to w_1 through $w_{r - k}$.

Now, I will throw in an extra set of constraints, x perpendicular to e_1 up to $e_{n - k}$. So, these are columns of a $n \times n$ identity matrix corresponding to columns $i = 1$ through $i = n$ minus k . So, I am adding extra constraints here. So, this maximum, the solution to this maximization problem may not be as big as the solution to this maximization problem. And that is why we have a greater than or equal to sign here.

So, the objective function is the same, $x^H A x$ over $x^H x$. Now, if x is perpendicular to all these vectors, then what I can do is to simply delete that corresponding row and column of A and then consider a reduced vector and then solve this over that reduced space. So, that reduced vector I will call it y and y will be perpendicular to these vectors w_1 through $w_{n - k}$ but with the indices, $i = 1$ through $i = n$ minus k delete it, and those I will call v_1 to $v_{r - k}$.

So, this is exactly equal to the minimum over vectors v_1 through the $r - k$ in C^r , the maximum over $y \neq 0$, $y \in C^r$, and y perpendicular to v_1 through $v_{r - k}$ of $y^H A_r y$ over $y^H y$, which is exactly by the Courant-Fischer theorem itself equal to λ_k of A_r . So, that proves this part of the inequality. And

similarly, λ_k of A . Now, we want to show an upper bound, so we will use the max-min version.

So, this is the maximum over w_1 through w_{k-1} in C to the n of the minimum over x not equal to 0, x in C to the n , x perpendicular to w_1 through w_{k-1} of $x^H A x$ over x Hermitian x . And now, I use the same trick again that this is less than or equal to if I throw an extra constraint on the minimum, I may not be able to minimize it as well as I am doing it here.

So, the final answer may turn out to be larger than whatever I get here. So, this is the max over w_1 through w_{k-1} in C to the n of the minimum x not equal to 0, x in C to the n x perpendicular to w_1 through w_{k-1} . And now, x also perpendicular to e_{i_1} through $e_{i_{r-1}}$ of $x^H A x$ over x Hermitian x . What is x is perpendicular to all these the entries i_1 through i_{r-1} of x are always equal to 0.

So, those particular rows and columns from A can just be deleted, because there is nothing to optimize over there. And correspondingly, I can delete those indices in w_1 through w_{k-1} and call them, call the resulting r -dimensional vectors as v_1 through v_{k-1} . So, this is exactly equal to the maximum over v_1 through v_{k-1} in C to the r the minimum over y not equal to 0, y belonging to C to the r and y perpendicular to v_1 through v_{k-1} of $y^H A y$ over y Hermitian y which is exactly equal to λ_k of A_r , which is the result we wanted to show.

So, that completes this proof. So, one immediate consequence of this, this result is something called the Poincare separation theorem. And this is very useful for example, in quantum mechanics in situations where one has information about $u_i^H A u_j$ for orthonormal vectors u_i and u_j . So, you do not get to observe the whole matrix A , but you get to observe projections of this matrix using a set of orthonormal vectors, and then what can we say about the eigenvalues of the original matrix in terms of the eigenvalues of the matrix obtained by forming these projections.

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Cor. $A \in \mathbb{C}^{n \times n}$, Herm. $1 \leq r \leq n$
 Let $u_1, \dots, u_r \in \mathbb{C}^n$ be r given orthonormal v.
 $(B_r)_{ij} = u_i^H A u_j$, $B_r \in \mathbb{C}^{r \times r}$
 If EVs of A and B_r are arranged in \uparrow order,
 $\lambda_k(A) \leq \lambda_k(B_r) \leq \lambda_{k+n-r}(A)$, $k=1, 2, \dots, r$
 Proof: If $r < n$, choose $(n-r)$ additional vecs u_{r+1}, \dots, u_n s.t.
 $\{u_1, \dots, u_n\}$ are an orthonormal set. $U \triangleq [u_1, \dots, u_n] \in \mathbb{C}^{n \times n}$.
 U is unitary $\Rightarrow \text{Evals}(U^H A U) = \text{Evals}(A)$
 $\Rightarrow B_r$ is a principal submatrix of $U^H A U$, obtained by
 deleting the last $(n-r)$ rows and cols. Now use prev. result.

So, here is the corollary, A is in \mathbb{C} to the n cross n Hermitian and 1 less than or equal to r less than or equal to n . So, r is some number between 1 and n let u_1 through u_r in \mathbb{C} to the n be r given orthonormal vectors. And define the matrix B_r with ij th element equal to $u_i^H A u_j$. And notice that B_r is a matrix in \mathbb{C} to the r cross r . If the eigenvalues of A and B are arranged in increasing order λ_k of A is less than or equal to λ_k of B_r is less than or equal to λ_{k+n-r} of A .

So, what this says is that instead of observing A , if we get to observe $u_i^H A u_j$ and then you arrange that in a matrix B_r and then you find the, so this is a smaller matrix possibly a much smaller matrix of size r cross r , then you can say something about the eigenvalues of A .

So, specifically, the k th eigenvalue of A is at most the k th eigenvalue of B_r and the k plus n minus r eigenvalue of A is at least equal to the k th eigenvalue of B_r . So, this allows you to bound the eigenvalues of A in terms of λ_k of B_r . So, the proof is very short it is just pointing to the previous results that we are going to use.

So, if r is strictly less than n , so, if r equals n , that is almost trivial but if r is less than n , I mean the next step that I am going to say is not required if r equals n , because u_1 to u_n if r equals n , u_1 to u_n are form an n cross n orthonormal matrix together when you stack them into a matrix, but if r is less than n , we can choose n minus r additional vectors u_{r+1} up to u_n such that this set u_1 through u_n form an orthonormal set. And let U be defined this is matrix u_1 through u_n in \mathbb{C} to the n cross n .

Now, u is unitary. So, which implies that the eigenvalues of u Hermitian Au are equal to the eigenvalues of A and that means that the given B_r is a principal submatrix of u Hermitian Au , just obtained by deleting the last $n - 1$ or $n - r$ rows and columns. So, that is it. So, now, we can use the previous theorem, just deleting $n - r$ rows and columns. And we can use the previous theorem and that is exactly what the previous theorem said that the eigenvalues have this relationship.

So, in fact, this result itself is very useful, we can use it to show many more results on many more variational results on eigenvalues and there are lots of results in the text. We just do not have the time to systematically cover them in this course, but you can look at the text and find many more interesting results.

Now, recall that the diagonal elements of Hermitian symmetric matrix are always real because if it is summation symmetric, A equals A Hermitian and if we equate the diagonal elements, it means A must be, A_{ii} must be equal to A_{ii}^* . In other words, diagonal entries must be real-valued. Also, the eigenvalues of a Hermitian symmetric matrix are real-valued, we have seen that also. Furthermore, the diagonal entries and the eigenvalues have the same sum that is the trace of a matrix is equal to the sum of its eigenvalues.