

Matrix Theory
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Gram-schmidt algorithm

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E2-212 Matrix Theory
14-10-2020.
Announcements:
- Practice assignment: TODAY at 6.30pm, due at 9.30pm.
Last time:
- Rank
- Inner product
- Cauchy-Schwarz inequality
Today:
- Gram-Schmidt Algo

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- Gram-Schmidt Algo
- Determinants.
Defn. A basis $\{v_1, v_2, \dots, v_n\}$ of a VS V is said to be an orthogonal basis w.r.t. $\langle \cdot, \cdot \rangle$ if $\{v_1, \dots, v_n\}$ is an orthogonal set.
Orthonormal basis w.r.t. $\langle \cdot, \cdot \rangle$ if orthogonal and $\langle v_i, v_i \rangle = 1 \forall i = 1, 2, \dots, n$.

That was the only announcement I made. So, today we will continue this discussion in particular, I am going to talk about the Graham Smith orthonormalization process. So I, there is one definition I want to put down before I begin this is the definition of an orthonormal or orthogonal

basis. So, if we are given a basis consisting of vectors v_1 through v_n of a vector space, vector space V is said to be an orthogonal basis with respect to an inner product.

So, in order to say whether a pair of vectors is orthogonal or not, you need to have some notion of an inner product and I denote that inner product by these braces with 2 arguments here and a comma between them. If this set v_1 to v_n is an orthogonal set, what is an orthogonal set we defined it in the previous class, a set of vectors are set to be orthogonal or mutually orthogonal if the inner product between any pair of vectors in that set is equal to 0. And we say that it, this basis is an orthonormal basis if it is orthogonal and v_i in a product with v_i equals 1 for all i .

That is 1 definition. So, 2 keywords that have come here orthogonal basis and an orthonormal basis. So, it turns out that any vector space V and in a product defined like this has an orthonormal basis. So, the question is how do you find such an orthonormal basis? So, if you are given a basis for a vector space, then you can use the Gram Schmidt process or the Gram Schmidt algorithm to find an orthonormal basis for the vector space V . And why are we interested in orthonormal basis? We will be clear as we go further in the discussion.

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Gram-Schmidt Process (Algo):

Input: $\{x_1, \dots, x_n\}$ LI in \mathbb{C}^m

Output: $\{z_1, \dots, z_n\}$ Orthonormal set of vecs. s.t.
 $\text{Span}\{z_1, \dots, z_n\} = \text{Span}\{x_1, x_2, \dots, x_n\}$

Procedure: Let $y_1 = x_1$
Set $z_1 = \frac{y_1}{\langle y_1, y_1 \rangle^{\frac{1}{2}}}$

Let $y_2 = x_2 - \langle x_2, z_1 \rangle z_1 (\Rightarrow y_2 \perp z_1)$
Set $z_2 = \frac{y_2}{\langle y_2, y_2 \rangle^{\frac{1}{2}}}$

Set $z_1 = \frac{y_1}{\|y_1\|}$

Let $y_2 = x_2 - \langle x_2, z_1 \rangle z_1 \Rightarrow y_2 \perp z_1$

Set $z_2 = \frac{y_2}{\|y_2\|}$

\vdots

Let $y_k = x_k - \langle x_k, z_1 \rangle z_1 - \langle x_k, z_2 \rangle z_2 - \dots - \langle x_k, z_{k-1} \rangle z_{k-1}$

Set $z_k = \frac{y_k}{\|y_k\|}$

Keep going till $k=n$.

So, the Gram Schmidt process or Algo. So, basically this is the input. So, it is a set of vectors say x_1 through x_n . And these are linearly independent vectors in \mathbb{C}^m . And what is going to be the output of this algorithm is a set of vectors z_1 through z_n is an orthonormal set of vectors such that span of this first set of vectors or z_1 through z_n is equal to the span of x_1 through x_n .

So, by the way, actually the correct way of writing it, writing a sequence is always like this, you have to always write out the first two elements and then separated by a comma, then a comma and exactly 3 dots, then a comma and then the last element of the set accent, you should not put 4 dots, 5 dots and so on. And they should be always these commas in between them. And you should always list the first two but sometimes as usual, I get lazy and I just write z_1 to z_n , where there is no confusion that I am not skipping anything in between, its just z_1 z_2 up to z_n .

So, this is how the procedure works. And I will first put down the procedure and then maybe make some remarks as to why this procedure will yield a set of orthonormal vectors such that the span of these vectors is exactly the same as the span of x_1 through x_n . So, I expect that you also seen this procedure previously. So, this is more of a recap.

So, you start out by saying let y_1 be equal to x_1 itself and then you normalize it. So, you set z_1 so I have already found out what z_1 is the first vector is going to be y_1 divided by the inner product of y_1 with itself power half. So, this means that z_1 is now normalized, I already mentioned this in the previous class, if you take any vector divided by the square root of the

inner product of that vector with itself, you will get a unit norm vector pointing in the same direction as the original vector. So, z_1 is now normalized.

Now, I want to find z_2 , which is orthogonal to z_1 , but span of z_1, z_2 will be span of x_1, x_2 . So, how do we do that, so, we let y_2 be equal to x_2 minus the, minus some scaled version of z_1 and the scaling factor is the inner product between x_2 and z_1 . So, now, what this means is that this y_2 is perpendicular to z_1 , why is that true? So, if I take the inner product between y_2 and z_1 that will be the inner product between x_2 and z_1 , inner products are linear.

So, it is the inner product between x_2 and z_1 minus this coefficient times the inner product of z_1 with itself, but z_1 is already unit now. And therefore, the inner product of z_1 with itself is one. So, it is the inner product of x_2 with z_1 minus the inner product of x_2 with z_1 which is 0. So y_2 is a vector that is perpendicular to z_1 . And then I normalize this and I set z_2 equal to y_2 divided by the inner product between y_2 and itself power half, so now z_2 is unit now and so on, so I proceed like this.

And so just to kind of make it clear in the k th $(())(10:01)$ I let y_k equal to x_k minus the inner product between x_k and z_{k-1} times z_{k-1} minus the inner product between x_k and z_{k-2} times z_{k-2} and so on inner product between x_k and z_1 times z_1 . So, what this means then is that y_k will be perpendicular to all the previous vectors z_1, z_2 up to z_{k-1} and so, we can set z_k equal to y_k divided by inner product of y_k with itself power half. So, this is the overall algorithm and you keep going up to k equal to n .

Student: Sir.

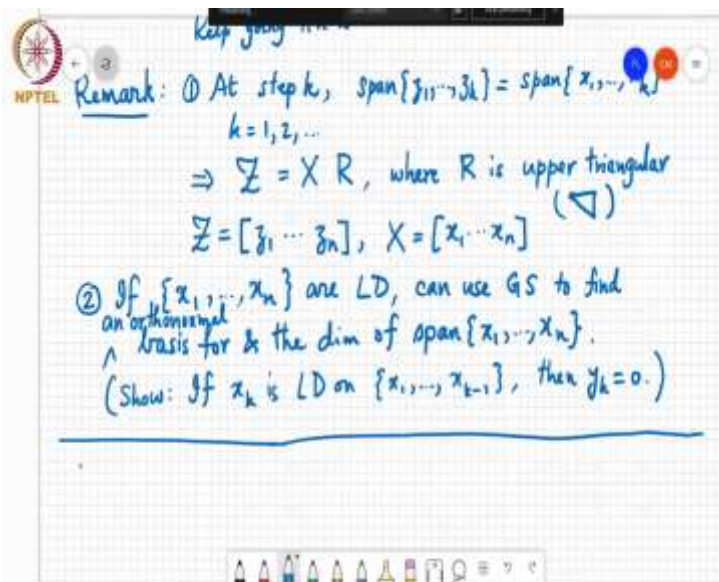
Professor: Yeah.

Student: So, can we say that orthogonal vectors are linearly independent?

Professor: So, if you remember in one of the previous classes, I did say that any set of non-zero orthogonal vectors are linearly independent. And I said you should try to write out a little proof for why that should be the case. So, obviously, if I take the 0 vector, the 0 vector is orthogonal to every other vector, you take the inner product of the 0 vector with any other vector, you will always get 0. So, orthogonal vectors are not necessarily linearly independent but non-zero orthogonal vectors are linearly independent.

Student: Yes Sir.

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Professor: So just to make some remarks about this just by construction. At step k we have that span of z_1 through z_k equals span of x_1 through x_k . And this is true for k equal to 1, 2 and so on. So, at every k this is actually true. So, what this means is that if I want to write a linear relationship between x and z , then I can write this matrix z whose columns are z_1, z_2 and so on. This is equal to the matrix X times R , where R is an upper triangular matrix.

So, going forward I will use this notation to write upper triangular in short, so, if you look at this, if R is upper triangular, what it means is that when I multiply so, just for the sake of completeness, I will say here, Z is this matrix formed by z_1 through z_n . And X is the matrix formed by x_1 through x_n . I do not want to put commas here. It is just stacking these next to each other.

So, if R is upper triangular. It means that if I look at the first column, remember I talked about how to view matrix multiplication. If I look at the first column of V , it is a linear combination involving only the first column of X . So basically that that is what is captured by this equation here. If I take the second column of Z , it is a linear combination of the first two columns of x and so it goes.

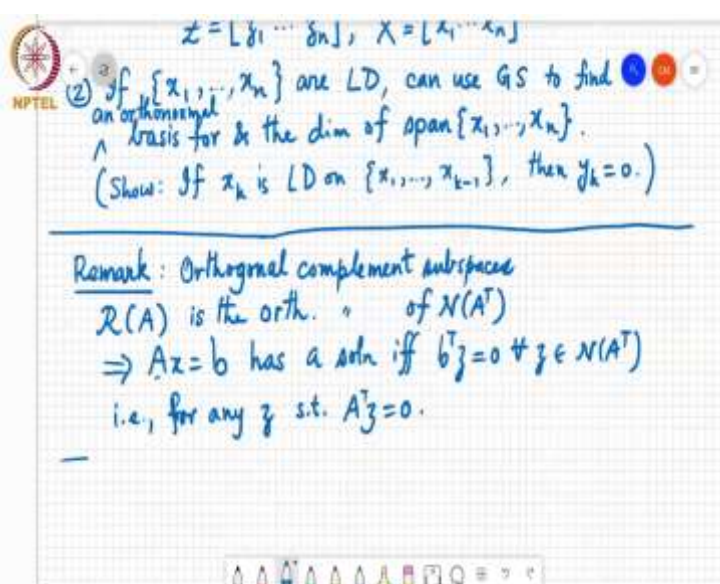
And the second remark I want to make is that if x_1 through x_n are linearly dependent, remember I presented the algorithm by assuming that x_1 to x_n are linearly independent vectors in C to the

M, but I can actually run this algorithm even if these vectors are linearly dependent. So, if x_1 through x_n linearly dependent if they are linearly dependent, we can still use Gram Schmidt to find basis and the dimension of span x_1 through x_n .

So, basically, how this happens is that if for example, x_k is linearly dependent on x_1 through x_{k-1} , then when you run this Gram Schmidt process, and if you compute this y_k here, it will turn out that y_k will become equal to 0. So, that is something you should convince yourself about, I will write it down for you. And you should again try to write out a small proof for that then what you can do is to skip x_k and then proceed, so you just do not compute a z_k , you skip the k th z and then you proceed with y_{k+1} and then you run the algorithm.

So, basically, this is something you should show if x_k is linearly dependent on x_1 through x_{k-1} then y_k equals 0. So, the end of the Gram Schmidt process, you will have an orthonormal basis for a span of x_1 to x_n . So, to be more clear, these are two remarks. Any questions about the Gram Schmidt process?

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So, I make one other small remark, this is it relates back to some things we discussed in the previous class, actually two classes ago. So, this is about, its a note about orthogonal complement subspaces. So, recall that the range space of A is the orthogonal complement of null space, of the null space of A transpose. So, that means that Ax equals b , if I take this system of

linear equations, this has a solution if and only if. So, this will have a solution only if and only if b lies in the range space of A , if b is not in the range space of A , then it will not have a solution.

So, if b lies in the range space of A it means that b must be orthogonal to any vector that lies in the null space of A transpose because the null space of A transpose is the orthogonal complement of the range space of A . So, that you know, so, to put that in words the way to write it is $b^T z$ must be equal to 0 for any vector belonging to the null space of any A transpose that is to say that for any z such that $A^T z = 0$. So, that is just a side remark I wanted to make about orthogonal complement subspaces.