

Advanced Matrix Theory and Linear Algebra for Engineers

Prof. R. Vittal Rao

Centre for Electronics Design and Technology

Indian Institute of Science, Bangalore

Lecture No. # 23

Inner Product and Orthogonality- Part 2

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The image shows a video lecture slide with handwritten mathematical content on a whiteboard. The content is as follows:

$$x, y \in \mathbb{R}^k$$
$$\underline{(x, y)} = \sum_{j=1}^k x_j y_j = \underline{y^T x} \text{ (or } \underline{x^T y})$$

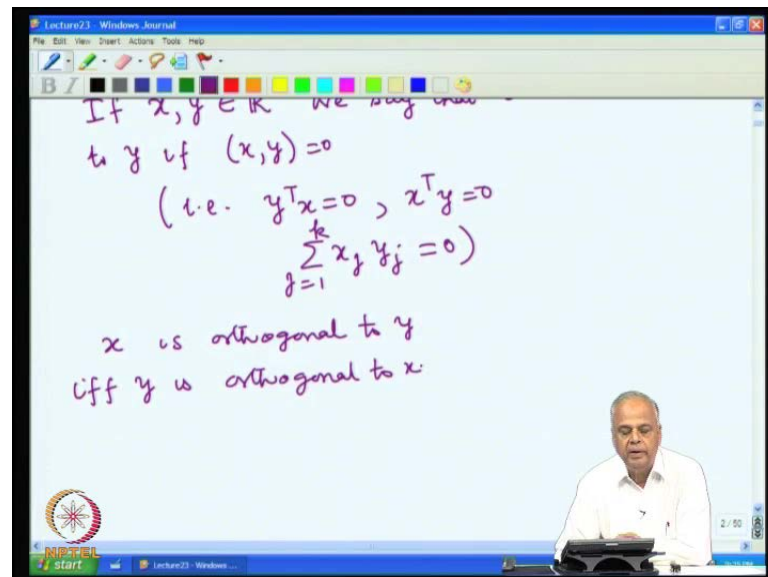
Orthogonality

$$x, y \in \mathbb{R}^3$$
$$x \cdot y = x_1 y_1 + x_2 y_2 + x_3 y_3$$
$$x \perp y \text{ iff } x \cdot y = 0$$

In the last lecture we introduce the notion of an inner product and we are looking at the geometry induced by this notion of inner product. How did we define the inner product suppose x and y are 2 vectors in \mathbb{R}^k . we defined and denoted the inner product but, x comma y and we defined it to be the sum of the product of the components which is just the generalization of the notion of the dot product. We had when we dealing with vector calculus into an 3 dimensions this can also be written as y transpose x or x transpose y all of them mean the same thing. So from now on when we say inner product we would be either denoting it by x comma y or we denoting by y transpose x or we shall denote it by x transpose y and all of them mean the same thing. The sum of the products of the components then we found some important properties of the inner product. Which was that the inner product was distributed and the inner product of a vector with itself. Gave the length square and that is 0 only when the vector is 0 and the most important thing that the inner product induces and which we shall be focussing is the notion of orthogonality.

What do we mean by this suppose we take 2 vectors in \mathbb{R}^3 for example, then we had the dot product in our earlier calculus courses, vector calculus courses. Which we defined as $x_2 y_2 + x_3 y_3$ and we found in the normal Euclidean geometry the x and y are perpendicular to each other if and only if this dot product 0.

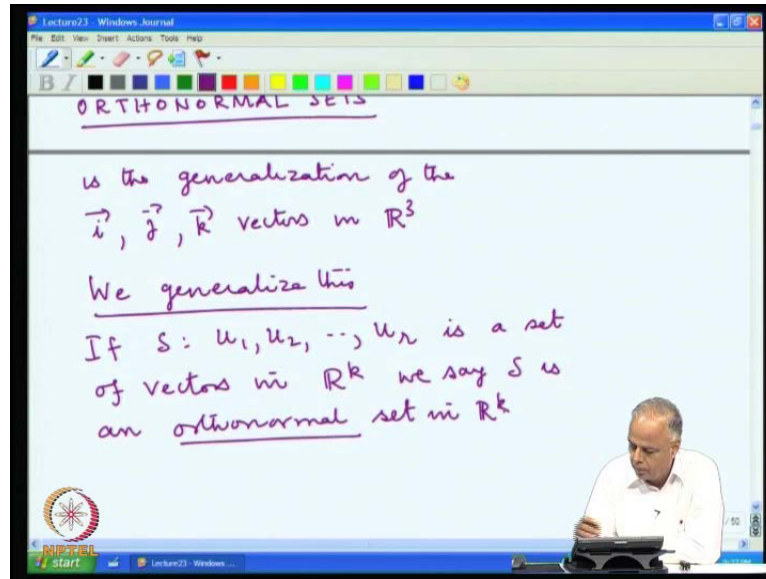
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And we now generalize this notion through the \mathbb{R}^k using this inner product if x and y belong to \mathbb{R}^k we say that x is orthogonal or perpendicular to orthogonal to y . If x comma y is equal to 0 that is the dot the inner product what does that mean that is y transpose x is 0 or we can write this as x transpose y is 0 or if we expand this we can write this as $x_j y_j$ equal to 0 so when we say x and y .

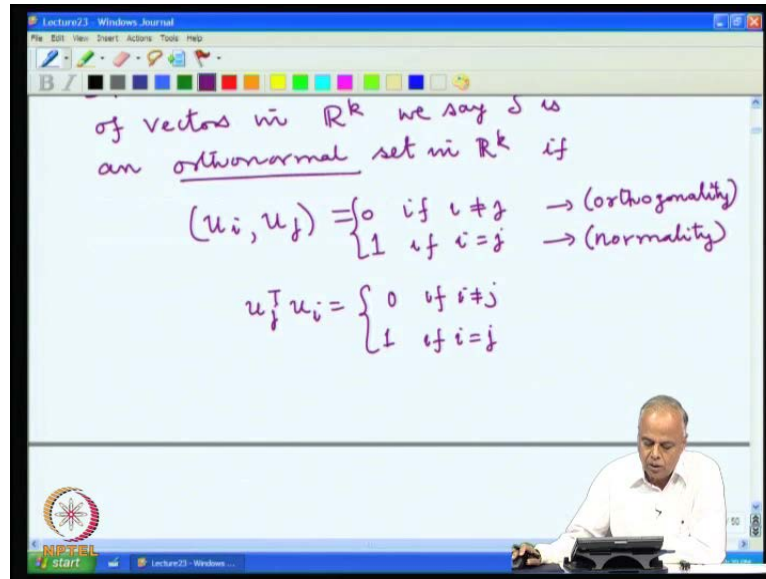
Are orthogonal we need all these things the notation is x comma y equal to 0 and that means that the y transpose x or x transpose y are sum of the products of the component is equal to 0 from the definition. The symmetry tells us that x is orthogonal to y if and only if y is orthogonal to x so from now on instead of a x is orthogonal to y and y is orthogonal to x we will just say x and y are orthogonal to each other x and y are orthogonal to each other. So the orthogonality comes from the fact that the inner product is 0 the inner product induces the notion of orthogonality and orthogonal is geometric notion so the inner product induces the idea of orthogonality.

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We next began looking at the notion of orthonormal sets this is the this notion is the generalization it is the generalization of the i, j, k vectors which we would have seen in vector algebra in \mathbb{R}^3 . This is the generalization of these 3 vectors what do these 3 vectors have special each vector is orthogonal to the other vector $i \cdot j$ is 0 $i \cdot k$ is 0 $k \cdot i$ is 0 so they are mutually orthogonal vectors and each vector has length 1. So this is a collection of vectors which have the special property that any 2 of them is orthogonal to each other and each vector has length 1. Now we generalize this idea in \mathbb{R}^k because we have the notion of orthogonality induce by the inner product. We have the notion of length which comes out as the inner product vector with itself and therefore, we can generalize this whole notion of orthonormality to the case of \mathbb{R}^k .

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We generalize this if $S = \{u_1, u_2, \dots, u_r\}$ is a set of vectors in \mathbb{R}^k we say S is an orthonormal set if it is orthonormal. Set in \mathbb{R}^k if any 2 of the vectors must be orthogonal to each other u_i and u_j must be equal to 0 if i is not equal to j that says if you.

Take any 2 different vectors from the set the dot product is 0 the inner product is 0. Which means they are orthogonal what do we mean by the length is 1. If we take i equal to j then we get $u_i \cdot u_i$. It has to give the length of u_i squared but we want that to be 1 so that means this must be equal to 1 if i equal to j . So the first condition is the orthogonality condition the fact that any 2 vectors are orthogonal the second 1 is the normalization condition normality. Condition each vector has been normalized to have length 1 and that is why we call the set as orthonormal set or if you want to write it in terms of the transpose notation this means $u_j^T u_i$ is equal to 0 if i not equal to j 1 if i equal to j . So the vectors are orthonormal if any pair of them is orthogonal to each other and every vector has length 1.

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Examples

(1) \mathbb{R}^3 $e_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$, $e_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$, $e_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$
is an orthonormal set in \mathbb{R}^k

(2) $s \cdot v_1 = \begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix}$, $v_2 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$
is an orthogonal set in \mathbb{R}^3 but not
an orthonormal set since
 $(v_1, v_1) = 2 \neq 1$
 $(v_2, v_2) = 2 \neq 1$

Let us look at some simple examples since we have seen that this notion of orthonormality itself is a generalization of the i, j, k vectors. The i, j, k vectors come out to be the first natural example of orthonormal sets. So we have \mathbb{R}^3 in \mathbb{R}^3 now we will use the vector space notation. We will denote the i vector as $\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$, this is the j vector $\begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$ and $e_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$ is an orthonormal set in \mathbb{R}^3 . Notice that the vector $v_1 = \begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix}$ and $v_2 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$ is an orthogonal set because the two vectors are orthogonal to each other. It is an orthogonal set in \mathbb{R}^3 but, it is not an orthonormal set because the normalization of length being 1 is not satisfied. The length of v_1 is $\sqrt{2}$ and the length of v_2 is also $\sqrt{2}$ but not an orthonormal set since $(v_1, v_1) = 2 \neq 1$ and $(v_2, v_2) = 2 \neq 1$. Now if we take the new vectors that we are going to form w_1 and w_2 which are obtained by normalizing v_1, v_2 . What is meant by normalizing v_1, v_2 they do not have length 1. Now we divide by the length then we get a unit vector so we take v_1 and divide by its length which is $\sqrt{2}$ and we take v_2 and divide by its length.

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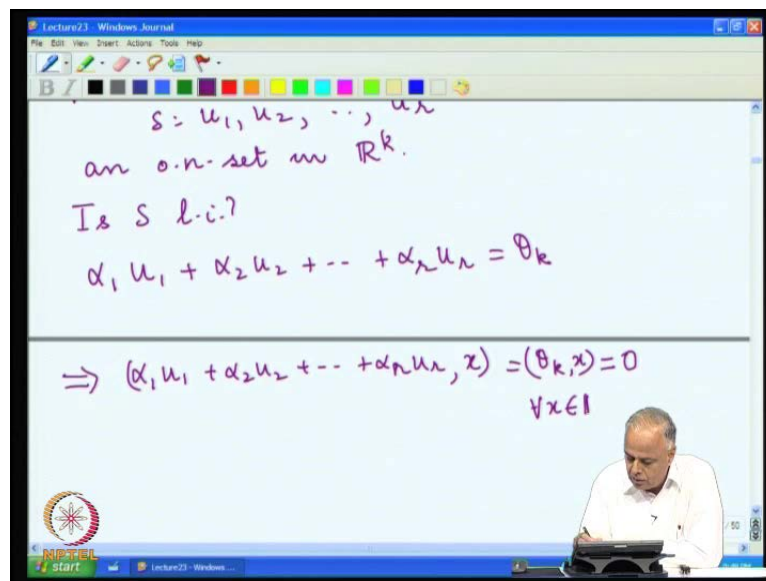
3) \mathbb{R}^4
 $u_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}, u_2 = \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix}, u_3 = \begin{pmatrix} 1 \\ 0 \\ -1 \\ 0 \end{pmatrix}$
 $(u_1, u_2) = 1 + (-1) + 1 + (-1) = 0$
 $(u_1, u_3) = 0 (= u_2, u_3)$
 \therefore This set is an orthogonal set
But $(u_1, u_1) = 1^2 + 1^2 + 1^2 + 1^2 = 4 \neq 1$
 $(u_2, u_2) = 1 + 1 + 1 + 1 = 4 \neq 1$
 $(u_3, u_3) = 1 + 0 + 1 + 0 = 2 \neq 1$

Now this set is an orthonormal set in \mathbb{R}^3 because now the u_1, u_2 are orthogonal to each other and each 1 of them has length 1 let us take \mathbb{R}^4 again in \mathbb{R}^4 look at these vectors u_1, u_2, u_3 . u_1 is equal to $(1, 1, 1, 1)$, u_2 is equal to $(1, 1, -1, -1)$, u_3 equal to $(1, 0, -1, 0)$. If you now look at u_1 comma u_2 the inner product of u_1 and u_2 which is simply the sum of the product of the components it is 1×1 which is 1 plus 1×1 which is 1 plus $1 \times (-1)$ which is -1 plus $1 \times (-1)$ which gives me 0 and therefore, we have that u_1 is orthogonal to u_2 similarly, u_1 is orthogonal to u_3 and u_2 is orthogonal to u_3 . So this u_1, u_2, u_3 are orthogonal to each other. Therefore, the set is an orthogonal set the set is an orthogonal set but, we have the length of u_1 square which is the (u_1, u_1) is $1^2 + 1^2 + 1^2 + 1^2$. The sum of the squares of the components which is 4 but, we want it to be 1 for normality. So it is not 1 similarly, (u_2, u_2) is again $1 + 1 + 1 + 1$ sum of the squares of the component that is not 1 (u_3, u_3) the dot product or inner product of u_3 with itself is $1^2 + 0^2 + (-1)^2 + 0^2$. Which is 2 which is not 1 so n of these vectors have length 1 but, they are orthogonal to each other. So this is not hence this is not an orthonormal. Set this is not an orthonormal set as before since we already have orthogonality we can force now.

Normality by dividing each 1 of these vectors by its length. Suppose we now take the set S consisting of these vectors v_1 which is obtained from we have to obtain v_1 from u_1 by dividing you have to take this vector u_1 and divide it by its length. We get 1 by 2

into $1 \ 1 \ 1 \ 1$ similarly, we divide u_2 by its length and we get u_3 by its length and then we get these vectors. Now this is an orthonormal set in \mathbb{R}^4 so thus the orthonormality we need 2 requirements for a set of vectors to be orthonormal. The name suggests is ortho and normal the word ortho refers to the fact any 2 vectors are mutually orthogonal to each other the word normal refers to the fact. That the vectors have been normalized to have length 1. So we now have this notion of orthonormality in an inner product space particularly \mathbb{R}^k with this inner product.

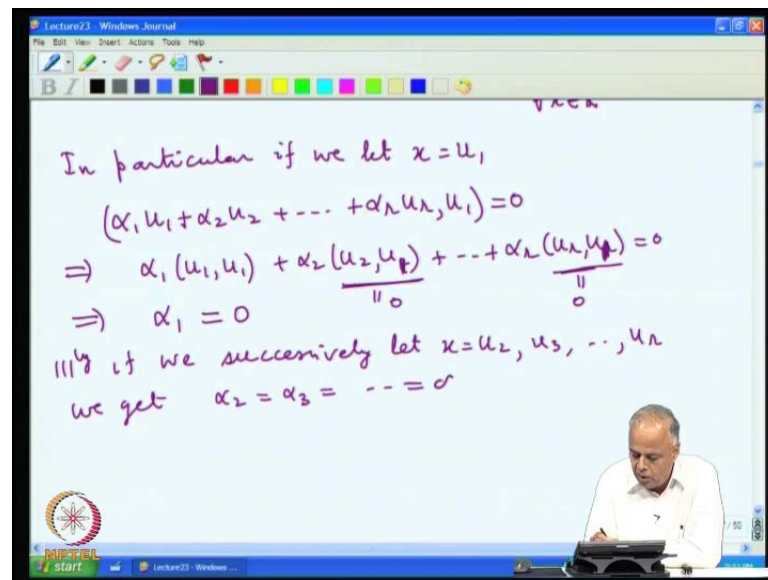
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Now we are going to look at a very important property of inner product. Orthonormal sets an important property of i will write o n sets for orthonormal sets. So we now look at a very important property of orthonormal set so suppose we have $u_1 \ u_2 \ u_r$ an orthonormal set in \mathbb{R}^k . Whenever we have a set of vectors in \mathbb{R}^k the first thing we investigate is whether the set is linearly independent or not. Whenever we get a set of vectors we always first look at the fact whether it is linearly independent or linearly dependent. If is linearly dependent now lot of redundant information we would like to throw it out. So first we check whether this set is linearly independent is S linearly

independent for this. We must check whether a linear combination of this u_1, u_2 are when it is the 0 vector thus forces all the coefficients to be 0. So we start with a linear combination of these vectors and suppose it is equal to the 0 vector. We want to investigate whether that will force all the coefficients to 0. If it forces all the coefficients to be 0 then we are linearly independent but, if you have non 0 coefficients we give 0 vector then we have linear dependent now this implies if we take any vector and take the inner product with the sum take any vector x and inner product with this that is the same as $\langle \sum u_i, x \rangle$. Because the sum is equal to 0 but the inner product of the 0 vector is always 0 with any vector. So this implies the inner product of the sum with any x is equal to 0 for every x in \mathbb{R}^k .

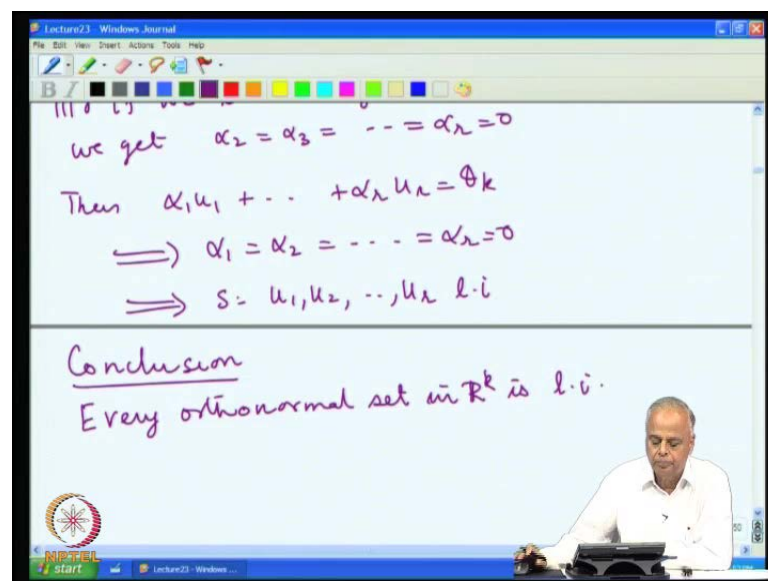
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Now if I particularly take in particular if we let x equal to u_1 what do we get we get therefore, $\alpha_1 u_1 + \alpha_2 u_2 + \dots + \alpha_n u_n$ must be equal to 0. Because this inner product is 0 whatever x I take in particular I have taken x is equal to u_1 . Now the inner product of a sum as the sum of the inner product which property we have seen last time and constants can be pulled out of the inner product. So this whole thing implies $\alpha_1 (u_1, u_1) + \alpha_2 (u_2, u_1) + \dots + \alpha_n (u_n, u_1) = 0$ because you are taking the inner product with u_1 . Now $\alpha_1 (u_1, u_1)$ is 1 why is u_1, u_1 because we are given that u_1, u_2, \dots, u_n is an orthonormal set. When you have an orthonormal set in that set every vector has length 1 u_1 is the member of that orthonormal set and hence it must have length 1. Therefore, $(u_1, u_1) = 1$ so the first term

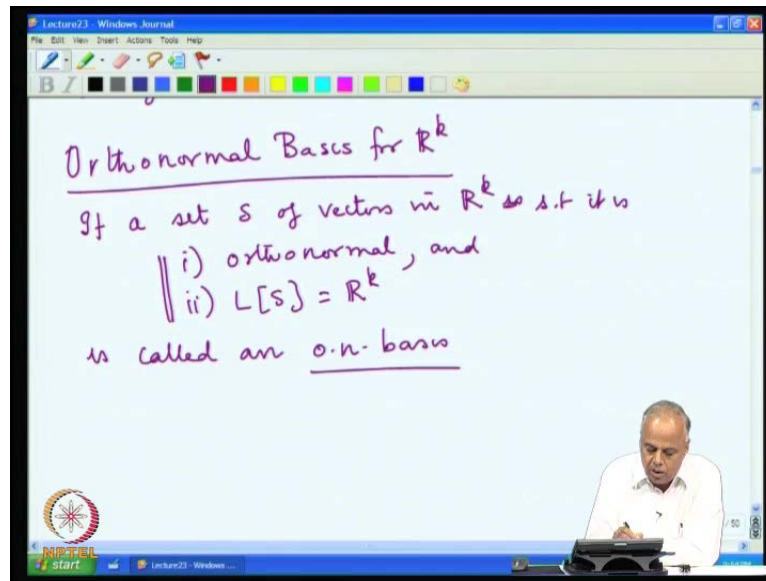
becomes u_1 now u_2 u_1 the second term u_2 u_1 is 0 because u_2 and u_1 are members of this. Orthonormal set and any 2 vectors in the orthonormal set are orthogonal to each other and therefore, their inner product is 0 and hence u_2 u_1 is 0. Similarly, u_3 u_1 is 0 u_r u_1 is 0 because all these vectors are in that set and any 2 vectors are orthogonal. So we simply get α_1 equal to 0 similarly, if we successively take let x equal to u_2 next then u_3 and so on when i let x equal to u_1 x α_1 is 0 if i let x equal to u_2 in this place and take this i get α_2 equal to 0 and so on we get α_2 equal to α_3 equal to α_r equal to 0.

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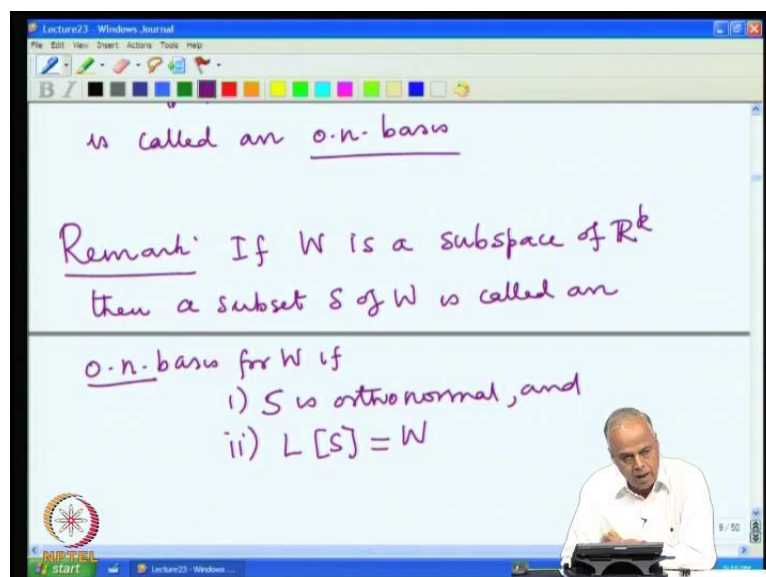
What we have this $\alpha_1 u_1$ plus $\alpha_r u_r$ equal to θk implies α_1 equal to α_2 equal to α_r equal to 0 this means that the set S of vectors. The set of vectors $u_1 u_2 r$ is linearly independent which implies the set of vectors $u_1 u_2 u_r$ linearly independent. So what we have shown is we start with any linearly any orthonormal set it is automatically forced to be linearly independent conclusion every orthonormal set is linearly independent. So conclusion every orthonormal set in $r k$ is linearly independent that is a very important property of orthonormal. But now let us look at what does mean an orthonormal set is automatically linearly independent and the moment you have a linearly independent. Set you wonder whether it is a basis for that to be a basis it must also span the space. So an orthonormal set will become a basis since it is already linearly independent the only requirement that will be force will be further required will be that its spansely space.

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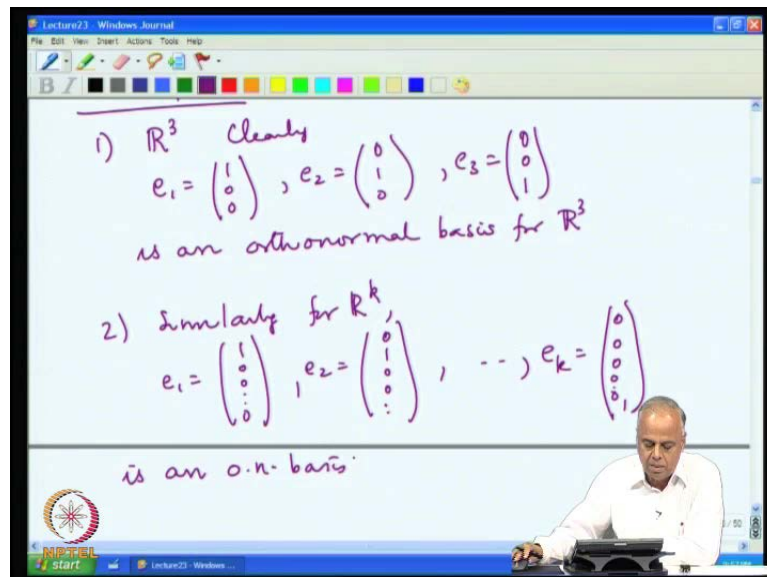
This links us to the notion of an orthonormal basis for \mathbb{R}^k . So if a set S of vectors in \mathbb{R}^k is orthonormal remember that when we said we want a basis we want linear independence and we want spanning. Now linear independence it can be now replace the orthonormal because orthonormal automatically implies linearly independent. So we want orthonormal and its spans \mathbb{R}^k the span of the set S is \mathbb{R}^k . Such a basis is called vectors in \mathbb{R}^4 such that it is orthonormal is called an orthonormal. Basis you put it this way so a set is an orthonormal basis if it is orthonormal and it is a spanning set so these are the 2 things required for a set to be an orthonormal basis.

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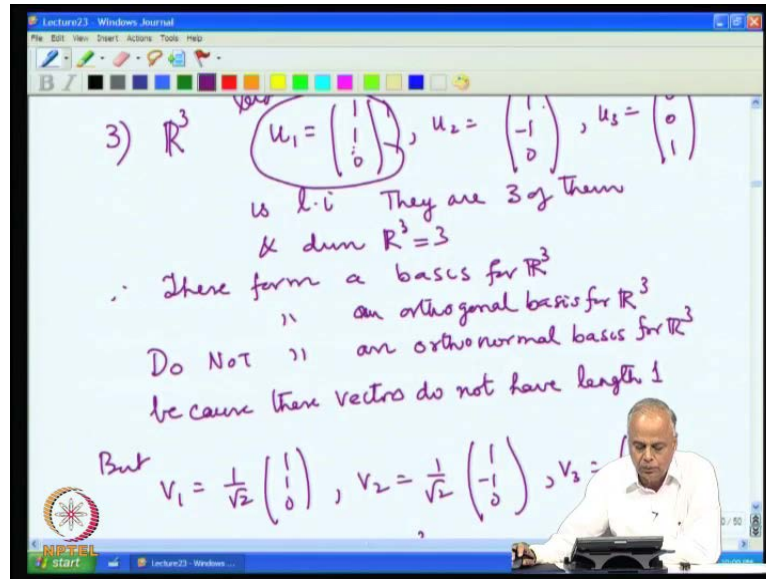
Remark similarly, if w is a subspace of \mathbb{R}^k then a subset s of w is called an orthonormal basis for w if s is orthonormal and s spans w . We want orthonormal so s must be orthonormal so we have s is orthonormal and we want it to span that means s must span w . It must span what now it must we are looking for a basis for w and therefore, it must span w so a orthonormal set in w which also spans w is called an orthonormal basis for w .

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So let us look at 1 of the simple example. Let us take \mathbb{R}^3 clearly e_1 equal to $(1, 0, 0)$ e_2 equal to $(0, 1, 0)$ e_3 equal to $(0, 0, 1)$ is an orthonormal basis for \mathbb{R}^3 . Why is it we know clearly that these are all orthogonal to each other. Because the dot product of any 1 of them is 0 with the other and then each 1 of them has length 1 and any vector x_1, x_2, x_3 or \mathbb{R}^3 . Obviously $x_1 e_1 + x_2 e_2 + x_3 e_3$. So the spans \mathbb{R}^3 so this is linearly independent this is orthonormal and spans and therefore, it is a basis so this is simplest example similarly, for \mathbb{R}^k e_1 equal to $(1, 0, 0, \dots, 0)$ with k components e_2 has second component 1 all other 0 and if go on like that e_k has the last component 1 the k th component all other 0 is an orthonormal basis these are very simple examples.

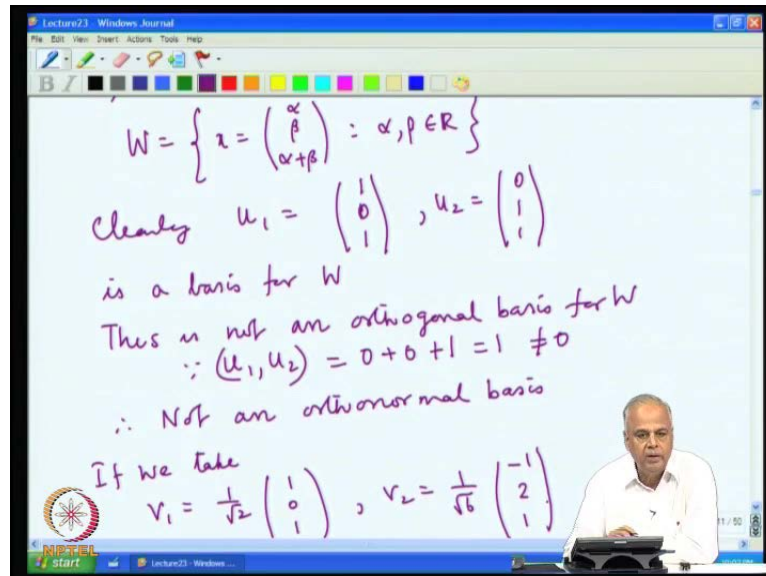
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Let us look at another example let us take \mathbb{R}^3 let us take the vectors u_1 equal to $\begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$ u_2 is equal to $\begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix}$ u_3 is equal to $\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$ this is a basis is easy to verify that this is linearly independent. This is there are 3 vectors for \mathbb{R}^3 for something to form a basis any 3 linearly independent vectors in \mathbb{R}^3 will form a basis for \mathbb{R}^3 there are 3 linearly independent vectors. So they are 3 of them and dimension of \mathbb{R}^3 is 3 therefore, these form a basis first thing, we know it is that these form a basis for \mathbb{R}^3 now every vector here is orthogonal to each other. Because the dot product of u_1 and u_2 is $1 \cdot 1 + 1 \cdot (-1) + 0 \cdot 0$ which is $1 - 1 = 0$. Similarly, u_2 and u_3 are orthogonal and u_3 and u_1 are orthogonal. So these vectors are orthogonal so if they form an orthogonal basis for \mathbb{R}^3 they form an orthogonal basis for \mathbb{R}^3 . However they do not form an orthonormal basis because the normality condition is not satisfied these vectors do not have length 1. Because these vectors do not have length 1 therefore, since we already have orthogonality in order to get normality. All we have to do is divide each 1 of these vectors by length 1. When we say that they do not have length 1 u_3 has length 1 but, u_1 and u_2 do not have length 1. Even if 1 vector fails to have length 1 we will use the normality condition. Therefore, if we now define v_1 to be $\frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$ this is obtained by dividing u_1 this vector u_1 by its length what is its length is $\sqrt{2}$. Therefore, we divide by the length $\sqrt{2}$. Similarly, we divide v_2 by its length and v_3 does not require any division because it has already has length 1 this is an orthonormal basis for \mathbb{R}^3 . Let therefore, even though this these original vectors u_1 u_2 u_3 did not

form a basis we have got a new basis by dividing them by the length. Because these vectors were already orthogonal we needed to do only normality.

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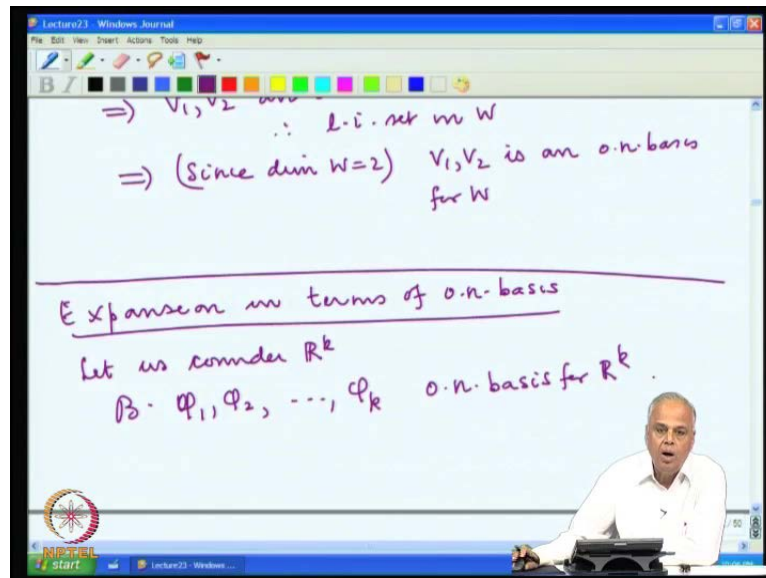


Let us now look at \mathbb{R}^3 consider the subspace w . It consists of all those vectors which are of this form $\alpha\beta\alpha + \beta\alpha\beta$ real numbers. What it means is all those vectors for which the third component is the sum of the first 2 components. All the third component is $\alpha + \beta$ which is the sum of the first 2 components α and β clearly $u_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, u_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}$ is a basis for w . Because these 2 vectors belong to w they are linearly independent and every vector in w is a linear combination of these vectors. So all the conditions required for basis is satisfied however this is not an orthogonal basis because the 2 vectors are not orthogonal to each other. Because $u_1 \cdot u_2$ the inner product is $1 \cdot 0 + 0 \cdot 1 = 0$ plus $0 \cdot 1 = 0$.

The product of the second components is $0 \cdot 1 = 0$ but the product of the third component is $1 \cdot 1 = 1$. So the $u_1 \cdot u_2 = 1 \neq 0$ and therefore, the vectors are not orthogonal and therefore, it does not form an orthogonal basis and therefore, not even orthonormal basis it is not even normal. So it does not have either orthogonality property or the normality property however if we take $v_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$ and $v_2 = \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ 2 \\ 1 \end{pmatrix}$ we see that v_1 belongs to w . Because v_1 is simply the multiple of the vector $u_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}$ by $\frac{1}{\sqrt{2}}$ multiple of the vector u_1 . We have here so v_1 is just the $\frac{1}{\sqrt{2}}$ multiple of u_1 and since u_1 is in w any multiple in w v_2 is a

vector in w why first of all. If we look at v_1, v_2 the third component is the sum of the first and the second and therefore, this part belongs to w and any multiple of that will belong to w and. Therefore v_1, v_2 belong to w that is the first thing that we observe secondly v_1, v_2 are orthogonal to each other because $1 \cdot 1 - 1 \cdot 1 + 1 \cdot 1 = 0$ so the dot product is 0 thirdly we observe that the length of v_1 is 1 and the length of v_2 is 1

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And therefore, v_1, v_2 is an orthonormal set in w and therefore, linearly independent set in w . Since v_1, v_2 is a basis for w the dimension of w we have seen that the v_1, v_2 be the basis for w . So dimension of w is 2 any 2 linearly independent vectors in w will form a basis which says since dimension w equal to 2. This implies that v_1, v_2 is an orthonormal basis for w . So we have a subspace here for which we have an orthonormal basis we have found the orthonormal basis. Now we shall look at what is effect of this orthonormal basis we have seen that whenever we have a basis every vector in that space can be expanded as a linear combination of the vectors.

In that basis and therefore, in particular if we have an orthonormal basis then every vector in that space can be expanded as a linear combination of this orthonormal basis. Let us look at this expansion so while call this the expansion in terms of orthonormal basis. So first let us look at \mathbb{R}^k it is considered \mathbb{R}^k and let us say b let us call it $\phi_1, \phi_2, \dots, \phi_k$ any. Basis must contain exactly k vectors so an orthonormal basis for \mathbb{R}^k or \mathbb{R}^k so suppose we have an orthonormal basis for \mathbb{R}^k .

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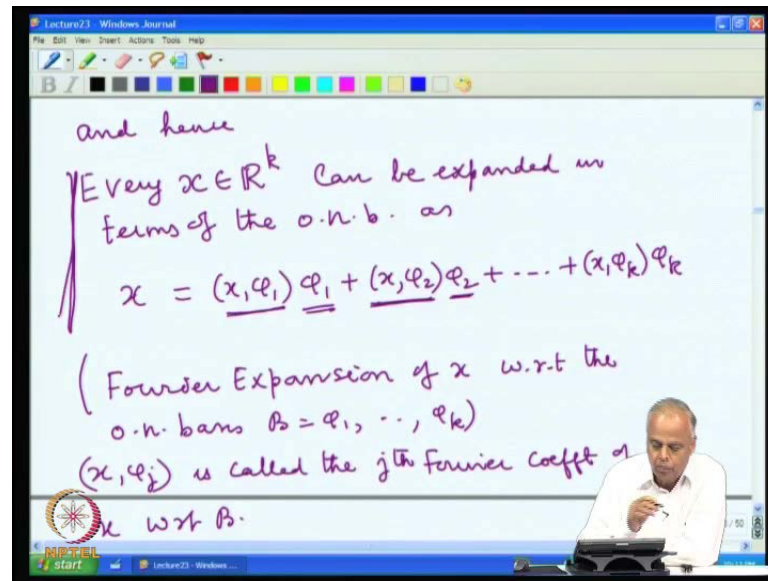
$x \in \mathbb{R}^k \Rightarrow \exists \alpha_1, \alpha_2, \dots, \alpha_k \in \mathbb{R} \text{ s.t.}$
 $x = \alpha_1 \phi_1 + \alpha_2 \phi_2 + \dots + \alpha_k \phi_k$

$\Rightarrow (x, \phi_1) = (\alpha_1 \phi_1 + \alpha_2 \phi_2 + \dots + \alpha_k \phi_k, \phi_1)$
 $\Rightarrow (x, \phi_1) = \alpha_1$
& similarly $(x, \phi_j) = \alpha_j$ for $j=1, 2, \dots, k$

and hence
Every $x \in \mathbb{R}^k$ can be expanded in terms of the o.n.b. as

Then any vector x in \mathbb{R}^k we can expand it as x is equal to $x_1 \phi_1$ plus $x_2 \phi_2$ plus $x_k \phi_k$. What we do not know what this x_1 x_2 x_k are so let us call them as α_1 α_2 α_k at the moment. We do not know what they are so given a vector x in \mathbb{R}^k all we can say is there exists numbers α_1 α_2 α_k . All of them are real such that x can be written as a linear combination the ϕ_1 ϕ_2 ϕ_k if this α is are the coefficients. Now suppose now I take the inner product $x \phi_1$ the dot product $x \phi_1$ that is the same as $\alpha_1 \phi_1$ plus $\alpha_2 \phi_2$ plus $\alpha_k \phi_k$ comma ϕ_1 . Because x is the sum again as before if we take the dot product $\phi_1 \phi_1$ will give 1 $\phi_2 \phi_1$ will give 0 $\phi_3 \phi_1$ will give 0 $\phi_k \phi_1$ will give 0. Because ϕ_1 ϕ_2 ϕ_k is an orthonormal set. So that says $x \phi_1$ is equal to α_1 so this where the coefficient of ϕ_1 in expansion of x is precisely the dot product or the inner product of x with ϕ_1 similarly, the coefficient of ϕ_2 will be the dot product of x with ϕ_2 .

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And similarly, $x \cdot \phi_j$ will be equal to α_j for j equal to 1 2 up to k and hence every x in \mathbb{R}^k can be expanded in terms of the orthonormal basis. As x is equal to $x \cdot \phi_1 \phi_1 + x \cdot \phi_2 \phi_2 + \dots + x \cdot \phi_k \phi_k$. So we know precisely how to find the coefficient what is that is much easier to find the coefficient in the expansion with respect to the orthonormal basis. Because to find the coefficient with respect to ϕ_1 we need to know only the relationship between x and ϕ_1 . Namely the dot product of $x \cdot \phi_1$ we find the coefficient corresponding to ϕ_1 . We need to know only the relationship between x and ϕ_2 . Namely the dot product and so on with and so on therefore, in these cases it is much easier to find this orthonormal expansion in terms of orthonormal basis.

In general situation when we deal with vector spaces abstract and abstract inner product. Which we generalize the dot product such expansions are reflective as in Fourier expansion. We generalize Fourier expansion of x with respect to the orthonormal basis b and the $x \cdot \phi_j$ is the coefficient the coordinate or the component of x with respect to this order basis b is called the j th Fourier coefficient of x with respect to this order basis b . We have an order here $\phi_1 \phi_2 \phi_k$ so let us treat this as an order orthonormal basis. Therefore, the first conclusion is that every vector can be expanded in this form. So this is the first important conclusion once we have an orthonormal basis every vector can be expanded in a Fourier expansion with respect to this orthonormal basis.

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$x = \begin{pmatrix} x_1 \\ \vdots \\ x_k \end{pmatrix}, y = \begin{pmatrix} y_1 \\ \vdots \\ y_k \end{pmatrix}, S: e_1 = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, e_2 = \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix}, \dots, e_k = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix}$

Fourier exp. of x, y wrt S

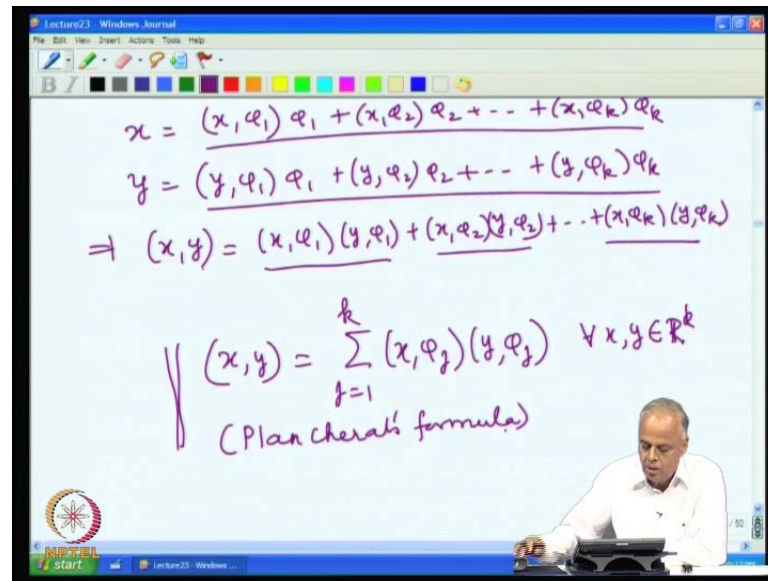
$x = \underline{x_1} e_1 + \underline{x_2} e_2 + \dots + \underline{x_k} e_k \quad x_j = (x, e_j)$
 $y = \underline{y_1} e_1 + \underline{y_2} e_2 + \dots + \underline{y_k} e_k \quad y_j = (y, e_j)$

$(x, y) = \underline{x_1 y_1} + \underline{x_2 y_2} + \dots + \underline{x_k y_k}$

Something interesting happens suppose we had x and we had the first. The standard basis we call this the standard basis $1\ 0\ 0\ 0$ e_2 as $0\ 1\ 0\ 0$ and so on and finally, e_k has $0\ 0\ 0\ 0$. This is the standard basis and if I have x which is $x_1\ x_2\ x_k$ then if I expand with respect to this standard or the Fourier expansion of x with respect to this basis is nothing but, x is equal to $x_1 e_1$ plus $x_2 e_2$ plus $x_k e_k$. Because x comma e_1 the dot product of x and e_1 picks up only the first coefficient the dot product of x and e_2 picks up the second coefficient and therefore, we have the Fourier expansion of x with respect to has as this and similarly, if I take a vector y which is $y_1\ y_2\ y_k$ then the Fourier expansion of y with respect to this will be $y_1 e_1$ plus $y_2 e_2$ plus $y_k e_k$ where x_j is actually.

Equal to $x e_j$ and y_j is equal to $y e_j$ now what is the dot product of x and y or the inner product of x and y it is $x_1 y_1$ plus $x_2 y_2$ plus $x_k y_k$ which is the sum of the products of the Fourier coefficients with respect to this basis S remember this $x_1\ x_2\ x_k$ and $y_1\ y_2\ y_k$ these are all the Fourier coefficients so this is the product of the first 2 Fourier coefficients of x and y this is the product of the Fourier coefficient of x second Fourier coefficients. This is the product of the k th Fourier coefficient so the inner product of the dot product is the sum of the products of the first k Fourier the k th Fourier coefficient

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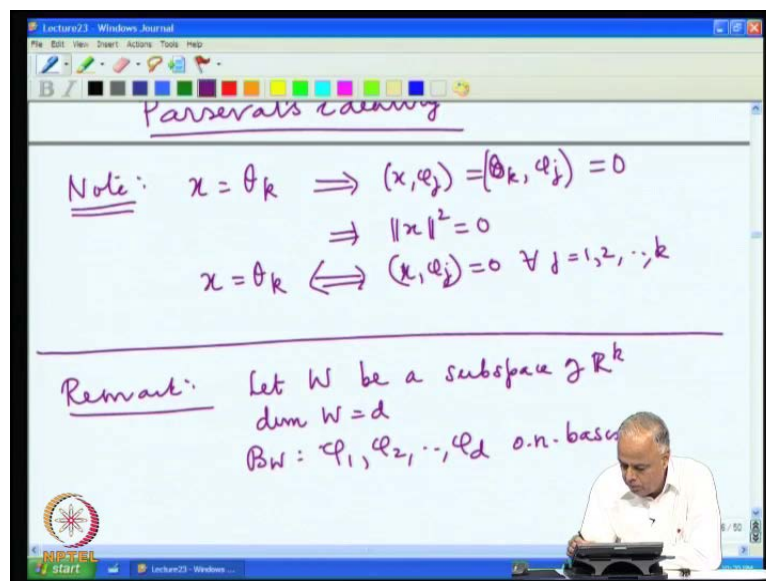
Now let us look at the Fourier expansion in terms of our orthonormal basis. General orthonormal basis $\phi_1, \phi_2, \dots, \phi_k$. Then we have $x = x_1 \phi_1 + x_2 \phi_2 + \dots + x_k \phi_k$ and so on. This is what the Fourier expansion we obtain that the Fourier expansion of any vector. The coefficients are simply the dot product of x with vectors. Similarly, $y = y_1 \phi_1 + y_2 \phi_2 + \dots + y_k \phi_k$. Now I take the dot product of x and y . I will have to take the dot product of this sum with respect to this sum. Now when we take the dot products the cross terms go away because $\phi_i \cdot \phi_j = 0$ if $i \neq j$ and the direct terms $\phi_i \cdot \phi_i = 1$ will give you 1 so this will simply be $x_1 y_1 + x_2 y_2 + \dots + x_k y_k$.

Which simply says again we get the inner product of x and y are the product of corresponding Fourier coefficients. So whether you choose this standard ordered basis you namely u_1, u_2, \dots, u_k or whether you choose any arbitrary orthonormal basis the inner product is always the sum of the product of the corresponding Fourier coefficients. Therefore, the next important property is $(x, y) = \sum_{j=1}^k x_j y_j$ for every $x, y \in \mathbb{R}^k$. This is referred to as the Plancherel formula. Once again this we put $y = x$. In the above we get $(x, x) = \|x\|^2 = \sum_{j=1}^k x_j^2$ which is the length of x squared. Now again this to same whatever ordered basis.

Whatever ordered orthonormal basis you choose the length square is always the sum of the corresponding Fourier coefficients squared in the standard ordered basis. We take this vector as $x = [x_1, x_2, \dots, x_k]^T$ the length is simply $x_1^2 + x_2^2 + \dots + x_k^2$. If you take an arbitrary ordered orthonormal basis then the length of x squared is the sum of the squares of the corresponding Fourier coefficients this is true for every $x \in \mathbb{R}^k$ and this is called the Parseval's identity. Now we have given an orthonormal basis.

We can expand every vector in terms of this orthonormal basis the coefficients are called the Fourier coefficients and whenever you want to take the inner product of 2 vectors. You have to simply take the sum of the products of the corresponding Fourier coefficients. Whenever you want to find the length square you have to only find the sum of the square of the Fourier coefficients of that vector with respect to this orthonormal basis. Whatever orthonormal basis we choose these identities hold these are very important facts.

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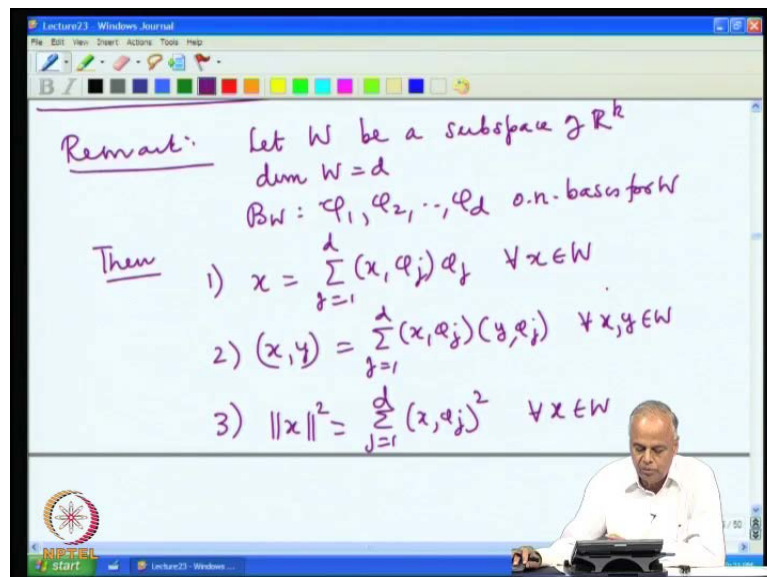


Note that if the vector x is θ_k then all these Fourier coefficients must be 0. Because $(x, \phi_j) = 0$ first of all it is equal to (θ_k, ϕ_j) that the inner product of this 0 vector with anything is 0. So all the Fourier coefficients are 0 and therefore, we get now $\|x\|^2 = 0$ which is what we want to look like the length of the vector is 0. So we have

whenever x is the 0 vector that says the fourier co efficient are all 0 for every j equal to 1 2 k conversely if $x \phi_j$ is 0 for all j then.

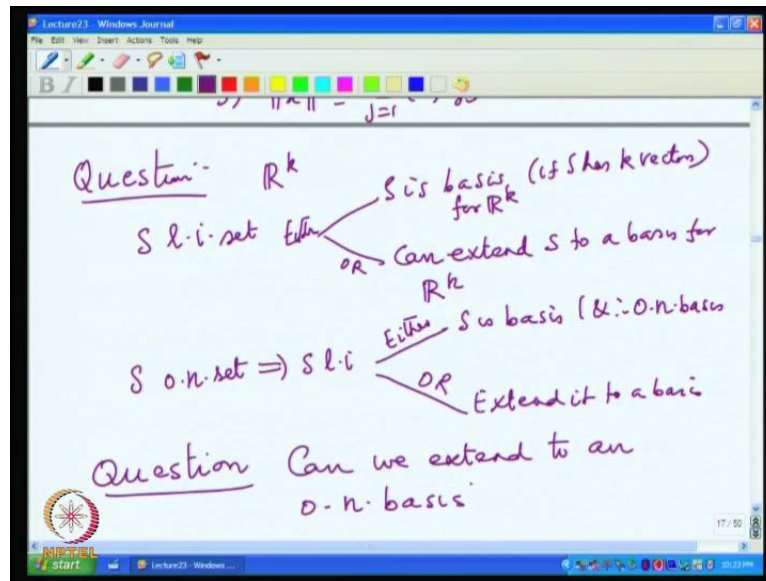
The fourier expansion tells you all the co efficient are 0 and therefore, the vector must be 0 so a vector is the 0 vector. If and only if it is orthogonal to all the basis vectors this is 1 criterian for $\phi_1 \phi_2 \phi_j$ to be a basis. We look at it later remark we can do the same thing in a sub space also, let w be a sub space of $r k$ dimension of w is d $b w$ is w 1 let me call it again the same ϕ notation for a orthonormal basis $\phi_1 \phi_2 \phi_d$ orthonormal basis for w .

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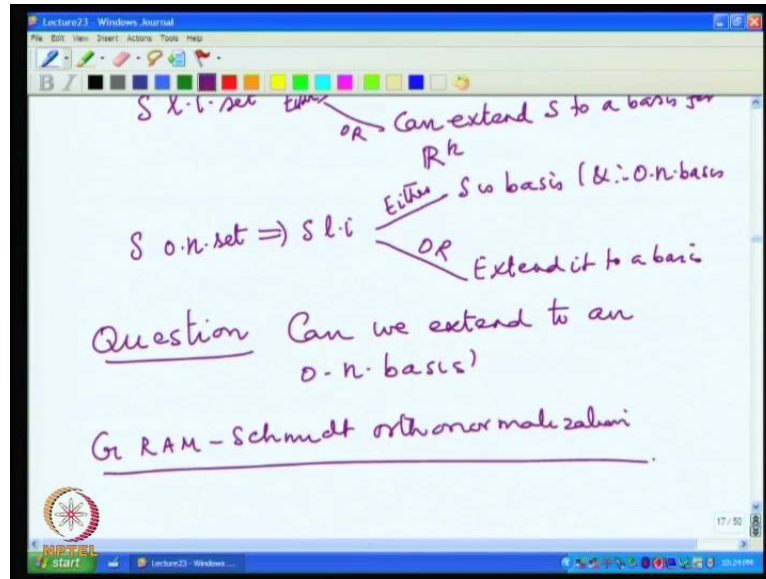
Then we can restrict our fourier expansion within w x is equal to summation j equal to 1 to d $x \phi_j \phi_j$ for every x in w . So every vector x in w can be expanded in the fourier expansion x comma y is equal to summation j equal to 1 to d $x \phi_j y \phi_j$ for every $x y$ in w and finally, this norm condition $\|x\|^2$ is equal to summation j equal to 1 to d $x \phi_j$ square for every x in w . So if you take w equal to $r k$ we get all the results we had before but, we can also restrict our self sub space and we get the corresponding.

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Now we raise a question we have \mathbb{R}^k , we have a linearly independent set, we saw that either S is basis this will happen if S has k vectors. So if S has k vectors because if we have k vectors and any k linearly independent vectors will form a basis. So if S has k vectors S is already a basis or can extend S to a basis for \mathbb{R}^k . This is a basis it is already a basis for \mathbb{R}^k or it can be extended to a basis for \mathbb{R}^k . Now if you start with S an orthonormal set we have seen that S is linearly independent and therefore, any linearly independent set is either S is basis and this will happen if S have a k vectors is observed now if it is a basis it is already orthonormal and therefore, orthonormal basis but now because S is a \mathbb{R}^k if it does not a k vectors. We can extend it to a basis but we do not know whether what we have extended to is an orthonormal basis. So question is can we extend to an orthonormal basis.

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So given any orthonormal set it is either a basis an orthonormal basis or it is a linearly independent set. Which can be extended to a basis the question is can we extend it to an orthonormal basis in other words is every orthonormal set a basis r can be converted to an orthonormal basis. Now we shall investigate this question the main ingredient that is required for this is what is known as the gram schmdt. Ortho normalization the main idea of the gram schmdt ortho normalization is the given any linearly independent set we convert it to an orthonormal. Set in such a way the space that we span are not lost we shall look at the details of this conversion in the next lecture.