

MITOCW | Part III: Linear Algebra, Lec 7: Dot Products

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HERBERT

Hi. Welcome to our lecture today in Calculus Revisited. And our topic is going to be the dot product. And by way of a preamble, let me point out that in our development of vector spaces in this block, up until now, we have deliberately not mentioned the concept of the dot product, even though dot product plays a very prominent role in the usual vector algebra of two- and three-dimensional space.

GROSS:

And the reason for this is that we wanted to emphasize the structure of a vector space. In a manner of speaking, mathematical structures are pretty much like an anatomy-type course, that one starts with a basic structure, exploits it, sees what ramifications it has, and then gradually adds on more sophisticated layers of nerves, nerve centers, skin grafts, and what have you. And ultimately, builds up a superstructure based on top of an underlying basic fundamental model.

Now, without going into that in more detail right now, let it suffice to say that I call today's lecture "Dot Products." And by way of review, notice that in the usual two- and three-dimensional case by the dot product of two vectors, we mean a real number. And if we want to keep this thing vague and not indicate the cosine of the angle between two vectors, et cetera, one usually says that a dot product is a mapping that carries ordered pairs of vectors into the real numbers.

This is the mathematical way of talking about what a dot product is without referring to angles or lines. It's a function which maps ordered pairs of vectors into real numbers. In particular, the mapping must have certain properties to be called a dot product. And again, emphasizing mathematical structure based on what we already know is the case from the two- and three-dimensional situation, what properties do we want the dot product to have?

Well, we would like $\alpha \cdot \beta$ to equal $\beta \cdot \alpha$, because that's certainly happened in the two- and three-dimensional case. We would like $\alpha \cdot \beta + \gamma$ to be $\alpha \cdot \beta + \alpha \cdot \gamma$. And if we have a scalar multiple of α dotted with β , we would like that to be the scalar c times the number $\alpha \cdot \beta$.

Or if we wanted to rewrite this in vector form, that the c could also be used as a scale of multiple of β . That $\alpha \cdot \beta$ is the same as $\alpha \cdot c \beta$. And where did these three rules come from? They came from the properties that the ordinary dot product has.

By the way, a dot product becomes known as a Euclidean dot product if, in addition to the given three properties, we also know that the dot product of a vector and itself, $\alpha \cdot \alpha$, is a non-negative real number. And that in particular, $\alpha \cdot \alpha$ can equal 0, if and only if α equals 0. By the way, let me point out that this fourth condition is independent of the other three.

That when one studies vector spaces in more abstract detail, one usually defines a dot product to have just the first three properties that we talked about. And if the fourth property happens to be present, then one talks about a positive-definite dot product. But not every dot product has to be positive definite, except that if we're trying to imitate the distance property of real vector spaces, then we add the positive-definite criterion. And that's explained in more detail in the study guide as we do the exercises.

But I did want to simply point out that once you know that you have a positive-definite form, that $\alpha \cdot \alpha$ is non-negative, then it makes sense to abstractly define the norm or the length of α to be the positive square root of $\alpha \cdot \alpha$. You see, this makes sense, because you know that $\alpha \cdot \alpha$ is a non-negative real number. Hence, it has a unique positive square root. And this is how we abstract the usual distance function.

At any rate, to show you how this works in abstract form, let's take a three-dimensional case. Let's suppose v is a three-dimensional vector space, that a particularly-chosen basis for v is u_1 , u_2 , and u_3 , and let's suppose that we have a positive-definite dot product. And I'll just make this up at random or semi-random here.

Let's suppose that I know what the dot product looks like on all of the pairs of basis elements. In other words, I know what $u_1 \cdot u_1$ is, what $u_2 \cdot u_1$ is, what $u_3 \cdot u_1$ is. And by the way, by the property, that $u_2 \cdot u_1$ must equal $u_1 \cdot u_2$, et cetera, by the commutative property. Notice that once I know what $u_2 \cdot u_1$ is, I also know what $u_1 \cdot u_2$ is. Once I know what $u_3 \cdot u_1$ is, I know what $u_1 \cdot u_3$ is, et cetera.

At any rate, there are nine possible combinations here. And just try to fix these in your mind, because I'll be referring to these as we go along. $u_1 \cdot u_1$ is 3. $u_1 \cdot u_2$ is 4. $u_1 \cdot u_3$ is 5. $u_2 \cdot u_2$ is 6. $u_2 \cdot u_3$ is 7. And $u_3 \cdot u_3$ is 9. I just happen to know that particular amount.

Let's also suppose that I now want to find the dot product of any two vectors in my space, v . My first claim is-- and again, this is an overview. I'll do this in more abstract detail in the exercises in the study guide. My first point, though, is that once we know what the dot product is for each pair of basis vectors, we know what the dot product is for all vectors and pairs of vectors in the space. That in particular, the four rules-- actually, the three rules that we have for defining a dot product tells us how to compute the dot product for any two elements.

For example, suppose I have one 3 tuple, and just suppose I have two vectors-- x_1u_1 plus x_2u_2 plus x_3u_3 , and y_1u_1 plus y_2u_2 plus y_3u_3 . Let's suppose I want to find that dot product. Notice that my distributive rule for multiplication, coupled with the commutative properties and how I can factor out scale in multiples, tells me that I multiply these two trinomials the same way as I would have had these been algebraic expressions.

In other words, I dot x_1u_1 with each of these three terms, I dot x_2u_2 with each of these three terms, and I dot x_3u_3 with each of these three terms. For example, this will give me x_1y_1 times $u_1 \cdot u_1$. But if you recall, I said that $u_1 \cdot u_1$ is 3, so this becomes $3x_1y_1$. And in a similar way, when I dot x_1u_1 with y_2u_2 , I get x_1y_2 , $u_1 \cdot u_2$. But I gave the fact that $u_1 \cdot u_2$ was 4, so this term becomes $4x_1y_2$.

And in a similar way, going through this, I get-- a term will be $5x_1y_3$. Then, dotting x_2u_2 with each of these three terms, I get three more terms-- $4x_2y_1$ plus $6x_2y_2$ plus $7x_2y_3$. Then I dot x_3u_3 with each of these three terms. Again, just to do this thing quickly.

x_3u_3 dotted with y_1u_1 is x_3y_1 times u_3 dotted with u_1 . And u_3 dotted with u_1 was given to be 5. In fact, it was the same as u_1 dotted with u_3 by commutativity, you see, which was also 5. At any rate, I get what? $5x_3y_1$ plus $7x_3y_2$ plus $9x_3y_3$.

By the way, at this particular stage, I would like to pause for a moment. And some of you may have picked this up better than others, but at this stage of the game, maybe you've already learned how to look at a system like this and write it in matrix form. Now, notice that these are what we call quadratic forms. Each term involves an x multiplied by a y .

I've written this so that the x's are always the left side factor and the y's are always on the right. Notice that there is a matrix of coefficients-- namely 3, 4, 5, 4, 6, 7, 5, 7, 9. And that consequently, I can write this array of nine terms simply as the following product.

I write the row matrix, $x_1 \ x_2 \ x_3$. Multiply that by the 3 by 3 matrix-- 3 4 5, 4 6 7, 5 7 9, and multiply that, in turn, by the column matrix, $y_1 \ y_2 \ y_3$. As a quick check, notice that this is a 1 by 3 matrix. This is 3 by 3. This is 3 by 1. And consequently, this will be a 1 by 1 matrix, or a number.

What number will it be? It will be this number here. And notice what I'm saying-- that $x_1, x_2, x_3, y_1, y_2, y_3$, are given numbers. And consequently, the dot product in question is determined as soon as I know these coefficients, which happen to be the dot products of the basis elements with one another.

So this shows two things. One, how we write this in matrix form. And two, how the dot product of each two vectors in v is determined by just knowing what happens to the pairs of basis vectors when we dot them. And this gives us still another way of seeing how matrices are used as a coding system.

In other words, every symmetric-- remember what symmetric means? You get the same matrix when you interchange rows and columns. Every symmetric n by n matrix codes a dot product. And conversely, every dot product is coded by a symmetric n by n matrix. You see, what does this matrix tell me?

This is the entry in the i -- the entry in the i -th row, j -th column is what happens when $u_{sub\ i}$ is dotted with $u_{sub\ j}$. Without meaning to belabor this point, let us notice that the array here-- 3 4 5, 4 6 7, 5 7 9-- is precisely the array that we had over here-- 3 4 5, 4 6 7, 5 7 9. This is what we mean when we talk about the matrix of the dot product. It's the array of how the basis vectors look when you dot them with one another.

By the way, as another aside, we agreed that when a vector with itself, that can be identified in a way with the length of the vector. In particular, going back to this example here, if the x's and the y's are chosen to be equal-- if I let x_1 equal y_1 , x_2 equal y_2 , and x_3 equals y_3 , this problem here reduces to this problem. Which in turn, just combining what I had above-- in other words, with the x's and the y's equal-- gives me that to find the square of the length of a vector, I have to solve this particular algebraic equation.

And this algebraic equation is called a quadratic form. You see, notice that each of the variables, x_1, x_2, x_3 , appears in each term here as a second-degree variable. See, here's an x_1 squared. Here's x_1 times x_2 . You see two factors-- x_1 times x_3 .

And what I'm driving at, again, is aside from any other connections, notice that to solve for the length of a particular vector, one has to wind up solving what we call quadratic forms. And these, for two and three dimensions, can be identified with certain curves in two- or three-dimensional space. But I don't want to belabor that point too much here, either. I just want you to get a buckshot overview of how one works abstractly with the dot product idea.

By the way, some new terminology. If v is an n dimensional vector space with basis u_1 up to u_n , we call the basis u_1 up to u_n an orthogonal basis relative to a given dot product if the dot product of any two different members of the basis is 0. In other words, if $u_i \cdot u_j = 0$ for all $i \neq j$, we call this an orthogonal basis, for the usual reason of what orthogonal means. When the dot product of two arrows was zero, we said the arrows were perpendicular, et cetera. This is just a carryover from that.

In particular, if in addition, the dot product of any vector with itself happens to be 1, then the basis is called an orthonormal basis. And this whole idea is modeled after the usual example that in three-dimensional space, i, j, k forms an orthonormal basis, relative to the usual dot product. In other words, $i \cdot j$, $i \cdot k$, and $j \cdot k$ are all 0. But $i \cdot i$, $j \cdot j$, and $k \cdot k$ are all 1.

Now, the interesting point is that in most textbooks, one always defines the dot product in much the same way as we do i, j , and k . One always assumes that somehow or other, we have an orthonormal basis. Now, obviously in the example I'm motivating today's lecture on, we don't have an orthonormal basis. Remember, we had something like $u_1 \cdot u_2$ was 4.

Well, see, to be orthonormal, $u_1 \cdot u_2$, first of all, would have to be 0, and $u_1 \cdot u_1$ would have to be 1. But in our example, $u_1 \cdot u_1$ is 3. So the question that comes up is, do we always have an orthonormal basis? And the answer is yes.

And in fact, if you like big words, the process by which we construct an orthonormal basis-- in fact, the process is easier than the name. The name is called the Gram-Schmidt orthogonalization process. And geometrically, what the method boils down to is that if I'm given two non-parallel vectors, u_1 and u_2 , to find the space spanned by u_1 and u_2 , I can replace u_2 by the component of u_2 , which is perpendicular to u_1 . Let's call that component u_2^* .

What I'm saying is that u_1 and u_2^* span the same space as u_1 and u_2 . But obviously, geometrically, it's easy to see that u_1 and u_2^* are orthogonal. Now, the question is, how could we get the same result without having to rely on geometry? And the answer is, we say, look it.

We know already in our course that in terms of spanning vectors, if you replace a vector by itself plus or minus a scalar multiple of another, you don't change the space spanned by the given set of vectors. So why not write u_2^* to be u_2 minus some suitable multiple of u_1 ? See, $u_2 - xu_1$, where we'll try to determine x in such a way that u_2^* , dotted with u_1 , will be 0.

You see, what we're going to try to do is replace u_2 by an equivalent vector, meaning that u_1 and u_2^* will span the same space as u_1 and u_2 , but with the additional property that u_1 and u_2^* will be orthogonal. Whereas, u_1 and u_2 might not have been orthogonal. And now you see, we can proceed axiomatically.

Namely, we say, OK. What we want to look at is $u_2^* \cdot u_1$. So let's start both sides of this equation with u_1 . You see, the left-hand side will become $u_2^* \cdot u_1$. The right-hand side becomes $u_2 - xu_1$, dotted with u_1 . But by our distributive property, this is the same as $u_2 \cdot u_1 - xu_1 \cdot u_1$.

Now, we didn't want x to be any old number. We wanted x to be that number, if one exists, that makes $u_2^* \cdot u_1$ equal to 0. Remember, $u_2 \cdot u_1$ and $u_1 \cdot u_1$ are numbers. Consequently, I treat this as an ordinary algebraic equation. Namely, this is a number. This is a number. I equate this to 0 and solve for x . In other words, x is $u_2 \cdot u_1$ divided by $u_1 \cdot u_1$.

And by the way, just as an aside, many mathematicians, as an abbreviation when they want to write the dot product of a vector and itself, they write it as the square of the given vector. Obviously, this cannot mean the usual squaring operation, because we don't multiply vectors by themselves. This obviously refers to the dot product. And I mention this in passing, simply so that if you see this in the literature, you will not be confused by it. I prefer to write $u_1 \cdot u_1$ rather than u_1 squared, but we'd like you to see this notation anyway.

At any rate, now knowing what x is, I replace x here into this equation, and I wind up with that u_2^* is u_2 minus $u_2 \cdot u_1$ over $u_1 \cdot u_1$ times u_1 . And if you want to check this thing geometrically, the u_2^* that I've computed this way is precisely the u_2^* that I get geometrically. The beauty of this technique is that it did not require geometry. And consequently, structurally, I should be able to use this in higher dimensions. And that's exactly what the Gram-Schmidt orthogonalization process is.

What you do is you start with a basis. You take the first vector in that basis and dot it with the second vector. If that dot product is 0, those two vectors are both eligible to be part of an orthogonal basis. Now, if that dot product isn't 0, you use the Gram-Schmidt orthogonalization process to replace the second vector, u_2 , by u_2^* , where $u_1 \cdot u_2^*$ is 0.

Now you take that new basis, which spans the same space as the original u_1 and u_2 , and compare that or take that in connection with u_3 and see if those three vectors form an orthogonal basis-- or orthogonal, meaning their dot product of different ones is 0. And if it is, fine. And if it isn't, you just inductively keep using the Gram-Schmidt orthogonalization process.

Now, to show you what this means in a specific case, let's suppose I have the following situation. Let's suppose I have a four-dimensional vector space for which a basis is u_1 , u_2 , u_3 , and u_4 . Suppose I also know that u_1 , u_2 , and u_3 form an orthogonal set.

That means I know that $u_1 \cdot u_2$, $u_1 \cdot u_3$, and $u_2 \cdot u_3$ are all 0. But I don't know that $u_4 \cdot u_1$, $u_4 \cdot u_2$, $u_4 \cdot u_3$ are 0 or anything like this. And the question that comes up now is, I would like to replace u_4 by an equivalent vector, which I'll call u_4^* , such that u_1 , u_2 , u_3 , and u_4^* span the same space, V . But that now with u_4 replaced by u_4^* , this becomes an orthogonal basis.

Well, the way I proceed is I use the fact that whenever I replace a vector by itself, plus or minus a linear combination of the other vectors, I don't change the space spanned by the vectors. So what I say is, let u_4^* be u_4 minus $x_1 u_1$ minus $x_2 u_2$ minus $x_3 u_3$. You see, I'm modeling this after what I did in the two-dimensional case. What I want to do is determine x_1 , x_2 , and x_3 such that $u_4^* \cdot u_1$, $u_4^* \cdot u_2$, and $u_4^* \cdot u_3$ will all be 0. And the trick is simply this.

Let me focus my attention on one of these coefficients, because the technique is the same for all the others. Let's suppose I want to find out what x_3 is. The trick is, I dot both sides of this equation with u_3 . Now, why do I do that? Remember, u_1 , u_2 , and u_3 are an orthogonal set. Consequently, when I dot u_1 with u_3 and u_2 with u_3 , those terms will be 0, and they will drop out.

In other words, dotting both sides of this equation with u_3 and using the fact that the dot product is distributive, I get $u_4^* \cdot u_3$ is $u_4 \cdot u_3$ minus $x_1 u_1 \cdot u_3$ minus $x_2 u_2 \cdot u_3$ minus $x_3 u_3 \cdot u_3$. And the key point is that by orthogonality, these two things here are 0. Consequently, $u_4^* \cdot u_3$ is $u_4 \cdot u_3$ minus $x_3 u_3 \cdot u_3$. Remember, these are numbers.

I would like $u_4 \cdot u_3$ to be 0, so all I have to do now is solve this algebraic equation for x_3 . And notice that x_3 algebraically simply turns out to be $u_4 \cdot u_3$ over $u_3 \cdot u_3$. Again, the only thing I have to be careful about is that the denominator not be 0. And notice that by positive definiteness, $u_3 \cdot u_3$ can only equal 0 if u_3 is the 0 vector. But if u_3 had been the 0 vector, it couldn't be part of a basis.

So you get the idea of how this works. This is the same Gram-Schmidt orthogonalization process that we used in two dimensions. Because once we know that all the vectors up to u_4 are orthogonal, whenever we dot one of them with the other three, we essentially reduce this to a two-dimensional problem, because all the other dot products drop out.

In a similar way, you see, I could have found x_2 and x_1 , leaving the details to you. The easiest way to remember this is every place I see a subscript 3 over here, let me replace it by a 2. And then every place I see the 3, let me replace it by a 1. And what I get is that u_4 star is u_4 . And then I subtract off these scalar multiples.

What scalar multiples are they? Notice that it's what? The coefficient of u_1 is $u_4 \cdot u_1$ over $u_1 \cdot u_1$. The coefficient of u_2 has as its denominator $u_2 \cdot u_2$. The numerator is u_4 dotted with u_2 . In other words, in a sense, it's like the projection of u_4 onto u_2 . And the coefficient of u_3 has as its denominator $u_3 \cdot u_3$, and its denominator is $u_4 \cdot u_3$.

Now, to show you how this works, let's come back to our original problem, which I've reproduced over here. Remember what we had. We had that $u_1 \cdot u_1$ is 3, $u_1 \cdot u_2$ is 4, $u_1 \cdot u_3$ is 5, et cetera. I'll refer to this as I need it. Let me show you how the Gram-Schmidt process allows me to find, from this, an orthogonal basis.

The first thing is that obviously, u_1 is not the 0 vector, because if it were the 0 vector, $u_1 \cdot u_1$ would be 0, not 3. So the first vector in my orthogonal basis, which I'll call u_1 star, can be u_1 itself. How do I find the second vector?

According to the Gram-Schmidt orthogonalization process, I replace u_2 by u_2 minus a suitable scalar multiple of u_1 star. And what scalar multiple is that? The denominator will be $u_1 \text{ star} \cdot u_1 \text{ star}$, and the numerator will be $u_2 \cdot u_1 \text{ star}$. Well, remember, $u_1 \text{ star}$ is equal to u_1 . So right from this array here, what do I have?

$u_2 \cdot u_1 \text{ star}$ is $u_2 \cdot u_1$. $u_2 \cdot u_1$ is 4. $u_1 \text{ star} \cdot u_1 \text{ star}$ is $u_1 \cdot u_1$. $u_1 \cdot u_1$ is 3. So this is simply what? Minus $4/3$ times u_1 . In other words, u_2 star is simply u_2 minus $4/3 u_1$.

And by the way, as a check, what was this supposed to do? If I replaced u_2 by u_2 star, these two vectors here should now be orthogonal. Are they? Let's start them. If I dot these two, I get what? $u_1 \cdot u_2$ minus $4/3 u_1 \cdot u_1$.

Notice that $u_1 \cdot u_2$ is 4. $u_1 \cdot u_1$ is 3. So coming down here as a check, $u_1 \text{ star} \cdot u_2 \text{ star}$ is $u_1 \cdot u_2$, which is 4, minus $4/3 u_1 \cdot u_1$, which is 3. The 3's cancel. 4 minus 4 is 0. This checks out fine.

How do I find u_3 star? Well, I subtract from u_3 suitable scalar multiples of u_1 star and u_2 star. You see what I've done. I orthogonalized one vector at a time. See, first I got u_2 star. Now I know that u_1 star and u_2 star are orthogonal, using u_1 star and u_2 star, the multiples that I subtract from u_3 are what?

For u_1^* , my denominator is $u_1^* \cdot u_1^*$, and my numerator is $u_3 \cdot u_1^*$. And for u_2^* , my denominator is $u_2^* \cdot u_2^*$, and my numerator is $u_3 \cdot u_2^*$. And now how do I evaluate what this thing really means?

Well, first of all, I know what $u_3 \cdot u_1^*$ is. That's just $u_3 \cdot u_1$, which happens to be 5. And I also know what $u_1^* \cdot u_1^*$ is. That's $u_1 \cdot u_1$, which is 3. I now have to compute what? $u_3 \cdot u_2^*$, and I have to compute $u_2^* \cdot u_2^*$.

Keep in mind that I've already computed that u_2^* is $u_2 - \frac{4}{3}u_1$. Consequently, $u_3 \cdot u_2^*$ is $u_3 \cdot u_2 - \frac{4}{3}u_3 \cdot u_1$. And now you see the mechanical algebra takes over again. I know what my axioms for dot products are.

This gives me $u_3 \cdot u_2 - \frac{4}{3}u_3 \cdot u_1$. I'm given that $u_3 \cdot u_2$ is 7. I'm given that $u_3 \cdot u_1$ is 5. So $u_3 \cdot u_2^*$ is $7 - \frac{4}{3} \cdot 5$. That's $\frac{1}{3}$ -- $\frac{21}{3} - \frac{20}{3}$, which is $\frac{1}{3}$.

So let's see what I know now. I know now how to handle this numerator. $u_3 \cdot u_2^*$ is $\frac{1}{3}$. How do I handle $u_2^* \cdot u_2^*$? u_2^* is $u_2 - \frac{4}{3}u_1$. So to find $u_2^* \cdot u_2^*$, I have to dot $u_2 - \frac{4}{3}u_1$ with itself.

If I do that-- and again, notice how these rules work the same way as for ordinary algebra. I get $u_2 \cdot u_2 - \frac{8}{3}u_1 \cdot u_2 + \frac{16}{9}u_1 \cdot u_1$. Well, I know that $u_2 \cdot u_2$ is 6. That was given. I know that $u_2 \cdot u_1$ is 4, and $u_1 \cdot u_1$ is 3.

So evaluating this, I wind up with the fact that $u_2^* \cdot u_2^*$ is $6 - \frac{16}{3}$, or $\frac{2}{3}$. Consequently, going back here, you see my numerator is $\frac{1}{3}$. My denominator is $\frac{2}{3}$, so the fraction is $\frac{1}{2}$. In other words, substituting into here, I get that u_3^* is $u_3 - \frac{5}{3}u_1 - \frac{1}{2}u_2 - \frac{4}{3}u_1$.

And retabulating my results to write them in the usual order of u_1 , u_2 , and u_3 components, notice that u_1^* is u_1 . u_2^* is $-\frac{4}{3}u_1 + u_2$. u_3^* is $-\frac{5}{3}u_1 - \frac{1}{2}u_2 + u_3$. Now, what property does this set of vectors have?

First of all, my claim is that they're orthogonal. And secondly, they span the same space as u_1 , u_2 , and u_3 . And it's clear why they span the same space as u_1 , u_2 , and u_3 . Namely, they're essentially suitable scalar multiples of u_1 , u_2 -- linear combinations of scalar multiples of u_1 , u_2 , and u_3 .

As a quick check-- and I'll leave some of the other details to you. Let's actually check that $u_1^* \cdot u_3^*$ is really 0. If I dot u_1^* with u_3^* , look at what I get. I get $-\frac{5}{3}u_1 \cdot u_1 - \frac{1}{2}u_1 \cdot u_2 + u_1 \cdot u_3$.

$u_1 \cdot u_1$ is 3. $u_1 \cdot u_2$ is 4. So this is $-\frac{5}{3} \cdot 3 - \frac{1}{2} \cdot 4 + 5$. That's $-5 - 2 + 5 = 0$. A similar check will show that $u_2^* \cdot u_3^*$ is 0.

We should also check to see what the lengths of u_1^* , u_2^* , and u_3^* are. In other words, $u_1^* \cdot u_1^*$ is what? That's $u_1 \cdot u_1$, which is 3. $u_2^* \cdot u_2^*$ -- well, we just found that over here. That's $\frac{2}{3}$. $u_3^* \cdot u_3^*$ -- well, u_3^* was $-\frac{5}{3}u_1 - \frac{1}{2}u_2 + u_3$.

Dotting that with itself-- and notice I used the square notation here to save space and not have this run too long. But dotting this, the same as I would the square of any trinomial, I get what? $u_3 \cdot u_3 + u_1 \cdot u_1 + \frac{1}{4}u_2 \cdot u_2 + u_3 \cdot u_3 + u_1 \cdot u_2 - \frac{10}{3}u_1 \cdot u_3 - u_2 \cdot u_3$.

Putting in the values for $u_1 \cdot u_1$, for $u_2 \cdot u_2$, $u_3 \cdot u_3$, $u_1 \cdot u_2$, $u_1 \cdot u_3$, and $u_2 \cdot u_3$ -- putting in these values, I find that $u_3 \cdot u_3$ is $1/2$. So I have an orthogonal basis. It's not orthonormal, but notice that it's easy to fix up the normality part, because all I have to do is divide each of these vectors by the square root of this number, and that will make the dot product 1.

For example, if I were to replace u_1 by u_1 over the square root of 3, then when I dotted these two vectors, I would have 3 divided by the square root of 3 times the square root of 3, which is 3. And $3/3$ is 1. So getting the lengths to be one is quite easy. The hard part is this Gram-Schmidt orthogonalization process to orthogonalize what's going on.

Now, this may seem rather complicated, but it's really one long piece of computation. We'll do this more slowly in the exercises. But the whole idea is what? I successively use the Gram-Schmidt orthogonalization process to replace each vector by a suitable linear combination of itself and the preceding ones to make sure that the new replacement is orthogonal to the remaining ones, and that doesn't change the space that I already have.

By the way, if you want to see what this means in terms of matrix multiplication, notice that we saw earlier that to dot a vector with itself, you write the vector as a row vector, then write down the matrix of coefficients for the basis elements, then write down that same vector as a column vector. The fact that u_1 is $u_1 + 0u_2 + 0u_3$ means that as a 3 tuple, it would be $1\ 0\ 0$. Its transpose would be $1\ 0\ 0$ -- the column vector.

And so when we take this vector and dot it with this vector, that should be the entry, $u_1 \cdot u_1$, in this particular matrix here. If we take this times this, this should be u_1 dotted with u_2 . And since u_1 and u_2 are orthogonal, that had better come out to be 0.

And going on in this way, what I claim is, if you now replace u_1 , u_2 , and u_3 by what 3 tuples they are, then also replace them as column vectors here, you will get a new 3 by 3 matrix which will be diagonal. In other words, if we change our basis from u_1 , u_2 , and u_3 -- if we change that basis to u_1 , u_2 , u_3 , notice that the new matrix that we get is a diagonal matrix. It's our way of saying that when you dot two different vectors, the dot product is 0.

The diagonal elements tell you what $u_1 \cdot u_1$ are-- $u_2 \cdot u_2$, $u_3 \cdot u_3$. You see, by using the diagonal matrix over here, this is a much simpler model to use. u_1 , u_2 , u_3 is a much nicer basis to use than u_1 , u_2 , and u_3 in order to determine what dot products are. I'll emphasize that in more detail later.

Let me make one remark before I get to our concluding remarks. And that is, have you begun to notice how complicated matrices are from the point of view that they are such a wonderful coding device that we use them to code many different things? For example, we have used matrices to code a linear transformation relative to various bases.

We're now using matrices to code the same dot product relative to different bases. We have used matrices to code equivalent row-reduced bases as bases for the same vector space. That at the end of this unit, what I will do is try to give you a summary in the study guide of the different kinds of matrix equivalents and where they're used. Because after a while, you tend to get mixed up if we don't see these pieces one bit at a time.

But to help you see what all this problem means, I have cheated-- that the place I got the data from for the u_1 , u_2 , and u_3 in this problem was that I thought of the following three vectors-- $i + j + k$, $2i + j + k$, $2i + j + 2k$ -- and used this to make up the data for u_1 , u_2 , and u_3 that was in this exercise. What you may find informative, and what I will do as a learning exercise, is have you go through the same exercise that we have just done as today's lesson and have you verify that this checks out with the equivalent geometric construction-- that one of the exercises in the homework will be to show what the Gram-Schmidt orthogonalization process means geometrically for these three vectors.

By the way, rather than to belabor that point for now, let me make one other aside. And that is, I had mentioned before that to find the dot product of two vectors, it may be more advantageous to use one basis rather than another. Remember, when we wanted to dot a vector with itself, using u_1 , u_2 , and u_3 as a basis, remember we got six different terms? We had an x_1 squared, x_2 squared, x_3 squared, an x_1x_2 , x_1x_3 , and x_2x_3 term.

Notice that when you pick an orthogonal basis, you only get three terms. Because once the basis is orthogonal, all you have to do is dot corresponding entries. Because you see, if I dot u_1 star with a term involving u_2 star or u_3 star, that will be 0 by orthogonality. If I didn't have an orthogonal basis, I couldn't neglect those terms.

So for example, to dot a vector with itself in this particular example, using u_1 star, u_2 star, and u_3 star as a basis, notice that what I wind up with is what? x_1 times x_1 . x_1 squared times u_1 star dot u_1 star, which is 3, et cetera. Meaning $3x_1$ squared plus $2/3 x_2$ squared plus $1/2 x_3$ squared, which is the square of the length of the vector that I'm looking for.

If I put everything over a common denominator, I get a very nice equation for an ellipsoid over here. You see a very nice equation with no mixed terms-- just perfect squares appearing over here. The mixed terms drop out, and that's one reason why we like orthogonal bases.

Still another reason that we like orthogonal bases-- and I'll conclude with this example-- is that if we know that the vectors u_1 up to u_n are orthonormal, say, and that x_1u_1 plus et cetera $x_n u_n$ is 0, then we automatically know that the u 's are-- that x_1 up to x_n are 0-- that these are linearly independent. And the proof is quite simple.

Namely, all we do is we dot both sides of this equation with, for example, $u_{sub 1}$. We could've used any one of the u 's that we wanted, but using $u_{sub 1}$, we dot $u_{sub 1}$ with both sides of this equation. Notice that this term gives me x_1u_1 dot u_1 . The next terms are what? u_1 dot u_2 up to u_1 dot u_n .

By the property of being orthogonal, all of these products are 0. Consequently, this scalar times x_1 must be 0. Consequently, x_1 itself must be 0. I've deliberately gone very rapidly here to give you an overview, and to also have you see, as I'm talking, what these computations look like.

I think by hearing this, as complicated as it may sound, I think when you now read the solutions to the exercises, you will have a better feeling for what's going on. And as I say, in the exercises, I will develop these topics much more slowly, and you can read these solutions as we go along. At any rate, this presents our overview of dot products. And so until next time, then, goodbye.

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