

You can preview this quiz, but if this were a real attempt, you would be blocked because:

This quiz is not currently available

Question **1**

Not complete

Points out of 4.00

First compute the [length/norm](#) of $\vec{w} = \begin{bmatrix} 2 \\ -1 \\ -5 \end{bmatrix}$.

Then create a unit [vector](#) pointing in the same direction.

Compute the [length/norm](#) and write your response precisely in the following format to represent the square root of a simplified integer, **like sqrt(1)**, with no extra characters or spaces

$$\|\vec{w}\| = \sqrt{\vec{w} \cdot \vec{w}} =$$

Next create a unit [vector](#) pointing in the same direction by dividing each coordinate of the [vector](#) by its [norm](#). Write your responses like $2/\text{sqrt}(1)$, with no extra characters or spaces.

Check

Question 2

Not complete

Points out of 2.00

Find a unit [vector](#) in the direction of the [vector](#) $\begin{bmatrix} -3 \\ 4 \end{bmatrix}$.

Type integers or simplified fractions with no extra spaces or characters, like -16/31

Question 3

Not complete

Points out of 4.00

Find the distance between $\vec{u} = \begin{bmatrix} 0 \\ -4 \\ 2 \end{bmatrix}$ and $\vec{v} = \begin{bmatrix} -4 \\ -1 \\ 9 \end{bmatrix}$

In 1.3 practice problems we saw that we could create the [line](#) connecting two [vectors](#) by making it parallel to $\vec{u} - \vec{v}$, the off-diagonal of the [parallelogram](#) they form.

We can use this reasoning here to find the distance between any two [vectors](#), by finding the [length](#) of $\|\vec{u} - \vec{v}\|$

First, what is $\vec{u} - \vec{v}$? Simplify your response.

What is the [length/norm](#) of $\vec{u} - \vec{v}$? Write your response like sqrt(1) without any extra characters or spaces.

Question 4

Not complete

Points out of 2.00

Determine if the following [vectors](#) are [orthogonal](#)

$$\vec{u} = \begin{bmatrix} 2 \\ -3 \end{bmatrix} \text{ and } \vec{v} = \begin{bmatrix} -4 \\ -2 \end{bmatrix}.$$

First, what is the [dot product](#) of the two [vectors](#)? Simplify your response.

Are the [vectors orthogonal](#)?

yes

no

Check

Question 5

Not complete

Points out of 2.00

Open

<https://www.geogebra.org/m/apayedjs>

which shows 2 [vectors](#) \vec{u}, \vec{v} , the coordinate axes in 3-space and the xy -[plane](#) shaded.

Turn the graph so that you can see whether the [vectors](#) are [orthogonal](#) or not. What is the [dot product](#) of the 2 [vectors](#)?

0

nonzero

Next, create a "[head on](#)" view of the [plane](#) the 2 [vectors](#) are on by dragging the [vectors](#) on top of each other and having the other 2 axes overlap. In that visualization, are they the same [length](#) or does one stick out further?

u and v are the same [lengths](#)

u is longer

v is longer

Check

Question 6

Not complete

Points out of 1.00

Determine if the following [vectors](#) are [orthogonal](#)

$$\vec{u} = \begin{bmatrix} 10 \\ 3 \\ -1 \end{bmatrix} \text{ and } \vec{v} = \begin{bmatrix} 1 \\ -3 \\ 1 \end{bmatrix}.$$

Are the [vectors orthogonal](#)?

yes

no

Check

Question 7

Not complete

Points out of 2.00

Open

<https://www.geogebra.org/m/gctjpnys>

from Juan Carlos Ponce Campuzano, University of Queensland, Australia, which we saw in 1.8 and 1.9. The [vectors](#) shown in the graph are the column [vectors](#) of the matrix, i.e. the image of the unit axes under the [linear transformation](#).

Which examples have columns that are all mutually [orthogonal](#)? We can see this algebraically by performing [dot products](#) on each pairing from the columns, or we can see this geometrically by looking at the transformed cube and seeing whether the faces stay [orthogonal](#) to each other, via a rectangular box or cube as the output or image of the transformed figure

Choose all that have columns that are all mutually [orthogonal](#). Choose all that apply!

Example 1

Example 2

Example 3

Example 4

Example 5

In Example 4, after you Apply T , turn the figure so that you can see the transformed cube on the top left of the screen. Does example 4 preserve the [orthogonality](#) of the cube?

yes

no, the cube has been distorted so that the faces are no longer [orthogonal](#)

Check

Question 8

Not complete

Points out of 3.00

Suppose the vector \vec{y} is orthogonal to both vectors \vec{u} and \vec{v} . We'll show that \vec{y} is orthogonal to every vector \vec{w} in the Span $\{\vec{u}, \vec{v}\}$.

The span is the set of linear combinations of the vectors $c_1\vec{u} + c_2\vec{v}$.

So take the dot product: $\vec{y} \cdot (c_1\vec{u} + c_2\vec{v})$, and we'll use linearity to pair \vec{y} with each of the vectors as follows:

Distribute \vec{y} among the sum, by linearity (write this out on paper).

Now apply the linearity property of pulling out the scalars (write this out on paper).

Then apply the fact that \vec{y} was orthogonal to \vec{u} and \vec{v} .

What do we have after this last step?

 c_1

 $+ c_2$

 $=$

Question 9

Not complete

Points out of 2.00

Look at $A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$. What linear transformation is this?

the identity acting on 2-space written in homogeneous coordinates

projection onto the $\begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$ plane in 3-space

Other

The nullspace of A^T , the transpose, is always orthogonal to the column space of A . Notice that in this example, $A^T = A$ but that usually won't be the case. To see the orthogonality, open

<https://www.geogebra.org/m/qxgg7vrm>

and move the sliders. What do we see?

the nullspace is the z -axis, which is orthogonal to the column space, the $\begin{bmatrix} x \\ y \\ 0 \end{bmatrix}$ plane

the nullspace is the origin and the column space is the entire space

Other

Question 10

Not complete

Points out of 4.00

Least squares analysis is very useful in many real-life applications where we want a best fit [line](#) (it's linear!). However, typically, no [line](#) exactly goes through all of the given points. We want to find the [line](#) that fits as closely as possible to all of the points (we minimize the squared vertical distance between the points and the [line](#) using the Pythagorean theorem).

Typically the matrix we are looking at isn't square, so we can't take its [inverse](#), but we can take the [inverse](#) of $(A^T A)$! Then the key to finding the y-intercept and [slope](#) $\begin{bmatrix} b \\ m \end{bmatrix} = (A^T A)^{-1} A^T \vec{y}$ comes from a property of [subspaces](#): The [null space](#) of A^T , the [transpose](#) of A is [orthogonal](#) to the [column space](#) of A .

Let's look at an example of $A = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix}$

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix} \xrightarrow{r'_2 = -r_1 + r_2} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 3 \end{bmatrix} \xrightarrow{r'_3 = -r_1 + r_3} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 0 & 2 \end{bmatrix} \xrightarrow{r'_3 = -2r_2 + r_3} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$$

So both column 1 and column 2 are [pivot](#) columns and $\left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \right\}$ is a [basis](#) for the [column space](#) of A

To find the [null space](#) of A^T , notice that $A^T = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 3 \end{bmatrix}$ and we want to solve for [solutions](#) of $A^T \vec{x} = \vec{0}$ and write a [basis](#). The

[augmented matrix](#) is $\begin{bmatrix} 1 & 1 & 1 & 0 \\ 1 & 2 & 3 & 0 \end{bmatrix}$ which reduces to $\xrightarrow{r'_2 = -r_1 + r_2} \begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & 2 & 0 \end{bmatrix}$

Here x_3 is free so set it to t .

Use row 2 to solve for $x_2 = -2t$.

Use row 1 to solve for $x_1 = -x_2 - x_3 = -(-2t) - t = t$.

Thus the [nullspace](#) is $t \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}$ and $\left\{ \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \right\}$ is a [basis](#) for that [line](#).

What is $\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$?

What is $\begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$?

This shows that the [basis vector](#) we found for the [nullspace](#) of A^T is

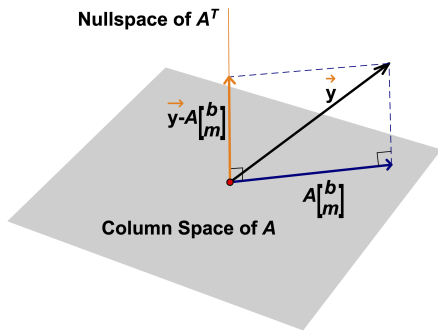
- parallel
 [orthogonal](#)

to both [basis vectors](#) we found for the [column space](#) of A .

Since the [basis vectors](#) generate the entire spaces, any [vector](#) in the [null space](#) of A^T must be

- parallel
 [orthogonal](#)

to any [vector](#) in the [column space](#) of A .



We can see that $A \begin{bmatrix} b \\ m \end{bmatrix}$ is the [vector](#) in the [column space](#) of A that is closest to \vec{y} , the [projection](#) of \vec{y} [onto](#) the [plane](#). In addition, $\vec{y} - A \begin{bmatrix} b \\ m \end{bmatrix}$ is in the [null space](#) of A^T , which gives us the way to compute best fit [lines](#)! Lots of course topics connect: [column space](#), [inverse](#), matrix algebra, [matrix multiplication](#), [nullspace](#), [orthogonality](#), [projection](#), solving linear equations, and [transpose](#).

Check

Question 11

Not complete

Points out of 1.00

To solidify and prepare for upcoming work, review and contemplate your knowledge and any questions that remain as related to definitions, concepts, computations, and examples from 6.1, including

- [inner product](#) of \vec{u} and \vec{v} and connection to the [dot product](#)
- [length](#) or [norm](#) of a [vector](#)
- [orthogonal vectors](#)

and consider 1.8 and 1.9, including

- [linear transformation](#): addition and scalar multiplication
- left multiplication matrix representations
- [dilation](#), [projection](#), [reflection](#), [rotation](#), [shear](#) (see Examples 2-5 in 1.8, Examples 2-3 in 1.9, and tables 1-4 in 2.8)
- the algebraic image of the unit axes as a way to find the matrix of the transformation
- [range of a linear transformation](#): the algebraic or geometric images or outputs, e.g. of the unit square as a way to visualize the transformation and understand its effects
- the [range](#), image or output of a [sheared](#) sheep

Since the material builds on itself, consider whether there is any material from before this module that you want to brush up on:

1.1

- algebra of linear equations: [coefficients](#) and variables
- geometry of linear equations in 2D and 3D: [lines](#) and [planes](#)
- [solution set](#): inconsistent: 0 [solutions](#); [consistent](#): 1 [unique](#) solution or [infinite solutions](#)
- matrix of a linear system: [coefficient](#) matrix, [augmented matrix](#), [triangular](#) form
- [row equivalent](#) systems
- algorithm for solving a linear system using [elementary row operations](#) of [replacement](#), [interchange](#), and [scaling](#)

1.2

- matrix of a linear system: [row echelon form](#) ([Gaussian](#)), [reduced row echelon form](#) ([Gauss-Jordan](#))
- [pivots](#): [pivot](#) position of a matrix, [pivot](#) column of a matrix
- row reduction algorithm we will most commonly use: [elimination](#) by forward phase and back substitution to [row echelon form](#)
- [solution set](#): inconsistent: 0 [solutions](#); [consistent](#): 1 [unique](#) solution or [infinite solutions](#) with [free variables](#) and [parametric solutions](#)

1.3

- algebra of [vectors](#): coordinates, [addition of vectors](#), [scalar multiplication of vectors](#), properties like [associativity](#) under addition (property ii on p. 29), a [linear combination](#) with [weights](#), zero [vector](#), [span](#) of a set of [vectors](#)=all the [linear combinations](#), is a [vector](#) in the [span](#)?, [vector](#) equation \rightarrow [augmented matrix](#)
- geometry of [vectors](#) in 2D and 3D: directed segment, [parallelogram](#) for addition, on same [line](#) for [scalar multiplication of vectors](#), origin=zero [vector](#), a [linear combination](#) geometrically in the [plane](#) or 3D, [span](#)=all the [linear combinations](#) geometrically in the [plane](#) or 3D, spaces of subsets of R^n [spanned](#) by [vectors](#)

1.4

- algebra of [matrix vector equation](#) $A\vec{x} = \vec{b}$:
 - [multiply a matrix and a column vector](#) by [linear combinations](#) of the columns of A using [weights](#) from \vec{x}
 - [span of the columns](#) of A = set of all [linear combinations](#) of the columns of A
 - [matrix vector equation](#) \rightarrow [vector](#) equation \rightarrow [augmented matrix](#)
 - equations [generic vectors](#) \vec{b} must satisfy to be in the [span](#) (Example 3)
 - [dot products](#) of rows of A with \vec{x} ,
- geometry of [solutions](#) of [matrix vector equation](#) $A\vec{x} = \vec{b}$: spaces of subsets of R^3 [spanned](#) by the column [vectors](#) of A , geometry of such spaces (Figure 1)
- Theorem 4: relationship of [consistency](#) of $A\vec{x} = \vec{b}$ to always being a [linear combination](#) to [spanning](#) the entire R^m , where m is the number of rows, to having a [pivot](#) position in every row of A .
- [identity matrix](#) I

1.5

- algebra of [homogeneous systems](#): $A\vec{x} = \vec{0}$
- algebraic [solutions](#) of homogenous systems always include the [trivial solution](#) $=\vec{0}$. nontrivial [solutions](#), if any exist, are [parameterized](#) in [parametric vector](#) form using [free variables](#) to express those as well as the variables with [pivots](#) and then decomposed algebraically to showcase the algebra and geometry giving $t\vec{v}$ or $s\vec{u} + t\vec{v}$ or similar, where each [free variable](#) is attached to a [vector](#).
- geometry of [solutions](#) of [homogeneous systems](#) are geometric spaces through the origin like [lines](#), [planes](#), or hyper[planes](#)
- algebra of nonhomogeneous systems: $A\vec{x} = \vec{b}$
- [solutions](#) of non[homogeneous system](#)s in [parametric vector](#) form can be decomposed algebraically to showcase the algebra and geometry like $\vec{p} + t\vec{v}$, [vectors](#) ending on the [line parallel](#) to \vec{v} or $\vec{p} + s\vec{u} + t\vec{v}$, [vectors](#) ending on the [plane](#) parallel to the one [spanned](#) by \vec{u}, \vec{v} ...
- geometry of [solutions](#) of non[homogeneous systems](#) are geometric spaces translated away from the origin via adding \vec{p}

1.7

- [linearly independent](#) set of [vectors](#) and connection to a [homogeneous equation](#) having only the [trivial](#) solution
- linearly dependent set of [vectors](#) and connection to nontrivial [solutions](#) existing and providing a dependence relation
- geometry of [linearly independent](#) set of 2 [vectors](#): independent directions in space versus along the same [line](#) (Figure 1)
- geometry of [linearly independent](#) set of 3 or more [vectors](#): no one [vector](#) is in the [span](#) of the rest, i.e. they are all needed to [span](#) the space versus redundancy in the geometric space they [span](#) in the sense that they aren't all needed to generate the same space under [linear combinations](#) (Figure 2)
- [linearly independent](#) columns of a matrix
- redundancy of $\vec{0}$ in a set of [vectors](#) $\{\vec{v}_1 = \vec{0}, \vec{v}_2, \dots, \vec{v}_n\}$ (Theorem 9)

2.1

- matrices: [diagonal matrix](#) [and [main diagonal](#)], zero matrix
- matrix operations: [matrix addition](#), [scalar multiplication of a matrix](#), [matrix multiplication](#), powers of a matrix, left (or right) multiplication, [transpose of a matrix](#)
- [matrix multiplication](#) by [linear combinations](#) of the columns of A using [weights](#) from the corresponding column of B or by the [dot products](#) of a row of A with the corresponding column of B.
- algebraic properties that do hold for [matrix multiplication](#): [associativity](#) and one-sided distributivity
- algebraic properties that don't hold for [matrix multiplication](#): [commutativity](#)

2.2

- matrices: [invertible \(nonsingular\)](#) matrix, [noninvertible \(singular\)](#) matrix, [elementary matrix](#)
- [determinant and inverse of a 2x2 matrix](#)
- connection between [invertibility](#) and [unique solutions](#)
- [inverse](#) of a product of matrices and [inverse](#) of a [transpose](#)

2.3

- [what makes a matrix invertible](#) for a square matrix (Theorem 8 statements aside from f. and i., which we haven't covered)
- [condition number](#) (numerical note on p. 123)

2.8

- [subspace](#) properties: closed under addition and scalar multiplication
- spaces associated to a matrix: [column space](#) and [null space](#)
- [basis](#): [linearly independent spanning set](#)
- [basis](#) for [column space](#) as the [pivot](#) columns
- [basis](#) for [null space](#) as the [vectors](#) attached to [free variables](#) in [parametric solutions](#) of the [homogeneous system](#) $A\vec{x} = \vec{0}$

2.9

- [dimension](#) of a space
- [rank](#) of a matrix ([dimension](#) of [column space](#))
- [nullity](#) of a matrix ([dimension](#) of [null space](#))
- [rank nullity theorem](#) (Theorem 14)
- [what makes a matrix invertible](#) continued: adding [rank](#) and [nullity](#) to Theorem 8 when the matrix is square

When you have finished reviewing and reflecting, select one of the following (both receive full credit)

I currently have no questions

I will continue solidifying and understand that help is available in Dr. Sarah's more extensive feedback that follows below each question after I finish and open back up an entire practice quiz (this is more extensive than the hints that I can access during the open quiz), in Dr. Sarah's glossary/Wiki which is embedded into ASULearn from the linked terms, in Dr. Sarah's office hours and forum, and in Math Lab and Tutoring

Check