

Here is the corrected version with the proper formula for vector projection:

## Linear Algebra Formula Guide

### **\*\*1. Vectors\*\***

- **\*\*Definition\*\***: A vector is an ordered set of numbers representing magnitude and direction in space.

$$\vec{v} = (v_1, v_2, \dots, v_n)$$

- **\*\*Scalars\*\***: A scalar is a single number that can scale a vector (e.g.,  $k$ ).

- **\*\*Vector Addition\*\***: The sum of two vectors is done element-wise.

$$\vec{v} + \vec{u} = (v_1 + u_1, v_2 + u_2, \dots, v_n + u_n)$$

- **\*\*Scalar Multiplication\*\***: Multiply each component of the vector by a scalar  $k$ .

$$k\vec{v} = (kv_1, kv_2, \dots, kv_n)$$

- **\*\*Dot Product (Inner Product)\*\***: The dot product of two vectors  $\vec{v}$  and  $\vec{u}$  is:

$$\vec{v} \cdot \vec{u} = v_1u_1 + v_2u_2 + \dots + v_nu_n$$

This yields a scalar.

- **\*\*Vector Projection\*\***: The projection of vector  $\vec{v}$  onto vector  $\vec{u}$  is:

$$Proj_{\vec{u}}\vec{v} = \frac{\vec{v} \cdot \vec{u}}{\|\vec{u}\|^2} \vec{u}$$

- **\*\*Cosine Similarity\*\***: The cosine of the angle between two vectors is given by:

$$\cos(\theta) = \frac{\vec{v} \cdot \vec{u}}{\|\vec{v}\| \|\vec{u}\|}$$

where  $\|\vec{v}\|$  is the norm (magnitude) of the vector.

- **\*\*Orthogonal Vectors\*\***: Two vectors are orthogonal if their dot product is zero:

$$\vec{v} \cdot \vec{u} = 0$$

- **\*\*Normal and Ortho-normal Vectors\*\***: - A **\*\*normal vector\*\*** has a magnitude (norm) of 1.

$$\|\vec{v}\| = 1$$

- **\*\*Ortho-normal vectors\*\*** are orthogonal and have a unit norm.

- **\*\*Vector Norm\*\***: The length (or magnitude) of a vector is:

$$\|\vec{v}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$$

- **\*\*Vector Space\*\***: A set of vectors that satisfies closure under addition and scalar multiplication.

- **\*\*Linear Combination\*\***: A vector  $\vec{v}$  is a linear combination of vectors  $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_k$  if:

$$\vec{v} = c_1\vec{u}_1 + c_2\vec{u}_2 + \dots + c_k\vec{u}_k$$

where  $c_1, c_2, \dots, c_k$  are scalars.

- **\*\*Linear Span\*\***: The set of all linear combinations of a set of vectors is called the span of those vectors.

- **\*\*Linear Independence\*\***: A set of vectors is linearly independent if none of the vectors can be expressed as a linear combination of the others.

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### **\*\*2. Matrices\*\***

- **Matrix Definition**: A matrix is a rectangular array of numbers arranged in rows and columns.

$$A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{pmatrix}$$

- **Matrix Addition**: Add corresponding elements of two matrices.

$$A + B = \begin{pmatrix} a_{11} + b_{11} & a_{12} + b_{12} & \dots & a_{1n} + b_{1n} \\ a_{21} + b_{21} & a_{22} + b_{22} & \dots & a_{2n} + b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} + b_{m1} & a_{m2} + b_{m2} & \dots & a_{mn} + b_{mn} \end{pmatrix}$$

- **Transpose of a Matrix**: Flip a matrix over its diagonal.

$$A^T = \begin{pmatrix} a_{11} & a_{21} & \dots & a_{m1} \\ a_{12} & a_{22} & \dots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{mn} \end{pmatrix}$$

- **Scalar Multiplication**: Multiply every element by a scalar  $k$ .

$$kA = \begin{pmatrix} ka_{11} & ka_{12} & \dots & ka_{1n} \\ ka_{21} & ka_{22} & \dots & ka_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ ka_{m1} & ka_{m2} & \dots & ka_{mn} \end{pmatrix}$$

- **Matrix Multiplication**: Multiply two matrices by summing the product of rows and columns.

$$(AB)_{ij} = \sum_{k=1}^n a_{ik}b_{kj}$$

- **Matrix Multiplication Properties**: 1. **Associativity**:  $A(BC) = (AB)C$  2. **Distributivity**:  $A(B + C) = AB + AC$  3. **Non-Commutativity**:  $AB \neq BA$  in general.

- **Hadamard Product**: Element-wise multiplication of two matrices.

$$(A \circ B)_{ij} = a_{ij}b_{ij}$$

- **Determinant**: For a  $2 \times 2$  matrix  $A$ , the determinant is:

$$\det(A) = a_{11}a_{22} - a_{12}a_{21}$$

For larger matrices, use cofactor expansion.

- **Identity Matrix**: A matrix with ones on the diagonal and zeros elsewhere.

$$I = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix}$$

- **Invertible Matrix and Inverse**: A matrix  $A$  is invertible if there exists a matrix  $A^{-1}$  such that:

$$AA^{-1} = A^{-1}A = I$$

- **Rank**: The rank of a matrix is the number of linearly independent rows or columns.

- **Trace**: The trace of a matrix is the sum of its diagonal elements.

$$\text{tr}(A) = a_{11} + a_{22} + \dots + a_{nn}$$

- **Symmetric Matrix**: A matrix is symmetric if  $A = A^T$ .

- **Diagonal Matrix**: A matrix is diagonal if all off-diagonal elements are zero.

- **Orthogonal Matrix**: A matrix is orthogonal if  $A^T A = I$ .

- **Ortho-Normal Matrix**: A matrix whose rows and columns are orthogonal unit vectors.

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### **3. Eigenvalues and Eigenvectors**

- **Eigenvalue Equation**: For a matrix  $A$ , a scalar  $\lambda$  is an eigenvalue if there exists a non-zero vector  $\vec{v}$  such that:

$$A\vec{v} = \lambda\vec{v}$$

$\vec{v}$  is the eigenvector corresponding to  $\lambda$ .

- **Characteristic Equation**: To find eigenvalues, solve the characteristic equation:

$$\det(A - \lambda I) = 0$$

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#### **4. Principal Components Analysis (PCA)**

- **Principal Components**: In PCA, the principal components are the eigenvectors of the covariance matrix of the data, and the eigenvalues represent the variance along those components.

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#### **5. Singular Value Decomposition (SVD)**

- **Definition**: For an  $m \times n$  matrix  $A$ , the singular value decomposition is:

$$A = U\Sigma V^T$$

where: -  $U$  is an  $m \times m$  orthogonal matrix. -  $\Sigma$  is an  $m \times n$  diagonal matrix with singular values. -  $V^T$  is the transpose of an  $n \times n$  orthogonal matrix  $V$ .