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| Scalars | What are scalars | A scalar is a single numeric quantity, fundamental in machine learning for computations, and deep learning for things like learning rates and loss values. | Ji | Importa |
| Vectors | What are Vectors | These are arrays of numbers that can represent multiple forms of data. In machine learning, vectors | | |
| | Row Vector and Column Vector | can represent data points, while in deep learning, they can represent features, weights, and biases. These are different forms of representing vectors. In both machine learning and deep learning, these representations matter because they affect computations like matrix multiplication, critical in areas | V | Very imp |
| | Distance from Origin | like neural network operations. This is the magnitude of the vector from the origin of the vector space. It's important in machine learning for operations like normalization, while in deep learning, it can help understand the magnitude | | |
| | Euclidean Distance between 2 vectors | This metric calculates the straight-line distance between two points or vectors. It's a common way to measure distance in many machine learning algorithms, including clustering and nearest neighbor | [L] L | Later |
| | Scalar Vector Addition/Subtraction(Shifting) | search, and also used in deep learning loss functions like Mean Squared Error. These operations can shift vectors, useful in machine learning for data normalization and centering. In deep learning, they are employed for operations like bias correction. | | |
| | Scalar Vector Multiplication/Division(Scaling) | Scalar and vector multiplication/division can be used for data scaling in machine learning. In deep learning, it's used to control the learning rate in optimization algorithms. | | |
| | Vector Vector Addition/Subtraction | These are fundamental operations used to combine or compare vectors, used across machine learning and deep learning for computations on data and weights. | | |
| | Dot Product of 2 vectors | This operation results in a scalar and is used in machine learning to compute similarity measures and perform computations in more advanced algorithms. In deep learning, it's crucial in operations like coloubles the work | | |
| | Angle between 2 vectors | calculating the weighted sums in a neural network layer. This can indicate the difference in direction between two vectors, useful in machine learning when comparing vectors in applications like recommender systems, and also in deep learning when examining the relationships between high-dimensional vectors. | | |
| | Unit Vectors | Unit vectors are important in machine learning for normalization and simplifying computations. They're equally significant in deep learning, particularly when it comes to generating directionally consistent | | |
| | Projection of a Vector | weight updates. The projection of a vector can be used for dimensionality reduction in machine learning and can be useful in deep learning for visualizing high-dimensional data or features. | | |
| | Basis Vectors | Basis vectors are used in machine learning for defining coordinate systems and working with transformations useful in algorithms like PCA and SVD. In deep learning, understanding basis vectors can be useful for interpreting the internal representations that a network learns. | | |
| | Equation of a Line in n-D | This generalizes the equation of a line to higher dimensions. It's used in machine learning for tasks like linear regression, and also crucial in deep learning where hyperplanes (an n-D extension of a line) are used to separate classes in high-dimensional space. | | |
| | Vector Norms[L] | Vector norms measure the length of a vector. In machine learning, they are fundamental in regularization techniques. In deep learning, they're used in measuring the size of weights, which can control the complexity of the model, and in normalization techniques such as batch and layer | | |
| | Linear Independence | normalization. Linear independence is a fundamental concept in many machine learning algorithms. | | |
| | Linear independence | Energy independence is a fundamental concept in many machine learning algorithms. For instance, in linear regression, if the predictor variables are not linearly independent (i.e., they are collinear), it can lead to issues like inflated variance and unstable estimates of parameters. PCA assumes that the principal components are linearly independent. | | |
| | Vector Spaces | The concept of a vector space is used throughout machine learning and deep learning. | | |
| | | In supervised learning, for example, the feature space (consisting of all possible feature vectors) and the output space (consisting of all possible output vectors) are vector spaces. In unsupervised learning, dustering algorithms often operate in a vector space, grouping together points that are close in this space. In deep learning, each layer of a neural network can be seen as transforming one vector space (the layer's input) into another vector space (the layer's output). | | |
| Matrix | What are Matrices? | A matrix is a two-dimensional array of numbers. In machine learning and deep learning, matrices are often used to represent sets of features, model parameters, or transformations of data. | | |
| | Types of Matrices | Different types of matrices (identity, zero, sparse, etc.) are used in various ways, such as the identity matrix in linear algebra operations, or sparse matrices for handling large, high-dimensional data sets efficiently. | | |
| | Orthogonal Matrices | Orthogonal matrices preserve the length and angle between vectors when they're multiplied. In machine learning, they're often used in PCA and SVD, which are dimension reduction techniques. In deep learning, orthogonal matrices are often used to initialize weights in a way that prevents vanishing or exploding gradients. | | |
| | Symmetric Matrices | These are matrices that are equal to their transpose. They're used in various algorithms because of their desirable properties, like always having real eigenvalues. Covariance matrices in statistics are an example of symmetric matrices. | | |
| | Diagonal Matrices | Diagonal matrices are used for scaling operations. In machine learning, they often appear in quadratic forms, while in deep learning, the diagonal matrix structure is used in constructing learning rate schedules for stoch | | |
| | Matrix Equality | Matrices are equal if they're of the same size and their corresponding elements are equal. This is fundamental to many machine learning and deep learning algorithms, for example, when checking convergence of algorithms. | | |
| | Scalar Operations on Matrices Matrix Addition and Subtraction | Scalar operations are used to adjust all elements of a natrix by a fixed value. This is used in machine learning and deep learning for data scaling, weight updates, and more. These operations are used to combine or compare datasets or model parameters, among other | | |
| | Matrix Multiplication | things. This operation is central to many algorithms in both machine learning and deep learning, like linear | | |
| | Transpose of a Matrix | regression or forward propagation in neural networks. Transposing a matrix is important for operations like computing the dot product between two vectors, or performing certain types of matrix multiplication. | | |
| | Determinant | The determinant of a matrix in machine learning is often used in statistics for tasks like multivariate normal distributions. In deep learning, the determinant is often used in advanced topics like volume-preserving transformations in flow-bosed models. | | |
| | Minor and Cofactor | These concepts are used in computing the inverse of a matrix or its determinant. While not directly used in many machine learning algorithms, they're fundamental to the underlying linear algebra. | | |
| | Adjoint of a Matrix | used in many machine learning algorithms, they're fundamental to the underlying linear algebra. The adjoint of a matrix is the transpose of the cofactor matrix. It's used in calculating the inverse of a matrix, which is crucial in solving systems of linear equations, often found in machine learning algorithms. | | |
| | Inverse of a Matrix | agoriums. The inverse of a matrix is used to solve systems of linear equations, which appears in methods like linear regression. In deep learning, pseudo-inverse matrices are used in techniques like Moore-Penrose inversion, which can be used to calculate weights in certain network architectures. | | |
| | Rank of a Matrix | The rank of a matrix is the maximum number of linearly independent rows or columns in the matrix. It's useful in machine learning for determining the solvability of linear systems (like in linear regression), and in deep learning, it's used to investigate the properties of weight matrices. | | |
| | Coulumn Space and Null Space[L] | The column space represents the set of all possible linear combinations of the vectors in the matrix. The null space represents the solutions to the homogeneous equation Ax=0. They are important for understanding the solvability of a system of equations, which can arise in algorithms like linear regression. | | |
| | Change of Basis [L] | The change of basis is used in machine learning and deep learning to transform data or model parameters between different coordinate systems. This is often used in dimensionality reduction | | |

| | Solving a System of linear equations | Many machine learning algorithms, including linear and logistic regression, essentially boil down to solving a system of linear equations. In deep learning, backpropagation can be seen as a process of solving a system of equations to find the best parameters. | |
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| | Linear Transormations | Linear transformations are used to map input data to a different space, preserving relationships between points. This is a fundamental operation in many machine learning and deep learning algorithms, from simple regression to complex neural networks. | |
| | 3d Linear Transformations | These transformations preserve points, lines, and planes. They're often used in machine learning for visualization and geometric interpretations of data. | |
| | Matrix Multiplication as Composition | In both machine learning and deep learning, sequential transformations can be compactly represented as a single matrix, created by multiplying the matrices representing the individual transformations. This is used extensively in deep learning where each layer of a neural network can be seen as a matrix transformation of the input. | |
| | Linear Transformation of Non-square Matrix | Non-square matrices are common in machine learning and deep learning because the number of features doesn't usually match the number of data points. Their transformations can be used for dimensionality reduction or feature construction. | |
| | Dot Product | Dot product is a way of multiplying vectors that results in a scalar. It's used in machine learning to compute similarity measures and in deep learning, for instance, to calculate the weighted sum of inputs in a neural network layer. | |
| | Cross Product [L] | The cross product of two vectors results in a vector that's orthogonal to the plane containing the original vectors. In machine learning, it's used less often due to its restriction to three dimensions, but it might appear in specific applications that involve 3D data. | |
| Tensors | What are Tensors | Tensors are a generalization of scalars, vectors, and matrices to higher dimensions. In machine learning and deep learning, they are used to represent and manipulate data of various dimensionalities, such as 1D for time series, 2D for images, or 3D for videos. | |
| | Importance of Tensors in Deep Learning Tensor Operations | Operations such as tensor addition, multiplication, and reshaping are common in deep learning | |
| | Data Representation using Tensors | algorithms for manipulating data and weights. In machine learning and deep learning, tensors are used to represent multidimensional data. For instance, an image can be represented as a 3D tensor with dimensions for height, width, and color channels. | |
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| Eigen Values and Vectors | Eigen Vectors and Eigen Values | These concepts are used in machine learning for dimensionality reduction (PCA), understanding linear transformations, and more. In deep learning, they're used to understand the behavior of optimization algorithms. | |
| | Eigen Faces [L] | This is a specific application of eigenvectors used for facial recognition. The 'eigenfaces' represent the directions in which the images of faces show the most variation. | |
| | Principal Component Analysis [L] | PCA is a dimensionality reduction technique used in machine learning to remove noise, visualize high-dimensional data, and more. While not used as often in deep learning, it's sometimes used for visualizing learned embeddings or activations. | |
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| Matrix Factorization | LU Decomposition[L] | LU decomposition is a method of solving linear equations, which can arise in machine learning models like linear regression. While not often used directly in deep learning, it's a fundamental linear algebra operation. | |
| | QR Decomposition[L] | QR decomposition can be used in machine learning for solving linear regression problems or for numerical stability in certain algorithms. In deep learning, it's often used in some optimization methods. | |
| | Eigen Decompositon[L] | This is used in machine learning to solve problems that involve understanding the underlying structure of data, like PCA. In deep learning, eigen decomposition can be used to analyze the weights of a model. | |
| | Singular Value Decomposition[L] | SVD is a method used in machine learning for dimensionality reduction, latent semantic analysis, and more. In deep learning, SVD can be used for model compression or initialization. | |
| | Non-Negative Matrix Factorization[L] | NMF is a matrix factorization technique often used in machine learning for dimensionality reduction and feature extraction in datasets where the data and the features are non-negative. In deep learning, NMF is less common, but might be used in some specific data preprocessing or analysis tasks. | |
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| Advanced Topics | Moore-Penrose Pseudoinverse[L] | The pseudoinverse provides a way to solve systems of linear equations that may not have a unique solution. This is useful in machine learning algorithms such as linear regression. In deep learning, it can be used in accluditing the weights of certain network architectures. | |
| | Quadratic Forms[L] | Quadratic forms appear in many machine learning algorithms such as support vector machines and Gaussian processes. In deep learning, they are often found in the formulation of loss functions and regularization terms. | |
| | Positive Definite Matrices[L] | Positive definiteness is a property of matrices that guarantees the existence of a unique solution to certain systems of equations, which is used in many machine learning algorithms. In deep learning, positive definite matrices appear in the analysis of optimization methods, ensuring certain desirable properties like convergence. | |
| | Hadamard Product[L] | The Hadamard product is the element-wise multiplication of matrices. It is used in machine learning in various ways, for instance, in computing certain types of features. In deep learning, it's used in operations such as gating in recurrent neural networks (RNNs). | |
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| Tools and Libraries | Numpy | Numpy is a fundamental library for numerical computation in Python and is used extensively in both machine learning and deep learning for operations on arrays and matrices. | |
| | Scipy[L] | Scipy is a library for scientific computing in Python that builds on Numpy. It's used in machine learning for tasks like optimization, statistical testing, and some specific models like hierarchical clustering. In deep learning, Scipy might be used for tasks like image processing or signal processing. | |