Application of matrices in real life

A student of computer science once struggled with understanding the applications of complex matrices in real-life scenarios. Despite having a strong background in linear algebra, they found themselves puzzled when it came to explaining how complex matrices could be used in everyday situations. The student's curiosity led them to explore various fields where complex matrices might have practical uses. They were informed about the role of electromagnetism and complex matrices, but found that this application was somewhat abstract. However, another area where linear maps play a crucial role is in geometry. The transformation represented by a matrix can be used to study rotations in a plane. For instance, the following matrix is typically utilized to describe rotations about the origin in a 2D plane: $$\begin{pmatrix} \cos(\phi) & -\sin(\phi)\\ \sin(\phi) & \cos(\phi) \end{pmatrix}$$ This technique seems unusual but is commonly used when solving physics problems. It enables the student to rotate coordinate systems, which simplifies their work and makes it more manageable. A real-life example of this concept can be found in computer graphics, where 3D models are often rotated and transformed to display them on a 2D screen. The QR decomposition of a matrix is essential in this process as it helps in decomposing the transformation into simpler components. When trading stocks, you should focus on complete units rather than fractional pieces. This eliminates confusion about the direction of transactions and allows for more straightforward calculations. Vector addition applies naturally to stock orders: selling two Microsoft stocks and buying one Apple stock can be combined with buying two Apples and five IBMs, resulting in a net change of (-2,3,5). The lack of a natural order for the basis (e.g., listing Microsoft first) is also beneficial. Multiplying by a scalar represents increasing or decreasing the number of stocks involved. The price function acts as a linear mapping from stock orders to money values, making it easy to calculate costs and earnings. This setup has several advantages over traditional Euclidean spaces, including no inherent scalar product. The absence of an intrinsic scalar product prevents meaningless calculations about multiplying certain orders with others. Determinants hold significant theoretical importance in mathematics but have limited practical use due to their computational complexity. Evaluating a determinant for large matrices (n > 1000) is often impractical unless the terms are close to unity, making it difficult for efficient computer calculations. In contrast, most numerical applications rely on matrix techniques for solving equations. Real-world problems typically involve systems of thousands or even millions of equations, but modern computers can handle such calculations efficiently. Examples include partial differential equations and large-scale optimization problems, which rely heavily on matrix operations for their solution. The heat equation, which models how temperature changes over time and space, leads to a tridiagonal matrix. To approximate its derivatives, we use backward difference for time and central difference for space. This results in a matrix that can be represented as (5), with special properties when using LU decomposition. LU decomposition is used to solve linear equations, which define linear spaces. The process of solving these equations can lead to various outcomes, such as no intersection, one point of intersection, or multiple points of intersection. Solving linear equations also has applications in geometry and matrix inversion, which is useful whenever working with matrices. Inverting a matrix allows us to solve equations like $AB = 10A$, where A and B are matrices. One practical application of matrix inversion is least squares regression. Given data arranged in a matrix X that predicts response values $\mathbf{y}$, the "best linear estimate" can be calculated using $(X^T X)^{-1} X^T \mathbf{y}$, where $\widehat{\beta}$ are the parameters. The text emphasizes that solving linear equations and working with matrices is not just about applying a specific algorithm, but also about understanding the underlying concepts and how they relate to geometry and other fields. Applying matrix inversion in real-world scenarios can be crucial due to its direct relevance to handling massive datasets. Since these datasets often equate to enormous matrices, computing their inverses rapidly poses significant challenges. Although methods such as QR/SVD/Cholesky factorisation exist for circumventing the inversion step when speed is a concern, they offer valuable alternatives that may warrant further exploration. Eigenvectors are pivotal in understanding the dimensions of data, essentially serving as axes along which these dimensions stretch. Eigenvalues represent how far apart these dimensions lie. The importance of eigenvectors lies in their utility with dimension reduction techniques like PCA (Principal Component Analysis), which significantly helps in scenarios where reducing the number of dimensions is essential for practical purposes. For instance, when attempting to find similarities among a large set of pictures and represent them in 2D without knowing the specific criteria or their count, simple non-guided dimension reduction can be used. This process not only aids in identifying partial clusters but also reveals how different criteria affect each other when combined. Eigenvectors play a fundamental role in face recognition by allowing for the association of names with images. They are essentially eigenfaces, which are crucial components in image classification tasks such as face recognition. Given that an image typically consists of numerous pixels (often over 1348 dimensions), reducing this to a more manageable number while preserving the essential features is critical. This is where PCA steps in by finding eigenvectors from input images. These eigenvectors can be seen as basis images from which complete images can be reconstructed, making them invaluable for pre-processing images before classification tasks like face recognition. The gain here is substantial, as not only is CPU workload reduced, but the information to store or process each image is significantly condensed into a vector of eigenvalues instead of a vast array of pixel values. EigenVectors Explain how much variance is lost in pixels, determined by eigenvector number and choice, also known as "number of components" after principal component analysis (PCA). PCA shows that using more eigenvectors allows us to reconstruct images with higher accuracy. For example, 32 eigenvectors can recover over 80% of the original picture, while 150 eigenvectors allow for recovery of more than 95%. The technique has applications similar to image compression but also enables direct relationships between images and names by training a classifier on known images. Applying mathematical concepts in real-world scenarios enables you to leverage existing knowledge and find solutions that meet your specific needs, ultimately providing a personalized approach to addressing challenges.

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