

Apply The Gram-Schmidt Orthonormalization Process To Transform The Given Basis For $\mathbb{R}^n$ Into An Orthonormal

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The Gram-Schmidt orthonormalization process is a fundamental algorithm in linear algebra that transforms a set of linearly independent vectors into an orthonormal set. When working within the Euclidean space $\mathbb{R}^n$, this process is particularly useful for simplifying problems such as projection, least squares approximation, and diagonalization of matrices. By converting a basis into an orthonormal basis, computations become more straightforward, and the geometric relationships between vectors are clarified. In this article, we explore the step-by-step procedure of the Gram-Schmidt process, its mathematical foundation, and practical applications through detailed examples.

Understanding the Foundations of Gram-Schmidt Orthonormalization

What Is a Basis in $\mathbb{R}^n$?

A basis in $\mathbb{R}^n$ is a set of n linearly independent vectors $\{v_1, v_2, \dots, v_n\}$ that spans the entire space. Any vector in $\mathbb{R}^n$ can be expressed as a linear combination of these basis vectors. The goal of the Gram-Schmidt process is to convert this basis into an orthonormal basis, where all vectors are mutually orthogonal and each has unit length.

Importance of Orthonormal Bases

Orthonormal bases simplify many linear algebra operations, including projections, coordinate transformations, and matrix computations. They allow for easy computation of vector coefficients, as the inner product of an orthonormal basis vector with any vector directly yields the coordinate component along that basis vector.

Mathematical Foundation of the Gram-Schmidt Process

Key Concepts and Definitions

- **Inner Product:** For vectors u and v in $\mathbb{R}^n$, the inner product is defined as $\langle u, v \rangle = u^T v$.
- **Orthogonality:** Two vectors u and v are orthogonal if $\langle u, v \rangle = 0$.
- **Orthonormal Vectors:** Vectors that are both orthogonal and of unit length, i.e., $\langle u, u \rangle = 1$.

Core Idea of Gram-Schmidt

The process constructs an orthogonal set $\{u_1, u_2, \dots, u_n\}$ from the original basis $\{v_1, v_2, \dots, v_n\}$ by sequentially removing components of vectors that are parallel to previously constructed vectors. Once the orthogonal set is obtained, it is normalized to produce an orthonormal basis.

Step-by-Step Procedure of the Gram-Schmidt Method

Initial Setup

1. Start with a linearly independent set of vectors $\{v_1, v_2, \dots, v_n\}$.
2. Set the first orthogonal vector u_1 as v_1 .

Iterative Construction of Orthogonal Vectors

For each subsequent vector v_k , perform the following:

1. Subtract the projection of v_k onto each of the previously computed orthogonal vectors u_j (for $j = 1, 2, \dots, k-1$):
2. Mathematically, this is expressed as:

$$u_k = v_k - \sum_{j=1}^{k-1} (\langle v_k, u_j \rangle / \langle u_j, u_j \rangle) u_j$$

Repeat this process for all vectors in the original basis to obtain a set of mutually orthogonal vectors $\{u_1, u_2, \dots, u_n\}$.

Normalization to Achieve Orthonormality

1. Normalize each orthogonal vector u_k to obtain the orthonormal vector e_k :

$$e_k = u_k / ||u_k||, \text{ where } ||u_k|| = \sqrt{\langle u_k, u_k \rangle}$$

The resulting set $\{e_1, e_2, \dots, e_n\}$ forms an orthonormal basis for $\mathbb{R}^n$.

Practical Example of Gram-Schmidt Orthonormalization

Given Basis Vectors

Suppose we have the basis vectors in $\mathbb{R}^3$:

$$v_1 = (1, 1, 0)$$

$$v_2 = (1, 0, 1)$$

$$v_3 = (0, 1, 1)$$

Constructing the Orthonormal Basis

Step 1: Compute u_1

$$u_1 = v_1 = (1, 1, 0)$$

Step 2: Compute u_2

$$\langle v_2, u_1 \rangle = (1)(1) + (0)(1) + (1)(0) = 1$$

$$\langle u_1, u_1 \rangle = 1^2 + 1^2 + 0^2 = 2$$

Projection of v_2 onto u_1 :

$$= (1 / 2) u_1 = (1/2)(1,1,0) = (0.5, 0.5, 0)$$

Now, u_2 :

$$= v_2 - \text{projection}$$

$$= (1, 0, 1) - (0.5, 0.5, 0) = (0.5, -0.5, 1)$$

Step 3: Compute u_3

$$\langle v_3, u_1 \rangle = (0)(1) + (1)(1) + (1)(0) = 1$$

$$\langle u_1, u_1 \rangle = 2 \text{ (from previous step)}$$

Projection of v_3 onto u_1 :

$$= (1/2) (1, 1, 0) = (0.5, 0.5, 0)$$

Similarly, $\langle v_3, u_2 \rangle$:

$$= (0)(0.5) + (1)(-0.5) + (1)(1) = (-0.5) + 1 = 0.5$$

$$\langle u_2, u_2 \rangle = (0.5)^2 + (-0.5)^2 + 1^2 = 0.25 + 0.25 + 1 = 1.5$$

Projection of v_3 onto u_2 :

$$= (0.5 / 1.5) u_2 = (1/3)(0.5, -0.5, 1) = (1/6, -1/6, 1/3)$$

Now, u_3

Frequently Asked Questions

What is the main purpose of the Gram-Schmidt process in linear algebra?

The Gram-Schmidt process is used to convert a set of linearly independent vectors into an orthonormal set, facilitating easier computations and analyses in vector spaces.

How do you apply the Gram-Schmidt process to a basis in R^n ?

To apply Gram-Schmidt, start with your original basis vectors, orthogonalize each by subtracting projections onto previous vectors, and then normalize each orthogonal vector to produce an orthonormal basis.

What are the key steps involved in the Gram-Schmidt orthonormalization process?

The key steps are: 1) Choose the first vector and normalize it; 2) For each subsequent vector, subtract its projections onto all previously orthogonalized vectors; 3) Normalize the resulting vectors to obtain an orthonormal set.

Can the Gram-Schmidt process be applied to any basis in $\mathbb{R}^n$?

Yes, it can be applied to any linearly independent set of vectors in $\mathbb{R}^n$ to produce an orthonormal basis spanning the same subspace.

What is the significance of normalization in the Gram-Schmidt process?

Normalization ensures that each vector in the orthogonal set has unit length, transforming the set into an orthonormal basis which simplifies many vector computations.

How do you handle zero vectors during the Gram-Schmidt process?

If a vector becomes zero during orthogonalization, it indicates linear dependence with previous vectors, and such vectors are typically omitted from the basis.

Is the Gram-Schmidt process unique for a given basis?

The process produces a unique orthonormal basis up to the order of vectors, but the specific vectors can vary depending on the order in which the basis vectors are processed.

What are common applications of the Gram-Schmidt orthonormalization in data science?

It is used in PCA (Principal Component Analysis), QR decomposition, signal processing, and in constructing orthonormal bases for subspaces to simplify computations.

Are there numerical stability concerns when applying

Gram-Schmidt, and how can they be addressed?

Yes, the classical Gram-Schmidt process can suffer from numerical instability; modified Gram-Schmidt is often used to improve stability in computational applications.

Can the Gram-Schmidt process be extended to infinite-dimensional spaces?

Yes, in functional analysis, the Gram-Schmidt process can be extended to infinite-dimensional inner product spaces, such as Hilbert spaces, with considerations for convergence.

Additional Resources

Apply The Gram-Schmidt Orthonormalization Process To Transform The Given Basis For $\mathbb{R}^n$ Into An Orthonormal

The Gram-Schmidt orthonormalization process is a fundamental technique in linear algebra, widely used for converting a set of linearly independent vectors into an orthonormal basis. This process is crucial in numerous applications, including numerical analysis, quantum mechanics, signal processing, and more. Understanding how to apply Gram-Schmidt to transform a given basis of $\mathbb{R}^n$ into an orthonormal basis is essential for both theoretical insights and practical computations.

In this detailed exploration, we will delve into the theoretical foundation of the Gram-Schmidt process, step-by-step methodology, detailed examples, common pitfalls, and practical considerations for implementation.

Understanding the Foundations of Gram-Schmidt Orthonormalization

What Is an Orthonormal Basis?

An orthonormal basis for $\mathbb{R}^n$ is a set of vectors $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n\}$ satisfying two key properties:

- Orthogonality: Each pair of distinct vectors is orthogonal, i.e., $\mathbf{u}_i \cdot \mathbf{u}_j = 0$ for $i \neq j$.
- Normalization: Each vector has unit length, i.e., $\|\mathbf{u}_i\| = 1$.

Having an orthonormal basis simplifies many computations, such as projections, coordinate transformations, and matrix diagonalization.

Linear Independence and the Need for Orthonormalization

Given a basis $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ for a subspace $(V \subseteq \mathbb{R}^n)$, the vectors are linearly independent but not necessarily orthogonal or of unit length. To facilitate easier calculations, it's advantageous to convert this basis into an orthonormal basis spanning the same subspace.

The Gram-Schmidt process provides a systematic way to do this, taking an initial linearly independent set and producing an orthonormal set that spans the same subspace.

The Gram-Schmidt Orthonormalization Process: Step-by-Step Explanation

Overview of the Procedure

Suppose you are given a basis $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ for a subspace (V) of $\mathbb{R}^n$. The goal is to produce an orthonormal basis $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\}$ for (V) .

The process involves iteratively orthogonalizing each vector against all previously obtained vectors and then normalizing it.

Mathematical Steps

Given vectors $(\mathbf{v}_1, \dots, \mathbf{v}_k)$:

1. Initialize:

$$\begin{aligned} \mathbf{u}_1 &= \frac{\mathbf{v}_1}{\|\mathbf{v}_1\|} \end{aligned}$$

2. Iterate for each $(j = 2, \dots, k)$:

- Orthogonalize:

$$\begin{aligned} \mathbf{w}_j &= \mathbf{v}_j - \sum_{i=1}^{j-1} (\mathbf{v}_j \cdot \mathbf{u}_i) \mathbf{u}_i \end{aligned}$$

Here, $(\mathbf{w}_j)$ is orthogonal to all previous $(\mathbf{u}_i)$.

- Normalize:

$$\begin{aligned} \mathbf{u}_j &= \frac{\mathbf{w}_j}{\|\mathbf{w}_j\|} \end{aligned}$$

3. Result:

The set $(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k)$ is orthonormal and spans the same subspace as the original set.

Applying Gram-Schmidt: A Concrete Example

Let's consider a specific example in $\mathbb{R}^3$:

Suppose the basis vectors are:

$$\begin{aligned} \mathbf{v}_1 &= \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{v}_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \quad \mathbf{v}_3 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \end{aligned}$$

Step 1: Normalize $(\mathbf{v}_1)$:

$$\begin{aligned} \mathbf{u}_1 &= \frac{\mathbf{v}_1}{\|\mathbf{v}_1\|} = \frac{1}{\sqrt{1^2 + 1^2 + 0^2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \end{aligned}$$

Step 2: Orthogonalize $(\mathbf{v}_2)$ against $(\mathbf{u}_1)$:

$$\text{Projection of } \mathbf{v}_2 \text{ onto } \mathbf{u}_1: \quad \left(\mathbf{v}_2 \cdot \mathbf{u}_1 \right) \mathbf{u}_1$$

Calculate the dot product:

$$\begin{aligned} \mathbf{v}_2 \cdot \mathbf{u}_1 &= \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \cdot \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \\ &= \frac{1}{\sqrt{2}} (1 \cdot 1 + 0 \cdot 1 + 1 \cdot 0) = \\ &= \frac{1}{\sqrt{2}} (1 + 0 + 0) = \frac{1}{\sqrt{2}} \end{aligned}$$

Projection:

$$\begin{aligned} \frac{1}{\sqrt{2}} \times \mathbf{u}_1 &= \frac{1}{\sqrt{2}} \times \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \end{aligned}$$

Orthogonal component:

$$\begin{aligned} \mathbf{w}_2 &= \mathbf{v}_2 - \text{projection} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = \\ &= \begin{bmatrix} 1 - \frac{1}{2} \\ 0 - \frac{1}{2} \\ 1 - 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \\ 1 \end{bmatrix} \end{aligned}$$

Normalize $(\mathbf{w}_2)$:

$$\begin{aligned} \|\mathbf{w}_2\| &= \sqrt{\left(\frac{1}{2}\right)^2 + \left(-\frac{1}{2}\right)^2 + 1^2} = \sqrt{\frac{1}{4} + \frac{1}{4} + 1} = \\ &= \sqrt{\frac{1}{2} + 1} = \sqrt{\frac{3}{2}} = \frac{\sqrt{6}}{2} \end{aligned}$$

Thus,

$$\begin{aligned} \mathbf{u}_2 &= \frac{\mathbf{w}_2}{\|\mathbf{w}_2\|} = \frac{2}{\sqrt{6}} \\ \begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \\ 1 \end{bmatrix} &= \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \end{aligned}$$

Step 3: Orthogonalize $(\mathbf{v}_3)$ against $(\mathbf{u}_1)$ and $(\mathbf{u}_2)$:

- Projection onto $(\mathbf{u}_1)$:

$$\mathbf{v}_3 \cdot \mathbf{u}_1 = \frac{1}{\sqrt{2}} (0 \cdot 1 + 1 \cdot 1 + 1 \cdot 0) = \frac{1}{\sqrt{2}} (0 + 1 + 0) = \frac{1}{\sqrt{2}}$$

Projection:

$$\frac{1}{\sqrt{2}} \cdot \mathbf{u}_1 = \frac{1}{\sqrt{2}}$$

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