1.4 Systems of Linear Equations

Question: When is \vec{b} found in $Span(\{\vec{v}_1, \vec{v}_2, ..., \vec{v}_n\})$?

Example: Let $\vec{b} = \langle -6, 4, 8 \rangle$. Is \vec{b} in:

- L : The line $Span(\{\langle 9, -6, -12 \rangle\})$?
- Π_1 : The plane with Cartesian equation 2x 4y + 5z = 0?
- Π_2 : The plane with Cartesian equation 2x + 9y 3z = 0?

Example: Decide if $\vec{b} = \langle 10, -9, -5, -7 \rangle$ is a member of the Span of the following five vectors from \mathbb{R}^4 :

$$\langle 3, -4, 1, -6 \rangle, \langle 2, -3, 2, -5 \rangle, \langle 1, 1, -9, 5 \rangle,$$

 $\langle 1, -2, 2, -4 \rangle, \langle 9, -7, -8, -3 \rangle$

If so, express \vec{b} as a linear combination of these five vectors in the simplest way possible.

Follow up:

Matrices

Definition: A matrix is a rectangular table of numbers organized into *m* rows and *n* columns. We say that the dimension of the matrix is $m \times n$, pronounced "*m* by *n*." If *A* is an $m \times n$ matrix, we call the number or entry in row *i* column *j* as $(A)_{i,j}$ or $a_{i,j}$. Thus we write:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix}$$

In particular, an $m \times 1$ matrix will be called a *column matrix*, and a $1 \times n$ matrix will be called a *row matrix*.

If $S = \{ \vec{v}_1, \vec{v}_2, ..., \vec{v}_n \}$ is a set of vectors from \mathbb{R}^m , and $\vec{b} \in \mathbb{R}^m$, we can form the $m \times (n+1)$ augmented matrix:

$$A = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_n & | & \vec{b} \end{bmatrix},$$

where we assemble the vectors in *S* into *columns*, and we separate the last column \vec{b} with a dashed line to indicate that it represents the right side of a system of equations. We normally use x_1 , x_2 , ..., x_n to be the variables *associated* to each column.

The Reduced Row Echelon Form or RREF

Definition: We will say that an $m \times (n + 1)$ augmented matrix is in **row echelon form** if it satisfies the following conditions:

1. All the rows consisting entirely of zeroes are at the *bottom* of the matrix.

2. The first non-zero entry of any row is the number 1. This entry is called a "*leading 1*."

3. If the next row is non-zero, its leading 1 is to the *right* of the previous leading 1.

Furthermore, we say that the matrix is in *reduced row echelon form*, or *rref*, if the matrix satisfies the additional condition:

4. All the entries *above* a leading 1 are also zeroes.

If column j contains a leading 1, we call x_j a *leading variable*, and column j is a *leading column*.

Otherwise, we call x_j a *free variable*.

Conditions 1 and 3 forces all entries *below* a leading 1 to be zeroes. Condition 4 forces all entries *above* the leading 1 to be zeroes as well.

The vectors $\vec{e}_1, \vec{e}_2, ..., \vec{e}_k$ will appear in the leading columns, in that order, for some $k \leq m$.

Example:

$$A = \begin{bmatrix} 1 & 0 & -4 & 0 & 9 & 2 & | & 6 \\ 0 & 1 & 3 & 0 & 6 & -5 & | & -9 \\ 0 & 0 & 0 & 1 & -2 & 7 & | & -4 \\ 0 & 0 & 0 & 0 & 0 & 0 & | & 0 \end{bmatrix}$$

Elementary Row Operations

Definition: An *elementary row operation* is any one of the following actions on a matrix:

Type:

Notation:

 $R_i \rightarrow cR_i$.

 $R_i \leftrightarrow R_j$.

- 1. Multiply row *i* by a nonzero scalar *c*
- 2. Exchange row *i* and row *j*
- 3. Add *c* times row *j* to row *i*

 $R_i \rightarrow R_i + cR_j$.

Invariance of Solution Sets

Theorem — The Invariance of Solution Sets:

An elementary row operation *does not change* the solution set of an augmented matrix. In other words, if A is an augmented matrix and B is obtained from A using an elementary row operation, then the solution set of the system corresponding to Ais exactly the same as the solution set of the system corresponding to B.

The Uniqueness of the RREF

Theorem — The Uniqueness of the Reduced Row Echelon Form:

The reduced row echelon form of a matrix is *unique*. Thus, if we start with a matrix A and arrive at two matrices H and J using a different sequence of row operations, and both H and J are in rref, then H = J.

The Gauss-Jordan Algorithm

The Gauss-Jordan Algorithm

1. Ignore all the leftmost columns that contain only zeros, if there are any.

2. Starting from the top row and going downward, find the first non-zero entry, called the *pivot*.

3. If the pivot is not in the top row, *exchange* the top row with the pivot's row (this is a Type 2 row operation).

4. Produce a leading 1 in the top row by *dividing* the entire top row by the pivot (this is a Type 1 row operation). We call this step *normalizing* the row.

5. Make the entries below the leading 1 *all zeroes* by adding suitable multiples of the top row to each row below it (these are Type 3 row operations).

6. Now, cover the top row, the leading column and all columns to its left, and repeat steps 1 through 5 on the smaller submatrix.

If we were to stop at Step 6, the algorithm above would be called *Gaussian Elimination*. It results in a matrix in *row echelon form*. Now we continue from *right to left*, working *upwards* as we go:

7. Starting at the rightmost leading 1, produce zeroes above the leading 1 by adding suitable multiples of this row to each row above it (again, these are Type 3 row operations).

8. Repeat Step 7 on the next rightmost leading 1, moving leftward until the matrix is in *reduced row echelon form*.

An Intelligent Modification:

To avoid fractions, produce a leading "1" using a Type 3 operation instead: multiply a row by a suitable constant and add it to another row to get a leading 1.

Success and Failure

 \vec{b} is **not** in Span(S) if we get a row consisting entirely of zeroes except for a non-zero entry in the rightmost column.