### Lecture 14

#### **Dimension and Rank**

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#### **Today's Lecture: Outline**

Today ... Dimension, rank

- 1. Basis and Dimension
- 2. Rank

Strang's book: Sec 3.3, 3.4

After this lecture, you should be able to

- 1. Identify basis of common spaces
- 2. Explain why the dimension of a linear space is a well-defined
- 3. Compute the number of solutions for different (r,m,n)

#### **Roadmap of Linear Systems**



# Review of Related Contents

The complete solution is

$$\mathbf{x}_p + N(A) = \mathbf{x}_p + \operatorname{span}\{\mathbf{v}_1, \dots, \mathbf{v}_m\}.$$

**Question**: Is there a "simpler" way to express span{ $v_1, ..., v_m$ }?

 $\mathbf{u}_1, \dots, \mathbf{u}_n$  are linearly independent iff the following holds:  $c_1\mathbf{u}_1 + \dots + c_k\mathbf{u}_k = 0$  only happens when  $c_1 = \dots = c_k = 0$ .

**General answer:** If M's columns are independent, then cannot use fewer vectors to express it.

## Part I Basis

Strang's book Sec. 3.4

Claim 14.1 (linear dependence and span) Suppose *V* is a linear space over  $\mathbb{R}$ . Suppose  $\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k \in V$ . If  $\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k$  are linear dependent, then there exists  $t \in \{1, ..., k\}$ such that: i)  $\mathbf{u}_t$  is a linear combination of  $\mathbf{u}_1, ..., \mathbf{u}_{t-1}, \mathbf{u}_{t+1}, ..., \mathbf{u}_k$ . ii) span $\{\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k\} = \text{span}(\{\mathbf{u}_1, ..., \mathbf{u}_{t-1}, \mathbf{u}_{t-1}, ..., \mathbf{u}_k\})$ 

#### In words:

**First,** LD <==> one element can be spanned by others.

Second, the span of these elements can be further simplified.

**Corollary**: If  $\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k$  are linear independent, then span  $\{\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k\}$  can NOT be simplified (i.e. expressed as the span of k - 1 elements)

4 unit vectors 
$$\begin{bmatrix} 1\\0\\0\\0\end{bmatrix}, \begin{bmatrix} 0\\1\\0\\0\end{bmatrix}, \begin{bmatrix} 0\\0\\1\\0\end{bmatrix}, \begin{bmatrix} 0\\0\\1\\0\end{bmatrix}, \begin{bmatrix} 0\\0\\0\\1\end{bmatrix}$$
 span  $\mathbb{R}^4$ .

**Q1**: Can we use 3 unit vectors to span  $\mathbb{R}^4$ ?

**Q2**: Are there 3 vectors that span  $\mathbb{R}^4$ ?

$$5 \text{ vectors} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 2 \\ 2 \\ 2 \\ 2 \end{bmatrix} \text{ span } \mathbb{R}^4.$$

**Q1**: Can we use 4 vectors in these 5 to span  $\mathbb{R}^4$ ?

**Q2**: Can we use 3 vectors in these 5 to span  $\mathbb{R}^4$ ?

Answer to Q1: No, because they are \_\_\_\_\_

Thus, {e<sub>1</sub>,...,e<sub>4</sub>} is not just a spanning set, but also a minimal spanning set (cannot be further simplified).
We will give such spanning set a name: Basis.

## Basis

#### **Definition 14.1 (basis)**

Suppose *V* is a linear space over  $\mathbb{R}$ . Suppose  $\mathscr{U} \triangleq \{\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k\} \subseteq V$ . We say  $\mathscr{U}$  is a basis if (i)  $\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k$  are linearly independent; (ii) span( $\mathscr{U}$ ) = *V*.

In words, a basis is a linearly independent set and span the whole space.

**Eg1** { $\mathbf{e}_1, \dots, \mathbf{e}_n$ } is a basis of  $\mathbb{R}^n$ . (called "standard basis")

**Eg2**  $\{u\}$  is a basis of span $\{u\}$ , if  $u \neq 0$ .

**Preparation**: Find a candidate set.

#### **First (independence)**

Check the elements are linearly independent.

#### Second (span)

Check any element can be expressed as a linear combination.

## **Basis: Exercise**

–Find a basis of  $\mathbb{R}^{2\times 2}$ .

-Find a basis of 
$$P_2 \triangleq \{f(x) = a_0 + a_1x + a_2x^2 : a_0, a_1, a_2 \in \mathbb{R}\}$$

$$- \mathsf{IS} \left\{ \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 1 \\ 4 \\ 5 \end{bmatrix} \right\} \text{ a basis of } \mathbb{R}^3?$$

$$--\mathbf{IS} \left\{ \begin{bmatrix} 1\\0\\0 \end{bmatrix}, \begin{bmatrix} 1\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\1\\1\\1 \end{bmatrix} \right\} \text{ a basis of } \mathbb{R}^3?$$

## **Basis of Matrix Space**

The set B consisting of

$$B_{11} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \ B_{12} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \ B_{21} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}, \ B_{22} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

is a basis of  $\mathbb{R}^{2 \times 2}$ . *B* is linearly independent. Also notice that  $\forall A \in \mathbb{R}^{2 \times 2}$ ,

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = aB_{11} + bB_{12} + cB_{21} + dB_{22}$$

In general,  $\{E_{ij}, i = 1, ..., m; j = 1, ..., n\}$  is a basis of  $\mathbb{R}^{m \times n}$ , where  $E_{ij}$  is a matrix with only (i, j)-th entry being 1 and other entries Being 0.

## **Basis of Polynomial Space**

1.  $V = P_1$  (polynomials of degree at most 1).

(1)  $\mathbf{p}_1(x) = 1$ ,  $\mathbf{p}_2(x) = x$ ,  $\mathbf{p}_3(x) = 2 - 3x$ . Is  $\mathcal{U} = {\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3}$  a basis for  $P_1$ ?

No!  $\mathcal{U}$  is linearly dependent since  $\mathbf{p}_3 = 2\mathbf{p}_1 - 3\mathbf{p}_2$ .

(2)  $U = \{1, x\}$  is a basis for  $P_1$ .

2. For  $V = P_n$  (polynomials of degree at most n),

 $\mathcal{U} = \{1, x, x^2, \cdots, x^n\}$  is a basis for  $P_n$ .

## Part II Dimension

Strang's book Sec. 3.4

{ $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ { $\mathbf{e}_1, \mathbf{e}_1 + \mathbf{e}_2, \mathbf{e}_1 + \mathbf{e}_2 + \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ { $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_1 + \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ 

**Question**: what is the next interesting quetion?

{ $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ { $\mathbf{e}_1, \mathbf{e}_1 + \mathbf{e}_2, \mathbf{e}_1 + \mathbf{e}_2 + \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ { $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_1 + \mathbf{e}_3$ } is a basis of  $\mathbb{R}^3$ 

**Question**: what is the next interesting quetion?

One answer:VoteQ1: What's the smallest basis?A) 3B) 2C) 1Q2: What's the biggest basis?A)  $\infty$ B) 3C) >3

## Too many vectors cannot be a basis

**Claim 14.2a**: The set of three vectors  $\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\} \subseteq \mathbb{R}^2$  is a linearly dependent set, thus not a basis of  $\mathbb{R}^2$ .

**Claim 14.2b**: columns of 
$$\begin{bmatrix} 1 & 5 & 8 \\ 3 & 8 & 27 \end{bmatrix}$$
 are linearly dependent.



**Proof:** 

## Rewriting the Proof in Shape

Claim 14.2a equivalent to:

Claim 14.3a' \_\_\_\_\_ has \_\_\_\_\_ solution

**Proof** (using shape of matrix, not concrete numbers):



## Wide Ax=0 has Non-zero Solution



**Claim 14.3**: Any (n + 1) vectors in  $\mathbb{R}^n$  are linearly dependent.

**Lemma 14.1** Suppose m > n. If  $\{\mathbf{v}_1, ..., \mathbf{v}_n\}$  is a basis of a linear space V, then any *m* elements  $\mathbf{u}_1, ..., \mathbf{u}_m$  are linearly dependent.

## **Unique Representation and Coordinate**

**Proposition 14.1** (unique representation) Suppose *V* is a linear space with a basis  $\mathscr{U} \triangleq \{\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_k\}$ . Any  $\mathbf{v} \in V$  can be written **uniquely** as a linear combination of  $\mathbf{u}_1, ..., \mathbf{u}_n$ , namely, there exist unique  $[\alpha_1, ..., \alpha_n]^\top \in \mathbf{R}^{n \times 1}$  s.t.  $\mathbf{x} = \alpha_1 \mathbf{u}_1 + ... + \alpha_n \mathbf{u}_n$ 

#### **Definition 14.1 (coordinates)**

 $\left[ \alpha \right]^{-}$ 

We say  $\alpha_1, \ldots, \alpha_n$  are the coordinates of **x** with respect to the basis  $\mathscr{U}$ ,

denoted as 
$$[\mathbf{x}]_{\mathcal{U}} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_n \end{bmatrix}$$

## **Coordinates of Elements in Matrix Space**

Eg. Matrix space.

Coordinates of  $\begin{bmatrix} 1 & 5 \\ 3 & 8 \end{bmatrix}$ 

## **Dimension = Size of Bases**

**Theorem 14.1** (bases have same size) If  $\{u_1, ..., u_m\}$  and  $\{v_1, ..., v_n\}$  are bases of a linear space V, then m = n.

All bases have the same size!! We call it "dimension"!

### **Proof**:

## **Dimension = Size of Bases**

**Theorem 14.1** (bases have same size) If  $\{\mathbf{u}_1, \dots, \mathbf{u}_m\}$  and  $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$  are bases of a linear space V, then m = n.

First "big" Theorem in this course!

All bases have the same size!! We call it "dimension"!

#### **Definition 14.1 (dimension)**

Suppose V is a linear space. If V has a basis  $\mathscr{U}$  with *n* elements, then we say the dimension of V is *n*, denoted as dim(V)=*n*, or V is *n*-dimensional.

Eq: dim( $\{0\}$ ) = 0, since  $\{0\}$  has no basis vector.

dim $(\mathbb{R}^n) = n$ , since  $\{\mathbf{e}_i, i = 1, \cdots, n\}$  is the standard

dim( $\mathbb{R}^{2\times 3}$ ) = 6, since

basis.

**Remark**: If there is no finite set of elements that can span V, we say V Is infinite dimensional.

## **Dimension Measures "Size" of Space**

We provide a perspective to understand dimension.

It comes from an old question: **Question**: Is a plane "larger" than a line?

You may say: surely larger; but in what sense?

**Option 1**: # of points.

**Option 2**: Dimension.



#### What is the dimension of the following linear spaces?

Space of  $n \times n$  diagonal triangular matrices

Space of  $n \times n$  upper triangular matrices

$$P_{n} = \left\{ \sum_{i=0}^{n} a_{i} x^{i} | a_{i} \in \mathbb{R} \right\}$$

$$C \left( \begin{bmatrix} 1 & 0 & a & 0 & c \\ 0 & 1 & b & 0 & d \\ 0 & 0 & 0 & 1 & e \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \right)$$

A basis is a linearly independent set and span the whole space.

#### For finite-dimensional linear space:

A basis is a minimal spanning set (deleting a vector from the basis cannot span the whole space),

Also a maximal independent set

(adding a vector to the basis makes the set linearly dependent)

## **Quicker Way to Check Basis**

#### **Proposition 14.2**

Consider a linear space V with  $\dim(V) = n$ . If  $\mathbf{u}_1, \ldots, \mathbf{u}_n$  are linearly independent, then they form a basis of V. If  $\mathbf{u}_1, \ldots, \mathbf{u}_n \in V$  can span V, then they form a basis of V.

**Remark:** For n vectors, only need to check either "span" or "lin. indep.", not both.

# E.g. $\begin{bmatrix} 1\\0\\1\\0\end{bmatrix}, \begin{bmatrix} 2\\1\\3\\1\end{bmatrix}$ are linearly independent, thus a basis of $\mathbb{R}^3$ .

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E.g. 
$$\begin{bmatrix} 1\\0\\0 \end{bmatrix}, \begin{bmatrix} 2\\1\\0 \end{bmatrix}, \begin{bmatrix} 2\\3\\1 \end{bmatrix}$$
 are linearly independent, thus a basis of  $\mathbb{R}^3$ .

Recall: Lec 13:

 $n \times n$  matrix A is invertible iff the *n* columns are linearly independent.

From Prop. 14.2, this is equivalent to:

- a) Its columns form a basis.
- b) Its columns span the whole space, i.e., Ax=b is solvable for any b.

## **Invertibility Conditions**

Theorem 14.2a (Equivalent Conditions for Invertibility) Let  $A \in \mathbb{R}^{n \times n}$ .

The following statements are equivalent:

- 1. A is invertible
- 2. The linear system  $A\mathbf{x} = 0$  has a unique solution  $\mathbf{x} = \mathbf{0}$
- 3. A is a product of elementary matrices
- 4. A has n pivots; or equivalently: rank(A) = n
- 5. The columns of A span  $\mathbb{R}^n$ .
- 6. The columns of A are linearly independent;
- 7. The columns of A form a basis;
- 8. dim(C(A)) = n.
- 9. Ax=b is solvable for any b



Most major concepts we learned so far are related to invertibility.

## Part III Rank

Strang's book Sec. 3.4

The number of pivots r is important.

It is so important that we give it a name.

**Definition 14.3 (rank)** The rank of a matrix A is the number of pivots, denoted as rank(A).

**Remark**: This is a computational definition.

In the future, we will introduce equivalent definitions that are more fundamental.

**Property**: For  $m \times n$  matrix, rank(A)  $\leq \min\{m, n\}$ .

#### # of Solutions for Different Cases of m, n and r

After proper re-ordering of columns, any RREF can be written as

$$\begin{bmatrix} I_r & F \\ \mathbf{0}_{(m-r)\times r} & \mathbf{0}_{(m-r)\times (n-r)} \end{bmatrix} \begin{bmatrix} x_P \\ x_F \end{bmatrix} = \begin{bmatrix} \hat{\mathbf{b}}_{r\times 1} \\ \mathbf{c}_{(m-r)\times 1} \end{bmatrix}$$

Case 1: r < m:[there are zero rows]IF  $\mathbf{c}_{(m-r) \times 1} \neq \mathbf{0}$ :[get 0 = non-zero]REPORT No solution.[get 0 = 0 equations]

Dependent on how large n,m,r, some of the blocks may disappear.

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Dependent on how large n,m,r, some of the blocks may disappear.

Four types for R $\begin{bmatrix} I \end{bmatrix}$  $\begin{bmatrix} I & F \end{bmatrix}$  $\begin{bmatrix} I & F \\ 0 \end{bmatrix}$  $\begin{bmatrix} I & F \\ 0 & 0 \end{bmatrix}$ Their ranksr = m = nr = m < nr = n < mr < m, r < n# of solutions1 $\infty$ 0 or 10 or  $\infty$ # of solutions1 $\infty$ 1 $\infty$ 

Thm 14.2 implies: rank(A) = n <==> dim(C(A)) = n.

Let's recall what it means.

rank(A) = n <==> n pivots <==> Ax=0 has unique solution 0 i.e. Ax=0 has no non-zero solution <==> n columns are linearly independent <==> C(A) has dimension n

[Def of rank]

[row transf. does not change solution]

[Def of lin. ind.]

[Fact 14.1; Def of dim]

Anything interesting to guess?

**Guess**: rank(A) = dim(C(A)), for any A.

## **Definition: Row Space**

**Definition 14.2 (row space)**  
Suppose 
$$A = \begin{bmatrix} \mathbf{a}_{(1)}^{\top} \\ \cdots \\ \mathbf{a}_{(m)}^{\top} \end{bmatrix} \in \mathbb{R}^{m \times n}$$
. is a linear space.  
Then span( $\{\mathbf{a}_{(1)}, \dots, \mathbf{a}_{(m)}\}$ )  $\subseteq \mathbb{R}^{n}$  is called the row space of A, denoted as **Row(A)**.

In words: A's row space is the span of A's row vectors.

Remark: Row(A) =  $C(A^{\top})$ .

Eg: C(
$$I_n$$
) =   
**Eg**: Row space of  $A = \begin{bmatrix} 1 & 0 \\ 4 & 3 \\ 2 & 3 \end{bmatrix}$  is the set  
 $\left\{ \alpha_1 \begin{bmatrix} 1, 0 \end{bmatrix}^{\mathsf{T}} + \alpha_2 \begin{bmatrix} 4, 3 \end{bmatrix}^{\mathsf{T}} + \alpha_3 \begin{bmatrix} 2, 3 \end{bmatrix}^{\mathsf{T}} \mid \alpha_1, \alpha_2 \in \mathbb{R} \right\}.$ 

#### What is dim(Row(R))?



**Observation 1**: Span{rows} = span { pivot rows}.

**Observation 2:** Pivot rows are linearly independent. Why?

Together: dim(Row(R)) = # of pivots = r.

**Definition 14.3** (row-rank and column rank) Row-rank of A is defined as dim(Row(A)), denoted as  $r_R(A)$ . Column-rank of A is defined as dim(C(A)), denoted as  $r_C(A)$ .

Theorem 14.3 Row-rank, column-rank and rank of a matrix are the same, i.e.,  $r_R(A) = r_C(A) = \operatorname{rank}(A)$ .

Equivalent expression: dim(Row(A)) = dim(C(A)) = # of pivots.

### Example

$$A = \begin{bmatrix} 1 & 2 & 1 & 2 \\ 2 & 4 & 3 & 3 \\ 1 & 2 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad \begin{array}{l} \operatorname{Row}(A) = \operatorname{Span}\left([1, 2, 0, 0]^{T}, [0, 0, 1, 0]^{T}, [0, 0, 0, 1]^{T}\right) \\ r_{R}(A) = 3. \end{array}$$

$$R = \begin{bmatrix} 1 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \qquad \begin{array}{l} \operatorname{C}(A) = \operatorname{Span}\left(\begin{bmatrix} 1 \\ 2 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 1 \\ 0 \end{bmatrix}\right) \\ r_{C}(A) = 3.$$

$$3 \text{ pivots,}$$
So rank(A) = 3.

Thus, 
$$r_R(A) = r_C(A) = \operatorname{rank}(A)$$
.

## Concluding Part

Strang's book Sec. 3.4

#### How to Fill the Gap Between Courses and Homework & Exam?

First, figure out all logic & proofs of the lectures

Second, work on more practice problems.

—Different from high school:

High school: Teachers (almost) provide you all needed problems.

University: You need to seek more practice problems yourself. [Active learning]

—Where? Textbook practice problems.

—Too many? Pick a few to work on. It is part of the challenge.

Summary Today (write Your Own)

**One sentence summary:** 

**Detailed summary:** 

### Summary Today (of Instructor)

#### **One sentence summary:**

Dimension, Rank and Nullity.

### **Detailed summary:**

#### 1. Basis and Dimension

- —Dimension of linear space = size of any basis.
- —Theorem 14.1: Any basis has the same size (size = # of vectors in the basis).

#### 2. Rank

Column/row-rank = dim of column/row space Rank theorem: row-rank = column-rank = rank (= # of pivots)

- 3. Nullity
  - -Nullity = dimension of null space.
  - -Nullity theorem: Nullity + rank = n.

**Byproduct**: Conditions for checking invertibility by

dim, rank, nullity, linear independence.

# Appendix: Proof of Rank = Row Rank = Column Rank

#### **Revisiting Solution Set of Ax=0**



 $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$  can express  $\mathbf{v}_4, \mathbf{v}_5$ . They are linearly independent. Fact 1: In RREF, free columns can be expressed as LC of pivot columns.



**Lemma 14.2** Elementary row operations do not change dimension of column space.

#### **Elementary Row Operation does Not Change LC Relation**



Consider the matrix  $\hat{R}$  that becomes R after one step of elementary row operation.

$$\hat{R} = \begin{bmatrix} 1 & 0 & a & -\beta & c - \beta e \\ 0 & 1 & b & 0 & d \\ 0 & 0 & 0 & 1 & e \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \xrightarrow{\beta R_3 + R_1} \begin{bmatrix} 1 & 0 & a & 0 & c \\ 0 & 1 & b & 0 & d \\ 0 & 0 & 0 & 1 & e \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\iff (-c)\mathbf{v}_1 + (-d)\mathbf{v}_2 + (-e)\mathbf{v}_4 + \mathbf{v}_5 = 0.$$

Check: 
$$(-c)\mathbf{v}_1 + (-d)\mathbf{v}_2 + (-e)\hat{\mathbf{v}}_4 + \hat{\mathbf{v}}_5 =$$

**Claim 14.1**: Elementary row operation does not change "linear combination" relation.

i.e. if  $\alpha_1 \cdot (\text{Column 1}) + \ldots + \alpha_n \cdot (\text{Column } n) = 0$  holds for M, then it holds for the row-transformed matrix too.

Consider the matrix  $\hat{R}$  that becomes R after one step of elementary row operation.

$$W = \begin{bmatrix} \mathbf{w}_1^{\mathsf{T}} \\ \mathbf{w}_2^{\mathsf{T}} \\ \mathbf{w}_3^{\mathsf{T}} \\ \mathbf{w}_3^{\mathsf{T}} \\ \mathbf{w}_4^{\mathsf{T}} \end{bmatrix} \stackrel{\beta R_3 + R_1}{\longrightarrow} \begin{bmatrix} \beta \mathbf{w}_3^{\mathsf{T}} + \mathbf{w}_1^{\mathsf{T}} \\ \mathbf{w}_2^{\mathsf{T}} \\ \mathbf{w}_2^{\mathsf{T}} \\ \mathbf{w}_3^{\mathsf{T}} \\ \mathbf{w}_4^{\mathsf{T}} \end{bmatrix} = \hat{W}.$$

$$\mathsf{Row}(W) = \mathsf{span}\{\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3, \mathbf{w}_4\}$$

 $\operatorname{span}\{\beta \mathbf{w}_3 + \mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3, \mathbf{w}_4\} = \operatorname{Row}(W).$ 

**Claim 14.2**: Elementary row operation does not change the row space.

**dim(Row(A)) = r**.

dim(Row(R)) = # of pivots = r