- New concepts:
 - Vector space sums
 - FTLA
 - FTLA step-by-step (question by question) proof
 - Rank-nullity theorem
 - $-\,$ Characterizing solutions to linear systems in terms of rank and nullity

Definition. Given two vector subspaces $(\mathcal{U}, \mathcal{S}, +)$, $(\mathcal{V}, \mathcal{S}, +)$ of the space $(\mathcal{W}, \mathcal{S}, +)$, the sum is the set $\mathcal{U} + \mathcal{V} = \{ u + v \mid u \in \mathcal{U}, v \in \mathcal{V} \}$.

Definition. Given two vector subspaces $(\mathcal{U}, \mathcal{S}, +)$, $(\mathcal{V}, \mathcal{S}, +)$ of the space $(\mathcal{W}, \mathcal{S}, +)$, the direct sum is the set $\mathcal{U} \oplus \mathcal{V} = \{u + v \mid \exists ! u \in \mathcal{U}, \exists ! v \in \mathcal{V}\}$. (unique decomposition)

Definition. Given two vector subspaces $(\mathcal{U}, \mathcal{S}, +)$, $(\mathcal{V}, \mathcal{S}, +)$ of the space $(\mathcal{W}, \mathcal{S}, +)$, the intersection is the set

$$\mathcal{U} \cap \mathcal{V} = \{ \boldsymbol{x} | \boldsymbol{x} \in \mathcal{U}, \boldsymbol{x} \in \mathcal{V} \}.$$

Definition. Two vector subspaces $(\mathcal{U}, \mathcal{S}, +)$, $(\mathcal{V}, \mathcal{S}, +)$ of the space $(\mathcal{W}, \mathcal{S}, +)$ are orthogonal subspaces, denoted $\mathcal{U} \perp \mathcal{V}$ if $\mathbf{u}^T \mathbf{v} = 0$ for any $\mathbf{u} \in \mathcal{U}, \mathbf{v} \in \mathcal{V}$.

Definition. Two vector subspaces $(\mathcal{U}, \mathcal{S}, +)$, $(\mathcal{V}, \mathcal{S}, +)$ of the space $(\mathcal{W}, \mathcal{S}, +)$ are orthogonal complements, denoted $\mathcal{U} = \mathcal{V}^{\perp}$, $\mathcal{V} = \mathcal{U}^{\perp}$ if they are orthogonal subspaces and $\mathcal{U} \cap \mathcal{V} = \{\mathbf{0}\}$, *i.e.*, the null vector is the only common element of both subspaces.

- A matrix $A \in \mathbb{R}^{m imes n}$ is a linear mapping from \mathbb{R}^n to \mathbb{R}^m , $A : \mathbb{R}^n \to \mathbb{R}^m$
- The transpose $A^T \in \mathbb{R}^{n \times m}$ is a linear mapping from \mathbb{R}^m to \mathbb{R}^n , $A^T : \mathbb{R}^m \to \mathbb{R}^n$
- To each matrix $oldsymbol{A} \in \mathbb{R}^{m imes n}$ associate four fundamental subspaces:
 - 1 Column space, $C(\mathbf{A}) = \{ \mathbf{b} \in \mathbb{R}^m | \exists \mathbf{x} \in \mathbb{R}^n \text{ such that } \mathbf{b} = \mathbf{A}\mathbf{x} \} \subseteq \mathbb{R}^m$, the part of \mathbb{R}^m reachable by linear combination of columns of \mathbf{A}
 - 2 Left null space, $N(\mathbf{A}^T) = \{ \mathbf{y} \in \mathbb{R}^m | \mathbf{A}^T \mathbf{y} = 0 \} \subseteq \mathbb{R}^m$, the part of \mathbb{R}^m not reachable by linear combination of columns of \mathbf{A}
 - 3 Row space, $R(\mathbf{A}) = C(\mathbf{A}^T) = \{ \mathbf{c} \in \mathbb{R}^n | \exists \mathbf{y} \in \mathbb{R}^m \text{ such that } \mathbf{c} = \mathbf{A}^T \mathbf{y} \} \subseteq \mathbb{R}^n$, the part of \mathbb{R}^n reachable by linear combination of rows of \mathbf{A}
 - 4 Null space, $N(\mathbf{A}) = \{\mathbf{x} \in \mathbb{R}^n | \mathbf{A}\mathbf{x} = 0\} \subseteq \mathbb{R}^n$, the part of \mathbb{R}^n not reachable by linear combination of rows of \mathbf{A}

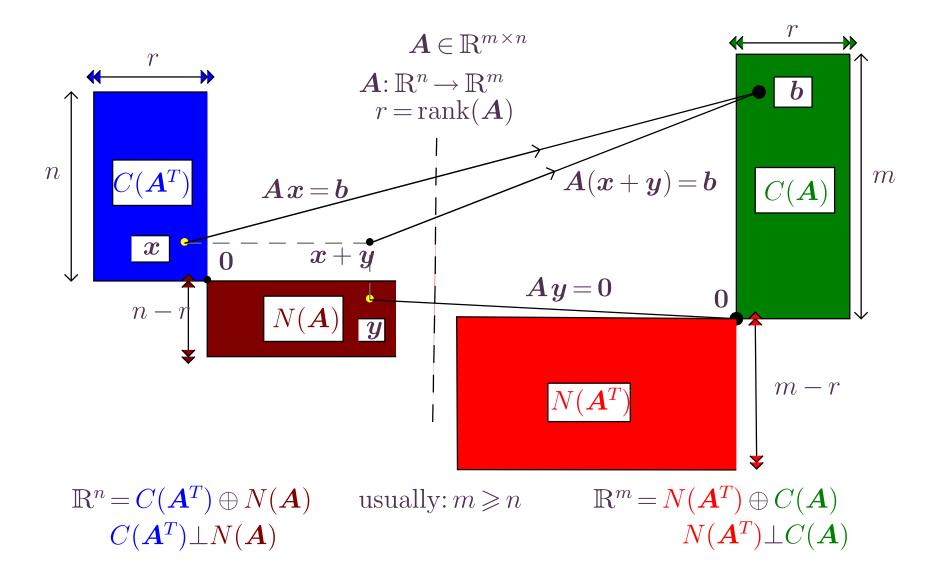
Theorem. Given the linear mapping associated with matrix $A \in \mathbb{R}^{m \times n}$ we have:

- 1. $C(A) \oplus N(A^T) = \mathbb{R}^m$, the direct sum of the column space and left null space is the codomain of the mapping
- 2. $C(\mathbf{A}^T) \oplus N(\mathbf{A}) = \mathbb{R}^n$, the direct sum of the row space and null space is the domain of the mapping
- 3. $C(\mathbf{A}) \perp N(\mathbf{A}^T)$ and $C(\mathbf{A}) \cap N(\mathbf{A}^T) = \{\mathbf{0}\}$, the column space is orthogonal to the left null space, and they are orthogonal complements of one another,

 $C(\mathbf{A}) = N(\mathbf{A}^T)^{\perp}, \ N(\mathbf{A}^T) = C(\mathbf{A})^{\perp}.$

4. $C(\mathbf{A}^T) \perp N(\mathbf{A})$ and $C(\mathbf{A}^T) \cap N(\mathbf{A}) = \{\mathbf{0}\}$, the row space is orthogonal to the null space, and they are orthogonal complements of one another,

 $C(\mathbf{A}^T) = N(\mathbf{A})^{\perp}, \quad N(\mathbf{A}) = C(\mathbf{A}^T)^{\perp}.$



- Understanding the FTLA is essential to applications
- Proofs of the FTLA help in:
 - $\,$ building the ability to recognize rigorous mathematical arguments as opposed to intuition $\,$
 - gaining an appreciation of the interplay between construction of mathematical concepts (formalized in a definition) and interaction between these concepts (propositions and theorems).
- Recall: linear algebra seeks construction of complex objects, vectors $b \in \mathbb{R}^m$ through linear combination of n column vectors organized into a matrix

$$A = [a_1 \dots a_n], b = T(x) = Ax, A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n$$
 scaling coefficients.

 $T: \mathbb{R}^n \to \mathbb{R}^m$ a linear mapping from domain \mathbb{R}^n to codomain \mathbb{R}^m .

A proof of the FTLA is now presented as answers (first informal, and then rigorous) to a series of natural questions arising from the initial goal:

- 1 What vectors can be obtained by the linear combination Ax?
- 2 Is there only one way to obtain a vector \boldsymbol{b} by linear combination?
- 3 Is there a preferred way to describe vectors b = Ax?
- 4 Is there a preferred way to describe vectors $m{y}$ that satisfy $m{A}\,m{y}\,{=}\,0?$
- 5 Is there anything different about organizing vectors into rows?

• Set of reachable vectors: defined by *column space* of A (range of mapping T)

 $C(\boldsymbol{A}) = \{\boldsymbol{b} | \exists \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{b} = \boldsymbol{A} \boldsymbol{x}\} \subseteq \mathbb{R}^m$

- C(A) has structure, it is a vector subspace of \mathbb{R}^m , $C(A) \leq \mathbb{R}^m$ Proof. $\forall u, v \in C(A) \Rightarrow \exists x, y \in \mathbb{R}^n$ such that u = Ax, v = Ay by definition of C(A). Then u + v = Ax + Ay = A(x + y), hence $u + v \in C(A)$.
- "Size" of a vector space has been characterized by the concept of dimension. Give a distinct name to the "size" of the set of reachable vectors.

Definition. The rank of a matrix $A \in \mathbb{R}^{m \times n}$ is the dimension of the column space

 $r = \dim C(\mathbf{A})$

- Suppose b = Ax, could b also be obtained differently, as b = A(x + y)?
- Subtracting the two linear combinations leads to Ay = 0, and the *null space*

$$N(\boldsymbol{A}) = \{\boldsymbol{y} \, | \, \boldsymbol{A} \, \boldsymbol{y} = \boldsymbol{0}\} \subseteq \mathbb{R}^n$$

- N(A) has structure, it is a vector subspace of \mathbb{R}^n , $N(A) \leq \mathbb{R}^n$ Proof. $\forall u, v \in N(A) \Rightarrow Au = 0, Av = 0 \Rightarrow A(u+v) = 0 \Rightarrow u+v \in N(A)$.
- Obviously, $\mathbf{0} \in N(\mathbf{A})$, but the null space might also contain non-zero vectors
- Even when A≠0 (i.e., A is not the zero matrix) and y≠0 (i.e., y is not the zero vector), there still might be choices of A and y such that Ay=0. This is different from a, x ∈ ℝ, where ax=0 ⇒ a=0 or x=0.
- Give a distinct name to the "size" of the set of such vectors.

Definition. The nullity of a matrix $A \in \mathbb{R}^{m \times n}$ is the dimension of the null space

 $z = \dim N(\boldsymbol{A})$

- Since $r = \dim C(\mathbf{A})$ and $C(\mathbf{A})$ is a vector subspace of \mathbb{R}^m , $r \leq m$.
- The above implies that only r of the n columns of \boldsymbol{A} are linearly independent
- Gather the linearly independent columns as the first r columns

$$oldsymbol{A} = [egin{array}{cccc} oldsymbol{A}_r & oldsymbol{A}_r \in \mathbb{R}^{m imes r}, oldsymbol{A}_{n-r} \in \mathbb{R}^{m imes (n-r)}] \end{array}$$

a block decomposition of A, with the index denoting number of columns.

• Since columns A_{n-r} are linearly dependent on those of A_r , $A_{n-r} = A_r B_{n-r}$

$$\boldsymbol{A} = \boldsymbol{A}_r [\boldsymbol{I}_r \ \boldsymbol{B}_{n-r}] = \boldsymbol{A}_r \boldsymbol{X}, \boldsymbol{X} \in \mathbb{R}^{r \times n}$$

The above states: "all the column vectors of A can be expressed as linear combinations of r linearly independent columns, A_r .

• Consider now $N(\mathbf{A})$: $\mathbf{A}\mathbf{u} = \mathbf{A}_r \mathbf{X}\mathbf{u} = \mathbf{0}$

Let v = Xu. A_r with linearly independent columns, A_r v = 0 ⇒ v = 0 ⇒ Xu = 0. Write this out in blocks

$$\left[egin{array}{cc} oldsymbol{I}_r & oldsymbol{B}_{n-r} \end{array}
ight] = oldsymbol{0} \Rightarrow oldsymbol{u} = \left[egin{array}{cc} -oldsymbol{B}_{n-r} \ oldsymbol{I}_{n-r} \end{array}
ight] oldsymbol{u}_{n-r} = oldsymbol{Y}_{n-r} oldsymbol{u}_{n-r}.$$

This states that columns of Y_{n-r} are a spanning set for N(A), $u = Y_{n-r} u_{n-r}$.

• Is it a minimal spanning set, i.e., a basis? Consider

$$Y_{n-r}w = 0 \Rightarrow \left[egin{array}{c} -B_{n-r} \ I_{n-r} \end{array}
ight] w = \left[egin{array}{c} -B_{n-r}w \ w \end{array}
ight] = \left[egin{array}{c} 0 \ 0 \end{array}
ight] \Rightarrow w = 0.$$

Indeed columns of Y_{n-r} are linearly independent, establishing that

$$z = \dim N(\mathbf{A}) = n - r$$

Theorem. (Rank-nullity theorem) For $A \in \mathbb{R}^{m \times n}$, r + z = n

- Matrix vector multiplication b = Ax = x₁a₁ + ··· + x_n a_n, expresses a linear combination of columns. Multiple linear combination of columns: B = AX.
- Organizing data into column vectors is an arbitrary choice, hence linear combinations of rows should also be possible, and indeed are expressed as

$$\boldsymbol{c}^{T} = \boldsymbol{y}^{T} \boldsymbol{A} \Rightarrow \boldsymbol{c} = \boldsymbol{A}^{T} \boldsymbol{y}.$$

 c^{T} : the row vector obtained by linear combination of rows of A with scaling coefficients gathered in the row vector y^{T} . Multiple linear combinations of rows

C = YA

Rows of C are linear combination of rows of A with scalings as rows of Y.

• The set of vectors reachable by linear combination of rows of ${m A}$ is $C({m A}^T)$

$$C(\boldsymbol{A}^{T}) = \{\boldsymbol{c} | \exists \boldsymbol{y} \in \mathbb{R}^{m}, \boldsymbol{c} = \boldsymbol{A}^{T} \boldsymbol{y} \} \leq \mathbb{R}^{n},$$

the row space or column space of the transpose, and is a subspace of \mathbb{R}^n .

• Let $p = \dim C(\mathbf{A}^T)$, the dimension of the row space.

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Proposition. The dimension of the column space equals that of the row space

 $r = \dim C(\mathbf{A}) = \dim C(\mathbf{A}^T) = p.$

Proof. Interpret $A = A_r X$ as stating that the rows of A can be obtained linear combinations of the rows of X with scalings contained in A_r . Since $X \in \mathbb{R}^{r \times n}$,

$$p = \dim C(\mathbf{A}^T) \leqslant r = \dim C(\mathbf{A}).$$

The above is true for any matrix M, dim $C(M^T) \leq \dim C(M)$. Choose $M = A^T$

$$\dim C((\boldsymbol{A}^T)^T) \leqslant \dim C(\boldsymbol{A}^T) \Rightarrow r = \dim C(\boldsymbol{A}) \leqslant \dim C(\boldsymbol{A}^T) = p.$$

Since $p \leqslant r$ and $r \leqslant p$, it results that r = p.

Results up to now can be used to prove:

- $C(\mathbf{A})$ is orthogonal to $N(\mathbf{A}^T)$. Proof. $\mathbf{u} \in C(\mathbf{A}) \Rightarrow \mathbf{u} = \mathbf{A}\mathbf{x}$, $\mathbf{v} \in N(\mathbf{A}^T) \Rightarrow \mathbf{A}^T \mathbf{v} = \mathbf{0}$. Compute $\mathbf{u}^T \mathbf{v} = \mathbf{x}^T \mathbf{A}^T \mathbf{v} = \mathbf{x}^T \mathbf{0} = \mathbf{0}$.
- 0 is the only vector both in C(A) and N(A^T).
 Proof. Assume there might be b ∈ C(A) and b ∈ N(A^T) and b ≠ 0. Since b ∈ C(A), ∃x ∈ ℝⁿ such that b = Ax. Since b ∈ N(A^T), A^Tb = A^T(Ax) = 0. Note that x ≠ 0 since x = 0 ⇒ b = 0, contradicting assumptions. Multiply equality A^TAx = 0 on left by x^T,

$$\boldsymbol{x}^{T}\boldsymbol{A}^{T}\boldsymbol{A}\boldsymbol{x} = \boldsymbol{0} \Rightarrow (\boldsymbol{A}\boldsymbol{x})^{T}(\boldsymbol{A}\boldsymbol{x}) = \boldsymbol{b}^{T}\boldsymbol{b} = \|\boldsymbol{b}\|^{2} = 0 \Rightarrow \boldsymbol{b} = 0.$$

C(A) ⊕ N(A^T) = ℝ^m. Rank-nullity theorem states dim C(A) + dim N(A^T) = m, thereby covering the entire codomain, ℝ^m.