

SC223 - Linear Algebra

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Lecture 35



November 3, 2023

Applications

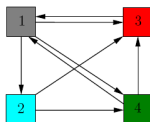
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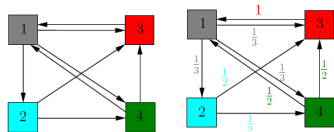
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Figure: Source: pi.math.cornell.edu

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{3} & \frac{1}{2} \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{3} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix}$$

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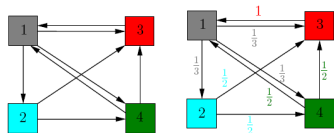


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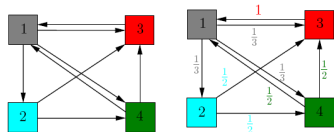


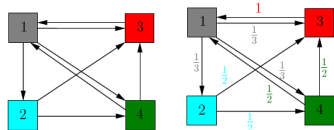
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- With the above model, after once click:

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f is C
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$$A(\lim_{n \rightarrow \infty} A^n x_0) = Ay$$

$$= \lim_{n \rightarrow \infty} A^{n+1} x_0 = y$$

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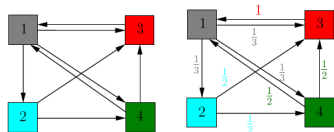


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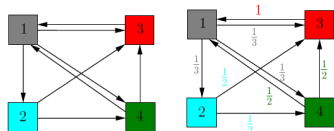


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- $\lim_{n \rightarrow \infty} A^n x_0 = y, Ay = y, y = [0.38, 0.12, 0.29, 0.19]^T$.

Projection

- Let V be a FDVS, and let U, W be subspaces of V such that $V = U \oplus W$.

Projection

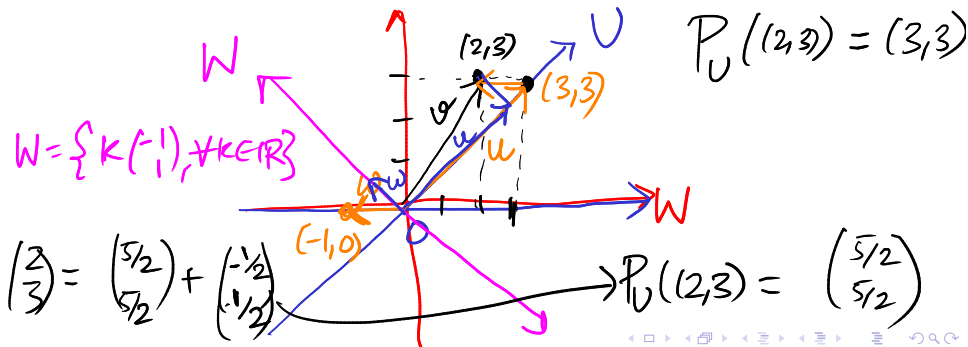
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Example:

① $V = \mathbb{R}^2$, $U = \{k \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \forall k \in \mathbb{R}\}$, $W = \{k \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \forall k \in \mathbb{R}\}$. $U \oplus W = \mathbb{R}^2$



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- Properties:

$$\textcircled{1} \quad N(P_U) = W, \quad \textcircled{2} \quad R(P_U) = U$$
$$V = R(P_U) \oplus N(P_U)$$

$$\textcircled{2} \quad \text{Let } v \in V, v = u + w, u \in U, w \in W.$$

$$\forall v \in V, \quad P_U(v) = u$$

$$P_U(P_U(v)) = P_U(u) = u$$

$$\Rightarrow P_U^2 = P_U \Rightarrow \underline{\text{Idempotent op.}}$$

- ③ Any Idempotent op. is diagonalizable
- ④ Eigenvalues are 0 & 1.
- ⑤ Let $T \in L(V)$ such that $T^2 = T$.
then T is a projection. (H.W)

————→ END of Class —————→

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- Is this the only way to define length?
- What are the necessary conditions for a function on vector space for it be called *length*?

Normed Vector space

- **Definition:** (Normed Vector Space) A normed vector space (NVS) is a vector space $(V, +, \cdot)$ over either \mathbb{R} or \mathbb{C} with a **norm**, a function $\|\cdot\| : V \rightarrow \mathbb{R}$ which satisfies the following properties:

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● Also note that given a NVS $(V, \|\cdot\|)$, we can define distance between two vectors x and y as $d(x, y) := \|x - y\|$. Such a distance or metric is called the **induced metric**.

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- L_2 norm on $\mathcal{P}_n([-1, 1])$: $\|x\|_{L_2} = \sqrt{\int_{-1}^1 (x(t))^2 dt}$.