



COMPUTER SCIENCE  
&  
APPLIED MATHEMATICS

MAA205 - ALGORITHMS FOR DISCRETE MATHEMATICS - FALL  
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**Part A - Graphs and Matrices**

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## Preface

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Prerequisites:

1. MAA106 - Introduction to Numerical Analysis
2. MAA104 - Algebra
3. MAA103 - Discrete Mathematics
4. CSE101 - Computer Programming

Mathematical Toolbox:

1. Graphs and Matrices
2. Probabilistic graphs

Python Notebooks:

1. Enumeration in graphs
2. Probabilistic graphs

Evaluation and Final Grade:

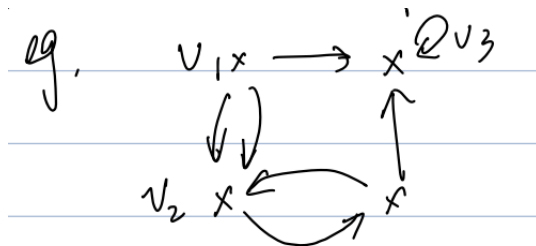
1. 50% Graded Labs (1 for every topic)
2. 50% Individual final project (report due at the end of the last Lab, no oral defense)

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# 1 Adjacency matrices 邻接矩阵 (review of CSE101)

Let  $G$  be a finite graph on a vertex set ( $V$  是顶点,  $E$  是边)  $V = \{v_1, \dots, v_n\}$



## 1.1 Definition

The adjacency matrix  $A_G$  of  $G$  is the  $n$  matrix  $(A_G) = (a_{ij})_{i,j \leq n}$  where  $a_{ij}$  = Number of edges going from  $v_i$  to  $v_j$ . 从点  $v_i$  到  $v_j$  的边的个数

What does  $(A_G)^2$  represent?

$$(A_G^2)_{i,j} = \sum_k a_{i,k} a_{k,j} = a_{i,1}a_{1,j} + a_{i,2}a_{2,j} + \dots + a_{i,n}a_{n,j}$$

# paths of length 2.  
 $v_i \rightarrow v_k \rightarrow v_j$

## 1.2 Proposition

For all  $k \geq 1$ ,  $(A_G)^k_{i,j}$  is the number of paths from  $v_i$  to  $v_j$  of length  $k$ .  $A^{100}$  是  $A$  经过 100 次方以后实际的运算结果.

$$Ex: A = \begin{bmatrix} 0 & 2 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\Rightarrow A^{100} = \begin{bmatrix} 0 & 0 & 99 & 2 \\ 0 & 1 & 50 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 50 & 1 \end{bmatrix}$$

### 1.3 (A glimpse of) spectral graph theory 谱系图理论

The maximal out-degree  $\Delta_{\rightarrow}$  of  $G$  is

$$\Delta_{\rightarrow} = \max_i \sum_j a_{ij}$$

**Theorem:** Let  $G$  be a graph with adjacency matrix  $A$ . Then

1. If  $0 < \varepsilon < \frac{1}{\Delta_{\rightarrow}}$  then  $(Id_n - \varepsilon A)$  is invertible.
2.  $G$  is connected <sup>(\*)</sup> 在一个无向图  $G$  中, 若从顶点  $v_i v_i$  到顶点  $v_j v_j$  有路径相连 (从  $v_j v_j$  到  $v_i v_i$  也一定有路径), 则称  $v_i v_i$  和  $v_j v_j$  是连通的。如果  $G$  是有向图, 那么连接  $v_i v_i$  和  $v_j v_j$  的路径中所有的边都必须同向。如果图中任意两点都是连通的, 那么图被称作连通图。  
 $\Leftrightarrow$  For all  $\varepsilon < \frac{1}{\Delta_{\rightarrow}}$ , even coefficient of  $(Id - \varepsilon A)^{-1} > 0$ .  
 $\Leftrightarrow \exists \varepsilon < \frac{1}{\Delta_{\rightarrow}}$  such that every coeff. of  $(Id - \varepsilon A)^{-1}$  is  $> 0$

$$\forall i, j, \quad \exists k \text{ s.t. } (A_G^h)_{i,j} \text{ is } > 0.$$

**Proof:**

1. Let  $\varepsilon$  be such that  $(Id - \varepsilon A)$  is not invertible  
 $\Rightarrow$  There exists  $\vec{x} = (x_1, \dots, x_n) \neq \vec{0} \cdot (0, 0, \dots, 0)$  st.  $(Id - \varepsilon A)\vec{x} = 0$ .

$$A\vec{x} = \frac{1}{\varepsilon}\vec{x}$$

$$\forall i, \sum_j a_{ij} x_j = \frac{1}{\varepsilon} x_i \quad (1)$$

Let  $i^*$  be such  $x_{i^*} = \max_{1 \leq i \leq n} x_i$ , we can assume  $x_{i^*}^* > 0$

Apply (1) to  $i^*$  we have

$$x_{i^*} \Delta_{\rightarrow} \geq x_{i^*} \sum_j a_{i^*,j} = \sum_j a_{i^*,j} \cdot x_{i^*} \geq \sum_j a_{i^*,j} \cdot a_j = \frac{1}{\varepsilon} x_{i^*}$$

We prove that  $\Rightarrow \Delta_{\rightarrow} \geq \frac{1}{\varepsilon}$

2.  $(1 - x)(1 + x + x^2 + \dots + x^k) = 1 - x^{k+1}$

Let  $x$  be real.  $(Id - \varepsilon A)(Id + \varepsilon A + \varepsilon^2 A^2 + \dots + \varepsilon^k A^k) = Id - \varepsilon^{k+1} A^{k+1}$  (every coefficient is  $\leq (\varepsilon \Delta_{\rightarrow})^{k+1}$ )

Let  $k \rightarrow +\infty$   $(Id - \varepsilon A)(Id + \varepsilon A + \varepsilon^2 A^2 + \dots) = Id$ .

$$(Id - \varepsilon A)^{-1} = Id + \varepsilon A + \varepsilon^2 A^2 + \dots + \varepsilon^k A^k + \dots$$

If  $G$  is connected, the every coefficient on  $RHS > 0 \quad \forall \varepsilon$  Fix  $\varepsilon$ , Assume every coefficient on  $RHS > 0$ .

## 2 Probabilistic Graphs 概率图谱 (Partly review of MAA103)

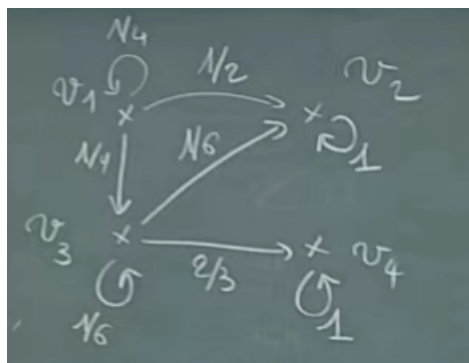
$$V = \{v_1, \dots, v_n\}$$

### 2.1 Definition of Probabilistic Graphs

A transition matrix on  $V$  is an  $n \times n$  matrix  $P = (P_{ij})_{ij \leq n}$  such that

1.  $\forall i, j, \quad 0 \leq p_{i,j} \leq 1$  个体概率小于 1
2.  $\forall i \leq n, \sum_j p_{i,j} = 1$  每行概率总和等于 1

$P_{ij}$  is interpreted as the probability of going from  $v_i$  to  $v_j$  in one-time step. For example:



$$P = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \frac{1}{6} & \frac{1}{6} & \frac{2}{3} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

### 2.2 Definition of Markov Chain 马尔可夫链

1.  $V$  be a vertex set  $\{v_1, \dots, v_m\}$
2.  $P$  be a transition matrix on  $V$ .
3.  $S \in V$

A Markov Chain with transition matrix  $P$  and starting point  $S$ . is a sequence of random variables  $X_0, X_1, X_2 \dots$  with value in  $V$  such that  $X_0 = S$  and  $\forall k \geq 1$

$$\mathbb{P}(X_1 = x_1, X_2 = x_2 \dots X_n = x_n) = p_{Sx_1} \times p_{x_1x_2} \times \dots \times p_{x_{n-1}x_n}$$

.

## 2.3 Proposition of Markov Chain

The coeff  $(P^k)_{i,j}$  is the probability of going from  $v_i$  to  $v_j$  Th exactly  $k$  times steps.

## 2.4 Absorbing Probability (on an example)

In the mathematical theory of probability, an **absorbing Markov chain** is a Markov chain in which every state can reach an absorbing state. An absorbing state is a state that, once entered, cannot be left.

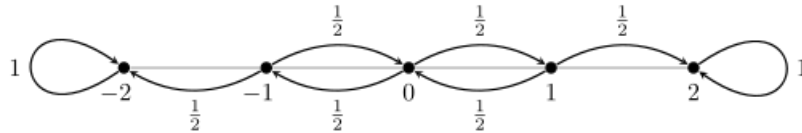


Figure 1: Sample of absorbing Markov chain

Put  $\Pi_{v'}^v = \mathbb{P}(\text{starting from } v, \text{ I am eventually stuck at } v')$

$\Pi_{v_1}^{v_2} = \mathbb{P}(\text{stuck at } v_2 | \text{1st step is } v_1) \times \mathbb{P}(\text{1st step is } v_1) + \mathbb{P}(\text{stuck at } v_2 | \text{1st step is } v_2) \times \mathbb{P}(\text{1st step is } v_2) + \mathbb{P}(\text{stuck at } v_2 | \text{1st step is } v_3) \times \mathbb{P}(\text{1st step is } v_3) = \Pi_{v_1}^{v_2} \times \frac{1}{4} + 1 \times \frac{1}{2} + \Pi_{v_3}^{v_2} \times \frac{1}{4}$