## 7. Markov Chains (Discrete-Time Markov Chains)

### 7.1. Introduction: Markov Property

7.2. Examples

- Two States
- Random Walk
- Random Walk (one step at a time)
- Gamblers' Ruin
- Urn Models
- Branching Process
7.3. Marginal Distribution of $X_{n}$
- Chapman-Kolmogorov Equations
- Urn Sampling
- Branching Processes

Nuclear Reactors
Family Names
7.4 Appendix: Notes on Matrices: I

### 7.1. Introduction: Markov Chains

Consider a system which can be in one of a countable number of states $1,2,3, \ldots$. The system is observed at the time points $n=0,1,2, \ldots$.

Define $X_{n}$ to be a random variable denoting the state of the system at "time" $n$. Suppose the history of the system up to time $n$ is:
$\left\{X_{0}, X_{1}, \ldots, X_{n}\right\}$. The probability distribution of $X_{n+1}$ would ordinarily depend on the past history; i.e.

$$
P\left\{X_{n+1} \mid X_{0}, X_{1}, \ldots, X_{n}\right\}
$$

The process is said to have the Markov property if

$$
P\left\{X_{n+1} \mid X_{0}, X_{1}, \ldots, X_{n}\right\}=P\left\{X_{n+1} \mid X_{n}\right\}
$$

$$
P\left\{X_{n+1} \mid X_{0}, \ldots, X_{n}\right\}=P\left\{X_{n+1} \mid X_{n}\right\}
$$

The stochastic process is called a Markov Chain. If the possible states are denoted by integers, then we have

$$
\begin{gathered}
P\left\{X_{n+1}=j \mid X_{n}=\right. \\
\left.i, X_{n-1}=i_{n-1}, X_{n-2}=i_{n-2}, \ldots, X_{0}=i_{0}\right\} \\
=P\left\{X_{n+1}=j \mid X_{n}=i\right\}
\end{gathered}
$$

Define

$$
p_{i j}(n)=P\left\{X_{n+1}=j \mid X_{n}=i\right\}
$$

If $S$ represents the state space and is countable, then the Markov Chain is called Time-Homogeneous if

$$
p_{i j}(n)=p_{i j} \quad \text { for all } i, j \in S \text { and } n \geq 0
$$

We will only be dealing with Time Homogeneous Markov Chains.

Note: Sometimes this process is referred to as a Discrete Time Markov Chain (DTMC).

Define $P=\left(p_{i j}\right)$.
If $S$ has $m$ states, then $P=\left(p_{i j}\right) \underline{m \times m}$ matrix.
$P$ is often called the one-step transition probability matrix.

Definition: A matrix $P=\left(P_{i j}\right)$ is called stochastic if
(i) $\quad p_{i j} \geq 0 \quad i, j \in S$
(ii) $\sum_{j \in S} p_{i j}=\sum_{j=1}^{m} p_{i j}=1$ for all $i \in S$.

$$
\begin{aligned}
X_{0} & =\text { initial state } \\
a_{i} & =P\left\{X_{0}=i\right\}=\text { Prob. of the initial state } X_{0}=i
\end{aligned}
$$

The probabilities $a_{i}$ and $P=\left(p_{i j}\right)$ completely determine the stochastic process.

Examples

$$
\begin{aligned}
P\left\{X_{0}=i_{0}, X_{1}=i_{1}\right\} & =P\left\{X_{1}=i_{1} \mid X_{0}=i_{0}\right\} P\left\{X_{0}=i_{0}\right\} \\
& =p_{i_{0} i_{1}} a_{i_{0}} \\
P\left\{X_{0}=i_{0}, X_{1}=i_{1}, X_{2}=i_{2}\right\} & =P\left\{X_{0}=i_{0}\right\} \cdot P\left\{X_{1}=i_{1} \mid X_{0}=i_{0}\right\} \\
& \cdot P\left\{X_{2}=i_{2} \mid X_{1}=i_{1}\right\} \\
& =a_{i_{0}} p_{i_{0} i_{1}} p_{i_{1} i_{2}}
\end{aligned}
$$

### 7.2. Examples

## Example: Two States

Suppose a person can be in one of two states - "healthy" or "sick". Let $\left\{X_{n}\right\} n=0,1, \ldots$ refer to the state at time $n$ where $X_{n}= \begin{cases}1 & \text { if healthy } \\ 0 & \text { if sick }\end{cases}$

Define

$$
\begin{aligned}
& P\left\{X_{n+1}=0 \mid X_{n}=0\right\}=\alpha \\
& P\left\{X_{n+1}=1 \mid X_{n}=1\right\}=\beta
\end{aligned}
$$

Transition Matrix

$$
P=\left[\begin{array}{cc}
\alpha & 1-\alpha \\
1-\beta & \beta
\end{array}\right]
$$

Transition Diagram


Ex. Independent Events
Let $\left\{X_{n}\right\}$ be iid with

$$
P\left\{X_{n}=k\right\}=p_{k} \text { for } k=0,1, \ldots
$$

and let the state space be $S=\{0,1,2, \ldots\}$

$$
\begin{aligned}
p_{j k}=P\left\{X_{n+1}\right. & \left.=k \mid X_{n}=j\right\}=P\left\{X_{n+1}=k\right\}=p_{k} \\
P & =\left[\begin{array}{cccc}
p_{0} & p_{1} & p_{2} & \ldots \\
p_{0} & p_{1} & p_{2} & \cdots \\
\vdots & \vdots & \vdots &
\end{array}\right]
\end{aligned}
$$

## Example: Random Walk on Non-negative Real Line

Define $\left\{Z_{n}\right\}$ to be iid with $p_{k}=P\left\{Z_{n}=k\right\}$ for $k=0,1,2, \ldots$
Define $X_{0}=0, \quad X_{n}=\sum_{k=1}^{n} Z_{k}$
Then $\left\{X_{n}\right\}$ is a Markov Chain with state space $S=\{0,1,2, \ldots\}$;

$$
\begin{gathered}
P\left\{X_{n+1}=j \mid X_{n}=i\right\}=P\left\{Z_{n+1}=j-i\right\}=p_{j-i} \\
P=\begin{array}{c}
\underline{0} \\
\underline{1} \\
0 \\
1 \\
2 \\
3 \\
\vdots
\end{array}\left[\begin{array}{ccccc}
p_{0} & p_{1} & p_{2} & p_{3} & \cdots \\
0 & p_{0} & p_{1} & p_{2} & \cdots \\
0 & 0 & p_{0} & p_{1} & \cdots \\
0 & 0 & 0 & p_{0} & \cdots \\
\vdots & & & &
\end{array}\right]
\end{gathered}
$$

Example: Random Walk (one step at a time)

$$
\begin{gathered}
P\left\{X_{n+1}=i+1 \mid X_{n}=i\right\}=p_{i}, P\left\{X_{n+1}=i+1 \mid X_{n}=j\right\}=0 \text { for } j \neq i \\
P\left\{X_{n+1}=i-1 \mid X_{n}=i\right\}=q_{i}, P\left\{X_{n+1}=i-1 \mid X_{n}=j\right\}=0 \text { for } j \neq i \\
P\left\{X_{n+1}=i \mid X_{n}=i\right\}=r_{i}=1-p_{i}-q_{i}
\end{gathered}
$$

State Space: $S=\{0,1,2, \ldots\}$
(i.) $\quad q_{0}=0$ means that state 0 is reflecting barrier.
(ii.) If $r_{0}=1$, then once in state 0 it can never leave.
(iii.) If $p_{N}=0 \Rightarrow S=\{0,1,2, \ldots, N\}$
(iv.) If $p_{N}=0$ and $r_{N}=1 \Rightarrow N$ is absorbing ( $r_{N}=0, N$ is reflecting barrier.)

## Example: Gambler's Ruin

Gamblers: $A, B$ have a total of $N$ dollars
Game: Toss Coin
If $H \Rightarrow A$ receives $\$ 1$ from $B$
$T \Rightarrow B$ receives $\$ 1$ from $A$

$$
P(H)=p, \quad P(T)=q=1-p
$$

$X_{n}=$ Amount of money $A$ has after $n$ plays

$$
P\left\{X_{n+1}=X_{n}+1 \mid X_{n}\right\}=p
$$

$$
P\left\{X_{n+1}=X_{n}-1 \mid X_{n}\right\}=q
$$

.....Game ends if $X_{n}=0$ or $X_{n}=N$

State space $=\{0,1,2, \ldots, N\}$

$$
X_{n+1}
$$

$$
\begin{aligned}
& \underline{0} \quad \underline{1} \quad \underline{2} \quad \underline{3} \quad \cdots \quad \underline{N-2} \underline{N-1} \underline{N} \\
& \begin{array}{c} 
\\
\\
X_{n}
\end{array} \begin{array}{c}
0 \\
1 \\
\\
\\
\\
\\
\\
\\
\\
\vdots \\
N
\end{array}\left[\begin{array}{cccccccc}
1 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
q & 0 & p & 0 & \cdots & 0 & 0 & 0 \\
0 & q & 0 & p & \cdots & 0 & 0 & 0 \\
& & & & & & & \\
0 & 0 & 0 & 0 & \cdots & q & 0 & p \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 1
\end{array}\right]
\end{aligned}
$$

Transition Diagram for
Gambler's Ruin


## Example: Urn Models (Ehrenfest Urn Model)

Two urns: $A, B$ each containing $N$ balls (Balls may be red or white).
Experiment consists of picking one ball at a time from each urn at random and placing them in the opposite urn.
$X_{n}=$ no. of white balls in urn $A$ after $n$ repetitions. Assume $X_{0}=N($ all white balls in $A)$.

If $X_{n}=i \Rightarrow \quad i$ white and $N-i$ red in $A$
$i$ red and $N-i$ white in $B$
$P\left\{X_{n+1}=i+1 \mid X_{n}=i\right\}=P\{$ white ball from $B$ and red ball from $A\}$

$$
=\left(1-\frac{i}{N}\right)^{2}=p_{i, i+1} \quad i \neq 0, N
$$

$$
P\left\{X_{n+1}=i-1 \mid X_{n}=i\right\}=P\{\text { white from } A \text { and red from } B\}
$$

$$
\begin{aligned}
= & \left(\frac{i}{N}\right)^{2}=p_{i, i-1} \\
P\left\{X_{n+1}=i \mid X_{n}=i\right\}= & P\{\text { white from } A \text { and } B\} \\
& +P\{\text { Red from } A \text { and } B\} \\
= & 2\left(\frac{i}{N}\right)\left(1-\frac{i}{N}\right)=p_{i i}
\end{aligned}
$$

## Example: Branching Process

$X_{n}=$ no. of individuals in $n^{t h}$ generation beginning with

$$
X_{0}=1(1 \text { individual })
$$

$Y_{i, n}=$ no. of offspring of the $i^{t h}$ person in the $n^{\text {th }}$ generation

$$
X_{n+1}=Y_{1, n}+Y_{2, n}+\ldots+Y_{X_{n}, n}=\sum_{i=1}^{X_{n}} Y_{i, n}
$$

Assume $\left\{Y_{i, n}\right\}$ are iid random variables.

$$
\begin{aligned}
p_{i j} & =P\left\{X_{n+1}=j \mid X_{n}=i\right\}=P\left\{\sum_{i=1}^{X_{n}} Y_{i, n}=j \mid X_{n}=i\right\} \\
& =P\left\{\sum_{r=1}^{i} Y_{r, n}=j\right\}
\end{aligned}
$$

Process: $\left\{X_{n}\right\}$ is called a branching process
How long does it take for a family to become extinct?
What is distribution of size in the $n^{\text {th }}$ generation?
7.3. Marginal Distribution of $X_{n}$

$$
\text { Define } \begin{aligned}
a_{j}^{(n)} & =P\left\{X_{n}=j\right\}=\sum_{i \in S} P\left\{X_{n}=j \mid X_{0}=i\right\} P\left\{X_{0}=i\right\} \\
& =\sum_{i \in S} P\left\{X_{n}=j \mid X_{0}=i\right\} a_{i} \\
p_{i j}^{(n)} & =\text { Prob. of going from } i \rightarrow j \text { in } n \text { steps } \\
p_{i j}^{(n)} & =\text { n-step transition probabilities }
\end{aligned}
$$

Th. Chapman-Kolmogorov Equations

$$
p_{i j}^{(n)}=\sum_{r \in S} p_{i r}^{(k)} p_{r j}^{(n-k)} \quad \underline{\text { Chapman-Kolmogorov Equations }}
$$

where $k$ is a fixed integer $0 \leq k \leq n$

Th. $\quad P^{(n)}=\left(p_{i j}^{(n)}\right)=P^{n}$
Proof. $P\left\{X_{0}=j \mid X_{0}=i\right\}=\left\{\begin{array}{lll}1 & \text { if } & i=j \\ 0 & \text { if } & i \neq j\end{array}\right.$
$\Rightarrow P^{0}=I$. Also $P^{1}=P$. Assume theorem is true for $n=k$. We will show it is true for $n=k+1$.

$$
P^{(k+1)}=P^{(k)} P=P^{k} P=P^{k+1}
$$

Th. $\quad a^{(n)}=$ row vector of $a_{j}^{(n)}=\left(a_{1}^{(n)}, a_{2}^{(n)}, \ldots\right)$

$$
a^{(n)}=a P^{n}
$$

Proof. $a^{(n)}=a^{(0)} P^{(n)}=a P^{n}$

Urn Sampling (Continuation)

$$
E\left(X_{n} \mid X_{0}\right)=\sum_{i=0}^{X_{0}} i P\left\{X_{n}=i \mid X_{0}\right\} \quad \begin{aligned}
& \text { Expected number of white } \\
& \\
& \text { balls in urn } A \text { with } n \\
& \\
& \\
& \\
& \\
& \\
& \text { draws given } X_{0}=\text { no. of } \\
&
\end{aligned}
$$

$$
=(0,0, \ldots, 1) P^{n}\left[\begin{array}{c}
0 \\
1 \\
2 \\
\vdots \\
X_{0}
\end{array}\right]
$$

Suppose $X_{0}=10$

| $\underline{n}$ | $\underline{E\left(X_{n} \mid X_{0}=10\right)}$ | $\underline{n}$ | $\underline{E\left(X_{n} \mid X_{0}=10\right)}$ |
| ---: | :---: | :--- | :---: |
| 2 | 8.2 | 12 | 5.3 |
| 4 | 7.0 | 14 | 5.2 |
| 6 | 6.3 | 16 | 5.14 |
| 8 | 5.8 | 18 | 5.09 |
| 10 | 5.5 | 20 | 5.06 |

## Ex. Branching Process (Continuation)

$$
\begin{gathered}
m_{n}=E\left(X_{n}\right), \quad \sigma_{n}^{2}=\operatorname{Var} X_{n}, \quad m=E\left(Y_{i, n}\right), \sigma^{2}=V\left(Y_{i}, n\right) \\
m_{n}=E\left(X_{n}\right)=E\left(\sum_{i=1}^{X_{n-1}} Y_{i, n-1}\right)=m E\left(X_{n-1}\right) \\
\Rightarrow \quad m_{n}=m m_{n-1} \\
\quad m_{n}=m^{n}, \quad m=E\left(Y_{i, n}\right) \\
\quad \operatorname{Var}\left(X_{n} \mid X_{n-1}\right)=\operatorname{Var}\left(\sum_{i=1}^{X_{n-1}} Y_{i, n}\right)=\sigma^{2} X_{n-1}
\end{gathered}
$$

Recall $\operatorname{Var} Z=E_{Y} \operatorname{Var}(Z \mid Y)+\operatorname{Var}_{Y} E(Z \mid Y)$
In our example $Z=X_{n}, \quad Y=X_{n-1}$
$\operatorname{Var}\left(X_{n} \mid X_{n-1}\right)=\operatorname{Var}\left(\sum_{1}^{X_{n-1}} Y_{i, n-1} \mid X_{n-1}\right)=X_{n-1} \sigma^{2}$, if $X_{n-1}$ fixed

$$
\begin{aligned}
& E\left(X_{n} \mid X_{n-1}\right)=E\left(\sum_{1}^{X_{n-1}} Y_{i, n-1} \mid X_{n-1}\right)=X_{n-1} m \\
& \therefore \operatorname{Var} X_{n}=\sigma^{2} E\left(X_{n-1}\right)+\operatorname{Var}\left(X_{n-1} m\right) \\
& \sigma_{n}^{2}=\sigma^{2} m_{n-1}+m^{2} \operatorname{Var} X_{n-1} \\
& \sigma_{n}^{2}=\sigma^{2} m_{n-1}+m^{2} \sigma_{n-1}^{2}
\end{aligned} \quad \begin{aligned}
\sigma_{n}^{2} & =\sigma^{2} m_{n-1}+m^{2} \sigma_{n-1}^{2} \\
m_{n} & =m^{n}
\end{aligned}
$$

Case 1: $\quad m=1\left(\sigma_{0}^{2}=0\right)$

$$
\begin{aligned}
& \sigma_{n}^{2}=\sigma^{2}+\sigma_{n-1}^{2} \\
& \Rightarrow \quad \sigma_{1}^{2}=\sigma^{2}, \sigma_{2}^{2}=2 \sigma^{2}, \sigma_{3}^{2}=3 \sigma^{2} \\
& \sigma_{n}^{2}=n \sigma^{2} \quad \text { if } m=1
\end{aligned}
$$

Case 2: $m \neq 1$

$$
\begin{aligned}
\sigma_{n}^{2}= & \sigma^{2} m^{n-1}+m^{2} \sigma_{n-1}^{2} \\
\sigma_{1}^{2}= & \sigma^{2} \quad\left(\sigma_{0}^{2}=0\right) \\
\sigma_{2}^{2}= & \sigma^{2} m+m^{2} \sigma_{1}^{2}=\sigma^{2} m\left[\frac{m^{2}-1}{m-1}\right] \\
\sigma_{3}^{2}= & \sigma^{2} m^{2}+m^{2} \sigma_{2}^{2}=\sigma^{2} m^{2}+m^{2}\left[\sigma^{2} m\left(\frac{m^{2}-1}{m-1}\right)\right] \\
= & \sigma^{2} m^{2}\left[\frac{m^{3}-1}{m-1}\right] \\
& \vdots \\
\vdots & \\
\sigma_{n}^{2}= & \sigma^{2} m^{n-1}\left[\frac{m^{n}-1}{m-1}\right] m \neq 1
\end{aligned}
$$

Use of Generating Functions

$$
\begin{aligned}
G(z) & =\sum_{n=1}^{\infty} \sigma_{n}^{2} z^{n} \quad\left(\sigma_{0}^{2}=0\right) \\
\sigma_{n}^{2} & =\sigma^{2} m^{n-1}+m^{2} \sigma_{n-1}^{2} \\
\sum_{1}^{\infty} \sigma_{n}^{2} z^{n} & =\sigma^{2} \sum_{1}^{\infty} m^{n-1} z^{n}+m^{2} \sum_{n=1}^{\infty} \sigma_{n-1}^{2} z^{n} \\
G(z) & =\sigma^{2} z \sum_{n=1}^{\infty}(m z)^{n-1}+m^{2} z \sum_{n=1}^{\infty} \sigma_{n-1}^{2} z^{n-1} \\
G(z) & =\sigma^{2} z \frac{1}{1-m z}+m^{2} z G(z) \\
G(z)\left[1-m^{2} z\right] & =\sigma^{2} z /(1-m z) \\
G(z) & =\sigma^{2} z /\left(1-m^{2} z\right)(1-m z)
\end{aligned}
$$

$$
\begin{aligned}
G(z) & =\sigma^{2} z /\left(1-m^{2} z\right)(1-m z) \\
& =\sigma^{2} z\left\{\sum_{r=0}^{\infty}\left(m^{2} z\right)^{r} \sum_{s=0}^{\infty}(m z)^{s}\right\} \\
& =\sigma^{2} z\left\{\sum_{r=0}^{\infty} \sum_{s=0}^{\infty} m^{2 r+s} z^{r+s}\right\}, n=r+s \quad 0 \leq r \leq n \\
& =\sigma^{2} z \sum_{n=0}^{\infty} z^{n} m^{n} \sum_{r=0}^{n} m^{r}=\sigma^{2} z \sum_{n=0}^{\infty} z^{n} m^{n}\left(\frac{1-m^{n+1}}{1-m}\right) \\
& =\sigma^{2} \sum_{0}^{\infty} z^{n+1} m^{n}\left(\frac{1-m^{n+1}}{1-m}\right) \\
\Rightarrow \sigma_{n+1}^{2} & =\sigma^{2} m^{n}\left(\frac{m^{n+1}-1}{m-1}\right) \text { or } \sigma_{n}^{2}=\sigma^{2} m^{n-1}\left(\frac{m^{n}-1}{m-1}\right) \\
m_{n} & =m^{n}
\end{aligned}
$$

If $m>1, m_{n} \rightarrow \infty$ as $n \rightarrow \infty$
If $m<1, \quad m_{n} \rightarrow 0$ as $n \rightarrow \infty$
If $m=1, m_{n}=m$ always

## Application: Nuclear Reactors

A neutron ( $0^{t h}$ generation) is introduced into a fissionable material. If it hits a nucleus it will produce a random number of new neutrons ( $1^{\text {st }}$ generation). This process continues as each new neutron behaves like the original neutron.

$$
X_{n}=\text { No. of neutrons after } n \text { collisions }
$$

$$
m_{n}=m^{n}
$$

If $m>1$, each neutron produces on average more than one neutron and reaction is explosive-(nuclear explosion or meltdown).

If $m<1$, reaction eventually dies out.

In nuclear power station, $m>1$ to reach "hot stage". Once hot, moderator rods are inserted to remove neutrons and reduce $m$. Hence reactor is controlled. The moderator rods are continually removed and inserted to keep temperature in a given range. (Heat is converted to electricity).

Application: Family Names

Consider only male offspring who will carry family name. If $m<1$, family name will eventually die out as $m^{n} \rightarrow 0$. Males in historical times would keep marrying until a wife could produce a male heir.
i.e. $P\left\{X_{n} \geq 1\right\}=1 \Rightarrow m \geq 1$.

### 7.4 Appendix: Notes on Matrices: I

$$
\text { Let } \begin{array}{ll}
A: & n \times n \text { matrix } \\
& x_{i}: \\
n \times 1 \text { vector }
\end{array}
$$

Eigenvalues:
$|A-\lambda I|=0 \quad$ Polynomial in $\lambda$ of degree $n$. The eigenvalues
$\lambda_{1}, \ldots, \lambda_{n}$ are the zeros of the polynomial.
$\underline{\text { Eigenvectors }}$
If $A x_{i}=\lambda_{i} x_{i} \quad i=1, \ldots, n$ then $x_{i}(n \times 1)$ are the right eigenvectors associated with $\lambda_{i}$.

If $y_{i}^{\prime} A=\lambda_{i} y_{i}^{\prime} \quad i=1, \ldots, n$ then $y_{i}(n \times 1)$ are the left eigenvectors associated with $\lambda_{i}$.

$$
\Rightarrow x_{i}^{\prime} y_{j}=0, \quad i \neq j
$$

Proof: $A x_{i}=\lambda_{i} x_{i}, y_{j}^{\prime} A x_{i}=\lambda_{j} y_{j}^{\prime} x_{i}=\lambda_{i} y_{j}^{\prime} x_{i}$
If $y_{j}^{\prime} x_{i} \neq 0$, then $\lambda_{i}=\lambda_{j}$ which is false. Hence $y_{j}^{\prime} x_{i}=0$.
Scale $x_{i}$, and $y_{i}$ so that $x_{i}^{\prime} y_{i}=1$
Define

$$
\begin{aligned}
X^{n \times n} & =\left[x_{1}, x_{2}, \ldots, x_{n}\right] \\
Y^{n \times n} & =\left[\begin{array}{c}
y_{1}^{\prime} \\
y_{2}^{\prime} \\
\vdots \\
y_{n}^{\prime}
\end{array}\right]
\end{aligned}
$$

Therefore $A X=X D$ and $Y A=D Y$ where $D=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)$. We can write $A=X D X^{-1}=Y^{-1} D Y$. Hence $X=Y^{-1}$.

Since

$$
\begin{aligned}
A & =X D X^{-1} \\
A^{2} & =X D X^{-1} X D X^{-1}=X D^{2} X^{-1} \\
A^{m} & =X D^{m} X^{-1}, \quad D^{m}=\operatorname{diag}\left(\lambda_{1}^{m}, \ldots, \lambda_{n}^{m}\right)
\end{aligned}
$$

Idempotent Decomposition $A^{m}=\sum_{i=1}^{n} \lambda_{i}^{m} x_{i} y_{i}^{\prime}=\sum_{i=1}^{n} \lambda_{i}^{m} E_{i}$

$$
E_{i}=x_{i} y_{i}^{\prime} \text { and } E_{i}^{2}=E_{i}, \quad E_{i} E_{j}=0 i \neq j
$$

If $A$ is stochastic $\underline{1}^{\prime} A=\underline{1}^{\prime}$ (columns add to unity), then $\lambda=1$ is the largest eigenvalue.

$$
\begin{aligned}
P & =\sum_{1}^{n} \lambda_{i} E_{i}, \quad P^{m}=\sum_{1}^{n} \lambda_{i}^{m} E_{i} \\
\text { as } m \rightarrow \infty, \lim _{m \rightarrow \infty} P^{m} & =E_{1}=y_{1} x_{1}^{\prime}
\end{aligned}
$$

