

woeh
45?

Intro to DS: Markov Chains.

def.
Pseudorandom

$$\mathcal{M} = \{0, 1, \dots, M-1\}$$

$$u_i \in \mathcal{M}$$

$$\frac{N_n(a)}{n} \xrightarrow[\text{how many numbers you see}]{\text{how many times a number appears}} \frac{1}{M} \text{ for any } a \in \mathcal{M}$$

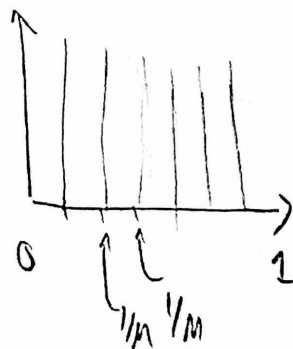
$$\begin{aligned} \text{seed} &= 1 \\ a &= 2 \\ b &= 1 \\ M &= 10 \\ u_{i+1} &= 3 \bmod 10 = 3. \end{aligned}$$

LCG

$$u_{i+1} = a \cdot u_i + b \bmod M$$

The correct choice of a, b, M gives u_i is pseudorandom sequence on \mathcal{M}

$$u_i \rightarrow \frac{u_i}{M} \in [0, 1]$$



as $M \rightarrow \text{infinity}$

Def Markov
Chain

A sequence of RVs X_1, \dots , is called a Markov chain if the distribution of X_t only depends on the previous state X_{t-1} .

Def.
Stochastic process

Stochastic process

✓ Sequence
of RVs

✓ think of this
as time.

$$(X_\alpha)_{\alpha \in \mathbb{N}}$$

Time 1, Time 2
etc. . . .

$$\alpha = \mathbb{R}$$

← continuous time

Def.
Finite Markov
Chain

$$(X_n)_{n \in \mathbb{N}}$$

Markov property
(Assumption)

$$\mathbb{P}(X_{t+1} = x \mid X_0, X_1, \dots, X_t) =$$

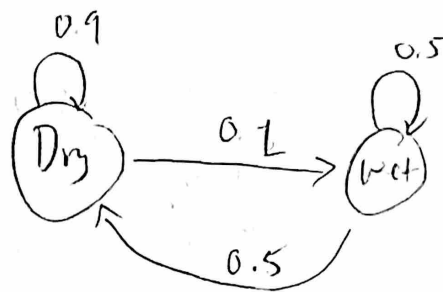
$$\mathbb{P}(X_{t+1} = x \mid X_t)$$

$$X_t \in X = \{0, 1, \dots, K\}$$

↑
state
space

finite as the state space is finite

Simple weather example



Transition matrix

We can write this as a matrix:

$$P = \begin{bmatrix} P(X_t = \text{"dry"} | X_{t-1} = \text{"dry"}) & P(X_t = \text{"wet"} | X_{t-1} = \text{"dry"}) \\ P(X_t = \text{"dry"} | X_{t-1} = \text{"wet"}) & P(X_t = \text{"wet"} | X_{t-1} = \text{"wet"}) \end{bmatrix}$$

The diagonal is always transitioning to itself.

Transition matrix

$$(P^t)_{xy} = P(X_t = y | X_{t-1} = x)$$

$$= \left[\begin{array}{l} \text{probability of going from} \\ x \text{ to } y \text{ at time } t. \end{array} \right]$$

the
ex

$$P_{t+1} = P_{t-1} = [P(X_{t-1} = \text{"dry"}), P(X_{t-1} = \text{"wet"})]$$

We want to compute $[P(X_t = \text{"dry"}), P(X_t = \text{"wet"})]$

$$P(X_t = \text{"dry"}) = P(X_t = \text{"dry"} | X_{t-1} = \text{"dry"}) \cdot P(X_{t-1} = \text{"dry"}) +$$

$$P(X_t = \text{"dry"} | X_{t-1} = \text{"wet"}) \cdot P(X_{t-1} = \text{"wet"})$$

= see next slide

the example
(continued...)

$$= (P^t)_{\text{drydry}} (q_{t-1})_{\text{dry}} + (P^t)_{\text{wetdry}} (q_{t-1})_{\text{wet}}$$

$$= (q_t)_{\text{dry}} \quad \text{column}$$

$$(P^t)_{\text{dry}} \quad \text{dry} \quad q_{t-1}$$

$$\quad \quad \quad \text{dot product}$$

$$q_{t-1} P^t = \begin{pmatrix} \text{row of } q_{t-1} \text{ dot product of } P^t \\ \text{is the first instance,} \\ \text{0.5, ...} \end{pmatrix}$$

$$= q_t$$

Repeat 2 get

$$q_0 P^{(1)} P^{(2)} P^{(3)} \dots P^{(t)} = q_t$$

index

In this case, the "wet-dry" case:

$$P^t = P \quad \forall t$$

$$q_0 (P)^t = q_t$$

~~np.log~~

$$-np.sum(Y \cdot \log(X) - (lam))$$

correlation threshold > 0.3

correlate Y with X.

Import np

$$P = \text{np.matrix} \begin{pmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{pmatrix}$$

$$p_0 = \text{np.array}([1, 0]) \quad \leftarrow \text{initial state is drug}$$

$$p_0 \cdot P$$

$$p_0 \times (P^{**10})$$

$$q_0 = \text{np.array}([0, 1]) \quad \text{initial state is wet}$$

Stationary distribution

$$P_0 P^t \rightarrow P_* \quad \forall P_0$$

$$P_* P = P_*$$

P_* is a left eigenvector.
eigenvalue 1

$$P^T P_*^T = P_*^T$$

$$(P_* P)^T = (P_*)^T$$

$$\text{eig.v. evecs} = \text{np.linalg.eig}(P.T)$$

$$\text{first_evec} = \text{evecs[:, 0]}$$

$$\text{np.array(first_evec) / np.sum(first_evec)}$$

homogenous
markov chain

= the markov chain is not dependent on
time

Homogenous: we need to observe for
a long time only one chain
Goal: estimate P . K^2 parameters.

inhomogenous: we need to observe multiple
chains.

Goal: estimate $P^{(0)}, P^{(1)}, P^{(2)}$
index

$0 \leq t \leq T$ $T \cdot K^2$ parameters

Property of P :

$$1) P_{x_0} = P(X_{t+1} = y \mid X_t = x)$$

transition from state x to any other state

$$= \sum_y P_{xy} = 1$$

Example
wet-dry
(continued)

$$E[\ln(P_n(X_1, \dots, X_n))]$$

start small

$$E[\ln P_2(x_1, x_2)] =$$

$$= E[\ln P(x_2 | x_1) P(x_1)] =$$

$$E[\ln P(x_2 | x_1)] + E[\ln P(x_1)]$$

$$\hat{R}(p) = - \sum_{i=0}^n \ln(p_{i,i}) n_{i,i} + \ln(1-p_{0,1}) n_{0,1} + \ln(1-p_{1,2}) n_{1,2}$$

$$\frac{\partial \hat{R}}{\partial p_{0,0}} = 0$$

$$\frac{\partial \hat{R}}{\partial p_{1,2}} = 0$$

Minimize

$$p_{0,0} = \frac{n_{0,0}}{n_{0,1} + n_{0,0}}$$

number of times we've seen this transition

all transitions from 0

$$n_{0,1} + n_{0,0}$$

$$p_{1,2} = \frac{n_{1,2}}{n_{1,0} + n_{1,2}}$$

Take: # of times we've seen transition 1,0 out of all transitions

RMP

Skapad med Tiny Scanner

$$P(x, w) \rightarrow \gamma$$

$$x = x_{t-1} \quad P(x_t | x_{t-1})$$

Example
wet-dry
continued

$$E[\ln(P_n(X_1, \dots, X_n))]$$

start small

$$\begin{aligned} E[\ln P_2(x_1, x_2)] &= \\ &= E[\ln P(x_2 | x_1) P(x_1)] = \\ &= E[\ln P(x_2 | x_1)] + E[\ln P(x_1)] \end{aligned}$$

$$\hat{R}(p) = - \sum_{i=0}^n \ln(p_{i,1}) n_{i,1} + \ln(1-p_{i,1}) n_{i,2} + \ln(1-p_{1,2}) n_{1,0}$$

$$\frac{\partial \hat{R}}{\partial p_{0,0}} = 0$$

$$\frac{\partial \hat{R}}{\partial p_{1,2}} = 0$$

minimize

$$p_{0,0} = \frac{n_{0,0}}{n_{0,1} + n_{0,0}}$$

$$p_{1,1} = \frac{n_{1,1}}{n_{1,0} + n_{1,2}}$$

number of times we've seen this transition

all transitions from 0

Total: # of times we've seen transition $n_{0,0}$ out of all transitions

RMP

$$P(x, w) \rightarrow y$$

Skapad med Tiny Scanner

$$P(P(x, w) = y) = P_{xy}$$

w_1, w_2, \dots, w_t i.i.d. uniform(0,1)

w is random variable