

IS 7033: Artificial Intelligence and Machine Learning

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<https://github.com/paulNrad/ProbabilisticGraphModels>

Markov and Hidden Markov Models (HMM)

Outline

- Time series
- Markov Chain
- Hidden Markov Model

Markov Chain

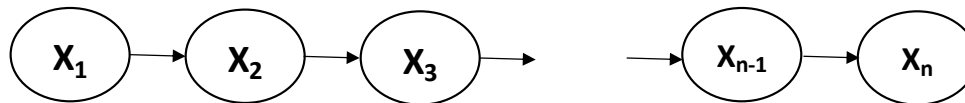
- A Markov chain describes a discrete stochastic process at successive times. The transitions from one state to any of all states including itself, are governed by a **probability distribution**.

$$P(X_t | X_1 \dots X_{t-1}) = P(X_t | X_{t-m} \dots X_{t-1})$$

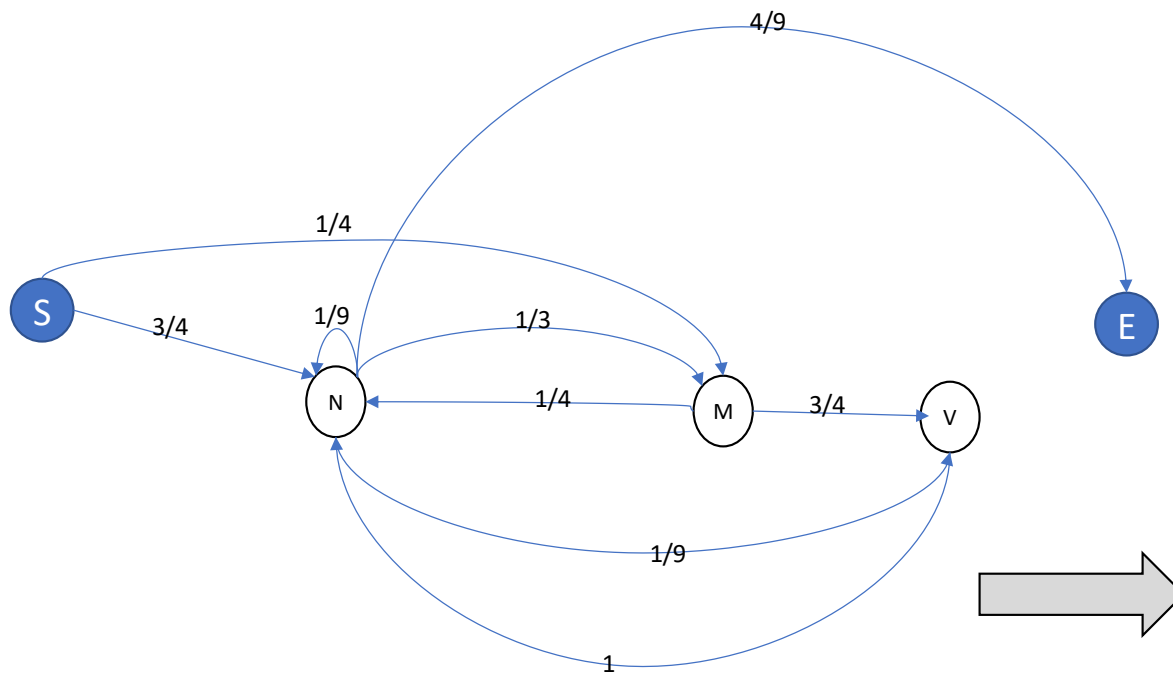
$$X_t = F(X_{t-1}, \dots X_{t-m}) \quad \text{m-order Markov Chain}$$

- A chain of random variables in which the next one depends (only) on the current one

$$P(X_t | X_1 \dots X_{t-1}) = P(X_t | X_{t-1})$$



Transition Probability

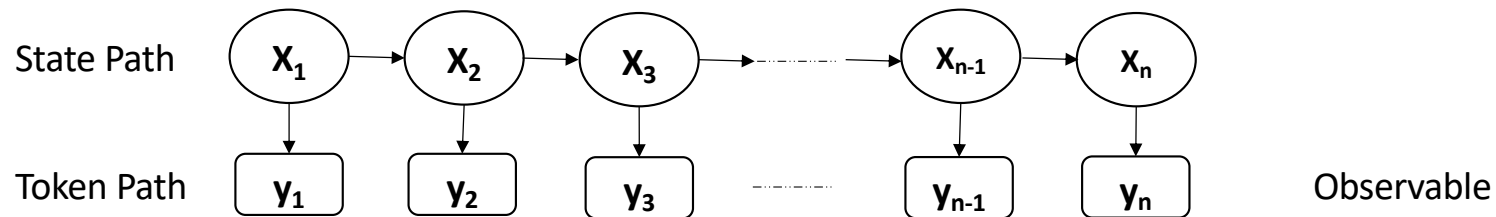


Transition Probabilities

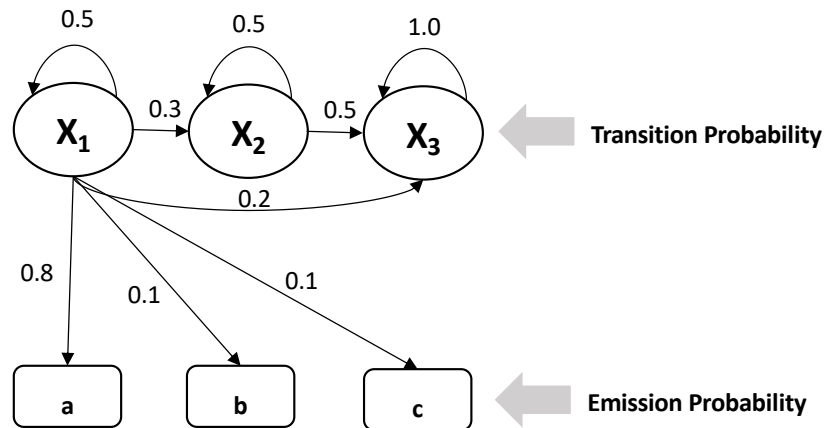
	N	M	V	End
Start	3/4	1/4	0	0
N	1/9	1/3	1/9	4/9
M	1/4	0	3/4	0
V	1	0	0	0

Hidden Markov Model (HMM)

- In addition to State **Transition Probability**, each state of HMM has a probability distribution over the possible output tokens (**Emission Probability**).
- Thus, a HMM is consist of two strings of information.
 - **The state path** is not directly visible
 - **The token path** (emitted sequence). Infer state path based on the observable token path.



Hidden Markov Model Example



	X_1		X_2		X_3	
	Out	Trans	Out	Trans	Out	Trans
a		0.8	a	0.2	a	0.7
b		0.1	b	0.6	b	0.3
c		0.1	c	0.2	c	0.1

What is the probability of HMM producing “a,a,b,c”?

Given a HMM, a sequence of tokens could be generated as following:

- When we “visit” a state, we emit a token from the state’s emission probability distribution.
- Then we choose which state to visit next, according to the state’s transition probability distribution.

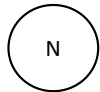
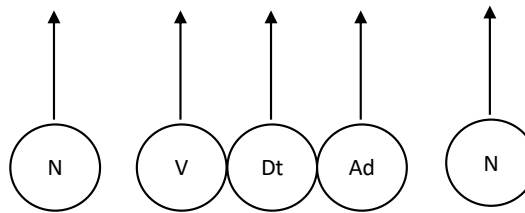
$$P(a,a,b,c) \text{ via } 1,1,2,3 = 0.8 \times 0.5 \times 0.8 \times 0.3 \times 0.6 \times 0.5 \times 0.1 = 0.004068$$

$$P(a,a,b,c) \text{ via } 1,2,3,3 = 0.8 \times 0.3 \times 0.2 \times 0.5 \times 0.3 \times 1 \times 0.1 = 0.00072$$

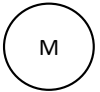
$$P(a,a,b,c) \text{ via } 1,3,3,3 = 0.8 \times 0.2 \times 0.7 \times 1.0 \times 0.3 \times 1.0 \times 0.1 = 0.00336$$

Example: Part of Speech Tagging

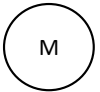
Mary had a little lamb.



Noun



Modal verb



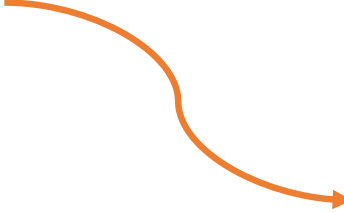
Verb

Jan can run


Look up Table

Given Data:

Mary saw Jane.
Jane saw Will.

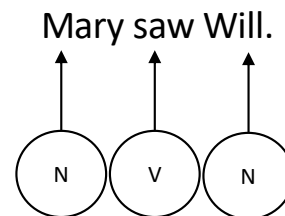


	N	V
Mary	1	0
saw	0	2
Jane	2	0
Will	1	0

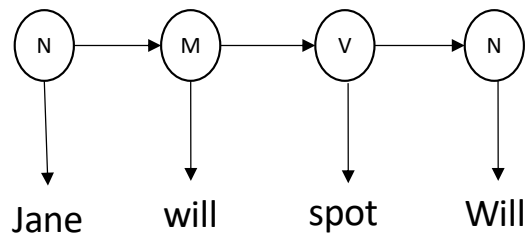


For
Mary saw Will.

Calculate:
Part of Speech Tagging?



Example: Part of Speech Tagging



Transition Probabilities

	N	M	V	End
Start	3/4	1/4	0	0
N	1/9	1/3	1/9	4/9
M	1/4	0	3/4	0
V	1	0	0	0

(N) (N) (M) (V) (N)

Mary Jane Can see Will.

(N) (M) (V) (N)

Spot will see Mary.

(M) (N) (V) (N)

Will Jane spot Mary?

(N) (M) (V) (N)

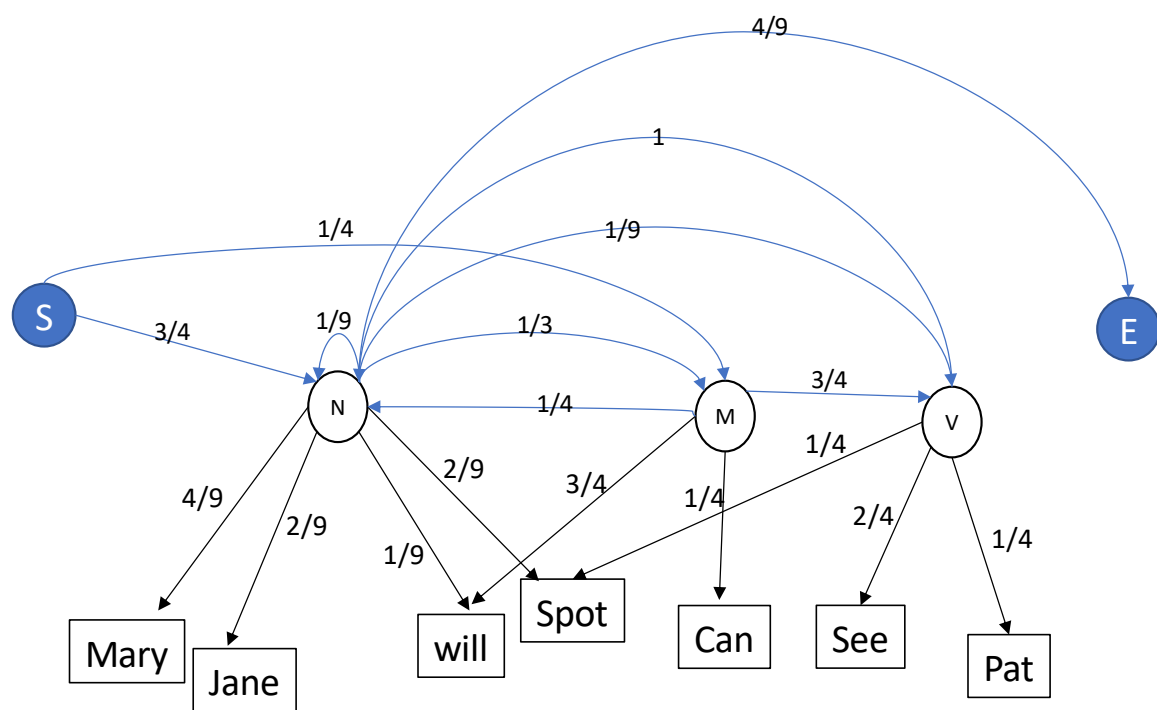
Mary will pat Spot.

Given Data

Emission Probabilities

	N	M	V
Mary	4/9	0	0
Jane	2/9	0	0
will	1/9	3/4	0
Spot	2/9	0	1/4
Can	0	1/4	0
See	0	0	2/4
Pat	0	0	1/4

Example: Hidden Markov Model (HMM)



Transition Probabilities

	N	M	V	End
Start	$3/4$	$1/4$	0	0
N	$1/9$	$1/3$	$1/9$	$4/9$
M	$1/4$	0	$3/4$	0
V	1	0	0	0

Emission Probabilities

	N	M	V
Mary	$4/9$	0	0
Jane	$2/9$	0	0
will	$1/9$	$3/4$	0
Spot	$2/9$	0	$1/4$
Can	0	$1/4$	0
See	0	0	$2/4$
Pat	0	0	$1/4$

Assignment

use the [Pomegranate](#) library or PyMC3 to build a hidden Markov model for part of speech tagging with a universal tagset library:

<http://www.petrovi.de/data/universal.pdf>