Artificial & Computational Intelligence

AIML CLZG557

M6: Reasoning over time

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Course Plan

M1	Introduction to AI
M2	Problem Solving Agent using Search
M3	Game Playing
M4	Knowledge Representation using Logics
M5	Probabilistic Representation and Reasoning
M6	Reasoning over time
M7	Ethics in AI

Reasoning Over Time

Learning Objective

1. Understand the relationship between Time & Uncertainty

1. Recognize the transition model of Markov Model

1. Relate to the application of the Hidden Markov Model

$0.5 \to P(H$

$0.5 \to P(L)$

Hidden Morkov Model

forward

Inference: Type -2

HHH

LLL

Most Likely Explanation : Veterbi Algorithm

(Find the pattern in pressure that might have caused this observation: $\boxed{\textbf{S-S-R}}$

argmax $X_{1...t}$: $P(X_{1...t} \mid E_{1...t})$)

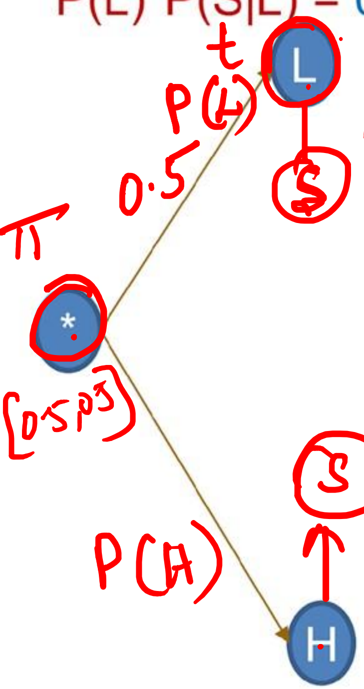
SSR

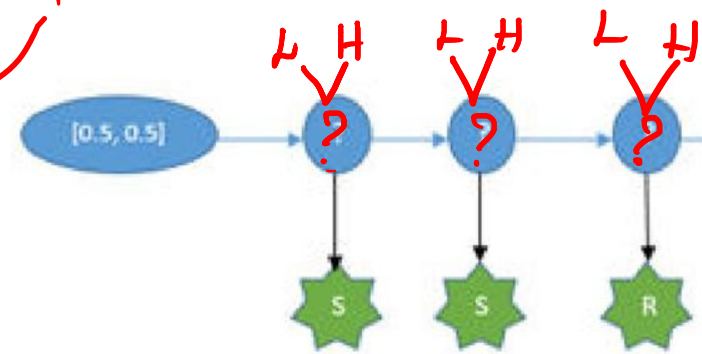
t t+1 t+2

MM Inf

$P(L)*P(S|L) = 0.5*0.2 = 0.1 \to 0.25$

$\frac{0.1}{0.1+0.3} \Rightarrow \frac{0.1}{0.4}$





Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

$\frac{0.3}{0.1+0.3} = 0.75$

$P(H)*P(S|H) = 0.5*0.6 = \boxed{0.3} \to 0.75$

Norm

Hidden Morkov Model

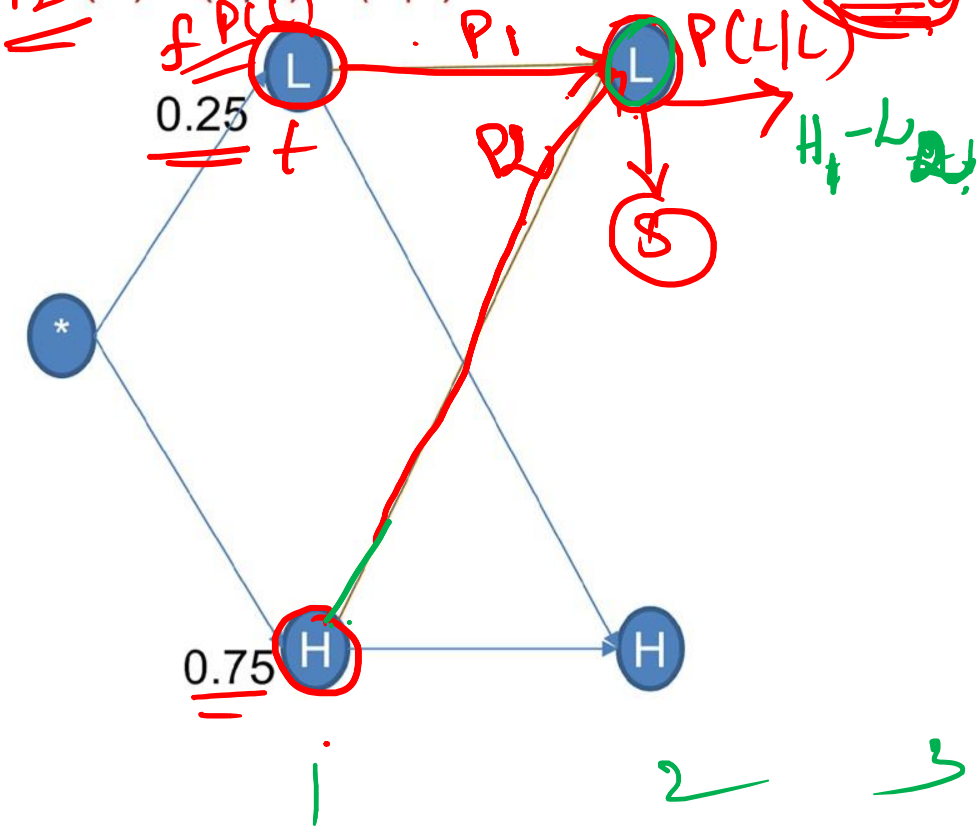
Veterbi Algorithm : S-S-R

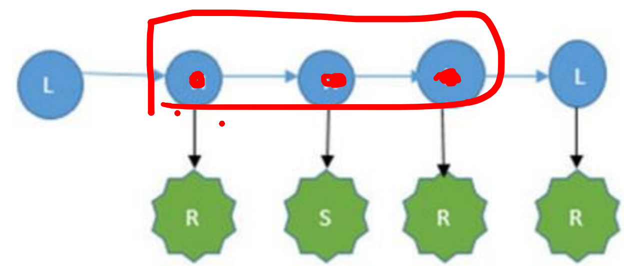
forw

P_1 P(L)*P(L|L)*P(S|L) = 0.25*0.5*0.2 = 0.025

P_2 P(H)*P(L|H)*P(S|L) = 0.75*0.2*0.2 = 0.030

max





Transition Model / Probability Matrix

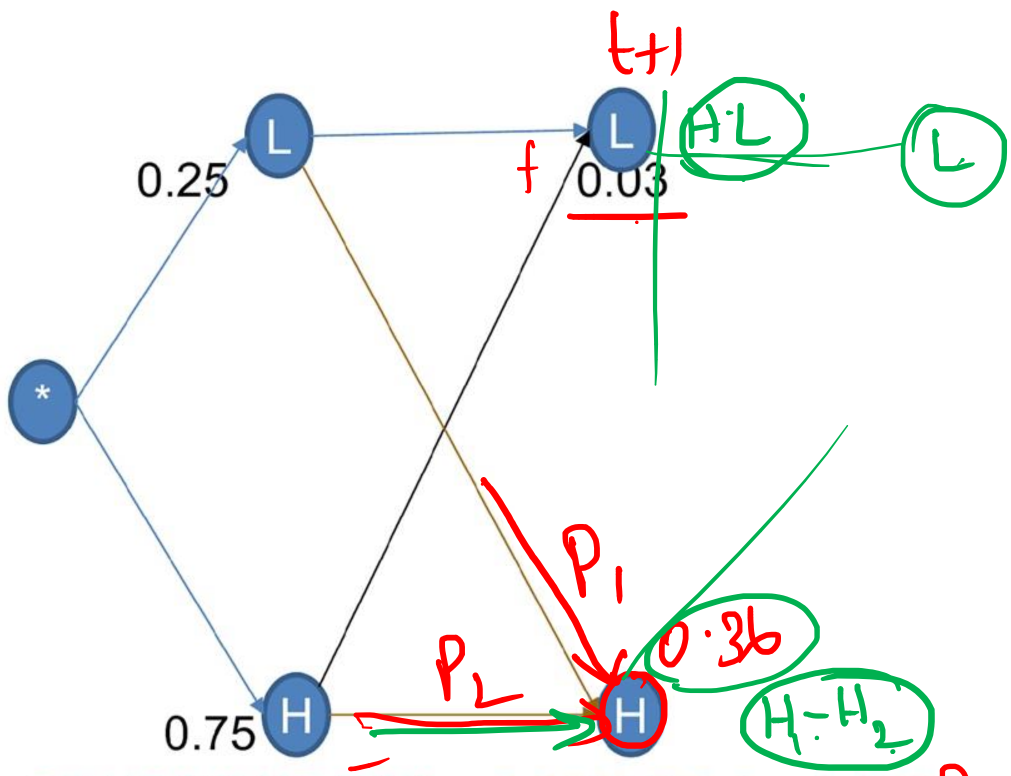
P(U_{t-1} = HP)	P(U_{t-1} = LP)	←Previous
0.2	0.5	P(U_t = LP)
0.8	0.5	P(U_t = HP)

Evidence / Sensor Model/ Emission Probability Matrix

P(X_t = LP)	P(X_t = HP)	←Unobserved Evidence v
0.8	0.4	P(E_t = Rainy)
0.2	0.6	P(E_t = Sunny)

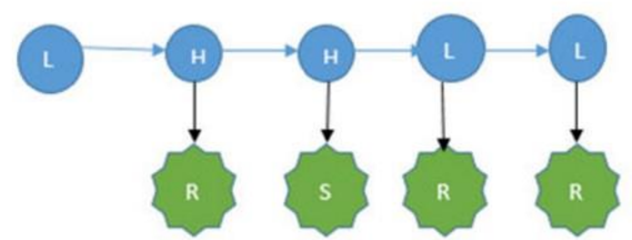
Hidden Morkov Model

Veterbi Algorithm : S-S-R



$$P(L)*P(H|L)*P(S|H) = 0.25*0.5*0.6 = 0.075$$
$$P(H)*P(H|H)*P(S|H) = 0.75*0.8*0.6 = 0.36$$

max



Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

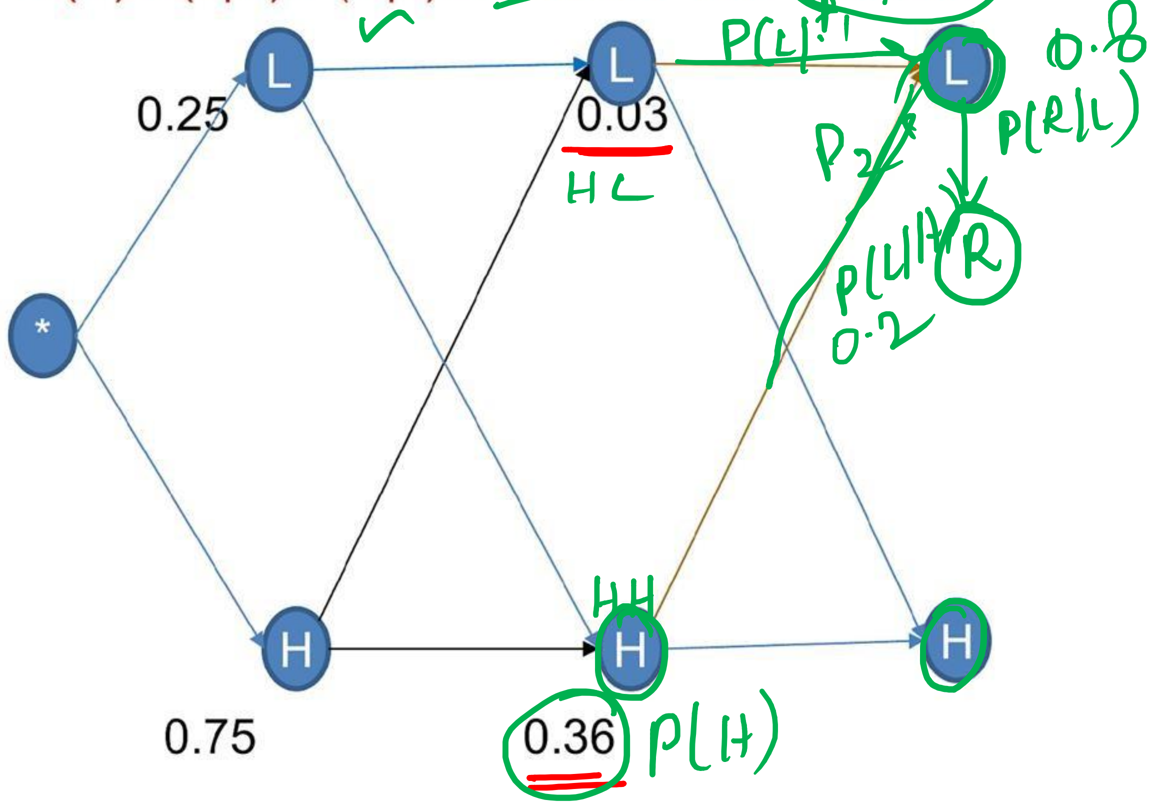
$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

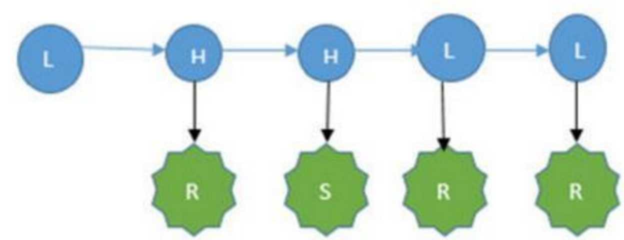
Hidden Morkov Model

Veterbi Algorithm : S-S-R

P(L)*P(L|L)*P(R|L) = 0.03*0.5*0.8 = 0.012

P(H)*P(L|H)*P(R|L) = 0.36*0.2*0.8 = 0.0576





Transition Model / Probability Matrix

P(U$_{t-1}$ = HP)	P(U$_{t-1}$ = LP)	←Previous
0.2	0.5	P(U$_t$ = LP)
0.8	0.5	P(U$_t$ = HP)

Evidence / Sensor Model/ Emission Probability Matrix

P(X$_t$ = LP)	P(X$_t$ = HP)	←Unobserved Evidence v
0.8	0.4	P(E$_t$ = Rainy)
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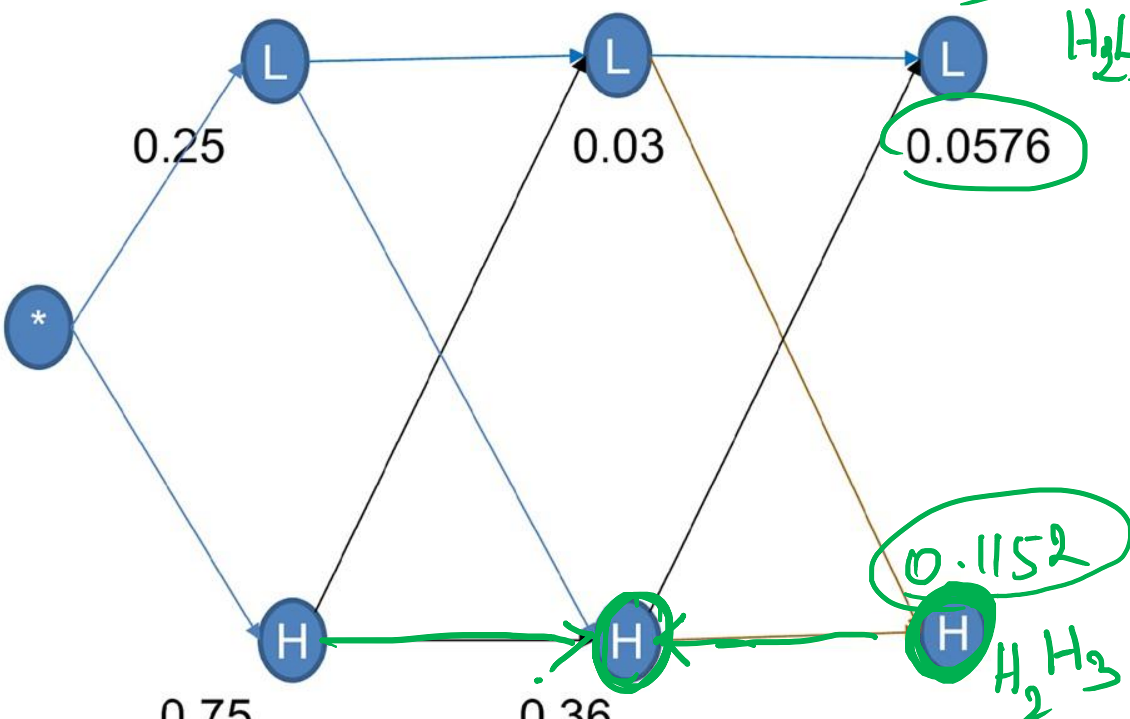
Hidden Morkov Model

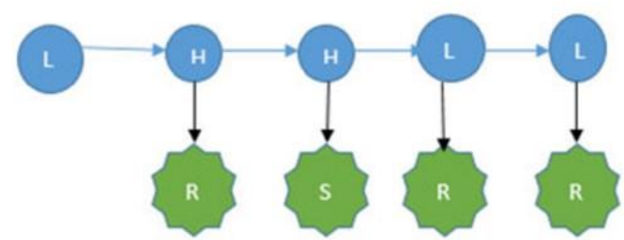
Veterbi Algorithm : S-S-R

t_3

H H

$P(SSR) \Rightarrow$ HHH





$$\left.\begin{array}{l} P(L)*P(H|L)*P(R|H) = 0.03*0.5*0.4 = 0.006 \\ P(H)*P(H|H)*P(R|H) = 0.36*0.8*0.4 = \underline{0.1152} \end{array}\right\} \max$$

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
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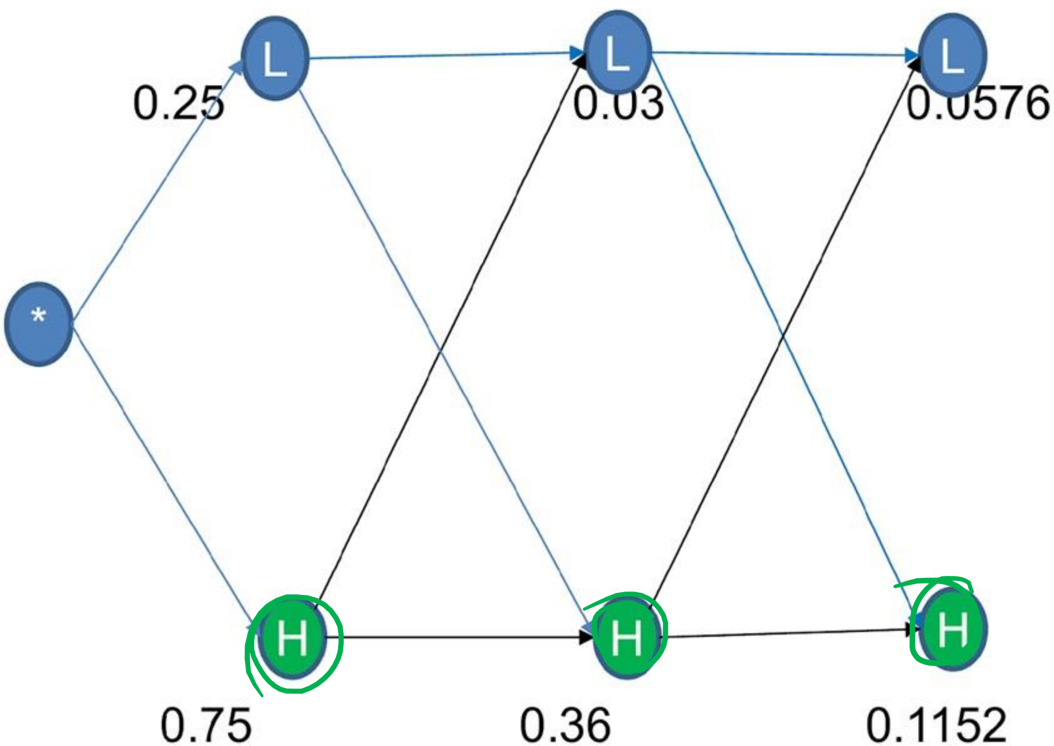
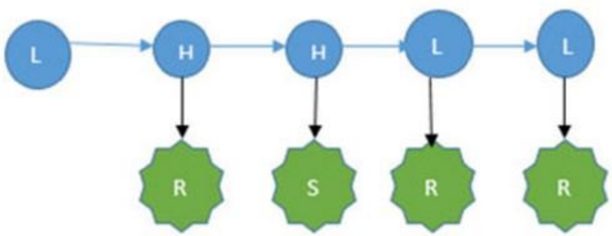
Hidden Morkov Model

Veterbi Algorithm : S-S-R





Transition Model / Probability Matrix

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0.2	0.6	$P(E_t = Sunny)$

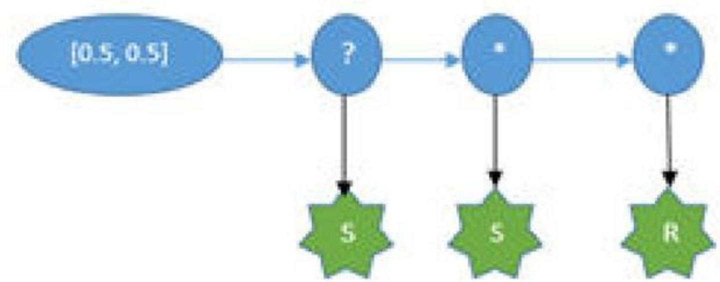
Hidden Morkov Model

Inference: Type -4

Smoothing : Backward Propagation Algorithm (Most Likely State Estimation)

Find the Pressure in past instance of time if sequence of following future weather observations recorded are: **S-S-R**

Intuition: $P(E_{1...t}) = \sum_{i=1}^{N} P(E_{1...t} \mid X_{1...t}) * P(X_{1...t}) = \sum_{i=1}^{N} \prod_{j=1}^{t} P(Ej \mid Xj) * P(Xj \mid Xj_{-1})$



Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	← Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	← Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Hidden Morkov Model

Inference: Type -4

Smoothing : Backward Propagation Algorithm

Find the Pressure in past instance of time if sequence of following future weather observations recorded are: **S-S-R**

Intuition: $P(Xt_{+1} | E_{1\ldots t+1}) = \boldsymbol{\alpha}\, P(et_{+1} | Xt_{+1}) * \sum_{X_t} P(X_{t+1}|X_t) * \boldsymbol{P}(\mathbf{X_t} | \mathbf{E_{1..t}})$

$$P(X_1 \mid SSR) = P(X_1 \mid S,S,R)$$

$$= \frac{\boldsymbol{P}(\boldsymbol{SR} \mid \mathbf{X_1}\ \boldsymbol{S}) * P(X_1 | S)}{P(SR)}$$

$$= \frac{P(X_1 | S) * \{\sum_{X_2} P(X_2|X_1) * \boldsymbol{P}(\mathbf{SR} \mid \mathbf{X_2}\ \mathbf{X_1})\}}{P(SR)}$$

$$= \frac{P(X_1 | S) * \{\sum_{X_2} P(X_2|X_1) * \boldsymbol{P}(\mathbf{SR} \mid \mathbf{X_2})\}}{P(SR)}$$

$$= \frac{P(X_1 | S) * \{\sum_{X_2} P(X_2|X_1) * P(S \mid X_2) * \boldsymbol{P}(\mathbf{R} \mid \mathbf{X_2})\}}{P(SR)}$$

$$= \frac{P(X_1 | S) * \{\sum_{X_2} P(X_2|X_1) * P(S \mid X_2) * \{\sum_{X_3} P(X_3|X_2) * P(R \mid X_3) * \boldsymbol{P}(. \mid \mathbf{X_3})\}\}}{P(SR)}$$

Transition Model / Probability Matrix

P(U$_{t-1}$ = HP)	P(U$_{t-1}$ = LP)	←Previous
0.2	0.5	P(U$_t$ = LP)
0.8	0.5	P(U$_t$ = HP)

Evidence / Sensor Model/ Emission Probab

P(X$_t$ = LP)	P(X$_t$ = HP)	←Unobserved Evidence v
0.8	0.4	P(E$_t$ = Rainy)
0.2	0.6	P(E$_t$ = Sunny)

$$P(Xt \mid E_{t+1,\, t+2\, \ldots\, z}) = \boldsymbol{\alpha} * \text{fwd msg} * \sum_{X_{t+1}} P(X_{t+1}|X_t) * P(e_{t+1}|X_{t+1}) * \boldsymbol{P}(\mathbf{E_{t+2..z}} | \mathbf{X_{t+1}})$$

transition

Msg

S S R
t t+1 t+2

Hidden Morkov Model

Backward Propagation Algorithm

Pressure sequence observation: **S-S-R**

Initialization Phase: Set value 1 for the terminal state

P_1 P(L|L)*P(R|L)*P(.|L) = 0.5*0.8 * 1= 0.40

P(H|L)*P(R|H)*P(.|H) = 0.5*0.4 *1= 0.2

0.60

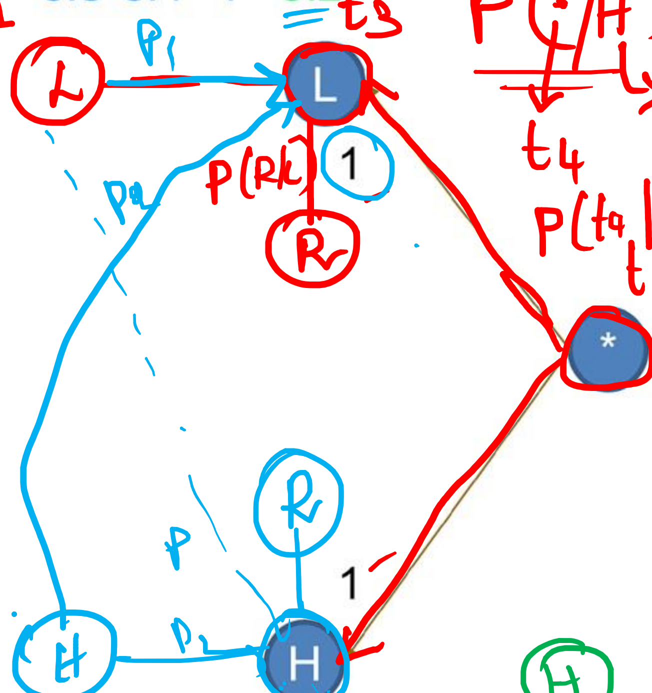
P(·|L) = 1

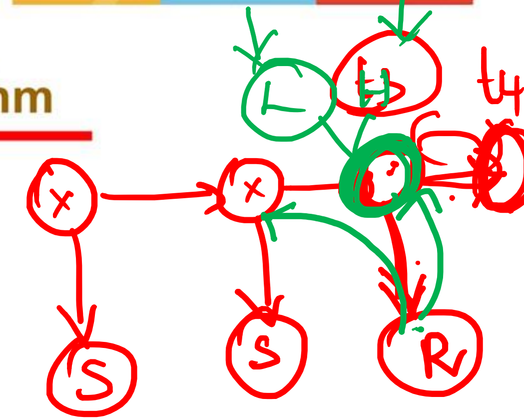
P(·|H) ⇒ 1

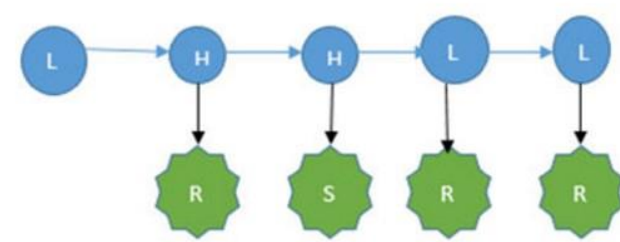
t3 t4

P(t4|t3)

t4 L







π^0

Transition Model / Probability Matrix

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0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

P(L|H)*P(R|L)*P(.|L) = 0.2*0.8 * 1= 0.16

P(H|H)*P(R|H)*P(.|H) = 0.8*0.4 *1= 0.32

+ } 0.48

H

Hidden Morkov Model

Backward Propagation Algorithm

Pressure sequence observation: **S-S-R**

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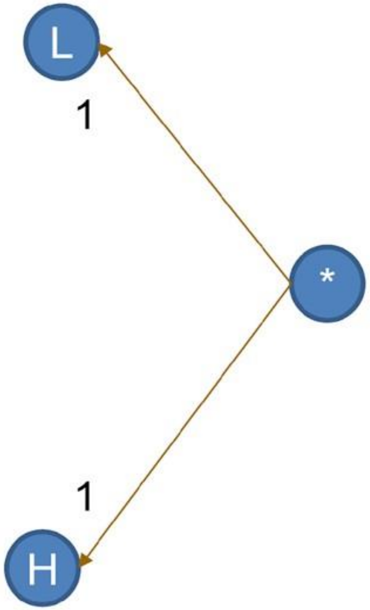

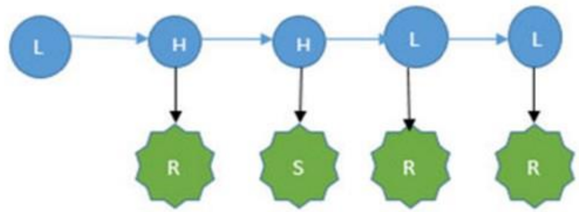

Transition Model / Probability Matrix

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0.8	0.5	$P(U_t = HP)$

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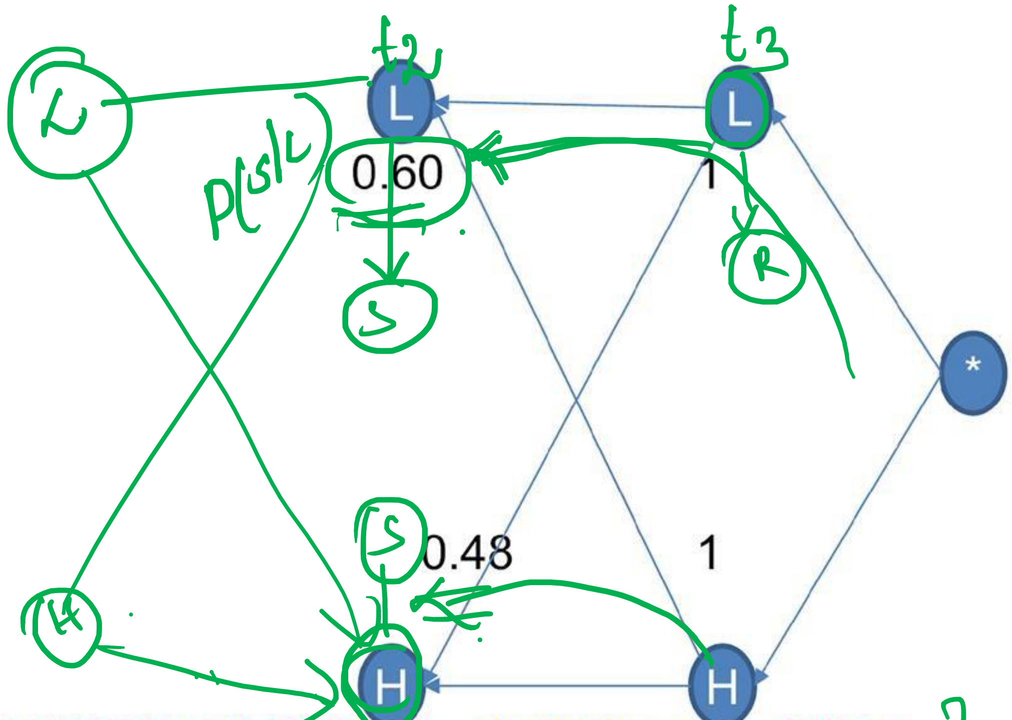
P(H|H)*P(R|H)*P(.|H) = 0.8*0.4 *1= 0.32

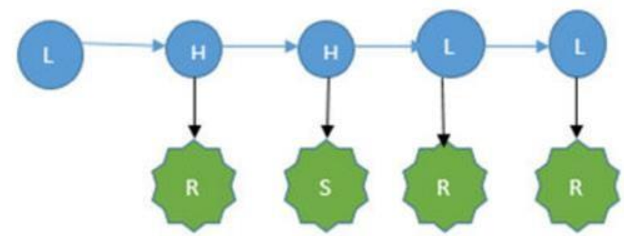
Hidden Morkov Model

Backward Propagation Algorithm : S-S-R

P(L|L)*P(S|L)*MSG(L`) = 0.5*0.2 * 0.60= 0.06
P(H|L)*P(S|H)*MSG(H`) = 0.5*0.6*0.48= 0.144

+ 0.204





P(L|H)*P(S|L)*MSG(L`) = 0.2*0.2 * 0.6= 0.024
P(H|H)*P(S|H)*MSG(H`) = 0.8*0.6 *0.48= 0.2304

Recursion Phase:

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
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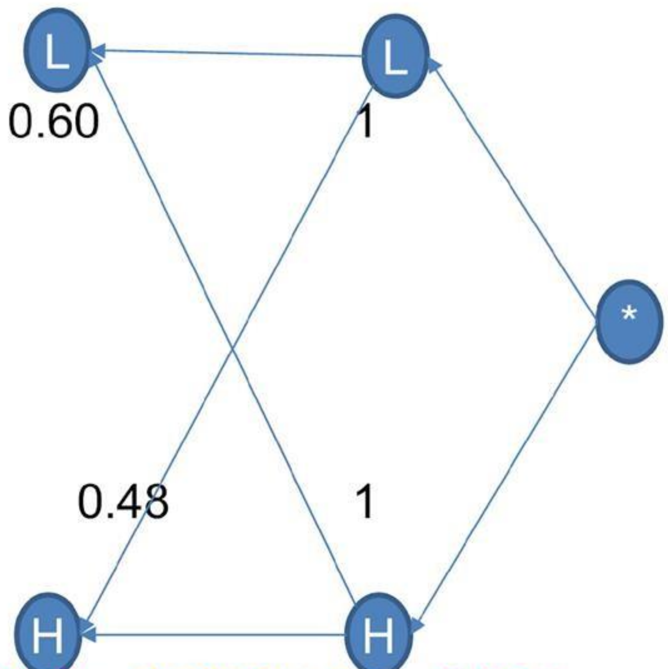
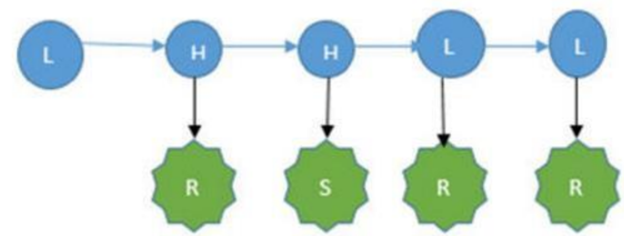
Hidden Morkov Model

Backward Propagation Algorithm : S-S-R

P(L|L)*P(S|L)*MSG(L`) = 0.5*0.2 * 0.60= 0.06

P(H|L)*P(S|H)*MSG(H`) = 0.5*0.6*0.48= 0.144





Transition Model / Probability Matrix

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$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

P(L|H)*P(S|L)*MSG(L`) = 0.2*0.2 * 0.6= 0.024

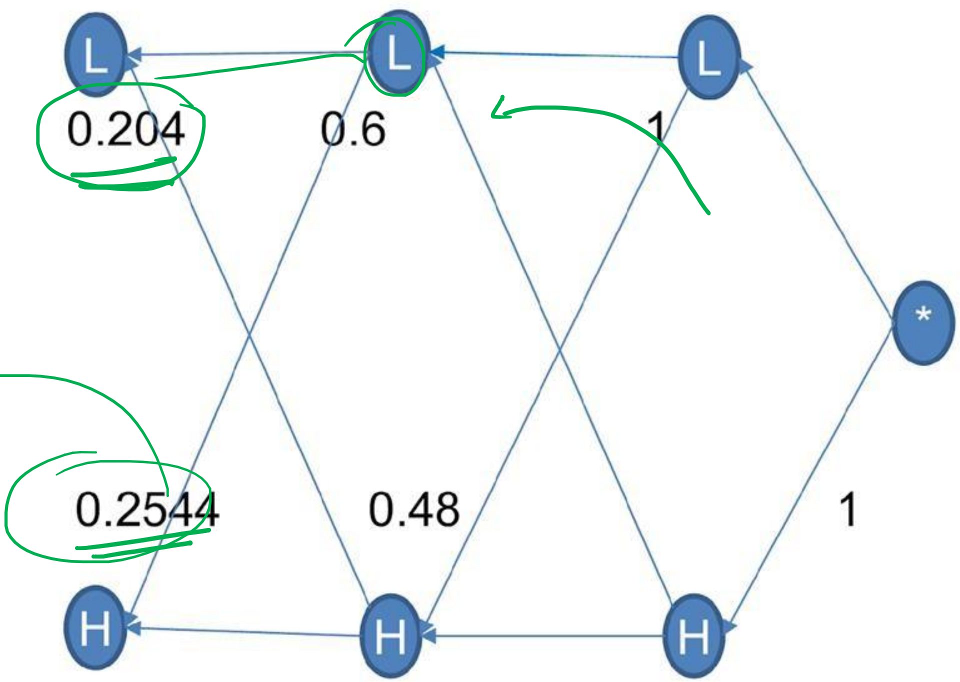
P(H|H)*P(S|H)*MSG(H`) = 0.8*0.6 *0.48= 0.2304

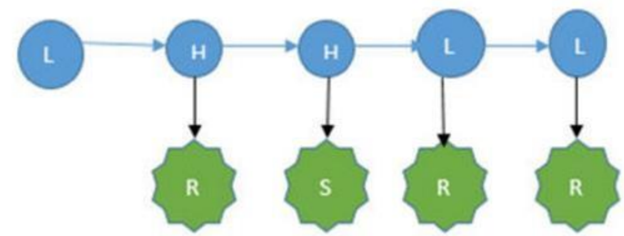
<u>Recursion Phase:</u>

Hidden Morkov Model

Backward Propagation Algorithm : S-S-R

S S S R R R





Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
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0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

<u>Recursion Phase: If it continues if needed !!!!</u>

Hidden Morkov Model

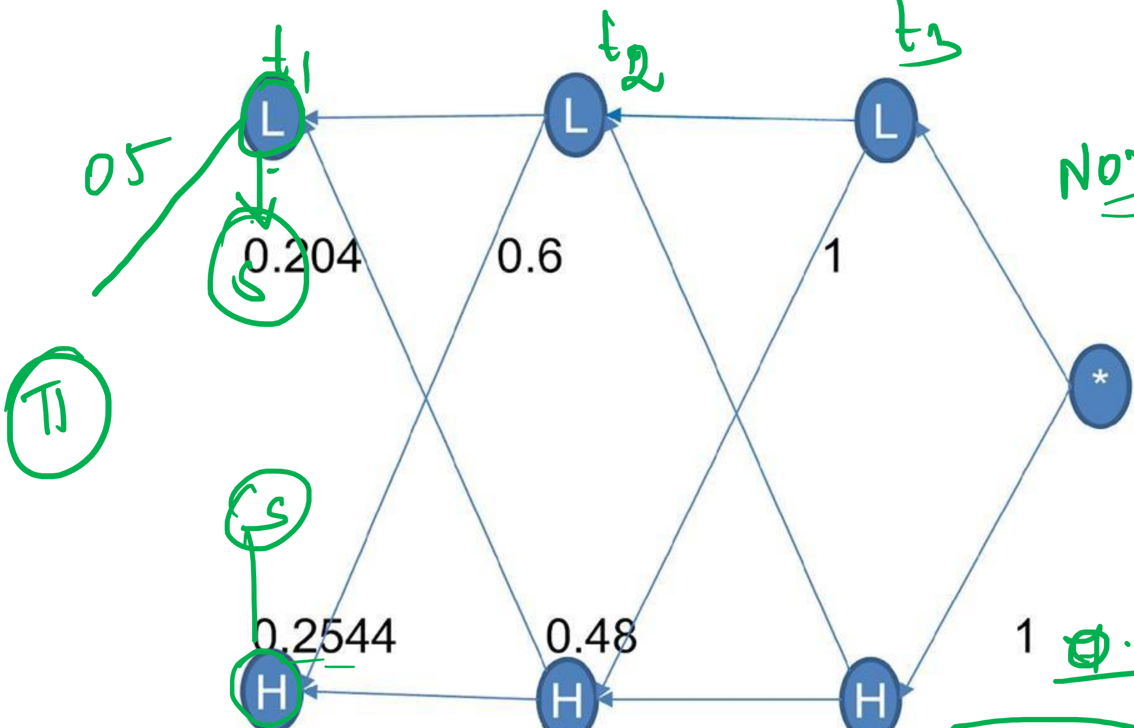
Backward Propagation Algorithm : S-S-R

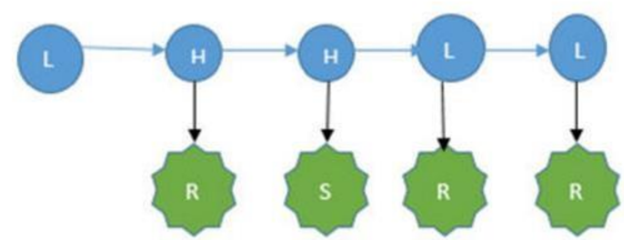
P(L)*P(S|L)*MSG(L`) = 0.5*0.2 * 0.204= 0.0204

0.0204

0.0204+0.07632

Normalize





Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

P(H)*P(S|H)*MSG(H`) = 0.5*0.6 * 0.2544= 0.07632

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Termination Phase: (0.2109,0.7891)

Normalize :Initial value * Emission at start* backMsg

Hidden Morkov Model F+B

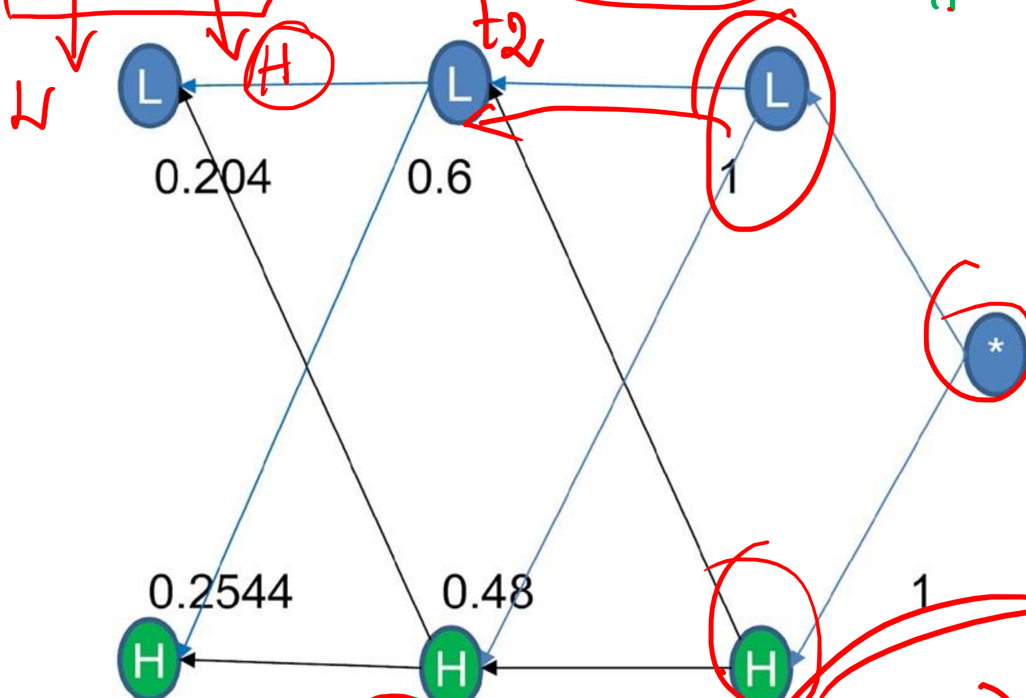
Smoothing

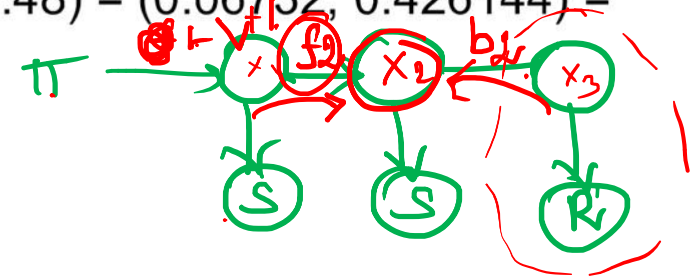
Forward Backward Propagation Algorithm : S-S-R

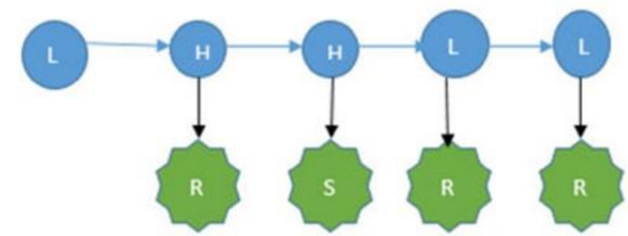
$P(X2 \mid SSR) = \alpha * P(X2|SS) * P(R|X2)$

$P(X2 \mid SSR) = \alpha * (0.1122, 0.8878) * (0.6, 0.48) = (0.06732, 0.426144) =$ $\boxed{(0.14, 0.86)}$

forward   L   H   Norma







Termination Phase (X2) = ??? → **X2 = H**

$X_2 \Rightarrow H$

SSR

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probability Matrix

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

$0.1122 * 0.6 \Rightarrow 0.06732$

$0.8878 * 0.48 \Rightarrow 0.426$

Forward Path Probability

$\alpha_t(j) = \alpha_{t-1}(i)\ a_{i,j}\ b_j(o_t)$

i

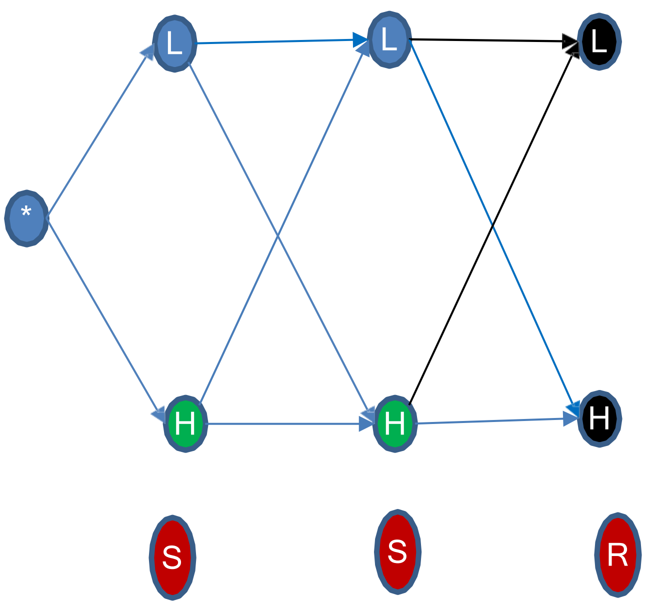
$P(O_{1..t} \mid \lambda)$

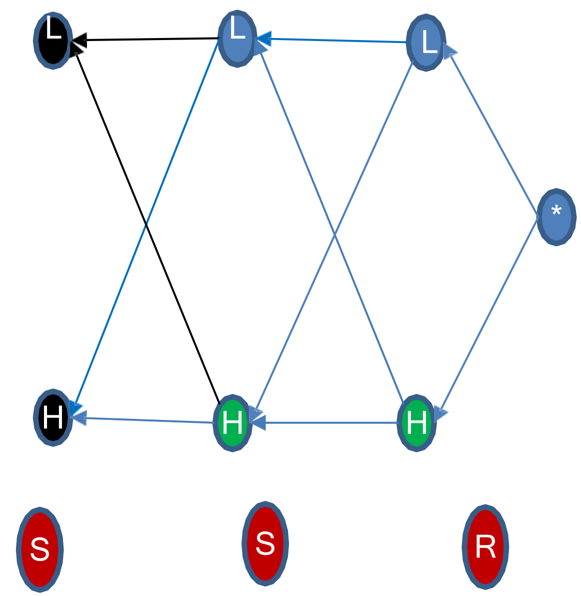
Backward Path Probability

$\beta_t(i) = {}_j\ \beta_{t+1}(j)\ a_{i,j}\ b_j(o_{t+1})$

$P(O_{t+1,\, t+2..t+k} \mid \lambda)$

$\gamma_t(i) = P(X_t \mid O_{1\ldots t\ \ldots t+1,\ t+2..t+k} \mid \lambda)$: Forward - Backward Algorithm





```
function FORWARD-BACKWARD(ev, prior) returns a vector of probability distributions
  inputs: ev, a vector of evidence values for steps 1, ..., t
          prior, the prior distribution on the initial state, P(X_0)
  local variables: fv, a vector of forward messages for steps 0, ..., t
                   b, a representation of the backward message, initially all 1s
                   sv, a vector of smoothed estimates for steps 1, ..., t

  fv[0] ← prior
  for i = 1 to t do
      fv[i] ← FORWARD(fv[i − 1], ev[i])
  for i = t downto 1 do
      sv[i] ← NORMALIZE(fv[i] × b)
      b ← BACKWARD(b, ev[i])
  return sv
```

Figure 15.4 The forward–backward algorithm for smoothing: computing posterior probabilities of a sequence of states given a sequence of observations. The FORWARD and BACKWARD operators are defined by Equations (15.5) and (15.9), respectively.

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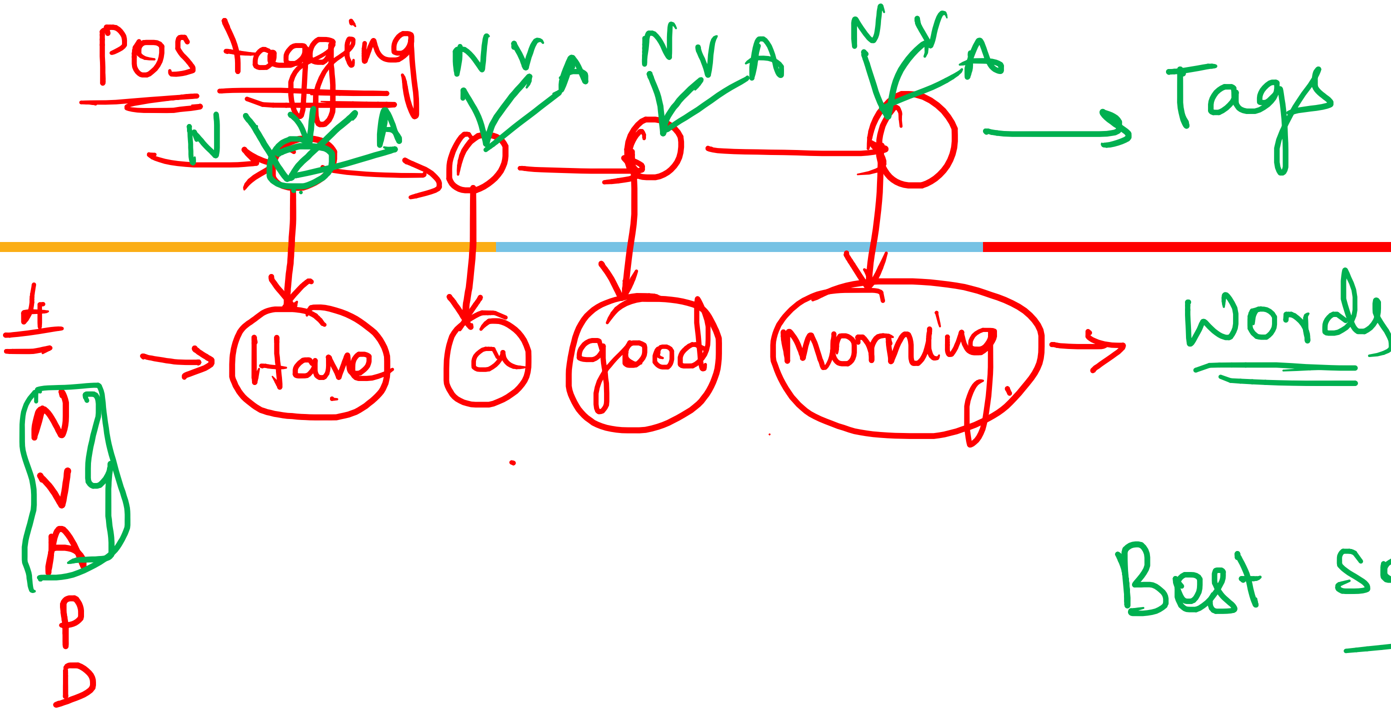

Best sequence of POS Tag

Text & Natural Language Processing

HMM Application

Initial	Prob
N	0.67
D	0.33
V	0
J	0
A	0
P	0

4/6

2/6

	N	D	V	J	A	P
N		01675		0.67		1
D			0.571			
V	0.63	0.1675	0.143			
J		0.33	0.143			
A						
P		0.1675				
E	0.37	0.1675	0.143	0.33		

P(N|N) P(D/N)

P(V/N) ⇒ NV → 5/8 → Noun Count

Given the corpus with tags to build training data:

1. Create initial probability matrix. → π
2. Transition probability matrix A
3. Emission probability matrix B
4. Use HMM Veterbi algorithm to predict the sequence of PoS Tags for given test data / sentence.

In the HMM model , the PoS tags act as the hidden states and the word in the given test sentence as the observed states.

training set

1. Boys are taller.
   N V J
2. This is the tree.
   D V D N
3. She is a tall girl.
   N V D J N
4. Trees are more.
   N V D
5. Girls are more than boys.
   N V D P N
6. The tall tree is falling.
   D J N V V

π, T, E

P(N|N

Pre

Cu

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Initial	Prob
N	0.67
D	0.33
V	0
J	0
A	0
P	0

π

A

N	D	V	J	A	P	
	01675		0.67		1	N
		0.571				D
0.63	0.1675	0.143				V
	0.33	0.143				J
						A
	0.1675					P
0.37	0.1675	0.143	0.33			E

B

N	D	V	J	A	P	
0.25						Boy s
		0.43				Are
			1			Tall
	0.17					This
		0.43				Is
	0.33					The
0.375						Tree
0.125						She
	0.17					A
0.25						Girl
	0.33					Mor e
					1	Tha n
		0.14				fall

Boys → N, D, V, J, A, P

$\frac{2}{8} = 0.25$

- Boys are taller.
  N V J
- This is the tree.
  D V D N
- She is a tall girl.
  N V D J N
- Trees are more.
  N V D
- Girls are more than boys.
  N V D P N
- The tall tree is falling.
  D J N V V

is → V ⇒ $\frac{3}{\text{verb count } 7}$ ⇒ 3/7 ⇒ 0.43

Initial	Prob
N	0.67
D	0.33
V	0
J	0
A	0
P	0

π

N	D	V	J	A	P	
	01675		0.67		1	N
		0.571				D
0.63	0.1675	0.143				V
	0.33	0.143				J
						A
	0.1675					P
0.37	0.1675	0.143	0.33			E

A

N	D	V	J	A	P	
0.25						Boy s
		0.43				Are
			1			Tall
	0.17					This
		0.43				Is
	0.33					The
0.375						Tree
0.125						She
	0.17					A
0.25						Girl
	0.33					Mor e
					1	Tha n
		0.14				fall

Exercise :

For the below test data/sentence, using the tables constructed using training data, predict the PoS tags.

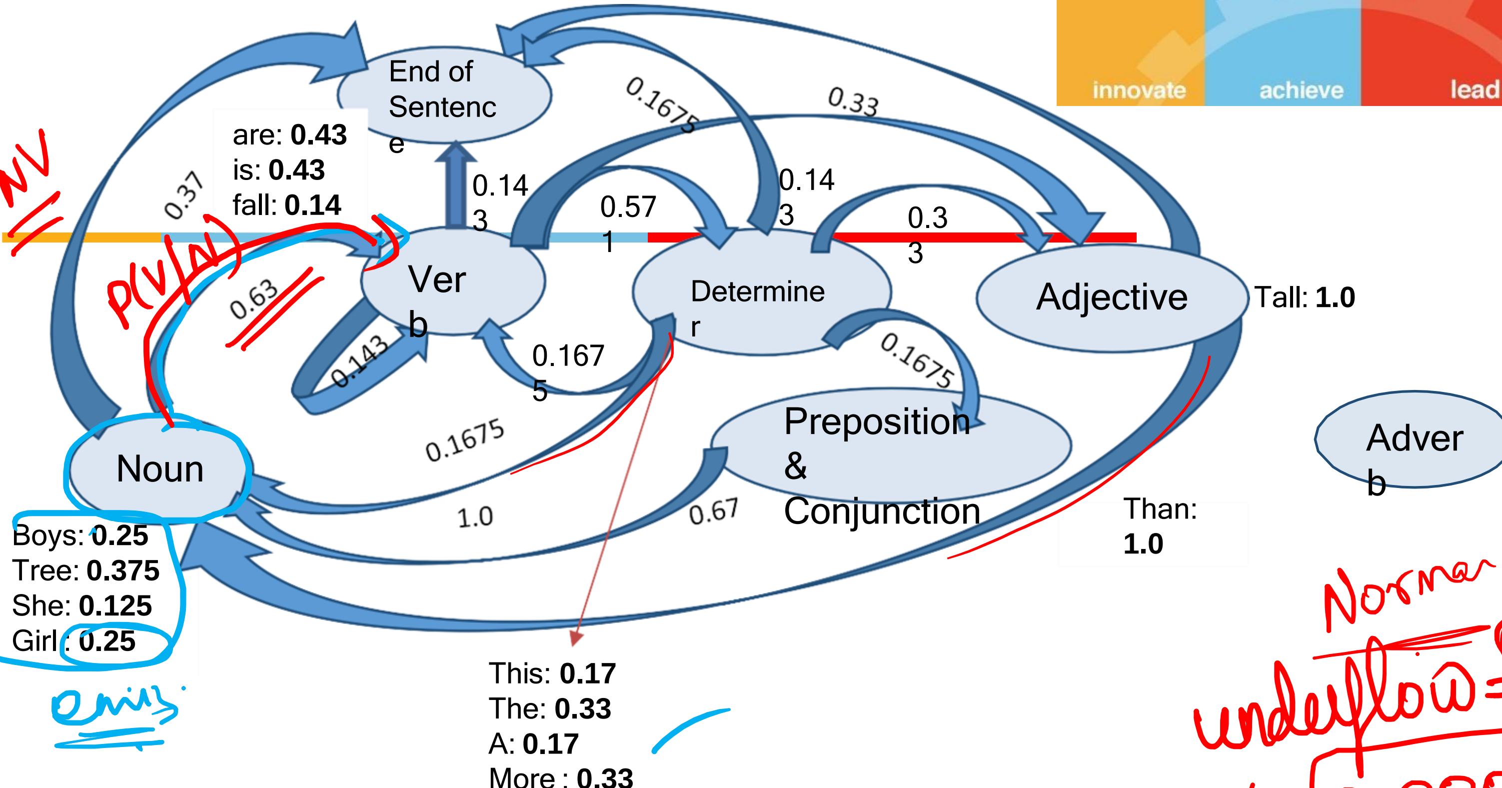
best Viterbi → max

"Girls are falling"

$P(H) = 0.5$

$P(L) = 0.5$

Initi	
N	0.67
D	0.33
V	0
J	0
A	0
P	0



NV

P(V|N)

emis

Normal
underflow 0
0.00000 001

"Girls are falling"

P(Girls , Noun) = P(Girl | Noun) * P(Noun | StartState) = 0.25 * 0.67 = **0.1675**

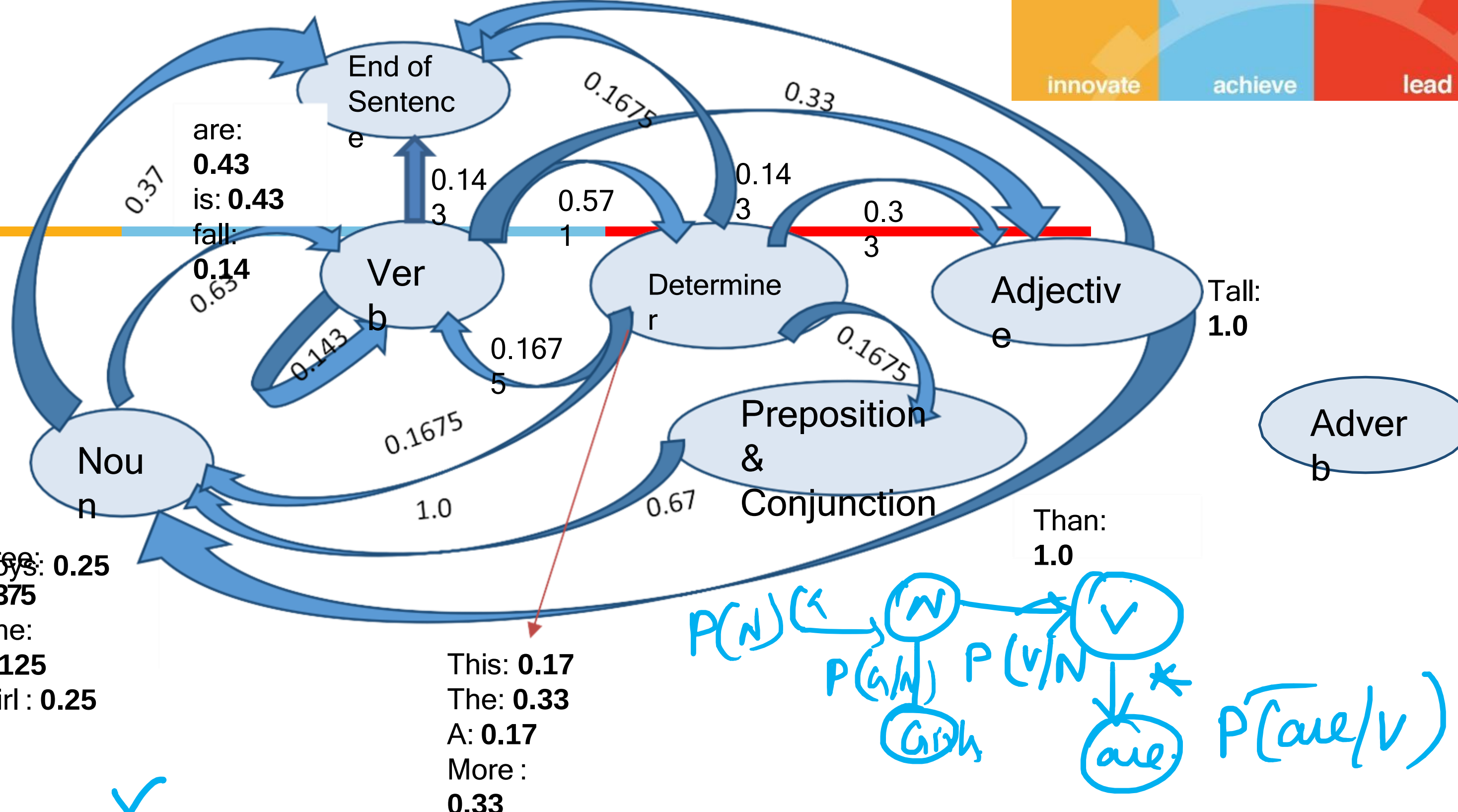
P(Girls , Verb) = P(Girl | Verb) * P(Verb | StartState) = 0 * 0 = 0 (Ideally with better corpus and the KB , for
most cases it might not be 0 but too low like 0.00000000000…..001.)

P(Girls , Determiner) = P(Girls , Adverb) = P(Girls , Adjective) =P(Girls , Preposition/Conjunction) = 0

StartState → Noun

π P(N) N Girls are falling

Initi	
N	0.67
D	0.33
V	0
J	0
A	0
P	0



"Girls are falling"

If Sequence is StartState →Noun

P(are , Verb)

= P(are| Verb) * P(Verb | Noun) * **P(Girls | Noun)**

 * **P(Noun | StartState)**

forwar

ms

= 0.43 * 0.63 * **0.1675**

= 0.04537

P(are, Noun) = P(are| Noun) * P(Noun | Noun) * **Noun** = 0 * 0 = 0

P(are, Determiner) = P(are, Adverb) = P(are , Adjective) =P(are , Preposition/Conjunction) = 0

StartState→ Noun→ Verb

If Sequence is StartState →Verb

P(are , Verb)

= P(are| Verb) * P(Verb | Verb) * **P(Girls | Verb)** *

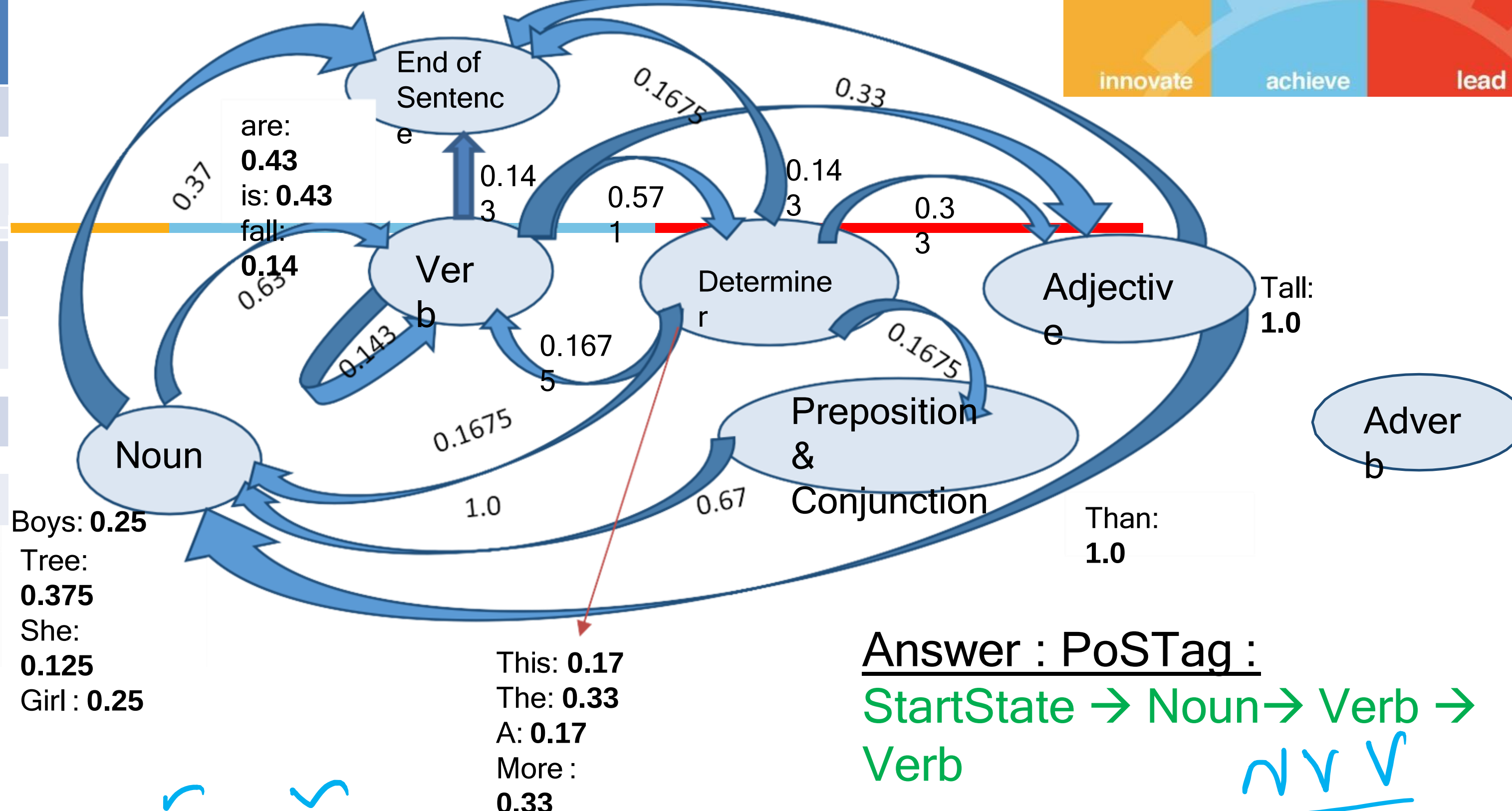
 P(Verb | StartState)

= 0.43 * 0.143 * **0 = 0**

P(are, Noun) = P(are| Noun) * P(Noun | Noun) * **Verb**= 0 * 0 = 0

P(are, Determiner) = P(are, Adverb) = P(are , Adjective) =P(are , Preposition/Conjunction) = 0

Initi	
N	0.67
D	0.33
V	0
J	0
A	0
P	0



"Girls are falling"

Answer : PoSTag :

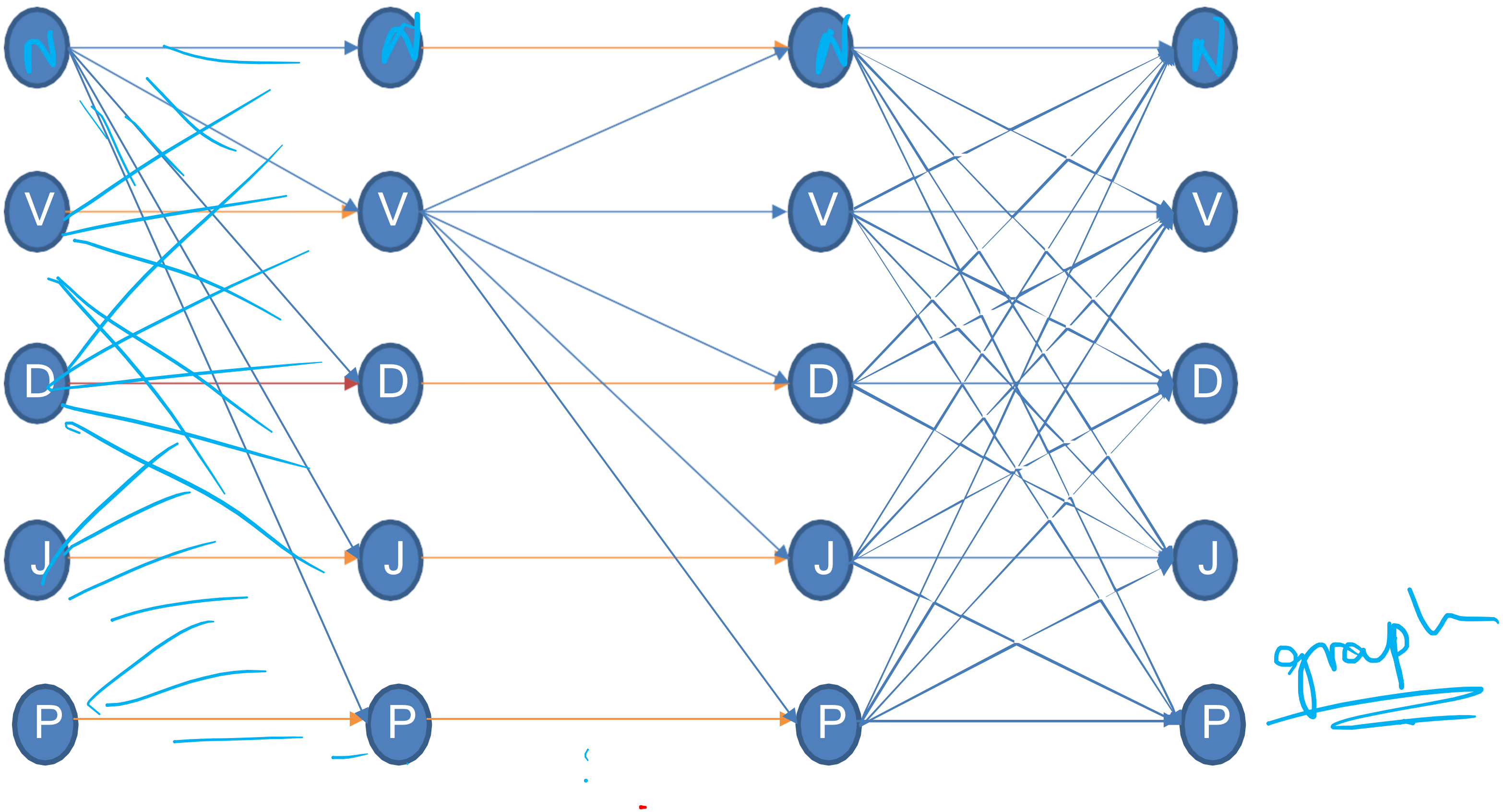
StartState → Noun→ Verb → Verb

N V V

If Sequence is StartState→ Noun →Verb	If Sequence is StartState→ Verb ->Adjective
P(falling, Verb) = P(falling|Verb)*P(Verb|Verb)***P(are| Verb) * P(Verb | Noun)** * **P(Girls | Noun) * P(Noun | StartState)** = 0.14 * 0.143 * **0.04537** **= 0.000908** P(are, Noun) = P(are| Noun) * P(Noun | Noun) * **Noun** = 0 * 0 = 0 P(are, Determiner) = P(are, Adverb) = P(are , Adjective) =P(are , Preposition/Conjunction) = 0	P(falling , Verb) = P(falling | Verb) * P(Verb | Verb) * P(are| Adjective) * P(Adjective | Verb) * P(Girls | Verb) * P(Verb | StartState) = 0.14 * 0.143 * **0 = 0** P(falling, Noun) = P(falling| Noun) * P(Noun | Adjective) * **Verb**= 0 * 0 = 0 P(falling, Determiner) = P(falling, Adverb) = P(falling , Adjective) =P(falling , Preposition/Conjunction) = 0

Sample Sequence under Test: Start □ Noun □ Verb □ … … … .

Assume Noun□ Verb is the maximum Value



innovate achieve lead

+M

E

Sta.

Kmeans

k=2

It 1

5.

π, A, B

Learning HMM Parameters

Parameter Estimation by EM Algorithm

(Baum-Welch re-estimation procedure)

Min SSE

Max

π A B

π A B

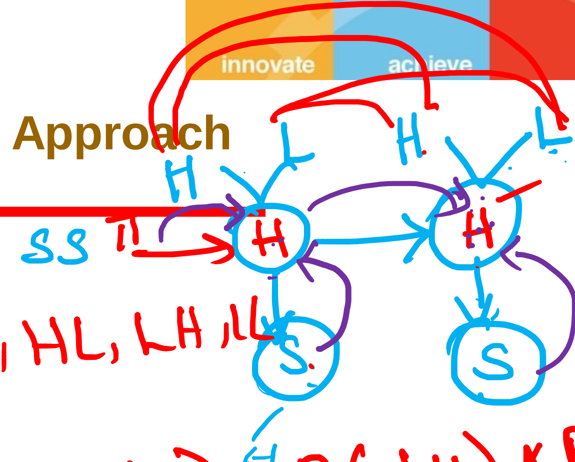
It 2

Conver

Parameter Estimation

π P(H) => 0.5
P(L) = 0.5

Learning Approach



Baum-Welch re-estimation procedure: Backward Propagation Algorithm

Given an observation sequence O(Evidence) and the set of possible states in the HMM, learn the HMM parameters A(Transition) and B(Emission).

HH, HL, LH, LL

P(H) * P(S|H) * P(H|H) * P(S|H)

0.5 * 0.6 * 0.8 * 0.6

Given set of weather observations recorded estimate the PARAMATERS:

{SS, SR, RR}

SS SR RR

	HH	HL	LH	LL
SS	**(0.5).(0.6).(0.8)(0.6) = 0.1440**	0.0120	0.03	0.01
SR	**0.0960**	0.048	0.02	0.04
RR	0.064	0.032	0.12	**0.16**
Total	0.304	0.092	0.17	0.21

Transition Model / Probability Matrix

P(U_{t-1} = HP)	P(U_{t-1} = LP)	←Previous
0.2	0.5	P(U_t = LP)
0.8	0.5	P(U_t = HP)

Evidence / Sensor Model/ Emission Probabi

P(X_t = LP)	P(X_t = HP)	←Unobserved Evidence v
0.8	0.4	P(E_t = Rainy)
0.2	0.6	P(E_t = Sunny)

Parameter Estimation

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Learning Approach

Baum-Welch re-estimation procedure: Backward Propagation Algorithm

Given an observation sequence O(Evidence) and the set of possible states in the HMM, learn the HMM parameters A(Transition) and B(Emission).

Given set of weather observations recorded estimate the PARAMATERS:

{SS, SR, RR}

	HH	HL	LH	LL	Best Seq	P(Best)
SS	**0.1440**	0.0120	0.03	0.01	HH	0.144
SR	**0.0960**	0.048	0.02	0.04	HH	0.096
RR	0.064	0.032	0.12	**0.16**	LL	0.16
Total	0.304	0.092	0.17	0.21		0.4
Normalize	0.76	0.23	0.425	0.525		

$\frac{0.76}{0.76+0.23}$ $\frac{0.23}{0.76+0.23}$ $\frac{0.425}{0.425+0.525}$ $\frac{0.525}{0.525+0.425}$

TM

HP	LP	
0.232323232	0.5526316	LP
0.767676768	0.4473684	HP

Prev

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probabi

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Parameter Estimation

Learning Approach

Baum-Welch re-estimation procedure: Backward Propagation Algorithm

Given an observation sequence O(Evidence) and the set of possible states in the HMM, learn the HMM parameters A(Transition) and B(Emission).

Given set of weather observations recorded estimate the PARAMATERS:

{SS, SR, RR}

H L

	HH	HL	LH	LL	Best Seq	P(Best)
SS	**0.1440**	0.0120	0.03	0.01	HH	0.144
SR	**0.0960**	0.048	0.02	0.04	HH	0.096
RR	0.064	0.032	0.12	**0.16**	LL	0.16
Total	0.304	0.092	0.17	0.21		0.4
Normalize	0.76	0.23	0.425	0.525		

HP	LP	
0.232323232	0.5526316	LP
0.767676768	0.4473684	HP

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probabi

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Parameter Estimation

$P(H) \Rightarrow \frac{0.5}{0.5}$

$P(L) = 0.5$

Learning Approach

$\rightarrow$ H

$\rightarrow$ L

Baum-Welch re-estimation procedure: Backward Propagation Algorithm

Given an observation sequence O(Evidence) and the set of possible states in the HMM, learn the HMM parameters A(Transition) and B(Emission).

Find set of weather observations recorded estimate the parAMATERS:

{SS, SR, RR}

After this step for the second iteration
Use the optimized tables
(Initial, Transition , Emission)
and repeat the algorithm till convergence

	Start(H)	Start(L)	Best Seq	P(Best)
SS	**0.1440**	0.03	HH	0.144
SR	0.0960	0.04	HH	0.096
RR	0.064	0.16	LL	0.16
	0.304	0.23		
Normalize	0.76	0.575		

$\frac{0.304}{0.4}$ $\frac{0.23}{0.4}$ 0.4

$\frac{0.76}{0.76+0.575}$ $\frac{0.575}{0.76+0.575}$

π P(H)

HP	LP
0.56929	0.4307

π

Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

E

Evidence / Sensor Model/ Emission Probability

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Parameter Estimation

Learning Approach

Baum-Welch re-estimation procedure: Backward Propagation Algorithm

Given an observation sequence O(Evidence) and the set of possible states in the HMM, learn the HMM parameters A(Transition) and B(Emission).

Find set of weather observations recorded estimate the parAMATERS:

{SS, SR, RR}

LP	HP	
0.615384615	0.4	R
0.384615385	0.6	S

	H→S	L→S	H→R	L→R	Best Seq	P(Seq)
SS	**0.1440**	0.01			HH	0.144
SR	0.0960	0.04	0.096	0.048	HH	0.096
RR			0.064	0.0320	LL	0.16
Total	0.24	0.05	0.16	0.08		
Normalize	0.6	0.125	0.4	0.2		

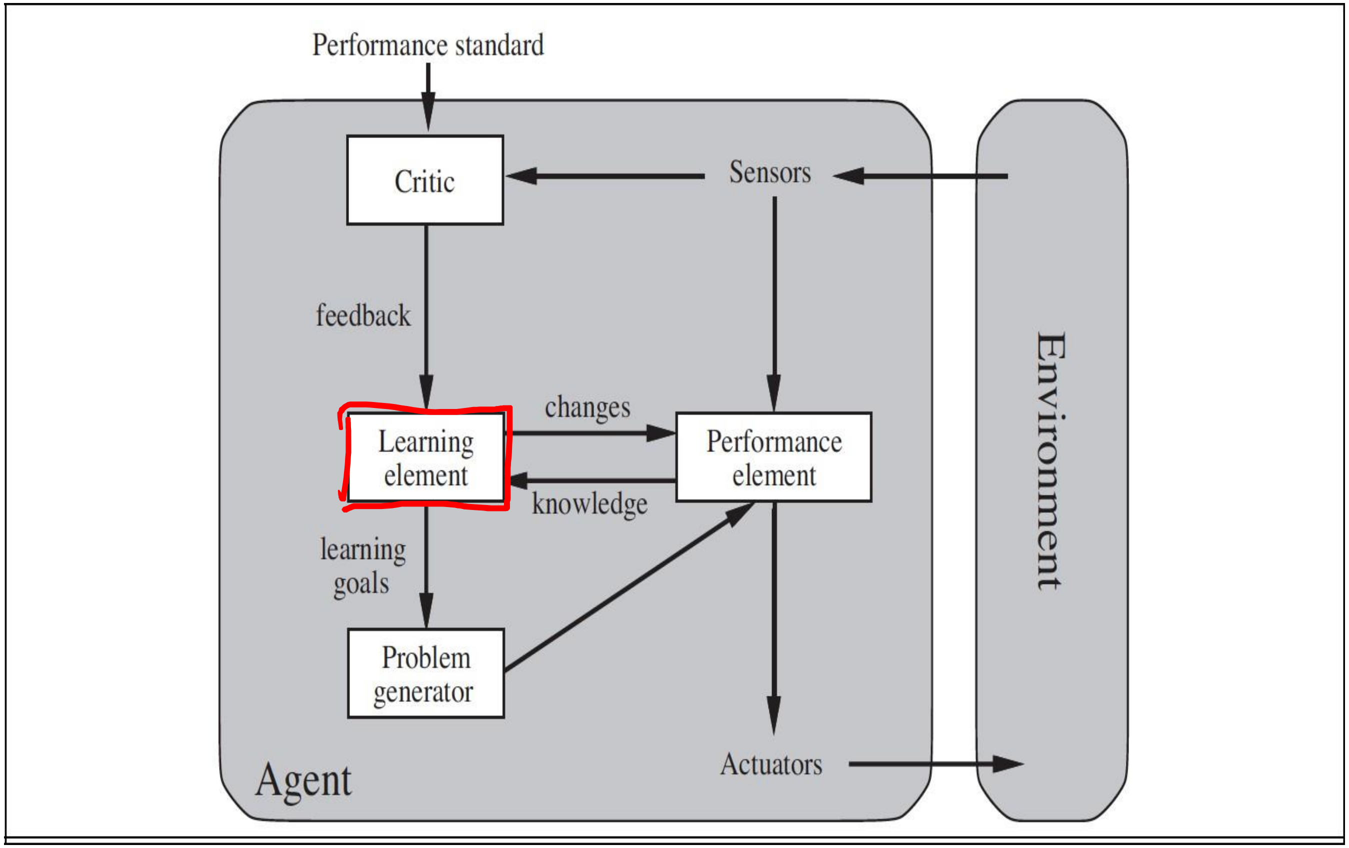
Transition Model / Probability Matrix

$P(U_{t-1} = HP)$	$P(U_{t-1} = LP)$	←Previous
0.2	0.5	$P(U_t = LP)$
0.8	0.5	$P(U_t = HP)$

Evidence / Sensor Model/ Emission Probabi

$P(X_t = LP)$	$P(X_t = HP)$	←Unobserved Evidence v
0.8	0.4	$P(E_t = Rainy)$
0.2	0.6	$P(E_t = Sunny)$

Ethics in Artificial Intelligence


Performance standard
Critic
Sensors
feedback
changes
Learning element
Performance element
knowledge
learning goals
Problem generator
Actuators
Agent
Environment

Recommendation System

REUTERS

Business Markets India Election 2019 TV More

TECHNOLOGY NEWS OCTOBER 10, 2018 / 9:13 AM / 5 MONTHS AGO

Insight - Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin

8 MIN READ

Amazon's Edinburgh engineering hub's goal was to develop AI that could rapidly crawl the web and spot candidates worth recruiting

Fairness : The absence of bias towards an individual or a group

Are the predictions ______?

- Fair
- Unbiased

Object Recognition System


Forbes
Billionaires Innovation Leadership Money Consumer Industry

44,931 views | Jul 1, 2015, 01:42pm

Google Photos Tags Two African-Americans As Gorillas Through Facial Recognition Software

Maggie Zhang Forbes Staff
I write about technology, innovation, and startups.

Are the Inferences_______?
- ➢ Correct
- ➢ Unbiased

Are the Predictions ______?
- ➢ Fair
- ➢ Universally Applicable

Building a Fair Model

No artificial model is a perfect one. But every model significantly influence the social , economic, cultural ethics impacting humanity.

Justify the design modelled & metric used to validate the model, is in fact the right choices fit in the context.

1. Is it fair to make an AI-ML system?
2. Is there a better technical approach to convert an existing AI system fair?
3. Are the results obtained by the AI system fair?

Building a Fair Model

1. Is it fair to make an AI-ML system?
2. Is there a better technical approach to convert an existing AI system fair?

Interpretable Results | Statistical Independence | Customized Metric

Interpretable Models

Are the results obtained by the AI system fair?

Interpretable models helps to trust the AI system by answering transparently to the specific questions like “Why the system is behaving under certain scenarios?”

- If a loan gets rejected, do we know the reasons?
- If a job application is accepted, is it biased towards a gender?
- If a bail is granted to an accused, is it based on their race?
- If a patient is diagnosed with a disease, what factors made the algorithm to classify it?

Interpretable Models

Example Based Explanations:

If SymptomInX ≡ SymptomInY

if DiseaseA infected X

then probably DiseaseB might have infected Y

If CustomerX ≡ CustomerY

if CustomerX purchased P1

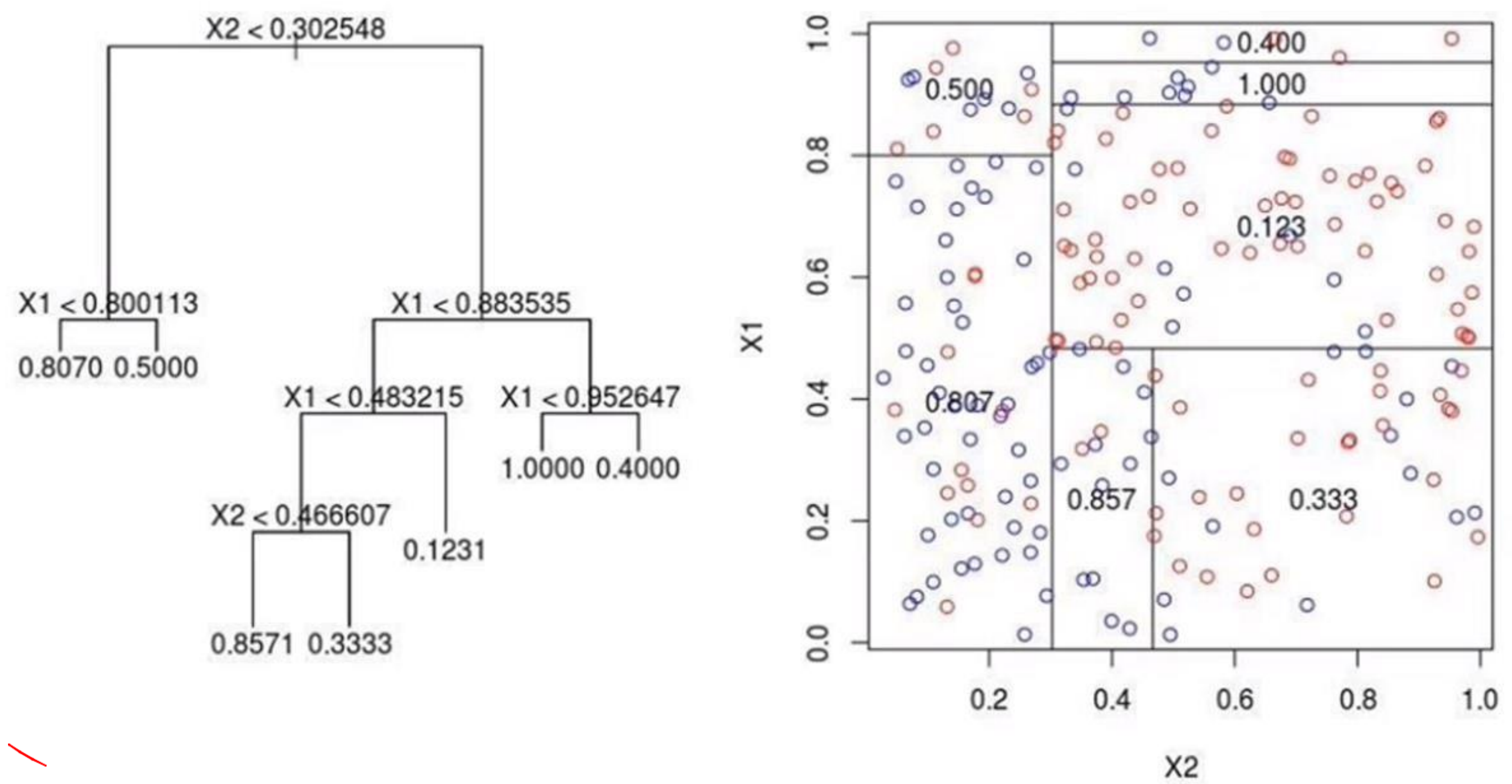
then probably CustomerY will purchase P1

Counterfactual Explanations:

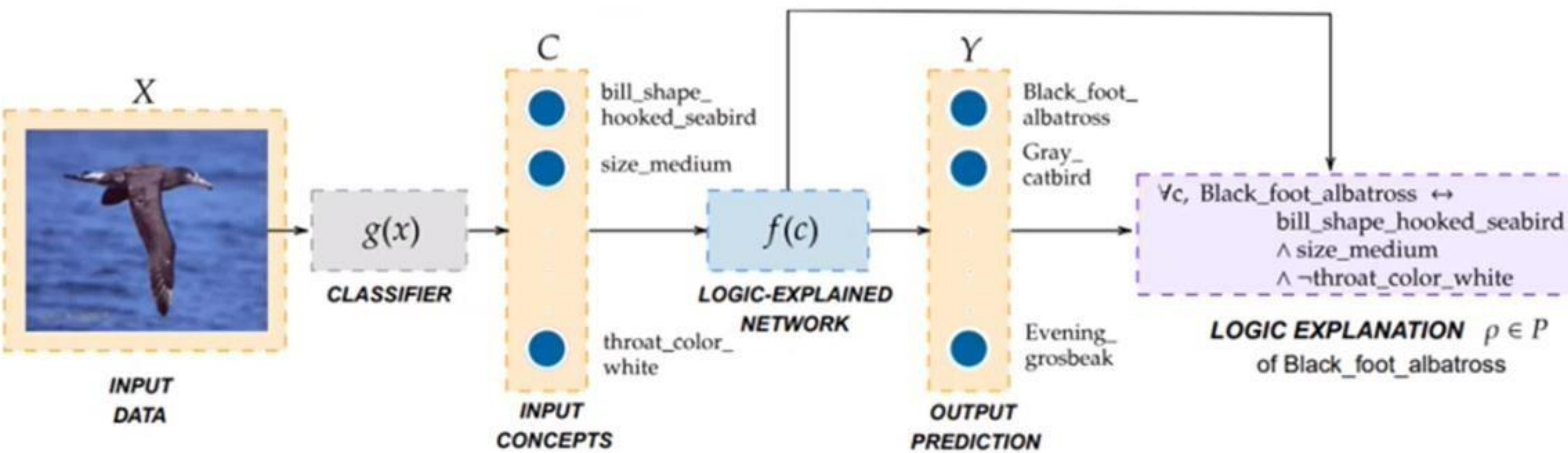
If customerX’s income level had not been less than L3

then the customer’s Loan might not have been rejected

Interpretable Models



In Deep Learning



Source Credit: 2021: **Logic Explained Networks**

HMM in Prevention of Network Security Threat

(Interesting Case Studies)

Hidden Morkov Model

Cyber Security

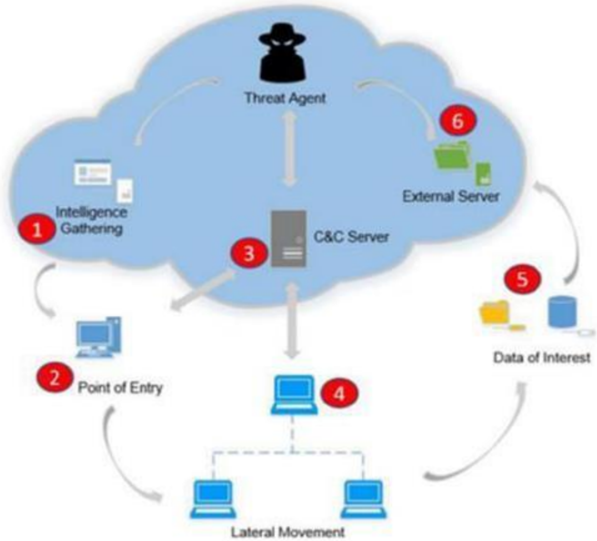
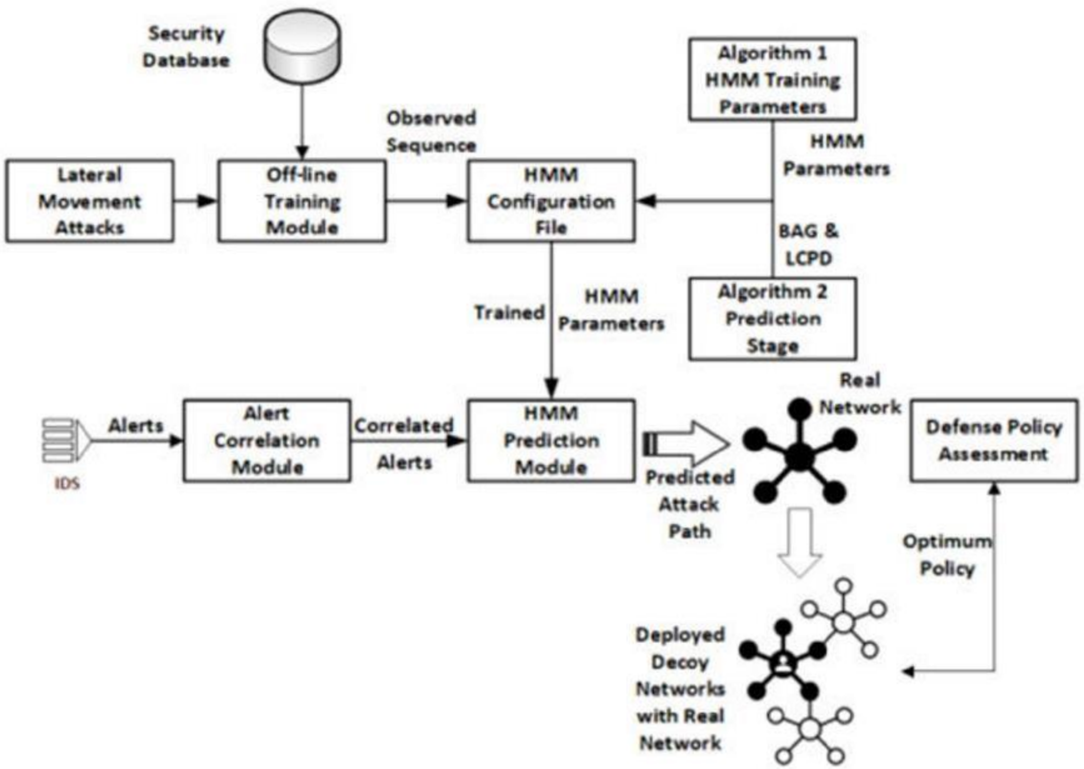


FIGURE 1. Typical stages of APT attack.

Source Credit : [2021 : Hidden Markov Model and Cyber Deception for the Prevention of Adversarial Lateral Movement]

Hidden Morkov Model

Cyber Security



Source Credit : [2021 : Hidden Markov Model and Cyber Deception for the Prevention of Adversarial Lateral Movement]

Hidden Morkov Model

Cyber Security

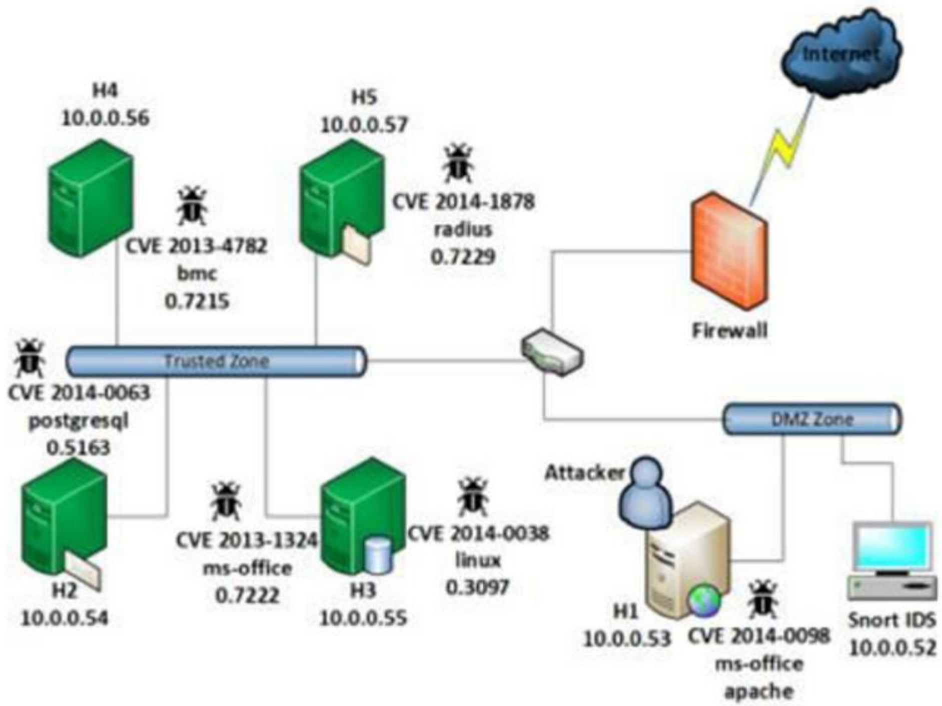


FIGURE 9. Experimental network topology.

Source Credit : [2021 : Hidden Markov Model and Cyber Deception for the Prevention of Adversarial Lateral Movement]()

Hidden Morkov Model

Cyber Security

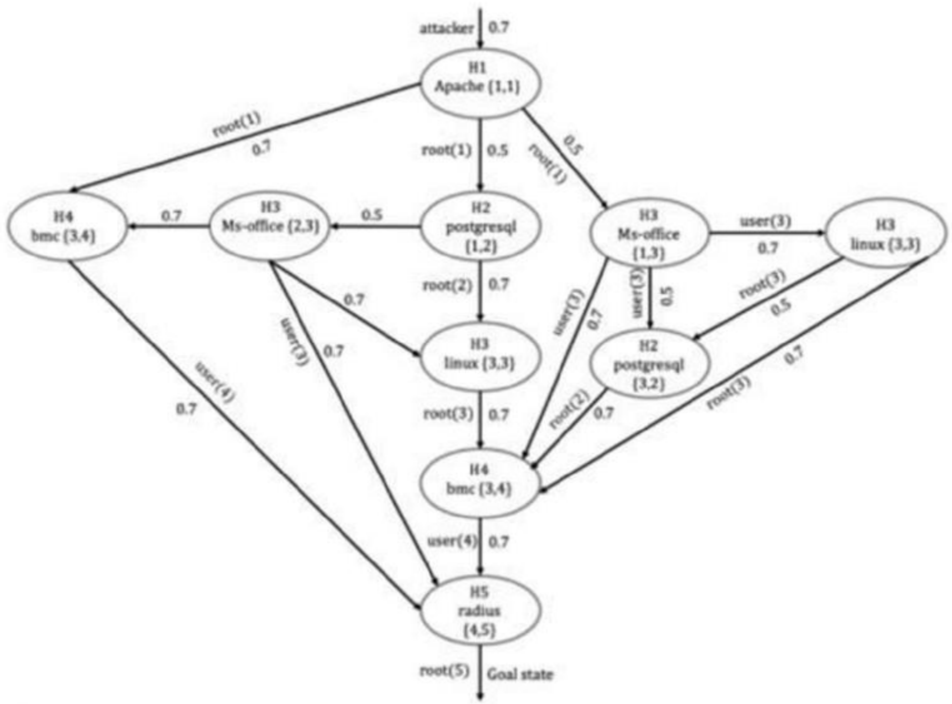


FIGURE 10. Attack graph of the experimental network.

Attack states description.

State	Description
S_1	Initial State
S_2	(H_1,root)
S_3	(H_2,root)
S_4	(H_3,user)
S_5	(H_3,root)
S_6	(H_4,user)
S_7	(H_5,root)

Source Credit : 2021 : Hidden Markov Model and Cyber Deception for the Prevention of Adversarial Lateral Movement

Hidden Morkov Model

Cyber Security

Attack states description.

State	Description
S_1	Initial State
S_2	(H_1,root)
S_3	(H_2,root)
S_4	(H_3,user)
S_5	(H_3,root)
S_6	(H_4,user)
S_7	(H_5,root)

TABLE 6. Possible attack paths.

Path Number	Attack Path
1	$S_1 \to S_2 \to S_6 \to S_7$
2	$S_1 \to S_2 \to S_3 \to S_4 \to S_7$
3	$S_1 \to S_2 \to S_3 \to S_6 \to S_7$
4	$S_1 \to S_2 \to S_3 \to S_4 \to S_5 \to S_6 \to S_7$
5	$S_1 \to S_2 \to S_3 \to S_5 \to S_6 \to S_7$
6	$S_1 \to S_2 \to S_4 \to S_6 \to S_7$
7	$S_1 \to S_2 \to S_4 \to S_3 \to S_6 \to S_7$
8	$S_1 \to S_2 \to S_4 \to S_5 \to S_3 \to S_6 \to S_7$
9	$S_1 \to S_2 \to S_4 \to S_5 \to S_6 \to S_7$

Source Credit : [2021 : Hidden Markov Model and Cyber Deception for the Prevention of Adversarial Lateral Movement]

Required Reading: AIMA - Chapter #15.1, #15.2, #15.3, #20.3.3

Thank You for all your Attention

Note : Some of the slides are adopted from AIMA TB materials