INT 404 (TW) Contd. from P- 120

20/3/2017.

Prolog 7.4

File → Consult

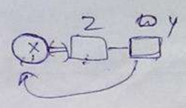
adjacent (1, 2)

fact.pl

```
fact(0,1).
fact(2,2).
fact(3,6).
```

prolog

```
?- fact(3,X).
- 6
```



Factorial Prog

```
factorial(0,1).

factorial(N,F) :-
    N > 0,
    N1 is N-1,
    factorial(N1,F1),
    F is N*F1.
```

```
grand-father(X,Y) :- father(X,W), father(W,Y).
grandfather(X,Y) :- mother(Z,Y), father(X,Z).
sister-in-law(X,Y) :- married(X,Z), brother(Z,Y).
```

Le Ch-7

Monotonicity – knowledge is complete.

Non-Monotonicity – Inconsistency, Incomplete knowledge, conflict arises.

Models, wff's, and Nonmonotonic Reasoning:

Model Logic

Default Logic → If A is provable and it is consistent to assume B then conclude C. $\frac{A:B}{C}$

$\frac{\neg A:B}{C}$ → Inheritance

Default Logic Vs Non-monotonic Logic

P.T.O.

(132)

AI

monotonic Deduction – if is given and find else part.

non-monotonic Abduction – else is given and find if.

E. Closed world Assumption / CWA

~~Af~~ If no rule is there, then result will be in negation of the predicate.

34-215 2 PM

Backward Rules using UNLESS

If → else

if → else } backward

Model View:

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M = Non monotonic ~~as~~ inconsistant.

The model statement should be consistant will all the rules of the knowledge based.

In non-monotonic, which statement is model statement. The model statement should be consistant.

In non-monotonic, we find out ~~and~~ any type inconsistancy in our knowledge based.

Default Logic:- In default logic, we try to remove inconsistancy.

$$\frac{A : B}{C}$$

Inheritance in Default Logic:

CWA:

eg. lion (x) ∧ ¬abnormal(x) → run (x)

lion (x)

Circumscription:

Whatever fact or rules are not given, we will not be able to give the answer of that.

Contd. on P-136

INT 404 | Contd. from P- 132 | 136

23/3/2017

Backward Rules using UNLESS

Forward Rules using UNLESS

How?

To overcome implementation issues

1. Augmenting Problem Solver → how to reach conclusion
2. Truth maintenance System →

Adj

24/3/2017

Statistical Reasoning :

Augmented PS → Backward Based, Forward Based

Truth maintenance → JTMS (Justification), LTMS (Logic), ATMS (Assumption)

Backward Rules using UNLESS

Suspect (x) ← Beneficiary (x) UNLESS Alibi (x)

Alibi (x) ← SomewhereElse (x)

SomewhereElse (x) ← RegisteredHotel (x, y) and farAway (y) UNLESS ForgedRegister (y)

~~SomewhereElse~~ Alibi (x) ← Defends (x, y) and farAway (y) UNLESS Lies (y)

SomewhereElse (x) ← PictureOf (x, y) and farAway (y)

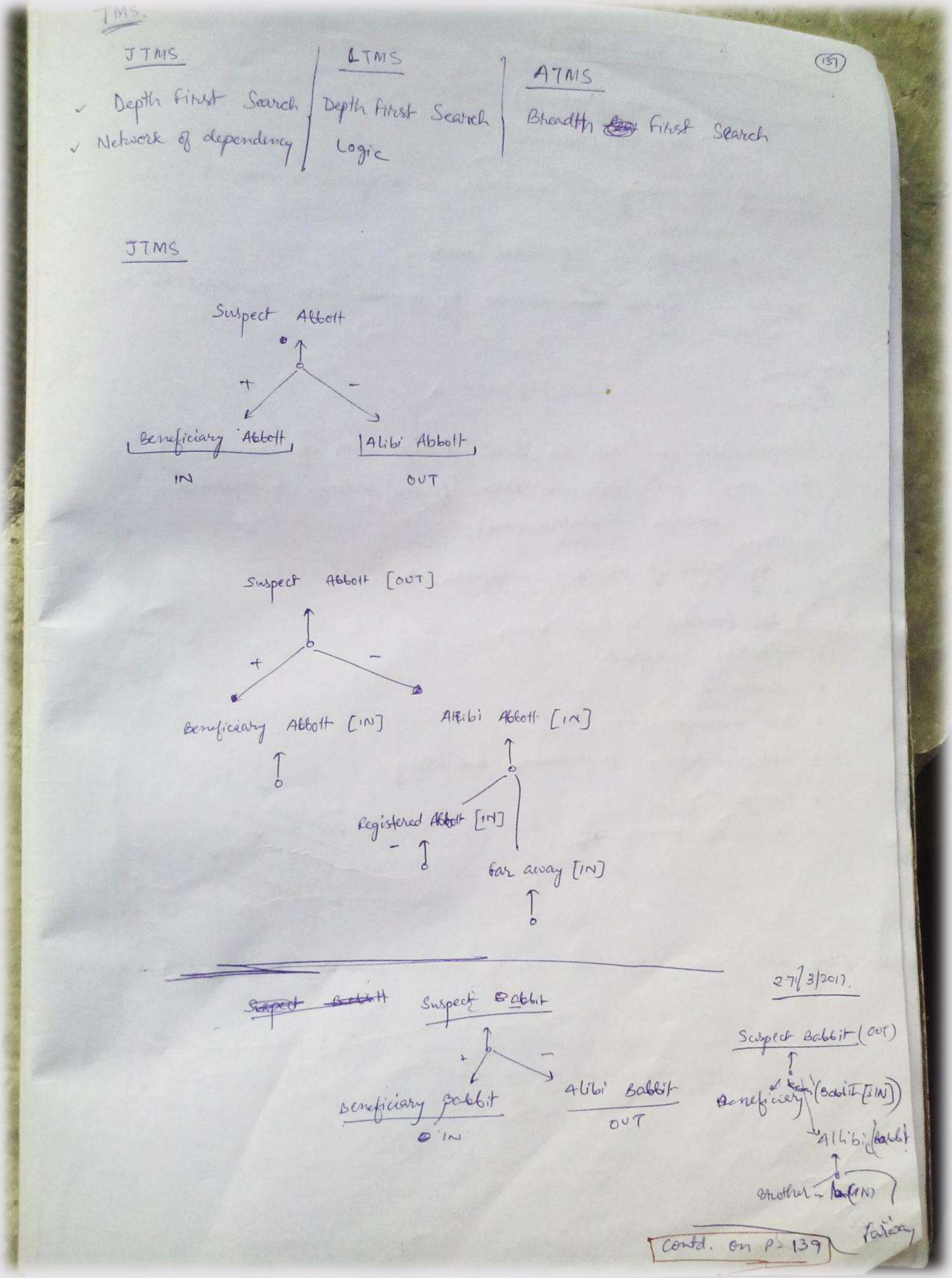
Contradiction ( ) ← TRUE UNLESS ∃x : Suspect (x)

Beneficiary (Abbott)

Beneficiary (Babbit)

Beneficiary (Cabot)

P.T.O.


TMS
JTMS
Depth First Search
Network of dependency
LTMS
Depth First Search
Logic
ATMS
Breadth First Search
137
JTMS
Suspect Abbott
Beneficiary Abbott
IN
Alibi Abbott
OUT
Suspect Abbott [OUT]
Beneficiary Abbott [IN]
Alibi Abbott [IN]
Registered Abbott [IN]
far away [IN]
27/3/2017
Suspect Babbit
Beneficiary Babbit
IN
Alibi Babbit
OUT
Suspect Babbit (OUT)
Beneficiary (Babbit [IN])
Alibi Babbit
Contd. on P-139

~~Bill~~

Suspect Cabbot [IN]

Beneficiary Cabbot [IN] Alibi Cabbot [OUT]

Suspect Cabbot [OUT]

Beneficiary Cabbot [IN] Alibi Cabbot [IN]

ATMS

A1 : Hotel Reg was forged.

A2. Hotel reg was not forged.

A3. Babbit B.I.L. lied

A4. Babbit B.I.L. did not lie.

A5. Cabbot lied.

A6. Cabbot did not lie.

A7. A, B, C are not only suspects.

A8. A, B, C. are only suspects.

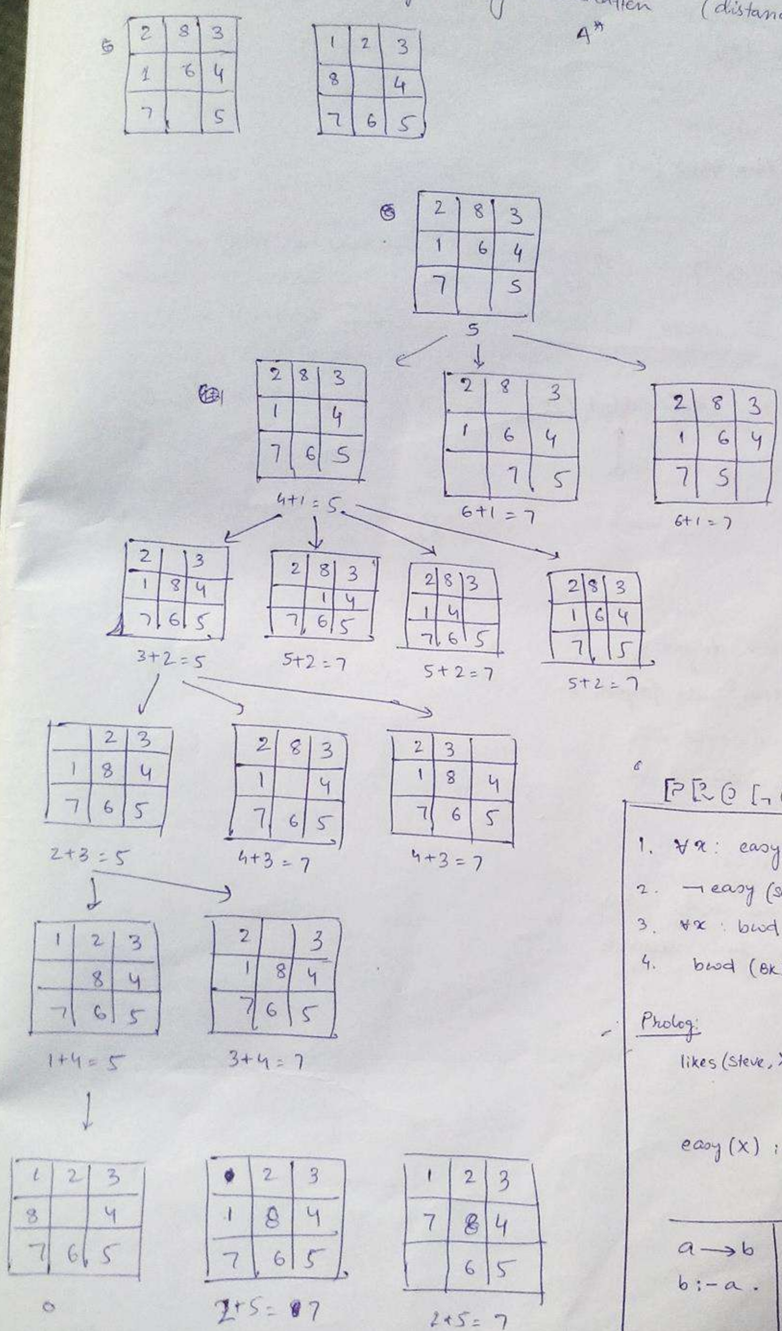
Contd. from P - 137

137

27/3/2017

Q. 8 puzzle problem by using Manhattan (distance of initial to final).

4*



1+2+0+1+1+1+0+0 = 5
~~1+2+0+1 = 4~~
1+2+0+1+1+1
1+2+0+1+1+1

1+0+1+1+
1+2+0+2+
1+2+0+1+1.
1+2+0+1+1.

1+1
1+2+1.
1+1+1+1.

1+1+1

PROLOG

1. $\forall x$: easy(x) → likes(steve, x)
2. ¬easy(science)
3. $\forall x$: bwd(x) → easy(x)
4. bwd(BK301)

Prolog:

likes(steve, X) :- easy(X).

easy(X) :- bwd(X).

a → b	a ∧ b → c	a ∨ b → c
b :- a.	c :- a, b.	c :- a. c :- b.

INT 404

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Chapter - 8

Bayes Theorem

The notion of conditional probability : ~~P(H/E)~~ ~~~~ P(H\E)

$$P(H_i|E) = \frac{P(E|H_i) \cdot P(H_i)}{[P(E|H_1) \cdot P(H_1)] + [P(E|H_2) \cdot P(H_2)] + [P(E|H_3) \cdot P(H_3)]} \quad k=3$$

Adding certainity factors to Rules:

Measures of Belief

$$\underbrace{CF(h,e)}_{\{-1,1\}} = \underbrace{mb(h,e)}_{\{0,1\}} - \underbrace{md(h,e)}_{\{0,1\}}$$

4.

Contd. on P- 23

INT 404 (Th) Contd. from P-19

23

3/4/17

Q. A basket has 12 marigolds and 8 roses. If we have break 2 flowers one by one. ~~How many~~ find probability to find a marigold and rose.

Sol: Marigold = 12

Roses = 8

Total = 20

$P(M) = \frac{12}{20}$

$P(R) = \frac{8}{20}$

$P(M \cap R) = P(M) \times P(R)$

$= \frac{\cancel{12}^{3}}{\cancel{20}_{5}} \times \frac{\cancel{8}^{2}}{\cancel{20}_{5}} = \frac{6}{25}$

Q. A basket has 6 black and 4 white marbles, 2 of them are drawn without replacement. Find the probability of getting a black and white marble.

Sol: Black = 6, white = 4, Total = 10

$P(B \cap W) = P(B) \times P(W)$

$= \frac{\cancel{6}^{2}}{\cancel{10}_{5}} \times \frac{\cancel{4}^{2}}{\cancel{9}_{3}} = \frac{4}{15}$

$P(W|B)$ = getting a white marble after getting a black marble.

Conditional Probabilities

Intersecting Events:

$P(C/X) = \frac{P(C \cap X)}{P(X)} = \frac{0.6}{0.8} = \frac{3}{4}$

P.T.O.

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Bayes Theorem :

— Inverse of conditional probability.

H = hypothesis
E = evidence

$$P(H|E) = \frac{P(E|H) \cdot P(H)}{\sum_{H=1}^{n} P(E_i|H_i)\, P_i(H) + P \cdots}$$

Q.

$P(A) = 0.35$ $\quad$ $P(D|A) = 0.015$

$P(B) = 0.35$ $\quad$ $P(D|B) = 0.010$

$P(C) = 0.30$ $\quad$ $P(D|C) = 0.020$

$$P(B|D) = \frac{P(D|B)\, P(B)}{P(D|A) \cdot P(A) + P(D|B) \cdot P(B) + P(D|C) \cdot P(C)}$$

$$= \frac{0.010 \times 0.35}{0.015 \times 0.35 + 0.010 \times 0.35 + 0.020 \times 0.30}$$

$$= \frac{0.0035}{0.00525 + 0.0035 + 0.006}$$

$$= \frac{0.0035}{0.01475} = \frac{35}{147.5} = \frac{\cancel{350}\ \cancel{70}\ 14}{\cancel{1475}\ \cancel{295}\ 59}$$

$$= \frac{14}{59} = 0.23$$

0.010 × 0.35 = .00350

35 × 15 = 175 ; .00525

.00525 + .00350 + .00600 = .01475

59) 140 (.23
118
220
177
43

Go to office By $\quad$ (L = late)

1. Train $P = 0.50$ $\quad$ $P(L|T) = 0.20$
2. car $P = 0.40$ $\quad$ $P(L|C) = 0.10$
3. Bus $P = 0.60$ $\quad$ $P(L|B) = 0.30$

$$P(B|L) = \frac{P(L|B) \cdot P(B)}{P(L|C) \cdot P(C) + P(L|T) \cdot P(T) + P(L|B) \cdot P(B)}$$

$$= \frac{0.30 \times 0.60}{0.30 \times 0.60 + 0.20 \times 0.50 + 0.40 \times 0.10}$$

$$= \frac{0.18}{0.18 + 0.10 + 0.04} = \frac{\cancel{18}\ 9}{\cancel{32}\ 16} = \frac{9}{16}$$

0.40 × 0.10 = .0400

.04 + .10 + .18 = .32

P.T.O.

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$cf(h, h_2, e_1) = Min[MB(h_1, e], MB[h_2, e]]$

$CF(h_1, e_1, e_2) = MB[h_1, e_1] + MB[h_1, e_2] \cdot [1 - MB[h_1, e_1]] - [MD[h_1, e_1] + MD[h_1, e_2] \cdot [1 - MD[h_1, e_1]]]$

$MB[h_1, e_1] = 0.2$

$MD[h_1, e_2] = 0.4$

$\boxed{Le}$

$cf = 1.$

Q2.

$\begin{bmatrix} 4B \\ 6G \end{bmatrix}$ U1 $\begin{bmatrix} 4G \\ 6B \end{bmatrix}$ U2 $\begin{bmatrix} 5G \\ 5B \end{bmatrix}$ U3

$P(G|U_1) = \frac{6}{10}$

$P(G|U_2) = \frac{4}{10}$

$P(G|U_3) = \frac{5}{10}$

$$P(U_1|G) = \frac{\frac{1}{3} \times \frac{6}{10}}{\frac{1}{3} \times \frac{6}{10} + \frac{1}{3} \times \frac{4}{10} + \frac{1}{3} \times \frac{5}{10}}$$

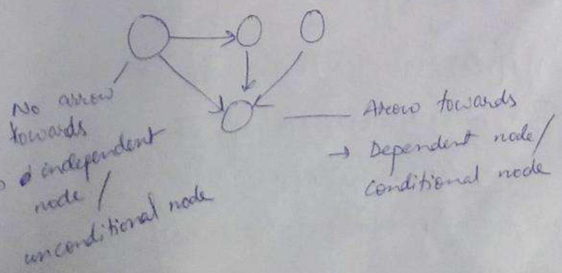
$$= \frac{\frac{1}{5}}{\frac{1}{5} + \frac{2}{15} + \frac{1}{6}} = \frac{30 \times 1}{5 \times (6+4+5)} = \frac{30}{65} = \frac{6}{13}$$

5 | 5, 15, 6
3 | 1, 3, 6
  1, 1, 2

Bayesian Belief Network (Acyclic graph)

Joint Probability distribution

→ Requires 2^n entries.



P.T.O.

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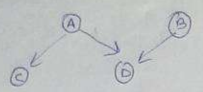
Conditional Probability Tables:



$$P(A|C) = \frac{P(A \cap C)}{P(C)}$$

$$= \frac{\sum_{D,B \in \{T,F\}} P(A \cap B \cap C \cap D)}{\sum_{A,B,D \in \{T,F\}} P(A \cap B \cap C \cap D)}$$

$$\sum_{D,B \in \{T,F\}} P(A \cap B \cap C \cap D) = P(A,B,C,D) + P(A,\neg B,C,D) + P(A,B,C,\neg D)$$

$$P(A,\neg B,C,\neg D)$$

$$= \underline{P(A) \times P(B) \times P(C|A) \times P(D|A,B)} + \underline{P(A) \times P(\neg B) \times P(C|A) \times P(D|A,B)}$$

$$= (0.3 \times 0.6 \times 0.4 \times 0.7) + (0.3 \times 0.4 \times 0.4 \times 0.4)$$

$$+ \underline{P(A) \times P(\neg B) \times P(C|A) \times P(\neg D|A,\neg B)} + P(A) \underline{\times P(\neg B) \times P(C|A) \times P(\neg D|A,\neg B)}$$

$$+ (0.3 \times 0.4 \times 0.4 \times 0.6) + (0.3 \times 0.4 \times 0.4 \times 0.6)$$

$$\sum_{A,B,D \in \{T,F\}} P(A \cap B \cap C \cap D)$$

$$= P(A,B,C,D) + P(A,B,C,\neg D) + P(A,\neg B,C,D)$$
$$+ P(A,\neg B,C,\neg D) + P(\neg A,B,C,D) + P(\neg A,B,C,\neg D)$$
$$+ P(\neg A,\neg B,C,D) + P(\neg A,\neg B,C,\neg D)$$

$$= [P(A) * P(B) . P(C|A) . P(D|AB)] + [P(A).P(B).P(C|A) + P(\neg D|A,B)]$$
$$+ [P(A)\,P(\neg B)\,P(C|A)\,P(D|A,\neg B)] + [P(A)\,P(\neg B)\,P(C|A)\,P(\neg D|A,\neg B)] +$$
$$[P(\neg A)\,P(B)\,P(C|\neg A)\,P(\neg D|A,B) + P(\neg A).P(B)\,P(C|\neg A)\,P(\neg D|\neg A,B)] +$$
$$[P(\neg A)\,P(\neg B) \cdot P(C|\neg A)\,P(D|\neg A,\neg B) + P(\neg A)\,P(\neg B)\,P(C|\neg A)\,P(\neg D|\neg A,\neg B)]$$

A	B	D
T	T	T
T	T	F
T	F	T
T	F	F
F	T	T
F	T	F
F	F	T
F	F	F

INT 404 | contd from P-

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6/4/2017

Dempster - Shafer Theory
(Based on set of evidences)

H	M	Bel	Pl
A is alive	0.2	0.2	0.5
A is dead	0.5	0.5,	0.8
either (A) Alive (A) dead	0.3	1	

~~Bel(s) = 1 − Pl(s̄)~~

Bel(s)

$Pl(s) = 1 - Bel(\bar{s})$

$Bel(s) \leq Pl(s)$

$Bel(s) \leq MB(h,s) \leq Pl(s)$

Plausibility - max extend to which we can believe a hypothesis.

m = probability density function (avg prob. of a set)

θ = frame of discernment

$x = \{a, b\}$ power set $= 2^n$

$\{\phi, \{a\}, \{b\}, \{a,b\}\}$

Fuzzy logic

value in between

K = measure of conflict

$\sum_{x \cap y = \phi} m_1(x) \cdot m_3(y)$

$\boxed{Bel + Pl = 1}$

Remaining space other than believe = Pl

When there is no conflict. –

$m_2(x) \rightarrow$ / $m_1(x) \downarrow$	{AFC} ·0.8	θ (0.2)
{FCP} 0.6	{FC} 0.6 × 0.8 = 0.48	{FCP} = 0.6 × 0.2 = 0.12
θ (0.4	{AFC} = 0.4 × 0.8 = 0.32	θ

θ = All / (A)

this whole becomes m3

$m_2(x) \rightarrow$ / $m_1(x) \downarrow$	{A} 0.9	θ (0.1)
{FC} = 0.48	ϕ = 0.48 × 0.9 = 0.432	{FC} = 0.048
{AFC} = 0.32	{A} = 0.288	{AFC} = 0.032
{FCP} = 0.12	ϕ = 0.108	{FCP} = 0.012
θ = 0.08	{A} = 0.072	θ = 0.008

measure of K (conflict)

7/4/2012

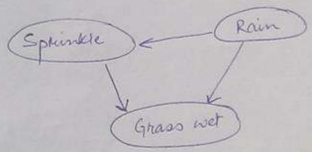
$\boxed{\text{INT 404}}$ $\boxed{\text{Contd. from P-34}}$

m_3 \ m_4	$\{A\}$ 0.9	Θ 0.1
$\{Flu, C\}$ 0.48	ϕ 0.432	$\{FC\}$ 0.048
$\{AFC\}$ 0.32	$\{A\}$ 0.288	$\{AFC\}$ 0.032
$\{FCP\}$ 0.12	ϕ 0.108	$\{FCP\}$ 0.012
Θ 0.08	$\{A\}$ 0.072	Θ 0.008

ϕ = 0.432
ϕ = 0.108
0.540

Q. Find the probability of raining given that grass is wet.

$P(\text{Rain} \mid \text{Grass-wet}) = ?$ $\qquad \dfrac{P(R \cap GW)}{P(GW)}$



$$P(R \mid GW) = \frac{\sum_{S \in \{T,F\}} P(R \cap GW)}{\sum_{S,R \in \{T,F\}} P(GW)}$$

$$= \frac{P(R \cap GW \cap S) + P(R \cap GW \cap \neg S)}{P(S \cap R \cap GW) + P(\neg S \cap R \cap GW) + P(S \cap \neg R \cap GW) + P(\neg S \cap \neg R \cap GW)}$$

$$= P(R \cap GW \cap S) + P(R \cap GW \cap \neg S)$$

$$= P(R) * P(GW \mid S, R) * P(S \mid R) + P(R) * P(GW \mid S, R) * P(\neg S \mid R)$$

$$= 0.2 * 0.99 * 0.01 + 0.2 * 0.8 * 0.99$$

$$= 0.00198 + 0.1584$$

$$= 0.16038$$

16
99
144
144
.15840
.00198
16038

P.T.O.

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And $P(S \cap R \cap GW) + P(\neg S \cap R \cap GW) + P(S \cap \neg R \cap GW) + P(\neg S \cap \neg R \cap GW)$

$= P(S|R) * P(R) * P(GW|S,R) + P(\neg S|R) * P(R) * P(GW|\neg S,R) + P(S|\neg R) * P(\neg R) * P(GW|S,\neg R)$

$+ P(\neg S|\neg R) * P(\neg R) * P(GW|\neg S,\neg R)$

DST

10/4/2017

m_1 = {Abbot, Babbit} = 0.3 $\quad \theta = 0.7$

m_2 = {Babbit, Cabbit} = 0.6 $\quad \theta = 0.4$

m_1 \ m_2	{Babbit, Cabbit} = 0.6	θ = 0.4
{Abbot, Babbit} 0.3	{Babbit} = 0.18	{Abbot, Babbit} 0.12
θ 0.7	{Babbit, Cabbit} = 0.42	θ = 0.28

m_3 : {Babbit} = 0.18

{Abbot, Babbit} = 0.12

{Babbit, Cabbit} = 0.42

θ = 0.28

m_4 : {Abbot, Ebbit} = 0.2

θ = 0.8

m_3 \ m_4	{Abbot, Ebbit} = 0.2	θ = 0.8
{Babbit} = 0.18	ϕ = 0.036	{Babbit} = 0.144
{Abbot, Babbit} = 0.12	{Abbot} = 0.024	{Abbot, Babbit} = 0.096
{Babbit, Cabbit} = 0.42	ϕ = 0.084	{Babbit, Cabbit} = 0.336
θ = 0.28	{Abbot, Ebbit} = 0.056	θ = 0.224

contd. on P-40

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10/4/2017

INT 404 | contd. from P-37

Probability Density Function

$$\frac{X \cap Y}{1 - (X \cap Y)_{\phi}}$$

$$= \frac{0.024 + 0.056 + 0.144 + 0.096 + 0.336 + 0.224}{1 - (0.036 + 0.084)}$$

$$= \frac{0.880}{1 - 0.120} = \frac{0.880}{0.880} = 1$$

$CF[h,e] = MB[h,e] - MD[h,e]$

Certainty factor — measure of belief — measure of disbelieve

$$MB[h_1, S_1 \wedge S_2] = \begin{cases} 0 & MD[h_1, S_1 \wedge S_2] = 1 \\ MB[h_1, S_1] + MB[h_1, S_2] * (1 - MB[h_1, S_1 \cap S_2]) & \text{otherwise} \end{cases}$$

$$MD[h_1, S_1 \wedge S_2] = \begin{cases} 0 & MB[h_1, S_1 \wedge S_2] = 1 \\ MD[h_1, S_1] + MD[h_1, S_2] * (1 - MD[h_1, S_1]) & \text{otherwise} \end{cases}$$

$MB[h_1 \wedge h_2, e] = \min(MB[h_1, e], MB[h_2, e])$

$MB[h_1 \vee h_2, e] = \max(MB[h_1, e], MB[h_2, e])$

$MD[h_1 \wedge h_2, e] = \min(MD[h_1, e], MD[h_2, e])$

$MD[h_1 \vee h_2, e] = \max(MD[h_1, e], MD[h_2, e])$

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Given:

$MB[h_1, S_1] = 0.4$

$MB[h_1, S_2] = 0.6$

$CF[h_1, S_1] = 0.4$

find a) $MB[h_1, S_1 \wedge S_2]$ b) $MD[h_1, S_1 \wedge S_2]$ c) $CF[h_1, S_1 \wedge S_2]$

a. $0.4 + 0.6 * (1 - 0.4)$ $= 0.4 + 0.036$
$= 0.76$

b. 0

c. 0.76

Lecture
Ch-9

Weak Slot and Filler Structures
↓ class ↓ value

- Are a form of object-oriented programming.
- Support both monotonic and Non monotonic inference.
- Make it easy to describe

Class – is a
Not a class – instance

weak Slot Filler
↳ Semantic N/w
↳ Frames.

A Semantic Structure

In the box → Slot
In the line → Filler

~~If there is no direct~~

Semantic networks are called weak slot filler structures because it is not able to generate relationship between those objects which are not directly connected / related.

eg. Relation between Brooklyn - Dodgers and Blue class.

P.T.O.

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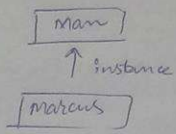
~~Unir~~ Unary Predicates

man (Marcus)

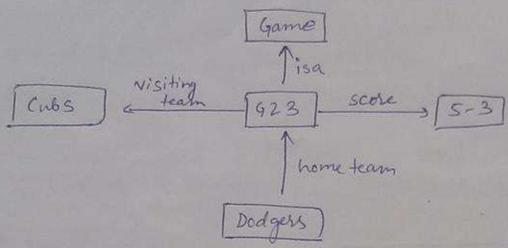
Binary Predicates

instance (Marcus, Man)



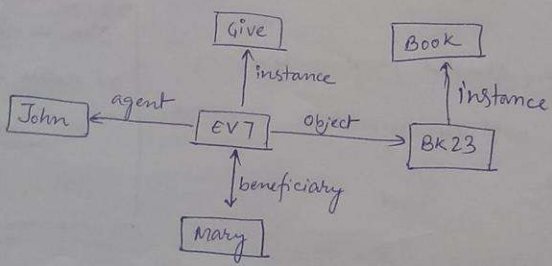
N-place predicates

score (Cubs, Dodgers, 5-3)



(Next week ~~For~~ CA3)

John gave the book to Mary.



Partitioned Semantic Nets

INT 404 contd. from P- 42

13/4/2017

Frames

cardinality - calculating the number.

Representing
(Meta class)

Tangled Heirarchies

when attributes are same then, ~~both~~ result will be same
if they are different, conflict arises.

Chapter 10 - Strong Slot and Fillers

In weak slot and filler structures, we will not having specified these forms.

We are not defining the objects.

Not specifying the particular actions.

→ In Strong slot and Fillers

1. CD - Conceptual ~~Def~~ Dependency
2. Script.

Primitive Action

1. ATRANS - Transfer of an abstract relationship
2. PTRANS - Transfer of the physical location of an object
3. PROPEL - Push
4. MOVE - Movement of body parts
5. GRASP - Grasping of an object

P.T.O.

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6. INGEST – eating something
7. EXPEL – Expulsion from the body.
8. MTRANS – to tell someone
9. MBUILD – to decide
10. SPEAK – Speaking
11. ATTEND – focus

CD Primitive Conceptual Categories

Dependencies

1. PP $\Leftrightarrow$ ACT — John $\overset{p}{\Leftrightarrow}$ PTRANS — John ran
2. PP $\Leftrightarrow$ PA — John $\Leftrightarrow$ height (> average) — John is tall
3. PP $\Leftrightarrow$ PA — John $\Leftrightarrow$ Doctor — John is a doctor
4. PP ↑ PA — ~~body~~ boy ↑ nice — A nice boy
5. PP ⇑ PA — dog ⇑ poss-by John — John's dog
6. ACT $\overset{o}{\Leftarrow}$ PP — John $\overset{p}{\Leftrightarrow}$ PROPEL $\overset{o}{\leftarrow}$ cart — John pushed the cart
7. ACT ← (→ PP, ← PP) — John $\overset{p}{\Leftrightarrow}$ ~~PROPEL~~ ATRANS $\overset{o}{\leftarrow}$ (→ John, ← Mary), ↑o book — John took book from Mary

ACTs – Actions
PPs – object
AAs – Modifier of action.
PAs –

contd on P– 52

(52)

INT 404 [contd. from P-49] 14/4/2017

Script

- Getting a Gun (Buy from gun shop)
- Holdi up a bank (Take money and shot, look after P)
- Escape with the money

Here the Props might be

- Gun, G.
- Loot, L
- Bag, B
- Get away Car. C

users.cs.cf.ac.uk/Dave.Marshall/AI2/node70.html

The Roles might be.

- Robber, S
- Cashier, M
- Bank Manager, O
- Policeman, P

The Entry Conditions might be

- S is poor
- S is destitute

The Results might be:

- S has more money
- O is angry
- M is in a state of shock
- P is shot

Scene I: Getting a gun

S PTRANS S into

Tu INT 404 contd. from P-52 17/4/2017

Write script of shopping mall :

Going to the Mall

Search for our desire product

Go to counter for payment

Come out from the mall

Step1 : Enter into the mall :

A = Customer
M = Shopping Mall
C = Counter
P = Product
R = Rupees (Money)

1. A PTRANS M
2. A ATTEND Eyes to P
3. If A found P
   - A MBUILD to buy
   - A GRASP P
   - A MOVE To C
   - A EXPEL R
   - R ATRANS C

   Else
   - A SPEAK To C for help
   - Go to 2

1. $$P(G|S,R) = \frac{P(G,S,R)}{P(S,R)}$$

$$= \frac{P(G|S,R) * P(S|R) * P(R)}{P(S|R) * P(R)}$$

2. $$P(R|G) = \frac{P(R,G)}{P(G)}$$

$$= \frac{R_T G_T S_T + R_T G_T S_F}{G_T R_F S_T + G_T R_F S_F + G_T R_T S_F + G_T R_T S_T}$$

P.T.O.

3. $P(G)$

$P(G|S,R) * P(S|R) * P(R)$. +
T T T   T T   T

$P(G|S,R) * P(S|R) * P(R)$ +
T F F   F F   F

FT ______ +

TF ______

Q. In a group of 100 sport cars wires 40 got alarm system, 30 purchased bucket sit and 20 purchased an alarm system and bucket sit. If a car wire is chosen at random got an alarm system. What is the probability that it also got bucket ~~sit~~ seat?

Sol $P(A) = \frac{40}{100}$

$P(B) = \frac{30}{100}$

$P(A \cap B) = \frac{20}{100}$

$P(B|A) = \frac{P(B \cap A)}{P(A)}$

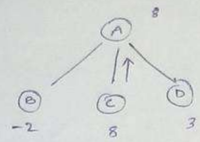
Q What are the advantages of
MIN-MAX algorithm
α-β algorithm

MIN-MAX Algorithm

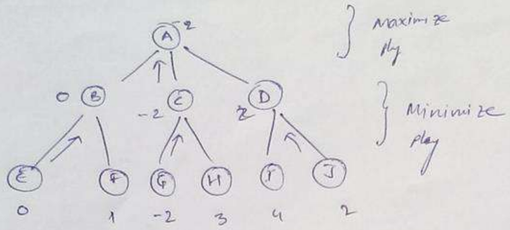
* It gives us a structured form which helps to determine the success or failure
* It does not require a large amount of knowledge space.

PTO

1) One ply search



2) Second ply Search



Functions

1. MOVEGEN (Position, Player)
2. STATIC (Position, Player)

Parameter

DEEP - ENOUGH → True - stop
→ False - continue

Initial

If turn of P1
based position, depth, player
MINIMAX (Current, 0, Player 1)

If turn of P2
MINIMAX (current, 0, Player 2)

1. DEEP-ENOUGH (Position, depth) → return the structure
VALUE = STATIC (Position, Player)
path = nil.

2. Otherwise generate one more ~~node~~ ply ~~like~~ by calling MOVEGEN (position, Player) and setting successor to the list.

P.T.O.

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3: If successors are emptied, then there are no moves to the so return the same structure in step 1.

4. If successors are not emptied, then examine each successor and keep the track of the test I.

Initialized ~~Best score~~ BEST-SCORE to the minimum value that STATIC can return.

For each element SUCC of successors do the following steps

a. Set ~~Result~~ RESULT-SUCC to MINIMAX (SUCC, Depth+1, Opposite.(player))

→ This is the recursive call that will actually carry out,