PART 1:

1)

Tower of Hanoi Problem:-

Init(peg(a) ^ peg(b) ^ peg(c) ^ on(d1,d2) ^ on(d2,a) ^ bigger(d2,d1)

clear(b) ^ clear(c))

Goal(on(d1,d2) ^ on(d2,c)).

Action(

moveToDisk(disk,source,destiDisk),

PreCond: clear(destiDisk),clear(disk),on(disk,source),bigger(destDisk,disk)

Effect: ~clear(destiDisk), on(disk, destiDisk),clear(source),~on(disk,source)

)

Action(

moveToPeg(disk,source,destiPeg),

PreCond: clear(disk),on(disk,source),clear(destiPeg),peg(destiPeg)

Effect: ~clear(destiPeg), on(disk, destiPeg),clear(source), ~on(disk,source)

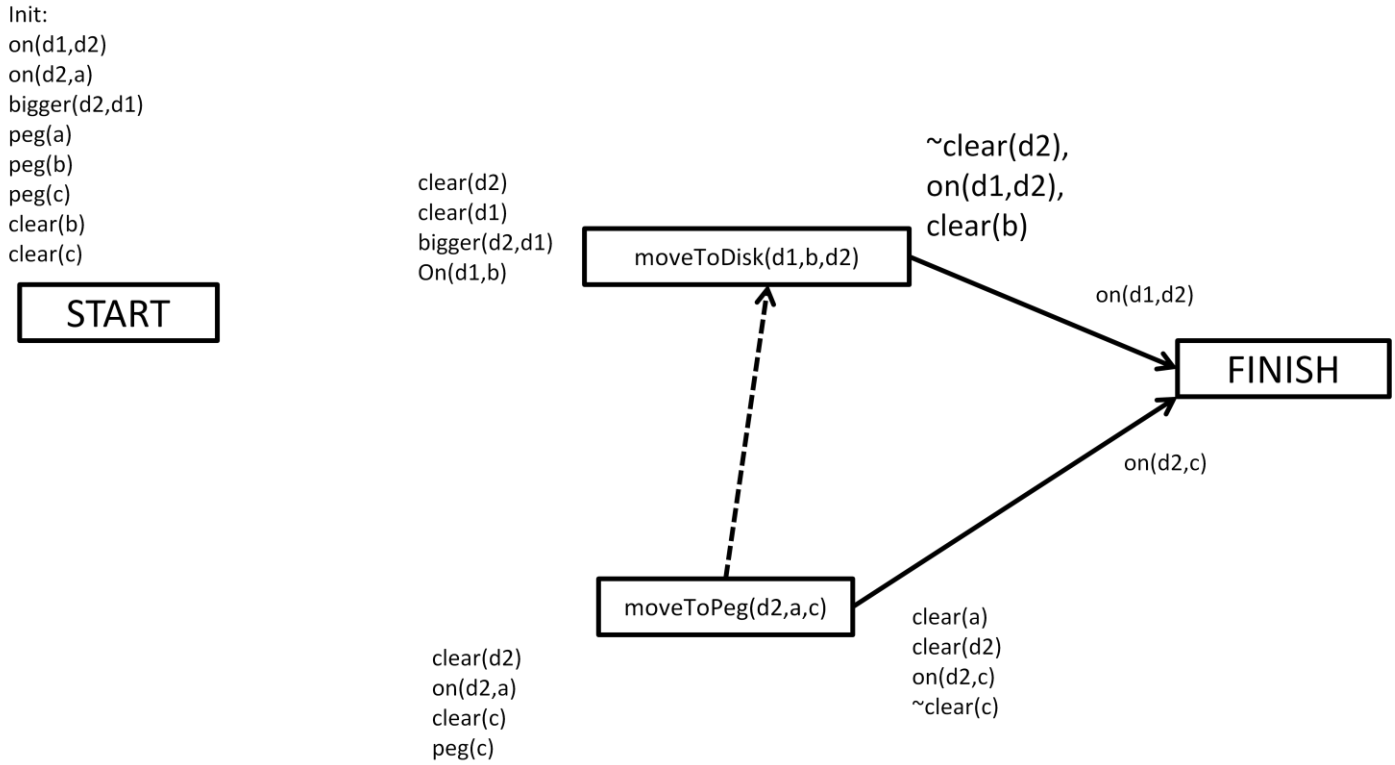
)

I have used symbol '~' as to denote negation

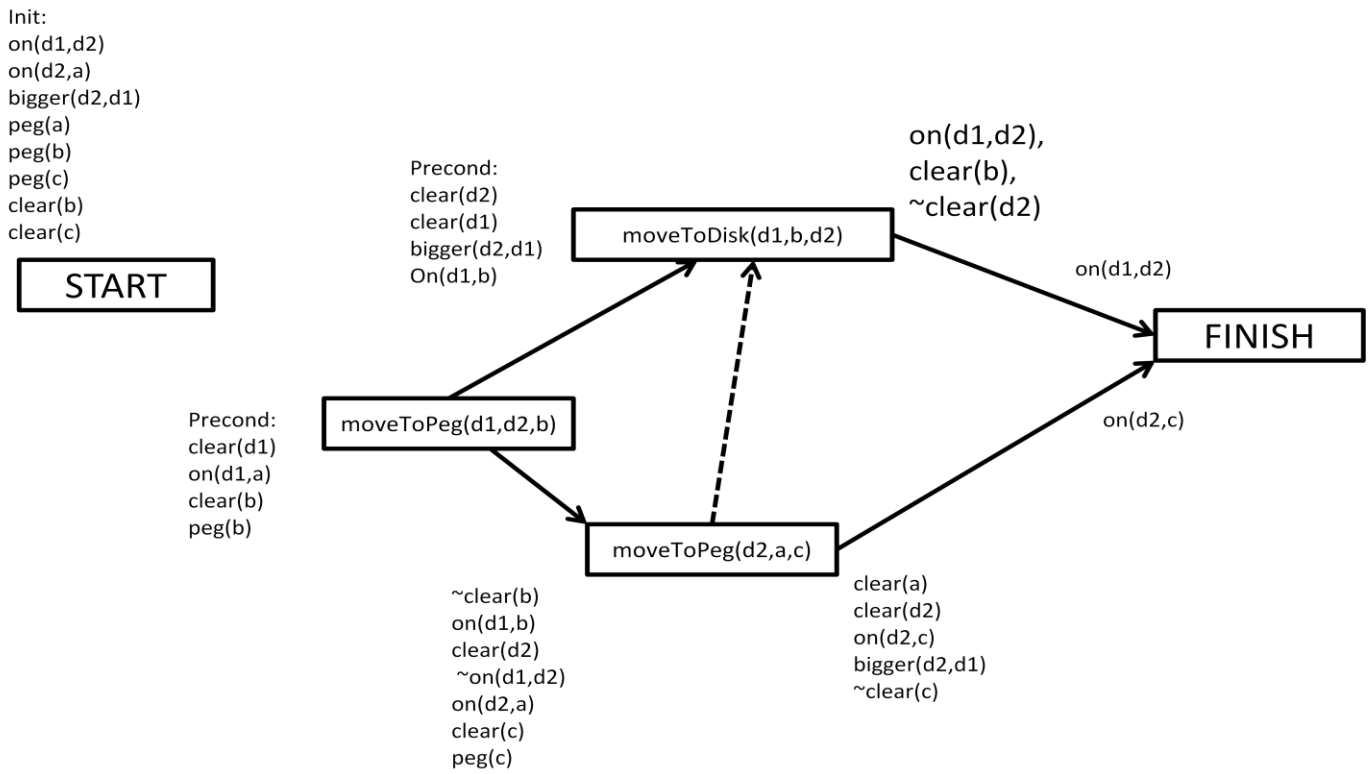
2)

1-

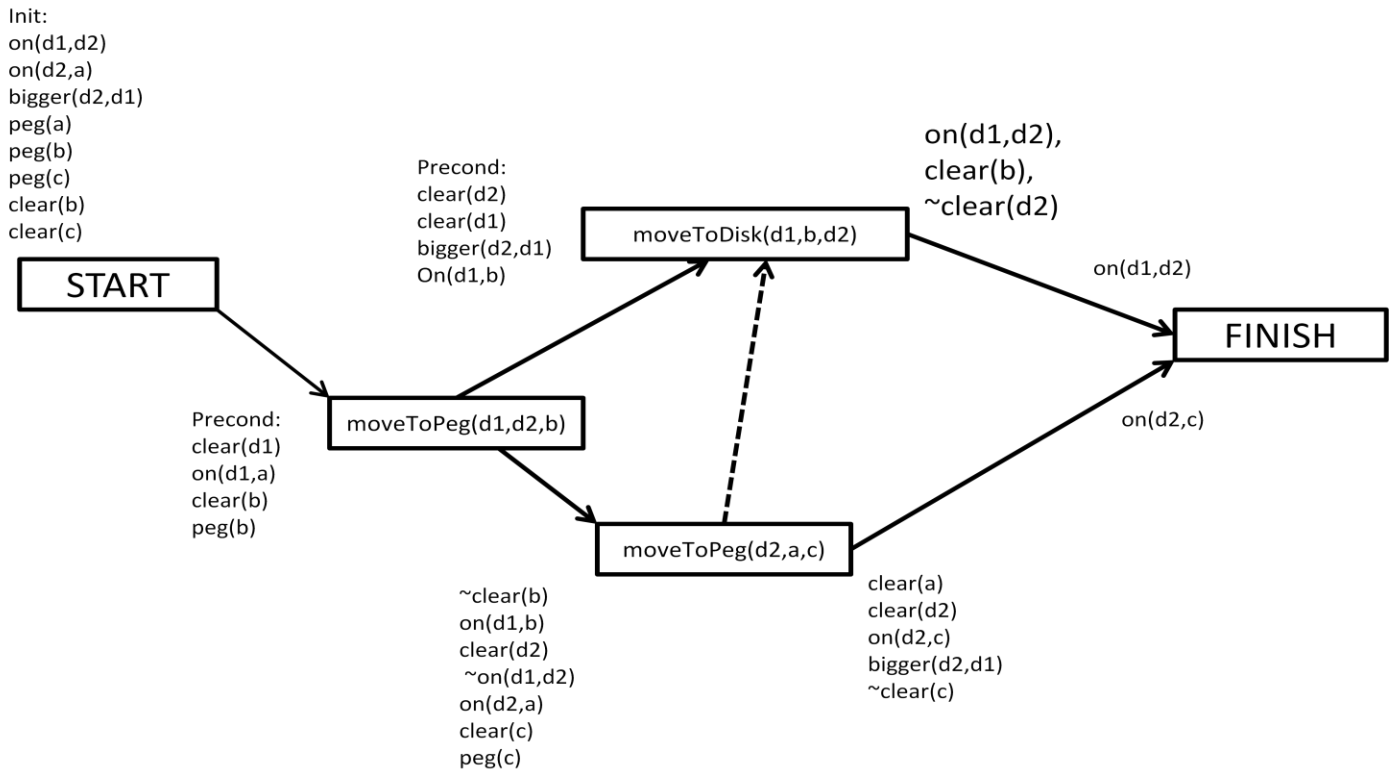
2- doing regression from sub-goals of final goal. trying to achieve each subgoal independetly.

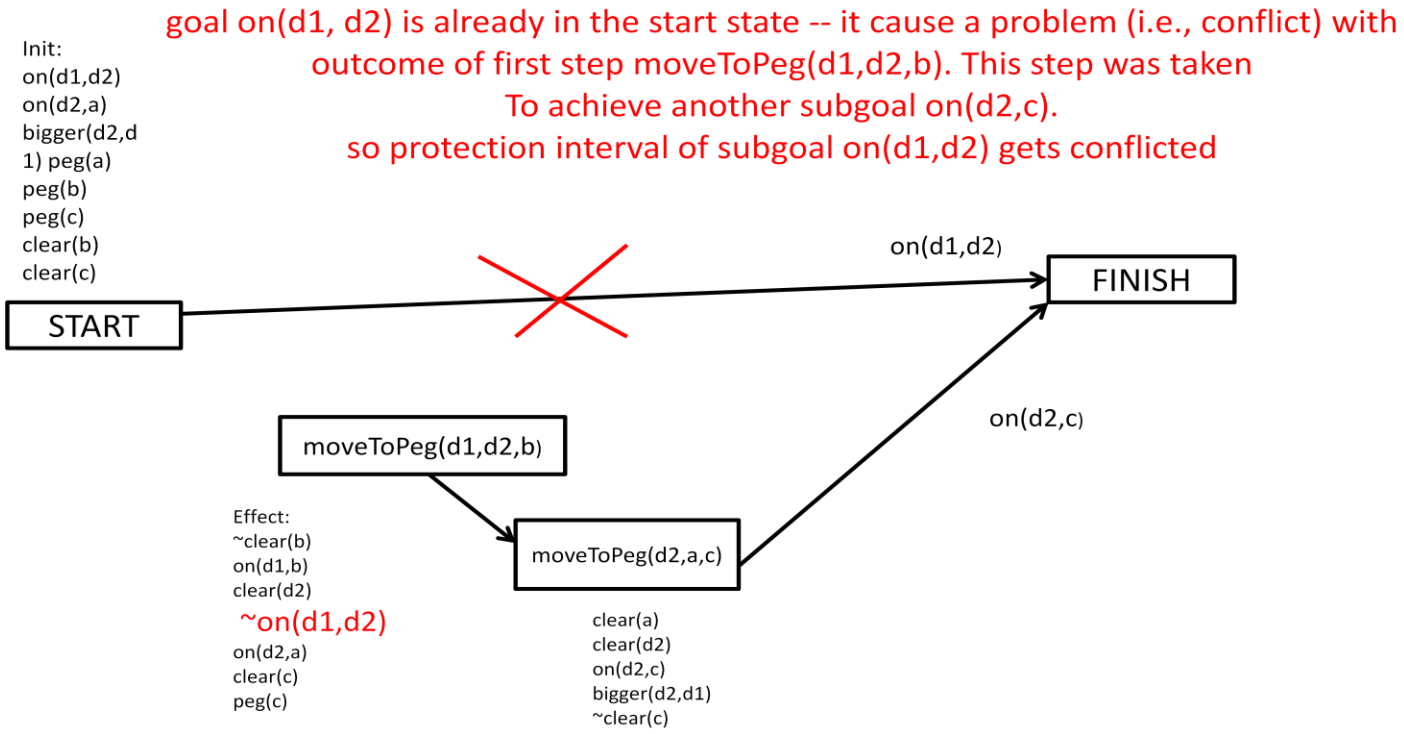


3-


Init:
on(d1,d2)
on(d2,a)
bigger(d2,d1)
peg(a)
peg(b)
peg(c)
clear(b)
clear(c)
START
Precond:
clear(d2)
clear(d1)
bigger(d2,d1)
On(d1,b)
moveToDisk(d1,b,d2)
on(d1,d2),
clear(b),
~clear(d2)
on(d1,d2)
FINISH
Precond:
clear(d1)
on(d1,a)
clear(b)
peg(b)
moveToPeg(d1,d2,b)
on(d2,c)
moveToPeg(d2,a,c)
~clear(b)
on(d1,b)
clear(d2)
~on(d1,d2)
on(d2,a)
clear(c)
peg(c)
clear(a)
clear(d2)
on(d2,c)
bigger(d2,d1)
~clear(c)

4- Final POP

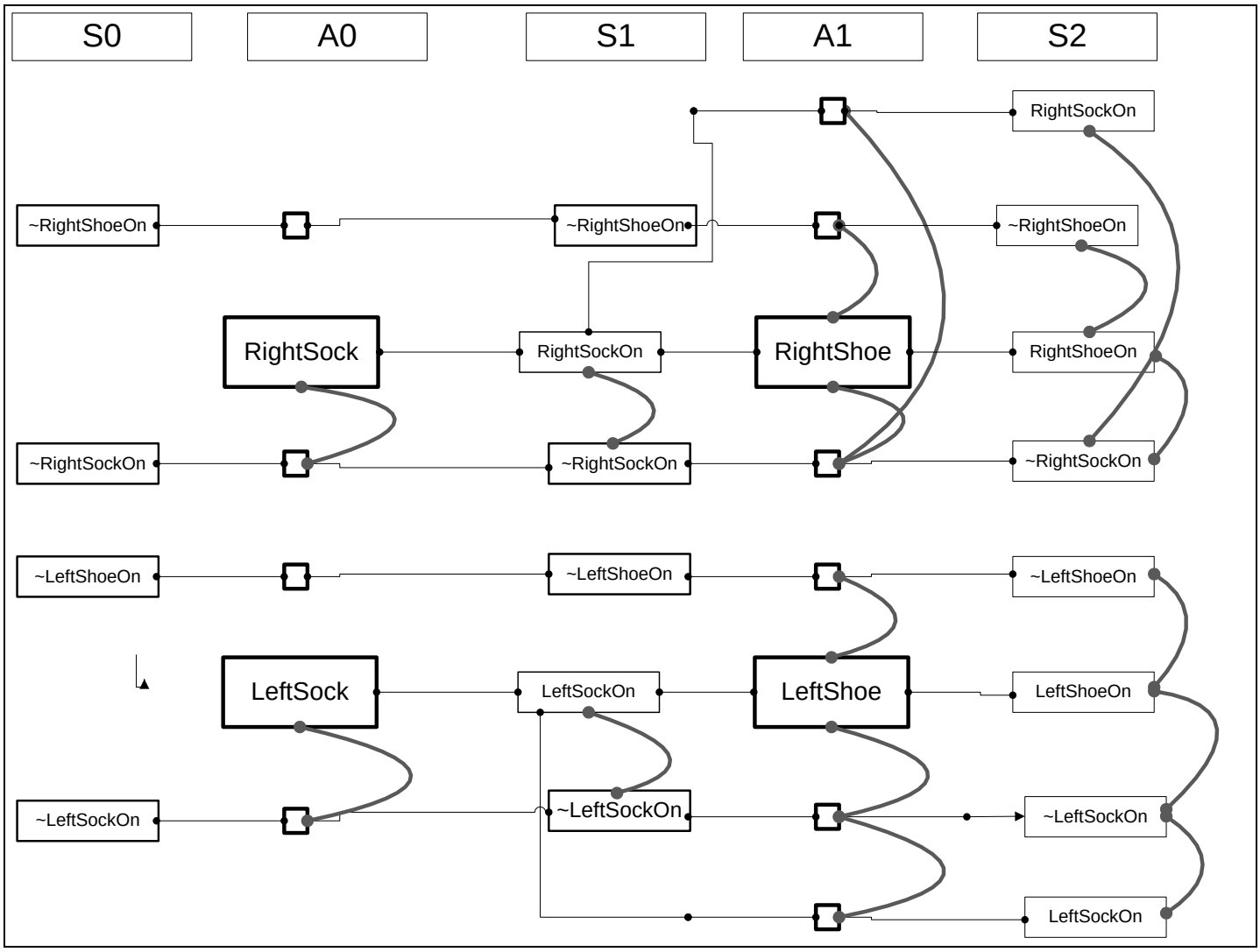

Init:
on(d1,d2)
on(d2,a)
bigger(d2,d1)
peg(a)
peg(b)
peg(c)
clear(b)
clear(c)
START
Precond:
clear(d2)
clear(d1)
bigger(d2,d1)
On(d1,b)
moveToDisk(d1,b,d2)
on(d1,d2),
clear(b),
~clear(d2)
on(d1,d2)
FINISH
Precond:
clear(d1)
on(d1,a)
clear(b)
peg(b)
moveToPeg(d1,d2,b)
on(d2,c)
moveToPeg(d2,a,c)
~clear(b)
on(d1,b)
clear(d2)
~on(d1,d2)
on(d2,a)
clear(c)
peg(c)
clear(a)
clear(d2)
on(d2,c)
bigger(d2,d1)
~clear(c)

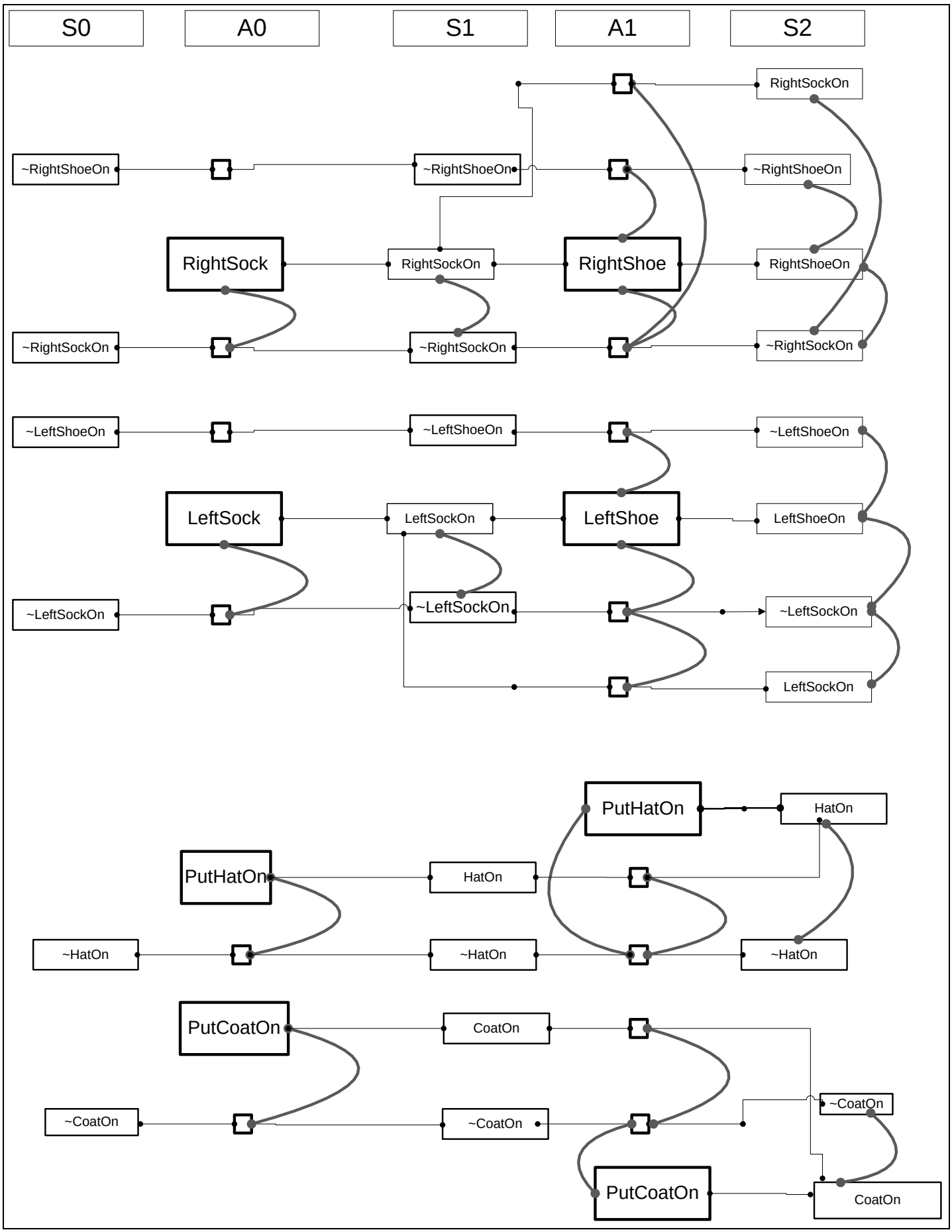


3)since init is empty & this is STRIPS, it means negation of every condition or literal by closed world principle. My formulation is Inspired from problem formulation in the book.

Init( ), Goal(LeftShoeOn ^ RightShoeOn ^ HatOn ^ CoatOn)
Action(LeftSock
PRECOND :
EFFECT : LeftSockOn),
Action(RightSock
PRECOND :
EFFECT : RightSockOn),
Action(LeftShoe
PRECOND : LeftSockOn
EFFECT : LeftShoeOn),
Action(RightShoe
PRECOND : RightSockOn
EFFECT : RightShoeOn)
Action(PutHatOn
PRECOND :
EFFECT : HatOn),
Action(PutCoatOn
PRECOND :
EFFECT : CoatOn),

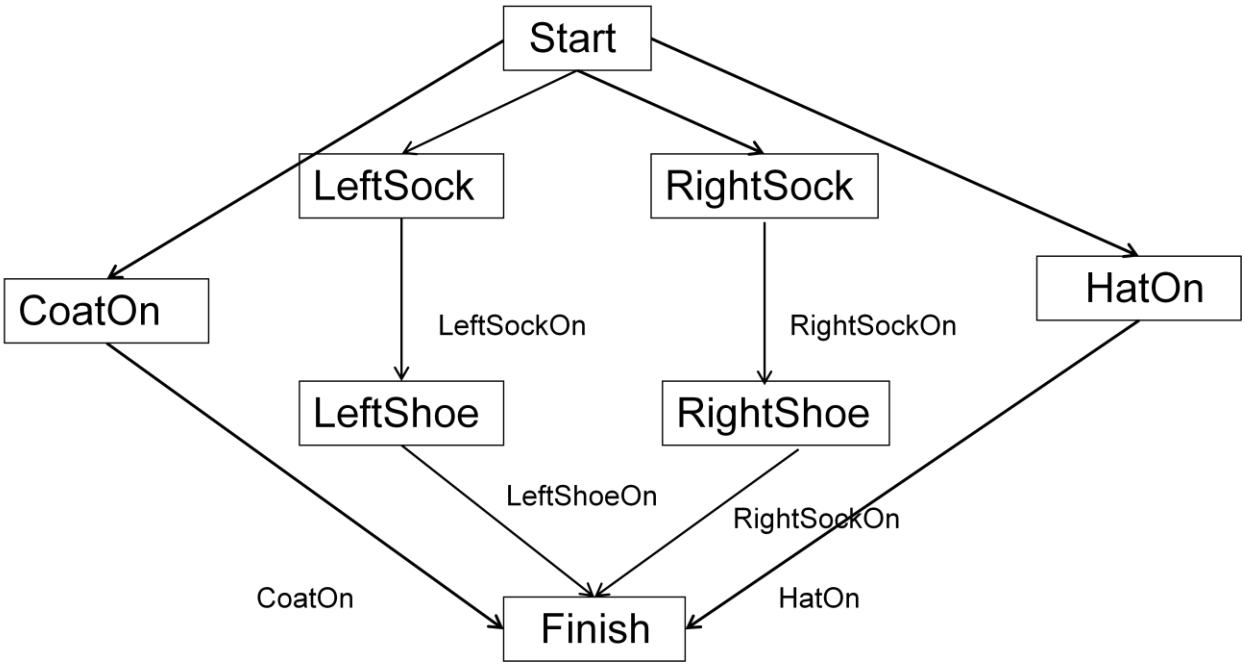
3-1

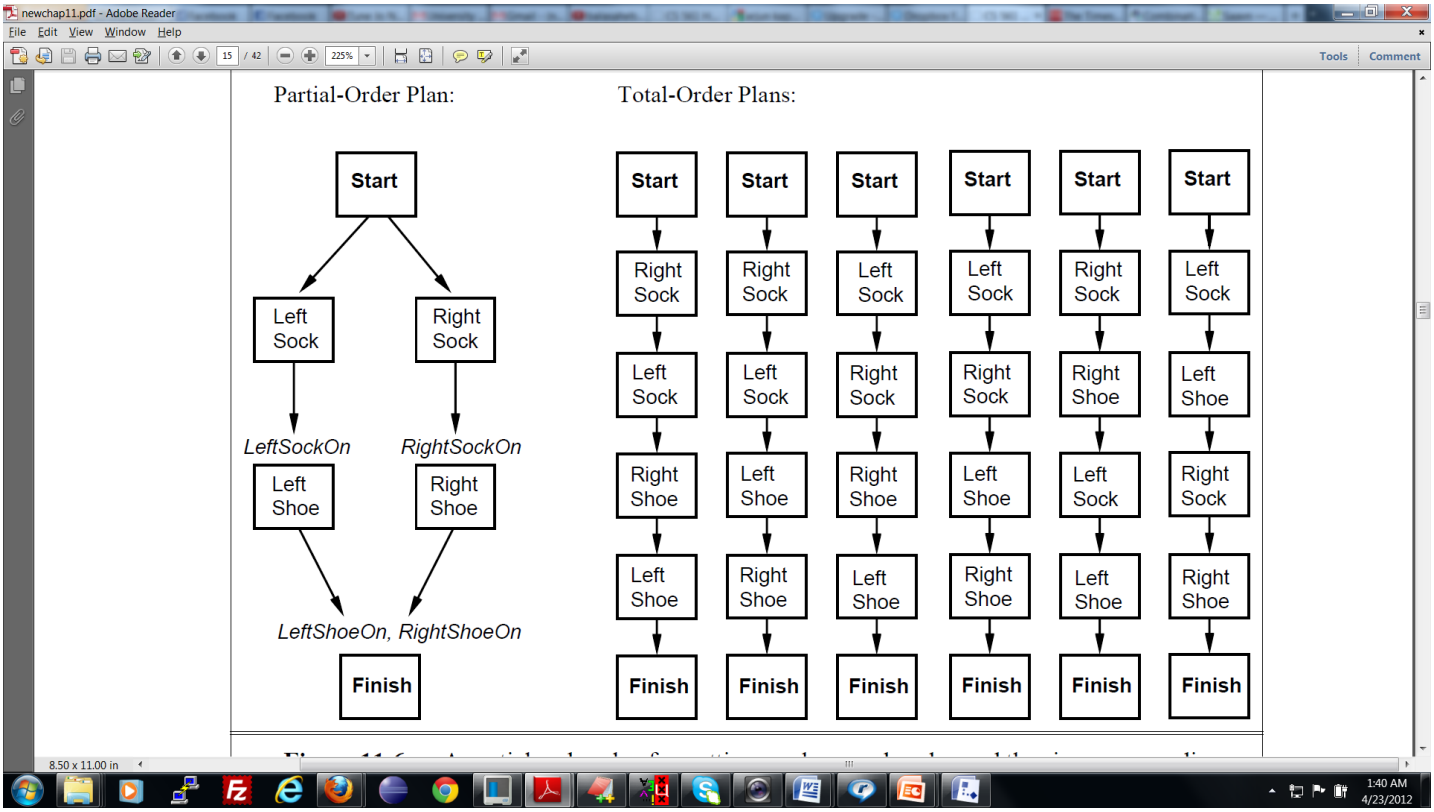

S0
A0
S1
A1
S2
RightSockOn
~RightShoeOn
~RightShoeOn
~RightShoeOn
RightSock
RightSockOn
RightShoe
RightShoeOn
~RightSockOn
~RightSockOn
~RightSockOn
~LeftShoeOn
~LeftShoeOn
~LeftShoeOn
LeftSock
LeftSockOn
LeftShoe
LeftShoeOn
~LeftSockOn
~LeftSockOn
~LeftSockOn
LeftSockOn


S0
A0
S1
A1
S2
RightSockOn
~RightShoeOn
~RightShoeOn
~RightShoeOn
RightSock
RightSockOn
RightShoe
RightShoeOn
~RightSockOn
~RightSockOn
~RightSockOn
~RightSockOn
~LeftShoeOn
~LeftShoeOn
~LeftShoeOn
LeftSock
LeftSockOn
LeftShoe
LeftShoeOn
~LeftSockOn
~LeftSockOn
~LeftSockOn
LeftSockOn
PutHatOn
HatOn
PutHatOn
HatOn
~HatOn
~HatOn
~HatOn
PutCoatOn
CoatOn
~CoatOn
~CoatOn
~CoatOn
PutCoatOn
CoatOn

3-2)

Partial Order Plan





For Shoe problem we know from the plan that, there are 6 linearization or total order plans each having 4 actions.

Hence we can have any one of

PutHatOn OR PutCoatOn

be placed anywhere before or after these 4 actions giving us 5 combination for each of these 6 plans. So total number of possible plans is 6 * 5=30

Now for each of these 30 plans, each having 5 actions in all(together with this new action), remaining action of PutHatOn OR PutCoatOn can be done in 6 ways. So total count by simple combinotorics is 30 * 6 = 180

3-3

What is the minimum number of different planning graph solutions needed to represent all 180 linearizations?

ANSWER: ***1***

PART 2: Natural Language

1: PP-attachment ambiguity

parse2(s,[the,man,eats,the,sushi,with,the,tuna]).

```
s(
  np(
    det(the)
    n(man))
  vp(
    vt(eats)
    np(
      np(
        det(the)
        n(sushi))
      pp(
        p(with)
        np(
          det(the)
          n(tuna))))))
true ;
s(
  np(
    det(the)
    n(man))
  vp(
    vp(
      vt(eats)
      np(
        det(the)
        n(sushi)))
    pp(
      p(with)
      np(
        det(the)
        n(tuna)))))
true ;
false.
```

2: relative-clause attachment ambiguity.

parse2(s,[the,man,eats,the,sushi,with,the,woman,who,likes,the,tuna]).

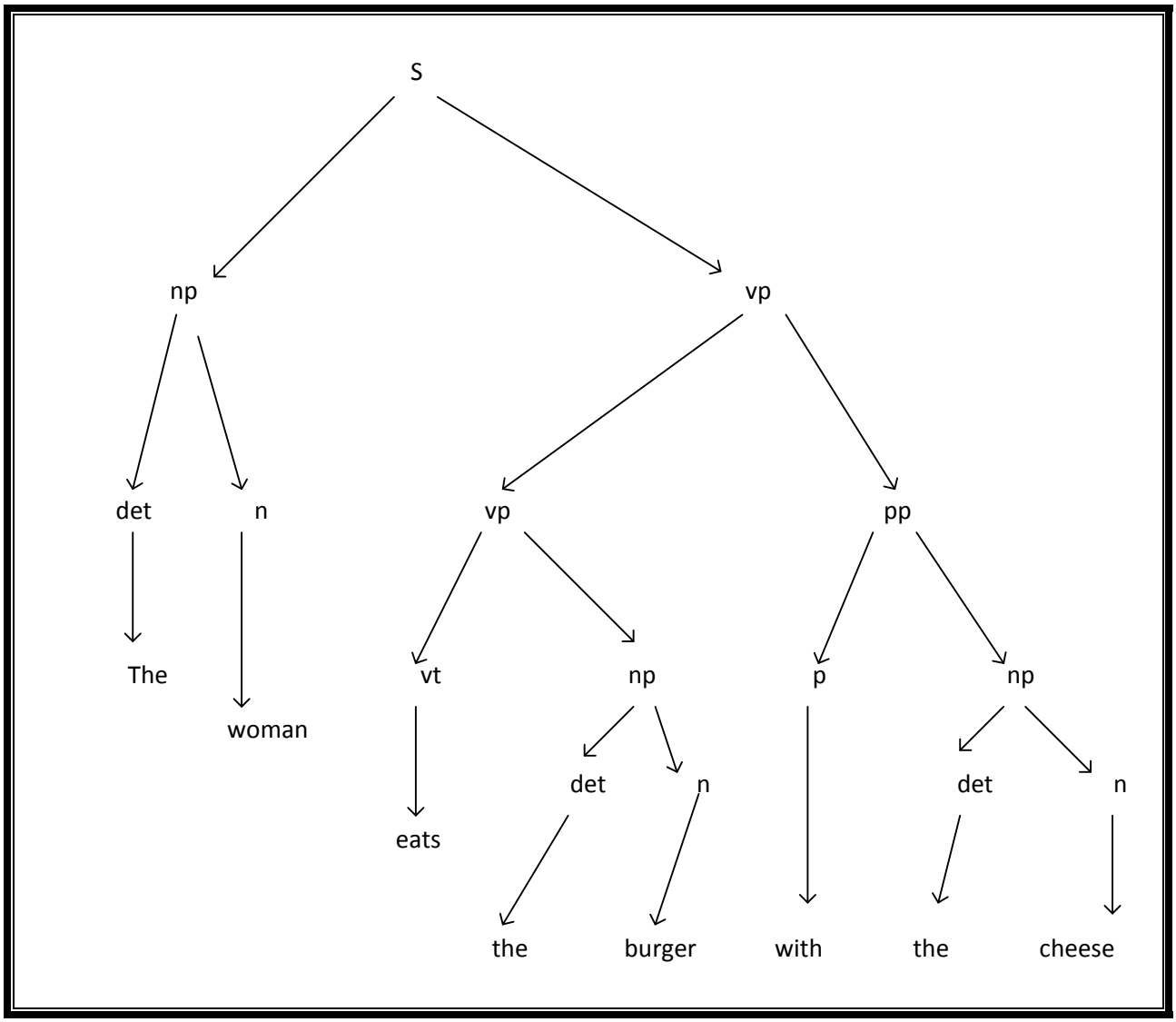
This generates 3 parse trees,& displayes it on the screen.

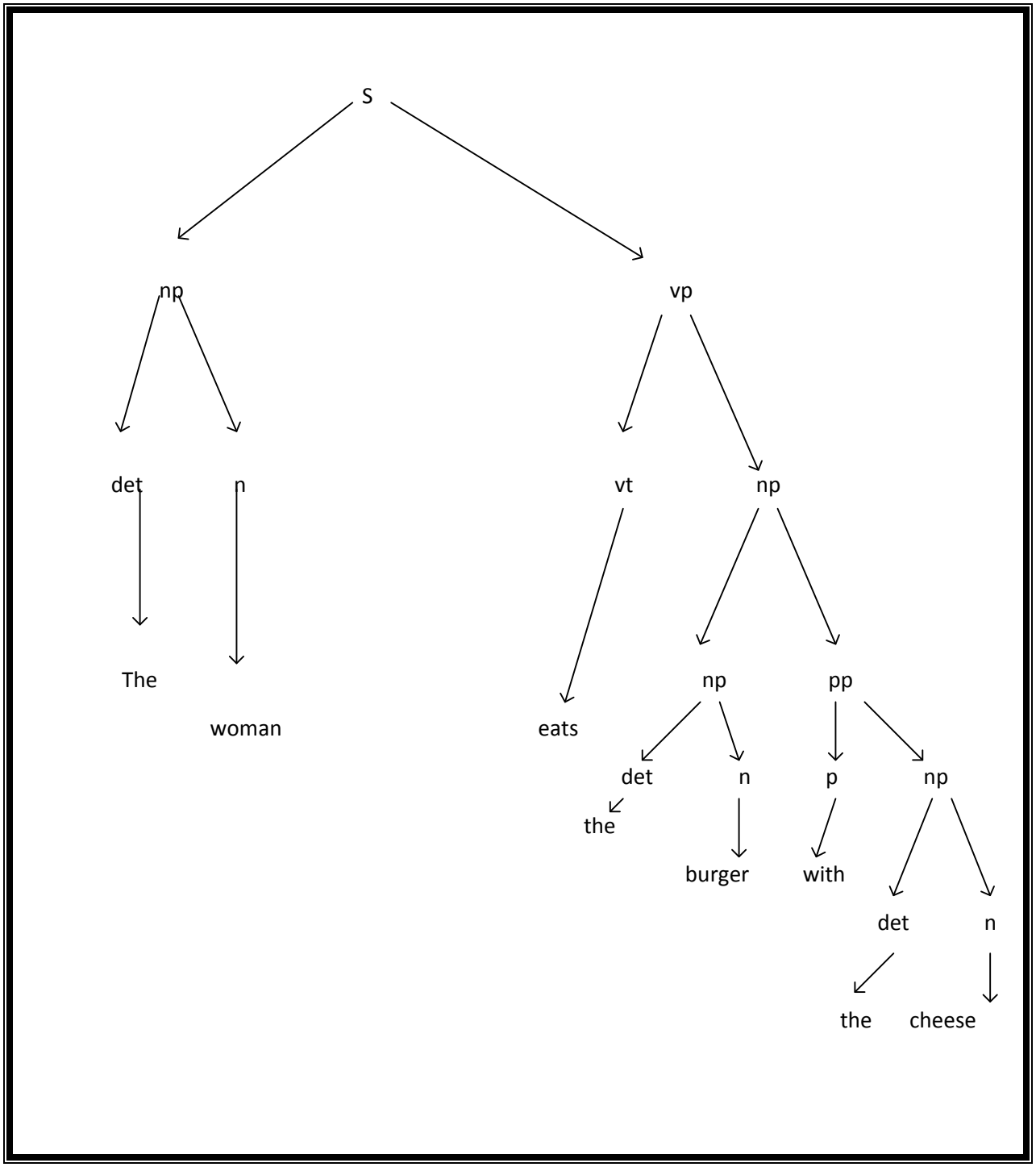
parse2(s,[the,man,eats,the,sushi,with,the,woman,who,eats,the,sushi,with,the,tuna]).

this generates 13 trees.

3: pretty format: First two inputs for 1 & 2 are already printed in pretty format

4:For original parse that is parse2 in my case , breaks given string 2 substrings(whose concatenation gives original string) in all possibilities & does this recursively. Also it applies every production rule to all of these strings. This is because of lack of memoisation found in dynamic programming.
moreover it solves same sub problems again & again. Hence it is exponential.




S
np
vp
det
n
vt
np
The
woman
eats
np
pp
det
n
p
np
the
burger
with
det
n
the
cheese

5-

for the input of

parse3(s,[the,man,eats,the,sushi,with,the,woman,who,eats,the,sushi,with,the,tuna]).

it shows signifcant improvement over parse2. for producing final false parse2 waits for 10 seconds while parse3 produces final false within less than a second.

improved complexity of parse3 is O(n^3 * G).n is number of words in a string & G size of CNF grammar. It employs bottom-up parsing and dynamic programming.

I am memoizing both if a string can or cannot be parsed by some production rule. So same recomputation is totally avoided.Two predicates asserted for this are already_parsed_successfully & cantbe_parsed_successfully respectively.

6:

```
parse4(s,[the,man,eats,the,sushi,with,the,tuna],P).
s(
 np(
  det(the)
  n(man))
 vp(
  vt(eats)
  np(
   np(
    det(the)
    n(sushi))
   pp(
    p(with)
    np(
     det(the)
     n(tuna))))))
P = 5.90625e-7 ;
false.
```

one can also try, parse4(s,[the,man,eats,the,sushi,with,the,woman,who,eats,the,sushi,with,the,tuna],P). it gives two trees with same probability. Even parse4 employs memoisation.
parse4(s,[the,man,eats,the,sushi,with,the,woman,who,eats,the,sushi,with,the,tuna],P).