

# Machine Learning for Data Science (CS4786)

## Lecture 23

### Approximate Inference

Course Webpage :

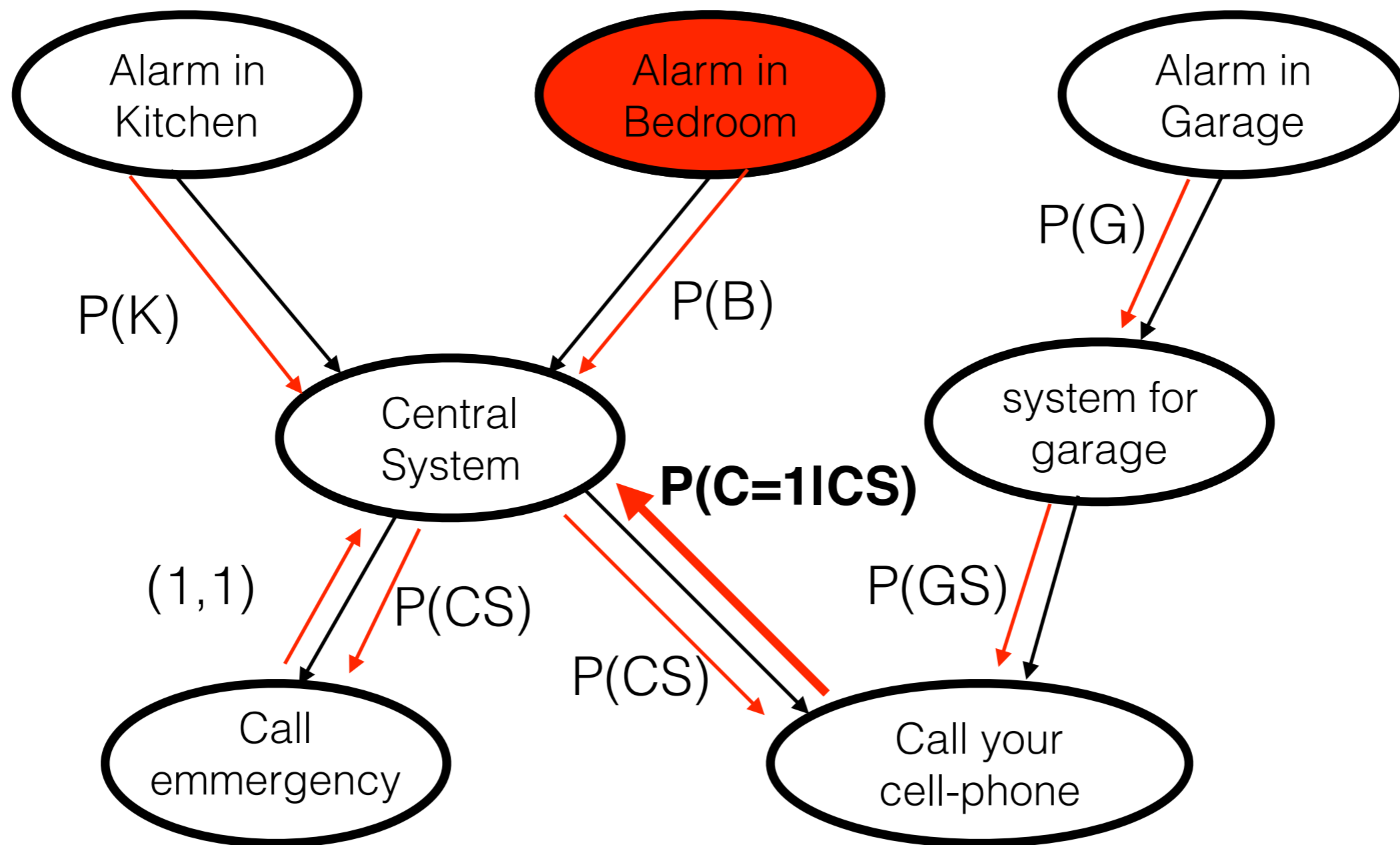
<http://www.cs.cornell.edu/Courses/cs4786/2017fa/>

# Announcement

- Homework 5 out, due in a week

# BELIEF PROPAGATION

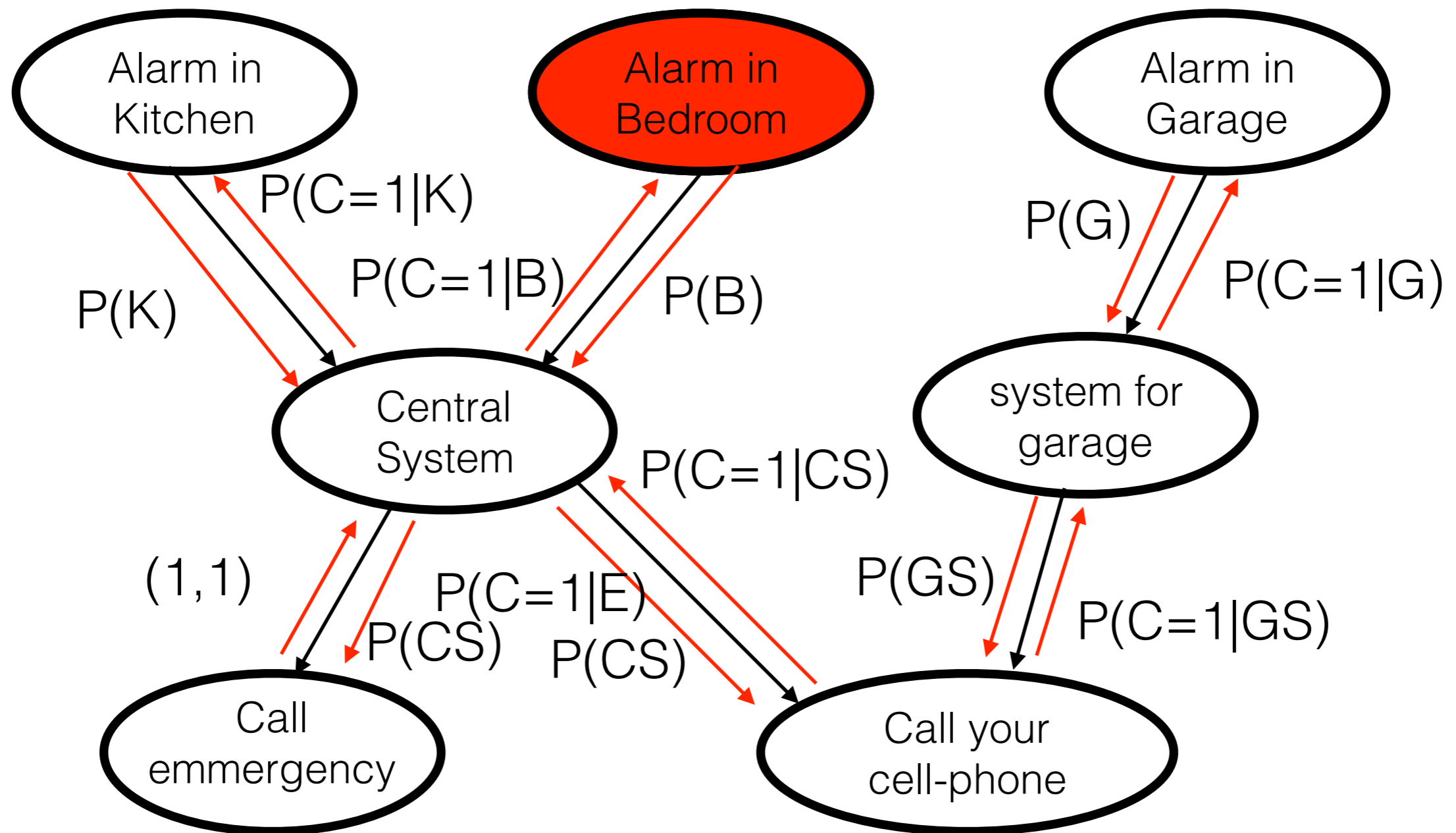
$i=1,2,3$



**You receive phone call**

# BELIEF PROPAGATION

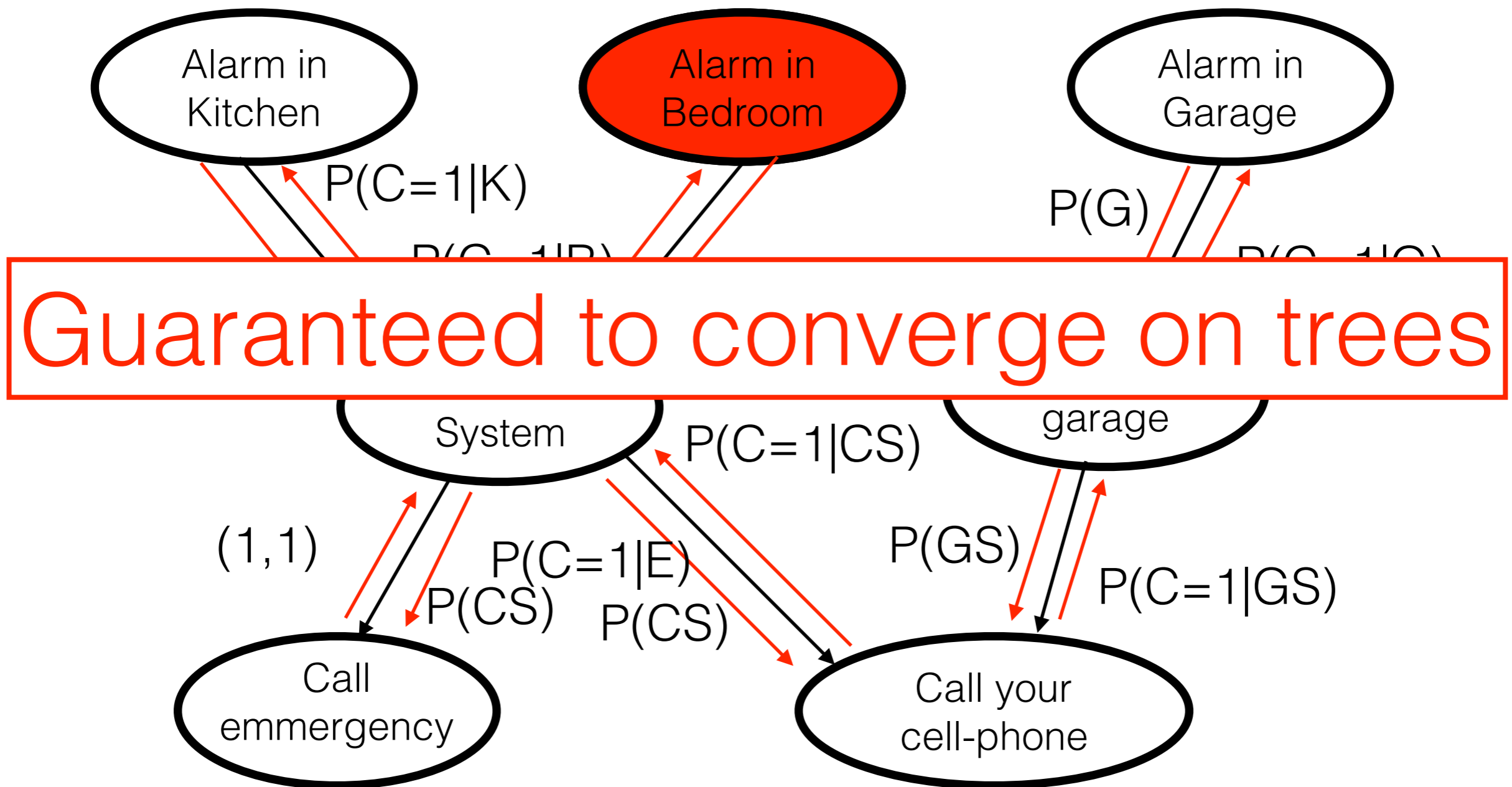
$i=1,2,3$



**You receive phone call**

# BELIEF PROPAGATION

$i=1,2,3$



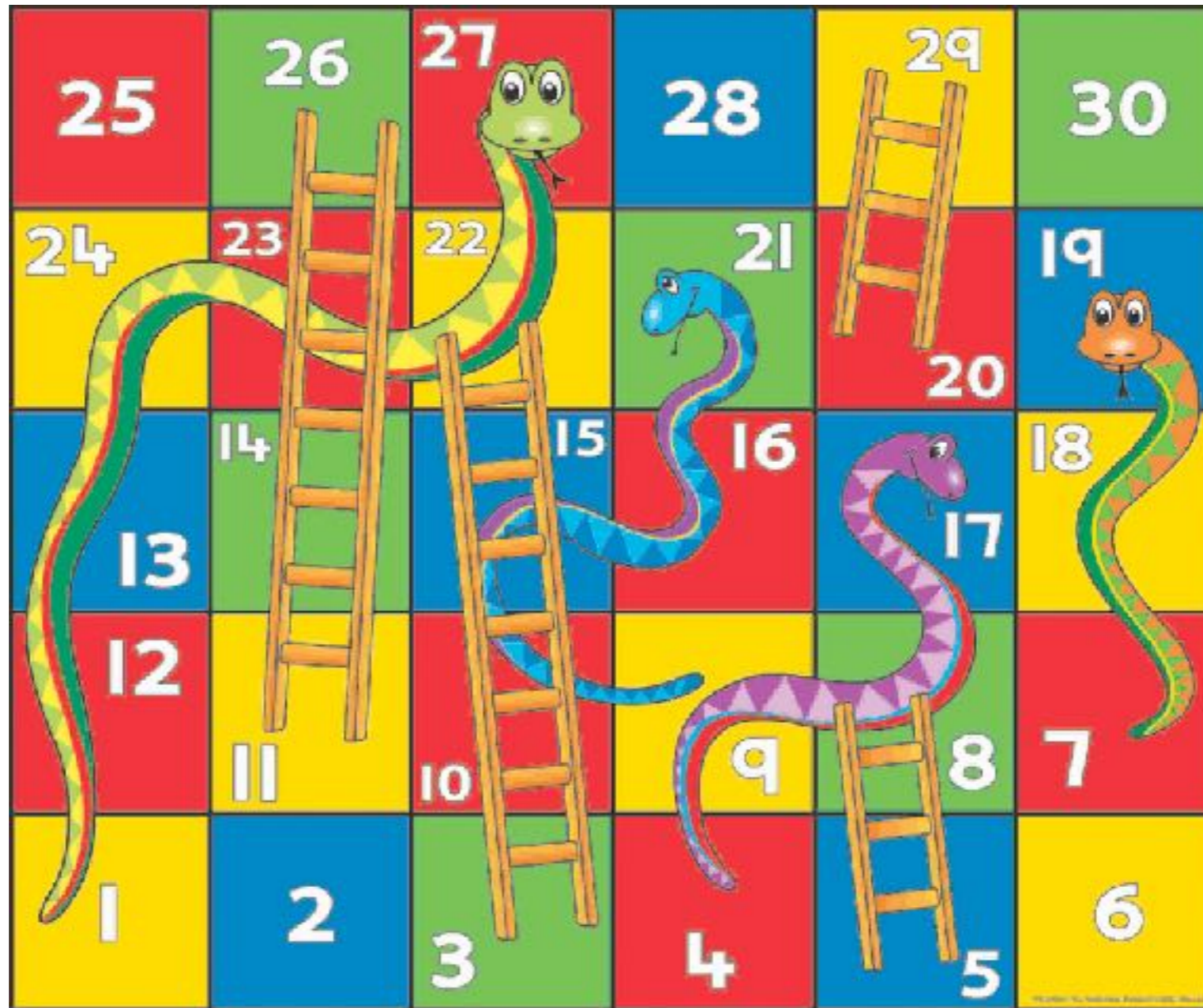
Guaranteed to converge on trees

**You receive phone call**

# Inference in General Graphs

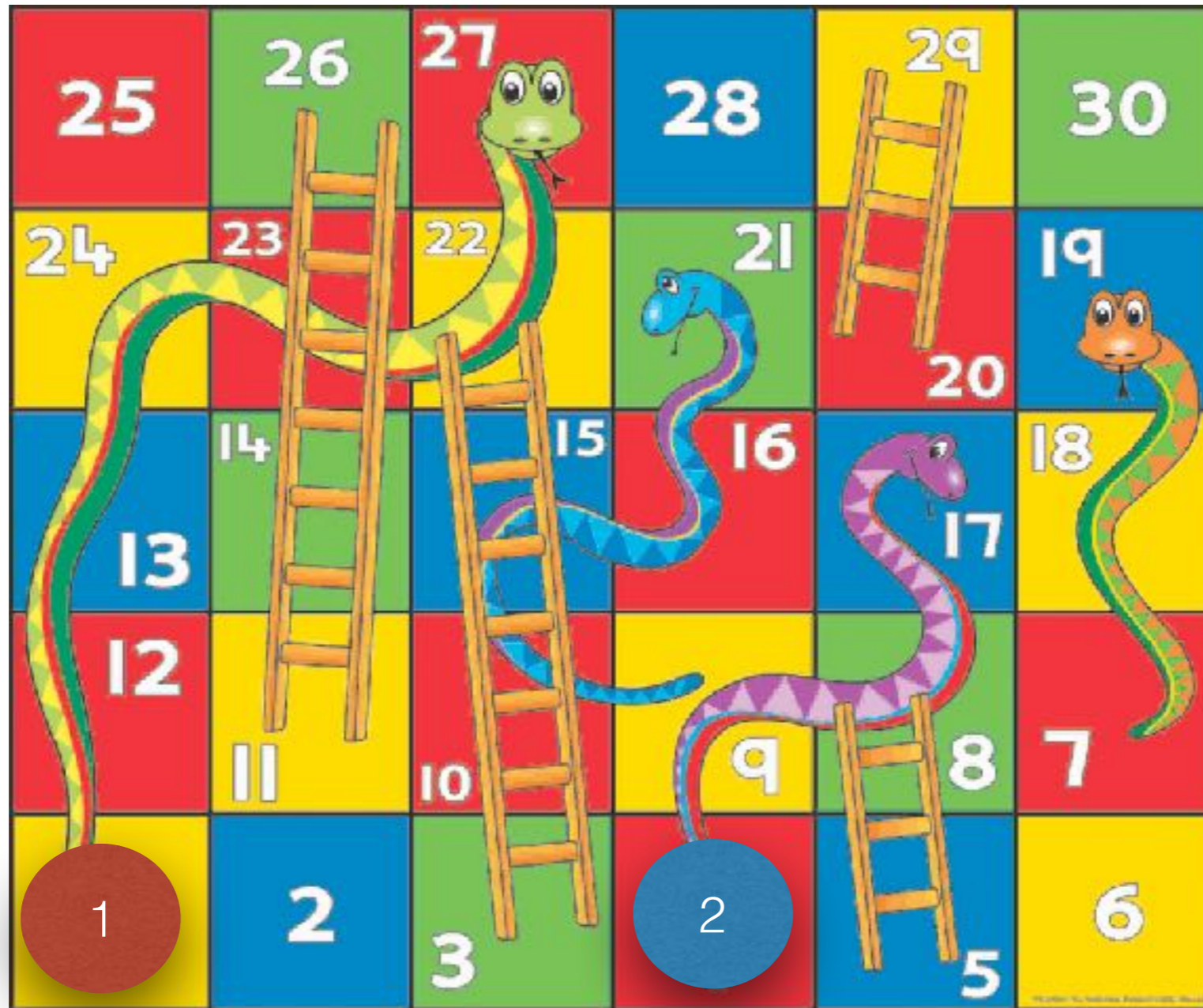
- Variable elimination is exact but can take exponential time
- Belief propagation is guaranteed to work only on trees
- In fact, in general inference problem is NP hard!
- Idea: Do approximate inference.

# INFERENCE



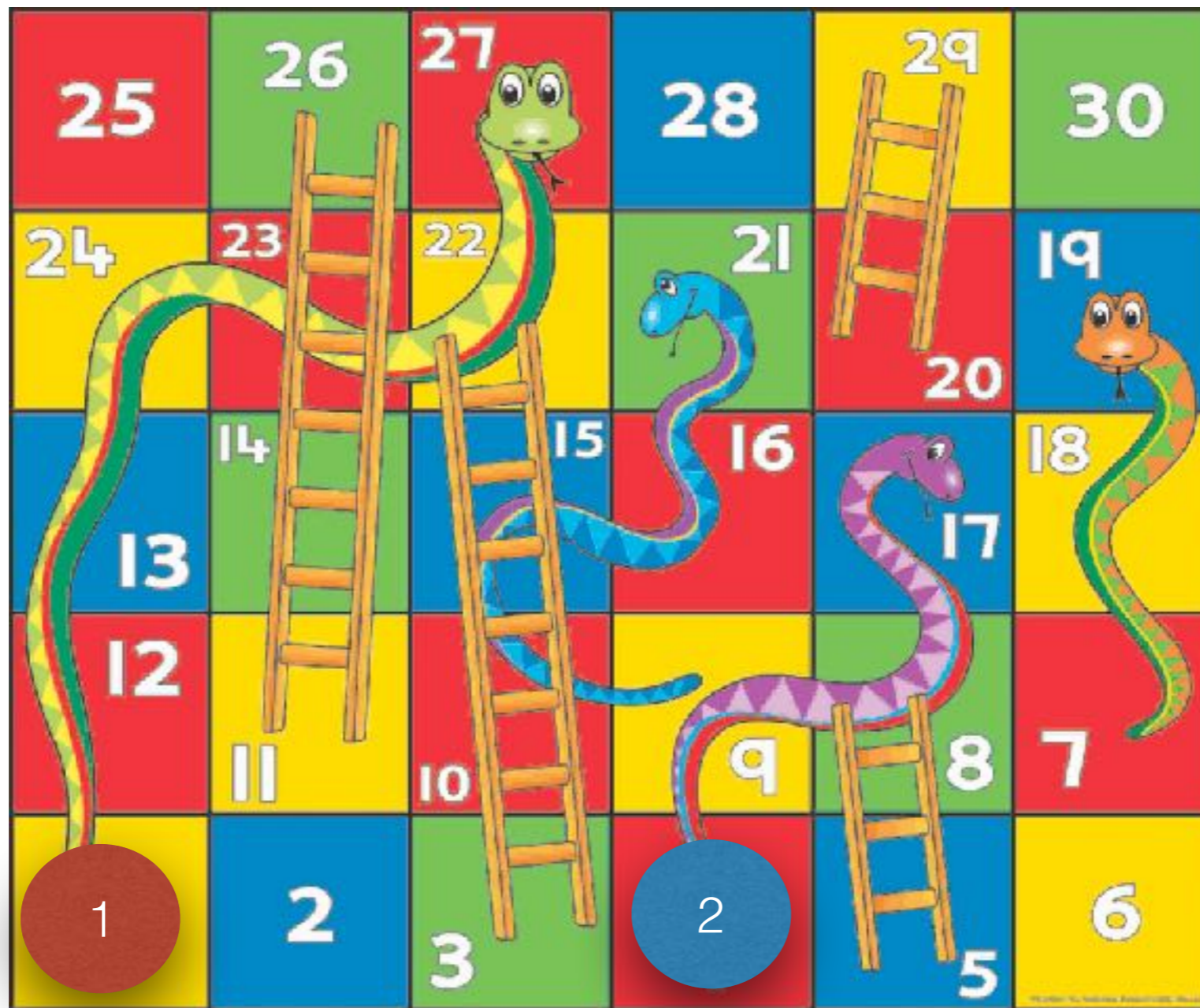


# INFERENCE



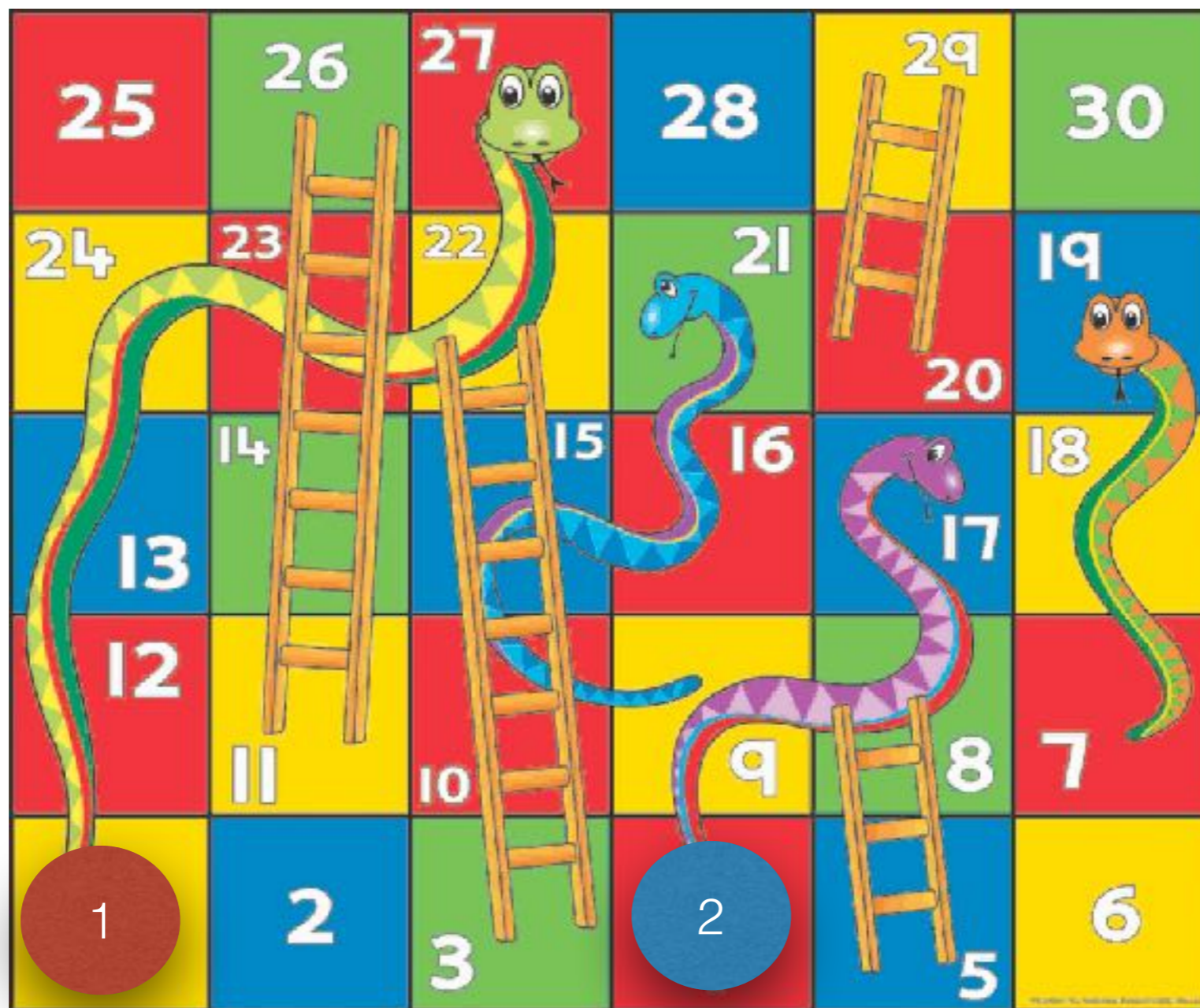


# INFERENCE



Who is more likely to win the game?

# INFERENCE

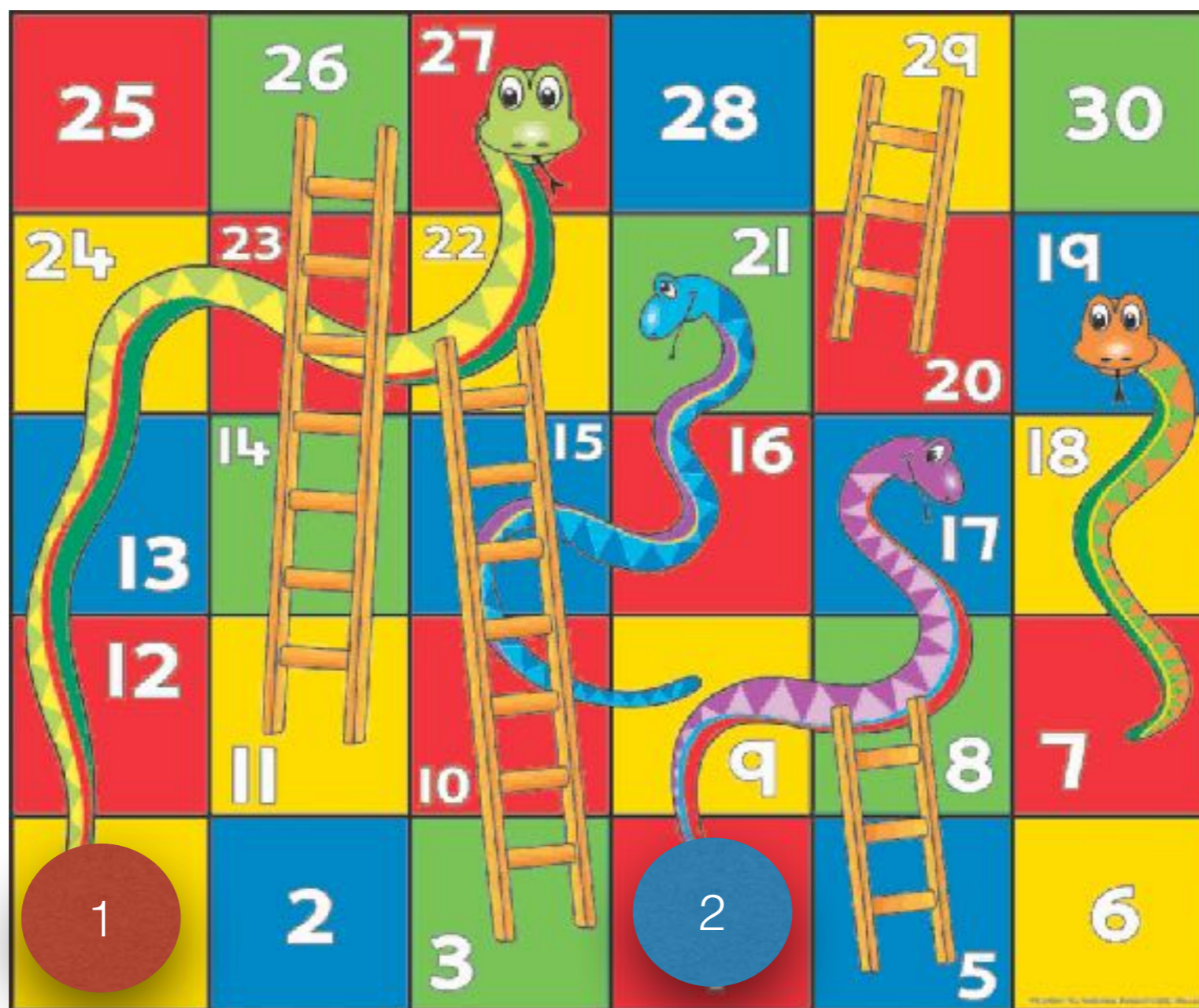


Who is more likely to win the game?

Compute sum of exact probabilities of all possible sequence of moves leading to Player 1's victory



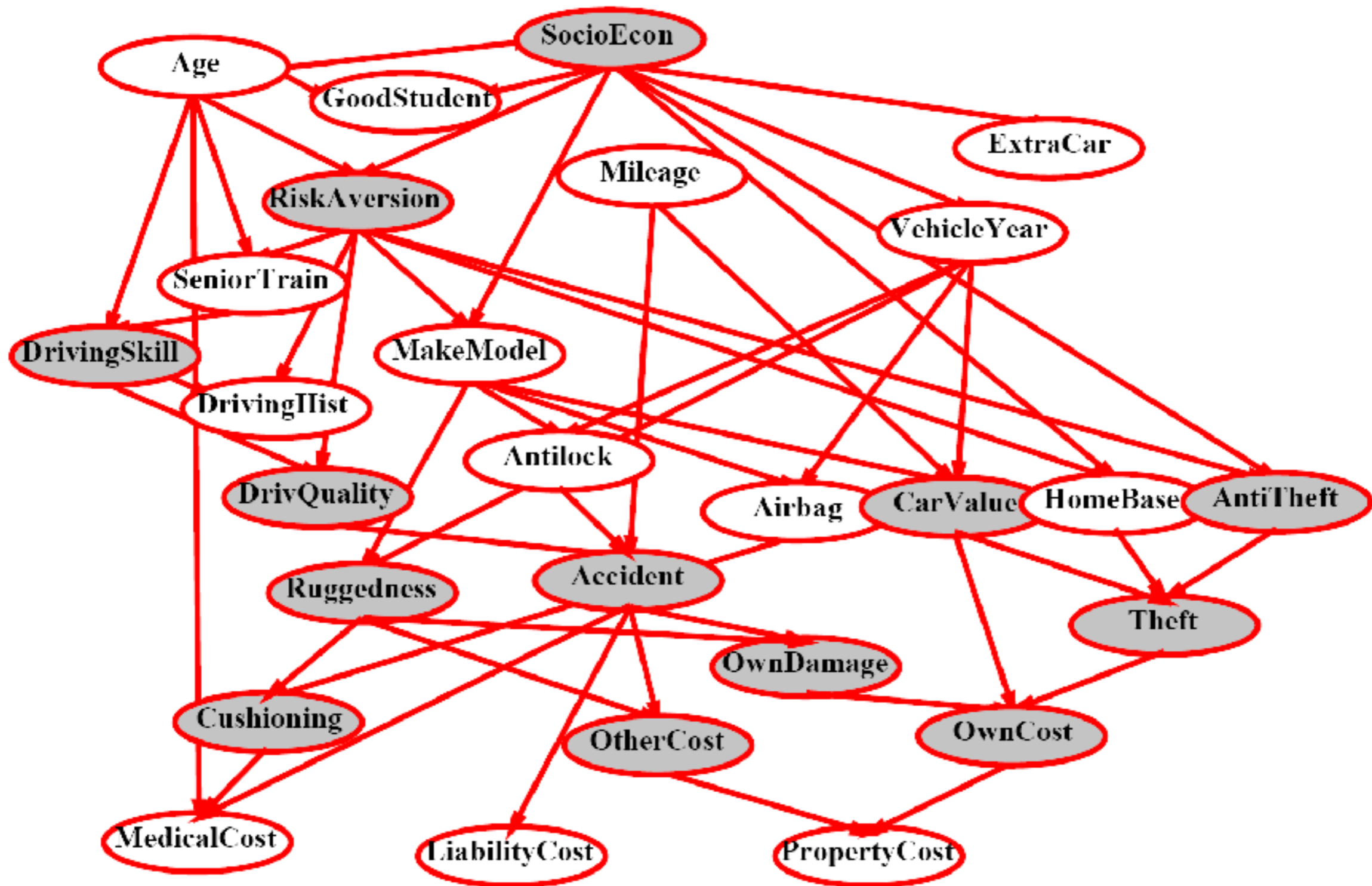
# INFERENCE



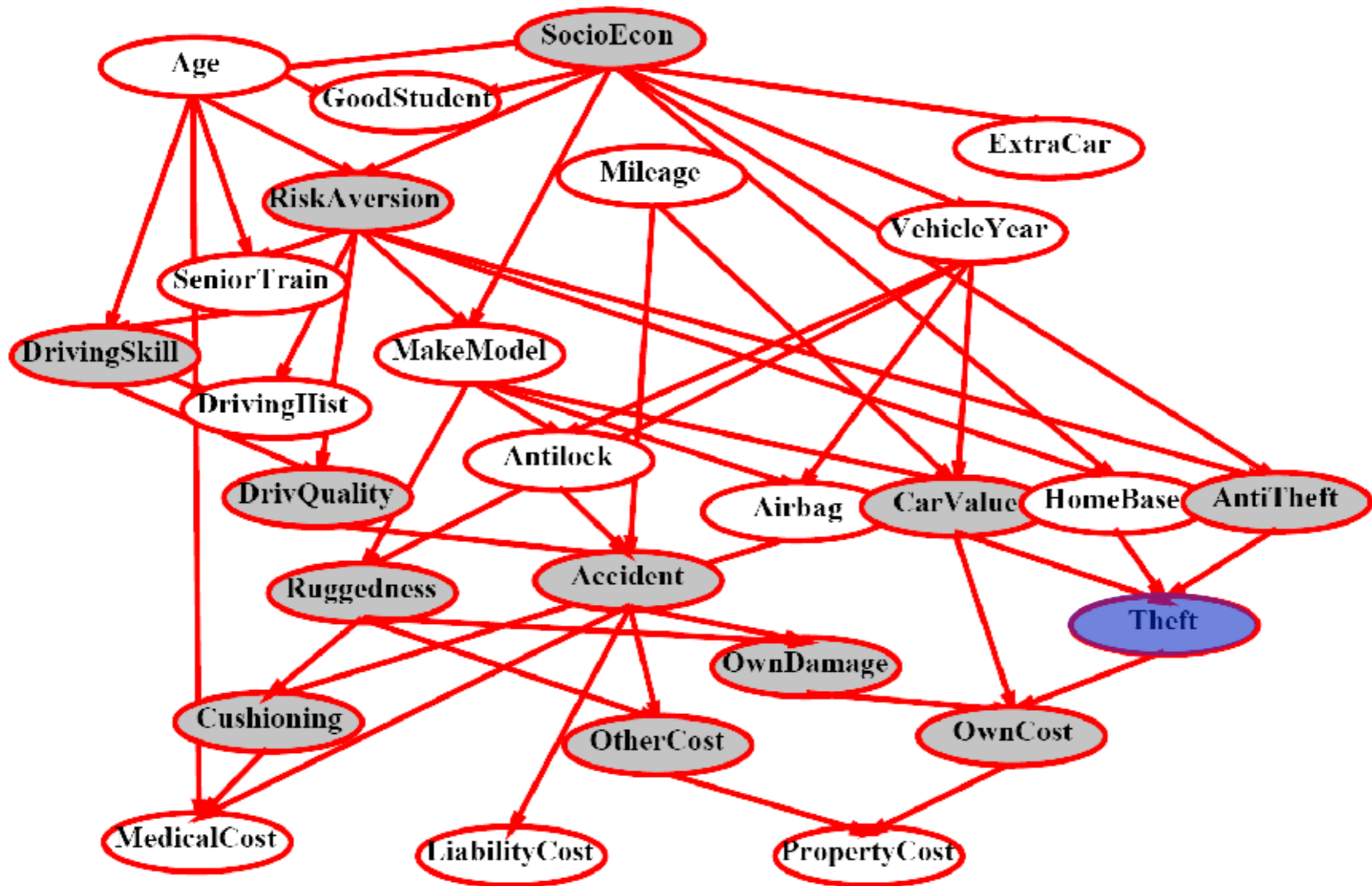
Who is more likely to win the game?

Throw dice and simulate multiple games, see who wins more often

# INFERENCE VIA SAMPLING



# INFERENCE VIA SAMPLING



# INFERENCE VIA SAMPLING

# INFERENCE VIA SAMPLING

- Draw  $n$  samples from the sampling distribution



# INFERENCE VIA SAMPLING

- Draw  $n$  samples from the sampling distribution
- Compute approximate probabilities by computing empirical frequencies

# INFERENCE VIA SAMPLING

- Draw  $n$  samples from the sampling distribution
- Compute approximate probabilities by computing empirical frequencies
- Why sampling?

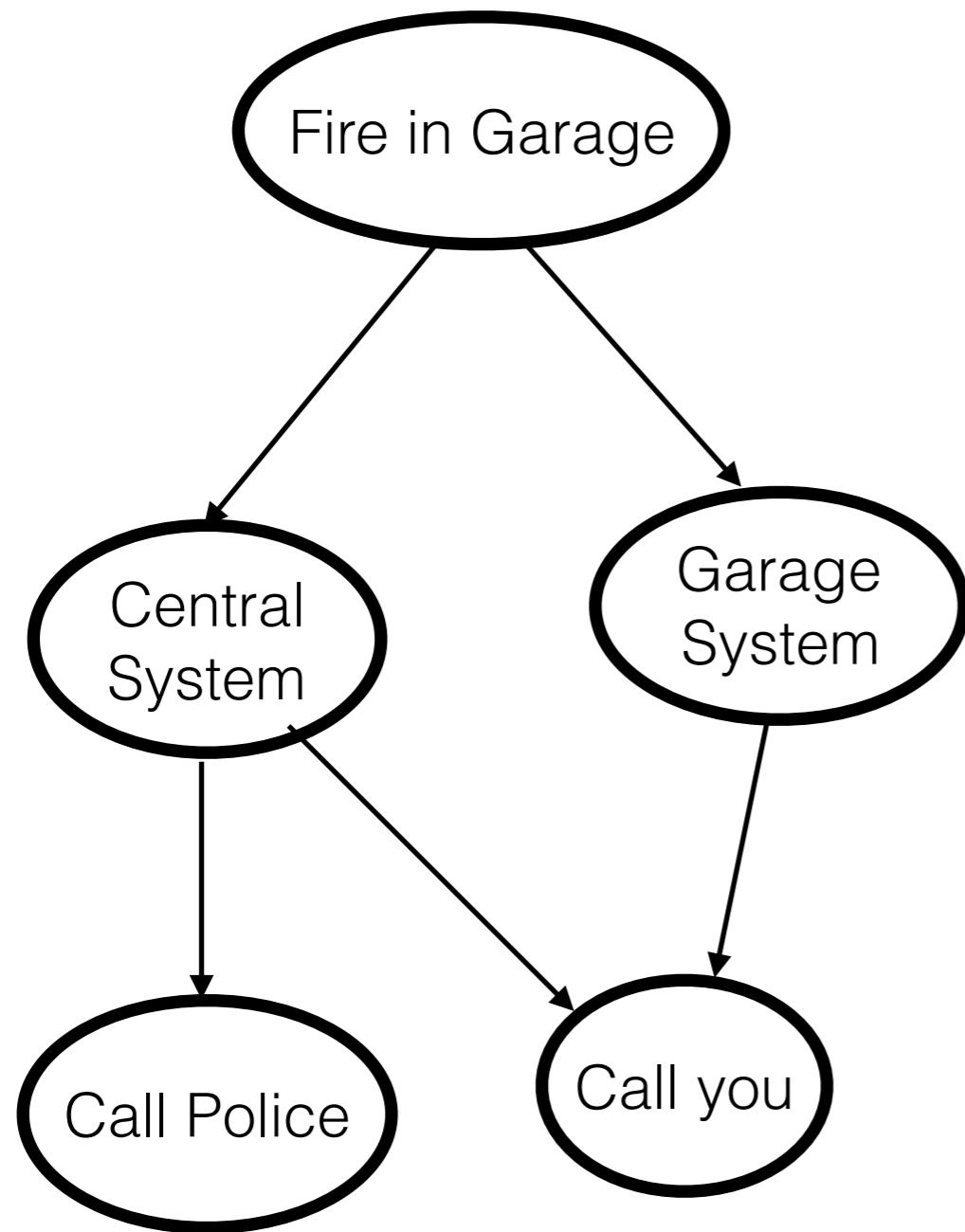
# INFERENCE VIA SAMPLING

- Draw  $n$  samples from the sampling distribution
- Compute approximate probabilities by computing empirical frequencies
- Why sampling?
  - Getting multiple samples often faster than computing exact probabilities (inference is hard)

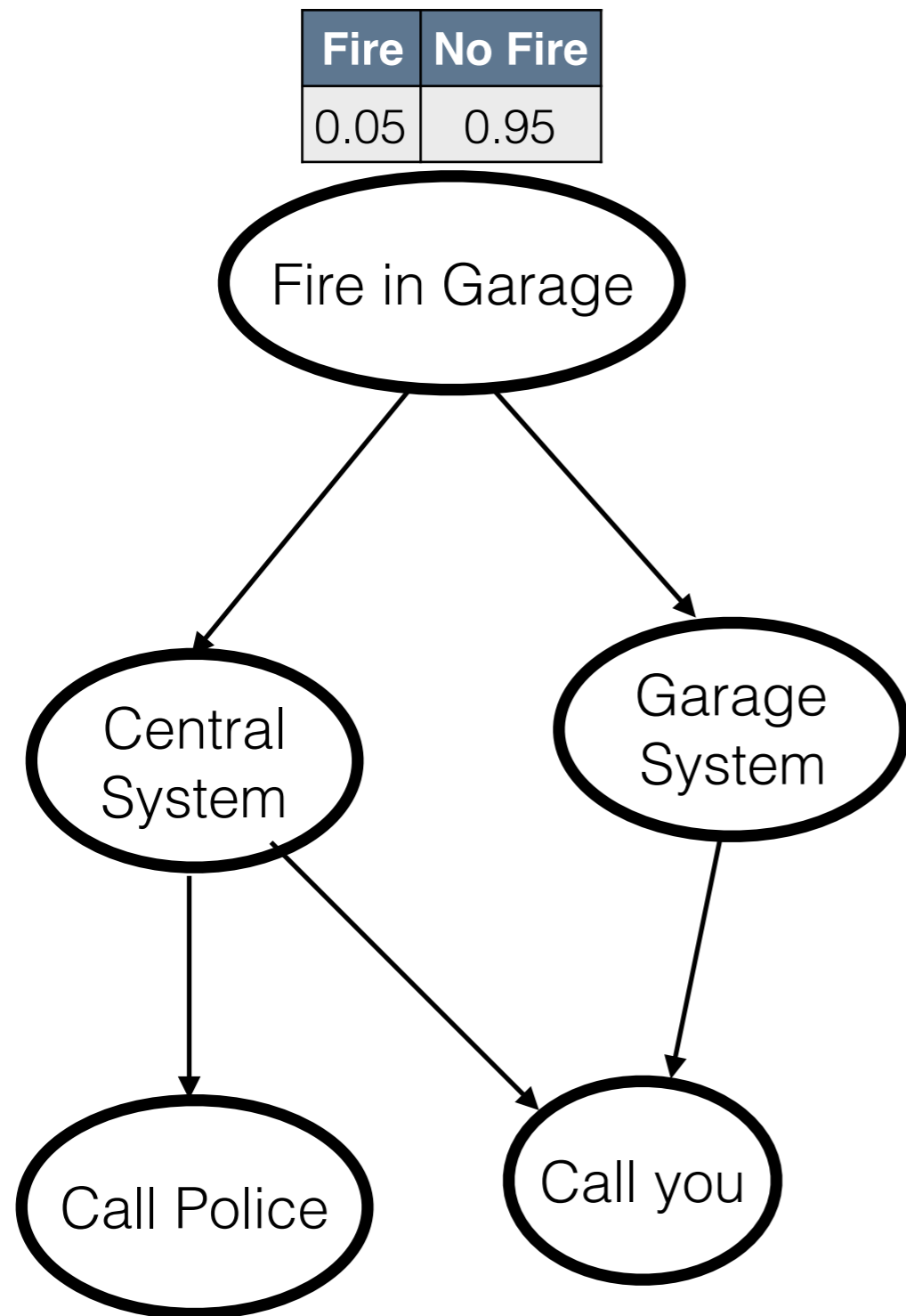
# INFERENCE VIA SAMPLING

- Draw  $n$  samples from the sampling distribution
- Compute approximate probabilities by computing empirical frequencies
- Why sampling?
  - Getting multiple samples often faster than computing exact probabilities (inference is hard)
  - Inference is key step in learning

# REJECTION SAMPLING



# REJECTION SAMPLING



# REJECTION SAMPLING

Fire	No Fire
0.05	0.95

Fire in Garage

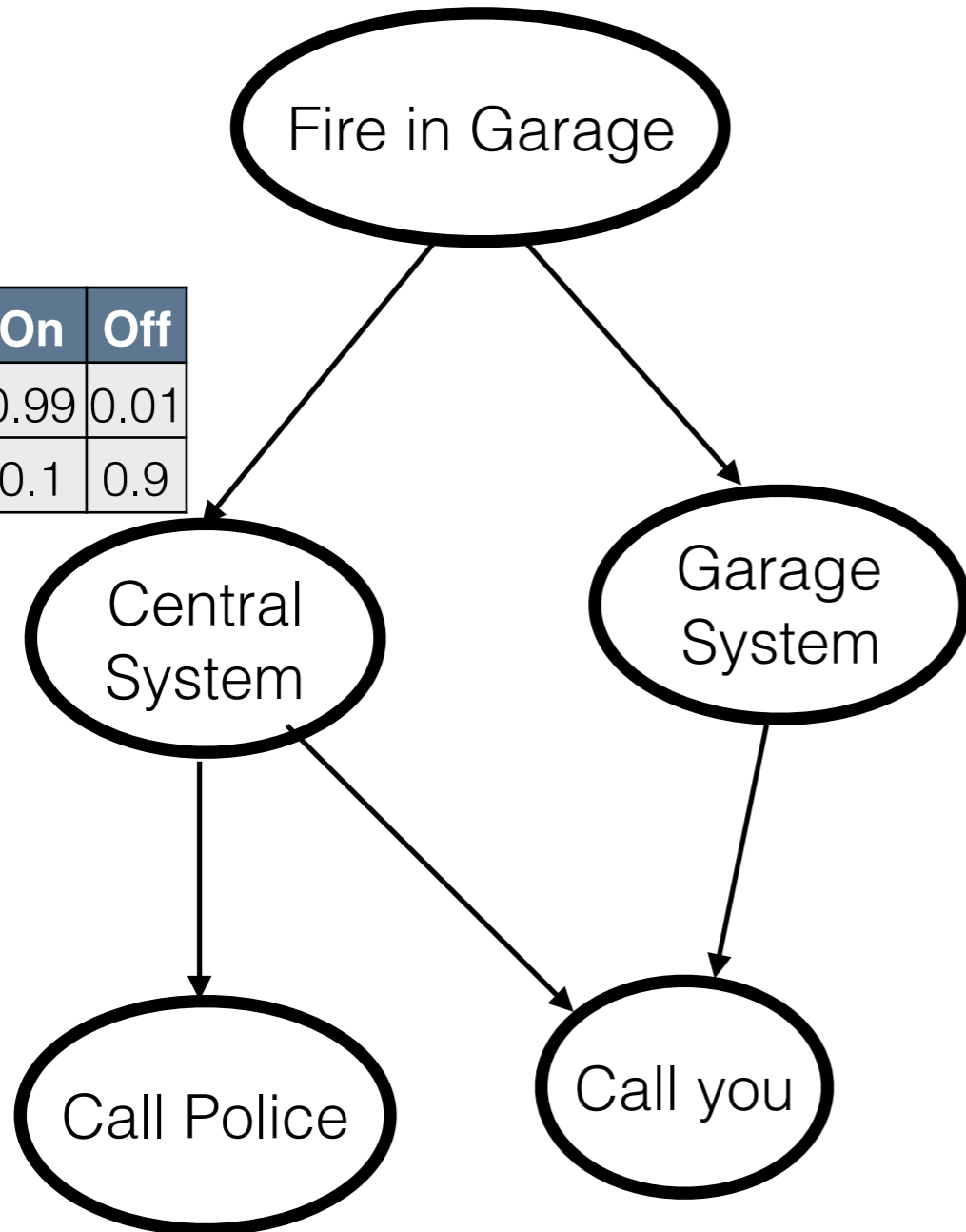
CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9

Central System

Garage System

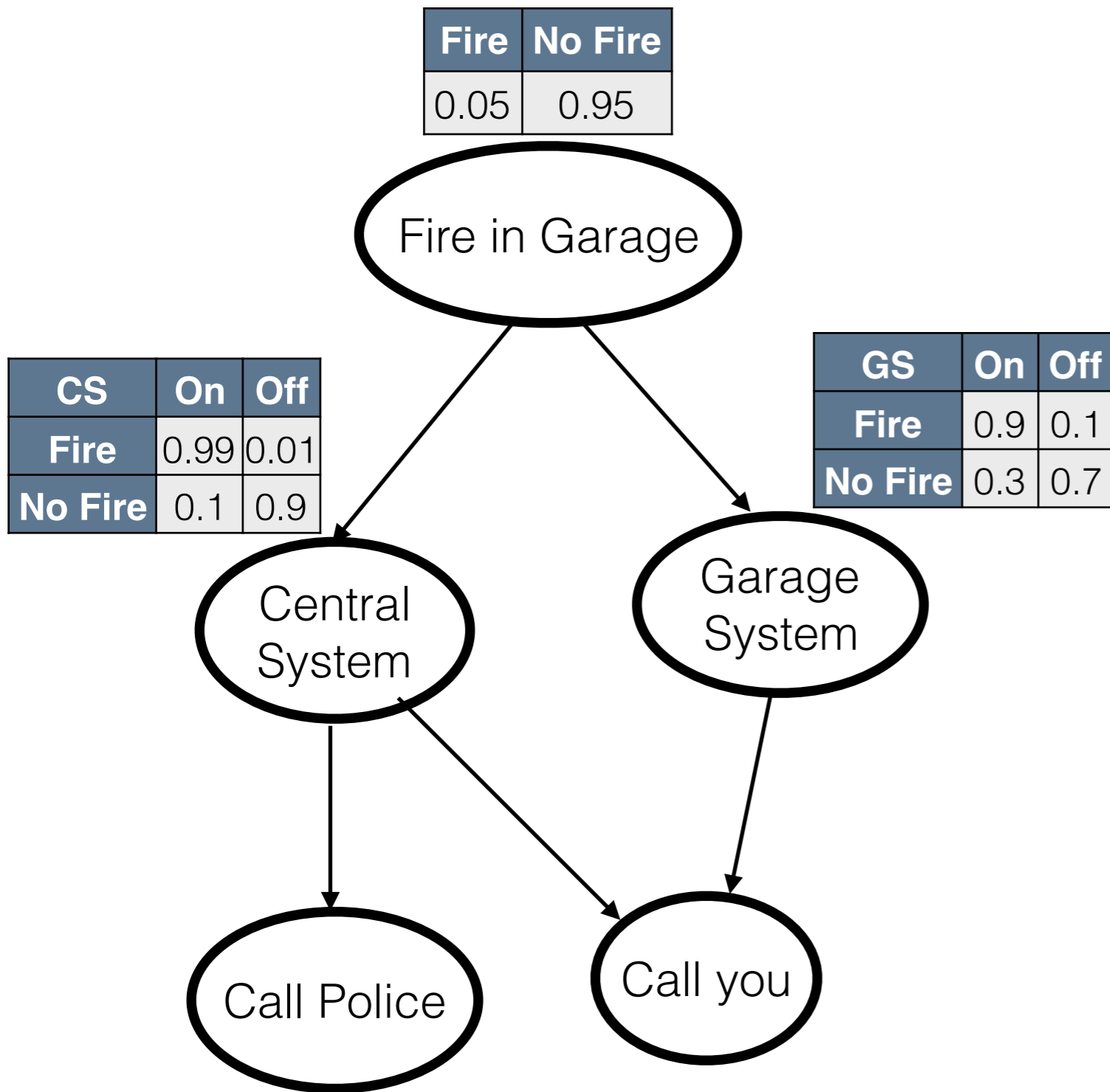
Call Police

Call you

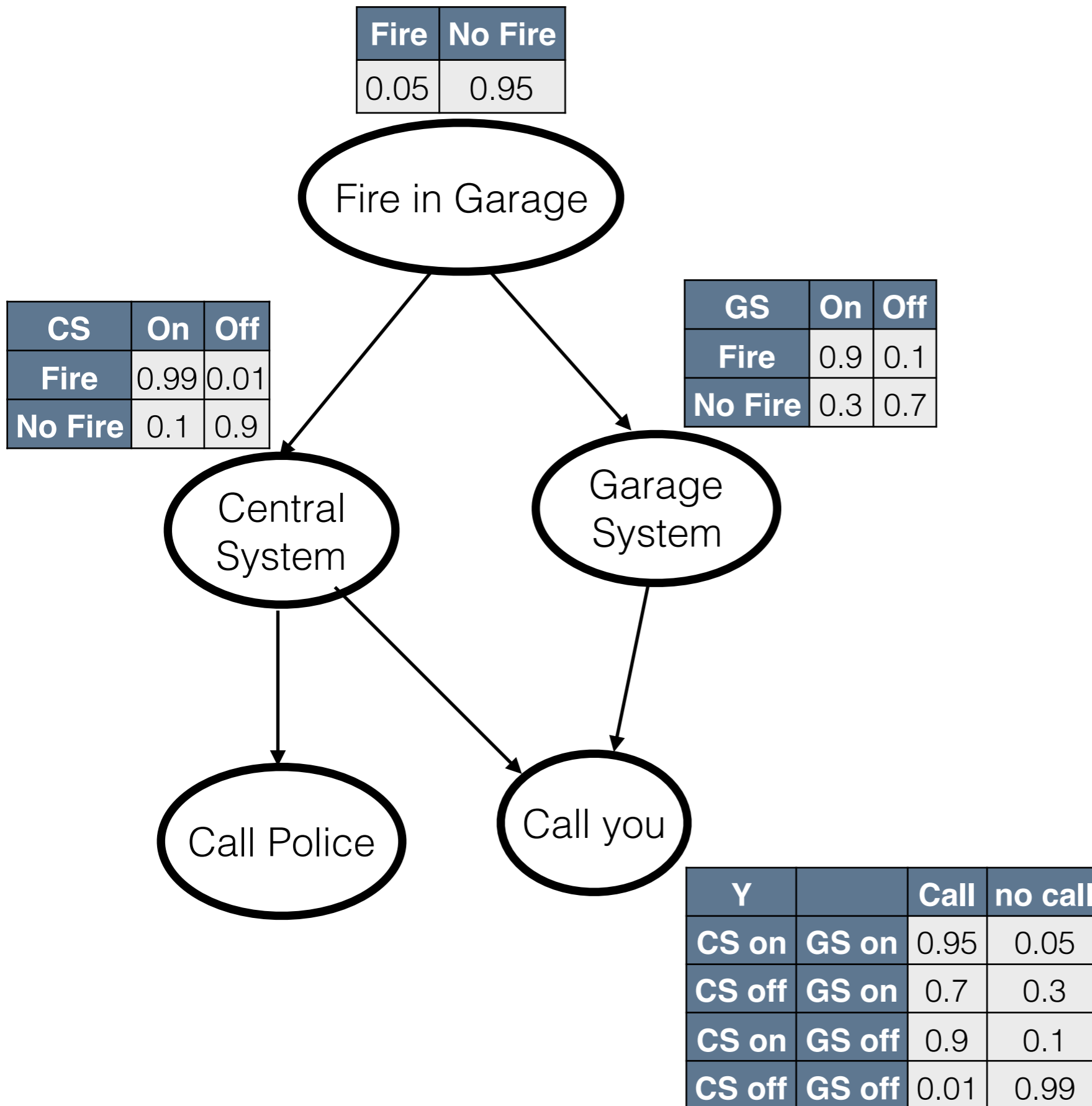




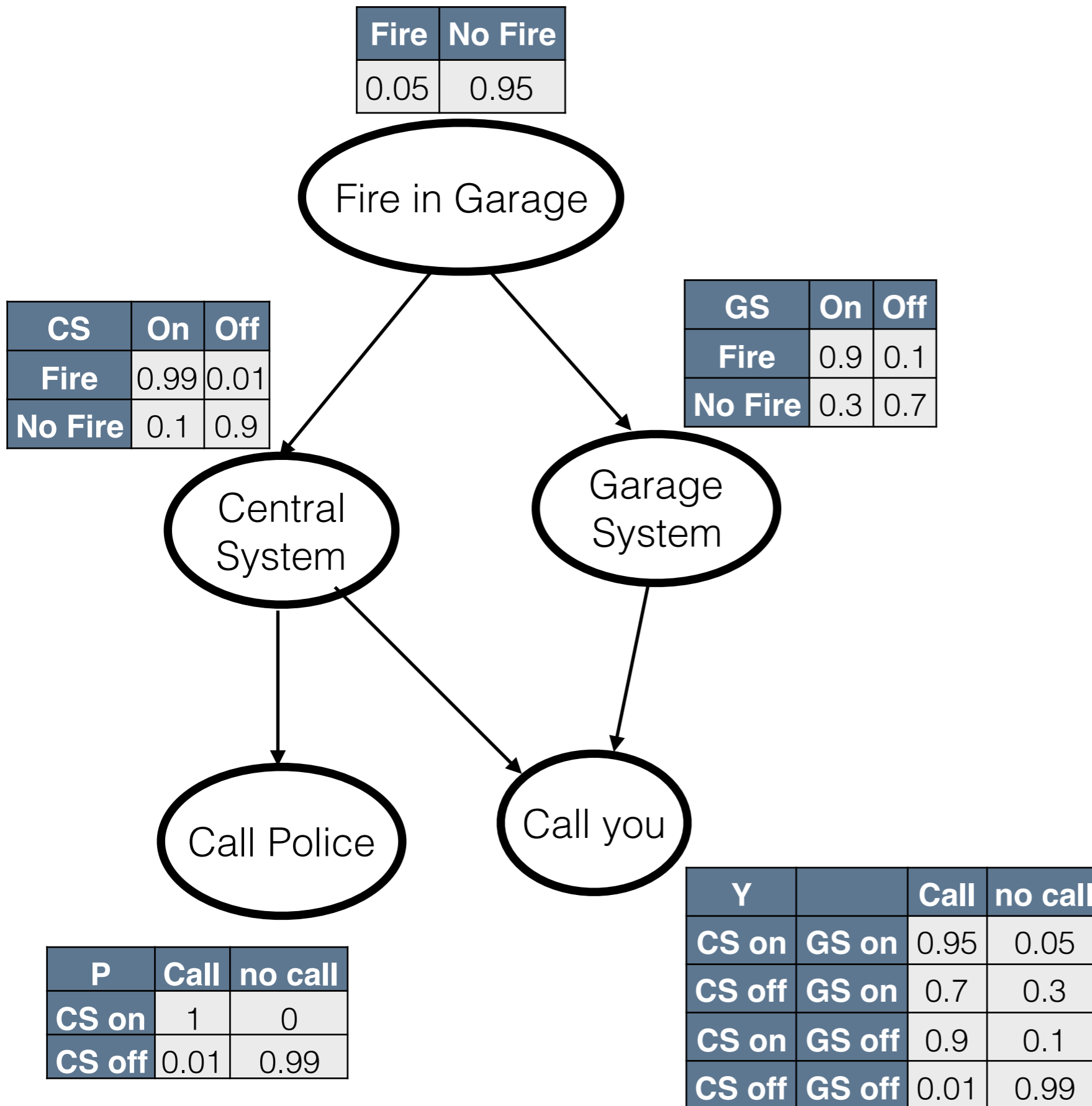
# REJECTION SAMPLING



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# REJECTION SAMPLING



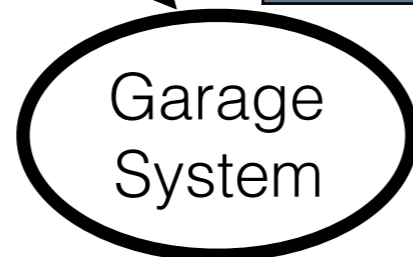
# REJECTION SAMPLING

	F	CS	GS	P	Y
1					

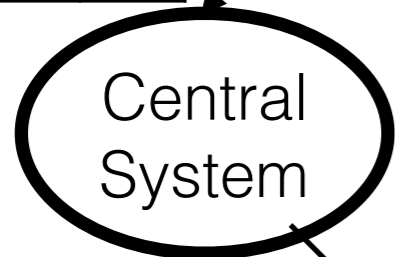
Fire	No Fire
0.05	0.95



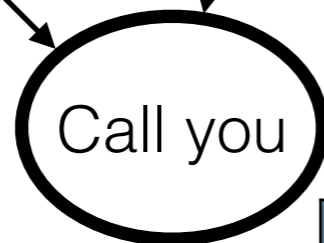
GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9

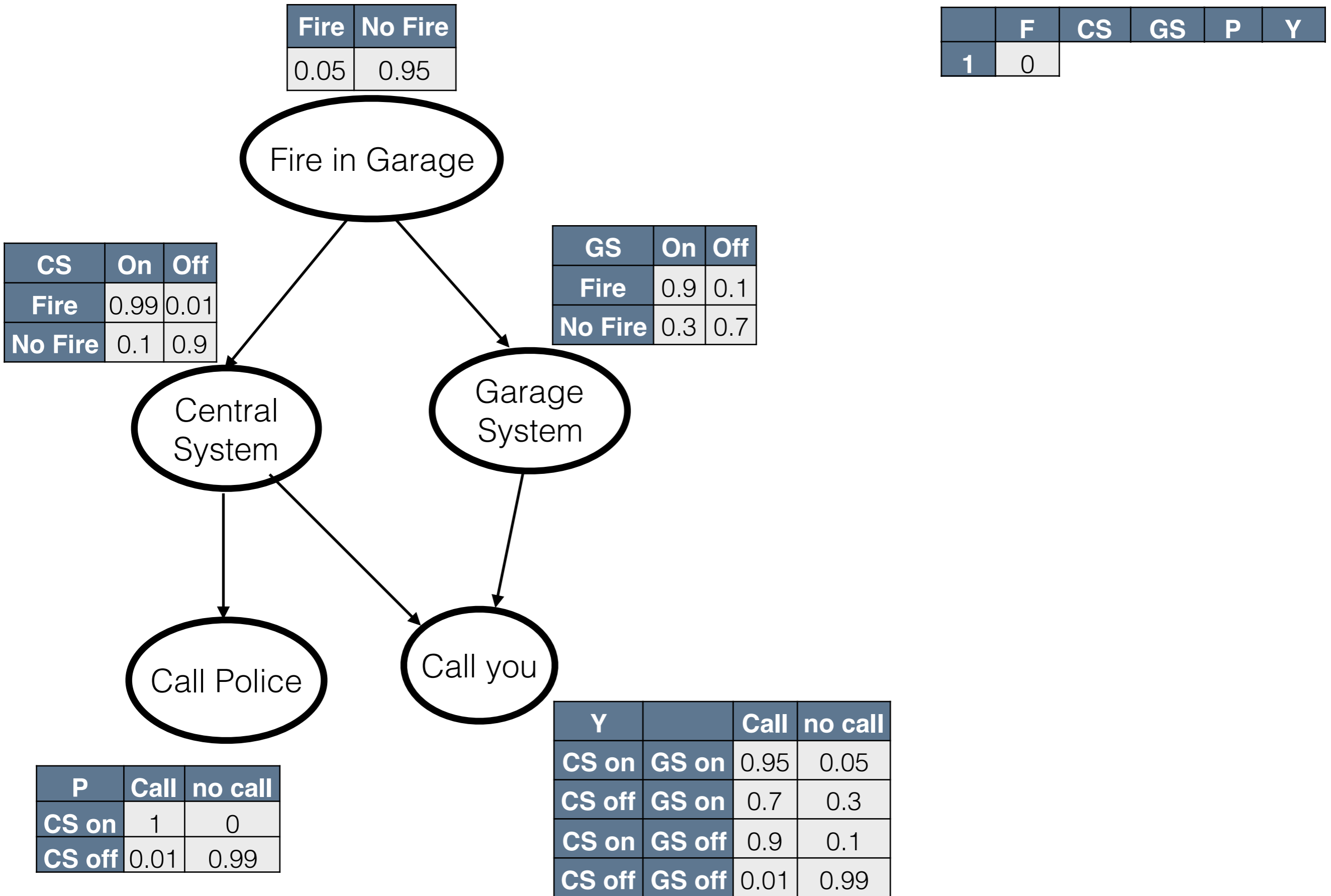


Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

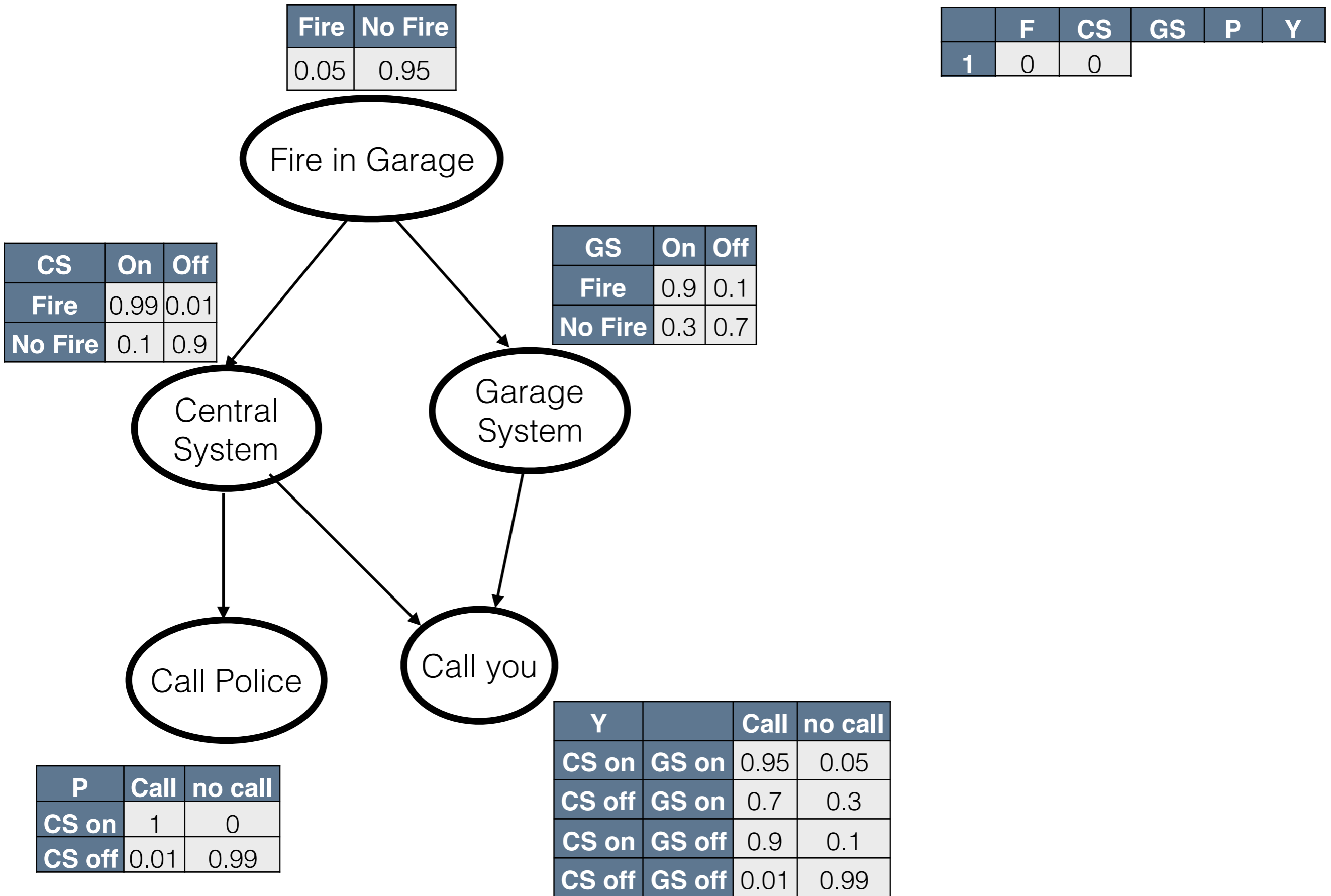


P	Call	no call
CS on	1	0
CS off	0.01	0.99

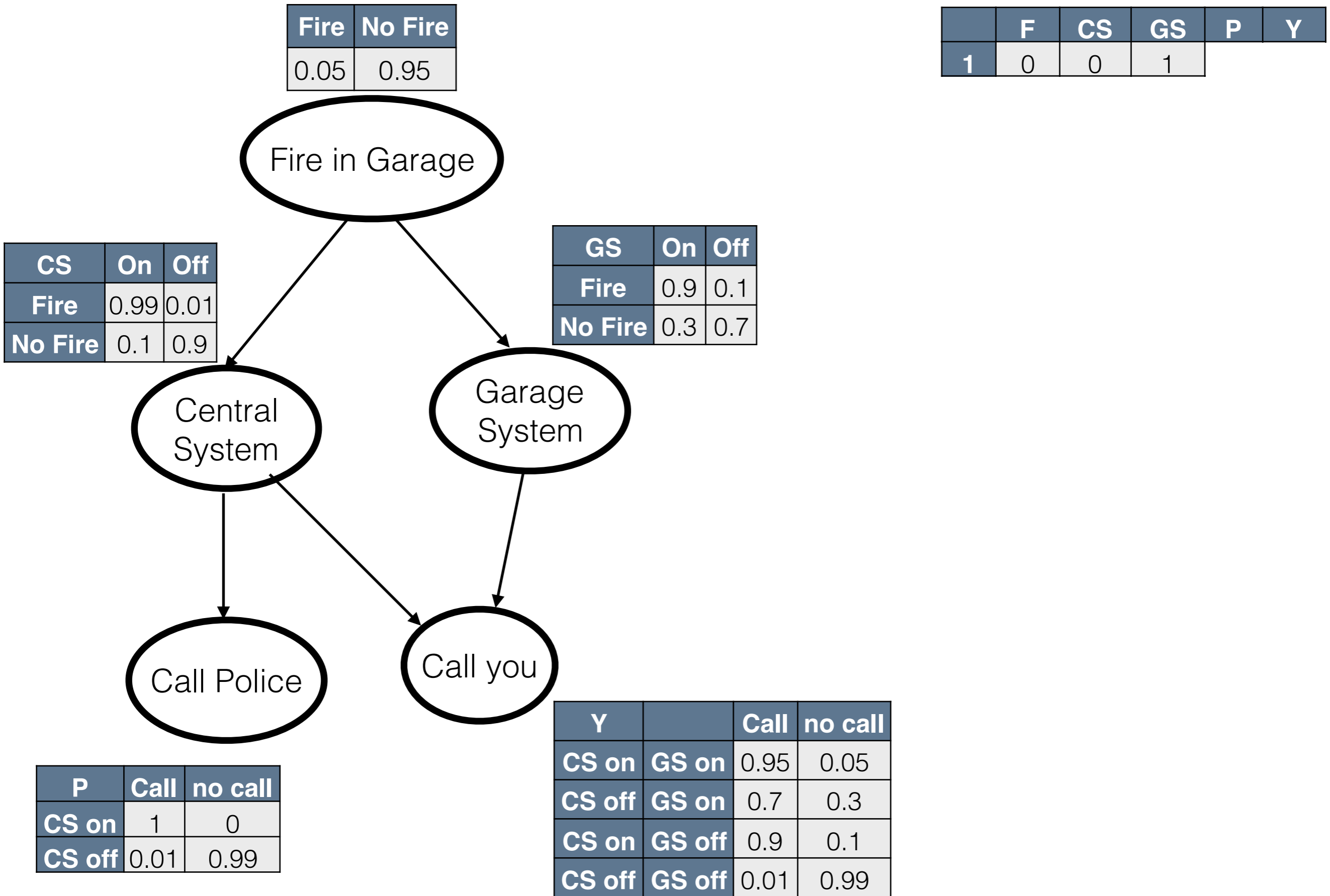
# REJECTION SAMPLING



# REJECTION SAMPLING

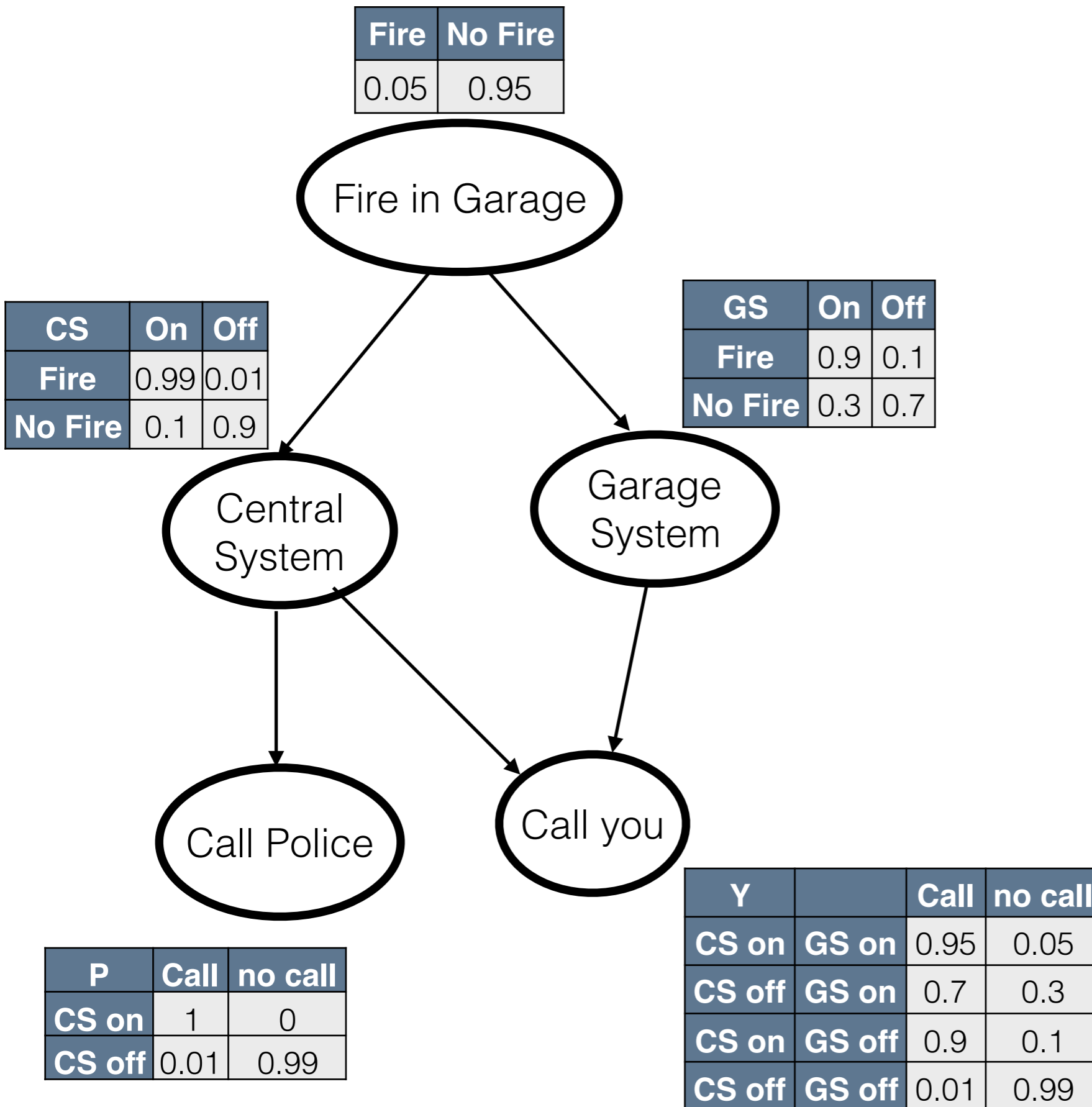


# REJECTION SAMPLING





# REJECTION SAMPLING



	F	CS	GS	P	Y
<b>1</b>	0	0	1	0	

# REJECTION SAMPLING

	F	CS	GS	P	Y
1	0	0	1	0	1

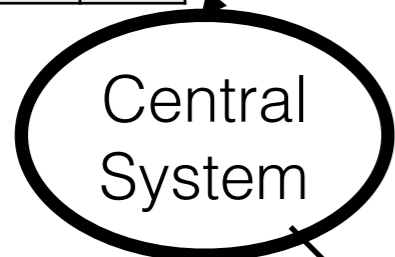
Fire	No Fire
0.05	0.95



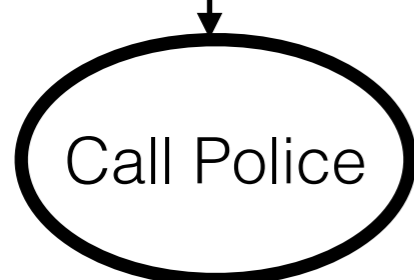
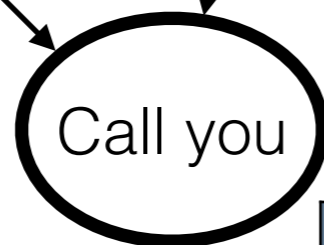
GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9

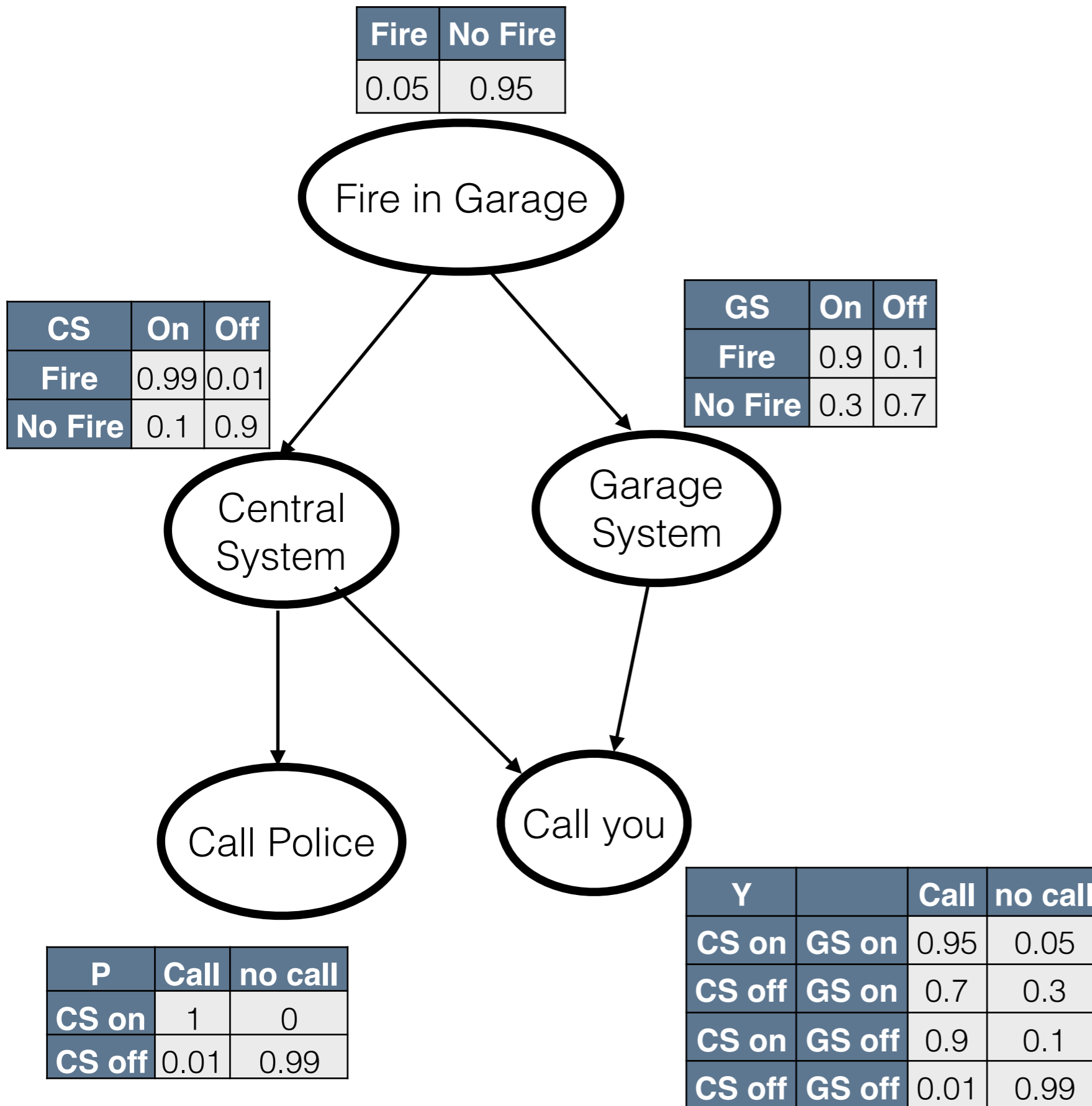


Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99



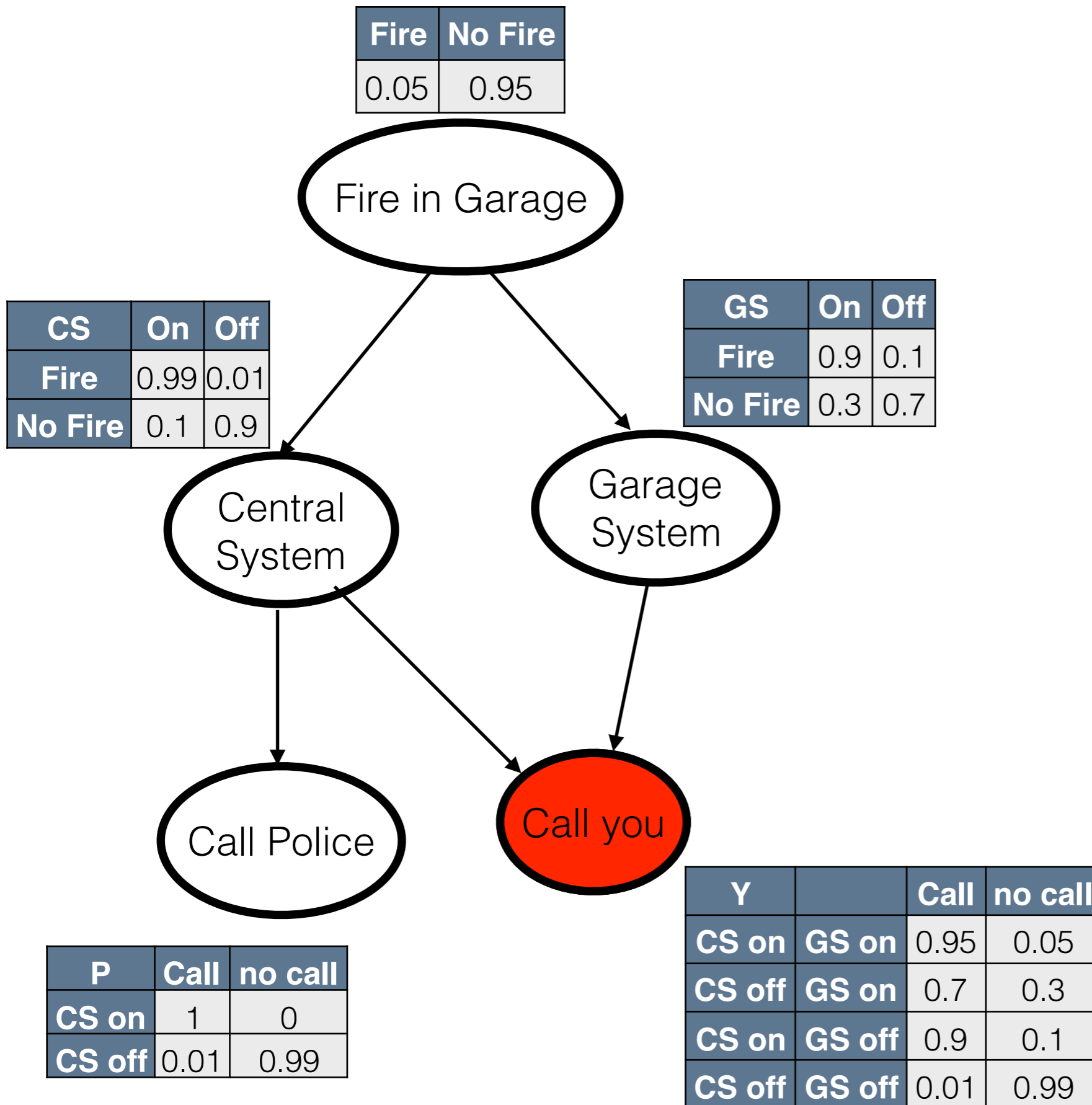
P	Call	no call
CS on	1	0
CS off	0.01	0.99

# REJECTION SAMPLING



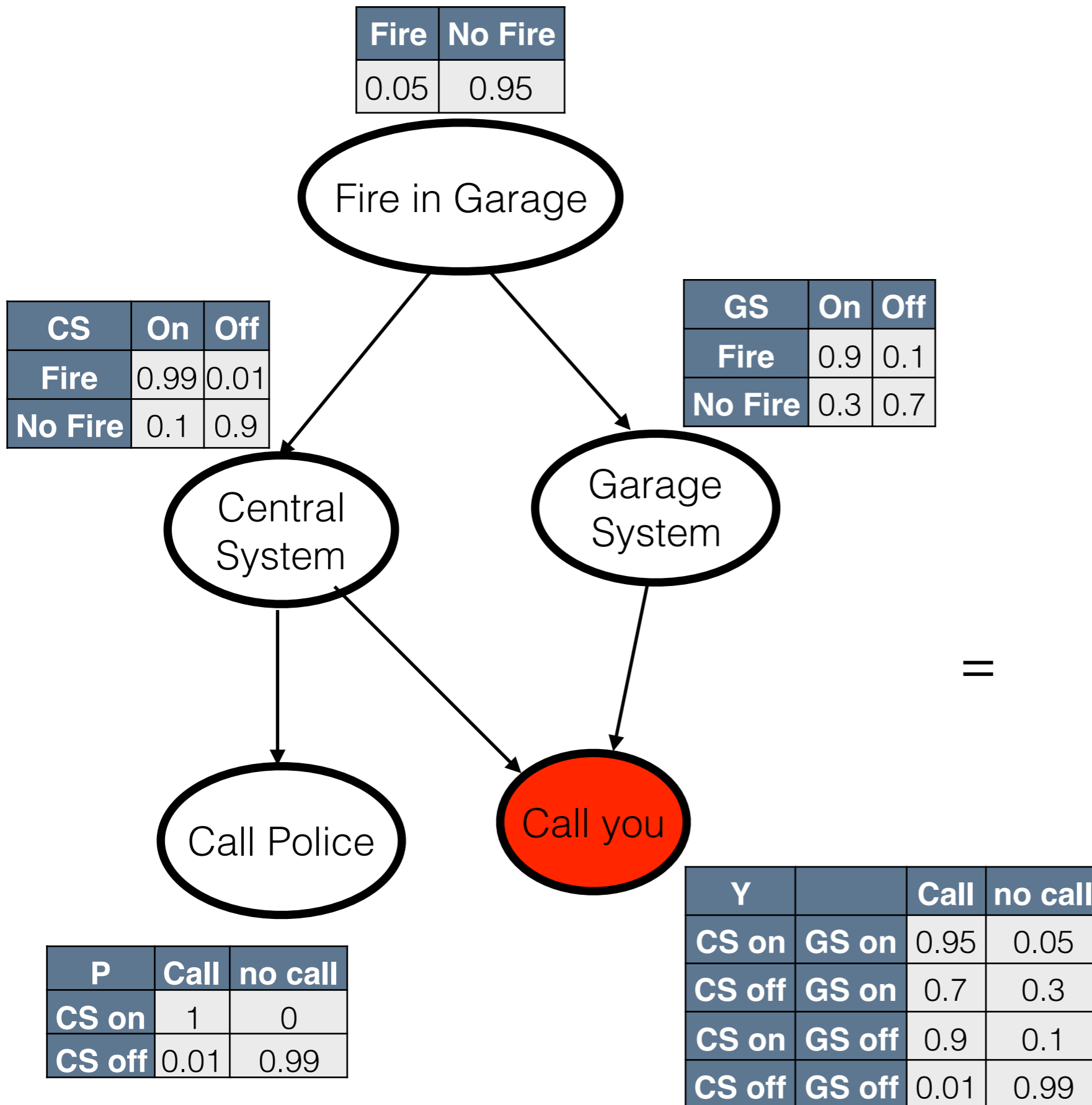
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

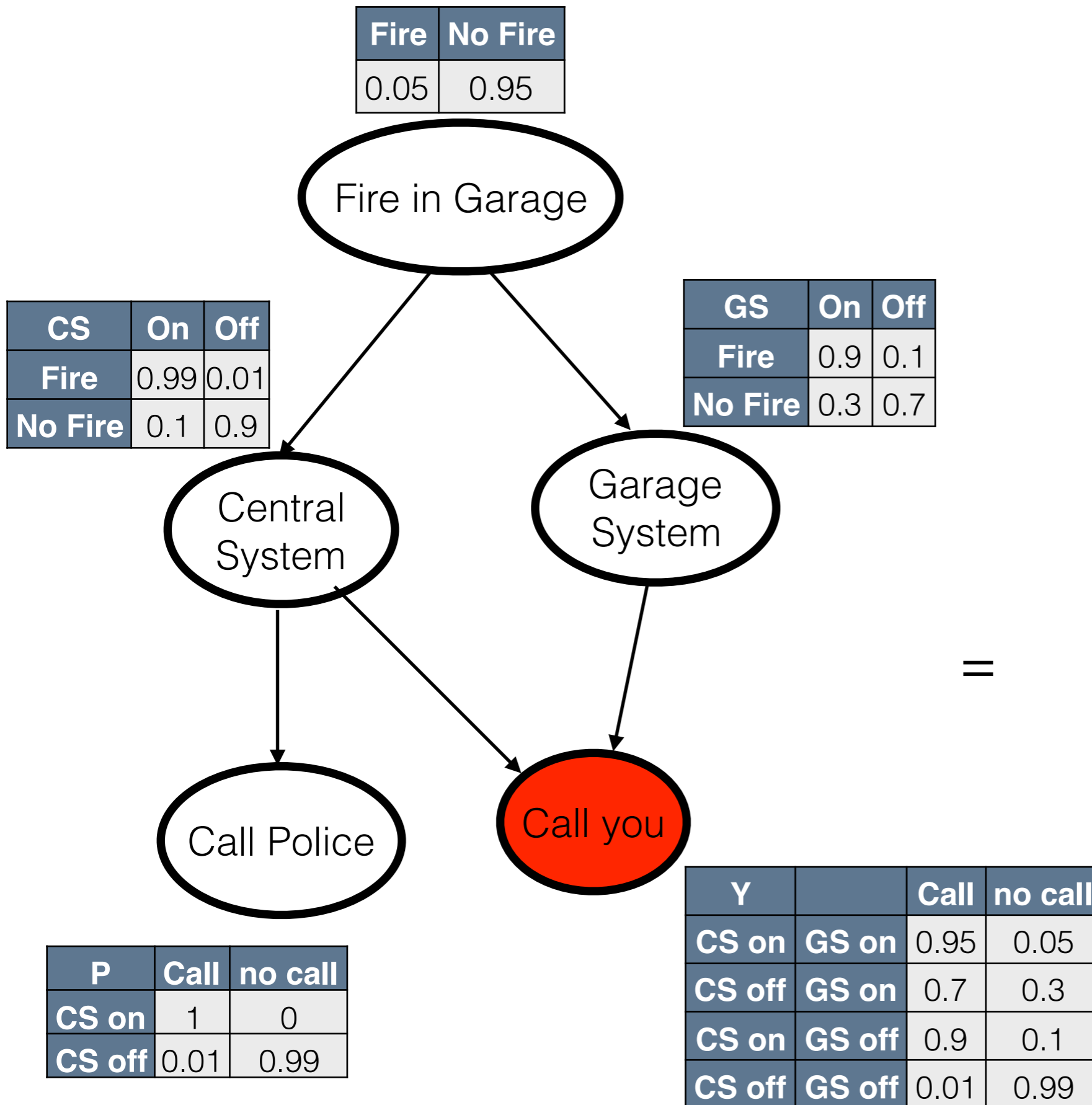
# REJECTION SAMPLING



=

	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

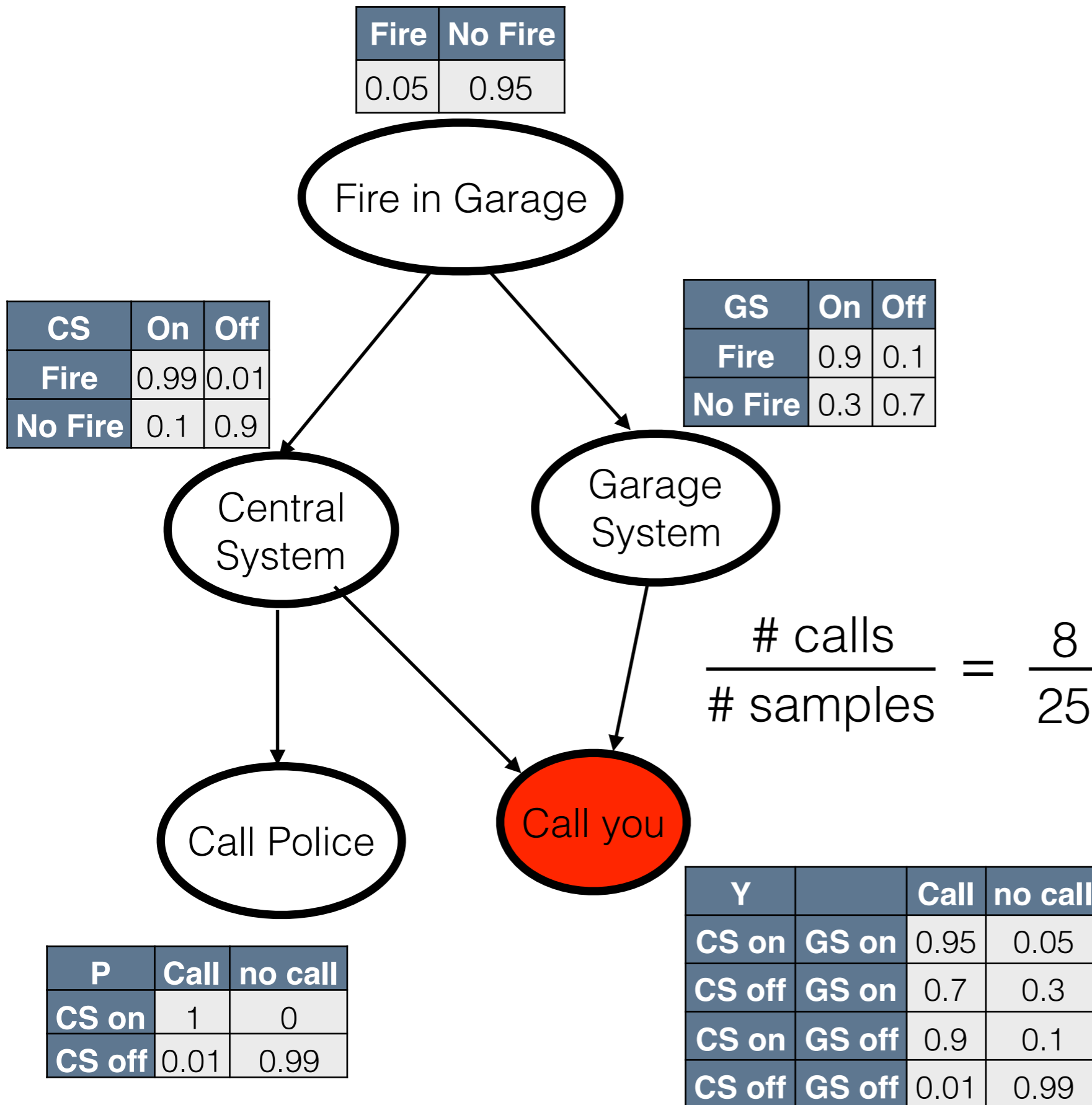
# REJECTION SAMPLING



=

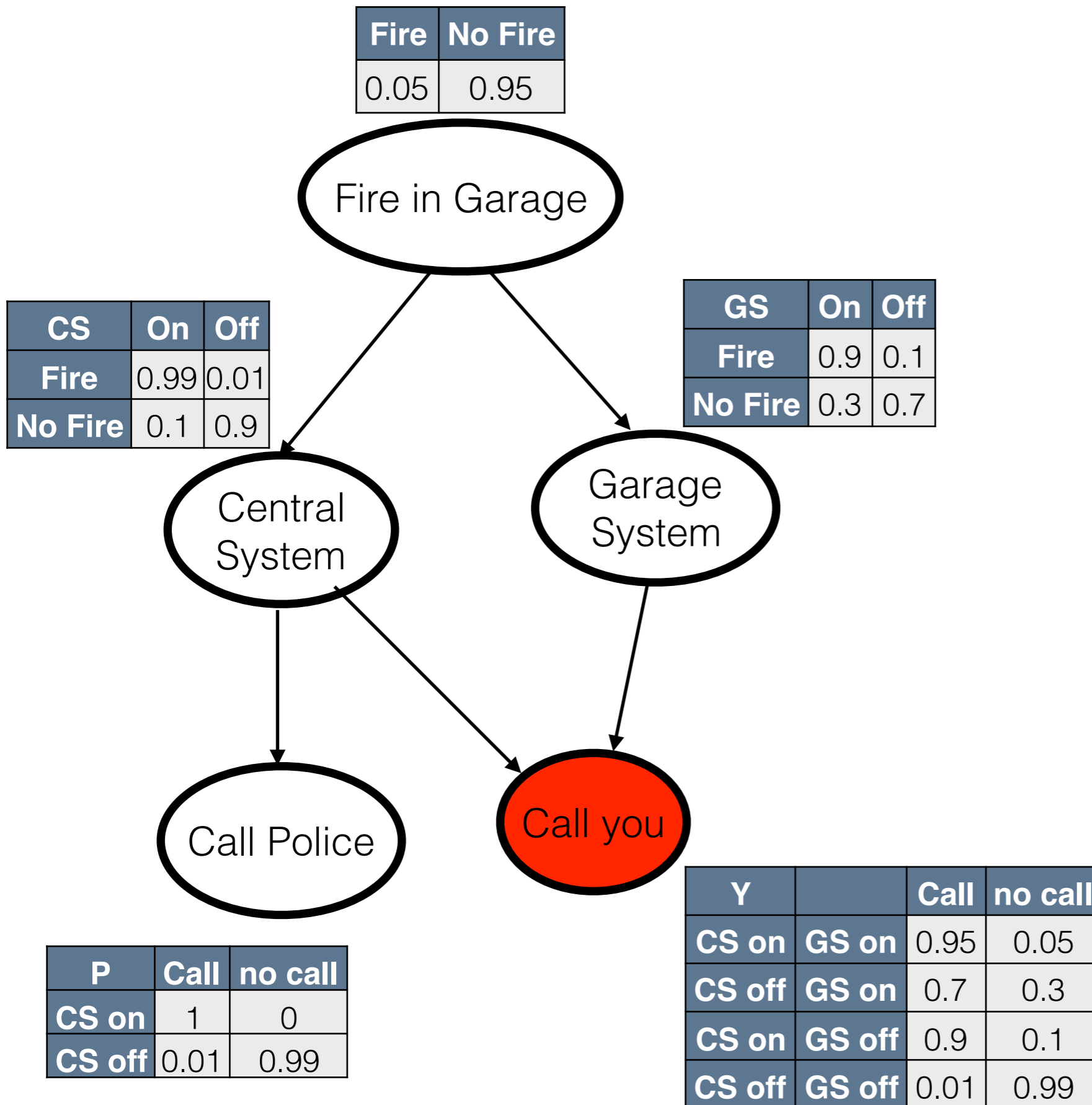
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

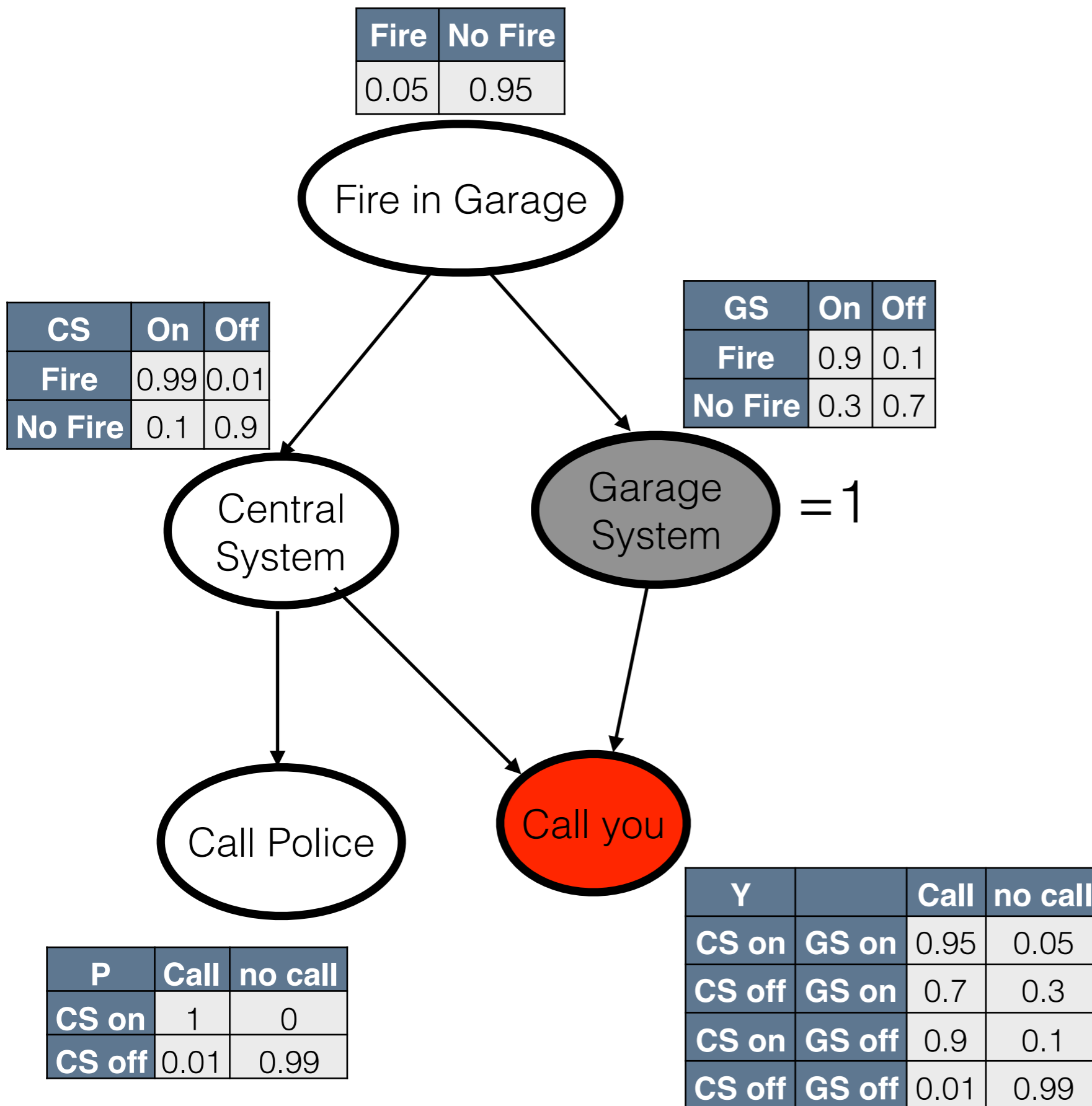
# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

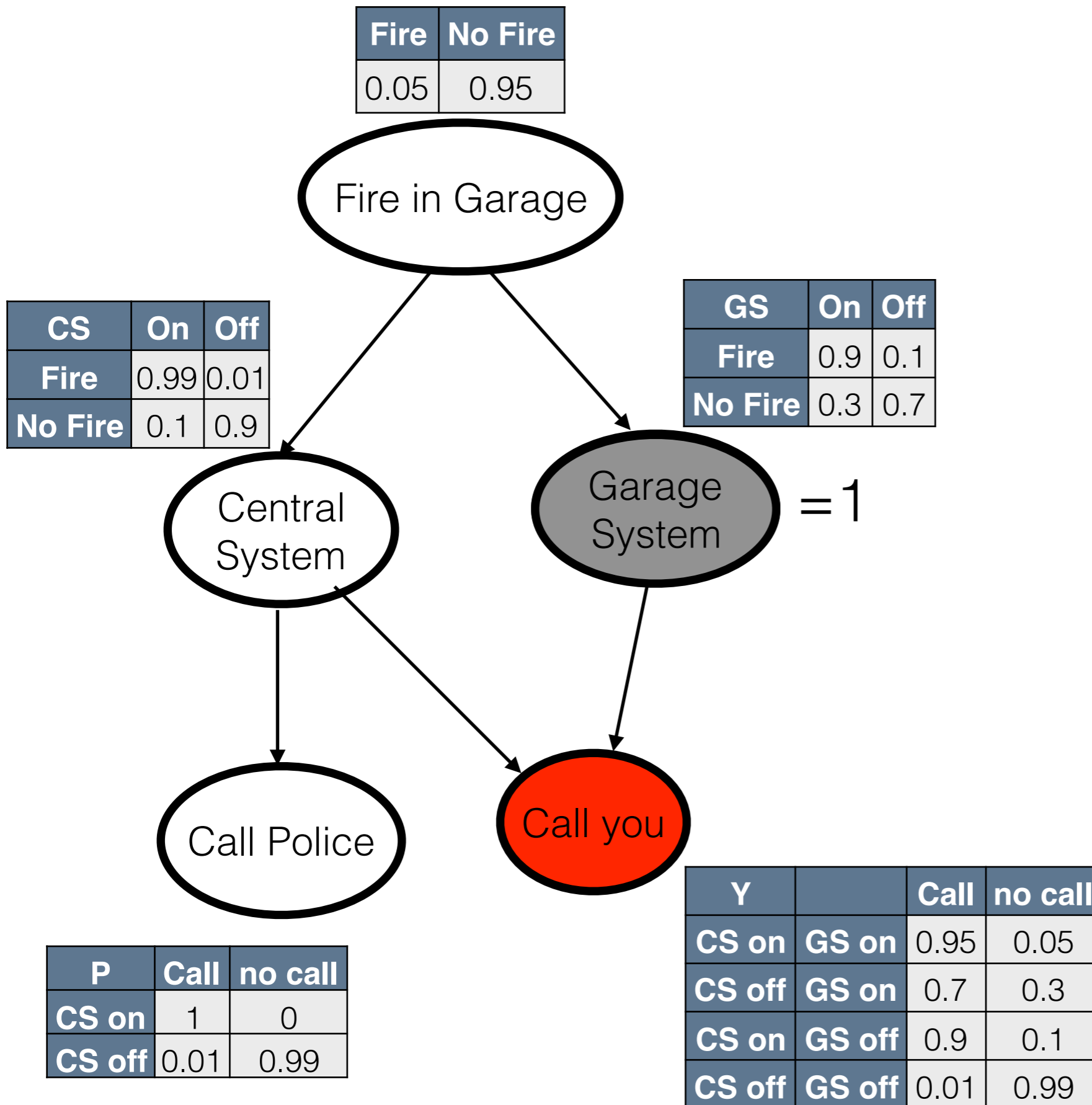


# REJECTION SAMPLING



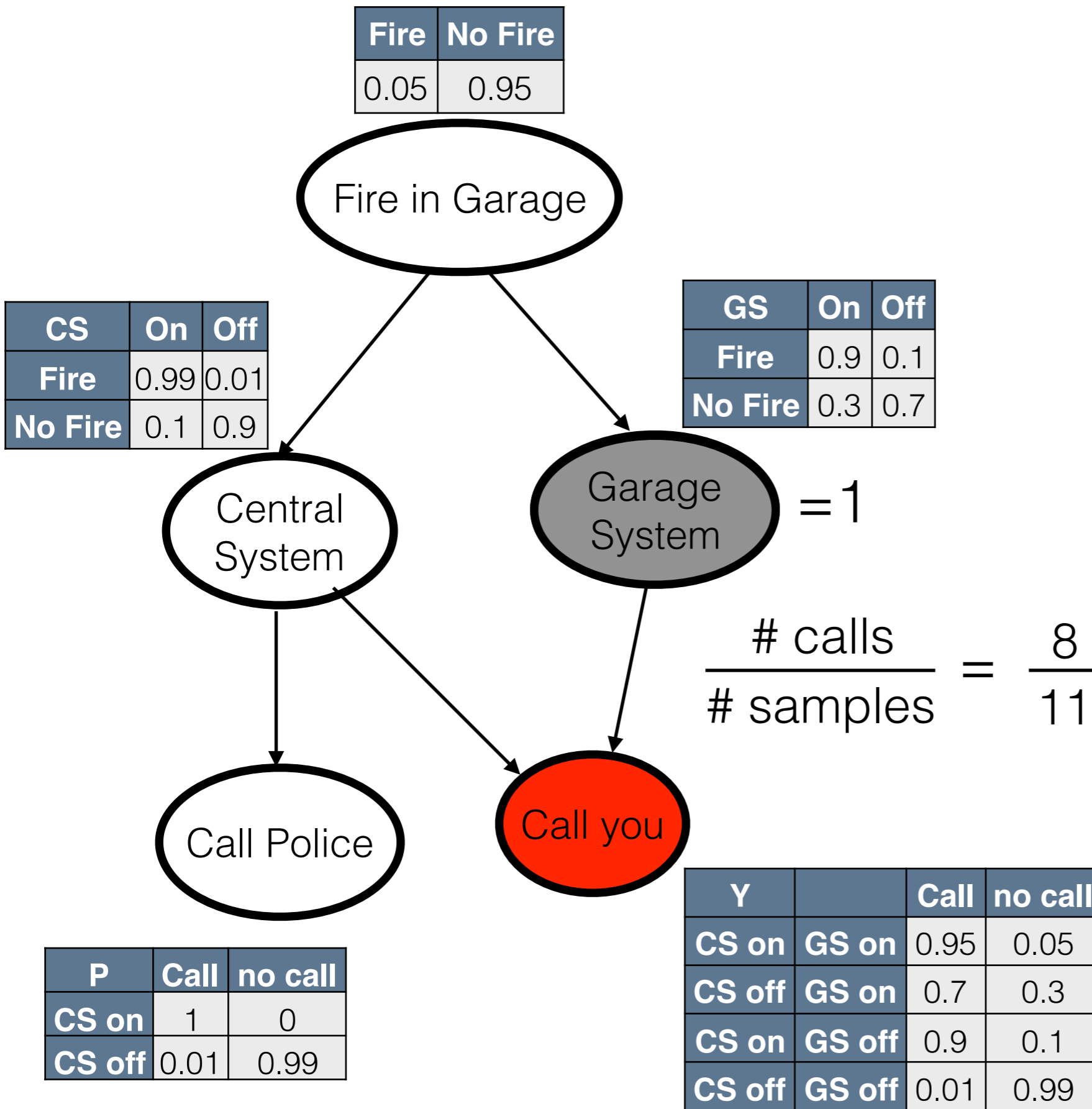
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING

Algorithm:

Topologically sort variables (parents first children later)

For  $t = 1$  to  $n$  (number of samples)

    For  $i = 1$  to  $N$  (number of variables in model)

        Sample  $x_i^t \sim P(X_i | \text{Parents}(X_i) \text{ already sampled})$

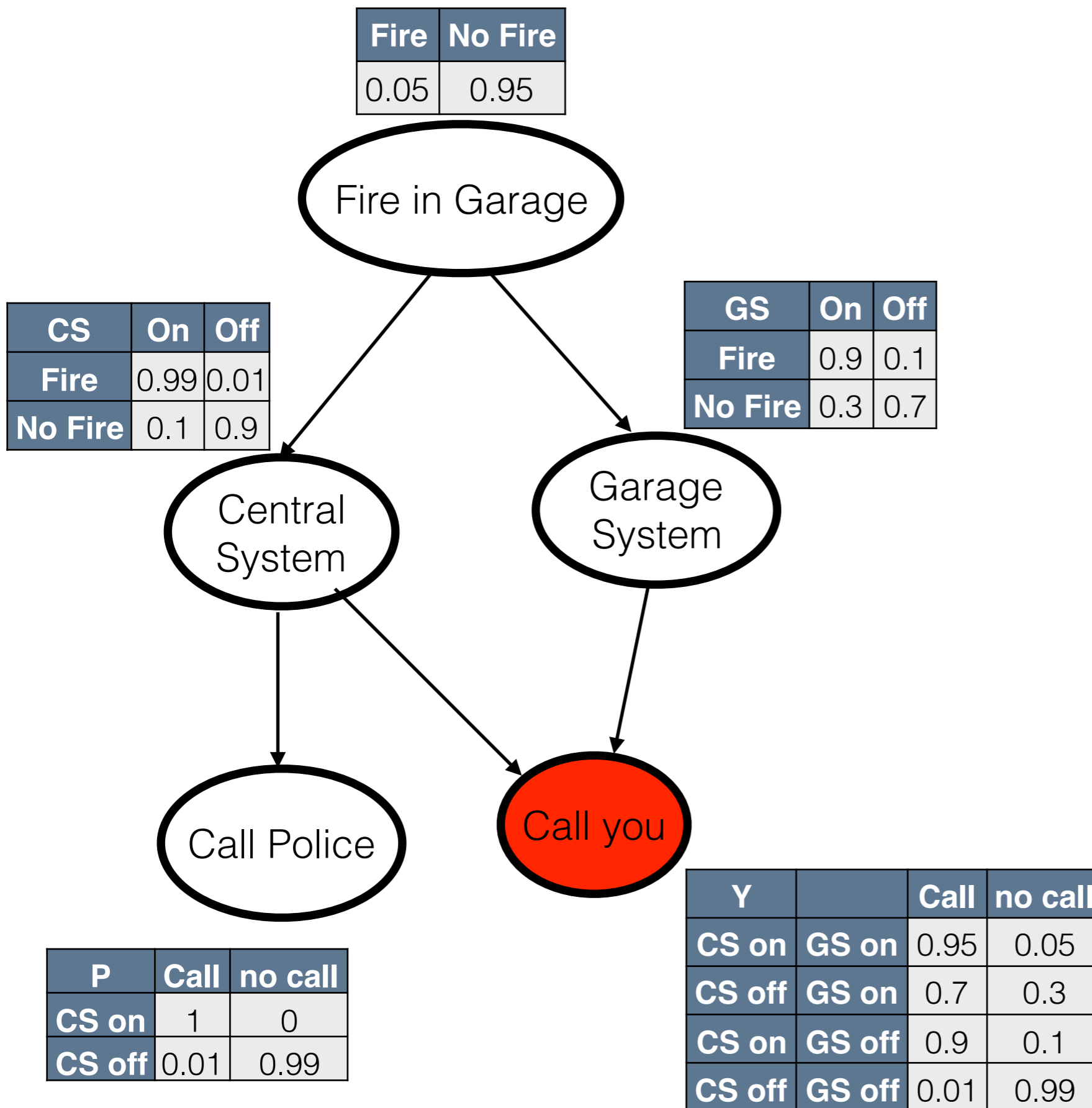
    End For

End For

Discard samples that do not match observations

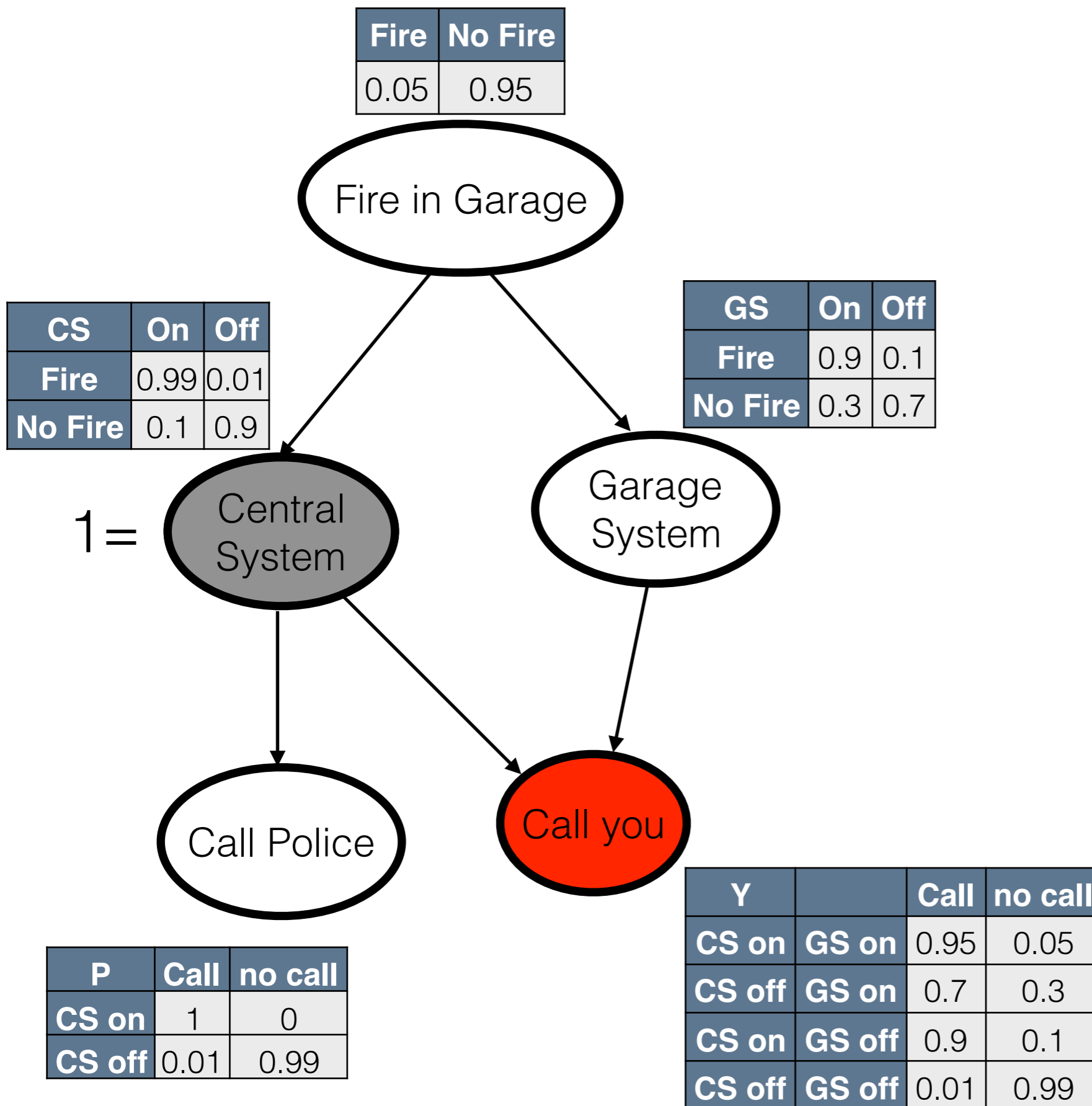
Compute empirical frequencies

# REJECTION SAMPLING



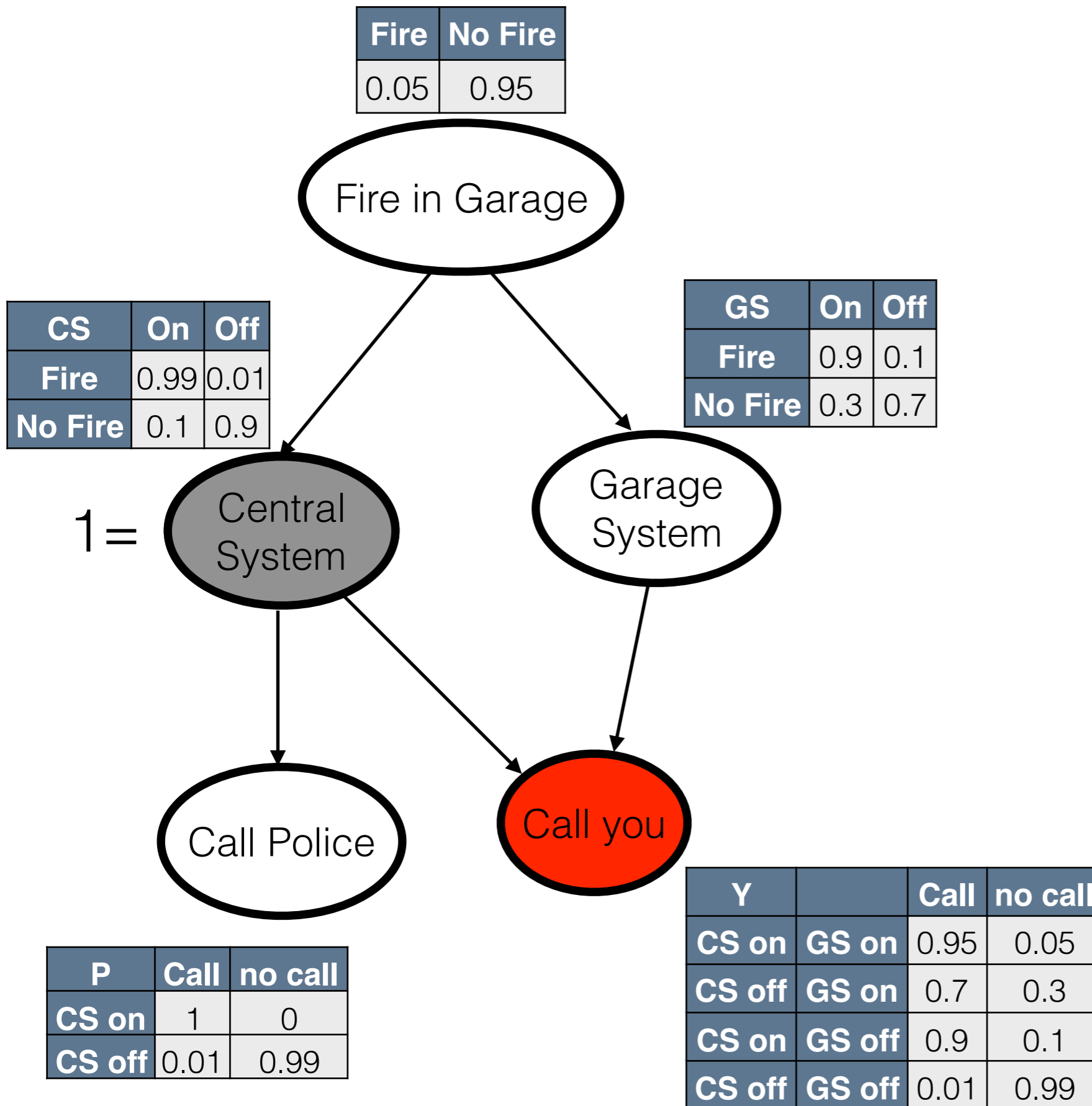
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

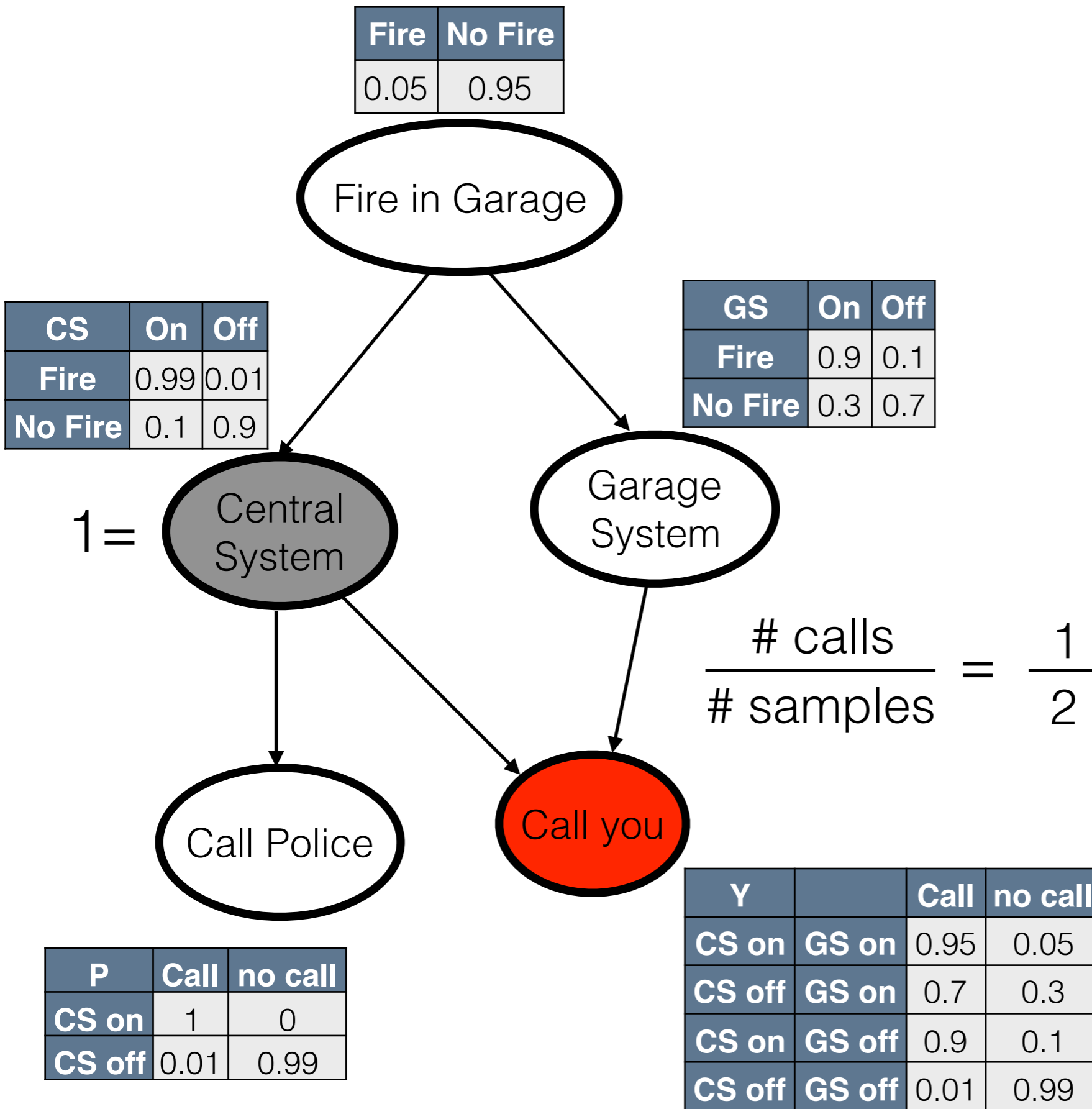
# REJECTION SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

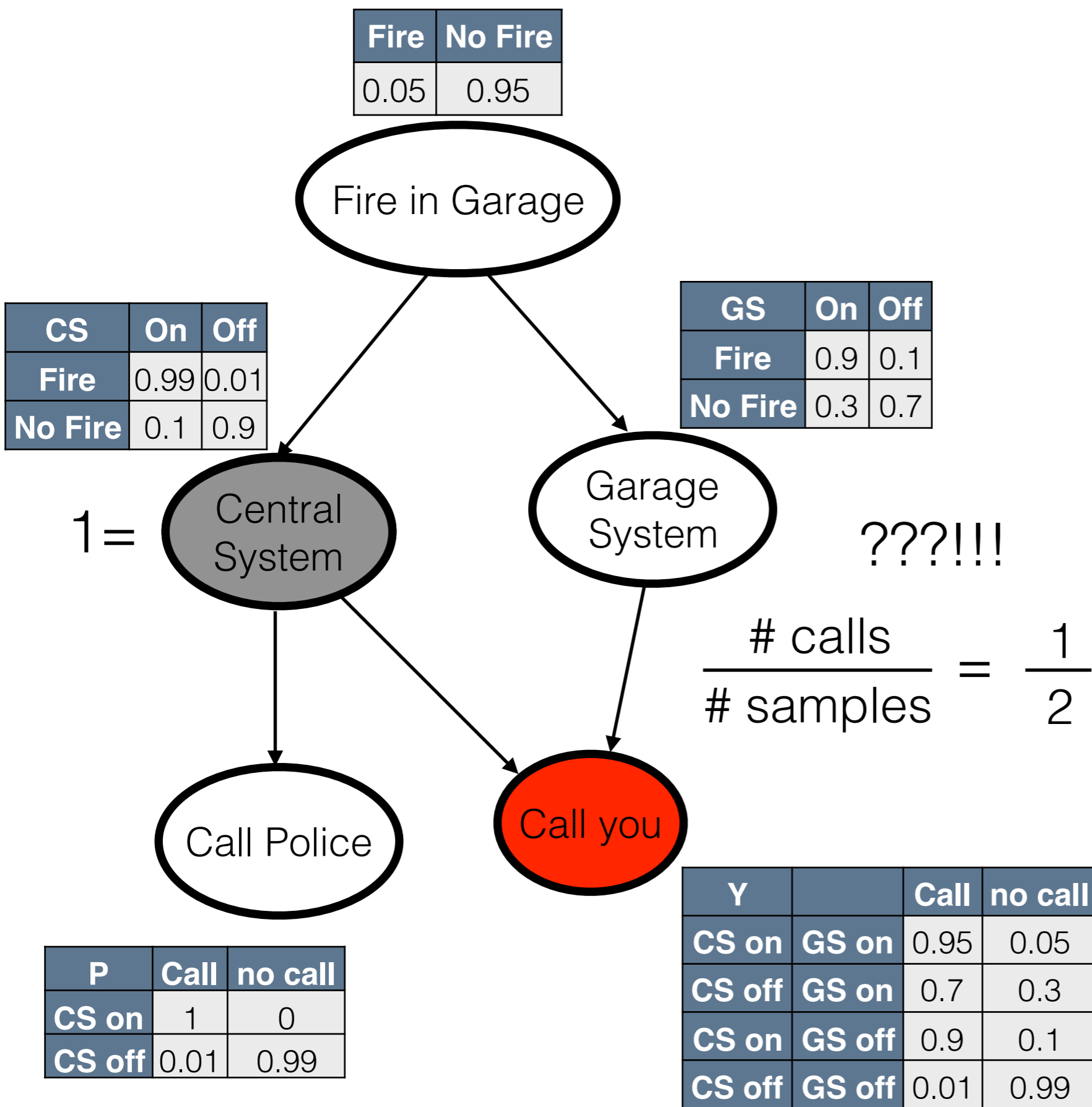


# REJECTION SAMPLING



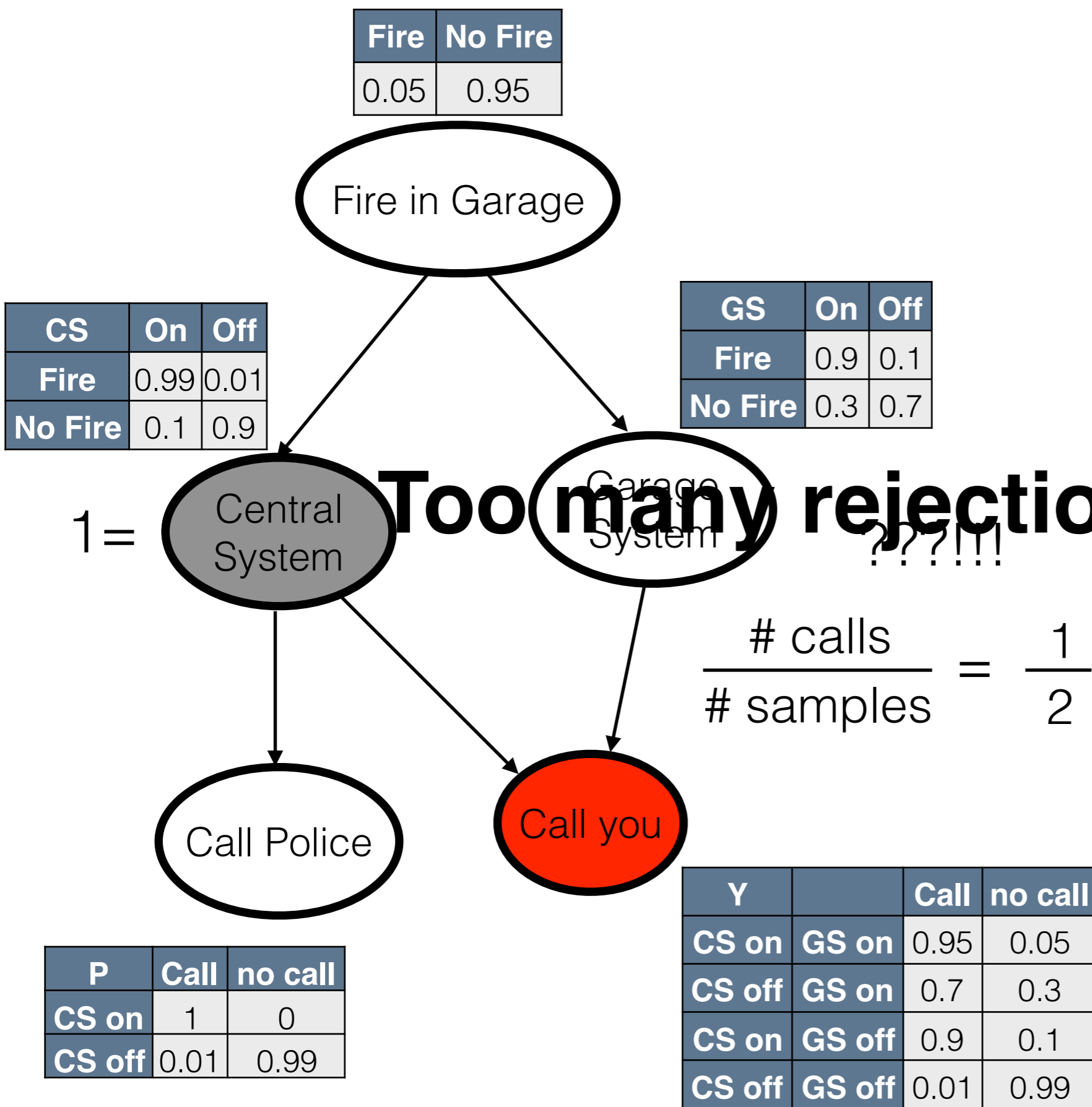
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



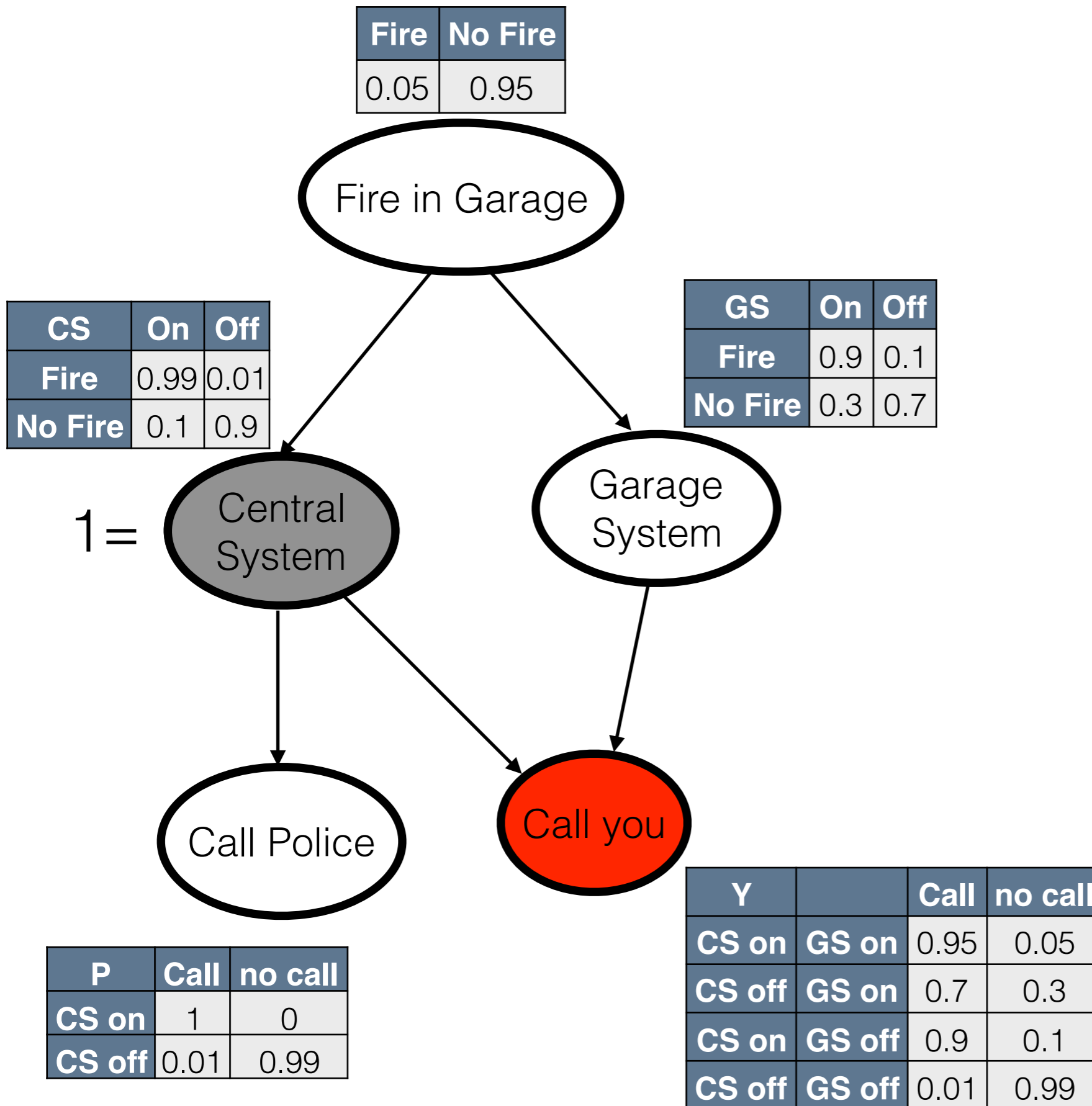
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# REJECTION SAMPLING



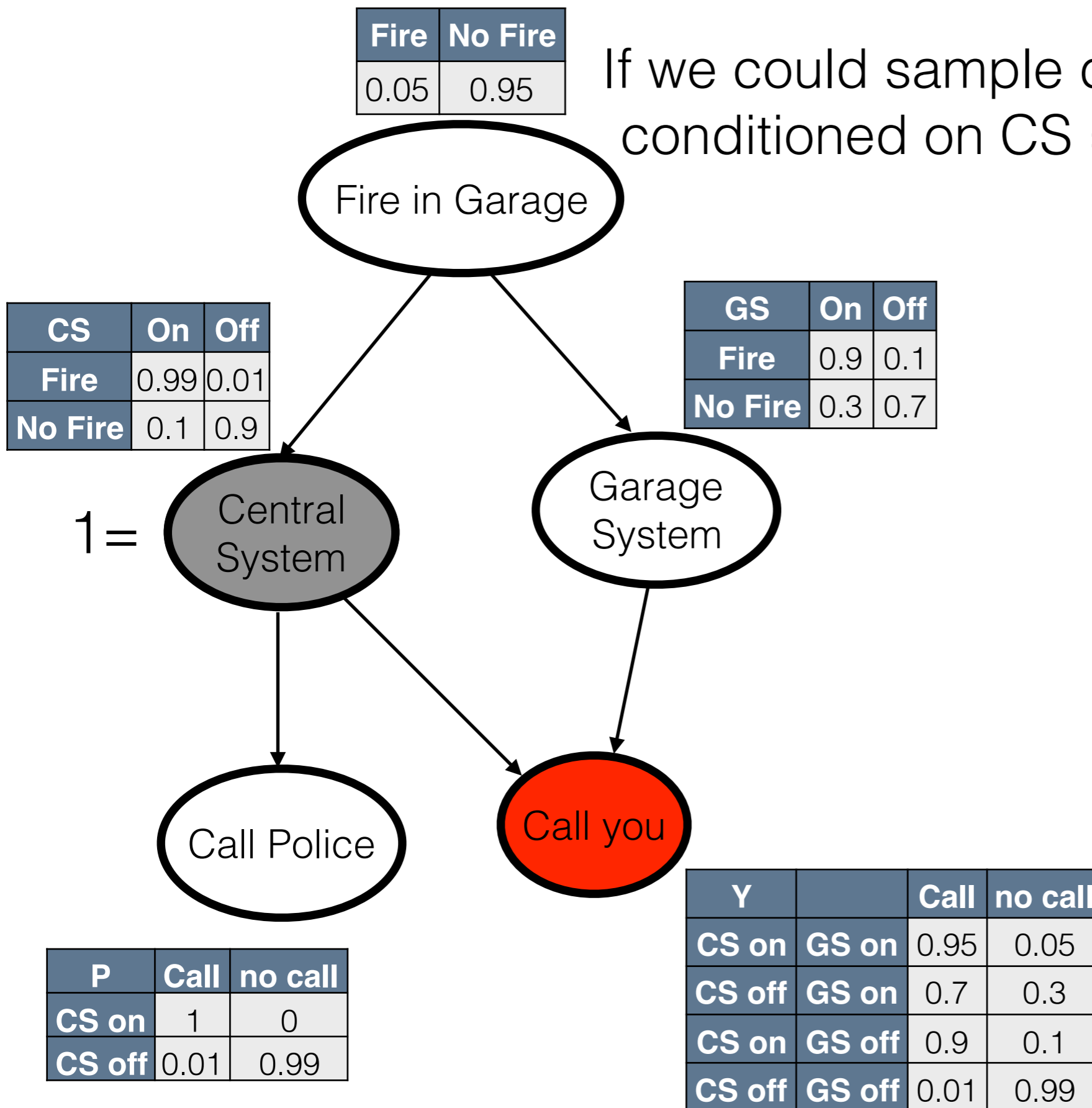
	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# IMPORTANCE SAMPLING

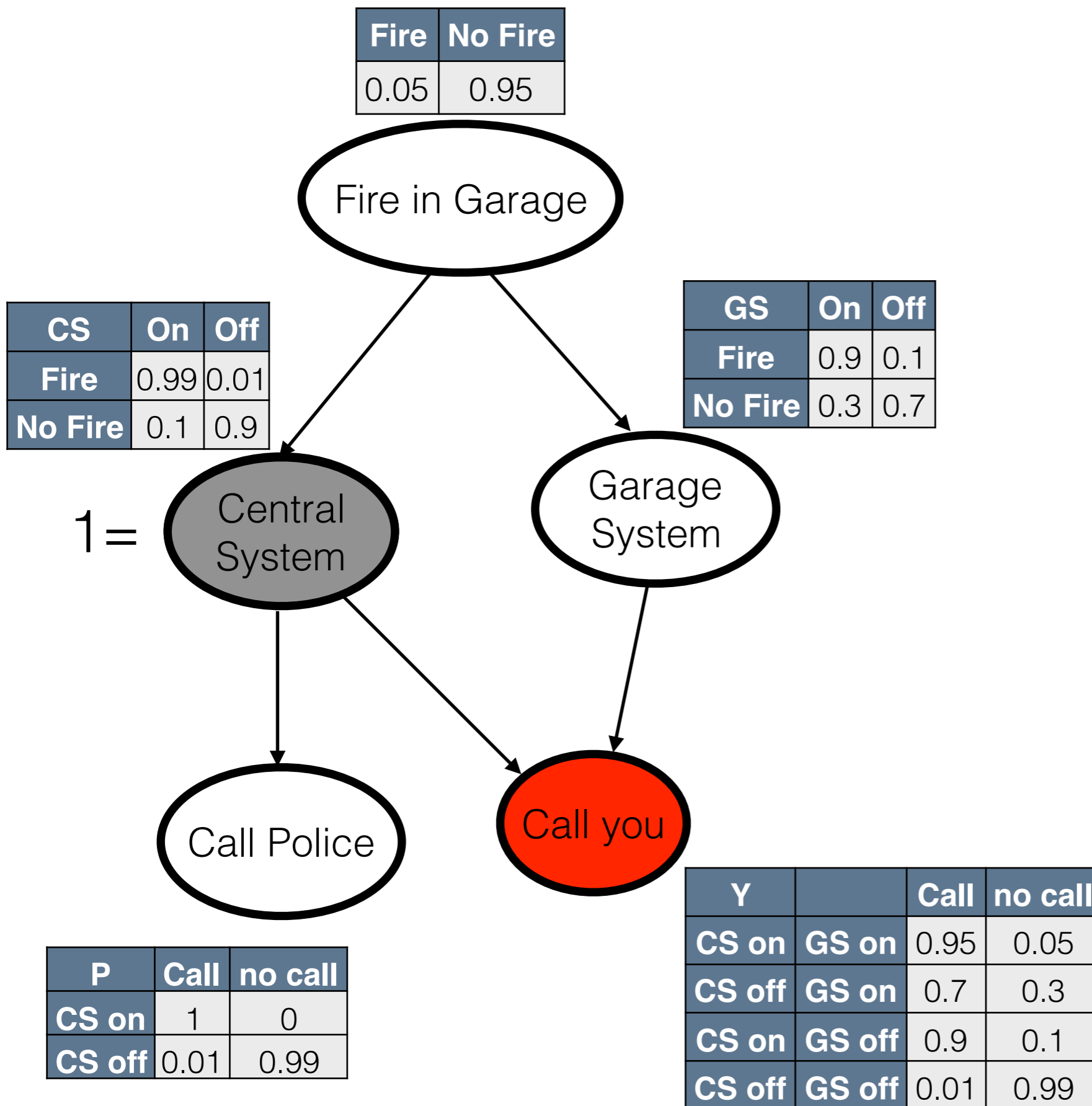


# IMPORTANCE SAMPLING

If we could sample directly from distribution conditioned on  $CS = 1$  it would be great!!!

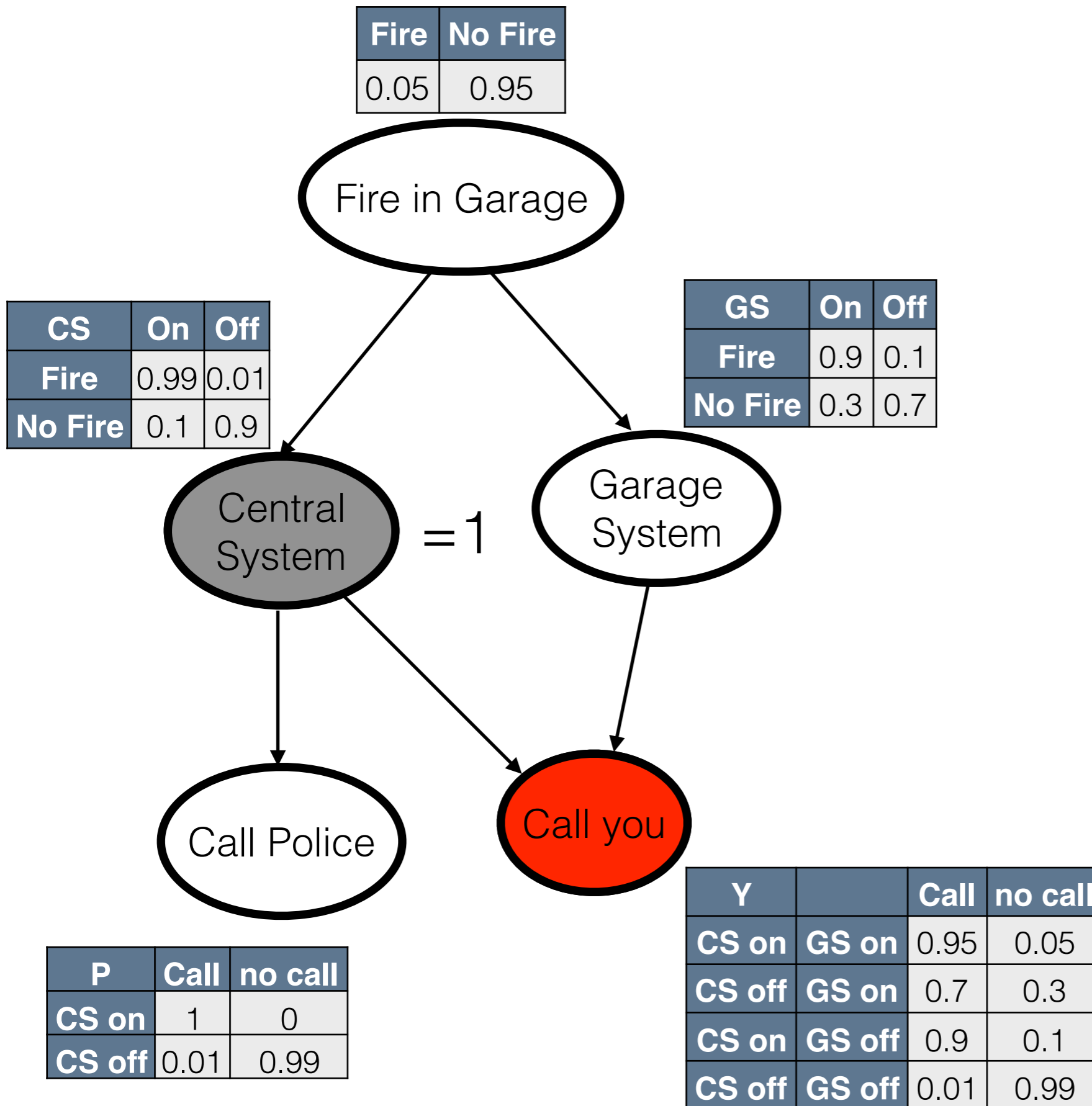


# IMPORTANCE SAMPLING



	F	CS	GS	P	Y
1	0	0	1	0	1
2	0	1	0	1	0
3	1	1	1	1	1
4	0	0	0	0	0
5	0	0	1	0	0
6	0	0	1	0	1
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	0	0	1	0	1
11	0	0	1	0	0
12	0	0	1	0	1
13	0	0	1	0	1
14	0	0	0	0	0
15	0	0	0	0	0
16	0	0	1	0	0
17	0	0	0	0	0
18	0	0	0	0	0
19	0	0	0	0	0
20	0	0	0	0	0
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0
24	0	0	0	0	0
25	0	0	1	0	1

# IMPORTANCE SAMPLING





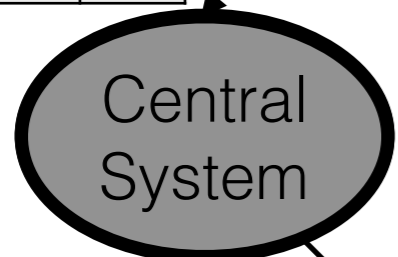
# IMPORTANCE SAMPLING

	F	CS	GS	P	Y
1					

Fire	No Fire
0.05	0.95

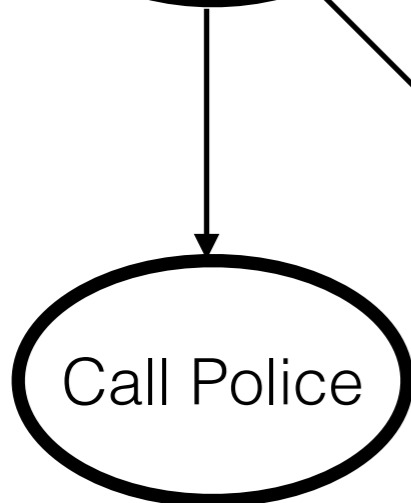
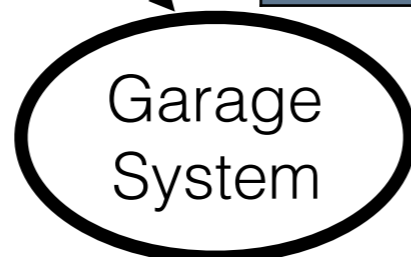


CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9



= 1

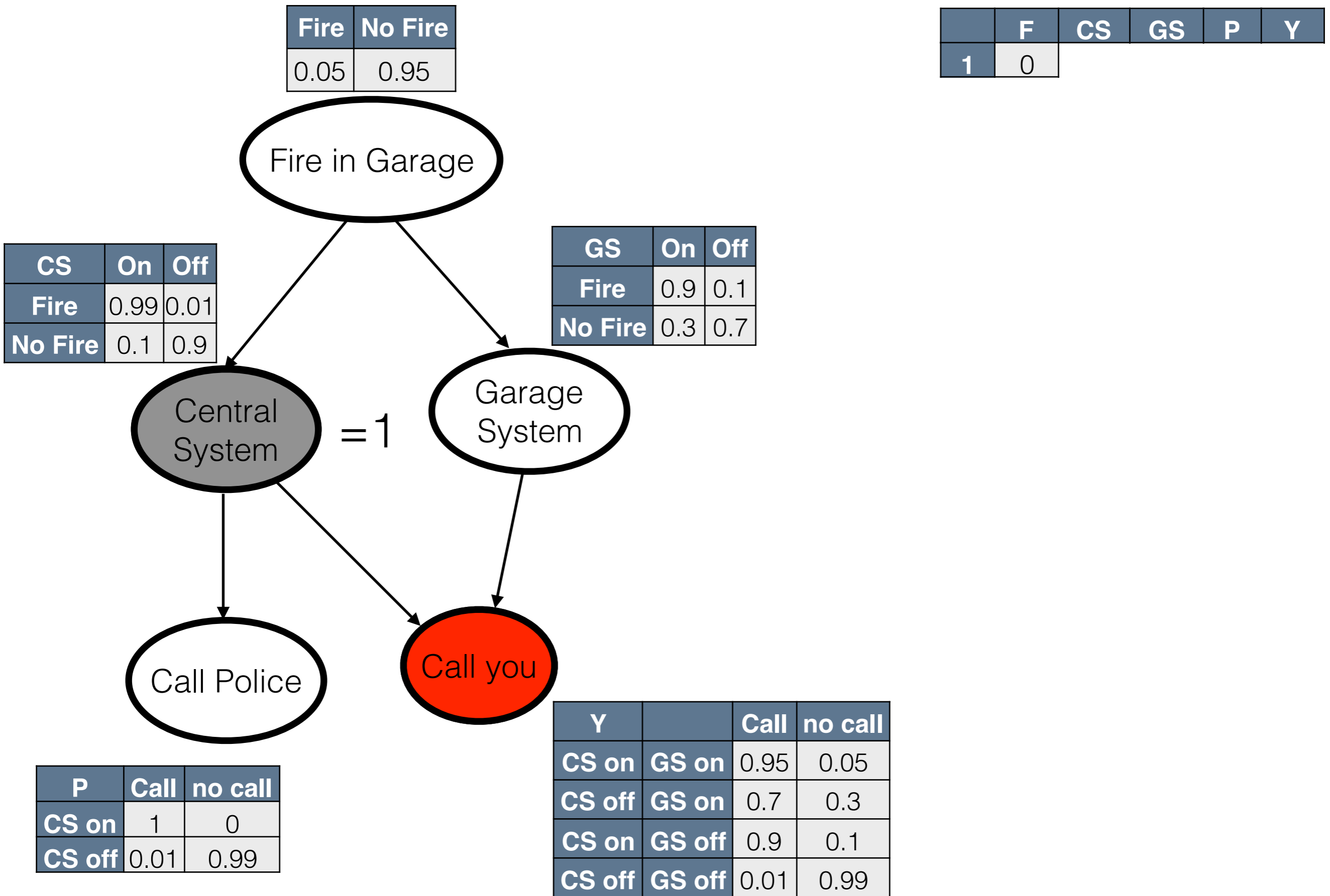
GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

# IMPORTANCE SAMPLING



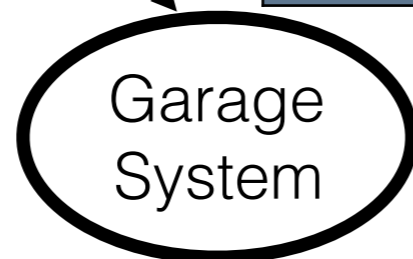
# IMPORTANCE SAMPLING

	F	CS	GS	P	Y
1	0	1			

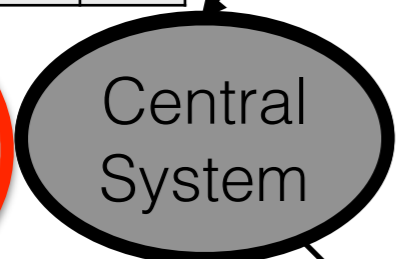
Fire	No Fire
0.05	0.95



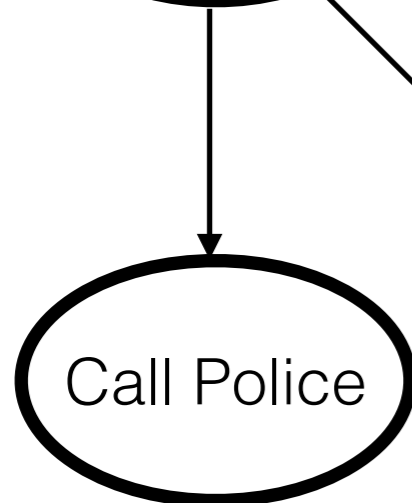
GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9



= 1



P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

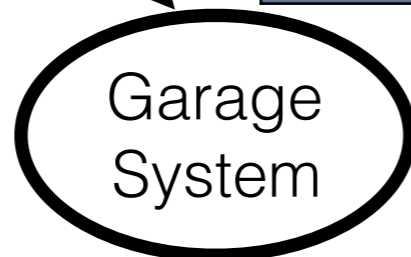
# IMPORTANCE SAMPLING

	F	CS	GS	P	Y
1	0	1	0		

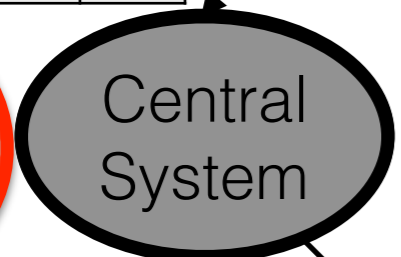
Fire	No Fire
0.05	0.95



GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9



= 1



P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

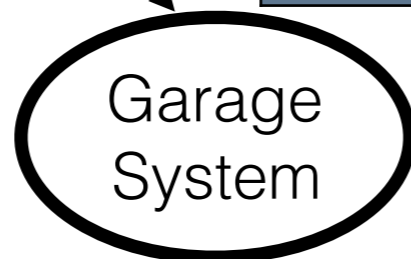
# IMPORTANCE SAMPLING

	F	CS	GS	P	Y
1	0	1	0	1	

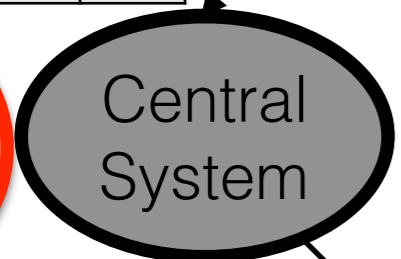
Fire	No Fire
0.05	0.95



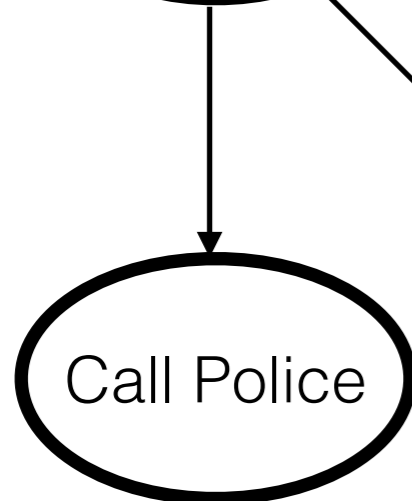
GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9



= 1



P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

# IMPORTANCE SAMPLING

	F	CS	GS	P	Y
1	0	1	0	1	0

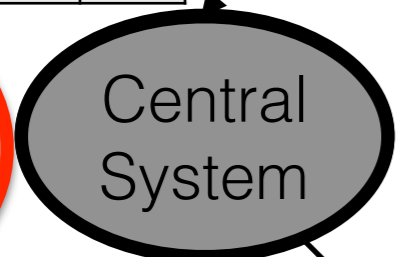
Fire	No Fire
0.05	0.95



GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7



CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9



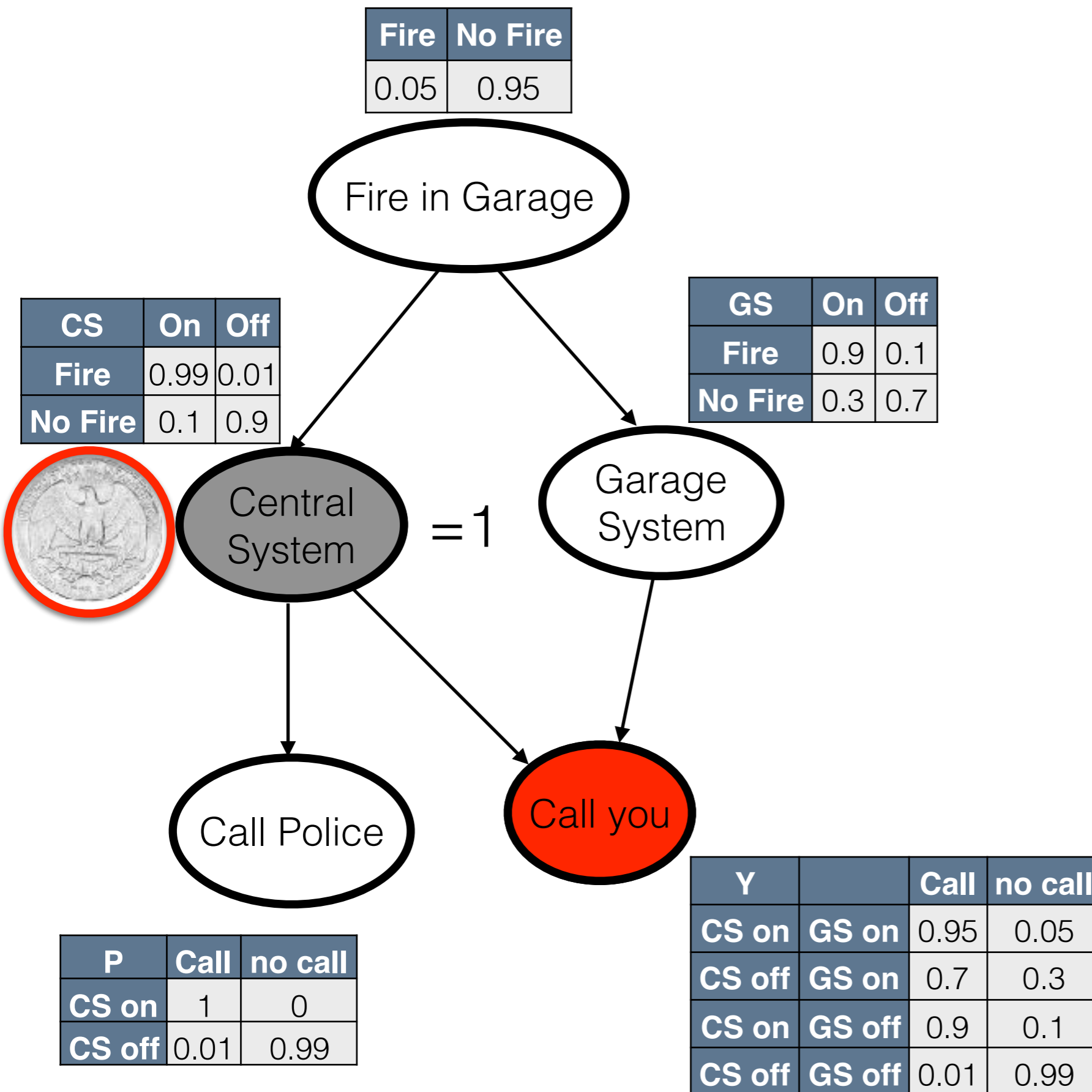
= 1



P	Call	no call
CS on	1	0
CS off	0.01	0.99

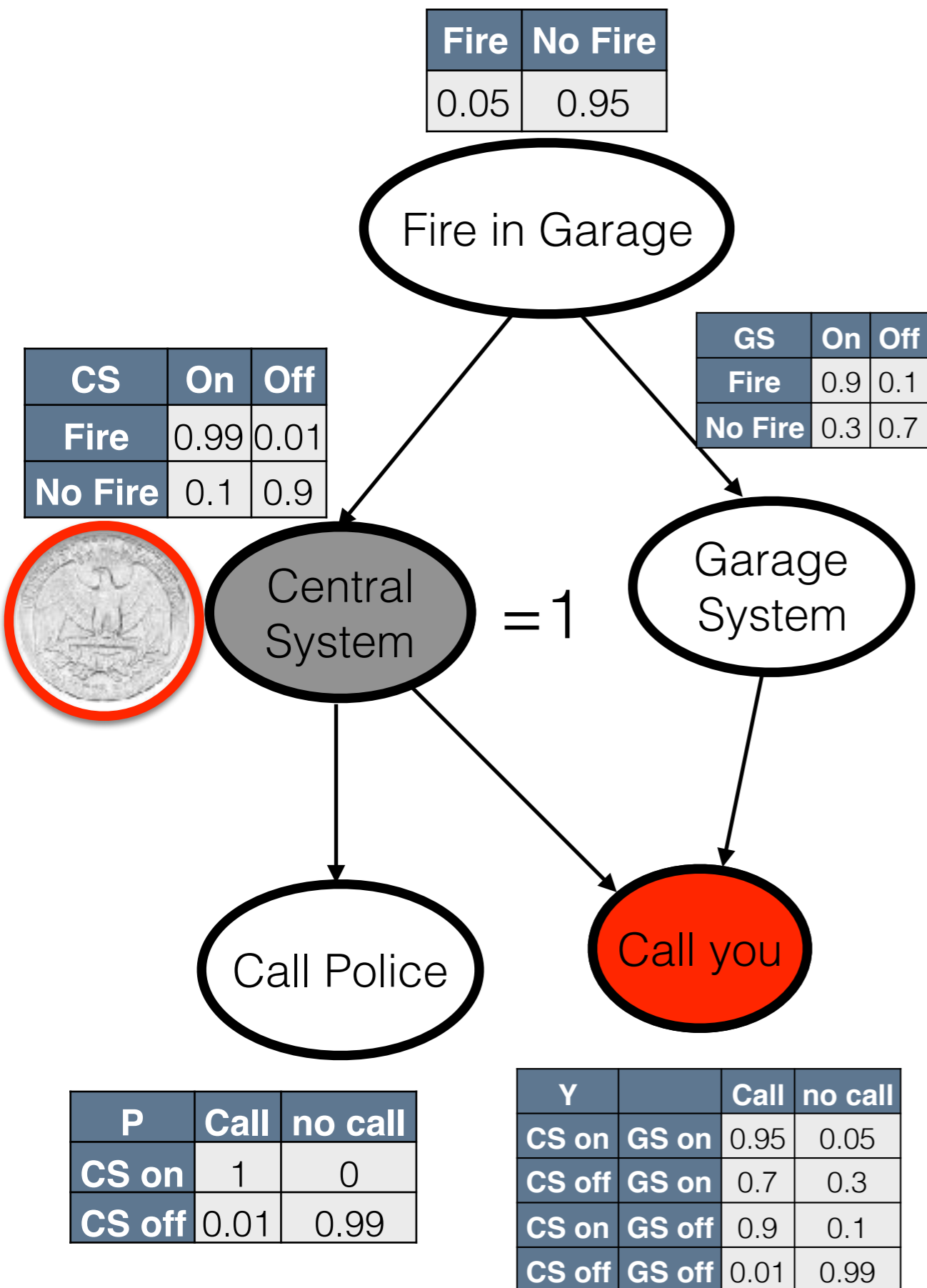
Y		Call	no call
CS on	GS on	0.95	0.05
CS off	GS on	0.7	0.3
CS on	GS off	0.9	0.1
CS off	GS off	0.01	0.99

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y
1	0	1	0	1	0
2	0	1	1	1	1
3	1	1	1	1	1
4	0	1	0	1	1
5	0	1	0	1	1
6	0	1	0	1	1
7	0	1	1	1	1
8	0	1	0	1	0
9	0	1	0	1	1
10	0	1	1	1	1
11	0	1	0	1	1
12	0	1	1	1	0
13	0	1	0	1	1
14	0	1	1	1	1
15	0	1	0	1	1
16	0	1	0	1	1
17	0	1	0	1	1
18	0	1	0	1	1
19	0	1	1	1	1
20	0	1	0	1	1
21	0	1	0	1	1
22	0	1	0	1	1
23	0	1	1	1	1
24	0	1	0	1	1
25	0	1	1	1	1

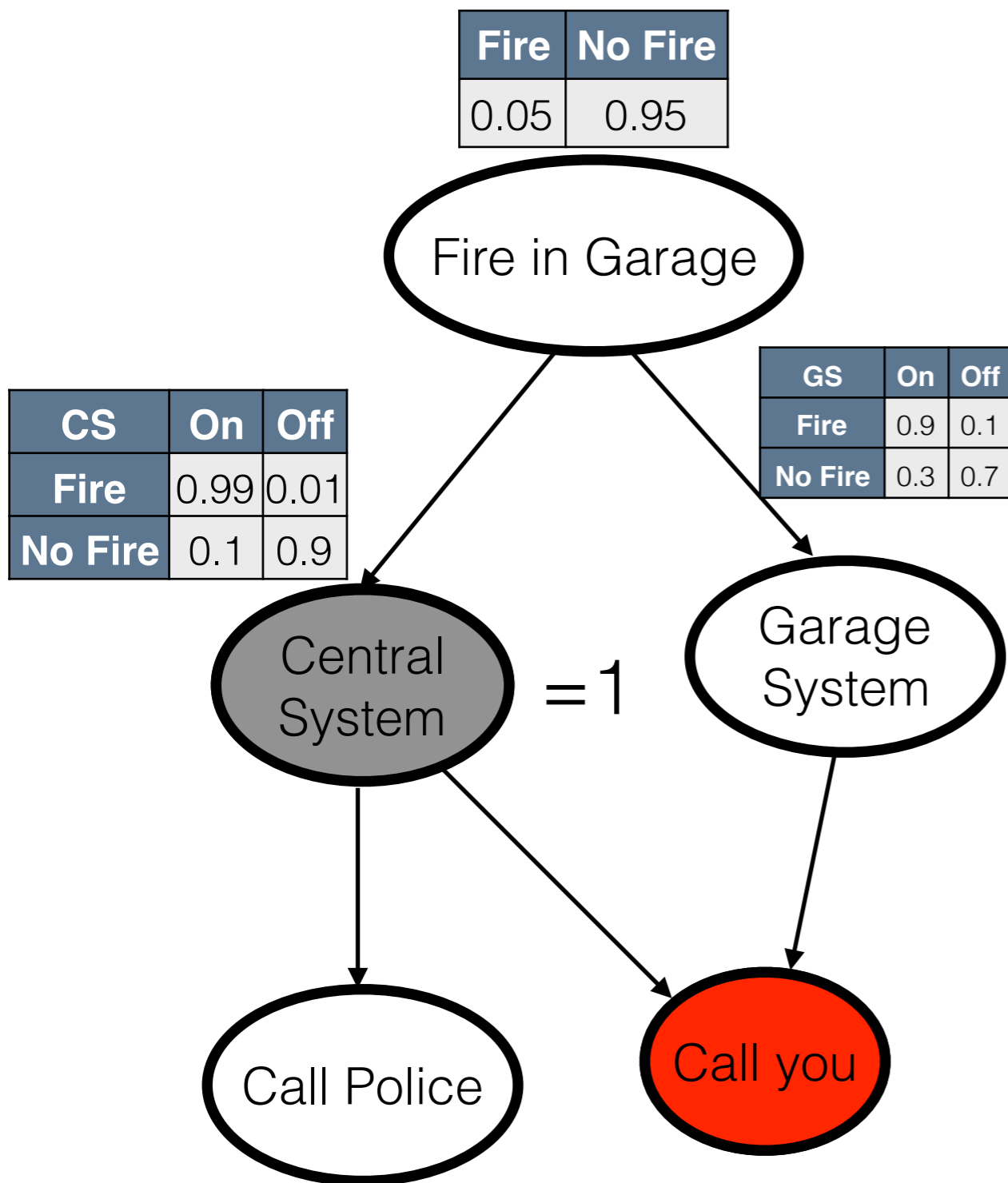
# IMPORTANCE SAMPLING



	F	CS	GS	P	Y
1	0	1	0	1	0
2	0	1	1	1	1
3	1	1	1	1	1
4	0	1	0	1	1
5	0	1	0	1	1
6	0	1	0	1	1
7	0	1	1	1	1
8	0	1	0	1	0
9	0	1	0	1	1
10	0	1	1	1	1
11	0	1	0	1	1
12	0	1	1	1	0
13	0	1	0	1	1
14	0	1	1	1	1
15	0	1	0	1	1
16	0	1	0	1	1
17	0	1	0	1	1
18	0	1	0	1	1
19	0	1	1	1	1
20	0	1	0	1	1
21	0	1	0	1	1
22	0	1	0	1	1
23	0	1	1	1	1
24	0	1	0	1	1
25	0	1	1	1	1



# IMPORTANCE SAMPLING



Fire	No Fire
0.05	0.95

GS	On	Off
Fire	0.9	0.1
No Fire	0.3	0.7

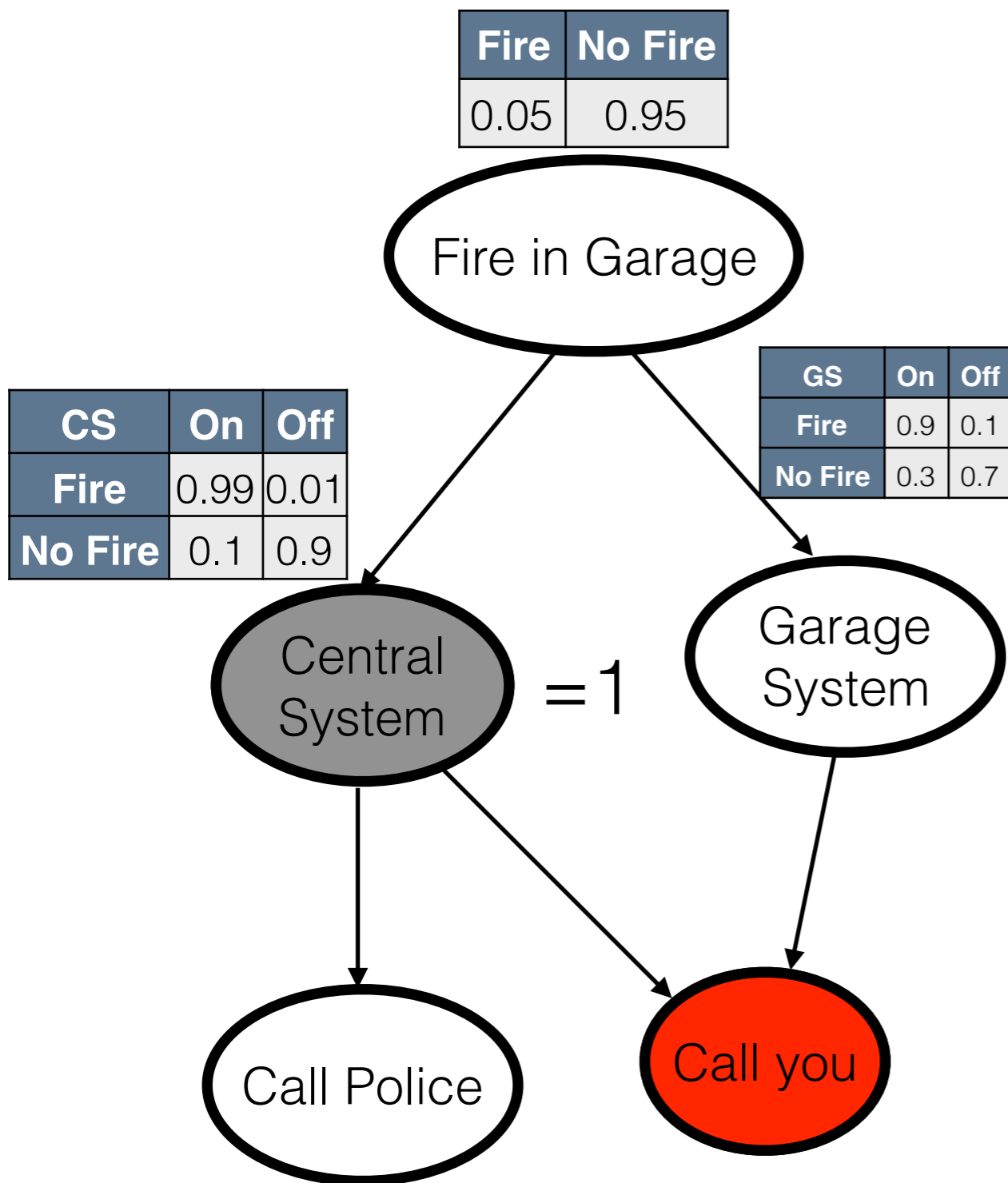
CS	On	Off
Fire	0.99	0.01
No Fire	0.1	0.9

P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no
CS	GS	0.95	0.05
CS	GS	0.7	0.3
CS	GS	0.9	0.1
CS	GS	0.01	0.99

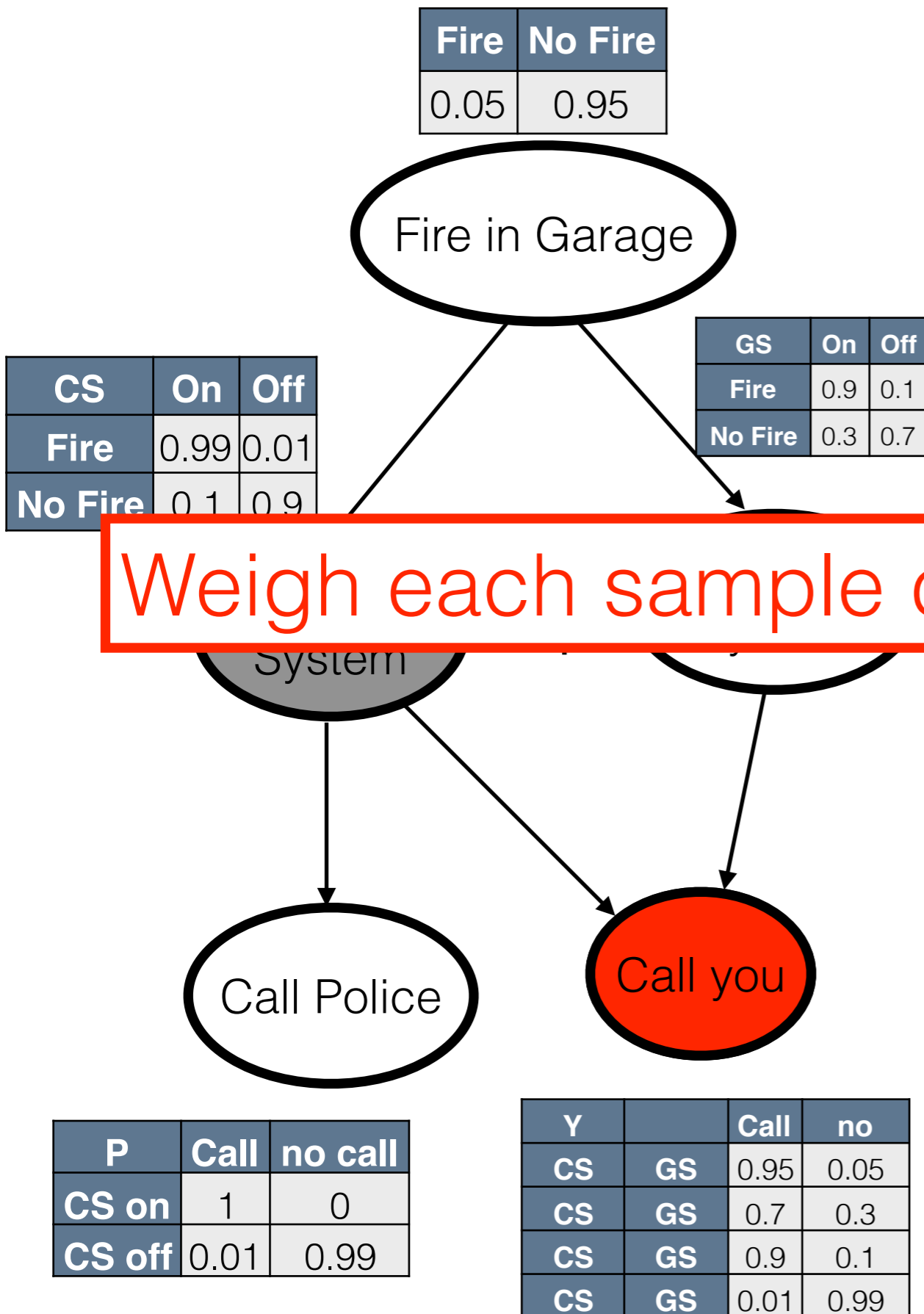
	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	
2	0	1	1	1	1	
3	1	1	1	1	1	
4	0	1	0	1	1	
5	0	1	0	1	1	
6	0	1	0	1	1	
7	0	1	1	1	1	
8	0	1	0	1	0	
9	0	1	0	1	1	
10	0	1	1	1	1	
11	0	1	0	1	1	
12	0	1	1	1	0	
13	0	1	0	1	1	
14	0	1	1	1	1	
15	0	1	0	1	1	
16	0	1	0	1	1	
17	0	1	0	1	1	
18	0	1	0	1	1	
19	0	1	1	1	1	
20	0	1	0	1	1	
21	0	1	0	1	1	
22	0	1	0	1	1	
23	0	1	1	1	1	
24	0	1	0	1	1	
25	0	1	1	1	1	

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	
2	0	1	1	1	1	
3	1	1	1	1	1	
4	0	1	0	1	1	
5	0	1	0	1	1	
6	0	1	0	1	1	
7	0	1	1	1	1	
8	0	1	0	1	0	
9	0	1	0	1	1	
10	0	1	1	1	1	
11	0	1	0	1	1	
12	0	1	1	1	0	
13	0	1	0	1	1	
14	0	1	1	1	1	
15	0	1	0	1	1	
16	0	1	0	1	1	
17	0	1	0	1	1	
18	0	1	0	1	1	
19	0	1	1	1	1	
20	0	1	0	1	1	
21	0	1	0	1	1	
22	0	1	0	1	1	
23	0	1	1	1	1	
24	0	1	0	1	1	
25	0	1	1	1	1	

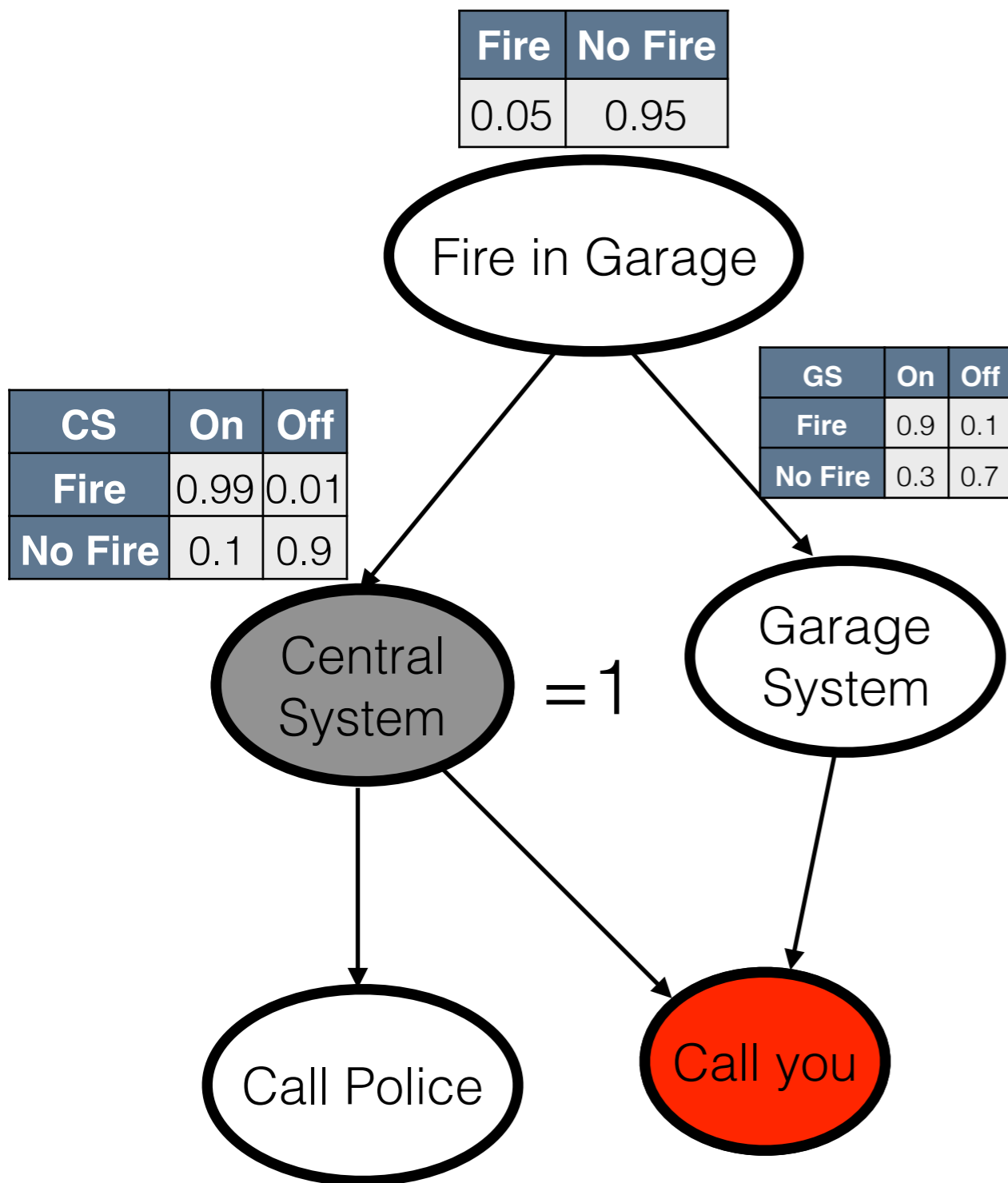
# IMPORTANCE SAMPLING



Weigh each sample differently!

	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	
2	0	1	1	1	1	
3	1	1	1	1	1	
4	0	1	0	1	1	
5	0	1	0	1	1	
6	0	1	0	1	1	
7	0	1	1	1	1	
8	0	1	0	1	0	
9	0	1	0	1	1	
10	0	1	1	1	1	
11	0	1	0	1	1	
12	0	1	1	1	0	
13	0	1	0	1	1	
14	0	1	1	1	1	
15	0	1	0	1	1	
16	0	1	0	1	1	
17	0	1	0	1	1	
18	0	1	0	1	1	
19	0	1	1	1	1	
20	0	1	0	1	1	
21	0	1	0	1	1	
22	0	1	0	1	1	
23	0	1	1	1	1	
24	0	1	0	1	1	
25	0	1	1	1	1	

# IMPORTANCE SAMPLING

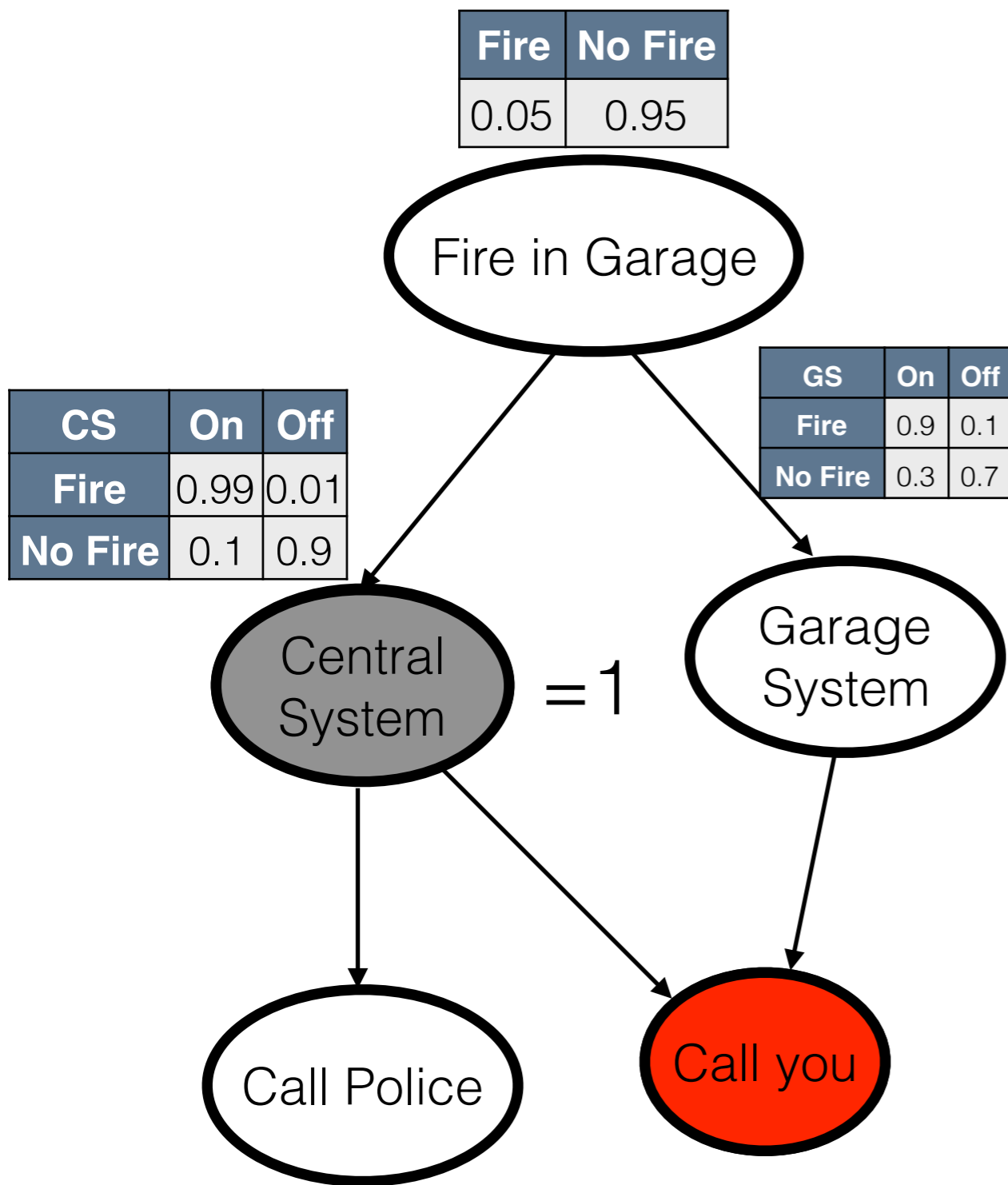


P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no
CS	GS	0.95	0.05
CS	GS	0.7	0.3
CS	GS	0.9	0.1
CS	GS	0.01	0.99

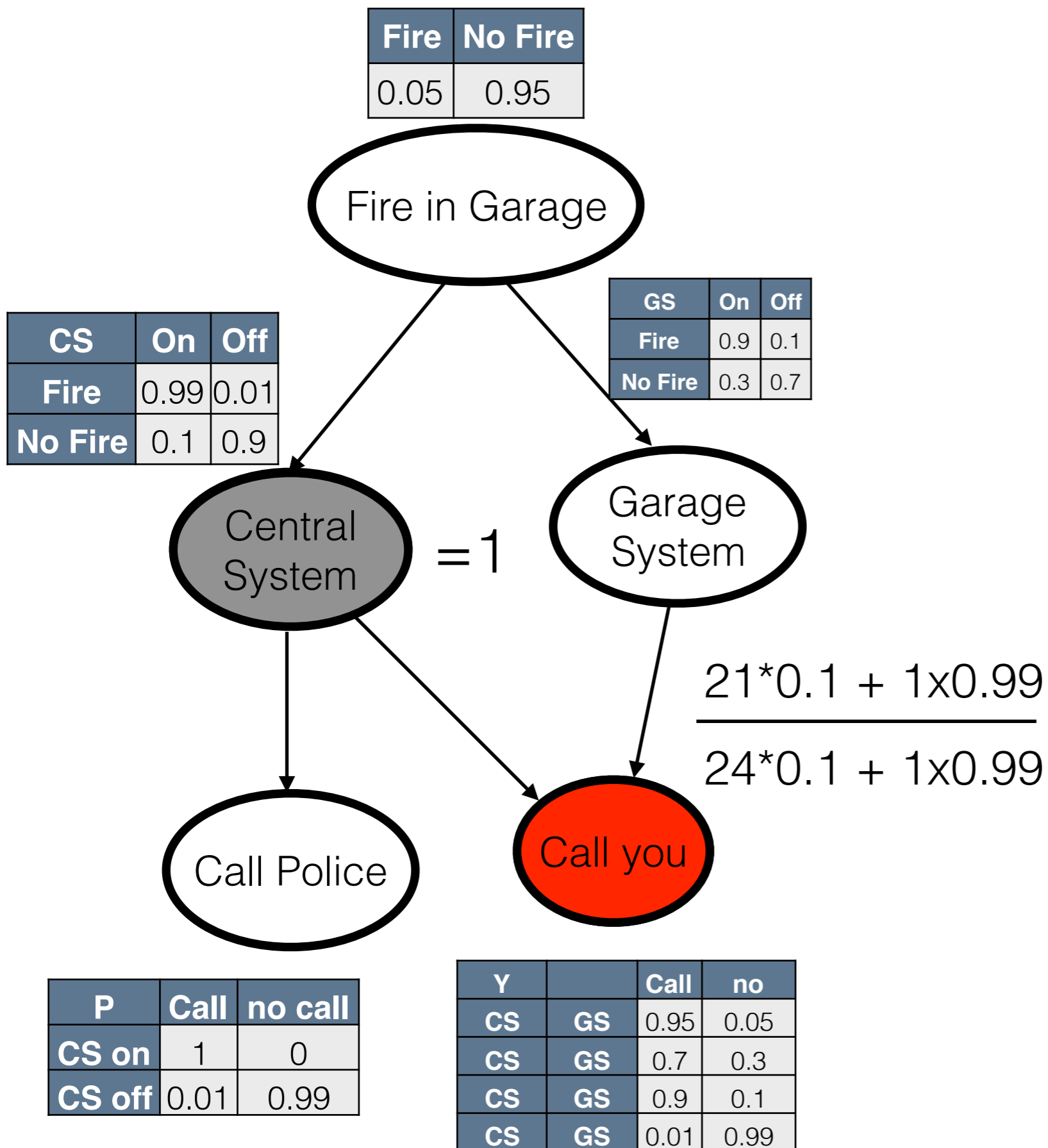
	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	0.1
2	0	1	1	1	1	0.1
3	1	1	1	1	1	0.99
4	0	1	0	1	1	0.1
5	0	1	0	1	1	0.1
6	0	1	0	1	1	0.1
7	0	1	1	1	1	0.1
8	0	1	0	1	0	0.1
9	0	1	0	1	1	0.1
10	0	1	1	1	1	0.1
11	0	1	0	1	1	0.1
12	0	1	1	1	0	0.1
13	0	1	0	1	1	0.1
14	0	1	1	1	1	0.1
15	0	1	0	1	1	0.1
16	0	1	0	1	1	0.1
17	0	1	0	1	1	0.1
18	0	1	0	1	1	0.1
19	0	1	1	1	1	0.1
20	0	1	0	1	1	0.1
21	0	1	0	1	1	0.1
22	0	1	0	1	1	0.1
23	0	1	1	1	1	0.1
24	0	1	0	1	1	0.1
25	0	1	1	1	1	0.1

# IMPORTANCE SAMPLING



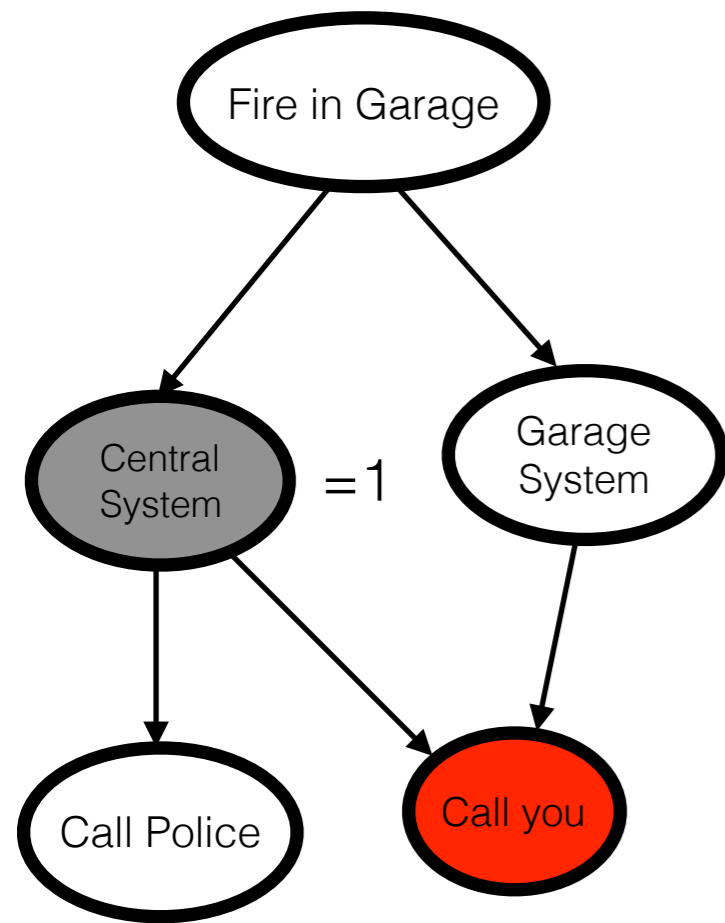
	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	0.1
2	0	1	1	1	1	0.1
3	1	1	1	1	1	0.99
4	0	1	0	1	1	0.1
5	0	1	0	1	1	0.1
6	0	1	0	1	1	0.1
7	0	1	1	1	1	0.1
8	0	1	0	1	0	0.1
9	0	1	0	1	1	0.1
10	0	1	1	1	1	0.1
11	0	1	0	1	1	0.1
12	0	1	1	1	0	0.1
13	0	1	0	1	1	0.1
14	0	1	1	1	1	0.1
15	0	1	0	1	1	0.1
16	0	1	0	1	1	0.1
17	0	1	0	1	1	0.1
18	0	1	0	1	1	0.1
19	0	1	1	1	1	0.1
20	0	1	0	1	1	0.1
21	0	1	0	1	1	0.1
22	0	1	0	1	1	0.1
23	0	1	1	1	1	0.1
24	0	1	0	1	1	0.1
25	0	1	1	1	1	0.1

# IMPORTANCE SAMPLING

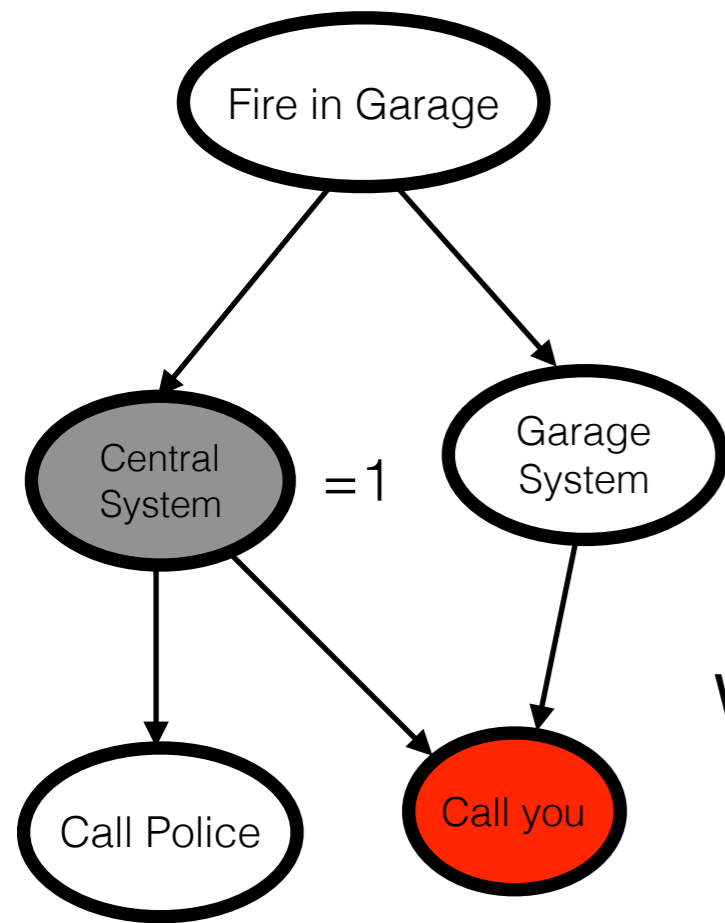


	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	0.1
2	0	1	1	1	1	0.1
3	1	1	1	1	1	0.99
4	0	1	0	1	1	0.1
5	0	1	0	1	1	0.1
6	0	1	0	1	1	0.1
7	0	1	1	1	1	0.1
8	0	1	0	1	0	0.1
9	0	1	0	1	1	0.1
10	0	1	1	1	1	0.1
11	0	1	0	1	1	0.1
12	0	1	1	1	0	0.1
13	0	1	0	1	1	0.1
14	0	1	1	1	1	0.1
15	0	1	0	1	1	0.1
16	0	1	0	1	1	0.1
17	0	1	0	1	1	0.1
18	0	1	0	1	1	0.1
19	0	1	1	1	1	0.1
20	0	1	0	1	1	0.1
21	0	1	0	1	1	0.1
22	0	1	0	1	1	0.1
23	0	1	1	1	1	0.1
24	0	1	0	1	1	0.1
25	0	1	1	1	1	0.1

# IMPORTANCE SAMPLING



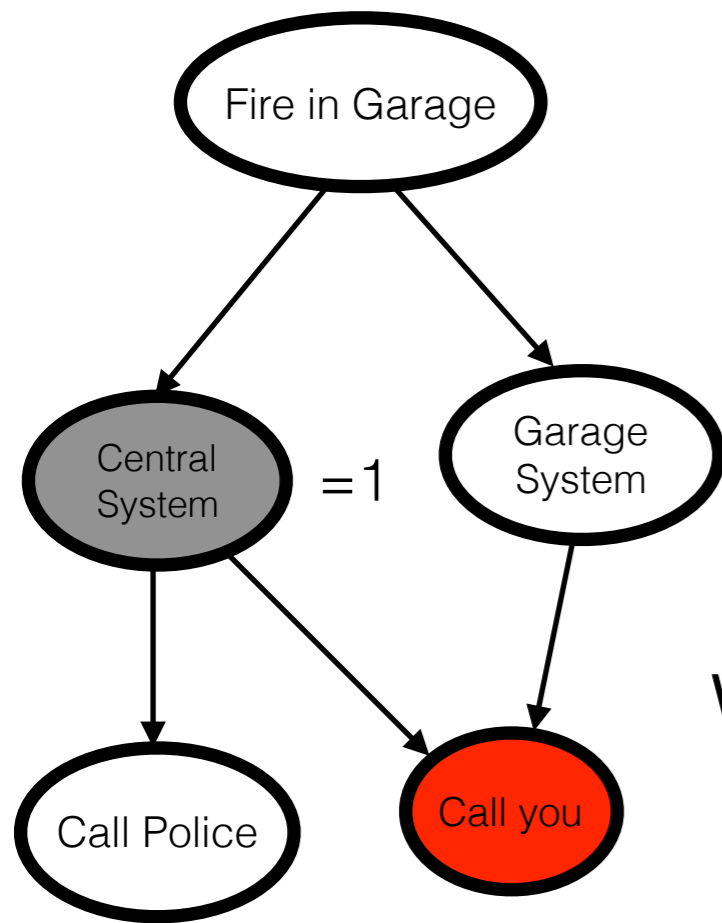
# IMPORTANCE SAMPLING



What we want: Draw from  $P(F,GS,P,Y | CS=1)$



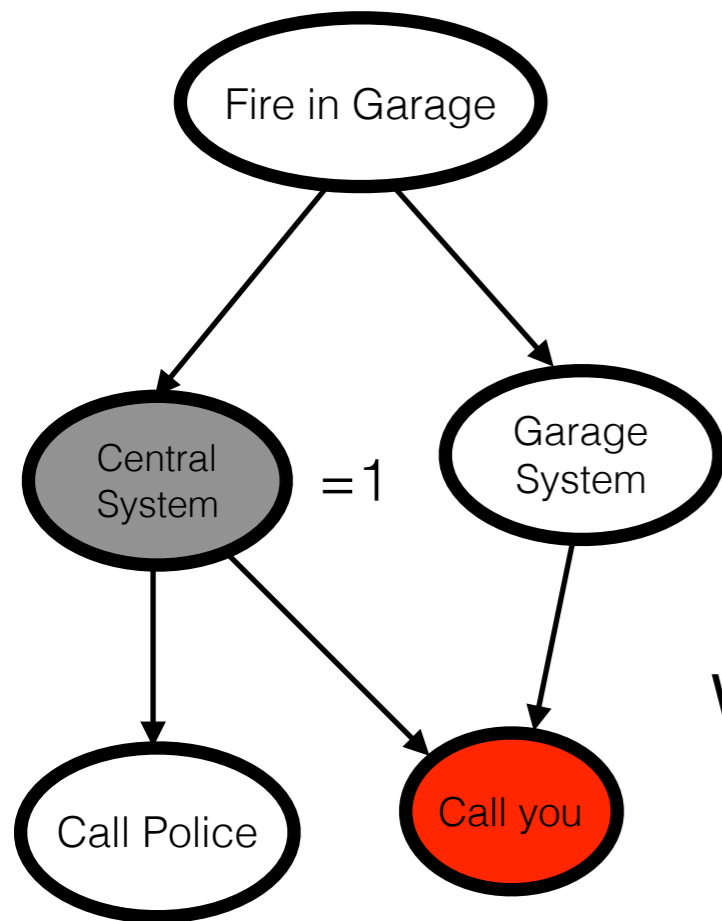
# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

What we want: Draw from  $P(F, GS, P, Y | CS=1)$

# IMPORTANCE SAMPLING

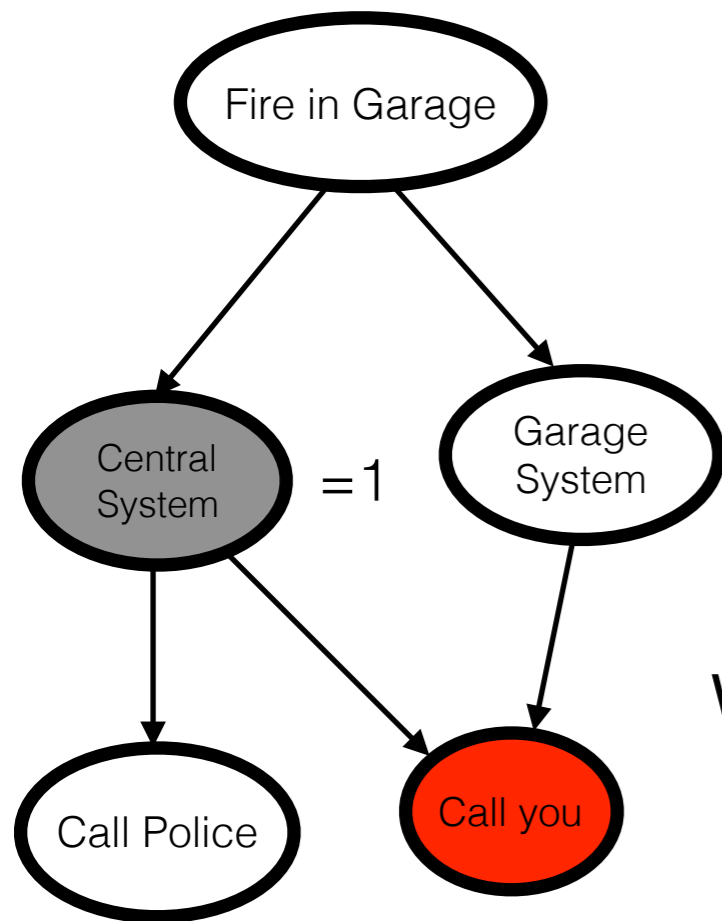


	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

# IMPORTANCE SAMPLING



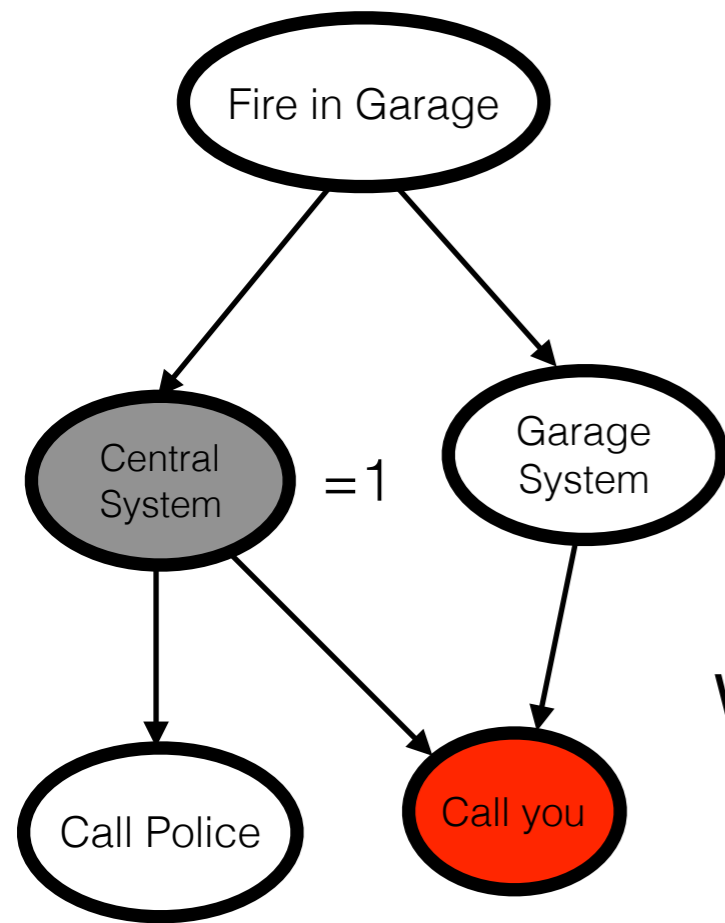
	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

Instead we draw from ?

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

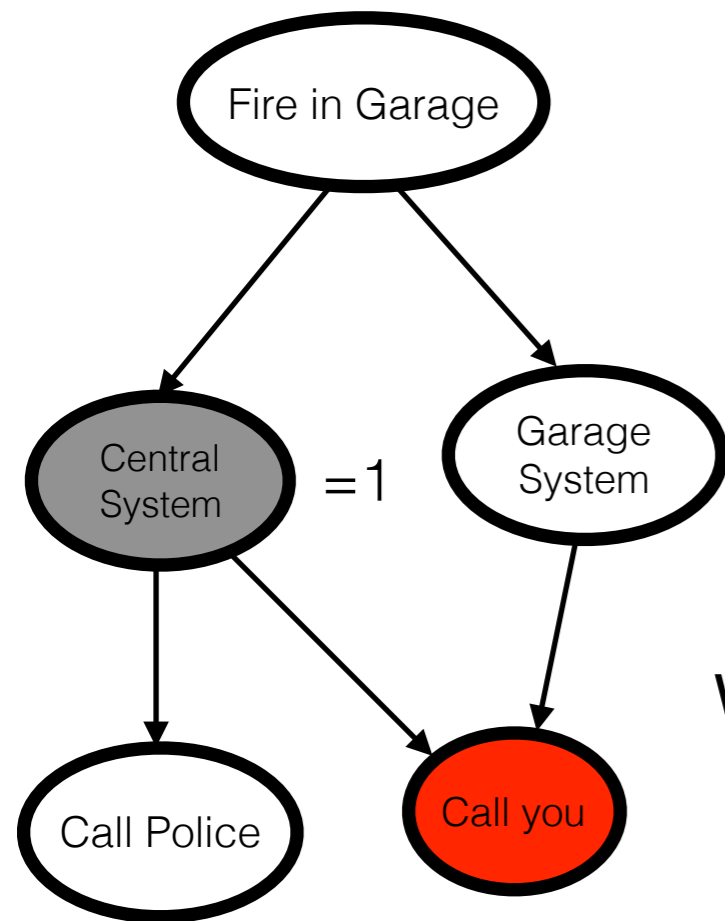
What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

Instead we draw from ?

$$P(F = 0)$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

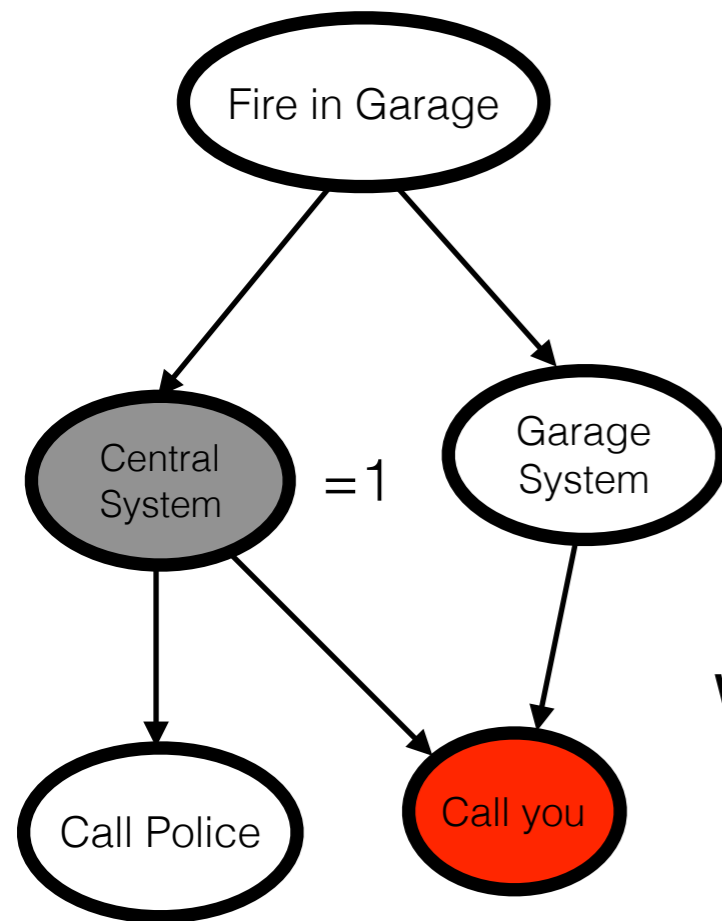
What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

Instead we draw from ?

$$P(F = 0) \times P(GS = 0 | F = 0)$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

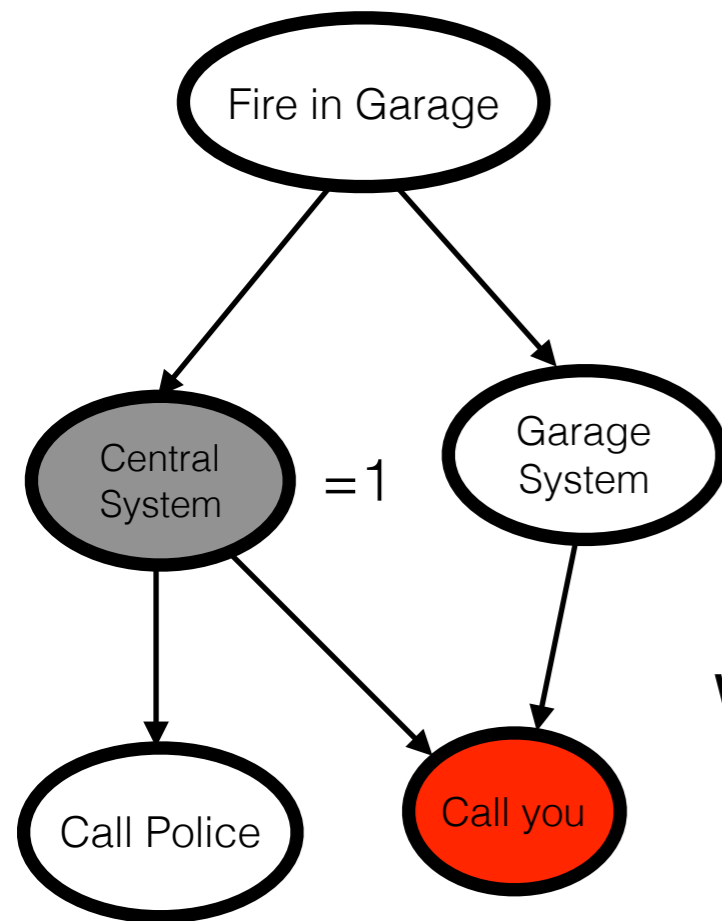
What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

Instead we draw from ?

$$P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1)$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

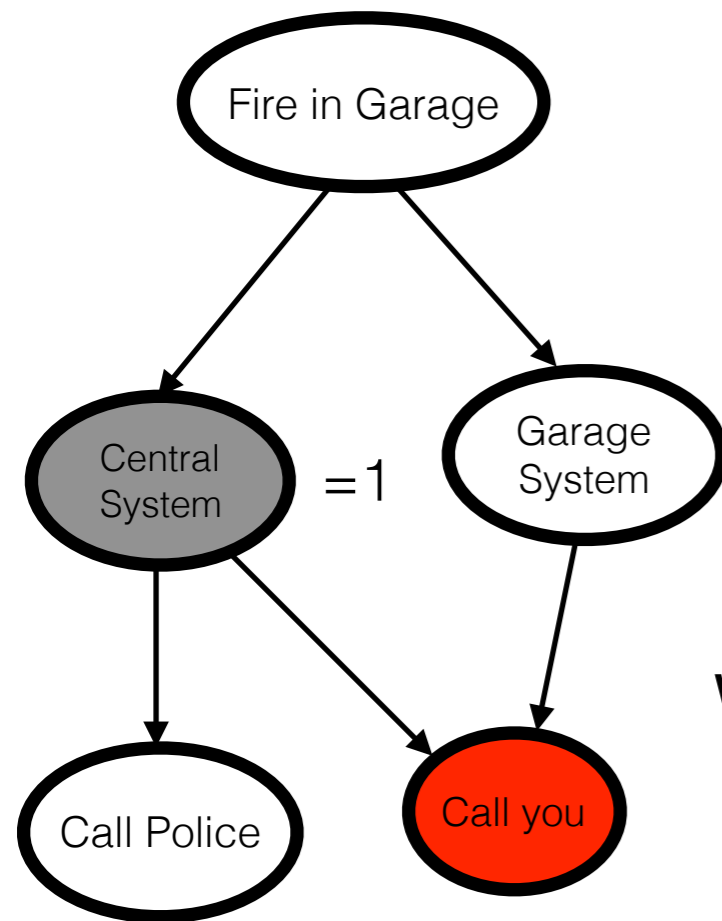
What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

Instead we draw from ?

$$P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 0 | CS = 1, GS = 0)$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

What we want: Draw from  $P(F, GS, P, Y | CS=1)$

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) :$$

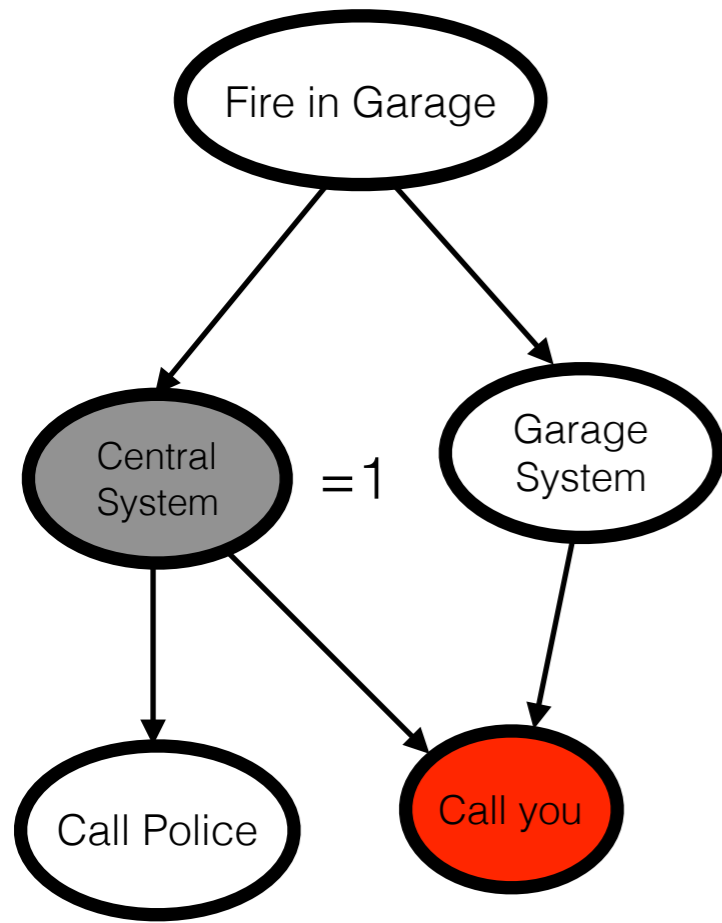
Instead we draw from ?

$$P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 0 | CS = 1, GS = 0)$$

Weigh each sample by ratio of Prob we want / Prob of draw

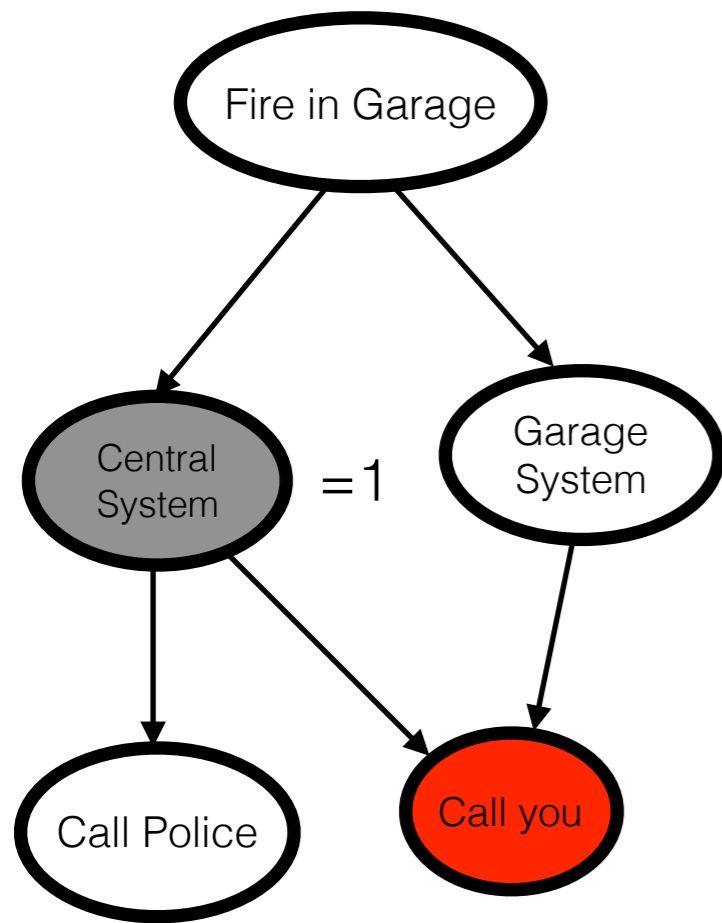


# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

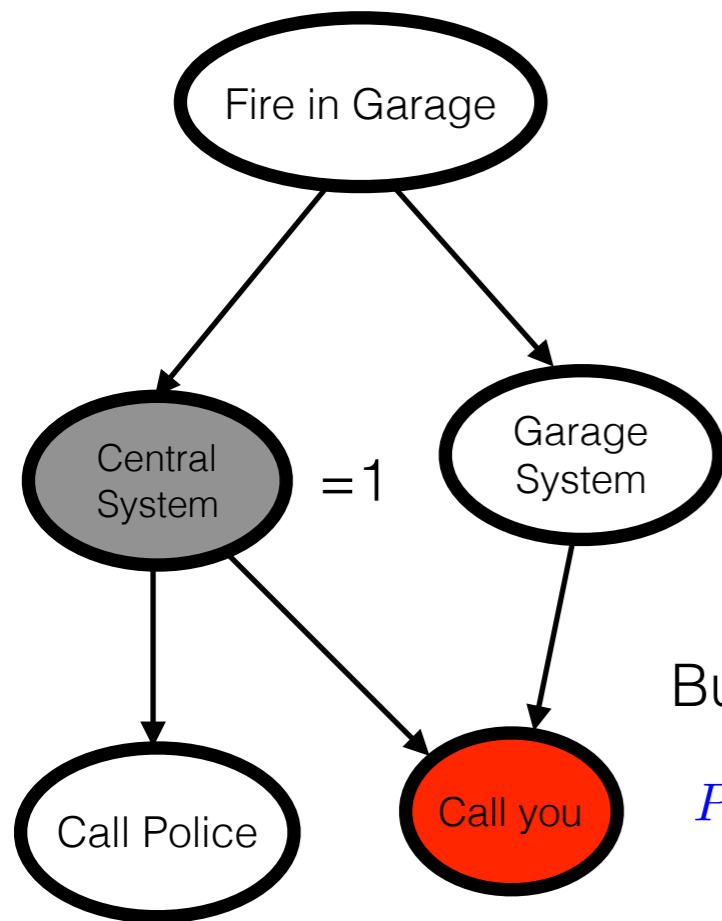
# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

$$\text{weight} \propto \frac{P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 1 | GS = 0, CS = 1)}$$

# IMPORTANCE SAMPLING



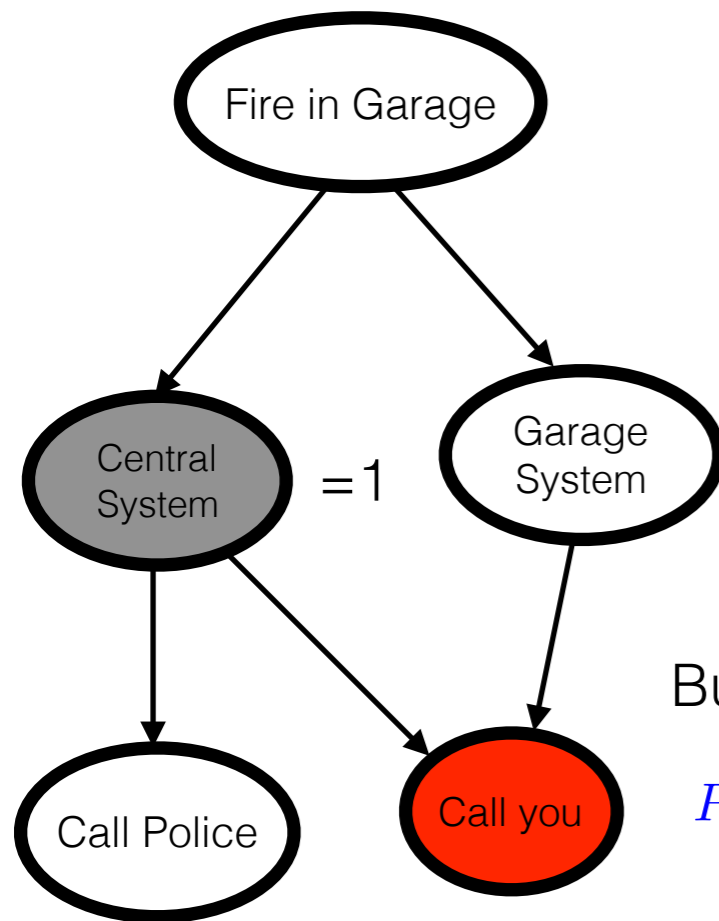
	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

But:

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) = \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(CS = 1)}$$

$$\text{weight} \propto \frac{P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 1 | GS = 0, CS = 1)}$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

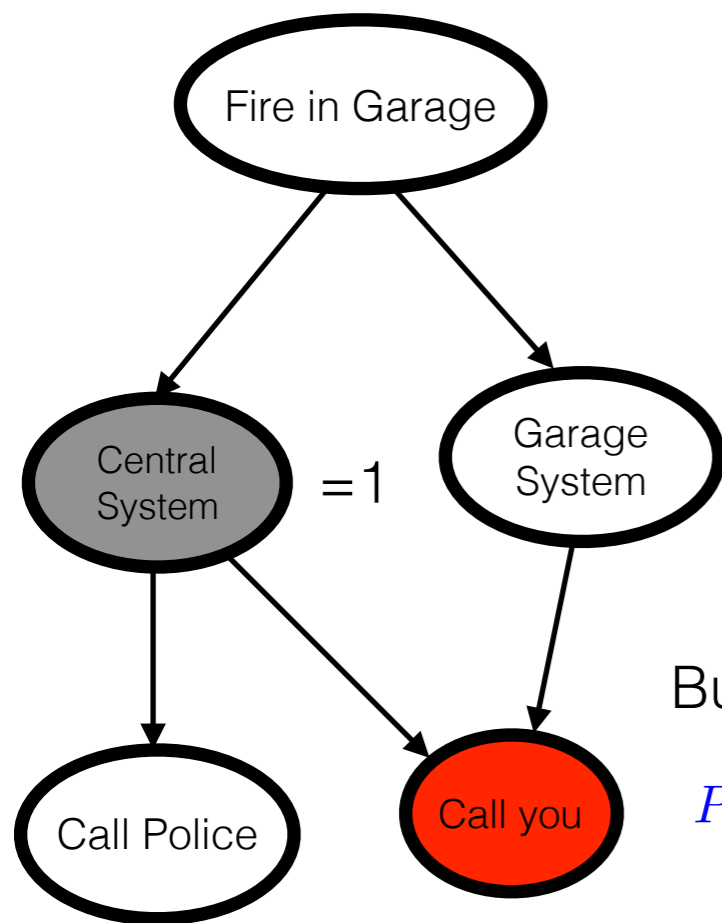
But:

$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) = \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(CS = 1)}$$

$$\text{weight} \propto \frac{P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 1 | GS = 0, CS = 1)}$$

$$\propto \frac{1}{P(CS = 1)} \cdot \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1), P(Y = 0 | CS = 1, GS = 0)}$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

But:

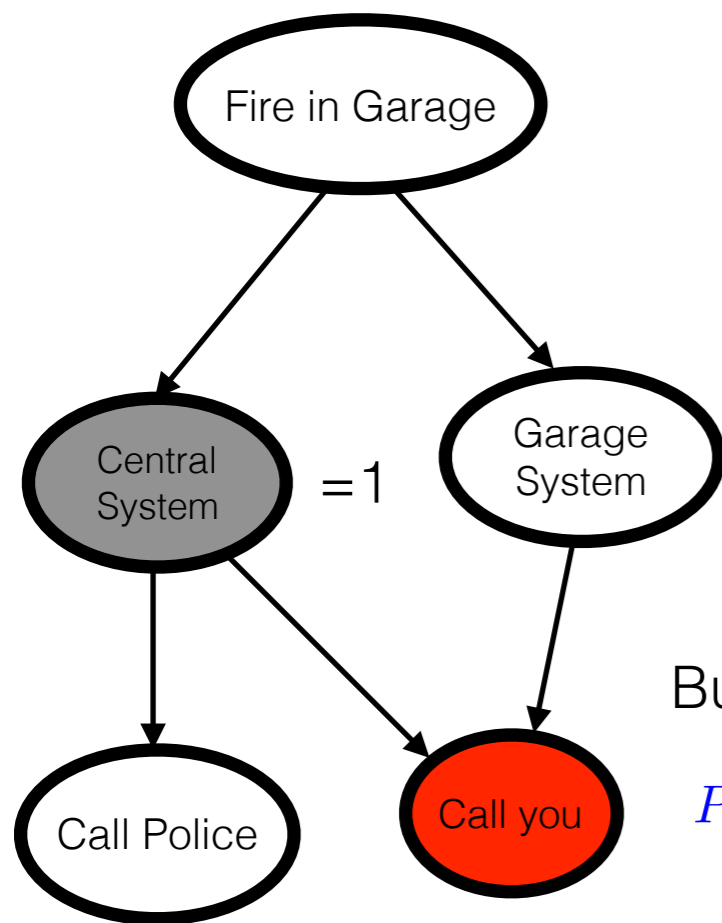
$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) = \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(CS = 1)}$$

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$$\propto \frac{1}{P(CS = 1)} \cdot \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1), P(Y = 0 | CS = 1, GS = 0)}$$

$$\propto \frac{P(CS = 1 | F = 0)}{P(CS = 1)}$$

# IMPORTANCE SAMPLING



	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	

But:

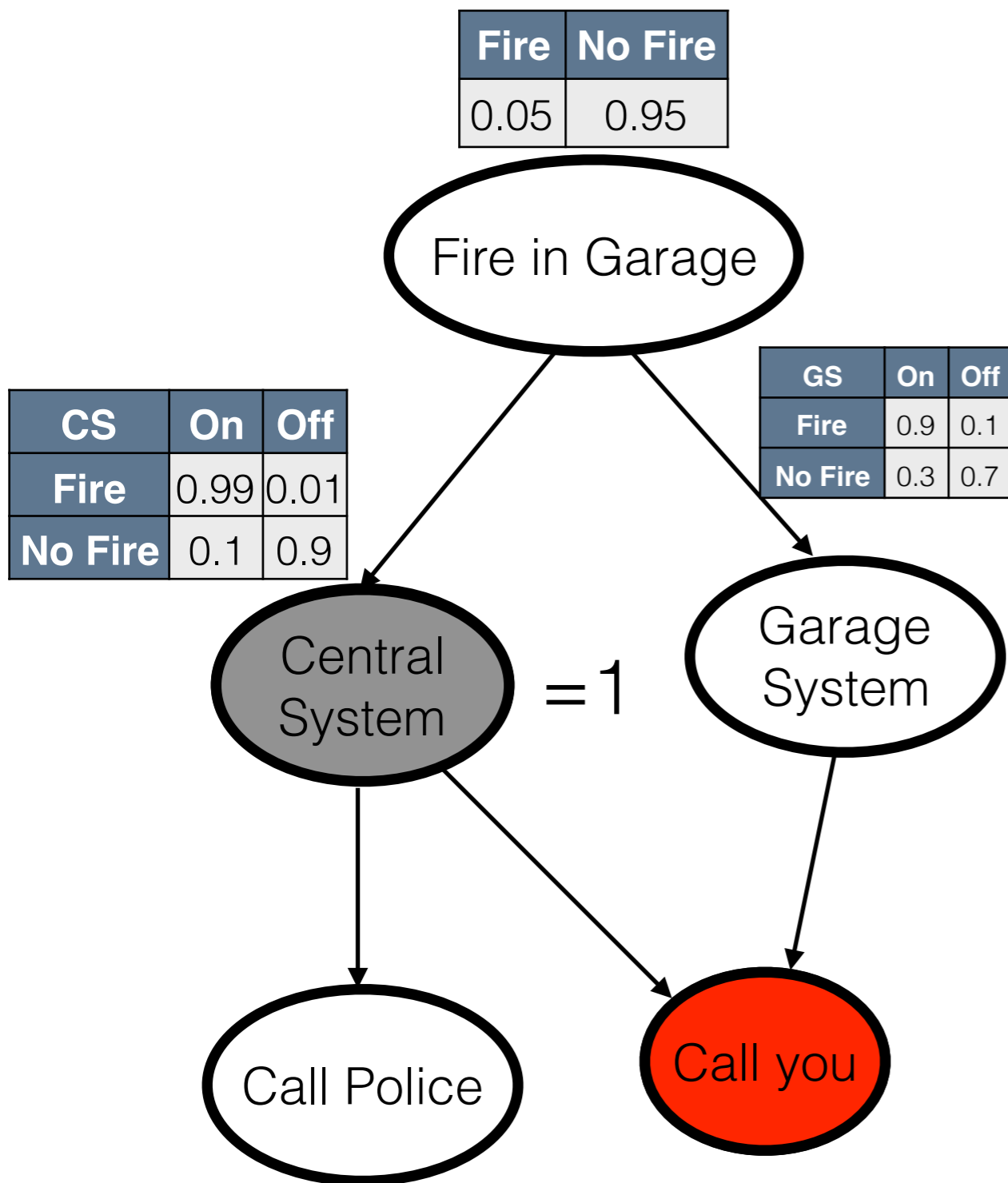
$$P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1) = \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(CS = 1)}$$

$$\text{weight} \propto \frac{P(F = 0, GS = 0, P = 1, Y = 0 | CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1) \times P(Y = 1 | GS = 0, CS = 1)}$$

$$\propto \frac{1}{P(CS = 1)} \cdot \frac{P(F = 0, GS = 0, P = 1, Y = 0, CS = 1)}{P(F = 0) \times P(GS = 0 | F = 0) \times P(P = 1 | CS = 1), P(Y = 0 | CS = 1, GS = 0)}$$

$$\propto \frac{P(CS = 1 | F = 0)}{P(CS = 1)} \propto P(CS = 1 | F = 0)$$

# IMPORTANCE SAMPLING



P	Call	no call
CS on	1	0
CS off	0.01	0.99

Y		Call	no
CS	GS	0.95	0.05
CS	GS	0.7	0.3
CS	GS	0.9	0.1
CS	GS	0.01	0.99

	F	CS	GS	P	Y	Weight
1	0	1	0	1	0	0.1
2	0	1	1	1	1	0.1
3	1	1	1	1	1	0.99
4	0	1	0	1	1	0.1
5	0	1	0	1	1	0.1
6	0	1	0	1	1	0.1
7	0	1	1	1	1	0.1
8	0	1	0	1	0	0.1
9	0	1	0	1	1	0.1
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# IMPORTANCE SAMPLING

Likelihood weighting:

Topologically sort variables (parents first children later)

For  $t = 1$  to  $n$  (number of samples)

Set  $w_t = 1$

For  $i = 1$  to  $N$  (number of variables)

If  $X_i$  is observed,

Set  $w_t \leftarrow w_t \cdot P(X_i = x_i | \text{Parents}(X_i) = \text{already sampled})$

Set  $x_i^t = x_i$  (the observed value)

Else, sample  $x_i^t \sim P(X_i | \text{Parents}(X_i) = \text{already sampled})$

End For

End For

Output,

$$P(\text{Variable} = \text{value} | \text{Observation}) = \frac{\sum_{t=1}^n w_t \mathbf{1}\{\text{Variable} = \text{value}\}}{\sum_{t=1}^n w_t}$$



# IMPORTANCE SAMPLING

- We really want to draw from distribution  $P$ .
- But we can only draw from distribution  $Q$  easily
- Trick:
  - Draw  $x_1, \dots, x_n \sim Q$
  - Re-weight each sample  $x_t$  by  $P(X = x_t)/Q(X = x_t)$

# IMPORTANCE SAMPLING

- Why does it work?

$$\mathbb{E}_{X \sim P}[f(X)] = \sum_x P(X = x)f(x)$$

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- Example:  $f(X) = \mathbf{1}\{X \in \text{Set}\}$ , then  $\mathbb{E}_{X \sim P}[f(X)] = P(X \in \text{Set})$

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- Example:  $f(X) = \mathbf{1}\{X \in \text{Set}\}$ , then  $\mathbb{E}_{X \sim P}[f(X)] = P(X \in \text{Set})$
- Hence, using importance weighted sampling,

$$P(X \in \text{Set}) \approx \frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \text{Set}\} \frac{P(X=x_t)}{Q(X=x_t)}$$

# IMPORTANCE SAMPLING



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$$P(1) = 0.9, \quad \forall j \neq 1 P(j) = 0.1/5$$

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What is  $P(\text{Set})$ ?

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What is  $P(\text{Set})$ ?

$$\frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \{2, 4, 6\}\} \frac{P(x_t)}{Q(x_t)} = \frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \{2, 4, 6\}\} \frac{0.1/5}{1/6}$$

# IMPORTANCE SAMPLING



$$P(1) = 0.9, \quad \forall j \neq 1 P(j) = 0.1/5$$



$$\forall j Q(j) = 1/6$$

$$\text{Set} = \{2, 4, 6\}$$

What is  $P(\text{Set})$ ?

$$\begin{aligned} \frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \{2, 4, 6\}\} \frac{P(x_t)}{Q(x_t)} &= \frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \{2, 4, 6\}\} \frac{0.1/5}{1/6} \\ &= 0.12 \times \frac{1}{n} \sum_{t=1}^n \mathbf{1}\{x_t \in \{2, 4, 6\}\} \approx 0.12 \times 0.5 = 0.06 \end{aligned}$$



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$$P(\text{Variable} = \text{value} | \text{Observation}) = \frac{\sum_{t=1}^n w_t \mathbf{1}\{\text{Variable} = \text{value}\}}{\sum_{t=1}^n w_t}$$