Programming Assignment 3

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5	Abstract			
6 7 8 9	In this programming assignment, we implemented a Bayesian Network and Rejection Sampling, Weighted Sampling, and Gibbs Sampling with a Markov Blanket.			
10	1 Con	tribution		
11 12 13	We worked collaboratively on the project at the same time. We split up typing up the data for this report, while the other person wrote up the calculations. We figured out the calculations by hand together as well as working together to code the sampling algorithms.			
14 15	2 Prob	oability Calculations		
16 17 18 19		Case 1 – P(J=1 B=0, E=0, E=1) = P(J and \sim B and E)/P(\sim		
20 21	(P(J ~B,E,M,A	$) + P(J \sim B,E,M,\sim A) + P(J \sim B,E,$	$\sim M,A) + P(J \sim B,E,\sim M,\sim A))/(P(\sim B)*P(E)) =$	
22 23 24	P(E) + P(J A)		+ $P(J \sim A) *P (M \sim A) * P(\sim A \sim B,E) * P(\sim B) * P(E) + P(J \sim A) * P(\sim M \sim A) * P(\sim A \sim B, E)$	
25 26	((0.9)*(0.7)*(0.29)*(0.999)*(0.002)+(0.05)*(0.01)*(0.71)*(0.999)*(0.002)+(0.9)*(0.3)*(0.29)*(0.999)*(0.002)+(0.05)*(0.99)*(0.71)*(0.999)*(0.002))/((0.999)*(0.002)) = 0.2965			
27		Case $2 - P(B=1 \mid J=1)$		
28	$P(B = 1 \mid J = 1)$	= P(B and J) / P(J) =		
29 30		$P(B \sim A, J, M) + P(B \sim B, A, J, M) + P(B E, A, M) + P(B E, A, M) + P(B E, A, M) + P(B E, M) + $	$(E,A,J,\sim M) + P(B \sim E,A,J,M) + P(B E,\sim A,J,\sim M)$ J, M)) / (P(J)) =	1
31 32 33 34 35	$ \begin{array}{l} (P(J \sim A) * P(\sim M \sim A) * P(\sim A B,\sim E) * P(B) * P(\sim E) + P(J \sim A) * P(M \sim A) * P(\sim A B,\sim E) * P(B) * P(\sim E) + P(J A) * P(\sim M A) * P(A B,\sim E) * P(B) * P(\sim E) + P(J A) * P(M A) * P(A B,\sim E) * P(B) * P(\sim E) + P(J \sim A) * P(\sim M \sim A) * P(\sim A B,E) * P(B) * P(E) + P(J \sim A) * P(M \sim A) * P(\sim A B,E) * P(B) * P(E) + P(J A) * P(M A) * P(\sim A B,E) * P(B) * P(E) + P(J A) * P(M A) * P(A B,E) * P(B) * P(E) + P(J A) * P(M A) * P(A B,E) * P(B) * P(E) + P(J A) * P(M A) * P(A B,E) * P(B) * P(E) + P(J A) * P(M A) * P(A B,E) * P(B) * P(E) + P(J A) * P(A B,E) * P(B) * P(E) + P(J A) * P(A B,E) * P(B) * P(E) + P(J A) * P(A B,E) * P(B) * P(E) + P(J A) * P(A B,E) * P(B) * P(E) + P(J A) * P(A B,E) * P(E) + P(E$)
36 37 38 39 40	94)*(0.001)*(0 02)+(0.05)*(0.	(0.998) + (0.9)*(0.7)*(0.94)*(0.00)	f(0.1)*(0.06)*(0.001)*(0.998)+(0.9)*(0.3)*(0. 1)*(0.998)+(0.05)*(0.99)*(0.05)*(0.001)*(0.0 9)*(0.3)*(0.95)*(0.001)*(0.002)+(0.9)*(0.7)*(368	

Sampling Results

3.1 Test Case 1 - P(J=1 | B=0, E=1)

For each case, it took about 1,000 trials to get a sample close to the actual result.

Sampling

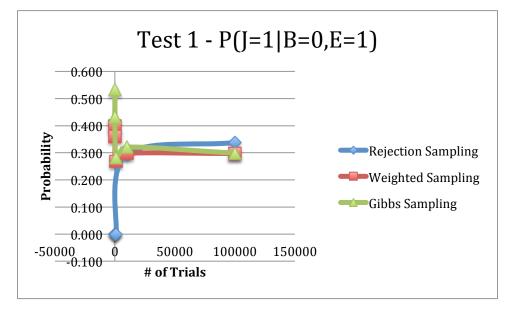
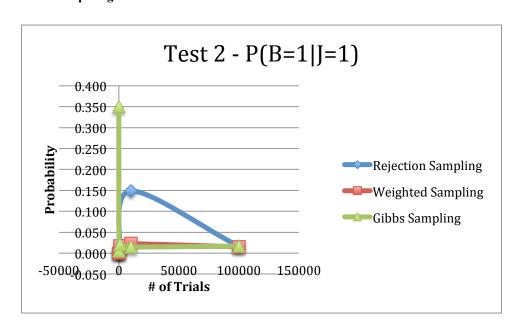


Figure 1: Test 1

Test Case $2 - P(B=1 \mid J=1)$ 3.2

For each case, it took about 10,000 trials to get a sample close to the actual result.

3.2.1 Sampling



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Figure 2: Test 2

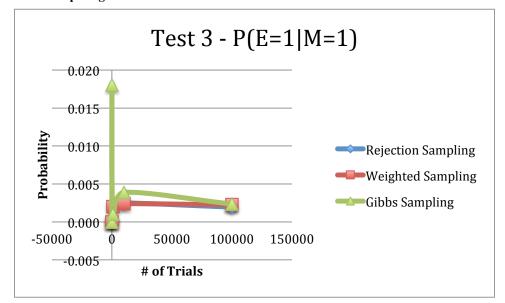
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3.3 Test Case $3 - P(E=1 \mid M=1)$

60 For each case, it took about 1,000 trials to get a sample close to the actual result.

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Sampling



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Figure 3: Test 3

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Gibbs Sampling 4

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- evidence variables E is set to given values
- non-evidence variables Z, all variables not in E, non-evidence variables are initialized to random values
- query variables Z
- Algorithm:

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for 1 to N
 for each zi in Z
    assign zi based on P(zi \mid mb(zi)) = P(zi \mid every other node)
    look at value of q
    if(Q = q){
      numTimesq + +
    numStateChanges = N * |Z|
```

return numTimesq/numStateChanges

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4.1 Markov Blanket

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      Markov Blanket (mb) of X includes:
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- 78 1) parents(X)
 - 2) children(X)
- 79 80 3) parents(children(X))