ex6.7:
The complexity of computing the normalisation constant:
$T = O(2^{2n-1} \times (n-1)) = O(n \cdot 2^{2n})$

The normalisation constant $log_n = 188.4774$ (The code for Q6.7 is in Appendix 'computeNormalisationConstant.m')

ex6.9
1.
The marginals of the symptoms is showed below, and the code for this question is is in Appendix 'q1_JT_diseaseNet.m').
P(s1=1) = 0.44183
P(s2=1) = 0.45668
P(s3=1) = 0.44141
P(s4=1) = 0.49127
P(s5=1) = 0.49389
P(s6=1) = 0.65748
P(s7=1) = 0.50456
P(s8=1) = 0.26869
P(s9=1) = 0.64908
P(s10=1) = 0.49074
P(s11=1) = 0.42255
P(s12=1) = 0.4291
P(s13=1) = 0.54502
P(s14=1) = 0.63296
P(s15=1) = 0.42954
P(s16=1) = 0.45879
P(s17=1) = 0.42756
P(s18=1) = 0.40426
P(s19=1) = 0.58209
P(s20=1) = 0.58959
P(s21=1) = 0.76127
P(s22=1) = 0.69559
P(s23=1) = 0.5087
P(s24=1) = 0.41996
P(s25=1) = 0.35194
P(s26=1) = 0.38961
P(s27=1) = 0.32597
P(s28=1) = 0.46962
P(s29=1) = 0.52287
P(s30=1) = 0.71731
P(s31=1) = 0.5242
P(s32=1) = 0.3537
P(s33=1) = 0.51268
P(s34=1) = 0.5294
P(s35=1) = 0.38575

P(s36=1) = 0.48909
P(s37=1) = 0.6336
P(s38=1) = 0.5896
P(s39=1) = 0.42316
P(s40=1) = 0.52823

2.

Since each symptom connects to 3 parent diseases, which is fixed, we can calculate P(si=1) by the basic Bayes' Rule:

$p(si = 1, pa(s_i)) = p(si|pa(s_i)) \cdot p(pa(si))$ & $p(s_i = 1) = \sum_{pa(s_i)} p(si = 1, pa(s_i))$

and the result showed below is the same with that using the Juntion Tree, and the code for this is 'q2_efficient_diseaseNet.m':

P(s1=1) = 0.44183
P(s2=1) = 0.45668
P(s3=1) = 0.44141
P(s4=1) = 0.49127
P(s5=1) = 0.49389
P(s6=1) = 0.65748
P(s7=1) = 0.50456
P(s8=1) = 0.26869
P(s9=1) = 0.64908
P(s10=1) = 0.49074
P(s11=1) = 0.42255
P(s12=1) = 0.4291
P(s13=1) = 0.54502
P(s14=1) = 0.63296
P(s15=1) = 0.42954
P(s16=1) = 0.45879
P(s17=1) = 0.42756
P(s18=1) = 0.40426
P(s19=1) = 0.58209
P(s20=1) = 0.58959
P(s21=1) = 0.76127
P(s22=1) = 0.69559
P(s23=1) = 0.5087
P(s24=1) = 0.41996
P(s25=1) = 0.35194
P(s26=1) = 0.38961
P(s27=1) = 0.32597
P(s28=1) = 0.46962
P(s29=1) = 0.52287
P(s30=1) = 0.71731
P(s31=1) = 0.5242
P(s32=1) = 0.3537

P(s33=1) = 0.51268
P(s34=1) = 0.5294
P(s35=1) = 0.38575
P(s36=1) = 0.48909
P(s37=1) = 0.6336
P(s38=1) = 0.5896
P(s39=1) = 0.42316
P(s40=1) = 0.52823

By this method, the complexity to calculate marginals is $T = O(2^3)$. Using Junction Tree, since each si has three parents d, a clique contains at least 4 variables, leading to the minimal computational complexity $O(2^3)$, but it can be larger. Therefore, the latter mathod is more efficient.

3.
the marginal for all diseases is showed below, and its code is 'q3_computeDisease.m', which is in the Appendix.
p(d1=1|s1:10)= 0.029776
p(d2=1|s1:10)= 0.38176
p(d3=1|s1:10)= 0.95423
p(d4=1|s1:10)= 0.39664
p(d5=1|s1:10)= 0.49647
p(d6=1|s1:10)= 0.43515
p(d7=1|s1:10)= 0.18749
p(d8=1|s1:10)= 0.70118
p(d9=1|s1:10)= 0.043127
p(d10=1|s1:10)= 0.61031
p(d11=1|s1:10)= 0.28732
p(d12=1|s1:10)= 0.48983
p(d13=1|s1:10)= 0.8996
p(d14=1|s1:10)= 0.61956
p(d15=1|s1:10)= 0.92048
p(d16=1|s1:10)= 0.7061
p(d17=1|s1:10)= 0.20125
p(d18=1|s1:10)= 0.90849
p(d19=1|s1:10)= 0.86497
p(d20=1|s1:10)= 0.88393

ex6.10
1.
[[[[[[[ex6.10_1.jpg]]]]]]]

Since all the variables are binary, the computational complexity of computing $p(x_T)$ is $O(2^T)$

2.

$p(x_T) = \sum_{x_1} p(x_1) \cdot \sum_{x2} p(x_2|x_1) \cdot \ldots \cdot \sum_{x_T} p(x_T|x_{T-1}) \cdot \sum_y p(y|x_1, x_2, \ldots, x_T)$

By passing messages in this way, the complexity of computing $p(x_T)$ is $O(2 \times T) = O(T)$