Introduction

A powerful framework for representing complex domains using probability distributions is probabilistic graphical model, with numerous applications in machine learning, computer vision, natural language processing and computational biology . among those different way of representing a graph we are try to implement Bayesian network and Markov networks in our graph with their conversion. Bayesian networks are directed graphical models that represent the joint distribution of a set of random variables. It uses nodes to represent the variable and the direct dependencies between variables and it encodes a set of conditional Independence's relations between variables. it accepts the principle of DAG and Independence's. similar to the Bayesian network, in the sense of Markov network, we can represent all the random variables in the form of nodes, but we represent the dependencies or interaction between these random variables with an undirected edge. in this assignment we will try to implement using library and from scratch.

Scenario

Network that will model the performance of a student on an exam. Let's assume that we're creating a Network that will model the Letter (L) of a student on his Grade. The Grade(G) will depend on:Difficulty of exam (D)-This is a discrete variable that can take two values, (difficult, easy) and the student intelligence(I)- discrete variable that can take two values (high, low). The Intelligence of the student will depend on the SAT(S) exam . The Grade will intern predict whether or not he/she will get admitted Letter to a university. The IQ will also predict the aptitude score (s) of the student.

Approach's

In the Bayesian network, we had a CPD associated with every node but in Markov network they don't have any directional influence or a parent-children relationship.so, instead of using CPDs, Markov network uses a more symmetric representation called factor.this Factor helps to know the maximal clique.

To construct a Markov network from a distribution, the mere concept of I-Maps is not enough. As in the case of Bayesian networks, a fully connected graph has no independence conditions and, hence, it can be an I-Map of any probability distribution. Therefore, we introduce the concept of the minimal I-Map in Markov networks as well. To construct a minimal I-Map, we can use the local Independencie conditions that we defined in the previous section.

Bayesian-network-Markov-Network-Conversion

when we convert Bayesian to Markov network two main perspectives are considered:

- From the perspective of **parameterization—probability distribution**.
  If we see the parameterization of the Bayesian network, we can also think of it as a parameterization of a Gibbs distribution. We can think of a CPD over a variable X to be a factor with a scope. This set of factors defines a Gibbs distribution with the partition function being equal to 1 or normalized.
- From the perspective of **independencie constraints—moralization.**
  Find out what kind of undirected graph would be an I-Map for this Gibbs distribution.most of the time Replace all the directed edges between the nodes with undirected edges. Add additional undirected edges between nodes that are parents of the node.

Markov-network-Bayesian-Network-Conversion

- From the perspective of **independencie constraints—immoralities.**
  From the perspective of independencie, Markov network involves pairwise and local independecies. so, To convert a Markov models to a Bayesian model requires us to add edges to the network to make it chordal. This process is known as triangulation.

Challenge

Identifying Independence's from Markov network to Bayesian network And also representation of factors into CPD.

Unlike CPDs, there is no notion of directionality or causal relationship among random variables in factors. Due to this, We can see that the moral graph of a Bayesian model loses some information between difficulty and intelligence in regarding the independencies and also which fails the concept of DAG in Bayesian network representation as we can see from the last figure result which forms a loop or cycle.

Result And Conclusion

Bayesian network case we need to D-separation which may require checking all possible paths to show conditional independence(huge problem with too many variables).Checking conditional independencies in Markov network, which amounts to graph separation, and which is relatively simpler. Problem with BN's is that there may be cases when you do not know and cannot estimate the actual dependence between your variables. In those cases, introducing independencies introduces a strong bias when modeling the joint distribution, thus it may lead to a difficult learning and prediction problem. On the other hand, MRF builds distributions by joint factors and does not assume any false independencies. The effect of independencies of course grows with the dimensionality of your data. As a whole, when independencies are not exact, using MRF is a safe choice.

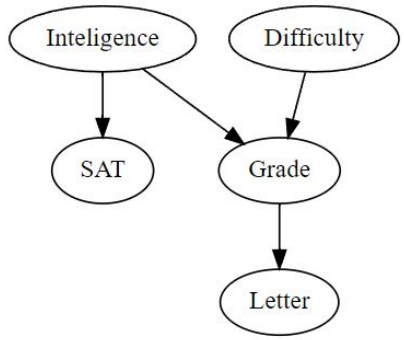

Figure 1: Bayesian-Network

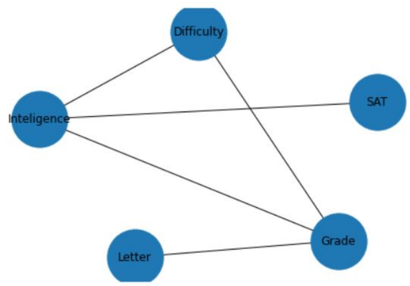

Figure 2: Bayesian network-TO-Markov-Network

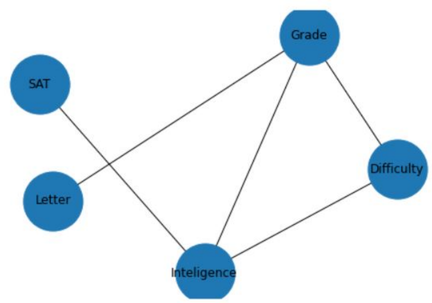

Figure 3: Markov-Network

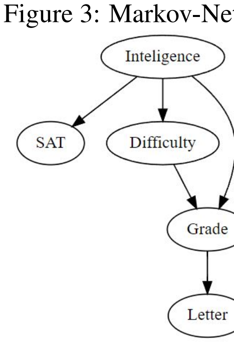

Figure 4: Markov-Network-To-Bayesian-network