Exp-1

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Aim: To Implement Inferencing with Bayesian Network in Python

Theory:

Bayesian Belief Networks (BBNs) are a key tool in Artificial Intelligence for representing and reasoning under uncertainty using probabilistic graphical models. A BBN consists of a **Directed Acyclic Graph (DAG)** where each node represents a random variable and each edge represents conditional dependency.

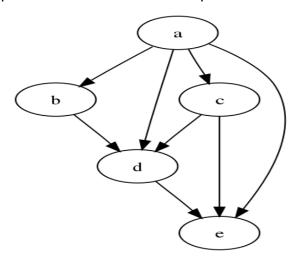
A Bayesian Network enables inferencing by using **Conditional Probability Tables (CPTs)** and algorithms like **Variable Elimination** to compute the probability of a variable given known evidence.

Applications of Bayesian Belief Networks:

- 1. **Medical Diagnosis** Predict diseases based on symptoms
- 2. Fault Diagnosis Detect faults in machines or IT systems
- 3. **Decision Support Systems** Aid business/environmental decisions
- 4. Al & Robotics Path planning and decision-making in uncertainty
- 5. Speech & Image Recognition NLP and computer vision tasks
- 6. **Bioinformatics** Gene expression analysis
- 7. **Finance** Risk assessment and portfolio management
- 8. Environmental Science Ecosystem modeling
- 9. **Forensics** Evidence-based scenario evaluation
- 10. **Education** Adaptive learning systems

Structure of Bayesian Network:

• DAG: Represents variables and their dependencies



• CPT: Specifies the probability distribution for each node given its parents

$$P(A \mid B) = rac{P(A \cap B)}{P(B)}$$

• Joint Probability Distribution:

```
P(X_1, X_2, ..., X_n) = \prod_{i=1}^n P(X_i \mid \operatorname{Parents}(X_i))
```

Test Cases:

- **Example 1:** P(Buy House,Marry | Salaried=1,Handsome=0)
- Example 2: P(Buy House, Marry | Salaried=0, Handsome=0)
- **Example 3:** P(Buy House, Marry | Salaried=0, Handsome=1)

Code Implementation (Python):

```
from pgmpy, models import DiscreteBayesianNetwork
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import VariableElimination
# Define the Bayesian Network structure
model = DiscreteBayesianNetwork([
  ('Salaried', 'Marry'),
  ('Handsome', 'Marry'),
  ('Marry', 'Buy House')
])
# Define the CPDs
cpd_salaried = TabularCPD(variable='Salaried', variable_card=2, values=[[0.2], [0.8]])
cpd_handsome = TabularCPD(variable='Handsome', variable_card=2, values=[[0.35], [0.65]])
cpd_marry = TabularCPD(variable='Marry', variable_card=2,
            values=[[0.05, 0.32, 0.47, 1.0],
                 [0.95, 0.68, 0.53, 0.0]]
            evidence=['Salaried', 'Handsome'],
            evidence_card=[2, 2])
cpd_buy_house = TabularCPD(variable='Buy House', variable_card=2,
               values=[[0.08, 0.79],
                   [0.92, 0.21]],
               evidence=['Marry'],
               evidence_card=[2])
# Add CPDs to the model
model.add_cpds(cpd_salaried, cpd_handsome, cpd_marry, cpd_buy_house)
assert model.check_model()
# Inference
inference = VariableElimination(model)
# Query example
query = inference.query(variables=['Buy House', 'Marry'],
             evidence={'Salaried': 1, 'Handsome': 0},
             joint=True)
print(query)
```

Output:

Test Case 1: Salaried=1, Handsome=0			
Buy House	Marry	phi(Buy House,Marry)	
Buy House(0)	Marry(0)	 0.0376	
Buy House(0)	Marry(1)	0.4187	
Buy House(1)	Marry(0)	0.4324	
Buy House(1) +			

Test Case 2: Salaried=0, Handsome=0			
Buy House	Marry	phi(Buy House,Marry)	
Buy House(0)	Marry(0)	0.0040	
Buy House(0)	Marry(1)	0.7505	
Buy House(1)	Marry(0)	0.0460	
Buy House(1)			

Test Case 3: Salaried=0, Handsome=1				
•		phi(Buy House,Marry) 		
Buy House(0)	Marry(0)	0.0256		
Buy House(0)	Marry(1)	0.5372		
Buy House(1)	Marry(0)	0.2944		
Buy House(1)				

Conclusion:

We have successfully implemented **inferencing with a Bayesian Network** in Python using the pgmpy library and verified its outputs on different inputs using variable elimination.