

Bayesian Network Model for Credit Worthiness

This script builds a Bayesian Network model to predict credit worthiness based on several factors like income, assets, debt ratios, and payment history.

```
In [52]: # Import necessary libraries
import pandas as pd
import bnlearn
from pgmpy.factors.discrete import TabularCPD

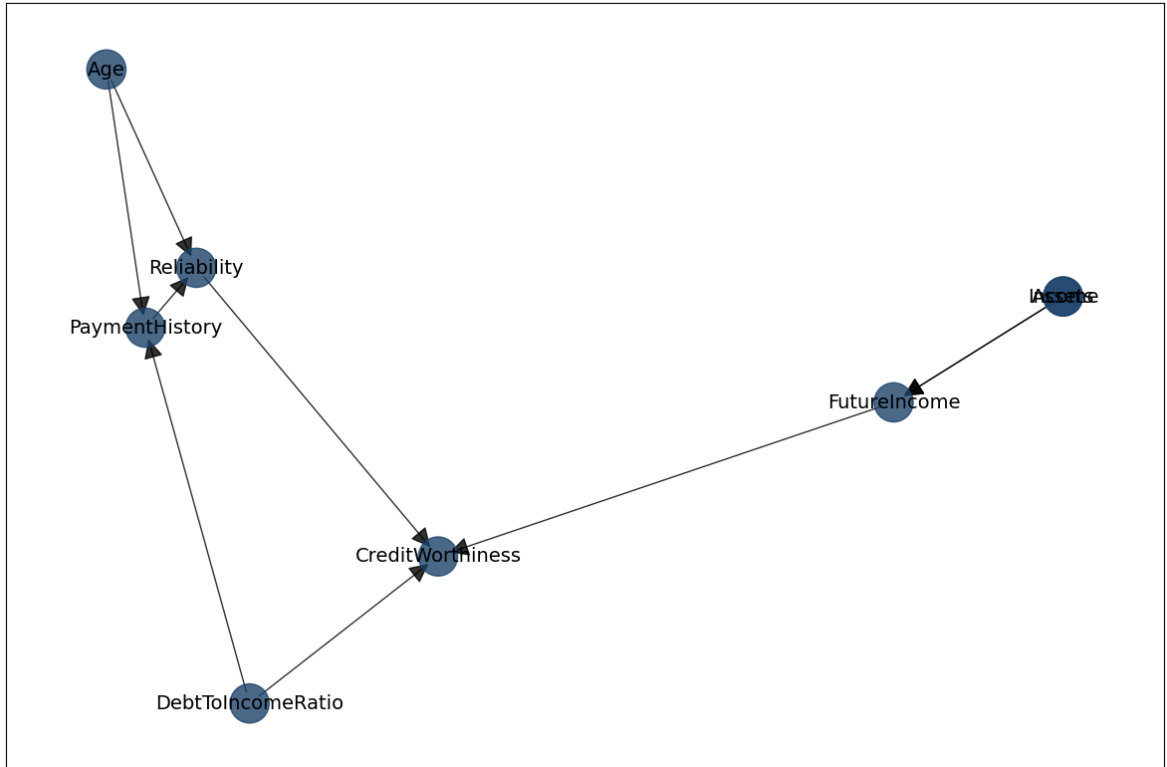
# Define nodes (variables) for the Bayesian Network
nodes = ['Income', 'PaymentHistory', 'Age', 'DebtToIncomeRatio', 'Assets', 'Reli

# Define edges (relationships) based on domain knowledge
edges = [
    ('PaymentHistory', 'Reliability'),
    ('Age', 'Reliability'),
    ('Age', 'PaymentHistory'),
    ('DebtToIncomeRatio', 'PaymentHistory'),
    ('Income', 'Assets'),
    ('Assets', 'FutureIncome'),
    ('Income', 'FutureIncome'),
    ('Reliability', 'CreditWorthiness'),
    ('FutureIncome', 'CreditWorthiness'),
    ('DebtToIncomeRatio', 'CreditWorthiness')
]

# Create the Bayesian Network structure (DAG)
DAG = bnlearn.make_DAG(edges)

bnlearn.plot(DAG)
```

```
[bnlearn] >bayes DAG created.
[bnlearn] >Set node properties.
[bnlearn] >Set edge properties.
[bnlearn] >Plot based on Bayesian model
```



```

Out[52]: {'fig': <Figure size 1500x1000 with 1 Axes>,
'ax': <Figure size 1500x1000 with 1 Axes>,
'pos': {'PaymentHistory': array([-0.50941915,  0.11031963]),
'Reliability': array([-0.43985395,  0.28725419]),
'CreditWorthiness': array([-0.11076964, -0.56557964]),
'Age': array([-0.56226778,  0.87328955]),
'DebtToIncomeRatio': array([-0.36734653, -1.          ]),
'Income': array([0.74011895, 0.20251795]),
'Assets': array([0.74011895, 0.20251795]),
'FutureIncome': array([ 0.50941915, -0.11031963])},
'G': <networkx.classes.digraph.DiGraph at 0x1a1e8d19b50>,
'node_properties': {'PaymentHistory': {'node_color': '#1f456e',
'node_size': 800},
'Reliability': {'node_color': '#1f456e', 'node_size': 800},
'Age': {'node_color': '#1f456e', 'node_size': 800},
'DebtToIncomeRatio': {'node_color': '#1f456e', 'node_size': 800},
'Income': {'node_color': '#1f456e', 'node_size': 800},
'Assets': {'node_color': '#1f456e', 'node_size': 800},
'FutureIncome': {'node_color': '#1f456e', 'node_size': 800},
'CreditWorthiness': {'node_color': '#1f456e', 'node_size': 800}},
'edge_properties': {('PaymentHistory', 'Reliability'): {'color': '#000000',
'weight': 1},
('Reliability', 'CreditWorthiness'): {'color': '#000000', 'weight': 1},
('Age', 'PaymentHistory'): {'color': '#000000', 'weight': 1},
('Age', 'Reliability'): {'color': '#000000', 'weight': 1},
('DebtToIncomeRatio', 'PaymentHistory'): {'color': '#000000', 'weight': 1},
('DebtToIncomeRatio', 'CreditWorthiness'): {'color': '#000000', 'weight': 1},
('Income', 'Assets'): {'color': '#000000', 'weight': 1},
('Income', 'FutureIncome'): {'color': '#000000', 'weight': 1},
('Assets', 'FutureIncome'): {'color': '#000000', 'weight': 1},
('FutureIncome', 'CreditWorthiness'): {'color': '#000000', 'weight': 1}}}

```

Run the following code for more interactive representation

```
In [53]: # bnlearn.plot(DAG, interactive=True, params_interactive = {'height':'800px', 'w
```

Bayesian Network: Conditional Probability Distributions (CPDs)

In this Bayesian network model, we define Conditional Probability Distributions (CPDs) to represent the relationships between various parameters that influence **creditworthiness**. The CPDs capture the likelihood of various states for each node based on its dependencies.

Parameter Levels

We define several parameters, each with a set of discrete levels. These are used to model different aspects of a client's financial status and their relationship with creditworthiness.

Parameters:

- **Income**
Levels:
0: high
1: medium
2: low
- **Assets**
Levels:
0: high
1: medium
2: low
- **Ratio of debts to income**
Levels:
0: high
1: low
- **Payment history**
Levels:
0: excellent
1: acceptable
2: unacceptable
- **Age**
Levels:
0: 16-21
1: 22-64
2: over 65
- **Client reliability**
Levels:

0: reliable

1: unreliable

- **Future income**

Levels:

0: promising

1: not promising

- **Ratio of debts to future income**

Levels:

0: low

1: high

Parameter Dependencies

In this model, we also capture how different parameters influence one another. These dependencies help structure the Bayesian Network and inform the probability distributions of the network's nodes.

Key Dependencies:

1. **Payment History**

- The better the payment history, the more likely the person is to be reliable.

2. **Age and Reliability**

- The older the person, the more likely they are to be reliable.
- Older people tend to have excellent payment histories.

3. **Debts to Income Ratio and Payment History**

- People with a high ratio of debts to income rarely have a good payment history.

4. **Income and Assets**

- The higher the income, the more likely the person has significant assets.

5. **Income, Assets, and Future Income**

- The greater the person's assets and income, the more likely they will have high future income.

6. **Reliability and Creditworthiness**

- More reliable people usually have higher creditworthiness.

7. **Future Income, Debts to Income Ratio, and Creditworthiness**

- People with promising future income and those with a low ratio of debts to income tend to have higher creditworthiness than others.

```
In [ ]: # CPD for 'Income' with three levels: high, medium, low
cpd_income = TabularCPD(variable='Income', variable_card=3, values=[[0.5], [0.35]

# CPD for 'PaymentHistory', dependent on 'Age' and 'DebtToIncomeRatio'
```

```

cpd_payment_history = TabularCPD(
    variable='PaymentHistory', variable_card=3,
    values=[[0.2, 0.25, 0.05, 0.25, 0.01, 0.1],
            [0.35, 0.35, 0.15, 0.3, 0.19, 0.3],
            [0.45, 0.4, 0.8, 0.45, 0.8, 0.6]],
    evidence=['Age', 'DebtToIncomeRatio'], evidence_card=[3, 2]
)

# CPD for 'Age' with three levels: 16-21, 22-64, over 65
cpd_age = TabularCPD(variable='Age', variable_card=3, values=[[0.2], [0.3], [0.5]

# CPD for 'DebtToIncomeRatio' with two levels: high, low
cpd_debt_to_income_ratio = TabularCPD(variable='DebtToIncomeRatio', variable_car

# CPD for 'Assets', dependent on 'Income'
cpd_assets = TabularCPD(
    variable='Assets', variable_card=3,
    values=[[0.7, 0.8, 0.1], [0.2, 0.15, 0.05], [0.1, 0.05, 0.85]],
    evidence=['Income'], evidence_card=[3]
)

# CPD for 'Reliability', dependent on 'PaymentHistory' and 'Age'
cpd_reliability = TabularCPD(
    variable='Reliability', variable_card=2,
    values=[[0.95, 0.9, 0.85, 0.75, 0.7, 0.6, 0.65, 0.6, 0.55],
            [0.05, 0.1, 0.15, 0.25, 0.3, 0.4, 0.35, 0.4, 0.45]],
    evidence=['PaymentHistory', 'Age'], evidence_card=[3, 3]
)

# CPD for 'FutureIncome', dependent on 'Income' and 'Assets'
cpd_future_income = TabularCPD(
    variable='FutureIncome', variable_card=2,
    values=[[0.65, 0.6, 0.55, 0.75, 0.7, 0.6, 0.95, 0.9, 0.85],
            [0.35, 0.4, 0.45, 0.25, 0.3, 0.4, 0.05, 0.1, 0.15]],
    evidence=['Income', 'Assets'], evidence_card=[3, 3]
)

# CPD for 'CreditWorthiness', dependent on 'Reliability', 'FutureIncome', and 'D
cpd_credit_worthiness = TabularCPD(
    variable='CreditWorthiness', variable_card=2,
    values=[[0.99, 0.8, 0.8, 0.4, 0.8, 0.4, 0.4, 0.01],
            [0.01, 0.2, 0.2, 0.6, 0.2, 0.6, 0.6, 0.99]],
    evidence=['Reliability', 'FutureIncome', 'DebtToIncomeRatio'], evidence_card
)

# Finalize the DAG with CPDs
DAG = bnlearn.make_DAG(DAG, CPD=[cpd_income, cpd_payment_history, cpd_age, cpd_d

```

```

In [61]: # Example 1: A 20-year-old with an excellent payment history
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Age'

# Example 2: High income, high assets, and low debt-to-income
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Inco

# Example 3: 70-year-old with medium assets and low income
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Age'

# Example 4: Promising future income and low debt-to-income ratio
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Futu

```

```
# Example 5: 22-year-old with low income, low assets, and excellent payment hist  
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Age'  
  
# Example 6: 40-year-old with high income, acceptable payment history  
print(bnlearn.inference.fit(DAG, variables=['CreditWorthiness'], evidence={'Age'
```

```

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]
+-----+-----+-----+
|      | CreditWorthiness |      p |
+=====+=====+=====+
|  0  |           0 | 0.672994 |
+-----+-----+-----+
|  1  |           1 | 0.327006 |
+-----+-----+-----+

+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) |           0.6730 |
+-----+-----+-----+
| CreditWorthiness(1) |           0.3270 |
+-----+-----+-----+

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]
+-----+-----+-----+
|      | CreditWorthiness |      p |
+=====+=====+=====+
|  0  |           0 | 0.823172 |
+-----+-----+-----+
|  1  |           1 | 0.176828 |
+-----+-----+-----+

+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) |           0.8232 |
+-----+-----+-----+
| CreditWorthiness(1) |           0.1768 |
+-----+-----+-----+

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]
+-----+-----+-----+
|      | CreditWorthiness |      p |
+=====+=====+=====+
|  0  |           0 | 0.754379 |
+-----+-----+-----+
|  1  |           1 | 0.245621 |
+-----+-----+-----+

+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) |           0.7544 |
+-----+-----+-----+
| CreditWorthiness(1) |           0.2456 |
+-----+-----+-----+

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]
+-----+-----+-----+
|      | CreditWorthiness |      p |
+=====+=====+=====+
|  0  |           0 | 0.917657 |
+-----+-----+-----+
|  1  |           1 | 0.0823425 |
+-----+-----+-----+

```

```

+----+-----+-----+
+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) | 0.9177 |
+-----+-----+-----+
| CreditWorthiness(1) | 0.0823 |
+-----+-----+-----+

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]

+----+-----+-----+
| | CreditWorthiness | p |
+=====+=====+=====+
| 0 | 0.672543 |
+-----+-----+-----+
| 1 | 0.327457 |
+-----+-----+-----+

+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) | 0.6725 |
+-----+-----+-----+
| CreditWorthiness(1) | 0.3275 |
+-----+-----+-----+

[bnlearn] >Variable Elimination.
[bnlearn] >Warning: variable(s) [None] does not exists in DAG.
[bnlearn] >Data is stored in [query.df]

+----+-----+-----+
| | CreditWorthiness | p |
+=====+=====+=====+
| 0 | 0.810688 |
+-----+-----+-----+
| 1 | 0.189312 |
+-----+-----+-----+

+-----+-----+-----+
| CreditWorthiness | phi(CreditWorthiness) |
+=====+=====+=====+
| CreditWorthiness(0) | 0.8107 |
+-----+-----+-----+
| CreditWorthiness(1) | 0.1893 |
+-----+-----+-----+

```