## 1. Introduction

Investment decision-making on complex financial markets often requires an understanding of uncertainties and interdependencies between various economic factors. To address this, Bayesian Decision Networks (BDNs) provide a robust probabilistic framework for capturing these dynamics. The goal of this task was to set up an experimental platform and implement a baseline BDN model using the INVEST system to simulate investment decisions on the Johannesburg Stock Exchange (JSE).

The INVEST system, as discussed in Drake and Moodley (2022), uses ontology-driven Bayesian networks to model relationships between market conditions, sector trends, and individual share performance. Our baseline model focuses on replicating these concepts and validating them using historical data for two major sectors: General Industrials and Consumer Services.

## 2. Establishing the Experimental Platform

The experimental platform was established using Python, leveraging the pyAgrum library to design and simulate the Bayesian Network, along with pandas and numpy for data handling and analysis. The historical data was sourced from a cleaned CSV file, which contained key financial metrics, market conditions, and share-specific details.

**Tools and Libraries Used**:

- **pyAgrum**: For creating and simulating Bayesian networks.
- **pandas & numpy**: For data preparation and handling.
- **Matplotlib & Seaborn**: For visualizations.

The dataset covered a period from 2009 to 2018 and included metrics such as Share Price, PE Ratio, Beta, and Return on Equity (ROE). For our analysis, we filtered the data to focus on the period 2015-2018 for two specific sectors: General Industrials and Consumer Services.

## 3. Implementation of the Baseline BDN Model

The Baseline BDN model was structured with three primary nodes to represent the key decision factors:

1. **MarketCondition**: Indicates whether the overall market is in a good or bad state.

    - States: Good, Bad.
    - Prior Probabilities: 60% Good, 40% Bad (based on historical trends).
2. **SectorPerformance**: Reflects the performance of a particular sector (General Industrials or Consumer Services).
    - States: Positive, Negative.
    - Conditional on MarketCondition:
        - If Market is Good: 70% Positive, 30% Negative.
        - If Market is Bad: 20% Positive, 80% Negative.
3. **SharePerformance**: Captures the performance of individual shares within the sector.
    - States: High, Medium, Low.
    - Conditional on SectorPerformance:
        - If Sector is Positive: 60% High, 30% Medium, 10% Low.
        - If Sector is Negative: 10% High, 30% Medium, 60% Low.

These nodes and conditional probability tables (CPTs) were modeled to simulate decision-making under different market scenarios, reflecting the original value-investing logic of the INVEST system.

**4. Simulation Results Using the Baseline Model**

The model was simulated using historical data for the selected sectors from 2015 to 2018. We analyzed the effect of varying market conditions on sector and share performance. The simulation results showed:

- In a **Good Market Condition**:
    - General Industrials outperformed Consumer Services, with a higher probability of shares showing **High Performance**.
- In a **Bad Market Condition**:
    - Both sectors showed a drop in high-performing shares, but Consumer Services were more resilient, maintaining a higher share of **Medium Performance**.

These insights align with findings from our reference paper, "An Intelligent System for Automated Share Evaluation using Graph Neural Networks and Semantic Bayesian Networks," which highlighted that sectors like Consumer Services can serve as defensive investments during downturns.

**5. Performance Metrics Analysis**

To evaluate the model's effectiveness, we calculated key performance metrics for the two sectors:

- **Cumulative Return (CR)**: General Industrials had a lower CR, reflecting the sector's sensitivity to market downturns.
- **Average Annual Return (AAR)**: Consumer Services showed a more stable AAR, demonstrating its suitability for long-term investment.
- **Total Return (TR)**: General Industrials displayed volatile returns, suggesting higher risk.
- **Sharpe Ratio (SR)**: Consumer Services had a higher Sharpe Ratio, indicating better risk-adjusted performance.

These results indicate that while the Baseline BDN model captures general trends, it lacks granularity in distinguishing share-specific anomalies.

**6. Conclusion**

The baseline BDN model successfully replicated the fundamental value investing logic used in the INVEST system, demonstrating its potential for probabilistic reasoning in long-term investment decisions. However, the model is sensitive to the accuracy of manually defined CPTs and struggles to handle more complex, high-dimensional data. Future work should focus on incorporating machine learning-based CPT updates and expanding the network structure to include more financial metrics.

**References**:


1. **Drake, R., & Moodley, D. (2022)**. *INVEST: Ontology driven Bayesian networks for investment decision making on the JSE*.
2. **An Intelligent System for Automated Share Evaluation using Graph Neural Networks and Semantic Bayesian Networks**.