Bayesian Network Analysis of Maritime Accidents

1. Introduction: This report investigates the causal relationships influencing maritime accidents in New Zealand between July 2022 and June 2024 by applying Bayesian network structure learning and inference. Using a combined dataset of maritime accident reports and local weather conditions, we explore and compare recent Bayesian structure learning algorithms to model dependencies between vessel features, accident outcomes, and environmental conditions. The best-performing model is then used for probabilistic reasoning and structural analysis.

2. Data Summary and Preprocessing: The accident data used in this study was obtained from *Maritime New Zealand*, while the weather data was sourced from *Visual Crossing*, a weather data platform. To collect the weather information dynamically across different dates and locations, Python's Selenium library was employed for web scraping, allowing for flexible and automated retrieval.

During preprocessing, "NULL" values were replaced with NaN, and relevant columns were converted to categorical types. The datasets were merged using a left join on latitude, longitude, and event date. Rows missing key weather or location information were removed. Categorical labels were cleaned, and continuous variables such as temperature, precipitation, wind, gross tonnage, and vessel length were discretized using equal-width binning. Outliers were filtered, and rows with sparse missing values were dropped to ensure a clean, categorical dataset suitable for Bayesian network modeling.

The final dataset contains around 450 records and includes key accident-related variables like *What Happened*, *Where Happened*, *Sector*, *Number of Injured Persons*, and *Safety System*. It also covers vessel metrics such as *Vessel Class*, *GT_bin*, and *LO_bin*, along with discretized weather features: *MaxTemp_bin*, *MinTemp_bin*, *Precip_bin*, and *Wind_bin*.

Descriptive visualizations highlighted trends such as risk concentration in domestic commercial sectors, accident prevalence in harbours, and common safety systems (e.g., "ISM", "MOSS").

3. Methodology Used for Bayesian Network Learning: We applied Bayesian structure learning using the bnlearn R package and compared four algorithms, including recent methods supported by literature.

Algorithms Used:

1. Tabu Search (BIC scoring): A score-based structure learning algorithm that uses Bayesian Information Criterion (BIC) for model evaluation. It maintains a tabu list to prevent revisiting recently explored structures, helping to escape local optima and explore the DAG space more effectively.
2. Max-Min Hill Climbing (MMHC):A hybrid approach that first uses the Max-Min Parents and Children (MMPC) algorithm to identify candidate parent sets, followed by a greedy hill-climbing search guided by a scoring function (e.g., BIC). This balances computational efficiency with structural accuracy.
3. Grow-Shrink (GS): A constraint-based algorithm that learns the network by iteratively growing a candidate Markov blanket for each node using conditional independence tests, and then shrinking it to remove spurious variables. It is well-suited for sparse, interpretable structures.
4. Fast-IAMB: An enhanced version of the Incremental Association Markov Blanket (IAMB) method, designed for fast and scalable structure learning. It improves the selection of relevant variables through a more efficient search and test strategy, particularly in large or high-dimensional datasets.

All models were trained using maximum likelihood estimation (MLE) via bn.fit(). Fully directed acyclic graphs (DAGs) were enforced using cextend() where necessary.

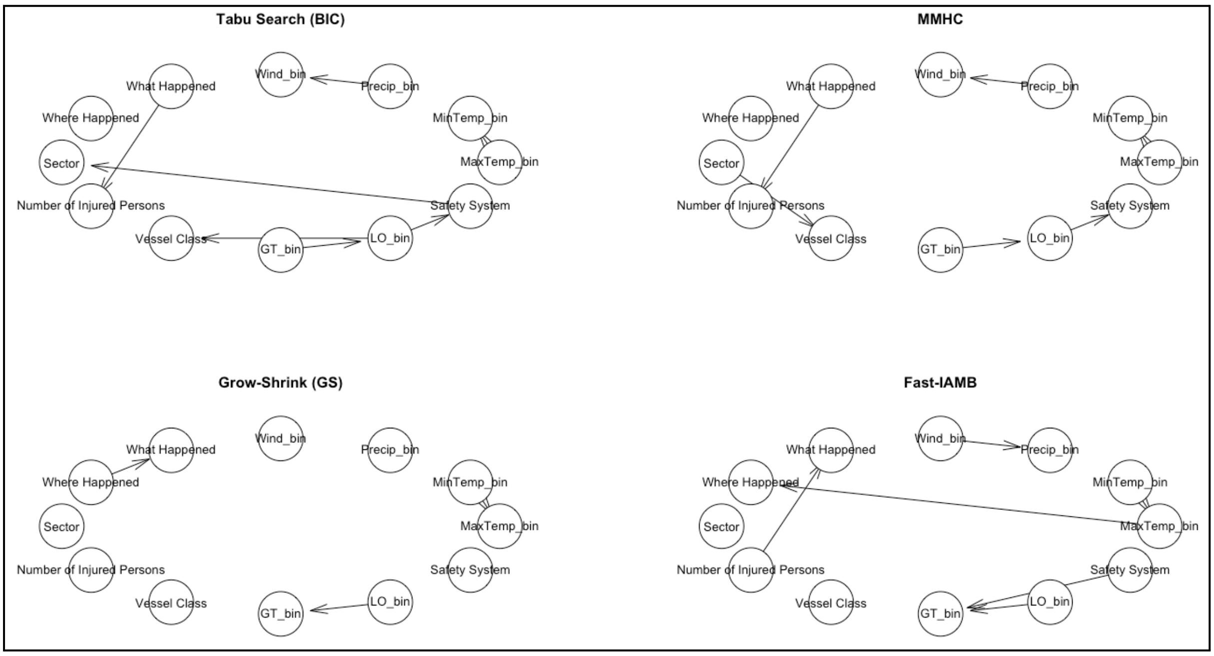
4. Model Evaluation & Comparison: Each learned network was evaluated on:

- BIC score: Lower is better (penalizes complexity).
- Structural differences: Edge-wise comparison of adjacency matrices.

Algorithm	**BIC Score**	**Edge Diff vs Tabu**
Tabu	-6901.43	0
MMHC	-7127.75	3
Fast-IAMB	-7414.33	13
Grow-Shrink	-8005.31	10

Interpretation: Among the four algorithms tested, Tabu Search produced the best Bayesian Information Criterion (BIC) score and yielded a structure that was both simple and informative, making it the most effective for modeling the data. MMHC performed comparably well and stands out as a strong alternative when a balance between constraint-based and score-based logic is preferred. In contrast, GS and Fast-IAMB underperformed, likely due to their reliance on conditional independence tests, which can be sensitive to noise and sparsity in real-world data.

5. Network Visualization: Plots were generated for each algorithm to visualize structural differences. Below are the plots. Tabu Search network is selected for further inference due to its superior score and structure.



Key dependencies in Tabu:

- Length Overall → Safety system.
- Safety system → Sector.
- What Happened → Number of injured persons.

6. Probabilistic Inference and Structural Analysis Using the Tabu Search Model:

Based on the learned structure:

- What Happened → Number of Injured Persons: The type of accident strongly influences the severity, with more serious incidents like collisions or capsizing leading to higher injury counts.
- Safety System → Sector: The choice of safety system is determined by the sector in which the vessel operates, as different sectors (e.g., domestic commercial vs. international) follow distinct safety regulations.
- GT_bin → LO_bin: Gross tonnage and vessel length are closely related — heavier ships are typically longer, reflecting standard vessel design characteristics.
- LO_bin → Safety System: Longer vessels are often equipped with more comprehensive safety systems, possibly due to regulatory requirements or operational complexity.

- MaxTemp_bin → MinTemp_bin: Daily maximum and minimum temperatures are naturally correlated, reflecting typical weather patterns.
- LO_bin → Vessel Class: Vessel length is a key determinant of class, with longer ships more likely falling into larger, more regulated categories.
- Precip_bin → Wind_bin: High precipitation levels are often accompanied by increased wind, indicating stormy conditions that can affect maritime safety.

These insights provide a basis for targeted safety interventions, such as enhancing regulations in specific sectors or during adverse weather.

7. Conclusion

This analysis demonstrated how Bayesian networks can effectively model the causal and probabilistic structure of maritime accidents. Tabu Search was found to be the most robust algorithm in this context, balancing model complexity and fit. It enabled interpretable and accurate inference of key accident patterns.

8. References

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