

Identifying Patterns in Arctic Ship Ship Route Planning

A PoGo–FRAM association-rule mining study
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Background:

Amazon From Association Rules: Customers Also Bought

1. Association Rule (From Data)

From historical purchase data, we find items that are frequently bought together.



Support: 2.8% Confidence: 65% Lift: 3.2

Meaning:

65% of customers who bought Item A also bought Item B.

Example Rule



iPhone Case

Screen Protector

Interpretation:

If a customer buys an **iPhone Case**, recommend a **Screen Protector**.

The image shows a screenshot of an Amazon product page for an iPhone 14 Case. The page features the Amazon logo, a search bar, and a shopping cart icon. The product is displayed with its image, name, ratings (4.6 stars from 1,568 ratings), price (\$15.99), and Prime eligibility. Below the product, there is a section titled 'Customers also bought' which displays four recommended items: iPhone 14 Screen Protector, iPhone Charger Cable (6ft), Car Phone Mount, and Wireless Earbuds. Each item is shown with its image, name, ratings, and price.

Product	Price	Prime
iPhone 14 Case	\$15.99	Yes
iPhone 14 Screen Protector	\$8.99	Yes
iPhone Charger Cable (6ft)	\$9.99	Yes
Car Phone Mount	\$12.99	Yes
Wireless Earbuds	\$25.99	Yes

Background:



1. Transaction Data

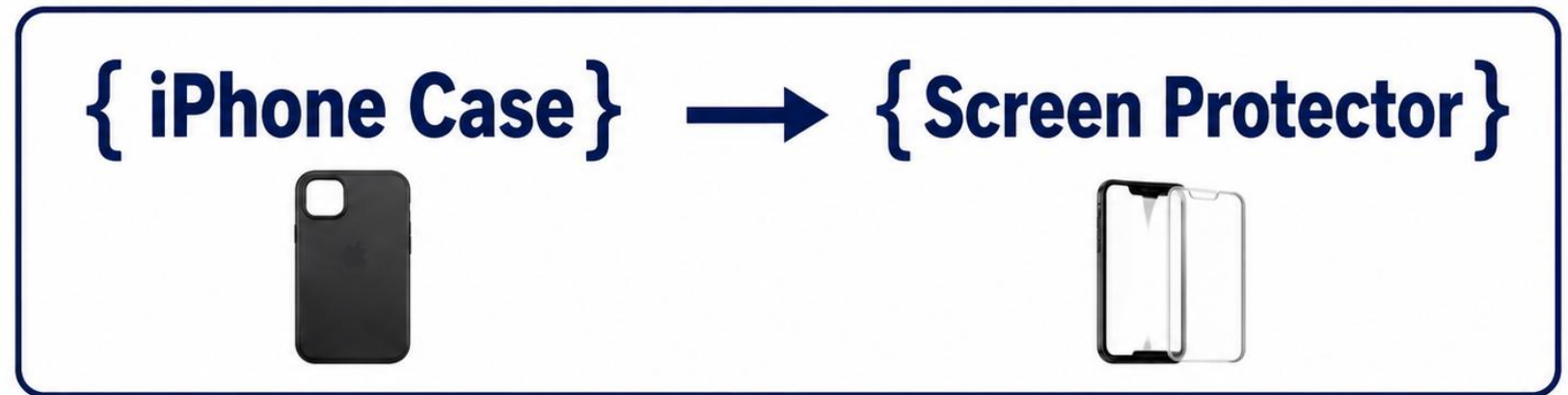
Each basket is one transaction.



Background:

2. Association Rule

A rule links items that are often bought together.



X = antecedent

If customers buy X, they are likely to also buy Y.

Y = consequent



Rule form: $\{X\} \rightarrow \{Y\}$



Example: customers who buy an iPhone Case often also buy a Screen Protector.

Background:



3A. Support

How often X and Y occur together.

Association Rule: {iPhone Case} $\rightarrow$ {Screen Protector}

$$\text{Support}(X \rightarrow Y) = \text{Support}(X \cup Y) = \frac{\text{Number of transactions containing both X and Y}}{\text{Total number of transactions}} = P(X \cap Y)$$

$X = \{\text{iPhone Case}\}$
 $Y = \{\text{Screen Protector}\}$

Transactions (Each basket is one transaction)				iPhone Case	Screen Protector	Contains both X and Y?
T_1			+			YES
T_2			+			NO
T_3			+			YES
T_4			+			NO
T_5			+ + +			YES

$$\text{Number of transactions containing both X and Y} = \frac{3}{5} = \frac{3}{5} = 0.60$$

(T_1, T_3, T_5) (Total transactions)



Support = 0.60 means **60%** of all transactions contain both the iPhone Case and the Screen Protector.

Background:

3B. Confidence

Among customers who bought X, how many also bought Y?

$\{\text{iPhone Case}\} \rightarrow \{\text{Screen Protector}\}$
 $X \qquad \qquad Y$

$$\text{Confidence}(X \rightarrow Y) = \frac{\text{Support}(X \cup Y)}{\text{Support}(X)} = P(Y | X)$$

Example: 5 Transactions



X = iPhone Case Y = Screen Protector

Customers who bought X (iPhone Case)

X appears in T₁, T₂, T₃, and T₅ → 4 transactions



Among these 4 transactions, Y appears in T₁, T₃, and T₅ → 3 transactions

$$\text{Confidence}(X \rightarrow Y) = \frac{\text{Support}(X \cup Y)}{\text{Support}(X)} = \frac{3}{4} = 0.75$$



Interpretation

Confidence = **0.75** means that **75%** of customers who bought the iPhone Case also bought the Screen Protector.

Background:



3C. Lift

How much stronger the rule is than random chance.

{iPhone Case} → {Screen Protector}

Formula

The lift of rule $X \rightarrow Y$ is defined as:

$$\text{Lift}(X \rightarrow Y) = \frac{\text{Confidence}(X \rightarrow Y)}{\text{Support}(Y)} = \frac{P(X \cap Y)}{P(X) P(Y)}$$

Example

Rule: {iPhone Case} → {Screen Protector}



Confidence($X \rightarrow Y$) = $P(Y | X)$ = 0.75
(From previous calculation)



Support(Y) = Support(Screen Protector)
= 4 / 5 = 0.80



Lift = 0.75 / 0.80 = 0.94

Visual Interpretation



Lift > 1:

positive association
(X increases the likelihood of Y)



Lift = 1:

independent
(X and Y occur together as by chance)



Lift < 1:

weaker than chance
(X decreases the likelihood of Y)

Conclusion



Lift = 0.94 means this rule is **slightly weaker** than random expectation in this small example.

For Arctic vessel route planning, which factor drives route selection?



Why Arctic route planning is difficult to optimize

A route-planning outcome is shaped by interacting environmental, technical, economic, and regulatory conditions.



Environment
region
ice-chart conditions

Vessel
type
ice class
resistance + speed

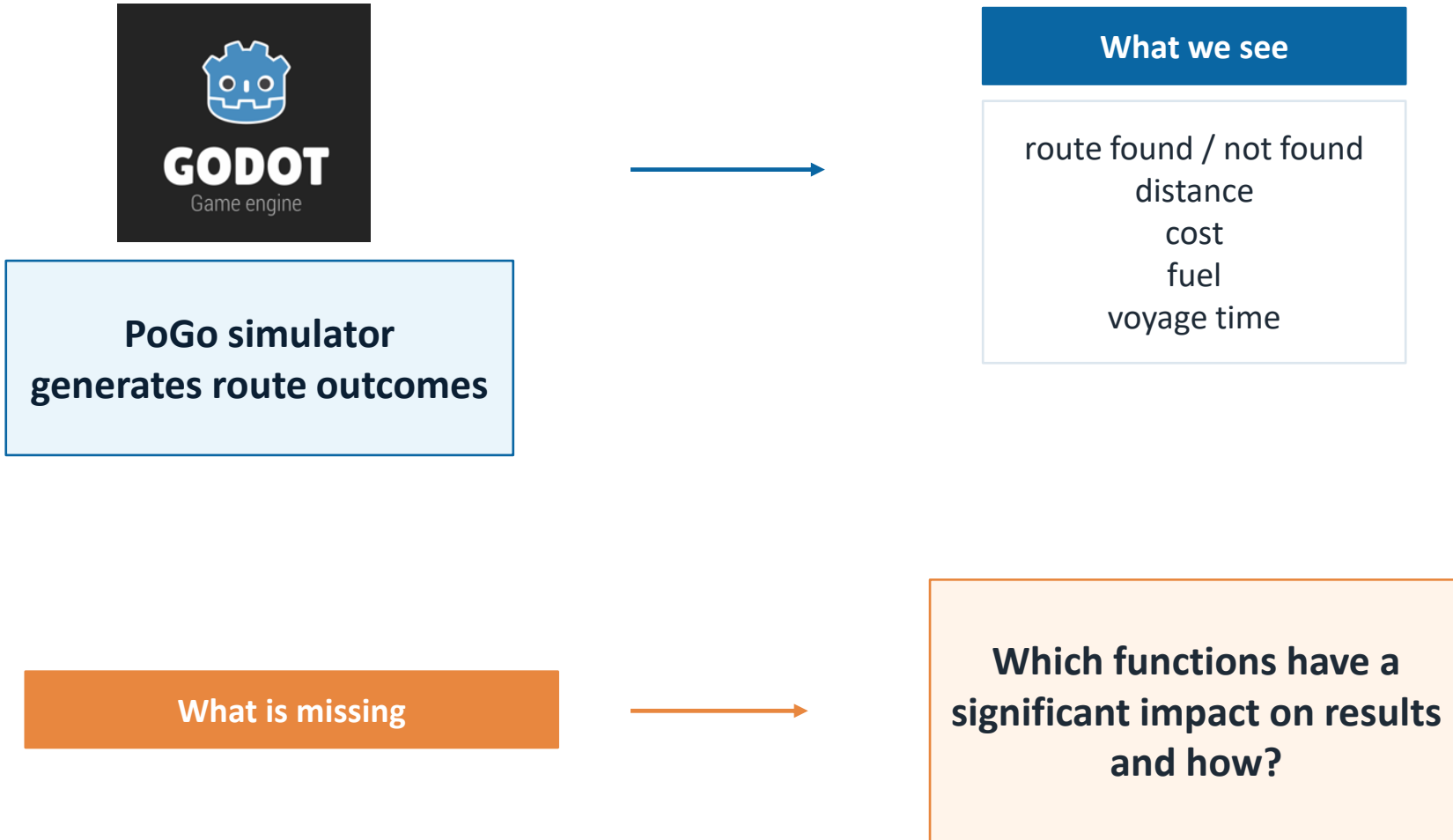
Economics
fuel + engine
parameters
voyage cost

Constraints
risk
CII
route feasibility

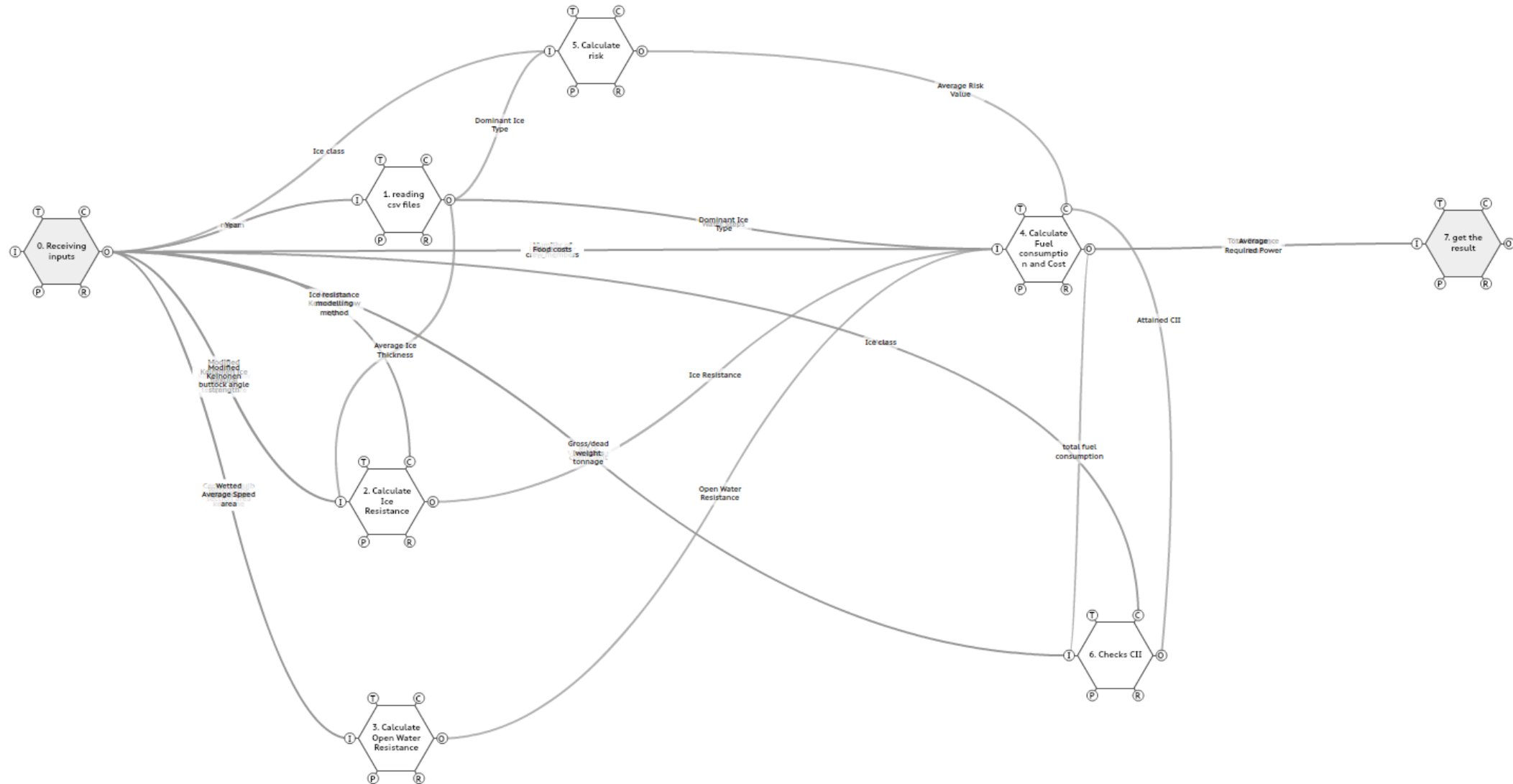


Route outcome
(distance, cost, fuel, feasibility)

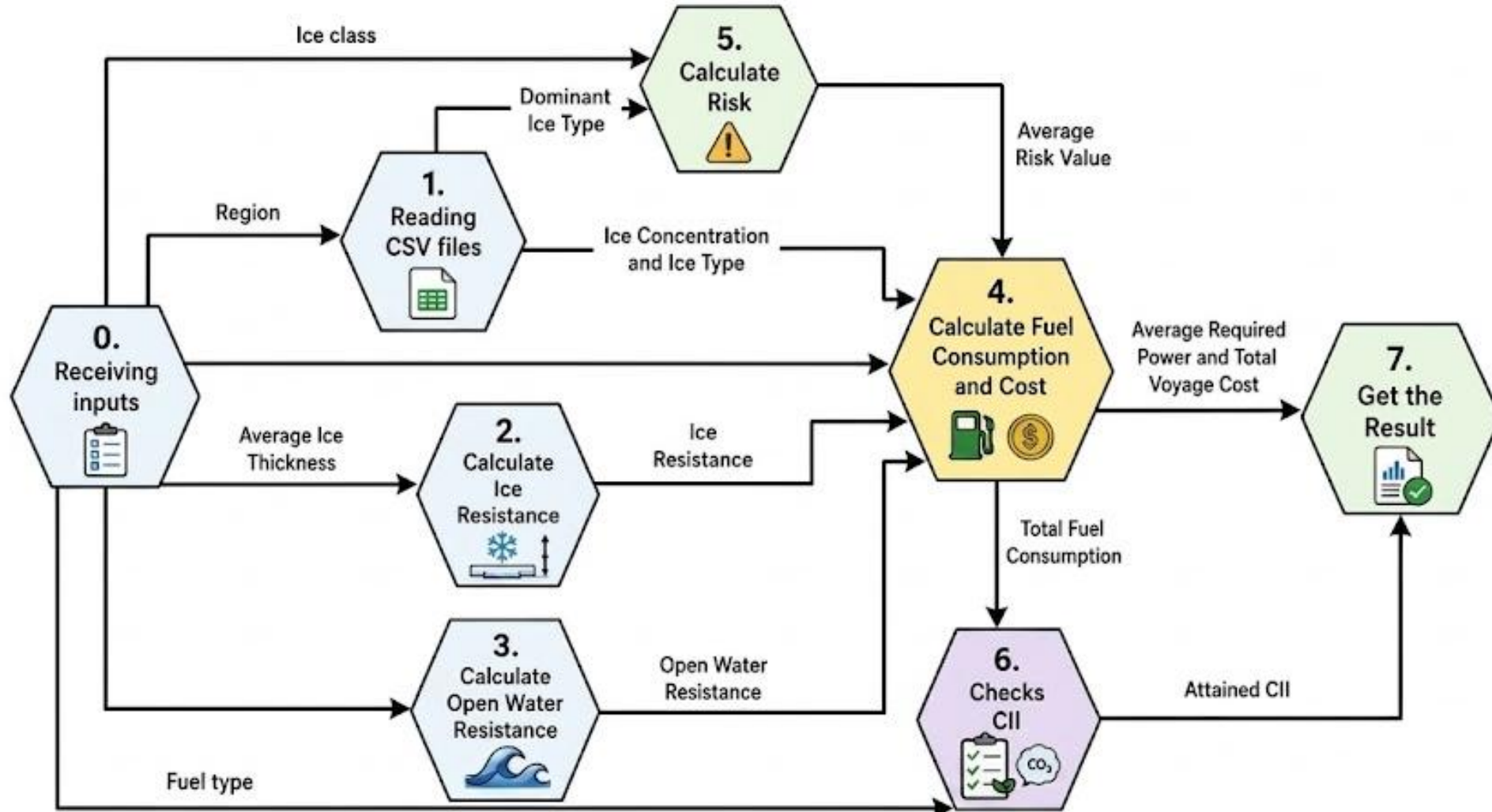
Research gap:



How FRAM is used in this study

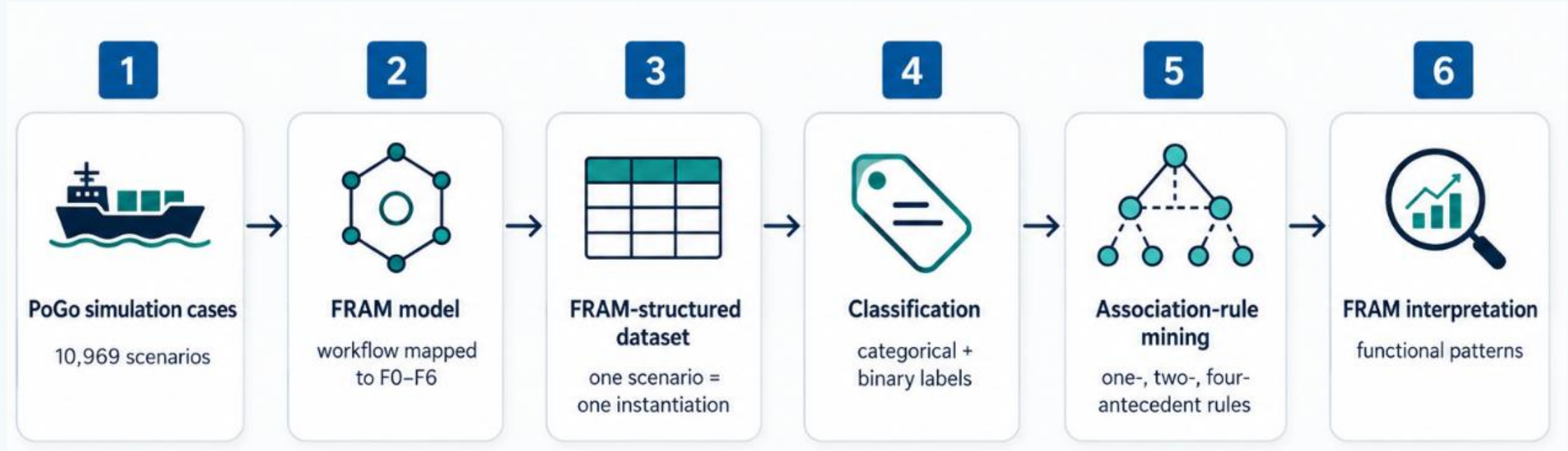


How FRAM is used in this study

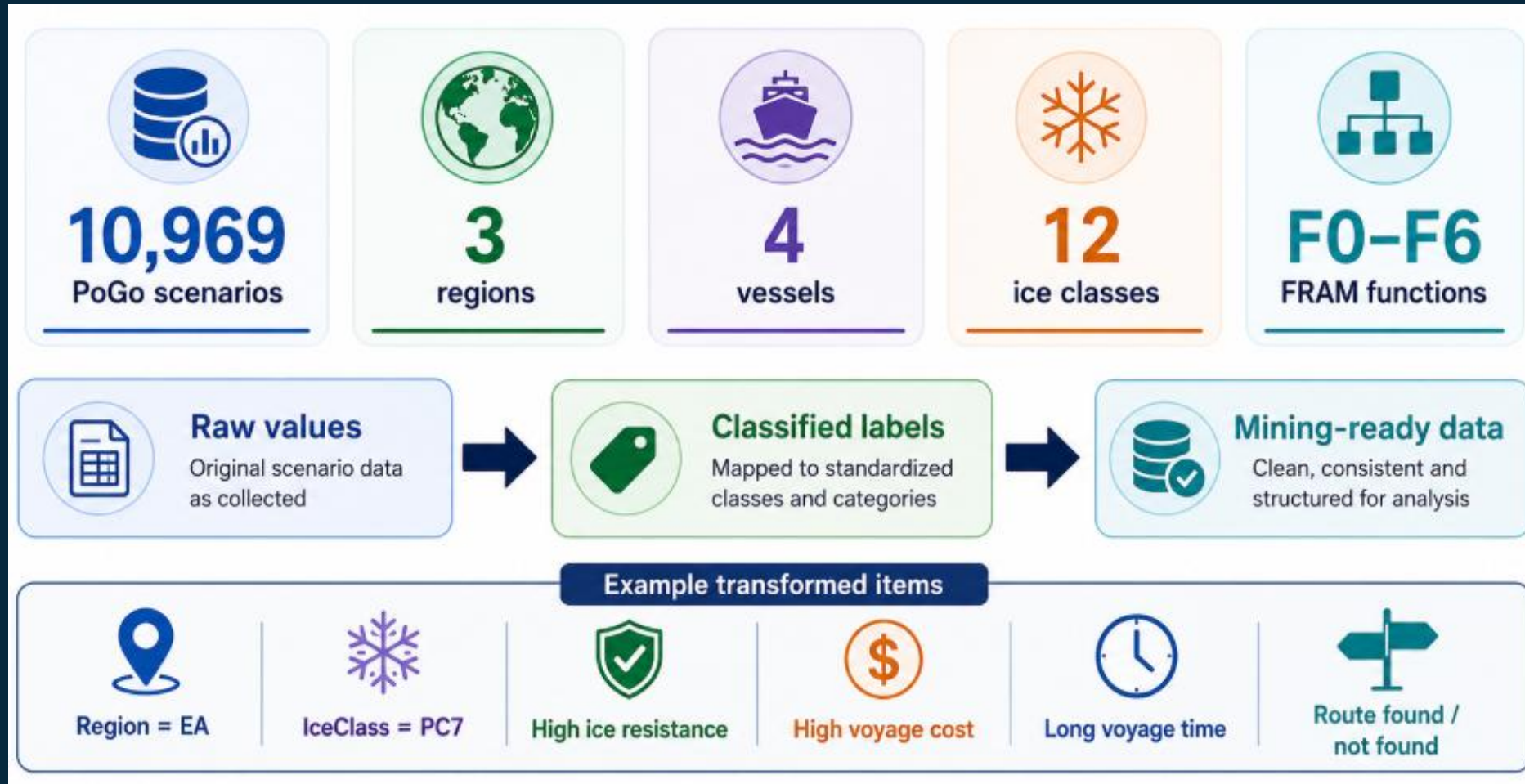


Method pipeline: from simulation to interpretable patterns

The key contribution is linking simulator outputs to FRAM functions and then to mined rules.



Scale of the analysis



Regions used in the final analysis: Eastern Arctic, Hudson Bay, Western Arctic

Classification step: making the data mineable

Categorical labels

Region → EA / HB / WA

Vessel → hl / ii / no / rd

Ice class → PC1...No_Ice_Class

Path status → Found / Not_Found

Continuous labels

Above median → “High” / “Long”

Below median → “Low” / “Not high”

Examples: High_Ice_Resistance,
High_Cost, Long_Distance

FRAM-structured data representation

Each row is one PoGo scenario / one FRAM instantiation.

FS	Antecedent Variables																Consequent Variables							
	F0: Receiving inputs				F1: reading csv files				F2: Calculate Ice Resistance		F3: Calculate Open Water Resistance		F5: Calculate risk		F6: Checks CII		F4: Calculate Fuel consumption and Cost							
FS	O0 (Region)	O0 (Ice Class)	A0	O (Ice Steps)	O1 (Avg Ice Thickness)	A1	O2 (Ice Resistance)	A2	O3 (Open Water Resistance)	A3	O5 (Average Risk Value)	A5	O6 (Attained CII)	A6	O4 (total fuel consumption)	O4 (Total Distance)	O4 (Path Found)	O4 (Total Voyage Cost)	O4 (Voyage Time)	F4 (Average Required Power)	A4			
FS1	Eastern Arctic	IA_SUPER	1	High	High	1	High	1	Low	0	High	0	High	0	High	High	High	Yes	High	High	High	1		
FS2	Western Arctic	PC1	1	low	High	1	High	1	High	0	Low	0	Low	0	Low	Low	Low	Yes	Low	Low	Low	1		
FS3	Western Arctic	No_Ice_Class	1	High	Low	1	High	1	Low	0	High	0	High	0	High	High	High	Yes	High	High	High	1		
FSn	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...		

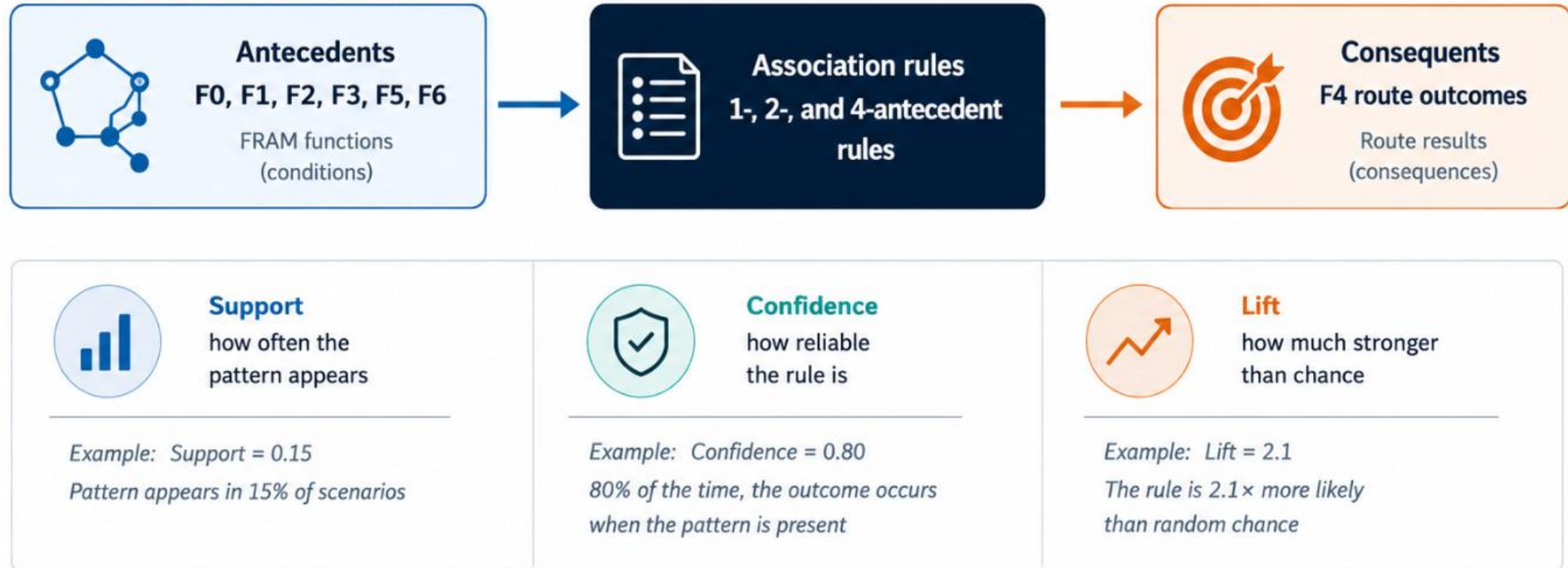
Antecedents: F0, F1, F2, F3, F5, F6

Consequents: F4 route-performance outcomes

A0–A6 = function active / inactive

Association-rule mining design

Rules were mined to identify repeated combinations, then interpreted through FRAM.



Selected rules used to interpret Association rule

Selected association rules:

No.	Association rule	FRAM functions involved	Outcome	Support	Confidence	Lift
1	Eastern Arctic + high ice steps + high ice resistance + high average ice thickness	F0, F1, F2 → F4	Long distance	0.229	1.000	1.752
2	Western Arctic + high ice resistance + high ice steps + high average ice thickness	F0, F1, F2 → F4	High cost	0.050	1.000	1.998
3	Western Arctic + high ice resistance + high ice steps + high average ice thickness	F0, F1, F2 → F4	Long voyage time	0.050	1.000	2.000
4	LFO fuel type + high ice resistance + high ice steps + high average ice thickness	F0, F1, F2 → F4	High required power	0.118	1.000	1.999
5	No ice class	F0 → F4	Route not found	0.055	0.809	1.784

Zooming into the clearest rule

Interpreted through FRAM, the rule becomes a functional signature.



Three takeaways

1

PoGo creates a useful simulated environment for studying route-planning logic.

2

FRAM gives structure to PoGo simulation data and interpretation makes those patterns explainable.

3

Association rules can highlight recurring patterns that can be interpreted using FRAM.

Thank you — questions and discussion