itaú

Underwriting Risk Estimation

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MITSloan MANAGEMENT

Problem Statement and Challenge

Itaú Unibanco, Latin America's largest financial institution, manages a diverse insurance portfolio. The current **SUSEP** (*Superintendência de Seguros Privados*) standard formula overestimates capital needs by ignoring Itaú's specific risk profile. Under **ORSA** (Own Risk and Solvency Assessment), insurers must assess solvency based on internal risk. Itaú's challenge is to develop a transparent internal model that accurately quantifies underwriting risk and improves capital efficiency.

Business Impact

- ✓ *Comply with ORSA regulation*
- ✓ *Estimation of required capital for each insurance product*
- ✓ *Optimization of reinsurance policy*

Possibly unlocking up to **$100 million** for investments

* *Upon internal model validation by regulators*

Portfolio Overview and Risk Modeling

PROPERTY | HOMEOWNER | TRAVEL | CARDS | LIFE & PENSION

5 products

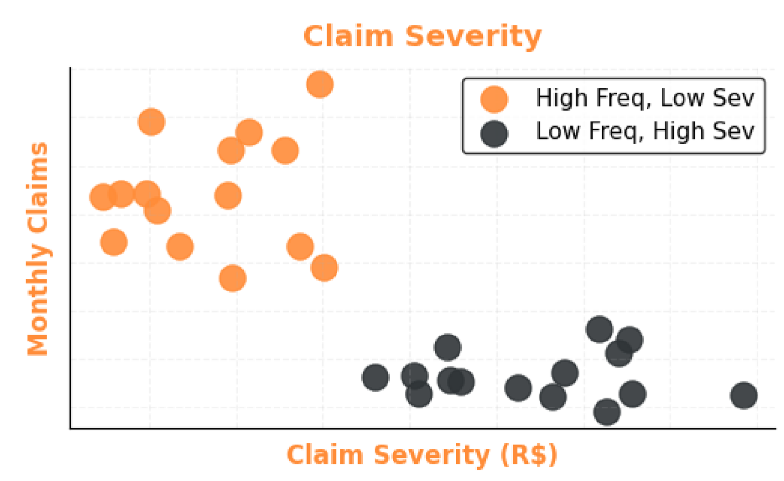
◆ **What Are We Trying to Model?**

We are modeling **underwriting risk**, specifically the **total annual claims cost** across multiple insurance products. This involves understanding both:

- **How often** claims occur **(Frequency)**
- **How large** each claim tends to be **(Severity)**

These two components are **modeled separately** and then **combined via Monte Carlo simulation** to estimate annual losses, which feed into capital requirement calculations.

Clustering



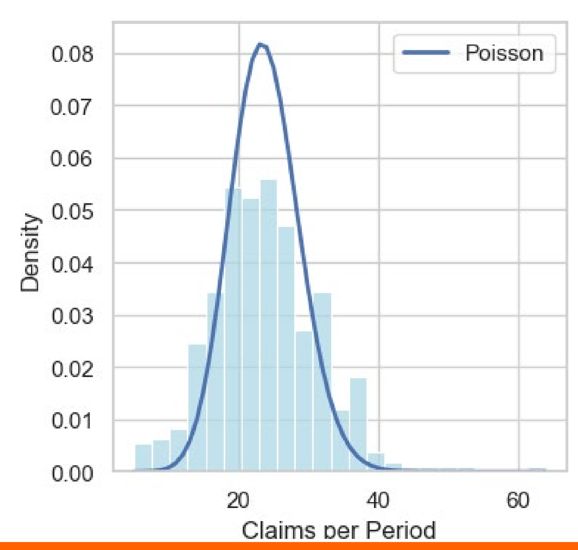
◆ **Why Clustering ?**

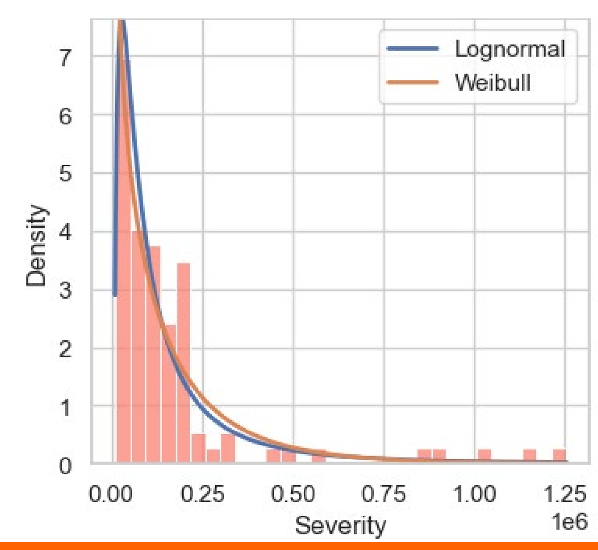
- **Different coverages** exhibit heterogeneous claim patterns (e.g., fire vs. theft).
- **Clustering** allows risk pooling across coverages with similar statistical behavior, improving model robustness.

◆ **How We Clustered ?**

- Used **tail-sensitive k-means** on statistical features of each coverage:
  - **Mean & variance of frequency**
  - **Mean & variance of severity**
- Grouped coverages into **homogeneous risk segments** for joint modeling.
- **Enabled cluster-specific** frequency (Poisson) and severity (Lognormal/Weibull) fitting.

Risk Simulation Pipeline





Fit distributions of claim frequency and severity

We assess how closely the simulation matches real-world data using **Relative Quantile Error (RQE):**

$$RQE = \frac{1}{|Q|}\sum_{q\in Q}\left|\frac{Q_q^{sim} - Q_q^{emp}}{Q_q^{emp}}\right|$$

Selected quantiles:

- **25%, 50%, 75%** → Represent **typical losses**
- **90%** → Captures **extreme tail risk** — critical for regulatory capital

◆ **Lower RQE = better match** between simulation and historical losses

◆ **Why it matters:**

High-tail accuracy ensures the model realistically reflects **worst-case scenarios**, strengthening capital planning and ORSA compliance

How Do We Evaluate the Fit Accuracy ?

Annual Loss Simulation with Reinsurance

❖ **Fit distribution parameters** for each cluster:
Model **claim frequency** and **severity** separately.

❖ **Simulate 1,000 annual scenarios** to account for variability in claims.

❖ **For each scenario:**

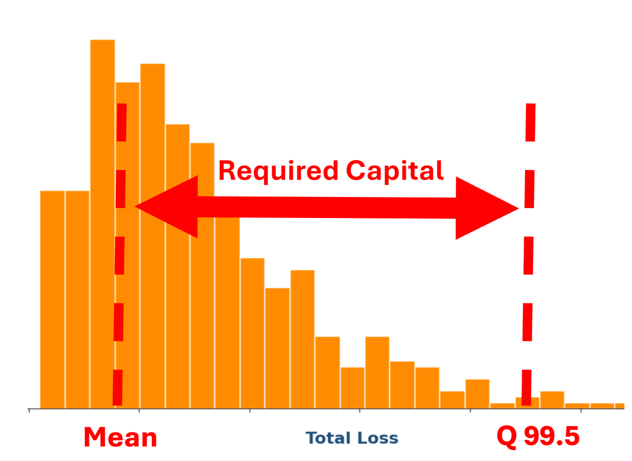
Step 1: Weekly Simulation
Sample annual **claim frequency** and distribute across 52 weeks.
Simulate **weekly claim severities** independently.

Step 2: Client Aggregation
Split total claims across clients using a **claim-to-client ratio**.
Enables realistic aggregation before applying reinsurance.

Step 3: Apply Reinsurance
Apply reinsurance contracts (e.g. per-client or aggregate retention).

❖ **After all scenarios: Capital Requirement**

- Plot the distribution of annual losses **with and without reinsurance**.
- Compute **key quantiles** (e.g., 99.5%) for capital estimation.
- Validate the model by comparing to **historical test losses**.



Results and Key Takeaways

Products	Refined Clustering	Per-Coverage Model	1-Cluster Baseline
Property	**21.34%**	102.45%	28.99%
Homeowner	**9.18%**	10.42%	10.02%
Travel	**34.66%**	101.83%	39.47%
Card	**20.78%**	22.89%	20.93%
Life & Pension	**4.87%**	23.92%	10.72%

Refined Clustering RQE

◆ The SUSEP standard formula **significantly overestimates** underwriting risk by ignoring portfolio structure and diversification.

◆ A **cluster-based internal model** enables more granular, data-driven segmentation, improving model accuracy and interpretability.

◆ **Capital requirements can be reduced** by **tuning reinsurance thresholds:** allowing for earlier reinsurance activation and more efficient risk transfer.

◆ **Backtesting with quantile errors** confirms the model's robustness and alignment with historical outcomes.

◆ The final model is **ready for ORSA deployment**, supported by a **Capital Optimization Dashboard** that enables data-driven decision-making and stress testing.

Practical applications

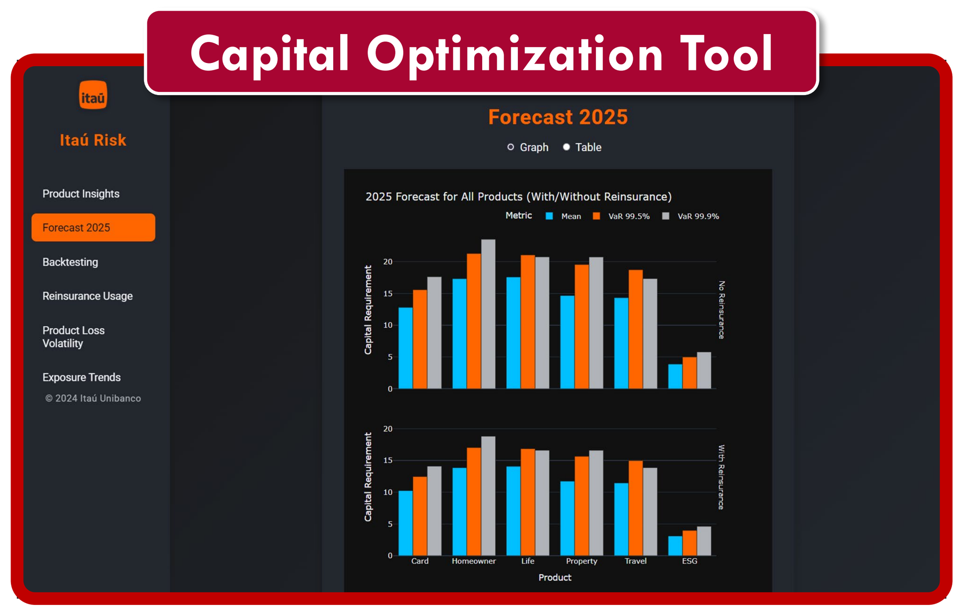
◆ **ORSA Reporting**: Aligns with regulatory expectations for internal model validation.

◆ **Capital Optimization**: Quantifies impact of reinsurance structures and tuning priority thresholds.

◆ **Portfolio Steering**: Identifies high-risk clusters to support product repricing or underwriting actions.

◆ **Scenario Testing**: Enables simulation under stressed environments to support risk planning.

Capital Optimization Tool



Team members

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