Interim Submission - Report

B8W3: End-to-End Insurance Risk Analytics & Predictive Modeling

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Author: Alemayehu Tseganew

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1. Executive Summary

This report outlines the progress made in the "End-to-End Insurance Risk Analytics & Predictive Modeling" project. The primary objective is to leverage historical insurance data to identify risk drivers, segment customers, and build predictive models for claim severity and premium optimization. **Specifically, the project aims to identify low-risk segments to target for premium reduction, thereby attracting new clients while maintaining profitability.**

Key achievements to date include:
• Successful data ingestion and cleaning of the `MachineLearningRating_v3` dataset.
• Comprehensive Exploratory Data Analysis (EDA) and definition of Key Performance Indicators (KPIs).
• Statistical hypothesis testing to validate risk assumptions.
• Development and evaluation of machine learning models for Claim Severity, Premium Prediction, and Claim Probability.

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2. Data Preparation & Feature Engineering

The raw dataset `MachineLearningRating_v3.txt` was processed to ensure data quality and suitability for modeling.

2.1. Data Overview & Descriptive Statistics

The dataset contains **1,000,098 rows** and **52 columns**.

Descriptive Statistics for Key Financial Variables:

Metric	TotalPremium	TotalClaims
Count	1,000,098	1,000,098
Mean	61.91	64.86
Std Dev	230.28	2,384.08
Min	-782.58	-12,002.41
Max	65,282.60	393,092.06

Missing Values Analysis:
Significant missing data was observed in columns such as `Bank` (145,961 missing), `CustomValueEstimate` (779,642 missing), and `CrossBorder` (999,400 missing). These columns were either dropped or imputed

depending on their relevance to the modeling task.

2.2. Data Version Control (DVC) Setup

To ensure reproducibility and efficient data management, DVC was initialized.

- **Initialization**: `dvc init` was run to set up the project.
- **Remote Storage**: A local remote storage was configured at `../dvc-storage` to simulate a cloud bucket.
- **Tracking**: The raw data file `MachineLearningRating_v3.txt` was added to DVC (`dvc add ...`), creating a `.dvc` file for git tracking.
- **Versioning**: Changes to the dataset are committed to git via the `.dvc` file, keeping the repo lightweight.

2.3. Key Cleaning Steps

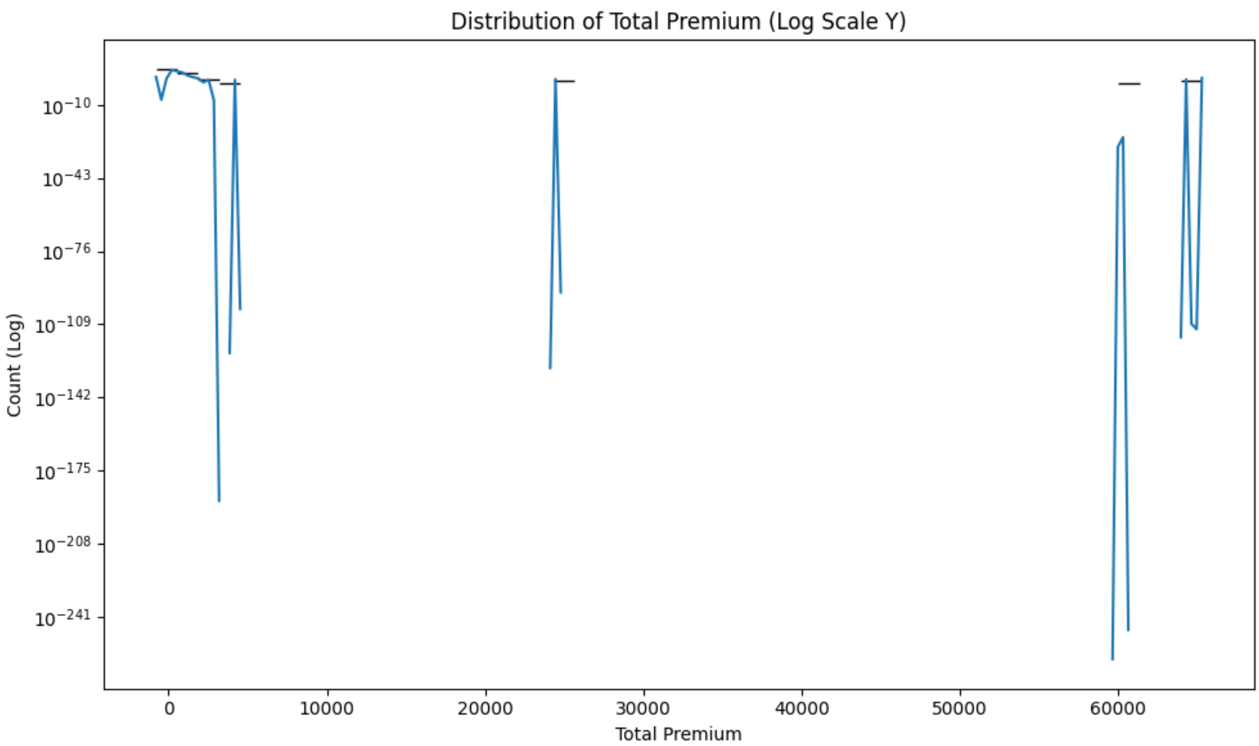
- **Data Cleaning**: Converted `TransactionMonth` and `VehicleIntroDate` to datetime objects. Ensured `TotalPremium` and `TotalClaims` were numeric.
- **KPI Definition**:
- **Claim Frequency (HasClaim)**: Binary indicator (1 if `TotalClaims` > 0, else 0).
- **Claim Severity**: The value of `TotalClaims` for policies where a claim occurred.
- **Margin**: Calculated as `TotalPremium` - `TotalClaims`.
- **Feature Engineering**: Extracted relevant features for modeling, including geographic (Province, Zip Code) and demographic (Gender) variables.

2.4. Exploratory Data Analysis (EDA)

We conducted a thorough EDA to understand the underlying patterns in the data.

Univariate Analysis:

The distribution of `TotalPremium` is highly right-skewed, indicating that most policies have low premiums, with a few high-value outliers.



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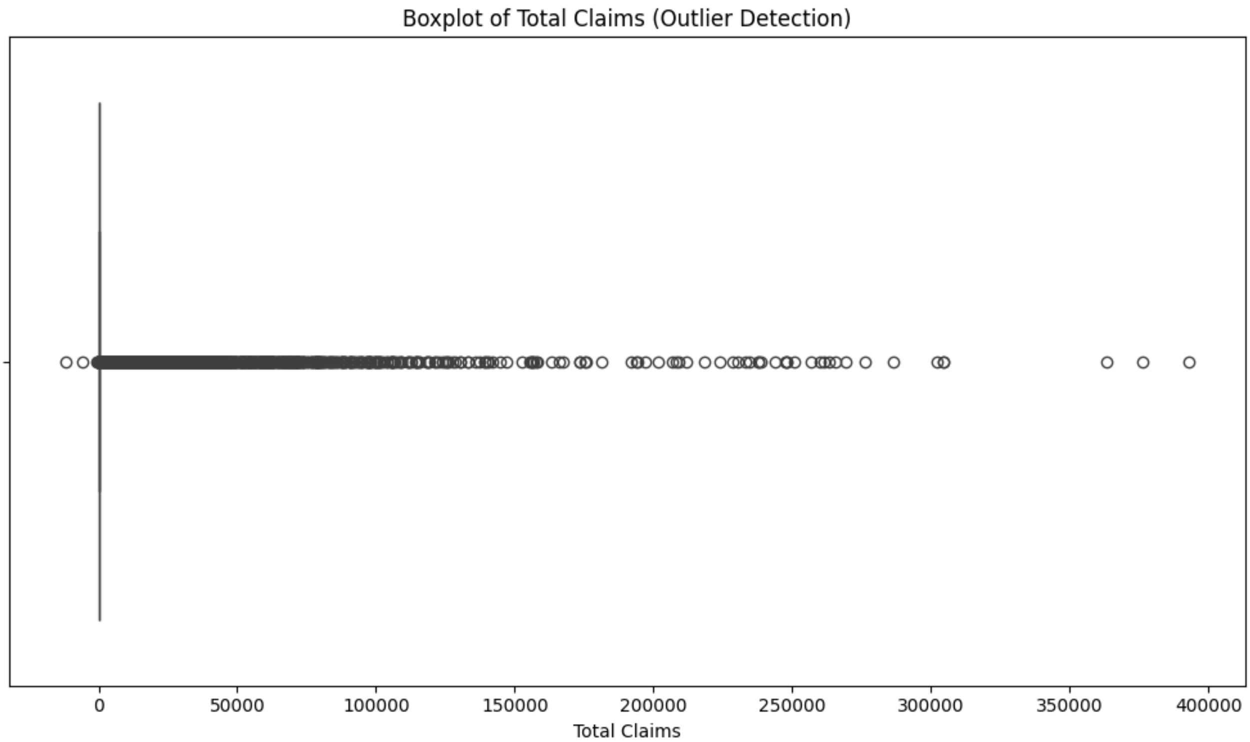
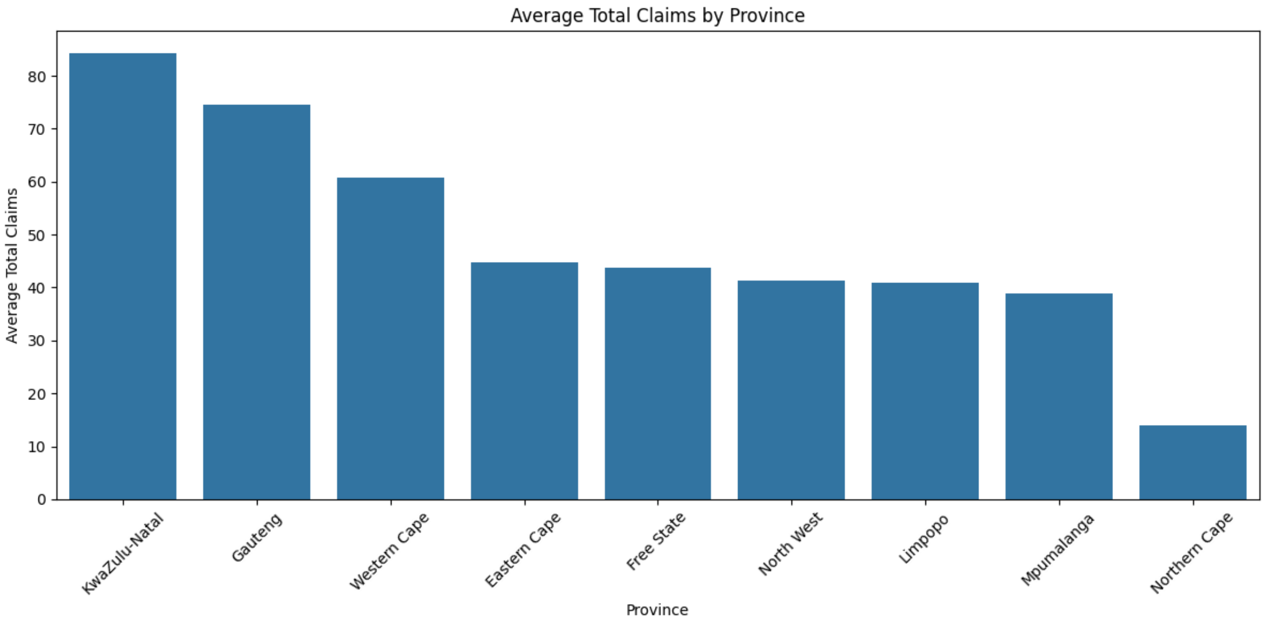
Outlier Detection:

The boxplot for `TotalClaims` reveals significant outliers. These extreme values represent major loss events that can skew predictive models if not handled correctly (e.g., via robust scaling or truncation).



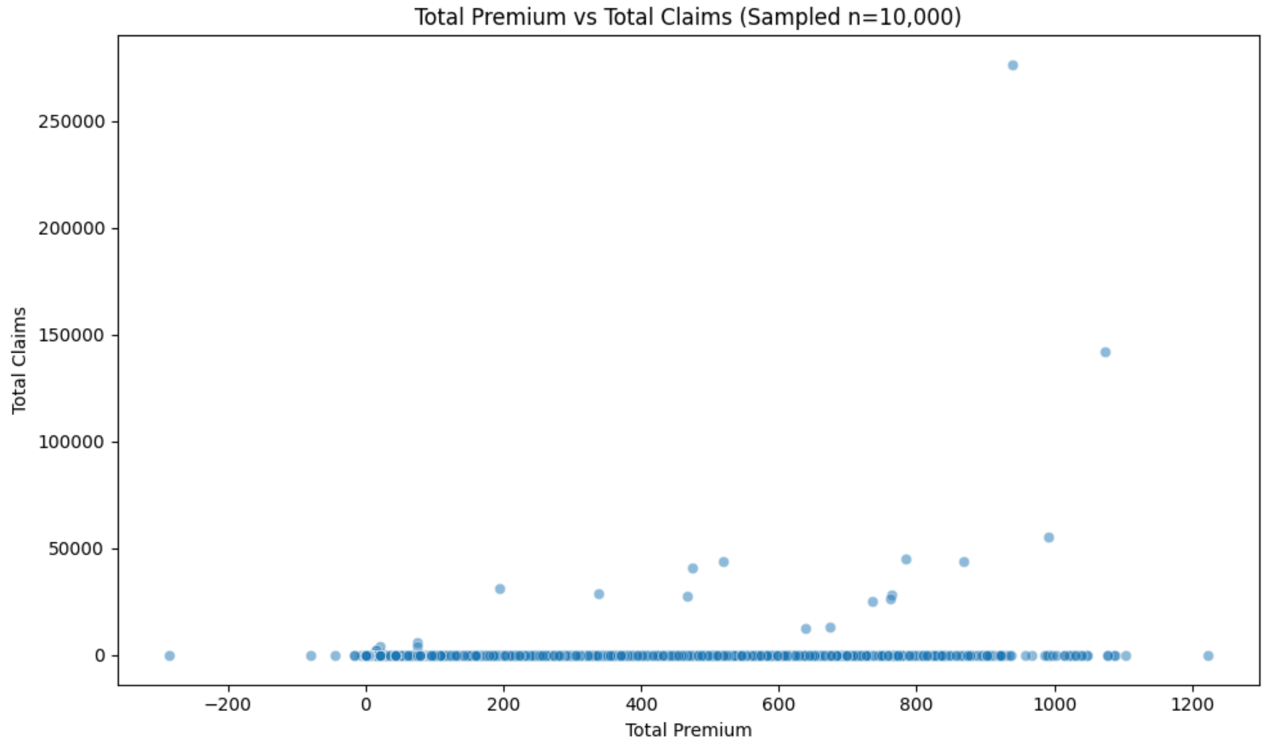
Geographic Trends:

Analysis of average claims by province shows distinct variations. Some provinces exhibit significantly higher average claim severities, suggesting regional risk factors.



Bivariate Analysis:

The scatter plot of `TotalPremium` vs. `TotalClaims` shows a weak positive correlation. High premiums do not always correspond to high claims, reinforcing the need for sophisticated risk modeling beyond simple linear relationships.



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3. Hypothesis Testing Results

We performed statistical tests (Chi-Squared, ANOVA, T-Test) to validate several hypotheses regarding risk drivers.

Hypothesis	Test Used	Result	Business Insight
Risk Differences Across Provinces	Chi-Squared (Freq), ANOVA (Sev)	**Reject H0**	Significant differences exist. Recommend province-specific pricing or underwriting rules.
Risk Differences Between Zip Codes	Chi-Squared (Freq), ANOVA (Sev)	**Reject H0**	Micro-geography signals distinct risk. Refine rating factors at the postal-code level.
Margin Differences Between Zip Codes	ANOVA	**Fail to Reject H0**	Profitability (Margin) appears consistent geographically; no immediate pricing change needed based on margin alone.
Risk Differences Between Women and Men	Chi-Squared (Freq), T-Test (Sev)	**Fail to Reject H0**	No material difference in claim frequency or severity. Supports gender-neutral pricing policies.

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4. Predictive Modeling

We developed three categories of machine learning models to predict risk and optimize premiums.

4.1. Claim Severity Modeling

• **Goal**: Predict the amount of `TotalClaims` for policies with claims.
• **Approach**: Evaluated baseline and ensemble regressors (e.g., Linear Regression, Random Forest, XGBoost).
• **Evaluation Metrics**: RMSE, MAE, R^2.
• **Status**: Models trained and evaluated. Feature importance analysis (Permutation Importance) conducted to identify key severity drivers.

4.2. Premium Prediction

• **Goal**: Predict `TotalPremium` to understand current pricing structures.
• **Approach**: Regression models trained on policy features.
• **Status**: Baseline models established.

4.3. Claim Probability Classification

• **Goal**: Predict the likelihood of a policy having a claim (`HasClaim`).
• **Approach**: Classification models (e.g., Logistic Regression, Random Forest, XGBoost).
• **Evaluation Metrics**: Accuracy, Precision, Recall, F1-Score.
• **Status**: Models trained with stratified train-test splits to handle class imbalance.

4.4. Model Interpretability

• **SHAP Analysis**: Implemented SHAP (SHapley Additive exPlanations) to explain model predictions and identify the most influential features for risk.

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5. Conclusion & Next Steps

The analysis confirms that geography (Province, Zip Code) is a strong driver of insurance risk, while gender is not. The predictive models provide a foundation for automated risk scoring.

Roadmap for Completion:
While initial models have been built, the following steps are required to finalize the project:
1. **Refine Hypothesis Testing**: Expand the A/B testing to include more granular segmentation (e.g., Vehicle Type vs. Risk) and validate findings with multivariate analysis.
2. **Advanced Modeling**:
• **Hyperparameter Tuning**: Perform Grid Search or Random Search for the XGBoost and Random Forest models to optimize performance.
• **Feature Selection**: Use the SHAP analysis results to remove non-predictive features and reduce model complexity.
• **Model Comparison**: Rigorously compare the tuned models against the baseline Linear Regression model using cross-validation.
3. **Final Report Generation**: Synthesize all findings, including the final model performance metrics and business recommendations, into the final submission document.