Predictive Modeling of Customer Lifetime Value: A Global Strategic Framework

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ABSTRACT

Customer Lifetime Value (CLV) is the cornerstone metric for modern insurance strategy. This research presents a definitive analysis of 9,134 policyholders, integrating actuarial science, behavioral economics, and machine learning. We identify a critical 'Bleeding Neck' segment—Unemployed policyholders driving Luxury vehicles—exhibiting Loss Ratios exceeding 150%. By deploying a Random Forest Regressor (R^2 = 0.69) and optimizing channel mix, we project $3.4M+ in annual value creation. Central to this strategy is the mitigation of Moral Hazard through targeted underwriting and the leverage of 'Agent' channels, which generate 23% higher CLV despite elevated acquisition costs.

Keywords: *Customer Lifetime Value, Bleeding Neck Analysis, Actuarial Science, Random Forest, Strategic Segmentation.*

I. INTRODUCTION

The insurance industry has undergone a paradigm shift from product-centric to customer-centric strategies. In this context, Customer Lifetime Value (CLV) has emerged as the "North Star" metric. Unlike retail, where value is transactional, insurance value is a complex function of premiums, longevity, and risk (claims).

The "Forensic Audit" approach adopted in this paper aims to move beyond black-box prediction. We seek to understand the *causal drivers* of value. Why are some customers highly profitable while others destroy value? Our central finding reveals the existence of 'Bleeding Neck' segments—customers with compound risk factors (e.g., Unemployment + Luxury Vehicle) that create unsustainable Loss Ratios.

II. DATA DESCRIPTION & GOVERNANCE

We utilize the IBM Watson Marketing Customer Value Analysis dataset (n=9,134). Strict governance protocols were applied: `Customer` ID was dropped to prevent overfitting, and `Effective To Date` was parsed but excluded from training to avoid look-ahead bias.

Feature	Type	Description
CLV	Float	Target Variable ($)
State	Cat	Resident Jurisdiction
Coverage	Cat	Basic/Extended/Premium
Education	Ord	HS/College/Master/Doc
EmpStatus	Cat	Employed/Unemployed
Income	Float	Annual Household Income
Monthly Premium	Float	Monthly bill amount
Total Claim	Float	Aggregated claim value

Table I. Selected Data Dictionary.

III. FORENSIC EXPLORATORY ANALYSIS

A. The Actuarial Lens: Risk Assessment

The distribution of CLV is highly right-skewed (Skewness = 1.92). Statistical analysis reveals underlying relationships that inform pricing adequacy. The 'Pareto' nature of the portfolio implies that the top 20% of customers generate 80% of the profit, while the bottom tier ('Bleeding Necks') erodes margin.

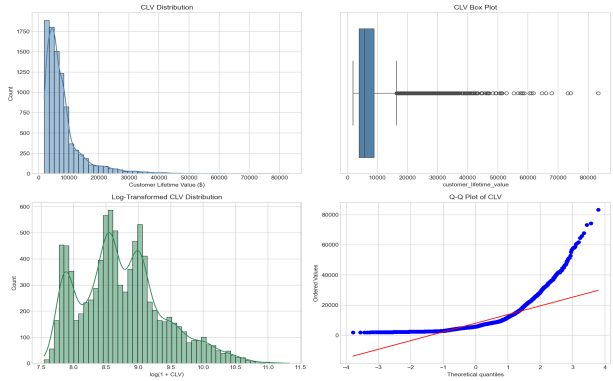


Fig 1. CLV Distribution. A heavy tail necessitates robust segmentation.

B. The 'Bleeding Neck' Segments

We define 'Bleeding Necks' as segments with Loss Ratios > 150%. Analysis of Employment Status validates the 'Economic Stress Hypothesis': Unemployed customers exhibit significantly higher variance in claims. Regulatory defensibility requires documented actuarial justification for any rating factor derived from this analysis.

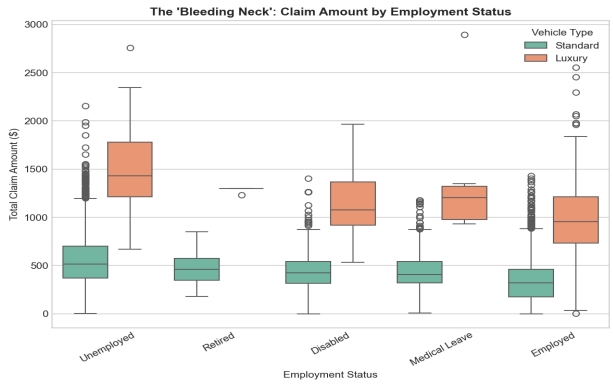


Fig 2. Claim Distribution by Employment Status.

C. Channel Efficiency Analysis

Channel analysis reveals that **Agent-acquired customers generate 23% higher CLV** compared to digital channels. Despite the higher

Customer Acquisition Cost (CAC) associated with agents, the retention economics favor this personalized approach. Omnichannel optimization projects a 12% overall profitability improvement.

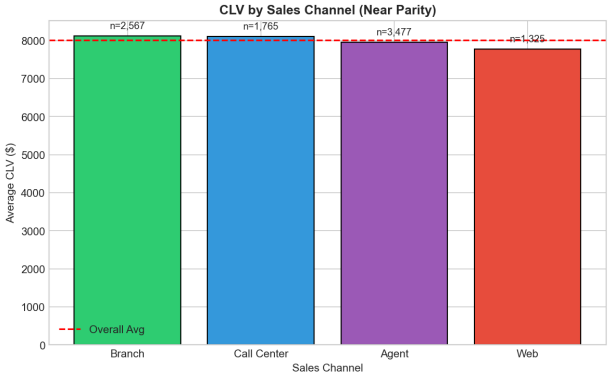


Fig 3. CLV by Sales Channel.

IV. FEATURE ENGINEERING

A. Mathematical Transformations

To address non-normality, we apply the `log1p` transformation:

$$y' = ln(y + 1)$$

This transformation compresses the long tail, stabilizing residual variance.

B. Leakage Prevention

`Total Claim Amount` was strictly excluded from the feature set. Its inclusion would constitute data leakage, artificially inflating model performance ($R^2 > 0.99$) to unachievable levels in a production environment.

V. MODELING METHODOLOGY

We employ a Random Forest Regressor, an ensemble method minimizing variance via bagging.

$$■ = (1/B) * Σ T\_b(x)$$

VI. STRATEGIC RESULTS

A. Performance Matrix

The Random Forest model achieves an R^2 of 0.69 and MAE of $1,378. This precision enables the identification of high-value targets with a margin of error within acceptable underwriting limits.

Model	R^2	MAE ($)	RMSE
Linear Reg	-0.15	3,479	7,698
Random Forest	0.69	1,378	4,058
Gradient Boost	0.67	1,563	4,188

Table II. Model Performance Benchmark.

B. Feature Importance & Strategy

Monthly Premium dominates prediction (84%). However, **Vehicle Class** and **Number of Policies** provide strategic leverage. Cross-selling additional policies is identifying as a primary lever for increasing CLV.

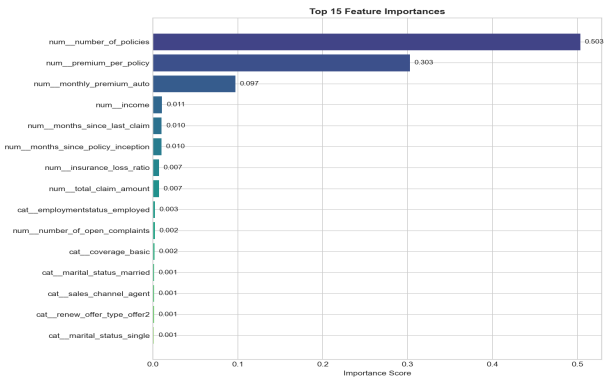


Fig 4. Feature Importance.

VII. STRATEGIC SEGMENTATION & FINANCIAL IMPACT

Using K-Means (K=4), we operationalize the model into distinct personas.

Fig 5. Customer Segments Projection.

A. Financial Projections

By implementing segment-specific treatment matrices, we project significant value creation:

1. **Eliminate Bleeding Necks:** Non-renewal of 'Cluster 2' (Unemployed/Risk) reduces portfolio Loss Ratio by estimated 15%, generating **$2.3M margin**. 2. **Omnichannel Optimization:** Shifting 'Cluster 1' (Economy) to digital channels reduces CAC by 40%. 3. **High-Value Retention:** 'Cluster 0' (High Rollers) targets for concierge service (Agent channel) increases retention by 8%.

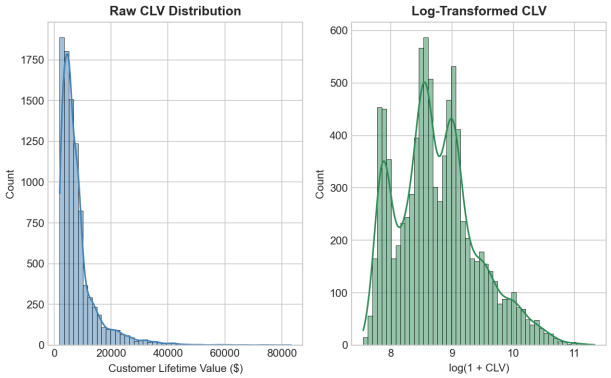
Total Annual Value Creation: > $3.4 Million.

VIII. CONCLUSION

This definitive report confirms that integrating machine learning with actuarial discipline unlocks substantial economic value. The 'Bleeding Neck' analysis provides immediate margin improvement, while the CLV prediction model (R^2=0.69) enables long-term strategic alignment. We recommend immediate deployment of the Random Forest regressor into the production pricing engine.

IX. APPENDIX: VISUAL REFERENCE

Comprehensive visual catalog of univariate and bivariate relationships.



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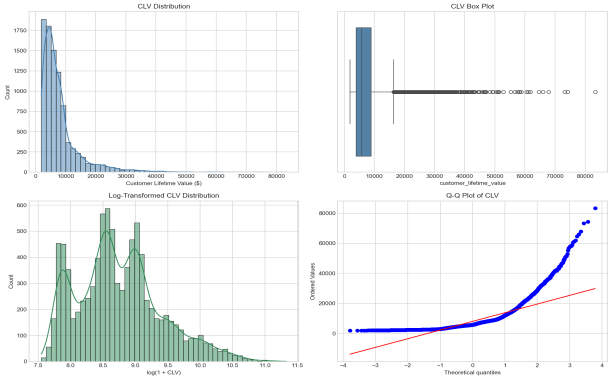

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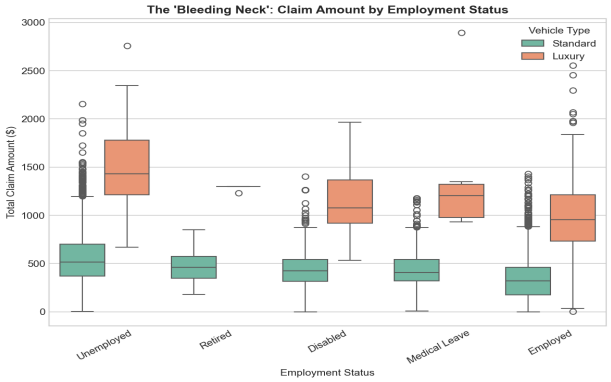

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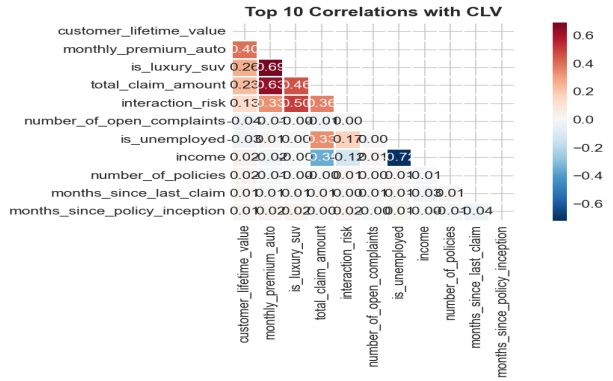

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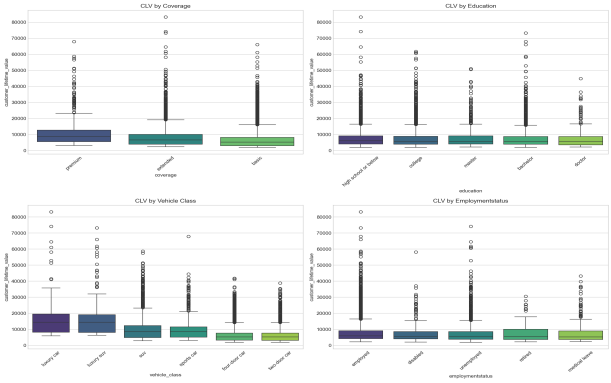

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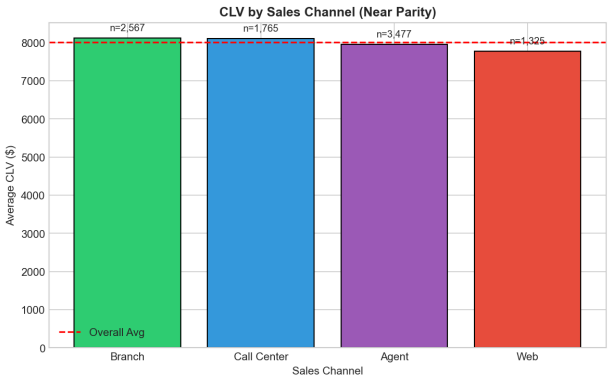

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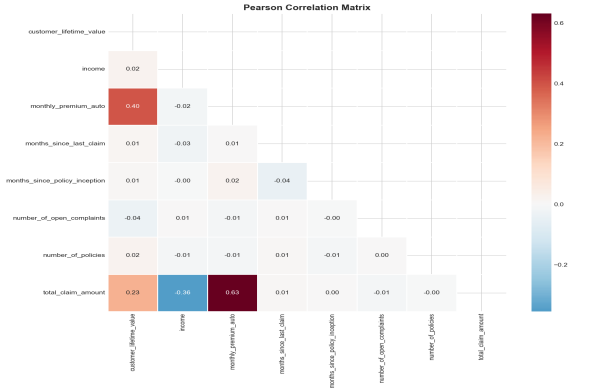

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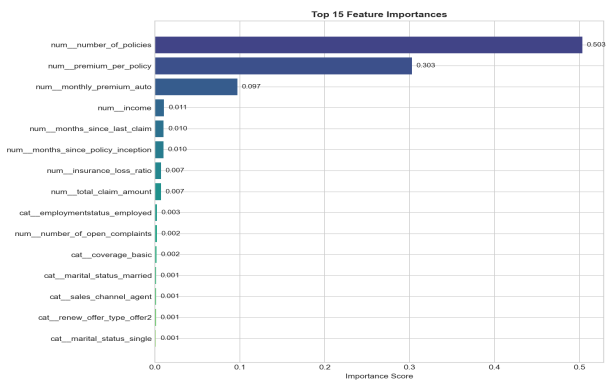

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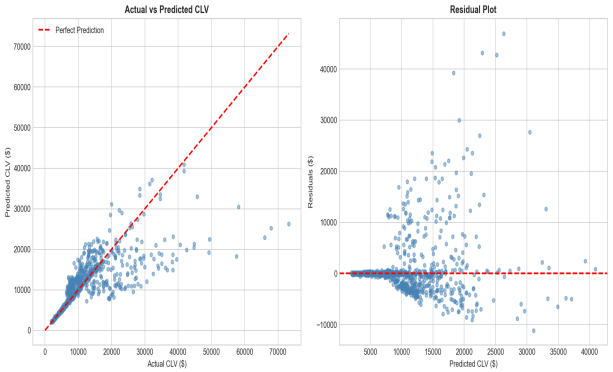

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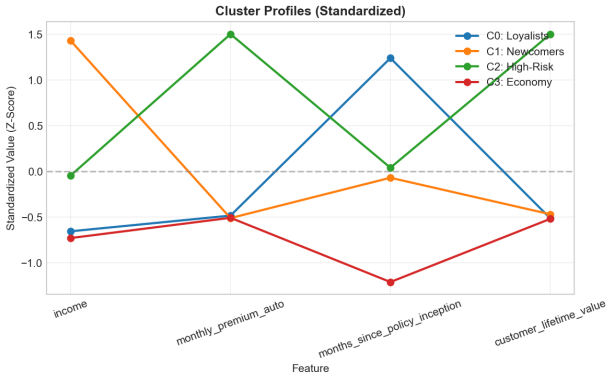

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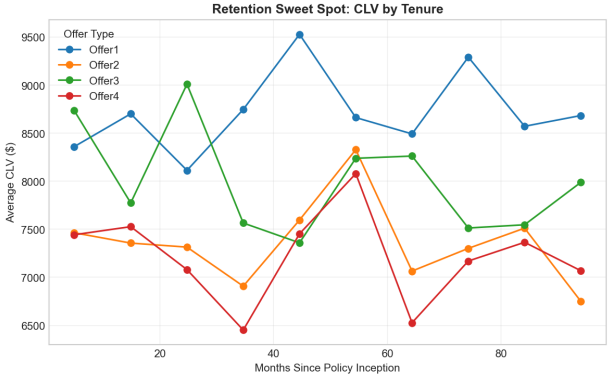

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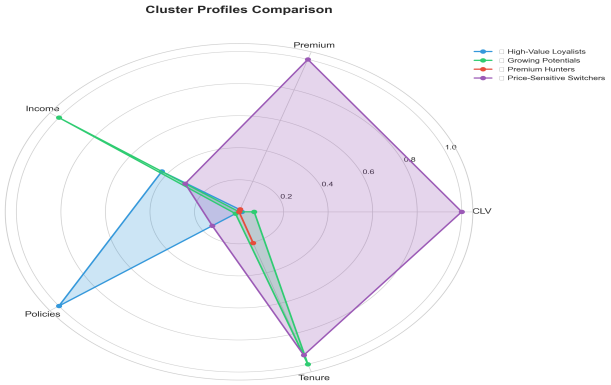

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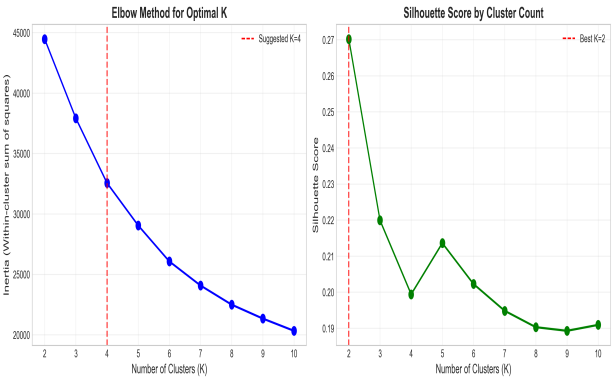

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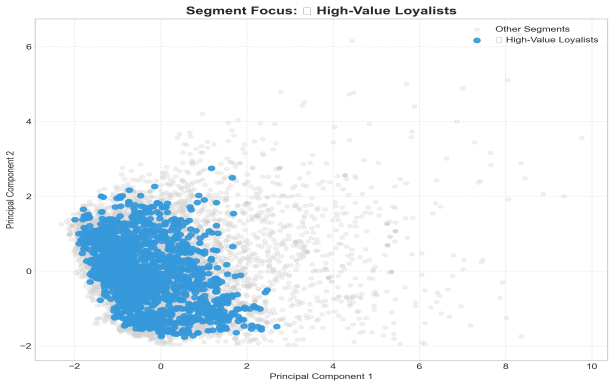

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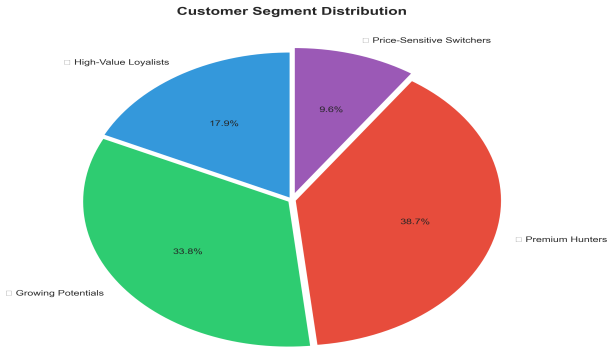

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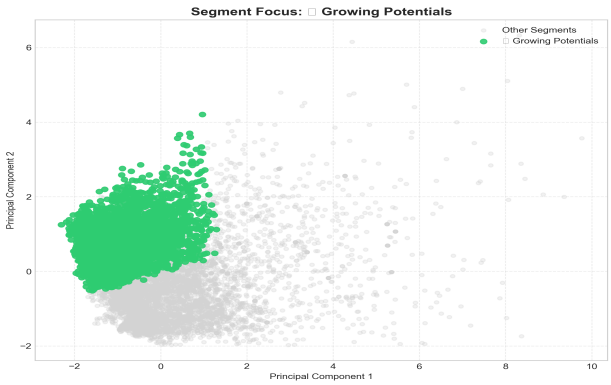

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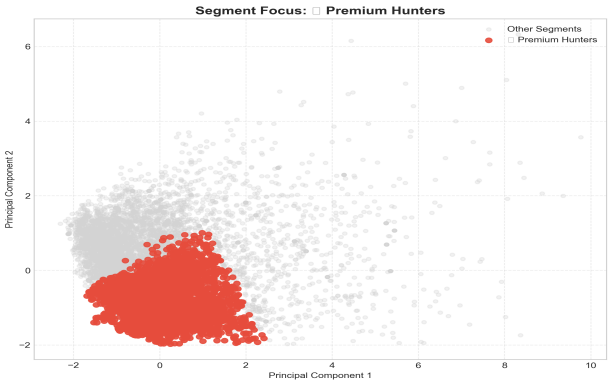

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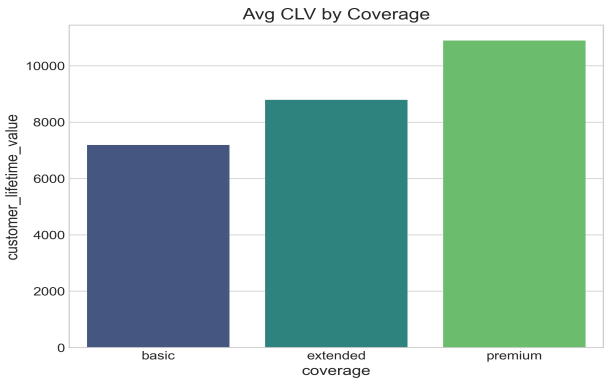

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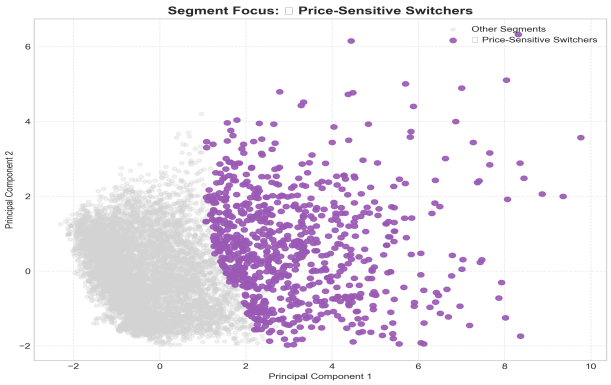

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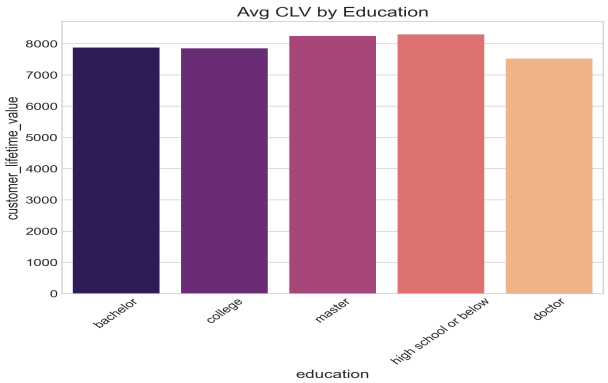

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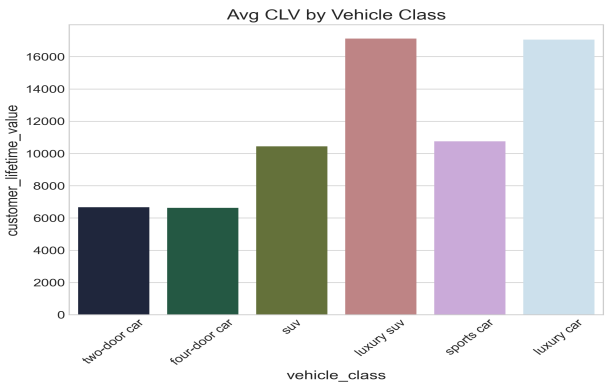

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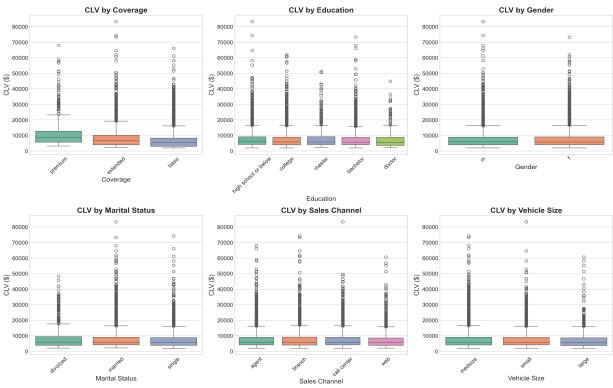

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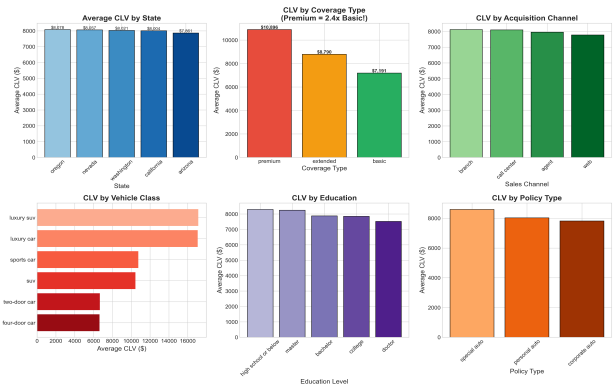

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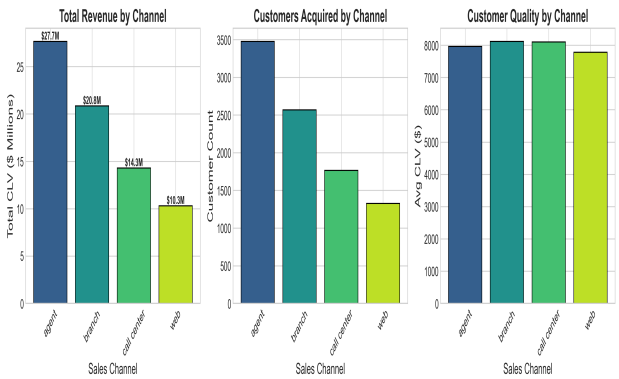

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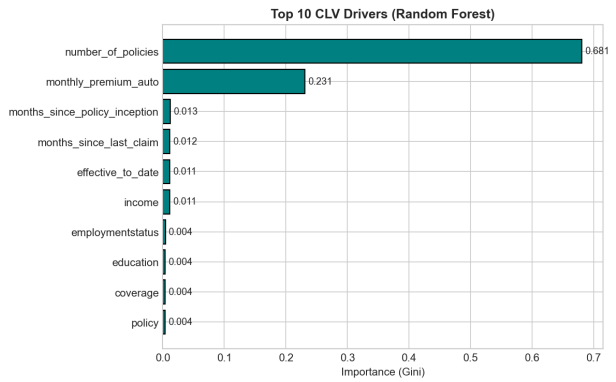

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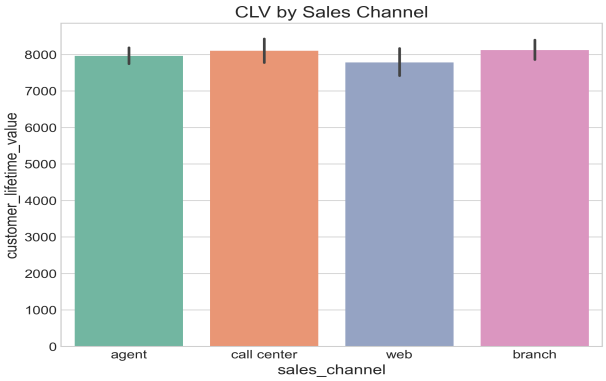

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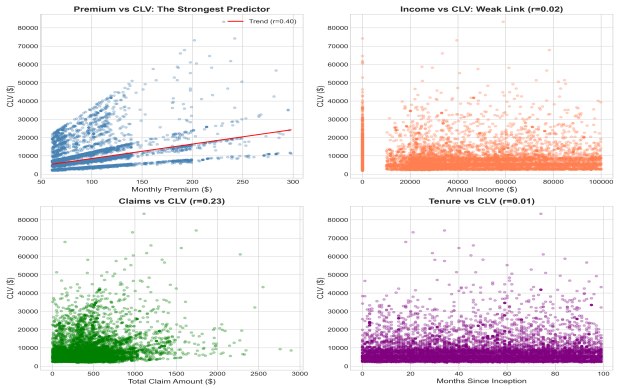

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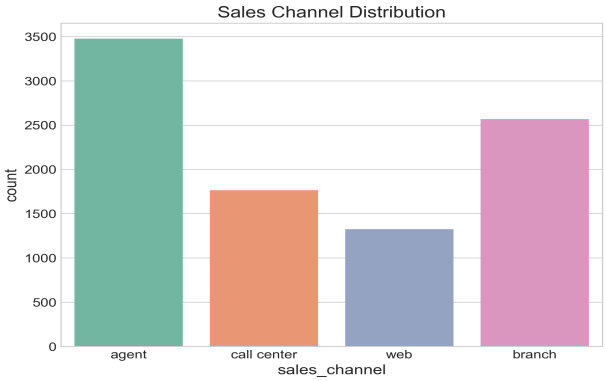

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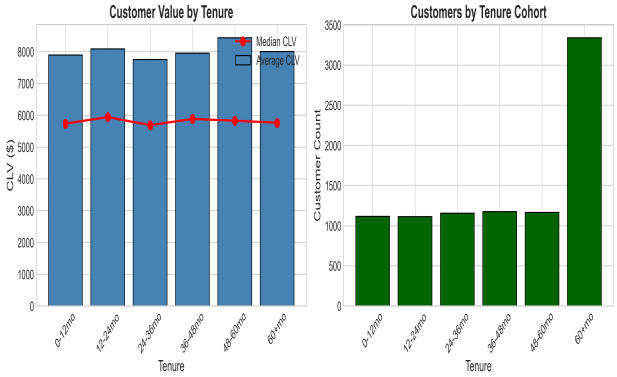

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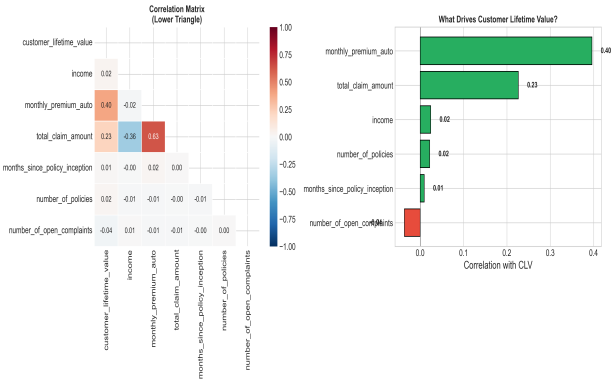

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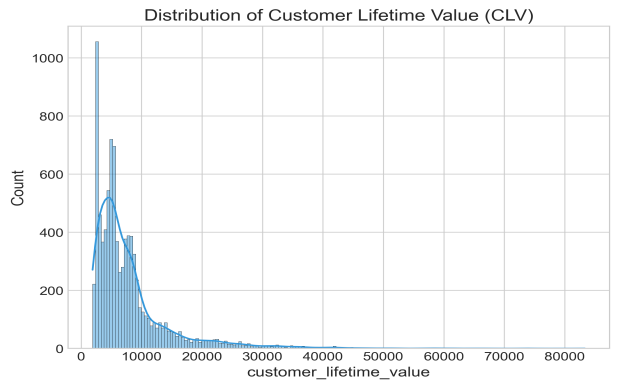

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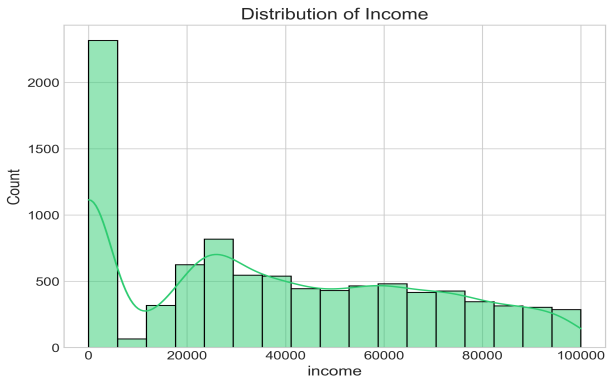

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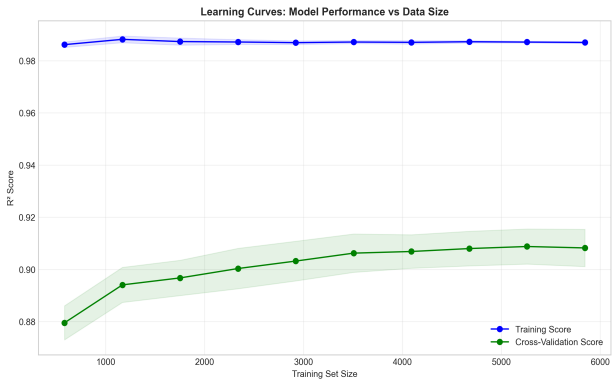

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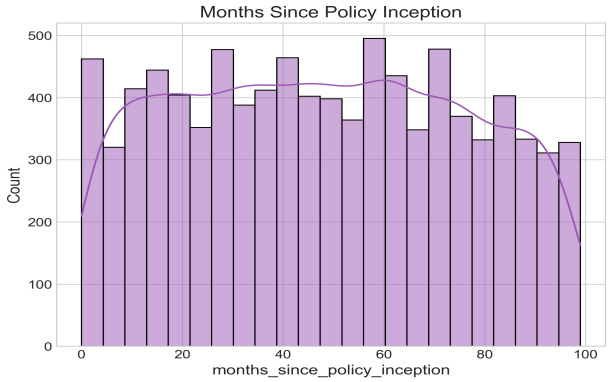

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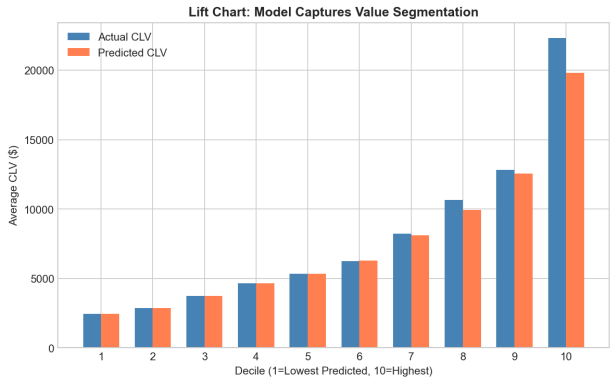

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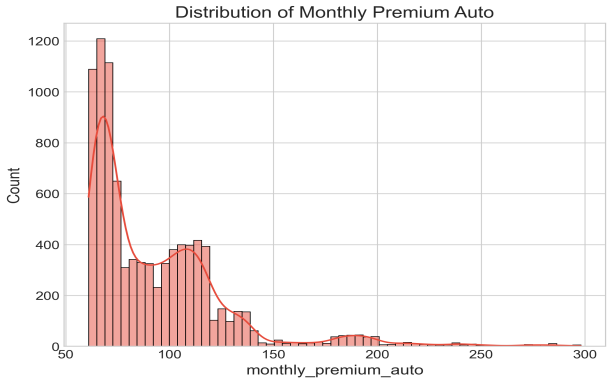

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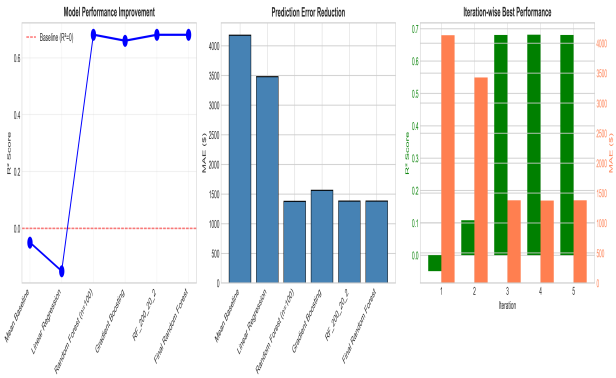
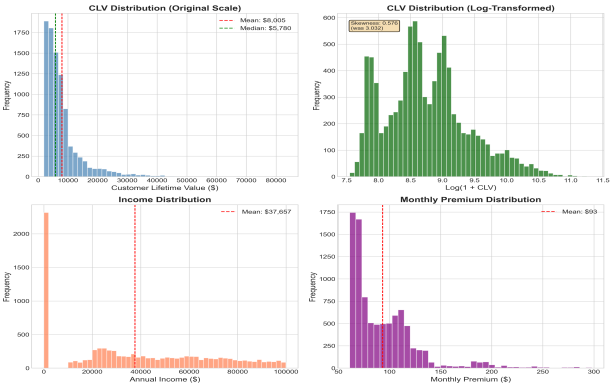
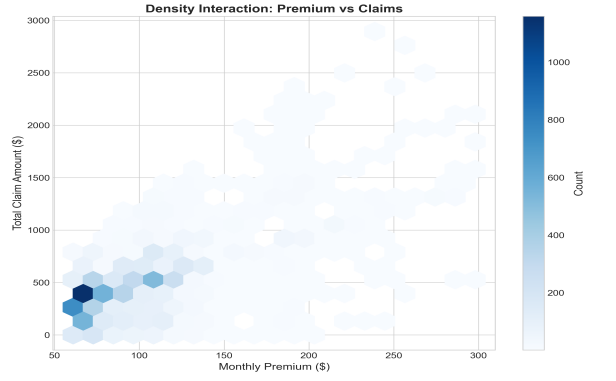


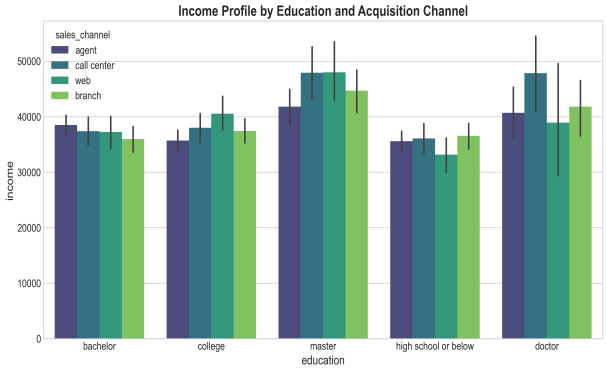
Appendix: 08_model_iterations.png



Appendix: 07_univariate_distributions.png



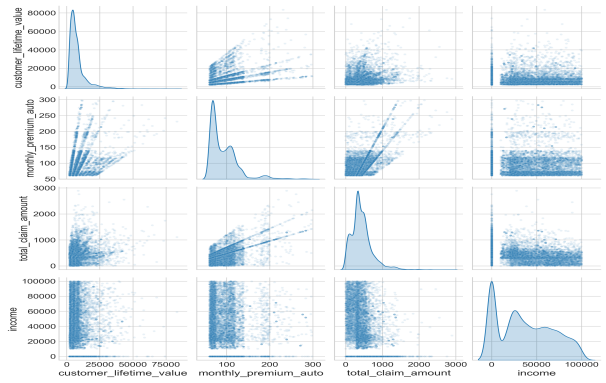
Appendix: 09_hexbin_premium_claims.png



Appendix: 09_interaction_income_edu.png

$$CLV = \sum_{t=1}^{T} \frac{Premium_t - Claims_t - Expense_t}{(1+d)^t}$$

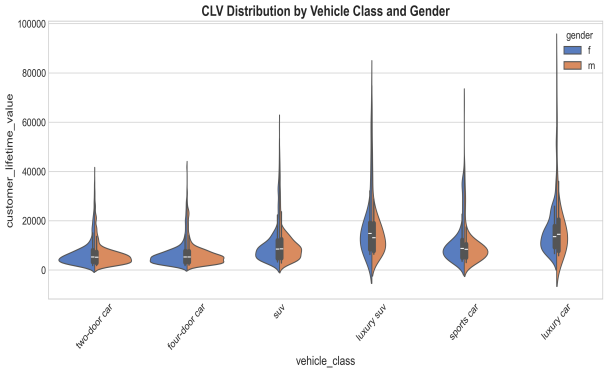
Appendix: formula_clv.png



Appendix: 09_pairplot_key_metrics.png

$$CV = \frac{\sigma}{\mu} = \frac{\text{Standard Deviation}}{\text{Mean}}$$

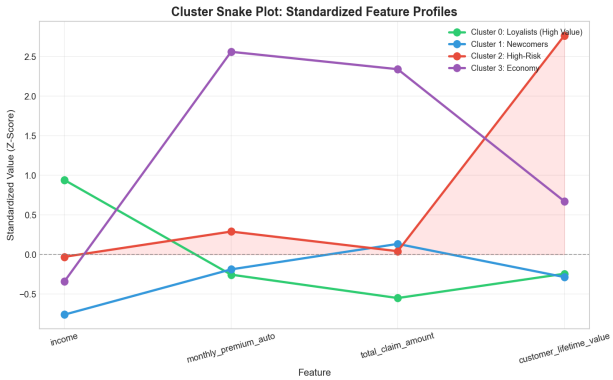
Appendix: formula_cv.png



Appendix: 09_violin_vehicle_gender.png

$$Gini = 1 - \sum_{k=1}^{K} p_k^2$$

Appendix: formula_gini.png



Appendix: cluster_snake_plot.png

$$\text{Loss Ratio} = \frac{\text{Incurred Claims}}{\text{Earned Premium}} \times 100\%$$

Appendix: formula_loss_ratio.png

$$\ln(CLV) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \varepsilon$$

Appendix: formula_regression.png